Crypto Connections: Unravelling African Stock Markets and Cryptocurrencies in the COVID-19 Era

by

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Declaration of original work

I, **Marcus Howard**, declare that this minor dissertation is my unaided work. Any assistance I have received has been duly acknowledged in the work. It is submitted in partial fulfilment of the requirements for the degree of MASTER OF MANAGEMENT in FINANCE AND INVESTMENTS at the University of the Witwatersrand. It has yet to be submitted for any degree or examination at this or any other University.

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Signature

Date

Abstract

Since their introduction in 2019, cryptocurrencies have become increasingly popular in the African markets. Cryptocurrencies are seen as disruptive technology based on cryptographical technologies and do not share features related to the real economy. Based on this characteristic, one hypothesises that these assets are a perfect diversification instrument during periods of high volatility, particularly as portfolio managers look for new avenues to manage risk. The main aim of this study was broadly focused on the interdependence and co-movement relationship of cryptocurrencies and African stock markets during periods of severe market stress, such as during the COVID-19 pandemic. This study was mainly concerned with those aspects of connectedness that relate to transmission through financial markets. This study sought to examine the co-movement relationships, determine the extent of integration and establish the direction of spillover by replicating modelling techniques proposed by Diebold and Yilmaz (2009; 2012) and Barunik and Krehlik (2018). These techniques measure connectedness using a spillover index, which follows a variance decomposition approach of a vector autoregressive model. The second technique allows for the estimation of connectedness to variables because of heterogeneous frequency responses to shocks.

By studying the connectedness of Bitcoin, Ethereum, Tether, Binance Coin, and XRP and the five largest African stock markets based on market capitalisation (South Africa, Nigeria, Morocco, Egypt, and Kenya), the study observed that the COVID-19 sub-sample period contributed most to connectedness at 31.79% relative to the pre-COVID period at 23.67%. The highest contributors to connectedness in both periods are Bitcoin and Ethereum, with Tether being the lowest. These results indicate that information flow mostly comes from the stock markets rather than cryptocurrencies.

Also, from the frequency-domain results, across both periods, the most significant contributor to connectedness is observed in the short-term being frequency 1, accounting for 17,74% and 24.77%, and frequency 2, 4.35% and 5.16% in the pre-COVID and COVID periods respectively, while the medium-term and long-term accounting for relatively more minor proportions. Thus, contagion is highest in the short term given connectedness results, thus leading to lower diversification across the short term; however, diversification benefits are noted across more extended term periods. In addition, in the longer-term period, the change in connectedness is relatively tiny. The findings of this study suggest that cryptocurrencies could be an alternative to diversifying risk in African equities. Diversification is essential for long-term investors and regulators as they build resilience in the financial markets during a crisis. This study informs policymakers and governments on the need to regulate markets to optimise diversification, safe haven, and hedging benefits across varied market conditions.

Keywords

African Stock Market, Connectedness, Contagion, Cryptocurrency, COVID-19, Frequency-domain, Time-domain

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List of abbreviations

ADF	Augmented Dickey-Fuller test
ARCH	Autoregressive Conditional Heteroscedasticity
BNB	Binance Coin
BTC	Bitcoin
COVID-19	Corona Virus Disease of 2019
CFVaR	Cornish-Fisher expansion
CSE	Casablanca Stock Exchange (Morocco)
cDCC	Corrected Dynamic Conditional Correlation
DCC	Dynamic Conditional Correlation
GARCH	Exponential Generalised Autoregressive Conditional Heteroscedasticity
EGX	The Egyptian Exchange (Egypt)
EMV	Equity Market Volatility
ETC	Ethereum
GARCH	Generalised Autoregressive Conditional Heteroscedasticity
GFVED	Generalised Forecast Error Variance Decomposition
GVAR	Generalised Vector Autoregressive
JSE	Johannesburg Stock Exchange (South Africa)
KPSS	Kwiatkowski-Phillips-Schmidt-Shin
MA	Moving Average
MENA	Middle East and North Africa
MSCI	Morgan Stanley Capital International Index
NGX	Nigeria Exchange Group (Nigeria)
NSE	Nairobi Securities Exchange (Kenya)
S&P500	Standard and Poor's 500
USDT	Tether
VAR	Vector Autoregressive
VIX	Volatility index
WHO	World Health Organisation
VaR	Value at Risk
XRP	XRP markets

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Dedication

To my beloved grandmother, Sophia Busisiwe Cebekhulu-Howard.

"*Beside each believer stands an angel as protector and shepherd, leading him to life***."**

-St. Basil the Great

Chapter 1 Introduction

1.1 INTRODUCTION

With the advent of globalisation and markets becoming increasingly integrated, understanding the links between markets has become imperative. Particularly as portfolio managers look to new avenues to manage risk, investors who seek to hold assets for the long term will seek to find markets or assets that share a different co-movement with their local economy (Chinzara & Aziakpono, 2009). Understanding the co-movement relationship amongst stock markets is an essential tool to aid portfolio managers in considering strategies to reduce risk and diversify portfolio risk. Where economies are less integrated, portfolio managers may consider these markets. Thus, where stock markets have no spillover effects, these stock markets become a better option for reducing risk (Gulzar *et al.*, 2019).

The COVID-19 pandemic is an example of event risk at the global level. It quickly brought to our attention how one event has far-reaching consequences to the extent that it exposed how vulnerable financial markets can be (Corbet *et al.*, 2020). The pandemic sparked different reactions across markets with varied portfolio flows across countries and asset classes, much driven by how various countries responded to the pandemic as cases began to increase (Hengge & Elfayoumi, 2021). In comparing the volatility of stock markets across different historical outbreaks driven by an infectious disease, such as the Spanish flu of 1918-19, the influenza pandemic of 1957-58, and the 1968 pandemic, Baker *et al.* (2020) discovered that no outbreak has had such a severe impact on US stock markets as the COVID-19 pandemic did. Using text-based methods such as newspaper-based Equity Market Volatility (EMV) tracker to explain stock movements, the study revealed that not a single jump could be attributable to previous outbreaks (from 1900 to 2019); however, with the COVID-19 pandemic period (24 February to 20 April 2020) there were at least two dozen jumps related to the pandemic. According to the World Health Organisation COVID-19 dashboard, as of 30 May 2023, 767,364,883 confirmed cases and 6,938,353 deaths arose because of the pandemic; the most significant proportion of cases reported in Europe, the Western Pacific, and the Americas accounted for

36,0%, 26.6% and 25.1% of all cases reported. Cases reported in Africa accounted for the lowest record of 1.2% of all cases compared to other World Health Organisation regions.[1]

Kumah and Odei-Mensah (2021) contend that cryptocurrency shocks may spill over African stock markets as markets become integrated, particularly at lower frequencies. As such, investors looking to hedge their risk in African stocks may not see benefits in the medium to long term but will likely achieve benefits in shorter timeframes. In applying a frequency-domain spillover index, the study's results also indicated that in the absence of solid integration between stock markets and cryptocurrencies, cryptocurrencies were significant spillover transmitters across various frequencies. In studying the integration of the stock markets of South Africa, Egypt, Kenya, Morocco, Nigeria, Tunisia, and Botswana and Bitcoin during the period 2011 and 2021, Nyakurukwa and Seetharam (2023) were able to show that the sample countries' integration was weak; however, the significant flow of information observed from Bitcoin to stock markets was where countries trade in higher volumes.

Contagion or spillover refers to how downside risk spreads between countries because of disturbances to the market. This downside risk was observed through the connections between asset classes and financial phenomena such as stock returns, exchange rate movements, bond spreads, and the flow of capital (Forbes & Rigobon, 1999; Masson, 1998; Wolf, 1999; Pritsker, 2001). Dornbusch *et al.* (2000a) observed further that contagion involves extensive interconnections across markets during periods of stress categorised into two categories: (1) spillovers that arise from normal market interconnectedness and (2) other effects that are linked to the behaviour and responses of investors rather than that which is observed in the macroenvironment. The term contagion has been a difficult concept to define for a long time. Forbes and Rigobon (2001) prefer the term shift-contagion, referring to cross-market linkages to one or more countries following a shock. Measured through the correlation of asset returns, probabilities of a speculative attack, and volatility measures, including transmission of shocks. Researchers use the terms spillover and contagion interchangeably with Collins and Biekpe (2003), referring to contagion as the increase in asset price correlation during periods of market distress. Understanding the contagion relationship continues to be topical amongst financial market researchers, given the essential role it plays in driving portfolio choices of investment managers and the development of financial markets (Chinzara & Aziakpono, 2009; Gulzar *et*

[1] Refer to https://covid19.who.int/ (accessed on 03 June 2023).

al., 2019; Van der Westerhuizen *et al*., 2022). Given a high-stress scenario as the pandemic, this raises the question of what type of relationship exists for the African market when we combine cryptocurrencies and stock markets.

Cryptocurrencies are interesting assets as they tend to hold high-risk, high-reward properties, with some studies indicating that Bitcoin has served as an effective hedge against the Standard and Poor's 500 (Bouri *et al*., 2017a; Tiwari *et al*., 2019). Cryptocurrencies differ from government-issued currency as they do not require financial intermediation from banks. Cryptocurrencies are seen as disruptive technology based on cryptographical technologies and do not share features related to the real economy. The government or a country's banking regulator does not control cryptocurrencies. Given these features, cryptocurrencies are perfect diversification instruments during periods of high volatility (Caferra & Vidal-Tomás, 2021). Researchers have ascribed many properties to cryptocurrencies, such as haven properties (Mariana *et al*., 2021) and a store of value (Corbet *et al*., 2020a). For these reasons, they play a pivotal role in an investor's portfolio as they consider the risks and returns around their portfolio (Gil-Alana *et al*., 2020).

Since its first introduction in 2009, the cryptocurrency market has grown into an industry that has a value of more than $1.15 trillion[2]. According to the 2022[3] Chain analysis report, Africa represents one of the fastest-growing cryptocurrency markets. Sub-Saharan Africa reported transaction volumes of $100.6 billion between July 2021 and June 2022, facilitated by deep penetration and integration, particularly in Nigeria, Kenya, and South Africa. On the other hand, North African countries such as Egypt and Morocco have accounted for the most significant year-on-year growth in traded volumes compared to the global cryptocurrency trade.

In exploring Bitcoin and Ethereum, Gil-Alana *et al*. (2020) hold that cryptocurrencies are critical in an investor's portfolio as they provide diversification options. Recent studies, particularly around the COVID-19 pandemic, have yet to reach a consensus about cryptocurrencies during periods of high volatility. In assessing returns and traded volumes for data from the period 01 January 2019 to 31 March 2020, Corbet *et al*. (2020a) found evidence

[2] Refer to https://coinmarketcap.com/ (Accessed 04 June 2023)
[3] Refer to https://go.chainalysis.com/rs/503-FAP-074/images/2022-Geography-of-Cryptocurrency.pdf (Accessed 04 June 2023)

that all the cryptocurrencies had higher traded volumes in the COVID-19 period than the prior period including significant generalised autoregressive conditional heteroscedasticity (GARCH-calculated) polarity scores with positive results for Bitcoin SV (+0.25), XRP markets (+0.10), Stellar (+0.09) and Ethereum (+0.06). The results indicate that even in a stressful period, cryptocurrencies continue to act as a store of value. Following an observation window from 01 July 2019 to 06 April 2020, Mariana *et al.* (2021) contend that the two major cryptocurrencies in the shorter term reveal a haven property, showing a negative dynamic correlation median of -0.0499 with Ethereum showing an even lower correlation than Bitcoin.

Studying spillover effects of the COVID-19 pandemic, looking particularly at four cryptocurrencies and their co-movements with global stock markets, Ampountolas (2023) found that significant spillover effects existed over short and long periods, with some cryptocurrencies showing varied behaviour during the early part of the pandemic. Bitcoin, for example, from January to December 2020, showed less value at risk than in the twelve months to December 2019. On the other hand, Ethereum shows a positive Cornish-Fisher expansion (CFVAR) compared to the other three cryptocurrencies. The Cornish-Fisher measures downside risk, a better loss estimate than Value at Risk (VaR), given that it accounts for negatively skewed returns. Conlon and McGee (2020) had a rather dim view of cryptocurrencies. They shunned Bitcoin as a risky asset that would not reduce the overall portfolio's risk, even if minimal allocations were added. Corbet *et al.* (2020b) supported this view. Caferra and Vidal-Tomás (2021), through the wavelet approach and Markov switching autoregressive model, concluded that a contagion existed between cryptocurrencies and stock markets at high frequencies, with minimal reduction in risk. In addition, cryptocurrencies showed a faster positive recovery than stock markets, with the COVID-19 impact being relatively short.

Over the recent years, several studies have focused on the effects of spillovers, particularly globally. For instance, some studies focussed on the Chinese stock market, gold, and cryptocurrencies (Corbet *et al.,* 2020b); the Standard and Poor’s 500 (S&P500) and Bitcoin (Nguyen, 2022; Conlon & McGee, 2020), and many others focussed on the major stock exchanges and cryptocurrencies (Gil-Alana *et al.,* 2020; Caferra & Vidal-Tomás, 2021; Mariana *et al.*, 2021; Ampountolas, 2023). Studies in the African context remain scarce, covering relatively short COVID-19 timeframes or with a limited number of countries within the scope of the study (Kumah *et al.*, 2021; Nkrumah-Boadu *et al.,* 2022; Nyakurukwa &

Seetharam, 2023) or outside of the scope of the COVID-19 period (Kumah & Odei-Mensah, 2021). Thus, there remains scope and interest in exploring the African market further during a high-stress environment such as the global financial crisis and the COVID-19 pandemic.

Against this background, using Diebold and Yilmaz's (2009; 2012) time-domain and the frequency-domain technique by Barunik and Krehlik (2018), this study looks at African stock markets and cryptocurrency spillovers during the COVID-19 pandemic. The COVID pandemic was an extreme volatility event that could be referenced very closely to the global financial market of 2008 and the East Asian crisis of 1997, which were vital in Diebold and Yilmaz's (2009) early study. Given that we are looking at cryptocurrencies, this study will further aim to understand the directional and magnitude of spillovers (Diebold & Yilmaz, 2012). Overall, the study adds to the existing body of knowledge on contagion and spillover effects in the African context provides additional knowledge on portfolio risk, and aids in directing policy.

1.2 PROBLEM STATEMENT

African stock markets differ from global stock markets, criticised for suffering from low-volume trading with a significant number of shares thinly traded; they are relatively small with high degrees of fragmentation, including issues in the regulatory environment (Yartey & Adjasi, 2007; Agu & Kindgom, 2020) and thus differing from global stock markets. Despite their development, they need to be firmly integrated into the continent (Kumah & Odei-Mensah, 2021).

The COVID-19 pandemic threatened vulnerabilities in the financial market (Corbet *et al.*, 2020b), requiring us to relook the views on contagion across various assets and the financial markets (Goodell, 2020). Global studies support varying views on cryptocurrencies, with some having positive sentiment (Corbet *et al*., 2020a; Iqbal *et al*., 2021; Mariana *et al.*, 2021; Ampountolas, 2023), while other researchers indicated that cryptocurrency did not possess hedging qualities and amplified losses (Conlon & McGee, 2020; Corbet *et al.*, 2020b; Caferra & Vidal-Tomás, 2021).

Recent studies on African stock markets in the COVID-19 era show that early evidence is beginning to support the idea that cryptocurrency may be an appropriate hedge. However, these studies take a limited country view, with only countries in the Morgan Stanley Capital

International Index (MSCI) included (Nyakuruwa & Seetharam, 2023); others covering short periods. Nkrumah-Boadu *et al.* (2022) covered a short COVID-19 period to 05 May 2020 in investigating cryptocurrencies, gold, and stock market safe havens, including only a limited cryptocurrency basket across Bitcoin, Dogecoin, Ripple and Ethereum. Critical aspects of the relationship between African stock markets and cryptocurrency have yet to be sufficiently explored; these include, but are not limited to, specific co-movement patterns, spillover effects, or risk dynamics. Goodell (2020) indicates that the pandemic extensively impacted financial markets, systems, and institutions, requiring us to relook at how assets co-move as financial market dynamics change, given changes in attitudes and behaviour. As such, the findings of this study become relevant to portfolio risk management, investment management, and diversification.

1.3 RESEARCH PURPOSE AND OBJECTIVES

1.3.1 Research Purpose

In establishing a balance of portfolio risk and return dynamics, portfolio managers are primarily concerned with the optimal asset allocation that minimises risks and ensures the highest return. The COVID-19 pandemic has had systemic effects on markets across the globe, affecting stock markets, including cryptocurrencies, which are primarily seen as unconventional assets (Ampountolas, 2023). This study aims to examine how African stock markets and cryptocurrencies co-move during the COVID-19 global pandemic and further investigate the spillover effects between these markets. The study aims to contribute to the existing body of knowledge on market interdependencies, risk management strategies, and portfolio diversification in the African context. By analysing the dynamics between African stock markets and cryptocurrencies during a severe crisis, the study intends to provide insights to aid investors, portfolio managers, and policymakers in making informed decisions during such challenging periods.

1.3.2 Research Objectives

This study focuses broadly on the interdependence and co-movement relationship of cryptocurrencies and African stock markets during severe market stress, such as the COVID-19 pandemic. The research objectives of this study are as follows:

I. To examine the co-movement relationship before and during a high-stress event.
II. To determine the extent of integration between cryptocurrencies and African stock markets about price movements.
III. To determine what spillover effects exist during the stress event and establish the direction of these spillovers.

1.4 RESEARCH QUESTIONS

This study aims to answer the following research questions:

1.4.1 Main Research Question

How do African stock markets co-move with cryptocurrencies during the COVID-19 pandemic, characterised by severe market stress and high volatility?

1.4.2 Secondary Research Questions

i. What is the co-movement relationship between African stock markets and cryptocurrencies before and during a high-stress event?
ii. To what extent are African stock markets and cryptocurrencies integrated regarding price movements during the COVID-19 pandemic?
iii. What are the volatility spillover effects between African stock markets and cryptocurrencies during the COVID-19 pandemic, and what is the direction of these spillovers?

1.5 IMPORTANCE AND BENEFITS OF THE STUDY.

There is a high likelihood that an event such as the global pandemic may reoccur; understanding market behaviour and dynamics during such events will be essential in guiding and aiding portfolio diversification.

This study makes several research contributions. Firstly, it extends the existing literature on cryptocurrencies and stock markets, particularly in Africa. Secondly, the findings will inform practical decisions for policymakers, investors, and portfolio managers, given cryptocurrencies' crucial role. Thirdly, given that there is no direct link to the real economy. Understanding the co-movement between stock markets and cryptocurrencies during volatile periods can guide hedging strategies, asset allocation decisions, and risk management approaches.

Given the potential regulatory implications of the study, it will also be of interest to the regulatory environment. Enhanced regulation and policy measures will aid in ensuring market stability and investor protection during market stress, including suggestions for regulatory frameworks, risk assessment methodologies, or market surveillance mechanisms.

There are broader implications for overall economic and financial stability. This study's insights will provide implications for potential systemic risks, assess financial contagion, and aid in the development of measures to mitigate such risks.

The study is essential for policymakers and investors to understand how stock markets and cryptocurrencies co-move during heightened periods of volatility to direct future policy. The results will be essential in guiding hedging strategies and enhancing regulation for these periods.

This study also has implications for the longer term, as the findings will contribute to building resilience and preparedness for future crises or similar events and aid in developing early warning systems, improving crisis management strategies, and enhancing market efficiency.

1.6 CHAPTER OUTLINES

Chapter One introduces this study, outlining the research problem and objectives, including the research questions under investigation. It further outlines the purpose of the study and its importance. Lastly, it outlines the benefits of this study.

Chapter Two reviews the existing research concerning the co-movement of stock markets and cryptocurrencies in the COVID-19 era. It then explores the definition of contagion and its mechanisms for transmission, crisis contingent and non-contingent theories, the properties of cryptocurrencies during COVID-19, and finally, the models and techniques employed in both the global and African contexts.

Chapter Three provides an overview of the data, the estimation techniques and the methods employed in the study, and the study's limitations.

Chapter Four analyses and discusses the results obtained from the time-domain, frequency-domain technique models, and the rolling window frequency spillover tests. Lastly, this section presents results obtained from the robustness checks performed at different VAR orders.

Chapter Five concludes this dissertation with a summary of the critical findings and recommends further research.

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Chapter 2 Literature review

2.1 INTRODUCTION

The literature review aims to explore and review the co-movement relationship between stock markets and cryptocurrencies. This chapter explores this relationship with a particular emphasis on the COVID-19 pandemic period, a severe market stress event that introduced turbulence across the globe. Secondly, this chapter explores the definition of contagion and outlines the channels and pathways for transmission. Thirdly, the chapter outlines the theories underpinning contagion across crisis and non-crisis contingencies. Fourthly, the chapter reviews the properties of cryptocurrencies during the COVID-19 pandemic and, finally, reviews the models employed in the global and African context.

2.2 CO-MOVEMENT OF STOCK MARKETS AND CRYPTOCURRENCIES

Nakamoto (2018) introduced Bitcoin as a peer-to-peer electronic cash system with the main aim of solving online payments such that the payment is sent directly between two parties without involving a financial institution. Financial institutions serve the intermediary role of the trusted third party facilitating these payments. The essence of the financial system relies heavily on trust and not cryptographic proof. As such, Bitcoin was introduced to solve this using digital signatures and cryptographic technology to avoid the double spending problem, which is the verification usually performed by a central bank or mint following a transaction.

Following the introduction of Bitcoin, several researchers focused on crucial aspects of cryptocurrencies, with the research taking on many branches of financial research. Market efficiencies were crucial, with Vidal-Tomas and Ibanez (2018) examining the semi-strong efficiency of Bitcoin with a particular focus on how a digital currency reacts to monetary policy, including events concerning Bitcoin. Many other researchers focussed on other aspects of market efficiency (Nadarajah & Chu, 2017; Bariviera, 2017). Some studies centred on aspects of volatility, including market returns (Ji *et al.*, 2018; Omane-Adjepong *et al.*, 2019b); other studies shifted to focus on the properties of the asset class, such as haven properties (Conlon & McGee, 2020); hedging and portfolio diversification properties (Bourie *et al*., 2017c; Bourie *et al.*, 2018a; Conlon & McGee, 2020; Corbet *et al.*, 2020a; Corbet *et al.*, 2020b), including looking at the behavioural aspects such as herding behaviour (Bouri *et al*., 2018b).

Some studies have also considered the inclusion of cryptocurrencies into the asset mix of a portfolio (Bouri *et al.,* 2017b; Omane-Adjepong *et al*., 2019a; Stensas *et al*., 2019), while others assessed the linkages that exist with different asset classes (Corbet *et al*., 2018). Recently, Gil-Alana *et al.* (2020) were particularly interested in cryptocurrencies' role in investment decisions, looking at the relationships between cryptocurrencies and stock markets. A key focus was showing the return and volatility transmission patterns contributing to investment decision-making. The study argues that cryptocurrencies have a significant role to play in the investor's portfolio, given that, as an asset class, they bring about a diversification element. Globally, many studies on stock markets and cryptocurrencies have been conducted; however, these studies are thin in the African context.

In the African context, examining bivariate co-movement between African stock returns and cryptocurrencies, Kumah and Odei-Mensah (2021) found that the Ghanaian, South African, and Kenyan stock markets were highly integrated with Bitcoin in the long term (a period denoted as greater than 64 days), while the Tunisian and Mauritian stock markets were highly integrated in both the medium (16-64 days) and the long term. The Moroccan stock market also shares a two-period time investment horizon integration for the short (2-16 days) and the long term. Egypt only shows integration during the medium term. When adding in Ethereum, a varying picture emerged. The results indicated that stock markets integrated into the long term were Egypt, Ghana, and Mauritius; medium and long term (Kenya, South Africa, and Tunisia); and short-term in Morocco. In examining cryptocurrencies and stock markets of the Middle East and North Africa (MENA) region through cointegration analysis and panel-specific forms of Granger causality, Sami and Abdallah (2020) established that a strong relationship existed between the cryptocurrency market and the performance of the stock market. The study focussed on Gulf countries and non-Gulf countries in the region. Gulf countries apply Sharia rules governed by Islamic religious practices, while non-Gulf countries apply flexibility around unjustified profits or taking on excessive risk. Gulf markets only encourage investment in real assets and not that of cryptocurrencies. The empirical results of this study indicate that for every 1% increase in cryptocurrency, a return of 0,15% (decrease) and 0,13% (increase) in stock market performance was noted for Gulf and non-Gulf stock markets, respectively. The implication is that in Gulf markets, investors may withdraw their investments in the stock market during a downturn and invest in the cryptocurrency market. At the same time, non-Gulf countries can add cryptocurrencies to their investment portfolio.

Following recent financial turbulence caused by the COVID-19 pandemic, a shift in research has led researchers to investigate and explore the co-movements relationship, properties, and contagion effects of cryptocurrencies on stock markets, particularly in the COVID-19 stress environment.

At the onset of the COVID-19 pandemic, stock markets and cryptocurrencies fell sharply, evidencing the presence of financial contagion. However, as time progressed, cryptocurrencies rebounded, with stock markets remaining bear markets (Caferra & Vidal-Tomás, 2021). In assessing contagion effects, looking at price volatility of the Shanghai and Shenzhen Stock exchanges and Bitcoin, Corbet *et al*. (2020b) concluded that cryptocurrencies were amplifiers of contagion, noting that the volatility relationship did evolve. Conlon and McGee (2020) supported this assertion in assessing whether Bitcoin during the COVID-19 bear market held properties of a safe haven or that of a risky asset; they established that no haven properties existed when examining a portfolio that contained the S&P500 and an allocation of Bitcoin. This study held that for all allocations of different weights of Bitcoin, the portfolio witnessed increased VaR and CVAR results. The study held further that any allocation of Bitcoin, which was more than 28%, led to a significant increase in downside risk (a quantum of at least 50%), holding the assertion that Bitcoin does not act as a safe haven. Corbet *et al*. (2020a) shared a differing view, as the results of their study proved that cryptocurrencies acted as a safe haven, similar to how precious metals behaved in previous crises. Mariana *et al.* (2021) concurred with this sentiment, particularly in the short term.

Bhattacharya *et al.* (2022), using dynamic conditional correlation and Diebold and Yilmaz (2012) volatility index examining Bitcoin, Ethereum, Binance Coin, Cardano, Tether, and Ripple with the CBOE volatility index, found that Ethereum and Ripple were adequate to be used in the construction of a portfolio. All the cryptocurrencies tested had spillovers in the long term, but no spillovers existed in the short term. Ampountolas (2023) also reported mixed results in their quantification, noting that VaR and CFVaR results differed across asset portfolios. The Dow and S&P500 showed the highest VaR loss, with Ethereum being the only cryptocurrency showing positive CFVaR results. Maitra *et al.* (2022), examining Bitcoin and Ethereum and eight stock markets using a pre-COVID-19 and COVID-19 sample period through copula techniques, proved that including cryptocurrencies in stock portfolios can yield hedging gains. The findings of these studies remain mixed.

In the African context, early evidence is beginning to support the position that cryptocurrency may be an appropriate hedge and provide diversification benefits (Nkrumah-Boadu *et al.*, 2022; Nyakuruwa & Seetharam, 2023), including embodying haven properties in the medium term (Kumah *et al.*, 2021). The existing literature is primarily skewed to the global context rather than to the African context. While some studies have examined the co-movement and integration between African stock markets and cryptocurrencies, there remains a lack of research specifically focused on the COVID-19 pandemic period. This research intends to address this gap by providing insights into the specific dynamics and interactions between African stock markets and cryptocurrencies by analysing the dynamics and volatility spillover effects during this unique period.

2.3 DEFINING CONTAGION

As mentioned earlier, Pritsker (2001) defined contagion as a shock occurring to one or a group of markets, countries, or institutions that can spread between any of the parts. This definition expands on the narrower definition used in previous studies and outlines the transmission mechanisms through which contagion is channelled. Forbes and Rigobon (2001) define contagion differently—which is not universally accepted—referring to a significant increase in cross-market linkages following a shock event to a specific country or a group of countries. This definition is premised on portfolio risk theory, with its effectiveness characterised by reducing portfolio risk during a crisis event. This definition uses correlation measures of asset returns, probabilities metrics, and volatility and shock transmission mechanisms. Thus, this definition outlines that contagion only exists not by mere correlation between markets but where this correlation is particularly significant.

2.4 CHANNELS FOR FINANCIAL CONTAGION

Transmission channels through which a shock can be transmitted can be linked to four key elements: the real sector, banks, financial markets, and non-bank financial market participants (Pritsker, 2001). The real sector refers to those sectors where goods and services are produced, transported, and sold and differs from the exchange of paper assets. The real sector is the foundation of a country's economy (Pirounakis, 1997). The banks in this context represent all those financial and non-financial firms that are either deposit-taking or are also in the market to provide loan financing. There are strong linkages between banks and the real sector, given that its consumer base represents participants in the real economy. Financial markets represent a marketplace where assets trade and, in essence, translate into the claims on the cashflows generated in the real economy. Non-bank financial market participants use general public funds and bank borrowing to participate in the financial markets (Pritsker, 2001).

2.4.1 Transmission of financial markets shocks to the real sector

Shocks to the real sector are transmitted in several ways. Firstly, through trade links and competitive devaluations, in the first instance, shocks in the local economy may impact that of another country, such that a trading partner may experience declining asset prices, leading to a decline in exports and weakening of its trade account. In the second instance where a country has experienced currency devaluation, this will reduce its export competitiveness (Corsetti *et al.*, 1999). Investor behaviour and actions can be why a shock spills over from one country to another, whether this behaviour is rational or not. This is because investors can take actions that lead to excessive co-movements (Dornbusch *et al.*, 2000b). Another reason is due to liquidity constraints and market incentives for investors. Global diversification involves cross-market hedging of macroeconomic risks such that where assets exhibit a high degree of co-movement with crisis-affected countries, there is likely to be transmission (Kaminsky & Reinhart, 1998). Financial links are also a way in which transmission may occur: a financial crisis in one country may affect another due to reduced trade credits and lower capital flows, including a reduction in foreign direct investment (Dornbusch *et al.*, 2000b).

2.4.2 Transmission pathways for real shocks

A real shock is a shock that affects the real sector of the economy—linked to several transmission channels through five different pathways, creating interlinkages. The first is through real linkages, which are goods and service trade. The second is via countries sharing a common lender, which occurs when a bank alters its lending position, favouring one country over another. Thirdly, through the financial markets, banks pull their deposits in different markets, causing run-on deposits. Fourthly, through financial institutions and the interaction of financial institutions and markets (Pritsker, 2001).

2.5 CRISIS-CONTINGENT THEORIES

This study is centred around the COVID-19 pandemic, so crisis-contingent theories are a significant literature review element. Crisis-contingent theories explain why there is a change in transmission mechanisms during a crisis. In addition, why can an increase in cross-market linkages be observed following a shock? These theories can be divided into three types: (1) multiple equilibria, (2) endogenous liquidity, and (3) political economy (Forbes & Rigobon, 2001). This is essential in this study given that the COVID-19 pandemic is a shock event that has displayed bear the vulnerabilities in the financial market (Corbet *et al.,* 2020b), requiring us to relook at our views on contagion across various assets and the financial markets (Goodell, 2020).

2.5.1 Multiple equilibria

Masson (1998) argued that true contagion exists where a model can exhibit multiple equilibria. Using a simple two-country balance of payments model to illustrate the multiple equilibria theory indicates that an investor's expectation may shift due to a crisis in one country, leading to a negative equilibrium in another. In addition, this study outlined several reasons for contagion across three categories: monsoonal effects, the second being spillovers, and lastly, a crisis in one country triggered by factors unrelated to the macroeconomic environment leading to changes in market sentiment. Forbes and Rigobon (2001) argue that when one market's prices shift on another, and a shock is transmitted because investors' expectations change, this qualifies as a crisis-contingent theory. Dornbusch *et al.,* (2000a) attribute these shifts in investor behaviour primarily to information asymmetries and differing views on an investor's expectation. A lack of information may cause an investor to believe that where a crisis is noted in one country, the likelihood of another country being affected may be as high. These expectations may be driven by both rational and irrational behaviour. In a later study, Luo and Tang (2007) highlight that capital controls have a dual nature on multiple equilibria; this is particularly important because, on the one hand, an open capital account increases economic development, leading to improved investments and capital inflows, but on the other hand it intensifies the probability of a crisis occurring in years to come.

2.5.2 Endogenous liquidity

A second crisis contingent theory is that of endogenous liquidity. This theory was demonstrated by Valdés (1996), who showed that when one country is experiencing a crisis, it is likely to cause a reduction in the liquidity of the participants in the market. To deal with the crisis, investors are likely to sell off assets in other markets to protect their interests in the crisis country and continue operating or meeting requirements stipulated by the regulatory environment. Depending on the magnitude of the liquidity shock, investors may have no option but to dispose of significant holdings of assets in other countries.

Calvo and Carmen (1996) developed a model that distinguishes between investors who are informed and those who are not. In both cases of investors, where a liquidity shock occurred, this increased the correlation of asset prices. Dornbusch *et al.*, (2000a) further indicate that individual agents' incentive structure may also drive a selloff in many markets. Where investors are incentivised to maintain a proportion of holdings in a country, they are likely to sell off to maintain the correct balance in their portfolios.

2.5.3 Political economy

Drazen (1998), in a study of currency devaluations, indicated that countries would want to maintain a fixed exchange rate with other countries. If this event does not occur, the presidents of these countries would be under political pressure to maintain the currency relationship. Where a country opts to abandon its peg, this would reduce political costs and thus increase the opportunity for a change in exchange rate. Financial crises often lead to a recession affecting investment in that country, leading to lower income and higher unemployment. To avoid further deterioration, governments would intervene to prevent further worsening of the economic condition. However, this intervention could expose the government to additional liabilities (O'Keeffe & Terzi, 2015). Secondly, distributional conflicts may arise, given that a crisis benefits certain economic groups, leading to incentives to deviate from the economically efficient solution (Walter, 2013).

2.6 NON-CRISIS CONTINGENT THEORIES

The other contagion theories relate to non-crisis contingent theories. These theories indicate that the transmission mechanisms following a shock are similar to those before the shock occurred, and as such, there is a continuation. The transmission mechanisms relate to linkages that can be termed real. These theories can be grouped into four channels: (1) trade, (2) policy coordination, (3) country re-evaluation, and (4) random aggregate shocks. Trade transmission can occur when a country's currency experiences a loss in value; this could lead to an increase in exports to another country and thus erode the sale of goods in that country's local economy. An increased loss in competitiveness of a country of a severe magnitude may lead to currency devaluation. Policy coordination occurs when one country's policy response to a shock may cause other countries to react similarly. Country re-evaluation involves the application of lessons learned, such that investors apply the lessons learned from a previous shock to other countries that share similar market mechanics to where the initial shock occurred. A pertinent example of this is where a country with a weak banking system may be at risk of a currency crisis, and investors could use this experience to evaluate the strength of the banking system in other countries. Lastly, random aggregate shocks indicate that global shocks could affect the fundamentals of many economies at the same time (Forbes & Rigobon, 2001).

2.7 PROPERTIES OF CRYPTOCURRENCIES DURING COVID-19

During COVID-19, several researchers tested properties related to cryptocurrencies and stock markets, including associated psychological biases. These properties, amongst others, include safe haven, hedge, diversification, and herding behaviour.

2.7.1 Safe haven

In studying Bitcoin and the S&P500 from March 2019 to March 2020, Conlon and McGee (2020) held that cryptocurrencies were not safe havens during periods of high volatility. Furthermore, the inclusion of Bitcoin would increase an investor's downside risk. Mariana *et al.* (2021), using dynamic conditional correlation (DCC) and corrected dynamic conditional correlation (cDCC) results, argue that Bitcoin and Ethereum act as safe havens for the S&P500, given that their results are negatively correlated. In this study, Ethereum fared better than Bitcoin as a safe haven. Using spillover frequency connectedness, which was first introduced by Barunik and Krehlik (2016) and later extended by Barunik and Krehlik (2018), Nyakurukwa and Seetharam (2023) over a period spanning 11 August 2015 to 28 August 2020, found that in the African context, haven properties of cryptocurrencies were present given that the results showed weak interconnectedness across markets.

2.7.2 Hedge

Conlon and McGee (2020) and Corbet *et al.* (2020b) contend that Bitcoin is an imperfect hedge during the pandemic. Contrary to this view is that of Corbet *et al.* (2020a), which indicates that prominent cryptocurrencies were a store of value during market stress. Given a weak correlation, Nkrumah-Boadu *et al.* (2022) revealed hedge benefits at specific times and frequency-domains for the cryptocurrencies and the Ghanaian stock market.

2.7.3 Diversification

Caferra and Vidal-Tomas (2021) argue that cryptocurrencies should be seen as perfect instruments for diversification given that they are not linked to the real economy and thus share fundamentals different from those of stock markets. An earlier study by Bourie *et al*. (2017c) found that Bitcoin was suitable for diversification purposes. In a study, Corbet *et al.* (2020a) found evidence that diversification benefits existed for cryptocurrencies.

2.7.4 Herding biases

In investigating herding biases by applying a multifractal analysis before and after the COVID-19 pandemic, Mnif *et al.* (2020) found that the pandemic positively impacted the efficiency of the cryptocurrency market. However, the study revealed evidence of herding behaviour when testing against the five largest cryptocurrency markets.

Many studies have explored the properties of cryptocurrencies during the crisis, but more research on the African perspective needs to be done. This study contributes to the literature by examining how African stock markets and cryptocurrencies behave during the COVID-19 pandemic, specifically regarding safe haven characteristics, hedging potential, diversification benefits, and herding behaviour.

2.8 MODELS AND TECHNIQUES IN THE GLOBAL CONTEXT

Techniques in the global sense vary across several studies, moving from the standard GARCH methodology of Bollerslev (1986) as employed by Corbet *et al*. (2020a) to variations such as the exponential generalised autoregressive conditional heteroscedasticity (EGARCH), DCC, VaR and CFVaR employed by Ampountolas (2023) to more complex techniques. Wavelet coherence and Markov Switching autoregressive model were employed by Caferra and Vidal-Tomás (2021), using continuous wavelet transform to analyse both time and frequency. This study showed that there is variation in price dynamics during the pandemic depending on the type of market. Baker *et al.* (2020) employed a varying text-based method technique, which entailed a two-step process. The first step included calculating the fraction of articles in eleven major US newspapers that contained specific terms relating to the economy, equity markets, and volatility. The results were then used to develop a newspaper-based Equity Market Volatility tracker alongside the Volatility Index (VIX). The second step entailed developing a Disease Equity Market Volatility tracker by identifying articles that contained terms related to the COVID-19 pandemic or other related infectious outbreaks. Mariana *et al*. (2021) applied the DCC-GARCH methodology to examine the dynamic correlation of cryptocurrency, gold, and S&P500 over an observation period from 01 July 2019 to April 2020. Bhattacharya *et al.* (2022) used the Diebold and Yilmaz (2012) volatility index, examining Bitcoin, Ethereum, Binance Coin, Cardano, Tether, and Ripple with the CBOE volatility index. The Diebold and Yilmaz technique was first born in 2009 through obtaining variance decompositions using a VAR approximating model with features of Cholesky factor identification. This embryonic idea was not aware of network theory, big data, and graphics. Diebold and Yilmaz (2012) made a shift to overcome these challenges and, as such, moved to generalised identification, which overcomes the issue of variable ordering. This approach also allowed for the consideration of total connectedness, including aspects of direction. The shortcomings of the 2012 model are that, like the 2009 model, it considers only small data.

2.9 MODELS AND TECHNIQUES IN THE AFRICAN CONTEXT

Using wavelet analysis, Nkrumah-Boadu *et al.* (2022) studied the safe haven, hedge, and diversification properties of cryptocurrencies for African stock markets. This study examined three cryptocurrencies, Ripple, Dogecoin, Bitcoin, gold, and five African stock markets. The main findings of this study indicate that gold and cryptocurrencies provide safe haven, diversification, and hedging benefits for investors who hold stock in African stock markets. This study is also of particular importance as it was able to indicate the diverse nature of participants' investment horizons. Nyakurukwa and Seetharam (2023) studied market integration of seven MSCI-classified African stock markets and Bitcoin using an information-theoretic framework that quantifies information flow across exchanges. This study observed a statistically insignificant information flow across stock markets, noting that South Africa was the only stock market with the most influence. While overall, African stock markets were not strongly integrated with Bitcoin. Kumah *et al.* (2021) adopted a Barunik and Krehlik (2018) frequency-domain spillover index technique, which explores the time-varying pair-wise connections among African stock markets, commodity indices, and cryptocurrencies. The findings depicted non-contagion risk, displaying that cryptocurrencies are safe havens for African stocks in the medium term.

2.10 CONCLUSION

In summary, Chapter 2 reviewed the literature on co-movement and contagion of cryptocurrencies and stock markets. The study reviewed literature in the global context and the African context. Although several studies have been conducted globally, they have not placed emphasis and attention on African Markets. This study explored the definition of contagion and channels for transmission, including the linkages across channels. The literature further explores contagion-related theories categorised across crisis-contingent and non-crisis-contingent theories, which remain relevant. The study further outlines the cryptocurrency and stock market properties tested during the COVID-19 stress event. Once again, only some studies are limited in the African context. Lastly, this study reviews the empirical models and techniques employed in the global and African contexts. This study contributes to the literature on how African stock markets and cryptocurrencies behaved during the COVID-19 pandemic by analysing the dynamics and volatility spillover effects, including what properties are present during this unique period, such as safe haven characteristics, hedging potential, diversification benefits, and herding behaviour.

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Chapter 3 Data and Research methodology

3.1 OVERVIEW

The approach taken in this study is quantitative, following two modelling techniques, the first being a time-domain approach employed by Diebold and Yilmaz (2009; 2012), which focuses on measuring connectedness, including price volatility, using a spillover index that follows a variance decomposition approach of a Vector Autoregressive (VAR) model. Although Diebold and Yilmaz (2009) focussed on global equities in the earlier studies, this study focuses on African stock markets and cryptocurrencies in the COVID-19 context. The approach is deemed appropriate given that Diebold and Yilmaz's measurement approach allows for both non-crisis and crisis episodes. Bhattacharya *et al*. (2022) supported this technique, mainly where cryptocurrencies are involved.

The second technique used is the frequency-domain approach by Barunik and Krehlik (2018). The technique extends the work of Diebold and Yilmaz (2009; 2012), allowing for the estimation of connectedness to variables because of heterogeneous frequency responses to shocks. This framework allows connectedness to be measured across various frequencies: short, medium, and long-term. This study examines the spillover effects between cryptocurrencies and stock markets by applying both techniques, including establishing direction and magnitude over several periods.

3.2 DATA DESCRIPTION

This study employs secondary data extracted from the EquityRT[4] platform for stock market data and CoinMarketCap[5] for cryptocurrency information. The dataset consists of data on the five largest cryptocurrencies based on market capitalisation: Bitcoin (BTC), Ethereum (ETC), Tether (USDT), Binance Coin (BNB), and XRP markets (XRP), in line with Bhattacharya *et al*. (2022) and the five largest African stock markets based on market capitalisation: Johannesburg Stock Exchange (JSE), Nigeria Exchange Group (NGX), Casablanca Stock

[4] Refer to https://0-www-equityrt-com.innopac.wits.ac.za/ (Accessed 02 September 2023)
[5] Refer to https://coinmarketcap.com/ (Accessed 02 September 2023)

Exchange (CSE), The Egyptian Exchange (EGX), and Nairobi Securities Exchange (NSE). Market capitalisation fluctuates from time to time. The data is extracted in USD to avoid exchange rate noise. These stock markets were selected because they account for approximately 73% of Africa's overall market capitalisation[6].

On 11 March 2020, 118,000 COVID-19 cases were reported in 114 countries, with 4,291 people having lost their lives. At this point, the World Health Organisation (WHO) declared COVID-19 a global pandemic based on its assessment of the virus's threat.[7] The study period spans 26 July 2017 to 05 May 2023 and is based on Monday-to-Friday returns, given that stocks do not trade on weekends, in line with Kumah *et al*. (2021) and Das and Kannadhasan (2018). The study analyses two distinct periods, being a pre-COVID period spanning 26 July 2017 to 10 March 2020, the start date guided by the availability of data as XRP data is only available at that date, and the end date guided by the declaration of COVID-19 as a global pandemic. The COVID period for this study spans 11 March 2020 to 05 May 2023. 05 March is the declaration of the end of the pandemic by the WHO[8].

The data selected allows the study to test events of both a bull and bear nature, given that it extends before and after the declaration date when COVID-19 was fully recognised as a global pandemic.

The study will be based on daily log returns with

$$r_t = logP_t / log_{t-1} \tag{1}$$

Where r_t refers to the log return

$logP_t$ refers to the current value

$logP_{t-1}$ the value in the previous period

[6] Refer to https://nairametrics.com/2023/12/09/top-10-largest-stock-markets-in-africa-based-on-market-capitalization/ (Accessed 14 March 2024)
[7] Refer to https://www.who.int/director-general/speeches/detail/who-director-general-s-opening-remarks-at-the-media-briefing-on-covid-19---11-march-2020 (Accessed 02 July 2023).
[8]Refer to https://www.who.int/europe/emergencies/situations/covid-19 (Accessed 21 October 2023)

3.3 TIME-DOMAIN TECHNIQUE

3.3.1 The basic spillover index

The study employs the spillover index to measure return and volatility spillovers, first introduced by Diebold and Yilmaz (2009), which is premised on Vector autoregressive (VAR) models that date back to Engle *et al*. (1990).

The spillover index focuses on variance decompositions, which allow for the aggregation of spillover effects across markets and compiles various data into a single measure.

The basic spillover index follows from variance decomposition with N-Variable VAR. For every asset i, the share of the forecast error variance received from the shock of asset j is added, in this case where $j \neq i$ then $i = 1, \ldots, N$

By deriving the simple first order two variable spillover index, it can be expressed as a percentage:

$$S = \frac{a_{0,12}^2 + a_{0,21}^2}{trace\left(A_0 A_0'\right)} * 100 \tag{2}$$

The simple spillover index can be further generalised to a more dynamic environment using a 1-step ahead forecast, in this case, a p^{th}-order for N-variable VAR.

$$S = \frac{\sum_{\substack{i,j=1 \\ i \neq j}}^{N} a_{0,ij}^2}{trace\left(A_0 A_0'\right)} \cdot 100 \tag{3}$$

Using H step ahead forecasts, the fully general case of p^{th}-order for N-variable VAR

$$S = \frac{\sum_{h=0}^{N} \quad \sum_{\substack{i,j=1 \\ i \neq j}}^{N} a_{0,ij}^2}{trace\left(A_0 A_0'\right)} \cdot 100 \tag{4}$$

3.3.2 Modelling connectedness

This study extends on the earlier work of Diebold and Yilmaz (2009). It applies the spillover index technique of Diebold and Yilmaz (2012) to measure the magnitude and direction of return spillover, including the system connectedness. This technique is premised on the generalised decomposition framework in a vector autoregressive environment (GVAR), which was developed by Koop *et al*. (1996) and Pesaran and Shin (1998).

The analysis is started by estimating the fraction of the H-step ahead forecast error variance for market i due to the shocks stemming from market j, where $i \neq j$.

In this study, there are two market blocks: cryptocurrency (c) and stocks (s)

In doing this, consider a covariance stationary p^{th}-order VAR(p) model

$$x_t = \sum_{i=1}^{p} \Theta_i x_{t-1} + \varepsilon_t \tag{5}$$

Where $x_t = (x_{ct}, x_{st})$ is a column vector of returns with non-orthogonal shocks.

Θ_i is an n x n parameter matrix

ε_t is an n x 1 vector of the error term

As a result of covariance stationary, the moving average (MA) representation of the VAR process is:

$$x_t = \mathrm{B(L)}\varepsilon_t, \varepsilon_t \sim (0, \sum) \tag{6}$$

Where $B(L) = B_0 + B_1 L + B_2 L^2 + \ldots + B_p L^p$ and $E(\varepsilon_t \varepsilon_t') = \sum$

B_0 is an n x n identity matrix with $B_i = 0$ for $i = 0$

Using H step ahead forecasts, the GVAR matrix contribution of market j to i is given by the following forecast-error variance:

$$\Theta_{ij}^{gH} = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e_i' B_h \sum e_j)^2}{\sum_{h=0}^{H-1} (e_i' B_h \sum B_h' e_i)} \tag{7}$$

Where e_j is a selection vector containing ones at the j^{th} element; otherwise, zero

B_h is the coefficient matric multiplying the h-lagged shock

$\sum$ is the covariance matrix of the shock

σ_{jj} is the j^{th} diagonal element of $\sum$

3.3.3 Total spillovers

Using the outputs from Koop *et al*. (1996) and Pesaran and Shin (1998), the KPPS variance decomposition, the total volatility may be constructed as follows:

$$S^g(\mathrm{H}) = \frac{\sum_{\substack{i,j=1 \\ j\neq i}}^{N} \Theta_{ij}^{g}(H)}{\sum_{i,j=1}^{N} \Theta_{ij}^{g}(H)} \cdot 100 = \frac{\sum_{\substack{i,j=1 \\ j\neq i}}^{N} \Theta_{ij}^{g}(H)}{N} \cdot 100 \qquad (8)$$

3.3.4 The direction of spillover

After establishing the spillover effect using the spillover index, it is imperative to establish the direction of spillover. The direction of spillover is to be calculated using a generalised variance decomposition matrix introduced by Diebold and Yilmaz (2012).

The directional volatility spillovers received from market i to market j are to be measured as

$$S_{i\cdot}^g(\mathrm{H}) = \frac{\sum_{\substack{j=1 \\ j\neq i}}^{N} \Theta_{ij}^{g}(H)}{\sum_{i,j=1}^{N} \Theta_{ij}^{g}(H)} \cdot 100 = \frac{\sum_{\substack{j=1 \\ j\neq i}}^{N} \Theta_{ij}^{g}(H)}{N} \cdot 100 \qquad (9)$$

With those spillovers that are transmitted from i to market j as:

$$S_{\cdot i}^g(\mathrm{H}) = \frac{\sum_{\substack{j=1 \\ j\neq i}}^{N} \Theta_{ji}^{g}(H)}{\sum_{i,j=1}^{N} \Theta_{ji}^{g}(H)} \cdot 100 = \frac{\sum_{\substack{j=1 \\ j\neq i}}^{N} \Theta_{ji}^{g}(H)}{N} \cdot 100 \qquad (10)$$

3.3.5 Net spillovers

In some instances, the stock markets may be net recipients or net transmitters, so it may be essential to calculate the net total spillover. The net spillover in this instance, which is the difference between gross volatility shocks transmitted and received, can be obtained as follows:

$$S_i^g(\mathrm{H}) = S_{\cdot i}^g - S_{i\cdot}^g \qquad (11)$$

3.3.6 Net pair-wise spillovers

Lastly, in line with Diebold and Yilmaz (2012), the net pair-wise spillover provides detail on how much can be attributable from one market to another and is defined as follows:

$$S_{ij}^{g}(\mathrm{H}) = \left(\frac{\Theta_{ji}^{g}(H)}{\sum_{i,k=1}^{N} \Theta_{ik}^{g}(H)} - \frac{\Theta_{ij}^{g}(H)}{\sum_{j,k=1}^{N} \Theta_{jk}^{g}(H)} \right) \cdot 100 = \frac{\Theta_{ji}^{g}(H) - \Theta_{ij}^{g}(H)}{N} \cdot 100 \qquad (12)$$

3.4 FREQUENCY-DOMAIN TECHNIQUE

The frequency-domain technique was first introduced by Barunik and Krehlik (2016) following the extensive work of Diebold and Yilmaz (2012), with this being further extended by Barunik and Krehlik (2018). The frequency-domain spillover index is premised on Dew-Becker and Giglio's (2016) spectral representation of variance decomposition. As such, the decomposition of the variance allows us to assess and quantify the extent of future uncertainty of one variable and its association with shocks in another variable. The system's relationship can be further explained by examining frequency dynamics across short-, medium- and long-term periods (Barunik & Krehlik, 2018).

The generalised impulse response function using the spectral behaviour of series X_t can be decomposed below following Barunik and Krehlik (2016):

$$S_x(w) = \sum_{h=0}^{\infty} E(X_t X_{t-H}) e^{-ihw} = \psi(e^{ihw}) \qquad (13)$$

Where w refers to the frequency, ∞ infinite horizon connectedness, and frequency response function $\psi(e^{-ihw})= \sum_{h=0}^{\infty} \psi(e^{-ihw})$ of Fourier convertible coefficients ψ_h with $i = \sqrt{-1}$

For frequency w, the unconditional generalised forecast error variance decomposition (GFVED) may be calculated as:

$$(\Theta(w))_{i,j} = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{\infty} (\psi(e^{-ihw})\Sigma)_{i,j}^{2}}{\sum_{h=1}^{\infty} (\psi(e^{-ihw}) \Sigma \psi(e^{ihw}))_{i,j}} \qquad (14)$$

Which could be further standardised to:

$$(\Theta(w))_{i,j} = \frac{(\Theta(w))_{i,j}}{\sum_{j=1}^{k}(\Theta(w))_{i,j}} \tag{15}$$

Barunik and Krehlik (2018) contend that frequency bands are more fitting when assessing short-, medium- or long-term connectedness. This allows us to understand better how some economic scenarios will likely play out. These bands can be expressed as $d = (a,); a, b\epsilon(-\pi, \pi), a < b)$. d may be expressed as:

$$(\Theta_d)_{i,j} = \int_a^b (\Theta(w))_{i,j} dw. \tag{16}$$

Given the band d, overall connectedness may be specified in (17) as:

$$C^d = \frac{\sum_{i=1,i\neq j}^{k}(\Theta_d)_{i,j}}{\sum_{i,j}(\Theta_d)_{i,j}} = 1 - \frac{\sum_{i=1}^{k}(\Theta_d)_{i,j}}{\sum_{i,j}(\Theta_d)_{i,j}} \tag{17}$$

With the "*within*" connectedness used to measure connectedness within each band using the *within from* connectedness specified as:

$$C_{i\leftarrow}^d = \sum_{i=1,i\neq j}^{k}(\Theta_d)_{i,j} \tag{18}$$

This is representative of the contribution of a market $i \neq j$ to a different market i. Similarly, the *within to* measure may be specified using:

$$C_{i\rightarrow}^d = \sum_{i=1,i\neq j}^{k}(\Theta_d)_{i,j} \tag{19}$$

The above is fundamental in generating the resultant spillovers across the various frequencies.

3.5 DATA LIMITATIONS

Stock markets do not typically trade over weekends, whereas cryptocurrencies trade more frequently, and as such, this needs to be accounted for. As with Kumah *et al*. (2021), Monday-to-Friday week frequency is employed to control for this.

Given the variation in stock market trading activities, the dataset will likely contain missing variables because of public holidays and non-trading days in various markets. Missing variables have been replaced with the previous day's closing value to account for this data discrepancy. Time bias may likely occur because the study focuses on the COVID-19 pandemic. Time bias occurs when results relate to a specific period with a single phenomenon, such as a bear or bull business cycle. To mitigate this, this study has separated the data into a pre-COVID and COVID period.

3.6 CONCLUSION

This study was premised broadly on replicating those techniques employed by Diebold and Yilmaz (2009; 2012). Its basis was first premised on measuring total connectedness, followed by establishing the direction of spillover, the net spillover and lastly the net pair-wise spillover. Further, this study extends its analysis to incorporate the seminal works of Barunik and Krehlik (2016; 2018), allowing for these spillovers to be analysed across various frequencies. This allows for deeper insights into how the various economic scenarios play out.

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Chapter 4 Empirical results and discussion

4.1 OVERVIEW

Chapter 4 outlines the study's empirical results, including an in-depth discussion. This study is centred on the time-domain model by Diebold and Yilmaz (2009; 2012) and the frequency-domain model by Barunik and Krehlik (2018). This study is concerned with those aspects of contagion that relate to transmission through financial markets, given that financial markets are a transmission pathway for real shocks. Real shocks are those shocks that affect the real sector (Pritsker, 2001). Understanding these shocks is of utmost importance, given that the real sector is the foundation of a country's economy (Pirounakis,1997).

To analyse the time-domain, a 10-variable VAR model is fitted to each series with a one (1) lag length, as guided by the Schwarz Criterion being the smallest at this lag length. Following this, a directional connectedness spillover index is constructed, pair-wise net directional spillover connectedness, and a rolling window spillover index as per the formula in Chapter 3. For the frequency-domain analysis, four frequency bands are selected: across the short, medium, and long term. In the economic sense, the spillover index provides colour to the system as the more significant the spillover index value, irrespective of this being positive or negative, the relationship within the system (i.e., cryptocurrencies and stock markets) is deemed to be strong. The sign indicates behaviour, such that it may explain which asset class is a net transmitter or net receiver.

4.2 DESCRIPTIVE STATISTICS

Figure A.1 and Figure A.2 in the appendices depict raw daily prices. This depiction shows that the data exhibits a random walk and is non-stationary. Figure A.3 and Figure A.4 represent the log returns. From these returns, a volatility clustering element is observed in the data. Volatility clustering is a phenomenon where small changes in asset prices follow small changes, and conversely, large changes follow large changes. Mandelbrot (1963) first noted this concept. Typical models used to solve this have been Engle's (1986) autoregressive conditional heteroscedasticity (ARCH) and Bollerslev's (1986) generalised autoregressive conditional heteroscedasticity (GARCH). However, in more modern times, models have moved to the time-domain (Diebold & Yilmaz, 2009; 2012) and the frequency-domain (Baranik & Krehlik, 2018). These models allow for studying crisis and non-crisis episodes, including catering for the trend element and bursts in spillovers (Diebold & Yilmaz, 2009).

Table 4.1 and Table 4.2 present the summary statistics for the five cryptocurrencies and stock markets studied. The pre-COVID period spans 685 observations, while the COVID period spans 823. Average daily log returns vary from -0.02% to 0.07% (pre-COVID) and -0.03% to 0.12% in the COVID period. These returns are comparable across both periods. Pre-COVID and during the COVID period, all cryptocurrencies had positive returns. However, the stock markets, on the other hand, had negative returns, namely JSE, NGX, and CSE pre-COVID and CSE, EGX, and NSE in the COVID period.

In terms of standard deviation, BNB and XRP had higher standard deviations in both periods, with USDT remaining relatively stable across the periods. The higher standard deviations suggest that BNB and XRP are more volatile than the other cryptocurrencies included in this study. JSE and CSE were the riskiest stock markets in both periods, displaying higher standard deviations.

The pre-COVID data is further observed to be 50:50 positive and negatively skewed. In contrast, the COVID data is more skewed, given that eight of the ten series are skewed negatively. Both periods display negative skewness in BTC, ETC, JSE, and EGX. Except for CSE, the kurtosis values in the tables below indicate values above 3, indicative of high peaks and leptokurtic and non-normal distributions. Non-normality is further confirmed by the results of the Shapiro-Wilk test; as such, the null hypothesis of normality is rejected. This evidence supports the use of asymmetric distributions.

This study performed unit rooting testing on each series using two tests, namely the Augmented Dickey-Fuller test (ADF) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS). The results in Table B.1 in the appendices indicate that all series are stationary at the 1% and 5% level of significance.

Table 4.1: Summary statistics of log returns (pre-COVID)

Pre-COVID	BTC	ETH	USDT	BNB	XRP	JSE	NGX	CSE	EGX	NSE
Obs.	685	685	685	685	685	685	685	685	685	685
Min	-0.1037	-0.1185	-0.0209	-0.3563	-0.1529	-0.0442	-0.0218	-0.0249	-0.0467	-0.0239
Max	0.0978	0.1075	0.0246	0.5185	0.2636	0.0233	0.0204	0.0264	0.0134	0.0131
Range	0.2015	0.2259	0.0455	0.8749	0.4164	0.0675	0.0422	0.0513	0.0601	0.037
Sum	0.4871	-0.0127	0.0008	2.2025	0.0761	-0.1305	-0.1651	-0.0379	-0.0321	-0.0197
Median	0.0006	-0.0003	0.0000	0.0006	-0.0016	0.0000	-0.0003	0.0000	0.0000	0.0000
Mean	0.0007	0.0000	0.0000	0.0032	0.0001	-0.0002	-0.0002	-0.0001	0.0000	0.0000
SE.mean	0.0008	0.0010	0.0001	0.0017	0.0012	0.0002	0.0002	0.0002	0.0002	0.0001
CI.mean.0.95	0.0016	0.0020	0.0002	0.0033	0.0024	0.0005	0.0003	0.0005	0.0004	0.0003
Var	0.0005	0.0007	0.0000	0.0019	0.0010	0.0000	0.0000	0.0000	0.0000	0.0000
std.dev	0.0213	0.0262	0.0026	0.0434	0.0315	0.0064	0.0039	0.0062	0.005	0.0039
coef.var	30.003	-1414.33	2177.176	13.512	283.539	-33.360	-16.352	-112.888	-105.938	-136.204
Skewness	-0.0157	-0.298	0.631	2.192	1.679	-0.769	0.320	0.182	-2.148	-0.507
skew.2SE	-0.0842	-1.5955	3.3816	11.7373	8.9933	-4.1215	1.7182	0.978	-11.5018	-2.7164
Kurtosis	3.4828	3.0412	20.2796	37.4323	13.2741	4.1277	4.4842	1.6703	14.842	4.3678
kurt.2SE	9.337	8.1532	54.368	100.353	35.5869	11.0661	12.0217	4.4779	39.7902	11.7098
normtest.W	0.9397	0.9438	0.8103	0.7442	0.8421	0.9619	0.9326	0.9393	0.8512	0.9401

Table 4.2: Summary statics of log returns (COVID)

COVID	BTC	ETH	USDT	BNB	XRP	JSE	NGX	CSE	EGX	NSE
Obs.	823	823	823	823	823	823	823	823	823	823
Min	-0.2018	-0.2392	-0.0228	-0.2359	-0.2391	-0.0539	-0.0851	-0.0426	-0.0719	-0.0244
Max	0.0832	0.1536	0.0232	0.2298	0.2722	0.0337	0.0878	0.0245	0.0376	0.0197
Range	0.2850	0.3928	0.0460	0.4657	0.5113	0.0876	0.1729	0.0671	0.1096	0.0441
Sum	0.5722	0.9973	-0.0003	1.2872	0.3432	0.1364	0.1558	-0.0665	-0.1057	-0.2816
Median	0.0006	0.0013	0.0000	0.0011	0.0006	0.0000	0.0000	0.0000	0.0000	-0.0001
Mean	0.0007	0.0012	0.0000	0.0016	0.0004	0.0002	0.0002	-0.0001	-0.0001	-0.0003
SE.mean	0.0007	0.0009	0.0001	0.0009	0.0011	0.0003	0.0002	0.0003	0.0002	0.0002
CI.mean.0.95	0.0013	0.0018	0.0001	0.0019	0.0021	0.0006	0.0004	0.0005	0.0005	0.0003
Var	0.0004	0.0007	0.0000	0.0007	0.001	0.0001	0.0000	0.0001	0.0000	0.0000
std.dev	0.0197	0.0261	0.0015	0.0272	0.0311	0.0081	0.0062	0.0079	0.007	0.0047
coef.var	28.363	21.575	-4070.973	17.393	74.479	48.602	32.855	-98.080	-54.840	-13.717
Skewness	-1.536	-1.059	0.574	-0.345	0.275	-0.675	-1.455	-0.226	-2.565	-0.251
skew.2SE	-9.0108	-6.216	3.3689	-2.0251	1.6151	-3.9613	-8.5405	-1.3302	-15.0485	-1.4729
Kurtosis	15.7835	12.4573	140.0117	16.795	16.0044	5.5901	107.9001	1.6726	26.0987	3.0503
kurt.2SE	46.3532	36.5849	411.1882	49.3238	47.0021	16.4171	316.8826	4.912	76.647	8.9581
normtest.W	0.8859	0.8942	0.3166	0.8441	0.8295	0.9395	0.4873	0.9353	0.7576	0.956

4.3 TIME-DOMAIN ANALYSIS

The directional spillover index in Table 4.3 and Table 4.4 display the system's total and net connectedness in pre-COVID and COVID-19 periods. The "FROM" indicates where the spillover originated, and the "TO" represents where the spillover was received. The results are reported as average percentages. The results indicate that the COVID-19 sub-sample period contributes most to connectedness at 31.79% relative to the pre-COVID period at 23.67%. The results above concur with Conlon and McGee (2020) and Corbet *et al.* (2020b) that cryptocurrencies increase overall portfolio risk during COVID-19. The risk increase is evidenced by system connectedness increasing from 23.67% to 31.79%.

The highest contributor to connectedness in both periods is BTC and ETH, with USDT being the lowest. However, USDT connectedness increased almost 4.68 (263.8%) times in the COVID period, with BNB increasing 39.5%. In line with Ji *et al*. (2018), this finding implies that shocks arising from these cryptocurrencies will likely affect the system most. The results of this study support Ji *et al*.(2018) assertion about BTC but contradict them when we consider ETC.

The net spillover indicates which cryptocurrency contributes to or receives from the total connectedness. The net spillover is calculated as the difference between the TO and FROM measures. BTC and ETH are net transmitters under both periods, with USDT and XRP net receivers, with ETH being the largest transmitter. BNB is ambiguous as it is a net receiver under the pre-COVID period but a net transmitter in the COVID period.

In assessing pair-wise directional spillover connectedness, the results indicate how much can be attributable from one cryptocurrency market to the stock market. A positive value indicates that the cryptocurrency is a net transmitter, while a negative value suggests that the cryptocurrency is a net receiver. From Table 4.5, the results suggest that BTC and ETH are net recipients across all stock market pairs in both periods (BTC-JSE, BTC-NGX, BTC-CSE, BTC-EGX, BTC-NSE, ETH-JSE, ETH-NGX, ETH-CSE, ETH-EGX, ETH-NSE). USDT is a net receiver except with JSE (pre-COVID) and NSE (COVID). BNB and XRP are net receivers in the COVID period but transmitters in the pre-COVID period to BNB-EGX and (XRP-NGX, XRP-CSE). The spillover effects of both periods are mainly negative, with the cryptocurrencies being recipients rather than transmitters. These results indicate that information flow mostly comes from the stock markets rather than cryptocurrencies. These results align with Bourie *et* *al*. (2018a) and Iqbal *et al*. (2021), who found that cryptocurrencies are not completely detached from other assets, with their returns, volatility, and spillovers likely to be related. The evidence from these studies shows that cryptocurrencies were more likely to receive a shock than transmit it to other assets. This evidence is essential and supports the assertion that cryptocurrencies provide diversification and hedging benefits for African stock markets (Kumah *et al.*, 2021). These findings contradict those of Nyakurukwa and Seetharam (2023), who state that there is a significant flow of information from Bitcoin to equities during a crisis.

The pair-wise relationships, however, are not significant, given that they range from -0.15 to 0.00. Considering the results from Table 4.3, Table 4.4, and Table 4.5, one sees the drawback of the time-domain technique. This technique aggregates total connectedness, giving the impression that there is more vital connectedness when, in fact, connectedness varies depending on the frequency.

Table 4.3: Time-domain directional spillover index results (pre-COVID)

Pre-COVID	**BTC**	**ETH**	**USDT**	**BNB**	**XRP**	**JSE**	**NGX**	**CSE**	**EGX**	**NSE**	**FROM**
BTC	48.40	24.09	0.49	14.82	11.63	0.10	0.08	0.07	0.23	0.10	5.16
ETH	22.54	45.21	0.39	12.56	18.44	0.40	0.03	0.01	0.37	0.04	5.48
USDT	1.43	1.17	94.18	0.47	2.05	0.13	0.24	0.09	0.14	0.09	0.58
BNB	17.59	15.93	0.30	57.49	7.05	0.44	0.05	0.28	0.24	0.62	4.25
XRP	13.35	22.47	0.06	6.95	55.50	0.54	0.12	0.15	0.43	0.43	4.45
JSE	0.60	0.87	0.04	0.93	1.52	90.69	0.58	1.27	2.38	1.10	0.93
NGX	0.20	0.77	0.25	0.18	0.04	2.36	92.73	0.48	1.26	1.73	0.73
CSE	0.15	0.18	0.39	0.36	0.12	1.17	0.29	95.58	0.76	1.01	0.44
EGX	0.28	0.38	0.50	0.18	0.63	4.76	0.48	0.65	90.96	1.17	0.90
NSE	0.22	0.35	0.10	0.62	0.56	1.86	0.97	1.00	1.82	92.52	0.75
TO	5.64	6.62	0.25	3.71	4.20	1.18	0.28	0.40	0.76	0.63	**23.67**
Net	0.48	1.14	-0.33	-0.54	-0.25	0.25	-0.44	-0.04	-0.14	-0.12	

Table 4.4:Time-Domain Directional spillover index results (COVID)

COVID	BTC	ETH	USDT	BNB	XRP	JSE	NGX	CSE	EGX	NSE	FROM
BTC	37.9	26.33	1.72	18.62	12.48	2.26	0.18	0.24	0.05	0.22	6.21
ETH	25.64	36.91	1.63	18.89	13.54	2.6	0.24	0.24	0.12	0.19	6.31
USDT	5.14	3.71	78.86	4.29	1.5	2.17	0.76	0.69	1.21	1.68	2.11
BNB	19.94	20.6	1.49	40.65	14.75	2.23	0.08	0.09	0.06	0.11	5.93
XRP	15.68	17.41	0.64	17.05	47.56	1.49	0	0.08	0.07	0.03	5.24
JSE	5.83	7.11	4.03	4.72	3.07	71.51	0.76	0.26	1.89	0.82	2.85
NGX	0.53	0.64	1.76	0.25	0.02	0.6	94.48	0.05	1.07	0.6	0.55
CSE	0.92	0.79	1.4	0.3	0.58	1.47	0.07	92.25	1.72	0.5	0.77
EGX	0.45	0.62	3.9	0.32	0.28	3.34	0.4	1.34	88.94	0.43	1.11
NSE	1.29	0.98	1.05	1.02	0.4	1.33	0.45	0.27	0.22	92.99	0.7
TO	7.54	7.82	1.76	6.55	4.66	1.75	0.29	0.33	0.64	0.46	**31.79**
Net	1.33	1.51	-0.35	0.61	-0.58	-1.10	-0.26	-0.45	-0.47	-0.24	

Table 4.5: Time-domain net pair-wise spillover results

	[1]	[2]		[1]	[2]
BTC-JSE	-0.0499	-0.3574	**BNB-JSE**	-0.0488	-0.2483
BTC-NGX	-0.0123	-0.0344	**BNB-NGX**	-0.0130	-0.0172
BTC-CSE	-0.0081	-0.0684	**BNB-CSE**	-0.0081	-0.0208
BTC-EGX	-0.0059	-0.0402	**BNB-EGX**	0.0058	-0.0261
BTC-NSE	-0.0121	-0.1066	**BNB-NSE**	-0.0003	-0.0913
ETH-JSE	-0.0466	-0.4508	**XRP-JSE**	-0.0981	-0.1583
ETH-NGX	-0.0739	-0.0403	**XRP-NGX**	0.0082	-0.0018
ETH-CSE	-0.0172	-0.0549	**XRP-CSE**	0.0030	-0.0504
ETH-EGX	-0.0004	-0.0499	**XRP-EGX**	-0.0200	-0.0214
ETH-NSE	-0.0308	-0.0791	**XRP-NSE**	-0.0124	-0.0369
USDT-JSE	0.0083	-0.1860			
USDT-NGX	-0.0005	-0.0992			
USDT-CSE	-0.0301	-0.0716			
USDT-EGX	-0.0360	-0.2695			
USDT-NSE	-0.0007	0.0624			

[1] Refers to pre-COVID, [2] Refers to COVID period

4.4 FREQUENCY-DOMAIN ANALYSIS

Barunik and Krehlik's (2018) technique measures the overall and net connectedness across different frequencies. This method relies on frequency reactions to innovations rather than impulse reactions. This method employs frequency bands, namely three frequencies, to determine the strength of connectedness across a range rather than one in the time-domain analysis. The rationale is that economic participants transact under various investment periods. The frequencies for this study are reflected in Table 4.6.

Table 4.6: Frequency-domain connectedness bands

Frequency	Band	Days
d_1	3.14-0.79	1-4 (short-term)
d_2	0.79-0.20	4-16 (short-term)
d_3	0.20-0.05	16-64 (medium-term)
d_4	0.05-0.00	64+ (long-term)

Table 4.7 and Table 4.8 display the total connectedness results of this study as computed using Barunik and Krehlik's (2018) modelling technique. The *to Absolute* (TO_ABS) is a quantification of skewness or Kurtosis spillovers from one market i to others, and the *from Absolute* (FROM_ABS) indicates from others to market i. The *within to* (TO_WTH) quantifies skewness or Kurtosis spillovers from one market i to others, including from its own innovations. In contrast, the *within from* (FROM_WTH) indicates from others to market i, including from its own innovations. The *within* (WTH) connectedness is of interest in these results, which use the power of the series based on the frequencies mentioned above. It can capture causality given that the *within* connectedness matches all ABS (absolute connectedness). In the pre-COVID period, the WTH increases as the forecast horizon increases; however, it decreases in the COVID period as the forecast horizon increases. This indicates that causality increases in the pre-COVID period but not in the COVID period. This is an interesting observation given that Corbet *et al.* (2020b) shunned cryptocurrencies as risky assets, and one would expect that the WTH would increase as the horizon increased. When assessing the absolute connectedness (ABS), this decreases with each forecast horizon and is less than WTH connectedness.

As displayed in Table 4.7 and Table 4.8, the ABS connectedness results indicate that connectedness increased during COVID-19. The increase in connectedness is observed across all frequencies, namely freq.1 to 24.77% (pre:17,74%), freq.2 to 5.16% (pre:4.35%), freq.3 to 1.49% (pre: 1.26%) and freq.4 to 0.37% (pre: 0.32%). Although we observed an increase across frequencies, these increases were not material, given that the significant change was mainly across freq.1 and 2, with a 7.03% and 0.81% rise, while freq.3 and freq.4 only recorded small movements of 0.23% and 0.05%, respectively.

From these results, we observe that across both periods, the most significant contributor to connectedness is observed in the short-term being frequency one, accounting for 17.74% and 24.77%, and frequency 2, 4.35%, and 5.16% in the pre-COVID and COVID periods, respectively, whilst the medium-term and long-term accounting for relatively more minor proportions. Thus, contagion is highest in the short term given connectedness results, thus leading to lower diversification across the short term; however, diversification benefits are noted across more extended term periods. In addition, in the longer-term period, the change in connectedness is relatively tiny. These results concur with findings from Kumah *et al.* (2021) and Ampountolas (2023) as they show weak interconnections in the medium to long term; however, they contradict the findings of Kumah and Odei-Mensah (2021) that investors may not see benefit in the medium to long term and should instead invest in the short term. Thus, from the above, investors might be better off in the long term to achieve haven properties, thus contradicting Mariana *et al.* (2021).

The FROM_ABS results across all frequencies indicate that BTC and ETH have the most dominant spillover, while USDT has the least dominant spillover in the pre-COVID period. A similar picture was also observed during the COVID period. Given that USDT indicates weak spillover, this has the potential for diversification and benefit for investors. When assessing the dominance of spillover spread in terms of the WTH, ETH is dominant across all frequencies in the pre-COVID period. However, in the COVID period, BTC is dominant in freq.2, freq.3, and freq.4. Put differently, in the COVID period, ETH has a stronger WTH connectedness than BTC in freq.1. BTC has a higher market capitalisation than ETH[9]. One would expect dominance from the largest cryptocurrency in all periods.

[9] Refer https://coinmarketcap.com/all/views/all/ (Accessed 15 March 2024)

The FROM_ABS and TO_ABS indicate which cryptocurrency contributes to and which receives from the total spillover effects within the various frequencies. In the pre-COVID period, BTC and ETH were major contributors and receivers of short- and long-term spillover. XRP and BNB display mixed results; USDT is the lowest contributor and receiver. In the COVID period, BTC contributed the most in freq.2, freq.3, and freq.4. ETH was the highest recipient of spillover in all frequencies. This concurs with Ji *et al*. (2018) that Bitcoin is one of the largest transmitters and receivers of spillover effects.

Net ABS is the difference between the TO_ABS and FROM_ABS. This measure outlines whether a cryptocurrency is a net transmitter or receiver of spillover. A positive measure indicates transmission and a negative measure indicates reception. Across all time horizons (freq.1 to freq.4), BTC and ETH are net transmitters in both the pre-COVID and COVID periods. BNB is a net recipient in all frequencies in the pre-COVID period but a net transmitter in the COVID period. USDT and XRP display mixed results across frequencies and periods. The two largest cryptocurrencies remain transmitters in both periods, and thus, these cannot be regarded as safe havens in the short term, which is in line with Mariana *et al.'s* (2021) assertion. The results support Caferra and Vidal-Tomás's (2021) position, which claims that contagion exists between cryptocurrencies and stock markets at high frequencies with minimal reduction in risk. The highest transmitter of spillover is BTC and ETH in the short-term horizon (freq.1) periods; however, ETH is highest across both cryptocurrencies. In the COVID period, BTC, ETH, USDT, and BNB are net transmitters in frequency 2-4, while XRP remains a net receiver. These results correspond closely to the time-domain results.

Table 4.9 depicts the net pair-wise spillover results. The results for BTC in the pre-COVID period indicate that BTC is a net recipient across all frequencies except for freq.3 (BTC-NGX), where BTC is a net transmitter. In freq.4, there was no connection between BTC-NGX and BTC-NSE. The results imply that the stock exchanges are net transmitters of spillover. The COVID period remains relatively unchanged for BTC from a net transmitter perspective, with no connection noted in freq. 4, BTC-NGX.

ETH is a net recipient in the pre-COVID period except for freq.2-4 (ETH-EGX), where ETH is a net transmitter. ETH is a net recipient across all stock markets in the COVID period. USDT is mainly a net transmitter in the pre-COVID period, except for freq.1 (USDT-CSE, USDT-EGX, USDT-NSE) and freq.2-4 (USDT-JSE, USDT-NGX). However, USDT is a net recipient in the COVID period, except for freq.1 (USDT-NSE) and freq.2-4 (USDT-JSE).

BNB was a net recipient in the pre-COVID period except across BNB-NSE in all frequencies where it was a net transmitter. In freq.4, there is no connection with BNB-NSE. BNB is a net recipient in the COVID period except with freq.2-3 with BNB-NGX.

XRP has mixed results in the pre-COVID period, being a net recipient for XRP-JSE XRP-EGX across all frequencies and a net transmitter across XRP-NGX and XRP-CSE. XRP-NSE is a net recipient for freq.1-2 and net-transmitter freq.3-4. In the COVID period, XRP is mainly a net recipient with no connection for freq.3-4 (XRP-NGX). A conclusion may be reached that, on average, the major stock exchanges are net transmitters of spillover effects in the pre-COVID period but more so in the COVID period. These results support the findings of Kumah *et al.* (2021). The results imply that where there are no connections, these could be considered safe havens, mainly BTC and XRP, for the Nigeria stock exchange. Overall, the results in line with the time-domain, Bourie *et al*. (2018a) and Iqbal *et al*. (2021) indicate that cryptocurrencies are more likely to receive a shock than transmit to the stock market. This is an interesting observation, given that cryptocurrencies are seen as disruptive technology based on cryptographical technologies and do not share features related to the real economy (Caferra & Vidal-Tomas, 2021).

One further note is that the pair-wise strength decreases with the COVID period compared to the pre-COVID period. The results imply that the pair-wise connections are relatively small. ETH has the most substantial pair-wise relation in the pre-and COVID periods, with XRP trailing behind ETH in the COVID period. BTC appears to have a strong connection with all stock market pairs in the COVID period, except the JSE.

Table 4.7: Frequency-domain directional spillover index results (pre-COVID)

Freq. 1	**BTC**	**ETH**	**USDT**	**BNB**	**XRP**	**JSE**	**NGX**	**CSE**	**EGX**	**NSE**	**FROM_ABS**	**FROM_WTH**
BTC	36.15	18.44	0.35	11.72	9.04	0.09	0.06	0.06	0.12	0.09	**4.00**	**5.31**
ETH	17.55	34.21	0.25	9.67	14.34	0.23	0.01	0.01	0.21	0.02	**4.23**	**5.62**
USDT	1.37	1.16	83.66	0.45	1.64	0.13	0.22	0.06	0.08	0.06	0.52	0.69
BNB	12.93	12.01	0.27	42.4	5.43	0.3	0.03	0.26	0.12	0.3	3.16	4.2
XRP	10.75	17.02	0.03	5.83	40.12	0.37	0.04	0.13	0.29	0.17	3.46	4.6
JSE	0.33	0.51	0.02	0.56	0.74	68.03	0.53	1.03	2.1	1.04	0.69	0.91
NGX	0.19	0.54	0.17	0.07	0.04	1.02	61.21	0.24	0.54	0.74	0.35	0.47
CSE	0.12	0.16	0.39	0.3	0.12	0.94	0.18	84.53	0.72	0.99	0.39	0.52
EGX	0.15	0.27	0.49	0.07	0.48	2.42	0.27	0.42	65.8	0.96	0.55	0.73
NSE	0.21	0.2	0.08	0.5	0.29	0.76	0.42	0.51	0.87	59.68	0.38	0.51
TO_ABS	4.36	5.03	0.21	2.92	3.21	0.62	0.18	0.27	0.5	0.44	**17.74**	
TO_WTH	5.79	6.68	0.27	3.87	4.26	0.83	0.24	0.36	0.67	0.58		**23.55**
Net ABS	0.36	0.8	-0.31	-0.24	-0.25	-0.07	-0.17	-0.12	-0.05	0.06		

Freq. 2	**BTC**	**ETH**	**USDT**	**BNB**	**XRP**	**JSE**	**NGX**	**CSE**	**EGX**	**NSE**	**FROM_ABS**	**FROM_WTH**
BTC	9.00	4.16	0.11	2.29	1.91	0.01	0.01	0.01	0.08	0.01	**0.86**	**4.75**
ETH	3.68	8.10	0.10	2.12	3.03	0.13	0.01	0.00	0.12	0.02	**0.92**	**5.10**
USDT	0.04	0.01	7.84	0.02	0.30	0.00	0.02	0.02	0.04	0.02	0.05	0.26
BNB	3.42	2.89	0.02	11.06	1.20	0.10	0.02	0.02	0.09	0.23	0.80	4.41
XRP	1.94	4.01	0.02	0.85	11.23	0.13	0.05	0.01	0.11	0.18	0.73	4.04
JSE	0.20	0.27	0.02	0.27	0.56	16.78	0.04	0.18	0.23	0.06	0.18	1.01
NGX	0.01	0.17	0.06	0.08	0.00	0.95	22.82	0.17	0.51	0.70	0.26	1.46
CSE	0.02	0.02	0.00	0.05	0.00	0.17	0.08	8.23	0.03	0.02	0.04	0.22
EGX	0.09	0.08	0.01	0.08	0.11	1.70	0.15	0.17	18.47	0.16	0.25	1.41
NSE	0.01	0.11	0.01	0.09	0.19	0.77	0.38	0.35	0.67	23.70	0.26	1.43
TO_ABS	0.94	1.17	0.03	0.58	0.73	0.40	0.08	0.09	0.19	0.14	**4.35**	
TO_WTH	5.21	6.48	0.19	3.23	4.04	2.19	0.42	0.52	1.04	0.77		**24.09**
Net ABS	0.08	0.25	-0.02	-0.22	0.00	0.22	-0.18	0.05	-0.06	-0.12		

Freq. 3	**BTC**	**ETH**	**USDT**	**BNB**	**XRP**	**JSE**	**NGX**	**CSE**	**EGX**	**NSE**	**FROM_ABS**	**FROM_WTH**
BTC	2.60	1.19	0.03	0.64	0.54	0.00	0.00	0.00	0.02	0.00	**0.24**	**4.61**
ETH	1.04	2.32	0.03	0.61	0.85	0.04	0.00	0.00	0.03	0.01	**0.26**	**4.97**
USDT	0.01	0.00	2.15	0.00	0.09	0.00	0.01	0.01	0.01	0.01	0.01	0.26
BNB	1.00	0.83	0.01	3.22	0.34	0.03	0.01	0.00	0.03	0.07	0.23	4.37
XRP	0.53	1.15	0.01	0.22	3.32	0.03	0.02	0.00	0.03	0.06	0.21	3.89
JSE	0.06	0.08	0.01	0.08	0.18	4.71	0.00	0.05	0.05	0.00	0.05	0.94
NGX	0.00	0.05	0.02	0.03	0.00	0.32	6.95	0.06	0.17	0.23	0.09	1.64
CSE	0.01	0.00	0.00	0.01	0.00	0.05	0.02	2.25	0.01	0.00	0.01	0.20
EGX	0.03	0.03	0.00	0.03	0.04	0.52	0.04	0.05	5.36	0.04	0.08	1.46
NSE	0.00	0.03	0.00	0.03	0.06	0.26	0.13	0.11	0.22	7.30	0.08	1.60
TO_ABS	0.27	0.34	0.01	0.16	0.21	0.13	0.02	0.03	0.06	0.04	**1.26**	

	BTC	ETH	USDT	BNB	XRP	JSE	NGX	CSE	EGX	NSE	FROM_ABS	FROM_WTH
TO_WTH	5.08	6.37	0.19	3.12	3.95	2.37	0.45	0.53	1.08	0.80		**23.94**
Net ABS	0.03	0.08	0.00	-0.07	0.00	0.08	-0.07	0.02	-0.02	-0.04		

Freq. 4	**BTC**	**ETH**	**USDT**	**BNB**	**XRP**	**JSE**	**NGX**	**CSE**	**EGX**	**NSE**	**FROM_ABS**	**FROM_WTH**
BTC	0.65	0.30	0.01	0.16	0.14	0.00	0.00	0.00	0.01	0.00	**0.06**	**4.60**
ETH	0.26	0.58	0.01	0.15	0.21	0.01	0.00	0.00	0.01	0.00	**0.07**	**4.96**
USDT	0.00	0.00	0.54	0.00	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.26
BNB	0.25	0.21	0.00	0.81	0.08	0.01	0.00	0.00	0.01	0.02	0.06	4.37
XRP	0.13	0.29	0.00	0.05	0.83	0.01	0.00	0.00	0.01	0.02	0.05	3.88
JSE	0.01	0.02	0.00	0.02	0.04	1.18	0.00	0.01	0.01	0.00	0.01	0.94
NGX	0.00	0.01	0.00	0.01	0.00	0.08	1.75	0.01	0.04	0.06	0.02	1.66
CSE	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.56	0.00	0.00	0.00	0.20
EGX	0.01	0.01	0.00	0.01	0.01	0.13	0.01	0.01	1.34	0.01	0.02	1.46
NSE	0.00	0.01	0.00	0.01	0.01	0.07	0.03	0.03	0.06	1.84	0.02	1.61
TO_ABS	0.07	0.08	0.00	0.04	0.05	0.03	0.01	0.01	0.01	0.01	**0.32**	
TO_WTH	5.07	6.36	0.19	3.11	3.95	2.39	0.45	0.53	1.08	0.81		**23.93**
Net ABS	0.01	0.01	0.00	-0.02	0.00	0.02	-0.01	0.01	-0.01	-0.01		

Table 4.8: Frequency-domain directional spillover index results (COVID)

Freq. 1	**BTC**	**ETH**	**USDT**	**BNB**	**XRP**	**JSE**	**NGX**	**CSE**	**EGX**	**NSE**	**FROM_ABS**	**FROM_WTH**
BTC	29.53	20.68	1.58	14.62	10.01	1.92	0.14	0.16	0.05	0.18	**4.94**	**6.35**
ETH	20.23	29.13	1.56	15.34	10.91	2.27	0.19	0.17	0.10	0.13	**5.09**	**6.55**
USDT	5.07	3.65	70.76	4.22	1.48	2.13	0.74	0.56	0.81	1.59	2.02	2.61
BNB	15.73	16.34	1.31	31.98	12.19	2.00	0.06	0.08	0.05	0.10	4.79	6.16
XRP	12.55	13.85	0.58	13.57	36.33	1.33	0.00	0.06	0.07	0.02	4.20	5.41
JSE	3.19	3.93	4.00	2.70	1.73	54.62	0.44	0.13	1.23	0.72	1.81	2.33
NGX	0.49	0.56	1.22	0.24	0.02	0.44	76.81	0.04	0.99	0.33	0.43	0.56
CSE	0.42	0.40	1.17	0.17	0.38	0.96	0.06	78.62	1.03	0.21	0.48	0.62
EGX	0.28	0.38	2.60	0.26	0.26	1.68	0.39	0.76	66.56	0.16	0.68	0.87
NSE	0.56	0.42	0.50	0.46	0.20	0.65	0.20	0.19	0.19	54.85	0.34	0.43
TO_ABS	5.85	6.02	1.45	5.16	3.72	1.34	0.22	0.22	0.45	0.34	**24.77**	
TO_WTH	7.53	7.75	1.87	6.64	4.79	1.72	0.28	0.28	0.58	0.44		**31.88**
Net ABS	0.91	0.93	-0.57	0.37	-0.48	-0.47	-0.21	-0.26	-0.23	0.00		

Freq. 2	**BTC**	**ETH**	**USDT**	**BNB**	**XRP**	**JSE**	**NGX**	**CSE**	**EGX**	**NSE**	**FROM_ABS**	**FROM_WTH**
BTC	6.18	4.17	0.10	2.95	1.83	0.25	0.03	0.06	0.00	0.03	**0.94**	**5.76**
ETH	3.99	5.75	0.05	2.63	1.95	0.24	0.04	0.05	0.01	0.04	**0.90**	**5.51**
USDT	0.06	0.05	6.04	0.07	0.02	0.04	0.02	0.09	0.29	0.07	0.07	0.44
BNB	3.12	3.15	0.14	6.42	1.91	0.18	0.02	0.01	0.00	0.01	0.85	5.22
XRP	2.31	2.63	0.04	2.57	8.27	0.12	0.00	0.01	0.00	0.01	0.77	4.71
JSE	1.91	2.31	0.03	1.47	0.97	12.43	0.24	0.09	0.49	0.07	0.76	4.64

NGX	0.03	0.06	0.39	0.01	0.00	0.12	13.09	0.01	0.06	0.19	0.09	0.54
CSE	0.36	0.28	0.17	0.09	0.14	0.37	0.00	10.09	0.50	0.20	0.21	1.30
EGX	0.12	0.16	0.96	0.04	0.02	1.19	0.00	0.42	16.42	0.19	0.31	1.89
NSE	0.51	0.40	0.39	0.39	0.14	0.48	0.18	0.06	0.02	27.12	0.26	1.57
TO_ABS	1.24	1.32	0.23	1.02	0.70	0.30	0.05	0.08	0.14	0.08	**5.16**	
TO_WTH	7.60	8.09	1.39	6.25	4.27	1.84	0.32	0.49	0.85	0.49		**31.59**
Net ABS	0.30	0.42	0.16	0.17	-0.07	-0.46	-0.04	-0.13	-0.17	-0.18		

Freq. 3	**BTC**	**ETH**	**USDT**	**BNB**	**XRP**	**JSE**	**NGX**	**CSE**	**EGX**	**NSE**	**FROM_ABS**	**FROM_WTH**
BTC	1.76	1.18	0.03	0.84	0.51	0.07	0.01	0.02	0.00	0.01	**0.27**	**5.57**
ETH	1.13	1.63	0.01	0.74	0.55	0.07	0.01	0.02	0.00	0.02	**0.25**	**5.33**
USDT	0.00	0.00	1.64	0.01	0.00	0.00	0.00	0.03	0.08	0.01	0.01	0.31
BNB	0.88	0.88	0.04	1.81	0.52	0.05	0.00	0.00	0.00	0.00	0.24	4.96
XRP	0.65	0.74	0.01	0.72	2.38	0.03	0.00	0.00	0.00	0.00	0.22	4.52
JSE	0.58	0.70	0.00	0.44	0.29	3.57	0.07	0.03	0.14	0.02	0.23	4.78
NGX	0.01	0.02	0.12	0.00	0.00	0.03	3.67	0.00	0.01	0.06	0.03	0.53
CSE	0.12	0.09	0.05	0.03	0.04	0.11	0.00	2.83	0.15	0.07	0.07	1.37
EGX	0.04	0.06	0.28	0.01	0.01	0.37	0.00	0.13	4.77	0.07	0.10	2.03
NSE	0.17	0.13	0.13	0.13	0.04	0.16	0.06	0.02	0.00	8.80	0.09	1.78
TO_ABS	0.36	0.38	0.07	0.29	0.20	0.09	0.02	0.02	0.04	0.03	**1.49**	
TO_WTH	7.50	7.96	1.39	6.12	4.12	1.87	0.33	0.51	0.84	0.55		**31.18**
Net ABS	0.09	0.13	0.06	0.05	-0.02	-0.14	-0.01	-0.05	-0.06	-0.06		

Freq. 4	**BTC**	**ETH**	**USDT**	**BNB**	**XRP**	**JSE**	**NGX**	**CSE**	**EGX**	**NSE**	**FROM_ABS**	**FROM_WTH**
BTC	0.44	0.29	0.01	0.21	0.13	0.02	0.00	0.00	0.00	0.00	**0.07**	**5.56**
ETH	0.28	0.41	0.00	0.18	0.14	0.02	0.00	0.00	0.00	0.00	**0.06**	**5.32**
USDT	0.00	0.00	0.41	0.00	0.00	0.00	0.00	0.01	0.02	0.00	0.00	0.30
BNB	0.22	0.22	0.01	0.45	0.13	0.01	0.00	0.00	0.00	0.00	0.06	4.94
XRP	0.16	0.18	0.00	0.18	0.59	0.01	0.00	0.00	0.00	0.00	0.05	4.51
JSE	0.15	0.17	0.00	0.11	0.07	0.89	0.02	0.01	0.04	0.01	0.06	4.79
NGX	0.00	0.00	0.03	0.00	0.00	0.01	0.92	0.00	0.00	0.02	0.01	0.53
CSE	0.03	0.02	0.01	0.01	0.01	0.03	0.00	0.71	0.04	0.02	0.02	1.38
EGX	0.01	0.01	0.07	0.00	0.00	0.09	0.00	0.03	1.19	0.02	0.02	2.04
NSE	0.04	0.03	0.03	0.03	0.01	0.04	0.02	0.00	0.00	2.22	0.02	1.80
TO_ABS	0.09	0.09	0.02	0.07	0.05	0.02	0.00	0.01	0.01	0.01	**0.37**	
TO_WTH	7.49	7.94	1.39	6.11	4.11	1.87	0.33	0.51	0.84	0.55		**31.15**
Net ABS	0.02	0.03	0.02	0.01	0.00	-0.04	-0.01	-0.01	-0.01	-0.01		

Table 4.9: Frequency-domain net pair-wise spillover results

Pre-COVID	Freq.1	Freq.2	Freq.3	Freq.4	COVID	Freq.1	Freq.2	Freq.3	Freq.4
BTC-JSE	-0.0234	-0.0192	-0.0058	-0.0014	**BTC-JSE**	-0.1263	-0.1666	-0.0515	-0.0130
BTC-NGX	-0.0123	-0.0002	0.0001	0.0000	**BTC-NGX**	-0.0342	-0.0004	0.0001	0.0000
BTC-CSE	-0.0058	-0.0017	-0.0005	-0.0001	**BTC-CSE**	-0.0257	-0.0302	-0.0099	-0.0025
BTC-EGX	-0.0031	-0.0017	-0.0009	-0.0002	**BTC-EGX**	-0.0236	-0.0116	-0.0039	-0.0010
BTC-NSE	-0.0118	-0.0001	-0.0002	0.0000	**BTC-NSE**	-0.0375	-0.0486	-0.0164	-0.0042
ETH-JSE	-0.0276	-0.0139	-0.0041	-0.0010	**ETH-JSE**	-0.1658	-0.2062	-0.0630	-0.0158
ETH-NGX	-0.0527	-0.0155	-0.0046	-0.0011	**ETH-NGX**	-0.0369	-0.0026	-0.0006	-0.0001
ETH-CSE	-0.0154	-0.0014	-0.0003	-0.0001	**ETH-CSE**	-0.0234	-0.0221	-0.0074	-0.0019
ETH-EGX	-0.0058	0.0042	0.0010	0.0002	**ETH-EGX**	-0.0280	-0.0150	-0.0055	-0.0014
ETH-NSE	-0.0182	-0.0092	-0.0027	-0.0007	**ETH-NSE**	-0.0294	-0.0350	-0.0117	-0.0030
USDT-JSE	0.0106	-0.0016	-0.0005	-0.0001	**USDT-JSE**	-0.1879	0.0014	0.0004	0.0001
USDT-NGX	0.0048	-0.0037	-0.0013	-0.0003	**USDT-NGX**	-0.0485	-0.0368	-0.0111	-0.0028
USDT-CSE	-0.0328	0.0019	0.0006	0.0002	**USDT-CSE**	-0.0605	-0.0083	-0.0022	-0.0005
USDT-EGX	-0.0409	0.0035	0.0011	0.0003	**USDT-EGX**	-0.1791	-0.0663	-0.0193	-0.0048
USDT-NSE	-0.0028	0.0014	0.0006	0.0002	**USDT-NSE**	0.1097	-0.0324	-0.0118	-0.0030
BNB-JSE	-0.0263	-0.0171	-0.0043	-0.0011	**BNB-JSE**	-0.0700	-0.1286	-0.0397	-0.0100
BNB-NGX	-0.0035	-0.0066	-0.0023	-0.0006	**BNB-NGX**	-0.0184	0.0008	0.0003	0.0001
BNB-CSE	-0.0043	-0.0027	-0.0009	-0.0002	**BNB-CSE**	-0.0098	-0.0079	-0.0025	-0.0006
BNB-EGX	0.0048	0.0008	0.0002	0.0000	**BNB-EGX**	-0.0204	-0.0040	-0.0013	-0.0003
BNB-NSE	-0.0202	0.0139	0.0048	0.0012	**BNB-NSE**	-0.0361	-0.0388	-0.0131	-0.0033
XRP-JSE	-0.0368	-0.0433	-0.0143	-0.0036	**XRP-JSE**	-0.0407	-0.0850	-0.0260	-0.0065
XRP-NGX	0.0005	0.0053	0.0019	0.0005	**XRP-NGX**	-0.0018	0.0000	0.0000	0.0000
XRP-CSE	0.0015	0.0011	0.0003	0.0001	**XRP-CSE**	-0.0323	-0.0131	-0.0040	-0.0010
XRP-EGX	-0.0188	-0.0003	-0.0007	-0.0002	**XRP-EGX**	-0.0190	-0.0016	-0.0007	-0.0002
XRP-NSE	-0.0125	-0.0007	0.0006	0.0002	**XRP-NSE**	-0.0186	-0.0130	-0.0042	-0.0011

4.5 ROLLING WINDOW FREQUENCY SPILLOVER

Figures 4.1 and 4.2 depict the overall spillover connectedness between the cryptocurrencies and stock markets using the rolling window approach. The horizontal axis represents the period under review, 26 July 2017 to 10 March 2020 for the pre-COVID period and 11 March 2020 to 05 May 2023 over a scale of 100 to 600. The vertical axis depicts the connectedness of the entire system. The results illustrate a consistent level of connectedness in both the pre-COVID and COVID periods. Across all four frequencies, it can be seen in both periods that cryptocurrencies and stock markets are highly connected in the short term but not so much in the medium to long run.

Figure 4.1: pre-COVID Rolling Window Frequency Spillover

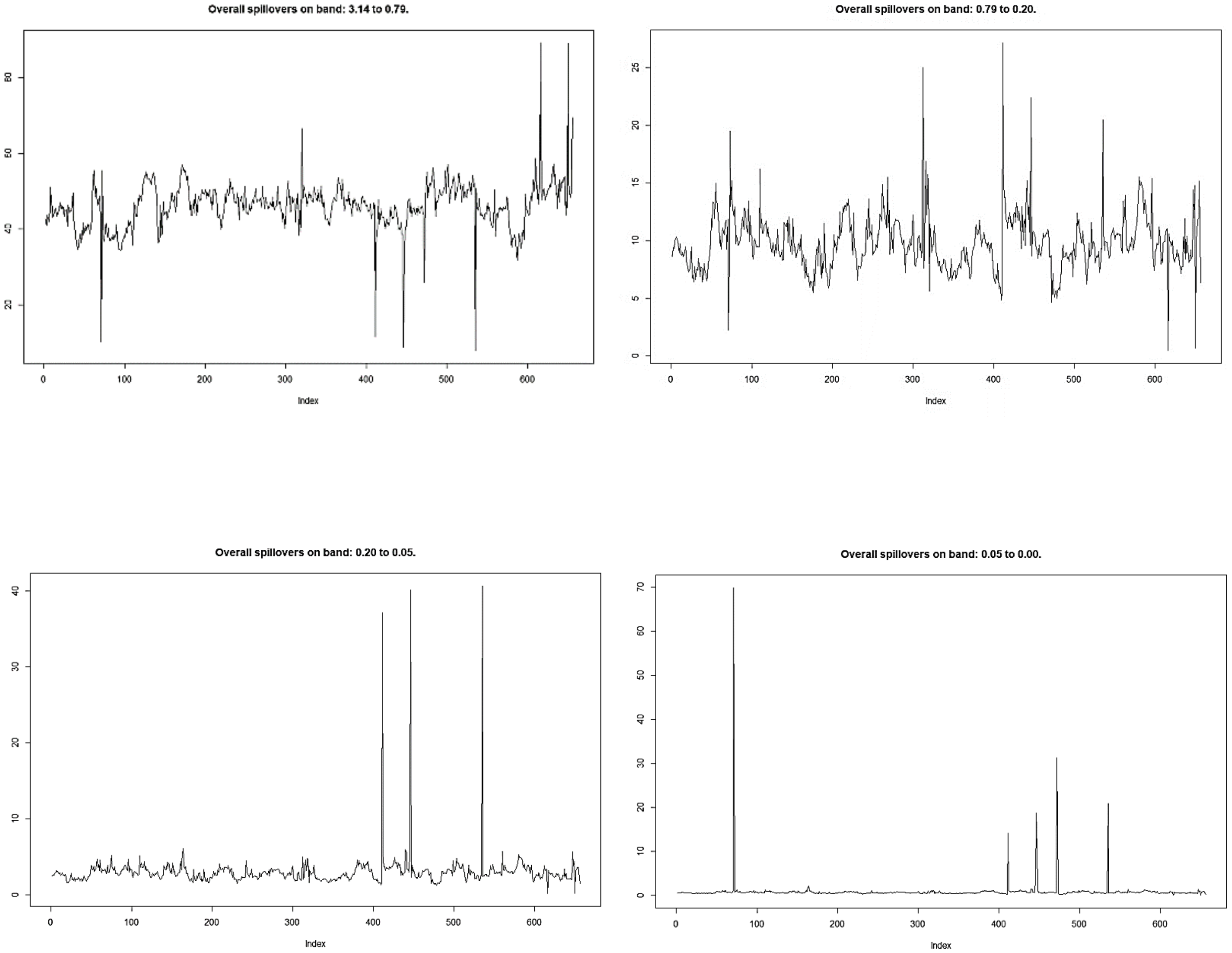
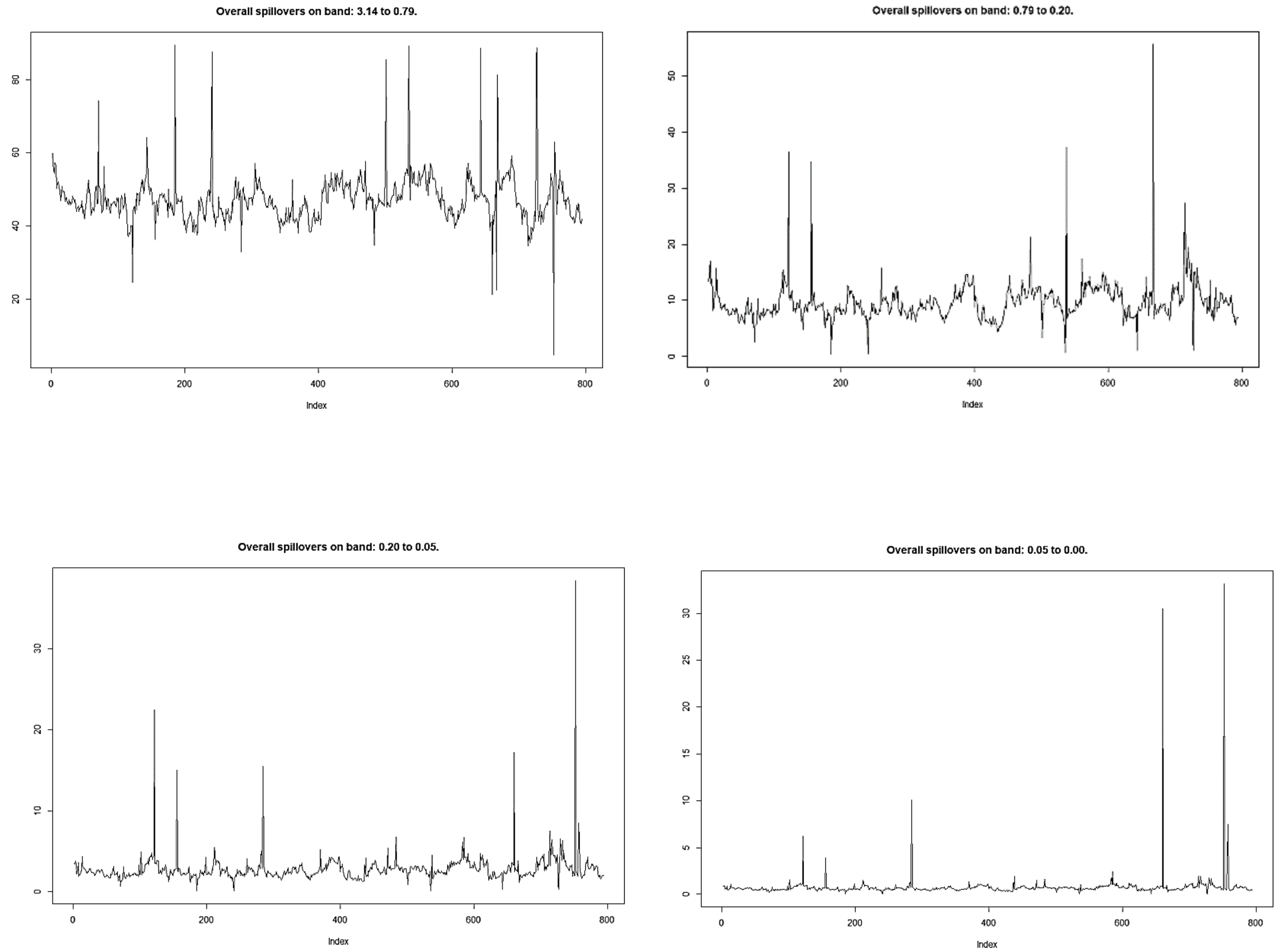


Figure 4.2: COVID Rolling Window Frequency Spillover



4.6 ROBUSTNESS CHECKS

This study performed robustness checks to obtain assurance regarding the reliability of the results. These tests were conducted using different VAR lag orders to assess changes in connectedness results given the change in VAR lag order in line with Fasanya *et al*. (2021). Barunik and Krehlik (2018) consider this a strong robustness check, particularly when looking at changes that occur at low frequencies. Table 4.10 depicts the results using a scenario analysis of VAR orders 2 to 6. The pre-COVID sensitivities are highest at lag order 6 (+6.4%) and lowest during the COVID period (-0.87%) compared to the base scenario. Under pre-COVID, sensitivities range from (+1.82% to 6.4%), while under the COVID period, these range from (-0.87% to -2.17%). Freq.1 accounts for the largest component of this movement, ranging from the pre-COVID and COVID periods (-1.81% to +3.87%). In considering both the pre-COVID and COVID period, particularly at freq.4, there are slight sensitivities to the base case, as evidenced in Table 4.10. Further, even at the higher frequencies, sensitivities are low. These results indicate that the calculated connectedness results are not sensitive to the VAR lag order structure; as such, one may conclude that the results are robust and that the model is appropriately specified, given its performance under the different VAR lag order.

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Table 4.10: Robustness checks for given VAR order

VAR order	Base case	p=2	p=3	p=4	p=5	p=6
Pre-COVID						
DY	**23.67**	25.49	26.28	27.8	29.15	30.07
BK freq.1	**17.74**	18.63	18.79	19.75	20.76	21.61
BK freq.2	**4.35**	4.97	5.29	5.43	5.05	4.93
BK freq.3	**1.26**	1.52	1.76	2.09	2.63	2.75
BK freq.4	**0.32**	0.38	0.44	0.53	0.72	0.78
COVID						
DY	**31.79**	29.62	30.12	29.66	29.93	30.92
BK freq.1	**24.77**	22	22.35	22.55	22.28	22.96
BK freq.2	**5.16**	5.55	5.79	5.14	5.55	5.83
BK freq.3	**1.49**	1.65	1.58	1.57	1.68	1.69
BK freq.4	**0.37**	0.41	0.39	0.4	0.42	0.44

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Chapter 5 Findings, conclusions and recommendations

5.1 INTRODUCTION

This study's primary aim broadly focused on the interdependence and co-movement relationship of cryptocurrencies and African stock markets during periods of severe market stress, such as during the COVID-19 pandemic. This study was mainly concerned with those aspects of connectedness that relate to transmission through financial markets. The objectives were to examine the co-movement relationship before and during a high-stress event. Secondly, determine the extent of integration between cryptocurrencies and African stock markets about price movements. Finally, determine what spillover effects exist during the stress event and establish the direction of these spillovers. The five sample cryptocurrencies studied were Ethereum (ETC), Tether (USDT), Binance Coin (BNB), and XRP markets (XRP). The five largest African stock markets based on market capitalisation are South Africa (JSE), Nigeria (NGX), Morocco (CSE), Egypt (EGX), and Kenya (NSE). The data is separated into two sub-sample periods, the first being a pre-COVID period spanning 26 July 2017 to 10 March 2020 and the second the COVID period for this study spanning 11 March 2020 to 05 May 2023.

5.2 SUMMARY OF KEY FINDINGS

The key finding of this study indicates that the COVID-19 sub-sample period contributes most to connectedness at 31.79% relative to the pre-COVID period at 23.67%. The results above concur with Conlon and McGee (2020) and Corbet et al. (2020b) that cryptocurrencies increase overall portfolio risk during COVID-19.

BTC and ETH contributed the most to connectedness in both periods, with USDT being the lowest. In line with Ji *et al*. (2018), this finding implies that shocks arising from these cryptocurrencies will likely affect the system most.

The spillover effects over both periods are mainly negative, with the cryptocurrencies being recipients rather than transmitters. These results indicate that information flow mostly comes from the stock markets rather than cryptocurrencies. These results align with Bourie *et al*. (2018a) and Iqbal *et al*. (2021), who found that cryptocurrencies are not completely detached from other assets, with their returns, volatility, and spillovers likely to be related. The evidence from these studies shows that cryptocurrencies were more likely to receive a shock than transmit it to other assets. This evidence is essential and supports the assertion that cryptocurrencies provide diversification and hedging benefits for African stock markets (Kumah *et al.*, 2021). These findings contradict those of Nyakurukwa and Seetharam (2023), who state that there is a significant flow of information from Bitcoin to equities during a crisis.

Frequency-domain findings share an in-depth view of the concentration of connectedness, which aids in overcoming the drawback of time-domain connectedness. This technique aggregates total connectedness such that it gives the impression that there is more vital connectedness when, in fact, connectedness varies depending on the frequency. From the frequency-domain results, across both periods, the most significant contributor to connectedness was observed in the short-term being frequency one, accounting for 17,74% and 24.77%, and frequency 2, 4.35%, and 5.16% in the pre-COVID and COVID periods, respectively, while the medium-term and long-term accounting for relatively more minor proportions. Thus, contagion is highest in the short term given connectedness results, thus leading to lower diversification across the short term; however, diversification benefits across more extended term periods. In addition, in the longer-term period, the change in connectedness is relatively tiny. These results concur with findings from Kumah (2021) and Ampountolas (2023) as they show weak interconnections in the medium to long term; however, they contradict the findings of Kumah and Odei-Mensah (2021) that investors may not see benefit in the medium to long term and should instead invest in the short term. Thus, from the above, investors might be better off in the long term to achieve haven properties, thus contradicting Mariana *et al.* (2021).

Across all time horizons (freq.1 to freq.4), BTC and ETH are net transmitters in both the pre-COVID and COVID periods. BNB is a net recipient in all frequencies in the pre-COVID period but a net transmitter in the COVID period. USDT and XRP display mixed results across frequencies and periods. The two largest cryptocurrencies remain transmitters in both periods, and thus, these cannot be considered safe havens in the short term, in line with Mariana *et* *al.'s.* (2021) assertion. The results support Caferra and Vidal-Tomás's (2021) findings that contagion exists between cryptocurrencies and stock markets at high frequencies, with minimal reduction in risk. The highest transmitters of spillover are BTC and ETH in the short-term horizon (freq.1) periods; however, ETH is the highest transmitter across the two cryptocurrencies. In the COVID period, BTC, ETH, USDT, and BNB are net transmitters in frequency 2-4, while XRP remains a net receiver.

In assessing pair-wise connections, the results indicate diversification and safe haven benefits in the medium to long term, given that the pair-wise strength decreases with the COVID period compared to the pre-COVID period. The results imply that the pair-wise connections are relatively small. The above findings contribute overall to understanding market interdependencies and stress the outcome of the actions of participants across different investment horizons.

5.3 POLICY IMPLICATIONS

The results presented above have several policy implications. Given that connectedness is lowest in the long term across the pre-COVID and COVID periods, cryptocurrencies can be considered an alternative to diversifying risk in African equities. Diversification is essential for long-term investors and regulators as they build resilience in the financial markets during a crisis. Secondly, these findings improve understanding of cryptocurrencies and stock markets during stressful events (Iqbal *et al*., 2021). In line with Nkrumah-Boadu *et al.* (2022), this study informs policymakers, including governments, on the need to regulate markets to optimise diversification, safe haven, and hedging benefits across varied market conditions. As cryptocurrencies become more integrated on the African continent, this could cripple financial systems, and as such, policymakers should be considerate of this (Nyakurukwa & Seetharam, 2023).

5.4 RECOMMENDATIONS FOR FUTURE RESEARCH

This study only focused on one event: the COVID-19 pandemic. Future research may incorporate behaviours of previous infectious disease outbreaks, including the global financial crisis. This study, in addition, was premised on African stock markets; future research may expand this to include other emerging markets to assess whether the patterns differed materially from those observed in African markets.

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Appendix A

Figure A.1: pre-COVID cryptocurrencies and stock market prices

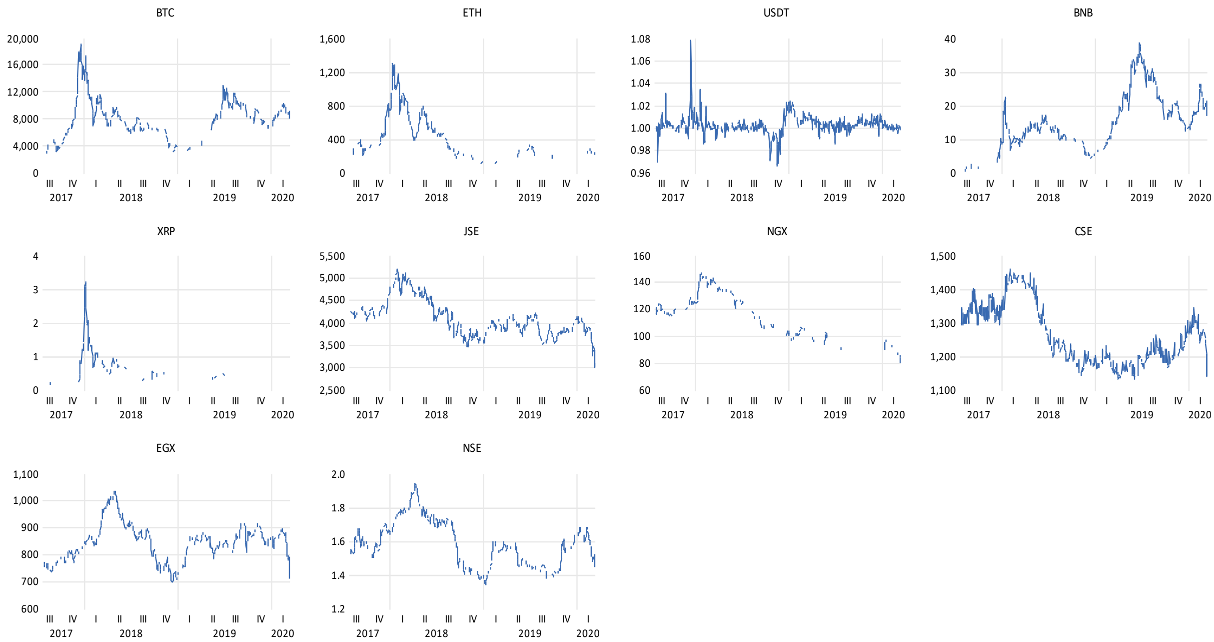


Figure A.2: COVID cryptocurrencies and stock market prices

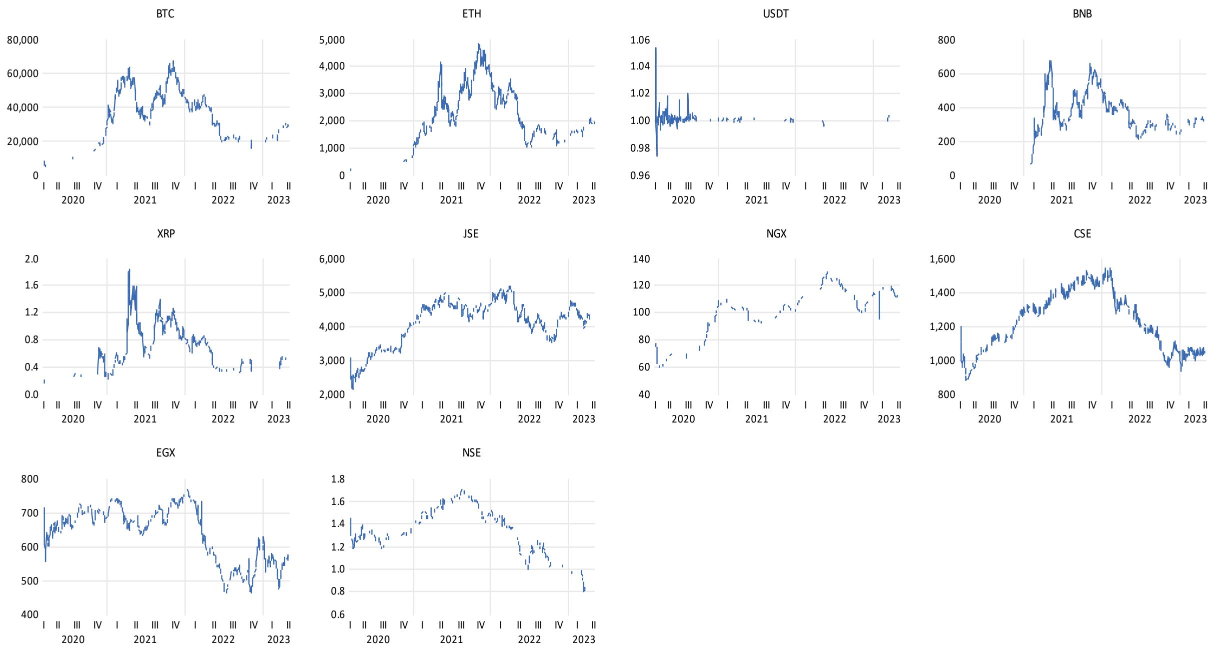


Figure A.3: pre-COVID log returns

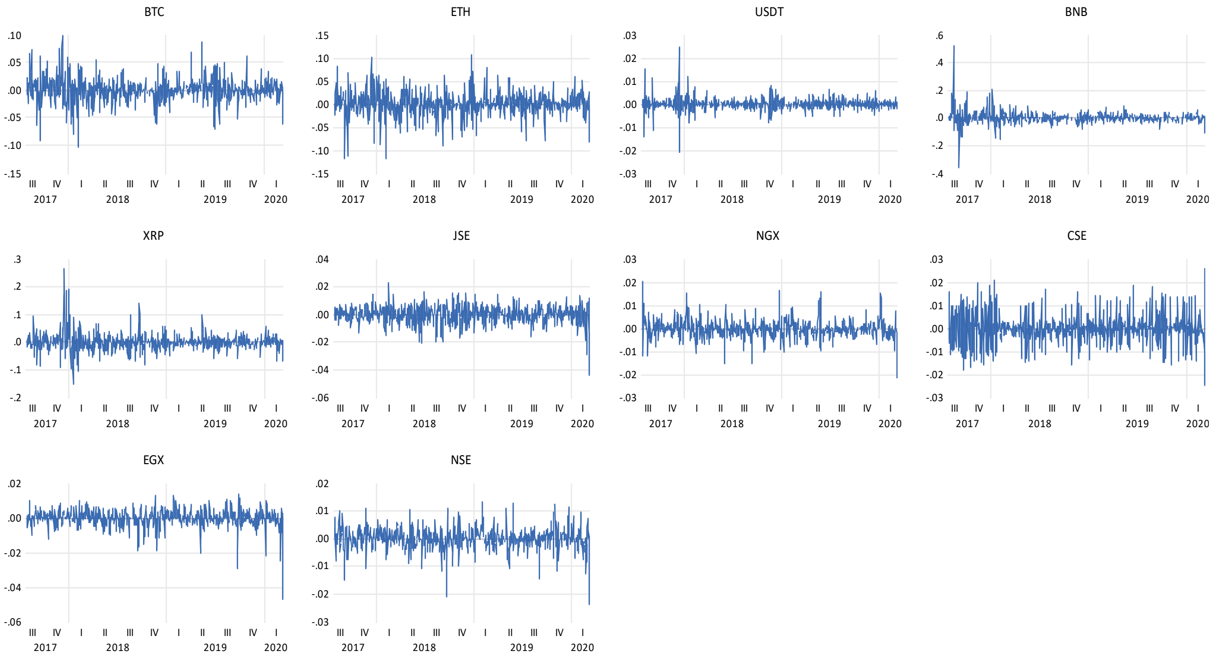
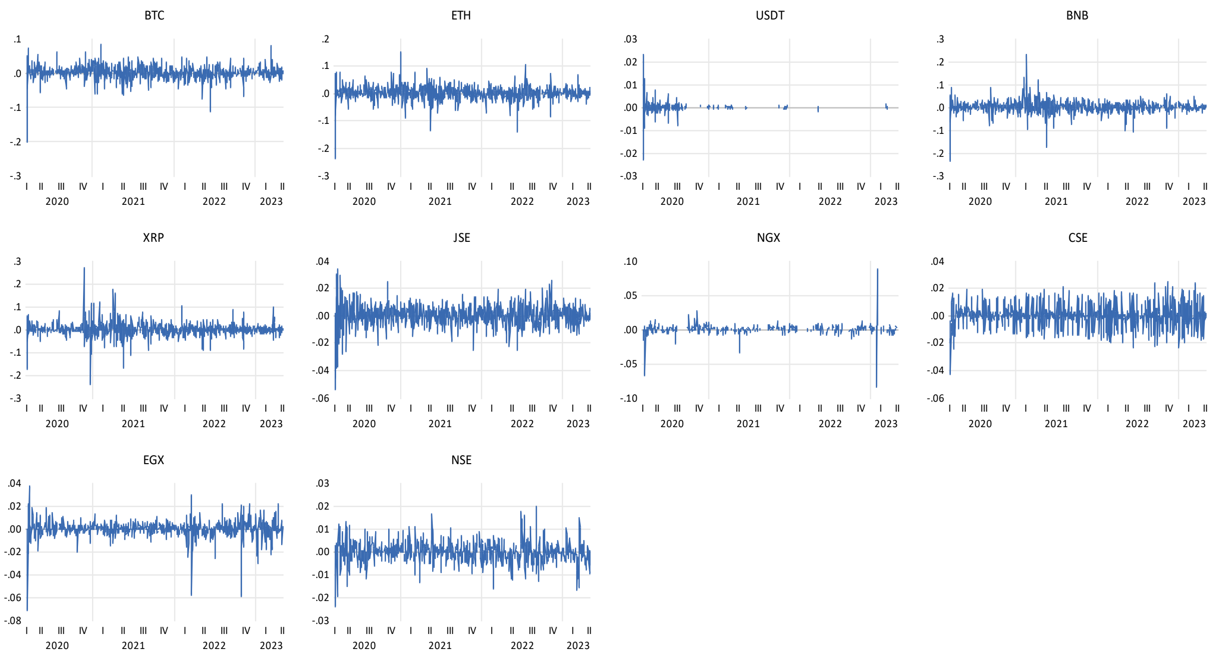


Figure A.4: COVID log returns



Appendix B

Table B.1: Unit root testing

	Augmented Dickey-Fuller Test (ADF)			**Kwiatkowski-Phillips-Schmidt-Shin (KPSS)**		
Pre-COVID	**Level**	**Significance level**	**Order**	**Level**	**Significance level**	**Order**
BTC	-25.1058	***	I(0)	0.1374	**	I(0)
ETH	-25.5144	***	I(0)	0.1300	**	I(0)
USDT	-38.4590	***	I(0)	0.0875	***	I(0)
BNB	-24.8004	***	I(0)	0.0952	***	I(0)
XRP	-23.9651	***	I(0)	0.0468	***	I(0)
JSE	-24.6623	***	I(0)	0.0589	***	I(0)
NGX	-20.4677	***	I(0)	0.0741	***	I(0)
CSE	-37.2291	***	I(0)	0.0922	***	I(0)
EGX	-23.6950	***	I(0)	0.0880	***	I(0)
NSE	-20.4770	***	I(0)	0.0953	***	I(0)
	Augmented Dickey-Fuller Test (ADF)			**Kwiatkowski-Phillips-Schmidt-Shin (KPSS)**		
COVID	**Level**	**1st difference**	**Order**	**Level**	**Significance level**	**Order**
BTC	-30.0005	***	I(0)	0.1242	**	I(0)
ETH	-30.7551	***	I(0)	0.0958	***	I(0)
USDT	-44.3799	***	I(0)	0.0302	***	I(0)
BNB	-30.3019	***	I(0)	0.1081	***	I(0)
XRP	-28.7506	***	I(0)	0.0430	***	I(0)
JSE	-29.1251	***	I(0)	0.0470	***	I(0)
NGX	-32.6971	***	I(0)	0.0860	***	I(0)
CSE	-37.3583	***	I(0)	0.0966	***	I(0)
EGX	-28.1373	***	I(0)	0.0495	***	I(0)
NSE	-20.5183	***	I(0)	0.0963	***	I(0)