Cryptocurrencies and African Financial Markets: Integration, Risk Analysis, and Diversification

By

Seyram Pearl Kumah

Student #: 2225980

A Doctoral Thesis Submitted in Fulfillment of the Requirements for the Award of Doctor of Philosophy Degree in the Field of Finance

The Graduate School of Business Administration, University of the Witwatersrand

Supervisor: Dr. Jones Odei-Mensah

ABSTRACT

The international financial system has witnessed cryptocurrencies as new financial instruments with increased growth in both volume and value and unique risk (return) benefits. The cryptocurrency market is integrating with financial markets which may induce increased investor participation with the chance of excessive liquidity in the cryptocurrency market. This can impair financial stability should there be shocks to the cryptocurrency markets. However, there is as yet little established scientific knowledge about the impact of cryptocurrencies on financial markets with African financial markets completely untouched. Such knowledge is critical since shocks to cryptocurrency markets may have rippling effects on the financial markets. The thesis contributes to fill this gap by investigating the nexus between cryptocurrencies and traditional asset classes in the African financial markets. This may help in understanding the microstructure of financial markets in general and the functioning of African markets in particular for regulating the general financial system. The thesis is organized into four empirical essays, each focusing on a research problem.

The first essay examines the level of integration between cryptocurrencies and African stock markets using wavelet-based methods. Findings suggest low degrees of integration between the markets at higher frequencies, but this grows stronger at medium frequencies and perfectly integrates at lower frequencies. Implying that stock markets in Africa are highly exposed to cryptocurrency market disruptions from the medium-term and international investors seeking to hedge their price risk in African stock markets using cryptocurrencies may have to look at the short-term. The phase difference arrow vectors and cross-correlation analysis implying lead (lag) effects are time-varying and heterogeneous, showing no particular cryptocurrency or stock market as leader or follower. Different markets have the potential to lead or lag other markets at varying scales which may induce arbitrage opportunities for international and local investors.

The second essay tests the ability of cryptocurrencies as viable alternatives to African fiat currencies during turbulent and tranquil currency conditions implementing the ensemble empirical mode decomposition-based quantile-in-quantile regression. The essay establishes that cryptocurrencies behave differently from African fiat currencies, showing significant negative relationship during extreme fiat currency regimes at medium and lower frequencies. This suggests

cryptocurrencies as viable alternative digital currencies and good hedges for African fiat currencies form the medium-term. This essay affords policymakers in Africa and across the globe seeking for viable alternative digital currencies to mitigate currency crises to consider cryptocurrencies from the medium-term. Forex traders may also compensate for losses from currency shocks by using cryptocurrencies to hedge USD/African fiat currency exchange rate risk.

In the third essay, we perform cryptocurrency market risk analysis focusing on tail risk and frequency spillover connectedness. The FZL function for joint Value-at-Risk and Expected Shortfall was used to measure tail risk, compare the level of risk, and capital adequacy of cryptocurrencies. Findings suggest Ethereum and Steller as less risky, followed by Monero, Das, Litecoin, Bitcoin, and Ripple, implying that Ethereum and Steller require the least capital to absorb losses. Investigating the time-varying interconnectedness across cryptocurrencies, the study posits that cryptocurrencies are strongely interconnected at high frequencies suggesting contagion risk in the cryptocurrency market and that diversification opportunity is low in the short-term. The essay also evidences time-varying volatility shock transmissions across cryptocurrencies. Economic actors interested in cryptocurrencies can follow this easy to hedge, calculate margins, and capital required to ensure financial stability in the global economy.

The fourth essay sheds light on the hedging properties of seven cryptocurrencies (Bitcoin, Litecoin, Ethereum, Das, Ripple, Monero, and Steller) for gold and crude oil price fluctuations at bear (bull) markets across time employing wavelet-based quantile-in-quantile regression. The essay finds that cryptocurrencies provide negative dependences for extreme gold and crude oil price fluctuations from the medium-term, and that all cryptocurrencies are hedges for gold price fluctuations but only four cryptocurrencies (Ethereum, Monero, Ripple, and Steller) are hedges for crude oil price volatilities. The essay also evidences bidirectional causal effects among the assets establishing that when the cryptocurrency market is bearish and the price of gold and crude oil is low, economic actors can hedge the downside risk of the commodities or cryptocurrencies across time using either of the assets. The essay provides precise information to economic agents on risk mitigating strategies for gold and crude oil markets.

Keywords: Cryptocurrencies; Traditional Assets; Integration; Spillover; Time-varying; Africa.

JEL Classification: *C40, C58, F31, F36, G10, G11, G15.*

LIST OF PUBLICATIONS AND OUTPUTS

Prior to submission, portions of the thesis have been published in peer reviewed journal while some others are under submission.

Peer-reviewed Journal Publication

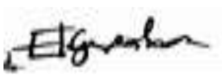
1. Kumah, P., S., & Mensah, J., O. (2020). Are Cryptocurrencies connected to Gold? A Wavelet-based Quantile-in-Quantile approach. *International Journal of Finance & Economics*. https://doi.org/10.1002/ijfe.2342.

Papers under Review

1. Kumah, P., S., & Mensah, O., J. (2020). Cryptocurrency and African Fiat Currencies: A Peaceful Coexistence?. *Journal of African Business.*
2. Kumah, P., S., & Mensah, O., J. (2020). Cryptocurrency Market Risk Analysis: Evidence from FZL Function. *Risk Finance.*
3. Kumah, P., S., & Mensah, O., J. (2020). Are Cryptocurrency and African stock markets integrated? *Quarterly Review of Finance and Economics.*
4. Kumah, P., S., & Mensah, O., J. (2020). Can altcoins become viable alternatives to African fiat currencies? *International Journal of Development Issue.*
5. Kumah, P., S., & Mensah, O., J. (2020). Co-movement of cryptocurrencies and African stock returns: A multiresolution analysis. *Journal of Economic Integeration.*

DECLARATION

I, **Seyram Pearl Kumah**, hereby declare that this research report is my own work except as indicated in the references and acknowledgments. It is submitted in fulfilment of the requirements for the award of Doctor of Philosophy degree in the field of Finance at the University of the Witwatersrand, Johannesburg. It has not been submitted before for any degree or examination in this or any other university.



Seyram Pearl Kumah

Signed at …………***Wits Business School (WBS)***………………………………………

On the ……***2nd*** ………………….. day of ……***July***…………………..……………….. ***2020***

DEDICATION

To Akusika Elinam Marfo, Nana Yaa Bediako Marfo & Kwabena Osei-Bonsu Marfo

ACKNOWLEDGEMENT

The Ph.D. journey would not have been completed without the favour of God, which I am extremely grateful. I extend my sincere gratitude to my supervisor Dr. Jones Odei-Mensah, for his motivation, patience, immense knowledge, and continuous support of my Ph.D. His guidance helped me in all the time of research and writing of the thesis. I could not have imagined having a better advisor and mentor for my Ph.D. I say, may God bless you and your generations and grant that thing on your heart quickly. I am deeply indebted to my family especially my mother (Ms. Patience Mensah) for supporting me financially, spiritually, and taking good care of my kids which allowed me time to complete the thesis. Thank you, my mother, brother, and sisters for holding the fort. To my friends at Wits Business School and around the world, you are one of the reasons why I am part of Ph.D. finance holders. Your efforts are duly acknowledged. To that person worth mentioning who I have not specifically acknowledged, I say, akpe na wo.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

Abbreviation	*Meaning*
AfDB	African Development Bank
ALD	Asymmetric Laplace
ARDL	Autoregressive Distributed Lag
AST	Asymmetric Student-t Distribution
BIS	Bank for International Settlements
BTC	Bitcoin
CAD	Canadian Dollar
Cap	Capitalization
CC	Correct Conditional Coverage
CFZL	Characteristic Fissler and Ziegel Loss Function
CHF	Swiss France
CMWT	Continuous Morlet Wavelet Transform
Cor	Correlation
Crp	Cryptocurrency
CSE	Casablanca Stock Exchange
DASH	Das
DCC	Dynamic Conditional Correlation
DQ	Dynamic Quantile
DWT	Discrete Wavelet Transform
EPA	Equal Predictive Accuracy
EMD	Empirical Mode Decomposition
EEMD	Ensemble Empirical Mode Decomposition
EGP	Egyptian Pound
EGX30	Egyptian Exchange

ETH	Ethereum
EUR	Euro (€)
EVT	Extreme Value Theory
ES	Expected Shortfall
Fcur	Fiat Currency
FZL	Fissler and Ziegel
GARCH	Generalized Autoregressive Conditional Heteroscedasticity
GAS	Generalized Autoregressive Score
GBP	Great British Pound
GSADF	Generalized Sup Augmented Dickey–Fuller
IMF	Intrinsic Mode Function
JPY	Japanese Yen
JSE	Johannesburg Stock Exchange
L	Lower Bound
LA	Daubechies Least Asymmetric
LTC	Litcoin
GFVED	Generalized Forecast Error Variance Decomposition
GSADF	generalized sup Augmented Dickey–Fuller
GSCI	Commodity Index
GSE	Ghana Stock Market
MAE	Mean Absolute Error
MDM	Multivariate Version of Mariano and Diebold
MF-ADCCA	Asymmetric Multifractal Detrended Cross-Correlation Analysis
MF-DFA	Multifractal Detrended Fluctuation Analysis
MODWT	Maximal Overlap Discrete Wavelet Transform
Nairobi.SE	Nairobi Stock Exchange
NSE	Nigeria Stock Exchange

QL	Quantile Loss
QR	Quantile Regression
QQR	Quantile-in-Quantile Regression
S&P500	Standard and Poor 500 Index
SEM	Stock Market of Mauritius
SNORM	Skewed-Gaussian
STD	Student-t Distribution
SSTD	Skewed-Student-t Distribution
SVAR	Structural Vector Autoressive
Tunnindex	Tunisia Stock Exchange
U	Upper Bound
UC	Correct Unconditional Coverage
USD	United States Dollar ($)
VaR	Value-at-Risk
VAR	Vector-Autoregressive
VIX	Volatility Index
WMC	Wavelet Multiple Correlation
WMCC	Wavelet Multiple Cross-Correlation
XLM	Steller
XMR	Monero
XRP	Ripple
ZAR	South African Rand

CHAPTER ONE

Introduction

1. Background to the thesis

Bill Gates in 1994 released the statement "Banking is necessary, banks are not" arguing on the obsolescence of Banks in the future despite being essential now (Filkorn, 2016; Bos and Economy, 2018). Even though this argument is far from being realized in recent years, an effort has been taken to create new innovations in the financial system that are not dependent on banks. This new financial innovations involving cryptocurrencies[1] gained massive popularity in the wake of the global financial crises in 2008/2009, European sovereign debt in 2010/2013, and other crises due to uncertainty and distrust in banks and other traditional assets (Huynh, 2019; Guadamuz and Marsden, 2015; Yaya, Ogbonna, and Olubusoye, 2018). Nakamoto (2009) created Bitcoin, the first and most popular decentralized currency to eliminate the need of banks or third parties in transactions. There are alternative digital currencies (hereafter altcoins[2]) among which are Ethereum, Ripple, Litecoin, Steller, Dash, Monero which went unnoticed years ago due to the domination of Bitcoin (Kristjanpoller and Bouri, 2019). All cryptocurrencies have similar features including decentralized network, requires access to the internet, and utilize peer-to-peer link in line with the ideas of Nakomoto, the creator of Bitcoin[3].

---

[1] Digital assets designed to work as alternative payment options which uses cryptography to regulate the production of extra units, secure financial transactions, and confirms the transfer of the coins.

[2] As noted by Huynh (2019), altcoins such as Ethereum was created to reduce trading time and transaction cost because of its decentralized platform that supports smart contracts. Ripple was born to allow free business transactions by creating currency and remittance network. Litecoin has an open source aimed to preserve the computing power and handle higher transaction volume. Steller was created to foster the transferring procedure with cross-border transactions of several cryptocurrencies. Dash is to improve privacy protection and provide faster transaction processing.

[3] A form of digital currency created using blockchain technology which was based on the ideas set out in a white paper by Satoshi Nakamoto, a person whose identity is yet to be verified, and which pioneered the blockchain movement.

Cryptocurrencies are secured by cryptography[4] and technology since they do not have tangible units, have no data repository, and central control. These virtual currencies have attractive properties including durability, means of payment, divisibility, and unit of account similar to government reserve currencies (Georgeson, 2018) and are increasingly becoming promising financial asset classes (Polasik, Piotrowska, Wisniewski, Kotkowski, and Lightfoot, 2015; Brandvold, Molnár, Vagstad, and Valstad, 2015; Huynh, 2019). Due to the dual[5] role played by cryptocurrencies in the international financial system, despite their excess volatilities, the empirical literature stresses the significance of investigating their behaviour relative to other assets classes in the traditional financial markets to uncover the risk and benefits of the digital currencies (Huynh, 2019; Bouri, Molnár, Azzi, Roubaud, and Hagfors, 2017a; Eisl, Gasser, and Weinmayer, 2015). However, most prior studies (Ji, Bouri, Gupta, and Roubaud, 2018; Polasik, Piotrowska, Wisniewski, Kotkowski, and Lightfoot, 2015; Bouri, Jalkh, Molnár, and Roubaud, 2017; Kristjanpoller and Bouri, 2019) produced inconsistent findings on the behaviour of cryptocurrencies, mostly proxied by Bitcoin relative to traditional assets in advanced financial markets, thus raising the need for further studies.

Further, there has been the development of several altcoins which also attract investor attention but their behaviour compared to traditional asset classes in the African financial market remains unexplored. Africa is likely to become the next big market for cryptocurrencies due to the local conditions experienced in the African financial system. For instance, the African stock markets though growing incredibly (see, Gourène and Mendy, 2014; Gourène, Mendy, and Lanciné, 2019) are illiquid, inefficient with low or no connection with advanced stock markets (Adjasi and Biekpe, 2006; Agyei-Ampomah, 2008; Boako and Alagidede, 2015; Peltomäki, Graham, and Alagidede. 2017; Mensah and Alagidede, 2017). The banking system of many African countries is challenged with mismanagement and cross-broader money transfer including high cost, low speed, and few

[4] Cryptography is essentially the practice of encrypting certain data or information so that it can be kept secret from third parties.

[5] As noted by Kim (2017), Bouri et al. (2017), and Kristjanpoller and Bouri (2019), cryptocurrencies can be a cost-effective alternative to the existing forex market and can also be used as an asset instead of a medium of exchange due to their liquidity, diversification, and hedging properties.

volumes of transactions which have led many Africans in search of alternative payment options (Naboulsi and Neubert, 2018). The continent is also characterized by political instability, exchange rate volatility, and high inflation leading to price volatility making investing in Africa highly risky (Kargbo, 2000; Owusu-Junior, Adam, and Tweneboah, 2017).

As indicated by Sousa (2019), Africa has already embraced cryptocurrencies with a 130% rise in the volume of cryptocurrency transactions in 2018, and as at 2019, an average trade per day of 17, 351 were carried out by crypto users in the region. Specifically,countries such as Kenya is already digital with more than half of the adult population holding M-Pesa digital wallet and currently leveraging its networks to allow for the transactional use of Bitcoin (see Holmes, 2017; McKenzie, 2018). In Zimbabwe, some citizens have turned to cryptocurrencies in the wake of the hyperinflation in 2008 which resulted in huge assets loss (Naboulsi and Neubert, 2018). Many Nigerians experienced financial instability when the central bank of Nigeria limited access to the US dollar in 2015. This choked off investment and caused some Nigerians to be attracted to cryptocurrencies (Hain and Jurowetzki, 2018). Bitcoin has been used to raise funds in 2014 for SOS children's villages in Botswana and has been visible in South Africa since 2014 with Bitcoin exchanges and mecharnts who accepts payment of goods and services with Bitcoin (Nieman, 2015). In 2016, the Ghana medical help received a donation from the creators of Dogecoin altcoin to purchase medical equipment and also created an endowment fund for donations in cryptocurrencies (Broni, Boateng, and Owusu, 2020; Scott, 2016). Aside from cryptocurrencies, South Africa uses blockchain technology to pay electricity bills for community schools, and Ghana is currently using blockchain technology known as Bitland to register land titles (see Holmes, 2017; McKenzie, 2018).

Africa can be transformed by turning challenges[6] into opportunities and pioneer transparency by considering cryptocurrencies as alternative currencies. Cryptocurrencies can help African countries expand their pool of available capital, provide volatile capital markets with stable alternatives, and rebuild trust in government, which can drive increased international investment

[6] As discussed by Das and Kannadhasan (2018) Corelli (2018), Kristjanpoller and Bouri (2019), cryptocurrencies which are deflationary and artificially scarce due to their fixed supply can hedge against inflation and tender a store of value when faith in local currencies is shaken.

across the region. The blockchain[7] technology behind cryptocurrencies is a potent tool for anti-corruption, and political risks that are paramount in African countries to curb bureaucratic and opaque processes involving public procurement. The distributed public ledger[8] enables the creation of transparent processes and structures that streamline business deals, minimize dubious procurement processes and back door deals, and introduce public oversight over government transactions (Fokuo, 2018). This could provide relief and instill confidence in Africans and international investors concerned with compliance with anti-corruption and bribery laws to invest in the continent.

In terms of methodology, most previous studies applied models that capture time information and ignored essential information relating to frequency domain in the time series of the variables of interest. Following the heterogeneous market hypothesis by Müller et al. (1993), financial market participants operate at different frequencies. Participants with short-, medium-, and long-term investment policies are focused on market fluctuations and co-movements at higher, medium, and lower frequencies respectively (Tiwari, Dar, Bhanja, and Shah, 2013; Skult, 2019). Moreover, heterogeneity of participants in the financial market is often cited as a major source of nonlinear dynamics[9] of financial series (Zhang, 2002). Therefore, modelling the dependence structure between assets across frequencies and economic conditions is a prudent way of managing the risk of portfolio and assets allocation across time (Mensi et al., 2016; Das and Kannadhasan, 2018).

Against this background, the thesis investigates the relationship between leading cryptocurrencies and conventional assets classes in the African financial markets (stocks, fiat currencies, gold, and crude oil) at different market conditions in a time-frequency space using a battery of tests. The thesis provides regulators, investors, academia. and the public with a comprehensive

[7] A distributed ledger technology which bundles transactions into groups called 'blocks' and cryptographically chains those blocks together and then broadcasts them to the nodes of a peer-to-peer network, in order to create a immutable, distributed database of those transactions.
[8] A technology developed in order to create a database that is consensually shared and synchronized across network spread across multiple sites, institutions or geographies.
[9] Nonlinear dynamics are not rare in financial series such as exchange rates, cryptocurrencies, stocks, and commodities. The time series of these variables are characterized by sudden and irregular jumps and neglecting nonlinear dependences may lead to inacurrate predictions (Zhang, 2002; Bisaglia and Gerolimetto, 2014).

understanding of the linkages between the markets. The thesis extensively covers the crypto-world and African financial markets.

1.1 Objectives of the thesis

The thesis explores the dynamic relationship between cryptocurrencies and the African financial markets, focusing on four main aspects. First, the returns of African stocks and cryptocurrencies are modelled with emphasis on their horizon-based integration and spillover effects for equity market risk management. Second, we examine the asymmetric linkages between cryptocurrencies and African fiat currencies at different currency regimes across time to test the viability of cryptocurrencies as alternatives and hedges for African fiat currencies. Third, the thesis performs cryptocurrency market risk analysis focusing on tail risk and time-varying volatility spillover across cryptocurrencies to enhance our understanding of the microstructure and functioning of the cryptocurrency market for effective regulation. Finally, an attempt is made to examine the interdependence between gold, crude oil, and cryptocurrencies across time and market conditions to address the timely question of whether cryptocurrencies exhibit hedging properties for gold and crude oil investmensts during turbulent market conditions and whether gold and crude oil exhibit similar property for extreme cryptocurrecy market.

1.2 Significance of the thesis

Cryptocurrencies are the most promising and latest addition to the digital payment sector as the world is moving towards a digital ecosystem. Africans are attracted to cryptocurrencies due to their attributes[10] which are more robust to the local conditions in the African financial system. However, the impact of cryptocurrencies on the African financial markets is significantly omitted in the literature. Few studies concentrated on Bitcoin and advanced financial markets (Dyhrberg, 2015a; Kristoufek, 2015; Elbahrawy et al., 2017; Corbet et al., 2018b; Gajardo et al., 2018; Carrick, 2016). Nonetheless, with innovations in financial assets, data generation processes, estimation techniques, and fleeting market conditions, further studies could still be undertaken to

[10] Following Kim (2017) cryptocurrencies have almost zero/no cost of transactions, high volume of transactions, speed of transactions, inflation proof, and hedge against exchange rate variability.

make significant and justifiable contributions to the limited literature on cryptocurrencies and financial markets.

The first contribution of the thesis addresses the dearth in the knowledge on the level of integration between cryptocurrencies and African stock markets across time. Stock indices are the barometer of financial and macroeconomic development as favorable and well-developed macroeconomic fundamentals may stimulate the demand for cryptocurrencies. Moreover, the low correlation between advanced stock markets and Bitcoin provides diversification benefits for global equity investors. However, the same for other cryptocurrencies and equity investors in African stock markets is unknown. Thus, an analysis of integration and spillover effects between African stocks and several cryptocurrencies is expected to advance our understanding of the relationship between the markets to hedge against equity market crises and extend the modern portfolio theory.

The second contribution is made in examining the capacity of cryptocurrencies as viable alternatives to African fiat currencies. Due to the liquidity, low cost of transactions, high volume of transactions, speed of transactions, hedging, and diversification properties of cryptocurrencies, countries are currently accepting them as legal currencies setting a standard for an institutionalized use. Meanwhile, empirical studies on cryptocurrencies and fiat currency interconnectedness are still sparse with no studies on African fiat currencies. African fiat currencies are characterized by high inflation and exchange rate volatility which affect financial stability and trade flow in the continent. Therefore, examining the value and volatility of several cryptocurrencies relative to African fiat currencies provides insight for the adoption of cryptocurrencies as complement to African fiat currencies, hedge against forex risk and extend the modern monetary theory.

Thirdly, an innovative way of performing risk analysis in the cryptocurrency market focusing on tail risk and frequency-domain spillover connectedness is fostered through this study. The application of Fissler and Ziegel (2016) joint loss dynamic models for ES and VaR jointly, and Barunik and Krehlik (2018) frequency domain spillover technique captures all the stylized facts exhibited by cryptocurrencies. This provides vibrant information to economic agents in the cryptocurrency market to enhance their trading and investment strategies to attain optimum utility and minimize risk in cryptocurrency investments. The thesis contributes to the cryptocurrency market risk management and extends the extreme value theory.

The last contribution of this thesis is the exploration of the hedging properties of cryptocurrencies for gold and crude oil risk management. The empirical literature on gold and crude oil show evidence of high price fluctuations of the commodities causing a fall in their value. Therefore, examining the interdependence between gold/cryptocurrencies and oil/cryptocurrencies at different market conditions across time contributes to commodity market risk management and extends portfolio optimization theory.

In addition to the contribution to the body of knowledge on cryptocurrencies and financial markets, the novelty in this thesis is also propagated through the data and variables employed in modelling the relationships between the variables. The econometric techniques used in this thesis are very scanty in the cryptocurrency literature. The methodologies provide nonlinear, asymmetric, and frequency-based results which are crucial as policy decisions are frequency-dependent, and financial markets associations are multi-scale, asymmetric, and nonlinear. This thesis has prospects of provoking renewed interests in cryptocurrencies and financial markets research in areas that may have been unexplored.

1.3 Literature Review

The literature on cryptocurrencies and financial markets is scant but varied. It covers areas such as cryptocurrencies and stock markets, cryptocurrencies and forex markets, cryptocurrencies and commodity markets among others. The literature review is focused on the specific concepts as per the research objectives and is organized into theoretical and empirical sub-sections.

1.3.1 Theoretical framework

The theoretical literature intends to navigate towards the theoretical framework postulated for the thesis. The sub-section focuses on the theories on co-movement, diversification, currencies, and volatility.

1.3.1.1 Fundamentals-based and Category-based Theories on Co-movement

The fundamentals-based theory on co-movement by Barberis, Shleifer and Wurgler (2005) argues that the co-movement in asset returns is as a result of co-movement in news about fundamental values. Under the fundamental view, correlated changes in rationally expected cashflows causes correlation in returns which in turn causes discount rates to be correlated when news about risk aversion or interest rate affect discount rates at the same time. The theory assumes constant investors risk aversion, constant risk-free rate and constant perception of risk making the discount rate to also be constant. Hence, the co-movement in news about fundamental values which is reflected in the co-movement in returns is simply the co-movement in news about future cash flows. The authors posit that common factors in returns including industry and strong market level factors in cashflow news explain the fundamentals-based co-movement. The fundamentals-based model is useful for understanding many instances of common factors in returns. The current study test the fundamentals-based co-movement theory in asset returns in the cryptocurrency and African stock markets integration across time.

The category-based theory on co-movement indicates that the fundamentals-based theory is not the only determinant of co-movement in asset returns but that co-movement can also be caused by investors trading patterns. Barberis et al. (2003; 2005) contends that many investors first of all group assets into categories based on some characteristic when making their portfolios and then allocate funds at the level of the categories rather than at the level of individual securities. Specifically, institutional investors are more attracted to investment in categories (e.g., stocks, bonds, gold, exchange rates, oil, cryptocurrencies). This makes the allocation of funds to a portfolio simple and provides a consistent and simplified way of evaluating the performance of a portfolio by fund managers. The category-based co-movement theory is tested in all the variables of interest by investigating the direction and degree of correlation of category of assets including cryptocurrencies and stocks, cryptocurrencies and fiat currencies, cryptocurrencies, gold and crude oil across time and market conditions.

1.3.1.2 Modern Portfolio Theory

The two main risk factors in investment are firm specific risk and market risk. Firm specific risk is determined by microeconomic factors that influence a particular firm and can be eliminated by diversification. Market risk is inherent to the investment in the market and cannot be excepted by diversification. This risk influences the entire market (see Bodie, Kane, and Markus, 2014). Several studies reported different results when they researched the number of assets needed to eliminate firm specific risk. Notable studies among them include Evans and Archer (1968) who reported an average of ten different stocks for an optimal portfolio while Statman (1987) reported forty different shares. Other studies, including Burnside et al. (2004), Malkiel (1999), and Graham (2009) document similar findings reporting an average of twenty-five different stocks. In periods of market turmoil, the correlations of stocks increase, reducing the efficiency of diversified portfolios (Forbes and Rigobon, 2002). Correlation values are essential for portfolio optimization and economic agents that subscribe to the modern portfolio theory target asset classes including stocks, commodities, bonds, currencies, and in today's market, cryptocurrencies to reduce correlation among the assets. These agents hedge downside risk whiles maximizing returns by choosing assets that are lowly or negatively correlated.

Bodie, Kane, and Markus (2014) argue that investments in negative or low correlated assets offer efficient diversification and that the number of assets in a portfolio is less important than efficient diversification which is in line with Malkiel (1999). Hedge or safe haven assets have negative correlations. The modern portfolio theory by Markowitz (1952) creates and optimizes investment portfolios by combining different types of assets that are negatively or lowly correlated. The theory contends that adding an asset to a portfolio should be considered in the light of its impact on the performance and risk of a portfolio of assets. In today's market, cryptocurrencies are digital assets with a unique reward (risk) profile and a brand new level of correlation to conventional assets classes which can add a previously unattainable level of asset mix to an investor's holdings, and impact the level of exposure and risk an investor has in a potentially positive way. Therefore, we test the modern portfolio theory in this thesis by exploring the hedge and diversification benefits of cryptocurrencies for African stocks, fiat currencies, gold, and crude oil risk management across time and market conditions.

1.3.1.3 Modern Monetary Theory

Monetary theory mostly focuses on factors such as the size of money supply, interest rates, price levels, and how they affect an economy through taxation, inflation, unemployment levels, and wage growth. The modern monetary theory by Wray (1998b) as cited in Fernandez-Villaverde and Sanches (2018), posits that many coexisting private currencies together with government reserve currencies are a possible outcome. The theory suggests that fiat currencies issued by government would be the dominant currency, provided the government controls inflation and whether the coexistence of private currencies was allowed by fiat currencies depends on government policy. This means that private currencies such as cryptocurrencies cannot compete with a 'good' fiat currency, but that cryptocurrencies can displace a 'bad' fiat currency associated with high inflation (Fernandez-Villaverde and Sanches, 2018). Therefore, cryptocurrencies can be unpopular in countries with low and stable inflation. In contrast, countries with high and unstable inflation could see their fiat currency pushed out and replaced by cryptocurrencies. The limited supply of cryptocurrencies makes them inherently deflationary which can serve as medium of exchange. Since Africa has high and unstable inflation, there is motivation to test the modern monetary theory by examining the viability of cryptocurrencies as suitable alternatives and hedges for African fiat currencies.

1.3.1.4 Volatility

The seminal paper of King and Wadhwani (1990) contends that the connection between international financial markets mainly depends on volatility and that co-movement between price changes in diverse financial markets increases (decreases) as volatility increases (decreases), causing market inter-linkages to strengthen or weaken. Specifically, inter-market relationships are stronger during periods of high volatility. The global financial crises have affected market participants and their investment decisions. Investors redistribute their investments into assets considered as safe haven such as gold and currencies during periods of economic turmoil. Many studies have investigated the volatility spillover of traditional asset classes such as stocks, commodities, bonds, and foreign exchange due to their volatile nature (Glosten, Jagannathan, and Runkle, 1993; Baur and McDermott, 2012). Cryptocurrencies do not meet all the three functions of money, several of them match the medium of exchange and unit of account exchange functions, nonetheless, it is hard to conciliate the store of value function given that all of them exhibit significant volatility which affects their fundamental value. Due to the extreme price volatility of cryptocurrencies we provide a comprehensive measure of tail risk as well as the time-varying volatility transmittions across cryptocurrencies. This has implications for economic actors especially financial institutions interested in cryptocurrency investment to manage their downside risk to ensure stability in the financial system.

1.3.2 Empirical Literature

The empirical literature review is focused on the specific themes as per the research objectives covering areas such as cryptocurrencies and stock markets, cryptocurrencies and forex markets, risk analysis in the cryptocurrency markets, and cryptocurrencies and commodity markets which together provide important and new insights to the field. We provide a summary of the literature with the key findings in this section. A thorough review of the literature on each objective can be accessed in the appended chapters.

The empirical studies on cryptocurrencies in recent years are focused on the addition of cryptocurrencies to a portfolio with traditional assets. Studies have examined the association between cryptocurrencies and stock markets focusing on Bitcoin and advanced stock markets. For instance, Baur, Hong, and Lee (2018) investigate the properties of Bitcoin as an asset or a medium of exchange and finds Bitcoin to be uncorrelated with traditional asset classes such as S&P 500s in periods of financial crises and normal times. Corbet, Meegan, Larkin, Lucey, and Yarovaya (2018) scrutinize the association among global stocks, commodities and three cryptocurrencies in a time-frequency space and evidence cryptocurrencies as isolated from the traditional asset in the short-time horizon. Thus, in the short investment horizon, cryptocurrencies may offer diversification benefits to investors. Using the spillover index technique, Trabelsi (2018) study the connectedness between cryptocurrencies and traditional assets (global stocks, currencies, and commodities) and reports that the traditional assets and cryptocurrencies are connected but have no major spillover effects. Most recently, Bouri, Shahzad, and Roubaud (2019) study the safe-haven and hedging characteristics of eight virtual currencies against ten developed equity sectors and the S&P 500. The authors make use of the cross-quantilogram approach and report that Monero and Litecoin are safe havens for some selected stocks and the aggregate US stock index. Bitcoin, Steller, and Ripple are safe havens for all US equity indices and Das, Ethereum, and Nem are hedges for a few equity sectors. What is lacking in the above literauture is whether a similar relationship observed in adavanced stock markets applies to African stock markets. Hence, we test the fundamentals-based theory and modern portfolio theory by investigating the level of integration between the cryptocurrency and African stock markets across time implementing wavelet-based methods.

A quick scan of the literature on cryptocurrencies and fiat currencies interconnectedness reveals no empirical studies on cryptocurrencies and African fiat currencies even though cryptocurrencies have desirable attributes that are robust to the stylized facts[11] of African currency market. Studies have mainly explored the interconnectedness between cryptocurrencies and global fiat currencies. Wu and Pandey (2014) investigate the value of Bitcoin as a currency against five reserve currencies (Euro, Yen, Australian dollar, Pound, and Canadian dollar) and finds Bitcoin to be lowly correlated with reserve currencies. Dyhrberg (2016a) examine the ability of Bitcoin to hedge USD/GBP, and USD/EUR exchange rates and finds Bitcoin to be positively related to dollar-sterling and dollar-euro exchange rates. In another study, Dyhrberg (2016b) makes use of asymmetric GARCH methodology to investigate the ability of Bitcoin to hedge against the USD in the short term and reports that Bitcoin behaves similarly to USD. Gajardo et al. (2018) apply MF-ADCCA technique to assess the asymmetric cross-correlations between Bitcoin and global reserve currencies and evidence shows that Bitcoin behaves differently from the major currencies. Corelli (2018) employs multivariate linear regression to scrutinize the relationship and causality between six cryptocurrencies and ten fiat currencies and finds some of the cryptocurrencies and fiat currencies connected. Applying MF-ADCC model, Kristjanpoller and Bouri (2019) explore the cross-correlation and asymmetric multifractality between cryptocurrencies (Litecoin, Bitcoin, Monero, Das, and Ripple) and global fiat currencies (Euro, Yen, Swiss Franc, Australian dollar, and British Pound). The findings show significant persistent asymmetric attribute of all cryptocurrencies, with

[11] The works of Fokuo (2018), Owusu-Junior, Adam, and Tweneboah (2017), Kargbo (2000) and Rainer (2017) suggest that African forex market exhibit stylized facts including high inflation, exchange rate variability, low speed and few volumes of transactions, and high cost of transactions.

Bitcoin and Litecoin showing high multifractal behavior compared to Ripple and Monero. In a different dimension, Carrick (2016) analyze the volatility and value of Bitcoin compared to the reserve currencies of emerging economies and documents Bitcoin as a suitable complement to emerging market currencies. Following this discussion we test the modern monetary theory in the cryptocurrency and African fiat currency space. We explore the asymmetric connections between the currencies to see if cryptocurrencies are suitable alternatives and hedges for African fiat currencies during turbulent and tranquil currency conditions implementing the ensemble empirical mode decomposition-based quantile-in-quantile regression.

The literature on risk analysis in the cryptocurrency market also focused on the predictable variance and missed a comprehensive measure of the risk of tail parameter as well as the time-varying volatility transmittions across cryptocurrencies eventhough the time series of cryptocurrencies display the features[12] of the time series of other financial assets. Notable studies in this regard include Catania et al. (2018) who apply Score Driven-GHSKT and GARCH model to Bitcoin, Ether, Litecoin, and Ripple and find long memory in the volatility process of the cryptocurrencies. The authors provide evidence of interdependence among the coins and also report asymmetric reactions of the volatility process to leverage effect. Bouri et al. (2019) find co-explosivity and multiple bubbles in the cryptocurrency market applying generalized sup Augmented Dickey–Fuller (GSADF). Employing generalized variance decomposition methodology, Corbet et al. (2018) examine the interdependence between traditional assets and cryptocurrencies and finds interdependence among the coins. Similarly, Omane-Adjepong, Alagidede, and Akosah, (2019) apply MODWT, and ARFIMA-FIGARCH class of models to explore the returns and volatility of cryptocurrencies but failed to account for the tail risk of the coins and reported volatility, trading horizons, and switching regimes in the cryptocurrency market. Yi et al. (2018) use LASSO-VAR3 approach to explore the volatility connectedness among fifty-two cryptocurrencies and confirm spillover effects across cryptocurrencies. In another study, Koutmos (2018) applies VAR methodology to study the volatility spillover and return among cryptocurrencies and indicate interdependence among the coins due to the spillover pattern

[12] As indicated in the works of Catania et al. (2018) and Borri (2019), the daily investments in cryptocurrencies comprises billions of USD but exhibit the stylized facts of traditional assets including extreme price volatility, extreme observations, time-varying asymmetry in volatility, are fat tailed and exposed to tail risk.

in the cryptocurrency market. Ji et al. (2018) scrutinize the connectedness between seven cryptocurrencies employing VAR model and report that cryptocurrencies are connected in terms of volatility and return and that Steller and Ethereum are the biggest recipients of spillovers risks whiles Bitcoin and Litecoin have more influence on other cryptocurrencies.

Applying multivariate extreme value theory, Gkillas, Bekiros, and Siriopoulos (2018) investigate the contemporaneous tail dependence structure of ten cryptocurrencies in a pairwise analysis and reports that cryptocurrencies are strongely interconnected at the tails of the conditional distributions. In another study, Gkillas and Katsiampa (2018) use expected shortfall and VAR methodology to explore tail behaviors among five cryptocurrencies and finds the existence of spillover risks among them. Incorporating time decomposition to spillover index, Trabelsi (2018) make use of VAR to scrutinize the interconnectedness within cryptocurrency markets and finds association among them. Examining the conditional tail-risk among cryptocurrency, Borri (2019) employs CoVAR and reports that Ethereum, Bitcoin, Ripple, and Litecoin are highly correlated with each other and exposed to tail-risk. Huynh (2019**)** apply Granger causality, VAR-SVAR, and Student's-t Copulas to examine the spillover risks among cryptocurrencies and indicate Bitcoin as the spillover effect recipient and Ethereum as isolated from other cryptocurrencies. Due to the extreme price volatility of cryptocurrencies, we examine their tail risk and time-varrying volatility spillover effects adopting Fissler and Ziegel (2016) joint loss dynamic models and Barunik and Krehlik (2018) frequency domain spillover technique.

In terms of an attempt to model the returns of cryptocurrencies with respect to gold and crude oil returns, some studies have made significant strides but ignored the nonlinearity[13] time-variability[14], and asymmetric[15] associations in the asset markets and produced conflicting results. For example, Bouri, Azzi, and Dyhrberg (2017) examine the hedge, safe-haven, and diversification abilities of Bitcoin for global commodities using the bivariate DCC model and evidence show

[13] Nonlinear dynamics are not rare in financial series such as gold, crude oil, and cryptocurrencies. The time series of these variables are characterized by sudden and irregular jumps and neglecting nonlinear dependences may lead to inacurrate predictions (Zhang, 2002; Bisaglia and Gerolimetto, 2014).
[14] As discussed by Zhang (2002), heterogeneity of participants in the financial market is often cited as a major source of nonlinear dynamics of financial series.
[15] Linear models do not allow for strong asymmetries in data which may lead to poorly behaved parameter estimates and models which miss important serieal dependencies (Bisaglia and Gerolimetto, 2014).

Bitcoin as a safe haven and a strong hedge against movements of commodity indices. Employing non-linear and quantile (ARDL) models, Bouri et al. (2018) explore the impact of aggregate commodity index and gold prices on Bitcoin price and finds non-linear, asymmetric, and quantile-dependent relationship between Bitcoin and aggregate commodity and between gold and Bitcoin. Kurka (2019) uses volatility spillovers framework to examine the nature of shock transmissions among stocks, commodities, financials, foreign exchange, and Bitcoin and reports that Bitcoin cannot be a hedge to the traditional assets because of its low correlation with the assets. Using the advanced cross-quantilogram technique, Shahzada et al. (2019) scrutinize the effects of Bitcoin on gold and commodity index and finds that Bitcoin has weak safe haven characteristics for gold and the commodity index.

Ciaian and Rajcaniova (2018) employ ARDL to explore the relationship between seventeen virtual currencies and control for crude oil price, stock indices, interest rate, gold, and exchange rate. The findings show that fluctuations in the price of Bitcoin impact fifteen altcoins and that Bitcoin and four altcoin prices cointegrate in the long-term. Similarly, Adebola, Gil-Alama, and Madigu (2019) apply cointegration and fractional integration techniques to cryptocurrencies and gold prices and examine their short-, and long-term relationship and their degree of persistence. The study reports a low degree of integration between the assets in the long-term. The study further report means reversion in some of the cryptocurrencies and gold prices. Ji, Bouri, Roubaud, and Kristoufek (2019) apply the transfer entropy technique to explore the information interdependence among cryptocurrencies, agricultural, metals, and energy commodities and report integration between cryptocurrencies and the commodities. The currency study sheds light on the hedging properties of seven cryptocurrencies for gold and crude oil price fluctuations at bear (bull) markets across time employing wavelet-based quantile-in-quantile regression.

The empirical literature above highlights different dimensions of the connections between cryptocurrencies and conventional assets classes in the advanced financial markets which deserve further examination. Further, it is evident from the literature that the connection between cryptocurrencies and traditional assets in the African financial markets have not been attempted even though African financial markets have different attributes (in terms of liquidity, stability, efficiency, integration etc) relative to advanced financial markets and that shocks emanating from the cryptocurrency markets may as well have rippling effects on African financial markets. Importantly, previous studies again failed to account for asymmetries, time-variablilities and non-linearities in the timeseries of the variables of interest even though heterogeneity of participants in the financial market is often cited as a major source of nonlinear dynamics of financial series (Zhang, 2002). Within this arena, the questions bothering on this study are: What is the level of integration between the cryptocurrency and African stock markets across time? What is the nature of asymmetric linkages between cryptocurrencies and African fiat currencies across market conditions and time? How do we model tail risk and time-varrying volatility spillover in the cryptocurrency market? To what extent do cryptocurrencies impact on gold, and crude oil across market conditions and time? This study seeks to find answers to these questions by modelling the relationship between cryptocurrencies and traditional assets (stocks, fiat currencies, gold, and crude oil) in the African financial markets using innovative financial instruments and statistical models suited to simultaneously capture all conventional moments without assuming normality in a time-frequency space.

1.4 Structure of the thesis

The thesis is organized into four empirical chapters in line with the objectives which highlight the contributions of each objective to literature. We provide a summary of methodologies, key findings, and contributions to literature from Chapters 2 to 5 in the paragraphs below. Interested readers can access details of each objective in the appended chapters.

Chapter Two investigates the level of integration between cryptocurrencies and African stock markets at different frequencies employing seven leading cryptocurrencies; Bitcoin (BTC), Ethereum (ETH), Litecoin (LTC), Ripple (XRP), Das (DASH), Steller (XLM), and Monero (XMR), and eight major African stock market indices; Egypt (EGX30), Nigeria (NSE), Ghana (GSE), Tunisia (Tunindex), Morocco (CSE), Mauritius (SEM), and Kenya (Nairobi.SE). The chapter dwells on two wavelet methods proposed by Morlet, Arens, Fourgeau, and Glad (1982) and Fern´andez-Macho (2012), the continuous morlet wavelet transform, and wavelet multiple correlations and cross-correlations respectively owing to their time-frequency decomposition properties.

The continuous morlet wavelet transform was used to examine the bivariate co-movement of the markets and is calculated by determining the wavelet power spectrum and wavelet coherence of two signals. The multivariate co-movement of cryptocurrencies and African stock returns was investigated applying the wavelet multiple correlations and cross-correlations. The wavelet multiple correlation was computed as the square root of the coefficient of determination of the regression formed by the linear combination of the wavelet coefficients such that the coefficient of determination is highest. Allowing thirty lags between the observed and fitted values formed by the same linear combination of wavelet coefficients at each of the wavelet scales we calculate the wavelet cross-correlation of the assets markets.

The results from both bivariate and multivariate co-movement of cryptocurrencies and African stock returns depict a high level of integration between the markets from medium to lower frequencies. This finding generally indicates that most stock markets in Africa are extremely vulnerable to discrepancies in the cryptocurrency market from the medium-term and that international investors seeking to hedge their price risk in African stock markets using cryptocurrencies may have to look at the short-time horizon. The results from phase difference vector arrows and cross-correlation analysis showing the lead (lag) association between the assets markets are contingent on the frequency under consideration suggesting that any cryptocurrency or stock markets have the possibility to lead (lag) other markets at different frequencies. The implication of this finding is that the returns of any of the assets markets can drive price changes in the other markets which may induce arbitrage opportunities for international investors. The results for the integration between cryptocurrencies and African stock markets contribute to inter-market linkages between cryptocurrencies and stock markets.

Chapter Three models the asymmetric behavior of exchange rate returns between cryptocurrencies and African fiat currencies focusing on five principal cryptocurrencies: Bitcoin (BTC), Ethereum (ETH), Litecoin (LTC), Ripple (XRP), and Das (DASH) and eight African fiat currencies: Egyptian Pound (Egypt), Niara (Nigeria), ZAR (South Africa), Rupee (Mauritius), Cedi (Ghana), Dinar (Tunisia), Dirham (Morocco) and Shilling (Kenya). We test the response of cryptocurrencies to positive (negative) shocks in African fiat currencies at high (low) currency regimes across time to see if cryptocurrencies are viable alternatives to African fiat currencies implementing the EEMD-based quantile-in-quantile regression.

We account for the time and frequency information in the time series of the currencies using the ensemble empirical mode decomposition (EEMD). We decompose the exchange rate return series of the currencies into higher, medium, and lower frequencies termed as Intrinsic Mode Functions (IMF1, IMF5, and IMF Residual) respectively. We then implement quantile regression (QR) and quantile-in-quantile regression (QQR) on the decomposed series to establish the association between cryptocurrencies and African fiat currencies over 19 quantiles ($\tau = 0.05\ to\ 0.95$). We choose the lower quantiles ($\tau = 0.05\ to\ 0.45$) as low currency state where the currencies are depreciating suggesting adverse shocks to the currencies, the medium quantile ($\tau = 0.50$) as normal state where the currencies are stable in value showing their normal strength, and upper quantiles ($\tau = 0.55\ to\ 0.95$) as high currency regime where the currencies are appreciating indicating positive shocks to currencies.

The results presented under QR and QQR framework indicate that cryptocurrencies reduce the variance of fiat currencies and are mostly negatively correlated with reserve currencies from the medium-term. Specifically, the QR results suggest that cryptocurrencies behave differently from fiat currencies providing negative associations to extreme fiat currencies fluctuations at medium and lower frequencies. This indicates that cryptocurrencies are viable alternative digital currencies and good hedges for African fiat currencies form the medium-term. The findings from QQR show bidirectional causal effects which demonstrate that cryptocurrencies can be good hedges and viable alternative currencies to African currencies from the medium-term when the fiat currencies are depreciating in value and the cryptocurrency market is less volatile.

This chapter has implication for policymakers on considering cryptocurrencies as alternatives to fiat currencies from the medium-term. Also, it provides vital information for multinational corporations, and forex traders on the ability of cryptocurrencies to hedge against the dollar/African fiat currencies exchange rate risk. The chapter contributes to the limited literature on cryptocurrency and fiat currency interconnectedness by extending the investigation into the African currency market to capture the African effects on cryptocurrencies and fill the gap in the literature that is focused on the reserve currencies of developed economies. The chapter further departs from earlier works by considering issues regarding time-frequency, asymmetries, and nonlinearities in the time series of currencies applying the EEMD-based quantile-in-quantile regression which provides comprehensive results compared to other models used in related studies.

Chapter Four performs risk analysis in the cryptocurrency market focusing on tail risk and volatility spillovers across seven large cryptocurrencies; Bitcoin, Litecoin, Ethereum, Ripple, Monero, Das, and Steller. The FZL function drawn from ES and VaR jointly was used to quantify tail risk. We applied six varying asymmetric distributions (STD, SNORM, SSTD, AST1, AST, and ALD) to the univariate GAS framework to capture fat-tails and volatility clusters that characterize cryptocurrency returns. Implementing the MDM, and MAE tests to the asymmetric distributions at both $\alpha = 0.01$ and $\alpha = 0.025$ levels, we checked the equal predictive accuracy of the distributions. Results show all models have equal predictive ability, but the ALD and SNORM appeared as the finest distributions showing the lowest MAE at the α levels.

As a typical out-of-sample forecasting procedure, we backtested the best distributions applying the CC, UC, DQ, and QL backtests to verify the forecast adequacy of the distributions. Except for the DQ test, the CC and UC tests accepted the ALD and SNORM distributions at their respective α levels as adequate and correctly specified. In line with Basel III, we compared the 1% models to 2.5% models by computing QL ratios and finds that the 1% models outperform the 2.5% models. We then estimate the characteristic FZL value to compare the capital adequacy and riskiness of the cryptocurrencies and finds that at both 1% and 2.5% risk thresholds, Ethereun and Steller have the least risk profile followed by Monero, Das, Litecoin, Bitcoin, and Ripple suggesting that Ethereum and Steller require the least capital to absorb losses at the risk levels.

Applying Barunik and Krehlik (2018) frequency-domain spillover index to the cryptocurrencies, we investigate the spillover frequency interconnectedness across the cryptocurrencies. We observe that cryptocurrencies are strongly interconnected at higher frequencies (short-term) than at medium and lower frequencies and that Bitcoin, Litecoin, and Das contribute most to total volatility in the cryptocurrency market. This finding suggests contagion risk in the cryptocurrency market, and that diversification and hedging opportunities are low in the short-term. We also find that the net transmitters and receivers of volatility spillover effects across cryptocurrencies are frequency-dependent and that all cryptocurrencies alternating between being receivers and transmitters of spillover effects across time suggest that Bitcoin is losing its dominant role in the cryptocurrency market. This chapter contributes to cryptocurrency market risk management by providing coherent risk measure estimation for enhanced investment and trading strategies for cryptocurrency portfolio optimization.

Chapter Five evaluates the impact of cryptocurrencies (Bticoin, Ethereum, Ripple, Litecoin, Das, Monero, and Steller) on gold and crude oil returns applying the wavelet-based Quantile-in-Quantile regression technique. We explore the asymmetric shock transmission mechanisms between the assets and uncover the hedging properties of the seven cryptocurrencies for extreme gold and crude oil price movements at different market states in a time-frequency space. We applied the Maximal Overlap Discrete Wavelet Transform to decompose the daily returns of cryptocurrencies, gold, and crude oil into wavelet scales D1, D4, and D6 which represent short-, medium-, and long-term fluctuations respectively. We then applied Quantile Regression (QR) and Quantile-in-Quantile Regression (QQR) on the decomposed series to establish the association between gold/cryptocurrencies and oil/cryptocurrencies over 19 quantiles ($\tau = 0.05\ to\ 0.95$). We chose the lower quantiles ($\tau = 0.05\ to\ 0.45$) as bear market where the price of the assets are low which exhibit downside risk in the market, the medium quantile ($\tau = 0.50$) as normal market where price is stable which shows normal gains in the market, and upper quantiles ($\tau = 0.55\ to\ 0.95$) as bull market where price is high which shows upside gains in the market.

The outcome of both QR and QQR highlights the heterogeneous effect of cryptocurrencies on gold and crude oil returns across quantiles and time-scales. Specifically, the QR results for gold/cryptocurrencies suggest all cryptocurrencies studied (Bitcoin, Ethereum, Litecoin, Das, Monero, Ripple, and Steller) as hedges for price fluctuations at bear (bull) gold markets (i.e. whether the price of gold is low, stable, or high) from the medium-term. However, the QR results for oil/cryptocurrencies undermine the hedging properties of Bitcoin, Litecoin, and Das markets as hedges for crude oil market oscillations suggesting shock transmissions from the cryptocurrencies to crude oil market across time and that hedging possibilities are feasible from the medium-term for crude oil investors/traders using Ethereum, Monero, Ripple, and Steller at bear (bull) crude oil markets.

The results from QQR for gold/cryptocurrencies and oil/cryptocurrencies pairs show negative associations between the commodities (gold and crude oil) and cryptocurrencies at bear market but positive relations at bull market. This suggests that market disruptions in any of the assets markets can spillover to the other when their market is bull, but the assets have hedging properties for each other when their market is bear. Thus, when the cryptocurrency market is bearish and the price of gold and crude oil is low, economic actors can hedge the downside risk of the commodities or cryptocurrencies across time using either of the assets. This chapter contributes to the empirical literature on cryptocurrencies and commodity market associations by showing that the connections between gold/cryptocurrencies and oil/cryptocurrencies are time-varying and also depends on the state of market.

We argue in line with the findings of this thesis that although cryptocurrencies exhibit excess price volatility, it would be very profitable if they are incorporated in a diversified portfolio with traditional asset classes in the African financial markets.

References

Adebola, S., S., Gil-Alana, A., L., & Madigu, G. (2019). Gold Prices and the Cryptocurrencies: Evidence of Convergence and Cointegration. *Physica A: Statistical Mechanics and its Applications,* 523, 1227-1236.

Adjasi, C., K.., D., & Biekpe, N., B., (2006). Co Integration and Dynamic Causal Links amongst African Stock Markets. *Investment Management and Financial Innovations,* 4, 102-119.

Agyei-Ampomah, S. (2008). An Empirical Examination of the Inter-Linkages between African Stock Markets. Available at SSRN 1311325.

Barberis, N., Shleifer, A., and Wurgler, J. (2005). Comovement. *Journal of Financial Economics,* 75(2), 283-317.

Barberis, N., and Shleifer, A. (2003). Style Investing," Forthcoming, *Journal of Financial Economics.*

Barunik, J., & Křehlík, T. (2018). Measuring the Frequency Dynamics of Financial Connectedness and Systemic Risk. *Journal of Financial Econometrics, 16*(2), 271-296. https://doi.org/10.1093/jjfinec/nby001.

Baur, D., G., Hong, K.., & Lee, A., D. (2018). Bitcoin: Medium of Exchange or Speculative Assets? *Journal of International Financial Markets, Institutions, and Money*, 54, 177–189. http://refhub.elsevier.com/.

Baur, D., G., & McDermott, T., K., J. (2012). Safe Haven Assets and Investor Behaviour under Uncertainty. Finance Discipline Group, UTS Business School Working Paper Series 173.

Bodie, Z., Kane, A., Marcus, L. J. (2014). *Investments*. (10th edn.) New York: McGraw-Hill McGraw-Hill/Irwin International Edition.

Boako, G., & Alagidede, P. (2015). Global Commodities and African Stocks: Insights for Hedging and Diversification Strategies. *Economic Research Southern Africa,* working paper 569.

von Böhm-Bawerk, E. (2002). Value, Cost, and Marginal Utility. *The Quarterly Journal of Austrian Economics*, 5(3), 37-79.

von Böhm-Bawerk, E. (1962). "The Ultimate Standard of Value." Annals of the Amen·can Academy of Political and Social Science. September 1894. In Shorter Classics of Eugen von BOhm-Bawerk, South Holland, III.

Bos, A., & Economy, G. P. (2018). *Cryptocurrencies and Regulation, a Master Thesis on the Best Practices for Regulating Cryptocurrencies within the EU* (Master's thesis).

Borri, N. (2019). Conditional Tail-Risk in Cryptocurrency Markets. *Journal of Empirical Finance*, 50, 1-19.

Bouri, E., Shahzad, S., J., H., & Roubaud, D. (2019). Cryptocurrencies as Hedges and Safe-havens for US Equity Sectors. *The Quarterly Review of Economics and Finance,* 1-14. https://doi.org/10.1016/j.qref.2019.05.001.

Bouri, E., Shahzad, S., J., H., & Roubaud, D. (2019). Co-explosivity in the Cryptocurrency Market. *Finance Research Letters,* 29, 178-183.

Bouri, E., Molnár, P., Azzi, G., Roubaud, D., & Hagfors, L., I. (2017a). On the Hedge and Safe Haven Properties of Bitcoin: Is it Really More Than a Diversifier? *Finance Research Letters*, 20, 192–198.

Bouri, E., Azzi, G., & Dyhrberg, A., H. (2017). On the Return-Volatility Relationship in the Bitcoin Market around the Price Crash of 2013. *Economics: The Open-Access, Open-*

Assessment E-Journal, 11(2), 1–16. http://dx.doi.org/10.5018/economics-ejournal.ja.2017-2.

Bouri, E., Jalkh, N., Molnár, P., & Roubaud, D. (2017). Bitcoin for Energy Commodities before and after the December 2013 Crash: Diversifier, Hedge or Safe Haven? *Applied Economics, 49*(50), 5063-5073.

Brandvold, M., Molnár, P., Vagstad, K., & Valstad, O., C., A. (2015). Price Discovery on Bitcoin Exchanges. *Journal of International Financial Markets, Institutions, and Money,* 36, 18–35. http://www.sciencedirect.com/science/article/pii/S104244311500027X.

Broni, F. E., Boateng, R., & Owusu, A. (2020). Preliminary Insights into the Adoption of Bitcoin in a Developing Economy: The Case of Ghana. In *Encyclopedia of Criminal Activities and the Deep Web* (pp. 945-963). IGI Global.

Burnside, D., J., Chambers, D., R., & Zdanowicz, J., S. (2004). How Many Stocks Do You Need to be Diversified. *AAII Journal*, 4(2), 16-19. http://www.aaii.com/journal/article/how-many-stocks-do-you-need-to-be-diversified-.touch.

Catania, L., Grassi, S., & Ravazzolo, F. (2018). Forecasting Cryptocurrencies Financial Time Series," In CAMP Working Paper Series, no. 5. Norwegian Business School.

Carrick, J. (2016). "Bitcoin as a Complement to Emerging Market Currencies," *Emerging Markets Finance and Trade* 52(10), 2321–2334.

Ciaian, P., & Rajcaniova, M. (2018). Virtual Relationships: Short-and Long-Run Evidence from Bitcoin and Altcoin Markets. *Journal of International Financial Markets, Institutions, and Money, 5*2, 173–195.

CoinMarketCap. (2019). Cryptocurrency Market Capitalizations and Data. Available online: https://coinmarketcap.com/ (accessed on 26th August 2019).

Corbet, S., Lucey, B., & Yarovaya, L. (2018b). Datestamping the Bitcoin and Ethereum Bubbles. *Finance Research Letters, 26,* 81-88.

Corbet, S., Meegan, A., Larkin, C., Lucey, B., & Yarovaya, L. (2018). Exploring the Dynamic Relationships between Cryptocurrencies and Other Financial Assets. *Economics Letters*, 165, 28–34. doi.org/10.1016/j.econlet.2018.01.004.

Corelli, A. (2018). Cryptocurrencies and Exchange Rates: A Relationship and Causality Analysis. *Risks*, 6, 111.

Das, D., & Kannadhasan, M. (2018). Do Global Factors Impact Bitcoin Prices? Evidence from Wavelet Approach. *Journal of Economic Research*, 23, 227-264.

Dyhrberg, A., H. (2016a). Hedging Capabilities of Bitcoin. Is it the Virtual Gold? *Finance Research Letters*, 16, 139–144.

Dyhrberg, A., H. (2016b). Bitcoin, Gold and the Dollar—A GARCH Volatility Analysis. *Finance Research Letters*, 16, 85–92.

Dyhrberg, A., H. (2015a). Hedging Capabilities of Bitcoin. Is it the Virtual Gold? *Finance Research Letters,* 16, 139–44.

ElBahrawy, A., Alessandretti, L., Kandler, A., Pastor-Satorras, R., & Baronchelli, A. (2017). Evolutionary Dynamics of the Cryptocurrency Market. *Royal Society open science*, 4(11), 170623.

Filkorn, M. (2016). "Banking Is Necessary, Banks Are Not; How Banks Can Survive in the Digital Age." Capgemini Worldwide, www.capgemini.com/consulting/2016/07/banking-is-necessary-banks-are-not-howbanks-can-survive-in-the/.

Eisl, A., Gasser, S., M., & Weinmayer, K. (2015). Caveat Emptor: Does Bitcoin Improve Portfolio Diversification? Available at SSRN 2408997. http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2408997.

Evans, J., & Archer, S. (1968). Diversification and the Reduction of Dispersion: An Empirical Analysis. *Journal of Finance*, 23, (5), 761-767,

Fern´andez-Macho, J. (2012). Wavelet Multiple Correlation and Cross-Correlation: A Multiscale Analysis of Eurozone Stock Markets. *Physica A: Statistical Mechanics and its Applications*,391,1097-1104. http://www.sciencedirect.com/science/article/pii/S0378437111008375.

Fernandez-Villaverde, J., & Sanches, D. (2018). Can Currency Competition Work? PIER Working Paper 16-008. http://ssrn.com/abstract=2760415.

Fissler, T., & Ziegel, J., F. (2016). Higher Order Elicitability and Osband's Principle. *The Annals of Statistics,* 44(4), 1680–1707.

Fokuo Jr, I., K. (2018). Blockchain can drive more Investment in Africa. *HR Future*, 30-31.

Forbes, K., J., & Rigobon, R. (2002). No Contagion, Only Interdependence: Measuring Stock Market Co-movements, *The Journal of Finance,* 57(5), 2223- 2261.

Gajardo, G., Kristjanpoller, W., D., & Minutolo, M. (2018). Does Bitcoin Exhibit the Same Asymmetric Multifractal Cross-Correlations with Crude Oil, Gold, and DJIA as the Euro, Great British Pound, and Yen? *Chaos, Solitons and Fractals*, 109, 195–205.

Georgeson, D., A. (2018). Cryptocurrencies as an Alternative to Fiat Monetary Systems.

Glosten, L., R., Jagannathan, R., & Runkle, D., E. (1993). On the Relation between the Expected Value and the Volatility of the Nominal Excess Return on Stocks. *The Journal of Finance*, 48(5). 1779-1801.

Gkillas, K., Bekiros, S., & Siriopoulos, C. (2018). Extreme Correlation in Cryptocurrency Markets. Available at SSRN 3180934.

Gkillas, K., & Katsiampa, P. (2018). An Application of Extreme Value Theory to Cryptocurrencies. *Economics Letters*, 164, 109–111. doi: 10.1016/j.econlet.2018.01.020.

Gourène, G., A., Z., Mendy, P., & Lanciné, D. (2019). Beginning an African Stock Markets Integration? A Wavelet Analysis. *Journal of Economic Integration*, 34(2), 370-394.

Gourène, G., A., Z., & Mendy, P. (2014). Beginning an African Stock Markets Integration? A Wavelet Analysis. *Munich Personal RePEc Archive*, 76048.

Graham, B. (2009). *The Intelligent Investor*, Revised Edition, Harper Collins.

Guadamuz, A., & Marsden, C. (2015). Blockchains and Bitcoin. *First Monday*, *20*(12), 6.

Hain, D., & Jurowetzki, R. (2018). Local Competence Building and International Venture Capital in Low Income Countries. *Journal of Small Business and Enterprise Development*, 25(3), 447-482, https://doi.org/10.1108/JSBED-03-2017-0092.

Holmes, T. (2017). No Magic Bullet: Cryptocurrencies and Complexities in Africa. https://www.africaportal.org/contributors/thalia-holmes/.

Huynh, T., L., D. (2019). Spillover Risks on Cryptocurrency Markets: A Look from VAR-SVAR Granger Causality and Student's-t Copulas. *Journal of Risk and Financial Management*, 12, 52. doi:10.3390/jrfm12020052.

Ji, Q., Bouri, E., Roubaud, D., & Kristoufek, L. (2019). Information Interdependence among Energy, Cryptocurrency and Major Commodity Markets. *Energy Economics*, 81, 1042-1055.

Ji, Q., Bouri, E., Gupta, R., & Roubaud, D. (2018). Network Causality Structures among Bitcoin and Other Financial Assets: A Directed Acyclic Graph Approach. *The Quarterly Review of Economics and Finance, 70, 203–13.*

Kargbo, J., M. (2000), "Impacts of Monetary and Macroeconomic Factors on Food Prices in Eastern and Southern Africa", *Applied Economics,* 32, 1373-1389.

Kim, T. (2017). On the transaction cost of Bitcoin. *Finance Research Letters,* 23, 300-305.

King, M., A., & Wadhwani, S. (1990). Transmission of Volatility between Stock Markets. *The Review of Financial Studies*, *3*(1), 5-33.

Koutmos, D. (2018). Return and Volatility Spillovers among Cryptocurrencies. *Economics Letters*, 173, 122–27.

Kristjanpoller, W., & Bouri, E. (2019). Asymmetric Multifractal Cross-Correlations between the Main World Currencies and the Main Cryptocurrencies. *Physica A: Statistical Mechanics and its Applications,* 523, 1057-1071.

Kristoufek, L. (2015). What are the Main Drivers of the Bitcoin Price? Evidence from Wavelet Coherence Analysis. *PLoS ONE,* 10: e0123923.

Krugman, P. (2013). Bitcoin is Evil. New York Times, Available at http://krugman.blogs.nytimes.com/2013/12/28/bitcoinisevil/?_php=true&_type=blogs&_php=true&_type=blogs&_php=true&_type=blogs&_r=2.

Kurkaa, J. (2019). Do Cryptocurrencies and Traditional Asset Classes Influence each other? *Finance Research Letters,* 38, 38-46.

LeRoux, C., D. (2014). Why Bitcoin Can Never Be Money. *Procesos de Mercado: Revista Europea de Economía Política, 11(1), 249-271.*

Malkiel, B., G. (1999). *A Random Walk Down Wall Street: Including a Life-Cycle Guide to Personal Investing* (7th edn), WW Norton & Company.

Markowitz, H. (1952). Portfolio Selection. *The Journal of Finance, 7*(1), 77-91.

McKenzie, B. (2018). Blockchain and Cryptocurrency in Africa: A Comparative Summary of the Reception and Regulation of Blockchain and Cryptocurrency in Africa. https://www.bakermckenzie.com//media/files/insight/publications/2019/02/report_blockchainandcryptocurrencyreg_feb2019.pdf.

Menger, C. (1871). *Principles of Economics*. Auburn, Ala: Ludwig von Mises Institute, 2005.

Menger, C. (1892). *On the Origins of Money.* Auburn, Ala: Ludwig von Mises Institute, 2009.

Mensi, W., Hammoudeh, S., & Tiwari, A., K. (2016). New Evidence on Hedges and Safe Havens for Gulf Stock Markets using the Wavelet-Based Quantile. *Emerging Markets Review,* 28, 155-183.

Mensah, J., O., & Alagidede, P. (2017). How are Africa's Emerging Stock Markets Related to Advanced Markets? Evidence from Copulas. *Economic Modelling*, 60, 1–10.

Mises, L., V. (1969). *Theory and History: An Interpretation of Social and Economic Evolution*. New Rochelle, New York: Arlington House.

Mises, L., V. (1953). *The Theory of Money and Credit*. (2nd edn.) Irvington-on-Hudson, New York: Foundation for Economic Education.

Morlet, J., Arens, G., Fourgeau, E., & Glard, D. (1982). Wave Propagation and Sampling Theory—Part I: Complex Signal and Scattering in Multilayered Media. *Geophysics*, 47(2), 203–221.

Müller, U., A., Dacorogna, M., M., Davé, R., D., Pictet, O., V., Olsen, R., B., & Ward, J., R. (1993). Fractals and Intrinsic Time: A Challenge to Econometricians. *Unpublished Manuscript, Olsen & Associates, Zürich*.

Murphy, R. (2013). "The Economics of Bitcoin," Library of Economics and Liberty Available at http://www econ lib org/library/Columns/ y2013/Murphy bitcoin html.

Naboulsi, N., & Neubert, M. (2018). Impact of Digital Currencies on Economic Development in Kenya. In *Proceedings of the ACBSP Region 8 Fall Conference, 2018* (pp. 368-387).

Nakomoto, S. (2009). Bitcoin: A Peer-to-Peer Electronic Cash System. https://bitcoin.org/bitcoin.pdf/.

Nieman, A. (2015). A few South African cents' worth on Bitcoin. *Potchefstroom Electronic Law Journal/Potchefstroomse Elektroniese Regsblad*, *18*(5), 1978-2010.

Omane-Adjepong, M., Alagidede, P., & Akosah, N., K. (2019). Wavelet Time-Scale Persistence Analysis of Cryptocurrency Market Returns and Volatility. *Physica A: Statistical Mechanics and its Applications*, 514(C), 105-120.

Owusu-Junior, P., Anokye M, A., & George, T. (2017). Co-movement of Real Exchange Rates in the West African Monetary Zone. *Cogent Economics & Finance*, 5(1), 1-18.

Patterson, T., C. (2014). Shell-Bead Money and the Mission Period Economy of Alta California. *Journal of Social Archaeology*, 14(1), 112-127.

Peltomäki, J., Graham, M., & Alagidede. P. (2017). Commodity-Driven Integration of Stock Markets in Africa. *Applied Economics Letters*, 24(11), 784-789. https://www.tandfonline.com/loi/rael20.

Polasik, M., Piotrowska, A., I., Wisniewski, T., P., Kotkowski, R., & Lightfoot, G. (2015). Price Fluctuations and the Use of Bitcoin: An Empirical Inquiry. *International Journal of Electronic Commerce*, 20, 9-49.

Scott, B. (2016). *How can cryptocurrency and blockchain technology play a role in building social and solidarity finance?* (No. 2016-1). UNRISD Working Paper.

Shahzada, H., J., S., Bourib, E., Roubaudc, D., Kristoufekd, L., & Lucey, B. (2019). Is Bitcoin a better Safe-haven Investment than Gold and Commodities? *International Review of Financial Analysis*, 63, 322–330.

Skult, R. (2019). Stock Market Co-movement in the Nordics: A Wavelet Analysis.

Sousa, F. (2019). Africa:Volume of Crypto Transactions Rose Significantly in 2018. https://ihodl.com/topnews/2019-01-29/africa-volume-crypto-transactions-rose-significantly-2018/.

Statman, M. (1987). How Many Stocks Make a Diversified Portfolio? *Journal of Financial and Quantitative Analysis*, 22(3), 353-363.

Tiware, A., K., Dar, A., B., Bhanja, N., & Shah, A. (2013). Stock Market Integration in Asian Countries: Evidence from Wavelet Multiple Correlations. *Journal of Economic Integration*, 441-456.

Trabelsi, N. (2018). Are There Any Volatility Spill-Over Effects among Cryptocurrencies and Widely Traded Asset Classes? *Journal of Risk and Financial Management*, 11(4), 66.

Wray, L., R. (1998). *Understanding Modern Money* (Vol. 11). Cheltenham: Edward Elgar.

Wu, C., Y., & Pandey, V., K. (2014). "The Value of Bitcoin in Enhancing the Efficiency of an Investor's Portfolio," *Journal of financial planning* 27(9), 44–52.

Yaya, S., O., Ogbonna, A., E., & Olubusoye, E., O. (2018). How Persistent and Dependent are Pricing of Bitcoin to other Cryptocurrencies Before and After 2017/18 Crash*? Munich Personal RePEc Archive*, 91253. https://mpra.ub.uni-muenchen.de/91253/.

Yi, S., Xu, Z., & Wang, G. (2018). Volatility Connectedness in the Cryptocurrency Market: Is Bitcoin a Dominant Cryptocurrency? *International Review of Financial Analysis*, 60, 98–114.

Yussof, S., A., & Al-Harthy, A. (2018). Cryptocurrency as an Alternative Currency in Malaysia: Issues and Challenges. *Islam and Civilisational Renewal* (ICR), 9(1), 48-65.

CHAPTER TWO

African Stock Markets Integration with Cryptocurrency Markets

2. Introduction

The rapid growth of cryptocurrencies has attracted a growing amount of academic literature in recent times (Dyhrberg, 2015a; Nakamoto, 2008; Hencic and Gourieroux, 2014; Brier et al., 2015; Kristoufek, 2015; Elbahrawy et al., 2017; Gajardo et al., 2018; Carrick, 2016). The increasing interest of investors, media, government, and the emergence of fledging finance and economic literature on cryptocurrencies have prompted researchers to investigate variety of issues associated with them. Cryptocurrencies are valid economic phenomenon which needs increasing attention due to their dual impact[16] on the economy. Recent studies on cryptocurrency focus on the integration of the cryptocurrency markets with stock markets and other financial markets (Trabelsi, 2018; Bouri, Molnar, Azzi, and Roubaud, 2017a; Briere, Oosterlinck, and Szafarz, 2015) with an aim to uncover the global portfolio diversification benefits and the potential to impair financial stability due to their excess volatility. However, the empirical literature has mostly focused on the connectedness between cryptocurrencies and advanced stock markets, with no study examining the connectedness between cryptocurrencies and African stock indices even though the African equity market is growing incredibly.

The advancement of stock markets in Africa can be evidenced by the Safaricom IPO at Nairobi in 2007 having a market capitalization similar to some companies listed on the New York stock exchange (Gourène, Mendy, and Diomande, 2019). In Nigeria, over $8 billion was invested in traded companies over the period 2007-2009. The market capitalization of the ten largest markets in Africa tripled from 2002 to 2008 (Gourène and Mendy, 2014; Gourène, Mendy, and Diomande, 2019). This advancement of African stock markets has raised the issue of its integration with other

[16] As noted by Kim (2017), cryptocurrency can be used as a cost-effective alternative to the existing forex market and can also be used as an asset instead of a medium of exchange due to its liquidity, diversification, and hedging properties (Bouri et al., 2017; Kristjanpoller and Bouri, 2019).

markets to enable African economies to benefit from international portfolio diversification and investment flows.

The fundamentals-based theory on co-movement by Barberis, Shleifer and Wurgler (2005) argues that the co-movement in asset returns is as a result of co-movement in news about fundamental values. The theory posits that common factors in asset returns including industry and strong market level factors in cashflow news explain the level of integration of asset markets. Financial market integration has implications for fund managers and international investors because the intensity of market integration impacts international diversification opportunities. As discussed by Mensah and Premaratne (2018) and Tiwari, Dar, Bhanja, and Shah (2013), markets that are highly integrated or co-move provides low benefits of international diversification, but portfolio managers can diversify and benefit from segmented markets. Policy-makers are also interested in financial market integration because events in one market can significantly impact other markets, as each market becomes an integral part of a single global market (Tiwari, Dar, Bhanja, and Shah, 2013; Mensah and Premaratne, 2018). Notably, high levels of integration can have monetary policy and macroeconomic implications, since an economy's monetary policy can be affected by the connections between the domestic capital market and other markets within the sub-region and globally.

Ever since the seminal works of Johansen (1998), Engle and Granger (1987), and Grubel (1968), on integration and international portfolio diversification benefits, a substantial body of literature has emerged on the integration of Africa's stock markets with global stock markets and other markets such as commodity and foreign exchange market as a result of the critical implications in asset pricing, policy formulation, risk-sharing across integrated markets, and portfolio diversification (Marashdeh and Shrestha, 2010). One strand of the literature on African stock markets focused on the integration between African equity markets and the global equity market, and evidence shows a low level of integration between the markets (Mensah and Alagidede, 2017; Adjasi and Biekpe, 2006; Alagidede, Panagiotidis, and Zhang, 2011). Another strand of the literature on African stock markets document studies that modelled the returns of African stocks and global commodities (Boako and Alagidede, 2015; Peltomaki, Graham, and Alagidede, 2017; Mongal and Eita, 2014; Omane-Adjepong and Dramani, 2017). The evidence emerging from such studies highlights both weak and strong connections among the markets. In terms of an attempt to model the returns of African stocks with respect to exchange rate, some studies have made significant strides and reported conflicting and inconclusive results (Mlambo, Maredza, and Sibanda, 2013; Sibanda, 2015; Boako, Omane-Adjepong, and Frimpong, 2016; Mitra, 2017; Owusu-Junior, Boafo, Awuye, Bonsu and Obeng-Tawiah, 2018).

Studies have also examined the connection between cryptocurrencies, mostly Bitcoin, and advanced equity markets, but the connection between cryptocurrencies and African stock returns are yet to be explored. For instance, Brière et al. (2015) analyze the portfolio diversification benefits of Bitcoin by employing the mean-variance spanning test and weekly data on both traditional assets (global stocks, bonds, currencies) and alternative investments (real estate, hedge funds, and commodities). The findings show a weak correlation between Bitcoin and the other assets classes and that investing in Bitcoin offers significant diversification benefits. Baur, Hong, and Lee (2018) investigate whether Bitcoin is a medium of exchange or an asset. The authors applied regression analysis to daily data for the period of July 2010 to June 2015. The findings show that Bitcoin is uncorrelated with traditional asset classes such as stocks (proxied with the S&P 500), commodities, and bonds both in periods of financial crises and normal times. Using time and frequency domains technique, Corbet, Meegan, Larkin, Lucey, and Yarovaya (2018) employ the generalized variance decomposition method by Diebold and Yilmaz (2012) to scrutinize the association between financial assets, such as stocks and commodities, and three cryptocurrencies using daily data for the period 2013 to 2017. The study report that cryptocurrencies are isolated from the traditional assets, therefore in the short investment horizon, cryptocurrencies may offer diversification benefits to investors.

Using spillover index technique, Trabelsi (2018) study the interconnectedness within cryptocurrency and traditional assets (global stock market indices, currencies, and commodities) markets. The findings show that financial market and cryptocurrency market are connected but have no major spillover effects. Ciaian and Rajcaniova (2018) employ ARDL to explore the relationship between seventeen virtual currencies, including Bitcoin and control for crude oil price, stock market index, interest rate, gold, and exchange rate. The findings show that shocks in Bitcoin price impact fifteen altcoins and in the long-run, Bitcoin, and four altcoin prices cointegrate.

Investigating the cross-correlation of the cryptocurrency market with Dow Jones Industrial Average, Zhang, Wang, Li, and Shen (2018) apply the generalized multifractal detrended fluctuation analysis (MF-DFA), and multifractal detrended cross-correlation analysis (MF-DCCA) to daily data between April 2013 to January 2018. Results show persistent cross-correlation between the variables. Aaltonen (2017) explores the relations between the US stock market and cryptocurrencies applying least squares, correlation, and orthogonalized impulse response functions. Results show insignificant relations between US equity and the cryptocurrency market.

The study of Al-Yahyaee, Mensi, and Yoon (2018) employ MF-DFA technique to investigate the efficiency of Bitcoin relative to stocks, gold and currency markets. The findings of the study show that Bitcoin markets multifractality and long-memory feature was stronger and that Bitcoin is inefficient more than currency, gold, and stock markets. Liu and Tsyvinski (2018) explore the risk and returns of Bitcoin, Ethereum, and Ripple, compared to precious metals, stocks, and currencies using daily data. The results of the study show that cryptocurrencies are not exposed to fiat currencies, commodities and stock market risk. Jarnstrom, Kane, and Knightly (2018) scrutinize the association among stock market, twitter sentiment, and the cryptocurrency market using data analytics life cycle and Socratic questioning technique. The findings show inverse connection among the variables. Klabbers (2017) employ Monte Carlo Simulation together with mean variance framework to explore the safe haven and hedging attributes of Bitcoin for global market portfolio consisting of stock indexes (FTSE, S&P 500, DAX, MSCI world, Nikkei, Shanghai A share), bond indexes (European, American, Asian), real estate, and commodity index. Results show Bitcoin as an inefficient hedge and diversifier for the traditional assets.

In another dimension, Ünvana (2019) explores the effects of Bitcoin on Japan (Nikkei 225), Turkey (BIST 100 index), USA (S&P 500), and China (SSE 380) stock markets using value-at-risk and causality analysis. The study employs weekly data for the period January 2016 to December 2018 and findings show bidirectional causal relations between Bitcoin and BIST100 but unidirectional causal linkages among Nikkei225, SSE380, and S&P500. Brière, Oosterlinck, and Szafarz (2015) study the portfolio diversification properties of Bitcoin for traditional assets, including global stocks using weekly data from 2010 to 2013. Their study shows that Bitcoin is lowly connected with conventional assets. Their spanning tests evidence Bitcoin as a diversifier to the traditional assets.

Most recently, Bouri, Shahzad, and Roubaud (2019) study the safe-haven and hedging characteristics of eight virtual currencies against ten developed equity sectors and the S&P 500. The authors make use of the cross-quantilogram approach and report that Monero and Litecoin exhibit safe-havens properties for selected stocks and the aggregate US stock index while Bitcoin, Steller, and Ripple have safe-haven characteristics for all US equity indices. The study reports Das, Ethereum, and Nem, to be hedges for a few equity sectors. In another study, Kurka (2019) uses volatility spillovers framework to examine the nature of shock transmissions among stocks, commodities, financials, foreign exchange, and Bitcoin. This study reports that Bitcoin can be a hedge to the traditional assets because of its low correlation with the assets. The study also reports a spillover from Bitcoins market disruptions to the conventional assets market.

Following the literature above, recent studies on the valuable role of cryptocurrencies, mostly Bitcoin, in portfolio diversification and risk management for advanced stock indices highlight no or weak connection between the markets, which provides hedging and diversification benefits for global equity investors. What is lacking in the literature is whether a similar relationship holds for African stocks. Even though the African stock market is openned to both domestic and international investors, the relationship between African stocks and cryptocurrencies remains unexplored and uncovering it could enable stock investors in Africa enhance the efficiency of their portfolios. From a macroeconomic perspective, there are reasons to believe that the behaviour of cryptocurrencies may vary internationally as studies including Baker, Bloom, and Davis (2016), Wang, Xie, Wen, and Zhao (2019a), Wu, Tong, Yang, and Derbali (2019), and Fang, Bouri, Gupta, and Roubaud (2019) document independence of cryptocurrencies in monetary policy. These studies motivate an investigation into the behaviour of cryptocurrencies relative to African stock market as monetary policy uncertainty is country-specific. From an economic development perspective, overexposure to cryptocurrencies can reduce the “depth” and “width” of national stock markets, as the excessive volatility of cryptocurrency prices translates into riskier and more expensive equity financing for local firms.

The empirical literature also notes that different stock markets exhibit different characteristics in terms of liquidity, efficiency, and integration with other markets and African stock markets have been evidenced to have weak connection with global stock markets (Adjasi and Biekpe, 2006; Emenalo, 2009; Agyei-Ampomah, 2008; Boako and Alagidede, 2015; Peltomӓki, Graham, and Alagidede, 2017; Mensah and Alagidede, 2017). Bouri et al. (2018) also note that the state of an economy′s stock market determines its relationship with cryptocurrencies. Therefore, we cannot assume that the relationship between Bitcoin and global stock indices apply to emerging and frontier stock markets in Africa.

Further, aside from Bitcoin, there are alternative cryptocurrencies including Ripple, Ethereum, Das, Monero, Steller, and Litecoin (hereafter altcoins) which also have anti-government[17] features and attracts the attention of fund managers. Yet, studies on these altcoins and African stock markets are missing from the literature. From a methodological perspective, prior studies employed models that assumed homogeneity in trading by market participants despite the multiscale nature of relationships in financial markets (i.e. relationships are dynamic and changes across time and frequencies). From the foregoing discussion, we ask the question "What is the level of integration between the cryptocurrency and African stock markets across time". There is therefore a motivation to seek answer to this question by modelling the returns of seven leading cryptocurrencies and eight major African stock indices and explore their level of integration. For African economies to benefit from such an international portfolio diversification and investment flows, there is a need to understand the nature and extent of integration between its financial markets and the cryptocurrency markets. This has implications for portfolio selection and regulatory authorities′ design of regulations on market integration.

We contribute to the limited literature on cryptocurrencies and stock markets integration by examining the level of integration between cryptocurrencies and African stock markets. We adopt a multiscale approach of analysis proposed by Morlet, Arens, Fourgeau, and Glad (1982) and

[17] The decentralized nature of cryptocurrencies makes it impossible for any entity or government to control it (Corelli, 2018).

Fern´andez-Macho (2012), the continuous morlet wavelet transform[18], and wavelet multiple correlation and cross-correlation[19] respectively. The methods permit bivariate and multivariate correlations and cross-correlations of asset markets at different time scales which is more indicative of financial markets behaviour. The results from both bivariate and multivariate co-movement of the asset markets suggest a weak integration between African stocks and cryptocurrency markets at higher frequencies which grows stronger at medium frequencies and perfectly integrates at lower frequencies. This finding generally indicates that most stock markets in Africa are extremely vulnerable to discrepancies in the cryptocurrency market from the medium-term and that international investors seeking to hedge their price risk in African stock markets using cryptocurrencies may have to look at the short-time horizon. The results from the lead (lag) association of the markets show that there is no particular cryptocurrency or stock market leader or follower: different markets have the possibility of leading or lagging other markets at varying scales suggesting that the returns of any of the assets markets under consideration can drive price changes in the other markets.

The rests of the chapter are organized as follows. Section 2.1 describes the methodology. Section 2.2 presents the data and statistical properties. Section 2.3 displays the results and discussion on the level of integration of the markets and section 2.4 delineate the conclusion and policy implications.

2.1 Methodology

The empirical literature on integration between financial markets has documented estimation techniques that have been proven to adequately measure integration (co-movement) between financial markets among which are cross-quantilogram, copulas, cointegration and error correction model, GARCH, Morlet wavelet transform, etc. (see Bouri et al., 2019; Mensah and Alagidede, 2017; Boako and Alagidede, 2015; Omane-Adjepong and Dramani, 2017; Adjasi and Biekpe,

[18] The continuous morlet wavelet transform is used to examine the bivariate co-movement of assets across time and frequency using the wavelet power spectrum, cross-wavelet coherency, and phase difference (Morlet, Arens, Fourgeau, and Glad, 1982).

[19] The wavelet multiple correlation and cross-correlation examines the multivariate co-movement of several asset markets across time and frequency (Fern'andez-Macho, 2012).

2006). The bivariate and multivariate wavelet-based techniques proposed by Morlet, Arens, Fourgeau, and Glad, (1982) and Fern´andez-Macho (2012) respectively have been chosen for this study owing to their time-scale decomposition properties which are more indicative of associations in financial markets.

Agents in financial markets have varying decision making timescales and wavelet analysis can be used to explore the association between market returns over different time and frequencies by decomposing a time series into multiple time series associated with varying time and frequencies. As indicated in the works of Crowley (2007) and Skult (2019), wavelets are small wave-like functions which begin at a finite point in time and die out at a later finite point in time. Wavelet can be used to compres (stretch) out the waves in a time series which can be delayed (advanced) in time. This allows an investivation into the influence an event has had at varying scales. We, first of all, present a synopsis of maximal overlap discrete wavelet transform (MODWT) and then move to bivariate and multivariate wavelet techniques.

2.1.1 Maximal Overlap Discrete Wavelet Transform (MODWT)

The maximal overlap discreet wavelet transform simultaneously localizes variations in signal in time and frequency and can be used to decompose the return series of cryptocurrencies and stocks at different timescales (Percival and Walden, 2000). As Ramsey (2002) notes, a function of time $f(t)$ can be represted with scaling function[20] also known as father wavelet (∅), and wavelet function[21] also known as mother wavelet (φ). Father wavelets integrate into one and are used to represent very long scale smooth components of the signal, whereas, mother wavelets integrate to zero and are used to describe deviations that occur in the smooth components. Scaling (smooth) coefficients are generated by father wavelets, whereas mother wavelets give rise to differencing (detail) coefficients.

[20] Scaling function simply means that the wavelet is stretched to capture the low frequency variations in the original time series that are associated with longer time horizons.
[21] Wavelet function simply means that the wavelet is compressed to capture variations in the original time series that are associated with shorter time horizons. In order to capture variations in the original time scales, the wavelet function (the basis function) is stretched to capture variations in the original time scales.

We define father wavelet as:

$$\emptyset_{j,k} = -2^{-j/2}\emptyset\left(\frac{t-2^{jk}}{2^j}\right) \quad with \quad \int \emptyset(t)\,dt = 1 \qquad (2.1)$$

and mother wavelet as:

$$\varphi_{j,k} = -2^{-j/2}\varphi\left(\frac{t-2^{jk}}{2^j}\right) \; with \int \varphi(t)\,dt = 0 \qquad (2.2)$$

The smooth coefficients generated by father wavelet are defined as:

$$S_{J,k} = \int f(t)\, \emptyset_{J,k} \qquad (2.3)$$

and detail coefficients generated by mother wavelet as:

$$d_{j,k} = \int f(t)\, \varphi_{J,k}\; with\; j = 1, \dots J \qquad (2.4)$$

The maximal scale of the former is 2^j, while the detailed are computed from the mother wavelets at all scales from 1 to *J*. The function *f* (.) from the coefficient above is defined as:

$$f(t) = \sum_k S_{J,k}\emptyset_{J,k}(t) + \sum_k d_{J,k}\,\varphi_{J,k}(t) \dots + \sum_k d_{J,k}\varphi_{j,k}(t) \dots + \sum_k d_{1,k}\varphi_{1,k}(t), \qquad (2.5)$$

which is simplified to

$$f(t) = S_J + D_J + D_{J-1} + \dots + D_j + \dots + D_1 \qquad (2.6)$$

with orthogonal components defined as:

$$S_J = \sum_k S_{J,k}\, \emptyset_{J,k(t)} \qquad (2.7)$$

$$D_J = \sum_k d_{J,k}\varphi_{J,k}(t).\, j = 1, \& \dots J \qquad (2.8)$$

The resulting multi horizon (multiresolution) breakdown of $f(t)$ is $\{S_{J,} D_{J-1,\dots,} D_1\}$. D_j calculates the *jth* level wavelet detail related to changes in the series at scale $\lambda_{j\dots}$. S_j denotes cumulative sum of alterations at each level and as *j* increases, S_j becomes smoother and smoother (Gençay et al., 2002). The study employs MODWT to estimate the scaling and wavelet coefficients because the MODWT produces a better resolution since it does not downsample data when generating the coefficients making it easy to compare decomposed and original series (Gençay et al., 2002; Percival and Mofjeld, 1997; Percival, 1995). The MODWT does not restrict the sample size to an integer multiple of 2^{J0} [22] unlike the Discrete Wavelet Transform and can be applied to a time series of any length (Percival and Walden, 2000).

The study applies Daubechies least asymmetric (LA) filter of length eight (LA8) to decompose the series due to its smooth correlation coefficients compared to HAAR wavelet filters which were widely applied in prior studies (Gençay et al., 2002). Cornish et al. (2006) documents that, the coefficients provided by LA (8) filter exhibit better uncorrelatedness across scales than the HAAR filter. In the study, the series were decomposed into wavelet coefficients $D_1 \, to \, D_7$. The detail coefficient D_j provides the resolution of data at scale 2^j to 2^{j+1}. The oscillations of periods of 2–4, 4–8, 8–16, 16–32, 32–64, 64–128, and 128 - 256 wavelet scales represent days $j_1, j_2, j_3, j_4, j_5, j_6, and \, j_7$ respectively. The wavelet smooth S_7 represents the long-term movements.

2.1.2 Continuous Morlet Wavelet Transform (CMWT)

The Continuous Morlet Wavelet Transform (CMWT) by Morlet, Arens, Fourgeau, and Glad, (1982) is used to study the integration of asset markets by determining the wavelet power spectrum and wavelet coherence of two signals. According to Grinsted, Moore, and Jevrejeva (2004), the CMWT allows isolation and identification of periodic signals between localization of time and frequency. The estimates of wavelet coherence, wavelet cross-correlation, and wavelet variance are principal in this study to examine the degree of integration between two time series.

In and Kim (2013), define CWMT as the integral over time of the product of signal and scaled, shifted versions of the wavelet function φ:

$$C(scale, position) = \int_{-\infty}^{\infty} x_t \, (scale, position, t) dt \qquad (2.9)$$

[22] The MODWT employs moving difference, and average operator and keeps the exact number of observations at each wavelet decomposition scale, whiles the DWT uses weighted differences and averages attached pairs of observations.

The CMWT results are several wavelet coefficients C, which are scale and position functions and can contain different values time series x_t. Gabor (1946), Grossman and Morlet (1984), Burrus, Gopinath, and Guo (1998) define the CMWT for two continuous variables as:

$$F(a,b) = \int x_t \, \varphi\left(\frac{t-a}{b}\right) dt \tag{2.10}$$

The Morlet wavelet can be simplified as

$$\varphi(\omega) = \pi^{-1/4} e^{i\omega\psi} e^{-\frac{\omega^2}{2}} \tag{2.11}$$

where, ω is a non-dimensional "time" parameter.

According to Boako and Alagidede (2016), to study co-movement between two variables, a finer version of wavelet coherence, is obtained from cross-wavelet, wavelet power spectrum, and phase difference. The bivariate cross-wavelet transform (XWT) of x_t and y_t defined by Torrence and Compo (1998) can be written as:

$$W^{xy} = W^x W^{y*} \tag{2.12}$$

Where W^x and W^y are the respective wavelet transforms which translate the Fourier co- and quadrature-spectra into frequency-time domain (Roesch and Schmidbauer, 2014). In line with Veleda, Montagne, and Araujo (2012), the wavelet power spectrum describes the local covariance between two time series which is specified as:

$$P^{xy}(s,\tau) = |W^{xy}(s,\tau)| \tag{2.13}$$

where s is the frequency and τ is the time. The wavelet power spectrum is challenged with regards to assessing the degree of integration of the two series which is solved by wavelet coherency (Roesch and Schmidbauer, 2014). As noted by Torrence and Webster (1999), the wavelet coherence is the local correlation coefficient in the time-frequency space similar to the traditional correlation coefficient. We specify the wavelet coherence of two time series x_t and y_t as:

$$R_t^2 = \frac{\left|S(W_t^{xy})(s)\right|^2}{S(s^{-1}\left|W_t^x(s)\right|^2).S(s^{-1}\left|W_t^y(s)\right|^2)} \tag{2.14}$$

where S is a smoothing operator. Wavelet coherence between two time series close to one indicates high level of integration between the series whereas coherence close to zero depicts no integration between the series (see Madaleno and Pinho, 2010a, 2010b; Uddin, Tiware, Arouri, and Teulon, 2013; Ftiti, Tiwari, Belanès, and Guesmi, 2015).

Torrence and Compo (1998), Madaleno and Pinho (2012) define the wavelet phase which shows lead (lag) associations between two time series at different frequencies as:

$$\theta_{xy} = \tan^{-1} \frac{I\left\{W_t^{xy}\right\}}{\Re\left\{W_t^{xy}\right\}}, \theta_{xy} \in [-\pi, \pi] \tag{2.15}$$

Two series are in-phase (out of phase) when an absolute value of θ_{xy} less (greater) than $\pi/2$ and refers to the instantaneous time as time origin and at the frequency under consideration, whereas the arrows of the phase exhibit which series is the leading one in the relationship.

2.1.3 Wavelet Multiple Correlation (WMC) and Wavelet Multiple Cross-Correlation (WMCC)

Fern´andez-Macho (2012) contends that the wavelet multiple correlations and wavelet multiple cross-correlation permit multiple correlations, and multiple cross-correlations in the multivariate set of varying time scales for many cryptocurrencies and stock returns, protect against type 1 errors and avoid spurious correlation.

The WMC and WMCC start with the maximal overlap discrete wavelet transform defined as follows: Let $X_t = x_{1t,} x_{2t,}, ..., x_{nt}$ be a multivariate stochastic process and $W_{jt} = w_{1jt,} w_{2jt,}, ..., w_{njt}$ denote their respective scale λ_j, wavelet coefficients are calculated by applying the MODWT. The wavelet multiple correlations $(WMC)\varphi X(\lambda_j)$ can be defined as a single set of multiscale correlations from equation (2.15) subsequently

$$\varphi X(\lambda_j) = \sqrt{1 - \frac{1}{maxdiag P_j^{-1}}} \tag{2.15}$$

For each λ_j , the square roots of the coefficients of determination of the regression is obtained by the linear combination of $w_{ijt,} i = 1, 2, ..., n$ variables, such that the coefficient of determination is highest. For the regression of a regressand z_t on a set of predictors $z_t \{z_{k,} k \neq i\}$, the coefficient of determination is calculated as $R_i^2 = 1 - 1/\rho^{ii,}\ i^{th}$, a diagonal element of the inverse of the complete correlation matrix P. P_j is the $(n \times n)$ correlation matrix of $W_{jt} = w_{1jt,} w_{2jt,}, ..., w_{njt}$, and maxdiag(.) selects the highest element in the diagonal argument.

The coefficient of determination in a regression theory is the squared correlation between the observed z_i and fitted $\hat{z}_i$ values. Thus, the WMC can also be expressed as equation (2.16), where w_{ij} is chosen to maximise $\varphi X(\lambda_j)$ and $\hat{w}_{ijt}$ are the fitted values in the regression of w_{ij} on the rest of the wavelet coefficients at scale λ_j;

$$\varphi X(\lambda_j) = \frac{Corr(w_{ijt}, \hat{w}_{ijt}) Cov(w_{ijt}, \hat{w}_{ijt})}{\sqrt{Var(w_{ijt}) Var(\hat{w}_{ijt})}} \tag{2.16}$$

Following Gençay et al. (2001), the corresponding wavelet covariances and variances can be estimated as;

$$Var(\tilde{w}_{ijt}) = \bar{\delta}_j^2 = \frac{1}{\tilde{T}_j} \sum_{t=:j-1}^{T-1} \tilde{w}_{ijt}^2 \tag{2.17}$$

$$Var(\hat{\tilde{w}}_{ijt}) = \bar{\vartheta}_j^2 = \frac{1}{\tilde{T}_j} \sum_{t=:j-1}^{T-1} \hat{\tilde{w}}_{ijt}^2 \tag{2.18}$$

$$Cov(\tilde{w}_{ijt}, \hat{\tilde{w}}_{ijt}) = \bar{\gamma}_j = \frac{1}{\tilde{T}_j} \sum_{t=L_j-1}^{T-1} \tilde{w}_{ijt}^2 \hat{\tilde{w}}_{ijt} \tag{2.19}$$

where $\tilde{w}_{ij}$ is such that the regression of the same on the set of regressors $\{\tilde{w}_{kj}, k \neq i\}$ maximises the coefficient of determination, $\hat{\tilde{w}}_{ij}$ denotes corresponding fitted values, and $L_j = (2^j - 1)(L - 1)$ is the number of wavelet coefficients affected by the boundary conditions associated with wavelet filter of length L and scale λ_j whereas $\tilde{T} = T - L_j + 1$ is the number of wavelet coefficients unaffected by the boundary conditions.

In this study, we perform multiple regression analysis to obtain the WMC for cryptocurrencies and African stock returns by regressing the wavelet coefficients of cryptocurrecies on the wavelet coefficients of the stock markets. We estimate seven regressions on each scale and the highest coefficient of determination is obtained. The WMC is the square root of the highest coefficients of determination at each scale.

Finaly, the wavelet multiple cross-correlation is computed by allowing a lag τ between observed and fitted values of the variables at each scale and can be calculated as;

$$\varphi X,\tau(\lambda_j) = \frac{Corr(\tilde{w}_{ijt},\hat{\tilde{w}}_{ijt+\tau})Cov(\tilde{w}_{ijt},\hat{\tilde{w}}_{ijt+\tau})}{\sqrt{Var((\tilde{w}_{ijt})\, Var(\hat{\tilde{w}}_{ijt+\tau})}} \tag{2.20}$$

In the case of cryptocurrencies and African stock returns, we calculate the WMCC by allowing thirty lags between the fitted and observed values of the assets returns. For seven decomposition scales, there is one curve with WMCC estimates formed by linearly combining the wavelet coefficients at each of the wavelet scales of the assets markets.

The confidence intervals is constructed on the assumption that $X_1 \ldots . X_T$ is the realisation of X in the estimation of wavelet multiple correlation and cross-correlation and hence for $X(\lambda_j)$ in (2.15) then $\tilde{z}_j \sim F\aleph(z_j, (T/2^j - 3)^{-1})$ where $z_j = arctan\,h\,(\varphi X(\lambda_j))$, $\tilde{z}_j = arctan\,h\,(\tilde{\varphi} X(\lambda_j))$, and $F\aleph$ symbolise the folded normal distribution. Therefore, an approximate $(1-\alpha)$ CI for the true value of WMC is given by $CI_{(1-\alpha)}(\varphi X(\lambda_j)) = tanh\left[\tilde{z}_j - \frac{c_2}{\sqrt{T/2^j-3}}; \tilde{z}_j + \frac{c_1}{\sqrt{T/2^j-3}}\right]$ where the $F\aleph$ critical values c_1, c_2 are such that $\phi(c_1) + \phi(c_1 - 2z^0) = 1 - \alpha/2$ and $\phi(c_2) + \phi(c_1 - 2z^0) = 2 - \alpha/2$ with $\phi(.)$ as the standard Gaussian probability distribution function and $tanh(z^0) = \varphi_X^0(\lambda)$ as the value of some wavelet multiple correlation as set under certain null hypothesis of no correlation. For a complete reading on DWT, CMWT, MODWT, WMC, and WMCC, (see Fern´andez-Macho, 2012; Carmona et al., 1998; In and Kim, 2013; Tiware et al., 2013; Nason, 2010).

2.2 Data description and statistical properties

To investigate the level of integration between cryptocurrencies and African stock markets, we apply bivariate (cross-wavelet coherency and phase difference) and multivariate (wavelet multiple correlation and wavelet multiple cross-correlation) to seven large cryptocurrencies: Bitcoin (BTC), Ethereum (ETH), Litecoin (LTC), Das (DASH), Ripple (XRP), Steller (XLM), and Monero (XMR) and eight African stock market indices: Egypt (EGX30), South Africa (JSE), Nigeria (NSE), Mauritius (SEM), Kenya (Nairobi.SE), Ghana (GSE), Tunisia (Tunindex), and Morocco (CSE). The cryptocurrencies and stock markets sampled are based on market capitalization and trading volume and can proxy for cryptocurrencies and stock markets in Africa respectively. Daily closing market indices for the period 10th August 2015 to 18th February 2019 are gleaned from Thomson Reuters Datastream and CoinMarketCap and expressed in a common currency (USD) to ease comparison and remove exchange rate noise. This practice has been justified in international financial market research (Pukthuanthong and Roll, 2009).

The availability of Ethereum data determines the start date of the period of analysis. Ethereum, which is the second-largest cryptocurrency market, started trading on 7th August 2015. We calculate Monday-to-Friday returns for cryptocurrencies due to stocks not traded on weekends. We remove non-synchronous data points to prevent the problem of underestimation of true correlations as did Martens and Poon (2001), Das and Kannadhasan (2018), and Yermack (2015). After matching the daily observations of the seven cryptocurrencies with the eight African stock indices, there were 822 observations. The availability of cryptocurrency price data constrained the period of analysis and the number of observations in this study. Taking the first differences of logarithm, the daily price data were converted to daily returns.

The summary statistics of the assets returns are displayed in Table 2.1. Cryptocurrencies show higher average returns and standard deviation relative to stocks. The average return of all cryptocurrencies is positive except Ethereum. The average stock return of Egypt (EGX30), Nigeria (NSE), Tunisia (Tunindex), and Ghana (GSE) is negative whiles that of South Africa (JSE), Mauritius (SEM), Kenya (Nairobi.SE), and Morocco (CSE) is positive. The largest standard deviation of Kenya (Nairobi.SE) implies that it is the most volatile market of the panel whiles Mauritius (SEM) is the least volatile market with the lowest standard deviation. Bitcoin, Ethereum, Egypt, Ghana, South Africa, Nigeria, and Mauritius are negatively skewed suggesting the domination of negative returns relative to positive returns across the markets. All the return series show leptokurtosis, heavy-tails and high peaks indicating asymmetry and non-normality. The Shapiro-Wilk tests confirms the non-normality in the assets returns by strongly rejecting the null hypothesis of normaly distributed returns. Further, the pictorial representation of cryptocurrencies and African stocks returns in Figure 2.1 in the Appendices exhibit fat tails, volatility clustering, and asymmetry suggesting nonlinearity. These features of the assets justify the use of wavelet techniques to model their returns and examine their level of integration across time.

Table 2. 1: Summary statistics of cryptocurrencies and African stock returns

Statistics	BTC	ETH	LTC	XRP	DASH	XLM	XMR
Observ.	822	822	822	822	822	822	822
Mean	0.0025	-0.0002	0.0005	0.0029	0.0023	0.0053	0.0017
Minimum	-0.2075	-0.3331	-0.3952	-0.6163	-0.2432	-0.3532	-0.2932
Maximum	0.2251	0.1119	-0.3952	1.0274	0.2877	0.9956	0.4516
Std. Dev.	0.0419	0.0197	0.0608	0.0692	0.0594	0.0946	0.0708
Skewness	-0.0875	-6.4865	1.2271	4.5801	0.3659	2.2342	0.6293
Kurtosis	4.9794	108.85	12.9304	75.398	3.5393	19.1241	4.9999
Normtest.W	0.907	0.6612	0.8383	0.5772	0.9418	0.851	0.937
Normtest.p	0	0	0	0	0	0	0

Statistics	EGX30	NSE	JSE	Nairob.SE	Tunindex	CSE	GSE	SEM
Observ.	822	822	822	822	822	822	822	822
Mean	-0.002	-0.0001	0.0002	0.0011	-0.0001	0.0001	-0.0003	0.0002
Minimum	-0.3331	-0.2323	-0.0734	-8.4708	-0.0561	-0.0206	-0.0503	-0.0428
Maximum	0.1119	0.0773	0.062	7.9933	0.0586	0.0376	0.0383	0.0236
Std. Dev.	0.0197	0.0167	0.0165	0.7680	0.0103	0.0068	0.0104	0.0056
Skewness	-6.4865	-3.905	-0.2769	0.2127	0.2395	0.3898	-0.3745	-0.3888
Kurtosis	108.85	52.4353	1.1249	97.8602	4.9973	2.3438	2.5383	6.2217
Normtest.W	0.6612	0.7571	0.9878	0.0935	0.9271	0.971	0.9566	0.9341
Normtest.p	0	0	0	0	0	0	0	0

Note: *Normtest.W designates Shapiro-Wilk test of normality. Observ.-observation and Std. Dev.-standard deviation. BTC-Bitcoin, ETH-Ethereum, LTC-Litecoin, XRP-Ripple, DASH-Das. XLM-Steller, XMR-Monero, EGX30-Egypt, NSE-Nigeria, JSE-South Africa, Nairobi.SE-Kenya, Tunindex-Tunisia, CSE-Morocco, GSE-Ghana, and SEM-Mauritius.*

2.3 Results and discussion

To investigate the level of integration between cryptocurrencies and African stock markets, we, first of all, paired each cryptocurrency with each African stock returns and examined their bivariate co-movement using cross-wavelet coherency and phase difference. We then combined all seven cryptocurrencies and eight African stocks returns and examined their multivariate correlation and cross-correlation using wavelet multiple correlation (WMC) and wavelet multiple cross-correlation (WMCC).

The maximal overlap discrete wavelet transform (MODWT) with Daubechies least asymmetric (LA) wavelet filter of length 8 was used to decompose cryptocurrencies and African stocks returns into different time scales and compute the smooth and detail coefficients. We choose MODWT over Discrete Wavelet Transform (DWT) because MODWT[23] produces a better resolution when generating the coefficients. Given a data points of 822 and the highest scales number of feasible decomposition of [Log_2 (N)][24], where N is the number of observations, we can decompose the assets returns into 9 details and 1 smooth component. Table 2.2 shows the time interpretation of different wavelet scales. The results and discussion for bivariate and multivariate co-movement of cryptocurrencies and African stock returns are presented in sections 2.3.1 and 2.3.2 respectively.

Table 2. 2: Time interpretation of Wavelet Scales

Wavelet Scales	Time interpretation	Time period
j =1	2-4 days	Intraweek
j =2	4-8 days	Weekly
j =3	8-16 days	Fortnightly
j =4	16-32 days	Monthly
j =5	32-64 days	Monthly to quarterly
j =6	64-128 days	Quarterly to biannual
j = 7	128– 258 days	Biannual to annual
j = 8	>256 days	More than one year

[23] An advantage of using MODWT is that, it does not restrict the sample size to an integer multiple to 2^{J0} unlike the Discreet Wavelet Transform and can be applied to a time series of any length (Percival and Walden, 2000). The MODWT produces a better resolution since it does not downsample dat when generating the scaling and wavelet coefficients and this makes it easy to compare decomposed series to original series (Gençay et al., 2002).
[24] $\text{Log}_2(822) = 9.7$

2.3.1 Bivariate co-movement between cryptocurrencies and African stocks returns

The cross-wavelet coherency results for the 56 pairs of seven cryptocurrencies and eight African stock returns are reported in Figure 2.2 (a-g). The plots explain the pairwise integration of the asset markets in the time-frequency space. We used wavelet coherency to measure the local correlation between the asset pairs, and phase difference to show the lead (lag) causal association between the pairs of assets markets. For the pairwise integration, we construct the cross-wavelet coherency from frequencies 4 days to 2048 days and choose three cycles to represents short-, medium-, and long-time movement of the markets as used by Boako and Alagided (2015). Specifically, the first cycle on the lower scales (4 – 16 days) is the higher frequencies and denotes short-term investment horizon. The second cycle on the middle scales (16 – 64 days) is the medium frequencies and indicates medium-term horizon. The third cycle on the long scale (> 64 days) is the lower frequencies and shows the long-term horizon as used by (Liow, Zhou, Qiang, and Huang, 2017; Das and Kannadhasan, 2018; Owusu-Junior, Tweneboah, and Adam, 2019).

The frequencies are depicted on the vertical axis of the plots, and the horizontal axis exhibit the time period from 2015 to 2019 sampled for the study. In each plot, the white contour lines inside the cone of influence show the 5% significance level estimated from Monte Carlo simulations. The lighter shade around the cone of influence depicts the boundary effects such that the region outside the boundary is statistically insignificant. This region shows faint red colour and should be interpreted with caution due to edge effect suffered from continuous wavelet transform analysis. The colour codes from red (high coherency, close to one), to blue (low coherency, close to zero) indicate a high degree of integration to a weak level of integration of the assets pairs respectively. A white contour with red colour at the top (bottom) of a plot shows strong integration at high (low) frequencies. A white contour with red colour at the left (right) hand of a plot exhibits strong level of integration at the start (end) of the sample period.

The arrows in the plots indicate the phase difference by showing the lead (lag) relationship and the direction of relationship between the series. The series are in-phase indicating positive correlation when the arrows point to the right (→). The first series leads the market when the arrows point to the right and up but when the arrows point to the right and down the first series lags the market.

The series are out of phase suggesting negative correlation when the arrows point to the left (←). Arrows that point to the left and up depicts that the first series is lagging the market whiles arrows that point to left and down means the first series is leading the market (see Liow, Zhou, Qiang, and Huang, 2017; Das and Kannadhasan, 2018; Owusu-Junior, Tweneboah, and Adam, 2019; Roesch and Schmidbauer, 2014).

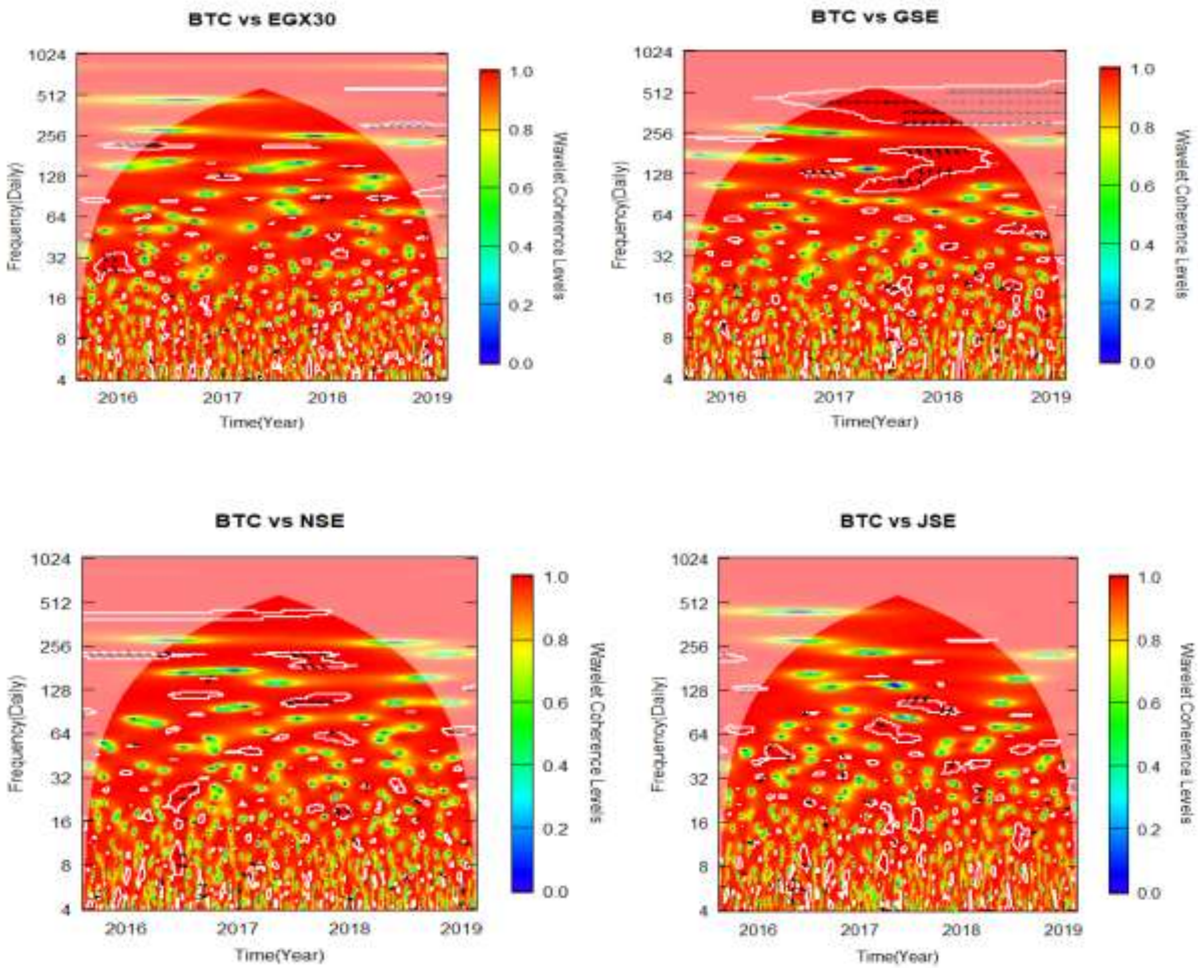
In general, the bivariate co-movement of cryptocurrencies and African stock returns displayed in Figure 2.2 (a-g) show a high level of integration between the markets as the red colour dominates all significant regions with the finest and stronger coherences occuring at the medium and long-terms. The co-movement relationship mainly reflects the long-term fundamental connections among the asset markets. This affirms the fundamentals-based theory on co-movement which states that common factors in returns including industry and strong market level factors in cashflow news causes stronger market integration in the long-term. The coherences that fell outside the cone of influence are not significant and therefore are to be ignored since they do not make any meaningful inferences. The phase difference arrow vectors are generally heterogenous across time since arrow vectors regularly points to right and left, and up and down indicating non-homogeneous relationship between the markets across time. We find the hedging abilities of the cryptocurrencies to be contingent on frequencies showing different cryptocurrencies as hedges for African stocks at different frequencies. This suggest that a study on co-movement without considering the scale effect is insufficient. We analyze individual cryptocurrency-stock pairs integration in sections 2.3.1.1 to 2.3.1.7. The name of the series on top of the plots in Figure 2.2 (a-g) shows the order of the series.

2.3.1.1 Bitcoin-Stock pairs

The coherence plots for Bitcoin-African stock pairs in Figure 2.2a show stronger co-movement of the markets from the medium-term with the stock markets significantly leading Bitcoin market except for South Africa (JSE) and Tunisia (Tunindex) stock markets as depicted by the phase difference arrow vectors. Specifically, we can observe from the plot that BTC-EGX30 pair is in-phase with EGX30 leading BTC at medium scales 16 to 40 days from 2015 to early 2016. The BTC-GSE duo exhibits a convincing GSE lead out of phase at long scales of 64 to 256 bands from the middle of 2016 to early 2018. In the BTC-NSE pair, NSE leads out of phase in the high 128 to 256 band and in-phase at scales 64 to 128 bands from the middle of 2017 to 2018. There is a conclusive in-phase BTC lead in the high 64 to 128 bands from 2017 to 2018 for the BTC-JSE pairs. In the case of BTC-Tunindex pair, BTC leads out of phase in the medium 20 to 64 bands and high 128 to 256 bands from early 2017 to the middle of 2018. Amidst the populated region of BTC-SEM duo, SEM leads in-phase in the medium 32 to 64 bands in 2017 and out of phase in the high 100 to 195 bands from 2015 to middle of 2016. The pairs BTC-CSE show CSE lead in-phase in the low 8 to 16 bands in 2017 and middle 32 to 64 bands from late 2017 to early 2018. Lastly, the high 120 to 150 band in 2016 depicts Nairobi.SE lead out of phase in BTC-Nairobi.SE duo.

The coherency results for the integration of Bitcoin with African stock markets indicate that Bitcoin (BTC) is highly integrated with Ghana (GSE), Nigeria (NSE), South Africa (JSE), and Kenya (Nairobi.SE) markets in the long-time horizon. Bitcoin is highly integrated with Tunisia (Tunindex), and the stock market of Mauritius (SEM) from the medium to long-term horizons. Bitcoin has high integration with Casablanca stock market (Morocco) in both short and long-term and with Egypt (EGX30) in the medium-term horizon. This strong time-varying integration between Bitcoin and African stock markets may be explained by the aggressive pursuit of African economies (i.e. trade openness, liberalization of markets, macroeconomic condination between countries etc) to ensure stronger ties of African financial markets with global financial markets (see AfDB, 2015). This results could also be due to a close economic tie between the cryptocurrency and African stock markets, because the long-term economic indicators are the major contributors of security market changes (Pretorius, 2002; Bracker et al, 1999).

The phase difference arrow vectors suggest positive effects of Bitcoin on Egypt in the medium-term, South Africa in the long-term, and Morocco in both short and long-terms. Adverse effects are visible for Tunisia from medium to long-term and in the long-terms of Kenya and Ghana stock markets. We find both positive and negative impacts in the long-term of Nigeria, but the medium (positive) and long (negative) terms of Mauritius stock market. These findings suggest that Bitcoin can be a hedge against extreme stock price movements in Ghana (long-term), Nigeria (long-term), Tunisia (from medium to long-term), Mauritius (long-term), and Kenya (long-term). We find the stock markets leading Bitcoin across the pairs except for South Africa and Tunisia stock markets where Bitcoin was in lead and thus volatilities of these stock markets affect the price of Bitcoin. These lead (lag) associations in the inter-market volatility correlations between Bitcoin and African stocks may enhance opportunities for arbitrage and diversification for international investors as investors will simultaneously buy and sell assets in different markets to take advantage of differing prices for the same asset as noted in the works o Madaleno and Pinho (2012).



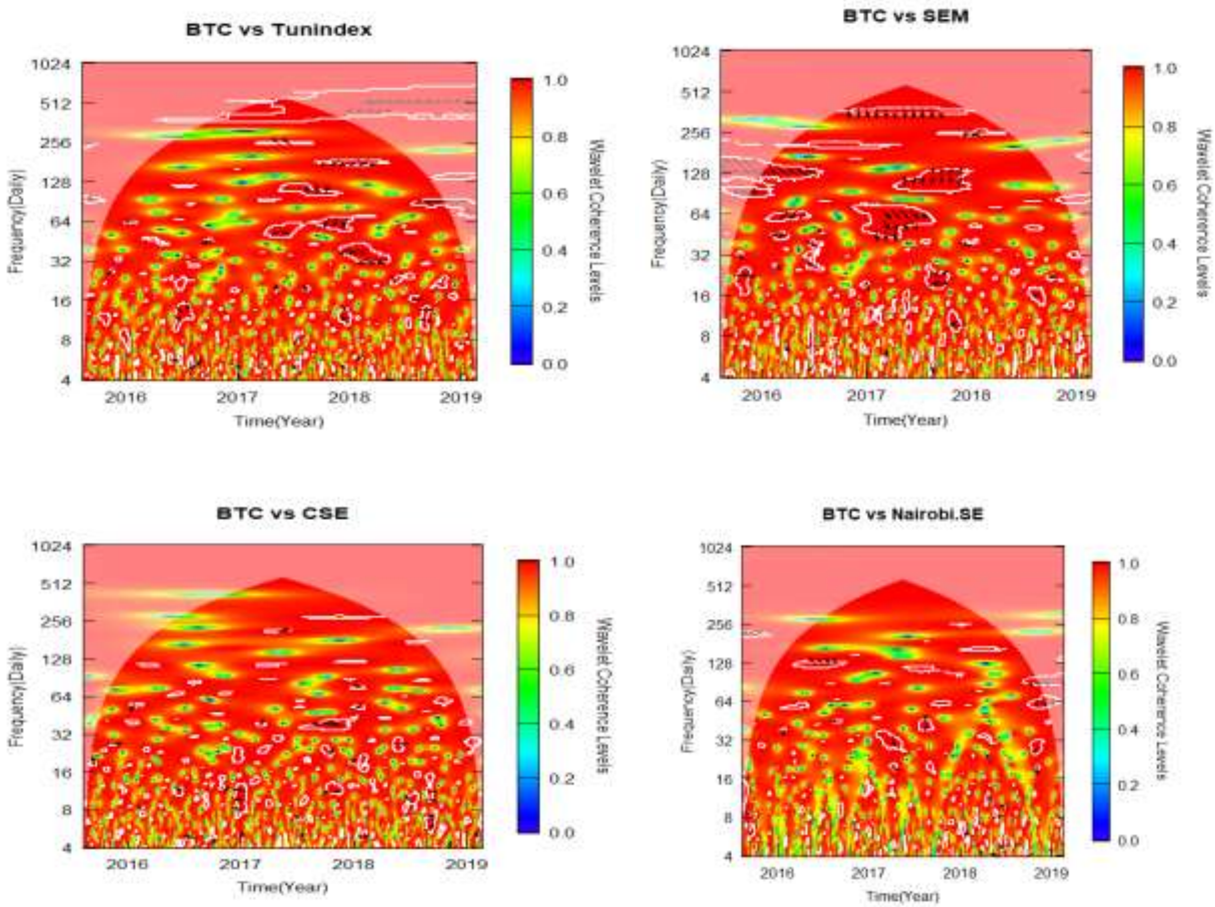


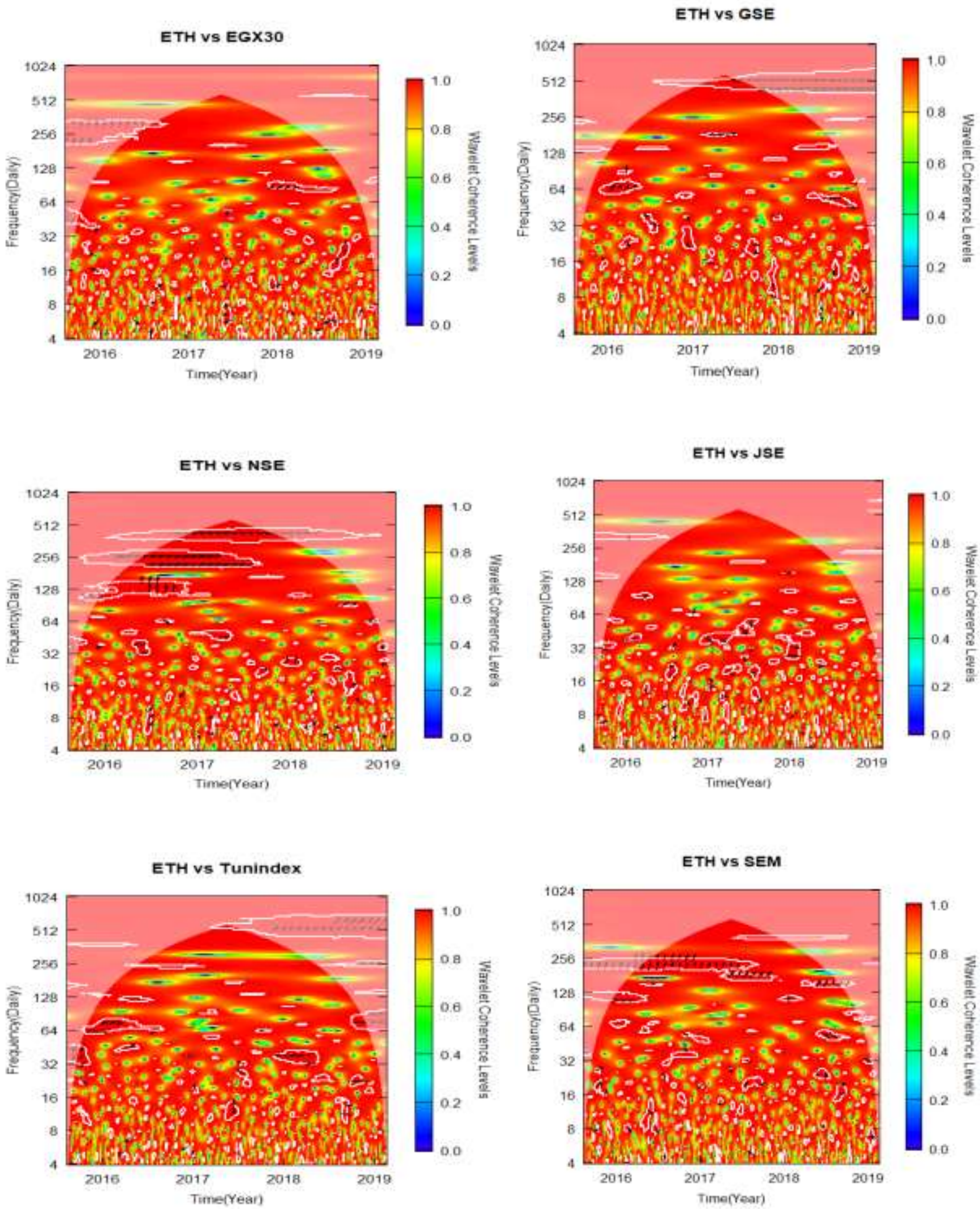
Figure 2.2 a: Bitcoin-African stocks cross-wavelet coherency

2.3.1.2 Ethereum-Stock pairs

The coherency plots in Figure 2.2b show the level of integration between Ethereum-African stock pairs and generally suggests stronger integration from the medium-term except for Nigeria stock market which is decoupled from Ethereum. Ethereum leads all stock markets except for South Africa, Morocco, and Kenya stock markets. As depicted in the plots, the ETH-EGX30 pair is out of phase with Ethereum lead in the high 64 to 128 bands in 2018. ETH-GSE pair shows an in-phase Ethereum lead in the high 64-day scale in early 2016. The ETH-NSE duo depicts no phase difference in the band 128 to 512 for mid-2016 to mid-2017. JSE leads in-phase in the middle 32 to 64 bands in 2017 for the ETH-JSE pair. There is Ethereum lead out of phase in the medium to high 32 to 90 bands from 2015 to early 2016 for the duo ETH-Tunindex. There are Ethereum leads in-phase at the long scales of 180 to 256 days for mid-2016 through to late 2018, and in 128 to 150 bands in late 2018 for the pairs ETH-SEM. Early 2017 and in the low 8 to 16 bands exhibit ETH lag in-phase for the ETH-CSE duo. In the case of ETH-Nairobi.SE pair, Ethereum lags out of phase in 2017 at the medium scales of 16 to 32 days and in-phase in the high of 100 to 128 days in 2016.

The findings of the bivariate co-movement of Ethereum and African stocks indicates that there is a strong level of integration of Ethereum (ETH) with Egypt, Ghana, South Africa, and Mauritius stock markets in the long-term. This can be due to the strong fundamental linkages between the assets markets including market liberalization, technological advances, removal of statutory controls, and volatility (Aamir and Ali Shah, 2018). The medium and long-terms of Kenya and Tunisia stocks show high integration with Ethereum. The short-term of Morocco stocks depict strong correlation whiles South Africa is highly integrated with Ethereum in the medium-term. This high degree of integration of the markets reflects the efforts at integrating African markets with regional and global markets over the past three decades which has been realized through market openness, intra-regional trade and advancement in total economic integration (Mougani, 2014). However, we find Nigeria stock market segmented from Ethereum which may reflect market imperfections such as illiquidity, political risk, high transaction cost, exchange rate exposure, high inflation, and lack of transparency leading to low levels of participation of foreign investors in the Nigeria stock market.

The homogeneous arrow vectors of phase difference indicate that Ethereum has positive associations in the long-term of Ghana, and Mauritius, but in the medium and short-terms of South Africa, and Morocco respectively. Nevertheless, the heterogeneous arrow vectors depict negative connections in the long-term of Egypt, and in both medium-, and long-terms of Tunisia. There are both negative and positive connections of Kenya stocks with Ethereum in the medium and long-term respectively. We find Nigeria stocks to be uncorrelated with Ethereum. This finding is indicative that Ethereum has hedging properties against stock market volatilities for Egypt, and Nigeria in the long-term, from medium-, to long-term for Tunisia, and in the medium-term horizon for Kenya stocks. We observe from the lead-lag association of the asset markets that Ethereum leads Egypt, Ghana, Tunisia, and Mauritius stock markets but lags South Africa, Morocco, and Kenya stock markets. Ethereum and Nigeria stock market are at par with neither lead nor lag. This suggests that the market volatility of Ethereum impacts all the stock markets except South Africa, Morocco, and Kenya stock markets where the reverse is true and that international investors may enhance arbitrage opportunities.



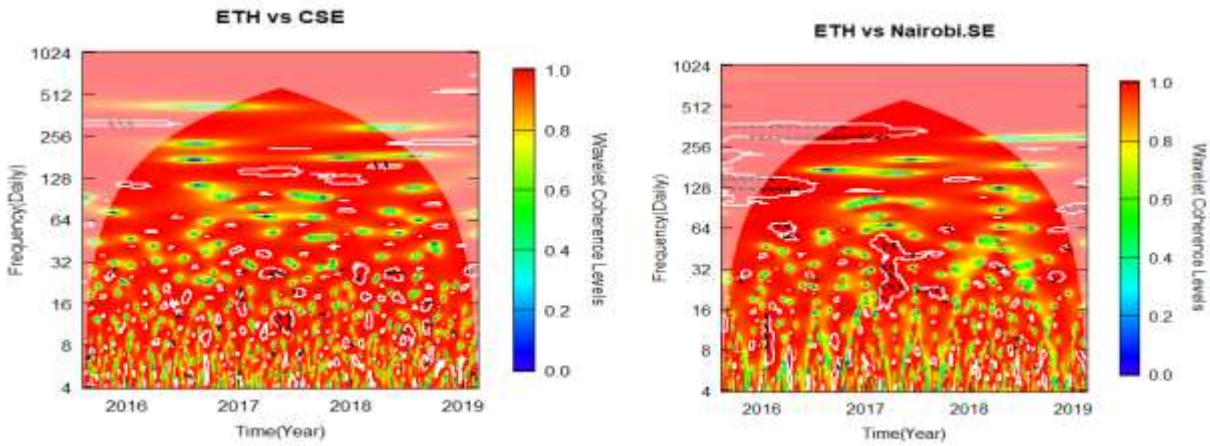
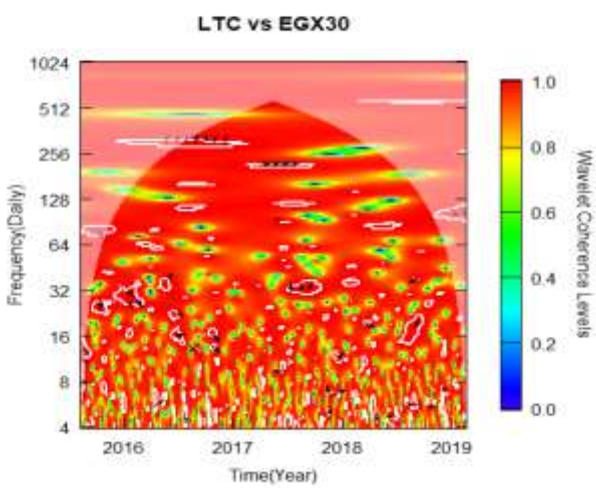


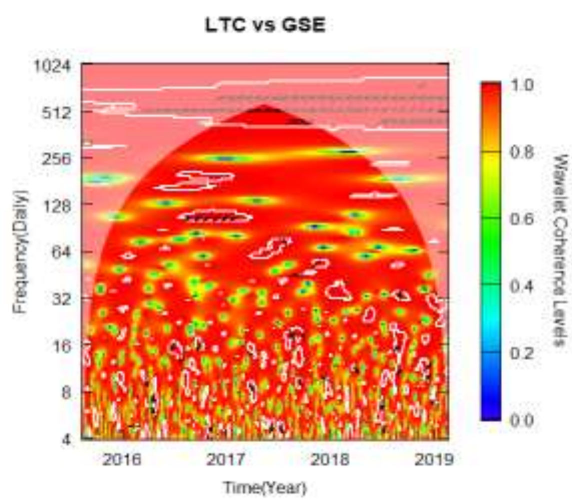
Figure 2.2 b: Ethereum-African stocks cross-wavelet coherency

2.3.1.3 Litecoin-Stock pairs

In line with Bitcoin and Ethereum stock pairs, the coherence plots for Litecoin-Stock pairs depicted in Figure 2.2c show the usual stronger association from the medium-term except for Johannesburg stock market which is uncorrelated with Litecoin. The phase relationship show Litecoin as the leading series except for Casablanca and Nairobi stock markets. Specifically, in the LTC-EGX30 pair, LTC leads in-phase at high scales 256 to 512, 250 to 256, and middle scale of 32 band from mid of 2016 to mid-2017 but lags in the medium of 16 to 32 bands from 2015 to late 2016. LTC leads anti-phase at high scales 64 to 128 from late 2016 to early 2017 in the LTC-GSE pair. The LTC-NSE pair shows LTC in-phase lead from medium 28 to 80 band in 2016 but anti-phase in the high 128days in 2017. There is no phase difference for LTC-JSE duo which indicates that the two markets are decoupled. There is LTC lead anti-phase in 2018 at medium of 32 to 64 bands in the pairs LTC-Tunindex. There is also LTC lead in-phase from 2017 to early 2019 in the bands of 20 to 256 for LTC-SEM pairs. CSE is the leading series in the LTC-CSE pair. The series are anti-phase (128 days) and in-phase (64 days) for 2017 and 2016 respectively. We also see Nairobi.SE in lead (in-phase) of LTC in the high 256 to 512 in 2016 in the LTC-Nairobi.SE pair.

The coherence for Litecoin-African stock pairs suggests strong integration between the markets from the medium to long-term as observed in Bitcoin and Ethereum stock pairs generally indicating that stock markets in Africa are extremely exposed to cryptocurrency market fluctuations in the long-term. This indicates that the gain from cryptocurrency diversification is relatively lower and less significant in the long-term. Specifically, the vector arrows in the phase difference indicate that Litecoin has positive effects on Egypt and Mauritius stock markets in the long-term, negative effects on Tunisia in the medium-term but long-term for Kenya and Ghana, both positive and negative effects in the medium-term of Morocco, but positive (medium-term) and negative (long-term) of Nigeria. Interestingly, we find no association between Litecoin and Johannesburg stock market even though the Johannesburg stock market has achieved higher liquidity and is strongly integrated with global markets. This indicates that Litecoin has hedging benefits in the long-term for Ghana, Nigeria, and Kenya stocks but medium-term for Tunisia and Morocco stock markets. We also observe Litecoin as the leading series in all stock markets except for Morocco and Kenya stock markets implying that changes in the price of Litecoin lead to changes in African stock prices except for Morocco and Kenya stocks where the reverse applies.





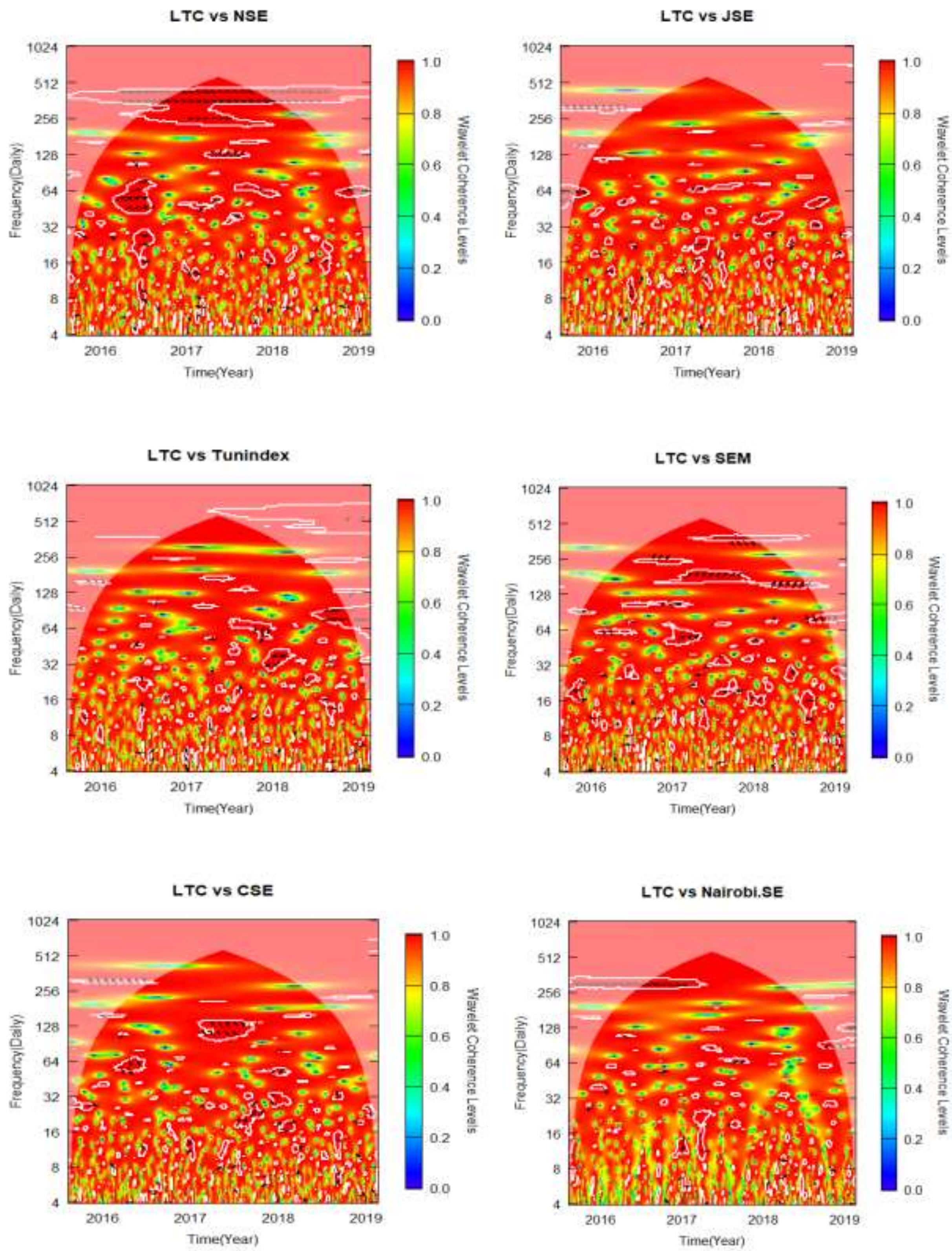
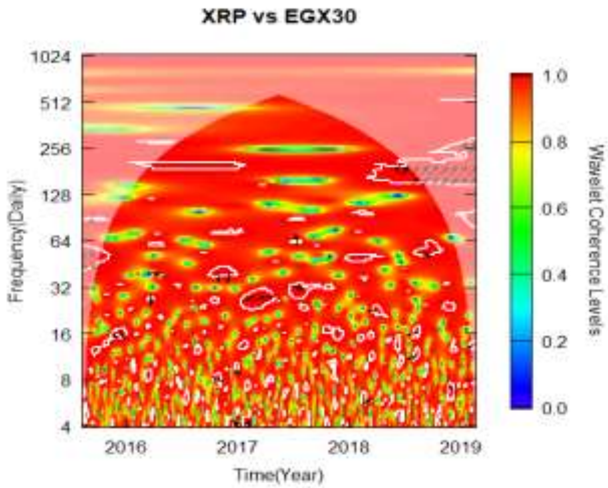


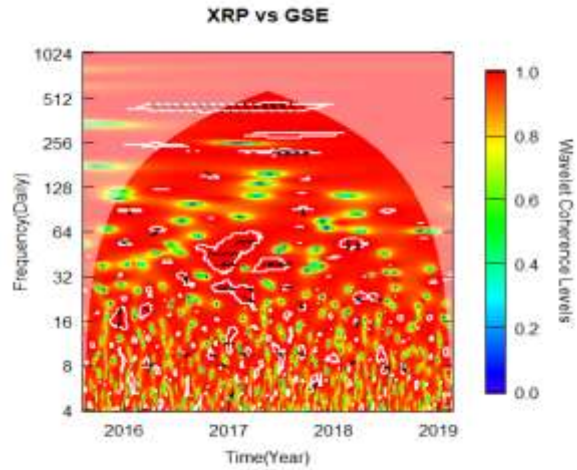
Figure 2.2 c: Litecoin-African stocks cross-wavelet coherency

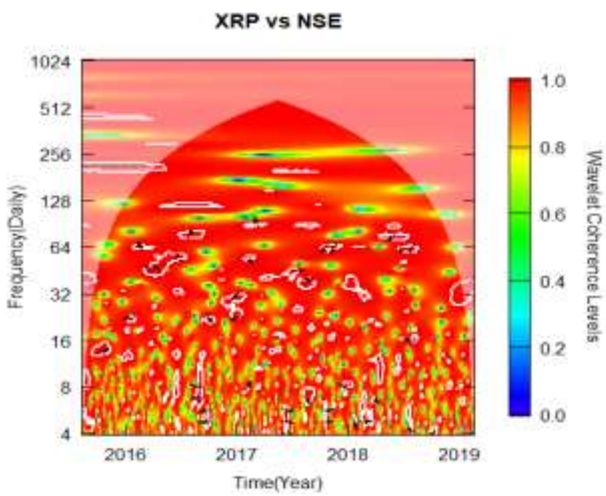
2.3.1.4 Ripple-Stock pairs

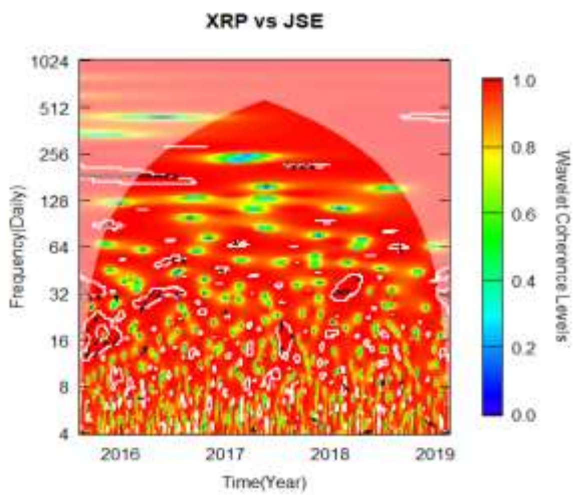
The coherence and phase difference of Ripple and African stock returns in Figure 2.2d depicts high connections in the medium and long-terms with Ripple having negative effects on all stock markets except for Egypt which shows positive efffect. Mauritius stock markets is segmented from Ripple. In particular, the interaction of the time series of XRP-EGX30 depicts XRP lead in-phase in the medium 16 to 32 band in 2017. GSE leads anti-phase in the high 256 to 512 band in 2017 for the XRP-GSE pair. Most of the scattered arrows in XRP-NSE pair are anti-phased and show NSE lead out of phase in the medium 32 to 64 band in 2016. The pair XRP-JSE shows that JSE lags the market anti-phase from the low 10 days to medium 32 days from 2015 to mid-2016, but in-phase at 32 day scale in 2018. Tunnindex leads out of phase in the band 250 to 256 in 2018 in the XRP-Tunindex pair. The pair XRP-SEM show no obvious phase difference. XRP leads CSE out of phase in XRP-CSE pair at medium scales of 32 to 64 in 2017. Lastly, the Nairobi stock market lags out of phase at long scales 64 to 128 in 2016 for the XRP-Nairobi.SE pair.

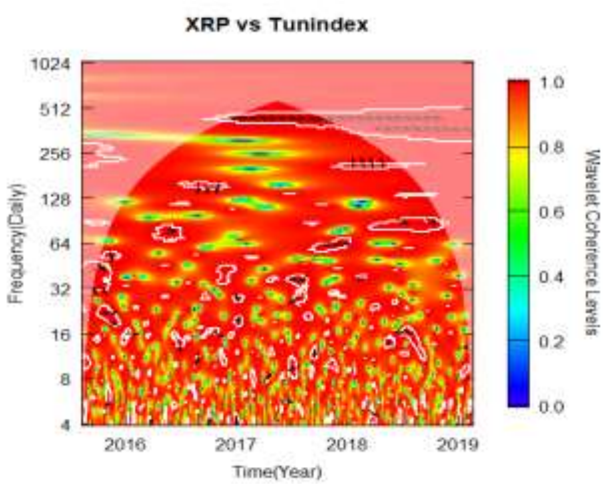
The findings suggest strong coherence for Ripple-African stocks returns in the medium-term (Egypt, Nigeria, South Africa, and Morocco) and long-term (Ghana, Tunisia, and Kenya) which implies that Ripple is highly integrated with African stock market from the medium-term. As discussed by Pretorius (2002), this finding could be due a close economic tie among the markets since long-term economic indicators are the main contributors of strong asset markets integration. We observe from the phase difference arrow vectors that the price of Ripple has inverse effects on all stock markets from the medium to long-term except for Egypt (positive) and Mauritius (no association). Clearly, except for Egypt stock market, Ripple can hedge fluctuations in all the other stock markets. Ripple leads Egypt, South Africa, Morocco, and Kenya stock markets but lags Ghana and Tunisia stock markets. There is neither lead nor lag between Ripple and Mauritius stock market showing SEM as the isolated African stock market. From these results, we can say that fluctuations in Ripple prices affect all the stock markets except Ghana, Tunisia, and Mauritius which shows the reverse.

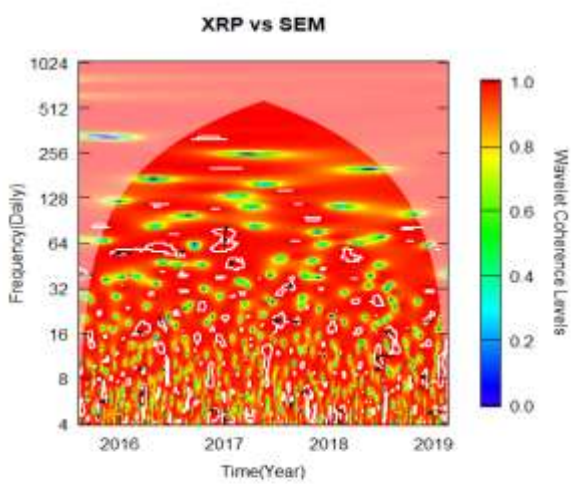

XRP vs EGX30
Frequency(Daily)
1024
512
256
128
64
32
16
8
4
2016
2017
2018
2019
Time(Year)
Wavelet Coherence Levels
1.0
0.8
0.6
0.4
0.2
0.0


XRP vs GSE
Frequency(Daily)
1024
512
256
128
64
32
16
8
4
2016
2017
2018
2019
Time(Year)
Wavelet Coherence Levels
1.0
0.8
0.6
0.4
0.2
0.0


XRP vs NSE
Frequency(Daily)
1024
512
256
128
64
32
16
8
4
2016
2017
2018
2019
Time(Year)
Wavelet Coherence Levels
1.0
0.8
0.6
0.4
0.2
0.0


XRP vs JSE
Frequency(Daily)
1024
512
256
128
64
32
16
8
4
2016
2017
2018
2019
Time(Year)
Wavelet Coherence Levels
1.0
0.8
0.6
0.4
0.2
0.0


XRP vs Tunindex
Frequency(Daily)
1024
512
256
128
64
32
16
8
4
2016
2017
2018
2019
Time(Year)
Wavelet Coherence Levels
1.0
0.8
0.6
0.4
0.2
0.0


XRP vs SEM
Frequency(Daily)
1024
512
256
128
64
32
16
8
4
2016
2017
2018
2019
Time(Year)
Wavelet Coherence Levels
1.0
0.8
0.6
0.4
0.2
0.0

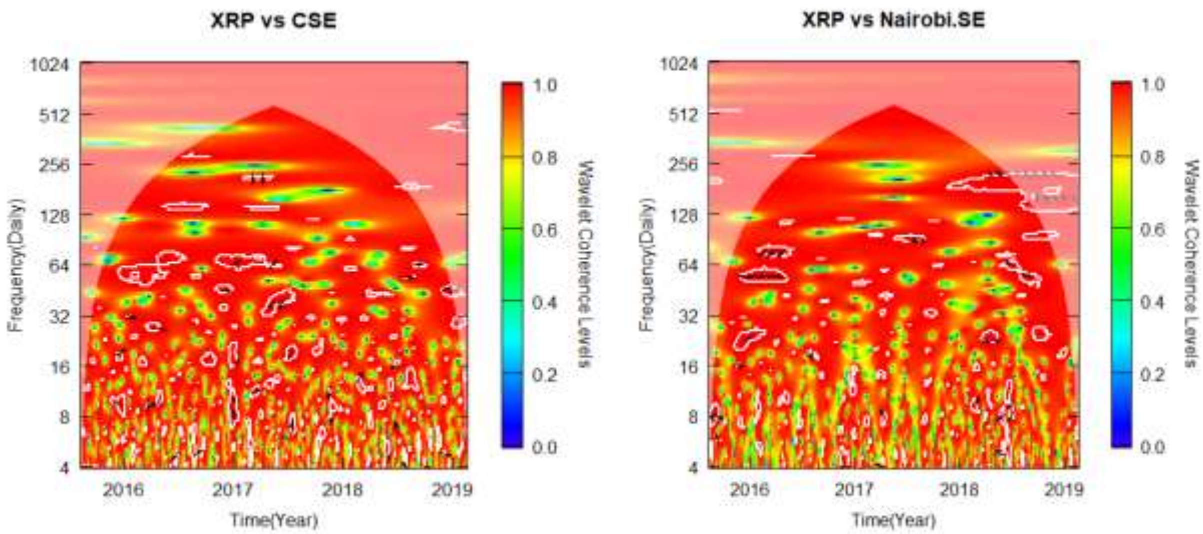
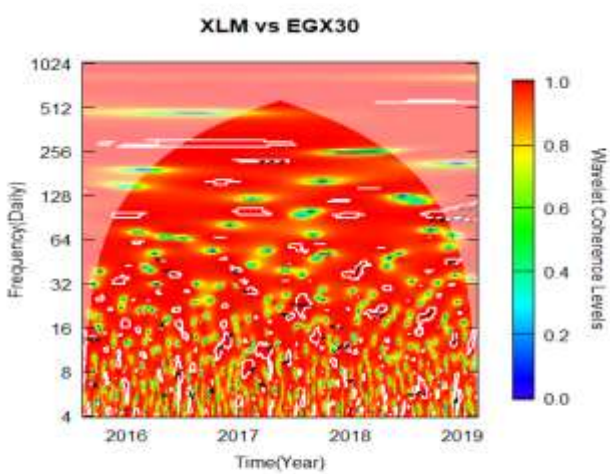


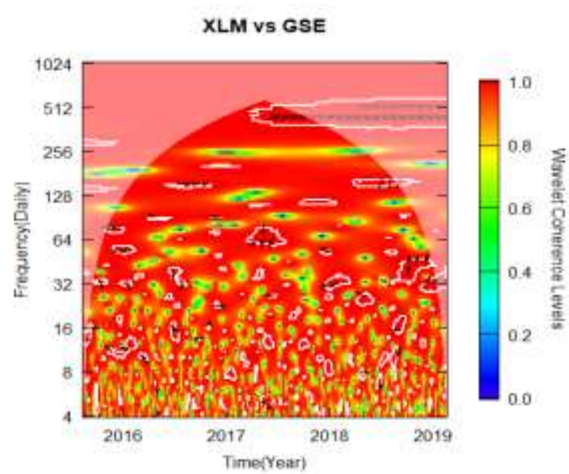
Figure 2.2 d: Ripple-African stocks cross-wavelet coherency

2.3.1.5 Steller-Stock pairs

The interaction between Steller and African stock returns displayed in Figure 2.2e generally suggest strong coherency across time showing a time-varying lead (lag) effects except for Egypt and Nigeria stock markets which are isolated from Ripple. In particular, the XLM-EGX30 plot shows no phase difference in any of the scales and period. There is a clear Steller lead out of phase (64-80 band) in 2017 and in-phase (32–64 band) in late 2018 in the XLM-GSE plot. Similar to XLM-EGX30 pair, the XLM-NSE pair also shows no phase difference in the bands 120 to 512. Johannesburg stock market lead anti-phase in the high 64 to 128 band in 2016 for the pair XLM-JSE. For XLM-Tunindex pair, Tunindex leads in-phase at 64 scale in 2015 but lags out of phase at 32 to 64 scales between 2017 and 2018. The plot for XLM-SEM show that SEM leads Steller in-phase (2017) but anti-phase (2018) in the medium 32 to 64 band but lags in-phase in the upper bands 128 to 256 in 2017. It is evident from XLM-CSE duo that the Casablanca stock market is leading Steller out of phase in the medium scales of 32 to 64 in 2016. In the plot of XLM-Nairobi.SE, we see a clear Steller lead in-phase in the 128 scale but lags in the 256 scale in 2016.

Analyzing the coherence between Steller and African stock returns, we can conclude that similar to Bitcoin, Ethereum, Litecoin, and Ripple, Steller is strongly integrated with African stock markets from the medium to long-term. The homogeneous phase arrow vectors are indicative of Stellers' positive connections with Kenya, Mauritius, and Tunisia in the long-term but medium-term for Ghana. However, the medium-term of Morocco, Mauritius, and Tunisia show negative associations but in the long-terms of Ghana and South Africa, as demonstrated by the heterogeneous phase arrow vectors. This finding means that Steller can hedge the market discrepancies of Tunisia, Mauritius, and Morocco stock markets in the medium-term but long-term for Ghana and South Africa. Importantly, we find Steller to be isolated from Egypt and Nigeria stock markets reflecting challenges including political unrest, illiquidity, and exchange rate exposure of the stock markets leading to inactive participation by foreign investors. Steller leads Ghana and Tunisia (medium-term), Mauritius (long-term), and Kenya stock markets, indicating that volatility in the price of Steller has the possibility of influencing the stock prices. Conversely, Steller lags South Africa and Mauritius (medium-term), Tunisia (long-term), and Morocco implying that stock price volatilities in these markets affect the price of Steller. Egypt and Nigeria stock market are at par with Steller with no lead (lag) effects.





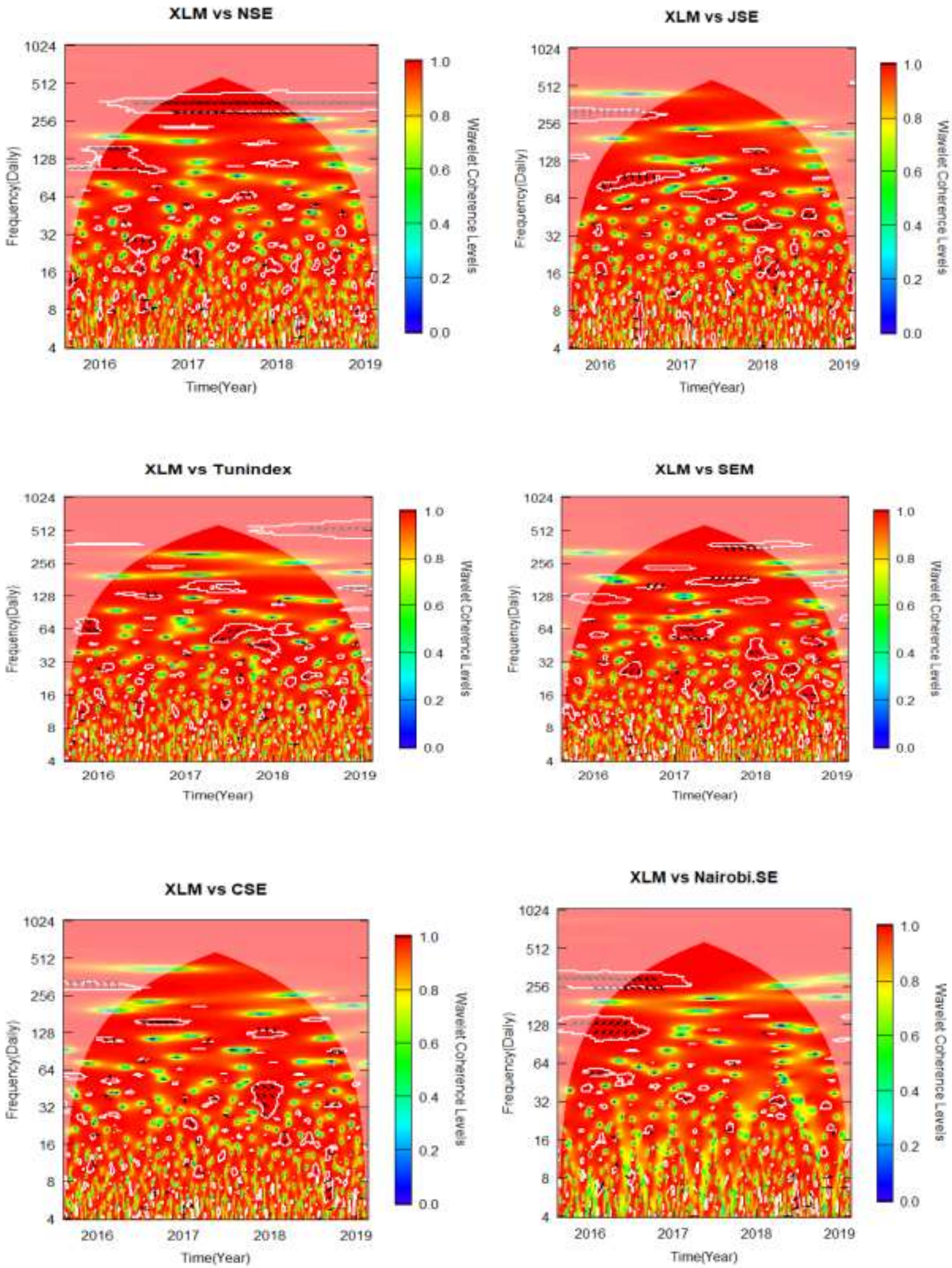
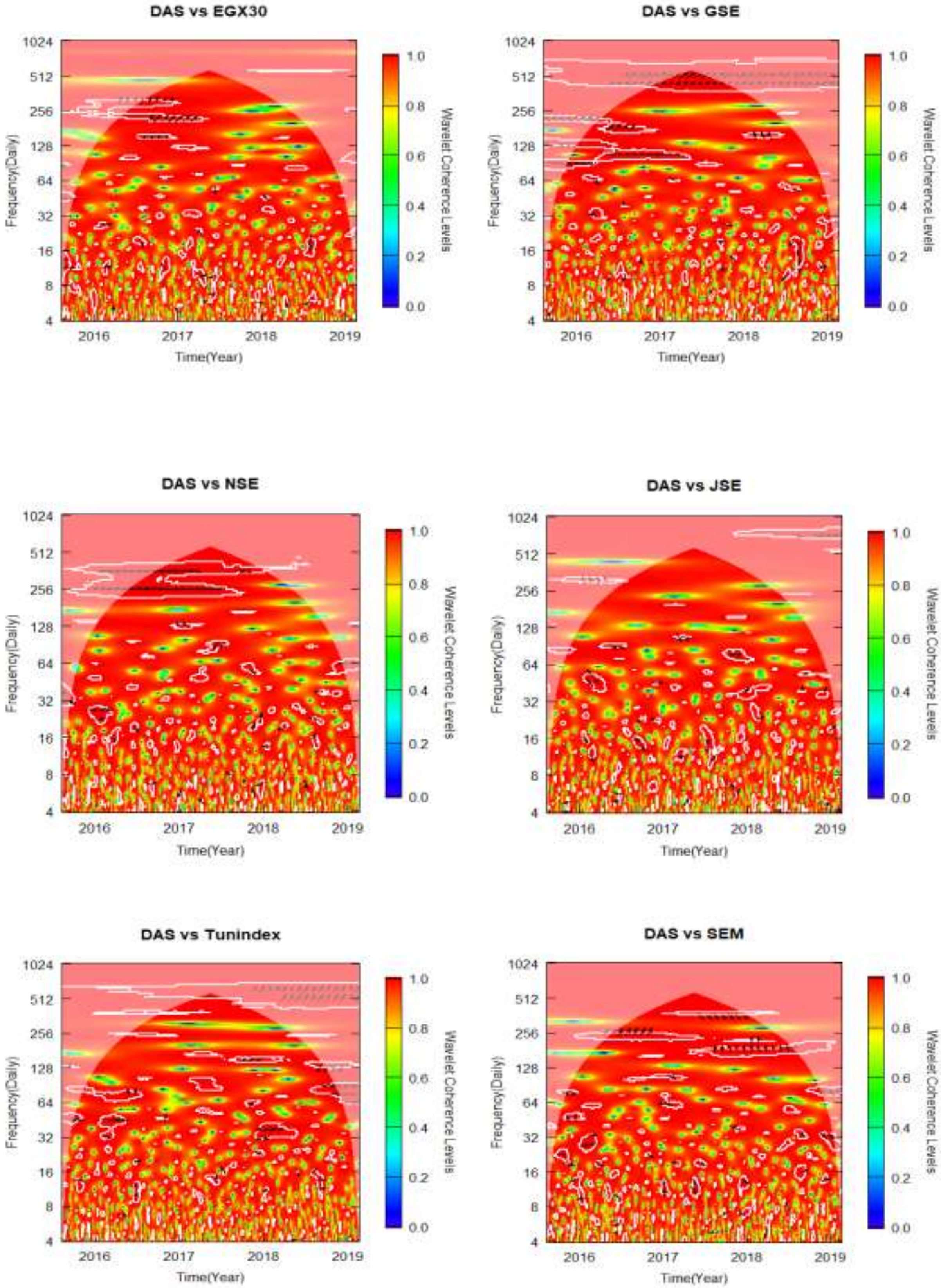


Figure 2.2 e: Steller-African stocks cross-wavelet coherency

2.3.1.6 Das-Stock pairs

A quick glance at the coherency plots for Das-Stock pairs show that Das is not yet integrated with some African stock markets and that Das significantly leads only three stock markets in Africa. Figure 2.2f presents the wavelet coherence and phase difference for Das and African stock returns. For DAS-EGX30 pair there is a substantial Das lead in-phase in the 200 to 300 band from mid-2016 to early-2017. Das lead in phase (mid of 2016) but lags out of phase (mid of 2018) in the high 128 to 256 band for DAS-GSE duo. The high 256 to 512 in DAS-NSE plot show phase indifference from mid-2016 to mid-2017. The DAS-JSE pair show similar pattern to DAS-NSE with no phase difference. Tunindex lags Das anti-phase in the medium 32 to 64 band in 2018 for DAS-Tunindex pair. Das once again leads SEM in-phase in the high 256 in 2016. The pair DAS-CSE show phase indifference similar to DAS-NSE, and DAS-JSE. There is a significant Nairobi.SE lead in-phase at scale 64 in 2016 in DAS-Nairobi.SE pair.

The results above highlights the obvious high level of integration between Das and African stock returns in the medium-term of Tunisia but long-term of Egypt, Ghana, Mauritius, and Kenya stock markets. Das is not yet integrated with Nigeria, South Africa, and Morocco stock markets in any of the time horizons as indicated by the coherency plots. It is evident from the phase arrow vectors that Das exhibit positive effects on Egypt, Mauritius, and Kenya stock markets in the long-term, adverse impact on Tunisia (medium-term), both positive and negative effects on Ghana (long-term) and no impact on Nigeria, South Africa, and Morocco stock markets. This means that Das can hedge against market crises of Tunindex in the medium-term and the long-term of Ghana stock market. Das significantly leads Egypt, Ghana, and Tunisia stock markets but lags Kenya stock market which means that extreme market volatilities of Das impact Egypt, Ghana, and Tunisia stocks except for Kenya where the reverse applies as depicted by the lead-lag effects in the plot and this may enhance arbitrage opportunities by international investors.


DAS vs EGX30
DAS vs GSE
DAS vs NSE
DAS vs JSE
DAS vs Tunindex
DAS vs SEM
Frequency(Daily)
1024
512
256
128
64
32
16
8
4
2016
2017
2018
2019
Time(Year)
1.0
0.8
0.6
0.4
0.2
0.0
Wavelet Coherence Levels

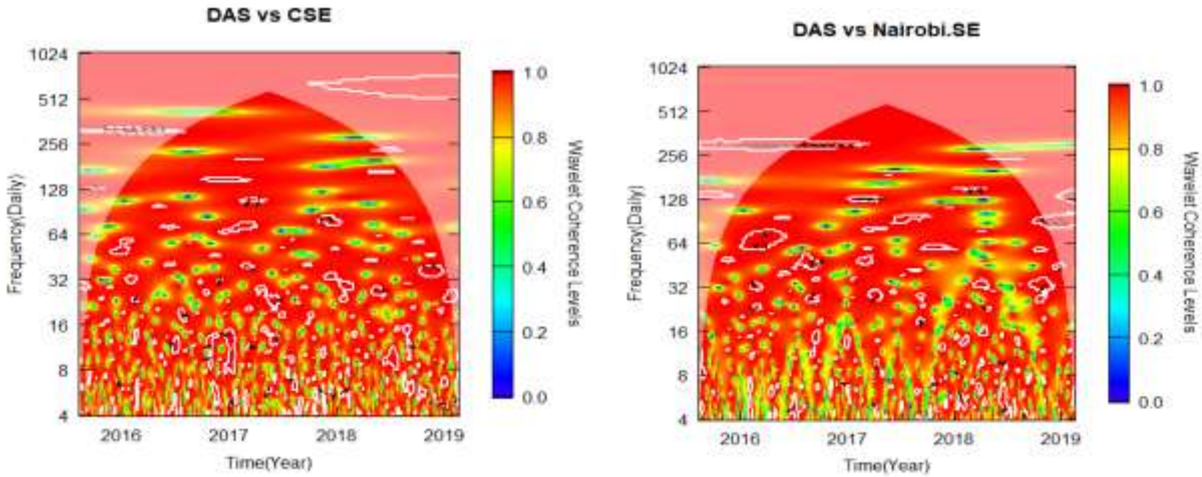
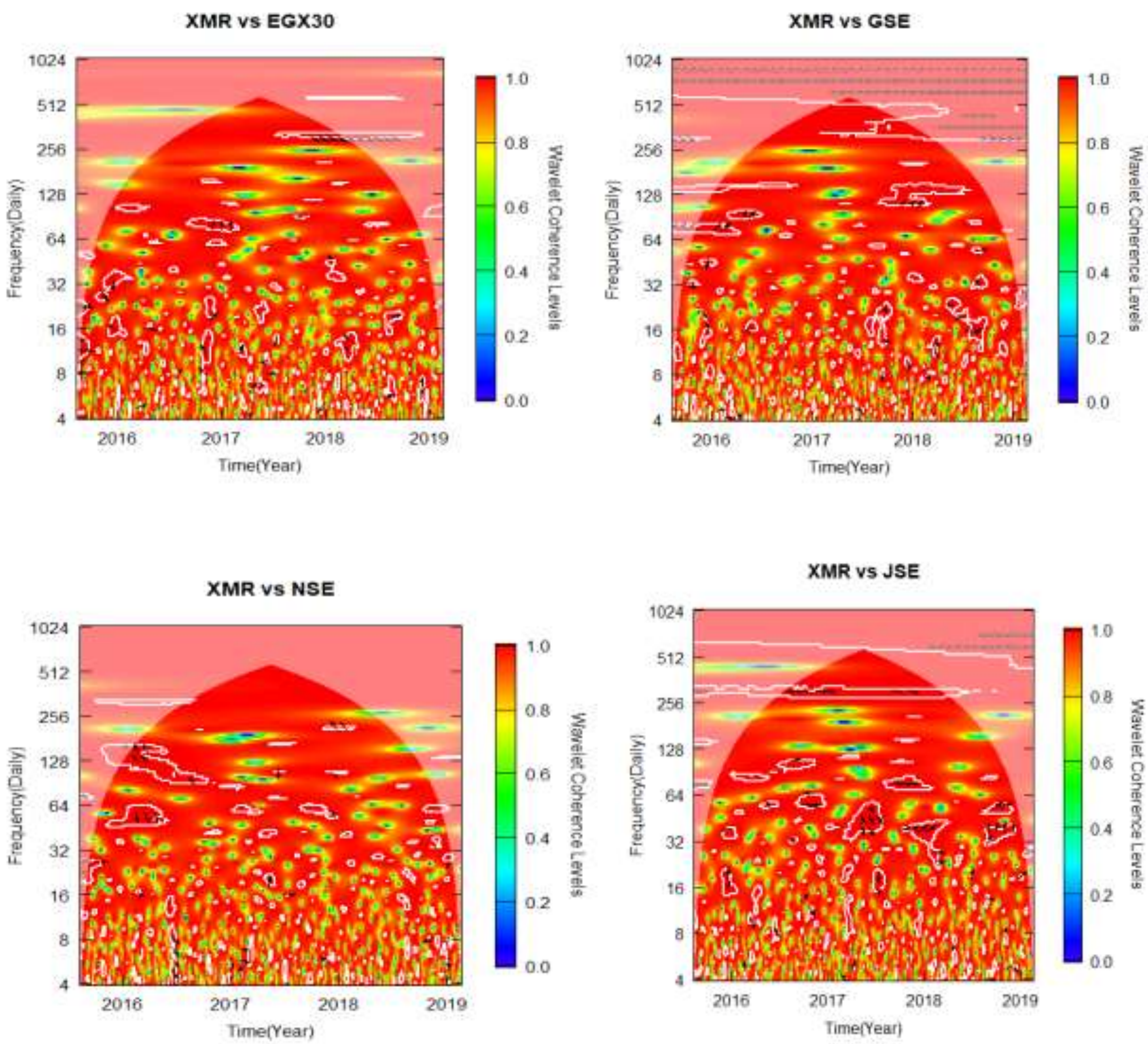


Figure 2.2 f: Das-African stocks cross-wavelet coherency

2.3.1.7 Monero-Stock pairs

The Monero-Stock pairs in Figure 2.2g exhibit the wavelet coherency and phase difference for the markets and confirms the obvious stronger coherency at medium and lower frequencies. The stock markets significantly leads Monero except for Ghana and Mauritius stock markets. In Figure 2.2g, the plot for XMR-EGX30 shows EGX30 lead in-phase at 64 and 256 band for 2017 and 2018 respectively. Monero leads Ghana stocks in the XMR-GSE pair. The series are in-phase in 64 to 128 band in 2016 and 2018. In the pair XMR-NSE, Nigeria stock market lead in-phase in the medium 50 to 64 band but out of phase in the high 70 to 140 band in 2016. Johannesburg stock market also leads Monero in-phase in 2017 at the band 32 to 64 for the XMR-JSE pair. The pair XMR-Tunindex depicts no phase difference in the band 32 to 64 in 2016 and 2018. For the XMR-SEM pair, XMR lead in-phase at 128 scale in late 2017. XMR-CSE and XMR-Nairobi.SE pairs show similar pattern to XMR-Tunindex with phase indifference.

The results for the co-movement of Monero and African stock returns confirm the apparent medium to long-term integration of the assets. We observe that movement of the price of Monero positively influences all the stock returns except the long-term of Nigeria stocks which shows negative effect. We also find Monero to be isolated from Tunisia, Morocco, and Kenya stocks. Monero leads Ghana and Mauritius stock markets in the long-term, demonstrating the positive response of the stock markets to the high price volatilities of Monero. Nevertheless, Egypt, Nigeria, and South Africa stock markets lead Monero, and thus Monero responds to the market fluctuations in these stock markets. The result further shows that Monero is decoupled from Tunindex (Tunisia), Casablanca stock market (Morocco) and Nairobi stock market (Kenya). Investors in the Nigeria stock market can hedge their positions using Monero in the long-term.



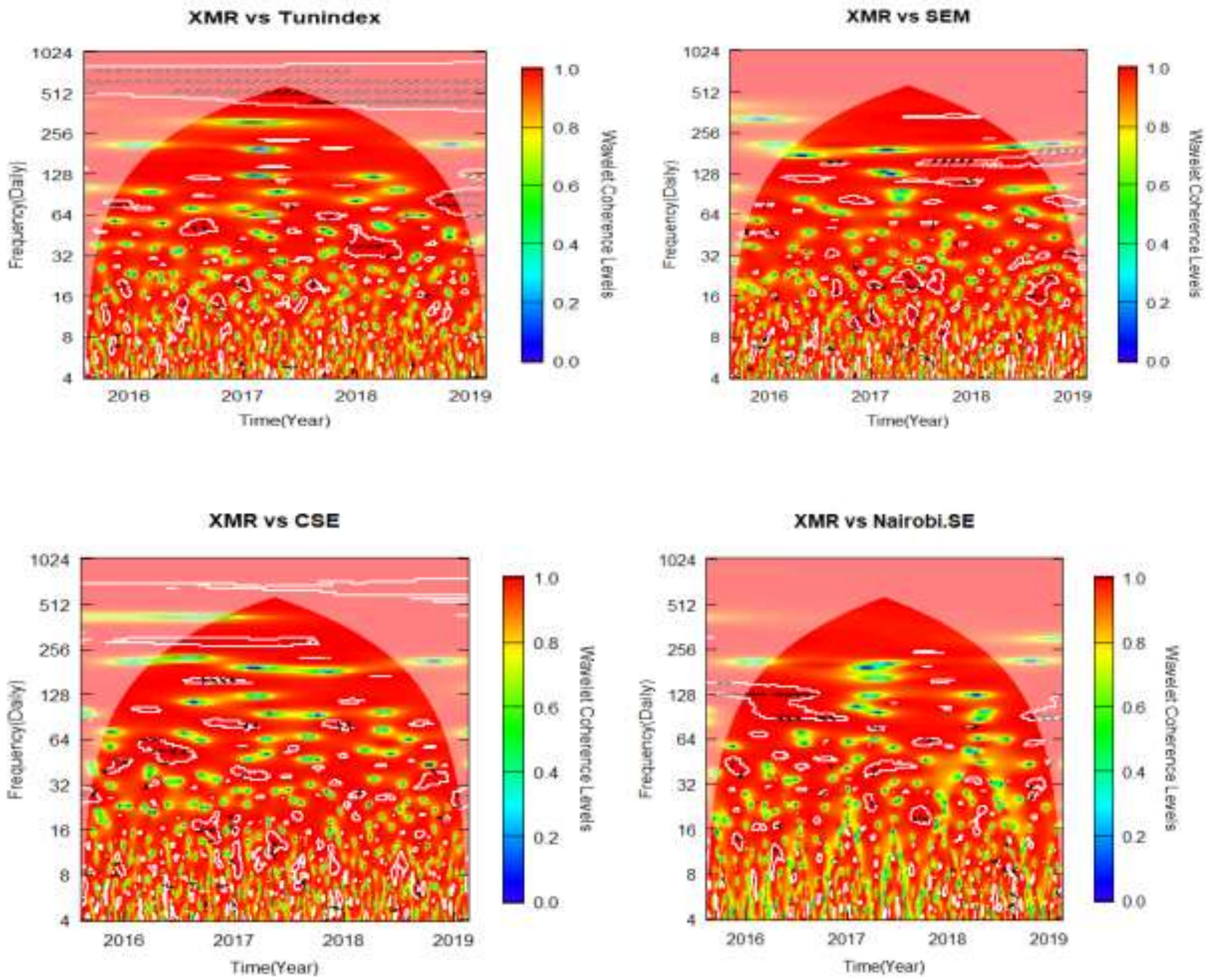


Figure 2.2 g: Monero-African stocks cross-wavelet coherency

To sum it all up, the bivariate co-movement of cryptocurrencies and African stock returns displayed in Figure 2.2 (a-g) is time-varying and dynamic suggesting a high level of integration between the markets from the medium to long-term. This is reflective of the enhanced economic integration (e.g. increasing market efficiency, easing investment and trade flows, granting economies of scale opportunities to reduce the cost of doing business, market openness, etc) laid down by policy decision makers in Africa to integrate African markets with global markets over the past three decades (see Mougani, 2014). The high level of integration between the markets from the medium to long-term suggest a close economic tie between the cryptocurrency and African stock markets in the long-term which affirms the fundamentals-based theory on co-movement tested in the chapter. The theory states that common factors in returns including industry and strong market level factors in cashflow news causes stronger market integration in the long-term. Our finding also implies that the gain from a cryptocurrency diversification is relatively low and less significant in the medium and long-terms.

We find the hedging abilities of the cryptocurrencies to be contingent on frequencies as the phase difference arrow vectors points to right and left across time scales, which implies that a study on co-movement association without considering scale effects is insufficient. However, in most cases, the arrow vectors point to the left showing negative relationship exhibiting the hedging properties of the cryptocurrencies. Specifically, Bitcoin has hedging properties for Ghana, Nigeria, Mauritius, and Kenya stock markets in the long-term but both medium and long-term for Tunisia stocks. Ethereum can hedge the market fluctuations of Egypt and Kenya stocks in the long-term but both medium and long-terms for Tunisia stocks. Hedging benefits are available for Ghana, Nigeria, and Kenya stocks in the long-term but medium-term for Tunisia and Mauritius stocks using Litecoin. Ripple clearly can hedge the market fluctuations of all the stock returns except EGX30. Investors in Tunisia, Morocco, and Mauritius stock markets can hedge their positions using Steller in the medium-term but in the long-term for Ghana and Nigeria stock investors. Stock investors in Tunindex and Ghana stock markets can hedge market risk using Das in the medium-term (Tunindex) and long-term (Ghana). Finally, Monero can only hedge Nigeria stock market crises in the long-term.

In terms of lead (lag) relationship in the market, the arrow vectors are non-homogeneous pointing up and down across scales. Specifically, we find Bitcoin leading JSE, and Tunindex. Ethereum leads EGX30, GSE, Tunindex, and SEM. Litecoin lags CSE, and Nairobi.SE, Ripple leads EGX30, JSE, CSE, and Nairobi.SE, Steller leads GSE, Tunindex, CSE, and Nairobi.SE. Das leads EGX30, GSE, and SEM, whiles Monero leads GSE and SEM. These lead (lag) associations in the inter-market volatility association between the cryptocurrencies and African stocks returns have implications for arbitrage opportunities which can aid investment decisions for international investors to buy and sell securities simultaneousely in different markets to take advantage of different prices for the same asset.

The findings for ETH-NSE, LTC-JSE, XRP-SEM, XLM-EGX30, XLM-NSE, DASH-NSE, DASH-JSE, DASH-CSE, XMR-Tunindex, XMR-CSE, and XMR-Nairobi.SE (11-pairs) provide evidence of no integration between the cryptocurrencies and stock returns in support of the works of Corbet, Meegan, Larkin, Lucey, and Yarovaya (2018), Liu and Tsyvinski (2018), and Gil-Alana, Abakah, and Rojo (2020). This segmentation of the assets markets across time could be due to several factors including exchange rate risk, illiquidity, inefficiency and undiversified characteristics hindering the nascent African markets which may account for low levels of international investor participation in the African stock markets. However, the majority of the cryptocurrency-stock pairs (45-pairs) confirm the findings of related studies including Ciaian and Rajcaniova (2018), Baur, Hong, and Lee (2018), and Bouri, Shahzad, and Roubaud (2019). These studies demonstrate the inter-market linkages and hedging abilities of cryptocurrencies for global stock indices.

2.3.2 Multivariate co-movement between cryptocurrencies and African stocks returns

To examine the multivariate co-movement and obtain the overall level of integration of the cryptocurrency market with African stock markets across time, we apply wavelet multiple correlation (WMC) and wavelet multiple cross-correlation (WMCC) to the decompose series of cryptocurrencies and stock returns. The series were decomposed into wavelet coefficients D_1 to D_7. The oscillations of periods of 2–4, 4–8, 8–16, 16–32, 32–64, 64–128, and 128- 256 days are represented by wavelet scales $j_1, j_2, j_3, j_4, j_5, j_6, and\ j_7$respectively. As indicated in section 2.3.1, we choose three cycles to represents short-, medium-, and long-time movements. Specifically, the first cycle on the lower scales (2 – 16 days) is the higher frequencies and denotes short-term movement. The second cycle on the middle scales (16 – 64 days) is the medium frequencies and indicates medium-term movement. The third cycle on the long scale (> 64 days) is the lower frequencies and shows the long-term movement as used by (Fern´andez-Macho, 2012; Das and Kannadhasan, 2018; Gourène, Mendy and Diomande, 2019; Gallegati, 2012).

2.3.2.1 WMC for Cryptocurrencies and African stock returns

The results of wavelet multiple correlation (WMC) with upper and lower bounds of 95 percent confidence intervals for multivariate co-movement of all cryptocurrencies and African stocks returns combined are shown in Table 2.3 and its plot shown in Figure 2.3. It can be seen that the correlations are weak at the higher frequencies and tend to grow at the lower frequencies. In particular, the correlations at higher frequencies $(j = 1, j = 2)$[25] falls from 0.725 to 0.675. The medium frequencies $(j = 3, j = 4)$[26] depicts an increasing correlation from 0.788 to 0.842. This association increases in magnitude at lower frequencies $(j = 5, j = 6, j = 7)$[27] reaching 0.999 at the lowest frequency. This finding indicates that cryptocurrencies and African stock markets are poorly integrated in the short-term but this integration increases in the medium-term and perfectly integrates in the long-term which confirms the results of the bivariate co-movement of the assets markets. This is probably mainly caused by long-term fundamental reasons between the markets.

Nevertheless, the returns attained in any of the cryptocurrency and stock markets at the lower and medium scales cannot be totally determined by the overall performance in other markets even though they are quite close. The discrepancies between African stock markets and the cryptocurrency market is high but they tend to dissipate in horizons close to one year. In general, the results indicate that the co-movement of cryptocurrencies and African stocks is strong at the medium and long time scales and that international portfolio diversification benefits within Africa are low for medium and longer investment horizons which is somewhat in line with the hypothesis that co-movement is stronger at longer time scales. This could be due to a strong fundamental linkages between the assets markets including market liberalization, technological advances, removal of statutory controls, and volatility (Aamir and Ali Shah, 2018) confirming the fundamentals-based theory tested in the chapter.

[25] Intraweek and weekly scales denotes short-term investment horizon
[26] Fortnightly and monthly scales depicts medium-term investment horizon
[27] From quarterly scale represent long-term investment horizon

Table 2. 3: WMC for cryptocurrencies and African stocks with the 95% confidence interval

Scale	Cor	Lower bound	Upper bound
j = 1	0.725	0.680	0.764
j = 2	0.675	0.601	0.737
j = 3	0.788	0.710	0.850
j = 4	0.842	0.749	0.902
j = 5	0.851	0.711	0.926
j = 6	0.986	0.960	0.995
j = 7	0.999	0.999	0.999

***Note: Cor** = correlation coefficient*

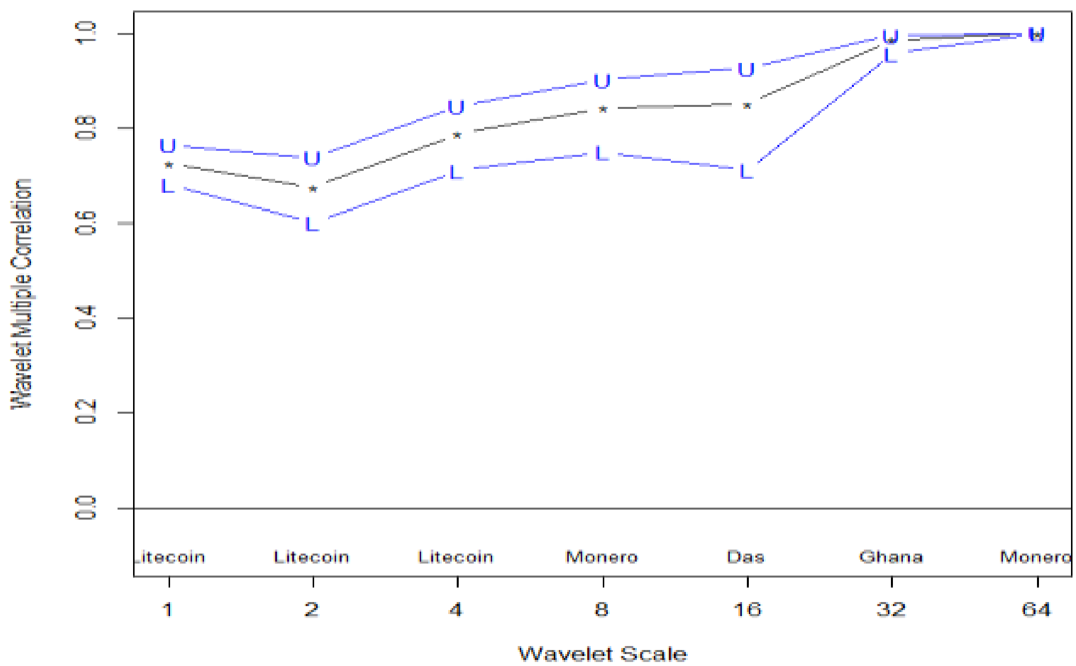


Figure *2.3*: WMC for cryptocurrencies and African stocks. The (U) and (L) lines respectively correspond to the Upper and Lower bounds of the 95% confidence interval.

2.3.2.2 WMCC for Cryptocurrencies and African stock returns

We present the result of multivariate cross-correlation of all cryptocurrencies and African stocks combined at varying wavelet scales with leads and lags up to 30 trading days (one month) on Table 2.4 (with localisations, time lag, lead/lag tendencies at the various scales) and its plots shown in

Figure 2.4. The name of the market that maximizes the multiple cross-correlations against the linear combination of other markets is shown on the right side of each wavelet scale in Figure 2.4.

This market can be a potential leader or follower for the other markets at various scales. The time lag at which the strongest or exact wavelet correlation coefficients are localised is indicated by the dashed lines (Figure 2.4). We observe that cross-correlations are stronger at lower frequencies (longer scales) which confirm the results of cross-wavelet coherency and WMC. In analysing the localisations vis-à-vis their time lags, we find that spillover effects are realised at longer scales $(> j = 16)$ since localisations do not occur at the point of symmetry (i.e. zero time lag). Thus, positive time lags are indicative of the lagging markets at a particular scale and the opposite is true for negative time lags.

Specifically, the short to medium scales $(j = 1 \; to \; j = 4)$ show that localizations occurred at the point of symmetry (i.e. zero time lag symmetry) which indicates no spillover effects from either market in the short-term and medium-term. However, the long scales $(j = 5, j = 6, j = 7)$ indicates that Monero (XMR), Das (DASH), and Ghana (GSE) maximizes the multiple cross-correlation against the linear combination of the rest of the markets. Monero (XMR) exhibit positive lag at 1 day (0.858), Das (DASH) shows negative lag at 1 day (0.986), and Ghana (GSE) depicts negative lag at 27 days (0.999). This finding depicts that in the long-term of cryptocurrencies and African stock markets associations, Monero (XMR) has the potential to lag other markets at scale $(j = 5)$, Das is a potential market leader at scale $(j = 6)$, and Ghana has the potential to lead other markets at the longest scale $(j = 7)$.

Table 2.4: WMCC for cryptocurrencies and African stocks returns

Scale	Localisation	Time lag	Leading/Lagging
j* = *1	0.725	0	symmetry
j* = *2	0.675	0	symmetry
j* = *3	0.788	0	symmetry
j* = *4	0.842	0	symmetry
j* = *5	0.858	1	Monero
j* = *6	0.986	-1	Das
j* = *7	0.999	-27	Ghana

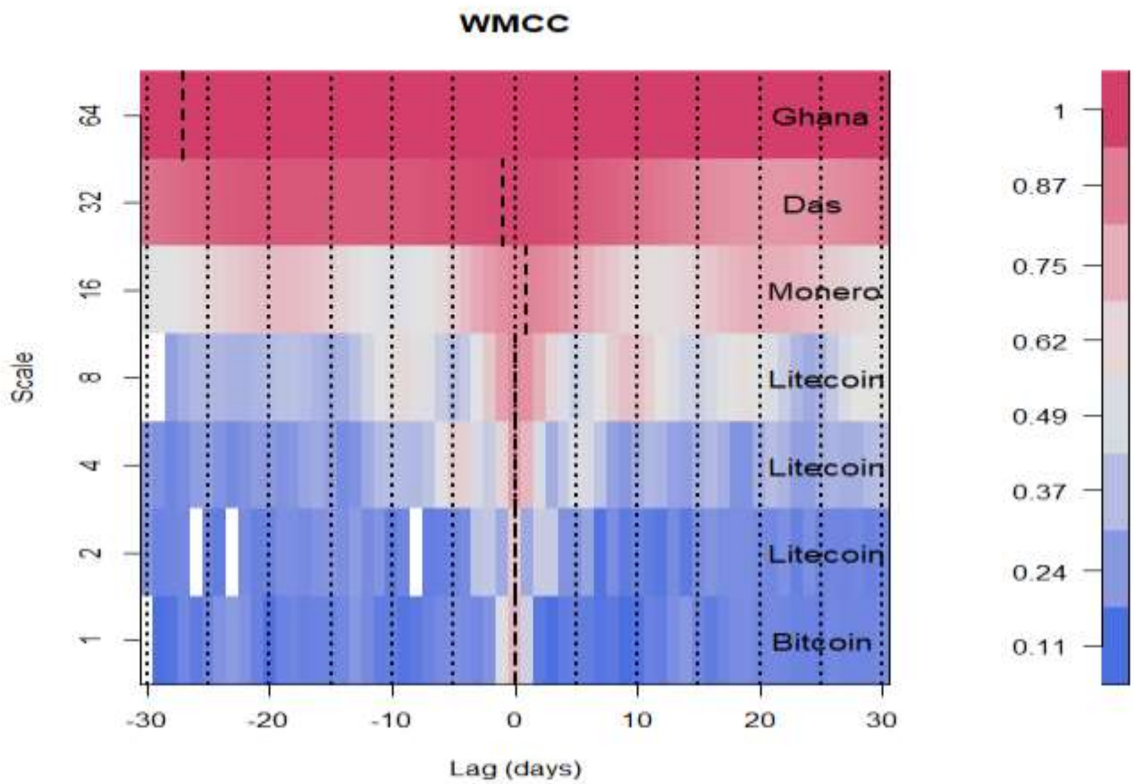


Figure *2.4*: WMCC for cryptocurrencies and African stocks. Areas in the plot in which the 95% interval extends to zero are indicated in white, and vertical long dotted lines indicate where the strongest wavelet correlation values are located.

In general, when the results are compared to other studies on cryptocurrencies and stock markets integration using different methods in advanced stock markets, our results are similar to the results of Brière et al. (2015), Ciaian and Rajcaniova (2018), Baur, Hong, and Lee (2018), Liu and Tsyvinski (2018), and Bouri, Shahzad, and Roubaud (2019). These studies report that cryptocurrencies offer diversification benefits for global stock markets. From the international investors′ perspective, cryptocurrencies, provide minimal benefits from international portfolio diversification for medium and long-term investment horizon investors in Africa, whereas cryptocurrencies offer higher benefits for the short-term horizons investors.

2.4 Conclusion and policy implication

Examining the level of integration between cryptocurrencies and African stock markets on multiple time scales, we applied the continuous morlet wavelet transform by Morlet, Arens, Fourgeau, and Glad, (1982) and wavelet multiple correlation and cross-correlation of Fern´andez-Macho (2012). The study employed seven leading cryptocurrencies; Bitcoin (BTC), Ethereum (ETH), Litecoin (LTC), Ripple (XRP), Das (DASH), Steller (XLM), and Monero (XMR), and eight major African stock market indices; Egypt (EGX30), Nigeria (NSE), Ghana (GSE), Tunisia (Tunindex), Morocco (CSE), Mauritius (SEM), and Kenya (Nairobi.SE) for the period August 2015 to February 2019 to achieve the set objective. In portfolio allocations and management, the level of integration (co-movement) of financial markets plays an important role. Apart from that, financial market participants operate at different frequencies, and that inter-market linkages are not necessarily the same over different time scales and frequencies which motivates the study to examine the inter-market linkages of cryptocurrencies and African stock markets in a time-frequency space.

We, first of all, paired each cryptocurrency with each African stock market and examined their bivariate co-movement using cross-wavelet coherency and phase difference. Evidence shows a high level of integration between the markets from the medium to long-term horizons, generally indicating the vulnerability of African stock markets to discrepancies in the cryptocurrency market from the medium-term. Testing the hedging and diversification properties of cryptocurrencies for African stocks following the description for hedge, safe haven, and diversification by Baur and McDermott (2010) and Baur and Lucey (2010)[28], we find Bitcoin as a hedge for Ghana, Nigeria, Mauritius, and Kenya stock markets in the long-term but both medium and long-term for Tunisia stocks. Ethereum can hedge the downside risk of Egypt and Kenya stocks in the long-term but both medium and long-terms of Tunisia stocks. Litecoin has hedging benefits for Ghana, Nigeria, and Kenya stocks in the long-term but medium-term for Tunisia and Mauritius stocks. Ripple can hedge the market fluctuations of all stock returns except EGX30. Investors in Tunisia, Morocco, and Mauritius stock markets can hedge their positions using Steller in the medium-term but in the

[28] Baur and Lucey (2010) and Baur and McDermott (2010) tested the safe haven, hedge, and diversification benefits of bonds and gold. However, we are not in anyway, suggesting that cryptocurrencies are like bonds or gold.

long-term for Nigeria and Ghana stock investors. Stock investors in Tunindex and Ghana stock markets can hedge price risk using Das in the medium-term (Tunindex) and long-term (Ghana). Finally, Monero can only hedge Nigeria stock market crises in the long-term. In terms of lead (lag) relationship in the market, we find Bitcoin leading JSE and Tunindex. Ethereum leads EGX30, GSE, Tunindex, and SEM. Litecoin lags CSE, and Nairobi.SE, Ripple leads EGX30, JSE, CSE, and Nairobi.SE, Steller leads GSE, Tunindex, CSE, and Nairobi.SE. Das leads EGX30, GSE, and SEM, whiles Monero leads GSE and SEM.

We then combined all seven cryptocurrencies and eight African stocks returns and examined their multivariate correlation and cross-correlation using wavelet multiple correlation and cross-correlation. The results of the wavelet multiple correlations show that the cryptocurrency market and African stock markets are poorly integrated at higher frequencies. However, this integration grows stronger at medium frequencies and perfectly integrates at the lowest frequency. The result based on the multivariate cross-correlation of cryptocurrencies and African stock markets shows that in the long-term of cryptocurrencies and African stock markets associations, Monero (XMR) has the potential to lag other markets at monthly to quarterly scale, Das is a potential market leader at quarterly to biannual scale, and Ghana has potential to lead other markets at biannual to annual scale respectively.

The empirical results of this study both support and contradict related literature. The results support the inter-market linkages between cryptocurrencies and global stock returns evidenced by Ciaian and Rajcaniova (2018), Liu and Tsyvinski (2018), and Bouri, Shahzad, and Roubaud (2019) and contradict Corbet, Meegan, Larkin, Lucey, and Yarovaya (2018) and Gil-Alana, Abakah, and Rojo (2020) who found no connection between the markets. In a nutshell, our results suggest that cryptocurrencies and African stocks returns are lowly integrated in the short-term inferring the possibility of hedging benefits across the cryptocurrencies. However, we find the medium to long-terms of the assets markets to be highly integrated, reflecting the aggressive pursuit of African economies to be integrated with the global economy in the long-term. Following these results, we recommend that international investors seeking to hedge their price risk in African stock markets using cryptocurrencies may have to look at the short-time horizon. More specifically, cryptocurrencies provide high portfolio diversification benefits for short-term market participants compared to their counterparts in the medium and long-term in the African stock markets. Our study as well suggest that there's no particular cryptocurrency or stock market leader on the continent. Different markets have the potential to lead at some point on the scales suggesting that the returns of any of the assets markets under consideration can drive price changes in the other markets.

The results for the integration between cryptocurrencies and African stocks returns, focusing on seven large cryptocurrencies and eight major African stock markets are the exclusive contribution of the chapter. Future studies could examine the integration of other cryptocurrencies and other African stock markets not covered in this study to enhance our understanding of the inter-market linkages. Future studies could also look at the regulatory and supervisory aspects of cryptocurrencies in Africa to allow for its successful integration in the region.

References

AfDB, OECD, UNDP (2015). African Economic Outlook 2015: Regional Development and Spatial Inclusion. http://www.google.com/url?sa=t&rct=j&q=&esrc=.

Aaltonen, A. (2017). Cryptocurrencies' Internal and External Relations: a Descriptive Analysis of Cryptocurrency Dynamics and Relations to the US Equity Market.

Adjasi, C., K.., D., & Biekpe, N., B. (2006). Co Integration and Dynamic Causal Links amongst African Stock Markets. *Investment Management and Financial Innovations*, 4, 102-119.

Agyei-Ampomah, S. (2008). An Empirical Examination of the Inter-Linkages between African Stock Markets. Available at SSRN 1311325.

Alagidede, P., Panagiotidis, T., & Zhang, X. (2011). Causal Relationship between Stock Prices and Exchange Rates. *The Journal of International Trade & Economic Development,* 20 (1), 67–86.

Al-Yahyaee, K., H., Mensi, W., & Yoon, S., M. (2018). Efficiency, Multifractality, and the Long-memory Property of the Bitcoin Market: A Comparative Analysis with Stock, Currency, and Gold Markets. *Finance Research Letters*, *27*, 228-234.

Baker, S., R., Bloom, N., & Davis, S., J. (2016). Measuring Economic Policy Uncertainty. *The Quarterly Journal of Economics, 131*(4), 1593-1636.

Baur, D., G., Hong, K.., & Lee, A., D. (2018). Bitcoin: Medium of Exchange or Speculative Assets? *Journal of International Financial Markets, Institutions, and Money*, 54, 177–189. http://refhub.elsevier.com/.

Baur, D., G., Dimpfl, T., & Kuck, K. (2018). Bitcoin, Gold and the US Dollar–A Replication and Extension. *Finance Research Letters*, 25, 103-110

Baur, D., G., & Lucey, B., M. (2010). Is Gold a Hedge or a Safe Haven? An Analysis of Stocks, Bonds and Gold. *Financial Review, 45*(2), 217-229.

Baur, D., & Mc Dermontt, T., K., J. (2010). Is Gold a Safe Haven? International Evidence, *Journal of Banking and Finance,* 34(8), 1886-1898.

Boako, G., Omane-Adjepong, M., & Frimpong, J., M. (2016). Stock Returns and Exchange Rate Nexus in Ghana: A Bayesian Quantile Regression Approach. *South African Journal of Economics,* 84(1), 149-179.

Boako, G., & Alagidede, P. (2016). Regionalization versus Internationalization of African Stock Markets: A Frequency-time Domain Analysis. Retrieved from https://www.researchgate.net/profile/Gideon_Boako/publication/309160305_Regionalization_versus_internationalization_of_African_stock_markets_A_frequency-time/links/5802068908ae6c2449f7c5fa.pdf

Boako, G., & Alagidede, P. (2015). Global Commodities and African Stocks: Insights for Hedging and Diversification Strategies. *Economic Research Southern Africa,* working paper 569.

Bouri, E., Shahzad, S., J., H., & Roubaud, D. (2019). Cryptocurrencies as Hedges and Safe havens for US Equity Sectors. *The Quarterly Review of Economics and Finance,* 1-14. https://doi.org/10.1016/j.qref.2019.05.001.

Bouri, E., Azzi, G., & Dyhrberg, A., H. (2017). On the Return-Volatility Relationship in the Bitcoin Market around the Price Crash of 2013. *Economics: The Open-Access, Open-Assessment E-Journal, 11*(2), 1–16. http://dx.doi.org/10.5018/economics-ejournal.ja.2017-2.

Bouri, E., Molnár, P., Azzi, G., Roubaud, D., & Hagfors, L., I. (2017a). On the Hedge and Safe Haven Properties of Bitcoin: Is it Really More Than a Diversifier? *Finance Research Letters*, 20, 192–198.

Bouri, E., Mahamitra, D., Gupta. R., & Roubaud, D. (2018). Spillovers Between Bitcoin and Other Assets During Bear and Bull Markets. *Applied Economics*, 50, 5935–49.

Bouri, E., Shahzad, S., J., H., & Roubaud, D. (2019). Co-explosivity in the Cryptocurrency market. *Finance Research Letters*, 29, 178 -183.

Bracker, K., Docking, D. S., & Koch, P. D. (1999). Economic Determinants of Evolution in International Stock Market Integration. *Journal of Empirical Finance, 6*(1), 1-27.

Brière, M., Oosterlinck, K., & Szafarz, A. (2015). Virtual Currency, Tangible Return: Portfolio Diversification with Bitcoin. *Journal of Asset Management,* 16(6), 365–373.

Burrus, C., S., Gopinath, R., & Guo, H. (1998). A Primer Introduction to Wavelets and Wavelet Transforms. *New Jersy: Prentice Hall*, *3*.

Carmona, R., Hwang, W.-L., & Torresani, B. (1998). *Practical Time-Frequency Analysis: Gabor and Wavelet Transforms, with an Implementation in S* (Vol. 9). Academic Press.

Carrick, J. (2016). "Bitcoin as a Complement to Emerging Market Currencies," *Emerging Markets Finance and Trade* 52(10), 2321–2334.

Ciaian, P., & Rajcaniova, M. (2018). Virtual Relationships: Short-and Long-Run Evidence from Bitcoin and Altcoin Markets. *Journal of International Financial Markets, Institutions and Money*, *5*2, 173–195.

CoinMarketCap. (2019). Cryptocurrency Market Capitalizations and Data. Available online: https://coinmarketcap.com/ (accessed on 26th August 2019).

Corbet, S., Meegan, A., Larkin, C., Lucey, B., & Yarovaya, L. (2018). Exploring the Dynamic Relationships between Cryptocurrencies and other Financial Assets. *Economics Letters*, 165, 28–34. doi.org/10.1016/j.econlet.2018.01.004.

Corelli, A. (2018). Cryptocurrencies and Exchange Rates: A Relationship and Causality Analysis. *Risks*, 6, 111.

Cornish, C., R., Bretherton, C., S., Percival, D., B., (2006). Maximal Overlap Wavelet Statistical Analysis with Application to Atmospheric Turbulence. *Boundary-Layer Meteorology*, 119 (2), 339–374.

Crowley, P. (2007). A Guide to Wavelets for Economists. *Journal of Economic Surveys*. 21 (2), 207-267.

Das, D., & Kannadhasan, M. (2018). Do Global Factors Impact Bitcoin Prices? Evidence from Wavelet Approach. *Journal of Economic Research*, *23*, 227-264.

Diebold, F. X., & Yilmaz, K. (2012). Better to Give than to Receive: Predictive Directional Measurement of Volatility Spillovers. *International Journal of Forecasting*, *28*(1), 57-66. https://doi.org/10.1016/j.ijforecast.2011.02.006.

Dyhrberg, A., H. (2015a). Hedging Capabilities of Bitcoin. Is it the Virtual Gold? *Finance ResearchLetters,*16, 139–44.

ElBahrawy, A., Alessandretti, L., Kandler, A., Pastor-Satorras, R., & Baronchelli, A. (2017). Evolutionary Dynamics of the Cryptocurrency Market. *Royal Society open science*, 4(11), 170623.

Emenalo, C. (2009). A Review of the Cost of Equity in Emerging and Frontier Markets. Available at SSRN 1517836. http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1517836.

Engle, R., F., Granger, C., W., J. (1987). Cointegration and Error Correction: Representation, Estimation and Testing. *Econometrica,* 55, 251–276.

Fang, L., Bouri, E., Gupta, R., & Roubaud, D. (2019). Does Global Economic Uncertainty Matter for the Volatility and Hedging Effectiveness of Bitcoin?. *International Review of Financial Analysis*, *61*, 29-36.

Fern´andez-Macho, J. (2012). Wavelet Multiple Correlation and Cross-Correlation: A Multiscale Analysis of Eurozone Stock Markets. *Physica A: Statistical Mechanics and itsApplications*,391,1097-1104. http://www.sciencedirect.com/science/article/pii/S0378437111008375.

Ftiti, Z., Tiwari, A., Belanès, A., & Guesmi, K. (2015). Tests of financial market contagion: Evolutionary cospectral analysis versus wavelet analysis. *Computational Economics*, 46(4), 575–611.

Gabor, D. (1946). Theory of communication. Part 1: The analysis of information. Journal of the Institution of Electrical Engineers-Part III: *Radio and Communication Engineering*, 93(26), 429–441.

Gajardo, G., Kristjanpoller, W., D., & Minutolo, M. (2018). Does Bitcoin Exhibit the Same Asymmetric Multifractal Cross-Correlations with Crude Oil, Gold and DJIA as the Euro, Great British Pound and Yen? *Chaos, Solitons and Fractals*, 109, 195–205.

Gallegati, M. (2012). A Wavelet-based Approach to Test for Financial Market Contagion. *Computational Statistics & Data Analysis*, *56*(11), 3491-3497.

Gençay, R., Selçuk, F., & Whitcher, B. J. (2001). *An Introduction to Wavelets and other Filtering Methods in Finance and Economics.* Academic Press. Retrieved from https://books.google.com/books?hl=en&lr=&id=3ZLTt50EUT8C&oi=fnd&pg=PP1&dq=time+varying+cointegration+wavelets&ots=aYiy-3Pdc6&sig=4-JZcc6hYHFCJZTqTH8vxA3Cyjo.

Gençay, R., Selçuk, F., & Whitcher, B., (2002). *An Introduction to Wavelets and Other Filtering Methods in Finance and Economics.* Academic Press, San Diego.

Gil-Alana, L. A., Abakah, E. J. A., & Rojo, M. F. R. (2020). Cryptocurrencies and Stock Market Indices. Are they related?. *Research in International Business and Finance*, *51*, 101063.

Gourène, G., A., Z., Mendy, P., & Diomande, L. (2019). Beginning an African Stock Markets Integration? A Wavelet Analysis. *Journal of Economic Integration,* 34(2), 370-394.

Gourène, G., A., Z., & Mendy, P. (2014). Beginning an African Stock Markets Integration? A Wavelet Analysis. *Munich Personal RePEc Archive,* 76048.

Grinsted, A., Moore, J., C., & Jevrejeva, S. (2004). Application of the Cross Wavelet Transform and Wavelet Coherence to Geophysical Time Series. *Nonlinear Processes in Geophysics*, 11(5/6), 561–566.

Grossman, A., & Morlet, J. (1984). Decomposition of Hardy Functions into Square Integrable Wavelets of Constant Shape. *SIAM Journal on Mathematics Analysis*, 15(4), 723-736.

Grubel, H., G. (1968). Internationally Diversified Portfolios: Welfare Gains and Capital Flows. *The American Economic Review*, *58*(5), 1299–1314.

Hencic, A., & Gourieroux, C. (2014). Noncausal Autoregressive Model in Application to Bitcoin/USD Exchange Rate, Econometrics of Risk, Series: Studies in Computational Intelligence, Springer International Publishing, 17-40.

Huynh, T., L., D. (2019). Spillover Risks on Cryptocurrency Markets: A Look from VAR-SVAR Granger Causality and Student's-t Copulas. *Journal of Risk and Financial Management,* 12, 52. doi:10.3390/jrfm12020052.

In, F., & Kim, S. (2013). An Introduction to Wavelet Theory in Finance: A Wavelet Multiscale Approach. World Scientific. Retrieved from https://books.google.com/books?

Jarnstrom, J., Kane, G., & Knightly, C. (2018). Predicting the Unpredictable: A Correlation of Cryptocurrencies, Twitter Sentiment, and Stock Markets.

Johansen, S. (1988). Statistical Analysis of Cointegration Vectors. *Journal of Economic Dynamics and Control*, 12 (2–3), 231–254.

Kim, T. (2017). On the Transaction Cost of Bitcoin. *Finance Research Letters*, 23, 300-305.

Klabbers, S. (2017). Bitcoin as an Investment Asset: The Added Value of Bitcoin in a Global Market Portfolio.

Kristjanpoller, W., & Bouri, E. (2019). Asymmetric Multifractal Cross-Correlations between the Main World Currencies and the Main Cryptocurrencies. *Physica A: Statistical Mechanics and its Applications,* 523, 1057-1071.

Kristoufek, L. (2015). What are the Main Drivers of the Bitcoin Price? Evidence from Wavelet Coherence Analysis. *PLoS ONE*, 10: e0123923

Kurkaa, J. (2019). Do Cryptocurrencies and Traditional Asset Classes Influence each other? *Finance Research Letters,* 38, 38-46.

Liow, K., H., Zhou, X., Qiang, L., & Huang, Y. (2017). Co-movements and Systematic risk of Asian Securitized Real Estate Markets: a Wavelet Analysis. *Available at SSRN 2971571*.

Liu, Y., & Tsyvinski, A. (2018). *Risks and Returns of Cryptocurrency* (No. w24877). National Bureau of Economic Research.

Madaleno, M., & Pinho, C. (2010a). Hedging Performance and Multiscale Relationships in the German Electricity Spot and Futures Markets. *Journal of Risk and Financial Management*, 3(1), 26–62.

Madaleno, M., & Pinho, C. (2010b). Relationship of the Multiscale Variability on World Indices. Revista De Economia Financiera, 20, 69–92.

Madaleno, M., & Pinho, C. (2012). International Stock Market Indices Co-movements: A New Look. *International Journal of Finance & Economics*, 17(1), 89–102.

Marashdeh, H., A., Shrestha, M., B. (2010). Stock Market Integration in the GCC Countries. *International Research Journal of Finance and Economics*, 37, 104–114.

Martens, M., & Poon, S., H. (2001). Returns Synchronization and Daily Correlation Dynamics between International Stock Markets. *Journal of Banking and Finance,* 25(10), 1805–1827.

Mensah, J., O., & Premaratne, G. (2018). Integration of ASEAN banking sector stocks. Journal of Asian Economics, 59, 48-60.

Mensah, J., O., & Alagidede, P. (2017). How are Africa's Emerging Stock Markets Related to Advanced Markets? Evidence from Copulas. *Economic Modelling*, 60, 1–10.

Mlambo, C., Maredza, A., & Sibanda, K. (2013). Effects of Exchange Rate Volatility on the Stock Market: A Case Study of South Africa. *Mediterranean Journal of Social Sciences,* 4(14), 561-570.

Mongal, I., & Eita, J., H. (2014). Commodity Prices and Stock Market Performance in South Africa. *Corporate Ownership and Control*, 11(4), 370-375.

Morlet, J., Arens, G., Fourgeau, E., & Glard, D. (1982). Wave Propagation and Sampling Theory—Part I: Complex Signal and Scattering in Multilayered Media. Geophysics, 47(2), 203–221.

Mougani, G., (2014). Challenges Towards Regional Financial Integration and Monetary Coordination in the West African Monetary Zone and the East African Community. *Regional Integration Policy Paper, African Development Bank*, 1-56.

Mitra, R. (2017). Stock Market and Foreign Exchange Market Integration in South Africa. *World Development Perspectives*, 6, 32–34. http://dx.doi.org/10.1016/j.wdp.2017.05.001.

Nakamoto, S. (2008). Bitcoin: A Peer-to-Peer Electronic Cash System. Unpublished Manuscript. Available online: http://pdos.csail.mit.edu/6.824/papers/bitcoin.pdf

Nakomoto, S. (2009). Bitcoin: A Peer-to-Peer Electronic Cash System. https://bitcoin.org/bitcoin.pdf/.

Nason, G. (2010). Wavelet Methods in Statistics with R. Springer Science & Business Media.

Omane-Adjepong, M., & Dramani, J., B. (2017). On the Dynamic Effects of Global Commodities on Stock Market Blocks in Africa. *Applied Economics Letters,* 1350-4851. *http://dx.doi.org/10.1080/13504851.2017.1368978.*

Owusu-Junior, P., Tweneboah, G., & Adam, A., M. (2019). Interdependence of Major Exchange Rates in Ghana: A Wavelet Coherence Analysis. *Journal of African Business*, 1-24.

Owusu-Junior, P., Boafo, B., K., Awuye, B., K., Bonsu, K., & Obeng-Tawiah, H. (2018). Co-movement of Stock Exchange Indices and Exchange Rates in Ghana: A Wavelet Coherence Analysis. *Cogent Business & Management*, 5, 1-24. https://doi.org/10.1080/23311975.2018.1481559.

Peltomäki, J., Graham, M., & Alagidede. P. (2017). Commodity-Driven Integration of Stock Markets in Africa. *Applied Economics Letters*, 24(11), 784-789. https://www.tandfonline.com/loi/rael20.

Percival, D., B., & Walden, A., T. (2000). *Wavelet Methods for Time Series Analysis, vol. 4 of Cambridge Series in Statistical and Probabilistic Mathematics*, Cambridge University Press, Cambridge, UK.

Percival, D., B., Mofjeld, H., O. (1997). Analysis of Subtidal Coastal Sea Level Fluctuations using Wavelets. *Journal of the American Statistical Association*, 92 (439), 868–880.

Percival, D., B. (1995). On Estimation of the Wavelet Variance. *Biometrika*, 82 (3), 619–631.

Pretorius, E. (2002). Economic Determinants of Emerging Stock Market Interdependence. *Emerging Markets Review*, *3*(1), 84-105.

Pukthuanthong, K., & Roll, R. (2009). Global Market Integration: An Alternative Measure and Its Application. *Journal of Financial Economics*, 94 (2), 214– 232. doi: 10.1016/j.jfineco.2008.12.004.

Ramsey, J., B. (2002). Wavelets in Economics and Finance: Past and Future. *Studies in Nonlinear Dynamics & Econometrics*, 6 (3), 1–29.

Roesch, A., & Schmidbauer, H. (2014). Package 'WaveletComp.' Retrieved from https://pbil.univlyon1.fr/CRAN/web/packages/WaveletComp/WaveletComp.pdf.

Skult, R. (2019). Stock Market Comovement in the Nordics: A Wavelet Analysis.

Sibanda, M. (2015). Stock Market Returns and Exchange Rate Movements in a Multiple Currency Economy: The Case of Zimbabwe. *Journal of Economic and Financial Sciences*, 8(3), 742-752.

Tiware, A., K., Dar, A., B., Bhanja, N., & Shah, A. (2013). Stock Market Integration in Asian Countries: Evidence from Wavelet Multiple Correlations. *Journal of Economic Integration*, 441-456.

Torrence, C., & Compo, G., P. (1998). A Practical Guide to Wavelet Analysis. *Bulletin of the American Meteorological Society*, 79(1), 61–78.

Torrence, C., & Webster, P., J. (1999). Interdecadal changes in the ENSO–Monsoon System. *Journal of Climate*, 12(8), 2679–2690.

Trabelsi, N. (2018). Are There Any Volatility Spill-Over Effects among Cryptocurrencies and Widely Traded Asset Classes? *Journal of Risk and Financial Management*, 11(4), 66.

Ünvana, Y. A. (2019). Impacts of Bitcoin on USA, Japan, China and Turkey stock market indexes: Causality analysis with value at risk method (VAR). *Communications in Statistics-Theory and Methods*, 1-16.

Uddin, G., S., Tiwari, A, K., Arouri, M., & Teulon, F. (2013). On the Relationship between Oil Price and Exchange Rates: A Wavelet Analysis. *Economic Modelling*, 35, 502–507.

Veleda, D., Montagne, R., & Araujo, M. (2012). Cross-wavelet bias Corrected by Normalizing Scales. *Journal of Atmospheric and Oceanic Technology*, 29(9), 1401–1408.

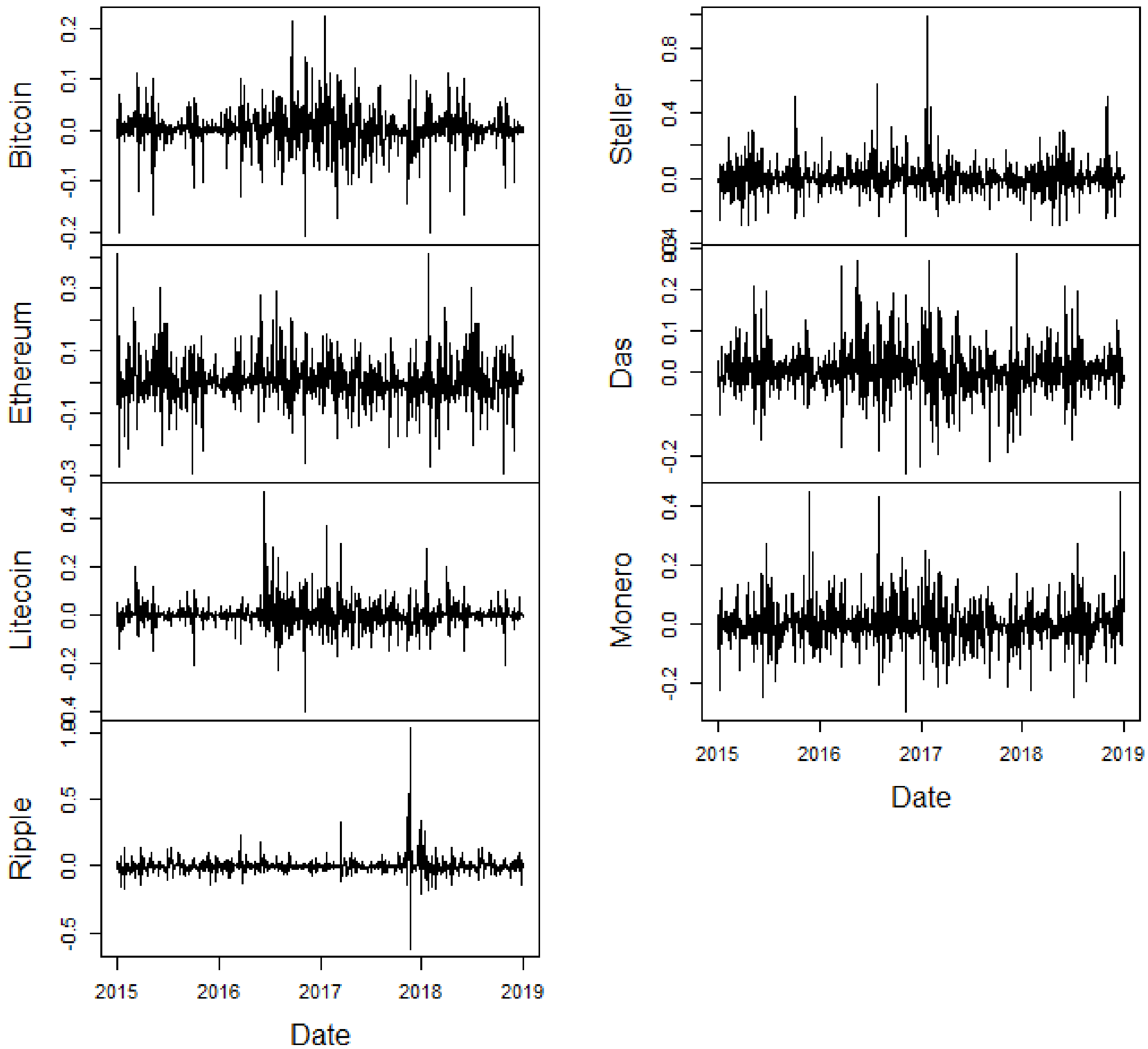
Wang, G., J., Xie, C., Wen, D., & Zhao, L. (2019). When Bitcoin meets Economic Policy Uncertainty (EPU): Measuring Risk Spillover Effect from EPU to Bitcoin. *Finance Research Letters*, *31*.

Wu, S., Tong, M., Yang, Z., & Derbali, A. (2019). Does Gold or Bitcoin Hedge Economic Policy Uncertainty?. *Finance Research Letters*, *31*, 171-178.

Yaya, S., O., Ogbonna, A., E., & Olubusoye, E., O. (2018). How Persistent and Dependent are Pricing of Bitcoin to other Cryptocurrencies Before and After 2017/18 Crash*? Munich Personal RePEc Archive*, 91253. https://mpra.ub.uni-muenchen.de/91253/.

Yermack, D. (2015): "Is Bitcoin a Real Currency?", in D Lee (ed), *The Handbook of Digital Currency*, Elsevier, pp 31–44.

Zhang, W., Wang, P., Li, X., & Shen, D. (2018). The Inefficiency of Cryptocurrency and its Cross-correlation with Dow Jones Industrial Average. *Physica A: Statistical Mechanics and its Applications*, *510*, 658-670.


Bitcoin
Ethereum
Litecoin
Ripple
Steller
Das
Monero
Date
Date
2015
2016
2017
2018
2019

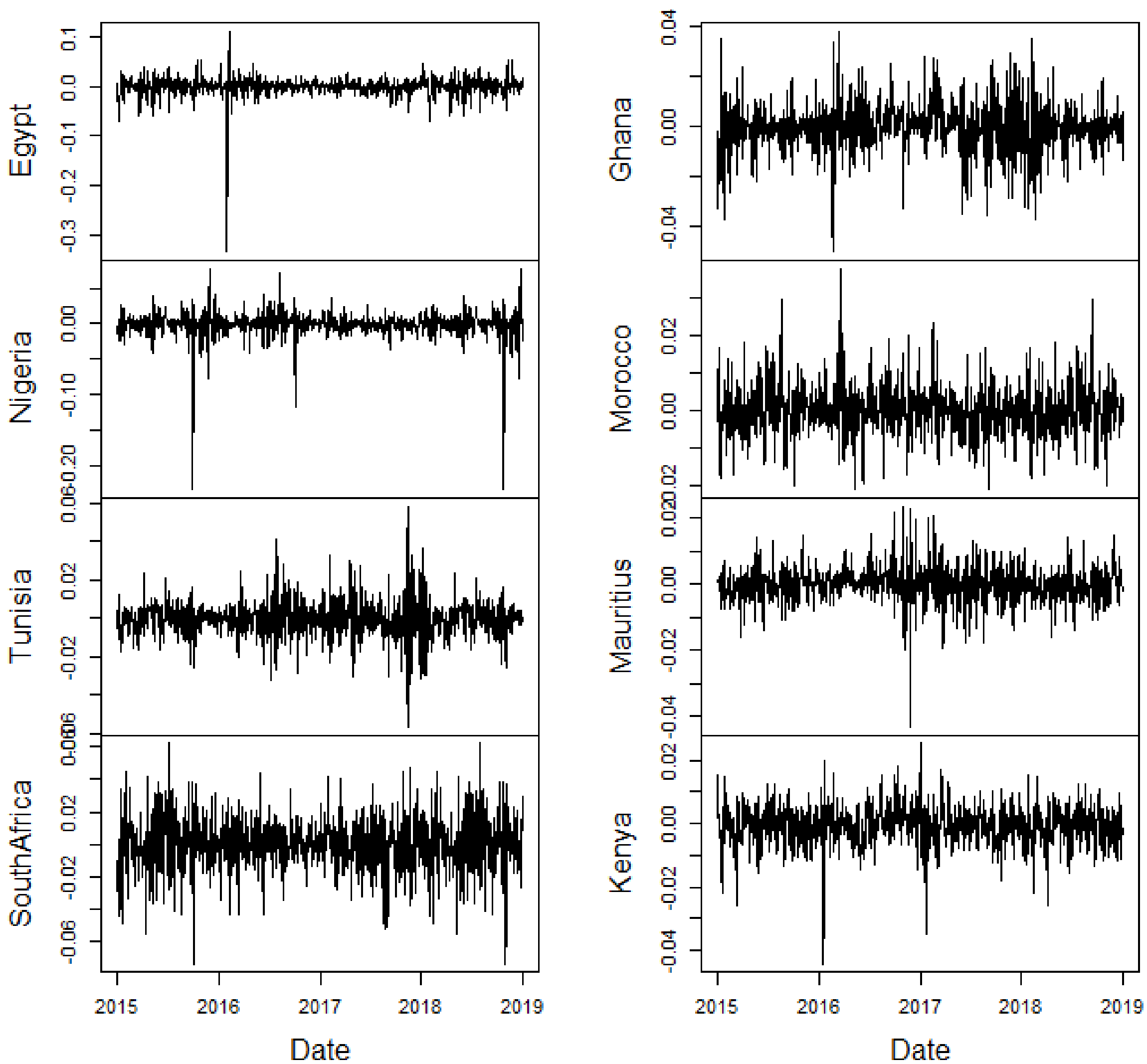


Figure 2. 1: Time series plot of selected Cryptocurrencies and African stock indices returns

CHAPTER THREE

Asymmetric Linkages between Cryptocurrencies and African Fiat Currencies

3. Introduction

In 1976, F. A. Hayek in his article "The Denationalization of Money" envisioned a system of private currencies in which banks would be induced by the forces of currency competition to provide a stable means of exchange in an economy. Hayek was worried about the high inflation in western countries in the 1970s which could not be tackled by central banks because of political constraints (Fernández-Villaverde and Sanches, 2018). Hayek argued against government monopoly in issuing a medium of exchange, and that market forces should be allowed to determine money-issuing in an economy. He contends that inflation in an economy can be controlled using a free market monetary system which allows for competition in currency markets within the economy (Hayek, 1976; Cermak, 2017; Fernández-Villaverde and Sanches, 2018). He believed that government reserve currencies and private currencies can coexist in an economy but government should control inflation otherwise people will switch to alternative currencies. However, Hayek's proposal was abandoned because it was not seen as a workable idea but instead as a curiosity. Nevertheless, this proposal has been made a reality by Satoshi Nakomoto in 2009 due to the development in technology in recent years. The development of computer science and cryptography has led to the creation of cryptocurrencies, privately issued currencies which are robust to over issuing, counterfeiting, and the double spending problem[29].

The theoretical root of cryptocurrencies can be traced to the Austrian business cycle theory, originated by Ludwig von Mises and Friedrich Hayek in the 1920s. The theory contends that occurrences in business cycles are not caused by natural phenomenon but by central banks manipulation of interest rates and money supply (Cermak, 2017). This implies that in an economy where the central bank influences entrepreneurs, an artificial signal is created through lower interest rates which mostly lead to over production and thereby destabilizes the economy. The Austrian business cycle theory holds that governments can avoid economic decline by finding

[29] The holder of the currency should not be able to spend the same token twice.

natural interest rates instead of pumping money arbitrarily into circulation (Georgeson, 2018). There is no central authority that determines the interest rates and the circulation of cryptocurrencies suggesting cryptocurrencies as theoretically linked to the Austrian business cycle theory. Cryptocurrencies have the potential to weaken the power of central banks as the sole issuer of means of exchange and can become an alternative currency in an economy when the inflation of the economy's fiat currency is too high.

Cryptocurrencies have gained traction as means of payment and financial instrument and have started to impact on the currency market threatening the supremacy of fiat currencies[30]. There has also been a search for an alternative to fiat currencies because of the often manipulation of fiat currencies for political and economic gains (Carrick, 2016; Staiger and Sykes, 2010). Cryptocurrencies have several advantages over fiat money. They are not subject to manipulation in terms of overprinting because they have fixed supply and also have no circulation cost because they are only virtually produced, thereby saving production cost. Currently, there are individuals, institutions, corporations, local and federal entities who are accepting cryptocurrencies as payments around the world setting a standard for their institutionalized use (Corelli, 2018). Cryptocurrencies at the moment operate alongside fiat currencies and cannot displace the position of fiat currencies as a country's dominant currency because of its volatility and few volumes. However, as the use and popularity of cryptocurrencies increase and algorithms improve to reduce its volatility, they can challenge the position of fiat currencies in economies. Investors are also asking if cryptocurrencies will replace fiat money in a short or long period and the consequences of such a takeover (Corelli, 2018).

Cryptocurrencies and government reserve currencies are connected as the worth of cryptocurrencies are measured in terms of fiat money. Implying that cryptocurrency transactions are quantified in fiat money, that is in this transaction, cryptocurrency is used as a medium of exchange while fiat money is used as a unit of account. This may reduce the competition between the currencies and perhaps lead them to a complete merger. As indicated in the work of Corelli

[30] The exchange rate between USD and Bitcoin broke the $20,000 mark on 17th December 2017, and closed at just above $19, 000 on the same day (see Coindesk, 2019).

(2018), cryptocurrencies may be legally adopted as alternative payment option in the future by failing countries and economies to stabilize the value and exchange rates of their fiat monies. Nevertheless, the empirical literature on cryptocurrencies and fiat currencies interconnectedness is still sparse, and focuses on the relationship, price dynamics, and speculative bubbles between Bitcoin and major world currencies with little or no published studies on altcoins and African fiat currencies. Notable studies in this regard include Hencic and Gourieroux (2014) who apply a noncausal autoregressive process with Cauchy errors to model and predict the USD and Bitcoin exchange rate using daily closing rates of Bitcoin and USD. The findings show episodes of local trends that can be modelled and interpreted as speculative bubbles due to the dynamics of daily Bitcoin/USD exchange rate. The authors suggest that the bubbles may arise from the speculative trading of Bitcoin. In a related study, Sapuric and Kokkinaki (2014) asses the volatility of Bitcoin exchange rate against six conventional currencies, using raw annualized data. They report high annualized volatility for the exchange rate of Bitcoin. However, the volatility of the exchange rate of Bitcoin stabilized when they accounted for the volume of Bitcoin trades.

Evaluating the validity of Bitcoin as a currency against the three required functions of money, Yermack (2013) posits that Bitcoin cannot be a store of value or a unit of account although it satisfies the role of a medium of exchange. Wu and Pandey (2014) investigated the value of Bitcoin as a currency against five reserve currencies (Euro, Yen, Australian dollar, Pound, and Canadian dollar). They reported Bitcoin to have low correlations with the reserve currencies. Yussof and Al-Harthy (2018) scrutinize the challenges and issues of cryptocurrencies as complement to Malaysian fiat currencies and recommended that due to the global trend[31] of cryptocurrencies, Malaysia should fully adopt a cryptocurrency to complement its fiat currency. In examining the volatility of Bitcoin relative to global fiat currencies, Cermak (2017) investigates whether Bitcoin can be an alternative to the fiat currencies of China, Japan, the European Union, and United States using GARCH (1, 1). Findings show that Bitcoin has safe-haven properties for China but behaves similar to the other reserve currencies except for Japan.

[31] That is using blockchain to develop Shariah complaint cryptocurrency backed by gold, and China developing its own cryptocurrency as complement to reserve currencies.

Dyhrberg (2016a) employs daily data to examine the hedging ability of Bitcoin for USD/GBP, and USD/EUR exchange rates and finds that Bitcoin has positive influence on dollar-sterling and dollar-euro exchange rates. Similarly, Dyhrberg (2016b) makes use of asymmetric GARCH methodology to investigate the ability of Bitcoin to hedge USD in the short-term. The study reports that Bitcoin has a positive correlation with the USD and can be a hedge for dollar/euro and dollar/pound exchange rates. In a different dimension, Gajardo et al. (2018) assess the asymmetry cross-correlations between Bitcoin and global reserve currencies. The authors applied MF-ADCCA, and evidence shows that Bitcoin behaves differently from the major currencies. Examining Bitcoin as a complement to emerging markets currency, Carrick (2016) examined the volatility and value of Bitcoin comparative to fiat currencies in emerging economies and evidenced Bitcoin as a viable alternative to emerging market currencies. In another study, Corelli (2018) employs multivariate linear regression to scrutinize the causal relationship between six cryptocurrencies and ten fiat currencies and reported association between some of the cryptocurrencies and fiat currencies.

Employing MF-ADCC model, Kristjanpoller and Bouri (2019) model the cross-correlation and asymmetric multifractality between cryptocurrencies (Litecoin, Bitcoin, Monero, Das, and Ripple) and global fiat currencies (Euro, Yen, Swiss Franc, Australian dollar, and British Pound) for the period June 2014 to February 2018. The authors evidenced significant persistent asymmetric attributes of all the cryptocurrencies, with Bitcoin and Litecoin showing high multifractal behavior compared to Ripple and Monero. Ehlers and Gauer (2019) compare the behavior of five principal cryptocurrencies (Bitcoin, Ripple, Ethereum, Litecoin, and Das) to the behavior of five global fiat currencies (GBP, EUR, CAD, CHF, and JPY) applying correlation, autocorrelation, variance ratio test, and Kolmogorov–Smirnov test. Findings of the study suggest that Bitcoin, Das, Ethereum, JPY, CAD, and EUR reduce the variance of mixed portfolio, whiles Bitcoin and Ripple have great impact in a portfolio with only cryptocurrencies. Drożdż, Minati, Oświęcimka, Stanuszek, and Wątorek (2019) model the multi-scale connection between Bitcoin, Ethereum, USD, and Euro for the period 2016 to 2018 and reported that the multi-scale characteristics of fluctuations in cryptocurrency exchange rates approach the exchange rate fluctuations of forex market and that there is no significant connection between Bitcoin/Ethereum and Euro/USD exchange rates.

The empirical literature shows evidence that related studies mostly explored the behavior of Bitcoin and major reserve currencies by capturing time information and ignored essential information relating to frequency domain leading us to ask the question "what is the nature of asymmetric linkages between cryptocurrencies and African fiat currencies across market conditions and time?. Following Pal and Mitra (2017), nonlinearities in time series investigation are mainly caused by ignoring frequency information. Generally, the connection between cryptocurrencies and fiat currencies is expected to be nonlinear[32] and our study addresses this issue. Importantly, cryptocurrencies are deflationary and artificially scarce due to their fixed supply and can offer a hedge against inflation, exchange rate risk, and provide a stable store of value for the African continent when adopted as alternative medium of exchange to African reserve currencies (see Fokuo, 2018; Naboulsi and Neubert, 2018; Georgeson, 2018). However, the behavior of cryptocurrencies relative to African fiat currencies remains unexplored despite the attractive attributes[33] of cryptocurrencies.

African fiat currencies are characterized by high inflation and exchange rate variability which denies a lot of Africans financial freedom (see, Rainer, 2017; Kargbo, 2000). As noted by Kargbo (2000), most countries in Africa record high volatility in prices due to high inflation and high exchange rates volatility since liberation in the 1980s. Studies on the relationship between inflation and exchange rates in Africa show that output reduces and inflation increases due to depreciation of African currencies (Alagidede, Tweneboah, and Adam, 2008) making investing in Africa highly risky hindering trade flows in the continent (Owusu-Junior, Anokye, and Tweneboah, 2017; Fokuo, 2018). Inflation discourages investments in fixed income instruments such as currencies and bonds. Fiat currencies depreciate in inflationary periods and probably cryptocurrencies can tender a store of value when faith in the local currency is shaken (see Das and Kannadhasan, 2018; Corelli, 2018; Kristjanpoller and Bouri, 2019). Although Africa is a diverse region, its nations share some key similarities and trends. Economic problems, from volatile currencies and high

[32] Nonlinear dynamics are not rare in financial series such as exchange rates and cryptocurrencies. The time series of these variables are characterized by sudden and irregular jumps and neglecting nonlinear dependences may lead to inacurrate predictions (Zhang, 2002; Bisaglia and Gerolimetto, 2014). In addition, heterogeneity of participants in the financial market is often cited as a major source of nonlinear dynamics of financial series (Zhang, 2002).

[33]Following Kristjanpoller and Bouri (2019), cryptocurrencies have hedging and safe-haven properties against inflation and forex risk, offer lower cost of transactions (Kim, 2017), and swift transactions (Fantazzini et al., 2016) relative to forex markets leading to ample liquidity in the cryptocurrency market.

inflation rates to financial issues such as capital controls and a lack of banking infrastructure, as well as demographic and societal trends make Africa well-suited to the rapid adoption of cryptocurrencies. While much of the focus elsewhere has been on speculation, trading, and investment, Africa, more than any other continent has a need for the utility of cryptocurrencies. The adoption of cryptocurrencies as complements to African currencies can help African countries expand their pool of available capital, provide volatile capital markets with stable alternatives, and rebuild trust in government which can drive increased international investment across the region.

Cryptocurrencies and fiat currencies are both impacting the world economy as several aspects of them are rolling on emerging economies (Muedini, 2018). Globally, cryptocurrencies have ceased the attention with their direct competitor of government fiat currencies by aggregate market capitalization (Lim, 2017; Islam, Nor, Al-Shaikhli, and Mohammed, 2018). There are thousands of cryptocurrencies in the market currently with Bitcoin as the most successful which is used as currency on its own (Islam, Nor, Al-Shaikhli, and Mohammed, 2018). The regulations of cryptocurrencies by central banks in many countries are still on-going since they are considered as better alternatives (e.g. low or no transaction cost, high volumes and swift transactions, hedges against inflation and forex risk, etc) relative to fiat currencies leading to ample liquidity in the cryptocurrency market (Kristjanpoller and Bouri, 2019; Kim, 2017; Fantazzini et al., 2016; Islam, Nor, Al-Shaikhli, and Mohammed, 2018). However, a quick scan of the cryptocurrencies and fiat currencies literature reveals no empirical studies on cryptocurrencies and African fiat currencies even though cryptocurrencies have desirable attributes that are robust to the stylized facts[34] of African currency market. Aside from that, related studies (e.g., Kristjanpoller and Bouri, 2019; Corelli, 2018; Gajardo et al., 2018; Ehlers and Gauer, 2019) mainly focused on global currencies and applied models that capture time information and ignored essential information relating to frequency domain. Thus, the motivation to examine the asymmetric linkages between five principal cryptocurrencies and eight major African reserve currencies to see if cryptocurrencies are well suited as complements to African fiat currencies. We implement the ensemble empirical mode decomposition-based quantile-in-quantile regression to explore the value and volatility of

[34] The works of Fokuo (2018), Owusu-Junior, Adam, and Tweneboah (2017), Kargbo (2000) and Rainer (2017) suggest that African forex market exhibit stylized facts including high inflation, exchange rate variability, low speed and few volumes of transactions, and high cost of transactions.

the currencies at different currency regimes in a time-frequency space. We account for the time and frequency information in the time series of the currencies using the ensemble empirical mode decomposition (EEMD). We then implement quantile regression (QR) and quantile-in-quantile regression (QQR) on the decomposed series to test the response of cryptocurrencies to shocks in African fiat currencies at high (low) currency regimes across time.

The QR results for cryptocurrencies and African fiat currencies associations suggest that cryptocurrencies behave differently from fiat currencies and that except for ZAR, Bitcoin is a viable alternative digital currency in the medium-term for Cedi, Naira, Rupee, Dirham, Shilling, and Dinar, but long-term for Egyptian Pound. Ethereum can be a viable alternative digital currency to Egyptian Pound and ZAR in the long-term, Dinar and Dirham in the medium-term, Cedi, Shilling, and Rupee from medium-term, and Naira in both short and long-terms. We observe from Litecoin-Fiat currency linkages that except for Cedi and ZAR, Litecoin can be a good alternative virtual currency for EGP, Naira, and Rupee in the long-term, both short and medium-term for Dinar and Dirham, but all periods for Shilling. Ripple-Fiat currency connectedness depicts that except for EGP, Ripple can supplement Cedi, Rupee, Dinar, Dirham, and Shilling in the long-term but medium-term for ZAR and Naira. Lastly, the Das-Fiat currency association exhibits hedging benefits for EGP, Cedi, ZAR, Naira, and Rupee in the long-term but from medium-term for Shilling suggesting that except for Dirham, Das can complement the fiat currencies from the medium-term. The findings from QQR demonstrate that cryptocurrencies are hedges and viable alternative currencies to African currencies from the medium-term when the fiat currencies are depreciation, and the cryptocurrency market is less volatile. Thus, Africa can adopt cryptocurrencies as complement to their fiat currencies from the medium-, to long-term but not the short-term.

This study has implications for policymakers on considering cryptocurrencies as alternative payment mechanism which may operate alongside government fiat currencies from the medium-term. The study also provides vital information for multinational corporations, and forex traders on the ability of cryptocurrencies to hedge against the dollar/African fiat currencies exchange rate risk. Technically, we may conclude that cryptocurrencies and African fiat currencies are complements for long-term sustainable currency market. Our study contributes to the limited literature on cryptocurrency and fiat currency interconnectedness by extending the investigation into the African currency market to capture the African effects on cryptocurrencies and fill the gap in the literature that is focused on the reserve currencies of developed economies. This study further departs from earlier works by considering issues regarding time-frequency, asymmetries, and nonlinearities in the time series of currencies applying the EEMD-based quantile-in-quantile regression which provides comprehensive results compared to other models used in related studies.

The rests of the chapter are organised as follows. Section 3.1 describes of the methodology. Section 3.2 explains the data and statistical properties. Section 3.3 presents the results and discussion on the asymmetric relations between the currencies. Section 3.4 discusses the conclusion and policy implications.

3.1 Methodology

The study employs the ensemble empirical mode decomposition (EEMD), quantile regression (QR), and Quantile-in-Quantile (QQ) regression techniques to achieve the set objective. The EEMD technique captures the time and frequency information in the return series of the currencies. Agents in financial markets have varying decision-making timescales and the EEMD can be used to decompose a time series into varying time and frequencies. The QR and QQR test the response of cryptocurrencies to shocks in African fiat currencies at high (low) currency regimes across time. The methodology comprises two steps where intrinsic mode functions (IMFs) are extracted from the return series of cryptocurrencies and the exchange rate/USD returns of fiat currencies with EEMD based on which QR, and the QQ regression are applied. In line with Ivanov (2013), IMFs designate the varying time scales of the original series showing the movements of the currencies at high, medium, and low frequencies and they are important in this study to address nonlinearity and nonstationarity within the return series of the variables.

3.1.1 Ensemble Empirical Mode Decomposition (EEMD)

The EEMD succeeds the empirical mode decomposition (EMD). As inidicated by Wu and Huang (2009), the EEMD is an improvement on the EMD by allowing a finer scale separation. The EEMD adds varying series of white noise into the signal in different trails. Notably, the resulting IMFs do not show any association with the corresponding IMFs across trails since the added white noise differ in every trails. The EEMD methodology describe here follows the approach of Wu and Huang (2009) .

The IMF is defined by the EEMD as the mean of an ensemble of trials, where each is made of the signal (data) and a white noise of finite amplitude. In generic terms, all data $x(t)$ are a sum of signal (i.e. actual data, $s(t)$) and noise $n(t)$ so that

$$x(t) = s(t) + n(t) \tag{3.1}$$

Although several data analysis methods have failed to eliminate the noise component, the added white noise eliminates weak signals and keeps the true signal presenting a fine-tuned data free from white noise for empirical investigation that can be reliably used for inferencing and forecasting.

From equation (3.1) an i^{th} artificial observation, $x_i(t)$ in equation (3.2) is obtained when a white noise of varying realisations is added, and $\omega_i(t)$ avoids mode mixing and offers a fairly uniform reference scale distribution to facilitate EMD.

$$x_i(t) = x(t) + \omega_i(t) \tag{3.2}$$

Nevertheless, the randomly added white noise series by the EEMD cancel out each other in the final rendition of the respective IMFs and mean IMFs reside within the natural dyadic filter windows which sidestep the mode mixing problem. The maximum number of IMFs s_i (and one residual r) of a data set is approximately $log_2 N$ where N denotes the number of observations and r can be denoted as $s_i - (s_i - 1)$.

3.1.2 The Quantile-in-Quantile Approach

The conventional quantile regression (QR) technique proposed by Koenker and Bassett (1978) has become a common tool to model and analyze the time-varying degree and dependence structure between time-series data. Unlike the classical linear or non-linear regression models, the quantile regression precisely and accurately measures the impact of explanatory variables on the different quantiles of a dependent variable of the given distribution enabling a comprehensive relationship between variables across different time periods (see Koenker, 2005). The QR extends the classical linear regression technique providing information on dependence in both upper[35] and lower[36] tails in addition to the median[37].

The major weakness of the QR approach is its inability to capture entire dependency. The QR does not accommodate the possibility of a bidirectional relationship between cryptocurrencies and fiat currencies, even though it can analyze and estimate the heterogeneous relationship between the currencies at various points of the conditional distribution. Hence, Sim and Zhou (2015) proposed a Quantile-in-Quantile (QQ) approach, which theoretically combineds QR with nonparametric estimations. The QQ technique has been utilized in the field of applied growth and energy economics (Atsalakis, Bouri, and Pasiouras, 2020; Mallick, Padhan, and Mahalik, 2019; Raza, Zaighum, and Shah, 2018) to empirically investigate how the quantiles that emerge from a variable affect the conditional quantiles of another variable.

Employing the QQ approach, we model the quantile of cryptocurrency returns (and its frequencies) as a function of the quantile of fiat currency returns of a country. The QQ approach provides a clear and more complete picture of dependence by capturing the diverse relationships between the dependent and independent variables at each point of their conditional distributions. The QQ technique is implemented by selecting quantiles of fiat currency returns and their various

[35] In this study, upper tail is when the currencies are gaining value
[36] Lower tail is when the currencies are losing value
[37] Median is when the currencies are stable in value.

frequencies on the various quantiles of cryptocurrency returns. The study follows Sim and Zhou (2015) single equation regression approach, which is also based on Ma and Koenker (2006).

Therefore, the QQ approach used in this study to model the effect of the quantiles of a country's fiat currency returns on the quantiles of cryptocurrency returns has its starting point of representation in the following nonparametric quantile regression equation:

$$Crp_t = \beta^{\theta}(Fcur_t) + u_t^{\theta} \tag{3.3}$$

where Crp_t denotes the exchange rate returns between cryptocurrency and the US dollar at period *t*, $Fcur_t$ denotes the exchange rate returns between fiat currency of a country and the US dollar in time *t*, θ is the θthquantile of the conditional distribution of Crp_t and u_t^{θ} is the quantile residual term whose conditional θthquantile is assumed to be zero. $\beta^{\theta}(\cdot)$ is an unknown function since we lack prior information on the relationship between the variables.

This quantile regression model empirically studies the asymmetric effects of movements of a country's fiat currency exchange rate returns on cryptocurrency returns while exploring the varying effects of cryptocurrency exchange rate returns across different quantiles of fiat currency returns in selected countries. The main advantage of this regression specification is the flexibility to capture the functional form of the dependency relationship between fiat currencies and cryptocurrencies returns in sample countries. Finally, the asymmetric effects of the fiat currency exchange rates return on cryptocurrency exchange rates returns are possible in response to both negative and positive shocks arising from cryptocurrency returns.

To establish the relationship between the θthquantile of fiat currencies and the τthquantile of cryptocurrency returns, the local linear regression is used to examine equation (3.3) in the neighbourhood of $Fcur^{\tau}$. Given that the value of $\beta^{\theta}(\cdot)$ is unknown, we can expand the regression function through a first order Taylor expansion around a quantile of $Fcur^{\tau}$ in the following way:

$$\beta^{\theta}(Fcur_t) \approx \beta^{\theta}(Fcur^{\tau}) + \beta^{\theta'}(Fcur^{\tau})(Fcur_t - Fcur^{\tau}) \tag{3.4}$$

We can redefine $\beta^{\theta}(Fcur^{\tau})$ and $\beta^{\theta'}(Fcur^{\tau})$ as $\beta_0(\theta,\tau)$ and $\beta_1(\theta,\tau)$, based on the study of Sim and Zhou (2015). Accordingly, equation 3.4 can be re-written as follows:

$$\beta^{\theta}(Fcur_t) \approx \beta_0(\theta,\tau) + \beta_1(\theta,\tau)(Fcur_t - Fcur^{\tau}) \qquad (3.5)$$

By substituting equation (3.5) into equation (3.3), we arrive at equation (3.6) as follows:

$$Crp_t = \underbrace{\beta_0(\theta,\tau) + \beta_1(\theta,\tau)(Fcur_t - Fcur^{\tau})}_{(*)} + \mu_t^{\theta} \qquad (3.6)$$

In that the conditional quantile of cryptocurrency returns denoted by (*) allows the exact connections among the quantile of cryptocurrency returns and that of gold/oil of β_0 and β_1 parameters with θ and τ indices. Applying a minimisation in line with ordinary least squares, we specify equation (3.7)

$$min_{b_0,b_1} \sum_i^n \rho\theta \left[Crp_t - b_0 - b_1\left(\widehat{Fcur}_t - \widehat{Fcur}^{\tau}\right)\right] K\left(\frac{F_n(\widehat{Fcur}_t - \tau)}{h}\right) \qquad (3.7)$$

where $\rho_{\theta}(u)$ is the quantile loss function representing as $\rho_{\theta}(u) = u\big(\theta - I(u < 0)\big)$, h, $K(\cdot)$, and i denote the kernel density bandwidth parameter, kernel density, and indicator functions respectively. The observations of Crp^{τ} are weighted by the kernel function where the minimum weight inversely relates to the distribution function of $\widehat{Crp}_t$ as $F_n\big(\widehat{Crp}_t\big) = \frac{1}{n}\sum_{k=1}^{n} I(\widehat{Crp}_k < \widehat{Crp}_t)$.

The choice of bandwidth is critical in nonparametric techniques as it smoothens the resulting estimate by determining the neighbourhood size at a targeted point. The bigger bandwidth produces robust estimation bias whiles the lesser bandwidth provides estimations with high variance bringing a balance between bias and variance. We use a bandwidth parameter $h = [0.05\ to\ 0.95]$ as used by Sim and Zhou (2015) in our analysis.

3.2 Data description and preliminary analysis

To examine the asymmetric connections between cryptocurrencies and African fiat currencies, the study focuses on eight major African fiat currencies: USD/EGP for Egyptian Pound, USD/ZAR for South African Rand, USD/NGN for Nigerian Naira, USD/GHS for Ghanaian Cedi, USD/MUR for Mauritian Rupee, USD/TND for Tunisian Dinar, USD/MAD for Moroccan Dirham and USD/KES for Kenyan Shilling. These currencies are sampled because they are the currencies of the eight major stock markets in Africa and fairly represent the regions within the African continent. We also sampled five principal cryptocurrencies: USD/BTC for Bitcoin, USD/ETH for Ethereum, USD/LTC for Litecoin, USD/DASH for Das and USD/XRP for Ripple based on market capitalization[38] and trading volume[39] and can proxy for the cryptocurrency market. Data spans 10th August 2015 to 18th February 2019 at daily frequency and sourced from Datastream and CoinMarketCap. We consider the exchange rate of a country's fiat currency and each cryptocurrency currently with US dollar to ease comparison and alleviate exchange rate noise (Pukthuanthong and Roll, 2009).

We follow Martens and Poon (2001) and remove non-synchronous data points to prevent the problem of underestimation of true correlations and regressions. After matching the daily observations of the five cryptocurrencies with the eight African fiat currencies, there were 826 observations. The availability of cryptocurrency price data constrained the period of analysis and the number of observations in this study. Taking the first differences of logarithm, the daily price data were converted to daily returns. The daily returns of the currencies are decomposed into frequencies termed IMFs based on the data points exhibiting fluctuations in the currencies at high, medium, and low frequencies as used by Wu and Huang (2009). In line with related studies, IMF 1, IMF 5, and IMF Residual denotes the short-term, medium-term, and long-term movements of the currencies (see Khaldi, El Afia, Chiheb, and Faizi, 2018; Wu and Huang, 2009).

[38] The market capitalization for cryptocurrencies includes: BTC - $136.36B, ETH - $14.47B, LTC - $2.67B, XRP - $19.56B, DAS - $408.38M (https://cryptocompare.com/; sourced 23-12-2019).

[39] The trading volume for cryptocurrencies includes:BTC - $ 294.79M, ETH - $22.82M, LTC – 7.24M, XRP - $19.56B, DAS - $408.38M (https://cryptocompare.com/; sourced 23-12-2019).

The exchange rate return summary statistics and their IMFs are displayed in Table 3.1; excess kurtosis and skewness corroborate the Jarque-Bera test confirming asymmetries and non-normality in the exchange rate returns of the currencies. The summary statistics of the decomposed series also exhibit fat-tails confirming the behaviour of the composite series showing the importance of implementing quantile-based techniques to model heavy tails of the currencies. Further, the return plots of the composite and decomposed series displayed in Figure 3.1 in the Appendices exhibit volatility clustering signifying time-varying risk transmissions from the currencies justifying the importance of employing IMF decomposition to model the frequency-dependent volatility of the series.

Table 3. 1: Summary statistics of return series and their IMFs

Statistic	**BTC**	**IMF1**	**IMF5**	**IMRes.**	**ETH**	**IMF1**	**IMF5**	**IMRes.**
Obs.	826	826	826	826	826	826	826	826
Mean	0.0024	0.0006	0.0005	0.0013	0.0044	-0.0008	-0.0022	0.0095
Std. Dev.	0.0419	0.0318	0.0069	0.0022	0.0719	0.0527	0.0151	0.0169
Skewness	-0.1643	0.0829	-0.2767	-0.9372	0.7067	0.072	-0.2817	0.682
Kurtosis	4.8135	2.1418	4.7066	8.4516	4.2099	1.2857	2.8966	8.0646
Jarque-Bera	801*	159*	18*	121*	679*	58*	300*	86*
Statistic	**LTC**	**IMF1**	**IMF5**	**IMRes.**	**XRP**	**IMF1**	**MF5**	**IMRes.**
Obs.	826	826	826	826	826	826	826	826
Mean	0.0011	0.0002	0.0002	0.0001	0.0026	-0.0004	-0.0007	0.0021
Std. Dev.	0.062	0.0457	0.009	0.004	0.068	0.0527	0.0092	0.011
Skewness	1.3402	-0.0882	-0.0347	-1.233	4.5226	0.2078	0.5256	0.5725
Kurtosis	12.7502	2.8032	9.4283	3.4262	75.6901	45.6328	3.3062	9.2129
Jarque-Bera	5842*	272*	31*	213.33*	199989*	71673*	414.23*	74.336*
Statistic	**Das**	**IMF1**	**IMF5**	**IMRes.**	**EGP**	**IMF1**	**IMF5**	**IMRes.**
Obs.	826	826	826	826	826	826	826	826
Mean	0.0022	-0.0006	0.0002	0.0013	-0.0007	-0.0003	0.0006	-0.0004
Std. Dev.	0.0593	0.0466	0.0079	0.003	0.0154	0.0116	0.0033	0.0013
Skewness	0.326	0.0075	-1.6904	-9.1579	-15.8112	-1.0931	4.1388	0.6097
Kurtosis	3.3782	9.6608	2.0753	-1.1753	345.5953	69.4337	8.1612	-1.0728
Jarque-Bera	407*	32.129*	152.16*	115.93*	4145008*	166089*	2315.9	90.779*
Statistic	**Cedi**	**IMF1**	**IMF5**	**IMRes.**	**ZAR**	**IMF1**	**IMF5**	**IMRes.**
Obs.	826	826	826	826	826	826	826	826
Mean	-0.0003	-0.0002	0.0001	-0.0005	-0.0001	0.0001	0.000	-0.0002
Std. Dev.	0.0081	0.0069	0.001	0.0005	0.0116	0.0089	0.0015	0.0008
Skewness	0.1844	-0.2116	-0.1654	-0.6601	-0.1871	-0.0269	0.0521	-0.9454

Kurtosis	5.5863	5.3712	2.4285	-0.8227	1.1022	-0.2724	0.0005	-0.0293
Jarque-Bera	1079*	999.07*	206.75*	83.278*	47*	2.6531*	0.37403*	123.06*
Statistic	**Naira**	**IMF1**	**IMF5**	**IMRes.**	**Rupee**	**IMF1**	**IMF5**	**IMRes.**
Obs.	826	826	826	826	826	826	826	826
Mean	-0.0006	-0.0003	-0.0001	-0.0005	0.0001	0.000	0.000	0.0001
Std. Dev.	0.013	0.011	0.0011	0.0006	0.0049	0.0042	0.0006	0.0001
Skewness	-9.1378	-0.265	0.4485	0.2011	-0.6608	0.0073	-0.2265	-1.2681
Kurtosis	151.7847	27.4307	4.2459	-1.5402	9.3928	5.0999	3.8739	0.7642
Jarque-Bera	804406*	25906*	648.16*	87.211	3097*	895.13	523.56*	241.49*
Statistic	**Dinar**	**IMF1**	**IMF5**	**IMRes.**	**Dirham**	**IMF1**	**IMF5**	**IMRes.**
Obs.	826	826	826	826	826	826	826	826
Mean	-0.0003	-0.0002	0.000	0.000	0.000	0.000	0.000	0.000
Std. Dev.	0.0095	0.0085	0.0006	0.0007	0.0036	0.0029	0.0029	0.0005
Skewness	0.358	-0.0098	0.0363	-1.2162	0.6515	-0.1336	-0.1336	0.4892
Kurtosis	7.5215	6.308	-0.4559	0.3119	5.0571	0.7048	0.7048	-0.9122
Jarque-Bera	1966.1*	1371*	7.0974*	206.64*	939.96*	19.884*	2822.2*	61.009*

Statistic	**Shilling**	**IMF1**	**IMF5**	**IMRes.**
Obs.	826	826	826	826
Mean	-0.0115	-0.5232	-1.6727	373.9145
Std. Dev.	1.9716	157.608	23.1369	21.2852
Skewness	1.9716	-0.0124	-0.2004	0.6403
Kurtosis	21.7688	-1.1727	0.2291	-0.8544
Jarque-Bera	16303*	46.711*	7.4351*	80.983*

Note: *BTC-Bitcoin returns, ETH-Ethereum returns, LTC-Litecoin returns, XRP-Ripple returns, EGP-Egyptian pound returns, IMF1, IMF 5, IMRes. - intrinsic mode function for short-term, medium-term, and long-term respectively, Obs. – number of observations, and Std. Dev. –standard deviation.*

3.3 Results and discussion

We present the results and discussion for Quantile Regression (QR) in section 3.3.1 and in Table 3.2(a-e), and Quantile-in-Quantile Regression (QQR) in section 3.3.2 and in Table 3.3(a-e). We explore the interconnectedness of the currencies at high (low) currency regimes across time and frequencies. We choose the lower quantiles ($\tau = 0.05\ to\ 0.45$) as low currency state where the currencies are depreciating suggesting adverse shocks to the currencies, the medium quantile ($\tau = 0.50$) as normal state where the currencies are stable in value showing their normal strength, and upper quantiles ($\tau = 0.55\ to\ 0.95$) as high currency regime where the currencies are appreciating indicating positive shocks to currencies. IMF 1, IMF 5, and IMF Residual show movement of the currencies at higher, medium, and lower frequencies,[40] respectively indicating the time horizons.

3.3.1 QR Results for Cryptocurrencies and African fiat currencies

3.3.1.1 Bitcoin and African fiat currencies

In general, the association between Bitcoin and African fiat currencies connectedness shows negative associations across quantiles at medium frequency but positive relations across quantiles at lower frequency exhibiting the hedging properties of Bitcoin in the medium-term for fiat currencies and the possibility of volatility transmissions from Bitcoin to fiat currencies in the long-term.

Table 3.2a shows the QR results of Bitcoin and African fiat currencies exchange rate returns. For the Egyptian Pound (EGP), we observe strong positive dependencies across all quantiles in the medium-term. We also find both positive and negative significant associations at the lower quantiles (0.05 to 0.25) and upper quantiles (0.55 to 0.95) respectively in the long- term movements of the currencies. However, the medium-term shows the strongest association. The Ghanaian Cedi exhibits strong negative relationship at upper quantiles (0.70 to 0.95) in the medium-term but positive associations across quantiles in the long-term with weaker magnitude. The South African Rand (ZAR) shows positive associations across all quantiles in both medium- and long- terms (strongest) only that the quantiles 0.85 and 0.90 in the medium-term exhibit negative associations. The Nigerian Naira presents a unique story showing increasing positive connection from the lower to the upper quantiles at the composite level except for the 0.05, 0.10, and 0.95 distributions. Except for the quantiles of 0.45 to 0.55, the medium-term movement of Naira depicts inverse association across all distributions with the strongest magnitude occurring at the lower quantiles (0.05 to 0.15). However, the long-term exhibit a decreasing positive connection from quantiles (0.05 to 0.70).

[40] In this study, higher, medium, and lower frequencies indicate short-term, medium-term, and long-term movement of the currencies respectively.

Mauritius Rupee has inverse association across all quantiles except for the lowest quantiles (0.10, 0.15) and highest quantiles (0.80 to 0.90) in the medium-term, whereas the long-term of Rupee depicts positive link across all quantiles with weaker coefficients at the quantiles of 0.25 to 0.55. Nevertheless, Rupee shows the strongest coefficients than all other currencies in the long-term. Tunisian Dinar exhibits decreasing negative effects on Bitcoin across all quantiles in the medium-term except quantiles 0.85 and 0.95 but an increasing positive association from quantiles 0.25 to 0.95 in the long-term. The Moroccan Dirham depicts inverse connections in both medium-term (from quantiles 0.05 to 0.70) and long-term (all quantiles). Lastly, Kenyan Shilling shows inverse associations in the short-term (lower quantiles 0.10 to 0.40), and all quantiles in both medium- and long-term horizons.

When the patterns are grouped in terms of countries, we observe Nigeria, Ghana, Mauritius, and Tunisia displaying negative dependencies at medium frequency but positive relations at lower frequency suggesting that Bitcoin is a viable alternative currency and a good hedge[41] for the currency risk of the countries in the medium-term but in the long-term, Bitcoin market discrepancies can transmit to the countries. The reserve currencies of South Africa and Egypt, on the contrary, depict all positive associations in the medium-, and long-terms but switches between negative and positive in long-term for Egypt implying that Bitcoin can complement Egyptian Pound in the long-term since it can hedge currency appreciation of the fiat currency. However, Bitcoin behaves similar to ZAR across frequencies and cannot complement ZAR in any of the time horizons. We find Morocco and Kenya currencies to exhibit negative influence across currency regimes at the medium and lower frequencies as well as low currency regimes in the short-term of Kenya which suggests that the countries can adopt Bitcoin as alternative to Shilling and Dirham from the medium-term to hedge against depreciation and forex risk.

The findings for Bitcoin-fiat currency indicate that except for ZAR, Bitcoin is a viable alternative digital currency for Cedi, Naira, Rupee, Dirham, Shilling, and Dinar at medium frequency, but

[41]Based on the definitional approach conducted by Kaul and Sapp (2006), Baur and Lucey (2010), Reboredo (2013), and Baur and McDermott (2010), the distinctive characteristics of an asset as a safe haven, hedge and diversifier is as follows: An asset is a hedge if it exhibits a negative correlation at all market states, a safe haven if it is negatively correlated with another asset in times of market turmoil and a diversifier if it is positively but weakly correlated with another asset on average.

lower frequency for Egyptian Pound. When we compare the findings for Bitcoin and African fiat currencies (excluding ZAR) to related studies, our finding is in line with the findings of Gajardo et al. (2016), Carrick (2016), Yussof and Al-harthy (2018), and Ehlers and Gaur (2019) who reports that Bitcoin has hedging properties for global fiat currencies and thus can alternate the currencies. However, the results for Bitcoin and ZAR confirm the study of Cermak (2017), and Dyherberg (2016a, 2016b) who noted that Bitcoin behaves similarly to the reserve currencies of US, China, GBP, and European Union and cannot complement the currencies.

Table 3.2 a: QR estimates for Bitcoin and African fiat currencies exchange rates

	EGP	EGP.IMF1	EGP.IMF5	EGP.IMRes.	Cedi	Cedi.IMF1	Cedi.IMF5	Cedi.IMRes.
Quantile	**Coef.**	**Coef.**	**Coef.**	**Coef.**	**Coef.**	**Coef.**	**Coef.**	**Coef.**
0.05	0.0165	-0.1015	0.8348[a]	0.7112[a]	-0.0678	-0.6013	0.7740[b]	4.7851[a]
0.10	0.0870[a]	0.0495	0.6121[a]	0.5010[a]	0.1414	0.147	0.1147	4.7879[a]
0.15	0.1303[a]	0.107	0.4939[a]	0.3443[a]	0.1451	-0.0648	0.4230	4.7921[a]
0.20	0.1581[a]	0.0491	0.3486[a]	0.2211[a]	0.1371	0.1279	0.5752[c]	4.7993[a]
0.25	0.1760[a]	0.0939	0.2502[a]	0.1318[c]	0.0936	0.1180	0.5003	4.8065[a]
0.30	0.0989	0.1243	0.1967[a]	0.0515	-0.0384	0.0894	0.5479	4.8173[a]
0.35	0.0899	0.1496[c]	0.1619[a]	-0.0095	0.006	0.0006	0.5463	4.8296[a]
0.40	0.0907	0.0818	0.1384[a]	-0.0594	-0.0687	0.0973	0.4420	4.8477[a]
0.45	0.0550	0.0911	0.1440[a]	-0.0999	-0.0103	0.1370	0.3416	4.8665[a]
0.50	0.0262	0.0811	0.1557[a]	-0.1319	0.0120	0.0962	0.1233	4.8917[a]
0.55	-0.0047	0.1036	0.1751[a]	-0.1621[c]	-0.0043	0.1316	-0.0211	3.0563[a]
0.60	0.0153	0.1400	0.1872[a]	-0.1801[c]	-0.0841	0.1416	-0.0355	3.0848[a]
0.65	0.0449	0.1849[a]	0.2338[a]	-0.1972[c]	-0.1230	0.1892	-0.3306	3.1094[a]
0.70	0.0716	0.1849[a]	0.3426	-0.2086[c]	0.0345	0.2329	-0.5752[b]	3.1297[a]
0.75	0.1035	0.1583[b]	0.4053[a]	-0.2196[c]	-0.0007	0.2589[c]	-0.5608[b]	3.1455[a]
0.80	0.1691	0.1239	0.4895[a]	-0.2303[c]	0.0838	0.3780b	-0.3287	3.1585[a]
0.85	0.1151	0.0749	0.5371[a]	-0.2358[c]	-0.1587	0.2581	-0.9722[a]	3.1669[a]
0.90	0.2351	0.0065	0.6689[a]	-0.2411[b]	-0.4469	0.4695[b]	-1.4366[a]	3.1742[a]
0.95	0.3939[a]	-0.1319[c]	-0.2591	-0.2413[a]	-0.8501	-0.025	-2.4537[a]	3.1781[a]

Note: *Values with [a] ([b]) [[c]] depict significance at the 0.01 (0.05) [0.10] levels. EGP – Egyptian Pound*

Table 3.2a: QR estimates for Bitcoin and African fiat currencies exchange rates cont.

Quantile	ZAR Coef.	ZAR.IMF1 Coef.	ZAR.IMF5 Coef.	ZAR.IMRes. Coef.	Naira Coef.	Naira.IMF1 Coef.	Naira.IMF5 Coef.	Naira.IMRes Coef.
0.05	0.5932	-0.0821	0.7538	2.7852[a]	0.3723	-0.3143[c]	-3.1372[a]	1.9302[a]
0.10	0.3793	-0.1127	1.4531[a]	2.7850[a]	0.1005	-0.2038	-2.5470[a]	1.5224[a]
0.15	0.0874	-0.1468	1.3313[a]	2.7856[a]	0.2138[c]	0.0005	-2.1510[a]	1.2365[a]
0.20	-0.0467	-0.1571	1.2045[a]	2.7858[a]	0.2467[b]	0.0321	-1.6145[a]	1.0367[a]
0.25	0.0019	-0.0663	1.0258[a]	2.7861[a]	0.1063[b]	0.0629	-1.3324[a]	0.8833[a]
0.30	0.0645	-0.0517	0.8556[a]	2.7869[a]	0.1231[b]	0.0982	-0.9988[a]	0.7694[a]
0.35	0.0681	-0.0028	0.7131[a]	2.7276[a]	0.1327[b]	0.0732	-0.7658[a]	0.6995[a]
0.40	0.0389	-0.0112	0.6639[a]	2.7289[a]	0.1430[a]	0.1215	-0.5018[b]	0.6248[a]
0.45	0.0434	0.0180	0.6455[a]	2.7293[a]	0.1525[a]	0.1102	-0.2093	0.5733[a]
0.50	0.0603	0.0248	0.4464[a]	2.7303[a]	0.1618[a]	0.0726	-0.0309	0.5283[a]
0.55	0.073	0.0204	0.3236[c]	2.7299[a]	0.1570[a]	0.0444	-0.1839	0.5003[b]
0.60	0.0584	0.0054	0.2943[c]	2.7308[a]	0.1693[a]	0.0447	-0.3831[c]	0.4775[b]
0.65	-0.0433	0.0072	0.3566[b]	2.7309[a]	0.1953[a]	0.0216	-0.9665[a]	0.4571[c]
0.70	0.0352	0.0876	0.3223[b]	2.7306[a]	0.1695[b]	-0.0119	-1.2749[a]	0.4401[c]
0.75	0.0293	0.0431	0.2592	2.7310[a]	0.2267[a]	-0.0497	-1.4606[a]	0.4268
0.80	0.1399	0.0551	-0.2033	2.7314[a]	0.2566[a]	-0.0621	-1.6677[a]	0.4156
0.85	0.1951	-0.0150	-0.4195[c]	2.7309[a]	0.2953[a]	-0.1721	-1.5255[a]	0.4177
0.90	0.2544	0.2748	-0.7532[b]	2.7310[a]	0.3515[a]	-0.2126[c]	-1.4798[a]	0.4115
0.95	-0.0721	0.3325	0.0437	2.7309[a]	0.246	-0.3108	-1.9284[a]	0.4080[b]

Note: *Values with [a] ([b]) [[c]] depict significance at the 0.01 (0.05) [0.10] levels.*

Table 3.2a: QR estimates for Bitcoin and African fiat currencies exchange rates cont.

Quantile	Rupee Coef.	Rupee.IMF1 Coef.	Rupee.IMF5 Coef.	Rupee.IMRes. Coef.	Dinar Coef.	Dinar.IMF1 Coef.	Dinar.IMF5 Coef.	Dinar.IMRes. Coef.
0.05	-0.4097	-0.0778	-2.4378[a]	44.3632[a]	-1.2033[a]	-0.3319[b]	-7.3479[a]	-0.9457[a]
0.10	-1.4009[b]	0.335	0.0234	44.2048[a]	-0.8096[a]	-0.2967	-8.7258[a]	-0.4642[a]
0.15	-0.9695[b]	-0.1129	-1.7127	44.0926[a]	-0.7258[b]	-0.1187	-7.7462[a]	-0.0939
0.20	-0.7606[b]	-0.1567	-2.3715[b]	44.0210[a]	-0.3879	-0.0971	-6.6824[a]	0.1842
0.25	-0.5329	-0.1378	-2.3457[b]	6.1975[a]	-0.1580	-0.0316	-6.2201[a]	0.4217[a]

0.30	-0.2784	-0.1568	-2.2131[b]	7.3180[a]	-0.1604	-0.0816	-6.3146[a]	0.6013[a]
0.35	-0.0053	-0.3659	-2.4858[a]	8.1948[a]	-0.0299	-0.0998	-6.2434[a]	0.7500[a]
0.40	-0.0378	-0.4815	-2.6888[a]	8.9298[a]	-0.0497	-0.0917	-5.3592[a]	0.8869[a]
0.45	0.0555	-0.4709	-2.3721[a]	9.5062[a]	-0.0984	0.1165	-4.8937[a]	0.9941[a]
0.50	-0.0165	-0.4916	-2.3129[a]	9.9526[a]	-0.0588	0.0915	-4.5809[a]	1.0812[a]
0.55	0.0026	-0.4092	-2.1367[a]	10.3517[a]	-0.0056	0.0763	-4.3832[a]	1.1576[a]
0.60	0.1200	-0.4658	-1.8069[b]	10.6604[a]	0.0370	0.0744	-4.2364[a]	1.2243[a]
0.65	-0.1267	-0.4494	-1.4549[c]	10.9158[a]	-0.0843	0.0411	-4.2532[a]	1.2816[a]
0.70	-0.1101	-0.5505	-1.1938[c]	11.1139[a]	0.0492	-0.0248	-4.1248[a]	1.3256[a]
0.75	0.0018	-0.3935	-1.2507[c]	11.2835[a]	-0.0270	0.0731	-3.8499[a]	1.3673[a]
0.80	0.1376	-0.2599	-0.9866	11.4023[a]	-0.0848	0.0450	-2.4077[a]	1.3970[a]
0.85	0.0518	-0.3712	-0.8326	11.4777[a]	0.0171	-0.1424	-0.7173	1.4155[a]
0.90	-0.0601	0.2901	-0.0308	11.5530[a]	0.2359	-0.1390	-1.5939[b]	1.4326[a]
0.95	0.231	0.3559	-1.1769[c]	11.5897[a]	0.6311[b]	-0.3584[b]	0.3192	1.4393[a]

Note: *Values with [a] ([b]) [[c]] depict significance at the 0.01 (0.05) [0.10] levels.*

Table 3.2a: QR estimates for Bitcoin and African fiat currencies exchange rates cont.

Quantile	Dirham Coef.	Dirham.IMF1 Coef.	Dirham.IMF5 Coef.	Dirham.IMFRes. Coef.	Shilling Coef.	Shilling.IMF1 Coef.	Shilling.IMF5 Coef.	Shilling.IMRes. Coef.
0.05	-1.7786	-0.8122	-1.4315[a]	-2.2449[a]	0.0015	-0.0004[a]	-0.0001	-0.0001[a]
0.10	-2.7957[a]	-1.0534	-2.0913[a]	-2.3765[a]	0.0020[b]	-0.0003[a]	-0.0009[a]	-0.0001[a]
0.15	-1.4012[c]	-0.6288	-1.9141[a]	-2.5271[a]	0.0013	-0.0002[b]	-0.0008[a]	-0.0001[a]
0.20	-0.7351	-0.6552	-2.6955[a]	-2.6614[a]	0.0009	-0.0001[c]	-0.0006[a]	-0.0001[a]
0.25	-0.2715	-0.3414	-3.1460[a]	-2.7796[a]	0.0009	-0.0001[c]	-0.0007[a]	-0.0001[a]
0.30	-0.2148	-0.5117	-3.6125[a]	-2.8988[a]	0.0006	-0.0002[b]	-0.0006[a]	-0.0001[a]
0.35	0.0877	-0.2390	-3.5061[a]	-3.0188[a]	0.0003	-0.0001[c]	-0.0005[a]	-0.0001[a]
0.40	0.0962	-0.0941	-3.3145[a]	-3.1221[a]	0.0000	-0.0001[c]	-0.0004[a]	-0.0001[a]
0.45	0.2189	0.2025	-3.0482[a]	-3.2086[a]	0.0002	-0.0001	-0.0003[a]	-0.0001[a]
0.50	0.0946	0.0976	-2.6959[a]	-3.2953[a]	0.0001	-0.0005	-0.0003[a]	-0.0007[a]
0.55	0.2408	-0.1330	-2.4277[a]	-3.3823[a]	0.0002	-0.0002	-0.0004[a]	-0.0007[a]
0.60	0.2784	-0.1968	-2.1777[a]	-3.4521[a]	0.0003	-0.0003	-0.0005[a]	-0.0007[a]
0.65	0.1786	-0.5441	-1.9762[a]	-3.5218[a]	0.0003	-0.0005	-0.0007[a]	-0.0007[a]
0.70	0.5043	-0.6927	-1.1726[c]	-3.5740[a]	0.0003	-0.0003	-0.0006[a]	-0.0007[a]

0.75	0.3903	-0.5181	-0.6223	-3.6261[a]	0.0006	-0.0006	-0.0008[a]	-0.0007[a]
0.80	0.6506	-1.0573	0.2739	-3.6605[a]	0.0007	-0.0008	-0.0005[a]	-0.0007[a]
0.85	1.3188	-0.8843	0.4315	-3.6772[a]	0.0017	-0.0008	-0.0006[a]	-0.0007[a]
0.90	0.9140[a]	-1.3651	1.4580[b]	-3.6933[a]	0.0029	-0.0008	-0.0008[a]	-0.0007[a]
0.95	0.8251	-2.7016[a]	2.2688[a]	-3.7111[a]	0.0032	-0.0001	-0.0005[b]	-0.0007[a]

Note: *Values with [a] ([b]) [[c]] depict significance at the 0.01 (0.05) [0.10] levels.*

3.3.1.2 Ethereum and African fiat currencies

Examining the associations between Ethereum and African fiat currencies, we observe both positive and negative dependencies across quantiles and time scales as shown on Table 3.2b. The Egyptian Pound (EGP) depicts positive association at the upper quantiles (0.80 to 0.95) at the composite level, positive linkages at all quantiles in the medium-term except the lowest quantile with the strongest magnitude occurring at the upper quantiles (0.80 to 0.95), and an increasing negative association across all quantiles in the long run. The Ghanaian Cedi exhibit both negative and positive association at quantiles (0.05 to 0.20) and (0.50 to 0.65) respectively at medium -, and long-terms, with the strongest magnitude at the lower quantiles (0.05 to 0.20). South African Rand (ZAR) shows an increasing positive connection at quantiles (0.15, 0.50, 0.70 to 0.85) at the composite level. The medium-term shows positive relationship from 0.20 to 0.9 quantiles but inverse association at the lowest quantiles (0.05, 0.10). The long-term of ZAR shows association that switches from positive at the lowest quantiles (0.05, 0.10) to a decreasing negative at quantiles (0.35 to 0.95) and these are highly significant. The long-term movement of ZAR shows the strongest magnitude.

The composite level of Naira exhibits negative association at 0.05, 0.75, and 0.80 quantiles, both positive (lowest quantiles of 0.05, 0.10) and decreasing negative association (quantiles from 0.35 to 0.95) in the short-term. The medium-term fluctuations of Naira depicts positive relationship across all quantiles whiles the long-term movement shows an increasing inverse association across quantiles. Rupee shows similar patterns to ZAR and Naira. The association at the medium-term switches between positive (lowest part of the distribution) to negative (upper half of the distribution), whereas the long-term of Rupee exhibit an increasing positive association (lower to upper quantiles) except for upper quantiles (0.80 to 0.95) that shows negative connections. With regards to Dinar, we observe a decreasing negative effect in the medium-term movement but an increasingly positive effect in the long-term movement of the currency. Dirham also depicts a decreasing inverse dependency at the lower quantiles in the medium-term but a decreasing positive dependency across quantiles in the long-time horizon. The medium-term movement of Shilling indicates negative connections across distribution, however, the long-term movement of the Shilling exhibits negative association at lower quantiles but positive relationships at the upper quantiles.

Following the patterns depicted by our results, Egypt and South Africa shows positive and negative connections in the medium -, and long-term respectively across currency regimes suggesting possible shock transmissions from EGP and ZAR to Ethereum in the medium-term but Ethereum can hedge the currency risk of the countries in the long-term. Ghana exhibit both negative (low state) and positive (high state) association in the medium-, and long-terms respectively indicating that Cedi can be hedged against depreciation using Ethereum in the medium-, and long-terms. Nigeria shows negative effects (all currency states) in its short-and long-term movement but positive effects (all currency states) in the medium-term implying that Naira can be hedged irrespective of its currency state in both short-, and long terms but shocks in Naira can spillover to Ethereum market in the medium-term.

Mauritius depicts positive and negative connections at low and high currency states in the medium -, and long-term respectively suggesting that Ethereum can hedge Rupee in both medium-, and long-term when Rupee is appreciating. The currencies of Tunisia and Morocco indicate adverse effects (all currency state) on Ethereum in the medium-term but positive effects at all currency regimes in the long-term showing Ethereum as a good hedge and can complement Dinar and Dirham in the medium-term. Lastly, the Kenyan Shilling shows negative association across all currency regimes in the medium-term whiles the long-term shows negative effects in low currency state but positive effects at high state. This implies that shocks to Shilling do not influence Ethereum in the medium-term and that Ethereum can be a viable alternative to Shilling in the medium term and long-term when Shilling is losing low.

We can conclude from these findings that Ethereum can be a viable alternative digital currency to EGP and ZAR in the long-term, Dinar, and Dirham in the medium-term, Cedi, Shilling, and Rupee from medium-, to long-term, and Naira in both short and long-terms.

Table 3.2 b: QR estimates for Ethereum and African fiat currencies exchange rates

Quantile	EGP Coef.	EGP.IMF1 Coef.	EGP.IMF5 Coef.	EGP.IMRes. Coef.	Cedi Coef.	Cedi.IMF1 Coef.	Cedi.IMF5 Coef.	Cedi.IMRes. Coef.
0.05	0.4735	-0.2603	-1.6658[a]	-7.6352[a]	0.7280[c]	0.7054[c]	-7.5725[a]	-7.5725[a]
0.10	0.7259[b]	0.1058	0.4002	-7.6525[a]	0.5874	0.5754	-5.4073[a]	-5.4073[a]
0.15	0.2077	0.0327	0.7498[a]	-7.7009[a]	0.1496	0.5574	-3.1957[a]	-3.1957[a]
0.20	-0.1194[c]	-0.1179	0.5341[a]	-7.7669[a]	0.0376	0.5415	-1.7535[b]	-1.7535[b]
0.25	-0.0969	0.092	0.3442[a]	-7.8630[a]	-0.0234	0.5228	-0.9357	-0.9357
0.30	-0.0736	-0.0911	0.2376[b]	-7.9812[a]	0.1067	0.3876	-0.3216	-0.3216
0.35	-0.0602	-0.0294	0.2611[b]	-8.1204[a]	-0.0349	0.3251	0.3217	0.3217
0.40	-0.0421	-0.0163	0.2728[b]	-8.2985[a]	-0.0354	0.1804	0.7350	0.7350
0.45	-0.0322	-0.0111	0.3459[a]	-8.5025[a]	-0.0189	0.3702	1.0590	1.0590
0.50	-0.0204	-0.0848	0.4231[a]	-8.7769[a]	0.0252	0.4081	1.5433[b]	1.5433[a]
0.55	-0.0079	-0.0111	0.5290[a]	-9.0838[a]	0.0985	0.1508	1.6214[a]	1.6214[a]
0.60	0.0061	-0.0166	0.6440[a]	-9.4537[a]	0.326	0.1305	1.4158[b]	1.4158[b]
0.65	0.0230	0.0329	0.7095[a]	-9.8817[a]	0.4389	0.0755	1.2316[b]	1.2316[b]
0.70	0.0461	0.0997	0.6920[a]	-10.3893[a]	0.4575	0.0656	0.7346	0.7346
0.75	0.0761	0.1601	0.9324[a]	-10.9940[a]	0.1176	0.1104	0.4614	0.4614
0.80	0.1107[c]	0.2293	1.0513[a]	-11.6865[a]	0.1924	0.0225	0.0396	0.0396
0.85	0.1688[a]	0.3377[a]	1.2219[a]	-12.5571[a]	0.2669	-0.1327	-0.4523	-0.4523
0.90	0.2455[a]	0.1874	1.4011[a]	-13.6237[a]	0.8541	0.3036	-0.6178	-0.6178
0.95	0.3605[a]	-0.2873	1.6155[a]	-15.0017[a]	1.4597	-0.1919	-1.3661[b]	-1.3661[b]

Note: *Values with [a] ([b]) [[c]] depict significance at the 0.01 (0.05) [0.10] levels. EGP – Egyptian Pound*

Table 3.2b: QR estimates for Ethereum and African fiat currencies exchange rates cont.

Quantile	ZAR Coef.	ZAR.IMF1 Coef.	ZAR.IMF5 Coef.	ZAR.IMRes. Coef.	Naira Coef.	Naira.IMF1 Coef.	Naira.IMF5 Coef.	Naira.IMRes Coef.
0.05	0.5003	0.1908	-3.8044[a]	2.1946[b]	-0.2702[a]	2.195[b]	4.4608[a]	-17.4749[a]
0.10	0.4565	0.195	-2.4132[a]	2.2298[c]	-0.148	2.2300[c]	2.4201[a]	-17.5617[a]
0.15	0.5564[b]	0.3582	-0.1383	2.2840	-0.0712	2.2840	2.4630[b]	-17.7126[a]
0.20	0.1844	0.5692[b]	1.9712[a]	2.3570	-0.0235	2.3570	1.8843	-17.8946[a]

0.25	0.0605	0.3708	2.0106[a]	2.4501	0.0117	2.4500	2.3928[b]	-18.1661[a]
0.30	0.2498	0.3537	1.7500[a]	2.5837	-0.1920	2.5840	2.8081[a]	-18.4835[a]
0.35	0.1932	0.3425	1.9686[a]	-17.7160[a]	-0.1392	-17.716[a]	2.5499[b]	-18.8857[a]
0.40	0.2866	0.3179	2.4259[a]	-17.1739[a]	-0.1454	-17.174[a]	2.4518[a]	-19.3623[a]
0.45	0.2692	0.4301[c]	2.3207[a]	-16.7554[a]	-0.0957	-16.755[a]	2.6257[a]	-19.8914[a]
0.50	0.3193[b]	0.3303	2.2981[a]	-16.3919[a]	-0.0600	-16.392[a]	2.5531[a]	-20.5380[a]
0.55	0.3124	0.2206	2.3508[a]	-16.1402[a]	-0.0947	-16.140[a]	2.7707[a]	-21.3064[a]
0.60	0.4225	0.1494	2.5049[a]	-15.8809[a]	-0.1452	-15.881[a]	2.2657[a]	-22.1989[a]
0.65	0.3181	0.0867	2.7572[a]	-15.6948[a]	-0.2461	-15.695[a]	1.8164[a]	-23.3068[a]
0.70	0.4727[b]	0.2104	3.0539[a]	-15.5548[a]	-0.3484	-15.555[a]	1.5333[a]	-24.5345[a]
0.75	0.6719[a]	0.2246	2.5807[a]	-15.4196[a]	-0.5334[a]	-15.420[a]	1.3524[a]	-26.0863[a]
0.80	0.9360[a]	0.1236	2.0566[a]	-15.3069[a]	-0.6532[b]	-15.307[a]	1.4616[a]	-28.0480[a]
0.85	0.7792[b]	0.3824	1.8120[a]	-15.2510[a]	-0.6205	-15.251[a]	1.3894[a]	-30.4572[a]
0.90	0.9984	0.3807	1.4197[a]	-15.1960[a]	-0.3083	-15.196[a]	0.9091[a]	-33.6141[a]
0.95	0.9878	0.5468	0.0692	-15.1586[a]	-0.3039	-15.159[a]	0.2916	-37.8644[a]

Note: *Values with [a] ([b]) [[c]] depict significance at the 0.01 (0.05) [0.10] levels.*

.

Table 3.2b: QR estimates for Ethereum and African fiat currencies exchange rates cont.

Quantile	Rupee Coef.	Rupee.IMF1 Coef.	Rupee.IMF5 Coef.	Rupee.IMRes. Coef.	Dinar Coef.	Dinar.IMF1 Coef.	Dinar.IMF5 Coef.	Dinar.IMRes. Coef.
0.05	-0.7738	0.0339	11.9593[a]	38.5226[a]	-0.3201	-0.1517	-19.7645[a]	8.9526[a]
0.10	-0.1962	-0.8889	4.9971[a]	38.8812[a]	-0.3747	-0.2235	-15.1175[a]	8.9830[a]
0.15	-0.3054	-0.3798	2.6571[b]	39.5994[a]	-0.1912	-0.0504	-11.0881[a]	9.0853[a]
0.20	-0.3787	-0.0461	0.7100	40.3502[a]	-0.0881	0.0195	-8.1458[a]	9.1867[a]
0.25	-0.4573	-0.2723	0.9813	41.4750[a]	0.0479	0.1399	-6.9181[a]	9.3607[a]
0.30	-0.2700	-0.4117	1.1751	42.9935[a]	0.0670	0.2459	-6.2649[a]	9.6110a
0.35	-0.0797	-0.4863	0.3801	44.7681[a]	0.0870	0.2965	-5.0330[a]	9.8653[a]
0.40	0.1644	-0.4834	0.1763	47.0165[a]	0.1825	0.4773	-5.0450[a]	10.2035[a]
0.45	0.2025	-0.0083	0.1730	49.5366[a]	0.1065	0.6754[b]	-5.2031[a]	10.5912[a]
0.50	0.2425	-0.3968	-1.5556	52.8992[a]	-0.0142	0.5376	-5.6858[a]	11.0344[a]
0.55	0.0483	-0.4077	-2.3587[b]	56.4205[a]	-0.0122	0.3842	-6.2174[a]	11.5392[a]
0.60	0.051	-0.1298	-2.9975[a]	60.9583[a]	0.0445	0.4755	-5.9050[a]	12.1583[a]
0.65	0.2434	-0.5686	-3.4427[a]	66.7367[a]	0.0078	0.4548	-5.1231[a]	12.9630[a]
0.70	0.098	-0.5320	-4.0575[a]	73.3177[a]	-0.0621	0.3421	-4.8144[a]	13.8215[a]
0.75	-0.0663	-0.3634	-4.1511[a]	81.6794[a]	0.1608	0.2219	-4.0692[a]	14.8585[a]
0.80	0.0065	-0.2538	-3.5519[a]	-187.8253[a]	-0.0039	0.1713	-3.8313[a]	16.2446[a]

0.85	-0.0551	0.0071	-3.1522[a]	-186.8256[a]	0.3090	-0.1168	-4.2910[a]	17.8578[a]
0.90	-0.879	-0.9690	-1.0873	-186.1985[a]	0.8454	-0.0155	-4.7461[a]	20.0019[a]
0.95	-4.1536[a]	-1.1314	0.3226	-185.7837[a]	1.5039[b]	-0.2387	-3.2642[a]	22.7866[a]

Note: *Values with ^{a} (^{b}) [^{c}] depict significance at the 0.01 (0.05) [0.10] levels.*

Table 3.2b: QR estimates for Ethereum and African fiat currencies exchange rates cont.

Quantile	Dirham Coef.	Dirham.IMF1 Coef.	Dirham.IMF5 Coef.	Dirham.IMFRes. Coef.	Shilling Coef.	Shilling.IMF1 Coef.	Shilling.IMF5 Coef.	Shilling.IMRes. Coef.
0.05	1.3356	1.1171	-12.4131[a]	39.6547[a]	0.0023[c]	-0.0001	-0.0001	-0.0014[a]
0.10	0.1484	-0.5696	-11.6548[a]	39.6366[a]	0.0013	-0.0002	0.0004	-0.0014[a]
0.15	0.6731	-0.4758	-7.6529[a]	39.5998[a]	-0.0007	-0.0003	-0.0008[b]	-0.0014[a]
0.20	0.6412	-0.4554	-6.2794[a]	39.5394[a]	-0.0002	-0.0002	-0.0008[b]	-0.0014[a]
0.25	0.2358	0.0638	-5.1400[a]	39.4478[a]	-0.0009	-0.0002	-0.0001[a]	-0.0015[a]
0.30	0.3372	0.2548	-4.1962[a]	39.3464[a]	-0.0013	-0.0008	-0.0001[a]	-0.0015[a]
0.35	0.1776	0.4957	-3.7674[a]	39.2150[a]	-0.0008	-0.0003	-0.0001[a]	-0.0016[a]
0.40	0.7479	0.5199	-3.2762[b]	39.0493[a]	-0.0004	-0.0004	-0.0001[a]	-0.0017[a]
0.45	0.4936	0.7841	-2.6647[c]	38.8611[a]	-0.0003	-0.0002	-0.0001[a]	-0.0018[a]
0.50	0.4404	0.1960	-1.8440	38.6434[a]	-0.0003	-0.0004	-0.0001[a]	-0.0019[a]
0.55	0.5097	0.2097	-1.5059	38.3757[a]	0.0000	-0.0003	-0.0001[a]	0.0060[a]
0.60	0.7798	-0.2837	-1.2431	38.0527[a]	-0.0001	-0.0010	-0.0001[a]	0.0059[a]
0.65	0.8032	-0.4896	0.1291	37.7025[a]	-0.0007	-0.0002	-0.0001[a]	0.0058[a]
0.70	0.7287	-0.1238	-0.2461	37.3113[a]	-0.0009	-0.0001	-0.0001	0.0057[a]
0.75	1.0139	0.3230	1.8156	36.8987[a]	-0.0017	-0.0004	-0.0001	0.0057[a]
0.80	1.2578	0.7236	2.1214	36.4658[a]	-0.0026[c]	-0.0002	-0.0001	0.0056[a]
0.85	1.7165	0.6723	3.0492	35.9907a	-0.0026	-0.0005	-0.0001[c]	0.0056[a]
0.90	1.8881[b]	1.1275	5.0276[a]	35.4907[a]	0.0003	-0.0002	-0.0001[a]	0.0056[a]
0.95	2.1861	0.4271	7.6875[a]	34.9962[a]	0.0002	0.0009	-0.0001	0.0056[a]

Note: *Values with ^{a} (^{b}) [^{c}] depict significance at the 0.01 (0.05) [0.10] levels.*

3.3.1.3 Litecoin and African fiat currencies

The QR estimates for Litecoin (LTC) and African fiat currencies exchange rate returns exhibit many variations across time and quantiles as displayed on Table 3.2c. At the composite level of the Egyptian Pound (EGP), we find an increasing positive association at the lower (0.20 to 0.35) and upper (0.80 to 0.95) quantiles. The medium-term of EGP shows positive connections at quantiles (0.20, 0.25, 0.30, and 0.90) but negative connections at the upper quantiles of (0.55, 0.60, 0.65, and 0.95). However, the long-term of EGP shows a decreasing highly significant negative association across all quantiles. The Cedi shows positive association across all quantiles at both medium -, and long-time horizons with the strongest coefficient occurring in the long-term. ZAR shows similar pattern to the Cedi with positive association at all quantiles in the medium -, and long-term. The long-term of ZAR and Cedi show similar magnitudes.

Naira displays positive influence at the quantiles of 0.25 to 0.40 and 0.75 to 0.95 at the composite level, highly significant positive connections across quantiles in the medium-term, and a decreasing highly significant inverse association at the long-term. Closely matching Naira is Rupee with a decreasing positive and negative association across quantiles in the medium -, and long-time horizons respectively, except that the composite level is not significant. We observe negative effects of Dinar at composite level (lower quantiles 0.05 to 0.15), short-time horizon (lower 0.05 to 0.20 and upper 0.70 to 0.95 quantiles), and all quantiles in the medium-term. Nevertheless, the long-term movements of Dinar exhibit positive influence across quantiles. The short-term (0.15 to 0.75) and medium-term (all quantiles) of Dirham has negative relationship with Litecoin but positive connections in all quantiles in the long-term. Shilling also shows negative effects on Litecoin in the short-term (0.15 to 0.55), medium-term (0.70 to 0.90), and all quantiles in the long-term.

Grouping the patterns by countries, we observe that South Africa and Ghana show positive relations in both medium -, and long-time horizons suggesting that fluctuations in Cedi and ZAR have positive influence on Litecoin which can lead to spillover effects in Litecoin market. We can conclude from this finding that Litecoin cannot be an alternative currency to Cedi and ZAR. Nigeria and Mauritius present positive relations in the medium-term but negative associations in the long-term, indicating that both positive and negative shocks to Naira and Rupee can be hedged using Litecoin in the long-term. Egypt distinctly exhibits both positive and negative relations in the medium-term, but negative relations in the long time horizon. This finding is indicative that Litecoin is not a good alternative to EGP in the medium-term since shocks to EGP has the potential of transmitting to the Litecoin market. However, the altcoin can coexist with EGP in the long-term due to its negative response to EGP signifying hedging properties for the fiat currency. Dinar and Dirham depict negative effects in the short-, and medium-term but positive effects in the long-term implying that Tunisia and Morocco can hedge their position against currency depreciation and forex risk in the short-, and medium-term when Litecoin is adopted as alternative currency in the countries. However, price shocks to Dinar and Dirham can affect the price of Litecoin in the long-term. With regards to Kenya, Shilling shows negative influence at low currency state in the short-term, high state in the medium-term and all currency states in the long-term. This shows that Litecoin is a good alternative to Shilling across time since the altcoin responds negatively to shocks in Shilling, implying that Litecoin is a good hedge for the currency crises of Shilling across time.

Table 3.2 c: QR estimates for Litecoin and African fiat currencies exchange rates

	EGP	EGP.IMF1	EGP.IMF5	EGP.IMRes.	Cedi	Cedi.IMF1	Cedi.IMF5	Cedi.IMRes.
Quantile	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.
0.05	-0.0757[a]	-0.3166[a]	-0.5135	-3.3530[a]	0.4964	0.2432	0.9096[b]	8.0177[a]
0.10	0.0032	-0.1631	-0.137	-3.2656[a]	0.6467[a]	0.4582	0.8640[b]	8.0279[a]
0.15	0.0472	-0.0461	0.2441	-3.1863[a]	0.2121	0.3999	1.3528[a]	8.0491[a]
0.20	0.0850[b]	0.0277	0.3439[a]	-3.1127[a]	0.1689	0.2711	1.5295[b]	8.0626[a]
0.25	0.1139[a]	-0.0035	0.2666[a]	-3.0349[a]	-0.0723	0.1101	1.1836[a]	8.0940[a]
0.30	0.1312[a]	0.0349	0.1596[a]	-2.9750[a]	-0.0996	0.089	1.3348[a]	8.1312[a]
0.35	0.1429[a]	0.0873	0.0726	-2.9109[a]	-0.0505	0.023	1.1387[a]	8.1813[a]
0.40	0.0809	0.1071	-0.0148	-2.8545[a]	-0.0195	0.0657	1.1821[a]	8.2384[a]
0.45	0.0457	0.0955	-0.0041	-2.8008[a]	-0.0024	0.0933	1.1664[a]	8.3041[a]
0.50	0.0246	0.1177	-0.0388	-2.7534[a]	0.0002	-0.0384	1.0504[a]	1.2953[a]
0.55	0.0425	0.0909	-0.1035[c]	-2.7153[a]	-0.0022	0.0535	1.1712[a]	1.4191[a]
0.60	0.0017	0.1185	-0.1717[b]	-2.6764[a]	-0.0153	0.211	1.0798[a]	1.5130[a]
0.65	0.0496	0.0928	-0.2268[b]	-2.6461[a]	0.0778	0.3034	1.0362[a]	1.5983[a]
0.70	0.0628	0.0794	-0.1413[c]	-2.6177[a]	0.093	0.0989	1.1716[a]	1.6614[a]
0.75	0.1138	0.1092	-0.0222	-2.5969[a]	-0.0472	-0.1282	0.9942[a]	1.7133[a]

0.80	0.1958[a]	-0.023	-0.1632	-2.5843[a]	-0.1376	0.0041	0.9257[b]	1.7513[a]
0.85	0.2869[a]	-0.1159	0.1402	-2.5712[a]	-0.0929	-0.1216	0.7356[c]	1.7852[a]
0.90	0.3423[a]	-0.2036	0.7501[a]	-2.5645[a]	-0.4544	-0.4448	1.7760[a]	1.8064[a]
0.95	0.4361[a]	-0.0175	-0.7086[c]	-2.5580[a]	0.1401	-1.1699[a]	2.2093[a]	1.8200[a]

Note: *Values with [a] ([b]) [[c]] depict significance at the 0.01 (0.05) [0.10] levels. EGP – Egyptian Pound*

Table 3.2c: QR estimates for Litecoin and African fiat currencies exchange rates cont.

Quantile	ZAR Coef.	ZAR.IMF1 Coef.	ZAR.IMF5 Coef.	ZAR.IMRes. Coef.	Naira Coef.	Naira.IMF1 Coef.	Naira.IMF5 Coef.	Naira.IMRes Coef.
0.05	0.6025	0.4165	-0.6251	6.4336[a]	0.0696	-0.3292	3.5482[a]	-7.9121[a]
0.10	0.3410	0.3400	-0.1004	6.4439[a]	0.4013	-0.2418	2.9550[a]	-7.3793[a]
0.15	0.1834	-0.1553	0.6941[b]	6.4618[a]	0.2748	-0.035	2.3246[a]	-6.8922[a]
0.20	0.4126[a]	-0.3727[c]	0.6748[b]	6.4855[a]	0.1087	0.0143	1.7129[a]	-6.4677[a]
0.25	0.1731	-0.2329	0.5606[b]	6.5158[a]	0.1479[b]	0.0095	1.2082[a]	-6.0904[a]
0.30	0.1345	-0.1544	0.6417[a]	6.5588[a]	0.1753[a]	0.0949	1.1324[a]	-5.7621[a]
0.35	-0.0213	-0.121	0.6833[a]	-0.1839	0.1934[a]	0.0873	1.0955[a]	-5.4598[a]
0.40	0.0096	-0.1618	0.5927[a]	0.0006	0.1802[b]	0.1811	1.1769[a]	-5.2130[a]
0.45	0.0044	-0.0707	0.5613[a]	0.1454	0.1464	0.1896	1.1625[a]	-4.9965[a]
0.50	0.0002	0.0167	0.6922[a]	0.2702[a]	0.1135	0.2333	1.1642[a]	-4.8124[a]
0.55	-0.0009	-0.0485	0.7124[a]	0.3600[a]	0.0788	0.2398	1.3176[a]	-4.6376[a]
0.60	0.0035	0.0465	0.7649[a]	0.4494[a]	0.1203	0.208	1.1657[a]	-4.4952[a]
0.65	0.0049	0.1003	0.6744[a]	0.5150[a]	0.1013	0.3753[a]	1.1686[a]	-4.3676[a]
0.70	-0.0289	0.1232	0.5881[a]	0.5654[a]	0.1389	0.2848[b]	1.1238[a]	-4.2604[a]
0.75	0.0537	0.0678	0.5751[a]	0.6122[a]	0.2671[a]	0.2402	1.2990[a]	-4.1764[a]
0.80	0.0392	-0.0011	0.5013[b]	0.6509[a]	0.2003	0.2770[c]	1.4264[a]	-4.1051[a]
0.85	0.1765	0.2910	0.5398[b]	0.6722[a]	0.4113[a]	0.1966	1.1326[a]	-4.0378[a]
0.90	0.1527	0.4878	1.0218[c]	0.6912[a]	0.4344[a]	0.3029	2.0899[a]	-3.9993[a]
0.95	0.5539	0.4529	1.5708[c]	0.7034[a]	0.6340[a]	0.2298	2.6358[b]	-3.9777[a]

Note: *Values with [a] ([b]) [[c]] depict significance at the 0.01 (0.05) [0.10] levels.*

Table 3.2c: QR estimates for Litecoin and African fiat currencies exchange rates cont.

Quantile	Rupee Coef.	Rupee.IMF1 Coef.	Rupee.IMF5 Coef.	Rupee.IMRes. Coef.	Dinar Coef.	Dinar.IMF1 Coef.	Dinar.IMF5 Coef.	Dinar.IMRes. Coef.
0.05	0.0129	-0.3292	3.5482[a]	-7.9121[a]	-1.0574[a]	-0.5219[c]	-5.8603[a]	5.2905[a]
0.10	-0.6622	-0.2418	2.9550[a]	-7.3793[a]	-0.8396[a]	-0.5615[b]	-5.4022[a]	5.2901[a]
0.15	-0.7905[b]	-0.035	2.3246[a]	-6.8922[a]	-0.4618[c]	-0.6460[b]	-6.1726[a]	5.2903[a]
0.20	-0.5032	0.0143	1.7129[a]	-6.4677[a]	-0.4604	-0.5309[c]	-6.6306[a]	5.2913[a]
0.25	-0.0431	0.0095	1.2082[a]	-6.0904[a]	-0.2124	-0.4090	-7.3747[a]	5.2927[a]
0.30	0.1017	0.0949	1.1324[a]	-5.7621[a]	-0.1914	-0.4034	-6.7552[a]	5.2948[a]
0.35	-0.0267	0.0873	1.0955[a]	-5.4598[a]	0.0103	-0.3226	-5.5112[a]	5.2973[a]
0.40	0.0718	0.1811	1.1769[a]	-5.2130[a]	-0.0462	-0.3389	-4.6963[a]	5.3002[a]
0.45	0.1718	0.1896	1.1625[a]	-4.9965[a]	0.0187	-0.4060	-4.7635[a]	5.3034[a]
0.50	0.1672	0.2333	1.1642[a]	-4.8124[a]	0.0281	-0.4791	-4.6274[a]	5.3070[a]
0.55	0.0069	0.2398	1.3176[a]	-4.6376[a]	0.0307	-0.4413	-4.5503[a]	5.3110[a]
0.60	0.1517	0.208	1.1657[a]	-4.4952[a]	-0.0426	-0.4012	-4.3958[a]	5.3150[a]
0.65	0.1134	0.3753[a]	1.1686[a]	-4.3676[a]	-0.1043	-0.4478	-4.0818[a]	5.3184[a]
0.70	0.0373	0.2848[b]	1.1238[a]	-4.2604[a]	-0.0826	-0.4946[c]	-3.3906[a]	5.3215[a]
0.75	-0.2317	0.2402	1.2990[a]	-4.1764[a]	-0.0823	-0.4482	-2.5934[a]	5.3243[a]
0.80	0.1817	0.2770[c]	1.4264[a]	-4.1051[a]	-0.1978	-0.3818[c]	-3.5565[a]	5.3271[a]
0.85	-0.1433	0.1966	1.1326[a]	-4.0378[a]	-0.1299	-0.4214[c]	-6.3329[a]	5.3300[a]
0.90	0.5506	0.3029	2.0899[a]	-3.9993[a]	-0.2976	-0.3879[c]	-9.2506[a]	5.3351[a]
0.95	-1.7570	0.2298	2.6358[b]	-3.9777[a]	-0.5654	-0.5280[b]	-8.0818[a]	5.3423[a]

Note: *Values with [a] ([b]) [[c]] depict significance at the 0.01 (0.05) [0.10] levels.*

Table 3.2c: QR estimates for Litecoin and African fiat currencies exchange rates cont.

Quantile	Dirham Coef.	Dirham.IMF1 Coef.	Dirham.IMF5 Coef.	Dirham.IMFRes. Coef.	Shilling Coef.	Shilling.IMF1 Coef.	Shilling.IMF5 Coef.	Shilling.IMRes. Coef.
0.05	-0.0609	-0.0069	-5.2975[a]	6.6710[a]	0.0027[b]	-0.0003	0.0004	-0.0002[a]
0.10	-1.0733	-0.6061	-7.7812[a]	6.4307[a]	0.0002	-0.0003[b]	0.0002	-0.0002[a]
0.15	-1.1654	-1.4956[c]	-5.9758[a]	6.1588[a]	0.0002	-0.0005[a]	-0.0008	-0.0002[a]
0.20	-1.6934[b]	-1.1273	-5.4085[a]	5.9138[a]	-0.0002	-0.0003[a]	0.0004	-0.0002[a]
0.25	-0.7824	-1.0142	-6.3227[a]	5.6962[a]	-0.0004	-0.0003[a]	0.0002	-0.0002[a]
0.30	-0.7983[c]	-1.2174[c]	-5.4775[a]	5.4775[a]	-0.0004	-0.0004[a]	0.0002	-0.0002[a]
0.35	-0.2680	-1.0905[c]	-4.8213[a]	5.2579[a]	-0.0009	-0.0003[a]	0.0002	-0.0002[a]
0.40	-0.2504	-1.2318[c]	-4.6260[a]	5.0668[a]	-0.0009	-0.0003[b]	0.0008	-0.0002[a]
0.45	-0.1059	-1.0685[c]	-4.3616[a]	4.9034[a]	-0.0006	-0.0002[b]	0.0002	-0.0002[a]

0.50	0.0000	-1.1035[c]	-4.1187[a]	4.7399[a]	-0.0005	-0.0002	0.0005	-0.0002[a]
0.55	0.0109	-1.6354[b]	-3.8597[a]	4.5767[a]	-0.0002	-0.0002[c]	-0.0004	-0.0004[a]
0.60	-0.0744	-1.8390[a]	-3.3021[a]	4.4418[a]	-0.0003	-0.0001	-0.0009	-0.0004[a]
0.65	-0.0826	-2.1052[a]	-2.6883[a]	4.3088[a]	-0.0003	-0.0001	-0.0002	-0.0004[a]
0.70	-0.0115	-1.7780[a]	-2.1756[a]	4.2044[a]	-0.0004	-0.0009	-0.0003[b]	-0.0004[a]
0.75	-0.1766	-1.8472[a]	-1.7925[a]	4.1012[a]	-0.0008	-0.0002	-0.0004[a]	-0.0004[a]
0.80	-0.4726	-1.8737[a]	-2.1445[a]	4.0274[a]	0.0000	-0.0005	-0.0004[a]	-0.0005[a]
0.85	0.2299	-1.2761	-3.5219[a]	3.9840[a]	0.0002	-0.0004	-0.0004[a]	-0.0005[a]
0.90	1.1141	-1.2615	-4.3679[a]	3.9433[a]	0.0022	-0.0002	-0.0004[b]	-0.0005[a]
0.95	1.5462	-0.9486	-5.4902[a]	3.9090[a]	0.0004	0.0006	-0.0002	-0.0005[a]

Note: *Values with [a] ([b]) [[c]] depict significance at the 0.01 (0.05) [0.10] levels.*

3.3.1.4 Ripple and African fiat currencies

The QR estimates for Ripple (XRP) and African fiat currencies exchange rate returns on Table 3.2d mostly displayed a significant negetaive effects across quantiles in the medium and long scales except for the Egyptian Pound. Specifically, the short and medium-term movements of Egyptian Pound (EGP) presents positive relations at quantiles (0.60 to 0.75), and at all levels of the distributions in the long-term movement of EGP with the strongest magnitude occurring in long-term. The Ghanaian Cedi shows a positive highly significant linkage across all quantiles in the medium-term. However, the long-term of Cedi displays an increasing positive relation at the lower half of the distributions (0.05 to 0.50), whereas the upper half of the distribution (0.55 to 0.95) displays a decreasing inverse relation. ZAR exhibit negative associations at lower quantiles (0.10 to 0.30) and higher quantiles (0.85 to 0.95) of the distribution in the medium time horizon, whereas the long time horizon of ZAR shows increasing positive relations at quantiles (0.05 to 0.65) but decreasing negative connections at quantiles (0.70 to 0.95). The composite level of Naira depicts negative connections at quantiles (0.05 to 0.20 and 0.45 to 0.60) of the distribution but positive association at higher quantiles (0.65 to 0.95) of the distribution in the long-term. Rupee shows similar pattern to Naira except that the composite level displays decreasing negative connections at upper quantiles (0.70 to 0.95), but an increasing positive relation at upper quantiles (0.65 to 0.95) in the long-term. The medium-term movement of Dinar exhibits positive dependencies at all quantiles, whereas the long-term movement shows a decreasing negative dependency across quantiles. Dirham depicts the strongest negative effects on Ripple across quantiles in its long-term movement whiles Shilling exhibits the weakest positive and negative effects across quantiles in its medium-term and long-term movements.

In general, we observe that Egyptian Pound show positive associations at high currency state in both short and medium-term movement of EGP but all currency states (low, stable, high) in the long-term indicating that volatility in EGP can affect the price of Ripple across time and thus the altcoin cannot hedge currency risk of EGP. South African Rand (ZAR) exhibit negative dependencies across currency states in the medium-term, but both negative (high state) and positive (low state) of ZAR in the long-term. This implies that South Africa in the medium-term can hedge depreciation and forex crises of ZAR using Ripple at all currency states but long-term when ZAR is depreciating in value. Ghanaian Cedi presents positive association in the medium-term (all currency regimes), and long-term (low state) whiles the high regime in the long-term shows negative dependencies which is indicative that Ripple has hedging properties against currency risk for Ghana in the long-term when the Cedi is gaining strength. Nigerian Naira depicts negative connections with Ripple when the Naira is low in the medium-term but positive effects in the long-term when the Naira is high. Rupee depicts negative dependencies with Ripple in the long-term when Rupee is in an upward trend. This indicates Ripple can hedge Naira and Rupee in the medium-, and long-term respectively. Dinar, Dirham, and Shilling have positive effects at all currency states in the medium-term but negative effects on Ripple in the long-term suggesting Ripple as a good hedge in the long-term when the currencies are losing or gaining value. We can conclude from this finding that Ripple is a viable alternative to all the fiat currencies from the medium to long-term except Egyptian Pound.

Table 3.2 d: QR estimates for Ripple and African fiat currencies exchange rates

Quantile	EGP Coef.	EGP.IMF1 Coef.	EGP.IMF5 Coef.	EGP.IMRes. Coef.	Cedi Coef.	Cedi.IMF1 Coef.	Cedi.IMF5 Coef.	Cedi.IMRes. Coef.
0.05	-0.0785[a]	-0.0756	-0.6157[a]	10.2100[a]	0.4458	-0.6232	1.0897[b]	4.8534[a]
0.10	-0.0284	-0.0029	-0.0667	9.7071[a]	0.1545	-0.2684	2.6533[a]	4.8938[a]
0.15	0.005	0.0963	0.2998[a]	9.3047[a]	0.0239	-0.2703	1.7449[a]	4.9550[a]
0.20	0.0302	0.1478	0.2783[a]	8.9881[a]	0.1181	-0.1257	1.6352[a]	5.0589[a]
0.25	0.044	0.0442	0.2396[a]	8.7399[a]	0.1371	-0.3225[c]	1.5042[a]	5.1643[a]
0.30	0.0534	0.0598	0.2539[a]	8.5517[a]	0.1507	-0.2331	1.5739[a]	5.3166[a]

0.35	0.0606	0.0603	0.2504[a]	8.4012[a]	0.0911	-0.3714[b]	1.7615[a]	5.4956[a]
0.40	0.0661	0.106	0.2396[a]	8.2820[a]	0.1168	-0.3047[c]	1.7832[a]	5.7534[a]
0.45	0.0306	0.1292	0.2434[a]	8.1943[a]	0.0974	-0.2519	1.8037[a]	6.0230[a]
0.50	0.0522	0.1266	0.2470[a]	8.1359[a]	0.0809	-0.1402	2.0503[a]	6.3869[a]
0.55	0.0749[b]	0.1459	0.2495[a]	8.0963[a]	0.0311	-0.1279	2.1264[a]	-15.7469[a]
0.60	-0.1673	0.1695[b]	0.2447[a]	8.0791[a]	-0.0195	-0.1105	2.1580[a]	-15.5031[a]
0.65	-0.223	0.1842[b]	0.2211[b]	8.0740[a]	-0.0258	-0.1156	1.9086[a]	-15.2909[a]
0.70	-0.2112	0.1668[b]	0.1918[b]	8.0879[a]	0.1441	-0.1567	2.2170[a]	-15.1051[a]
0.75	-0.2424	0.1625[b]	0.1213	8.1198[a]	0.1601	-0.2613	2.4804[a]	-14.9667[a]
0.80	-0.223	0.113	0.0637	8.1655[a]	-0.0084	-0.202	2.6429[a]	-14.8505[a]
0.85	-0.1517	0.0835	0.2301	8.2230[a]	-0.1876	0.0591	2.6424[a]	-14.7982[a]
0.90	-0.086	-0.0254	0.4991[a]	8.2930[a]	-0.0747	-0.085	2.9810[a]	-14.7207[a]
0.95	0.3275[a]	-0.1569[b]	0.6144[b]	8.3750[a]	-1.4253[a]	0.0113	2.1512[a]	-14.6831[a]

Note: *Values with [a] ([b]) [[c]] depict significance at the 0.01 (0.05) [0.10] levels. EGP – Egyptian Pound*

Table 3.2d: QR estimates for Ripple and African fiat currencies exchange rates cont.

Quantile	ZAR Coef.	ZAR.IMF1 Coef.	ZAR.IMF5 Coef.	ZAR.IMRes. Coef.	Naira Coef.	Naira.IMF1 Coef.	Naira.IMF5 Coef.	Naira.IMRes. Coef.
0.05	0.0478	-0.7190	0.6454	4.0063[a]	-0.3427[a]	-0.1996	-0.1223[a]	-0.0131
0.10	-0.0646	-0.2483	-1.3999[a]	4.0375[a]	-0.2234[a]	-0.2654	-0.0208	-0.0177
0.15	-0.0138	-0.1484	-1.0966[a]	4.0845[a]	-0.2486[a]	-0.2227[b]	0.0160	-0.0189
0.20	0.0969	0.0893	-0.8165[a]	4.1323[a]	-0.1682[a]	-0.1318	0.0215	-0.0097
0.25	0.0017	0.0977	-0.4759[b]	4.2289[a]	-0.0811	-0.1051	0.0059	0.00340
0.30	-0.0463	0.1128	-0.4491[b]	4.3448[a]	-0.0657	-0.0607	0.0329	0.00230
0.35	-0.0001	0.0676	-0.1105	4.4647[a]	-0.0488	-0.0897	0.0493[b]	0.01590
0.40	-0.0217	-0.0100	-0.0687	4.6241[a]	-0.0661	-0.0508	0.0308	0.01230
0.45	-0.0225	-0.0838	-0.0627	4.8463[a]	-0.1451[b]	-0.0319	0.0264	-0.02100
0.50	-0.0138	-0.1162	0.0026	5.0619[a]	-0.1362[b]	-0.0542	0.0209	-0.02340
0.55	0.013	-0.0927	0.0446	5.3734[a]	-0.1235[c]	-0.0789	0.01210	-0.00740
0.60	-0.0143	-0.0532	0.0965	5.7323[a]	-0.1131[c]	-0.0765	0.00440	0.05710
0.65	-0.0667	-0.0280	0.1254	6.1973[a]	-0.1432	-0.1499	0.00170	0.1227[b]
0.70	-0.1313	-0.0690	0.1277	-11.2979[a]	-0.209	-0.0856	0.01040	0.1799[a]
0.75	-0.2259[b]	0.0087	0.0967	-11.1822[a]	-0.2332	-0.0453	0.00700	0.1588[c]
0.80	-0.1915	0.0435	-0.0996	-11.1014[a]	-0.2959	-0.0945	0.00310	0.2042[a]
0.85	-0.1749	0.0583	-0.3413[c]	-11.0380[a]	-0.3013	-0.1859	-0.0015	0.2355[a]
0.90	-0.2572	-0.0665	-1.2291[a]	-10.9903[a]	-0.5974[c]	-0.1598	0.0172	0.3062[a]

0.95	-0.151	-0.8417[c]	-3.8371[a]	-10.9613[a]	-0.1828	0.1277	0.0479	0.2913[a]

Note: *Values with [a] ([b]) [[c]] depict significance at the 0.01 (0.05) [0.10] levels.*

Table 3.2d: QR estimates for Ripple and African fiat currencies exchange rates cont.

Quantile	Rupee Coef.	Rupee.IMF1 Coef.	Rupee.IMF5 Coef.	Rupee.IMRes. Coef.	Dinar Coef.	Dinar.IMF1 Coef.	Dinar.IMF5 Coef.	Dinar.IMRes. Coef.
0.05	0.4793	-0.1996	-0.1223[a]	-0.0131	0.4127	-0.1041	7.5593[a]	-16.2045[a]
0.10	-0.3935	-0.2654	-0.0208	-0.0177	0.0724	-0.0844	4.5753[a]	-15.3154[a]
0.15	-0.3573	-0.2227[b]	0.0160	-0.0189	-0.0505	-0.1346	2.6321[a]	-14.6308
0.20	-0.2162	-0.1318	0.0215	-0.0097	-0.1132	0.0427	1.5127[a]	-14.1154[a]
0.25	-0.2616	-0.1051	0.0059	0.0034	-0.1300	-0.2067	1.2514[b]	-13.6712[a]
0.30	-0.2499	-0.0607	0.0329	0.0023	-0.0766	-0.0957	1.5852[a]	-13.3412[a]
0.35	-0.2076	-0.0897	0.0493[b]	0.0159	-0.0283	-0.1503	1.3498[b]	-13.0683[a]
0.40	-0.2202	-0.0508	0.0308	0.0123	0.0149	-0.1445	0.8555	-12.8098[a]
0.45	-0.1536	-0.0319	0.0264	-0.0210	-0.0025	-0.1470	0.5257	-12.6131[a]
0.50	-0.2358	-0.0542	0.0209	-0.0234	-0.0125	-0.1127	0.9361[b]	-12.4525[a]
0.55	-0.2098	-0.0789	0.0121	-0.0074	0.0045	-0.1623	1.1437[b]	-12.3114[a]
0.60	-0.1473	-0.0765	0.0044	0.0571	-0.0182	-0.1682	1.2914[b]	-12.1877[a]
0.65	-0.3317	-0.1499	0.0017	0.1227[b]	-0.0457	-0.1886	1.6640[a]	-12.0788[a]
0.70	-0.4603[b]	-0.0856	0.0104	0.1799[a]	-0.0318	-0.2367	1.9267[a]	-11.9980[a]
0.75	-0.5451[b]	-0.0453	0.007	0.1588[c]	0.1448	-0.1871	2.3907[a]	-11.9166[a]
0.80	-0.8443[a]	-0.0945	0.0031	0.2042[a]	0.2857	-0.2996	2.4894[a]	-11.8609[a]
0.85	-1.0864[a]	-0.1859	-0.0015	0.2355[a]	0.0256	-0.2063	4.1834[a]	-11.8298[a]
0.90	-1.7986[c]	-0.1598	0.0172	0.3062[b]	-0.0161	-0.2077	6.5510[a]	-11.7966[a]
0.95	-3.1944[a]	0.1277	0.0479	0.2913[a]	-0.0730	0.0077	10.0105[a]	-11.7900[a]

Note: *Values with [a] ([b]) [[c]] depict significance at the 0.01 (0.05) [0.10] levels.*

Table 3.2d: QR estimates for Ripple and African fiat currencies exchange rates cont.

Quantile	Dirham Coef.	Dirham.IMF1 Coef.	Dirham.IMF5 Coef.	Dirham.IMFRes. Coef.	Shilling Coef.	Shilling.IMF1 Coef.	Shilling.IMF5 Coef.	Shilling.IMRes. Coef.
0.05	-0.3014	-0.3014	-1.5334	-20.7649[a]	0.0001	-0.0004[b]	0.0002[a]	-0.0001[a]
0.10	0.0413	0.0413	2.6853[a]	-20.7894[a]	0.0001	-0.0003	0.0002[a]	-0.0001[a]
0.15	0.2931	0.2931	1.3178[b]	-20.8139[a]	0.0008	-0.0006	0.0002[a]	-0.0001[a]

0.20	0.3093	0.3093	0.4371	-20.8242[a]	0.0006	-0.0005	0.0002[a]	-0.0001[a]
0.25	0.3154	0.3154	-0.1537	-20.8629[a]	0.0005	-0.0005	0.0001[a]	-0.0001[a]
0.30	0.1758	0.1758	-0.5311	-20.9329[a]	0.0005	-0.0004	0.0010[a]	-0.0001[a]
0.35	0.1079	0.1079	-1.1166	-20.9903[a]	0.0003	0.0002	0.0010[a]	-0.0001[a]
0.40	0.0077	0.0077	-0.9089[b]	-21.0803[a]	0.0003	-0.0002	0.0009[a]	-0.0001[a]
0.45	0.0774	0.0774	-0.6108[b]	-21.1532[a]	0.0004	-0.0002	0.0008[a]	-0.0001[a]
0.50	0.0616	0.0616	-0.3152	-21.2588[a]	0.0004	-0.0006	0.0006[a]	0.0004[a]
0.55	0.0907	0.0907	-0.2135	-21.3516[a]	0.0004	-0.0003	0.0005[a]	0.0004[a]
0.60	0.0599	0.0599	-0.1850	-21.4316[a]	0.0005	0.0001	0.0007[a]	0.0004[a]
0.65	0.1159	0.1159	0.0470	-21.5458[a]	0.0006	0.0001	0.0008[a]	0.0004[a]
0.70	0.2250	0.2250	0.2354	-21.6869[a]	0.0008	0.0003	0.0009[a]	0.0003[a]
0.75	0.5276	0.5276	0.3834	-21.8149[a]	0.0013[b]	0.0003	0.0001[a]	0.0003[a]
0.80	0.4050	0.4050	0.6210	-21.9296[a]	0.0016[a]	0.0009	0.0001[a]	0.0003[a]
0.85	0.3052	0.3052	1.1849	-22.0693[a]	0.0014[a]	0.0002[c]	0.0001[a]	0.0003[a]
0.90	0.8653	0.8653	3.0937[a]	-22.2435[a]	0.0029[a]	0.0003[c]	0.0002[a]	0.0003[a]
0.95	3.3612	3.3612	7.1301[a]	-22.3665[a]	-0.0013	0.0004[b]	0.0002[a]	0.0003[a]

Note: *Values with [a] ([b]) [[c]] depict significance at the 0.01 (0.05) [0.10] levels.*

3.3.1.5 Das and African fiat currencies

The dependences between Das and African fiat currencies exchange rate returns in Table 3.2e suggest Das as a viable alternative payment option and a good hedge for all fiat currencies from the medium-term except for Dirham. For Egyptian Pound (EGP) we find a decreasing negative association at the lower quantiles (0.05 to 0.35) at the composite level and in the long-term. The lower quantiles (0.05 to 0.35) in the long time horizon of the Ghanaian Cedi depicts a decreasing inverse association. The composite level of ZAR shows positive connections at the lower quantiles (0.05 and 0.10) and upper quantiles (0.70 to 0.85), whereas the long-term of ZAR depicts a decreasing inverse association at lower quantiles (0.05 to 0.35). The Nigerian Naira displays decreasing negative relations at the 0.20 to 0.45 quantiles of the distribution at the composite level and decreasing inverse connections at the lower quantiles (0.05 to 0.35) of the distribution in the long-term. The Rupee depicts similar patterns to EGP, Cedi, ZAR, and Naira with decreasing negative connections at the lower quantiles (0.05 to 0.35) in the long time horizon. Dinar shows inverse dependencies across quantiles in the medium-term but positive relations in the long-term.

The long-term movement of Dirham show positive relationship whereas both medium-, and long-term of Shilling have negative effects on Das.

Specifically, we find Egypt, Ghana, South Africa, Nigeria, and Mauritius displaying negative association when their fiat currencies are losing value, Dinar and Dirham show positive dependencies at all regimes of their fiat currencies in the long-term as well as negative relations in the medium-term for Dinar. Shilling presents all negative dependencies at all currency states in both medium and long-term movements of the Shilling. Thus, hedging benefits are feasible for Egypt, Ghana, South Africa, Nigeria, and Mauritius in the long-term when their fiat currencies are depreciating. Das can hedge forex risk of Tunisia in the medium-term when Dinar is low, stable, or high, and Kenya in both medium and long-term when the Shilling is bear, stable or bull. In the case of Morocco, Das cannot act as a hedge against forex risk since it behaves just like the Dirham across time. We can conclude from these findings that except for Dirham, Das can complement the fiat currencies from the medium-term.

Table 3.2 e: QR estimates for DAS and African fiat currencies exchange rates

Quantile	EGP Coef.	EGP.IMF1 Coef.	EGP.IMF5 Coef.	EGP.IMRes. Coef.	Cedi Coef.	Cedi.IMF1 Coef.	Cedi.IMF5 Coef.	Cedi.IMRes. Coef.
0.05	-0.2984[a]	-0.1194	-0.0581[a]	-0.0947[a]	0.9496[c]	-0.1194	-0.0581[a]	-0.0947[a]
0.10	-0.2206[a]	-0.1088	-0.0114	-0.0752[a]	0.3148	-0.1088	-0.0114	-0.0752[a]
0.15	-0.1713[a]	0.0241	-0.0026	-0.0534[b]	0.5184	0.0241	-0.0026	-0.0534[b]
0.20	-0.1595[a]	-0.0679	0.0071	-0.0517[a]	0.3901	-0.0679	0.0071	-0.0517[a]
0.25	-0.1330[b]	-0.1510	0.0119	-0.0440[b]	0.4162	-0.1510	0.0119	-0.0440[b]
0.30	-0.1128[c]	-0.1565	0.0257	-0.0375[b]	0.249	-0.1565	0.0257	-0.0375[b]
0.35	-0.0947	-0.2103	0.0145	-0.0302[c]	0.055	-0.2103	0.0145	-0.0302[c]
0.40	-0.0813	-0.1669	0.0279	-0.0235	0.0953	-0.1669	0.0279	-0.0235
0.45	-0.0571	-0.0946	0.0302	-0.0200	0.1229	-0.0946	0.0302	-0.0200
0.50	-0.0564	-0.1681	0.0211	-0.0135	0.0046	-0.1681	0.0211	-0.0135
0.55	-0.048	-0.1025	-0.0064	-0.0078	0.0607	-0.1025	-0.0064	-0.0078
0.60	-0.0311	-0.0329	0.0057	-0.0029	-0.0923	-0.0329	0.0057	-0.0029
0.65	-0.0118	0.0549	-0.005	0.0008	-0.0495	0.0549	-0.0050	0.0008
0.70	0.0096	0.0783	-0.0729[c]	-0.0003	0.1422	0.0783	-0.0729[c]	-0.0003

0.75	0.0302	0.1127	-0.0692	0.0008	0.1069	0.1127	-0.0692	0.0008
0.80	-0.0938	0.0185	-0.0423	0.0021	0.0322	0.0185	-0.0423	0.0021
0.85	-0.0553	-0.0075	-0.0192	0.0031	-0.2567	-0.0075	-0.0192	0.0031
0.90	0.1315^{a}	0.1246	0.0009	0.0005	-0.2223	0.1246	0.0009	0.0005
0.95	0.2185^{a}	0.3414	0.0399	0.0008	1.1958^{b}	0.3414	0.0399	0.0008

Note: *Values with ^{a} (^{b}) [^{c}] depict significance at the 0.01 (0.05) [0.10] levels.* *EGP – Egyptian Pound*

Table 3.2e: QR estimates for DAS and African fiat currencies exchange rates cont.

Quantile	ZAR Coef.	ZAR.IMF1 Coef.	ZAR.IMF5 Coef.	ZAR.IMRes. Coef.	Naira Coef.	Naira.IMF1 Coef.	Naira.IMF5 Coef.	Naira.IMRes Coef.
0.05	0.9150^{b}	-0.1194	-0.0581^{a}	-0.0947^{a}	0.6088	-0.1194	-0.0581^{a}	-0.0947^{a}
0.10	0.4948^{c}	-0.1088	-0.0114	-0.0752^{a}	0.0483	-0.1088	-0.0114	-0.0752^{a}
0.15	0.2602	0.0241	-0.0026	-0.0534^{b}	-0.1626	0.0241^{b}	-0.0026	-0.0534^{b}
0.20	-0.0097	-0.0679	0.0071	-0.0517^{a}	-0.3074^{a}	-0.0679	0.0071	-0.0517^{a}
0.25	-0.0283	-0.151	0.0119	-0.0440^{b}	-0.2721^{a}	-0.151	0.0119	-0.0440^{b}
0.30	0.0909	-0.1565	0.0257	-0.0375^{b}	-0.2226^{b}	-0.1565	0.0257	-0.0375^{b}
0.35	0.0246	-0.2103	0.0145	-0.0302^{c}	-0.2141^{b}	-0.2103	0.0145	-0.0302c
0.40	-0.005	-0.1669	0.0279	-0.0235	-0.1034	-0.1669	0.0279	-0.0235
0.45	0.0493	-0.0946	0.0302	-0.02	-0.1793^{c}	-0.0946	0.0302	-0.0200
0.50	0.1402	-0.1681	0.0211	-0.0135	-0.1237	-0.1681	0.0211	-0.0135
0.55	0.2176	-0.1025	-0.0064	-0.0078	-0.143	-0.1025	-0.0064	-0.0078
0.60	0.2091	-0.0329	0.0057	-0.0029	-0.1181	-0.0329	0.0057	-0.0029
0.65	0.2499	0.0549	-0.0005	0.0008	-0.0894	0.0549	-0.0050^{c}	0.0008
0.70	0.4141^{b}	0.0783	-0.0729^{c}	-0.0003	-0.0579	0.0783	-0.0729	-0.0003
0.75	0.4199^{b}	0.1127	-0.0692	0.0008	-0.0272	0.1127	-0.0692	0.0008
0.80	0.4850^{b}	0.0185	-0.0423	0.0021	0.0047	0.0185	-0.0423	0.0021
0.85	0.5204^{b}	-0.0075	-0.0192	0.0031	0.0521	-0.0075	-0.0192	0.0031
0.90	0.5148	0.1246	0.0009	0.0005	0.1280^{c}	0.1246	0.0009	0.0005
0.95	0.7323	0.3414	0.0399	0.0008	-0.5706	0.3414	0.0399	0.0008

Note: *Values with ^{a} (^{b}) [^{c}] depict significance at the 0.01 (0.05) [0.10] levels.*

Table 3.2e: QR estimates for DAS and African fiat currencies exchange rates cont.

Quantile	Rupee Coef.	Rupee.IMF1 Coef.	Rupee.IMF5 Coef.	Rupee.IMRes. Coef.	Dinar Coef.	Dinar.IMF1 Coef.	Dinar.IMF5 Coef.	Dinar.IMRes. Coef.
0.05	-0.6036	-0.1194	-0.0581[a]	-0.0947[a]	-1.0833[b]	0.2064	-8.1049[a]	2.5464[a]
0.10	0.1439	-0.1088	-0.0114	-0.0752[a]	-0.4545	-0.2358	-6.1948[a]	2.8817[a]
0.15	-0.7598	0.0241	-0.0026	-0.0534[b]	-0.2953	-0.1649	-5.6704[a]	3.1394[a]
0.20	-0.4283	-0.0679	0.0071	-0.0517[a]	-0.2038	0.0169	-5.3232[a]	3.3324[a]
0.25	-0.0191	-0.151	0.0119	-0.0440[b]	-0.1576	0.2112	-5.1552[a]	3.4959[a]
0.30	0.1829	-0.1565	0.0257	-0.0375[b]	-0.0791	0.4455	-4.6287[a]	3.6212a
0.35	0.2343	-0.2103	0.0145	-0.0302[c]	0.0222	0.4048	-4.1236[a]	3.7251[a]
0.40	0.2001	-0.1669	0.0279	-0.0235	0.0237[c]	0.5752	-3.9504[a]	3.8186[a]
0.45	0.1458	-0.0946	0.0302	-0.0200	0.0948[a]	0.8231	-2.9091[a]	3.8934[a]
0.50	0.0878	-0.1681	0.0211	-0.0135	0.2117[b]	0.7696	-2.6259[a]	3.9541[a]
0.55	0.1392	-0.1025	-0.0064	-0.0078	0.2249	0.4975	-2.8123[a]	4.0072[a]
0.60	0.1193	-0.0329	0.0057	-0.0029	0.2935	0.2623	-2.7846[a]	4.0533[a]
0.65	-0.0224	0.0549	-0.005	0.0008	0.3039	0.1279	-3.0355[a]	4.0923[a]
0.70	0.1388	0.0783	-0.0729[c]	-0.0003	0.2959	-0.1308	-2.8815[a]	4.1230[a]
0.75	-0.1532	0.1127	-0.0692	0.0008	0.3302	-0.3125	-2.6588[a]	4.1506[a]
0.80	-0.4178	0.0185	-0.0423	0.0021	0.0090	-0.3191	-2.9386[a]	4.1710[a]
0.85	-0.5241	-0.0075	-0.0192	0.0031	-0.0955	-0.1578	-3.2377[a]	4.1847[a]
0.90	-0.9415	0.1246	0.0009	0.0005	-0.1029	-0.5757	-4.3154[a]	4.1961[a]
0.95	-0.039	0.3414	0.0399	0.0008	0.1683[b]	-0.5636[a]	-8.3051[a]	4.2023[a]

Note: *Values with [a] ([b]) [[c]] depict significance at the 0.01 (0.05) [0.10] levels.*

Table 3.2e: QR estimates for DAS and African fiat currencies exchange rates cont.

Quantile	Dirham Coef.	Dirham.IMF1 Coef.	Dirham.IMF5 Coef.	Dirham.IMFRes. Coef.	Shilling Coef.	Shilling.IMF1 Coef.	Shilling.IMF5 Coef.	Shilling.IMRes. Coef.
0.05	0.3322	-0.6489	-6.1427[a]	2.4952[a]	0.0019	-0.0003[c]	-0.0006[b]	-0.0001[a]
0.10	0.0937	0.0095	-1.1686	2.3401[a]	0.0005	-0.0003[c]	-0.0002	-0.0001[a]
0.15	0.3364	0.6497	1.3765[a]	2.1526[a]	0.0015	-0.0002	-0.0005[a]	-0.0001[a]
0.20	0.5866	0.0912	1.1270[a]	1.9899[a]	-0.0005	-0.0009	-0.0006[a]	-0.0001[a]
0.25	0.5158	0.3063	0.6920	1.8490[a]	-0.0002	-0.0002	-0.0007[a]	-0.0002[a]
0.30	0.3021	0.4303	0.4094	1.7033[a]	-0.0007	-0.0002	-0.0002[a]	-0.0002[a]
0.35	-0.0050	0.0461	-0.0135	1.5528[a]	-0.0001	-0.0002	-0.0008[a]	-0.0002[a]

0.40	-0.0737	-0.2774	-0.4841	1.4254[a]	0.0003	-0.0003[b]	-0.0008[a]	-0.0002[a]
0.45	0.0681	-0.1263	-0.8451[b]	1.3235[a]	0.0006	-0.0003[b]	-0.0009[a]	-0.0002[a]
0.50	0.0253	0.5318	-1.3927[a]	1.2174[b]	0.0005	-0.0003[b]	-0.0008[a]	-0.0002[a]
0.55	0.2464	0.5241	-1.1228[a]	1.1073[b]	0.0005	-0.0002	-0.0007[a]	-0.0001[a]
0.60	0.7225	0.3536	-0.7070[c]	1.0227	0.0007	-0.0002	-0.0006[a]	-0.0001[a]
0.65	1.1215[c]	0.4148	-0.1048	0.9330	0.0008	-0.0001	-0.0007[a]	-0.0001[a]
0.70	1.3477[b]	0.2681	0.6600	0.8689	0.0007	-0.0008	-0.0008[a]	-0.0001[a]
0.75	0.9592	0.1120	1.1381	0.8013	0.0003	-0.0005	-0.0009[a]	-0.0001[a]
0.80	0.6414	-0.0338	1.5655[b]	0.7592	0.0002	-0.0002	-0.0007[a]	-0.0001[a]
0.85	0.0608	-0.0500	2.1009[a]	0.7417	0.0015	-0.0002	-0.0006[a]	-0.0001[a]
0.90	1.6933	-0.6138	2.9118[a]	0.7209	0.0022	-0.0003	-0.0001[a]	-0.0001[a]
0.95	0.6178	-1.0171	-1.0683	0.6973	0.0054[a]	-0.0008	-0.0009[a]	-0.0001[a]

Note: *Values with [a] ([b]) [[c]] depict significance at the 0.01 (0.05) [0.10] levels.*

The QR results for cryptocurrencies and African fiat currencies are indicative that cryptocurrencies reduce the variance of fiat currencies and are mostly negatively correlated with reserve currencies from the medium-term. We confirm the findings of Dyhrberg (2016a, 2016), Cermak (2017), Corelli (2018) and Kristjanpoller and Bouri (2019) who reported that some cryptocurrencies and fiat currencies are connected. However, our findings contradict the works of Drożdż, Minati, Oświęcimka, Stanuszek, and Wątorek (2019) who finds no significant connections between cryptocurrencies and reserve currencies. Our results provide evidence in support of Yussof and Al-Harthy (2018) who recommend that due to the hedging benefits and global trend of cryptocurrencies, countries should fully adopt them as complements to their reserve currencies.

3.3.2 QQR Results for Cryptocurrencies and African fiat currencies

The QQR investigates the bidirectional association (reverse causality) between cryptocurrencies and fiat currencies at different quantiles of both cryptocurrencies and fiat currencies, unlike the QR which only explore the unidirectional effects of fiat currencies on cryptocurrencies at varying quantiles of fiat currencies. Therefore, we combined the two approaches to explore the entire dynamic dependencies of the virtual and fiat currencies. As a nonparametric model the coefficients of QQR do not show level of significant, unlike the QR model which is parametric. However, QQR coefficients can be validated with QR coefficients since QQR estimates are obtained by averaging QR estimates (Bouri, Gupta, Tiwari, and Roubaud, 2017) and thus the latter can confirm the former. We report QQR estimates of cryptocurrencies and African fiat currencies exchange rate returns on Table 3.3 (a- e). It is clear from Table 3.3 (a- e) that except for Shilling, the QQR shows weaker estimates relative to QR and has more inverse dependencies and variations across time and quantiles.

Specifically, Bitcoin shows negative association across quantiles at the composite level of EGP and Naira, all time periods of EGP and Dirham, the long- term of Cedi, Naira, Dinar, and ZAR, and lower quantiles (0.05 to 0.45) in the short-, and medium-term movement of Cedi, Naira, Rupee, ZAR, Dinar, and Shilling. However, the higher quantiles (0.50 to 0.95) of all fiat currencies display positive associations in the short-, and medium-terms except for Shilling which depicts all positive dependencies across quantiles in the long-term. The other cryptocurrencies; Ethereum, Litecoin, Ripple, and Das exhibit similar patterns to Bitcoin except that Das shows negative influence at 0.70 and 0.80 quantiles at the composite level of Naira and EGP but up to the 50th quantile at all time periods for the other fiat currencies. Clearly, the QQR findings for the dependencies between cryptocurrencies and African fiat currencies suggest cryptocurrencies as viable alternatives to African fiat currencies from the medium-term. This indicates that when the cryptocurrency market is less volatile and fiat currencies are depreciating, cryptocurrencies can be used to hedge against inflation and currency risk of African fiat currencies. However, market discrepancies from either of the currency markets have the potential of spilling over to the other when fiat currencies are appreciating and the cryptocurrency market is highly volatile. The dependence dynamics of the QQR are shown in Tables 3a, 3b, 3c, 3d, and 3e for Bitcoin, Ethereum, Litecoin, Ripple, and Das pairs with African fiat currencies respectively.

We tested the validity of QQR as against standard QR by plotting their coefficients in Figure 3. 2 (in the Appendices). We find the QR estimates significantly confirming the QQR estimates across time and quantiles of all cryptocurrencies and African fiat currencies exchange rate returns except Ethereum (Residual in EGP, IMF 1 in Cedi and Rupee, all levels of ZAR and Naira) and the plots for Shilling. This is evident in the QQR-QR coefficient plots in Figure 3.2 in the Appendices. Hence, the confidence that the QQR is a robust technique which quantifies the frequency-dependent asymmetric associations between cryptocurrencies and fiat currencies exchange rate returns in Africa, and also shows what those relations are.

Table 3.3 a: QQR estimates for Bitcoin and African fiat currencies exchange rates

	EGP	EGP.IMF1	EGP.IMF5	EGP.IMRes.	Cedi	Cedi.IMF1	Cedi.IMF5	Cedi.IMRes.
Quantile	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.
0.05	-0.3552	-0.1248	-0.0148	-0.0017	-0.0503	-0.0433	-0.0043	-0.0016
0.10	-0.3318	-0.1101	-0.0132	-0.0015	-0.0445	-0.0385	-0.0039	-0.0015
0.15	-0.3084	-0.0955	-0.0115	-0.0012	-0.0387	-0.0337	-0.0035	-0.0014
0.20	-0.2850	-0.0809	-0.0099	-0.0010	-0.0329	-0.0289	-0.0030	-0.0013
0.25	-0.2616	-0.0662	-0.0082	-0.0008	-0.0271	-0.0241	-0.0026	-0.0012
0.30	-0.2382	-0.0516	-0.0066	-0.0006	-0.0213	-0.0193	-0.0022	-0.0011
0.35	-0.2148	-0.0369	-0.0049	-0.0004	-0.0155	-0.0145	-0.0017	-0.0010
0.40	-0.1914	-0.0223	-0.0033	-0.0002	-0.0097	-0.0097	-0.0013	-0.0009
0.45	-0.1680	-0.0077	-0.0016	0.0001	-0.0040	-0.0049	-0.0008	-0.0008
0.50	-0.1446	0.0070	0.0000	0.0003	0.0018	-0.0001	-0.0004	-0.0008
0.55	-0.1212	0.0216	0.0017	0.0005	0.0076	0.0047	0.0000	-0.0007
0.60	-0.0977	0.0363	0.0033	0.0007	0.0134	0.0095	0.0005	-0.0006
0.65	-0.0743	0.0509	0.0050	0.0009	0.0192	0.0143	0.0009	-0.0005
0.70	-0.0509	0.0655	0.0066	0.0012	0.0250	0.0191	0.0013	-0.0004
0.75	-0.0275	0.0802	0.0083	0.0014	0.0308	0.0239	0.0018	-0.0003
0.80	-0.0041	0.0948	0.0099	0.0016	0.0366	0.0287	0.0022	-0.0002
0.85	0.0193	0.1095	0.0116	0.0018	0.0424	0.0335	0.0026	-0.0001
0.90	0.0427	0.1241	0.0132	0.0020	0.0482	0.0383	0.0031	0.0000
0.95	0.0661	0.1387	0.0149	0.0022	0.0540	0.0431	0.0035	0.0001

Table 3.3a: QQR estimates for Bitcoin and African fiat currencies exchange rates cont.

Quantile	ZAR Coef.	ZAR.IMF1 Coef.	ZAR.IMF5 Coef.	ZAR.IMRes. Coef.	Naira Coef.	Naira.IMF1 Coef.	Naira.IMF5 Coef.	Naira.IMRes Coef.
0.05	-0.0471	-0.0330	-0.0047	-0.0024	-0.2359	-0.0897	-0.0038	-0.0012
0.10	-0.0416	-0.0294	-0.0042	-0.0022	-0.2186	-0.0790	-0.0033	-0.0011
0.15	-0.0361	-0.0257	-0.0037	-0.0020	-0.2014	-0.0683	-0.0029	-0.0010
0.20	-0.0306	-0.0220	-0.0033	-0.0019	-0.1842	-0.0576	-0.0024	-0.0009
0.25	-0.0251	-0.0184	-0.0028	-0.0017	-0.1669	-0.0469	-0.0019	-0.0009
0.30	-0.0196	-0.0147	-0.0023	-0.0015	-0.1497	-0.0362	-0.0015	-0.0008
0.35	-0.0141	-0.0111	-0.0019	-0.0014	-0.1324	-0.0255	-0.0010	-0.0007
0.40	-0.0086	-0.0074	-0.0014	-0.0012	-0.1152	-0.0148	-0.0005	-0.0006
0.45	-0.0031	-0.0038	-0.0009	-0.0010	-0.0979	-0.0041	-0.0001	-0.0005
0.50	0.0024	-0.0001	-0.0005	-0.0009	-0.0807	0.0066	0.0004	-0.0004
0.55	0.0079	0.0036	0.0000	-0.0007	-0.0634	0.0173	0.0009	-0.0003
0.60	0.0134	0.0072	0.0005	-0.0005	-0.0462	0.0280	0.0013	-0.0002
0.65	0.0189	0.0109	0.0009	-0.0004	-0.0289	0.0387	0.0018	-0.0001
0.70	0.0244	0.0145	0.0014	-0.0002	-0.0117	0.0494	0.0023	-0.0001
0.75	0.0299	0.0182	0.0018	0.0000	0.0056	0.0602	0.0028	0.0000
0.80	0.0354	0.0218	0.0023	0.0001	0.0228	0.0709	0.0032	0.0001
0.85	0.0409	0.0255	0.0028	0.0003	0.0401	0.0816	0.0037	0.0002
0.90	0.0464	0.0291	0.0032	0.0005	0.0573	0.0923	0.0042	0.0003
0.95	0.0518	0.0328	0.0037	0.0006	0.0746	0.1030	0.0046	0.0004

Table 3.3a: QQR estimates for Bitcoin and African fiat currencies exchange rates cont.

Quantile	Rupee Coef.	Rupee.IMF1 Coef.	Rupee.IMF5 Coef.	Rupee.IMRes. Coef.	Dinar Coef.	Dinar.IMF1 Coef.	Dinar.IMF5 Coef.	Dinar.IMRes. Coef.
0.05	-0.0396	-0.0246	-0.0022	-0.0002	-0.0547	-0.0534	-0.0015	-0.0021
0.10	-0.0359	-0.0218	-0.0020	-0.0002	-0.0486	-0.0474	-0.0013	-0.0019
0.15	-0.0321	-0.0189	-0.0017	-0.0001	-0.0425	-0.0413	-0.0012	-0.0018
0.20	-0.0283	-0.0161	-0.0015	-0.0001	-0.0363	-0.0353	-0.0010	-0.0016
0.25	-0.0246	-0.0132	-0.0012	-0.0001	-0.0302	-0.0293	-0.0009	-0.0014
0.30	-0.0208	-0.0104	-0.0010	-0.0001	-0.0241	-0.0233	-0.0007	-0.0013
0.35	-0.0171	-0.0076	-0.0008	0.0000	-0.0179	-0.0172	-0.0005	-0.0011
0.40	-0.0133	-0.0047	-0.0005	0.0000	-0.0118	-0.0112	-0.0004	-0.0010
0.45	-0.0096	-0.0019	-0.0003	0.0000	-0.0057	-0.0052	-0.0002	-0.0008
0.50	-0.0058	0.0010	-0.0001	0.0000	0.0004	0.0009	-0.0001	-0.0007
0.55	-0.0021	0.0038	0.0002	0.0001	0.0066	0.0069	0.0001	-0.0005

0.60	0.0017	0.0067	0.0004	0.0001	0.0127	0.0129	0.0002	-0.0004
0.65	0.0055	0.0095	0.0006	0.0001	0.0188	0.0190	0.0004	-0.0002
0.70	0.0092	0.0124	0.0009	0.0001	0.0250	0.0250	0.0006	-0.0001
0.75	0.0130	0.0152	0.0011	0.0002	0.0311	0.0310	0.0007	0.0001
0.80	0.0167	0.0181	0.0013	0.0002	0.0372	0.0371	0.0009	0.0002
0.85	0.0205	0.0209	0.0016	0.0002	0.0434	0.0431	0.0010	0.0004
0.90	0.0242	0.0237	0.0018	0.0002	0.0495	0.0491	0.0012	0.0005
0.95	0.0280	0.0266	0.0021	0.0003	0.0556	0.0552	0.0014	0.0007

Table 3.3a: QQR estimates for Bitcoin and African fiat currencies exchange rates cont.

Quantile	Dirham Coef.	Dirham.IMF1 Coef.	Dirham.IMF5 Coef.	Dirham.IMFRes. Coef.	Shilling Coef.	Shilling.IMF1 Coef.	Shilling.IMF5 Coef.	Shilling.IMRes. Coef.
0.05	-0.0145	-0.0121	-0.0019	-0.0007	-9.9500	-324.0228	-67.6213	350.1421
0.10	-0.0122	-0.0106	-0.0016	-0.0006	-8.8422	-286.7208	-60.5677	354.1740
0.15	-0.0098	-0.0092	-0.0013	-0.0005	-7.7344	-249.4187	-53.5142	358.2060
0.20	-0.0075	-0.0078	-0.0010	-0.0004	-6.6267	-212.1167	-46.4606	362.2379
0.25	-0.0052	-0.0064	-0.0007	-0.0003	-5.5189	-174.8146	-39.4071	366.2698
0.30	-0.0029	-0.0049	-0.0005	-0.0002	-4.4111	-137.5126	-32.3535	370.3018
0.35	-0.0006	-0.0035	-0.0002	-0.0001	-3.3033	-100.2106	-25.3000	374.3337
0.40	0.0018	-0.0021	0.0001	0.0000	-2.1956	-62.9085	-18.2464	378.3656
0.45	0.0041	-0.0006	0.0004	0.0001	-1.0878	-25.6065	-11.1929	382.3976
0.50	0.0064	0.0008	0.0007	0.0001	0.0200	11.6956	-4.1393	386.4295
0.55	0.0087	0.0022	0.0010	0.0002	1.1278	48.9976	2.9142	390.4614
0.60	0.0110	0.0037	0.0012	0.0003	2.2356	86.2997	9.9677	394.4934
0.65	0.0134	0.0051	0.0015	0.0004	3.3433	123.6017	17.0213	398.5253
0.70	0.0157	0.0065	0.0018	0.0005	4.4511	160.9038	24.0748	402.5572
0.75	0.0180	0.0080	0.0021	0.0006	5.5589	198.2058	31.1284	406.5892
0.80	0.0203	0.0094	0.0024	0.0007	6.6667	235.5078	38.1819	410.6211
0.85	0.0226	0.0108	0.0026	0.0008	7.7744	272.8099	45.2355	414.6530
0.90	0.0250	0.0123	0.0029	0.0009	8.8822	310.1119	52.2890	418.6850
0.95	0.0273	0.0137	0.0032	0.0010	9.9900	347.4140	59.3426	422.7169

Table 3.3 b: QQR estimates for Ethereum and African fiat currencies exchange rates

Quantile	EGP Coef.	EGP.IMF1 Coef.	EGP.IMF5 Coef.	EGP.IMRes. Coef.	Cedi Coef.	Cedi.IMF1 Coef.	Cedi.IMF5 Coef.	Cedi.IMRes. Coef.
0.05	-0.3552	-0.1248	-0.1248	-0.0017	-0.0503	-0.0433	-0.0043	-0.0043
0.10	-0.3318	-0.1101	-0.1101	-0.0015	-0.0445	-0.0385	-0.0039	-0.0039
0.15	-0.3084	-0.0955	-0.0955	-0.0012	-0.0387	-0.0337	-0.0035	-0.0035
0.20	-0.2850	-0.0809	-0.0809	-0.0010	-0.0329	-0.0289	-0.0030	-0.0030
0.25	-0.2616	-0.0662	-0.0662	-0.0008	-0.0271	-0.0241	-0.0026	-0.0026
0.30	-0.2382	-0.0516	-0.0516	-0.0006	-0.0213	-0.0193	-0.0022	-0.0022
0.35	-0.2148	-0.0369	-0.0369	-0.0004	-0.0155	-0.0145	-0.0017	-0.0017
0.40	-0.1914	-0.0223	-0.0223	-0.0002	-0.0097	-0.0097	-0.0013	-0.0013
0.45	-0.1680	-0.0077	-0.0077	0.0001	-0.0040	-0.0049	-0.0008	-0.0008
0.50	-0.1446	0.0070	0.0070	0.0003	0.0018	-0.0001	-0.0004	-0.0004
0.55	-0.1212	0.0216	0.0216	0.0005	0.0076	0.0047	0.0000	0.0000
0.60	-0.0977	0.0363	0.0363	0.0007	0.0134	0.0095	0.0005	0.0005
0.65	-0.0743	0.0509	0.0509	0.0009	0.0192	0.0143	0.0009	0.0009
0.70	-0.0509	0.0655	0.0655	0.0012	0.0250	0.0191	0.0013	0.0013
0.75	-0.0275	0.0802	0.0802	0.0014	0.0308	0.0239	0.0018	0.0018
0.80	-0.0041	0.0948	0.0948	0.0016	0.0366	0.0287	0.0022	0.0022
0.85	0.0193	0.1095	0.1095	0.0018	0.0424	0.0335	0.0026	0.0026
0.90	0.0427	0.1241	0.1241	0.0020	0.0482	0.0383	0.0031	0.0031
0.95	0.0661	0.1387	0.1387	0.0022	0.0540	0.0431	0.0035	0.0035

Table 3.3b: QQR estimates for Ethereum and African fiat currencies exchange rates cont.

Quantile	ZAR Coef.	ZAR.IMF1 Coef.	ZAR.IMF5 Coef.	ZAR.IMRes. Coef.	Naira Coef.	Naira.IMF1 Coef.	Naira.IMF5 Coef.	Naira.IMRes Coef.
0.05	-0.0471	-0.0330	-0.0330	-0.0024	-0.2359	-0.0024	-0.0038	-0.0012
0.10	-0.0416	-0.0294	-0.0294	-0.0022	-0.2186	-0.0022	-0.0033	-0.0011
0.15	-0.0361	-0.0257	-0.0257	-0.0020	-0.2014	-0.0020	-0.0029	-0.0010
0.20	-0.0306	-0.0220	-0.0220	-0.0019	-0.1842	-0.0019	-0.0024	-0.0009
0.25	-0.0251	-0.0184	-0.0184	-0.0017	-0.1669	-0.0017	-0.0019	-0.0009
0.30	-0.0196	-0.0147	-0.0147	-0.0015	-0.1497	-0.0015	-0.0015	-0.0008
0.35	-0.0141	-0.0111	-0.0111	-0.0014	-0.1324	-0.0014	-0.0010	-0.0007
0.40	-0.0086	-0.0074	-0.0074	-0.0012	-0.1152	-0.0012	-0.0005	-0.0006
0.45	-0.0031	-0.0038	-0.0038	-0.0010	-0.0979	-0.0010	-0.0001	-0.0005
0.50	0.0024	-0.0001	-0.0001	-0.0009	-0.0807	-0.0009	0.0004	-0.0004

0.55	0.0079	0.0036	0.0036	-0.0007	-0.0634	-0.0007	0.0009	-0.0003
0.60	0.0134	0.0072	0.0072	-0.0005	-0.0462	-0.0005	0.0013	-0.0002
0.65	0.0189	0.0109	0.0109	-0.0004	-0.0289	-0.0004	0.0018	-0.0001
0.70	0.0244	0.0145	0.0145	-0.0002	-0.0117	-0.0002	0.0023	-0.0001
0.75	0.0299	0.0182	0.0182	0.0000	0.0056	0.0000	0.0028	0.0000
0.80	0.0354	0.0218	0.0218	0.0001	0.0228	0.0001	0.0032	0.0001
0.85	0.0409	0.0255	0.0255	0.0003	0.0401	0.0003	0.0037	0.0002
0.90	0.0464	0.0291	0.0291	0.0005	0.0573	0.0005	0.0042	0.0003
0.95	0.0518	0.0328	0.0328	0.0006	0.0746	0.0006	0.0046	0.0004

Table 3.3b: QQR estimates for Ethereum and African fiat currencies exchange rates cont.

	Rupee	**Rupee.IMF1**	**Rupee.IMF5**	**Rupee.IMRes.**	**Dinar**	**Dinar.IMF1**	**Dinar.IMF5**	**Dinar.IMRes.**
Quantile	**Coef.**	**Coef.**	**Coef.**	**Coef.**	**Coef.**	**Coef.**	**Coef.**	**Coef.**
0.05	-0.0396	-0.0246	-0.0022	-0.00018	-0.0547	-0.0534	-0.0015	-0.0021
0.10	-0.0359	-0.0218	-0.0020	-0.00015	-0.0486	-0.0474	-0.0013	-0.0019
0.15	-0.0321	-0.0189	-0.0017	-0.00013	-0.0425	-0.0413	-0.0012	-0.0018
0.20	-0.0283	-0.0161	-0.0015	-0.00010	-0.0363	-0.0353	-0.0010	-0.0016
0.25	-0.0246	-0.0132	-0.0012	-0.00008	-0.0302	-0.0293	-0.0009	-0.0014
0.30	-0.0208	-0.0104	-0.0010	-0.00006	-0.0241	-0.0233	-0.0007	-0.0013
0.35	-0.0171	-0.0076	-0.0008	-0.00003	-0.0179	-0.0172	-0.0005	-0.0011
0.40	-0.0133	-0.0047	-0.0005	-0.00001	-0.0118	-0.0112	-0.0004	-0.0010
0.45	-0.0096	-0.0019	-0.0003	0.00001	-0.0057	-0.0052	-0.0002	-0.0008
0.50	-0.0058	0.0010	-0.0001	0.00004	0.0004	0.0009	-0.0001	-0.0007
0.55	-0.0021	0.0038	0.0002	0.00006	0.0066	0.0069	0.0001	-0.0005
0.60	0.0017	0.0067	0.0004	0.00009	0.0127	0.0129	0.0002	-0.0004
0.65	0.0055	0.0095	0.0006	0.00011	0.0188	0.0190	0.0004	-0.0002
0.70	0.0092	0.0124	0.0009	0.00013	0.0250	0.0250	0.0006	-0.0001
0.75	0.0130	0.0152	0.0011	0.00016	0.0311	0.0310	0.0007	0.0001
0.80	0.0167	0.0181	0.0013	0.00018	0.0372	0.0371	0.0009	0.0002
0.85	0.0205	0.0209	0.0016	0.00021	0.0434	0.0431	0.0010	0.0004
0.90	0.0242	0.0237	0.0018	0.00023	0.0495	0.0491	0.0012	0.0005
0.95	0.0280	0.0266	0.0021	0.00025	0.0556	0.0552	0.0014	0.0007

Table 3.3b: QQR estimates for Ethereum and African fiat currencies exchange rates cont.

Quantile	Dirham Coef.	Dirham.IMF1 Coef.	Dirham.IMF5 Coef.	Dirham.IMFRes. Coef.	Shilling Coef.	Shilling.IMF1 Coef.	Shilling.IMF5 Coef.	Shilling.IMRes. Coef.
0.05	-0.0145	-0.0121	-0.0019	-0.0007	-9.9500	-324.0228	-67.6213	350.1421
0.10	-0.0122	-0.0106	-0.0016	-0.0006	-8.8422	-286.7208	-60.5677	354.1740
0.15	-0.0098	-0.0092	-0.0013	-0.0005	-7.7344	-249.4187	-53.5142	358.2060
0.20	-0.0075	-0.0078	-0.0010	-0.0004	-6.6267	-212.1167	-46.4606	362.2379
0.25	-0.0052	-0.0064	-0.0007	-0.0003	-5.5189	-174.8146	-39.4071	366.2698
0.30	-0.0029	-0.0049	-0.0005	-0.0002	-4.4111	-137.5126	-32.3535	370.3018
0.35	-0.0006	-0.0035	-0.0002	-0.0001	-3.3033	-100.2106	-25.3000	374.3337
0.40	0.0018	-0.0021	0.0001	0.0000	-2.1956	-62.9085	-18.2464	378.3656
0.45	0.0041	-0.0006	0.0004	0.0001	-1.0878	-25.6065	-11.1929	382.3976
0.50	0.0064	0.0008	0.0007	0.0001	0.0200	11.6956	-4.1393	386.4295
0.55	0.0087	0.0022	0.0010	0.0002	1.1278	48.9976	2.9142	390.4614
0.60	0.0110	0.0037	0.0012	0.0003	2.2356	86.2997	9.9677	394.4934
0.65	0.0134	0.0051	0.0015	0.0004	3.3433	123.6017	17.0213	398.5253
0.70	0.0157	0.0065	0.0018	0.0005	4.4511	160.9038	24.0748	402.5572
0.75	0.0180	0.0080	0.0021	0.0006	5.5589	198.2058	31.1284	406.5892
0.80	0.0203	0.0094	0.0024	0.0007	6.6667	235.5078	38.1819	410.6211
0.85	0.0226	0.0108	0.0026	0.0008	7.7744	272.8099	45.2355	414.6530
0.90	0.0250	0.0123	0.0029	0.0009	8.8822	310.1119	52.2890	418.6850
0.95	0.0273	0.0137	0.0032	0.0010	9.9900	347.4140	59.3426	422.7169

Table 3.3 c: QQR estimates for Litecoin and African fiat currencies exchange rates

Quantile	EGP Coef.	EGP.IMF1 Coef.	EGP.IMF5 Coef.	EGP.IMRes. Coef.	Cedi Coef.	Cedi.IMF1 Coef.	Cedi.IMF5 Coef.	Cedi.IMRes. Coef.
0.05	-0.3552	-0.1248	-0.0148	-0.0017	-0.0503	-0.0433	-0.0043	-0.0016
0.10	-0.3318	-0.1101	-0.0132	-0.0015	-0.0445	-0.0385	-0.0039	-0.0015
0.15	-0.3084	-0.0955	-0.0115	-0.0012	-0.0387	-0.0337	-0.0035	-0.0014
0.20	-0.2850	-0.0809	-0.0099	-0.0010	-0.0329	-0.0289	-0.0030	-0.0013
0.25	-0.2616	-0.0662	-0.0082	-0.0008	-0.0271	-0.0241	-0.0026	-0.0012
0.30	-0.2382	-0.0516	-0.0066	-0.0006	-0.0213	-0.0193	-0.0022	-0.0011
0.35	-0.2148	-0.0369	-0.0049	-0.0004	-0.0155	-0.0145	-0.0017	-0.0010
0.40	-0.1914	-0.0223	-0.0033	-0.0002	-0.0097	-0.0097	-0.0013	-0.0009
0.45	-0.1680	-0.0077	-0.0016	0.0001	-0.0040	-0.0049	-0.0008	-0.0008
0.50	-0.1446	0.0070	0.0000	0.0003	0.0018	-0.0001	-0.0004	-0.0008
0.55	-0.1212	0.0216	0.0017	0.0005	0.0076	0.0047	0.0000	-0.0007

0.60	-0.0977	0.0363	0.0033	0.0007	0.0134	0.0095	0.0005	-0.0006
0.65	-0.0743	0.0509	0.0050	0.0009	0.0192	0.0143	0.0009	-0.0005
0.70	-0.0509	0.0655	0.0066	0.0012	0.0250	0.0191	0.0013	-0.0004
0.75	-0.0275	0.0802	0.0083	0.0014	0.0308	0.0239	0.0018	-0.0003
0.80	-0.0041	0.0948	0.0099	0.0016	0.0366	0.0287	0.0022	-0.0002
0.85	0.0193	0.1095	0.0116	0.0018	0.0424	0.0335	0.0026	-0.0001
0.90	0.0427	0.1241	0.0132	0.0020	0.0482	0.0383	0.0031	0.0000
0.95	0.0661	0.1387	0.0149	0.0022	0.0540	0.0431	0.0035	0.0001

Table 3.3c: QQR estimates for Litecoin and African fiat currencies exchange rates cont.

Quantile	ZAR Coef.	ZAR.IMF1 Coef.	ZAR.IMF5 Coef.	ZAR.IMRes. Coef.	Naira Coef.	Naira.IMF1 Coef.	Naira.IMF5 Coef.	Naira.IMRes Coef.
0.05	-0.0471	-0.0330	-0.0047	-0.0024	-0.2359	-0.0897	-0.0038	-0.0012
0.10	-0.0416	-0.0294	-0.0042	-0.0022	-0.2186	-0.0790	-0.0033	-0.0011
0.15	-0.0361	-0.0257	-0.0037	-0.0020	-0.2014	-0.0683	-0.0029	-0.0010
0.20	-0.0306	-0.0220	-0.0033	-0.0019	-0.1842	-0.0576	-0.0024	-0.0009
0.25	-0.0251	-0.0184	-0.0028	-0.0017	-0.1669	-0.0469	-0.0019	-0.0009
0.30	-0.0196	-0.0147	-0.0023	-0.0015	-0.1497	-0.0362	-0.0015	-0.0008
0.35	-0.0141	-0.0111	-0.0019	-0.0014	-0.1324	-0.0255	-0.0010	-0.0007
0.40	-0.0086	-0.0074	-0.0014	-0.0012	-0.1152	-0.0148	-0.0005	-0.0006
0.45	-0.0031	-0.0038	-0.0009	-0.0010	-0.0979	-0.0041	-0.0001	-0.0005
0.50	0.0024	-0.0001	-0.0005	-0.0009	-0.0807	0.0066	0.0004	-0.0004
0.55	0.0079	0.0036	0.0000	-0.0007	-0.0634	0.0173	0.0009	-0.0003
0.60	0.0134	0.0072	0.0005	-0.0005	-0.0462	0.0280	0.0013	-0.0002
0.65	0.0189	0.0109	0.0009	-0.0004	-0.0289	0.0387	0.0018	-0.0001
0.70	0.0244	0.0145	0.0014	-0.0002	-0.0117	0.0494	0.0023	-0.0001
0.75	0.0299	0.0182	0.0018	0.0000	0.0056	0.0602	0.0028	0.0000
0.80	0.0354	0.0218	0.0023	0.0001	0.0228	0.0709	0.0032	0.0001
0.85	0.0409	0.0255	0.0028	0.0003	0.0401	0.0816	0.0037	0.0002
0.90	0.0464	0.0291	0.0032	0.0005	0.0573	0.0923	0.0042	0.0003
0.95	0.0518	0.0328	0.0037	0.0006	0.0746	0.1030	0.0046	0.0004

Table 3.3c: QQR estimates for Litecoin and African fiat currencies exchange rates cont.

Quantile	Rupee Coef.	Rupee.IMF1 Coef.	Rupee.IMF5 Coef.	Rupee.IMRes. Coef.	Dinar Coef.	Dinar.IMF1 Coef.	Dinar.IMF5 Coef.	Dinar.IMRes. Coef.
0.05	-0.0396	-0.0897	-0.0038	-0.0012	-0.0547	-0.0534	-0.0015	-0.0021
0.10	-0.0359	-0.0790	-0.0033	-0.0011	-0.0486	-0.0474	-0.0013	-0.0019
0.15	-0.0321	-0.0683	-0.0029	-0.0010	-0.0425	-0.0413	-0.0012	-0.0018
0.20	-0.0283	-0.0576	-0.0024	-0.0009	-0.0363	-0.0353	-0.0010	-0.0016
0.25	-0.0246	-0.0469	-0.0019	-0.0009	-0.0302	-0.0293	-0.0009	-0.0014
0.30	-0.0208	-0.0362	-0.0015	-0.0008	-0.0241	-0.0233	-0.0007	-0.0013
0.35	-0.0171	-0.0255	-0.0010	-0.0007	-0.0179	-0.0172	-0.0005	-0.0011
0.40	-0.0133	-0.0148	-0.0005	-0.0006	-0.0118	-0.0112	-0.0004	-0.0010
0.45	-0.0096	-0.0041	-0.0001	-0.0005	-0.0057	-0.0052	-0.0002	-0.0008
0.50	-0.0058	0.0066	0.0004	-0.0004	0.0004	0.0009	-0.0001	-0.0007
0.55	-0.0021	0.0173	0.0009	-0.0003	0.0066	0.0069	0.0001	-0.0005
0.60	0.0017	0.0280	0.0013	-0.0002	0.0127	0.0129	0.0002	-0.0004
0.65	0.0055	0.0387	0.0018	-0.0001	0.0188	0.0190	0.0004	-0.0002
0.70	0.0092	0.0494	0.0023	-0.0001	0.0250	0.0250	0.0006	-0.0001
0.75	0.0130	0.0602	0.0028	0.0000	0.0311	0.0310	0.0007	0.0001
0.80	0.0167	0.0709	0.0032	0.0001	0.0372	0.0371	0.0009	0.0002
0.85	0.0205	0.0816	0.0037	0.0002	0.0434	0.0431	0.0010	0.0004
0.90	0.0242	0.0923	0.0042	0.0003	0.0495	0.0491	0.0012	0.0005
0.95	0.0280	0.1030	0.0046	0.0004	0.0556	0.0552	0.0014	0.0007

Table 3.3c: QQR estimates for Litecoin and African fiat currencies exchange rates cont.

Quantile	Dirham Coef.	Dirham.IMF1 Coef.	Dirham.IMF5 Coef.	Dirham.IMFRes. Coef.	Shilling Coef.	Shilling.IMF1 Coef.	Shilling.IMF5 Coef.	Shilling.IMRes. Coef.
0.05	-0.0145	-0.0121	-0.0019	-0.0007	-9.9500	-324.0228	-67.6213	350.1421
0.10	-0.0122	-0.0106	-0.0016	-0.0006	-8.8422	-286.7208	-60.5677	354.1740
0.15	-0.0098	-0.0092	-0.0013	-0.0005	-7.7344	-249.4187	-53.5142	358.2060
0.20	-0.0075	-0.0078	-0.0010	-0.0004	-6.6267	-212.1167	-46.4606	362.2379
0.25	-0.0052	-0.0064	-0.0007	-0.0003	-5.5189	-174.8146	-39.4071	366.2698
0.30	-0.0029	-0.0049	-0.0005	-0.0002	-4.4111	-137.5126	-32.3535	370.3018
0.35	-0.0006	-0.0035	-0.0002	-0.0001	-3.3033	-100.2106	-25.3000	374.3337
0.40	0.0018	-0.0021	0.0001	0.0000	-2.1956	-62.9085	-18.2464	378.3656
0.45	0.0041	-0.0006	0.0004	0.0001	-1.0878	-25.6065	-11.1929	382.3976
0.50	0.0064	0.0008	0.0007	0.0001	0.0200	11.6956	-4.1393	386.4295
0.55	0.0087	0.0022	0.0010	0.0002	1.1278	48.9976	2.9142	390.4614

0.60	0.0110	0.0037	0.0012	0.0003	2.2356	86.2997	9.9677	394.4934
0.65	0.0134	0.0051	0.0015	0.0004	3.3433	123.6017	17.0213	398.5253
0.70	0.0157	0.0065	0.0018	0.0005	4.4511	160.9038	24.0748	402.5572
0.75	0.0180	0.0080	0.0021	0.0006	5.5589	198.2058	31.1284	406.5892
0.80	0.0203	0.0094	0.0024	0.0007	6.6667	235.5078	38.1819	410.6211
0.85	0.0226	0.0108	0.0026	0.0008	7.7744	272.8099	45.2355	414.6530
0.90	0.0250	0.0123	0.0029	0.0009	8.8822	310.1119	52.2890	418.6850
0.95	0.0273	0.0137	0.0032	0.0010	9.9900	347.4140	59.3426	422.7169

Table 3.3 d: QQR estimates for Ripple and African fiat currencies exchange rates

	EGP	**EGP.IMF1**	**EGP.IMF5**	**EGP.IMRes.**	**Cedi**	**Cedi.IMF1**	**Cedi.IMF5**	**Cedi.IMRes.**
Quantile	**Coef.**	**Coef.**	**Coef.**	**Coef.**	**Coef.**	**Coef.**	**Coef.**	**Coef.**
0.05	-0.3552	-0.1248	-0.0148	-0.0017	-0.0503	-0.0433	-0.0043	-0.0016
0.10	-0.3318	-0.1101	-0.0132	-0.0015	-0.0445	-0.0385	-0.0039	-0.0015
0.15	-0.3084	-0.0955	-0.0115	-0.0012	-0.0387	-0.0337	-0.0035	-0.0014
0.20	-0.2850	-0.0809	-0.0099	-0.0010	-0.0329	-0.0289	-0.0030	-0.0013
0.25	-0.2616	-0.0662	-0.0082	-0.0008	-0.0271	-0.0241	-0.0026	-0.0012
0.30	-0.2382	-0.0516	-0.0066	-0.0006	-0.0213	-0.0193	-0.0022	-0.0011
0.35	-0.2148	-0.0369	-0.0049	-0.0004	-0.0155	-0.0145	-0.0017	-0.0010
0.40	-0.1914	-0.0223	-0.0033	-0.0002	-0.0097	-0.0097	-0.0013	-0.0009
0.45	-0.1680	-0.0077	-0.0016	0.0001	-0.0040	-0.0049	-0.0008	-0.0008
0.50	-0.1446	0.0070	0.0000	0.0003	0.0018	-0.0001	-0.0004	-0.0008
0.55	-0.1212	0.0216	0.0017	0.0005	0.0076	0.0047	0.0000	-0.0007
0.60	-0.0977	0.0363	0.0033	0.0007	0.0134	0.0095	0.0005	-0.0006
0.65	-0.0743	0.0509	0.0050	0.0009	0.0192	0.0143	0.0009	-0.0005
0.70	-0.0509	0.0655	0.0066	0.0012	0.0250	0.0191	0.0013	-0.0004
0.75	-0.0275	0.0802	0.0083	0.0014	0.0308	0.0239	0.0018	-0.0003
0.80	-0.0041	0.0948	0.0099	0.0016	0.0366	0.0287	0.0022	-0.0002
0.85	0.0193	0.1095	0.0116	0.0018	0.0424	0.0335	0.0026	-0.0001
0.90	0.0427	0.1241	0.0132	0.0020	0.0482	0.0383	0.0031	0.0000
0.95	0.0661	0.1387	0.0149	0.0022	0.0540	0.0431	0.0035	0.0001

Table 3.3d: QQR estimates for Ripple and African fiat currencies exchange rates cont.

Quantile	ZAR Coef.	ZAR.IMF1 Coef.	ZAR.IMF5 Coef.	ZAR.IMRes. Coef.	Naira Coef.	Naira.IMF1 Coef.	Naira.IMF5 Coef.	Naira.IMRes Coef.
0.05	-0.0471	-0.0330	-0.0047	-0.0024	-0.2359	-0.0897	-0.0897	-0.0897
0.10	-0.0416	-0.0294	-0.0042	-0.0022	-0.2186	-0.0790	-0.0790	-0.0790
0.15	-0.0361	-0.0257	-0.0037	-0.0020	-0.2014	-0.0683	-0.0683	-0.0683
0.20	-0.0306	-0.0220	-0.0033	-0.0019	-0.1842	-0.0576	-0.0576	-0.0576
0.25	-0.0251	-0.0184	-0.0028	-0.0017	-0.1669	-0.0469	-0.0469	-0.0469
0.30	-0.0196	-0.0147	-0.0023	-0.0015	-0.1497	-0.0362	-0.0362	-0.0362
0.35	-0.0141	-0.0111	-0.0019	-0.0014	-0.1324	-0.0255	-0.0255	-0.0255
0.40	-0.0086	-0.0074	-0.0014	-0.0012	-0.1152	-0.0148	-0.0148	-0.0148
0.45	-0.0031	-0.0038	-0.0009	-0.0010	-0.0979	-0.0041	-0.0041	-0.0041
0.50	0.0024	-0.0001	-0.0005	-0.0009	-0.0807	0.0066	0.0066	0.0066
0.55	0.0079	0.0036	0.0000	-0.0007	-0.0634	0.0173	0.0173	0.0173
0.60	0.0134	0.0072	0.0005	-0.0005	-0.0462	0.0280	0.0280	0.0280
0.65	0.0189	0.0109	0.0009	-0.0004	-0.0289	0.0387	0.0387	0.0387
0.70	0.0244	0.0145	0.0014	-0.0002	-0.0117	0.0494	0.0494	0.0494
0.75	0.0299	0.0182	0.0018	0.0000	0.0056	0.0602	0.0602	0.0602
0.80	0.0354	0.0218	0.0023	0.0001	0.0228	0.0709	0.0709	0.0709
0.85	0.0409	0.0255	0.0028	0.0003	0.0401	0.0816	0.0816	0.0816
0.90	0.0464	0.0291	0.0032	0.0005	0.0573	0.0923	0.0923	0.0923
0.95	0.0518	0.0328	0.0037	0.0006	0.0746	0.1030	0.1030	0.1030

Table 3.3d: QQR estimates for Ripple and African fiat currencies exchange rates cont.

Quantile	Rupee Coef.	Rupee.IMF1 Coef.	Rupee.IMF5 Coef.	Rupee.IMRes. Coef.	Dinar Coef.	Dinar.IMF1 Coef.	Dinar.IMF5 Coef.	Dinar.IMRes. Coef.
0.05	-0.0396	-0.0897	-0.0897	-0.0897	-0.0547	-0.0534	-0.0015	-0.0021
0.10	-0.0359	-0.0790	-0.0790	-0.0790	-0.0486	-0.0474	-0.0013	-0.0019
0.15	-0.0321	-0.0683	-0.0683	-0.0683	-0.0425	-0.0413	-0.0012	-0.0018
0.20	-0.0283	-0.0576	-0.0576	-0.0576	-0.0363	-0.0353	-0.0010	-0.0016
0.25	-0.0246	-0.0469	-0.0469	-0.0469	-0.0302	-0.0293	-0.0009	-0.0014
0.30	-0.0208	-0.0362	-0.0362	-0.0362	-0.0241	-0.0233	-0.0007	-0.0013
0.35	-0.0171	-0.0255	-0.0255	-0.0255	-0.0179	-0.0172	-0.0005	-0.0011
0.40	-0.0133	-0.0148	-0.0148	-0.0148	-0.0118	-0.0112	-0.0004	-0.0010
0.45	-0.0096	-0.0041	-0.0041	-0.0041	-0.0057	-0.0052	-0.0002	-0.0008

0.50	-0.0058	0.0066	0.0066	0.0066	0.0004	0.0009	-0.0001	-0.0007
0.55	-0.0021	0.0173	0.0173	0.0173	0.0066	0.0069	0.0001	-0.0005
0.60	0.0017	0.0280	0.0280	0.0280	0.0127	0.0129	0.0002	-0.0004
0.65	0.0055	0.0387	0.0387	0.0387	0.0188	0.0190	0.0004	-0.0002
0.70	0.0092	0.0494	0.0494	0.0494	0.0250	0.0250	0.0006	-0.0001
0.75	0.0130	0.0602	0.0602	0.0602	0.0311	0.0310	0.0007	0.0001
0.80	0.0167	0.0709	0.0709	0.0709	0.0372	0.0371	0.0009	0.0002
0.85	0.0205	0.0816	0.0816	0.0816	0.0434	0.0431	0.0010	0.0004
0.90	0.0242	0.0923	0.0923	0.0923	0.0495	0.0491	0.0012	0.0005
0.95	0.0280	0.1030	0.1030	0.1030	0.0556	0.0552	0.0014	0.0007

Table 3.3d: QQR estimates for Ripple and African fiat currencies exchange rates cont.

	Dirham	**Dirham.IMF1**	**Dirham.IMF5**	**Dirham.IMFRes.**	**Shilling**	**Shilling.IMF1**	**Shilling.IMF5**	**Shilling.IMRes.**
Quantile	**Coef.**	**Coef.**	**Coef.**	**Coef.**	**Coef.**	**Coef.**	**Coef.**	**Coef.**
0.05	-0.0145	-0.0145	-0.0019	-0.0007	-9.9500	-324.0228	-67.6213	350.1421
0.10	-0.0122	-0.0122	-0.0016	-0.0006	-8.8422	-286.7208	-60.5677	354.1740
0.15	-0.0098	-0.0098	-0.0013	-0.0005	-7.7344	-249.4187	-53.5142	358.2060
0.20	-0.0075	-0.0075	-0.0010	-0.0004	-6.6267	-212.1167	-46.4606	362.2379
0.25	-0.0052	-0.0052	-0.0007	-0.0003	-5.5189	-174.8146	-39.4071	366.2698
0.30	-0.0029	-0.0029	-0.0005	-0.0002	-4.4111	-137.5126	-32.3535	370.3018
0.35	-0.0006	-0.0006	-0.0002	-0.0001	-3.3033	-100.2106	-25.3000	374.3337
0.40	0.0018	0.0018	0.0001	0.0000	-2.1956	-62.9085	-18.2464	378.3656
0.45	0.0041	0.0041	0.0004	0.0001	-1.0878	-25.6065	-11.1929	382.3976
0.50	0.0064	0.0064	0.0007	0.0001	0.0200	11.6956	-4.1393	386.4295
0.55	0.0087	0.0087	0.0010	0.0002	1.1278	48.9976	2.9142	390.4614
0.60	0.0110	0.0110	0.0012	0.0003	2.2356	86.2997	9.9677	394.4934
0.65	0.0134	0.0134	0.0015	0.0004	3.3433	123.6017	17.0213	398.5253
0.70	0.0157	0.0157	0.0018	0.0005	4.4511	160.9038	24.0748	402.5572
0.75	0.0180	0.0180	0.0021	0.0006	5.5589	198.2058	31.1284	406.5892
0.80	0.0203	0.0203	0.0024	0.0007	6.6667	235.5078	38.1819	410.6211
0.85	0.0226	0.0226	0.0026	0.0008	7.7744	272.8099	45.2355	414.6530
0.90	0.0250	0.0250	0.0029	0.0009	8.8822	310.1119	52.2890	418.6850
0.95	0.0273	0.0273	0.0032	0.0010	9.9900	347.4140	59.3426	422.7169

Table 3.3 e: QQR estimates for DAS and African fiat currencies exchange rates

	EGP	EGP.IMF1	EGP.IMF5	EGP.IMRes.	Cedi	Cedi.IMF1	Cedi.IMF5	Cedi.IMRes.
Quantile	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.
0.05	-0.3552	-0.0897	-0.0897	-0.0897	-0.0503	-0.0897	-0.0897	-0.0897
0.10	-0.3318	-0.0790	-0.0790	-0.0790	-0.0445	-0.0790	-0.0790	-0.0790
0.15	-0.3084	-0.0683	-0.0683	-0.0683	-0.0387	-0.0683	-0.0683	-0.0683
0.20	-0.2850	-0.0576	-0.0576	-0.0576	-0.0329	-0.0576	-0.0576	-0.0576
0.25	-0.2616	-0.0469	-0.0469	-0.0469	-0.0271	-0.0469	-0.0469	-0.0469
0.30	-0.2382	-0.0362	-0.0362	-0.0362	-0.0213	-0.0362	-0.0362	-0.0362
0.35	-0.2148	-0.0255	-0.0255	-0.0255	-0.0155	-0.0255	-0.0255	-0.0255
0.40	-0.1914	-0.0148	-0.0148	-0.0148	-0.0097	-0.0148	-0.0148	-0.0148
0.45	-0.1680	-0.0041	-0.0041	-0.0041	-0.0040	-0.0041	-0.0041	-0.0041
0.50	-0.1446	0.0066	0.0066	0.0066	0.0018	0.0066	0.0066	0.0066
0.55	-0.1212	0.0173	0.0173	0.0173	0.0076	0.0173	0.0173	0.0173
0.60	-0.0977	0.0280	0.0280	0.0280	0.0134	0.0280	0.0280	0.0280
0.65	-0.0743	0.0387	0.0387	0.0387	0.0192	0.0387	0.0387	0.0387
0.70	-0.0509	0.0494	0.0494	0.0494	0.0250	0.0494	0.0494	0.0494
0.75	-0.0275	0.0602	0.0602	0.0602	0.0308	0.0602	0.0602	0.0602
0.80	-0.0041	0.0709	0.0709	0.0709	0.0366	0.0709	0.0709	0.0709
0.85	0.0193	0.0816	0.0816	0.0816	0.0424	0.0816	0.0816	0.0816
0.90	0.0427	0.0923	0.0923	0.0923	0.0482	0.0923	0.0923	0.0923
0.95	0.0661	0.1030	0.1030	0.1030	0.0540	0.1030	0.1030	0.1030

Table 3.3e: QQR estimates for DAS and African fiat currencies exchange rates cont.

	ZAR	ZAR.IMF1	ZAR.IMF5	ZAR.IMRes.	Naira	Naira.IMF1	Naira.IMF5	Naira.IMRes
Quantile	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.
0.05	-0.0471	-0.0897	-0.0897	-0.0897	-0.2359	-0.0897	-0.0897	-0.0897
0.10	-0.0416	-0.0790	-0.0790	-0.0790	-0.2186	-0.0790	-0.0790	-0.0790
0.15	-0.0361	-0.0683	-0.0683	-0.0683	-0.2014	-0.0683	-0.0683	-0.0683
0.20	-0.0306	-0.0576	-0.0576	-0.0576	-0.1842	-0.0576	-0.0576	-0.0576
0.25	-0.0251	-0.0469	-0.0469	-0.0469	-0.1669	-0.0469	-0.0469	-0.0469
0.30	-0.0196	-0.0362	-0.0362	-0.0362	-0.1497	-0.0362	-0.0362	-0.0362
0.35	-0.0141	-0.0255	-0.0255	-0.0255	-0.1324	-0.0255	-0.0255	-0.0255
0.40	-0.0086	-0.0148	-0.0148	-0.0148	-0.1152	-0.0148	-0.0148	-0.0148
0.45	-0.0031	-0.0041	-0.0041	-0.0041	-0.0979	-0.0041	-0.0041	-0.0041
0.50	0.0024	0.0066	0.0066	0.0066	-0.0807	0.0066	0.0066	0.0066

0.55	0.0079	0.0173	0.0173	0.0173	-0.0634	0.0173	0.0173	0.0173
0.60	0.0134	0.0280	0.0280	0.0280	-0.0462	0.0280	0.0280	0.0280
0.65	0.0189	0.0387	0.0387	0.0387	-0.0289	0.0387	0.0387	0.0387
0.70	0.0244	0.0494	0.0494	0.0494	-0.0117	0.0494	0.0494	0.0494
0.75	0.0299	0.0602	0.0602	0.0602	0.0056	0.0602	0.0602	0.0602
0.80	0.0354	0.0709	0.0709	0.0709	0.0228	0.0709	0.0709	0.0709
0.85	0.0409	0.0816	0.0816	0.0816	0.0401	0.0816	0.0816	0.0816
0.90	0.0464	0.0923	0.0923	0.0923	0.0573	0.0923	0.0923	0.0923
0.95	0.0518	0.1030	0.1030	0.1030	0.0746	0.1030	0.1030	0.1030

Table 3.3e: QQR estimates for DAS and African fiat currencies exchange rates cont.

	Rupee	**Rupee.IMF1**	**Rupee.IMF5**	**Rupee.IMRes.**	**Dinar**	**Dinar.IMF1**	**Dinar.IMF5**	**Dinar.IMRes.**
Quantile	**Coef.**	**Coef.**	**Coef.**	**Coef.**	**Coef.**	**Coef.**	**Coef.**	**Coef.**
0.05	-0.0396	-0.0897	-0.0897	-0.0897	-0.0547	-0.0534	-0.0015	-0.0021
0.10	-0.0359	-0.0790	-0.0790	-0.0790	-0.0486	-0.0474	-0.0013	-0.0019
0.15	-0.0321	-0.0683	-0.0683	-0.0683	-0.0425	-0.0413	-0.0012	-0.0018
0.20	-0.0283	-0.0576	-0.0576	-0.0576	-0.0363	-0.0353	-0.0010	-0.0016
0.25	-0.0246	-0.0469	-0.0469	-0.0469	-0.0302	-0.0293	-0.0009	-0.0014
0.30	-0.0208	-0.0362	-0.0362	-0.0362	-0.0241	-0.0233	-0.0007	-0.0013
0.35	-0.0171	-0.0255	-0.0255	-0.0255	-0.0179	-0.0172	-0.0005	-0.0011
0.40	-0.0133	-0.0148	-0.0148	-0.0148	-0.0118	-0.0112	-0.0004	-0.0010
0.45	-0.0096	-0.0041	-0.0041	-0.0041	-0.0057	-0.0052	-0.0002	-0.0008
0.50	-0.0058	0.0066	0.0066	0.0066	0.0004	0.0009	-0.0001	-0.0007
0.55	-0.0021	0.0173	0.0173	0.0173	0.0066	0.0069	0.0001	-0.0005
0.60	0.0017	0.0280	0.0280	0.0280	0.0127	0.0129	0.0002	-0.0004
0.65	0.0055	0.0387	0.0387	0.0387	0.0188	0.0190	0.0004	-0.0002
0.70	0.0092	0.0494	0.0494	0.0494	0.0250	0.0250	0.0006	-0.0001
0.75	0.0130	0.0602	0.0602	0.0602	0.0311	0.0310	0.0007	0.0001
0.80	0.0167	0.0709	0.0709	0.0709	0.0372	0.0371	0.0009	0.0002
0.85	0.0205	0.0816	0.0816	0.0816	0.0434	0.0431	0.0010	0.0004
0.90	0.0242	0.0923	0.0923	0.0923	0.0495	0.0491	0.0012	0.0005
0.95	0.0280	0.1030	0.1030	0.1030	0.0556	0.0552	0.0014	0.0007

Table 3.3e: QQR estimates for DAS and African fiat currencies exchange rates cont.

Quantile	Dirham Coef.	Dirham.IMF1 Coef.	Dirham.IMF5 Coef.	Dirham.IMFRes. Coef.	Shilling Coef.	Shilling.IMF1 Coef.	Shilling.IMF5 Coef.	Shilling.IMRes. Coef.
0.05	-0.0145	-0.0121	-0.0019	-0.0007	-9.9500	-324.0228	-67.6213	350.1421
0.10	-0.0122	-0.0106	-0.0016	-0.0006	-8.8422	-286.7208	-60.5677	354.1740
0.15	-0.0098	-0.0092	-0.0013	-0.0005	-7.7344	-249.4187	-53.5142	358.2060
0.20	-0.0075	-0.0078	-0.0010	-0.0004	-6.6267	-212.1167	-46.4606	362.2379
0.25	-0.0052	-0.0064	-0.0007	-0.0003	-5.5189	-174.8146	-39.4071	366.2698
0.30	-0.0029	-0.0049	-0.0005	-0.0002	-4.4111	-137.5126	-32.3535	370.3018
0.35	-0.0006	-0.0035	-0.0002	-0.0001	-3.3033	-100.2106	-25.3000	374.3337
0.40	0.0018	-0.0021	0.0001	0.0000	-2.1956	-62.9085	-18.2464	378.3656
0.45	0.0041	-0.0006	0.0004	0.0001	-1.0878	-25.6065	-11.1929	382.3976
0.50	0.0064	0.0008	0.0007	0.0001	0.0200	11.6956	-4.1393	386.4295
0.55	0.0087	0.0022	0.0010	0.0002	1.1278	48.9976	2.9142	390.4614
0.60	0.0110	0.0037	0.0012	0.0003	2.2356	86.2997	9.9677	394.4934
0.65	0.0134	0.0051	0.0015	0.0004	3.3433	123.6017	17.0213	398.5253
0.70	0.0157	0.0065	0.0018	0.0005	4.4511	160.9038	24.0748	402.5572
0.75	0.0180	0.0080	0.0021	0.0006	5.5589	198.2058	31.1284	406.5892
0.80	0.0203	0.0094	0.0024	0.0007	6.6667	235.5078	38.1819	410.6211
0.85	0.0226	0.0108	0.0026	0.0008	7.7744	272.8099	45.2355	414.6530
0.90	0.0250	0.0123	0.0029	0.0009	8.8822	310.1119	52.2890	418.6850
0.95	0.0273	0.0137	0.0032	0.0010	9.9900	347.4140	59.3426	422.7169

3.4. Conclusion and policy implication

The chapter examines the asymmetric linkages between Cryptocurrencies and African fiat currencies, applying the Ensemble Empirical Mode Decomposition (EEMD)-based Quantile-in-Quantile regression technique to obtain robust results and draw solid implications. First of all, we decomposed the exchange rate returns series of the currencies into higher, medium, and lower frequencies termed as Intrinsic Mode Functions (IMF1, IMF5, and IMF Residual) respectively to eliminate the noise from the daily returns and capture the time horizons. We then implemented the parametric Quantile Regression (QR) and nonparametric Quantile-in-Quantile Regression (QQR) proposed by Koenker and Bassett (1978) and Sim and Zhou (2015) respectively to explore the association between cryptocurrencies and African fiat currencies over 19 quantiles (0.05 through to 0.95). The outcomes presented under QR and QQR approach indicate heterogeneous effects in the influence of the movement of African fiat currencies exchange rate returns on cryptocurrencies.

From QR results, the Bitcoin-Fiat currency connectedness indicates that except for ZAR, Bitcoin is a viable alternative digital currency in the medium-term for Cedi, Naira, Rupee, Dirham, Shilling, and Dinar, but long-term for Egyptian Pound. We can conclude from Ethereum-Fiat currency dependences that Ethereum can be a viable alternative digital currency to Egyptian Pound and ZAR in the long-term, Dinar and Dirham in the medium-term, Cedi, Shilling, and Rupee from medium-term, and Naira in both short and long-terms. For Litecoin-Fiat currency linkages, we observe that except for Cedi and ZAR, Litecoin might be a good alternative virtual currency for EGP, Naira, and Rupee in the long-term, both short and medium-term for Dinar and Dirham, but all time periods for Shilling. Ripple-Fiat currency connectedness depicts that, except for EGP, Ripple can supplement Cedi, Rupee, Dinar, Dirham, and Shilling in the long-term but medium-term for ZAR and Naira. Lastly, Das-Fiat currency association exhibits hedging benefits for EGP, Cedi, ZAR, Naira, and Rupee in the long-term but from medium-term for Shilling suggesting that except for Dirham, Das can complement the fiat currencies from the medium-term.

The findings from QQR demonstrate that cryptocurrencies can be good hedges and alternative currencies to African currencies from the medium-term when the cryptocurrency market is less volatile and fiat currencies are depreciating. Thus, policymakers in Africa seeking alternative digital currencies to mitigate currency crises can consider cryptocurrencies from the medium-term. Forex traders may also compensate for losses from currency shocks by using cryptocurrencies to hedge USD/African fiat currency exchange rate risk. We inferred the validation and analysis of QQR estimates from QR and found that the techniques match each other, only differing in magnitudes. As a nonparametric technique, QQR is validated by the closeness with which it matches QR across both quantiles and time in all cryptocurrencies and African fiat currencies pairs except for Ethereum-fiat currencies pairs. Following the outcome of our study, the modern monetary theory can be applied in Africa since cryptocurrencies are good hedges and suitable alternatives to African fiat currencies.

The results for currency interconnectedness between cryptocurrencies and African fiat currencies are the unique contribution of this study. In general, when the results are compared to other studies on cryptocurrencies and fiat currencies connectedness using different methods, our findings show similarity to the findings of Wu and Pandey (2014), Dyhrberg (2016b), Carrick (2016) Gajardo et al. (2018), who reported that cryptocurrencies offer hedging benefits for global fiat currencies. Our findings are indicative that cryptocurrencies reduce the variance of fiat currencies and are mostly negatively correlated with reserve currencies from the medium-term as reported by Ehlers and Gauer (2019). Our results provide evidence in support of the study of Yussof and Al-Harthy (2018) who recommend that cryptocurrency should be fully adopted to complement reserve currencies due to its global trend and hedging properties.

The chapter focused on the asymmetric linkages between cryptocurrencies and African fiat currencies using five principal cryptocurrencies and eight major African fiat currencies. Future studies could examine the connectedness of other cryptocurrencies and other African fiat currencies not covered in this study to enhance our understanding of the inter-market linkages. Future studies could also look at the regulatory and supervisory aspects of cryptocurrencies in Africa to allow for its successful integration in the region.

References

Alagidede, P., Tweneboah, G., & Adam, A., M. (2008). Nominal Exchange Rates and Price Convergence in the West African Monetary Zone. *International Journal of Business and Economics,* 7, 181.

Atsalakis, G., S., Bouri, E., & Pasiouras, F. (2020). Natural Disasters and Economic Growth: A Quantile on Quantile Approach. *Annals of Operations Research*, 1-27.

Baur, D. G., & Lucey, B. M. (2010). Is gold a hedge or a safe haven? An analysis of stocks, bonds, and gold. *Financial Review*, *45*(2), 217-229.

Baur, D., & Mc Dermontt, T., K., J. (2010). Is Gold a Safe Haven? International Evidence, *Journal of Banking and Finance,* 34(8), 1886-1898.

Bouri, E., Gupta, R., Tiwari, A. K., & Roubaud, D. (2017). Does Bitcoin hedge global uncertainty? Evidence from wavelet-based quantile-in-quantile regressions. *Finance Research Letters*, *23*, 87-95.

Carrick, J. (2016). "Bitcoin as a Complement to Emerging Market Currencies," *Emerging Markets Finance and Trade* 52(10), 2321–2334.

Cermak, V. (2017). Can bitcoin become a viable alternative to fiat currencies? An empirical analysis of bitcoin's volatility based on a GARCH model. *An Empirical Analysis of Bitcoin's Volatility Based on a GARCH Model*. SSRN Electronic Journal.

CoinMarketCap. (2019). Cryptocurrency Market Capitalizations and Data. Available online: https://coinmarketcap.com/ (accessed on 26th August 2019).

Corelli, A. (2018). Cryptocurrencies and Exchange Rates: A Relationship and Causality Analysis. *Risks*, 6, 111.

Das, D., & Kannadhasan, M. (2018). Do Global Factors Impact Bitcoin Prices? Evidence from Wavelet Approach. *Journal of Economic Research*, 23, 227-264.

Drożdż, S., Minati, L., Oświęcimka, P., Stanuszek, M., & Wątorek, M. (2019). Signatures of crypto-currency market decoupling from the Forex. *arXiv preprint arXiv:1906.07834*, 11 (7) (2019), p. 154.

Dyhrberg, A., H. (2016a). Hedging Capabilities of Bitcoin. Is it the Virtual Gold? *Finance Research Letters*, 16, 139–144.

Dyhrberg, A., H. (2016b). Bitcoin, Gold and the Dollar—A GARCH Volatility Analysis. *Finance Research Letters*, 16, 85–92.

Ehlers, S., & Gauer, K. (2019). Beyond Bitcoin: A Statistical Comparison of Leading Cryptocurrencies and Fiat Currencies and Their Impact on Portfolio Diversification. *The Journal of Alternative Investments*, 22(2) jai-2019. DOI: https://doi.org/10.3905/jai.2019.1.072.

Fantazzini, D., Nigmatullin, E., Sukhanovskaya, V., & Ivliev, S. (2016). Everything You Always wanted to know about Bitcoin Modelling but were afraid to ask. Available at SSRN: https://ssrn.com/abstract=2794622.

Fernández-Villaverde, J., & Sanches, D. R. (2018). On the economics of digital currencies.

Fokuo Jr, I., K. (2018). Blockchain can drive more Investment in Africa. *HR Future*, 30-31.

Gajardo, G., Kristjanpoller, W., D., & Minutolo, M. (2018). Does Bitcoin Exhibit the Same Asymmetric Multifractal Cross-Correlations with Crude Oil, Gold, and DJIA as the Euro, Great British Pound, and Yen? *Chaos, Solitons and Fractals,* 109, 195–205.

Georgeson, D., A. (2018). Cryptocurrencies as an Alternative to Fiat Monetary Systems.

Hayek, F., A. (1976). *Choice in currency: a way to stop inflation* (Vol. 48). Ludwig von Mises Institute.

Hencic, A., & Gourieroux, C. (2014). Noncausal Autoregressive Model in Application to Bitcoin/USD Exchange Rate, Econometrics of Risk, Series: Studies in Computational Intelligence, Springer International Publishing, 17-40.

Islam, M., R., Nor, R., M., Al-Shaikhli, I., F., & Mohammad, K., S. (2018, July). Cryptocurrency vs. Fiat Currency: Architecture, Algorithm, Cashflow & Ledger Technology on Emerging Economy: The Influential Facts of Cryptocurrency and Fiat Currency. In *2018 International Conference on Information and Communication Technology for the Muslim World (ICT4M)* (pp. 69-73). IEEE.

Ivanov, S., I. (2013). The Influence of ETFs on the Price Discovery of Gold, Silver, and Oil. *Journal of Economics and Finance*, *37*(3), 453–462.

Kargbo, J., M. (2000), "Impacts of Monetary and Macroeconomic Factors on Food Prices in Eastern and Southern Africa", *Applied Economics,* 32, 1373-1389.

Kaul, A., & Sapp, S. (2006). Y2K fears and safe haven trading of the US dollar. *Journal of international money and finance*, *25*(5), 760-779.

Khaldi, R., El Afia, A., Chiheb, R., & Faizi, R. (2018). Forecasting of Bitcoin Daily Returns with EEMD-ELMAN Based Model. In *Proceedings of the International Conference on Learning and Optimization Algorithms: Theory and Applications* 1-6).

Koenker, R., & Bassett, G. (1978). Regression Quantiles. *Econometrica,* 46 (1), 33–50.

Koenker, R. (2005). *Quantile Regression*. Cambridge University Press, New York, NY.

Kim, T. (2017). On the Transaction Cost of Bitcoin. *Finance Research Letters,* 23, 300–305. https://doi.org/10.1016/j.frl.2017.07.014.

Kristjanpoller, W., & Bouri, E. (2019). Asymmetric Multifractal Cross-Correlations between the Main World Currencies and the Main Cryptocurrencies. *Physica A: Statistical Mechanics and its Applications*, 523, 1057-1071.

Lim, B., S. (2017). Cover Story: The Cryptocurrency Conundrum: The Edge Malaysia.

Ma, L., & Koenker, R. (2006). Quantile Regression Methods for Recursive Structural Equation Models. *Journal of Economics*, 134, 471–506.

Mallick, H., Padhan, H., & Mahalik, M., K. (2019). Does Skewed Pattern of Income Distribution Matter for the Environmental Quality? Evidence from Selected BRICS Economies with an Application of Quantile-on-Qauntile Regression (QQR) Approach. *Energy Policy*, *129*, 120-131.

Martens, M., & Poon, S., H. (2001). Returns Synchronization and Daily Correlation Dynamics between International Stock Markets. *Journal of Banking and Finance,* 25(10), 1805–1827.

Muedini, F. (2018). The Compatibility of Cryptocurrencies and Islamic Finance. *European Journal of Islamic Finance,* (10).

Nakomoto, S. (2009). Bitcoin: A Peer-to-Peer Electronic Cash System. https://bitcoin.org/bitcoin.pdf/.

Owusu-Junior, P., Anokye M, A., & George, T. (2017). Co-movement of Real Exchange Rates in the West African Monetary Zone. *Cogent Economics & Finance,* 5(1), 1-18.

Pal, D., & Mitra, S., K. (2017). Time-frequency Contained Co-movement of Crude Oil and World Food Prices: a Wavelet-based Analysis. *Energy Economics*, 62, 230‑239.

Pukthuanthong, K., & Roll, R. (2009). "Global Market Integration: An Alternative Measure and Its Application." *Journal of Financial Economics,* 94 (2), 214– 232. doi: 10.1016/j.jfineco.2008.12.004.

Rainer M., P. (2017). Cryptocurrency is the Great African Opportunity. https://www.howwemadeitinafrica.com/author/rainer-michael-preiss/).

Reboredo, J., C. (2013). Modeling EU allowances and oil market interdependence. Implications for portfolio management. *Energy Economics*, *36*, 471-480.

Sapuric, S., & Kokkinaki, A. (2014). Bitcoin is Volatile! Isn't that right? Business Information Systems Workshops, Lecture Notes in Business Information Processing; 255–265.

Sim, N., Zhou, A. (2015). Oil Prices, US Stock Return, and the Dependence between their Quantiles. *Journal of Banking and Finance,* 55, 1–8.

Staiger, R. W., & Sykes, A., O. (2010). Currency Manipulation and World Trade. *World Trade Review* 9 (04):583–627. doi:10.1017/S1474745610000340.

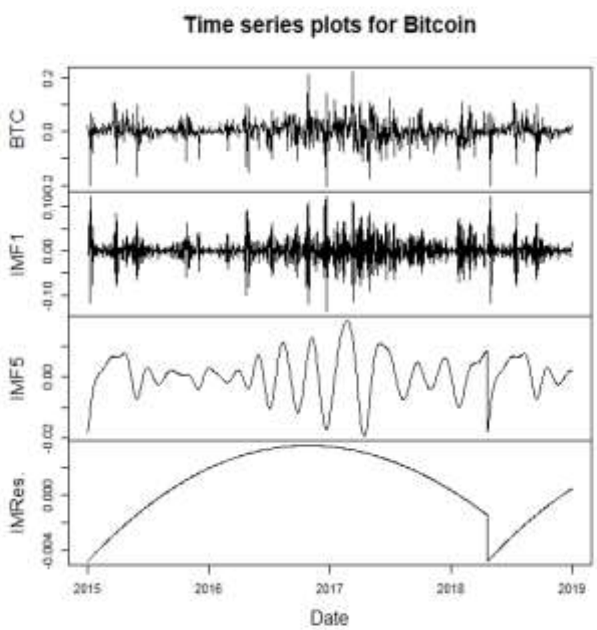
Wu, Z., & Huang, N., E. (2009). Ensemble Empirical Mode Decomposition: a Noise-assisted Data Analysis Method. *Advances in Adaptive Data Analysis*, *01*(01), 1–41.

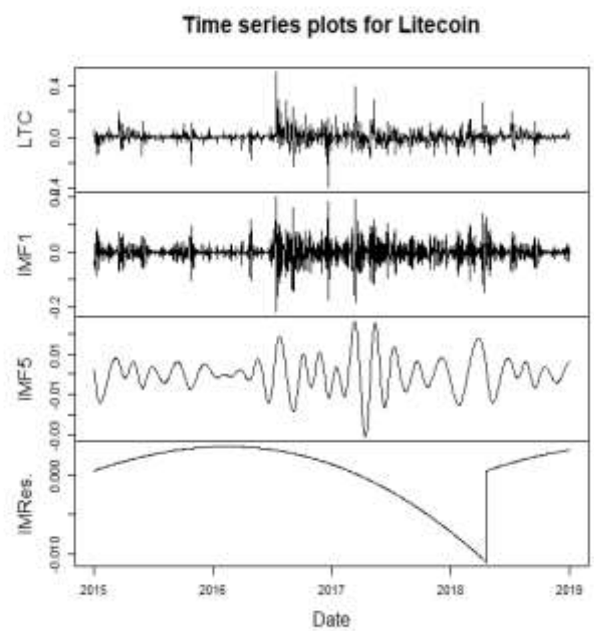
Wu, C., Y., & Pandey, V., K. (2014). "The Value of Bitcoin in Enhancing the Efficiency of an Investor's Portfolio," *Journal of financial planning* 27(9), 44–52.

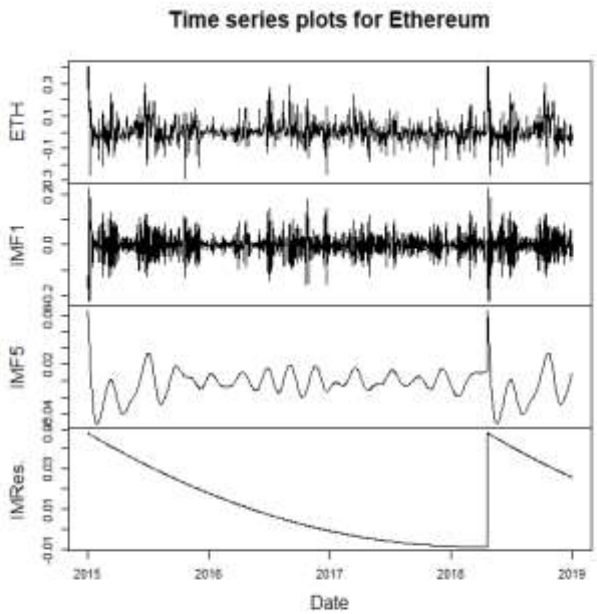
Yermack, D. (2013). Is Bitcoin a Real Currency? An Economic Appraisal. (No. w19747). National Bureau of Economic Research. http://www.nber.org/papers/w19747.

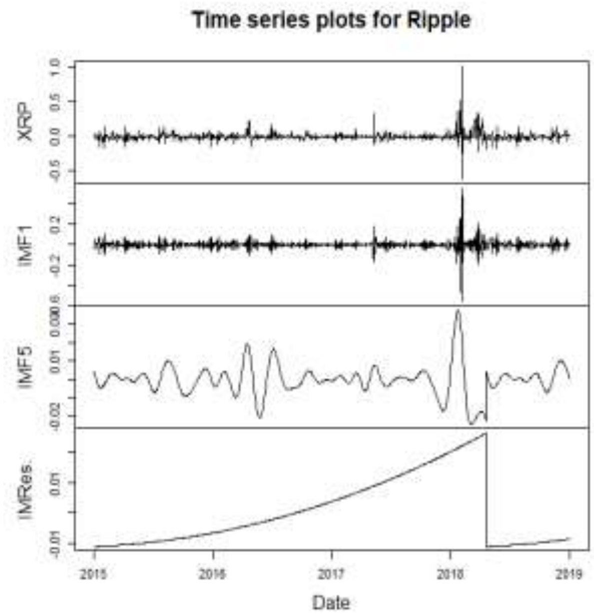
Yussof, S. A., & Al-Harthy, A. (2018). Cryptocurrency as an Alternative Currency in Malaysia: Issues and Challenges. *Islam and Civilisational Renewal (ICR)*, *9*(1), 48-65.

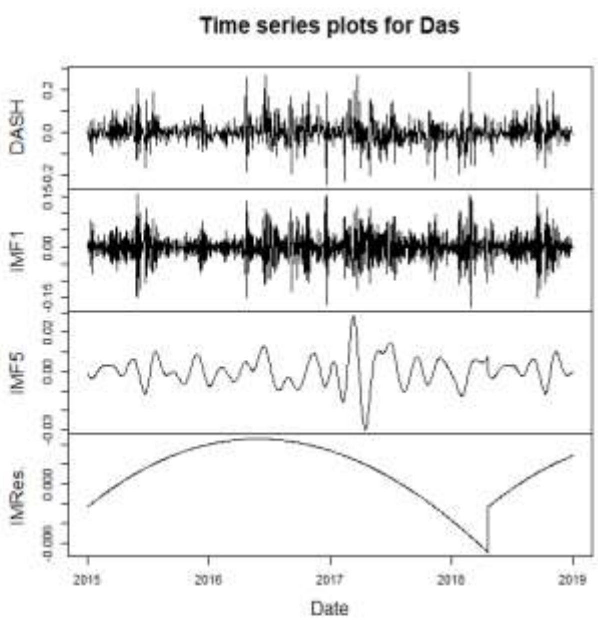
Appendices

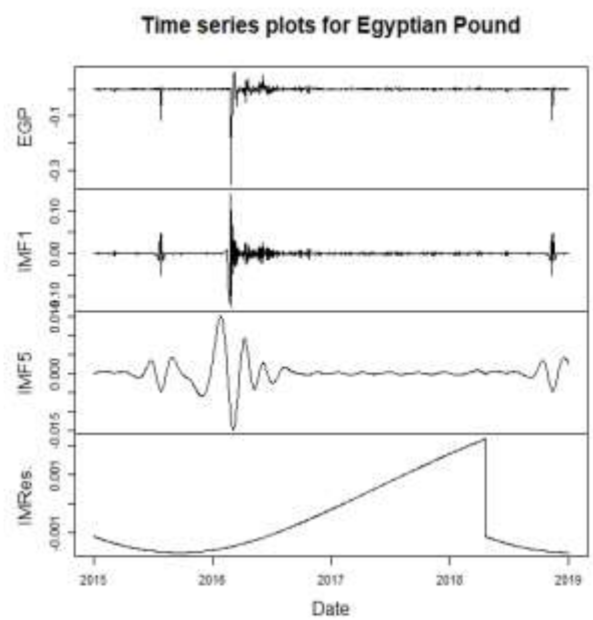


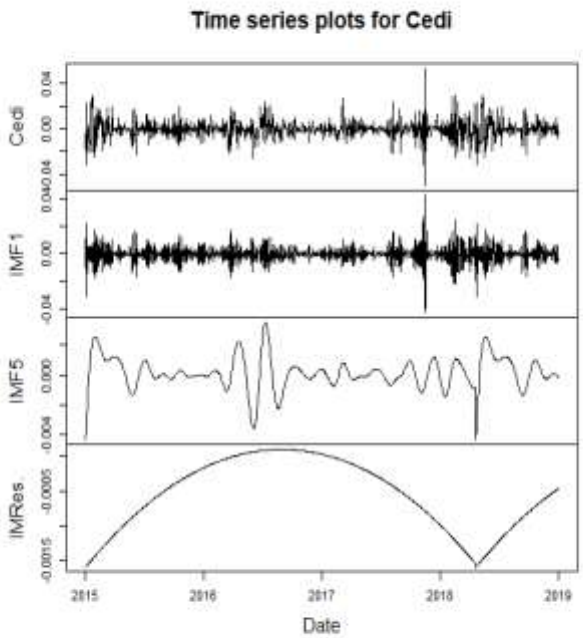


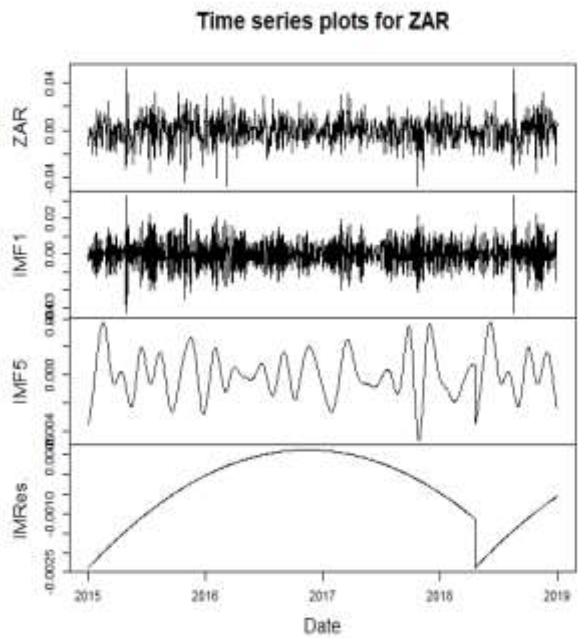

Time series plots for Ethereum
ETH
IMF1
IMF5
IMRes.
2015
2016
2017
2018
2019
Date

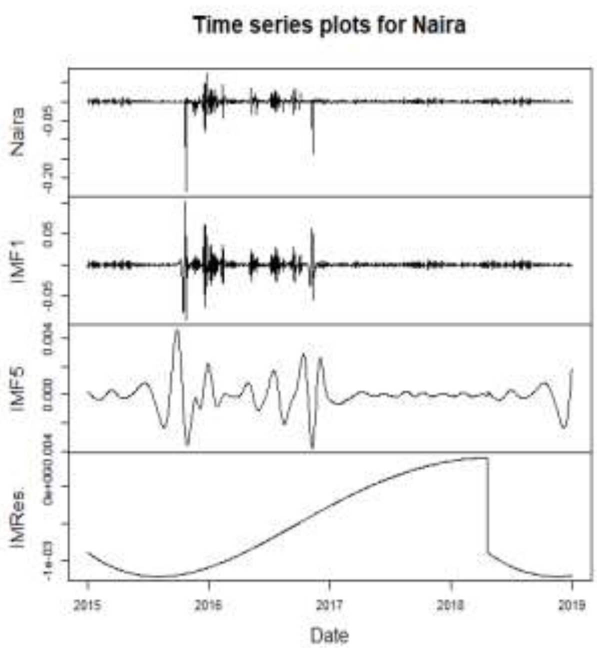

Time series plots for Ripple
XRP
IMF1
IMF5
IMRes.
2015
2016
2017
2018
2019
Date

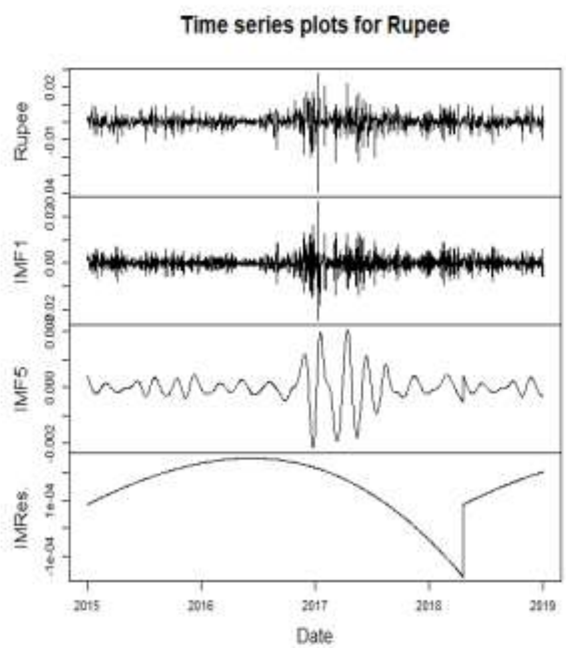

Time series plots for Das
DASH
IMF1
IMF5
IMRes.
2015
2016
2017
2018
2019
Date


Time series plots for Egyptian Pound
EGP
IMF1
IMF5
IMRes.
2015
2016
2017
2018
2019
Date


Time series plots for Cedi
Cedi
IMF1
IMF5
IMRes.
2015
2016
2017
2018
2019
Date


Time series plots for ZAR
ZAR
IMF1
IMF5
IMRes.
2015
2016
2017
2018
2019
Date


Time series plots for Naira
Naira
IMF1
IMF5
IMRes.
2015
2016
2017
2018
2019
Date


Time series plots for Rupee
Rupee
IMF1
IMF5
IMRes.
2015
2016
2017
2018
2019
Date

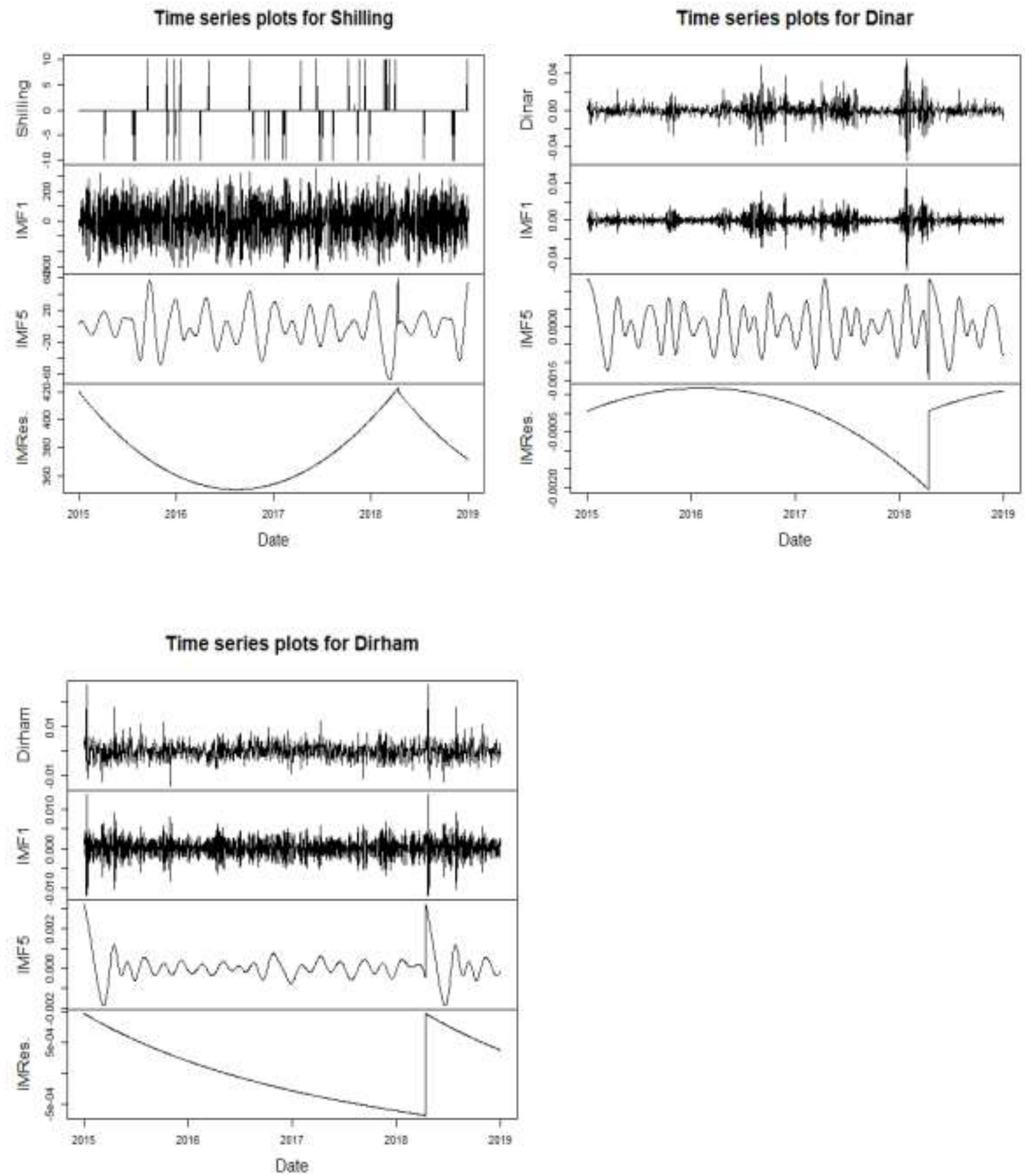
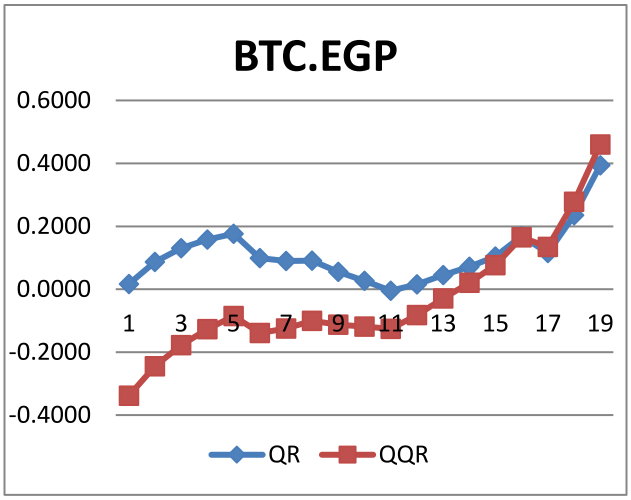
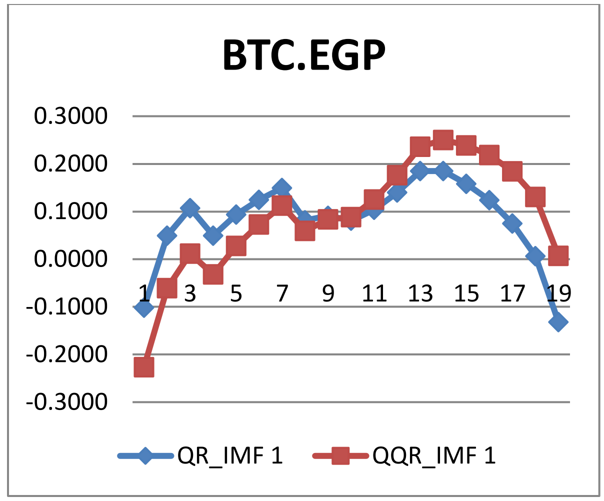
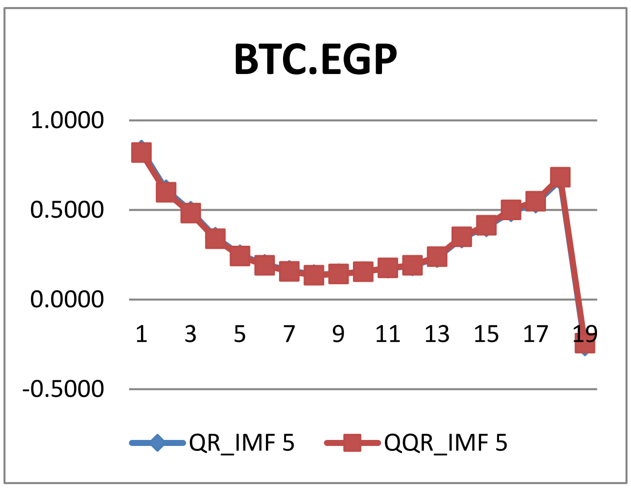
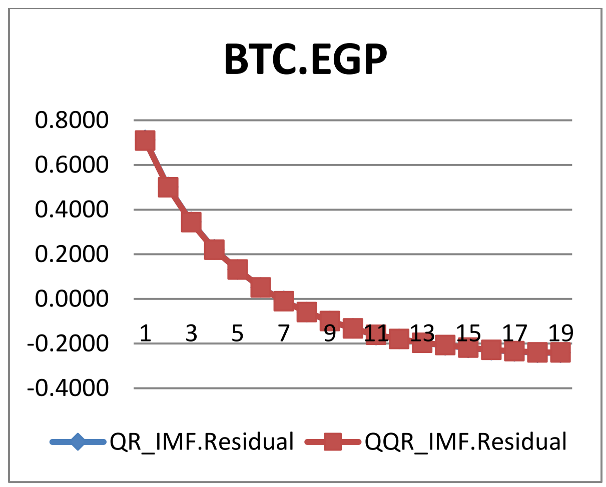


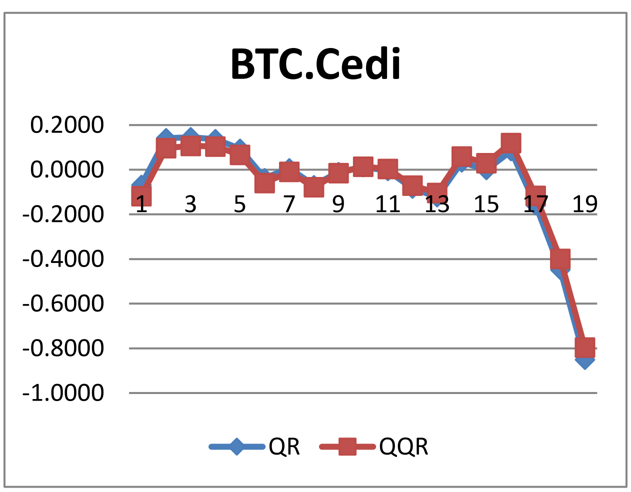
Figure 3. 1: Time series plots for composite and decomposed series of Cryptocurrencies and African fiat currencies exchange rates returns.

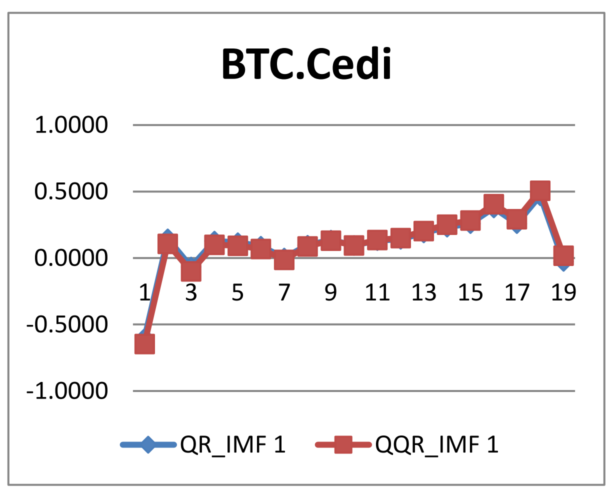

BTC.EGP
0.6000
0.4000
0.2000
0.0000
-0.2000
-0.4000
1 3 5 7 9 11 13 15 17 19
QR
QQR

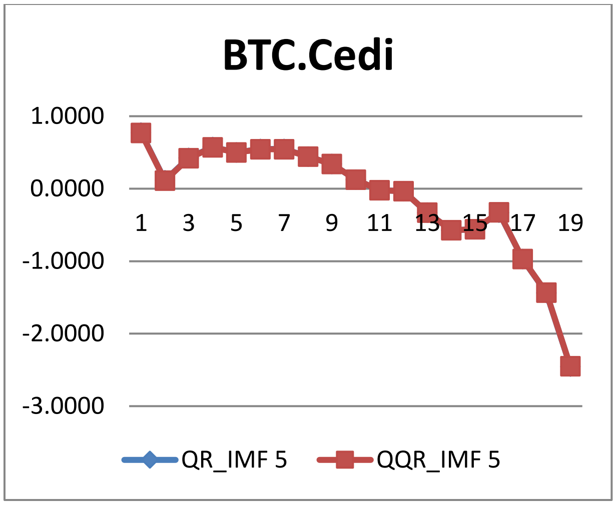

BTC.EGP
0.3000
0.2000
0.1000
0.0000
-0.1000
-0.2000
-0.3000
1 3 5 7 9 11 13 15 17 19
QR_IMF 1
QQR_IMF 1

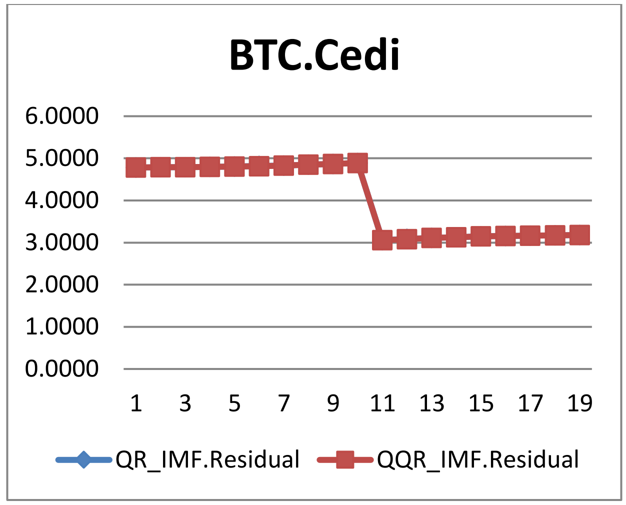

BTC.EGP
1.0000
0.5000
0.0000
-0.5000
1 3 5 7 9 11 13 15 17 19
QR_IMF 5
QQR_IMF 5

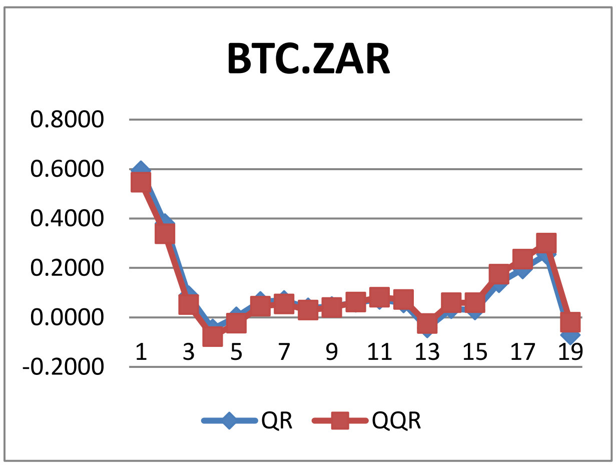

BTC.EGP
0.8000
0.6000
0.4000
0.2000
0.0000
-0.2000
-0.4000
1 3 5 7 9 11 13 15 17 19
QR_IMF.Residual
QQR_IMF.Residual

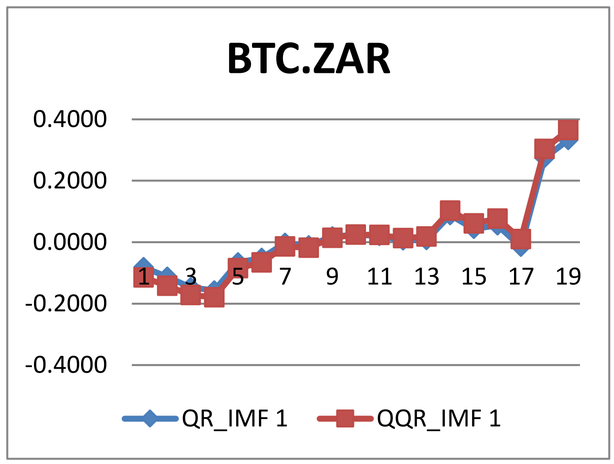

BTC.Cedi
0.2000
0.0000
-0.2000
-0.4000
-0.6000
-0.8000
-1.0000
1 3 5 7 9 11 13 15 17 19
QR
QQR

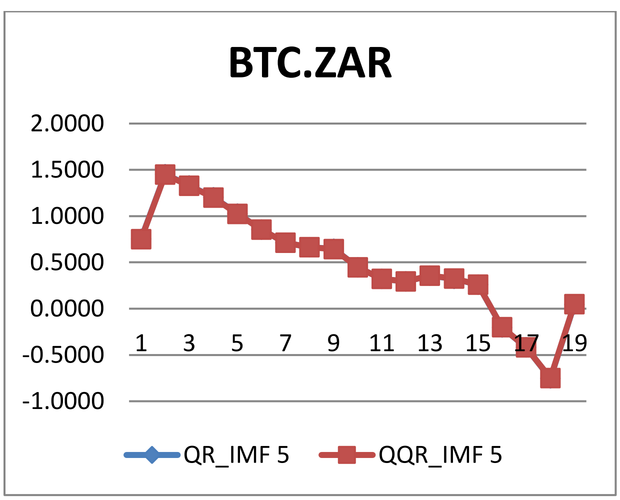

BTC.Cedi
1.0000
0.5000
0.0000
-0.5000
-1.0000
1 3 5 7 9 11 13 15 17 19
QR_IMF 1
QQR_IMF 1

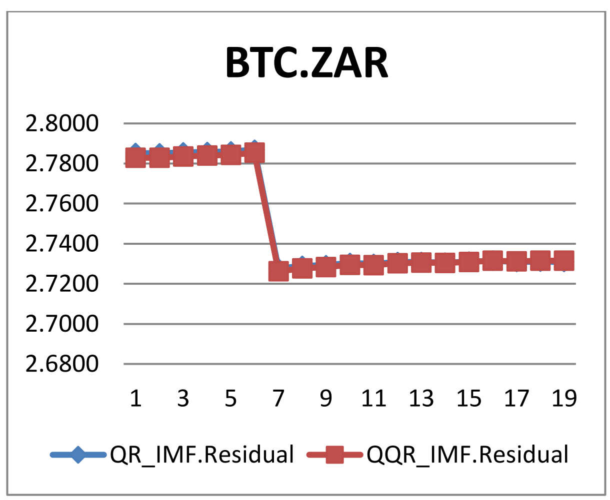

BTC.Cedi
1.0000
0.0000
-1.0000
-2.0000
-3.0000
1 3 5 7 9 11 13 15 17 19
QR_IMF 5
QQR_IMF 5

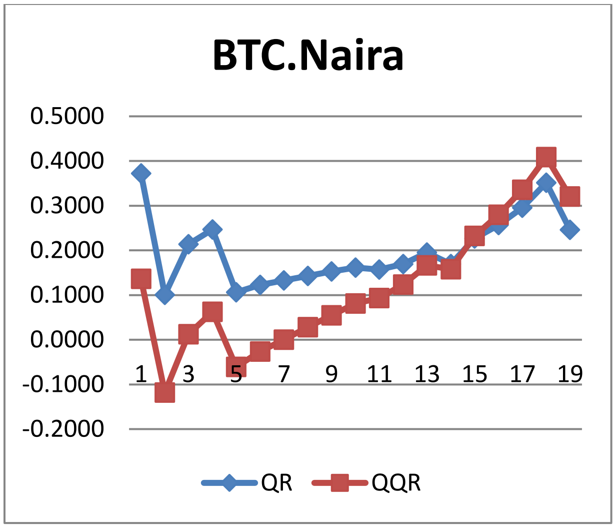

BTC.Cedi
6.0000
5.0000
4.0000
3.0000
2.0000
1.0000
0.0000
1 3 5 7 9 11 13 15 17 19
QR_IMF.Residual
QQR_IMF.Residual

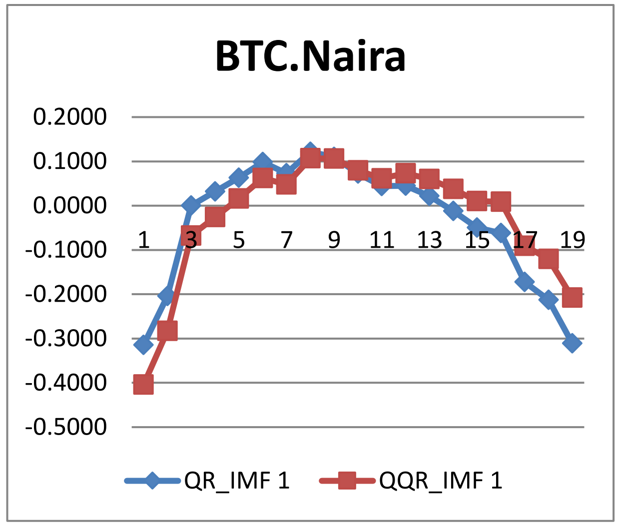

BTC.ZAR
0.8000
0.6000
0.4000
0.2000
0.0000
-0.2000
1 3 5 7 9 11 13 15 17 19
QR
QQR

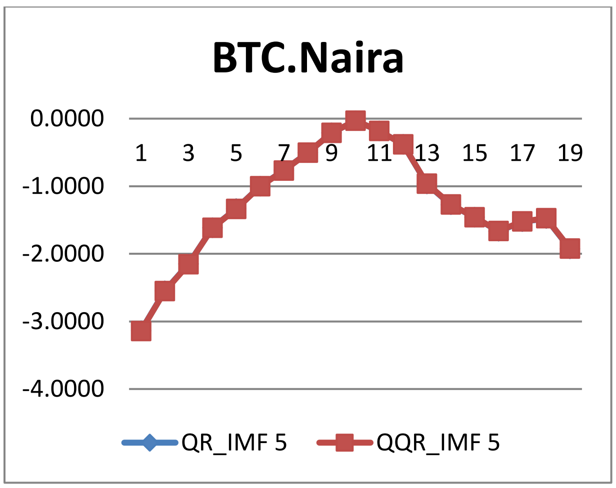

BTC.ZAR
0.4000
0.2000
0.0000
-0.2000
-0.4000
1 3 5 7 9 11 13 15 17 19
QR_IMF 1
QQR_IMF 1

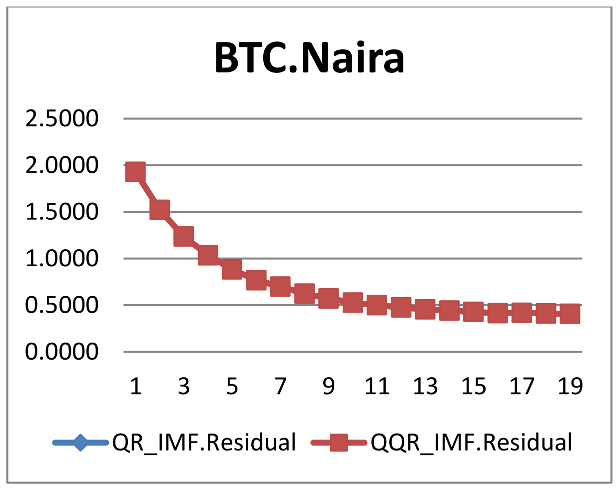

BTC.ZAR
2.0000
1.5000
1.0000
0.5000
0.0000
-0.5000
-1.0000
1 3 5 7 9 11 13 15 17 19
QR_IMF 5
QQR_IMF 5

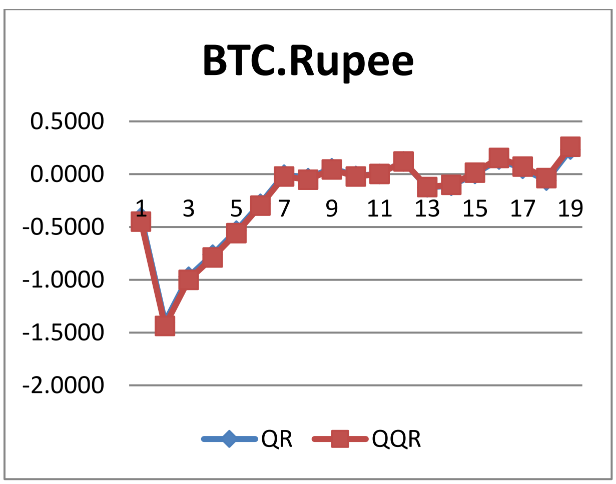

BTC.ZAR
2.8000
2.7800
2.7600
2.7400
2.7200
2.7000
2.6800
1 3 5 7 9 11 13 15 17 19
QR_IMF.Residual
QQR_IMF.Residual

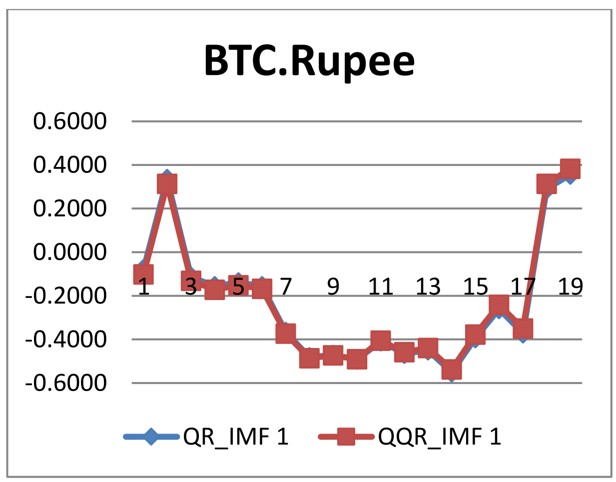

BTC.Naira
0.5000
0.4000
0.3000
0.2000
0.1000
0.0000
-0.1000
-0.2000
1 3 5 7 9 11 13 15 17 19
QR
QQR

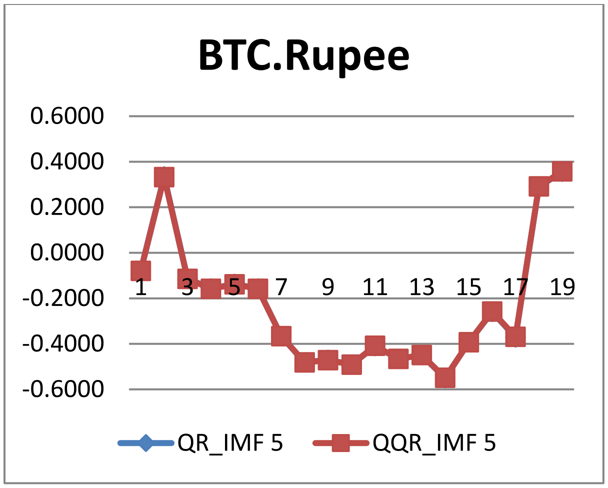

BTC.Naira
0.2000
0.1000
0.0000
-0.1000
-0.2000
-0.3000
-0.4000
-0.5000
1 3 5 7 9 11 13 15 17 19
QR_IMF 1
QQR_IMF 1


BTC.Naira
0.0000
-1.0000
-2.0000
-3.0000
-4.0000
1 3 5 7 9 11 13 15 17 19
QR_IMF 5
QQR_IMF 5

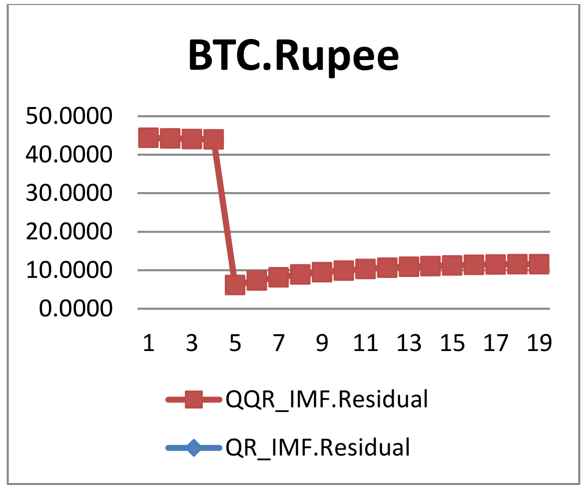

BTC.Naira
2.5000
2.0000
1.5000
1.0000
0.5000
0.0000
1 3 5 7 9 11 13 15 17 19
QR_IMF.Residual
QQR_IMF.Residual


BTC.Rupee
0.5000
0.0000
-0.5000
-1.0000
-1.5000
-2.0000
1 3 5 7 9 11 13 15 17 19
QR
QQR

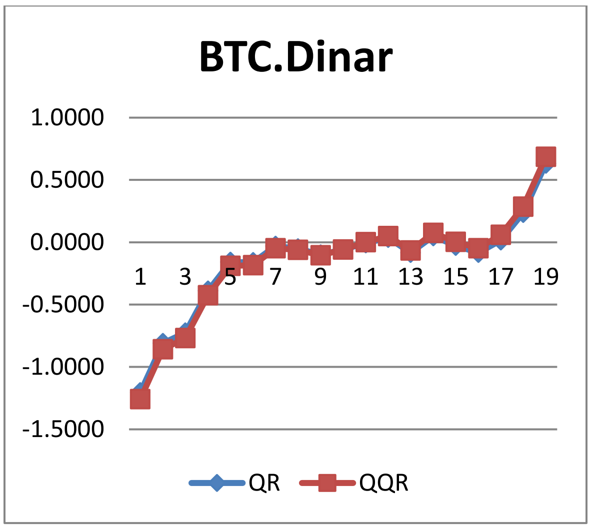

BTC.Rupee
0.6000
0.4000
0.2000
0.0000
-0.2000
-0.4000
-0.6000
1 3 5 7 9 11 13 15 17 19
QR_IMF 1
QQR_IMF 1



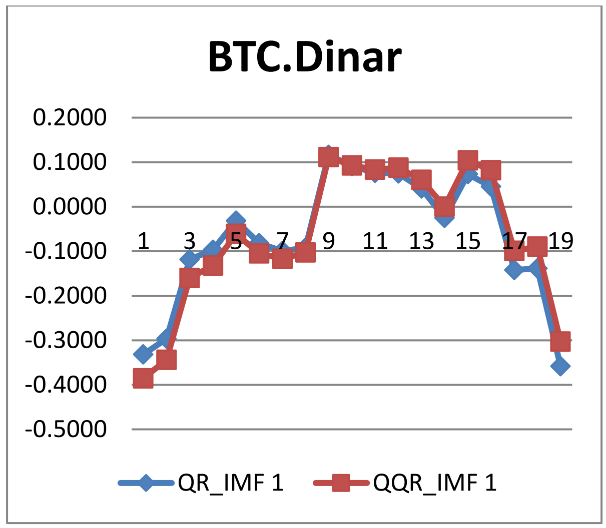
BTC.Rupee
0.6000
0.4000
0.2000
0.0000
-0.2000
-0.4000
-0.6000
1 3 5 7 9 11 13 15 17 19
QR_IMF 5
QQR_IMF 5



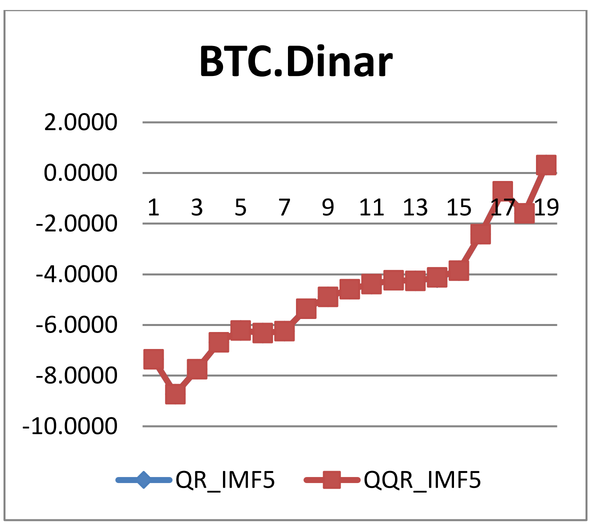
BTC.Rupee
50.0000
40.0000
30.0000
20.0000
10.0000
0.0000
1 3 5 7 9 11 13 15 17 19
QQR_IMF.Residual
QR_IMF.Residual



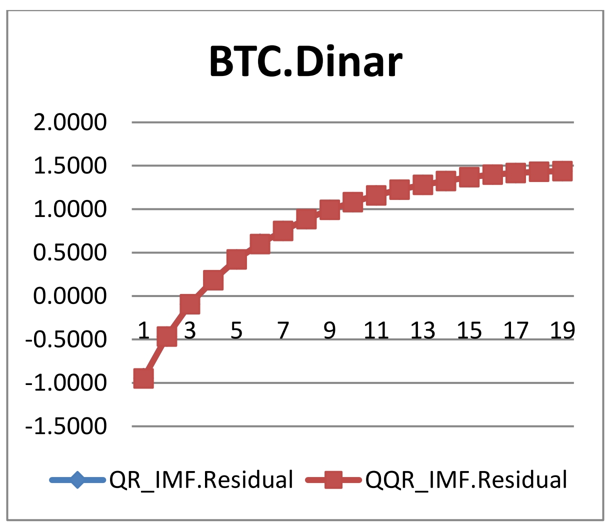
BTC.Dinar
1.0000
0.5000
0.0000
-0.5000
-1.0000
-1.5000
1 3 5 7 9 11 13 15 17 19
QR
QQR



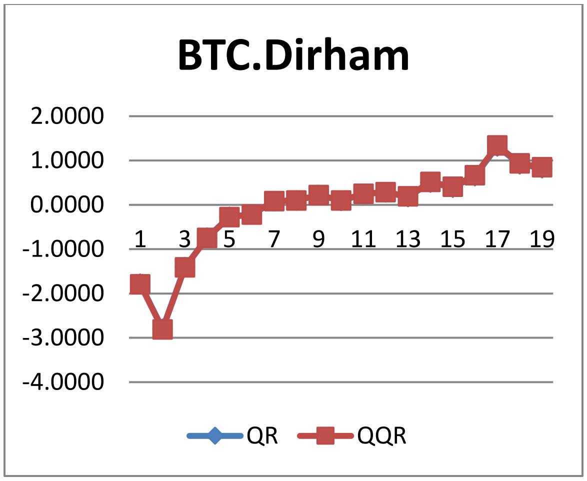
BTC.Dinar
0.2000
0.1000
0.0000
-0.1000
-0.2000
-0.3000
-0.4000
-0.5000
1 3 5 7 9 11 13 15 17 19
QR_IMF 1
QQR_IMF 1

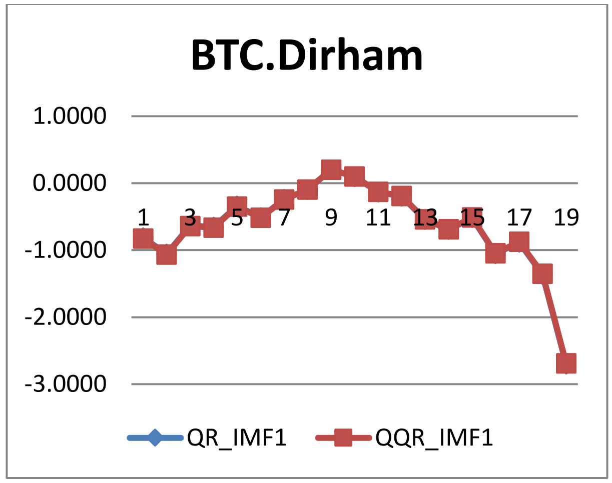


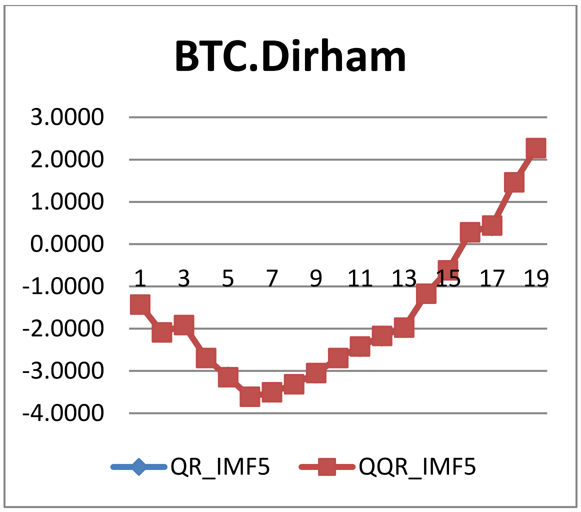
BTC.Dinar
2.0000
0.0000
-2.0000
-4.0000
-6.0000
-8.0000
-10.0000
1 3 5 7 9 11 13 15 17 19
QR_IMF5
QQR_IMF5

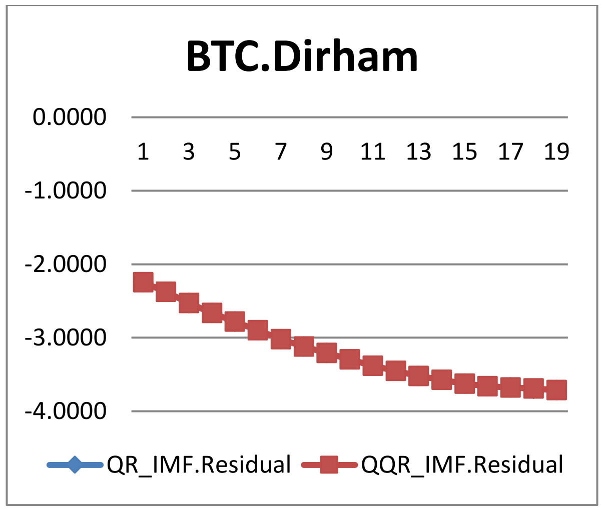


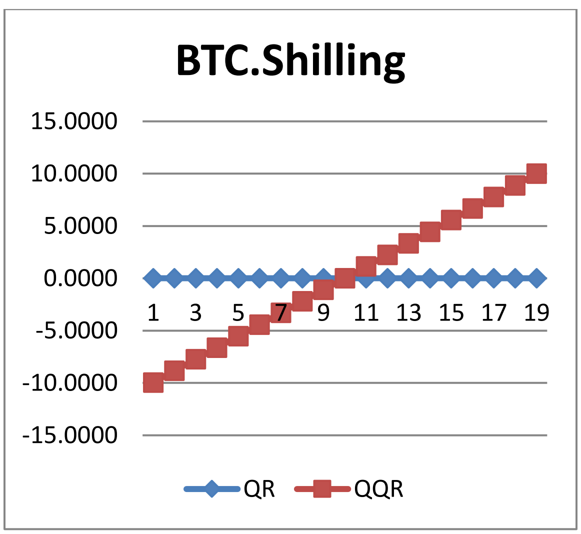
BTC.Dinar
2.0000
1.5000
1.0000
0.5000
0.0000
-0.5000
-1.0000
-1.5000
1 3 5 7 9 11 13 15 17 19
QR_IMF.Residual
QQR_IMF.Residual

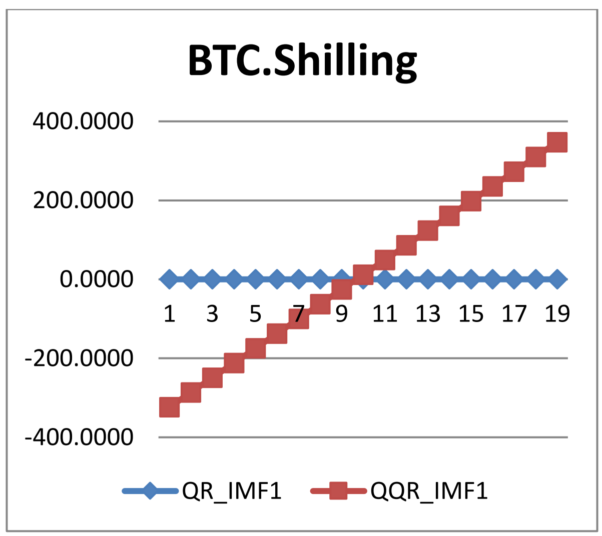

BTC.Dirham
2.0000
1.0000
0.0000
-1.0000
-2.0000
-3.0000
-4.0000
1 3 5 7 9 11 13 15 17 19
QR
QQR

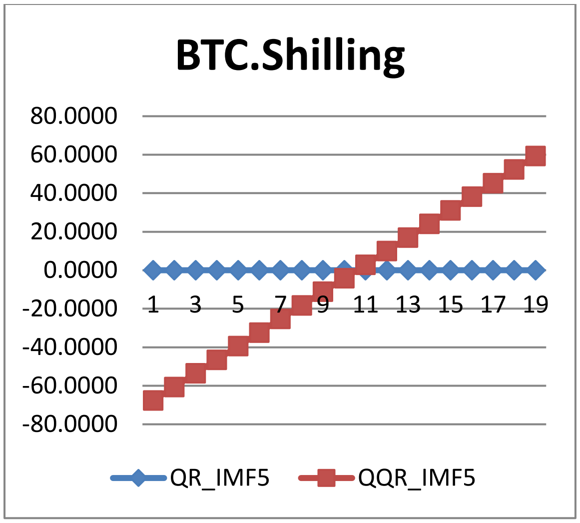

BTC.Dirham
1.0000
0.0000
-1.0000
-2.0000
-3.0000
1 3 5 7 9 11 13 15 17 19
QR_IMF1
QQR_IMF1

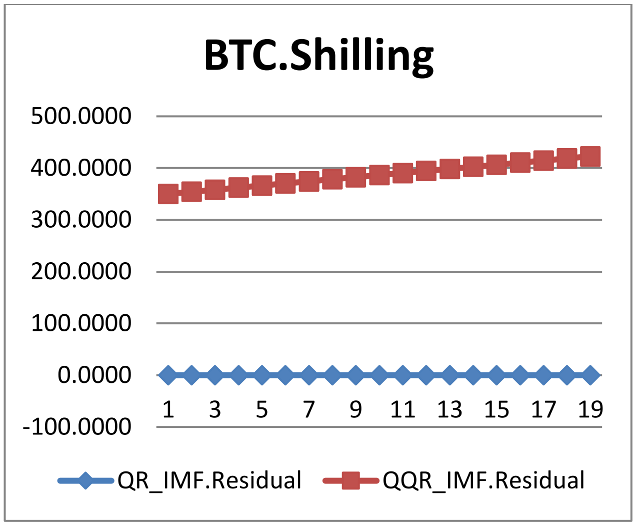

BTC.Dirham
3.0000
2.0000
1.0000
0.0000
-1.0000
-2.0000
-3.0000
-4.0000
1 3 5 7 9 11 13 15 17 19
QR_IMF5
QQR_IMF5

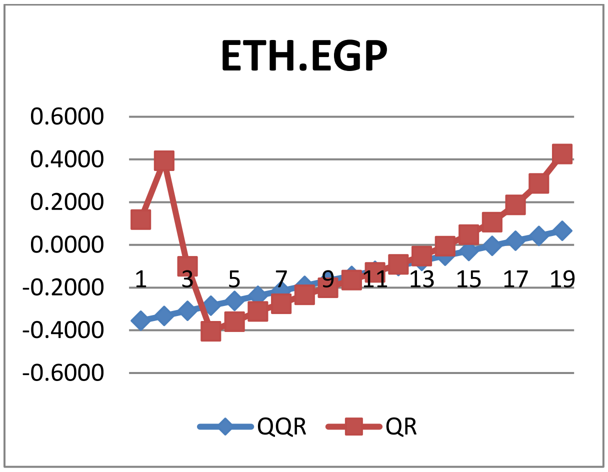

BTC.Dirham
0.0000
-1.0000
-2.0000
-3.0000
-4.0000
1 3 5 7 9 11 13 15 17 19
QR_IMF.Residual
QQR_IMF.Residual

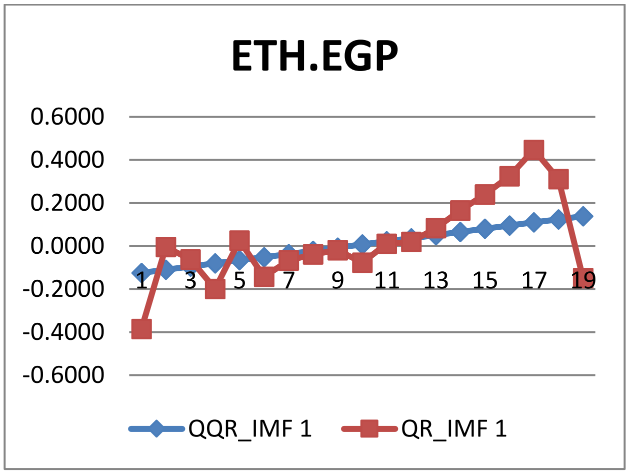

BTC.Shilling
15.0000
10.0000
5.0000
0.0000
-5.0000
-10.0000
-15.0000
1 3 5 7 9 11 13 15 17 19
QR
QQR

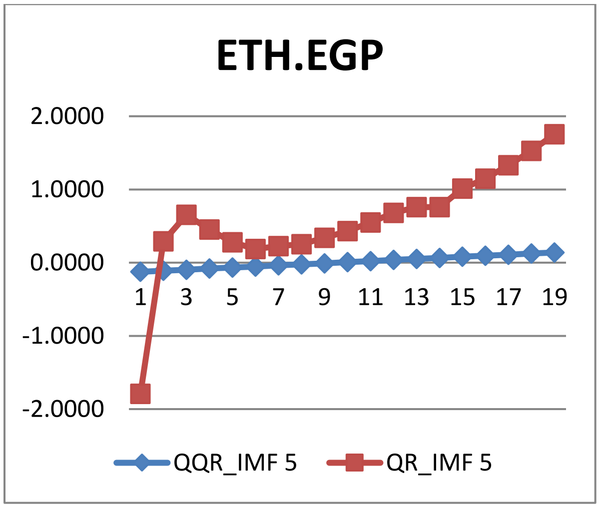

BTC.Shilling
400.0000
200.0000
0.0000
-200.0000
-400.0000
1 3 5 7 9 11 13 15 17 19
QR_IMF1
QQR_IMF1

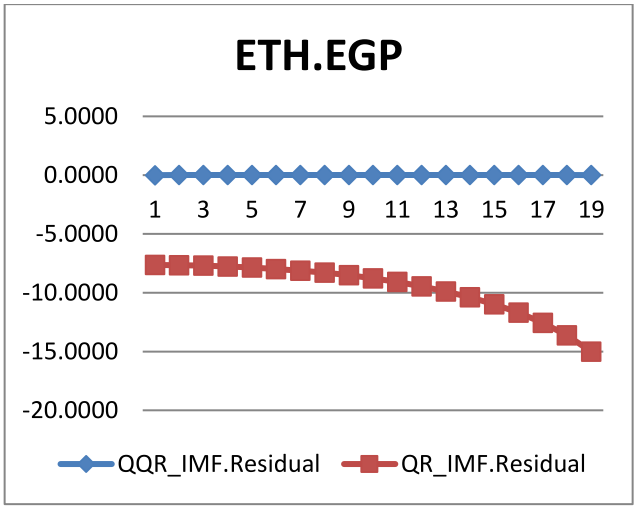

BTC.Shilling
80.0000
60.0000
40.0000
20.0000
0.0000
-20.0000
-40.0000
-60.0000
-80.0000
1 3 5 7 9 11 13 15 17 19
QR_IMF5
QQR_IMF5

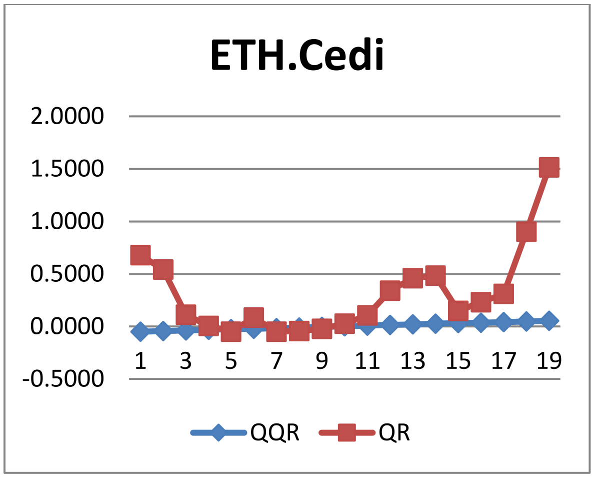

BTC.Shilling
500.0000
400.0000
300.0000
200.0000
100.0000
0.0000
-100.0000
1 3 5 7 9 11 13 15 17 19
QR_IMF.Residual
QQR_IMF.Residual

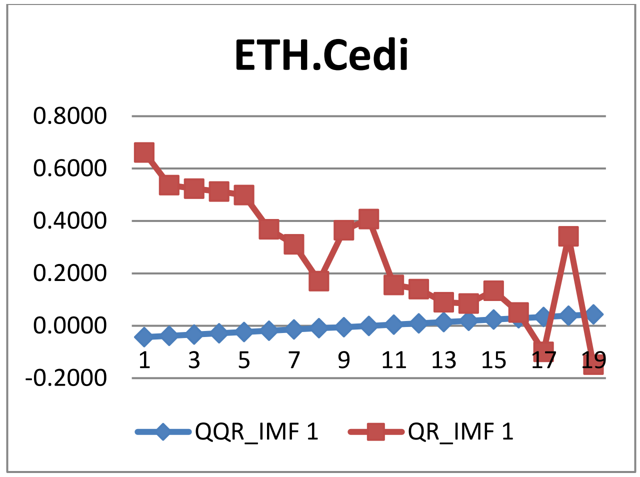

ETH.EGP
0.6000
0.4000
0.2000
0.0000
-0.2000
-0.4000
-0.6000
1 3 5 7 9 11 13 15 17 19
QQR
QR

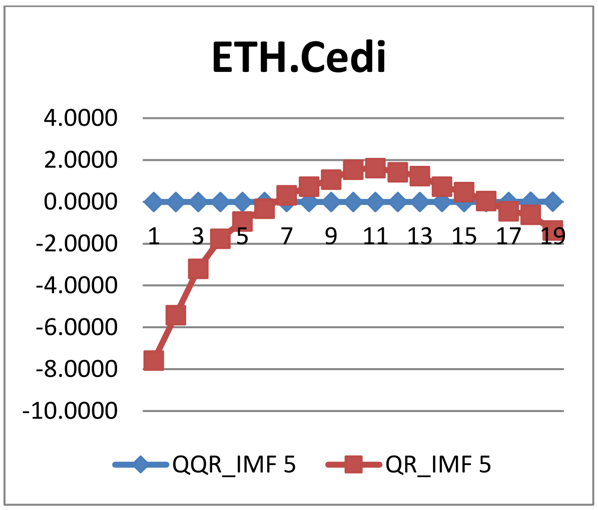

ETH.EGP
0.6000
0.4000
0.2000
0.0000
-0.2000
-0.4000
-0.6000
1 3 5 7 9 11 13 15 17 19
QQR_IMF 1
QR_IMF 1

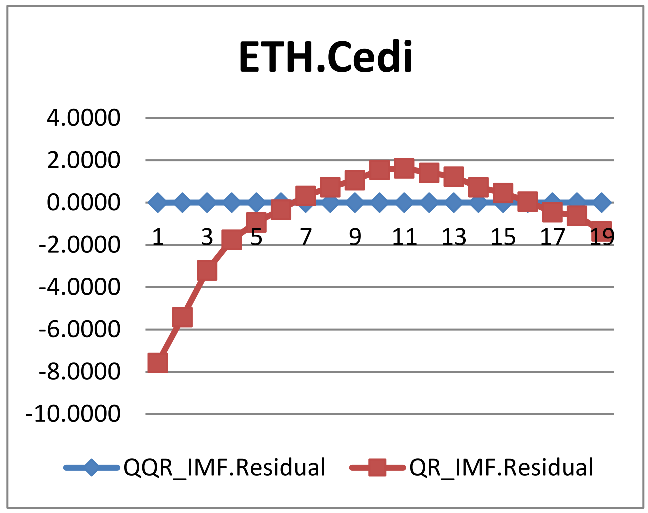

ETH.EGP
2.0000
1.0000
0.0000
-1.0000
-2.0000
1 3 5 7 9 11 13 15 17 19
QQR_IMF 5
QR_IMF 5

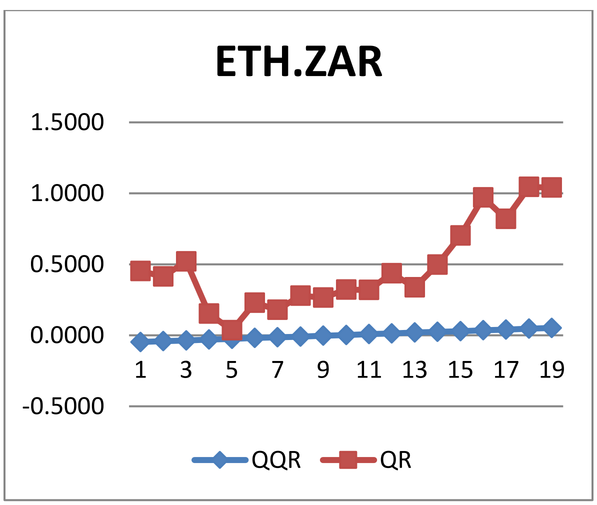

ETH.EGP
5.0000
0.0000
-5.0000
-10.0000
-15.0000
-20.0000
1 3 5 7 9 11 13 15 17 19
QQR_IMF.Residual
QR_IMF.Residual

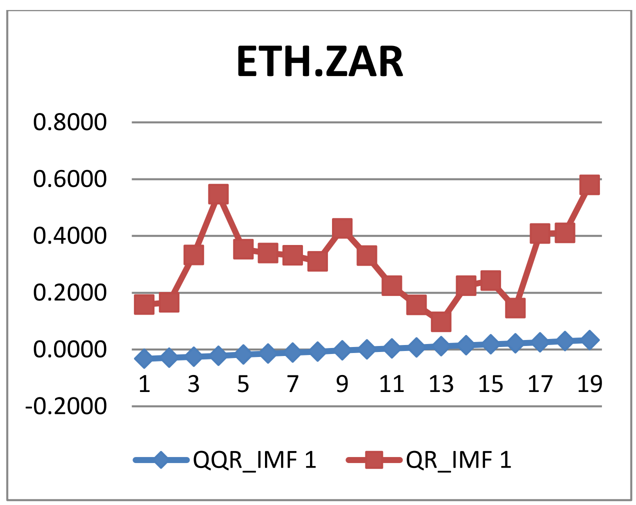

ETH.Cedi
2.0000
1.5000
1.0000
0.5000
0.0000
-0.5000
1 3 5 7 9 11 13 15 17 19
QQR QR

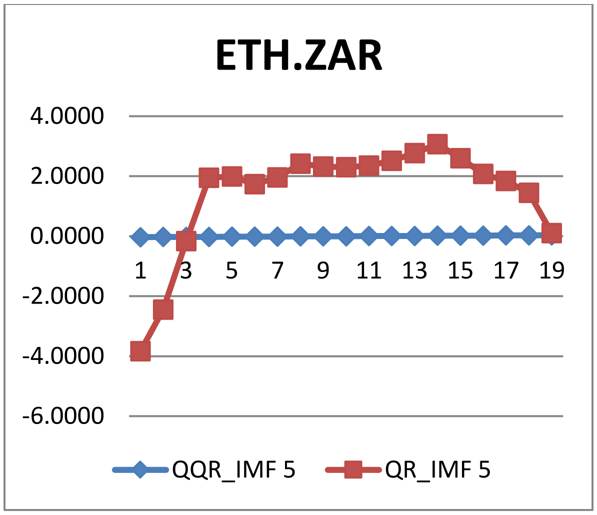

ETH.Cedi
0.8000
0.6000
0.4000
0.2000
0.0000
-0.2000
1 3 5 7 9 11 13 15 17 19
QQR_IMF 1 QR_IMF 1

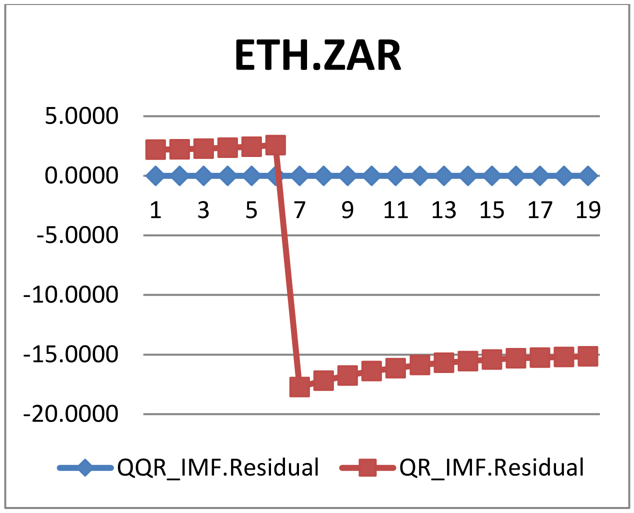

ETH.Cedi
4.0000
2.0000
0.0000
-2.0000
-4.0000
-6.0000
-8.0000
-10.0000
1 3 5 7 9 11 13 15 17 19
QQR_IMF 5 QR_IMF 5

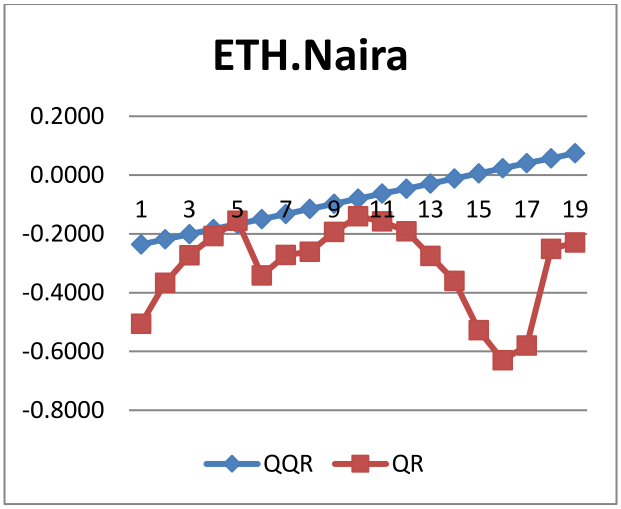

ETH.Cedi
4.0000
2.0000
0.0000
-2.0000
-4.0000
-6.0000
-8.0000
-10.0000
1 3 5 7 9 11 13 15 17 19
QQR_IMF.Residual QR_IMF.Residual

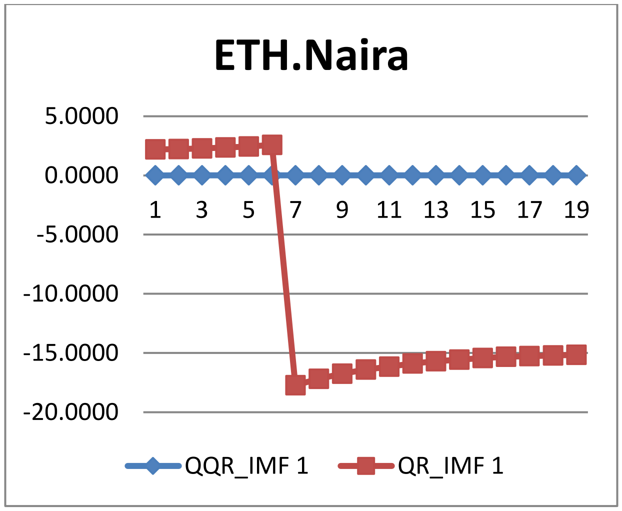

ETH.ZAR
1.5000
1.0000
0.5000
0.0000
-0.5000
1 3 5 7 9 11 13 15 17 19
QQR QR

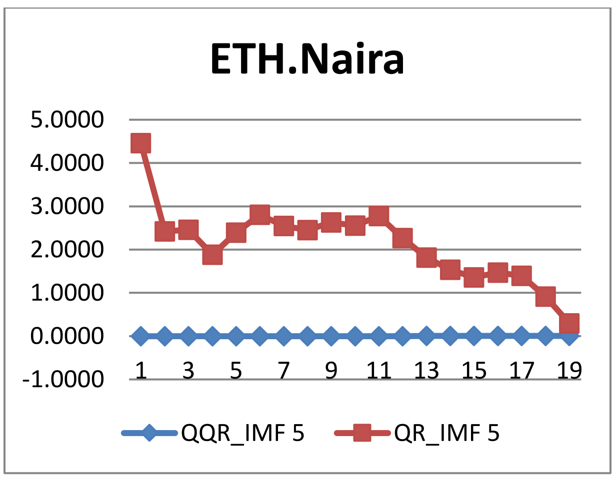

ETH.ZAR
0.8000
0.6000
0.4000
0.2000
0.0000
-0.2000
1 3 5 7 9 11 13 15 17 19
QQR_IMF 1 QR_IMF 1

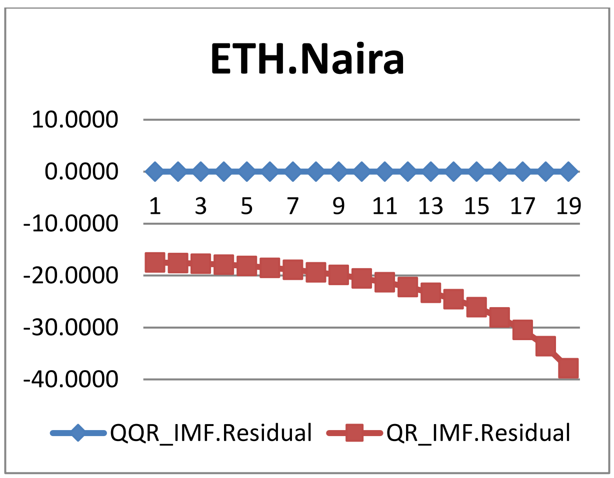

ETH.ZAR
4.0000
2.0000
0.0000
-2.0000
-4.0000
-6.0000
1 3 5 7 9 11 13 15 17 19
QQR_IMF 5
QR_IMF 5

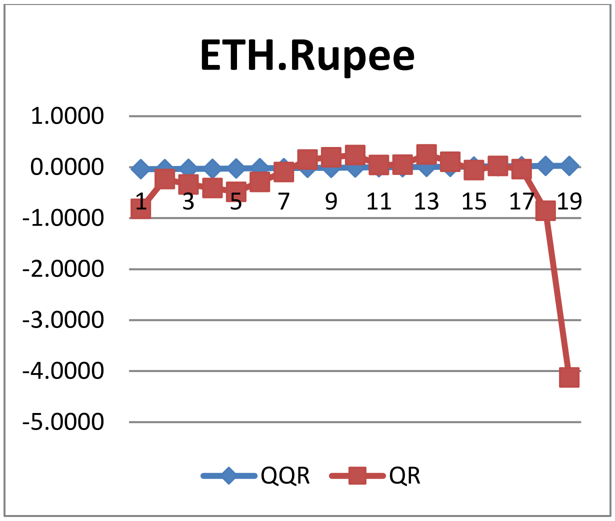

ETH.ZAR
5.0000
0.0000
-5.0000
-10.0000
-15.0000
-20.0000
1 3 5 7 9 11 13 15 17 19
QQR_IMF.Residual
QR_IMF.Residual

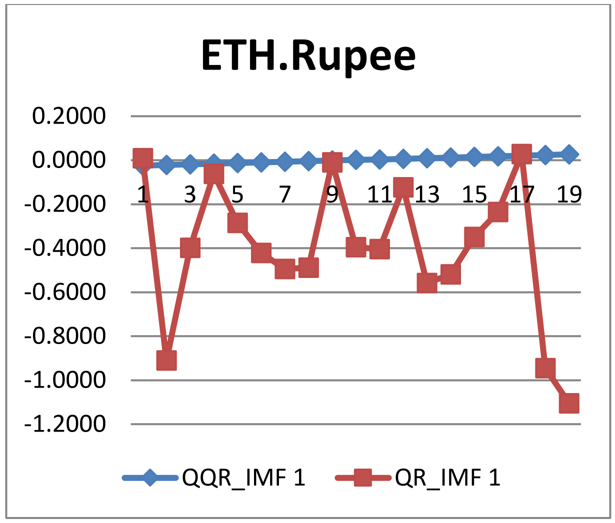

ETH.Naira
0.2000
0.0000
-0.2000
-0.4000
-0.6000
-0.8000
1 3 5 7 9 11 13 15 17 19
QQR
QR

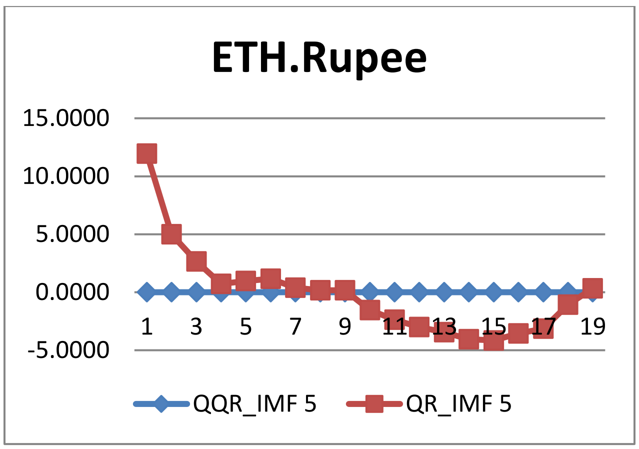

ETH.Naira
5.0000
0.0000
-5.0000
-10.0000
-15.0000
-20.0000
1 3 5 7 9 11 13 15 17 19
QQR_IMF 1
QR_IMF 1

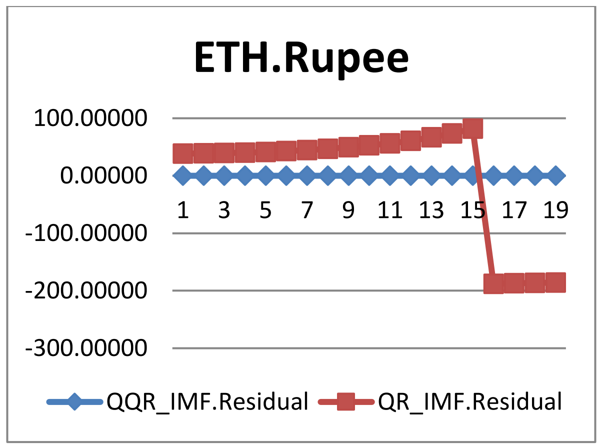

ETH.Naira
5.0000
4.0000
3.0000
2.0000
1.0000
0.0000
-1.0000
1 3 5 7 9 11 13 15 17 19
QQR_IMF 5
QR_IMF 5

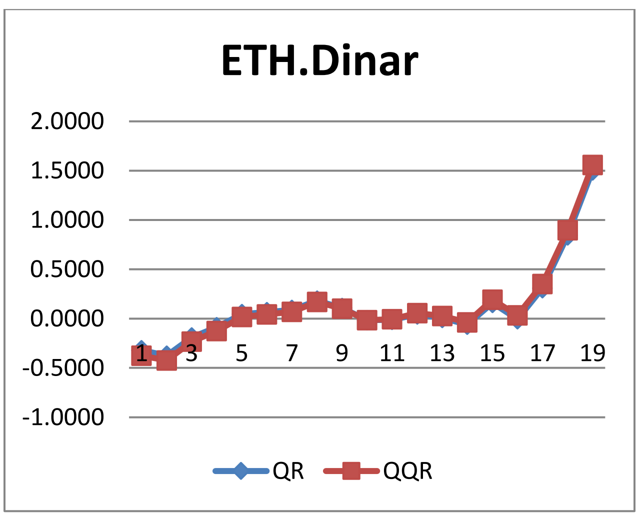

ETH.Naira
10.0000
0.0000
-10.0000
-20.0000
-30.0000
-40.0000
1 3 5 7 9 11 13 15 17 19
QQR_IMF.Residual
QR_IMF.Residual

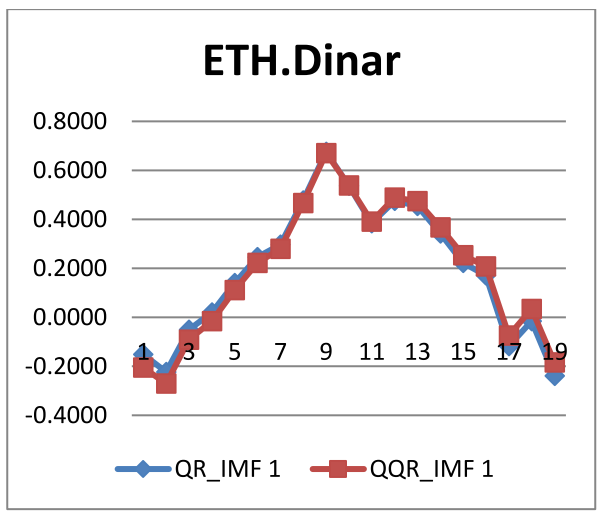

ETH.Rupee
1.0000
0.0000
-1.0000
-2.0000
-3.0000
-4.0000
-5.0000
1 3 5 7 9 11 13 15 17 19
QQR
QR

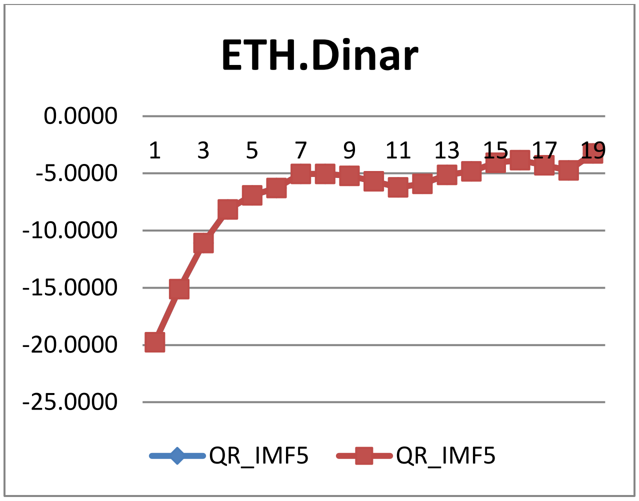

ETH.Rupee
0.2000
0.0000
-0.2000
-0.4000
-0.6000
-0.8000
-1.0000
-1.2000
1 3 5 7 9 11 13 15 17 19
QQR_IMF 1
QR_IMF 1

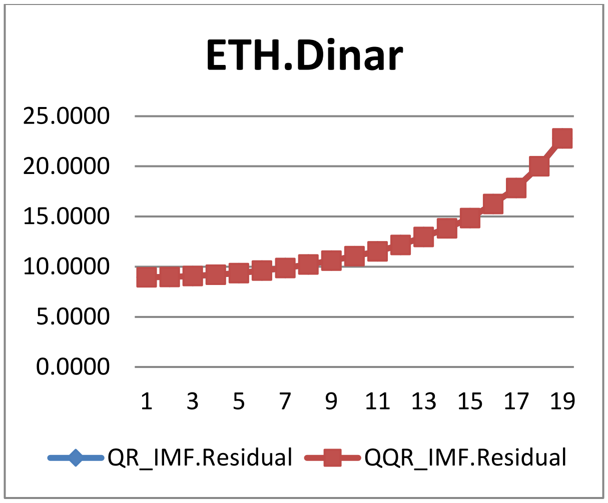

ETH.Rupee
15.0000
10.0000
5.0000
0.0000
-5.0000
1 3 5 7 9 11 13 15 17 19
QQR_IMF 5
QR_IMF 5

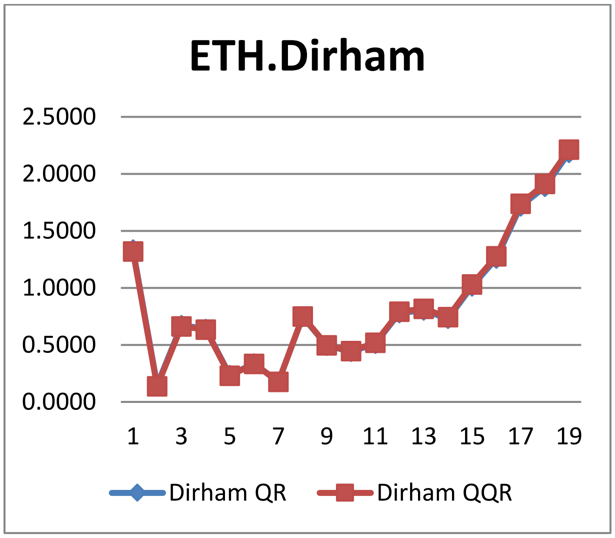

ETH.Rupee
100.00000
0.00000
-100.00000
-200.00000
-300.00000
1 3 5 7 9 11 13 15 17 19
QQR_IMF.Residual
QR_IMF.Residual

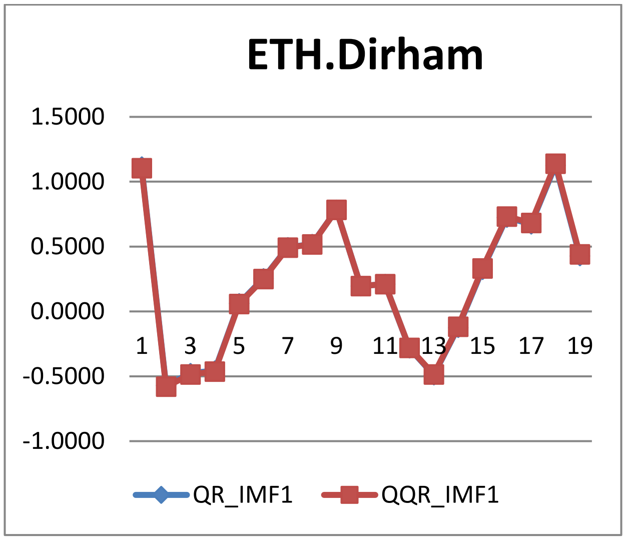

ETH.Dinar
2.0000
1.5000
1.0000
0.5000
0.0000
-0.5000
-1.0000
1 3 5 7 9 11 13 15 17 19
QR
QQR

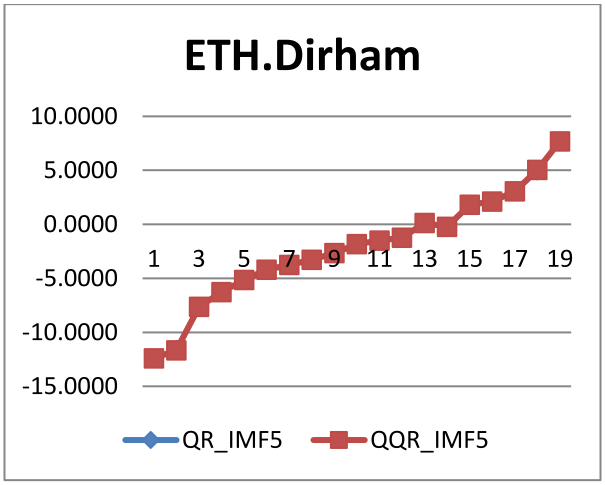

ETH.Dinar
0.8000
0.6000
0.4000
0.2000
0.0000
-0.2000
-0.4000
1 3 5 7 9 11 13 15 17 19
QR_IMF 1
QQR_IMF 1

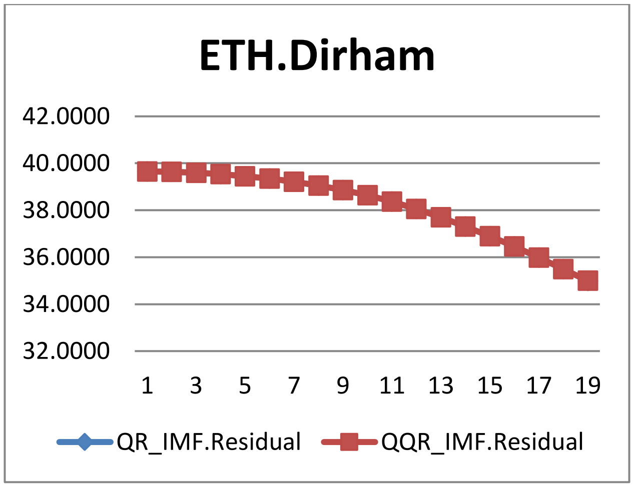

ETH.Dinar
0.0000
-5.0000
-10.0000
-15.0000
-20.0000
-25.0000
1 3 5 7 9 11 13 15 17 19
QR_IMF5
QR_IMF5

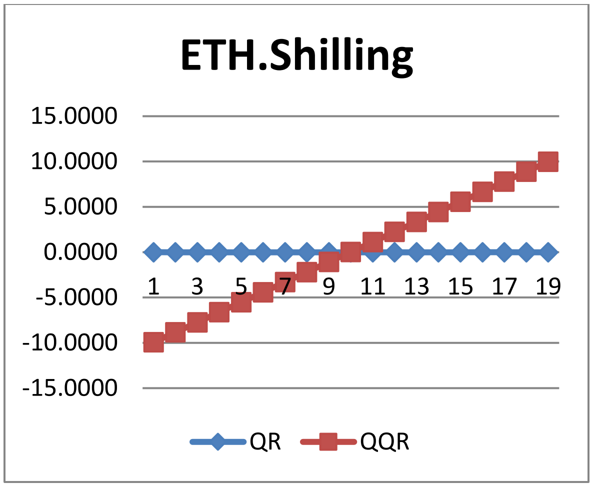

ETH.Dinar
25.0000
20.0000
15.0000
10.0000
5.0000
0.0000
1 3 5 7 9 11 13 15 17 19
QR_IMF.Residual
QQR_IMF.Residual

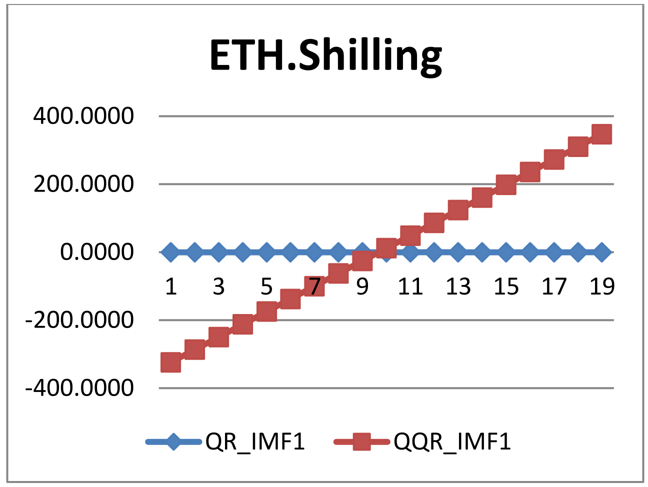

ETH.Dirham
2.5000
2.0000
1.5000
1.0000
0.5000
0.0000
1 3 5 7 9 11 13 15 17 19
Dirham QR
Dirham QQR

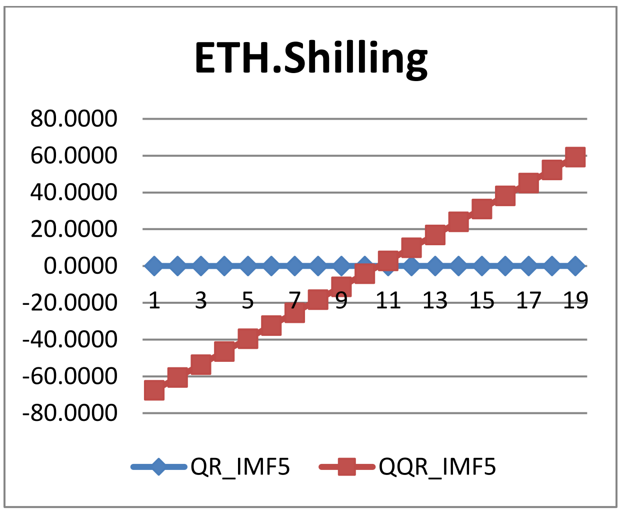

ETH.Dirham
1.5000
1.0000
0.5000
0.0000
-0.5000
-1.0000
1 3 5 7 9 11 13 15 17 19
QR_IMF1
QQR_IMF1

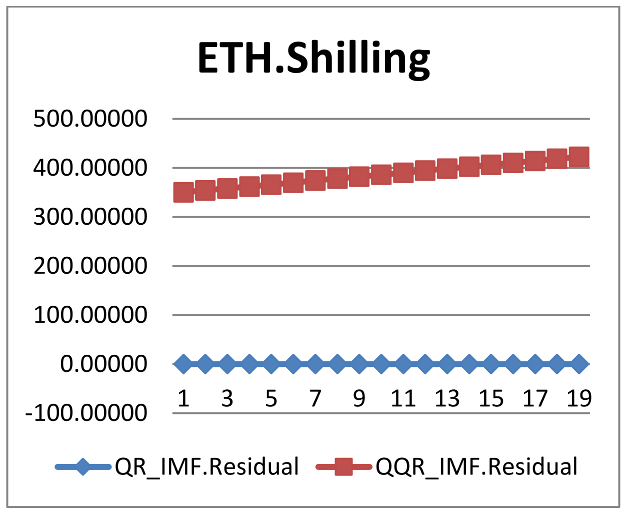

ETH.Dirham
10.0000
5.0000
0.0000
-5.0000
-10.0000
-15.0000
1 3 5 7 9 11 13 15 17 19
QR_IMF5
QQR_IMF5

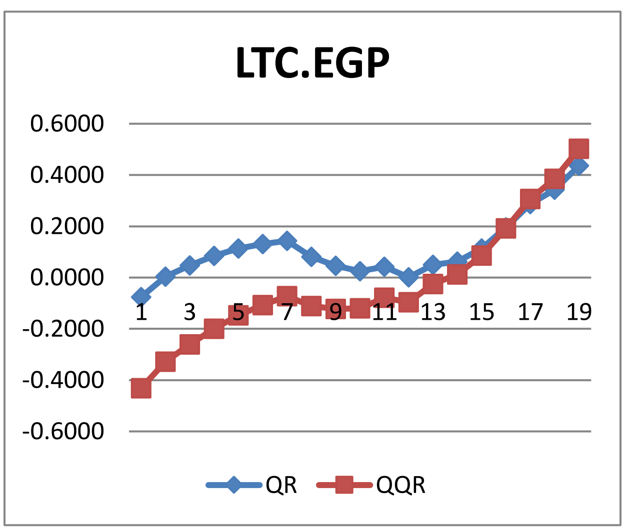

ETH.Dirham
42.0000
40.0000
38.0000
36.0000
34.0000
32.0000
1 3 5 7 9 11 13 15 17 19
QR_IMF.Residual
QQR_IMF.Residual

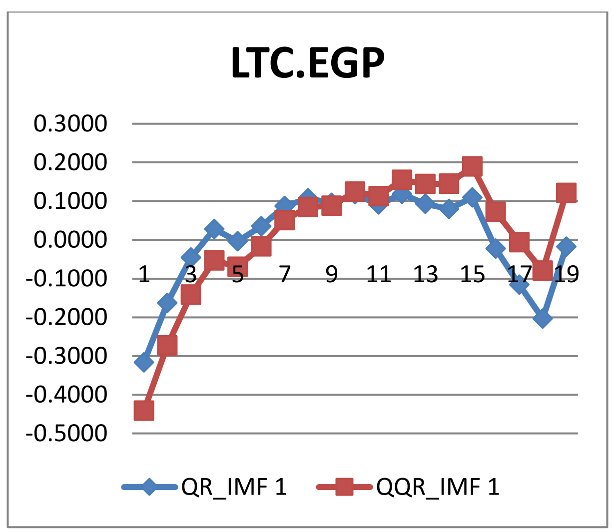

ETH.Shilling
15.0000
10.0000
5.0000
0.0000
-5.0000
-10.0000
-15.0000
1 3 5 7 9 11 13 15 17 19
QR
QQR

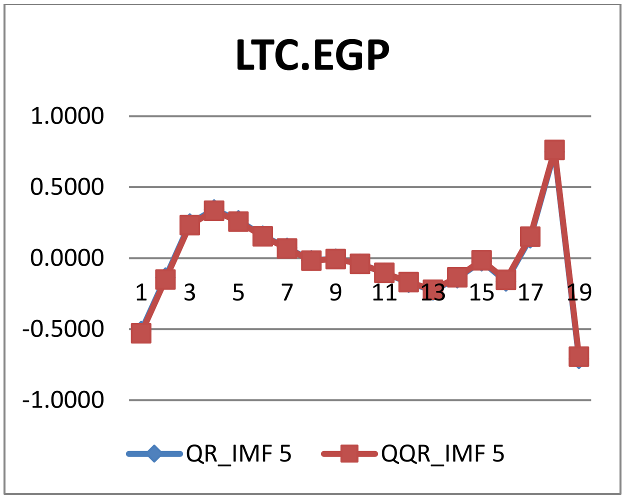

ETH.Shilling
400.0000
200.0000
0.0000
-200.0000
-400.0000
1 3 5 7 9 11 13 15 17 19
QR_IMF1
QQR_IMF1

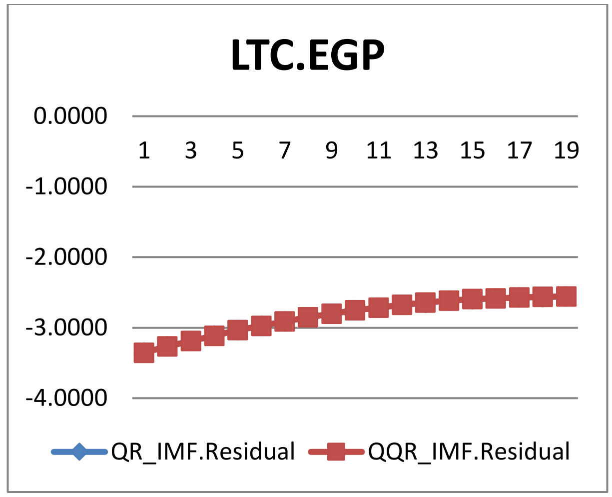

ETH.Shilling
80.0000
60.0000
40.0000
20.0000
0.0000
-20.0000
-40.0000
-60.0000
-80.0000
1 3 5 7 9 11 13 15 17 19
QR_IMF5
QQR_IMF5

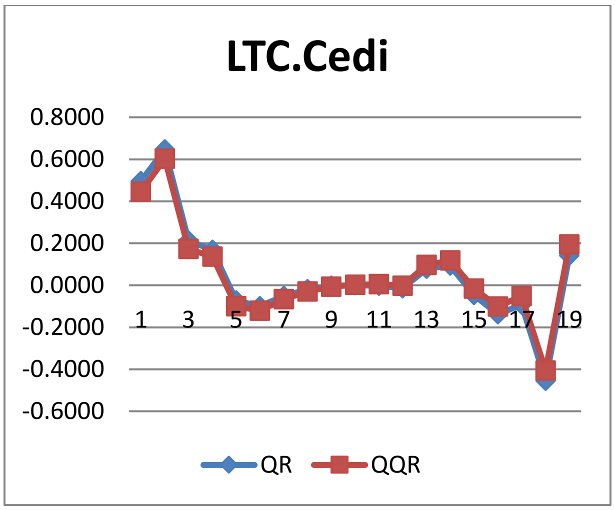

ETH.Shilling
500.00000
400.00000
300.00000
200.00000
100.00000
0.00000
-100.00000
1 3 5 7 9 11 13 15 17 19
QR_IMF.Residual
QQR_IMF.Residual

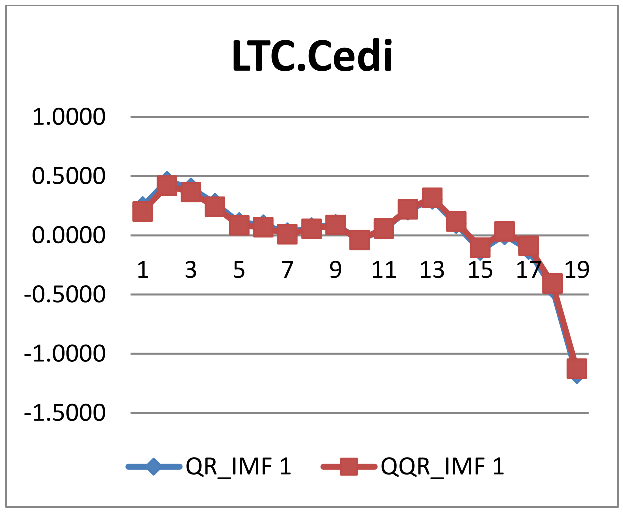

LTC.EGP
0.6000
0.4000
0.2000
0.0000
-0.2000
-0.4000
-0.6000
1 3 5 7 9 11 13 15 17 19
QR
QQR

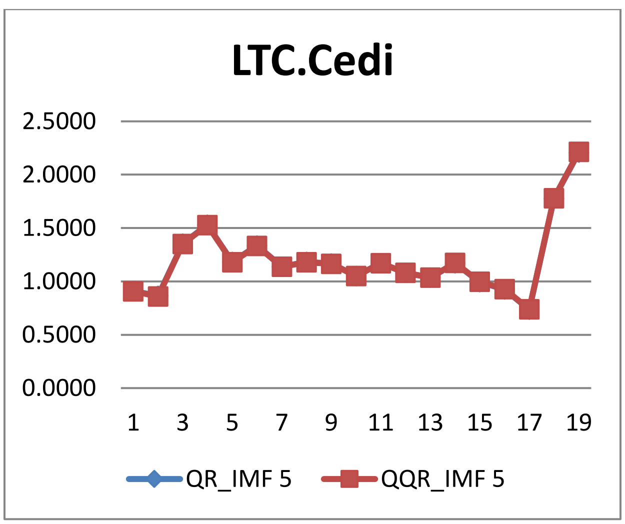

LTC.EGP
0.3000
0.2000
0.1000
0.0000
-0.1000
-0.2000
-0.3000
-0.4000
-0.5000
1 3 5 7 9 11 13 15 17 19
QR_IMF 1
QQR_IMF 1

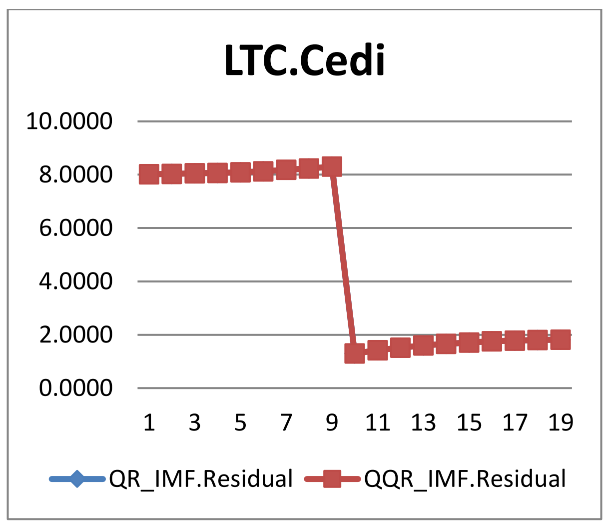

LTC.EGP
1.0000
0.5000
0.0000
-0.5000
-1.0000
1 3 5 7 9 11 13 15 17 19
QR_IMF 5
QQR_IMF 5

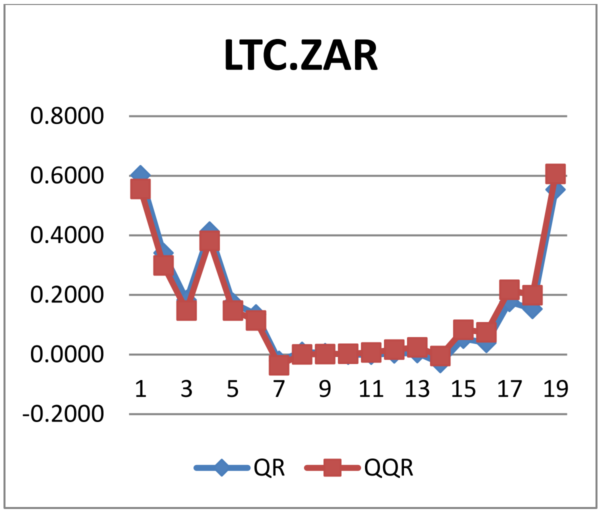

LTC.EGP
0.0000
-1.0000
-2.0000
-3.0000
-4.0000
1 3 5 7 9 11 13 15 17 19
QR_IMF.Residual
QQR_IMF.Residual

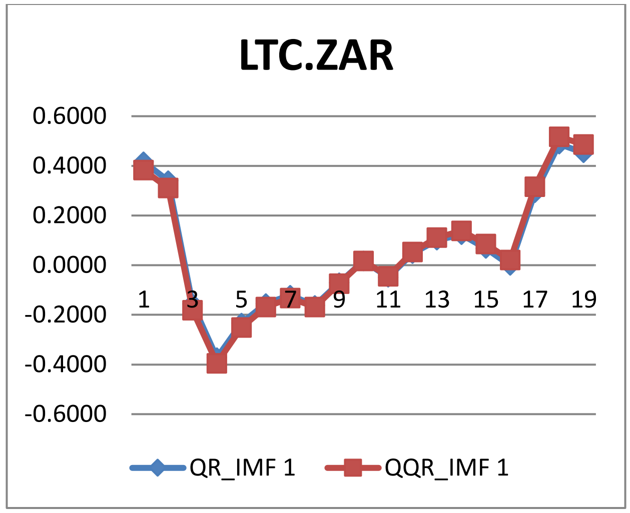

LTC.Cedi
0.8000
0.6000
0.4000
0.2000
0.0000
-0.2000
-0.4000
-0.6000
1 3 5 7 9 11 13 15 17 19
QR
QQR

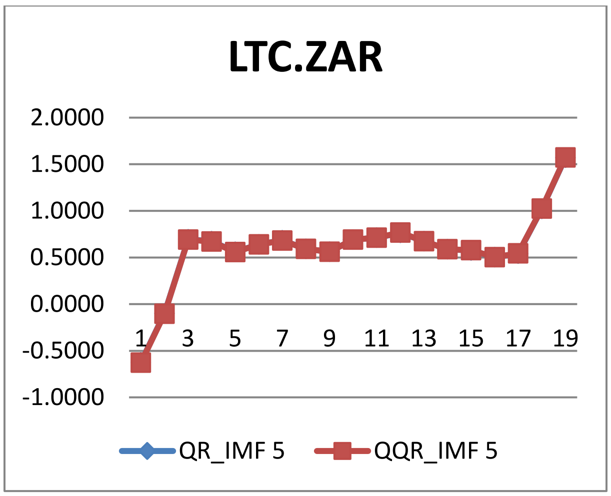

LTC.Cedi
1.0000
0.5000
0.0000
-0.5000
-1.0000
-1.5000
1 3 5 7 9 11 13 15 17 19
QR_IMF 1
QQR_IMF 1

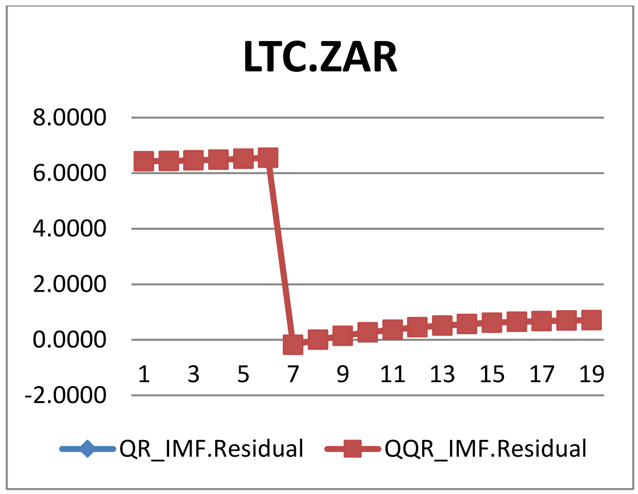

LTC.Cedi
2.5000
2.0000
1.5000
1.0000
0.5000
0.0000
1 3 5 7 9 11 13 15 17 19
QR_IMF 5
QQR_IMF 5

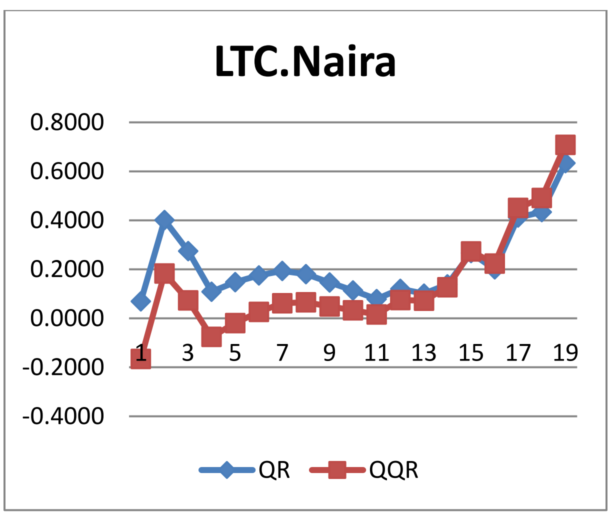

LTC.Cedi
10.0000
8.0000
6.0000
4.0000
2.0000
0.0000
1 3 5 7 9 11 13 15 17 19
QR_IMF.Residual
QQR_IMF.Residual

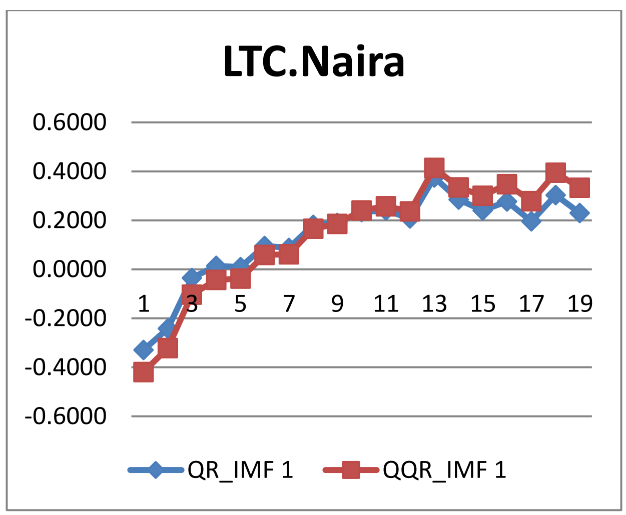

LTC.ZAR
0.8000
0.6000
0.4000
0.2000
0.0000
-0.2000
1 3 5 7 9 11 13 15 17 19
QR
QQR

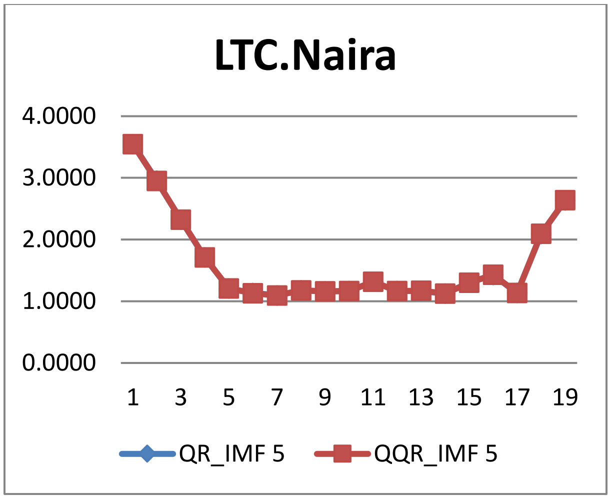

LTC.ZAR
0.6000
0.4000
0.2000
0.0000
-0.2000
-0.4000
-0.6000
1 3 5 7 9 11 13 15 17 19
QR_IMF 1
QQR_IMF 1

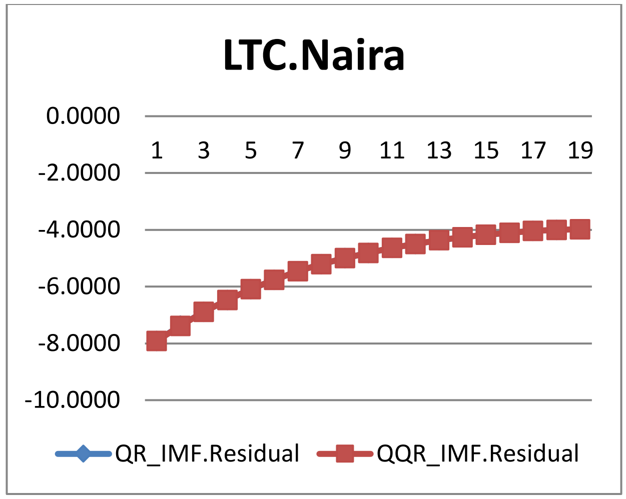

LTC.ZAR
2.0000
1.5000
1.0000
0.5000
0.0000
-0.5000
-1.0000
1 3 5 7 9 11 13 15 17 19
QR_IMF 5
QQR_IMF 5

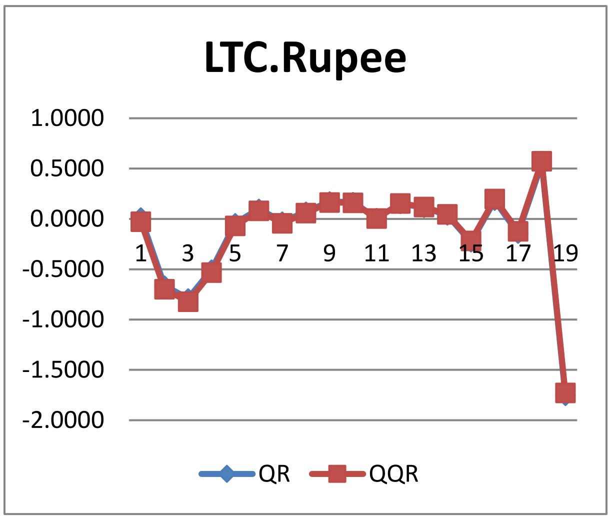

LTC.ZAR
8.0000
6.0000
4.0000
2.0000
0.0000
-2.0000
1 3 5 7 9 11 13 15 17 19
QR_IMF.Residual
QQR_IMF.Residual

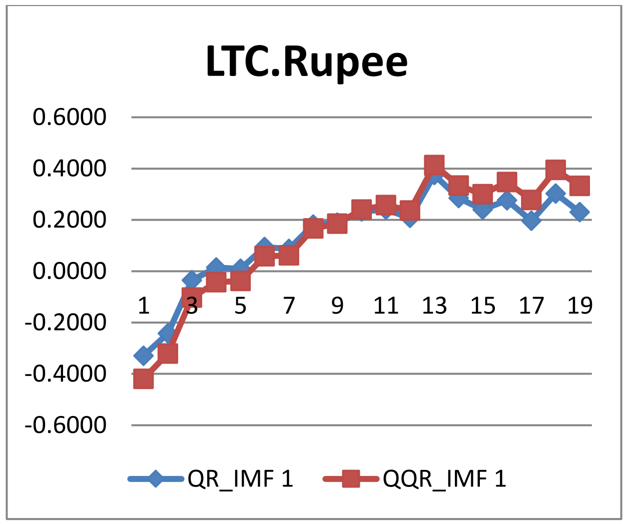

LTC.Naira
0.8000
0.6000
0.4000
0.2000
0.0000
-0.2000
-0.4000
1 3 5 7 9 11 13 15 17 19
QR
QQR

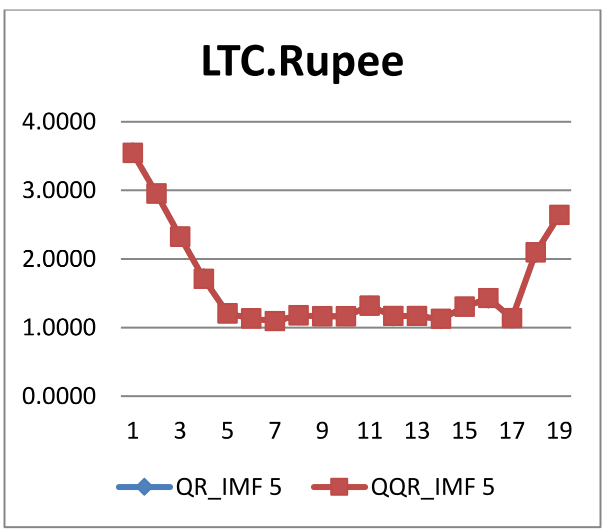

LTC.Naira
0.6000
0.4000
0.2000
0.0000
-0.2000
-0.4000
-0.6000
1 3 5 7 9 11 13 15 17 19
QR_IMF 1
QQR_IMF 1

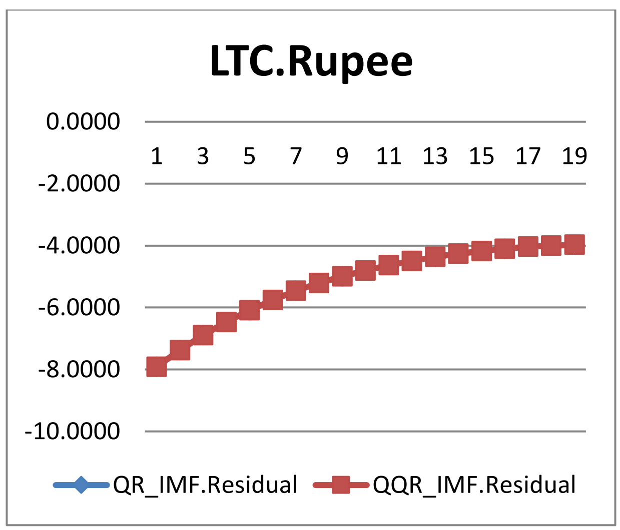

LTC.Naira
4.0000
3.0000
2.0000
1.0000
0.0000
1 3 5 7 9 11 13 15 17 19
QR_IMF 5
QQR_IMF 5

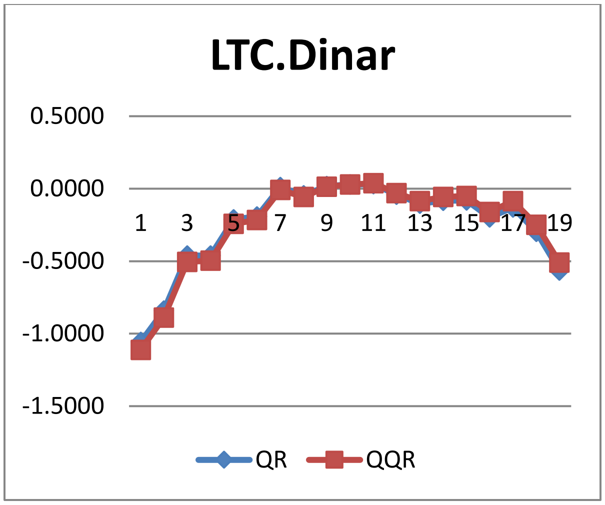

LTC.Naira
0.0000
-2.0000
-4.0000
-6.0000
-8.0000
-10.0000
1 3 5 7 9 11 13 15 17 19
QR_IMF.Residual
QQR_IMF.Residual

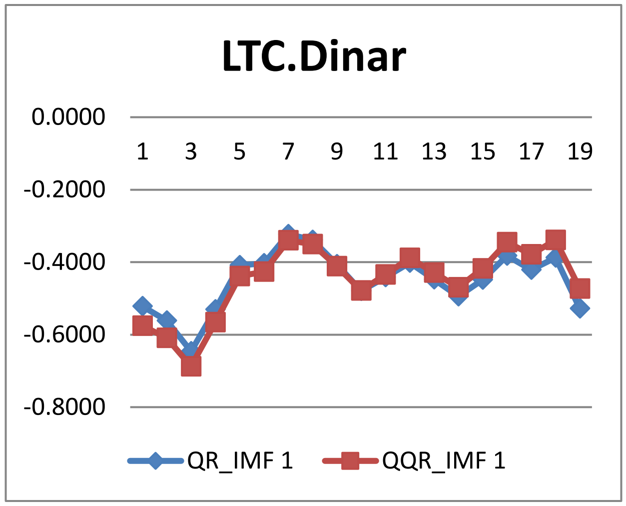

LTC.Rupee
1.0000
0.5000
0.0000
-0.5000
-1.0000
-1.5000
-2.0000
1 3 5 7 9 11 13 15 17 19
QR
QQR

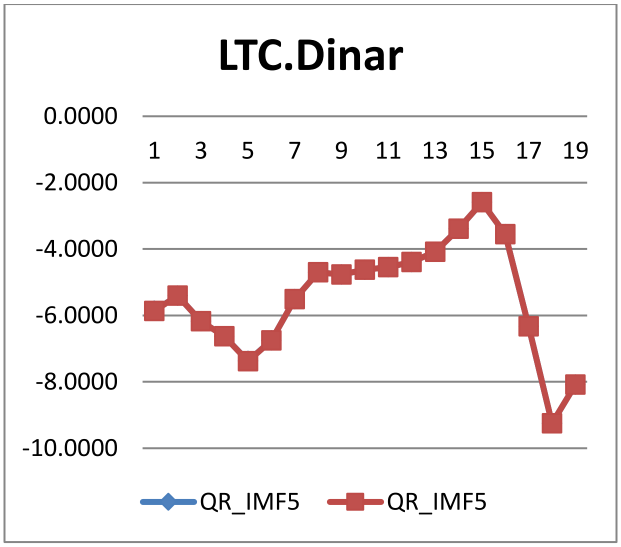

LTC.Rupee
0.6000
0.4000
0.2000
0.0000
-0.2000
-0.4000
-0.6000
1 3 5 7 9 11 13 15 17 19
QR_IMF 1
QQR_IMF 1

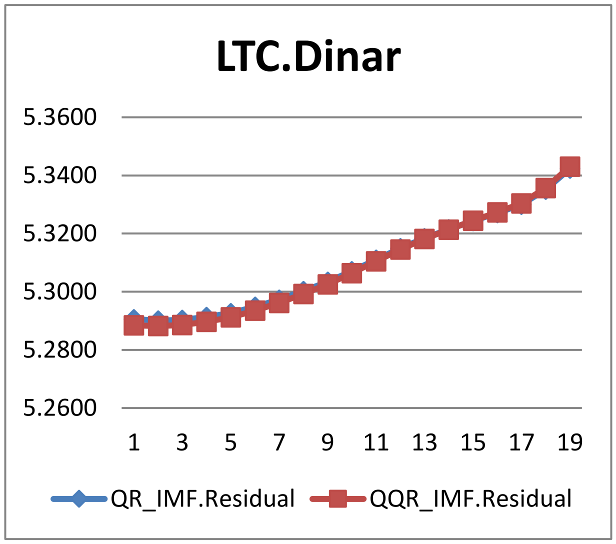

LTC.Rupee
4.0000
3.0000
2.0000
1.0000
0.0000
1 3 5 7 9 11 13 15 17 19
QR_IMF 5
QQR_IMF 5

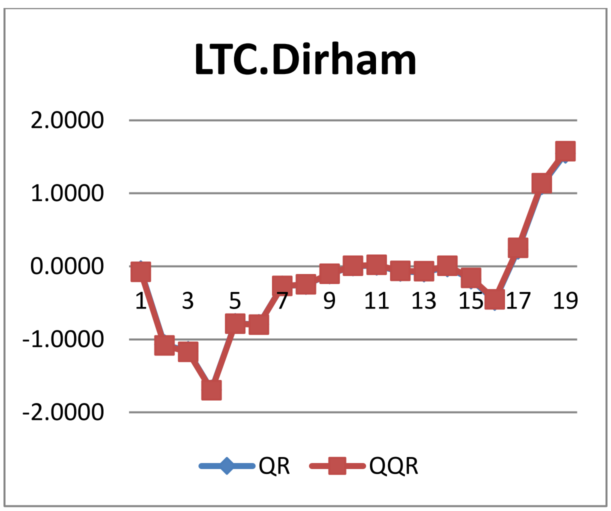

LTC.Rupee
0.0000
-2.0000
-4.0000
-6.0000
-8.0000
-10.0000
1 3 5 7 9 11 13 15 17 19
QR_IMF.Residual
QQR_IMF.Residual

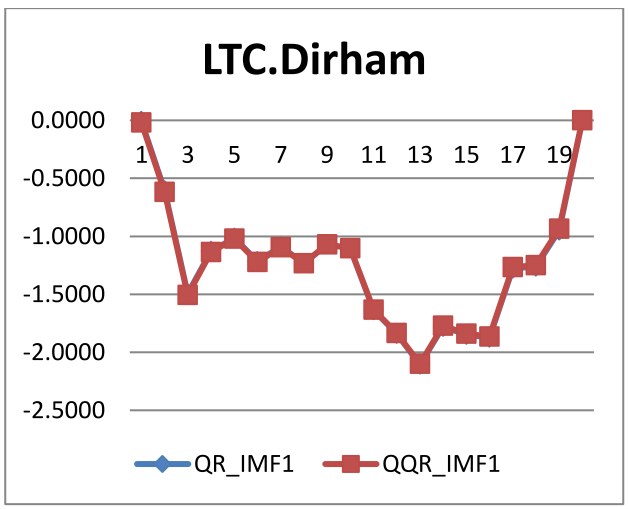

LTC.Dinar
0.5000
0.0000
-0.5000
-1.0000
-1.5000
1 3 5 7 9 11 13 15 17 19
QR
QQR

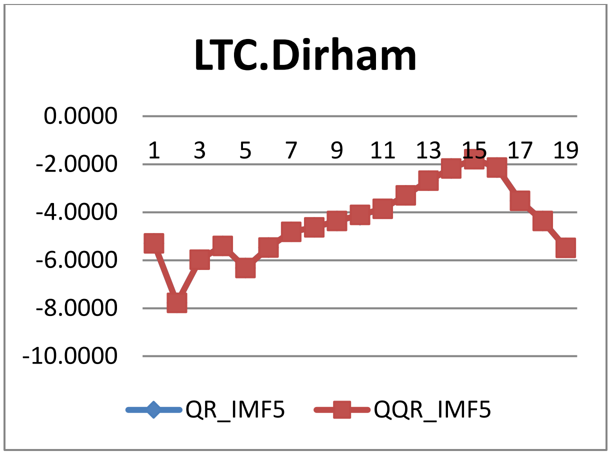

LTC.Dinar
0.0000
-0.2000
-0.4000
-0.6000
-0.8000
1 3 5 7 9 11 13 15 17 19
QR_IMF 1
QQR_IMF 1

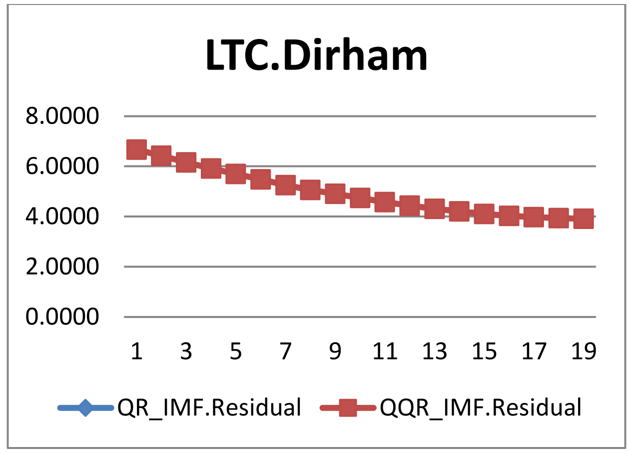

LTC.Dinar
0.0000
-2.0000
-4.0000
-6.0000
-8.0000
-10.0000
1 3 5 7 9 11 13 15 17 19
QR_IMF5
QR_IMF5

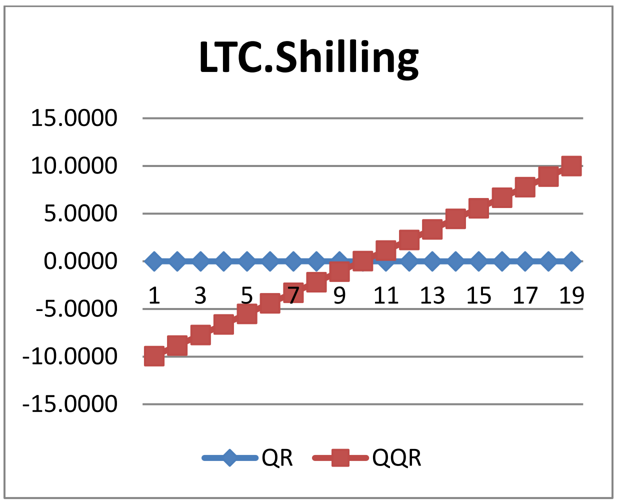

LTC.Dinar
5.3600
5.3400
5.3200
5.3000
5.2800
5.2600
1 3 5 7 9 11 13 15 17 19
QR_IMF.Residual
QQR_IMF.Residual

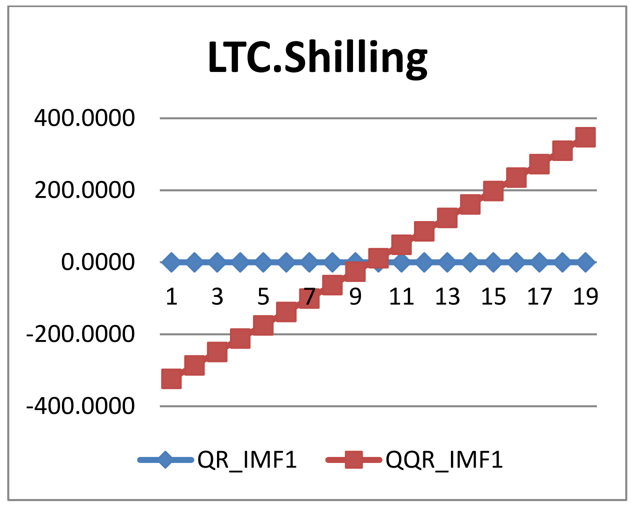

LTC.Dirham
2.0000
1.0000
0.0000
-1.0000
-2.0000
1 3 5 7 9 11 13 15 17 19
QR
QQR

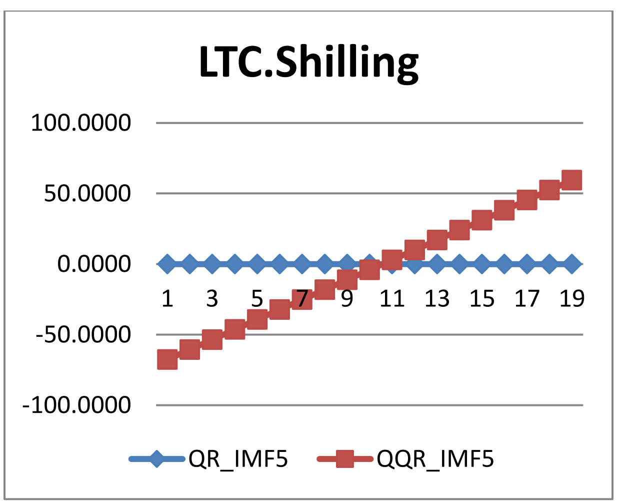

LTC.Dirham
0.0000
-0.5000
-1.0000
-1.5000
-2.0000
-2.5000
1 3 5 7 9 11 13 15 17 19
QR_IMF1
QQR_IMF1

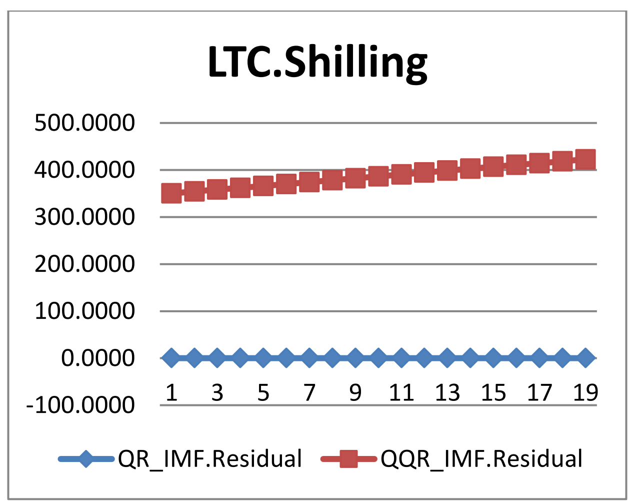

LTC.Dirham
0.0000
-2.0000
-4.0000
-6.0000
-8.0000
-10.0000
1 3 5 7 9 11 13 15 17 19
QR_IMF5
QQR_IMF5

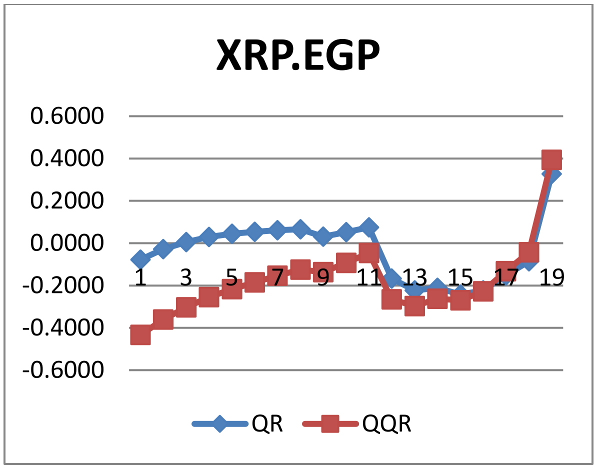

LTC.Dirham
8.0000
6.0000
4.0000
2.0000
0.0000
1 3 5 7 9 11 13 15 17 19
QR_IMF.Residual
QQR_IMF.Residual

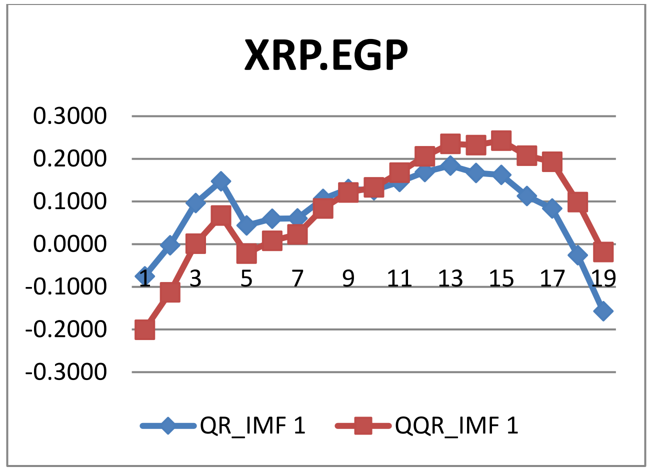

LTC.Shilling
15.0000
10.0000
5.0000
0.0000
-5.0000
-10.0000
-15.0000
1 3 5 7 9 11 13 15 17 19
QR
QQR

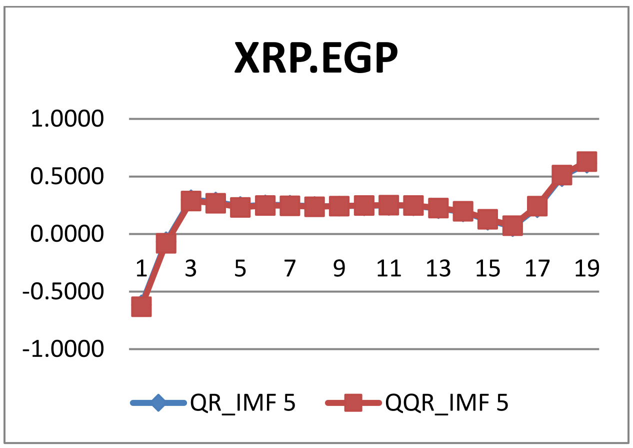

LTC.Shilling
400.0000
200.0000
0.0000
-200.0000
-400.0000
1 3 5 7 9 11 13 15 17 19
QR_IMF1
QQR_IMF1

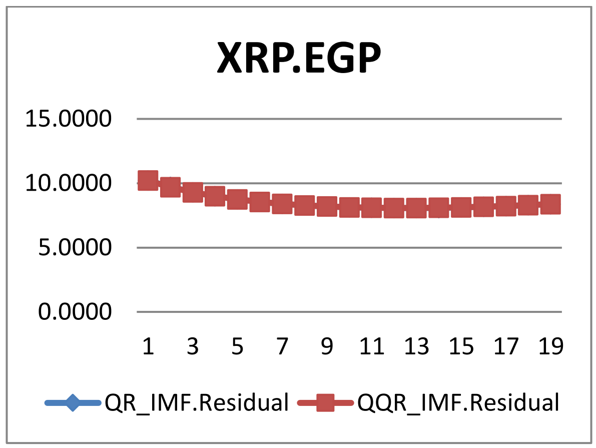

LTC.Shilling
100.0000
50.0000
0.0000
-50.0000
-100.0000
1 3 5 7 9 11 13 15 17 19
QR_IMF5
QQR_IMF5

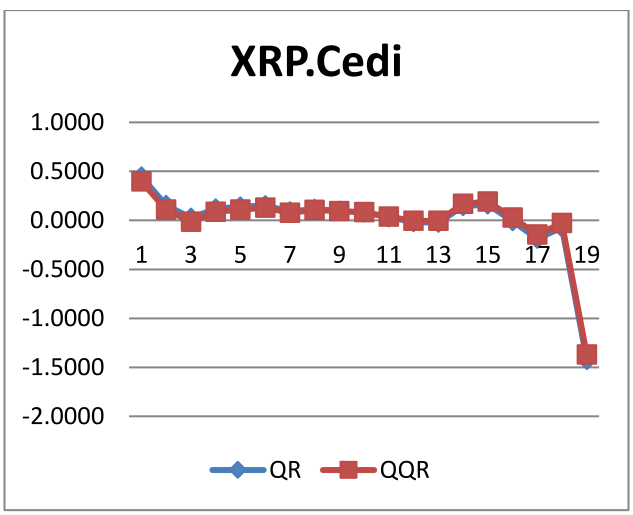

LTC.Shilling
500.0000
400.0000
300.0000
200.0000
100.0000
0.0000
-100.0000
1 3 5 7 9 11 13 15 17 19
QR_IMF.Residual
QQR_IMF.Residual

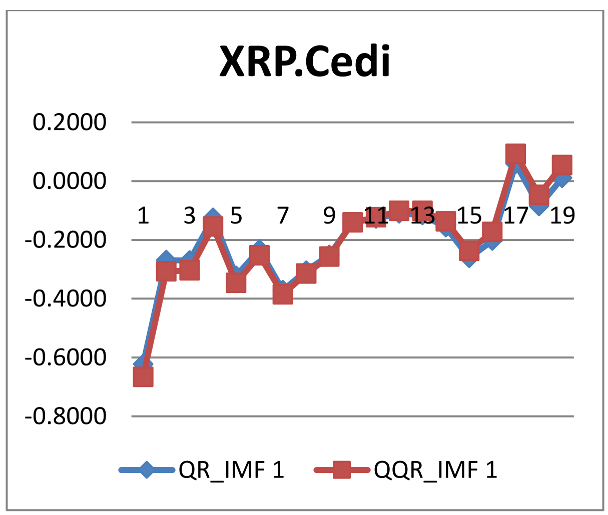

XRP.EGP
0.6000
0.4000
0.2000
0.0000
-0.2000
-0.4000
-0.6000
1 3 5 7 9 11 13 15 17 19
QR
QQR

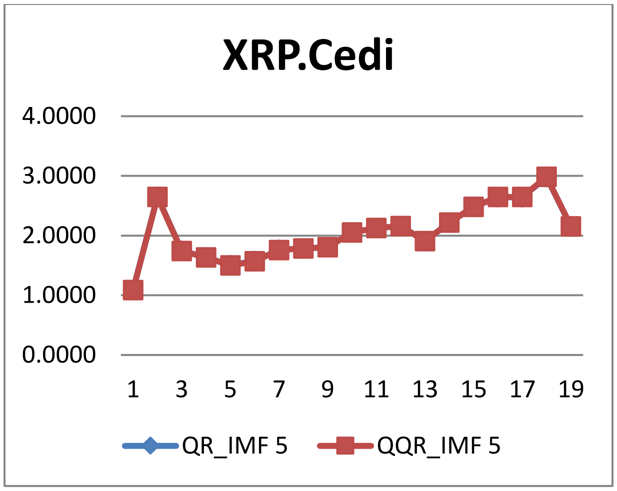

XRP.EGP
0.3000
0.2000
0.1000
0.0000
-0.1000
-0.2000
-0.3000
1 3 5 7 9 11 13 15 17 19
QR_IMF 1
QQR_IMF 1

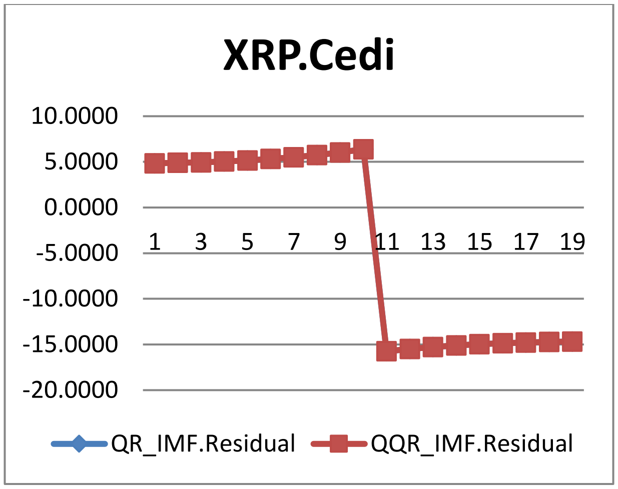

XRP.EGP
1.0000
0.5000
0.0000
-0.5000
-1.0000
1 3 5 7 9 11 13 15 17 19
QR_IMF 5
QQR_IMF 5

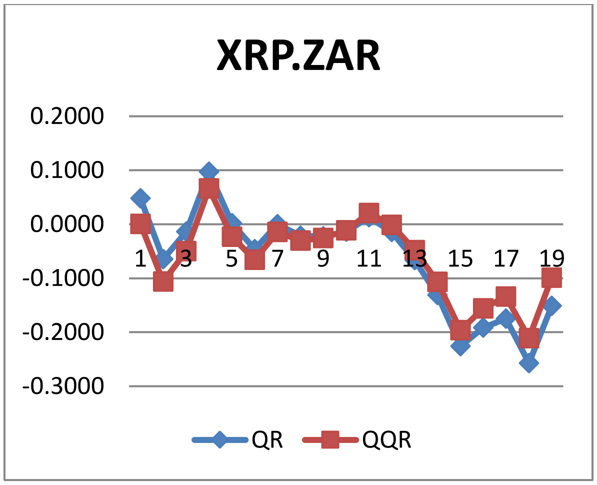

XRP.EGP
15.0000
10.0000
5.0000
0.0000
1 3 5 7 9 11 13 15 17 19
QR_IMF.Residual
QQR_IMF.Residual

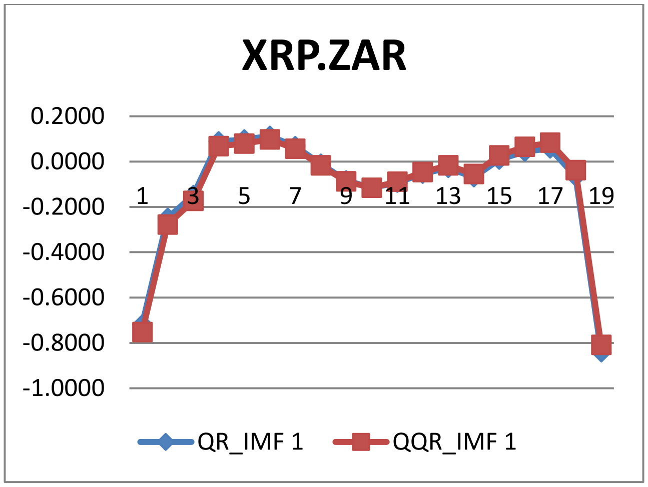

XRP.Cedi
1.0000
0.5000
0.0000
-0.5000
-1.0000
-1.5000
-2.0000
1 3 5 7 9 11 13 15 17 19
QR
QQR

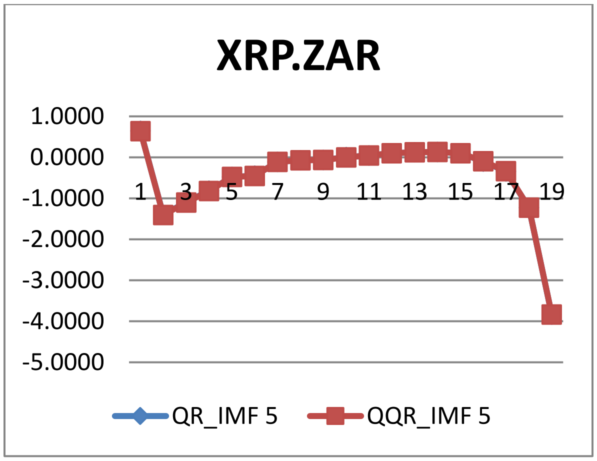

XRP.Cedi
0.2000
0.0000
-0.2000
-0.4000
-0.6000
-0.8000
1 3 5 7 9 11 13 15 17 19
QR_IMF 1
QQR_IMF 1

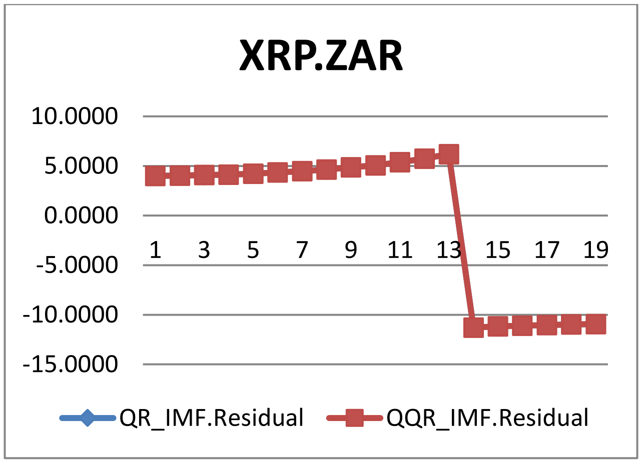

XRP.Cedi
4.0000
3.0000
2.0000
1.0000
0.0000
1 3 5 7 9 11 13 15 17 19
QR_IMF 5
QQR_IMF 5

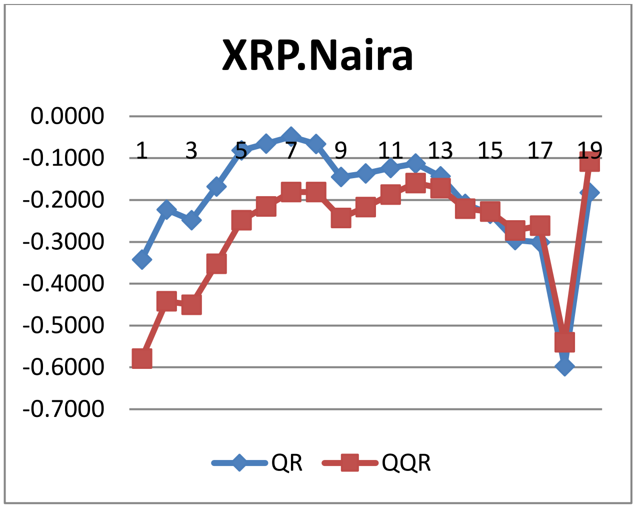

XRP.Cedi
10.0000
5.0000
0.0000
-5.0000
-10.0000
-15.0000
-20.0000
1 3 5 7 9 11 13 15 17 19
QR_IMF.Residual
QQR_IMF.Residual

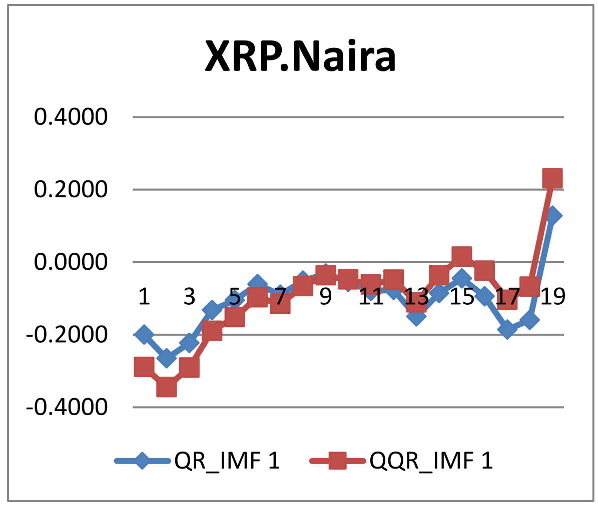

XRP.ZAR
0.2000
0.1000
0.0000
-0.1000
-0.2000
-0.3000
1 3 5 7 9 11 13 15 17 19
QR
QQR

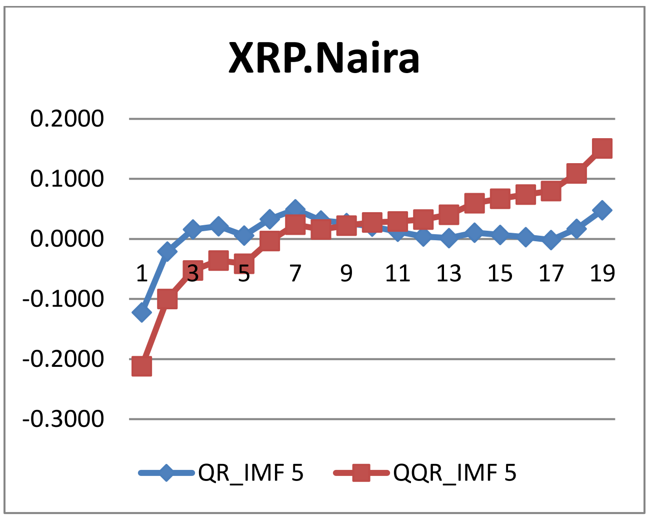

XRP.ZAR
0.2000
0.0000
-0.2000
-0.4000
-0.6000
-0.8000
-1.0000
1 3 5 7 9 11 13 15 17 19
QR_IMF 1
QQR_IMF 1

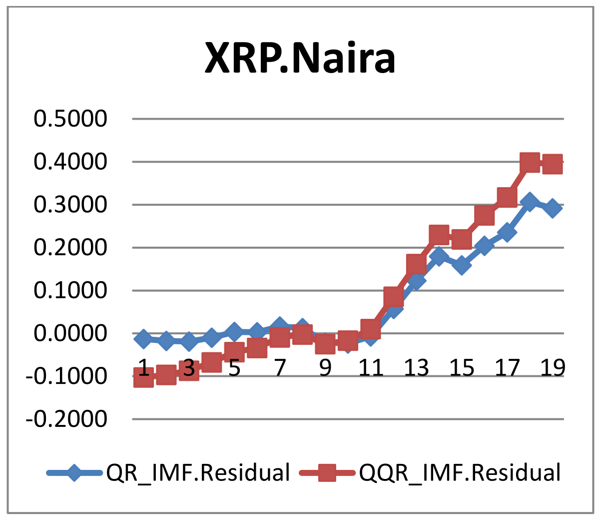

XRP.ZAR
1.0000
0.0000
-1.0000
-2.0000
-3.0000
-4.0000
-5.0000
1 3 5 7 9 11 13 15 17 19
QR_IMF 5
QQR_IMF 5

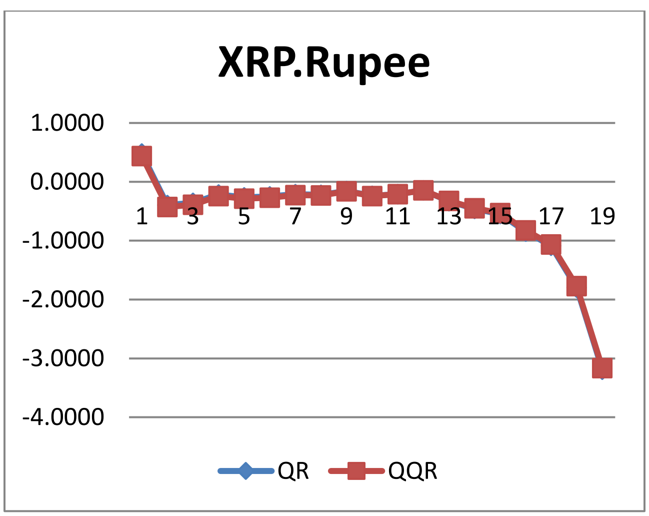

XRP.ZAR
10.0000
5.0000
0.0000
-5.0000
-10.0000
-15.0000
1 3 5 7 9 11 13 15 17 19
QR_IMF.Residual
QQR_IMF.Residual

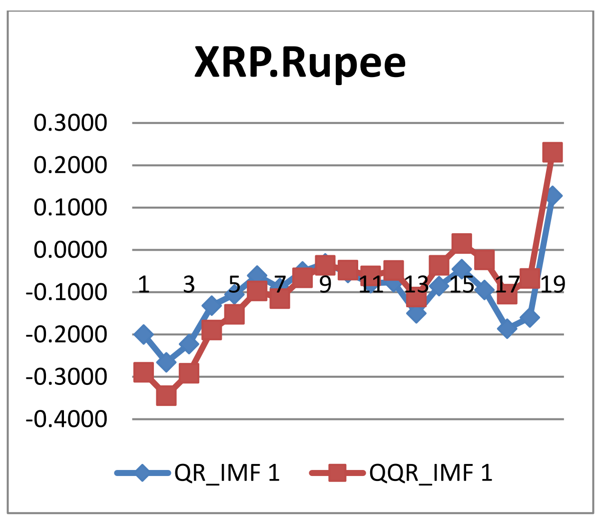

XRP.Naira
0.0000
-0.1000
-0.2000
-0.3000
-0.4000
-0.5000
-0.6000
-0.7000
1 3 5 7 9 11 13 15 17 19
QR
QQR

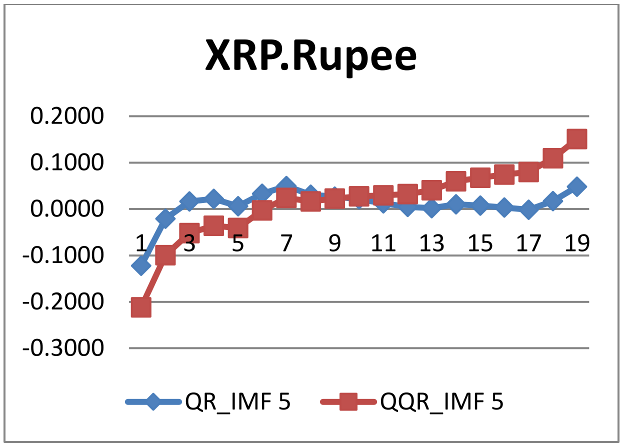

XRP.Naira
0.4000
0.2000
0.0000
-0.2000
-0.4000
1 3 5 7 9 11 13 15 17 19
QR_IMF 1
QQR_IMF 1

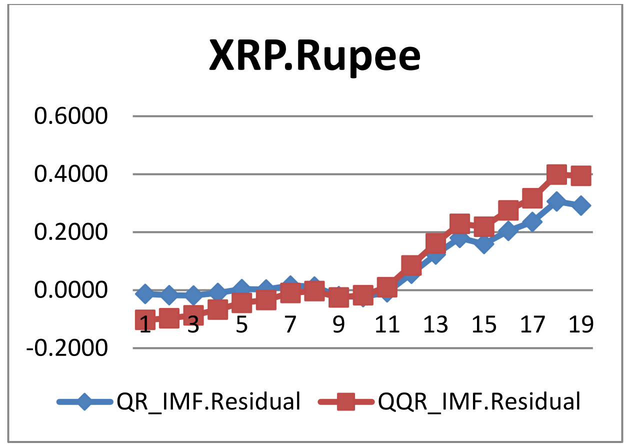

XRP.Naira
0.2000
0.1000
0.0000
-0.1000
-0.2000
-0.3000
1 3 5 7 9 11 13 15 17 19
QR_IMF 5
QQR_IMF 5

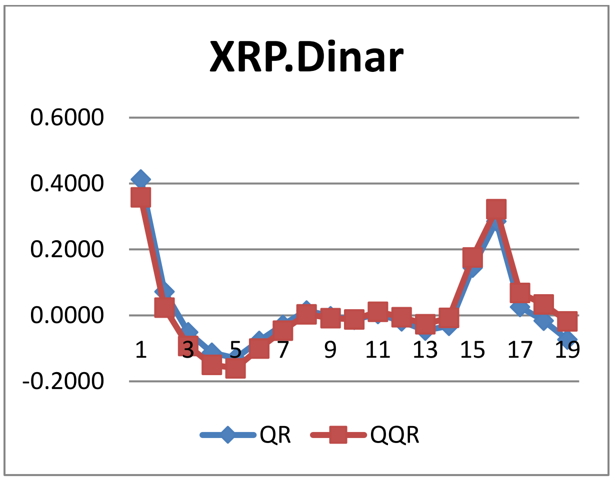

XRP.Naira
0.5000
0.4000
0.3000
0.2000
0.1000
0.0000
-0.1000
-0.2000
1 3 5 7 9 11 13 15 17 19
QR_IMF.Residual
QQR_IMF.Residual

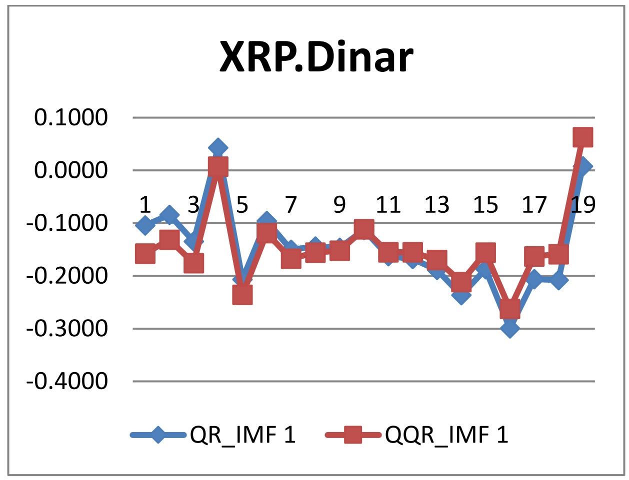

XRP.Rupee
1.0000
0.0000
-1.0000
-2.0000
-3.0000
-4.0000
1 3 5 7 9 11 13 15 17 19
QR
QQR

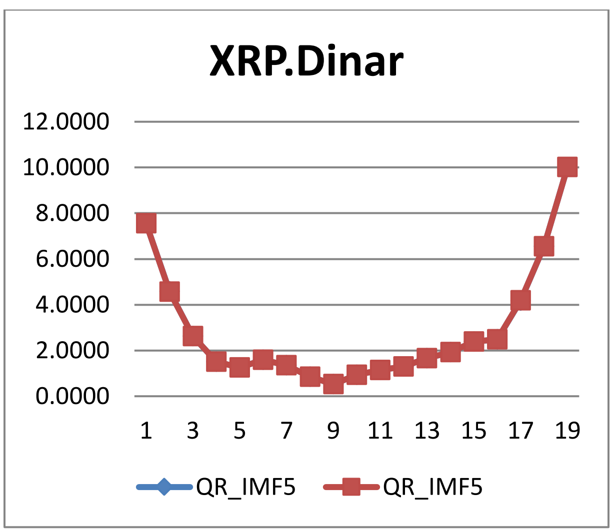

XRP.Rupee
0.3000
0.2000
0.1000
0.0000
-0.1000
-0.2000
-0.3000
-0.4000
1 3 5 7 9 11 13 15 17 19
QR_IMF 1
QQR_IMF 1

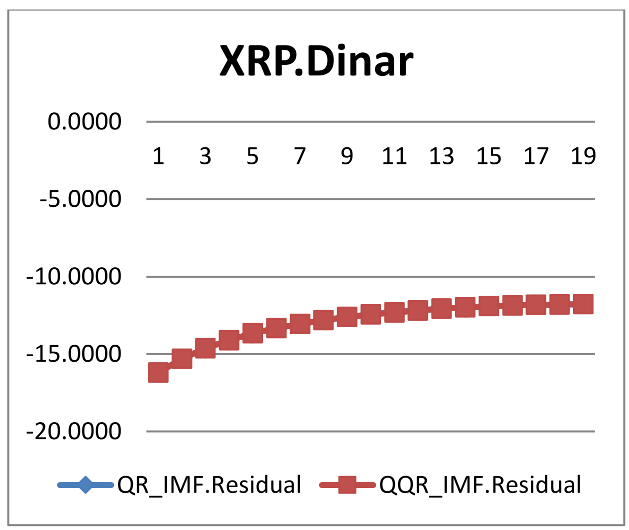

XRP.Rupee
0.2000
0.1000
0.0000
-0.1000
-0.2000
-0.3000
1 3 5 7 9 11 13 15 17 19
QR_IMF 5
QQR_IMF 5

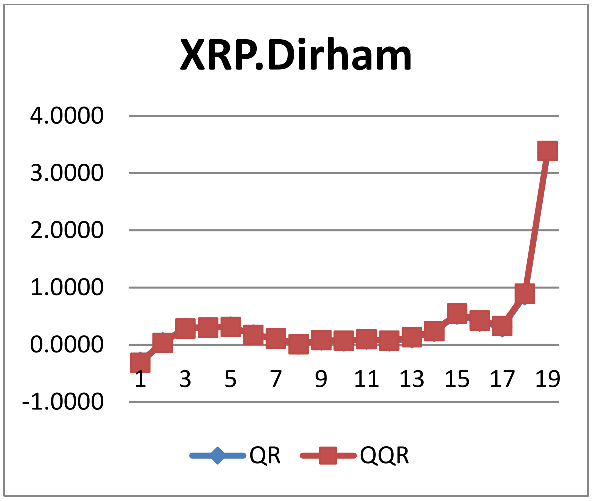

XRP.Rupee
0.6000
0.4000
0.2000
0.0000
-0.2000
1 3 5 7 9 11 13 15 17 19
QR_IMF.Residual
QQR_IMF.Residual

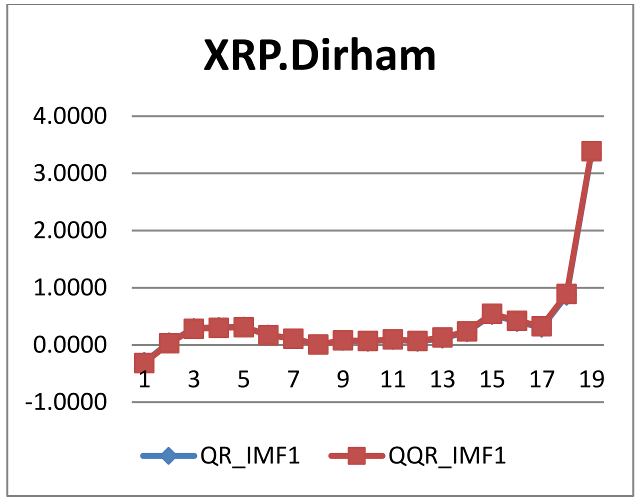

XRP.Dinar
0.6000
0.4000
0.2000
0.0000
-0.2000
1 3 5 7 9 11 13 15 17 19
QR
QQR

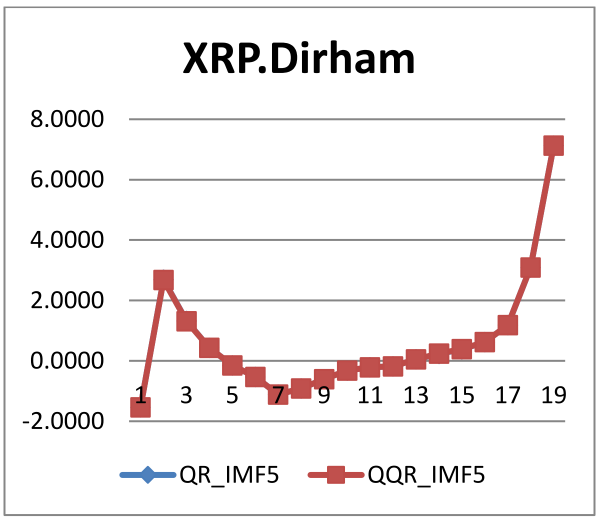

XRP.Dinar
0.1000
0.0000
-0.1000
-0.2000
-0.3000
-0.4000
1 3 5 7 9 11 13 15 17 19
QR_IMF 1
QQR_IMF 1

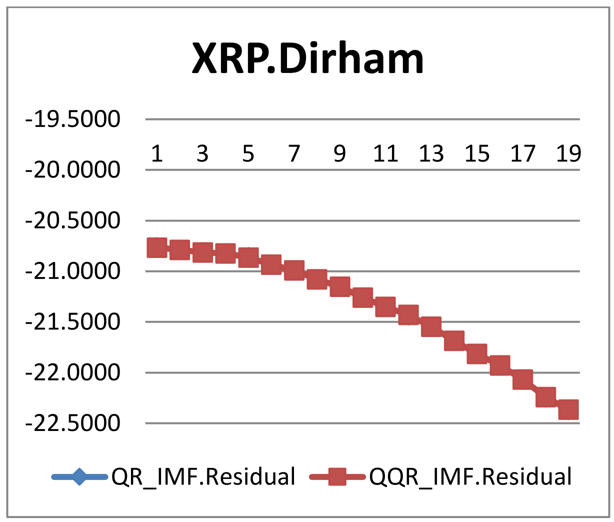

XRP.Dinar
12.0000
10.0000
8.0000
6.0000
4.0000
2.0000
0.0000
1 3 5 7 9 11 13 15 17 19
QR_IMF5
QR_IMF5

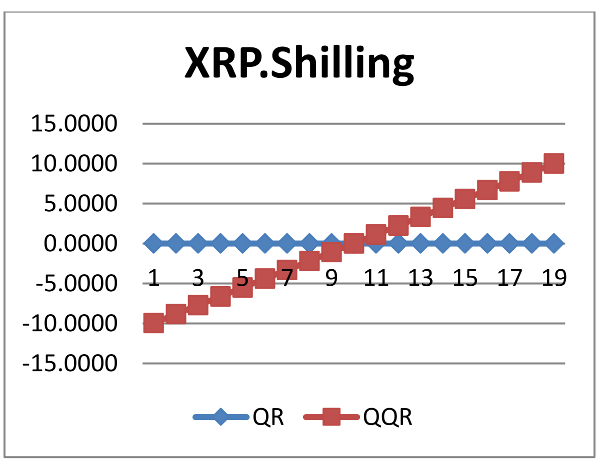

XRP.Dinar
0.0000
-5.0000
-10.0000
-15.0000
-20.0000
1 3 5 7 9 11 13 15 17 19
QR_IMF.Residual
QQR_IMF.Residual

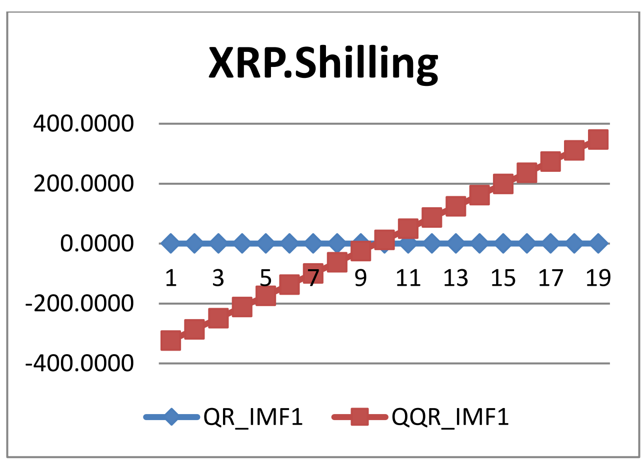

XRP.Dirham
4.0000
3.0000
2.0000
1.0000
0.0000
-1.0000
1 3 5 7 9 11 13 15 17 19
QR
QQR

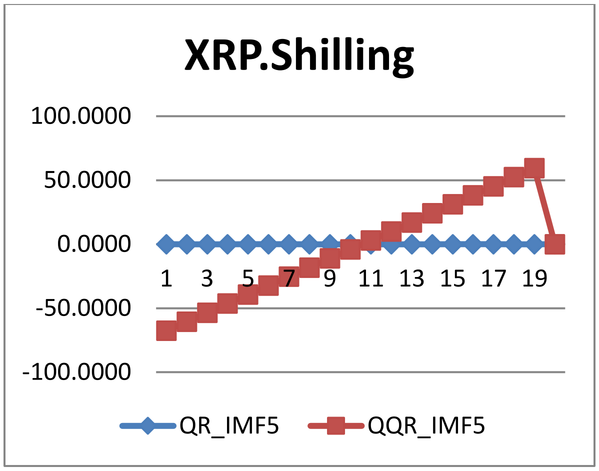

XRP.Dirham
4.0000
3.0000
2.0000
1.0000
0.0000
-1.0000
1 3 5 7 9 11 13 15 17 19
QR_IMF1
QQR_IMF1

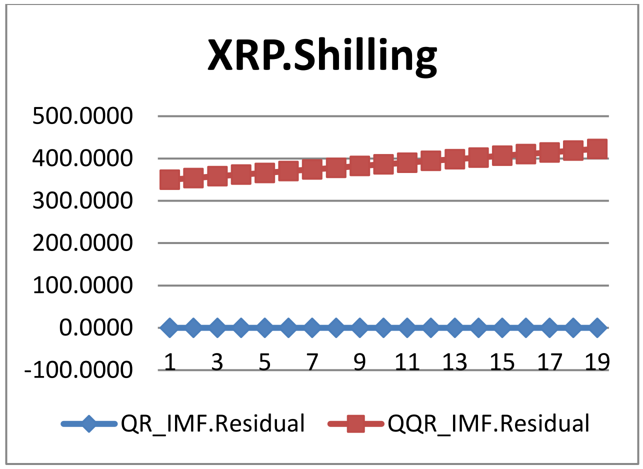

XRP.Dirham
8.0000
6.0000
4.0000
2.0000
0.0000
-2.0000
1 3 5 7 9 11 13 15 17 19
QR_IMF5
QQR_IMF5

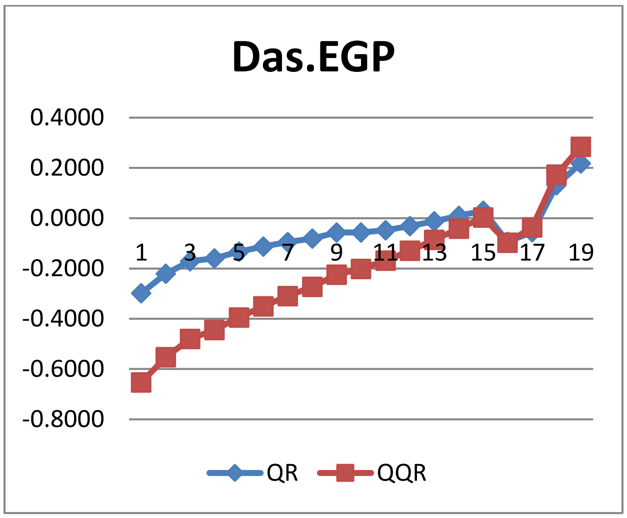

XRP.Dirham
-19.5000
-20.0000
-20.5000
-21.0000
-21.5000
-22.0000
-22.5000
1 3 5 7 9 11 13 15 17 19
QR_IMF.Residual
QQR_IMF.Residual

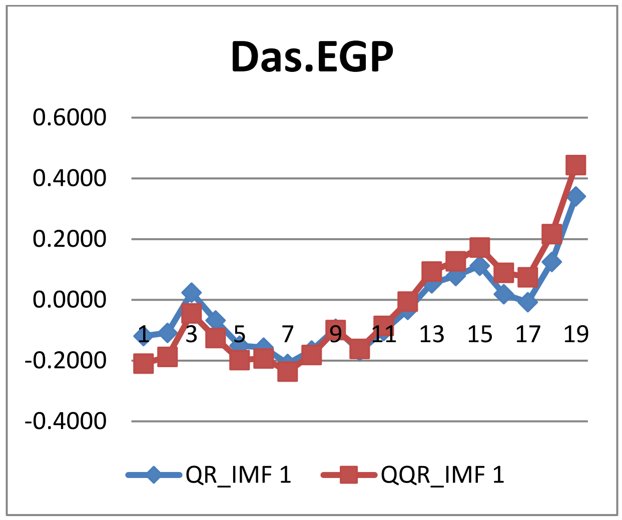

XRP.Shilling
15.0000
10.0000
5.0000
0.0000
-5.0000
-10.0000
-15.0000
1 3 5 7 9 11 13 15 17 19
QR
QQR

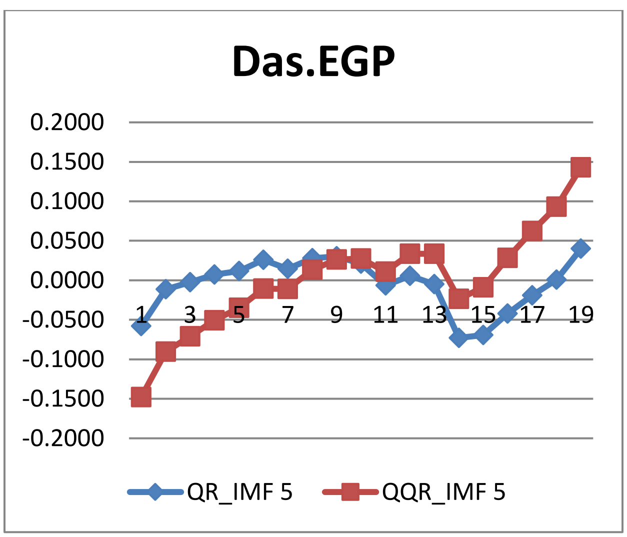

XRP.Shilling
400.0000
200.0000
0.0000
-200.0000
-400.0000
1 3 5 7 9 11 13 15 17 19
QR_IMF1
QQR_IMF1

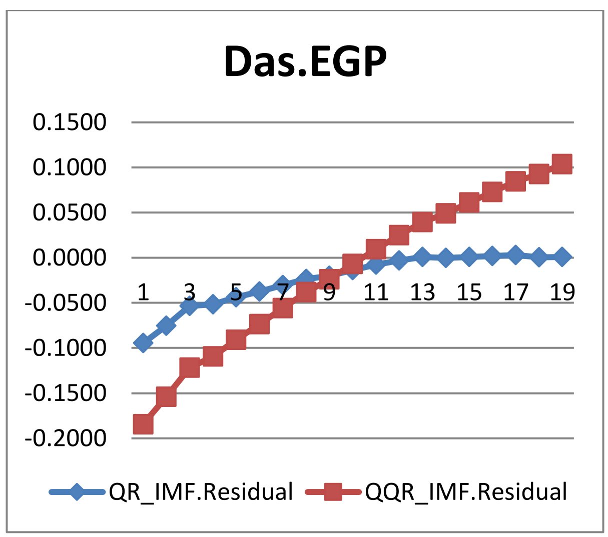

XRP.Shilling
100.0000
50.0000
0.0000
-50.0000
-100.0000
1 3 5 7 9 11 13 15 17 19
QR_IMF5
QQR_IMF5

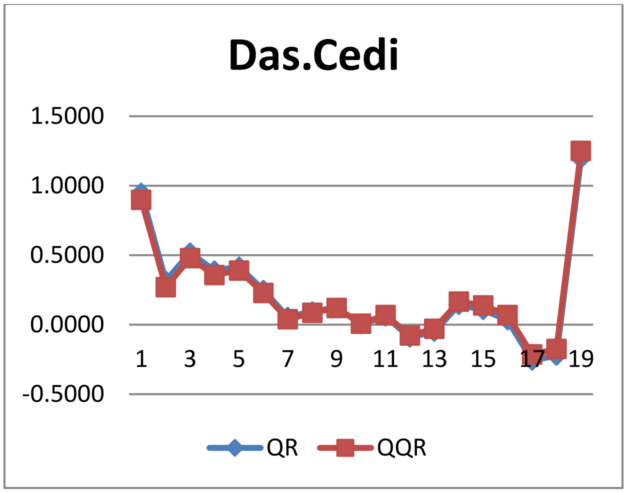

XRP.Shilling
500.0000
400.0000
300.0000
200.0000
100.0000
0.0000
-100.0000
1 3 5 7 9 11 13 15 17 19
QR_IMF.Residual
QQR_IMF.Residual

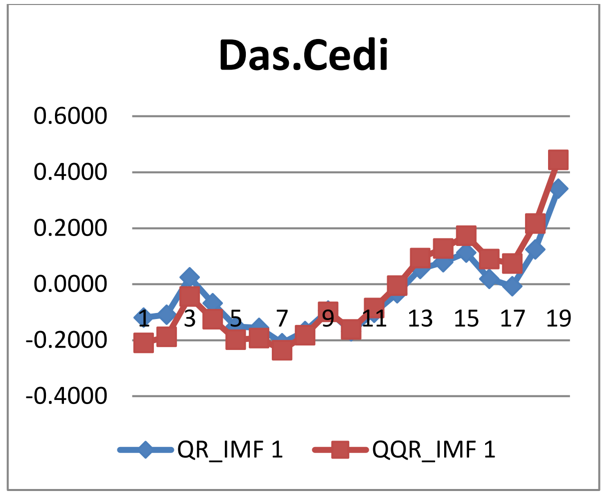

Das.EGP
0.4000
0.2000
0.0000
-0.2000
-0.4000
-0.6000
-0.8000
1 3 5 7 9 11 13 15 17 19
QR
QQR

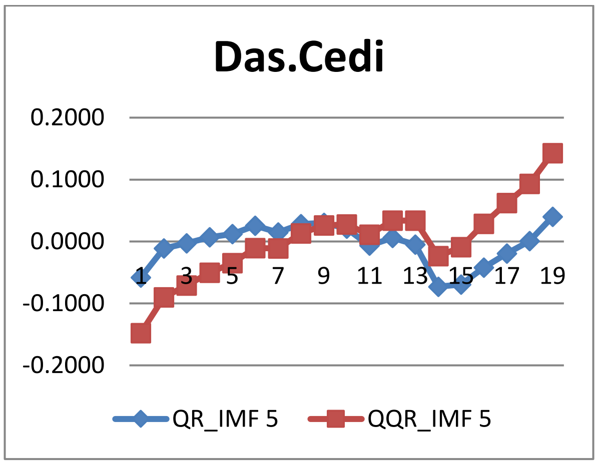

Das.EGP
0.6000
0.4000
0.2000
0.0000
-0.2000
-0.4000
1 3 5 7 9 11 13 15 17 19
QR_IMF 1
QQR_IMF 1

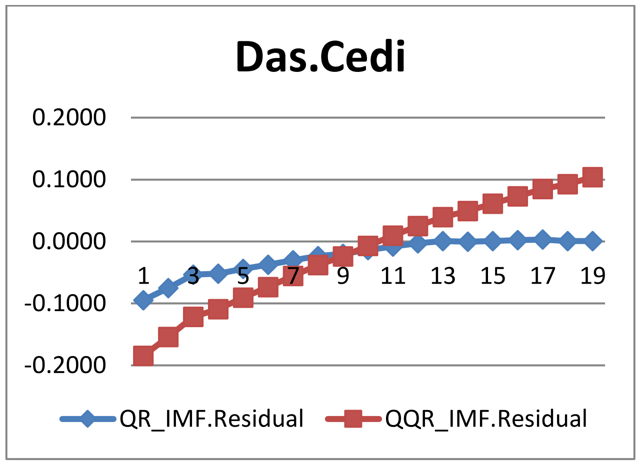

Das.EGP
0.2000
0.1500
0.1000
0.0500
0.0000
-0.0500
-0.1000
-0.1500
-0.2000
1 3 5 7 9 11 13 15 17 19
QR_IMF 5
QQR_IMF 5

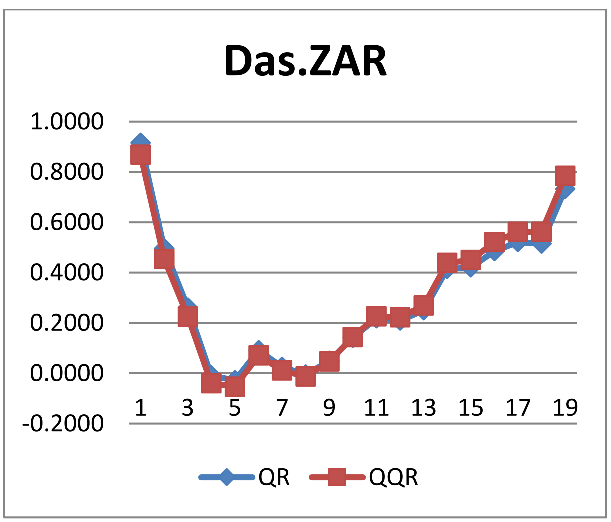

Das.EGP
0.1500
0.1000
0.0500
0.0000
-0.0500
-0.1000
-0.1500
-0.2000
1 3 5 7 9 11 13 15 17 19
QR_IMF.Residual
QQR_IMF.Residual

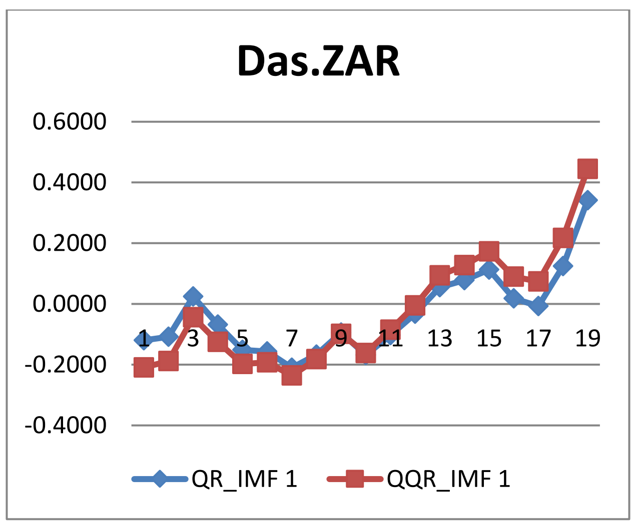

Das.Cedi
1.5000
1.0000
0.5000
0.0000
-0.5000
1 3 5 7 9 11 13 15 17 19
QR
QQR

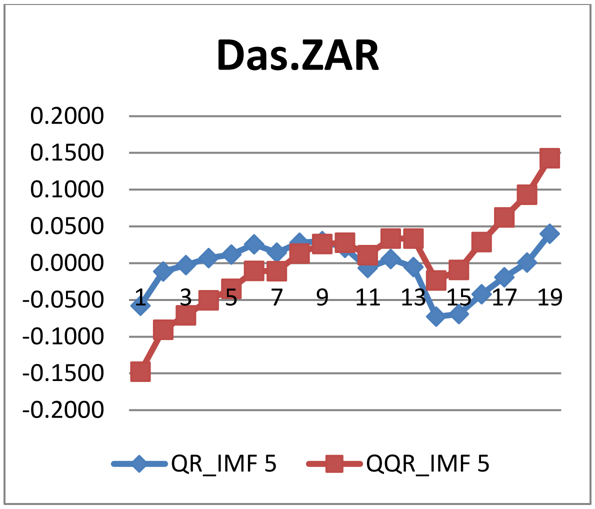

Das.Cedi
0.6000
0.4000
0.2000
0.0000
-0.2000
-0.4000
1 3 5 7 9 11 13 15 17 19
QR_IMF 1
QQR_IMF 1

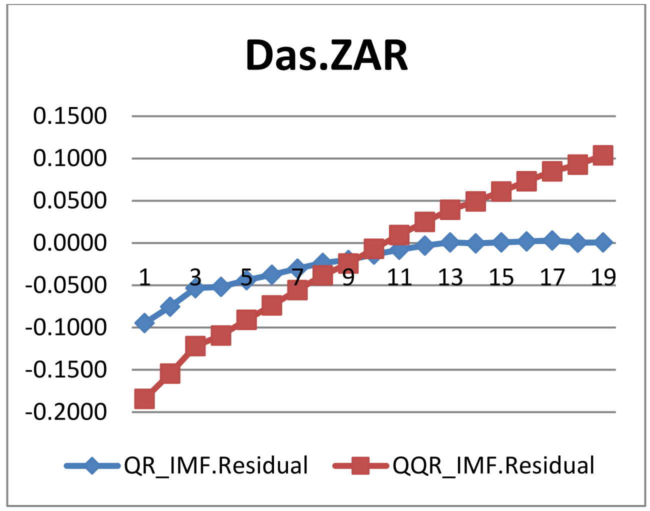

Das.Cedi
0.2000
0.1000
0.0000
-0.1000
-0.2000
1 3 5 7 9 11 13 15 17 19
QR_IMF 5
QQR_IMF 5

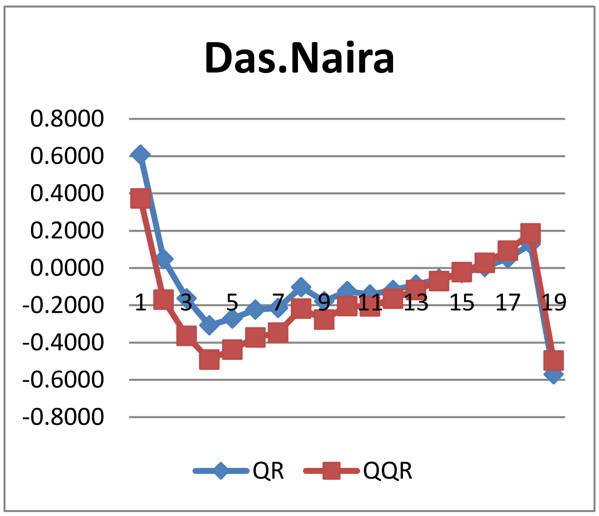

Das.Cedi
0.2000
0.1000
0.0000
-0.1000
-0.2000
1 3 5 7 9 11 13 15 17 19
QR_IMF.Residual
QQR_IMF.Residual

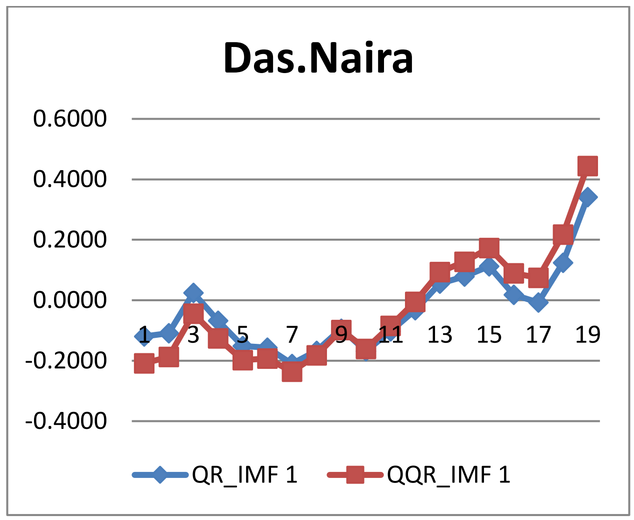

Das.ZAR
1.0000
0.8000
0.6000
0.4000
0.2000
0.0000
-0.2000
1 3 5 7 9 11 13 15 17 19
QR
QQR

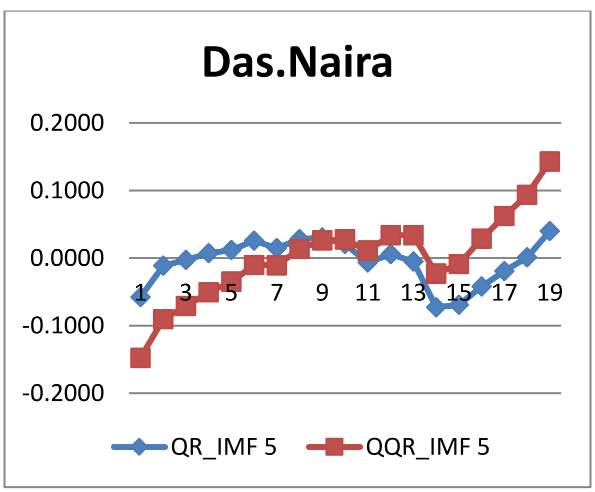

Das.ZAR
0.6000
0.4000
0.2000
0.0000
-0.2000
-0.4000
1 3 5 7 9 11 13 15 17 19
QR_IMF 1
QQR_IMF 1

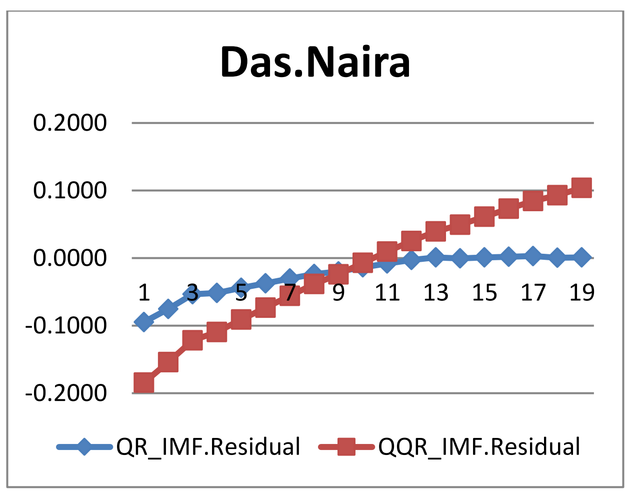

Das.ZAR
0.2000
0.1500
0.1000
0.0500
0.0000
-0.0500
-0.1000
-0.1500
-0.2000
1 3 5 7 9 11 13 15 17 19
QR_IMF 5
QQR_IMF 5

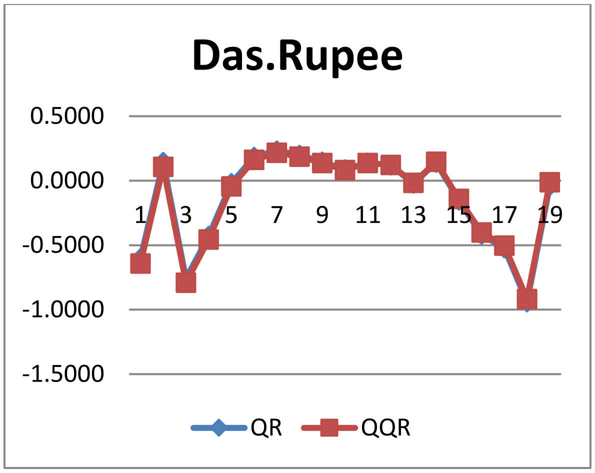

Das.ZAR
0.1500
0.1000
0.0500
0.0000
-0.0500
-0.1000
-0.1500
-0.2000
1 3 5 7 9 11 13 15 17 19
QR_IMF.Residual
QQR_IMF.Residual

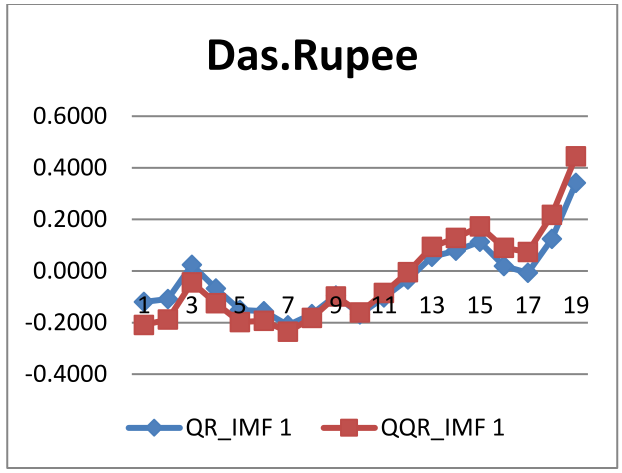

Das.Naira
0.8000
0.6000
0.4000
0.2000
0.0000
-0.2000
-0.4000
-0.6000
-0.8000
1 3 5 7 9 11 13 15 17 19
QR
QQR

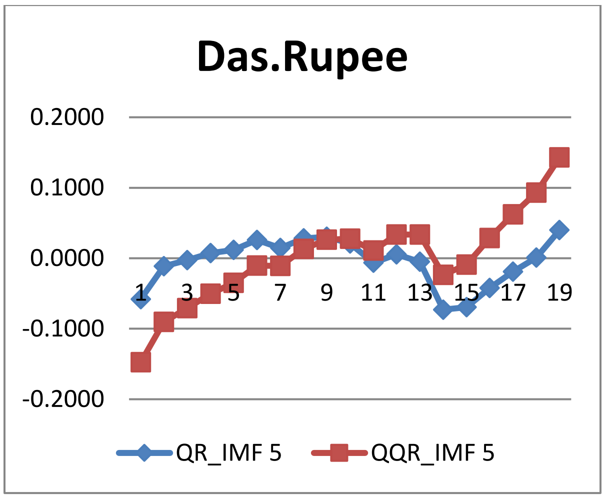

Das.Naira
0.6000
0.4000
0.2000
0.0000
-0.2000
-0.4000
1 3 5 7 9 11 13 15 17 19
QR_IMF 1
QQR_IMF 1

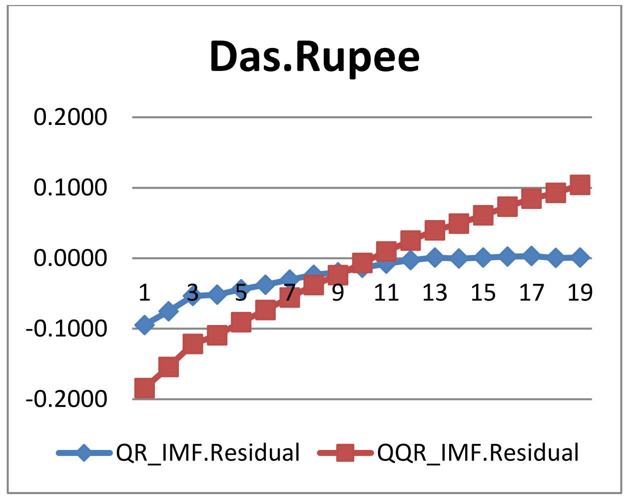

Das.Naira
0.2000
0.1000
0.0000
-0.1000
-0.2000
1 3 5 7 9 11 13 15 17 19
QR_IMF 5
QQR_IMF 5

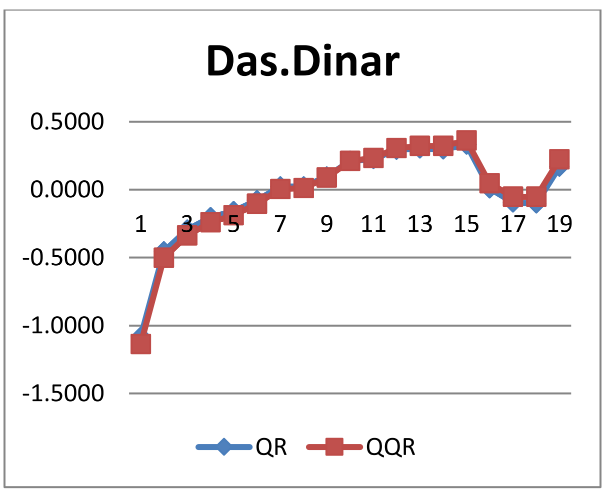

Das.Naira
0.2000
0.1000
0.0000
-0.1000
-0.2000
1 3 5 7 9 11 13 15 17 19
QR_IMF.Residual
QQR_IMF.Residual

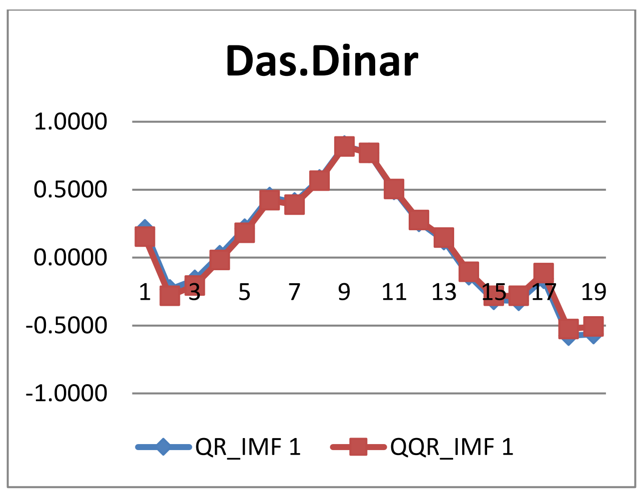

Das.Rupee
0.5000
0.0000
-0.5000
-1.0000
-1.5000
1 3 5 7 9 11 13 15 17 19
QR QQR

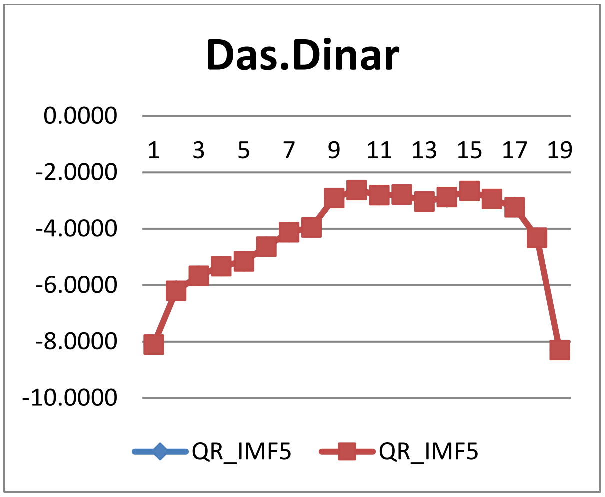

Das.Rupee
0.6000
0.4000
0.2000
0.0000
-0.2000
-0.4000
1 3 5 7 9 11 13 15 17 19
QR_IMF 1 QQR_IMF 1

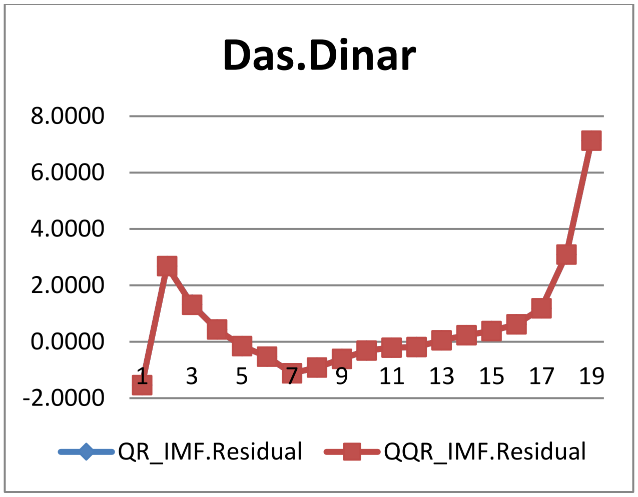

Das.Rupee
0.2000
0.1000
0.0000
-0.1000
-0.2000
1 3 5 7 9 11 13 15 17 19
QR_IMF 5 QQR_IMF 5

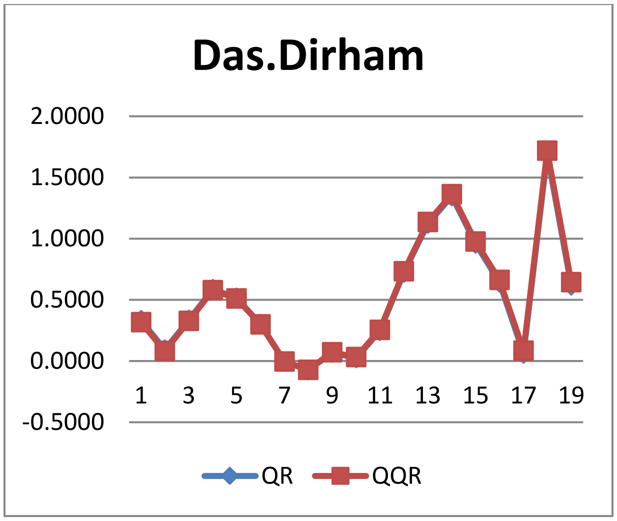

Das.Rupee
0.2000
0.1000
0.0000
-0.1000
-0.2000
1 3 5 7 9 11 13 15 17 19
QR_IMF.Residual QQR_IMF.Residual

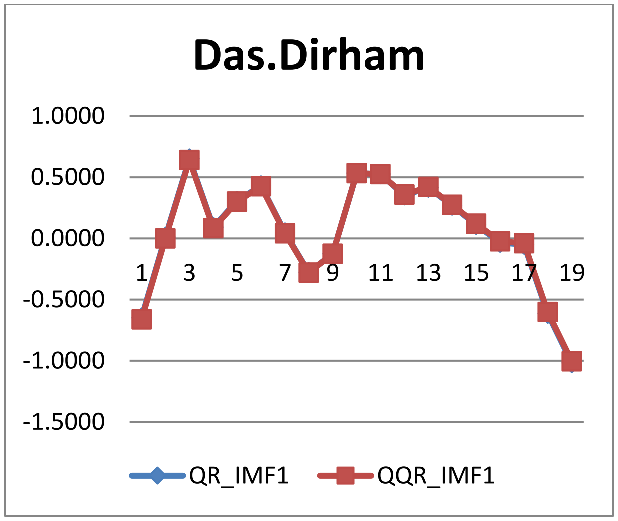

Das.Dinar
0.5000
0.0000
-0.5000
-1.0000
-1.5000
1 3 5 7 9 11 13 15 17 19
QR QQR

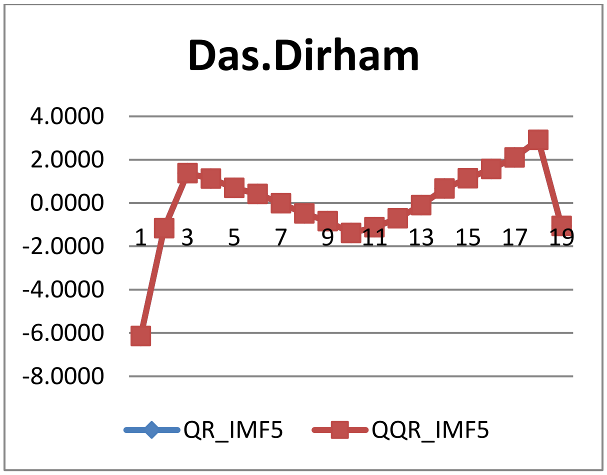

Das.Dinar
1.0000
0.5000
0.0000
-0.5000
-1.0000
1 3 5 7 9 11 13 15 17 19
QR_IMF 1 QQR_IMF 1

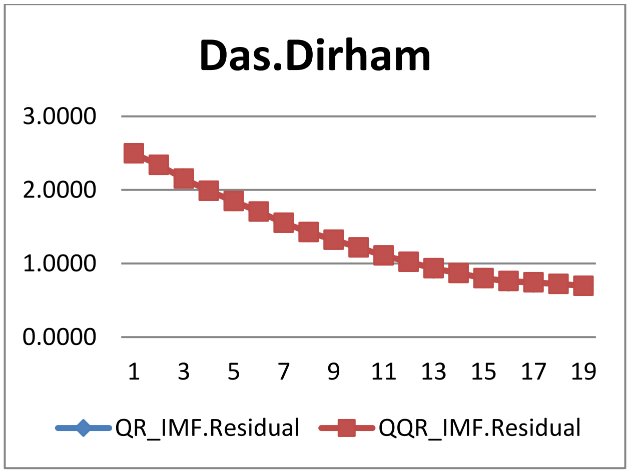

Das.Dinar
0.0000
-2.0000
-4.0000
-6.0000
-8.0000
-10.0000
1 3 5 7 9 11 13 15 17 19
QR_IMF5
QR_IMF5


Das.Dinar
8.0000
6.0000
4.0000
2.0000
0.0000
-2.0000
1 3 5 7 9 11 13 15 17 19
QR_IMF.Residual
QQR_IMF.Residual


Das.Dirham
2.0000
1.5000
1.0000
0.5000
0.0000
-0.5000
1 3 5 7 9 11 13 15 17 19
QR
QQR


Das.Dirham
1.0000
0.5000
0.0000
-0.5000
-1.0000
-1.5000
1 3 5 7 9 11 13 15 17 19
QR_IMF1
QQR_IMF1


Das.Dirham
4.0000
2.0000
0.0000
-2.0000
-4.0000
-6.0000
-8.0000
1 3 5 7 9 11 13 15 17 19
QR_IMF5
QQR_IMF5


Das.Dirham
3.0000
2.0000
1.0000
0.0000
1 3 5 7 9 11 13 15 17 19
QR_IMF.Residual
QQR_IMF.Residual

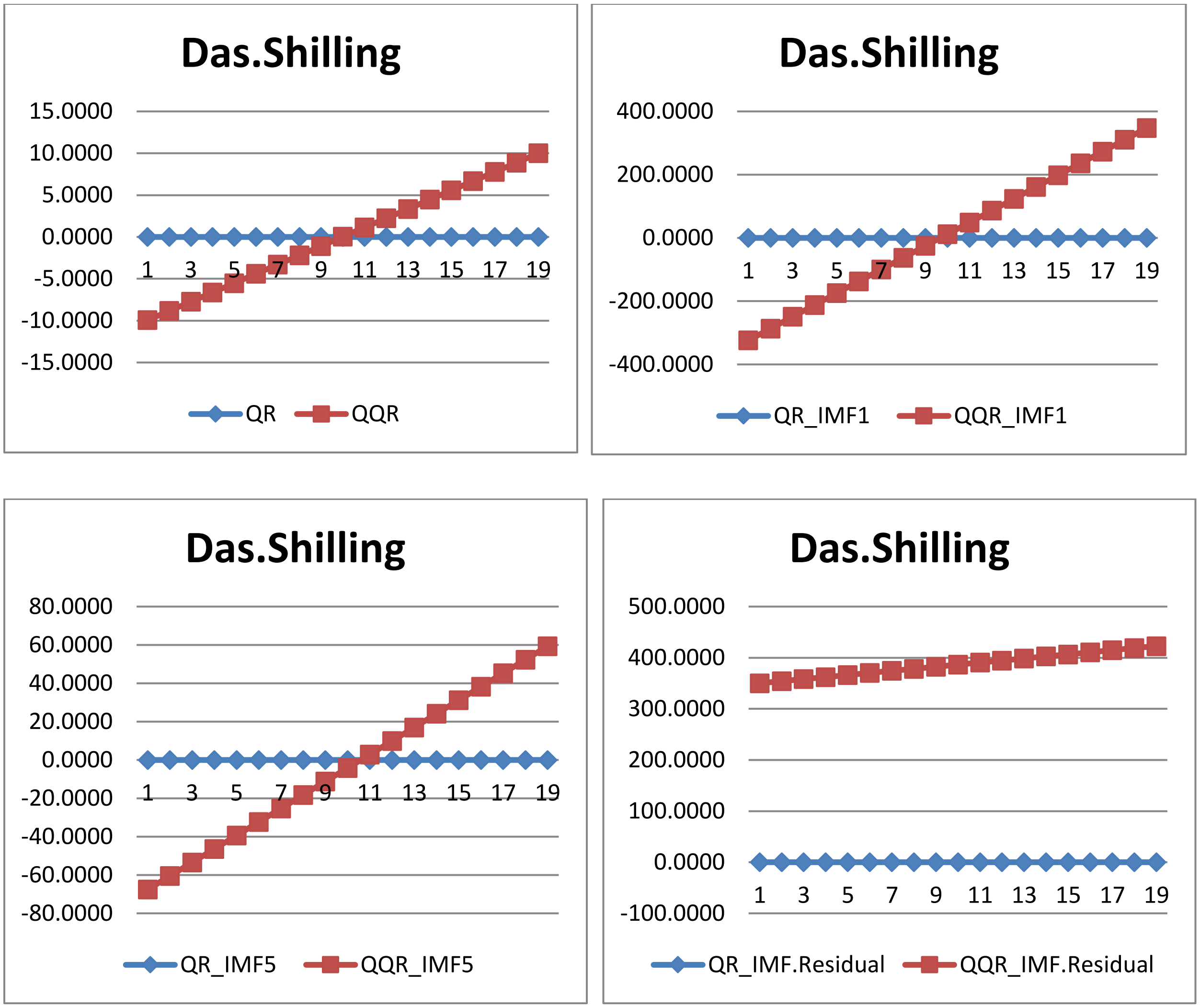


Figure 3. 2: QR-QQR coefficient plots

CHAPTER FOUR

Cryptocurrency Market Risk Analysis

4. Introduction

Following Basel III international regulatory framework on the development of enhanced risk management system for financial institutions after the global financial crises in 2008/2009, the international financial system witnessed the introduction of cryptocurrencies,[42] decentralized digital currencies with excess price volatility (Caporale and Zekokh 2019; Ji, Bouri, Lau, and Roubaud, 2019). Cryptocurrencies have become an inextricable part of the society as they are actively permeating all spheres of life. Businesses are adopting them as alternative payment option by implementing crypto accounting mechanisms into their process and individuals are as well investing in cryptocurrencies and paying for goods and services with them (Corelli, 2018). Subsequently, central banks have been directed by the U.S. Federal Reserve Board Chair to study the risk and benefits of the new innovations (blockchain, cryptocurrencies[43], and distributed ledger technologies) in the financial industry due to the global interest in cryptocurrencies (Chan, Chu, Nadarajah, and Osterrieder, 2017). Besides, the regulation of cryptocurrencies by central banks of many countries are on-going as they are considered as better alternatives to the traditional payment system (Nor, Al-Shaikhli, and Mohammad, 2018).

Consequently, studies have examined the volatility and returns in the cryptocurrency market yet disregarded the volatility of the extreme tails, as well as the time-varying volatility transmissions across cryptocurrencies. Notably, tail events as a distributional property of returns largely reflect extreme market situations. Tail events and the time-varying volatility transmissions across

---

[42] The transaction times and fees, transparency, and lack of geographical boundaries continue to be the cryptocurrency advantage over fiat money and the traditional banking platform (Fantazzini et al., 2016).

[43] Following Chan, Chu, Nadarajah, and Osterrieder (2017), A growing number of Chinese and IT companies are stockpiling cryptocurrencies to defend against ransomware. The UK government in 2016 demonstrated it support for Bitcoin and Blockchain by considering the payment of research grant in Bitcoin. As inidicated in the work of Islam, Nor, Al-Shaikhli, and Mohammad (2018), central banks of many countries are regulating cryptocurrencies.

cryptocurrencies are crucial for understanding the microstructure and functioning of the cryptocurrency market for effective portfolio optimization and risk management.

The empirical literature on risk analysis in the cryptocurrency market largely concentrates on the predictable volatility and unexplored the tail distribution of the cryptocurrencies. For instance, Bouri, Shahzad, and Roubaud (2019) find co-explosivity and multiple bubbles in the cryptocurrency market applying the generalized sup Augmented Dickey–Fuller (GSADF) model. Employing generalized variance decomposition methodology, Corbet, Meegan, Larkin, Lucey, and Yarovaya (2018) examine the interdependence amid traditional assets and cryptocurrencies and finds dependence among the coins. Similarly, Omane-Adjepong, Alagidede, and Akosah (2019) apply MODWT, and ARFIMA-FIGARCH class of models to explore the returns and volatility of cryptocurrencies and finds volatility, trading horizons, and switching regimes in the cryptocurrency market. In a related study, Omane-Adjepong and Alagidede (2019) investigate cryptocurrency market connectedness employing wavelet-based methods and finds that the market interconnectedness of cryptocurrencies is frequency-dependent.

Appling Score Driven-GHSKT and GARCH models to Bitcoin, Ethereum, Litecoin, and Ripple, Catania et al. (2018) find long memory in the volatility process of the cryptocurrencies. The authors show evidence of interdependence among the coins and also report asymmetric reactions of the volatility process to leverage effect. Katsiampa (2019) applied asymmetric diagonal BEKK multivariate GARCH technique together with Student-t distribution to explore the volatilities of Bitcoin, Litecoin, Ripple, Ethereum, and Steller and provided evidence that past covariances of the distributions affected the conditional covariances and that a positive association exists among the coins. The empirical literature show evidence of other approaches including VAR technique used to examine risk in the cryptocurrency market. For example, Yi et al. (2018) use LASSO-VAR3 approach to explore the volatility connectedness among fifty-two cryptocurrencies and confirmed strong interconnection leading to spillover effects across the cryptocurrencies. Similarly, Koutmos (2018) applies VAR methodology to explore the risk and return among cryptocurrencies and indicated interdependence among the coins due to the spillover pattern in the cryptocurrency market. In a related study, Ji et al. (2018) scrutinize the connectedness between seven cryptocurrencies employing VAR model and report that cryptocurrencies are connected in terms of volatility and return and that Steller and Ethereum are the biggest recipients of spillover risks whiles Bitcoin and Litecoin have more influence on other cryptocurrencies. Nevertheless, all the above studies ignored the tail behaviour of the cryptocurrencies.

Studies have also investigated the tail dependence structure and volatility spillovers among cryptocurrencies but missed a comprehensive measure of the risk of tail parameter as well as the time-varrying volatility transmittions across cryptocurrencies. For instance, Gkillas, Bekiros, and Siriopoulos (2018) explore the contemporaneous tail dependence structure of ten cryptocurrencies in a pairwise analysis. Their findings suggest cryptocurrencies as extremely dependent at the tails of the conditional distributions. Incorporating time decomposition to spillover index, Trabelsi (2018) make use of VAR to study the spillover effects across cryptocurrencies and finds the cryptocurrency market connected. In examining the conditional tail-risk in the cryptocurrency market, Borri (2019) implement CoVaR and reports that Ethereum, Bitcoin, Ripple, and Litecoin are highly correlated with each other and exposed to tail-risk. In a different dimension, Huynh et al. (2018) apply both parametric (Copulas with Normal, Gumbel, and Clayton) and nonparametric (Kendall-plots and chi-plots) techniques and reported contagion risks in the cryptocurrency markets. More recently, Huynh (2019**)** apply Granger causality, VAR-SVAR, and Student's-t Copulas to investigate the spillover risks across cryptocurrencies and finds that Bitcoin is the spillover effect recipient while Ethereum is the independent coin in the market. The study further reports a negative change of the coins when the extreme end was captured.

The empirical literature also has studies that attempted to fit and forecast Expected Shortfall (ES) and Value-at-Risk (VaR) in the cryptocurrency market. Notable studies in this regard include Caporale and Zekokh (2018) who implemented GARCH technique to explore the risk in Ethereum, Bitcoin, Ripple, and Litecoin in a one-step ahead prediction of Expected Shortfall and Value-at-Risk. The authors indicated that GARCH technique inaccurately predicts VaR and ES and this may affect effective portfolio optimization, derivative pricing, and risk management, and thus suggested asymmetric distributions for such analysis. In another study, Troster, Tiware, Shahbaz, and Macedo (2018) apply GARCH and GAS technique to explore Bitcoin's return and risk and finds that Generalized Autoregressive Score (GAS) models invloving fat-tailed asymmetric distributional innovations provides finest goodness-of-fit and out-of-sample prediction relative to fat-tailed GARCH techiques. The work of Angelini and Emili (2018) forecast the volatility of six cryptocurrencies implementing the simple GARCH, EGARCH, GARCH-M, TGARCH, and APARCH in a one-step ahead forecast recursively and indicated that the EGARCH performs very well compared to the other GARCH frameworks. Gkillas and Katsiampa (2018) employ the extreme value method to evaluate ES and VaR of five cryptocurrencies including Bitcoin Cash, Ethereum, Bitcoin, Litecoin, and Ripple and report spillover risk among the coins and that Litecoin and Bitcoin are the less risky cryptocurrencies whiles Bitcoin cash is the riskiest.

The studies that modelled the volatility of cryptocurrencies using VAR and GARCH techniques (Trabelsi, 2018; Borri, 2019; Huynh, 2019; Huynh et al., 2018; Caporale and Zekokh, 2018) among others missed a comprehensive measure of the risk for tail parameter of the cryptocurrencies. Notably, GARCH and VAR techniques have the strength to forecast in linear shape but cannot forecast complex structures of asset distribution. The strength of the novel technique copula as a measure of tail risk is because of the ability to model the marginal distributions of returns. However, copulas provide a single parametric measure of the tail of returns. They thus fall short of offering a comprehensive measure of return distributions. The studies that fit and forecast VaR and ES of cryptocurrencies (Angelini and Emili, 2018; Gkillas and Katsiampa, 2018; Troster, Tiware, Shahbaz, and Macedo, 2018; Caporale and Zekokh, 2018) also missed out on the coherent risk measure, Fissler and Ziegel (FZL) joint loss dynamic model for combined VaR and ES in a univariate GAS framework.

Following the work of Catania et al. (2018), the return series of cryptocurrencies display features similar to the return series of traditional assets including extreme observations, leptokurtosis, time-varying asymmetric variability, and heteroscedasticity although cryptocurrencies once invested at the correct period provide immense profit to their owners. Studies including Huynh (2019), Borri (2019), Corbet et al. (2018), and Troster, Tiware, Shahbaz, and Macedo (2018) confirmed the stylized facts noting that the cryptocurrency market comprises billions of USD everyday but exposed to tail risk, excess price fluctuations, and are heavey-tailed which need coherent risk metrics including Expected Shortfall and Value-at-Risk in a framework that can capture all conventional moments with non-normality assumption. In line with Aas and Haff (2006), Value-at-Risk quantifies a quantile of the return distributions of an asset and disregards crucial details regarding the tails after the quantile, whereas Expected Shortfall capture an assets average return conditional that the assets return is beneath the VaR level. Following Patton, Ziegel, and Chen (2019), Basel Committee (2011), and BIS (2013), the Expected Shortfall as a coherent tail risk measure was implemented by Basel III[44] subsequent to the global financial crises to partly substitute or complement Value-at-Risk which provides a restricted measure for tail risk.

As indicated in BIS (2013), the Expected Shortfall is basically Value-at-Risk adjusted to turbulent market situations with adequate regulatory capital for both turbulent and tranquil market states. Nevertheless, unlike VaR, the ES even though is a comprehensive tail risk measure is not comparable (elicitable[45]) and robust in estimation procedures (Artzner, Delbaen, Eber, and Heath, 1999; Burzoni, Peri, and Ruffo, 2017; Fissler and Ziegel, 2016; Cont, Deguest, and Scandolo, 2010; Nolde and Ziegel, 2017; Fissler, Ziegel, and Gneiting, 2015). However, the work of Fissler and Ziegel (2016) depicts that ES and VaR can be jointly elicited at higher order. Accordingly, a joint loss function (hereafter FZL) which allows comparative backtesting relative to Basel III traditional backtesting was proposed by the authors. The extreme price volatility of cryptocurrencies coupled with their exposure to tail risk calls for an estimation of enhanced risk metrics by selecting appropriate asymmetric distributions that can effectively capture skewness, tail risk, and volatility clusters that characterize cryptocurrency returns for effective hedging, risk management, calculate margins, and capital requirement to ensure stability in the global financial system. The thesis contributes to the empirical literature by empirically applying the FZL function for joint VaR and ES to analyze tail risk in the cryptocurrency market. This technique has proven worthy of tail risk quantification to capture skewness, fat-tails, and time-varying shape parameters in cryptocurrency returns. This has implications for economic actors interested in cryptocurrency investments to effectively manage their price risk.

[44] Basel III will be fully phased in 1st January 2027 but has initial implementation date of 1st January 2019 (Patton, Zeigel, and Chen, 2019; https://www.bis.org/press/p181004.htm).
[45] In line with Fissler, Ziegel, and Gneiting (2015) and Patton, Ziegel, and Chen (2019), a risk measure with a loss function is elicitable in that the risk measure minimizes the expected loss and that elicitability is vital since it enables model comparison, ranking, estimation, and selection.

The intuition is drawn from Fisher and Tippett (1928) Extreme Value Theory (EVT)[46] which concerns itself with tail risk quantification and its critical consequences. The theory identifies extreme observations as significant stylised facts for estimating risk measures. In line with Cecchinato (2010), best fitting models can be chosen when the stylized facts of financial series are known as risk can be underestimated when stylized facts including time-varying volatility, heavy tails, skewness, and leptokurtosis are ignored. This may cause a default by participants (eg. firms, financial institutions, investors) leading to financial instability. The outcome from the joint loss function (FZL) suggests Ethereum and Steller as the less risky cryptocurrencies followed by Monero, Das, Litecoin, Bitcoin, and largest for Ripple at both $\alpha = 0.01$ and $\alpha = 0.025$ risk thresholds. In the case of financial institutions, the findings implies that the capital required to absorb losses in cryptocurrencies is least for Ethereum and Steller followed by Monero, Das, Litecoin, Bitcoin, and Ripple at the risk thresholds.

Even though the joint loss dynamic models (FZL) for joint VaR and ES in a univariate GAS framework provides coherent risk measure estimates for comparing the riskiness, required capital, and tail risk of cryptocurrencies for effective portfolio optimization and risk management, it does not capture the time-varying volatility transmissions across cryptocurrencies. Following Omane-Adjepong and Alagidede (2019), and Omane-Adjepong, Alagidede, and Akosah (2019), adequate knowledge of time-varying volatility transmissions are crucial for understanding market microstructure in general and the functioning of the crypto market in particular. Therefore, the chapter further analyzes and captures the time-varying volatility spillovers among the cryptocurrencies. The international financial market has witness cryptocurrencies as new financial instruments (Corbet, Meegan, Larkin, Lucey, and Yarovaya, 2018) with increased growth in both the number and value of the digital currencies (Ji, Bouri, Lau, and Roubaud, 2019) suggesting active investor participation in the cryptocurrency market. However, there is still limited empirical evidence on the time-varying volatility connectedness of the coins.

[46] Ramadhani, Nurrohmah and Novita (2017) contends that the extreme value theory offers strong theoretical underpinning for estimating statistical models that describe extreme events.

Related studies including Omane-Adjepong and Alagidede (2019), Omane-Adjepong, Alagidede, and Akosah (2019), and Trabelsi (2018) have uncovered the time-varying volatility spillovers among cryptocurrencies following the works of Catania et al. (2018), Huynh (2019), Gkillas and Katsiampa (2018), and Chan et al. (2017) that demonstrate that the returns of cryptocurrencies are highly volatile and exhibit stylized facts[47] common in traditional assets. Nevertheless, the cryptocurrencies that mainly transmits and recieves the spillovers across time is still an open question. The cryptocurrency market is shallow and exhibits excess price volatility compared to the traditional financial market, and this can trigger a collapse in the cryptocurrency market should there be fluctuations or shocks to the market leader (Kumar, and Ajaz, 2019). Further, the integration of cryptocurrencies with traditional assets (Henriques and Sadorsky, 2018; Guesmi, Saadi, Abid, and Ftiti, 2019; Klein, Thu, and Walther, 2018) has the potential of increasing investor attention with the chance of excessive liquidity in the cryptocurrency market. Such phenomenon requires extensive knowledge of how leading cryptocurrencies connect over time to help economic agents interested in cryptocurrencies to devise trading and investment strategies for portfolio optimization and risk management.

Accordingly, the chapter further captures the time-varying volatility transmissions across the cryptocurrencies implementing the frequency domain spillover method by Barunik and Krehlik (2018). Employing this approach, we decomposed the contribution of each cryptocurrency to total volatility at varying frequencies and also captured the cryptocurrencies that mainly transmits and recieves spillover effects across time. Our result is suggestive of a strong connection among cryptocurrencies at higher frequencies (short-term) relative to medium and lower frequencies showing Bitcoin, Das, and Litecoin as contributing most to total volatility in the cryptocurrency market. This finding is indicative of contagion risk in the cryptocurrency market, and that diversification and hedging opportunities are low in the short-term. We also find that the net transmitters and receivers of volatility spillover effects across cryptocurrencies are contingent on the frequency under consideration.

[47] As discussed by Catania et al. (2018), Huynh (2019), Gkillas and Katsiampa (2018), Chan, Chu, Nadarajah, and Osterrieder, (2017), the return series of cryptocurrencies depicts the features of traditional assets data including extreme observations, leptokurtosis, time-varying asymmetric volatility, and heteroscedasticity.

The rest of the chapter is organized as follows. Section 4.1 describes the methodology adopted. Section 4.2 provides an explanation of data and statistical properties. Section 4.3 presents the results and discussion on GAS FZL and frequency domain spillover effects. Section 4.4 provides the conclusion and policy implications.

4.1 Methodology

The section describes the approach used to apply the FZL function for ES and VaR jointly and the frequency domain spillover index to the cryptocurrencies. The FZL function is constructed on the univariate GAS framework because both models are score driven. Thus, the GAS model can adequately estimate the FZL due to their fundamental score driven function. The frequency-domain spillover index technique is based on Barunik and Krehlik (2018) approach which allows time-varying volatility spillover across cryptocurrencies.

4.1.1 Univariate GAS model specification

The univariate GAS model otherwise called Dynamic Conditional Score (DCS) and Score Driven (SD) models proposed by Harvey (2013) and Creal et al. (2013) is a comprehensive tool for forecasting assets distributions that are skewed, and fat-tailed with volatility clustering (Troster, Tiware, Shahbaz, and Macedo, 2018; Ardia, Boudt, and Catania, 2018). GAS models introduce a driving mechanism for time-varying parameters by using the score function of the predictive model density at time t instead of only higher moments and means and can model all types of time series data. GAS models encompass popular models such as the autoregressive conditional duration, generalized autoregressive conditional heteroskedasticity, autoregressive conditional intensity, poisson count models with time-varying mean, and the dynamic copula models (Creal, Koopman, and Lucas, 2012). The empirical application of GAS model for financial risk forecasting includes; Oh and Patton (2016) for systematic risk, Blasques, Koopman, Lucas, and Schaumburg (2016b) for spatial econometrics, Harvey and Thiele (2016) for dependence modelling, and Harvey and Sucarrat (2014) for market risk.

The thesis follows the GAS technique suggested by Harvey (2013) and Creal et al. (2013), which is specified as:

$$r_t | F_{t-1} \sim p(r_t; \theta_t) \quad (4.1)$$

where F_{t-1} represents the historical values of cryptocurrency returns (r_t) up to $t-1$, $\theta_t \in \Theta \subseteq \Re^J$ represents a time-varying parameters' vector that fully identifies $p(.)$, and $p(r_t;\theta_t)$ is the returns conditional distribution.

The GAS model in equation (4.1) is specified with autoregressive component as:

$$\theta_{t+1} = \omega + A s_t + B\theta_t, \quad (4.2)$$

$$s_t = S_t(\theta_t)\frac{\partial \log p(r_t;\theta_t)}{\partial \theta_t}, \quad (4.3)$$

where ω is a vector of constant, A, and B are coefficient matrices, s_t is the steps of the scaled-score vector, $\frac{\partial \log p(r_t;\theta_t)}{\partial \theta_t}$ is the score of (4.1) that is appraised at θ_t, and $S_t(\theta_t)$ [48] is a positive definite scaling matrix that adjusts the shape of the score specified as:

$$S_t(\theta_t) = E_{t-1}\left[\frac{\partial \log p(r_t;\theta_t)}{\partial \theta_t}\frac{\partial \log p(r_t;\theta_t)'}{\partial \theta_t}\right]^{-1} \quad (4.4)$$

Where E_{t-1} denotes an expectation with respect to $p(r_t;\theta_t)$.

Equations (4.1) to (4.4) express the GAS technique, and $GAS(1,1)$ is employed for the estimations as used by Mensah and Alagidede (2017), Ardia, Boudt, and Catania (2016, 2018), and Creal et al. (2013).

[48] Note that, as mentioned by Creal et al. (2013), the scaling matrix $S_t(\theta_t)$ can take the form of an identity matrix, inverse fisher information matrix, or pseudo inverse square root, leading to different types of GAS models. Following Troster et al. (2018), the study looks at only the inverse fisher information matrix.

4.1.2 Selected distributions for the univariate GAS model

We specify in the univariate GAS framework distributions[49] such as student-t (STD), skewed-Gaussian (SNORM), skewed-student-t (SSTD) (Fernández and Steel, 1998), asymmetric student-t with two tail decay parameters (AST), asymmetric student-t with one tail decay parameter (AST1) (Zhu and Galbraith, 2010, 2011), and asymmetric Laplace (ALD) (Kotz et al., 2012). The distributions have the flexibility of incorporating the features of assets returns (heavy-tails, skeweness, and volatility clustering) in estimating the FZL for cryptocurrencies returns (McNeil, Frey, and Embrechts, 2015).

4.1.2.1. STD, SSTD, and SNORM

A skewness parameter basically checks asymmetries in the centre of a distribution. In financial risk modelling, STD, SNORM, and SSTD with one tail parameter have been aplied to evaluate fat (tin) tails and skewness in conditional distribution of assets returns (Zhu and Galbraith, 2010; Fernández and Steel, 1998). The STD, SSTD, and SNORM distributions are generally specified as:

$$r_t|\mathcal{F}_{t-1} \sim SSTD(r_t, \mu, \sigma_t, \zeta, v) \tag{4.5}$$

where $\mathcal{F}_{t-1}$ designates autoregressive conditional distribution of r_t, $\mu \in \mathbb{R}$ denotes the location parameter, $\sigma_t > 0$ represents time-varying scale, $\nu > 2$ is shape parameter, and $\zeta > 0$ represents skewness. As used by Ardia, Boudt, and Catania (2016; 2018), and Bauwens and Laurent (2005) we parameterize equation (4.5) so that $Var_{t-1}[r_t] = \sigma_t^2$, and $\mathbb{E}_{t-1}[r_t] = \mu$. We recover as exceptional cases SSTD imposing SNORM when $\zeta = \infty$, and SSTD imposing STD when $\zeta = 1$.

[49] There are several non-Gaussian distributions that can be selected but the chapter employed SNORM, STD, SSTD, AST, AST1, and ALD together with GAS to capture skewed, fat-tails and volatility clusters that characterise cryptocurrency returns (Troster et al., 2018).

4.1.2.2. AST, AST1

The AST distributions have skewness and two tail parameters that check the left (right) tail behaviour of asset returns. The two tail parameters enhance the ability to evaluate assets returns at the tails and this is vital for managing risk (Zhu and Galbraith, 2010). The AST and AST1 distributions in this study have zero location parameter, unity (one) scale parameter with probability density function expressed as:

$$AST(r_t;\theta) = \begin{cases} \frac{1}{\sigma}\left[1+\frac{1}{\vartheta_1}\left(\frac{r_t-\mu}{2\alpha\sigma\mathrm{K}(\vartheta_1)}\right)^2\right]^{-(\vartheta_1+1)/2}, r_t \le \mu \\ \frac{1}{\sigma}\left[1+\frac{1}{\vartheta_2}\left(\frac{r_t-\mu}{2(1-\alpha)\sigma\mathrm{K}(\vartheta_2)}\right)^2\right]^{-(\vartheta_2+1)/2}, r_t > \mu, \end{cases} \tag{4.6}$$

where $\theta = (\alpha, \vartheta_1, \vartheta_2, \mu, \sigma)^T$, α is skewness, $\vartheta_1$is left tail, ϑ_2 is right tail, μ is location, σ is scale parameter, with $\mathrm{K}(\vartheta) = (\Gamma(\vartheta+1)\backslash 2)/[\sqrt{\pi\vartheta}\Gamma(\vartheta/2)]$, for $\{\vartheta_1, \vartheta_2\} \in \vartheta$.

4. 1.2.3. ALD

The most suitable skewed simplification of classical Laplace law which robustly measure fat-tail, skewness, and leptokurtic characteristics of financial returns is ALD (Kotz et al., 2012; Zhao et. al., 2015) with probability density function specified as:

$$f(r_t;\theta,\sigma,\kappa) = \frac{\kappa(1-\kappa)}{\sigma} exp\left(-\frac{(r_t-\theta)}{\sigma}[\kappa - I(r_t \le \theta)]\right), \tag{4.7}$$

where $-\infty < \theta < \infty$ is location parameter, $\sigma > 0$ is scale parameter, and $0 < \kappa < 1$is skewness with indication function as $I(.)$.

We employ Kotz et al. (2012), Blasques, Koopman, and Lucas (2014) maximum likelihood estimator jointly with one-step ahead forecast to estimate the parameters in all the distributions.

4.1.3. FZL Function for joint VaR and ES

The two typical techniques applied to compute risk in asset returns include Value-at-Risk (VaR) and Expected Shortfall (ES) (Jorion, 1997; Ardia, Boudt, and Catania, 2018). However, these two standard risk measures fall short in their own rights under the properties of a coherent risk measure (Acerbi and Szekely, 2014; Acerbi and Tasche, 2002). Value-at-Risk is elicitable utilizing the quantile loss function but not sub-additive while ES cannot be elicited since it has no loss function but coherent and comonotonically additive (Ziegel, 2016; Bellini and Bignozzi, 2015). Nonetheless, Fissler and Ziegel (2016) demonstrate that the ES and VaR combined is elicitable and therefore built a joint loss dynamic model refered to as FZL for them. The FZL function which allows comparative backtesting replaces the traditional backtesting in Basel III. Following Fissler and Ziegel (2016), we implement the FZL technique for combined VaR and ES in a univariate GAS framework.

As discussed by Artzner et al. (1999), the VaR $\alpha \in (0,1)$ for a random variable X with a distribution function F is defined as:

$$VaR_{\alpha}(X) = inf\{x|F(x) \leq \alpha\}. \tag{4.8}$$

ES is specified as:

$$E(X|X > VaR_{\alpha}) \tag{4.9}$$

As indicated in Fissler and Ziegel (2016), ES and VaR can jointly be elicited as the values of $e_t and\ v_t$ that curtail the sample average of the loss function:

$$FZ(r_t, v_t, e_t, \alpha, G_1, G_2) \equiv (d_t - \alpha)\left(G_1(v_t) - G_1(r_t) + \frac{1}{\alpha}G_2(e_t)v_t\right)$$

$$-G_2(e_t)\left(\frac{1}{\alpha}d_t r_t - e_t\right) - G_{2(e_t),} \tag{4.10}$$

where $G_1$and G_2 are strictly increasing, $G_2 = 0$, and $\mathbb{G}_2' = G_2$. Following Ardia et al. (2018), Patton et al. (2017), we assume strictly inverse values for VaR and ES by setting $G_1(x) = 0$ and $G_2(x) =$

$-1/_{x}$. We specify the associated FZ loss function for predicting VaR and ES at α risk level at time t as:

$$FZL_t^\alpha \equiv \frac{1}{\alpha ES_t^\alpha} d_t(r_t - VaR_t^\alpha) + \frac{VaR_t^\alpha}{ES_t^\alpha} + log(-ES_t^\alpha) - 1, \tag{4.11}$$

for $ES_t^\alpha \leq VaR_t^\alpha \leq 0$. We average FZ losses over the OOS period to calculate the QL.

4.1.4. FZL backtesting and model comparison

The thesis follows a typical out-of-sample exercise using in-sample (IS) period of length M to estimate model parameters, forecast conditional distribution in the out-of-sample (OOS) period H, and compare models based no their out-of-sample performance. Thus, h-step (($h = 1$) ahead daily prediction of the return distribution of cryptocurrencies at time $M + h$ is generated along with corresponding FZL level recursively until the end of the series T.

Following the work of Blazsek and Hernandez (2018), we test the forecasting ability of the distributional properties as equal predictors of the FZL forecast applying the Mariano and Preve (2012), and Diebold and Mariano (2002) multivariate model (MDM) and calculate the mean absolute error (MAE) $1/T_f \sum_{t=1}^{T_f} |p_t - \bar{p}_t|$ between predicted and realized values to rank and select the distributions with lowest MAE to backtest their FZL forecast.

To validate forecast accuracy and scrutinize that the unconditional and conditional left-tail of log-returns are correctly covered, we implement on the FZL forecasts at risk levels[50] $\alpha = 0.01; and\ \ \alpha = 0.25$, four backtesting procedures including correct unconditional coverage (UC), correct conditional coverage (CC), dynamic quantile (DQ), and quatile loss (QL) by Kupiec (1995), Christoffersen (1998), Engle and Manganelli (2004), and Koenker and Bassett (1978) respectively. The UC checks if the left-tail of the marginal distribution of returns are correctly covered. The CC investigates the conditional density of returns. The DQ concurrently tests for

[50] The BIC (2013) and Ardia, Boudt, and Catania (2016, 2018) postulate that the FZL model is computed by typically setting the risk threshold to $\alpha = 0.01$; $\alpha = 0.025$ for which a loss in an asset is not anticipated to be exceeded at a given period of time.

conditional and unconditional coverage and is more robust relative to the UC and CC. The QL helps in choosing the finest FZL model if two models realize CC/UC.

4.1.5 Spillover frequency connectedness

The chapter further investigates the volatility spillovers across cryptocurrencies employing Barunik and Krehlik (2018) frequency domain spillover index which is based on Dew-Becker and Giglio (2016) spectral representations of variance decomposition. The technique is theoretically linked to Diebold and Yilmaz (2012), however, the frequency-domain interconnectedness was initially proposed by Barunik and Krehlik (2016) and extended by Barunik and Krehlik (2018).

In line with Barunik and Krehlik (2016), the generalized impulse response function is decomposed considering the spectral behaviour of series X_t as:

$$S_x(w) = \sum_{h=0}^{\infty} E(X_t X_{t-h}) e^{-ihw} = \psi\left(e^{ihw}\right), \tag{4.12}$$

where w is frequency, ∞ is infinite horizon connectedness, and $\psi\left(e^{-ihw}\right) = \sum_{h=0}^{\infty} \psi\left(e^{-ihw}\right)$. The unconditional generalized forecast error variance decomposition (GFVED) is calculated on a particular frequency w as:

$$(\Theta(w))_{i,j} = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{\infty} (\psi(e^{-ihw}) \Sigma)_{i,j}^2}{\sum_{h=1}^{\infty} (\psi\left(e^{-ihw}\right) \Sigma \psi\left(e^{ihw}\right))_{i,j}}, \tag{4.13}$$

which is standardized to:

$$(\Theta(w))_{i,j} = \frac{(\Theta(w))_{i,j}}{\sum_{j=1}^{k} (\Theta(w))_{i,j}}. \tag{4.14}$$

We follow Barunik and Krehlik (2016) and express accumulative connectedness table over an arbitrary frequency band $d = (a;, b)$ as:

$$(\Theta_d)_{i,j} = \int_a^b (\Theta(w))_{i,j} dw. \tag{4.15}$$

We then specify the overall connectedness within a frequency band d as:

$$C^d = \frac{\sum_{i=1, i \neq j}^{k} (\Theta_d)_{i,j}}{\sum_{i,j} (\Theta_d)_{i,j}} = 1 - \frac{\sum_{i=1}^{k} (\Theta_d)_{i,i}}{\sum_{i,j} (\Theta_d)_{i,j}}. \tag{4.16}$$

In the spectral band $d = (a; , b)$, high connectedness is exhibited when C^d is close to unity. The contribution of a market $(i \neq j)$ to another i on the spectral band d is measured using the *within from* connectedness specified as:

$$C_{i\leftarrow}^{d} = \sum_{j=1, i\neq j}^{k} (\Theta_d)_{i,j}. \tag{4.17}$$

whereas the contribution to a market $(i \neq j)$ from another i on the spectral band d is measured using the *within to* connectedness specified as:

$$C_{i\rightarrow}^{d} = \sum_{j=1, i\neq j}^{k} (\Theta_d)_{i,j}. \tag{4.18}$$

In line with Diebold and Yilmaz (2012), we measure total connectedness as $Sg(H) = \sum_d C^d$ and pairwise connectedness as $\theta_{ij} \neq \theta_{ji}$.

4.2 Data description and preliminary analysis

The chapter focuses on seven cryptocurrencies: Bitcoin (BTC), Ethereum (ETH), Litecoin (LTC), Das (DASH), Ripple (XRP), Monero (XMR), and Steller (XLM) for the cryptocurrency market risk analysis. The cryptocurrencies sampled have been in existence for the past five years with market capitalization above 1 billion USD. These cryptocurrencies are among the top fifteen currencies by market capitalization and can proxy for the cryptocurrency market. Data spans 10th August 2015 to 18th February 2019 at daily frequency and gleaned from CoinMarketCap. The availability of Ethereum data determined the start date of the period of analysis. Ethereum, which is the second largest market, started trading on 7th August 2015. Daily returns are computed as change in log price for Monday-to-Friday series.

For the joint loss function (FZL) for combined VaR and ES, we divide the period of analysis (10/8/2015 – 18/2/2019) into in-sample (IS) (10/8/2015 – 11/12/2017) showing the estimation period and out-of-sample (OOS) (12/12/2017 – 18/2/2019) depicting the forecasting period as per out-of-sample predicting exercise. We select the OOS as the forecast length since backtesting periods are based on the forecast length. As prescribed by BIS (2013), the OOS is a minimum of one year with 99 and 97.5 percentiles.

Table 4.1 shows the descriptive statistics of log returns of the seven cryptocurrencies. Panel one of Table 4.1 displays the composite descriptive statistics with average daily return ranging between 0.2% (Bitcoin/Ethereum) and 0.55% (Steller). The daily volatility of the currencies vary between 0.18% and 0.88% for Bitcoin/Ethereum and Steller respectively. Except for Bitcoin and Ethereum which show negative skeweness, all other cryptocurrencies exhibit positive skewness. In panel two, the in-sample descriptive statistics shows the lowest average return of -0.026% (Ripple) and highest return of 0.084% (Ethereum) with daily volatility ranging between 0.03% (Das) and 0.059% (Ethereum). Bitcoin is negatively skewed but positive skeweness in all other cases. As can be observed from the out-of-sample descriptive statistics displayed in panel three, there is positive average return for Ethereum but negative average returns in all other cryptocurrencies, daily volatility varies between 0.02% (Bitcoin) and 0.099% (Ripple), with Bitcoin, Ethereum, Monero depicting negative skewness. There is a general leptokurtosis and skewness across board indicating non-normality in the returns series of cryptocurrencies. The Shapiro-Wilk test also rejects the normality assumption at all conventional levels of significance confirming the abnormality of cryptocurrency returns. These provide evidence in support of the use of asymmetric distributions in performing risk analysis in the cryptocurrency market.

Table 4. 1: Summary statistics of cryptocurrencies

Composite	**Bitcoin**	**Ethereum**	**Litecoin**	**Ripple**	**Das**	**Monero**	**Steller**
Observ.	885	885	885	885	885	885	885
Mean	0.002	0.002	0.0007	0.0026	0.0021	0.0026	0.0055
Variance	0.0018	0.0018	0.0038	0.0044	0.0035	0.0044	0.0088
Skewness	-0.2356	-0.2356	1.2575	4.5132	0.2983	4.5132	2.1108
Kurtosis	4.7234	4.7234	12.1915	76.4051	3.383	76.4051	17.9168
Normtest.W	0.914	0.914	0.8425	0.5981	0.9463	0.5981	0.8568
Normtest.p	0	0	0	0	0	0	0
In-sample							
Observ.	590	590	590	590	590	590	590
Mean	0.0055	0.0084	0.0042	-0.0026	0.007	0.0047	0.0123
Variance	0.0016	0.0059	0.0037	0.0016	0.003	0.0052	0.0104
Skewness	-0.1033	0.7087	1.3649	0.8047	0.3981	0.9364	2.2475

Kurtosis	6.8739	4.0117	15.9088	6.2963	3.7041	6.2583	17.7008
Normtest.W	0.8752	0.9254	0.7784	0.8876	0.9373	0.9128	0.8447
Normtest.p	0	0	0	0	0	0	0
Out-of-sample							
Observ.	295	295	295	295	295	295	295
Mean	-0.0048	-0.006	-0.0062	0.0128	-0.0078	-0.006	-0.008
Variance	0.002	0.0037	0.0041	0.0099	0.0043	0.0046	0.0053
Skewness	-0.3551	-0.0008	1.1381	3.6817	0.3133	-0.1485	0.6361
Kurtosis	1.7404	1.6286	6.5447	42.5311	2.8943	1.196	5.5911
Normtest.W	0.9616	0.9661	0.9217	0.553	0.9556	0.9813	0.9351
Normtest.p	0	0	0	0	0	0	0

Period of analysis: 10/8/2015 – 18/2/2019 (Out-of -sample: 12/12/2017 – 18/2/2019, In-sample: 10/8/2015 – 11/12/2017). Observ. – observations, Shapiro-Wilk test rejects the normality assumption at all conventional levels of significance.

4.3 Results and Discussion

To conduct the cryptocurrency market risk analysis, we, first of all, evaluate and forecast the tail risk of cryptocurrencies implementing the GAS FZL functions drawn from both Value-at-Risk (VaR) and Expected Shortfall (ES). We then examine the time-varying volatility spillover amongst the cryptocurrencies implementing frequency domain spillover index technique. The results and discussions for FZL functions and spillover effects are displayed in sections 4.3.1 and 4.3.2 respectively.

4.3.1 FZL functions

4.3.1.1 Predicting univariate GAS FZL functions

We employ six varying distributional innovations (STD, SNORM, SSTD, AST, AST1, and ALD)[51] specified in a univariate GAS model to a one-step ahead FZL in the OOS period at $\alpha = 0.01$ and $\alpha = 0.025$ levels. We next applied MDM to the competitive distributions to test the null hypothesis of equal predictive adequacy (EPA) of the distributions. Except for Litecoin at 1% risk

[51]The distributions have the flexibility of capturing all the stylized facts including fat-tails, skewness, and volatility clusters of cryptocurrency returns (McNeil, Frey, and Embrechts, 2015) .

level, the MDM test of EPA in Table 4.2 did not reject the null hypothesis of EPA at both 1% and 2.5% risk levels of the cryptocurrencies. This confirms the robustness of the six asymmetric distributions as adequate tail risk measures for cryptocurrencies. However, all the distributional innovations cannot be selected as models of choice in our study since Litecoin was rejected at the 1% level and this requires further investigations. Table 4.2 exhibits the EPA by the MDM test.

Table 4. 2: Multivariate Diebold-Mariano (2012) test of model equal predictive accuracy

Cryptocurrency	α	W	p-value
Bitcoin	1%	44.213	1.00
	2.5%	75.524	1.00
Ethereum	1%	37.979	1.00
	2.5%	58.048	1.00
Litecoin	1%	**-429.38**	**0.000**
	2.5%	777.07	1.00
Ripple	1%	37.965	1.00
	2.5%	111.92	1.00
Das	1%	25.211	0.9999
	2.5%	44.686	1.00
Monero	1%	23.129	0.9997
	2.5%	42.397	1.00
Steller	1%	45.452	1.00
	2.5%	341.43	1.00

Except for Litecoin at 1% threshold (in boldface), the MDM fails to reject the null hypothesis of EPA for all the cryptocurrencies at the risk levels. W denote MDM test statistics.

4.3.1.2 MAE ranking of univariate GAS FZL forecasts per distributional innovation

The six distributional innovations can be ranked in order of predictive ability since the FZL has consistent scoring function which allows comparative tests on competing models. Therefore, we follow Blazsek and Hernández (2018) and quantify the MAE for each distributional innovation across currencies at the risk thresholds to order them, which is displayed in Table 4.3. Innovations with the lowest value of Mean Average Error are elected. As can be observed in Table 4.3, the

ALD is the best innovation as it shows the lowest MAE at both $\alpha = 0.01$ and $\alpha = 0.025$ thresholds supporting Taylor (2019), who asserts that the ALD is suitable for estimating and forecasting the ES and VaR jointly. The thesis affirms the ALD as robust and most appropriate skewed simplified classical laplace law as indicated in the works of Kotz et al. (2012) and Zhao et al. (2015). Nonetheless, in a couple of cases, the SNORM also showed up as the finest innovation at the risk thresholds. The AST1 and AST exhibit equal and higher MAE affirming the work of Zhu and Galbraith (2010) which show that the distributions can equally establish the profit (loss) in an assets returns at the right(left) tails. As evident in Table 4.3, we select the ALD and SNORM distributions to backtest their FZL estimate.

Table 4. 3: MAE ranking of univariate GAS FZL forecasts per distributional innovation

	α = 1%		**α =2.5%**	
	MAE	**Rank**	**MAE**	**Rank**
Bitcoin (BTC)				
snorm	3.1607	2	2.9999	2
std	3.9029	3	3.3759	4
sstd	3.9763	4	3.3655	3
ast	5.8154	5	4.2653	5
ast1	5.8154	5	4.2653	5
ald	**2.6573**	**1**	**2.8173**	**1**
Ethereum (ETH)				
snorm	**1.7797**	**1**	**1.9538**	**1**
std	3.0435	3	2.7099	3
sstd	3.0859	4	2.6973	2
ast	5.2219	5	3.8057	5
ast1	5.2219	5	3.8057	5
ald	2.1056	2	2.8195	4
Litecoin (LTC)				
snorm	2.1092	2	2.2452	2
std	2.8942	4	2.5461	4
sstd	2.8028	3	2.4974	3
ast	5.8835	5	4.3849	5

ast1	5.8834	5	4.3848	5
ald	**1.9575**	**1**	**2.1843**	**1**
Ripple (XRP)				
snorm	4.4938	5	3.5477	5
std	2.4745	3	2.5393	3
sstd	2.4007	2	2.4929	2
ast	3.4519	4	3.2062	4
ast1	3.4519	4	3.2062	4
ald	**2.1808**	**1**	**2.4527**	**1**
Das (DASH)				
snorm	2.900	3	2.7387	3
std	2.8931	2	2.759	4
sstd	2.9778	4	2.7259	2
ast	4.113	5	3.2817	5
ast1	4.113	5	3.2817	5
ald	**2.1163**	**1**	**2.2972**	**1**
Monero (XMR)				
snorm	2.200	2	2.203	2
std	2.3881	4	2.4007	4
sstd	2.3862	3	2.3839	3
ast	3.7679	5	3.1475	5
ast1	3.7678	5	3.1475	5
ald	**1.7868**	**1**	**2.1214**	**1**
Steller (XLM)				
snorm	1.4993	2	**1.6549**	**1**
std	2.098	4	2.2129	4
sstd	2.0391	3	2.1228	3
ast	3.5717	5	3.084	5
ast1	3.5717	5	3.084	5
ald	**1.4405**	**1**	1.7435	2

The boldface shows the finest distributions.

4.3.1.3 Backtesting and model ranking of FZL function

We backtested the FZL forecast of the finest distributional innovations (ALD and SNORM) implementing the CC, UC, DQ, and QL at the risk levels. Nevertheles, all the backtesting models (excluding DQ) show evidence that the ALD and SNORM at the respective α levels[52] are correctly specified. The test statistics of CC, UC, and DQ show p-values and models with p-values closs to unity are preferred. The QL test statistics provides loss values and distributions with smaller Quantile losses are preferred. Table 4.4 exhibits the results for backtesting.

As can be seen in Table 4.4, the distributions can robustly estimate the FZL forecast for cryptocurrencies as they are not rejected by the UC and CC test as inadequate and incorrectly specified at the α levels although the DQ test did not accept them as correctly specified. The outcome of DQ test affirms the study of Braione and Scholtes (2016) which claims that the DQ is robust and generally accounts for a temporal interdependence among series of violations. In estimating the single value FZL to enable comparison of the cryptocurrencies in terms of their risk exposure and capital required for loss absorption, the distributions that are elected by any of the UC, CC, and DQ as appropriately specified is further analysed. Hence, we subject the ALD and SNORM at the α levels for futhur investigations.

The Quantile Loss ratios computed as $QLR = QL_{1\%}/QL_{2.5\%}$ from the FZL forecast backtested enable us to compare the performance of the 1% and 2.5% models in line with Basel III and this is shown in the last column of Table 4.4. As Ardia et al. (2016c, 2018) note, the 1% model performs better than the 2.5% when $QLR < 1$ and vice versa. It is evident in Table 4.4 that the 1% FZL models performs better than the 2.5% FZL models varying between 9% to 61% in five cryptocurrency markets excluding Bitcoin (2%), and Das (1%) which provides supports in favour of the 2.5% FZL model.

[52] In order to be consistent, we carry all tests at the same α levels in line with 99 and 97.5 percentiles of the FZL forecasts.

Table 4. 4: Backtesting results of selected univariate GAS FZL models

Cryptocurrency	Distribution	α	UC	CC	DQ	QL	QL ratio	QL ratio (%)
Bitcoin	ald	1%	2.45(0.12)	2.70(0.26)	284.75(0.00)	0.587981		-0.02*
	ald	2.5%	2.51(0.11)	3.53(0.17)	251.72(0.00)	0.575433	1.021806	
Ethereum	snorm	1%	0.35(0.55)	0.38(0.83)	200.09(0.00)	0.096554		0.38
	snorm	2.5%	0.28(0.59)	0.55(0.77)	187.04(0.00)	0.155926	0.619229	
Litecoin	ald	1%	1.19(0.27)	1.36(0.50)	471.52(0.00)	0.293236		0.09
	ald	2.5%	0.02(0.87)	0.36(0.83)	226.57(0.00)	0.323699	0.905891	
Ripple	ald	1%	1.19(0.27)	5.13(0.08)	278.39(0.00)	0.075128		0.46
	ald	2.5%	1.89(0.17)	1.98(0.37)	118.30(0.00)	0.138782	0.541342	
Das	ald	1%	0.34(0.56)	0.45(0.79)	307.06(0.00)	0.410231		-0.01*
	ald	2.5%	0.86(0.35)	1.57(0.46)	220.21(0.00)	0.404281	1.014719	
Monero	ald	1%	2.45(0.12)	2.70(0.25)	500.14(0.00)	0.20253		0.39
	ald	2.5%	0.34(0.56)	0.91(0.63)	304.48(0.00)	0.333679	0.606961	
Steller	ald	1%	0.001(0.98)	6.79(0.03)	83.57(0.00)	0.041684		0.61
	snorm	2.5%	5.63(0.02)	5.66(0.06)	69.24(0.00)	0.106585	0.39109	

**The 2.5% FZL model performs better than the 1% FZL model when QL ratio show negative percentage.*

4.3.1.4. Characteristic FZL estimates for 1% and 2.5% univariate GAS models

The characteristic FZL (CFZL) values (single values of FZL) was obtained from the unconditional[53] location parameters from the OOS FZL forecast of the ALD and SNORM to compare the risk exposure and capital required for loss absorption of the cryptocurrencies. As displayed in Table 4.5, the values for CFZL are ordered ascendingly with the smallest negative CFZL ranked 1 and 7 for the highest inverse. Lower values are preferred to higher ones. We can observe from Table 4.5 that Ethereum shows the lowest level of risk at 1% followed by Steller, Monero, Das, Litecoin, Bitcoin and largest for Ripple suggesting that among the cryptocurrencies studied, the risk exposure of Ethereum is less and thus requires the lowest capital for loss absorption whereas Ripple is the riskiest and requires the highest capital for loss absorption.

[53] Conditional parameters are the case in which the scale parameter is set to be time-varying in the typical GAS models used for FZL estimation and forecasting. The unconditional parameters have not time-varying assumptions.

Nonetheless, at the 2.5% level, Steller exhibit the lowest risk profile and thus require the lowest capital for loss absorption followed by Ethereum, Monero, Das, Litecoin, Bitcoin, and largest for Ripple.This suggests Steller as less risky relative to other cryptocurrencies whiles Ripple is the riskiest. The results show Monero, Das, Litecoin, Bitcoin, and Ripple maintaining their third, fourth, fifth, sixth, and seventh positions respectively at both 1% and 2.5% risk thresholds whiles Ethereum and Steller alternate the first and second positions. Our results suggest that at 1% and 2.5% risk levels, Ethereum and Steller are the safest cryptocurrencies which provide evidence against the study of Gkillas and Katsiampa (2018) which reported Litecoin and Bitcoin as cryptocurrencies with the least risk esposure adopting the extreme value technique to estimate VaR and ES of five cryptocurrencies.

In line with the findings of this study, economic actors (eg. investors, hedge funds, market makers, traders) in the cryptocurrency market may adopt the rankings in this study to enhance their trading and investment strategies for optimum utility and minimized risk. The thesis affirms the study of Patton et al. (2019) and Owusu-Junior and Alagidede (2020) which contends that FZL values drawn from both VaR and ES provide a better empirical risk modelling than either VaR and ES separately. Our approach offers coherent risk measure estimates which can be used by market participants interested in cryptocurrencies for effective portfolio optimization and risk management.

Table 4. 5: Characteristic FZL forecast values for selected distributional innovations

α = 1%				**α =2.5%**			
Cryptocurrency	**Innovation**	**CFZL**	**Rank**	**Cryptocurrency**	**Innovation**	**CFZL**	**Rank**
Ethereum	snorm	-1.2098	1	Steller	snorm	-1.1231	1
Steller	ald	-1.5654	2	Ethereum	snorm	-1.3340	2
Monero	ald	-1.9100	3	Monero	ald	-2.2004	3
Das	ald	-1.9913	4	Das	ald	-2.2727	4
Litecoin	ald	-2.0031	5	Litecoin	ald	-2.3274	5
Bitcoin	ald	-2.5041	6	Bitcoin	ald	-2.7877	6
Ripple	ald	-2.5631	7	Ripple	ald	-2.8269	7

CFZL – characteristic FZL forecast

4.3.2 Spillover frequency connectedness

Even though the characteristic FZL values drawn from both VaR and ES provides a better empirical risk modelling for comparing the capital requirement, tail risk, and riskiness of the seven cryptocurrencies for effective portfolio optimization and risk management, it does not capture the volatility spillover frequency connectedness across the cryptocurrencies. The empirical literature generally suggests a stronger inter-market relationship during periods of high volatility leading to spillover effects which negatively affect portfolio diversification and stability in the global financial system (Shahzad et al., 2018; King and Wadhwani, 1990). Following the approach of Barunik and Krehlik (2018), and as used in the works of Qarni, Gulzar, Fatima, Khan, and Shafi (2019), and Tiwari, Cunado, Gupta, and Wohar (2018), we uncover the time-varying volatility spillovers among the cryptocurrencies. We, first of all, estimate a seven variable VAR with two (2) lag lengths. We then construct the directional spillover connectedness index, the pairwise net directional spillover connectedness, and the rolling window spillover and results discussed in sections 4.3.2.1, 4.3.2.2, and 4.3.2.3 respectively. As noted by Barunik and Krehlik (2016, 2018), the spillover table has 4 frequency bands and we choose the first and second bands[54] (freq. 1 and 2) as short-term connectedness, third band[55] (freq. 3) as medium-term connectedness, and fourth band[56] (freq. 4) as long-term connectedness of cryptocurrencies.

4.3.2.1 Directional spillover connectedness

The directional spillover connectedness table was constructed by implementing a variance decomposition forecasting horizon (H) of 100 period ahead since Barunik and Krehlik (2018) approach does not support a forecasting horizon less than 100 (H<100) and outcomes displayed in Table 4.6. From the decomposed spillover exhibited in Table 4.6, we observe that the shortest horizon (freq. 1) contributes most (30.46%) of total connectedness followed by freq. 2 which is also a short-time horizon (7.88%). The medium-term (freq. 3) contributes (2.57%) to total connectedness whiles the long-term movement of the currencies (freq. 4) contributes only (0.43%) to total connectedness. We can conclude from this result that the total spillover connectedness

[54] The spillover table for first band (freq. 1) 3.14 to 0.79 roughly corresponds to 1 to 4 days, and second band (freq. 2) 0.79 to 0.20 roughly corresponds to 4 to 16 days.
[55]The spillover table for third band (freq. 3) 0.20 to 0.05 roughly corresponds to 16 to 64 days.
[56] The spillover table for fourth band (freq. 4) 0.05 to 0.00 roughly corresponds to more than 64 days.

index among the seven cryptocurrencies is high at higher frequencies than medium and lower frequencies suggesting contagion risk and that portfolio diversification benefits are low in the short-term. The result for total spillover connectedness supports the findings of Trabelsi (2018) which incorporates time-decomposition to VAR to investigate the volatility spillover effects among cryptocurrencies and reports connectedness within the cryptocurrency market.

The across frequencies FROM_ABS (TO_ABS) exhibit the cryptocurrency that highly contributes to (receives from) the total spillover effects across frequencies. From Panels 1 and 2 of Table 4.6, it is evident that Bitcoin is the major contributor and receiver of total spillover effects in the short-term (freq. 1 and 2), followed by Litecoin, Das, Monero, Ethereum, Steller, and Ripple. However, Panels 3 and 4 which show the medium-term (freq. 3) and long-term (freq.4) respectively depict Litecoin, Bitcoin, and Das markets as the major contributors and receivers of total spillover effects. This finding is in line with Ji, Bouri, Lau, and Roubaud (2018, 2019) who document Bitcoin and Litecoin as the two largest transmitters and receivers of spillover effects from other cryptocurrencies. Ripple neither contributes to nor receives spillover effects from any of the cryptocurrencies suggesting Ripple as the independent coin among the cryptocurrencies which contradict the findings of Huynh (2019) that support Ethereum as the independent coin in the cryptocurrency market applying Granger causality, VAR-SVAR, and Student's-t Copulas. From this result, we suggest that Bitcoin, Litecoin, and Das markets should be given regulatory initiatives since these cryptocurrencies contribute and receive most of the total volatility spillovers in the cryptocurrency market.

The difference between TO_ABS and FROM_ABS (TO_ABS – FROM_ABS) measures the net directional spillover connectedness (Net_ABS) of cryptocurrencies across time. This shows the cryptocurrencies that are net transmitters (positive values) and recipients (negative values) of spillover effects to (from) other cryptocurrencies across frequencies. We observe from Table 4.6 that the shortest horizon (freq.1) shows Bitcoin, Litecoin, and Das as the net transmitters of spillover effects, whiles Ethereum, Ripple, Monero, and Steller are the net recipients of spillover effects. Nevertheless, frequencies 2, 3, and 4 depict Bitcoin, Ethereum, and Steller as the net transmitters of spillover effects whiles Litecoin, Ripple, Das, and Monero are the net recipients of spillover effects. We once again confirm the findings of Ji, Bouri, Lau, and Roubaud (2019) which shows Bitcoin and Litecoin as the largest net transmitters of spillovers and Ethereum and Das as the largest net spillover effect receivers.

Table 4. 6: Directional Spillover index results

Freq. 1	**BTC**	**ETH**	**LTC**	**XRP**	**DASH**	**XMR**	**XLM**	**FROM_ABS**	**FROM_WTH**
BTC	32.50	4.76	13.20	0.02	9.39	9.44	4.55	5.91	7.95
ETH	7.10	42.73	7.34	0.01	7.51	6.21	2.39	4.36	5.87
LTC	13.49	4.97	32.86	0.00	8.08	7.31	5.48	5.62	7.56
XRP	0.09	0.02	0.08	71.41	0.20	0.05	0.16	0.09	0.11
DASH	9.91	5.52	8.40	0.02	38.30	8.95	3.91	5.24	7.06
XMR	11.07	4.47	8.37	0.01	9.32	40.77	2.94	5.17	6.96
XLM	6.87	2.61	8.66	0.01	6.16	4.16	48.42	4.07	5.47
TO_ABS	6.93	3.19	6.58	0.01	5.81	5.16	2.77	**30.46**	
TO_WTH	9.33	4.30	8.85	0.01	7.82	6.94	3.73		40.99
Net _ABS	1.0226	-1.1708	0.9610	-0.0747	0.5647	-0.0089	-1.2938		
Freq. 2									
BTC	8.29	1.16	3.56	0.00	1.82	2.34	1.72	1.51	8.19
ETH	1.24	12.99	1.45	0.00	1.72	1.14	0.82	0.91	4.92
LTC	3.55	1.40	8.66	0.00	1.94	2.04	2.54	1.64	8.86
XRP	0.04	0.00	0.01	19.19	0.01	0.00	0.06	0.02	0.09
DASH	2.32	1.69	2.24	0.00	7.87	2.16	1.80	1.46	7.89
XMR	2.46	1.69	2.07	0.01	2.20	7.28	1.06	1.36	7.33
XLM	1.86	0.95	2.09	0.00	1.08	0.88	10.02	0.98	5.30
TO_ABS	1.64	0.98	1.63	0.00	1.25	1.22	1.14	**7.88**	
TO_WTH	8.86	5.33	8.83	0.02	6.77	6.61	6.18		42.59
Net _ABS	0.1246	0.0741	-0.0050	-0.0144	-0.2071	-0.1334	0.1613		
Freq. 3									
BTC	2.74	0.38	1.17	0.00	0.56	0.77	0.59	0.50	8.03
ETH	0.39	4.37	0.45	0.00	0.51	0.32	0.27	0.28	4.49
LTC	1.18	0.48	2.83	0.00	0.59	0.66	0.86	0.54	8.73
XRP	0.01	0.00	0.00	7.39	0.00	0.00	0.02	0.01	0.09
DASH	0.81	0.57	0.76	0.00	2.44	0.71	0.63	0.50	8.06
XMR	0.81	0.56	0.69	0.00	0.69	2.26	0.36	0.45	7.23
XLM	0.62	0.31	0.66	0.00	0.31	0.27	3.15	0.31	5.05
TO_ABS	0.55	0.33	0.53	0.00	0.38	0.39	0.39	**2.57**	
TO_WTH	8.86	5.32	8.67	0.02	6.16	6.32	6.35		41.68

Net _ABS	0.0509	0.0514	-0.0039	-0.0043	-0.1177	-0.0564	0.0799		
Freq. 4									
BTC	0.46	0.06	0.19	0.00	0.09	0.13	0.10	0.08	8.01
ETH	0.06	0.73	0.07	0.00	0.08	0.05	0.04	0.05	4.45
LTC	0.20	0.08	0.47	0.00	0.10	0.11	0.14	0.09	8.71
XRP	0.00	0.00	0.00	1.25	0.00	0.00	0.00	0.00	0.08
DASH	0.14	0.10	0.13	0.00	0.40	0.12	0.11	0.08	8.07
XMR	0.14	0.09	0.12	0.00	0.11	0.37	0.06	0.07	7.22
XLM	0.10	0.05	0.11	0.00	0.05	0.05	0.52	0.05	5.03
TO_ABS	0.09	0.05	0.09	0.00	0.06	0.06	0.07	**0.43**	
TO_WTH	8.85	5.32	8.65	0.02	6.11	6.29	6.35		41.58
Net _ABS	0.0086	0.0089	-0.0007	-0.0007	-0.0202	-0.0095	0.0136		

***Note**: Freq. 1& 2 = short-term (1 to 16 days), freq. 3 = medium-term (16 to 64 days), and freq. 4 = long-term (> 64 days) connectedness of the currencies. WTH and ABS = within and absolute in the estimated system respectively.*

4.3.2.2 Pairwise directional spillover connectedness

Furthermore, we investigate the results in more detail by constructing a net-pairwise directional spillover connectedness of the currencies and results shown in Table 4.7. The net-pairwise directional spillover effect from one currency to another is measured by subtracting the second variable from the first. A negative (positive) value depicts that the first cryptocurrency is a net receiver (transmitter) of spillover effects from (to) the corresponding cryptocurrency. It is evident from Table 4.7 that the net-pairwise directional spillover effects switch between positive and negative connectedness indicating that at any given point of time, each cryptocurrency can act as a net transmitter or receiver of spillover effects. Specifically, all Bitcoin pairs (BTC-ETH, BTC-LTC, BTC-XRP, BTC-DASH, BTC-XMR, BTC-XLM) exhibit negative connectedness across frequencies indicating Bitcoin as net spillover effect recipient from corresponding currencies.

The Ethereum pairs ETH-LTC and ETH-DASH (except freq. 3 and 4), ETH-XRP (except freq. 1), show positive connectedness depicting Ethereum as net spillover effect transmitter to corresponding currencies across the frequencies, however, except for freq. 1 of ETH-XMR pairs, Ethereum receives spillover effects from Monero and Steller. The Litecoin pairs LTC-XRP, LTC-DASH, LTC-XMR, and LTC-XLM (only freq.1) indicate Litecoin as net receiver of spillover effects from corresponding cryptocurrencies across time. The Steller pairs XRP-DASH (except freq. 3), XRP-XMR (only freq. 1) and XRP-XLM show Steller as a net transmitter of spillover effects to corresponding currencies. DASH-XMR (freq. 2 and 3), DASH-XLM (freq. 2 to 4), and XMR-XLM (freq. 2 to 4) depict Das and Monero as the net transmitters of spillover effects to corresponding currencies. From this result, we can conclude that the net connectedness between pairs of cryptocurrencies is mostly negative and Bitcoin is the largest spillover effect receiver from other cryptocurrencies. This finding provides evidence in support of Huynh (2019) study which indicates Bitcoin as the spillover effect recipient in the cryptocurrency market.

Table 4. 7: Net-pairwise Spillover

Currencies	**Freq. 1**	**Freq. 2**	**Freq.3**	**Freq.4**
BTC-ETH	-0.3334	-0.0123	-0.0014	-0.0002
BTC-LTC	-0.0402	0.0024	-0.0012	-0.0002
BTC-XRP	-0.0105	-0.0047	-0.0014	-0.0002
BTC-DASH	-0.0736	-0.0724	-0.0355	-0.0061
BTC-XMR	-0.2334	-0.0171	-0.0058	-0.0010
BTC-XLM	-0.3316	-0.0206	-0.0055	-0.0009
ETH-LTC	0.3382	0.0075	-0.0038	-0.0007
ETH-XRP	-0.0011	0.0001	0.0000	0.0000
ETH-DASH	0.2838	0.0039	-0.0094	-0.0017
ETH-XMR	0.2488	-0.0795	-0.0346	-0.0059
ETH-XLM	-0.0323	-0.0183	-0.0050	-0.0008
LTC-XRP	-0.0116	-0.0016	-0.0006	-0.0001
LTC-DASH	-0.0456	-0.0426	-0.0244	-0.0042
LTC-XMR	-0.1510	-0.0040	-0.0047	-0.0008
LTC-XLM	-0.4547	0.0631	0.0286	0.0048
XRP-DASH	0.0257	0.0007	-0.0001	0.0000
XRP-XMR	0.0053	-0.0011	-0.0006	-0.0001
XRP-XLM	0.0205	0.0086	0.0029	0.0005
DASH-XMR	-0.0525	-0.0057	0.0023	0.0004
DASH-XLM	-0.3219	0.1024	0.0460	0.0078
XMR-XLM	-0.1738	0.0261	0.0130	0.0022

***Note**: Freq. 1& 2 = short-term (1 to 16 days), freq. 3 = medium-term (16 to 64 days), and freq. 4 = long-term (> 64 days) connectedness of the currencies.*

4.3.2.3 Rolling window analysis

To better appreciate and visualize the direction, strength, and structure of spillovers, we capture the time-varying net-pairwise directional and overall spillover connectedness among the cryptocurrencies using the rolling window approach. Figure 4.2 exhibits the overall spillover connectedness of cryptocurrencies at frequency bands. The horizontal axis of the graphs depicts the period of analysis where 200, 400, 600, and 800 represent connectedness in 2015/2016, 2016/2017, 2017/2018, and 2018/2019 respectively which corresponds to our period of analysis. The vertical axis indicates the level of connectedness of the system. We observe that the overall spillover connectedness at the various frequency bands (Figure 4.2) confirms the results of the directional spillover connectedness (Table 4.6) which indicates that cryptocurrencies are highly connected in the short-term than medium and long-terms. This result is in line with previous studies (Barunik and Krehlik, 2018; Tiwari, Cunado, Gupta, and Wohar, 2018; Qarni, Gulzar, Fatima, Khan, and Shafi, 2019; Belke and Gokus, 2014) that documents a time-varying volatility spillover effects among traditional assets. Even though the returns of cryptocurrencies exhibit the stylized facts[57] of traditional assets (Huynh, 2019), the cryptocurrency market is shallow and exhibits excess price volatility compared to the traditional financial market which can trigger a collapse in the cryptocurrency market. In line with our findings we argue that economic agents interested in cryptocurrencies should devise risk management strategies to mitigate losses in the short-term.

[57] As discussed by Catania et al. (2018), Huynh (2019), Gkillas and Katsiampa (2018), Chan, Chu, Nadarajah, and Osterrieder, (2017), the return series of cryptocurrencies depicts the features of traditional assets data including extreme observations, leptokurtosis, time-varying asymmetric volatility, and heteroscedasticity.

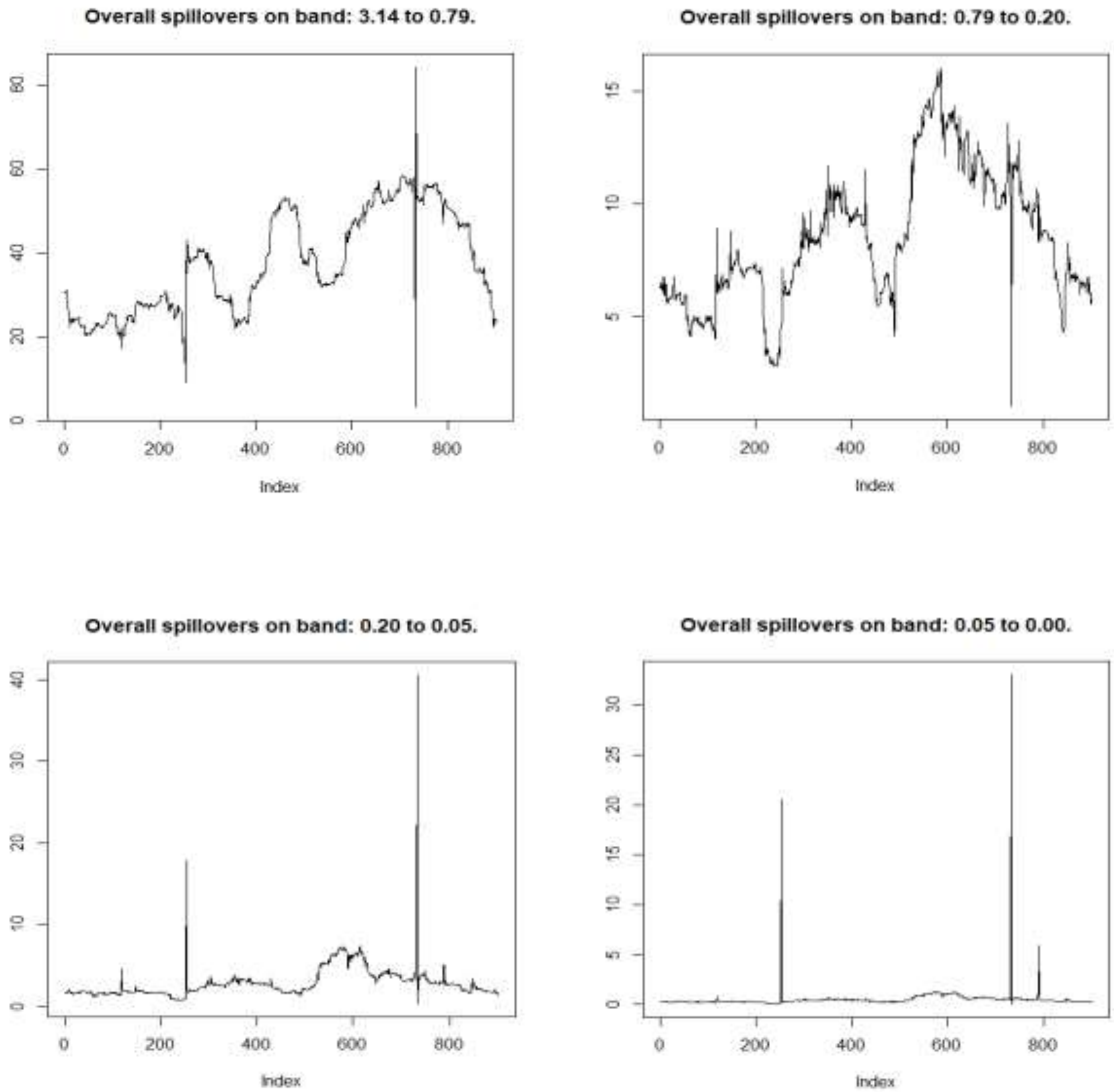
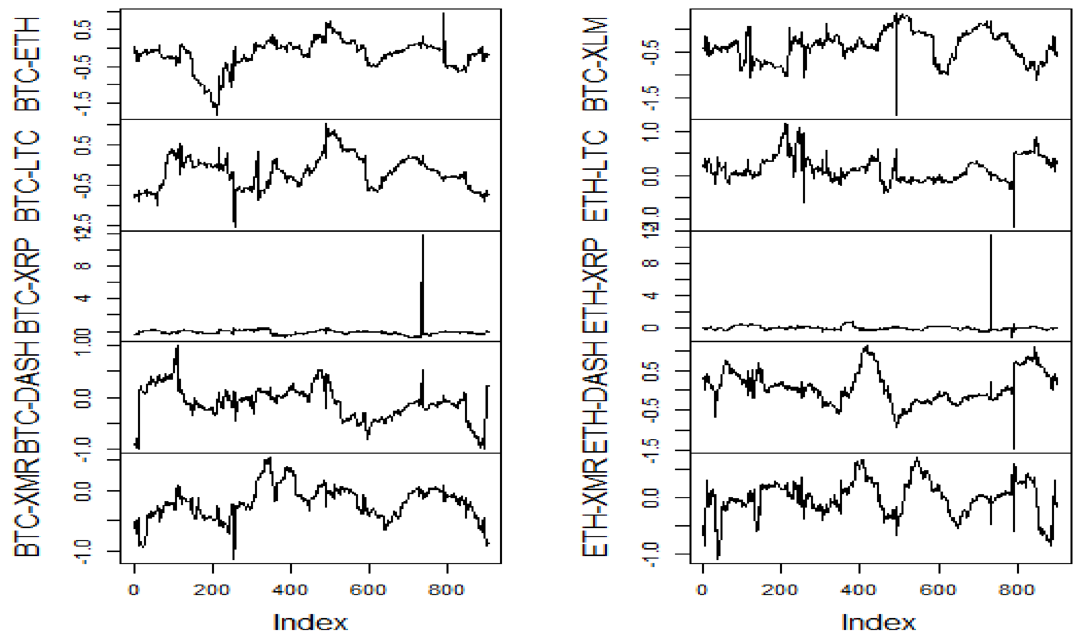


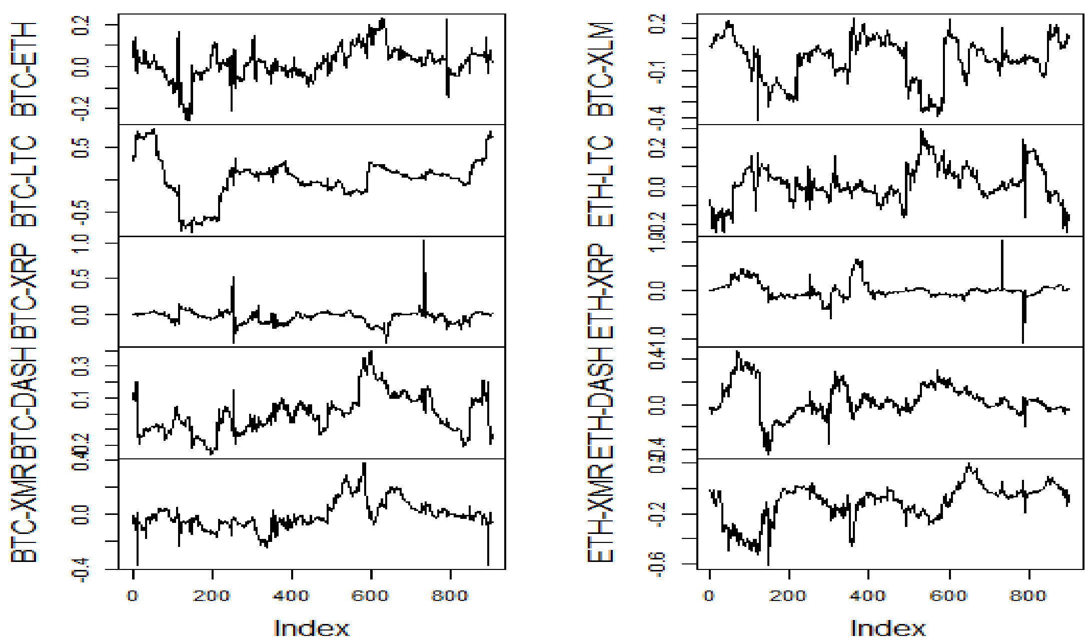
Figure ***4.2:*** **Overall across-frequencies spillovers**

The net-pairwise directional connectedness between cryptocurrencies in Figure 4.3 shows high volatility with mostly negative connections, especially for Bitcoin pairs in line with the results in Table 4.7. This suggests a stronger inter-market relationship during periods of high volatility leading to spillover effects which negatively affect portfolio diversification and stability in the cryptocurrency market especially the Bitcoin market (Shahzad et al., 2018; King and Wadhwani, 1990).

Pairwise spillovers on band: 3.14 to 0.79.



Pairwise spillovers on band: 0.79 to 0.20.



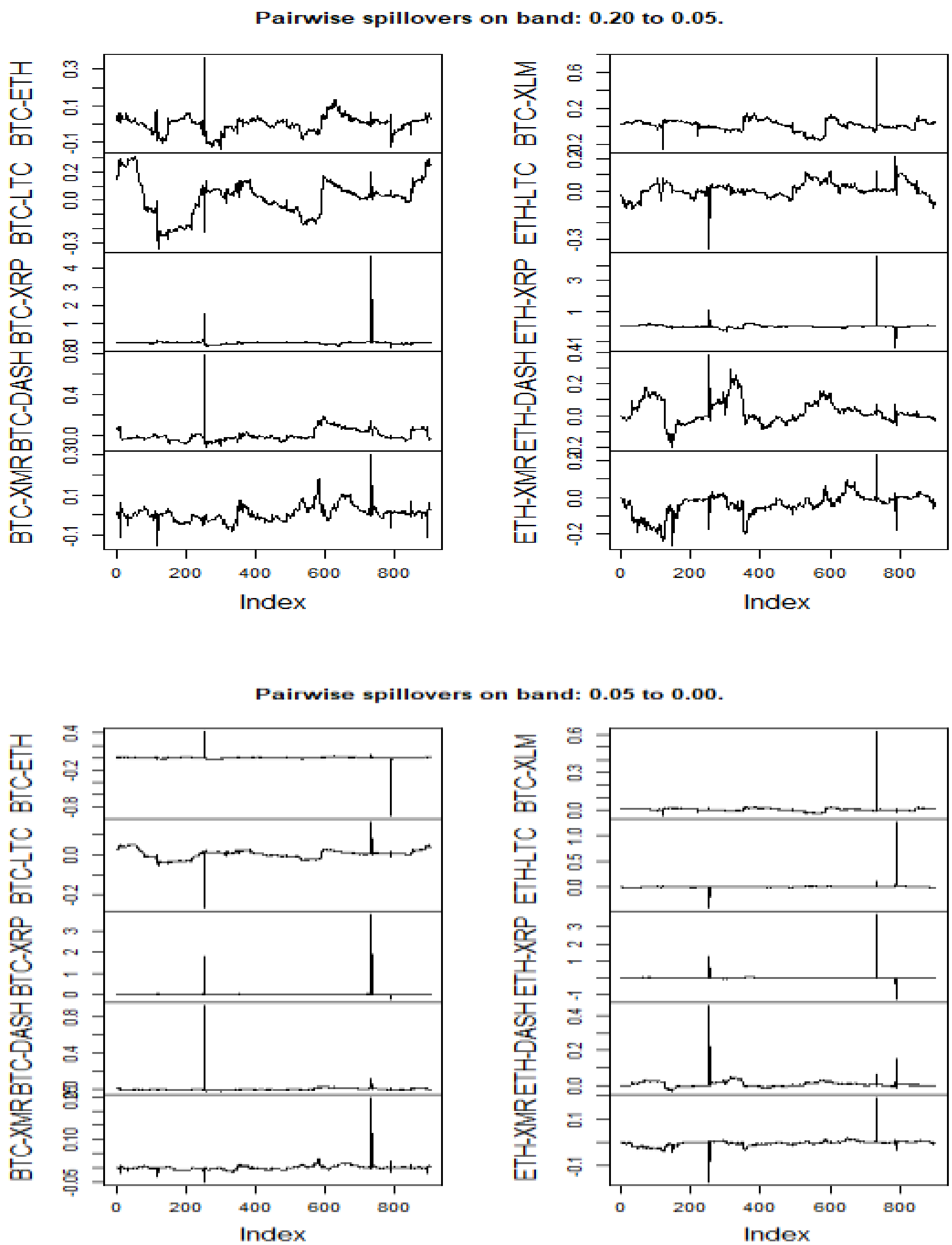


Figure *4.3:* Pairwise net directional connectedness across-frequencies.

4.4 Conclusion and policy implication

The chapter performs cryptocurrency market risk analysis focusing on seven large cryptocurrencies applying the FZL dynamic models for joint ES and VaR and the frequency domain spillover index. The FZL functions drawn from both ES and VaR which is conducive for comparative backtesting of competing forecasting models via ranking according to a consistent scoring function was used to measure tail risk. We accounted for fat-tails and volatility clustering in the return series of the cryptocurrencies applying the STD, SNORM, SSTD, AST, AST1, and ALD distributions to the univariate GAS framework. The forecast ability of the distributions were tested implementing the MDM test and findings show that all distributions can equally forecast the FZL for the cryptocurrencies except that Litecoin was rejected at the 1% level. Further test was carried out applying the MAE to the distributions to rank and select the finest distributions to backtest their FZL forecast and results suggested the ALD and SNORM as the finest innovations at the risk levels. We bactested the FZL forecasts provided by the ALD and SNORM implementing the CC, UC, DQ, and QL test and finds that except for DQ, the CC and UC did not reject the distributions as inadequate and incorrectly specified. Computing the QL ratios, we observe that the 1% models outperformed the 2.5% models. Estimating the characteristic FZL value, we find that the risk exposure of Ethereum and Steller is low relative to other cryptocurrencies and that Ripple has the highest risk profile.

The extreme price volatility of cryptocurrencies coupled with their exposure to tail risk makes them risky currencies since the financial impact of tail risk could be large despite their small likelihood of occurrence. Hence, the application of FZL function for joint VaR and ES to cryptocurrencies provides coherent risk measure estimation for enhanced investment and trading strategies for cryptocurrency portfolio optimization. The results for FZL dynamic model goes beyond other models used by related studies which mainly described the volatility dynamics of cryptocurrencies (Troster, Tiware, Shahbaz, and Macedo, 2018; Angelini and Emili, 2018; Gkillas and Katsiampa, 2018) by estimating risk measures which is a major contribution of this study. We provide evidence in support of the study of Patton et al. (2019) which argues that FZL values drawn from both VaR and ES provide a better empirical risk modelling than either VaR or ES separately.

The chapter further analyzes and captures the volatility spillover effects across the cryptocurrencies following the approach of Barunik and Krehlik (2018). The outcome from time-varying directional spillover index is indicative of a strong total interconnectedness across cryptocurrencies at high frequencies relative to medium and low frequencies signifying low diversification opportunities in the short-term. However, the net transmitters and receivers of volatility spillovers across cryptocurrencies are frequency dependent. This finding provides evidence in support of the works of Corbet et al. (2018), and Ji, Bouri, Lau, and Roubaud (2019) that leading cryptocurrencies are interconnected but differs in showing that the interconnectedness is time-varying and that stronger interconnectedness occurs at higher frequencies. The evidence of all cryptocurrencies alternating between being receivers and transmitters of spillover effects across time suggest that Bitcoin is losing its dominant role in the cryptocurrency market.

Examining the pairwise spillover, we observe a dominant negative net interconnectedness across pairs of cryptocurrencies showing Bitcoin as the major reciepient of spillover effects from other cryptocurrencies. Accordingly, the rolling window investigation affirms the outcomes shown by the directional and pairwise spillover tables. The evidence of weak and negative connections in the medium and lower frequencies may benefit economic agents interested in investing in cryptocurrencies to enhance hedging and portfolio diversifications in the medium and long-term. The frequency-based inteconnectedness across cryptocurrencies is significant as the result highlights the need for proper regulation of the Bitcoin, Litecoin, and Das markets across all frequencies particularly at high frequencies to decrease risk globally.

The chapter focused on seven principal cryptocurrencies; Bitcoin, Ethereum, Litecoin, Ripple, Das, Monero, and Steller to investigate risk in the cryptocurrency market implementing the joint loss function (FZL) of VaR and ES and the frequency domain spillover index techniques. Future studies can replicate this study by extending the enquiry into several cryptocurrencies and other financial instruments not captured in this chapter to broaden our understanding of market microstructure and volatility of financial instruments. Future studies could also look at the regulatory and supervisory aspects of cryptocurrencies in Africa to allow for its successful integration in the region.

References

Acerbi, C., & Szekely, B. (2014). Back-testing Expected Shortfall. *Risk*, 27(11), 76–81.

Acerbi, C., & Tasche, D. (2002). Expected Shortfall: a Natural Coherent Alternative to Value at Risk. *Economic Notes*, 31(2), 379–388.

Angelini, G., & Emili, S. (2018). Forecasting Cryptocurrencies: A Comparison of GARCH Models. *Available at SSRN 3195704*. https://dx.doi.org/10.2139/ssrn.3195704.

Ardia, D., Boudt, K., & Catania, L. (2016). Downside Risk Evaluation with the R Package GAS (SSRN Scholarly Paper No. ID 2871444). Retrieved from Social Science Research Network website: https://papers.ssrn.com/abstract=2871444.

Ardia, D., Boudt, K., & Catania, L. (2018). Downside Risk Evaluation with the R Package GAS. *R Journal*, *10*(2), 410-421.

Artzner, P., Delbaen, F., Eber, J. M., & Heath, D. (1999). Coherent measures of risk. *Mathematical finance*, *9*(3), 203-228.

Aas, K., & Haff, I. H. (2006). The Generalized Hyperbolic Skew Student'st-distribution. *Journal of Financial Econometrics*, *4*(2), 275-309.

Barunik, J., & Křehlík, T. (2018). Measuring the Frequency Dynamics of Financial Connectedness and Systemic Risk. *Journal of Financial Econometrics*, *16*(2), 271-296. https://doi.org/10.1093/jjfinec/nby001.

Barunik, J., & Krehlik, T. (2016). Measuring the Frequency Dynamics of Financial and Macroeconomic Connectedness (No. 54). *FinMaP-Working Paper*.

Bauwens, L., & Laurent, S. (2005). A New Class of Multivariate Skew Densities, With Application to Generalized Autoregressive Conditional Heteroscedasticity Models. *Journal of Business and Economic Statistics*, 23(3), 346–354. https://doi.org/10.1198/073500104000000523.

Basel Committee on Banking Supervision (2011), "Messages from the academic literature on risk measurement for the trading book", BCBS Working Paper No. 19, Basel, 31 January 2011.

Bellini, F., & Bignozzi, V. (2015). On Elicitable Risk Measures. *Quantitative Finance*, *15*(5), 725-733.

Belke, A., & Gokus, C. (2014). Volatility Patterns of CDS, Bond and Stock Markets before and during the Financial Crisis: Evidence from Major Financial Institutions. *International Journal of Economics and Finance,* 6, 53–70.

BIS, B. (2013). Fundamental Review of the trading book. October 31. Retrieved from http://www.bis.org/publ/bcbs265.pdf.

Blasques, F., Koopman, S., J., Lucas, A., & Schaumburg, J. (2016b). Spillover Dynamics for Systemic Risk Measurement Using Spatial Financial Time Series Models. *Journal of Econometrics,* 195(2), 211–223. doi:10.1016/j.jeconom.2016.09.001.

Blasques, F., Koopman, S. J., & Lucas, A. (2014). *Maximum likelihood estimation for generalized autoregressive score models* (No. 14-029/III). Tinbergen Institute Discussion Paper.

Blazsek, S., & Hernández, H. (2018). Analysis of Electricity Prices for Central American Countries using Dynamic Conditional Score Models. *Empirical Economics*, 55(4), 1807–1848. https://doi.org/10.1007/s00181-017-1341-3.

Bouri, E., Shahzad, S., J., H., & Roubaud, D. (2019). Co-explosivity in the Cryptocurrency Market. *Finance Research Letters*, 29, 178-183.

Borri, N. (2019). Conditional Tail-Risk in Cryptocurrency Markets. *Journal of Empirical Finance*, 50, 1-19.

Braione, M., & Scholtes, N. K. (2016). Forecasting Value-at-Risk under Different Distributional Assumptions. *Econometrics*, 4(1), 3. https://doi.org/10.3390/econometrics4010003.

Burzoni, M., Peri, I., & Ruffo, C. M. (2017). On the Properties of the Lambda Value at Risk: Robustness, Elicitability, and Consistency. *Quantitative Finance*, 17(11), 1735–1743.

Caporale, G., M., & Zekokh, T. (2019). Modelling volatility of cryptocurrencies using Markov-Switching GARCH models. *Research in International Business and Finance*, *48*, 143-155.

Catania, L., Grassi, S., & Ravazzolo, F. (2018). Forecasting Cryptocurrencies Financial Time Series," In CAMP Working Paper Series, no. 5. Norwegian Business School.

Cecchinato, N. (2010). Forecasting time-varying value-at-risk. Queensland University of Technology. Retrieved from http://eprints.qut.edu.au/32185/.

Chan, S., Chu, J., Nadarajah, S., & Osterrieder, J. (2017). A Statistical Analysis of Cryptocurrencies. *Journal of Risk and Financial Management*, 10 (12), 1–23.

Christoffersen, P., F. (1998). Evaluating Interval Forecasts. *International Economic Review*, 39, 841–862.

CoinMarketCap. (2019). Cryptocurrency Market Capitalizations and Data. Available online: https://coinmarketcap.com/ (accessed on 26th August 2019).

Cont, R., Deguest, R., & Scandolo, G. (2010). Robustness and Sensitivity Analysis of Risk Measurement Procedures. *Quantitative Finance*, 10(6), 593–606.

Corbet, S., Meegan, A., Larkin, C., Lucey, B., & Yarovaya, L. (2018). Exploring the Dynamic Relationships between Cryptocurrencies and Other Financial Assets. *Economics Letters*, 165, 28–34. doi.org/10.1016/j.econlet.2018.01.004.

Creal, D., Koopman, S. J., & Lucas, A. (2013). Generalized Autoregressive Score Models with Applications. *Journal of Applied Econometrics*, 28(5), 777–795.

Creal, D., Koopman, S., J., & Lucas, A. (2012). Generalized Autoregressive Score Models.

Dew-Becker, I., & Giglio, S. (2016). Asset Pricing in the Frequency Domain: Theory and Empirics. *The Review of Financial Studies, 29*(8), 2029-2068. https://doi.org/10.1093/rfs/hhw027.

Diebold, F. X., & Yilmaz, K. (2012). Better to Give than to Receive: Predictive Directional Measurement of Volatility Spillovers. *International Journal of Forecasting*, *28*(1), 57-66. https://doi.org/10.1016/j.ijforecast.2011.02.006.

Diebold, F. X., & Mariano, R. S. (2002). Comparing Predictive Accuracy. *Journal of Business & economic statistics*, *20*(1), 134-144.

Engle, R., F., & Manganelli, S. (2004). CAViaR: Conditional Autoregressive Value at Risk by Regression Quantiles. *Journal of Business & Economic Statistics*, 22(4), 367–381

Fantazzini, D., Nigmatullin, E., Sukhanovskaya, V., & Ivliev, S. (2016). Everything You Always wanted to know about Bitcoin Modelling but were afraid to ask. Available at SSRN: https://ssrn.com/abstract=2794622.

Fernández, C., & Steel, M., F., J. (1998). On Bayesian Modeling of Fat Tails and Skewness. *Journal of the American Statistical Association*, 93(441), 359–371. doi:10.1080/01621459.1998. 10474117.

Fisher, R., A., & Tippett, L., H., C. (1928). Limiting Forms of the Frequency Distribution of the Largest or Smallest Member of a Sample. In *Mathematical Proceedings of the Cambridge Philosophical Society*, 24(2), 180-190.

Fissler, T., & Ziegel, J. F. (2016). Higher Order Elicitability and Osband's Principle. The Annals of Statistics, 44(4), 1680–1707.

Fissler, T., Ziegel, J. F., & Gneiting, T. (2015). Expected Shortfall is jointly Elicitable with Value at Risk-Implications for Backtesting. ArXiv Preprint ArXiv:1507.00244.

Gkillas, K., & Katsiampa, P. (2018). An Application of Extreme Value Theory to Cryptocurrencies. *Economics Letters*, 164, 109–111. doi: 10.1016/j.econlet.2018.01.020.

Gkillas, K., Bekiros, S., & Siriopoulos, C. (2018). Extreme Correlation in Cryptocurrency Markets. *Available at SSRN 3180934*.

Guesmi, K., Saadi, S., Abid, I., & Ftiti, Z. (2019). Portfolio Diversification with Virtual Currency: Evidence from Bitcoin. *International Review of Financial Analysis*, *63*, 431-437. https://doi.org/10.1016/j.irfa.2018.03.004.

Harvey, A., C., & Thiele, S. (2016). Testing against Changing Correlation. *Journal of Empirical Finance*, 38(B), 575–589. doi:10.1016/j.jempfin.2015.09.003.

Harvey, A., C., & Sucarrat, G. (2014). EGARCH Models with Fat Tails, Skewness, and Leverage. *Computational Statistics and Data Analysis*, 76, 320–338. doi:10.1016/j.csda.2013.09.022.

Harvey, A., C. (2013). Dynamic Models for Volatility and Heavy Tails: with Applications to Financial and Economic Time Series (Vol. 52). Cambridge University Press.

Henriques, I., & Sadorsky, P. (2018). Can Bitcoin Replace Gold in an Investment Portfolio? *Journal of Risk and Financial Management*, 11:48.

Huynh, T.L.D., Nguyen, S.P., Duong, D. (2018). Contagion Risk Measured by Return among Cryptocurrencies. *In: International Econometric Conference of Vietnam. Springer*, 987–998.

Huynh, T., L., D. (2019). Spillover Risks on Cryptocurrency Markets: A Look from VAR-SVAR Granger Causality and Student's-t Copulas. *Journal of Risk and Financial Management*, 12, 52. doi:10.3390/jrfm12020052.

Islam, M., R., Nor, R., M., Al-Shaikhli, I., F., & Mohammad, K., S. (2018). Cryptocurrency vs. Fiat Currency: Architecture, Algorithm, Cashflow & Ledger Technology on Emerging Economy: The Influential Facts of Cryptocurrency and Fiat Currency. In *2018 International Conference on Information and Communication Technology for the Muslim World (ICT4M)* (pp. 69-73). IEEE.

Ji, Q., Bouri, E., Lau, C., K., M., & Roubaud, D. (2019). Dynamic Connectedness and Integration in Cryptocurrency Markets. I*nternational Review of Financial Analysis*.63, 257-272.

Ji, Q., Bouri, E., Lau, C., K., M., & Roubaud, D. (2018). Dynamic Connectedness and Integration in Cryptocurrency Markets. I*nternational Review of Financial Analysis*.

Jorion, P. (1997). Value at Risk. McGraw–Hill, New York, 410. URL https://doi.org/10.1036/0071464956.

Katsiampa, P. (2019). An empirical investigation of volatility dynamics in the cryptocurrency market. *Research in International Business and Finance*, 50, 322-335. https://dx.doi.org/10.2139/ssrn.3202317.

King, M., A., & Wadhwani, S. (1990). Transmission of Volatility between Stock Markets. *The Review of Financial Studies*, *3*(1), 5-33.

Klein, T., Thu, H. P., & Walther, T. (2018). Bitcoin is not the New Gold–A Comparison of Volatility, Correlation, and Portfolio Performance. *International Review of Financial Analysis*, *59*, 105-116.

Koenker, R., & Bassett, G. (1978). Regression Quantiles. *Econometrica*, 46 (1), 33–50.

Kotz, S., Kozubowski, T., & Podgorski, K. (2012). The Laplace distribution and generalizations: a revisit with applications to communications, economics, engineering, and finance. Springer Science and Business Media.

Koutmos, D. (2018). Return and Volatility Spillovers Among Cryptocurrencies. *Economics Letters*, 173, 122–27.

Kumar, A. S., & Ajaz, T. (2019). Co-movement in Cryptocurrency Markets: Evidences from Wavelet Analysis. *Financial Innovation*, *5*(1), 33.

Kupiec, P. (1995). Techniques for Verifying the Accuracy of Risk Measurement Models. *The Journal of Derivatives,* 3(2), 73–84.

Mariano, R. S., & Preve, D. (2012). Statistical Tests for Multiple Forecast Comparison. *Journal of Econometrics,* 169(1), 123–130. https://doi.org/10.1016/j.jeconom.2012.01.014.

McNeil, A., J., Frey, R., & Embrechts, P. (2015). Quantitative Risk Management: Concepts, Techniques, and Tools-revised edition. Princeton University Press.

Mensah, J., O., & Alagidede, P. (2017). How are Africa's Emerging Stock Markets Related to Advanced Markets? Evidence from Copulas. *Economic Modelling*, *60*, 1-10.

Nolde, N., & Ziegel, J. F. (2017). Elicitability and Backtesting: Perspectives for Banking Regulation. *The Annals of Applied Statistics*, 11(4), 1833–1874.

Oh, D., H., & Patton, A., J. (2018). Time-varying Systemic Risk: Evidence from a Dynamic Copula Model of CDS Spreads. *Journal of Business and Economic Statistics*, *36*(2), 181-195.

Omane-Adjepong, M., Alagidede, P., & Akosah, N., K. (2019). Wavelet Time-Scale Persistence Analysis of Cryptocurrency Market Returns and Volatility. *Physica A: Statistical Mechanics and its Applications,* 514(C), 105-120.

Owusu-Junior, P. & Alagidede, I. (2020). Risks in Emerging Markets Equities: Time-varying versus Spatial Risk Analysis. *Physica A: Statistical Mechanics and its Applications*, *542*, 123474.

Omane-Adjepong, M., & Alagidede, I. P. (2019). Multiresolution Analysis and Spillovers of Major Cryptocurrency Markets. *Research in International Business and Finance*, *49*, 191-206.

Patton, A. J., Ziegel, J. F., & Chen, R. (2017). Dynamic Semiparametric Models for Expected Shortfall (and Value-at-Risk). ArXiv:1707.05108 [q-Fin]. Retrieved from http://arxiv.org/abs/1707.05108.

Patton, A. J., Ziegel, J. F., & Chen, R. (2019). Dynamic Semiparametric Models for Expected Shortfall (and Value-at-Risk). *Journal of Econometrics.* https://doi.org/10.1016/j.jeconom.2018.10.008.

Qarni, M., O., Gulzar, S., Fatima, S., T., Khan, M., J., & Shafi, K. (2019). Inter-markets Volatility Spillover in US Bitcoin and Financial Markets. *Journal of Business Economics and Management*, *20*(3), 526-546.

Ramadhani, F., A., Nurrohmah, S., & Novita, M. (2017, July). Extreme Value Theory (EVT) Application on Estimating the Distribution of Maxima. In *AIP Conference Proceedings* (Vol. 1862, No. 1, p. 030156). AIP Publishing LLC.

Shahzad, S., J., H., Hernandez, J., A., Rehman, M., U., Al-Yahyaee, K., H., & Zakaria, M. (2018). A Global Network Topology of Stock Markets: Transmitters and Receivers of Spillover Effects. *Physica A: Statistical Mechanics and its Applications*, *492*, 2136–2153.

Taylor, J., W. (2019). Forecasting Value at Risk and Expected Shortfall Using a Semiparametric Approach Based on the Asymmetric Laplace Distribution. *Journal of Business and Economic Statistics*, 37(1), 121–133. https://doi.org/10.1080/07350015.2017.1281815.

Tiwari, A., K., Cunado, J., Gupta, R., & Wohar, M., E. (2018). Volatility Spillovers across Global Asset Classes: Evidence from Time and Frequency Domains. *The Quarterly Review of Economics and Finance*, *70*, 194-202.

Troster, V., Tiwari, A., K., Shahbaz, M., & Macedo, D., N. (2019). Bitcoin returns and risk: A general GARCH and GAS analysis. *Finance Research Letters*, *30*, 187-193.

Trabelsi, N. (2018). Are There Any Volatility Spill-Over Effects among Cryptocurrencies and Widely Traded Asset Classes? *Journal of Risk and Financial Management*, 11(4), 66.

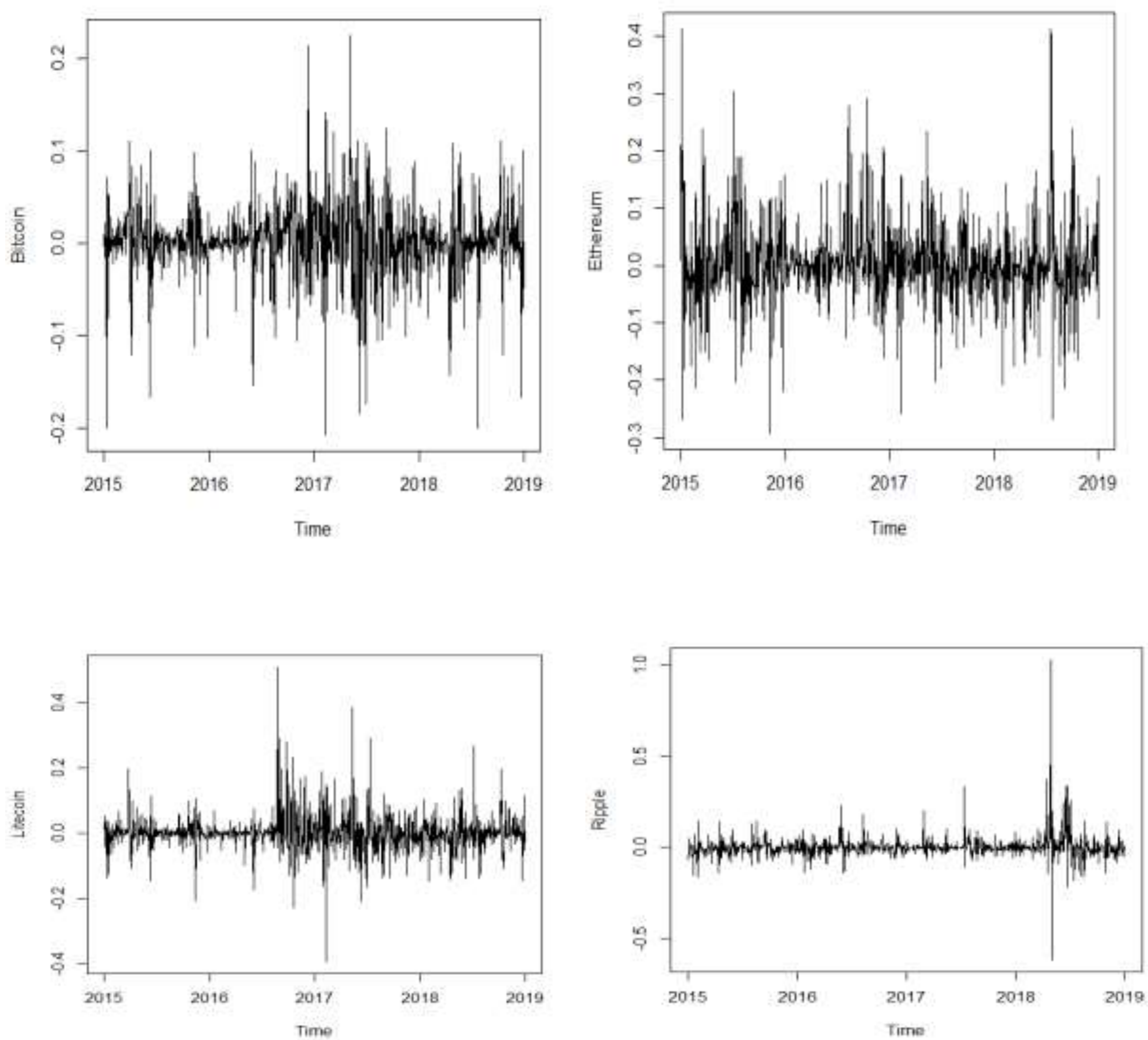
Yi, S., Xu, Z., & Wang, G. (2018). Volatility Connectedness in the Cryptocurrency Market: Is Bitcoin a Dominant Cryptocurrency? *International Review of Financial Analysis*, 60, 98–114.

Zhao, S., Lu, Q., Han, L., Liu, Y., & Hu, F. (2015), A Mean-CVaR-Skewness Portfolio Optimization Model Based on Asymmetric Laplace Distribution', *Annals of Operations Research*, 226, 727– 739.

Zhu, D., & Galbraith, J., W. (2010). A Generalized Asymmetric Student-t Distribution with Application to Financial Econometrics. *Journal of Econometrics*, 157(2), 297–305. doi: 10.1016/j.jeconom.2010.01.013.

Ziegel, J. F. (2016). Coherence and Elicitability. *Mathematical Finance,* 26(4), 901–918.

Appendice



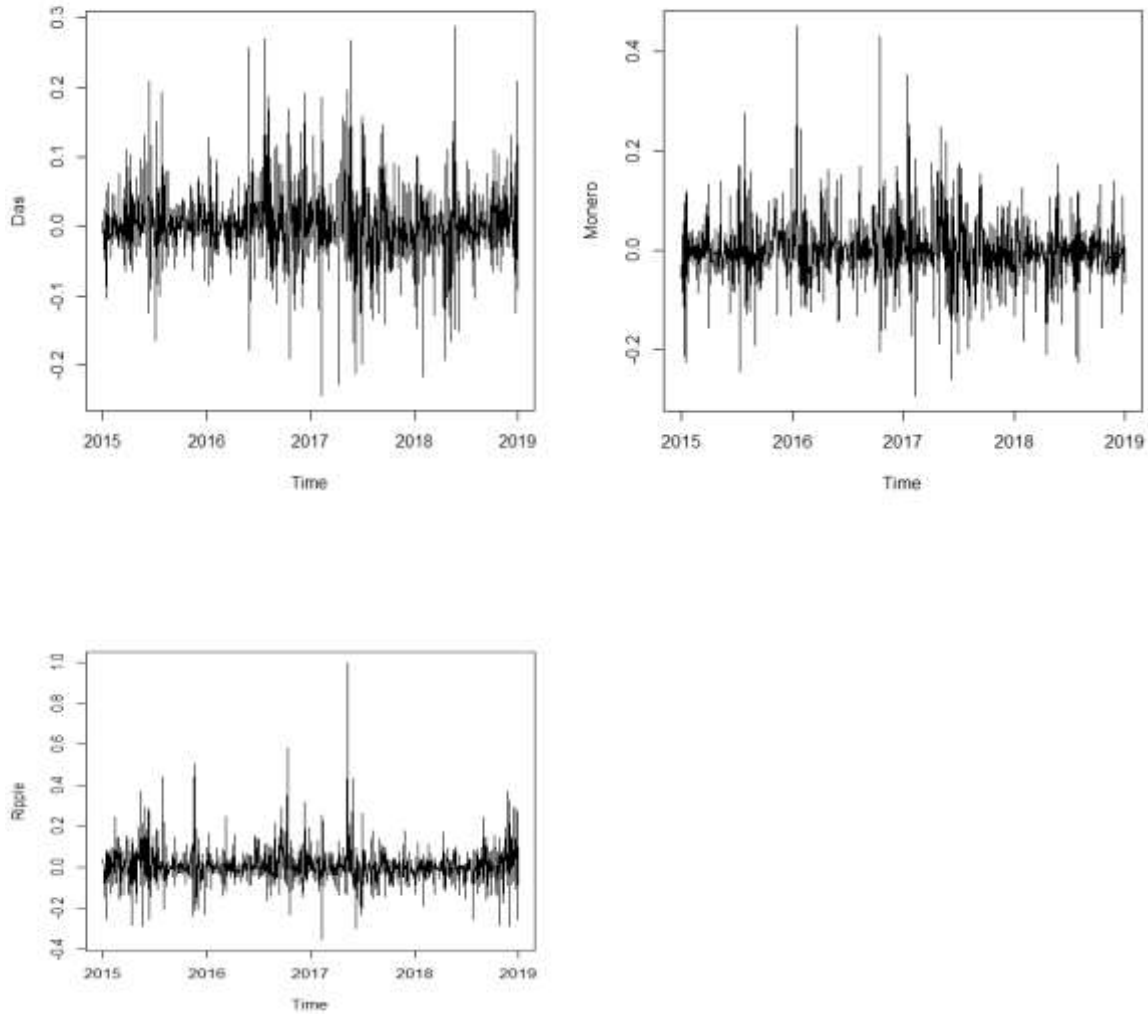


Figure *4.1*: Time series plot of selected Cryptocurrencies.

CHAPTER FIVE

Impact of Cryptocurrencies on Gold, and Crude Oil

5. Introduction

Interest in cryptocurrencies have risen considerably in recent years with intensified debate on whether cryptocurrencies behave as commodities, currencies, or synthetic commodity (Ji Bouri, Roubaud, and Kristoufek, 2019; Polasik, Piotrowska, Wisniewski, Kotkowski, and Lightfoot, 2015; Yermack, 2013). Cryptocurrencies have become a global phenomenon with many features including alternative monetary system (Fantazzini, Nigmatullin, Sukhanovskaya, Ivliev, 2016; Rogojanu and Badea, 2014; Das and Kannadhasan, 2018), speculative or investment vehicles (Corbet, Meegan, Larkin, Lucey, and Yarayova, 2018; Baek and Elbeck, 2015; Ji et al., 2019; Yermack, 2013), hedges and diversifiers for gold and crude oil market fluctuations (Selmi Mensi Hammoudeh and Jamal Bouoiyour, 2018; Al-Yahyaee, Mensi, Al-Jarrah, Hamdi, and Kang, 2019), and assets with high volatility (Catania et al., 2018; Huynh, 2019; Gkillas and Katsiampa, 2018; Chan et al., 2017). The works of Rogojanu and Badea (2014), and Popper (2015) consider cryptocurrencies as digital gold owing to their hedge and safe haven characteristics. Financial market participants are using cryptocurrencies, mostly Bitcoin, to hedge against extreme price fluctuations in the commodity market (Al-Yahyaee, Mensi, Al-Jarrah, Hamdi, and Kang, 2019).

Gold and Crude oil are strategic and essential commodities for investors, Africa, and the global economy. These commodities are the primary exports of Africa even though the continent is dominated by several natural resources. Africa's gold mining industry has seen major mines including South Deep (the largest gold mine in the world in terms of reserves and currently owned by Harmony Gold), Mponeng (operated by AngloGold Ashanti and the deepest mine in the world), Driefontein (owned by Sibanye-Stillwater), Kinross Gold, and Newmont Gold active in the region. In line with NS Energy (2020), the top five gold producing countries in the continent as at 2019 include Ghana which mined 142 metric tonnes which accounts for 49% of the country's total exports value. Ghana's gold reserves have been estimated to be 1,000 metric tonnes. South Africa mined 137 metric tonnes and 118.2 metric tonnes in 2018 and 2019 respectively contributing more than 29% of the country's total exports. The Witwatersrand Basin, an underground geological formation in South Africa, holds one of the largest gold placer deposits in the world. Sudan produced more than 76 metric tonnes in 2019 accounting for 70% of its total exports. This was, however, a big drop from the 93 tonnes produced the previous year and the 107 tonnes in 2017. Mali produced more than 71 metric tonnes of gold in 2019, a sizeable jump from the 61.2 tonnes in 2018 accounting for 72% of the country's total exports. Mali's gold mines make a significant contribution to the country's economy. Mali is estimated to have 800 metric tonnes of gold reserves. Burkina Faso's 62 metric tonnes of gold produced in 2019 places it in fifth position and accounts for 70% of the country's total exports. The country has one of the most dynamic mining sectors in West Africa. Burkina Faso's gold reserves are estimated to be about 154 metric tonnes.

With specific regards to crude oil, Faria (2021) discussed that Nigeria was the leading oil producer and exporter in Africa as of 2019. Oil production amounted to 101.4 million metric tonnes and exports of more than two million barrels per day in the country. Angola followed by 69.1 million metric tonnes and exports volume of 1.31 million barrels per day. Algeria produced 64.3 million metric tonnes, and exported 584.2 thousand barrels per day. Lybia sold 1.03 million barrels per day to the international market. West and North Africa's contribution to the global oil exports reached nearly 10 percent. In total the African output of oil per day amounted to some 8.4 million barrels in 2019, variating minimally compared to the previous year. Africa's crude oil reserves remained stable in 2020, accumulating to 125.8 billion barrels. From a country perspective, Libya had the largest amount of crude oil reserves in the continent, 48.36 billion barrels, while the Nigerian reserves amounted to 36.97 billion barrels. When it comes to oil refining, Egypt led, with a refinery capacity of 814 thousand barrels daily.

In line with Das and Kannadhasan (2018), an economy's inflation and general price movement is measured by movements of crude oil price suggesting crude oil price as the harbinger of inflationary conditions in an economy. Studies by Krugman (2008), and Palombizio and Morris (2012) demonstrate that crude oil price is the major cause of cost and demand pressures in an economy suggesting that the general price level may change due to fluctuations in crude oil price. Nonetheless, the study of Ciaian et al. (2016) argues that cryptocurrencies may be diversifies for crude oil price fluctuations. Gold has played a role as a safe haven and hedge against equity market crises (Baur and McDermott, 2010), currency market turmoil (Sakemoto, 2018), and oil market downturns (Reboredo, 2013b).

However, there is high variability of gold prices in recent times (Tan et al., 2014), with evidence of volatility spillover from gold market to other markets (Jian and Xu, 2019). Further, empirical studies (e.g. Ciner et al., 2013; Baur and McDermott, 2010; Bampinas and Panagiotidis, 2015) show evidence of substantial change in the relationship between gold and other assets classes during periods of extreme market fluctuations. These show the importance of investigating the interdependences between gold/cryptocurrencies and oil/cryptocurrencies returns at different market regimes in a time-frequency space to uncover the shock transmission mechanisms and hedging benefits of cryptocurrencies for gold and crude oil risk management across time. The thesis departs from earlier works by addressing the timely question of whether cryptocurrencies exhibit hedging properties for gold and crude oil investmensts during turbulent market conditions and whether gold and crude oil exhibit similar property for extreme cryptocurrency market by proposing a new definition for turbulent and tranquil market conditions.

The modern portfolio theory propounded by Markowitz (1952) contends that adding an asset to a portfolio should be considered in the light of its impact on the performance and risk of the portfolio of assets. In today's market, cryptocurrencies are digital assets with unique reward/risk profile with brand new level of correlation to conventional asset classes which can add previously unattainable level of asset mix to an investor's holdings, and impact the level of exposure and risk an investor has in a potentially positive way. The empirical literature on cryptocurrencies in a portfolio, including gold and crude oil mainly focused on Bitcoin and produced different effects of Bitcoin on the commodities. For instance, Bouri, Azzi, and Dyhrberg (2017) subject movement in the price of Bitcoin, energy commodities, and commodities in general to regression analysis using bivariate DCC model. The authors investigated the hedge, safe-haven, and diversification abilities of Bitcoin and evidence show Bitcoin as a safe haven and a strong hedge against movements of commodity indices at the pre-crash period but a diversifier in the post-crash period. Baur, Dimpfl, and Kuck, (2018) use GARCH model to explore the effects of Bitcoin on US dollar and gold and reports that Bitcoin shows different correlation, return and volatility characteristics compared to US dollar and gold.

Employing non-linear and quantile ARDL models, Bouri, Mahamitra, Gupta and Roubaud (2018) investigate the impact of aggregate commodity index and gold prices on Bitcoin price and finds non-linear, asymmetric, and quantile-dependent relationship between Bitcoin and aggregate commodity and between gold and Bitcoin. Dyhrberg (2016) scrutinized the connection among gold, USD, and Bitcoin applying GARCH technique and evidenced Bitcoin as a hedge for gold and US dollar market crises. Similarly, Baur, Hong, and Lee (2018) use GARCH model to explore the effects of Bitcoin on US dollar, and gold and finds Bitcoin to be uncorrelated with the assets. Using conditional and unconditional Quantile-in-Quantile regression techniques, Selmi, Mensi, Hammoudeh, and Bouoiyour (2018) study the impact of gold and Bticoin on crude oil market and finds that gold and Bitcoin can hedge crises in oil markets. Investigating the behavior of Bitcoin in portfolio including gold and crude oil, Guesmi, Saadi, Abid, and Ftiti (2018) employ VARMA-DCC-GARCH framework and reports that Bitcoin can reduce portfolio risk when included in portfolio made up of gold and oil. Applying empirical mode decomposition, Bouoiyour and Selmi (2017) model the correlation among gold, silver, Bitcoin and US stock and finds that Bitcoin and the commodities have lost their safe haven properties as their correlation decreased over time.

More recently, Kurka (2019) uses volatility spillover framework to examine the nature of shock transmissions among stocks, commodities, financials, foreign exchange, and Bitcoin and reports that Bitcoin cannot be a hedge to the traditional assets because of its low correlation with the assets. The study also reports a spillover from Bitcoin's market disruptions to the traditional assets market. Using the advanced cross-quantilogram technique, Shahzada et al. (2019) scrutinize the safe haven property of gold, Bitcoin, and commodity index. Their findings show that Bitcoin has weak safe haven characteristics against gold and the commodity index. Al-Yahyaee, Mensi, Al-Jarrah, Hamdi, and Kang (2019) apply GARCH model to gold, oil, and Bitcoin and examined the ability of Bitcoin and gold as hedges for oil market volatility and evidenced gold and Bitcoin as good hedges for oil market risk management.

Studies have also analyzed the relationship between several cryptocurrencies and commodities including gold and crude oil. Ciaian and Rajcaniova (2018) employ ARDL to explore the relationship between seventeen virtual currencies, including Bitcoin and control for crude oil price, stock market index, interest rate, gold, and exchange rate. The findings show that shocks in Bitcoin price impact fifteen altcoins and in the long-term, Bitcoin, and four altcoin prices cointegrate. Similarly, Adebola, Gil-Alama, and Madigu (2019) apply cointegration and fractional integration techniques to cryptocurrencies and gold prices and examined their short and long-term relationship. The authors again test their degree of persistence and report a low degree of integration between gold and cryptocurrencies in the long-term. The study further report means reversion in some of the cryptocurrencies and gold prices. Ji, Bouri, Roubaud, and Kristoufek (2019) apply the transfer entropy technique to explore information interdependence among cryptocurrencies, agricultural, metals, and energy commodities and evidenced integration between cryptocurrencies and the commodities. Further, Corbet, Meegan, Larkin, Lucey, and Yarayova (2018) model the co-movements of Bitcoin, Litecoin Ripple, gold, S&P500 index, bond, forex, VIX, and GSCI index using time and frequency technique and findings show investors can use cryptocurrencies to diversify and hedge their positions during extreme price fluctuations of the traditional assets in the short investment horizon.

In recent times, empirical research on cryptocurrencies is focused on analysing their safe haven and hedging characteristics as an investment instrument relative to commodities such as gold and crude oil (Bouri, Jalkh, Molnr, Roubaud, 2017; Dyhrberg, 2015b: Baur et al., 2018; Bouri et al., 2017; Bouri et al., 2018; Shahzada et al., 2019). However, the majority of these studies focus solely on Bitcoin and omit altcoins. Following Lee, Guo, and Wang (2018), Selmi et al. (2018), and Corbet et al. (2018), Bitcoin and altcoins are new investment opportunities that can reduce the risk of a well-diversified portfolio. Further, most past studies also ignored the nonlinearity[58] time-variability[59], and asymmetric[60] associations in the asset markets and produced conflicting results.

[58] Nonlinear dynamics are not rare in financial series such as gold, crude oil, and cryptocurrencies. The time series of these variables are characterized by sudden and irregular jumps and neglecting nonlinear dependences may lead to inacurrate predictions (Zhang, 2002; Bisaglia and Gerolimetto, 2014).
[59] As discussed by Zhang (2002), heterogeneity of participants in the financial market is often cited as a major source of nonlinear dynamics of financial series.
[60] Linear models do not allow for strong asymmetries in data which may lead to poorly behaved parameter estimates and models which miss important serieal dependencies (Bisaglia and Gerolimetto, 2014).

Notably, these assets markets though essential to investors and the global economy are characterized by nonlinear relationships, unusual dependencies and exhibit high volatility in prices (Selmi et al., 2018; Al-Yahyaee, Mensi, Al-Jarrah, Hamdi, and Kang, 2019). As accurate measurement of association between different assets is critical for portfolio optimization and has implication for hedging, diversification, and risk analysis, it is important to comprehensively investigate the connectedness between gold/cryptocurrencies and oil/cryptocurrencies during different market episodes (i.e. bear, normal and bull market regimes) across time to deepen the academic, regulators, and international investors' knowledge on the potential benefits and risk of these asset markets. As discussed by Vandezande (2017), the behaviour of cryptocurrencies compared to other assets should be robustly analysed to provide regulatory bodies and policymakers with the risk and benefits of cryptocurrencies as financial instruments.

Motivated by the above discourse, we employ nonparametric wavelet-based Quantile-in-Quantile technique to model the effects of cryptocurrencies on gold and crude oil at different market states in a time-frequency space. Following the heterogeneous market hypothesis by Müller et al. (1993)[61], we decompose the time series of the variables into high, medium, and low frequencies using wavelet to account for the multi-scale nature of relationship in assets market as did Das and Kannadhasan (2018). We complement the study of Selmi et al. (2018) by examining the dependencies between gold/cryptocurrencies and oil/cryptocurrencies at bear (bull) markets applying Quantile Regression (QR) and Quantile-in-Quantile Regression (QQR) on the decomposed series of the assets to capture the nonlinear and asymmetric associations in the return series of the assets across time and frequencies. The use of QR technique captures both lower and upper tail dependencies in addition to average dependence conditional on varying gold/cryptocurrencies and oil/cryptocurrencies market regimes where gold and oil prices are low, stable or high. The QQR approach models the reverse causality where the quantile of cryptocurrency returns with its various frequencies is expressed as a function of gold and crude oil returns. This provides precise information to investors to hedge against their downside risk across time and market regimes.

[61]The heterogeneous market hypothesis propounded by Müller et al. (1993) argues that economic agents in financial markets are not homogeneous, all possessing the same information and objectives and thus operates at the same time and frequency.

The outcome of both QR and QQR highlight the heterogeneous effect of cryptocurrencies on gold and crude oil returns across quantiles and time-scales. Specifically, the QR results for gold/cryptocurrencies suggest all cryptocurrencies studied (Bitcoin, Litecoin, Ethereum, Das, Monero, Steller, and Ripple) as hedges for price fluctuations at bear (bull) gold markets (i.e. whether the price of gold is low, stable, or high) from the medium-term. However, the QR results for oil/cryptocurrencies undermine the hedging properties of Bitcoin, Litecoin, and Das markets as hedges for crude oil market oscillations suggesting shock transmissions from the cryptocurrencies to crude oil market across time and that hedging possibilities are feasible from the medium-term for crude oil investors/traders using Ethereum, Monero, Ripple, and Steller at bear (bull) crude oil markets. The results from QQR for gold/cryptocurrencies and oil/cryptocurrencies pairs show negative associations between the commodities (gold and crude oil) and cryptocurrencies at bear market but positive relations at bull market. This suggests that market disruptions in any of the assets markets can spillover to the other when their market is bull but the assets have hedging properties for each other when their market is bear. Thus, when the cryptocurrency market is bearish and the price of gold and crude oil is low, economic actors can hedge the downside risk of the commodities or cryptocurrencies across time using either of the assets across time. We validate QQR by the closeness with which it matches QR across quantiles and time.

Our study departs from earlier works (Kurka, 2019; Shahzad et al., 2019; Henriques and Sadorsky, 2018; Klein et al., 2018; Selmi et al., 2018) by showing that the connections between gold/cryptocurrencies and oil/cryptocurrencies are time-varying and also depends on the state of market. We argue in line with the findings of this study that although cryptocurrencies exhibit excess price volatility, they may provide diversification benefits for gold and crude oil investors which is consistent with the findings of Eisl et al. (2015), Bouri, Molnár, Azzi, Roubaud, Hagfors (2017), and Halaburda and Gandal (2014). The choice of cryptocurrencies, gold, and crude oil is not arbitrary but because gold and crude oil are the two major commodities traded in commodity exchanges and can proxy for the broader commodity market. There has also been a creation of blockchain platform[62] which facilitate crude oil trade between firms in the commodity industry.

[62] https://www.coindesk.com/blockchain-oil-trading-platform-backed-by-shell-and-bp-is-now-live.

Gold has similarities with cryptocurrencies in that they are both speculative assets. In line with van Wijk (2013), crude oil and gold prices drive the price formation of cryptocurrencies, therefore, the response of cryptocurrencies to gold and crude oil price shocks is crucial for risk management and assets allocation.

The remainders of the study are structured as follows. Section 5.1 explains the methodology adopted for the study. Section 5.2 delineates the data and statistical properties. Section 5.3 captures the results and discussion on the impact of cryptocurrencies on gold and crude oil. Section 5.4 discusses the conclusion and policy implications.

5.1 Methodology

The chapter implements Maximal Overlap Discrete Wavelet Transform (MODWT), Quantile Regression (QR), and Quantile-in-Quantile Regression (QQR) to model the interactions between gold/cryptocurrencies and oil/cryptocurrencies at bear (bull) markets across time. The MODWT captures the time and frequency information in the time series of the variables whiles the QR and QQR examines the nonlinear and asymmetric associations across time and frequencies of the assets returns. The methodology involves a two-step approach of using MODWT to decompose the series into various wavelet scales based on which QR, and the QQ regressions are applied. Pertinent studies that have used this approach include Mishra, Sharif, Khuntiia, Meo, and Khan (2019), and Bouri, Gupta, Tiwari, and Roubaud (2017).

5.1.1 Maximum Overlap Discrete Wavelet Transform (MODWT)

Following Percival and Walden (2000), the maximal overlap discreet wavelet transform simultaneously localizes variations in signal in time and frequency space which is used in this study to decompose cryptocurrencies, gold, and crude oil returns into different timescales. As discussed by Ramsey (2002), a function of time can be represented with scaling and wavelet functions[63] commonly known as father($\emptyset$), and mother (φ) wavelets respectively. Father wavelets

[63]Scaling function simply means that the wavelet is stretched to capture the low frequency variations in the original time series that are associated with longer time horizons. Wavelet function simply means that the wavelet is compressed to capture variations in the original time series that are associated with shorter time horizons. In order to

integrate into one and are used to represent very long scale smooth components of the signal, whereas, mother wavelets integrate to zero and are used to represent deviations that occur in the smooth components. Scaling coefficients are generated by father wavelets, whereas mother wavelets give rise to differencing coefficients.

We define father wavelet as:

$$\emptyset_{j,k} = -2^{-j/2}\emptyset\left(\frac{t-2^{jk}}{2^j}\right) \quad with \quad \int \emptyset(t)\,dt = 1 \tag{5.1}$$

and mother wavelet as:

$$\varphi_{j,k} = -2^{-j/2}\varphi\left(\frac{t-2^{jk}}{2^j}\right) \; with \int \varphi(t)\,dt = 0 \tag{5.2}$$

From the father and mother wavelets, the basic functions which define the sequence of coefficients is constituted. The fathers' wavelet smooth coefficients are defined as:

$$S_{J,k} = \int f(t)\,\emptyset_{J,k} \tag{5.3}$$

and mother wavelets detail coefficients as:

$$d_{j,k} = \int f(t)\,\varphi_{J,k}\; with\; j = 1, \dots J \tag{5.4}$$

The maximal scale of the former is 2^j , while the detailed are computed from the mother wavelets at all scales from 1 to *J*. The function *f* (.) from the coefficient above is defined as:

$$f(t) = \sum_k S_{J,k}\emptyset_{J,k}(t) + \sum_k d_{J,k}\,\varphi_{J,k}(t) \dots + \sum_k d_{J,k}\varphi_{j,k}\,(t) \dots + \sum_k d_{1,k}\varphi_{1,k}(t), \tag{5.5}$$

which is simplified to

$$f(t) = S_J + D_J + D_{J-1} + \dots + D_j + \dots + D_1 \tag{5.6}$$

with orthogonal components defined as:

$$S_J = \sum_k S_{J,k}\,\emptyset_{J,k(t)} \tag{5.7}$$

$$D_J = \sum_k d_{J,k}\varphi_{J,k}(t).\, j = 1, \& \dots J \tag{5.8}$$

---

capture variations in the original time scales, the wavelet function (the basis function) is stretched to capture variations in the original time scales.

The resulting multi horizon breakdown of $f(t)$ is $\{S_{J,}D_{J-1,...,}D_1\}$. D_j calculates the *jth* level wavelet detail related with changes in the series at scale $\lambda_{j...}$. S_j denotes cumulative sum of alterations at each level and as *j* increases, S_j becomes smoother and smoother (Gençay et al., 2002). We employ MODWT[64] to estimate the scaling and wavelet coefficients as MODWT can be used for a time series of any length and does not restrict the sample size to an integer multiple of 2^{J0} unlike the Discrete Wavelet Transform (Percival and Walden, 2000). This makes it easy to compare composite series to decomposed series.

In line with extant literature, we apply Daubechies least asymmetric (LA)[65] filter of length eight (LA8) to decompose the series due to its smooth correlation coefficients compared to HAAR wavelet filters (Gençay et al., 2002). Since feasible wavelet coefficients get smaller for higher level decompositions[66], we decompose the series into wavelet coefficients D_1 *to* D_6. The detail coefficient D_j provides the resolution of data at scale 2^j to 2^{j+1}. The oscillations of periods, 2–4, 4–8, 8–16, 16–32, 32–64, and 64–128 days represent wavelet scales $D_1, D_2, D_{3,} D_4, D_{5,}$ *and* D_6 respectively. The wavelet smooth S_6 represents the long-term movement of the assets.

5.1.2 The Quantile-in-Quantile Approach

Since the inception of the conventional quantile regression (QR) technique proposed by Koenker and Bassett (1978), it has become a common tool to model the time-varying degree and dependence structure between time-series data. Compared to the classical linear (non-linear) regression models, the QR model precisely and accurately measure the impact of covariates on the different quantiles of a response variable of a given distribution enabling a comprehensive

---

[64] The smooth and detail coefficients of a MODWT are allied with zero phase filters, which helps to align the features of original time series with that of multi resolution analysis (MRA), and DWT-based estimators are asymptotically less efficient compared to MODWT (Gençay et al., 2002; Percival and Mofjeld, 1997; Percival, 1995). Additionally, the MODWT employs moving difference and average operator and keeps the exact number of observations at each wavelet decomposition scale unlike the DWT which employs weighted differences and averages attached pairs of observations.

[65] As discussed by Cornish et al. (2006), the coefficients provided by LA (8) filter exhibit better uncorrelated coefficients across scales than the HAAR filter.

[66] With 877 number of observations, we can have 9 details and 1smooth component from $[Log_2(N)]^2$, where $N$is the number of observations.

investigation of the association between variables across different time periods (see Koenker, 2005). The QR technique as an extension of the classical linear regression model provides information on upper (lower) tails in addition to the median of the assets returns. Specifically, the QR can analyze and estimate the heterogeneous relationship between gold/cryptocurrencies and oil/cryptocurrencies at various points of the conditional distribution of gold and crude oil returns.

However, the QR approach does not capture entire dependency since it does not accommodate the possibility that movements of gold and crude oil prices (response variable) may also influence the hedging properties of cryptocurrencies. Consequently, Sim and Zhou (2015) proposed a Quantile-in-Quantile (QQ) approach, which theoretically combines QR and nonparametric estimations. The QQ technique has been exploited in the field of applied growth and energy economics to empirically investigate how the quantiles that emerge from a variable affect the conditional quantiles of another variable (Atsalakis, Bouri, and Pasiouras, 2020; Mallick, Padhan, and Mahalik, 2019; Raza, Zaighum, and Shah, 2018).

In this study, we apply the QQ[67] technique to model the quantile of gold and crude oil returns (and their frequencies) as a function of the quantile of cryptocurrency returns. This approach provides a clear and more complete picture of dependence by capturing the diverse relationships between the response (gold and crude oil), and covariates (cryptocurrencies) returns at each point of their conditional distributions. The study follows Sim and Zhou (2015) single equation regression approach as used by Ma and Koenker (2006).

Therefore, the QQ approach used in this study to model the quantile effect of cryptocurrency returns on the quantiles of gold and crude oil returns has its starting point of representation in the following nonparametric quantile regression equation:

$$GO_t = \beta^\theta (Crp_t) + \mu_t^\theta \tag{5.9}$$

[67] The QQ technique is implemented by selecting a number of quantiles of cryptocurrency returns and its various frequencies on the various quantiles of gold and oil returns. The QQR empirically studies the impact of movements of cryptocurrency returns on gold/oil returns while exploring the varying effects of gold/oil returns across different quantiles of cryptocurreny returns (reverse causality).

Where GO_t denotes gold and crude oil returns at period *t*, Crp_t denotes cryptocurrency returns at period *t*, θ is the θthquantile of the conditional distribution of GO_t and u_t^{θ} is the quantile residual term whose conditional θth quantile is assumed to be zero. $\beta^{\theta}(\cdot)$ is an unknown function since we lack prior information on the relationship between gold/cryptocurrencies and oil/cryptocurrencies returns.

The main advantage of this regression specification is the flexibility to capture the functional form of the dependency relationship between gold/cryptocurrencies and oil/cryptocurrencies returns. Finally, the asymmetric effects of cryptocurrency returns on gold/oil returns are possible in response to both negative and positive shocks arising from gold/oil returns.

Notably, to establish the relationship between the θth quantile of cryptocurrency returns and the τth quantile of gold/oil returns, the local linear regression is used to examine equation (5.9) in the neighbourhood of Crp^{τ}. Given that the value of $\beta^{\theta}(\cdot)$ is unknown, we can expand the regression function through a first order Taylor expansion around a quantile of Crp^{τ} in the following way:

$$\beta^{\theta}(Crp_t) \approx \beta^{\theta}(Crp^{\tau}) + \beta^{\theta\prime}(Crp^{\tau})(Crp_t - Crp^{\tau}) \qquad (5.10)$$

We can redefine $\beta^{\theta}(Crp^{\tau})$ and $\beta^{\theta\prime}(Crp^{\tau})$ as $\beta_0(\theta,\tau)$ and $\beta_1(\theta,\tau)$, based on the study of Sim and Zhou (2015). Accordingly, equation (5.10) can be re-written as follows:

$$\beta^{\theta}(Crp_t) \approx \beta_0(\theta,\tau) + \beta_1(\theta,\tau)(Crp_t - Crp^{\tau}) \qquad (5.11)$$

By substituting equation (5.11) into equation (5.9), we arrive at the equation (5.12) as follows:

$$GO_t = \underbrace{\beta_0(\theta,\tau) + \beta_1(\theta,\tau)(Crp_t - Crp^{\tau})}_{(*)} + \mu_t^{\theta} \qquad (5.12)$$

In that the conditional quantile of cryptocurrency returns denoted by (*) allows the exact connections among the quantile of cryptocurrency returns and that of gold/oil of β_0 and β_1 parameters with θ and τ indices. Applying a minimisation in line with ordinary least squares, we specify equation (5.13)

$$min_{b_0,b_1} \sum_i^n \rho\theta \left[GO_t - b_0 - b_1\left(\widehat{Crp}_t - \widehat{Crp}^\tau\right)\right] K\left(\frac{F_n(\widehat{Crp}_t - \tau)}{h}\right) \qquad (5.13)$$

where $\rho_\theta(u)$ is the quantile loss function representing as $\rho_\theta(u) = u\big(\theta - I(u < 0)\big)$, h, $K(\cdot)$, and i denote the kernel density bandwith parameter, kernel density, and indicator functions respectively. The observations of Crp^τ are weighted by the kernel function where the minimum weight inversely relates to the distribution function of $\widehat{Crp}_t$ as $F_n\big(\widehat{Crp}_t\big) = \frac{1}{n}\sum_{k=1}^{n} I(\widehat{Crp}_k < \widehat{Crp}_t)$.

The choice of bandwidth is critical in nonparametric techniques as it smoothens the resulting estimate by determining the neighbourhood size at a targeted point. The bigger bandwidth produces robust estimation bias whiles the lesser bandwidth provides estimations with high variance bringing a balance between bias and variance. We use a bandwidth parameter $h = [0.05\ to\ 0.95]$ as used by Sim and Zhou (2015) in our analysis.

5.2 Data description and preliminary analysis

To examine the impact of cryptocurrencies on gold and crude oil returns, we employ seven leading cryptocurrencies: Bitcoin (BTC), Ethereum (ETH), Litecoin (LTC), Das (DASH), Ripple (XRP), Monero (XMR), and Steller (XLM) and two global commodities: Brent crude oil prices, and Gold (Bullion LBM U$/troy ounce) prices. The cryptocurrencies sampled for the study have been in existence for the past five years and are part of the top fifteen currencies by market capitalization. The included commodities are produced on commercial scale and have significance in international trade and can proxy for the commodity market. Daily closing market data for the period 10th August 2015 to 18th February 2019 are gleaned from CoinMarketCap for the cryptocurrencies and Bloomberg database for the gold and crude oil and expressed in US dollar to ease comparison and alleviate exchange rate noise (Pukthuanthong and Roll, 2009).

The availability of cryptocurrency price data constrained the period of analysis and the number of observations in this study. We calculate Monday-to-Friday returns for cryptocurrencies due to the commodities not traded on weekends. There is 877 observations when we removed the non-synchronous data points and matched the daily observations of the cryptocurrencies to gold and crude oil to prevent the problem of underestimation of true correlations and regressions following Martens and Poon (2001). Taking the log difference, the indices were converted to daily returns.

The daily returns of the assets are decomposed into frequencies based on the number of observations indicating the high-, medium-, and low frequencies of the assets. Specifically, wavelet scales D1, D4, and D6 indicate the short-, medium-, and long-term fluctuations of the assets as used by Das and Kannadhasan (2018). The summary statistics of cryptocurrencies, gold and crude oil returns at composite and decomposed levels are reported in Table 5.1. The daily average returns of the assets are close to zero at composite level with cryptocurrencies showing the highest average return, followed by gold, and then crude oil whereas the decomposed levels show zero average returns. The values for standard deviation depicts that cryptocurrencies are more volatile relative to gold and crude oil, with gold showing less volatility across the board.

The skewness and kurtosis of the series indicate that all the returns are skewed and leptokurtic indicating asymmetry and heavy tail. This non-normality is confirmed by Shapiro-Wilk test which shows asymmetry in the cryptocurrency returns. Further, the return plots of the composite and decomposed series reported in Figure 5.1 in the Appendices exhibit volatility clustering, fat tails, and asymmetry suggesting nonlinearity. These stylized facts justify the motivation to use wavelet decomposition to model the frequency-dependent volatility of the series and quantile-based techniques to model heavy tails of cryptocurrencies, gold, and crude oil and examine their association in bullish, normal, and bearish market states.

Table 5. 1: Summary statistics of cryptocurrencies, gold, and crude oil returns

Statistics	BTC	BTC.D1	BTC.D4	BTC.D6	ETH	ETH.D1	ETH.D4	ETH.D6	LTC	LTC.D1	LTC.D4	LTC.D6
Observ.	877	877	877	877	877	877	877	877	877	877	877	877
Mean	0.0021	0	0	0	0.003	0	0	0	0.0006	0	0	0
Std. Dev.	0.042	0.0291	0.0104	0.0051	0.072	0.048	0.0173	0.0111	0.0619	0.0418	0.016	0.0079
Skewness	-0.2386	-0.1611	0.2303	0.0228	0.622	-0.0225	0.4484	0.0787	1.2638	0.2161	0.6704	0.6036
Kurtosis	4.8188	4.0184	1.424	0.8112	4.013	2.0671	1.3257	0.2202	12.322	21.745	3.5507	1.4248
Normtest.W	0.9118	0.9362	0.9795	0.9807	0.933	0.9659	0.9809	0.988	0.8407	0.9105	0.934	0.9554
Normtest.p	0	0	0	0	0	0	0	0	0	0	0	0
Statistics	**XMR**	**XMR.D1**	**XMR.D4**	**XMR.D6**	**XRP**	**XRP.D1**	**XRP.D4**	**XRP.D6**	**XLM**	**XLM.D1**	**XLM.D4**	**XLM.D6**
Observ.	877	877	877	877	877	877	877	877	877	877	877	877
Mean	0.0014	0	0	0	0.0026	0	0	0	0.0053	0	0	0
Std. Dev.	0.0709	0.0517	0.0151	0.0094	0.0666	0.0485	0.0155	0.0091	0.094	0.0663	0.0193	0.0144
Skewness	0.6324	0.174	0.2473	-0.0524	4.5593	-0.2875	0.6259	-0.7791	2.1125	0.6004	0.5311	0.3434
Kurtosis	5.0718	2.836	0.2586	0.0847	77.2562	102.802	8.889	3.0518	17.8319	8.5355	2.6301	1.1458
Normtest.W	0.9355	0.9679	0.9943	0.99	0.5919	0.5474	0.8626	0.9308	0.8567	0.9174	0.9691	0.9762
Normtest.p	0	0	0	0	0	0	0	0	0	0	0	0
Statistics	**DASH**	**DASH.D1**	**DASH.D4**	**DASH.D6**	**GOLD**	**GOLD.D1**	**GOLD.4**	**GOLD.6**	**OIL**	**OIL.D1**	**OIL.D4**	**OIL.D6**
Observ.	877	877	877	877	877	877	877	877	877	877	877	877
Mean	0.0021	0	0	0	0.001	0	0	0	0.0003	0	0	0
Std. Dev.	0.0588	0.0418	0.0138	0.0069	0.008	0.0058	0.002	0.0009	0.0219	0.0163	0.0054	0.0027
Skewness	0.3105	0.2444	0.3464	0.4308	-0.377	-0.1038	0.0846	-0.2929	0.0778	-0.103	0.1336	-0.283
Kurtosis	3.4902	2.3709	1.339	0.2888	2.9526	1.9902	-0.2365	0.8967	2.3307	1.9324	1.5837	0.1506
Normtest.W	0.9446	0.9651	0.9807	0.9798	0.9646	0.9778	0.9977	0.9701	0.9708	0.9791	0.9839	0.9863
Normtest.p	0	0	0	0	0	0	0	0	0	0	0	0

Note: *Normtest.W denote Shapiro-Wilk test of normality,. D1, D4, D6 show the high-, medium-, and low frequencies respectively. BTC-Bitcoin, ETH-Ethereum, LTC-Litecoin, XRP-Ripple, XMR-Monero, XLM-Steller, DASH-Das. Observ.-observation and Std. Dev.-standard deviation.*

5.3 Results and discussion

To investigate the impact of cryptocurrencies on gold and crude oil returns to uncover the shock transmission mechanisms among the assets and their hedging[68] properties at different market states across varying time scales, we propose a new definition for tranquil and turbulent market conditions within a bivariate QR and QQR approach. We choose the lower quantiles ($\tau = 0.05\ to\ 0.45$) as bear market where the price of the assets are low which exhibit the downside risk in the market, the medium quantile ($\tau = 0.50$) as normal market where prices are stable which shows normal gains in the market, and upper quantiles ($\tau = 0.55\ to\ 0.95$) as bull market where prices are high which shows upside gain in the market as used by Selmi Mensi Hammoudeh and Jamal Bouoiyour (2018) and Mensi, Hammoudeh, and Tiwari (2016). The D1, D4, and D6 scales respectively depicts short-term, medium-term, and long-term trading horizons. We present the results and discussion for Quantile Regression (QR) in section 5.3.1 and Quantile-in-Quantile Regression in section 5.3.2.

5.3.1 QR Results for Gold and Cryptocurrencies

The QR estimates for gold/cryptocurrencies returns are reported in Table 5.2a and the plot of these estimates is shown in Figure 5.2 (in the Appendices) for further appreciation of the dynamics. The QR estimates on the impact of cryptocurrencies on gold reported in Table 5.2a display significant effects of cryptocurrencies on gold at some composite levels and some wavelet scales.

For Bitcoin (BTC), we find a significant positive but weak connections at the upper quantiles (0.85 to 0.95) in the medium scale (D4) of the distribution whiles the long scale (D6) shows positive association at lower quantiles (0.05 through to 0.35) and inverse connection at upper quantiles (0.60 to 0.95). The quantiles (0.05, 0.10, 0.90, and 0.95) at the long scale (D6) show the strongest magnitude. This result indicates that Bitcoin in the medium-term is a diversifier that behaves just like gold at bull state where the price of gold is high implying that investors can benefit from

[68] Based on the definitional approach conducted by Kaul and Sapp (2006), Baur and Lucey (2010), Reboredo (2013), and Baur and McDermott (2010), the distinctive characteristics of an asset as a safe haven, hedge and diversifier is as follows: An asset is a hedge if it exhibits a negative correlation in normal states. An asset is a safe haven if it is negatively correlated with another asset in times of market turmoil. An asset is a diversifier if it is positively but weakly correlated with another asset on average.

holding both Bitcoin and gold in the medium-term when gold price is high. The long-term of Bitcoin depicts that Bitcoin cannot hedge against turmoil in gold market at bearish regime (where gold price is very low) but can only hedge gold market crises when the price of gold is gaining value. This finding confirms the results of Guesmi, Saadi, Abid, and Ftiti (2019), Baur, Dimpfl, and Kuck (2018), and Selmi Mensi Hammoudeh and Jamal Bouoiyour (2018) who reports that Bitcoin has diversification and hedging properties for extreme gold price movements.

The composite level of Ethereum (ETH) exhibits significant negative association from lower to upper quantiles (0.20 to 0.80). The medium-term (D4) and long-term (D6) movements of Ethereum show highly significant negative association across all quantiles except for the highest quantiles of 0.90 and 0.95 in the medium scale (D4). The long scale of Ethereum exhibits the strongest effects on gold returns. The result implies that Ethereum can hedge gold market risk at all market states of gold (whether gold price is low, stable or high) in both medium and long-term horizons except for the bull market in the medium-term. In the case of Litecoin (LTC), we observe positive effects of Litecoin on gold returns at the quantiles (0.05 to 0.35) but negative effects at the quantiles (0.40 to 0.95) at the lower frequency indicating that price volatilities in Litecoin can affect gold price when gold market is bear in the long-term since gold behaves just like Litecoin at bear state. Nevertheless, Litecoin can hedge price volatilities of gold in normal and bull markets (where gold price is stable and high). The long-term of Litecoin shows the strongest effect on gold. We confirm the findings of Corbet, Meegan, Larkin, Lucey, and Yarayova (2018) that support the hedging properties of Litecoin for gold.

Monero (XMR) depicts similar pattern to Litecoin except that Monero has a highly significant negative effects on gold across all quantiles at the long scale (D6) except for the lowest (0.05) and highest (0.95) quantiles. The implication of this finding is that gold traders or investors can use Monero to hedge price fluctuations in gold market at all market regimes (bear, normal, and bull) whether gold price is in low, stable, or high states in the long-term. With regards to Ripple (XRP), we observe an inverse effect on gold returns from quantiles (0.25 to 0.45) and from (0.65 to 0.95) at the composite scale. The short scale (D1) shows negative effect on gold returns from (0.15 to 0.85) quantiles. The medium scale (D4) also depicts negative connections with gold at lower quantiles (0.05, 0.1, 0.15) and upper quantiles (0.85, 0.90, 0.95). However, the long scale (D6) exhibit highly significant positive effects of Ripple on gold returns across all quantiles. This clearly shows that hedging strategies are feasible for economic actors in gold market at all market states of gold in the short-term (i.e. whether gold price is low, stable, or high) but bearish regime where gold price is very low, and bullish regime where gold price is very high in the medium-term. However, price fluctuations in Ripple can influence gold price in the long-term and that market participants in gold market cannot hedge extreme gold price movements using Ripple in the long-term. Our result for gold/Ripple is consistent with the results of Corbet, Meegan, Larkin, Lucey, and Yarayova (2018) which show Ripple as a good hedge for gold.

For Das (DASH), we find negative relationship from lower to medium quantiles (0.30 to 0.50) and positive association at upper quantiles (0.85 to 0.95) at the medium scale (D4). We also find negative effects of Das on gold returns across all quantiles at the long scale (D6). This implies that Das is a good hedge against gold market downturns at bear market state (where gold price is low) in the medium-term, but all market states (whether gold price is in downside, normal, or upside regimes) in the long-time horizon. Steller exhibit negative impact on gold at lower quantiles of (0.15 to 0.25) at the medium scale (D4) and across all quantiles at the long scale (D6) which indicates that Steller has hedging properties for gold in bearish market condition where gold price is falling in the medium-term but all market conditions in the long-term no matter the price of gold.

To sum it all up, our results suggest that Bitcoin, Litecoin, and Monero can hedge price fluctuations of gold at all market states of gold (bear, normal, bull) whether the price of gold is low, stable, or high in the long-term. Das and Steller can hedge the downside risk of gold in the medium-term at both bear and bull gold markets and across all market states in the long-term when gold price is low, stable, or high. Ripple can hedge against extreme gold price movements across market regimes in the short-term whether gold price is in the downside, middle, or upside regimes and in the medium-term when gold price is very low and very high. Lastly, in both medium and long-time horizons, economic agents can hedge against extreme gold price movements using Ethereum in the downside, normal, and upside price regimes of gold.

Our findings on gold/cryptocurrencies complement the findings of Guesmi, Saadi, Abid, and Ftiti (2019), Dyhrberg (2016), Bouri et al. (2017), Al-Khazali et al. (2018), Selmi Mensi Hammoudeh and Jamal Bouoiyour (2018), and Bouri et al. (2018). The findings of these studies show that cryptocurrencies have hedging characteristics that can curtail adverse effects of gold market fluctuations and thus should be included in a portfolio with gold. Conversely, our findings contradict the work of Baur, Dimpfl, and Kuck (2018) that report Bitcoin to be isolated from gold market. Our finding of cryptocurrencies having hedging properties for gold is in line with the modern portfolio theory which contends that adding an asset to a portfolio should be considered in the light of its impact on the performance and risk of the portfolio of assets.

Table 5.2 a: QR estimates for gold/cryptocurrencies returns

	BTC	BTC.D1	BTC.D4	BTC.D6	ETH	ETH.D1	ETH.D4	ETH.D6	LTC	LTC.D1	LTC.D4	LTC.D6
Quantile	**Coef.**	**Coef.**	**Coef.**	**Coef.**	**Coef.**	**Coef.**	**Coef.**	**Coef.**	**Coef.**	**Coef.**	**Coef.**	**Coef.**
0.05	0.0080	0.0234	0.0103	0.1157[a]	-0.0077	0.0036	-0.0161[a]	-0.0412[a]	0.0027	-0.0097	0.0045	0.0627[a]
0.10	-0.0116	0.0068	-0.0010	0.0944[a]	-0.0042	0.0030	-0.0167[a]	-0.0491[a]	0.0033	0.0067	0.0014	0.0464[a]
0.15	-0.0024	0.0013	0.0003	0.0408[a]	-0.0030	-0.0035	-0.0191[a]	-0.0509[a]	-0.0014	0.0014	-0.0011	0.0299[a]
0.20	-0.0059	0.0038	-0.0103	0.0120[c]	-0.0096[b]	-0.0008	-0.0258[a]	-0.0376[a]	-0.0073	0.0018	-0.0075	0.0119[a]
0.25	-0.0106	0.0015	-0.0095	0.0174[a]	-0.0112[a]	-0.0008	-0.0300[a]	-0.0338[a]	-0.0097[c]	0.0022	-0.0060	0.0119[a]
0.30	-0.0078	0.0008	-0.0117	0.0159[a]	-0.0095[b]	0.0009	-0.0324[a]	-0.0280[a]	-0.0077	0.0006	-0.0062	0.0091[a]
0.35	-0.0076	0.0002	-0.0149	0.0128[a]	-0.0064	-0.0007	-0.0315[a]	-0.0278[a]	-0.0050	-0.0018	-0.0068	0.0078[b]
0.40	-0.0053	-0.0014	-0.0168[c]	0.0035	-0.0076[c]	-0.0011	-0.0351[a]	-0.0268[a]	-0.0027	-0.0003	-0.0095	0.0023
0.45	-0.0073	0.0025	-0.0174[c]	-0.0018	-0.0072[c]	-0.0003	-0.0328[a]	-0.0274[a]	-0.0020	0.0018	-0.0106	-0.0013
0.50	-0.0045	0.0044	-0.0160	-0.0034	-0.0064	0.0016	-0.0276[a]	-0.0259[a]	-0.0025	0.0047	-0.0079	-0.0057[c]
0.55	0.0015	0.0036	-0.0135	-0.0056	-0.0066	0.0016	-0.0251[a]	-0.0274[a]	0.0018	0.0036	-0.0073	-0.0081[a]
0.60	0.0019	0.0025	-0.0077	-0.0089[c]	-0.0069[c]	0.0026	-0.0214[a]	-0.0285[a]	0.0010	0.0014	-0.0041	-0.0096[a]
0.65	0.0050	-0.0016	-0.0012	-0.0109[b]	-0.0061	0.0045	-0.0163[a]	-0.0312[a]	0.0024	-0.0019	0.0006	-0.0121[a]
0.70	0.0095	-0.0056	-0.0022	-0.0122[a]	-0.0082[b]	0.0054	-0.0213[a]	-0.0329[a]	0.0049	-0.0016	-0.0006	-0.0139[a]
0.75	0.0134[b]	-0.0045	0.0001	-0.0115[b]	-0.0080[c]	0.0051	-0.0186[a]	-0.0329[a]	0.0064	-0.0026	-0.0018	-0.0154[a]
0.80	0.0081	-0.0018	0.0113	-0.0089	-0.0077[c]	-0.0001	-0.0149[a]	-0.0364[a]	0.0022	-0.0008	0.0020	-0.0180[a]
0.85	0.0070	-0.0005	0.0222[b]	-0.0014	-0.0068	0.0022	-0.0132[a]	-0.0405[a]	-0.0016	0.0005	0.0070	-0.0222[a]
0.90	0.0106	0.0142	0.0223[a]	0.0594[a]	-0.0055	0.0101	-0.0073	-0.0467[a]	0.0061	0.0070	0.0068	-0.0061
0.95	0.0067	0.0078	0.0224[b]	0.0581[a]	0.0046	0.0055	0.0048	-0.0555[a]	0.0062	-0.0073	0.0137[b]	0.0292[b]

Note: *Values with [a] ([b]) [[c]] respectively denotes significance at the 0.01 (0.05) [0.10] levels. BTC - Bitcion, ETH – Ethereum, LTC - Litecoin*

Table 5.2a: QR estimates for gold/cryptocurrencies returns cont.

	XMR	XMR.D1	XMR.D4	XMR.D6	XRP	XRP.D1	XRP.D4	XRP.D6
Quantile	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.
0.05	-0.0037	-0.0134[c]	0.0045	-0.0069	0.0022	0.0003	-0.0200[a]	0.0494[a]
0.10	-0.0040	-0.0085	0.0026	-0.0425[a]	-0.0012	-0.0042	-0.0180[a]	0.0302[a]
0.15	-0.0028	-0.0040	0.0005	-0.0345[a]	-0.0031	-0.0060[c]	-0.0152[b]	0.0108[a]
0.20	-0.0013	-0.0034	-0.0030	-0.0259[a]	-0.0050	-0.0075[b]	-0.0097	0.0091[a]
0.25	-0.0009	0.0002	-0.0049	-0.0213[a]	-0.0063[c]	-0.0087[a]	-0.0075	0.0093[a]
0.30	-0.0015	0.0008	-0.0047	-0.0283[a]	-0.0075[b]	-0.0096[a]	-0.0116[c]	0.0138[a]
0.35	-0.0025	0.0023	-0.0043	-0.0347[a]	-0.0080[b]	-0.0081[c]	-0.0060	0.0190[a]
0.40	-0.0017	0.0022	-0.0079	-0.0334[a]	-0.0088[a]	-0.0073	-0.0055	0.0199[a]
0.45	-0.0008	0.0044	-0.0070	-0.0309[a]	-0.0072[c]	-0.0089[b]	-0.0049	0.0193[a]
0.50	-0.0014	0.0059	-0.0063	-0.0279[a]	-0.0066	-0.0124[a]	-0.0036	0.0191[a]
0.55	0.0005	0.0056	-0.0018	-0.0252[a]	-0.0042	-0.0129[a]	-0.0054	0.0218[a]
0.60	-0.0013	0.0034	0.0013	-0.0240[a]	-0.0046	-0.0126[a]	-0.0034	0.0263[a]
0.65	-0.0003	0.0036	0.0032	-0.0222[a]	-0.0076[c]	-0.0123[a]	-0.0036	0.0265[a]
0.70	0.0038	0.0038	0.0068	-0.0199[a]	-0.0077[c]	-0.0114[a]	-0.0050	0.0262[a]
0.75	0.0066	0.0030	0.0108	-0.0190[a]	-0.0119[a]	-0.0102[a]	-0.0047	0.0291[a]
0.80	0.0058	0.0036	0.0098	-0.0219[a]	-0.0161[a]	-0.0090[a]	-0.0057	0.0327[a]
0.85	0.0054	0.0039	0.0161[b]	-0.0238[a]	-0.0171[a]	-0.0095[b]	-0.0147[a]	0.0395[a]
0.90	0.0102	0.0033	0.0286[a]	-0.0223[a]	-0.0186[a]	-0.0080	-0.0189[a]	0.0425[a]
0.95	0.0194[b]	-0.0001	0.0239[a]	0.0041	-0.0218[a]	-0.0016	-0.0224[a]	0.0511[a]

Note: Note: *Values with [a] ([b]) [[c]] respectively denotes significance at the 0.01 (0.05) [0.10] levels. XMR – Monero, and XRP – Ripple.*

Table 5.2a: QR estimates for gold/cryptocurrencies returns cont.

Quantile	DASH Coef.	DASH.D1 Coef.	DASH.D4 Coef.	DASH.D6 Coef.	XLM Coef.	XLM.D1 Coef.	XLM.D4 Coef.	XLM.D6 Coef.
0.05	0.0053	0.0178	0.0117[c]	0.0583[a]	0.0003	0.0143[a]	-0.0033	-0.0302[a]
0.10	-0.0042	-0.0043	0.0050	-0.0223	-0.0042	0.0019	-0.0058	-0.0268[a]
0.15	-0.0020	-0.0026	-0.0020	-0.0266[a]	-0.0021	0.0016	-0.0108[b]	-0.0276[a]
0.20	0.0013	-0.0029	-0.0091	-0.0144[a]	0.0005	-0.0011	-0.0146[a]	-0.0266[a]
0.25	-0.0002	-0.0019	-0.0083	-0.0229[a]	0.0024	0.0004	-0.0142[a]	-0.0275[a]
0.30	-0.0053	-0.0018	-0.0120[b]	-0.0270[a]	0.0011	-0.0003	-0.0071	-0.0265[a]
0.35	-0.0048	-0.0014	-0.0174[a]	-0.0303[a]	-0.0005	-0.0008	-0.0057	-0.0250[a]
0.40	-0.0045	-0.0006	-0.0138[a]	-0.0271[a]	0.0016	-0.0001	-0.0064	-0.0235[a]
0.45	-0.0027	0.0025	-0.0158[a]	-0.0249[a]	0.0021	0.0001	-0.0039	-0.0227[a]
0.50	-0.0022	0.0037	-0.0120[b]	-0.0223[a]	0.0012	0.0045	-0.0015	-0.0215[a]
0.55	0.0008	0.0031	-0.0094	-0.0190[a]	0.0019	0.0009	-0.0009	-0.0194[a]
0.60	-0.0003	0.0023	-0.0030	-0.0174[a]	0.0011	0.0020	0.0017	-0.0184[a]
0.65	0.0014	0.0018	-0.0035	-0.0188[a]	0.0021	0.0027	0.0017	-0.0175[a]
0.70	0.0031	0.0036	-0.0041	-0.0181[a]	0.0028	0.0018	0.0041	-0.0177[a]
0.75	0.0050	0.0008	-0.0067	-0.0172[a]	0.0034	0.0014	0.0029	-0.0163[a]
0.80	-0.0020	-0.0008	0.0012	-0.0190[a]	-0.0010	0.0014	-0.0012	-0.0171[a]
0.85	0.0011	0.0056	0.0188[b]	-0.0207[a]	0.0035	0.0017	0.0051	-0.0216[a]
0.90	0.0107	0.0101	0.0303[a]	-0.0238[a]	0.0071	0.0025	0.0074	-0.0263[a]
0.95	0.0024	-0.0058	0.0392[a]	0.0283[c]	0.0151	0.0000	0.0055	-0.0359[a]

Note: *Values with [a] ([b]) [[c]] respectively denotes significance at the 0.01 (0.05) [0.10] levels. DASH – Das, XLM - Steller*

5.3.2 QR Results for Crude Oil and Cryptocurrencies

Table 5.2b exhibits the QR estimates for oil/cryptocurrencies return and the plot of these estimates shown in Figure 5.2 (in the Appendices) for a further appreciation of the dynamics. The QR estimates on the impact of cryptocurrencies on crude oil returns reported in Table 5.2b displays a significant effect of cryptocurrencies on crude oil at some composite levels and some wavelet scales.

For Bitcoin (BTC), the medium-term (D4) and long-term (D6) movements depict positive effects on crude oil across quantiles suggesting that market discrepancies in Bitcoin can transmit to crude oil market from the medium to long-term. This implies that Bitcoin cannot hedge extreme oil price movements across the time-horizons since it behaves similarly to crude oil at all market conditions of crude oil price. This finding contradicts the results of Bouri, Azzi, and Dyhrberg (2017), Al-Yahyaee, Mensi, Al-Jarrah, Hamdi, and Kang (2019), Selmi Mensi Hammoudeh and Jamal Bouoiyour (2018), Guesmi, Saadi, Abid, and Ftiti (2018) who finds Bitcoin as a good hedge which can reduce the portfolio risk of crude oil. Conversely, the finding for oil/Bitcoin is consonant with Kurka (2019) who reports Bitcoin as not a hedge for traditional assets due to its positive correlation with the assets.

Ethereum (ETH) displays negative effects on crude oil at the lowest quantile (0.15, 0.10) in its short-term (D1) and medium-term (D4) movements indicating that Ethereum can hedge shocks to crude oil prices at bear state where oil price is very low in the short-, and medium-terms. However, Ethereum shows positive effects on crude oil across quantiles in the long scale (D7), suggesting possible shock transmissions from Ethereum market to crude oil market at all market regimes. We observe from Litecoin (LTC)/crude oil pairs that Litecoin has positive influence on crude oil prices across quantiles at both medium (D4) and long (D6) scales which indicates that price volatilities in Litecoin directly affect crude oil prices and that Litecoin is not a good hedge for extreme volatilities in crude oil market at all market states across the trading horizons. Monero (XMR) depicts positive effect on crude oil at the short scale (D1) at quantiles (0.30 to 0.90), negative effects at lower and upper quantiles (0.05, 0.10) and (0.90, 0.95) respectively but positive effects at quantiles (0.30 to 0.50) in the medium scale (D4). Nonetheless, the long scale of Monero shows positive association across all distribution. This finding shows the possibility of market disruptions spilling over from Monero market to crude oil market in the short-, and long-terms and that hedging strategy are only feasible at bear and bull market states in the medium-term for oil traders/investors when oil price is very low and very high.

In the case of Ripple (XRP), we find negative association from (0.35 to 0.80) at the composite scale, the quantiles (0.35 to 0.60) at the short scale (D1), across all quantiles at the medium scale (D4), and at lower quantiles (0.05 to 0.15) at the long scale (D6). The quantiles (0.20 through to 0.85) depict highly significant positive connections with crude oil at the long scale (D6). The implication of the results is that economic participants in the crude oil market can use Ripple to hedge oil market crises at bear and normal market conditions where oil price is low and stable in the short-term, all market conditions in the medium-term (whether oil price is in upside, normal, or downside regime), and bearish regime in the long-term (where oil price is very low). With regards to Das (DASH), we observe positive effects on crude oil at both medium and long scales which implies that Das cannot hedge oil market turmoil at any of the market states across the horizons since Das behaves just like crude oil across all quantiles in the various investment horizons. Steller (XLM) exhibit positive impact on crude oil at short scale (D1) (0.05 to 0.30), all quantiles in the medium scale (D4), but negative impact at lower quantiles (0.05, 0.10) and upper quantiles (0.70 to 0.95) at the long scale (D6). This result indicates that Steller has hedging properties for crude oil investors and traders at bear and bull markets in the long-term (where oil price is very low and very high).

To sum it all up, our findings depict that Bitcoin, Litecoin, and Das do not have hedging characteristics for extreme oil price movements at the various market conditions across the time horizons and that price volatilities in the cryptocurrencies can influence the price of crude oil across time. Conversely, Ethereum can hedge against oil market turmoil at bearish regime when oil price is very low in the short-, and medium-time horizons. Hedging properties are feasible using Monero in the medium-term at both bull and bear regimes. In all time scales and across market states, Ripple can hedge against oil market crises. Lastly, investors can use Steller to hedge oil crises in the long-term when oil price is in very low and high states.

In general, the findings for Bitcoin, Litecoin, and Dash markets contradict the findings of Al-Yahyaee, Mensi, Al-Jarrah, Hamdi, and Kang (2019), Selmi et al. (2018), Dyhrberg (2016), Bouri et al. (2017), Al-Khazali et al. (2018), Corbet, Meegan, Larkin, Lucey, and Yarayova (2018) who reported cryptocurrencies as safe havens, diversifiers, and hedges for crude oil price fluctuations implementing different techniques. Conversely, our findings on Ethereum, Monero, Steller, and Ripple complement previous studies including Lee, Guo, and Wang (2018), Corbet et al. (2018) and Selmi et al. (2018) which argued that digital currencies are new tools to diversify portfolios and reduce risk.

Table 5.2 b: QR estimates for oil/cryptocurrencies returns

Quantile	BTC Coef.	BTC.D1 Coef.	BTC.D4 Coef.	BTC.D6 Coef.	ETH Coef.	ETH.D1 Coef.	ETH.D4 Coef.	ETH.D6 Coef.	LTC Coef.	LTC.D1 Coef.	LTC.D4 Coef.	LTC.D6 Coef.
0.05	0.0624	0.0267	0.0425	0.2895[a]	-0.0004	-0.0456[b]	-0.0381[b]	0.1928[a]	0.0400	0.0193	0.0233	0.1799[a]
0.10	0.0255	0.0350	0.0803[a]	0.2416[a]	0.0035	-0.0353[b]	-0.0471[a]	0.1671[a]	0.0185	0.0080	0.0610[a]	0.1465[a]
0.15	0.0296	0.0142	0.0843[a]	0.1796[a]	-0.0059	-0.0179	-0.0205	0.1101[a]	-0.0011	-0.0005	0.0662[a]	0.1051[a]
0.20	0.0072	0.0252	0.0822[a]	0.1378[a]	-0.0039	-0.0097	0.0000	0.0962[a]	0.0064	0.0135	0.0544[a]	0.0963[a]
0.25	0.0067	0.0203	0.0850[a]	0.1172[a]	0.0025	-0.0014	0.0124	0.0905[a]	0.0143	0.0107	0.0495[a]	0.1075[a]
0.30	0.0004	0.0056	0.0781[a]	0.1008[a]	-0.0042	-0.0028	0.0238[c]	0.0828[a]	0.0114	0.0093	0.0415[a]	0.1047[a]
0.35	0.0013	-0.0074	0.0830[a]	0.0837[a]	-0.0080	-0.0073	0.0292[b]	0.0677[a]	0.0135	0.0062	0.0491[a]	0.0983[a]
0.40	-0.0225	0.0119	0.0990[a]	0.0659	-0.0092	-0.0024	0.0369[a]	0.0517[a]	0.0069	0.0074	0.0607[a]	0.1044[a]
0.45	-0.0126	0.0138	0.1018[a]	0.0659[a]	-0.0053	0.0019	0.0321[b]	0.0337[a]	0.0036	0.0096	0.0582[a]	0.1056[a]
0.50	-0.0145	0.0030	0.0999[a]	0.0841[a]	-0.0068	0.0023	0.0258[c]	0.0342[a]	0.0032	0.0119	0.0520[a]	0.0925[a]
0.55	-0.0044	0.0054	0.1017[a]	0.1024[a]	-0.0018	0.0032	0.0257[c]	0.0329[a]	0.0069	0.0085	0.0442[a]	0.1052[a]
0.60	-0.0021	0.0004	0.0896[a]	0.1285[a]	-0.0027	-0.0045	0.0234[b]	0.0416[a]	0.0060	0.0036	0.0383[a]	0.1235[a]
0.65	0.0017	0.0148	0.0924[a]	0.1579[a]	-0.0126	-0.0054	0.0316	0.0435[a]	0.0032	-0.0048	0.0432[a]	0.1514[a]
0.70	-0.0047	0.0074	0.0997[a]	0.1774[a]	-0.0096	-0.0138	0.0147	0.0572[a]	0.0027	0.0025	0.0432[a]	0.1602[a]
0.75	0.0111	0.0110	0.1081[a]	0.1935[a]	0.0066	-0.0168	0.0127	0.0696[a]	0.0128	0.0013	0.0493[a]	0.1492[a]
0.80	0.0040	0.0140	0.1239[a]	0.2332[a]	0.0068	-0.0231	0.0020	0.0806[a]	0.0142	0.0004	0.0562[a]	0.1446[a]
0.85	-0.0153	0.0229	0.1103[a]	0.2564[a]	-0.0065	-0.0266	0.0035	0.0863[a]	0.0024	0.0041	0.0493[a]	0.1566[a]
0.90	-0.0375	0.0352	0.0931[a]	0.2013[a]	-0.0224	-0.0209	-0.0054	0.1006[a]	0.0041	0.0215	0.0248	0.1950[a]
0.95	0.0075	0.0451	0.0210	0.0985	-0.0233	-0.0249	-0.0253[c]	0.1008[a]	0.0097	-0.0296	-0.0291[a]	0.1377[a]

Note: *Values with [a] ([b]) [[c]] respectively denotes significance at the 0.01 (0.05) [0.10] levels. BTC – Bitcoin, ETH – Ethereum, LTC – Litecoin.*

Table 5.2b: QR estimates for oil/cryptocurrencies returns cont.

	XMR	XMR.D1	XMR.D4	XMR.D6	XRP	XRP.D1	XRP.D4	XRP.D6
Quantile	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.
0.05	0.0067	0.0069	-0.0519[a]	0.1309[a]	-0.0613[c]	0.0109	-0.0637[c]	-0.1036[a]
0.10	0.0170	0.0246	-0.0328[c]	0.1407[a]	-0.0161	-0.0292	-0.0580[b]	-0.0598[a]
0.15	-0.0019	0.0216	-0.0143	0.0981[a]	-0.0221	-0.0259	-0.0820[a]	-0.0338[a]
0.20	0.0085	0.0231	0.0046	0.0855[a]	-0.0304	-0.0221	-0.0820[a]	-0.0165
0.25	0.0075	0.0196	0.0174	0.0779[a]	-0.0349[b]	-0.0173	-0.0690[a]	-0.0129
0.30	0.0079	0.0289[b]	0.0228[c]	0.0794[a]	-0.0342[b]	-0.0239	-0.0737[a]	0.0105
0.35	0.0192[c]	0.0297[b]	0.0269[b]	0.0852[a]	-0.0268[a]	-0.0301[a]	-0.0868[a]	0.0294[a]
0.40	0.0172	0.0282[b]	0.0335[a]	0.0748[a]	-0.0203[b]	-0.0276[a]	-0.0886[a]	0.0350[a]
0.45	0.0141	0.0233[c]	0.0363[a]	0.0702[a]	-0.0223[a]	-0.0254[b]	-0.0899[a]	0.0321[a]
0.50	0.0094	0.0280[b]	0.0298[b]	0.0717[a]	-0.0252[a]	-0.0254[a]	-0.0946[a]	0.0306[a]
0.55	0.0105	0.0311[a]	0.0189	0.0792[a]	-0.0268[a]	-0.0277[a]	-0.1047[a]	0.0346[a]
0.60	0.0134	0.0297[b]	0.0130	0.0819[a]	-0.0178[c]	-0.0209[b]	-0.1032[a]	0.0398[a]
0.65	0.0207[c]	0.0257[b]	0.0103	0.0914[a]	-0.0204[c]	-0.0155	-0.0944[a]	0.0510[a]
0.70	0.0207[c]	0.0314[a]	0.0081	0.0983[a]	-0.0218[b]	-0.0130	-0.0913[a]	0.0617[a]
0.75	0.0205	0.0200	0.0072	0.0979[a]	-0.0304[a]	-0.0102	-0.0951[a]	0.0690[a]
0.80	0.0252[c]	0.0295[b]	0.0086	0.1102[a]	-0.0291[a]	-0.0076	-0.1003[a]	0.0576[a]
0.85	0.0106	0.0318[b]	-0.0031	0.1179[a]	-0.0190	-0.0035	-0.0819[a]	0.0389[a]
0.90	0.0124	0.0377[b]	-0.0509[b]	0.1479[a]	-0.0170	0.0019	-0.0648[a]	0.0110
0.95	0.0041	0.0023	-0.0923[a]	0.1599[a]	-0.0128	-0.0021	-0.0383[a]	-0.0003

Note: *Values with [a] ([b]) [[c]] respectively denotes significance at the 0.01 (0.05) [0.10] level. XMR - Monero, XRP - Ripple*

Table 5.2b: QR estimates for oil/cryptocurrencies returns cont.

Quantile	DASH Coef.	DASH.D1 Coef.	DASH.D4 Coef.	DASH.D6 Coef.	XLM Coef.	XLM.D1 Coef.	XLM.D4 Coef.	XLM.D6 Coef.
0.05	0.0509[b]	0.0206	0.0287	0.1385[a]	0.0212	0.0322[b]	0.0513[a]	-0.0521[a]
0.10	0.0275	0.0358	0.0021	0.1272[a]	0.0219	0.0293[a]	0.0746[a]	-0.0431[a]
0.15	0.0317	0.0287	0.0269	0.0716[a]	0.0182	0.0224[b]	0.0618[a]	-0.0145
0.20	0.0307[c]	0.0273	0.0381[b]	0.0670[a]	0.0080	0.0240[a]	0.0541[a]	0.0002
0.25	0.0208	0.0245	0.0530[a]	0.0729[a]	0.0085	0.0158	0.0523[a]	0.0063
0.30	0.0153	0.0347[b]	0.0593[a]	0.0758[a]	0.0042	0.0186[b]	0.0633[a]	0.0066
0.35	0.0194	0.0296[b]	0.0606[a]	0.0594[a]	0.0077	0.0151	0.0661[a]	0.0120[b]
0.40	0.0193	0.0235	0.0620[a]	0.0452	0.0042	0.0126	0.0653[a]	0.0097
0.45	0.0205	0.0234	0.0642[a]	0.0251	-0.0014	0.0111	0.0581[a]	0.0070
0.50	0.0215	0.0177	0.0631[a]	0.0177	0.0004	0.0116	0.0539[a]	0.0001
0.55	0.0151	0.0145	0.0559[a]	0.0117	0.0038	0.0061	0.0431[a]	-0.0030
0.60	0.0156	0.0239	0.0553[a]	0.0351[b]	0.0061	0.0019	0.0373[a]	-0.0067
0.65	0.0184	0.0349[b]	0.0493	0.0720[a]	0.0040	0.0043	0.0372[a]	-0.0060
0.70	0.0193	0.0352[b]	0.0393[b]	0.0986[a]	0.0101	0.0100	0.0458[a]	-0.0144[c]
0.75	0.0251[c]	0.0312[b]	0.0373[b]	0.1221[a]	0.0106	0.0045	0.0545[a]	-0.0270[a]
0.80	0.0378[a]	0.0341	0.0448[a]	0.1096[a]	0.0092	0.0089	0.0718[a]	-0.0399[a]
0.85	0.0460[a]	0.0280	0.0351[c]	0.1269[a]	0.0134	0.0079	0.0709[a]	-0.0496[a]
0.90	0.0137	0.0658[a]	0.0257	0.1428[a]	0.0345	0.0096	0.0873[a]	-0.0699[a]
0.95	0.0726	0.0655[c]	-0.0209	0.1532[a]	0.0161	0.0422[b]	0.0840[a]	-0.0742[a]

Note: *Values with [a] ([b]) [[c]] respectively denotes significance at the 0.01 (0.05) [0.10] levels. DASH – Das, XLM – Steller.*

5.3.3 QQR Results for Gold, Crude Oil, and Cryptocurrencies

The QR estimates the heterogeneous response of gold and crude oil to cryptocurrencies across quantiles of the conditional distribution of gold and crude oil returns. However, it neglects the possibility that gold and crude oil prices in low, normal or high regimes can also impact the hedging properties of cryptocurrencies. Specifically, the QR estimate a unidirectional effect of cryptocurrencies on gold and crude oil returns while QQR investigates the bidirectional association (reverse causality) between gold/cryptocurrencies, and oil/cryptocurrencies returns. Consequently, we combine these two approaches to explore the entire dynamic dependencies between the assets.

The QQR as a nonparametric model does not show significance level in the estimates reported in Table 5.3(a, b) but these estimates can be validated with QR coefficients which is parametric since the estimates generated by QR are decomposed into the specificied quantiles of the covariates by the QQR as discussed in the work of Bouri, Gupta, Tiwari, and Roubaud (2017).

The QQR estimates on the effects of cryptocurrencies on gold and crude oil returns show larger coefficients relative to QR estimates. The upper half of the distribution depicts negative associations between gold/cryptocurrencies and oil/cryptocurrencies at quantiles (0.05 to 0.50) across all time scales (short, medium, and long scales) whiles the lower half of the distribution exhibit positive effects between the assets at quantiles (0.55 to 0.95) across the time scales. The implication of this finding is that under bearish and normal market states ($\tau = 0.05\ to\ 0.50$), negative shocks to the price of cryptocurrencies cannot influence gold and crude oil prices whiles negative shocks to gold and crude oil prices cannot also affect the price of cryptocurrencies suggesting that the assets (gold/crude oil and cryptocurrencies) can hedge the price fluctuations of each other across time when gold and crude oil prices are in low and normal regimes and the price of cryptocurrencies is low and stable. However, extreme market discrepancies from the commodities or cryptocurrencies can spillover to the other at bull regimes across time implying that neither the commodities (gold and crude oil) nor cryptocurrencies can hedge extreme price volatilities of the other when their market is bull. This finding is in line with Lee, Guo, and Wang (2018), Corbet et al. (2018) and Selmi et al. (2018), who depict that cryptocurrencies are new tool to diversify portfolios and reduce risk. The QQR estimates for gold/cryptocurrencies are shown in Table 5.3a whiles oil/ cryptocurrencies are shown in Table 5.3b.

We plot the coefficients of both QR and QQR to test the validity of QQR. The line plots of the coefficients of QR and QQR in Figure 5.2 (in the Appendices) depict that QR estimates largely confirms QQR by the closeness in pattern of both QQR and QR across time-scales and quantiles which only differ in magnitude thereof. This shows the appropriateness of employing both techniques in this study. The pictorial view shown by the line plots of QQR and QR displays the bear and bull trends in gold, crude oil, and cryptocurrency markets.

Table 5.3 a: QQR estimates for gold/cryptocurrencies returns

	BTC	BTC.D1	BTC.D4	BTC.D6	ETH	ETH.D1	ETH.D4	ETH.D6	LTC	LTC.D1	LTC.D4	LTC.D6
Quantile	**Coef.**	**Coef.**	**Coef.**	**Coef.**	**Coef.**	**Coef.**	**Coef.**	**Coef.**	**Coef.**	**Coef.**	**Coef.**	**Coef.**
0.05	-0.2075	-0.1473	-0.0339	-0.0141	-0.2917	-0.2025	-0.0512	-0.0281	-0.3952	-0.2479	-0.0503	-0.0186
0.10	-0.1835	-0.1310	-0.0296	-0.0124	-0.2526	-0.1803	-0.0444	-0.0250	-0.3448	-0.2174	-0.0430	-0.0161
0.15	-0.1595	-0.1147	-0.0253	-0.0108	-0.2135	-0.1580	-0.0377	-0.0219	-0.2945	-0.1869	-0.0358	-0.0136
0.20	-0.1354	-0.0985	-0.0210	-0.0091	-0.1744	-0.1358	-0.0309	-0.0187	-0.2442	-0.1564	-0.0285	-0.0111
0.25	-0.1114	-0.0822	-0.0167	-0.0075	-0.1353	-0.1136	-0.0242	-0.0156	-0.1939	-0.1259	-0.0213	-0.0086
0.30	-0.0873	-0.0659	-0.0124	-0.0058	-0.0962	-0.0914	-0.0174	-0.0125	-0.1436	-0.0955	-0.0140	-0.0061
0.35	-0.0633	-0.0496	-0.0081	-0.0042	-0.0570	-0.0692	-0.0107	-0.0094	-0.0933	-0.0650	-0.0067	-0.0036
0.40	-0.0393	-0.0334	-0.0038	-0.0026	-0.0179	-0.0470	-0.0039	-0.0062	-0.0430	-0.0345	0.0005	-0.0011
0.45	-0.0152	-0.0171	0.0005	-0.0009	0.0212	-0.0247	0.0028	-0.0031	0.0073	-0.0040	0.0078	0.0014
0.50	0.0088	-0.0008	0.0048	0.0007	0.0603	-0.0025	0.0096	0.0000	0.0576	0.0265	0.0150	0.0039
0.55	0.0328	0.0155	0.0091	0.0024	0.0994	0.0197	0.0163	0.0032	0.1079	0.0570	0.0223	0.0064
0.60	0.0569	0.0317	0.0134	0.0040	0.1385	0.0419	0.0231	0.0063	0.1582	0.0875	0.0296	0.0089
0.65	0.0809	0.0480	0.0177	0.0057	0.1776	0.0641	0.0298	0.0094	0.2085	0.1180	0.0368	0.0114
0.70	0.1049	0.0643	0.0220	0.0073	0.2168	0.0863	0.0366	0.0126	0.2588	0.1484	0.0441	0.0139
0.75	0.1290	0.0806	0.0263	0.0090	0.2559	0.1086	0.0433	0.0157	0.3091	0.1789	0.0513	0.0163
0.80	0.1530	0.0968	0.0306	0.0106	0.2950	0.1308	0.0501	0.0188	0.3594	0.2094	0.0586	0.0188
0.85	0.1770	0.1131	0.0349	0.0122	0.3341	0.1530	0.0568	0.0219	0.4097	0.2399	0.0659	0.0213
0.90	0.2011	0.1294	0.0392	0.0139	0.3732	0.1752	0.0636	0.0251	0.4600	0.2704	0.0731	0.0238
0.95	0.2251	0.1457	0.0435	0.0155	0.4123	0.1974	0.0703	0.0282	0.5103	0.3009	0.0804	0.0263

Note: *BTC – Bitcoin, ETH – Ethereum, LTC - Litecoin*

Table 5.3a: QQR estimates for gold/cryptocurrencies returns cont.

	XMR	XMR.D1	XMR.D4	XMR.D6	XRP	XRP.D1	XRP.D4	XRP.D6
Quantile	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.
0.05	-0.2932	-0.2360	-0.0412	-0.0230	-0.6163	-0.7096	-0.0752	-0.0359
0.10	-0.2518	-0.2071	-0.0360	-0.0203	-0.5250	-0.6318	-0.0656	-0.0326
0.15	-0.2104	-0.1781	-0.0307	-0.0175	-0.4336	-0.5540	-0.0561	-0.0292
0.20	-0.1690	-0.1492	-0.0254	-0.0148	-0.3423	-0.4762	-0.0465	-0.0258
0.25	-0.1277	-0.1202	-0.0202	-0.0120	-0.2510	-0.3984	-0.0369	-0.0224
0.30	-0.0863	-0.0913	-0.0149	-0.0092	-0.1597	-0.3205	-0.0274	-0.0190
0.35	-0.0449	-0.0623	-0.0096	-0.0065	-0.0684	-0.2427	-0.0178	-0.0156
0.40	-0.0035	-0.0334	-0.0044	-0.0037	0.0229	-0.1649	-0.0083	-0.0122
0.45	0.0378	-0.0044	0.0009	-0.0010	0.1142	-0.0871	0.0013	-0.0088
0.50	0.0792	0.0245	0.0061	0.0018	0.2055	-0.0093	0.0109	-0.0054
0.55	0.1206	0.0535	0.0114	0.0046	0.2969	0.0685	0.0204	-0.0020
0.60	0.1620	0.0824	0.0167	0.0073	0.3882	0.1464	0.0300	0.0014
0.65	0.2034	0.1114	0.0219	0.0101	0.4795	0.2242	0.0395	0.0048
0.70	0.2447	0.1403	0.0272	0.0128	0.5708	0.3020	0.0491	0.0082
0.75	0.2861	0.1693	0.0325	0.0156	0.6621	0.3798	0.0587	0.0116
0.80	0.3275	0.1982	0.0377	0.0183	0.7534	0.4576	0.0682	0.0150
0.85	0.3689	0.2272	0.0430	0.0211	0.8447	0.5355	0.0778	0.0184
0.90	0.4102	0.2561	0.0483	0.0239	0.9360	0.6133	0.0873	0.0218
0.95	0.4516	0.2851	0.0535	0.0266	1.0274	0.6911	0.0969	0.0252

Note: *XMR – Monero, XRP - Ripple*

Table 5.3a: QQR estimates for gold/cryptocurrencies returns cont.

	DASH	DAS.D1	DASH.D4	DASH.D6	XLM	XLM.D1	XLM.D4	XLM.D6
Quantile	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.
0.05	-0.2432	-0.1630	-0.0428	-0.0140	-0.3532	-0.3179	-0.0737	-0.0429
0.10	-0.2137	-0.1437	-0.0374	-0.0121	-0.2782	-0.2686	-0.0643	-0.0379
0.15	-0.1842	-0.1244	-0.0321	-0.0102	-0.2033	-0.2193	-0.0550	-0.0329
0.20	-0.1547	-0.1052	-0.0268	-0.0082	-0.1284	-0.1701	-0.0456	-0.0279
0.25	-0.1252	-0.0859	-0.0215	-0.0063	-0.0534	-0.1208	-0.0362	-0.0228
0.30	-0.0957	-0.0667	-0.0162	-0.0044	0.0215	-0.0715	-0.0268	-0.0178
0.35	-0.0662	-0.0474	-0.0109	-0.0024	0.0964	-0.0222	-0.0174	-0.0128
0.40	-0.0367	-0.0282	-0.0056	-0.0005	0.1713	0.0271	-0.0080	-0.0078
0.45	-0.0073	-0.0089	-0.0003	0.0014	0.2463	0.0764	0.0014	-0.0028
0.50	0.0222	0.0103	0.0050	0.0033	0.3212	0.1257	0.0108	0.0023
0.55	0.0517	0.0296	0.0103	0.0053	0.3961	0.1750	0.0202	0.0073
0.60	0.0812	0.0488	0.0156	0.0072	0.4711	0.2243	0.0295	0.0123
0.65	0.1107	0.0681	0.0209	0.0091	0.5460	0.2736	0.0389	0.0173
0.70	0.1402	0.0873	0.0262	0.0110	0.6209	0.3229	0.0483	0.0223
0.75	0.1697	0.1066	0.0315	0.0130	0.6959	0.3722	0.0577	0.0274
0.80	0.1992	0.1258	0.0368	0.0149	0.7708	0.4215	0.0671	0.0324
0.85	0.2287	0.1451	0.0421	0.0168	0.8457	0.4708	0.0765	0.0374
0.90	0.2582	0.1643	0.0474	0.0187	0.9206	0.5201	0.0859	0.0424
0.95	0.2877	0.1836	0.0527	0.0207	0.9956	0.5694	0.0953	0.0474

Note: *DASH – Das, XLM - Steller*

Table 5.3 b: QQR estimates for oil/cryptocurrencies returns

	BTC	BTC.D1	BTC.D4	BTC.D6	ETH	ETH.D1	ETH.D4	ETH.D6	LTC	LTC.D1	LTC.D4	LTC.D6
Quantile	**Coef.**	**Coef.**	**Coef.**	**Coef.**	**Coef.**	**Coef.**	**Coef.**	**Coef.**	**Coef.**	**Coef.**	**Coef.**	**Coef.**
0.05	-0.2075	-0.1473	-0.0339	-0.0141	-0.2917	-0.2025	-0.0512	-0.0281	-0.3952	-0.2479	-0.0503	-0.0186
0.10	-0.1835	-0.1310	-0.0296	-0.0124	-0.2526	-0.1803	-0.0444	-0.0250	-0.3448	-0.2174	-0.0430	-0.0161
0.15	-0.1595	-0.1147	-0.0253	-0.0108	-0.2135	-0.1580	-0.0377	-0.0219	-0.2945	-0.1869	-0.0358	-0.0136
0.20	-0.1354	-0.0985	-0.0210	-0.0091	-0.1744	-0.1358	-0.0309	-0.0187	-0.2442	-0.1564	-0.0285	-0.0111
0.25	-0.1114	-0.0822	-0.0167	-0.0075	-0.1353	-0.1136	-0.0242	-0.0156	-0.1939	-0.1259	-0.0213	-0.0086
0.30	-0.0873	-0.0659	-0.0124	-0.0058	-0.0962	-0.0914	-0.0174	-0.0125	-0.1436	-0.0955	-0.0140	-0.0061
0.35	-0.0633	-0.0496	-0.0081	-0.0042	-0.0570	-0.0692	-0.0107	-0.0094	-0.0933	-0.0650	-0.0067	-0.0036
0.40	-0.0393	-0.0334	-0.0038	-0.0026	-0.0179	-0.0470	-0.0039	-0.0062	-0.0430	-0.0345	0.0005	-0.0011
0.45	-0.0152	-0.0171	0.0005	-0.0009	0.0212	-0.0247	0.0028	-0.0031	0.0073	-0.0040	0.0078	0.0014
0.50	0.0088	-0.0008	0.0048	0.0007	0.0603	-0.0025	0.0096	0.0000	0.0576	0.0265	0.0150	0.0039
0.55	0.0328	0.0155	0.0091	0.0024	0.0994	0.0197	0.0163	0.0032	0.1079	0.0570	0.0223	0.0064
0.60	0.0569	0.0317	0.0134	0.0040	0.1385	0.0419	0.0231	0.0063	0.1582	0.0875	0.0296	0.0089
0.65	0.0809	0.0480	0.0177	0.0057	0.1776	0.0641	0.0298	0.0094	0.2085	0.1180	0.0368	0.0114
0.70	0.1049	0.0643	0.0220	0.0073	0.2168	0.0863	0.0366	0.0126	0.2588	0.1484	0.0441	0.0139
0.75	0.1290	0.0806	0.0263	0.0090	0.2559	0.1086	0.0433	0.0157	0.3091	0.1789	0.0513	0.0163
0.80	0.1530	0.0968	0.0306	0.0106	0.2950	0.1308	0.0501	0.0188	0.3594	0.2094	0.0586	0.0188
0.85	0.1770	0.1131	0.0349	0.0122	0.3341	0.1530	0.0568	0.0219	0.4097	0.2399	0.0659	0.0213
0.90	0.2011	0.1294	0.0392	0.0139	0.3732	0.1752	0.0636	0.0251	0.4600	0.2704	0.0731	0.0238
0.95	0.2251	0.1457	0.0435	0.0155	0.4123	0.1974	0.0703	0.0282	0.5103	0.3009	0.0804	0.0263

Note: *BTC – Bitcoin, ETH – Ethereum, LTC - Litecoin*

Table 5.3b: QQR estimates for oil/cryptocurrencies returns cont.

	XMR	XMR.D1	XMR.D4	XMR.D6	XRP	XRP.D1	XRP.D4	XRP.D6
Quantile	**Coef.**	**Coef.**	**Coef.**	**Coef.**	**Coef.**	**Coef.**	**Coef.**	**Coef.**
0.05	-0.2932	-0.2360	-0.0412	-0.0230	-0.6163	-0.7096	-0.0752	-0.0359
0.10	-0.2518	-0.2071	-0.0360	-0.0203	-0.5250	-0.6318	-0.0656	-0.0326
0.15	-0.2104	-0.1781	-0.0307	-0.0175	-0.4336	-0.5540	-0.0561	-0.0292
0.20	-0.1690	-0.1492	-0.0254	-0.0148	-0.3423	-0.4762	-0.0465	-0.0258
0.25	-0.1277	-0.1202	-0.0202	-0.0120	-0.2510	-0.3984	-0.0369	-0.0224
0.30	-0.0863	-0.0913	-0.0149	-0.0092	-0.1597	-0.3205	-0.0274	-0.0190
0.35	-0.0449	-0.0623	-0.0096	-0.0065	-0.0684	-0.2427	-0.0178	-0.0156
0.40	-0.0035	-0.0334	-0.0044	-0.0037	0.0229	-0.1649	-0.0083	-0.0122
0.45	0.0378	-0.0044	0.0009	-0.0010	0.1142	-0.0871	0.0013	-0.0088
0.50	0.0792	0.0245	0.0061	0.0018	0.2055	-0.0093	0.0109	-0.0054
0.55	0.1206	0.0535	0.0114	0.0046	0.2969	0.0685	0.0204	-0.0020
0.60	0.1620	0.0824	0.0167	0.0073	0.3882	0.1464	0.0300	0.0014
0.65	0.2034	0.1114	0.0219	0.0101	0.4795	0.2242	0.0395	0.0048
0.70	0.2447	0.1403	0.0272	0.0128	0.5708	0.3020	0.0491	0.0082
0.75	0.2861	0.1693	0.0325	0.0156	0.6621	0.3798	0.0587	0.0116
0.80	0.3275	0.1982	0.0377	0.0183	0.7534	0.4576	0.0682	0.0150
0.85	0.3689	0.2272	0.0430	0.0211	0.8447	0.5355	0.0778	0.0184
0.90	0.4102	0.2561	0.0483	0.0239	0.9360	0.6133	0.0873	0.0218
0.95	0.4516	0.2851	0.0535	0.0266	1.0274	0.6911	0.0969	0.0252

Note: *XMR – Monero, XRP – Ripple*

Table 5.3b: QQR estimates for oil/cryptocurrencies returns cont.

	DASH	DAS.D1	DASH.D4	DASH.D6	XLM	XLM.D1	XLM.D4	XLM.D6
Quantile	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.
0.05	-0.2432	-0.1630	-0.0428	-0.0140	-0.3532	-0.3179	-0.0737	-0.0429
0.10	-0.2137	-0.1437	-0.0374	-0.0121	-0.2782	-0.2686	-0.0643	-0.0379
0.15	-0.1842	-0.1244	-0.0321	-0.0102	-0.2033	-0.2193	-0.0550	-0.0329
0.20	-0.1547	-0.1052	-0.0268	-0.0082	-0.1284	-0.1701	-0.0456	-0.0279
0.25	-0.1252	-0.0859	-0.0215	-0.0063	-0.0534	-0.1208	-0.0362	-0.0228
0.30	-0.0957	-0.0667	-0.0162	-0.0044	0.0215	-0.0715	-0.0268	-0.0178
0.35	-0.0662	-0.0474	-0.0109	-0.0024	0.0964	-0.0222	-0.0174	-0.0128
0.40	-0.0367	-0.0282	-0.0056	-0.0005	0.1713	0.0271	-0.0080	-0.0078
0.45	-0.0073	-0.0089	-0.0003	0.0014	0.2463	0.0764	0.0014	-0.0028
0.50	0.0222	0.0103	0.0050	0.0033	0.3212	0.1257	0.0108	0.0023
0.55	0.0517	0.0296	0.0103	0.0053	0.3961	0.1750	0.0202	0.0073
0.60	0.0812	0.0488	0.0156	0.0072	0.4711	0.2243	0.0295	0.0123
0.65	0.1107	0.0681	0.0209	0.0091	0.5460	0.2736	0.0389	0.0173
0.70	0.1402	0.0873	0.0262	0.0110	0.6209	0.3229	0.0483	0.0223
0.75	0.1697	0.1066	0.0315	0.0130	0.6959	0.3722	0.0577	0.0274
0.80	0.1992	0.1258	0.0368	0.0149	0.7708	0.4215	0.0671	0.0324
0.85	0.2287	0.1451	0.0421	0.0168	0.8457	0.4708	0.0765	0.0374
0.90	0.2582	0.1643	0.0474	0.0187	0.9206	0.5201	0.0859	0.0424
0.95	0.2877	0.1836	0.0527	0.0207	0.9956	0.5694	0.0953	0.0474

Note: *DASH – Das, XLM - Steller*

5.4. Conclusion and policy implication

The chapter evaluates the impact of cryptocurrencies (Bticoin, Litecoin, Ethereum, Ripple, Monero, Das, and Steller) on gold and crude oil returns applying the wavelet-based Quantile-in-Quantile regression technique. We explored the asymmetric shock transmission mechanisms between the assets and uncovered the hedging properties of the seven cryptocurrencies for extreme gold and crude oil price movements at different market states in a time-frequency space. Applying the MODWT, we decomposed the cryptocurrencies, crude oil, and gold returns into wavelet scales D1, D4, and D6 showing fluctuations of the assets returns at high, medium, and low frequencies respectively also indicating the trading horizons. We implemented the nonparametric Quantile-in-Quantile Regression (QQR), and parametric Quantile Regression (QR) proposed by Sim and Zhou (2015), and Koenker and Bassett (1978) respectively on the decomposed series of the assets to establish the association between gold/cryptocurrencies and oil/cryptocurrencies over 19 quantiles ($\tau = 0.05\ to\ 0.95$).

Both QR and QQR results confirm the heterogeneous effect of the movement of cryptocurrencies on gold and crude oil returns across quantiles and time-scales. Specifically, the QR results for gold/cryptocurrencies suggest all cryptocurrencies studied (Bitcoin, Litecoin, Ethereum, Das, Monero, Steller, and Ripple) as hedges for price fluctuations at bear (bull) gold markets (i.e. whether the price of gold is low, stable, or high) from the medium-term. However, the QR results for oil/cryptocurrencies suggest that Bitcoin, Litecoin, and Das do not have hedging characteristics for extreme oil price movements at bear (bull) markets across time suggesting a possible price shock transmissions from the cryptocurrencies to crude oil price and that hedging possibilities are feasible from the medium-term for crude oil investors/traders using Ethereum, Monero, Ripple, and Steller. The results from QQR for gold/cryptocurrencies and oil/cryptocurrencies pairs show negative associations between the commodities (gold and crude oil) and cryptocurrencies at bear market but positive relations at bull market indicating hedging possibilities for the assets at bear market. Thus, economic actors can hedge their downside risk across time using either of the assets at bear market where the price of gold and crude oil is low, and the cryptocurrency market is bearish. We validate QQR by the closeness with which it matches QR across quantiles and time.

Our finding is consistent with Bernanke et al. (1996) flight to safety phenomenon where investors and traders use less risky assets to hedge their positions during economic crises. The empirical literature highlights different dimensions of the effects of cryptocurrencies on gold and crude oil returns (Kurka, 2019; Shahzad et al., 2019; Henriques and Sadorsky, 2018; Selmi et al., 2018; Klein et al., 2018). Our findings go beyond the outcomes of these studies by demonstrating that the connections among the assets are sensitive to different market conditions in different horizons. This study has practical implications for gold/cryptocurrencies, and oil/cryptocurrencies dynamic dependencies for hedging in order to reduce downside risk in gold and crude oil markets. Although cryptocurrencies exhibit excess price volatility, our study shows that it would be very profitable if investors incorporate them in a diversified portfolio which is consistent with the findings of Eisl et al. (2015), Bouri et al. (2017c), and Halaburda and Gandal (2014). Our study departs from prior studies by showing that the connections between gold/cryptocurrencies and oil/cryptocurrencies are time-varying and also depend on the state of market. Future studies can explore the impact of cryptocurrencies on the broader commodity market controlling for global uncertainties. Future studies could also look at the regulatory and supervisory aspects of cryptocurrencies in Africa to allow for its successful integration in the region.

References

Adebola, S., S., Gil-Alana, A., L., & Madigu, G. (2019). Gold Prices and the Cryptocurrencies: Evidence of Convergence and Cointegration. *Physica A,* 523, 1227–1236.

Al-Khazali, O., Elie, B., & Roubaud, D. (2018). The Impact of Positive and Negative Macroeconomic News Surprises: Gold versus Bitcoin. *Economics Bulletin*, *38*(1), 373-382.

Al-Yahyaee, K., H., Mensi, W., Al-Jarrah, I., M., W., Hamdi, A., & Kang, S., H. (2019). Volatility Forecasting, Downside Risk and Diversification Benefits of Bitcoin and Oil and International Commodity Markets: A Comparative Analysis with Yellow Metal. *The North American Journal of Economics and Finance*, *49,* 104-120.

Atsalakis, G. S., Bouri, E., & Pasiouras, F. (2020). Natural Disasters and Economic Growth: A Quantile on Quantile Approach. *Annals of Operations Research*, 1-27.

Baek, C., & Elbeck, M. (2015). Bitcoins as an Investment or Speculative Vehicle? A First Look. *Applied Economics Letters*, *22*(1), 30-34.

Bampinas, G., Panagiotidis, T. (2015). Are Gold and Silver a Hedge against Inflation? A Two Century Perspective. *International Review of Financial Analysis*, 41, 267–276.

Baur, D., G., Hong, K.., & Lee, A., D. (2018). Bitcoin: Medium of Exchange or Speculative Assets? *Journal of International Financial Markets, Institutions and Money*, 54, 177–189. http://refhub.elsevier.com/.

Baur, D., G., Dimpfl, T., & Kuck, K. (2018). Bitcoin, Gold and the US Dollar–A Replication and Extension. *Finance Research Letters*, 25, 103-110.

Baur, D. G., & Lucey, B. M. (2010). Is Gold a Hedge or a Safe Haven? An Analysis of Stocks, Bonds, and Gold. *Financial Review*, *45*(2), 217-229.

Baur, D., & McDermontt, T., K., J. (2010). Is Gold a Safe Haven? International Evidence, *Journal of Banking and Finance*, 34(8), 1886-1898.

Bernanke, B., Gertler, M., & Gilchrist, S. (1996). *The Financial Accelerator and the Flight to Quality* (No. w4789). National Bureau of Economic Research.

Bisaglia, L., & Gerolimetto, M. (2014). Testing for (Non) Linearity in Economic Time Series: A Monte Carlo Comparison.

Bouri, E., Mahamitra, D., Gupta. R., & Roubaud, D. (2018). Spillovers between Bitcoin and Other Assets during Bear and Bull Markets. *Applied Economics*, 50, 5935–49.

Bouri, E., Shahzad, S., J., H., & Roubaud, D. (2018b). Co-explosivity in the Cryptocurrency market. *Finance Research Letters*. Forthcoming.

Bouri, E., Azzi, G., & Dyhrberg, A., H. (2017). On the Return-Volatility Relationship in the Bitcoin Market around the Price Crash of 2013. *Economics: The Open-Access, Open-Assessment E-Journal*, *11*(2), 1–16. http://dx.doi.org/10.5018/economics-ejournal.ja.2017-2.

Bouri, E., Gupta, R., Tiwari, A. K., & Roubaud, D. (2017). Does Bitcoin Hedge Global Uncertainty? Evidence from Wavelet-based Quantile-in-Quantile Regressions. *Finance Research Letters*, *23*, 87-95.

Bouri, E., Jalkh, N., Molnr, P., Roubaud, D. (2017). Bitcoin for Energy Commodities before and after the December 2013 Crash: Diversifier, Hedge or Safe Haven? *Applied Economics*, 49 (50), 5063–5073.

Bouri, E., Molnár, P., Azzi, G., Roubaud, D., & Hagfors, L., I. (2017). On the Hedge and Safe Haven Properties of Bitcoin: Is it Really More Than a Diversifier?. *Finance Research Letters*, *20*, 192-198.

Bouoiyour, J., & Selmi, R. (2017). The Bitcoin Price Formation: Beyond the Fundamental Sources. *arXiv preprint arXiv:1707.01284*.

Ciaian, P., & Rajcaniova, M. (2018). Virtual Relationships: Short-and Long-Run Evidence from Bitcoin and Altcoin Markets. *Journal of International Financial Markets, Institutions, and Money, 5*2, 173–195.

Ciaian, P., Rajcaniova, M., & Kancs, D. A. (2016). The Economics of Bitcoin Price Formation. *Applied Economics*, *48*(19), 1799-1815.

Catania, L., Grassi, S., & Ravazzolo, F. (2018). Forecasting Cryptocurrencies Financial Time Series," In CAMP Working Paper Series, no. 5. Norwegian Business School.

Chan, S., Chu, J., Nadarajah, S., Osterrieder, J. (2017). A Statistical Analysis of Cryptocurrencies. *Journal of Risk and Financial Management*, 10 (12), 1–23.

Ciner, C., Gurdgiev, C., & Lucey, B. M. (2013). Hedges and Safe Havens: An Examination of Stocks, Bonds, Gold, Oil, and Exchange Rates. *International Review of Financial Analysis*, *29*, 202-211.

CoinMarketCap. (2019). Cryptocurrency Market Capitalizations and Data. Available online: https://coinmarketcap.com/ (accessed on 26th August 2019).

Corbet, S., Meegan, A., Larkin, C., Lucey, B., & Yarayova, L. (2018). Exploring the Dynamic Relationships between Cryptocurrencies and other Financial Assets. *Economics Letters*, *165*, 28‑34.

Cornish, C., R., Bretherton, C., S., Percival, D., B., (2006). Maximal Overlap Wavelet Statistical Analysis with Application to Atmospheric Turbulence. *Boundary-Layer Meteorology*, 119 (2), 339–374.

Das, D., & Kannadhasan, M. (2018). Do Global Factors Impact Bitcoin Prices? Evidence from Wavelet Approach. *Journal of Economic Research*, 23, 227-264.

Dyhrberg, A., H. (2016). Bitcoin, Gold and the Dollar–A GARCH Volatility Analysis. *Finance Research Letters*, *16*, 85-92.

Dyhrberg, A., H. (2015b). Bitcoin, Gold and the Dollar – A GARCH Volatility Analysis. *Finance Research Letters*, 16, 85–92.

Eisl, A., Gasser, S., M., Weinmayer, K. (2015). Caveat Emptor: Does Bitcoin Improve Portfolio Diversification? (Available at SSRN 2408997).

Fantazzini, D., Nigmatullin, E., Sukhanovskaya, V., & Ivliev, S. (2016). Everything you always wanted to know about Bitcoin Modelling but were afraid to ask. Available at SSRN: https://ssrn.com/abstract=2794622.

Faria, J. (2021). Main Oil Producing Countries in Africa 2019. https://www.statista.com/aboutus/our-research-commitment. Accessed 9th March 2021.

Gençay, R., Selçuk, F., & Whitcher, B. (2002). *An Introduction to Wavelets and Other Filtering Methods in Finance and Economics.* Academic Press, San Diego.

Gkillas, K., & Katsiampa, P. (2018). An Application of Extreme Value Theory to Cryptocurrencies. *Economics Letters*, 164, 109–111. doi: 10.1016/j.econlet.2018.01.020.

Guesmi, K., Saadi, S., Abid, I., & Ftiti, Z. (2019). Portfolio Diversification with Virtual Currency: Evidence from Bitcoin. *International Review of Financial Analysis*, *63*, 431-437.

Halaburda, H., Gandal, N. (2014). Competition in the Cryptocurrency Market (Available at SSRN 2506463).

Henriques, I., & Sadorsky, P. (2018). Can Bitcoin Replace Gold in an Investment Portfolio?. *Journal of Risk and Financial Management*, *11*(3), 48.

Huynh, T., L., D. (2019). Spillover Risks on Cryptocurrency Markets: A Look from VAR-SVAR Granger Causality and Student's-t Copulas. *Journal of Risk and Financial Management*, 12, 52. doi:10.3390/jrfm12020052.

Ji, Q., Bouri, E., Roubaud, D., & Kristoufek, L. (2019). Information Interdependence among Energy, Cryptocurrency and Major Commodity Markets. *Energy Economics*, 81, 1042-1055.

Kaul, A., & Sapp, S. (2006). Y2K Fears and Safe Haven Trading of the US Dollar. *Journal of International Money and Finance*, *25*(5), 760-779.

Klein, T., Thu, H., P., & Walther, T. (2018). Bitcoin is not the New Gold–A Comparison of Volatility, Correlation, and Portfolio Performance. *International Review of Financial Analysis*, *59*, 105-116.

Koenker, R., & Bassett, G. (1978). Regression Quantiles. *Econometrica*, 46 (1), 33–50.

Koenker, R. (2005). *Quantile Regression*. Cambridge University Press, New York, NY.

Krugman, P., R. (2008). *International Economics: Theory and policy, 8/E*. Pearson Education India.

Kurkaa, J. (2019). Do Cryptocurrencies and Traditional Asset Classes Influence each other? *Finance Research Letters*, 38, 38-46.

Lee, D., K., C., Guo, L., & Wang, Y. (2018). Cryptocurrency: A New Investment Opportunity? *The Journal of Alternative Investments*, *20*, 16‑40.

Ma, L., & Koenker, R. (2006). Quantile Regression Methods for Recursive Structural Equation Models. *Journal of Economics*, 134, 471–506.

Mallick, H., Padhan, H., & Mahalik, M., K. (2019). Does Skewed Pattern of Income Distribution Matter for the Environmental Quality? Evidence from Selected BRICS Economies with an Application of Quantile-on-Qauntile Regression (QQR) approach. *Energy policy*, *129*, 120-131.

Markowitz, H. (1952). Portfolio Selection. *The Journal of Finance*, *7*(1), 77-91.

Martens, M. & Poon, S., H. (2001). Returns Synchronization and Daily Correlation Dynamics between International Stock Markets. *Journal of Banking and Finance,* 25(10), 1805–1827.

Mensi, W., Hammoudeh, S., & Tiwari, A., K. (2016). New Evidence on Hedges and Safe Havens for Gulf Stock Markets using the Wavelet-based Quantile. *Emerging Markets Review*, 28, 155-183.

Mishra, S., Sharif, A., Khuntia, S., Meo, S. A., & Khan, S. A. R. (2019). Does Oil Prices Impede Islamic Stock Indices? Fresh Insights from Wavelet-based Quantile-on-Quantile Approach. *Resources Policy*, *62*, 292-304.

Müller, U., A., Dacorogna, M., M., Davé, R., D., Pictet, O., V., Olsen, R., B., & Ward, J., R. (1993). Fractals and Intrinsic Time: A Challenge to Econometricians. *Unpublished manuscript, Olsen & Associates, Zürich*.

NS Energy. (2020). Top Five Gold Mining Countries of Africa from Ghana to Burkina Faso https://www.nsenergybusiness.com/news/top-gold-mining-countries-africa/# Accessed 28th August 2020.

Palombizio, E., & Morris, I. (2012). Forecasting Exchange Rates using Leading Economic Indicators Open Access Scientific Reports, 1(8), 1–6. doi: 10.4172/scientificreports.

Percival, D., B., & Walden, A., T. (2000). *Wavelet Methods for Time Series Analysis, vol. 4 of Cambridge Series in Statistical and Probabilistic Mathematics*, Cambridge University Press, Cambridge, UK.

Percival, D., B., Mofjeld, H., O. (1997). Analysis of Subtidal Coastal Sea Level Fluctuations using Wavelets. *Journal of the American Statistical Association*, 92 (439), 868–880.

Percival, D., B. (1995). On Estimation of the Wavelet Variance. *Biometrika*, 82 (3), 619–631.

Polasik, M., Piotrowska, A. I., Wisniewski, T. P., Kotkowski, R., & Lightfoot, G. (2015). Price Fluctuations and the Use of Bitcoin: An Empirical Inquiry. *International Journal of Electronic Commerce*, *20*(1), 9-49.

Popper, N. (2015). Digital gold: The Untold Story of Bitcoin. Penguin UK.

Pukthuanthong, K., & Roll, R. (2009). "Global Market Integration: An Alternative Measure and Its Application." *Journal of Financial Economics,* 94 (2), 214– 232. doi: 10.1016/j.jfineco.2008.12.004.

Ramsey, J., B. (2002). Wavelets in Economics and Finance: Past and Future. *Studies in Nonlinear Dynamics & Econometrics*, 6 (3), 1–29.

Raza, S., A., Zaighum, I., & Shah, N. (2018). Economic Policy Uncertainty, Equity Premium and Dependence between their Quantiles: Evidence from Quantile-on-Quantile Approach. *Physica A: Statistical Mechanics and its Applications*, *492*, 2079-2091.

Reboredo, J., C. (2013). Modelling EU Allowances and Oil Market Interdependence. Implications for Portfolio Management. *Energy Economics*, *36*, 471-480.

Rogojanu, A., & Badea, L. (2014). The Issue of Competing Currencies. *Theoretical and Applied Economics,* 21(1), 103–114.

Sakemoto, R. (2018). Do Precious and Industrial Metals Act as Hedges and Safe Havens for Currency Portfolios? *Finance Research Letters, 24*, 256‑262.

Selmi, R., Mensi, W., Hammoudeh, S., & Bouoiyour, J. (2018). Is Bitcoin a Hedge, a Safe Haven or a Diversifier for Oil Price Movements? A Comparison with Gold. *Energy Economics*, *74*, 787-801.

Shahzada, H., J., S., Bourib, E., Roubaudc, D., Kristoufekd, L., & Lucey, B. (2019). Is Bitcoin a better Safe-Haven Investment than Gold and Commodities? *International Review of Financial Analysis*, 63, 322–330.

Sim, N., Zhou, A. (2015). Oil Prices, US Stock Return, and the Dependence between their Quantiles. *Journal of Banking and Finance*, 55, 1–8.

Tan, K., L., Kang, C., K., Koh, W., H., Lau, H., Y., & Ng, C., Y. (2014). *The Nexus Between Stock Market Performance and Gold Price: The Case of Hang Seng Index* (Doctoral dissertation, UTAR).

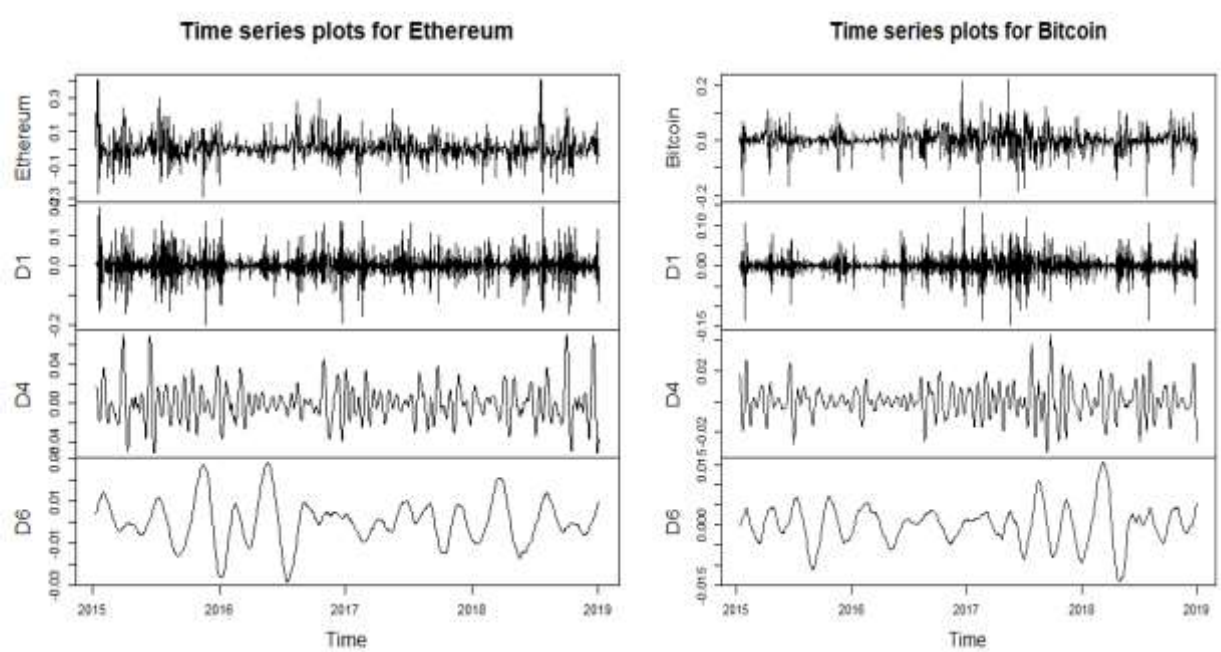
van Wijk, D. (2013). *What can be expected from the Bitcoin? Working Paper No. 345986.* Rotterdam: Erasmus Rotterdam Universiteit.

Vandezande, N. (2017). Virtual Currencies under EU Anti-money Laundering Law. *Computer law & security review*, *33*(3), 341-353.

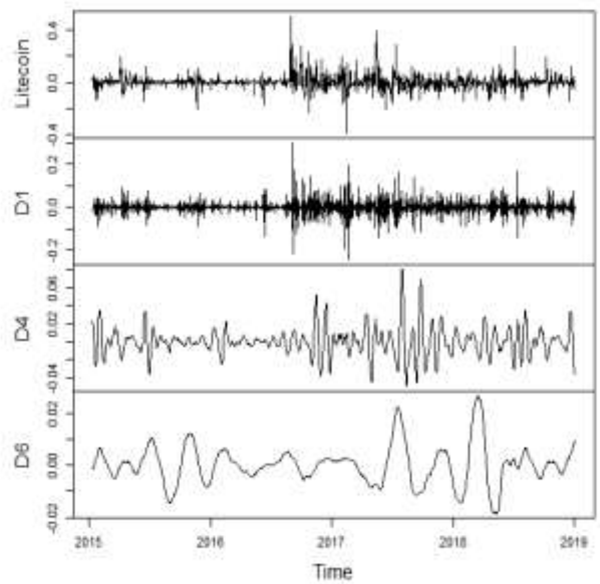
Yermack, D. (2013). Is Bitcoin a Real Currency? An Economic Appraisal. (No. w19747). National Bureau of Economic Research. http://www.nber.org/papers/w19747.

Zhang, Y. (2002). Testing for Nonlinearities in Time Series with an Application to Exchange Rates.

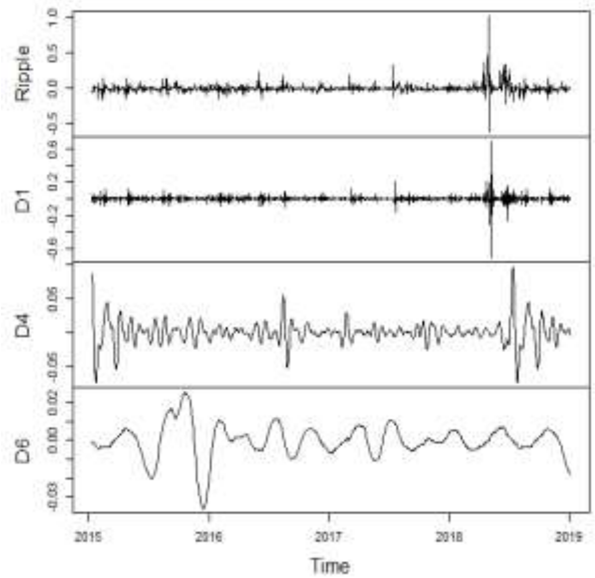
Appendices



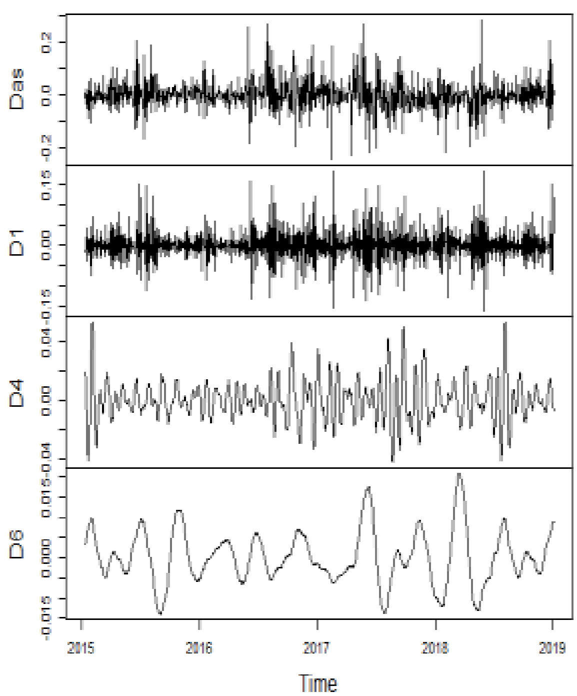
Time series plots for Litecoin



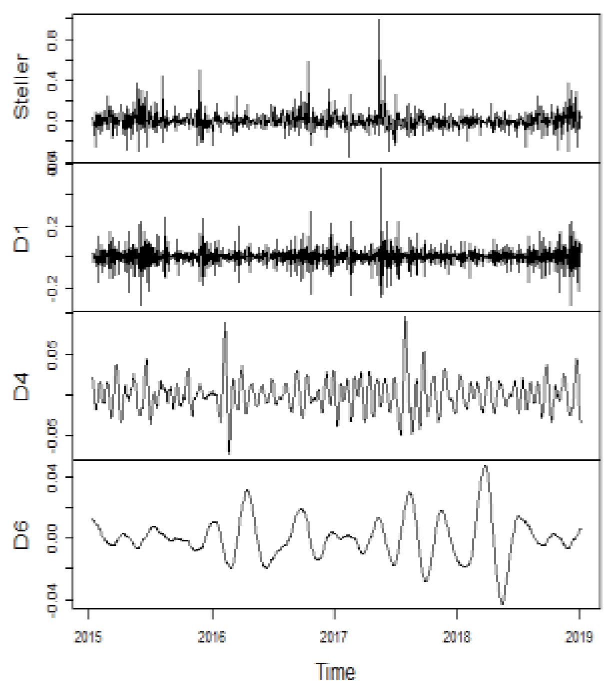
Time series plots for Ripple



Time series plots for Das



Time series plots for Steller



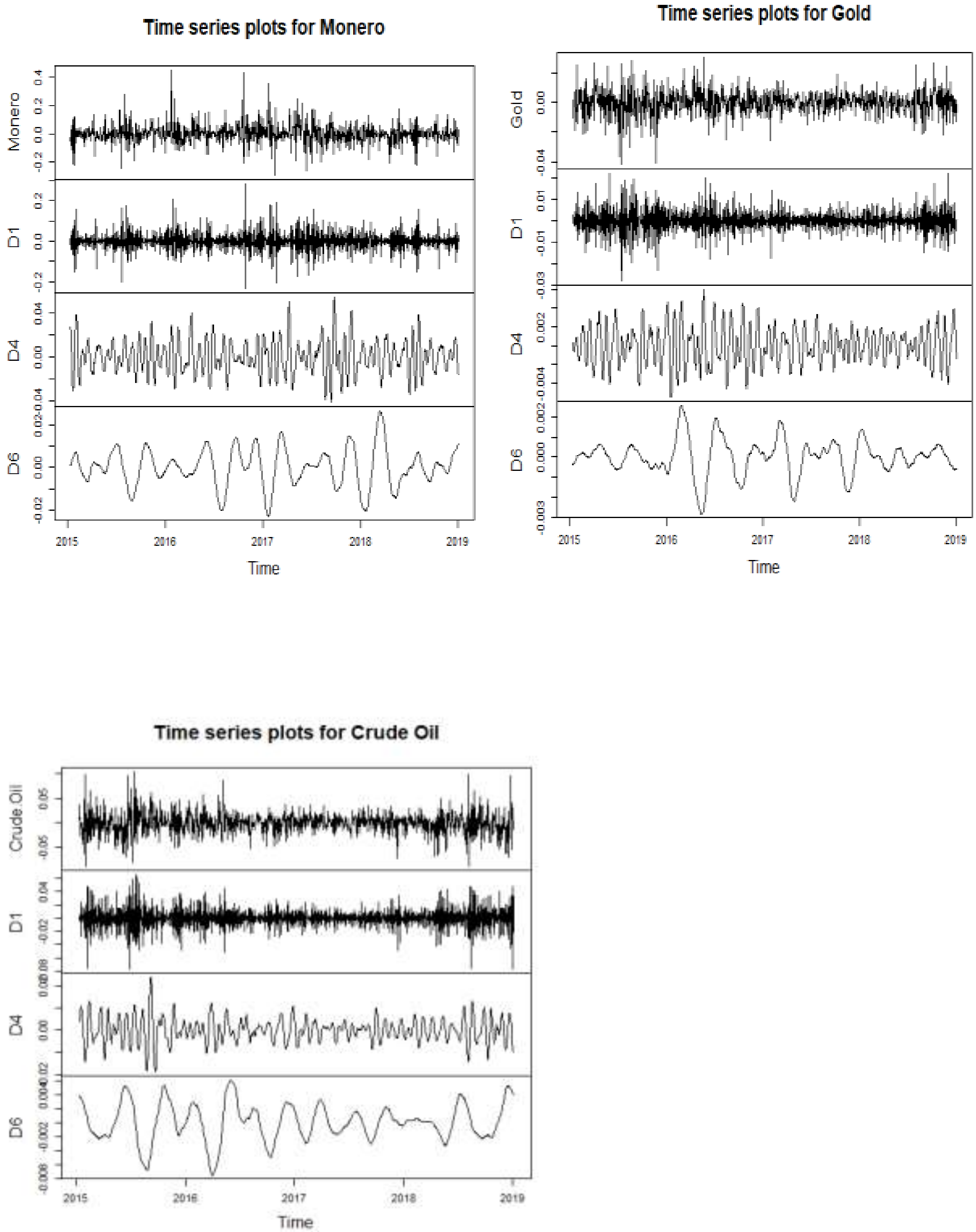
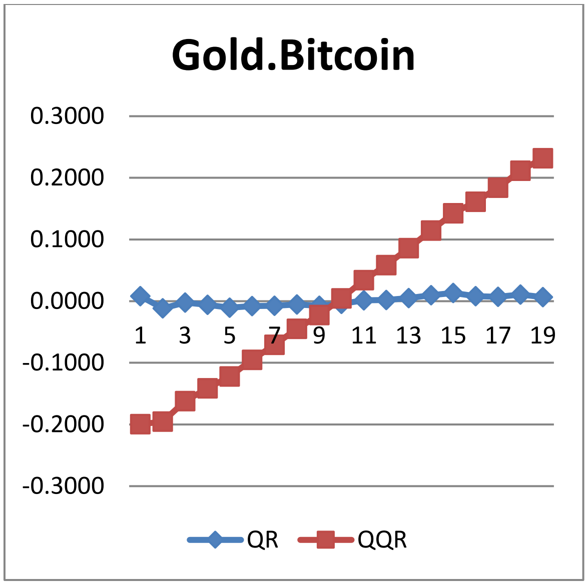
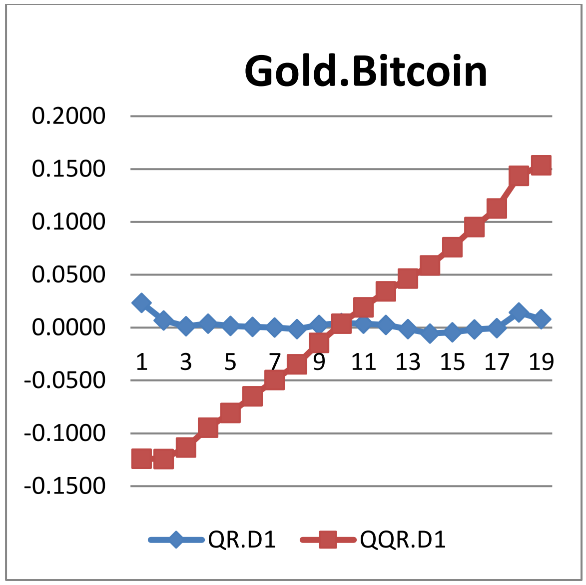
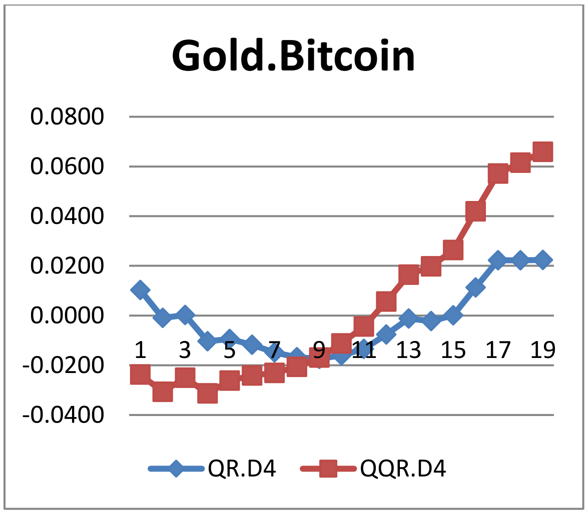
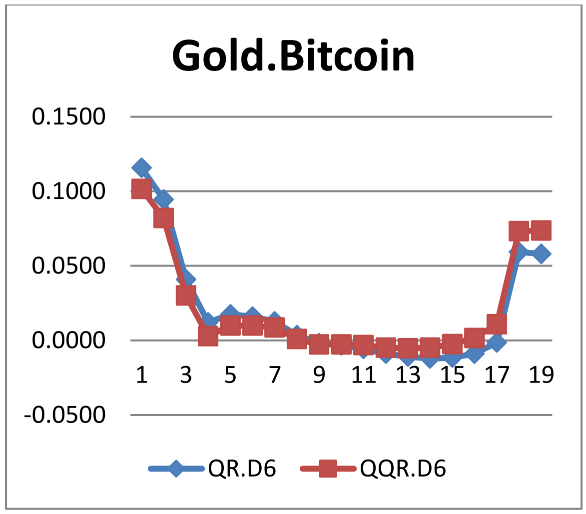


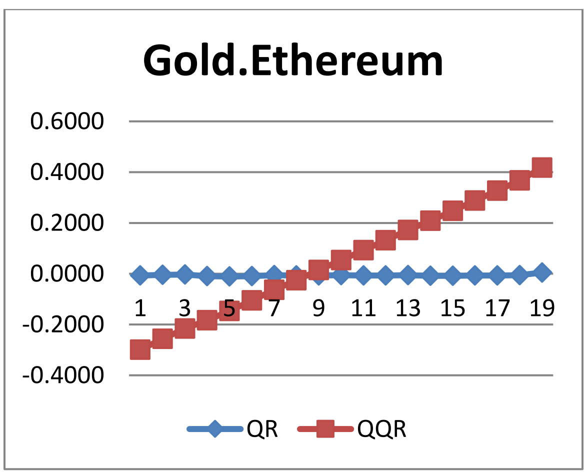
Figure 5. 1: Time series plots gold, crude oil, and cryptocurrencies returns.

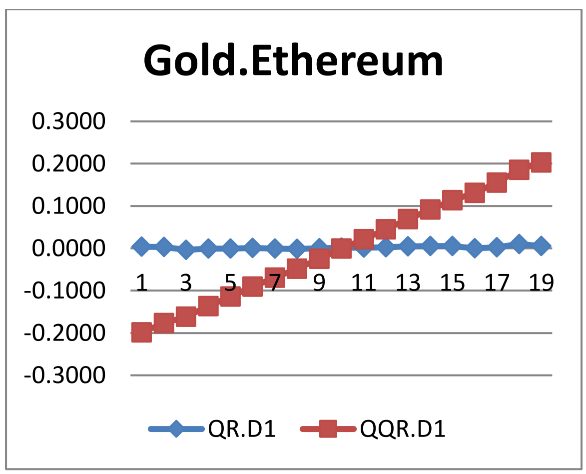

Gold.Bitcoin
0.3000
0.2000
0.1000
0.0000
-0.1000
-0.2000
-0.3000
1 3 5 7 9 11 13 15 17 19
QR
QQR

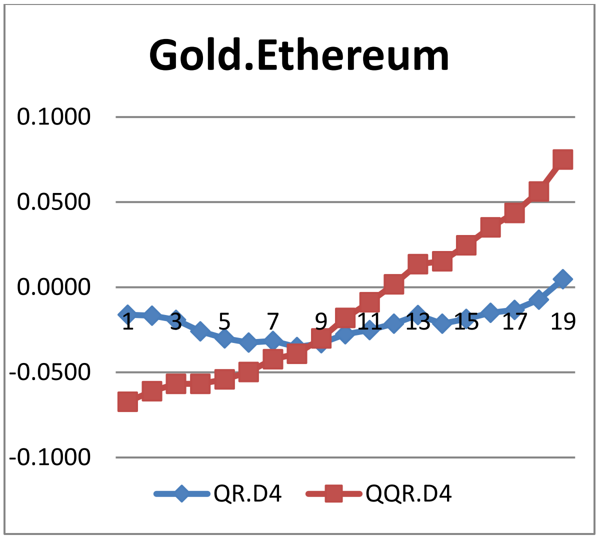

Gold.Bitcoin
0.2000
0.1500
0.1000
0.0500
0.0000
-0.0500
-0.1000
-0.1500
1 3 5 7 9 11 13 15 17 19
QR.D1
QQR.D1

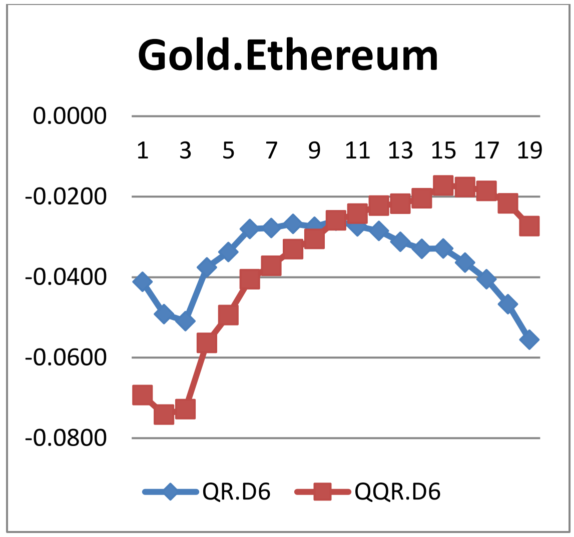

Gold.Bitcoin
0.0800
0.0600
0.0400
0.0200
0.0000
-0.0200
-0.0400
1 3 5 7 9 11 13 15 17 19
QR.D4
QQR.D4

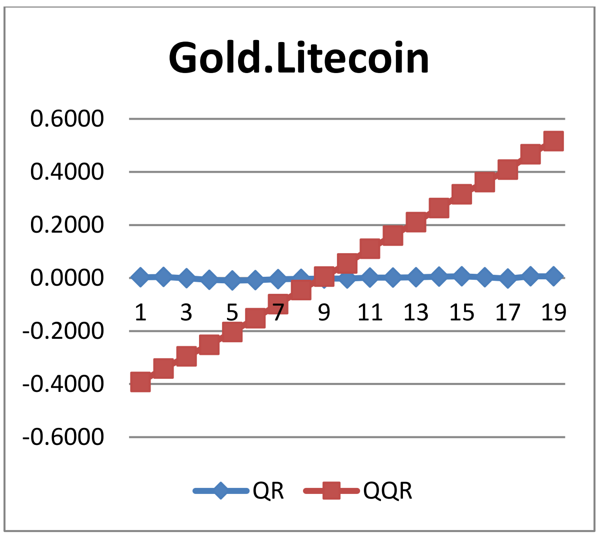

Gold.Bitcoin
0.1500
0.1000
0.0500
0.0000
-0.0500
1 3 5 7 9 11 13 15 17 19
QR.D6
QQR.D6

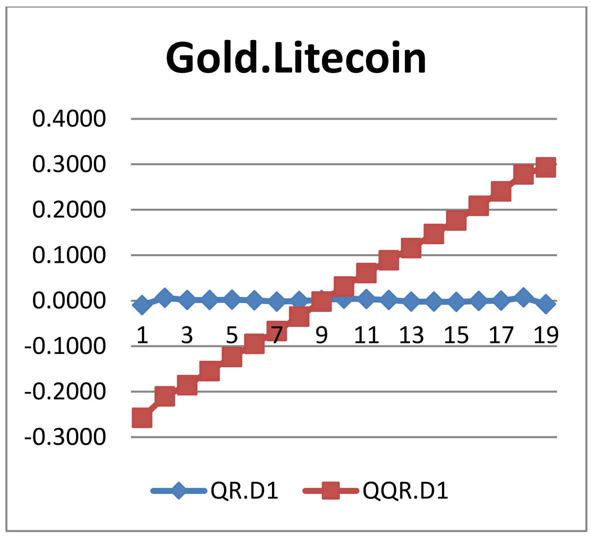

Gold.Ethereum
0.6000
0.4000
0.2000
0.0000
-0.2000
-0.4000
1 3 5 7 9 11 13 15 17 19
QR
QQR

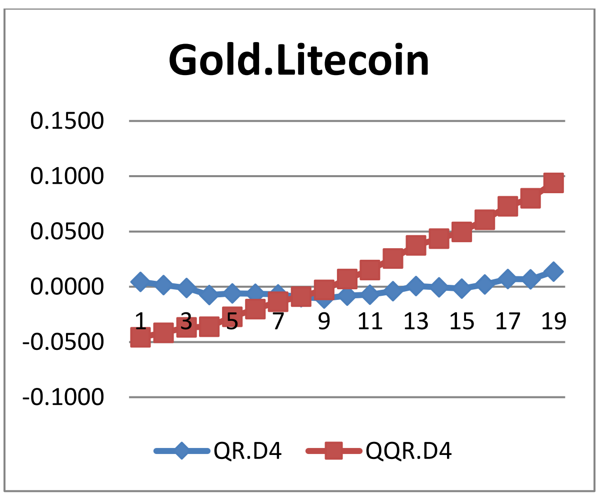

Gold.Ethereum
0.3000
0.2000
0.1000
0.0000
-0.1000
-0.2000
-0.3000
1 3 5 7 9 11 13 15 17 19
QR.D1
QQR.D1

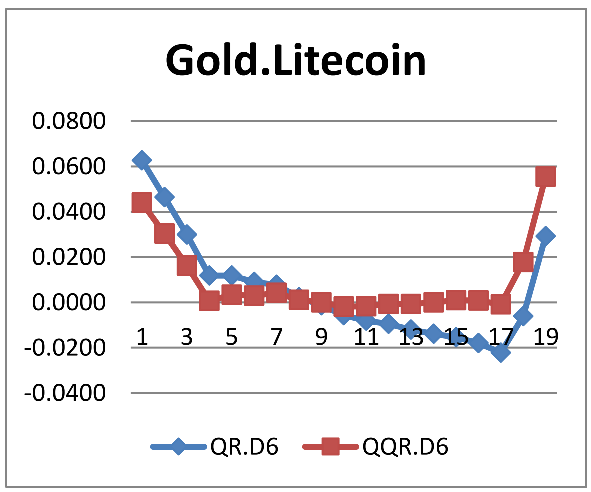

Gold.Ethereum
0.1000
0.0500
0.0000
-0.0500
-0.1000
1 3 5 7 9 11 13 15 17 19
QR.D4
QQR.D4

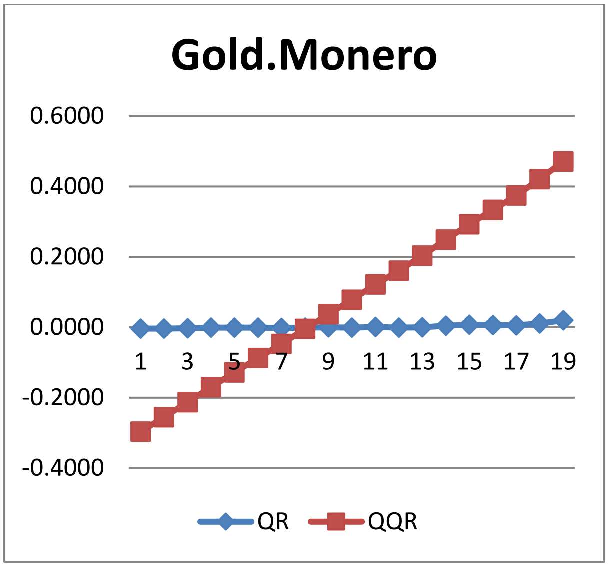

Gold.Ethereum
0.0000
-0.0200
-0.0400
-0.0600
-0.0800
1 3 5 7 9 11 13 15 17 19
QR.D6
QQR.D6

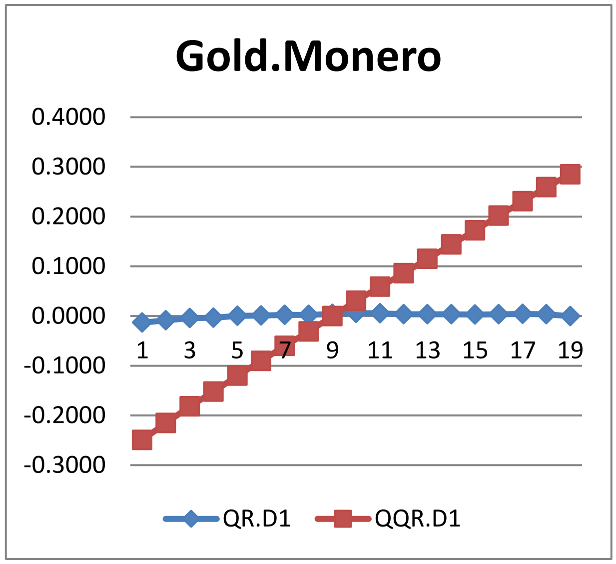

Gold.Litecoin
0.6000
0.4000
0.2000
0.0000
-0.2000
-0.4000
-0.6000
1 3 5 7 9 11 13 15 17 19
QR
QQR

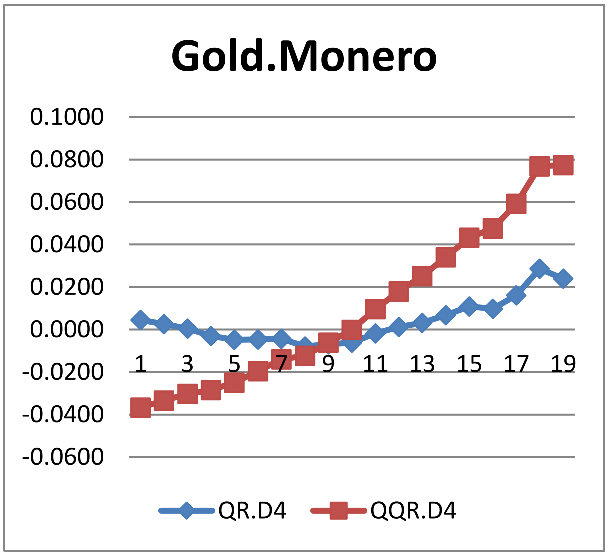

Gold.Litecoin
0.4000
0.3000
0.2000
0.1000
0.0000
-0.1000
-0.2000
-0.3000
1 3 5 7 9 11 13 15 17 19
QR.D1
QQR.D1

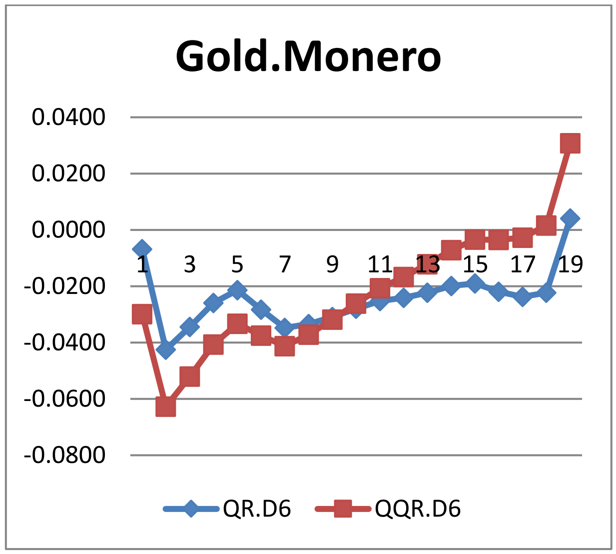

Gold.Litecoin
0.1500
0.1000
0.0500
0.0000
-0.0500
-0.1000
1 3 5 7 9 11 13 15 17 19
QR.D4
QQR.D4

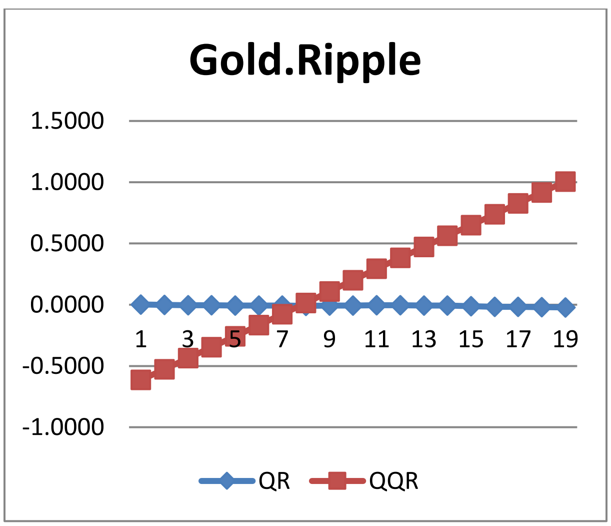

Gold.Litecoin
0.0800
0.0600
0.0400
0.0200
0.0000
-0.0200
-0.0400
1 3 5 7 9 11 13 15 17 19
QR.D6
QQR.D6

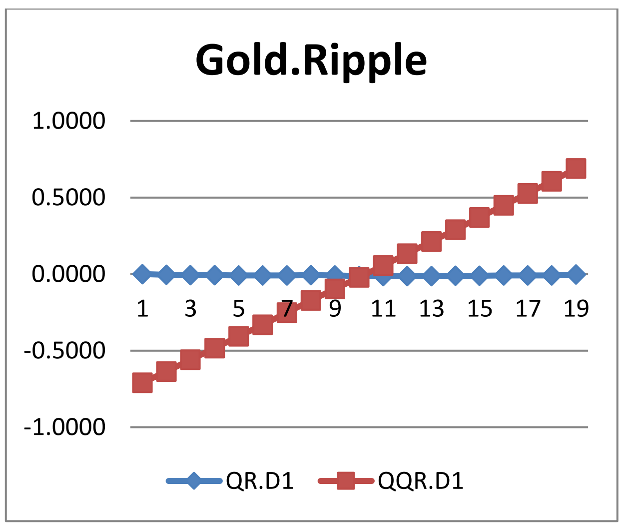

Gold.Monero
0.6000
0.4000
0.2000
0.0000
-0.2000
-0.4000
1 3 5 7 9 11 13 15 17 19
QR QQR

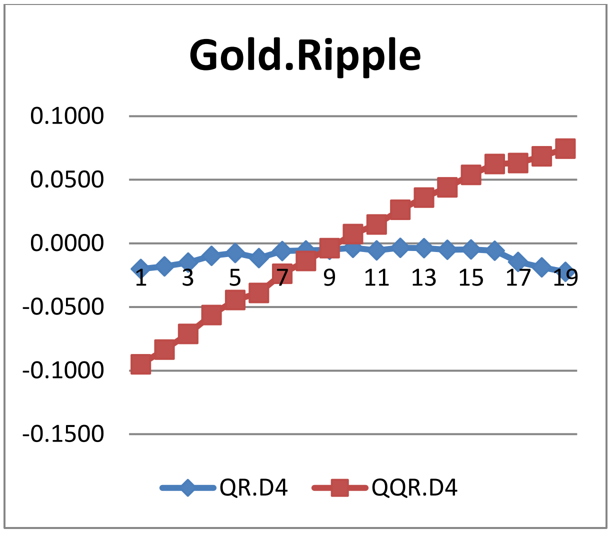

Gold.Monero
0.4000
0.3000
0.2000
0.1000
0.0000
-0.1000
-0.2000
-0.3000
1 3 5 7 9 11 13 15 17 19
QR.D1 QQR.D1

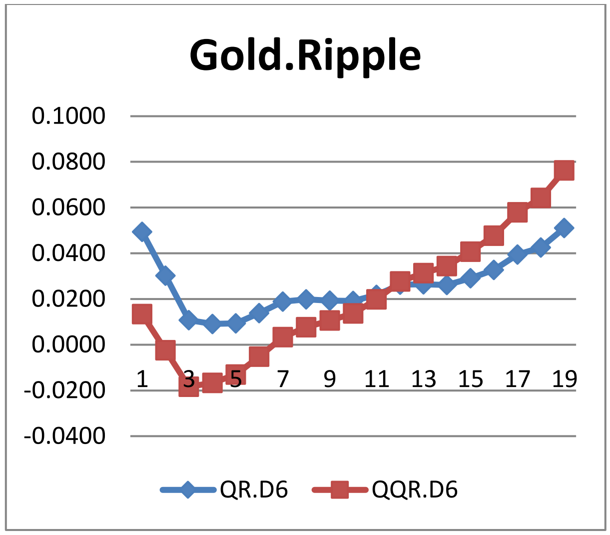

Gold.Monero
0.1000
0.0800
0.0600
0.0400
0.0200
0.0000
-0.0200
-0.0400
-0.0600
1 3 5 7 9 11 13 15 17 19
QR.D4 QQR.D4

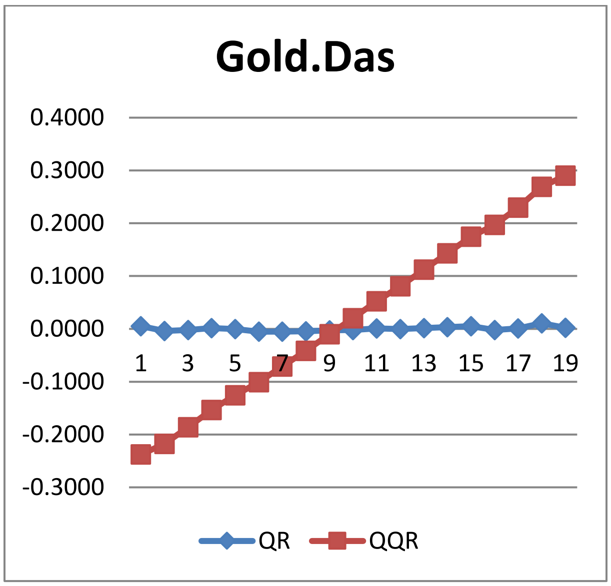

Gold.Monero
0.0400
0.0200
0.0000
-0.0200
-0.0400
-0.0600
-0.0800
1 3 5 7 9 11 13 15 17 19
QR.D6 QQR.D6

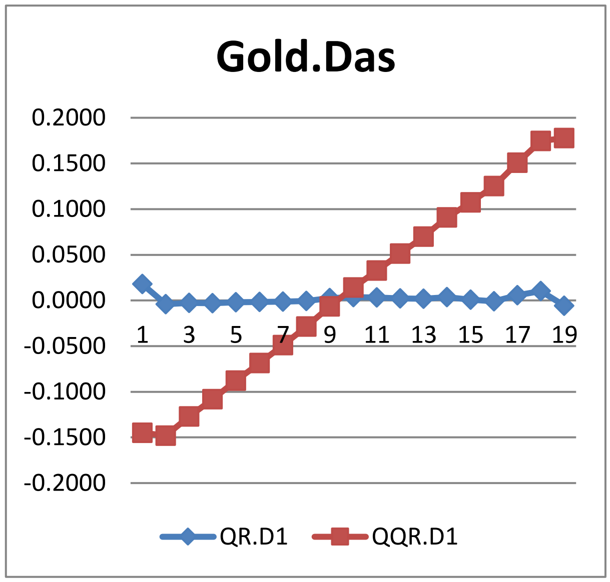

Gold.Ripple
1.5000
1.0000
0.5000
0.0000
-0.5000
-1.0000
1 3 5 7 9 11 13 15 17 19
QR QQR

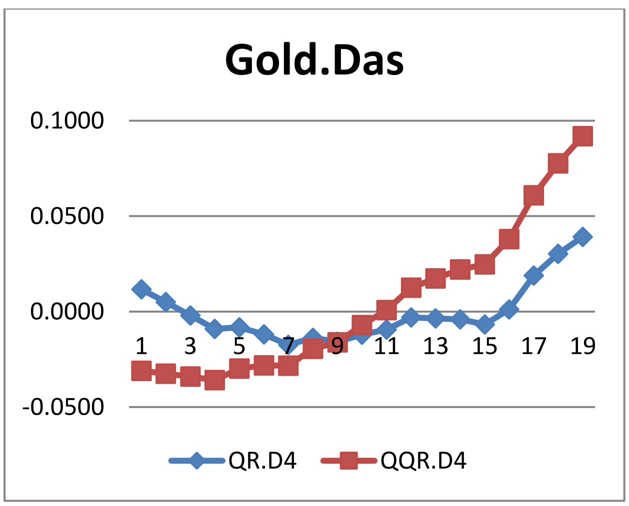

Gold.Ripple
1.0000
0.5000
0.0000
-0.5000
-1.0000
1 3 5 7 9 11 13 15 17 19
QR.D1 QQR.D1

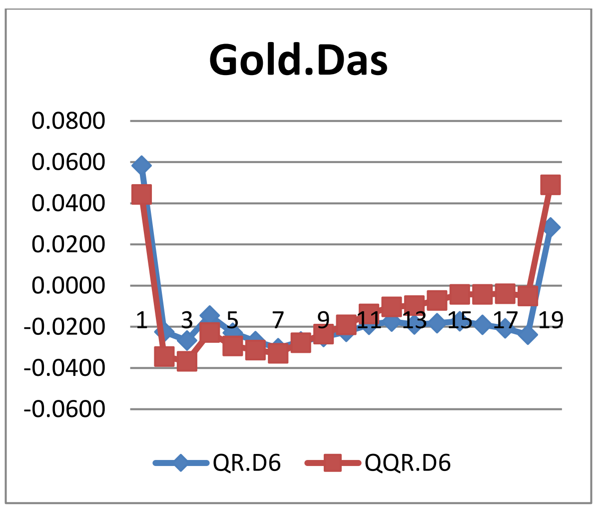

Gold.Ripple
0.1000
0.0500
0.0000
-0.0500
-0.1000
-0.1500
1 3 5 7 9 11 13 15 17 19
QR.D4
QQR.D4

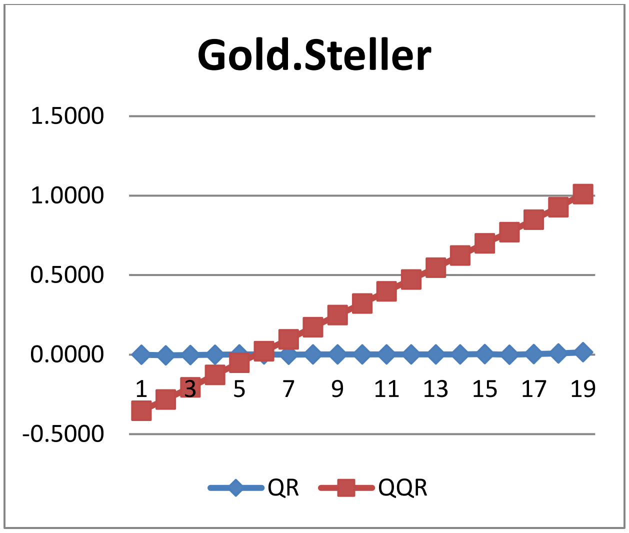

Gold.Ripple
0.1000
0.0800
0.0600
0.0400
0.0200
0.0000
-0.0200
-0.0400
1 3 5 7 9 11 13 15 17 19
QR.D6
QQR.D6

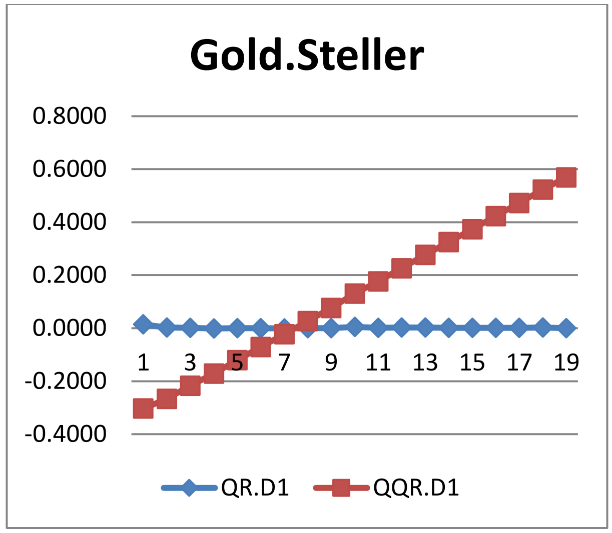

Gold.Das
0.4000
0.3000
0.2000
0.1000
0.0000
-0.1000
-0.2000
-0.3000
1 3 5 7 9 11 13 15 17 19
QR
QQR

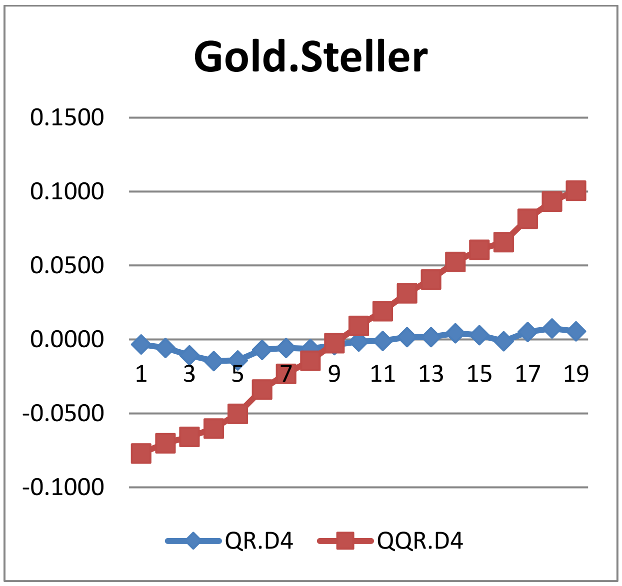

Gold.Das
0.2000
0.1500
0.1000
0.0500
0.0000
-0.0500
-0.1000
-0.1500
-0.2000
1 3 5 7 9 11 13 15 17 19
QR.D1
QQR.D1

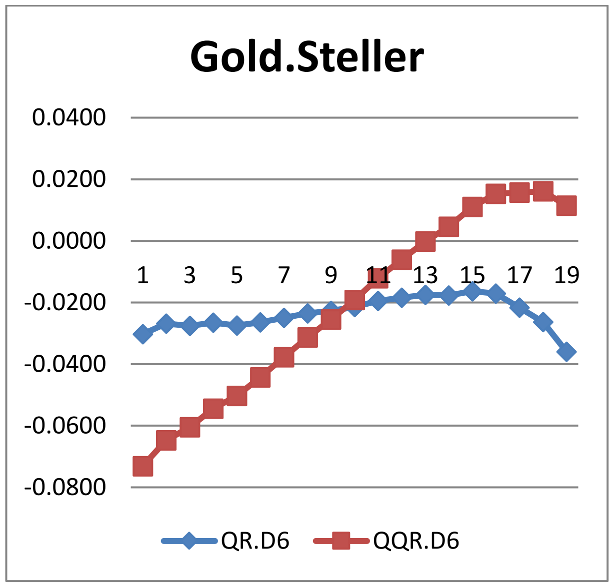

Gold.Das
0.1000
0.0500
0.0000
-0.0500
1 3 5 7 9 11 13 15 17 19
QR.D4
QQR.D4

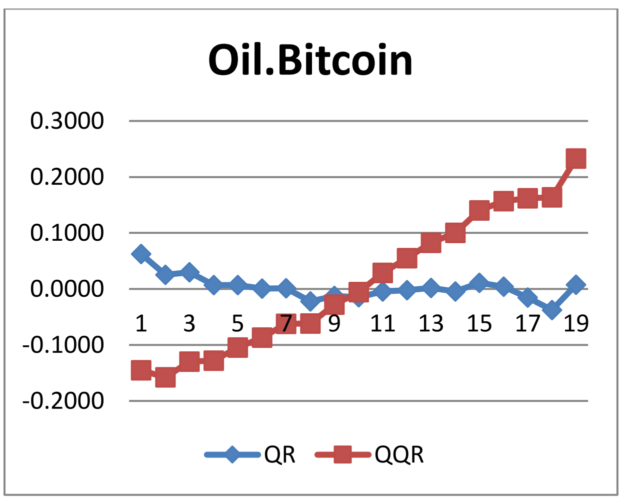

Gold.Das
0.0800
0.0600
0.0400
0.0200
0.0000
-0.0200
-0.0400
-0.0600
1 3 5 7 9 11 13 15 17 19
QR.D6
QQR.D6

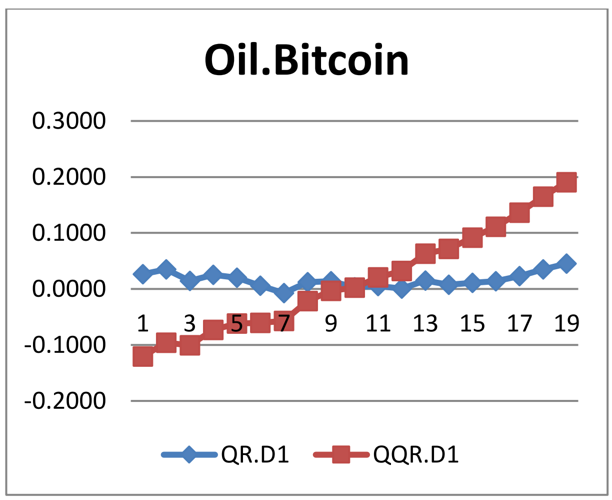

Gold.Steller
1.5000
1.0000
0.5000
0.0000
-0.5000
1 3 5 7 9 11 13 15 17 19
QR
QQR

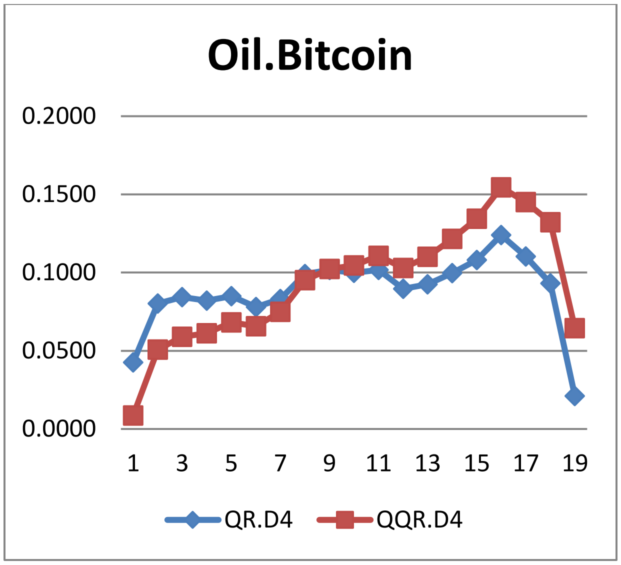

Gold.Steller
0.8000
0.6000
0.4000
0.2000
0.0000
-0.2000
-0.4000
1 3 5 7 9 11 13 15 17 19
QR.D1
QQR.D1


Gold.Steller
0.1500
0.1000
0.0500
0.0000
-0.0500
-0.1000
1 3 5 7 9 11 13 15 17 19
QR.D4
QQR.D4

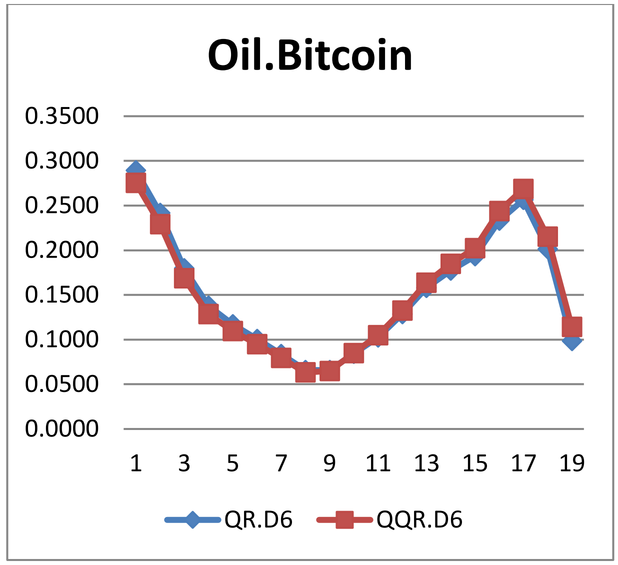

Gold.Steller
0.0400
0.0200
0.0000
-0.0200
-0.0400
-0.0600
-0.0800
1 3 5 7 9 11 13 15 17 19
QR.D6
QQR.D6


Oil.Bitcoin
0.3000
0.2000
0.1000
0.0000
-0.1000
-0.2000
1 3 5 7 9 11 13 15 17 19
QR
QQR

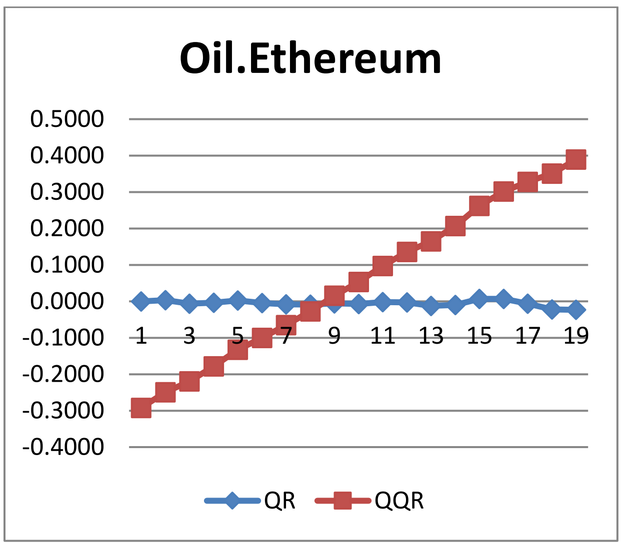

Oil.Bitcoin
0.3000
0.2000
0.1000
0.0000
-0.1000
-0.2000
1 3 5 7 9 11 13 15 17 19
QR.D1
QQR.D1



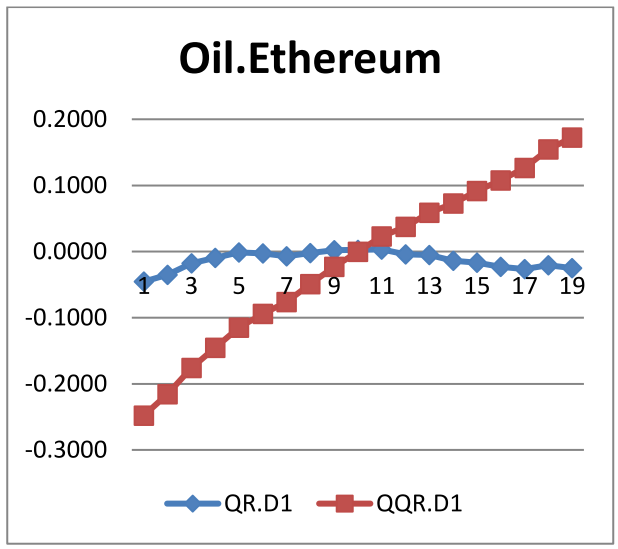
Oil.Bitcoin
0.2000
0.1500
0.1000
0.0500
0.0000
1 3 5 7 9 11 13 15 17 19
QR.D4
QQR.D4



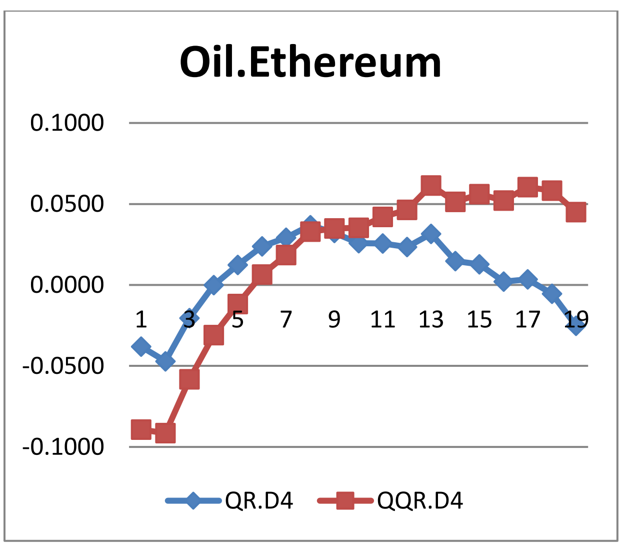
Oil.Bitcoin
0.3500
0.3000
0.2500
0.2000
0.1500
0.1000
0.0500
0.0000
1 3 5 7 9 11 13 15 17 19
QR.D6
QQR.D6



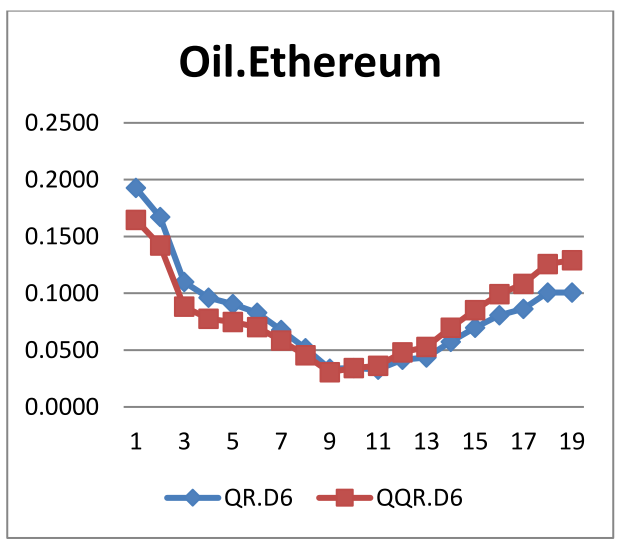
Oil.Ethereum
0.5000
0.4000
0.3000
0.2000
0.1000
0.0000
-0.1000
-0.2000
-0.3000
-0.4000
1 3 5 7 9 11 13 15 17 19
QR
QQR



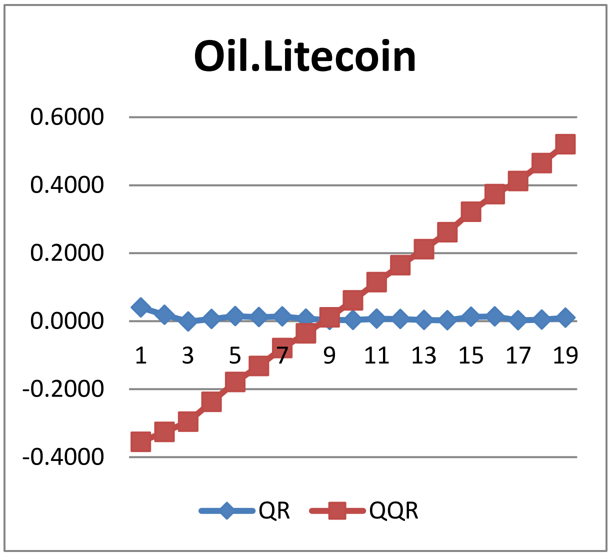
Oil.Ethereum
0.2000
0.1000
0.0000
-0.1000
-0.2000
-0.3000
1 3 5 7 9 11 13 15 17 19
QR.D1
QQR.D1

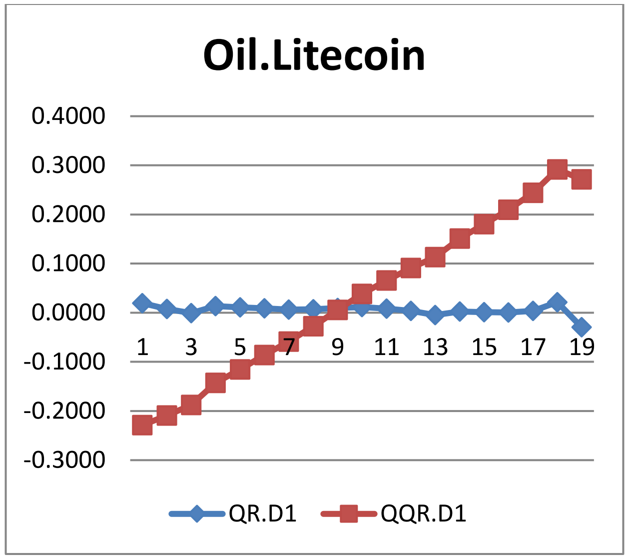


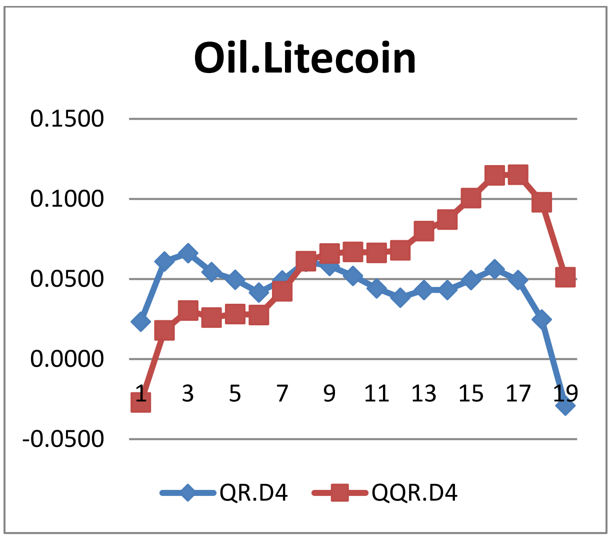
Oil.Ethereum
0.1000
0.0500
0.0000
-0.0500
-0.1000
1 3 5 7 9 11 13 15 17 19
QR.D4
QQR.D4

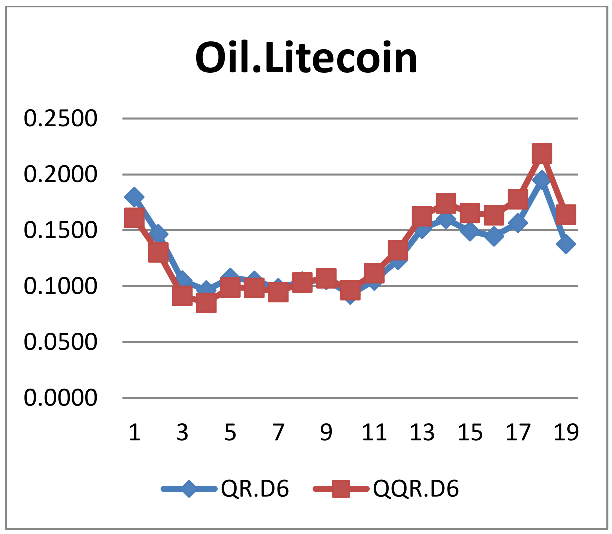


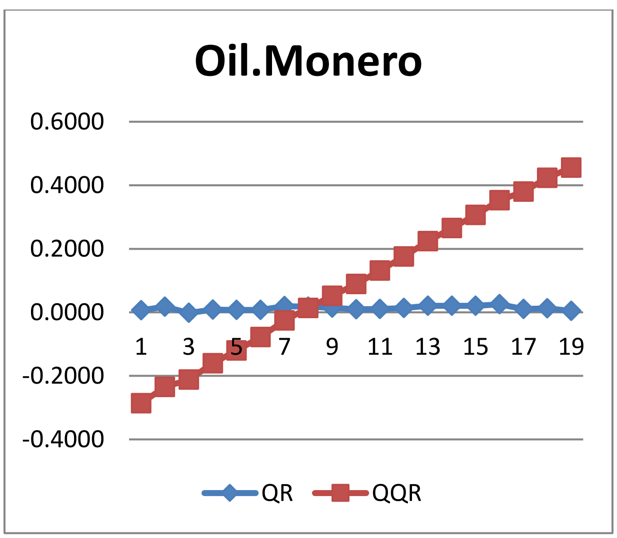
Oil.Ethereum
0.2500
0.2000
0.1500
0.1000
0.0500
0.0000
1 3 5 7 9 11 13 15 17 19
QR.D6
QQR.D6

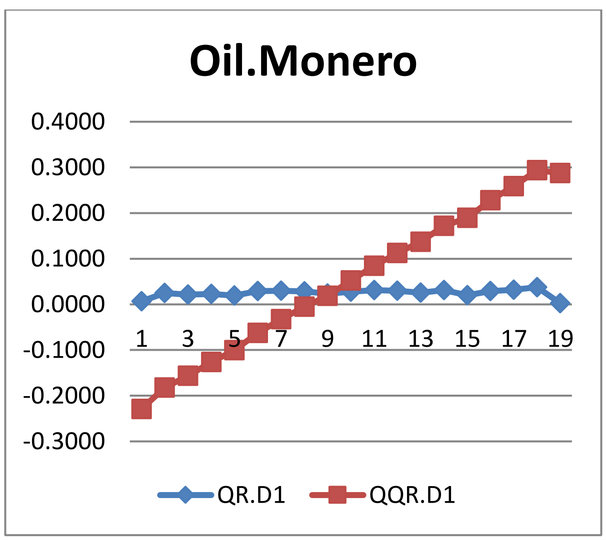

Oil.Litecoin
0.6000
0.4000
0.2000
0.0000
-0.2000
-0.4000
1 3 5 7 9 11 13 15 17 19
QR
QQR

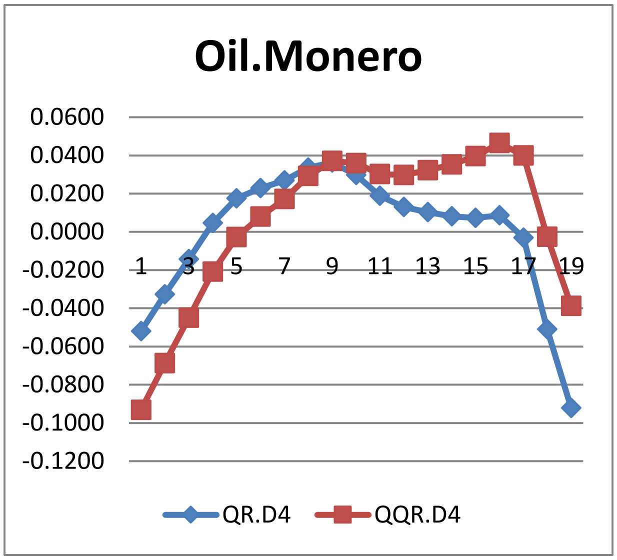

Oil.Litecoin
0.4000
0.3000
0.2000
0.1000
0.0000
-0.1000
-0.2000
-0.3000
1 3 5 7 9 11 13 15 17 19
QR.D1
QQR.D1

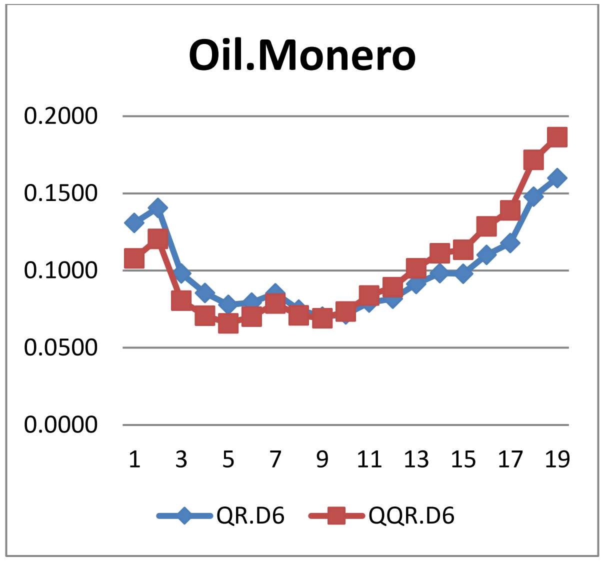

Oil.Litecoin
0.1500
0.1000
0.0500
0.0000
-0.0500
1 3 5 7 9 11 13 15 17 19
QR.D4
QQR.D4

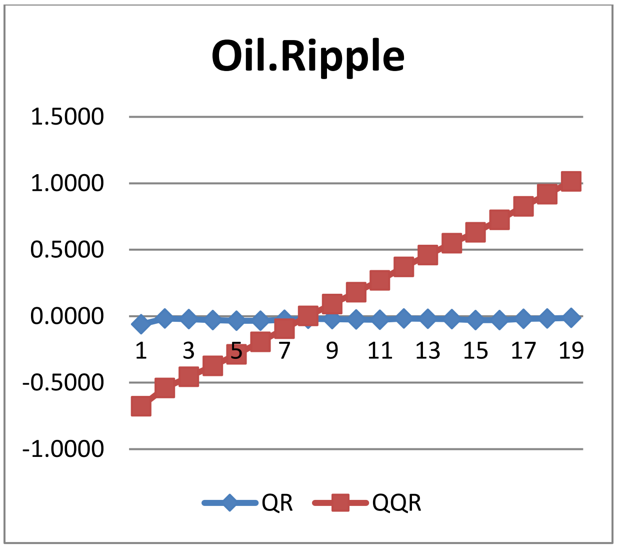

Oil.Litecoin
0.2500
0.2000
0.1500
0.1000
0.0500
0.0000
1 3 5 7 9 11 13 15 17 19
QR.D6
QQR.D6

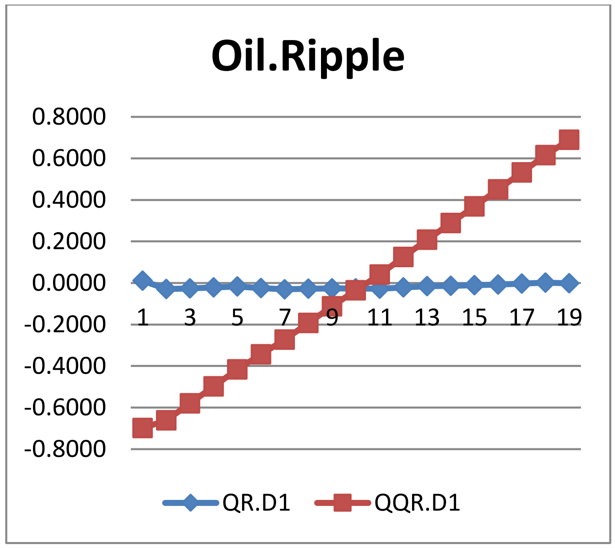

Oil.Monero
0.6000
0.4000
0.2000
0.0000
-0.2000
-0.4000
1 3 5 7 9 11 13 15 17 19
QR
QQR

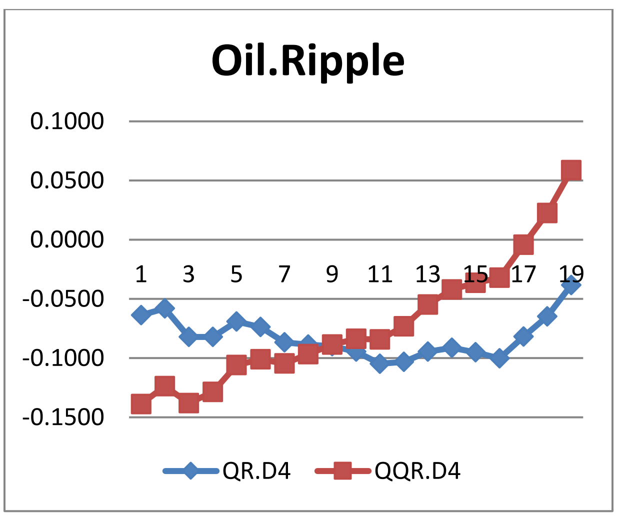

Oil.Monero
0.4000
0.3000
0.2000
0.1000
0.0000
-0.1000
-0.2000
-0.3000
1 3 5 7 9 11 13 15 17 19
QR.D1
QQR.D1

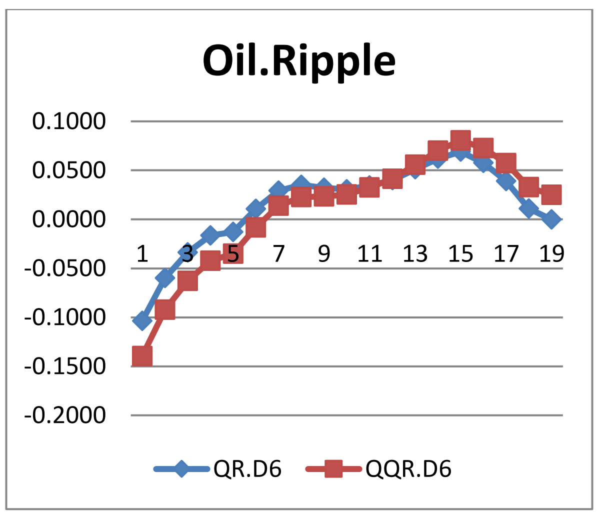

Oil.Monero
0.0600
0.0400
0.0200
0.0000
-0.0200
-0.0400
-0.0600
-0.0800
-0.1000
-0.1200
1 3 5 7 9 11 13 15 17 19
QR.D4
QQR.D4

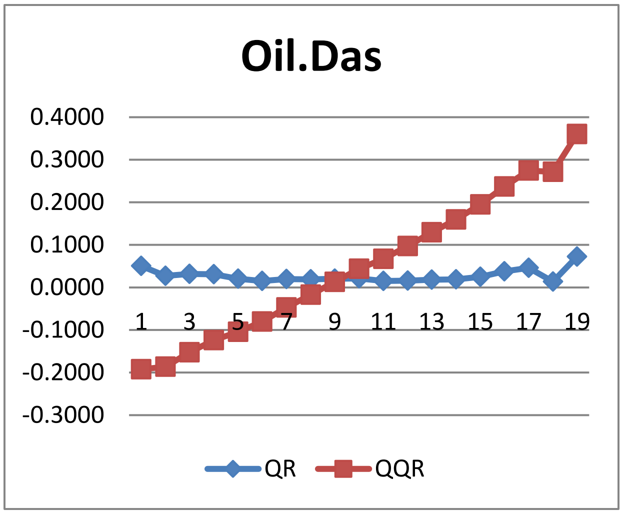

Oil.Monero
0.2000
0.1500
0.1000
0.0500
0.0000
1 3 5 7 9 11 13 15 17 19
QR.D6
QQR.D6

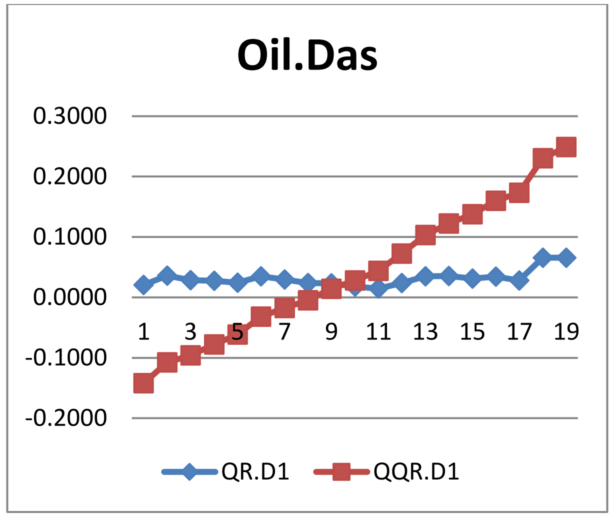

Oil.Ripple
1.5000
1.0000
0.5000
0.0000
-0.5000
-1.0000
1 3 5 7 9 11 13 15 17 19
QR
QQR

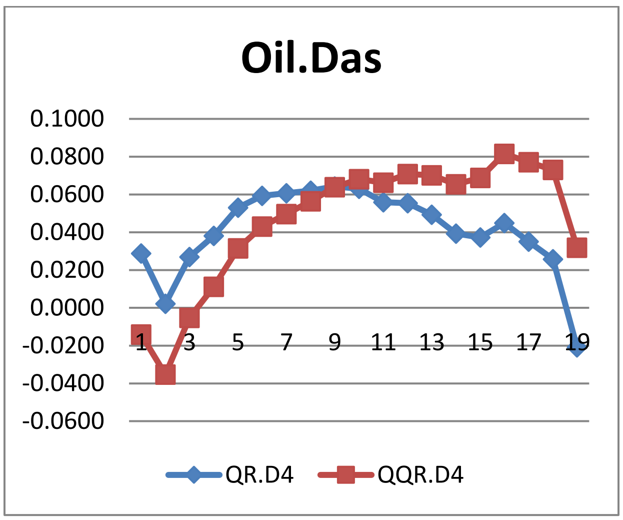

Oil.Ripple
0.8000
0.6000
0.4000
0.2000
0.0000
-0.2000
-0.4000
-0.6000
-0.8000
1 3 5 7 9 11 13 15 17 19
QR.D1
QQR.D1

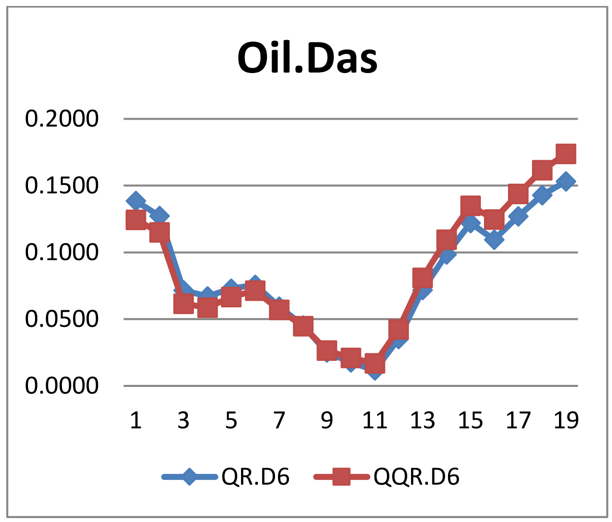

Oil.Ripple
0.1000
0.0500
0.0000
-0.0500
-0.1000
-0.1500
1 3 5 7 9 11 13 15 17 19
QR.D4
QQR.D4

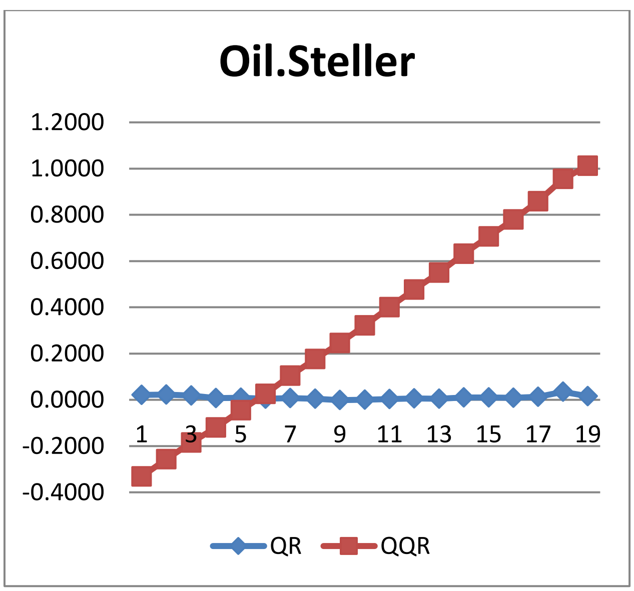

Oil.Ripple
0.1000
0.0500
0.0000
-0.0500
-0.1000
-0.1500
-0.2000
1 3 5 7 9 11 13 15 17 19
QR.D6
QQR.D6

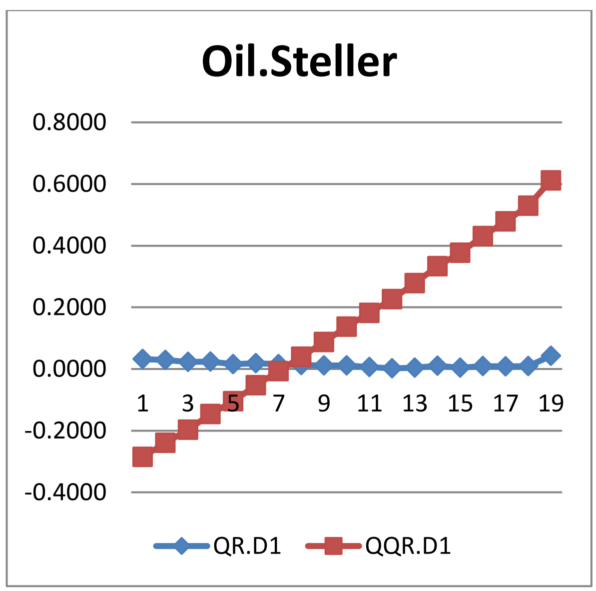

Oil.Das
0.4000
0.3000
0.2000
0.1000
0.0000
-0.1000
-0.2000
-0.3000
1 3 5 7 9 11 13 15 17 19
QR
QQR


Oil.Das
0.3000
0.2000
0.1000
0.0000
-0.1000
-0.2000
1 3 5 7 9 11 13 15 17 19
QR.D1
QQR.D1


Oil.Das
0.1000
0.0800
0.0600
0.0400
0.0200
0.0000
-0.0200
-0.0400
-0.0600
1 3 5 7 9 11 13 15 17 19
QR.D4
QQR.D4


Oil.Das
0.2000
0.1500
0.1000
0.0500
0.0000
1 3 5 7 9 11 13 15 17 19
QR.D6
QQR.D6


Oil.Steller
1.2000
1.0000
0.8000
0.6000
0.4000
0.2000
0.0000
-0.2000
-0.4000
1 3 5 7 9 11 13 15 17 19
QR
QQR


Oil.Steller
0.8000
0.6000
0.4000
0.2000
0.0000
-0.2000
-0.4000
1 3 5 7 9 11 13 15 17 19
QR.D1
QQR.D1

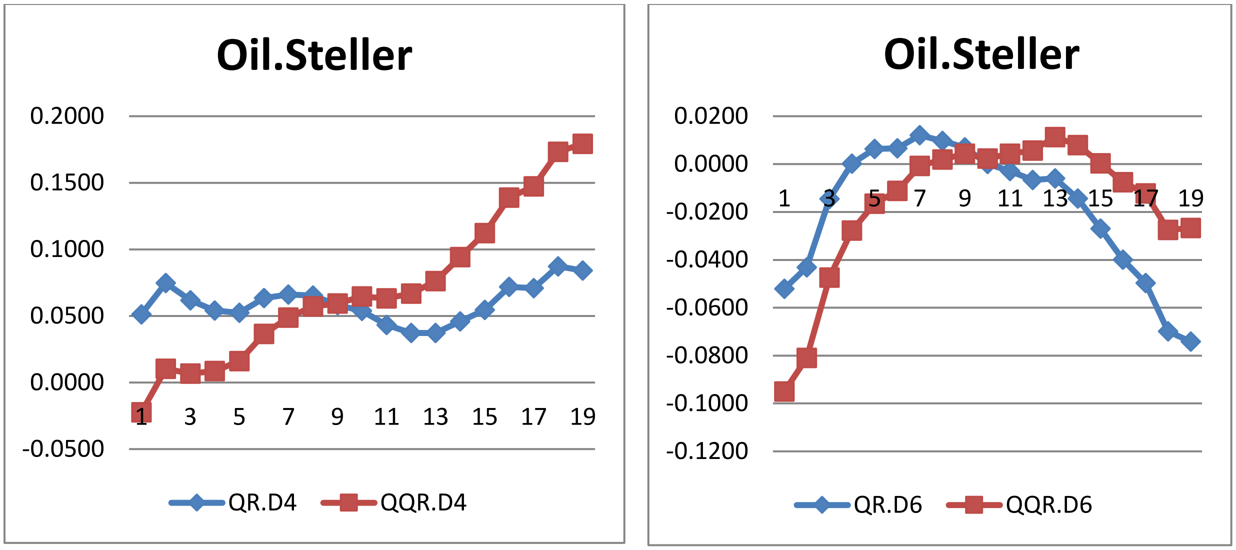


Figure 5. 2: Plot of QR and QQR coefficients of gold, crude oil, and cryptocurrency