Investigating the relationship between cryptocurrencies and exchange rates: Evidence from selected African countries

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Declaration

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DEDICATION

I dedicate this dissertation with deep gratitude to my beloved wife Sithembile, whose steadfast support and astute observations made this endeavour both possible and incredibly fulfilling. Your support is the cornerstone that supports this accomplishment, and your impact permeates every word. With sincere appreciation, this effort honours your lasting influence on my academic endeavours.

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ABSTRACT

The rise of cryptocurrencies has had a significant impact on the financial system, the world of finance and financial markets. After being written off as a passing fad, cryptocurrencies have come to be accepted as real investment assets with some hedging capabilities. Some even regard them as a form of payment, which has led to many businesses, financial institutions, and policy makers, including reserve banks examining the technology more closely and considering possible returns. This study aimed to, firstly, examine the connection between the fiat currencies for African countries and cryptocurrencies. It focused on the fiat currencies for the top eight economies in Africa with nominal Gross Domestic Product above $100 billion - Algeria, Egypt, South Africa, Morocco, Nigeria, Angola, Ethiopia, and Kenya - and the top three cryptocurrencies, Bitcoin, Ethereum and Binance coin which together represent more than 66% of the cryptocurrency market by market capitalisation. Secondly, the study assessed the relationship between cryptocurrencies, Bitcoin and Ethereum and the five main fiat currencies (the South African Rand, British Pound, Swiss Franc, Euro, and Australian Dollar) traded in South Africa's fiat currency market. These crypto and fiat currencies were analysed using the daily market price returns from 1 March 2018 to 12 May 2023. Time as well as time frequency information in the time series of cryptocurrencies and fiat currencies were captured using ensemble empirical mode decomposition (EEMD), while quantile regression (QR) was applied on the decomposed time series data to examine the connection between cryptocurrencies and fiat currencies under various currency regimes. The results revealed that QR adequately captured the asymmetric behaviour of cryptocurrencies and fiat currencies that changes with time. They illustrate that the connection between fiat currencies and cryptocurrencies at different magnitudes ranges from very strong to weak dependencies, although both positive and negative across different quantiles. In the African context, the study found that Bitcoin has some hedging characteristics against the Egyptian Pound, Ethiopian Birr, and South African Rand. Binance coin can also be used as a hedge against the depreciating Ethiopian Birr, while Ethereum can be utilised as a hedge against loss in the Egyptian Pound, and South African Rand. Furthermore, Bitcoin and Ethereum can be employed for diversification purposes in a portfolio with the Kenyan Shilling and Bitcoin and Ethereum are suitable alternatives to the Egyptian Pound, the Moroccan Dirham, Nigerian Naira, and South African Rand for transacting. Binance coin can be utilised as alternative to the Ethiopian Birr, Kenyan Shilling and South African Rand, Algerian Dinar, and Moroccan Dirham. In the case

of South Africa, Bitcoin can be used as a hedge against the depreciating value of the Australian Dollar, Euro, and South African Rand. Similarly, Ethereum can be used as a hedge against the Australian Dollar as well as the British Pound.

The research contributes to the existing literature on the subject by providing further empirical evidence on the connection between cryptocurrency and African fiat currencies, and the association between cryptocurrency and the fiat currencies traded in South Africa. Based on the results, it is recommended that policy makers, forex dealers and investors should adopt Binance coin, Bitcoin and Ethereum as a substitute for fiat currency in Africa and particularly South Africa to mitigate currency depreciation on the continent.

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LIST OF ACRONYMS

ACX	African Currency Exchange
AIIB	Asian Infrastructure Investment Bank
AOA	Angolan Kwanza, the currency of Angola
AR	Abnormal Returns
AUD	Australian Dollar, the currency of Australia
AUM	Assets Under Management
BCH	Bitcoin Cash cryptocurrency
BNB	Binance Coin cryptocurrency
BOA	Bank of America
BOT	Bank of Thailand
BRL	Brazilian Real, the currency of Brazil
BSE	Bombay Stock Exchange
BTC	Bitcoin cryptocurrency
CAD	Canadian Dollar, the currency of Canada
CAR	Cumulative Abnormal Returns
CBDC	Central Bank Digital Currency
CFPB	Consumer Financial Protection Bureau
CHF	Swiss Franc, the currency of Switzerland
CNH	Offshore Chinese Yuan, the currency of China
CRYPTO	Cryptocurrency, digital currency
DEA	Data Envelopment Analysis
DZD	Algerian Dinar, the currency of Algeria
EBA	European Banking Authority
ECB	European Central Bank
EGP	Egyptian Pound, the currency of Egypt
ETB	Ethiopian Birr, the currency of Ethiopia
ETF	Exchange Traded Fund
ETH	Ethereum cryptocurrency
EUR	Euro, the currency of Europe
FDI	Foreign Direct Investment
FED	Federal Reserve System, the United States' central bank
FII	Foreign Institutional Investors

LIST OF ACRONYMS (continued)

FNB	First National Bank
FX	Foreign Exchange
GBP	British Pound, the currency of Britain
GDP	Gross Domestic Product
HSBC	Hong Kong and Shanghai Banking Corporation
ICBC	Industrial and Commercial Bank of China
INR	Indian Rupee, the currency of India
IPO	Initial Public Offering
JPY	Japanese Yen, the currency of Japan
JSE	Johannesburg Stock Exchange
KES	Kenyan Shilling, the currency of Kenya
LTC	Litecoin cryptocurrency
MAD	Moroccan Dirham, the currency of Morocco
MENA	Middle East and North Africa
NEDBANK	National Equity Development Bank
NGN	Nigerian Naira, the currency of Nigeria
NYSE	New York Stock Exchange
RUB	Russian Ruble, the currency of Russia
SA	South Africa
SARB	South African Reserve Bank
SBSA	Standard Bank of South Africa
SCX	Foreign Exchange traded in South Africa
SEC	Securities and Exchange Commission
SENSEX	Benchmark index of the BSE in India, the 30 largest & most traded stocks
SWIFT	Society for Worldwide Interbank Financial Telecommunication
UNCTAD	United Nations Conference on Trade and Development
USA	United States of America
USD	United States Dollar, the currency of the United States
XRP	Ripple cryptocurrency
ZAR	South African Rand, the currency of South Africa

CHAPTER 1: INTRODUCTION

1.1 Introduction

This study investigated the connection between the fiat currencies for African countries and cryptocurrencies. It focused on the fiat currencies for the top eight African economies by Gross Domestic Product (GDP), whose individual nominal GDP is above US$100 billion – Algeria, Egypt, South Africa, Morocco, Nigeria, Angola, Ethiopia, and Kenya and the top three cryptocurrencies – Bitcoin (BTC), Ethereum (ETH) and Binance Coin (BNB), which together represent more than 66% of the cryptocurrency market by market capitalisation. This chapter presents the background of the study, the problem statement, and the research objectives and hypotheses. It discusses the study's significance, delimitations, assumptions and limitations, defines the key terms and presents an outline of the dissertation.

1.2 Background of the Study

A number of studies have highlighted a significant connection between fiat and digital currencies with a few showing insignificant correlation between the two currencies. All these studies conclude that the connection between fiat and cryptocurrencies is largely influenced by coexistence between the two currencies and the regulatory environment under which both, especially crypto, operate. This section discusses the infusion of cryptocurrency into the financial market, the difference between South Africa and other African countries, the coexistence of foreign exchange (FX) and cryptocurrency and lastly cryptocurrency's development, regulation and future.

1.2.1 Infusion of cryptocurrency into the financial market

The world of finance and its financial systems have been drastically impacted by the emergence of cryptocurrency (Şanlisoy & Çiloğlu, 2019). The digital currency has had a significant impact on global financial markets (Ehlers & Gauer, 2019). Once seen as a fleeting trend, it has now become a legitimate investment asset with some hedging characteristics (Czapliński &

Nazmutdinova, 2019; Elsayed et al., 2022). According to Chemkha et al. (2021) and Jaag and Bach (2017), some see cryptocurrency as a means of payment, prompting many policy makers, companies and financial institutions, including reserve banks to take a closer look at the technology and its potential benefits. The first cryptocurrency was created by Satoshi Nakamoto in 2008 and was followed by the creation of other cryptocurrencies across the world (Chuen et al., 2017).

Mandeng (2018) describes cryptocurrency as a type of digital currency or decentralised financial payment system that is designed with encryption for security and anti-counterfeiting purposes. Cryptocurrency has made cross-border payments faster and more convenient, with a fraction of the costs (Chapman and Wilkins (2018) Onyeke (2020). Furthermore, it has become increasingly popular with investors, who have seen the potential for huge investment gains (Czapliński & Nazmutdinova, 2019). This has led to more companies, including some financial institutions offering cryptocurrency-related services in some countries (Ertz & Boily, 2019; Hsieh, 2018) and has thus influenced the stock price of companies in the financial sector (Anagnostopoulos, 2018; Attaran & Gunasekaran, 2019; Cortina Lorente & Schmukler, 2018; Dranev et al., 2019; Jaag & Bach, 2017; Romānova & Kudinska, 2016; Vives, 2017).

Virtual currencies like Bitcoin, Litecoin, Ripple, and Ethereum emerged in financial markets from 2008, and in recent years, they have almost completely replaced traditional currencies (Onyeke, 2020). According to Chemkha et al. (2021), Tesla started accepting Bitcoin as a form of payment for its goods on 8 February 2021, after revealing that it had purchased the cryptocurrency for $1.5 billion. The Bitcoin trading platform Coinbase went public on NASDAQ on 14 April 2021 and as a result of this and other factors, the price of Bitcoin witnessed a stunning rise to more than $63 000 (Chemkha et al., 2021). However, on 12 May 2021, Tesla ceased using Bitcoin as a form of payment, and China's central bank reaffirmed that digital currency cannot be used as a medium of exchange. Nonetheless, Chemkha et al. (2021) note that El Salvador accepted it in September 2021 as means of payment, heralding its recovery, with many investors wondering which country would be next.

Cryptocurrencies have attracted much media and academic attention since the beginning of 2013 due to extreme fluctuations in their pricing (Elsayed & Sousa, 2022; Luchkin et al., 2020). Various commodities in financial markets, including forex currencies have been impacted by cryptocurrencies due to their continued development and rising global popularity. Luchkin et al. (2020) raised concern about how cryptocurrencies would affect the value of global currency pairs and financial markets in general. Since the turn of the century, international investment has increased, as the most liquid market, the FX market helps buyers and sellers to enter and exit the market more easily, reducing trading costs, volatility, and slippage (Kim, 2023).

Acho (2021), BenSaïda (2023a) and Onyeke (2020) caution that digital currency's infusion into financial markets has also had drawbacks. Duarte et al. (2023) research concluded that cryptocurrencies still have a long way to go before meeting all the criteria for being classified as a currency, particularly in terms of their ability to serve as a unit of account as well as a store of value. Luchkin et al. (2020) posit that, due to their potential to disrupt traditional monetary institutions, payment systems, and even financial stability (Böhme et al., 2015), digital currencies should be the subject of research by economists and financiers.

The proliferation of cryptocurrency has undermined FX currencies and the financial market industry in general (Mensi, Rehman, et al., 2019). A review of the literature on this issue reveals that the dependency between FX markets and the cryptocurrency market is not fully understood (Schultz, 2016). Research on interactions between traditional currencies and digital currencies is still in its infancy despite the fact that various scholars have explored connections with financial markets over the previous decade (BenSaïda (2023a).

1.2.2 Distinction between South Africa and other African Countries

South Africa is ranked top among African countries when it comes to technology including research and development, followed by Egypt and Nigeria (Muhammad, 2022). It is also ranked high on the United Nations e-government development index when it comes to digitalisation, including E-payments (Domingo & Shiferaw, 2022). Indeed, Mpofu and Mhlanga (2022) describe South Africa as one of the leaders of the digital economy in Africa. Based on its superior internet access, large, sophisticated banking industry, and comprehensive

legislative framework that protects consumers and their data, South Africa appears to be a leader in e-commerce on the continent (Lemma et al., 2022). Lemma et al. (2022) add that it is the leading digital trade market on the African continent. According to Campbell-Verduyn and Giumelli (2022) South Africa takes the lead in Africa when it comes to crypto-jurisdictions.

The few empirical studies that have been conducted on the connections between African financial markets have found that South Africa has strong ties to Western markets but only moderate integration with other African nations (Nyakurukwa & Seetharam, 2023b). While African stock exchanges are weakly integrated with cryptocurrency, South Africa has the most influential financial markets in Africa and is ranked among the top African nations when it comes to cryptocurrency trading in currency value (Nyakurukwa & Seetharam, 2023b). The profile of the South African financial market appears to be empirically different and somewhat superior in relation to those of other African countries. This study's second objective was thus to examine the impact of these different characteristics on the connection between cryptocurrency and FX currencies in South Africa.

1.2.3 Coexistence of foreign exchange and cryptocurrency

Froot and Thaler (1990) and King et al. (2012) define foreign exchange, commonly shortened to forex or FX, as the international currency trading industry. It is the decentralised, interconnected system of financial institutions, governments, businesses, and private traders that trade various national currencies for and in competition with one another (King et al. (2012). Foreign exchange markets enable participants to convert one currency into another in order to facilitate international trade and investment (Froot & Thaler, 1990; King et al., 2012). In forex trading, exchange rates which are based on supply and demand, are important because they affect the relative values of different currencies (Senner & Sornette, 2019). As defined by ElBahrawy et al. (2017) and Rice (2019), cryptocurrency is a type of virtual or digital money that runs on decentralised networks built on blockchain technology.

The global FX market is one of the biggest markets that traded around US$2.4 quadrillion in 2022 (Nekhili et al., 2023). It is also said to be the most liquid market, with staggering daily trading volumes of more than US$7.5 trillion (Nekhili et al. (2023). In contrast, the daily trading volume for cryptocurrency was around US$99 billion on 8 May 2022, $248 billion in

November 2018 and $1.8 trillion in January 2022 (Brauneis et al., 2022). Trading operations for any asset, including cryptocurrencies, depend on liquidity (Nekhili et al., 2023). Due to its tremendous liquidity, Bitcoin's bid-ask spreads are smaller than those of traditional assets like equities and bonds and are commensurate with FX markets. Any market that is illiquid is susceptible to volatility (Brauneis et al., 2022; Nekhili et al., 2023).

Analysts have hitherto either regarded cryptocurrencies as a whimsy with little intrinsic value or significance or as the payment and currency system of the future that will take the place of currencies backed by governments (Abu & Ohiaeri, 2023; Hairudin et al., 2022). It should be borne in mind that digital assets at an estimated value of $3 trillion are held on the global market.

1.2.4 Cryptocurrency development, regulation and the future

Despite the fact that many people have invested in Bitcoin in anticipation of earning large returns, its future is uncertain (Abu & Ohiaeri, 2023; Nugroho, 2023; Sauchande, 2023). Governments have repeatedly warned their citizens about the risks involved in dealing in the crypto market or in digital currencies that are not backed by the state through the central bank and regulators (Senner, 2018). The Chartalism monetary theory of fiat currency, which states that fiat currency is referred to as legal tender because it is created by government, would discourage governments from granting permission for digital assets to be used as a means of exchange (Lavoie, 2013; Peters et al., 2015). However, Senner (2018) asserts that although crypto-currency technology creates regulatory risks, it has useful economic applications. Foreign trade is facilitated by crypto, particularly at the micro level, and it has the potential to promote financial inclusion as it is also less expensive and quicker for foreign remittances (Pantin, 2023).

Melnyk (2019) submits that digital currency has the potential to promote modest foreign trade. Furthermore, cryptocurrency may enable domestic business owners in developing economies who find it difficult to gain entry to global payment networks to export their products (Nyamongo et al., 2012). The lack of a central authority has been highlighted by numerous scholars as the primary feature of digital currencies (Kadam, 2018; Mukhopadhyay et al., 2016;

Nabilou, 2019). Governments have also drawn attention to the risks associated with investing in an unregulated as well as highly unpredictable market. Given cryptocurrency's rapid development and the fact that the literature notes that the connection between it and fiat currencies has not yet been fully established, particularly in the African financial market system, there is a need for further research on this issue.

1.3 Problem Statement

Cryptocurrencies, especially Bitcoin and Ethereum, are regarded as a means of trading (Levulytė & Šapkauskienė, 2021). Rehman et al. (2023), and Sinlapates et al. (2023) also highlight the potential rewards of investing in cryptocurrency, although Nugroho (2023), and Sauchande (2023) caution that the lack of a recognised legal framework for such trading remains a challenge for many governments and regulatory authorities around the world. The benefits include the use of digital currencies as a hedge against inflation and depreciating fiat currencies (Esparcia & Lopez, 2023; Klein et al., 2018). Diversification in a fiat currency portfolio using crypto is another advantage noted by Baumöhl (2019), and an interesting characteristic of digital currency is the ability to store value using crypto during economic meltdown (Baur & Dimpfl, 2021). However, research on this issue has produced mixed findings, with some scholars arguing that cryptos benefit the economy (Baumöhl (2019) Baur and Dimpfl (2021) Cermak (2017) Esparcia and Lopez (2023) Klein et al. (2018) whilst others disagree (Dierksmeier and Seele (2018) Morton (2020) Ramos et al. (2021). Furthermore, the majority of studies on the influence of cryptocurrency including Bhullar and Bhatnagar (2020), Donmez et al. (2021), (Dranev et al., 2019), Khaled (2020) and Sami and Abdallah (2021) focused on developed countries. There is a paucity of research on developing countries and most studies conducted on similar topics focused on the Middle East and North Africa (MENA) region, Europe, India and China. The few studies on the African continent produced mixed results. A review of the literature also reveals that the structure of dependency between FX markets and the digital currency market is not fully understood. Assessment of the interactions between fiduciary currencies and digital currencies is still in its infancy, despite the fact that various scholars have explored connections with financial markets over the past decade. Furthermore, the connection between cryptocurrency and African fiat currencies represents a problem that requires attention.

1.4 Objectives of the Study

The study's objectives were to:

1.4.1 Assess the connection between cryptocurrencies (BTC, ETH and BNB) and the fiat currencies in the African context.

1.4.2 Examine the connection between cryptocurrencies (BTC and ETH) and the fiat currencies traded in South Africa.

1.5 Research Hypotheses

1.5.1 Hypotheses for Objective 1 (Connection between African fiat currencies and cryptocurrency)

Null Hypotheses

First Null – H_0: No significant connection exists among the fiat currencies and BTC return.

Second Null – H_0: No significant connection exists among the fiat currencies and ETH return.

Third Null – H_0: No significant connection exists among the fiat currencies and BNB return.

Alternative Hypotheses

First alternative – H_1: A significant connection exists among the fiat currencies and BTC return.

Second alternative – H_2: A significant connection exists among the fiat currencies and ETH return.

Third alternative – H_3: A significant connection exists among the fiat currencies and BNB return.

1.5.2 Objective 2 (Connection between South African fiat currencies and cryptocurrency)

Null Hypotheses

Fourth Null – H_0: No significant connection exists among the fiat currencies and BTC return.

Fifth Null – H_0: No significant connection exists among the fiat currencies and ETH return.

Alternative Hypotheses

Fourth alternative – H_4: There is a significant connection among the fiat currencies and BTC return.
Fifth alternative – H_5: There is a significant connection among the fiat currencies and ETH return.

1.6 Significance of the Study

As detailed below, the study's findings will assist a variety of stakeholders within their respective roles in the financial markets and the economy in general.

1.6.1 Banks and forex dealers

Given that banks and central banks are the primary gatekeepers of the financial system, (Berentsen & Schär, 2018), it is essential to understand how the market for FX behaves in relation to cryptocurrency market performance. Banks and forex dealers can use the findings of this study to understand how their FX services relate to cryptocurrency and adjust their operations to ensure they remain competitive and relevant. This research shows how African foreign currencies behave with cryptocurrency. Accordingly, through their central banks, governments can use the findings to achieve their macroeconomic goals such as preserving price stability, fostering economic growth, and controlling inflation and monetary policy (Nayyar, 2011; Sahay et al., 2015). As highlighted by Hristov and Roth (2022), economic uncertainty creates systemic vulnerabilities and financial crises. Similarly, central banks can use the results to consider all risks and benefits emanating from the connection between foreign currencies and cryptocurrencies to manage systematic vulnerabilities and create stability in the financial markets to protect market participants.

1.6.2 Investors

The study's results offer investors insights into how to adjust their investment strategies to take advantage of the new asset class. For example, understanding that cryptocurrency moves alongside or against the markets for foreign currency and how volatile it is will assist investors to diversify their portfolio according to their risk appetite. Mallick and Mallik (2021) regard

cryptocurrency as a hedging asset which can be used by investors to diversify their portfolios. Researchers such as El Montasser et al. (2022), Mokni et al. (2022), Narayan (2021), Soni and Nandan (2022), Umar et al. (2021) and Xu and Lien (2022) note the substantial surge in the market for cryptocurrencies over the past few years, alongside a spike in demand for fiat currencies, particularly in light of the COVID-19 pandemic. Demand for the two currencies is rising, but this has resulted in wide fluctuations in exchange rates and the value of virtual currencies. However, they are still seen as worthwhile investment prospects, whether for speculating, mitigating risk, or diversifying a portfolio. Demir et al. (2022) observe that cryptocurrencies are seen as a potential answer to sudden changes in the financial and economic landscape. Giving cryptocurrencies' growing significance as an investment vehicle, the interconnection between them needs to be modelled in order to make investment decisions (Bouri et al., 2021).

1.6.3 Regulators

Regulators can use this research to better understand how the cryptocurrency market relates to the FX market system in order to develop policies and regulations for the creation of a safe and secure environment for market participants. Corelli (2018) connection and causality analysis between cryptocurrencies and exchange rates concluded that there is causality and a correlation effect between cryptocurrency and exchange rates. The author notes the need for further research on this topic to determine the reasons for such a connection and causality and how these can be used to influence monetary policy and regulations.

1.6.4 Academics and Researchers

Researchers and academics can benefit by learning more about the connections between these variables in the African setting. Scholars with an interest in cryptocurrencies, financial markets, and foreign currency rates will also find the study useful. Furthermore, the study adds to the body of knowledge in these fields and points to new directions for future investigations. Ultimately, it provides valuable insights into how the financial system has been reshaped since the introduction of cryptocurrency. Isaksson (2022), examined the markets for and the movements of cryptocurrency in Europe and found that cryptocurrency is a very speculative

asset with high volatility. The author calls for further research on cryptocurrency and financial markets in order to gain more insight into this new asset class and its influence on the market. Lastly, the study's results will inform researchers and academics' academic projects and teaching.

1.7 Delimitations of the Study

This study examined the relationship between cryptocurrency (BTC, ETH and BNB) and African fiat currencies (the NGN, ZAR, EGP, DZD, AOA, MAD, ETB and KES), and the association between cryptocurrency (BTC and ETH) and the fiat currencies traded in South Africa (the ZAR, EUR, GBP, CHF and AUD). It focused on the daily market price movements for fiat and digital currencies from 1 March 2018 to 12 May 2023 in Africa and South Africa.

1.8 Assumptions of the Study

It was assumed that the market price data used in this study is true and accurate for both foreign currencies and cryptocurrencies. It follows that the sample size is thought to be a reasonable representation of the entire fiat and cryptocurrency markets in Africa and South Africa. Furthermore, it is believed that the study's conclusions fairly depict developing economies, particularly South Africa and other African nations.

1.9 Limitations of the Study

Only eight countries were sampled; therefore, the results from the African dataset cannot be generalised to all the countries on the continent. Similarly, five foreign currencies were sampled in the South African dataset and accordingly the results cannot be generalised to all the foreign currencies traded in this country. The sample period was confined to 1 March 2018 to 12 May 2023; therefore, the study's output cannot be extrapolated beyond this period.

The study recognises some inherent limitations related to its scope and design. To begin with, there are just eight nations in the African dataset: Nigeria (NGN/USD), South Africa (ZAR/USD), Egypt (EGP/USD), Algeria (DZD/USD), Angola (AOA/USD), Morocco

(MAD/USD), Ethiopia (ETB/USD), and Kenya (KES/USD). Although these nations have substantial nominal GDPs over $100 billion and a considerable economic influence, they do not adequately represent the continent. Over 50 countries make up Africa, and each has its own economic climate, set of laws, and degree of cryptocurrency adoption. As a result, it is not possible to extrapolate the findings from this sample to all of Africa since they may not accurately represent the variety of economic conditions and bitcoin dynamics that exist throughout the continent.

Comparably, only five foreign currencies are included in the South African dataset: ZAR/USD, EUR/USD, GBP/USD, CHF/USD, JPY/USD, and AUD/USD. These currencies, which act as stand-ins for the wider range of foreign exchange currencies traded in the nation, were selected based on their popularity in South Africa's foreign exchange market. But there are a lot of other currencies that are traded in South Africa as well, and they might all interact with cryptocurrencies in different ways. Because of this, the study's conclusions are limited to the currencies that were sampled and might not apply to the whole range of foreign currencies that are traded on the South African market.

Additionally, the study's temporal scope is limited to the months of March 2018 through May 12, 2023. In order to include current trends and advancements in the foreign exchange and cryptocurrency markets, this time span was chosen. However, a wide range of factors, such as macroeconomic events, regulatory changes, and technological breakthroughs, have a significant impact on the extremely dynamic financial markets. Because of this, the conclusions drawn from this study are restricted to the time frame given and cannot be extended beyond it. It is important to use caution when extrapolating these findings to later periods since future market conditions can differ dramatically from those that were experienced during the study period.

1.10 Sampling biases and data source limitations

The selection of cryptocurrencies and fiat currencies in this study was done strategically in order to mitigate any potential sampling biases. Bitcoin, Ethereum, and Binance Coin were selected for the cryptocurrency sample because between them they account for over 66% of the total market capitalisation of cryptocurrencies. The chosen sample is very typical of the whole cryptocurrency sector thanks to this sizeable market share. Thus, the study reduces the

danger of missing important market dynamics by concentrating on these prominent cryptocurrencies and capturing the key trends and behaviours that are likely to affect and be influenced by the fiat currencies in question.

The study focusses on the top eight African economies with nominal GDPs more than US$100 billion for the fiat currency sample. The significant economic influence these nations have on the continent led to the selection of this criterion. NGN/USD (Nigeria), ZAR/USD (South Africa), EGP/USD (Egypt), DZD/USD (Algeria), AOA/USD (Angola), MAD/USD (Morocco), ETB/USD (Ethiopia), and KES/USD (Kenya) are among the currencies that are covered. These nations were selected so that the study would concentrate on the most influential African economies due to their substantial economic activity and high GDPs. The research attempts to capture the fundamental economic connections and market behaviours that are most pertinent to the goals of the study by choosing these top economies.

The sites utilised to get the data, CoinMarketCap and Investing.com, are reliable and popular providers of current and accurate financial data. By depending on these reliable sources, the study further reduces the possibility of biases resulting from inconsistent or erroneous data by ensuring the quality and trustworthiness of the data.

In summary, the study effectively tackles potential sampling biases by focussing on the top eight African economies with considerable nominal GDPs and choosing the three largest cryptocurrencies by market capitalisation. By using this method, a representative sample that captures the essential market characteristics required to comprehend the relationships between cryptocurrencies and fiat currencies is ensured.

1.11 Dissertation outline

The dissertation is presented in the following five chapters:

Chapter 1: Introduction

This chapter presents the introduction and background of the study, the problem statement, the study's objectives, and the research hypotheses. It also discusses the significance of the study

as well as its assumptions, delimitations and limitations, and presents an outline of the dissertation.

Chapter 2: Literature review

Chapter 2 presents a theoretical literature review that provides a framework for the study and an empirical literature review that provides an overview of existing literature on similar research topics. The latter also presents empirical evidence on the impact of cryptocurrency and identifies the research gaps which this study aimed to fill.

Chapter 3: Research methodology

This chapter presents the research methodology employed to conduct the study, including the research paradigm and design, the study population and sample, and data sources and selection of variables. It also discusses the model specification and analysis, diagnostic inspection, estimation procedure, the quantile regression results, data validity and reliability, and the ethical considerations taken into account in conducting the study.

Chapter 4: Data presentation and analysis

Chapter 4 presents and analyses the data. The researcher carefully examined the dataset to find patterns, correlations, and trends that provide empirical evidence to bolster the study's assertions. The chapter presents the preliminary analysis which includes the tests for outliers, descriptive statistics, correlation analysis, variance inflation factors and unit root tests. This is followed by the model design which includes Jarque Bera normality tests, IMF summary statistics, the quantile regression model, quantile process estimates, quantile slope equality tests and symmetric quantiles tests. Lastly, the connection between fiat currencies and cryptocurrencies is discussed.

Chapter 5: Summary, conclusions and recommendations

This chapter presents a summary of the research, conclusions and recommendations. The summary provides a concise synopsis of the complete study, including the key findings, the

techniques utilised, and the wider implications of the research. The conclusion outlines the findings in further detail, evaluating the information and responding to the study questions and hypotheses.

1.12 Summary

This chapter commenced by sketching the background to this study that highlighted that since the introduction of cryptocurrency in 2008, particularly Bitcoin, a number of altcoins (other digital currencies) have entered the cryptocurrency market, disrupting financial markets around the world. It also noted that some investors regard cryptocurrency as a new asset class with some hedging characteristics and a store of value. Furthermore, the disruption caused by cryptocurrency is affecting financial markets to the extent that some investors have seized the arbitrage opportunity caused by cryptocurrency price fluctuations, as it is highly volatile. While some studies have concluded that there is a significant connection between fiat currencies and cryptocurrencies, others point to insignificant correlation. This connection has been observed to be largely influenced by the regulatory environment in which cryptocurrency trades.

The chapter also presented the problem statement, the study's objectives and research hypotheses, its significance and its delimitations and limitations. It concluded by outlining the structure of the dissertation.

The following chapter presents a conceptual literature review, theoretical literature review, and empirical literature review.

CHAPTER 2: LITERATURE REVIEW

2.1 Introduction

This chapter critically reviews the existing literature on the connection between cryptocurrency and FX currencies around the world since the introduction of cryptocurrency in financial markets. It also critically evaluates the theoretical frameworks and concepts that serve as the foundation for current research on the relationship between digital and fiat currencies.

A theoretical literature review explores the underlying theories, models, and frameworks that support a particular research topic, while a standard literature review summarises empirical studies, methodology, or findings on the subject. This literature review also discusses the different research methodologies applied and identifies gaps in the literature.

2.2 Conceptual Literature Review

Conceptually, cryptocurrency is considered as a blockchain system that digitalises money and employs encryption for online transactions. This technology is characterised by decentralisation, accountability, and its unchanging nature (Fakunmoju et al., 2022). Cryptocurrencies have the potential to enhance financial inclusion, improve fund transparency, and ameliorate poverty and could thus promote development in poor nations (Nakamoto & Bitcoin, 2008). Digital currency can yield substantial profits by overcoming a lack of social confidence and increasing access to financial services (Ammous, 2018). Examples of cryptocurrencies include Monero, Libra, Bitcoin Cash, Ripple, Dash, Litecoin, Ethereum, Bitcoin, and others (Agu & Kindgom, 2020).

In general, the concept of a financial instrument under IAS 38 and IFRS 9 does not apply to cryptocurrencies (Pramana et al., 2023). However, either the cost model or the revaluation model can be utilised under the IAS 38 valuation approach in cases where cryptocurrency is exchanged on a trading platform. The fair value of the intangible asset must be accurately measured in order to use the IAS 38 revaluation model. In specific situations, it might be suitable for an entity to account for cryptocurrency assets like Bitcoin as inventory assets for

commodity brokers in accordance with IAS 2 'Inventories'. IAS 2 requires that inventory be measured using the lower of cost or net realisable value. Commodity brokers accordingly measure their inventories at fair value less costs of sale, with changes in fair value less costs of sale being recorded in loss or profit in the period of change. IAS 2 does not mandate physical inventories, but they must contain assets held for sale in the normal course of business (Pramana et al., 2023).

According to Holtmeier and Sandner (2019), cryptocurrencies offer a number of benefits. First, they include crucial elements that promote trust such as transparency and accountability. This enables free exchanges between parties with a sense of confidence. Second, governments are powerless to stop the decentralisation of cryptocurrencies. As a result, Bitcoin can be exchanged anywhere in the world. Third, removing middlemen/women increases the speed of money transfers. Fourth, financial inclusion of adults who have been shut out of the traditional financial system is improved through a digital financial system. Fifth, mining cryptocurrencies create job prospects.

However, cryptocurrencies have a number of drawbacks, particularly in emerging economies (Fakunmoju et al., 2022). They are vulnerable to cyber-attacks and because the government is not involved, can be utilised for money laundering. Furthermore, hackers take advantage of cryptocurrencies' various security flaws and they exhibit a significant degree of volatility, which causes investors to become fearful. Lastly, cryptocurrencies are not subject to government regulations (Fakunmoju et al., 2022).

2.3 Theoretical Literature Review

The study was premised on the Efficient Market Hypothesis (EMH), and institutional and legitimacy theories that are outlined below.

2.3.1 Efficient Market Hypothesis

Developed by Fama in 1965, the EMH can be used to conceptualise the capital market (Bodie et al., 2013; Fox & Sklar, 2009; Lo, 2007; Ţiţan, 2015). It holds that capital markets are effective and that the prices of traded assets already reflect all available knowledge. As a result, they are impartial since they reflect the shared expectations of all investors for the future. The long-term dependency of equity returns served as the foundation for the EMH's previous empirical test results. It demonstrates how historical data has been used to more accurately forecast outcomes (Abu & Ohiaeri, 2023; Lo, 2007). The EMH posits that arbitrage chances are swiftly taken advantage of and removed. Thus, if there are arbitrage opportunities between cryptocurrencies and conventional currencies, these are swiftly eliminated (Zhan et al., 2022). A market that processes information effectively is referred to as an efficient capital market. Transactional efficiency and information efficiency occur in a market where securities prices react quickly to any new information, at which point the current value of an asset will accurately reflect all information at hand. The prices of securities at any time in an informationally efficient market are based on a "correct" evaluation of all information available at the time. The following assumptions form the foundation for the EMH: (i) Numerous independent, profit-maximising competitors should exist to analyse and assess securities. (ii) New information is received on a random basis. (iii) Rival investors try to quickly adjust prices in line with fresh knowledge (Bodie et al., 2013; Fox & Sklar, 2009; Lo, 2007; Ţiţan, 2015).

In order to comprehend information dynamics and asset pricing in the financial and digital currency markets, it is useful to consider the implications of the EMH for this study on the connection between cryptocurrencies and exchange rates. The EMH is connected to this study in the following ways:

(i) *News and Events' Impact*: The EMH postulates that news and events are swiftly included in pricing. Analysing the relationship between exchange rate markets and cryptocurrencies may shed light on how effectively these markets handle information, as the theory proposes.

(ii) *Arbitrage possibilities*: According to the EMH, arbitrage possibilities are promptly taken advantage of and removed. If there are arbitrage opportunities between cryptocurrencies and fiat currencies, this investigation may demonstrate them as well as the speed at which they are taken advantage of.

(iii) *Fiat Market Anomalies and Cryptocurrency Pricing*: The EMH concedes that market efficiency may not always be ideal and that anomalies may arise. This study could reveal discrepancies in the way cryptocurrencies are priced with respect to currency rates.

(iv) *Information and Market Efficiency*: According to the EMH, financial markets process and reflect all available information efficiently. Within the framework of this research, it could become apparent how effectively cryptocurrency information and pertinent economic elements are factored into exchange prices. Significant changes in cryptocurrency prices may be swiftly reflected in exchange rates if markets are extremely efficient, which would provide little opportunity for steady profit margins.

(v) *Behavioural Biases and Market Inefficiencies*: Although the EMH presumes that market participants are rational and take into account all available information, behavioural biases can lead to departures from efficiency. Examining the association between digital currency and cryptocurrencies may reveal behavioural elements that impact the connection between cryptocurrencies and exchange rates. For example, enduring patterns or inefficiencies may indicate the existence of behavioural biases that produce recognisable patterns in the market.

2.3.2 Institutional Theory

This theory suggests that companies tend to adopt and conform to institutional norms and practices such as the International Financial Reporting Standard (IFRS) framework to gain legitimacy and social acceptance (Eltweri et al., 2022; Modell, 2022). Ontologically, this theory stems from the objectivist position that social entities like accounting professional bodies and the International Accounting Standards Board (IASB) shape the accounting profession to conform to norms and standards that are generally accepted (Bell et al., 2022). Therefore, according to institutional theory, investors and traders are likely to embrace cryptocurrency when they see others adopting digital currencies.

The current study on the connection between cryptocurrency prices and exchange rates could benefit from knowledge of the role that formal and informal institutions play in forming and

influencing market behaviour. Institutional theory as a framework could be linked to this study as follows:

(i) *Institutional influences on Market Participants*: According to institutional theory, market participants' behaviour can be influenced by normative, coercive, and mimetic institutional influences. For instance, changes to regulations may put market players under pressure to follow the new requirements. Examining the relationship between digital currency and fiat currency could shed light on how these factors affect choices about cryptocurrencies and exchange rates.

(ii) *Legitimacy and Cryptocurrency Markets*: According to institutional theory, organisational behaviour depends heavily on legitimacy. The findings may reveal how concerns about legitimacy affect traditional financial institutions' and the market's adoption of cryptocurrencies in the context of our investigation of the relationship between fiat money and cryptocurrencies. The degree to which cryptocurrencies are accepted as legitimate could also have an effect on how well they integrate into the financial system and how exchange rates behave.

(iii) *The Regulatory Environment and Adoption of Cryptocurrencies*: According to institutional theory, formal rules and regulations have a significant impact on how organisations behave. This study's examination of the relationship between digital and fiat currencies could assist in clarifying how South Africa's and Africa's legislative frameworks impact the uptake and integration of cryptocurrencies with fiat money.

(iv) *Informal and Cultural Institutions*: The theory proposes that in addition to legal restrictions, behaviour can also be shaped by cultural and informal institutions. Common standards and values are important. This study could demonstrate how cultural elements in South Africa and Africa affect how people view and use cryptocurrencies in regard to their association with fiat currencies.

2.3.3 Legitimacy Theory

Legitimacy theory is a theoretical framework that seeks to explain how organisations use accounting information to maintain their social legitimacy in the eyes of various stakeholders such as shareholders, customers, employees, regulators, and the general public (Herbert & Graham, 2022; Modell, 2022). It's proposition that an organisation's identity is not uniform but frequently contradictory and vague and is intended to provide evidence to support claims of legitimacy among both internal and external audiences, is of particular theoretical significance (Bell et al., 2022). Accordingly, investors as well as traders may deal in digital currency when they see others doing so in order to remain legitimate in the eyes of their customers.

2.4 Empirical Literature Review

Numerous studies have examined the relationship between fiat currencies and cryptocurrencies, producing a range of conclusions. Some have established a noteworthy correlation between these two types of currencies, emphasising their interdependence and possible causality relationship. These studies frequently examine variables such as macroeconomic data, legislative changes, and market sentiment in an effort to understand the intricate relationship between cryptocurrencies and conventional fiat currency. Conversely, other studies have proposed that there is no meaningful correlation and that the movement of cryptocurrencies is generally unrelated to traditional fiat currency systems. The research results exhibit a duality that highlights the complex interaction between cryptocurrencies and fiat currencies, warranting further examination in both the financial and academic domains. These studies are discussed below.

2.4.1 Positive and inverse connection between fiat and cryptocurrency

According to the theory of supply and demand, a currency's value will increase if there is a rise in demand for it (Obstfeld, 1995). When it comes to cryptocurrency trading, an increase in the number of traded cryptocurrencies indicates rising demand, which may then fuel increased demand for the local currency to support these transactions (Hayes, 2017). In comparison to other fiat currencies, the value of the local currency rises due to increased demand, which

causes the exchange rate to rise (Obstfeld, 1995). This is in line with recent research that examines how much cryptocurrency is traded and how this affects exchange prices. For instance, Lombardi et al. (2022) found that increased cryptocurrency trading volumes were positively correlated with rising exchange rates in a number of regions. Their findings imply that rising demand for cryptocurrencies and ensuing demand for local currencies are factors in the appreciation of exchange rates. In support of this association, Lin et al. (2021) show that higher cryptocurrency trade volumes are related to higher exchange rates.

Isaksson (2022) observes that, unlike the gold market, cryptocurrency has a positive connection with the fiat currency market. These results are similar to those of Mallick and Mallik (2021) study that used daily data from December 2019 to June 2021 to examine the connection among official Indian fiat currency (the YEN, EUR, GBP, as well as the USD) and cryptocurrency rates (BTC, ETH, BNB, and Litecoin). The results point to a significant link among Bitcoin, Ethereum, and Binance Coin, as well as between Binance Coin and Litecoin and Ethereum, Bitcoin, and Binance Coin. Conversely, the study observed that because there is an inverse connection between Litecoin and the USD, the former can be used to diversify and hedge risks. The study also found that Indian FX markets had very little influence on cryptocurrency markets (Isaksson, 2022).

Levulytė and Šapkauskienė (2021) examined three cryptocurrencies, namely, Bitcoin, Ethereum, and Ripple. The South African Rand, Argentine Peso, Mexican Peso, Russian Ruble, Chinese Yuan, Australian Dollar, Swiss Franc, Japanese Yen, Swedish Krona and United States Dollar were among the other significant currencies for which data was gathered about the Euro (Levulytė & Šapkauskienė, 2021). Lastly, the S&P500, FTSE, and commodity gold were selected as the three main stock market indices for analysis. Using statistical analytic techniques, including cluster analysis, linear regression, and Spearman correlation, the authors concluded that there is a positive connection between fiat currencies and cryptocurrency with a time lag of about four months between the movement of fiat currency which is followed by a move in the same direction by the cryptocurrency (Levulytė & Šapkauskienė, 2021). Mallick and Mallik's (2021) study also established a positive connection between the United States Dollar and cryptocurrency (BNB). (Mallick & Mallik, 2021) (Mallick & Mallik, 2021) (Mallick & Mallik, 2021) (Mallick & Mallik, 2021) (Mallick & Mallik, 2021)

Khaled (2020) compared the exchange rate returns of the eight different Arabian currencies with the top three digital currencies (Bitcoin, Ethereum, and Ripple). The sample covered the period 1 January 2017 to 1 January 2020 and data on daily closing prices (against the USD) were gathered from several sources. While the findings revealed no notable correlations between the fiat currencies in the Arabian region and the cryptocurrency exchange rate, a positive connection was found between the Iraqi dinar and XRP, the Moroccan Dirham (MAD) and ETH, and the Lebanese lira and BTC and XRP. The findings also revealed a sizable positive correlation between Bitcoin and Arabian currencies (Khaled, 2020).

Levulytė and Šapkauskienė (2021) research on how well cryptocurrencies function as an accounting unit, a wealth storage mechanism, and a medium of exchange found that Bitcoin and Ethereum serve as borderless means of exchange with less transaction costs (Levulytė & Šapkauskienė, 2021). Elsayed et al. (2022) examined causality between cryptocurrency and major foreign currencies. Nine significant FX currencies and three prominent cryptocurrencies—Bitcoin, Litecoin, and Ripple—were selected for analysis. Using the Diebold-Yilmaz method, the authors estimated the measure of currency markets' spillover from cryptocurrencies and applied a Bayesian graphical structural vector. The study revealed that Bitcoin and Yuan have a negative connection while other fiat currencies exhibit insignificant connection (Elsayed et al., 2022).

Mokni and Ajmi (2021) focused on different economic times like crises and upswings. They covered the period prior to and during the COVID-19 pandemic to gain an understanding of how cryptocurrency and FX currencies behave. The top-five digital currencies (the BTC, ETH, LTC, XRP and BCH) and the United States Dollar were analysed to establish their causal connections. The Granger causality text revealed that the quantiles pre and during the pandemic showed a significant causal association between the cryptocurrency and FX currencies, particularly during COVID-19. The authors thus concluded that there is a negative connection between the USD and cryptocurrencies during economic crises (Mokni & Ajmi, 2021).

Khaled (2020) observed that the Ripple and the Iraqi Dinar have a negative connection and added that investors can benefit from diversification and hedging in their portfolios. The author used various statistical techniques such as multiple regression analyses to examine the connection between the rate of exchange returns of the major three cryptocurrencies at the time and eight of the currencies in the Arab world (Khaled, 2020).

Research conducted in the Gulf region by Sami and Abdallah (2020) on the connection between the stock markets and cryptocurrency concluded that cryptocurrency has a negative connection with the markets; thus, crypto assets are a substitute for securities in the stock market. The study showed that for every 1% increase in the crypto markets, there is a 0.17% decline in the markets (Sami & Abdallah, 2020). A similar study in the MENA region (Sami and Abdallah (2021) indicated that for every 1% increase in the digital currency market, there is a 0.15% drop in stock markets. Similar to the current study, Fernandes, Kristjanpoller, et al. (2023) used two cryptocurrencies with the biggest market capitalisation and traded volume (Bitcoin and Ethereum) and three significant high-frequency fiat currencies: the EUR, YEN, and the British pound (GBP) to investigate the cross-correlation between cryptocurrencies and fiat currencies during the COVID-19 pandemic. The results point to positive correlation between fiat and digital currencies, suggesting that investing in major cryptocurrencies (BTC and ETH) and major fiat currencies at the same time can lower portfolio risk and boost investment returns (Fernandes, Kristjanpoller, et al., 2023).

Drożdż et al. (2023) used a time series of log returns (similar to our study) for 22 conventional financial instruments and 70 cryptocurrencies. The sample included contracts for difference representing the returns of 12 fiat currencies (the AUD, CAD, CHF, CNH, EUR, GBP, JPY, MXN, NOK, NZD, PLN, and ZAR); four commodities, West Texas Intermediate crude oil, high-grade copper, silver, and gold; four US stock market indices, Nasdaq 100, SP500, Down Jones Industrial Average, and Russell 2000; the primary German stock index DAX 40, and the Japanese Nikkei 225. The authors established substantial positive correlation between Bitcoin and Ethereum and the conventional financial markets throughout the COVID-19 pandemic and the 2022 bear market. In contrast, they reached the intriguing conclusion that pre the COVID-19 pandemic, cryptocurrencies had a negative connection to fiat currencies (Drożdż et al., 2023).

Dumitrescu et al. (2023) assessed whether Bitcoin returns have any impact on the evolution of fiat currencies for countries outside of Europe. Nine currencies were selected to weigh the possibility of heterogeneities in this relationship based on fluctuations in the national currencies. The findings demonstrated that, under normal market conditions, appreciation in the price of Bitcoin caused the fiat currencies in their sample to appreciate, but the relationship changed during the COVID-19 pandemic when the connection became negative. Furthermore,

the connection included heterogeneities dependent on changes in nominal exchange rates. This study's major finding was that changes in the value of Bitcoin could impact how monetary policy is implemented via the exchange rate channel. Using quantile regression analysis similar to that used to our study, Dumitrescu et al. (2023) found a negative association between Bitcoin returns and the development of the currencies in the sample starting at the 25th quantile under normal market conditions. As a result, an increase in the nominal exchange rate was linked to a positive return on Bitcoin. The authors note that cryptocurrency investors can gain from diversification by adding both types of assets to their portfolios, as can investors in various financial assets denominated in the currencies in their sample (Dumitrescu et al., 2023).

Kristjanpoller and Bouri (2019) employed several non-linear techniques to demonstrate the existence of major asymmetric traits related to the cryptocurrency and currency markets. Their conclusions support the literature that shows a positive connection between cryptocurrencies and fiat currencies. (BenSaïda, 2023a) and (Ji et al., 2018) found that digital currency is positively correlated to the Canadian Dollar (CAD), the EUR, the Japanese Yen (JPY), the GBP and the USD. Palazzi et al. (2021) concluded that the EUR and GBP have a direct, positive impact on cryptocurrency (Kristjanpoller & Bouri, 2019). In line with Zhu et al. (2017) results, the study highlights the strength of the long- and short-term interdependencies between cryptocurrency returns and the rates at which EU currencies are traded. The findings point to modest correlation between BTC and all the currencies (CNY, EUR, CHF and JPY), with a large and positive correlation between BTC and EUR as well as GBP (Palazzi et al., 2021).

Esparcia and Lopez (2023) analysis of the intraday portfolio performance considered the diversification advantages of cryptocurrency for forex investors. The study covered the period 1 January 2019 to 31 May 2021, which included part of the COVID-19 era. It investigated the benefits of diversification in portfolios of main fiat currencies quoted against the USD by including large-cap and highly liquid cryptocurrencies. The pandemic weakened the USD, with the Nominal Broad USD Index decreasing steadily from mid-March to December 2020, losing 12% of its value after reaching a record high of 126.14 on 23 March 2020. Under these circumstances, it was crucial for investors in the forex market to consider diversification, hedging, and a safe haven. The study employed a method that extended beyond the examination of dependent structures between cryptocurrencies and fiat currencies to explore the role of

digital currencies as diversifiers, hedges, or safe havens against USD depreciation. Esparcia and Lopez (2023) highlight that forex traders can use cryptocurrencies to diversify their portfolios as both fiat and digital currencies enjoy a negative connection.

Esparcia and Lopez (2023) used hourly data for the five cryptocurrencies with the highest market caps as at May 2021: Bitcoin, Ethereum, Litecoin, Ripple, and Bitcoin Cash. Bouri et al. (2020) and El Montasser et al. (2022) also used these cryptocurrencies in their recent studies. For fiat currencies, Esparcia and Lopez (2023) employed the GBP, Swiss Franc (CHF), Australian Dollar (AUD), CAD, EUR, and JPY, the six USD crosses for which they collected hourly data. Similar to Dumitrescu et al. (2023), they conclude that, given the comparatively stronger (and largely negative) average correlations between fiat currency and crypto markets during the pandemic compared to the pre-pandemic period, diversification through cryptocurrency investments was more likely to benefit forex investors during the turbulent period associated with the COVID-19 crisis (Esparcia & Lopez, 2023). Furthermore, in contrast to the negative connections, JPY was positively linked to cryptocurrencies (Esparcia & Lopez, 2023).

Kim (2023) explored liquidity and volatility across major fiat currencies and cryptocurrency markets on decentralised exchanges (DEXs). The study consists of three parts; however, for the purposes of the current study that focused on the connection between cryptocurrency and fiat currencies in Africa, we cover Kim (2023) investigation of recurring trends in the market for FX, focusing on the currency pairs JPY/USD and EUR/USD, and contrasting them with those in the cryptocurrency market. As at April 2022, the spot market for FX had a daily trading volume of almost $2.1 trillion, making it the largest financial market. Compared to the spot market for digital currencies within the same time period, this amount is around 50 times larger. The FX market trades through numerous markets throughout the world, as opposed to cryptocurrencies, which are continuously traded 24 hours per day on each exchange. On weekdays, 24-hour trading is possible thanks to the rotating trading hours of major markets including London, New York, and Tokyo. The frequent opening and closing of these markets leave recognisable marks in the volatility and liquidity patterns. The volatility of the markets for FX exhibits day-of-the-week and intraday patterns (see (Andersen et al., 2019), among others). For the two major fiat currency pairings with the biggest trading volume, EUR/USD

and JPY/USD, Kim (2023) examined periodicity in liquidity and volatility which provide weekday, intraday, and minute-by-minute patterns and contrasted them with market patterns for cryptocurrencies. The author concluded that fiat and digital currency markets are positively correlated (Kim, 2023).

Han et al. (1999) and Harvey and Huang (1991) found that there were less intense fluctuations on Mondays and more intense fluctuations on Thursdays and Fridays in the foreign currency market. The authors hypothesised that this may be due to big news breaking more frequently on Thursdays and Fridays. Further investigation revealed that, even after controlling for economic indicators announcements, both the Deutsche Mark and the JPY exhibited strong positive day-of-the-week trends. Using relative volatility measures, Kim (2023) found that this occurred on Mondays and Thursdays, but not Fridays. No discernible weekday influence was noted in the Bitcoin market (Han et al., 1999; Harvey & Huang, 1991).

Andersen and Bollerslev (1998) demonstrated the intraday pattern in the DM/USD market that was attributed to the combined impact of U-shaped operations in markets in various time zones. Yamada and Ito (2017) were among the first to investigate the effects of fixing rates on the FX markets, while Han et al. (1999) showed the effect of economic indicator announcements on FX intraday patterns. Surges in volatility and volume were observed around the release of economic indicators (13:30 or 15:00), and the setting of rates in Tokyo (00:55) and London (16:00), as well as Federal Open Market Committee (FOMC) announcements (19:00 on Wednesdays). Similar to the intraday pattern of fiat currency, (Yamada & Ito, 2017) assessment of the intraday price pattern of Bitcoin showed no connection between foreign currency and cryptocurrency. Kim (2023) also found no evidence that these frequent occurrences affect the intraday trend in the Bitcoin market. Yamada and Ito (2017) state that it is common knowledge that there are correlations between intraday returns, volume, volatility, and liquidity, and that both equity markets and currencies display intraday patterns. Nevertheless, there is no proof that the intraday price movement of cryptocurrencies and fiat currency are connected in any way (Yamada & Ito, 2017).

One of the few studies on the connection between cryptocurrency and fiat currencies in Africa is that by Abu and Ohiaeri (2023) which analysed how cryptocurrencies affect the value of

currency in Nigeria. The research covered the period 1 January 2019 to 31 December 2022 and the study drew on data on the adoption rate and volume of trade for cryptocurrency from investing.com. For the local fiat currency, the Naira, the authors selected the monetary policy rate and inflation rate that were sourced from the Central Bank of Nigeria. The study found that with proper regulation, cryptocurrency adoption can have positive impact on the value of the fiat currency.

Abu and Ohiaeri (2023) postulate that according to economic theories and empirical data, there is an affirmative connection between inflation and exchange rates. The positive coefficient estimate for IFR (3 = 0.433399, p = 0.0000) supports this hypothesis. The purchasing power parity (PPP) theory states that as inflation rises, a currency's value declines and the exchange rate falls. Imported items become comparatively more expensive as a result of rising inflation, which also diminishes demand for the local currency. In order to illustrate the relative buying power of currencies, the exchange rate is adjusted. This suggests that inflationary pressures may be a factor in the devaluation of the Naira (Abu & Ohiaeri, 2023).

Nam (2023) studied the effects of cryptocurrency on financial markets by sampling BTC, ETH, LTC, AUD, EUR, GBP, CAD, JPY, VND, GOLD, OIL and SP500 from investing.com between 1 January 2014 and 28 February 2021. Like other studies, the sample period covered different economic downswings and upswings. The findings suggest that cryptocurrencies affect the financial industry. In particular, it found that cryptocurrency (BTC, ETH, LTC) and currency pairs (AUD, EUR, GBP, CAD, JPY) had an inverse effect on one another as well as on cryptocurrencies (Nam, 2023).

Eisl et al. (2015) state that investors typically hold a portfolio of investments rather than a single investment that needs to be diversified. They note that the way in which Bitcoin performs in a portfolio is a topic of debate in the literature, largely due to questions regarding the nature of its function. While Kliber et al. (2019) and Zhang et al. (2018) demonstrate safe haven options, cryptocurrencies are inversely correlated with a fiat currency. A portfolio of assets as a whole could experience a range of effects with the addition of Bitcoin. Due to its high fluctuation as well as a poor relationship with other assets, Bitcoin is difficult to evaluate for portfolio inclusion (Klein et al. (2018). Since digital currency cannot be hedged against any

equity investments, it has no use in a basket of investments other than to diversify risky assets. However, given the multiple reasons why Bitcoin might be included, this assumption could be overblown. There is evidence that digital currency, and Bitcoin in particular, has a positive effect on the proportion of risk to return of a portfolio. According to a study by (Eisl et al., 2015), Bitcoin can have a favourable impact on the risk-return ratios of an ideal portfolio. This shows that traders as well as investors might benefit from Bitcoin's features of being both high risk and offering significant reward (Eisl et al., 2015).

Abid et al. (2023) compared fiat currencies, JPY, EUR and GBP in relation to Bitcoin with other financial markets including stock, fixed income and commodity indices. Their research covered the period 2010 to 2022 which included economic downswings, the COVID-19 pandemic and the war in Ukraine. Due to fiat and cryptocurrency's limited sensitivity to the negative risks associated with fixed-income and gold markets, the authors found similarities in the market behaviours of fiat currency and Bitcoin during bear markets. Notably, they identified a negative relationship between JPY and Bitcoin. The study also concluded that there is a clear difference between Bitcoin and fiat currencies' interactions with the stock and crude oil markets based on the temporal dynamic upside and downside risk spillovers. Stock and crude oil market investors should thus consider diversifying their portfolios with fiat currencies, but also use short Bitcoin to protect themselves from extreme downside events like the COVID-19 pandemic and the Russia-Ukraine conflict (Abid et al., 2023). This affirms the inverse connection between cryptocurrency and fiat currencies (Abid et al., 2023).

Rehman et al. (2023) investigated the risk escalation and excessive reliance between the fiat currencies of the G7 and the BRICS economies. They found that all the currencies and Bitcoin were correlated over time. Furthermore, Bitcoin exerted considerable influence on most other currencies, with the South African Rand and the Brazilian Real carrying the biggest downside and upside risks prior to and following the COVID-19 pandemic, respectively. The Japanese Yen had the largest downside risk spillovers in relation to Bitcoin. Lastly, the authors observed asymmetric spillovers between extreme upward and negative movements and concluded that, during the course of the sampling period, there was positive correlation between Bitcoin and all other FX markets. However, the Indian Rupee (INR) was inversely connected with digital currency (Rehman et al., 2023).

Li et al. (2023) note that the volatility of the cryptocurrency market and its interactions with other financial markets point to unequal distribution of volatility spillovers when major economic events like COVID-19 occur. Instead, it appears that during such times, the Bitcoin market serves as a form of risk cover or shelter for investors (Li et al. (2023). This is in line with Rehman et al. (2023) findings. Li et al. (2023) sampled BTC, the Chinese Shanghai Index (CSI 300), Hang Seng Index (HK), RMB exchange rate (USD/CNY), CSI Universal Bond (RATE), Shanghai copper futures (CU2104), Shanghai gold futures (AU), and the Energy and Real Estate Index (RE) covering different economic conditions from 2013 to 2021. They conclude that Bitcoin enjoys an inverse relationship with the RMB exchange rate (Li et al., 2023).

Charfeddine et al. (2020) highlight that there are two threads to the dynamic interactions between Bitcoin and conventional assets: yield (or price) and risk. Analysis from the viewpoint of yield (or price) primarily focuses on the portfolio (Conlon et al., 2020; Jana & Das, 2020) and dynamic correlation coefficient (Charfeddine et al., 2020). There is no consensus on the asset qualities of Bitcoin, although the volatility spillover effect is the major focus of the investigation from a risk standpoint (Charfeddine et al., 2020). Bouri, Vo and Saeed (2021) employed the BTGARCH-M model to examine the ripple effects of Bitcoin's volatility on traditional global assets in bull and bear markets. The TVP-VAR approach was used by Dahir et al. (2020) and Mensi, Al-Yahyaee, et al. (2019) to determine the impact of Bitcoin's dynamic volatility on the stock markets of the BRICS countries. Mensi, Al-Yahyaee, et al. (2019) selected the DY index and concluded that there were notable asymmetric volatility spillover effects between Bitcoin and the US precious metals markets, with Bitcoin serving as the net recipient. The authors unanimously agree that digital currency is negatively connected to fiat currency especially during a bear market (Charfeddine et al., 2020; Dahir et al., 2020; Kristjanpoller & Bouri, 2019; Mensi, Rehman, et al., 2019).

Numerous studies focus on the volatility spillovers between Bitcoin and market indicators such as market size, trading volume, investor sentiment, and global financial uncertainty in an effort to further investigate the source and transmission mechanism of risk associated with the cryptocurrency (Yi et al., 2018). Yi et al. (2018) analysed the dynamics and volatility spillovers

between the Bitcoin market and the Chinese financial markets. In contrast to previous studies, which focused solely on frequency spillovers between Bitcoin and a particular asset, they broadened their focus to China's key financial markets and employed the BK index to investigate frequency spillovers with an economic justification. During the period 2016 to 2018 digital currencies such as Bitcoin (BTC), Ripple (XRP), Litecoin (LTC), Peercoin (PPC), Namecoin (NMC), Feathercoin (FTC), Novacoin (NVC) and Terracoin (TRC) showed a positive correlation with fiat currency markets (Yi et al., 2018).

Al-Shboul et al. (2023) investigated the dynamic spillover between fiat currencies and cryptocurrencies before and after the COVID-19 crisis and assessed how economic policy uncertainty (EPU) influenced this spillover. The traditional currencies in the sample included the CHF, INR, EUR, GBP, Chinese Yuan, Korean Won, CAD, and JPY Yen. Bitcoin, Ethereum, Litecoin and Ripple comprised the cryptocurrency group. The complete dataset spanned 2 January 2017 to 6 October 2022. The selection of the sample period considered two main issues: (i) the significant decline in the price of digital currencies shortly after the beginning of 2018 and indices for currency markets generally as a result of the scepticism caused by the ongoing COVID-19 crisis; and (ii) the significant decline in the value of digital currencies after the beginning of 2018. The virtual and traditional currencies selected were determined by their value in US dollars. Refinitiv's DataStream database was employed to gather traditional currencies and Coinmarketcap.com for cryptocurrency. The study found evidence of currency spillover effects, which increased significantly during the pandemic. Furthermore, the findings imply that during the COVID-19 period in particular, all cryptocurrencies continued to serve as a safe haven against market volatility. In addition, fiat and cryptocurrency exhibit positive connectivity, particularly during the COVID-19 pandemic, while the Yen had very high significant positive correlation with digital currencies (Al-Shboul et al., 2023).

Economic policy uncertainty has increased significantly since the 2008 global economic crisis, suggesting a growing impact on financial markets, particularly those for FX (Urom et al., 2020). Lucey et al. (2022) note that new economic uncertainty indices utilising data from news stories for significant economies have been extensively used in the recent literature. For instance, Corbet et al. (2020) found that currency exchange rates are adversely impacted by EPU. Other studies concluded that modifications to EPU also impact cryptocurrencies (Cheng

& Yen, 2020; Karim et al., 2022; Paule-Vianez et al., 2020). Urom et al. (2020) found a strong positive correlation between Bitcoin and fiat currency markets. Furthermore, under normal economic conditions Bitcoin's connection with the fiat currency market becomes significantly weak while remaining positive (Urom et al., 2020).

Nekhili et al. (2023) investigated the liquidity spillover between fiat currencies and cryptocurrency markets. According to them, this is one of the first studies to cover this topic from a liquidity perspective. The study employed intraday hourly spot prices (open, close, high, and low) for seven major currencies, including the SEK, AUD, CAD, JPY, GBP, CHF, and EUR, as well as five major digital currencies, namely, ETH, LTC, BCH, XRP, and BTC. The currencies were divided into six groups that make up the dollar index (DXY). Since each of these currencies has a long history, it is impossible to overestimate their significance as important reserve currencies. In addition, their respective economies account for almost 60% of global GDP. The authors highlight a strong positive association between Bitcoin, Litecoin, Ripple, and the major FX markets of the GBP, JPY, and EUR (Nekhili et al., 2023).

Hsu (2022) validated the fluctuating volatility of the correlation between cryptocurrency and currency markets in various economic time zones during several risk events including the trade war between the US and China, the COVID-19 pandemic, and the conflict between Russia and Ukraine. Using the Diagonal BEKK model, the study found that there was a notable shift in the co-volatility spillover effects between the returns of cryptocurrencies (BTC and ETH) and other currencies (GBP, CNY, EUR, JPY and RUB), apart from Tether and the US dollar index. The biggest impacts and swings were caused by the co-volatility spillover effects between cryptocurrencies and the EUR. Furthermore, there was a higher co-volatility spillover effect between large-cap cryptocurrencies like Ethereum and Bitcoin and other currencies. Interestingly, the results revealed a positive connection between ETH and fiat currencies apart from DXY and CNY where the connection was negative. Substantial negative correlation was established between Bitcoin and both GBP and CNY (Hsu, 2022).

Investigating the interdependence of liquidity between traditional and digital currencies can assist market participants and policymakers to understand the liquidity of such markets at the macro and micro levels and identify liquidity problems. According to BenSaïda (2023b),

liquidity affects traders' positions and portfolio management in addition to derivative pricing. The identity of net transmitters and recipients of liquidity spillover shocks, as well as how spillovers change over time, are revealed in intriguing ways. Because both the forex and virtual currency markets are open 24 hours a day, seven days a week, proof of liquidity spillover is crucial. Numerous studies emphasise cryptocurrency's steep price rise and connection to fiat money.

Corelli (2018) examined the causal connections between 11 traditional currencies as well as six virtual currencies. Fiat and digital currencies are inversely linked to each other (BenSaïda, 2023a). Corelli (2018) analysed the link between the most popular cryptocurrencies and a variety of fiat currencies. Because of their close ties to the Blockchain system, which is where they originated, cryptocurrencies are currently very popular in the finance industry and are typically seen as a component of the global financial revolution that is currently underway. This novel study analysed this developing relationship by carefully examining the data, and their characteristics and connections. The study showed that Bitcoin has a positive relationship with the Thai Baht and an inverse connection with the Taiwan Dollar; and ETH exhibits an affirmative link with the Euro Indian Rupee and Chinese Yuan, but not the Swiss Franc, the Thai Baht and the Taiwan Dollar, where the link is negative. The Thai Baht and Chinese Yuan are negatively connected to XRP, while the Taiwan Dollar has a positive connection with XRP. The Taiwan Dollar, Indian Rupee, Malaysian Ringgit, Japanese Yen, and Euro are all negatively associated with Litecoin, Monero and Dash. Lastly, the results show a positive link between the Thai Baht, Chinese Yuan, Thai Baht, Taiwan Dollar, and Chinese Yuan and Litecoin, Monero and Dash (Corelli, 2018).

Baumöhl (2019) used the quantile cross-spectral technique to explain how major FX currencies and cryptocurrencies are related. Six foreign currencies and six cryptocurrencies were included in the sample, which spanned 1 September 2015 to 29 December 2017. The quantile cross-spectral technique yields superior information on the dependence structure across various quantiles and frequencies when compared to standard correlations and detrended moving-average cross-correlation analysis (DMCA) results. The finding that intra-group dependencies are positive and inter-group dependencies are negative in the lower extreme quantiles is most intriguing. From both the short- and long-term viewpoints, this outcome is valid. This suggests

that investors would be well-advised to diversify their holdings between these two currency groups. The analysis showed that XEM was, on average, unrelated to any other currency in the dataset, which is also intriguing. However, the lower quantiles were found to be positively correlated with LTC and negatively correlated with two foreign currencies (JPY and CHF), with XEM exhibiting positive correlation with EUR, GBP, and CAD at higher quantiles. Furthermore, the correlation between CAD and ETH, XRP, and XLM was negative (Baumöhl, 2019).

Palazzi et al. (2021) aimed to determine whether there is a nonlinear relationship between Bitcoin and the following six currencies: US dollar-denominated Yen, Ruble, Renminbi, Euro, Pound Sterling, and Swiss Franc. The study used a multivariate filtering strategy based on BEKK-GARCH residuals and the suggested nonparametric causality test to regulate the conditional heteroskedasticity on daily log-returns from July 2010 to April 2020. The Bitcoin dataset was divided into two samples: one prior to a structural break and one subsequent to it. The resulted showed that the Euro had a direct impact on Bitcoin; however, Renminbi only influenced Bitcoin in the post-break sample. The results offer insight into the dynamics of nonlinear relationships between currencies and whether Bitcoin's behaviour can be predicted using fiat currencies. While there was modest correlation between BTC and all the currencies, there was large, positive correlation between the EUR and GBP (Palazzi et al., 2021).

According to Chemkha et al. (2021), there is large positive dependence between Bitcoin, Litecoin, and Ripple and the major foreign currency markets of the EUR, JPY, and GBP. Raza et al. (2022) concluded that there was a nonlinear relationship between cryptocurrencies and FX markets in a variety of exchange markets that fluctuated over quantiles of cryptocurrencies and foreign currency pairs. As confirmed by Nikolova (2023), an asset is deemed a diversifier by Baumöhl (2019) if it has an average weak positive connection with another asset. In contrast, an asset that is, on average, uncorrelated (negatively correlated) with another asset is a weak (strong) hedge. (Baumöhl, 2019)) showed that at a lower quantile, XEM was negatively associated with two forex currencies (JPY, CHF) and positively associated with LTC. At the higher quantiles, its extreme positive returns were positively connected to extreme positive returns on EUR, GBP, CAD, and XLM and negatively connected with BTC (Baumöhl, 2019).

2.4.2 Negligible Relationship Between Cryptocurrency and Fiat Money

Khaled (2020) researched the connection between FX currencies and cryptocurrencies in the MENA region. The sample included the top three cryptocurrencies (BTC, ETH and XRP) and the Saudi Arabian Riyal, Tunisian Dinar, Qatari Riyal, Omani Riyal, MAD, Lebanese Lira and Iraqi Dinar as well as the Egyptian Pound which are the eight fiat currencies of the Arab world, all against the US Dollar. Data for the period 1 January 2017 to 1 January 2020 were obtained from various sources using the daily exchange rate closing price versus US dollars. Using analysis of multiple regression, unit root tests, and correlations, the author established that there was no significant connection between the FX currencies for the MENA region and cryptocurrencies (Khaled (2020).

Mallick and Mallik (2021) employed the link between FX and cryptocurrencies used in India to gain an in-depth understanding of their behaviour. Daily data from December 2019 to June 2021 was used to sample exchange rates between official Indian currencies (USD, GBP, EUR, YEN) and cryptocurrency (Bitcoin, Ethereum, Binance Coin, Litecoin). The data was analysed using correlation, Durbin-Watson (DW), and multiple regression analysis. The study demonstrated that Indian markets for FX have limited influence on digital currency markets, which may be related to the government's not recognising cryptocurrency, influencing public perception and leading to poor uptake (Mallick & Mallik, 2021).

Ehlers and Gauer (2019) found no significant connection between digital currencies and European fiat currencies. The authors aimed to understand how cryptocurrencies behave when compared with each other and when compared with FX currencies. They sampled BTC, ETH, XRP, Litecoin, and Dash and fiat currencies EUR, GBP, CHF, CAD, and JPY, all measured against the US Dollar by analysing the daily closing prices for each variable. Fundamental statistical concepts, including correlation and return autocorrelation were examined. The next step was a variance ratio test with heteroscedasticity adjustment and a Kolmogorov-Smirnov test. Lastly, they provided solutions to more than 4 800 optimisation issues to examine how different crypto and fiat currencies affect portfolio diversity (Ehlers & Gauer, 2019).

Recent events in global financial markets showed that cryptocurrencies grew quickly as a result of blockchain technology's rising popularity and changing role in the digital finance sector (Donmez et al., 2021). Donmez et al. (2021) observe that the emergence of cryptocurrencies

has caused economists to re-evaluate conventional wisdom in the financial sector. To learn more about the precise connections and contrasts between the most important cryptocurrencies and fiat currencies, researchers are particularly interested in the interplay between two different forms of financial marketplaces. Donmez et al. (2021) found no significant connection between cryptocurrency and European currencies. This study used cross-correlation, hierarchical tree, and minimal spanning tree approaches to analyse 50 various conventional currencies as well as Bitcoin, the most well-known cryptocurrency on the market (Donmez et al., 2021).

Bhullar and Bhatnagar (2020) examination of the connection between stock markets in China (the SSIC stock index) and Bitcoin established that there is no causal connection between BTC and the movements of stock markets. They observed that this infers that investors can invest in both Chinese stocks and cryptocurrency in order to diversify. Dumitrescu (2017) reviewed research conducted on China and other countries. Bitcoin is not permitted in China's financial system although citizens are able to engage in Bitcoin services like mining and buying Bitcoin from trading platforms around the world. China and Nigeria are among the countries that are unfriendly when it comes to Bitcoin services. Similarly, Asena DENİZ and Teker (2020) research found that cryptocurrency price movements do not impact the fiat currency rates movement. These findings are contrary to those of Mokni and Ajmi (2021) who concluded that there is a negative connection between the United States dollar and cryptocurrencies (Asena DENİZ & Teker, 2020).

Gil-Alana et al. (2020) used cryptocompare.com data to study cryptocurrencies and indices (Total Return by S&P GSCI Commodity, S&P 500 Composite, VIX, and S&P Bond Index, US Nominal Dollar Broad Index, and S&P GSCI Gold Total Return) to establish if there is a connection between crypto and any index. They sampled the top six cryptocurrencies valued at more than $1B representing 80.22% of total market capitalisation as at 5 October 2018. The analysis of the data for the period 7 May 2015 to 5 October 2018 concluded that cryptocurrency has no bearing on the price movements for any of the indices. The top three cryptocurrencies with more than 66% market capitalisation of the crypto market from 1 March 2018 to 12 May 2023 were used to investigate the connection between crypto and fiat currencies (Gil-Alana et al., 2020).

Isaksson (2022) asserted that the high volatility of cryptocurrency does not deter investors from investing in it. While there has been robust debate among investors on the benefits of

cryptocurrency (Isaksson, 2022), it was established that the markets have no connection with cryptocurrency movements. The research employed Nasdaq 100 data and cryptocurrency market movements from 1 July 2018 to 15 May 2022 (Isaksson, 2022).

Ji et al. (2018) employed the directed acyclic graph, a data-driven methodology, to identify the lagged and contemporaneous relationships between Bitcoin and other asset classes. The authors explain that without depending on presumptions, the methodology enables determination of causal networks based on measurements of observed correlations and partial correlations (Ji et al., 2018). The contemporaneous analysis' findings show that no single asset (including the USD) has a significant impact on the Bitcoin market, and that the cryptocurrency is isolated from all other markets (Ji et al., 2018).

In support of Donmez et al. (2021), Ehlers and Gauer (2019), Gil-Alana et al. (2020) and Ji et al. (2018) but contrary to Bakhtiar et al. (2023), Kohli (2021) and Cermak (2017) indicate that there is no link between fiat currency and cryptocurrency. Cermak (2017) clarifies that digital currency like bitcoin does not meet the requirements to be classified as a currency because it is not a store of value, a unit of account, or a means of exchange, but a digital good with limited supply.

2.4.3 Critical Analysis of Conflicting Findings and the Limitations of Existing Studies

Due to its exceptional volatility and quick development, the cryptocurrency market has drawn the attention of academics, investors, regulators, and researchers alike (Conlon et al., 2024; Hansen et al., 2024). Berdiev et al. (2024) denote that despite the growing attention, there are still many contradicting research results and interpretations in the field, which contributes to the complicated and frequently contradictory understanding of cryptocurrency and its correlation with fiat currencies. This section of chapter aims to analyse these contradictory findings and provide light on the numerous reasons that contribute to the discrepancies observed in different studies. As observed by Colombo and Yarovaya (2024) the intrinsic volatility of cryptocurrencies, which has the power to significantly change market conditions and study outcomes, is a major cause of divergence. Accurate and trustworthy data are also difficult to extract because of data restrictions, such as the limited historical records and

inconsistent quality between exchanges (Fieberg et al., 2024). Asif and Unar (2024) add that these divergent study conclusions are exacerbated by research methodological variations since researchers use a variety of models and analytical procedures, each with its own set of assumptions and restrictions. These studies also have different goals; some concentrate on investment possibilities such as Kiruba DR et al. (2024) and Setyawan et al. (2024), some focus on technological innovation (Jegerson et al., 2024) and (Kayani & Hasan, 2024) (Jegerson et al., 2024; Kayani & Hasan, 2024), while Uzougbo et al. (2024a) and Uzougbo et al. (2024b) in two separate studies focused on the effects of regulations.

Another degree of complexity is introduced by the constantly changing legal and regulatory environment, since these shifts can have a significant and immediate impact on how the market behaves (Uzougbo et al., 2024a). Technological developments as witnessed by Boczko (2024) and Ofori et al. (2024) are also very important since innovation is happening so quickly that it is always changing the dynamics of the market. It is difficult to obtain reliable conclusions because behavioural factors bring additional variability, such as market manipulation and investor psychology (Abdeldayem & Aldulaimi, 2024; Alzyoud et al., 2024). Finally, the complex interactions between cryptocurrencies and fiat currencies further complicate matters because these interactions are frequently erratic and impacted by a wide range of outside variables highlighted above (Zhou, 2024).

2.4.3.1 Market Volatility

Ahmed et al. (2024) and Chen et al. (2024) observe that extreme volatility is a well-known feature of cryptocurrencies that distinguishes them from more conventional financial instruments. There are multiple reasons for this volatility, first is speculative nature (Ahmed et al., 2024). The authors continue to note that speculative trading, in which investors purchase and sell assets based on transient price fluctuations rather than inherent worth, is a common driving force behind cryptocurrencies. Rapid price swings brought on by this speculative conduct can make it challenging for studies to identify long-term patterns (Dudek et al., 2024). Second is market sentiment, the state of the market has a significant impact on the cryptocurrency market (Doroslovački et al., 2024; Osman et al., 2024). Unpredictable and abrupt price changes can result from investor behaviour being immediately influenced by news

events, social media trends, and public opinions (Chowdhury et al., 2024; Mou et al., 2024; Roumeliotis et al., 2024). As a result, research done throughout several sentiment cycles may yield contradicting findings. Third is liquidity issues: Cryptocurrency markets are susceptible to liquidity problems, in contrast to traditional financial markets, which usually have significant levels of liquidity (Deng & Zhou, 2024; Yao et al., 2024). Price fluctuations may be made worse by low liquidity, particularly when there is a lot of trading activity or market stress (Hansen et al., 2024; P. Zhang et al., 2024). Because the effect of liquidity on price behaviour might change based on the particular market conditions at the time of the study, this can lead to conflicting conclusions across studies (Ahmed, 2024; Tripathi & Sharma, 2024).

2.4.3.2 Research Methodological Differences

The methodologies used in cryptocurrency research can have a big impact on the findings because different strategies can lead to diverse interpretations of the same data. Such as quantitative versus qualitative approaches. In certain research, price data, trade volumes, and other metrics are analysed using statistical models in a quantitative manner such as (Das, 2024). Others such as Campino and Yang (2024) investigate market sentiment, the effects of regulations, or technical advancements using qualitative methodologies. Different viewpoints and results can result from different approach choices as seen with (Das, 2024) and Campino and Yang (2024). Another is the time frame selection; the analysis's chosen time frame might significantly affect the findings of the investigation.

2.4.3.3 Diverse Objectives and Perspectives

The goals and viewpoints of researchers can influence the direction and results of studies on cryptocurrencies. Some researchers are investment focus such that research on cryptocurrencies as investment assets, including portfolio diversification, risk management, and return potential, may be the subject of some research (Abdeldayem & Aldulaimi, 2024; Alzyoud et al., 2024). Metrics including volatility, correlation with other assets, and Sharpe ratios may be given priority in these studies as witnessed in Pandurugan and Al Shammakhi (2024), which could produce different results than studies that focus on other areas. Some research such as Boczko (2024) and Ofori et al. (2024) focuse on technology. This includes the

security characteristics, consensus processes, or blockchain technology of cryptocurrencies. More so than their financial properties, these researches like Al-Omoush et al. (2024) and Berdiev et al. (2024), Cheah et al. (2024), Pandurugan and Al Shammakhi (2024) and (Sakariyahu et al., 2024) might shed light on the technological innovation and possible applications of cryptocurrencies. While Animashaun (2024), Asif and Unar (2024) and Wronka (2024) focus on regulatory and policy analysis. Research may also concentrate on the cryptocurrency-related regulatory and policy landscape. These studies could look at how regulations affect financial stability, investor protection, or market behaviour. Depending on the regulatory environment and the particular problems being studied, the results of these kinds of studies may vary.

2.4.3.4 Regulatory and Legal Environment

The highly changeable regulatory and legal landscape surrounding cryptocurrency can have a substantial impact on research outcomes (Malala & Adeyemo, 2024). Jurisdictional differences are a case in point. Although cryptocurrencies are used worldwide as Rehman et al. (2023) observed, different nations have quite different regulatory frameworks. While some nations have welcomed cryptocurrencies, others have enacted stringent laws or outright banned them (Apatu & Goudar, 2024; Yuliana & Iswardhana, 2024). The outcomes of studies carried out in disparate regulatory settings could be contradicted by these variations in legal frameworks. Regulatory Shifts is another regulatory factor. Animashaun (2024) posits that the cryptocurrency market is prone to regular regulatory shifts that can have a significant and rapid impact on market dynamics. Market mood and price adjustments can happen quickly when new rules, enforcement actions, or tax treatment changes are announced (Asif & Unar, 2024; Chen et al., 2024; Conlon et al., 2024; Hansen et al., 2024). Research carried out prior to and following these modifications may produce disparate findings. The legal uncertainty is another factor where there may be room for interpretation and ambiguity over the legal standing of cryptocurrencies and associated activities (such initial coin offerings and crypto lending) (Uzougbo et al., 2024a). Sakariyahu et al. (2024) acknowledge that the unpredictability of the market can pose hazards to investors and other participants, impacting their actions and the general dynamics of the market. Research that ignores this legal ambiguity could overlook important market-influencing aspects.

2.4.3.5 Technological Developments

The swift advancement of technology in the bitcoin realm may result in varying study findings. The cryptocurrency market is always changing, and new blockchain platforms and cryptocurrencies are appearing on a regular basis (Ofori et al., 2024). The introduction of novel features, consensus processes, and use cases by these new players may have an impact on investor preferences and market dynamics the author added. As a result, studies that concentrate on various time periods could draw different conclusions about the industry. As this blockchain technology is new, the utility and allure of cryptocurrencies can be affected by technological developments such as enhancements to blockchain security, scalability solutions like layer-2 protocols, or the adoption of proof-of-stake consensus processes (Kayani & Hasan, 2024). Syaeh and Fahriany (2024) remark that the market behaviour may be impacted by the growing integration of cryptocurrencies with conventional financial systems, such as through the creation of crypto derivatives, custodial services, or crypto ETFs. These modifications may result in different study outcomes by altering the characteristics of market participants and the forces influencing price movements (Boczko, 2024).

2.4.3.6 Behavioural Factors

Alzyoud et al. (2024) exclaim that the digital currency market is significantly influenced by behavioural characteristics, which also have an impact on the results of other studies. A wide spectrum of players, including individual investors, institutional investors, and tech enthusiasts, are drawn to the cryptocurrency market, Abdeldayem and Aldulaimi (2024) added. The author continues to highlight that psychological elements including fear, greed, and herd mentality can have an impact on these participants' actions. Diverse market sectors may be the subject of studies that provide disparate behavioural patterns and results. Hype and speculation are another behavioural factor (Pandurugan & Al Shammakhi, 2024; Sakariyahu et al., 2024). New projects, tokens, or technological advancements frequently cause a lot of enthusiasm and media attention, and this drives the market. Price bubbles and their following crashes may come from this, causing unstable market conditions that may affect the findings of studies (Osman et al., 2024; J. Zhang, H. Wang, et al., 2024). Due to its relative lack of regulation noted by Campino

and Yang (2024), other authors add that the cryptocurrency market is vulnerable to strategies like wash trading and pump-and-dump schemes, i.e. market manipulation (J. Zhang, H. Wang, et al., 2024). These actions have the potential to skew market data and affect investor behaviour, producing conclusions that could not fairly represent the underlying principles of the market (Osman et al., 2024; J. Zhang, H. Wang, et al., 2024).

2.4.3.7 Complex Interrelationships

Research findings may be complicated by the intricate links that exist between cryptocurrencies and other financial assets or economic indices (Zhou, 2024). The correlations between cryptocurrencies and conventional financial assets such as stocks, fiat currencies, bonds, or commodities might vary. Macroeconomic variables, investor mood, and market conditions can all affect these connections over time. Diverse assets or time periods may yield varying degrees of correlation in studies, which could lead to contradictory findings (Ibrahim et al., 2024; Toudas et al., 2024). As observed by some authors such as (Gaies et al., 2024; Kumah, 2024; Wahyuni et al., 2024) both traditional financial markets and cryptocurrencies can be impacted by macroeconomic variables like interest rates, inflation, or geopolitical events. These variables can have different effects based on investor opinions and the state of the economy, the authors remark (Asif & Unar, 2024; Ullah et al., 2024). Research that ignores these more general economic circumstances run the risk of missing significant factors influencing market behaviour, these are sentiments shared by Asif and Unar (2024) and Ullah et al. (2024). Complex dynamics that are difficult to describe and forecast might result from the interaction of regulatory changes, market behaviour, and technical advancements (Malala & Adeyemo, 2024; Wronka, 2024). For instance, the implementation of new laws may encourage technical advancements meant to ensure compliance, which may then have an impact on consumer behaviour (Animashaun, 2024). Accordingly, the research that concentrates on a single factor may miss these complex relationships.

2.4.3.8 Summary

In a nutshell, the contradictory results of bitcoin research highlight how complex and dynamic this world of digital assets is. Ahmed et al. (2024); (Asif & Unar, 2024; Chen et al., 2024;

Ibrahim et al., 2024) demonstrate in their research extreme volatility of cryptocurrencies, together with data restrictions and a variety of methodology used, frequently results in inconsistent results that call into question the dependability and consistency of study findings. The diverse goals and viewpoints of scholars, encompassing everything from technological discovery such as Muqeet et al. (2024) and Zaidi et al. (2024) to investment analysis in studies like Porfirenko et al. (2024) and Su (2024), add to the fractured comprehension of the market. Diverse jurisdictions have different laws and regulations, and the regulatory landscape is constantly changing, which adds another level of complexity and affects research findings and market dynamics (Asif & Unar, 2024; Malala & Adeyemo, 2024). The industry is always changing due to technological improvements as noted by Boczko (2024) and confirmed by (Ofori et al., 2024) who go further to indicate that technological advancement in crypto also introduce new aspects that may not have been taken into account in previous studies.

The unpredictability that is introduced by behavioural elements, such as market manipulation and speculative conduct, makes it more difficult to analyse market patterns (Pandurugan & Al Shammakhi, 2024; Radu & Deak, 2024). Furthermore, there is a dynamic interaction between cryptocurrencies and conventional financial assets substantiated by Faisal and Donduran (2024) that is subject to change depending on the state of the economy due to the intricate relationships between them. Together, these elements draw attention to the difficulties in generating reliable and consistent results in bitcoin research (Cheah et al., 2024; Fang et al., 2024). Recent studies Alzyoud et al. (2024), Chen et al. (2024), Pandurugan and Al Shammakhi (2024) and J. Zhang, H. Wang, et al. (2024) suggest that future research must use more complex models and take these intricacies into consideration in order to produce more insightful results, especially as the market develops and more complete data becomes accessible. However, the current corpus of work offers insightful—if occasionally contradictory—viewpoints that advance our understanding of this emerging discipline (Hoechenberger et al., 2024; Yashwini et al.).

2.4.4 Gaps in the literature

The empirical literature review shows that studies in developed economies in Europe, Asia and the US point to the existence of a relationship between cryptocurrency and fiat currencies.

However, there are mixed findings, with some researchers reporting a positive relationship and others a negative one depending on the economic circumstances during the period under study as well as the region.

There is a paucity of research on this issue in developing countries, particularly on the African continent. The literature review showed that the few studies conducted focused on Nigeria and South Africa. Accordingly, the African continent is uncharted territory when it comes to this type of research.

Furthermore, previous research in this field has mainly focused on the connections between one digital currency (BTC) and the main fiat currencies (CAD, EUR, JPY, GBP and American Dollar), with little known of the relationship with other digital currencies as well as other fiat currencies (BenSaïda, 2023a; Dumitrescu et al., 2023; Rehman et al., 2023). Other studies, such as those by Mensi, Al-Yahyaee, et al. (2019) and Wei et al. (2020) focused on Bitcoin and Ethereum and only explored connectivity among cryptocurrencies. The current study included other cryptocurrencies such as BNB and compared it with other fiat currencies in Africa.

A further body of research assessed the relationship between conventional currencies and other financial assets like stocks, bonds, commodities, and oil prices (Fernandes, Silva, et al., 2023; Kumari et al., 2023; Lopez-Lira & Tang, 2023), while this study examined digital currency and its connection with foreign currencies, particularly in Africa.

Lastly, little research has been done on the connection between fiat currencies and digital currencies on the African continent taking into account economic downturns, which is covered by our study.

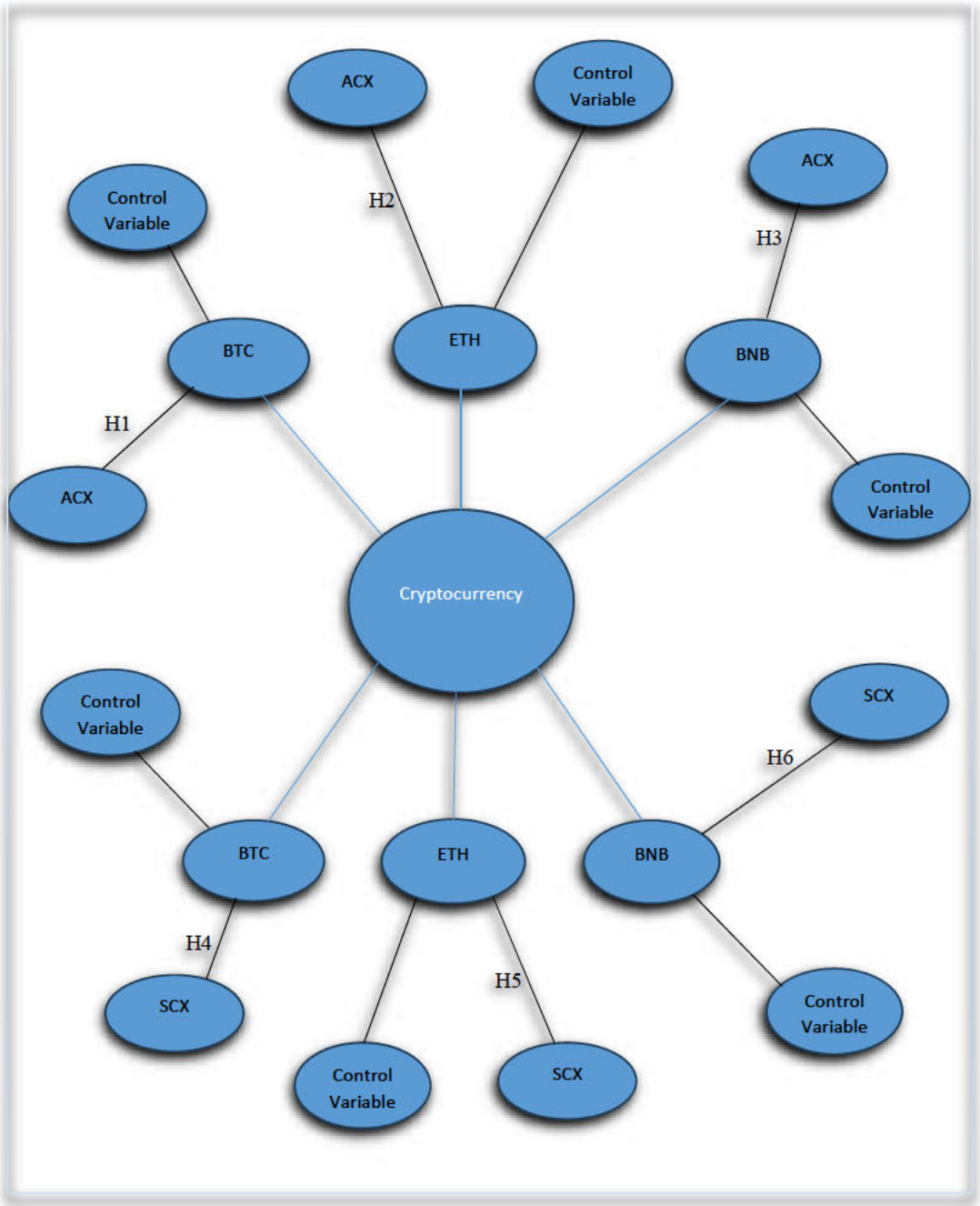
This study aimed to address the research gaps and add to the current body of knowledge by establishing how the introduction of digital currency as a new asset class is connected to fiat currencies in Africa's developing economies during economic upswings and downswings. It did so by addressing two main objectives. Firstly, it investigated the returns on currencies for eight African economies, including NGN/USD, ZAR/USD, EGP/USD, DZD/USD, AOA/USD, MAD/USD, ETB/USD, and KES/USD. Secondly, the study examined the FX environment from a South African perspective, analysing the currencies AUD, ZAR, EUR,

GBP, CHF, and JPY. The analysis incorporated daily market price returns of these currencies alongside cryptocurrency data from 1 March 2018 to 15 May 2023.

2.4.5 Conceptual Framework

Figure 2.1 presents a conceptual framework showing how the study's primary variables interact with the hypotheses used. There is strong evidence that there is a significant connection between fiat currency and digital currency (Hayes, 2017; Khaled, 2020; Lin et al., 2021; Lombardi et al., 2022; Mokni & Ajmi, 2021; Sami & Abdallah, 2020). However, Nugroho (2023) and Sauchande (2023) observe that the legal environment in which a cryptocurrency operates impacts the kind of connection.

Figure 2.1: Conceptual Framework



Source: Researcher's formulation

2.5 Summary

This chapter began with conceptual literature review followed by the theoretical literature and a review of empirical literature. It is empirically evident that there is a connection between FX currencies and cryptocurrency markets and that this is influenced by other factors like the legal framework of the market environment under study (Khaled (2020). It has been observed that, conceptually, companies holding cryptocurrencies in their financial statement should hold them at fair value for accurate reporting. The theoretical literature review established that the price of cryptocurrencies and fiat currencies in the market already includes all available knowledge to arrive at market prices. It further demonstrates that, as posited by legitimacy and institutional theories, when traders or investors adopt cryptocurrency and/or fiat currency, others will likely follow suit. The empirical literature review showed that studies on the relationship between fiat currencies and cryptocurrencies have produced mixed results. Some point to a significant association between these two forms of currencies, underlining their interdependence and potential causative relationship. These studies usually employ variables such as macroeconomic statistics, legal developments, and market sentiment in order to better comprehend the complex link between cryptocurrencies and traditional fiat currency. However, other studies conclude that there is no relevant association and that cryptocurrency fluctuations are mainly unrelated to traditional fiat currency systems. These mixed findings highlight the duality that underlines the complicated relationship between cryptocurrencies and fiat currencies, calling for further investigation and analysis in both the financial and academic spheres.

The following chapter presents the research methodology employed to conduct this study.

CHAPTER 3: RESEARCH METHODOLOGY

3.1 Introduction

This chapter outlines the methodological approach employed to conduct this study. It discusses the research paradigm and research design, the population and sample, and data sources. It also covers variable selection, model specification and analysis, diagnostic inspection, the estimation procedure, the assessment of the unit root, the quantile regression results, data validity and reliability, and the ethical considerations taken into account in conducting the study.

3.2 Research paradigm

(Kivunja & Kuyini, 2017) define a research paradigm as the conceptual lens researchers use to decide on the research techniques to be applied and the data analysis strategy. They add that paradigms are human constructs that deal with guiding principles that reveal the researcher's perspective and help to create meaning from the data analysed. Yasseen (2019) states that quantitative research can be used to measure the success of a product or service, test theories, and explore connections between variables Kivunja and Kuyini (2017) note that the positivist paradigm promotes the use of quantitative research methods to provide a precise description of the parameters and coefficients in the data that are collected, analysed, and interpreted. The researcher thus adopted a positivist epistemological position. According to Al-Saadi (2014), positivism is an epistemological viewpoint that maintains that the researcher has no influence on the external world and emphasises the need for objectivity and evidence in the search for truth.

3.3 Research Design

Qualitative research aims to provide a detailed and comprehensive description of a particular topic. It is anthropological and interpretive in nature and the linguistic features found in the data are not assigned frequencies. Because the data need not be forced into a limited number

of classes, qualitative analysis enables precise distinctions to be made (Ochieng, 2009). Conversely, the scientific research paradigm, commonly referred to as the quantitative research paradigm, is empirical in nature. By using rigorous definition, clarification, or pilot experimentation, the paradigm assures validity. This entails evaluating the tools beforehand to confirm their applicability and using statistical tests to gauge their validity and reliability (Ochieng, 2009). This study adopted a quantitative research design. Researchers like Khaled (2020) and Mallick and Mallik (2021) used a similar approach to investigate the connection between cryptocurrencies and FX currencies or other stock markets in the MENA region, India, Europe, the USA and other developing economies (Chemkha et al., 2021; Levulytė & Šapkauskienė, 2021; Shahzad et al., 2022). Quantitative research collects and analyses data to draw conclusions and make predictions (Yasseen, 2019). It can be used to measure the success of a product or service, test theories, and explore connections between variables (Yasseen, 2019).

3.4 Research Population

Bell et al. (2022) define the research population as the entire group of objects that are studied, with each object having one or more similar qualities. The research population for this study comprised of cryptocurrencies trading in the market between 1 March 2018 and 12 May 2023 and official rates of exchange for the African countries.

3.5 Research Sample

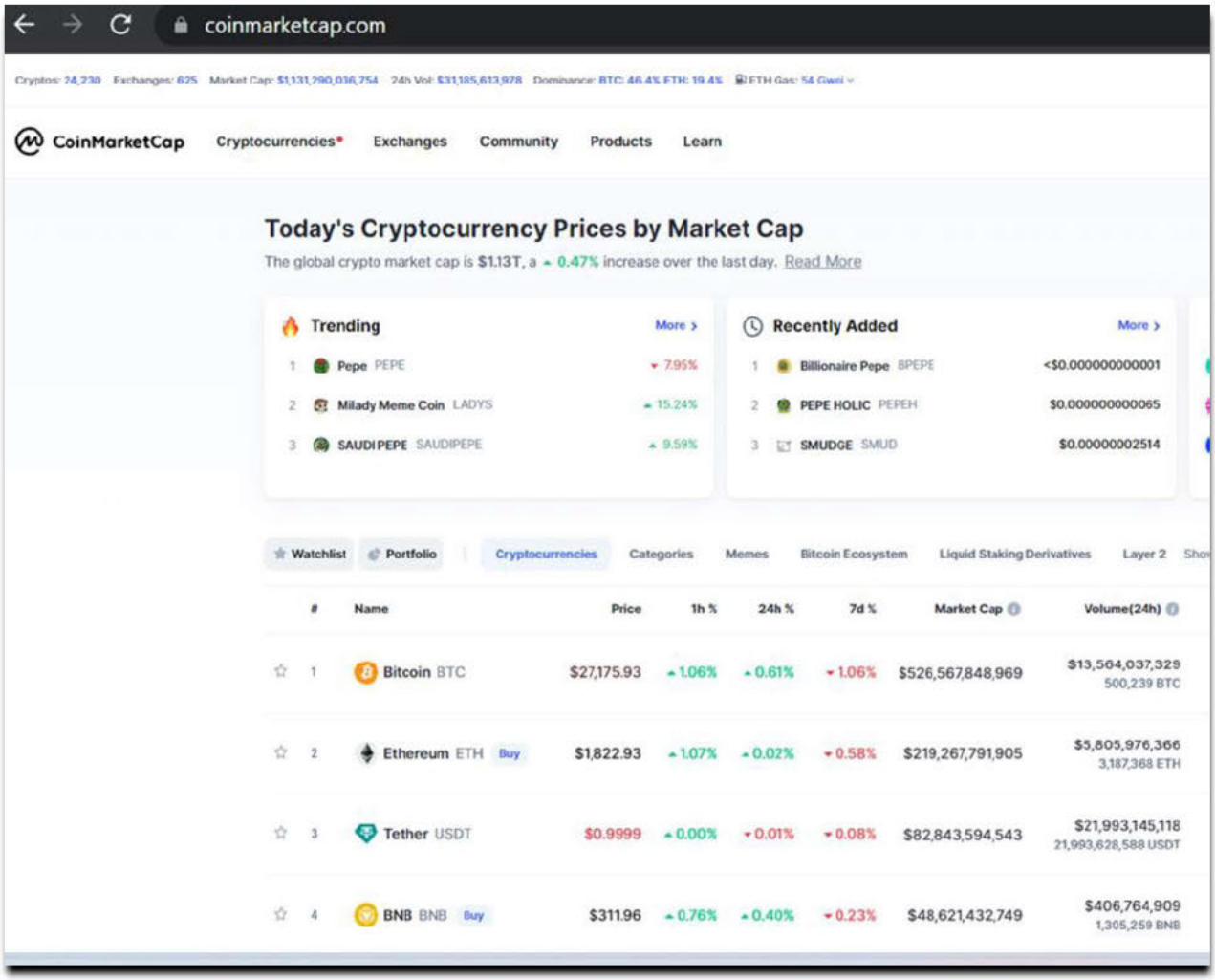
The segment or subgroup of the population under investigation is called a sample and it is a representation of the entire population (Bell et al., 2022). This study employed non-probability sampling, which involves choosing a sample based on factors other than randomness. Thus, not every element of the population (cryptocurrency or foreign/local currency) has a comparable likelihood of being selected for the sample.

The first cryptocurrency, Bitcoin, was introduced in the crypto market in July 2010 (Chuen et al., 2017). According to coinmarketcap.com, more than 24 000 cryptocurrencies are trading on

the market. Due to time and other constraints, the researcher opted for a sample size that represents the majority of the crypto market as proxies for the total. Three cryptocurrencies represent more than 66% of the crypto market by market capitalisation, namely, Bitcoin, Ethereum and BNB (coinmarketcap website). They were thus selected to represent the entire crypto population (Chemkha et al., 2021; Levulytė & Šapkauskienė, 2021; Mallick & Mallik, 2021; Shahzad et al., 2022).

The sample for objective one was Bitcoin, Ethereum and BNB that represent more than 66% of digital currencies in the African currency market by market capitalisation, and the fiat currencies of the top eight African economies whose individual nominal GDP is above US$100 billion, namely, NGN/USD, ZAR/USD, EGP/USD, DZD/USD, AOA/USD, MAD/USD, ETB/USD and KES/USD. For objective two in relation to the South African currency market, the sample was ZAR/USD, EUR/USD, GBP/USD, CHF/USD and AUD/USD as well as Bitcoin and Ethereum trading between 1 March 2018 and 12 May 2023.

Figure 3.1: Coinmarketcap Platform



Source: https://coinmarketcap.com/ December 2023

Tether USD was excluded purely because it is a stable coin, and its price is always 1 Dollar as it is pegged against the USD. The foreign currencies are the fiat currencies used by each African country against the United States Dollar. Three cryptocurrencies represent more than 66% of the crypto market by market cap, namely, Bitcoin, Ethereum and BNB. Similar to other studies, these were selected to represent the entire crypto population (Chemkha et al., 2021; Levulytė & Šapkauskienė, 2021; Mallick & Mallik, 2021; Shahzad et al., 2022).

For fiat currency selection, we opted for the biggest economies by GDP with a nominal GDP of more than $100 billion. These eight fiat currencies were used as proxies for total African

foreign currencies. For the second objective, the researcher opted for the top trading foreign currencies in South Africa which were proxies for all official FX currencies traded in this country. According to Tradefx.co.za, the top five foreign currencies traded in South Africa are ZAR/USD, EUR/USD, GBP/USD, CHF/USD, JPY/USD, and AUD/USD. Accordingly, these were chosen as the sample representing the total foreign currencies traded in South Africa.

3.6 Data sources and selection of variables

The data sources and selection of dependent and independent variables are discussed below:

3.6.1 Data sources

All the variables used the US Dollar as a base since it is the global currency reserve and the most widely exchanged fiat currency in the world (Lyzun et al. (2019) Yeyati (2021). In order to produce meaningful, reliable statistical results when analysing data, the research must have the maximum number of observations (Lakens, 2022); therefore, the daily market rates were chosen for analysis.

Cryptocurrencies and fiat currencies were sampled based on market capitalisation and the country's nominal GDP, respectively. The data was extracted from investing.com and the daily market prices data from 1 March 2018 to 12 May 2023 was used for the cryptocurrencies. For fiat currencies, the daily exchange rates for the same period were applied using the same data source. Both fiat currencies and cryptocurrencies use the United States Dollar as the base to avoid different exchange rates noise and to smoothen statistical inferences (Kumah, 2023). Secondary data was used for the daily market price movements for FX currencies traded in Africa. The FX rate data was obtained from the investing.com website. For the cryptocurrencies, data was obtained from the coinmarketcap.com database. Several researchers have used coinmarketcap.com and investing.com databases (Asena DENİZ and Teker (2020) Khaled (2020) Mallick and Mallik (2021) to analyse the interaction between cryptocurrency and commodities like gold, silver and oil as well as FX currencies. Bunjaku et al. (2017) also

sourced data from coinmarketcap.com to identify the advantages and disadvantages of cryptocurrency. From the daily market price, the daily returns were calculated as follows:

$$\text{Return}_{i,t} = \ln(R_t / R_{t-1}) \quad (1)$$

Where the natural logarithm of the closing price at time t is indicated by ln(Rt).

Our sample period covered 1 March 2018 to 12 May 2023 which included 1 295 observations each for the African and South African datasets. Given that the study focused on the African continent and used African currencies and that ETB/USD started trading on 1 March 2018, all the variables for analysis needed to start from this date for meaningful statistical analysis. The sample period was therefore 1 March 2018 to 12 May 2023 which is the day this study was crafted. The non-trading days for any forex pair must be discounted on all other variables to obtain an equal number of observations for all variables. Examples include weekends, public holidays, religious holidays, etc. when the forex markets are closed.

Several considerations for objective one, including their notable market capitalisation, extensive acceptance, and representativeness of the larger cryptocurrency sector, support the choice of Bitcoin, Ethereum, and BNB as the sample for objective one. These three digital assets represent the most significant and powerful players between 1 March 2018 and 12 May 2023, with a combined market capitalisation of over 66% of all cryptocurrencies. Because of their huge market share as noted by Radu and Deak (2024), any investigation of their actions is guaranteed to yield insightful information about the general dynamics and trends of the cryptocurrency industry. Furthermore, as the original cryptocurrency, Bitcoin acts as a standard for the market according to Osman et al. (2024), Radu and Deak (2024) and Wang and Hausken (2024), and additional levels of value and market relevance are provided by Ethereum's smart contract capabilities and BNB's affiliation with the Binance exchange, the authors added. Accordingly, BTC, ETH and BNB are viable options to be sampled because of these qualities to capture the multifarious nature of digital assets, such as their use as speculative investments, storage of value, and mediums of exchange.

There are solid statistical and economic foundations for the choice of fiat currencies, which include NGN/USD, ZAR/USD, EGP/USD, DZD/USD, AOA/USD, MAD/USD, ETB/USD, and KES/USD. By representing the top eight economies in Africa with nominal GDPs over US$100 billion, these currencies guarantee that a substantial percentage of the continent's economic activity is covered by the sample. The study can gain a better understanding of the influence of cryptocurrencies on more developed and influential markets in Africa by concentrating on economies with significant GDPs. Also observed by Gershon et al. (2024) as well as Ofori et al. (2024) in their study, these nations also display a variety of economic patterns, from more diversified economies like South Africa and Egypt to resource-dependent ones like Algeria and Nigeria. This variety offers a thorough picture of the ways in which various economic contexts engage with the bitcoin market. Furthermore, by including these particular fiat currencies, a more detailed examination of the potential correlations between cryptocurrency prices and macroeconomic factors like economic growth and exchange rates is made possible, offering a comprehensive understanding of the relationship between fiat and digital currencies.

Additionally, the chosen fiat currencies and cryptocurrencies represent a range of economic scenarios and market behaviours, which makes them a perfect sample for analysing the intricate relationship between traditional and digital assets. By ensuring that the study contains both key regional fiat currencies and major global cryptocurrencies, this selection technique also helps to mitigate selection bias. Because of this, conclusions drawn from this sample can be applied more consistently to the larger picture of the cryptocurrency market and how it interacts with fiat money, providing insightful information to scholars, investors, and decision-makers.

In the case of objective two and given that ZAR/USD, EUR/USD, GBP/USD, CHF/USD, JPY/USD, and AUD/USD are the most traded foreign currencies in South Africa (Huang et al., 2024), their selection for the second aim makes sense. These currencies serve as stand-ins for all officially traded foreign exchange (FX) currencies in the nation, offering a representative sample for examining how cryptocurrencies and conventional fiat currencies interact in this particular setting.

First and foremost, the US Dollar's importance in international trade and its function as the main currency for transactions abroad are the main reasons ZAR/USD (South African Rand/US Dollar) is mentioned (Huang et al., 2024). Understanding the relationship between South Africa's national currency and the most powerful currency in the world—which in turn reflects global economic trends and the effects of monetary policy—requires an understanding of the ZAR/USD pair. The fact that the euro is the second most traded currency in the world justifies its inclusion in the EUR/USD (Euro/US Dollar) pair (Vasileiou, 2024). South Africa's trade balance and economic stability may be significantly impacted by changes in the EUR/USD exchange rate, since the Eurozone is one of the country's main trading partners (Vasileiou, 2024). By examining this combination, one can better understand how the economic climate in Europe affects the currency market in South Africa.

Another important currency combination is GBP/USD (British Pound/US Dollar) as per Afuecheta et al. (2024), considering the historical and economic links between South Africa and the UK. The British Pound is still a significant currency in the foreign exchange market, and its presence offers valuable information about how changes in the UK economy affect the dynamics of South Africa's currency, Hart (2024) added. Because of the Swiss Franc's standing as a safe-haven currency, CHF/USD (Switzerland Franc/US Dollar) is included. The stability of the Swiss economy and the appeal of the Franc in uncertain economic times make this combination crucial for comprehending South African investor behaviour and risk management tactics (Adeleye et al., 2024).

The Japanese Yen/US Dollar, or JPY/USD, is a symbol of Asia's economic power, especially in Japan, one of the biggest economies in the world. The introduction of the Yen facilitates analysis of how monetary policy and economic conditions in Asia affect the foreign exchange market in South Africa (Abakah, Ullah, et al., 2024). Finally, because both South Africa and Australia have economies that are resource-rich, AUD/USD (Australian Dollar/US Dollar) was chosen. The performance of the Australian Dollar can offer comparative insights into how international trade relations and commodity prices impact the South African Rand (Abakah, Ullah, et al., 2024).

3.6.2 Dependent variables

Bell et al. (2022) define the dependent variable as a variable the researcher seeks to explain. The dependent variables were cryptocurrencies (BTC - Bitcoin, ETH - Ethereum and BNB – Binance Coin).

3.6.3 Independent variables

Bell et al. (2022), define the independent variable as the variable used to explain the dependent variable. The independent variables that represented African and South African currencies were African exchange rates (NGN/USD - Nigerian Naira, ZAR/USD - South African Rand, EGP/USD - Egyptian Pound, DZD/USD - Algerian Dinar, AOA/USD - Angolan Kwanza, MAD/USD - Moroccan Dirham, ETB/USD - Ethiopian Birr and KES/USD - Kenyan Shilling) and South African exchange rates (ZAR - South African Rand, EUR - Euro, GBP - British Pound Sterling, CHF and AUD), respectively.

3.7 Model Specification and Analysis

Using the log difference, the daily returns from 1 March 2018 to 12 May 2023 were calculated. This approach was adopted by scholars such as Erdas and Caglar (2018), Nyakurukwa and Seetharam (2023a), Nyakurukwa and Seetharam (2023b) and Sim and Zhou (2015) to eliminate the asynchronous data points and avoid the challenge of underestimation of real links as well as regressions. The total number of observations once all the daily returns were calculated was 1 256. Similar to the studies conducted by Kumah (2020), Kumah (2023) and Yang et al. (2020) on the link between bitcoin and fiat currencies in Africa, we utilised Ensemble Empirical Mode Decomposition (EEMD) to decompose the daily return series into Intrinsic Mode Function (IMF) which exhibits the short-, medium- and long-term dynamics. Accordingly, IMF1, IMF5 and IMF residuals were considered to represent the short-, medium- and long-term, respectively (Kumah, 2023).

Koenker and Hallock (2001) asserted that the QR model is most suitable when normality, homoscedasticity and linearity do not exist. This was confirmed by Zohuri et al. (2022) recent assessment of the link between oil prices and US stock returns. The Jarque-Bera normality test confirmed excess kurtosis and skewness of the time series data for this study; hence, the adopted approach of quantile regression techniques. Quantile regression is an extension of linear regression. It assumes that there is no strong normal distribution and therefore the parameters pertaining to linear regression like normality, homoscedasticity and linearity cannot be satisfied (Koenker, 2017; Koenker & Hallock, 2001; Kyriazis, 2022; Sim & Zhou, 2015).

Similar to Kumah (2023) investigation of the correlation between fiat and cryptocurrency, this study used EEMD-based quantile regression to provide a comprehensive outcome. The models are presented in the following section. Quantile regression IMFs data was a statistically appropriate input for the regression analysis as the time series data of composite as well as decomposed data series presented in Appendices 7 to 13 exhibited volatility clusters, indicating time-varying risk from the series.

3.7.1 Ensemble Empirical Mode Decomposition (EEMD)

By using an objective intermittence test on white noise-added signal (data), EEMD enhances the EMD and enables the mean to be regarded as the ultimate actual results (Kumah, 2023). Accordingly, EMD can be replaced by the EEMD. In accordance with the EEMD as a time-space analysis approach, the EEMD technique filters through the original series with an adequate number of iterations and adds white noise to create a uniform reference in the time-frequency space that was necessary for this study. The EEMD technique that follows is predicated on (Kumah, 2023). The EEMD defines the IMF components as the mean of an ensemble of trials, each consisting of the signal (data) and a finite-amplitude white noise, so that:

$$x(t) = s(t) + n(t). \quad (2)$$

where:

$x(t) = all\ data$

$s(t) = signal$

$n(t) = noise$

While many data processing algorithms have sought in vain to eliminate this noise component, according to Kumah (2023), the EEMD introduces white noise in order to eliminate weak signals while preserving the original signal. For any empirical analysis, this provides well-tuned data free of white noise, which can be used for trustworthy forecasting and inferencing. The i^{th} synthetic observation, $x_i\ (t)$, in the equation below is realised by adding a white noise of various realisations, $\omega_i(t)$, which prevents mode mixing and offers a reasonably uniform reference scale distribution to aid with EMD. This equation emanates from the above equation such that:

$$x_i\ (t) = x\ (t) + \omega_i(t). \tag{3}$$

where:

$x_i\ (t)$ = artificial observation

$x\ (t)$ = all data

$\omega_i(t)$ = white noise of different realisations

Kumah (2023) concludes that the EEMD is favoured due to its ability to avoid mode mixing by having mean IMFs dwell within natural dyadic filter windows and randomly introduced white noise series cancel each other out in the final rendition of the corresponding IMFs. A dataset has the greatest number of IMFs s_i (and one residual r) of about $\log_2 N$, where N is the total number of data points. One way to express r is as follows $s_i - (s_i - 1)$:

$$r = s_i - (s_i - 1) \tag{4}$$

where:

r = residual

s_i = the large number of IMFs

This research methodology is especially beneficial since it combines quantile regression (QR) with ensemble empirical mode decomposition (EEMD) for a number of reasons. With the help

of data-driven methods like EEMD, a time series may be efficiently broken down into a collection of intrinsic mode functions (IMFs), each of which represents a distinct frequency component of the original series (Kumah, 2024; J. Zhang, K. Cai, et al., 2024). Given the intrinsic volatility and non-linearity of the fiat currency and cryptocurrency markets, this decomposition makes it possible to capture both temporal and time-frequency information (Faisal & Donduran, 2024; Saâdaoui, 2024). As Jin and Tian (2024) find, a more sophisticated knowledge of the dynamic interactions between cryptocurrencies and fiat currencies can be obtained by employing EEMD to separate and analyse the numerous underlying patterns and trends within the data.

The decomposed time series data is then subjected to quantile regression (QR) in order to investigate the relationships under various market or currency regimes (Faisal & Donduran, 2024; Jin & Tian, 2024; Kumah, 2024; C. Zhang et al., 2024). By estimating the conditional quantiles of the dependent variable distribution, QR offers a more thorough analysis than ordinary least squares (OLS) regression, which concentrates on calculating the mean of the dependent variable, the authors continue. This makes it possible for the study to evaluate the correlations between cryptocurrencies and fiat money over the whole distribution, identifying any potential asymmetries and tail dependencies that conventional mean-based approaches would have overlooked as per El Abaji and A Haraty (2024) and Kumah (2024) studies. In financial markets, where extreme events and tail risks significantly influence market behaviour, such an approach is especially pertinent (El Abaji & A Haraty, 2024).

Other approaches like generalised autoregressive conditional heteroskedasticity (GARCH) models, autoregressive integrated moving average (ARIMA) models, or ordinary least squares regression might not be as appropriate for this study. Despite being commonly used in studies such as Ani et al. (2024) , Berdiev et al. (2024) as well as Smales (2024), OLS regression makes two assumptions about data: a linear connection and homoscedasticity, which are frequently broken in financial time series data that exhibit non-linearity and volatility clustering. While ARIMA models work well for short-term forecasting and linear dependencies, they may not be able to handle the complex patterns and non-stationarity that are characteristic of cryptocurrency markets (Alkamali, 2024; Chauhan & Chaudhary, 2024; Cheng et al., 2024). In contrast, GARCH models as used in Alam et al. (2024) and Guo and Zhang (2024) are

intended to represent and predict volatility; however, their primary focus is on conditional variance, which may not fully account for the multi-scale structure of the data or the distributional characteristics investigated by quantile regression .

For time-frequency analysis, techniques such as wavelet transforms (Noureen et al., 2024; Trichilli et al., 2024), or Fourier analysis could also be taken into consideration (Afshan et al., 2024; Li & Xia, 2024). However, these techniques may be less flexible and accurate in capturing the complex and adaptive patterns in the fiat currency and cryptocurrency markets since they sometimes call for assumptions about the stationarity of the time series or the use of particular basis functions. These restrictions are circumvented by EEMD since it is data-driven and adaptive and permits intrinsic data decomposition without the need for preset basis functions such as Kumah (2024) approach in his study.

Accordingly, a solid and adaptable framework for capturing the intricate, non-linear, and multi-scale connections between cryptocurrencies and fiat currencies is provided by the EEMD-based quantile regression methodology. It is the best option for this study since it makes use of EEMD's advantages in time-frequency decomposition and QR's advantages in distributional feature analysis (Boczko, 2024; Kumah, 2024). Alternative approaches might not offer the same degree of thorough and in-depth insights required to comprehend the complex dynamics at work in these financial markets, even though they might be helpful in some situations.

3.7.2 Objective 1 – African dataset

The following model specification was used to assess the link between cryptocurrencies and African foreign currencies:

$$CRC_{i,t} = \beta_0 + \beta\,(ACX_{i,t}) + \varepsilon_{i,t} \quad (5)$$

Where:

$CRC_{i,t}$ = *cryptocurrency return against USD$ for crypto i at time t*

β_0 = Intercept

β = coefficient

USD$ = United States Dollar, the currency

For objective one, quantile regression was used in this model. Objective one sought to assess the connection between cryptocurrencies and African FX currencies. Eight foreign currency pairs: NGN/USD, ZAR/USD, EGP/USD, DZD/USD, AOA/USD, MAD/USD, ETB/USD and KES/USD were the independent variables. The three cryptocurrencies, BTC, ETH and BNB were the dependent variables. The researcher ran the three QR models with the dependent variables (BTC, BNB and ETH) and independent variables (AOA, DZD, EGP, ETB, KES, MAD, NGN and ZAR) to establish the connection between cryptocurrency and African fiat currencies as follows:

$$BTC=\beta 0 + \beta_1 NGN + \beta_2 ZAR + \beta_3 EGP + \beta_4 DZD + \beta_5 AOA + \beta_6 MAD + \beta_7 ETB + \beta_8 KES + \varepsilon 1 \quad (6)$$

$$ETH = \beta 0 + \beta_1 NGN + \beta_2 ZAR + \beta_3 EGP + \beta_4 DZD + \beta_5 AOA + \beta_6 MAD + \beta_7 ETB + \beta_8 KES + \varepsilon 2 \quad (7)$$

$$BNB = \beta 0 + \beta_1 NGN + \beta_2 ZAR + \beta_3 EGP + \beta_4 DZD + \beta_5 AOA + \beta_6 MAD + \beta_7 ETB + \beta_8 KES + \varepsilon 3 \quad (8)$$

Where:

BTC = Bitcoin

ETH = Ethereum

BNB = Binance Coin

NGN = Nigerian Naira

ZAR = South African Rand

EGP = Egyptian Pound

DZD = Algerian Dinar

AOA = Angolan Kwanza

MAD = Moroccan Dirham

ETB = Ethiopian Birr

KES = Kenyan Shilling

$\beta 0$ = Intercept

β_1 to β_8 are regression coefficients

$\varepsilon 1$ to $\varepsilon 3$ are error terms

Given the above models, for objective one, the hypotheses to be tested were as follows:

Null hypothesis

First null - H_0: No significant impact exists on BNB due to African fiat currency exchange.

Second null - H_0: No significant impact exists on BTC due to African fiat currency exchange.

Third null - H_0: No significant impact exists on ETH due to African fiat currency exchange.

Alternative hypothesis

H_1: There is a significant impact on BNB due to African fiat currency exchange.

H_2: There is a significant impact on BTC due to African fiat currency exchange.

H_3: There is a significant impact on ETH due to African fiat currency exchange.

If the Probability value is < 0.05, reject H_0.

3.7.3 Objective 2 – South African dataset

The following model specification was used to examine the connection between cryptocurrencies and South African foreign currencies:

$CRC_{i,t} = \beta_0 + \beta\ (SCX_{i,t}) + \varepsilon_{i,t}$: for the second objective (5)

Where:

ACX*i,t* = *Return of currency exchange rate against USD$ for African country i at time t*

$\varepsilon i,t$ = *Error term for i at time t*

SCX*i,t* = *Return of currency exchange rate against USD$ for South African country i at time t.*

The quantile regression used in this model for objective two can be elaborated as follows. The study analysed the connection between cryptocurrency (BTC and ETH) and the official rates of exchange in South Africa (ZAR, GBP, EUR, CHF and AUD), with the following foreign currency pairs selected: ZAR/USD, EUR/USD, GBP/USD, CHF/USD and AUD/USD which were also independent variables. The two cryptocurrencies, BTC and ETH were dependent variables. The researcher also run the QR model with the dependent variables (BTC and ETH) and dependent variables (AUD, CHF, EUR, GBP and ZAR) to assess the link between South African fiat currencies and digital currencies as follows:

$$BTC = \beta_0 + \beta_1 AUD + \beta_2 CHF + \beta_3 GBP + \beta_4 EUR + \beta_5 ZAR + \varepsilon 1 \quad (9)$$

$$ETH = \beta_0 + \beta_1 AUD + \beta_2 CHF + \beta_3 GBP + \beta_4 EUR + \beta_5 ZAR + \varepsilon 2 \quad (10)$$

Where:

BTC = Bitcoin

ETH = Ethereum

BNB = Binance Coin

AUD = Australian Dollar

CHF = Swiss Franc

GBP = British Pound

EUR = Euro

ZAR = South African Rand

β_0 to β_5 are the regression coefficients

ε1 to ε3 are the error terms

Accordingly, the hypotheses to be tested for objective two were as follows:

Null hypothesis

First null - H_0: No significant impact exists on BTC due to South African fiat currency exchange.

Second null - H_0: No significant impact exists on ETH due to South African fiat currency exchange.

Alternative hypothesis

H_1: There is a significant impact on BTC due to South African fiat currency exchange.

H_2: There is a significant impact on ETH due to South African fiat currency exchange.

If the Probability value is < 0.05, reject H_0.

3.8 Diagnostic Inspection

Performance diagnostics was performed to assess and analyse the performance of the models for the study and to identify their strengths, weaknesses and inefficiencies (Patwardhan & Shah, 2002). Below is the performance diagnostics for our study on objectives 1 and 2.

3.8.1 Jarque-Bera normality test - Africa

The Jarque-Bera normality test was used to assess the performance or effectiveness of the designed models. The researcher tested for normality in the distribution of data for the research. As seen in Figure 4.1 in the following chapter, the Jarque-Bera normality test results confirmed excess kurtosis and skewness, indicating that the distribution of the data was not normal. At this point we considered the use of the Quantile Regression model. As explained by Koenker

and Hallock (2001), this model is appropriate when the conditions of normality, homoscedasticity and linearity do not exist, as in our study. When the conditions of linear regression such as normality, linearity or homoscedasticity are not met, the use of quantile regression is statistically justified since it has no normal distribution assumption (Koenker & Hallock, 2001; Kumah, 2023).

The Jarque-Bera normality test hypotheses for objective one were as follows:

H_0 = Time series data is normally distributed; reject null if P value < 0.05

H_1 = Time series data is not normally distributed; reject H_1 if P value is > 0.05

3.8.2 Jarque-Bera normality test – South Africa

The Jarque-Bera normality test hypotheses for objective two were:

H_0 = Time series data is normally distributed; reject null if P value < 0.05

H_1 = Time series data is not normally distributed; reject H_1 if P value is > 0.05

3.8.3 Quantile process estimates – Africa and South Africa

The researcher also ran the quantile process estimates for the African and South African datasets to understand the connection between variables across different covariate levels (see Tables 4.14 and 4.18. in the following chapter). This provides insight into how the dependent variable behaves at each quantile (Kumah, 2023).

3.8.4 Quantile slope equality test – Africa

Following the quantile process estimates, we ran the quantile slope equality test to probe whether the connection between the variables was consistent across different distribution quantiles (Bera et al., 2014; Buchinsky, 1998). The hypotheses for the quantile slope equality tests were as follows for objective one:

Null hypothesis

First null - H_0: The quantile slope equality is not different across quantile levels for BTC.

Second null - H_0: The quantile slope equality is not different across quantile levels for BNB.

Third null - H_0: The quantile slope equality is not different across quantile levels for ETH.

Alternative hypothesis

H_1: The quantile slope equality is different across quantile levels for BTC.

H_2: The quantile slope equality is different across quantile levels for BNB.

H_3: The quantile slope equality is different across quantile levels for ETH.

If the probability value is < 0.05, reject H_0.

As noted by (Buchinsky, 1998), heterogeneity in the effects is indicated by the occurrence of distinct slopes between quantiles. (Hao & Naiman, 2007) note that it indicates that for various regions of the response distribution, the relationship between the independent and dependent variables varies in intensity or direction. Koenker and Hallock (2001) stated that this calls into question the normal distribution assumption. As the general linear regression model assumed a normal distribution (Limpert & Stahel, 2011), this assumption was violated for our study, confirming that the quantile regression model was appropriate.

3.8.5 Quantile slope equality test – South Africa

The hypotheses for the quantile slope equality tests were as follows for objective two:

Null hypothesis

First null - H_0: The quantile slope equality is not different across quantile levels for BTC.

Second null - H_0: The quantile slope equality is not different across quantile levels for ETH.

Alternative hypothesis

H_1: The quantile slope equality is different across quantile levels for BTC.

H_2: The quantile slope equality is different across quantile levels for ETH.

If the probability value is < 0.05, reject H_0.

3.8.6 Symmetric quantiles test – Africa

After conducting the quantile slope equality test, the researcher ran the symmetric quantiles test to assess the presence of asymmetry or skewness in the distribution (Barber & Jennison, 1999; Chiang et al., 2006). The hypotheses for objective 1 were as follows:

Null hypothesis

First null - H_0: There is no evidence of skewness or asymmetry in the distribution for BTC.

Second null - H_0: There is no evidence of skewness or asymmetry in the distribution for BNB.

Third null - H_0: There is no evidence of skewness or asymmetry in the distribution for ETH.

Alternative hypothesis

H_1: There is evidence of skewness or asymmetry in the distribution for BTC.

H_2: There is evidence of skewness or asymmetry in the distribution for BNB.

H_3: There is evidence of skewness or asymmetry in the distribution for ETH.

If the probability value is < 0.05, reject H_0.

3.8.7 Symmetric quantiles test – South Africa

The hypotheses for objective 2 were as follows.

Null hypothesis

First null - H_0: There is no evidence of skewness or asymmetry in the distribution for BTC.

Second null - H_0: There is no evidence of skewness or asymmetry in the distribution for ETH.

Alternative hypothesis

H_1: There is evidence of skewness or asymmetry in the distribution for BTC.

H_2: There is evidence of skewness or asymmetry in the distribution for ETH.

If the probability value is < 0.05, reject H_0.

3.9 Estimation procedure

The following steps were followed in sequence to process and analyse the data:

3.9.1 Data presentation and detection of outliers

Detection and treatment of outliers are necessary to achieve appropriate statistical results from reliable and meaningful data behaviour. Hawkins (1980) described outliers as observations that deviate from other observations such that they create suspicion that they were generated from a different source or mechanism. This was confirmed by Osborne and Overbay (2004) and Zuur et al. (2010), who defined outliers as a few data points that are further away from the other normal data points in a dataset.

3.9.2 Descriptive statistics

Descriptive statistics provides a statistical perspective of a study's variables. Vetter (2017) explains that within the field of statistical analysis, descriptive statistics involves gathering, organising, summarising, and presenting data in order to give the reader a concise and insightful picture of its key characteristics. Its main objective is to provide insights into central tendencies, variability, and distribution patterns by describing and synthesising a dataset's basic

features (Vetter, 2017). The author adds that central tendency measures like the mean, median, and mode are frequently used in descriptive statistics to represent the average value of a dataset (Vetter, 2017).

3.9.3 Pearson correlation tests

Pearson correlation tests establish the linear link among the variables. Yang et al. (2020) analysis of cryptocurrency market price movement used Pearson's correlation to measure the correlation between variables. A study on the hedging characteristics of cryptocurrencies also employed this method to determine the correlation between cryptocurrencies, oil and gas prices and other stock prices (Bossman et al., 2023). Kim et al. (2020) used Pearson's correlation to examine the connection between gold and US stock prices. The current study employed this method for the time series data. The test results indicated no significant correlation among the variables, meaning that there was no multicollinearity.

3.9.4 Variance Inflation Factor

The multicollinearity test is conducted using Variance Inflation Factor (VIF). The VIF tests for multicollinearity in the regression analysis were conducted prior to the assessment of the relationship between fiat and digital currencies in Africa and South Africa and the design of the model specifications. They were used to test the correlation between the independent variables. Daoud (2017), Dormann et al. (2013) and Khaled (2020) used VIF to verify whether there was linear multicollinearity among the independent variables when investigating the connection between variables. The presence of multicollinearity among the independent variables in the regression model may result in adverse regression results (Daoud, 2017). Daoud (2017) affirmed that certain variables become statistically insignificant when they should be statistically significant due to multicollinearity, which raises the standard errors, with adverse consequences for the reliability of the regression model.

3.9.5 Assessment of the unit root

The data used for this study is time series data, and accordingly, its stationarity had to be assessed before performing any further statistical analysis. Levin et al. (2002) noted that, when studying relationships between macroeconomic variables (such as in this study) the unit root often exists. They note that this can have a substantial impact on test statistics and the asymptotic characteristics of the time series regression estimations. Thus, if a unit root is present in a time series, it can significantly impact the behaviour of statistical estimates obtained from time series regression analysis, as well the properties of test statistics used to make inferences about the data (Levin et al., 2002). Levin et al. (2002) state that these effects are particularly relevant in the asymptotic (large sample) context, which highlights the importance of considering the existence of a unit root when analysing time series data (Levin et al., 2002; Maddala & Wu, 1999; Pesaran, 2007).

If statistical properties like the mean, variance and covariance of the distribution are constant over a period of time, the time series data is referred to as stationary time series data; i.e., the time series data shows no trend (Dickey & Fuller, 1979). The literature notes that the Phillips-Perron (PP) and augmented Dickey-Fuller (ADF) should be used to test for stationarity when studying the unit root in time series data with macroeconomic variables (Choi (2001) Elliott et al. (1992) Levin et al. (2002) Maddala and Wu (1999). The following hypotheses were used for the unit root test:

3.9.5.1 Unite root test – Africa

The following hypotheses were tested for objective one in the African dataset:

H_0: A Unit Root exists in the time series data (series is non-stationary)

H_1: A Unit Root does not exist in the time series data (series is stationary)

If the probability value is < 1%, reject H_0.

3.9.5.2 Unit root test – South Africa

The following hypotheses were tested for objective two in the South African dataset:

H_0: A Unit Root exists in the time series data (series is non-stationary)

H_1: A Unit Root does not exist in the time series data (series is stationary)

If the probability value is < 1%, reject H_0.

3.10 Quantile regression results

The results of the quantile regression model and the findings on the link between digital currencies and the FX currencies in Africa and South Africa were captured.

3.11 Data Validity and Reliability

The study used secondary data sourced from reliable, reputable sources used by many researchers, namely, investing.com and coinmarketcap.com. The performance of the models was evaluated using the Jarque-Bera normality test. The secondary data was cryptocurrency and fiat currency market prices and quantitative research methods were employed. Olabode et al. (2019) observed that secondary data is reliable to use for research and quantitative research methods provide reliable research outputs (Apuke, 2017). Accordingly, the data for this study can be trusted and produced reliable results.

3.12 Ethical Considerations

This study did not involve human subjects or the collection of primary data which is private, privileged or classified. It only employed historical secondary data that is publicly available. Prior to obtaining the data, the researcher obtained ethical clearance from the University of KwaZulu-Natal (Ethical clearance number 00021991).

3.13 Summary

This chapter set out the methodological approach adopted for this study. It discussed the research paradigm and design, the population and sample, data sources and selection of variables, model specification and analysis, performance diagnostics, the estimation procedure, data validity and reliability and the ethical considerations taken into account.

The following chapter presents and analyses the data.

CHAPTER 4: DATA PRESENTATION AND ANALYSIS

4.1. Introduction

This chapter focuses on data presentation and analysis. It begins with a presentation on the detection and elimination of outliers to achieve appropriate statistical results from reliable and meaningful data behaviour. This is followed by the presentation of the descriptive statistics, which provides a statistical perspective of the study's variables; the Spearman Rho correlation coefficient to establish the relationships between the variables; the multicollinearity test using the VIF; the assessment of the unit root test; and the results of the quantile regression model and the findings of the generalised linear regression model on the connection between digital currencies and FX currencies in Africa for objective one and South Africa for objective two. Lastly, the results are discussed in line with the literature reviewed.

4.2 Preliminary analysis

4.2.1 Test for outliers and winsorising

Before conducting any statistical examination, the researcher assessed the existence of any outliers from both datasets (for Africa and South Africa). The data is graphically presented in boxplot graphs, normal QQ plots and histograms (see Appendices A1 to Appendix A3) to identify any outliers. The boxplot graphs in Appendix A1 show that there were data points located outside the boxes; accordingly, these were considered outliers. Koenker and Hallock (2001) performed a similar procedure to identify and eliminate outliers. Similarly, Appendices A2 and A3 present the QQ plot graphs and histograms that illustrate the existence of outliers for the African currency and South African currency datasets as they depict data points away from the line and those isolated from the other data group, respectively.

After initially winsorising extreme data points at the distribution's 5^{th} and 95^{th} percentiles, the African dataset still exhibited some outliers. This prompted further winsorising at a higher quantile of 0.13 lowest observations and quantile 0.87 highest observations that led to the winsorisation of all the outliers for this dataset. The results are presented in Appendices A4 to

A6. For the South African dataset, winsorising was initially performed at quantile 0.05 lowest observations and quantile 0.95 highest observations of the dataset which resulted in the elimination of outliers. The results are graphically presented in Appendices A4 to A6 in boxplots, normal QQ plots and histograms. Tiwari et al. (2020) utilised similar instruments to detect and eliminate outliers in their analysis of stock price movements and the relationship between variables.

4.2.2 Descriptive statistics

The descriptive statistics are presented below in Tables 4.1 and 4.2 for Africa and South Africa, respectively. Descriptive statistics provide a comprehensive overview by quantifying and summarising the key characteristics and attributes inherent within datasets, thereby illuminating their significant features and facilitating deeper understanding of their underlying structures and distributions.

Table 4.1: Descriptive statistics (for cryptocurrencies and African fiat currencies)

Variable	Status	Mean	Max	Min	Std. Dev.	Skewness	Kurtosis
AOA/USD	Unwinsorised	-0.0006	0.0626	-0.0529	0.0073	-0.2288	15.4594
	Winsorised	-0.0006	0.0626	-0.0529	0.0073	-0.2288	15.4594
BNB/USD	Unwinsorised	0.0049	0.8817	-0.4396	0.0667	2.5590	36.9125
	Winsorised	0.0049	0.8817	-0.4396	0.0667	2.5590	36.9125
BTC/USD	Unwinsorised	0.0017	0.2138	-0.3818	0.0440	-0.3066	6.9524
	Winsorised	0.0017	0.2138	-0.3818	0.0440	-0.3066	6.9524
DZD/USD	Unwinsorised	-0.0001	0.0136	-0.0133	0.0022	-0.1094	3.5890
	Winsorised	-0.0001	0.0136	-0.0133	0.0022	-0.1094	3.5890
EGP/USD	Unwinsorised	-0.0004	0.0134	-0.1487	0.0067	-16.7985	336.3648

	Winsorised	-0.0004	0.0134	-0.1487	0.0067	-16.7985	336.3648
ETB/USD	Unwinsorised	0.0043	2.7157	-0.8497	0.1137	11.6598	268.6138
	Winsorised	-0.0005	0.0177	-0.0288	0.0040	-1.0771	9.6136
ETH/USD	Unwinsorised	0.0024	0.4308	-0.4470	0.0597	0.1657	7.0180
	Winsorised	0.0024	0.4308	-0.4470	0.0597	0.1657	7.0180
KES/USD	Unwinsorised	-0.0002	0.0160	-0.0093	0.0017	1.1037	12.7793
	Winsorised	-0.0002	0.0160	-0.0093	0.0017	1.1037	12.7793
MAD/USD	Unwinsorised	-0.0001	0.0201	-0.0177	0.0034	-0.0912	3.4848
	Winsorised	-0.0001	0.0201	-0.0177	0.0034	-0.0912	3.4848
NGN/USD	Unwinsorised	-0.0003	0.0333	-0.1774	0.0067	-15.2564	387.2343
	Winsorised	-0.0003	0.0333	-0.1774	0.0067	-15.2564	387.2343
ZAR/USD	Unwinsorised	-0.0003	0.0288	-0.0405	0.0098	-0.3137	0.5993
	Winsorised	-0.0003	0.0288	-0.0405	0.0098	-0.3137	0.5993

For African fiat currencies and cryptocurrencies, the standard deviation, skewness, kurtosis, mean, maximum, and minimum did not change after winsorising apart from ETB for which all descriptive statistics changed as follows after winsorising: mean – from 0.0043 to 0.0005; maximum – from 2.7157 to 0.0177; minimum – from -0.8497 to -0.0288; standard deviation – from 0.1137 to 0.0040; skewness – from 11.6598 to -1.0771 and kurtosis – from 268.6138 to 9.6138 (see Table 4.1 above). This shows that the African data's central tendency, variability, and distributional shape were not significantly changed by the winsorising procedure.

Table 4.2: Descriptive statistics (for cryptocurrencies and South African fiat currencies)

Variable	Status	Mean	Max	Min	Std. Dev.	Skewness	Kurtosis
AUD_USD	Unwinsorised	-0.0001	0.0325	-0.0386	0.0067	-0.1005	5.9727
	Winsorised	-0.0001	0.0103	-0.0106	0.0055	-0.0590	2.3652
BTC_USD	Unwinsorised	0.0017	0.2138	-0.3818	0.0440	-0.3063	9.9209
	Winsorised	0.0020	0.0768	-0.0628	0.0345	0.2042	2.8591
CHF_USD	Unwinsorised	0.0000	0.0284	-0.0203	0.0046	0.3577	5.6392
	Winsorised	0.0000	0.0072	-0.0070	0.0038	0.1126	2.2987
ETH_USD	Unwinsorised	0.0024	0.4308	-0.4470	0.0597	0.1656	9.9863
	Winsorised	0.0023	0.0935	-0.0837	0.0454	0.0982	2.6158
EUR_USD	Unwinsorised	-0.0001	0.0214	-0.0204	0.0047	-0.0071	4.4507
	Winsorised	-0.0001	0.0074	-0.0075	0.0040	-0.0238	2.3403
GBP_USD	Unwinsorised	-0.0001	0.0314	-0.0363	0.0060	-0.0671	6.3745
	Winsorised	-0.0001	0.0093	-0.0092	0.0049	0.0179	2.3701
ZAR_USD	Unwinsorised	-0.0003	0.0288	-0.0405	0.0098	-0.3133	3.5924
	Winsorised	-0.0003	0.0145	-0.0169	0.0087	-0.1783	2.1991

For South African FX currencies and cryptocurrency data, the mean remained unchanged after winsorising apart from the mean values of BTC and ETH as tabulated in Table 4.2 above. The values of standard deviation, skewness, kurtosis, maximum, and minimum all changed after winsorising the original South African dataset. This implies that the data's central tendency did not change after winsorising apart from the variability and distributional shape, which were slightly changed by the winsorising procedure.

4.2.3 Multicollinearity tests

The following multicollinearity tests were conducted for this study:

4.2.3.1 Correlation analysis

Using the Pearson correlation tests, the examination of multicollinearity in the regression was conducted prior to assessment of the relationship between fiat and digital currencies for Africa and South Africa. Tables 4.3 and 4.4 below show the Pearson correlation metrics for the African and South African dataset of variables, respectively. For the African dataset, overall,

the Pearson Correlation matrix demonstrates that there is no multicollinearity between variables. In addition, the results show that at 0.05 level of significance MAD and ETB, DZD and ETB, DZD and AOA, BTC and KES, ETH and KES, ETH and DZD, BNB and ETB have no significant levels of multicollinearity. At a level of 0.01 significance, DZD and MAD, EGP and AOA, BTC and ETB, BTC and MAD, BTC and DZD, ETH and ETB, ETH and MAD, ETH and BTC indicate that there is no multicollinearity between the variables. A negative coefficient signifies the inverse direction of correlation between variables.

For the South African dataset, overall, the Pearson Correlation matrix demonstrates that there is no multicollinearity between variables. The correlation matrix shows that at 0.01 level of significance, CHF and AUD, GBP and AUD, GBP and CHF, EUR and AUD, ERU and CHF, EUR and GBP, BTC and AUD, BTC and CHF, BTC and GBP, BTC and EUR, ETH and AUD, ETH and GBP, ETH and EUR, ETH and BTC show no indication of significant correlation. Lastly, the correlation matrix shows that at a level of 0.05 significance, ZAR and CHF, ETH and CHF are not significantly correlated.

Table 4.3: Pearson Correlation matrix – for cryptocurrency and African fiat currencies

Variable	ZAR/USD	KES/USD	ETB/USD	MAD/USD	AOA/USD	DZD/USD	EGP/USD	NGN/USD	BTC/USD	ETH/USD	BNB/USD
ZAR/USD	1.0000										
KES/USD	-0.0058	1.0000									
ETB/USD	0.0089	0.0210	1.0000								
MAD/USD	0.0274	0.0450	0.067*	1.0000							
AOA/USD	-0.0154	0.0267	-0.0384	0.0064	1.0000						
DZD/USD	-0.0154	0.0488	0.055*	0.458**	0.058*	1.0000					
EGP/USD	-0.0039	0.0140	-0.0014	-0.0071	0.103**	-0.0245	1.0000				
NGN/USD	-0.0538	0.0449	0.0173	-0.0333	-0.0144	-0.0296	0.0143	1.0000			
BTC/USD	0.0304	0.055*	0.402**	0.108**	-0.0281	0.072**	0.0132	0.0333	1.0000		
ETH/USD	0.0286	0.057*	0.343**	0.080**	-0.0144	0.071*	0.0038	0.0205	0.806**	1.0000	
BNB/USD	0.0026	0.0372	0.071*	-0.0391	0.0233	-0.0294	-0.0078	0.0007	0.0087	0.0128	1.0000

* Significant connection at the 0.05 level (two-tailed)

** Significant connection at the 0.01 level (two-tailed)

Table 4.4: Pearson Correlation matrix – for crypto and South African fiat currencies

Variable	AUD/USD	CHF/USD	GBP/USD	EUR/USD	ZAR/USD	BTC/USD	ETH/USD
AUD/USD	1.0000						
CHF/USD	0.346**	1.0000					
GBP/USD	0.414**	0.542**	1.0000				
EUR/USD	0.392**	0.755**	0.671**	1.0000			
ZAR/USD	-0.011	0.060*	0.025	0.024	1		
BTC/USD	0.167**	0.075**	0.149**	0.125**	0.030	1.0000	
ETH/USD	0.200**	0.071*	0.140**	0.119**	0.029	0.806**	1.0000

* Significant connection at the 0.05 level (two-tailed)
** Significant connection at the 0.01 level (two-tailed)

4.2.3.2 Variance Inflation Factor (VIF)

Thereafter, a VIF test was conducted for both datasets. Tables 4.5 to 4.7 below display the collinearity statistic results.

4.2.4.1 Variance Inflation Factor – for crypto and African fiat currencies

Table 4.5: Collinearity statistics: dependent variable BNB – Africa

Model		Unstandardized Coef.		Standardized Coef.	t	Sig.	Collinearity	
		B	Std. Error	Beta			Tolerance	VIF
ACX	(Const)	0.0029	0.0011		2.6584	0.0079		
	AOA_USD	0.0662	0.3073	0.0060	0.2153	0.8295	0.9967	1.0033
	DZD_USD	0.0345	0.6831	0.0016	0.0505	0.9597	0.7285	1.3728
	EGP_USD	-0.3409	0.6643	-0.0144	-0.5132	0.6079	0.9843	1.0159
	ETB_USD	-0.6616	1.0599	-0.0174	-0.6242	0.5326	0.9868	1.0134
	KES_USD	2.0373	1.0682	0.0531	1.9072	0.0567	0.9956	1.0044
	MAD_USD	-0.7544	0.4563	-0.0535	-1.6533	0.0985	0.7368	1.3572
	ZAR_USD	-0.2288	0.1198	-0.0531	-1.9106	0.0563	0.9967	1.0033
	NGN_USD	-0.5971	6.6241	-0.0025	-0.0901	0.9282	0.9899	1.0102

Table 4.6: Collinearity statistics: dependent variable BTC – Africa

Model		Unstandardized Coef.		Standardized Coef.	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
ACX	(Constant)	0.0022	0.0009		2.5547	0.0107		
	AOA_USD	-0.1978	0.2467	-0.0222	-0.8019	0.4228	0.9967	1.0033
	DZD_USD	0.1881	0.5485	0.0111	0.3430	0.7317	0.7285	1.3728
	EGP_USD	0.1605	0.5334	0.0084	0.3010	0.7635	0.9843	1.0159
	ETB_USD	-0.1812	0.8510	-0.0059	-0.2129	0.8314	0.9868	1.0134
	KES_USD	1.5991	0.8577	0.0516	1.8643	0.0625	0.9956	1.0044
	MAD_USD	1.3445	0.3664	0.1180	3.6700	0.0003	0.7368	1.3572
	ZAR_USD	0.0873	0.0962	0.0251	0.9080	0.3641	0.9967	1.0033
	NGN_USD	3.7475	5.3188	0.0195	0.7046	0.4812	0.9899	1.0102

Table 4.7: Collinearity statistics: dependent variable ETH – Africa

Model		Unstandardized Coef.		Standardized Coef.	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
ACX	(Constant)	0.0031	0.0012		2.5833	0.0099		
	AOA_USD	-0.1197	0.3404	-0.0097	-0.3516	0.7252	0.9967	1.0033
	DZD_USD	0.8368	0.7569	0.0358	1.1056	0.2691	0.7285	1.3728
	EGP_USD	0.2152	0.7360	0.0081	0.2924	0.7700	0.9843	1.0159
	ETB_USD	-0.5659	1.1743	-0.0134	-0.4819	0.6299	0.9868	1.0134
	KES_USD	2.2834	1.1835	0.0535	1.9294	0.0539	0.9956	1.0044
	MAD_USD	1.3605	0.5055	0.0867	2.6914	0.0072	0.7368	1.3572
	ZAR_USD	0.0046	0.1327	0.0010	0.0345	0.9725	0.9967	1.0033

	NGN_USD	11.0129	7.3389	0.0417	1.5006	0.1337	0.9899	1.0102

The results show that 99.67% of the Angolan Kwanza is unique to the variable itself and cannot be accounted for or explained by any other dependent variable (BNB, BTC or ETH). As a result of insignificant collinearity, the standard error is 1.0033 times more. This is the case with all the other dependent variables for AOA as can be observed by the 0.9967 level of tolerance and 1.0033 variance inflationary factor in Tables 4.5 to 4.7. Turning to the independent variable DZD, it is observed from the above table that 72.85% of the DZD is unique to the independent variable itself and it cannot be explained by any other dependent variable (BNB, BTC or ETH). Similarly, the standard error is 1.3728 times more as there is insignificant collinearity. Furthermore, with this variable, the VIF and the tolerance values remain constant for all other dependent variables, BTC and ETH, suggesting that 72.85% of the DZD is unique to it and cannot be explained by BTC and ETH which are dependent variables. The absence of multicollinearity in the case of EGP is also observed from the three collinearity tables (Tables 4.5 to 4.7 above) which results in the standard error being 1.0159 times more for this dependent variable. This is confirmed by the 98.43% which is unique to the EGP and cannot be explained by any other dependent variable. Again, insignificant collinearity for the EGP cuts across all the other models.

The rest of the dependent variables, ETB, KES, MAD, ZAR and NGN demonstrate insignificant multicollinearity whereby 98.68%, 99.56%, 73.68%, 99.67% and 98.99% of the respective dependent variable is unique to itself and is not accounted for or explained by another dependent variable (BNB, BTC or ETH), respectively. With insignificant collinearity, the standard errors for ETB, KES, MAD, ZAR and NGN are 1.0134, 1.0044, 1.3572, 1.0033 and 1.0102 times more, respectively. The coefficients in the regression model are stable and can be deemed reliable. This implies that the results of the regression model can be interpreted with reliability (see Tables 4.5 to 4.7).

4.2.4.2 Variance Inflation Factor – for crypto and South African fiat currencies

In the South African context, 83.00% of the AUD is unique to the variable itself and cannot be accounted for or explained by any other dependent variable, i.e.., BTC (see Table 4.8 below).

Due to insignificant collinearity, the standard error is 1.2048 times more. As demonstrated in Table 4.9 below, the results for the other dependent variable ETH are similar.

Table 4.8: Collinearity statistics: dependent variable BTC – South Africa

Model		Unstandardized Coef.		Standardized Coef.	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
SCX	(Constant)	0.0023	0.0009		2.3867	0.0171		
	AUD_USD	0.6806	0.1869	0.1093	3.6409	0.0003	0.8300	1.2048
	CHF_USD	-0.6338	0.3689	-0.0705	-1.7181	0.0860	0.4442	2.2510
	EUR_USD	0.7106	0.4029	0.0822	1.7638	0.0780	0.3438	2.9084
	GBP_USD	0.6541	0.2666	0.0924	2.4538	0.0143	0.5276	1.8952
	ZAR_USD	0.1005	0.1087	0.0254	0.9248	0.3552	0.9948	1.0052

Table 4.9: Collinearity statistics: dependent variable ETH – South Africa

Model		Unstandardized Coef.		Standardized Coef.	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
SCX	(Constant)	0.0026	0.0012		2.0936	0.0365		
	AUD_USD	1.3116	0.2447	0.1600	5.3593	0.0000	0.8300	1.2048
	CHF_USD	-0.9594	0.4830	-0.0811	-1.9864	0.0472	0.4442	2.2510
	EUR_USD	0.8588	0.5274	0.0755	1.6283	0.1037	0.3438	2.9084
	GBP_USD	0.7433	0.3490	0.0797	2.1299	0.0334	0.5276	1.8952
	ZAR_USD	0.0608	0.1423	0.0116	0.4272	0.6693	0.9948	1.0052

The other dependant variables, CHF, EUR, GBP and ZAR, ZAR and NGN, all demonstrate insignificant multicollinearity, whereby 44.42%, 34.38%, 52.76%, and 99.48% of the respective dependent variable (CHF, EUR, GBP and ZAR, ZAR or NGN) is unique to itself and is not accounted for or explained by another dependent variable (BTC or ETH). The collinearity is insignificant and as a result the standard errors for CHF, EUR, GBP and ZAR, ZAR and NGN are 2.2510, 2.9084, 1.8952 and 1.0052 times more, respectively (see Tables 4.8 and 4.9).

4.2.4 Unit Root Test

Tables 4.10 and 4.11 below depict the outcome of the unit root tests for the study's time series.

4.2.4.1 Unit Root Test hypothesis – for cryptocurrency and African fiat currencies

Table 4.10: Unit root tests results – Africa

UNIT ROOT TEST TABLE (PP)												
At Level												
		BNB	**BTC**	**ETH**	**AOA**	**DZD**	**EGP**	**ETB**	**KES**	**MAD**	**NGN**	**ZAR**
With Const	t-Statistic	-39.0324	-37.2264	-37.4803	-39.3877	-40.3618	-44.5277	-42.1590	-33.0396	-34.7776	-44.4601	-36.4759
	Prob.	0.0000	0.0000	0.0000	0.0000	0.0000	0.0001	0.0000	0.0000	0.0000	0.0001	0.0000

		***	***	***	***	***	***	***	***	***	***	***
With Const & Trend	t-Statistic	-39.0229	-37.2132	-37.5148	-38.6753	-40.4967	-45.7800	-41.9732	-32.6276	-34.7648	-43.9941	-36.4643
	Prob.	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
		***	***	***	***	***	***	***	***	***	***	***
Without Const & Trend	t-Statistic	-38.7024	-37.1100	-37.4098	-41.3224	-39.9711	-44.3862	-48.4720	-35.7147	-34.7906	-42.8954	-36.4754
	Prob.	0.0000	0.0000	0.0000	0.0000	0.0000	0.0001	0.0001	0.0000	0.0000	0.0001	0.0000
		***	***	***	***	***	***	***	***	***	***	***
At First Difference												
		d(BNB)	**d(BTC)**	**d(ETH)**	**d(AOA)**	**d(DZD)**	**d(EGP)**	**d(ETB)**	**d(KES)**	**d(MAD)**	**d(NGN)**	**d(ZAR)**
With Const	t-Statistic	-1075.471	-419.1023	-577.1600	-268.3425	-426.6007	-596.0173	-491.8151	-330.9599	-868.1688	-278.9685	-848.9893
	Prob.	1.0000	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001
		no	***	***	***	***	***	***	***	***	***	***
With Const & Trend	t-Statistic	-1329.128	-418.6447	-579.0614	-268.3627	-426.3929	-594.7875	-495.0064	-331.8844	-930.8804	-278.7524	-909.4356
	Prob.	1.0000	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001
		no	***	***	***	***	***	***	***	***	***	***
Without Const & Trend	t-Statistic	-1030.093	-419.4360	-577.2967	-268.4514	-427.0447	-595.9808	-491.9884	-330.5105	-663.8332	-279.0088	-798.4782

	Prob.	1.0000	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001
		no	***	***	***	***	***	***	***	***	***	***
UNIT ROOT TEST TABLE (ADF)												
At Level												
		BNB	**BTC**	**ETH**	**AOA**	**DZD**	**EGP**	**ETB**	**KES**	**MAD**	**NGN**	**ZAR**
With Const	t-Statistic	-39.0618	-37.2467	-37.4904	-15.9222	-40.3476	-13.2877	-12.2707	-20.8424	-34.7334	-5.3581	-36.4699
	Prob.	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
		***	***	***	***	***	***	***	***	***	***	***
With Const & Trend	t-Statistic	-39.0517	-37.2329	-37.5347	-16.4552	-40.3909	-14.0226	-12.4775	-21.6173	-34.7202	-5.8372	-36.4585
	Prob.	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
		***	***	***	***	***	***	***	***	***	***	***
Without Const & Trend	t-Statistic	-38.7890	-37.0898	-37.3682	-8.6123	-40.1052	-13.1314	-4.5710	-6.3937	-34.7295	-4.1214	-36.4700
	Prob.	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
		***	***	***	***	***	***	***	***	***	***	***
At First Difference												
		d(BNB)	**d(BTC)**	**d(ETH)**	**d(AOA)**	**d(DZD)**	**d(EGP)**	**d(ETB)**	**d(KES)**	**d(MAD)**	**d(NGN)**	**d(ZAR)**
With Const	t-Statistic	-18.2544	-18.6630	-23.3738	-15.6989	-17.5620	-16.8467	-18.9288	-15.7627	-16.9170	-19.0136	-18.3504

	Prob.	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
		***	***	***	***	***	***	***	***	***	***	***
With Const & Trend	t-Statistic	-18.2474	-18.6561	-23.3664	-15.6940	-17.5552	-16.8400	-18.9237	-15.7580	-16.9090	-19.0061	-18.3435
	Prob.	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
		***	***	***	***	***	***	***	***	***	***	***
Without Const & Trend	t-Statistic	-18.2607	-18.6706	-23.3827	-15.7052	-17.5689	-16.8533	-18.9362	-15.7631	-16.9238	-19.0210	-18.3569
	Prob.	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
		***	***	***	***	***	***	***	***	***	***	***
Notes: (*) Significant at the 10% level; (**) Significant at the 5% level; (***) Significant at the 1% level;(no) Not Significant												
*MacKinnon (1996) one-sided p-values.												

The unit root tables above reveal that all the variables (BNB, BTC, ETH, AOA, DZD, EGP, ETB, KES, MAD, NGN and ZAR) are stationary at level on both the Phillips-Perron (PP) and augmented Dickey-Fuller (ADF) test methods. This inference is made from the calculated probability results of less than 0.01 significance levels. Accordingly, the researcher rejects the null hypothesis. With those test results at level which confirm that the data series is stationary for all variables, the researcher saw no merit in applying differencing to confirm stationarity. The unit root test indicates that there is no unit root for the African dataset.

4.2.4.2 Unit Root Test hypothesis – for cryptocurrency and South African fiat currencies

Table 4.11: Unit root tests results – South Africa

UNIT ROOT TEST TABLE (PP)								
At Level								
		BTC	**ETH**	**AUD**	**CHF**	**EUR**	**GBP**	**ZAR**
With Const.	t-Statistic	-36.5258	-37.0358	-36.3782	-34.5869	-35.9922	-35.6948	-36.6886
	Prob.	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
		***	***	***	***	***	***	***
With Const & Trend	t-Statistic	-36.5162	-37.0550	-36.3658	-34.5753	-35.9844	-35.7086	-36.6744
	Prob.	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
		***	***	***	***	***	***	***
Without Const & Trend	t-Statistic	-36.4837	-37.0001	-36.3729	-34.5999	-35.9791	-35.6983	-36.6698
	Prob.	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
		***	***	***	***	***	***	***
At First Difference								
		d(BTC)	**d(ETH)**	**d(AUD)**	**d(CHF)**	**d(EUR)**	**d(GBP)**	**d(ZAR)**

With Const	t-Statistic	-494.9893	-615.1819	-426.3038	-523.3274	-351.4801	-404.9756	-986.2433
	Prob.	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001
		***	***	***	***	***	***	***
With Const & Trend	t-Statistic	-494.2637	-617.5944	-427.8710	-527.2249	-351.3456	-404.5553	-1086.7792
	Prob.	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	1.0000
		***	***	***	***	***	***	n0
Without Const & Trend	t-Statistic	-495.6296	-615.3372	-426.4378	-523.9418	-352.0195	-405.6795	-853.3420
	Prob.	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001
		***	***	***	***	***	***	***
UNIT ROOT TEST TABLE (ADF)								
At Level								
	BTC	**ETH**	**AUD**	**CHF**	**EUR**	**GBP**	**ZAR**	

With Const	t-Statistic	-36.4440	-37.0174	-36.2720	-34.5937	-35.9159	-35.5799	-36.6926
	Prob.	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
		***	***	***	***	***	***	***
With Const & Trend	t-Statistic	-36.4348	-37.0442	-36.2593	-34.5824	-35.9055	-35.5714	-36.6784
	Prob.	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
		***	***	***	***	***	***	***
Without Const & Trend	t-Statistic	-36.3302	-36.9330	-36.2735	-34.6066	-35.9117	-35.5869	-36.6701
	Prob.	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
		***	***	***	***	***	***	***
At First Difference								
		d(BTC)	**d(ETH)**	**d(AUD)**	**d(CHF)**	**d(EUR)**	**d(GBP)**	**d(ZAR)**
With Const	t-Statistic	-18.6629	-18.8025	-19.5405	-17.1265	-18.5079	-16.0438	-19.2051
	Prob.	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
		***	***	***	***	***	***	***

With Const & Trend	t-Statistic	-18.6566	-18.7982	-19.5315	-17.1205	-18.5008	-16.0375	-19.1983
	Prob.	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
		***	***	***	***	***	***	***
Without Const & Trend	t-Statistic	-18.6706	-18.8094	-19.5482	-17.1335	-18.5151	-16.0500	-19.2120
	Prob.	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
		***	***	***	***	***	***	***
Notes: (*) Significant at the 10% level; (**) Significant at the 5% level; (***) Significant at the 1% level; (no) Not Significant								
*MacKinnon (1996) one-sided p-values.								

For the South African dataset, the unit root test outcome shows that all variables (AUD, CHF, EUR, GBP and ZAR) are stationary at level using both the Phillips-Perron (PP) and augmented Dickey-Fuller (ADF) methods of test. The researcher made inferences from the calculated probability results which are below 0.01 significance level. The null hypothesis is accordingly rejected. The researcher found no reason to use differencing to confirm stationarity given these test findings at the level that validates that the data series is stationary for all variables. The unit root test indicates that there is no unit root for the South African dataset.

4.3 Presentation of Results

To probe the connection between cryptocurrencies and the ACX, the researcher used BNB/USD, BTC/USD as well as ETH/USD for the virtual currencies and AOA/USD, DZD/ USD, EGP/ USD, ETB/ USD, KES/ USD, MAD/ USD, NGN/ USD and ZAR/ USD for African fiat currencies. BTC and ETH and other dependent variables AUD, CHF, EUR, GBP and ZAR, all against the USD, were used to assess the link between cryptocurrencies and South African fiat currencies.

4.3.1 Objective 1: The connection between cryptocurrencies (BTC, ETH and BNB) and the fiat currencies in the African context

4.3.1.1 IMF Summary Statistics – Africa

Summary statistics with IMFs are displayed in Table 4.12 below.

Table 4.12: Summary statistics of return series and their IMFs – Africa

Statistic	AOA	AOA_IMF1	AOA_IMF5	AOA_RES	BNB	BNB_IMF1	BNB_IMF5	BNB_RES
Mean	-0.0003	-0.0004	0.0000	-0.0004	0.0044	0.0008	0.0001	-0.0008
Median	-0.0001	0.0000	0.0000	-0.0007	0.0011	0.0019	0.0000	-0.0005
Maximum	0.0626	0.0626	0.0295	0.0050	0.8817	0.8817	0.3289	0.0458
Minimum	-0.0529	-0.0529	-0.0310	-0.0048	-0.4396	-0.4396	-0.3508	-0.0424
Std. Dev.	0.0044	0.0066	0.0042	0.0010	0.0636	0.0527	0.0142	0.0028
Skewness	-0.6010	-0.2269	0.0362	0.9575	2.7015	0.3123	-0.0761	0.0595
Kurtosis	50.3389	17.7777	12.3709	6.7258	43.7528	17.9402	102.4215	21.1431
Jarque-Bera	5323869.0	518959.9	208494.9	41663.7	4012292.0	530860.2	23467817.0	781538.6
Probability	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Sum	-18.04529	-20.76363	2.103186	-25.31999	249.6248	43.54852	5.110512	-47.07099
Sum Sq. Dev.	1.0949	2.4878	1.0073	0.0530	230.3646	158.0186	11.4330	0.4335
Observations	1295	1295	1295	1295	1295	1295	1295	1295
Statistic	**BTC**	**BTC_IMF1**	**BTC_IMF5**	**BTC_RES**	**DZD**	**DZD_IMF1**	**DZD_IMF5**	**DZD_RES**
Mean	0.0011	-0.0002	0.0000	-0.0007	-0.0006	-0.0001	0.0000	-0.0001
Median	-0.0002	-0.0006	0.0000	-0.0007	-0.0009	-0.0001	0.0000	-0.0001
Max	0.2138	0.2138	0.1877	0.0223	0.0136	0.0136	0.0079	0.0011

Min	-0.3818	-0.3818	-0.1821	-0.0225	-0.0133	-0.0133	-0.0080	-0.0011
Std. Dev.	0.0399	0.0349	0.0144	0.0041	0.0016	0.0020	0.0013	0.0003
Skewness	-0.2947	-0.0709	-0.0581	0.2171	0.6788	-0.1033	-0.0284	0.2459
Kurtosis	12.0300	7.1965	18.3104	6.1969	12.4009	5.9997	6.5685	3.2232
Jarque-Bera	194414.7	41858.8	556559.5	24712.3	214196.0	21464.5	30240.8	692.6
Prob	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Sum	63.1970	-11.5220	0.2161	-38.2076	-34.1790	-3.8593	0.0205	-6.3035
Sum Sq. Dev.	90.5696	69.5726	11.8790	0.9485	0.1391	0.2318	0.0920	0.0048
Obs	1295	1295	1295	1295	1295	1295	1295	1295

Statistic	**EGP**	**EGP_IMF1**	**EGP_IMF5**	**EGP_RES**	**ETB**	**ETB_IMF1**	**ETB_IMF5**	**ETB_RES**
Mean	-0.0003	-0.0002	0.0000	-0.0002	-0.0003	-0.0004	0.0000	-0.0001
Median	0.0000	0.0000	0.0000	-0.0002	-0.0003	-0.0002	0.0000	-0.0001
Max	0.0134	0.0620	0.0620	0.0067	0.0177	0.0177	0.0125	0.0014
Min	-0.1487	-0.1487	-0.0577	-0.0081	-0.0288	-0.0288	-0.0112	-0.0016
Std. Dev.	0.0050	0.0061	0.0037	0.0009	0.0017	0.0039	0.0029	0.0005
Skewness	-22.7228	-10.0740	-0.9759	1.0251	-2.8279	-0.9774	0.0077	-0.0893
Kurtosis	619.5989	244.7890	137.8672	33.9293	68.4290	12.1849	6.5893	2.9310
Jarque-Bera	908000000.0	140000000.0	43193130.0	2281158.0	10239636.0	209363.5	30588.0	86.9
Prob	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Sum	-18.1903	-12.7232	-1.2380	-12.3283	-17.4965	-23.5798	-0.2659	-8.1816
Sum Sq. Dev.	1.4132	2.1207	0.7878	0.0479	0.1711	0.8624	0.4646	0.0137
Obs.	1295	1295	1295	1295	1295	1295	1295	1295
Statistic	**ETH**	**ETH_IMF1**	**ETH_IMF5**	**ETH_RES**	**KES**	**KES_IMF1**	**KES_IMF5**	**KES_RES**
Mean	0.00161	0.00035	-0.00025	-0.00121	-0.00084	-0.00021	-0.00002	-0.00004
Median	-0.00035	-0.00058	-0.00057	-0.00116	-0.00089	-0.00010	-0.00001	-0.00002
Max	0.43082	0.43082	0.22176	0.03225	0.01603	0.01603	0.00530	0.00162
Min	-0.44703	-0.44703	-0.23483	-0.02937	-0.00928	-0.00928	-0.00567	-0.00165
Std. Dev.	0.05095	0.04899	0.02332	0.00627	0.00054	0.00161	0.00103	0.00036
Skewness	0.23796	0.12684	0.08041	0.18268	6.05934	1.04861	-0.17048	0.19490
Kurtosis	13.72789	7.86390	13.84528	5.37980	151.75520	15.95277	6.27754	7.46785
Jarque-Bera	273775.0	56319.6	279311.4	13762.9	52884498.0	408766.5	25780.0	47753.1
Prob	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
Sum	91.96563	19.69458	-14.41939	-68.79037	-47.79251	-11.83114	-1.20236	-2.40665
Sum Sq. Dev.	147.90490	136.72840	30.99684	2.23949	0.01650	0.14828	0.05999	0.00725
Obs	1295	1295	1295	1295	1295	1295	1295	1295
Statistic	**MAD**	**MAD_IMF1**	**MAD_IMF5**	**MAD_RES**	**NGN**	**NGN_IMF1**	**NGN_IMF5**	**NGN_RES**

Mean	-0.0004	0.0000	0.0000	0.0000	-0.0003	-0.0002	0.0000	-0.0003
Median	-0.0006	0.0000	0.0000	-0.0001	0.0000	0.0000	0.0000	-0.0002
Max	0.0201	0.0201	0.0079	0.0023	0.0333	0.0795	0.0795	0.0020
Min	-0.0177	-0.0177	-0.0077	-0.0023	-0.1774	-0.1774	-0.0803	-0.0024
Std. Dev.	0.0018	0.0031	0.0020	0.0005	0.0054	0.0068	0.0039	0.0004
Skewness	0.4364	-0.0946	-0.0539	0.3663	-19.0596	-5.5720	-1.5668	0.6261
Kurtosis	21.7255	6.5511	4.4189	7.4614	609.2901	168.5414	193.1960	7.9061
Jarque-Bera	834293.4	30024.7	4807.7	48529.3	876000000.0	65356424.0	85907634.0	60866.9
Prob	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Sum	-25.3312	-2.5702	0.1009	-2.3257	-18.1345	-11.5960	-2.4116	-15.0839
Sum Sq. Dev.	0.1855	0.5559	0.2326	0.0119	1.6482	2.6524	0.8616	0.0081
Obs.	1295	1295	1295	1295	1295	1295	1295	1295

Statistic	**ZAR**	**ZAR_IMF1**	**ZAR_IMF5**	**ZAR_RES**				
Mean	-0.0000	-0.0003	0.0000	-0.0000				
Median	-0.0001	0.0003	0.0001	-0.0001				
Max	0.8817	0.0288	0.0205	0.0032				
Min	-0.4470	-0.0405	-0.0201	-0.0035				
Std. Dev.	0.0194	0.0098	0.0071	0.0013				
Skewness	2.6740	-0.3119	0.0022	-0.0283				

Kurtosis	174.7105	3.6001	2.3922	2.4444				
Jarque-Bera	70 069 047.0	1 779.1	877.0	740.5				
Prob	0.0000	0.0000	0.0000	0.0000				
Sum	- 1.5614	- 18.3941	1.3612	- 2.5195				
Sum Sq. Dev.	21.3618	5.4327	2.9124	0.0945				
Obs.	1295	1295	1295	1295				

The IMF summary statistic results in Table 4.12 above for the African data series affirm that the data is not normally distributed and also affirm the earlier statistical inference to use the quantile regression model for this study. Similar to the studies by Kumah (2023) and Y. Wang et al. (2023), IMF data is presented for the IMF1, IMF5 and IMF residuals to represent short-, medium- and long-term dynamics.

4.3.1.2 Quantile regression model (QR Model) – Africa

The quantile regression model results are presented and discussed below.

Table 4.13: Quantile regression output – Africa

Method: Quantile Regression									
Huber Sandwich Standard Errors and Covariance									
Sparsity method: Kernel (Epanechnikov) using residuals									
Bandwidth method: Hall-Sheather, bw=0.025248									
Estimation successfully identifies unique optimal solution									
Dep Variable	**BNB**			**BTC**			**ETH**		
Indep. Variable	**Coef.**	**Prob.**	***S or I***	**Coef.**	**Prob.**	***S or I***	**Coeff.**	**Prob.**	***S or I***
AOA	-0.1213	0.0000	*S*	-0.2696	0.0000	*S*	-0.0725	0.1758	*I*
AOA_IMF1	0.0553	0.0186	*S*	0.0916	0.0000	*S*	-0.0002	0.9680	*I*
AOA_IMF5	-0.0613	0.0279	*S*	-0.1406	0.0000	*S*	0.0002	0.9766	*I*
AOA_RES	-0.5723	0.0000	*S*	-0.2545	0.0012	*S*	0.0005	0.9858	*I*
DZD	-0.0471	0.7413	*I*	1.5630	0.0000	*S*	0.8097	0.0000	*S*
DZD_IMF1	-0.3577	0.0003	*S*	-0.2106	0.0047	*S*	0.0003	0.9902	*I*
DZD_IMF5	0.2043	0.0727	*I*	0.3487	0.0001	*S*	-0.0001	0.9956	*I*
DZD_RES	-0.4538	0.2692	*I*	0.1036	0.7444	*I*	-0.0026	0.9812	*I*
EGP	-0.0786	0.0000	*S*	0.0320	0.3033	*I*	0.1392	0.0000	*S*
EGP_IMF1	-0.0551	0.0015	*S*	0.1180	0.0003	*S*	0.0002	0.9683	*I*
EGP_IMF5	-0.0392	0.1235	*I*	-0.0226	0.0364	*S*	-0.0002	0.9718	*I*
EGP_RES	-0.0059	0.9254	*I*	-0.2709	0.0035	*S*	-0.0004	0.9791	*I*
ETB	-0.4944	0.0015	*S*	-0.1051	0.1493	*I*	0.0017	0.9859	*I*
ETB_IMF1	0.0277	0.5143	*I*	-0.0404	0.1269	*I*	0.0001	0.9930	*I*
ETB_IMF5	-0.2168	0.0000	*S*	0.0864	0.0117	*S*	-0.0001	0.9960	*I*
ETB_RES	-0.7068	0.0136	*S*	-0.2407	0.1980	*I*	-0.0004	0.9960	*I*

KES	1.3028	0.0142	*S*	0.8571	0.0013	*S*	1.2833	0.0000	*S*
KES_IMF1	0.3717	0.0092	*S*	-0.2852	0.0000	*S*	-0.0002	0.9921	*I*
KES_IMF5	-0.1752	0.3357	*I*	0.9821	0.0000	*S*	0.0012	0.9707	*I*
KES_RES	0.5182	0.1842	*I*	2.9857	0.0000	*S*	0.0032	0.9693	*I*
MAD	-0.1989	0.1012	*I*	-0.0835	0.3898	*I*	1.2302	0.0000	*S*
MAD_IMF1	-0.1755	0.0016	*S*	0.4362	0.0000	*S*	0.0004	0.9783	*I*
MAD_IMF5	0.2374	0.0021	*S*	-0.1778	0.0018	*S*	-0.0002	0.9884	*I*
MAD_RES	1.6554	0.0000	*S*	0.8450	0.0000	*S*	0.0018	0.9752	*I*
NGN	-0.4169	0.0000	*S*	-0.1013	0.0000	*S*	0.0687	0.3313	*I*
NGN_IMF1	0.1321	0.0018	*S*	0.0130	0.3767	*I*	0.0002	0.9650	*I*
NGN_IMF5	-0.0053	0.7830	*I*	-0.0041	0.7494	*I*	-0.0001	0.9864	*I*
NGN_RES	-0.7528	0.0013	*S*	0.1768	0.2529	*I*	-0.0024	0.9719	*I*
ZAR	-0.0038	0.0787	*I*	0.0431	0.0000	*S*	0.0000	0.9986	*I*
ZAR_IMF1	0.0552	0.0057	*S*	0.1142	0.0000	*S*	0.0001	0.9763	*I*
ZAR_IMF5	-0.2282	0.0000	*S*	-0.0347	0.0674	*I*	-0.0001	0.9859	*I*
ZAR_RES	0.1333	0.2381	*I*	-0.1308	0.0864	*I*	0.0000	0.9987	*I*
C	0.0016	0.0012	*S*	0.0012	0.0000	*S*	0.0023	0.0000	*S*
Where *S* = Statistically significant, *I* = Statistically insignificant									

4.3.1.3 Impact on BNB due to African fiat currency exchange

The quantile regression results in Table 4.13 above show that, for BNB, AOA, EGP, ETB and NGN are significant with a P value of less than 0.05. DZD, MAD and ZAR are not significant as the P value is more than 0.05. A 1% appreciation in the value of AOA, EGP, and NGN results in a 0.1213%, 0.0786%, 0.4944% and 0.4169% decrease, respectively in BNB. In addition, for every 1% appreciation in the value of KES, the value of BNB increases by 1.3028%. Accordingly, AOA, EGP, ETB and NGN are negatively connected to BNB while KES exhibits an inverse relationship with BNB. Finally, the QR tests results show that there is no significant connection between BNB and the other independent variables (MAD, DZD and ZAR). This implies that in the case of BNB with MAD, DZD and ZAR, we reject the alternative

hypothesis; however, in the case of BNB with AOA, EGP, NGN and KES, the null hypothesis is renounced.

4.3.1.4 Impact on BTC due to African fiat currency exchange

The results show that in terms of BTC, the P value is significant for AOA, DZD, KES, NGN and ZAR (see Table 4.13 above). In contrast, EGP and MAD are not significant as the P value is more than 0.05. If there is a 1% increase in the value of AOA and NGN, there is a 0.2696% and 0.1013% respective decrease in the value of BTC. However, for every 1% increase in DZD, KES and ZAR, the value of BTC increases by 1.5630%, 0.8571% and 0.0431%, respectively. In terms of the results in Table 4.14 below, BTC exhibits an inverse relationship between AOA and NGN while it shows a positive relationship with DZD, EGP, KES and ZAR. Therefore, the alternative hypothesis is repudiated for the link between BTC and the independent variables (EGP, ETB and MAD) but the null hypothesis is rejected for the connection between BTC and the other independent variables (AOA, NGN, KES, DZD and ZAR).

4.3.1.5 Impact on ETH due to African fiat currency exchange

Lastly, the quantile regression results in Table 4.13 above reveal that, in terms of ETH, the P value is significant for DZN, EGP, KES and MAD, while it is not significant for AOA, ETB, NGN and ZAR, with a P value of more than 0.05. This implies that the null hypothesis is renounced for DZN, EGP, KES and MAD, while the alternative hypothesis is repudiated for AOA, ETB, NGN and ZAR. The results indicate that when DZN, EGP, KES and MAD increase by 1% each, ETH reacts by 0.8097%, 0.1392%, 1.2833% and 1.2302%, respectively, all in the positive direction. Accordingly, there is positive relationship between BTC and the dependent variables (DZN, EGP, KES and MAD).

4.3.1.6 Jarque-Bera normality test – Africa

The Jarque-Bera test output is presented below:

Jarque-Bera Test results

Figure 4.1: Jarque-Bera normality test

BNB = β0 + β (ACXi,t) + εi,t

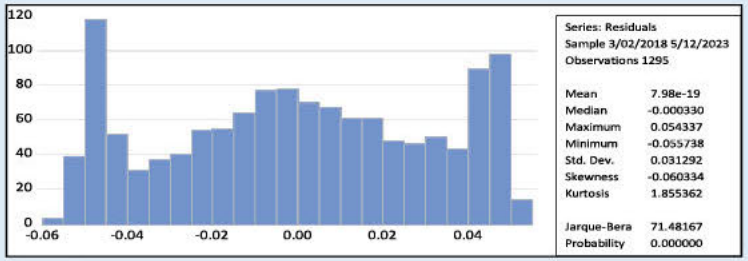


Figure 1

BTC = β0 + β (ACXi,t) + εi,t

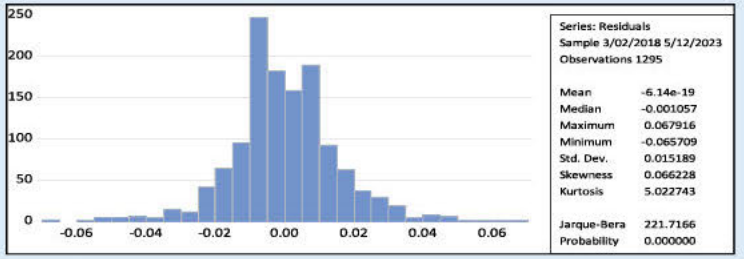


Figure 2

ETH = β0 + β (ACXi,t) + εi,t

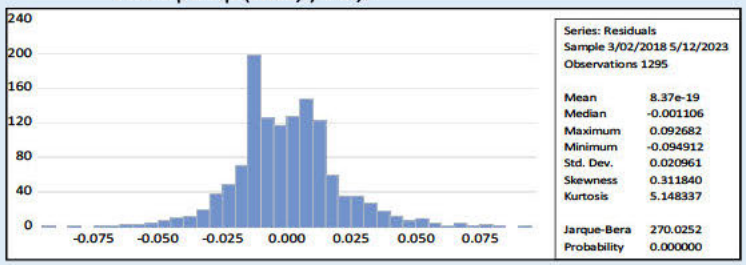


Figure 3

BTC = β0 + β (SCXi,t) + εi,t

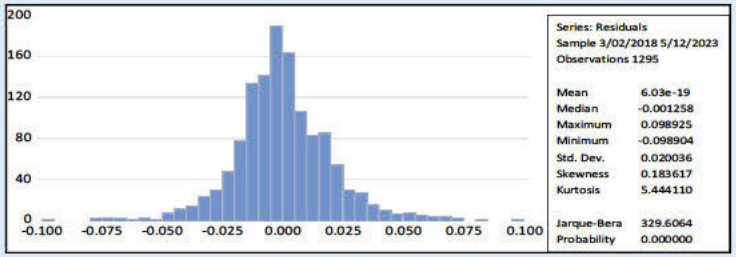


Figure 4

ETH = β0 + β (SCXi,t) + εi,t

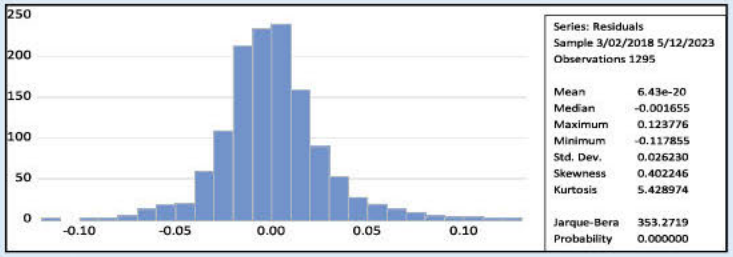


Figure 5

The Jarque-Bera test results in Figure 4.1 above indicate that all P values are less than 0.05 and accordingly, the null hypothesis for objective 1 is rejected. Given that the P value is less than 0.05 for all the models, the researcher inferred that the residuals are not normally distributed (Nyakurukwa & Seetharam, 2023b; Tiwari et al., 2020). These results corroborate that the data series is asymmetric, which provide the basis for the use of quantile regression to analyse the return on cryptocurrencies and fiat currencies to investigate the connection between the crypto and fiat currencies in Africa. Our approach is corroborated by research on a similar topic by Kumah (2023).

4.3.1.7 Quantile process estimates – Africa

The quantile process results in Table 4.14 illustrate that the P value is significant at various levels of quantiles, while not significant at some quantiles.

Table 4.14: Quantile process estimates results - Africa

Quantile Process Estimates				
Estimated equation quantile tau = 0,5				
Number of process quantiles: 10				
Variables		**BNB**	***BTC***	***ETH***
	Quantile	**Coefficient**	**Coefficient**	**Coefficient**
AOA	0.1	0.5391	-0.1706	-0.0565
	0.2	0.2868	-0.0195	0.2610
	0.3	0.1213	-0.0864	0.1753
	0.4	-0.0444	-0.1319	0.0272
	0.5	-0.1213	-0.2696	-0.0142
	0.6	-0.0653	-0.2707	-0.0754
	0.7	-0.0121	-0.2177	-0.1813
	0.8	-0.0399	-0.3577	-0.2807
	0.9	-0.2249	-0.2168	-0.0544
AOA_IMF1	0.1	0.3825	-0.5921	-0.3458
	0.2	0.1947	-0.2438	-0.2814
	0.3	0.0625	-0.0813	-0.1641

	0.4	0.0363	0.0179	-0.0294
	0.5	0.0553	0.0916	-0.0177
	0.6	0.0633	0.0815	0.0262
	0.7	0.1253	0.0407	0.1216
	0.8	0.1221	0.0535	0.2142
	0.9	0.0364	0.1651	0.3531
AOA_IMF5	0.1	0.4215	0.3395	0.1388
	0.2	0.2935	0.1524	0.2162
	0.3	0.0476	0.0526	0.1664
	0.4	-0.0342	-0.0460	0.0198
	0.5	-0.0613	-0.1406	0.0149
	0.6	-0.0576	-0.1374	-0.0325
	0.7	-0.0732	-0.1236	-0.0906
	0.8	0.0654	-0.1681	-0.2270
	0.9	-0.1364	-0.2201	-0.1476
AOA_RESIDUAL	0.1	3.6865	4.8215	7.0903
	0.2	1.7689	1.8209	3.9065
	0.3	0.7498	0.6100	1.7427
	0.4	0.1924	0.1177	0.2055
	0.5	-0.5723	-0.2545	0.0190
	0.6	-1.3575	-0.9701	-0.3248
	0.7	-2.1106	-1.7082	-1.9072
	0.8	-2.3669	-2.9113	-3.8179
	0.9	-3.5451	-4.7139	-6.1239
DZD	0.1	1.0150	0.1492	-0.2966
	0.2	0.1834	0.2241	0.1728
	0.3	-0.3541	0.3447	0.2549
	0.4	-0.4950	1.1021	-0.0399
	0.5	-0.0471	1.5630	0.6254
	0.6	-0.3177	1.4268	2.3263
	0.7	-0.2215	1.3154	2.9397
	0.8	-0.0709	0.9565	2.7177

	0.9	-0.2868	1.1312	2.5391
DZD_IMF1	0.1	-0.6437	-0.9660	-1.8258
	0.2	-0.5975	-0.1223	-0.1459
	0.3	-0.6005	-0.3300	0.0569
	0.4	-0.2205	-0.3182	0.0333
	0.5	-0.3577	-0.2106	0.0076
	0.6	-0.5197	-0.0227	-0.0501
	0.7	-0.3424	0.1218	-0.2251
	0.8	0.1569	0.3229	-0.1205
	0.9	-0.8057	0.7694	0.9187
DZD_IMF5	0.1	1.3675	0.7138	-0.0000
	0.2	0.4979	0.1720	0.5225
	0.3	0.2042	0.2009	0.3374
	0.4	0.0508	0.3624	-0.0193
	0.5	0.2043	0.3487	0.0003
	0.6	0.2639	0.1138	0.0721
	0.7	0.3692	0.0693	0.2644
	0.8	0.0379	0.3588	0.4675
	0.9	-1.2396	0.1683	0.5686
DZD_RESIDUAL	0.1	1.5623	1.9591	1.5522
	0.2	2.2764	1.8110	5.5088
	0.3	1.0411	1.7679	2.5509
	0.4	0.1910	1.3146	0.4837
	0.5	-0.4538	0.1036	-0.2762
	0.6	0.8831	0.0657	-2.3528
	0.7	2.6383	-0.8527	-6.6967
	0.8	4.6125	0.9407	-9.2232
	0.9	2.6042	-1.2672	-3.5803
EGP	0.1	-0.2871	-0.1378	-0.1190
	0.2	-0.3022	-0.0760	-0.0578
	0.3	-0.2141	0.0080	0.0026
	0.4	-0.0987	0.0502	0.0948

	0.5	-0.0786	0.0320	0.1254
	0.6	-0.0840	0.1164	0.1346
	0.7	-0.0667	0.2026	0.0781
	0.8	0.0231	0.2494	0.2077
	0.9	0.1660	0.3344	0.2282
EGP_IMF1	0.1	-0.3102	0.3150	0.1685
	0.2	-0.0373	0.1945	0.0366
	0.3	-0.0198	0.1451	0.1092
	0.4	-0.1225	0.1223	0.0175
	0.5	-0.0551	0.1180	0.0367
	0.6	0.0147	0.1019	0.0732
	0.7	0.0725	0.0798	0.0957
	0.8	0.0955	0.1261	0.2508
	0.9	0.2329	-0.0466	0.2394
EGP_IMF5	0.1	0.5127	-0.4228	-0.6132
	0.2	0.1862	-0.2760	-0.2821
	0.3	0.0843	-0.1330	-0.1315
	0.4	0.0217	-0.0894	-0.0141
	0.5	-0.0392	-0.0226	-0.0269
	0.6	-0.1191	0.0169	-0.0869
	0.7	-0.1933	0.0616	-0.0760
	0.8	-0.0152	-0.0627	-0.2654
	0.9	0.1472	0.2083	-0.0391
EGP_RESIDUAL	0.1	1.9332	-2.8086	1.0834
	0.2	0.3021	-1.3086	0.9536
	0.3	0.6456	-0.6477	0.3915
	0.4	0.4097	-0.6231	-0.0045
	0.5	-0.0059	-0.2709	-0.0629
	0.6	-0.4697	-0.0272	-0.2243
	0.7	-1.3094	-0.3102	-0.6097
	0.8	-1.7079	-0.7907	-1.4660
	0.9	-0.5529	0.7698	-2.8086

ETB	0.1	-0.7286	-0.3020	-0.5153
	0.2	-0.6357	-0.0539	-0.3448
	0.3	-0.4309	-0.0812	-0.2560
	0.4	-0.3843	-0.2253	-0.3048
	0.5	-0.4944	-0.1051	-0.2997
	0.6	-0.1524	-0.1927	-0.1725
	0.7	-0.0239	-0.1934	-0.1087
	0.8	-0.2403	-0.1077	-0.1740
	0.9	0.2156	0.4439	0.3297
ETB_IMF1	0.1	0.4950	-0.1433	0.3878
	0.2	0.4815	-0.0063	-0.0940
	0.3	0.0954	-0.0058	-0.0900
	0.4	0.0459	-0.0242	-0.0259
	0.5	0.0277	-0.0404	0.0107
	0.6	0.0298	0.0133	0.0346
	0.7	0.0804	-0.0366	0.0034
	0.8	0.1659	0.0154	0.0363
	0.9	-0.1774	0.7157	-0.5365
ETB_IMF5	0.1	-1.3070	0.1117	-0.2733
	0.2	-1.1784	0.0337	-0.0580
	0.3	-0.6859	0.0002	0.0746
	0.4	-0.3033	0.0199	0.0212
	0.5	-0.2168	0.0864	-0.0057
	0.6	-0.4164	0.0919	-0.0382
	0.7	-0.7597	0.2289	0.0266
	0.8	-0.7547	-0.1408	0.0988
	0.9	-1.0985	-0.1995	0.6116
ETB_RESIDUAL	0.1	-8.3409	-3.6126	-9.5518
	0.2	-5.0411	-1.0703	-1.2072
	0.3	-2.6246	-0.8598	0.3720
	0.4	-2.0222	-0.5467	0.0762
	0.5	-0.7068	-0.2407	-0.0906

	0.6	-0.4950	-0.6020	-0.6611
	0.7	-1.0791	-0.8622	-0.8324
	0.8	-2.0912	-1.8450	-0.0854
	0.9	-4.7057	-3.6360	2.9060
KES	0.1	-0.8976	2.0153	-0.3435
	0.2	-0.4374	0.9367	0.2452
	0.3	-0.0227	0.4486	0.0541
	0.4	0.0736	0.7618	-0.5255
	0.5	1.3028	0.8571	1.2044
	0.6	1.4544	1.7494	2.1169
	0.7	1.8017	1.3620	2.2412
	0.8	1.4256	1.4372	2.0823
	0.9	3.5136	0.4526	3.1782
KES_IMF1	0.1	-0.6884	1.1038	-0.9426
	0.2	-0.0363	-0.0716	-0.5086
	0.3	0.3613	-0.3755	-0.2578
	0.4	0.3070	-0.3013	-0.0134
	0.5	0.3717	-0.2852	0.0736
	0.6	1.2231	-0.2081	0.1623
	0.7	2.0959	0.3266	0.5019
	0.8	2.1515	0.2211	0.9548
	0.9	1.9574	-0.4021	2.3914
KES_IMF5	0.1	0.6330	2.7033	4.6888
	0.2	-0.7062	1.9761	1.8408
	0.3	-0.3056	1.2191	1.1018
	0.4	-0.3075	0.8392	0.1912
	0.5	-0.1752	0.9821	0.0246
	0.6	-0.2260	1.2203	0.0694
	0.7	-0.0606	0.8649	0.8219
	0.8	-0.9118	2.0824	1.0355
	0.9	0.3236	2.6361	-1.7239
KES_RESIDUAL	0.1	-1.1543	10.3390	12.2836

	0.2	4.1716	8.4640	9.7836
	0.3	2.4672	5.3734	5.3163
	0.4	0.4558	3.2590	0.7427
	0.5	0.5182	2.9857	0.1003
	0.6	0.3367	4.5456	0.5980
	0.7	1.8706	3.2100	2.3358
	0.8	4.1036	4.5090	3.6982
	0.9	16.7046	3.9547	1.2661
MAD	0.1	-0.9120	0.7269	-0.0925
	0.2	-0.5037	0.2818	-0.1110
	0.3	-0.3091	0.3468	0.0188
	0.4	-0.4501	0.0462	-0.2020
	0.5	-0.1989	-0.0835	-0.1412
	0.6	0.2715	0.4531	0.3623
	0.7	0.2671	0.5405	0.4038
	0.8	-0.1467	0.6043	0.2288
	0.9	-0.2012	0.7811	0.2899
MAD_IMF1	0.1	-0.7457	1.1983	1.5369
	0.2	-0.5514	0.9450	0.9898
	0.3	-0.3810	0.7095	0.4584
	0.4	-0.3279	0.5577	0.0111
	0.5	-0.1755	0.4362	0.0374
	0.6	-0.0809	0.3493	0.1483
	0.7	-0.3552	0.5676	0.5398
	0.8	-1.0652	1.0989	0.7224
	0.9	-0.9932	0.5009	0.0547
MAD_IMF5	0.1	-0.0648	-0.4856	-0.9037
	0.2	0.0510	-0.4310	-0.2517
	0.3	0.1858	-0.2793	-0.1441
	0.4	0.2499	-0.2769	0.0009
	0.5	0.2374	-0.1778	-0.0232
	0.6	0.3795	-0.2428	-0.0971

	0.7	0.5429	-0.2354	-0.2109
	0.8	0.7481	-0.4135	0.2501
	0.9	1.1483	0.3282	0.2553
MAD_RESIDUAL	0.1	10.9158	4.6950	10.5265
	0.2	7.3439	2.4151	3.0429
	0.3	2.8808	1.2604	1.7517
	0.4	2.1522	0.9087	0.2077
	0.5	1.6554	0.8450	0.1075
	0.6	1.0747	-0.0922	0.3870
	0.7	2.7432	-1.2455	0.1754
	0.8	-0.0217	-3.6315	2.3324
	0.9	-2.1447	0.9510	0.0289
NGN	0.1	1.0592	0.6160	0.8376
	0.2	0.2512	0.0544	0.1528
	0.3	-0.1246	-0.1527	-0.1386
	0.4	-0.3352	-0.1320	-0.2336
	0.5	-0.4169	-0.1013	-0.2591
	0.6	-0.4528	-0.0934	-0.2731
	0.7	-0.6418	-0.0781	-0.3600
	0.8	-0.5174	-0.0289	-0.2732
	0.9	-0.3291	0.1148	-0.1071
NGN_IMF1	0.1	0.1016	0.2449	0.1114
	0.2	0.4083	0.0118	0.0457
	0.3	0.1578	0.0728	0.0713
	0.4	0.0847	0.0414	0.0575
	0.5	0.1321	0.0130	0.0290
	0.6	0.2013	0.0715	0.1077
	0.7	0.2982	0.1003	0.1963
	0.8	0.3112	0.1347	0.1215
	0.9	0.0091	0.1153	0.2572
NGN_IMF5	0.1	0.1407	0.1281	-0.1261
	0.2	0.2365	-0.0320	-0.1499

	0.3	0.0371	-0.0121	-0.0908
	0.4	-0.0046	-0.0249	-0.0165
	0.5	-0.0053	-0.0041	-0.0045
	0.6	0.0824	-0.0430	-0.0015
	0.7	0.1932	-0.0093	0.0563
	0.8	0.1486	0.0021	0.1383
	0.9	-0.2224	0.1156	0.0187
NGN_RESIDUAL	0.1	4.0666	6.9536	18.1221
	0.2	3.4338	7.1834	11.5379
	0.3	1.5724	4.2817	6.5678
	0.4	0.8327	2.2435	1.0013
	0.5	-0.7528	0.1768	-0.1733
	0.6	-3.4602	-2.4085	-4.0347
	0.7	-3.2581	-6.1700	-10.9516
	0.8	-1.6652	-9.1162	-14.2876
	0.9	-0.0570	-12.6218	-21.6550
ZAR	0.1	0.0437	0.2182	0.1310
	0.2	0.0261	0.1359	0.0810
	0.3	0.0142	0.0659	0.0400
	0.4	0.0007	0.0440	0.0223
	0.5	-0.0038	0.0431	0.0197
	0.6	-0.0128	0.0546	0.0209
	0.7	-0.0299	0.0999	0.0350
	0.8	-0.0461	0.1757	0.0648
	0.9	-0.0848	0.2696	0.0924
ZAR_IMF1	0.1	0.5707	0.6627	0.2613
	0.2	0.1586	0.1557	0.2326
	0.3	-0.0549	0.0981	0.0785
	0.4	0.0198	0.0916	0.0130
	0.5	0.0552	0.1142	0.0107
	0.6	0.0616	0.0795	0.0242
	0.7	0.1629	0.1053	0.0815

	0.8	0.4602	0.1592	0.1830
	0.9	0.5709	0.1173	0.1310
ZAR_IMF5	0.1	-1.1593	-0.5362	-0.1050
	0.2	-0.6886	-0.1200	-0.1082
	0.3	-0.4331	-0.0752	-0.0708
	0.4	-0.2651	-0.0332	-0.0030
	0.5	-0.2282	-0.0347	-0.0044
	0.6	-0.4273	-0.0277	-0.0101
	0.7	-0.8028	-0.0372	-0.1215
	0.8	-0.9999	-0.1793	-0.4194
	0.9	-1.2644	-0.1118	-0.5014
ZAR_RESIDUAL	0.1	-2.4793	-2.4566	-1.9806
	0.2	-0.1531	-0.9569	-1.1046
	0.3	0.5133	-0.4603	-0.4772
	0.4	0.6387	-0.2843	-0.0435
	0.5	0.1333	-0.1308	-0.0139
	0.6	0.4822	-0.3285	-0.1283
	0.7	0.7801	-0.7013	-0.6416
	0.8	-0.2019	-1.1907	-0.8561
	0.9	-1.5052	-3.0463	0.3272
C	0.1	-0.0489	-0.0331	-0.0387
	0.2	-0.0253	-0.0153	-0.0157
	0.3	-0.0122	-0.0075	-0.0064
	0.4	-0.0045	-0.0026	-0.0014
	0.5	0.0016	0.0012	0.0014
	0.6	0.0083	0.0064	0.0050
	0.7	0.0193	0.0106	0.0105
	0.8	0.0336	0.0195	0.0221
	0.9	0.0591	0.0383	0.0464

4.3.1.8 Impact on BNB due to African fiat currency exchange (see Table 4.14)

For AOA at the 10th quantile level, BNB increases by 0.5391%, then decreases to 0.2868% in the 20th quantile and drops further to 0.1213% in the 30th quantile. At the 40th, 70th and 80th quantiles, the P value is not significant. From the 50th quantile, BNB starts to experience an inverse relationship with AOA where it decreases by 0.1213%, and by 0.0653% in the 60th quantile. In the 90th quantile, the negative relationships become stronger as BNB decreases to 0.2349%.

As shown in Table 4.14, for DZD, in the case of the 10th quantile, BNB increases to 1.0150%, then in the 30th and 40th quantiles to 0.3541% and 0.4950%, respectively. Only in the 10th quantile do BNB and DZD show a positive relationship, contrary to the 30th and 40th quantiles where there is a negative relationship. For the rest of the quantiles, the P value is not significant as the value is more than 0.05.

For EGP, the P value is significant for all quantiles except for the 80th quantile, as tabulated in Table 4.14 above. BNB decreases to -0.2871% and further to -0.3022% in the 10th and 20th quantiles, respectively. From the 30th to the 50th quantiles, it starts to increase slightly from -0.2141% to -0.0786%. From this point it goes down slightly to -0.0840% in the 60th quantile and then starts to increase in the 70th to 90th quantiles from -0.0667% to 0.1660%. BNB and EGP mainly show a negative relationship.

For ETB, BNB decreases to -0.7286% in the 10th quantile and then shows an increase to -0.6357% in the 20th quantile and to -0.3843 in the 40th quantile and finally drops to 0.4944% in the 50th quantile. In all other quantiles the P value for ETB is not significant. There is a negative relationship between BNB and ETB.

For KES, BNB increases to 1.3028% in the 50th quantile and then increases to 1.4544% and 1.8017% in the 60th and 70th quantiles, respectively. It drops slightly to 1.4256% in the 80th quantile and then increases to 3.5136%. The relationship between BNB and KES is positive.

As Table 4.14 indicates, the P value in the first four quantiles (10th, 20th 30th and 40th) is not significant.

For MAD, in the case of the 10th quantile, BNB decreases to -0.9120%, then increases to -0.5037% and -0.3091% in the 20th and 30th quantiles, respectively. It drops slightly to -0.4501% in the 40th quantile and then moves up to 0.2715% in the 60th and drops to 0.2671% in the 70th quantile. The relationship between BNB and MAD is mainly negative.

For NGN, in the case of the 10th quantile, BNB increases to 1.0592%, then drops to 0.2512% in the 20th quantile, right down to -0.6418% in the 70th quantile and eventually starts to increase to 0.5174% in the 80th quantile and to -0.3291% in the 90th quantile. As demonstrated in Table 4.14, the P value is significant for all quantiles and there a negative relationship between BNB and NGN.

For ZAR, in the 10th quantile, BNB increases to 0.0437% and then drops to 0.0261% in the 20th. After this point it drops all the way down to -0.0848% in the 90th quantile. The P value is not significant from the 40th and 50th quantiles and the relationship between BNB and ZAR is negative.

The output for the quantile process estimates is tabled in Table 4.14 above which indicates the relationship between BNB and AOA. BNB is positively connected to AOA at the 10th, 20th and 30th quantiles and then from the 50th, 60th and 90th, the relationship is negative. For DSD, BNB exhibits a positive relationship only at the 10th quantile and shows a negative relationship in the 30th and 40th quantiles. From the 10th quantile up to the 70th quantile, BNB is negatively correlated with EGP. However, in the 90th quantile, the relationship shows an inverse connection. ETB and KES exhibit a consistent negative and consistent positive relationship, respectively, with BNB. For NGN, the connection is only positive in the 10th and 20th quantiles. From the 30th quantile to the 90th quantile the link is negative with BNB. Similar to NGN, ZAR starts with a positive connection with BNB in the first three quantiles, then switches to a negative relationship from the 60th to the 90th quantiles.

4.3.1.9 Impact on BTC due to African fiat currency exchange (see Table 4.14)

For AOA, in the case of BTC, the P value is not significant from the 10th to 30th quantiles, but is significant from the 40th quantile to the 90th quantile as BTC decreases to 0.1319% in the 40th quantile, then decreases further to 0.2610% and 0.2707% in the 50th and 60th quantiles, respectively. In the 70th quantile, it starts to lose momentum and decreases to 0.2177%. It then regains its momentum to decrease further to 0.3577% in the 80th quantile and records a 0.2168% decrease in the 90th quantile. BTC and AOA exhibit an inverse relationship.

BTC increases to 0.3447% in the case of the 30th quantile for DZD, then increases to 1.1021% and 1.5630% in the 40th and 50th quantiles, respectively. In the 60th, 70th and 80th quantiles, it drops to 1.4268%, 1.3154% and 0.9565%, respectively. Finally, in the 90th quantile, it increases to 1.1312%. The P value in not significant for BTC in the 10th and 20th quantiles as the level of significance is more than 0.05. There is a positive relationship between BTC and DZD.

BTC decreases to -0.1378% in the case of the 10th quantile for EGP, then starts increase to -0.0760% to 0.3344% from the 20th quantile all the way to the 90th quantile. BTC and EGP are positively correlated.

BTC drops to -0.3020% in the 10th quantile for ETB, then increases from -0.2253% in the 40th quantile to 0.4439% in the 90th quantile. In the rest of the quantiles, the P value is not significant for ETB. The relationship between BTC and ETB is negative.

In the case of BTC, the P value is not significant in the 30th and 90th quantiles as it is more than 0.05 level of significance. BTC increases to 2.0153% in the 10th quantile for KES, then drops to 0.9367% and 0.7618% in the 20th and 40th quantiles, respectively. In the 50th quantile, it increases to 0.8571%, then drops to 1.7494% and 1.3620% in the 60th and 70th quantiles, respectively and finally rises to 1.4372% in the 80th quantile. The relationship between BTC and KES is positive.

BTC increases to 0.7269% in the 10th quantile for MAD, then drops to 0.2818% in the 20th quantile. It increases from 0.4368% in the 30th quantile right up to 0.7811% in the 90th quantile. MAD and BTC exhibit a positive relationship. Only in the 40th and the 50th quantiles, is the P value not significant.

BTC increases to 0.6160% in the 10th quantile for NGN, then goes all the way up from -0.1527% in the 30th quantile to 0.1148% in the 90th quantile. The P value is not significant in the 20th and the 80th quantiles and the relationship between BTC and NGN is negative.

BTC increases to 0.2182% in the 10th quantile for ZAR, then in the 20th, 30th, 40th, and 50th quantiles it drops from 0.1359% to 0.0431%. It starts to increase from the 60th quantile to 0.0546% right up to 0.2696% in the 90th quantile. For all quantile levels the P value is significant and the relationship between ZAR and BTC is positive.

Table 4.14 above presents the results for the quantile process estimates and shows the correlation between BTC and BNB. The relationship between BTC and the independent variables (DZD, KES, MAD and ZAR) is consistently positive across all significant quantiles. In addition, AOA has a consistent, but negative connection with BTC across all significant quantiles. EGP starts to show a negative correlation with BTC in the 10th and 20th quantiles, then becomes positive from the 40th to 90th quantiles. Similarly, ETB shows a negative link to BTC in the 10th, 40th and 70th quantiles, with the relationship only becoming positive in the 90th quantile. The exceptional relationship is exhibited by NGN where a connection starts to be positive in the 10th quantile, switching to negative from the 30th to 70th quantiles and back to positive in the 90th quantile.

4.3.1.10 Impact on ETH due to African fiat currency exchange (see Table 4.14)

Similarly, for AOA, in the case of ETH, the P value is significant at some quantile levels (20th, 30th, 70th and 80th quantiles). ETH increases to 0.2610% and 0.1705% in the 20th and 30th

quantiles, respectively. For the 70th and 80th quantiles, it exhibits an inverse relationship with AOA, decreasing to 0.1813% and 0.2807%, respectively.

ETH increases to 0.6254% in the case of the 50th quantile for DZD, then increases further to 2.3263% and 2.9397% in the 60th and 70th quantiles, respectively. It drops to 2.7177% and 2.5391%, respectively, in the 80th and 90th quantiles. There is a positive relationship between ETH and AZD according to the results of quantile process estimates.

ETH decreases to -0.1190% in the 10th quantile for EGP, then starts to increase to -0.0578% from the 20th quantile all the way to 0.2282% in the 90th quantile with a slight drop to 0.0781% in the 70th quantile. ETH has a positive relationship with EGP.

For ETH, the P value is not significant for all the quantiles except the 10th and 40th quantiles where the results show that ETH drops to -0.5152% and increases to -0.3048% in the 40th quantile. There is inverse relationship between ETH and ETB.

ETH starts to increase to 1.2044% in the 50th quantile for KES, drops slightly to 2.823% in the 80th quantile, then proceeds all the way to 3.1782% in the 90th quantile. There is a positive relationship between ETH and KES.

ETH decreases to -0.0925% in the 10th quantile and drops further to -0.1110% in the 20th quantile. From the 30th quantile, it starts to increase from 0.0188% to 0.3623% in the 60th quantile and to 0.4038% in the 70th quantile. The relationship between ETH and MAD is mainly positive.

ETH increases to 0.8376% in the 10th quantile for NGN, then decreases to -0.1386% in the 30th quantile and all the way down to -0.3600% in the 70th quantile, after which it starts to increase to -0.2732% in the 80th quantile and settles slightly up to -0.1071%. The P value is only not significant in the 20th quantile and there is an inverse relationship between ETH and NGN.

ETH increases to 0.1310% in the 10th quantile for ZAR, then drops to 0.0810% in the 20th quantile, dropping all the way to 0.0197% in the 50th quantile. From the 60th quantile, its starts to increase from 0.0209% to 0.0924% in the 90th quantile. Only in the 40th quantile is the P value not significant and there is an affirmative connection between ZAR and ETH.

The relationship between ETH and the dependant variables is shown in Table 4.14 that presents the results for the quantile process estimates. There is a positive correlation between BNB and the dependent variables (DZD, KES and ZAR) across all significant quantiles apart from ETB, where the connection is negative. The connection with ETH varies for the other variables and starts from positive in the lower quantiles to negative in the upper quantiles in the case of AOA and NGN. Lastly, for EGP and MAD, the correlation proceeds from negative in the lower quantiles to positive in the upper quantiles.

4.3.1.11 Quantile Slope Equality Test – Africa

For objective 1, the test results in Table 4.15 below show that the Chi square value of the slope equality test is 132, 132 and 116 for BNB, BTC and ETH, respectively according to the Wald test which is statistically significant. The null hypothesis is repudiated which means that the equality of the slope is different across the quantile levels. According to the quantile slope equality test, there is inconsistency in the independent variable's impact or effect across all quantiles of the dependent variable. Stated differently, there exists a quantile-specific link between the two variables.

4.3.1.12 Symmetric quantiles test – Africa

Table 4.15: Symmetric quantiles test

Symmetric Quantiles Test													
Estimated equation quantile tau = 0.5													
Number of test quantiles: 10													
Test statistic compares all coefficients													
Restriction Detail: b(tau) + b(1-tau) - 2*b(.5) = 0													
		BNB				***BTC***				***ETH***			
Test Summary		Chi-Sq. Statistic	Chi-Sq. d.f.	Prob.		Chi-Sq. Statistic	Chi-Sq. d.f.	Prob.		Chi-Sq. Statistic	Chi-Sq. d.f.	Prob.	
Wald Test		3407.9837	132	0.0000		3492.7229	132	0.0000		3464.5	116	0.0000	
Quantiles	Variable	Restr. Value	Std. Error	Prob.	*S or I*	Restr. Value	Std. Error	Prob.	*S or I*	Restr. Value	Std. Error	Prob.	*S or I*

0.1, 0.9	AOA	0.5568	0.1239	0.0000	*S*	0.1517	0.0917	0.0978	*I*	-0.0824	0.1831	0.6527	*I*
	AOA_IMF1	0.3084	0.1314	0.0189	*S*	-0.6102	0.1071	0.0000	*S*	0.0426	0.1374	0.7565	*I*
	AOA_IMF5	0.4077	0.1998	0.0413	*S*	0.4005	0.1352	0.0030	*S*	-0.0386	0.1674	0.8175	*I*
	AOA_RES	1.2860	0.7762	0.0976	*I*	0.6165	0.4609	0.1810	*I*	0.9284	0.6433	0.1490	*I*
	DZD	0.8224	0.5892	0.1628	*I*	-1.8456	0.5758	0.0014	*S*	0.9917	0.6379	0.1200	*I*
	DZD_IMF1	-0.7339	0.4955	0.1386	*I*	0.2245	0.3212	0.4846	*I*	-0.9224	0.5976	0.1227	*I*
	DZD_IMF5	-0.2808	0.6792	0.6793	*I*	0.1848	0.4613	0.6887	*I*	0.5680	0.8766	0.5170	*I*
	DZD_RES	5.0741	3.1854	0.1112	*I*	0.4848	2.1623	0.8226	*I*	-1.4757	3.1959	0.6443	*I*
	EGP	0.0362	0.0423	0.3927	*I*	0.1327	0.0643	0.0389	*S*	-0.1415	0.0597	0.0177	*S*
	EGP_IMF1	0.0330	0.1243	0.7907	*I*	0.0324	0.1289	0.8014	*I*	0.3347	0.1173	0.0043	*S*
	EGP_IMF5	0.7382	0.7074	0.2967	*I*	-0.1692	0.2606	0.5162	*I*	-0.5985	0.1735	0.0006	*S*
	EGP_RES	1.3921	1.0604	0.1892	*I*	-1.4969	1.4588	0.3048	*I*	-1.5993	1.4924	0.2839	*I*
	ETB	0.4757	0.4191	0.2564	*I*	0.3520	0.1649	0.0327	*S*	0.4138	0.2920	0.1446	*I*
	ETB_IMF1	0.2622	0.2540	0.3018	*I*	0.6533	0.1453	0.0000	*S*	-0.1701	0.2391	0.4770	*I*
	ETB_IMF5	-1.9719	0.4591	0.0000	*S*	-0.2606	0.2305	0.2583	*I*	0.3497	0.3909	0.3710	*I*
	ETB_RES	-11.6332	1.6041	0.0000	*S*	-6.7672	1.2143	0.0000	*S*	-6.4646	1.7655	0.0003	*S*
	KES	0.0105	1.6279	0.9949	*I*	0.7536	0.7094	0.2881	*I*	0.4259	2.0288	0.8337	*I*
	KES_IMF1	0.5256	0.6084	0.3877	*I*	1.2720	0.3418	0.0002	*S*	1.3017	0.6510	0.0456	*S*
	KES_IMF5	1.3070	0.8701	0.1331	*I*	3.3753	0.5664	0.0000	*S*	2.9157	0.6934	0.0000	*S*
	KES_RES	14.5139	2.0832	0.0000	*S*	8.3224	1.2453	0.0000	*S*	13.3490	2.9039	0.0000	*S*
	MAD	-0.7154	0.3868	0.0644	*I*	1.6751	0.2971	0.0000	*S*	0.4799	0.3420	0.0322	*S*

	MAD_IMF1	-1.3880	0.3169	0.0000	*S*	0.8268	0.2405	0.0006	*S*	1.5168	0.3223	0.0000	*S*
	MAD_IMF5	0.6087	0.4986	0.2222	*I*	0.1982	0.3338	0.5527	*I*	-0.6020	0.4663	0.1967	*I*
	MAD_RES	5.4603	1.3640	0.0001	*S*	3.9559	1.1436	0.0005	*S*	10.3403	2.1157	0.0000	*S*
	NGN	1.5640	0.1485	0.0000	*S*	0.9335	0.1845	0.0000	*S*	1.2487	0.1665	0.0000	*S*
	NGN_IMF1	-0.1535	0.1208	0.2039	*I*	0.3342	0.1141	0.0034	*S*	0.3106	0.2555	0.2241	*I*
	NGN_IMF5	-0.0711	0.1615	0.6596	*I*	0.2520	0.0955	0.0083	*S*	-0.0984	0.2478	0.6911	*I*
	NGN_RES	5.5153	2.4125	0.0222	*S*	-6.0218	1.4296	0.0000	*S*	-3.1863	0.8430	0.0002	*S*
	ZAR	-0.0336	0.0317	0.2894	*I*	0.4016	0.0158	0.0000	*S*	0.1840	0.0237	0.1447	*I*
	ZAR_IMF1	1.0312	0.1272	0.0000	*S*	0.5516	0.0985	0.0000	*S*	0.3708	0.1075	0.0006	*S*
	ZAR_IMF5	-1.9673	0.1739	0.0000	*S*	-0.5786	0.1261	0.0000	*S*	-0.5975	0.1392	0.0000	*S*
	ZAR_RES	-4.2512	0.6750	0.0000	*S*	-5.2413	0.4413	0.0000	*S*	-1.6256	0.6644	0.0144	*S*
	C	0.0070	0.0018	0.0001	*S*	0.0027	0.0010	0.0084	*S*	0.0049	0.0020	0.0166	*S*
0.2, 0.8	AOA	0.4895	0.1060	0.0000	*S*	0.1619	0.0688	0.0187	*S*	0.0088	0.0606	0.8841	*I*
	AOA_IMF1	0.2063	0.0704	0.0034	*S*	-0.3735	0.0400	0.0000	*S*	-0.0318	0.0511	0.5336	*I*
	AOA_IMF5	0.4815	0.1350	0.0004	*S*	0.2654	0.0633	0.0000	*S*	-0.0407	0.0849	0.6314	*I*
	AOA_RES	0.5466	0.3981	0.1697	*I*	-0.5815	0.2290	0.0111	*S*	0.0506	0.3069	0.8691	*I*
	DZD	0.2067	0.3016	0.4931	*I*	-1.9454	0.2271	0.0000	*S*	1.6398	0.2470	0.0000	*S*
	DZD_IMF1	0.2749	0.3034	0.3649	*I*	0.6217	0.1672	0.0002	*S*	-0.2816	0.2499	0.2599	*I*
	DZD_IMF5	0.1272	0.3961	0.7482	*I*	-0.1665	0.2425	0.4923	*I*	0.9895	0.4251	0.0199	*S*
	DZD_RES	7.7965	1.5256	0.0000	*S*	2.5446	0.9778	0.0093	*S*	-3.1621	1.3198	0.0166	*S*
	EGP	-0.1218	0.0704	0.0835	*S*	0.1095	0.0529	0.0385	*S*	-0.1008	0.0382	0.0083	*S*

	EGP_IMF1	0.1685	0.1464	0.2498	*I*	0.0846	0.0569	0.1367	*I*	0.2140	0.0479	0.0000	*S*
	EGP_IMF5	0.2493	0.0522	0.0000	*S*	-0.2934	0.0460	0.0000	*S*	-0.4937	0.0820	0.0000	*S*
	EGP_RES	-1.3939	0.4781	0.0036	*S*	-1.5574	0.2591	0.0000	*S*	-0.3866	0.2985	0.1953	*I*
	ETB	0.1127	0.2601	0.6648	*I*	0.0485	0.1399	0.7286	*I*	0.0806	0.2000	0.6967	*I*
	ETB_IMF1	0.5921	0.1351	0.0000	*S*	0.0899	0.0637	0.1580	*I*	-0.0792	0.1055	0.4530	*I*
	ETB_IMF5	-1.4996	0.1600	0.0000	*S*	-0.2799	0.0965	0.0037	*S*	0.0522	0.1126	0.6427	*I*
	ETB_RES	-5.7188	0.8805	0.0000	*S*	-2.4339	0.5166	0.0000	*S*	-1.1114	0.7237	0.1246	*I*
	KES	-1.6173	0.8693	0.0628	*I*	0.6597	0.4374	0.1315	*I*	-0.0814	0.7162	0.9095	*I*
	KES_IMF1	1.3718	0.3136	0.0000	*S*	0.7199	0.1991	0.0003	*S*	0.2991	0.2112	0.1569	*I*
	KES_IMF5	-1.2676	0.4779	0.0080	*S*	2.0943	0.2855	0.0000	*S*	2.8272	0.4365	0.0000	*S*
	KES_RES	7.2388	1.3549	0.0000	*S*	7.0017	0.8104	0.0000	*S*	13.2811	1.2972	0.0000	*S*
	MAD	-0.2527	0.2197	0.2500	*I*	1.0532	0.1681	0.0000	*S*	0.4002	0.1939	0.1250	*I*
	MAD_IMF1	-1.2657	0.1909	0.0000	*S*	1.1714	0.1107	0.0000	*S*	1.6373	0.1539	0.0000	*S*
	MAD_IMF5	0.3242	0.2543	0.2024	*I*	-0.4888	0.1821	0.0073	*S*	0.0448	0.2433	0.8540	*I*
	MAD_RES	4.0114	0.9127	0.0000	*S*	-2.9065	0.6074	0.0000	*S*	5.1602	0.7702	0.0000	*S*
	NGN	0.5677	0.1103	0.0000	*S*	0.2281	0.0649	0.0004	*S*	0.3979	0.0876	0.0002	*S*
	NGN_IMF1	0.4553	0.1144	0.0001	*S*	0.1205	0.0371	0.0012	*S*	0.1092	0.0502	0.0297	*S*
	NGN_IMF5	0.3956	0.1756	0.0243	*S*	-0.0216	0.0707	0.7606	*I*	-0.0027	0.1468	0.9856	*I*
	NGN_RES	3.2743	0.9806	0.0008	*S*	-2.2864	0.4055	0.0000	*S*	-2.4031	0.4841	0.0000	*S*
	ZAR	-0.0125	0.0104	0.2289	*I*	0.2254	0.0112	0.0000	*S*	0.1064	0.0108	0.1144	*I*
	ZAR_IMF1	0.5084	0.0674	0.0000	*S*	0.0866	0.0435	0.0468	*S*	0.3941	0.0556	0.0000	*S*

	ZAR_IMF5	-1.2322	0.0855	0.0000	*S*	-0.2300	0.0527	0.0000	*S*	-0.5188	0.0814	0.0000	*S*
	ZAR_RES	-0.6217	0.3242	0.0552	*I*	-1.8860	0.2004	0.0000	*S*	-1.9329	0.2891	0.0000	*S*
	C	0.0051	0.0010	0.0000	*S*	0.0017	0.0005	0.0003	*S*	0.0036	0.0007	0.0000	*S*
0.3, 0.7	AOA	0.3519	0.0557	0.0000	*S*	0.2351	0.0558	0.0000	*S*	0.0225	0.0932	0.8091	*I*
	AOA_IMF1	0.0773	0.0390	0.0475	*S*	-0.2237	0.0247	0.0000	*S*	-0.0071	0.0303	0.8148	*I*
	AOA_IMF5	0.0970	0.0590	0.1002	*I*	0.2102	0.0341	0.0000	*S*	0.0460	0.0411	0.2634	*I*
	AOA_RES	-0.2162	0.2115	0.3068	*I*	-0.5893	0.1464	0.0001	*S*	-0.2025	0.1544	0.1896	*I*
	DZD	-0.4814	0.2004	0.0163	*S*	-1.4660	0.1747	0.0000	*S*	1.9439	0.2398	0.0000	*S*
	DZD_IMF1	-0.2274	0.1599	0.1549	*I*	0.2129	0.1055	0.0435	*S*	-0.1835	0.1382	0.1843	*I*
	DZD_IMF5	0.1648	0.2559	0.5194	*I*	-0.4271	0.1261	0.0007	*S*	0.6012	0.1707	0.0004	*S*
	DZD_RES	4.5870	0.9007	0.0000	*S*	0.7081	0.5771	0.2199	*I*	-3.5935	0.5770	0.0000	*S*
	EGP	-0.1235	0.0415	0.0029	*S*	0.1466	0.0534	0.0060	*S*	-0.1701	0.0421	0.0001	*S*
	EGP_IMF1	0.1629	0.0963	0.0908	*I*	-0.0111	0.0474	0.8144	*I*	0.1315	0.0506	0.0093	*S*
	EGP_IMF5	-0.0306	0.0613	0.6174	*I*	-0.0262	0.0405	0.5188	*I*	-0.1536	0.0527	0.0035	*S*
	EGP_RES	-0.6519	0.3190	0.0410	*S*	-0.4160	0.1812	0.0217	*S*	-0.0923	0.0871	0.2889	*I*
	ETB	0.5339	0.2076	0.0101	*S*	-0.0644	0.1096	0.5570	*I*	0.2347	0.1586	0.2836	*I*
	ETB_IMF1	0.1205	0.0746	0.1064	*S*	0.0384	0.0520	0.4602	*I*	-0.1081	0.0563	0.0548	*S*
	ETB_IMF5	-1.0120	0.1069	0.0000	*S*	0.0562	0.0674	0.4042	*I*	0.1126	0.0770	0.1436	*I*
	ETB_RES	-2.2903	0.5287	0.0000	*S*	-1.2406	0.3271	0.0001	*S*	-0.2791	0.4772	0.5585	*I*
	KES	-0.8265	0.6992	0.2372	*I*	0.0964	0.3612	0.7897	*I*	-0.1136	0.3605	0.7527	*I*
	KES_IMF1	1.7138	0.2187	0.0000	*S*	0.5215	0.1178	0.0000	*S*	0.0970	0.1254	0.4391	*I*

	KES_IMF5	-0.0158	0.2933	0.9570	*I*	0.1199	0.1755	0.4947	*I*	1.8745	0.2005	0.0000	*S*
	KES_RES	3.3015	0.6933	0.0000	*S*	2.6121	0.4658	0.0000	*S*	7.4514	0.4785	0.0000	*S*
	MAD	0.3558	0.1660	0.0321	*S*	1.0544	0.1315	0.0000	*S*	0.7051	0.1488	0.0161	*S*
	MAD_IMF1	-0.3853	0.0987	0.0001	*S*	0.4047	0.0705	0.0000	*S*	0.9234	0.0834	0.0000	*S*
	MAD_IMF5	0.2538	0.1323	0.0551	*I*	-0.1591	0.0854	0.0627	*S*	-0.3085	0.1095	0.0048	*S*
	MAD_RES	2.3132	0.5596	0.0000	*S*	-1.6751	0.3367	0.0000	*S*	1.7121	0.3786	0.0000	*S*
	NGN	0.0675	0.0563	0.2311	*I*	-0.0280	0.0175	0.1100	*I*	0.0197	0.0369	0.1705	*I*
	NGN_IMF1	0.1919	0.0583	0.0010	*S*	0.1470	0.0310	0.0000	*S*	0.2095	0.0405	0.0000	*S*
	NGN_IMF5	0.2408	0.0431	0.0000	*S*	-0.0131	0.0479	0.7851	*I*	-0.0255	0.0400	0.5231	*I*
	NGN_RES	-0.1800	0.6082	0.7673	*I*	-2.2419	0.2687	0.0000	*S*	-4.0372	0.6270	0.0000	*S*
	ZAR	-0.0082	0.0087	0.3478	*I*	0.0796	0.0076	0.0000	*S*	0.0357	0.0081	0.1739	*I*
	ZAR_IMF1	-0.0024	0.0391	0.9505	*I*	-0.0250	0.0221	0.2592	*I*	0.1385	0.0309	0.0000	*S*
	ZAR_IMF5	-0.7796	0.0536	0.0000	*S*	-0.0431	0.0271	0.1120	*I*	-0.1835	0.0400	0.0000	*S*
	ZAR_RES	1.0268	0.1835	0.0000	*S*	-0.9000	0.1166	0.0000	*S*	-1.0910	0.1536	0.0000	*S*
	C	0.0040	0.0007	0.0000	*S*	0.0006	0.0004	0.0830	*I*	0.0013	0.0004	0.0009	*S*
0.4, 0.6	AOA	0.1329	0.0311	0.0000	*S*	0.1365	0.0431	0.0015	*S*	-0.0197	0.0383	0.6065	*I*
	AOA_IMF1	-0.0109	0.0281	0.6966	*I*	-0.0839	0.0167	0.0000	*S*	0.0322	0.0064	0.0000	*S*
	AOA_IMF5	0.0308	0.0370	0.4050	*I*	0.0977	0.0213	0.0000	*S*	-0.0426	0.0081	0.0000	*S*
	AOA_RES	-0.0205	0.1292	0.8742	*I*	-0.3435	0.0857	0.0001	*S*	-0.1573	0.0340	0.0000	*S*
	DZD	-0.7185	0.1673	0.0000	*S*	-0.5971	0.1501	0.0001	*S*	1.0357	0.1087	0.0000	*S*
	DZD_IMF1	-0.0248	0.1057	0.8145	*I*	0.0802	0.0757	0.2893	*I*	-0.0320	0.0260	0.2190	*I*

	DZD_IMF5	-0.0939	0.1245	0.4508	*I*	-0.2211	0.0892	0.0132	*S*	0.0523	0.0288	0.0695	*I*
	DZD_RES	1.9817	0.5036	0.0001	*S*	1.1732	0.3318	0.0004	*S*	-1.3168	0.1245	0.0000	*S*
	EGP	-0.0254	0.0214	0.2350	*I*	0.1027	0.0376	0.0063	*S*	-0.0213	0.0175	0.2233	*I*
	EGP_IMF1	0.0024	0.0330	0.9413	*I*	-0.0117	0.0340	0.7300	*I*	0.0173	0.0115	0.1320	*I*
	EGP_IMF5	-0.0191	0.0876	0.8275	*I*	-0.0273	0.0184	0.1387	*I*	-0.0472	0.0062	0.0000	*S*
	EGP_RES	-0.0482	0.0997	0.6289	*I*	-0.1084	0.1039	0.2969	*I*	-0.1030	0.0181	0.0000	*S*
	ETB	0.4520	0.1863	0.0153	*S*	-0.2079	0.0781	0.0078	*S*	0.1221	0.1322	0.0115	*I*
	ETB_IMF1	0.0203	0.0494	0.6810	*I*	0.0700	0.0286	0.0142	*S*	-0.0127	0.0104	0.2227	*I*
	ETB_IMF5	-0.2861	0.0623	0.0000	*S*	-0.0610	0.0363	0.0933	*I*	-0.0056	0.0126	0.6599	*I*
	ETB_RES	-1.1038	0.3033	0.0003	*S*	-0.6673	0.1889	0.0004	*S*	-0.4037	0.0950	0.0000	*I*
	KES	-1.0776	0.6389	0.0917	*I*	0.7969	0.2666	0.0028	*S*	-0.8174	0.2948	0.0056	*I*
	KES_IMF1	0.7868	0.1586	0.0000	*S*	0.0609	0.0725	0.4007	*I*	0.0018	0.0280	0.9483	*I*
	KES_IMF5	-0.1832	0.1920	0.3402	*I*	0.0954	0.1133	0.3998	*I*	0.2114	0.0338	0.0000	*S*
	KES_RES	-0.2439	0.4999	0.6257	*I*	1.8333	0.2872	0.0000	*S*	1.1400	0.0984	0.0000	*I*
	MAD	0.2191	0.1249	0.0795	*I*	0.6664	0.0928	0.0000	*S*	0.4427	0.1089	0.0398	*I*
	MAD_IMF1	-0.0579	0.0584	0.3212	*I*	0.0345	0.0486	0.4778	*I*	0.0845	0.0171	0.0000	*S*
	MAD_IMF5	0.1545	0.0800	0.0535	*I*	-0.1641	0.0559	0.0033	*S*	-0.0498	0.0197	0.0116	*S*
	MAD_RES	-0.0839	0.3426	0.8066	*I*	-0.8735	0.2123	0.0000	*S*	0.3797	0.0689	0.0000	*I*
	NGN	0.0459	0.1013	0.6504	*I*	-0.0226	0.0191	0.2360	*I*	0.0116	0.0602	0.4432	*I*
	NGN_IMF1	0.0218	0.0453	0.6298	*I*	0.0869	0.0389	0.0254	*S*	0.1072	0.0246	0.0000	*S*
	NGN_IMF5	0.0884	0.0253	0.0005	*S*	-0.0596	0.0275	0.0302	*S*	-0.0091	0.0095	0.3380	*I*

	NGN_RES	-1.1218	0.2916	0.0001	*S*	-0.5186	0.1683	0.0021	*S*	-2.6867	0.2774	0.0000	*S*
	ZAR	-0.0046	0.0038	0.2257	*I*	0.0124	0.0041	0.0024	*S*	0.0039	0.0039	0.1141	*I*
	ZAR_IMF1	-0.0291	0.0242	0.2286	*I*	-0.0573	0.0155	0.0002	*S*	0.0157	0.0050	0.0016	*S*
	ZAR_IMF5	-0.2361	0.0312	0.0000	*S*	0.0085	0.0188	0.6518	*I*	-0.0042	0.0064	0.5150	*I*
	ZAR_RES	0.8542	0.1343	0.0000	*S*	-0.3512	0.0781	0.0000	*S*	-0.1439	0.0265	0.0000	*S*
	C	0.0007	0.0006	0.2096	*I*	0.0013	0.0003	0.0000	*S*	0.0008	0.0003	0.0035	*S*

For objective 1, the symmetric quantiles test results in Table 4.15 indicate that the P value is statistically significant. The Chi square statistic value is 3407.98, 3492.72 and 3464.5 for BNB, BTC and ETH, respectively, according to the Wald test. There is evidence of skewness or asymmetry in the distribution as the P value is less than 0.05 and, accordingly, the null hypothesis is rejected.

4.3.2 Objective 2: The connection between cryptocurrencies (BTC and ETH) and the fiat currencies traded in South Africa

4.3.2.1 IMF Summary Statistics – South Africa

Table 4.16: Summary statistics of return series and their IMFs – South Africa

Statistic	AUD_IMF1	AUD_IMF5	AUD_RES	AUD_USD	BTC_IMF1	BTC_IMF5	BTC_RES	BTC_USD	CHF_IMF1	CHF_IMF5
Mean	0.0001	0.0000	-0.0009	-0.0001	-0.0006	0.0000	-0.0017	0.0017	0.0000	0.0000
Median	0.0002	0.0000	-0.0009	0.0001	-0.0012	0.0000	-0.0016	0.0009	0.0001	0.0000

Max	0.0153	0.0051	0.0005	0.0325	0.1877	0.0223	0.0027	0.2138	0.0115	0.0025
Min	-0.0147	-0.0046	-0.0024	-0.0386	-0.1819	-0.0221	-0.0065	-0.3818	-0.0116	-0.0023
Std. Dev.	0.0049	0.0012	0.0008	0.0067	0.0330	0.0083	0.0026	0.0440	0.0033	0.0007
Skewness	0.0010	0.0961	-0.0101	-0.1005	0.0127	0.0166	-0.0767	-0.3063	-0.0425	-0.0436
Kurtosis	2.6387	5.8345	1.8145	5.9727	4.8709	2.7550	1.8470	9.9209	2.8551	4.0031
Jarque-Bera	7.0432	435.5245	75.8558	479.0143	188.8994	3.2974	72.9971	2604.8051	1.5219	54.7038
Prob	0.0296	0.0000	0.0000	0.0000	0.0000	0.1923	0.0000	0.0000	0.4672	0.0000
Sum	0.1501	0.0005	-1.1811	-0.1258	-0.7326	0.0492	-2.2492	2.1751	0.0179	0.0106
Sum Sq. Dev.	0.0308	0.0018	0.0009	0.0573	1.4072	0.0899	0.0089	2.5078	0.0141	0.0006
Obs.	1295	1295	1295	1295	1295	1295	1295	1295	1295	1295
Statistic	**CHF_RES**	**CHF_USD**	**ETH_IMF1**	**ETH_IMF5**	**ETH_RES**	**ETH_USD**	**EUR_IMF1**	**EUR_IMF5**	**EUR_RES**	
Mean	0.0000	0.0000	-0.0003	-0.0002	-0.0014	0.0024	0.0000	0.0000	-0.0001	
Median	0.0000	-0.0001	-0.0002	-0.0006	-0.0012	0.0007	0.0000	0.0000	-0.0001	

Max	0.0001	0.0284	0.2214	0.0315	0.0074	0.4308	0.0103	0.0018	0.0001	
Min	-0.0001	-0.0203	-0.2341	-0.0291	-0.0110	-0.4470	-0.0107	-0.0019	-0.0003	
Std. Dev.	0.0001	0.0046	0.0449	0.0105	0.0052	0.0597	0.0035	0.0006	0.0001	
Skewness	-0.0321	0.3577	0.0527	-0.0194	-0.1041	0.1656	-0.0092	0.0633	-0.0866	
Kurtosis	1.8118	5.6392	4.4056	2.8501	1.8458	9.9863	2.6330	3.1242	1.8225	
Jarque-Bera	76.4044	403.4532	107.2097	1.2934	74.2220	2639.5706	7.2841	1.6968	76.4357	
Prob	0.0000	0.0000	0.0000	0.5238	0.0000	0.0000	0.0262	0.4281	0.0000	
Sum	0.0252	0.0609	-0.4027	-0.2761	-1.8329	3.0588	-0.0101	-0.0067	-0.1309	
Sum Sq. Dev.	0.0000	0.0273	2.6112	0.1440	0.0354	4.6193	0.0155	0.0004	0.0000	
Obs.	1295	1295	1295	1295	1295	1295	1295	1295	1295	
Statistic	**EUR_USD**	**GBP_IMF1**	**GBP_IMF5**	**GBP_RES**	**GBP_USD**	**ZAR_IMF1**	**ZAR_IMF5**	**ZAR_RES**	**ZAR_USD**	
Mean	-0.0001	0.0000	0.0000	-0.0002	-0.0001	0.0000	0.0000	-0.0008	-0.0003	
Median	0.0000	0.0001	0.0000	-0.0002	0.0000	0.0003	0.0000	-0.0008	0.0003	

Max	0.0214	0.0185	0.0036	0.0001	0.0314	0.0205	0.0034	-0.0007	0.0288	
Min	-0.0204	-0.0200	-0.0033	-0.0006	-0.0363	-0.0201	-0.0035	-0.0008	-0.0405	
Std. Dev.	0.0047	0.0043	0.0009	0.0002	0.0060	0.0073	0.0013	0.0000	0.0098	
Skewness	-0.0071	0.0013	0.0488	-0.1760	-0.0671	0.0022	-0.1462	-0.5772	-0.3133	
Kurtosis	4.4507	3.6326	4.6527	1.9038	6.3745	2.2823	2.4645	1.9055	3.5924	
Jarque-Bera	113.5657	21.5969	147.8945	71.5242	615.3968	27.7954	20.0855	136.5423	40.1204	
Prob	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	
Sum	-0.1090	0.0614	0.0137	-0.2703	-0.0771	0.0296	0.0280	-0.9882	-0.4285	
Sum Sq. Dev.	0.0281	0.0242	0.0011	0.0001	0.0470	0.0693	0.0023	0.0000	0.1247	
Obs	1295	1295	1295	1295	1295	1295	1295	1295	1295	

The IMF summary statistics results in Table 4.16 above for the South African data series confirm that the data is not normally distributed and affirm the earlier statistical inference to use the quantile regression model for this study. Similar to other studies by Kumah (2023) andL. Wang et al. (2023), IMF data is presented for the IMF1, IMF5 and IMF residuals to represent short-, medium- and long-term dynamics.

4.3.2.2 Quantile regression model (QR Model) – South Africa

The quantile regression model results are presented and discussed below.

Table 4.17: Quantile regression output – South Africa

Method: Quantile Regression						
Dependent Variable:	**BTC**			**ETH**		
Indep. Variable	**Coef.**	**Prob.**	***S Or I***	**Coef.**	**Prob.**	***S Or I***
AUD_IMF1	0.0469	0.0000	*S*	-0.0009	0.0000	*S*
AUD_IMF5	-0.0343	0.0000	*S*	0.0008	0.0000	*S*
AUD_RES	-0.0761	0.0000	*S*	-0.0023	0.0000	*S*
AUD_USD	-0.0146	0.0000	*S*	0.4975	0.0000	*S*
CHF_IMF1	0.0276	0.0000	*S*	-0.0002	0.1167	*I*
CHF_IMF5	-0.0241	0.0003	*S*	0.0006	0.0016	*S*
CHF_RES	0.1774	0.0000	*S*	0.0063	0.0000	*S*
CHF_USD	-0.0346	0.0030	*S*	-0.0026	0.0000	*S*
EUR_IMF1	0.0436	0.0000	*S*	-0.0002	0.3207	*I*
EUR_IMF5	-0.0495	0.0000	*S*	-0.0003	0.1574	*I*
EUR_RES	-0.2581	0.0000	*S*	-0.0155	0.0000	*S*
EUR_USD	0.0537	0.0000	*S*	0.0001	0.5149	*I*
GBP_IMF1	0.0170	0.0002	*S*	0.0003	0.0210	*S*
GBP_IMF5	0.0047	0.3868	*I*	0.0001	0.3891	*I*
GBP_RES	0.0587	0.0034	*S*	-0.0036	0.0000	*S*

GBP_USD	0.0180	0.0047	*S*	-0.0003	0.0695	*I*
ZAR_IMF1	0.0397	0.0000	*S*	0.0001	0.0044	*S*
ZAR_IMF5	-0.0319	0.0000	*S*	-0.0002	0.0276	*S*
ZAR_RES	-0.2807	0.0000	*S*	0.0004	0.5326	*I*
ZAR_USD	-0.0185	0.0000	*S*	-0.0002	0.0000	*S*
Where *S* = Statistically significant, *I* = statistically insignificant						

4.3.2.3 Impact on BTC due to South African fiat currency exchange

The quantile regression results (see Table 4.17 above) reveal that, for BTC, except for GBP IMF5 all the variable results are significant with a P value of less than 0.05. The null hypothesis is accordingly rejected for all variables except for GBP IMF5, where the alternative hypothesis is renounced. A 1% increase in the value of AUD, CHF and ZAR results in a 0.0146%, 0.0346% and 0.0185% decrease, respectively, in the value of BTC. In contrast, for every 1% increase in the value of EUR and GBP, the value of BTC increases by 0.0537% and 0.0180%, respectively. Therefore, as indicated in Table 4.18 below, BTC is positively correlated with EUR and GBP, but negatively correlated with AUD and ZAR.

4.3.2.4 Impact on ETH due to South African fiat currency exchange

The P value is significant with a value of less than 0.05% of AUD, CHF and ZAR for ETH, while EUR and GBP are not significant with a P value of more than 0.05% (see Table 4.17 above). We therefore reject the null hypothesis for AUD, CHF and ZAR, but reject the alternative hypothesis for EUR and GBP. A 1% increase in the value of AUD, CHF and ZAR for ETH results in a 0.4975% increase, 0.0026% decrease and 0.0002% decrease, respectively, in the value of ETH. As shown in Table 4.18 below, CHF and ZAR are inversely correlated with ETH, except for AUD which shows a positive connection with ETH.

BTC is inversely connected to AUD, CHF, and ZAR, while it is positively correlated with EUR and GBP (see Table 4.17 above). Similarly, it is observed that ETH exhibits a positive link

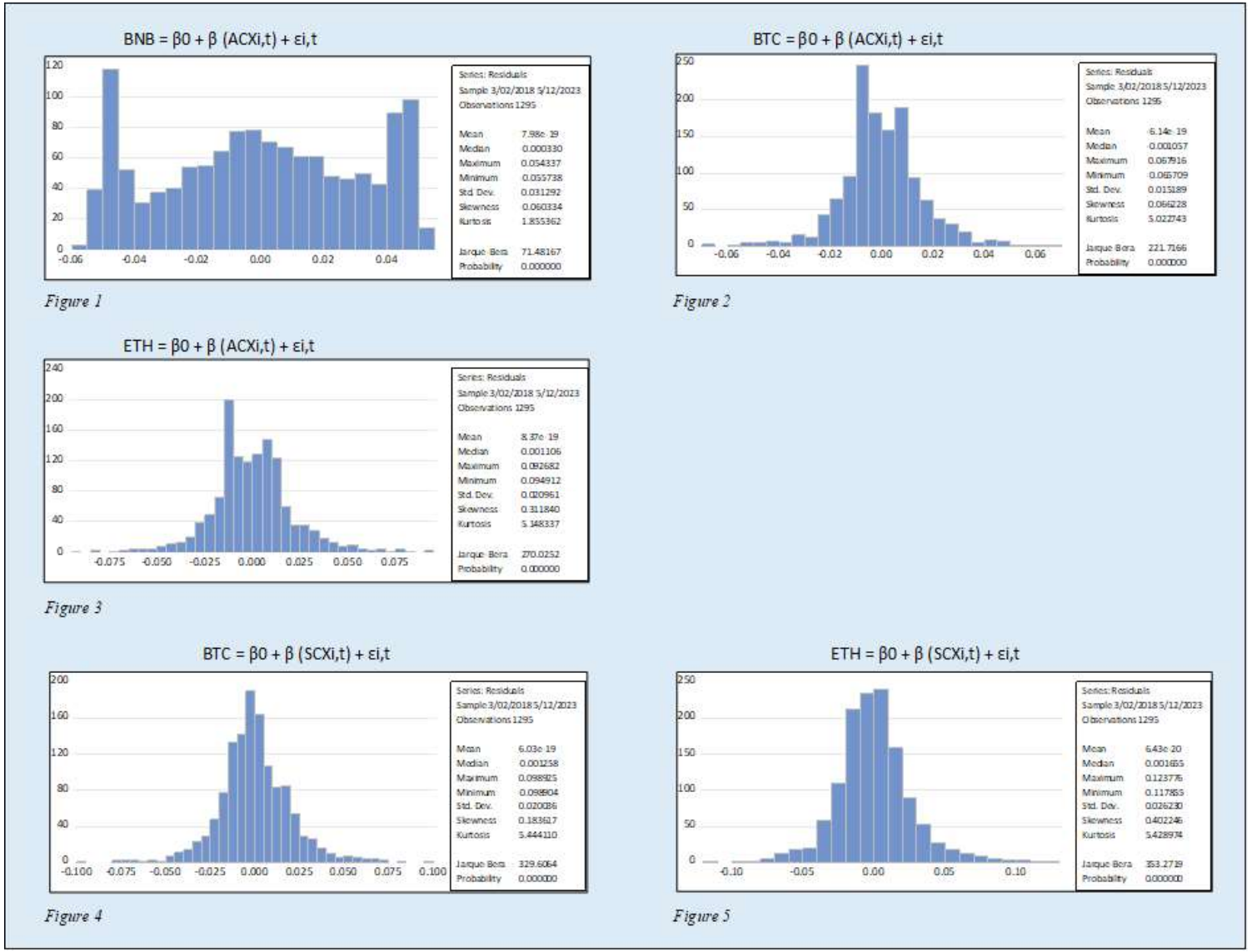
with AUD. However, as shown in Table 4.17 above, ETH is negatively connected to CHF and ZAR.

4.3.2.5 Jarque-Bera normality test – South Africa

Figure 4.2 below presents the Jarque-Bera test output.

Jarque-Bera Test results

Figure 4.2: Jarque-Bera Test results



The Jarque-Bera test results in Figure 4.2 above indicate that all the P values are less than 0.05 and, accordingly, the null hypothesis for objective 2 of the study is rejected. The P value is less than 0.05 for all the models and based on this, the researcher makes the inference that residuals are not normally distributed (Nyakurukwa & Seetharam, 2023b; Tiwari et al., 2020). These results corroborate that the data series is asymmetric which provides the basis for the use of quantile regression to analyse the return on cryptocurrencies and return on fiat currencies in order to investigate the connection between the crypto and fiat currencies in Africa. Our approach is corroborated by Kumah (2023) study on a similar topic.

4.3.2.6 Quantile process estimates – South Africa

The results of the quantile process estimates for objective 2 are set out in Table 4.18.

Table 4.18: Quantile process estimates results – South Africa

Variables	**Quantile**	***BTC***	***ETH***
		Coef.	**Coef.**
AUD_IMF1	0.1	0.0526	-0.0602
	0.2	0.0842	-0.0193
	0.3	0.0709	-0.0005
	0.4	0.0513	-0.0008
	0.5	0.0469	-0.0009
	0.6	0.0637	-0.0004
	0.7	0.0978	0.0000
	0.8	0.1522	0.0002
	0.9	0.2493	0.0601
AUD_IMF5	0.1	0.0280	0.0772
	0.2	-0.0309	0.0217
	0.3	-0.0410	0.0004
	0.4	-0.0318	0.0008
	0.5	-0.0343	0.0008
	0.6	-0.0480	0.0004
	0.7	-0.0675	-0.0001

	0.8	-0.1100	-0.0007
	0.9	-0.2168	-0.0849
AUD_RES	0.1	1.7032	0.7677
	0.2	0.5009	0.1153
	0.3	0.1573	0.0012
	0.4	0.0079	0.0009
	0.5	-0.0761	-0.0023
	0.6	-0.1978	-0.0063
	0.7	-0.4430	-0.0095
	0.8	-0.8424	-0.0182
	0.9	-2.1103	-1.4646
AUD_USD	0.1	-0.0783	0.2031
	0.2	-0.0955	0.4378
	0.3	-0.0741	0.4933
	0.4	-0.0387	0.4958
	0.5	-0.0146	0.4975
	0.6	0.0081	0.4989
	0.7	0.0420	0.5005
	0.8	0.0987	0.5009
	0.9	0.2734	0.5207
CHF_IMF1	0.1	0.0428	0.0652
	0.2	0.0465	0.0171
	0.3	0.0528	0.0000
	0.4	0.0389	0.0000
	0.5	0.0276	-0.0002
	0.6	0.0380	0.0001
	0.7	0.0447	0.0002
	0.8	0.0456	0.0001
	0.9	-0.0799	-0.0454
CHF_IMF5	0.1	0.0364	-0.1326
	0.2	0.0371	-0.0194
	0.3	0.0125	-0.0002

	0.4	-0.0251	0.0000
	0.5	-0.0241	0.0006
	0.6	-0.0165	0.0002
	0.7	0.0265	0.0000
	0.8	0.0939	0.0001
	0.9	0.2474	0.0352
CHF_RES	0.1	-0.7520	-0.1121
	0.2	0.0287	-0.0247
	0.3	0.0740	0.0026
	0.4	0.1211	0.0058
	0.5	0.1774	0.0063
	0.6	0.2444	0.0055
	0.7	0.3977	0.0031
	0.8	0.6526	0.0111
	0.9	1.8419	1.3868
CHF_USD	0.1	-0.3755	-0.2364
	0.2	-0.2261	-0.1173
	0.3	-0.1554	-0.0061
	0.4	-0.0968	-0.0031
	0.5	-0.0346	-0.0026
	0.6	-0.0156	-0.0022
	0.7	-0.0016	-0.0010
	0.8	0.0283	-0.0007
	0.9	0.2742	0.0663
EUR_IMF1	0.1	0.0804	-0.0049
	0.2	0.1221	0.0028
	0.3	0.0965	0.0001
	0.4	0.0556	0.0001
	0.5	0.0436	-0.0002
	0.6	0.0475	-0.0001
	0.7	0.0691	-0.0001
	0.8	0.0323	-0.0005

	0.9	-0.1259	-0.0589
EUR_IMF5	0.1	-0.1354	0.0840
	0.2	-0.2014	0.0005
	0.3	-0.1447	0.0000
	0.4	-0.0678	-0.0002
	0.5	-0.0495	-0.0003
	0.6	-0.0690	-0.0001
	0.7	-0.1220	-0.0001
	0.8	-0.1288	0.0010
	0.9	-0.0013	0.0600
EUR_RES	0.1	-1.8130	-1.4256
	0.2	-1.5258	-0.3595
	0.3	-0.7906	-0.0093
	0.4	-0.3440	-0.0173
	0.5	-0.2581	-0.0155
	0.6	-0.3405	-0.0111
	0.7	-0.3746	-0.0080
	0.8	0.1415	-0.0112
	0.9	0.6637	-0.6542
EUR_USD	0.1	0.1938	0.0919
	0.2	0.1342	0.0108
	0.3	0.0898	0.0003
	0.4	0.0733	0.0003
	0.5	0.0537	0.0001
	0.6	0.0548	0.0002
	0.7	0.0903	0.0000
	0.8	0.1310	0.0004
	0.9	0.2336	0.0609
GBP_IMF1	0.1	0.0473	-0.0070
	0.2	0.0482	-0.0014
	0.3	0.0352	0.0000
	0.4	0.0255	0.0001

	0.5	0.0170	0.0003
	0.6	0.0278	0.0002
	0.7	0.0447	0.0001
	0.8	0.0637	0.0005
	0.9	0.1251	0.0154
GBP_IMF5	0.1	-0.0014	-0.0449
	0.2	0.0459	-0.0040
	0.3	0.0208	0.0000
	0.4	-0.0013	0.0001
	0.5	0.0047	0.0001
	0.6	0.0076	0.0000
	0.7	0.0129	0.0001
	0.8	0.0373	-0.0001
	0.9	0.0595	0.0583
GBP_RES	0.1	-0.5659	-0.7289
	0.2	-0.1560	-0.0826
	0.3	-0.0152	-0.0001
	0.4	0.0659	-0.0015
	0.5	0.0587	-0.0036
	0.6	0.0671	-0.0022
	0.7	0.0673	0.0001
	0.8	0.2469	0.0008
	0.9	0.8366	0.6795
GBP_USD	0.1	0.1630	0.0586
	0.2	0.0745	0.0057
	0.3	0.0471	0.0000
	0.4	0.0277	-0.0002
	0.5	0.0180	-0.0003
	0.6	0.0078	-0.0003
	0.7	0.0049	-0.0001
	0.8	-0.0067	-0.0009
	0.9	-0.1054	-0.1015

ZAR_IMF1	0.1	0.1986	-0.0009
	0.2	0.1244	-0.0004
	0.3	0.0695	0.0000
	0.4	0.0483	0.0002
	0.5	0.0397	0.0001
	0.6	0.0500	0.0000
	0.7	0.0774	0.0000
	0.8	0.1286	0.0000
	0.9	0.2369	-0.0046
ZAR_IMF5	0.1	-0.1495	-0.0062
	0.2	-0.0864	-0.0002
	0.3	-0.0553	-0.0001
	0.4	-0.0427	-0.0002
	0.5	-0.0319	-0.0002
	0.6	-0.0388	-0.0001
	0.7	-0.0639	-0.0001
	0.8	-0.0865	-0.0004
	0.9	-0.1213	0.0341
ZAR_RES	0.1	1.4457	0.4505
	0.2	0.4848	0.0944
	0.3	0.0887	0.0018
	0.4	-0.1356	0.0012
	0.5	-0.2807	0.0004
	0.6	-0.4329	-0.0003
	0.7	-0.7150	-0.0010
	0.8	-1.1136	-0.0022
	0.9	-1.8769	-0.1685
ZAR_USD	0.1	-0.0903	0.0166
	0.2	-0.0608	0.0022
	0.3	-0.0354	0.0000
	0.4	-0.0230	-0.0002
	0.5	-0.0185	-0.0002

	0.6	-0.0240	-0.0001
	0.7	-0.0375	-0.0001
	0.8	-0.0622	-0.0001
	0.9	-0.1192	0.0111
C	0.1	-0.0070	-0.0045
	0.2	-0.0034	-0.0016
	0.3	-0.0019	-0.0011
	0.4	-0.0010	-0.0011
	0.5	-0.0004	-0.0010
	0.6	0.0000	-0.0010
	0.7	0.0008	-0.0010
	0.8	0.0023	-0.0010
	0.9	0.0065	0.0018

4.3.2.7 Impact on BTC due to South African fiat currency exchange (see Table 4.18)

For AUD in the case of BTC, the P value is significant at all quantile levels apart from the 10th quantile. It is observed that from the 20th to the 50th quantile, AUD and BTC have an inverse relationship, where BTC decreases to 0.0955%, 0.0741%, 0.0387% and 0.0146% in the 20th, 30th, 40th, and 50th quantiles, respectively. From the 60th to the 90th quantiles, AUD and BTC exhibit a positive relationship, with BTC increasing by 0.0081% in the 60th quantile and to 0.0420% in the 70th quantile. In the 80th quantile, it increases further to 0.0987% and reaches its peak of 0.2734% in the 90th quantile.

For CHF, the P value is not significant in the 60th, 70th and 80th quantiles. In the case of the 10th quantile, BTC decreases to -0.3755, then increases in the 20th quantile to -0.2261% and all the way to -0.0346 in the 50th quantile. In the 90th quantile, BTC increases by 0.2742%. In all the quantiles where the P value is significant, BTC and CHF have a negative relationship apart from the 90th quantile where there is a positive relationship.

In the relationship between BTC and EUR, the P value is significant in all quantiles except for the 10th quantile. The outcome shows an affirmative connection between BTC and EUR. In the 20th quantile, BTC increases by 0.1342% and in the 30th, 40th and 50th quantiles, it decreases to 0.0898%, 0.0733%, 0.0537%, respectively. From the 60th quantile, it increases to 0.0548% and further to 0.0903% in the 70th quantile, increasing to 0.1310% in the 80th quantile and reaching its summit at 0.2336% in the 90th quantile.

For GBP, the P value is significant in all quantiles except for the 60th, 70th and 80th. BTC increases to 0.1632% in the 10th quantile, decreases to 0.0745% in the 20th, drops further to 0.0471% in the 30th quantile, and drops again to 0.0180% in the 50th quantile. Up to this point BTC and GBP show a positive relationship which switches in the 90th quantile to a negative one. BTC finally settles by a drop to -0.1054%.

For ZAR, in the 20th quantile, BTC decreases to -0.0608%, then starts to increase to -0.0354%, -0.0230%, -0.0185% in the 30th, 40th, and 50th quantiles, respectively. However, from the 60th quantile BTC starts to decrease to -0.0240% and to -0.0375%, -0.0622% and -0.1192% in the 70th, 80th and 90th quantiles, correspondingly. The results show that BTC and ZAR exhibit an inverse relationship.

Table 4.18 above shows the correlation between BTC and the independent variables, summarising the quantile process estimates. From the 20th quantile to the 50th quantile, BTC exhibits an inverse correlation with AUD, then from the 60th to the 90th quantile, the relationship shifts to positive. Similarly, BTC and CHF start exhibiting a negative relationship from the 20th to the 50th quantile, then switch to a positive connection in the 90th quantile. EUR and ZAR show a positive and negative correlation with BTC, respectively for all significant quantiles. Lastly, for GBP, the connection starts to be positive with BTC from the 10th quantile to the 50th quantile and finally switches to negative in the 90th quantile.

AUD and EUR are positively connected to ETH at all significant quantiles. CHF starts exhibiting a negative connection with ETH from the 10th to the 70th quantile and then switches

to positive in the 90th quantile. This is contrary to CHF, GBP and ZAR, where the positive correlation with ETH starts on the 10th and 20th quantiles and changes to negative from the 40th quantile up to the last significant quantiles.

4.3.2.8 Impact on ETH due to South African fiat currency exchange (see Table 4.18)

ETH decreases to -0.2364% in the 10th quantile for CHF, then starts to increase to -0.1173% in the 20th quantile and all the way to the 90th quantile when it reaches 0.0663%. The P value is significant for all quantiles apart from the 80th. There is a negative relationship between ETH and CHF.

ETH increases to 0.0919% in the 10th quantile for EUR, then decreases to 0.0108% in the 20th quantile and further decreases to 0.0003% in the 30th quantile after which it starts to increase to 0.0004% in the 80th quantile and to 0.0609% in the 90th. The relationship between ETH and EUR is positive.

ETH increases to 0.0586% in the 10th quantile for GBP, then drops in the 20th, 40th, 60th, 80th and 90th quantiles to 0.0057%, -0.0002%, -0.0003%, -0.0009%, -0.1015%, respectively. The relationship between ETH and GBP is negative.

ETH increases to 0.0166% in the case of the 10th quantile for ZAR, then starts to decrease to 0.0022% in the 20th quantile. In the 40th quantile, ETH decreases to -0.0002% and remains constant in the 50th quantile at -0.0002%. It then drops to -0.0001% in the 60th quantile and remains the same at -0.0001% in the 70th. ETH is inversely connected to ZAR and the P value is not significant for the 30th, 80th and 90th quantiles.

4.3.2.9 Quantile Slope Equality Test – South Africa

The results of the quantile slope equality test are displayed below.

Table 4.19: Quantile slope equality test results – South Africa

		BTC			*ETH*		
Test Summary:		Chi-Sq. Statistic	Chi-Sq. d.f.	Prob.	Chi-Sq. Statistic	Chi-Sq. d.f.	Prob.
Wald Test:		6855.16	160	0.0000	24682.96	160	0.0000
Quantiles	Variable	Restr. Value	Std. Error	Prob.	Restr. Value	Std. Error	Prob.
0.1, 0.2	AUD_IMF1	-0.0317	0.0135	0.0192	-0.0409	0.0097	0.0000
	AUD_IMF5	0.0589	0.0239	0.0137	0.0556	0.0157	0.0004
	AUD_RES	1.2023	0.0716	0.0000	0.6524	0.0643	0.0000
	AUD_USD	0.0172	0.0123	0.1607	-0.2347	0.0102	0.0000
	CHF_IMF1	-0.0038	0.0224	0.8670	0.0482	0.0223	0.0310
	CHF_IMF5	-0.0007	0.0389	0.9855	-0.1133	0.0340	0.0009
	CHF_RES	-0.7807	0.1875	0.0000	-0.0875	0.1362	0.5209
	CHF_USD	-0.1494	0.0272	0.0000	-0.1192	0.0242	0.0000
	EUR_IMF1	-0.0416	0.0321	0.1942	-0.0077	0.0188	0.6804
	EUR_IMF5	0.0659	0.0602	0.2730	0.0835	0.0196	0.0000
	EUR_RES	-0.2873	0.2754	0.2969	-1.0661	0.2132	0.0000
	EUR_USD	0.0596	0.0263	0.0234	0.0811	0.0180	0.0000
	GBP_IMF1	-0.0010	0.0210	0.9638	-0.0056	0.0137	0.6808
	GBP_IMF5	-0.0473	0.0458	0.3016	-0.0409	0.0297	0.1688
	GBP_RES	-0.4099	0.1228	0.0008	-0.6463	0.2005	0.0013
	GBP_USD	0.0886	0.0172	0.0000	0.0529	0.0120	0.0000
	ZAR_IMF1	0.0742	0.0124	0.0000	-0.0005	0.0074	0.9459
	ZAR_IMF5	-0.0631	0.0460	0.1700	-0.0060	0.0165	0.7157
	ZAR_RES	0.9609	0.0678	0.0000	0.3562	0.0728	0.0000
	ZAR_USD	-0.0295	0.0117	0.0114	0.0144	0.0061	0.0185
0.2, 0.3	AUD_IMF1	0.0133	0.0074	0.0709	-0.0188	0.0021	0.0000
	AUD_IMF5	0.0101	0.0104	0.3326	0.0212	0.0025	0.0000
	AUD_RES	0.3436	0.0351	0.0000	0.1141	0.0117	0.0000

	AUD_USD	-0.0214	0.0067	0.0013	-0.0555	0.0062	0.0000
	CHF_IMF1	-0.0063	0.0122	0.6087	0.0170	0.0029	0.0000
	CHF_IMF5	0.0246	0.0170	0.1468	-0.0192	0.0036	0.0000
	CHF_RES	-0.0453	0.0637	0.4765	-0.0273	0.0129	0.0341
	CHF_USD	-0.0707	0.0140	0.0000	-0.1112	0.0113	0.0000
	EUR_IMF1	0.0256	0.0122	0.0360	0.0027	0.0024	0.2662
	EUR_IMF5	-0.0567	0.0229	0.0132	0.0005	0.0034	0.8777
	EUR_RES	-0.7351	0.1749	0.0000	-0.3502	0.0540	0.0000
	EUR_USD	0.0443	0.0110	0.0001	0.0105	0.0026	0.0000
	GBP_IMF1	0.0130	0.0092	0.1574	-0.0014	0.0015	0.3700
	GBP_IMF5	0.0251	0.0132	0.0582	-0.0040	0.0022	0.0637
	GBP_RES	-0.1408	0.0521	0.0069	-0.0825	0.0135	0.0000
	GBP_USD	0.0274	0.0084	0.0012	0.0057	0.0018	0.0015
	ZAR_IMF1	0.0549	0.0055	0.0000	-0.0004	0.0008	0.6145
	ZAR_IMF5	-0.0312	0.0132	0.0179	-0.0002	0.0016	0.9245
	ZAR_RES	0.3961	0.0345	0.0000	0.0926	0.0130	0.0000
	ZAR_USD	-0.0253	0.0046	0.0000	0.0023	0.0008	0.0042
0.3, 0.4	AUD_IMF1	0.0197	0.0044	0.0000	0.0003	0.0000	0.0000
	AUD_IMF5	-0.0092	0.0056	0.1017	-0.0003	0.0001	0.0000
	AUD_RES	0.1495	0.0175	0.0000	0.0003	0.0003	0.2860
	AUD_USD	-0.0354	0.0036	0.0000	-0.0025	0.0002	0.0000
	CHF_IMF1	0.0139	0.0061	0.0238	0.0000	0.0001	0.9992
	CHF_IMF5	0.0375	0.0099	0.0001	-0.0002	0.0001	0.0321
	CHF_RES	-0.0471	0.0317	0.1379	-0.0032	0.0004	0.0000
	CHF_USD	-0.0586	0.0092	0.0000	-0.0030	0.0015	0.0441
	EUR_IMF1	0.0409	0.0075	0.0000	0.0001	0.0001	0.4193
	EUR_IMF5	-0.0769	0.0114	0.0000	0.0002	0.0001	0.1264
	EUR_RES	-0.4466	0.0794	0.0000	0.0080	0.0007	0.0000
	EUR_USD	0.0165	0.0068	0.0147	0.0000	0.0001	0.7472
	GBP_IMF1	0.0097	0.0048	0.0443	-0.0001	0.0001	0.0653
	GBP_IMF5	0.0221	0.0070	0.0017	-0.0001	0.0001	0.1742
	GBP_RES	-0.0811	0.0313	0.0096	0.0014	0.0003	0.0000

	GBP_USD	0.0194	0.0050	0.0001	0.0002	0.0001	0.0003
	ZAR_IMF1	0.0212	0.0032	0.0000	-0.0001	0.0000	0.0000
	ZAR_IMF5	-0.0125	0.0046	0.0065	0.0001	0.0000	0.0031
	ZAR_RES	0.2244	0.0180	0.0000	0.0006	0.0003	0.0186
	ZAR_USD	-0.0124	0.0026	0.0000	0.0002	0.0000	0.0000
0.4, 0.5	AUD_IMF1	0.0043	0.0029	0.1274	0.0000	0.0001	0.4839
	AUD_IMF5	0.0026	0.0033	0.4361	0.0000	0.0001	0.6679
	AUD_RES	0.0839	0.0112	0.0000	0.0032	0.0003	0.0000
	AUD_USD	-0.0241	0.0022	0.0000	-0.0017	0.0001	0.0000
	CHF_IMF1	0.0113	0.0040	0.0052	0.0003	0.0001	0.0036
	CHF_IMF5	-0.0010	0.0051	0.8517	-0.0006	0.0001	0.0000
	CHF_RES	-0.0563	0.0188	0.0027	-0.0005	0.0005	0.2685
	CHF_USD	-0.0622	0.0070	0.0000	-0.0005	0.0002	0.0360
	EUR_IMF1	0.0120	0.0043	0.0055	0.0002	0.0001	0.0283
	EUR_IMF5	-0.0183	0.0055	0.0008	0.0001	0.0001	0.5758
	EUR_RES	-0.0859	0.0310	0.0055	-0.0018	0.0008	0.0229
	EUR_USD	0.0196	0.0052	0.0001	0.0001	0.0001	0.1998
	GBP_IMF1	0.0085	0.0033	0.0113	-0.0002	0.0001	0.0243
	GBP_IMF5	-0.0060	0.0043	0.1581	0.0000	0.0001	0.7969
	GBP_RES	0.0072	0.0161	0.6546	0.0021	0.0004	0.0000
	GBP_USD	0.0096	0.0041	0.0189	0.0001	0.0001	0.3836
	ZAR_IMF1	0.0086	0.0019	0.0000	0.0000	0.0000	0.5682
	ZAR_IMF5	-0.0108	0.0025	0.0000	0.0000	0.0001	0.8532
	ZAR_RES	0.1450	0.0089	0.0000	0.0008	0.0004	0.0413
	ZAR_USD	-0.0045	0.0015	0.0021	0.0000	0.0000	0.6494
0.5, 0.6	AUD_IMF1	-0.0168	0.0028	0.0000	-0.0004	0.0001	0.0000
	AUD_IMF5	0.0136	0.0032	0.0000	0.0004	0.0001	0.0000
	AUD_RES	0.1217	0.0110	0.0000	0.0040	0.0003	0.0000
	AUD_USD	-0.0227	0.0022	0.0000	-0.0014	0.0001	0.0000
	CHF_IMF1	-0.0103	0.0044	0.0185	-0.0004	0.0001	0.0001
	CHF_IMF5	-0.0076	0.0049	0.1196	0.0004	0.0001	0.0007
	CHF_RES	-0.0670	0.0162	0.0000	0.0009	0.0005	0.0626

	CHF_USD	-0.0190	0.0084	0.0240	-0.0005	0.0002	0.0101
	EUR_IMF1	-0.0039	0.0043	0.3601	0.0000	0.0001	0.7379
	EUR_IMF5	0.0194	0.0059	0.0009	-0.0002	0.0001	0.0742
	EUR_RES	0.0824	0.0297	0.0055	-0.0044	0.0007	0.0000
	EUR_USD	-0.0011	0.0051	0.8343	0.0000	0.0001	0.7833
	GBP_IMF1	-0.0108	0.0031	0.0005	0.0000	0.0001	0.4682
	GBP_IMF5	-0.0029	0.0038	0.4435	0.0001	0.0001	0.1549
	GBP_RES	-0.0084	0.0144	0.5617	-0.0014	0.0005	0.0022
	GBP_USD	0.0102	0.0041	0.0120	0.0000	0.0001	0.8029
	ZAR_IMF1	-0.0103	0.0020	0.0000	0.0001	0.0000	0.0001
	ZAR_IMF5	0.0068	0.0030	0.0236	-0.0002	0.0001	0.0103
	ZAR_RES	0.1522	0.0113	0.0000	0.0007	0.0004	0.0605
	ZAR_USD	0.0055	0.0015	0.0001	-0.0001	0.0000	0.0362
0.6, 0.7	AUD_IMF1	-0.0341	0.0038	0.0000	-0.0005	0.0001	0.0000
	AUD_IMF5	0.0196	0.0049	0.0001	0.0005	0.0001	0.0000
	AUD_RES	0.2452	0.0171	0.0000	0.0032	0.0004	0.0000
	AUD_USD	-0.0339	0.0032	0.0000	-0.0016	0.0001	0.0000
	CHF_IMF1	-0.0067	0.0065	0.2968	-0.0001	0.0001	0.4473
	CHF_IMF5	-0.0429	0.0083	0.0000	0.0002	0.0001	0.0065
	CHF_RES	-0.1533	0.0291	0.0000	0.0023	0.0003	0.0000
	CHF_USD	-0.0141	0.0101	0.1626	-0.0012	0.0002	0.0000
	EUR_IMF1	-0.0215	0.0064	0.0007	-0.0001	0.0001	0.2464
	EUR_IMF5	0.0530	0.0104	0.0000	0.0000	0.0001	0.8925
	EUR_RES	0.0341	0.0541	0.5286	-0.0031	0.0007	0.0000
	EUR_USD	-0.0355	0.0065	0.0000	0.0001	0.0001	0.0937
	GBP_IMF1	-0.0170	0.0048	0.0004	0.0001	0.0001	0.2600
	GBP_IMF5	-0.0052	0.0068	0.4405	-0.0001	0.0001	0.1839
	GBP_RES	-0.0002	0.0266	0.9932	-0.0022	0.0005	0.0000
	GBP_USD	0.0029	0.0060	0.6311	-0.0002	0.0001	0.0444
	ZAR_IMF1	-0.0274	0.0030	0.0000	0.0000	0.0000	0.5766
	ZAR_IMF5	0.0252	0.0047	0.0000	0.0000	0.0001	0.9930
	ZAR_RES	0.2821	0.0190	0.0000	0.0007	0.0004	0.0749

	ZAR_USD	0.0135	0.0024	0.0000	-0.0001	0.0000	0.0361
0.7, 0.8	AUD_IMF1	-0.0544	0.0054	0.0000	-0.0002	0.0001	0.0520
	AUD_IMF5	0.0424	0.0079	0.0000	0.0006	0.0001	0.0000
	AUD_RES	0.3994	0.0263	0.0000	0.0087	0.0014	0.0000
	AUD_USD	-0.0566	0.0054	0.0000	-0.0004	0.0001	0.0001
	CHF_IMF1	-0.0009	0.0112	0.9356	0.0001	0.0002	0.3321
	CHF_IMF5	-0.0675	0.0135	0.0000	-0.0001	0.0002	0.4938
	CHF_RES	-0.2550	0.0507	0.0000	-0.0080	0.0014	0.0000
	CHF_USD	-0.0299	0.0174	0.0858	-0.0002	0.0004	0.6191
	EUR_IMF1	0.0367	0.0121	0.0024	0.0005	0.0001	0.0004
	EUR_IMF5	0.0068	0.0179	0.7049	-0.0011	0.0002	0.0000
	EUR_RES	-0.5161	0.1086	0.0000	0.0031	0.0018	0.0744
	EUR_USD	-0.0407	0.0105	0.0001	-0.0003	0.0001	0.0155
	GBP_IMF1	-0.0189	0.0074	0.0106	-0.0004	0.0002	0.0102
	GBP_IMF5	-0.0245	0.0102	0.0169	0.0002	0.0001	0.0568
	GBP_RES	-0.1796	0.0527	0.0007	-0.0008	0.0007	0.2529
	GBP_USD	0.0116	0.0098	0.2363	0.0008	0.0002	0.0002
	ZAR_IMF1	-0.0512	0.0047	0.0000	0.0000	0.0001	0.9152
	ZAR_IMF5	0.0226	0.0114	0.0468	0.0004	0.0001	0.0066
	ZAR_RES	0.3986	0.0484	0.0000	0.0012	0.0006	0.0514
	ZAR_USD	0.0247	0.0041	0.0000	0.0000	0.0001	0.8099
0.8, 0.9	AUD_IMF1	-0.0971	0.0144	0.0000	-0.0598	0.0100	0.0000
	AUD_IMF5	0.1069	0.0216	0.0000	0.0842	0.0123	0.0000
	AUD_RES	1.2679	0.0628	0.0000	1.4465	0.0522	0.0000
	AUD_USD	-0.1748	0.0156	0.0000	-0.0198	0.0118	0.0944
	CHF_IMF1	0.1255	0.0234	0.0000	0.0454	0.0142	0.0014
	CHF_IMF5	-0.1535	0.0412	0.0002	-0.0351	0.0298	0.2389
	CHF_RES	-1.1893	0.1408	0.0000	-1.3757	0.0781	0.0000
	CHF_USD	-0.2459	0.0298	0.0000	-0.0671	0.0204	0.0010
	EUR_IMF1	0.1582	0.0307	0.0000	0.0584	0.0203	0.0040
	EUR_IMF5	-0.1274	0.0440	0.0038	-0.0590	0.0329	0.0731
	EUR_RES	-0.5222	0.2085	0.0123	0.6430	0.1644	0.0001

	EUR_USD	-0.1025	0.0248	0.0000	-0.0605	0.0145	0.0000
	GBP_IMF1	-0.0615	0.0195	0.0017	-0.0148	0.0158	0.3485
	GBP_IMF5	-0.0221	0.0298	0.4576	-0.0585	0.0202	0.0039
	GBP_RES	-0.5897	0.0977	0.0000	-0.6786	0.0623	0.0000
	GBP_USD	0.0988	0.0250	0.0001	0.1006	0.0133	0.0000
	ZAR_IMF1	-0.1083	0.0110	0.0000	0.0047	0.0097	0.6290
	ZAR_IMF5	0.0348	0.0310	0.2621	-0.0345	0.0196	0.0778
	ZAR_RES	0.7632	0.0972	0.0000	0.1663	0.0586	0.0045
	ZAR_USD	0.0571	0.0096	0.0000	-0.0112	0.0071	0.1168

For objective 2, the test results in Table 4.19 show that the Chi square value of the slope equality test is 160 for both BTC and ETH according to Wald test, which is statistically significant. The null hypothesis is repudiated which means that the equality of the slope is different across the quantile levels. According to the quantile slope equality test, there is inconsistency in the independent variable's impact or effect across all quantiles of the dependent variable. Stated differently, there exists a quantile-specific link between the two variables.

4.3.2.10 Symmetric quantiles test – South Africa

Similarly, for objective 2, the symmetric quantiles test results indicate that the P value is statistically significant, with a value of less than 0.05. According to Wald test, the Chi square statistic value is 2736.75 and 4286.68 for BTC and ETH, respectively. The null hypothesis is repudiated and accordingly it is concluded that there is evidence of skewness or asymmetry in the distribution.

Based on the symmetric quantiles test results, Koenker and Hallock (2001) state that asymmetry is a sign of abnormalities in the distribution of data. Therefore, the validity of the general linear regression results might be impacted by the presence of skewness, as many statistical tests and models, including general linear regression, surmise normal distribution (Buchinsky, 1998; Hao & Naiman, 2007; Limpert & Stahel, 2011). Accordingly, the

justification for using quantile regression for this study is affirmed as Kumah (2023) used it to investigate the connection between digital currencies and fiat currencies.

4.4 Discussion

The study results presented in Table 4.14 for African fiat currencies and Table 4.18 for South African FX currencies are discussed in this section.

4.4.1 The connection between African fiat currencies and cryptocurrency

When all the African fiat currencies' interaction is compared in the short, medium and long term, a pattern emerges which indicates that BNB is positively correlated with ETB in the short or medium term and negatively connected in the long term. BTC shows a similar connection with EGP, ETB and ZAR. Similarly, ETH is positively connected to EGP and ZAR in the short or medium term and inversely related in the long term. These results suggest that digital currencies (BNB, BTC and ETH) cannot be used as alternative means of trade in the short or medium term but can be used as a hedge against depreciating fiat currencies (EGP, ETB and ZAR) over the long term. In similar vein, Kumah (2023) study found that cryptocurrencies can be used as a hedge against depreciating fiat currencies, but not as a means of trade.

KES is an exceptional case when it comes to its correlation with BTC and ETH as it moves in the same direction in both the medium and long term as well as with DZD, but only in the medium term. Accordingly, digital currencies (BTC and ETH) cannot be used as an alternative to KES and DZD (in the medium term) to hedge against depreciating fiat currency or inflation in Kenya and Algeria, respectively. These results are similar to those of Beerbaum (2023) and Kumah (2023) who concluded that digital currency cannot be used as an alternative to fiat currency to hedge against inflation or depreciating fiat currency. In addition, these results suggest that BTC and ETH can be used as diversification assets in a portfolio with KES in the medium and long term and with DZD only in the medium term. In support of this outcome, Huang et al. (2023) and James and Menzies (2023) found that cryptocurrency can be utilised as a diversification asset in a portfolio of fiat currencies.

In the long term, BNB, BTC and ETH switch correlation between positive and negative with AOA and NGN. Furthermore, EGP is connected with BNB in the long term, switching from positive to negative. This pattern indicates that cryptocurrency (BNB, BTC and ETH) has some hedging traits against the AOA and NGN during bearish markets when fiat currencies depreciate. The conclusion is the same for the connection between BNB and EGP. These results are in sync with those of Gbolahan (2023) and Kumah (2023) who concluded that cryptocurrency can be used as a hedge against depreciating currencies in bear markets.

In the realm of African fiat currencies, but only in the medium term, our results show that BTC and ETH are negatively correlated with EGP, MAD, NGN and ZAR. Furthermore, the connection between BNB and ETB, KES, and ZAR is negative in the medium term. These results suggest that Bitcoin and Ethereum can be used as an alternative to fiat currencies for EGP, MAD, NGN, and ZAR in the medium term, while Binance coin can be utilised as an alternative to ETB, KES and ZAR. Affirming our findings, Kumah (2023) asserts that cryptocurrency, particularly Bitcoin, is a viable alternative to the NGN. Similarly, DZD and MAD are negatively connected to BNB, but only in the short term, indicating that Binance coin is a suitable alternative currency to DZD and MAD. Only in the case of ZAR do our results suggest that all three cryptocurrencies are viable alternatives to the Rand as means of transacting.

In contrast, the rest of the results reveal disparities in that, while BNB with DZD, KES, MAD, and ZAR are inversely correlated in the short or medium term, they are positively connected in the long term. The same can be observed when it comes to the connection between MAD and BNB, BTC and ETH. This indicates that BNB can be used as diversification in a portfolio with DZD, KES, MAD, and ZAR in the long term. Similarly, BTC and ETH can be utilised to diversify a portfolio with MAD. Our results are in harmony with studies that established that digital currency is a suitable diversifier in a portfolio (Huang et al., 2023; James & Menzies, 2023; Kumah, 2023).

In terms of the magnitude of the correlation between cryptocurrencies and fiat currencies in Africa, our results point to a peculiar pattern where the connection becomes intense in the long term when compared to the short or medium term across all fiat currencies. When it comes to the long-term strong correlation, it is further observed that the strength of the connection is intense from the lower quantiles 0.1 to 0.3, becomes less intense in the mid-quantiles (0.4 to 0.6) and then switches back to more intense in the higher quantiles (0.7 to 0.9) across all African fiat currencies. For example, the effect for quantile 0.1 in the case of BNB and ETB is -8.3409, suggesting a relatively strong negative link in the lower tail of the distribution between ETB and Binance coin. On the other hand, the effect is -0.4950 at quantile 0.6, indicating a less strong negative association near the middle of the distribution. From -1.0791 in the 0.7 quantile to -4.7057 in the 0.9 quantile which is the higher tail end of the distribution, the link becomes stronger again as it moves towards the higher quantiles. There is variability in the link between ETB and Binance coin, as evidenced by the variations in the effects between quantiles. This implies that the relationship can change based on the distribution level of the dependent variable (BNB). Kumah (2023) found similar patterns when investigating the coexistence of cryptocurrency and fiat currencies and concluded that there is a heterogeneous relationship between cryptocurrencies and fiat currencies at various points of the conditional distribution of cryptocurrencies.

4.4.2 The connection between the South African fiat currency market and cryptocurrency

In the South African context, BTC exhibits a positive connection with AUD, EUR, and ZAR in the short or medium term but negative correlation in the long term. ETH is also positively connected with AUD and GBP in the short or medium term but negative in the long term. This implies that, first, in the short or medium term, digital currencies (BTC and ETH) are suitable diversifiers in a portfolio where fiat currencies (AUD, EUR, and ZAR) are included in the same basket, and second, that in the long term, digital currencies (BTC and ETH) can be used as a hedge against depreciating fiat currencies (AUD, EUR and ZAR). (Abid et al., 2023), (Nugroho, 2023) and (Rodriguez & Colombo, 2024) corroborate the outcome of our study as they established that cryptocurrency hedges against depreciating currencies.

The South Africa Rand is, however, negatively connected to ETH in the short or medium term but positively correlated with it in the long term. This means that ETH can be used as an alternative currency to ZAR in the short or medium term, and in the long term, it can be used as diversification in a portfolio that includes ZAR. Parallel to the findings of this study, Nugroho (2023) concluded that cryptocurrencies are a suitable alternative to fiat currencies. Other studies affirm our finding that digital currencies diversify a portfolio with fiat currencies (Abakah, Brahim, et al., 2024; James & Menzies, 2023). Similarly, the results demonstrate that Bitcoin is inversely correlated to AUD and EUR in the medium term, suggesting that Bitcoin can serve as an alternative to the AUD and the EUR. Turning to Ethereum, it is negatively connected to AUD but in the short term, which implies that Ethereum can be utilised as an alternative to the AUD in the short term.

In the case of the other fiat currencies in the South African context, BTC is positively correlated with CHF and GBP in both the short and long term. A similar pattern is followed by ETH as it is positively connected to CHF in the short and long term. This indicates that virtual currency (BTC) is a suitable diversifying currency in a portfolio with CHF and GBP. The same strategy can be used in ETH with CHF in the same portfolio. Abid et al. (2023) and Huang et al. (2023) affirm the results of our study by indicating that cryptocurrencies possess diversification characteristics in a portfolio with fiat currencies. ETH is inversely correlated with EUR in the long term, signalling that it can be used as a hedge against depreciating EUR in the long term. In line with our conclusion, Gbolahan (2023) and Kumah (2023) conclude that virtual currencies are catalysts in the hedge against depreciating fiat currencies.

In examining the dynamics of South Africa's FX markets, the analysis reveals a nuanced relationship between fiat currencies such as the AUD, CHF, EUR, and GBP, and cryptocurrencies. Notably, these fiat currencies exhibit a weak correlation with cryptocurrencies, as evidenced by coefficients measuring less than one. This observation contrasts sharply with the robust correlation observed between cryptocurrencies and African fiat currencies over the long term. Interpreting these findings within the framework of quantile regression analysis sheds light on the nature of this relationship. A coefficient below one signifies that the influence exerted by the aforementioned fiat currencies on cryptocurrencies is less than proportional. In practical terms, this suggests that fluctuations in fiat currencies

(AUD, CHF, EUR and GBP) have a mitigated impact on cryptocurrencies, indicating cryptocurrencies' subdued responsiveness to changes in fiat currencies compared to their counterparts in African fiat currencies.

4.5 Summary

This chapter presented and analysed the data, including the detection and elimination of outliers to achieve appropriate statistical results from reliable and meaningful data behaviour; the descriptive statistics which provided a statistical perspective of the variables; the use of Pearson Correlation and the Variance Inflation Factor to test multicollinearity among the variables; and the assessment of the unit root. The results were then discussed using the quantile regression model that established the link between virtual currencies and the FX currencies in Africa for objective one and South Africa for objective two. Lastly, the results were discussed and interpreted in line with the literature.

Summary of Hypothesis Test		Accepted/ Rejected	Supported or n/a
Connection between African currencies exchange and cryptocurrency			
The Null Hypotheses			
First Null – H_0:	There is no significant connection between the ACX and BTC return.	Rejected	n/a
Second Null – H_0:	There is no significant connection between the ACX and ETH return.	Rejected	n/a
Third Null – H_0:	There is no significant connection between the ACX and BNB return.	Rejected	n/a
The Alternative Hypotheses			
H_1:	There is a significant connection between the ACX and BTC return.	Accepted	Supported
H_2:	There is a significant connection between the ACX and ETH return.	Accepted	Supported
H_3:	There is a significant connection between the ACX and BNB return.	Accepted	Supported
Connection between South African currencies exchange and cryptocurrency			
The Null Hypotheses			
Fourth Null – H_0:	There is no significant connection between the SCX and BTC return.	Rejected	n/a
Fifth Null – H_0:	There is no significant connection between the SCX and ETH return.	Rejected	n/a
The Alternative Hypotheses			
H_4:	There is a significant connection between the SCX and BTC return.	Accepted	Supported
H_5:	There is a significant connection between the SCX and ETH return.	Accepted	Supported

The following chapter presents a summary, conclusions and recommendations as well as suggestions for future studies.

CHAPTER 5: SUMMARY, CONCLUSIONS AND RECOMMENDATIONS

5.1 Introduction

This chapter presents a summary of the study, conclusions and recommendations based on the findings, and suggestions for further studies.

5.2 Summary of the study

While cryptocurrency users see cryptocurrencies as an investment that is not impacted by inflation, a means of transacting and a value storage without central bank restrictions (Bondarenko et al., 2019), some researchers like Raymaekers (2015) regard cryptocurrency as a disruption in the financial industry. These diverse views motivated this study that assessed the link between cryptocurrency and African FX currencies. A theoretical and empirical literature review were conducted to gain an understanding of the connection between cryptocurrency and fiat currency in Africa and the South African fiat currency market.

The empirical literature review revealed that there is some connection between FX currencies and cryptocurrency markets and that this is influenced by other factors like the legal framework of a particular market environment (Vujović, 2023). For example, Khaled (2020) found that while the Iraqi Dina and Ripple showed a negative connection, the lack of government legal recognition of cryptocurrencies may explain why exchange markets in Arabian nations have no impact on the markets for cryptocurrencies. The review and our data analysis revealed that the connection is sometimes positive and other times negative. It was also concluded that economic downturns and upswings impact the correlation between fiat and digital currency.

Overall, while some scholars point to insignificant correlation between fiat currencies and cryptocurrencies (Asena DENİZ and Teker (2020) Donmez et al. (2021), the literature indicates a notable relationship. For instance, Isaksson (2022), Mallick and Mallik (2021) and Fernandes, Kristjanpoller, et al. (2023) observed a positive correlation between cryptocurrency and fiat currency, as did Levulytė and Šapkauskienė (2021) and Khaled (2020). These authors suggest

that digital currencies can serve as a diversification tool within a portfolio alongside fiat currencies. However, Elsayed et al. (2022), Drożdż et al. (2023) and Sami and Abdallah (2020) suggest an inverse correlation between fiat currencies and digital currencies. Many other researchers align with this perspective, concluding that digital currencies can serve as a hedge against depreciating fiat currencies (Baumöhl, 2019; Esparcia & Lopez, 2023; Klein et al., 2018). Moreover, there is consensus that cryptocurrencies can be a sound investment strategy with no exposure to inflation, reduced risk and enhanced returns within a portfolio (Bondarenko et al., 2019; Fernandes, Silva, et al., 2023). Some scholars have found a negative correlation between cryptocurrency and fiat currencies (Mokni & Ajmi, 2021). Consequently, Bondarenko et al. (2019), Levulytė and Šapkauskienė (2021) and Nugroho (2023) suggest that digital currencies could potentially function as an alternative to fiat currencies.

This study adopted a positivist epistemological position and a quantitative approach to investigate the connection between fiat currencies and cryptocurrencies on the African continent. Time frequency information in the time series of cryptocurrencies and fiat currencies was captured using ensemble empirical mode decomposition (EEMD) and quantile regression (QR) was applied on the decomposed time series data to examine the connection between cryptocurrencies and fiat currencies under various currency regimes.

The research population consisted of all cryptocurrencies trading in the market between 1 March 2018 and 12 May 2023 and the official rates of exchange for the African countries. A sample of three cryptocurrencies (Bitcoin, Binance coin and Ethereum) which represent more than 66% of cryptocurrencies by market capitalisation was selected. For fiat currencies we selected the top eight African economies whose individual nominal GDP is above US$100 billion from investing.com and coinmarketcap. In the case of the South African dataset, we selected five traded foreign currencies in the country's forex market. We then selected cryptocurrencies (Bitcoin, Binance coin and Ethereum) as dependent variables while all fiat currencies (NGN/USD, ZAR/USD, EGP/USD, DZD/USD, AOA/USD, MAD/USD, ETB/USD, KES/USD and EUR, GBP, CHF, and AUD were selected as the dependent variables. Our study used EEMD-based quantile regression to provide a comprehensive outcome, and diagnostic inspection was performed using the Jarque-Bera normality test, quantile process estimates, quantile slope equality tests, and symmetric quantiles tests to

analyse the performance of the models and identify their strengths, weaknesses and inefficiencies. The estimation procedure used was the treatment of outliers followed by descriptive statistics providing a statistical perspective of the variables. Thereafter, Pearson correlation tests and VIF tests were conducted to examine multicollinearity. Lastly, the unit root test was conducted to test the stationarity of the time series data.

In the African context, the study found that across various African fiat currencies, digital currencies like BNB, BTC, and ETH exhibit varying correlations over the short, medium, and long term. While BNB and BTC show positive short-term correlations and negative long-term correlations with certain fiat currencies, ETH demonstrates short- to medium-term positive correlations with the others and long-term inverse correlation. These findings suggest that while digital currencies cannot replace traditional payment methods in the short or medium term, they can serve as long-term hedges against declining fiat currencies. Moreover, BTC and ETH can function as diversification assets in portfolios holding specific fiat currencies in the medium term and the others in both the long and medium term. In addition, the study highlighted the evolving nature of correlations between digital currencies and specific fiat currencies over time, particularly during bearish markets. Cryptocurrencies like BNB, BTC, and ETH develop hedging characteristics against certain fiat currencies during such periods. Notably, ETH can serve as a hedge against the long-term depreciation of specific fiat currencies. Furthermore, while BNB exhibits positive long-term relationships with certain fiat currencies, its short- and medium-term correlations are inverse, indicating its potential use for diversification in portfolios including those fiat currencies.

For fiat currencies traded in South Africa, BTC and ETH demonstrate short- to medium-term positive correlations with certain fiat currencies like AUD, EUR, and ZAR, but long-term negative correlations with them. This implies that digital currencies can serve as diversifiers in portfolios containing these fiat currencies in the short to medium term and as hedges against their depreciation in the long run. Conversely, the ZAR displays a short- to medium-term negative correlation with ETH but a long-term positive correlation, indicating ETH's potential use as a substitute for ZAR in the short and medium term and as a diversification asset in the long run. BTC and ETH also exhibit positive correlations with GBP and CHF, suggesting their suitability to diversify portfolios alongside these fiat currencies. Moreover, the inverse long-

term correlation between ETH and EUR implies ETH's potential utility as a hedge against EUR depreciation in the long term.

Similar to other studies such as those by Levulytė and Šapkauskienė (2021) and Mallick and Mallik (2021), which point to a positive connection between fiat currency and cryptocurrency, our results indicate that fiat currencies are positively connected to digital currencies. For the African dataset, BNB is positively connected to KES in the long term. BTC exhibits a positive correlation with KES, DZD, and ZAR in the short to medium term. The positive connection is also revealed by the results of the South African dataset whereby BTC relates positively to AUD, EUR, and ZAR in the long term, while ETH connects positively with AUD and GBP. These results are affirmed by Chemkha et al. (2021) who found a positive link between fiat and cryptocurrency.

The results indicate that there are both positive and negative relationships between cryptocurrencies and fiat money, indicating that these relationships are complicated and influenced by a variety of variables. This adds to the continuing discussion concerning cryptocurrencies' use as speculative or hedging assets. The study deepens our understanding of cryptocurrencies' functional significance in financial markets by proving that they can display both hedging features and the potential for portfolio diversification.

This study also emphasises how regional currency regimes and economic situations have a significant impact on how fiat currencies and cryptocurrencies interact. The need to take into account local economic settings when analysing cryptocurrency marketplaces is highlighted by the different outcomes for major global currencies and African currencies. For financial institutions, investors, and politicians involved with or interested in African markets, this regional focus provides useful insights.

This research also highlights how cryptocurrencies may affect financial stability and monetary policy in developing nations. The identification of both divergences and convergences in the behaviours of currencies encourages more research into the potential effects of

cryptocurrencies on cross-border transactions, exchange rates, and inflation. Furthermore, quantile regression analysis reveals evidence of asymmetric correlations and tail dependencies, which highlights the significance of risk management techniques in bitcoin investing.

In short, this study challenges preexisting paradigms that mostly focus on large global currencies while simultaneously contributing to the body of knowledge by offering a thorough analysis of the interactions between cryptocurrencies and a variety of fiat currencies. In light of the fast-changing cryptocurrency environment, it highlights the need for more focused and nuanced research and provides insightful information that may be used to guide future investigations, legislative choices, and investment plans.

5.3 Conclusions

The study investigated the relationship between cryptocurrencies and exchange rates in the selected African countries. Our focus was on the African continent and also zoomed in to the fiat currencies trading in South Africa. An EEMD-based QR technique was applied on the fiat exchange rate returns. To capture the time and frequency information in the currency time series, the exchange rate return series of the fiat currencies were first divided into the short-, medium-, and long-term proportion known as Intrinsic Mode Functions (IMF1, IMF5, and IMF residuals), respectively. Second, to establish the relationship between cryptocurrencies and African fiat currencies, including fiat currencies traded in South Africa over nine quantiles (0.1 through to 0.9), parametric QR was applied to the decomposed series. This helped to empirically examine connections between the return series.

The results displayed using the QR framework show that there is variation in the relationships between the exchange rates of African fiat currencies and digital currencies. Among all the African fiat currencies, only in the case of EGP, MAD, NGN and ZAR can digital currencies BTC and ETH be a viable alternative to the fiat currencies. Our study also established that cryptocurrencies can be utilised as a hedge against depreciating fiat currencies such as ETB, EGP, ZAR, AOA, and NGN over a long period. However, when it comes to KES and DZD, the results showed that cryptocurrency can be utilised to diversify a portfolio where these fiat

currencies are included in the medium and the long term, while digital currency can be utilised to diversify a portfolio with MAD. Rehman et al. (2023) came to a similar conclusion and indicated that Bitcoin can act as short-term diversifier for the AUD, CAD, and JPY. The authors further observed that Bitcoin can be used to diversify portfolios with the EUR, GBP, CAD, Brazilian real, Chinese Yuan, and ZAR. Majdoub et al. (2021) corroborate the findings of our study that Bitcoin can be viewed as a short-term hedge for the CHF, EUR, and GBP, and as a diversifier for the AUD, CAD, and JPY.

Overall, this study underscores the intricate interplay between fiat currencies and cryptocurrencies within South Africa's FX landscape, revealing differential effects across currency pairs and emphasising the need for nuanced analysis to comprehensively understand the underlying dynamics. The results indicate that both BTC and ETH exhibit positive connections with AUD, EUR, and ZAR in the short to medium term, but display negative correlations in the long term. This suggests that digital currencies can serve as diversifiers in portfolios alongside these fiat currencies in the short to medium term and as hedges against depreciation in the long term. These findings are supported by previous studies such as those by Abid et al. (2023) and Duarte et al. (2023), which underline the hedging potential of cryptocurrencies against depreciating fiat currencies.

Conversely, the ZAR demonstrates a negative correlation with ETH in the short to medium term, but a positive correlation in the long term. This indicates that ETH can function as an alternative currency to ZAR in the short to medium term and as a diversification asset in portfolios containing ZAR in the long term. These observations are echoed by Nugroho (2023) and other studies, which highlight cryptocurrencies' viability as alternatives to fiat currencies and their role in portfolio diversification. In addition, BTC and ETH display positive correlations with CHF and GBP in both the short and long term, suggesting their utility as diversifying assets alongside these fiat currencies. This aligns with Abid et al. (2023) and Huang et al. (2023) findings, further emphasising the diversification potential of cryptocurrencies in fiat currency portfolios. Furthermore, the inverse correlation between ETH and EUR in the long term indicates ETH's potential as a hedge against EUR depreciation, a conclusion consistent with studies by (Gbolahan, 2023; Kumah, 2023).

Accordingly, alternative hypotheses H_1, H_2, H_3, H_4, and H_5 are all accepted as they are supported by empirical evidence that correlation exists between fiat and digital currencies. However, we reject all the null hypotheses (first, second, third, fourth and fifth null).

First Null – H_0: No significant connection exists among the fiat currencies and BTC return - rejected.

Second Null – H_0: No significant connection exists among the fiat currencies and ETH return - rejected.

Third Null – H_0: No significant connection exists among the fiat currencies and BNB return - rejected.

First alternative - H_1: A significant connection exists among the fiat currencies and BTC return - accepted.

Second alternative - H_2: A significant connection exists among the fiat currencies and ETH return- accepted.

Third alternative - H_3: A significant connection exists among the fiat currencies and BNB return - accepted.

Fourth Null – H_0: No significant connection exists among the fiat currencies and BTC return - rejected.

Fifth Null – H_0: No significant connection exists among the fiat currencies and ETH return - rejected.

Fourth alternative - H_4: There is a significant connection among the fiat currencies and BTC return - accepted.

Fifth Alternative - H_5: There is a significant connection among the fiat currencies and ETH return - accepted.

5.4 Recommendations

Based on the study's finding of an inverse connection between cryptocurrency and fiat currencies and that cryptocurrency has some hedging characteristics, it is recommended that cryptocurrency can be used as a hedge against depreciating fiat currencies in a portfolio. In

particular, those who invest in FX markets could include digital currency in their portfolios to hedge against risks. However, the appropriateness of utilising cryptocurrency as a diversifier is contingent on the investor's risk appetite and investing objectives. While some investors may welcome the potential benefits of diversification, others could be wary because of the volatility in digital currencies. Some investors may use digital currency as a store of value during economic downturns. It should be borne in mind, however, that cryptocurrency does not meet the requirements to be classified as a currency as it will not be a reliable (stable) unit of account or medium of exchange because of its volatility under stable economic conditions.

Evidence indicates that digital currency is highly volatile as it is influenced by a number of factors like regulation, technology and market sentiments. While some investors with an appetite for high risk may use digital currency for arbitrage opportunities, caution should be exercised as the market can move quite rapidly in any direction, creating exposure to huge losses in trade. Given that the literature points to a lack of regulation in the cryptocurrency market (Oladipupo & Amodu, 2022), it is also recommended that the authorities consider regulating this asset class which has been adopted by many investors throughout the world (Ankenbrand and Bieri (2018) Bunjaku et al. (2017) Mensi, Rehman, et al. (2019).

While our literature review revealed that cryptocurrency is volatile, we advise that forex traders include digital currency in their portfolios to hedge against losses resulting from depreciation in fiat currencies in the short to medium and long term. We also recommend that policymakers use the results of this study to understand cryptocurrency's movements and its connections with African fiat currencies to design appropriate legislation that protects all currencies in the best interests of citizens of the African continent to create a stable financial system. In addition, to guard against ripple effects in the financial system, we advise that central banks use the results of this study to understand the correlation between fiat and digital currencies in order to protect fiat currencies against depreciation by using cryptocurrencies as a hedge fund against fiat currency loss. In instances where the connection is positive, we recommend that central banks invest in digital currencies to diversify the fiat currency portfolio. As cryptocurrency is not subject to inflation, we strongly advise that African governments consider the use of digital currencies as an alternative to fiat currency.

We strongly recommend that regulation should move with speed so that customers/traders are protected from cryptocurrency-related abnormal risks such as fraud and market manipulation. Once regulation is in place, we urge African governments to embrace cryptocurrency to mitigate against the continent's depreciating fiat currencies. Nonetheless, the authorities should navigate the constantly changing regulatory landscape brought about by evolving digital currencies by finding a careful balance between promoting the use of digital currencies and managing related risks.

5.5 Suggestions for further study

Our study focused on the correlation between cryptocurrencies (Binance coin, Bitcoin and Ethereum) and eight major fiat currencies in Africa (NGN, ZAR, EGP, DZD, AOA, MAD, ETB and KES) and then delved deeper into the connection between five major fiat currencies trading in the South African forex market (AUD, CHF, GBP, EUR and ZAR) and digital currencies Bitcoin and Ethereum. Further studies should include many other cryptocurrencies to increase the sample size as we only used the top three. This can also be applied to the fiat currencies used in future studies, with the number of foreign currencies increased to cover a wider range of fiat currencies for African countries. Furthermore, our study's results point to a positive and negative connection between fiat and cryptocurrencies, with very limited links in the case of some fiat and digital currencies. Therefore, further research should delve deeper to understand why these few fiat and digital currencies exhibit limited correlation.

The issue of causality is another area for future research. It would be very interesting to gain an understanding of what causes the cryptocurrency to increase or decrease when the fiat currency decreases or increases and vice versa. The already known connection between cryptocurrencies and fiat currencies suggests that digital currencies could be used as an alternative to fiat currencies especially in cross-border payments and as a medium of exchange within and outside the African continent. This should be further probed to gain an understanding of how it may benefit those using cross-border payments and those who use it as a medium of exchange, including the benefits and risks in African economies.

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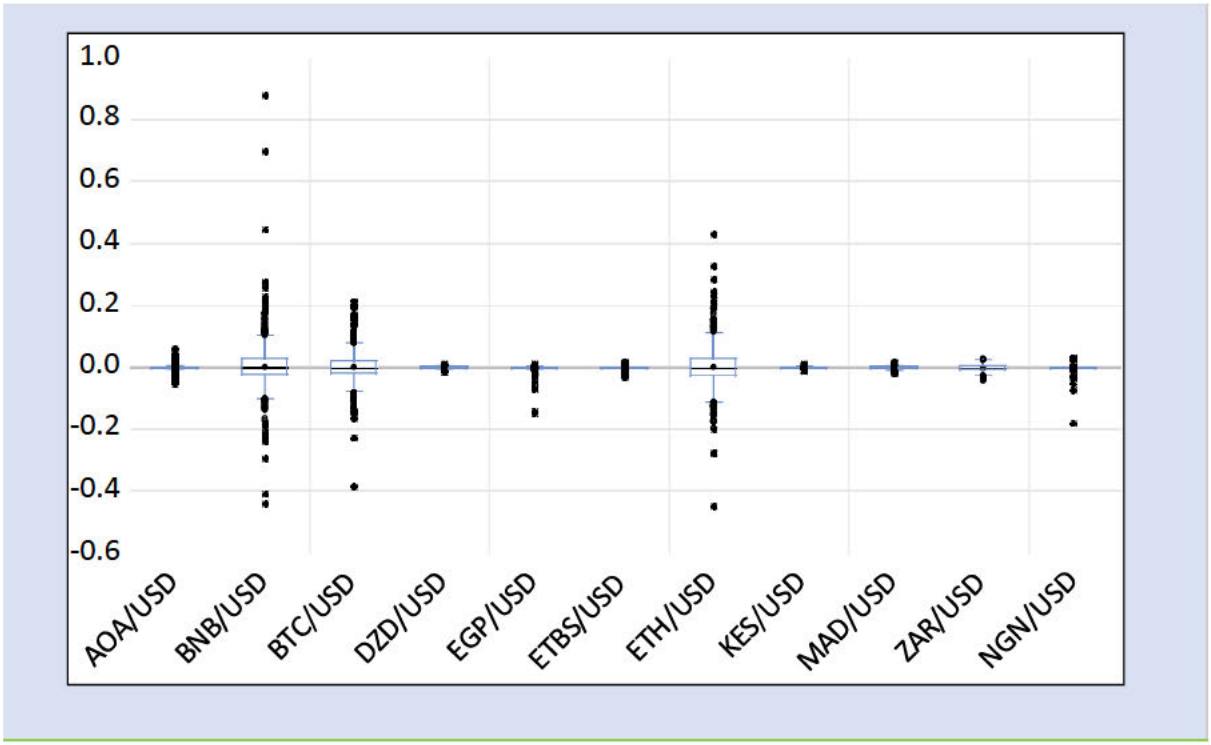
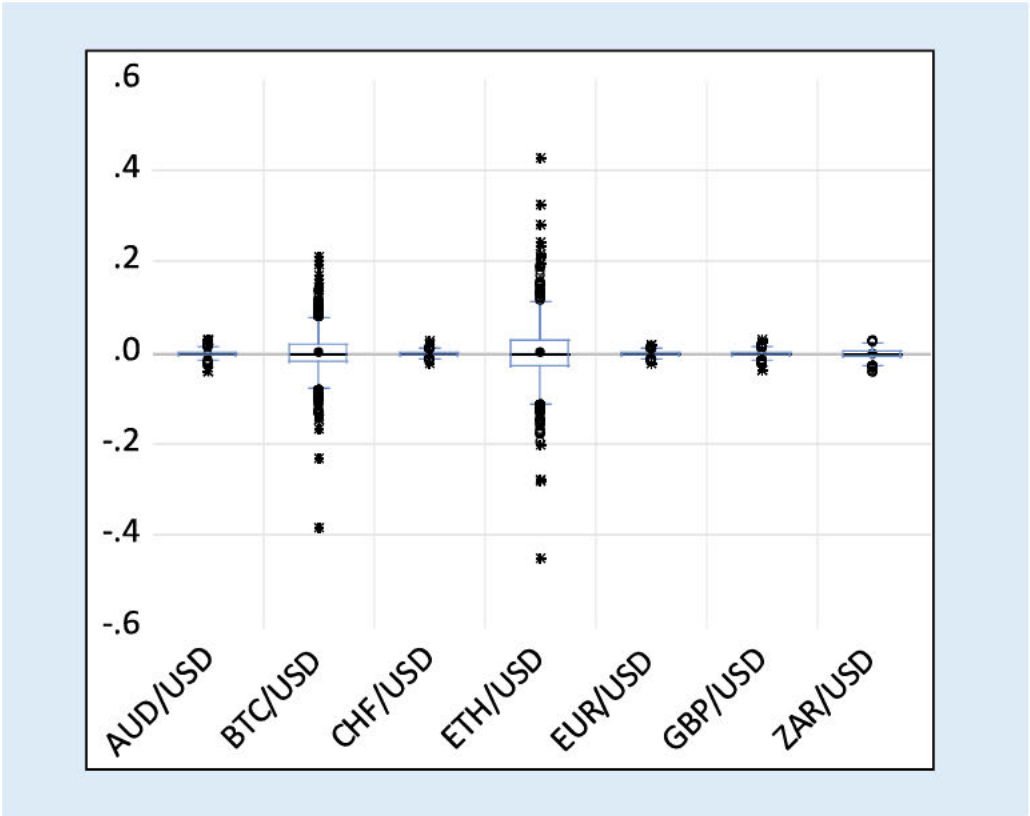
APPENDIX A1: OUTLIER DETECTION GRAPHS

Boxplots – ACX

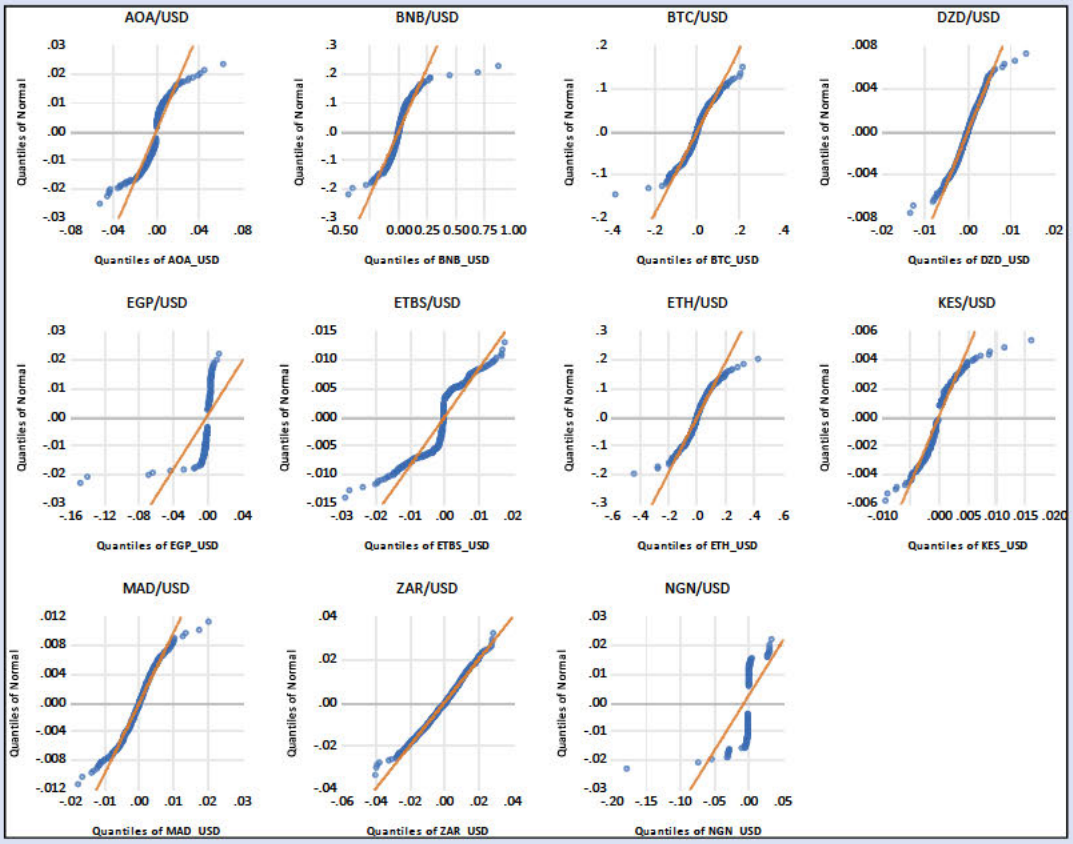


Boxplots – SCX

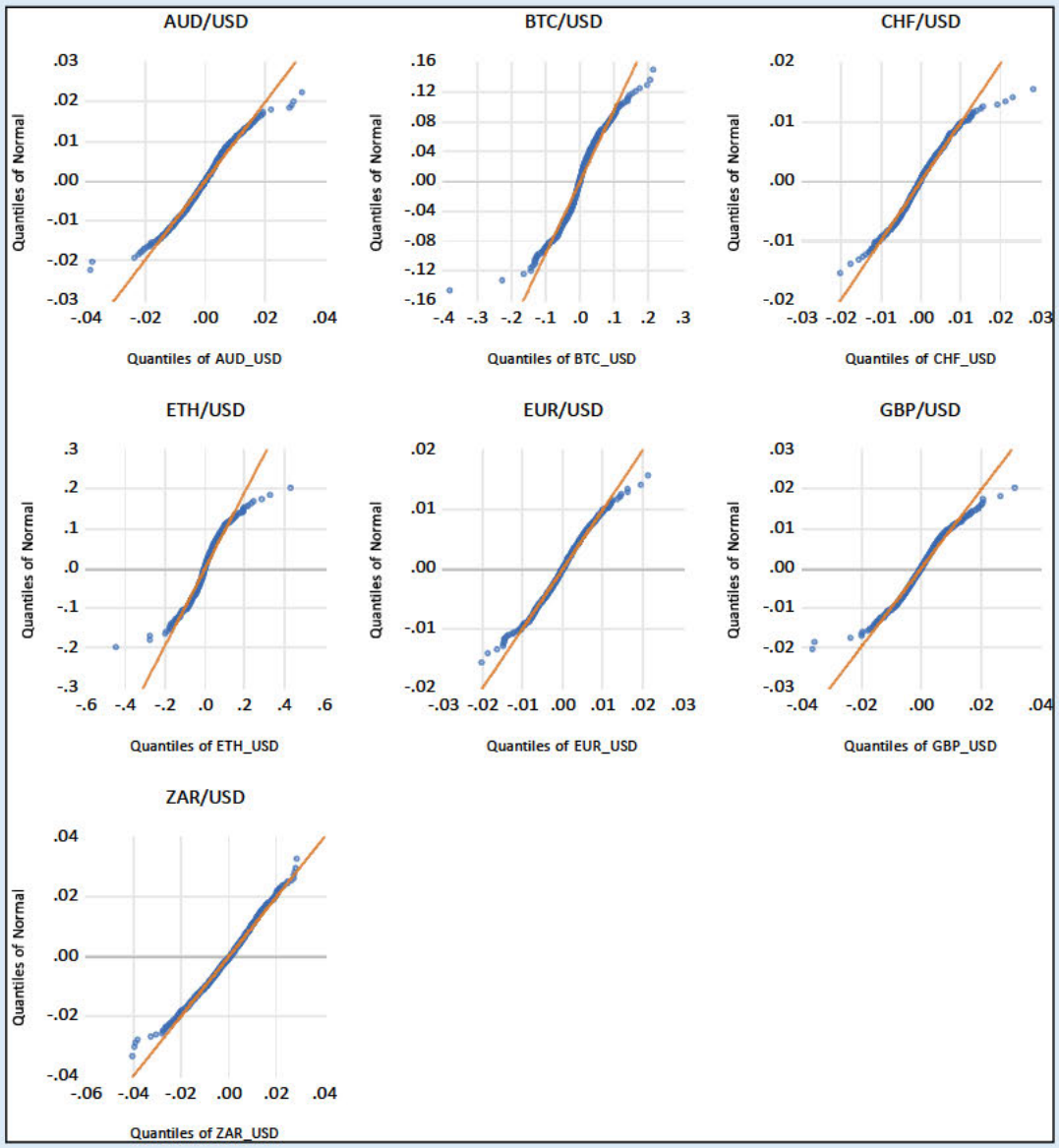


APPENDIX A2: OUTLIER DETECTION GRAPHS

Normal QQ Plots – ACX

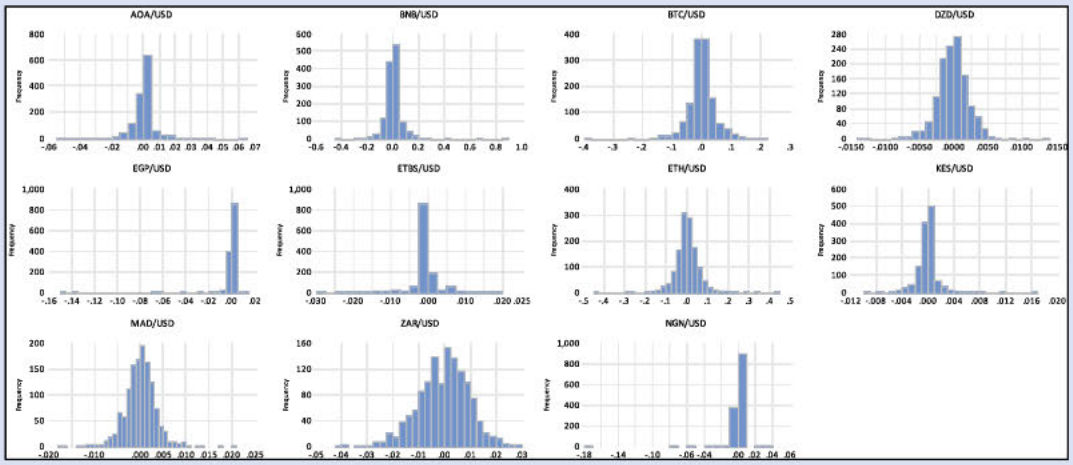


APPENDIX A2.1: NORMAL QQ PLOTS – SCX

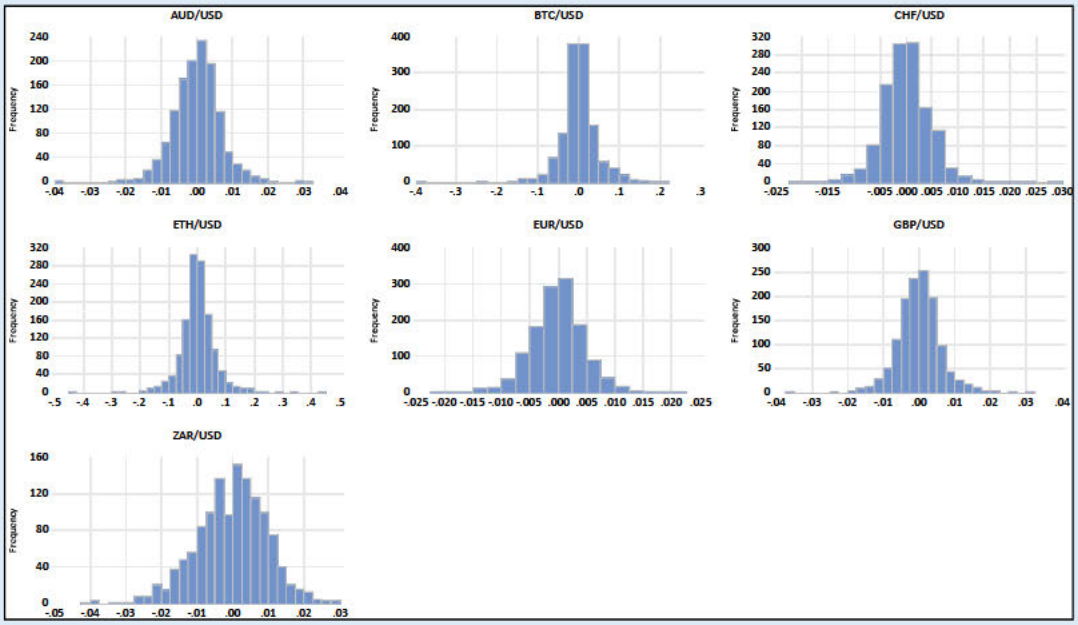


APPENDIX A3: OUTLIER DETECTION GRAPHS

Histograms - ACX

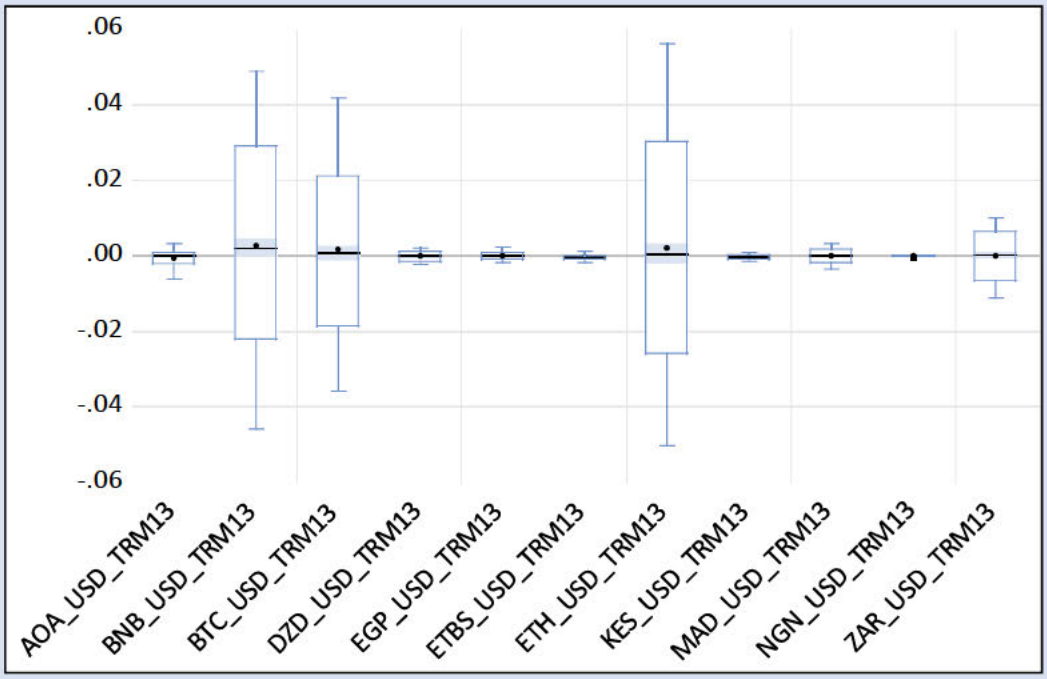


Histograms – SCX

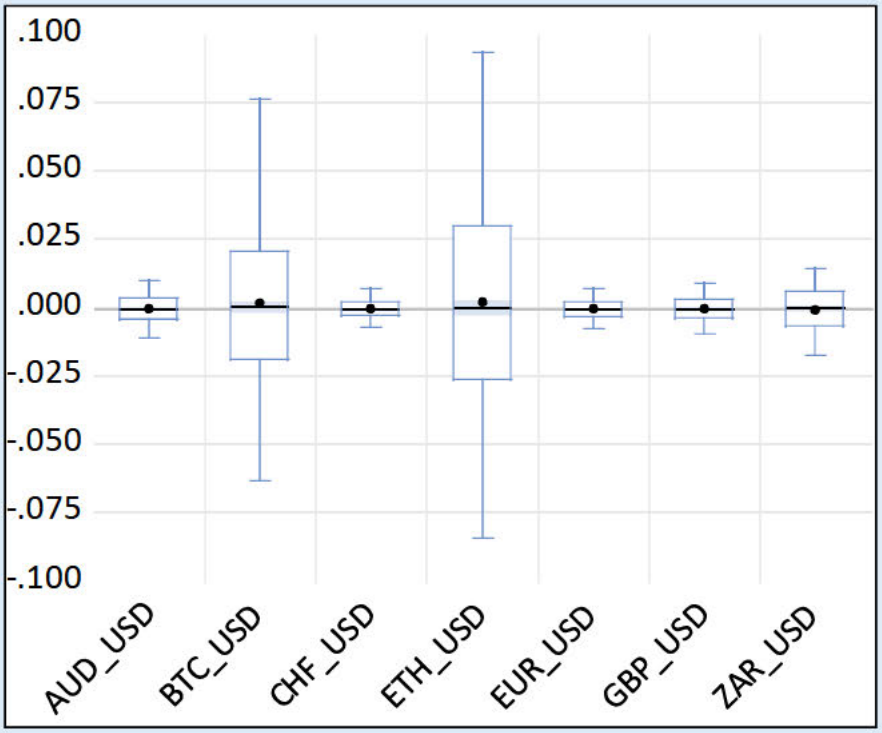


APPENDIX A4: OUTLIER ELIMINATION RESULTS

Boxplots after winsorising – ACX

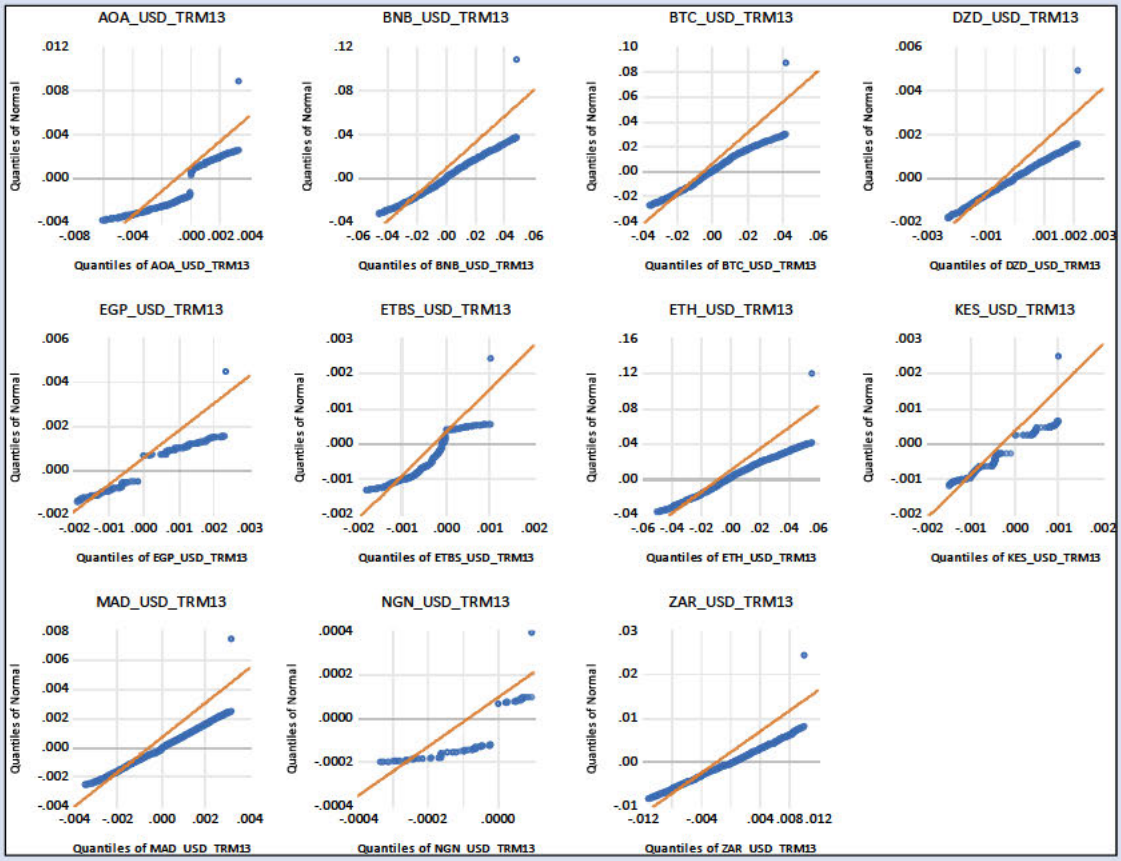


Boxplots after winsorising – SCX

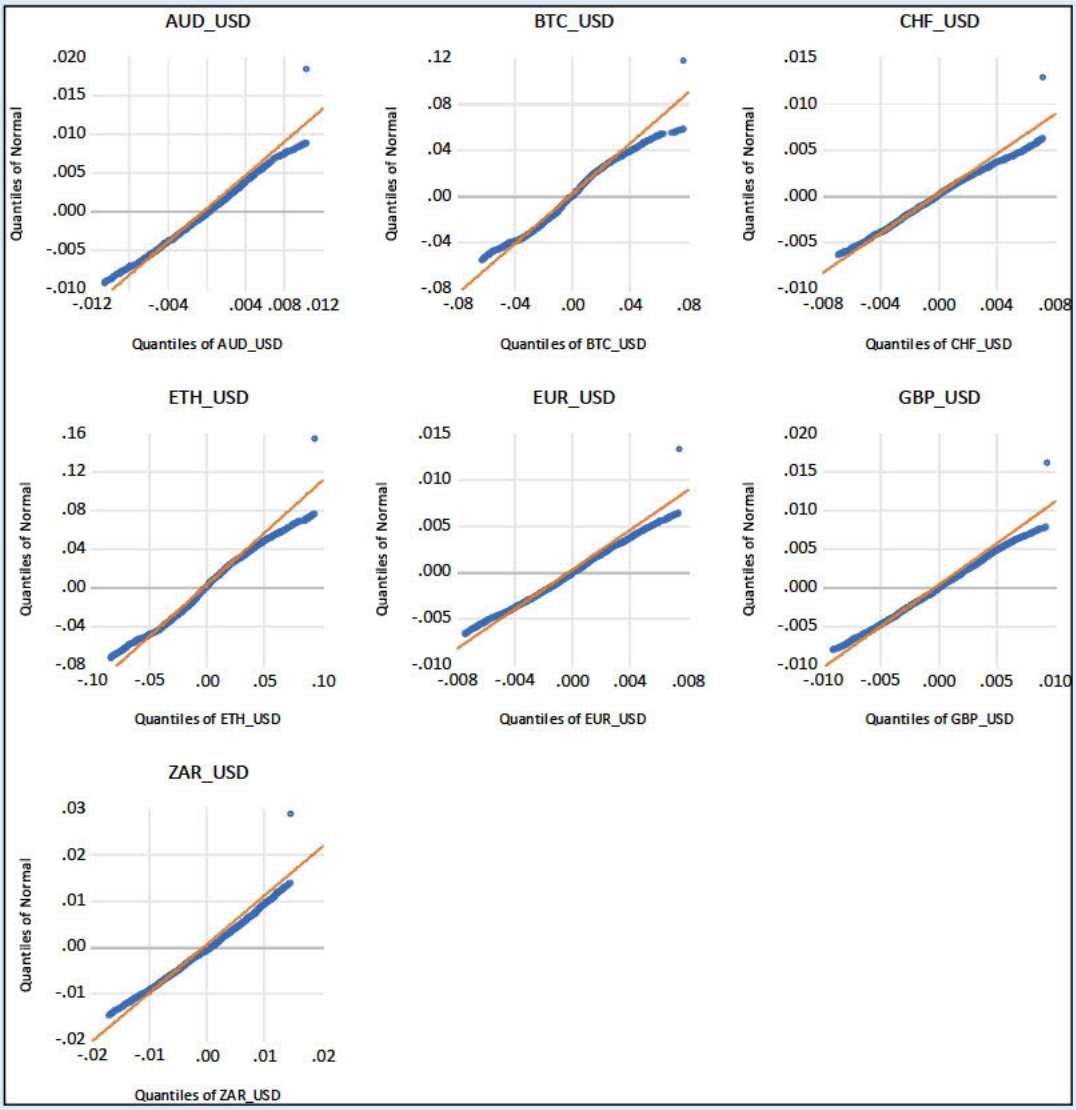


APPENDIX A5: OUTLIER ELIMINATION RESULTS

Normal QQ Plots after winsorising – ACX

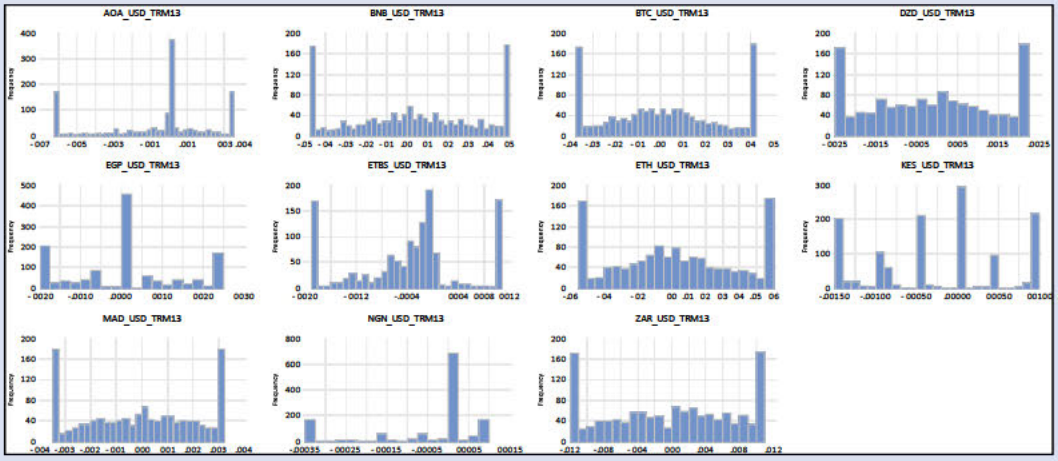


APPENDIX A5.1: NORMAL QQ PLOTS AFTER WINSORISING – SCX

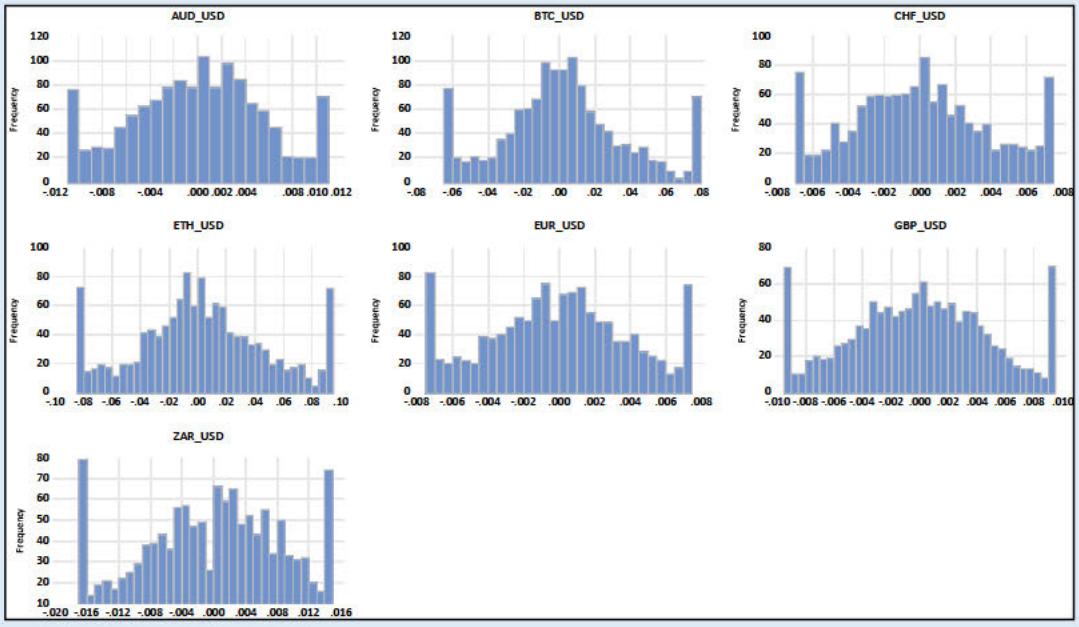


APPENDIX A6: OUTLIER ELIMINATION RESULTS

Histograms after winsorising – ACX

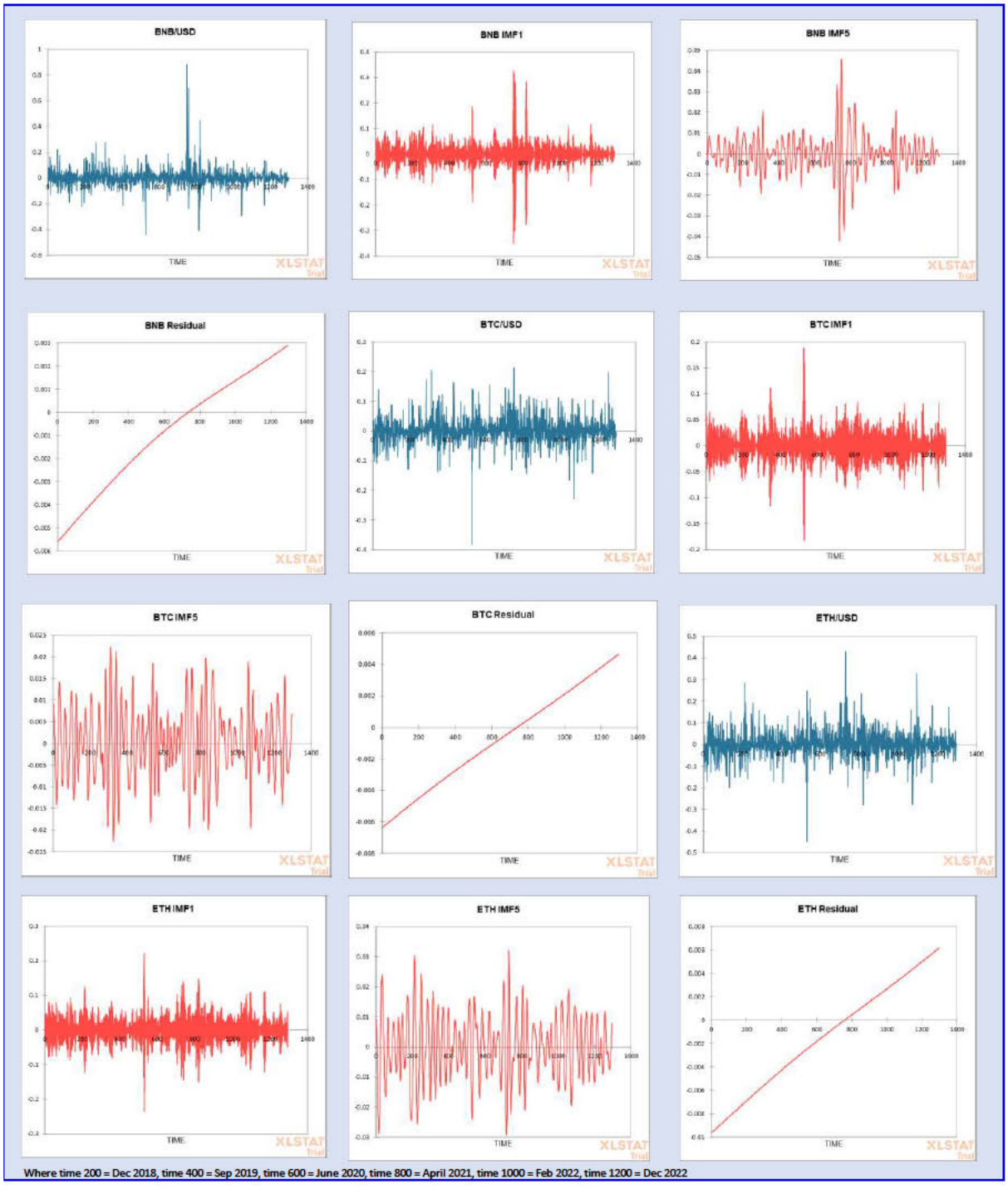


Histograms after winsorising – SCX



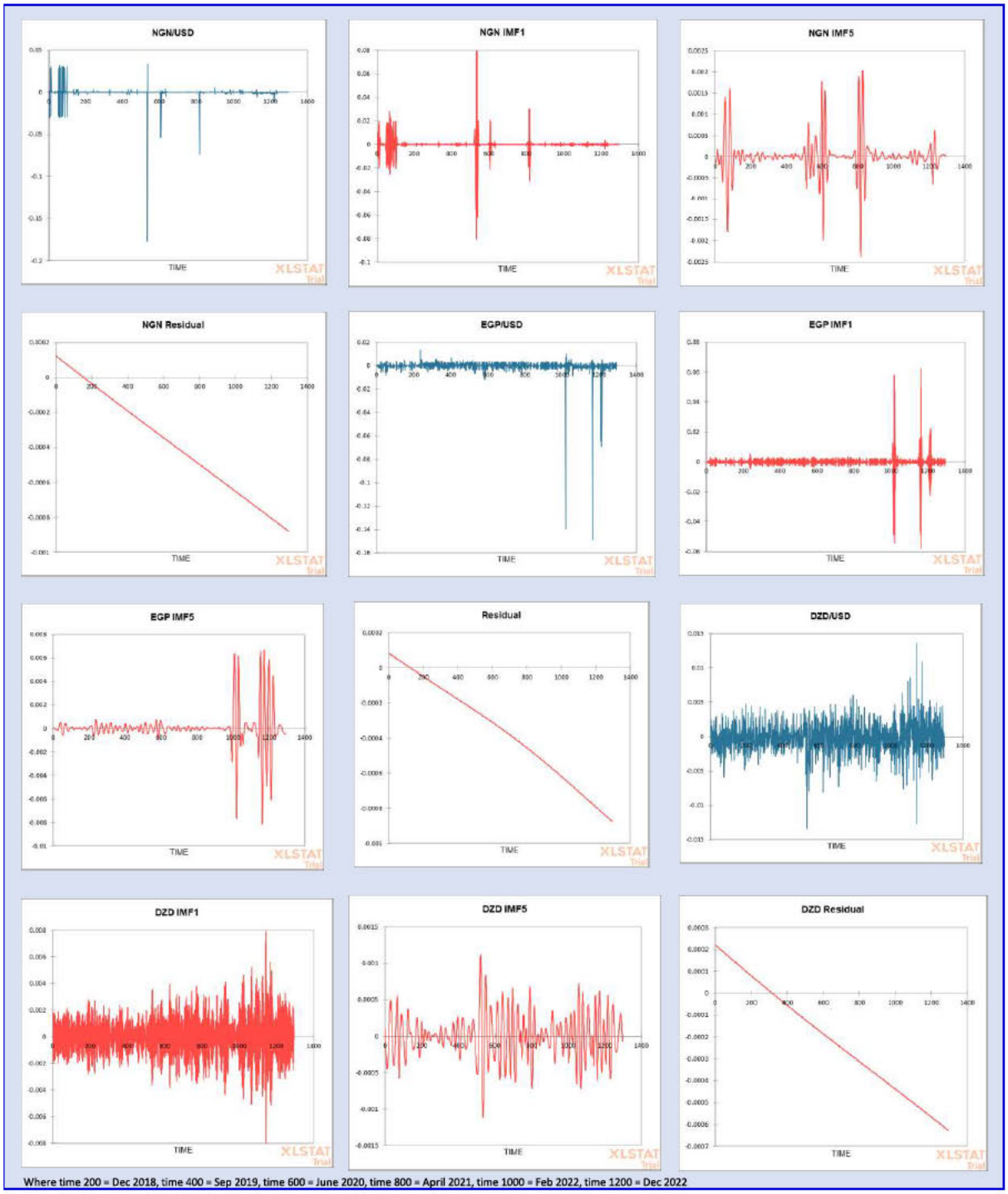
APPENDIX A7: COMPOSITE & DECOMPOSED TIME SERIES

Composite & Decomposed time series - ACX



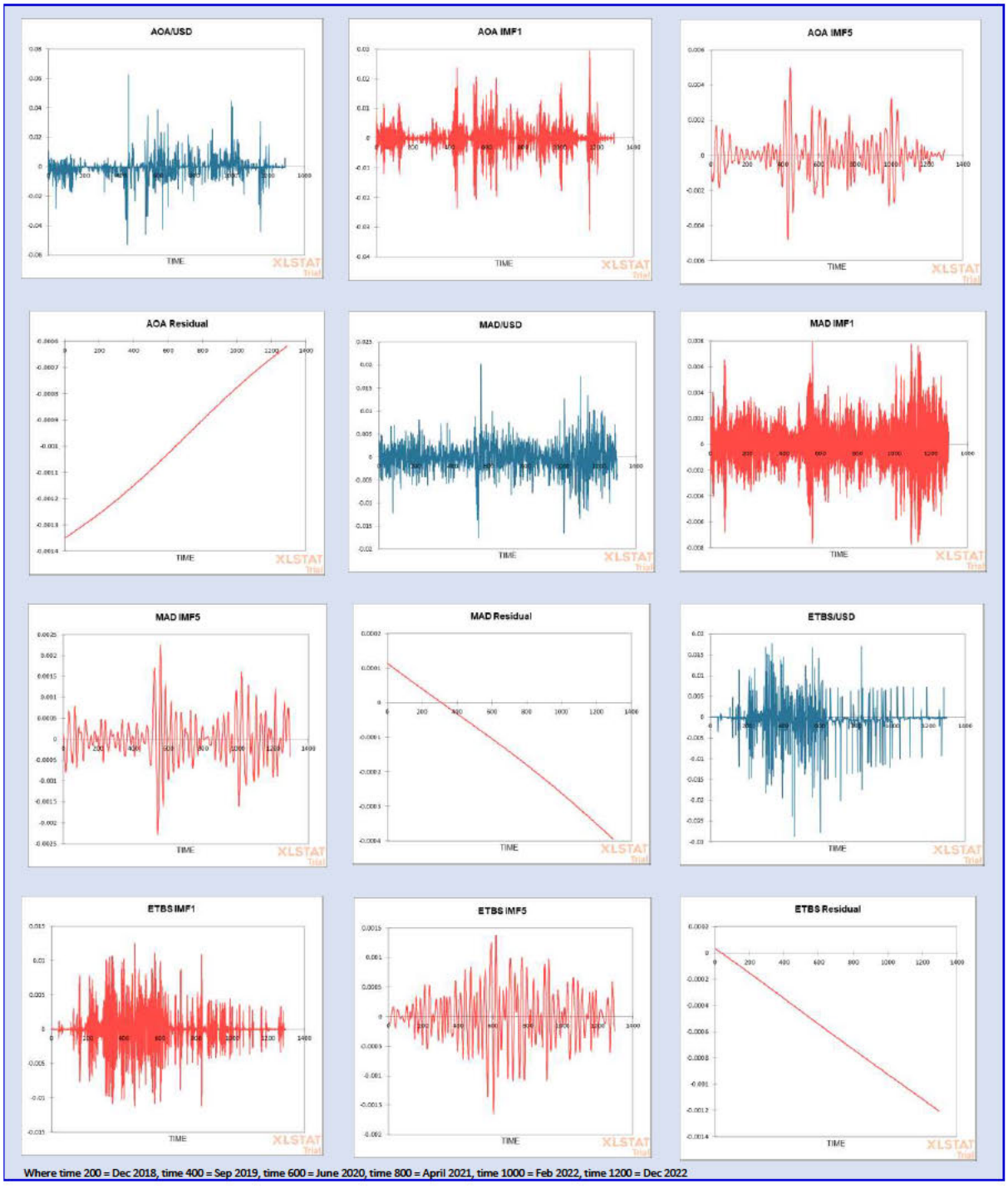
APPENDIX A8: COMPOSITE & DECOMPOSED TIME SERIES

Composite & Decomposed time series - ACX



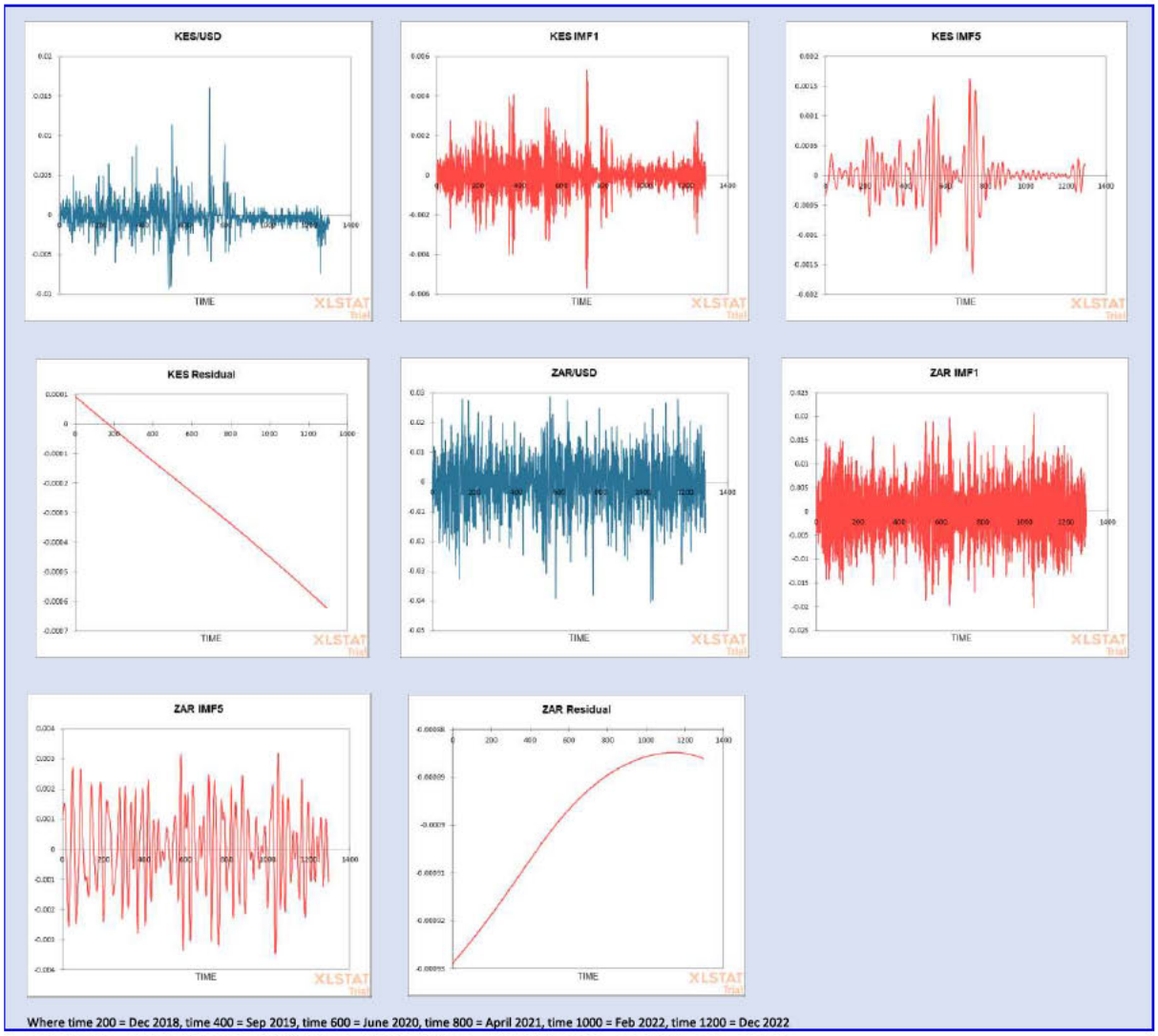
APPENDIX A9: COMPOSITE & DECOMPOSED TIME SERIES

Composite & Decomposed time series - ACX



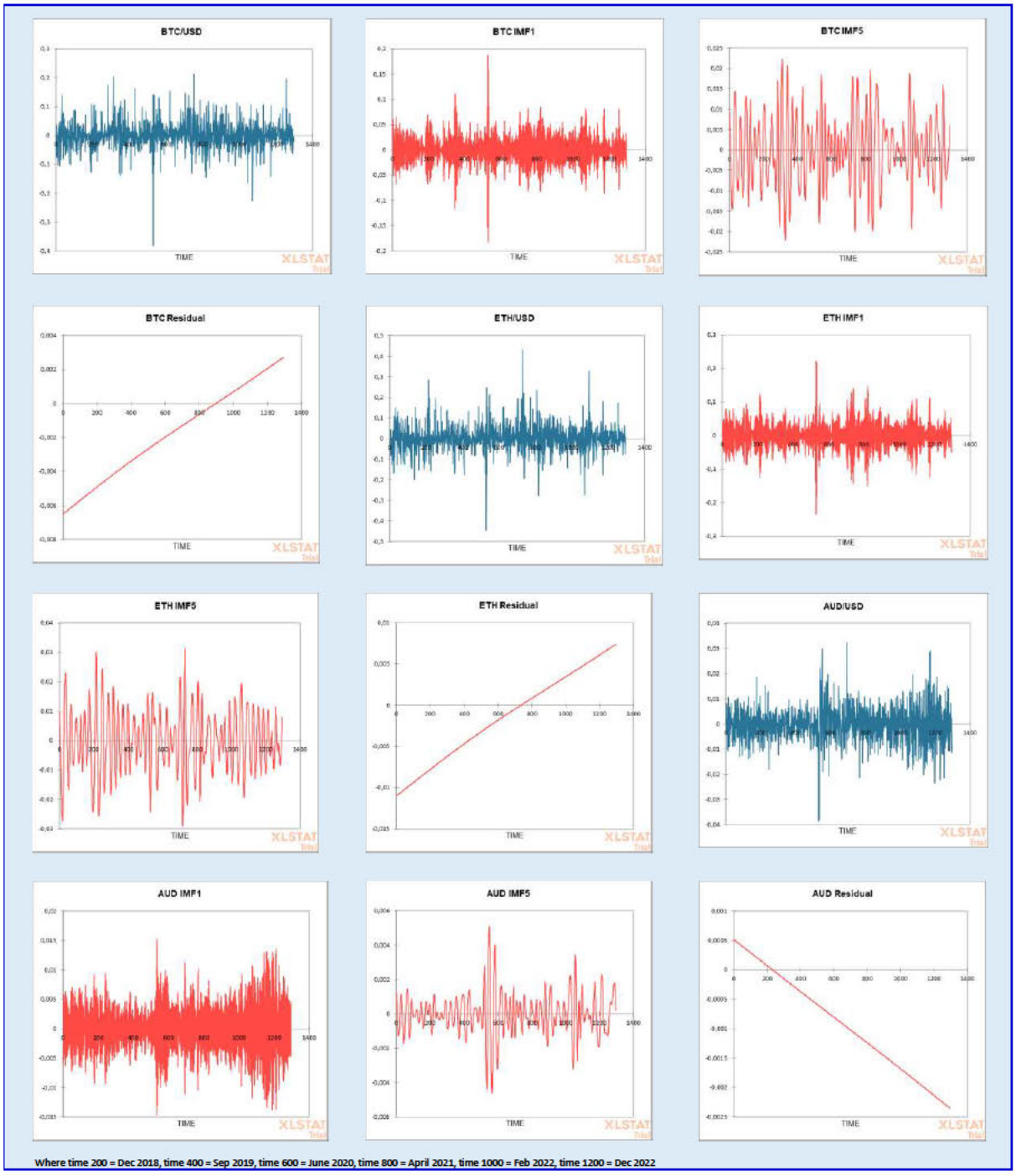
APPENDIX A10: COMPOSITE & DECOMPOSED TIME SERIES

Composite & Decomposed time series - ACX



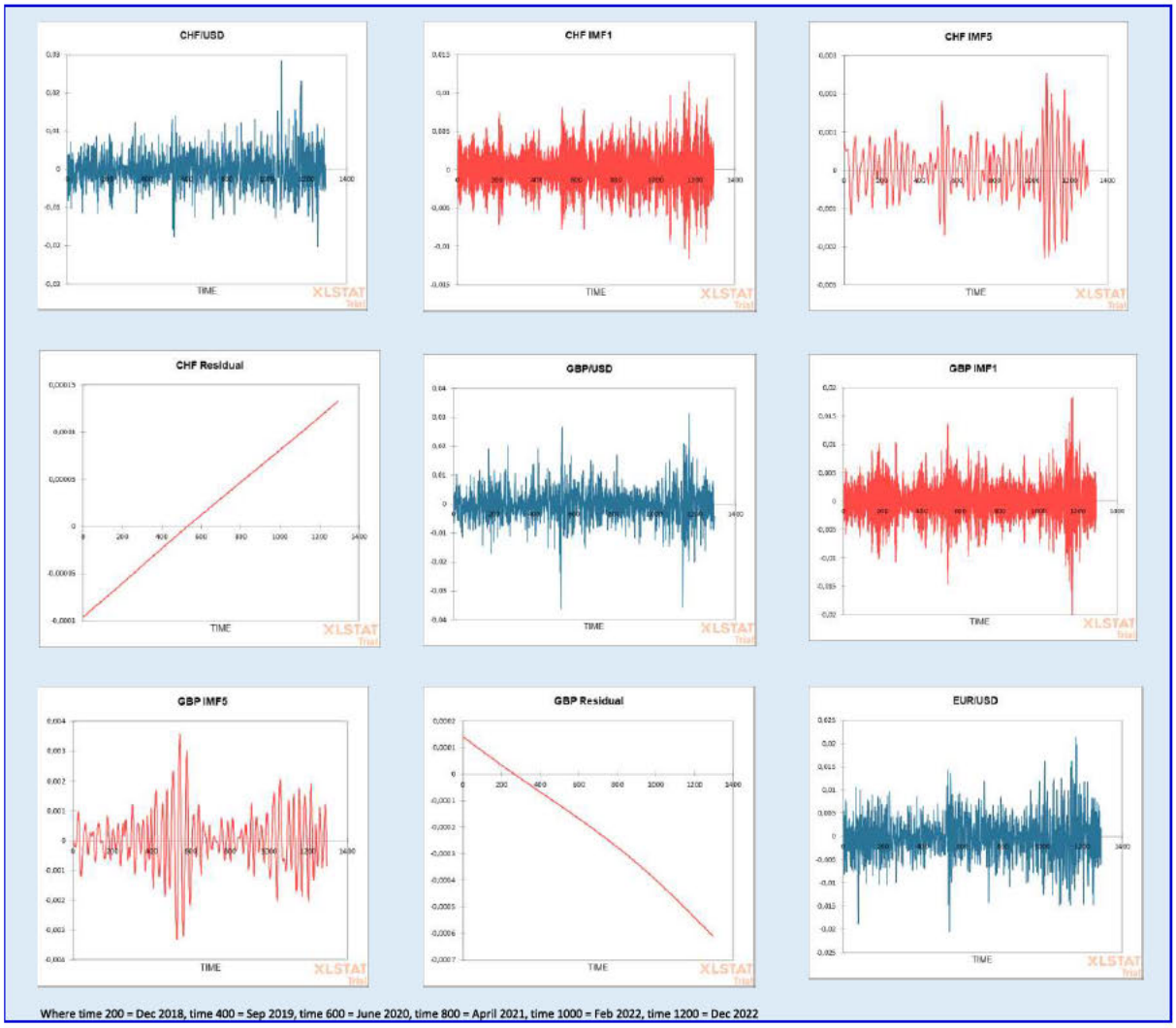
APPENDIX A11: COMPOSITE & DECOMPOSED TIME SERIES

Composite & Decomposed time series - SCX



APPENDIX A12: COMPOSITE & DECOMPOSED TIME SERIES

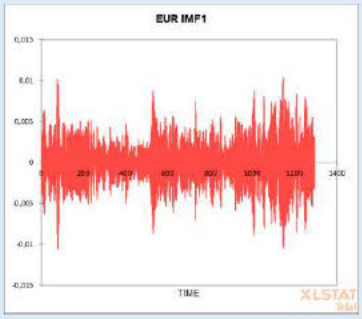
Composite & Decomposed time series - SCX

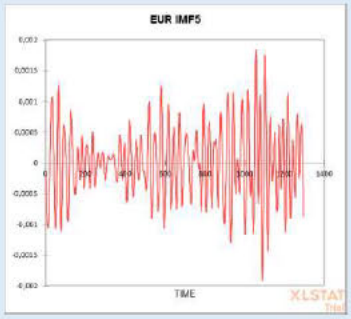


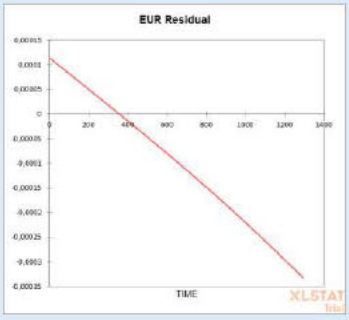
Where time 200 = Dec 2018, time 400 = Sep 2019, time 600 = June 2020, time 800 = April 2021, time 1000 = Feb 2022, time 1200 = Dec 2022

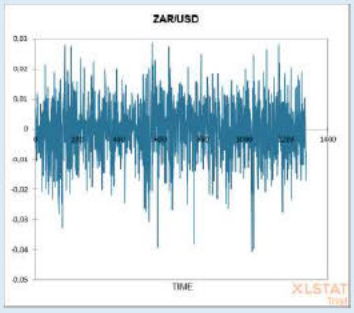
APPENDIX A13: COMPOSITE & DECOMPOSED TIME SERIES

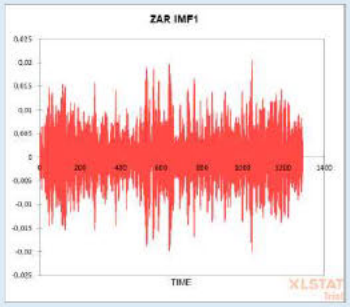
Composite & Decomposed time series - SCX

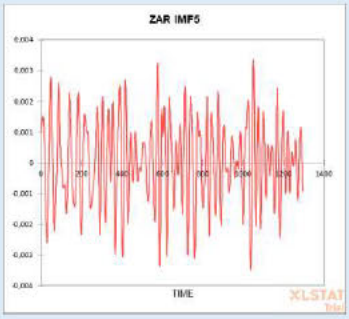


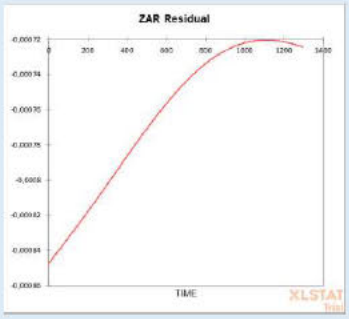












Where time 200 = Dec 2018, time 400 = Sep 2019, time 600 = June 2020, time 800 = April 2021, time 1000 = Feb 2022, time 1200 = Dec 2022

APPENDIX A14: QUANTILE PROCESS ESTIMATES RESULTS

Quantile Process Estimates				
Estimated equation quantile tau = 0,5				
Number of process quantiles: 10				
Equation:		BNB = β0 + β (ACXi,t) + εi,t	*BTC = ϐ0 + ϐ (ACXi,t) + εi,t*	*ETH = ϐ0 + ϐ (ACXi,t) + εi,t*
Specification:		CRCi,t = β0 + β (ACXi,t) + εi,t	*CRCi,t = ϐ0 + ϐ (ACXi,t) + εi,t*	*CRCi,t = ϐ0 + ϐ (ACXi,t) + εi,t*
	Quantile	**Coefficient**	**Coefficient**	**Coefficient**
AOA	0.1	0.5391	-0.1706	-0.0565
	0.2	0.2868	-0.0195	0.2610
	0.3	0.1213	-0.0864	0.1753
	0.4	-0.0444	-0.1319	0.0272
	0.5	-0.1213	-0.2696	-0.0142
	0.6	-0.0653	-0.2707	-0.0754
	0.7	-0.0121	-0.2177	-0.1813
	0.8	-0.0399	-0.3577	-0.2807
	0.9	-0.2249	-0.2168	-0.0544
AOA_IMF1	0.1	0.3825	-0.5921	-0.3458
	0.2	0.1947	-0.2438	-0.2814
	0.3	0.0625	-0.0813	-0.1641
	0.4	0.0363	0.0179	-0.0294
	0.5	0.0553	0.0916	-0.0177
	0.6	0.0633	0.0815	0.0262
	0.7	0.1253	0.0407	0.1216
	0.8	0.1221	0.0535	0.2142
	0.9	0.0364	0.1651	0.3531
AOA_IMF5	0.1	0.4215	0.3395	0.1388
	0.2	0.2935	0.1524	0.2162
	0.3	0.0476	0.0526	0.1664
	0.4	-0.0342	-0.0460	0.0198
	0.5	-0.0613	-0.1406	0.0149
	0.6	-0.0576	-0.1374	-0.0325
	0.7	-0.0732	-0.1236	-0.0906
	0.8	0.0654	-0.1681	-0.2270
	0.9	-0.1364	-0.2201	-0.1476
AOA_RESIDUAl	0.1	3.6865	4.8215	7.0903
	0.2	1.7689	1.8209	3.9065
	0.3	0.7498	0.6100	1.7427
	0.4	0.1924	0.1177	0.2055
	0.5	-0.5723	-0.2545	0.0190
	0.6	-1.3575	-0.9701	-0.3248
	0.7	-2.1106	-1.7082	-1.9072
	0.8	-2.3669	-2.9113	-3.8179
	0.9	-3.5451	-4.7139	-6.1239
DZD	0.1	1.0150	0.1492	-0.2966
	0.2	0.1834	0.2241	0.1728
	0.3	-0.3541	0.3447	0.2549
	0.4	-0.4950	1.1021	-0.0399
	0.5	-0.0471	1.5630	0.6254
	0.6	-0.3177	1.4268	2.3263
	0.7	-0.2215	1.3154	2.9397
	0.8	-0.0709	0.9565	2.7177
	0.9	-0.2868	1.1312	2.5391
DZD_IMF1	0.1	-0.6437	-0.9660	-1.8258
	0.2	-0.5975	-0.1223	-0.1459
	0.3	-0.6005	-0.3300	0.0569
	0.4	-0.2205	-0.3182	0.0333
	0.5	-0.3577	-0.2106	0.0076
	0.6	-0.5197	-0.0227	-0.0501
	0.7	-0.3424	0.1218	-0.2251
	0.8	0.1569	0.3229	-0.1205
	0.9	-0.8057	0.7694	0.9187

APPENDIX A4.14 (continued)

DZD_IMF5	0.1	1.3675	0.7138	-0.0000
	0.2	0.4979	0.1720	0.5225
	0.3	0.2042	0.2009	0.3374
	0.4	0.0508	0.3624	-0.0193
	0.5	0.2043	0.3487	0.0003
	0.6	0.2639	0.1138	0.0721
	0.7	0.3692	0.0693	0.2644
	0.8	0.0379	0.3588	0.4675
	0.9	-1.2396	0.1683	0.5686
DZD_RESIDUAL	0.1	1.5623	1.9591	1.5522
	0.2	2.2764	1.8110	5.5088
	0.3	1.0411	1.7679	2.5509
	0.4	0.1910	1.3146	0.4837
	0.5	-0.4538	0.1036	-0.2762
	0.6	0.8831	0.0657	-2.3528
	0.7	2.6383	-0.8527	-6.6967
	0.8	4.6125	0.9407	-9.2232
	0.9	2.6042	-1.2672	-3.5803
EGP	0.1	-0.2871	-0.1378	-0.1190
	0.2	-0.3022	-0.0760	-0.0578
	0.3	-0.2141	0.0080	0.0026
	0.4	-0.0987	0.0502	0.0948
	0.5	-0.0786	0.0320	0.1254
	0.6	-0.0840	0.1164	0.1346
	0.7	-0.0667	0.2026	0.0781
	0.8	0.0231	0.2494	0.2077
	0.9	0.1660	0.3344	0.2282
EGP_IMF1	0.1	-0.3102	0.3150	0.1685
	0.2	-0.0373	0.1945	0.0366
	0.3	-0.0198	0.1451	0.1092
	0.4	-0.1225	0.1223	0.0175
	0.5	-0.0551	0.1180	0.0367
	0.6	0.0147	0.1019	0.0732
	0.7	0.0725	0.0798	0.0957
	0.8	0.0955	0.1261	0.2508
	0.9	0.2329	-0.0466	0.2394
EGP_IMF5	0.1	0.5127	-0.4228	-0.6132
	0.2	0.1862	-0.2760	-0.2821
	0.3	0.0843	-0.1330	-0.1315
	0.4	0.0217	-0.0894	-0.0141
	0.5	-0.0392	-0.0226	-0.0269
	0.6	-0.1191	0.0169	-0.0869
	0.7	-0.1933	0.0616	-0.0760
	0.8	-0.0152	-0.0627	-0.2654
	0.9	0.1472	0.2083	-0.0391
EGP_RESIDUAL	0.1	1.9332	-2.8086	1.0834
	0.2	0.3021	-1.3086	0.9536
	0.3	0.6456	-0.6477	0.3915
	0.4	0.4097	-0.6231	-0.0045
	0.5	-0.0059	-0.2709	-0.0629
	0.6	-0.4697	-0.0272	-0.2243
	0.7	-1.3094	-0.3102	-0.6097
	0.8	-1.7079	-0.7907	-1.4660
	0.9	-0.5529	0.7698	-2.8086
ETBS	0.1	-0.7286	-0.3020	-0.5153
	0.2	-0.6357	-0.0539	-0.3448
	0.3	-0.4309	-0.0812	-0.2560
	0.4	-0.3843	-0.2253	-0.3048
	0.5	-0.4944	-0.1051	-0.2997
	0.6	-0.1524	-0.1927	-0.1725
	0.7	-0.0239	-0.1934	-0.1087
	0.8	-0.2403	-0.1077	-0.1740
	0.9	0.2156	0.4439	0.3297

APPENDIX A4.14 (continued)

ETBS_IMF1	0.1	0.4950	-0.1433	0.3878
	0.2	0.4815	-0.0063	-0.0940
	0.3	0.0954	-0.0058	-0.0900
	0.4	0.0459	-0.0242	-0.0259
	0.5	0.0277	-0.0404	0.0107
	0.6	0.0298	0.0133	0.0346
	0.7	0.0804	-0.0366	0.0034
	0.8	0.1659	0.0154	0.0363
	0.9	-0.1774	0.7157	-0.5365
ETBS_IMF5	0.1	-1.3070	0.1117	-0.2733
	0.2	-1.1784	0.0337	-0.0580
	0.3	-0.6859	0.0002	0.0746
	0.4	-0.3033	0.0199	0.0212
	0.5	-0.2168	0.0864	-0.0057
	0.6	-0.4164	0.0919	-0.0382
	0.7	-0.7597	0.2289	0.0266
	0.8	-0.7547	-0.1408	0.0988
	0.9	-1.0985	-0.1995	0.6116
ETBS_RESIDUA	0.1	-8.3409	-3.6126	-9.5518
	0.2	-5.0411	-1.0703	-1.2072
	0.3	-2.6246	-0.8598	0.3720
	0.4	-2.0222	-0.5467	0.0762
	0.5	-0.7068	-0.2407	-0.0906
	0.6	-0.4950	-0.6020	-0.6611
	0.7	-1.0791	-0.8622	-0.8324
	0.8	-2.0912	-1.8450	-0.0854
	0.9	-4.7057	-3.6360	2.9060
KES	0.1	-0.8976	2.0153	-0.3435
	0.2	-0.4374	0.9367	0.2452
	0.3	-0.0227	0.4486	0.0541
	0.4	0.0736	0.7618	-0.5255
	0.5	1.3028	0.8571	1.2044
	0.6	1.4544	1.7494	2.1169
	0.7	1.8017	1.3620	2.2412
	0.8	1.4256	1.4372	2.0823
	0.9	3.5136	0.4526	3.1782
KES_IMF1	0.1	-0.6884	1.1038	-0.9426
	0.2	-0.0363	-0.0716	-0.5086
	0.3	0.3613	-0.3755	-0.2578
	0.4	0.3070	-0.3013	-0.0134
	0.5	0.3717	-0.2852	0.0736
	0.6	1.2231	-0.2081	0.1623
	0.7	2.0959	0.3266	0.5019
	0.8	2.1515	0.2211	0.9548
	0.9	1.9574	-0.4021	2.3914
KES_IMF5	0.1	0.6330	2.7033	4.6888
	0.2	-0.7062	1.9761	1.8408
	0.3	-0.3056	1.2191	1.1018
	0.4	-0.3075	0.8392	0.1912
	0.5	-0.1752	0.9821	0.0246
	0.6	-0.2260	1.2203	0.0694
	0.7	-0.0606	0.8649	0.8219
	0.8	-0.9118	2.0824	1.0355
	0.9	0.3236	2.6361	-1.7239
KES_RESIDUAL	0.1	-1.1543	10.3390	12.2836
	0.2	4.1716	8.4640	9.7836
	0.3	2.4672	5.3734	5.3163
	0.4	0.4558	3.2590	0.7427
	0.5	0.5182	2.9857	0.1003
	0.6	0.3367	4.5456	0.5980
	0.7	1.8706	3.2100	2.3358
	0.8	4.1036	4.5090	3.6982
	0.9	16.7046	3.9547	1.2661

APPENDIX A4.14 (continued)

MAD	0.1	-0.9120	0.7269	-0.0925
	0.2	-0.5037	0.2818	-0.1110
	0.3	-0.3091	0.3468	0.0188
	0.4	-0.4501	0.0462	-0.2020
	0.5	-0.1989	-0.0835	-0.1412
	0.6	0.2715	0.4531	0.3623
	0.7	0.2671	0.5405	0.4038
	0.8	-0.1467	0.6043	0.2288
	0.9	-0.2012	0.7811	0.2899
MAD_IMF1	0.1	-0.7457	1.1983	1.5369
	0.2	-0.5514	0.9450	0.9898
	0.3	-0.3810	0.7095	0.4584
	0.4	-0.3279	0.5577	0.0111
	0.5	-0.1755	0.4362	0.0374
	0.6	-0.0809	0.3493	0.1483
	0.7	-0.3552	0.5676	0.5398
	0.8	-1.0652	1.0989	0.7224
	0.9	-0.9932	0.5009	0.0547
MAD_IMF5	0.1	-0.0648	-0.4856	-0.9037
	0.2	0.0510	-0.4310	-0.2517
	0.3	0.1858	-0.2793	-0.1441
	0.4	0.2499	-0.2769	0.0009
	0.5	0.2374	-0.1778	-0.0232
	0.6	0.3795	-0.2428	-0.0971
	0.7	0.5429	-0.2354	-0.2109
	0.8	0.7481	-0.4135	0.2501
	0.9	1.1483	0.3282	0.2553
MAD_RESIDUA	0.1	10.9158	4.6950	10.5265
	0.2	7.3439	2.4151	3.0429
	0.3	2.8808	1.2604	1.7517
	0.4	2.1522	0.9087	0.2077
	0.5	1.6554	0.8450	0.1075
	0.6	1.0747	-0.0922	0.3870
	0.7	2.7432	-1.2455	0.1754
	0.8	-0.0217	-3.6315	2.3324
	0.9	-2.1447	0.9510	0.0289
NGN	0.1	1.0592	0.6160	0.8376
	0.2	0.2512	0.0544	0.1528
	0.3	-0.1246	-0.1527	-0.1386
	0.4	-0.3352	-0.1320	-0.2336
	0.5	-0.4169	-0.1013	-0.2591
	0.6	-0.4528	-0.0934	-0.2731
	0.7	-0.6418	-0.0781	-0.3600
	0.8	-0.5174	-0.0289	-0.2732
	0.9	-0.3291	0.1148	-0.1071
NGN_IMF1	0.1	0.1016	0.2449	0.1114
	0.2	0.4083	0.0118	0.0457
	0.3	0.1578	0.0728	0.0713
	0.4	0.0847	0.0414	0.0575
	0.5	0.1321	0.0130	0.0290
	0.6	0.2013	0.0715	0.1077
	0.7	0.2982	0.1003	0.1963
	0.8	0.3112	0.1347	0.1215
	0.9	0.0091	0.1153	0.2572
NGN_IMF5	0.1	0.1407	0.1281	-0.1261
	0.2	0.2365	-0.0320	-0.1499
	0.3	0.0371	-0.0121	-0.0908
	0.4	-0.0046	-0.0249	-0.0165
	0.5	-0.0053	-0.0041	-0.0045
	0.6	0.0824	-0.0430	-0.0015
	0.7	0.1932	-0.0093	0.0563
	0.8	0.1486	0.0021	0.1383
	0.9	-0.2224	0.1156	0.0187

APPENDIX A4.14 (continued)

NGN_RESIDUA	0.1	4.0666	6.9536	18.1221
	0.2	3.4338	7.1834	11.5379
	0.3	1.5724	4.2817	6.5678
	0.4	0.8327	2.2435	1.0013
	0.5	-0.7528	0.1768	-0.1733
	0.6	-3.4602	-2.4085	-4.0347
	0.7	-3.2581	-6.1700	-10.9516
	0.8	-1.6652	-9.1162	-14.2876
	0.9	-0.0570	-12.6218	-21.6550
ZAR	0.1	0.0437	0.2182	0.1310
	0.2	0.0261	0.1359	0.0810
	0.3	0.0142	0.0659	0.0400
	0.4	0.0007	0.0440	0.0223
	0.5	-0.0038	0.0431	0.0197
	0.6	-0.0128	0.0546	0.0209
	0.7	-0.0299	0.0999	0.0350
	0.8	-0.0461	0.1757	0.0648
	0.9	-0.0848	0.2696	0.0924
ZAR_IMF1	0.1	0.5707	0.6627	0.2613
	0.2	0.1586	0.1557	0.2326
	0.3	-0.0549	0.0981	0.0785
	0.4	0.0198	0.0916	0.0130
	0.5	0.0552	0.1142	0.0107
	0.6	0.0616	0.0795	0.0242
	0.7	0.1629	0.1053	0.0815
	0.8	0.4602	0.1592	0.1830
	0.9	0.5709	0.1173	0.1310
ZAR_IMF5	0.1	-1.1593	-0.5362	-0.1050
	0.2	-0.6886	-0.1200	-0.1082
	0.3	-0.4331	-0.0752	-0.0708
	0.4	-0.2651	-0.0332	-0.0030
	0.5	-0.2282	-0.0347	-0.0044
	0.6	-0.4273	-0.0277	-0.0101
	0.7	-0.8028	-0.0372	-0.1215
	0.8	-0.9999	-0.1793	-0.4194
	0.9	-1.2644	-0.1118	-0.5014
ZAR_RESIDUAL	0.1	-2.4793	-2.4566	-1.9806
	0.2	-0.1531	-0.9569	-1.1046
	0.3	0.5133	-0.4603	-0.4772
	0.4	0.6387	-0.2843	-0.0435
	0.5	0.1333	-0.1308	-0.0139
	0.6	0.4822	-0.3285	-0.1283
	0.7	0.7801	-0.7013	-0.6416
	0.8	-0.2019	-1.1907	-0.8561
	0.9	-1.5052	-3.0463	0.3272
C	0.1	-0.0489	-0.0331	-0.0387
	0.2	-0.0253	-0.0153	-0.0157
	0.3	-0.0122	-0.0075	-0.0064
	0.4	-0.0045	-0.0026	-0.0014
	0.5	0.0016	0.0012	0.0014
	0.6	0.0083	0.0064	0.0050
	0.7	0.0193	0.0106	0.0105
	0.8	0.0336	0.0195	0.0221
	0.9	0.0591	0.0383	0.0464

APPENDIX A15: QUANTILE PROCESS ESTIMATES RESULTS SCX

Quantile Process Estimates			
Estimated equation quantile tau = 0.5			
Number of process quantiles: 10			
Equation:		*BTC = ϐ0 + ϐ (ACXi,t) + εi,t*	*ETH = ϐ0 + ϐ (ACXi,t) + εi,t*
Specification:		*CRCi,t = ϐ0 + ϐ (ACXi,t) + εi,t*	*CRCi,t = ϐ0 + ϐ (ACXi,t) + εi,t*
	Quantile	**Coefficient**	**Coefficient**
AUD_IMF1	0.1	0.0526	-0.0602
	0.2	0.0842	-0.0193
	0.3	0.0709	-0.0005
	0.4	0.0513	-0.0008
	0.5	0.0469	-0.0009
	0.6	0.0637	-0.0004
	0.7	0.0978	0.0000
	0.8	0.1522	0.0002
	0.9	0.2493	0.0601
AUD_IMF5	0.1	0.0280	0.0772
	0.2	-0.0309	0.0217
	0.3	-0.0410	0.0004
	0.4	-0.0318	0.0008
	0.5	-0.0343	0.0008
	0.6	-0.0480	0.0004
	0.7	-0.0675	-0.0001
	0.8	-0.1100	-0.0007
	0.9	-0.2168	-0.0849
AUD_RES	0.1	1.7032	0.7677
	0.2	0.5009	0.1153
	0.3	0.1573	0.0012
	0.4	0.0079	0.0009
	0.5	-0.0761	-0.0023
	0.6	-0.1978	-0.0063
	0.7	-0.4430	-0.0095
	0.8	-0.8424	-0.0182
	0.9	-2.1103	-1.4646
AUD_USD	0.1	-0.0783	0.2031
	0.2	-0.0955	0.4378
	0.3	-0.0741	0.4933
	0.4	-0.0387	0.4958
	0.5	-0.0146	0.4975
	0.6	0.0081	0.4989
	0.7	0.0420	0.5005
	0.8	0.0987	0.5009
	0.9	0.2734	0.5207
CHF_IMF1	0.1	0.0428	0.0652
	0.2	0.0465	0.0171
	0.3	0.0528	0.0000
	0.4	0.0389	0.0000
	0.5	0.0276	-0.0002
	0.6	0.0380	0.0001
	0.7	0.0447	0.0002
	0.8	0.0456	0.0001
	0.9	-0.0799	-0.0454
CHF_IMF5	0.1	0.0364	-0.1326
	0.2	0.0371	-0.0194
	0.3	0.0125	-0.0002
	0.4	-0.0251	0.0000
	0.5	-0.0241	0.0006
	0.6	-0.0165	0.0002
	0.7	0.0265	0.0000
	0.8	0.0939	0.0001
	0.9	0.2474	0.0352
CHF_RES	0.1	-0.7520	-0.1121
	0.2	0.0287	-0.0247
	0.3	0.0740	0.0026
	0.4	0.1211	0.0058
	0.5	0.1774	0.0063

APPENDIX A15 (continued)

	Quantile	Coefficient	Coefficient
	0.6	0.2444	0.0055
	0.7	0.3977	0.0031
	0.8	0.6526	0.0111
	0.9	1.8419	1.3868
CHF_USD	0.1	-0.3755	-0.2364
	0.2	-0.2261	-0.1173
	0.3	-0.1554	-0.0061
	0.4	-0.0968	-0.0031
	0.5	-0.0346	-0.0026
	0.6	-0.0156	-0.0022
	0.7	-0.0016	-0.0010
	0.8	0.0283	-0.0007
	0.9	0.2742	0.0663
EUR_IMF1	0.1	0.0804	-0.0049
	0.2	0.1221	0.0028
	0.3	0.0965	0.0001
	0.4	0.0556	0.0001
	0.5	0.0436	-0.0002
	0.6	0.0475	-0.0001
	0.7	0.0691	-0.0001
	0.8	0.0323	-0.0005
	0.9	-0.1259	-0.0589
EUR_IMF5	0.1	-0.1354	0.0840
	0.2	-0.2014	0.0005
	0.3	-0.1447	0.0000
	0.4	-0.0678	-0.0002
	0.5	-0.0495	-0.0003
	0.6	-0.0690	-0.0001
	0.7	-0.1220	-0.0001
	0.8	-0.1288	0.0010
	0.9	-0.0013	0.0600
EUR_RES	0.1	-1.8130	-1.4256
	0.2	-1.5258	-0.3595
	0.3	-0.7906	-0.0093
	0.4	-0.3440	-0.0173
	0.5	-0.2581	-0.0155
	0.6	-0.3405	-0.0111
	0.7	-0.3746	-0.0080
	0.8	0.1415	-0.0112
	0.9	0.6637	-0.6542
EUR_USD	0.1	0.1938	0.0919
	0.2	0.1342	0.0108
	0.3	0.0898	0.0003
	0.4	0.0733	0.0003
	0.5	0.0537	0.0001
	0.6	0.0548	0.0002
	0.7	0.0903	0.0000
	0.8	0.1310	0.0004
	0.9	0.2336	0.0609
GBP_IMF1	0.1	0.0473	-0.0070
	0.2	0.0482	-0.0014
	0.3	0.0352	0.0000
	0.4	0.0255	0.0001
	0.5	0.0170	0.0003
	0.6	0.0278	0.0002
	0.7	0.0447	0.0001
	0.8	0.0637	0.0005
	0.9	0.1251	0.0154
GBP_IMF5	0.1	-0.0014	-0.0449
	0.2	0.0459	-0.0040
	0.3	0.0208	0.0000
	0.4	-0.0013	0.0001
	0.5	0.0047	0.0001
	0.6	0.0076	0.0000
	0.7	0.0129	0.0001
	0.8	0.0373	-0.0001
	0.9	0.0595	0.0583

APPENDIX A15 (continued)

	Quantile	Coefficient	Coefficient
GBP_RES	0.1	-0.5659	-0.7289
	0.2	-0.1560	-0.0826
	0.3	-0.0152	-0.0001
	0.4	0.0659	-0.0015
	0.5	0.0587	-0.0036
	0.6	0.0671	-0.0022
	0.7	0.0673	0.0001
	0.8	0.2469	0.0008
	0.9	0.8366	0.6795
GBP_USD	0.1	0.1630	0.0586
	0.2	0.0745	0.0057
	0.3	0.0471	0.0000
	0.4	0.0277	-0.0002
	0.5	0.0180	-0.0003
	0.6	0.0078	-0.0003
	0.7	0.0049	-0.0001
	0.8	-0.0067	-0.0009
	0.9	-0.1054	-0.1015
ZAR_IMF1	0.1	0.1986	-0.0009
	0.2	0.1244	-0.0004
	0.3	0.0695	0.0000
	0.4	0.0483	0.0002
	0.5	0.0397	0.0001
	0.6	0.0500	0.0000
	0.7	0.0774	0.0000
	0.8	0.1286	0.0000
	0.9	0.2369	-0.0046
ZAR_IMF5	0.1	-0.1495	-0.0062
	0.2	-0.0864	-0.0002
	0.3	-0.0553	-0.0001
	0.4	-0.0427	-0.0002
	0.5	-0.0319	-0.0002
	0.6	-0.0388	-0.0001
	0.7	-0.0639	-0.0001
	0.8	-0.0865	-0.0004
	0.9	-0.1213	0.0341
ZAR_RES	0.1	1.4457	0.4505
	0.2	0.4848	0.0944
	0.3	0.0887	0.0018
	0.4	-0.1356	0.0012
	0.5	-0.2807	0.0004
	0.6	-0.4329	-0.0003
	0.7	-0.7150	-0.0010
	0.8	-1.1136	-0.0022
	0.9	-1.8769	-0.1685
ZAR_USD	0.1	-0.0903	0.0166
	0.2	-0.0608	0.0022
	0.3	-0.0354	0.0000
	0.4	-0.0230	-0.0002
	0.5	-0.0185	-0.0002
	0.6	-0.0240	-0.0001
	0.7	-0.0375	-0.0001
	0.8	-0.0622	-0.0001
	0.9	-0.1192	0.0111
C	0.1	-0.0070	-0.0045
	0.2	-0.0034	-0.0016
	0.3	-0.0019	-0.0011
	0.4	-0.0010	-0.0011
	0.5	-0.0004	-0.0010
	0.6	0.0000	-0.0010
	0.7	0.0008	-0.0010
	0.8	0.0023	-0.0010
	0.9	0.0065	0.0018

ANNEXURE A16: QUANTILE SLOPE EQUALITY TEST RESULTS – ACX

Quantile Slope Equality Test

Estimated equation quantile tau = 0.5
Number of test quantiles: 10
Test statistic compares all coefficients

Restriction Detail: b(tau_h) - b(tau_k) = 0

Equation:	BNB = β0 + β (ACXi,t) + εi,t	BTC = β0 + β (ACXi,t) + εi,t	ETH = β0 + β (ACXi,t) + εi,t
Specification:	CRCi,t = β0 + β (ACXi,t) + εi,t	CRCi,t = β0 + β (ACXi,t) + εi,t	CRCi,t = β0 + β (ACXi,t) + εi,t

Test Summary	Chi-Sq. Statistic	Chi-Sq. d.f.	Prob.	Chi-Sq. Statistic	Chi-Sq. d.f.	Prob.	Chi-Sq. Statistic	Chi-Sq. d.f.	Prob.
Wald Test	20805.301	256	0.0000	19910.071	256	0.0000	37896.42895	224	0.0000

Quantiles	Variable	Restr. Value	Std. Error	Prob.	S or I	Restr. Value	Std. Error	Prob.	S or I	Restr. Value	Std. Error	Prob.	S or I
0.1, 0.2	AOA	0.2524	0.0948	0.0078	S	-0.1511	0.0522	0.0038	S	-0.3176	0.1325	0.0166	S
	AOA_IMF1	0.1878	0.0881	0.0330	S	-0.3482	0.0560	0.0000	S	-0.0644	0.1021	0.5281	I
	AOA_IMF5	0.1280	0.1531	0.4031	I	0.1871	0.0896	0.0369	S	-0.0774	0.1057	0.4642	I
	AOA_RES	1.9176	0.4691	0.0000	S	3.0006	0.2847	0.0000	S	3.1838	0.3911	0.0000	S
	DZD	0.8316	0.4279	0.0520	I	-0.0749	0.2860	0.7934	I	-0.4694	0.4588	0.3063	I
	DZD_IMF1	-0.0462	0.3499	0.8950	I	-0.8437	0.2137	0.0001	S	-1.6800	0.3525	0.0000	S
	DZD_IMF5	0.8696	0.5003	0.0822	I	0.5418	0.3487	0.1202	I	-0.5225	0.5012	0.2972	I
	DZD_RES	-0.7141	2.2829	0.7544	I	0.1481	1.4619	0.9193	I	-3.9565	1.9878	0.0465	S
	EGP	0.0151	0.0638	0.8129	I	-0.0619	0.0215	0.0040	S	-0.0612	0.0328	0.0621	I
	EGP_IMF1	-0.2729	0.1643	0.0967	I	0.1205	0.0522	0.0210	S	0.1320	0.0711	0.0634	I
	EGP_IMF5	0.3265	0.7016	0.6417	I	-0.1467	0.1323	0.2674	I	-0.3311	0.0429	0.0000	S
	EGP_RES	1.6311	0.6999	0.0198	S	-1.5000	0.9433	0.1118	I	0.1299	0.7622	0.8647	I
	ETBS	-0.0929	0.2515	0.7117	I	-0.2481	0.1122	0.0270	S	-0.1705	0.1818	0.3693	I
	ETBS_IMF1	0.0135	0.1670	0.9356	I	-0.1370	0.0711	0.0542	I	0.4819	0.1621	0.0029	S
	ETBS_IMF5	-0.1285	0.2925	0.6603	I	0.0780	0.0951	0.4123	I	-0.2153	0.2643	0.4155	I
	ETBS_RES	-3.2998	1.0992	0.0027	S	-2.5423	0.6538	0.0001	S	-8.3446	1.2547	0.0000	S
	KES	-0.4602	0.5652	0.4155	I	1.0786	0.4911	0.0281	S	-0.5886	1.6785	0.7258	I
	KES_IMF1	-0.6521	0.3040	0.0319	S	1.1754	0.2501	0.0000	S	-0.4340	0.3627	0.2314	I
	KES_IMF5	1.3392	0.6508	0.0396	S	0.7272	0.3211	0.0235	S	2.8480	0.4003	0.0000	S
	KES_RES	-5.3259	1.5805	0.0008	S	1.8750	0.8031	0.0196	S	2.5000	2.2697	0.2707	I
	MAD	-0.4082	0.2680	0.1277	I	0.4451	0.1221	0.0003	S	0.0184	0.1950	0.0640	I
	MAD_IMF1	-0.1943	0.2188	0.3747	I	0.2533	0.1639	0.1222	I	0.5471	0.2201	0.0129	S
	MAD_IMF5	-0.1158	0.2895	0.6892	I	-0.0546	0.2716	0.8405	I	-0.6520	0.3217	0.0427	S
	MAD_RES	3.5719	1.1038	0.0012	S	2.2799	0.8706	0.0088	S	7.4835	1.4594	0.0000	S
	NGN	0.8080	0.1202	0.0000	S	0.5616	0.1535	0.0003	S	0.6848	0.1369	0.0001	S
	NGN_IMF1	-0.3067	0.0947	0.0012	S	0.2331	0.0992	0.0188	S	0.0657	0.2379	0.7825	I
	NGN_IMF5	-0.0958	0.1130	0.3968	I	0.1600	0.0703	0.0228	S	0.0238	0.1857	0.8980	I
	NGN_RES	0.6328	1.7034	0.7103	I	-0.2297	1.0479	0.8265	I	6.5842	0.5840	0.0000	S
	ZAR	0.0176	0.0077	0.0214	S	0.0823	0.0081	0.0000	S	0.0500	0.0079	0.0107	S
	ZAR_IMF1	0.4121	0.0871	0.0000	S	0.5070	0.0582	0.0000	S	0.0287	0.0620	0.6432	I
	ZAR_IMF5	-0.4706	0.1280	0.0002	S	-0.4161	0.0682	0.0000	S	0.0032	0.0830	0.9692	I
	ZAR_RES	-2.3262	0.4657	0.0000	S	-1.4997	0.2535	0.0000	S	-0.8760	0.3351	0.0089	S
0.2, 0.3	AOA	0.1655	0.0755	0.0284	S	0.0669	0.0372	0.0722	I	0.0857	0.0496	0.0840	S
	AOA_IMF1	0.1322	0.0473	0.0052	S	-0.1626	0.0192	0.0000	S	-0.1173	0.0242	0.0000	S
	AOA_IMF5	0.2459	0.0787	0.0018	S	0.0998	0.0292	0.0006	S	0.0498	0.0424	0.2408	I
	AOA_RES	1.0191	0.2565	0.0001	S	1.2109	0.1196	0.0000	S	2.1638	0.1170	0.0000	S
	DZD	0.5375	0.1665	0.0012	S	-0.1205	0.1234	0.3287	I	-0.0821	0.1373	0.5497	I
	DZD_IMF1	0.0030	0.1882	0.9874	I	0.2077	0.0951	0.0291	S	-0.2027	0.1195	0.0898	I
	DZD_IMF5	0.2936	0.2235	0.1888	I	-0.0289	0.1314	0.8257	I	0.1852	0.1879	0.3243	I
	DZD_RES	1.2353	0.9523	0.1946	I	0.0431	0.4466	0.9232	I	2.9579	0.5805	0.0000	S
	EGP	-0.0881	0.0487	0.0706	I	-0.0839	0.0100	0.0000	S	-0.0604	0.0165	0.0002	S
	EGP_IMF1	-0.0175	0.1057	0.8688	I	0.0495	0.0207	0.0168	S	-0.0726	0.0382	0.0573	I
	EGP_IMF5	0.1018	0.0508	0.0449	S	-0.1431	0.0276	0.0000	S	-0.1506	0.0298	0.0000	S
	EGP_RES	-0.3435	0.2834	0.2254	I	-0.6609	0.1613	0.0000	S	0.5620	0.1935	0.0037	S
	ETBS	-0.2048	0.1341	0.1269	I	0.0273	0.0850	0.7483	I	-0.0887	0.1096	0.4376	I
	ETBS_IMF1	0.3861	0.0765	0.0000	S	-0.0005	0.0361	0.9885	I	-0.0040	0.0312	0.8984	I
	ETBS_IMF5	-0.4926	0.0979	0.0000	S	0.0336	0.0614	0.5848	I	-0.1326	0.0418	0.0015	S
	ETBS_RES	-2.4165	0.5642	0.0000	S	-0.2106	0.2775	0.4479	I	-1.5792	0.2824	0.0000	S
	KES	-0.4147	0.4712	0.3789	I	0.4882	0.2191	0.0259	S	0.1911	0.2963	0.5189	I

ANNEXURE A16 (continued)

	KES_IMF1	-0.3976	0.2168	0.0667	*I*	0.3039	0.0996	0.0023	*S*	-0.2508	0.0959	0.0089	*S*
	KES_IMF5	-0.4006	0.3325	0.2283	*I*	0.7571	0.1260	0.0000	*S*	0.7390	0.2062	0.0003	*S*
	KES_RES	1.7043	1.0563	0.1066	*I*	3.0907	0.4399	0.0000	*S*	4.4673	0.3289	0.0000	*S*
	MAD	-0.1947	0.1098	0.0762	*I*	-0.0649	0.0908	0.4746	*I*	-0.1298	0.1003	0.2754	*I*
	MAD_IMF1	-0.1704	0.1059	0.1078	*I*	0.2355	0.0563	0.0000	*S*	0.5314	0.0613	0.0000	*S*
	MAD_IMF5	-0.1348	0.1271	0.2890	*S*	-0.1516	0.0927	0.1020	*I*	-0.1076	0.1184	0.3634	*I*
	MAD_RES	4.4631	0.6138	0.0000	*I*	1.1546	0.3064	0.0002	*S*	1.2912	0.3236	0.0001	*S*
	NGN	0.3758	0.0866	0.0000	*S*	0.2070	0.0604	0.0006	*S*	0.2914	0.0735	0.0003	*S*
	NGN_IMF1	0.2505	0.0723	0.0005	*S*	-0.0609	0.0234	0.0092	*S*	-0.0256	0.0318	0.4219	*I*
	NGN_IMF5	0.1994	0.0792	0.0118	*S*	-0.0199	0.0337	0.5552	*I*	-0.0592	0.0901	0.5112	*I*
	NGN_RES	1.8614	0.5631	0.0009	*S*	2.9017	0.2061	0.0000	*S*	4.9701	0.2352	0.0000	*S*
	ZAR	0.0119	0.0061	0.0537	*I*	0.0701	0.0055	0.0000	*S*	0.0410	0.0058	0.0269	*S*
	ZAR_IMF1	0.2135	0.0474	0.0000	*S*	0.0577	0.0239	0.0159	*S*	0.1541	0.0248	0.0000	*S*
	ZAR_IMF5	-0.2555	0.0589	0.0000	*S*	-0.0448	0.0276	0.1042	*I*	-0.0374	0.0371	0.3128	*I*
	ZAR_RES	-0.6664	0.2027	0.0010	*S*	-0.4966	0.1191	0.0000	*S*	-0.6274	0.1393	0.0000	*S*
0.3, 0.4	AOA	0.1657	0.0261	0.0000	*S*	0.0455	0.0331	0.1694	*I*	0.1481	0.0455	0.0011	*S*
	AOA_IMF1	0.0263	0.0222	0.2375	*I*	-0.0991	0.0151	0.0000	*S*	-0.1347	0.0165	0.0000	*S*
	AOA_IMF5	0.0818	0.0322	0.0112	*S*	0.0986	0.0185	0.0000	*S*	0.1466	0.0252	0.0000	*S*
	AOA_RES	0.5573	0.1054	0.0000	*S*	0.4923	0.0767	0.0000	*S*	1.5372	0.0904	0.0000	*S*
	DZD	0.1409	0.0837	0.0924	*I*	-0.7574	0.0807	0.0000	*S*	0.2948	0.1357	0.0299	*S*
	DZD_IMF1	-0.3799	0.0831	0.0000	*S*	-0.0118	0.0571	0.8367	*I*	0.0235	0.0758	0.7561	*I*
	DZD_IMF5	0.1534	0.1407	0.2756	*I*	-0.1615	0.0712	0.0233	*S*	0.3567	0.1052	0.0007	*S*
	DZD_RES	0.8501	0.4395	0.0531	*I*	0.4533	0.3747	0.2264	*I*	2.0672	0.3325	0.0000	*S*
	EGP	-0.1154	0.0408	0.0046	*S*	-0.0422	0.0138	0.0021	*S*	-0.0922	0.0210	0.0000	*S*
	EGP_IMF1	0.1027	0.0970	0.2898	*I*	0.0227	0.0318	0.4755	*I*	0.0917	0.0503	0.0682	*I*
	EGP_IMF5	0.0627	0.0528	0.2355	*I*	-0.0435	0.0307	0.1557	*I*	-0.1174	0.0204	0.0000	*S*
	EGP_RES	0.2360	0.2720	0.3856	*I*	-0.0246	0.1429	0.8635	*I*	0.3960	0.0609	0.0000	*S*
	ETBS	-0.0466	0.1274	0.7144	*I*	0.1441	0.0742	0.0520	*I*	0.0487	0.1008	0.3832	*I*
	ETBS_IMF1	0.0495	0.0430	0.2498	*I*	0.0183	0.0247	0.4577	*I*	-0.0641	0.0306	0.0363	*S*
	ETBS_IMF5	-0.3826	0.0588	0.0000	*S*	-0.0198	0.0296	0.5040	*I*	0.0534	0.0420	0.2028	*I*
	ETBS_RES	-0.6024	0.2606	0.0208	*S*	-0.3131	0.1801	0.0822	*I*	0.2959	0.2518	0.2399	*I*
	KES	-0.0963	0.2154	0.6548	*I*	-0.3133	0.2096	0.1351	*I*	0.5795	0.2556	0.0234	*S*
	KES_IMF1	0.0542	0.0689	0.4314	*I*	-0.0742	0.0592	0.2107	*I*	-0.2445	0.0642	0.0001	*S*
	KES_IMF5	0.0019	0.1265	0.9881	*I*	0.3798	0.0908	0.0000	*S*	0.9106	0.0958	0.0000	*S*
	KES_RES	2.0114	0.3195	0.0000	*S*	2.1144	0.2580	0.0000	*S*	4.5736	0.2810	0.0000	*S*
	MAD	0.1411	0.0681	0.0382	*S*	0.3006	0.0703	0.0000	*S*	0.2208	0.0692	0.0191	*S*
	MAD_IMF1	-0.0531	0.0631	0.3999	*I*	0.1518	0.0435	0.0005	*S*	0.4473	0.0455	0.0000	*S*
	MAD_IMF5	-0.0641	0.0776	0.4088	*I*	-0.0024	0.0520	0.9632	*I*	-0.1450	0.0637	0.0229	*S*
	MAD_RES	0.7286	0.3337	0.0290	*S*	0.3518	0.2006	0.0795	*I*	1.5440	0.2481	0.0000	*S*
	NGN	0.2106	0.0733	0.0041	*S*	-0.0207	0.0141	0.1433	*I*	0.0950	0.0437	0.0737	*I*
	NGN_IMF1	0.0731	0.0264	0.0056	*S*	0.0313	0.0245	0.2017	*I*	0.0138	0.0282	0.6255	*I*
	NGN_IMF5	0.0417	0.0259	0.1077	*I*	0.0128	0.0159	0.4200	*I*	-0.0743	0.0206	0.0003	*S*
	NGN_RES	0.7397	0.2761	0.0074	*S*	2.0382	0.1399	0.0000	*S*	5.5665	0.1937	0.0000	*S*
	ZAR	0.0135	0.0039	0.0006	*S*	0.0219	0.0035	0.0000	*S*	0.0177	0.0037	0.0003	*S*
	ZAR_IMF1	-0.0747	0.0185	0.0001	*S*	0.0065	0.0124	0.5986	*I*	0.0655	0.0223	0.0033	*S*
	ZAR_IMF5	-0.1680	0.0246	0.0000	*S*	-0.0420	0.0151	0.0053	*S*	-0.0678	0.0259	0.0089	*S*
	ZAR_RES	-0.1254	0.0938	0.1812	*I*	-0.1759	0.0627	0.0050	*S*	-0.4338	0.1027	0.0000	*S*
0.4, 0.5	AOA	0.0769	0.0230	0.0008	*S*	0.1377	0.0237	0.0000	*S*	0.0415	0.0229	0.0708	*I*
	AOA_IMF1	-0.0190	0.0161	0.2372	*I*	-0.0737	0.0096	0.0000	*S*	-0.0117	0.0036	0.0011	*S*
	AOA_IMF5	0.0271	0.0205	0.1856	*I*	0.0946	0.0125	0.0000	*S*	0.0049	0.0044	0.2610	*I*
	AOA_RES	0.7648	0.0754	0.0000	*S*	0.3722	0.0486	0.0000	*S*	0.1865	0.0179	0.0000	*S*
	DZD	-0.4479	0.0878	0.0000	*S*	-0.4609	0.0865	0.0000	*S*	-0.6652	0.0700	0.0000	*S*
	DZD_IMF1	0.1372	0.0708	0.0527	*I*	-0.1076	0.0501	0.0318	*S*	0.0257	0.0145	0.0767	*I*
	DZD_IMF5	-0.1535	0.0855	0.0726	*I*	0.0137	0.0584	0.8140	*I*	-0.0196	0.0160	0.2213	*I*
	DZD_RES	0.6448	0.3096	0.0373	*S*	1.2111	0.2199	0.0000	*S*	0.7598	0.0682	0.0000	*S*
	EGP	-0.0201	0.0064	0.0016	*S*	0.0182	0.0264	0.4890	*I*	-0.0306	0.0042	0.0000	*S*
	EGP_IMF1	-0.0674	0.0116	0.0000	*S*	0.0043	0.0258	0.8664	*I*	-0.0192	0.0064	0.0026	*S*
	EGP_IMF5	0.0608	0.0349	0.0813	*I*	-0.0668	0.0104	0.0000	*S*	0.0128	0.0035	0.0002	*S*
	EGP_RES	0.4156	0.0693	0.0000	*S*	-0.3522	0.0788	0.0000	*S*	0.0584	0.0102	0.0000	*S*
	ETBS	0.1100	0.1024	0.2828	*I*	-0.1202	0.0460	0.0090	*S*	-0.0051	0.0742	0.1459	*I*
	ETBS_IMF1	0.0182	0.0255	0.4754	*I*	0.0163	0.0161	0.3125	*I*	-0.0366	0.0064	0.0000	*S*
	ETBS_IMF5	-0.0865	0.0336	0.0101	*S*	-0.0665	0.0213	0.0018	*S*	0.0269	0.0075	0.0004	*S*
	ETBS_RES	-1.3155	0.1901	0.0000	*S*	-0.3060	0.1195	0.0104	*S*	0.1668	0.0470	0.0004	*S*
	KES	-1.2292	0.3889	0.0016	*S*	-0.0953	0.1589	0.5487	*I*	-1.7299	0.1828	0.0000	*S*
	KES_IMF1	-0.0647	0.0997	0.5168	*I*	-0.0162	0.0444	0.7158	*I*	-0.0869	0.0144	0.0000	*S*
	KES_IMF5	-0.1323	0.1143	0.2470	*I*	-0.1428	0.0633	0.0240	*S*	0.1666	0.0202	0.0000	*S*
	KES_RES	-0.0624	0.2533	0.8054	*I*	0.2733	0.1860	0.1417	*I*	0.6423	0.0537	0.0000	*S*
	MAD	-0.2513	0.0733	0.0006	*S*	0.1297	0.0599	0.0302	*S*	-0.0608	0.0666	0.0154	*S*
	MAD_IMF1	-0.1525	0.0401	0.0001	*S*	0.1215	0.0329	0.0002	*S*	-0.0264	0.0089	0.0029	*S*
	MAD_IMF5	0.0125	0.0570	0.8267	*I*	-0.0991	0.0385	0.0100	*S*	0.0241	0.0106	0.0230	*S*
	MAD_RES	0.4968	0.2316	0.0319	*S*	0.0637	0.1406	0.6508	*I*	0.1002	0.0364	0.0060	*S*
	NGN	0.0818	0.0772	0.2895	*I*	-0.0306	0.0145	0.0352	*S*	0.0256	0.0459	0.1624	*I*
	NGN_IMF1	-0.0474	0.0264	0.0725	*I*	0.0284	0.0292	0.3306	*I*	0.0285	0.0119	0.0168	*S*
	NGN_IMF5	0.0007	0.0170	0.9684	*I*	-0.0207	0.0120	0.0845	*I*	-0.0120	0.0035	0.0005	*S*
	NGN_RES	1.5855	0.1626	0.0000	*S*	2.0667	0.1057	0.0000	*S*	1.1746	0.0562	0.0000	*S*
	ZAR	0.0045	0.0014	0.0011	*S*	0.0008	0.0025	0.7347	*I*	0.0027	0.0019	0.3679	*I*
	ZAR_IMF1	-0.0354	0.0129	0.0060	*S*	-0.0226	0.0095	0.0167	*S*	0.0022	0.0030	0.4539	*I*
	ZAR_IMF5	-0.0369	0.0182	0.0422	*S*	0.0015	0.0126	0.9034	*I*	0.0015	0.0038	0.7012	*I*
	ZAR_RES	0.5054	0.0780	0.0000	*S*	-0.1535	0.0483	0.0015	*S*	-0.0295	0.0149	0.0469	*S*

0.5, 0.6	AOA	-0.0560	0.0199	0.0048	S	0.0012	0.0269	0.9657	I	0.0612	0.0301	0.0423	S
	AOA_IMF1	-0.0081	0.0234	0.7306	I	0.0101	0.0124	0.4151	I	-0.0439	0.0054	0.0000	S
	AOA_IMF5	-0.0037	0.0310	0.9055	I	-0.0032	0.0159	0.8414	I	0.0475	0.0071	0.0000	S
	AOA_RES	0.7852	0.1067	0.0000	S	0.7156	0.0674	0.0000	S	0.3438	0.0298	0.0000	S
	DZD	0.2706	0.1461	0.0641	I	0.1362	0.0890	0.1260	I	-1.7009	0.0787	0.0000	S
	DZD_IMF1	0.1620	0.0748	0.0304	S	-0.1879	0.0476	0.0001	S	0.0577	0.0228	0.0114	S
	DZD_IMF5	-0.0596	0.0858	0.4873	I	0.2349	0.0558	0.0000	S	-0.0719	0.0253	0.0044	S
	DZD_RES	-1.3369	0.3839	0.0005	S	0.0378	0.2217	0.8645	I	2.0766	0.1080	0.0000	S
	EGP	0.0054	0.0207	0.7954	I	-0.0845	0.0225	0.0002	S	-0.0093	0.0178	0.6034	I
	EGP_IMF1	-0.0698	0.0336	0.0377	S	0.0161	0.0249	0.5176	I	-0.0365	0.0067	0.0000	S
	EGP_IMF5	0.0799	0.0696	0.2510	I	-0.0395	0.0129	0.0022	S	0.0600	0.0056	0.0000	S
	EGP_RES	0.4638	0.0637	0.0000	S	-0.2438	0.0690	0.0004	S	0.1614	0.0159	0.0000	S
	ETBS	-0.3420	0.1006	0.0007	S	0.0877	0.0749	0.2422	I	-0.1272	0.0878	0.1214	I
	ETBS_IMF1	-0.0021	0.0463	0.9636	I	-0.0538	0.0243	0.0268	S	-0.0239	0.0084	0.0043	S
	ETBS_IMF5	0.1996	0.0565	0.0004	S	-0.0055	0.0321	0.8648	I	0.0325	0.0105	0.0019	S
	ETBS_RES	-0.2117	0.2340	0.3657	I	0.3613	0.1391	0.0094	S	0.5705	0.0867	0.0000	S
	KES	-0.1516	0.3235	0.6394	I	-0.8922	0.1813	0.0000	S	-0.9125	0.2243	0.0000	S
	KES_IMF1	-0.8514	0.1037	0.0000	S	-0.0771	0.0552	0.1623	I	-0.0887	0.0253	0.0004	S
	KES_IMF5	0.0508	0.1384	0.7135	I	-0.2382	0.1013	0.0187	S	-0.0448	0.0277	0.1065	I
	KES_RES	0.1815	0.4628	0.6949	I	-1.5600	0.1845	0.0000	S	-0.4976	0.0864	0.0000	S
	MAD	-0.4703	0.0768	0.0000	S	-0.5367	0.0608	0.0000	S	-0.5035	0.0688	0.0000	S
	MAD_IMF1	-0.0945	0.0404	0.0192	S	0.0870	0.0300	0.0038	S	-0.1108	0.0156	0.0000	S
	MAD_IMF5	-0.1420	0.0552	0.0100	S	0.0650	0.0351	0.0644	I	0.0739	0.0177	0.0000	S
	MAD_RES	0.5807	0.2553	0.0229	S	0.9372	0.1382	0.0000	S	-0.2795	0.0622	0.0000	S
	NGN	0.0359	0.0489	0.4629	I	-0.0080	0.0090	0.3742	I	0.0139	0.0289	0.4185	I
	NGN_IMF1	-0.0692	0.0378	0.0671	I	-0.0585	0.0189	0.0019	S	-0.0787	0.0195	0.0001	S
	NGN_IMF5	-0.0877	0.0194	0.0000	S	0.0388	0.0236	0.0994	I	-0.0029	0.0085	0.7277	I
	NGN_RES	2.7073	0.2336	0.0000	S	2.5853	0.1272	0.0000	S	3.8613	0.2703	0.0000	S
	ZAR	0.0091	0.0037	0.0130	S	-0.0115	0.0033	0.0006	S	-0.0012	0.0035	0.0068	S
	ZAR_IMF1	-0.0063	0.0207	0.7598	I	0.0347	0.0099	0.0005	S	-0.0135	0.0040	0.0009	S
	ZAR_IMF5	0.1991	0.0261	0.0000	S	-0.0070	0.0120	0.5611	I	0.0057	0.0054	0.2924	I
	ZAR_RES	-0.3489	0.1057	0.0010	S	0.1977	0.0502	0.0001	S	0.1144	0.0221	0.0000	S
0.6, 0.7	AOA	-0.0532	0.0403	0.1866	I	-0.0531	0.0201	0.0083	S	0.1059	0.0542	0.0509	I
	AOA_IMF1	-0.0620	0.0270	0.0217	S	0.0407	0.0141	0.0038	S	-0.0954	0.0187	0.0000	S
	AOA_IMF5	0.0156	0.0368	0.6715	I	-0.0138	0.0212	0.5160	I	0.0581	0.0227	0.0106	S
	AOA_RES	0.7531	0.1420	0.0000	S	0.7381	0.0932	0.0000	S	1.5824	0.0878	0.0000	S
	DZD	-0.0963	0.1446	0.5057	I	0.1115	0.0811	0.1695	I	-0.6134	0.1527	0.0001	S
	DZD_IMF1	-0.1773	0.0999	0.0760	I	-0.1445	0.0546	0.0082	S	0.1750	0.0860	0.0418	I
	DZD_IMF5	-0.1053	0.1539	0.4939	I	0.0444	0.0590	0.4513	I	-0.1923	0.0952	0.0434	S
	DZD_RES	-1.7552	0.5768	0.0023	S	0.9184	0.2783	0.0010	S	4.3439	0.3334	0.0000	S
	EGP	-0.0173	0.0203	0.3933	I	-0.0861	0.0281	0.0022	S	0.0566	0.0300	0.0592	I
	EGP_IMF1	-0.0578	0.0367	0.1155	I	0.0221	0.0137	0.1079	I	-0.0225	0.0138	0.1039	I
	EGP_IMF5	0.0742	0.0725	0.3059	I	-0.0447	0.0132	0.0007	S	-0.0110	0.0402	0.7853	I
	EGP_RES	0.8397	0.0989	0.0000	S	0.2830	0.0367	0.0000	S	0.3854	0.0436	0.0000	S
	ETBS	-0.1284	0.0685	0.0607	I	0.0006	0.0742	0.9932	I	-0.0639	0.0713	0.5269	I
	ETBS_IMF1	-0.0507	0.0508	0.3183	I	0.0499	0.0349	0.1522	I	0.0312	0.0362	0.3881	I
	ETBS_IMF5	0.3433	0.0678	0.0000	S	-0.1370	0.0458	0.0028	S	-0.0648	0.0487	0.1833	I
	ETBS_RES	0.5841	0.3485	0.0937	I	0.2602	0.1945	0.1811	I	0.1713	0.2896	0.5542	I
	KES	-0.3474	0.3136	0.2679	I	0.3873	0.1809	0.0323	S	-0.1242	0.2630	0.6366	I
	KES_IMF1	-0.8728	0.1388	0.0000	S	-0.5347	0.0739	0.0000	S	-0.3396	0.0783	0.0000	S
	KES_IMF5	-0.1654	0.1975	0.4022	I	0.3554	0.1168	0.0023	S	-0.7525	0.1379	0.0000	S
	KES_RES	-1.5339	0.5652	0.0066	S	1.3356	0.2630	0.0000	S	-1.7378	0.2756	0.0000	S
	MAD	0.0043	0.0654	0.9473	I	-0.0874	0.0634	0.1683	I	-0.0415	0.0644	0.5578	I
	MAD_IMF1	0.2742	0.0533	0.0000	S	-0.2184	0.0331	0.0000	S	-0.3916	0.0531	0.0000	S
	MAD_IMF5	-0.1635	0.0806	0.0426	S	-0.0074	0.0449	0.8685	I	0.1138	0.0648	0.0790	I
	MAD_RES	-1.6685	0.3519	0.0000	S	1.1534	0.1839	0.0000	S	0.2116	0.1989	0.2875	I
	NGN	0.1890	0.0604	0.0018	S	-0.0153	0.0087	0.0784	S	0.0869	0.0346	0.0401	S
	NGN_IMF1	-0.0969	0.0415	0.0195	S	-0.0288	0.0185	0.1185	I	-0.0885	0.0175	0.0000	S
	NGN_IMF5	-0.1107	0.0230	0.0000	S	-0.0337	0.0296	0.2542	I	-0.0578	0.0227	0.0110	S
	NGN_RES	-0.2021	0.3915	0.6057	I	3.7615	0.1694	0.0000	S	6.9169	0.4050	0.0000	S
	ZAR	0.0171	0.0051	0.0008	S	-0.0453	0.0049	0.0000	S	-0.0141	0.0050	0.0004	S
	ZAR_IMF1	-0.1013	0.0270	0.0002	S	-0.0258	0.0123	0.0361	S	-0.0573	0.0141	0.0001	S
	ZAR_IMF5	0.3755	0.0382	0.0000	S	0.0095	0.0150	0.5241	I	0.1114	0.0214	0.0000	S
	ZAR_RES	-0.2979	0.1211	0.0139	S	0.3729	0.0679	0.0000	S	0.5133	0.0785	0.0000	S
0.7, 0.8	AOA	0.0279	0.0470	0.5534	I	0.1400	0.0431	0.0012	S	0.0994	0.0635	0.1175	I
	AOA_IMF1	0.0033	0.0362	0.9284	I	-0.0128	0.0269	0.6350	I	-0.0926	0.0313	0.0031	S
	AOA_IMF5	-0.1386	0.0770	0.0717	I	0.0445	0.0407	0.2743	I	0.1365	0.0515	0.0081	S
	AOA_RES	0.2563	0.2102	0.2226	I	1.2031	0.1371	0.0000	S	1.9107	0.2185	0.0000	S
	DZD	-0.1506	0.1567	0.3365	I	0.3589	0.0900	0.0001	S	0.2220	0.1770	0.2096	I
	DZD_IMF1	-0.4994	0.1638	0.0023	S	-0.2011	0.0851	0.0181	S	-0.1046	0.1376	0.4471	I
	DZD_IMF5	0.3313	0.2350	0.1586	I	-0.2895	0.1399	0.0385	S	-0.2031	0.2596	0.4342	I
	DZD_RES	-1.9742	0.7826	0.0116	S	-1.7934	0.6324	0.0046	S	2.5264	0.8125	0.0019	S
	EGP	-0.0897	0.0164	0.0000	S	-0.0468	0.0191	0.0144	S	-0.1297	0.0313	0.0000	S
	EGP_IMF1	-0.0230	0.0186	0.2158	I	-0.0463	0.0193	0.0163	S	-0.1551	0.0171	0.0000	S
	EGP_IMF5	-0.1780	0.0288	0.0000	S	0.1242	0.0253	0.0000	S	0.1895	0.0523	0.0003	S

	EGP_RES	0.3985	0.3305	0.2280	I	0.4805	0.1383	0.0005	S	0.8563	0.1420	0.0000	S
	ETBS	0.2164	0.0927	0.0195	S	-0.0856	0.0660	0.1945	I	0.0654	0.0793	0.1070	I
	ETBS_IMF1	-0.0855	0.0779	0.2721	I	-0.0520	0.0393	0.1853	I	-0.0329	0.0778	0.6724	I
	ETBS_IMF5	-0.0049	0.0909	0.9566	I	0.3696	0.0530	0.0000	S	-0.0723	0.0717	0.3134	I
	ETBS_RES	1.0120	0.4630	0.0288	S	0.9828	0.2927	0.0008	S	-0.7469	0.4608	0.1050	I
	KES	0.3761	0.3333	0.2591	I	-0.0752	0.1712	0.6606	S	0.1589	0.5786	0.7836	I
	KES_IMF1	-0.0556	0.1665	0.7387	I	0.1055	0.1218	0.3864	I	-0.4528	0.1235	0.0002	S
	KES_IMF5	0.8513	0.2417	0.0004	S	-1.2174	0.1835	0.0000	S	-0.2136	0.2442	0.3816	I
	KES_RES	-2.2330	0.5946	0.0002	S	-1.2990	0.4503	0.0039	S	-1.3624	1.0066	0.1759	I
	MAD	0.4139	0.0920	0.0000	S	-0.0638	0.0733	0.3847	I	0.1751	0.0827	0.1923	I
	MAD_IMF1	0.7100	0.1221	0.0000	S	-0.5312	0.0687	0.0000	S	-0.1825	0.1010	0.0709	I
	MAD_IMF5	-0.2052	0.1729	0.2353	I	0.1781	0.1171	0.1284	I	-0.4610	0.1294	0.0004	S
	MAD_RES	2.7649	0.4630	0.0000	S	2.3859	0.3679	0.0000	S	-2.1569	0.4586	0.0000	S
	NGN	-0.1244	0.0298	0.0000	S	-0.0491	0.0125	0.0001	S	-0.0868	0.0211	0.0001	S
	NGN_IMF1	-0.0129	0.0603	0.8299	I	-0.0344	0.0225	0.1258	I	0.0748	0.0292	0.0104	S
	NGN_IMF5	0.0446	0.1288	0.7293	I	-0.0114	0.0406	0.7787	I	-0.0820	0.0706	0.2450	I
	NGN_RES	-1.5929	0.5233	0.0023	S	2.9461	0.2352	0.0000	S	3.3360	0.4088	0.0000	S
	ZAR	0.0162	0.0056	0.0038	S	-0.0758	0.0064	0.0000	S	-0.0298	0.0060	0.0019	S
	ZAR_IMF1	-0.2973	0.0333	0.0000	S	-0.0539	0.0254	0.0335	S	-0.1015	0.0319	0.0015	S
	ZAR_IMF5	0.1970	0.0493	0.0001	S	0.1421	0.0321	0.0000	S	0.2979	0.0460	0.0000	S
	ZAR_RES	0.9821	0.1607	0.0000	S	0.4894	0.1040	0.0000	S	0.2144	0.1513	0.1564	I
0.8, 0.9	AOA	0.1850	0.0546	0.0007	S	-0.1409	0.0524	0.0072	S	-0.2263	0.1048	0.0308	S
	AOA_IMF1	0.0856	0.0722	0.2353	I	-0.1116	0.0731	0.1271	I	-0.1388	0.0606	0.0219	S
	AOA_IMF5	0.2018	0.1074	0.0601	I	0.0520	0.0748	0.4871	I	-0.0795	0.0926	0.3909	I
	AOA_RES	1.1782	0.4792	0.0140	S	1.8026	0.2714	0.0000	S	2.3060	0.3482	0.0000	S
	DZD	0.2160	0.2962	0.4659	I	-0.1747	0.4316	0.6856	I	0.1786	0.3030	0.5555	I
	DZD_IMF1	0.9626	0.2702	0.0004	S	-0.4465	0.1621	0.0059	S	-1.0392	0.3340	0.0019	S
	DZD_IMF5	1.2775	0.3477	0.0002	S	0.1905	0.1892	0.3140	I	-0.1011	0.4754	0.8316	I
	DZD_RES	2.0083	1.6232	0.2160	I	2.2079	1.1590	0.0568	I	-5.6429	1.6827	0.0008	S
	EGP	-0.1429	0.0217	0.0000	S	-0.0851	0.0308	0.0057	S	-0.0205	0.0448	0.6478	I
	EGP_IMF1	-0.1374	0.0397	0.0005	S	0.1727	0.0992	0.0816	I	0.0113	0.0764	0.8823	I
	EGP_IMF5	-0.1624	0.0556	0.0035	S	-0.2710	0.1908	0.1555	I	-0.2263	0.1622	0.1628	I
	EGP_RES	-1.1549	0.6227	0.0637	I	-1.5605	0.8811	0.0765	I	1.3426	1.0809	0.2142	I
	ETBS	-0.4559	0.2294	0.0469	S	-0.5516	0.0739	0.0000	S	-0.5037	0.1517	0.0234	S
	ETBS_IMF1	0.3434	0.1493	0.0215	S	-0.7003	0.1061	0.0000	S	0.5727	0.1260	0.0000	S
	ETBS_IMF5	0.3437	0.2765	0.2138	I	0.0587	0.1759	0.7385	I	-0.5128	0.1940	0.0082	S
	ETBS_RES	2.6145	0.8508	0.0021	S	1.7910	0.8037	0.0259	S	-2.9915	0.7552	0.0001	S
	KES	-2.0880	1.2933	0.1064	I	0.9847	0.2642	0.0002	S	-1.0959	0.6454	0.0895	I
	KES_IMF1	0.1940	0.4459	0.6635	I	0.6233	0.1694	0.0002	S	-1.4366	0.4289	0.0008	S
	KES_IMF5	-1.2354	0.3901	0.0015	S	-0.5537	0.3778	0.1427	I	2.7595	0.3875	0.0000	S
	KES_RES	-12.6010	1.1276	0.0000	S	0.5543	0.7380	0.4526	I	2.4321	1.1648	0.0368	S
	MAD	0.0545	0.1815	0.7642	I	-0.1768	0.2272	0.4364	I	-0.0612	0.2043	0.6003	I
	MAD_IMF1	-0.0720	0.1744	0.6798	I	0.5980	0.1378	0.0000	S	0.6676	0.1687	0.0001	S
	MAD_IMF5	-0.4002	0.3171	0.2069	I	-0.7416	0.1350	0.0000	S	-0.0052	0.2046	0.9796	I
	MAD_RES	2.1230	0.6753	0.0017	S	-4.5824	0.5513	0.0000	S	2.3035	0.9789	0.0186	S
	NGN	-0.1884	0.0475	0.0001	S	-0.1437	0.0138	0.0000	S	-0.1660	0.0306	0.0000	S
	NGN_IMF1	0.3021	0.0821	0.0002	S	0.0194	0.0265	0.4645	I	-0.1357	0.0426	0.0014	S
	NGN_IMF5	0.3710	0.1242	0.0028	S	-0.1135	0.0480	0.0181	S	0.1196	0.0859	0.1638	I
	NGN_RES	-1.6082	1.1105	0.1476	I	3.5056	0.6731	0.0000	S	7.3674	0.5058	0.0000	S
	ZAR	0.0387	0.0275	0.1596	I	-0.0939	0.0101	0.0000	S	-0.0276	0.0188	0.0798	S
	ZAR_IMF1	-0.1107	0.0771	0.1511	I	0.0420	0.0617	0.4962	I	0.0520	0.0622	0.4029	I
	ZAR_IMF5	0.2645	0.0770	0.0006	S	-0.0675	0.0847	0.4257	I	0.0819	0.0746	0.2721	I
	ZAR_RES	1.3033	0.3573	0.0003	S	1.8556	0.2761	0.0000	S	-1.1833	0.4149	0.0043	S

Where S = Statistically signifint, I = statistically insignificant

ANNEXURE A17: QUANTILE SLOPE EQUALITY TEST RESULTS – SCX

Quantile Slope Equality Test									
Estimated equation quantile tau = 0.5									
Number of test quantiles: 10									
Test statistic compares all coefficients									
Restriction Detail: b(tau_h) - b(tau_k) = 0									
Equation:		$BTC = \beta 0 + \beta (ACXi,t) + \varepsilon i,t$				$ETH = \beta 0 + \beta (ACXi,t) + \varepsilon i,t$			
Specification:		$CRCi,t = \beta 0 + \beta (ACXi,t) + \varepsilon i,t$				$CRCi,t = \beta 0 + \beta (ACXi,t) + \varepsilon i,t$			
Test Summary:		Chi-Sq. Statistic	Chi-Sq. d.f.	Prob.		Chi-Sq. Statistic	Chi-Sq. d.f.	Prob.	
Wald Test:		6855.16	160	0.0000		24682.96	160	0.0000	
Quantiles	**Variable**	**Restr. Value**	**Std. Error**	**Prob.**	***S or I***	**Restr. Value**	**Std. Error**	**Prob.**	***S or I***
0.1, 0.2	AUD_IMF1	-0.0317	0.0135	0.0192		-0.0409	0.0097	0.0000	
	AUD_IMF5	0.0589	0.0239	0.0137		0.0556	0.0157	0.0004	
	AUD_RES	1.2023	0.0716	0.0000		0.6524	0.0643	0.0000	
	AUD_USD	0.0172	0.0123	0.1607		-0.2347	0.0102	0.0000	
	CHF_IMF1	-0.0038	0.0224	0.8670		0.0482	0.0223	0.0310	
	CHF_IMF5	-0.0007	0.0389	0.9855		-0.1133	0.0340	0.0009	
	CHF_RES	-0.7807	0.1875	0.0000		-0.0875	0.1362	0.5209	
	CHF_USD	-0.1494	0.0272	0.0000		-0.1192	0.0242	0.0000	
	EUR_IMF1	-0.0416	0.0321	0.1942		-0.0077	0.0188	0.6804	
	EUR_IMF5	0.0659	0.0602	0.2730		0.0835	0.0196	0.0000	
	EUR_RES	-0.2873	0.2754	0.2969		-1.0661	0.2132	0.0000	
	EUR_USD	0.0596	0.0263	0.0234		0.0811	0.0180	0.0000	
	GBP_IMF1	-0.0010	0.0210	0.9638		-0.0056	0.0137	0.6808	
	GBP_IMF5	-0.0473	0.0458	0.3016		-0.0409	0.0297	0.1688	
	GBP_RES	-0.4099	0.1228	0.0008		-0.6463	0.2005	0.0013	
	GBP_USD	0.0886	0.0172	0.0000		0.0529	0.0120	0.0000	
	ZAR_IMF1	0.0742	0.0124	0.0000		-0.0005	0.0074	0.9459	
	ZAR_IMF5	-0.0631	0.0460	0.1700		-0.0060	0.0165	0.7157	
	ZAR_RES	0.9609	0.0678	0.0000		0.3562	0.0728	0.0000	
	ZAR_USD	-0.0295	0.0117	0.0114		0.0144	0.0061	0.0185	
0.2, 0.3	AUD_IMF1	0.0133	0.0074	0.0709		-0.0188	0.0021	0.0000	
	AUD_IMF5	0.0101	0.0104	0.3326		0.0212	0.0025	0.0000	
	AUD_RES	0.3436	0.0351	0.0000		0.1141	0.0117	0.0000	
	AUD_USD	-0.0214	0.0067	0.0013		-0.0555	0.0062	0.0000	
	CHF_IMF1	-0.0063	0.0122	0.6087		0.0170	0.0029	0.0000	
	CHF_IMF5	0.0246	0.0170	0.1468		-0.0192	0.0036	0.0000	
	CHF_RES	-0.0453	0.0637	0.4765		-0.0273	0.0129	0.0341	
	CHF_USD	-0.0707	0.0140	0.0000		-0.1112	0.0113	0.0000	
	EUR_IMF1	0.0256	0.0122	0.0360		0.0027	0.0024	0.2662	
	EUR_IMF5	-0.0567	0.0229	0.0132		0.0005	0.0034	0.8777	
	EUR_RES	-0.7351	0.1749	0.0000		-0.3502	0.0540	0.0000	
	EUR_USD	0.0443	0.0110	0.0001		0.0105	0.0026	0.0000	
	GBP_IMF1	0.0130	0.0092	0.1574		-0.0014	0.0015	0.3700	
	GBP_IMF5	0.0251	0.0132	0.0582		-0.0040	0.0022	0.0637	
	GBP_RES	-0.1408	0.0521	0.0069		-0.0825	0.0135	0.0000	
	GBP_USD	0.0274	0.0084	0.0012		0.0057	0.0018	0.0015	
	ZAR_IMF1	0.0549	0.0055	0.0000		-0.0004	0.0008	0.6145	
	ZAR_IMF5	-0.0312	0.0132	0.0179		-0.0002	0.0016	0.9245	
	ZAR_RES	0.3961	0.0345	0.0000		0.0926	0.0130	0.0000	
	ZAR_USD	-0.0253	0.0046	0.0000		0.0023	0.0008	0.0042	

ANNEXURE A17 (continued)

Quantiles	Variable	Restr. Value	Std. Error	Prob.	*S or I*	Restr. Value	Std. Error	Prob.	*S or I*
0.3, 0.4	AUD_IMF1	0.0197	0.0044	0.0000		0.0003	0.0000	0.0000	
	AUD_IMF5	-0.0092	0.0056	0.1017		-0.0003	0.0001	0.0000	
	AUD_RES	0.1495	0.0175	0.0000		0.0003	0.0003	0.2860	
	AUD_USD	-0.0354	0.0036	0.0000		-0.0025	0.0002	0.0000	
	CHF_IMF1	0.0139	0.0061	0.0238		0.0000	0.0001	0.9992	
	CHF_IMF5	0.0375	0.0099	0.0001		-0.0002	0.0001	0.0321	
	CHF_RES	-0.0471	0.0317	0.1379		-0.0032	0.0004	0.0000	
	CHF_USD	-0.0586	0.0092	0.0000		-0.0030	0.0015	0.0441	
	EUR_IMF1	0.0409	0.0075	0.0000		0.0001	0.0001	0.4193	
	EUR_IMF5	-0.0769	0.0114	0.0000		0.0002	0.0001	0.1264	
	EUR_RES	-0.4466	0.0794	0.0000		0.0080	0.0007	0.0000	
	EUR_USD	0.0165	0.0068	0.0147		0.0000	0.0001	0.7472	
	GBP_IMF1	0.0097	0.0048	0.0443		-0.0001	0.0001	0.0653	
	GBP_IMF5	0.0221	0.0070	0.0017		-0.0001	0.0001	0.1742	
	GBP_RES	-0.0811	0.0313	0.0096		0.0014	0.0003	0.0000	
	GBP_USD	0.0194	0.0050	0.0001		0.0002	0.0001	0.0003	
	ZAR_IMF1	0.0212	0.0032	0.0000		-0.0001	0.0000	0.0000	
	ZAR_IMF5	-0.0125	0.0046	0.0065		0.0001	0.0000	0.0031	
	ZAR_RES	0.2244	0.0180	0.0000		0.0006	0.0003	0.0186	
	ZAR_USD	-0.0124	0.0026	0.0000		0.0002	0.0000	0.0000	
0.4, 0.5	AUD_IMF1	0.0043	0.0029	0.1274		0.0000	0.0001	0.4839	
	AUD_IMF5	0.0026	0.0033	0.4361		0.0000	0.0001	0.6679	
	AUD_RES	0.0839	0.0112	0.0000		0.0032	0.0003	0.0000	
	AUD_USD	-0.0241	0.0022	0.0000		-0.0017	0.0001	0.0000	
	CHF_IMF1	0.0113	0.0040	0.0052		0.0003	0.0001	0.0036	
	CHF_IMF5	-0.0010	0.0051	0.8517		-0.0006	0.0001	0.0000	
	CHF_RES	-0.0563	0.0188	0.0027		-0.0005	0.0005	0.2685	
	CHF_USD	-0.0622	0.0070	0.0000		-0.0005	0.0002	0.0360	
	EUR_IMF1	0.0120	0.0043	0.0055		0.0002	0.0001	0.0283	
	EUR_IMF5	-0.0183	0.0055	0.0008		0.0001	0.0001	0.5758	
	EUR_RES	-0.0859	0.0310	0.0055		-0.0018	0.0008	0.0229	
	EUR_USD	0.0196	0.0052	0.0001		0.0001	0.0001	0.1998	
	GBP_IMF1	0.0085	0.0033	0.0113		-0.0002	0.0001	0.0243	
	GBP_IMF5	-0.0060	0.0043	0.1581		0.0000	0.0001	0.7969	
	GBP_RES	0.0072	0.0161	0.6546		0.0021	0.0004	0.0000	
	GBP_USD	0.0096	0.0041	0.0189		0.0001	0.0001	0.3836	
	ZAR_IMF1	0.0086	0.0019	0.0000		0.0000	0.0000	0.5682	
	ZAR_IMF5	-0.0108	0.0025	0.0000		0.0000	0.0001	0.8532	
	ZAR_RES	0.1450	0.0089	0.0000		0.0008	0.0004	0.0413	
	ZAR_USD	-0.0045	0.0015	0.0021		0.0000	0.0000	0.6494	
0.5, 0.6	AUD_IMF1	-0.0168	0.0028	0.0000		-0.0004	0.0001	0.0000	
	AUD_IMF5	0.0136	0.0032	0.0000		0.0004	0.0001	0.0000	
	AUD_RES	0.1217	0.0110	0.0000		0.0040	0.0003	0.0000	
	AUD_USD	-0.0227	0.0022	0.0000		-0.0014	0.0001	0.0000	
	CHF_IMF1	-0.0103	0.0044	0.0185		-0.0004	0.0001	0.0001	
	CHF_IMF5	-0.0076	0.0049	0.1196		0.0004	0.0001	0.0007	
	CHF_RES	-0.0670	0.0162	0.0000		0.0009	0.0005	0.0626	
	CHF_USD	-0.0190	0.0084	0.0240		-0.0005	0.0002	0.0101	
	EUR_IMF1	-0.0039	0.0043	0.3601		0.0000	0.0001	0.7379	
	EUR_IMF5	0.0194	0.0059	0.0009		-0.0002	0.0001	0.0742	
	EUR_RES	0.0824	0.0297	0.0055		-0.0044	0.0007	0.0000	
	EUR_USD	-0.0011	0.0051	0.8343		0.0000	0.0001	0.7833	
	GBP_IMF1	-0.0108	0.0031	0.0005		0.0000	0.0001	0.4682	
	GBP_IMF5	-0.0029	0.0038	0.4435		0.0001	0.0001	0.1549	
	GBP_RES	-0.0084	0.0144	0.5617		-0.0014	0.0005	0.0022	
	GBP_USD	0.0102	0.0041	0.0120		0.0000	0.0001	0.8029	
	ZAR_IMF1	-0.0103	0.0020	0.0000		0.0001	0.0000	0.0001	
	ZAR_IMF5	0.0068	0.0030	0.0236		-0.0002	0.0001	0.0103	
	ZAR_RES	0.1522	0.0113	0.0000		0.0007	0.0004	0.0605	
	ZAR_USD	0.0055	0.0015	0.0001		-0.0001	0.0000	0.0362	

ANNEXURE A17 (continued)

Quantiles	Variable	Restr. Value	Std. Error	Prob.	*S or I*	Restr. Value	Std. Error	Prob.	*S or I*
0.6, 0.7	AUD_IMF1	-0.0341	0.0038	0.0000		-0.0005	0.0001	0.0000	
	AUD_IMF5	0.0196	0.0049	0.0001		0.0005	0.0001	0.0000	
	AUD_RES	0.2452	0.0171	0.0000		0.0032	0.0004	0.0000	
	AUD_USD	-0.0339	0.0032	0.0000		-0.0016	0.0001	0.0000	
	CHF_IMF1	-0.0067	0.0065	0.2968		-0.0001	0.0001	0.4473	
	CHF_IMF5	-0.0429	0.0083	0.0000		0.0002	0.0001	0.0065	
	CHF_RES	-0.1533	0.0291	0.0000		0.0023	0.0003	0.0000	
	CHF_USD	-0.0141	0.0101	0.1626		-0.0012	0.0002	0.0000	
	EUR_IMF1	-0.0215	0.0064	0.0007		-0.0001	0.0001	0.2464	
	EUR_IMF5	0.0530	0.0104	0.0000		0.0000	0.0001	0.8925	
	EUR_RES	0.0341	0.0541	0.5286		-0.0031	0.0007	0.0000	
	EUR_USD	-0.0355	0.0065	0.0000		0.0001	0.0001	0.0937	
	GBP_IMF1	-0.0170	0.0048	0.0004		0.0001	0.0001	0.2600	
	GBP_IMF5	-0.0052	0.0068	0.4405		-0.0001	0.0001	0.1839	
	GBP_RES	-0.0002	0.0266	0.9932		-0.0022	0.0005	0.0000	
	GBP_USD	0.0029	0.0060	0.6311		-0.0002	0.0001	0.0444	
	ZAR_IMF1	-0.0274	0.0030	0.0000		0.0000	0.0000	0.5766	
	ZAR_IMF5	0.0252	0.0047	0.0000		0.0000	0.0001	0.9930	
	ZAR_RES	0.2821	0.0190	0.0000		0.0007	0.0004	0.0749	
	ZAR_USD	0.0135	0.0024	0.0000		-0.0001	0.0000	0.0361	
0.7, 0.8	AUD_IMF1	-0.0544	0.0054	0.0000		-0.0002	0.0001	0.0520	
	AUD_IMF5	0.0424	0.0079	0.0000		0.0006	0.0001	0.0000	
	AUD_RES	0.3994	0.0263	0.0000		0.0087	0.0014	0.0000	
	AUD_USD	-0.0566	0.0054	0.0000		-0.0004	0.0001	0.0001	
	CHF_IMF1	-0.0009	0.0112	0.9356		0.0001	0.0002	0.3321	
	CHF_IMF5	-0.0675	0.0135	0.0000		-0.0001	0.0002	0.4938	
	CHF_RES	-0.2550	0.0507	0.0000		-0.0080	0.0014	0.0000	
	CHF_USD	-0.0299	0.0174	0.0858		-0.0002	0.0004	0.6191	
	EUR_IMF1	0.0367	0.0121	0.0024		0.0005	0.0001	0.0004	
	EUR_IMF5	0.0068	0.0179	0.7049		-0.0011	0.0002	0.0000	
	EUR_RES	-0.5161	0.1086	0.0000		0.0031	0.0018	0.0744	
	EUR_USD	-0.0407	0.0105	0.0001		-0.0003	0.0001	0.0155	
	GBP_IMF1	-0.0189	0.0074	0.0106		-0.0004	0.0002	0.0102	
	GBP_IMF5	-0.0245	0.0102	0.0169		0.0002	0.0001	0.0568	
	GBP_RES	-0.1796	0.0527	0.0007		-0.0008	0.0007	0.2529	
	GBP_USD	0.0116	0.0098	0.2363		0.0008	0.0002	0.0002	
	ZAR_IMF1	-0.0512	0.0047	0.0000		0.0000	0.0001	0.9152	
	ZAR_IMF5	0.0226	0.0114	0.0468		0.0004	0.0001	0.0066	
	ZAR_RES	0.3986	0.0484	0.0000		0.0012	0.0006	0.0514	
	ZAR_USD	0.0247	0.0041	0.0000		0.0000	0.0001	0.8099	
0.8, 0.9	AUD_IMF1	-0.0971	0.0144	0.0000		-0.0598	0.0100	0.0000	
	AUD_IMF5	0.1069	0.0216	0.0000		0.0842	0.0123	0.0000	
	AUD_RES	1.2679	0.0628	0.0000		1.4465	0.0522	0.0000	
	AUD_USD	-0.1748	0.0156	0.0000		-0.0198	0.0118	0.0944	
	CHF_IMF1	0.1255	0.0234	0.0000		0.0454	0.0142	0.0014	
	CHF_IMF5	-0.1535	0.0412	0.0002		-0.0351	0.0298	0.2389	
	CHF_RES	-1.1893	0.1408	0.0000		-1.3757	0.0781	0.0000	
	CHF_USD	-0.2459	0.0298	0.0000		-0.0671	0.0204	0.0010	
	EUR_IMF1	0.1582	0.0307	0.0000		0.0584	0.0203	0.0040	
	EUR_IMF5	-0.1274	0.0440	0.0038		-0.0590	0.0329	0.0731	
	EUR_RES	-0.5222	0.2085	0.0123		0.6430	0.1644	0.0001	
	EUR_USD	-0.1025	0.0248	0.0000		-0.0605	0.0145	0.0000	
	GBP_IMF1	-0.0615	0.0195	0.0017		-0.0148	0.0158	0.3485	
	GBP_IMF5	-0.0221	0.0298	0.4576		-0.0585	0.0202	0.0039	
	GBP_RES	-0.5897	0.0977	0.0000		-0.6786	0.0623	0.0000	
	GBP_USD	0.0988	0.0250	0.0001		0.1006	0.0133	0.0000	
	ZAR_IMF1	-0.1083	0.0110	0.0000		0.0047	0.0097	0.6290	
	ZAR_IMF5	0.0348	0.0310	0.2621		-0.0345	0.0196	0.0778	
	ZAR_RES	0.7632	0.0972	0.0000		0.1663	0.0586	0.0045	
	ZAR_USD	0.0571	0.0096	0.0000		-0.0112	0.0071	0.1168	

Where *S* = Statistically signifint, *I* = statistically insignificant

ANNEXURE A18: SYMMETRIC QUANTILES TEST - ACX

Symmetric Quantiles Test

Estimated equation quantile tau = 0.5
Number of test quantiles: 10
Test statistic compares all coefficients

Restriction Detail: b(tau) + b(1-tau) - 2*b(.5) = 0

Equation:	BNB = β0 + β (ACXi,t) + εi,t				BTC = θ0 + θ (ACXi,t) + εi,t				ETH = θ0 + θ (ACXi,t) + εi,t			
Specification:												
	CRCi,t = θ0 + θ (ACXi,t) + εi,t				CRCi,t = θ0 + θ (ACXi,t) + εi,t				CRCi,t = θ0 + θ (ACXi,t) + εi,t			
Test Summary	Chi-Sq. Statistic	Chi-Sq. d.f.	Prob.		Chi-Sq. Statistic	Chi-Sq. d.f.	Prob.		Chi-Sq. Statistic	Chi-Sq. d.f.	Prob.	
Wald Test	3407.9837	132	0.0000		3492.7229	132	0.0000		3464.5	116	0.0000	

Quantiles	Variable	Restr. Value	Std. Error	Prob.	S or I	Restr. Value	Std. Error	Prob.	S or I	Restr. Value	Std. Error	Prob.	S or I
0.1, 0.9	AOA	0.5568	0.1239	0.0000	S	0.1517	0.0917	0.0978	I	-0.0824	0.1831	0.6527	I
	AOA_IMF1	0.3084	0.1314	0.0189	S	-0.6102	0.1071	0.0000	S	0.0426	0.1374	0.7565	I
	AOA_IMF5	0.4077	0.1998	0.0413	S	0.4005	0.1352	0.0030	S	-0.0386	0.1674	0.8175	I
	AOA_RES	1.2860	0.7762	0.0976	I	0.6165	0.4609	0.1810	I	0.9284	0.6433	0.1490	I
	DZD	0.8224	0.5892	0.1628	I	-1.8456	0.5758	0.0014	S	0.9917	0.6379	0.1200	I
	DZD_IMF1	-0.7339	0.4955	0.1386	I	0.2245	0.3212	0.4846	I	-0.9224	0.5976	0.1227	I
	DZD_IMF5	-0.2808	0.6792	0.6793	I	0.1848	0.4613	0.6887	I	0.5680	0.8766	0.5170	I
	DZD_RES	5.0741	3.1854	0.1112	I	0.4848	2.1623	0.8226	I	-1.4757	3.1959	0.6443	I
	EGP	0.0362	0.0423	0.3927	I	0.1327	0.0643	0.0389	S	-0.1415	0.0597	0.0177	S
	EGP_IMF1	0.0330	0.1243	0.7907	I	0.0324	0.1289	0.8014	I	0.3347	0.1173	0.0043	S
	EGP_IMF5	0.7382	0.7074	0.2967	I	-0.1692	0.2606	0.5162	I	-0.5985	0.1735	0.0006	S
	EGP_RES	1.3921	1.0604	0.1892	I	-1.4969	1.4588	0.3048	I	-1.5993	1.4924	0.2839	I
	ETBS	0.4757	0.4191	0.2564	I	0.3520	0.1649	0.0327	S	0.4138	0.2920	0.1446	I
	ETBS_IMF1	0.2622	0.2540	0.3018	I	0.6533	0.1453	0.0000	S	-0.1701	0.2391	0.4770	I
	ETBS_IMF5	-1.9719	0.4591	0.0000	S	-0.2606	0.2305	0.2583	I	0.3497	0.3909	0.3710	I
	ETBS_RES	-11.6332	1.6041	0.0000	S	-6.7672	1.2143	0.0000	S	-6.4646	1.7655	0.0003	S
	KES	0.0105	1.6279	0.9949	I	0.7536	0.7094	0.2881	I	0.4259	2.0288	0.8337	I
	KES_IMF1	0.5256	0.6084	0.3877	I	1.2720	0.3418	0.0002	S	1.3017	0.6510	0.0456	S
	KES_IMF5	1.3070	0.8701	0.1331	I	3.3753	0.5664	0.0000	S	2.9157	0.6934	0.0000	S
	KES_RES	14.5139	2.0832	0.0000	S	8.3224	1.2453	0.0000	S	13.3490	2.9039	0.0000	S
	MAD	-0.7154	0.3868	0.0644	I	1.6751	0.2971	0.0000	S	0.4799	0.3420	0.0322	S
	MAD_IMF1	-1.3880	0.3169	0.0000	S	0.8268	0.2405	0.0006	S	1.5168	0.3223	0.0000	S
	MAD_IMF5	0.6087	0.4986	0.2222	I	0.1982	0.3338	0.5527	I	-0.6020	0.4663	0.1967	I
	MAD_RES	5.4603	1.3640	0.0001	S	3.9559	1.1436	0.0005	S	10.3403	2.1157	0.0000	S
	NGN	1.5640	0.1485	0.0000	S	0.9335	0.1845	0.0000	S	1.2487	0.1665	0.0000	S
	NGN_IMF1	-0.1535	0.1208	0.2039	I	0.3342	0.1141	0.0034	S	0.3106	0.2555	0.2241	I
	NGN_IMF5	-0.0711	0.1615	0.6596	I	0.2520	0.0955	0.0083	S	-0.0984	0.2478	0.6911	I
	NGN_RES	5.5153	2.4125	0.0222	S	-6.0218	1.4296	0.0000	S	-3.1863	0.8430	0.0002	S
	ZAR	-0.0336	0.0317	0.2894	I	0.4016	0.0158	0.0000	S	0.1840	0.0237	0.1447	I
	ZAR_IMF1	1.0312	0.1272	0.0000	S	0.5516	0.0985	0.0000	S	0.3708	0.1075	0.0006	S
	ZAR_IMF5	-1.9673	0.1739	0.0000	S	-0.5786	0.1261	0.0000	S	-0.5975	0.1392	0.0000	S
	ZAR_RES	-4.2512	0.6750	0.0000	S	-5.2413	0.4413	0.0000	S	-1.6256	0.6644	0.0144	S
	C	0.0070	0.0018	0.0001	S	0.0027	0.0010	0.0084	S	0.0049	0.0020	0.0166	S
0.2, 0.8	AOA	0.4895	0.1060	0.0000	S	0.1619	0.0688	0.0187	S	0.0088	0.0606	0.8841	I
	AOA_IMF1	0.2063	0.0704	0.0034	S	-0.3735	0.0400	0.0000	S	-0.0318	0.0511	0.5336	I
	AOA_IMF5	0.4815	0.1350	0.0004	S	0.2654	0.0633	0.0000	S	-0.0407	0.0849	0.6314	I
	AOA_RES	0.5466	0.3981	0.1697	I	-0.5815	0.2290	0.0111	S	0.0506	0.3069	0.8691	I
	DZD	0.2067	0.3016	0.4931	I	-1.9454	0.2271	0.0000	S	1.6398	0.2470	0.0000	S
	DZD_IMF1	0.2749	0.3034	0.3649	I	0.6217	0.1672	0.0002	S	-0.2816	0.2499	0.2599	I
	DZD_IMF5	0.1272	0.3961	0.7482	I	-0.1665	0.2425	0.4923	I	0.9895	0.4251	0.0199	S
	DZD_RES	7.7965	1.5256	0.0000	S	2.5446	0.9778	0.0093	S	-3.1621	1.3198	0.0166	S
	EGP	-0.1218	0.0704	0.0835	S	0.1095	0.0529	0.0385	S	-0.1008	0.0382	0.0083	S
	EGP_IMF1	0.1685	0.1464	0.2498	I	0.0846	0.0569	0.1367	I	0.2140	0.0479	0.0000	S
	EGP_IMF5	0.2493	0.0522	0.0000	S	-0.2934	0.0460	0.0000	S	-0.4937	0.0820	0.0000	S
	EGP_RES	-1.3939	0.4781	0.0036	S	-1.5574	0.2591	0.0000	S	-0.3866	0.2985	0.1953	I
	ETBS	0.1127	0.2601	0.6648	I	0.0485	0.1399	0.7286	I	0.0806	0.2000	0.6967	I
	ETBS_IMF1	0.5921	0.1351	0.0000	S	0.0899	0.0637	0.1580	I	-0.0792	0.1055	0.4530	I
	ETBS_IMF5	-1.4996	0.1600	0.0000	S	-0.2799	0.0965	0.0037	S	0.0522	0.1126	0.6427	I
	ETBS_RES	-5.7188	0.8805	0.0000	S	-2.4339	0.5166	0.0000	S	-1.1114	0.7237	0.1246	I
	KES	-1.6173	0.8693	0.0628	I	0.6597	0.4374	0.1315	I	-0.0814	0.7162	0.9095	I
	KES_IMF1	1.3718	0.3136	0.0000	S	0.7199	0.1991	0.0003	S	0.2991	0.2112	0.1569	I
	KES_IMF5	-1.2676	0.4779	0.0080	S	2.0943	0.2855	0.0000	S	2.8272	0.4365	0.0000	S
	KES_RES	7.2388	1.3549	0.0000	S	7.0017	0.8104	0.0000	S	13.2811	1.2972	0.0000	S
	MAD	-0.2527	0.2197	0.2500	I	1.0532	0.1681	0.0000	S	0.4002	0.1939	0.1250	I
	MAD_IMF1	-1.2657	0.1909	0.0000	S	1.1714	0.1107	0.0000	S	1.6373	0.1539	0.0000	S
	MAD_IMF5	0.3242	0.2543	0.2024	I	-0.4888	0.1821	0.0073	S	0.0448	0.2433	0.8540	I
	MAD_RES	4.0114	0.9127	0.0000	S	-2.9065	0.6074	0.0000	S	5.1602	0.7702	0.0000	S
	NGN	0.5677	0.1103	0.0000	S	0.2281	0.0649	0.0004	S	0.3979	0.0876	0.0002	S
	NGN_IMF1	0.4553	0.1144	0.0001	S	0.1205	0.0371	0.0012	S	0.1092	0.0502	0.0297	S
	NGN_IMF5	0.3956	0.1756	0.0243	S	-0.0216	0.0707	0.7606	I	-0.0027	0.1468	0.9856	I
	NGN_RES	3.2743	0.9806	0.0008	S	-2.2864	0.4055	0.0000	S	-2.4031	0.4841	0.0000	S
	ZAR	-0.0125	0.0104	0.2289	I	0.2254	0.0112	0.0000	S	0.1064	0.0108	0.1144	I
	ZAR_IMF1	0.5084	0.0674	0.0000	S	0.0866	0.0435	0.0468	S	0.3941	0.0556	0.0000	S
	ZAR_IMF5	-1.2322	0.0855	0.0000	S	-0.2300	0.0527	0.0000	S	-0.5188	0.0814	0.0000	S
	ZAR_RES	-0.6217	0.3242	0.0552	I	-1.8860	0.2004	0.0000	S	-1.9329	0.2891	0.0000	S
	C	0.0051	0.0010	0.0000	S	0.0017	0.0005	0.0003	S	0.0036	0.0007	0.0000	S
0.3, 0.7	AOA	0.3519	0.0557	0.0000	S	0.2351	0.0558	0.0000	S	0.0225	0.0932	0.8091	I
	AOA_IMF1	0.0773	0.0390	0.0475	S	-0.2237	0.0247	0.0000	S	-0.0071	0.0303	0.8148	I
	AOA_IMF5	0.0970	0.0590	0.1002	I	0.2102	0.0341	0.0000	S	0.0460	0.0411	0.2634	I
	AOA_RES	-0.2162	0.2115	0.3068	I	-0.5893	0.1464	0.0001	S	-0.2025	0.1544	0.1896	I
	DZD	-0.4814	0.2004	0.0163	S	-1.4660	0.1747	0.0000	S	1.9439	0.2398	0.0000	S
	DZD_IMF1	-0.2274	0.1599	0.1549	I	0.2129	0.1055	0.0435	S	-0.1835	0.1382	0.1843	I

	DZD_IMF5	0.1648	0.2559	0.5194	I	-0.4271	0.1261	0.0007	S	0.6012	0.1707	0.0004	S
	DZD_RES	4.5870	0.9007	0.0000	S	0.7081	0.5771	0.2199	I	-3.5935	0.5770	0.0000	S
	EGP	-0.1235	0.0415	0.0029	S	0.1466	0.0534	0.0060	S	-0.1701	0.0421	0.0001	S
	EGP_IMF1	0.1629	0.0963	0.0908	I	-0.0111	0.0474	0.8144	I	0.1315	0.0506	0.0093	S
	EGP_IMF5	-0.0306	0.0613	0.6174	I	-0.0262	0.0405	0.5188	I	-0.1536	0.0527	0.0035	S
	EGP_RES	-0.6519	0.3190	0.0410	S	-0.4160	0.1812	0.0217	S	-0.0923	0.0871	0.2889	I
	ETBS	0.5339	0.2076	0.0101	S	-0.0644	0.1096	0.5570	I	0.2347	0.1586	0.2836	I
	ETBS_IMF1	0.1205	0.0746	0.1064	S	0.0384	0.0520	0.4602	I	-0.1081	0.0563	0.0548	S
	ETBS_IMF5	-1.0120	0.1069	0.0000	S	0.0562	0.0674	0.4042	I	0.1126	0.0770	0.1436	I
	ETBS_RES	-2.2903	0.5287	0.0000	S	-1.2406	0.3271	0.0001	S	-0.2791	0.4772	0.5585	I
	KES	-0.8265	0.6992	0.2372	I	0.0964	0.3612	0.7897	I	-0.1136	0.3605	0.7527	I
	KES_IMF1	1.7138	0.2187	0.0000	S	0.5215	0.1178	0.0000	S	0.0970	0.1254	0.4391	I
	KES_IMF5	-0.0158	0.2933	0.9570	I	0.1199	0.1755	0.4947	I	1.8745	0.2005	0.0000	S
	KES_RES	3.3015	0.6933	0.0000	S	2.6121	0.4658	0.0000	S	7.4514	0.4785	0.0000	S
	MAD	0.3558	0.1660	0.0321	S	1.0544	0.1315	0.0000	S	0.7051	0.1488	0.0161	S
	MAD_IMF1	-0.3853	0.0987	0.0001	S	0.4047	0.0705	0.0000	S	0.9234	0.0834	0.0000	S
	MAD_IMF5	0.2538	0.1323	0.0551	I	-0.1591	0.0854	0.0627	S	-0.3085	0.1095	0.0048	S
	MAD_RES	2.3132	0.5596	0.0000	S	-1.6751	0.3367	0.0000	S	1.7121	0.3786	0.0000	S
	NGN	0.0675	0.0563	0.2311	I	-0.0280	0.0175	0.1100	I	0.0197	0.0369	0.1705	I
	NGN_IMF1	0.1919	0.0583	0.0010	S	0.1470	0.0310	0.0000	S	0.2095	0.0405	0.0000	S
	NGN_IMF5	0.2408	0.0431	0.0000	S	-0.0131	0.0479	0.7851	I	-0.0255	0.0400	0.5231	I
	NGN_RES	-0.1800	0.6082	0.7673	I	-2.2419	0.2687	0.0000	S	-4.0372	0.6270	0.0000	S
	ZAR	-0.0082	0.0087	0.3478	I	0.0796	0.0076	0.0000	S	0.0357	0.0081	0.1739	I
	ZAR_IMF1	-0.0024	0.0391	0.9505	I	-0.0250	0.0221	0.2592	I	0.1385	0.0309	0.0000	S
	ZAR_IMF5	-0.7796	0.0536	0.0000	S	-0.0431	0.0271	0.1120	I	-0.1835	0.0400	0.0000	S
	ZAR_RES	1.0268	0.1835	0.0000	S	-0.9000	0.1166	0.0000	S	-1.0910	0.1536	0.0000	S
	C	0.0040	0.0007	0.0000	S	0.0006	0.0004	0.0830	I	0.0013	0.0004	0.0009	S
0.4, 0.6	AOA	0.1329	0.0311	0.0000	S	0.1365	0.0431	0.0015	S	-0.0197	0.0383	0.6065	I
	AOA_IMF1	-0.0109	0.0281	0.6966	I	-0.0839	0.0167	0.0000	S	0.0322	0.0064	0.0000	S
	AOA_IMF5	0.0308	0.0370	0.4050	I	0.0977	0.0213	0.0000	S	-0.0426	0.0081	0.0000	S
	AOA_RES	-0.0205	0.1292	0.8742	I	-0.3435	0.0857	0.0001	S	-0.1573	0.0340	0.0000	S
	DZD	-0.7185	0.1673	0.0000	S	-0.5971	0.1501	0.0001	S	1.0357	0.1087	0.0000	S
	DZD_IMF1	-0.0248	0.1057	0.8145	I	0.0802	0.0757	0.2893	I	-0.0320	0.0260	0.2190	I
	DZD_IMF5	-0.0939	0.1245	0.4508	I	-0.2211	0.0892	0.0132	S	0.0523	0.0288	0.0695	I
	DZD_RES	1.9817	0.5036	0.0001	S	1.1732	0.3318	0.0004	S	-1.3168	0.1245	0.0000	S
	EGP	-0.0254	0.0214	0.2350	I	0.1027	0.0376	0.0063	S	-0.0213	0.0175	0.2233	I
	EGP_IMF1	0.0024	0.0330	0.9413	I	-0.0117	0.0340	0.7300	I	0.0173	0.0115	0.1320	I
	EGP_IMF5	-0.0191	0.0876	0.8275	I	-0.0273	0.0184	0.1387	I	-0.0472	0.0062	0.0000	S
	EGP_RES	-0.0482	0.0997	0.6289	I	-0.1084	0.1039	0.2969	I	-0.1030	0.0181	0.0000	S
	ETBS	0.4520	0.1863	0.0153	S	-0.2079	0.0781	0.0078	S	0.1221	0.1322	0.0115	I
	ETBS_IMF1	0.0203	0.0494	0.6810	I	0.0700	0.0286	0.0142	S	-0.0127	0.0104	0.2227	I
	ETBS_IMF5	-0.2861	0.0623	0.0000	S	-0.0610	0.0363	0.0933	I	-0.0056	0.0126	0.6599	I
	ETBS_RES	-1.1038	0.3033	0.0003	S	-0.6673	0.1889	0.0004	S	-0.4037	0.0950	0.0000	I
	KES	-1.0776	0.6389	0.0917	I	0.7969	0.2666	0.0028	S	-0.8174	0.2948	0.0056	I
	KES_IMF1	0.7868	0.1586	0.0000	S	0.0609	0.0725	0.4007	I	0.0018	0.0280	0.9483	I
	KES_IMF5	-0.1832	0.1920	0.3402	I	0.0954	0.1133	0.3998	I	0.2114	0.0338	0.0000	S
	KES_RES	-0.2439	0.4999	0.6257	I	1.8333	0.2872	0.0000	S	1.1400	0.0984	0.0000	I
	MAD	0.2191	0.1249	0.0795	I	0.6664	0.0928	0.0000	S	0.4427	0.1089	0.0398	I
	MAD_IMF1	-0.0579	0.0584	0.3212	I	0.0345	0.0486	0.4778	I	0.0845	0.0171	0.0000	S
	MAD_IMF5	0.1545	0.0800	0.0535	I	-0.1641	0.0559	0.0033	S	-0.0498	0.0197	0.0116	S
	MAD_RES	-0.0839	0.3426	0.8066	I	-0.8735	0.2123	0.0000	S	0.3797	0.0689	0.0000	I
	NGN	0.0459	0.1013	0.6504	I	-0.0226	0.0191	0.2360	I	0.0116	0.0602	0.4432	I
	NGN_IMF1	0.0218	0.0453	0.6298	I	0.0869	0.0389	0.0254	S	0.1072	0.0246	0.0000	S
	NGN_IMF5	0.0884	0.0253	0.0005	S	-0.0596	0.0275	0.0302	S	-0.0091	0.0095	0.3380	I
	NGN_RES	-1.1218	0.2916	0.0001	S	-0.5186	0.1683	0.0021	S	-2.6867	0.2774	0.0000	S
	ZAR	-0.0046	0.0038	0.2257	I	0.0124	0.0041	0.0024	S	0.0039	0.0039	0.1141	I
	ZAR_IMF1	-0.0291	0.0242	0.2286	I	-0.0573	0.0155	0.0002	S	0.0157	0.0050	0.0016	S
	ZAR_IMF5	-0.2361	0.0312	0.0000	S	0.0085	0.0188	0.6518	I	-0.0042	0.0064	0.5150	I
	ZAR_RES	0.8542	0.1343	0.0000	S	-0.3512	0.0781	0.0000	S	-0.1439	0.0265	0.0000	S
	C	0.0007	0.0006	0.2096	I	0.0013	0.0003	0.0000	S	0.0008	0.0003	0.0035	S

ANNEXURE A19: SYMMETRIC QUANTILES TEST - SCX

Symmetric Quantiles Test									
Estimated equation quantile tau = 0.5									
Number of test quantiles: 10									
Test statistic compares all coefficients									
Restriction Detail: b(tau) + b(1-tau) - 2*b(.5) = 0									
Equation:		*BTC = ϐ0 + ϐ (ACXi,t) + εi,t*				*ETH = ϐ0 + ϐ (ACXi,t) + εi,t*			
Specification:		*CRCi,t = ϐ0 + ϐ (ACXi,t) + εi,t*				*CRCi,t = ϐ0 + ϐ (ACXi,t) + εi,t*			
Test Summary:		Chi-Sq. Statistic	Chi-Sq. d.f.	Prob.		Chi-Sq. Statistic	Chi-Sq. d.f.	Prob.	
Wald Test:		2736.75	84	0.0000		4286.68	84	0.0000	
Quantiles	**Variable**	**Restr. Value**	**Std. Error**	**Prob.**	***S or I***	**Restr. Value**	**Std. Error**	**Prob.**	***S or I***
0.1, 0.9	AUD_IMF1	0.2080	0.0243	0.0000	*S*	0.0016	0.0152	0.9179	*I*
	AUD_IMF5	-0.1201	0.0399	0.0026	*S*	-0.0093	0.0218	0.6686	*I*
	AUD_RES	-0.2549	0.1182	0.0310	*S*	-0.6923	0.0907	0.0000	*S*
	AUD_USD	0.2243	0.0244	0.0000	*S*	-0.2712	0.0161	0.0000	*S*
	CHF_IMF1	-0.0924	0.0401	0.0210	*S*	0.0203	0.0288	0.4809	*I*
	CHF_IMF5	0.3320	0.0698	0.0000	*S*	-0.0986	0.0488	0.0434	*S*
	CHF_RES	0.7350	0.2911	0.0116	*S*	1.2621	0.1681	0.0000	*S*
	CHF_USD	-0.0320	0.0502	0.5235	*I*	-0.1648	0.0347	0.0000	*S*
	EUR_IMF1	-0.1327	0.0547	0.0153	*S*	-0.0635	0.0299	0.0339	*S*
	EUR_IMF5	-0.0377	0.0925	0.6836	*I*	0.1446	0.0407	0.0004	*S*
	EUR_RES	-0.6332	0.4412	0.1512	*I*	-2.0488	0.2882	0.0000	*S*
	EUR_USD	0.3199	0.0442	0.0000	*S*	0.1526	0.0252	0.0000	*S*
	GBP_IMF1	0.1384	0.0354	0.0001	*S*	0.0079	0.0226	0.7278	*I*
	GBP_IMF5	0.0486	0.0663	0.4641	*I*	0.0132	0.0385	0.7320	*I*
	GBP_RES	0.1533	0.1972	0.4370	*I*	-0.0423	0.2189	0.8469	*I*
	GBP_USD	0.0215	0.0369	0.5607	*I*	-0.0423	0.0195	0.0305	*S*
	ZAR_IMF1	0.3560	0.0206	0.0000	*S*	-0.0058	0.0131	0.6572	*I*
	ZAR_IMF5	-0.2070	0.0680	0.0023	*S*	0.0283	0.0275	0.3028	*I*
	ZAR_RES	0.1301	0.1492	0.3831	*I*	0.2813	0.1011	0.0054	*S*
	ZAR_USD	-0.1725	0.0189	0.0000	*S*	0.0281	0.0101	0.0055	*S*
	C	0.0004	0.0002	0.0948	*I*	-0.0006	0.0002	0.0001	*S*

ANNEXURE A19 (continued)

Quantiles	Variable	Restr. Value	Std. Error	Prob.	S or I	Restr. Value	Std. Error	Prob.	S or I
0.2, 0.8	AUD_IMF1	0.1426	0.0122	0.0000	S	-0.0174	0.0021	0.0000	S
	AUD_IMF5	-0.0721	0.0175	0.0000	S	0.0193	0.0025	0.0000	S
	AUD_RES	-0.1893	0.0587	0.0013	S	0.1017	0.0118	0.0000	S
	AUD_USD	0.0323	0.0116	0.0053	S	-0.0563	0.0063	0.0000	S
	CHF_IMF1	0.0368	0.0220	0.0946	S	0.0176	0.0029	0.0000	S
	CHF_IMF5	0.1792	0.0292	0.0000	S	-0.0204	0.0036	0.0000	S
	CHF_RES	0.3265	0.1106	0.0032	S	-0.0262	0.0129	0.0423	S
	CHF_USD	-0.1286	0.0296	0.0000	S	-0.1127	0.0122	0.0000	S
	EUR_IMF1	0.0672	0.0230	0.0035	S	0.0026	0.0024	0.2747	I
	EUR_IMF5	-0.2311	0.0396	0.0000	S	0.0021	0.0033	0.5291	I
	EUR_RES	-0.8682	0.2826	0.0021	S	-0.3397	0.0537	0.0000	S
	EUR_USD	0.1578	0.0201	0.0000	S	0.0109	0.0025	0.0000	S
	GBP_IMF1	0.0779	0.0157	0.0000	S	-0.0013	0.0015	0.3723	I
	GBP_IMF5	0.0738	0.0228	0.0012	S	-0.0044	0.0021	0.0392	S
	GBP_RES	-0.0265	0.1014	0.7940	I	-0.0746	0.0134	0.0000	S
	GBP_USD	0.0317	0.0170	0.0618	I	0.0054	0.0018	0.0022	S
	ZAR_IMF1	0.1735	0.0098	0.0000	S	-0.0006	0.0008	0.4508	I
	ZAR_IMF5	-0.1091	0.0222	0.0000	S	-0.0002	0.0016	0.8927	I
	ZAR_RES	-0.0675	0.0773	0.3823	I	0.0914	0.0130	0.0000	S
	ZAR_USD	-0.0859	0.0083	0.0000	S	0.0026	0.0008	0.0011	S
	C	-0.0003	0.0001	0.0041	S	-0.0005	0.0001	0.0000	S
0.3, 0.7	AUD_IMF1	0.0749	0.0073	0.0000	S	0.0013	0.0002	0.0000	S
	AUD_IMF5	-0.0398	0.0093	0.0000	S	-0.0013	0.0002	0.0000	S
	AUD_RES	-0.1335	0.0311	0.0000	S	-0.0037	0.0008	0.0000	S
	AUD_USD	-0.0029	0.0061	0.6306	I	-0.0012	0.0003	0.0000	S
	CHF_IMF1	0.0422	0.0112	0.0002	S	0.0007	0.0002	0.0008	S
	CHF_IMF5	0.0871	0.0162	0.0000	S	-0.0014	0.0003	0.0000	S
	CHF_RES	0.1169	0.0548	0.0330	S	-0.0069	0.0011	0.0000	S
	CHF_USD	-0.0877	0.0175	0.0000	S	-0.0018	0.0015	0.2453	I
	EUR_IMF1	0.0783	0.0124	0.0000	S	0.0004	0.0002	0.0978	I
	EUR_IMF5	-0.1676	0.0195	0.0000	S	0.0005	0.0003	0.1285	I
	EUR_RES	-0.6491	0.1217	0.0000	S	0.0136	0.0016	0.0000	S
	EUR_USD	0.0727	0.0121	0.0000	S	0.0001	0.0003	0.7595	I
	GBP_IMF1	0.0459	0.0086	0.0000	S	-0.0004	0.0002	0.0255	S
	GBP_IMF5	0.0242	0.0124	0.0500	S	-0.0001	0.0002	0.5279	I
	GBP_RES	-0.0653	0.0522	0.2110	I	0.0071	0.0010	0.0000	S
	GBP_USD	0.0159	0.0099	0.1063	I	0.0005	0.0003	0.0622	I
	ZAR_IMF1	0.0674	0.0055	0.0000	S	-0.0002	0.0001	0.0020	S
	ZAR_IMF5	-0.0554	0.0081	0.0000	S	0.0003	0.0001	0.0188	S
	ZAR_RES	-0.0650	0.0322	0.0435	S	0.0000	0.0009	0.9787	I
	ZAR_USD	-0.0359	0.0044	0.0000	S	0.0003	0.0001	0.0000	S
	C	-0.0002	0.0000	0.0000	S	0.0000	0.0000	0.2104	I
0.4, 0.6	AUD_IMF1	0.0211	0.0040	0.0000	S	0.0005	0.0001	0.0000	S
	AUD_IMF5	-0.0111	0.0046	0.0160	S	-0.0005	0.0001	0.0005	S
	AUD_RES	-0.0378	0.0157	0.0163	S	-0.0008	0.0005	0.1271	I
	AUD_USD	-0.0014	0.0031	0.6543	I	-0.0003	0.0001	0.0007	S
	CHF_IMF1	0.0216	0.0059	0.0003	S	0.0006	0.0002	0.0000	S
	CHF_IMF5	0.0067	0.0071	0.3489	I	-0.0009	0.0002	0.0000	S
	CHF_RES	0.0106	0.0248	0.6675	I	-0.0014	0.0008	0.0731	I
	CHF_USD	-0.0431	0.0109	0.0001	S	0.0000	0.0003	0.9967	I
	EUR_IMF1	0.0159	0.0061	0.0089	S	0.0002	0.0002	0.1332	I
	EUR_IMF5	-0.0377	0.0080	0.0000	S	0.0003	0.0002	0.1560	I
	EUR_RES	-0.1684	0.0431	0.0001	S	0.0025	0.0012	0.0318	S
	EUR_USD	0.0207	0.0074	0.0054	S	0.0002	0.0002	0.3831	I
	GBP_IMF1	0.0192	0.0045	0.0000	S	-0.0002	0.0001	0.0659	I
	GBP_IMF5	-0.0031	0.0057	0.5819	I	-0.0001	0.0001	0.3043	I
	GBP_RES	0.0156	0.0217	0.4721	I	0.0035	0.0007	0.0000	S
	GBP_USD	-0.0006	0.0059	0.9210	I	0.0001	0.0002	0.5322	I
	ZAR_IMF1	0.0189	0.0027	0.0000	S	-0.0001	0.0000	0.0354	S
	ZAR_IMF5	-0.0177	0.0039	0.0000	S	0.0002	0.0001	0.0684	I
	ZAR_RES	-0.0072	0.0140	0.6051	I	0.0001	0.0006	0.9223	I
	ZAR_USD	-0.0101	0.0021	0.0000	S	0.0001	0.0000	0.1217	I
	C	-0.0001	0.0000	0.0005	I	0.0000	0.0000	0.9379	I

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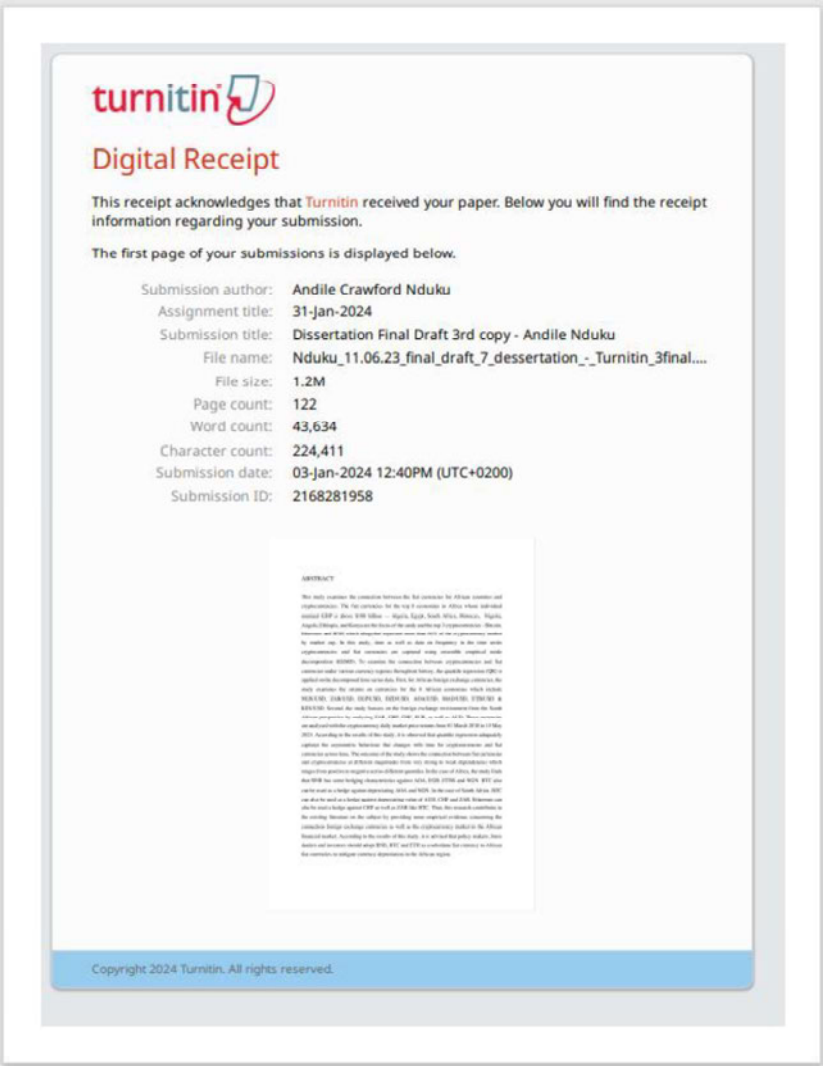

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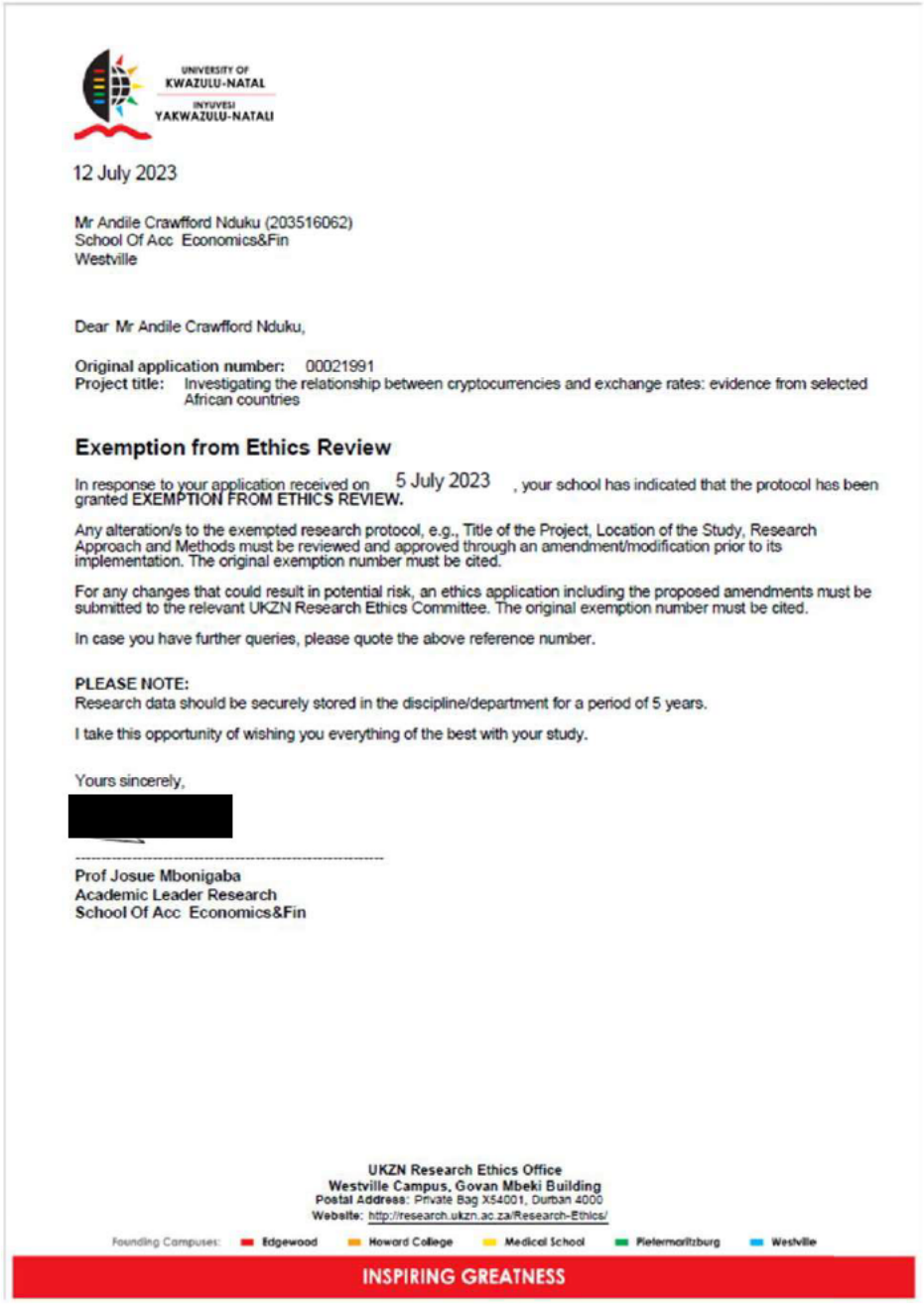

UNIVERSITY OF KWAZULU-NATAL
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12 July 2023

Mr Andile Crawfford Nduku (203516062)
School Of Acc Economics&Fin
Westville

Dear Mr Andile Crawfford Nduku,

Original application number: 00021991
Project title: Investigating the relationship between cryptocurrencies and exchange rates: evidence from selected African countries

Exemption from Ethics Review

In response to your application received on 5 July 2023 , your school has indicated that the protocol has been granted **EXEMPTION FROM ETHICS REVIEW.**

Any alteration/s to the exempted research protocol, e.g., Title of the Project, Location of the Study, Research Approach and Methods must be reviewed and approved through an amendment/modification prior to its implementation. The original exemption number must be cited.

For any changes that could result in potential risk, an ethics application including the proposed amendments must be submitted to the relevant UKZN Research Ethics Committee. The original exemption number must be cited.

In case you have further queries, please quote the above reference number.

PLEASE NOTE:
Research data should be securely stored in the discipline/department for a period of 5 years.

I take this opportunity of wishing you everything of the best with your study.

Yours sincerely,

[redacted]

Prof Josue Mbonigaba
Academic Leader Research
School Of Acc Economics&Fin

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