UNIVERSITY OF CAPE COAST

MULTI-SCALE ANALYSIS OF THE RELATIONSHIP BETWEEN COMMODITY PRICES AND MACROECONOMIC FUNDAMENTALS IN SUB-SAHARAN AFRICA

RICHARD TAKYI OPOKU

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BY

RICHARD TAKYI OPOKU

Thesis submitted to the School of Business, College of Humanities and Legal Studies, University of Cape Coast, in partial fulfilment of the requirements for the award of Doctor of Philosophy Degree in Business Administration.

FEBRUARY 2023

DECLARATION

Candidate's Declaration

I hereby declare that this thesis is the result of my own original research and that no part of it has been presented for another degree in this university or elsewhere.

Candidate's Signature………………………… Date………………………

Name: Richard Takyi Opoku

Supervisors' Declaration

We hereby declare that the preparation and presentation of this thesis were supervised in accordance with the guidelines on supervision of thesis laid down by the University of Cape Coast.

Principal Supervisor's Signature………………… Date…………………

Name: Prof. Anokye Mohammed Adam

Co-supervisor's Signature…………………….. Date…………………...

Name: Dr. Zangina Mohammed Isshaq

ABSTRACT

This thesis explored the multiscale relationship between commodity prices (oil, gold, and cocoa) and macroeconomic fundamentals (inflation and exchange rate), focusing on predictability, systemic risk, information flow, and contagion. These issues are important to global investors seeking to reduce risk and maximise investment returns, as well as to policymakers who must craft appropriate policy responses even in the midst of financial turmoil. Multiscale relationships are assessed using a cross-quantilogram, complete ensemble empirical mode decomposition (CEEMDAN), transfer entropy, and Barunik and Krehlik (BK18) spillover index. These techniques are robust to weaknesses in methods like vector autoregressive (VAR) and generalised autoregressive conditional heteroscedasticity (GARCH) used in the prior literature. The results show that commodity prices have an inconsistent prediction pattern for inflation but are more successful at the extreme quantiles than the medium ones. Systemic risk from commodities reaches different countries at different times but is higher at the upper quantiles. Also, it was observed that the information flow between commodity prices and exchange rates is asymmetric and is both time- and frequency-dependent. Again, it was revealed that, while oil and cocoa are net transmitters of spillovers, commodity exporting countries' exchange rates dominate spillover propagation. The results also show that countries differ in their responses to spillover, which are both time- and frequency-varying. It was recommended that inflation and exchange rate policies be country-specific. Again, hedging and diversification strategies should be quantile dependent, frequency-dependent, and time-varying.

KEYWORDS

Commodity prices

Inflation and exchange rate

Information flow

Interdependence and contagion

Multi-scale analysis

Systemic risk

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DEDICATION

To my wife, Hannah Adjoa Asabil Opoku, my daughter, Animuonyan Tanaa Opoku and all my siblings.

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LIST OF ACRONYMS

AMH	Adaptive Market Hypothesis
AFCFTA	Africa Continental Free Trade Area
AU	Africa Union
AEC	Agricultural Exporting Countries
ApEn	Approximate Entropy
ADF	Augmented Dickey-Fuller
ARMA	Autoregressive Moving Average
BK18	Barunik and Krehlik (2018)
CEC	Commodity Exporting Countries
CP	Commodity Price(s)
CEEMDAN	Complete Ensemble Empirical Mode Decomposition
CMH	Competitive Market Hypothesis
CoVAR	Conditional Value at Risk
CCC	Constant Conditional Correlation
CPI	Consumer Price Index
CWT	Continuous Wavelet Transform
CQ	Cross-Quantilogram
DRC	Democratic Republic of Congo
DY12	Diebold and Yilmaz (2012)
DWT	Discrete Wavelet Transform
DCC	Dynamic Conditional Correlation
ETE	Effective Transfer Entropy
EEC	Energy-Exporting Countries
EMH	Efficient Market Hypothesis

EMD	Empirical Mode Decomposition
EEMD	Ensemble Empirical Mode Decomposition
ER	Exchange Rate(s)
FQGLS	Feasible Quasi-Generalized Least Squares
FDI	Foreign Direct Investment
FX	Foreign Exchange
GARCH	Generalised Autoregressive Conditional Heteroscedasticity
GFECVDs	Generalised Forecast Error Variance Decompositions
GMM	Generalised Method of Moment
GFC	Global financial crisis
GP	Gold Price
GDP	Gross Domestic Product
HMH	Heterogeneous Market Hypothesis
IFI	International Financial Integration
IFS	International Financial Statistics
IMF	International Monetary Fund
IMFs	Intrinsic Mode Functions
MEC	Metal Exporting Countries
NARDL	Non-Linear Autoregressive Distributed Lag
NGCaVaR	Nonparametric Generalised Conditional Value at Risk
OP	Oil Price
OECD	Organisation for Economic Co-Operation and Development
PP	Philip-Perron
PSTR	Panel Smooth Transition Regression
RER	Real Exchange Rate

RE	Renyi Entropy
SCT	Shift-Contagion Theory
SIFT	Situated Information Flow Theory
STFT	Short-Time Fourier Transform
SSA	Sub-Saharan Africa
TOT	Terms of Trade
TVCC	Time-Varying Conditional Correlation
TVPSAR	Time-Varying Parameter Structural Autoregressive
TE	Transfer Entropy
UNCTAD	United Nation Commission on Trade and Development
VAR	Vector Autoregressive
VECM	Vector Error Correction Model
WT	Wavelet Transform

CHAPTER ONE

INTRODUCTION

In light of recent disruptions in the commodity markets—such as the significant declines in oil, gold, and cocoa prices in 2013 and 2017, which harmed the economies of numerous Sub-Saharan African (SSA) countries (UNCTAD, 2019)—it is more crucial than ever to comprehend the way in which global commodity prices impact the economic fundamentals of SSA countries that rely heavily on exports for revenue. The motivation to examine the relationship arises not solely from a risk-averse stance but also from an aim to optimise investment gains and propose suitable policy adjustments during a period of economic instability. Although researchers have conducted extensive studies on the interaction between commodity prices and macroeconomic fundamentals, the majority of these studies have focused on homogeneous static time analysis. While such examinations are still relevant, they fail to furnish countries in SSA with the comprehensive understanding required to formulate optimal investment and policy judgements. By examining additional information dimensions pertaining to macroeconomic fundamentals and commodity prices at multiple scales, this thesis aims to provide a more comprehensive outlook that can inform prudent investment and risk management strategies.

Background to the Study

Every country aims to achieve some level of price stability in the economic fundamentals of interest rates, exchange rates, and inflation. Economic price stability serves as the foundation that propels a country towards growth (Zafar & Khan, 2022; Tien, 2022). It is also the sound footing that businesses need to plan and forecast into the future (Zafar & Khan, 2022). This is why the focus of monetary policy is to bring about stability in the economic fundamentals (Fernández et al., 2017). Ismail et al. (2020) indicated that a critical mandate of monetary authorities in countries is forecasting and maintaining inflation, which brings about price stability. Indeed, Khalfaoui (2020) has indicated that exchange rate, interest rate, and inflation can each have different effects on money demand, and as such, their uncertainty can bring about instability in the general economy. Global factors usually threaten the achievement of economic stability. One such factor is global commodity prices, whose uncertainties usually have implications for economic management (Chen & Regov, 2003; Thornton & García-Herrero, 1997).

Commodities have emerged as a crucial asset class in the global economy (Floros & Galyfianakis, 2020). However, investors' interest in commodities became stronger after the 2007 global financial crisis (GFC) due to the interconnection between the commodities market and other markets like currency and stock markets (Tiwari et al., 2020). This interaction among markets helps in portfolio diversification (Tiwari et al., 2020). The recent COVID-19 pandemic has also generated further interest in commodities as assets for hedging. This has resulted in increased commodity trading activity in the markets over the years. Clearly, the increasing investment in the commodities market has made them more volatile. This has implications for macroeconomic variables.

Although interest in commodities has always existed, the development of the commodities market has reached a whole new level of growth in the past two decades (UNCTAD, 2019). According to the 2021 report of the

United Nations Conference on Trade and Development (UNCTAD), the nominal value of global commodity exports increased to $4.38 trillion in 2018–2019, an increase of $700 billion (19%) from 2008–2009. Fuels and energy remained the biggest exported group over the period accounting for 63% of all commodity exports in 2008-2009 (17% of global merchandise exports) and 54% of total commodity exports in 2018-2019 (13% of total merchandise exports). The report shows that, due to the decline in prices between 2008–2009 and 2018–2019 (-22.3%) and the increase in exports of other commodity groups, fuels' proportion of global commodity trade has drastically dropped. The value of the minerals and metals exports (together referred to as mining exports) increased by more than 50% between 2008–2009 and 2018–2019, whereas agricultural exports increased by 44% during the same period (UNCTAD, 2021). This trend has been projected to continue into 2023 by UNCTAD.

Globally, many countries have become commodity-dependent due to the significant contributions of commodities to their economies. The World Bank has indicated that more than half of the countries in the world (53%) are classified as commodity-dependent, which represents an increase from 93 countries in 2009 to 101 countries in 2019 (UNCTAD, 2021). A country is classified as commodity-dependent if at least 60% of its export revenue comes from commodity exports.

The aforementioned statistics notwithstanding, commodity dependence is more prevalent in Sub-Saharan Africa and Latin America. In SSA, approximately 80% of export revenue came from commodities between 2013 and 2017, and it was as high as 95% in Western and Central Africa

(UNCTAD, 2019). It goes without saying that such revenue was very crucial for the survival of those countries. The UNCTAD (2021) report show that while dependence on commodities slowed down for developed countries, that for developing countries, which include many countries in Africa, it increased between 2009 and 2019 and was higher in Africa than in other parts of the world. Specifically, almost half of the commodity-dependent countries in the world (44.6%) were in Africa from 2018–2019, with over 90% of countries in SSA classified as commodity-dependent, a trend expected to continue in the 2023 report (UNCTAD, 2021). In order to run their economies well, many of these countries do not just need to know commodity prices; they also need to analyse, forecast, and identify the drivers of those prices and the link they have with macroeconomic variables like inflation and the exchange rate.

Commodity prices (CP), however, have been volatile since the development of the market due the high interest and investment in commodities. This volatility, is often driven by economic, social and geopolitical factors (Singhal et al., 2019). Indeed, these factors have contributed to a substantial bubble in CP at different times, like in 1998, 2002, 2008, 2012, 2013, and 2017. For instance, between 2011 and 2013, monthly oil prices rose from $93 per barrel to $118 per barrel, but the figure fell to as low as $29 per barrel in 2016 (Tule et al., 2019) and even under $20 per barrel in 2020. The same holds true for cocoa, whose price per metric tonne decreased from $3000 to $2000 in 2017. Several countries in SSA experienced a deterioration of their debt-to-GDP ratio by a minimum of 20% as a result of a 28.5% decline in energy prices and a 38.7% decline in mineral prices between 2013 and 2017 (UNCTAD, 2019). The fact that commodity prices are prone to possibly large fluctuations at different times within a year and probably at higher frequencies creates a big challenge for countries (Hooker, 1996; Hernaiz, 2018; Tule et al., 2019). This is because the uncertainties in price fluctuations bring about uncertainty in the management of the macroeconomy, including difficulty in revenue projection, difficulty in targeting inflation, and problems in exchange rate management. Indeed, Rao and Goyal (2018) noted that one of the issues that has impacted policy-making and macroeconomic performance in many emerging economies is commodity and oil price fluctuations.

Commodities are primarily used as inputs in the production of many goods, so the general impact of commodity price shocks on the economy is thought to manifest itself in changes in the price level of goods in a country. The assumption, therefore, is that commodity prices are leading indicators of inflation rates in an economy. This idea is premised on the overshooting theory of commodities by Frankel (1986), who builds on the original overshooting theory by Dornbusch (1976). The argument from this theory has been that commodities respond quicker to monetary policy changes because of the flexible nature of the commodities markets, and this usually causes an overestimation of commodity prices in the short term. The theory explains that due to the sticky nature of the goods market, its response to monetary policy lags in the short term (Frankel, 1986). However, since commodities are inputs for many industrial products, increases in commodity prices are eventually passed on to the prices of goods, leading to inflation. This suggests a positive relationship between commodity prices and inflation.

The deduction from the theory supports the argument that commodities' prices can be used to forecast inflation. This proposition has been investigated by several studies, particularly in the context of developed countries, but results vary from commodity to commodity, either for a different country or the same country at different times (see, for instance, Barsky & Kilian, 2004; Chen, 2009; Du et al., 2010; Bala & Chin, 2018). Complicating matters was the study by Bloomberg and Harris (1995), who suggested a nuanced relationship. The authors demonstrated that although commodity prices had a strong predictive power for inflation in the 1980s, this may have changed in the 1990s. This makes monetary policy decisions more complicated to implement. There is therefore a need for fresh evidence on the nature of the interaction between commodity prices and inflation to enhance policy on economic stability measures and investor portfolio selection decisions.

Moreover, commodities are traded on the international market, with the dollar as the main currency for trading. Therefore, the exchange rate (ER) is identified as the conduit through which shocks from commodity prices are first transmitted to the local economy due to the information they present. This idea is consistent with the overshooting theory. The theory indicates that the flexible nature of commodity and currency markets allows them to respond more rapidly to changes in market conditions (Dornbush, 1976). According to the theory, a surge in global market demand for commodities will promptly result in a rise in commodity prices (Dornbush, 1976; Frankel, 1986). But since the US dollar is the main trading currency on the commodities market, there will be an immediate increase in demand for dollars for transactions, which will lead to an increase in the exchange rate (Gylfason, 2001; Papyrakis & Gerlagh, 2004; Frankel, 2010). This suggests that commodity prices relate positively to ER. But the idea of information transfer in the financial market hinges on the efficient market hypothesis (EMH) by Fama (1970). The EMH postulates that markets are efficient, so all information is reflected in asset prices. The EMH indicates that investor behaviour is homogeneous, and as a result, all investors react to information in the same way, usually uninfluenced by time or circumstance. Accordingly, asset prices change due to investors reacting similarly to information.

The indication that commodity prices interact positively with the exchange rate has led to several empirical examinations of the link between the two variables. However, findings have been inconsistent, with different outcomes. For instance, while some studies have shown that CP increases lead to ER appreciation (Sabai & Nouri, 2015; Jain & Biswal, 2019; Lui et al., 2020), others have shown a contrary view (see Singhal et al., 2019; Mo et al., 2018; and Buah, 2019). The differences in the outcomes of these studies may be due to the time-wise linear and homogeneous approaches used in line with the EMH. But evidence (see Shafiullah et al., 2020; Scarcioffolo et al., 2019) suggests that variables like commodities and exchange rates are non-linear, so there is a need to employ different methods to secure new insight of the relationships.

It has also been argued that the relationship between CP and ER can be contagious in developing countries, leading to possible contagion among exchange rates. This is more likely for countries that are trading partners or share boundaries with one another. From the perspective of contagion theorists, emerging and developing countries stand the risk of suffering shocks from global commodity prices due to their dependence on global economic activities. On the other hand, the proponents of the decoupling hypothesis are of the opinion that emerging economies are now controlling the activities of the global economy and, as such, are at low risk of global shocks from advanced countries (Dervis, 2012). However, while some empirical studies have obtained evidence of contagion from global markets to African markets (see Louis et al., 2009; Daryl & Biekpe, 2002), others obtain no such evidence (see Alagidede, 2008; Forbes & Rigobon, 2002). Since there is limited evidence on the level of contagion between the global commodities market and the currency markets in SSA, it is necessary to investigate the level of contagion between these two markets to enhance risk management and portfolio diversification strategies.

Further, from the perspective of EMH, when there is a global crisis or market turmoil, prices may fall. However, the excessive volatility, mean reversion, the January effect, market overreaction, and the delayed effect of price responses to information (Mishkin & Eakins, 2018; Jensen, 1978) provide context for the empirical investigation, as do other counterexamples. Moreover, investors' patterns of behaviour tend to vary over time, especially in uncertain times like crises and pandemics, and since markets do not function in a vacuum, prices reflect the asymmetric and time-based behaviour of investors (Owusu Junior et al., 2021). So decomposing these prices, like commodities and currencies, into various scales provides more information about the dynamic behaviour of investors and other market participants. Indeed, two main theories—the heterogeneous market hypothesis (HMH) by

Muller et al. (1993) and the adaptive market hypothesis (AMH) by Lo (2004)—support investor heterogeneity.

The HMH indicates that there are differences among market participants based on their risk profiles, the degree of information they have, constraints in institutions, their market perception, their geographical location, or even their beliefs. It was thus argued that the multiple differences in market agents will lead to investors responding differently to different volatilities at different time horizons (Muller et al., 1993). As a result, long-term market participants, such as institutional investors, are less likely to act on short-term fluctuations, which are often fuelled by panic, unlike speculators. This calls for a proper assessment of each layer of information. The AMH, on the other hand, posits that classifying all investors as rational is unrealistic. Some investors make rational decisions, while others make just reactive decisions due to several factors, and as such, there must be a blend of homogeneity and heterogeneity in analysing prices to reinforce variation in investor behaviour. These two theories, therefore, support the idea of multi-scale analysis of commodity prices and macroeconomic fundamentals due to heterogeneity in the behaviour of market participants at high-, medium- and low-frequencies.

Accordingly, the thesis argues that understanding the multi-scale dynamics of commodity price volatilities will help policymakers implement policies that respond to different volatilities to bring about stability in the macroeconomic fundamentals and help investors in their portfolio selection and diversification. Indeed, Gourene and Mendy (2018) found that using multiple scales when studying commodity prices and macroeconomic variables provides policymakers with more information than traditional homogeneous methods such as vector autoregressive (VAR) and generalised autoregressive conditional heteroscedasticity (GARCH). So, getting new evidence on multiple scales will help us to appreciate the nature of the relationship better and make it easier to make relevant policy decision.

This thesis takes a deeper look at interdependence, systemic risk, information flow, and contagion between commodity prices and macroeconomic fundamentals (inflation and exchange rate), focusing on countries in SSA for several reasons. First, over 90 percent of the countries in SSA are resource-dependent countries, as they obtain over 60% of their export revenues from commodity exports (UNCTAD, 2019–2021). This makes the SSA very prime for this type of study, as countries in this region are more vulnerable to global commodity price uncertainties than other parts of the world. Second, these countries are all developing countries that belong to one regional bloc, the African Union (AU). They are mainly neighbours who share boundaries, and as such, events in one country can easily spill over into the other country. Ralston et al. (1992) indicated that there are usually cultural and traditional overlaps between countries that are connected geographically. The implementation of the Africa Continental Free Trade Area (AFCFTA) have brought them together economically in trade relations. Understanding the nature of the interaction between commodity prices (CP) and macroeconomic fundamentals will help policymakers in SSA mount appropriate monetary policy responses to global uncertainties and for hedging purposes. It will also help investors who are looking to channel their resources into the region make effective portfolio selections and enhance their diversification strategies.

It should be noted, however, that despite the similarities among SSA countries, there are differences that must be acknowledged. In the first place, these countries differ in the commodities they export, and as such, the impact of changes in commodity prices on each country will differ. For instance, a fall in the price of crude oil will have a bigger impact on the Nigerian economy, which obtains over 90% of its export revenue from it, than on the Kenyan economy, which is a predominantly agricultural-dependent country (UNCTAD, 2019). Second, there is the issue of Francophone and Anglophone blocks in the sub-region, which affect the way these economies are structured. Indeed, while each of the Anglophone countries has an individual central bank, all the Francophone countries in West Africa share one currency and one central bank. There is therefore a stronger likelihood of spillovers among Francophone countries than among in the Anglophone block. However, those countries have differences that require individual analysis rather than block analysis. Despite its proximity to South Africa, Swaziland has a distinct political system. This simply suggests that there are no two perfect countries in the region.

It is on this basis that, in studying the relationship between commodity prices and macroeconomic fundamentals, the thesis considers the specific country effect to guide policy. This thesis, therefore, examines how commodity prices predict inflation and the systemic risk implication of the relationship, quantifies information flow between commodity prices (CP) and exchange rates, and investigates the contagious nature of the relationship between commodity prices and exchange rates among commodity-exporting countries (CEC) in SSA.

For a variety of reasons, the study focuses on macroeconomic fundamentals such as interest rates, inflation, and exchange rates that influence price stability. To begin with, commodities serve as indispensable inputs for the operation of numerous industries, including manufacturing, transportation, agriculture, and energy (Hanson & McMahon, 2016). Variations in their valuations have an immediate and direct effect on expenditures related to production, trade, and consumer goods, which in turn have repercussions on inflation, interest rates, and exchange rates (Hanson & McMahon, 2016). Secondly, commodity prices are susceptible to boom-and-bust cycles caused by weather, geopolitical events, and technological advancements, among other variables (Kilian, 2009). Unanticipated changes of this nature have the potential to instigate substantial and swift fluctuations in interest rates, exchange rates, and inflation, necessitating vigilant surveillance and policy adaptations (Kilian, 2009). However, in light of the lack of consistent monthly interest rate data for the majority of the countries incorporated in the thesis, the interest rate was omitted from the study.

Statement of the Problem

Commodity prices, due to their unpredictable nature, pose a substantial risk to the macroeconomic fundamentals of countries in the SSA, specifically the exchange rate, interest rate, and inflation (Rao & Goyal, 2018; Tiwari et al., 2020). The transmission of over 70% of global commodity price volatility to the local economy is primarily attributed to the exchange rate, inflation, and interest rate (Fernandez et al., 2017; Mensi et al., 2018). Commodity price fluctuations introduce uncertainties in managing the macroeconomy, leading to challenges in projecting revenue, managing exchange rates, targeting inflation and interest rates, and promoting growth. Several African countries experienced a deterioration of their debt-to-GDP ratio by a minimum of 20% as a result of a 28.5% decline in energy prices and a 38.7% decline in mineral prices between 2013 and 2017 (UNCTAD, 2019). This is why countries in SSA do not only need to know commodity prices but also analyse, forecast, and identify the drivers of those prices and the link they have with macroeconomic variables like inflation and the exchange rate.

The primary concern revolves around the impact of participants' behaviour in the commodities, currencies, and goods markets on their relationship, given that these participants are distinct and their behaviour is influenced by varying circumstances. Empirically analysing the diverse behaviours of market players is crucial to understanding the impact of commodity prices and macroeconomic fundamentals on countries in the SSA. These countries seek consistent policy prescriptions to effectively manage their economies on a global scale. The purpose of this thesis is therefore to examine the interactions between global commodity prices and macroeconomic fundamentals, particularly inflation and exchange rate, using a multiscale approach. In order to achieve the objective of the thesis, three overarching themes have been explored, as outlined below:

Interdependence and Systemic Risk between Commodity Prices and Inflation

Commodity prices (CP) are considered leading indicators of inflation, according to Frankel (1986), who builds on Dornbusch's (1976) framework. Frankel (1986) argues that commodities have flexible prices, so in the short term, commodity prices shoot up immediately when there is an expansion in the money supply. However, goods prices respond with a lag due to their fixed nature in the short term. Therefore, commodity prices signal a possible movement in inflation. This notion has resulted in commodities, whether metal, energy, or agricultural, being considered important determinants of inflation, particularly in commodity-exporting countries (CEC).

The problem, however, is that the nature of the relationship has been shifting over time for developed countries like the US, as indicated by Frankel (2006). For instance, it has been observed that the relationship was stronger in the 1970s and early 1980s, became weaker in the 1990s, then turned stronger again in the late 2000s (see, Blomberg & Harris, 1995; Kilian, 2009). The concern of this study is in relation to developing countries that depend a lot on commodities for survival, like those in SSA, and is not just about the prediction but the systemic risk implications of the interaction between commodity price (CP) and inflation which has been neglected. Previous studies have concentrated on capturing systemic risk of institutions within the same sector like among banks (Black et al., 2016; Huang et al., 2017) or equity markets (Acharya et al., 2017) but not institutions across different sectors. Also, prior studies have mostly neglected the impact of extreme events in forecasting inflation with commodities, with more focus on the mean-to-mean forecast (see Tule et al., 2019; Fasanya and Awodimila, 2019; Chen et al., 2014). Such analyses only present information about normal market conditions, making them less reliable.

The 2008 GFC, the 2014 terms-of-trade shocks, the commodity price collapse from 2016–2017, and the Ebola virus epidemic in Africa between 2013 and 2015 are among some of the extreme or crisis situations that impacted the global commodities market and the economies of countries in

SSA. For instance, while the GFC contributed to an average fiscal deficit per annum of 1.6% of GDP, the terms of the trade shock increased it further by 3.6% of GDP, and oil-exporting countries accumulated an average annual debt of 59% of GDP between 2014 and 2017 (Coulibaly, 2019). Understanding the role such situations play in the relationship will help countries in SSA deal with inflation risk since commodity price booms and busts are key contributors to the risk of inflation in SSA (Fernández et al., 2017). This study fills the knowledge gap by concentrating on measuring the level of systemic risk present in the relationship between CP and inflation at different distributional quantiles. The outcome of the study offers information to policymakers on managing commodity revenue, such as the accumulation of reserve funds and hedging, to bring about stability in their economies.

Multi-Frequency Information Flow between Commodity Prices and Exchange Rates

The relationship between commodity price (CP) and exchange rates (ER) has received considerable attention in the literature. But the focus has been on linear and time-wise homogeneous interaction in line with the assumptions of the efficient market hypothesis (EMH) and has therefore produced conflicting outcomes. For instance, while some studies (see, Sabai & Nouri, 2015; Jane & Biswal, 2019; Lui et al., 2020) have found a positive relationship, others (for instance, Mo et al., 2018; Buah, 2019) have found an inverse relation, and yet others have found no relationship (see, Seyyedi, 2017; Singal et al., 2019). Also, since the study of Baur and Lucey (2010), several studies have looked at the hedging or safe-haven potential of commodities for exchange rates, but even that appears to change from commodity to commodity and from time to time (Joy, 2011; Omag, 2012; Seyyedi, 2017; Qureshi et al., 2018).

The empirical literature has, however, not given considerable attention to quantifying the strength of information flow between these variables at multiple time horizons for different currencies, particularly currencies developing countries. The few existing ones have concentrated on major currencies but not weaker ones like those in SSA (see, for instance, Tiwari et al., 2013; Alterturi et al., 2018; Tiwari, Raheem, et al., 2020). Major currencies like the US dollar and the British pounds belong to countries with stronger institutions and systems capable of reducing the impact of commodity price volatilities on the currencies better than those in SSA. As a result, it is important to examine the situation in SSA since many countries have weak financial systems and institution to manage global shocks.

Again, most prior studies have relied on methods like VAR, GARCH, and wavelets. But while VAR and GARCH methods may contain information about the time domain, they usually exclude information on the frequency domain, contributing to the inconsistency of empirical findings (Pal and Mitra, 2017). Moreover, with all its abilities, the wavelet is nonadaptive in nature and suffers from counterintuitive interpretation (Huang et al., 1998), creating room for a more improved approach to be employed to enhance outcome. In filling the gaps in the literature, the thesis concentrates on quantifying information flow in a multiple time horizon in line with the HMH and takes a bi-directional view of the relationship, as opposed to many existing studies that take a unidirectional view (see, Wang & Lee, 2022; Kassouri & Altintas, 2020: Buah, 2019). Providing information in the frequency domain will help policymakers and investors in SSA discern recurring patterns that endure across short-term variations, medium-term trends, and long-term cycles (Tiwari et al., 2013). Policymakers will therefore be able to comprehend the market's dynamics at various degrees of specificity. It will also enhance the forecasting of commodity prices and exchange rates through the integration of data from diverse time horizons. Long term models can offer valuable insights into fundamental structural dynamics, whereas short-term models are capable of capturing immediate trends (Kassouri & Altintas, 2020). The integration of data that captures the fundamental structural dynamics of short, medium, and long trends will result in forecasts that are more resilient and all-encompassing.

Time-Varying Connectedness and Contagion between commodity prices and exchange rates

The numerous extreme events over the years like the 2007/2008 global financial crisis (GFC), the commodity price collapse between 2016 and 2017, the 2014 terms-of-trade shock, and apparent interdependence among countries either as trading partners or in proximity to each other have intensified the research interest in interdependence and contagion among financial markets (Jiang et al., 2022; Diebold & Yilmaz, 2009). However, many of the existing studies on financial contagion have widely placed emphasis on the equity markets (see Owusu Junior et al., 2020; Pula & Peltonen, 2009; Diebold & Yilmaz, 2009), between equity and currency markets (see Bouri et al., 2017; Boako & Alagidede, 2017), and among commodity markets (see Shen et al., 2022; Ji & Fan, 2012), with less focus on the contagion between commodities and currency markets, particularly in SSA. Only major international currencies are considered by the few existing ones, such as Dai et al. (2020). Including commodities will allow the study to determine if there is a substantial premium for commodity price risk in African currency markets. Also, the few studies on commodities and ER in SSA have emphasised on static time analysis at the expense of time-frequency analysis (see, for instance, Nandelenga et al., 2021). This gap needs attention since measuring contagion at the frequency level provides an added avenue for dealing with systemic risk (Barunik & Krehlik, 2018).

Additionally, the debate over contagion vs. decoupling of emerging markets from shocks in developed markets exists. But examining the state of decoupling of SSA's currency market from commodity prices at different time horizons remain largely unexplored. This study fills the knowledge gap by investigating contagion between CP and ER in static frequency, and time-frequency (time-varying) analyses for commodity exporting countries (CEC) in SSA. This provides a foundation for both academia interested in testing the robustness of static vs. time-varying data, as well as policymakers and investors looking for comprehensive information to make informed decisions.

Purpose of the Study

The main purpose of this thesis is to conduct a multi-scale analysis of the relationship between commodity prices and macroeconomic fundamentals (inflation and exchange rates) in SSA, with a focus on interdependence, systemic risk, information flow, and contagion.

Objectives of the Study

The study seeks to achieve the following:

1. Investigate the nature of interdependence and systemic risk between commodity prices and inflation rates for commodity-exporting countries in SSA.
2. Analyse the level of multi-frequency information flow between commodity prices and exchange rates among commodity-exporting countries in SSA.
3. Examine the time-varying connectedness and contagion between commodity prices and exchange rates in SSA's commodity-producing countries.

Research Questions

In order to reach the goals listed above, the study tries to find answers to the following:

1. What is the nature of interdependence and systemic risk between commodity prices and inflation rates in SSA commodity-exporting countries?
2. What is the level of multi-frequency information flow between commodity prices and exchange rates among commodity-exporting countries in SSA?
3. What is the nature of the connectedness and contagion between commodity prices and exchange rates in SSA?

Significance of the Study

The consensus among economists is that commodity prices have implications for macroeconomic fundamentals in practically every country. The belief is that having a good forecast of commodity price volatility will bring about certainty and stability in the exchange rate, inflation, interest rate, and growth. As a result, having a clear understanding of the behaviour of commodity prices and how they relate to macroeconomic fundamentals is the best way to implement fiscal policy to enhance price stability. This study adds to the existing literature on commodity prices and macroeconomic fundamental interactions in several ways.

First, the study focuses on measuring systemic risk between commodity prices and inflation at different distributional quantiles. In this process, the extreme events that can easily change the inflation forecast are captured to help with risk management strategies. The employment of the cross-quantilogram (CQ) method enabled the study to capture direction, duration, and magnitude at the same time. The use of the CQ method enabled the study to forecast over a long period of time as opposed to other methods, which are only able to do so within a short period of time. Central banks in SSA, like the Bank of Ghana, who have been relying on a normal situation in their inflation forecast, can incorporate the distributional quantile in their analysis for an accurate outcome, enhancing their decision on when to hedge inflation with commodities.

Second, the study concentrates on quantifying information in a multiple-frequency manner in line with the HMH and AMH. This is done in a bi-directional way as opposed to many existing studies that take a unidirectional view and, as such, provide mutual information for better decision-making. In doing this, the study employed a noise-assisted technique called complete ensemble empirical mode decomposition (CEEMDAN) to decompose the series into intrinsic mode functions (IMFs). This method has the ability to reduce noise in the data to its lowest point and thus enhance the accuracy of decision-making. Many central banks in SSA have been assessing commodity price information for ER based on linear and homogeneous analysis; incorporating frequency dynamics is more important for accuracy in decision making as the relationship is frequency dependent. They can clearly distinguish between actual long-term trends and panic behaviour by following the method employed in this study.

Third, the study provides evidence of contagion from static time analysis, static frequency analysis, and time-frequency analysis (time variation) at the same time. This provides a foundation for both academia interested in testing the robustness of static vs. time-varying data, as well as policymakers and investors looking for comprehensive information to make informed decisions. Next, the study examined the *"shift contagion hypothesis"* and the *"decoupling hypothesis"* with currency markets in SSA, which have received less attention. By employing the rolling window procedure in the Barunik and Krehlik (2018) framework, the study has provided evidence that countries that export oil and cocoa suffer more contagion from global activities at higher frequencies. However, there is marginal evidence of decoupling for gold exporters at low frequencies. The significant implication is that gold provides a better hedge against inflation than crude oil and cocoa.

Further, the use of multiple commodities in the study provides comprehensive information to policymakers and investors at large. The study's findings improve diversification policy, risk management decisions, and hedging strategies. This is because different countries export different commodities in SSA, so having a study with multiple commodities provides a better outcome to enhance knowledge.

Delimitation

The study focuses on analysing the multiscale relationship between commodity prices and macroeconomic variables in sub-Saharan African (SSA) countries. The focus was on forecasting inflation based on the informational content of commodities and the systemic risk implications of the relationship. This was done based on the distributional quantiles of the variables rather than the mean. In studying the relationship between commodities and ER, emphasis was placed on quantifying the strength of information flow to aid in hedging and diversification strategies. This was accomplished using a noise removal assisted technique. The study also investigated the interdependence and contagion between commodity prices and ERs, as well as how ERs in SSA countries are connected. The concentration was on determining the most dominant contributor to contagion to help with risk management measures.

In this study, emphasis was placed on SSA because almost all the countries in the region are classified as commodity-dependent countries by the World Bank. Over a 29-year period, the study included over 30 commodity exporting countries as well as three commodities (oil, gold, and cocoa). The essence of using these countries over a longer period was to provide a broader view of information to policymakers and investors as opposed to existing studies that have limited information for decision-making. Focusing on this period enabled the study to capture the structural adjustment programme that started on the continent in the 1980s, different financial crises, and pandemics, among other important events over the period. This contributes to a better understanding of the relationship between policymakers and policy implementation.

Limitations

In interpreting the findings of the study, the following limitations must be considered. First, this study did not include data on the COVID-19 pandemic period due to the possible impact it might have on the overall results. The lack of daily frequency data on ER for countries in SSA prevented a possible estimation of the partial effect of COVID-19, hence, the exclusion.

Second, the study was limited to 29-year monthly data point observations. The use of monthly data instead of daily frequency might hide certain information. Daily frequency may have enhanced the outcome due higher observations. However, such data frequencies were not available for countries in SSA. Third, the study relied on commodity prices and not export revenue since such data was not available at high frequencies. The differences in currencies may lead to different amounts of net revenue flowing to different countries for the same quantity of commodities exported.

In spite of the limitations, the study has provided vital information which is helpful, particularly, in the context of developing countries which is significant to both policymakers and academicians. Providing country-specific evidence is helpful to monetary policy authorities in making risk management decisions.

Organization of the Study

The thesis is organised into seven chapters, with three of them being empirical chapters. Chapter 1, which is the introduction, provides an overview of the thesis. It highlights the problem identified, the research objectives, and the contribution of the study to existing knowledge. This chapter also considers the study's limitations, significance, and organization. Chapter two reviews the existing theoretical and empirical reviews related to the topic. Chapter three of the thesis discusses the general methodological issues relating to this study. It also discusses research paradigms, research approaches, and the various theoretical models used for the study.

Chapters 4, 5, and 6 present the empirical studies, which comprise an introduction, theoretical and empirical models, data descriptions, analysis, and discussion of findings. More specifically, chapter four examines the interdependence and systemic risk between CP and inflation. In chapter five, the focus is on investigating and discussing the results of multi-frequency information flow between CP and exchange rates. The thesis then concentrates on the analysis and discussion of the results on connectedness and contagion between CP and the exchange rate in Chapter 6. Finally, chapter seven consists of a general thesis summary, conclusions, and policy recommendations.

CHAPTER TWO

LITERATURE REVIEW

Introduction

This chapter of the thesis focuses on providing the theoretical foundation and empirical review of systemic risk, information flow, and contagion for the study. The chapter summarises the literature review for the three thematic areas that serve as the foundation for the following three chapters: Chapters 4, 5, and 6. The chapter is organised into two sections. The first section reviews the main theories that form the basis for the study, giving it the necessary foundation for its take-off. Theories covered are the overshooting theory, the contagion theory, and information flow theories, including the efficient market hypothesis (EMH), the heterogeneous market hypothesis (HMH), the adaptive market hypothesis (AMH), and the situated information flow theory (SIFT). The final section concentrates on the empirical review in relation to the main thematic areas of systemic risk, information flow, interdependence, and contagion.

Theoretical Review

The Overshooting Theory of Commodities

Commodity prices (CP) are typically determined through auctions or flexible-price markets, so they may react rapidly to changes in supply and demand (both actual and anticipated) (Frankel, 1986). In contrast, the prices of most final goods and services only slowly catch up to commodity prices due to constraints imposed by contractual arrangements and other frictions (Frankel, 1986; Blomberg & Harris, 1995). In effect CPs are like the hare in Aesop's story: they surge forward early in inflationary cycles but eventually decline (Blomberg & Harris, 1995).

The idea that CP serve as a leading indicator of the consumer price index (CPI) or inflation rests on the overshooting theory of Dornbusch (1976). In the original overshooting theory by Dornbusch, the idea was to explain the behaviour of exchange rate responses to changes in monetary policy. According to the theory, due to the flexible nature of the currency market, exchange rates overshoot their value in the short-term whenever an expansionary monetary policy is implemented, although the situation is corrected in the long-term. The idea behind this was then extended and improved on to form the theoretical foundation to explain how commodity behaviour is a leading indicator of price level changes in the goods market and thus inflation.

Among the proponents who built on the overshooting theory to create a formal model for commodity behaviour and inflation were Frankel (1986), Boughton and Branson (1991), and Fuhrer and Moore (1992). The main strategy in these models was to replace the exchange rate with commodities, and once the exchange rate for commodities is adjusted, Dornbusch's overshooting model can be used to explain why commodity prices react more than proportionally to changes in the monetary policy rate and serve as a leading indicator for inflation.

For instance, substituting the exchange rate for commodities in Dornbusch's overshooting model, Frankel (1986) created an overshooting model of commodities by imposing no-arbitrage requirements. Given the flexibility of commodity prices, the impact of monetary policy should be nearly instantaneous and manifest as overshooting behaviour that is reversed in subsequent periods. Frankel argues that the general price level must increase by the same percentage as the increase in the nominal money supply. Though prices of industrial goods lag commodity prices in the short-term due to the sticky nature of the goods market, they eventually take over in the long-term. This means that commodity price behaviour signals likely change in inflation.

Similar arguments were made by Boughton and Branson (1991) and Fuhrer and Moore (1992) in their theoretical frameworks. In general, commodities are treated as assets in these models, with price "jumps" serving to balance the monetary and commodity markets. Consequently, when there is a sudden increase in aggregate demand (such as when the money supply suddenly expands), the price of commodities rises sharply while the price of finished items lags. The key tenet of this strategy is that a change in monetary policy will cause commodity prices to rise beyond their long-term averages. Therefore, commodity prices rise above their short-term equilibrium as real interest rates fall. The increase in price leads to a rise in commodity supply, causing businesses to stock up in the hope of making more profit from further price increases. However, futures demand falls as investors conclude prices are already at or near their equilibrium levels. This correction is accompanied by a general rise or fall in the prices of goods that mirrors the direction of change in commodity prices.

Building on these fundamental theoretical frameworks, the empirical literature on commodities presents three distinct explanations for the correlations between commodity prices and overall inflation. These stories, sometimes known as "commodity fables," illustrate how commodity prices can serve as an early warning system for inflation.

First, as the story of the tortoise and the hare shows, rising commodity prices may serve as an early warning signal of an inflationary spike in aggregate demand (Bloomberg & Harris, 1995). Although the inflation push could originate in the markets for finished goods, the first obvious increase in prices could occur in the flexible-price commodity markets as a result of the increased demand for these commodities. Given the global nature of commodity trading, a strong local demand signal would be expected while overseas demand is relatively weak. In empirical models, commodity prices are commonly modelled because of global economic activity warning signal of an inflationary spike in aggregate demand (Bloomberg & Harris, 1995). Much of these commodity price increases due to increased demand would likely affect industrial materials.

Second, commodities are a significant input into production, accounting for around one-tenth of the value of output in the United States, suggesting a possible direct link between commodity prices and broad inflation. With all factors remaining constant, a rise in the cost of raw materials ought to be reflected in the ultimate price of finished products. Historically, food and energy commodities have borne the brunt of large direct input price effects.

Third, commodity prices and projected inflation have three interconnected factors. Investors may view commodities as a good inflation hedge due to their responsive price levels. As a result, investors are more likely to buy commodities like gold and silver in anticipation of inflation if they are widely believed to be reliable inflation hedges. In this way, inflation can be stabilised by investing in a variety of commodities, although precious metals have long been considered the most practical. These foundations have formed the basis for this study's estimation of the relationship between commodity prices and inflation.

However, the commodities and goods markets are made up of different market players whose behaviours are impacted by different situations, with such behaviour having implications for the relationship between commodities and inflation. Such thinking is in line with the adaptive market hypothesis (AMH) proposed by Lo (2004). According to the AMH, market efficiency is not a constant across markets or over time but rather fluctuates in response to bubbles, crashes, and crises. As a result, the concept of market efficiency is defined as highly context-dependent and dynamic, originating from evolutionary principles (Lo, 2004). Accordingly, changes in the market structure influence the establishment of markets, leading to the achievement of market efficiency driven by time variation. This means that not only do different events influence the decisions of participants in the commodities market but also the decisions of policymakers in an attempt to stabilise inflation. As a result, not recognising the dynamic behaviours of the market players in the relationship may lead to misleading conclusions. Therefore, chapter 4 of this thesis employs the overshooting theory of commodities and the adaptive market hypothesis (AMH) to study the relationship between commodity prices and inflation and to detect possible systemic risk flowing from global commodity prices to inflation. This reveals information at the extremes of market conditions, like bearish and bullish, instead of just normal situations, which is significant for hedging decisions.

Information Flow Theories in Financial Markets

Generally, the traditional theories explaining information flow in financial markets are predicated on the assumption of investor homogeneity. The representative agent is the main feature of this paradigm, which assumes that all investors are homogeneous in terms of their preferences, expectations, and investment strategies. Prominent among these theories in modern finance is Eugene Fama’s (1970) efficient market hypothesis (EMH), which assumes that if the market is strongly efficient, the current price contains all available information and that past prices cannot be used to predict future prices. Earlier, Fama et al. (1969) indicated that the price generation of financial assets is based on their response to information. Accordingly, the ability of capital markets to respond to information renders them efficient (Fama, 1970; Fama, 1998). According to the EMH, prices follow a "random walk," so changes are unpredictable and random. As a result, investors cannot produce superior long-term returns. Therefore, Grossman and Stiglitz (1980) emphasise that investors are willing to spend time and resources searching for new information only if it is worthwhile to do so, and only under these conditions can they provide higher investment returns. For a long time, many researchers and practitioners have debated the EMH, and the debate is still ongoing and continues to preoccupy many researchers (Bodie et al., 2014). The EMH may still have some use, but the different kinds of market participants and how they change over time, market overreaction, mean reversion, excessive volatility, and all the other strange things that happen on the market are all reasons to investigate information flows about commodities and exchange rates at different times.

Supporting the concept of information flow, Benthal (2019) has argued through the situated information flow theory (SIFT) that financial markets and assets share mutual information, so it is possible to retrieve interrelationships. It must be pointed out here that the foundation of SIFT is derived from two sources: (1) the philosophy of Odegard (1982) and (2) the statistical quantification of intrinsic information, which is common between two random variables and developed by Pearl (1982). The assumption in SIFT is because, if there are two random variables and there is a possibility of knowing about one variable by making an inference to the state of the other variable, then the two variables share mutual information. Based on such an understanding, there is a high possibility that commodities and exchange rates will observe each other under different dynamics over the period based on the intrinsic mutual information shared by them in the context of this study. Therefore, our proposition here is that, due to the complex nature of investors, the interrelationship between the two markets would possibly differ across different levels of investment, which could result in diversification or hedging potential between commodities and currencies.

Multi-Frequency Matters in Information Flow

The complexities in investor behaviour and multiple policies implemented by different monetary authorities have called into question the assumption of the efficient market hypothesis. The argument here is that there is high information flow in the markets, and investors relying on available information will look for assets that are relatively safe to put their money in as a means of portfolio diversification, particularly during crisis times. As a result, their risk appetite dictates their investment choices, making each respond to volatility differently in their attempt to get the most out of their portfolio. These lines of argument are what have led to the emergence of the heterogeneous market hypothesis (HMH) by Muller et al. (1993) and the adaptive market hypothesis (AMH) by Lo (2004) and more recently, the competitive market hypothesis (CMH) by Owusu Junior et al. (2021).

The HMH, for instance, proposes that the decision of investors about their risk-reward trade-off corresponds to different time scales, and this is influenced by events of the past and present. According to the AMH, market efficiency is not a constant across markets or over time, but rather fluctuates in response to bubbles, crashes, and crises (Lo, 2004). According to these theories, when conducting empirical analysis, it is critical to consider different time scales, as this brings out the dynamic behaviours of market participants classified as high-, intermediate-, and low-frequencies. The CMH suggests that investors' pursuit of competing rewards and risks in order to satisfy their portfolio goals contributes to the already high levels of information flow and spillover between markets of the same and different asset classes. The dynamism in investor behaviour as a result of heterogeneity, adaptability and competitiveness renders asset prices in the financial market nonlinear, nonstationary, and noisy. Because of this, empirical studies of financial assets need to use methods and approaches that reflect these changes.

Moreover, Markowitz's (1952) modern portfolio theory has indicated that investors are interested in alternative markets when establishing a portfolio based on the risk-reward trade-off. Investors are therefore interested in adding an asset to a portfolio if it generates higher returns with lower risk. And with different investors having different investment objectives, there can be conflict as different times present different choices to be made. As such, with heterogeneity in market participants' behaviour presented by HMH, AMH coupled with CMH and modern portfolio theory, which brings about conflict in portfolio allocation, investors are always making different choices at different times depending on market conditions at the time, and as such, they see the exchange rate market and the commodities market as two different markets that they can switch one for the other or combine in their portfolio. At the same time, monetary policymakers are more interested in the time when commodities offer any safe-haven or hedging potential for their currencies in their policy decisions, at the heart of which is the nature and strength of information flow. As a result, chapter five of the current study rely on these theories to quantify information flow between commodity prices and exchange rates at multiple scales to capture different behaviours of market participants.

Contagion Theory

One topic that is very popular in the financial economics literature is contagion. But its popularity has also generated more debate about its meaning since several definitions have been assigned to it. However, empirical findings will only make sense if they are situated within a clear theoretical foundation. In many instances, the source of shock propagation is used as the theoretical foundation to define or classify contagion. One school of thought says that contagion spreads in three ways: (1) aggregate shocks that affect the economic fundamentals of many countries; (2) country-specific shocks that affect other countries; and (3) shocks that can't be explained by fundamentals and are called "pure contagion" (Forbes & Rigobon, 2002).

The first classification occurs when situations like rising global interest rates, reduced global capital availability, and weakening global demand dampen economic expansion in several countries. There is a high possibility that financial markets in the affected nations will move together, so cross-market correlations could increase after the shock. In the second instance, there is a likelihood that volatility in one country's fundamentals can affect another country's economic fundamentals due to the link between them. The main channel for such shock propagation is trade relations. A recent case in point is how the Russian invasion of Ukraine is impacting the fundamentals of many European countries due to the cut in the supply of gas from Russia to Europe. The actions of one trading partner, like the devaluation of a currency, can lead to other trading partners taking a similar measure if it is badly affected. In the third case, contagion occurs when there is a rise in market co-movement that is not based on the scenario in the first and second instances.

Theoretically, the two main types of contagion mentioned in the financial literature are pure or irrational-based contagion and fundamental-based contagion. According to proponents of pure contagion, when a shock spreads from one country or market to another without idiosyncratic factors, there is contagion. As the name suggests, the irrational behaviour of investors is believed to be the main cause of contagion. As per Kaminsky et al. (2003), this irrational and enthusiastic investor behaviour has the possibility of altering the pattern of capital flows and worsening financial market booms and busts. Conversely, the fundamental-based theory defines contagion as shock diffusion from one nation or market to another through the real sector or macroeconomic factors. To them, a substantial rise in the connection between two markets shows there is contagion (Bekaert et al., 2005; Pritsker, 2000). The fundamental-based theory has come under serious criticism, although it is the most commonly used definition. The main point of the fundamentalists is that it is hard to prove contagion without looking at the right fundamentals and even harder without cross-market hedging (Pritsker, 2000).

The lack of clarity on the exact meaning of contagion in the existing theories led Forbes and Rigobon (2002) to propose the "shift-contagion" theory (SCT) to bring precision to the meaning of contagion. Their definition differentiated between interdependence and contagion. To them, interdependence is when only linkages occur between markets without significant cross-market linkages. But when there is a shift or change in cross-market correlation, there is a contagion, hence their description of "shift contagion." However, their definition did not indicate how the shift occurs. In line with Forbes and Rigobon (2002), Celik (2012) examined financial contagion between emerging and developed countries during the U.S. subprime crisis and found that unconditional correlations increased in crisis periods relative to pre-crisis periods. Similar findings were also obtained by King and Wadhawani (1990). Despite what Forbes and Rigobon describe as the strengths of their shift-contagion theory, proponents of the pure contagion theory disagree and point out that contagion occurs whenever shocks are transmitted from one market or country to another, and it doesn't matter if cross-market linkages change.

To unify the various channels of financial contagion, Pericoli and Sbracia (2003) proposed six channels of financial contagion after adding one channel to the five existing channels they identified in the finance literature. Based on the five channels they identified—fundamental panics, incomplete information, learning, and updating by international investors—they proposed three types of contagion, if the last two cause discontinuities in the international transmission of the initial crisis. Forbes and Rigobón's shift-contagion theory from 2002 says that the last two channels are contagious, but the first channel is just interdependence.

Bekaert et al. (2014) proposed a theoretical and empirical definition of contagion. To them, when the factor framework indicates that the co-movement between markets is beyond the factor, there is contagion (Bekaert et al., 2014). They originally proposed four types of contagion, but further statistical examination forced them to reject two of their hypotheses. However, the inconsistency in their hypotheses still makes Forbes and Rigobon's idea important for understanding how contagion works, and this study's way of measuring contagion is in line with Forbes and Rigobon's (2002).

To keep the debate going, Boako and Alagidede (2017), after examining the shift contagion (SCT) among African stock markets and global exchange rate, demonstrated that contagion usually continues after a crisis moment, so there is *"delayed contagion"* (DC). They argue that it is not enough to limit episodes of contagion to only the crisis period since, in many instances, the episodes prolong over time, as seen in the 2007 global financial crisis, which extended into 2009 in many European countries. Recently, Owusu Junior et al. (2020) proposed a *"shape shift-contagion"* (SSC) theory as a new way of thinking about financial contagion. The view of the SSC is that the higher moments of return distribution exhibit shocks better, irrespective of the transmission channels. It is therefore important to analyse contagion on the basis of the shape parameters of the distribution. The DC and SSC provide added dimensions to the concept of contagion, but are still extensions of the SCT.

Generally, contagion theorists argue that emerging and developing countries stand the risk of suffering shocks from global commodity prices due to their dependence on global economic activities (Louis et al., 2009; Daryl & Biekpe, 2002). This presupposes that shocks from the global commodities market can spillover to the currency markets in SSA and cause possible contagion due to the cross-market linkages. Although the decoupling theorists argue to the contrary, there is not much empirical support for their contention in SSA. Chapter six of the thesis employs the shift contagion theory to study connectedness and contagion between global commodities markets and the currency markets in SSA. The significance of shift contagion theory (SCT) is based on two main things: (1) it differentiates between interdependence and contagion by indicating that contagion occurs when there is a change in the linkages across markets, and (2) it accounts for heteroscedasticity in measuring correlation, leading to an efficient conclusion contrary to many existing studies.

As important as the shift contagion theory (SCT) is in explaining financial contagion, it focuses on contagion happening across time with no emphasis on frequency dynamics. The multiplicity of investors and different market participants in the financial markets calls for the consideration of time variation in measuring contagion. The heterogeneous market hypothesis (HMH) posits that there is a need to segregate markets into different investment horizons (short-, medium-, and long-term) to satisfy the behaviour of different market participants. Adding to that is the adaptive hypothesis (AMH), which indicates that different events influence the formation of markets, so market efficiency is time-varying. Based on these theoretical propositions, it is important to consider the heterogeneous nature of market participants in studying the contagion between commodity prices and exchange rates.

In this thesis, the shift contagion theory (SCT) is employed together with HMH and AMH to study the connectedness and contagion between the global commodities markets and the currency markets in SSA. Connectedness and contagion are defined through non-parametric correlation coefficients derived from the time- and time-frequency domain connectedness of Barunik and Krehlik (2018) (BK18). This is because the dynamic connection across markets changes over time and at different investment horizons, which is consistent with SCT. The BK18 framework is used in this study to assess contagion and connectedness based on its ability to capture the dynamics of cross-market linkages in frequency- and time-varying ways. The BK18 method has the ability to decompose series into time and frequency at the same time, thus making room to create higher and lower frequencies. Also, the BK18 framework appeals to HMH and AMH. Moreover, BK18 possesses a rolling window in their estimation, which enables it to overcome the SCT heteroscedasticity bias. The focus on exchange rates of commodity-dependent developing economies in SSA distinguishes this study from previous efforts, which have primarily focused on developed and emerging economies stock markets.

Empirical Review

The empirical literature has been done in line with the three main thematic areas of the study, which are interdependence, information flow, and contagion.

Relationship between Commodity Prices and Inflation

The link between commodity prices (CP) and inflation has received extensive attention in the literature, but the findings are far from consistent. Again, several studies have also examined the predictive power of commodities to forecast inflation, and those have also had mixed outcomes. Several factors, including the different methods, the measurement of inflation, and the commodities involved, may have contributed to the differences in results.

Some studies have shown that there are variations in the movement of CP and consumer price inflation, but they sometimes cointegrate. For instance, Cody and Mills (1991) investigated how monetary policy responds to commodity price volatility to see whether it would help stabilise the US economy after the war. The conclusion was that commodity prices and inflation move in the same direction, so responding to shocks in commodities would stabilise US inflation. In a similar vein, Browne and Cronin (2007) use a pure exchange economy framework to investigate the connection between commodity prices, consumer good prices, and the money supply. This paper delves into the question of whether or not commodity and consumer goods market price disequilibria are the result of an exogenous change in the money supply, and how indicators of such price disequilibria can be used to predict future changes in CPI inflation. In the long run, they find that commodity and consumer prices are proportional to the movement of the money stock. Further, they discover that commodity prices adjust more quickly and do not overshoot their new equilibrium level in response to a money shock, while consumer prices adjust more slowly and do. Last but not least, the subsequent CPI inflation can be explained by the commodity price deviation from its long-run values. But these studies only looked at the American economy and didn't pay much attention to other situations.

Soni and Parashar (2015) investigated the rise in the demand for gold and how that affect inflation in India by focusing on a single commodity. Using monthly secondary data from 2002 to 2012, the study analysed prices of gold and equity returns in the Indian economy. The Augmented Dickey-Fuller and Johansen co-integrated tests, as well as the Granger causality test, were used in this study. The findings of the study show that gold price is a significant predictor of inflation in India.

Chen et al. (2014) investigated the forecasting ability of commodity prices for inflation for commodity-exporting countries (Canada, Australia, Chile, New Zealand, and South Africa). Quarterly data from 1983–2010 was analysed based on the VAR model. The authors found that world CP have strong predictive power for inflation, especially when they consider a possible structural change. Gerlos and Ustyugova (2017) sought to find out how countries differ in terms of their inflation response to commodity prices. Their findings indicated that countries are very prone to sustained inflation from commodity prices if they have high food components in their CPI, high fuel intensity, and pre-existing inflation. Similarly, Inoue and Okimoto (2017) examine the impact of CP hikes (oil and food) on general price levels (inflation) and production in Asian economies and other thirteen countries, including the US. Using the global VAR model on monthly data from 2001–2015, the findings show that Asian economies are very vulnerable to commodity price shocks due to their overdependence on commodity exports.

Studies have also considered the long- and short-term relationship between commodity prices and macroeconomic fundamentals like inflation and the exchange rate. Moreira (2014) studied the association between commodity price volatility and expected inflation in net exporting countries. Several methods, including VAR, ARMA-GARCH, and VEC, were applied to monthly data from 2005–2013 with a focus on obtaining short- and long-term effects. The empirical result suggests that an increase in commodity price volatility in the long-term leads to higher expected inflation and lower GDP. This result means that commodity prices have a positive relationship with inflation.

Another strand of empirical literature has shown that the predictive influence of commodities to forecast inflation has weakened over the years. One such study is Bloomberg and Harris (1995), who studied the connection between CP and consumer price inflation in the US economy. This study was done to find out whether the notion of commodity prices serving as principal pointers of inflation was based on fact or fable. Using eight commonly used commodity indexes to test the relationship, the findings revealed that commodities have had some ability to predict inflation in the past, particularly in the 1980s, but that power has waned in the 1990s. Bloomberg and Harris maintain that the diminishing role of commodities in the US economy may be responsible for the shift in the diminishing predictive powers of commodities for inflation.

Similar evidence was provided by Acharya et al. (2010), who investigated how movements in commodity prices relate to inflation in the US economy. Relying on the VAR model, the study findings were that the relationship between commodity prices and inflation has changed over time because it was greater in the past than in the 2000s. The authors believe that the changes in the structure of the US economy to be more service-led, which uses fewer commodities, may have contributed to that. It can be inferred from these two studies that changes in the structure of an economy can easily change the strength of the relationship between commodities and inflation, and since countries evolve over time, it is necessary for re-examination from time to time.

Kilian (2009) agrees with the shifting nature of the association, and indicates that the link between oil prices and industrial goods has not been consistent because of changes in the constituents of shock. Kilian believe that the effect of each shock on oil prices and macroeconomic factors like inflation is different, hence the unstable nature of the relationship. Therefore, Delle Chiaie et al. (2017) demonstrated that the importance of international economic activities in explaining variations in commodity prices increased in the 2000s compared to previous years. While this may be true for the US economy, the situation may be very different in countries that are developing like those in SSA due to their high dependence on commodity exports for revenue.

Others studies, however, reject the potential of commodity prices (CPs) to predict inflation in any form. For instance, when Durand and Blondal (1988) examined the use of CP trends in predicting the development of prices in OECD countries, the outcome was different. The study tested both integration and cointegration between the two variables using both commodity indexes and individual commodities. Results from the study indicate that no clear equilibrium relation exists but that some relationship exists between metals, agricultural commodities, and inflation. Their findings were supported by Thornton and Herrero (1997), who examined whether commodity price movement predicts retail prices of goods in the UK economy by way of co-movement and whether the information in short-term commodity prices conveys future retail price movement. After employing both the cointegration test and the granger causality test, the finding was that there is no cointegration and no granger causality in both directions. Aside from the fact that these studies only looked at advanced economies, the methods used were linear and not very reliable.

Financial economics oriented studies concentrated on the hedging potential of commodities against inflation. Here too, inconsistency exists in the outcome, making it difficult to establish a consistent policy direction. One such study is Hoang et al. (2016), which studied the relationship between the gold price and inflation in China, India, Japan, France, the United Kingdom, and the United States. Following the non-linear autoregressive distributed lag (NARDL), the study concluded that gold was not a hedge for inflation in the long run for all the countries observed. A similar conclusion was drawn earlier by Erb and Harvey (2013), who indicated that gold is not an effective hedge against unexpected inflation in both the short- and long-terms. This was the outcome of their study that sought to find out whether gold is a good hedge against inflation or not. The general conclusion was that the golden constant of gold no longer exists.

The AMH have indicated that different events in the commodities market impact the behaviour of market participants and policy makers differently, which can also change a normal market situation into an abnormal one. As a result, a positive relationship can easily turn negative due to the impact of extreme events. Accordingly, forecasting inflation with commodities for risk management without considering varying events in the market may lead to erroneous conclusions. But this has been overlooked in the existing literature. One exception is Lucey et al. (2016), who studied the connection between gold prices and inflation. Their study tried to establish the stability of the relationship over time across several inflation measures. Three developed economies—the US, UK, and Japan—were used for the study based on the assumption that the US and the UK are the leading centres of trading gold in the world. Monthly data covering a period of 40 years were used from January 1974 to January 2014. A co-integration was done following the VECM method, while the ARIMA model was used to conclude the connection between gold and inflation. From the findings of the study, gold prices show a time-varying co-integration association with inflation over the period of the study. Although the study considered time variation in its analysis, the models VECM and ARIMA could not properly decompose the series to give both normal (mean) and abnormal (quantile) effects, making them unreliable for such purposes.

Mukhtarov et al. (2019) examined the impact of commodity prices (oil) on macroeconomic fundamentals (growth, exports, inflation, and exchange rate) in Azerbaijan. The Johansen cointegration and vector error correction model (VECM) methods were used on monthly data from 2005–2017. Findings from the study show that a positively significant relationship exists between oil prices and inflation. The problem is that this study considered a single country, which is very limited as different countries depend on different commodities.

The situation in SSA is even worse, as existing studies have completely ignored quantile analysis that can bring out different market conditions. For instance, Jumah and Kunst (2007) focused on how cocoa prices influence inflation in five West African economies. In their study, annual data from 1975–2001 was employed for Benin, Cameroun, Cote d'Ivoire, Ghana, and Togo with the least square regression. The results revealed that cocoa prices have a stronger significant influence on inflation in the countries studied. This could probably be due to the significant amount of revenue these countries obtain from cocoa exports to run their economies. Similar observations were made by Salisu et al. (2019), who examined the consistency of cocoa in predicting inflation in net exporting and importing countries using a panel regression approach. In the end, Salisu confirmed the earlier findings of Jumah and Kunst (2007) in the case of net exporting countries. The weakness here is that the panel methodology employed could not present different market dynamics like bearish and bullish conditions in the relationship which will enhance risk management policies.

In a study to examine the strength of CPs in forecasting inflation, Fasanya and Awodimila (2020) focused on core and headline inflation for two African countries, South Africa and Nigeria. They discovered that CP indexes are good predictors of inflation in the two countries studied using the feasible quasi-generalized least squares (FQGLS) estimation. A more recent study by Abaidoo and Agyapong (2022) examined the impact of globally traded commodities on inflationary conditions and inflation uncertainties in sub-Saharan African countries. The study spans 32 countries from 1996 to 2019. The study employed the two-stage generalised method of moments (GMM) in its estimation procedure. The findings from the study are that the impacts of gold, oil, and cocoa on inflation and inflation uncertainties are positive and significant. However, cotton has a negative impact on inflation but a positive effect on inflation uncertainties. Apart from these studies considering all markets to be the same, they also suffer from problems with the panel methodology stated earlier.

Despite the plethora of studies on commodity prices and inflation, several gaps exist in the literature. First, studies using commodities to forecast inflation have mainly concentrated on the US and other developed economies with less attention paid to developing economies, particularly those in SSA. However, countries in SSA have a stronger dependence on commodities than those in other parts of the world. Second, existing studies have ignored the impact of varying events in forecasting inflation with commodities. They have thus mainly assumed normal market conditions, with only a handful addressing the extreme event. These extreme events usually emanate from global markets, like the impact of the 2008 GFC on the global commodities market and the eventual effect on the economies of countries in SSA.

Third, the systemic risk between commodity prices and inflation has received very little attention, and the situation in SSA is more serious. Fourth, methodologically, VAR and panel analysis dominate the empirical studies on the connection between commodity prices and inflation. The weakness of these methods is that they are either linear or limited in presenting the impact of varying events on the relationship. But empirical evidence suggests that commodity prices are mostly nonlinear. Moreover, these methods cannot be used to forecast over a longer period of time due to the limited number of lags they take.

This study fills the gaps in the literature by doing the following: (1) focusing on countries in SSA that have higher inflation than the rest of the world and are highly dependent on commodity exports for survival. The countries in the study are categorised into three groups according to the commodities they export (agricultural, metals, and energy). In so doing, three commodities, one from each, are selected for the study, which include cocoa, gold, and crude oil. (2) This study appeals to HMH and AMH to present evidence on varying events in the relationship. In the process, different quantiles are used, which can detect different market states like bullish, bearish, and normal situations. (3) the study measures systemic risk and dependence using the cross-quantilogram method proposed by Han et al. (2016). This method has the ability to make a forecast over a longer period of time, which other methods like quantile regression cannot do.

Information Flow between Commodity Prices and Exchange rate

Several studies have been conducted on the interaction between commodity prices and exchange rates. While many of these studies have taken a unidirectional approach, the few bidirectional ones have not approached the subject with superior techniques applied in this study. For instance, Clement and Fry (2008) used a bidirectional approach to investigate the relationship between commodity prices and exchange rates, focusing on the New Zealand, Australian, and Canadian dollars. The Kalman filter method was used with data from 1975 to 2005 on five commodity indices. Testing for "commodity currency" and "currency commodity," they observed that the relationship moves in both directions. In a related study to examine the causal return and volatility spillovers between commodities and currencies in developed and emerging markets, Belasen and Demirer (2019) found several instances of causality between commodities and ERs, specifically between gold and the New Zealand dollar, oil and the Brazilian real, and copper and the Chilean peso. Their study used daily commodity prices and indexes from 2007 to 2016 and found that causality became widespread during the 2007–2008 global financial crisis (GFC). The problem with these studies is that they used commodity indices, which hide the fact that different countries have different economic policies because of the different goods they export.

There are those who have relied on a commodity price index to determine their relationship with the exchange rate. For instance, Chen and Regoff (2003) created monthly commodity price indices based on 44 commodities for 58 commodity-exporting countries and examined their effects on real exchange rates. The authors introduced the commodity-currency hypothesis in their study to explain the implications of commodity price fluctuations for real exchange in small, open commodity-exporting countries. In the end, Chen and Regoff demonstrated that a higher commodity price improves the trade balance of commodity exporters and may result in currency appreciation in countries that rely heavily on commodity exports. The authors discovered that commodity currencies are used by roughly one-third of the commodity-exporting countries in their sample. In a related study, Cashin et al. (2004) studied the exchange rate determinants of three countries: Australia, New Zealand, and Canada, using quarterly data from 1973 to 2001. Based on the terms of trade index, they observed that commodity prices have a stable influence on the exchange rate, but this is particularly true for New Zealand and Australia. Even though these two studies were very important, the way they looked at the relationship was linear and one-sided, which goes against new evidence that shows the relationship is not linear.

Al-Abri (2013) was interested in the interaction among real exchange rates (RER), commodity terms of trade (TOT), and international financial integration (IFI) in primary commodity exporting countries across the globe. A panel of 53 countries was used, with data ranging from 1980 to 2007. The focus was on the interactive role of IFI in reducing RER volatilities. In the end, the finding was that IFI causes a reduction in the impact of TOT on EER, and the reduction becomes bigger when foreign direct investment (FDI) is used as an IFI.

Similarly, in a sample of 42 commodity-exporting countries, Boubakri et al. (2019) investigated the impact of real commodity prices on the real exchange rate, taking into consideration the role of financial market integration. The countries were grouped into four panels: energy; metal; raw materials; and food and beverage. Both the linear causality test and the nonlinear panel smooth transition regression (PSTR) methods were employed with four commodity indices and data from 1980 to 2016. Findings reveal that a nonlinear relationship exists between commodity prices and RER and that this relationship depends on commodity market financialization. Aside from the fact that these studies only looked in one direction, the use of panel methodology eliminate the country-specific effect, which makes them less reliable because different countries export different commodities.

Moving away from using the commodity price index, others have studied this relationship by using one or two commodities, albeit with mixed outcomes. One such study is Seyyedi (2017), who studied how exchange rates respond to changes in commodity price volatilities (oil and gold prices). Different approaches, including Johansen's co-integration test, the vector autoregressive (VAR) model, and the impulse response function, were used on monthly data from January 2004 to April 2015 for the Indian economy. It was concluded from the study that commodity prices and exchange rates are independent of each other, so policies must be detached. However, when Singhal (2019) used the same commodities (gold and oil) to investigate return and volatility linkages between commodity prices and exchange rates in Mexico, the outcome was different. Indeed, after using ARDL bound testing co-integration on daily data, the result was that oil price has a negative impact on the exchange rate in the long-run, but the gold price has no significant effect on the exchange rate in the long-run. This means that different commodities can have different influences on the exchange rate at different times, creating the need to examine individual commodities separately. Again, the studies were linear and one-directional, thus ignoring the mutual information.

Jain and Biswal (2016) examine the interrelatedness between gold prices, oil prices, and exchange rates in India using DCC-GARCH models. Findings from empirical results show that a decrease in commodity prices leads to a decrease in the value of the Indian rupee. In a more recent study to investigate the link between four markets: foreign exchange, crude oil, gold, and stocks, Thakolsri (2021) used monthly data from January 2000 to December 2018 for Thailand. Both the Johansen co-integration and Granger causality tests were employed in the study. Findings show that all assets can act as hedges for each other, but the gradient of causality runs only from the gold and stock markets to the exchange rate markets. But the modelling in these studies were either linear, unidirectional, or both, hence suffering from the weaknesses identified earlier.

Focusing on Africa, Buah (2019) examines the effect of cocoa prices on the exchange rate in Ghana using monthly data. The study followed both the VECM and GARCH models in estimating the relationship based on the theory of purchasing price parity. Findings from the study indicate that a negative relationship exists between commodity prices (cocoa) and the exchange rate. The problem is that the study does not capture heterogeneity in investor behaviour. To improve that, Kassouri and Altintas (2020) examined how shocks from commodity terms of trade impact the rear exchange rate (RER) for 23 countries in Africa. Four commodity indexes were used to cover energy, metals, agriculture, and food and beverage subgroups, and countries were classified accordingly. The findings from the autoregressive distributed lag (ARDL) show that the response of RER to TOT is asymmetric and differs across commodity subgroups, with energy and metals receiving the strongest asymmetry shocks. However, not only is this study unidirectional, but the outcome is also not country-specific, denying countries specific policies in relation to the commodities they export. Additionally, ARDL lacks the capacity to quantify the strength of information between the two variables.

Others studies, realising the importance of investor heterogeneity in line with HMH and AMH, incorporates time variation in the analysis. Tiwari et al. (2013) investigated the linear and non-linear Granger causalities between oil prices and effective exchange rates using the Indian currency. In the study, the real effective exchange rate was used as the dependent variable, which was obtained from the Reserve Bank of India website. The study employed the discrete wavelet transform (DWT) to decompose the data after transforming all the variables into a logarithmic form. The study found no causal relationship between oil prices and real exchange rates in the standard normal time domain. However, causality was discovered between oil prices and RER at the higher time scale but not at the lower time scale. While this study shows the importance of decomposition, the wavelet methodology due to the counterintuitive interpretation problem, making it less reliable.

Reboredo and Rivera-Castro (2014) employed the copula model to study the correlation between gold and the US dollar exchange rate. In the study, a distinction was made between extreme market conditions and normal conditions. The study suggests that gold acts as a good hedge and a haven for the US dollar in extreme market movements, but the study did not distinguish between time frames. In a related study, Alterturi et al. (2018) conducted a three-way analysis of oil, gold, and the USD. The study finds that in the short-to-medium-term, the exchange rate influences the price of gold and oil, but the reverse happens in the long-term. Like the prior studies, the wavelet method is weak in reducing noise in the data, thus reducing the reliability of the outcome. In a recent study, Wang and Lee (2022) looked at the safe-haven properties of gold for the exchange rate of five major currencies in the world using data from 1999 to 2018. Using TVP-VAR, the finds that gold serves as a safe haven for the pounds, dollars, and euro only in the short term but not the yen and renminbi. But the method used does not properly separate a series into its intrinsic modes and the study also focuses only on the major currencies.

We note that many of the methods used in the existing studies either do not measure frequency dynamics in the relationship or do not quantify the strength of information flow. Besides, different crisis events like the GFC and the COVID-19 pandemic present multiple dynamics in the commodities and currency markets, which carry a lot of information that can turn the seemingly negative relationship into a positive one. With the possibility of such changes in the direction of the relationship, it is important to use a method that can measure how information flows through these markets in the financial system.

From a theoretical perspective, there is a possibility of measuring information between two or more variables in terms of the one pushing the information and the one responding to the information. According to Schreiber (2000), such a process is called transfer entropy (TE). In recent times, the use of transfer entropy for information transfer among financial markets has been expanding (see Bossman et al., 2022; Owusu Junior et al., 2021; Adams, 2020;

Behrendt, 2019). However, these studies were only limited to stock markets. In the commodities market, Huynh (2020) employed transfer entropy to determine the effect of uncertainties on precious metals and concluded that gold is still the dominant commodity among precious metals. But the focus of that study was on the drivers of commodity prices, and no decomposition among the variables was done. Similarly, Tapia et al. (2020) employed the entropy method to examine the behaviour of the copper price, but their study only considered the long-term behaviour of the copper price, thus limiting its focus.

The literature clearly shows that not only do we lack evidence from commodity-dependent countries in SSA, but to the best of author's knowledge, no study has quantified the strength of information flow between commodity prices and exchange rates. Furthermore, studies capturing information flow in frequency dynamics are completely lacking in relation to SSA. Considering the weaknesses above, we contribute to the literature on the commodity price-exchange rate nexus by employing the transfer entropy approach, which is data-driven and based on CEEMDAN decomposition, to study the information flow between the gold price and the exchange rate, focusing on commodity-exporting countries in SSA on three commodities (cocoa, gold, and crude oil). By doing so, we can determine whether these commodities are diversifiers, hedgers, or safe haven assets for the SSA exchange rate.

Connectedness and Contagion of Commodity Prices and Exchange Rates

Despite the ongoing debate on the concept of contagion, empirical studies abound in the literature, with inconsistencies probably due to the multiplicity of measurements. Several studies in this area have concentrated on the return and volatility spillovers between the exchange rates of major currencies in the world, with varying outcomes. Bubák et al. (2011) conducted a study on volatility transmission between the currencies of Central European (CE) countries and the EUR/USD exchange rate, relying on model-free estimates of daily exchange rate volatility. The findings showed that in the Central European markets, there are statistically significant intra-day spillovers among the currencies. Except for the Czech Republic and Poland, there were no spillovers from EUR/USD markets to CE markets. In a study to examine the volatility spillover and exchange rate co-movement before and after the Euro introduction, Anthonakakis (2012) utilised a VAR-based spillover index for major currencies in Europe and the US dollar. The results show that spillovers were important, but on average they were smaller after the euro was introduced than they were before. This shows that spillovers change over time and need to be looked at from time to time.

Similarly, Salisu et al. (2018) examined the return and volatility spillovers in the global exchange rate markets, focusing on the six most traded currency pairs (Aussie, Cable, Euro, Gropher, Loonie, and Swissy) in the world using daily data from January 1999 to December 2014. The result from the DY12 model indicates that interdependence exists among major currency pairs, but while return spillovers exhibit mild trends, volatility spillovers exhibit no trend at all. It must be pointed out that, apart from the study focusing on only major currencies in the world, the analysis was only done in the time domain, which falls short of bringing out the total dynamics at different levels.

In a related study, Kocenda and Moravcová (2019) investigated spillovers, co-movement, and hedging costs in the EU forex markets with monthly data from 1999 to 2018. They concluded that correlation and spillovers were unstable; the correlation becomes negative during turbulent times, and cross-currency spillovers rise at the time of crisis. Not only do their findings contradict some aspects of Antonakakis (2012), but they also assumed a time domain analysis. More recently, Huynh et al. (2020) considered the role of trade policy uncertainties in studying connectedness and spillovers in the foreign exchange market over the period from 1999 to 2019 for nine major US dollar exchange rate currencies. It came out that connectedness and spillovers are present only after considering trade policy, albeit at a higher level of volatility than the return. This study, just like previous studies, ignores the weaker currencies and is also limited to only time-domain analysis.

Other contagion studies have focused on exchange rates and stock market relationships. For example, Lin (2012) focused on the emerging Asian market by studying the co-movement between exchange rates and stock markets. The autoregressive distributed lag (ARDL) was used, and the findings show that spillovers become stronger during crisis times, which is a sign of contagion during turbulent times. But while the study attempts to differentiate between connectedness and contagion, the method used is more linear in nature, which defeats the nonlinear nature of financial data like stock prices and exchange rates. In a similar vein, Moore and Wang (2014) examined the dynamic linkages between real exchange rates and stock returns, focusing on the US market and the emerging Asian markets. Using the dynamic conditional correlation (DCC) approach, they discovered that trade balance is a key influencer of the relationship between Asian and US markets, while interest rate differential is the primary influencer on US markets. But, like Lin (2012), this study is limited by the fact that linear models cannot show the whole picture of what's going on.

A more comprehensive study was done by Boako and Alagidede (2017), who examined the existence of "shift contagion" in African stock markets based on extreme events (downside movement) from the global exchange rate and developed stock markets using weekly data. The conditional value at risk (CoVAR) based on the copula method was employed, and the findings show that, based on "shift contagion," there is evidence of contagion from some developed stock markets and exchange rates to African stock markets. They argued that shocks do not happen only during crisis times but can also happen post-crisis times, so there is "delayed-shift contagion." While we share the view that there can be a delay in contagion, a simple extension of the study period does not necessarily defeat the implicit assumptions of the SCT since SCT still captures shocks after crisis period. However, the mathematical assumptions in implementing shift contagion (SCT) might be its main weakness, an issue this thesis seeks to correct.

Some studies have used multi-scale analysis to study the nonlinear connection between commodities and foreign exchange markets, albeit with a focus on major currency markets and mostly one commodity (oil or gold). For instance, Benhmad (2012) studied the nonlinear causality between oil prices and the US dollar, relying on the wavelet approach. The findings show that the causality relationship was bi-directional and varied over frequency but was unidirectional at the first frequency, running only from oil to exchange rate. In a similar fashion, Reboredo and Rivera-Castro (2014) examined the importance of gold to exchange rate risk management in terms of hedging and downside risk. The analysis was done at different investment horizons using wavelet multiresolution analysis. The findings show that over the period 2000–2013, the depreciation of gold and the US dollar have a positive dependence on other currencies used in the study at all-time scales. Despite these two studies using the same approach but with different commodities, the findings are not consistent for both. While the former does not obtain a consistent relationship at all frequencies, the latter does. This creates room for an assessment of this relationship between different commodities and different currencies. Moreover, the wavelet method used in both studies has the probability of smearing the energy of the decomposed frequencies, thus making their reliability suspect.

Uncertainty in the results is also evidence in Wen et al. (2017) who sought to assess the nonlinear Granger causality and time-varying effect between crude oil and the US dollar. In this study, multiple methods were applied, including the Hiemstra and Jones test, the Diks and Panchenkotest, and the time-varying parameter structural autoregressive model (TVPSAR). The finding of the study was that exchange rate does not cause oil price, but rather the other way around: the exchange rate has a more stable negative effect on the oil price. Despite the multiple methods used in Wen et al. (2017), none of them has the capability of proper decomposition to present the frequency-level information.

In a recent study, Yildirim et al. (2022) investigated volatility transmission between real exchange rates and real commodity prices for three emerging economies: Mexico, Indonesia, and Turkey. The study suggests that a bidirectional causality exists between the CP and ER but that the relationship varies with time and that volatility transfer disappears in times of crisis, particularly during the COVID-19 pandemic. Yildirim et al. (2022) also revealed that, though both precious metals and oil have safe-haven potential for the exchange rate, risk transfer from oil only happens in Indonesia and not in the other two countries. One weakness of this study is that it is a time-domain study with no frequency dimension. Again, the study also confirms the importance of studying different commodities and different exchange rates due to the inconsistencies in the outcomes for both oil and gold in the same study.

Contagion studies on African currency markets have primarily been linear or time-domain analyses. For instance, Katusiime (2018) investigated price volatility spillovers from commodities to the exchange rate in Uganda using dynamic conditional correlation (DCC), constant conditional correlation (CCC), and time-varying conditional correlation (TVCC). The study found that market interconnectedness and volatility spillover are generally low but increase during times of crisis, using data from January 1992 to April 2017. Atenga and Moutoue (2021) study return and volatility spillover to African currencies using data from 2000 to 2019. The empirical results of the DY12 model show that African currencies respond more to themselves than to global factors, except for Botswana, Morocco, Tunisia, and South Africa, which may be linked to other currencies.

The forgoing literature presents the following issues and weaknesses: (1) that most empirical evidence has focused on major currencies in developed economies; (2) that there are inconsistencies in empirical findings when different commodities are used for different currency markets or even when the same commodity is used for different currencies; (3) that many existing studies concentrate on linear interaction; (4) that there is a paucity of empirical evidence on time-variation particularly in SSA; and (5) that there is lack of studies testing the *"decoupling hypothesis"* in the frequency domain of the currency market in SSA from global CP. Based on the weaknesses identified in the literature, this study fills the gaps by: (1) using three commodities (oil, gold, and cocoa) and the exchange rates of 27 commodity-producing countries in SSA; (2) appealing to the HMH and presenting evidence in frequency domain; and (3) employing the BK18 approach. In the process, we differentiate between connectedness and contagion similar to Forbes and Rigobon (2012), Owusu Junior et al. (2020) and make an inference about the decoupling hypothesis in SSA. We take frequency heterogeneity into account in our analysis, which gives investment and policy decisions a more complete picture.

Chapter Summary

An overview of the theoretical and empirical literature that forms the basis of this study is provided in this chapter. This section reviews the relevant literature concerning the study's three overarching themes: systemic risk, multi-frequency information flow, and time-varying interdependence and contagion. First, it is evident from the literature that, in spite of several attempts to study the link between commodity prices and inflation, the systemic risk implications of the relationship have received little or no attention, particularly in SSA. Also, most of the existing studies have focused on mean-to-mean analysis at the expense of quantiles of the distribution.

Second, it is clear in the literature that most studies on information flow between commodity prices and exchange rates have been time-wise homogeneous and linear in nature, in line with EMH. Studies in SSA have thus paid little attention to quantifying the strength of information flow at a multi-scale level to reflect the dynamic behaviours of investors and other market participants. Third, numerous studies on financial market contagion abound, but the emphasis has been on commodity and stock markets, with less emphasis on commodity and currency markets in SSA. Moreover, there is more focus on static time analysis at the expense of time-frequency analysis. As a result, the complex behaviour of the multiple market participants is mostly missing from the outcome, leading to inconsistent results.

The gaps above present the trend of literature from studies that focus on SSA in terms of commodity prices and macroeconomic fundamentals. Based on the knowledge gaps, this study offers a novel strategy for revealing the hidden parallels and divergences among SSA nations. The focus of this thesis is on these unarticulated aspects of SSA countries.

The literature review in this chapter forms the foundation for the empirical chapters 4–6. As a result, references should be made to this chapter for a detailed review after reading the introductions to each of those chapters.

CHAPTER THREE

RESEARCH METHODS

Introduction

The primary goal of this thesis is to conduct a multi-scale analysis of the relationship between commodity prices and macroeconomic fundamentals focusing on interdependence, systemic risk, information flow and contagion. To achieve that, this chapter provides a detailed research design, theoretical models used for the study, and a discussion of data and data sources for the study. The section begins with the research design and proceeds to the research paradigm and research approach. This is followed up with discussions of the various theoretical models employed in the study. The final part then looks at the nature of the data used for the study.

Research Design

A very important foundation of every research project is its design. The research design provides a guide for data collection, measurement, and analysis. The research design has been observed as providing direction to a study, which helps in time usage and resource cost reduction (Sarantakos, 2013). Robson (2002) describes three types of study designs: exploratory, descriptive, and explanatory. As each design is intended to do something different, he bases his categorization on the purpose. The goal of a descriptive study, for instance, is to paint a picture of some aspect of a situation, person, or event, or to demonstrate the interconnectedness and inherent order of things (Blumberg et al., 2005). However, when not enough is known about a phenomenon and an issue that has not been precisely characterised, researchers do exploratory studies (Saunders et al., 2007). Although it does delve into the topic at hand, an exploratory study is not meant to be an exhaustive treatment of the questions at hand.

By contrast, the goal of an explanatory study is to provide an explanation for, or at least an explanation that accounts for, the descriptive data. The goal of explanatory research is to find the root of a problem or the rationale behind a phenomenon in order to either confirm or disprove a hypothesis. This study employed the explanatory design because it researched the causes of a phenomenon that has already been described by exploratory methods. The purpose of this investigation is to identify and document connections between elements of the phenomenon being investigated. The purpose is achieved by using time series data over a 29-year period.

Research Philosophy

The reality of life is that every individual holds different beliefs, and these beliefs influence their actions. In research, these sets of beliefs are described as paradigms, and Barker (1992) has viewed them as modelling the world around us. In the view of Patton (1978), research paradigms influence how we try to find knowledge, our philosophy of life, and generally our view of the world's complexities. It is believed that the way data is collected and eventually analysed has a lot to do with our philosophies and worldview (Bajpai, 2011). To avoid misinterpretation of the work, researchers should clearly lead their readers with their world views.

Several classifications of research philosophies have been propounded over time, but Henn et al. (2006) believe they can all be grouped into two, which are positivism and interpretivism. The specific philosophy used in a study, however, must be influenced by the types of questions being answered and the nature of the data available. The positivist philosophy believes that the concept of absolute truth in knowledge is suspect, and as such, it is very important to examine factors that cause an outcome of events (Bryman & Bell, 2011). The assumption here is that there are rules and laws that govern social events, so implementing these rules can help us understand the world better. In general, positivism aims to develop testable hypotheses. One of the main advantages of positivism is that it recognises that absolute claims of knowledge are impossible to make when studying human behaviour and behaviours (Creswell, 2009).

In this thesis, the positivist worldview or paradigm is employed as the baseline philosophical approach. This is because the study seeks to draw some conclusions from its findings that may lead to some generalization, which is consistent with the positivist viewpoint. The field of finance and economics is dominated by the testing of hypotheses against the backdrop of objective reality. This thesis, therefore, follows a scientific procedure similar to the methodology in the natural sciences and thus supports the positivist ideology. Again, the study analyses secondary time series data but not the behaviour of individuals which makes positive view ideal for the analysis.

Research Approach

A very important stage in research is thinking about the approach to adopt for a study. Two main approaches have been identified: the qualitative and the quantitative approaches, and the choice made between them is very important for a particular research method (Bryman, 2002). The quantitative approach is built on deductive reasoning, which proceeds from general to specific issues. It must be noted that the link between variables that are measured scientifically and mathematically is investigated using a quantitative research technique (Saunders et al. 2012). On the other hand, qualitative research, according to Westerman (2006), is interpretative, constructionist, and founded on inductive reasoning. However, it has been claimed by Bryman (2012) that all studies, quantitative or qualitative, entail some sort of examination of the relationship between a dependent and independent variable. Furthermore, Collis and Hussey (2003) propose that researchers should be aware of the framework's dependability and validity, whether quantitative or qualitative. The positivism philosophy promotes objectivity, and so the quantitative approach that supports such thinking was employed in this thesis. The use of this approach allowed for some level of generalisation from the conclusions drawn from the study.

Data Source

This thesis seeks to achieve three main objectives. To accomplish that, 29 years of monthly closing data from January 2009 to December 2019 were utilized. The choice of the period is to enable the study to capture the impact of various reforms on the continent that started in the 1980s, the various commodity price collapses, and the financial crises in the 2000s.

Two macroeconomic variables (inflation and exchange rate) and three commodities (crude oil, gold, and cocoa) were used. The choice of exchange rate is because all commodities are traded on the international market and are usually denominated in the US dollar. As a result, volatility in various countries is first felt in the exchange rate when funds are converted to the country's currency. In relation to inflation, this is the variable that mainly reflects stability or instability in a country. The target of monetary policy is usually to bring about stability in these variables due to their overall impact on the general economy, making them very important. All monthly figures for inflation and exchange rate were collected from the International Financial Statistics (IFS) database of the IMF. The IFS database contained monthly and quarterly data for these variables for all countries, which gives uniformity instead of collecting from individual countries. All SSA countries with complete data were included in the study.

With respect to commodities, the World Bank classifies them into three main groups, comprising energy/fuel, mining/metals, and agriculture (UNCTAD, 2019). Agricultural commodities are often divided into two categories: food and beverages and raw materials. For this study, a commodity is selected from the three main groups, which are crude oil from energy, gold from metals, and cocoa from agriculture. These commodities are chosen because they are the largest contributors of export revenue in their respective subcategories to SSA and because they were the most traded in the international markets over the period. Monthly data for these commodities was sourced from the World Bank's commodity price database, popularly called the "pink sheet," which is publicly available.

Ethical Considerations

This study did not encounter any specific ethical issues as it relied on secondary data. All data were sourced from IMF and World Bank databases which can be verified.

Data Processing and Analysis

This section concentrates on how the data for the study was analysed. Different theoretical models were used to analyse the three main objectives of the study. The section begins by discussing the cross-quantilogram model, which was used in forecasting and estimating systemic risk in the relationship between commodity prices and inflation. The second part focuses on time-frequency decomposition methods, with a specific emphasis on complete ensemble empirical mode decomposition (CEEMDAN). The estimation technique for transfer entropy for information flow is then followed. Finally, the estimation of connectedness in time-varying networks using Diebold and Yilmaz's (2012) framework and Barunik and Krehlik's (2018) framework is reviewed.

The Cross-Quantilogram Method

In studying the predictive powers of commodity prices in forecasting inflation and the systemic risk involved in the relationship, the cross-quantilogram (CQ) of Han et al. (2016) was used. Indeed, since the influential work of Frankel (1986), which indicated that commodities are leading indicators of inflation, several attempts at forecasting inflation have been made with varying methods. But most of the existing studies have used methods that either focus on the centre or make projections over a short period of time. However, the advancement in computers has created a platform for new methods that can forecast based on the distributional quantiles of the series. One such method is the cross-quantilogram (CQ), proposed by Han et al. (2016) and developed from the quantilogram approach. The CQ is model-free and is able to measure the correlation between variables across distributional quantiles.

The quantilogram was first developed by Linton and Whang (2007) to evaluate the amount of predictability present in various portions of the distribution of a stationary time series. The quantilogram is based on the correlogram of "quantile hits." They used it to test the notion that a certain time series lacked the ability to be predicted in any one direction. To complete the test, you will need to compare the quantilogram to a pointwise confidence band. This is a good addition to the large body of research on judging predictability with signs or rank statistics, which includes the work of Cowles and Jones (1937), Dufour et al. (1998), and Christoffersen and Diebold (2002), among others.

When compared to other test statistics, the quantilogram has various advantages, particularly in terms of its directional predictability. It has an appealing conceptual structure and is simple to grasp the meaning of. Because the method is predicated on quantile hits, it does not call for moment conditions like the ordinary correlogram or statistics like the variance ratio that are derived from it, according to Mikosch and Starica (2000). As a result, the method is useful for analysing heavy-tailed series and performs particularly well in this context. As a result of the fact that most financial time series have heavy tails (see, for example, Mandelbrot, 1963; Fama, 1965; Embrechts et al., 1997; Rachev & Mittnik, 2000; Ibragimov et al., 2009; Ibragimov, 2009), this is an essential factor to take into account when applying theory to practise. In addition, in contrast to methods that are based on regression, such as Engle and Manganelli's (2004), this type of strategy enables researchers to take into consideration very lengthy lags.

The CQ can make a forecast over a long period of time due to its ability to include several lags. It must be pointed out that the original quantilogram was built for the univariate case, but CQ expanded it to multivariate situations, making it more appealing. Several applications of the CQ methods in finance are available, particularly in forecasting commodity prices and stock values (see Han et al., 2016; Bouri et al., 2018; Zhou et al., 2018; Shahzad et al., 2020). In Chapter 4, the CQ method is used to investigate the directional predictability and systemic risk between commodity prices and inflation in SSA commodity-exporting countries. By using this method, the study can capture the impact of extreme events on the relationship.

Time-Frequency Decomposition Methods

The thesis' second objective is estimating the information flow between CP and ER. To do that, this sub-section reviews the CEEMDAN method used to decompose the series into multiple frequencies, which is followed by a discussion of the transfer entropy in the next sub-section used to quantify the information flow. Usually, economic time series are frequently examined in the time domain. This method, however, does not provide any information about the frequency components of the studied time series. As a result, the distinction between low-frequency, medium-frequency, and high-frequency fluctuations in time is made in this study because transforming data to the frequency domain allows for better series analysis.

The HMH classifies traders based on their typical time horizons or dealing frequencies. Speculators and market makers are classified as high-frequency traders, while institutional investors and central banks are classified as low-frequency traders. Expectations, beliefs, risk profiles, informational sets, and many other factors differentiate these market participants. Market heterogeneity results in different dealing frequencies and, as a result, different reactions to the same news in the same market. Each market component has its own reaction time to the information, which is determined by its time horizon and dealing frequency (Dacorogna et al., 2001).

Traditional Fourier spectral analysis can be used to identify and quantify the various frequency components of a time series (for example, trends, cycles, seasonality, and noise). However, because it is based on a stationary assumption, it appears to be overly restrictive, as economic and financial time series are frequently subject to regime shifts, jumps, volatility clustering, outliers, or long-term trends. To address this issue, the short-time Fourier transform (STFT) (also known as the Gabor or windowed Fourier transform) was created. To estimate the frequencies, it divides the sample into subsamples and performs the Fourier transform on these subsamples over a time period (the window) less than the number of observations T. Many other suggestions for developing time-varying spectra were made (Priestley, 1965). The issue with the STFT is the correct window selection and its consistency over time.

The wavelet transform (WT) was then introduced to overcome the weaknesses seen in the STFT. The wavelet transforms, which derives from Fourier analysis, is unique in that its window is automatically adjusted to a high or low frequency, as it uses a short window for high frequency and a long window for low frequency by employing time compression or dilatation rather than frequency variation in the modulated signal. This is accomplished by dividing the time axis into successively smaller segments (Percival and Walden, 2000). The discrete wavelet transform (DWT) transforms a time series by dividing it into time domain segments known as "scales" or frequency "bands." The scales represent progressively higher, medium, and low-frequency fluctuations, from shortest to largest.

As a result, wavelets overcome the limitations of Fourier analysis because they combine information from both the time domain and the frequency domain, do not require stationariness, and allow for the extraction of the different frequencies. They, especially the continuous wavelet transform (CWT), can drive any macroeconomic variable in the time domain by decomposing it into time-scale components, each of which reflects the signal's evolution through time at a specific frequency. However, both the STFT and CWT have a significant flaw in that they smear the energy of the superimposed instantaneous frequencies around their centre frequencies (Daubechies and Maes, 1996). Barnes (1993) says that the spectral bandwidth is equal to the standard deviation around the main frequency.

To study non-linear and non-stationary signals, an adaptive method called Empirical Mode Decomposition (EMD) was developed (Huang et al., 1998). It consists of splitting a signal into rapid and slow oscillations in a local, data-driven manner. EMD is a fully data-driven method for dividing a signal into components known as IMFs (Huang et al., 1998). The signal is separated into high and low oscillatory components using recursive empirical operations (the sifting process; see Huang et al., 1998). The original signal is reproduced by the sum of all the individual components. However, due to signal intermittency, some mode mixing occurs in the classic EMD method, which can cause difficulties in interpreting the resulting time-frequency distribution (Huang et al., 1999, 2003). This realisation prompted the development of ensemble EMD (Wu & Huang, 2009), a noise-injection technique. Prior to decomposition, noise is introduced, and ensemble averages for the resulting IMFs are computed. This helps with independent mode separation but does not guarantee perfect reconstruction.

Despite the improvement in mode separation achieved with the noise-assisted technique, reconstruction from individual components is critical, and Torres et al. (2011) propose a simple solution in complete ensemble empirical mode decomposition (CEEMDAN). At each stage of the decomposition, an appropriate noise signal is added to the CEEMDAN, resulting in a unique signal residual for computing the next IMF (Torres et al., 2011; Han and Van der Baan, 2013). The desired time-frequency representation is then produced by computing the instantaneous frequencies for each IMF (Han and Van der Baan, 2013). Although the application of CEEMDAN to financial data is very recent, few empirical studies have shown its effectiveness. For instance, Owusu Junior et al. (2021) used CEEMDAN to decompose the series when they studied information flow from COVID-19 to global equity markets, and Asafo-Adjei et al. (2022) used it as a baseline decomposition in a study on global commodities and uncertainties.

Generally, the EMD-based alternative performs better than the STFT and WT when it comes to spectral resolution. A more detailed analysis of how CEEMDAN outperforms the EMD and EEMD can be found in Torres et al. (2011). In this study, the CEEMDAN method is used to decompose commodity prices and exchange rates before examining the strength of information from each frequency in Chapter 5.

Transfer Entropy Method

The mathematician Claude Shannon laid the foundations for current information theory and ergodic theory with his concept of the entropy of random variables and processes. In particular, ever since the publication of his seminal work "A Mathematical Theory of Communications" in 1948 (Shannon, 1948), it has been common knowledge that entropy is connected to the idea of uncertainty. As a result, higher Shannon entropy values result in greater uncertainty and, as a result, less predictable series behaviour. The idea has also been extended to non-stationary signals. It is found by monitoring the behaviour of entropy over time that the value of entropy corresponds to "the predictivity of signals" (Takizawa & Fukasawa, 1989). Along the entropy curves, as time goes on, the entropy value goes down and the predictability goes up.

Numerous studies around entropy-based analysis of financial markets have been written because of this idea. Darbellay and Wuertz (2000) provide evidence supporting the applicability of the entropy method for studying financial time series. Next, an empirical method, known as the approximation entropy (ApEn), is proposed by Pincus and Kalman (2004) to assess the entropy of a series. ApEn obtains the entropy estimation by tweaking the maximum entropy approach (or Kolmogorov–Sinai entropy), an exact regularity statistic. In particular, the authors use the approximation entropy method as a sign of the market's stability. Sharp rises could mean that a financial factor is about to change in a big way.

Foreign exchange (Oh et al., 2007) and stock market (Risso, 2008, 2009; Zunino et al., 2009; Gradojevic & Gencay, 2011) efficiencies have both been quantified using entropy, and it has also been used to shed light on the development of aggregate market expectations (Gençay & Gradojevic, 2010; Gradojevic & Gençay, 2008). Recently, entropy-based research has been applied to the study of energy commodity markets. For instance, Martina et al. (2011) provides an entropy study of crude oil price movements, while Ortiz-Cruz et al. (2012) explore the use of information entropy analysis to assess the efficacy of crude oil markets. Then, Kristoufek and Vosvrda (2014) talk about an ApEn-based market efficiency indicator and use it to look at different energy commodities.

A major drawback of Shannon entropy is that it is unable to assign equal weight to all possible realisations in a specific probability distribution. It is therefore not able to accommodate heavy tails, which are very common with financial and economic data, specifically price and returns. Renyi (1961) came in with Renyi's transfer entropy to deal with such weaknesses. Renyi entropy's capacity to give varying weights to events depending on their significance is a major selling point when applied to financial data. This is because the relative importance of different parts of the distribution is determined by the value of the parameter q (Adam, 2020; Behrendt et al., 2019). This thesis, therefore, employs Renyi’s transfer entropy in chapter five to quantify information flow between commodity prices and exchange. The novelty of the study is the application of transfer entropy to a decomposed series from CEEMDAN to quantify information flow in the frequency domain.

Measuring Connectedness in Time and Frequency Domain

The third objective of the study examined the contagion between commodity prices and inflation and, by extension, the connectedness among exchange rates in commodity-exporting countries in SSA. The study used Barunik and Krehlik's (2018) framework, known as BK18, to accomplish this in both the time and frequency domains.

Diebold and Yilmaz (2012) proposed a framework (also known as DY12) for measuring connectedness in the time domain. The DY12 calculates connectedness from generalised forecast error variance decompositions (GFEVDs), which are based on the matrix of vector autocorrelation (VAR) model of local covariance stationarity. Variance decompositions from a vector autoregression approximating model can be used to characterise system connectedness (Diebold & Yilmaz, 2012, 2009).

Variance decompositions reveal how much of the future uncertainty in the variable *i* is due to shocks in the variable *j*. The aggregation of information in variance decompositions for many variables can be used to measure how the system is interconnected. Diebold and Yilmaz (2014) argue that variance decompositions are also closely related to modern network theory and recently proposed measures of various types of systemic risk, such as expected shortfall (Acharya et al., 2017) and CoVaR (Adrian & Brunnermeier, 2016).

A major drawback of measuring connectedness in the time domain is, however, the aggregation of heterogeneous frequency responses to volatilities (Barunik & Krehlik, 2018). Since agents in the financial markets operate at different investment horizons, it is logical to incorporate the frequency dimension in line with HMH. Consider the spectral representation of variance decompositions based on frequency responses to shocks as a natural way to describe the frequency dynamics (long-term, medium-term, or short-term) of connectedness. Stiassny (1996) established the first concept of spectral representation for variance decompositions, albeit in a limited context. But Barunik and Krehlik (2018) used their framework to show how the general spectral representation of variance decompositions can be used to define frequency-dependent connectedness measures.

Variance decomposition spectral representations can also be viewed as a more general way of measuring causality in the frequency domain. Geweke (1982) proposes a frequency domain decomposition of the standard likelihood ratio test statistic for Granger causality, and Dufour and Renault (1998); Breitung and Candelon (2006); Yamada and Yanfeng (2014) provide a formal framework for testing causality at different frequencies. Geweke (1984) and Granger (1969) develop a multivariate extension, but all of the analysis is done with partial cross-spectra, leaving out the indirect causality chains. Because of this result, Barunik and Krehlik (2018) came up with a more general framework called BK18 to test connectedness and causality in the frequency domain. This was done to fix the problems with earlier frameworks.

The BK18 builds on the method of measuring connectedness introduced by Diebold and Yilmaz (2012) using generalised forecast error variance decompositions (GFEVD). This thesis followed the BK18 framework to measure connectedness in the frequency domain due to the advantages it has over other approaches. First, the BK18 possesses the strength to calculate in three ways: time domain, frequency domain, and time-frequency domains. The BK18 not only introduces the frequency dimension but is also able to examine the impact of cross-sectional correlation on connectedness. This is very significant because having a high contemporaneous correlation does not necessarily suggest a connection, but most of the existing literature has measured connections that way.

Chapter Summary

This chapter has described the methods, theoretical models and data employed in achieving the objectives of the study. The explanatory design with quantitative approach based on the positivist philosophy was adopted to achieve the three main objectives for the study. Secondly data for the study were sourced from World Bank primary commodity data base and IFS data base of IMF. To model the relationship between commodity prices and inflation to capture systemic risk, the cross-quantilogram method proposed by Han et al. (2016) was used. This method has been discussed in this chapter with emphasis on its ability to capture the quantile behaviour as the main motivation for it use. In modelling the multi-frequency information between commodity prices and exchange rate, the CEEMDAN method was used to decompose the series and followed up with Renyi's transfer entropy to capture information flow. The dynamic behaviour of different market was thus reflected in the results. Finally, contagion between commodity prices and exchange rate were specified using Barunik and Krehlik (BK18) framework. The subsequent three empirical chapters provide details of empirical estimation and the discussion of the results.

CHAPTER FOUR

INTERDEPENDENCE AND SYSTEMIC RISK BETWEEN COMMODITY PRICES AND INFLATION RATES IN SSA

Introduction

A primary concern for policymakers worldwide is inflation's risk or uncertainties. Inflation risk is important in the central bank's determination of appropriate monetary policies to implement, investors' decisions on the amount to invest, and even the nature of consumption and savings made by individuals and households (Zafar & Khan, 2022). Extant literature shows that stabilising inflation is key to bringing certainty to the business environment, heightening investment, making a country more competitive externally, and propelling the country for growth (Mavikela et al., 2019; Garratt & Petrella, 2021; Zafar & Khan, 2022; Tien, 2022).

Inflation forecasting and management are therefore at the heart of monetary policy decisions and the economic stability programme of policymakers. A primary strategy for forecasting the risk of inflation involves identifying the sources of such uncertainties and using them to predict inflation. Global commodity prices have been identified as the primary source of risk that presents volatilities from global economic activities to macroeconomic fundamentals, particularly inflation (Fernandez et al., 2017). However, employing the right method to model a formal link between commodity prices and inflation is hotly debated (Garratt & Petrella, 2021; Bao et al., 2007) and still an unanswered question in economics.

The overshooting theory originally proposed by Dornbusch (1976) and extended by Frankel (1986) has indicated that commodities and inflation move in the same direction. The theory argues that due to the flexible nature of the commodities markets, an increase in demand usually comes from an increase in money supply, which leads to commodity price jumps in the short term (Franke, 1986). But the prices of goods increase with a lag compared to commodity prices since the prices of goods in the goods markets are fixed in the short term (Franke, 1986). Again, commodities are inputs to manufactured goods, so an increase in commodity prices leads to high goods prices, which about inflation (Dornbusch, 2000). The overshooting theory thus indicates that commodity prices are a leading indicator or act as a signal for inflation.

While this relationship has received considerable attention, empirical evidence suggests that it has been shifting over the years and can change depending on a demand or supply shift for commodities (see, for instance, Kilian, 2009). For instance, it was stronger for the US economy in the early 1970s and 1980s but became weaker in the late 1990s and 2000s (see Whitt, 1988; Furlong, 1989; Blomberg & Harris, 1995; Kilian, 2009). This suggests that the relationship has to be studied from time to time and from country to country due to its non-static nature. However, studies that systematically investigate the mechanisms and dynamics of these two variables as systemic risk are scarce. Prior studies on systemic risk has focused on risk transmission from one institution to another within the same sector like banks (Black et al., 2016; Huang et al., 2017) and stock markets (Acharya et al., 2017) but not across different sectors.

Furthermore, many studies on commodity prices and inflation have relied on volatility or the return of the mean in interdependence and forecasting inflation (see, for instance, Kose, 2002; Neely & Rapach, 2011;

Gelos & Ustyugova, 2017; Fernandez et al., 2017; Knotekl & Zaman, 2017; Davarzani, 2022). The literature on dependence and forecasting based on quantiles is emerging but still scant. Prominent among them are Han et al. (2016), Bouri et al. (2018), and Scarcioffolo & Ettiene (2019). These studies either focused on stock markets or commodities without any emphasis on inflation. For instance, Jiang et al. (2016) focused on directional predictability among agricultural commodities of the US and Chinese markets; in Shafiulla et al. (2020), emphasis was on quantile causality between crude oil and metal commodities using quantile regression. Tiwari et al. (2019) capture systemic risk between crude oil and the BRICS exchange rate using quantile coherency and nonparametric generalised conditional value at risk (NGCoVaR) methods. As a result, studies on systemic risk and dependence on returns or volatility at various quantiles of commodity prices and inflation are scarce and desperately needed.

In developing countries like those in SSA, interdependence studies in quantiles about commodity prices and inflation to capture the impact of extreme events are almost non-existent. This is a gap that needs addressing as these countries suffer most from commodity price volatility given the high commodity dependence in SSA compared to the rest of the world. Specifically, 44.6% of commodity-dependent countries in the world were located in Africa, with over 80% of countries in SSA being classified as commodity-dependent from 2018 to 2019 (UNCTAD, 2021). A few exceptions are Chen et al. (2014), Tule et al. (2019), and Fasanya and Awodimila (2019), who explored the forecasting potential of commodity prices on inflation for selected countries in Africa. However, apart from these studies focusing on South Africa and Nigeria only, none of them provided information on the various quantiles. In addition, those studies could only provide a forecast for a short period since the methods used could not predict over a longer period. Accordingly, countries in this region need an improved approach to assess the systemic risk of inflation presented by commodity price changes and eventually assess the state of dependence between these variables to inform policy on economic stability measures and investor portfolio diversification strategies.

This study examines the dependence structure and systemic risk between commodity prices and inflation by departing from prior studies in a number of ways. First, the study comprehensively examines the predictability of inflation by looking at commodity prices at different quantiles rather than the mean. This is motivated by the need to understand and model the relationship between financial data like commodities at the extremes of the distribution due to the information such analysis carries. This has become necessary because of lessons from the various crises, including the Asian, Mexican, and Brazilian crises, the 2008 global financial crisis (GFC), and the recent COVID-19 pandemic, which has heightened the impact of extreme events on modelling financial data. Most of the previous studies have usually investigated mean-to-mean with some time variation using GARCH models with different dynamics. The correlation structure emanating from tail dependence is usually missing from such studies, making them incomplete.

Second, the study contributes to the empirical literature by presenting evidence from commodity export-dependent developing countries in SSA. Prior studies have mainly concentrated on developed and emerging economies that have proper systems in place to manage commodity price volatility as opposed to developing countries. However, available data show that Africa is more dependent on commodities than the rest of the world, with nine out of every ten SSA countries classified as commodity-dependent between 2013 and 2017 (UNCTAD, 2019). In doing so, the study makes use of the three most important commodities in their respective commodity categories in terms of revenue contribution to SSA economies. The use of specific commodities instead of a commodity index is to help avoid the situation where the individual effect is swallowed by the index, knowing that different countries produce and export different commodities. This study can tell a complete story about individual commodities in different countries in order to help them manage inflation more effectively.

Third, the study examines the dependency structure under different commodity market conditions, such as bearish (low quantile), normal (medium quantiles), and bullish (high quantile). This is achieved by applying the adaptive markets hypothesis to the study of African economies, which has not been done before the era of extreme occurrences. In line with the AMH, investors are likely to respond to emerging markets and the different market dynamics in a period of extreme events like the 2008 global financial crisis, especially in the search for an optimal portfolio, and as suggested by Lo (2004) through the AMH, varying events and structural changes result in the evolution of markets. This highlights the need to re-evaluate the function of traditional hedging instruments in the post-crises world of volatile markets. Using the AMH as a worldview, the interaction between commodities and inflation is looked at in a new way in the context of extreme events.

Fourth, this study simultaneously captures the relationship's magnitude, duration, and direction, which is very significant for hedging and portfolio diversification. This is made possible by using the cross-quantilogram (CQ) method proposed by Han et al. (2016). This is unique about CQ since an alternative method like quantile regression cannot do all three things at the same time. Again, instead of relying on pre-set quantiles, the cross-quantilogram allows for the selection of arbitrary quantiles. Additionally, this method makes room for utilising large lags, which are made possible by the stationary bootstrap method used to construct the critical values. In this process, the study provides evidence of systemic risk between commodity prices and inflation over a longer period due to large lags.

Theoretical Model and Empirical Methodology

This section goes over the theoretical and empirical models that were used in the chapter. The section describes the procedure used to calculate the dependence and directional predictability of inflation by commodity prices (crude oil, gold, and cocoa), as well as the systemic risk present in the relationship for various quantiles. The cross-quantilogram approach has been selected for the examination.

Cross-Quantilogram Method

The overshooting theory of commodities by Frankel (1986) has explained that the flexible nature of the commodities market makes commodities jump in value in the short-term, making it a leading indicator for inflation due to the sticky nature of the goods markets. However, the literature on financial markets has shown that different events call for different reactions by market participants because of the impact of such events, particularly the extreme ones, on commodities markets. Indeed, the impact that varying events have on the structure of the market can bring about evolution due to investors' reactions. The above lines of argument are the thinking behind the HMH and AMH. Accordingly, this study seeks to investigate the relationship between commodity prices and inflation with an emphasis on quantile distribution to capture the different events in the commodities markets using the cross-quantilogram method proposed by Han et al. (2016).

Over the past few decades, advancements in time series modelling have taken modelling in the lead-lag of cross-correlation, particularly in the multivariate case to a new level, moving away from the traditional reliance on the conditional mean. One such development was the extremogram developed by Davis et al. (2009, 2012, 2013) with an emphasis on tail events rather than the mean. The key focus of the extremogram was to detect correlation only at the extreme end of the quantile. Bollerslev et al. (2011, 2013) followed from there by incorporating jumps in their method of estimating lead-lag cross-correlation. All these methods were extensions of the quantilogram method introduced by Linton and Whang (2007).

The exploit of Linton and Whang (2007) to develop the quantilogram method was a major breakthrough in calculating cross-correlation at different quantiles after years of struggle by earlier researchers. The purpose of the quantilogram was to detect directional predictability at different quantiles of the distribution. The key assumption is that the time series must be stationary as it focuses on the "quantile hits" of the correlogram. The major weakness of the quantilogram approach was that it was limited to univariate cases. This is how Han et al. (2016) extended the quantilogram to the multivariate case using a method called the cross-quantilogram. The key advantage of the cross-quantilogram (CQ) is that it is more flexible and can simultaneously calculate the correlation between data series at different quantiles. The confidence interval created by CQ is generally valid for dependence structure and is based on conditional quantiles, enabling it to control for information during prediction (Han et al., 2016).

In this study, the cross-quantilogram (CQ) approach developed by Han et al. (2016) is employed in studying the link between commodity prices and inflation. Using the CQ method, the study also captures the quantile dependence between commodity prices and inflation and determines the directional predictability of inflation by commodity prices. In that way, the systemic risk present in the relationship can be determined. It is model-free when it is able to measure the correlation between variables. The advantage of the CQ method over many traditional approaches is that it is able to measure correlation across the quantiles of the distribution. Like many financial data points, commodity prices lend themselves well to the CQ method due to their large tails. The CQ method can capture information on different market conditions, like bearish, normal, and bullish, in line with HMH and AMH. By so doing, the study is able to capture the asymmetric dependence of the series used in the study. The key assumption that should be met for the CQ to be applied is that the series to be used must be stationary.

Let us define x_t and y_t as representing two underlying stationary series (in this case commodity price and inflation, respectively). If we follow the assumption that $x_t = (x_{1t}, x_{2t})^T \in \mathbb{R}^{d1} \times \mathbb{R}^{d2}$ and $y_t = (y_{1t}, y_{2t})^T \in \mathbb{R}^2$, then the conditional distribution will be given as $F_{yi|xi}(.|x_{it})$ and quantile function can be defined as $q_{it}(\alpha_i) = \inf[v: F_{(yi|xi)}(\text{v}|x_{it}) \geq \alpha_i$ for any $\alpha_i \in (0,1)$. Under the assumption above, the CQ of the various quantiles can be stated as

$$\rho_\alpha(k) = \frac{E[\psi_{\alpha_1}\left(y_{1,t} - q_{1,t}(\alpha_1)\right)\psi_{\alpha_2}\left(y_{2,t-k} - q_{2,t-k}(\alpha_2)\right)]}{\sqrt{E[\psi^2{}_{\alpha_1}\left(y_{1,t} - q_{1,t}(\alpha_1)\right)]}\sqrt{E[\psi^2{}_{\alpha_2}\left(y_{1,t-k} - q_{1,t-k}(\alpha_2)\right)]}} \quad (1)$$

For $k = 0, \pm1, \pm2, \ldots,$ where the indicator function is given by $\psi_a(u) \equiv 1[u < 0] - a, 1[.]$ with the quantile-hit process expressed as $1[y_{1,t} \leq q_i(\alpha_i)]$. Looking at equation 1, the CQ captures the serial dependence between two series for different quantiles. It is worthy of note that in a situation where the series is a single one, the CQ will be the same as the quantilogram proposed by Linton and Whang (2007). The simplified version of the CQ based on observations can be expressed as;

$$\hat{\rho}_\alpha(k) = \frac{\sum_{t=k+1}^{T}\psi_{\alpha_1}\left(y_{1,t} - \hat{q}(\alpha_1)\right)\psi_{\alpha_2}\left(y_{2,t-k} - \hat{q}_{2,t-k}(\alpha_2)\right)}{\sqrt{\sum_{t=k+1}^{T}\psi^2{}_{\alpha_1}\left(y_{1,t} - \hat{q}_{1,t}(\alpha_1)\right)}\sqrt{\sum_{t=k+1}^{T}\psi^2{}_{\alpha_2}\left(y_{1,t-k} - \hat{q}_{1,t-k}(\alpha_2)\right)}}, \quad (2)$$

for $k = 0, \pm1, \pm2, \ldots$. If there are given quantiles, the focus of the CQ will be to use the direction of deviation from quantiles to determine dependence which then helps in measuring directional predictability from one event to another. Equation 2 is a very useful mechanism for describing dependence. This can be achieved by creating, $\hat{\rho}_\alpha(k) \in [-1,1]$ with $\hat{\rho}_\alpha(k) = 0$ which signifies a situation of no directional predictability. Accordingly, if we have an l dimensional multivariate situation with an $(i,j)th$ entry having a corresponding cross-correlation matrices $\Gamma_{\bar{\alpha}}(k)$, equation 2 can be applied on a pair of variables $(y_{it,}\, x_{it})$ and $(y_{it,-k\,,}\, x_{it-k})$ with a pair of conditional quantiles given as $(\hat{q}_{i,t}(\alpha_i), \hat{q}_{j,t-k}(\alpha_j)))$ for $\bar{\alpha} = (\alpha_1, \ldots, \alpha_l)^T$ which obtain generalised statistics. In this case, the symmetric properties of $\Gamma_{\bar{\alpha}}(k) = \Gamma_{\bar{\alpha}}(-k)^T$ is exhibited by the cross-correlation matrices when $\alpha_1 = \cdots = \alpha_d$.

The focus of this study is to evaluate the conditional dependence/directional predictability which is done based on a null hypothesis of no conditional dependence or no directional predictability ($H_0: \rho_\alpha(1) = \cdots = \rho_\alpha(p) = 0$) with the alternative hypothesis being different from zero as follows ($H_1: \rho_\alpha(k) \neq 0$, for $k \in \{1, \ldots, p\}$). This test can be done up to p lags $\{y_{2,t-k} \leq q_{2,t-k}(\alpha_1): k = 1, \ldots, p\}$ for $\{y_{1,t} \leq q_{1,t}(\alpha_1)\}$. Han et al (2016) have proposed that in conducting this test, it is ideal to use the Box-Ljung test for statistical inference which is expressed as follows;

$$\hat{Q}_\alpha(p) = T(T+2)\sum_{k=1}^{p}\frac{\hat{\rho}^2(k)}{T-k} \tag{3}$$

Following the suggestion of Han et al. (2016), the stationary bootstrap (SB) of Politis and Romano (1994) is utilised to determine confidence intervals. The benefits of this method is that it is able to account for any potential misspecification with the no directional predictability null hypothesis and, at the same time, secure the stationary property of each event based on the bootstrapping process for each series.

Data and Preliminary Analysis

This study relied on 29 years of monthly data, from January 1990 to December 2019. The sample period covers many of the reforms embarked on in SSA in the 1990s, the 2008 global financial crisis, the Ebola virus epidemic in west Africa from 2013 to 2015, the commodity terms of trade shock in 2014, the collapse of oil, gold, and cocoa prices between 2016 and 2017, and other extreme events that led to several countries in SSA accumulating more debt. The World Bank has grouped commodities into three categories: energy/fuel, metal, and agricultural, which usually have two categories (food and beverage and raw materials). To this study, a commodity was selected from the first three classifications. The focus was to consider the most important commodity in each category with the biggest impact on the sub-region. This is mainly based on the biggest revenue contribution and active trading activities on the international markets. Accordingly, crude oil, gold, and cocoa were selected from energy, metal, and agriculture, respectively. The commodity prices were sourced from the World Bank's Commodity Price Pink Sheet.

The consumer price index (CPI) for each country was used as a measure of inflation. Inflation represents a measure of changes in the price level of the country's consumer price index (CPI). These series were collected for each country included in the study from the International Financial Statistics (IFS) database of the IMF. In all, fourteen countries that produce and export agricultural commodities, ten metal-producing countries, and ten fuel-producing countries in Sub-Saharan Africa (SSA) were selected. The emphasis on countries that rely on exports is driven by the pivotal role that revenue from commodity exports plays in these economies. First, the amount of revenue received by these countries has implications for the currency exchange rate due to the conversion between the US dollar, which is the main currency of global commodity trading, and the local currency (Benassy-Quere et al., 2020). Next, the amount of revenue from commodity exports can also swing demand and supply conditions in these countries in different directions, which has implications for the prices of goods and hence inflation. We focused on the classification of UNCTAD (2019–2021) for the selection of the countries.

A country is classified as fuel or energy dependent if at least 60% of its merchandise exports are energy commodities; similarly, metal and agriculture dependents. Few countries appear in more than one group due to their level of production in the commodities studied. Ghana, for instance, is in all the groups because they are among the top five producing countries of cocoa, gold, and crude oil in SSA. All prices and series were closing prices, and their log returns were used. The use of returns for prices in in this thesis was to reduce the challenges associated with non-stationarity, heteroscedasticity, autocorrelation, and other such factors which is associated using price directly (Han et al., 2016). These factors have the capacity to complicate the interpretation and analysis of the collected data. Moreover, returns are frequently favoured because they reflect the actual performance of an asset or investment by considering capital gains in addition to income from dividends or interest (Moreira, 2014). The log returns of commodity prices and inflation were calculated as the log difference as $r_t = \mathrm{lo}_{t+1}) - \log(P_t)$ where r_t represent return from time t to time $t+1$, P_t and P_{t+1} represent price observation at time t and time $t+1$, respectively.

Table 1: Summary statistics and test of stationarity

Country	Obs[a].	mean	SD	skewness	Kurtosis[b]	SW	ADF***	PP***
Inflation for commodity-producing countries								
Comoros	359	0.001	0.032	6.044	76.385	0.687***	-12.502	-16.228
C. d'Ivoire	359	0.003	0.010	2.544	15.099	0.812***	-10.106	-13.063
Eswatini	359	0.006	0.02	1.572	43.789	0.440***	-17.780	-27.858
Ethiopia	359	0.008	0.021	0.689	3.844	0.940***	-10.070	-12.816
Gambia	359	0.005	0.009	0.465	7.073	0.819***	-11.488	-16.960
Kenya	359	0.009	0.016	2.359	10.438	0.808***	-9.892	-14.056
Madagascar	359	0.009	0.016	0.993	12.303	0.801***	-12.225	-12.291
Malawi	359	0.015	0.032	0.298	0.371	0.990**	-8.137	-11.629
Mauritius	359	0.004	0.008	0.932	4.411	0.903***	-11.784	-16.697
Seychelles	359	0.003	0.018	2.034	86.290	0.445***	-11.727	-15.756
Uganda	359	0.005	0.012	1.777	11.656	0.892***	-11.632	-13.133
Angola	359	0.030	0.064	5.479	42.727	0.474***	-8.6186	-11.178
Cameroon	359	0.003	0.010	3.787	30.795	0.731***	-9.9101	-12.635
Chad	359	0.003	0.027	0.109	7.552	0.910***	-11.482	-15.360
Congo	359	0.027	0.090	2.904	19.226	0.528***	-9.059	-18.334
E. Guinea	359	0.004	0.029	1.276	12.200	0.700***	-16.188	-23.478
Gabon	359	0.002	0.014	2.544	21.863	0.783***	-10.828	-15.211
Mauritania	359	0.004	0.010	2.688	27.994	0.763***	-13.041	-19.578
Niger	359	0.002	0.018	1.848	14.114	0.868***	-11.368	-13.640
Nigeria	359	0.013	0.019	1.033	2.541	0.908***	-8.526	-11.782
Botswana	359	0.006	0.005	1.001	2.729	0.928***	-11.318	-16.260
Burundi	359	0.008	0.021	1.387	7.041	0.916***	-13.228	-19.797
DRC	359	0.003	0.021	2.242	14.579	0.826***	-13.193	-19.073
Mali	359	0.001	0.012	0.071	0.501	0.994	-8.651	-10.250
Ghana	359	0.014	0.016	1.268	6.803	0.924***	-13.041	-19.578
Rwanda	359	0.006	0.013	0.659	2.528	0.959***	-11.649	-11.665
S. Africa	359	0.005	0.005	0.630	1.260	0.969***	-9.4975	-13.657
Tanzania	359	0.007	0.019	5.130	47.427	0.655***	-8.9034	-13.001
Zambia	359	0.020	0.027	2.607	8.449	0.713***	-6.906	-9.454
Commodity price returns								
Oil returns	359	0.002	0.085	-0.321	4.690	0.939***	-11.664	-13.981
Gold return	359	0.001	0.043	-0.015	3.009	0.951***	-14.446	-17.068
Cocoa returns	359	0.002	0.059	0.097	0.843	0.993*	-12.598	-16.225

*Note: [a] = observations; [b] = excess kurtosis; *** $p < 0.01$, * $p < 0.1$; SD = standard deviation; SW = normality test. The ADF and PP tests include both intercept and trend.*

Source: Field Data (2023)

Descriptive Statistics

The plots of the log-return series and summary statistics of the data used for the study are shown in Figure 15 (Appendix A) and Table 1, respectively. The log-return plots exhibit varied fluctuations, but the fluctuations cluster, which is consistent and common to financial time series like commodity prices. With respect to the summary statistics, the Shapiro-Wilk test rejected the assumption of normality for all variables except Mali's inflation, indicating a situation of non-normality of the series common with financial data.

Commodity prices and inflation skewness figures for numerous nations were both positive. This means that over the period of the study, increases recorded in inflation and commodity returns exceeded the decreases, which confirms the non-normality of the data. There is also evidence of leptokurtic behaviour in the data based on the excess kurtosis results. The suggestion is that returns on commodities and inflation are heavy-tailed, which is very suitable for the method of analysis in this study. Finally, a stationarity test was conducted using the Augmented Dickey-Fuller (ADF) and Philip-Perron (PP) tests. At 1% significant level, all the log-return series were stationary, making them convenient for the cross-quantilogram analysis.

Estimation Results

This section discusses the results of the estimation, along two themes, dependence and systemic risk. The first section examines the dependence of inflation on commodity prices and, in the process, assesses the predictability of inflation through the lens of commodity prices. The second section discusses the estimation results of systemic risk in commodity prices and inflation. The estimation results all followed the cross-quantilogram by Han et al. (2016).

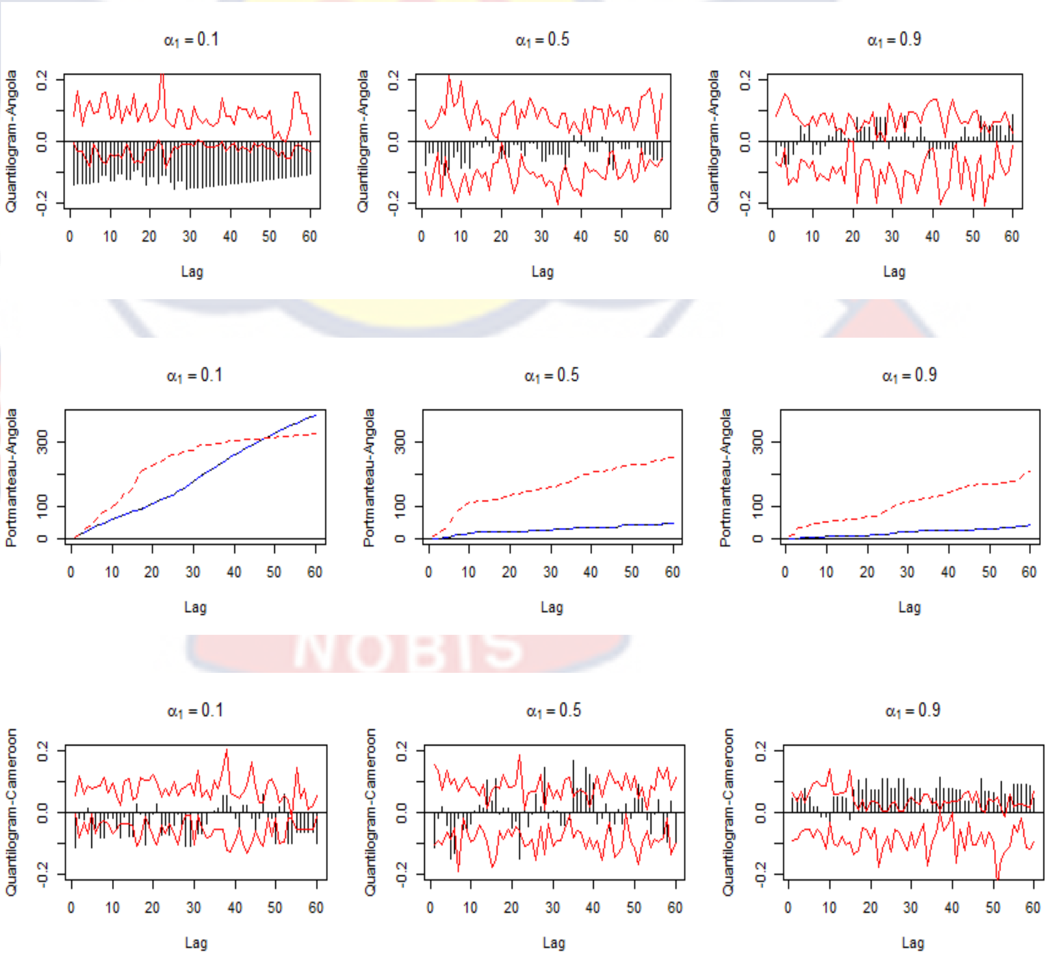
Dependence of Inflation on Commodity Prices

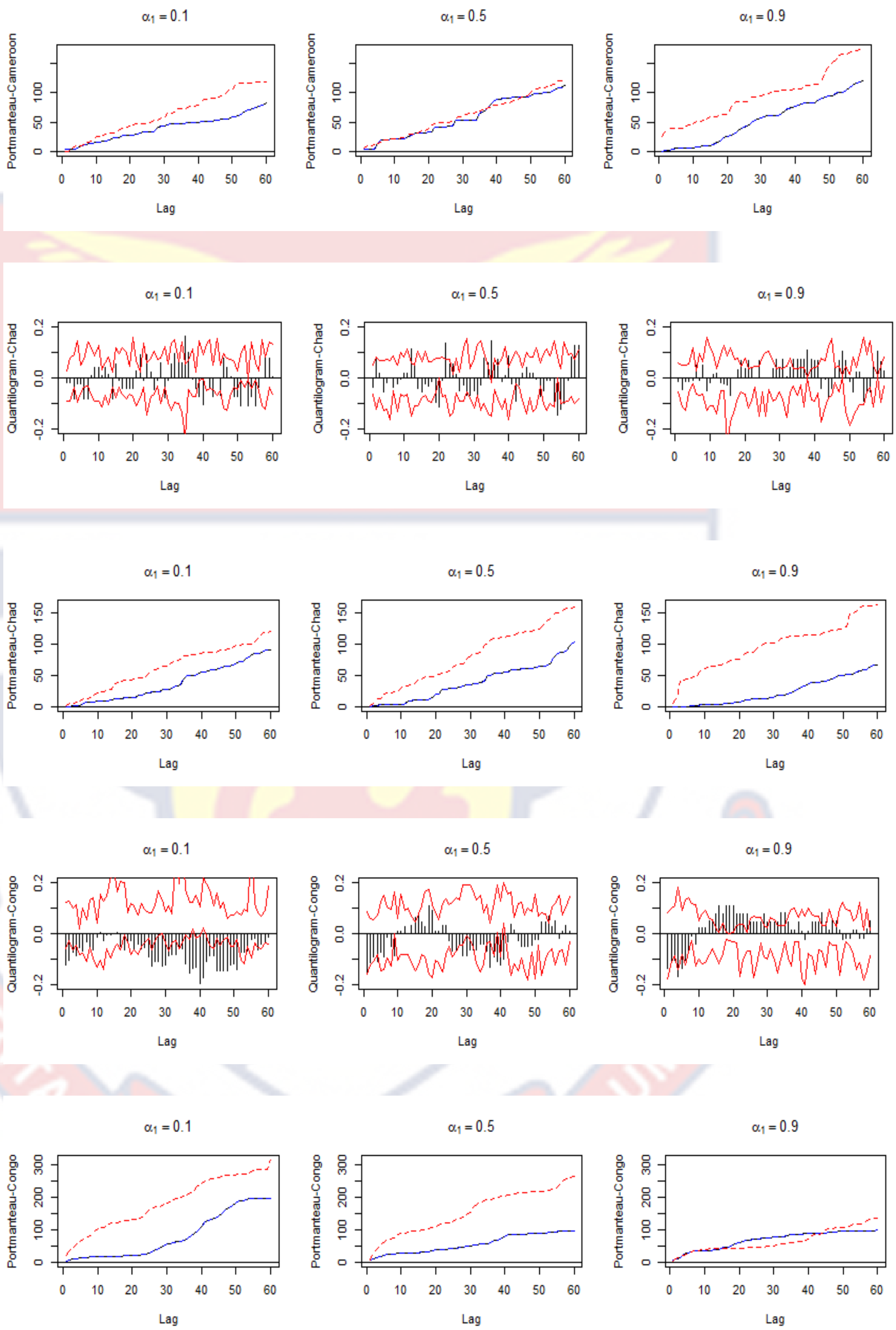
To examine the nature of the dependence of inflation on commodity prices, the cross-quantilogram $\hat{\rho}_\alpha(k)$ by Han et al. (2016) has been followed to undertake the analysis. Both the cross-quantilogram and the Box-Ljung statistics test have been provided for each country.

The goal is to investigate the situation for inflation at different quantiles, so 0.1, 0.5, and 0.9 have been selected for the low quantile, medium quantile, and high quantile, respectively, $q_1(\alpha_1)$ in line with the empirical literature. Evidence from empirical studies shows that quantile 0.1 reflects general activities at the lower quantiles (bearish conditions), while quantile 0.9 exhibits most of the activities at the upper quantiles (bullish conditions), with general activities at the medium quantile (normal conditions) demonstrating in quantile 0.5 (see Jiang et al. 2016; Bouri et al. 2018). In the case of commodity price returns, the focus is when they are in the low and high quantiles, corresponding to 0.1 and 0.9, respectively for $q_2(\alpha_2)$. For each country, the upper diagram represents cross-quantilogram results, while the lower graph represents the Box-Ljung test of statistics. The 95% bootstrap confidence interval with 1000 bootstrapped replicates is used to show no directional predictability in both graphs. The number of lags is set at $k = 60$, representing a five-year window of analysis. Lags 1–12 represent short-term, 13–36 represent medium-term horizons, and 37–60 show a long-term trend. To be significant, the bar graphs must cross the red line or the blue line must be above the red dash line. The red lines (including red dash) represents 95% bootstrap confidence interval.

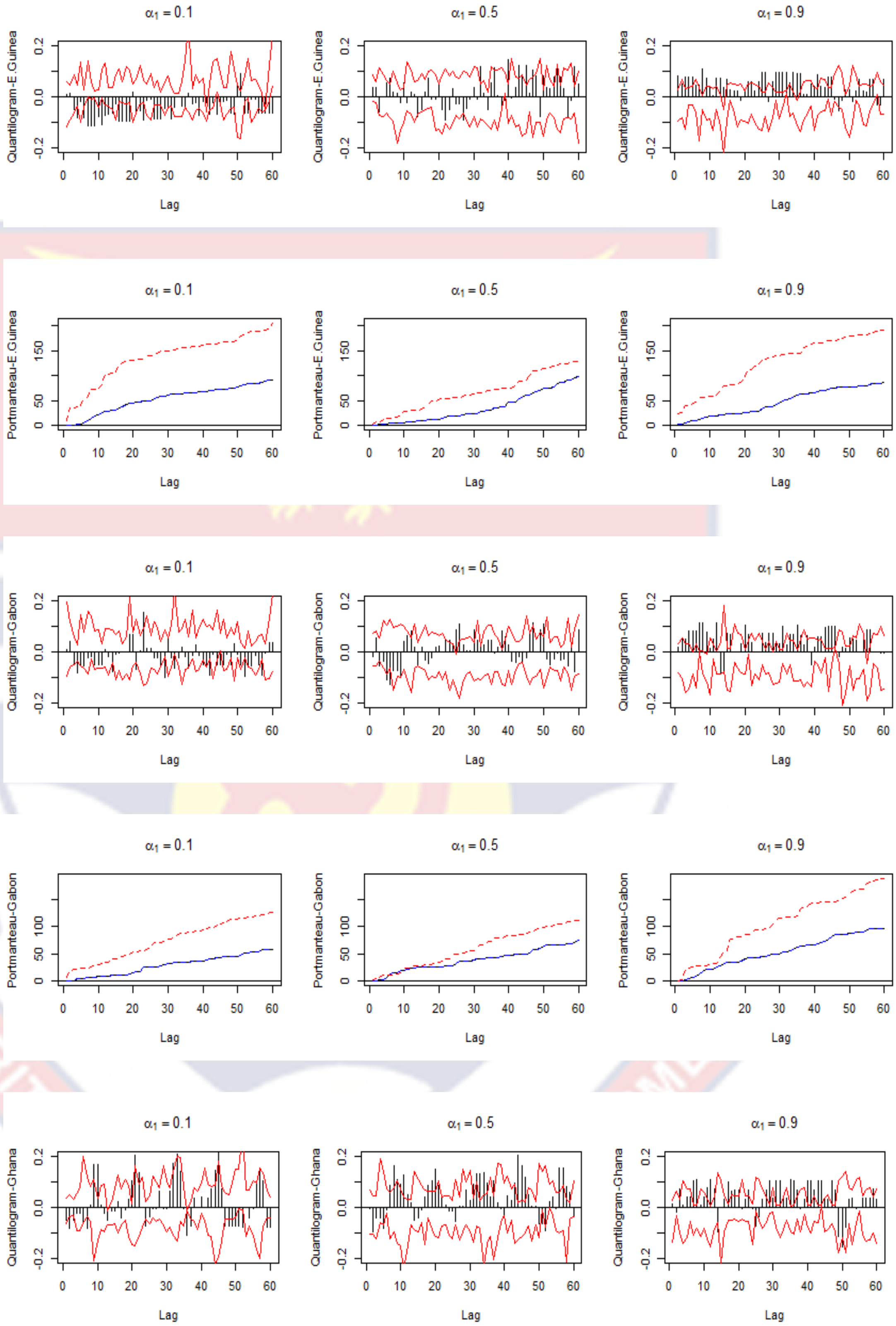
The dependence of inflation on crude oil price

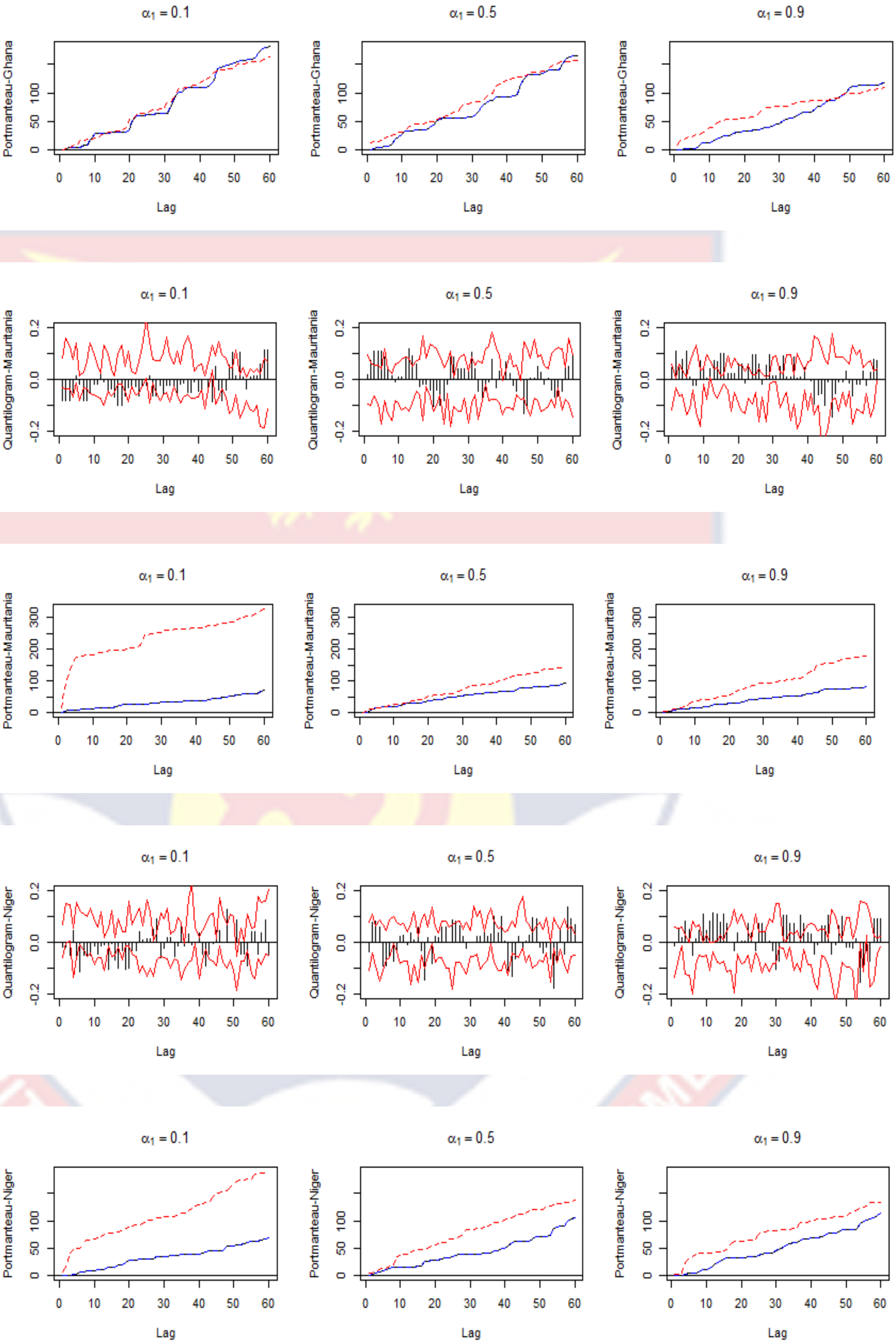
In Figures 1 and 16, the thesis demonstrates the interaction between crude oil price and inflation for energy-exporting countries (EEC) in sub-Saharan Africa (SSA). Ten energy-exporting countries were included, and the results for the low quantile of crude oil $[q_2(\alpha_2) = 0.1]$ are presented in Figure 1. Figure 16 (Appendix B) depicts the results for the high quantile $[q_2(\alpha_2) = 0.9]$ of crude oil. The results for the low quantile of crude oil price $(\alpha_2 = 0.1)$ show more significant negatives for many lags at the low quantile of inflation and more significant positives for many lags at the high quantile of inflation for many countries.





$\alpha_1 = 0.1$
$\alpha_1 = 0.5$
$\alpha_1 = 0.9$
Portmanteau-Cameroon
Quantilogram-Chad
Portmanteau-Chad
Quantilogram-Congo
Portmanteau-Congo
Lag


α1 = 0.1
α1 = 0.5
α1 = 0.9
Quantilogram-E.Guinea
Portmanteau-E.Guinea
Quantilogram-Gabon
Portmanteau-Gabon
Quantilogram-Ghana
Lag


$\alpha_1 = 0.1$
$\alpha_1 = 0.5$
$\alpha_1 = 0.9$
Portmanteau-Ghana
Quantilogram-Mauritania
Portmanteau-Mauritania
Quantilogram-Niger
Portmanteau-Niger
Lag

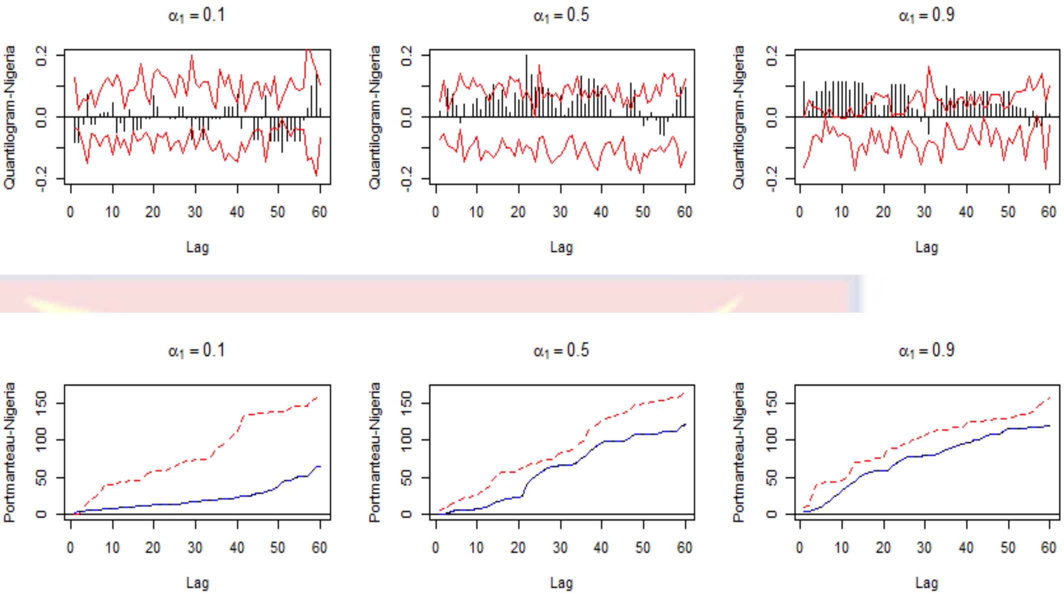


Figure 1: Sample cross-quantilogram from crude oil returns to inflation with $\boldsymbol{\alpha_2 = 0.1}$ and $\boldsymbol{\alpha_1 = 0.1, 0.5, and\ 0.9}$.

Note: *The first diagram for each country represents the cross-quantilogram where the bar graph describes the sample cross-quantilogram. The red line/red dashed lines are the 95% bootstrapped confidence interval with 1000 replicates. For each country, the second diagram is the Box-Ljung test statistics. Lag k = 60 representing a 5-year window.*

Source: Field Data (2023)

Specifically, the results of the cross-quantilogram for Angola show that the cross-quantilogram from oil price to inflation is significant and negative at the low quantile ($\alpha_1 = 0.1$). This means that when risk in crude oil price is low, it is less likely that inflation in Angola will also record very large negative changes throughout the five-year window. On the flip side, at $\alpha_1 = 0.9$ more positive lags are recorded, but few are significant. This suggests that when risk in return on crude oil is low, it is less likely that inflation in Angola will be high. The results at the medium quantile of inflation are mainly insignificant, meaning that at the lower quantile of crude oil changes, predicting whether inflation is located below or above the median is practically not helpful. The Box-Ljung statistics for Angola are insignificant at the medium and upper quantiles of inflation but partially significant at the lower quantile, suggesting that the oil price is only helpful in predicting inflation at the lower quantile, especially in the long term. The findings for Angola on the dependence of inflation on the crude oil returns are consistent with Garratt & Petrella (2021) whose findings show the importance of the tail behaviour of commodity prices in predicting inflation. The practical implication is that bearish market conditions in the crude oil market reduce revenue inflow into Angola, which affects demand for goods, leading to lower inflation, consistent with empirical evidence (Garratt & Petrella, 2021).

On the other hand, the result in Figure 16 (see Appendix B) shows the situation where crude oil returns are in the high quantile ($\alpha_2 = 0.9$). The results for dependence in Angola are mainly positive and significant at $\alpha_1 = 0.1$, but produce a mixed pattern at $\alpha_1 = 0.9$, with a more positive and significant predictability in the short-term and a more significant negative relationship in the long-term. The results suggest that when risk in crude oil price is high (higher than 0.9 quantiles), there is more likelihood of recording large positive changes in inflation in Angola at the lower quantile. However, at the high quantile of inflation, the possibility of recording large positive changes in inflation is only likely in the short term, particularly in the first, third, and sixth months, but large negative changes will be recorded in the long term. The results on the high quantile of crude oil returns are consistent with those of Mukhtarov et al. (2019), who obtained similar results for crude oil and inflation. The practical implication here is that bullish market conditions in the crude oil market, which is riskier, present more revenue to Angola, leading to higher demand for goods and high inflation in the country. Here also, the results of the portmanteau test (Box-Ljung test) indicate that the oil price is only good at predicting inflation when inflation is in the lower quantile.

With respect to other countries, similar results are recorded at the low quantile of crude oil returns ($\alpha_2 = 0.1$) albeit with more long-lived significant positive predictability recorded at the high quantile of inflation ($\alpha_1 = 0.9$). Nigeria, a leading producer of crude oil in Sub-Saharan Africa, however, presents a little different scenario from that of Angola. In the case of Nigeria, when crude oil returns are in the low quantile, that is ($\alpha_2 = 0.1$), an inconsistent pattern in terms of the direction of the linkage is revealed at the low quantile ($\alpha_1 = 0.1$). Negative predictability is recorded in the first two months and drops after that. The directional predictability of inflation is predominantly positive at high quantiles ($\alpha_2 = 0.9$), with many significant lags. The findings imply that when there is a high level of risk in crude oil price, inflation is less likely to experience two-month large negative changes, followed by an inconsistent outcome at the low quantile. However, at the high quantile of inflation, more positive changes will be recorded in response to changes in crude oil price than at the low quantile ($\alpha_2 = 0.1$).

Contrary to what happens at the low quantile of crude oil return, a more consistent pattern in terms of direction is observed at the high quantile of crude oil return ($\alpha_2 = 0.9$). While crude oil has a higher degree of influence at $\alpha_1 = 0.1$, the opposite is true for inflation at $\alpha_1 = 0.9$. The findings suggest that when risk in crude oil return is high, inflation at the lower quantile is more likely to record more positive figures, albeit less significant, changes, whereas inflation at the high quantile is more likely to record more negative significant changes or low inflation. The results of the Nigeria portmanteau test show that the crude oil price is only useful for predicting inflation in the short- to medium-term when both the oil price and inflation are in the high quantile.

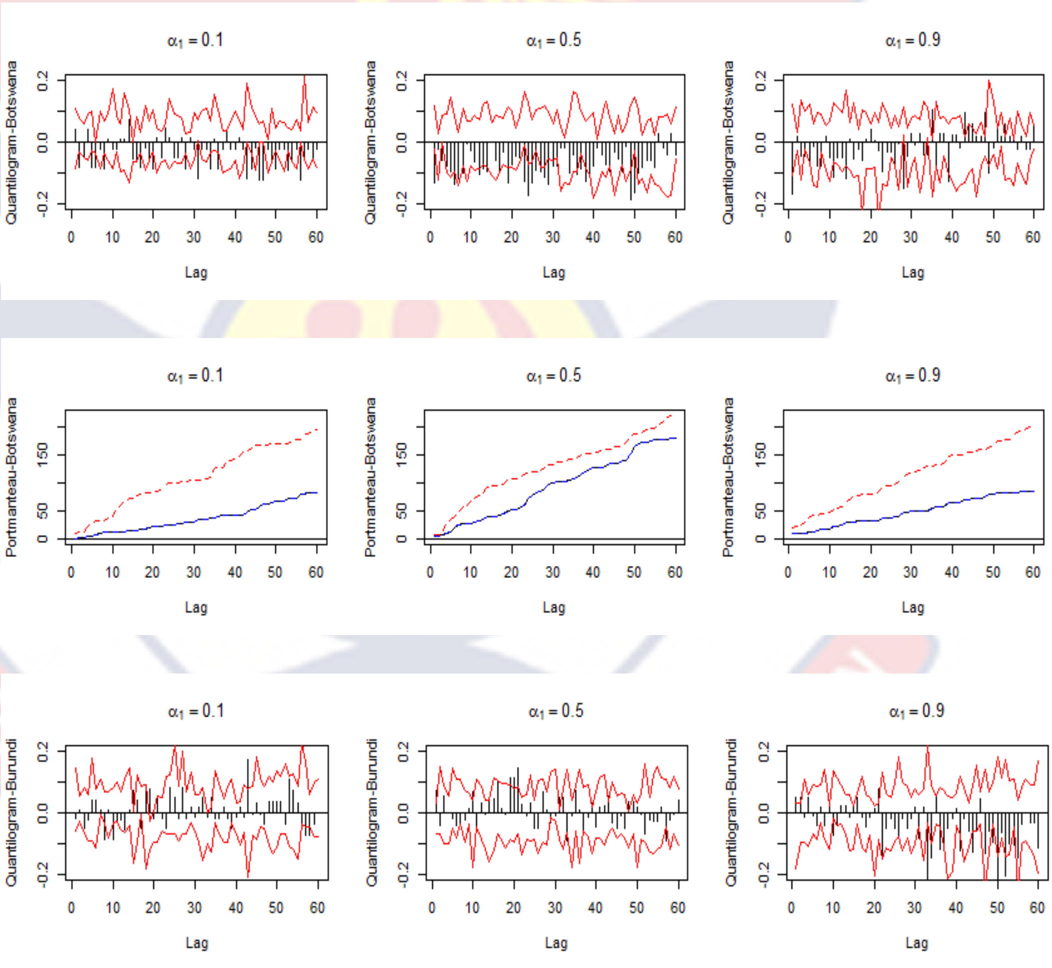
The study also observed a number of intriguing findings from the results in Figures 1 and 16. First, it is observed that the return on crude oil is stronger at influencing inflation when inflation is at the low or high quantile but weak at the medium quantile. The results show that some level of prediction flows to inflation at the medium quantiles for some countries, but this occurs for only a few lags. This is in line with Tien's (2022) findings that the relationship between oil price and macroeconomic fundamentals is stronger at the tail because extreme events drive many decisions. Second, for the two leading crude oil producers in SSA (Nigeria and Angola), there is a contrasting relationship between the oil price and inflation. While crude oil has a strong and consistent influence on inflation in Angola's low quantile, it has a stronger and more consistent influence in Nigeria's high quantile. This means that, no matter what the market condition is (bearish, normal, or bullish), it will be easier for decision-makers in Nigeria to predict their inflation with crude oil when their economy is experiencing a booming situation. The opposite is true for Angola.

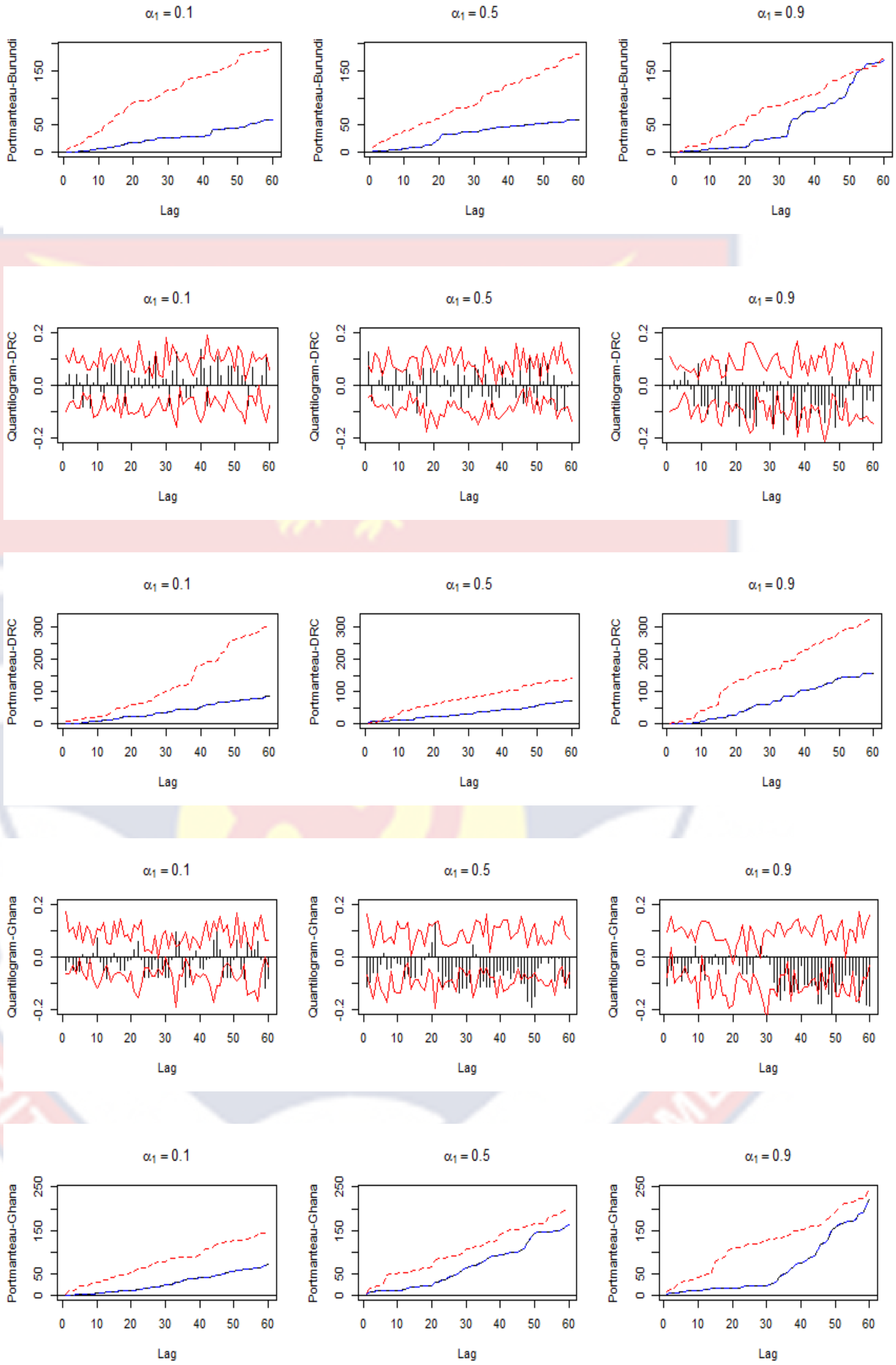
The dependence of inflation on gold price

Having dealt with the situation with crude oil prices, we now focus on the dependence of inflation on the prices of gold, with an emphasis on countries that produce and export metal commodities. The results are presented in Figures 2 and 17. For the study, ten SSA countries with a high reliance on metal commodities for export revenue were considered. These countries are Botswana, Burundi, the Democratic Republic of Congo, Ghana, Mali, Mauritania, Rwanda, South Africa, Tanzania, and Zambia. The results on inflation show a more negative correlation at the low quantile than at the high quantile for many countries.

Concentrating on the two leading producers of gold in SSA (South Africa and Ghana), similar outcomes are observed. When gold returns are at the low quantile ($\alpha_2 = 0.1$), there is predominantly negative predictability from gold returns to inflation across all quantiles, low (0.1), medium (0.5), and high (0.9), albeit with limited significant lags. For example, at the low quantile of inflation, gold price significantly predict inflation in the first and third months, but then decline until the tenth month. But at the high quantile of inflation, gold price influence inflation in the first month, a drop until the fourth month, and continued growth for the next six months. The middle quantile of inflation follows the same pattern as the high and low levels.

The situation in Ghana is very similar to that of South Africa, except that at the low quantile of inflation, significant influence happens in the 12th month and drops until a year later (at lag 24). The result suggests a negative dependence between gold price and inflation in South Africa and Ghana, which contradicts the findings of Lucey et al. (2016), who obtained positive co-integration for three developed countries. The findings of the sample cross-quantilogram are however, not supported by the Box-Ljung test statistics for each country since they are insignificant at all quantiles. The implication is that, gold price is not helpful in predicting inflation in Ghana and South Africa. At the low and high quantiles of inflation, the results for countries like Botswana, Rwanda, Tanzania, and Zambia are very similar to the leading producing countries of gold. Mali and Mauritania have the opposite outcome at the low quantile of inflation, as there is positive cross-quantilogram from gold price to their inflation. Burundi and the DRC are the two countries whose inflation receives the most inconsistent cross-quantilogram from gold prices, especially at the low quantile of inflation. Here too, the results for Mali and the DRC follow a very inconsistent pattern, making forecasting more complex and indicating a sign of asymmetry and dependence in the relationship. Zambia is the only country with a significant result from the Box-Ljung test statistics at the medium and high quantiles of inflation.

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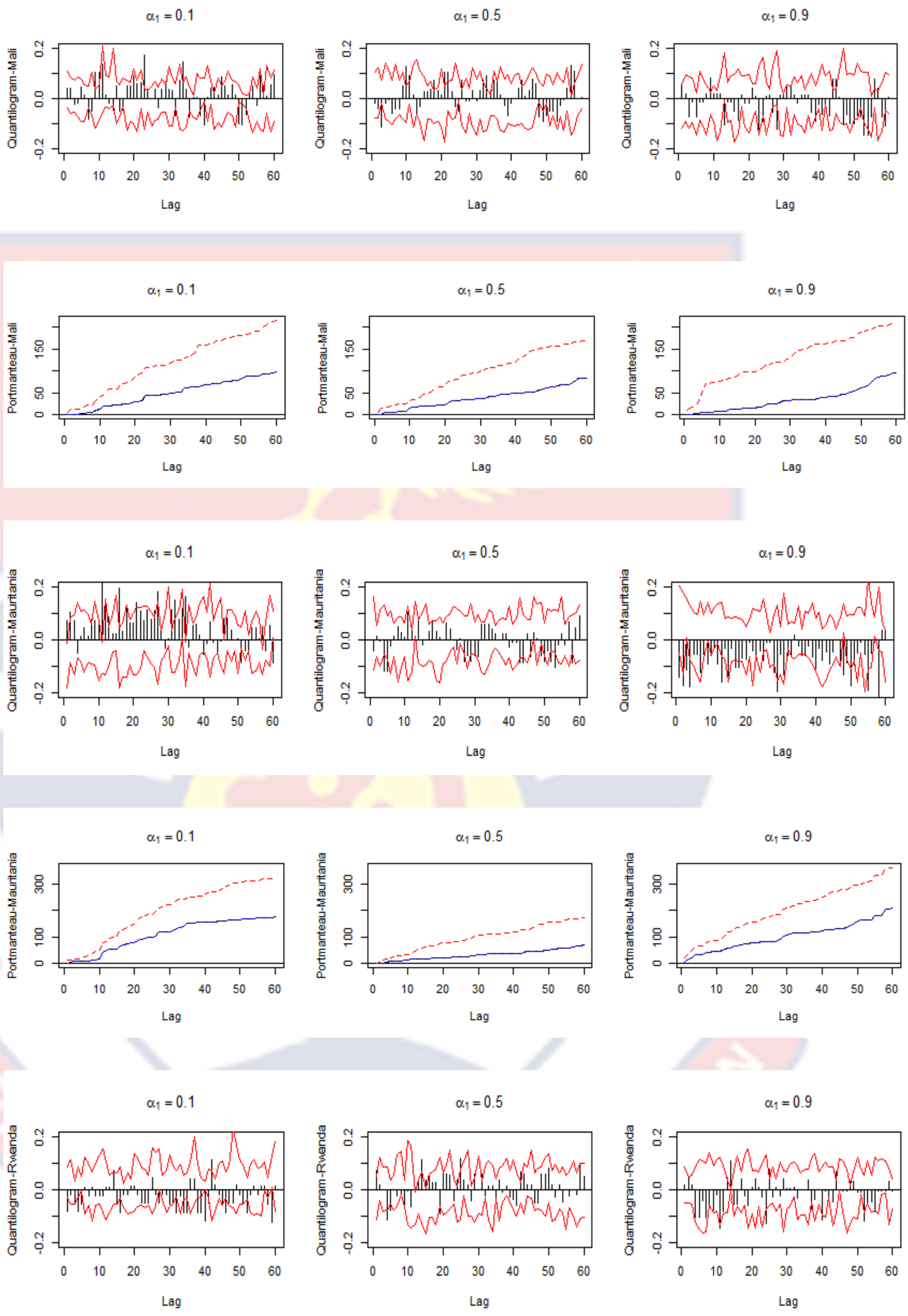
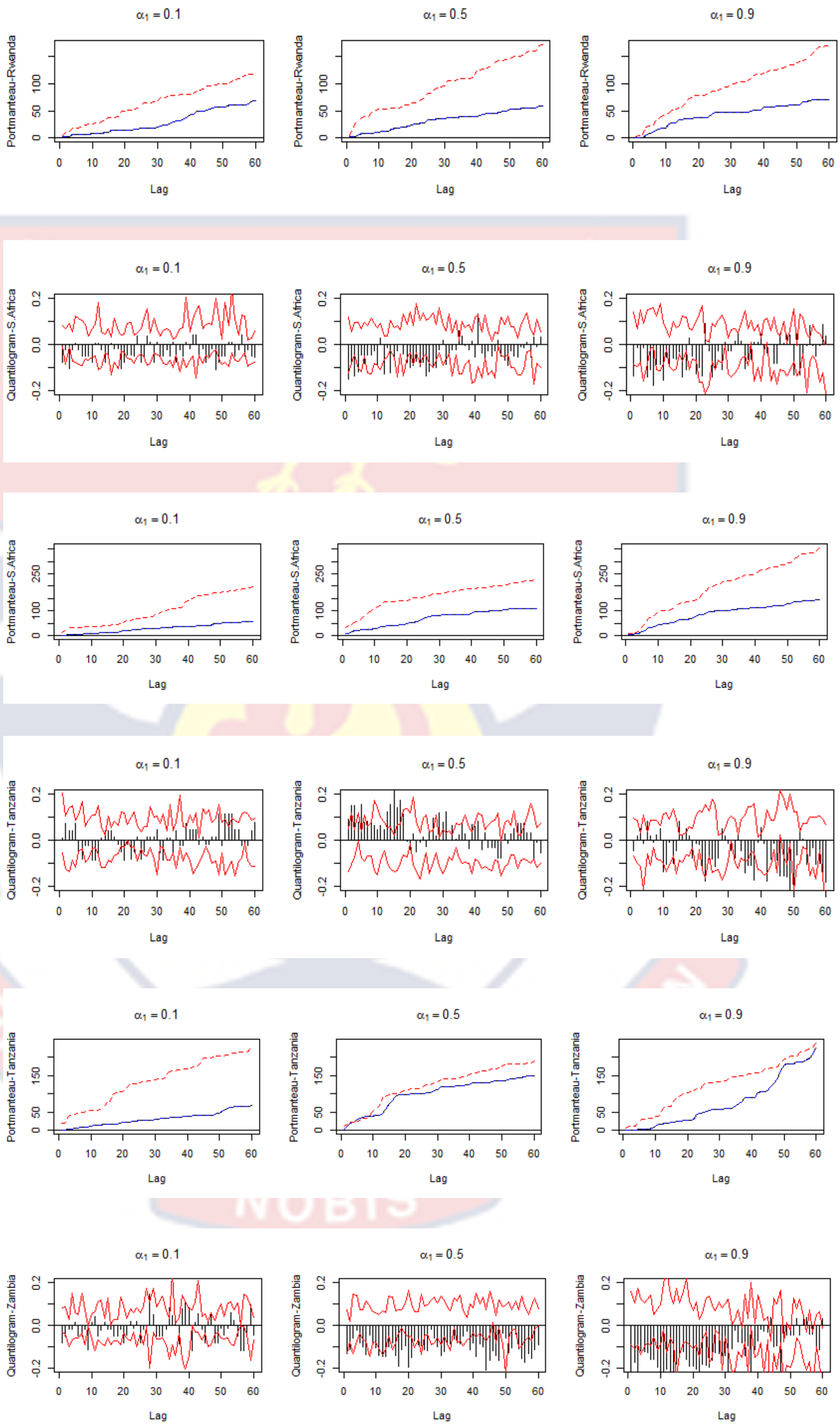
$\alpha_1 = 0.5$
$\alpha_1 = 0.9$
Portmanteau-Burundi
Quantilogram-DRC
Portmanteau-DRC
Quantilogram-Ghana
Portmanteau-Ghana
Lag


$\alpha_1 = 0.1$
$\alpha_1 = 0.5$
$\alpha_1 = 0.9$
Quantilogram-Mali
Portmanteau-Mali
Quantilogram-Mauritania
Portmanteau-Mauritania
Quantilogram-Rwanda
Lag



$\alpha_1 = 0.1$
$\alpha_1 = 0.5$
$\alpha_1 = 0.9$
Portmanteau-Rwanda
Quantilogram-S.Africa
Portmanteau-S.Africa
Quantilogram-Tanzania
Portmanteau-Tanzania
Quantilogram-Zambia
Lag

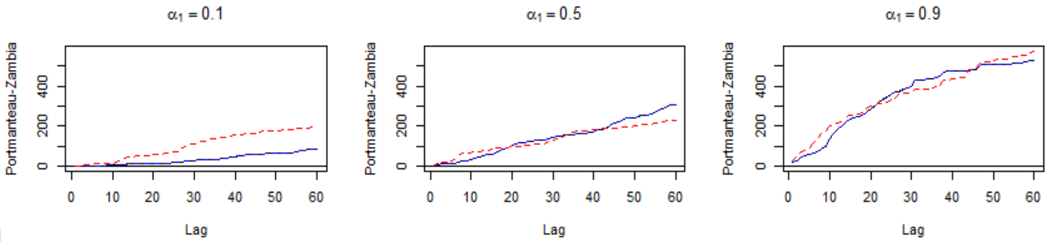


Figure 2: Sample cross-quantilogram from gold returns to inflation with $\boldsymbol{\alpha_2 = 0.1}$ and $\boldsymbol{\alpha_1 = 0.1, 0.5, and\ 0.9}$.

Note: *The first diagram for each country represents the cross-quantilogram where the bar graph describes the sample cross-quantilogram The red line/red dashed lines are the 95% bootstrapped confidence interval with 1000 replicates. For each country, the second diagram is the Box-Ljung test statistics. Lag k = 60 representing a 5-year window.*

Source: Field Data (2023)

Turning the attention to relationship at the high quantile of gold price ($\alpha_2 = 0.9$), the results are displayed in Figure 17 (Appendix B). The findings show that gold price are positively related to inflation in Ghana and South Africa. This indicates that when changes in gold returns are high and positive, it is more likely that changes in inflation will also record high and positive changes in the two countries. This study finds evidence to support the impact of gold on inflation, in line with existing studies (see Erb & Harvey, 2013; Soni & Parashar, 2015; Rao & Guyal, 2018). Rwanda and Zambia exhibit similar outcomes to Ghana and South Africa.

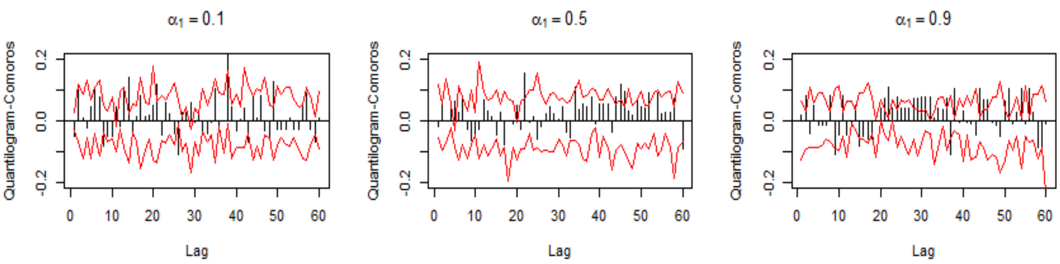
One significant observation is the fact that the relationship is stronger at the high quantile of inflation than at the low quantile, as the absolute figures are relatively higher at the high quantile. For instance, in the case of Ghana, the highest absolute figure is just above 0.1 at the lower quantile, while at the upper quantile, the highest absolute figure is above 0.2, which usually happens in the long term. The portmanteau test (Box-Ljung test) to detect the direction of predictability is, however, insignificant for many countries. Zambia is the country with the most significant portmanteau test results in the medium- to long-term when inflation is in the high quantile. The implication of the findings in terms of gold price and exchange rate is that higher risk in the global market of gold has a huge potential to cause high inflation in metal exporting countries in SSA, probably due to the high inflow of money into those economies. The reverse is true in the case of low-risk situations in the gold market influenced by downside risk.

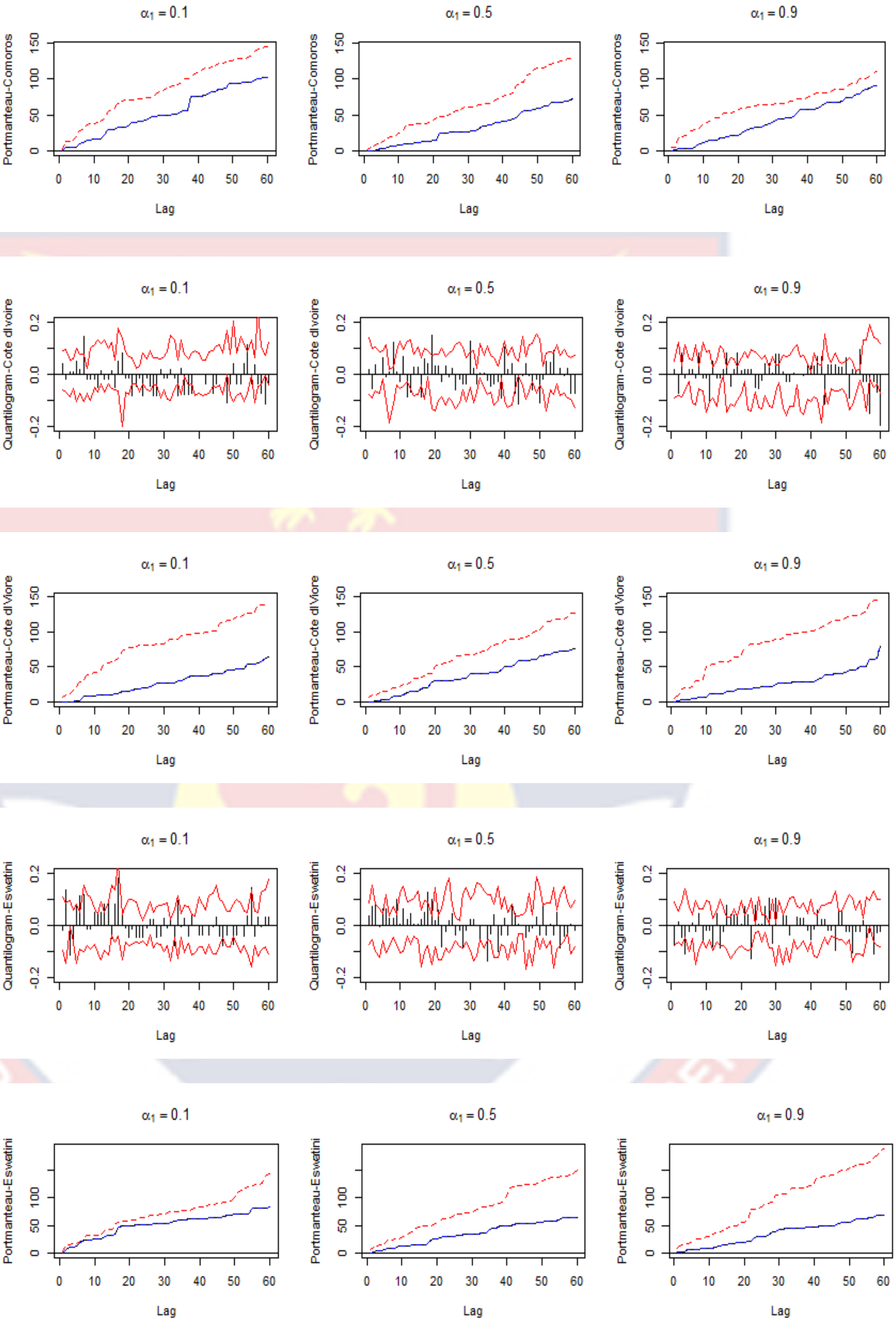
The dependence of inflation on cocoa prices

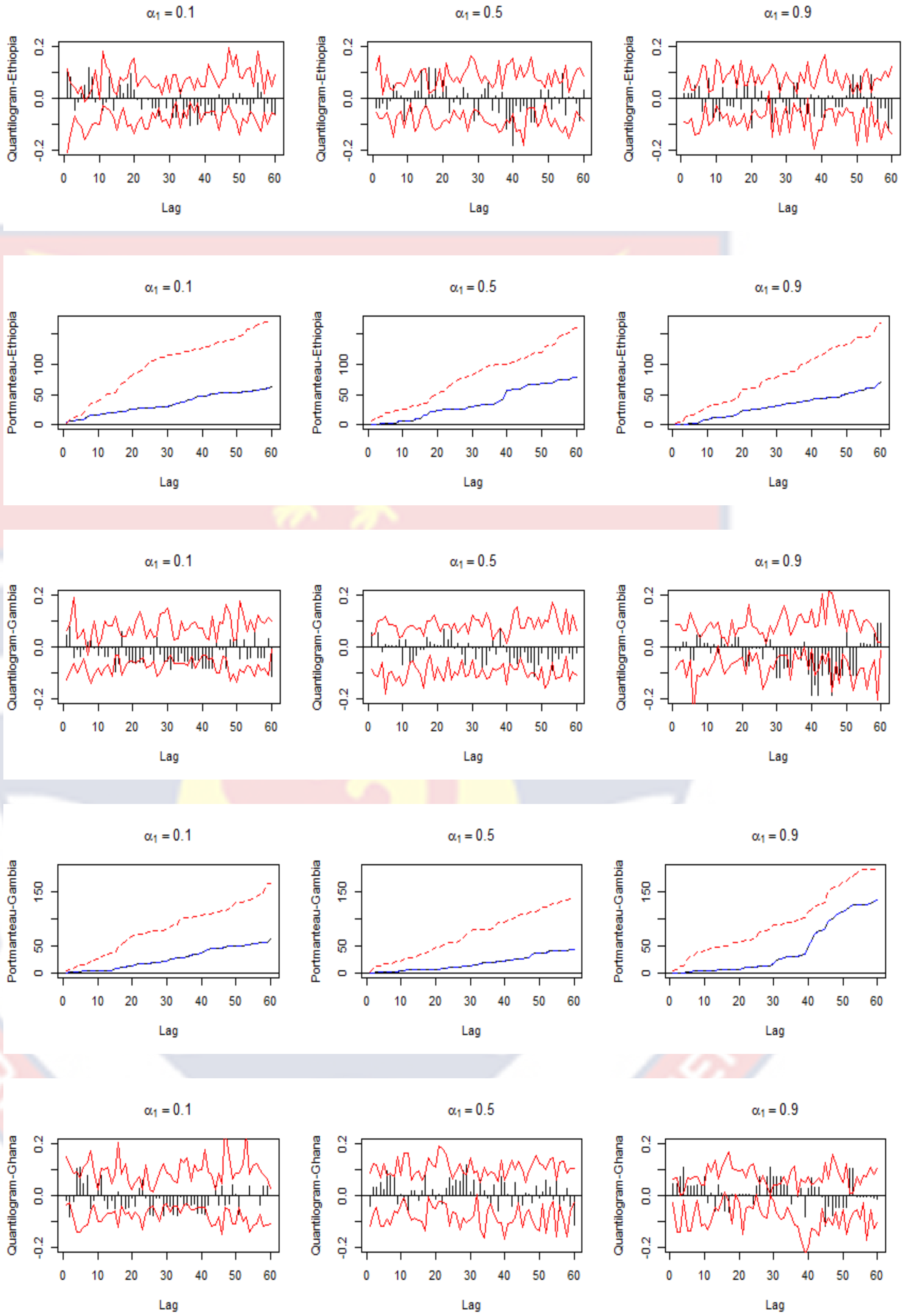
A major agricultural commodity that is predominantly produced in Africa is cocoa. Indeed, Cote d'Ivoire and Ghana alone produce more than half of the world's cocoa production. The reliance on cocoa exports for revenue is very high in Sub-Saharan Africa (SSA), where many of the population are farmers. Policymakers in this region are more interested in how changes in cocoa prices on the global market influence their inflation. Departing from existing studies like Salisu et al. (2019), the study focused on this relationship in quantiles following equation 2.

The results of cocoa price and inflation for thirteen countries in SSA that predominantly depend on agricultural production for export are shown in Figures 3 for the low-quantile of cocoa price $(\alpha_2 = 0.1)$ and 18 (see Appendix B) for the high-quantile of cocoa price $\alpha_2 = 0.9$. Generally, the results show that when changes in cocoa prices are low, the effects on inflation at the low quantile are usually positive in the short term and negative in the long term, but at the high quantile of inflation, the effect is mainly positive for bigger producing countries. Using Cote d'Ivoire, the world's largest cocoa producer, as an example, the results show that at $\alpha_2 = 0.1$, a significant positive impact occurs only at lag seven and drops to negative at lag eleven when $\alpha_1 = 0.1$.

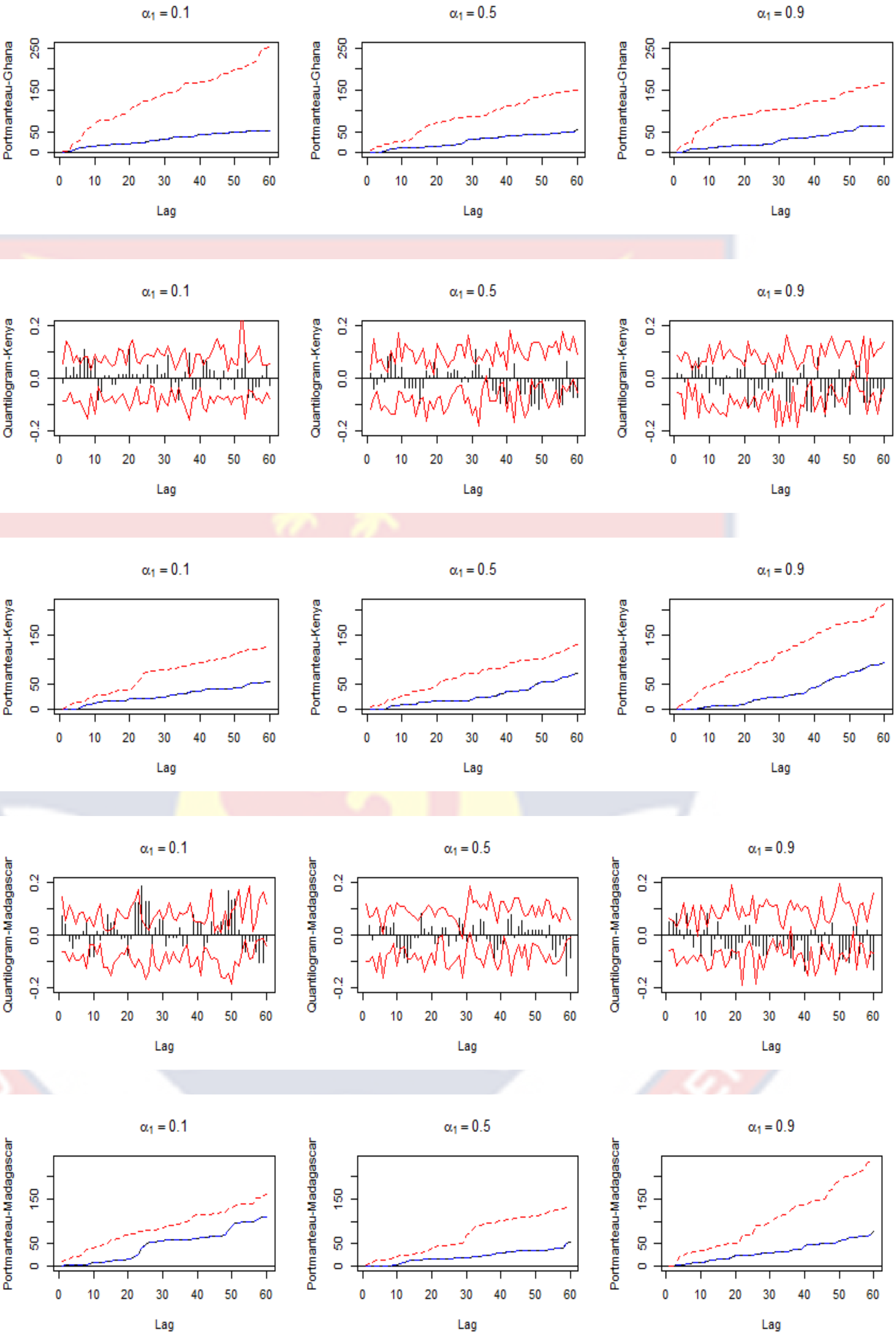
On the other hand, at $\alpha_1 = 0.9$ positive significant effect happens at the 3rd and 8th lags and drops to negative at the 11th lag. The results suggest that when risk in cocoa price are low, there is less likelihood of recording higher positive changes in inflation in the 7th month when inflation is in the low quantile and in the 3rd and 8th months when inflation is at the high quantile in Cote d'Ivoire. However, in each case, high negative changes in inflation are recorded in the eleventh month. Ghana presents similar results with some variations. For example, at $\alpha_1 = 0.1$ significant negative influence happens in the 2nd month and moves to positive in the 4th month, and continues for four months. But at $\alpha_1 = 0.9$ significant positive prediction happens in the 3rd, 5th, and 11th months. In many cases, the Box-Ljung test statistics for a number of countries are insignificant, making it impossible to forecast inflation using cocoa prices. The findings make predicting inflation with cocoa returns complicated, as the pattern swings from positive to negative with no uniformity. So, policymakers need more time and work to keep an eye on cocoa prices in the international market so they can make inform decision.

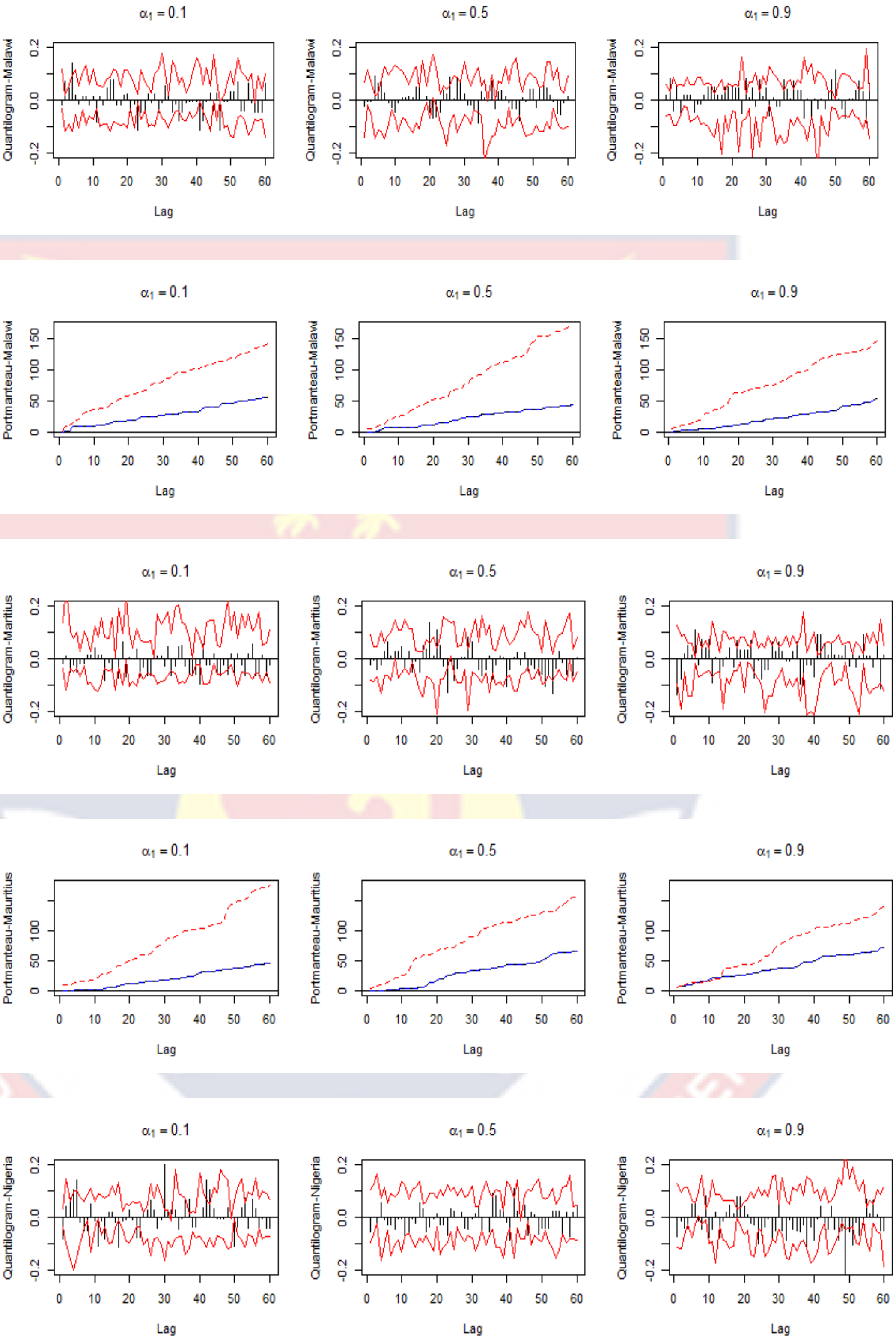



α1 = 0.1
α1 = 0.5
α1 = 0.9
Portmanteau-Comoros
Quantilogram-Cote dIvoire
Portmanteau-Cote dIvore
Quantilogram-Eswatini
Portmanteau-Eswatini
Lag



$\alpha_1 = 0.1$
$\alpha_1 = 0.5$
$\alpha_1 = 0.9$
Quantilogram-Ethiopia
Portmanteau-Ethiopia
Quantilogram-Gambia
Portmanteau-Gambia
Quantilogram-Ghana
Lag


α1 = 0.1
α1 = 0.5
α1 = 0.9
Portmanteau-Ghana
Quantilogram-Kenya
Portmanteau-Kenya
Quantilogram-Madagascar
Portmanteau-Madagascar
Lag



$\alpha_1 = 0.1$
$\alpha_1 = 0.5$
$\alpha_1 = 0.9$
Quantilogram-Malawi
Portmanteau-Malawi
Quantilogram-Martius
Portmanteau-Mauritius
Quantilogram-Nigeria
Lag

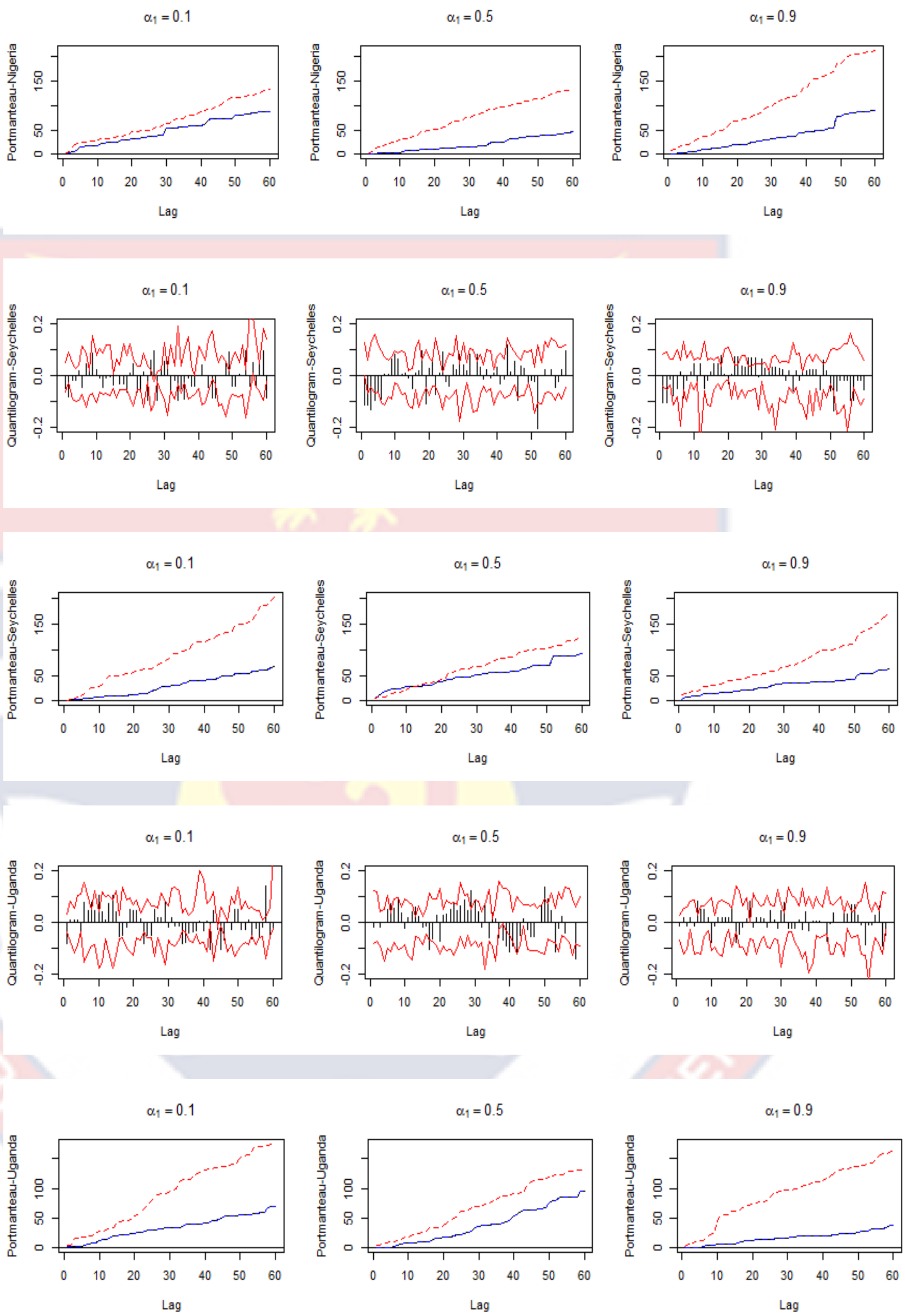


Figure 3: Sample cross-quantilogram from cocoa returns to inflation with $\boldsymbol{\alpha_2 = 0.1}$ and $\boldsymbol{\alpha_1 = 0.1, 0.5, and\ 0.9}$.

Note: *The first diagram for each country represents the cross-quantilogram where the bar graph describes the sample cross-quantilogram. The red line/red dashed lines are the 95% bootstrapped confidence interval with 1000 replicates. For each country, the second diagram is the Box-Ljung test statistics. Lag k = 60 representing a 5-year window.*

Source: Field Data (2023)

With the high quantile of cocoa returns, $(\alpha_2 = 0.9)$ the situation becomes more complicated. With respect to Cote d'Ivoire, the results start with negative significant correlation at the 3rd and 4th lags and reverse to positive significant correlation at the 11th lag at the low quantile of inflation. But at the high quantile, significant positive correlation happens in lag 9 and from there starts moving between negatives and positives. In Ghana, the sixth, twelfth, and thirteenth lags at the end of the low quantiles of the distribution show a primarily positive and significant correlation between cocoa price and inflation. However, the significant risk of cocoa to inflation at the high quantile of inflation is primarily negative. This means that, while the situation in Cote d'Ivoire is inconsistent, Ghana's situation is more consistent at both low and high quantiles of inflation. The results in Ghana are in line with Salisu et al. (2019) but with emphasis on the quantile importance. The results suggest that the influence of cocoa prices on inflation in SSA under all market conditions is inconsistent and very difficult to predict. An important observation from these findings is that the level of dependence of inflation on cocoa returns varies from country to country and quantile to quantile, and as such, policies to deal with volatilities in inflation must be looked at from country to country.

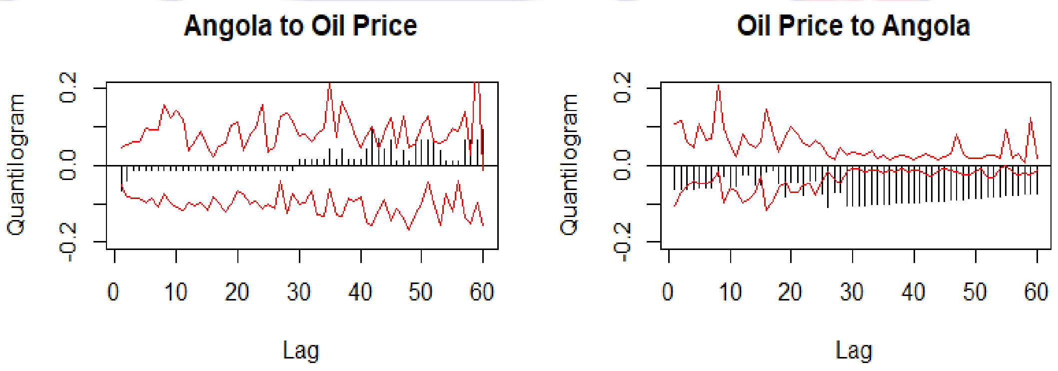
Systemic Risk Estimation

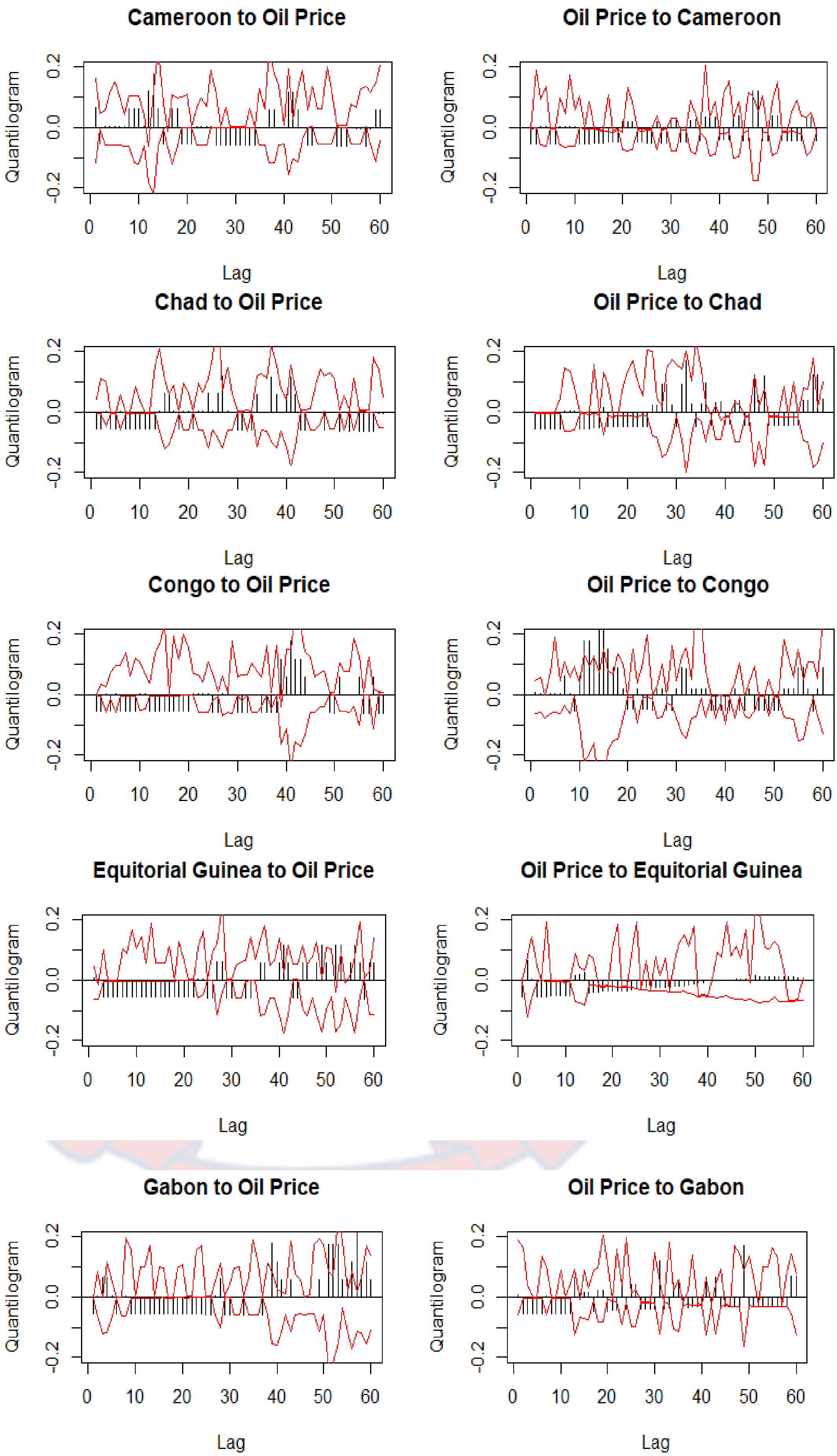
This section of the chapter focuses on examining the systemic risk between commodity prices and inflation. Several approaches have been proposed to measure systemic risk. According to Bisias et al. (2012), systemic risk measures can be put into four main categories, which are: (a) tail measurement; (b) network models; (c) dynamic stochastic macroeconomic models; and (d) contingent claims analysis. A commonly established fact is that financial data are heavy-tailed, usually based on the fact that they are impacted by extreme events like financial crises, pandemics, and the like. As a result, the tail measures are more suitable for analysing financial data like commodity prices and macroeconomic variables. In this thesis, the cross-quantilogram method proposed by Han et al. (2016) was followed to measure the systemic risk between commodity prices and inflation. Han et al. (2016) used this method because it can show how two-time series depend on each other in quantiles.

The results of the CQ are discuss below according to the different commodities. We first examine the cross-quantilogram of crude oil prices and inflation in SSA EEC in the first section. Next, the CQ between the gold prices and the inflation of metal-exporting countries (MEC) in the second subsection. Finally, the returns on cocoa and the inflation of agriculture-dependent countries are considered in the last subsection. In doing the analysis, the number of lags is set at k = 60, and commodity price and inflation rate are considered at the same quantile $\alpha_1 = \alpha_2 = 0.05$ for the low quantile and $\alpha_1 = \alpha_2 = 0.95$ for high quantile in line with Han et al. (2016). The results are presented in Figures 4-6 and 19-21, and in all instances, the 95% bootstrap confidence interval for no quantile dependence with 1000 bootstrapped replicates was utilised. The analysis is bi-directional in nature, giving us a two-way impact analysis. Note that the graphs in the left panel present the cross-quantilogram from the individual country's inflation to the commodity prices, while the graph on the right side presents the CQ from commodity returns to the individual country's inflation. For any bar graph to be considered significant, it must cross the red line.

Systemic risk between crude oil and inflation

Figure 4 depicts the results of crude oil prices and inflation in the lower quantile $\alpha_1 = \alpha_2 = 0.05$ for the ten EEC in SSA. Generally, the CQ between crude oil price and inflation is negative in the short- to medium-term and turns positive in the long-term for many countries. In Nigeria, a leading oil producer in Sub-Saharan Africa, the CQ from inflation to oil returns is predominantly negative and significant for many lags but has a weak impact. meaning that systemic risk in Nigeria's inflation moves in the opposite direction from systemic risk in oil price. The result in Angola is the opposite of the situation in Nigeria. The significant cross-quantilogram from inflation to oil price is mainly positive but for a few lags at k = 42, 45, 57, and 59. This means that it takes about three and a half years for distress in Angola's inflation to reach oil prices, which is a long time. The results from the other countries either follow Nigeria's trend or that of Angola, with a few having a blend of negatives and positives at different lags.




Cameroon to Oil Price
Oil Price to Cameroon
Chad to Oil Price
Oil Price to Chad
Congo to Oil Price
Oil Price to Congo
Equitorial Guinea to Oil Price
Oil Price to Equitorial Guinea
Gabon to Oil Price
Oil Price to Gabon
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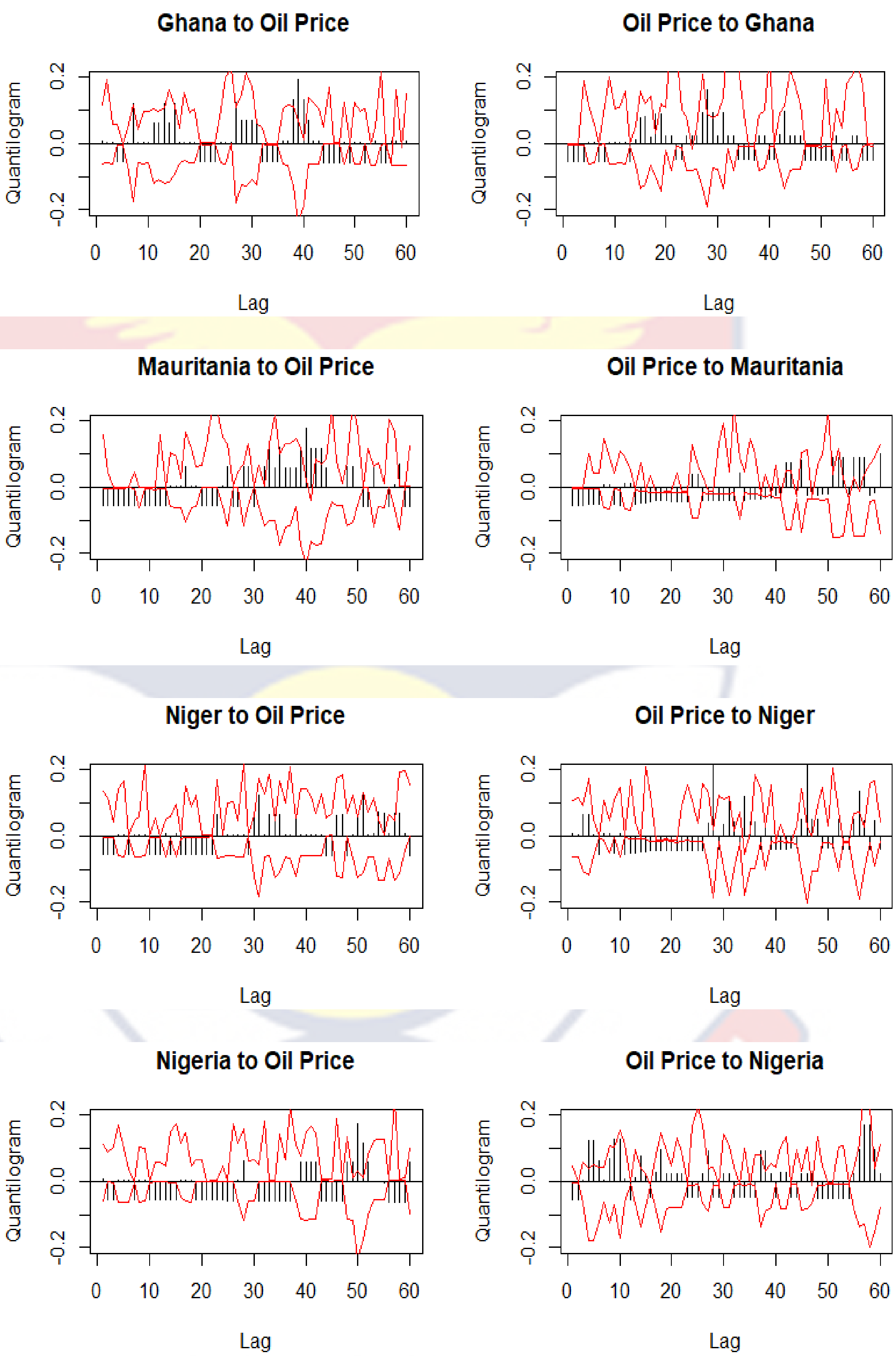


Figure 4: Sample cross-quantilogram to detect systemic risk between oil price returns and inflation for fuel-producing countries in SSA at $\alpha_1 = \alpha_2 = 0.05$.
Note: The bar graph describes the sample cross-quantilogram and the red lines are the 95% bootstrap confidence interval centred at zero.
Source: Field Data (2023)

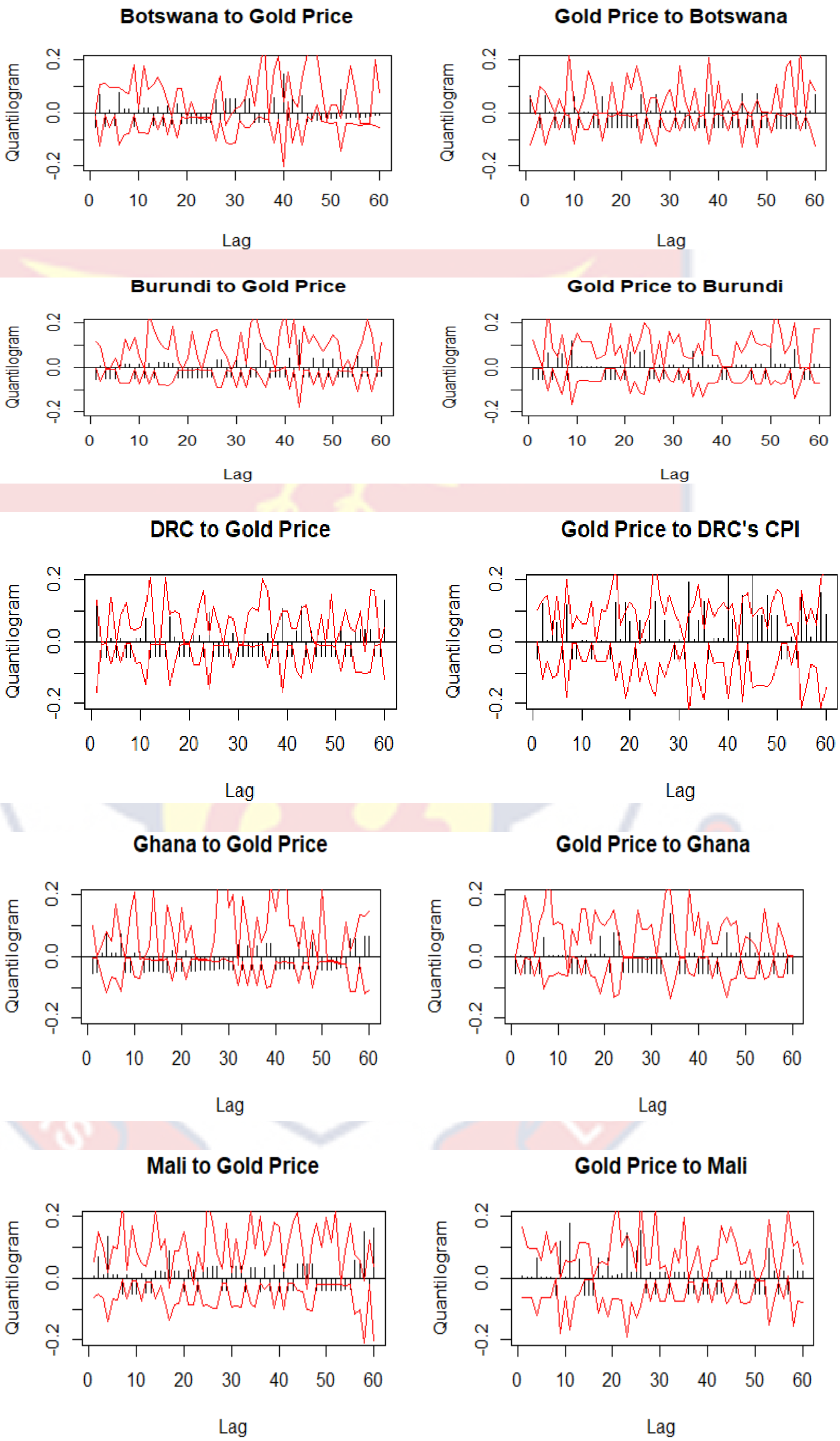
However, on the right side of the diagram, we observe significant positive CQ from oil price to Nigeria's inflation in the short term from lag k = 3, suggesting that distress in oil price causes distress in inflation starting from the third month. In the case of Angola, the significant cross-quantilogram from crude oil returns to inflation is negative. This is a confirmation of the findings of Inoue and Okimoto (2017), who observed a negative relationship between oil prices and inflation under normal market condition but extended to include the extreme situations. Many other oil-producing countries find themselves in a similar situation, but with minor variations in terms of size and direction. The results suggest the possibility for investors to hedge against inflation in asset value with crude oil, particularly in the short-term.

Moving to the higher quantile $(\alpha_1 = \alpha_2 = 0.95)$ (see Figure 19/Appendix C) which represent high risk, we observe that inflation in EEC produces an inconsistent pattern when they are in distress, with a mixture of positives and negatives. However, most of the significant lags in Nigeria, Angola, Cameroon, Equatorial Guinea, and Ghana are negative, although they mostly peak with positive figures. For instance, the systemic risk from inflation to the oil price peaks at lags 20, 1, 8, and 16 for Nigeria, Angola, Cameroon, and Ghana, respectively. This means that at the high quantile, systemic risk from inflation to oil price takes 20 months to peak in Nigeria, 1 month in Angola, 8 months in Cameroon, and 16 months in Ghana.

On the right side of Figure 8, the systemic risk from oil prices to inflation is shown, and the results reveal that the significant systemic risk from oil prices to inflation is mainly negative with few positive significant outcomes. Oil-exporting countries typically bear the brunt of the negative impact of systemic risk from oil prices to inflation in the short- to medium-terms. The results indicate that, though systemic risk from oil price moves to inflation in the short-term, the effect is mainly negative, with few positive figures recorded. The peaks from oil price distress to inflation occurs in the long-term for many countries. It also implies that when oil prices are in distress and very high, oil exporting countries are more likely to experience high inflation, particularly in the short- to medium-terms.

Systemic risk between gold price and inflation

In Figure 5, the results of the cross-quantilogram between gold returns and inflation at the low quantile $\alpha_1 = \alpha_2 = 0.05$ are presented. The dominant outcome from both the right side and the left side is that a significant negative relationship exists between gold returns and inflation for metal-producing countries in SSA. Starting with the leading producer (Ghana), we observe that a significant cross-quantilogram from Ghana's inflation to gold returns is mainly negative for many lags and persists for a longer period. Surprisingly, the opposite is similar, as evidenced by a negative significant cross-quantilogram shift from gold returns to inflation in Ghana. The only significant positive cross-quantilogram from gold returns occurs at k = 7. The inference from Ghana's results is that systemic risk in gold returns and systemic risk in inflation moves in the opposite direction in the case of Ghana. The findings also support the fact that gold can be a good hedge against inflation in metal-exporting countries in SSA, as revealed in the existing literature (see, for instance, Bampinas & Panagiotidis, 2015; Hoang et al., 2016).


Botswana to Gold Price
Gold Price to Botswana
Burundi to Gold Price
Gold Price to Burundi
DRC to Gold Price
Gold Price to DRC's CPI
Ghana to Gold Price
Gold Price to Ghana
Mali to Gold Price
Gold Price to Mali
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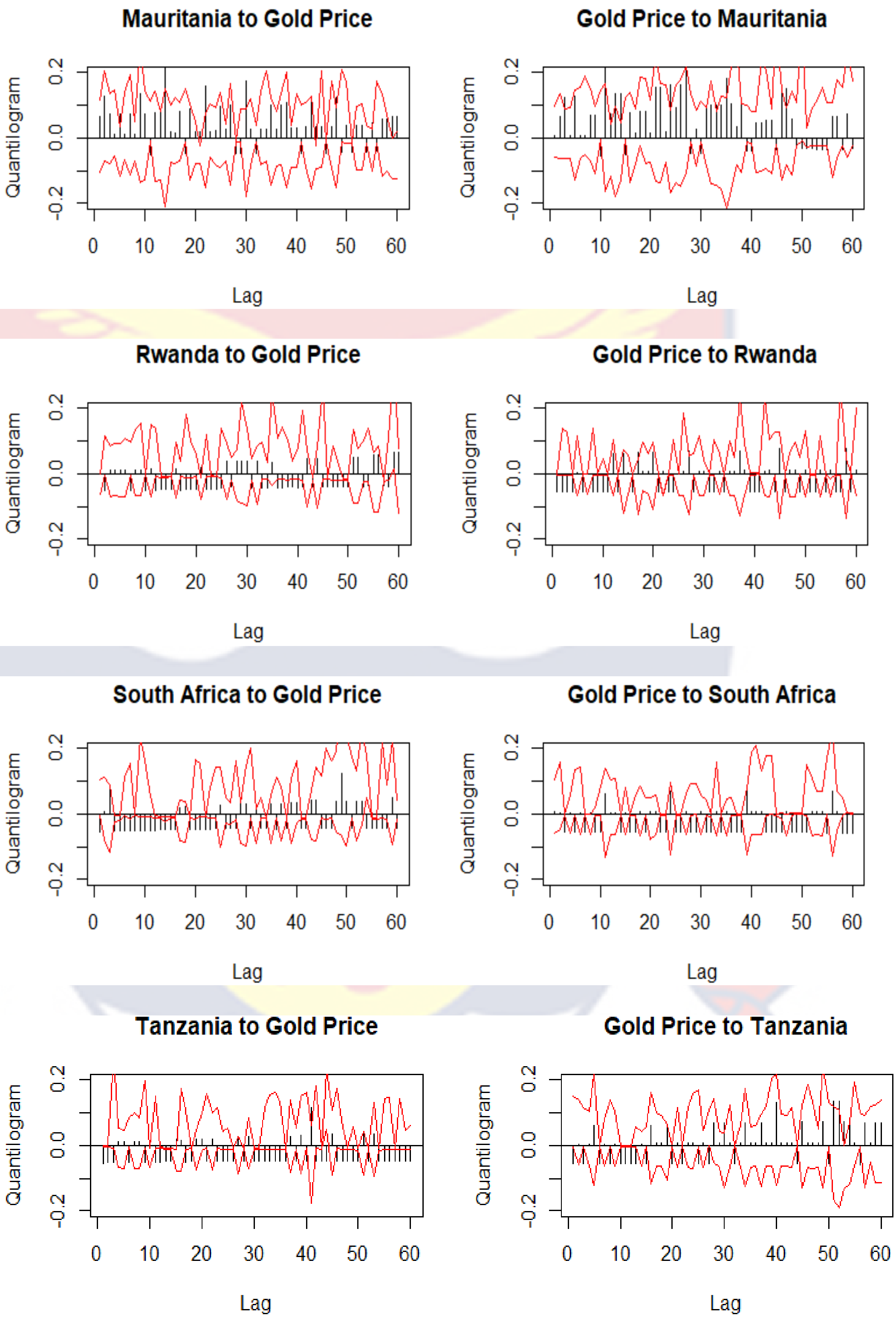
Mauritania to Gold Price
Gold Price to Mauritania
Rwanda to Gold Price
Gold Price to Rwanda
South Africa to Gold Price
Gold Price to South Africa
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Gold Price to Tanzania
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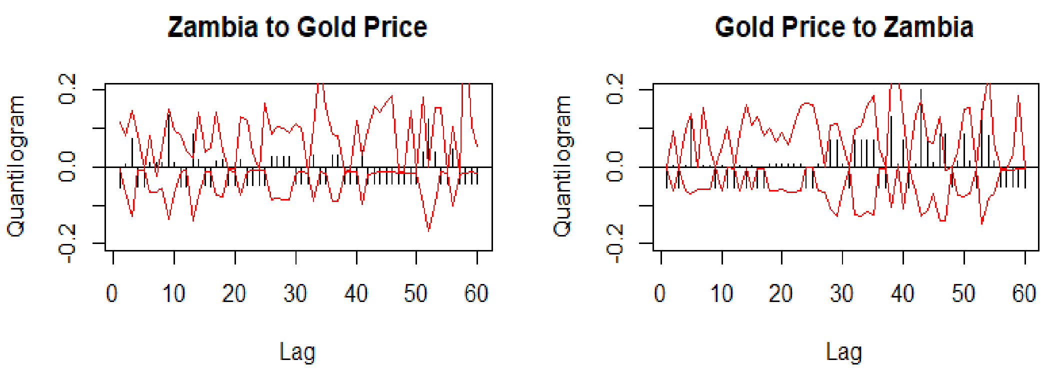


Figure 5: Sample cross-quantilogram to detect systemic risk between gold returns and inflation for metal-producing countries in SSA at $\boldsymbol{\alpha_1 = \alpha_2 = 0.05}$.

Note: *The bar graph describes the sample cross-quantilogram and the red lines are the 95% bootstrap confidence interval centred at zero.*

Source: Field Data (2023)

The results for South Africa and several other countries are not different from Ghana's. Mauritania, the DRC, and Zambia are the ones with a little deviation from the general case. In these three countries, significant positive cross-quantilogram flows occur in both directions. From gold price to inflation, significant positive CQ reaches the DRC at k = 2, Mauritania at k = 3, and Zambia at k = 5, and it is stronger and more persistent for many lags in the DRC and Mauritania. It means that within 2 months, systemic risk in gold price increases systemic risk in inflation in the DRC and does the same thing in Mauritania in 3 months. It means that in the DRC and Mauritania, gold does not offer protection against inflation, so investors can easily lose value in their assets if the systemic risk in gold price is high.

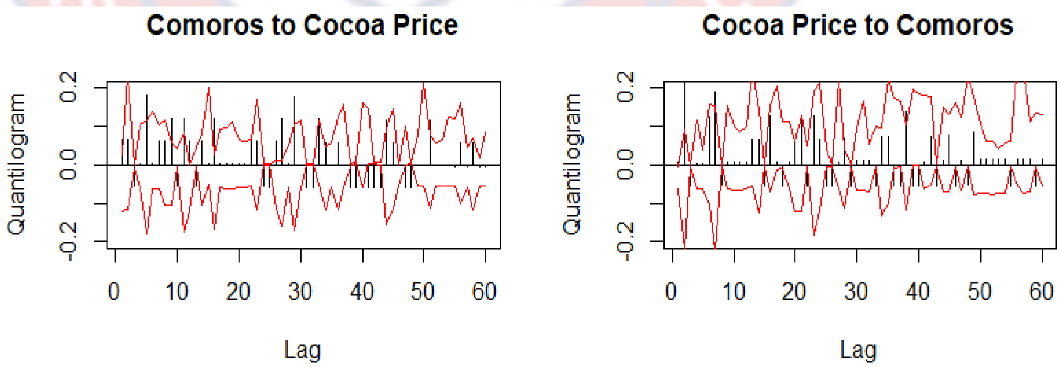
Moving to the high quantile ($\alpha_1 = \alpha_2 = 0.95$), the results are presented in Figure 20. (Appendix C). It is observed that if individual countries' inflation is distressing; they produce inconsistent patterns of impact on gold prices. In Ghana, distress inflation has both positive and negative impacts on gold prices, but all the positives are insignificant, with many of the negative lags being significant. The significant negative impact lasts longer in the long-term than the short-term, which occurs only in the second and fifth months. The situation in South Africa is similar to that in Ghana, except that the peak in South Africa happens to be significant and positive at k = 25. This means that the systemic risk posed by South African inflation to the gold price takes more than two years to peak. All the other metal-exporting countries have similar outcomes, with more significant negative impacts and fewer significant positive effects on gold prices.

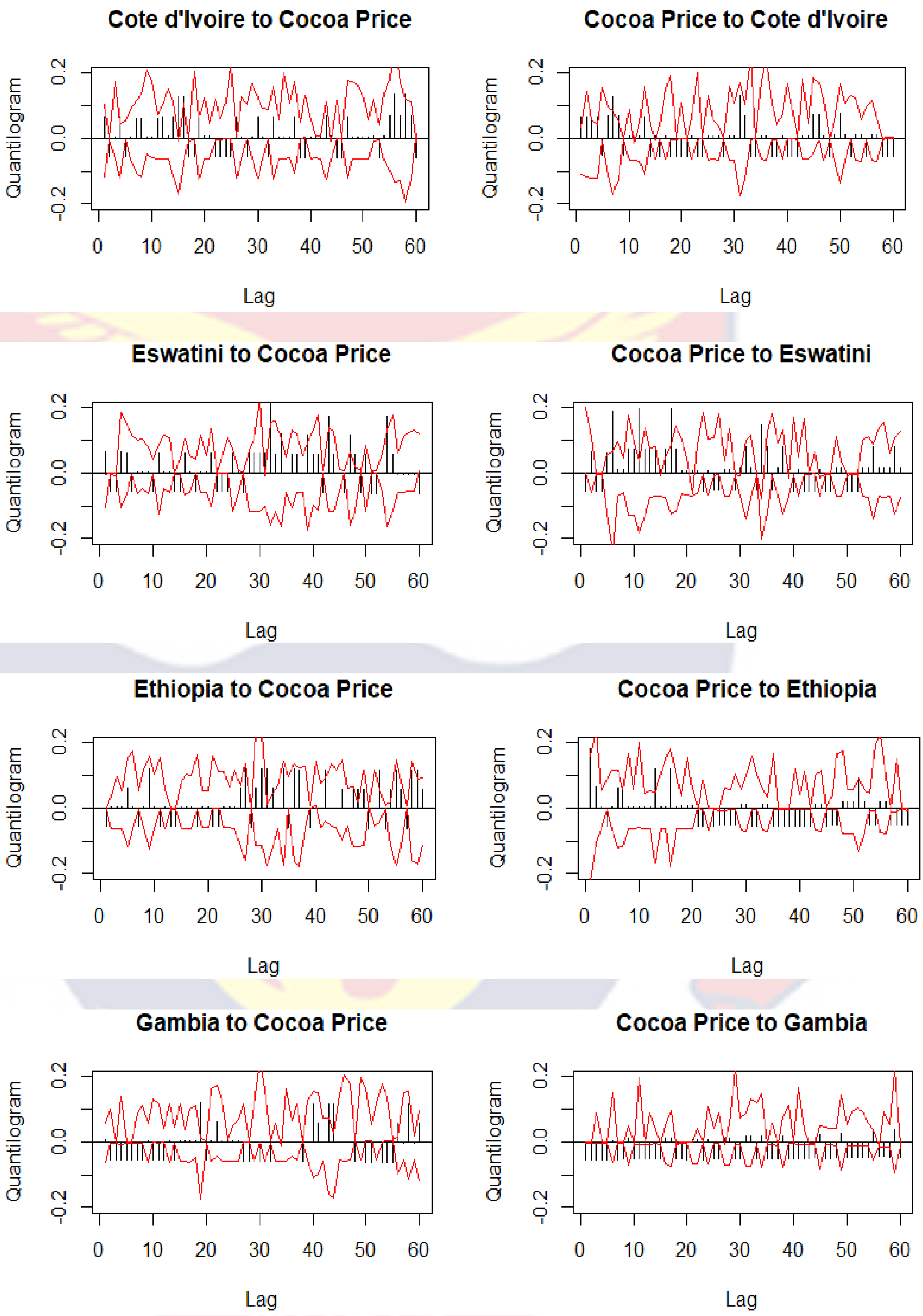
The right side of Figure 20 is used to examine how systemic risk from the gold price affects inflation at the high quantile. It is observed that the impact on inflation also has both positive and negative aspects for all countries. From the gold price to Ghana's inflation, it was mainly negative in the short-term and the early part of the medium-term before turning positive in the latter part of the medium-term and the long-term. The case of South Africa is no different from Ghana, particularly in the short- to medium-term, except that the impact of the gold price on inflation in South Africa is predominantly negative in the long term. The situation is the same in several other countries, except that three countries produce more consistent patterns. The systemic risk from the gold price to inflation is primarily positive and significant for several lags in Tanzania and Zambia, but it is primarily negative in Botswana. The results suggest that when the gold price is distressed and very high, it has a different impact on each country's inflation at different times and with different magnitudes, which is consistent with AMH. It also shows that gold can be a hedge against inflation in different countries at different times.

Systemic risk between cocoa price and inflation

We now turn to the bi-directional systemic risk between cocoa and inflation for countries that produce agricultural commodities. As indicated earlier in this chapter, more than half of the world's cocoa production comes from SSA, with Cote d'Ivoire and Ghana being the leading producers. As a result, examining the systemic risk from cocoa to inflation will help with economic stability measures for these countries. The results of the cross-quantilogram between cocoa and inflation at $\alpha_1 = \alpha_2 = 0.05$ are presented in Figure 6 and at $\alpha_1 = \alpha_2 = 0.95$ in Figure 21 in Appendix C.

Focusing on the top four producers of cocoa in SSA included in this study, it is observed that the risk of inflation affecting cocoa returns comes in different forms and peaks at different times in the lower quantile ($\alpha_1 = \alpha_2 = 0.05$). The significant cross-quantilogram from inflation to cocoa returns reaches its peak as follows; (0.12) at k = 15 for Cote d'Ivoire, (0.13) at k = 49 for Ghana, (0.2) at k = 23 for Nigeria, and (0.18) at k = 26 for Uganda. This means that systemic risk, from inflation to cocoa returns, reaches its peak in the 15th month for Cote d'Ivoire, the 49th month for Ghana, the 23rd month for Nigeria, and the 26th month for Uganda. The implication is that systemic risk from inflation to cocoa returns takes a long time to produce the highest impact.




Cote d'Ivoire to Cocoa Price
Cocoa Price to Cote d'Ivoire
Eswatini to Cocoa Price
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Gambia to Cocoa Price
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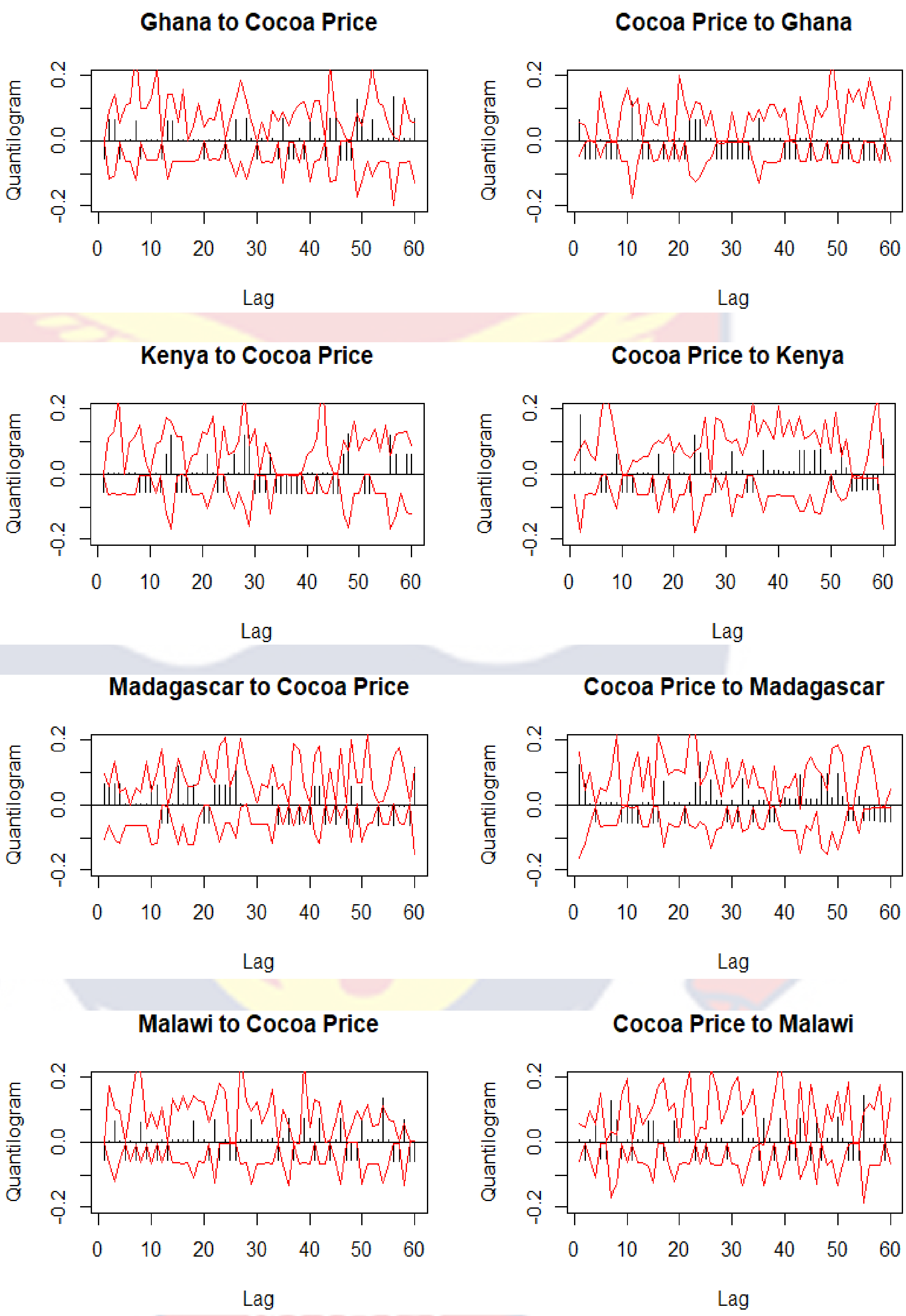
Ghana to Cocoa Price
Cocoa Price to Ghana
Kenya to Cocoa Price
Cocoa Price to Kenya
Madagascar to Cocoa Price
Cocoa Price to Madagascar
Malawi to Cocoa Price
Cocoa Price to Malawi
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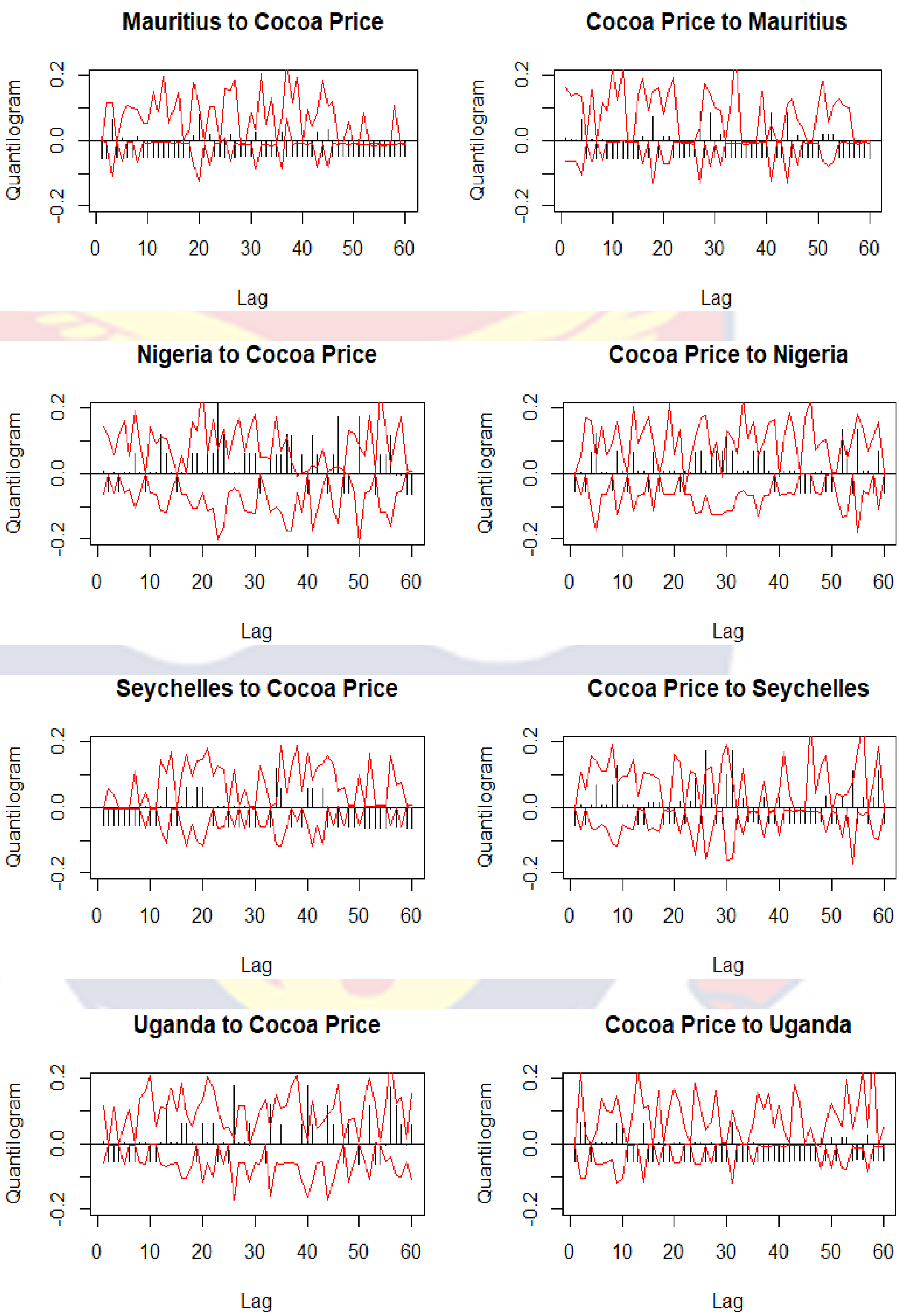


Figure 6: Sample cross-quantilogram to detect systemic risk between cocoa price returns and inflation for food & Beverage-producing countries in SSA at $\boldsymbol{\alpha_1 = \alpha_2 = 0.05}$.

Note: *The bar graph describes the sample cross-quantilogram and the red lines are the 95% bootstrap confidence interval centred at zero.*

Source: Field Data (2023)

The right side of Figure 6 presents the cross-quantilogram from cocoa price to inflation, and here too the results vary in terms of direction, magnitude, and duration. In terms of direction and timing, significant positive CQ from cocoa returns to inflation reaches Cote d'Ivoire at k = 7, Ghana at k = 11, Nigeria at k = 5, and Uganda at k = 3. However, in all the countries, it is short-lived as it does not persist for a longer period. The results of this study show that systemic low risk in cocoa returns takes 7 months to affect inflation in Cote d'Ivoire, 11 months to affect inflation in Ghana, 5 months to affect inflation in Nigeria, and 3 months to affect inflation in Uganda.

The nature of the relationship in other countries is similar to the situation in these four countries. The Gambia is the only country whose inflation receives only a significant negative cross-quantile from cocoa prices. The results here show the inherent heterogeneity in the relationship between cocoa price and inflation, which is consistent with Salisu et al. (2019). In their study, they have contended that the non-inclusion of heterogeneous behaviour in studying the relationship between cocoa price and inflation may lead to a wrong conclusion. The differences in behaviour in different countries may have led to different outcomes for different countries in this study.

Moving to the higher quantile in Figure 21 (Appendix C), it is observed that the patterns differ from country to country. Inflation in Cote d'Ivoire has a more positive than negative impact on cocoa prices, and this is understandable since they are the leading producer of cocoa in the world. And the highest impact of 12% happens in the 15th month, when it reaches its peak. The other countries follow similar lines, like Cote d'Ivoire, with a more positive impact. For instance, in Ghana, systemic risk from inflation to cocoa prices peaks at k = 56; in Nigeria, it peaks at k = 23; and in Uganda, it peaks at k = 26. The results indicate that when inflation in individual cocoa-producing countries is distressed and very high (above 0.95), its biggest impact on global cocoa prices is positive, though it happens at different times.

The impact of the cocoa price on inflation, on the other hand, is more negative than positive at the high quantile. For Cote d'Ivoire, the systemic risk from the cocoa price to inflation is positive in the short-term but turns negative in the medium-term and long-term. The biggest positive impact occurs in the seventh month at 12%. In the case of Ghana, the systemic risk from the cocoa price has a positive effect in the first month, changing to negative for about six months before recording its highest positive figure in the eleventh month. After recording its peak, the consistent impact on inflation in Ghana, which is long-lived from the medium-term to the long-term, is negative. The other countries have similar patterns to these two, albeit with minor variations. The results suggest that when the cocoa price is distressed and very high (higher than 0.95), it is more likely to record high inflation in many cocoa exporting countries, particularly in the medium to long term.

Sensitivity Analysis

We conducted a robustness analysis to assess the consistency of the results in different situations. To do that, the cross-quantilogram method proposed by Han et al. (2016), which is already utilised in this thesis, was followed, but with a different quantile of 0.25 for the lower quantile and 0.75 for the upper quantile. Figure 23 in Appendix E shows the results of the sensitivity analysis.

The results for energy-exporting countries show that the cross-quantilogram from commodity prices to inflation exhibits more negative and significant values for several lags at the lower quantile and more positive values at the upper quantile, with minor variations observed across different countries. For instance, while the case of Nigeria has more variation in dependence, that of Angola is very consistent throughout the period. Here too, the portmanteau test is only significant for Angola and Ghana in the long term but insignificant for the other countries. The results are therefore similar to the ones reported earlier and thus confirm the earlier conclusions.

Conclusion and Recommendations

The dependence of inflation on commodity prices in commodity-producing countries in Sub-Saharan Africa is examined in this chapter by considering quantile dynamics in the relationship. Three commodities (crude oil, gold, and cocoa) were considered due to their important contribution to revenue for countries in SSA. The study period is from January 1990 to December 2019. The countries were divided into three groups depending on which commodities they produced and exported. The cross-quantilogram (CQ) method proposed by Han et al. (2016) was followed to estimate the directional predictability from commodity price to exchange rate and inflation in three different quantiles (low, medium, and high). The CQ method was used due to its ability to capture the extreme or tail behaviour of the series in line with AMH. Overall, the results suggest possible directional predictability from commodity prices to the inflation rate across all quantiles, albeit with weaker prediction at the medium quantile.

First, the results show that the influence of commodities on inflation is stronger in the low and high quantiles than in the medium quantiles. This goes to show the importance of the tails in the relationship between commodity prices and inflation. In many instances, the cross-quantilogram is stronger for major commodity-producing countries than for small commodity-producing countries. The implication is that in forecasting inflation in SSA with commodities, policymakers must be interested in tail behaviour as extreme situations usually influence the behaviour of market participants in the commodities market. Again, due to the insignificant nature of the Box-Ljung test statistics for many countries, it is a bit risky to rely on just CP to predict inflation.

Second, we observe that the systemic risk between inflation and commodity returns is mainly negative. The negative systemic risk relationship is stronger for crude oil and gold than cocoa, where there is more inconsistency in the pattern. It is also more long-lived in the short-term than in the long-term at the low quantile, but more long-lived in the long-term at the high quantile. This finding offers an opportunity for countries to seek protection in commodities for their inflation. This can be done by hedging inflation with commodities during distress situations in the short-, medium-, and long-terms. This will help sustain the value of assets and bring about stability in the macroeconomic environment.

The results also show heterogeneity in the relationship as we move from one commodity to another and from one country to another. This is evident throughout the study as the same commodity generates different outcomes at different or the same quantiles for different countries, which is in line with AMH. In estimating systemic risk, the relationship between cocoa and inflation exhibited a higher level of heterogeneous behaviour than the other two commodities (gold and crude oil) and inflation. The implication for many SSA countries is that having a single inflation policy for all countries may not be ideal due to differences in market participants' and consumers' behaviour in different countries and commodities exported. It is therefore important that each country consider its individual uniqueness when making inflation policies that respond to the specific needs of the people.

CHAPTER FIVE

MULTI-FREQUENCY INFORMATION FLOW BETWEEN COMMODITY PRICES AND EXCHANGE RATES

Introduction

The foreign exchange (FX) market has recently seen big currency fluctuations, including those in the US, Switzerland, Canada, Russia, and Europe. More importantly, the FX market's increased volatility has serious effects on market participants; hence, it is crucial to comprehend exchange rate behaviour. Due to the impact of severe exchange rate swings on a company's foreign currency balance sheet items, central banks have undertaken policy tools to stabilise the macroeconomic environment and defend against ER volatility (Liu et al., 2021). In this context, commodity prices are seen as important exchange rate volatility drivers. Many governments incorporate commodities like gold and oil in the currency basket and maintain reserves to deal with fluctuations and manage exchange rate volatility (Shakil, 2017).

In international trade, for instance, commodities are predominantly quoted in the US dollar (Benassy-Quere et al., 2020), and that opens a door for their relationship with the exchange rate as all participating countries trade their commodities in the dollar before translating it to their local currencies. In this sense, the exchange rate (ER) creates an avenue through which volatilities from commodity prices (CP) are transmitted to the local economy (Mo et al., 2018). The implication is that there is interdependence between commodities markets and currency markets since information flows between them. Policymakers in Sub-Saharan Africa (SSA), whose economies are predominantly commodity dependent, will therefore be interested in quantifying, analyzing, and understanding the content of information flow between CPs and ERs in order to make possible risk management decision like financial hedging, diversification and debt repayment structuring.

Commodities, because of their interaction with exchange rates, can also be used to diversify, hedge, or provide a safe haven for ER. In this direction, gold is very popular among investors and countries because of its perceived hedging potential. Following the definition of Baur and Lucey (2010), an asset provides a hedge if it correlates negatively or has no correlation with another asset or portfolio on average. And if such a negative correlation happens during market turmoil, then the asset also provides a safe haven. While the hedging or safe-haven capabilities of gold for the exchange rate are still debatable (see, Joy et al., 2011; Wang & Lee, 2021), not much is known about other commodities, particularly those from the energy and agriculture sectors. Accordingly, this study seeks to quantify information transfer between commodity prices and ER in SSA as a means of determining the hedging or safe-haven potentials of commodities for the exchange rate. Quantifying the information transfer between CPs and ERs would help identify individual exchange rates that are vulnerable to information that is due to fluctuations in the global commodities markets and their environment as a whole.

The idea of information flow in the financial market hinges on the efficient market hypothesis (EMH) by Fama (1970). The EMH has indicated that investor behaviour is homogeneous, and as a result, all investors react to information in the same way, usually uninfluenced by time or circumstance.

Accordingly, asset prices change due to investors reacting similarly to information. This has led to more linear and static time analyses in previous studies. But changing investor behaviour and altering economic situations contradict the EMH. The heterogeneous market hypothesis (HMH) by Muller et al. (1993) and the adaptive market hypothesis (AMH) by Lo (2004) support investors' asymmetric and time-varying behaviour. According to the HMH, market participants base investment decisions on risk and return preferences, as well as historical and present news. The AMH, for its part, says that markets evolve, adapting to events and structural changes, and market efficiency varies over time. Also, investors and policymakers may overreact to information during times of crisis, such as during the 2007 global financial crisis (GFC), which contributed to financial data such as CP and ER becoming non-linear, non-stationary, and noisy. As a result, it is important to use the best technique to account for investor heterogeneity and deal with noise effectively when analysing financial data like commodities and ER.

Furthermore, Benthal (2019) demonstrated that information between financial assets is causal in nature using the situated information flow theory (SIFT). The SIFT builds on the philosophy of Odegard (1982) and the statistics of Pearl (1982) to show that if there are two random variables and there is a possibility of knowing about one variable by making an inference to the state of the other variable, then the two share mutual information. Based on such an understanding, there is a high possibility that commodities and exchange rates will observe each other under different dynamics over the period based on the intrinsic mutual information shared by them in the context of this study. Drawing on the theoretical propositions above, this study proposes that understanding the bi-directional information flow between commodity prices and exchange rates at multi-scale levels offers the best means for investors and policymakers to make the right diversification and hedging decisions. A bi-directional analysis presents information on how two variables interact simultaneously, thus providing causal information.

Unfortunately, empirical papers on commodity price volatility and ER have mostly focused on developed countries and a single commodity, either crude oil or gold. For instance, several studies (see Kilian, 2009; Reboredo and Rivera-Castro, 2013; Kumar, 2019; Malik and Umar, 2019; Zhu and Chen, 2019) have concentrated on oil. Other studies (see Baur & McDermott, 2010; Joy, 2011; Qureshi et al., 2018; Wang & Lee, 2022) have focused on gold. They have therefore neglected the potential for heterogeneity in agriculture and food markets. Still, the results are mixed and vary from one currency to another and from one commodity to another. This suggests that the CP-ER nexus must be contextual, so countries in SSA that depend a lot on commodity exports need to study how their ERs react to changes in the informational content of individual commodity prices; hence, the current study. Moreover, these studies did not quantify the flow of information at different points in time over the period. They did not therefore account for the different behaviour of market agents, which varies at different investment horizons.

Additionally, prior work has mostly relied on VAR, GARCH, and, to a lesser extent, wavelets. While VAR and GARCH can contain time-domain information, they frequently exclude frequency-domain information, leading to inconsistent empirical results (Pal and Mitra, 2017). On the other hand, a wavelet can capture discontinuity well, but its nonadaptive nature and counterintuitive interpretation allow for additional ways to improve results. This study took the frequency dimension into account by using the intrinsic time mode, which works for short-, medium-, and long-time scales. Dealing with these issues necessitates the use of a more robust approach that incorporates divergent investor behaviour into the analysis.

The study's contributions are as follows: First, the study evaluated market heterogeneity using three significant commodities (crude oil, gold, and cocoa) and 27 commodity-exporting nations in SSA. Oil, gold, and cocoa were picked from each of the three main categories of energy, metals, and agriculture based on revenue and international trading. We look at information flow from the point of view of a developing country's currency market by providing individual country effects for 27 countries in SSA. Previous studies in SSA have mostly used one commodity or provided a panel effect, making it difficult for country-specific policy. More than 60% of the export earnings of these countries come from commodities (UNCTAD, 2021; 2019), making them subject to global commodity price swings.

Second, by employing various commodity and exchange rate frequencies, the study emphasises a multi-scale examination of information flow. Many studies in this manner have focused on the time domain and failed to depict the genuine intrinsic behaviour of various financial market participants (see Buah, 2019; Kassouri & Altintas, 2020). The analysis's use of the frequency domain accounts for the impact of short-, medium-, and long-term dynamics of commodity prices on the exchange rate, which appeals to

HMH and AMH. The study, therefore, covers non-linear and non-parametric multiple-frequency causality.

Third, to the best of our knowledge, this study is one of the first to adopt a noise-assisted technique in complete ensemble empirical mode decomposition (CEEMDAN) to evaluate the information flow between CP and ER in SSA. The advantage of this technique is that it reduces the impact of extreme reactions on data by decomposing it into intrinsic mode functions, each representing different investor behaviour. This strategy is better at reducing noise since it decomposes series into several time scales to represent investors' complex connection assessments. Noise in data series often obscures the genuine picture, but CEEMDAN's decomposition method reduces it. CEEMDAN reduces noise better than EMD and EEMD.

Fourth, the study uses transfer entropy to measure commodity price and exchange rate information transfer. Transfer entropy (TE) from information theory is used to calculate a time series' correlation richness. It measures time-series heterogeneity, surprises, and shocks (Altieri et al., 2018b). The uniqueness of TE is its ability to quantify the strength of the information flow by assigning the required weight to the tails of the distribution. This way of assessing information flow in the financial economics literature is emerging (see Bossman et al., 2022; Owusu Junior et al., 2021; Adams, 2020; Osei & Adams, 2020; Tapia et al., 2020). The study uses Renyi's (1961) transfer entropy (RTE), which is better for financial data than Shanon's (1948) transfer entropy. This method is effective because it captures important tail information in the result. After all, financial data is fat-tailed, and deleting tail information can impact the result's quality. Renyi's transfer entropy will help policymakers and investors get non-linear and non-parametric causal information flow for portfolio allocation and risk management decisions. Renyi entropy can discriminate between positive (low-risk) and negative (high-risk) assets. This information helps investors enhance their diversification and hedging strategies.

Methodology

In this study, a two-stage methodological approach was followed to examine the flow of information between CP and ER. The first stage involves the use of the CEEMDAN method to decompose the data series into intrinsic mode functions (IMFs), which differentiate between short-term, medium-term, and long-term dynamics, respectively. The study is thus able to analyse the nature of the interaction between commodity prices and ER at different investment horizons of decision-making in line with HMH and AMH. The second stage involves using Renyi's transfer entropy (RTE) to estimate effective transfer entropies (ETEs). The good thing about this method is the ability to assign more weight to the tails of the distributions since financial data is mostly fat-tailed. By combining these two methods, we can overcome the problems of non-linearity and non-stationarity and also deal with information asymmetry in a non-parametric way. We have chosen a bi-directional flow of information because empirical evidence (Peng et al., 2020) suggests the flow of information between the price of gold and the exchange rate is in both directions. Moreover, for better comparison, the analysis has been done both at the composite level and at the decomposed levels.

Complete Ensemble Empirical Mode Decomposition

Researchers have never doubted that financial and economic time series data exhibit trends and seasonality and are, as such, non-stationary and noisy. This is because investors respond to volatility differently and, as such, operate at different investment horizons. It has therefore been the case that such data must be analysed in a multiscale manner. What has been the problem in the past, however, is the tools for undertaking such analysis. This is no longer the case, as tools for decomposing time series data into different time domains at various frequencies are now available. One such technique is the CEEMDAN proposed by Torres et al. (2011). CEEMDAN overcome the problems of mode mixing and reconstruction associated with EMD and EEMD discussed in chapter three. The CEEMDAN overcomes the residual noise problem by adding white noise to the previous iteration's residual instead of adding to the original signal. The noise reduction strength of CEEMDAN lends itself to its usage in this study. The CEEMDAN algorithm is implemented using the *Rlibeemd* package in this study. The CEEMDAN method consists of the following steps:

Step 1: Assume the following, original signal $x(t)$, actual signal $s(t)$, noise $n(t)$, Gaussian white noise $\omega_j(t)$. The process begins by adding the Gaussian white noise with different amplitudes into the original signal $x(t)=s(t)+n(t)$. In the end, multiple new signals will emerge as;

$$x_j(t)=x(t)+\omega_j(t) \tag{4}$$

Step 2: Next is the derivation of the initial IMF by applying the EMD method on (4) which serves as the basis to generate others.

Step 3: The process continues by computing the mean of the first IMF as follows.

$$\overline{\mathrm{IMF}_1(n)} = \frac{1}{\mathrm{K}}\sum_{k=1}^{\mathrm{K}} \mathrm{IMF}_{1k}(t) \tag{5}$$

Step 4: Next, the original signal is used to compute the remaining components C_n of the signal as;

$$C_n = \begin{cases} x(t) - \mathrm{IMF}_1(t), n = 1 \\ C_{n+1} - \mathrm{IMF}_1(t), n > 1 \end{cases} \tag{6}$$

Step 5: Next, we need the ρ^{th} component proceeding EMD of the signal which is represented by E_ρ. Consequently, components (L + IMFs) can be calculated as follows;

$$\mathrm{IMF}_{L+1}(n) = \frac{1}{\mathrm{K}}\sum_{k=1}^{\mathrm{K}} E_L\{C_L(t) + \sigma_L E_L(\omega_k(t))\} \tag{7}$$

Step 6: The final process involves reconstruction to derive the original signal which will give *n* steady-state IMFs as follows;

$$x(t) = C(t) + \sum_{m=1}^{\mathrm{M}} \overline{\mathrm{IMF}_m}(t) \tag{8}$$

It must be noted that CEEMDAN produces a certain number of IMFs with one residue from a time series data in the form of $log_2 N$, where N is equal to the number of observations (T). Additional information on CEEMDAN can be obtained from Torres et al. (2011), Wang et al. (2020), and Peng et al. (2020).

Renyi Transfer Entropy

Transfer entropy has its origins in information theory as an econophysics technique for capturing uncertainty or direction of information.

Shanon (1948) is credited with developing transfer entropy as the basis for measuring information flow. It has been widely used in many fields due to its ability to measure contagion, uncertainty, surprise, and heterogeneity, among others (Altieri et al., 2018b). Assume a discrete random variable Y with a probability distribution of $p(y_t)$, then, the mean number of bits needed to efficiently encode independent draws is given as;

$$\mathrm{H}_Y = -\sum_{y=1}^{n} p(y)\log_2 p(y) \tag{9}$$

The process of information flow measurement of Shanon entropy for two-time series has its foundation in the distance model by Kullbacks & Leibler (1951) under the Markov assumption. In this paper, two discrete random variables are presented as X and Y with their respective probability distributions as $p(x)$ and $p(y)$. Together, they have a joint probability of $p(x,y)$ and they follow a dynamic Markov process in the form k (process X) and l (process Y). Based on the features of Markov, there is the probability of observing time $t+1$ in a state x conditional on previous observations of k as; $p(x_{t+1}|x_t,...,x_{t+k+1}) = p(x_{t+1}|x_t,...,x_{t-k})$. There is a mean number of bits that are needed to encode in other to observe the values of k at time $t+1$ and this is given by;

$$h_X(k) = -\sum_{x} p(x_{t+1}, x_t^{(k)})\log_2 p(x_{t+1}|x_t^{(k)}) \tag{10}$$

Where $x_t^{(k)} = (x_t,...,x_{t-k+1})$. It must be noted that equation (10) follows a similar Markov process for Y. In dealing with a bivariate case, Schreiber's method is followed where information flow process Y to process X is derived by calculating the deviation from the generalised Markov property

$p(x_{t+1}, x_t^{(k)}) = p(x_{t+1} | x_t^{(k)}, y_t^{(l)}$ which in this case l is the order for Markov process Y. When there is no information flow from Y to X, preceding observations of Y have no effect on the conditional probabilities of X. Schreiber (2000) thus relied on Kullbacks-Leibler distance model to define Shanon entropy as;

$$T_{X \to Y}(k,l) = \sum p(x_{t+1}, x_t^{(k)}, y_t^{(l)}) \log_2 \frac{p(x_{t+1} | x_t^{(k)}, y_t^{(l)})}{p(x_{t+1} | x_t^{(k)})} \qquad (11)$$

In (11), $T_{Y \to X}$ measure the flow of information from process Y to Process X and $T_{X \to Y}$ similarly measure the flow of information from process X to Process Y through an analogous procedure. Interestingly, transfer entropy is asymmetric, as a result, the dominant direction of information can be determined by computing the difference between $T_{Y \to X}$ and $T_{X \to Y}$.

One major weakness of Shannon entropy is its inability to assign equal weight to all possible realisations in a specific probability distribution. The problem here is that it is unable to accommodate heavy tail which is very rampant with financial and economic data with specific reference to price and returns. This is where Renyi's transfer entropy comes in handy to deal with such weakness. Renyi (1961) transfer entropy (RE) can assign equal weight through a weighting parameter q in a process defined as;

$$H_Y^q = \frac{1}{1-q} \log_2 \sum_y P^q(y) \qquad (12)$$

Where $q > 0$. whenever $q = 1$, RE and Shannon entropy will be the same. In a situation where $0 < q < 1$ higher weight is assigned to a low probability event, whiles a lower weight is assigned to a high probability event where $q > 1$. What makes Renyi entropy more appealing to financial data is its ability to assign different weights based on the importance of the event. This is because based on the parameter q different portion of the distribution receives their weight (Adam, 2020; Behrendt et al., 2019). Additionally, RE can normalise the weighted distribution through escort function in a situation where $q > 0$ as $\phi_q(y) = p^q(y) / \sum_y p^q(y)$. Accordingly, RE can be obtained as;

$$RE_{Y \to X}(k,l) = \frac{1}{1-q} p(x_{t+1}, x_t^{(k)}, y_t^{(l)}) \log_2 \frac{\Sigma_x \phi_q(x_t^{(k)}) p^q(x_{t+1} | x_t^{(k)})}{\Sigma_{x,y} \phi_q(x_t^{(k)} y_t^{(l)}) p^q(x_{t+1} | x_t^{(k)} y_t^{(l)})} \tag{13}$$

It is important to note that transfer entropy is based on discrete variables, but continuous data is required to estimate equation (13). Consequently, continuous data must be partitioned into discretized values. The option here is to partition the data into bins. The ideal option would be partitioning the data into higher bins, but this will require a higher number of observations to accomplish that, which is not available in this case. As a result, the trajectory of the most dominant symbolic approach is followed to partition our data set into a finite set of bins. The process is described as "symbolic encoding" by Behrendt et al. (2019). Therefore, given data set y_t, with n number of bins and bounds $q_1, q_2, q_3, ..., q_{n-1}$ $(q_1 < q_2 < q_3 < \ldots < q_{n-1}$ the symbolic encoding for S_t time series can be derived as follows:

$$S_t = \begin{cases} 1, y_t \le q_1 \\ 2, q_1 < y_t < q_2 \\ \vdots \\ n-1, q_{n-2} < y_t < q_{n-1} \\ n, y_t \ge q_{n-1} \end{cases} \tag{14}$$

The size and distribution of the observed time series must inform the number of bins chosen. Binning is frequently based on the empirical quantiles of the left and right tails because tail observations are important. This is simply accomplished by setting the bottom and upper boundaries of the bins to the 5 percent and 95 percent empirical quantiles, respectively. This yields three symbolic encodings, with the first bin (5%) including negative extreme returns (lower tail), the third bin (95%) capturing positive extreme returns (upper tail), and the second bin (middle 90%) containing normal returns. Using the chain rule on the symbolic encoding, conditional probabilities can be represented as fractions of joint probabilities. In that situation, the relative frequencies of all conceivable realisations can be used to derive the probabilities in equations (13) and (14).

A note of caution is that one can obtain negative figures when computing RE. In such situations, critical care must be taken with the history of the events. For this study, negative values indicate higher risk, and positive values are indications of low risk.

Moreover, transfer entropy requires very high data observations, as stated earlier. However, larger data sets are rarely available for SSA countries. The consequence of fewer data points is the possibility of biassed outcomes. To overcome this weakness, Marschinski and Kantz (2002) proposed the calculation of effective transfer entropy (ETE) as follows:

$$ETE_{Y\to X}(k,l) = T_{Y\to X}(k,l) - T_{Yshuffled\to X}(k,l) \qquad (15)$$

Where $T_{Y\to X}(k,l)$ represent the transfer entropy with series Y shuffled. The process is set up in such a way that there is a repeated random drawing of the distribution of Y, which is then realigned to create new time series. By so doing, the serial dependence of the Y series is destroyed by the process, but the statistical dependencies between Y and X are kept. Accordingly, there is a convergence at zero based on a larger sample size, and any non-zero values are a result of a smaller sample effect. To secure a favourable outcome, the shuffling process is repeated to obtain an average shuffled transfer entropy approximation for all replications, which represents an estimator for small sample bias. Lastly, the bias-corrected ETE estimates are found by taking the estimates after shuffling away from the estimates before shuffling.

To check the statistical significance of the transfer entropy approximations, the Markov block bootstrap approach can be employed (Owusu Junior et al., 2021). This process involves maintaining dependencies between Y and X but, contrary to shuffling, eliminates any statistical dependencies between the two variables (Behrendt et al., 2019). The null hypothesis provided to be tested under this approach is 'no information flow' with a p-value of $1-\hat{q}T$. The $\hat{q}T$ provided stands for the quantile of the simulation estimation determined by the transfer entropy estimates (Behrendt et al., 2019; Owusu Junior et al., 2021).

Data and Preliminary Analysis

In this study, monthly data from a sample of 27 African countries spanning a 29-year period from January 1990 to December 2019 was used. Three panels were created out of the sample based on the main commodity exported by each country. The commodity groupings were done based on the International Monetary Fund (IMF) commodity classification system and previous research. The categories were: thirteen agricultural exporting countries (AEC), five energy exporting countries (EEC) and thirteen metal exporting countries (MEC). Ghana appears in all categories because it is among the top five exporters of all the commodities used for the study. Nigeria and Mauritania appear in two categories each due to similar reasons. Table 1 contain the list of countries used in the study.

These countries represent all SSA's regions. In this regard, the study provides a comprehensive picture of the relationship between commodity markets and ER dynamics for the entire region. Furthermore, the use of monthly time series data over a long-time span allowed for the accommodation of various extreme events, such as the 1997 Asian crisis, the 2008 GFC, the Arab Spring (2011), and the 2000–2001 financial recession. These events could have caused structural shifts in the currency and commodity markets, which higher-frequency data can perfectly capture (Bildirici & Turkmen, 2015).

In this study, the monthly ER of each country to the US dollar was used as reported in the International Financial Statistics (IFS) database of the International Monetary Fund (IMF). Following the IMF commodity classification, one commodity from each was selected: agricultural (cocoa), metal (gold), and energy (crude oil). The prices of the three commodities used were obtained from the World Bank's primary commodity price database, popularly called the "pink sheet." All commodity prices and the exchange rates were converted to log returns and were derived as the log difference of the closing price/rate as $r_t = \log(P_{t+1}) - \log(P_t)$ where r_t represents the return from time t to time $t+1$, P_t and P_{t+1} represent price observation at time t and time $t+1$, respectively.

Figures 7 and 22 (Appendix D) present the results of the graphical behaviour of the data series. In both cases, the left side shows the trend of the original price series, while the right side presents the return price series behaviour. The graphs in Figures 7 and 22 show that the original series' behaviour is unstable. For instance, the cocoa price has recorded the most inconsistent outcome over the period, but the gold price presents the most sustained upward trend. All commodities recorded sharp price drops between 2007 and 2009, with crude oil experiencing the most significant change. The sharp change in price may have been due to the global financial crisis (GFC) at the time. The right side of Figure 7 shows that the log-return series for commodities exhibits a stable trend with regular volatilities. The exchange rate plots in Figure 22 (Appendix D) follow a similar trend, with the original series on the left-hand side showing more instability, although most of them were trending upward. The log-return series, however, has a stable trend with some volatility over the period.

Summary Statistics

The result of the descriptive statistics is presented in Table 2. The average monthly gold price return is approximately 0.36%, as shown in Table 2. This is the highest monthly commodity price average, while cocoa prices have the lowest monthly price average return of about 0.25%. In terms of monthly growth in oil price return, the mean value for the period is 0.32%. Among the commodities, oil returns exhibited the most volatile situation over the period in terms of the standard deviation, followed by cocoa and the exchange rate, which is not surprising. During that time, all exchange rates were recorded as positive, which means that the value of all currencies went up or grew.

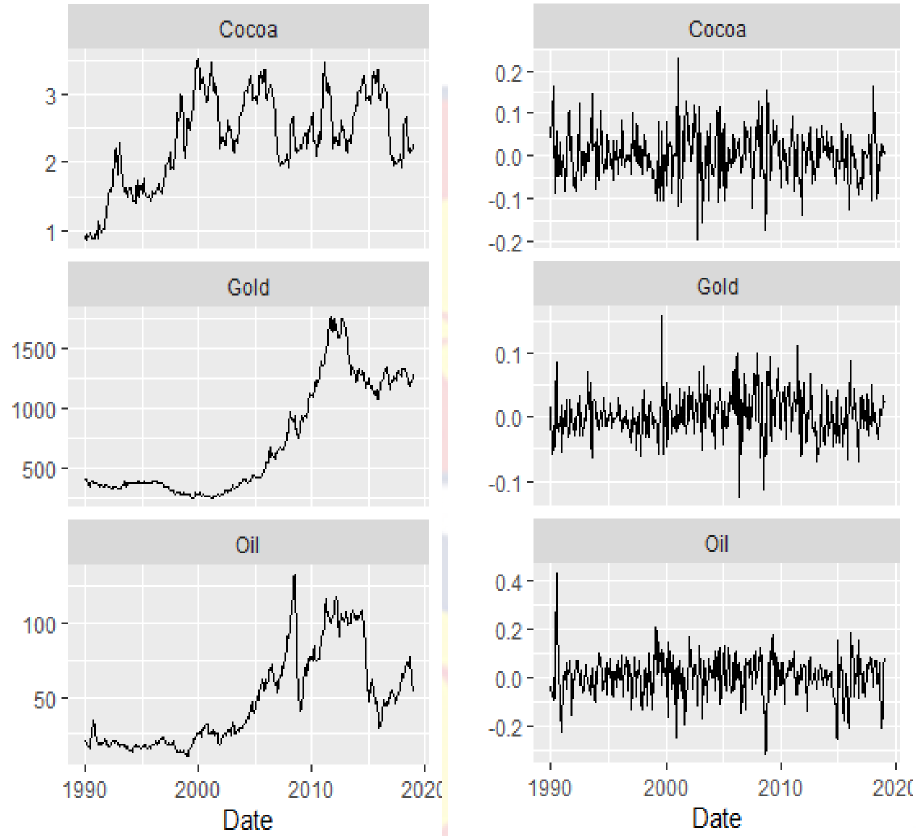


Figure 7: Time series plots of commodity prices and returns
Source: Field Data (2023)

Unsurprisingly, the assumption of normality was rejected for all the series, as seen in the test of normality (N. test). The rejection happened at 1%, except for cocoa, where the rejection happened at 10%, meaning that the series is not normal, which is particularly common with financial data. The returns of two commodities (gold and cocoa) are positively skewed, but the oil return is negatively skewed. All the exchange rates are positively skewed, apart from the two countries and the Gambia. The skewed nature of the series confirms that they are not normal, as demonstrated by the normality test. In terms of kurtosis, all commodities and exchange rates recorded excess kurtosis over the period. The implication is that the series exhibited fat-tailed behaviour, which is normal with financial data.

Table 2: Summary statistics and test of stationarity

	Obs	mean	SD	skewness	kurtosis	N.test	ADF	PP
Commodity price returns								
Oil return	359	0.0032	0.0851	-0.3516	2.494	0.960***	-11.264***	-13.548***
Gold return	359	0.0036	0.0349	0.3655	1.548	0.979***	-14.446***	-17.068***
Cocoa return	359	0.0025	0.0581	0.0861	0.810	0.993*	-12.588***	-16.315***
Oil Producing countries								
Angola	359	0.03	0.1074	8.072	83.352	0.318***	-9.283***	-13.437***
Cameroon	359	0.002	0.044	11.382	179.649	0.440***	-12.868***	-17.561***
Ghana	359	0.0145	0.0343	2.877	18.905	0.603***	-11.288***	-18.037***
Mauritania	359	0.0042	0.0271	5.833	74.915	0.481***	-14.081***	-20.293***
Nigeria	359	0.0102	0.0813	13.757	216.648	0.164***	-13.301***	-17.993***
Metal producing countries								
Botswana	359	0.0049	0.027	0.629	8.921	0.879***	-12.622***	-15.922***
Burundi	359	0.0066	0.0226	2.412	13.326	0.770***	-12.979***	-16.32***
DRC	359	0.0335	0.1165	5.100	36.868	0.460***	-11.446***	-14.799***
Ghana	359	0.0145	0.0343	2.8769	18.905	0.603***	-11.288***	-18.037***
Guinea	359	0.0075	0.0301	-0.291	21.679	0.619***	-10.946***	-13.068***
Mali	359	0.002	0.044	11.382	179.649	0.440***	-12.868***	-17.562***
Mauritania	359	0.0042	0.0271	5.833	74.915	0.481***	-14.081***	-20.293***
Mozambique	359	0.012	0.0325	1.204	4.708	0.866***	-9.438***	-12.416***
Namibia	359	0.0048	0.0371	0.803	3.570	0.946***	-11.993***	-16.833***
Rwanda	359	0.0069	0.04	10.792	128.665	0.230***	-12.832***	-17.631***
South Africa	359	0.0048	0.0343	0.627	5.062	0.939***	-12.221***	-14.119***
Tanzania	359	0.0069	0.0201	2.768	17.693	0.739***	-12.231***	-13.512***
Zambia	359	0.0183	0.0645	2.0261	9.809	0.782***	-11.406***	-15.819***
Agricultural producing countries								
Comoros	359	0.0012	0.0321	6.044	76.385	0.687***	-12.502***	-16.228***
Cote d'Ivoire	359	0.002	0.044	11.382	179.650	0.440***	-12.868***	-17.561***
Eswatini	359	0.0048	0.0343	0.627	5.062	0.939***	-12.221***	-14.119***
Ethiopia	359	0.0076	0.0484	16.558	293.408	0.108***	-13.446***	-18.756***
Gambia	359	0.0052	0.029	-0.718	8.463	0.817***	-12.309***	-15.92***
Ghana	359	0.0145	0.0343	2.877	18.905	0.603***	-11.288***	-18.038***
Kenya	359	0.0043	0.03	1.346	17.525	0.717***	-10.869***	-12.352***
Madagascar	359	0.0069	0.0413	6.451	80.716	0.635***	-11.614***	-15.78***
Malawi	359	0.0157	0.0482	3.920	22.979	0.610***	-11.46***	-11.882***
Mauritius	359	0.0025	0.0183	0.702	3.775	0.937***	-11.817***	-12.483***
Nigeria	359	0.0102	0.0813	13.757	216.649	0.164***	-13.301***	17.993***
Seychelles	359	0.0026	0.0391	11.407	184.424	0.353***	-11.695***	-14.945***
Uganda	359	0.0064	0.025	0.734	3.743	0.921***	-9.637***	-13.493***

Note: *The asterisk (***), (**), and (*) represent the level of significance at 1%, 5%, and 10% respectively. N. test stands for normality test and the ADF and PP tests include both intercept and trend.*
Source: Field Data (2023)

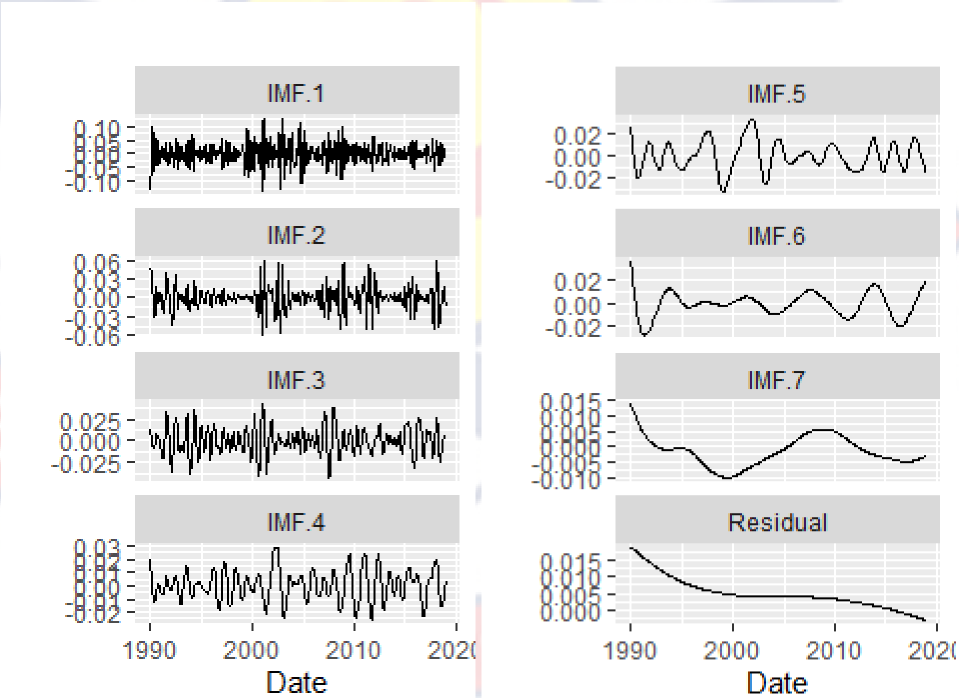
Two tests were done to assess the stationarity behaviour of the series using the Augmented Dickey-Fuller (ADF) test and the Philip Peron (PP) test. The results are presented in Table 2. Both the ADF and PP tests show that all the series are stationary at a 1% significance level. This means that they can be used for the analysis in this study.

Results and Discussion

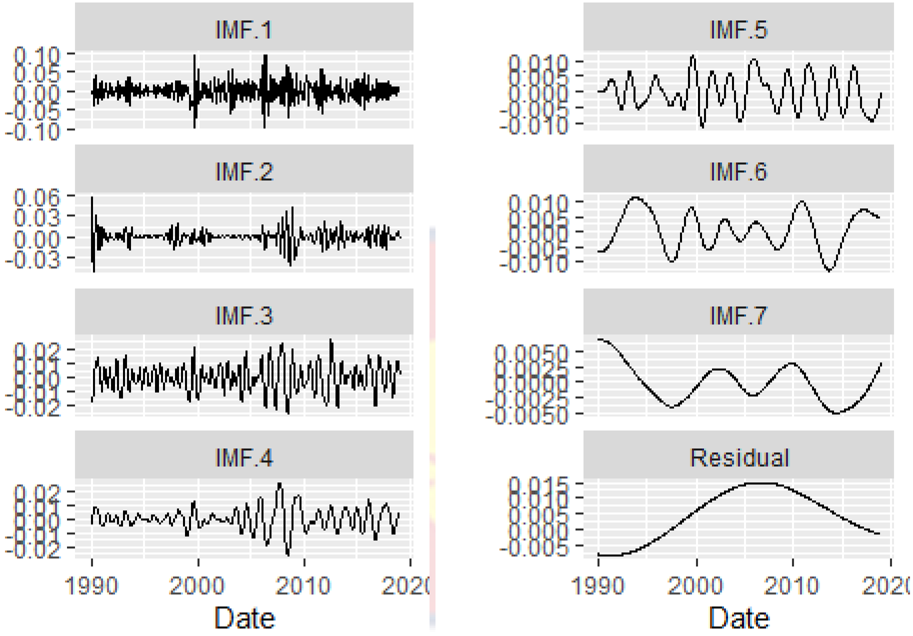
CEEMDAN and Reconstruction

In this study, the CEEMDAN method was utilised to decompose the series of commodity price returns and exchange rate returns into different sets of intrinsic mode functions (IMFs) having different scales. In doing that, the number of realizations, which is often set at 300 with a Gaussian noise amplitude α of 0.2, was followed in line with the suggestion of Colominas et al. (2012). The CEEMDAN method was used to decompose the series into eight IMFs, each of different frequencies, including one residual. The plot of IMFs for commodity returns is represented in Figure 8. The IMFs are classified in line with existing literature (see Bossman et al., 2022; Owusu Jr. et al., 2021; Zhu et al., 2019) as the short-term behaviour represented by IMFs 1-3, the medium-term dynamic represented by IMFs 4–7, and the long-term trend represented by the Residual.

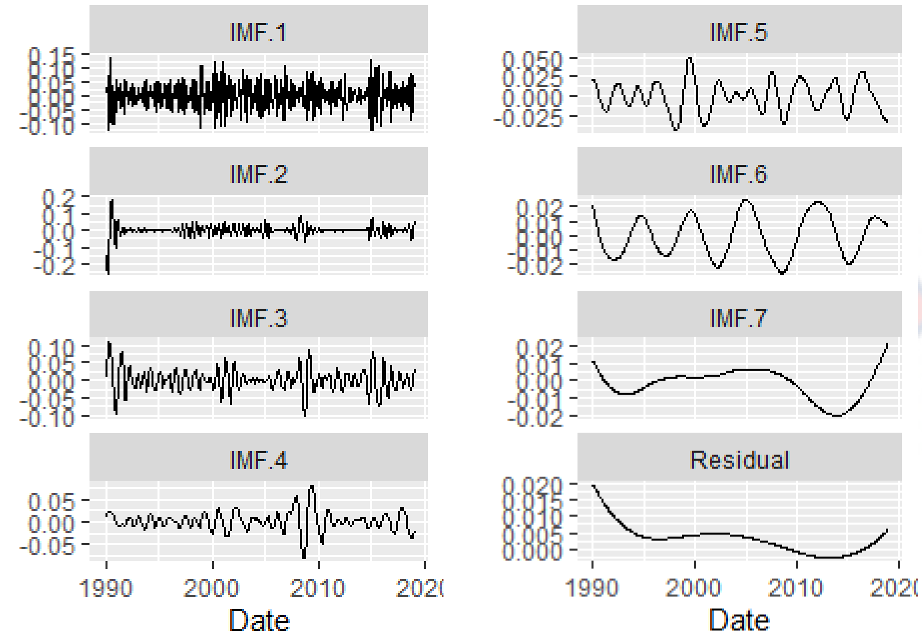
Empirical evidence (see, for instance, Peng et al., 2020; Zhu et al., 2019) shows that the IMFs 1-3, which are the short-term frequencies, usually exhibit normal market volatility and are mainly determined by demand and supply disequilibrium from individual activities of market participants. Similarly, IMFs 4–7 portray the impact on prices that emanates from significant events and, as such, show medium-term dynamics, while the residual is regarded as the long-term trend of activities on price. Based on this classification, we can differentiate between commodities and exchange rate markets, allowing us to examine how shocks in one market, in this case commodities, can affect another market, in this case the exchange rate market, based on different periods of information asymmetry. The decomposing of the series into various IMFs helps to understand the different dynamics of the various markets, particularly for countries that must constantly deal with exchange rate volatility and investors looking for safe-haven assets like gold. This is even more crucial in a crisis period when investors are trying to see whether short-term and medium-term events provided by the entropies in IMFs 1–7 will project into the long term as provided by the entropies in the residual.



(a) IMF plots for cocoa returns
Figure 8: continued



(b) IMF plots for gold returns



(c) IMF plots for oil returns

Figure 8: IMF plots for commodity returns
Source: Field Data (2023)

A close examination of the IMF plots for the three commodities indicates in Figure 8 that most of the volatilities in commodity prices are exhibited at high frequencies. The low frequency presents the fewest variations in commodity behaviour. This suggests that the high frequency presents the most dominant mode for all commodities, contrary to Adam et al.'s (2022) observation of the residual as the dominant mode. It means that the short-term is very critical for stability measures in all countries that policymakers/investors must put measures in place to overcome such volatility.

Results of Renyi's Effective Transfer Entropy

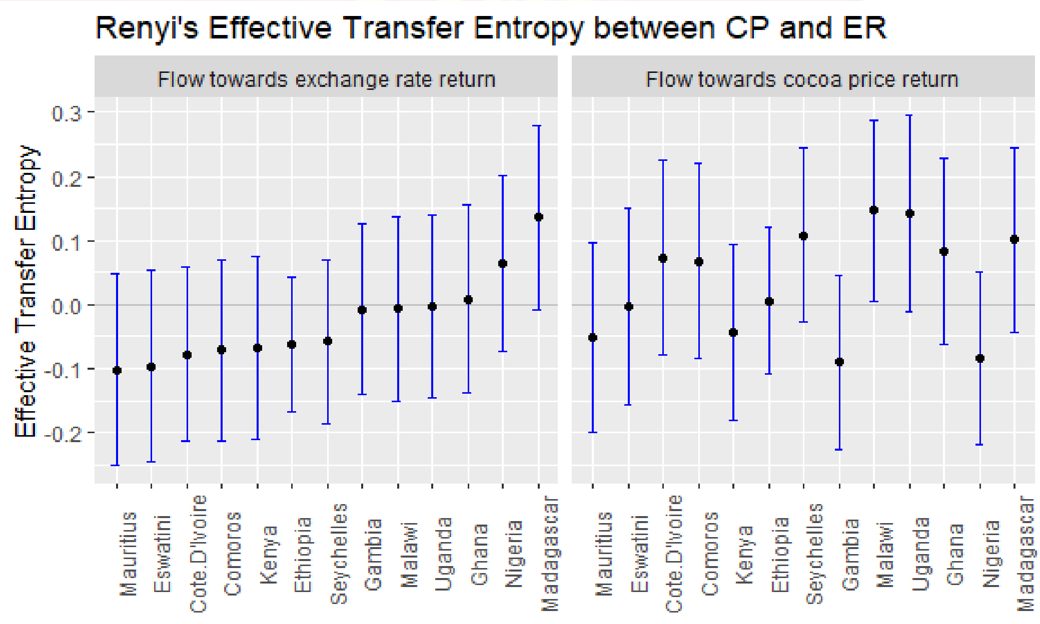
The main purpose of this study was to examine the information flow between commodity price returns and exchange rate returns for commodity-exporting countries in SSA, and this section focuses on addressing that. To test the hypothesis of no information flow between commodity returns and exchange rate returns, the study relied on Renyi's effective transfer entropy (ETE) to achieve its purpose. A bi-directional information transmission was conducted because, just as commodity prices can influence the exchange rate, vice versa also holds. There is thus a mutual interdependence between commodities and the exchange rate. From the framework of Renyian entropy, a negative effective transfer entropy (ETE) represents a high risk, while a positive ETE shows a low risk. It is a known fact that financial data is fat-tailed, and therefore, this behaviour is catered to in both commodity returns and exchange rates by utilising a fault weight of 0.3, which is in line with Behrendt (2019).

All frequency information flows were done based on IMF 1–7 and the residual. It must be noted that commodity returns represent the first asset, while the exchange rate (ER) represents the second asset. Receiving negative information on the exchange rate (ER) from commodity returns indicates that the ER is less vulnerable to shocks from commodity information, with the opposite being true for commodity returns. In all instances, the ETEs are black spots or points in blue or red bars. These blue or red bars, whose length represents 95% confidence level (5% significance), must be in the positive region or the negative region if the study is to fail to accept the null hypothesis of "no information flow." Any situation where overlaps of the bars cross the origin shows that information flow is not significant. The results are presented in two stages. The first stage presents information flow at the composite level for commodity returns and exchange rates **(Figure 9).** In the second stage, we focus on the information flow between the frequency levels of both commodity returns and the exchange rate **(Figures 10–12),** thus providing a more complete picture of the situation.

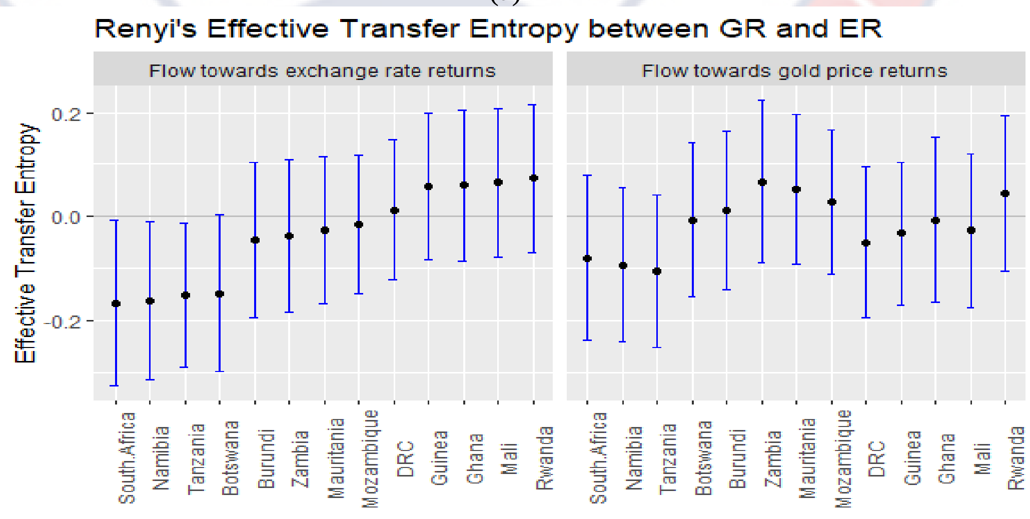
Composite Analysis of Information Flow

This section presents results and a discussion on information flow between commodity prices and exchange rates at the composite level. The results are presented in Figure 9 in three panels (a, b, and c) for cocoa, gold, and oil, respectively. The results in Panel A show that seven countries (Mauritius, Eswatini, Cote d'Ivoire, Comoros, Kenya, Ethiopia, Seychelles, and the Gambia) receive negative information from cocoa price returns (CR), which is consistent with Buah (2019). Three countries (Ghana, Nigeria, and Madagascar) receive positive information from CR, though Ghana's own is almost zero, with other countries receiving no information. The implication is that, except for Nigeria and Madagascar, cocoa prices are not likely to cause shocks in the exchange rates of countries that export agricultural goods.

However, all the information is insignificant, creating room for possible diversification. The right side of panel A, which indicates information flow from exchange rate to CR, shows that apart from Mauritius, Gambia, Kenya, and Nigeria, all the countries transmit positive entropy to CR. Only Malawi, however, transmits significant positive information. The results suggest that volatilities in exchange in agricultural-exporting countries (AEC) have a positive influence on CR. Due to negative or no information on CR, CR provides a hedge for ER in Mauritius, Kenya, the Gambia, Eswatini, and Ethiopia. The results also mean that, at the composite level, information flows in both directions, except for Malawi, Eswatini, and Uganda.

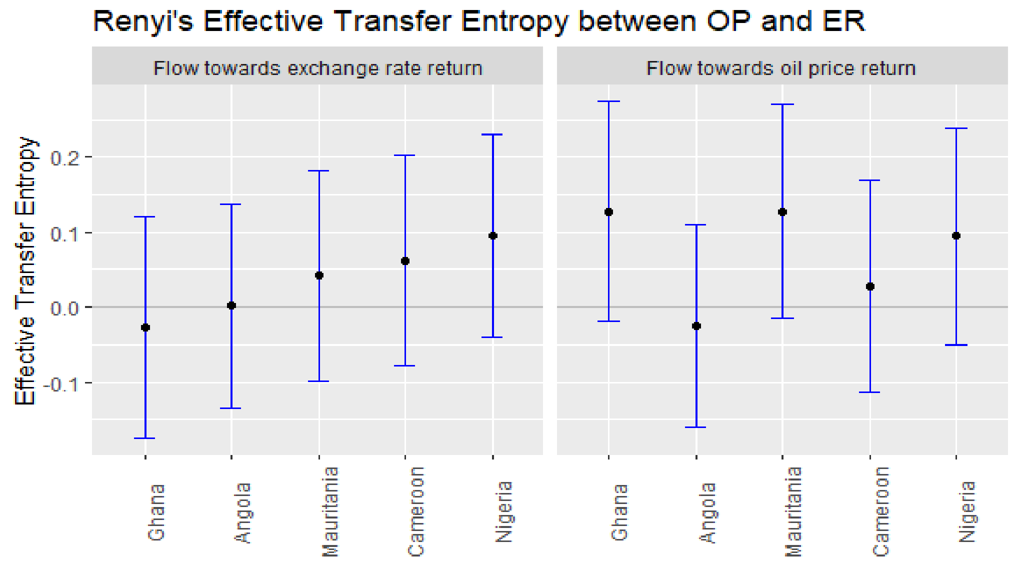


(a)



(b)

Figure 9 Continued



(c)

Figure 9: Renyian effective transfer entropy between commodities and exchange rate at the composite level. (a) Cocoa price and ER of food and beverage exporting countries. (b) Gold price and ER of metal exporting countries. (c) Oil price and ER of energy exporting countries.
Source: Field Data (2023)

In panel B of figure 9, the results of the information flow between gold return (GR) and exchange rates of metal-exporting countries at the composite level are shown. It can be observed that the information flow from gold returns (GR) to the ER of several countries, including South Africa, Tanzania, Botswana, Namibia, Burundi, Zambia, Mauritania, and Mozambique, which are all Southern African countries, is negative. This finding is in line with Reboredo and Rivera-Castro (2014). But the flow of information to countries like the DRC, Guinea, Ghana, Mali, and Rwanda, mainly West African countries apart from Rwanda, is positive. The implication is that shocks from GR are risky for the economies of countries in West Africa but not for those in Southern Africa. So, because there is a lot of information flow, the economies of southern African countries, especially South Africa, Tanzania, Namibia, and Botswana, have chances to diversify their portfolios.

Focusing on the right hand, gold can serve as a hedge for the ER of South Africa, Namibia, Tanzania, Botswana, the DRC, Guinea, and Mali as they transmit negative information to the GR in line with several empirical studies (Baur & Lucey, 2010; Baur & McDermott, 2010; Reboredo & Rivera-Castro, 2014; Sinton, 2014; Qureshi et al., 2018). The remaining countries do not have such protection because of the positive information they receive on gold.

Except for Ghana, all countries receive positive entropy at the composite level when the relationship between oil prices (OP) and ER is examined in panel C of Figure 9. Clearly, oil price shocks pose a greater risk to oil exporting countries in SSA. Not surprisingly, Nigeria appears to face a bigger risk than other countries due to its high dependence on oil exports for revenue. The situation is not so different from the right side of the figure, as only the exchange rate of Angola transmits negative information, with the rest all transmitting positive information to OP. Although all the information flow was insignificant, the risk is still visible.

Frequency Analysis of Information Flow

The results from the composite level present a situation of no information asymmetry in the relationship between commodity prices and the exchange rate, which suggests that the two markets observed each other based on mutual information and were therefore symmetrical. There is, however, a need to account for information asymmetry in the interaction between the commodity price and exchange rate. This is achieved by focusing on the frequency domain by using the IMFs, which bring out the complex behaviour of participants in the two markets. The HMH by Muller et al. (1993) and the

AMH by Lo (2004) have established that investors respond to volatility at different investment horizons. So, it's important to look at how information moves between different financial assets at different frequencies.

The effective transfer entropy (ETE) is used to examine the entropies that are transmitted in the frequency domain. The idea is that the markets for commodities and exchange rates have different participants whose behaviour is influenced by different things and, as such, they react differently to information. It is therefore important to segregate the behaviour of these participants, like speculators, who are mostly interested in the short-term, from institutional investors and monetary policy authorities, who are more focused on long-term trends. The entropies obtained from IMFs 1-3 (short-term dynamics), IMFs 4–7 (medium-term dynamics), and IMF residuals (long-term trend) give us the various behaviours of the different market participants. Figures 10–12 show the result of bidirectional multi-frequency information flow between decomposed CP and ER, GR and ER, and OP and ER, respectively.

The flow of information between the cocoa price and the exchange rate

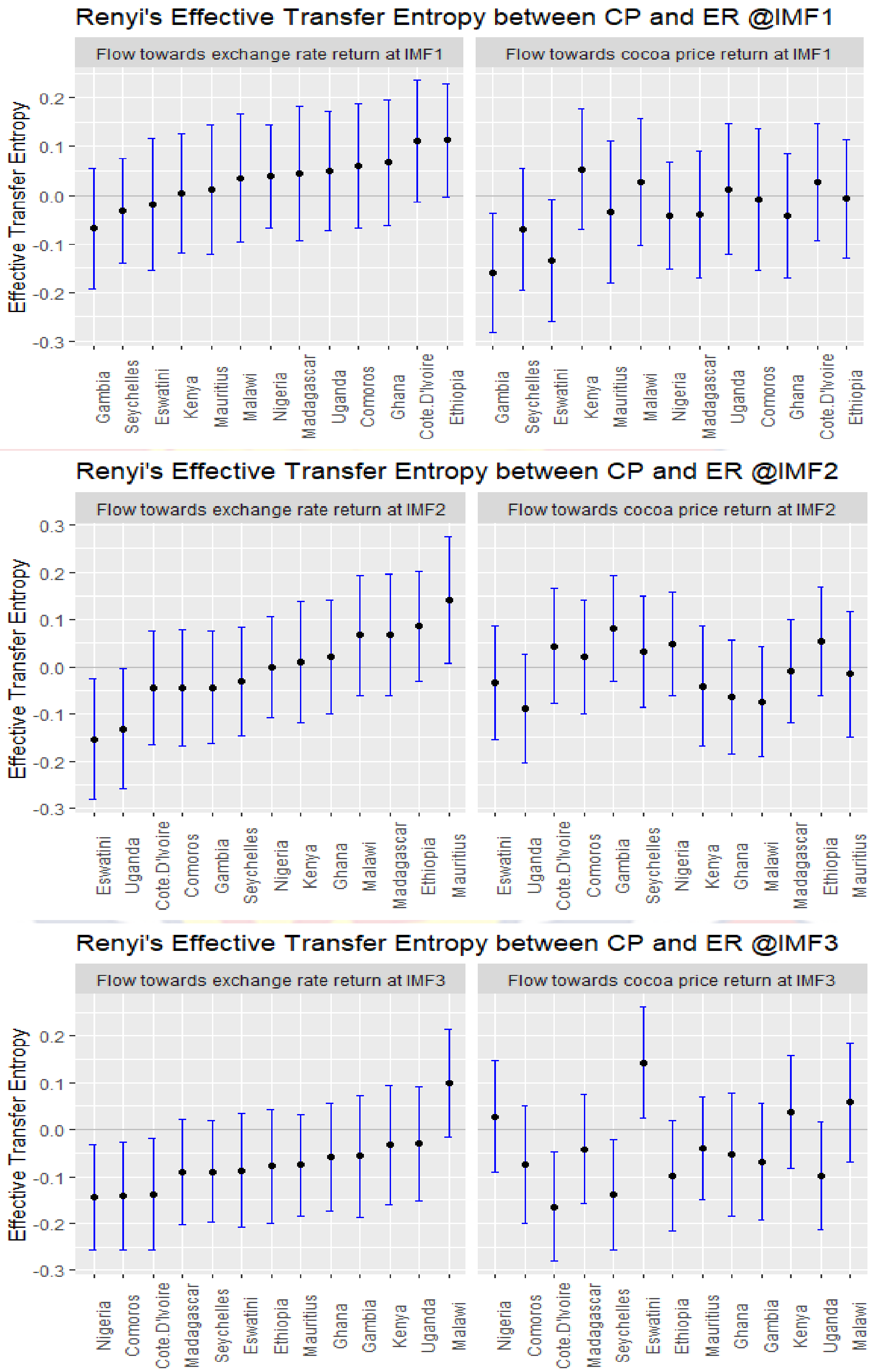
Figure 10 depicts the multi-frequency information transfer between the cocoa price CP and the SSA food and beverage exporting countries' exchange rates (ER). It can be seen in IMF1-4, which represents the high frequency with which more countries received positive information at the beginning but the reverse happened at the end. Specifically, except for Gambia, Seychelles, and Eswatini, all the other ten countries received positive information from cocoa returns at IMF1. At IMF2, the situation became evenly spread, with six countries (Kenya, Ghana, Malawi, Madagascar, Ethiopia, and Mauritius) receiving positive information and six others (Eswatini, Uganda, Cote d'Ivoire, Comoros, Gambia, and the Seychelles) receiving negative information. At IMF3 and IMF4, information from cocoa returns to ER became more negative, apart from Malawi at IMF3 and Nigeria, Madagascar, and Ghana at IMF4. The implication is that the beginning of high frequency presents high-risk shocks to ER in food and beverage exporting countries, but the latter part presents a low risk of shocks to ER in these countries. The results also show that there are several opportunities for diversification in the short-term. Because cocoa has a strong negative entropy effect on the currencies of Eswatini, Cote d'Ivoire, Comoros, Mauritius, Seychelles, and Gambia, these countries' currencies can be paired with cocoa investments.

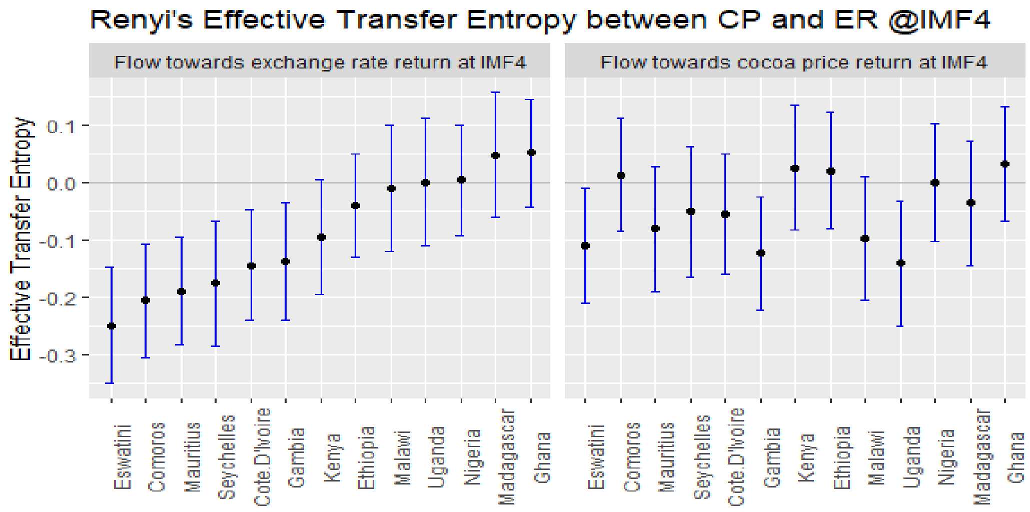
It can also be observed from the right side that there is a similar pattern of information transfer from ER to cocoa price in the short term. At IMF1, Kenya, Malawi, Uganda, and Cote d'Ivoire transmit positive entropy to cocoa returns, with the rest being negative. At IMF2, six countries (Eswatini, Uganda, Kenya, Ghana, Malawi, and Mauritius) transmit negative information about cocoa prices, and another six countries (Cote d'Ivoire, Comoros, Gambia, Seychelles, Nigeria, and Ethiopia) transmit positive information about cocoa prices. At IMF3-4, at least nine countries transmit negative information about cocoa returns. This means that about nine countries can use cocoa as a hedge or haven when their exchange rates are in trouble, which is in line with Buah's (2019) results.

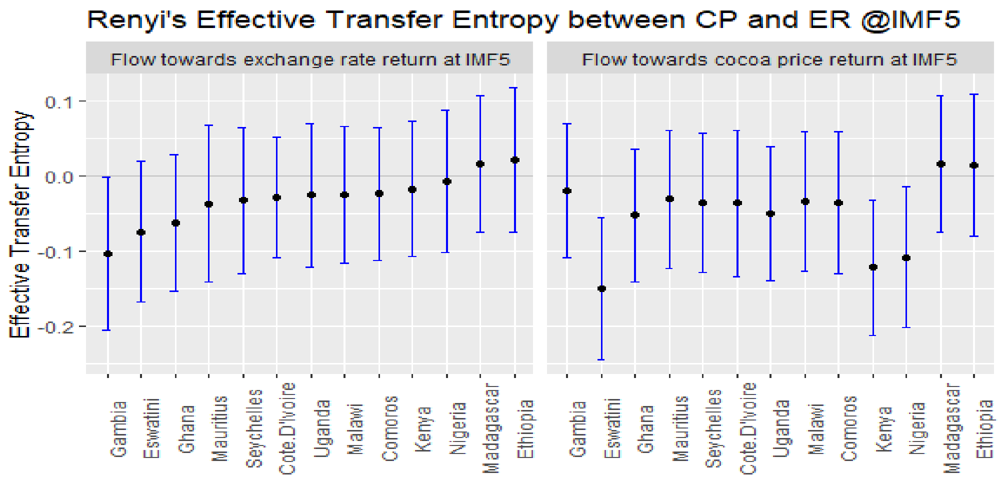
Moving to medium frequencies, the information flow from cocoa to the exchange rate is predominantly negative. The only countries that received positive information are Madagascar and Ethiopia at IMF5, and Ghana at

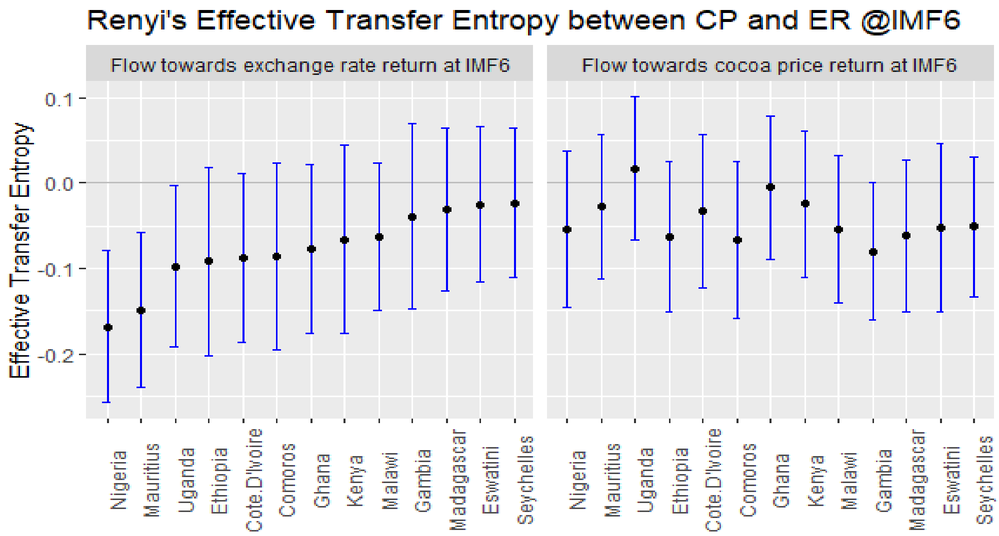
IMF7. All the other countries received negative information about cocoa at IMF5-IMF7, making them safer from shocks emanating from cocoa price volatility. Gambia, Nigeria, Mauritius, and Uganda are the only ones that receive significant negative information. On the other hand, Madagascar and Ethiopia transmit positive information about cocoa at IMF5, and Uganda does the same at IMF6, putting them at risk of losing protection in cocoa because of their exchange rates. The results indicate that the nature of information flow is asymmetric, which is consistent with the findings of Kassouri and Altintas (2020) for African commodity exporters. As a result, cocoa serves as a diversifier, hedge, and safe haven for about nine SSA food and beverage exporting countries.

Finally, in the long-term, the exchange rates of all countries receive negative information from cocoa prices, and all of them transmit significant negative information to cocoa prices apart from Seychelles, as seen in the residual. All the exchange rates also receive negative information from cocoa returns, indicating a bidirectional negative information flow between cocoa price and exchange rate in the long term. The results show that, except for Seychelles, all countries that export food and beverages are safe from changes in the price of cocoa and can also protect their exchange rates.


Renyi's Effective Transfer Entropy between CP and ER @IMF1
Flow towards exchange rate return at IMF1
Flow towards cocoa price return at IMF1
Effective Transfer Entropy
Gambia
Seychelles
Eswatini
Kenya
Mauritius
Malawi
Nigeria
Madagascar
Uganda
Comoros
Ghana
Cote.D'Ivoire
Ethiopia
Renyi's Effective Transfer Entropy between CP and ER @IMF2
Flow towards exchange rate return at IMF2
Flow towards cocoa price return at IMF2
Renyi's Effective Transfer Entropy between CP and ER @IMF3
Flow towards exchange rate return at IMF3
Flow towards cocoa price return at IMF3


Renyi's Effective Transfer Entropy between CP and ER @IMF4
Flow towards exchange rate return at IMF4
Flow towards cocoa price return at IMF4
Effective Transfer Entropy
0.1
0.0
-0.1
-0.2
-0.3
Eswatini
Comoros
Mauritius
Seychelles
Cote.D'Ivoire
Gambia
Kenya
Ethiopia
Malawi
Uganda
Nigeria
Madagascar
Ghana


Renyi's Effective Transfer Entropy between CP and ER @IMF5
Flow towards exchange rate return at IMF5
Flow towards cocoa price return at IMF5
Effective Transfer Entropy
0.1
0.0
-0.1
-0.2
Gambia
Eswatini
Ghana
Mauritius
Seychelles
Cote.D'Ivoire
Uganda
Malawi
Comoros
Kenya
Nigeria
Madagascar
Ethiopia


Renyi's Effective Transfer Entropy between CP and ER @IMF6
Flow towards exchange rate return at IMF6
Flow towards cocoa price return at IMF6
Effective Transfer Entropy
0.1
0.0
-0.1
-0.2
Nigeria
Mauritius
Uganda
Ethiopia
Cote.D'Ivoire
Comoros
Ghana
Kenya
Malawi
Gambia
Madagascar
Eswatini
Seychelles

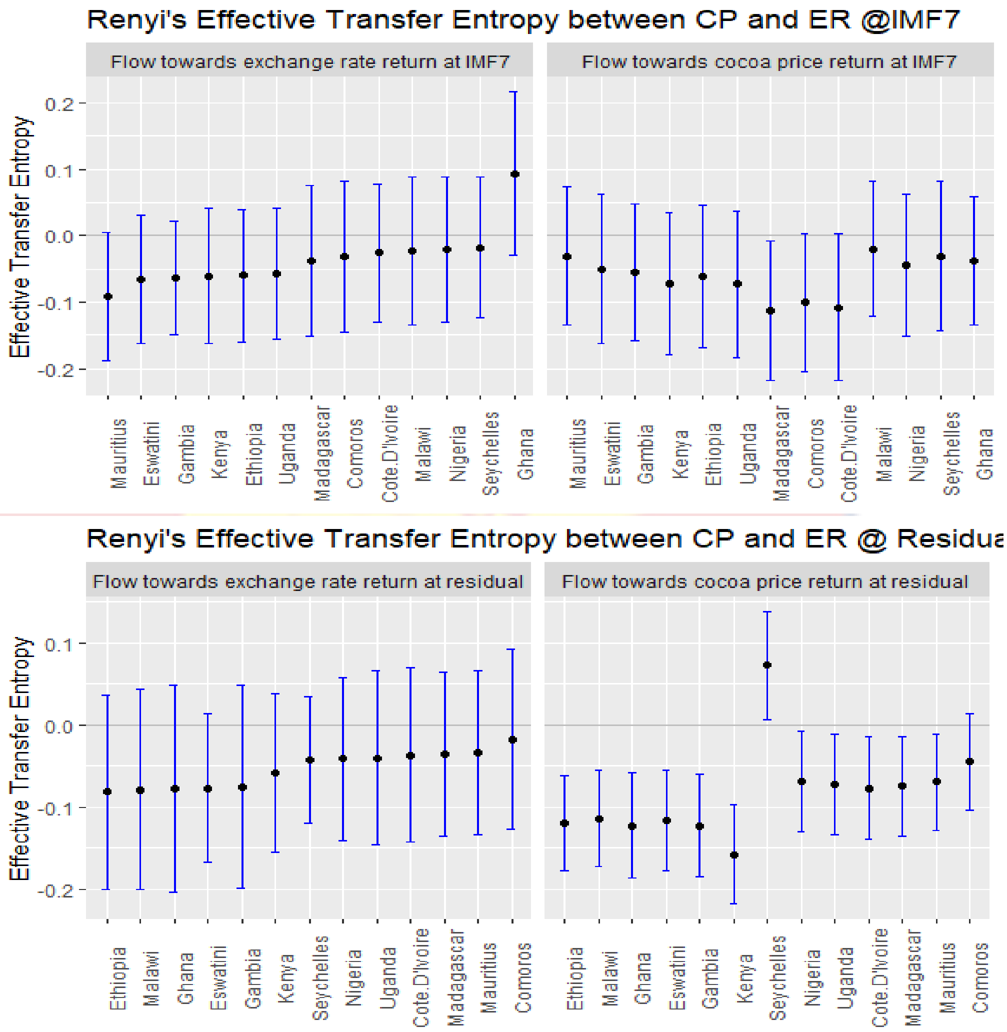
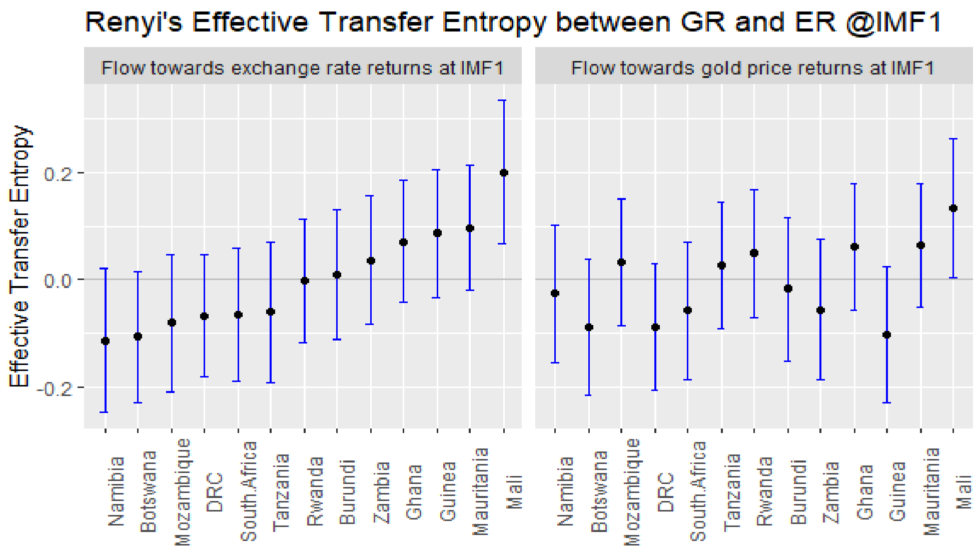
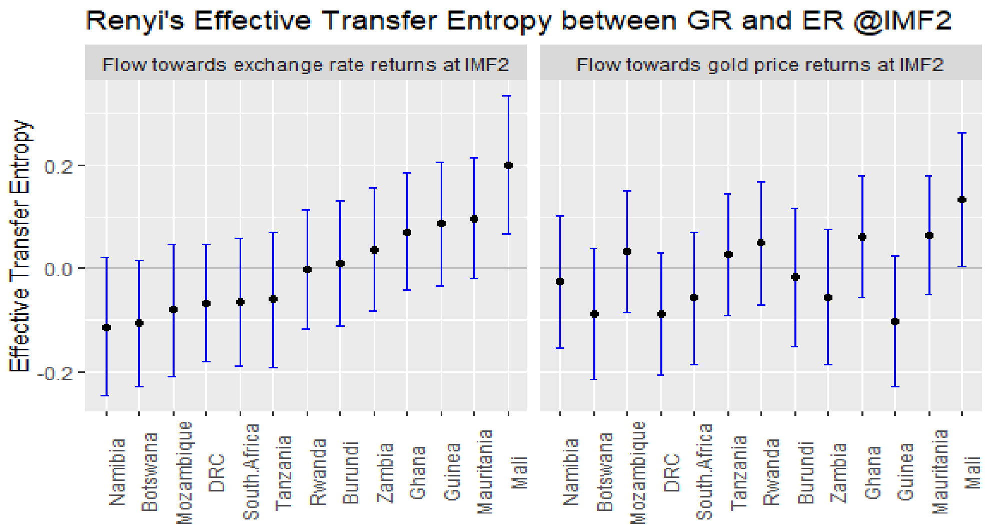
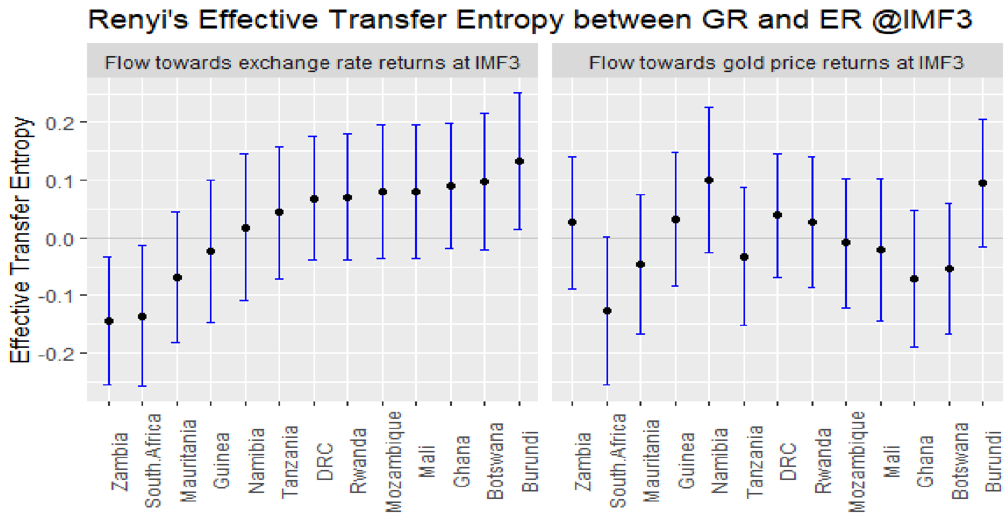


Figure 10: Renyian effective transfer entropy between the frequency levels of both cocoa price returns and exchange rate returns for food and beverage commodity-exporting countries in SSA.
Source: Field Data (2023)

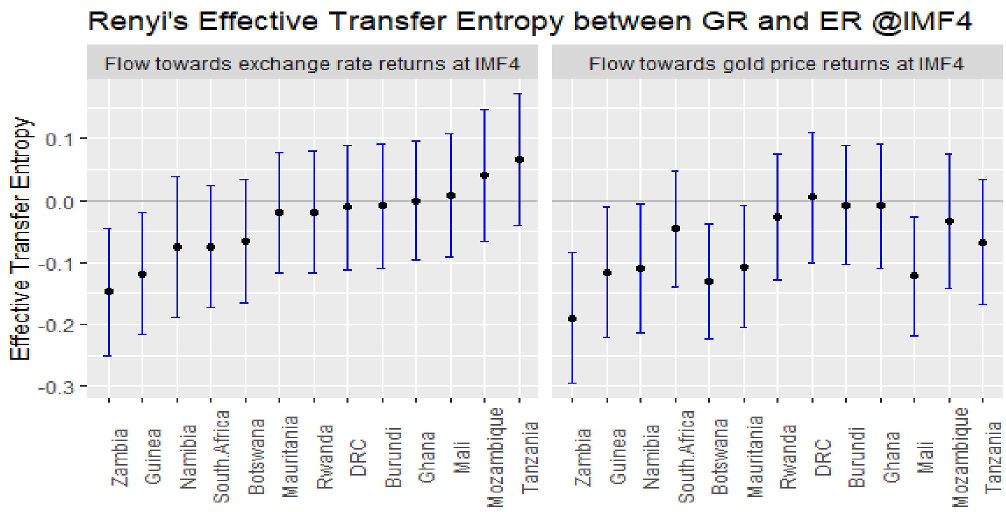




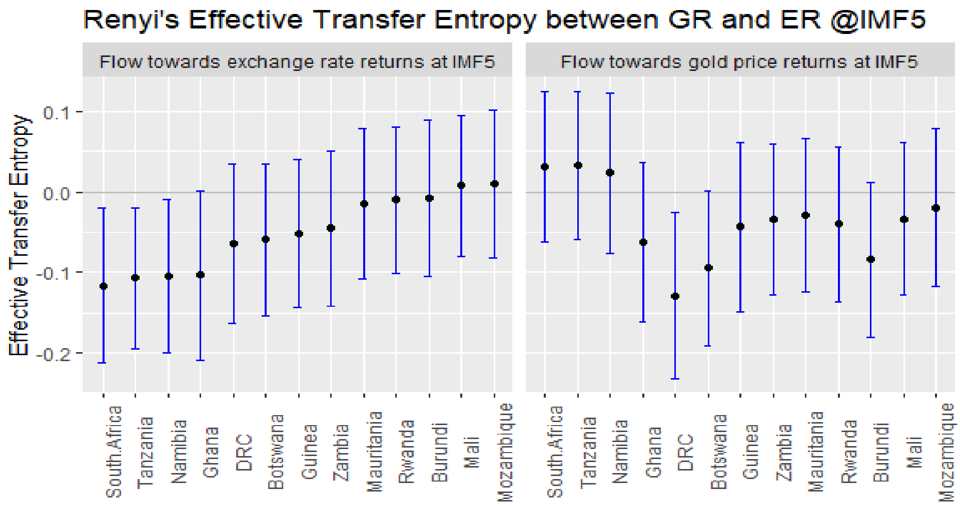
Renyi's Effective Transfer Entropy between GR and ER @IMF2
Flow towards exchange rate returns at IMF2
Flow towards gold price returns at IMF2
Effective Transfer Entropy
0.2
0.0
-0.2
Namibia
Botswana
Mozambique
DRC
South.Africa
Tanzania
Rwanda
Burundi
Zambia
Ghana
Guinea
Mauritania
Mali

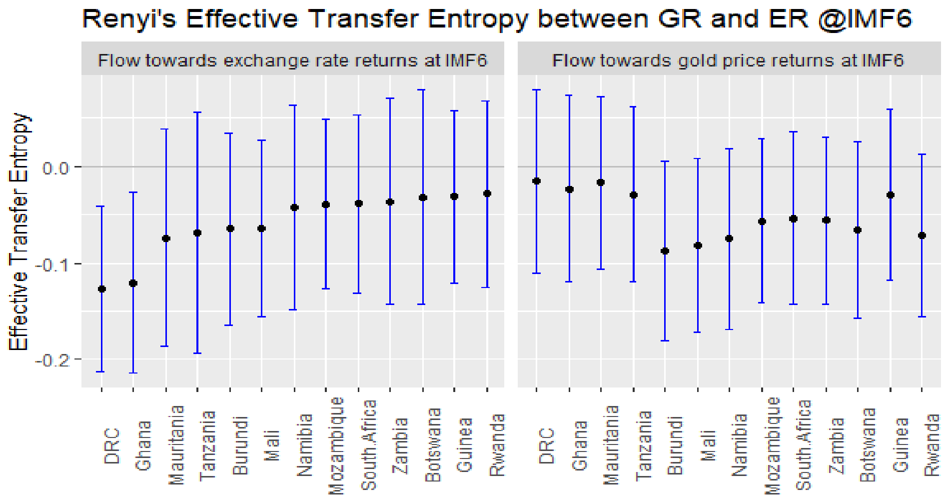


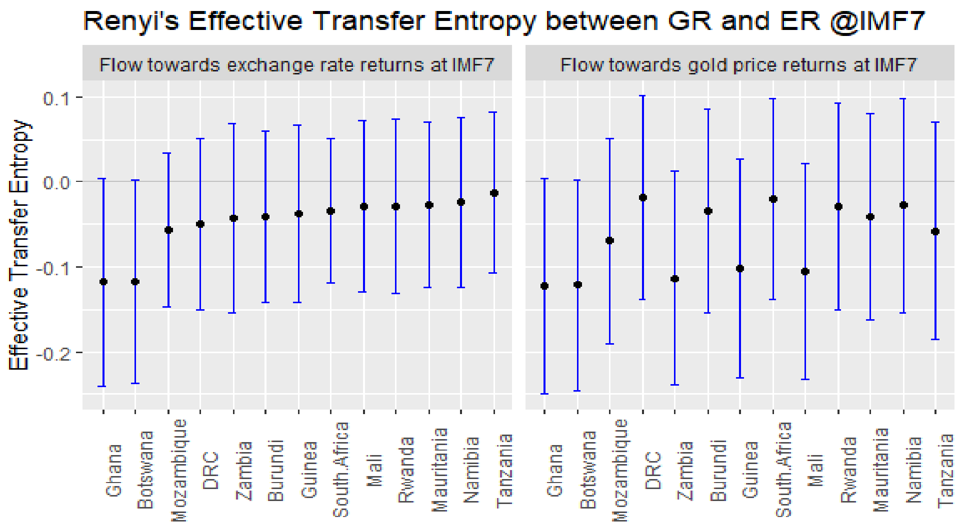
Renyi's Effective Transfer Entropy between GR and ER @IMF3
Flow towards exchange rate returns at IMF3
Flow towards gold price returns at IMF3
Effective Transfer Entropy
0.2
0.1
0.0
-0.1
-0.2
Zambia
South.Africa
Mauritania
Guinea
Namibia
Tanzania
DRC
Rwanda
Mozambique
Mali
Ghana
Botswana
Burundi



Renyi's Effective Transfer Entropy between GR and ER @IMF4
Flow towards exchange rate returns at IMF4
Flow towards gold price returns at IMF4
Effective Transfer Entropy
0.1
0.0
-0.1
-0.2
-0.3
Zambia
Guinea
Namibia
South.Africa
Botswana
Mauritania
Rwanda
DRC
Burundi
Ghana
Mali
Mozambique
Tanzania


Renyi's Effective Transfer Entropy between GR and ER @IMF5
Flow towards exchange rate returns at IMF5
Flow towards gold price returns at IMF5
Effective Transfer Entropy
0.1
0.0
-0.1
-0.2
South.Africa
Tanzania
Namibia
Ghana
DRC
Botswana
Guinea
Zambia
Mauritania
Rwanda
Burundi
Mali
Mozambique


Renyi's Effective Transfer Entropy between GR and ER @IMF6
Flow towards exchange rate returns at IMF6
Flow towards gold price returns at IMF6
Effective Transfer Entropy
0.0
-0.1
-0.2
DRC
Ghana
Mauritania
Tanzania
Burundi
Mali
Namibia
Mozambique
South.Africa
Zambia
Botswana
Guinea
Rwanda


Renyi's Effective Transfer Entropy between GR and ER @IMF7
Flow towards exchange rate returns at IMF7
Flow towards gold price returns at IMF7
Effective Transfer Entropy
0.1
0.0
-0.1
-0.2
Ghana
Botswana
Mozambique
DRC
Zambia
Burundi
Guinea
South.Africa
Mali
Rwanda
Mauritania
Namibia
Tanzania

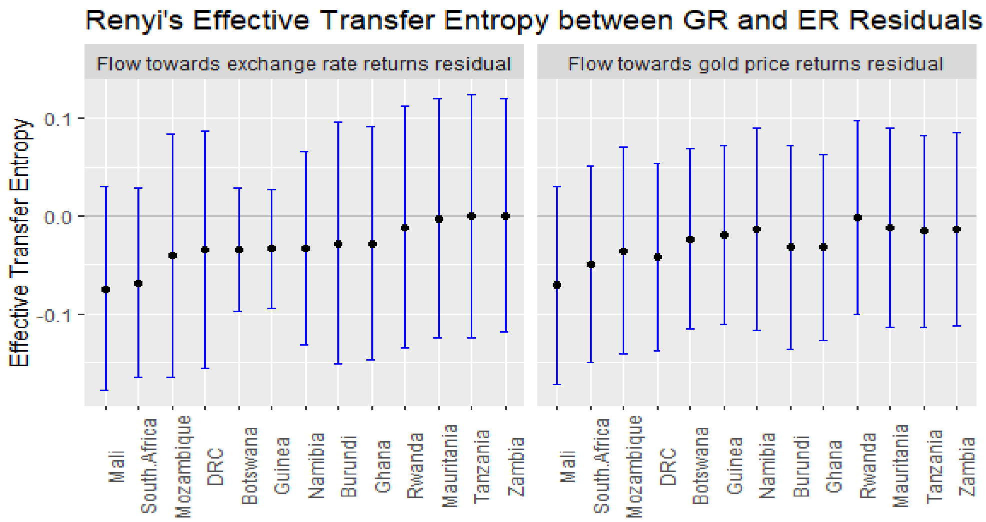
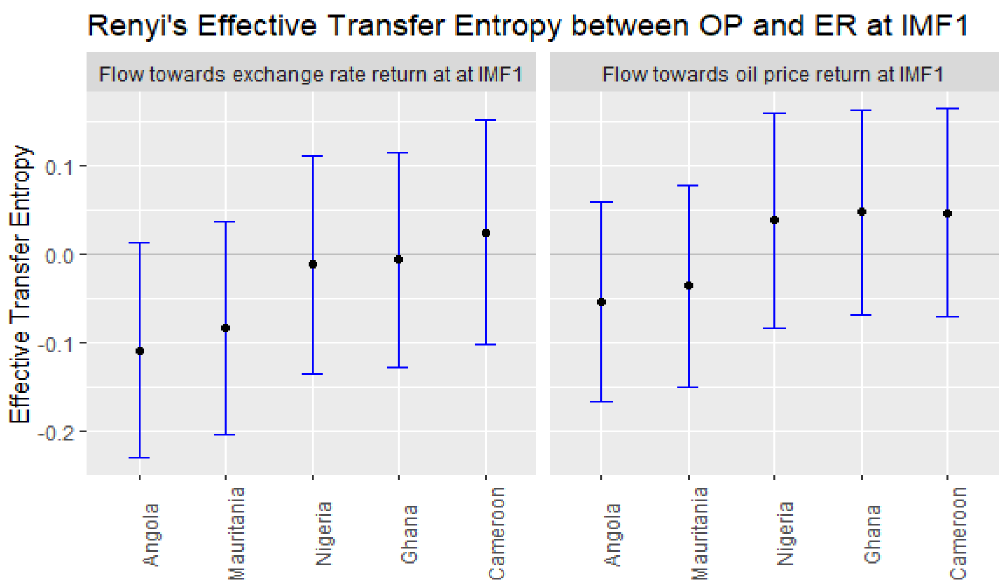
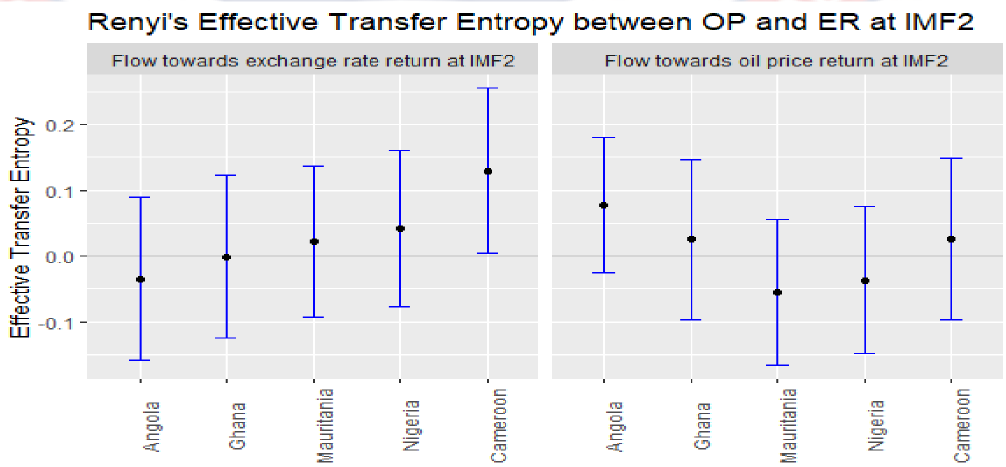
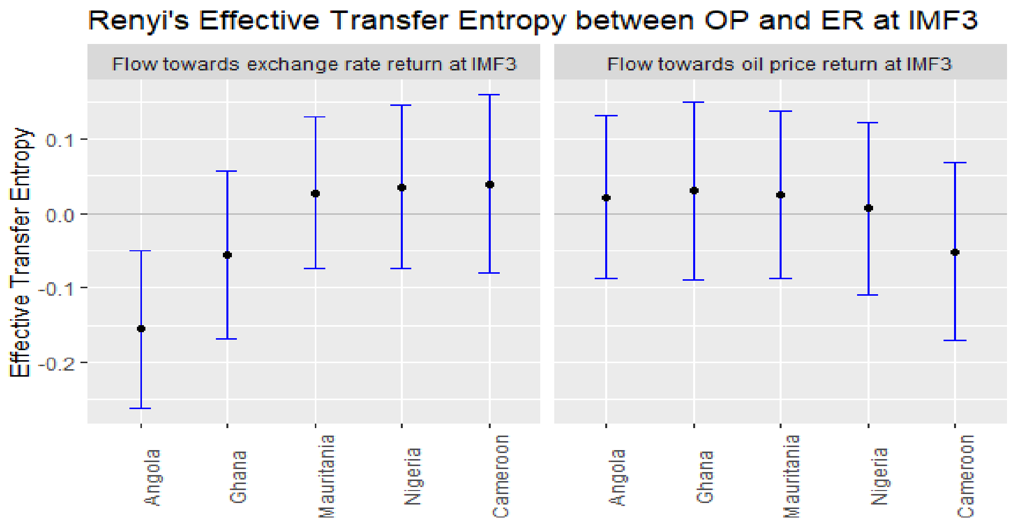
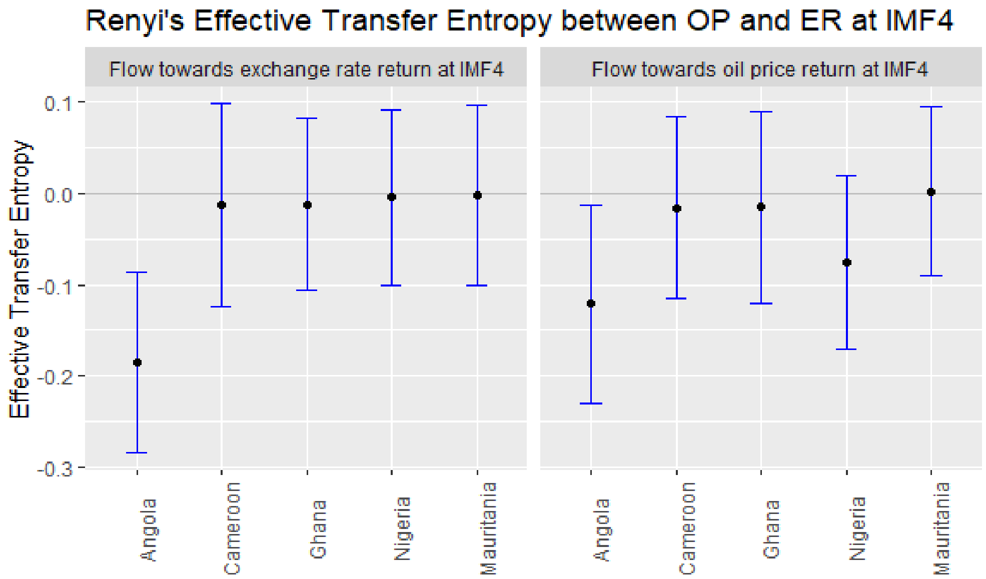


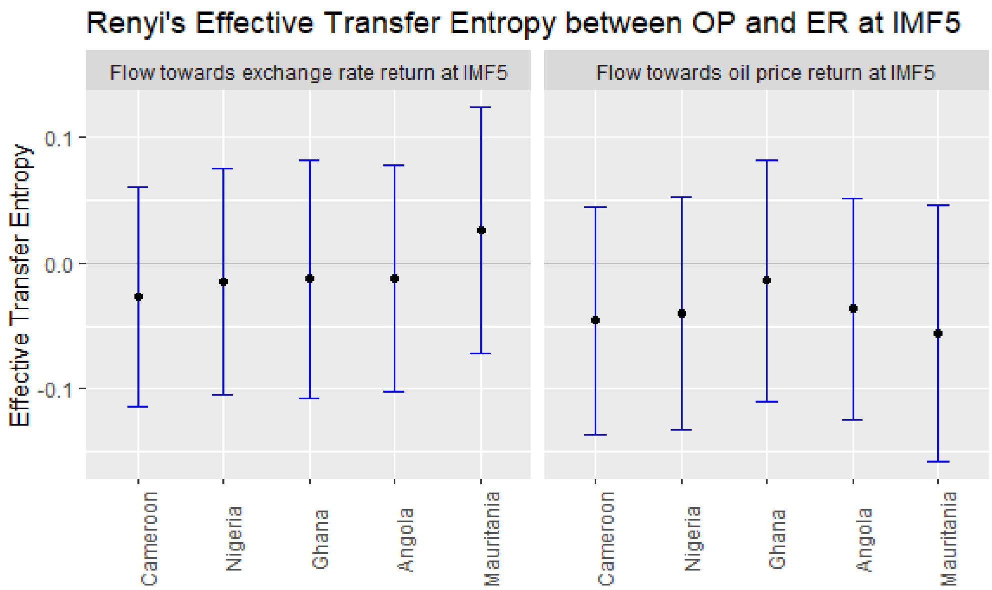
Figure 11: Renyian effective transfer entropy between the frequency levels of both gold price returns and exchange rate returns of metal commodity-exporting countries in SSA.
Source: Field Data (2023)






Renyi's Effective Transfer Entropy between OP and ER at IMF3
Flow towards exchange rate return at IMF3
Flow towards oil price return at IMF3
Effective Transfer Entropy
Angola
Ghana
Mauritania
Nigeria
Cameroon


Renyi's Effective Transfer Entropy between OP and ER at IMF4
Flow towards exchange rate return at IMF4
Flow towards oil price return at IMF4
Effective Transfer Entropy
Angola
Cameroon
Ghana
Nigeria
Mauritania


Renyi's Effective Transfer Entropy between OP and ER at IMF5
Flow towards exchange rate return at IMF5
Flow towards oil price return at IMF5
Effective Transfer Entropy
Cameroon
Nigeria
Ghana
Angola
Mauritania

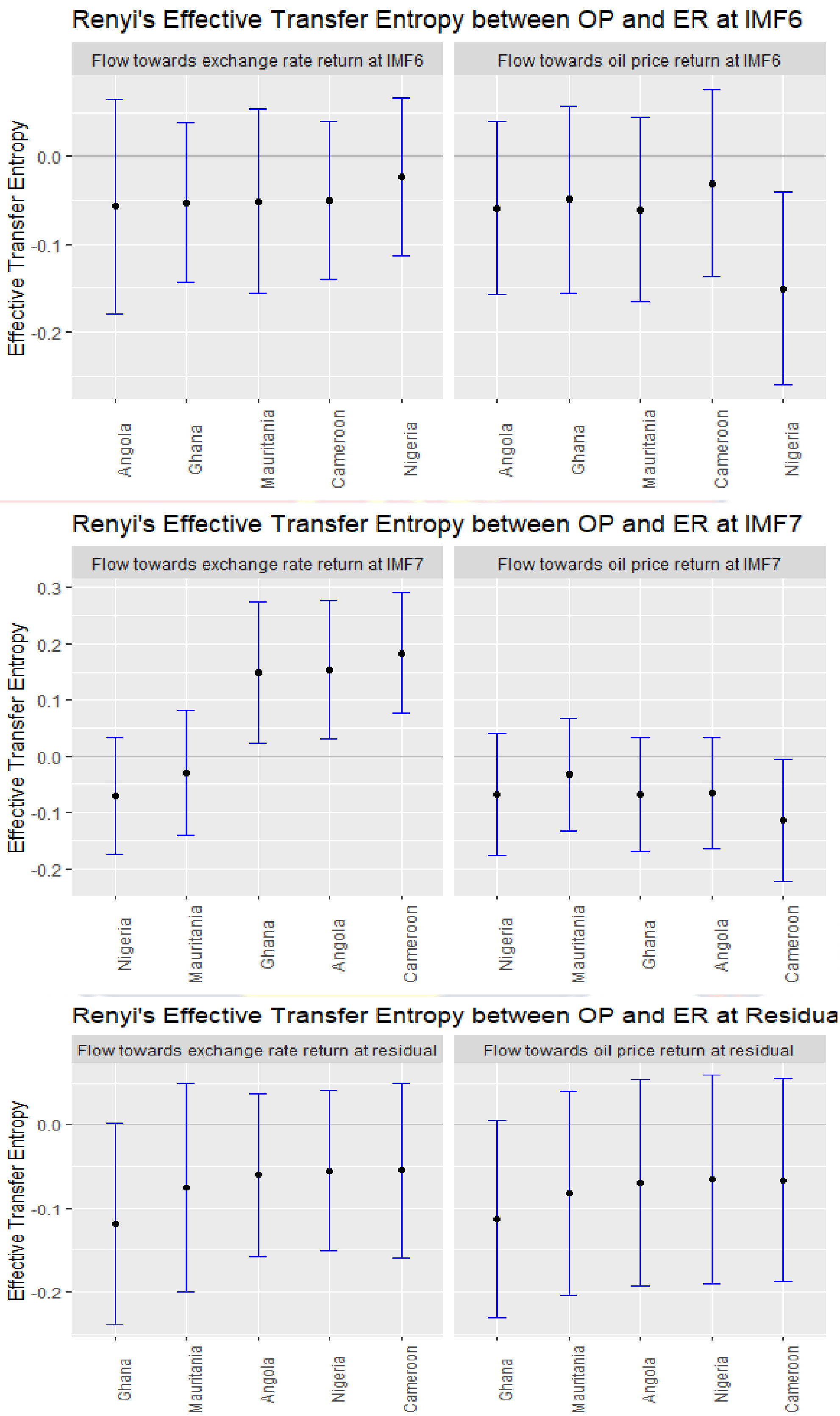


Figure 12: Renyian effective transfer entropy between the frequency levels of both oil price returns and exchange rate returns of energy commodity-exporting countries in SSA.
Source: Field Data (2023)

The flow of information between gold price and exchange rate

The results of the multi-frequency flow of information between gold and ER are found in figure 11. At the high frequencies (IMF1-4), there is a mixture of negative and positive information between gold and the exchange rate. Specifically, at IMF 1, Ghana, Mauritania, and Mali are three countries that receive and transmit positive information, while Namibia, Botswana, the DRC, and South Africa receive and transmit negative information. While IMF3 has more countries receiving positive information from gold prices, those of IMF2 and IMF4 are very similar to IMF1. The results mean that there is more variability in the information flow at high frequency, but West African countries face greater risk than those in Southern Africa.

The medium frequencies present a more consistent outcome in terms of information transfer. Only IMF5 comes with a few variations: South Africa, Tanzania, and Namibia receive negative information from the gold price but, in turn, transmit positive information to the gold price; Mali and Mozambique receive positive information but return negative information to the gold price. The flow of information at IMF6-7 is consistently negative in both directions between GR and ER. The implication from the results is that all metal exporting countries have a good hedge and safe haven protection in gold for their ER in the medium term, in support of several empirical studies (see Baur & McDermott, 2010; Reboredo & Rivera-Castro, 2014; Sinton, 2014; Qureshi et al., 2018).

Focusing on the residual, the nature of information flow in the long-term, representing low frequency, is observed. The residual shows a similar pattern of build-up on the medium frequencies. In the long term, information flow is predominantly negative and bi-directional, though Tanzania and Zambia received no information. This means that, in the long term, the exchange rates in metal-exporting countries are relatively safe from gold price shocks. It also suggests that gold is a good hedge for the exchange rate in the long-term, which is consistent with Thakolski (2021), who obtains a similar outcome. Low-frequency investors can also get long-term diversification in gold and exchange rates.

The flow of information between oil price and exchange rate

In examining the information flow between the crude oil price (OP) and ER, five EEC were included because the remaining major exporting countries in SSA used CFA and so have the same ER as Cameroon. The results are presented in Figure 12. From the results, there is a high frequency of both negative and positive information in the short-term. For instance, at IMF1, Cameroon is the only country whose ER receives and transmits positive information, putting it at a high risk of oil price shocks. Angola and Mauritania were the countries' most secure from oil shocks at the beginning of high frequency. At IMFs 2 and 3, the risk increases as three countries (Mauritania, Nigeria, and Cameroon) receive positive information from gold returns. Tiwari et al. (2013) have shown that causality between oil price and exchange rate exists at a high frequency, which this study has found evidence to support. The situation eases at the end of the high frequency, where information flows in both directions and moves into the negative. The inference is that there is an asymmetry of information flow between oil prices and the ER of energy exporting countries in the short term. In line with the findings of Jain and Biswal (2016), crude oil may not be a good hedge for many oil-exporting countries in SSA.

At the intermediate frequencies, there is more negative information flow between the two variables. IMFs 5 and 6 produce predominantly negative information in both directions, but the ER of Ghana, Angola, and Cameroon receives positive information from gold returns. Inferring from the medium-frequency results, the ER of many countries can have some protection from crude oil shocks, but Cameroon is one country that faces greater risk from oil price shocks in the medium-term. This result is also applicable to the francophone oil exporting countries in SSA since they use the same currency as Cameroon, putting them all at risk.

The lower frequency provides a safer zone for all SSA energy-exporting countries. As seen in the residual, the information flow from and to oil prices is negative about all exchange rates, which supports the findings of Singhal (2019) in the long term. Ghana is the country able to secure the most protection from oil price shocks in the long term. As a result of the significant negative information, the Ghanaian currency offers stronger diversification to crude oil investors. An interesting finding is that Nigeria, which is the major exporter of crude oil in SSA, is consistently secured against shocks in oil prices, from the medium to the long-term.

Sensitivity analysis with wavelet bivariate correlation

A sensitivity analysis using wavelet bivariate partial correction was conducted to check the robustness of the results. According to Frimpong et al. (2021), the bivariate wavelet can be employed to deduce interdependence (at low frequency) and contagion (at high frequency). The results, which are presented in Figure 24 in Appendix E, indicates that crude oil transmits positive information to most countries at high frequencies and that the connection is mainly negative at low frequencies. Such results are still consistent with those obtained by the CEEMDAN-based transfer entropy method.

Summary of the Study

The purpose of this study was to examine the flow of information between commodity prices and exchange rates at a multi-scale level among commodity-exporting countries in SSA. Existing studies have either focused on the unidirectional approach or have not quantified the strength of information between these variables. Entropy was used with the noise-assisted complete ensemble empirical mode decomposition (CEEMDAN) method to do this. The study relied on logarithm returns of 29-year monthly data for three commodities (cocoa, gold, and oil) and exchange rates for thirteen food and beverage commodity-exporting countries, thirteen metal-exporting countries, and five energy-exporting countries spanning from 1990 to 2019. Using large data points is more suitable for the methods employed in the study.

In conducting the analysis, two main steps were followed: In the first stage, the CEEMDAN method was employed to decompose the series into eight intrinsic mode functions (IMFs), including the residual, which represent short-, intermediate-, and long-term dynamics. By so doing, the study was able to remove noise that could easily blur the actual outcome from the data and appreciate the dynamics involved in different investor behaviour and participants' attitudes in the two markets. Again, this study appeals to HMH and AMH, hence making CEEMDAN a more suitable method. The next step involved the application of Renyi's effective transfer entropy (ETE) to the undecomposed and decomposed series at various frequencies. To account for the tailed behaviour present in the data, a fault weight of 0.3 was adopted, which also differentiates between positive ETE (low risk) and negative ETE (high risk).

The results at the composite level produce inconsistent patterns of information flow, particularly for cocoa and gold. Indeed, the bi-directional information flow between commodities (cocoa and gold) and exchange rate presents a mixture of positives and negatives, with a more positive information flow to countries in West Africa than those in Southern Africa. However, the case of oil and the exchange rate at the composite level is consistently positive for all but one country. The results point out that oil prices present a higher risk than gold and cocoa at the composite level.

The results at the frequency level indicate that the nature of the information transmitted and the significance levels change at different frequencies. The study's findings show that the information flow between global commodities and exchange rates is mostly negative in the long run. Investors looking to diversify during uncertain commodity times may find it profitable. However, the study observed both positive and negative information flows between the variables in the short- and medium-terms, which represent the high and medium frequencies. The short-term frequencies produce a higher level of risk for both commodities and the exchange rate as more positive information flows in both directions. In relation to the medium frequencies, the early part presents more positive information flow, but the later frequencies produce more negative information flow in both directions. This means that the flow of negative information increases from short to long-term.

Policy Implication

In general, the findings provide useful inferences for portfolio diversification, policy decisions, investment risk, and risk management strategies in global commodities. The support is contingent on the negative information flow between global commodities and market volatilities at various investment horizons for the sake of asset allocation and risk management. Several factors, such as financial crises and political uncertainties in large commodity-producing countries, among others, may be attributed to the uncertainties in global commodity prices (Singhal et al., 2019). To manage shocks from commodity returns effectively, policymakers must incorporate the frequency dynamics into their decisions on the ER and policy rate. This is to enable them to target different timescales with different policy strategies with more precision, which gives a high probability of success in dealing with shocks in commodity prices. Although the shocks in commodity prices pose a significant danger to some ER in the short-term, particularly those in West and Central Africa, there are, however, hedging opportunities available in the medium-term for some countries due to the negative information transmitted to commodities at different frequencies. Policymakers need dynamic policies to monitor and deal with the volatility that emanates from commodity returns to their ER during short-term turbulence usually triggered by the crisis, as fluctuations in the ER have repercussions for the interest rate and inflation.

Concerning investors, it is critical that they incorporate frequency information into their portfolio strategies because the behaviour of investors differs from each other as they operate at different investment time horizons. The asymmetric nature of the information in the exchange rate markets of commodity-exporting countries in SSA creates some avenues for portfolio diversification in the short- to medium-term, either among African markets or for international diversification. Investors can find some safe havens in some local currencies with negative information at certain frequencies in the medium- to long-term. The increasing nature of short-term negative information flow indicates that investors can effectively rebalance their portfolios to maximise their returns. The increasing flow of negative information clearly indicates that currency market volatility and global commodities act as safe havens for one another, in line with Baur & Lucey (2010).

CHAPTER SIX

TIME-VARYING CONNECTEDNESS AND CONTAGION BETWEEN COMMODITY PRICES AND EXCHANGE RATES

Introduction

The financial economics literature has shown significant interest in connectedness and contagion, mainly driven by financial catastrophes like the Asian, Mexican, and Russian crises, the 2007/2008 global financial crisis (GFC), the 2013 oil price drop, and the COVID-19 pandemic (see, for instance, Jiang et al., 2022; Boako & Alagedede, 2017; Diebold & Yilmaz, 2009). The growing interdependence of countries as economic partners or neighbours has also opened the door to shock spillovers and, as a result, interest in contagion (Owusu Junior et al., 2020). Again, high market integration, especially for nations in the same economic bloc, contributes to high interest in contagion research and financial market expansion as investors seek secure assets (Tiwari et al., 2019).

The numerous academic interests in contagion have generated a debate on what constitutes financial contagion. From the perspective of fundamental contagion theorists, contagion occurs when there is shock transmission from one country or market to another through the real sector or macroeconomic factors (Bekaert et al., 2005; Forbes & Rigobon, 2002; Pritsker, 2000). On the contrary, the pure contagion theorists are of the belief that when shocks are transmitted from one country or market to another without any idiosyncratic factors, there is contagion (see Kaminsky et al., 2003; Dornbusch et al., 2000). The lack of clarity in the meaning of contagion led Forbes and Rigobon (2002) to propose *"shift contagion,"* (SC), which is a significant shift in cross-market linkages. To them, a cross-market linkage without any significant change in spillover constitutes connectedness. Despite the contribution of SC, the definition and measurement of contagion are still the subject of an ongoing and contentious debate. Contagion is therefore an empirical issue that is contextual in nature; hence, this study seeks to examine connectedness and contagion between global commodity prices (CP) and exchange rates (ER) in SSA. In line with Forbes and Rigobon (2002) we separate connectedness from contagion and make inferences about any possible decoupling between the two markets.

The focus on commodities and ER is motivated by the high dependence of countries in SSA on commodity exports for revenue. Indeed, nine out of ten countries in SSA are classified as commodity dependent (UNCTAD, 2021), and since these commodities are traded mainly in US dollars on the international market, there is a high probability of shocks emanating from commodity prices to ER in SSA. At the same time, these countries see commodities as assets that can be relied on to hedge their currencies, especially in turbulent times. As a result, understanding the dynamics of interdependence and possible contagion between these two variables will be helpful in the hedging and risk management decisions of policymakers in SSA.

Moreover, information from crises like the GFC and the 2017 commodity price collapse usually triggers a reaction from market participants and agents to look for alternative assets to put in their portfolios, either for hedging purposes or for diversification. These economic agents could either be rational or irrational, and because of the heterogeneity in their behaviour, they may be following the heterogeneous market hypothesis (HMH) by Muller et al. (1993) or the adaptive market hypothesis proposed by Lo (2004). The idea behind these theories is that the differences among investors cause them to operate at different investment horizons as they respond to volatility differently. Investors' behaviour is thus frequency varying over time, contrary to the proposition of the efficient market hypothesis (EMH) that sees investors behave similarly. Market participants seeking an efficient portfolio, particularly during times of crisis, look for assets that are uncorrelated or negatively correlated to provide a safe haven (Baur & Lucey, 2010). This is because contagion between assets diminishes portfolio diversification possibilities since it increases correlation (Gulko, 2002).

Financial markets in Africa, including the forex and stocks markets, have become attractive to global investors because there is a perception fuelled by some studies that the African markets, like many in other developing economies, are decoupled from global economic activities (see Kose & Prasad, 2010; Kose, 2008; World Development Outlook, 2007). These studies posit that economic activities in advance markets and the developing and emerging world are uncorrelated contrary to the views of contagion theorists. The implication is that returns from FX markets in SSA and the global commodities market won't be related in a normal way, meaning they won't be tied together. This belief has led to increased capital inflows to SSA markets (Atenga & Mougoué, 2021; World Bank, 2018; Nyang'ro, 2017). The question then is: do the currency markets in SSA offer any diversification opportunities to commodity investors and does commodities provide hedging potentials for currencies in SSA? The answer to the question hinges on the nature of any possible connectedness and or contagion between the two variables, and since not much is known in this direction, this study seeks to provide a possible guide to investors and policymakers.

Further, several studies on financial contagion in the financial economics literature have focused on contagion between stock markets (Owusu Junior et al., 2020; Caporin et al., 2018; Diebold & Yilmaz, 2009), between commodities (Shen et al., 2022; Bouri et al., 2017; Ji & Fan, 2012), and between currencies (see Huynh et al., 2020; Kocenda & Moravcová, 2019; Salisu et al., 2018; Anthonakakis, 2012; Bubák et al., 2011). Yet, contagion between commodity markets and currency markets has received limited attention. The few exceptions, like Dai et al. (2020) and Jiang et al. (2022), focused on only major currencies at the expense of those of weaker economies. The situation in SSA is even worse, as studies on contagion between global commodities and exchange rates (ER) hardly exist. Mention can be made of Katusiime (2018), but apart from the study being limited to only one country (Uganda), no differentiation was made between connectedness and contagion. This gap needs immediate attention due to the high dependence of countries in SSA on commodity exports. Including commodities will allow policymakers to determine if there is a substantial premium for commodity price risk in African currency markets and if the currency markets in SSA offer diversification opportunities to global commodity traders.

Additionally, previous connectedness and contagion studies between commodities and ER in SSA have concentrated on linear and static time analysis in line with EMH with little or no attention to the time-frequency dimension. This is a significant gap because Muller et al. (1993) found that agents in financial markets respond to volatility differently at different investment horizons corresponding to high, medium and low frequencies. Understanding the frequency dynamics of connectedness is critical to finding the origins of connectivity in an economic system since economic shocks have various impacts on variables at different frequencies and intensities. Again, measuring connections in the frequency domain provides another source for managing systemic risk between assets (Barunik & Krehlik, 2018). Moreover, most prior studies have relied on GARCH, transfer entropy, and DY12 methods. Although, these methods contain information about static time-domain analysis, they are limited in their ability to examine the frequency information of contagion over time. There is therefore a need to utilise a more robust method capable of capturing the dynamic behaviour of market agents.

This study differs from others by focusing on returns as the source of contagion in commodity-dependent developing countries and makes the following contributions: First, the study provides novel understandings of the ways in which dependence and contagion spread both within and between ERs in SSA and between global commodities and ERs in SSA by disaggregating return volatility. Such analysis provides more information about the heterogeneous behaviour of investors, which varies across different times (short-, medium-, and long-terms) and may be hidden from studies focusing on composite behaviour (Owusu Junior et al., 2022). The information provided by the study is helpful to investors and policymakers for risk management.

Second, it examines the dynamic interdependence between commodities and ER at different frequencies (high, medium, and low) and over time. This provides information about how complex connections between CP and ER have evolved over time. Such analyses appeal to HMH, which has indicated that the differences in investor expectations and appetite for risk, among others, make them operate at different investment horizons at different times. Therefore, while institutional investors and monetary policy authorities are more interested in medium and low frequencies, which correspond to medium- and long-terms, speculators focus on high frequencies, which correspond to short-term. Findings here will therefore be more useful to different participants in the markets making hedging decisions than other studies that focus on only time at the expense of time variation.

Third, we quantify connectedness and contagion using the non-parametric method of Barunik and Krehlik's (2018) time-domain, frequency-domain and time-frequency domain framework (BK18). This method captures non-linear and non-stationary returns. Non-stationarity and non-linearity are becoming important in spillover research. To the best of our knowledge, this method has not been applied to commodities and currency markets in SSA, as prior studies have mostly applied the Diebold and Yilmaz (2012) (DY12) spillover index and GARCH methods, which are limited in accounting for the frequency dimension of the relationship. Again, BK18 accounts for causality in the frequency domain by using "within" connectivity, contrary to DY12. The BK18 considers composite and pairwise (bi-directional) spillover at different frequencies and timings. It estimates net spillovers by comparing "from" and "to" spillovers. BK18 calculates spillovers like several current studies (see Saiti et al., 2015; Adam, 2013; Diebold & Yilmaz, 2009). BK18's contagion measurement is consistent with Forbes and Regobon's (2002) "shift contagion" measurement. It captures contagion asymmetry, which benefits investors and policymakers.

Fourth, we present evidence of currency market contagion in 27 commodity-producing and largely commodity-dependent SSA countries. Commodity-dependent countries need to know whether they should spend more time dealing with external shocks from global commodity prices or dealing with shocks from the exchange rates of other commodity-exporting countries within the continent. The use of three major commodities (oil, gold, and cocoa) and several countries provides a broader understanding of the situation in specific countries to aid investor and policy decision-making. The methods employed in this study (BK18) can determine the system's most dominant contributor to spillovers. This is important for systemic risk management and portfolio diversification. By using BK18, the study can determine whether a specific country at a specific frequency is a net receiver of return shocks in pairs or as a whole, which other methods are unable to do.

Theoretical Models and Empirical Estimation

This section of the chapter discusses the theoretical and empirical models used to estimate commodity price and exchange rate connectedness and contagion. We provide details of the Barunik and Krehlik (2018) spillover methods, which was relied on to achieve the purpose of the study.

Barunik and Krehlik Frequency-Domain Spillover Method

Barunik and Krehlik (2018) spillover method, commonly called BK18 was motivated by Diebold and Yilmaz's (2012) method (DY 12), which estimates connectedness among variables in the time domain. Barunik and Krehlik extended the DY model to incorporate the frequency domain in estimating connectedness. The benefit of the BK18 method is its ability to account for connections in the time domain, frequency domain, and time-frequency domain. We begin the discussion of the methods with Diebold and Yilmaz's (2012) framework, herein called DY12. The DY12 calculates connectedness from generalised forecast error variance decompositions (GFEVDs), which are based on the matrix of vector autocorrelation (VAR) model of local covariance stationarity. For instance, if we denote $K-variance$ process as $Y_t = (y_{1,t}, \ldots, y_{k,t})'$ at $t = 1, \ldots, T$, then, the $VAR_{(\rho)}$ may be expressed as;

$$Y_t = \sum_{i=1}^{p} \emptyset_i \, y_{t-1} + \epsilon_t \tag{16}$$

From equation (16), $\emptyset_i$ and ϵ_t represent coefficient matrix and white noise respectively with (possibly non-diagonal) covariance matrix Π. In the equation above, the system makes it possible to regress each of the variables on its own ρ lags and the ρ lags of other variables. This makes $\emptyset$ have complete information of the connection between all the variables. It must be indicated that it is helpful to work with $(K \, x \, K)$ matrix lag-polynomial $(I_K - \emptyset_1 L - \cdots - \emptyset_p L^p)$ with identity I_K. In this process, if the root of $|\theta(Z)|$ lies outside the unit circle, then the VAR process contains a vector moving average $(i.e., \mathrm{MA}(\infty))$ expressed as

$$Y_t = \psi(L)\epsilon_{t,} \tag{17}$$

Where $\psi(L)$ is an infinitely lag polynomial. Building on Diebold & Yilmaz (2012) the GFEVD can be expressed as;

$$(\Theta_H)_{j,k} = \frac{\sigma_{kk}^{-1}\Sigma_{h=0}^{H}(\psi_h\Pi)_{j.k})^2}{\Sigma_{h=0}^{H}(\psi_h\Pi_{h'})_{j.k}} \tag{18}$$

Where ψ_h is KxK matrix having a coefficient corresponding to h lags $(i.e., h = 1, \dots, H)$ and $\sigma_{kk} = (\Pi)_{k,k}$ and represent the contribution of the k_{th} variable to the variance of the forecast error of the element j. It is worth noting that the sum of each row does not necessarily add up to one, so each element of the decomposition matrix is normalized as follows;

$$(\widetilde{\Theta}_H)_{j.k} = \frac{(\Theta_H)_{j.k}}{\Sigma_{k=1}^{H}(\Theta_h)_{j.k}} \tag{19}$$

It should be noted that $(\widetilde{\Theta}_H)_{j.k}$ provides a pairwise connectedness measure from j to i at horizon H that can be aggregated by design. The connectedness measure is defined by Diebold and Yilmaz (2012) as the amount of variance in forecasts contributed by errors other than own errors or the ratio of the sum of the off-diagonal element to the sum of the entire matrix, which is expressed as

$$C_H = 100 * \frac{\Sigma_{j\neq k}(\widetilde{\Theta}_H)_{j.k}}{\Sigma\widetilde{\Theta}_H} = 100 * \left(1 - \frac{Tr\{\widetilde{\Theta}_H\}}{\Sigma\widetilde{\Theta}_H}\right) \tag{20}$$

From (20), $Tr\{*\}$ is the trace operator, and the denominator stand for the sum of all the elements of $\widetilde{\Theta}_H$ Matrix. Accordingly, connectedness is the relative contribution of the other variables in the system to the forecast variances. Until now, the link between commodity prices and exchange rates has been clearly demonstrated in time domain. We can also measure spillovers from one country to another. Barunik and Krehlik extended the DY model to incorporate the frequency domain in estimating connectedness. As a foundation, if we consider a frequency response function $\psi(e)^{-i\omega} = \Sigma_h e^{-i\omega h}\psi_h$ of Fourier transformable coefficient ψ_h with $i = \sqrt{-1}$, then, a spectral density of Y_t at a frequency ω can be expressed as $MA(\infty)$ filters series as follows;

$$S_{y(\omega)} = \sum_{h=\infty}^{\infty} E(Y'Y_{t-h})\, e^{-i\omega h} = \psi(e^{-i\omega})\Pi\psi'(e^{+i\omega}) \qquad (21)$$

The power spectrum $S_{y(\omega)}$ expresses how the variance of the Y_t is distributed over the frequency component ω and is very important in understanding the frequency dynamics. The generalized causation spectrum over $\omega \epsilon = (-\pi, \pi)$ is expressed as:

$$(\mathcal{F}(\omega))_{j,k} = \frac{\sigma_{kk}^{-1}|\psi(e^{-i\omega})\Pi_{j,k}|^2}{\psi(e^{-i\omega})\Pi\psi'(e^{+i\omega}))_{j,j}} \qquad (22)$$

The $(\mathcal{F}(\omega))_{j,k}$ indicate the portion of the ith variable at a given frequency ω due to shocks in the kth variable. From that, we can interpret the quantity as within-frequency causation based on the denominator which shows a spectrum of jth variable at a frequency of ω. The most logical thing to do now is to weigh $(\mathcal{F}(\omega))_{j,k}$ by the frequency share of the variance of the jth variable to get the natural decomposition of GFEVD to frequencies. This is expressed as

$$\Gamma_j = \frac{\psi(e^{-i\omega})\Pi\psi'(e^{+i\omega}))_{j,j}}{\frac{1}{2\pi}\int_{-\pi}^{\pi}(\psi(e^{-i\lambda})\Pi\psi'(e^{+i\lambda}))_{j,j}d\lambda} \qquad (23)$$

The weighted function defined in (23) is the power of (jth) variable at a given frequency which sums up the value of real numbers through to 2π. Indeed, it is appropriate to measure connectedness over time horizons if we have proper financial application. Therefore, measuring connectedness at different frequency bands instead of just at a single frequency is very necessary. So as a general representation, if we have a frequency band $d = (a, b) : a, b\ \epsilon\ (-\pi, \pi), a < b$, then, the GFEVDs can be expressed as

$$(\Theta_d)_{j,k} = \frac{1}{2\pi}\int_a^b \Gamma_j(\omega)\,(\mathcal{F}(\omega))_{j,k}d\omega \qquad (24)$$

From (24), a scale generalized variance decomposition can be expressed over the same frequency band d as follows.

$$(\widetilde{\Theta}_d)_{j,k} = (\Theta_d)_{j,k} / \sum_k (\Theta_\infty)_{j,k} \qquad 25$$

Consequently, (24) and (25) respectively define the within-frequency and frequency connectedness over d as follows

$$C_d^W = 100.\left(1 - \frac{\mathrm{T}_r\{\widetilde{\Theta}_d\}}{\Sigma\widetilde{\Theta}_d}\right) \qquad (26)$$

$$C_d^F = 100.\left(\frac{\Sigma\widetilde{\Theta}_d}{\Sigma\widetilde{\Theta}_\infty} - \frac{\mathrm{T}_r\{\widetilde{\Theta}_d\}}{\Sigma\widetilde{\Theta}_\infty}\right) = C_d^W.\left(\frac{\Sigma\widetilde{\Theta}_d}{\Sigma\widetilde{\Theta}_\infty}\right) \qquad (27)$$

Based on the estimation of Barunik & Krehlik (2018), C_d^W measures the connectedness within a frequency band which is exclusively weighted by the power of the series. The C_d^F on the contrary decomposes the original connectedness into separate parts which add up to the original connectedness measure. In this study, the frequency bands $(\pi + 0.00001, \pi/4, \pi/12, 0)$ as seen in Barunik & Krehlik (2018) and Tiwari et al. (2019) are used.

Data and Preliminary Analysis

The data series used as input for the VAR analysis were the monthly return series for three commodities and the exchange rate. The series covered log returns from January 1990 to December 2019 for commodity-producing countries in sub-Saharan Africa following IMF classification. Three commodities (gold, cocoa, and crude oil) were utilised for the study based on their massive revenue contribution to countries in SSA, and data on commodity prices were gleaned from the World Bank commodity price database, commonly called the "Pink Sheet." These three commodities were selected from three categories: metal commodities, food and beverage agricultural commodities, and energy commodities, respectively.

Data on exchange rates were sourced from the International Financial Statistics (IFS) database of the IMF for countries included in the study. The exchange rate is the measure of the rate between a particular country's currency and the US dollar. Countries selected for the study were grouped into three based on their level of dependence on a particular commodity or commodities. The connection between gold and ER was calculated for metal-producing countries; that of cocoa and ER for agricultural-exporting countries was done; and finally, the estimation of oil and exchange rates for energy-exporting countries was done.

Refer to Table 2 in chapter five for the presentation of the stationarity test results and the series' descriptive statistics. Also, results on the graphical behaviour of both the original and return series of the commodities can be found in figure 7 in chapter five and that of ER in Figure 22 in appendix D. The Augmented Dickey-Fuller (ADF) test by Dickey and Fuller (1979) and the Phillips-Perron (PP) test by Phillips and Perron (1988) indicated that all the return series were stationary at 1% significant level. In conducting the analysis, the entire set of 359 data points was used to calculate the spillover in the time domain and the frequency domain. The data was then rolled over to account for the time-frequency domain, with a window size of 100 and a forecast horizon of 12 months ahead maintained. The lag selected for the VAR model was done in order to minimise the AIC. It is worth noting that, when using the BK18 method, it is unnecessary to exogenously designate the start and end times of the crisis when using the rolling window approach. By visualising the resulting spillover indices, we can take into consideration significant alterations in the shape of spillovers as we roll the data across the whole sample period (Yilmaz, 2010). The Diebold-Yilmaz and Barunik-Krehlik spillover frameworks have this as a major advantage over other methods.

Table 3 displays the selected bands' interpretations in the BK18 framework. The selected bands were to help in accounting for time-frequency spillovers in the short-, medium-, and long-terms, respectively.

Table 3: Time-scale and frequency interpretation

	BK18		
Band	Frequency	Months	Interpretation
d_1	3.14 ~ 0.79	1 ~ 4	Short-term
d_2	0.79 ~ 0.26	4 ~ 12	Medium-term
d_3	0.26 ~ 0.00	12 ~ □	Long-term

Source: Author’s estimation (2023)

Estimation Results

In this section, emphasis is placed on discussing the results obtained from the Barunik and Krehlik (2018) framework. The analysis is presented in three sections. The first part focuses on the on results from the frequency domain classified as static analysis (Diebold & Yilmaz, 2011; Baruník & Krehlík 2018). The analysis then proceeds to the second section for the results of the rolling window, which is described as the time-frequency variation by the extant literature (see Diebold & Yilmaz, 2014; Polanco-Martinez et al., 2018; Baruník & Krehlík, 2018; Polanco-Martinez, 2019).

The Static Frequency-Domain Analysis

The BK18 framework is used to present the result of the total spillovers between commodity price returns and exchange rates in a bi-directional form. In this static analysis, three frequencies are selected, and the results (see Table 4) are presented in three panels, A, B, and C, for oil and energy-exporting countries, gold and metal-exporting countries, and cocoa and agricultural-exporting countries, respectively. The expected contribution from commodity/exchange rate *j* innovations to the forecast error variance in commodity/exchange rate *i* is represented by the *ijth* entry. The proportion of the commodity's or exchange rate's forecast error variance that is attributable to its own innovations is shown by diagonal entries *(i = j)* (shocks). These are the table's greatest values, which makes sense given their size.

When discussing the overall connectedness results in Table 4, the emphasis is on within connectedness (WTH) rather than absolute (ABS) connectedness. This is motivated by the fact that, although it is intriguing to discover that total connection adds up to absolute connectedness when dissected into frequency bands, within connectedness has the crucial additional function of pointing out causality in the system. In the view of Baruník and Krehlík (2018), cross-sectional dependence on connectedness can distort causal effects when using variance decomposition. As a result, by using the cross-sectional correlations, they modify the correlation matrix of the VAR residuals, which Diebold & Yilmaz (2014) also pointed out.

Again, we need to point out that the results in Table 4 can be interpreted as causality within connectedness. This is because there is a corresponding within-connection value for each of the absolute connection values, which signifies an element of causation. The observation in Table 4 gives a clear picture of the causality because, throughout the results, values of within-connectedness are higher than those of absolute connectedness. This suggests that the main reason for the lower absolute connectivity is the smaller number of correlations happening at the same time.

Also, in line with Anas et al. (2020), the decoupling hypothesis is accepted when a commodity contributes negative, zero, or less than 1% to within or net spillovers. In other words, if a commodity is contributing negative or zero spillovers within the system, it is a sign of a negative or no connection, but where it is positive and less than one, it’s still an indication of a weak connection with the exchange rate.

The first part of the results in Table 4 (Panel A) concentrates on the spillovers between oil returns and exchange rate returns of fuel-producing countries in SSA. It can be observed from the results in Panel A that the average *absolute (to)* spillovers are 3.48 for Band 1, 1.57 for Band 2, and 1.01 for Band 3. This indicates that the short-term dominates spillovers and the long-term has the lowest spillovers between the oil price and exchange rate. Surprisingly, spillovers in band 1 are dominated by Ghana and oil returns, with Angola and Nigeria, the two largest crude oil producers, among the least contributors. The trend in bands 2 and 3 is very similar to band 1, where oil returns dominate, followed by Ghana, Mauritania, and Angola, which recorded the least spillovers. Together with Ghana's exchange rate, crude oil return is therefore a dominant propagator of the average *absolue (to)* spillovers for energy-exporting countries in the frequency domain. However, Cameroon and Mauritania are the biggest recipients of spillovers from other countries.

The result on crude oil returns and the ER has some implications for market participants. For starters, diversification in the long-term can be advantageous over diversification in the short-term with stronger spillovers.

This can be achieved by combining crude oil and an exchange rate or by combining ERs. Second, the major oil-producing countries do not dominate spillovers, as smaller producing countries do in most cases. The indication is that when one relies on returns as the source of spillovers, there is a less dominant effect from large markets. Finally, because oil returns are the most dominant propagator of spillovers at all frequencies, they transmit significant spillovers in relative terms. The findings here support several empirical studies that have observed the crude oil price as the bigger transmitter of global shocks to oil-producing countries (see, for instance, Benhmad, 2012; Wen et al., 2017).

In a nutshell, when it comes to exchange rate returns, oil-producing countries in SSA must exercise caution when it comes to policies of integration or dependence among themselves rather than with countries outside Sub-Saharan Africa. Moreover, it can also be suggested that the spillovers among ER of many oil-producing countries are not stronger than the impact emanating from crude oil, and so countries must consider hedging their ER against crude oil volatilities. The results also show that oil-producing countries are not separated from shocks in crude oil prices because there is a connection at all frequencies.

In Panel B of Table 4, we find the results of spillovers between gold returns and ER returns for metal-exporting countries in sub-Saharan Africa. In terms of correlation dynamics, it's fascinating to see that the average absolute and within-connectedness follow a similar pattern like Panel A. The exception in Panel B is that the magnitude of the average connectedness is higher in the case of gold than in the case of oil. For example, in the case of gold returns and metal-exporting countries' ERs, the average spillovers within those bands are 16.77%, 6.88%, and 4.85%, respectively. In spillovers, the short-term also outweighs the medium- to long-term. Other findings are that in band 1, which represents the short-term frequency, South Africa (3.64%), Botswana (3.38%), and Namibia (3.29%), which are all southern African countries, dominate *absolute* spillovers. Rwanda (0.28%) and the Democratic Republic of the Congo (0.28%) recorded the lowest contribution to spillovers. In band 2, South Africa dominates, followed by Namibia and Botswana, with the lowest coming from the Democratic Republic of the Congo and Rwanda. Band 3 has the same countries dominating spillovers, but the most negligible spillovers come from the DRC, which is followed by Rwanda. The *absolute-to* spillovers for gold returns are 0.58, 0.15, and 0.09 for bands 1, 2, and 3, respectively.

The findings have some implications for the spillovers between gold returns and exchange rate returns in SSA metal-producing countries. First, owing to the strength of spillovers in the short-term, it will not be advisable for investors to undertake diversification in the short-term. They should rather consider the long-term for such an investment, as the weakness in spillovers will make it more beneficial. Shocks from gold returns are transmitted more strongly in the short-term than in the medium- and long-term. It must be pointed out that the gold return is among the least likely to shock the exchange rate, making it less risky for metal-producing countries in SSA. This finding is consistent with several empirical findings that have identified the gold price as a weak transmitter of shocks to the exchange rate (see Ciner et al., 2013; Reboredo, 2013; Wang & Lee, 2016). Moreover, policymakers must be cautious with integration policies like the African Continental Free Trade Area

(ACFTA) since a strong dependence can easily trigger spillovers among the ER of these countries. The results in Panel B provide evidence in support of the *"decoupling hypothesis"* at all frequencies.

We now move to the results in Panel C, which focus on spillovers between cocoa returns and the exchange rate of countries that produce agricultural commodities. Thirteen countries are included for this purpose. Surprisingly, the results in Panel C are like those in Panels A and B in terms of the correlation of average absolute and within connectedness. The averages *absolute spillovers for* bands 1, 2, and 3 are 16.41%, 6.28%, and 3.68%, respectively, which are like those between gold and the exchange rate. Just like in the case of Panels A and B, band 1 dominates bands 2 and 3 in terms of spillovers. In bands 1 to 3, the *absolute (to)* spillovers from cocoa returns are 1.3%, 0.45%, and 0.21%, in that order. But cocoa returns do not produce the most dominant spillovers, as that position is taken by exchange rates in the Comoros and Cote d'Ivoire, with figures of **1.45% and 1.06,** respectively, in band 1, with the lowest coming from Nigeria and Ethiopia. Moving to bands 2 and 3, the situation is not different from band 1 because Comoros and Cote d'Ivoire are still dominant with *absolute (to)* spillovers with Mauritius in the mix. For these last two bands, Ethiopia produces the fewest spillovers, followed by Nigeria. In terms of the policy and investment implications, the explanation provided in panel B at the average *absolute (to)* connected levels is also applicable here.

At this stage, it is necessary to bring out the issues relating to net spillovers. The earlier discussion in Table 4 concentrated on spillovers "*from"* and "*to*" between commodity returns and the exchange rate. To determine the net position of a commodity or exchange rate in terms of spillovers, it is necessary to find the difference between spillovers *(from)* and spillovers *(to)*, which represent *net spillovers.* A positive net spillover makes a commodity or an exchange rate a **net transmitter** of spillovers, while vice versa makes a commodity or an exchange rate a **net recipient** of spillovers. The results of net spillovers are found in the last rows of each band in Table 4. The results in Table 4 show that oil returns in Panel A are a **net transmitter** of spillovers, but this is very weak in the short-term, which confirms the existence of the *"decoupling hypothesis"* only in the short-term. The cocoa return is found in Panel C and is also a **net transmitter** of spillovers to the ER of food and beverage-producing countries in the short- and long-terms, but zero in the medium-term. The implication is that food and beverage commodity exporting countries are insulated from short- to medium-term shocks from cocoa returns. However, the gold return in Panel B is a **net recipient** of spillovers from the exchange rate in metal-producing countries, which is also across all bands. The dynamics here make gold a good asset for portfolio diversification and have great potential for hedging ER, particularly for metal-producing countries.

For energy-exporting countries, Angola, Cameroon, and Mauritania are the **net recipients** of spillovers, while Nigeria and Ghana are the **net transmitters** of spillovers across all bands, as seen in Panel A. As a result, combining crude oil with the ER of either Ghana or Nigeria is a good possibility for portfolio selection. In terms of metal-producing countries, the ER of Burundi, the Democratic Republic of the Congo, Guinea, Mali, Mauritania, and Rwanda are net recipients of spillovers, whereas Botswana, Ghana, Mozambique, Namibia, South Africa, and Zambia are net transmitters across all bands. South Africa is the biggest net transmitter, which is not surprising since it is the biggest economy among metal-producing countries and a leading producer of gold in SSA. Concerning countries that focus more on the production of agricultural commodities, seven out of the thirteen countries (Ethiopia, Gambia, Kenya, Madagascar, Malawi, Nigeria, and the Seychelles) are consistently **net recipients** of spillovers, with Comoros, Cote d'Ivoire, Mauritius, and Uganda also **net transmitters** of spillovers across all bands.

A close examination of the results in Panel C of Table 4 indicates that two countries (Eswatini and Ghana) are **net recipients** and **net transmitters** at the same time. When it comes to shock transmission, there is a big-producing country effect for oil and metal-exporting countries, but both small and big countries for cocoa-producing countries. To stabilise the ER, oil-exporting countries should make policies that specifically target shocks from global oil prices as well as the ER of Nigeria due to their consistent net transmission of shocks. Similarly, policies from countries that produce cocoa must focus on dealing with fluctuations in cocoa returns and those from ERs for Cote d'Ivoire, Comoros, Mauritius, and Uganda. Since gold is a net recipient of shocks, metal-exporting countries should not have many problems with shocks emanating from gold but should rather worry inwardly about shocks coming from the exchange rates of southern African countries and from Ghana, a leading producer of gold. Investors should also keep in mind that the dynamics are not only static but also frequency dependent, so policies must be considered on a country-by-country basis rather than as a blanket policy for all countries.

To finish the static frequency analysis, it is logical to consider the pairwise connectedness to get a complete picture of the whole situation. The benefit of considering pairwise analysis it provides information relevant for portfolio selection of two assets and policies relating to the bilateral relationship. The results are presented in Table 5 in three panels, A, B, and C, for energy-exporting countries, metal-exporting countries, and agricultural-exporting countries, respectively. Consider the commodity returns and ER, it can be observed from the table that the results of pairwise connectedness are frequency-dependent in terms of magnitude and direction. Investors and policymakers must therefore target their strategies on a frequency-by-frequency basis and not make general decisions for all frequencies since there is a mix of both positives and negatives at different frequencies. The few countries that have consistent negative pairwise connections at all frequencies have a good chance of hedging their exchange rate with commodities, and investors can take advantage of such countries for diversification purposes.

Table 4: Total spillover and Net spillover indices between commodity price returns and exchange rate of commodity-producing countries in SSA

	Oil Return	Angola	Cameroon	Ghana	Mauritania	Nigeria	FROM_ABS[a]	FROM_WTH[b]
Panel A: Oil returns and fuel-producing countries								
Band 1: 3.14 to 0.79 corresponds to 1 month to 4 months								
Oil Return (OR)	56.68	0.23	0.68	0.18	0.59	1.75	0.57	0.84
Angola (AN)	0.48	49.12	0.05	0.38	0.15	0.19	0.21	0.31
Cameroon (CM)	0.56	0.04	67.66	3.71	0.48	0.12	0.82	1.21
Ghana (GH)	0.52	0.08	1.64	65.87	0.03	0.31	0.43	0.63
Mauritania (MT)	1.32	0.15	0.04	5.01	72.63	0.28	1.13	1.67
Nigeria (NR)	1.03	0.27	0.17	0.11	0.34	73.88	0.32	0.47
TO_ABS	0.65	0.13	0.43	1.57	0.27	0.44	**3.48**	
TO_WTH	0.96	0.19	0.63	2.31	0.39	0.65		**5.14**
Net	0.08	-0.08	-0.39	1.14	-0.87	0.12		
Band 2: 0.79 to 0.26 correspond to 4 months to 12 months								
Oil Return	23.94	0.29	0.48	0.1	0.28	0.61	0.29	1.47
Angola	0.2	26.36	0.03	0.25	0.07	0.02	0.09	0.47
Cameroon	1.22	0.01	15.17	1.18	0.25	0.06	0.45	2.26
Ghana	0.32	0.18	0.76	18.11	0	0.04	0.22	1.08
Mauritania	1.11	0.03	0.06	1.17	11.01	0.06	0.41	2.03
Nigeria	0.33	0.04	0.07	0.09	0.09	15.94	0.11	0.53
TO_ABS[a]	0.53	0.09	0.23	0.47	0.11	0.13	**1.57**	
TO_WTH[b]	2.65	0.46	1.17	2.33	0.57	0.65		**7.84**
Net	0.24	-0.00	-0.22	0.25	-0.29	0.024		
Band 3: 0.26 to 0.00, correspond to 12 months to infinity								
Oil Return	13.13	0.21	0.23	0.04	0.18	0.4	0.18	1.44
Angola	0.2	22.11	0.03	0.28	0.06	0.02	0.1	0.81
Cameroon	0.83	0	7.86	0.7	0.15	0	0.28	2.3
Ghana	0.18	0.21	0.49	1.27	0	0	0.15	1.19
Mauritania	0.72	0.04	0.05	0.72	5.59	0.01	0.26	2.09
Nigeria	0.13	0	0.04	0.06	0.06	7.34	0.05	0.39
TO_ABS[a]	0.34	0.08	0.14	0.3	0.08	0.07	**1.01**	
TO_WTH[b]	2.82	0.62	1.14	2.45	0.62	0.59		**8.23**
Net	**0.17**	**-0.02**	**-0.14**	**0.15**	**-0.18**	**0.02**		

Table 4 Continued: Panel B: Gold returns and metal-producing countries

	GR	BT	BU	DRC	GH	GU	ML	MT	MZ	NB	RW	SA	TZ	ZM	FROM_ABS[a]	FROM_WTH[b]
Band 1: 3.14 to 0.79 corresponds to 1 month to 4 months																
Gold Return (GR)	57.8	3.34	0.34	0.23	1.03	0.18	0.77	0.59	0.24	2.56	0.2	3.12	0.6	0.51	0.98	1.51
Botswana (BT)	1.01	25.42	0.14	0.13	0.1	0.67	1.23	1.04	1.82	15.41	0.42	17.45	1.06	0.36	2.92	4.49
Burundi (BU)	0.77	0.37	59.75	0.92	0.67	1.38	1.41	1.64	0.25	0.3	0.31	0.35	0.24	0.49	0.65	1
DRC	0.41	0.25	2.11	55.18	0.11	0.4	0.08	0.24	0.14	0.09	0.57	0.13	0.3	0.37	0.37	0.57
Ghana (GH)	0.77	0.7	0.41	0.17	58.38	0.07	1.57	0.08	0.58	0.23	0.22	0.23	3.93	1.18	0.72	1.11
Guinea (GU)	0.79	1.96	0.1	0.09	0.26	51.77	0.1	1.92	0.13	1.07	0.02	1.4	0.33	0.18	0.6	0.92
Mali (ML)	1.03	2.54	0.56	0.28	2.9	0.14	53.88	0.41	0.35	1.7	0.62	1.91	2.49	2.81	1.27	1.95
Mauritania (MT)	0.9	2.94	0.87	0.31	4.22	0.91	0.13	59.03	1.06	2.19	0.23	2.77	0.83	0.43	1.27	1.96
Mozambique (MZ)	0.14	0.89	0.26	0.04	0.48	0.14	0.03	0.04	38.29	0.12	1.05	0.11	0.93	0.28	0.32	0.5
Namibia (NB)	0.81	15.48	0.23	0.09	0.11	0.41	0.69	0.77	0.15	25.58	0.01	21.8	0.35	0.32	2.94	4.53
Rwanda (RW)	0.22	0.68	0.32	0.86	0.52	0.04	0.9	0.17	1.77	0.03	63.77	0.05	0.05	3.19	0.63	0.97
South Africa (SA)	0.87	16.45	0.23	0.12	0.08	0.5	0.74	0.79	0.27	20.46	0.03	23.45	0.28	0.3	2.94	4.52
Tanzania (TZ)	0.26	1.06	0.15	0.28	2.94	0.48	0.21	0.33	1.61	0.75	0.26	0.63	49.25	0.74	0.69	1.07
Zambia (ZB)	0.11	0.7	0.55	0.35	0.15	0.19	0.78	1.19	0.14	1.07	0.02	1.02	0.28	53.23	0.47	0.72
TO_ABS[a]	0.58	3.38	0.45	0.28	0.97	0.39	0.62	0.66	0.61	3.29	0.28	3.64	0.83	0.8	**16.77**	
TO_WTH[b]	0.89	5.21	0.69	0.43	1.49	0.6	0.95	1.01	0.93	5.06	0.44	5.6	1.28	1.23		**25.81**
Net	-0.40	0.46	-0.20	-0.09	0.24	-0.20	-0.65	-0.62	0.29	0.34	-0.35	0.70	0.14	0.33		
Band 2: 0.79 to 0.26 correspond to 4 months to 12 months																
Gold Return	13.09	1.24	0.22	0.29	0.18	0.28	0.28	0.07	0.04	1.04	0.03	1.16	0	0.79	0.4	1.88
Botswana	0.37	7.32	0.01	0.05	0.09	0.44	0.42	0.33	0.37	5.9	0.01	6.65	0.09	0.32	1.08	5.05
Burundi	0.36	0.67	15.08	0.03	0.61	0.22	0.12	1.2	0.06	0.73	0.09	0.85	0.16	0.01	0.36	1.71
DRC	0	0.13	2.3	20.68	0.27	0.03	0	0.11	0.19	0.1	0.21	0.12	0.24	0.04	0.27	1.26
Ghana	0.02	0.44	0.74	0.05	16.38	0.01	0.42	0.05	0.26	0.07	0.09	0.07	0.29	0.79	0.24	1.1
Guinea	0.08	0.36	0.01	0.09	0.08	23.54	0.16	0.13	0.02	0.22	0.04	0.35	0.21	0.03	0.13	0.6
Mali	0.12	0.96	0.47	0.06	0.8	0.15	12.13	0.31	0.16	0.58	0.11	0.64	0.12	1.77	0.45	2.09
Mauritania	0.08	1.02	0.18	0.02	0.97	0.31	0.03	9.06	0.05	0.84	0.03	0.88	0.03	0.59	0.36	1.68
Mozambique	0.01	0.04	0.13	0.06	0.77	0.18	0.01	0.15	19.94	0.29	0.98	0.19	3.03	0.91	0.48	2.27
Namibia	0.39	5.1	0.03	0.05	0.06	0.25	0.32	0.24	0.04	7.38	0	7.34	0.08	0.39	1.02	4.79
Rwanda	0.02	0.18	0.22	0.23	0.13	0.03	0.64	0.09	0.37	0.02	15.21	0.02	0.02	0.64	0.19	0.87
S. Africa	0.38	5.62	0.04	0.06	0.07	0.3	0.35	0.26	0.06	7.34	0	8.15	0.06	0.43	1.07	5.02
Tanzania	0.03	0.44	0.1	0.25	0.35	0.13	0.15	0.5	1.41	0.86	0.06	0.68	16.94	1.52	0.46	2.17
Zambia	0.2	0.37	0.68	0.07	0.24	0.19	0.16	1.14	0.06	0.74	0.01	0.7	0.09	17.69	0.33	1.57

TO_ABS[a]	0.15	1.18	0.37	0.09	0.33	0.18	0.22	0.33	0.22	1.34	0.12	1.4	0.32	0.59	**6.83**	
TO_WTH[b]	0.69	5.56	1.72	0.43	1.55	0.85	1.03	1.54	1.03	6.28	0.56	6.59	1.48	2.76		**32.08**
Net	-0.25	0.11	0.00	-0.18	0.00	0.05	-0.23	-0.03	-0.26	0.32	-0.07	0.34	-0.15	0.26		
Band 3: 0.26 to 0.00, correspond to 12 months to infinity																
Gold Return	6.36	0.72	0.21	0.18	0.1	0.2	0.12	0	0.03	0.61	0	0.67	0	0.58	0.24	1.78
Botswana	0.19	3.7	0.02	0.02	0.06	0.29	0.22	0.16	0.17	2.97	0	3.37	0.01	0.18	0.55	4
Burundi	0.24	0.45	7.7	0.05	0.45	0.01	0	0.76	0	0.55	0.03	0.62	0.07	0.03	0.23	1.7
DRC	0	0.03	1.54	12.57	0.3	0	0	0.07	0.25	0.05	0.22	0.05	0.05	0.04	0.19	1.36
Ghana	0.01	0.35	0.54	0.03	9.8	0.01	0.17	0.02	0.27	0.08	0.02	0.09	0.02	0.41	0.14	1.05
Guinea	0.02	0.16	0	0.12	0.04	13.57	0.13	0	0.02	0.09	0.02	0.15	0.19	0.06	0.07	0.52
Mali	0.06	0.66	0.38	0.04	0.57	0.08	5.76	0.24	0.17	0.41	0.01	0.46	0.02	1.13	0.3	2.2
Mauritania	0.02	0.81	0.19	0	0.69	0.15	0.02	5.14	0.04	0.7	0	0.73	0.03	0.55	0.28	2.04
Mozambique	0.01	0.23	0.2	0.07	1.5	0.07	0	0.48	20.05	0.71	1.08	0.55	3.81	1.73	0.75	5.44
Namibia	0.21	2.69	0.04	0.03	0.05	0.16	0.18	0.15	0.02	3.86	0	3.84	0.02	0.28	0.55	3.99
Rwanda	0	0.07	0.08	0.03	0.08	0.02	0.32	0.01	0.47	0	7.96	0	0.01	0.56	0.12	0.87
S. Africa	0.21	2.95	0.05	0.03	0.06	0.19	0.2	0.17	0.03	3.83	0	4.26	0.02	0.31	0.57	4.19
Tanzania	0	0.48	0	0.24	0.73	0.04	0.12	0.68	1.69	0.9	0.05	0.74	10.3	1.66	0.52	3.81
Zambia	0.21	0.49	0.56	0.03	0.33	0.05	0.08	1.01	0.11	0.88	0	0.83	0	13.24	0.33	2.39
TO_ABS[a]	**0.09**	**0.72**	0.27	0.06	0.35	0.09	0.11	0.27	0.23	**0.84**	0.1	**0.86**	0.3	0.54	**4.85**	
TO_WTH[b]	0.62	5.25	1.99	0.44	2.58	0.66	0.82	1.96	1.7	6.14	0.75	6.29	2.22	3.91		**35.33**
Net	-0.16	0.17	0.04	-0.13	0.21	0.02	-0.19	-0.19	-0.51	0.29	0.02	0.29	-0.22	0.21		

Table 4 continued: Panel C: Cocoa returns and food and beverage producing countries

	CR	CoM	CD	ES	ET	GM	GH	KN	MG	MW	MS	NR	SEY	UG	FROM_ABS[a]	FROM_WTH[b]
Band 1: 3.14 to 0.79; corresponds to 1 month to 4 months																
Cocoa return (CR)	54.43	3.28	2.6	1.09	0.3	0.83	0.14	0.27	0.25	0.2	2.58	0.36	2.34	2.33	1.18	1.82
Comoros (CoM)	1.98	28.17	27.07	1.65	0.38	0.67	1.64	0.32	1.19	0.06	5.91	0.1	0.83	0.15	3	4.61
Cote d'Ivoire (CD)	1.57	29.57	32.28	0.97	0.34	0.42	1.83	0.16	0.69	0.05	3.4	0.06	0.5	0.14	2.84	4.36
Eswatini (ES)	2.35	3.15	1.75	50.76	0.2	0.99	0.18	0.74	0.66	0.6	2.39	0.02	0.72	0.75	1.03	1.59
Ethiopia (ET)	0.79	0.51	0.44	0.13	64.75	0.23	7.6	0.07	0.45	0.09	1.76	0.07	1.08	0.24	0.96	1.48
Gambia (GM)	0.55	1.59	0.9	0.03	0.21	57.87	0.45	0.3	0.14	0.49	3.85	0.25	1.07	0.2	0.72	1.1
Ghana (GH)	0.3	1.66	1.82	0.09	0.28	1.37	56.97	0.19	1.81	0.17	0.71	0.31	0.04	0.08	0.63	0.97
Kenya (KN)	0.49	0.76	0.39	1.37	0.1	0.18	0.78	46.36	0.1	0.37	1.04	0.46	0.15	0.95	0.51	0.79
Madagascar (MG)	1.66	2.89	1.57	1.72	0.38	0.38	0.58	0.06	49.35	2.03	3.89	0.16	0.02	0.55	1.14	1.75
Malawi (MW)	0.61	3.11	4.18	0.24	0.22	0.75	0.39	1.28	0.04	43.47	0.14	0.24	0.02	0.44	0.83	1.28
Mauritius (MS)	2.16	8.28	4.73	1.63	0.86	2.2	0.83	0.73	0.9	0.28	34.84	0.1	1.38	0.42	1.75	2.69
Nigeria (NR)	0.39	0.26	0.16	0.43	0.11	0.16	0.11	0.18	0.27	0.18	0.14	70.24	0.97	0.53	0.28	0.43
Seychelles (SEY)	2.71	1.36	0.75	4.21	0.63	0.28	0.1	0.24	0.17	0.03	1.9	0.17	46.45	1.47	1	1.54
Uganda (UG)	1.06	1.06	1.34	0.33	0.02	0.18	0.31	1.1	0.02	0.85	0.81	0.49	0.03	44.59	0.54	0.84
TO_ABS[a]	**1.19**	**4.1**	**3.41**	0.99	0.29	0.62	1.07	0.4	0.48	0.39	2.04	0.2	0.66	0.59	**16.41**	
TO_WTH[b]	1.83	6.31	5.24	1.53	0.44	0.95	1.64	0.62	0.73	0.59	3.13	0.3	1.01	0.91		**25.24**
Net	0.00	1.11	0.57	-0.04	-0.67	-0.00	0.44	-0.11	-0.66	-0.45	0.28	-0.08	-0.35	0.05		
Band 2: 0.79 to 0.26; correspond to 4 months to 12 months																
CR	14.21	1.08	0.73	0.38	0.02	0.03	0.15	0.07	0.05	0.19	0.59	0.57	0.15	0.94	0.35	1.58
CoM	0.53	7.57	6.52	0.75	0	0.17	0.8	0.13	0.2	0	2.64	0.06	0.13	0.05	0.86	3.84
CD	0.37	7.45	7.39	0.4	0	0.09	0.67	0.06	0.11	0	1.63	0.03	0.09	0.08	0.78	3.52
ES	0.2	1.47	0.8	17.46	0.03	0.14	0.15	0.57	0.1	0.19	1.62	0.00	0.17	0.05	0.39	1.76
ET	0.06	0.15	0.16	0.02	13.19	0.01	0.92	0.02	0.01	0.04	0.07	0.01	0.06	0.04	0.11	0.5
GM	0.4	0.91	0.49	0.01	0.03	16.46	0.4	0.01	0.03	0.25	1.93	0.02	0.33	0.06	0.35	1.56
GH	0.05	1.15	0.79	0.06	0.21	0.4	16.83	0.22	0.44	0	0.78	0.01	0.04	0.06	0.3	1.35
KN	0.15	0.22	0.09	0.42	0	0.19	0.44	22.99	0.01	0.26	1.08	0.39	0.09	1.64	0.35	1.59
MG	0.24	1.07	0.48	1.11	0.16	0.04	0.05	0.02	17.24	0.41	1.17	0.03	0.04	0.12	0.35	1.59
MW	0.23	1.77	2.33	0.43	0.06	0.16	0.14	1.25	0.01	23.01	0.06	0.04	0.01	0.03	0.46	2.08
MS	1.22	3.36	1.66	1.97	0.25	0.91	0.84	0.38	0.2	0.13	14.76	0	0.46	0.18	0.82	3.7
NR	0.67	0.18	0.08	0.08	0.03	0.09	0.07	0.01	0.02	0.01	0.21	15	0.13	0.28	0.13	0.6
SEY	1.82	1.25	0.64	2.89	0.12	0.25	0.08	0.41	0.04	0.04	1.93	0.17	15.35	0.64	0.73	3.29
UG	0.3	0.2	0.03	0.13	0	0.05	0.05	0.84	0.02	0.44	1.02	0.2	0.05	23.3	0.24	1.06
TO_ABS[a]	**0.45**	**1.45**	**1.06**	0.62	0.07	0.18	0.34	0.28	0.09	0.14	**1.05**	0.11	0.12	0.3	**6.25**	
TO_WTH[b]	2	6.49	4.74	2.77	0.3	0.81	1.52	1.28	0.4	0.62	4.72	0.49	0.55	1.34		**28.01**
Net	0.09	0.59	0.27	0.23	-0.05	-0.17	0.04	-0.07	-0.27	-0.33	0.23	-0.02	-0.61	0.06		

Band 3: 0.26 to 0.00; corresponds to 12 months to infinity

CR	7.06	0.64	0.4	0.13	0.02	0	0.13	0.08	0.01	0.05	0.26	0.41	0	0.65	0.2	1.57
CoM	0.27	3.85	3.15	0.49	0	0.07	0.45	0.15	0.13	0	1.61	0.04	0.11	0	0.46	3.65
CD	0.19	3.83	3.64	0.28	0	0.03	0.37	0.08	0.08	0	1.03	0.02	0.08	0.01	0.43	3.39
ES	0.02	0.59	0.23	8.82	0	0.09	0.07	0.55	0.03	0.01	1.14	0	0.12	0.13	0.21	1.68
ET	0.02	0.07	0.08	0.02	6.3	0	0.43	0	0.03	0.02	0	0	0.07	0	0.05	0.41
GM	0.2	0.48	0.25	0	0	8.29	0.27	0.03	0.01	0.08	1.02	0	0.15	0.01	0.18	1.41
GH	0.05	0.84	0.52	0.09	0.13	0.23	9.99	0.17	0.24	0.01	0.75	0.01	0.05	0.06	0.22	1.77
KN	0.09	0.13	0.01	0.18	0	0.19	0.27	14.24	0	0.32	0.97	0.25	0.01	1.88	0.31	2.42
MG	0.1	0.7	0.37	0.76	0.06	0	0	0		0.15	0.56	0.01	0.04	0	0.2	1.55
MW	0.05	1.03	1.28	0.33	0.01	0.04	0.08	0.54	0.02	11.81	0.06	0.04	0	0.08	0.25	2.01
MS	0.5	1.63	0.67	1.2	0.09	0.46	0.51	0.46	0.07	0.01	8.26	0	0.3	0.18	0.43	3.43
NR	0.41	0.12	0.04	0.05	0.02	0.06	0.03	0.02	0	0.01	0.15	7.86	0.04	0.23	0.08	0.65
SEY	0.91	0.66	0.27	1.48	0.03	0.19	0.08	0.35	0	0.02	1.31	0.07	7.98	0.56	0.42	3.33
UG	0.08	0.1	0	0.07	0	0.01	0	0.92	0.02	0.02	0.91	0.12	0.09	18.85	0.17	1.32
TO_ABS[a]	**0.21**	**0.77**	**0.52**	0.36	0.03	0.1	0.19	0.24	0.05	0.05	**0.7**	0.07	0.07	0.27	**3.62**	
TO_WTH[b]	1.63	6.1	4.1	2.86	0.2	0.77	1.53	1.87	0.36	0.39	5.5	0.55	0.59	2.13		**28.59**
Net	0.01	0.31	0.09	0.14	-0.03	-0.08	-0.03	-0.07	-0.15	-0.20	0.26	-0.01	0.26	-0.01		

Note: [a]*Absolute to* measure return spillovers from commodity/country *j* to other countries. *Absolute from* measure return spillovers from other countries to commodity/country *j*. [b]*Within to* measure return spillovers from commodity/country *j* to other countries, including from own innovation to commodity/country *k*. *Within from* measure return spillovers from other countries to commodity/country *j*, including from own innovation to commodity/country *k* (Tiwari et al. 2019). The three largest contributors to spillovers are in bold for all frequencies.

Source: Field Data (2023)

Table 5: Pairwise net directional spillover between commodity price returns and exchange rate of commodity-producing countries in Sub-Saharan Africa

Panel A: Oil returns and fuel-producing countries

Band 1: 3.14 to 0.79; corresponds to 1 month to 4 months

OR-AN	OR-CM	OR-GH	OR-MT	OR-NR	AN-CM	AN-GH	AN-MT	AN-NR	CM-GH	CM-MT	CM-NR	GH-MT	GH-NR	MT-NR
-0.041	0.0198	-0.056	-0.1219	0.1206	0.00177	0.0496	-0.0002	-0.0122	0.346	-0.010	0.074	-0.008	0.830	0.033

Band 2: 0.79 to 0.26; corresponds to 4 months 12 months

OR-AN	OR-CM	OR-GH	OR-MT	OR-NR	AN-CM	AN-GH	AN-MT	AN-NR	CM-GH	CM-MT	CM-NR	GH-MT	GH-NR	MT-NR
0.015	-0.123	-0.035	-0.139	0.046	0.003	0.012	0.005	-0.004	0.069	-0.006	0.030	-0.003	-0.195	-0.009

Band 3: 0.26 to 0.00; corresponds to 12 months to infinity

OR-AN	OR-CM	OR-GH	OR-MT	OR-NR	AN-CM	AN-GH	AN-MT	AN-NR	CM-GH	CM-MT	CM-NR	GH-MT	GH-NR	MT-NR
0.001	-0.101	-0.022	-0.091	0.046	0.005	0.012	0.004	0.003	0.035	-0.0086	0.017	-0.006	0.118	0.010

Panel B: Gold returns and metal-producing countries

Band 1: 3.14 to 0.79; corresponds to 1 month to 4 months

GR-BT	GR-BU	GR-DRC	GR-GH	GR-GU	GR-ML	GR-MT	GR-MZ	GR-NB	GR-RW	GR-SA	GR-TZ	GR-ZB	BT-BU	BT-DRC
0.166	-0.030	-0.013	0.019	-0.044	-0.018	-0.022	0.007	0.125	-0.002	0.161	0.0239	0.028	-0.017	-0.009
BT-GH	BT-GU	BT-ML	BT-MT	BT-MZ	BT-NB	BT-RW	BT-SA	BT-TZ	BT-ZB	BU-DRC	BU-GH	BU-GU	BU-ML	BU-MT
-0.043	-0.092	-0.094	-0.136	0.066	-0.005	-0.019	0.071	0.0003	-0.025	-0.085	0.018	0.091	0.060	0.055
BU-MZ	BU-NB	BU-RW	BU-SA	BU-TZ	BU-ZB	DRC-GH	DRC-GU	DRC-ML	DRC-MT	DRC-MZ	DRC-NB	DRC-RW	DRC-SA	DRC-TZ
-0.001	0.005	-0.001	0.009	0.006	-0.005	-0.005	0.022	-0.014	-0.005	0.007	0.0002	-0.020	0.001	0.002
DRC-ZB	GH-GU	GH-ML	GH-MT	GH-MZ	GH-NB	GH-RW	GH-SA	GH-TZ	GH-ZB	GU-ML	GU-MT	GU-MZ	GU-NB	GU-RW
0.001	-0.014	-0.095	-0.296	0.007	0.009	-0.021	0.011	0.071	0.073	-0.003	0.072	-0.001	0.047	-0.001
GU-SA	GU-TZ	GU-ZB	ML-MT	ML-MZ	ML-NB	ML-RW	ML-SA	ML-TZ	ML-ZM	MT-MZ	MT-NB	MT-RW	MT-SA	MT-TZ
0.064	-0.010	-0.001	0.021	0.023	0.072	-0.020	0.083	0.163	0.145	0.073	0.101	0.004	0.142	0.036

MT-ZB	MZ-NB	MZ-RW	MZ-SA	MZ-TZ	MZ-ZB	NB-RW	NB-SA	NB-TZ	NB-ZB	RW-SA	RW-TZ	RW-ZB	SA-TZ	SA-ZB
-0.054	-0.002	-0.051	-0.011	-0.048	0.010	-0.001	0.096	-0.029	-0.054	0.002	-0.015	0.226	-0.025	-0.052
TZ-ZB														
0.033														

Band 2: 0.79 to 0.26; corresponds to 4 months to 12 months

GR-BT	GR-BU	GR-DRC	GR-GH	GR-GU	GR-ML	GR-MT	GR-MZ	GR-NB	GR-RW	GR-SA	GR-TZ	GR-ZB	BT-BU	BT-DRC
0.062	-0.010	0.020	0.011	0.014	0.012	-0.0003	0.0017	0.047	0.001	0.056	-0.002	0.042	-0.047	-0.006
BT-GH	BT-GU	BT-ML	BT-MT	BT-MZ	BT-NB	BT-RW	BT-SA	BT-TZ	BT-ZB	BU-DRC	BU-GH	BU-GU	BU-ML	BU-MT
-0.025	0.006	-0.038	-0.049	0.024	0.057	-0.012	0.074	-0.024	-0.004	-0.162	-0.009	0.015	-0.025	0.073
BU-MZ	BU-NB	BU-RW	BU-SA	BU-TZ	BU-ZB	DRC-GH	DRC-GU	DRC-ML	DRC-MT	DRC-MZ	DRC-NB	DRC-RW	DRC-SA	DRC-TZ
-0.005	0.050	-0.010	0.058	0.004	-0.048	0.016	-0.004	-0.004	0.006	0.009	0.003	-0.001	0.004	-0.001
DRC-ZB	GH-GU	GH-ML	GH-MT	GH-MZ	GH-NB	GH-RW	GH-SA	GH-TZ	GH-ZB	GU-ML	GU-MT	GU-MZ	GU-NB	GU-RW
-0.002	-0.005	-0.027	-0.066	-0.036	0.001	-0.003	0.0002	-0.004	0.039	0.001	-0.012	-0.011	-0.002	0.001
GU-SA	GU-TZ	GU-ZB	ML-MT	ML-MZ	ML-NB	ML-RW	ML-SA	ML-TZ	ML-ZM	MT-MZ	MT-NB	MT-RW	MT-SA	MT-TZ
0.004	0.005	-0.011	0.020	0.012	0.018	-0.038	0.021	-0.002	0.115	-0.008	0.043	-0.004	0.044	-0.034
MT-ZB	MZ-NB	MZ-RW	MZ-SA	MZ-TZ	MZ-ZB	NB-RW	NB-SA	NB-TZ	NB-ZB	RW-SA	RW-TZ	RW-ZB	SA-TZ	SA-ZB
-0.039	0.018	0.044	0.010	0.116	0.061	-0.001	0.0003	-0.055	-0.025	0.001	-0.003	0.045	-0.044	-0.019
TZ-ZB														
0.102														

Band 3: 0.26 to 0.00; corresponds to 12 months to infinity

GR-BT	GR-BU	GR-DRC	GR-GH	GR-GU	GR-ML	GR-MT	GR-MZ	GR-NB	GR-RW	GR-SA	GR-TZ	GR-ZB	BT-BU	BT-DRC
3.79E-02	-2.13E-03	1.26E-02	6.31E-03	1.29E-02	4.30E-03	-1.11E-03	1.43E-03	2.87E-02	-3.06E-04	3.29E-02	-2.45E-05	2.58E-02	-3.11E-02	-1.06E-03
BT-GH	BT-GU	BT-ML	BT-MT	BT-MZ	BT-NB	BT-RW	BT-SA	BT-TZ	BT-ZB	BU-DRC	BU-GH	BU-GU	BU-ML	BU-MT
-2.02E-02	9.44E-03	-3.12E-02	-4.60E-02	-3.74E-03	2.02E-02	-4.63E-03	2.94E-02	-3.35E-02	-2.16E-02	-1.06E-01	-6.63E-03	8.56E-04	-2.70E-02	4.04E-02
BU-MZ	BU-NB	BU-RW	BU-SA	BU-TZ	BU-ZB	DRC-	DRC-	DRC-	DRC-	DRC-	DRC-	DRC-	DRC-SA	DRC-TZ

						GH	GU	ML	MT	MZ	NB	RW		
-1.44E-02	3.63E-02	-3.86E-03	4.13E-02	4.85E-03	-3.81E-02	1.95E-02	-8.48E-03	-2.32E-03	4.56E-03	1.28E-02	1.74E-03	1.40E-02	1.81E-03	-1.34E-02
DRC-ZB	GH-GU	GH-ML	GH-MT	GH-MZ	GH-NB	GH-RW	GH-SA	GH-TZ	GH-ZB	GU-ML	GU-MT	GU-MZ	GU-NB	GU-RW
1.31E-03	-2.22E-03	-2.85E-02	-4.74E-02	-8.80E-02	1.72E-03	-4.26E-03	1.77E-03	-5.08E-02	5.73E-03	3.38E-03	-1.03E-02	-3.93E-03	-4.63E-03	2.55E-04
GU-SA	GU-TZ	GU-ZB	ML-MT	ML-MZ	ML-NB	ML-RW	ML-SA	ML-TZ	ML-ZM	MT-MZ	MT-NB	MT-RW	MT-SA	MT-TZ
-2.95E-03	1.09E-02	5.32E-04	1.59E-02	1.20E-02	1.63E-02	-2.20E-02	1.84E-02	-6.69E-03	7.49E-02	-3.15E-02	3.92E-02	-8.79E-04	4.00E-02	-4.62E-02
MT-ZB	MZ-NB	MZ-RW	MZ-SA	MZ-TZ	MZ-ZB	NB-RW	NB-SA	NB-TZ	NB-ZB	RW-SA	RW-TZ	RW-ZB	SA-TZ	SA-ZB
-3.35E-02	4.96E-02	4.33E-02	3.72E-02	1.52E-01	1.16E-01	-7.75E-05	4.10E-04	-6.31E-02	-4.28E-02	1.55E-04	-2.83E-03	4.00E-02	-5.15E-02	-3.71E-02
TZ-ZB														
1.18E-01														

Panel C: Cocoa returns and food and beverage-producing countries

Band 1: 3.14 to 0.79; correspond to 1 month to 4 months

CR-CO	CR-CD	CR-ES	CR-ET	CR-GM	CR-GH	CR-KN	CR-MG	CR-MW	CR-MS	CR-NR	CR-SEY	CR-UG	CO-CD	CP-ES
0.094	0.074	-0.090	-0.035	0.020	-0.011	-0.016	-0.101	-0.030	0.030	-0.002	-0.026	0.091	-0.179	-0.107
CO-ET	CO-GM	CO-GH	CO-KN	CO-MG	CO-MW	CO-MS	CO-NR	CO-SEY	CO-UG	CD-ES	CD-ET	CD-GM	CD-GH	CD-KN
-0.001	-0.065	-0.001	-0.031	-0.122	-0.217	-0.169	-0.012	-0.037	-0.065	-0.055	-0.007	-0.034	0.001	-0.017
CD-MG	CD-MW	CD-MS	CD-NR	CD-SEY	CD-UG	ES-ET	ES-GM	ES-GH	ES-KN	ES-MG	ES-MW	ES-MS	ES-NR	ES-SEY
-0.001	-0.065	-0.001	-0.031	-0.122	-0.217	-0.169	-0.012	-0.037	-0.065	-0.055	-0.007	-0.034	0.001	-0.017
ES-UG	ET-GM	ET-GH	ET-KN	ET-MG	ET-MW	ET-MS	ET-NR	ET-SEY	ET-UG	GM-GH	GM-KN	GM-MG	GM-MW	GM-MS
0.030	0.001	0.522	-0.002	0.005	-0.009	0.064	-0.002	0.032	0.015	-0.066	0.008	-0.017	-0.019	0.118
GM-NR	GM-SEY	GM-UG	GH-KN	GH-MG	GH-MW	GH-MS	GH-NR	GH-SEY	GH-UG	KN-MG	KN-MW	KN-MS	KN-NR	KN-SEY

0.006	0.056	0.001	-0.042	0.088	-0.016	-0.008	0.014	-0.004	-0.017	0.003	-0.065	0.022	0.020	-0.007
KN-UG	MG-MW	MG-MS	MG-NR	MG-SEY	MG-UG	MW-MS	MW-NR	MW-SEY	MW-UG	MS-NR	MS-SEY	MS-UG	NR-SEY	NR-UG
-0.011	0.142	0.213	-0.008	-0.011	0.038	-0.010	0.005	-0.001	-0.030	-0.003	-0.037	-0.028	0.058	0.003
SEY-UG														
0.103														
Band 2: 0.79 to 0.26; correspond to 4 months to 12 months														
CR-CO	CR-CD	CR-ES	CR-ET	CR-GM	CR-GH	CR-KN	CR-MG	CR-MW	CR-MS	CR-NR	CR-SEY	CR-UG	CO-CD	CP-ES
0.039	0.025	0.013	-0.003	-0.026	0.007	-0.005	-0.014	-0.003	-0.045	-0.007	-0.119	0.046	-0.067	-0.051
CO-ET	CO-GM	CO-GH	CO-KN	CO-MG	CO-MW	CO-MS	CO-NR	CO-SEY	CO-UG	CD-ES	CD-ET	CD-GM	CD-GH	CD-KN
-0.011	-0.053	-0.025	-0.007	-0.062	-0.126	-0.051	-0.009	-0.080	-0.011	-0.029	-0.011	-0.028	-0.009	-0.002
CD-MG	CD-MW	CD-MS	CD-NR	CD-SEY	CD-UG	ES-ET	ES-GM	ES-GH	ES-KN	ES-MG	ES-MW	ES-MS	ES-NR	ES-SEY
-0.027	-0.166	-0.002	-0.004	-0.039	0.003	0.001	0.009	0.006	0.011	-0.073	-0.017	-0.025	-0.006	-0.194
ES-UG	ET-GM	ET-GH	ET-KN	ET-MG	ET-MW	ET-MS	ET-NR	ET-SEY	ET-UG	GM-GH	GM-KN	GM-MG	GM-MW	GM-MS
-0.005	-0.001	0.051	0.001	-0.011	-0.002	-0.013	-0.002	-0.004	0.003	0.0002	-0.013	-0.001	0.006	0.073
GM-NR	GM-SEY	GM-UG	GH-KN	GH-MG	GH-MW	GH-MS	GH-NR	GH-SEY	GH-UG	KN-MG	KN-MW	KN-MS	KN-NR	KN-SEY
-0.005	0.006	0.001	-0.016	0.028	-0.010	-0.004	-0.004	-0.003	0.001	-0.001	-0.071	0.050	0.027	-0.023
KN-UG	MG-MW	MG-MS	MG-NR	MG-SEY	MG-UG	MW-MS	MW-NR	MW-SEY	MW-UG	MS-NR	MS-SEY	MS-UG	NR-SEY	NR-UG
0.057	0.028	0.069	0.001	0.0003	0.008	-0.005	0.003	-0.003	-0.030	-0.015	-0.105	-0.060	-0.003	0.006
SEY-UG														
0.043														
Band 3: 0.26 to 0.00; corresponds to 12 months to infinity														
CR-CO	CR-CD	CR-ES	CR-ET	CR-GM	CR-GH	CR-KN	CR-MG	CR-MW	CR-MS	CR-NR	CR-SEY	CR-UG	CO-CD	CP-ES
2.64E-02	1.51E-02	7.88E-03	-8.91E-05	-1.41E-02	6.04E-03	-1.03E-03	-6.52E-03	5.66E-04	-1.75E-02	-2.96E-04	-6.48E-02	4.11E-02	-4.85E-02	-7.79E-03
CO-ET	CO-GM	CO-GH	CO-KN	CO-MG	CO-MW	CO-MS	CO-NR	CO-SEY	CO-UG	CD-ES	CD-ET	CD-GM	CD-GH	CD-KN

-5.18E-03	-2.95E-02	-2.77E-02	1.49E-03	-4.05E-02	-7.39E-02	-1.68E-03	-5.77E-03	-3.86E-02	-7.20E-03	3.36E-03	-5.38E-03	-1.52E-02	-1.10E-02	4.89E-03
CD-MG	CD-MW	CD-MS	CD-NR	CD-SEY	CD-UG	ES-ET	ES-GM	ES-GH	ES-KN	ES-MG	ES-MW	ES-MS	ES-NR	ES-SEY
-2.01E-02	-9.13E-02	2.57E-02	-1.89E-03	-1.40E-02	6.25E-04	-1.45E-03	6.15E-03	-1.29E-03	2.64E-02	-5.24E-02	-2.28E-02	-4.19E-03	-3.26E-03	-9.78E-02
ES-UG	ET-GM	ET-GH	ET-KN	ET-MG	ET-MW	ET-MS	ET-NR	ET-SEY	ET-UG	GM-GH	GM-KN	GM-MG	GM-MW	GM-MS
4.42E-03	1.32E-04	2.10E-02	3.35E-05	-2.31E-03	5.27E-04	-6.60E-03	-1.05E-03	2.89E-03	1.05E-04	2.81E-03	-1.21E-02	1.06E-03	2.71E-03	4.03E-02
GM-NR	GM-SEY	GM-UG	GH-KN	GH-MG	GH-MW	GH-MS	GH-NR	GH-SEY	GH-UG	KN-MG	KN-MW	KN-MS	KN-NR	KN-SEY
-3.99E-03	-2.73E-03	-3.13E-04	-7.34E-03	1.68E-02	-5.60E-03	1.72E-02	-1.28E-03	-2.26E-03	3.95E-03	-1.82E-04	-1.55E-02	3.64E-02	1.64E-02	-2.41E-02
KN-UG	MG-MW	MG-MS	MG-NR	MG-SEY	MG-UG	MW-MS	MW-NR	MW-SEY	MW-UG	MS-NR	MS-SEY	MS-UG	NR-SEY	NR-UG
6.89E-02	9.51E-03	3.50E-02	5.03E-04	2.71E-03	-1.36E-03	3.63E-03	1.94E-03	-1.05E-03	4.05E-03	-1.03E-02	-7.24E-02	-5.20E-02	-2.45E-03	7.21E-03
SEY-UG														
3.35E-02														

Note: All figures are in percentages

Source: Field Data (2023)

Time-Frequency-Domain (Time-Varying) Analysis

In the previous analysis, the assumption was that the direction of spillovers does not change over time but only changes at different frequencies, which makes them static. This assumption is not entirely accurate, as the nature and direction of shocks change with time, hence their time-varying nature. This is particularly true considering the impact of financial market regime changes and the changing nature of the business cycle. For instance, extreme events like financial crises and changes in the regulations of financial markets have tended to change the narrative on shock transmission at various times. Thus, spillovers transmitted from one asset to another are likely time-varying and, as such, not static. To incorporate the time-frequency domain in the analysis, a rolling window approach in the BK18 framework has been utilised with a window size of 100 and a 12-month forecast horizon. The results are presented in Figure 13 for rolling total spillovers and Figure 14 for rolling pairwise net spillovers. Looking at the multiplicity of pairs generated out of the study for three bands 46 pairs for fuel-producing countries, 247 for metal-producing countries, and 274 for food and beverage-producing countries), only pairs involving commodity returns and exchange rates in the short-, medium-, and long-term are presented here as it will be impractical to show all the pairs.

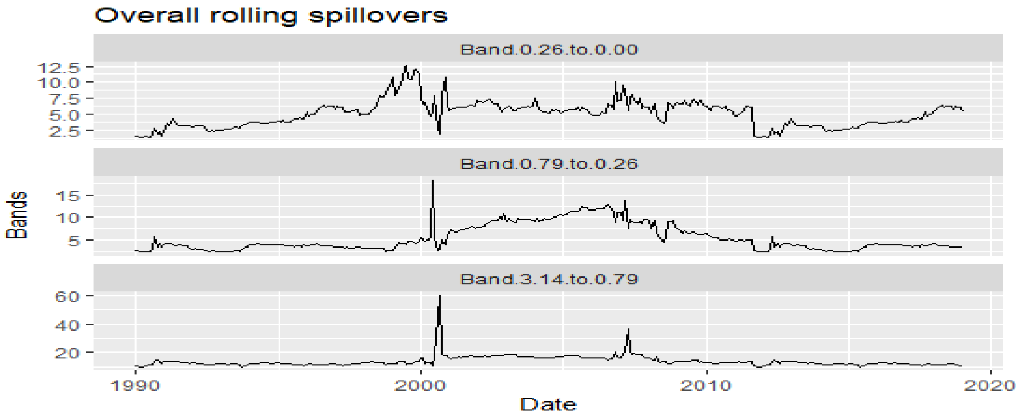
Concerning oil and energy-exporting countries as seen in Figure 13 (a), an increase in frequency is accompanied by an increase in the magnitude of overall connectedness. It is observed that in the short-term (band 3.14 to 0.79), the fluctuation is between 10% and 20%; in the medium-term (band 0.79 to 0.26), it is between 1% and 15%; and it fluctuates between 1% and 12.5% in the long-term (band 0.26 to 0.00). The return spillovers, however, exhibit some situations of sharp contagion at different frequencies. For instance, in the short-term, an episode of a sharp increase in spillovers to about 60% was observed around 2001, which may be due to the 2000 global recession. In the medium-term, a similar incident was recorded between 2000 and 2001 at about 18%. In band 3 (0.26 to 0.00), which represents the long-term, there were upward changes in spillovers from 5% to about 12.5% between 1998 and 2000. The sharp changes in the short- and medium-terms were very steep but short-lived; however, those in the long term persisted for a while though not as high as those in the short- and medium-terms.

For gold and metal exporting countries (Figure 13 (b)), we observe increasing frequency with increasing overall connectedness. The fluctuation in the spillovers was between 30% and 85% in the short-term, between 5% and 20% in the medium-term, and between 1% and 15% in the long-term. Strangely, no episode of connectedness or contagion was recorded between 1990 and 1997 or between 2012 and 2018 at all frequency bands. This is an exhibition of the "*decoupling hypothesis"* between gold returns and exchange rates for metal-producing countries. However, 1997 witnessed sharp upward return spillovers for all frequencies, though different in magnitude. The increases were 75% for band 1, 21% for band 2, and 13% for band 3. Then, around 2001, another sharp change occurred, but this time in different directions for different frequencies. For instance, while band 1 recorded a steep increase in spillover episodes to about 90%, bands 2 and 3 had a sharp downward trend to 2.5% and 1%, respectively. This period was characterised by what was called the "Brown Bottom" (the sale of about half of the UK's gold reserve), which had a massive impact on gold prices (Mound, 2007).

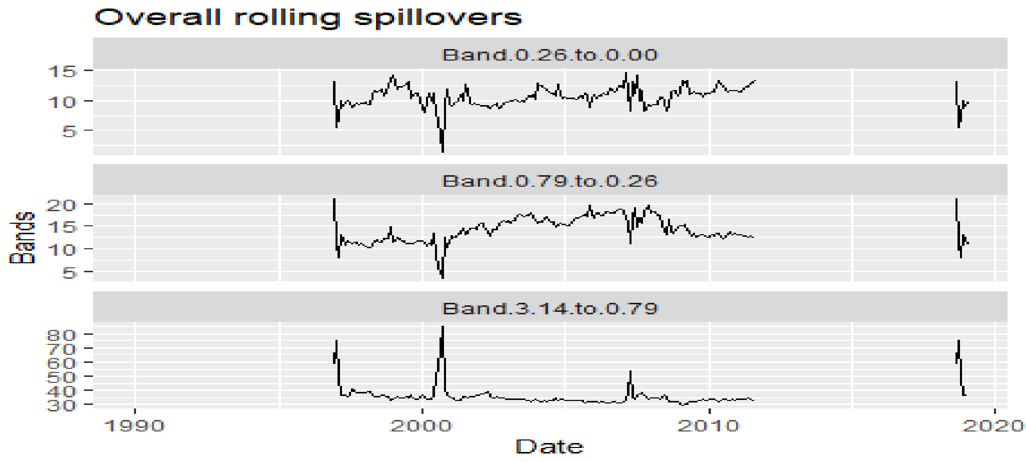
Shifting attention to Figure 13 (c), which relates cocoa to agricultural exporting countries, similar observations to (a) and (b) were made. Following increasing magnitude in overall relation to increasing frequency, the average fluctuations were between 35% and 60% for band 1, 10% to 20% for band 2, and 22% for band 3. Concerning band 1 (3.14 to 0.79), sharp upward contagion incidence was seen in 2004 and 2007, with 68% and 60%, respectively. In band 2, there was a sharp increase in spillovers to about 50% in 2001. But while the situation in bands 1 and 2 was mainly one-off events, several episodes of sharp increases occurred in the long term (band 3) between 1998 and 2008, with the highest of about 26% happening around 2002.

All in all, the strength of contagion is higher in the short-term than in both the medium- and long-term for all commodities when time variation is considered. Again, an interesting observation is that contagion is short-lived in many instances. This may be a result of lessons learned from the previous commodity price collapse in the late 1980s and early 1990s, which prepared many countries in the sub-region to manage it better. Worth mentioning is the fact that many of the contagion episodes occurred during or just after the crisis period. For instance, the energy-exporting countries recorded contagion of about 60% around 2001, and in the same period, both metal-exporting countries and food and agricultural-exporting countries recorded contagion of about 90% and 50%, respectively. These events were probably driven by the impact of the recession from 2000 to 2001 in many developed countries and the delayed impact of the Asian financial crisis, which affected global trade in commodities. The 2007–2009 global financial crisis and the Eurozone crisis also produced similar episodes of contagion. It is safe to say that the results here have an element of delay contagion based on spillovers coming after a crisis moment. Also, there are instances of a sudden change in spillovers, which is also in line with the "*shift contagion hypothesis*" and the "*decoupling hypothesis,*" which shows up at some point specifically between gold returns and exchange rates. This study, however, demonstrates that contagion in the currency markets in SSA are frequency varying.

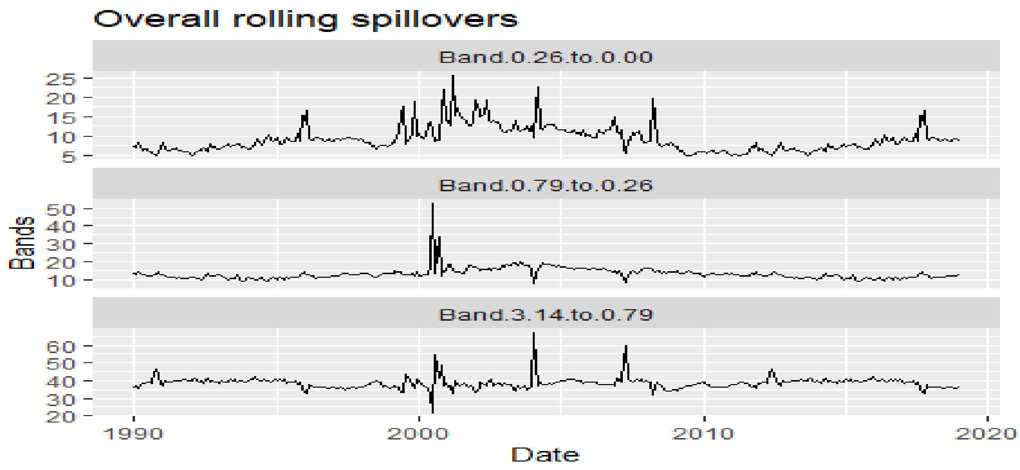
In summary, the results point to some important lessons that policymakers must look at. It is clear from the results that there is always a danger posed by the immediate aftermath of a commodity price crisis or financial crisis, which must be a concern. However, there are instances where spillovers were delayed or prolonged, as happened after the 2007–2008 financial crisis and the Eurozone recession. There is therefore the possibility of delayed spillovers from an extreme event, which should not be ignored. The results also point to the fact that connectedness is not just time-dependent but also frequency-dependent. But the strength of dependence is higher at the higher frequencies than at the lower frequencies, though the persistence is greater at low frequencies. This suggests that diversification between commodities and the exchange rate of commodity-producing countries in SSA will be more beneficial in the long- and medium-terms than in the short-term due to the strong interdependence.



(a) Oil and exchange rate

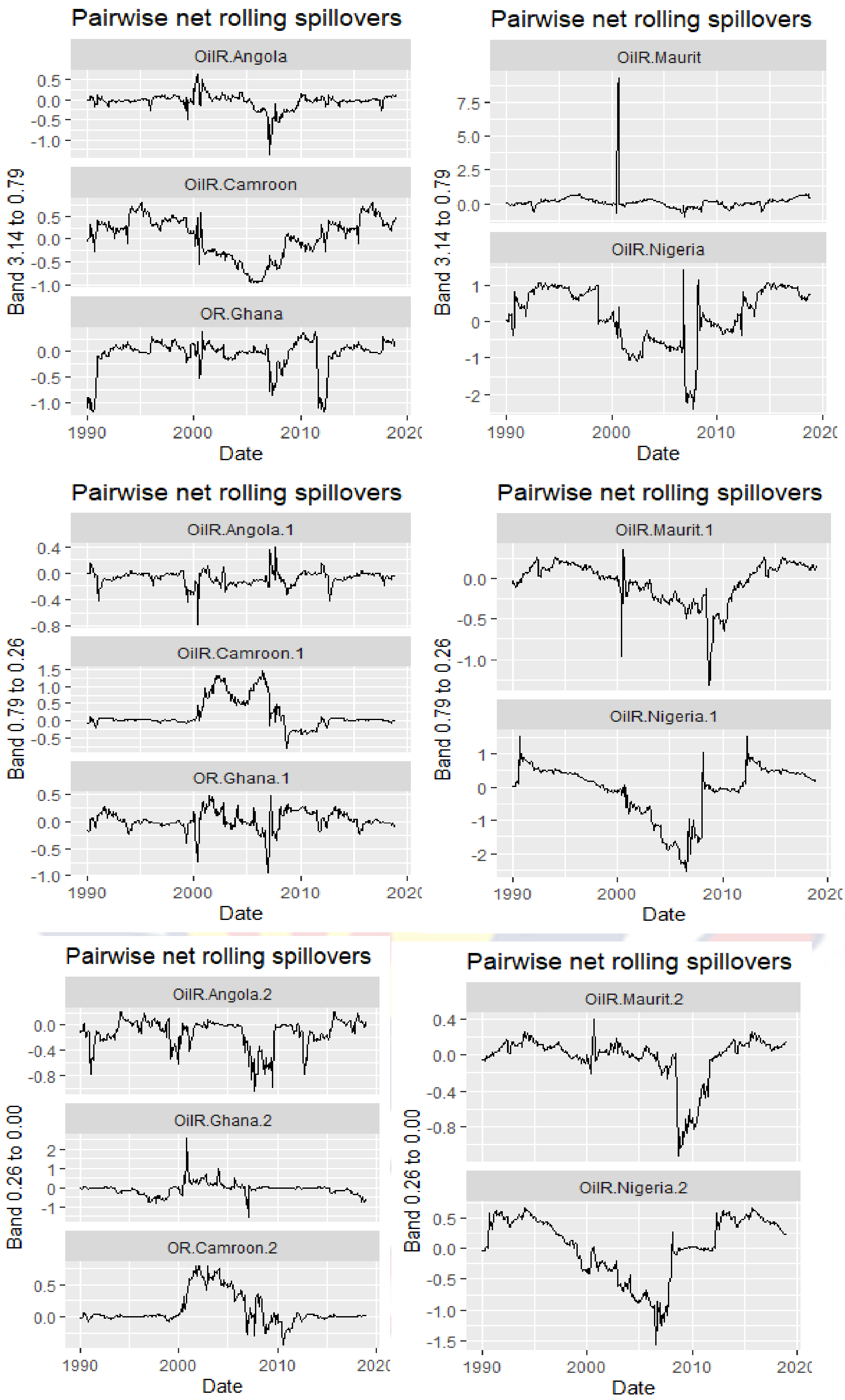


(b) Gold and exchange rate

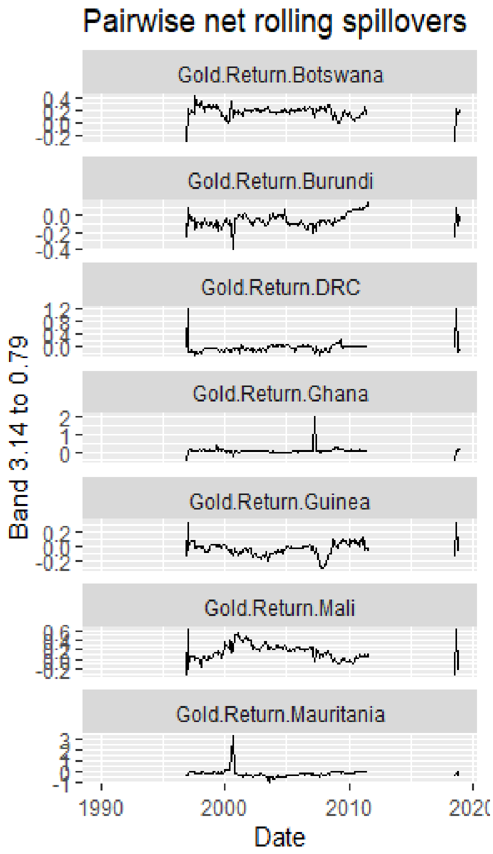


(c) Cocoa and exchange rate

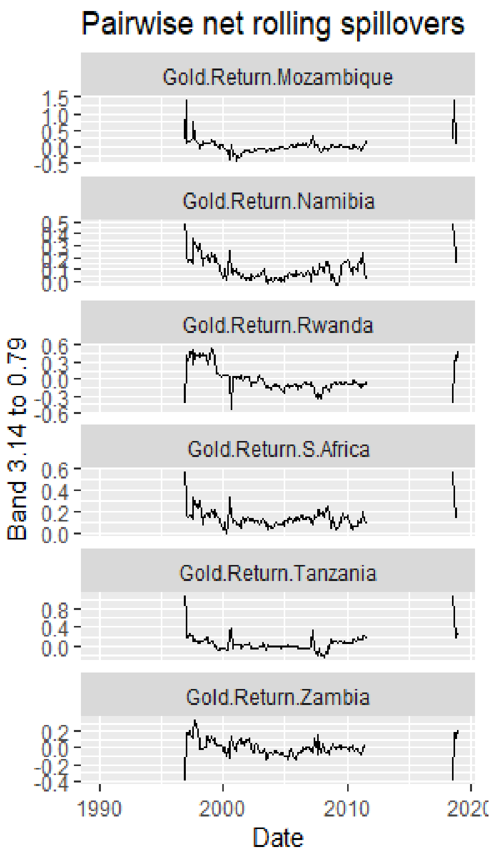
Figure 13: Overall rolling spillovers between commodity prices and exchange rate of Sub-Saharan African countries.
Source: Field Data (2023)



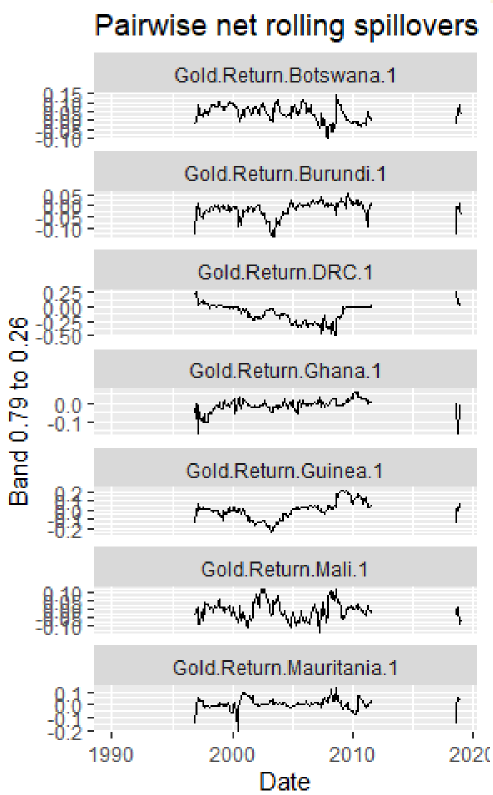
(a) Oil and exchange rate



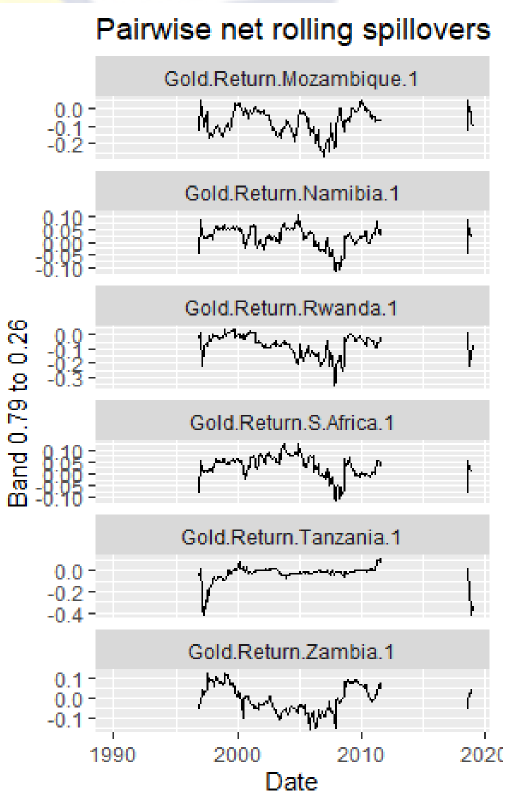
Pairwise net rolling spillovers
Gold.Return.Botswana
Gold.Return.Burundi
Gold.Return.DRC
Gold.Return.Ghana
Gold.Return.Guinea
Gold.Return.Mali
Gold.Return.Mauritania
Band 3.14 to 0.79
Date



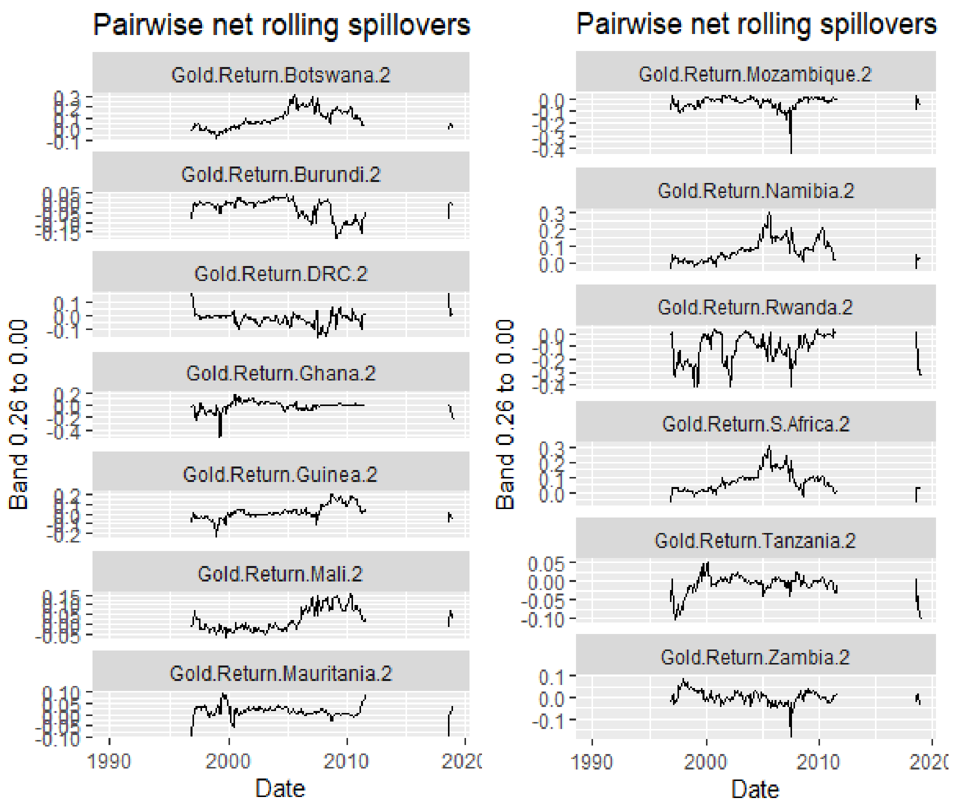
Pairwise net rolling spillovers
Gold.Return.Mozambique
Gold.Return.Namibia
Gold.Return.Rwanda
Gold.Return.S.Africa
Gold.Return.Tanzania
Gold.Return.Zambia
Band 3.14 to 0.79
Date



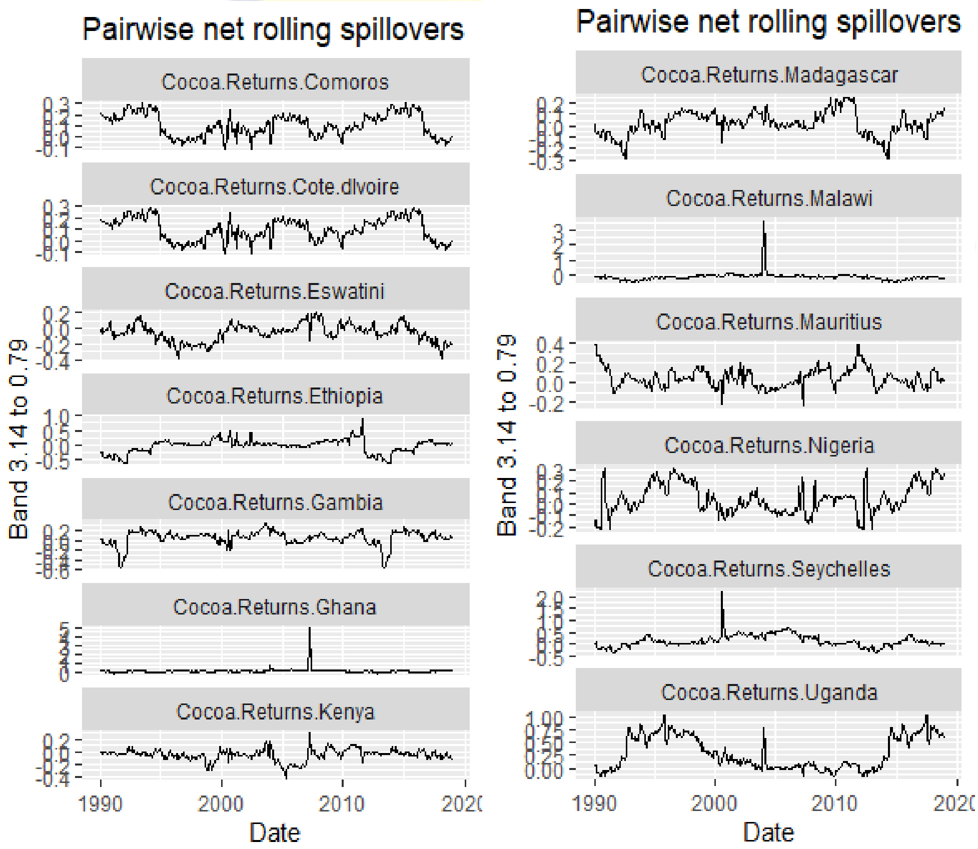
Pairwise net rolling spillovers
Gold.Return.Botswana.1
Gold.Return.Burundi.1
Gold.Return.DRC.1
Gold.Return.Ghana.1
Gold.Return.Guinea.1
Gold.Return.Mali.1
Gold.Return.Mauritania.1
Band 0.79 to 0.26
Date

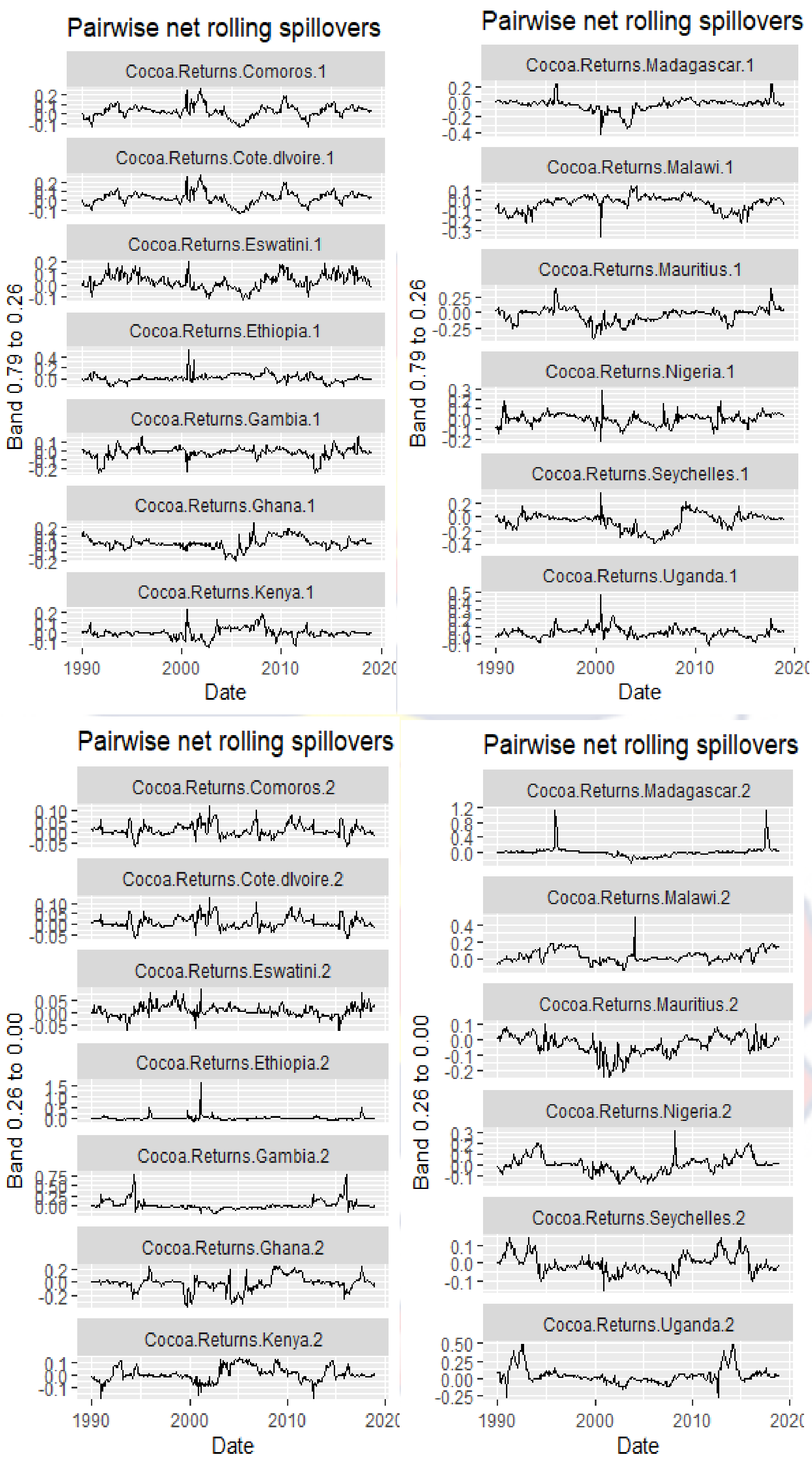


Pairwise net rolling spillovers
Gold.Return.Mozambique.1
Gold.Return.Namibia.1
Gold.Return.Rwanda.1
Gold.Return.S.Africa.1
Gold.Return.Tanzania.1
Gold.Return.Zambia.1
Band 0.79 to 0.26
Date



(b) Gold and exchange rate





(c) Cocoa and exchange rate

Figure 14: Pairwise net rolling spillovers between commodity prices and exchange rates of Sub-Saharan African countries

Source: Field Data (2023)

To conclude the discussion on the time-varying analysis, we turn to pairwise net rolling spillovers. The results are presented in Figures 14 a, b, and c for energy-exporting countries, metal-exporting countries, and agricultural-exporting countries, respectively. As explained earlier, we have chosen to present only the pairs involving commodities and exchange rates due to the impracticality of presenting all the generated pairs from the analysis. It can be observed that the pairwise net spillovers between commodities and exchange rates have both positive and negative outcomes, except in a few cases. Even so, the few cases of positive pairs only happen in one frequency, not all frequencies. The implication here is that these associations or pairs are both **time-varying net recipients** and **time-varying net transmitters** of spillovers. Connectedness is stronger in the short- and medium-terms than in the long-term. Again, there are observations of sharp episodes of connectedness in contagion. For instance, in Figure 14a, sharp episodes are attributed to oil and Mauritania in 2001 for band 1 and between 2007 and 2008 for all bands. Similarly, oil and Nigeria exhibit sudden episodes between 2007 and 2008 for all frequencies, which confirms the impact of the 2007/2008 financial crisis on the interaction between commodity prices and exchange rates.

The results in Figures 14b and 14c show similar trends to those in Figure 14a. There is an observation of both sharp increases and decreases in connected contagion and delay contagion across all frequencies. Mention can be made of gold and South Africa, which exhibit a sudden shift in contagion around 2001 and between 2007 and 2008. The pairwise spillovers between gold returns and exchange rates also show no connection before 1997 and no connection between 2012 and 2018, implying the existence of the decoupling hypothesis during those time periods. And for cocoa and exchange rates, sudden increases are observed for many countries within 2001, which is not surprising looking at the events of the early 2000 recession. In all instances, connectedness appears stronger in the short term than in the long term. Based on the bivariate case too, the study found evidence supporting the time-varying contagion for specific country exchange rates and commodities.

Robustness analysis with wavelet multiple cross correlation

We check the robustness of return spillover between commodities and exchange rate using wavelet multiple cross-correlation (WMCC) proposed by (Fernández-Macho, 2012) which capture the frequency connectedness dynamics in the relationship. Fernández-Macho (2012) define wavelet multiple correlation ($\phi X(\lambda_j)$) as a single set of multi-scale correlations. The results are presented in Figure 25 in Appendix E.

The results indicate that while there is market leadership at some scales for oil-exporting countries, there is no market leadership for metal-exporting countries or agricultural exporting countries. Ghana dominates spillover propagation at the higher scale, and crude oil and Nigeria dominate spillovers at the intermediate scales for oil-exporting countries. For metal-exporting countries, South Africa is the most dominant propagator of spillovers but has no market leadership, followed by Namibia. Comoros dominates spillover propagation, although it has no market leadership, followed by Cote d'Ivoire. The results of the WMCC are therefore quite similar to those of BK18.

Conclusions and recommendations

The study focused on the connectedness and contagion between commodity prices and exchange rates of commodity-exporting countries in

Sub-Saharan Africa (SSA). The extant literature has concentrated on spillovers among stock markets and commodities in developed and emerging markets, with little emphasis on developing countries like those in SSA. This study concentrated on the returns of commodities and the exchange rate as the origin of contagion and thus emphasised the role of cross-sectional correlation in the origin of connectedness.

In this study, monthly log-return series for crude oil, gold, and cocoa were computed, as were the ER of five energy-exporting countries, thirteen metal-exporting countries, and thirteen agricultural-exporting countries. Commodities are used as propagators of spillovers. Spillovers in the system were captured with the static frequency domain (BK18), and the time-varying frequency domain (BK18).

The findings of the study show that there are differences in spillovers and contagion for different commodities. In the time domain, no commodity dominates spillover propagation, although crude oil is an important contributor to spillovers among oil-exporting countries. There was higher total return connectedness between gold- and metal-exporting countries and cocoa- and agricultural-exporting countries than oil- and energy-exporting countries. However, oil returns have a more significant contribution to overall connectedness than gold and cocoa. Additionally, when frequency levels rise, connectedness rises as well, and short-lived outbreaks of contagion eventually give way to dependency. The results also revealed that in the medium- to long-terms, within-connection levels are lower than in the long-term so diversification advantages can be realised from both static and time-varying perspectives.

There is no clear evidence from the results of the study that the exchange rates of large commodity-exporting countries are the dominant propagators of spillovers. We also found that gold and cocoa do not dominate spillover transmission to exchange rates in Sub-Saharan Africa, although oil returns and cocoa returns are **net transmitters** of spillovers to oil-exporting countries and agricultural-exporting countries, respectively. Surprisingly, gold returns happen to be a **net receiver** of spillovers, with the exchange rates of South Africa, Namibia, and Botswana (all southern African countries) dominating spillover transmission among the metal-exporting countries. Oil returns were dominant among oil-producing countries, while Comoros and Cote d'Ivoire dominate the agricultural-producing countries. Further, Mauritania and Nigeria have a passing contagious association with oil returns in the net's pairwise directional connectedness. The same can be said for South Africa and gold returns and the Comoros and cocoa returns.

Since the study concentrated on contagion and connectedness between commodities and exchange rates, the findings are significant for improving portfolio diversification, risk management, and the stability of the financial market. Policymakers and investors should thus understand and monitor the connection between these markets and their interaction with global shock factors for effective decision-making. Again, instead of focusing on external shocks from commodities, policies aiming at reducing the impact of external shocks on exchange rates should rather be heavy on other commodity-producing countries' exchange rates. Also, when it comes to how return shocks spread, policymakers should look at the exchange rates of both small and large commodity-producing countries.

In general, this study demonstrates that not only does contagion in the currency market shift or delay, it is also time-frequency dependent. For the energy exporting countries (EEC) and agricultural exporting countries (AEC), decoupling is rejected but partially accepted in the metal exporting countries (MEC). The study has therefore examined the *"decoupling hypothesis"* in the currency market of CEC in SSA, which was not previously done. This is new evidence that is critical for hedging and risk management decisions, as well as portfolio diversification strategies, for commodity exporting countries that are also commodity dependent. In line with the HMH, policy and investment decisions in SSA's currency market should take into account the short-, medium-, and long-terms. This is because different factors may affect the movement in each time frame.

CHAPTER SEVEN

SUMMARY, CONCLUSION AND RECOMMENDATIONS

Introduction

A challenge faced by many countries in Sub-Saharan Africa (SSA) is maintaining stability in their economic fundamentals, particularly inflation rates, exchange rates, and interest rates. Excessive dependence on commodity exports for revenue significantly contributes to the challenge due to fluctuations in global commodity prices. There is therefore a need to reinvestigate the interaction between commodity prices and economic fundamentals to guide the development of more consistent policies to deal with global fluctuations.

Motivated by the fact that participants in the commodities markets, the goods markets, and the currency markets are different and their behaviours are impacted differently by different situations, the thesis employed the heterogeneous market hypothesis (HMH) and the adaptive market hypothesis (AMH) to conduct a multiscale analysis of the relationship between commodity prices and macroeconomic fundamentals (inflation and exchange rates) in SSA. The specific objectives were:

1. To investigate the nature of interdependence and systemic risk between commodity prices and inflation rates for commodity-exporting countries in SSA.

2. To analyse the level of multi-frequency information flow between commodity prices and exchange rates among commodity-exporting countries in SSA.

3. Examine the time-varying connectedness and contagion between commodity prices and exchange rates in SSA's commodity-producing countries.

To accomplish the research objectives, empirical papers were conducted for each of the three objectives. The study adopted a quantitative approach based on monthly secondary data from January 1990 to December 2019 collected from the World Bank and IMF databases. The study also utilised modern econometric techniques such as the cross-quantilogram proposed by Han et al. (2016), effective transfer entropy by Renyi (1961) based on complete ensemble empirical mode decomposition by Torres et al. (2011), and spillover index proposed by Barunik and Krehlik (2018). These methods enabled the study to reveal more information that would otherwise be missing from traditional methods like vector autoregressive (VAR), generalised autoregressive conditional heteroscedasticity (GARCH), and ordinary least squares (OLS) regression.

This chapter presents a summary and conclusion to the three empirical studies conducted on the relationship between commodity prices and macroeconomic fundamentals. The chapter commences with a concise summary of the principal discoveries. It subsequently progresses to the concluding section, which addresses the practical implications of the study's results, contributions to theoretical and empirical frameworks, policy and practice recommendations, and finally, proposals for future research.

Summary of Findings

The purpose of the thesis was to conduct a multi-scale analysis of the relationship between commodity prices and microeconomic fundamentals (inflation and exchange rates) in SSA, with a focus on interdependence, systemic risk, information flow, and contagion. To achieve the research objectives, we presented empirical papers for each of the three objectives. The subsequent three paragraphs provide a synopsis of each of the three papers:

The perspective of the overshooting theory is that changes in commodity prices signal possible changes in inflation. But with commodities markets dominated by players with different behaviours who are also impacted differently by different market situations, the first objective sought to find out how such behaviours impact interdependence and systemic risk between commodity prices and inflation in SSA countries. As shown in Chapter 4, the objective revealed that the interdependence between commodity prices and inflation is mainly significant and negative at the lower quantile and mainly significant and positive at the upper quantile. The result suggests that it is more likely to record higher inflation in SSA countries when risk in commodity prices is high, but less likely to record high inflation in SSA when risk in commodity prices is low. The study also observed mainly negative systemic risk patterns, albeit with limited consistency as it peaked with positive numbers. The implication is that the possibility of risk in commodity prices causing systemic risk in inflation in SSA is inconsistent, short-lived, and takes longer to record the highest impact in SSA. Further analysis shows that the predictive power of commodities to forecast inflation in SSA is very weak since the portmanteau test was insignificant for several countries.

Chapter 5 examines the information flow between commodity prices and exchange rates of commodity-exporting countries in the SSA, based on objective two. The focus of the objective was to quantify the strength of information flow at multiple frequencies to reveal the complex behaviour of agents in the financial market in line with the heterogeneous market hypothesis (HMH). The findings of the objective revealed that at the composite level, information flow is negative from cocoa and gold to the exchange rate. But from crude oil to exchange rates, the information flow is positive for all but one country. At the frequency level, information flows in both directions, from short- to long-term, with more positive information at higher frequencies, more negative information at intermediate frequencies, and only negative information at low frequencies. The results suggest that high commodity prices present a high risk to the exchange rate in SSA during economic turmoil and that commodities provide a hedge to exchange rates in the medium to long term, but only a few countries can obtain a good hedge in commodities in the short term.

The final empirical chapter (Chapter 6) investigates the level of connectedness between commodity prices and exchange rates and how contagious the relationship is, according to Objective 3. The study also draws conclusions about the decoupling hypothesis in SSA commodity-exporting countries. The findings show that the connectedness and contagion dynamics between commodity prices and exchange rates vary only slightly across commodities. The study discovered instances of possible diversification opportunities in both static and time-varying stages. The study also observed that commodities do not dominate connectedness and contagion, although crude oil is among the significant contributors to contagion. Indeed, cocoa and crude oil are net transmitters of spillovers, but gold is the net receiver of spillovers. There are also instances of both small and large commodity-exporting countries dictating contagion. A case in point is Comoros and Cote d'Ivoire, which dictate spillovers for agricultural exporting countries. The results mean that the impact of extreme events on market players' behaviours increases the level of connectedness and interdependence between commodities and exchange rates in SSA.

Conclusions

The conclusion drawn from the first objective is that anytime commodity prices in the global markets record very high prices, countries in Sub-Saharan Africa are more likely to record high inflation, but the reverse will happen whenever commodity prices record low prices. The study also concludes that the possibility of shocks in commodity prices causing systemic risk in inflation in SSA is low, and when it happens, it does not last longer. Again, while predicting inflation in SSA based on commodity prices is a bit risky, doing so based on the lower quantile increases the success rate.

The findings from Objective 2 conclude that information transmission between commodity prices and exchange rates is frequency-dependent and asymmetric, as more positive information is transmitted from commodity prices to exchange rates at high frequency and more negative information at medium- to long-term. The practical implication is that in the short term, high commodity prices lead to high exchange rates in Sub-Saharan Africa, but the situation normalises and reverses, moving from the medium to the long term, where market participants do not panic in their decision-making. It also suggests that it is important to consider the differences in the behaviour of market players in the commodities market and the currency markets in SSA countries when learning about the interaction between the two markets. The study adds that the hedging potential of commodities for exchange rates in SSA is stronger in the medium to long term but weaker in the short term.

Based on the findings from objective three, the study concludes that cross-market linkages between global commodities markets and the currency markets in SSA increase whenever there is a crisis in the global market, as was evidenced in 2001, 2008, and 2011, among others. The study also concludes that since crude oil and cocoa are net transmitters of spillovers, they present a significant amount of risk to exchange rates in SSA countries whenever their prices increase, with gold behaving the opposite. Again, during the period of the study, there were instances of disconnect (1990–1997 and 2012–2017) between the currency markets and the gold market, which suggests that the global market of gold offered no risk to the currency markets in SSA during those periods. The implication is that energy-exporting countries and agricultural-exporting countries should be more concerned about shocks emanating from global markets of crude oil and cocoa, respectively, since that can trigger contagion among the currency markets in SSA commodity-exporting countries. The study also rejects the decoupling between the currency markets in SSA and those of the oil and cocoa markets, but partially accepts it between the gold and currency markets.

Contribution to Knowledge

Empirically, the study adds to knowledge by providing evidence of systemic risk between commodity prices and inflation in the context of commodity-dependent developing countries. Previous studies have looked at the predictive powers of commodities for inflation but have ignored the systemic risk implications of the relationship. The study's findings indicate that there is a high likelihood of high inflation in SSA when commodity price risks are high, particularly for energy and agricultural exporting countries. By providing empirical evidence based on the distributional quantiles, the study is one of the first to extend the argument of the adaptive market hypothesis (AMH) to the situation in SSA.

The study also contributes to knowledge on commodity returns as the origin of contagion and information flow in the currency market of the SSA at multiple frequencies. Prior research has examined the relationship between commodity prices and exchange rates but has primarily focused on volatility at static time levels. Such analysis fails to elucidate crucial hidden information that is relevant for policy and investment decisions. The findings of the study indicate that at high frequency levels, more positive information flows from commodities to the ER, but this turns mainly negative at low frequency. Furthermore, the returns of ERs of commodity exporting countries (CEC), particularly for countries that export metal and agricultural commodities, take the position of dominating spillovers to the currency markets in SSA, providing additional evidence that commodities do not hold this role.

Theoretically, the study contributes by examining HMH and AMH in the currency markets of commodity-dependent countries. The application of these theories has provided more evidence to add to what is already known about the stronger currencies in developed countries. Findings from the study show that participants exhibit heterogeneity in the currency market, which provides a guide for policy and investment decisions.

Finally, the study investigated the existence or otherwise of the decoupling hypothesis in the currency market in SSA. The novelty of this study is that decoupling was examined at both time and frequency levels, thus providing evidence for effective comparison. The study's findings reject the existence of decoupling in EEC and AEC but partially accept it in MEC. To the best of our knowledge, the thesis is one of the first empirical studies to test the decoupling hypothesis in time variation between global commodity markets and the currency markets in SSA.

Recommendations

The empirical evidence from the study shows that the cross-quantilogram from commodity prices to inflation in countries in the SSA is significantly negative at the lower quantile and significantly positive at the upper quantile. The results show how extreme situations in the global commodities market influence the relationship. The study recommends that policymakers should put in place strategies that can detect early warning signals of extreme situations in the global commodities markets in order to prepare for such situations. There should be constant monitoring of activities on the global market to identify extreme situations like an outbreak of war in a major producing country, financial crises, and global pandemics. Such monitoring can provide valuable information for policy preparedness. It is recommended that commodity-backed loans, which many countries in the SSA have contracted with China and other multilateral companies, must be well designed to favour countries in the SSA. For instance, countries contracting commodity-backed loans, such as Ghana, Chad, Angola, and Zambia, among others, should link the repayment not only to commodity revenue but also to growth indicators to reduce the possibility of developing systemic debt due to volatile commodity prices. The study also recommends that, to avoid any possibility of systemic risk in inflation emanating from global commodity prices, central banks in the SSA should establish clear inflation goals and modify interest rates in order to maintain inflation levels within the desired range. This fosters the establishment of inflation expectations and enhances stability in the financial system. A longer-term strategy is that countries in the SSA should gradually reduce their dependence on commodities by diversifying their economies to reduce the impact of global commodity prices on their inflation.

The findings from the thesis show that information transmission between commodity prices and the exchange rate is frequency-dependent since information flow changes from more positive at high frequencies (short-term) to more negative at low frequencies (long-term). The thesis recommends segregating policies to manage global shocks on exchange rates based on short-term, medium-term, and long-term frequencies, corresponding to high, intermediate, and low frequencies, respectively. For instance, in the short term (high frequency), there is a need for policymakers to provide more timely and accurate information to participants in the currency market to reduce panic reactions to uncertainties emanating from global commodities markets. In the medium to long term, authorities can hedge their currencies with commodities, especially gold and cocoa, through commodity futures and options markets, which will help bring about stability in the currency markets in SSA.

Findings from the third objective show that when extreme situations happen in the global markets, there are more cross-market links between the global commodities market and the currency markets in SSA. This makes it more likely that one market will spread to other markets. However, the impact of shocks on the currency markets in SSA may worsen during the crisis period and even become stronger after the crisis period, as seen in the case of the 2007 GFC spreading to the latter part of 2008 and early 2009 in many countries in SSA. As a result, the thesis recommends that policies to reduce the possible impact of shocks emanating from commodities markets to currency markets in SSA should focus on stopping the spread of the shocks at the latter part of the crisis rather than the early part. This is because most countries in the SSA do not have adequate resources, the requisite technology, or know how to manage the immediate impact of crises. To avoid possible spillovers from the currency markets of other commodity-exporting countries in the subregion, the study recommends that more effort be put into having a common currency in SSA as part of the integration process. As trading partners, they will only need to worry about global commodity price shocks, which can be easily managed as an economic block, reducing the need for conversion among themselves.

Suggestions for Future Research

This study relied on commodity prices and not export revenue since such data was not available for SSA countries at high frequencies. The differences in currencies may lead to different amounts of net revenue flowing to different countries for the same quantity of commodities exported. Due to the differences in the exchange rates, future studies can analyse the forecasting ability of net commodity export revenue for inflation.

This study did not include data on the COVID-19 pandemic period due to the possible impact it might have on the overall results. The lack of daily frequency data on ER for countries in SSA prevented a possible estimation of the partial effect of COVID-19, hence the exclusion. It will be interesting to quantify the partial and overall information transmitted by the pandemic period once high frequency ER data for SSA become available. This may provide information for future risk management strategies in the currency market.

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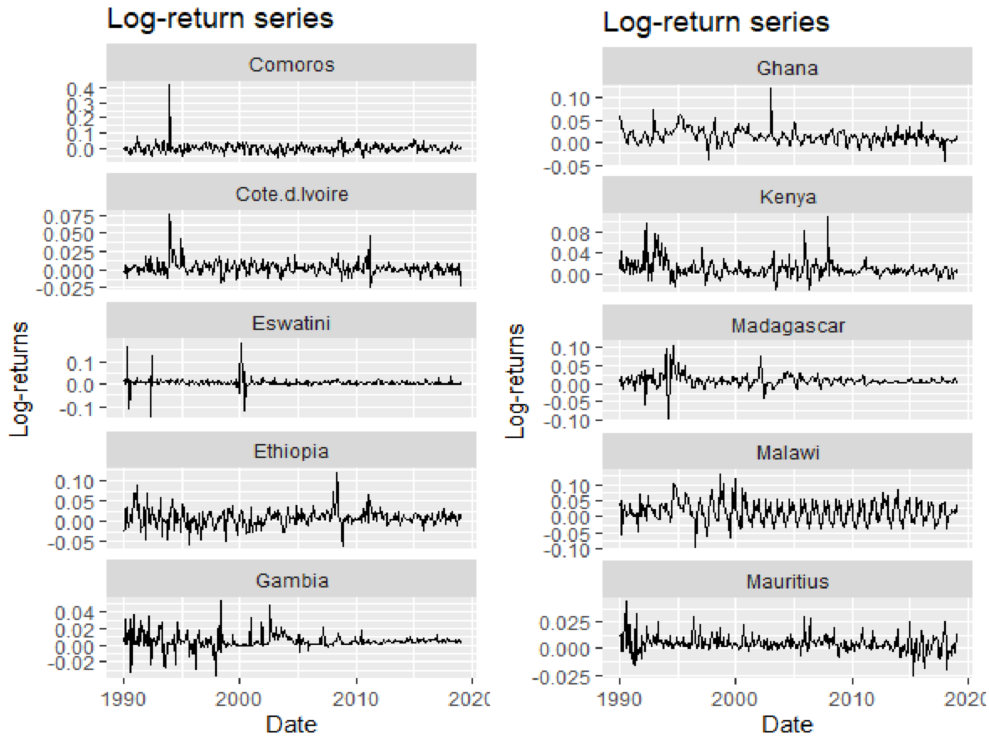
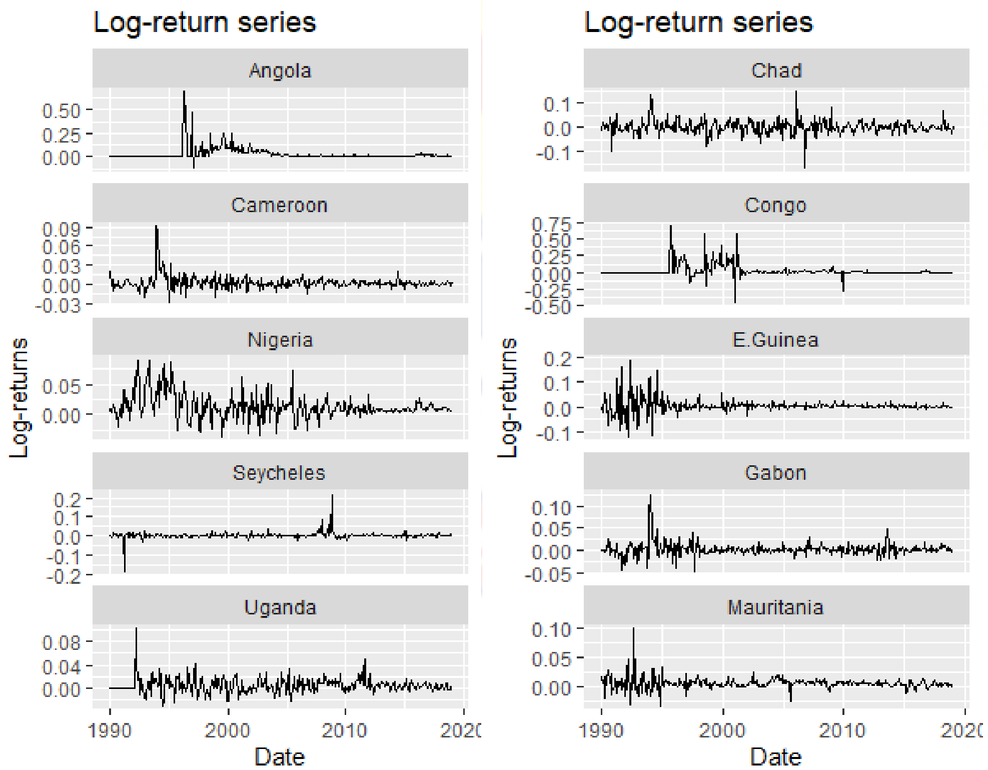
APPENDICES

APPENDIX A

PLOTS OF LOG-RETURN SERIES FOR INFLATION AND COMMODITY PRICES





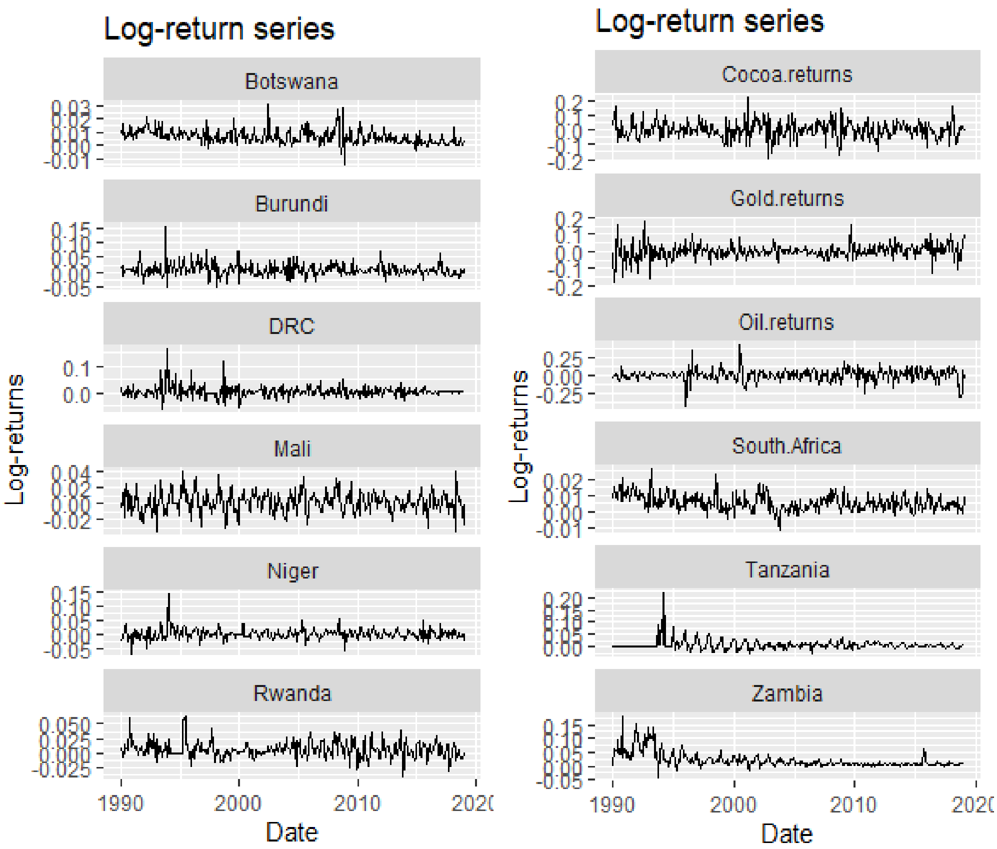
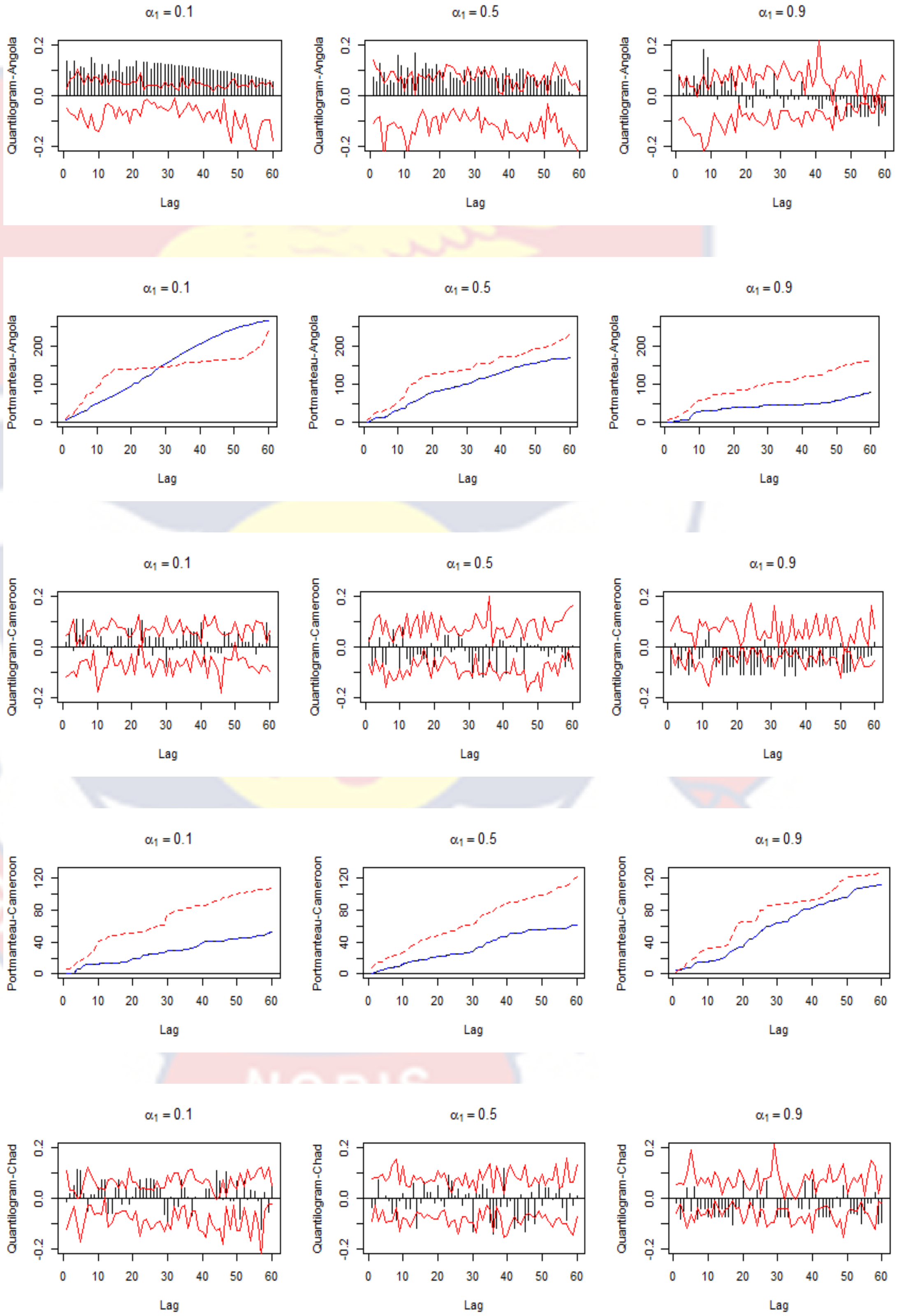
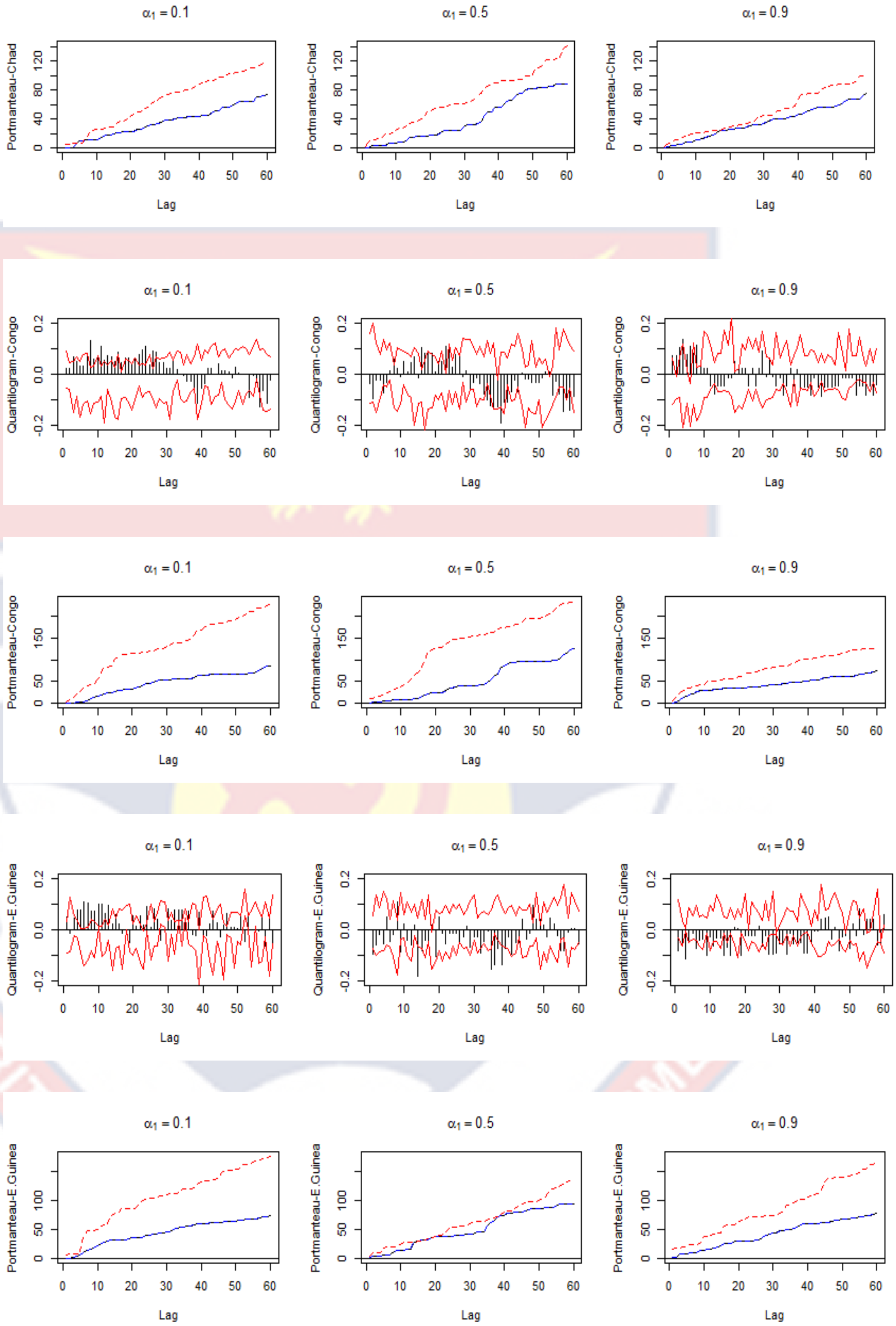


Figure 15: Log-return plots of inflation and commodity prices for Sub-Saharan African countries from January 1990 – December 2019.
Source: Field Data (2023)

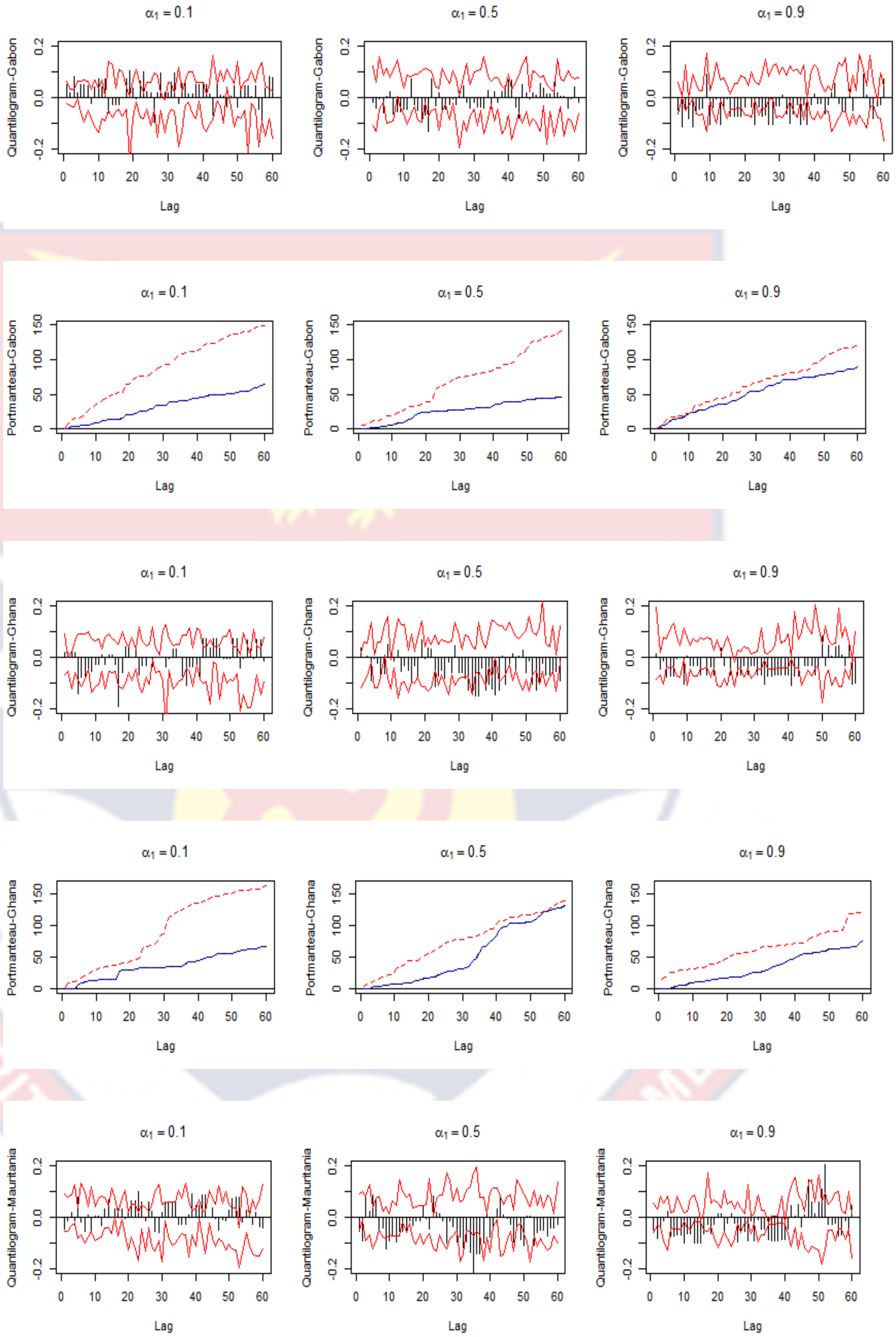
APPENDIX B

PLOTS OF DIRECTIONAL PREDICTABILITY FROM OIL RETURNS, GOLD RETURNS AND COCOA RETURNS TO INFLATION AT $\alpha_2 = 0.9$.





α1 = 0.1
α1 = 0.5
α1 = 0.9
Portmanteau-Chad
Quantilogram-Congo
Portmanteau-Congo
Quantilogram-E.Guinea
Portmanteau-E.Guinea
Lag



$\alpha_1 = 0.1$
$\alpha_1 = 0.5$
$\alpha_1 = 0.9$
Quantilogram-Gabon
Portmanteau-Gabon
Quantilogram-Ghana
Portmanteau-Ghana
Quantilogram-Mauritania
Lag

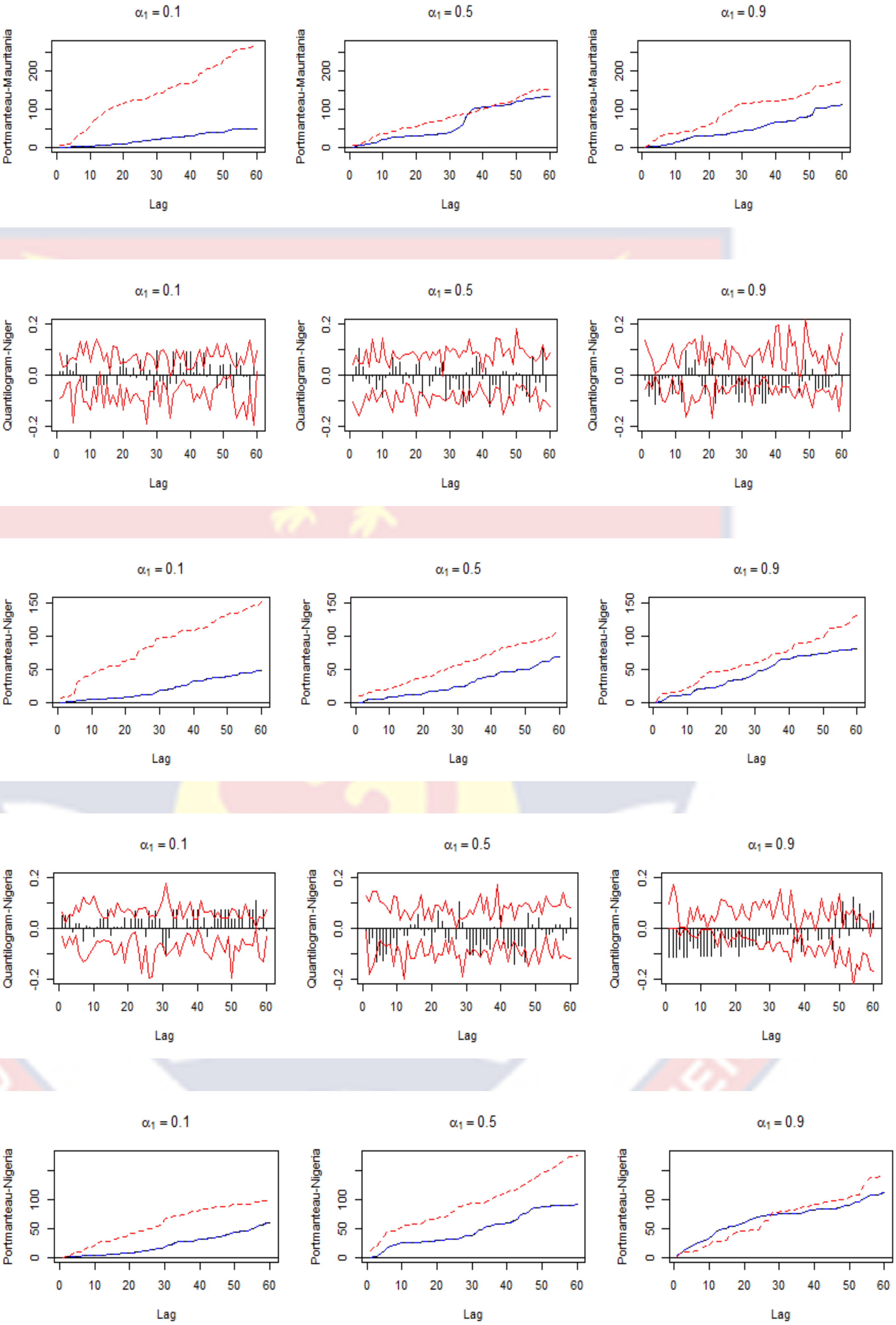
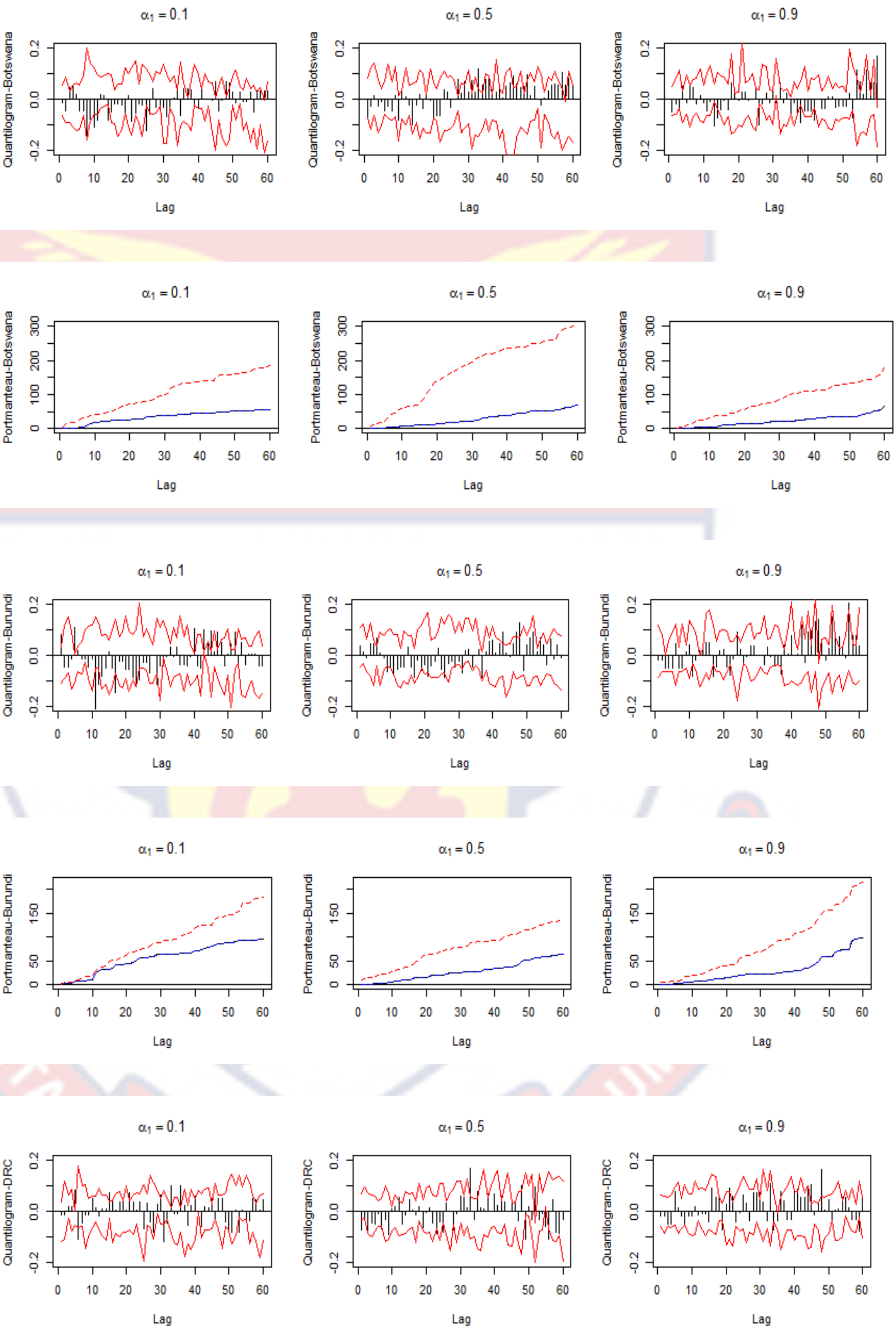


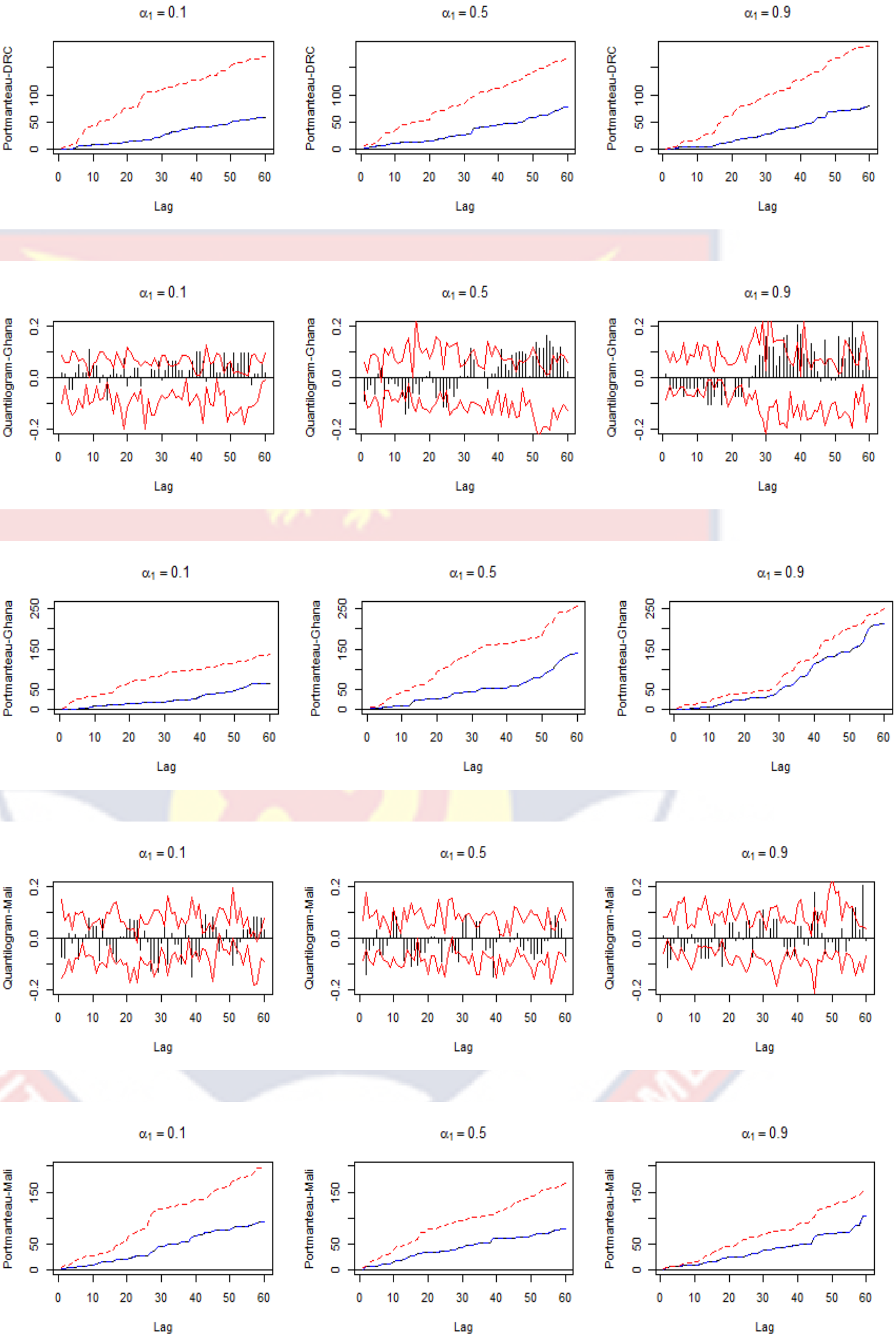
Figure 16: Sample cross-quantilogram from crude oil returns to inflation with $\alpha_2 = 0.9$ and $\alpha_1 = 0.1, 0.5, and\ 0.9$.

Note: *The first diagram for each country represents the cross-quantilogram where the bar graph describes the sample cross-quantilogram. The red dashed lines are the 95% bootstrapped confidence interval with 1000 replicates. For each country, the second diagram is the Box-Ljung test statistics. Lag k = 60 representing a 5-year window.*

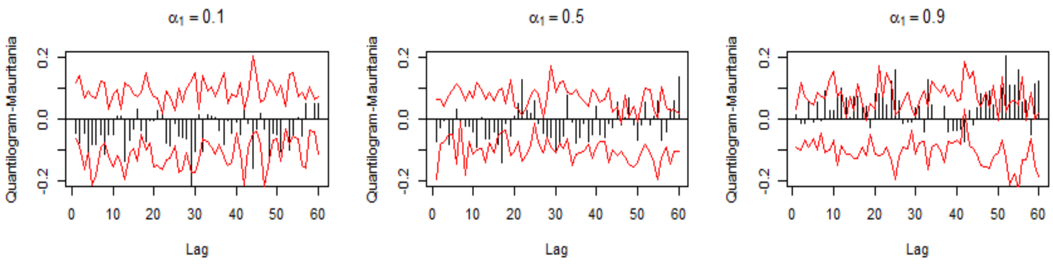
Source: Field Data (2023)

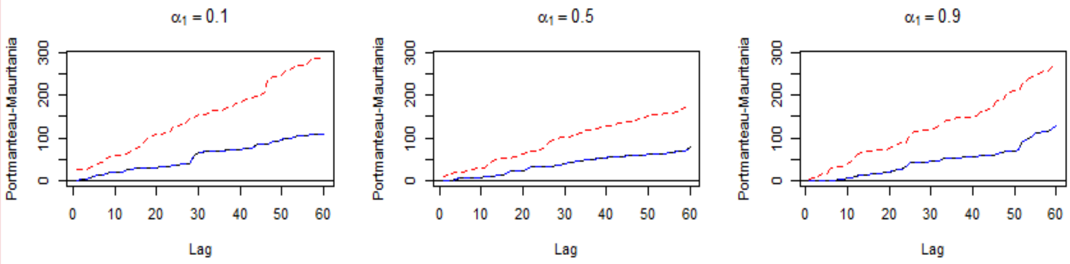


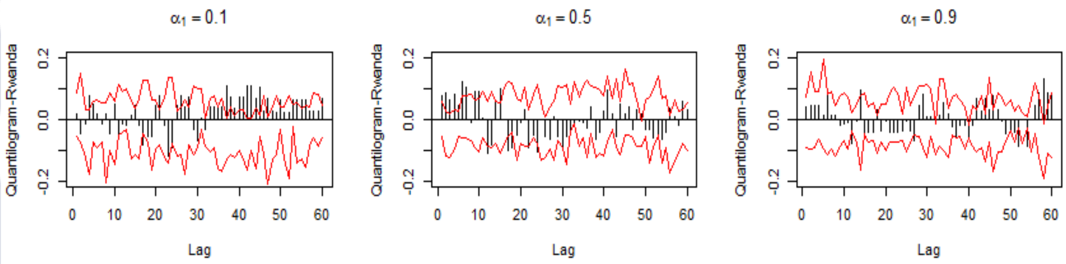
α1 = 0.1
α1 = 0.5
α1 = 0.9
Quantilogram-Botswana
Lag
Portmanteau-Botswana
Quantilogram-Burundi
Portmanteau-Burundi
Quantilogram-DRC

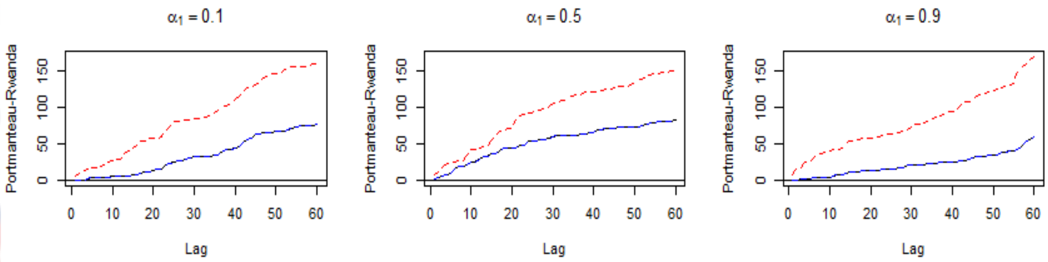


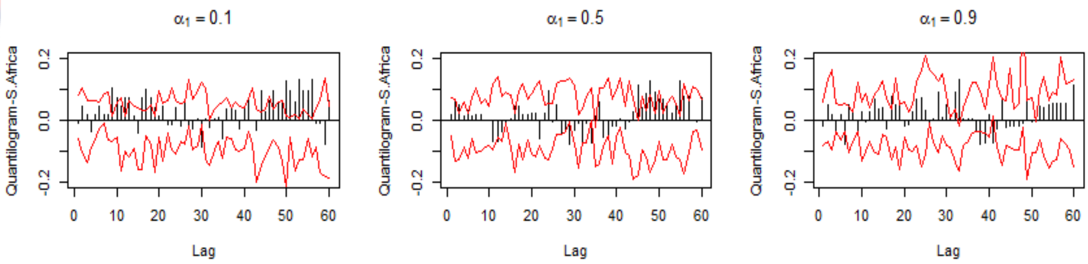
$\alpha_1 = 0.1$
$\alpha_1 = 0.5$
$\alpha_1 = 0.9$
Portmanteau-DRC
Quantilogram-Ghana
Portmanteau-Ghana
Quantilogram-Mali
Portmanteau-Mali
Lag


α1 = 0.1
α1 = 0.5
α1 = 0.9
Quantilogram-Mauritania
Lag


α1 = 0.1
α1 = 0.5
α1 = 0.9
Portmanteau-Mauritania
Lag


α1 = 0.1
α1 = 0.5
α1 = 0.9
Quantilogram-Rwanda
Lag


α1 = 0.1
α1 = 0.5
α1 = 0.9
Portmanteau-Rwanda
Lag


α1 = 0.1
α1 = 0.5
α1 = 0.9
Quantilogram-S.Africa
Lag

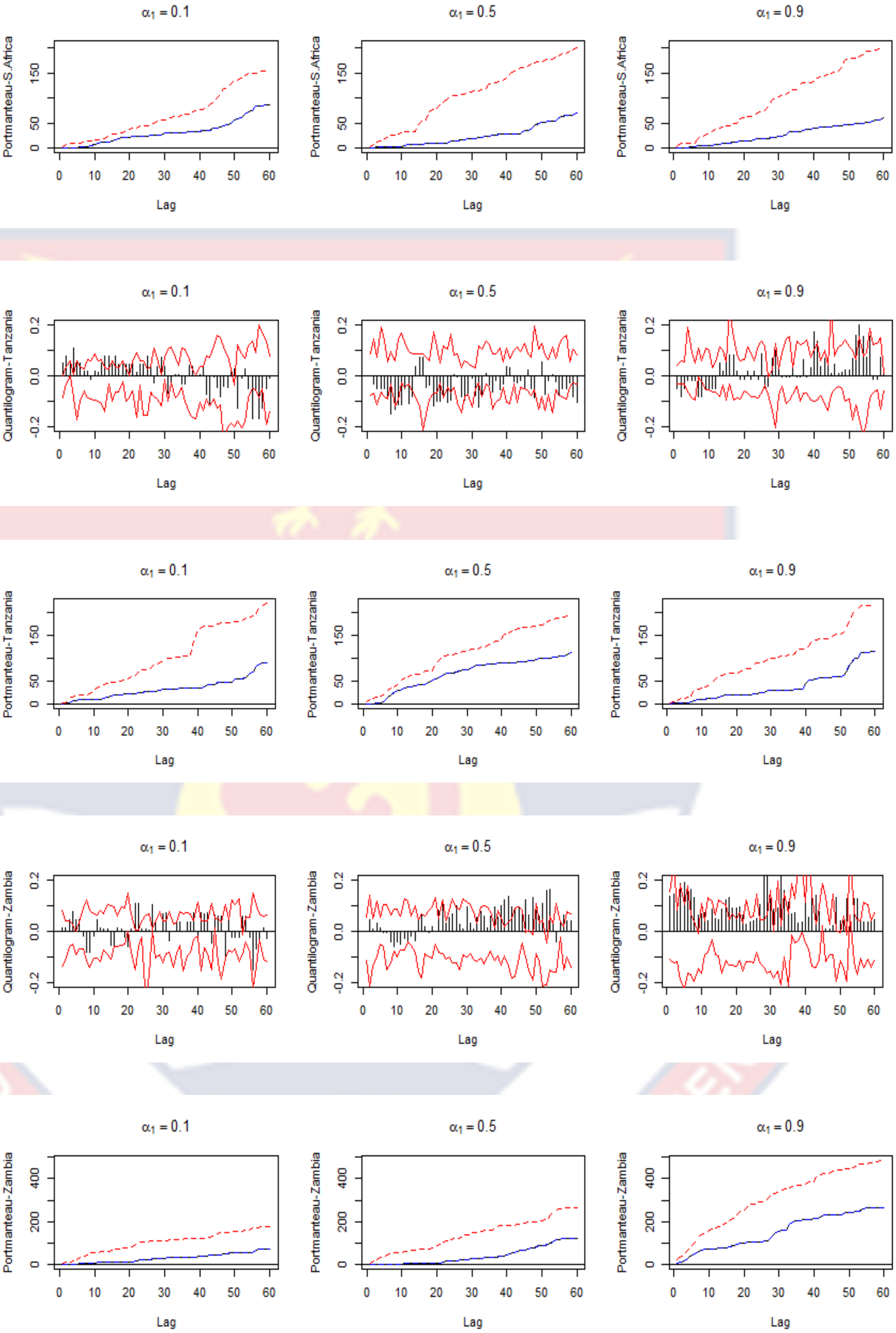
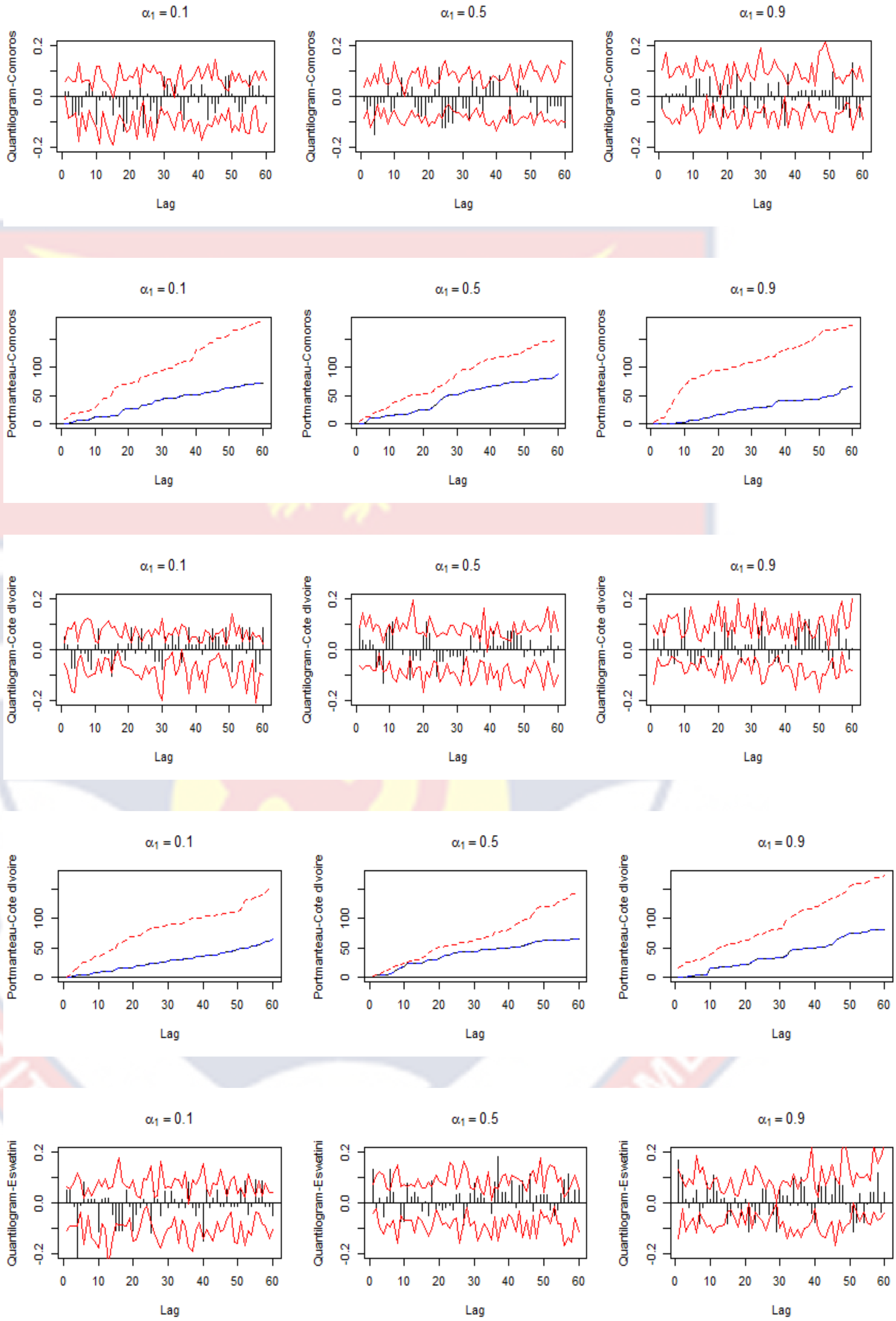


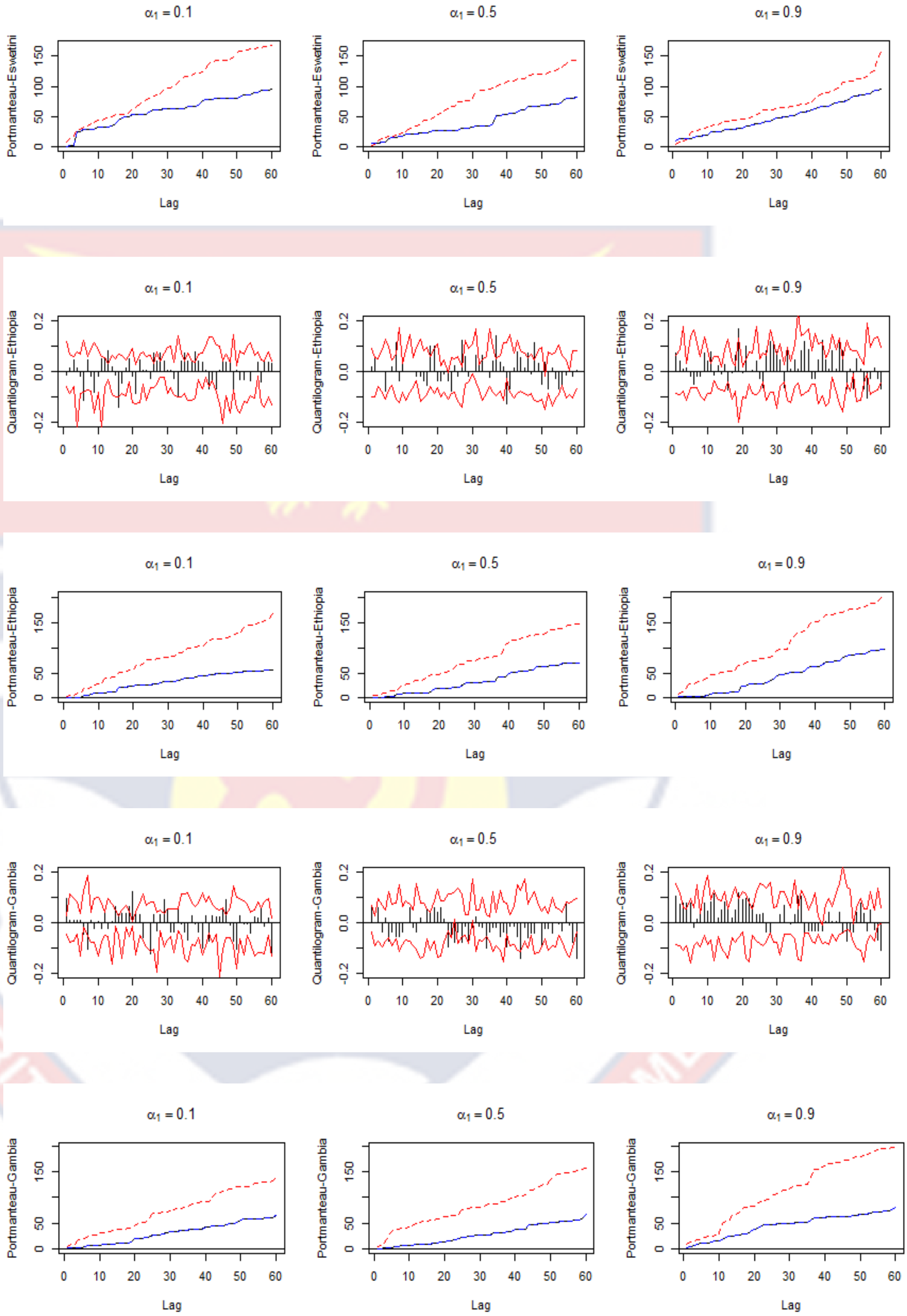
Figure 17: Sample cross-quantilogram from gold returns to inflation with $\alpha_2 = 0.9$ and $\alpha_1 = 0.1, 0.5, and\ 0.9$.

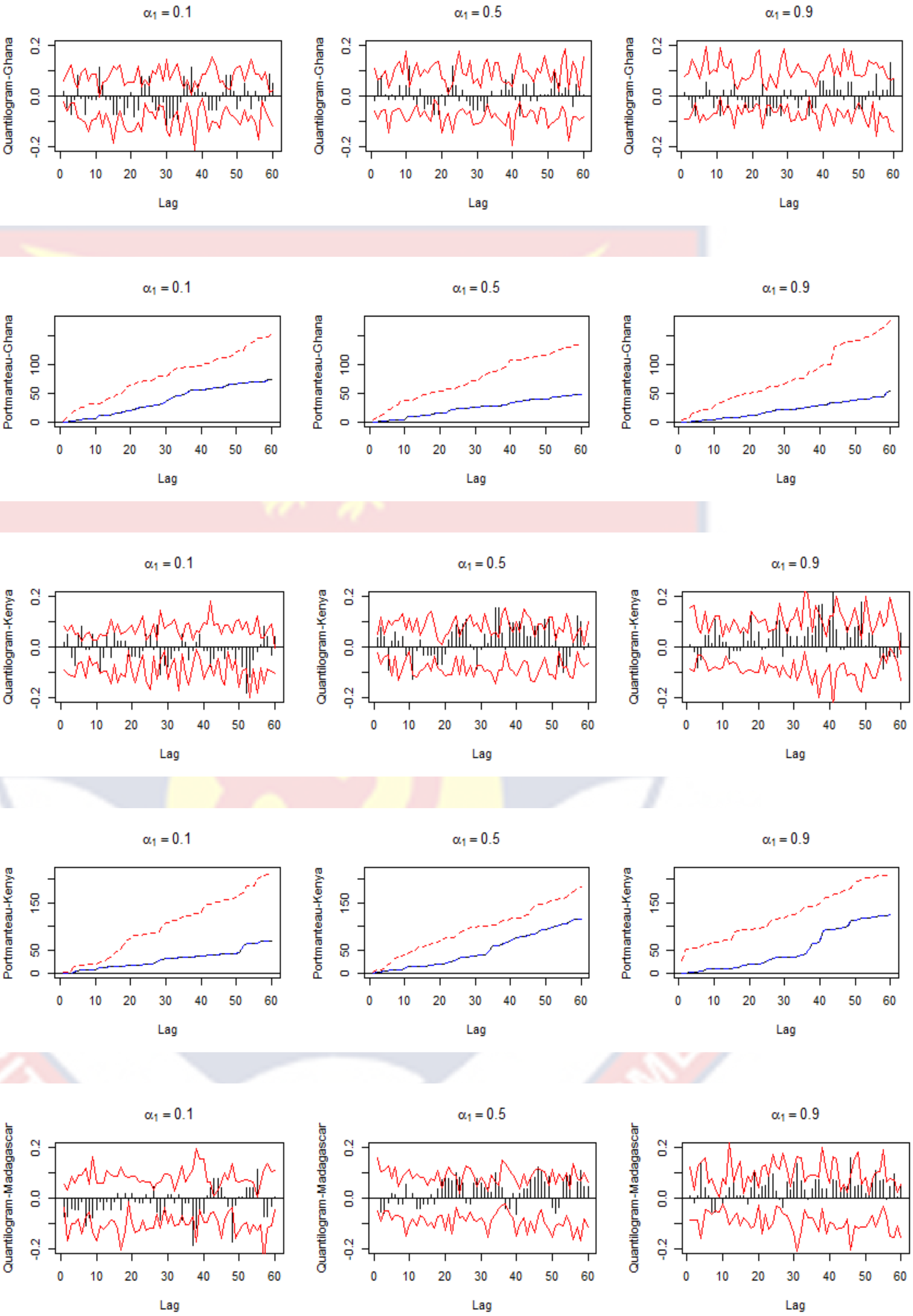
Note: *The first diagram for each country represents the cross-quantilogram where the bar graph describes the sample cross-quantilogram. The red dashed lines are the 95% bootstrapped confidence interval with 1000 replicates. For each country, the second diagram is the Box-Ljung test statistics. Lag k = 60 representing a 5-year window.*

Source: Field Data (2023)

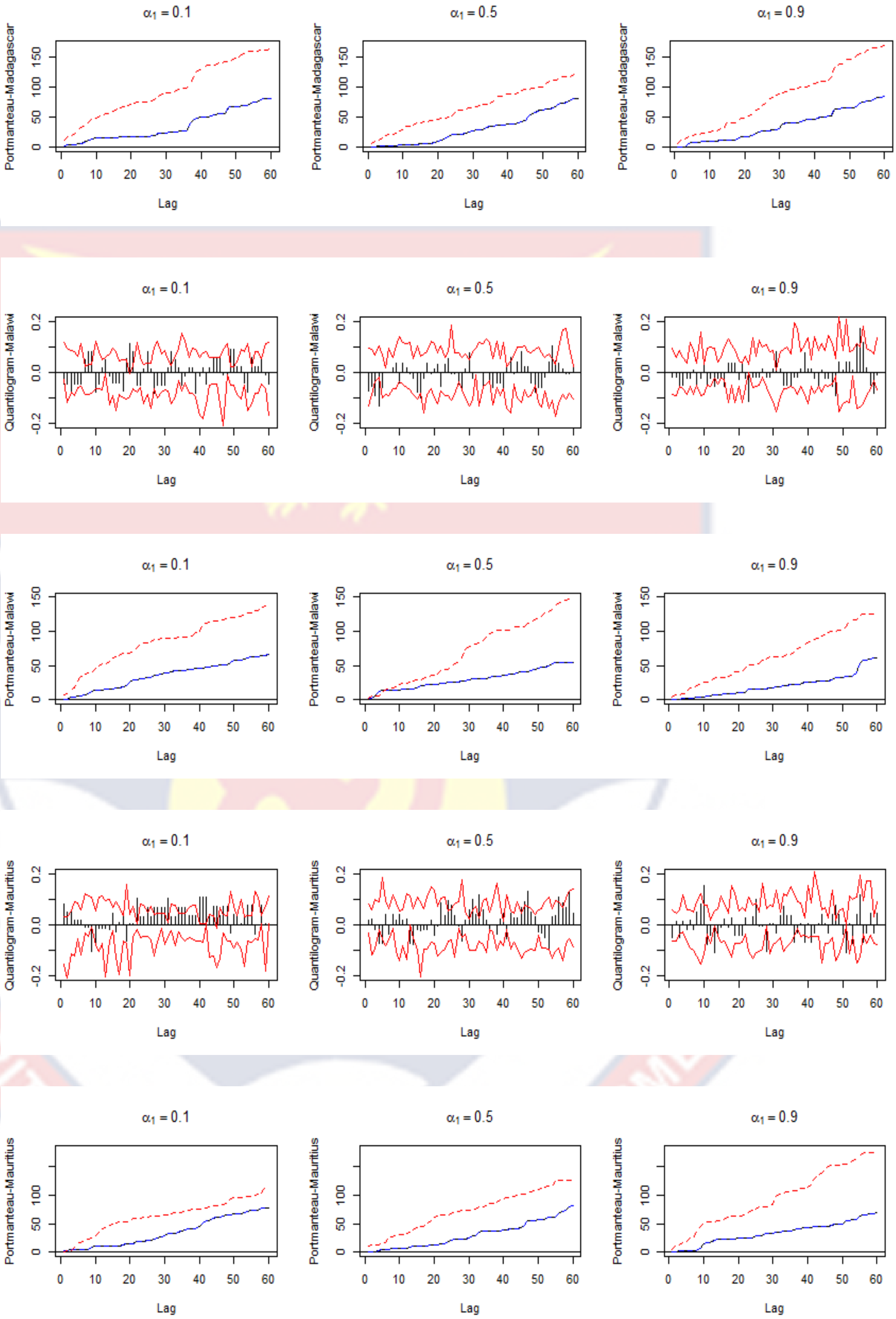


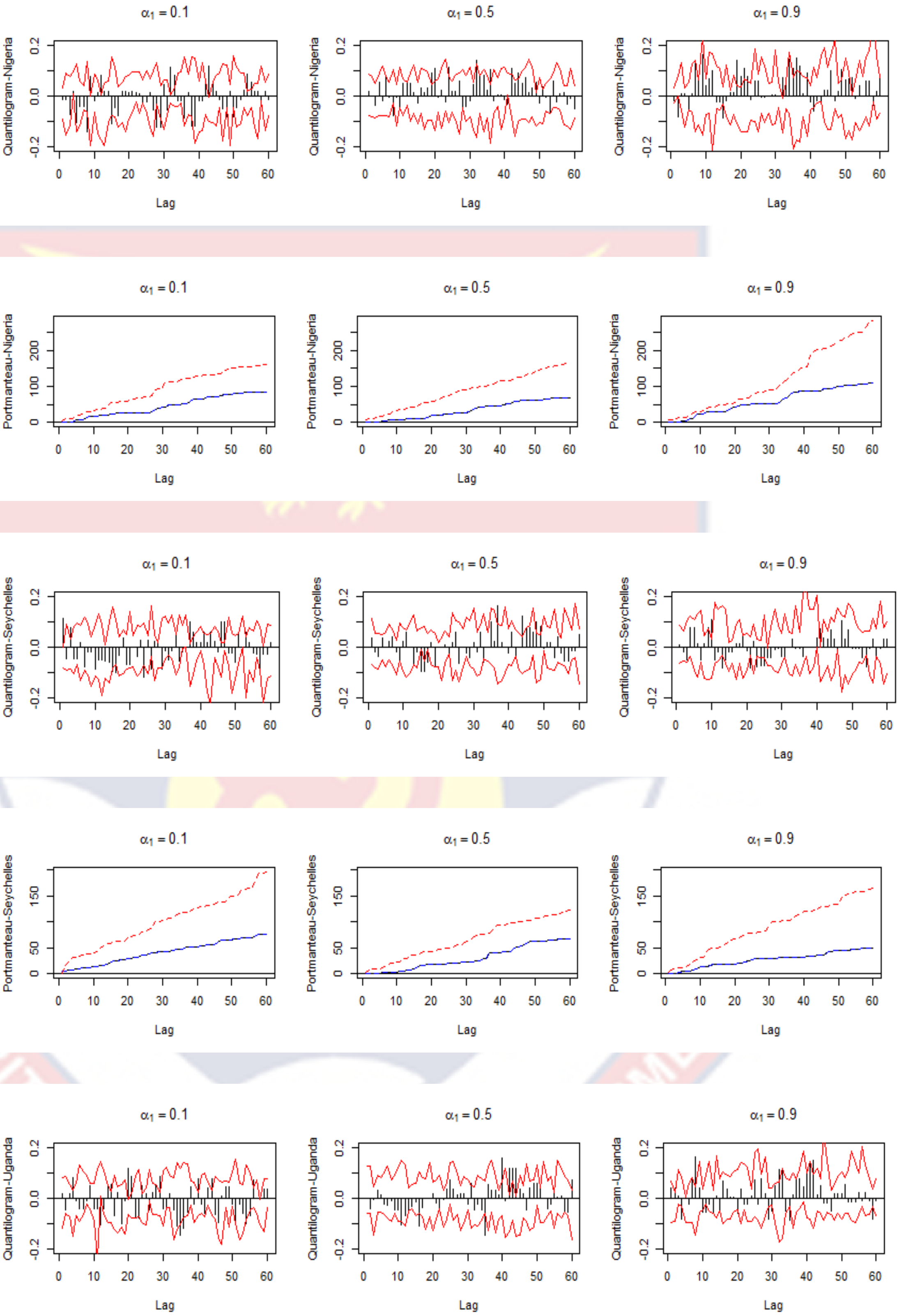
$\alpha_1 = 0.1$
$\alpha_1 = 0.5$
$\alpha_1 = 0.9$
Quantilogram-Comoros
Portmanteau-Comoros
Quantilogram-Cote dIvoire
Portmanteau-Cote dIvoire
Quantilogram-Eswatini
Lag


$\alpha_1 = 0.1$
$\alpha_1 = 0.5$
$\alpha_1 = 0.9$
Portmanteau-Eswatini
Quantilogram-Ethiopia
Portmanteau-Ethiopia
Quantilogram-Gambia
Portmanteau-Gambia
Lag



$\alpha_1 = 0.1$
$\alpha_1 = 0.5$
$\alpha_1 = 0.9$
Quantilogram-Ghana
Portmanteau-Ghana
Quantilogram-Kenya
Portmanteau-Kenya
Quantilogram-Madagascar
Lag
0 10 20 30 40 50 60
-0.2 0.0 0.2
0 50 100
0 50 150


$\alpha_1 = 0.1$
$\alpha_1 = 0.5$
$\alpha_1 = 0.9$
Portmanteau-Madagascar
Quantilogram-Malawi
Portmanteau-Malawi
Quantilogram-Mauritius
Portmanteau-Mauritius
Lag


$\alpha_1 = 0.1$
$\alpha_1 = 0.5$
$\alpha_1 = 0.9$
Quantilogram-Nigeria
Portmanteau-Nigeria
Quantilogram-Seychelles
Portmanteau-Seychelles
Quantilogram-Uganda
Lag

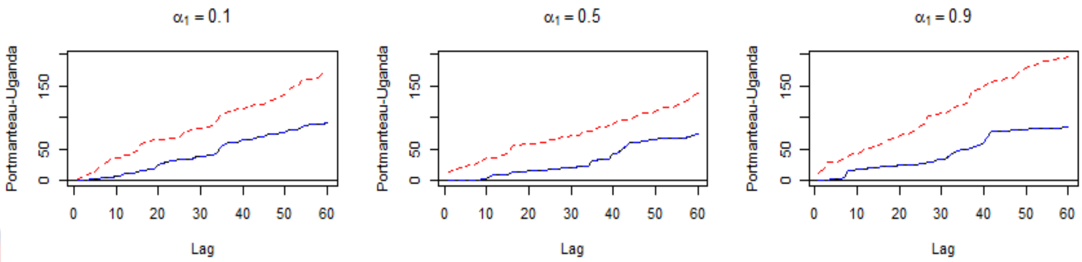


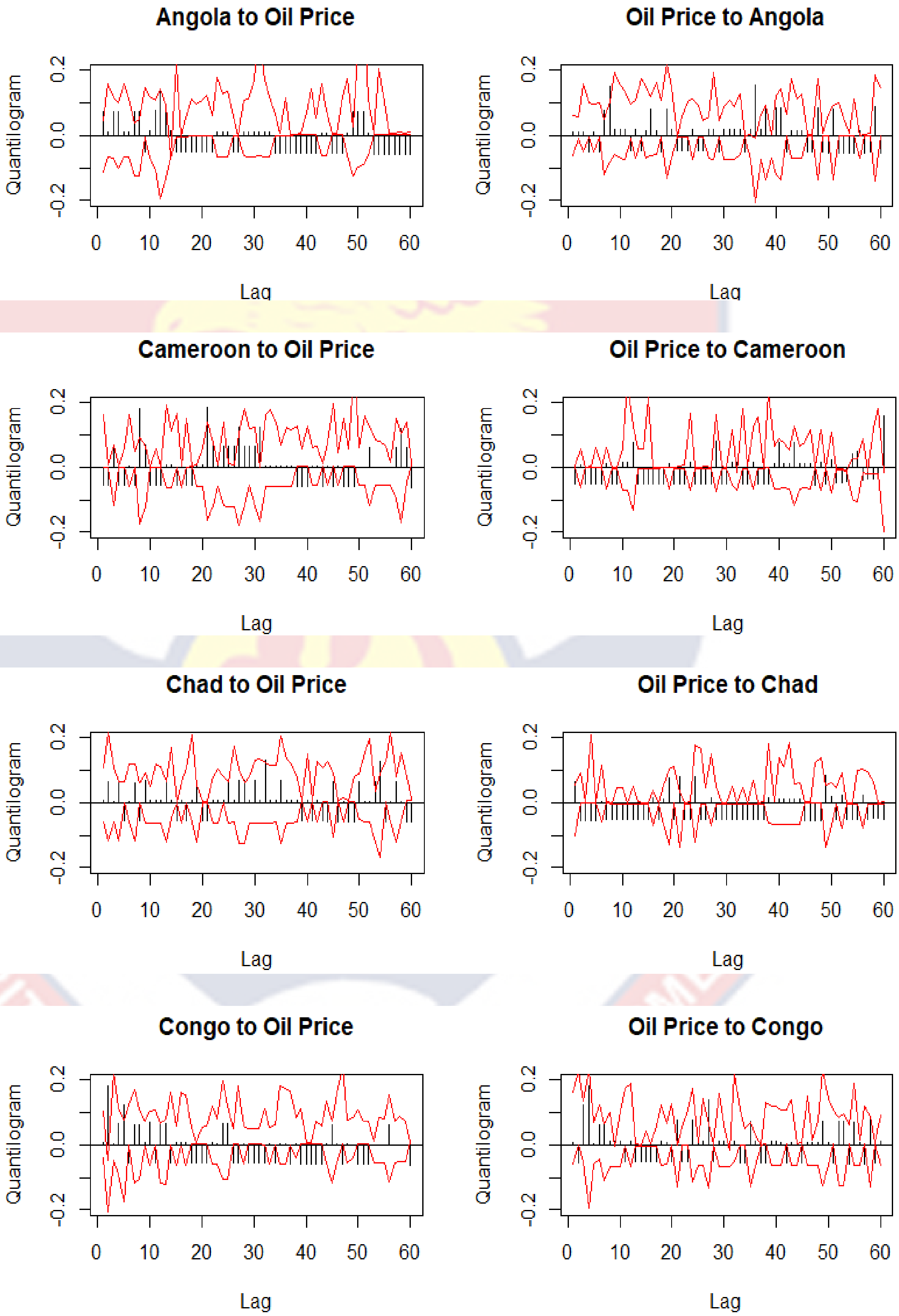
Figure 18: Sample cross-quantilogram from cocoa returns to inflation with $\alpha_2 = 0.9$ and $\alpha_1 = 0.1, 0.5, and\ 0.9$.

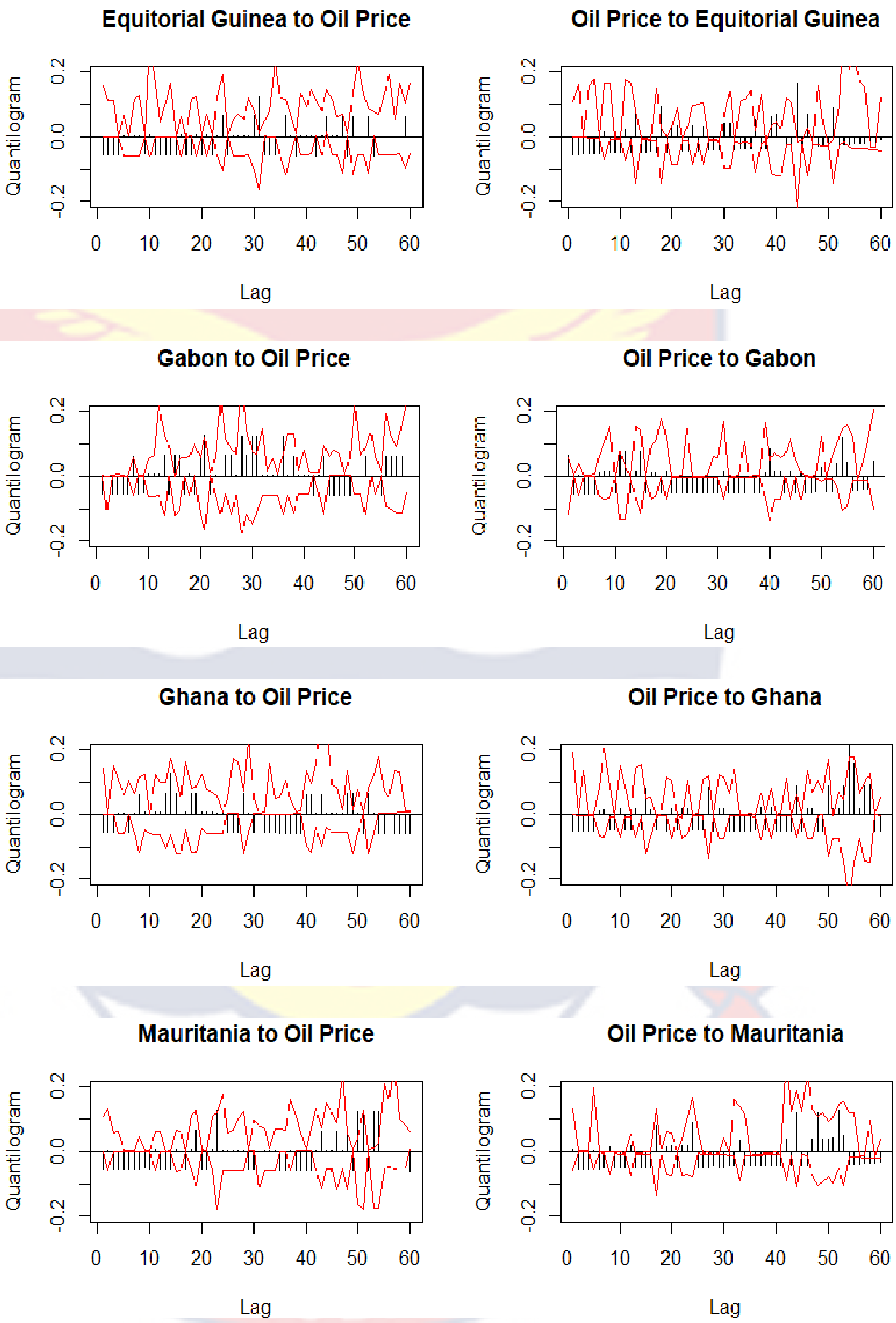
Note: *The first diagram for each country represents the cross-quantilogram where the bar graph describes the sample cross-quantilogram. The red dashed lines are the 95% bootstrapped confidence interval with 1000 replicates. For each country, the second diagram is the Box-Ljung test statistics. Lag k = 60 representing a 5-year window.*

Source: Field Data (2023)

APPENDIX C

PLOTS OF SYSTEMIC RISK BETWEEN COMMODITY PRICES AND INFLATION $\alpha_1 = \alpha_2 = 0.95$.




Equitorial Guinea to Oil Price
Oil Price to Equitorial Guinea
Gabon to Oil Price
Oil Price to Gabon
Ghana to Oil Price
Oil Price to Ghana
Mauritania to Oil Price
Oil Price to Mauritania
Quantilogram
Lag
-0.2
0.0
0.2
0
10
20
30
40
50
60

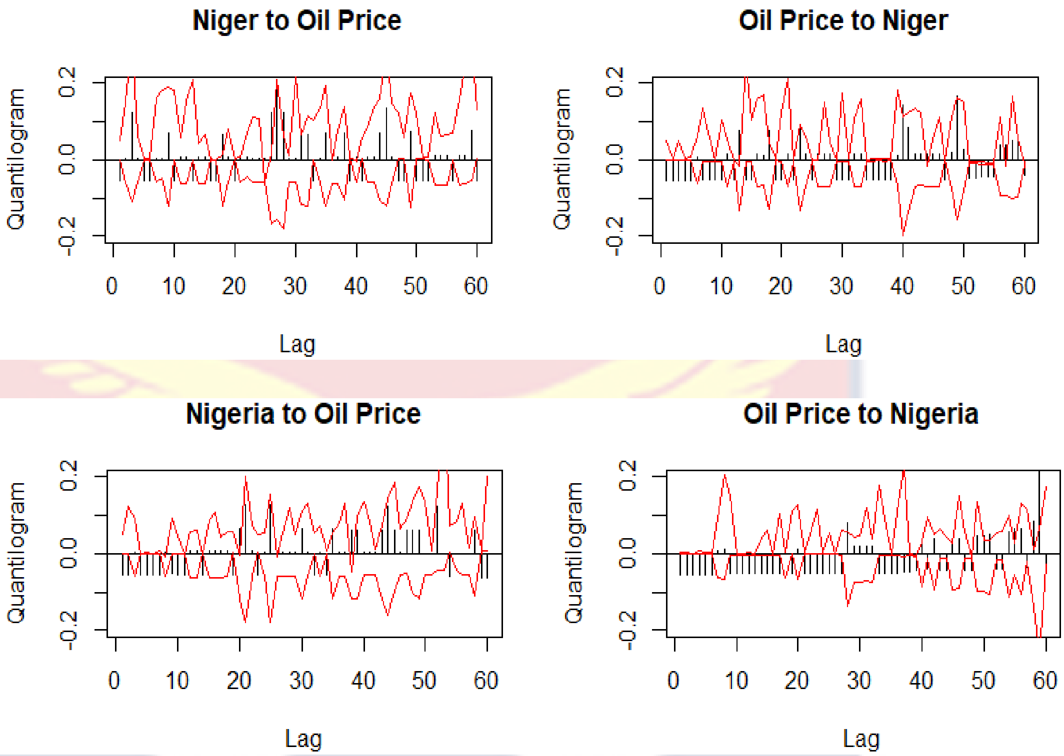
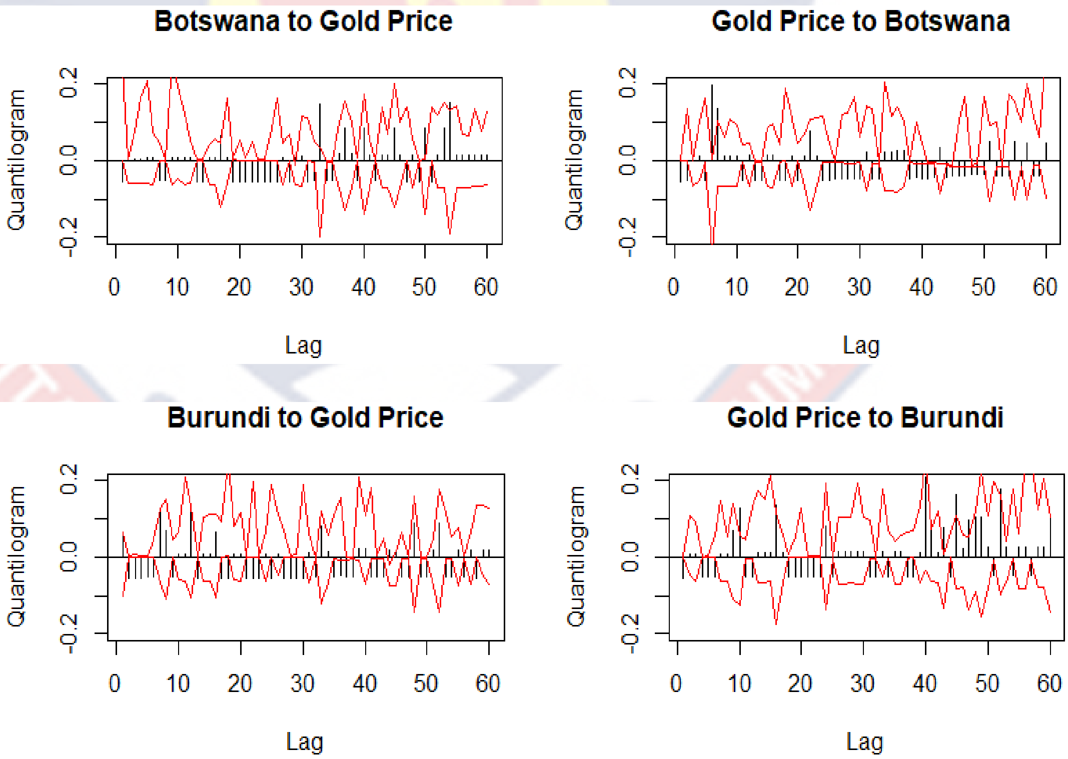
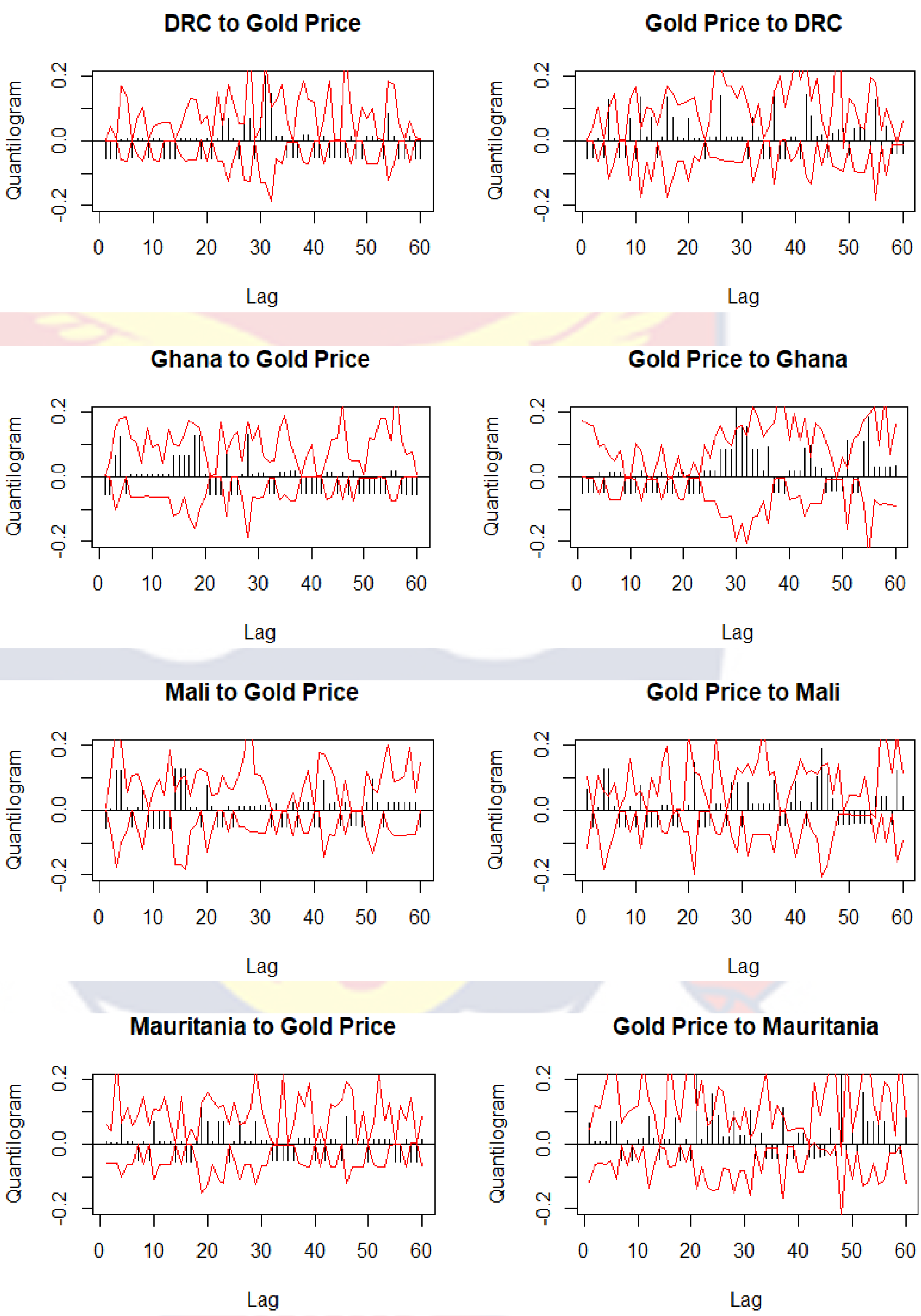


Figure 19: Sample cross-quantilogram to detect systemic risk between oil returns and inflation for fuel-producing countries in SSA at $\alpha_1 = \alpha_2 = 0.95$.
Note: *The bar graph describes the sample cross-quantilogram and the red lines are the 95% bootstrap confidence interval centred at zero.*
Source: Field Data (2023)




DRC to Gold Price
Gold Price to DRC
Ghana to Gold Price
Gold Price to Ghana
Mali to Gold Price
Gold Price to Mali
Mauritania to Gold Price
Gold Price to Mauritania
Quantilogram
-0.2
0.0
0.2
0
10
20
30
40
50
60
Lag

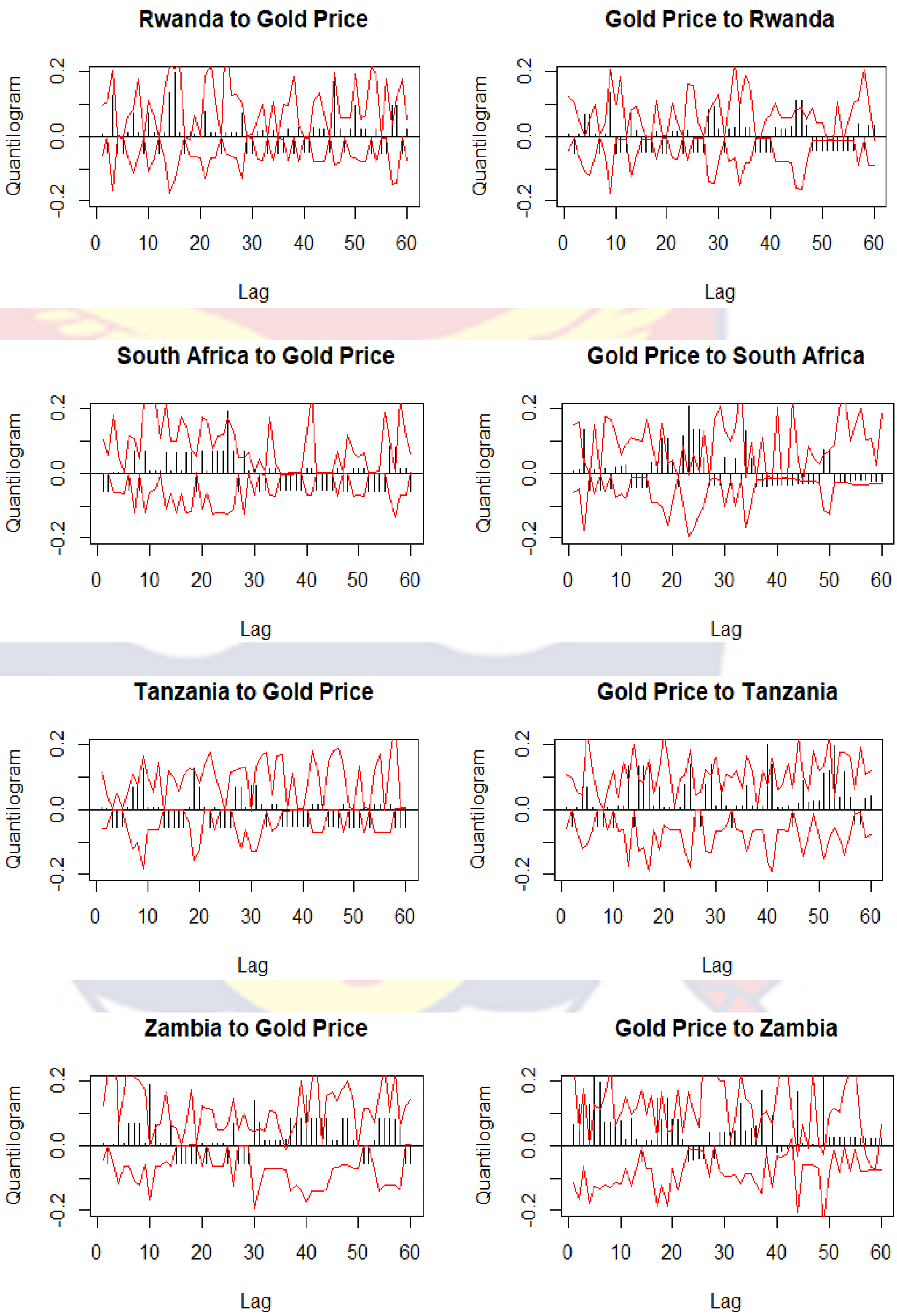
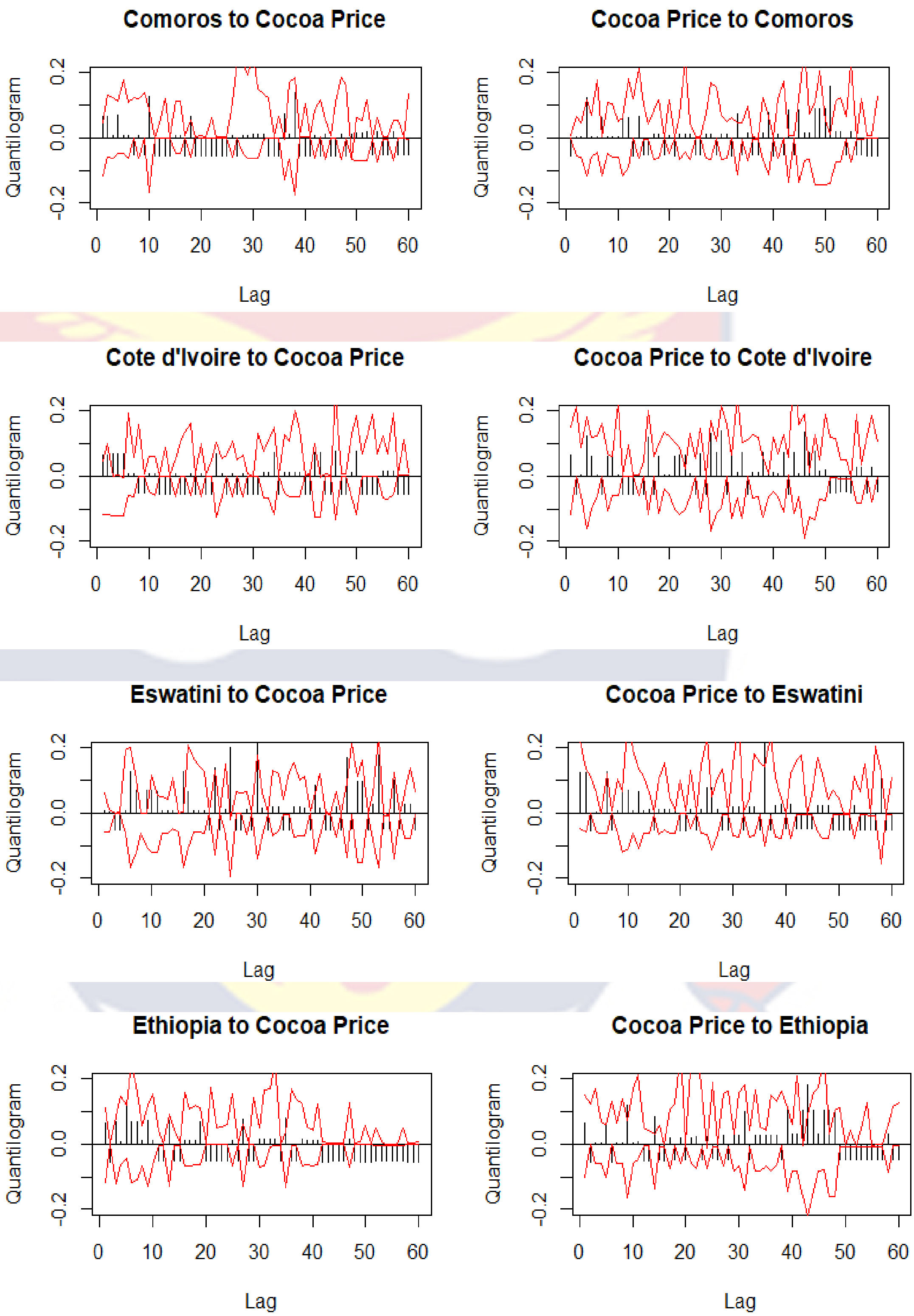
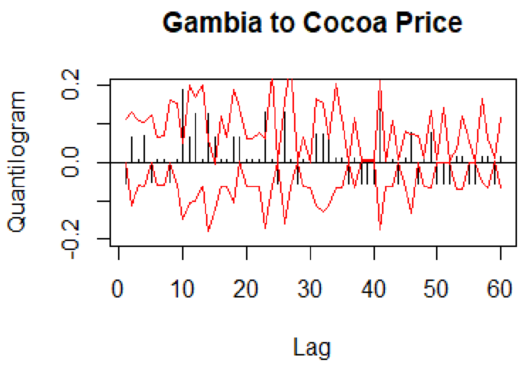
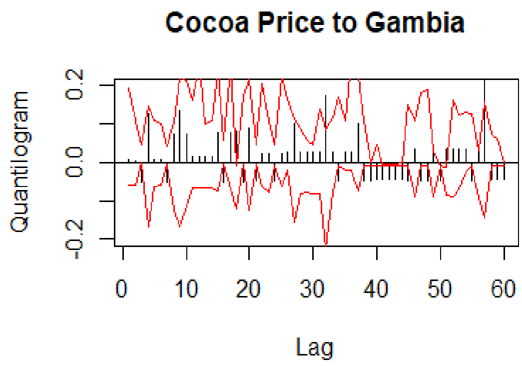
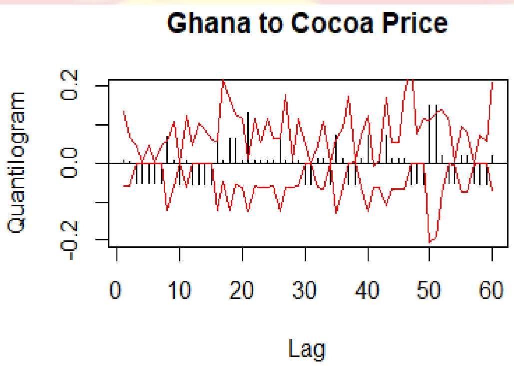


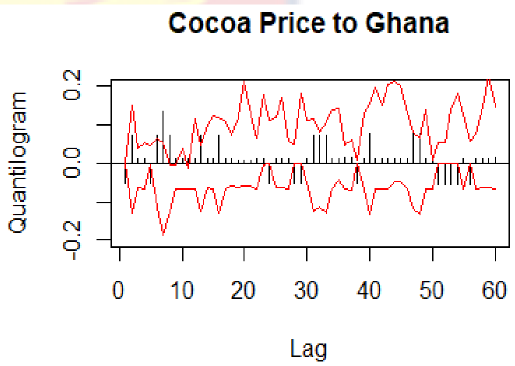
Figure 20: Sample cross-quantilogram to detect systemic risk between gold returns and inflation for metal-producing countries in SSA at $\alpha_1 = \alpha_2 = 0.95$.
Note: *The bar graph describes the sample cross-quantilogram and the red lines are the 95% bootstrap confidence interval centred at zero.*
Source: Field Data (2023)

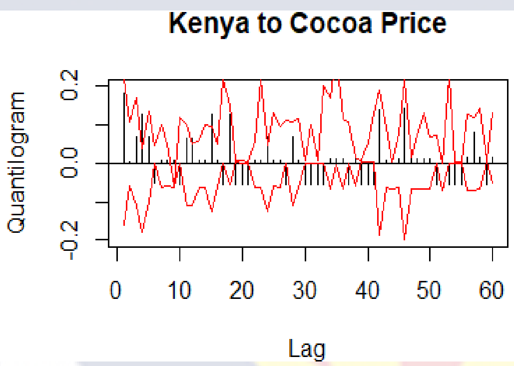

Comoros to Cocoa Price
Cocoa Price to Comoros
Cote d'Ivoire to Cocoa Price
Cocoa Price to Cote d'Ivoire
Eswatini to Cocoa Price
Cocoa Price to Eswatini
Ethiopia to Cocoa Price
Cocoa Price to Ethiopia
Quantilogram
-0.2 0.0 0.2
0 10 20 30 40 50 60
Lag

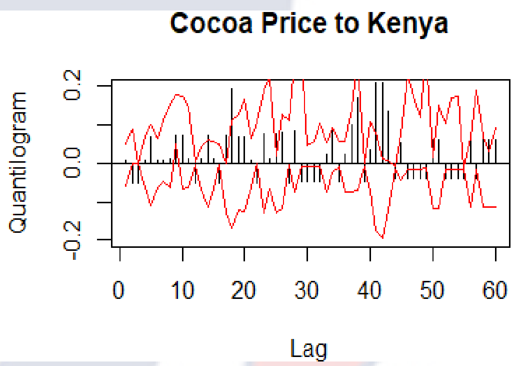

Gambia to Cocoa Price
Quantilogram
0.2 0.0 -0.2
0 10 20 30 40 50 60
Lag

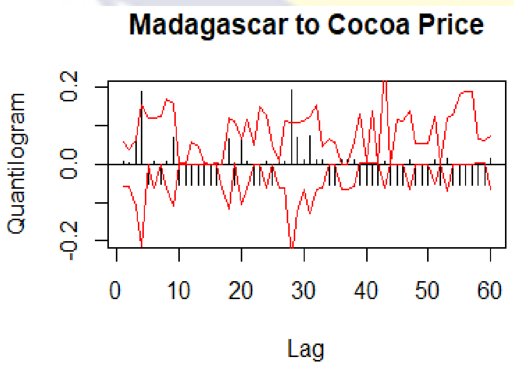

Cocoa Price to Gambia
Quantilogram
0.2 0.0 -0.2
0 10 20 30 40 50 60
Lag

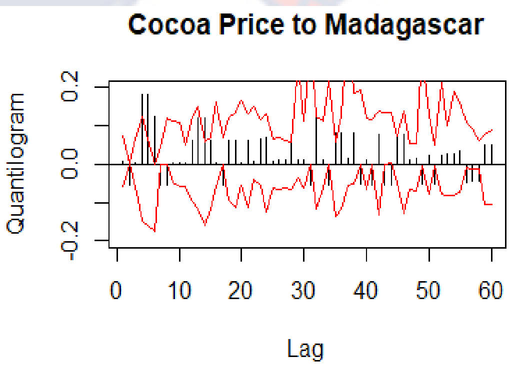

Ghana to Cocoa Price
Quantilogram
0.2 0.0 -0.2
0 10 20 30 40 50 60
Lag

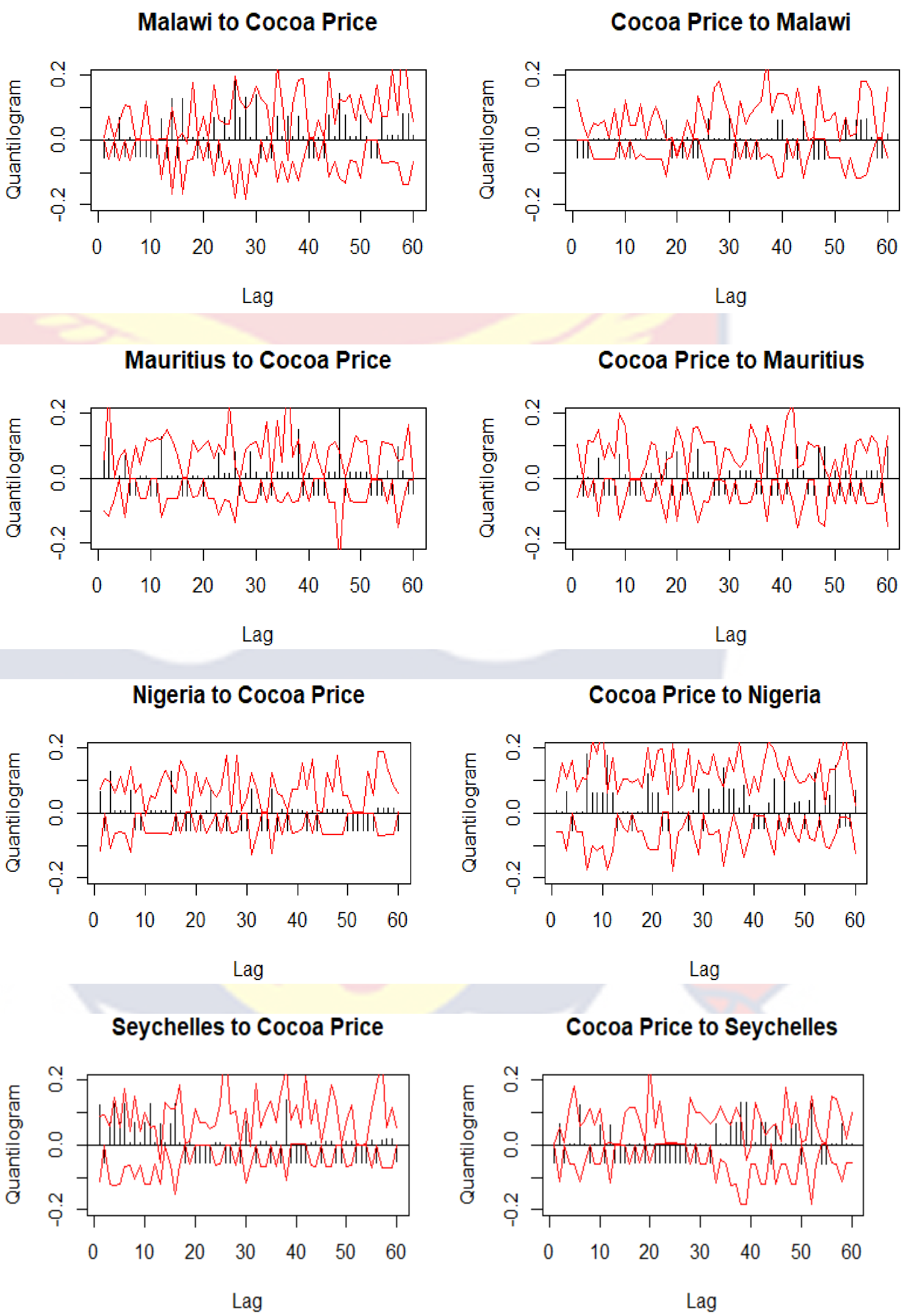

Cocoa Price to Ghana
Quantilogram
0.2 0.0 -0.2
0 10 20 30 40 50 60
Lag


Kenya to Cocoa Price
Quantilogram
0.2 0.0 -0.2
0 10 20 30 40 50 60
Lag


Cocoa Price to Kenya
Quantilogram
0.2 0.0 -0.2
0 10 20 30 40 50 60
Lag


Madagascar to Cocoa Price
Quantilogram
0.2 0.0 -0.2
0 10 20 30 40 50 60
Lag


Cocoa Price to Madagascar
Quantilogram
0.2 0.0 -0.2
0 10 20 30 40 50 60
Lag


Malawi to Cocoa Price
Cocoa Price to Malawi
Mauritius to Cocoa Price
Cocoa Price to Mauritius
Nigeria to Cocoa Price
Cocoa Price to Nigeria
Seychelles to Cocoa Price
Cocoa Price to Seychelles
Quantilogram
-0.2 0.0 0.2
0 10 20 30 40 50 60
Lag

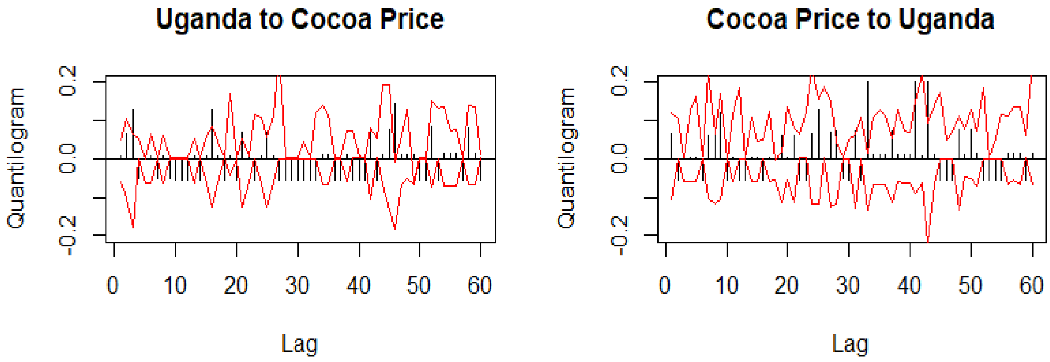


Figure 21: Sample cross-quantilogram to detect systemic risk between cocoa price returns and inflation for food & Beverage-producing countries in SSA at $\alpha_1 = \alpha_2 = 0.95$.
Note: *The bar graph describes the sample cross-quantilogram and the red lines are the 95% bootstrap confidence interval centred at zero.*
Source: Field Data (2023)

APPENDIX D

PLOTS OF PRICES AND LOG-RETURN SERIES FOR EXCHANGE RATE

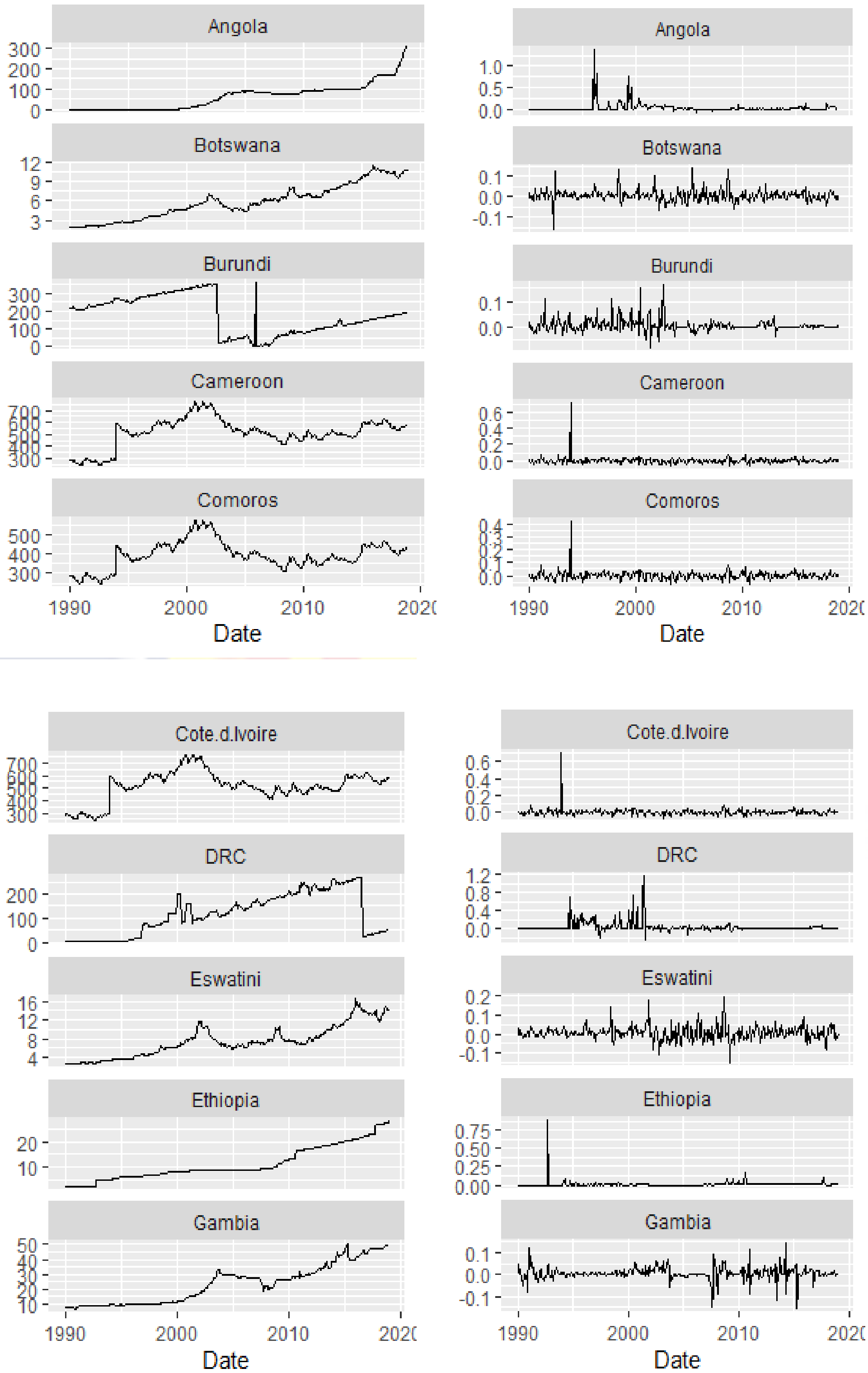


Figure 15 continued

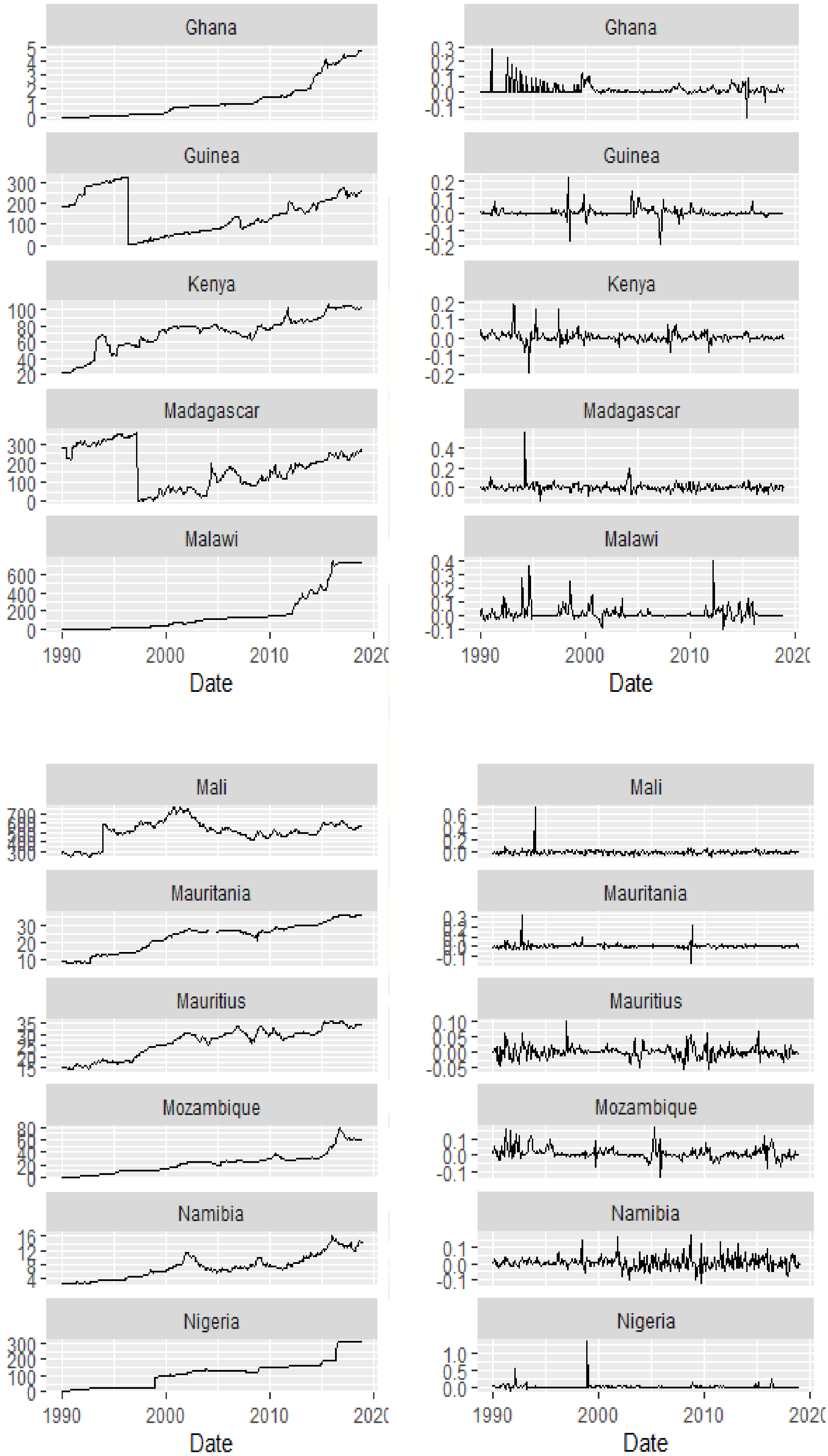


Figure 15 continued

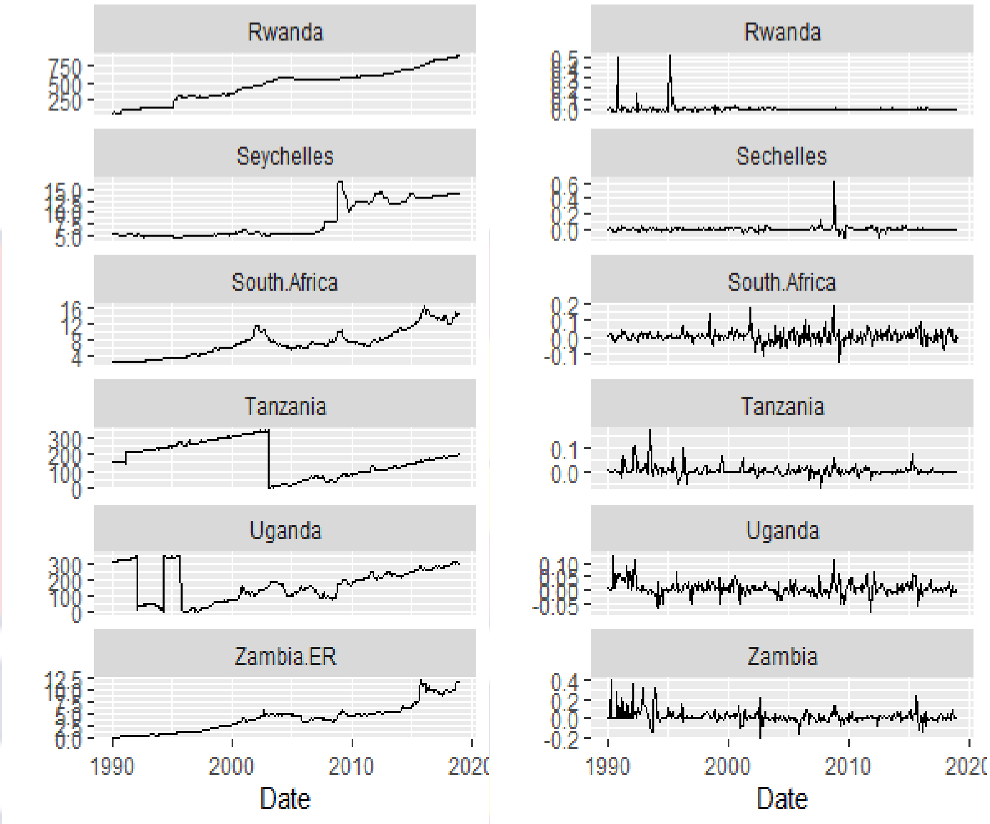
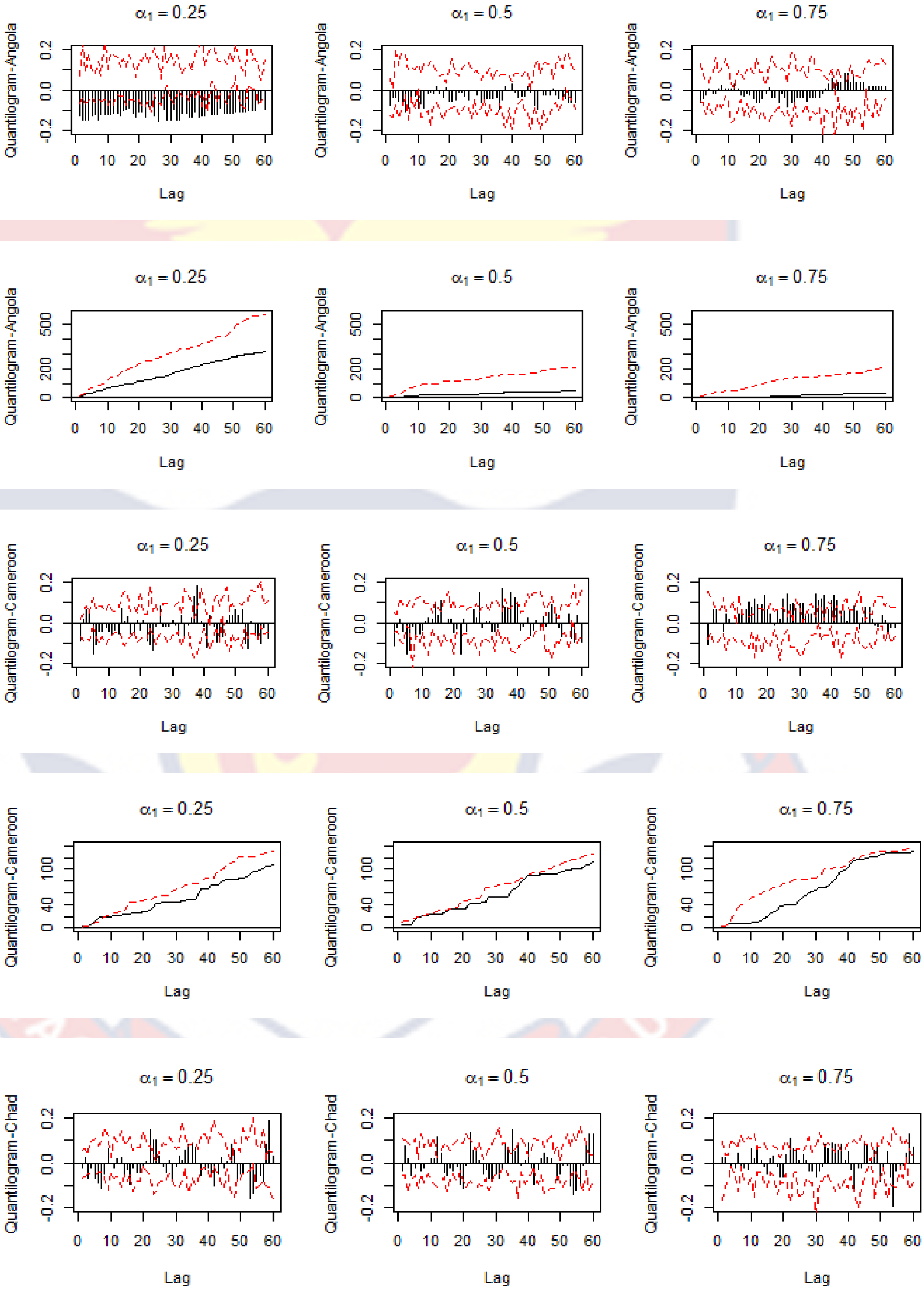
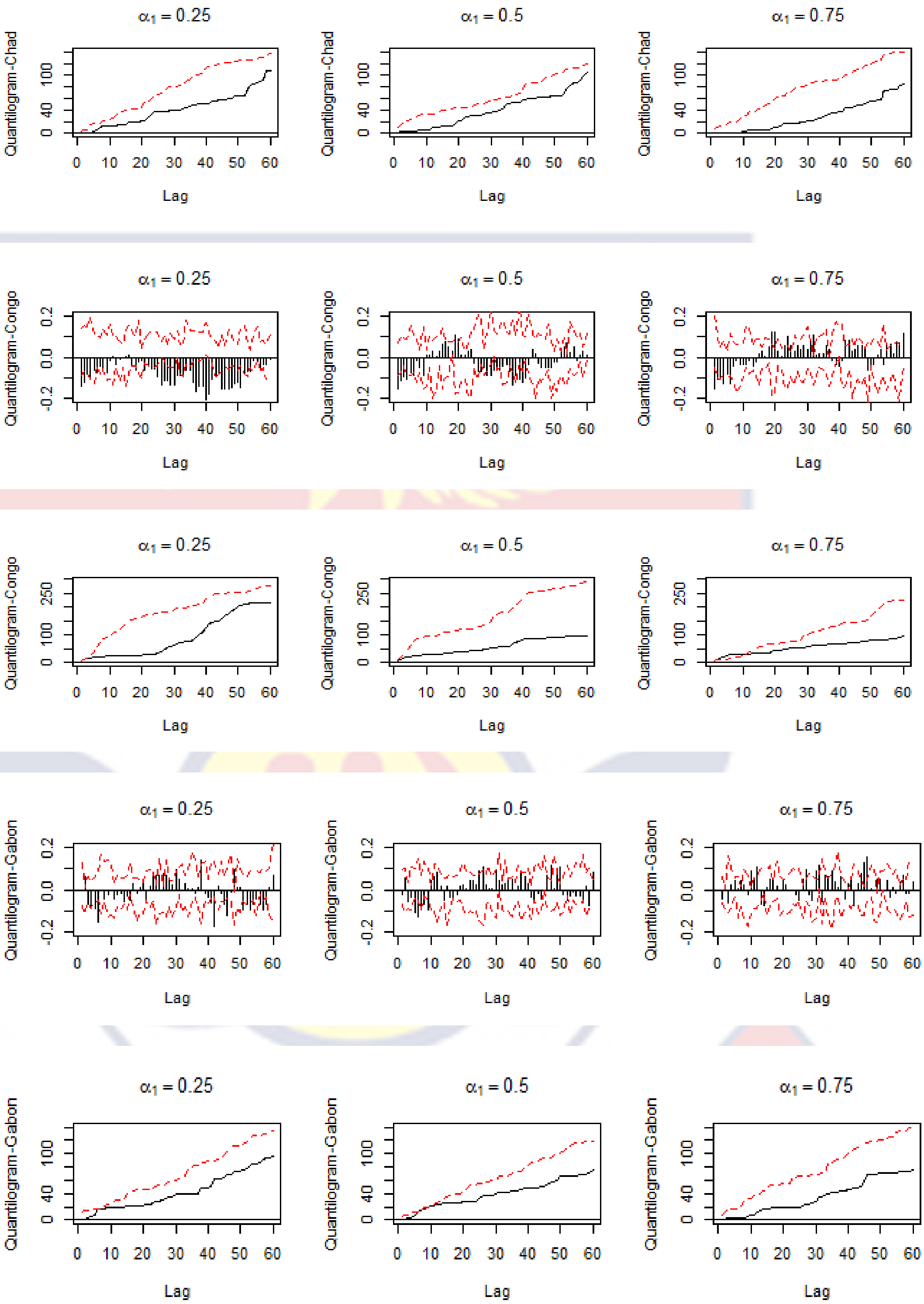


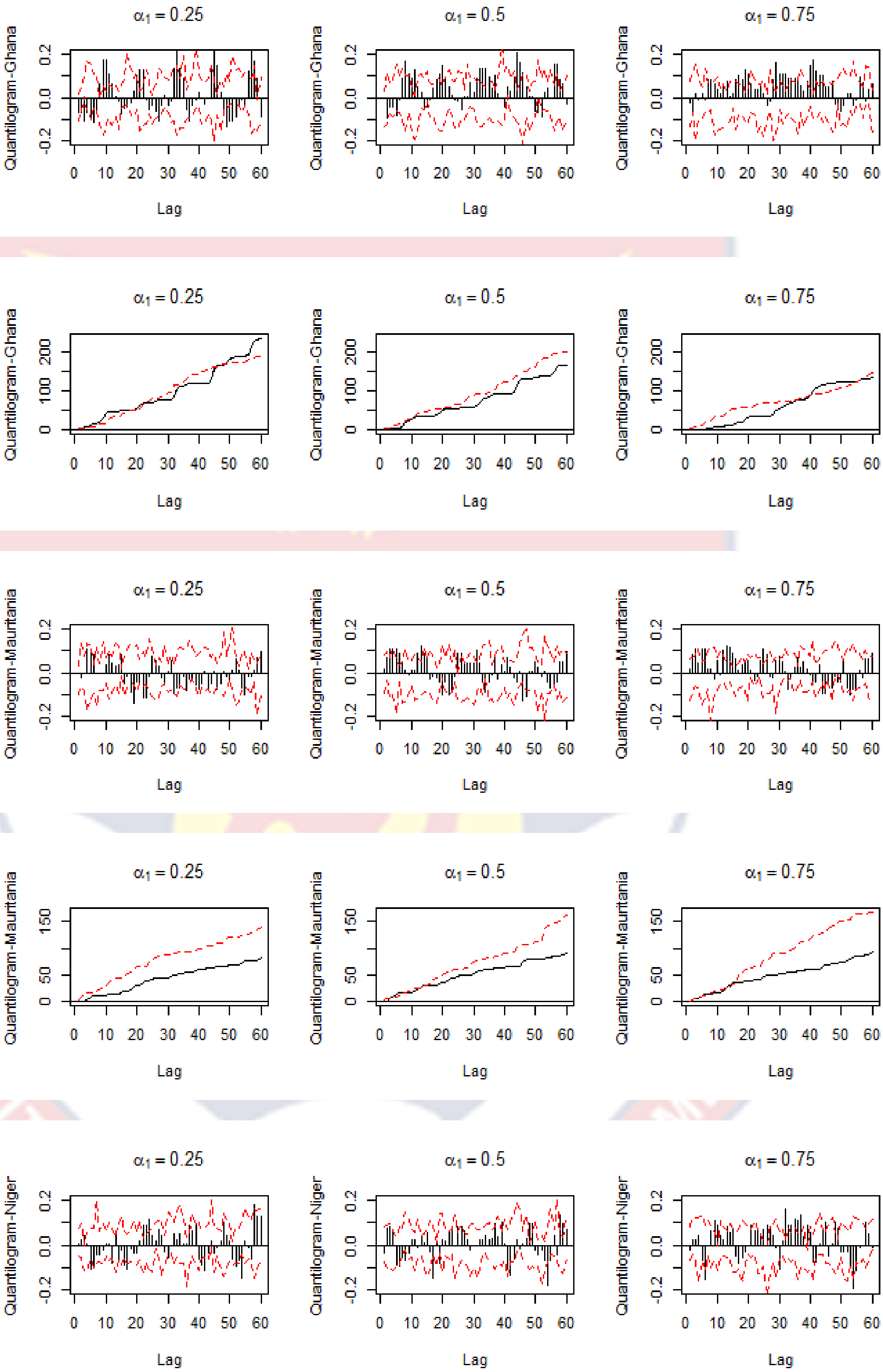
Figure 22: Time series plots of exchange rate prices and returns
Source: Field Data (2023)

APPENDIX E

PLOTS FOR ROBUSTNESS ANALYSIS




$\alpha_1 = 0.25$
$\alpha_1 = 0.5$
$\alpha_1 = 0.75$
Quantilogram-Chad
Quantilogram-Congo
Quantilogram-Gabon
Lag
0 10 20 30 40 50 60


$\alpha_1 = 0.25$
$\alpha_1 = 0.5$
$\alpha_1 = 0.75$
Quantilogram-Ghana
Quantilogram-Mauritania
Quantilogram-Niger
Lag
0 10 20 30 40 50 60
-0.2 0.0 0.2
0 100 200
0 50 150

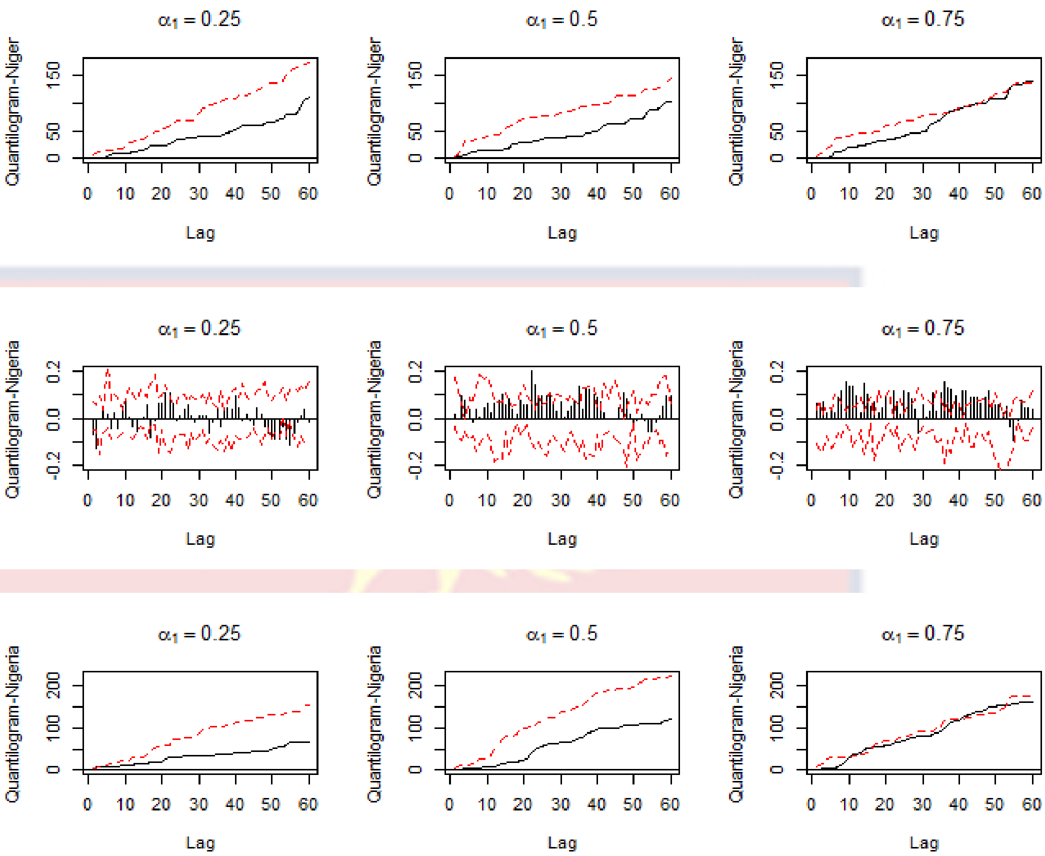


Figure 23: Sample cross-quantilogram from crude oil returns to inflation with $\alpha 2$=0.1 and $\alpha 1$=0.25, 0.5, *and* 0.75.

Note: *The first diagram for each country represents the cross-quantilogram where the bar graph describes the sample cross-quantilogram. The red dashed lines are the 95% bootstrapped confidence interval with 1000 replicates. For each country, the second diagram is the Box-Ljung test statistics. Lag k = 60 representing a 5-year window.*

Source: Field Data (2023)

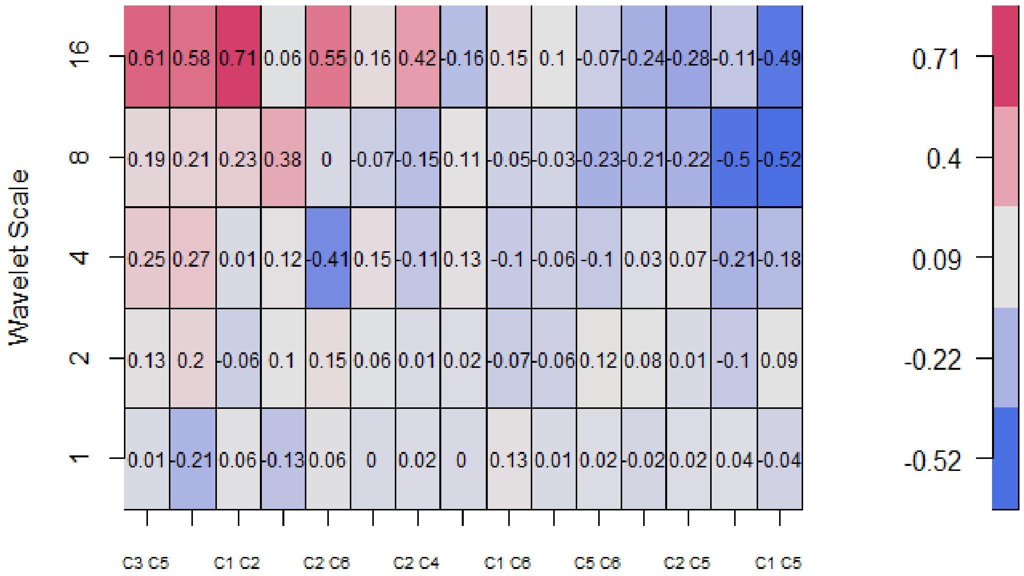
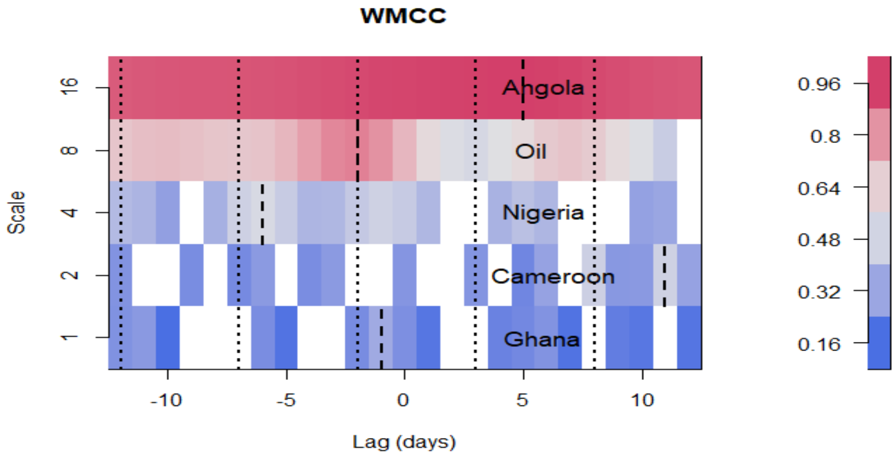
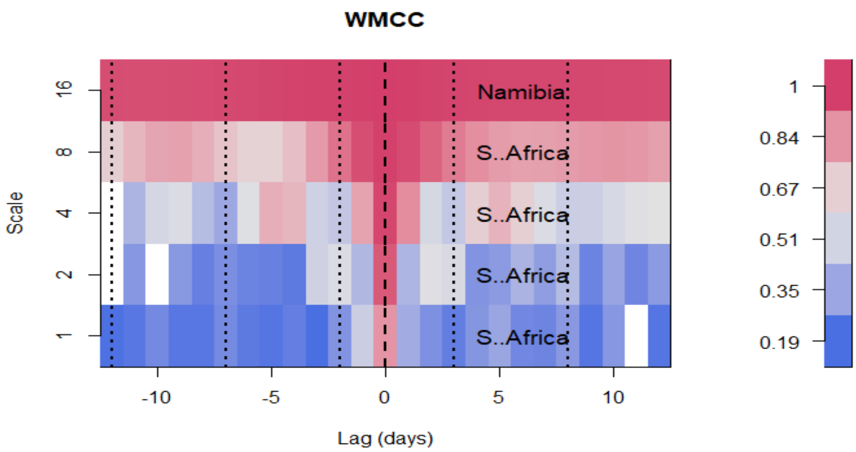


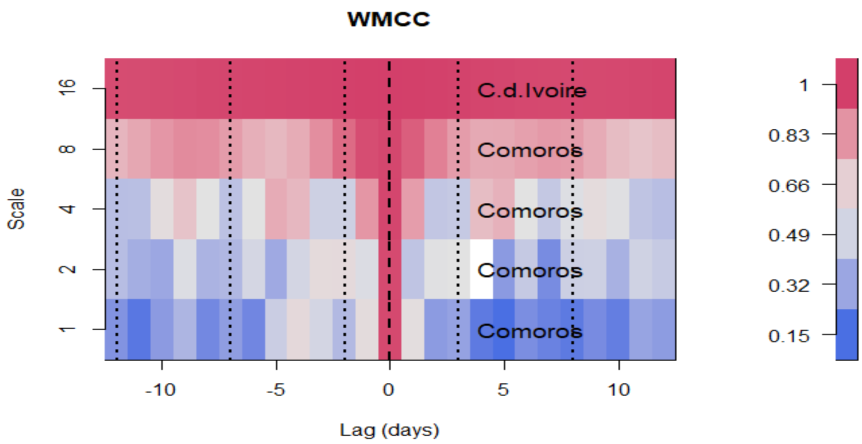
Figure 24: Wavelet bivariate correlation matrix between crude oil price and exchange rate.
Note: C1, C2, C3, C4, C5, C6 represent oil, Angola, Cameroon, Ghana, Mauritania and Nigeria respectively.
Source: Field Data (2023)



(a) Oil-exporting countries



(b) Metal-exporting countries



(c) Agricultural-exporting countries

Figure 25: Wavelet multiple cross-correlation of commodities and exchange rates
Note: Dashed-lines indicate localisations
Source: Field Data (2023)

APPENDIX F

DEFINITION AND MEASUREMENT OF VARIABLES

Table 10: Definition, Measurement and source of key variables

Variable	Definition and Measurement	Source
Inflation	Inflation represents a measure of changes in the price level of a country's consumer price index (CPI).	IMF database
Exchange rate	It is a measure of the rate between a particular country's currency and the US dollar.	IMF database
Crude oil price	It is the average monthly closing price of crude oil recorded by the World Bank.	World Bank commodity price database
Gold price	It is the average monthly closing price of gold recorded by the World Bank.	World Bank commodity price database
Cocoa price	It is the average monthly closing price of cocoa recorded by the World Bank.	World Bank commodity price database

Source: Field Survey, 2023