Volatility spillovers and interconnectedness between cryptocurrencies and traditional asset classes in emerging markets

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DECLARATION

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ABSTRACT

Cryptocurrencies have emerged significantly in financial markets as a medium of exchange, seeking to disrupt traditional financial systems by allowing individuals to conduct peer-to-peer transactions without the interference of the third party. However, cryptocurrencies are marked by highly volatile prices due to their detachment from the traditional financial system. This volatility significantly spills over among cryptocurrencies and is suspected to extend to traditional asset classes, particularly in emerging markets. This is because emerging markets are often characterized by significant price fluctuations, driven by factors such as inflation rates, economic and political instability, and exchange rate volatility.

As such, this study seeks to investigate volatility spillovers and interconnectedness between cryptocurrencies and traditional asset classes in emerging markets. To achieve the objective of this research, the study uses Bitcoin, Ethereum, Tether, Ripple, Litecoin, and Bloomberg Galaxy Cryptocurrency Index against the traditional asset indices of stocks, bonds, and commodities. The study incorporates daily closing prices from the 6th of October 2019 to the 31st of January 2024 and applies the Diebold and Yilmaz spillover approach to examine the nature of volatility spillovers between these cryptocurrencies and traditional assets. In order to capture the non-linear and time-varying nature of these volatility spillovers, the study employs the Time-Varying Parameter Vector Autoregressive (TVP-VAR) model which offers a more comprehensive analysis of the spillover effects over time.

For the robustness of the results, the sample period was divided into two segments, (1) the whole sample period and (2) the period during the COVID-19 pandemic. The findings suggest time-varying volatility spillovers during both market crises and stable periods. However, cryptocurrencies exhibit greater internal influence than external influence, indicating that they operate within their own isolated market, with a weak connection to stocks, bonds, and commodities. These findings indicate that investors can view cryptocurrencies as a distinct asset, offering potential diversification benefits when combined with stocks, bonds and commodities in emerging markets. For policymakers, the weak connection between the two markets highlights the need to focus on internal market dynamics and regulations tailored to address risks within the cryptocurrency market without relying on traditional market mechanisms.

GLOSSARY OF ACRONYMS

ADF – Augmented Dickey-Fuller

AIC – Akaike Information Criteria

AMH – Adaptive Market Hypothesis

BCOMPRI – Bloomberg Commodity Index for Precious Metals

BGCI – Bloomberg Galaxy Commodity Index

BGCII – Bloomberg Galaxy Cryptocurrency Index[1]

BTC – Bitcoin

DY – Diebold and Yilmaz

EMBI – Emerging Market Bond Index

EMH -Efficient Market Hypothesis

ETH - Ethereum

FCA – Financial Conduct Authority

FCT – Financial Contagion Theory

FEVD – Forecast Error Variance Decomposition

FOMO – Fear of Missing out

GFEVD – Generalized Forecast Error Variance Decomposition

GIRF – Generalized Impulse Response Function

GVAR – Generalized Autoregresision

HQIC - Hannan-Quinn Information Criterion

I.M.F – International Monetary Fund

ICO -Initial Coin Offering

IPO – Initial Public Offering

KPSS - Kwiatkowski-Phillips-Schmidt-Shin

LogL – Log Likelihood

LIT - Litecoin

MPT – Modern Portfolio Theory

MSCIEMI – Morgan Stanley Capital International Emerging Market Index

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[1] The extra "I" is to differentiate between the Bloomberg Galaxy Crypto Index and Bloomberg Galaxy Commodity Index.

PP – Phillips-Perron

SBIC – Schwartz Bayesian Information Criteria

SEC – Securities and Exchange Commission

TET - Tether

TVP-VAR - Time-Varying Parameter Vector Autoregression

VAR – Vector Autoregression

XRP – Rippl**e**

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CHAPTER ONE: INTRODUCTION

1.1 Introduction and Background

The increasing use of cryptocurrencies[2] in financial markets has changed the old traditional financial system, as how social media has altered the traditional media space (Joseph et al., 2024). Urquhart and Zhang (2019) reveal that cryptocurrencies have experienced tremendous growth since the 2008 global financial crisis, indicating that people are becoming less reliant on the traditional financial system. Accordingly, Ali (2024) describes traditional financial system as a centralized network of banks, markets, and regulators that facilitates financial services. During crisis periods, the prices of traditional assets such as stocks and real estate typically decline as this was witnessed during the Great Recession (Lo, 2022). However, the response of cryptocurrencies, which are digital, decentralized, cryptographic financial assets, to a downturn may differ, as they are not subject to control by a central authority and operate separately from the traditional financial system (Vukovic et al., 2021). An example is Bitcoin, which usually behaves inversely to traditional asset classes highlighting that it can provide diversification benefits in market downturns as during the COVID-19 pandemic, its prices increased by a significant 300 percent as opposed to traditional assets which were facing a decline (Sarkodie et al., 2022).

Cryptocurrency emerged in 2008 as a response to the global financial crisis, which led to widespread loss of confidence in the traditional monetary system (Trabelsi, 2018). Since then, its history has been both compelling and divisive, with its prices increasing significantly (Bhattacharya, 2022). The first cryptocurrency ever produced was Bitcoin and it is currently the most valued and famous cryptocurrency in the world with a current market value of approximately $66 757 (Coin Codex, 2025). Cryptocurrencies seek to eliminate the need for banks, allowing people to finance projects and transfer funds directly without a third party (Pernice and Scott, 2021). This system deviates significantly from the regular financial system where instead of depending on banks and governments, people have the option to conduct financial activities directly through online networks (Jumde and Cho, 2020). In more direct terms, the decentralized nature of cryptocurrencies implies that individuals can make financial transactions without the interference of regulatory agencies such as the government, thus influencing significant growth in the cryptocurrency market (Joseph et al., 2024).

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[2] Cryptocurrencies throughout the study will be sometimes referred to as digital assets.

The cryptocurrency market has been growing at a rapid rate, with over 21 000 additional cryptocurrencies developed since the inception of Bitcoin in 2009 (Rowland and Kiviat, 2024). According to Primeiq Research (O.P.C) Private Limited (2023), the cryptocurrency market is projected to increase from $1.54 billion in 2022 to $13.17 billion by 2030, with a growth rate of 30.80 percent during this period. This projection indicates that the market size will grow significantly throughout the forecasted period, and the critical factor driving the market's growth is the expansion of distributed ledger technology, increased digital investments in venture capital, and growing acceptance of cryptocurrencies as a medium of exchange (Baboshkin et al., 2022). Accordingly, Miller and Prondzinski (2023) mention that the growing use of cryptocurrencies has seen even developing markets adopting digital money as a medium of exchange for financial transactions. Figure 1.1 below illustrates the number of cryptocurrency users from 2016 to 2024, showing a consistent upward trend over the years.

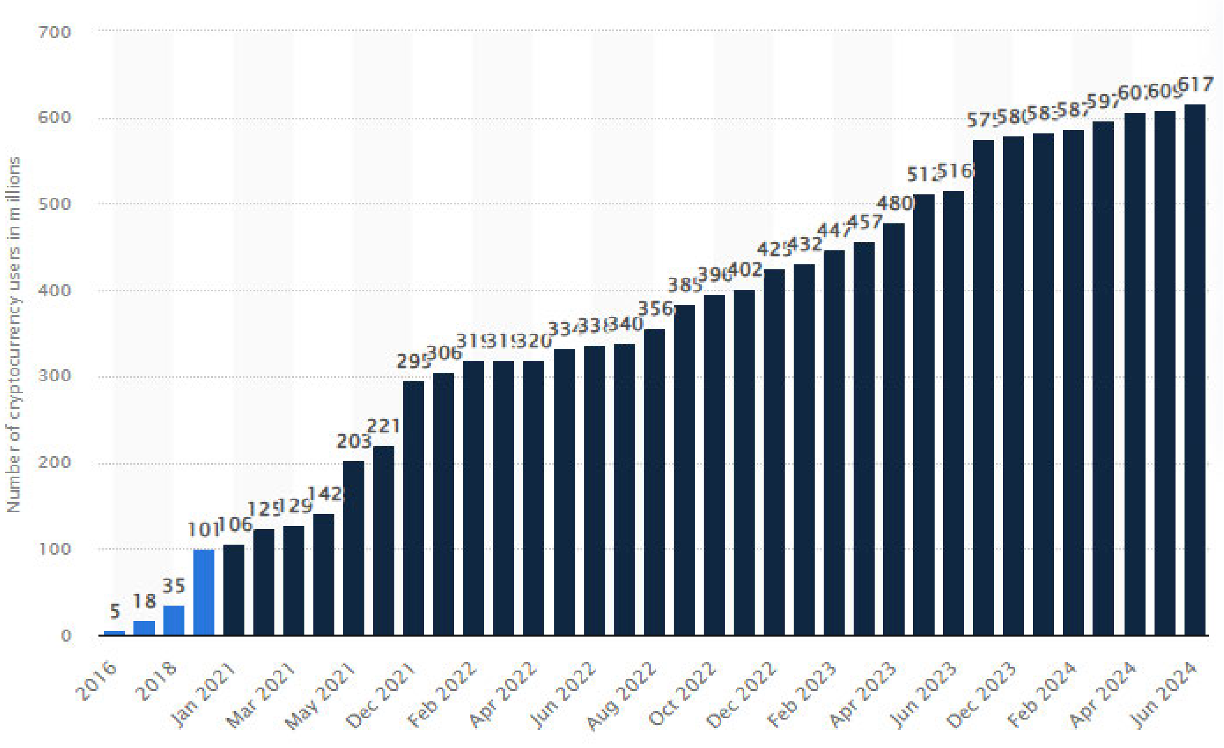

Figure 1.1: Cryptocurrency users from 2016 to 2024

Source: Statista (2024)

Out of the several factors influencing growth in the cryptocurrency market, Baur and Hoang (2021) highlight the decentralized nature of blockchain technology as a key driver of this growth, as it fosters peer-to-peer interactions by enabling transparent and tamper-resistant transactions, and boosters' confidence in the cryptocurrency market. Moreover, consensus techniques in the blockchain network such as Proof-of-Work[3] and Proof-of-stake[4] ensure the integrity and consensus of transactions in the cryptocurrency market (Nakamoto, 2008; Buterin, 2014). Furthermore, Poon and Dryja (2016) report that off-chain transactions and layer-two protocols scaling solutions are used to address the scalability issues posed by cryptocurrencies by enabling higher efficiency and transactions throughout. Subsequently, programmable features and smart contracts have increased the capabilities of cryptocurrencies, encouraging the creation of decentralized apps. As such, Eldomiaty and Mohab (2024) confirm that technological developments are one of the key factors improving the usability and usefulness of cryptocurrencies and assisting them to gain popularity and remain viable over time.

However, the prices of cryptocurrencies are highly volatile, often leading to significant gains or losses in a short period of time. For instance, on April 3rd, 2023, Dogecoin's value declined by a significant 21 percent in a single day (Tan, 2023), while Bitcoin experienced a substantial price swing in November 2022, with a 10-day volatility exceeding 100 percent (Winkel and Härdle, 2023). Cryptocurrency prices fluctuate frequently due to their detachment from conventional assets such as gold and diamonds, lack of any underlying asset that stabilizes their value and their relative immaturity as compared to the traditional assets. In this context, Liu et al., (2019) mention that fluctuations in the cryptocurrency market can be linked to the performance of other investment types such as commodities, stocks and bonds. These asset classes, which exhibit varying levels of volatility, consequently lead to different correlation patterns among them. For instance, bonds are less volatile than stocks, but commodities are more volatile than both bonds and stocks (Jacquet, 2021).

Understanding volatility linkages among assets of different natures, such as cryptocurrencies and traditional financial instruments is crucial for assessing their role in portfolio diversification and risk management. If volatility shocks in one asset class significantly influence another, it could diminish the potential diversification benefits of including those assets together in a portfolio. As such, Bouri et al. (2021) emphasize the importance of analysing the transmission of second moments within return distributions to capture these cross-asset volatility dynamics accurately. While such analyses are well established in traditional financial markets, Lee et al. (2018) note that this area remains understudied in the

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[3] Proof-of-work – a technique used by cryptocurrencies to verify the accuracy of new transactions that are added to a blockchain

[4] Proof-of-stake - a consensus mechanism used to verify new cryptocurrency transactions.

context of cryptocurrencies, despite their increasing prominence as speculative and investment instruments. This gap is partly due to the relatively recent emergence of the cryptocurrency market, which is characterized by significantly higher price volatility than traditional asset classes. As such, this study includes stocks, bonds, and commodities as the traditional asset classes of interest, given their distinct volatility profiles and fundamentally different characteristics within financial markets

The stock market, which refers to various exchanges where publicly held firm shares are bought and traded, is ought to be influenced by cryptocurrencies. Therefore, Jeris et al., (2022) highlight that the stock market can be significantly influenced by cryptocurrencies and the safety of a cryptocurrency can be assessed by analysing diverse stock markets, the duration of investment intentions, and individual's perspective on investing. However, Gil-Alana et al., (2020) suggest that investors could benefit from spreading their investments by including cryptocurrencies in their portfolio, as they typically move in the opposite direction of the stock market. In contrast, Conrad et al., (2018) uncover that the fluctuations in the S&P 500 and the Baltic Dry Index are reflected in Bitcoin's long-term volatility and the higher risk premiums in the S&P 500 further increase Bitcoin's volatility, highlighting its connection to global economic conditions. This connection is suspected to extend to the bond market as well.

As such, Kartal and Can (2022) note that a larger number of factors influence the connection between the bond market and cryptocurrency market due to the complicated relationship that exists between them. The bond market is where investors engage in trading debt assets like bonds and these bonds can be issued by either corporations or governments (Bosse and Coughlan, 2016). Bonds are traditionally seen as constant low-risk assets, and their prices frequently move opposite to interest rates. In contrast, cryptocurrencies can see significant value fluctuations due to factors like market sentiment, new regulations, and advancements in technology. For instance, the U.S stock does not influence the cryptocurrency market but the U.S bond market is more influential to the cryptocurrency market (Harb et al., 2024). Therefore, during market downturns, it is recommended that investors seeking to escape the losses in the bond market may benefit from investing in cryptocurrencies such as Ethereum, as it surged from $729 to $1000 in just six weeks in 2021 (Rahahleh and Qurashi, 2024)

Furthermore, there are significant economic developments and investor emotions that frequently influence the volatility between commodities and cryptocurrencies. The commodity market operates with raw materials or natural resources, not items that have been processed or manufactured and the returns are mainly independent of stock and bond returns (Sraffa, 2016). During economic uncertainty, investors may gravitate to traditional commodities like gold as a safe haven asset, causing prices to rise. Simultaneously, some investors may perceive cryptocurrencies, particularly Bitcoin, as a digital store of wealth, causing higher demand during market stress. As a result, Mo et al., (2022) report that the total spillovers from commodity markets to the cryptocurrency market alternated[5] during the COVID-19 pandemic, and the system is most susceptible to risks through the use of cryptocurrencies. Subsequently, Sraffa (2016) indicates that following the COVID-19 pandemic, cryptocurrencies emerged as a reliable safeguard against systemic risk, particularly in mitigating risk in the stock market.

This dynamic is also reflected in emerging markets, such as Brazil, Russia, India, China, and South Africa (BRICS), which are becoming increasingly influential in the global economy (Marquis and Raynard, 2015). Emerging markets are experiencing rapid growth due to their extraction and sale of natural resources and their extensive use of cheap labour in manufacturing processes. However, Nyopa and Khumalo (2022) note that investments in emerging markets are often characterized by greater volatility in returns than investments in more developed markets due to several factors such as currency risk heightening in emerging markets, as their currencies are typically more susceptible to sudden shifts. Thus, the main aim of this study is to investigate the volatility spillovers and interconnectedness between cryptocurrencies and traditional asset classes in emerging markets. The following section provides a problem statement of the current study.

1.2 Problem statement

Cryptocurrencies are transforming the financial landscape by offering a decentralized alternative to traditional financial systems. However, they experience highly volatile prices influenced by regulatory changes, market manipulation and macroeconomic trends (Gupta and Chaudhary, 2022). This volatility raises concerns about their reliability as a hedge against risk or as diversification tools, particularly during market downturns, like the early stages of the COVID-19 pandemic, where cryptocurrencies moved in the same direction with traditional assets by experiencing significant price declines (Vukovic et al., 2021).

While studies such as Trabelsi (2018) suggest weak correlations between cryptocurrencies and traditional assets, evidence presented by Ghorbel and Jeribi (2021) revealed that

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[5] Alternated in this context implies that the transmission of volatility or shocks from commodity markets to the cryptocurrency market varied over time during the COVID-19 pandemic.

cryptocurrency market shifts can influence traditional markets, particularly during economic downturns as investors seek safer investments. This dynamic becomes more complicated in emerging markets, which, like cryptocurrencies, experience high volatility and speculative swings (De santis, 1997; Pagliari and Hannan, 2024). As a results, it becomes crucial to examine whether cryptocurrencies intensify risk in the emerging markets traditional asset classes or complement them as diversification tools (Charfeddine et al., 2020).

Studies conducted by Jareno et al., (2020); Jeribi and Masmoudi (2021) and Iyer and Popescu (2023) have explored the volatility spillovers between cryptocurrencies and traditional assets, however; there is a notable gap in emerging markets. Furthermore, the findings of the existing studies are conflicting as some suggest weak connection, whilst others suggest a strong connection between cryptocurrencies and traditional assets. As such, this study seeks to add in the existing literature about the connection between digital assets and traditional assets, focusing on emerging markets and further reveal the assets that are a source of risk transmission and the connection strength between these assets during the crisis and non-crisis periods.

1.3 Research aim and objectives

The aim of this study is:

- To investigate volatility spillovers and interconnectedness between cryptocurrencies and traditional asset classes in emerging markets.

The study intends to achieve this aim through the following objective:

- To investigate volatility spillovers and interconnectedness between cryptocurrencies and stocks, bonds and commodities in emerging markets.

1.4 Research questions

The study seeks to achieve the objectives by answering the following research questions:

- What is the nature of volatility spillovers and connectedness between cryptocurrencies and stocks, bonds and commodities in emerging markets?

1.5 Scope and method of this study

1.5.1 Scope of the study

Cryptocurrencies are highly volatile assets making them riskier investments, especially during times of increased volatility in financial markets. To fulfil the research objectives, this study uses the emerging markets' traditional asset classes to assess their volatility spillovers and interconnectedness with the cryptocurrencies. The study employs five cryptocurrencies based on popularity and on how long the cryptocurrency has been existing which are Bitcoin, Ethereum, Ripple, Tether and Litecoin and the study further incorporates the cryptocurrency index (Bloomberg Galaxy Crypto Index) as a proxy of cryptocurrency markets, to purposely examine spillovers effects from the whole market of cryptocurrencies to traditional asset classes. Accordingly, three traditional assets class indices representing stocks, bonds and commodities are selected, these are Morgan Stanley Capital International Emerging Market Index for stocks, Emerging Market Bond Index for bonds and because commodities are not country specific, Bloomberg Commodity Index is used for precious metals and Bloomberg Galaxy Commodity Index is used for all commodities. Since cryptocurrencies are a relatively new market compared to traditional asset classes, the study period was chosen based on the inception dates of cryptocurrencies, ranging from October 2019 to January 2024. This period is deemed long enough to capture volatility spillover effects during non-market and market crises, with the COVID-19 pandemic serving as the reference point of this study. The price of cryptocurrencies fluctuates significantly, therefore; daily closing prices were considered to be more accurate to sufficiently capture all the trends in the cryptocurrency market.

1.5.2 Method of the study

To investigate the volatility spillovers and interconnectedness between cryptocurrencies and traditional asset classes in emerging markets, the Diebold and Yilmaz connectedness approach is applied. However, the DY approach has several drawbacks such as the rolling window size being predetermined with no specific criteria of selecting the optimal window size. Therefore, to overcome the drawbacks of the rolling window VAR approach, the study supplements these results with the modified approach of Diebold and Yilmaz which is the TVP-VAR method. All the objectives of this study were achieved through these two empirical methods, with the TVP-VAR having more reliable results as compared to the DY approach.

1.6 Significance of the study

This study makes a significant contribution to the existing literature for several reasons. Firstly, while numerous studies, including those by Bouri, Gupta, Lahiani, and Shahbaz (2018); Symitsi and Chalvatzis (2018); Urquhart and Zhang (2019); Zeng, Yang, and Shen (2020); Wang, Liu, and Wu (2022) and Attarzadeh and Balcilar (2022) have examined the relationship between cryptocurrencies and traditional assets, they primarily focus on Bitcoin, overlooking other important cryptocurrencies such as Ethereum and Tether. As such, this study incorporates a variety number of cryptocurrencies including the cryptocurrency index to demonstrate how the whole market of cryptocurrencies is connected to traditional financial market. Furthermore, Tether is utilized as a stable coin to evaluate its role as a stability cryptocurrency during market downturn.

Secondly, several existing studies such as Jareno et al., (2020); Jeribi and Masmoudi (2021) and Iyer and Popescu (2023) focuses more on developed markets, thus leaving a significant gap in emerging markets. As such, this study focuses on the traditional asset of emerging markets as they are essential participants in the world economy, with unique economic framework. This provides an insight as to how cryptocurrencies are connected with traditional asset classes in emerging markets by examining how shocks in asset may spillover to another.

Lastly, the study looks to advance knowledge of the changing financial environment among academics. This information will benefit the scholars and investors, financial analysts, and legislators who must negotiate the complex workings of a world monetary system that is becoming more interconnected daily. Moreover, the study's importance ultimately stems from its capacity to enhance risk assessment and guide decision-making of investments in emerging markets.

1.7 Structure of the thesis

This study compromises of six chapters. Chapter 1 examined the significant volatility spillovers and rapid growth of cryptocurrencies, along with their connection with traditional asset classes. It further outlined the problem statement, research aim and objectives, research questions, and the study's scope and significance. Chapter 2 covers two key components: first, it explores the theoretical frameworks that underpin the current study, and second, it provides a comprehensive discussion of cryptocurrencies and traditional asset classes. Chapter 3 examines the empirical evidence on the relationship between cryptocurrencies and traditional asset classes. It is organized into three sections: firstly, a review of general studies that are not specific to any country or market; secondly, a review of studies on developed markets; and finally, a review of studies centered on developing markets. Chapter 4 discusses the data and sample used in the study and further discusses the empirical models that are used to achieve the objectives of this study. Chapter 5 displays the results as per the method discussed in Chapter 4 and provides a detailed analysis and discussion of the findings. Chapter 6 summarizes the findings of the study in line with the research questions and further outlines the implication of the findings to the market participants, policymakers and academics and provides recommendations for similar future studies

1.8 Summary and concluding remarks

This chapter provided a significant background of this study by thoroughly outlining all the crucial key concepts associated with the study. Cryptocurrencies were evaluated and explained accordingly by highlight their volatile nature which possess both the benefits and gains to the market participants. Furthermore, the traditional assets were discussed and their possibly connection with the cryptocurrencies was assessed with a specific focus on emerging markets. The chapter further covered the problem statement, research objectives, research questions, scope, method, significance and structure of the study. The following chapter discusses the theories underpinning the current study and the important concepts associated with the study.

CHAPTER TWO: THEORETICAL FOUNDATIONS

2.1 Introduction

Theoretical foundations are equally important in research by ensuring coherence and linking prior studies to the current study. This linkage highlights a research contribution to the body of knowledge in the field. By summary, cryptocurrencies are emerging as a modern medium of exchange, built on a blockchain system that eliminates the need for banks, enabling peer-to-peer transactions. However, their high volatility makes them a risky investment, particularly in developing markets, which are also marked by significant volatility and growth fluctuations. As such, this chapter provides a theoretical background of cryptocurrencies and traditional asset classes. Therefore, Section 2.2 discusses different theories underpinning the current study by explaining how they align and interact with the research. Section 2.3 analyses the cryptocurrency market, examining its history, functionality, benefits and limitations. Finally, Section 2.4 discusses the selected traditional assets with a specific focus on emerging markets.

2.2 Theories underpinning the study

This study identifies three key theories that are highly relevant to understanding linkages in financial markets pertaining the study, these are inclusive of the Modern Portfolio Theory, Financial Contagion Theory, and the Adaptive Market Hypothesis. As such, this section provides a concise discussion of each theory and further highlights its relevance to the current research. By examining these theories, the study enhances a strong theoretical framework to examine the volatility spillovers and interconnectedness between cryptocurrencies and traditional asset classes in emerging markets

2.2.1 Modern Portfolio Theory

The modern portfolio theory (MPT) has played a crucial role in linking markets globally by providing a more structured framework of understanding relationships between various types of assets across diverse markets (Surtee and Alagidede, 2023). The MPT developed by Harry Markowitz in 1952, is an investment theory that seeks to optimize a portfolio's expected return by adjusting and choosing the proportions of different assets in the portfolio (Francis and Kim, 2013). The MPT asserts that all investors are risk-averse and will prefer the investment with lower risk if two options offer the same expected returns (Swisher and Kasten, 2005; Martellini, 2008). However, the theory further highlights that investors will accept an increased risk only compensated with increased returns (Beyhaghi and Hawley, 2013). Therefore, in the context of this study, the MPT provides a guiding principle for how investors in emerging markets should balance their portfolio between cryptocurrencies and traditional assets. As such, investors attempt to minimize a specific risk by choosing a diversified portfolio called efficient portfolio[6] (Orman and Duggan, 1999; Lukomnik and Hawley, 2021). The MPT contributes enormously in making decisions that decreases portfolio volatility by considering all assets together and it encourages investors to assess their risk profile and tailor their portfolio accordingly. As a result, the theory is heavily used in psychology as it serves as one of the foundations for behavioural finance and economics (Ou, 2023). Furthermore, Elton and Gruber (1997) emphasise that a combination of client's risk tolerance and return expectations are considered as the best way to design a portfolio in order to maximise the level of expected return for a given level of risk.

As such, Francis and Kim (2013) mention that in the MPT a combination of assets such as digital assets, stocks, bonds and real estate can be used to achieve diversification benefits, adding to the main emphasis of the theory which is to reduce portfolio volatility without sacrificing returns by combining assets with low and negative correlation. Therefore, the introduction of cryptocurrencies presented both challenges and opportunities to the main emphasis of the MPT. These contrasting views of cryptocurrencies to the MPT are in line with Letho et al., (2022) who highlighted that cryptocurrencies such as Bitcoin and Ethereum are highly volatile with minimal correlation to traditional asset classes, thus introducing risk and gains to a portfolio. However; Chen, (2023) states that having the cryptocurrencies on the traditional MPT framework must be substantiated by a full understanding of unique traits of crypto market, attraction of investors alpha[7] particularly in periods of market downturn and the extreme fluctuations posing risks of destabilizing a portfolio. Therefore, this theory advocates a balance of the potential benefits of diversification with cryptocurrencies against their inherent risks.

Diversification in the Modern Portfolio Theory

Diversification is a core concept associated with the MPT as it plays a vital role in assisting investors to maximise full returns while minimising the risks (Biswas, 2015). Accordingly, financial wisdom has always advised against putting all eggs in one basket, encouraging the practise of diversification (Lecraw, 1984). As such, analysing the correlation patterns between cryptocurrencies and traditional assets is crucial for an effective investment strategy for the

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[6] An efficient portfolio, also referred to as an "optimal portfolio," delivers the highest expected return for a given level of risk or, alternatively, the lowest risk for a specified expected return.

[7] Alpha describes an investment strategy capability of beating the market or its edge.

investors in emerging markets. Elton and Grubear (1997); Dhir and Dhir (2015) state that investing all of your money in investments with highly correlated returns is not a rational approach, regardless of the little possibility of any individual investment collapsing. If one investment collapses, the other investments are likely to follow suit, resulting in the entire portfolio collapsing. This contradicts with the popular Efficiency Market Hypothesis (E-M-H) developed by Eugene Fama in 1960 which posits that investors are always rational (Timmermann and Granger, 2004)

Furthermore, Reinholtz et al. (2021) emphasise that diversifying investments across low to moderately correlated assets assist in reducing the volatility of an investment portfolio. This aligns with Cohen and Handy (2001), who proposed that monitoring correlations is crucial strategy to effective diversification since it assist to minimize a portfolio's vulnerability. The evidence presented Asuero et al., (2006) revealed that correlations between asset types, such as fixed income, stocks, real estate, and digital assets, is minimal. This happens because different asset classes react differently to changing market conditions, which can be influenced by factors like geopolitical events and adjustments in monetary policies. Therefore, this presents a great opportunity of achieving diversification between cryptocurrencies and traditional assets.

2.2.2 Theoretical Perspective on Financial Contagion

One of the most crucial consideration in the financial markets, particularly relevant to this study, is the Financial Contagion Theory (FCT) which explains how financial shocks or crises can spread across markets leading to severe economic crisis (Seth and Panda, 2018). Rigobon (2002) highlights contagion as one of the least understood yet most referenced phenomena in international finance. This followed after the 1997 Asian crisis and the 1998 Russian financial crisis, during which investors became increasingly wary of contagion risks and began to doubt the advantages of international diversification, especially in emerging markets (Rigobon, 2002). Contagion occurs when one or more assets experience a shock, leading to a considerable rise in cross-market links (Imen and Rim, 2012). In essence, contagion is the spread of financial disruptions between markets. However, Kaminsky and Reinhart (2000) argue that contagion occurs when standard shocks and all routes of potential interconnectivity are either absent or controlled highlighting that contagion is not a one-way street.

As such, Roberto Rigobon's 2002 paper outlined several methods through which shocks are transmitted across markets (Rigobon, 2002). Bilateral links are seen as the primary and most straightforward propagation channels, while indirect connections serve as less apparent means of transmission. Corsetti et al., (2011) mention that even if two markets do not possess bilateral links, a shock in one may be transmitted to the other through a third market that is correlated to both. Additionally, Pritzker (2001) highlights investor behaviour as another transmission mechanism, where a shock in one market prompts investors to re-evaluate risk in other markets with comparable characteristics. Lastly, Rodriguez (2007) identified liquidity links as another shock transmission mechanism, where a disruption in one market triggers margin calls, prompting investors to sell assets in other markets as they adjust their portfolios.

Conventionally, financial contagion occurs through channels such as the interconnectedness of financial institutions, common exposures to risk factors and investor panic or herding behaviour (Baur, 2012). These channels can propagate a shock hitting one market amplifying volatility and triggering widespread sell-offs across between cryptocurrencies and traditional asset classes. Cryptocurrencies operate independently of traditional financial institutions and have regulatory frameworks, which can shield them from certain contagion channels affecting traditional assets (Ferreira and Pereira, 2019). However, their integration into global financial markets through trading platforms and investment vehicles has increased their interconnectedness with traditional assets which can thus leading to contagion between the two assets. Kolb (2011) identifies two distinct types of contagion: "pure contagion," which occurs independent of fundamental factors, and "fundamentals-based contagion," which is driven by underlying economic or financial factors.

2.2.2.1 Pure contagion

Pure contagion is one of the most prevalent forms of contagion, primarily driven by the behavioural and psychological factors influencing investor decisions (Kaufman, 1994). In essence, pure contagion explains a situation where shocks arising from economic distress may spread rapidly from one market to another, regardless of the minimal or absence of correlation that exists between them which can largely occur between cryptocurrencies and traditional assets (Kanas, 2005). The market sentiments such as speculative pressures and panic selling are the primary drivers of this contagion by intensifying volatility, thus undermining the benefits of diversification (Ludwig, 2014). Groening and Kanuri (2013) state that investors tend to react irrational during economic downturns, leading to herd behaviour and extensive sell-offs across uncorrelated assets. As such, pure contagion challenges traditional risk management strategies that rely on correlations and economic fundamentals, highlighting the importance of understanding and mitigating behavioural biases in financial markets to prevent cascading effects during periods of market stress or uncertainty particularly in emerging markets (Kumar and Persaud, 2002).

2.2.2.2 Fundamentals-based contagion

Fundamentals based contagion differs significantly from true contagion. Chang and Majnoni (2002) describe fundamentals-based contagion as a situation that occurs during an economic downturn where shocks in one market spreads to others, controlled by the underlying economic factors rather than market sentiment and irrational panic. Amid the COVID-19 pandemic, this type of contagion has been evident in the interactions between cryptocurrencies and traditional assets in emerging markets (Ullah, 2024). However, Fundamentals-based contagion often occurs when markets are interconnected through investment or sharing economic policies (Gallegati, 2012). As such, Gómez-Puig and Sosvilla-Rivero (2016) highlight that this form of contagion emphasizes spillovers that stem from the normal interdependence between market economies. Such interdependence means that shocks, whether global or local, can be transmitted across markets due to their real and financial connections. Accordingly, Manz (2010) points out that while these movements would typically not be classified as contagion, they can be considered as such if they happen during a crisis and have a negative impact.

2.2.3 Adaptive Market Hypothesis

Introducing a different perspective compared to the two theories discussed above is the Adaptive Market Hypothesis (A-M-H). The AMH which was developed by Lo in 2004, is a combination of a well-known EMH and Behavioural Finance Theories (BFT). Lo (2004) identifies that individuals are rational but can sometimes overreact during times of heightened market volatility opening up buying opportunities, which remains relevant for cryptocurrencies and traditional assets during the COVID-19 pandemic. He further suggests that investor behaviours like loss aversion, overconfidence, and overreaction align with evolutionary models of human behaviour, which encompass actions such as competition, adaptation, and natural selection. The AMH suggests that investors learn from their mistakes and form future predictions based on previous experiences (Urquhart and McGroarty, 2016). In this approach, Ghazani and Araghi (2014) reveal that investors use trial and error method, if the investment strategy fails, investors are likely to take another strategy next time and if the strategy succeed, they are likely to try it again.

Furthermore, Ghazani and Araghi (2014) highlight that the AMH merges the concepts of the EMH, which posits that markets are rational and efficient, with the perspective of behavioural of finance, which asserts that markets are irrational and inefficient. The EMH has long been the prevailing theory, asserting that it is impossible to outperform the market because all securities are traded at their fair value, making it unfeasible to purchase undervalued stocks or sell them at inflated prices (Khursheed et al., 2020). In contrast, behavioural finance theory emerged in an attempt to explain market anomalies through psychological based theories, it states that investors are irrational and stocks are not trading at fair value during market crisis and uncertainties (Shleifer, 2000). Therefore, the AMH integrates these opposing perspectives to explain investor and market behaviour, suggesting that both rationality and irrationality coexist, and it applies evolutionary and behavioral principles to financial interactions. (Saritepeci, Kapusuzoglu and Ceylan, 2023).

The AMH contends that investors are largely, but not perfectly, rational and they participate in satisficing behaviour rather than maximizing behaviour, and they build market heuristics based on a market's natural selection mechanism (Tripathi and Dixit, 2020). This causes markets to function primarily rationally, comparable to the EMH, in situations where those heuristics apply. However, during significant changes or economic shocks, the market's evolutionary environment is altered, causing previously adaptive heuristics to become maladaptive (Mörke, 2018; Chalamandaris, 2020). This mean that under periods of rapid change, stress, or abnormal conditions, the EMH may not hold. Accordingly, the characteristics of AMH can be summed up as follows, people behave in their own best interests, people make mistakes, people learn from them and adapt, competition promotes innovation and adaptation, natural selection shapes the market's ecology and evolution establishes the dynamics of the market (Li, Li and Xiao, 2021).

As a result, Dhankar and Shankar (2016) mention the AMH acknowledges the time-varying fluctuations that exists in financial markets. Therefore; in cryptocurrencies and traditional asset, the AMH suggests that market efficiency varies and adapts based on the dynamics of investor behaviour, market conditions, and the overall economic environment (Brini and Lenz, 2024). For instance, the rapid innovation and high volatility in the cryptocurrency market may lead to periods of inefficiency as investors adapt to new information and technologies. Conversely, traditional asset classes, while generally more stable, can also experience shifts in efficiency due to changing economic policies, technological advancements, and evolving market structures. The interplay between these two markets can further illustrate AMH as events in one market may lead to adaptive behaviours in the other thus reflecting contagion (Parfenov, 2022). Building on the discussion and the relevance of the theories discussed, cryptocurrencies emerge as the central variables of this research. Therefore, the following section delves deeper into cryptocurrencies, providing a comprehensive overview of these digital assets and their broader implications.

2.3 An overview of cryptocurrencies

Similar to how the internet marked a turning point in the development of communication, cryptocurrencies have a potential of representing the next step in the evolution of finance in this rapidly growing technological era (Joseph et al, 2022). Cryptocurrencies do not require banks to authenticate transactions as they are a digital payment. In more technical terms, cryptocurrencies are a peer-to-peer system that allows anybody, anywhere to send and receive payments (Zohuri et al., 2022). Kumar (2018) highlights that cryptocurrency payments are made through digital entries in an online database that records individual transactions, unlike physical money that is used and exchanged in the real world. A public ledger records all cryptocurrency transactions, documenting the transfer of funds, while crypto wallets are used to store the cryptocurrencies. Zohuri et al, (2022) highlight that cryptocurrencies acquired the name because they utilize encryption to verify transactions, this means advanced coding is involved in storing and transporting cryptocurrency data between wallets and to public ledgers and the purpose of encryption is to ensure safety and security.

Kumar (2018) further explains that cryptocurrencies rely on blockchain, a decentralized public database that records all transactions, with updates managed and stored by the currency holders. Accordingly, Caliskan (2020) points out that cryptocurrency units are generated through a process called mining, which involves using computational power to solve intricate mathematical problems. Additionally, users can buy cryptocurrencies from brokers and store or spend them in secure wallets. Moreover, Caliskan (2020) explains that the key difference between fiat currency and cryptocurrency is that the latter exists as a digital form of value, unlike fiat money, which takes a physical form such as paper or coins. Fauzi et al. (2020) state that cryptocurrencies and blockchain technology are still in the early phases of financial development, with future applications expected. Consequently, the technology could eventually be used for transactions involving bonds, equities, and other financial assets.

The term cryptocurrency became popular after Bitcoin's rise in 2009 following the global financial crisis of 2008 as a response to traditional financial system which perceived lack of trust (Brini and Lenz, 2024). Bitcoin is the most commonly known and used cryptocurrency in the world with the current market capitalization of just over 10 billion US dollars (Coin Market

Cap, 2025). Bitcoin was originally introduced by Satoshi Nakomoto as a strictly peer-to-peer electronic payment system and a solution to the problem of double-spending (D’Alfonso, Langer and Vandelis, 2016; Fauzi et al, 2020). As such, Bitcoin aims to eliminate the need for financial institutions or trusted third-party entities by reducing fraud, enhancing efficiency, and providing objective proof-of-work for transaction legitimacy and security. As a distinct market to the traditional financial systems, cryptocurrencies operate with their own unique activities.

Lahajnar and Rozanec (2018) state that the cryptocurrency market hosts an Initial Coin Offering (ICO) to finance projects in the blockchain development which is similar to Initial Public Offering (IPO) in the stock market. As a result, Barsan (2017) highlight ICO in cryptocurrencies has a potential of making sizeable profits, however a lack of regulation makes them extremely risky. One of the most prominent cryptocurrencies, Ethereum was initially funded through ICO, where during a period of 22nd July and 2nd September 2014, a campaign raised a total amount of 18 million US dollars (Coin Market Cap, 2014). Investors in the Ethereum ICO received Ethereum in return for Bitcoin, and more than 2.2 million US dollars in Ethereum were sold within 24 hours of the ICO's launch. However, Kumar (2018) state that despite Ethereum growing at a significant rate over the past years, its market capitalization is approximately 10 percent of Bitcoin, demonstrating the dominance of Bitcoin in the cryptocurrency market.

Bitcoin's dominance has shifted significantly over the years. In its early stages, BTC dominated the cryptocurrency sector significantly as it was relatively small and consisted of only Bitcoin and a few smaller ventures (Kulal, 2021). Figure 2.2 below depicts the dominance of Bitcoin in the cryptocurrency sector from 2014 to 2024. However; over time, a lot more resources and capital have been invested in the cryptocurrency and blockchain sectors. As a result, projects such as Ethereum have delivered technological advancements while also earning considerable valuations (Choudhary, 2021). The year 2017 was particularly significant, since the rise of "altcoins" caused Bitcoin dominance to decline drastically (Nguyen et at., 2019).

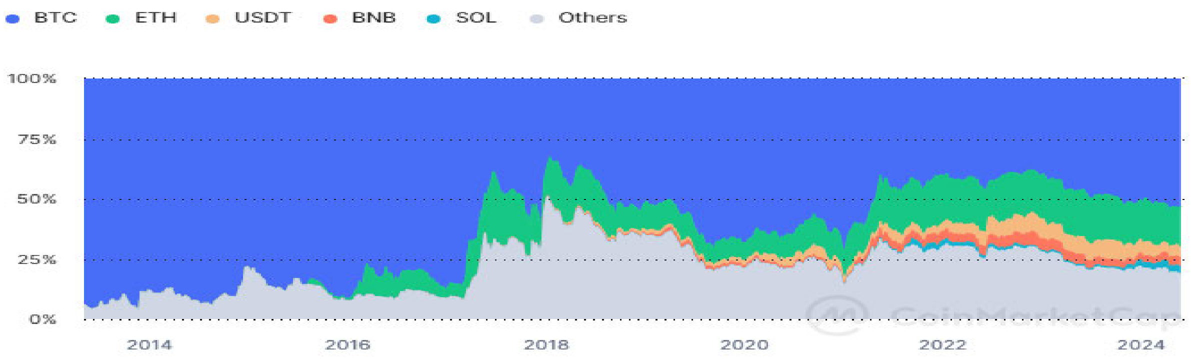

Figure 2.2: Market capitalization of Bitcoin and other cryptocurrencies

Source: Coin Market Cap (2024)

There have been several debates with the classification of cryptocurrencies, as there are thousands of cryptocurrencies but they are not all the same (Hossain, 2021). Accordingly, Pele et al., (2020) mention that cryptocurrencies lack a general accepted definition that aligns with current economic theories. Therefore; the argument is that despite several cryptocurrencies sharing a blockchain technology infrastructure, there are some significant differences between them. The I.M.F report (2019) states that cryptocurrencies can be separated into two branches: Bitcoin-like crypto assets (BLCA) (Coins) and digital tokens.

BLCAs are digital coins that use distributed ledger technology as a medium of exchange, examples include Bitcoin, Ethereum, Ripple, Bitcoin Cash, EOS, Stellar, and Litecoin (I.M.F, 2019). A coin is any cryptocurrency with its own independent blockchain. Bitcoin, for example, is classified as a "coin" because it is supported by its own technology. Similarly, Ethereum operates on the Ethereum blockchain. Subsequently, the term "altcoin" refers to an alternative coin other than Bitcoin (Spurr and Ausloos, 2021). Many cryptocurrencies operate similarly to Bitcoin, however; others, like Dogecoin, are very different. Doge, for example, has an unlimited quantity of coins, whereas Bitcoin has a limit of 21 million coins (Pele et al., 2020). Similar to coins, digital tokens are also electronic assets that can be bought or sold, however; digital tokens fall into four kinds based on their economic function (IMF, 2019). Table 2.1 below illustrates the four kinds of digital tokens.

Table 2.1: Four kinds of digital tokens

Token type	Definition
Payment tokens	Are meant to become BLCAs and be used as units of account, stores of value, and payment methods globally not just on a particular platform, example includes Litecoin
Utility tokens	Enables future access to services through DLT-based applications. Examples of such applications include file storage, social messaging, and trading such as Ether, Binance currency, and Filecoin
Asset tokens	Are those that represent debt or equity claims on the issuer. These instruments offer interest or a portion of the company's future earnings
Hybrid tokens	Are ones that function as both a utility token and an asset or payment token.

Source: Construction based on IMF (2019)

Furthermore, cryptocurrencies have several benefits and limitations in the financial systems, this is line with many researchers such as Alqaryouti, Siyam, Alkashri and Shaalan, (2019); Zakarneh, Qaroush and Dawabsheh, (2022) and Darmawansyah, Polindi, Fitriani, Aguspriyani, Setiadi and Sanawi (2023) who have conducted studies based on the benefits and limitations of cryptocurrencies. Thus, the subsequent sections discuss the benefits and limitations of cryptocurrencies.

2.3.1 Benefits of cryptocurrencies

The high growth in cryptocurrency market capitalization can be explained by the several benefits that these digital currencies offer as compared to traditional currencies. For instance, Bunjaku et al. (2017) believe that transparency is the key driver of cryptocurrency success. That is because, everyone in the system may view the financial transactions of the other participants, making the system incredibly transparent unlike the traditional bank method of payments, where the client has only information about its own account. Bunjaku et al. (2017) further state that cryptocurrencies offer anonymity, privacy and confidentiality. Moreover, Inshyn et al, (2018) uncover that cryptocurrencies have an advantage of eliminating the need for intermediaries, leading to faster and cheaper transactions that are cost-effective, with no banking fees, simplifying international trade and providing strong security.

Sanneh (2022) also emphasizes that cryptocurrencies are borderless, transactions within this system are irreversible, and the coins cannot be counterfeit, duplicated, or reused. These features maintain the system's integrity, leading to a continuous increase in the number of online businesses, resources, and companies that accept Bitcoin each month. (Zakarneh, Qaroush and Dawabsheh, 2022). Furthermore, the decentralization of cryptocurrencies offers an advantage to the network by eliminating the need for a central governing authority. Malherbe et al. (2019) emphasize that the network is distributed across all users, with every computer mining bitcoins acting as a member of the system. This implies that a central authority cannot enforce rules on bitcoin owners, and even if a section of the network fails, the payment system will remain operational (Frebowitz, 2018).

Additionally, Bunjaku et al. (2017) explain that cryptocurrencies are user-friendly, especially when compared to traditional banking procedures. For example, opening an account with a Ukrainian bank can be complex and may be denied without reason, making Bitcoin a more convenient option for businesses. The company takes about five minutes to setup a cryptocurrency wallet and immediately starts using it without any questions or commissions (Tredinnick, 2019). Darmawansyah et al., (2023) present the unlimited transactions possibilities as another advantage of cryptocurrencies as each wallet holder can pay anyone, anywhere, and for any amount. This is because the transaction cannot be regulated or blocked, funds can be transferred to anyone in the world who has a Bitcoin wallet.

Another benefit of the cryptocurrency market is its increasing recognition as an asset class that is not correlated with traditional markets (Almeida and Gonçalves, 2022). In theory, cryptocurrency markets function mostly independently from traditional markets, with their price movements driven by factors distinct from those influencing traditional assets. Therefore, Kurka (2019) state that cryptocurrencies offer investors with diversification with another vehicle of growing their money outside of stocks, EFTs or bonds as crypto has its own unique risks, but it is another avenue for potential returns for investors. Furthermore, Bitcoin can act as a hedge for inflation (Conlon, Corbet and McGee, 2021). This is based on the evidence presented by Wagenaar (2022) that the maximum number of coins is accurately limited to 21 million Bitcoins, therefore, there is no chance of inflation developing in the system because neither political forces nor corporations have the ability to change this arrangement.

2.3.2 Limitations of cryptocurrencies

Despite cryptocurrencies offering numerous benefits, they also have drawbacks that limit their market growth. One of the most feared phenomena in the cryptocurrency market is volatility. Yen and Cheng (2021) define volatility as a measure of the extent to which prices fluctuate over a given period. Cryptocurrency prices often fluctuate significantly due to their detachment from traditional assets. While this volatility can lead to quick gains, it can also cause big financial losses for investors, particularly when the price of cryptocurrency experience sudden drops. This volatility can be a risky financial decision, particularly for those seeking steady returns (Yen and Cheng, 2021). Bunjaku et al. (2017) highlight that almost all of the ups and downs in the cryptocurrencies value are directly correlated with the announced comments of governments in different countries and this volatility causes a concern in the short run. The following highlights the most prominent factors that lead to high volatility in cryptocurrencies.

2.3.2.1 Price discovery

It is widely recognized that all new ideas take time to establish and be accepted, and this holds true for cryptocurrencies as well. Investors are still trying to find their feet within this market in its early age and driven by high growth phases (Tang, 2024). Except for Bitcoin, which has been around for approximately 15 years, most cryptocurrencies are still in the price discovery phase. This suggests that price fluctuations will continue as new participants join the market, working to determine the fair value of digital assets (Fang et al., 2024). Maturity in the market and growing acceptance goes hand in hand, therefore; Fang et al. (2024) state that until investors gain more confidence in the long-term utility and regulatory clarity of cryptocurrencies, the price discovery process will remain a significant factor driving volatility in the cryptocurrency market.

2.3.2.2 Immature markets

The crypto market is still very much in development phases as compared to asset classes like stocks and bonds, leading to investors not gaining enough exposure to the crypto market and making them retail heavy (Brini and Lenz, 2024). The exposure of investors to cryptocurrencies is constrained due to the increasing institutional adoption of cryptocurrencies and the derivative products and other ways of hedging are still in their early stages. Kleist (2024) notes that cryptocurrencies have limited liquidity and market depth, making it difficult for larger traders to operate, as the total market capitalization of cryptocurrency is only a small portion of the U.S. stock market's size. As a result, large players find it challenging to enter or exit the market in significant amounts without influencing prices and causing market movements.

2.3.2.3 Supply and demand dynamics

The balance between supply and demand is a key factor in determining the volatility and price fluctuations of any asset. However, this relationship is especially complex in the cryptocurrency market due to the differences in supply characteristics of various digital assets. (Asif and Unar, 2024). The sudden increased demand in cryptocurrencies is often created by the limited supply of certain assets leading to greater upward pressure on prices, increasing volatility with Bitcoin being the most prominent example of fixed supply with a limited supply of 21 million coins (Al-Murisi, 2024). This pressure can increase when big investors buy or sell large amounts of a specific asset, possibly causing its price to rise or fall sharply. Kukacka and Kristoufek (2023) note that the crypto market still lacks the efficiency to handle supply and demand shocks without causing noticeable price fluctuations. Because of limited liquidity, smaller assets are especially vulnerable to the effects of large trades, making them more volatile and riskier

2.3.2.4 Market sentiment

Investor sentiment plays a significant role in the crypto markets. The market's immaturity means that both negative and positive opinions can spread rapidly, much like a contagion (Doroslovački et al., 2024). Accordingly, Chen et al. (2019) mention that this can be attributed to the psychology of cryptocurrency investors, who are usually individual or retail investors. These investors tend to be less informed and more influenced by market sentiment compared to experienced traditional investors. One key factor in speculative assets is the fear of missing out (FOMO), where investors often hear stories of rising prices during a bull market and others profiting, which motivates them to jump in and encourage their friends and family to do the same. This can lead to a self-reinforcing cycle, where excessive and unsustainable demand for an asset drives significant price fluctuations (Abraham, 2024).

2.3.2.5 Lack of regulation

Unlike traditional financial markets, the crypto market lacks global regulation by government authorities, which contributes to instability, as regulation plays a crucial role in controlling market volatility (Xiong and Luo, 2024). The digital and decentralized nature of cryptocurrencies poses significant challenges for regulators worldwide. Uzougbo et al. (2024) note that while key figures within the cryptocurrency industry have consistently pushed for regulation to safeguard consumers and give legitimacy to the sector, policymakers have made slow progress in addressing these calls. The absence of clear regulations hinders exchanges from listing assets that are being investigated by regulatory authorities as part of legal proceedings.

Cryptocurrencies are completely anonymous, as a result they are commonly employed by crime syndicates and other individuals engaging in illegal activities (Rice, 2019). Offenders believe that using cryptocurrencies to launder money is the greatest option because they are not subject to government regulation and this can present challenges for investors because the market is totally anonymous (Ozturk and Sulungur, 2021). Therefore, it is possible that investors are supporting these money laundering schemes without even being aware of it, as such investors who deal in cryptocurrencies run the risk of becoming involved in legal issues (Bondarenko et al., 2019). Several investors are trying to avoid this problematic scenario by avoiding to invest in cryptocurrencies altogether, whilst issuing and accepting of cryptocurrency has been declared illegal in different countries and investors trading these currencies despite the ban may face legal repercussions.

Fama (1970) posits that a market is efficient when prices reflect all available historical information. Cryptocurrencies, being relatively new, lack a long history of reliable data, limiting investor’s ability to forecast their future performance (Fauzi et al., 2020). Since Bitcoin’s inception in 2009, the absence of historical depth and institutional anchoring has made the market prone to speculation. As a result, the crypto market has exhibited characteristics consistent with speculative bubbles, where prices deviate significantly from intrinsic values due to irrational exuberance, herd behavior, or media hype (Cheah and Fry, 2015; Urquhart, 2016). These speculative bubbles manifesting in sharp price surges followed by severe crashes that are increased by the lack of regulatory oversight, which fails to impose mechanisms that could lesses excessive volatility or enforce valuation-based trading. The absence of investor protections or circuit breakers found in traditional markets has allowed crypto prices to be heavily swayed by sentiment, often disconnected from fundamentals. As Cheah and Fry (2015) and Urquhart (2016) suggest, the volatility, price bubbles, and sudden crashes observed in cryptocurrency markets could be mitigated by introducing more transparent systems to track transactions and hold asset values stable.

Moreover, cryptocurrencies are relatively new, hence there is still confusion about how the gains from these investments should be taxed, since the rules are not entirely clear (Cong et al., 2023). As such, Thiemann (2021) presents that the majority of nations do not have tax benefits from cryptocurrency in their tax legislation. Investors are required to declare and pay taxes on the income, even if this has not been done specifically. Since governments lack a reliable process for determining the exact income from cryptocurrencies. Cong et al. (2023) state that some investors have attempted to avoid paying taxes on them and this has led them into troubles with the tax authorities. In many situations, investors truly wanted to pay their obligations. However, due to confusion regarding the exact form of the tax that must be imposed to cryptocurrencies, they have been unable to do so. As a result, paying taxes on cryptocurrency is a complicated process with high transaction costs (Basson, 2020)

2.4 An overview of traditional assets classes

Traditional assets form the backbone of many investment portfolios and have been widely utilized in financial markets due to their reliability, established valuation metrics, and historical performance. They are often favoured for their ability to provide stability, predictable returns, and a foundation for long-term wealth accumulation. As such, Alles and Athanassakos (2006) highlight that something gains popularity whenever it becomes beneficial to people and when something becomes popularity, it has the potential to become an asset class. However, only when something becomes essential does it acquire the status of a recognized asset class. Alles and Athanassakos (2006) further state that once an idea or object of value is essential to the survival or efficient operation of society and the economy, individuals will seek ownership, and the concept is rooted in the foundation of society and the economy. An example is human beings, who have long regarded certain objects as essential assets, such as food, housing, clothing, and water (Walker, 2015). Therefore; stocks, bonds and commodities are valuable because they enable people to participate in the production of new assets and creates wealth. Thus, the following part discusses the characteristics of each selected traditional asset class in this study.

2.4.1 Selected traditional asset classes

Several traditional asset classes exist worldwide, primarily because they are well-established investment types that are widely accepted across many countries. Among these, stocks, bonds, and commodities are identified as the most relevant for achieving the objectives of this study. These asset classes represent varying levels of risk and are integral components of investment portfolios due to their diverse characteristics and widespread utilization. Therefore, this section discusses these traditional assets in more details.

2.4.1.1 Stocks

Stocks play an important role in the global economy by providing companies with the funds they need to grow and innovate. For investors, they offer a way to share in the success and growth of businesses, making them a key part of traditional asset classes. As such, Gil-Alana et al. (2020) define stocks as a portion of a company's ownership, including a claim to its profits and assets and as a result shareholder own a portion of the business, the value of the stock changes in accordance with the business's worth. Stocks are generally bought and sold electronically through stock exchanges, such as the Johannesburg Stock Exchange (JSE) in South Africa and the Shanghai Stock Exchange (SSE) in China. However, some companies sell stock directly to investors, most only sell stock through a brokerage such as Schwab[8] (Chung, 2000).

Jacquet (2021) state that stocks are often the most susceptible to market volatility, as their values are influenced by a multitude of factors such as economic conditions, company performance, and investor sentiment. Stock prices can drop sharply or rise quickly during times of strong market volatility. For example, the 2008 global financial crisis led to significant volatility in the stock market, causing the value of several equities to decline, especially in emerging markets that were prone to high volatility. Investors who had spread their holdings throughout several industries and geographical areas were better equipped to endure the economic downturn (Jacquet, 2021). Bhowmik and Wang (2020) highlight that investing in stocks requires diversification and an investor's exposure to the volatility of individual equities can be lessened by diversifying their investments across sectors, industries, and countries.

Musonera and Safari (2008) state that emerging equities[9] offer exposure to fast growing economies and are the key divers of global growth as several entities in developing markets are relatively inexpensive compared to developed markets. As such, Hoeft et al. (2019) emphasize that diversifying investments across a broad spectrum of emerging market stocks, including well-known companies and smaller, lesser-known securities, provides investors with extensive diversification and the opportunity to achieve alpha. For instance, a portfolio that includes both the MSCI Emerging Markets Index and the MSCI World Index of developed market equities would have provided superior risk-adjusted returns over the past two decades compared to one made up only of the MSCI World Index.

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[8] Schwab brokerage - refers to the investment and trading services offered by Charles Schwab Corporation, a leading U.S. based financial services firm.

[9] Stocks can sometimes be referred as equities.

2.4.1.2 Bonds

Also known as debt securities, a bond is any debt that can be bought or sold in the market before it matures. Its structure resembles a debt owing by an issuer (the government, an organization, or a firm) to an investor who serves as a lender. McCauley et al. (2013) mention that bonds are designed for consumers who seek investments with a consistent amount of return. These fixed-income securities have a predetermined interest income (coupons) and maturity term and can be sold before they mature. In this case, the bond price will be determined by the market conditions at the time of sale, as well as the level of interest rates. Municipalities, governments, and corporations are among the entities that sell bonds to investors, companies frequently use the earnings from the sale of bonds to fund new ventures, acquisitions, and continuous operations (Kuehn and Schmid, 2014).

Levy and Levy (2019) point out that bonds offer more stable returns compared to stocks, making them valuable for investors looking to create a well-diversified portfolio. Subsequently, Ranosz (2017) confirms that some bond types are less dependent on market performance than stocks and might be an attractive option for risk-averse investors, such as those who are about to retire or have already retired. However, Maltais and Nykvist (2020) argue that while bonds are generally considered a safer investment than stocks, they still have certain risks one of which being interest rate risk. Interest rates can have a major impact on bond prices as when interest rates rise, bond prices generally fall, and vice versa. Bond default represents a major risk for bond investors, as it may lead to a loss of principal and/or interest if the borrower fails to repay the loan. Generally, the likelihood of default is low for investment-grade bonds.

Bonds in emerging markets are more preferred investment types than bonds in developed markets (Dittmar and Yuan, 2008). While emerging market bonds carry risks, they offer significant potential advantages, particularly in terms of portfolio diversification, as their returns are generally less correlated with those of traditional asset classes. Additionally, many investors seeking to mitigate currency risk in their portfolios choose to invest in emerging market bonds denominated in local currencies, viewing them as an effective hedge against such risks (Bunda et al., 2009). Moreover, developing countries grow rapidly which enhances returns, thus resulting in higher yield returns in emerging debt than those of U.S. treasuries.

2.4.1.3 Commodities

Commodities are crucial for producing goods and services, and their prices often impact the costs of industries worldwide. As a result, commodities are important for economic growth and play a key role in global trade and financial markets. Sraffa (2016) defines commodities as the raw materials used to make the goods that people purchase, such as food, furniture, and gasoline. Commodities include agricultural products such as wheat and cattle, energy products such as oil and natural gas, and metals such as gold, silver and aluminium. Sraffa (2016) also mentions that commodities have developed into a distinct asset class since the 1990s, with the creation of commodity futures indices and the subsequent introduction of investment vehicles that serve as benchmarks for these indices. Nowadays, investors have a wide range of options when it comes to investing in the commodities futures markets, ranging from mutual funds to exchange-traded funds or notes, covering exposures to individual commodities to sector-based and broad-based commodity exposures.

Corbet et al. (2018) emphasize that commodities tend to be more volatile than stocks and bonds, primarily due to their lower liquidity and trading volumes compared to other asset classes, as well as their ongoing vulnerability to weather conditions and production related challenges that can impact supply and demand. Commodities are also very prone to volatility around geopolitical events, as the placement of reserves is specific to different locations. Typically, energy commodities are the most volatile, whereas agricultural commodities see less significant price fluctuations. Baffes et al. (2018) suggest that emerging economies relies more on commodity exports as they are characterized by richness in natural resources and minerals.

2.5 Chapter summary

This chapter discussed the theories underpinning the current study in relation to the investor behaviour towards the cryptocurrencies and traditional asset classes. This was followed by a thoroughly discussion of cryptocurrencies and the selected traditional assets classes as concepts. In summary, the modern portfolio theory strongly recommends diversification within the cryptocurrencies and traditional assets as they may possess a negative relationship particularly in periods of market crisis. Furthermore, the contagion theory is more likely to occur between cryptocurrencies and traditional asset classes as a shock in one asset may spill over to another. The adaptive market hypothesis stresses the time-varying fluctuations within these assets and further asserts that efficiency and inefficiency can co-exist in the digital and traditional market. In addition, most researchers revealed that investing in emerging markets assets is more preferred as compared to developed markets assets. The following chapter will discuss the existing literature between digital assets and traditional assets.

CHAPTER THREE: REVIEW OF EMPIRICAL STUDIES

3.1 Introduction

The preceding chapter explored the theoretical underpinnings of volatility spillovers across different assets and markets, including both cryptocurrency and traditional markets. Expanding on this foundation, the current chapter focuses on empirical studies that analyze volatility spillovers and the interconnectedness between cryptocurrencies and traditional asset classes. This study intends to investigate volatility spillovers between cryptocurrencies and traditional asset classes in emerging markets, however the existing literature addresses several interrelated dimensions of this relationship which includes volatility spillovers, hedging capabilities and connectedness and diversification. As such, the studies are grouped into three subheadings of (1) Spillover effects; (2) Hedging capabilities and (3) Connectedness and diversification, this grouping largely depends on the outcomes of the conducted studies.

3.2 Spillover effects

Bouri, Gupta, Lahiani, and Shahbaz (2018) utilized a range of advanced autoregressive distributed lag (ARDL) models to analyze the dynamic, asymmetric, and quantile-specific influences of the overall commodity index and gold prices on Bitcoin. To capture asymmetries in both the short- and long-term, the study employed a nonlinear ARDL model, alongside the quantile ARDL approach, to assess distributional asymmetry using daily data spanning from July 17, 2010, to February 2, 2017. The findings demonstrated that Bitcoin's price could be predicted based on movements in the aggregate commodity index and gold prices. Additionally, the study revealed that the relationships among gold, Bitcoin, and the commodity index were nonlinear, exhibited asymmetries, and varied across different quantiles. This suggests the necessity for using non-standard cointegration models to capture the complex interactions between Bitcoin and traditional asset classes. The study further highlighted the time-varying nature of these relationships, emphasizing the importance of regular monitoring of Bitcoin in conjunction with traditional assets for investment.

While Bouri et al. found evidence of predictive spillovers from commodities to Bitcoin, other studies suggest a weaker or even negligible level of interconnectedness, Trabelsi (2018) used the Diebold and Yilmaz (2012) model to assess the interconnectedness between the cryptocurrency market, the Bitcoin Price Index (BPI), and key asset classes like stock market indices and commodities. The study used daily dataset spanning from October 2010 to February 2018. The basic idea behind the proposal of Diebold and Yilmaz (2009) was its effectiveness in ranking the assets by their systemic importance (Trabelsi, 2018). Following the original approach of Diebold and Yilmaz (2009), the study utilized Forecast Error Variance Decomposition (FEVD) networks derived from an n-variable vector autoregressive (VAR) model to construct weighted and directed networks from market data. Furthermore, in Diebold and Yilmaz (2012), the Perasan and Shin (1998) generalized variance decompositions (herein, GVD) were proposed which are invariant to variable ordering, to reveal unrelated structural shocks from correlated reduced form shocks. The n-variate stationary process is described as $Yt = (Yt, 1, \dots \dots \dots Yt, n)$ by structural VAR(p) at $t = 1, \dots \dots T$ as:

$$\phi(L)y_t = u_t \tag{3.1}$$

Equation (3.1) follows the generalized forecast error decomposition method of Diebold and Yilmaz (2012). The equation was used to achieve the investigating of spillovers of forecast error variation in an asset "k" due to shock to an asset "j" at a specific time horizon. Trabelsi (2018) further defines the own variance spillovers in line with Diebold and Yilmaz (2018) as the fractions of the H-step-ahead error in forecasting Yj that are due to shocks in Yj for $j = 1,2 \dots, n$ and across variance spillovers as the fractions of the H-step-ahead error variances in forecasting Yj that are due to shocks to Yk for $k = 1,2 \dots, n$ such that $j \neq k$. The equation is estimated as follows:

$$(\theta_H)_{j,k} = \frac{\left((\Sigma)_{k,k}\right)^{-1} \sum_{h=0}^{\mathrm{H}-1} \left((\psi_h \Sigma)_{j,k}\right)^2}{\sum_{h=0}^{H-1} \left(\psi_h \Sigma \, \psi_h'\right)_{j,j}} \tag{3.2}$$

Where ψ is the n x n matrix of coefficients corresponding to lag h and $\sigma_{k,k} = (\Sigma)_{k,k}$ and $(\theta_H)_{j,k}$ captures the Pearson-Shin GFEVD partial contribution from asset k to asset j. The findings indicated that there were no significant volatility spillovers between the cryptocurrency market and traditional financial markets, implying that cryptocurrencies function independently and do not pose a risk to financial system stability. Additionally, the study identified a time-frequency dynamic nature of connectedness within the cryptocurrency market, highlighting its speculative nature, as the total spillover index was largely influenced by short-term fluctuations (2–4 days). These results suggest that cryptocurrencies, along with other financial assets such as commodities and stock indices, can serve as effective instruments for portfolio diversification due to the absence of strong linkages between these asset classes.

Symitsi and Chalvatzis (2018) complicated this picture by showing substantial return and volatility spillovers from energy and technological firms to Bitcoin using asymmetric VAR-GARCH and BEKK models. Their evidence of both unilateral and bidirectional spillovers contradicts Trabelsi (2018) isolation finding, instead reinforcing Bouri et al., (2018) results that cryptocurrency interactions with traditional sectors can be highly dynamic and asymmetric. Okorie and Lin (2020) using the VAR, MGARCH, GJR, and BEKK models similarly revealed bidirectional volatility spillovers between cryptocurrencies and crude oil markets, further validating the existence of shock transmission mechanisms across asset classes. These findings indicate that in specific sectors, especially energy and technology cryptocurrency assets are actively interconnected and may exert a significant systemic impact rather than remaining isolated.

Nonetheless, the strength and direction of these spillovers are largely dependent on the prevailing market conditions. For example, Andrada-Félix et al. (2020), using both Diebold and Yilmaz (2014) and TVP-VAR methods, found that spillovers between cryptocurrencies and traditional fiat currencies were relatively weak, accounting for only 34.43% of forecast error variance. This largely confirms Trabelsi (2018) earlier findings of weak inter-asset linkages but adds differences by identifying volatility spillovers intensifying during market downturns. This aligns with Hsu, Sheu and Yoon (2021); who, using BEKK models, showed that co-volatility between cryptocurrencies, fiat currencies, and gold intensified during the COVID-19 pandemic. Their findings also emphasize time-varying hedging capabilities and reveal that negative return shocks have a larger impact than positive ones, underlining the asymmetric nature of cryptocurrency behavior.

Contrasting perspectives are further illustrated by Klein, Thu, and Walther (2018), who found that Bitcoin exhibits asymmetric volatility dynamics similar to precious metals, using APARCH and FIAPARCH models. However; unlike gold, Bitcoin failed to act as a hedge during market downturns, suggesting its safe-haven status is exaggerated. A more distinct view emerges from Jeribi and Masmoudi (2021), who applied the DCC-MGARCH model and found that the previously low correlations between cryptocurrencies and traditional assets increased significantly during the COVID-19 pandemic. This supports the time-varying connectedness findings of Hsu, Sheu and Yoon (2021) who, using the BEKK model and daily data from August 2015 to June 2020, investigated risk spillovers from the three leading cryptocurrencies to ten major fiat currencies and two gold prices (gold spot and gold future). Similar dynamics are evident in Iyer and Popescu (2023), who found generally weak return and volatility spillovers between crypto assets and financial markets but acknowledged robust links with global equities, the VIX index, and gold using the Diebold and Yilmaz (2009,2012) spillover index. They also documented shifts in spillover directions during financial instability, further underscoring the context-specific nature of interconnectedness.

In emerging market contexts, regional dynamics play an important role. Akdağ and Emsen (2021), focusing on Turkey and using the BEKK-MGARCH method, identified bi-directional return and volatility spillovers between Bitcoin and traditional Turkish financial assets such as the BIST100 and gold futures. Similarly, Li, Mo, and Nie (2023) studied the dynamic time-frequency connectedness between cryptocurrencies and traditional financial assets in China, utilizing a weekly dataset covering the period from September 2015 to March 2022, found that cryptocurrencies were net transmitters of risk to traditional assets, particularly during periods of economic stress, such as the COVID-19 pandemic. These findings indicate that, within emerging markets, cryptocurrencies may serve as systemic risk amplifiers rather than passive stores of value or diversifiers. Furthermore, Liu et al., (2024) provided evidence of strong spillovers from the cryptocurrency-implied exchange rate discount in BRICS countries to US financial markets using TVP-VAR and DCC-GARCH models. Their findings challenge earlier studies suggesting weak spillovers and highlight the growing global interconnectedness of cryptocurrency markets. Notably, Brazil and Russia emerged as dominant spillover sources, while the US Financial Stress Index was particularly sensitive to changes in the BRICS crypto landscape. This emphasizes the increasingly international character of crypto-related volatility transmission, which has important implications for global market stability and coordination of regulatory responses.

3.3 Hedging

The hedging role of Bitcoin in financial markets is on conditional basis, reflecting both its evolving market status and varying relationships with different asset classes. While some studies emphasize Bitcoin's potential as a hedge, others underline its limitations, particularly under markets distress. Kurka (2019), using the Diebold and Yilmaz spillover framework, provides compelling evidence that despite the generally low average connectedness between Bitcoin and traditional assets such as commodities, foreign exchange, and stocks, there are relatively weak but significant transmissions of market shocks. This asymmetry suggests that Bitcoin's hedging function varies depending on current conditions, under stable market conditions, it may offer diversification benefits, but during economic turmoil, its tendency to propagate shocks diminishes its protective role. These differences challenge the narrative of

Bitcoin as a reliable hedge and emphasizes its vulnerability to systemic disruptions, especially as its market capitalization grows and integrates more deeply into the financial system.

Contrastingly, Urquhart and Zhang (2019) take a high-frequency perspective using the ADCC-GARCH model and reveal that Bitcoin exhibits stronger hedging characteristics against specific fiat currencies, such as the CHF, EUR, and GBP. Their findings highlight that Bitcoin can function not only as a hedge but also as a safe haven during periods of extreme stress for certain currencies. This dynamic behavior is not uniform across all currencies; rather, Bitcoin's role varies, acting as a diversifier for the AUD, CAD, and JPY reflecting heterogeneous relationships across currency markets. However, the absence of intraday hedging and diversification capabilities points to the temporal instability of Bitcoin's protective features, thereby limiting its utility for high-frequency or short-term risk management strategies.

Dyhrberg (2016) further reinforces the case for Bitcoin's strategic hedging role by drawing parallels with gold. Employing an asymmetric GARCH model, the study demonstrates Bitcoin's ability to hedge against movements in both the FTSE Index and the U.S. dollar, particularly in the short term. These findings strengthen the argument that Bitcoin, like gold, can be used as a partial shield against equity market downturns and fiat currency depreciation. The observed negative or weak correlations imply that, under specific macroeconomic or financial conditions, Bitcoin can offer targeted hedging benefits, particularly when used in combination with traditional safe-haven assets.

3.4 Diversification and Connectedness

The literature presents a distinct and time-varying picture of the diversification benefits and connectedness between Bitcoin and traditional financial assets. While early studies, such as Zeng, Yang, and Shen (2020), highlight weak systemic connectedness between Bitcoin and conventional markets, particularly noting asymmetric spillover effects where negative shocks dominate, this weak linkage is far from static. Their use of the Diebold and Yilmaz (2009, 2012, 2014) VAR-based framework suggests that although Bitcoin offers moderate diversification opportunities, its growing spillover intensity over time reflects an evolving risk transmission role. This time-dependence and asymmetry are further reinforced by Charfeddine, Benlagha, and Maouchi (2020), whose findings using time-varying copula and DCC-GARCH models show that the correlation between digital and traditional assets is weak but non-negligible, and it amplifies in response to external economic shocks. Yet, the practical utility of cryptocurrencies in portfolio diversification is hindered by poor hedging performance, a finding supported by their portfolio analysis.

The argument for Bitcoin's distinctiveness and portfolio value gains further strength from Bouri et al., (2020), who employ wavelet coherency to uncover that Bitcoin exhibits lower dependence on global stock markets than gold or commodities across all time scales. Their wavelet-at-risk assessment reveals that Bitcoin, in fact, demonstrates greater diversification potential than these traditional hedging assets, but only under specific time-frequency conditions. This reinforces the conclusion that Bitcoin's role as a diversifier depends on market conditions, dependent on investors' risk horizons and market timing. However, these benefits are not consistent across all market states. For instance, Attarzadeh and Balcilar (2022), using the TVP-VAR model, found that Bitcoin's connectedness with financial and energy markets surges during crises, such as the 2018 crypto crash and the COVID-19 pandemic contradicting the assumption of Bitcoin's structural independence. Their evidence points to a form of latent systemic integration, where the crypto market, though loosely connected in stable market conditions, becomes systemically strong under market turmoil.

This crisis dependent behavior is confirmed by Wang, Liu, and Wu (2022), whose ADDC-GARCH analysis shows that Bitcoin's correlation with traditional financial assets is conditional and intensifies under stress, revealing its dual role as both a diversifier and a transmitter of financial shocks. They argue convincingly that Bitcoin mimics the behavior of a risk asset, particularly during market extremes, while still showing potential as a hedge against the USD and safe haven for specific assets like U.S. stocks and crude oil over longer horizons. Adding further the empirical aspect, Salem, Fakhfekh, and Jeribi (2023) demonstrate that Bitcoin contributed significant diversification benefits during the COVID-19 crisis, a finding that emphasizes its practical value in volatile market environments. This complements the observation by Baur, Hong, and Lee (2018) that Bitcoin's statistical properties depart from those of both currencies and traditional assets, making it a novel financial instrument. Their analysis of Bitcoin's public ledger also suggests that investors predominantly treat Bitcoin as an investment asset, further distancing it from currency-like functions and supporting its case as a diversification tool.

Moreover, the work of Jareno et al. (2020) introduces a deeper layer of complexity by examining Bitcoin's sensitivity to global risk factors using quantile regression and nonlinear ARDL models. They find strong asymmetric relationships between Bitcoin and traditional market indicators like the VIX, STLFSI, interest rates, and oil prices. Importantly, Bitcoin exhibits safe-haven behavior under extreme market stress, particularly in lower quantiles, while also maintaining a positive long-term cointegration with gold, suggesting a hybrid identity as both risk asset and safe-haven asset depending on the prevailing market regime. Moreover, Khalfaoui, Hammoudeh, and Rehman (2023), using a quantile VAR framework, expose the nonlinear and regime-switching spillover dynamics between BRICS Islamic financial markets and major cryptocurrencies. Their network analysis demonstrates that cryptocurrencies can act as both shock transmitters and absorbers, with connectedness being market condition dependent. This challenges the simplistic differences between cryptocurrency and traditional markets, instead suggesting a structural convergence that becomes more evident during periods of financial stress.

3.5 Gap in existing literature

One notable gap in the existing literature is that several studies use Bitcoin to demonstrate the relationship between cryptocurrencies and traditional asset classes. This study will fill this gap by employing several cryptocurrencies, including the crypto index to reveal the interactions between these markets. Furthermore, the study will incorporate the stable coin cryptocurrency (Tether) which existing literature have ignored as it was created to maintain stability in the cryptocurrency market. The existing literature, as evidenced by relatively few studies, has primarily focused on developed markets, highlighting a significant research gap in developing markets. These markets are characterized by heightened price volatility, making them an important area of study. Therefore, this research aims to address this gap by exploring the relationship between cryptocurrencies and traditional assets within the context of emerging markets.

3.6 Chapter summary

Chapter 3 reviewed the existing empirical studies based on the volatility spillovers and interconnectedness between cryptocurrencies and traditional assets classes. The studies reviewed were broken into three subsets of evidence from general literature, evidence from developed markets and evidence from developing markets. The summary of results for the reviewed studies is presented in Table 3.1.

The results are inconsistent despite some studies using the same methods[10], Kurka (2019) and employed the Diebold and Yilmaz method and found significant shocks and volatility spilliovers between cryptocurrencies and traditional asset classes whereas Andrada-Félix, Fernandez-Perez and Sosvilla-Rivero (2020), Trabelsi (2018); Zeng, Yang and Shen (2020) and Iyer and Popescu (2023) employing the same model found weak connectedness and volatility spillovers in the respective markets. However, Symitsi and Chalvatzis (2018); Okorie and Lin (2020); Hsu, Sheu and Yoon (2021); Klein, Thu and Walther (2018) and Akdağ and Emsen (2021) all using BEKK method found significant shocks and volatility spillovers across the two markets and Klein, Thu and Walther (2018) further revealed that Bitcoin cannot hedge against traditional assets.

Moreover, Charfeddine, Benlagha and Maouchi (2020) using GARCH methods found weak connection and that Bitcoin hedge against traditional assets whereas Urquhart and Zhang (2019); Okorie and Lin (2020); Wang, Liu and Wu (2022); Dyhrberg (2016); Jeribi and Masmoudi (2021) using the same methods found that Bitcoin can hedge serve as a hedge against traditional assets.

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[10] There are studies who employed more than two methods such as Andrada-Félix, Fernandez-Perez and Sosvilla-Rivero (2020); Liu et al, (2024); Okorie and Lin (2020); and Klein, Thu and Walther (2018);

Table 3.1: Summary of reviews studies

Findings	Authors
No major spillover effects between the cryptocurrency market and other financial markets suggesting that cryptocurrencies are independent digital instruments posing no danger to financial system stability	Trabelsi (2018); Andrada-Félix et al., (2020); Zeng, Yang and Shen (2020); Charfeddine, Benlagha and Maouchi (2020); Wang, Liu and Wu (2022); Klein, Thu and Walther (2018); Baur, Hong and Lee (2018); Jeribi and Masmoudi (2021); Iyer and Popescu (2023); Akdağ and Emsen (2021); Salem, Fakhfekh and Jeribi (2023).
Significant return spillover from energy and technology stocks to Bitcoin and Short-run volatility spills over from technological companies.	Kurka (2019); Symitsi and Chalvatzis (2018); Hsu, Sheu and Yoon (2021); Attarzadeh and Balcilar (2022); Li, Mo and Nie (2023); Liu et al, (2024); Khalfaoui, Hammoudeh and Rehman (2023).
Relations between Bitcoin and aggregate commodity and between Bitcoin and gold are asymmetric, nonlinear.	Bouri et al., (2018); Bouri et al., (2020);
Cryptocurrencies particularly Bitcoin can serve as a hedge against the traditional financial system	Dyhrberg (2016); Urquhart and Zhang (2019); Okorie and Lin (2020); Liu and Wu (2022); Jeribi and Masmoudi (2021)

Source: Author own estimation (2024)

CHAPTER 4: DATA AND METHODOLOGY

4.1 Introduction

The previous chapter reviewed the existing empirical literature examining the volatility spillovers and connectedness between the cryptocurrencies and traditional asset classes in both developed and emerging markets. The reviewed studies employed several techniques and methods in identifying the volatility spillovers and connectedness between these assets, each with its own benefits and limitations. The current chapter describes the sample period and the dataset used in the study such as the cryptocurrency data and the traditional asset classes data in emerging markets. This chapter further discusses the preliminary tests and empirical methodologies that are used to achieve the aim of this study; that is, investigating the volatility spillovers and interconnectedness between cryptocurrencies and traditional asset classes in emerging markets.

4.2 Dataset and sample period

This study employs the daily closing prices which are the secondary data obtained from the Bloomberg terminal. The use of daily closing prices is consistent with Comerton-Forde and Putniņš (2011); Ju and Zhu (2024), who mentioned that daily closing prices provide a consistent and standardized reference point for measuring asset performance across different periods and markets. Furthermore, the trading on cryptocurrencies occurs daily, therefore, daily closing prices serve as a perfect measure to capture fluctuations in cryptocurrencies and traditional assets (Hudson and Urquhart, 2021). Additionally, several studies investigating the relationship involving cryptocurrencies often use daily closing prices, this includes Cohen and Qadan (2022); Petukhina, Reule and Härdle, (2021) and Chhabra (2022).

Contrastingly, Boido and Fasano (2009) mention that while other traditional asset classes such as bonds and equities have been existing for more than 400 years, the idea of cryptocurrency market was introduced in 2008 by Satoshi Nakamoto with the inception of Bitcoin in 2009. The age disparity between these assets highlights the relative immaturity of cryptocurrencies when compared to the long-established traditional asset classes. Thus, the daily dataset employed in this study are spanning from the 06th of October 2019 to the 31st of January 2024 and to account for public holidays and weekends for traditional market[11], the data interpolation was conducted in line with Borna and Moore (2022). This period is selected to account for

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[11] Traditional markets close on specific public holidays and weekends.

significant structural breaks that are believed to have an impact on the outcomes of this study, such as the COVID-19 pandemic as well as the Russian-Ukraine war. Furthermore, the period is selected to account for the nascent stage of cryptocurrencies, as the daily closing prices for some of them on the Bloomberg terminal are only available starting from the 6th of October 2019. This highlights that, while certain cryptocurrencies may have been developed much earlier, their daily price data is not widely accessible, reflecting market inefficiency. To fully demonstrate the robustness of the results, the data is divided into two segments, (1) Whole sample period, (2) During the COVID-19 pandemic. Therefore; the data for "during the COVID-19" was from the 31st of December 2019 where the first case of the COVID-19 was officially declared and ended on the 5th of May 2023 where the end of the COVID-19 pandemic was declared (WHO, 2023).

Table 4.1 presents the sample of cryptocurrencies. The selection criteria for the cryptocurrencies was based on popularity and on how long the cryptocurrency has been existing. It is important to note that, for the interest of this study, the cryptocurrencies were not ranked according to the market capitalization. This is because most cryptocurrencies with the highest market capitalization were developed in recent years, an example is Solana which was launched in 2020 with its idea dating back to 2017 (Coin Market Cap, 2024). Therefore, this would have led in the study not capturing enough trends between the cryptocurrencies and traditional assets. However, all the selected cryptocurrencies were inside the top 10 in terms of the market performance when the data was collected. The cryptocurrency index is further incorporated to demonstrate how the whole market of cryptocurrencies is connected with the traditional asset classes with a specific focus on emerging markets. Similarly, Table 4.2 presents the sample for traditional asset classes and to ensure consistency in the selection of the types of bonds, stocks, and commodities, the study opted to use indices as representative measures for these asset classes.[12]

Table 4.1: Sample of cryptocurrencies

Cryptocurrency name	Year incepted	Data availability from
Bitcoin	2009	06 October 2019
Ethereum	2015	06 October 2019
Tether	2014	06 October 2019
Ripple	2012	06 October 2019
Litecoin	2011	06 October 2019
Bloomberg Galaxy Crypto Index	2018	06 October 2019

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[12] The justification for these cryptocurrencies and traditional asset classes is provided in this chapter.

Source: Authors own estimation (2024)

Table 4.2: Sample of traditional asset classes

Traditional assets	Index name	Ticker
Bonds	Emerging Markets Bond Index	EMBI
Stocks	MSCI Emerging Market Stock Index	MSCIEMI
Commodities	Bloomberg Galaxy Commodity Index	BGCI
	Bloomberg Commodity Index for Precious Metals	BCOMPRI

Source: Authors own estimation (2024)

The secondary data analysis includes daily closing prices and returns for all cryptocurrencies and traditional asset classes in the sample. This is because, daily returns provide a regular and detailed measure of an asset's performance, helping investors to track short-term trends and assess the impact of daily market events (Wen et al., 2023). The daily closing prices were used to construct the daily returns in the following logarithmic conversion:

$$R_t = \ln\left(\frac{p_t}{p_{t-1}}\right) * 100 \tag{4.1}$$

Where: R_t is the daily compounded return at time t, with p_t and p_{t-1} the current closing price of the asset and the previous day's closing price, respectively. Multiplying the equation by 100 is to convert the log returns to percentages for easy use and interpretation.

4.3 Delimitation of the study

This study is delimited to the use of daily data for both cryptocurrencies and traditional asset classes. While high-frequency data (e.g., hourly or intraday) are commonly employed in the literature to better capture short-term volatility and spillover effects, the use of daily data in this study is justified by practical constraints related to data availability and computational intensity, as well as a focus on medium- to longer-term market dynamics. Although 2018 was a year marked by significant market stress, particularly in global equity and cryptocurrency markets, the absence of this data is a limitation stemming from source availability rather than deliberate scope exclusion.

4.4 Cryptocurrency data

Cryptocurrencies, as previously mentioned, are a relatively new market, introduced in 2008. Their high price volatility often makes market participants hesitant to invest, as they lack confidence in their stability. However, Jindal (2024) highlights that the recent surge in Bitcoin has attracted attention from investors worldwide which reflects a renewed confidence and interest in the cryptocurrency market. Therefore, this study employs 5 cryptocurrencies based on popularity and on how long the cryptocurrency has been existing. The inclusion of long-established cryptocurrencies ensures a reliable historical dataset, allowing for more accurate analysis of their performance and risk profiles over time. This approach is particularly valuable for investors, as it offers insights into cryptocurrencies with proven market relevance and stability, enabling an informed decision-making and portfolio diversification. Furthermore, the Bloomberg Galaxy Crypto Index (BGCII)[13] is used to track how the whole market of cryptocurrencies is connected with the traditional asset classes in emerging markets. Thus, the following section provides a concise overview of each cryptocurrency selected for the study and offers additional details about the Bloomberg Galaxy Crypto Index.

4.4.1 Bitcoin

Bitcoin (BTC) was the first ever cryptocurrency to be created and it is now the most valued and well-known cryptocurrency worldwide (Julie Pinkerton, 2024). Despite the idea of cryptocurrency being around for over 40 years, Bitcoin made it a reality in 2009 and its 15-year trading history has been an exhilarating ride, fuelled by increasing interest from younger investors. Armaan (2024) notes that Bitcoin maintains its leading role in the cryptocurrency market, with its price demonstrating resilience amid market volatility and a highly positive technical rating, highlighting its robust standing. Bitcoin has recorded a 3-month performance of 66.45, Bitcoin’s stability and widespread adoption making it a preferred choice for investors seeking long-term value and stability in the volatile crypto landscape (Saikia, Maurya and Verma 2024).

4.4.2 Ethereum

Ahn, Yi and Kim (2024) state that Ethereum is the second-largest cryptocurrency by market capitalization behind Bitcoin and according to Coin Market Cap (2024), the statement holds as the current market capitalization for Ethereum is the second-biggest after Bitcoin. Jani (2017) notes that Ethereum, created by Russian-Canadian programmer Vitalik Buterin in 2013 and launched in 2015, has since emerged as a significant player in the fields of cryptocurrency and blockchain technology. As such, Armaan (2024) highlights that Ethereum's technical rating remains highly positive, reflecting strong confidence in its fundamental aspects, with a 3-month

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[13] The second I; as it reads BGCII, is used to illustrate the difference between this index and Bloomberg Galaxy Commodity Index (BGCI)

performance of 73.69. Ethereum has attracted both developers and investors by leading in the development of decentralized applications and smart contracts.

4.4.3 Tether

Tether is a stable coin[14] cryptocurrency which was founded in 2014 by the trio of Reeve Collins, Craig Sellars, and Brock Pierce (Aggarwal and Kumar, 2021). Tether is a blockchain-based platform that enables the digital use of fiat currencies. It allows users to transact in traditional currencies through a blockchain network and its technologies, reducing the volatility and complexity typically associated with digital currencies. Armaan (2024) highlights that Tether, as a prominent stable coin, maintains price stability, offering liquidity and security to traders and investors, with a 3-month performance of -0.87. Additionally, Tether acts as a dependable safeguard during market volatility, providing a safe option for capital preservation.

4.4.4 Ripple

Ripple Labs company based in the U.S is the main idea behind the development of Ripple (Armknecht et al., 2015). Ripple was created with the goal of enhancing the efficiency of cross-border payments, especially within the banking industry. As such, Ripple can be transferred directly, eliminating the need for an intermediary, which makes it a highly efficient tool for quickly bridging two currencies. Accordingly, it is currently ranked number seven largest crypto project by market capitalization, boasting a total market capitalization of $26.73 billion (Coin Market Cap, 2024). According to the reports of Ripple Labs (2015), a single unit of XRP is priced low due to the large supply of coins in circulation (over 45 billion), making it attractive for many investors to include in their portfolios. Its relatively inexpensive price compared to other top 10 projects in the cryptocurrency space can be particularly appealing to investors.

4.4.5 Litecoin

Litecoin is a well-established cryptocurrency that has been active for over nine years (Reed, 2017). With a strong technical foundation, this cryptocurrency has managed to secure its position as one of the top 30 cryptocurrencies by market capitalization and popularity. Yu et al., (2024) highlights that despite the recent discussions around Litecoin's declining popularity, the cryptocurrency continues to demonstrate resilience and potential for future growth. Accordingly, in a bullish market scenario where positive market sentiment prevails, Litecoin's

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[14] Stable coin - refers to a type of cryptocurrency that tries to tackle price fluctuations to maintain a more stable price by linking the stable coin's market value to some external reference, most commonly a fiat currency like the USD, although some stable coins are linked to commodities, such as a precious metal like gold (Ante, Fiedler and Strehle, 2021)

prices are likely to experience significant growth. According to Coin Market Cap (2024), the current market capitalization of Litecoin is $6,083,390,948. Despite being one of the most popular cryptocurrencies, one attribute that played a role in the inclusive of Litecoin in this study is that Litecoin shares a codebase with Bitcoin (Tu and Xue, 2019). Therefore, the study sought to observe the similarities between these cryptocurrencies.

4.4.6 Bloomberg Galaxy Crypto Index

Wout (2023) highlight that the coin market capitalisation of cryptocurrencies offers a wide variety of indices that are used individually or collectively to track the performance of cryptocurrencies. Among the various indices available in the Coin Market Crypto Index, this study utilizes the Bloomberg Galaxy Crypto Index. This index tracks the performance of the top 10 cryptocurrencies and was further selected for its comprehensive data availability on the Bloomberg terminal. The use of BGCI is consistent with Jayawardhana and Colombage (2024); Rapp and Thorwaldsson (2022) and Häusler and Xia (2022).

4.5 Selected traditional asset classes data

As previously mentioned, traditional asset classes such as bonds and equities have been existing for over 400 years (Boido and Fasano, 2009). Accordingly, traditional assets form an integral part of this study, as such the study selects three traditional asset classes which are stocks, bonds and commodities. These assets are selected because they capture diverse risk profiles and economic dynamics. Bonds reflect stability and interest rate trends (Lagos, 2013), whereas stocks represent economic growth (Liu et al., 2023), and commodities respond to inflation and supply-demand shifts (Culyer, 2002). Therefore, their inclusion allows for a comprehensive analysis of cryptocurrencies' interaction with traditional markets and potential diversification benefits. The interest of this study is in emerging markets, as such the data for these traditional assets classes is collected in emerging markets.

Campbell (2005) state that there are several types of bonds and stocks that exists worldwide. Therefore, to avoid the inconsistent selection of the asset types, the study uses the emerging market index for each traditional asset class. However, the evidence presented by Boakye, Heimonen and Junttila (2024) reveals that commodities are not country-specific as they are influenced by worldwide economic performance rather than country-specific factors. As such the study employs two indices for commodity markets (Commodity Markets Index[15] and

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[15] This index tracks the performance of all commodities without being country specific or market specific such as emerging markets or developed markets

Emerging markets precious metals index[16]). The following section discusses the characteristics of each selected traditional asset class under emerging markets.

4.5.1 Morgan Stanley Capital International Emerging Market Stock Index

Michelson, Philipova, and Srotova (2008) point out that the MSCI Emerging Markets Index is a collection of stocks aimed at monitoring the financial performance of major companies in rapidly growing countries. It is one of several indices developed by MSCI Inc., previously known as Morgan Stanley Capital International. The MSCI Emerging Markets Index tracks the performance of large-cap and mid-cap companies across 25 countries classified as emerging markets. That is, the economies of these countries, or certain sectors within them, are expanding quickly and engaging vigorously with global markets (Patel, 2021).

Öner (2022) mentions that the MSCI Emerging Markets Index comprises stocks from companies located in countries such as Brazil, Chile, China, Colombia, Czech Republic, Egypt, Greece, Hungary, India, Indonesia, Korea, Kuwait, Malaysia, Mexico, Peru, Philippines, Poland, Qatar, Russia, Saudi Arabia, South Africa, Taiwan, Thailand, Turkey, and the United Arab Emirates. The index was created in 1988 and at that time, companies in only 10 nations were represented. However, the index has evolved as it is now widely used to measure the economic performance of emerging market companies and it is used by emerging market ETFs and mutual funds as a benchmark against which to measure their own performance (Arzova and Sahin, 2023).

4.5.2 Emerging Market Bond Index (EMBI)

The emerging markets bond index (EMBI) is a benchmark index that measures the total return performance of international government and corporate bonds issued by emerging market countries that meet specific liquidity and structural requirements (Erb, Harvey and Viskanta, 2000). Kennedy and Palerm (2014) mention that despite their increased riskiness relative to developed markets, emerging market bonds offer several potential benefits such as portfolio diversity as their returns are not closely correlated with other asset classes. However, Jüttner, Chung and Leung (2006) state that emerging market bonds tend to be more volatile than developed market bonds, influenced by global interest rate changes, commodity price fluctuations, and local economic policies. Moreover, this index is weighted on the basis of the market capitalization of government bonds, but it is the sub-index with the greatest liquidity

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[16] Precious metals are technically commodities; this index tracks the performance of precious metals in emerging markets in line with achieving objective 3 of this study

requirements, so some markets are excluded. Studies, including Arslanalp et al. (2020), have utilized this index.

4.5.3 Commodity Market Index

Since commodities are not country-specific (Boakye, Heimonen, and Junttila, 2024), this study employs two indices to represent the commodity market. The first index tracks the performance of all commodities and is used to examine the connection between the commodity market and cryptocurrencies. The second index focuses on the performance of precious metals, such as gold, silver, and platinum, within emerging markets. This aligns with the third objective of the study, which focuses on emerging markets, where precious metals are considered commodities (Richards, 2006). Additionally, the study by Ben et al., (2024) also utilized a range of Bloomberg indices, including the two indices mentioned here.

4.5.3.1 Bloomberg Galaxy Commodity Index

The report of Federal Bank of St Louis (2024) highlights that the Bloomberg Galaxy Commodity Index (BGCI) is a purely identified index that measures the overall price changes of a broad basket of commodities across the world. This index provides a brief overview of how the various primary goods and raw materials changing overtime reflecting global economic conditions, supply and demand dynamics, and other market factors (Zaremba, 2015)

4.5.3.2 Bloomberg Commodity Index for Precious Metals

The BCOMPR index is a benchmark that measures the performance of the companies in the precious metals and mining sector under emerging markets (Lazzarino, Berrill and Šević, 2022). The Bloomberg Commodity Index employs production and liquidity measures to determine the weighting of each commodity which ensures that the sub-index reflects the relative importance of each precious metal in the global market (Aoraki and Matsumoto, 2017).

4.6 Methods of analysis[17]

The aim of this study is the centre of all the objectives; in essence, the objectives of this study are derived from the aim, that investigating volatility spillovers and interconnectedness between cryptocurrencies and traditional asset classes in emerging markets. To ensure that the study produces reliable results and estimates, the preliminary tests are equally important. As such, Section 4.3.1 discusses all the relevant preliminary tests for this study and highlighting their importance. Moreover, Section 4.3.2 discusses the Diebold and Yilmaz spillover approach

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[17] Cryptocurrencies are regarded as digital assets; therefore, from time to time in this section cryptocurrencies and traditional asset classes involved in the study will all be referred to as assets.

to achieve the objectives of the study and Section 4.3.3 discusses the modified approach of DY, that is the Time-Varying Parameter Vector Autoregressive model (TVP-VAR).

4.6.1 Preliminary tests

Keselman, Othman and Wilcox (2013), mention that preliminary tests are essential in quantitative research as they ensure reliability, validity and the robustness of the data and the models used. As such, this study conducts the following preliminary tests.

4.6.1.1 Descriptive Statistics

The descriptive statistics that is analysed in this study, includes the following:

i. Mean

Brown and Kass (2009) define the mean as the central value of a set of numbers. It is determined by dividing the sum of all the numbers by the total count of values in the set.

ii. Standard Deviation

Standard deviation quantifies the level of variation or dispersion in a dataset (Lee, In, and Lee, 2015). It is a key indicator of the risk or volatility associated with a financial asset or portfolio. A higher standard deviation reflects greater fluctuations in returns, signifying increased risk, while a lower value indicates more consistent returns and reduced risk. The calculation of standard deviation follows this formula.

$$Standard\ Deviation = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n} (x_i - \bar{x})^2}$$

Where x_i represents individual data points, $\bar{x}$ is the mean of the sample and n is the total number of observations in the sample.

iii. Skewness

Skewness assesses the asymmetry of a distribution relative to its mean (Doane and Seward, 2011). It identifies whether the data is symmetrically distributed, exhibits left skewness (negative skewness), or shows right skewness (positive skewness). The formula to compute the skewness of the sample is presented as follows:

$$Skewness = \frac{n}{(n-1)(n-2)}\sum_{i=1}^{n} \frac{(x_i-\bar{x})^3}{s^3} \tag{4.2}$$

Where x_i is the individual data points, $\bar{x}$ is the mean of the sample, n is the total number of observations in the sample and s is the standard deviation as calculated in equation 4.2.

iv. Kurtosis

Kurtosis is a statistical measure that characterizes the shape of a dataset's distribution, emphasizing the tails and the sharpness of its peak (Bai and Ng, 2005). It offers insights into the presence of outliers and the likelihood of extreme values. By analysing kurtosis, one can distinguish between normal and non-normal distribution patterns. The formula for calculating kurtosis is as follows:

$$Kurtosis = \frac{n(n+1)}{(n-1)(n-2)(n-3)} \sum_{i=1}^{n} \left(\frac{x_i - \bar{x}}{5}\right)^4 - \frac{3(n-1)^2}{(n-2)(n-3)} \tag{4.3}$$

Where x_i is the individual data points, $\bar{x}$ is the mean of the sample, n is the total number of observations in the sample and s is the standard deviation as calculated in equation 4.2. The accepted value of kurtosis that indicates a normal distribution is 3, thus, a kurtosis value that is greater (less) than 3 indicates that the series distribution is peaked (flat).

v. Jarque-Bera

The Jarque-Bera test evaluates whether a dataset conforms to a normal distribution by assessing its skewness and kurtosis, then comparing them to those of a standard normal distribution. The JB statistic is determined using the following formula:

$$JB = n\left(\frac{s^2}{6} + \frac{(k-3)^2}{24}\right) \tag{4.4}$$

Where n is the number of observations is the sample, s represents skewness as calculated in equation 4.2 and k represents kurtosis as calculated in equation 4.3.

4.6.1.2 Correlation

Taylor (1990) defines correlation as a measure that indicates the extent to which two variables move in relation to one another. It quantifies both the strength and direction of the linear relationship between the variables. In this study, the Pearson correlation coefficient, r, is calculated as follows:

$$r = \frac{\sum_{i}^{n} (x_i - \bar{x})(x - \bar{y})}{\sqrt{\sum_{i=1}^{n} (x_i - \bar{x})^2 \sum_{i=1}^{n} (y_i - \bar{y})^2}} \tag{4.5}$$

Where r represents the Pearson correlation (ranges from -1 to 1), x_i and y_i are individual data points for x and y and $\bar{x}$; $\bar{y}$ are the mean values for x and y respectively. The correlation coefficient ranges between -1 and +1. A positive correlation means that both variables change in the same direction; if one increases or decreases, the other follows the same pattern. On the other hand, a negative correlation signifies that the variables move in opposite directions; as one variable increases, the other decreases, and vice versa. If there is no relationship between the variables' movements, the correlation coefficient will be zero.

4.6.1.3 Stationarity and Unit Roots Tests

In ensuring that the study does not produce spurious results, the stationarity tests of the dataset is conducted. As such, this study employs three techniques of conducting stationarity tests, each with its benefits. Firstly, the Augmented Dickey-Fuller Test (A.D.F.), which examines the impact of periodic aggregation on the test's power attributes and detects stationarity (Paparoditis and Politis, 2018) is employed. The second test that will be conducted is the Phillips-Perron (P.P.) test which corrects any heteroscedasticity and serial correlation in the errors by altering the test statistics directly and the third test that is employed is Kwiatkowski-Phillips-Schmidt-Shin (K.P.S.S.) test which is widely used in empirical research as a complement to the standard unit root tests and ensuring that seasonal dummies do not affect it (Hadri and Rao, 2008). The following section explains each method in detail and highlights its importance in detecting the unit root and non-stationary series.

i. Augmented Dickey-Fuller Test

The A.D.F test is only valid if the error term (U_t) is white noise and subsequently if the error term is autocorrelated, the solution is to augment the test using *p* lags of the dependent variable. The equation of A.D.F can be written as follows:

$$\Delta Y_t = \psi Y_{t-1} + \sum_{i=1}^{p} \gamma_i \Delta Y_{t-1} + U_t \tag{4.6}$$

Where: ψ is the unit root; γ is the time trend (it is only included when it is necessary) *p* represents the number of lags and U_t is the white noise disturbance. The ideal lag for the dependent variable is identified using information criteria (Vrieze, 2012), which consist of the Akaike Information Criterion (AIC) (1973), Schwarz's Bayesian Information Criterion (SBIC) (1978), and the Hannan and Quinn Information Criterion (HQIC) (1979). The mathematical expressions for these three criteria are as follows:

$$AIC = 2K - 2\ln(L) \tag{4.7}$$

$$SBIC = \ln(n)k - 2\ln(L) \tag{4.8}$$

$$HQIC = -2k + 2k\ln(\ln(L)) \tag{4.9}$$

Where: L is the maximized value of the likelihood function of the model, n is the number of data points and K is the number of free parameters to be estimated. Vrieze (2012) explains that the Akaike Information Criterion is more appropriate for small samples as it tends to select longer lag orders, whereas the Schwarz's Bayesian Information Criterion is more effective for large samples and favours shorter lag orders. The Hannan and Quinn Information Criterion falls in between the AIC and SBIC criterions. Using the ADF test, the hypothesis is drawn as follows:

H_0: The series has a unit root

H_1: The series is stationary

If the test statistic is less than the critical value (more negative), the null hypothesis is rejected at the specified level of significance. To account for the structural breaks in the sample period such as the COVID 19 pandemic and the Ukraine-Russian war, the ADF t-min structural break test introduced by Ling, Nor, Saud and Ahmad (2013) is used. The ADF min-t structural break test statistic can be expressed as follows:

$$\Delta y_t = \psi_{t-1} + \mu DL + \alpha_t + \sum_{p_{i=1}}^{Bi} \Delta_{yt-i} + \mu_i \tag{4.10}$$

Where: ψ is the unit root test, μ represents the intercept, DL and B_1 represent break point parameters, α is the trend line (Included when necessary), p shows the number of lags and μ_i represents the white noise disturbance. The hypothesis for the ADF min-t structural break test is stated as follows:

H_0: The series has a unit root with an unknown of structural breaks.

H_1: The series is stationary with an unknown number of structural breaks.

The null hypothesis is rejected if the test statistic is more negative than the critical value at the given level of significance.

ii. Phillips-Perron Test

The PP is used as another method of testing for stationarity in the series. The PP (1988) test that a variable has a unit root. The null hypothesis assumes that the variable has a unit root, while the alternative hypothesis suggests that the variable was generated by a stationary process. PP uses Newey–West (1987) standard errors to account for serial correlation, whereas the ADF test uses additional lags of the first-differenced variable. The equation for the PP test can be written as follows:

$$\Delta y_t = \alpha + \beta t + \gamma_{yt-1} + \mu_t \tag{4.11}$$

Where y_t is the time series tested, α is the intercept, β is the trend term (included when it is necessary), γ is the coefficient on the lagged level of the series and μ_t is the error term. The PP test modifies the ADF by adjusting the test statistic to account for autocorrelation and heteroscedasticity in the residuals. The PP test statistic equation is written as follows:

$$\text{PP Test Statistic} = \frac{\hat{\gamma}}{SE(\hat{\gamma})} \tag{4.12}$$

Where $\hat{\gamma}$ is the estimated coefficient from the regression and $SE(\hat{\gamma})$ is the standard error of the coefficient adjusted for autocorrelation and heteroscedasticity using a non-parametric method. The null and alternative hypotheses for the test are:

H_o: The series has a unit root test (non-stationary)

H_1: The series is stationary

When the probability value is greater than the stated level of significance, the null hypothesis cannot be rejected, indicating that the is not stationary. Conversely, the null hypothesis of unit root in the univariate times series is rejected when the probability value is smaller than the stated level of significance and the data is stationary.

iii. Kwiatkowski-Phillips-Schmidt-Shin

Kagalwala (2022) mention that the KPSS test was developed to complement unit root tests as the ADF and PP tests above have low power with respect to near unit-root and long-run trend processes. The equation of KPSS can be written as follows:

$$x_t = r_t + \beta_t + \mu_t \tag{4.13}$$

The KPSS is explained by 3 variables, r_t is the random walk, β_t is a deterministic trend and μ_t is the stationary error. The hypothesis for KPSS are as follows:

H_0: The series is stationary

H_1: The series is not stationary

The null hypothesis is rejected if the test statistic is larger than (or more negative than) the critical value at the designated significance level. The KPSS tests are designed to complement unit root tests. If the outcomes from the unit root tests contradict the results from the KPSS test, the KPSS test is preferred over the ADF and PP tests (Sjösten, 2022). This preference arises because the KPSS tests a null hypothesis of stationarity, while the ADF and PP tests examine the presence of a unit root. A null hypothesis can only be rejected or confirmed, not proven.

4.6.3 Investigating volatility spillovers

Volatility spillovers refers to the market shocks transferred from one market to another. Accordingly, spillover effects form an integral part of this study with a specific focus on emerging markets. As such, this section discusses the empirical models that are used to assess how volatility in cryptocurrencies may affect the traditional assets which are represented by stocks, bonds, and commodities, and vice versa.

4.6.3.1 Diebold and Yilmaz (2012,2014) Model

To achieve the aim and the subsequent objectives, this study uses the Diebold and Yilmaz (2012,2014) model which is a spillover index proposed by Diebold and Yilmaz in 2009 and also called the DY[18] index. This technique is based on the forecast error variance decomposition (FEVD) in vector autoregressive (VAR) models. It represents the extent to which changes in one variable can be explained by another variable when a unit of exogenous shock occurs (Fu and Qiao, 2021). Diebold and Yilmaz (2009) assert that this model can be employed to reveal and analyse the formation of networks by utilizing daily asset return and volatility data to investigate how shocks propagate across a group of assets and markets over time. Additionally, the model assesses the measurement of connectedness among financial markets and institutions globally, an issue that has been of concern to policymakers since the 2008 global financial crisis.

Kashyap (2023) states that the DY (2012,2014) model offers several benefits, such as allowing the study of the impact of directional spillovers by analysing markets' net exposure to other markets, and it measures the directional spill-overs from one asset to another, allowing for the identification of dominant transmission channels and the assessment of asymmetric effects. Moreover, Diebold and Yilmaz (2012,2014) capture the net volatility spillovers from each asset to all other assets in the sample, accounting for positive and negative spillovers. As a result, an

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[18] DY is short for Diebold and Yilmaz.

asset spreading shocks positively is regarded as the net transmitter whereas an asset spreading shock negatively is regarded as the net receiver. Thus, contributing to the demonstration of the direction in which the shocks are moving and the degree of influence exerted by each asset.

However; the Diebold and Yilmaz (2012,2014) approach uses a VAR rolling window method which according to Liu and Gong (2020), is viewed simple to implement but it is associated with several shortcomings such as the rolling window size being predetermined. The findings vary depending on the size of the window, and it is challenging to decide on the optimal window size thus leading to variability in findings based on the chosen window size. Caloia, Cipollini and Muzzioli (2019) further highlight that the rolling window method may not react quickly to sudden changes in market conditions which can be critical during periods of increased volatility and economic distress. However, a rolling window V.A.R. method assists businesses and researchers in becoming flexible by providing a rolling window of future events (Huhtakangas, 2020). This means that forecast plans are updated as new data becomes available, allowing business decisions to be made based on the most current information. Therefore, to overcome the drawbacks of the rolling window V.A.R. method whilst utilizing its benefits, this study employs both the traditional V.A.R. method and the rolling window V.A.R. method.

This study uses a 200-day rolling window size because it provides a balance between capturing longer-term trends and being responsive to short-term fluctuations and the size is neither too narrow, which could lead to excessive noise, nor too large, which might obscure important changes in market dynamics (Inoue, Jin and Rossi, 2017). Furthermore, the 200-day window is specifically chosen to account for potential structural breaks and economic downturns, thus allowing the analysis to be more robust in the face of significant market events that could impact volatility and interconnectedness (Hällman, 2017). Additionally, a larger window size, like 200 days, can provide a clearer view of market changes and assist in capturing longer-term trends and patterns, which is essential for understanding the dynamics of volatility spillovers and connectedness (Kartal, Ghosh and Adebayo, 2023). The Diebold and Yilmaz (2012,2014) uses two techniques that complements one another in capturing the volatility spillovers from one asset to another as outlined below.

i. Variance decomposition for connectedness

In the approach of the Diebold and Yilmaz, variance decomposition is a method of quantifying the contribution of shocks from one variable to the forecast error variance of another variable

(Diebold and Yılmaz, 2014). In this study, the variance decomposition will play key role in measuring the spillovers and interconnectedness between cryptocurrencies and traditional asset classes in line with the research objectives. Zhang, Chen and Ma (2020) state that connectedness measured based on variance decompositions are appealing for several reasons.

Firstly, they make obvious intuitive sense, answering a key question, which are the most granular pairwise level like "How much of asset *i's* future uncertainty at horizon H is due to shocks arising not with asset *i*, but rather with asset *j*". Secondly, they allow for different connectedness at different horizons, facilitating examination of a variety of horizons and selection of a preferred horizon if desired which is important because, for instance, 1-day connectedness may be very different from 10- or 30-day connectedness (Zhang, Chen and Ma, 2020). Lastly, they are closely linked to modern network theory, in particular the degree distribution and mean degree, and they are also closely linked to proposed measures of various types of systemic risk, such as marginal expected shortfall.

ii. VAR approximate models and Connectedness measure

To evaluate the directional connectivity across the different assets, a covariance stationary V.A.R.(p) as described by Diebold and Yilmaz (2012) was assumed as follows:

$$y_t = \sum_{i=1}^{p} \Phi_i y_{t-1} + \varepsilon_t \tag{4.14}$$

Where: Φ_i is $N \times N$ autoregressive coefficient matrices, and ε_t is a vector of uncorrelated error terms. y_t is an $M \times 1$ vector of endogenous variables which are the volatility returns of the assets included in the study. The moving average representation is $Y_t = \sum_{j=0}^{\infty} A_j \varepsilon_i$, where the $N \times N$ coefficient matrices A_j follow a recursion of $A_j = \Phi_1 A_{j-1} + \Phi_2 A_{j-2} + .. + \Phi_p A_{j-p}$ with A_0 being the $M \times M$ identity matrix and $A_j = 0$ for $j < 0$.

Korobilis and Yilmaz (2018) point out that in high-dimensional situations, identification becomes challenging, with standard methods like Cholesky factorization relying on the ordering of the variables, which introduces significant complications. This study adopts the generalized identification framework of Koop, Pesaran, and Potter (1996) and Pesaran and Shin (1980), as outlined by Diebold and Yilmaz (2012), which produces variance decompositions that are invariant to ordering. Rather than orthogonalizing shocks, the generalized approach accommodates correlated shocks while properly addressing their correlation. Therefore, the H-step-ahead generalized forecast error variance decomposition used the generalized vector-autoregression framework, such that:

$$\theta_{ij}(H) = \frac{\sigma_{jj}{}^{-1} \sum_{h=0}^{H-1} (e'iA_h \sum e_j)^2}{\sum_{h=0}^{H-1} (e'iA_h \sum A'{}_h e_i)} \tag{4.15}$$

Where e, and σ_{ij} denotes the error term’s and standard deviation of the j^{th} equation, e_i is an $M \times 1$ vector with one on the i^{th} element and zero otherwise, Σ represents the vector of errors' variance matrix and the connectedness index is composed of an $M \times M.$ $\theta(H) = \left[\theta_{ij}(H)\right]_{i,j} = 1{,}2$ where each entry represents asset $j's$ contribution to the forecast error variance of asset i.

This study adopts Koop–Pesaran–Potter–Shin generalized VAR framework, therefore the variance shares do not necessarily add to 1, that is: $\sum_{j=1}^{N} \theta_{ij}^{g}(H) \neq 1$ hence the study normalizes each entry of the generalized variance decomposition matrix by the row sum to obtain pairwise directional connectedness from asset *j* to asset *i*. Using the generalized decomposition each member of the variance decomposition matrix is normalized by its row sum as follows:

$$\ddot{\theta}_{ij}\,(H) = \frac{\theta_{IJ}\,(H)}{\sum_{j=1}^{n} \theta_{ij}\,(H)} \tag{4.16}$$

In this equation, $\ddot{\theta}_{ij}\,(H)$ at horizon H, gives a metric of pairwise directional connectivity from j to i, this channelling is described as a $C_{i\leftarrow j}(H)$ and the pairwise direction link is evaluated as $C_{j\leftarrow i}\,(H)$, where the channelling is now from $i\ to\ j$. $\sum_{j=1}^{n} \theta_{ij}\,(H) = 1$ and $\sum_{j=1}^{n} \theta_{ij}\,(H) = n$ by construction and to calculate the net pairwise directional link, Equation 4.13 is used.

$$C_{ij} = C_{i\leftarrow j}\,(H) \text{-} C_{j\leftarrow i}\,(H) \tag{4.17}$$

Where: C_{ij} represents the net directional pairwise link between asset i and j, $C_{i\leftarrow j}\,(H)$ represents directional connectivity from asset *j* to asset *i* at horizon H and $C_{j\leftarrow i}\,(H)$ represents directional connectivity from asset *i* to asset *j* at horizon *H*. In achieving the aim of this study, Equation (4.15) provides a measure of how interconnected the assets are by assessing the extent to which shocks to one asset contribute to the forecast error of another asset. The total directional connectivity was aggregated to determine how each asset contribute to a single asset. Using directional connectivity, three more volatility spillovers and interconnectedness are constructed:

(a) Spillover to asset *i* from all other assets is computed as:

$$C_{i\leftarrow\cdot}\,(H) = \frac{\sum_{\boldsymbol{j=1}\,\boldsymbol{j\neq i}}^{\boldsymbol{N}} \ddot{\theta}_{\boldsymbol{ij}}\,(\boldsymbol{H})}{\sum_{\boldsymbol{ij=1}}^{\boldsymbol{N}} \ddot{\theta}_{\boldsymbol{ij}}\,(\boldsymbol{H})} \times 100 = \frac{\sum_{\boldsymbol{j=1}\,\boldsymbol{j\neq i}}^{\boldsymbol{N}} \ddot{\theta}_{\boldsymbol{ij}}\,(\boldsymbol{H})}{\boldsymbol{N}} \times 100 \tag{4.18}$$

(b) Spillover from asset *i* to all other assets is computed as:

$$C_{\cdot\leftarrow i}\,(H) = \frac{\sum_{j=1\; j\neq i}^{N} \ddot{\theta}_{ij}\,(H)}{\sum_{ij=1}^{N} \ddot{\theta}_{ij}\,(H)} \times 100 = \frac{\sum_{j=1\; j\neq i}^{N} \ddot{\theta}_{ij}\,(H)}{N} \times 100 \qquad (4.19)$$

(c) The total spillover of asset that measures spillovers across all assets is computed as:

$$C\,(H) = \frac{\sum_{ij=1\; i\neq j}^{N} \ddot{\theta}_{ij}\,(H)}{\sum_{ij=1}^{N} \ddot{\theta}_{ij}\,(H)} \times 100 = \frac{\sum_{ij=1\; i\neq j}^{N} \ddot{\theta}_{ij}\,(H)}{N} \times 100 \qquad (4.20)$$

In achieving the study's objectives, the variables in Equation 4.18 are the ratio of the sum of individual shocks and those from other assets. Thus, the asset analyses the entire flow of information across all assets. Diebold and Yilmaz (2014, 2016) use the variance decomposition matrix as an adjacency matrix for a weighted directed network, which helps to construct the network topology that illustrates the connectivity across all markets. $C_{i\leftarrow j(H)}$ pairwise directional link is denoted by the variables of the adjacency matrix, the row sums of the adjacency matrix and total directional interconnectedness "from," $C_{i\leftarrow\cdot}(H)$; and the column sums of the adjacency matrix as the total directional connectedness "to," $\mathrm{C} \cdot\leftarrow i(H)$.

4.6.3.2 Modified approach of Diebold and Yilmaz (2012, 2014)

As mentioned, that the Diebold and Yilmaz (2012, 2014) approach has several drawbacks and limitations, as such Primiceri (2005) introduced the time-varying parameter vector autoregression (TVP-VAR) which was extended by Antonakakis and Gabauer (2017) to overcome the limitations of the DY approach. Therefore, Ari (2022) states that indeed the TVP-VAR does overcome the drawbacks of Diebold and Yilmaz model (2012,2014) and it has several benefits over the rolling window V.A.R approach. These benefits include 1) its capacity to capture the net connectivity of assets across the system, 2) it highlights the dynamic potential of financial contagion and volatility spillovers across the entire market system over time, and 3) its capacity to identify potential linkages and structural gaps within time series data. Furthermore, Koop and Korobilis (2014) state that the TVP-VAR method does not need the window size to be adjusted if there are some factors forgotten and it further makes it flexible for the variance to differ through Kalman Filter estimations, thus removing quick response to deviations and loss of observations. Moreover, the TVP-VAR method is quicker in responding to events as compared to the rolling window size which exaggerate and reduce shocks.

The TVP-VAR differ from the standard fixed coefficient V.A.Rs in that it allows coefficient in linear VAR model to vary over time following a specified law of motion (Lubik and Matthes, 2015). Additionally, the TVP-VAR often include the stochastic volatility which allows for time variation in the variances of the error processes that affect the V.A.R. The equation for the model is estimated as follows:

$$y_t = \beta_t y_{t-1} + \varepsilon_t \qquad \varepsilon_t | F_{t-1} \sim N(0, S_t)$$

$$\beta_t = \beta_{t-1} + \upsilon_t \qquad \upsilon_t | F_{t-1} \sim N\,(0, R_t)$$

$$y_t = A_t \varepsilon_{t-1} + \varepsilon \tag{4.21}$$

Where: y_t is a $k \times 1$, vector with an $M_p \times 1$ lagged vector. The lagged values of β_t are an $M \times M_p$ error matrix with an $M_p \times M_p$ variance-covariance matrix. β_t is an $M \times M_p$ coefficient matrix and is an $M \times 1$ error disturbance vector with S_t a $M \times M$ variance-covariance matrix. This study will calculate the H-day forward generalized forecast error variance decomposition (G.F.E.V.D.), as it does not quickly respond to the ordering of variables.

G.F.E.V.D. was the preferred framework as an arbitrarily set selection of error structure may give invalid results. To calculate both the generalized impulse response functions (G.I.R.F.) and the G.F.E.V.D., the TVP-VAR was transformed into a TVP-Vector Moving Average (TVP-VMA) model based on the Wold theorem[19] as follows:

$$y_t = A_t + e_t$$

$$Y_t = A_t \varepsilon_t$$

$$A_{0,t} = I$$

$$A_{i,t} = \beta_{1,t} A_{i-1} + \cdots + \beta_{p,t} A_{i-p,t} \tag{4.22}$$

Where $A_{i,t}$ and $\beta_{i,t}$ are $N \times N$-dimensional parameter matrices.

The utilization of the scaled G.F.E.V.D. ($\tilde{\phi}^{g}_{ij,t}\,(H)$), as indicated in Equation 4.20, normalizes the unscaled G.F.E.V.D. ($\phi^{g}_{ij,t}\,(H)$) from Equation 4.19; this resulted in each row adding up to one. $\tilde{\phi}^{g}_{ij,t}(H)$ measures the impact of asset j to asset i in terms of its share in forecast error variance, which is defined as the spillover from asset j to asset i, or the pairwise directional connectedness and this in line with the primary objective. The spillover effect was computed as follows:

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[19] Wold theorem decomposes stationary time series into deterministic and stochastic components, aiding in the analysis and forecasting of asset return behavior.

$$\phi_{ij,t}^{g}(H) = \frac{S_{ii,t}^{-1}\Sigma_{t=1}^{H-1}(\iota_i' A_t S_t \iota_j)2}{\Sigma_{j=1}^{k}\Sigma_{t=1}^{H-1}(\iota_i' A_t S_t A_t' \iota_i)} \tag{4.23}$$

$$\tilde{\phi}_{ij,t}^{g}(H) = \frac{\phi_{ij,t}^{g}(H)}{\Sigma_{j=1}^{k}\phi_{ij,t}^{g}(H)} \tag{4.24}$$

Where $\Sigma_{j=1}^{k}\phi_{ij,t}^{g}(H)$ equals one, $\Sigma_{i,j=1}^{k}\tilde{\phi}_{ij,t}^{g}(H)$ equals κ, and ι_j represents a vector with unity on the j^{th} position and zero otherwise. Using the G.F.E.V.D. framework, connectedness between two assets is expressed as:

$$To_{jt} = \Sigma_{i=1,j\neq i}^{k}\tilde{\phi}_{ij,t}^{g}(H) \tag{4.25}$$

$$From_{jt} = \Sigma_{j=1,j\neq i}^{k}\tilde{\phi}_{ij,t}^{g}(H) \tag{4.26}$$

$$Net_{jt} = To_{jt} - From_{jt} \tag{4.27}$$

$$TCI_t = \frac{1}{k}\Sigma_{j=1}^{k} To_{jt} \equiv \frac{1}{k}\Sigma_{j=1}^{k} From_{jt} \tag{4.28}$$

Equation 4.26 estimates the spill over of asset j to all other assets, which is the sum directional interconnectedness to other assets. The impact of all assets on asset j is estimated in Equation 4.25 which represents the total directional connectedness from other assets. The difference between Equations 4.25 and 4.26 indicate whether an asset is a primary receiver or transmitter of shocks within the system represented in Equation 4.27. The total connectedness index (T.C.I.) in Equation 4.28 measures the total average impact of all the spillovers between the assets where a high T.C.I. indicates a strong presence of interconnectedness between the assets, and vice versa.

4.7 Chapter summary

Chapter 4 reviewed the dataset as well as the empirical models applied in this study. The chapter gave a detailed discussion of the dataset employed for both the cryptocurrencies and traditional asset classes starting from the 06th of October 2019 to the 31st of January 2024. The merits of selecting the cryptocurrencies were based on popularity and on how long the cryptocurrency has been existing. This was followed by a brief discussion of the traditional asset classes selected, which possess different risk attributes. Additionally, the chapter has examined the empirical models used, such as the Diebold and Yilmaz (2012, 2014) framework and the TVP-VAR model, emphasizing their advantages and drawbacks in fulfilling the study's objectives. Prior to the estimation of these models, preliminary data analyses, such as descriptive statistics, correlations analysis, stationarity checks, and unit root tests, were conducted to ensure the suitability of the time series data for estimation. The following chapter discusses the results obtained when estimating the empirical models.

CHAPTER 5: RESULTS AND ANALYSIS

5.1 Introduction

The previous chapter discussed the sample period of the study, the data that is used to achieve the aim and the subsequent objectives. The chapter further discussed the preliminary tests and the empirical models that are used in this study. The current chapter presents and discusses the estimated results found when conducting the tests of the above methodologies. The descriptive statistics is estimated for both the cryptocurrencies and traditional asset indices, followed by the correlation results and the stationarity and unit roots tests results. The later part of this chapter discusses the results of the Diebold and Yilmaz and the TVP-VAR models.

5.2 Descriptive statistics

The main aim of descriptive statistics is to help describe key characteristics of the data by summarizing it in an informative way, both numerically and graphically (Holcomb (2016). As such, the descriptive statistics of daily returns for the cryptocurrencies are presented in Table 5.1 below, whereas Table 5.2 present the descriptive statistics of daily returns for the traditional asset indices.

5.2.1 Descriptive statistics for cryptocurrencies

All the returns of the cryptocurrencies were positive excluding Ripple which demonstrated a negative return of -0.073 percent. Bitcoin had the highest return of 10.065 percent, followed by Ethereum with a return of 7.036 percent which made economic sense as both Bitcoin and Ethereum are leading in terms of market capitalization and popularity (Coin Market Cap, 2024). The crypto index (BGCII) had a third largest return of 6.995 percent reflecting how the whole market of cryptocurrencies is performing whereas Litecoin had a return of 4.440 percent and the stable coin in Tether had a return of 0.004 percent.

In accordance with Renz and Vogel (2022), one of the key drives for the negative returns in Ripple are the regulatory challenges faced by this cryptocurrency. In December 2020, a lawsuit was filed against Ripple by the U.S. Securities and Exchange Commission (SEC) alleging that XRP was a security and that the company had conducted an unregistered security offering. This legal battle casted a shadow of uncertainty over the future of XRP, leading to a lack of confidence among investors and causing the price to drop. Tether had a lowest positive return because it is not exposed to price fluctuations, as it is a stable coin created to maintain a stable price and it is pegged to a US dollar (Wei, 2018)

Table 5.1: Descriptive statistics for the returns of cryptocurrencies

	BTC	ETH	TETHER	XRP	LTC	BGCII
Mean	10.065	7.036	0.004	-0.073	4.440	6.995
Maximum	11.123	8.476	0.012	0.602	5.923	8.261
Minimum	8.498	4.697	-0.015	-1.975	3.467	5.384
Std. Dev.	0.640	1.019	0.001	0.540	0.512	0.710
Skewness	-0.464	-0.844	0.893	0.124	0.561	-0.359
Kurtosis	2.086	2.379	28.238	2.302	2.426	2.121
Jarque-Bera	110.820*	211.263*	41770.98*	35.771*	103.695*	84.006*
Probability	0.000	0.000	0.000	0.000	0.000	0.000

** Denote the level of significance at 1%.*

Source: Authors own estimations (2024)

The highest returns on Bitcoin and Ethereum could be due to their stability compared to the other three cryptocurrencies. While both the Bitcoin and Ethereum market experience significant volatility, these cryptocurrencies are more stable due to their high market capitalization and reputation in the market due to their continuous adoption. The crypto index (BGCII) reflects that cryptocurrency are growing as a medium of exchange with Bitcoin playing a huge role as it acts as the gold standard of the cryptocurrency market, and it usually provides the cue for price direction for other coins and tokens (Avatrade, 2023).

Bitcoin had the highest maximum return of 11.123 percent as compared to the other cryptocurrencies which further demonstrates the powers of the cryptocurrency in terms of market capitalization and popularity. Ethereum had the second largest highest maximum return of 8.476 percent, this was expected as the cryptocurrency is behind Bitcoin in terms of market capitalization and popularity. This increase in both Bitcoin and Ethereum could be because they are speculative assets, and positive sentiment around them has the tendency to multiply (Badari and Chaudhury, 2021). Notably, the crypto index had a maximum return of 8.261 percent which purely demonstrates the performance of cryptocurrencies during the period. Tether had a lowest maximum return of 0.012 percent which was expected as tether has a reduced volatility. Additionally, Bitcoin recorded the highest minimum returns at 8.498 percent, followed by BGCII, which surpassed Ethereum with a minimum return of 5.384 percent. In contrast, Tether and Ripple were the only cryptocurrencies to experience negative minimum returns of -0.015 percent and -1.975 percent respectively.

Ethereum possessed a highest risk out of all the cryptocurrencies with a standard deviation of 1.019 percent, followed by the crypto index 0.710 percent and notable Tether had the lowest standard deviation of 0.001 percent. Ethereum is suspected to be largely affected by issues in the market, such as sell-offs and spillovers from other cryptocurrencies. Ethereum is the second largest after Bitcoin in terms of market capitalization and its markets is believed to be more stable; however, the cryptocurrency is prone to volatile price movements due to investors trading (Dwivedi and Surana, 2024). Despite Ripple being ranked the highest cryptocurrency with the highest risk, in the examined sample the cryptocurrency performed better than Ethereum. Bitcoin had a lowest standard deviation than BGCII, demonstrating its ability as a largest and a stable cryptocurrency.

Table 5.1 revealed a negative skewness of -0.464 and -0.844 for Bitcoin and Ethereum respectively, whereas all the other cryptocurrencies including BGCII had positive skewness values. The negative values indicated that both Ethereum and Bitcoin had larger daily closing prices while the positive values indicated smaller daily closing prices for the other cryptocurrencies (Boylan and Cho, 2012). Furthermore, the negative skewness for Bitcoin and Ethereum are undesirable property as it indicates that more returns were below the mean while the positive skewness indicates that returns were above the mean. This indicates that during the bearish conditions, Bitcoin and Ethereum performed poorly than the other cryptocurrencies in the sample.

Based on Kurtosis, all the cryptocurrencies had the positive values indicating a more peaked distribution. Notably, Tether had a highest kurtosis value of 28.238 indicating a nonlinear and chaotic behaviour in nature, this is line with; Maiti, Grubisic and Vukovic (2020), who found that the behaviour of Tether cryptocurrency daily average return time series pattern is highly nonlinear and chaotic in nature, whereas the other four cryptocurrencies (namely Bitcoin, Ethereum, XRP and Bitcoin Cash) daily average return time series were found to be linear in nature. The Jarque-Bera test results indicate that all cryptocurrencies were rejected at the 1 percent significance level, confirming that their returns are not normally distributed, consistent with Tong, Chen and Zhu, (2022) and Chaim and Laurini (2019).

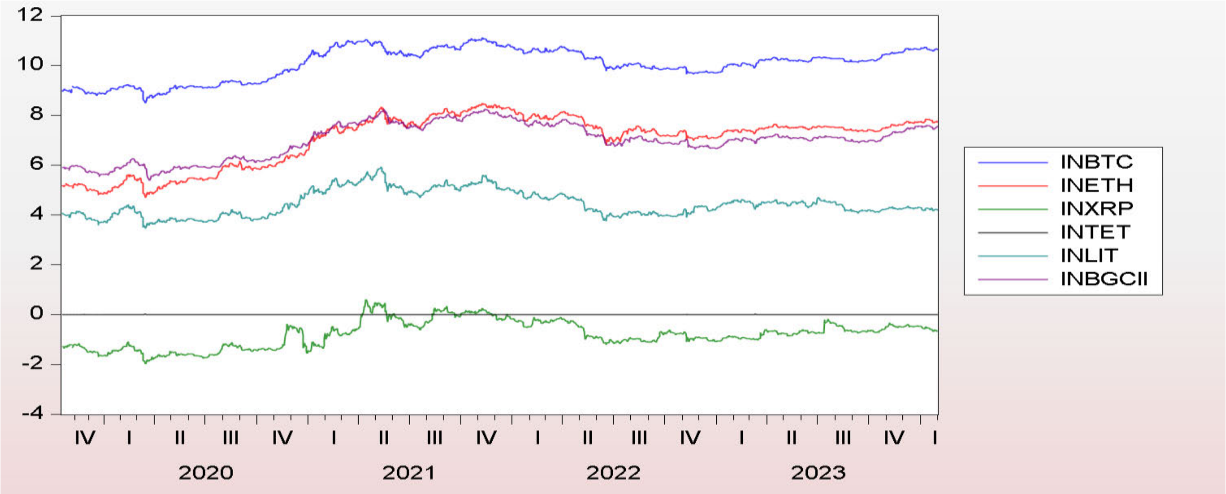

Figure 5.1: Log returns of cryptocurrencies

Source: Author own depiction (2024)

Figure 5.1 above depicts the log returns of the cryptocurrencies during the sample period. As shown in the figure, Bitcoin had the highest returns which is supported by the highest market capitalization among the cryptocurrencies. Ethereum and the crypto index (BGCII) are interchanging in terms of having the highest returns with Tether and Litecoin having positive returns as well. Notably, Ripple demonstrated negative returns during the period with slightly positive returns in the second to the third quarter of 2021 which confirms the negative return value in Table 5.1 as well.

5.2.2 Descriptive statistics for traditional asset indices

All the indices demonstrated the positive returns across the sample with MSCIEMI having a highest return of 6.988 percent, followed by the EMBI with 6.734 percent, BCOMPRI with 5.364 percent and BGCI had the least return of 4.539 percent. This demonstrated how well the traditional asset classes represented by these indices have been performing in emerging markets, which makes economic sense as emerging markets are regarded as fast-growing economies. Accordingly, the indices demonstrated positive highest maximum and minimum returns, with MSCIEMI having higher returns as compared to other traditional asset indices. Moreover, BGCI had a highest risk with a standard deviation of 0.205 percent, followed by MSCIEMI with 0.134 percent, EMBI with 0.080 percent and BCOMPRI was the least risk asset with 0.073 percent.

Table 5.2: Descriptive statistics for the returns of traditional asset indices

	BGCI	EMBI	MSCIEMI	BCOMPRI
Mean	4.539	6.734	6.988	5.364
Maximum	4.917	7.131	7.276	5.543
Minimum	4.086	6.223	6.631	5.121
Std. Dev.	0.205	0.080	0.134	0.073
Skewness	-0.407	-0.364	0.305	-0.675
Kurtosis	2.201	3.245	2.088	3.047
Jarque-Bera	84.985*	38.483*	78.461*	118.941*
Probability	0.000	0.000	0.000	0.000

**Denote the level of significance at 1%.*

Source: Authors own estimations (2024)

Based on Skewness, BGCI, EMBI and BCOMPRI had negative values of -0.407, -0.364 and -0.675 respectively, with MSCIEMI being the only index with a positive value of 0.305. This indicated that only the assets in the MSCIEMI performed better during the bearish markets conditions as it indicates that more returns were above the mean.

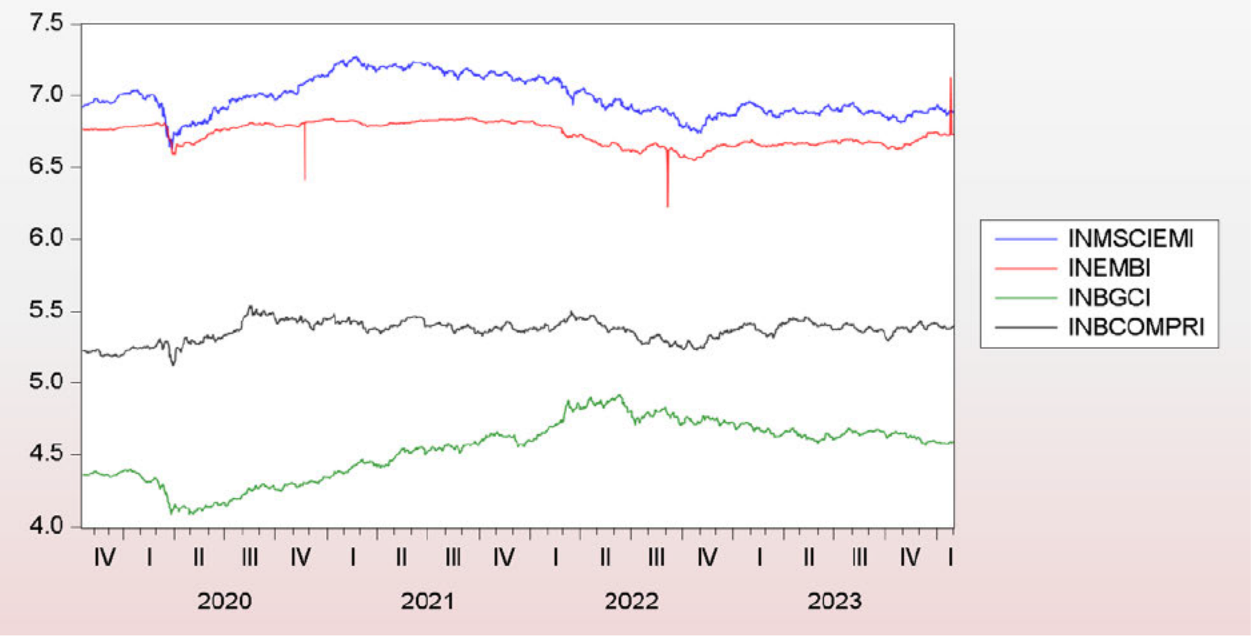

Figure 5.2: Log returns of traditional asset classes indices

Source: Author own depiction (2024)

Figure 5.2 above depicts the log returns of the traditional asset classes indices during the sample period. All the indices demonstrated positive returns with MSCIEMI having the highest returns followed by EMBI, BCOMPRI and BGCI respectively.

5.2.3 Summary: Cross-comparison of cryptocurrencies and traditional asset classes

The analysis reveals that cryptocurrencies such as Bitcoin and Ethereum offer significantly higher average and maximum returns compared to traditional asset indices like MSCIEMI and EMBI. However, these high returns come with substantially greater volatility and risk, as seen in the higher standard deviations and negative skewness of Bitcoin and Ethereum. Traditional asset classes, while delivering lower returns, are more stable, with consistent positive minimum returns and lower volatility, making them more suitable for risk-averse investors. Tether stands out as a stable coin with minimal return and volatility, reflecting its peg to the U.S. dollar. All assets in the study displayed non-normal return distributions, confirmed by the Jarque-Bera test, indicating the need for more advanced risk modelling techniques. Overall, the findings suggest that while cryptocurrencies are suited for high-risk, high-return strategies, traditional assets provide stability. A diversified portfolio that includes both asset types can offer improved risk-adjusted performance, especially in the context of emerging markets.

5.3 Correlation analysis

Senthilnathan (2019) describes correlation as the measure of closeness between two assets. As such, Table 5.3 depicts the correlation between the cryptocurrencies and the traditional asset indices. The correlation is analyzed in two segments, Panel A which is for the whole sample period and Panel B which is during the COVID-19 pandemic. The reason to divide the segments, is to examine how the cryptocurrencies are correlated with the traditional assets during different market conditions bearish and stable. Therefore; the data for "during the COVID-19" was from the 31st of December 2019 where the first case of the COVID-19 was officially declared and ended on the 5th of May 2023 where the end of the COVID-19 pandemic was declared (WHO, 2023)[20].

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[20] This division applies everywhere in the study concerning Panel A and Panel B.

Table 5.3: Correlation results

Panel A: Correlation for the whole sample period										
	BTC	**ETH**	**TET**	**XRP**	**LIT**	**BGCII**	**MSCIEMI**	**EMBI**	**BCOMPRI**	**BGCI**
BTC	1.000									
ETH	0,642	1.000								
TET	0,207	0,189	1.000							
XRP	0,370	0,474	0,019	1.000						
LIT	0,713	0,721	0,142	0,500	1.000					
BGCII	0,276	0,264	0,913	-0,014	0,181	1.000				
MSCIEMI	-0,029	-0,01	0,011	-0,031	-0,029	0,011	1.000			
EMBI	-0,001	0,012	0,011	0,115	0,046	0,018	0,011	1.000		
BCOMPRI	0,002	0,029	0,007	0,018	0,021	0,010	0,060	0,037	1.000	
BGCI	-0,044	-0,038	0,103	-0,028	-0,044	0,119	-0,021	0,017	0,012	1.000

Panel B: Correlation during the COVID-19 pandemic										
	BTC	**ETH**	**TET**	**XRP**	**LIT**	**BCGII**	**MSCIEMI**	**EMBI**	**BCOMPRI**	**BGCI**
BTC	1.000									
ETH	0,792	1.000								
TET	0,047	-0,002	1.000							
XRP	0,569	0,640	0,006	1.000						
LIT	0,768	0,812	0,016	0,652	1.000					
BCGII	-0,011	-0,019	-0,048	-0,005	-0,051	1.000				
MSCIEMI	0,071	0,038	-0,071	0,042	0,02	0,133	1.000			
EMBI	0,009	0,076	-0,013	0,036	0,026	0,025	0,032	1.000		
BCOMPRI	-0,005	-0,007	0,021	-0,014	0,001	-0,042	0,033	0,021	1.000	
BGCI	-0,001	-0,057	-0,02	-0,014	-0,001	0,044	0,068	0,015	0,018	1.000

Source: Author own estimations (2024)

There exist positive correlations among the cryptocurrencies in Panel A, demonstrating the tendency to move in the same direction. Notably, Bitcoin and Ethereum are moderately correlated with 0.642, reflecting their shared market drivers and leadership in the cryptocurrency market. The strong positive correlation of 0.713 between Bitcoin and Litecoin is because these cryptocurrencies share the same codebase with Litecoin being the derivative of Bitcoin (Tu and Xue, 2019). Moreover, there is strong positive correlation of 0.721 between Ethereum and Litecoin. Tether being the stable coin shows weak positive correlation with all the cryptocurrencies except for the crypto index (BGCII) with a correlation of 0.913, indicating that it is largely influenced by the crypto market dynamics. Ripple also demonstrates weak positive correlation with all the cryptocurrencies which is marked by a negative interaction with BGCII, highlighting the existence of diversification benefits between the two cryptocurrencies.

Similarly, the correlations between traditional asset indices in Panel A are weak positive showing no significance co-movements between these assets. Commodities exhibit a negative correlation of -0.021 with the stock markets, presenting an opportunity to achieve diversification. This is consistent with Tuna (2019), who revealed that commodities are effective portfolio diversification tools for developed Islamic stock markets. Furthermore, Bitcoin has negative interactions with stocks, bonds and commodities, as such; investors can benefit in creating a portfolio mixing this combination in line with the MPT. Overall, there is weak correlation between the cryptocurrencies and traditional asset indices in Panel A, indicating that these markets are not highly integrated with each other.

Panel B reveals an increased interaction between the cryptocurrencies during the COVID-19 pandemic as a result of volatility heightening. This is supported by a significant increased correlation between Litecoin and Ethereum of 0.812. However, Tether showed weak positive correlation with all the cryptocurrencies during the COVID-19 pandemic and negative relationship with Ethereum of -0.002 indicating safe haven capabilities. One notable change in traditional asset indices during the COVID-19 pandemic is the correlation between stocks and commodities becoming weak positive to 0.068. This shows that these assets were heavily affected by the market shifts during the crisis. BGCII possessed a weak, positive correlation with MSCIEMI, EMBI and BGCI of 0.133, 0.025 and 0.044 respectively. Despite these correlation values being positive, this demonstrate that during the COVID-19 pandemic the cryptocurrencies were not closely correlated with the traditional asset classes as the correlation are weak positive. This is further supported by the weak correlation between the individual cryptocurrencies and the traditional asset indices.

Moreover, BGCII possessed a weak, negative correlation with BCOMPRI of -0.042 revealing that the cryptocurrencies moved in opposite direction with the precious metals during the COVID-19 pandemic. The correlations of Bitcoin, Ethereum and Ripple with precious metals further support these findings. In line with Karim et al., (2024) who revealed a negative correlation between gold and cryptocurrencies during the COVID-19 pandemic, this suggests that during the market crisis, cryptocurrencies and the precious could be used to achieve the diversification benefits. The findings reaffirm cryptocurrencies' position as assets that operate in an isolated market from traditional assets like gold and this independence makes them a valuable addition to a diversified portfolio.

Overall, the results solidify the importance of cryptocurrencies as a tool for achieving diversification benefits, particularly when combined with the precious metals. The weak correlations between these markets highlights the isolated nature of cryptocurrencies making them valuables assets in a diversified portfolio. However, the increased interconnectedness among the cryptocurrencies during the market crisis reveals the need for cautious portfolio creation, as shocks can intensify volatility within the cryptocurrency market. The stronger correlation between Bitcoin and equity indices during the COVID-19 pandemic suggests that investors may have treated Bitcoin more like a risk asset than a hedge during periods of heightened uncertainty. This shift indicates a potential convergence between crypto and traditional markets in times of crisis, reducing its usefulness as a diversification tool. Post-pandemic, the return to weaker correlations might reflect renewed investor differentiation between asset classes, reinstating the potential role of cryptocurrencies in portfolio diversification.

5.4. Stationarity and unit root tests for cryptocurrencies and traditional asset indices

Understanding stationarity and conducting proper unit root testing are crucial steps in time series modeling. Therefore, Hlouskova and Wagner (2006) highlight that stationarity and unit root tests are essential because they assist in determining whether a time series is non-stationary which can affect how the series is analyzed and modelled. As such, Table 5.4 below and appendix A13 illustrates the results of the ADF, PP and KPSS tests for cryptocurrencies and traditional asset indices. The value on top depicts the test statistic for the ADF and PP tests and the probability value lies below the test statistic whilst the KPSS test has the Lagrange Multiplier (LM) statistic value only.

The tests were conducted at first difference with an intercept because all the variables except Tether demonstrated non-stationarity at levels with an intercept. Tether was found to be stationary because it is a stable coin that maintains stability and these findings are consistent with Shao and Rajapaksa (2024) who found Tether to be stationary without the need for differencing. The probability values for all the variables were 0 and the test statistic were more negative which meets the criteria for unit root testing based on the ADF and PP tests. Therefore, the null hypothesis for the presence of unit root was rejected at all conventional significance levels as the p value is smaller than 1 percent, 5 percent and 10 percent respectively.

In the KPSS test using the LM statistic, all variables were less than the values represented by the conventional significance levels. As such, the null hypothesis of the series is stationary cannot be rejected. Furthermore, the unit root test with the structural break was tested based on the ADF mini t statistic which can account for structural breaks. The notable structural breaks associated with this study are the COVID-19 pandemic and the Ukraine-Russian war. All the variables were significant at 1 percent level indicating that the data was stationary even when the structural breaks were considered.

Table 5.4: Unit root and stationarity tests for cryptocurrencies and traditional asset indices

Variables	**ADF Test**	**P.P Test**	**KPSS Test**
Unit Root and Stationarity Test at First Difference with an Intercept			
BTC	-39.958* (0.000)	-39.977* (0.000)	0.049***
ETH	-40.545* (0.000)	-40.552* (0.000)	0.050***
XRP	-39.332* (0.000)	-39.372* (0.000)	0.041***
TET	-7.724* (0.000)	-33.591* (0.000)	0.141***
LIT	-40.569* (0.000)	-40.562* (0.000)	0.125***
BGCII	-24.827* (0.000)	-36.765* (0.000)	0.044***
MSCIEMI	-12.637* (0.000)	-45.538* (0.000)	0.030***
EMBI	-25.251* (0.000)	-104.248* (0.000)	0.272***
BCOMPRI	-39.618* (0.000)	-39.671* (0.000)	0.024***
BGCI	-36.153* (0.000)	-36.266* (0.000)	0.018***
Break-Point Unit Root Tests at First Difference with an Intercept			
BTC	-41.211* (<0.01)	NONE	
ETH	-41.949* (<0.01)		
XRP	-41.101* (<0.01)		
TET	-61.308* (<0.01)		
LIT	-41.574* (<0.01)		
BGCII	-36.736* (<0.01)		
MSCIEMI	-45.938* (<0.01)		
EMBI	-60.261* (<0.01)		
BCOMPRI	-40.498* (<0.01)		
BGCI	-36.736 (<0.01)		

**Denote the level of significance at 1%*

Source: Author own estimation (2024)

5.5 Information Criterion Tests

Information criterion tests, like AIC, BIC, and HQIC, are useful for choosing the best model. They help prevent overfitting by adding a penalty for complexity, encouraging simpler models that still fit the data well. Claeskens and Hjort (2003) state that the spillovers calculated based on the Diebold and Yilmaz model heavily depends on the correct lag length for the underlying VAR model. Furthermore, Hu (2007) stressed that selecting too few lags may lead to omitted bias while selecting too large lags may lead to overfitting and unnecessary noise, as such information criteria provides a standardized method of selecting an accurate lag length by balancing model complexity and goodness of fit. Table 5.7 provides the results of the Akaike Information, Schwarz's Bayesian Information and Hannan and Quinn Information respectively. The column "Lag" represents the number of lags as default selected by the EViews software, whereas "LogL" stands for Log Likelihood measuring how well the model explains the observed data. Based on the Schwartz Bayesian Information Criterion, lag length 2 is the most appropriate lag for this study as the results of the SBIC are the most preferred out of the three methods. This is because the SBIC is the best fit for the large sample period (Vrieze, 2013 and Watanabe, 2013).

Table 5.5: AIC, SBIC and HQIC results

Lag	LogL	AIC	SBIC	HQIC
0	-65926,66	85,13	85,17	85,15
1	-42361,37	54,84	55,22*	54,98
2	-42012,99	54,52	55,24	54,79*
3	-41828,67	54,41	55,48	54,81
4	-41684,54	54,35	55,77	54,88
5	-41576,52	54,34	56,1	54,99
6	-41276,18	54,08*	56,19	54,86
7	-41184,94	54,09	56,54	55
8	-41110,8	54,13	56,92	55,17

** Denotes the lag selected by each criterion*

Source: Authors own estimation (2024)

5.6 Volatility spillovers co-movements in the assets

In this section, volatility spillovers between cryptocurrencies and traditional asset indices are examined in line with all the objectives of this study. As such, dynamic volatility spillovers estimated from the Diebold and Yilmaz approach and the TVP-VAR model were analyzed. To demonstrate the volatility spillovers during economic crises, the analysis was divided into two segments, Panel A which is for the whole sample period and Panel B which is during the COVID-19 pandemic. Therefore, Table 5.6 and Table 5.7 illustrates the matrix table results from the estimation of the DY approach and the TVP-VAR respectively.

To make the analysis clearer, it is worthy to mention that; a row represents a target asset, and a column represents a source shock. The "From" table column sums the share of volatility spillovers in the total variance of the forecast error and the "To others" row represents the contribution to the forecast error variances from one asset to other assets respectively. The net spillovers reflect the dominance of a particular asset in transmitting or receiving information to and from other assets. A positive value suggests the net transmitter of shocks, while a negative value suggests a net receiver of shocks for a given asset and every spillover value ranges between 0 to 100, indicating the percentage impact of one asset on another or on itself. The results of the two methods are discussed in the following section.

5.6.1 Analysis volatility spillover using Diebold and Yilmaz approach

The Diebold and Yilmaz (2012,2014) spillover approach built on the VAR framework with optimum lag as suggested by the Schwartz Bayesian Information Criterion was estimated. The spillover approach is structured for 10 variables, 10-step ahead (h=10) FEVD setup, in line with Oyewole and Fasanya (2018) and; Balcilar and Bekun (2018). Moreover, the study is aligned with the FEVD built on VAR framework to estimate the pairwise spillovers, directional spillovers, net spillovers and finally, the total spillovers indices. Table 5.7 illustrates the results from the estimation of Diebold and Yilmaz index for both Panel A and Panel B.

Table 5.6: Dynamic connectedness matrix table – Diebold and Yilmaz approach

Panel A – Sample Period

	BTC	ETH	XRP	LIT	TET	BCGII	EMBI	BCOMPRI	MSCIEMI	BGCI	From Others
BTC	32,72	23,29	14,22	20,06	2,76	1,01	1,91	1,13	1,49	1,39	67,28
ETH	22,96	32,74	15,63	20,58	2,44	1,02	1,29	0,96	1,35	1,03	67,26
XRP	15,44	17,42	39,56	17,64	2,82	1,02	2,05	1,26	1,57	1,24	60,44
LIT	20,23	21,19	16,01	33,8	2,54	1,04	1,61	1,05	1,28	1,26	66,2
TET	6,16	6,25	6,37	8,16	61,97	2,22	2,24	1,84	2,12	2,67	38,03
BCGII	15,5	15,71	10,06	12,26	3,78	35,54	2,01	1,7	1,79	1,66	64,46
EMBI	2,12	2,46	2,93	2,24	2,61	2,49	74,13	2,19	4,46	4,36	25,87
BCOMPRI	2,42	2,5	2,89	2,2	3,13	2,3	4,24	71,7	3,72	4,89	28,3
MSCIEMI	4,58	4,97	4,16	4,09	3,29	2,72	5,09	2,08	65,45	3,58	34,55
BGCI	2,89	2,82	2,27	2,76	2,9	4,49	3,26	5,06	5,05	68,5	31,5
To Others	92,29	96,62	74,54	89,99	26,26	18,32	23,7	17,26	22,81	22,09	483,89
Inc. Own	125,02	129,35	114,1	123,79	88,23	53,86	97,83	88,96	88,26	90,59	cTCI/TCI
NET	25,02	29,35	14,1	23,79	-11,77	-46,14	-2,17	-11,04	-11,74	-9,41	53,77/48,39

Panel B - During the COVID-19 Pandemic

	BTC	ETH	XRP	LIT	TET	BCGII	EMBI	BCOMPRI	MSCIEMI	BGCI	From Others
BTC	31,7	22,54	15,31	21,42	2,29	0,86	1,83	1,03	1,58	1,45	68,3
ETH	22,39	31,96	16,48	21,65	2,08	0,84	1,14	0,98	1,41	1,07	68,04
XRP	16,61	18,28	36,43	19,28	2,85	0,92	1,89	1,06	1,39	1,3	63,57
LIT	21,09	21,49	17,28	31,95	2,15	0,96	1,54	0,93	1,28	1,33	68,05
TET	6,49	6,42	7,21	8,42	60,39	2,34	2,22	1,56	2,3	2,64	39,61
BCGII	13,34	13,42	9,38	11,87	3,42	41,04	1,86	1,92	2,01	1,74	58,96
EMBI	2,07	2,5	2,8	2,24	2,65	2,31	74,11	2,35	4,46	4,52	25,89
BCOMPRI	2,56	2,55	2,5	2,32	2,74	2,47	3,34	72,89	3,68	4,94	27,11
MSCIEMI	4,96	5,05	4,42	4,01	3,03	2,72	2,98	1,99	67,87	2,96	32,13
BGCI	3,12	2,72	2,36	2,62	3,02	4,58	2,92	5,48	5,87	67,32	32,68
To Others	92,63	94,97	77,75	93,83	24,23	18	19,72	17,3	23,97	21,95	484,35
Inc. Own	124,33	126,93	114,17	125,78	84,62	59,05	93,83	90,19	91,83	89,26	cTCI/TCI
NET	24,33	26,93	14,17	25,78	-15,38	-40,95	-6,17	-9,81	-8,17	-10,74	53,82/48,44

Source: Author own estimation (2024)

As observed in Panel A, the spillover effect of assets due to their own contributions ranges from 32.72 percent to 74.13 percent as represented by the diagonal cells of the matrix. The spillover effect slightly decreased during the COVID-19 pandemic as it ranged from 31.70 percent to 74.11 percent, demonstrating that the cryptocurrencies, bonds, stocks and commodities depend less on their own contribution during the COVID-19 pandemic. In Panel A, the off-diagonal cells showing the portion of forecast error variance explained by shocks coming from one asset to another, revealed that cryptocurrencies send more shocks among themselves as compared to the traditional assets. This is explained by Ethereum contributing 23.29 percent of shocks to Bitcoin, but only contributed 2.46 percent, 2.5 percent, 4.97 percent and 2.82 percent to EMBI, BCOMPRI, MSCIEMI and BGCI respectively. Similarly, this trend was noted during the COVID-19 pandemic as the cryptocurrencies had more shocks to other cryptocurrencies as compared to the traditional asset classes. One notable observation in both Panel A and Panel B is that Tether and BGCII had less shocks to either cryptocurrencies and traditional assets.

The finding of Tether having less shocks was somehow expected, as Tether is a stable coin created to maintain stability (Wu and Leung, 2023) and this further suggest the abilities of Tether to serve as a diversification tool by having a low correlation in line with the MPT. The total spillover index is shown at the bottom of the matrix in the final row, summing up the overall level of interconnectedness among all the assets over the analyzed time period. Panel A had a total spillover index of 483.89 percent, with Ethereum having the highest contribution to others by 96.62 percent, followed by Bitcoin with 92.29 percent and in traditional assets, EMBI contributed more to others with 23.70 percent, followed by MSCIEMI with 22.81 percent. This finding summarizes the dominance of Bitcoin and Ethereum within the cryptocurrency market by having more influence on other cryptocurrencies, marked by highly volatile prices. Panel B was slightly above Panel A in terms of total spillover index as it accounted for 484.35 percent highlight a significant total spillover within the time domain.

In Panel A, Bitcoin received more volatility shocks from other assets accounting for 67.28 percent, followed by Ethereum with 67.26 percent and Litecoin was third with 66.2 percent. This suggests that the prices of these cryptocurrencies are significantly influenced by the movement of other assets in the sample, thus limiting their diversification benefits and presenting the traits of contagion in line with the FCT. Notable, Tether received less volatility spillovers from other assets accounting for 38.03 percent which is relatively low as compared to the other cryptocurrencies, indicating less dependence from other assets. In traditional assets, MSCIEMI received more shocks of 34.55 percent, followed by BGCI with 31.5 percent, whereas BCOMPRI and EMBI had 28.3 percent and 25.87 percent respectively. In Panel B, the shocks received from other assets for all the cryptocurrencies and traditional assets were slightly above than Panel A due to heightened volatility during the COVID-19 pandemic. Notable, Litecoin received more shocks of 68.05 percent than Ethereum (68.04 percent). This might be due to shifts in investor sentiments and speculative trading during the COVID-19 pandemic.

By manually calculating the contribution of each traditional asset index to the cryptocurrencies[21] in panel A, stock markets had the highest contribution of shocks to cryptocurrencies with 23.81 percent, followed by the commodities with 18.13 percent, precious metals with 15.44 percent and bonds with 14.85 percent. Following the similar approach in Panel B, bonds had the highest contribution of 10.48 percent, followed by the MSCIEMI with 9.97 percent, commodities with 9.53 percent and precious metals with 7.48 percent. These findings suggest that the stock markets are more connected with the cryptocurrencies in general, however; during the COVID-19 the bonds in emerging markets were more connected with the cryptocurrencies. Moreover, the low spillovers of precious metals in both Panels indicate that they can be used as a diversification tool for the cryptocurrencies particularly during the COVID-19 pandemic aligning perfectly with the MPT.

These findings are in line with Yousaf and Ali (2021), who found that the volatility spillovers between the cryptocurrencies and US stock were not significant during the COVID-19 pandemic, moreover Syed et al., (2022) discovered that the cryptocurrency market was attached to the US bond market during the COVID-19 pandemic. Lastly, Rehman and Vo (2020) revealed that in short-run, copper[22] provides maximum diversification opportunities for investors with all cryptocurrencies, even under extreme market conditions, and for medium and long-run periods, Rehman and Vo (2020) highlighted that precious metals under extreme positive returns distribution are not integrated with extreme negative cryptocurrencies returns, thereby implying diversification opportunities for investors.

Looking at the volatility transmission between the cryptocurrencies and traditional assets in both Panels, there appears to be very low spillovers between these assets suggesting that

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[21] Summing up all the total contributions of each traditional asset class index to the cryptocurrencies alone including the crypto index. For example; EMBI (1,83 + 1.14 + 1.89 + 1.54 + 2.22 + 1.86) = 10.48 total spillovers to the cryptocurrencies.

[22] Copper falls under precious metals.

cryptocurrencies operate in their own isolated market, even during market crisis. This is because there are more spillover effects among the cryptocurrencies alone, as compared to spillover effects going to the traditional assets' indices. Similarly, the effects are less from the traditional asset indices to the cryptocurrencies and it is less even among themselves. This aligns with the findings of Corbet et al., (2021) who revealed that the cryptocurrency market operates in isolation from financial markets such as Gold and S&P 500, making cryptocurrencies to have more influence among themselves.

Furthermore, in Panel A; Ethereum is the net transmitter of shocks by 29.5 percent, followed by Bitcoin with 25.02 percent, Litecoin with 23.79 percent and Ripple with 14.10 percent. This implies that these cryptocurrencies significantly influence other assets in the sample by acting as the source of risk transmission. Notably, Tether and BGCII moved in separate direction with the rest of the cryptocurrencies by being the net receivers, meaning that they do not transfer shocks to other assets. All the traditional asset indices are the net receivers of shocks within the system with MSCIEMI receiving more shocks of -11.74 percent, followed by BCOMPRI with -11.04 percent, BGCI with -9.41 percent and EMBI with -2.17 percent. However, the volatility spillover influencing traditional assets might be from external factors because there exist weak spillover effects between them and cryptocurrencies indicating that these markets are not highly integrated. Similarly, cryptocurrencies such as Ethereum, Bitcoin, Litecoin and Ripple act as a source of risk transmission for other cryptocurrencies than for the traditional asset indices indicating a greater internal influence.

The findings of Panel B support the findings of Panel A in terms of the cryptocurrencies that are the net transmitter and net receivers of shocks, and accordingly for the traditional asset indices as well. However, Tether appears to receive more shocks during the COVID-19 of -15.38 percent as compared to the -11.78 percent of the whole sample period. This demonstrates that Tether served as safe haven, particularly for the cryptocurrencies during the COVID-19 pandemic which is in line with Syuhada et al., (2022) who discovered that Tether was a consistent safe haven for oil and Bitcoin mixed with any allocation. Furthermore, these findings are consistent with Bouri et al., (2021) who found Bitcoin, Ethereum and Litecoin to be net transmitter of shocks during the COVID-19 pandemic. Additionally, commodities received more shocks in Panel B of -10.74 percent, followed by the precious metals with -9.81 percent, indicating their safe haven abilities during the COVID-19 pandemic. The heat map in appendix A1 reflects the movements of cryptocurrencies and traditional asset indices using the Diebold and Yilmaz approach.

The above findings indicate a significant distinct between the cryptocurrency market and the traditional financial system. The high volatility spillovers observed in the cryptocurrency market implies that shocks in one asset propagated across the market, thus highlighting the importance a thoroughly risk assessment within the crypto ecosystem. The attribute of Tether and BGCII as net receivers of shocks indicate their utility as stabilizing forces and further highlight their systemic importance within the cryptocurrencies. For traditional assets, the findings support their insulation from cryptocurrency market volatility, revealing that traditional financial markets are not affected by the movements in the cryptocurrency market. Overall, this segmentation provides investors with diversification opportunities by allocating across these two distinct asset classes in emerging markets and further strengthens their knowledge in financial markets in line with the AMH.

5.6.2 Analysis of the volatility spillover using TVP-VAR model

The TVP-VAR model is employed to further assess the time-varying relationship between cryptocurrencies and traditional asset classes. Table 5.8 illustrate the matrix table results estimated using the TVP-VAR method for both panel A and Panel B. Revisiting some benefits of the TVP-VAR method over the standard VAR approach of Diebold and Yilmaz approach, the following was highlighted (Ari, 2022):

1) TVP-VAR specifies the dynamic potential impact of financial contagion and volatility spillovers on the overall system of the markets over time.
2) TVP-VAR has an ability to identify possible linkages and structural gaps in time series data.
3) TVP-VAR is quicker in responding to events as compared to the rolling window size which exaggerate and reduce shocks.

The volatility spillovers of the assets due to their shocks as observed in the diagonal matrix ranges from 33.88 percent to 84.74 percent in Panel A and for Panel B, the range was from 33.05 percent to 84.94 percent. This observation is relatively higher as compared to the DY index observation; this is because the TVP-VAR model provide more insights by capturing time-varying patterns whereas the DY index relies on fixed matrix which may not reflect real-time market dynamics. The overall total spillovers coming from the cryptocurrency market (BGCII) to all traditional asset indices on the sample was 9.88 percent and from the traditional asset indices to the cryptocurrencies was 8.54 percent. This minimal connection was somehow expected as there were less spillovers from individual cryptocurrencies to the traditional asset indices and vice versa.

Analyzing the assets individually, Litecoin appears to send more shocks to EMBI of 3.14 percent in Panel A and 3.35 percent in Panel B respectively, demonstrating no significant changes in and out of the crisis time. Similar to the DY index, cryptocurrencies continued to have more influence among themselves as there more spillover shocks internal than external i.e., 23.08 percent of shocks from Ethereum to Bitcoin in Panel A. Moreover, Tether continued to demonstrate its attributes as a stable coin with relatively less influence on both the cryptocurrencies and the traditional asset indices. This supports the abilities of this cryptocurrency to achieve diversification benefits in both the cryptocurrencies and asset classes such as bonds, stocks and commodities.

Table 5.7: Dynamic connectedness using the TVP-VAR model

Panel A- Whole sample period										
	BTC	**ETH**	**XRP**	**LIT**	**TET**	**BCGII**	**EMBI**	**BCOMPRI**	**MSCIEMI**	**BBCGI**	**From Others**
BTC	38,34	23,08	12,78	20,46	1,36	0,8	0,99	0,85	0,77	0,57	61,66
ETH	21,3	33,88	16,8	21,46	1,03	0,83	1,95	0,99	0,97	0,78	66,12
XRP	14,7	19,65	41,28	18,59	0,99	0,84	1,83	0,88	0,66	0,58	58,72
LIT	19,03	22,13	15,71	35,6	1,25	0,98	2,34	1,29	0,75	0,93	64,4
TET	2,58	1,88	1,85	2,61	83,03	1,44	2,16	1,06	1,03	2,35	16,97
BCGII	1,96	2,37	2,13	2,36	2,7	79,81	2,18	1,71	2,37	2,41	20,19
EMBI	1,24	2,01	1,96	3,14	1,09	1,05	82,78	3,35	2,01	1,38	17,22
BCOMPRI	0,8	1,35	1,02	1,61	1	1,55	6,41	82,05	1,71	2,5	17,95
MSCIEMI	1,28	1,15	1,26	1,45	1,02	3,94	1,94	1,42	84,75	1,78	15,25
BBCGI	1,11	1,41	0,98	2,28	1,75	3,02	2,64	4,4	1,15	81,25	18,75
To Others	64,01	75,04	54,49	73,96	12,18	14,45	22,43	15,95	11,42	13,29	357,24
Inc. Own	102,35	108,93	95,77	109,56	95,21	94,26	105,22	97,99	96,17	94,54	cTCI/TCI
NET	2,35	8,93	-4,23	9,56	-4,79	-5,74	5,22	-2,01	-3,83	-5,46	39,69/35,72
Panel B - During the COVID-19 pandemic											
	BTC	**ETH**	**XRP**	**LIT**	**TET**	**BCGII**	**EMBI**	**BCOMPRI**	**MSCIEMI**	**BBCGI**	**From Others**
BTC	37,75	21,75	13,41	20,66	1,38	0,95	1,1	1,17	0,93	0,9	62,25
ETH	19,97	33,05	18,05	22,17	0,97	0,8	2,16	1,26	0,89	0,7	66,95
XRP	14,6	20,54	38,46	19,4	1,17	0,95	2,25	1,49	0,63	0,51	61,54
LIT	18,86	22,33	16,9	33,61	1,28	1,32	2,52	1,44	0,75	0,99	66,39
TET	2,14	2,41	2,73	2,94	82,19	1,4	2,29	1,14	1,01	1,74	17,81
BCGII	1,74	2,47	2,52	2,51	2,83	79,38	1,93	1,65	2,61	2,35	20,62
EMBI	1,24	2,07	2,18	3,35	1,14	0,91	81,57	4,22	1,95	1,38	18,43
BCOMPRI	0,85	1,5	1,17	1,9	0,95	1,51	7,49	80,43	1,57	2,63	19,57
MSCIEMI	1,37	1,17	1,1	1,29	0,75	4,29	2,13	1,16	84,94	1,81	15,06
BBCGI	1,34	1,26	0,78	1,91	1,44	3,17	2,91	4,86	1,27	81,06	18,94
To Others	62,12	75,5	58,83	76,13	11,91	15,29	24,78	18,38	11,61	13,02	367,57
Inc. Own	99,87	108,55	97,29	109,74	94,1	94,67	106,35	98,82	96,55	94,08	cTCI/TCI
NET	-0,13	8,55	-2,71	9,74	-5,9	-5,33	6,35	-1,18	-3,45	-5,92	40,84/36,76

Source: Author own estimation (2024)

Observing the results in Panel A, Ethereum sends more shocks to others with 75.04 percent, followed by Litecoin with 73.96 percent, Bitcoin with 64.01 percent and Ripple with 54.49 percent. However, during the COVID-19 pandemic, Litecoin appears to send more shocks with 76.13 percent showing an increased volatility as compared to the whole sample. This is because the COVID-19 pandemic shocks spurred Litecoin by 3.20 to 3.84 percent, higher than any other cryptocurrency (Sarkodie et al., 2022). Notably, the shock transmissions for all the cryptocurrencies in Panel B increased except for Bitcoin, who faced a declined to 62.12 percent. In traditional asset indices, EMBI sends more shocks in both Panels, followed by BCOMPRI, BGCI and MSCIEMI, however; shocks are increased during the COVID-19 pandemic as compared to the sample period.

In panel A, Ethereum, Litecoin, Bitcoin and Ripple receives more shocks from other assets of 66.12 percent, 64.40 percent, 61.66 percent and 58.72 percent respectively. Tether and BGCII continued to have less influence within the system as they received shocks of 16.97 percent and 20.19 percent respectively. Traditional asset indices received relatively low shocks in the system as compared to the cryptocurrencies, with BGCI receiving more shocks of 18.75percent, followed by BCOMPRI with 17.95 percent, EMBI with 17.22 percent and MSCIEMI with 15.25 percent. Notably, the shocks increased significantly for the cryptocurrencies during the COVID-19 pandemic, particularly for Ripple and Litecoin, however; the sequence did not change as Ethereum continued to receive more shocks. Similarly, the shocks increased for traditional asset indices during the COVID-19 pandemic except for MSCIEMI, which resulted in a sequence change as BCOMPRI received more shocks of 19.57 percent, followed by BGCI, EMBI and MSCIEMI with 18.94 percent, 18.43 percent and 15.96 percent respectively.

These findings significantly differ with the earlier results of the DY index. Firstly, the directional spillovers in the DY index, particularly the "To" spillovers are relatively high as compared to the TVP-VAR model, indicating the incompetence of the DY index by not responding quicker to events and shocks, thus leading to exaggerating or reducing shocks. Secondly, the DY index did not account for the time-varying aspect of Litecoin, who transferred more and received increased shocks in return, during the COVID-19 pandemic in the TVP-VAR model. Moreover, in the DY index, Ethereum sends more shocks to the MSCIEMI whereas in the TVP-VAR, it is Litecoin that has a significant impact to EMBI. In terms of volatility transmission within the system, both the DY index and TVP-VAR model move in the same direction, highlight significant volatility spillovers among the cryptocurrencies themselves and the weak connection that exists between cryptocurrencies and traditional assets in emerging markets.

Litecoin was the net transmitter of shocks in the sample period with 9.56 percent, followed by Ethereum with 8.93 percent and Bitcoin with 2.53 percent. Notable, Ripple was the net receiver of shocks with -4.23 percent opposing the earlier findings of the DY index. This might be due to the case[23] that was filed by the U.S authorities against Ripple. Similar to the findings of the DY index, Tether, BGCII and the traditional asset indices except for EMBI continued to be the net receiver of shocks. Panel B of Table 5.8 report a significant change during the COVID-19 pandemic as Bitcoin had a slightly role of being the net receiver of shocks with -0.13 percent, highlighting the heightened volatility and possible integration between cryptocurrencies and traditional asset during the crisis. There were no significant changes in other assets during the crisis, as Litecoin alongside Ethereum and EMBI were the net transmitters. Based on the TVP-VAR, the study can conclude that Litecoin was the net transmitter of shocks in the sample period, opposing Ethereum as suggested by the earlier findings of the DY index.

The findings of Panel A and B of the TVP-VAR model move in the same direction by supporting the earlier findings of the DY index that the cryptocurrency market and traditional financial system operate in segmentation. However, the TVP-VAR model revealed major time-varying relationships which are very crucial when analyzing the market during the crisis times. An example includes Bitcoin temporarily serving as net receiver during the COVID-19 pandemic, moreover Ripple was found to be the net receiver in both Panels. This completely differs with the results of the DY index which found these two cryptocurrencies to be always the net transmitters of shocks. Moreover, bonds were found to be the net transmitters of shocks in the system in both Panels using the TVP-VAR. These findings imply that the assets movement are time-varying particularly during the crisis period thus enforcing the importance of diversification and proactive risk management by the market participants. Appendix A2 highlights the movement that occurred in the assets when using the TVP-VAR model.

5.6.3 Directional spillover analysis

This section focuses on the rolling window size and the time-varying parameter analysis and by default, the COVID-19 pandemic fluctuations are incorporated as the study period extends beyond the pandemic. The table matrix results above and the corresponding interpretations are static, reporting the "average" of the spillover dynamics among the investigated cryptocurrencies and traditional asset indices. Moreover, the above VAR analysis were built on the assumptions that the spillover coefficients are time invariant indicating that coefficients are constant over time. As such, the time invariant assumption of coefficients is inadequate given that it fails to capture fluctuations and this may lead to false and misleading direction in

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[23] The case was explained in the subsequent chapters.

the period of jumps. For example, during the COVID-19 pandemic which influenced the whole world, the general expectation is to experience observable spillovers varying over-time.

Therefore, this study employs a 200-day rolling window size of the DY approach and the TVP-VAR model to enable time-varying and nonlinear spillover characteristics to be investigated. This approach is opposing the static framework which may miss the effects of a myriad changes that have been occurring in the cryptocurrency market and traditional system market that may have been affected the interconnectedness between these markets. As such, the figures below demonstrate the spillover fluctuations among the cryptocurrencies and the traditional asset indices.

5.6.3.1 Pairwise dynamic spillover analysis

Figure 5.3 and Figure 5.4 below depicts the pairwise dynamic spillovers estimated from the 200-day rolling window size and the TVP-VAR model between the cryptocurrency index (BGCII) to the traditional asset indices. For this purpose, only the cryptocurrency index (BGCII) was considered to demonstrate how the whole market of cryptocurrencies move with the selected traditional asset classes rather than individual cryptocurrencies. The spillovers fluctuate significantly during the period for both approaches. Notably, in the 200-day analysis, the plot of BGCII to EMBI recorded a high spillover impact of almost 100 percent in late 2020 demonstrating the impact of the COVID-19 pandemic on these assets. The trend is noted in the TVP-VAR figures in late 2019 with the spillover average of 70 percent for each asset. The fluctuations are high throughout the period for both Figures 5.3 and 5.4 plots and this could be due to the COVID-19 pandemic and based on the static results above, one could conclude that the cryptocurrencies are the reason for these fluctuations. However; these fluctuations differ significantly between these two approaches, revealing that indeed the approaches offers diverse advantages.

The pairwise dynamic spillovers for each cryptocurrency to the traditional asset class index and vice versa can be observed in Appendix A6 and A11. Based on these Appendices, it can be noted that there exist less volatility spillovers between the cryptocurrencies and traditional asset indices. Significant interactions are observed in the cryptocurrency market between Bitcoin, Ethereum, Ripple and Litecoin with less influence to the traditional asset indices. Furthermore, Tether and BGCII demonstrates less spillovers between them and the other cryptocurrencies, indicating that they can be used to achieve diversification benefits in the cryptocurrency market. Overall, these pairwise dynamic spillovers support the earlier findings of the static approach about these markets operating in segmentation.

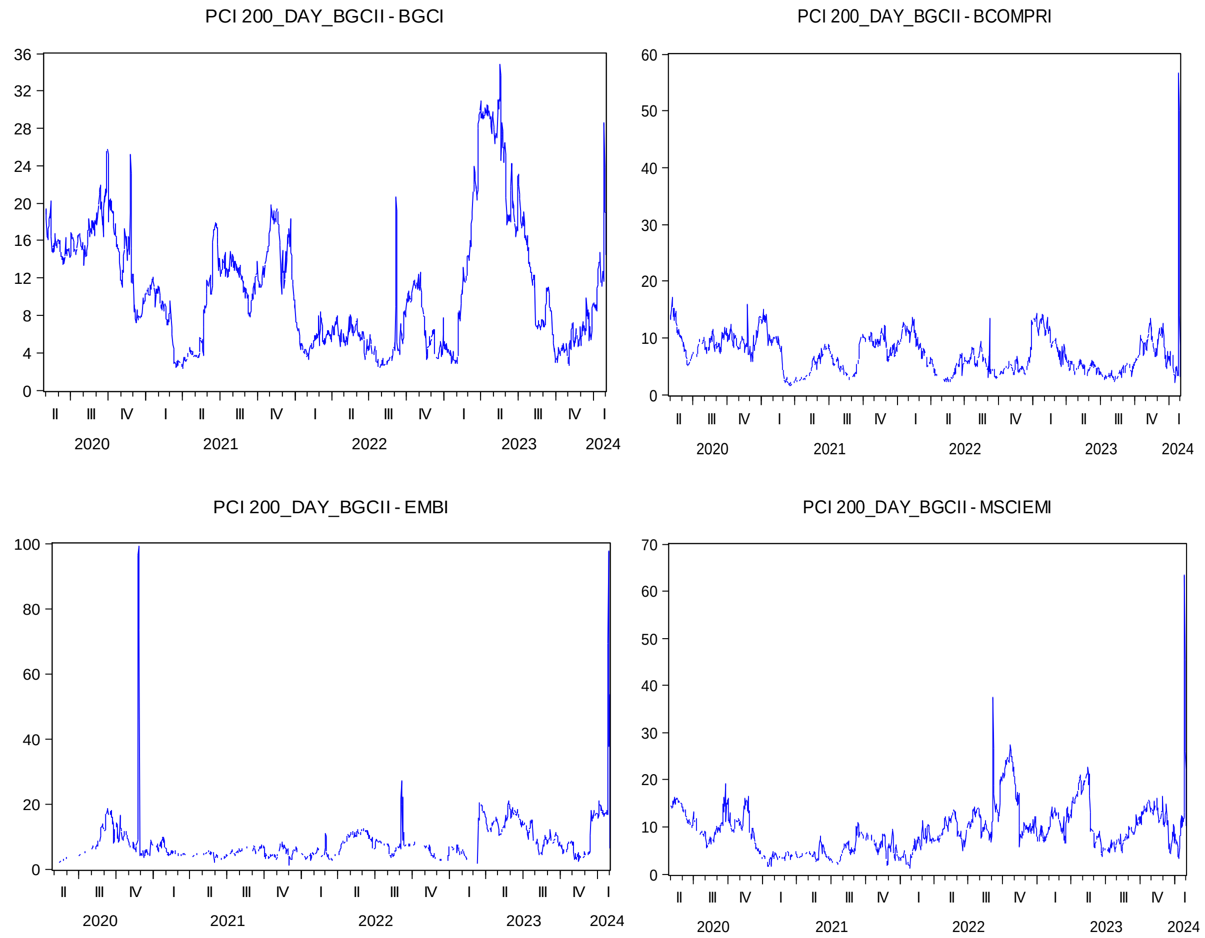
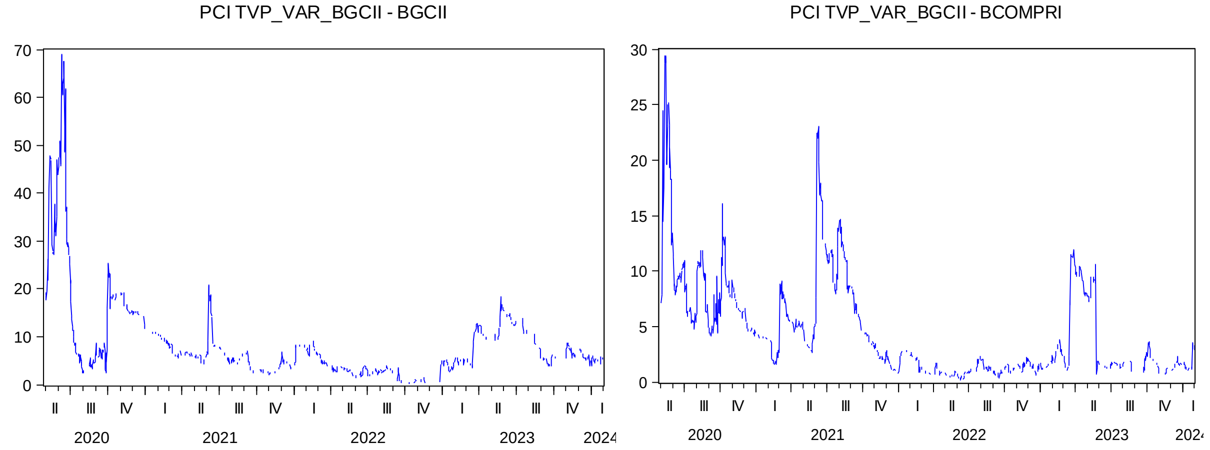


Figure 5.3: The 200-day pairwise dynamic spillovers

Source: Author own depiction (2024)



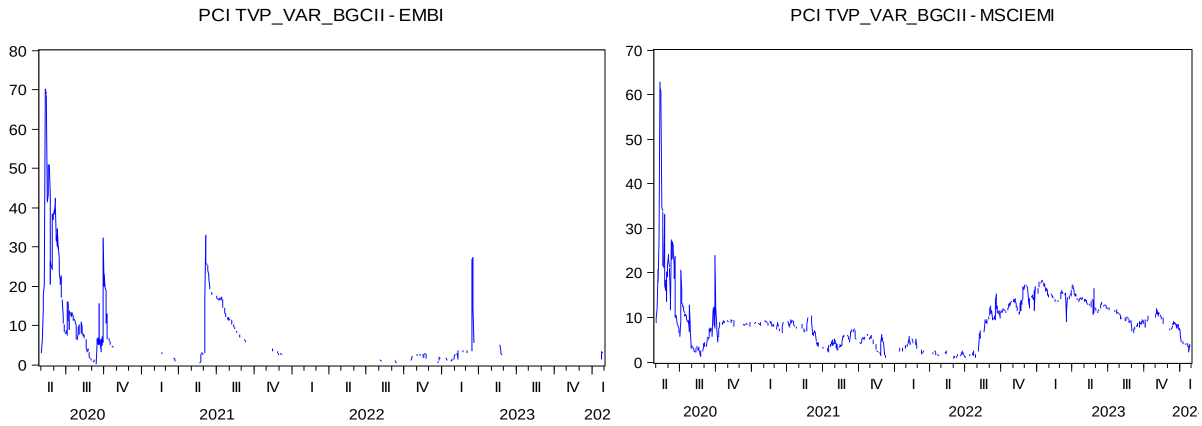


Figure 5.4: TVP-VAR pairwise dynamic spillovers

Source: Author own depiction (2024)

5.6.3.2 Directional spillover analysis

The study proceeds to investigate the directional dynamic spillover effect after the pairwise dynamic spillovers. For more robust discussion on the direction of the spillovers as expressed in Equations 4.18 and 4.19 for DY approach and 4.25 and 4.26 for TVP-VAR model in the methodology section, the need to examine the directional spillover is crucial. The directional spillover of “To” and “From” are illustrated in figure 5.5 and 5.6. The plots of directional spillovers “From” and “To” show that the shock transmission “To” reveals more volatility relative to “From” transmission for both approaches.

Figure 5.5 show the trend of high fluctuations in cryptocurrencies particularly for Bitcoin, Ethereum, Ripple and Litecoin with an average of almost 120 percent in 2022 for the DY index and averaging 100 percent for the TVP-VAR model. The high fluctuations in the DY index might be due to the assumption that the rolling window approach exaggerate shocks. Despite EMBI having the heightened volatility in late 2022 for possibly hours or days, the cryptocurrencies dominated the volatility spillovers throughout the period. This supports the evidence presented by Tan (2023) about the high volatile prices during economic downturns for the cryptocurrency assets. Similarly, the “FROM” plots in Figure 5.6 show a similar trend of cryptocurrencies dominating the volatility spillovers transmitted as compared to the traditional asset classes. Notable, the cryptocurrency index exhibits different patterns in both approaches, with more spillovers in 2020 for the TVP-VAR whereas the DY demonstrates more spillovers from 2021 to 2024.

Overall, both Figures demonstrate the increased interconnectedness of the cryptocurrencies in times of market distress as marked by increased volatility spillovers. However, stable coins like Tether shows minor variations indicating their role as net receivers of shocks in times of market downturns. Traditional asset indices remain relatively stable, highlighting their weak connection with the cryptocurrency market. These visualizations align with previous findings that major cryptocurrencies are significant transmitters of volatility, while traditional assets and stable coins' act as receivers or stabilizers during turbulent periods. More directional spillovers of this nature can be observed in Appendix 4,5,8 and 9 for both the DY index and the TVP-VAR model.

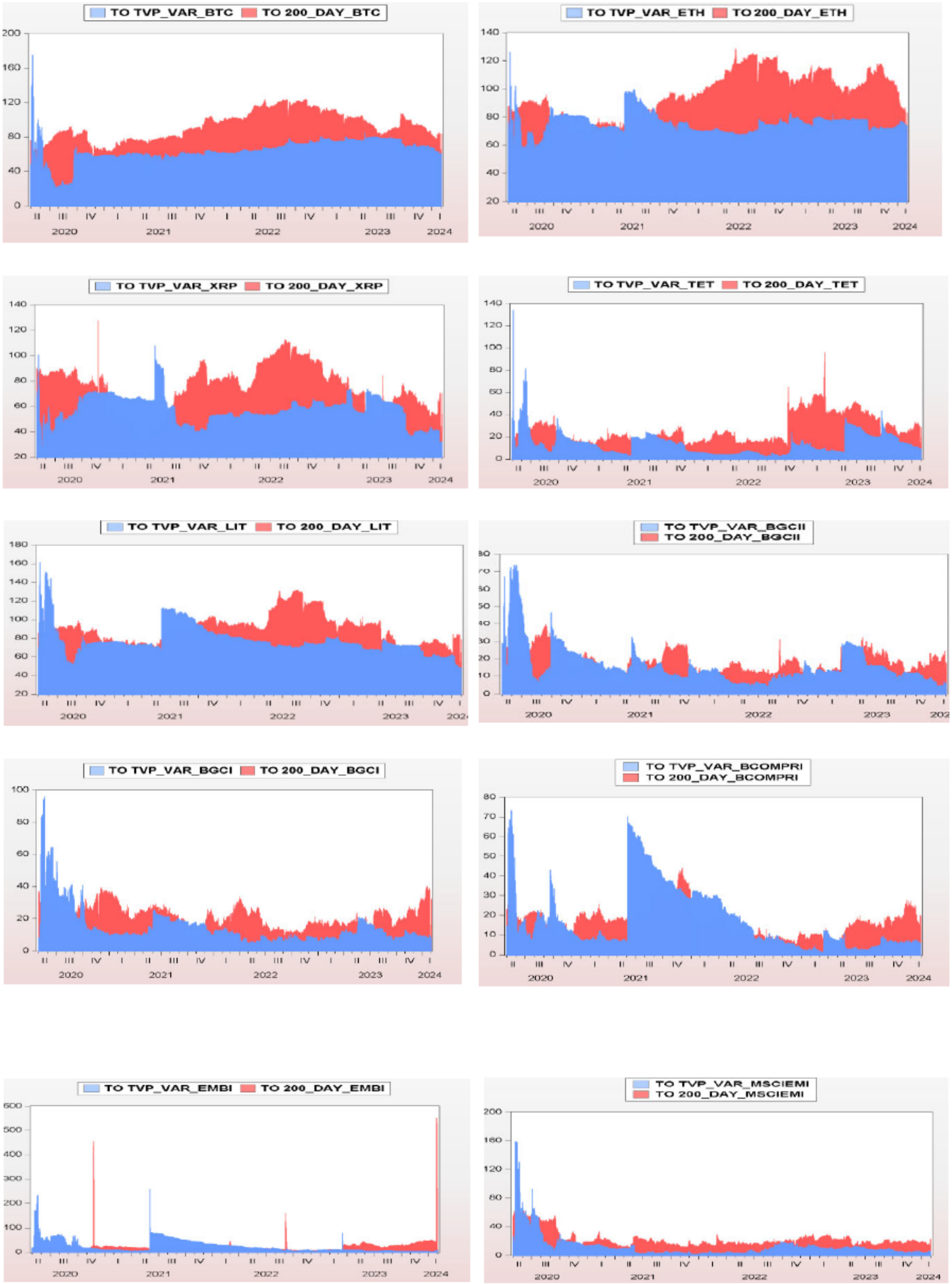


Figure 5.5: Total dynamic spillovers "To" cryptocurrencies and traditional asset indices

Source: Author own depiction (2024)

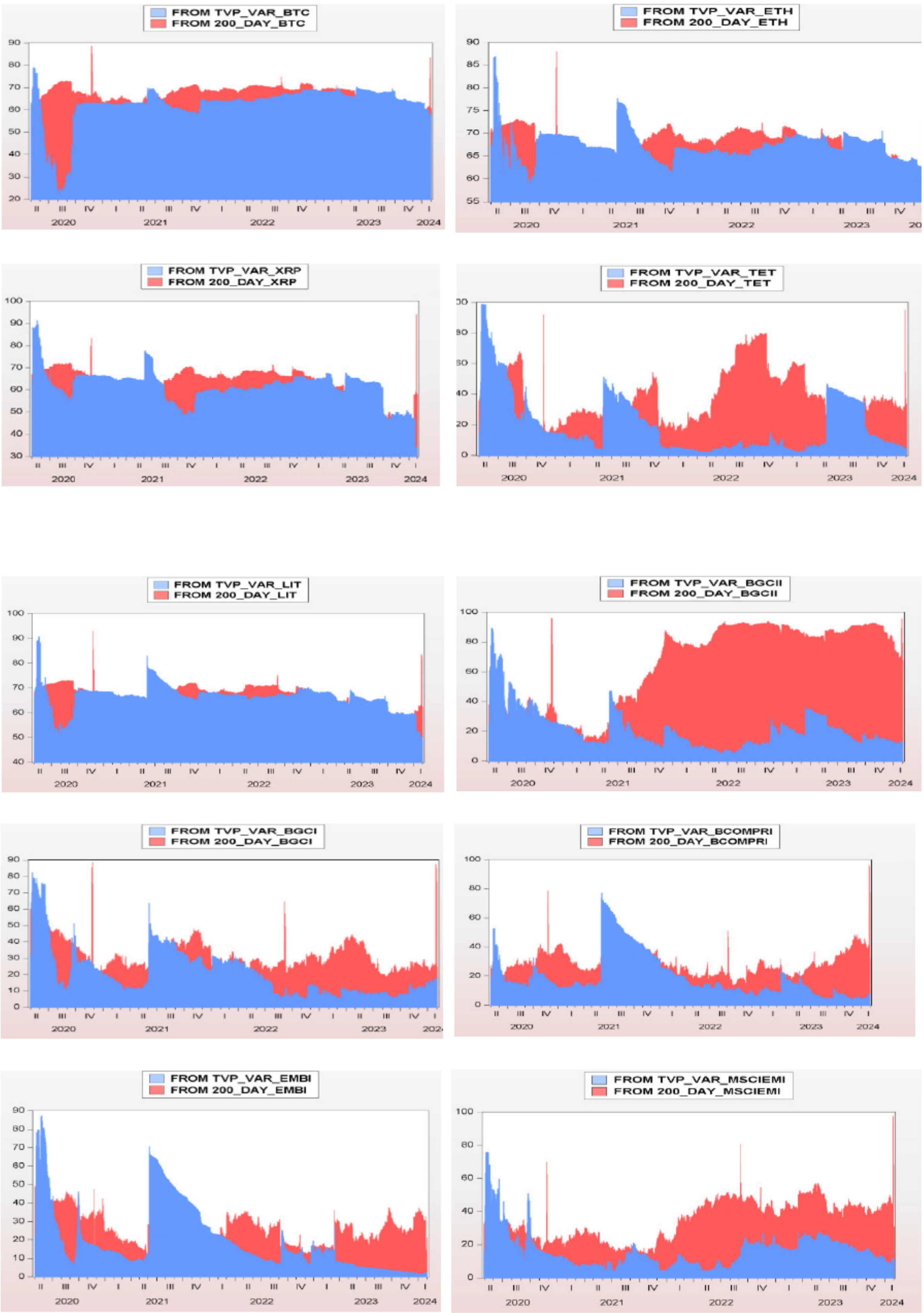
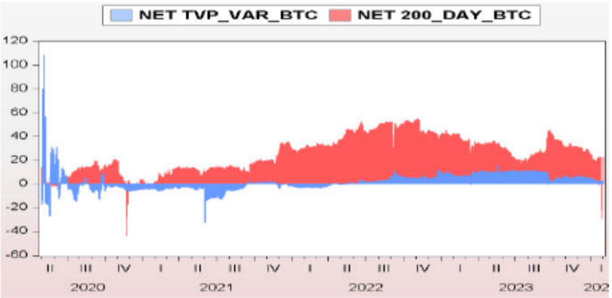


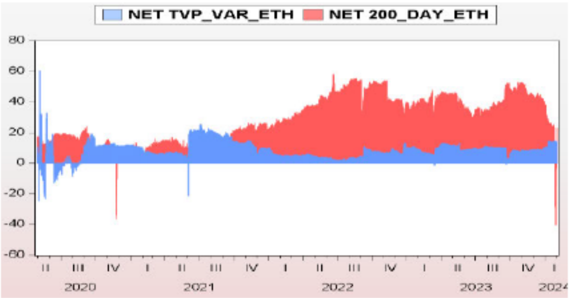
Figure 5.6: Total dynamic spillovers “From” cryptocurrencies and traditional asset indices

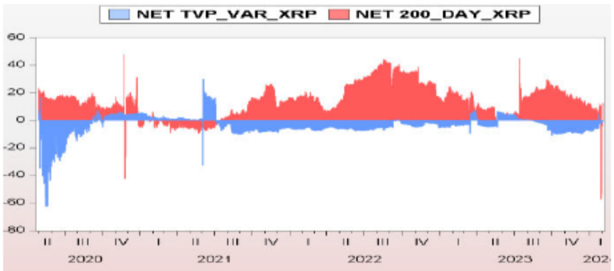
Source: Author own depiction (2024)

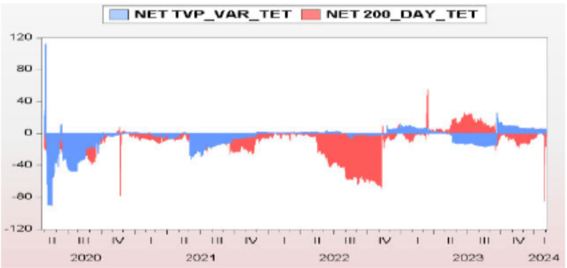
5.6.3.3 Net spillover analysis

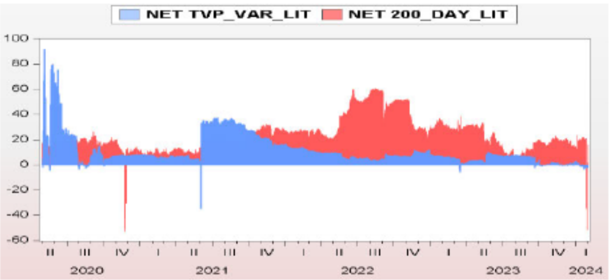
In order to reveal the net transmitters and net receivers to the total spillover, the need to investigate the net directional spillover of the “FROM” and “TO” above was crucial. As such, figure 5.9 renders the time varying volatility spillovers between the cryptocurrencies and traditional asset classes. Figure 5.7 reports that Bitcoin, Ethereum, Ripple and Litecoin are the net transmitters of shocks within the system averaging at 40 percent whereas Tether and BGCII together with the traditional asset indices (BGCI, BCOMPRI, EMBI, MSCIEMI) are net receivers of shocks within the system in the DY approach. The TVP-VAR model reveals significant fluctuations within the assets, demonstrating both periods of being the net transmitter and net receiver of shocks. A trend of heightened net recipients of the spillovers is noted in late 2020 for all the assets except for EMBI which had a heightened trend of being the net transmitter (for hours or a day). However; as noted in Table 5.6 and 5.7 that these markets tend to have internal influence than external influence particularly the cryptocurrencies. The net dynamic spillover plots indicate that there are less volatility spillovers from cryptocurrencies to the traditional asset classes and vice versa, thus reporting a weak connection existing between these two assets in emerging markets and supporting the evidence of cryptocurrencies being detached from traditional financial systems.











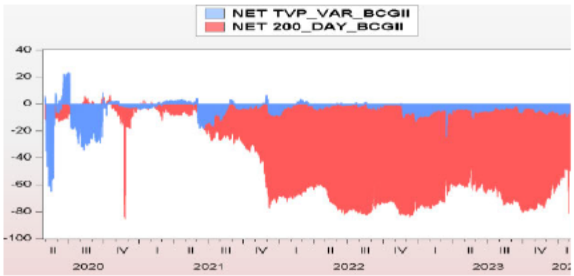


Figure 5.7: The net dynamic volatility spillovers between the crypto index and traditional asset indices

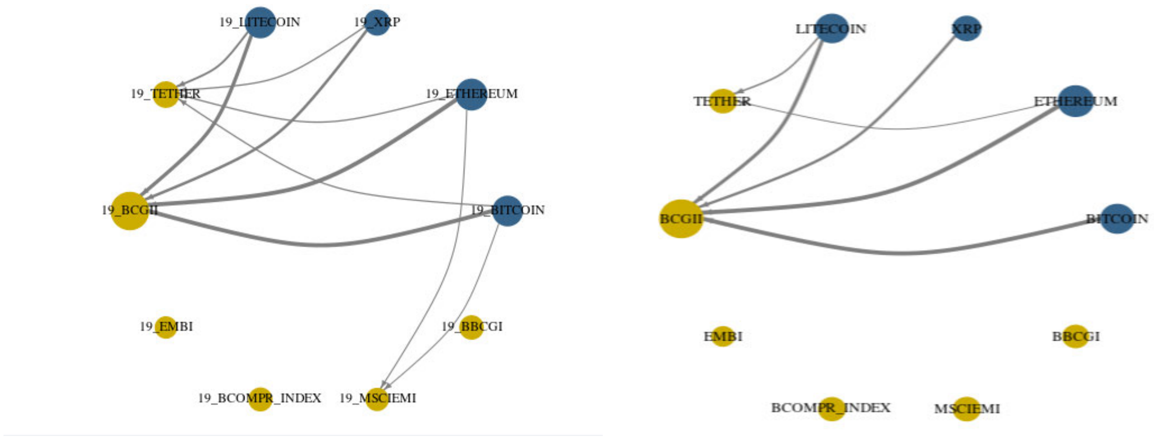
Source: Author own depiction (2024)

5.6.3.4 Analysis of network plots

To further solidify the net dynamic spillover results above, the network plots for the assets using both the DY approach and TVP-VAR model were analyzed. Figure 5.8 and 5.9 below depicts the network plot for both models. The assets colored “yellow” marks those who are net receivers of shocks within the system and colored “dark blue” presents the assets which are net transmitters of shocks. The larger the circle means the more the net receiver or net transmitter of shocks and vice versa, additionally the transfer of shocks is conducted for each individual asset and the thickness of the line represents the strength of the connection. The during COVID-19 plots are marked with “19” at the beginning of the asset name.

In Figure 5.8 during the COVID-19 pandemic, all the cryptocurrencies transfer shocks to Tether and the crypto index (BCGII) than to the traditional asset classes. Notably, Bitcoin and Ethereum are the only cryptocurrencies which transfer shocks to MSCIEMI indicating that the cryptocurrencies have slightly influence in the stock markets. The isolated traditional asset classes such as EMBI, BGCI and BCOMPRI are net receivers which are not significantly affected by other assets within the scope of this analysis. For the whole sample period, Cryptocurrencies have less influence on the traditional asset classes and vice versa. Despite the traditional asset classes being the net receivers of shocks, cryptocurrencies possibly have minimal effects on those shocks as there is no direct connection from any of the cryptocurrencies to the traditional asset class index. This suggests the traditional asset classes might be receiving shocks from other external factors such as geopolitical events or economic indicators. Furthermore, cryptocurrencies have more influence on the crypto index as marked by the strong connection.

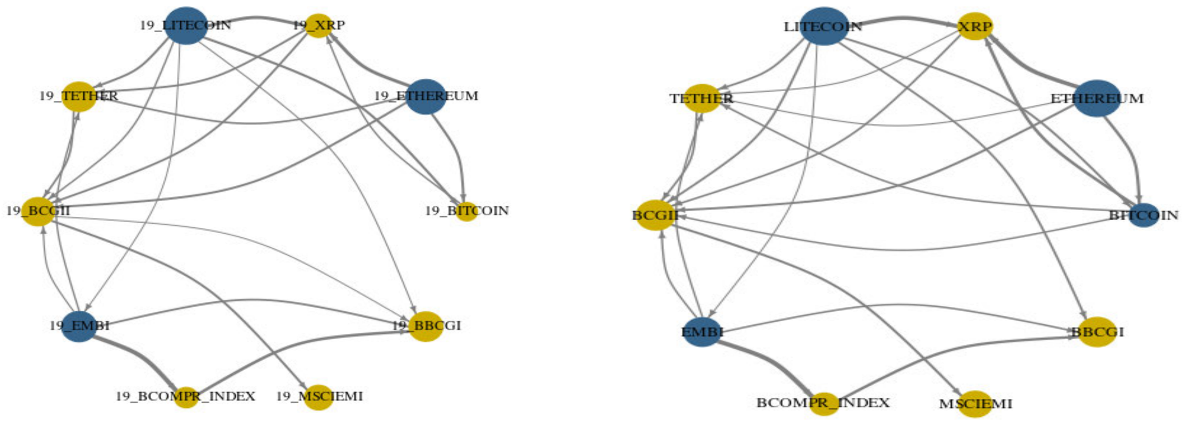
In Figure 5.9, there exists a variability of volatility spillovers between the cryptocurrencies and traditional asset indices. Notably, there were more spillovers coming from both the cryptocurrencies and the traditional asset indices in particular EMBI, to the cryptocurrency market as presented by BGCII. This is because the cryptocurrency market is still immature and it is largely affected by the negative news such as the one imposed by the COVID-19 pandemic (Mtiraoui and obeid, 2024). Bitcoin appears to be the net receiver of shocks during the COVID-19 as it was largely influenced by the strong spillovers coming from Ethereum and Litecoin. All the traditional asset indices except EMBI were the net receivers of spillovers during this period, however there were minor shocks coming from the cryptocurrencies suggesting that it was influenced by other external factors. Notably, for the whole sample period, Bitcoin changed to be net transmitter demonstrating its power and ability to responds to negative shocks and this is could be the surge in Bitcoin after the COVID-19 pandemic renewed the investor confidence. Overall, the network plot for both methods support the idea of cryptocurrencies operating as an isolated market.



COVID-19 Plot Sample Period Plot

Figure 5.8: Network plots for the DY approach

Source: Author own depiction (2024)



COVID-19 Plot

Sample Period Plot

Figure 5.9: Network plots for the TVP-VAR model

Source: Author own depiction (2024)

5.6.3.5 Total spillover analysis

All the above spillover analysis approach eventually leads to the total dynamic spillover index. As such, Figure 5.10 reports the results of the total dynamic spillover index for both the DY index and the TVP-VAR model. There are high volatility spillovers associated with the TVP-VAR model in late 2019, slightly above 90 percent demonstrating the impact of the COVID-19 pandemic. The total spillover averaged 60 percent for the DY index during the sample period and it is suspected that cryptocurrencies contributed more spillovers based on the results above for both models.

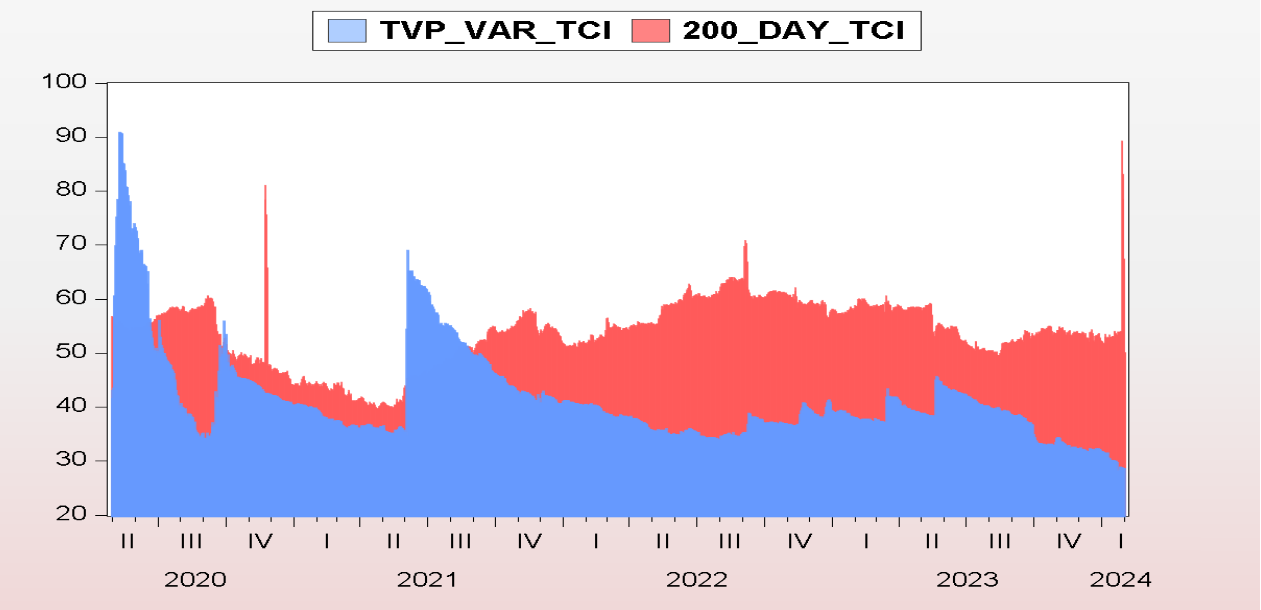


Figure 5.10: The total dynamic spillover index

Source: Author own depiction (2024)

5.7 Analysis of generalized impulse response function

The TVP-VAR model eventually leads to the estimation of the impulse responses for the traditional asset indices against the cryptocurrencies. As such, the impulse responses are computed by fixing the initial shock size equal to the time-series average of stochastic volatility for traditional asset classes for the whole sample and using the simultaneous relations at each point in time. Therefore, Figures 5.11, 5.12 and 5.13 represents the impulse response for traditional asset indices at 6-month horizon, 12-month horizon and 18-month horizon respectively. Figure 5.11 shows that all the traditional asset indices except for the MSCIEMI responded positively to the changes of the cryptocurrency market in the early stages of the COVID-19 with a significant shift in the middle of the pandemic as the response became positively. The MSCIEMI started with negative response but the time continued, the response became positive during the 6-month horizon.

Figure 5.12 shows a significant response pattern with BGCI, EMBI and MSCIEMI starting off positively to the shocks of the cryptocurrency market and the precious metals (BCOMPRI) were the only assets starting with a negative response. One noticeable trend in the 12-month horizon is that, overtime the traditional asset indices responded negatively and thereafter the responses were neutral at (0.00) for all the traditional asset indices. The 18-month horizon in Figure 5.13 starting point was similar to the 6-month horizon as the traditional asset indices were positive except for MSCIEMI which was negative. Overtime, the responses became neutral towards the shocks in the cryptocurrency market. Overall, it is safe to conclude that the 18-month horizon responses combined the response of 6-month and 12- month respectively, with 6-month horizon showing no specific direction overtime whereas both the 12-month and 18-month demonstrated a neutral response to cryptocurrency market shocks.

The impulse response results have several implications for investment strategies. Firstly, the findings suggest that shocks from the cryptocurrency market tend to have short-lived effects on traditional asset classes, with responses fading to neutrality over longer horizons. This indicates that long-term investors in traditional assets may not be significantly affected by cryptocurrency volatility, supporting the case for buy-and-hold strategies. However, in the short-term, particularly during periods of market stress such as the early stages of the COVID-19 pandemic, some traditional assets responded positively to cryptocurrency shocks. This implies that active investors may find value in short-term tactical adjustments based on cryptocurrency market movements. The shift from initial positive or negative reactions to eventual neutrality also highlights the limited long-term integration between the crypto and traditional markets, which preserves the diversification potential of cryptocurrencies in multi asset portfolios. Moreover, the delayed and evolving response of emerging market stocks

(MSCIEMI) suggests that emerging markets may be more sensitive to crypto volatility in the medium term. Finally, the absence of a consistent inverse relationship between cryptocurrencies and traditional assets suggests that traditional markets do not act as safe havens during periods of crypto market stress. Overall, investors should recognize that while cryptocurrencies can exert influence on traditional assets, this influence is mostly transitory, reinforcing the role of cryptocurrencies as a potentially diversifying but volatile asset class in long-term investment portfolios.

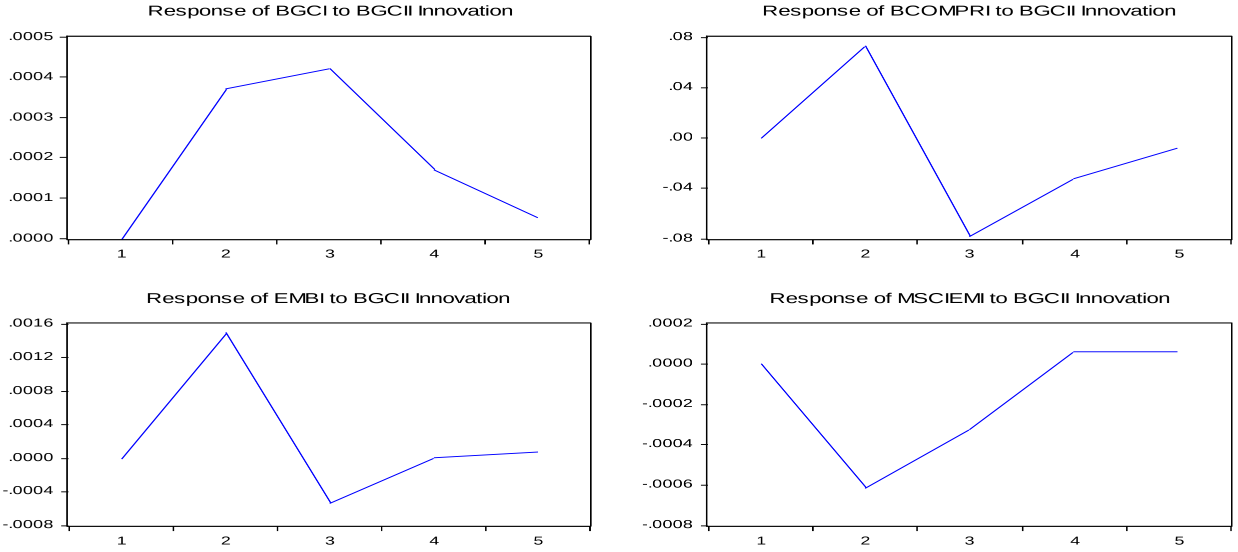


Figure 5.11: Generalized impulse response over a 6-month horizon

Source: Author own depiction (2024)

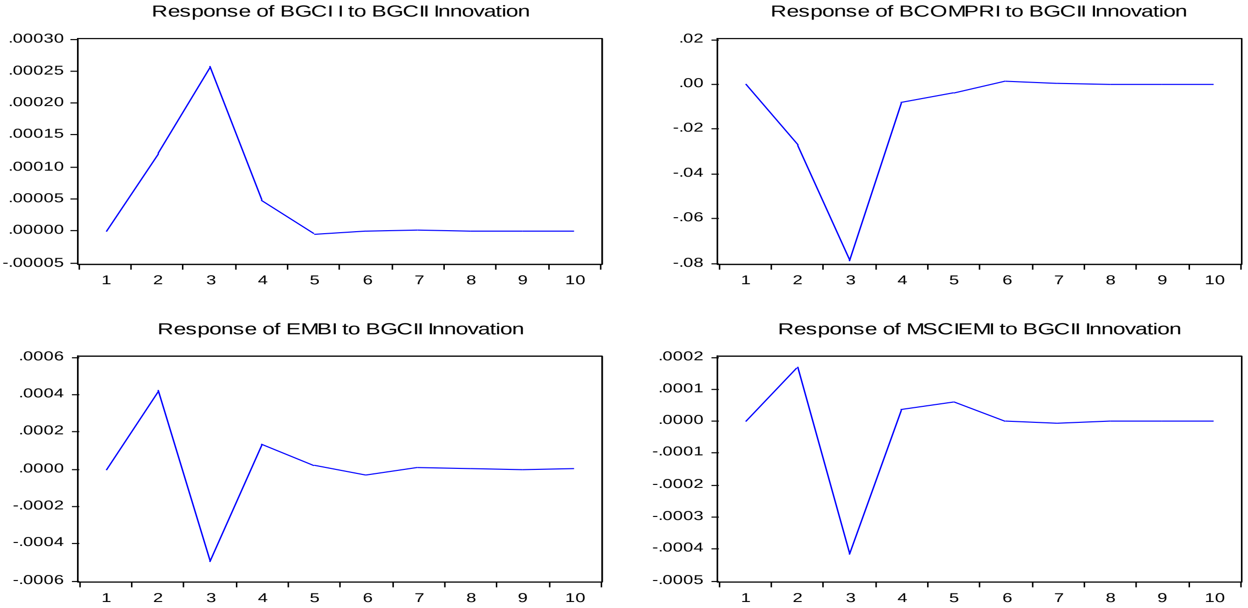
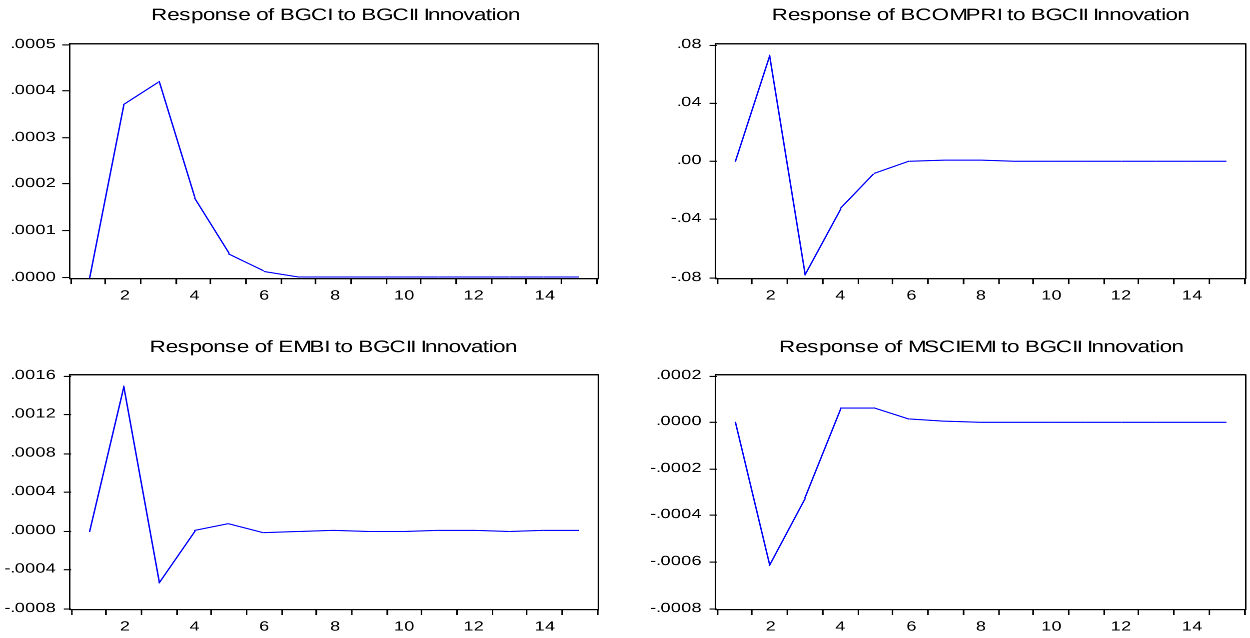


Figure 5.12: Generalized impulse response over a 12-month period

Source: Author own depiction (2024)


Response of BGCI to BGCII Innovation

Response of BCOMPRI to BGCII Innovation

Response of EMBI to BGCII Innovation

Response of MSCIEMI to BGCII Innovation

Figure 5.13: Generalized impulse response over an 18-month period

Source: Author own depiction (2024)

5.8 Chapter Summary

This chapter reported the results of the tests that were carried out to achieve the main aim of the study, that is, investigating volatility spillovers and interconnectedness between cryptocurrencies and traditional asset classes in emerging markets. Firstly, the descriptive statistics results were reported for both the cryptocurrencies and the traditional asset indices to reveal the returns that these assets experienced during the sample period, this was followed by the correlation analysis to assess the relationship between these two assets. The stationarity tests were carried out to ensure that the estimation of the models does not lead to spurious results. To specifically achieve the aim of the study, the Diebold and Yilmaz and the TVP-VAR models were employed in line with, Andrada-Félix, Fernandez-Perez and Sosvilla-Rivero (2020). The results of these models move in the same direction by confirming that there exist low volatility spillovers between the cryptocurrency market and traditional asset classes in emerging markets, suggesting that cryptocurrencies operate in isolation from the traditional financial system. Additionally, within the cryptocurrency market itself, cryptocurrencies were found to be net transmitters of shocks during the whole sample period. These findings are consistent, as they reflect the limited interaction between cryptocurrencies and traditional markets, while highlighting the significant interconnectedness and volatility transmission within the cryptocurrency market.

CHAPTER 6: CONCLUSION AND RECOMMENDATIONS

6.1 Introduction

The development of cryptocurrencies in the recent years has been widely supported by the widespread adoption by new financial asset companies, market participants and several countries. The factors driving this adoption includes technological advancements, security and decentralization and financial inclusion of cryptocurrencies in regions with limited access to traditional financial system. Moreover, the improvement in the blockchain system and cryptocurrency infrastructure such as faster transaction times and scalability enhance the user experience and thus driving the adoption of this market. As such, the development of other technologies within the cryptocurrency setup such as smart contracts which provide speed, accuracy, safety and autonomy are monitored by certain countries aiming to regulate and implement cryptocurrency as an official form of payment.

However; one notable drawback of the cryptocurrencies is the high price volatility often leading to significant gains and losses within a short period of time. The volatility in the cryptocurrency market is mainly due because they are not backed by an underlying asset such as gold or silver but rather they operate in their own isolated market. Notably, these fluctuations in the cryptocurrency market can be connected to the performance of other investment types such as commodities, stocks and bonds. The connections between these assets are mostly observed during market crisis where there is a movement of investors seeking to achieve diversification benefits. As such, investigating volatility spillovers and interconnectedness between cryptocurrencies and traditional asset classes becomes crucial for investors and policy makers particularly in emerging markets which has less empirical evidence on this issue and it is highly volatile.

Based on this background, this study set out to achieve three key objectives: to investigate the volatility spillovers and interconnectedness between cryptocurrencies and stocks in emerging markets, to examine the volatility spillovers and interconnectedness between cryptocurrencies and bonds in these markets, and to explore the relationship between cryptocurrencies and commodities in emerging markets. Each of these objectives have been successfully addressed, providing valuable insights into how cryptocurrencies interact with traditional asset classes in emerging markets. The findings offer a crucial understanding of whether cryptocurrencies serve as sources of risk transmission or effective diversification tools, contributing meaningfully to the existing literature.

In line with the above objectives, the study employed five cryptocurrencies based on popularity and on how long the cryptocurrency has been existing, which are Bitcoin, Ethereum, Ripple, Tether and Litecoin. Furthermore, the cryptocurrency market index (BGCII) was used as a proxy for the cryptocurrencies. Subsequently, three traditional asset classes were employed, namely; stocks, bonds and commodities and the indices of each traditional asset were used as proxies, which are MSCIEMI for stocks, EMBI for bonds and BCOMPRI and BGCI for precious metals and commodities respectively. The study used the daily dataset spanning from the 6th of October 2019 to the 31st of January 2024, employing Diebold and Yilmaz and the TVP-VAR models to assess the volatility spillovers between these assets. The section below discusses the summary of findings.

6.2 Summary of findings

This section presents a summary of the results aligned with the research questions of the study. Each research question is thoroughly analyzed in conjunction with the findings to provide a comprehensive understanding of the study's outcomes. The analysis aims to clearly articulate how the results address the objectives and contribute to the goals of the research.

6.2.1 Research question one: nature of volatility spillovers and connectedness between cryptocurrencies and stocks in emerging markets.

The correlation matrix of the full sample period reported a negative correlation for all the cryptocurrencies to the stock assets suggesting diversification benefits, except for Tether and BGCII which were positively correlated. However, due to heightened volatility during the COVID-19 pandemic, the relationship changed significantly as all the cryptocurrencies were positively correlated with stock assets except for Tether. Moreover, the results of the DY index and TVP-VAR model report weak volatility spillovers between cryptocurrencies and stocks in and out of the market crisis. However; comparing the two approaches, Ethereum led in transmitting more shocks to stock assets in the DY approach whereas in the TVP-VAR model, the crypto index had more spillovers going to the stock assets.

Furthermore, the co-movement of Tether were found to be negatively correlated with the equities during the COVID-19 pandemic. Based on these findings, the study can conclude that Tether appears to be an important safe haven for stock assets during times of market turmoil. Overall, the positive correlations between cryptocurrencies and stock assets appears to be weak, suggesting that using the two assets in an investment portfolio, investors can achieve diversification benefits. This suggests that there are low volatility spillovers existing between the cryptocurrencies and stock assets in emerging markets.

6.2.2 Research question two: nature of volatility spillovers and connectedness between cryptocurrencies and bonds in emerging markets.

The correlation matrix table reported that all the cryptocurrencies were positively correlated with bonds, except for Bitcoin who demonstrated a negative correlation with bonds. During the COVID-19, the correlation matrix table reported a weak positive correlation between cryptocurrencies and bonds, except for Tether which had a negative correlation. Both the results of the DY index and the TVP-VAR model revealed weak volatility spillovers from cryptocurrencies to bonds and vice versa, suggesting less intermarket links between the two assets. However, the major difference arose when the DY indicated that bonds are the net receivers of shocks, whereas the TVP-VAR indicated that they are the net transmitter of shocks.

Based on these conflicts views, the results of the TVP-VAR model are more preferred as it overcomes the drawbacks of the rolling window VAR approach. As such, the study concludes that both cryptocurrencies and bonds are the net transmitter of shocks during the sample period, however with less shocks of each asset affecting another asset. The study further indicates that there exist weak volatility spillovers between cryptocurrencies and bonds during crisis and non-crisis periods. This suggests that these two assets can be used by market participants to achieve diversification benefits in emerging markets.

6.2.3 Research question three: nature of volatility spillovers and connectedness between cryptocurrencies and commodities in emerging markets.

Analyzing the full sample period of the correlation matrix table, all the cryptocurrencies were positively correlated with the precious metals, thus limiting diversification benefits. However, the correlations were weakly positive indicating that diversification benefits can still be achieved. During the COVID-19 pandemic, all the cryptocurrencies except Tether were negatively correlated with the precious metals, indicating a shift in their relationship based on market conditions. This suggest that during the crisis, cryptocurrencies such as Bitcoin and commodity assets such as gold could be used to achieve the diversification benefits. Additionally, there exist negative correlations between cryptocurrencies and commodities during crisis and non-crisis periods. The findings of the DY index and TVP-VAR model revealed less volatility spillovers of the cryptocurrencies to both the precious metals and commodities and vice versa. Overall, there are no observable connections of volatility spillovers between the cryptocurrencies and the commodities including the precious metals, suggesting that these assets can be used to achieve diversification benefits in emerging markets.

6.3 Implications of the study

The Modern Portfolio Theory assert that all investors are risk averse, that if two investments offer identical expected returns, investors would prefer the one with less risk. The theory further introduced the concept of diversification to mitigate risks based on the connectedness of the assets. As such, these findings offer valuable insights to investors and policy makers with regards to achieving diversification benefits in emerging markets. The following discusses the implications of these findings to the investors, policy makers and scholars.

- Investors by mixing a portfolio of cryptocurrencies and traditional asset classes of emerging market could potentially benefit in terms of mitigating risks as there are less volatility spillovers between these assets. This implies that these assets have less interconnected risk making them an ideal for portfolio diversification. However, monitoring the spillovers overtime is crucial as the relationship can change in response to market conditions, possibly altering the diversification benefits. Therefore, investors should seek the assistance of the professional before embarking on this journey.

- Policy makers should seek ways of reducing volatility particularly in the cryptocurrency market. As they become increasingly integrated in the financial systems, more companies, countries, individuals and investors will adopt them as a medium of exchange which can cause more harm than good if their volatile nature is not well monitored. Furthermore, the spillovers in the long-run might increase posing danger in the investment portfolio consisting of cryptocurrencies.

- Scholars can gain a valuable knowledge about the market of cryptocurrencies which is relatively new and thus enriching their knowledge about the diverse nature of this markets and its connection with the traditional asset classes in emerging markets.

6.4 Recommendations for future studies

This study had few limitations, mainly arising from the immature market of the cryptocurrencies relative to the traditional asset classes. The desired cryptocurrency data is hard to find, thus making it difficult to examine a large sample size to reveal more robustness on the spillover movements. Furthermore, emerging markets serves as a bracket for several countries making it difficult to assess how individuals' countries connects with the cryptocurrencies. As such, following these research limitations, the following gaps have been identified to contribute to the existing literature between the cryptocurrencies and traditional asset classes.

- The period of the current study was relatively small (5 years) due to the availability of data. With the cryptocurrencies marked with high volatility, extending the study periods becomes crucial to reveal more fluctuations in the market. Therefore, future research could examine the relationship between cryptocurrencies and traditional asset classes by extending the study period to at least 10 or 15 years. However, that also depends on the availability of data indicating that the study can be applicable in the year of 2030s.

- The study examined the emerging markets as a whole and with different countries forming emerging markets it becomes difficult to clearly outline which one is more affected and which one is not. Therefore, future research could examine this relationship on specific individuals emerging countries or a group such as BRICS.

- Future research could also incorporate more methods in the analysis such as modelling conditional volatilities using Multivariate GARCH models before revealing the volatility spillovers and connectedness in these markets.

6.5 Conclusion

By combining the Diebold and Yilmaz spillover index and the TVP-VAR model, this study aimed at investigating volatility spillovers and interconnectedness between cryptocurrencies and traditional asset classes in emerging markets. The study employed a variety of cryptocurrencies based on popularity and on how long the cryptocurrency has been existing, which are Bitcoin, Ethereum, Tether, Ripple, Litecoin and further incorporated the Bloomberg Galaxy Crypto Index. These cryptocurrencies were used to assess the volatility spillovers against the traditional asset indices of stocks, bonds and commodities. The results of the DY index and the TVP-VAR moved in the same direction by highlighting weak connectedness between the digital assets and traditional assets. However, the spillovers were time-varying during the analyzed period influenced by different market conditions. The study revealed that the transmission of shocks between the two assets is more internal rather than external, particularly for the cryptocurrencies as they operate in their own market. Therefore, based on the above findings, the study concludes that there are minimal volatility spillovers between cryptocurrencies and traditional asset classes in emerging markets, suggesting that a combination of cryptocurrencies with stocks, bonds and commodities can be used to achieve diversification benefits.

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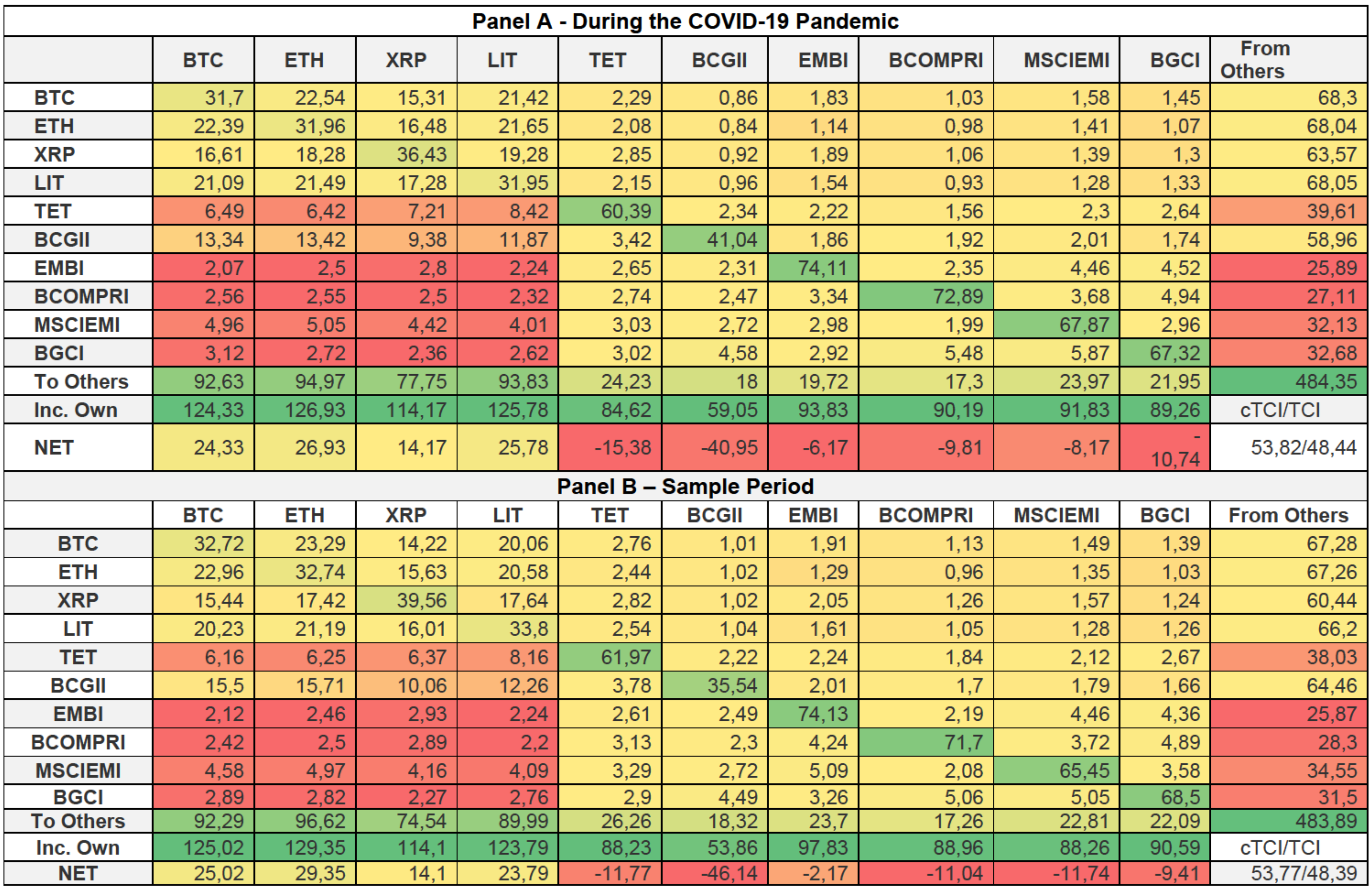
APPENDICES

Appendix A: Additional estimations

Appendix A1: Diebold and Yilmaz Results heat map



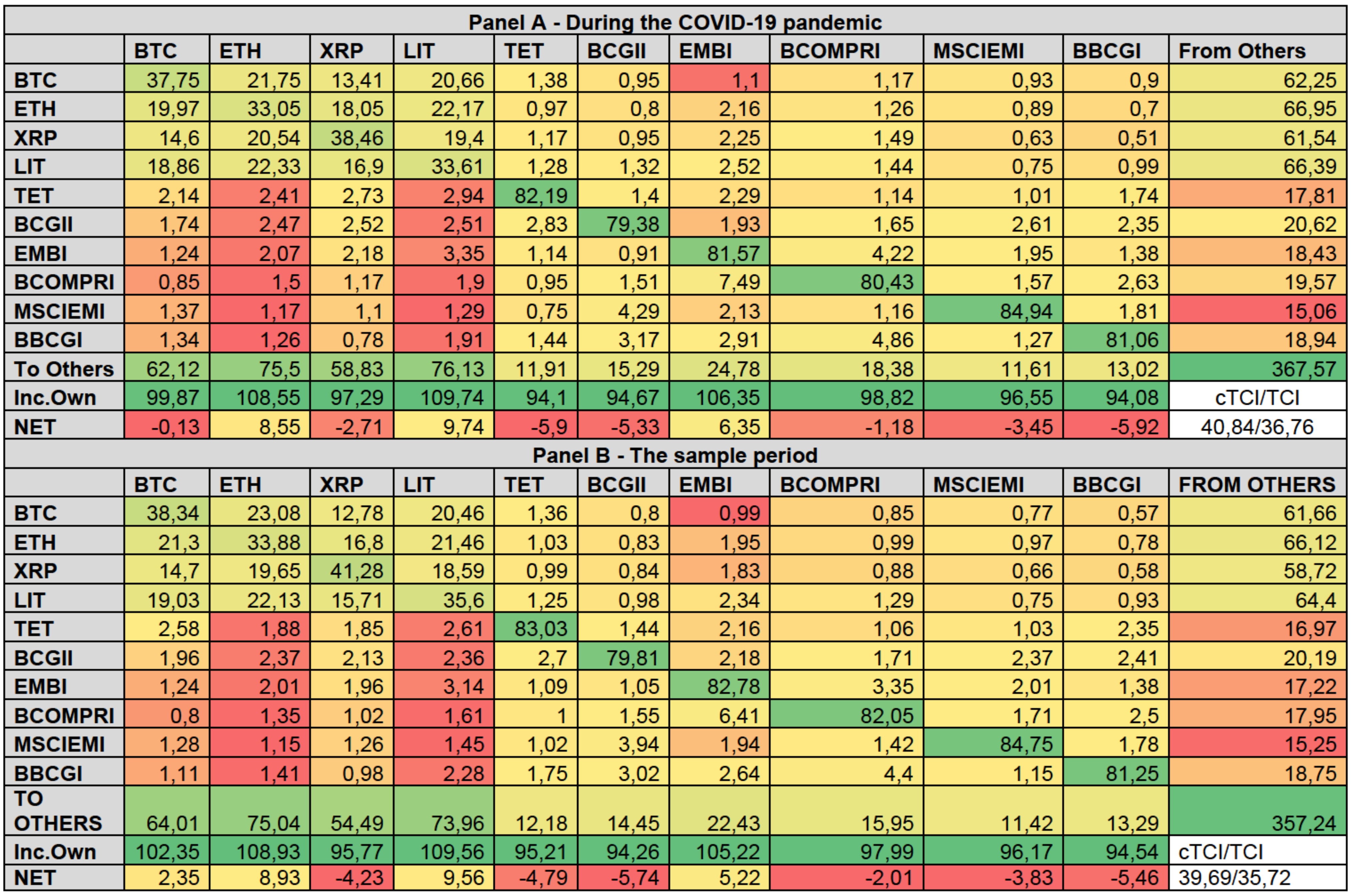
Panel A - During the COVID-19 Pandemic

	BTC	ETH	XRP	LIT	TET	BCGII	EMBI	BCOMPRI	MSCIEMI	BGCI	From Others
BTC	31,7	22,54	15,31	21,42	2,29	0,86	1,83	1,03	1,58	1,45	68,3
ETH	22,39	31,96	16,48	21,65	2,08	0,84	1,14	0,98	1,41	1,07	68,04
XRP	16,61	18,28	36,43	19,28	2,85	0,92	1,89	1,06	1,39	1,3	63,57
LIT	21,09	21,49	17,28	31,95	2,15	0,96	1,54	0,93	1,28	1,33	68,05
TET	6,49	6,42	7,21	8,42	60,39	2,34	2,22	1,56	2,3	2,64	39,61
BCGII	13,34	13,42	9,38	11,87	3,42	41,04	1,86	1,92	2,01	1,74	58,96
EMBI	2,07	2,5	2,8	2,24	2,65	2,31	74,11	2,35	4,46	4,52	25,89
BCOMPRI	2,56	2,55	2,5	2,32	2,74	2,47	3,34	72,89	3,68	4,94	27,11
MSCIEMI	4,96	5,05	4,42	4,01	3,03	2,72	2,98	1,99	67,87	2,96	32,13
BGCI	3,12	2,72	2,36	2,62	3,02	4,58	2,92	5,48	5,87	67,32	32,68
To Others	92,63	94,97	77,75	93,83	24,23	18	19,72	17,3	23,97	21,95	484,35
Inc. Own	124,33	126,93	114,17	125,78	84,62	59,05	93,83	90,19	91,83	89,26	cTCI/TCI
NET	24,33	26,93	14,17	25,78	-15,38	-40,95	-6,17	-9,81	-8,17	-10,74	53,82/48,44

Panel B – Sample Period

	BTC	ETH	XRP	LIT	TET	BCGII	EMBI	BCOMPRI	MSCIEMI	BGCI	From Others
BTC	32,72	23,29	14,22	20,06	2,76	1,01	1,91	1,13	1,49	1,39	67,28
ETH	22,96	32,74	15,63	20,58	2,44	1,02	1,29	0,96	1,35	1,03	67,26
XRP	15,44	17,42	39,56	17,64	2,82	1,02	2,05	1,26	1,57	1,24	60,44
LIT	20,23	21,19	16,01	33,8	2,54	1,04	1,61	1,05	1,28	1,26	66,2
TET	6,16	6,25	6,37	8,16	61,97	2,22	2,24	1,84	2,12	2,67	38,03
BCGII	15,5	15,71	10,06	12,26	3,78	35,54	2,01	1,7	1,79	1,66	64,46
EMBI	2,12	2,46	2,93	2,24	2,61	2,49	74,13	2,19	4,46	4,36	25,87
BCOMPRI	2,42	2,5	2,89	2,2	3,13	2,3	4,24	71,7	3,72	4,89	28,3
MSCIEMI	4,58	4,97	4,16	4,09	3,29	2,72	5,09	2,08	65,45	3,58	34,55
BGCI	2,89	2,82	2,27	2,76	2,9	4,49	3,26	5,06	5,05	68,5	31,5
To Others	92,29	96,62	74,54	89,99	26,26	18,32	23,7	17,26	22,81	22,09	483,89
Inc. Own	125,02	129,35	114,1	123,79	88,23	53,86	97,83	88,96	88,26	90,59	cTCI/TCI
NET	25,02	29,35	14,1	23,79	-11,77	-46,14	-2,17	-11,04	-11,74	-9,41	53,77/48,39

Appendix A2: TVP-VAR Results heat-map



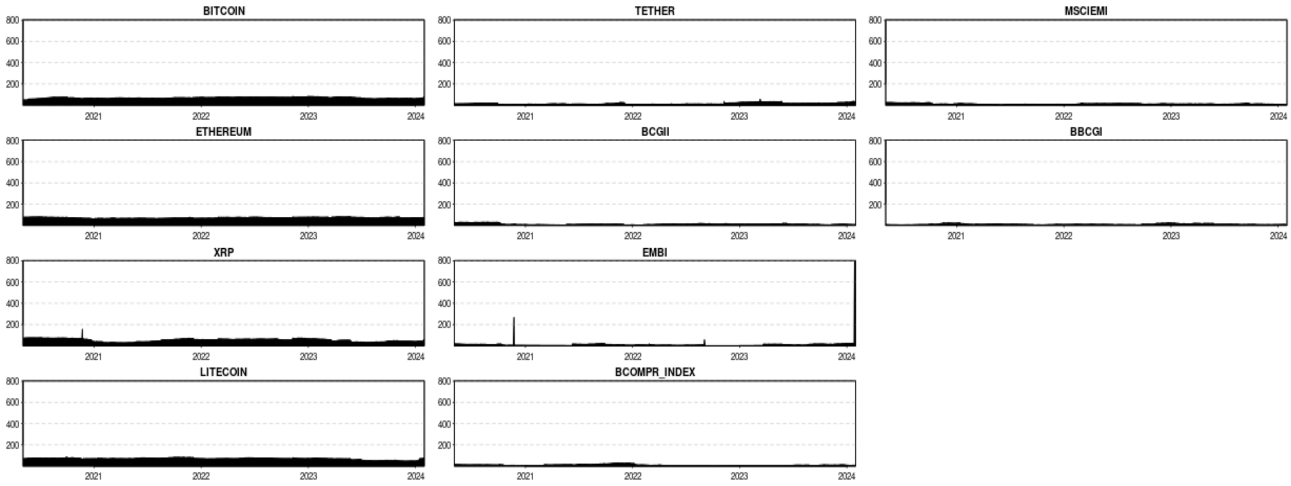
Panel A - During the COVID-19 pandemic

	BTC	ETH	XRP	LIT	TET	BCGII	EMBI	BCOMPRI	MSCIEMI	BBCGI	From Others
BTC	37,75	21,75	13,41	20,66	1,38	0,95	1,1	1,17	0,93	0,9	62,25
ETH	19,97	33,05	18,05	22,17	0,97	0,8	2,16	1,26	0,89	0,7	66,95
XRP	14,6	20,54	38,46	19,4	1,17	0,95	2,25	1,49	0,63	0,51	61,54
LIT	18,86	22,33	16,9	33,61	1,28	1,32	2,52	1,44	0,75	0,99	66,39
TET	2,14	2,41	2,73	2,94	82,19	1,4	2,29	1,14	1,01	1,74	17,81
BCGII	1,74	2,47	2,52	2,51	2,83	79,38	1,93	1,65	2,61	2,35	20,62
EMBI	1,24	2,07	2,18	3,35	1,14	0,91	81,57	4,22	1,95	1,38	18,43
BCOMPRI	0,85	1,5	1,17	1,9	0,95	1,51	7,49	80,43	1,57	2,63	19,57
MSCIEMI	1,37	1,17	1,1	1,29	0,75	4,29	2,13	1,16	84,94	1,81	15,06
BBCGI	1,34	1,26	0,78	1,91	1,44	3,17	2,91	4,86	1,27	81,06	18,94
To Others	62,12	75,5	58,83	76,13	11,91	15,29	24,78	18,38	11,61	13,02	367,57
Inc.Own	99,87	108,55	97,29	109,74	94,1	94,67	106,35	98,82	96,55	94,08	cTCI/TCI
NET	-0,13	8,55	-2,71	9,74	-5,9	-5,33	6,35	-1,18	-3,45	-5,92	40,84/36,76

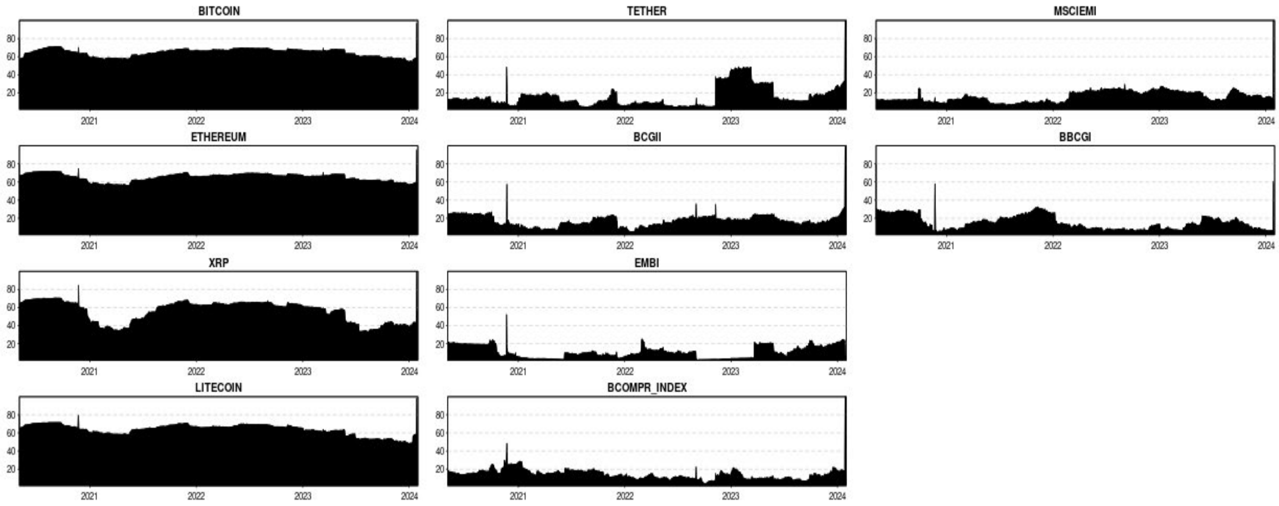
Panel B - The sample period

	BTC	ETH	XRP	LIT	TET	BCGII	EMBI	BCOMPRI	MSCIEMI	BBCGI	FROM OTHERS
BTC	38,34	23,08	12,78	20,46	1,36	0,8	0,99	0,85	0,77	0,57	61,66
ETH	21,3	33,88	16,8	21,46	1,03	0,83	1,95	0,99	0,97	0,78	66,12
XRP	14,7	19,65	41,28	18,59	0,99	0,84	1,83	0,88	0,66	0,58	58,72
LIT	19,03	22,13	15,71	35,6	1,25	0,98	2,34	1,29	0,75	0,93	64,4
TET	2,58	1,88	1,85	2,61	83,03	1,44	2,16	1,06	1,03	2,35	16,97
BCGII	1,96	2,37	2,13	2,36	2,7	79,81	2,18	1,71	2,37	2,41	20,19
EMBI	1,24	2,01	1,96	3,14	1,09	1,05	82,78	3,35	2,01	1,38	17,22
BCOMPRI	0,8	1,35	1,02	1,61	1	1,55	6,41	82,05	1,71	2,5	17,95
MSCIEMI	1,28	1,15	1,26	1,45	1,02	3,94	1,94	1,42	84,75	1,78	15,25
BBCGI	1,11	1,41	0,98	2,28	1,75	3,02	2,64	4,4	1,15	81,25	18,75
TO OTHERS	64,01	75,04	54,49	73,96	12,18	14,45	22,43	15,95	11,42	13,29	357,24
Inc.Own	102,35	108,93	95,77	109,56	95,21	94,26	105,22	97,99	96,17	94,54	cTCI/TCI
NET	2,35	8,93	-4,23	9,56	-4,79	-5,74	5,22	-2,01	-3,83	-5,46	39,69/35,72

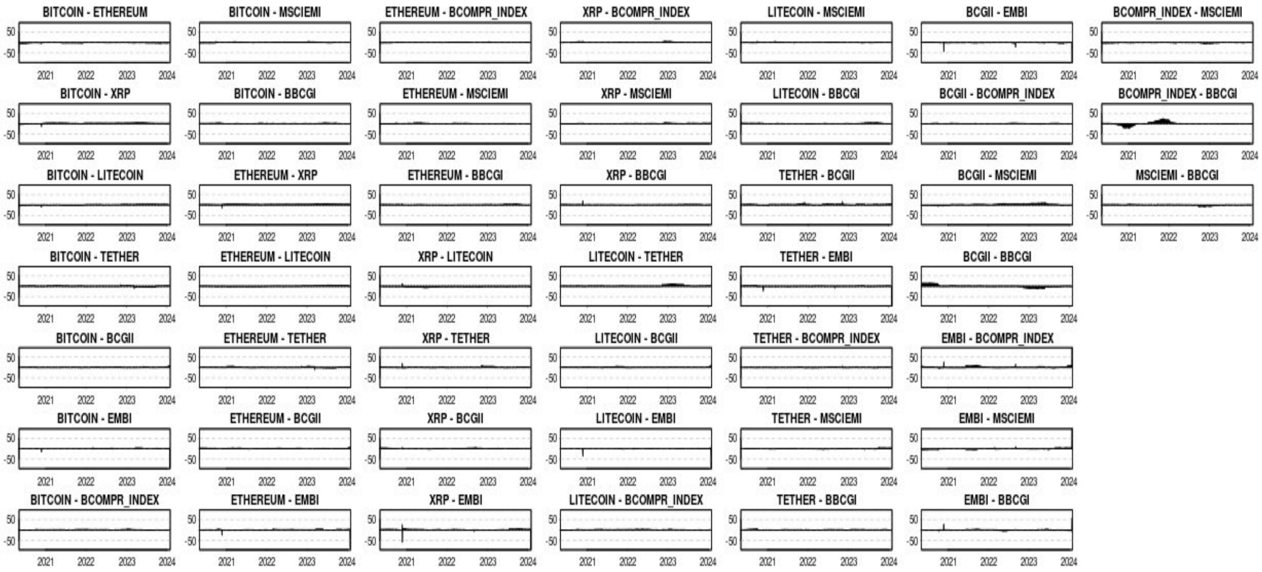
Appendix A3: Spillovers "To" using Diebold and Yilmaz model



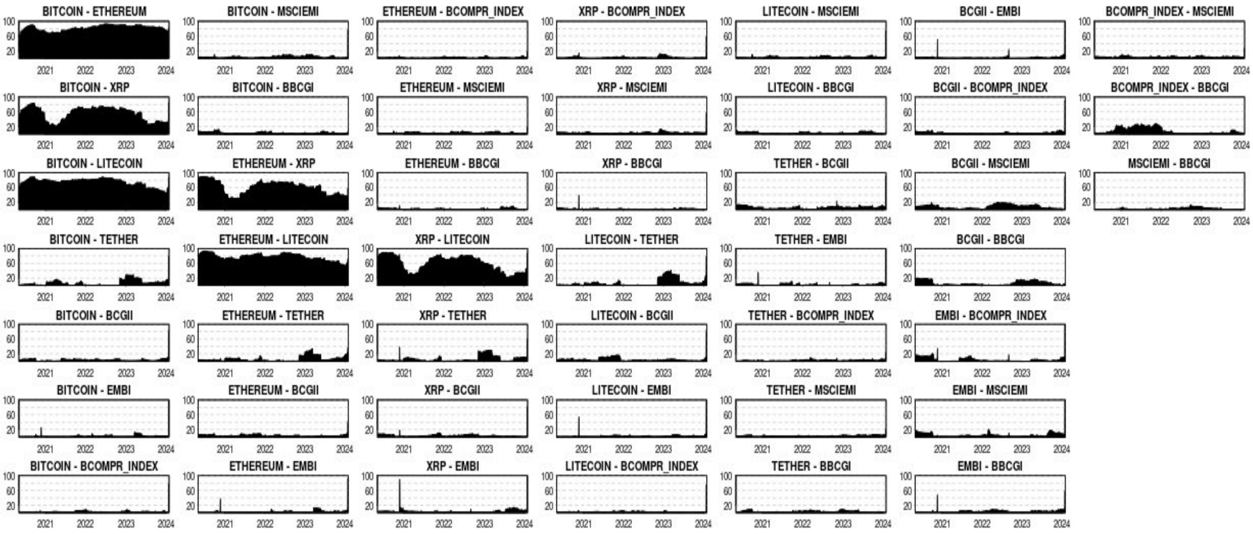
Appendix A4: Spiilovers "From" using Diebold and Yilmaz model



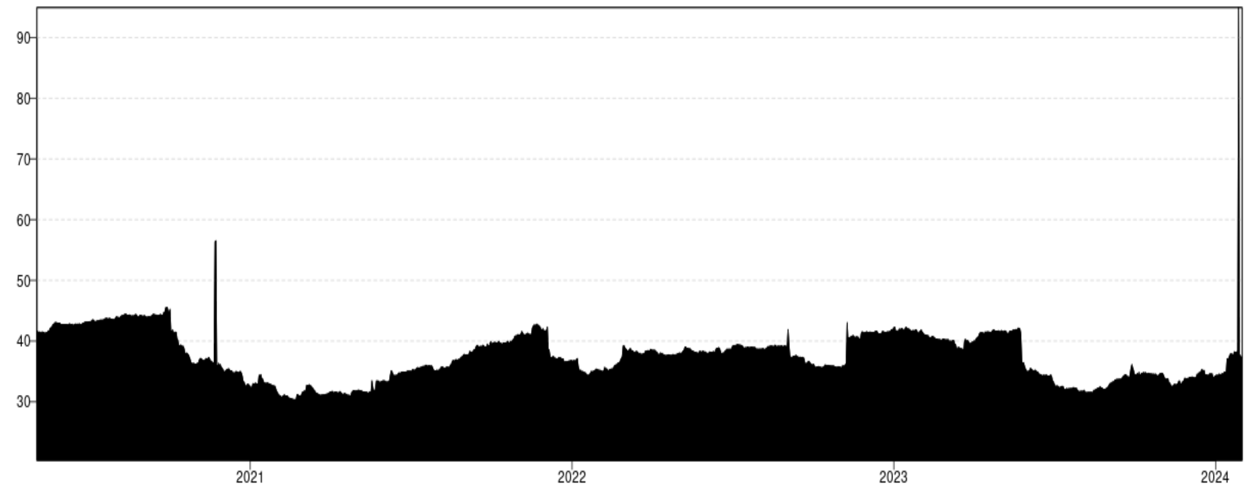
Appendix A5: Net pairwise spillovers using Diebold and Yilmaz



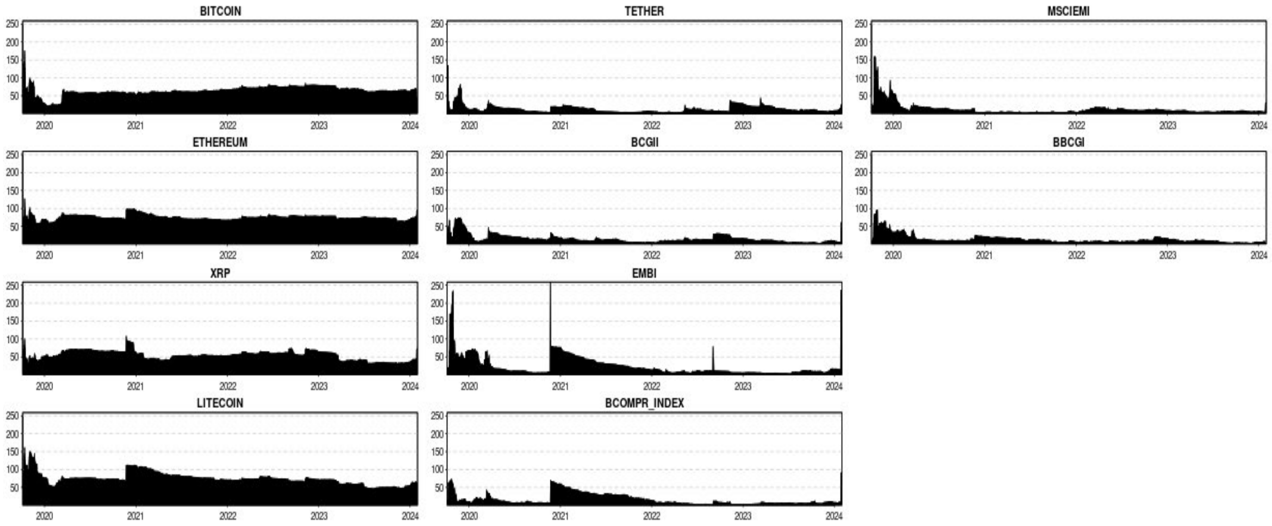
Appendix A6: Dynamic pairwise spillovers using Diebold and Yilmaz model



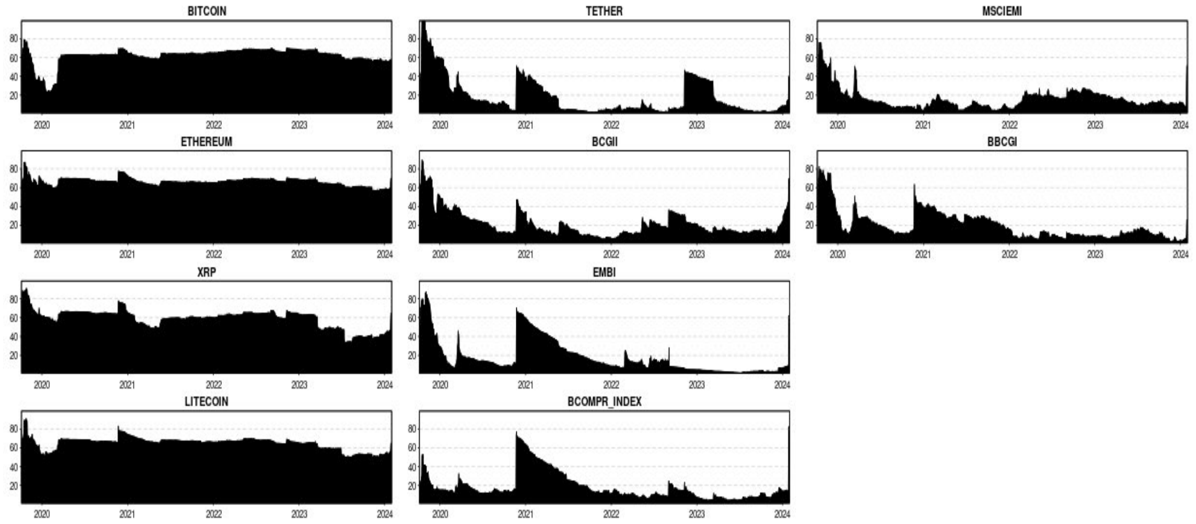
Appendix A7: Dynamic total connectedness for Diebold and Yilmaz model



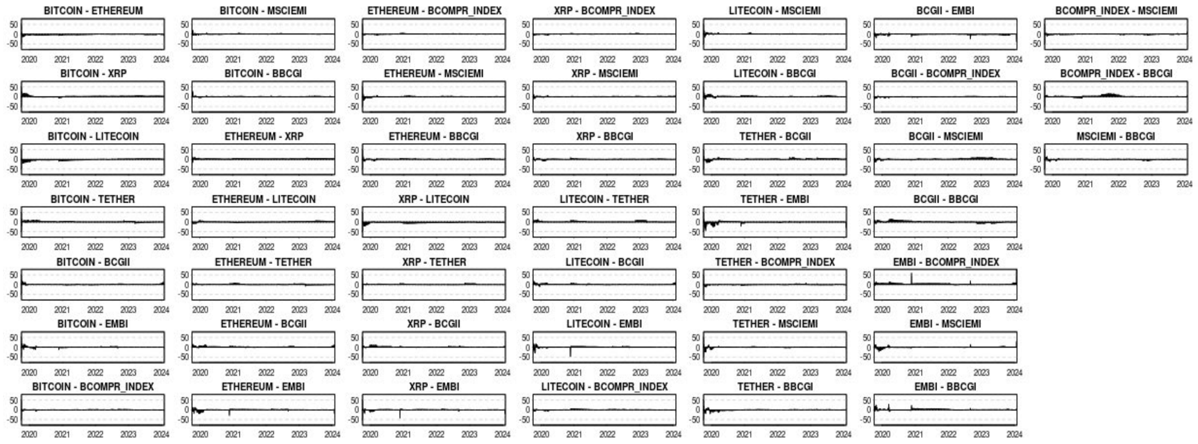
Appendix A8: Spillovers “To” using TVP-VAR model



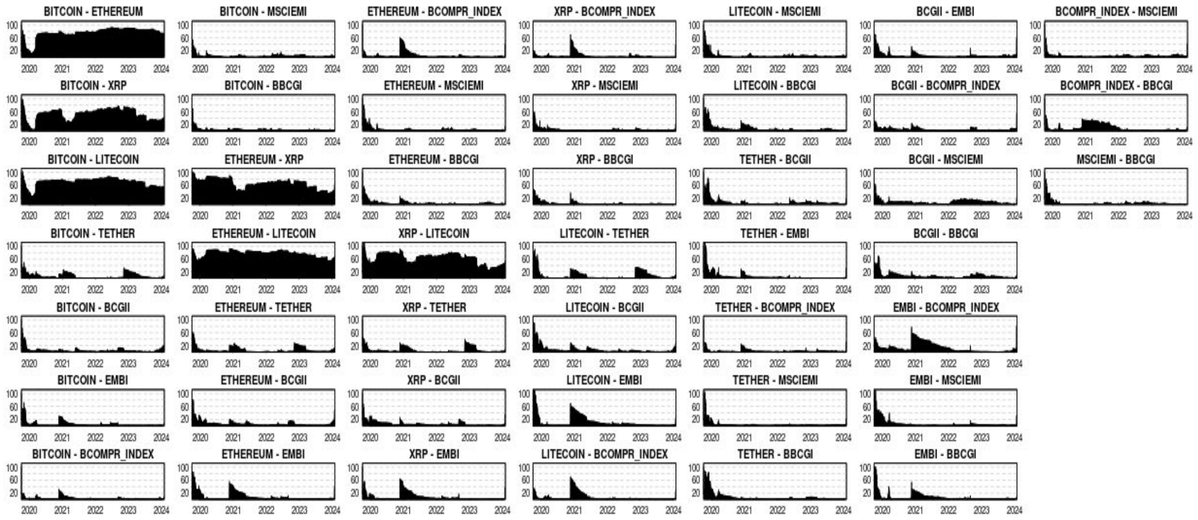
Appendix A9: Spillovers “From” using TVP-VAR model



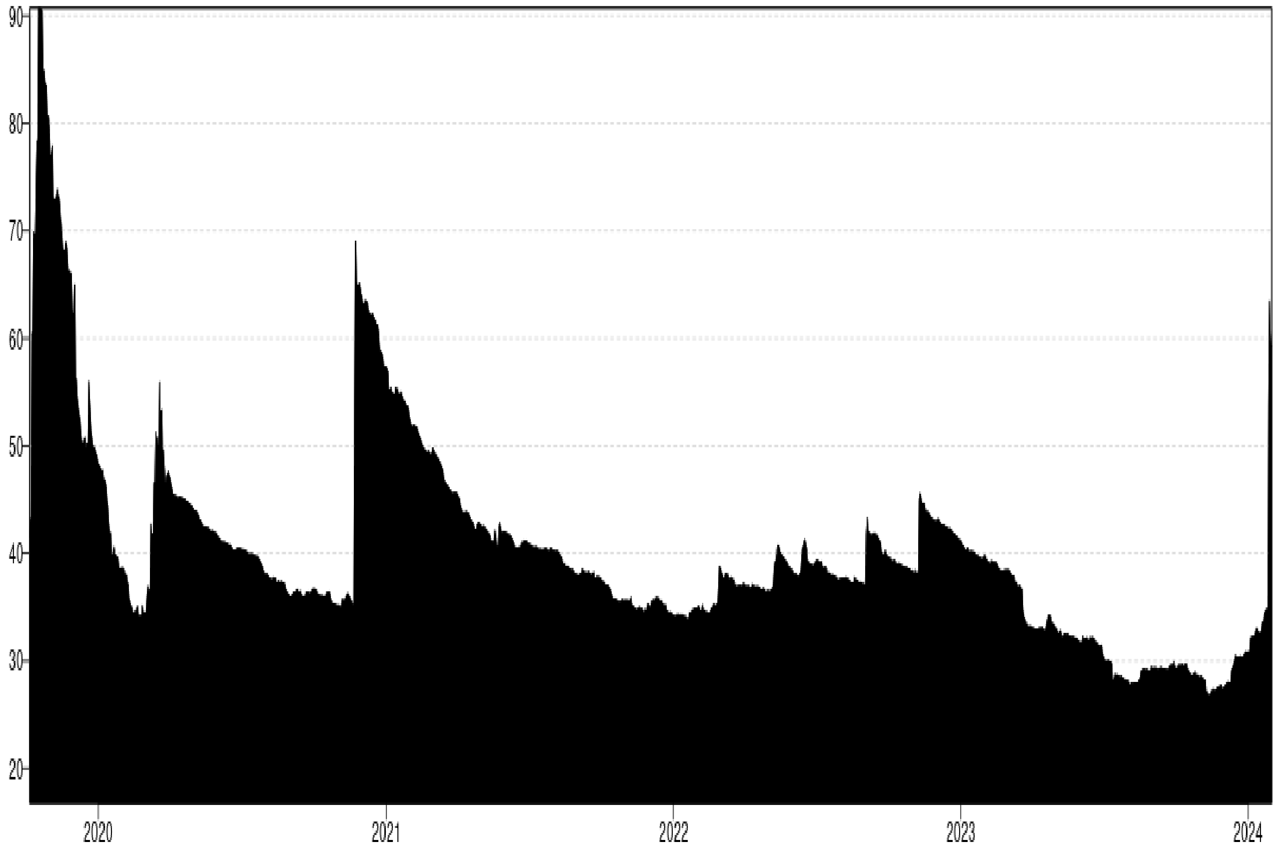
Appendix A10: Net pairwise spillover using TVP-VAR model



Appendix A11: Dynamic pairwise spillovers using TVP-VAR



Appendix A12: Dynamic total connectedness using TVP-VAR



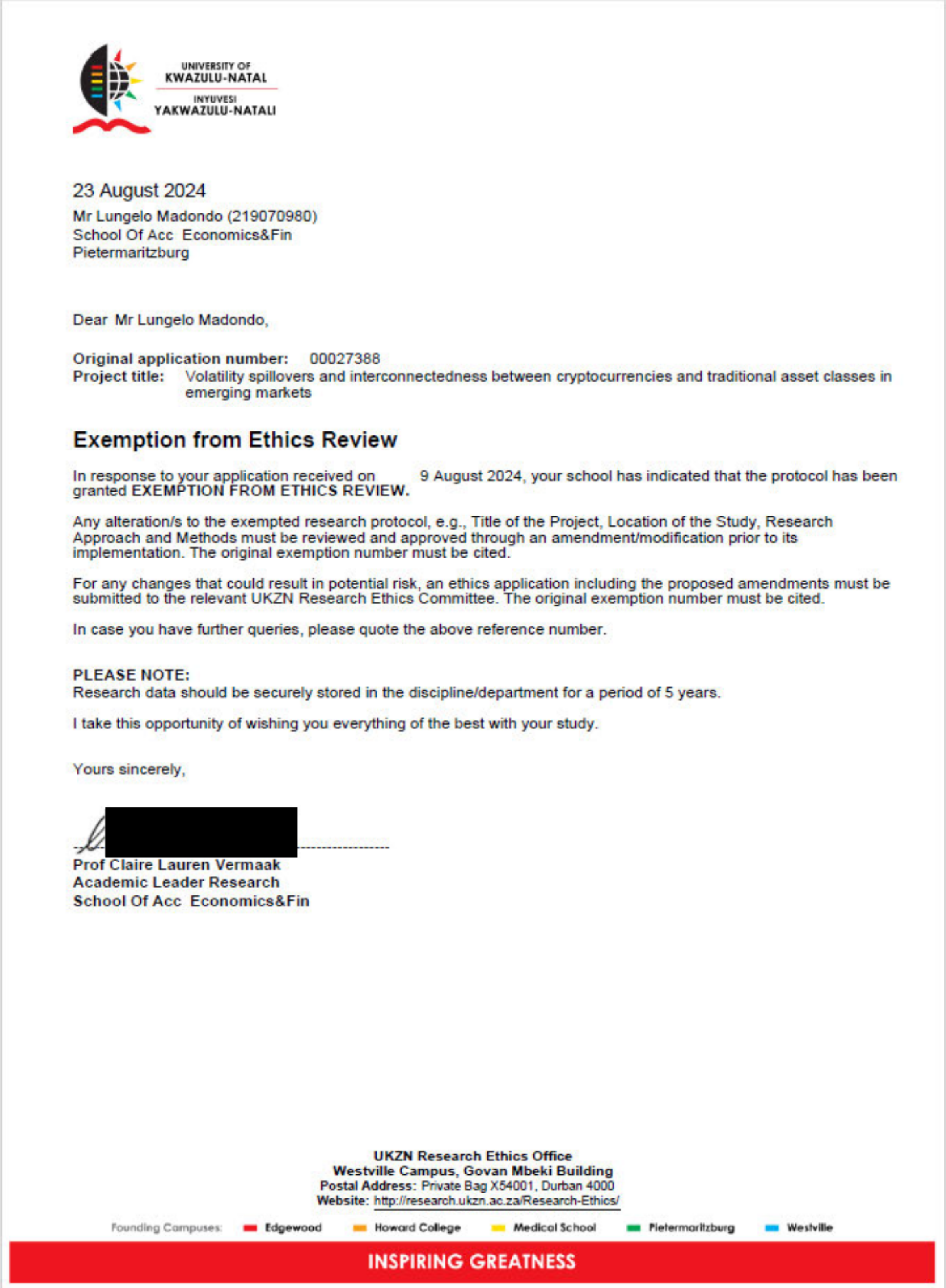
Appendix A13: Unit root and stationarity tests for cryptocurrencies and traditional asset indices during COVID-19

Variables	ADF Test	P.P Test	KPSS Test
Unit Root and Stationarity Test at First Difference with an Intercept			
BTC	-17.117* (0.000)	-481.892* (0.000)	0.046***
ETH	-18.072* (0.000)	-355.687* (0.000)	0.045***
XRP	-20.422* (0.000)	-319.250* (0.000)	0.035***
TET	-7.126* (0.000)	-30.485* (0.000)	0.085***
LIT	-18.056* (0.000)	-411.015* (0.000)	0.108***
BGCII	-15.813* (0.000)	-345.181* (0.000)	0.022***
MSCIEMI	-17.412* (0.000)	-197.746* (0.000)	0.007***
EMBI	-17.908* (0.000)	-923.481* (0.000)	0.160***
BCOMPRI	-16.010* (0.000)	-572.134* (0.000)	0.026***
BGCI	-16.613* (0.000)	-399.555* (0.000)	0.047***
Break-Point Unit Root Tests at First Difference with an Intercept			
BTC	-63.948* (<0.01)	NONE	
ETH	-64.772* (<0.01)		
XRP	-60.107* (<0.01)		
TET	-55.673* (<0.01)		
LIT	-64.079* (<0.01)		
BGCII	-62.233* (<0.01)		
MSCIEMI	-64.144* (<0.01)		
EMBI	-70.297* (<0.01)		
BCOMPRI	-65.091* (<0.01)		
BGCI	-61.338* (<0.01)		

Denote the level of significance at 1%

Source: Author own estimation (2024)

Appendix B: Ethical clearance letter



UNIVERSITY OF
KWAZULU-NATAL
INYUVESI
YAKWAZULU-NATALI

23 August 2024

Mr Lungelo Madondo (219070980)
School Of Acc Economics&Fin
Pietermaritzburg

Dear Mr Lungelo Madondo,

Original application number: 00027388
Project title: Volatility spillovers and interconnectedness between cryptocurrencies and traditional asset classes in emerging markets

Exemption from Ethics Review

In response to your application received on 9 August 2024, your school has indicated that the protocol has been granted **EXEMPTION FROM ETHICS REVIEW.**

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

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

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

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

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

Yours sincerely,

[redacted]

Prof Claire Lauren Vermaak
Academic Leader Research
School Of Acc Economics&Fin

UKZN Research Ethics Office
Westville Campus, Govan Mbeki Building
Postal Address: Private Bag X54001, Durban 4000
Website: http://research.ukzn.ac.za/Research-Ethics/

Founding Campuses: 🟥 Edgewood 🟧 Howard College 🟨 Medical School 🟩 Pietermaritzburg 🟦 Westville

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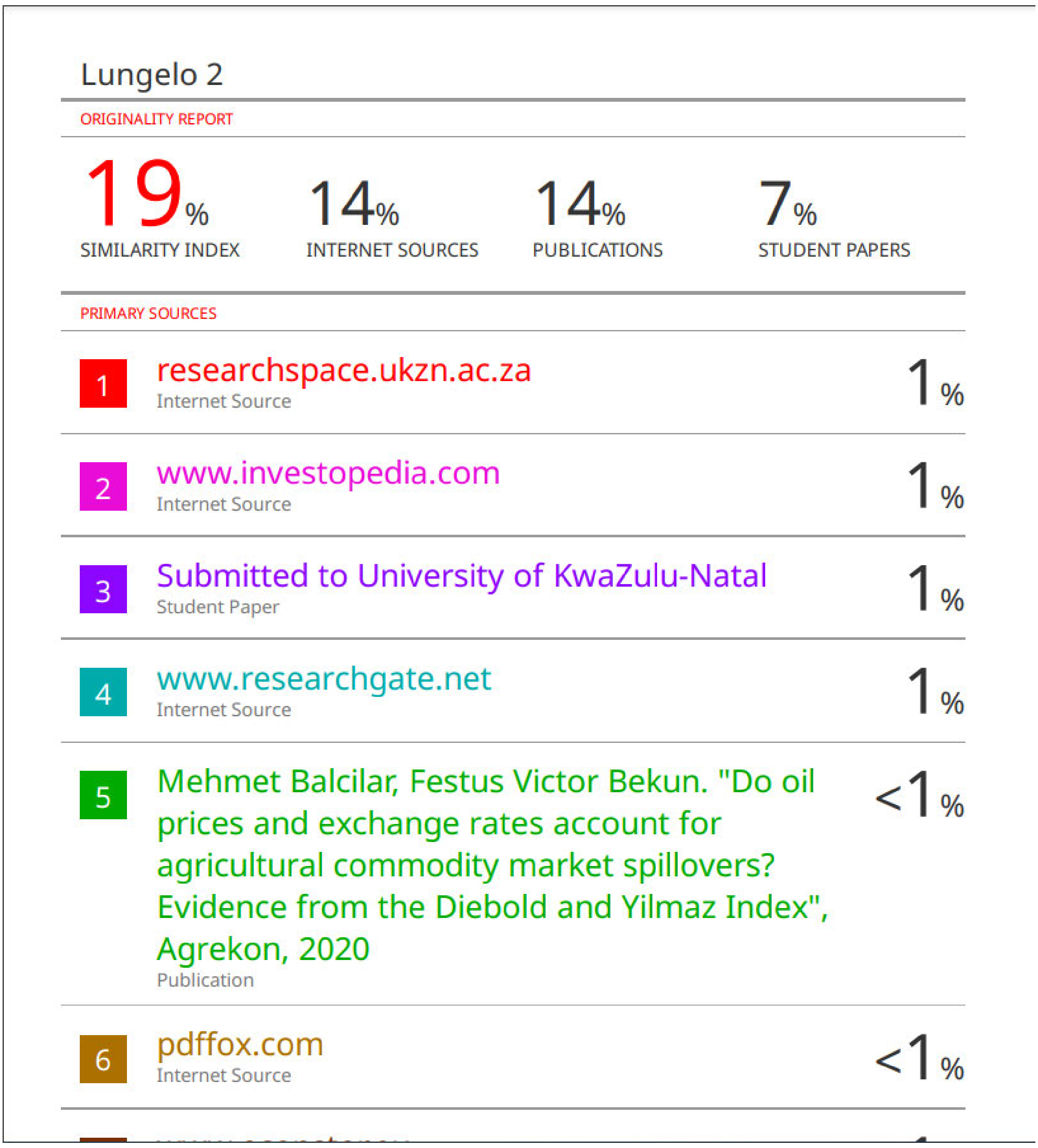
Appendix C: Turntin report



Lungelo 2

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6	pdffox.com Internet Source	<1%