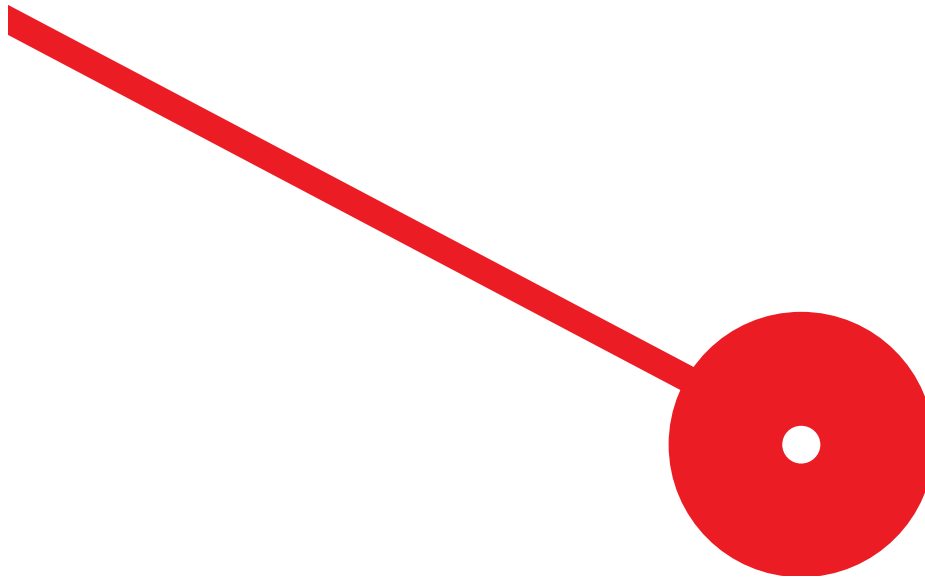




Cryptocurrencies and stocks: spillovers across developed and emerging markets and in bear and bull phases

Bernardo Silva Andrade

07/2024

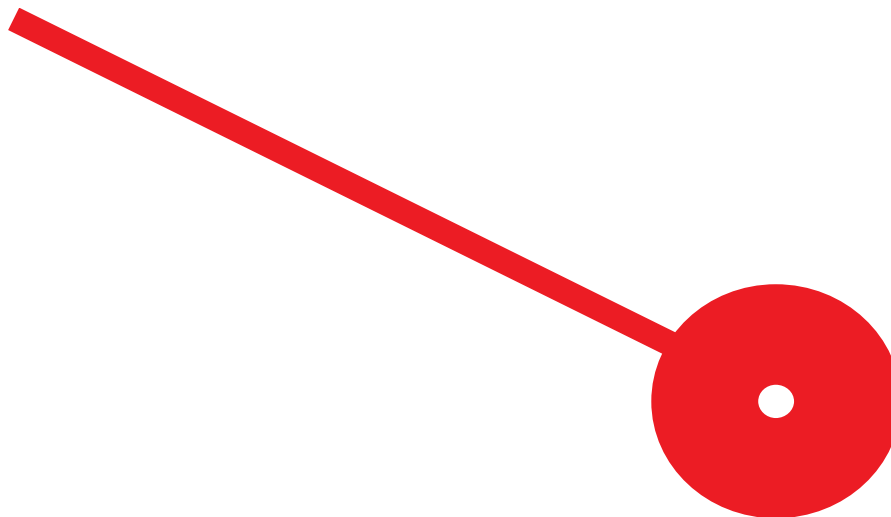




Cryptocurrencies and stocks: spillovers across developed and emerging markets and in bear and bull phases

Bernardo Silva Andrade

Dissertação de Mestrado apresentado ao Instituto Superior de Contabilidade e Administração do Porto para a obtenção do grau de Mestre em Contabilidade e Finanças, sob orientação da Professora Doutora Celsa Maria de Carvalho Machado e da Professora Doutora Ana Paula Ferreira Ribeiro



Agradecimentos

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Resumo:

As criptomoedas ganharam uma popularidade crescente como classe de ativos, mas também suscitaram preocupações quanto às suas potenciais implicações para a estabilidade financeira devido à extrema volatilidade dos preços.

Este estudo examina as repercussões em termos de rendibilidade e volatilidade entre as três principais criptomoedas de capitalização bolsista e os índices bolsistas, no período de 1 de janeiro de 2016 a 30 de abril de 2024. Contribui para a literatura ao avaliar se a intensidade e os efeitos líquidos destas repercussões diferem em mercados em alta e em baixa, e entre economias emergentes e avançadas. Quanto à estratégia empírica, alargámos a abordagem de conectividade de Diebold e Yilmaz para incluir potenciais diferenças de spillover em períodos de mercados em alta e em baixa, estimadas utilizando o algoritmo de Lunde e Timmermann (2004).

As conclusões deste estudo indicam que as criptomoedas e as ações mantêm características de classes de ativos separadas, mas há provas de uma interligação mais estreita durante os períodos de baixa. Sugerem também a inexistência de qualquer assimetria nas repercussões entre as criptomoedas e os mercados bolsistas das economias avançadas e emergentes, apesar da popularidade das criptomoedas nestes últimos.

Palavras chave: Criptomoedas; Mercados de ações; Conexão entre retorno e volatilidade; Regimes de mercado

Abstract:

Cryptocurrencies have gained increasing popularity as an asset class, but they have also raised concerns about their potential financial stability implications due to extreme price volatility.

This study examines the return and volatility spillovers between the top three market capitalization cryptocurrencies and stock market indices, over the period from January 1, 2016, to April 30, 2024. It contributes to the literature by assessing whether the intensity and net effects of these spillovers differ in bull and bear markets, and between emerging and advanced economies. As for the empirical strategy, we extended Diebold and Yilmaz's connectedness approach to include potential spillover differences in bull and bear market periods, estimated using Lunde and Timmermann's (2004) algorithm.

The findings of this study indicate that cryptocurrencies and stocks maintain characteristics of separate asset classes, but there is evidence of closer interconnection during bearish periods. They also suggest the inexistence of any asymmetry on the spillovers between cryptocurrencies and the stock markets of advanced and emerging economies, despite the the popularity of cryptocurrencies in the latter.

Key words: Cryptocurrencies; Stock Markets; Return and Volatility Connectedness; Market Regimes

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LIST OF ABBREVIATIONS

VAR - Autorregressive Vector

BTC - Bitcoin

ETH - Ethereum

XRP - Ripple

ETF - Exchange-traded funds

VT - Vanguard Total World Stock ETF

MCHI - iShares MSCI China ETF

VEA - Vanguard FTSE Developed Markets ETF

VWO - Vanguard FTSE Emerging Markets ETF

TNX - CBOE Interest Rate 10 Year T No

BCO - Brent Crude Oil Last Day Financ

S&P 500 - Standard and Poor 500

TCI - Total connectedness index

H1 - Hipotesis 1

H2 - Hipotesis 2

CHAPTER - INTRODUCTION

Chapter - Introduction

Cryptocurrencies markets began with Bitcoin in 2008, created by Satoshi Nakamoto, using blockchain technology to guarantee transparent and secure transactions. Other cryptocurrencies, such as Litecoin, Ripple, and Ethereum, emerged with different functionalities. The growing popularity of cryptocurrencies has led to their adoption by large financial companies, integrating them into the traditional financial system, requiring the creation of a specific regulation framework in several countries.

Cryptocurrencies, especially Bitcoin, offer advantages such as decentralization, with no need for intermediaries, reduced transaction costs, greater security, and financial inclusion. However, they also face significant disadvantages, including high volatility, lack of regulation, vulnerability to hacker attacks, and technical complexity, hindering their mass adoption. Anonymity in transactions can also facilitate illegal activities and scalability can be limited in times of high demand.

Digital transformation in financial markets, with electronic trading platforms, has reduced costs, and enabled more global access to these markets. Financial innovations such as ETFs and complex derivatives allow for more efficient risk management. Robust regulation is thus crucial to protect investors and prevent fraud. In this context, the introduction of digital currencies by central banks is reshaping the financial landscape, raising questions about the future of private cryptocurrencies. Despite the challenges, cryptocurrencies are seen as a new asset class with high return potential, redefining traditional investment and finance paradigms.

Cryptocurrencies are a recent phenomenon worthy of attention in economic and financial research. There is a need to investigate their relationship with traditional financial assets, especially related to their portfolio diversification potential, for guidance for investors and policymakers. While there is already substantial research on the linkages between cryptocurrencies and other financial assets, the findings are still inconclusive, and there is limited investigation of potential asymmetries in these linkages. More specifically, research on whether these linkages are sensitive to stock market states (bull and bear markets) or to the nature of the stock markets (advanced and emerging economies) is still scarce. Indeed, one would expect higher connectivity between different asset markets during “bad times”, when investors try harder to seek out alternative assets, including options beyond traditional

investments. Potential spillovers between cryptocurrencies and stock markets may also differ across advanced and emerging economies, given the popularity of cryptocurrencies in the latter.

The main objective of this dissertation is to assess the return and volatility spillovers between cryptocurrencies and stock market indices. We aim at assessing whether the intensity and net effects of these spillovers differ under bear and bull markets, and between emerging and advanced economies, filling a gap in the literature.

As far as we know, Bouri et al. (2018) is the sole study attempting to fill this gap in the empirical literature, covering daily data from 2010 to 2017. However, their study represents the crypto market solely with Bitcoin and employs a different (VAR-asymmetric GARCH) methodology. Also, they do not study spillovers with stock indices specific to advanced economies.

Instead, we quantify directional connectivity between different time series of financial assets returns/volatilities by following the Diebold and Yilmaz (2012, 2014) connectedness methodology and estimate VAR models considering stock market indices of emerging and advanced economies while extending the analysis for bull and bear stock market periods. Lunde and Timmermann (2004) algorithm was used to identify bull and bear periods on the S&P500 index and create bear and bull dummies.

In addition, we considered more recent daily data from January 1, 2016, to April 30, 2024, for the top-three most historic cryptocurrencies as of 2024 (Bitcoin, Ethereum, and Ripple), and also alternative selected stock market indices for world (VT), advanced (S&P 500 and VEA), and emerging (MCHI and VWO) markets, the 10-year US Treasury bonds (TNX), and a commodity, crude oil price (BCO).

This study has the following structure: chapter 1 presents an overview of the context of cryptocurrencies; in chapter 2, we review the empirical literature on recent research into cryptocurrencies and their main topics of interest; chapter 3 provides information on the data and methodology used in the study; chapter 4 discusses the results and chapter 5 concludes.

CHAPTER I – BACKGROUND CONTEXT: CRYPTOCURRENCY

The aim of this section is to enhance our understanding of cryptocurrencies market and its connection with the financial markets. We start by exploring the history of the development of the cryptocurrencies market to better frame its evolution and origins, including its main assets. Then, we highlight its key merits and drawbacks. Finally, we will examine the relationship between cryptocurrency and financial markets. We will cover the origins and evolution of financial markets, explore ETFs and cryptocurrencies, and discuss the role of cryptocurrencies on financial markets.

1.1 Foundations of Cryptocurrencies: Definition, History, and Key Cryptocurrencies

The concept of cryptocurrency began with the launch of Bitcoin in 2008 by Satoshi Nakamoto, an anonymous entity. Nakamoto published a whitepaper entitled "Bitcoin: A Peer-to-Peer Electronic Cash System," describing a decentralized digital currency that allows direct transactions without intermediaries, using blockchain technology to guarantee transparency and security. Following Bitcoin's introduction, it rapidly developed in the global financial market, leading to a comprehensive body of literature on the subject (Aydogan and Vardar, 2021).

The blockchain is a distributed digital ledger that records all transactions in a transparent and immutable way. Each block contains a set of transactions linked to the previous block, forming a continuous chain. This guarantees the security and integrity of the data. Once the computer effort has been expended to make it satisfy the proof-of-work, the block cannot be changed without redoing the work. As later blocks are chained after it, the work to change the block would include redoing all the blocks after it (Nakamoto, 2008).

The first Bitcoin transaction was mined by Nakamoto in January 2009. In May 2010, a programmer paid 10,000 BTC for two pizzas, marking the beginning of Bitcoin's use as a currency. In the following years, its popularity grew among technology enthusiasts and financial privacy advocates. More investors began to accept Bitcoin, and cryptocurrency transactions were established, allowing Bitcoin to be bought and sold with fiat currencies. Bitcoin originated using a scheme outlined by Satoshi Nakamoto, who introduced the first 50 Bitcoins into circulation in 2009 (Ismail and Basah, 2021).

Despite challenges such as scalability, volatility, and regulation, Bitcoin's technology has inspired the development of other cryptocurrencies and blockchain applications. The launch of Bitcoin in 2008 marked the beginning of a financial revolution, introducing a new form of decentralized and secure digital currency. Bitcoin remains the best-known and most

valuable cryptocurrency, paving the way for the development of the cryptocurrency market. Bitcoin, the largest crypto asset by market capitalization, recently found its way beyond private markets with El Salvador becoming the first country to adopt Bitcoin as legal tender in September 2021 (Lyer, 2022).

Blockchain technology, fundamental to cryptocurrencies, is a distributed and immutable digital ledger that records all transactions across a network of computers. This technology ensures the integrity of transactions and eliminates the need for financial intermediaries. According to Nakamoto (2008), once the computer effort has been expended to satisfy the proof-of-work, the block cannot be changed without redoing the work. As later blocks are chained after it, the work to change the block would include redoing all the subsequent blocks.

After Bitcoin's initial success, several other cryptocurrencies emerged, known as altcoins, each with different functionalities and purposes. Notable examples include Litecoin (2011), Ripple (2012), and Ethereum (2015), which introduced technological innovations and specific use cases. According to Lyer (2022), Bitcoin and Ethereum have ranked among the world's top 20 traded assets, competing with the market capitalization of some of the world's largest companies. Additionally, the market capitalization and trading volume of stablecoins have also increased, highlighting the growing diversity and significance of the cryptocurrency market.

With the rise in popularity and market value of cryptocurrencies, financial regulators around the world have begun to develop guidelines and regulations for their use. Countries such as the United States, Japan, and various members of the European Union have initiated the creation of legal frameworks to regulate cryptocurrency exchanges, initial coin offerings, and the use of cryptocurrencies as a means of payment. At the same time, financial institutions and large companies have started to adopt and invest in cryptocurrencies and blockchain technology. This regulatory evolution and institutional adoption signify the growing acceptance and integration of cryptocurrencies into the traditional financial system.

Main cryptocurrencies

Figure 1 represents the market capitalization of the three top cryptocurrencies in 2023. Bitcoin (BTC) is the first and best-known cryptocurrency, created in 2008 by an anonymous entity known as Satoshi Nakamoto. It was designed to be a decentralized digital currency and a store of value. Bitcoin's main innovation is the use of blockchain technology,

a public and immutable record of all transactions carried out on the network. Each transaction is verified by a decentralized network of nodes, guaranteeing security and transparency without the need for intermediaries such as banks.

Bitcoin is often referred to as "digital gold" due to its limited supply of 21 million coins. This limit was set by Nakamoto to mimic the scarcity of gold and create a hedge against inflation. As the number of Bitcoins in circulation approaches this limit, mining becomes more difficult, increasing the potential value of the cryptocurrency.

In addition to being a currency, Bitcoin is seen as a store of value and a form of portfolio diversification. Investors and financial institutions consider Bitcoin a hedge against inflation and an alternative to traditional assets such as shares and gold.

Ethereum (ETH) is a decentralized platform launched in 2015 by Vitalik Buterin with the aim of expanding the capabilities of blockchain technology beyond simple financial transactions. Ethereum's main innovation is the introduction of smart contracts, which are self-executing contracts with the terms of the agreement written directly into the code. These contracts enable the creation of decentralized applications that operate autonomously and transparently.

The Ethereum network uses its own native cryptocurrency, Ethereum (ETH), which is used to pay transaction fees and computing services on the network. The versatility of smart contracts and decentralized Apps has made Ethereum a popular platform for a wide range of applications, from decentralized finance to non-fungible tokens. According to Lyer (2022), Bitcoin and Ethereum have ranked among the world's top 20 traded assets, competing with the market capitalization of some of the world's largest companies, and the market capitalization and trading volume of stablecoins have also increased.

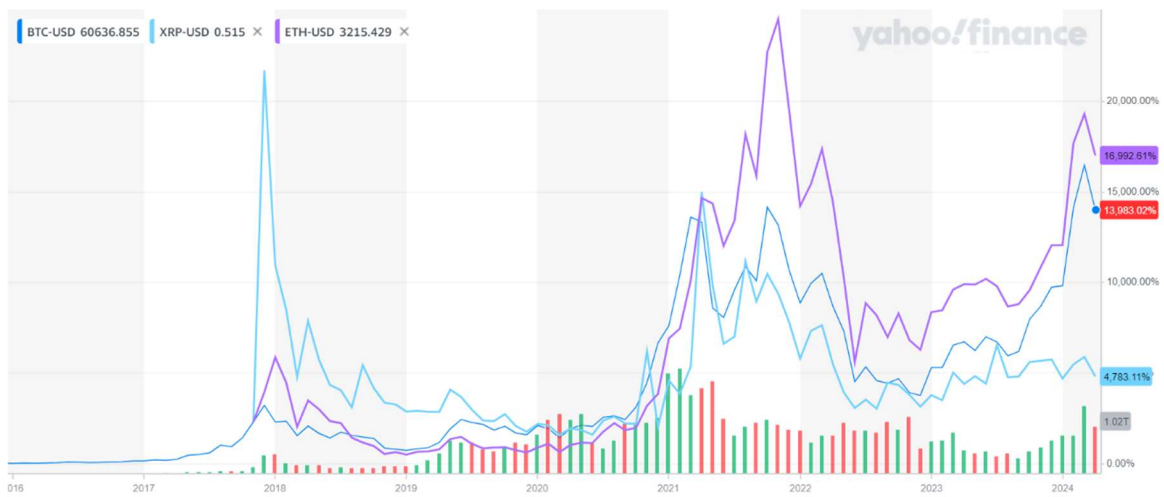
Ethereum is also in the process of transitioning to a new version called Ethereum 2.0, which aims to improve the scalability and security of the network by adopting a proof-of-stake consensus mechanism, replacing the current proof-of-work. This transition is expected to significantly enhance the network's efficiency and reduce its environmental impact.

Ripple (XRP), created in 2012 by Ripple Labs, is a cryptocurrency and digital payment platform designed to collaborate with financial institutions to improve the efficiency of cross-border transactions. Unlike many other cryptocurrencies aiming to replace the traditional banking system, Ripple works alongside it. Its main innovation is its

consensus protocol, enabling fast, low-cost transaction confirmations without the need for mining. Ripple uses a distributed ledger called the XRP Ledger, maintained by a network of independent servers. The platform's native cryptocurrency, XRP, acts as a "bridge" between different fiat currencies, facilitating liquidity and reducing the costs of international transfers. Ripple's partnerships with several large financial institutions and banks worldwide leverage its technology to enhance the speed and efficiency of international money transfers. This practical application to real-world financial issues sets Ripple apart from other cryptocurrencies.

The functionality of Ripple contrasts with that of Bitcoin and Ethereum, which aim to decentralize finance and expand blockchain applications, respectively. Bitcoin, introduced by Satoshi Nakamoto in 2008, focuses on being a decentralized digital currency and store of value. Ethereum, launched in 2015 by Vitalik Buterin, extends blockchain capabilities by enabling smart contracts and decentralized applications. The emergence of these cryptocurrencies highlights the diversification and specialization within the crypto space, with each offering unique solutions to various financial and technological challenges.

Figure 1 – Cryptocurrencies Market Capitalization



Source: Yahoo Finance. The sample is from 01/01/2016 to 30/04/2024. All the coin are compared with BTC. BTC are present in dark blue, XRP in light blue and ETH in purple.

1.2 Advantages and Disadvantages of Cryptocurrencies

Bitcoin has some key features: decentralization, operating on a network of nodes without the need for a central bank; transparency, with all transactions publicly visible on the blockchain; security, using advanced cryptography to protect transactions and balances; and limited supply, with a maximum supply of 21 million coins. These attributes make Bitcoin and other cryptocurrencies attractive as new financial investment instruments for investors in the financial system. They offer high return expectations, a decentralized nature, exemption from strict government regulations, and tax advantages, thereby providing new opportunities for portfolio diversification (Aydogan and Vardar, 2021).

Moreover, cryptocurrencies offer several advantages over fiat money. Firstly, as decentralized currencies, they are based on a vast network of interconnected users, making it impossible for any individual or government to exert control. Secondly, the set supply of cryptocurrencies prevents manipulation, unlike fiat money, which can be overprinted, leading to devaluation (Ismail and Basah, 2021). These factors contribute to the growing appeal of cryptocurrencies as innovative financial assets.

1.2.1 Advantages

Cryptocurrencies offer numerous advantages due to their decentralized nature. They operate on decentralized networks, eliminating the need for intermediaries such as banks and financial institutions. This allows for direct transactions between users, reducing costs and increasing efficiency. The decentralized nature of cryptocurrencies, as highlighted by Ismail and Basah (2021), ensures that no central authority can control transactions. This makes it challenging for governments or other entities to censor or block cryptocurrency transactions, thus providing greater economic freedom. Blockchain technology, which underpins cryptocurrencies, confirms and records transactions securely and transparently, reinforcing the resilience and autonomy of the cryptocurrency network.

Security is another significant advantage of cryptocurrencies. Transactions are protected by advanced encryption, making them highly secure against fraud and cyber-attacks. This ensures that only the intended recipients can access the funds. Furthermore, blockchain technology ensures data integrity and transparency by making transactions immutable; once recorded, they cannot be altered or deleted. This feature prevents fraud and manipulation. Additionally, Ismail and Basah (2021) note that there are centralized virtual

or digital tokens that leverage blockchain technologies, aiming to enhance privacy and confidentiality, though their effectiveness varies.

Cryptocurrencies also enhance transparency. All transactions are recorded in a public, distributed ledger known as a blockchain. This means anyone can access and verify transactions, increasing transparency and trust in the system. In terms of accessibility and financial inclusion, cryptocurrencies can be accessed by anyone with an internet connection, including those who do not have access to traditional banking services. This is particularly beneficial in regions with limited banking infrastructure. Cryptocurrencies allow people from countries with unstable financial systems to participate in the global market, promoting financial inclusion and offering viable alternatives for local economies.

Transaction costs are significantly reduced with cryptocurrencies. Transactions generally have lower fees compared to traditional methods, especially for international transfers. This is particularly advantageous for remittances and cross-border payments. Nakamoto (2008) points out that cryptocurrencies facilitate near-instant transfers, particularly for international transactions, which traditionally take several days to process. Traditional financial systems incur high mediation costs, increasing transaction fees and limiting the practicality of small, casual transactions. Moreover, these systems often prevent non-reversible payments for non-reversible services, adding an additional layer of cost and complexity. By eliminating intermediaries, cryptocurrencies reduce these costs and enhance the efficiency and feasibility of small-scale transactions.

1.2.2 Disadvantages

Although cryptocurrencies offer many advantages, they also have notable disadvantages. The lack of regulation creates an environment of uncertainty for both investors and creators. The absence of clear regulation can lead to fraudulent practices and risky investment schemes. There is also the risk that some countries will ban or restrict the use of cryptocurrencies, as mentioned by Nakamoto (2008), which creates uncertainty for users and limits adoption.

Security issues further complicate the use of cryptocurrencies. Exchanges and cryptocurrency wallets are vulnerable to hacking, and once funds are stolen, recovering them is nearly impossible, leading to significant user losses. Additionally, if a user loses their private key, they permanently lose access to their cryptocurrencies with no possibility of recovery (Ismail and Basah, 2021).

The technical complexity of cryptocurrencies also poses a barrier. Understanding and using cryptocurrencies and blockchain technology can be complicated for those unfamiliar with the subject, hindering mass adoption. Furthermore, irreversible errors in transactions can result in the permanent loss of funds, and the lack of customer support in many cases exacerbates this problem.

Cryptocurrencies' anonymity can be exploited for illegal activities such as money laundering and terrorist financing, posing a challenge for regulators and authorities. Nakamoto (2008) acknowledged that a certain percentage of fraud is unavoidable, but implementing routine escrow mechanisms could protect buyers and computationally impractical-to-reverse transactions could protect sellers from fraud.

Lastly, scalability problems present significant challenges. Many cryptocurrencies face technical limitations, such as long processing times and high transaction fees during periods of high demand, which can limit the network's ability to handle a large volume of transactions efficiently (Ismail and Basah, 2021).

These points provide a detailed overview of the advantages and disadvantages of cryptocurrencies, highlighting both their transformative potential and the challenges and risks that need to be managed to promote safe and efficient adoption.

1.3 The impact of cryptocurrencies on financial markets

1.3.1 Development of financial markets

Financial markets play a fundamental role in the global economy, facilitating the purchase, sale, and trading of a variety of financial assets such as stocks, bonds, currencies, commodities, and derivatives. Historically concentrated in major financial centers like New York, London, Tokyo, Frankfurt, and Hong Kong, these markets have evolved in response to economic needs and technological and regulatory changes (Song & Kang, 2019).

Digital transformation has been a significant catalyst in this development, with the emergence of electronic trading platforms and the use of trading algorithms. These innovations have enabled real-time trading, reduced transaction costs, and increased accessibility for retail investors worldwide (Demirgüç-Kunt et al., 2017).

However, a robust regulatory environment is essential to ensure the efficient and fair operation of financial markets. Regulators such as the Securities and Exchange Commission in the US, the Financial Conduct Authority in the UK, and the Securities and Exchange

Commission in Brazil establish rules to protect investors, ensure transparency, and prevent fraud and market manipulation (Chiu & Koepl, 2017).

Financial innovation also plays a crucial role in market development, with the creation of new financial instruments such as exchange-traded funds (ETFs), complex derivatives, and structured products. These instruments allow for more efficient risk management and capital leverage (Natarajan et al., 2019).

In the context of cryptocurrencies, regulation varies widely between countries, with some jurisdictions adopting a favourable approach while others impose severe restrictions (Ciaian et al., 2016). The introduction of own digital currencies by central banks, such as the European Central Bank and the Federal Reserve, is reshaping the global financial landscape and raises questions about the future of private cryptocurrencies (Benedetti and Kostovetsky, 2021).

Despite regulatory and security challenges, cryptocurrencies are viewed by many investors as a new asset class with high return potential. Specific investment strategies, such as holding and trading, are being adopted to capitalize on the opportunities offered by this constantly evolving market (Golumbia, 2015).

In conclusion, financial markets play a crucial role in efficiently allocating resources and managing risks in the global economy. The evolution of markets, driven by technological and regulatory innovation, will continue to shape the future of the financial system, while cryptocurrencies emerge as a promising but challenging asset class that is redefining traditional investment and finance paradigms (Benedetti and Kostovetsky, 2021).

1.3.2 The role of cryptocurrencies in development of financial markets

1.3.2.1 Protection against inflation and economic instability provided by cryptocurrencies

Cryptocurrencies have emerged as a tangible response to the economic fluctuations and monetary instability characterizing many economies worldwide (Narayanan et al., 2016). Particularly in regions with histories of high inflation and volatile currencies, such as Venezuela, Argentina, and Zimbabwe, cryptocurrencies have been seen as a promising alternative and, in some cases, as a solution to the economic challenges faced by local citizens.

One of the main ways in which cryptocurrencies are used in these regions subject to constant devaluation, stablecoins are a reliable alternative for storing value and carrying out transactions without worrying about significant losses due to inflation or economic instability. Faced with a local currency constantly losing value due to uncontrolled inflation, residents have sought to store their wealth in assets unaffected by government economic policies or market fluctuations. Bitcoin has been considered a safe harbour in the midst of the economic storm, with many individuals converting part of their assets into cryptocurrencies to protect their long-term purchasing power. In addition, stablecoins have played an important role in providing stability of value in regions with high inflation and volatile currencies. These cryptocurrencies, whose value is pegged to a fiat currency or stable asset, offer a way of accessing stable currencies and hedging against the volatility of local currencies (Yermack, 2015 and Antonopoulos, 2014).

Additionally, cryptocurrencies have been seen as a capital flight mechanism in countries with strict capital controls and currencies subject to constant devaluations. When governments impose restrictions on money movement or implement monetary policies that devalue the local currency, citizens often seek alternatives to protect their assets and preserve their wealth. Cryptocurrencies offer a digital solution that allows individuals to transfer funds abroad quickly and efficiently, bypassing restrictions imposed by local governments (Dwyer, 2015).

In addition to serving as a store of value and a means of capital flight, cryptocurrencies have also been incorporated into investment portfolio diversification strategies. In a scenario where fiat currencies are subject to economic instability and exchange rate risks, including cryptocurrencies in investment portfolios can help reduce overall risk and improve portfolio resilience in the face of economic turbulence. Case studies and data analyses demonstrate how including cryptocurrencies can improve the risk-return relationship of a portfolio, providing an additional form of diversification amid turbulent markets (Narayanan et al., 2016).

In summary, cryptocurrencies have played an increasingly important role in protecting against inflation and economic instability in regions affected by economic crises. Whether as a store of value, a means of capital flight, portfolio diversification, cryptocurrencies offer a promising alternative for individuals and communities seeking to protect their wealth and preserve their purchasing power amid economic turbulence.

However, it is important to recognize that cryptocurrencies also present challenges and risks, and their adoption and use should be carefully considered in light of each country's specific economic and regulatory circumstances.

1.3.2.2 Challenges and Barriers to financial inclusion with cryptocurrencies

Cryptocurrencies have sparked considerable interest as potential drivers of financial inclusion worldwide. However, despite their potential, there are still numerous challenges and barriers to be overcome for cryptocurrencies to effectively fulfil this role and achieve their full utility.

One of the main concerns is access to technology. In many unbanked or economically underdeveloped regions, the lack of technological infrastructure, such as smartphones and internet connectivity, can be a significant barrier to the adoption of cryptocurrencies. Without access to basic devices or reliable connectivity, individuals in these communities may face difficulties in participating in the cryptocurrency-based digital economy (World Bank, 2018). Addressing this issue requires initiatives aimed at providing access to affordable technological devices and reliable connectivity, such as subsidized smartphone distribution programs or investments in telecommunications infrastructure in remote and disadvantaged areas (Narayanan et al., 2016).

In addition to access to technology, the lack of knowledge and financial education also represents a significant obstacle to cryptocurrency adoption. Many people in marginalized communities may not be familiar with the concept of cryptocurrencies or the underlying blockchain technology (Catalini and Gans, 2016). This can lead to concerns about security and inadequate understanding of how cryptocurrencies work, which in turn can discourage their adoption. To combat this lack of knowledge, comprehensive financial education programs are needed to increase digital and financial literacy in these populations (Frost et al., 2019).

Another significant challenge faced by cryptocurrencies is their volatility and the associated risks (Benedetti and Kostovetsky, 2021). The highly volatile nature of cryptocurrency prices can pose a significant risk to individuals and businesses relying on financial stability. Price fluctuations can lead to substantial value losses in short periods of time, making cryptocurrencies a risky investment option for many. Strategies to mitigate these risks include portfolio diversification, the use of risk management tools such as futures and options contracts, and the development of stablecoins, whose value is anchored to less

volatile assets such as fiat currencies or commodities. However, despite the potential benefits of cryptocurrencies as a store of value and protection against inflation and economic instability, there are also challenges and limitations to consider. The inherent volatility of cryptocurrencies, for example, can pose a significant risk to investors, especially in regions where local currencies are subject to extreme fluctuations in value. Additionally, the lack of regulation and legal security in some countries may hinder the widespread adoption of cryptocurrencies as a means of payment and store of value (Ciaian et al., 2016).

In summary, while cryptocurrencies have the potential to promote financial inclusion worldwide, it is crucial to recognize and address the various challenges and barriers that currently limit their adoption and widespread use. From access to technology and financial education to regulation and legal security, a comprehensive and collaborative approach is needed to overcome these obstacles and enable cryptocurrencies to fulfil their role in protecting against inflation and economic instability, while promoting financial inclusion on a global scale.

CHAPTER II – REVIEW OF EMPIRICAL LITERATURE

In this section, we present a literature overview regarding return and volatility spillovers between cryptocurrencies and between cryptocurrencies and stock markets. Table 1 systematizes empirical studies of this literature review.

BTC has, since its inception in 2008, evolved in the cryptocurrencies markets. Among cryptocurrencies, the rise of BTC as an investment asset has earned increasing attention from investors and academics since its introduction by Nakamoto (2008). This study analyses various research exploring different aspects of BTC and cryptocurrencies in general, and how these markets interact with financial markets.

2.1 Interconnections within crypto assets

Kumar and Anandarao (2019) revealed, through the DCC GARCH model, that there are significant spillovers between all the returns of the cryptocurrencies studied. Among these cryptocurrencies, the return spillover values are highest between Bitcoin and Litecoin, followed by Ripple and Litecoin, indicating a strong interconnection and influence between these digital currencies. Kumar and Anandarao (2019) also found negative return correlations between Bitcoin and Ethereum during periods of turbulence, suggesting that the returns of these cryptocurrencies tend to move in opposite directions in times of high volatility and uncertainty. The analysis also showed a significant correlation between the returns of Bitcoin and Ripple, highlighting a strong interconnection between these cryptocurrencies.

In addition, Kumar and Anandarao (2019) observed that there is a synchronization of returns between all cryptocurrencies during the analysis period, suggesting that shocks in one cryptocurrency can quickly spread to others, reflecting a high interconnectivity in the cryptocurrency market. This interconnectedness was corroborated by Koutmos (2018), who used the VAR model to analyse the "Contributions to Others" and the "Contributions of Others" in relation to cryptocurrency returns. Koutmos (2018) found that Bitcoin transmits disproportionately more return shocks to other cryptocurrencies.

Bouteska, et al. (2023) used the GARCH model to analyse the volatility of cryptocurrencies and found that Bitcoin and Dash have negative skewness, with distributions skewed to the left and high kurtosis, indicating leptokurtic returns. This implies that both cryptocurrencies have return distributions that deviate from normality. Bouteska, et al. (2023) also observed significant bidirectional spillovers between Bitcoin and other

cryptocurrencies (ETH, LTC and XMR), suggesting that these smaller cryptocurrencies also play significant roles in the market.

Baur and Dimpfl (2018), using the Quantile Autoregressive (QAR) model, showed that for most cryptocurrencies, negative shocks increase volatility less than positive shocks. BTC was not identified as a dominant player in the cryptocurrency markets, although BTC shocks transmitted to other cryptocurrencies had a longer duration.

Corbet et al. (2018) used the Diebold and Yilmaz method to conclude that Bitcoin volatility explains less than Ripple and Litecoin volatility, while Litecoin volatility has a greater impact on both Bitcoin and Ripple, so the net spillover from Litecoin and ripple to BTC is stronger than if the opposite were indicated. These results indicate that both Bitcoin and Ripple may be susceptible to volatility shocks transmitted by Litecoin.

In Iyer (2023), total connectivity across all samples exhibits significant values for both returns and volatilities. In 2014, these values indicated that cryptocurrency markets were highly interconnected. BTC is the largest emitter of return spillovers, but this is also true for volatility. After 2017, though, Ethereum became the largest transmitter of return spillovers. Overall, both return and volatility spillovers reveal a similar picture in both samples, although with some differences in magnitudes.

Indeed, until around December 2017, it coincided with the first big boom in the cryptocurrency market. During this period, the connectivity of both returns and volatility remained relatively low, suggesting that, despite the rise in the price of Bitcoin and the growing prominence of crypto assets in the mainstream, the degree of interconnectivity between crypto assets, as measured by spillovers, remained modest. The COVID-19 pandemic in March 2020 brought another wave of volatility within the cryptocurrency market. This period of recovery was accompanied by a decrease in spillover indices, indicating a decrease in interconnectivity between crypto assets (Iyer, 2023).

2.2 Interconnections between crypto and other financial assets

Uzonwanne (2021), using VARMA-AGARCH, found that the market returns spillovers of Bitcoin to CAC40 were negative, but positive to DAX30, FTSE100, NIKKEI225 and S&P500 markets. Some links showed no connection, while others had unidirectional long-term spillovers (BTC - DAX 30 and BTC - FTSE 100) and short-term spillovers (BTC - Nikkei 225) and bidirectional spillovers in both terms (BTC - Nikkei 225).

In the short term, the return spillover from the Bitcoin market to the S&P 500 market was statistically significant, but not significant from the S&P 500 market to the Bitcoin market.

Aydogan et al. (2022), using MGARCH, for the E7 countries, the results show a bidirectional volatility spillover between Ethereum and Bitcoin and the Indian stock indices (BSE Sensex). Unidirectional stock market volatility spillovers for Ethereum exist only in Indonesia (JKSE) and Brazil (Bovespa), while for Bitcoin they exist in Indonesia (JKSE) and Russia (RTS). The effects of cryptocurrencies on stock market returns are significant in Russia (RTS) and China (Shanghai SEE) for Ethereum, and in Brazil (Bovespa) and China (Shanghai SEE) for Bitcoin. For the G7 countries, there is a bidirectional volatility spillover effect between cryptocurrencies and stock markets. In the UK, there is a unidirectional volatility spillover from the FTSE 100 to cryptocurrencies.

Basah and Ismail (2021), using the VECM (Vector Error Correction Model), found that the JP225 (Nikkei) and the WTI (West Texas Intermediate) had negative and significant values at the 5% level, confirming the existence of a long-term relationship with Bitcoin. In addition, the results indicate that the Dow Jones and oil prices have an impact on Bitcoin, with a positive connection between the Dow Jones and Bitcoin price movements.

Trabelsi (2018) used the VAR model, where he highlighted a limited interconnection between cryptocurrency markets (Bitcoin, Ethereum, Ripple and Litecoin) and traditional stocks (S&P500, NASDAQ, FTSE100, Hang Seng and Nikkei225). This disparity can be attributed to different profitability factors in each market segment. BTC emerges as a relatively minor and inconsequential transmitter and receiver of shock channels. This observation emphasises the minimal impact of BTC on the broader financial markets, suggesting that its influence on knock-on effects is marginal compared to more traditional assets. Overall, their analysis emphasises the unique characteristics of cryptocurrency markets and their comparatively limited integration into conventional financial systems.

Elsayed, Gozgor and Lau (2020), used the VAR model, where they studied the repercussions of returns in the foreign exchange (FX) and cryptocurrency markets. They found that BTC, the Australian dollar (AUD), the euro (EUR) and the Swedish krona (SEK) acted as net transmitters of return spillovers, while others, such as Ripple (XRP), the British pound (GBP) and the Canadian dollar (CAD), were net receivers. BTC emerged as the most significant net transmitter of volatility spillovers, contrary to its position in. Interestingly, contrary to its position in the feedback network analysis, Litecoin was found to be a net receiver of spillovers. The findings of the spillover approach confirmed that both return

indices and volatility spillover indices are highly reactive and sensitive to international shocks and economic and financial turbulence.

Omri (2023) used the VAR model to examine the relationship between BTC returns and those of various stock market indices in different regions. Specifically, in developed markets, the Nikkei 225 index in Japan has a negative impact on BTC returns, suggesting that an increase in the returns of this index leads to a decrease in BTC returns. In contrast, South Korea's Kospi Composite index and Sweden's OMX Stockholm 30 index have a positive impact on BTC returns. In emerging markets, the QE index in Qatar and the TASI in Saudi Arabia positively affect BTC returns, which implies that increases in the returns of these indices correspond to increases in BTC returns. Omri (2023) concluded that BTC responded mainly to shocks from developing markets, acting as a net receiver of shocks from these markets.

Zang and He (2021), using the DC-GC-MSV model, found that BTC volatility Granger causes the Dow Jones stock market. The volatility of BTC is evidently higher than that of the stock market. However, there is no significant spillover between BTC and the stock index. By way of exception, this study also showed that BTC has a lower volatility compared to the Dow Jones index, suggesting that the Dow Jones index has a higher volatility persistence than BTC, while still being a negligible value. Consequently, the spillover relationship between BTC and the stock index shows no significant spillover effects.

Malhotra and Gupta (2019), using the Diagonal BEKK model, concluded that the spillover effects of volatility itself (ARCH effects) are positive and significant for the five Asian currency markets (S&PBSE (Indian stock exchange), PSE (Philippine Stock Exchange), SGX (Singapore Stock Exchange), HNX (Vietnam Stock Exchange), BUR (Malaysian Stock Exchange)) and for the four cryptocurrencies (BTC (Bitcoin), LTC (Litecoin), DASH, XMR (Monero)). Cross-volatility spillovers are higher than own-volatility spillovers in all markets, indicating that BTC has a more significant effect on the Asian market than the other cryptocurrencies. The study highlighted BTC's unique position in the financial markets, acting as an intermediary between a fiat currency and a commodity. The analysis also revealed that for all stock indices, with the exception of the Vietnam stock exchange and the Philippine stock exchange, the correlation coefficient in volatility is negative.

Wang et al. (2022), using the TVP-VAR model, demonstrated a relatively strong information spillover effect between Bitcoin, gold, commodities and three stock markets. This means that the risk of one market is likely to be transferred to other markets. Global and developed stock markets act as net transmitters of spillovers, while Bitcoin, gold, commodities and emerging stock markets are net receivers. The global stock index is the largest net transmitter of spillovers, which demonstrates that the global stock market occupies the leading position. The emerging stock market is the smallest net transmitter of spillovers, which reflects its lesser development and openness. Bitcoin, gold and commodities are defined as net recipients of spillovers, with the total directional spillovers from other markets to Bitcoin increasing rapidly.

Jiang et al. (2022) carried out a comprehensive analysis of volatility spillovers in financial markets using TVP-VAR models. The authors categorised financial markets into two types based on net spillovers, with BTC identified as a net spillover market, which transmits more volatility than it receives. In contrast, the stock market and the crude oil market acted as volatility receivers. The stock market receives the highest number of spillovers and produces the lowest number of spillovers to other markets, making it the largest recipient of volatility among all the main financial markets, significantly influenced by BTC price fluctuations. The authors observed that the BTC market is fully involved and integrated into the global financial market volatility co-movement system. Markets with positive net spillovers, including the BTC, gold, foreign exchange and natural gas markets, act as volatility communicators, while markets with negative net spillovers, such as the stock market and the crude oil market, act as volatility receivers.

Qarni et al. (2019), using VAR, found that the US BTC market receives and transmits the lowest volatility spillover among selected US markets. During calm periods, volatility spillover in financial markets is lower, but during turbulent periods, it gradually increases. Both the stock and currency markets exhibit the most reactive behaviour to global financial events, with high volatility spillovers. BTC is considered the lowest volatility spillover receiver among all other US financial markets throughout the sample period.

Iyer (2022), used VAR, where he highlighted the growing connection between the cryptocurrency market and the stock market during the period from 2017 to 2021. The correlation between BTC price volatility and the S&P 500 index increased more than fourfold before the COVID-19 pandemic. BTC's contribution to the change in S&P 500 volatility also increased significantly after the pandemics. Return spillovers from BTC to the

S&P 500 increased, and vice versa, between 2017-19 and 2020-21. This increase was accompanied by a significant increase in the correlation between the returns of BTC and the S&P 500, indicating a more robust influence of BTC on stock market movements. Both BTC and the MSCI emerging markets index showed increasing contributions to each other's returns before and after the pandemics.

Iyer (2022) reported that the COVID-19 crisis triggered a significant increase in directional volatility spillovers between the cryptocurrency and stock markets, indicating greater interconnectedness and impact between these markets. Specifically, it was found that stocks emit a greater amount of volatility spillovers to the cryptocurrency market compared to the spillovers emitted by cryptocurrencies to the stock market.

Iyer and Popescu's (2023) analysis also revealed significant bilateral spillovers between financial asset pairs and within the crypto market. The MSCI World Equity Index and the S&P 500 show the strongest bidirectional spillover effects with cryptocurrencies, with return spillovers from cryptocurrencies to these indices being more dominant. Volatility spillovers are more prominent between cryptocurrencies and riskier emerging market stock markets. The analysis also records significant bilateral spillovers between pairs of financial assets, and within the cryptocurrency market itself, indicating strong integration.

A significant part of the literature studies how the spillovers across markets change according to the state of the stock market, when the market is on the rise, economically sound phase (bull market), or otherwise (bear market).

Khalfaoui et al. (2022) used GARCH models and concluded that, in rising markets, all markets contribute and receive greater spillovers, with the spillovers being net in a crisis market, higher in a normal market and much lower in a rising market. In the stock market, the S&P 500 transfers risks to Bitcoin. There are pairs of high volatility spillover connectivity in a bull market, with the BTC, S&P 500 markets showing strong volatility spillover connectivity.

The study by Bouri et al. (2018) used the Glosten-Jagannathan-Runkle Generalised Autoregressive Conditional Heteroskedasticity and Dynamic Conditional Correlation model to investigate the spillover effects between BTC returns and the returns of other assets during bull and bear market regimes. Regarding volatility, the study concluded that BTC - MSCI China have a greater influence on each other, and thus there is greater connectivity. The summary statistics of Bouri et al. (2018) reveal notable trends in return spillovers during bull and bear markets. Positive return spillovers from global and emerging markets to BTC are

observed in bull markets, while in bull markets there are also negative return spillovers from BTC to global equities, energy, gold and bonds. Similarly, negative spillovers in US dollar returns are observed for BTC in bull market conditions. Conversely, in bear markets, return spillovers from global and emerging markets to BTC become negative, while positive return spillovers from BTC to global, emerging and Chinese stock markets emerge. Furthermore, in bear markets, positive spillovers are observed in the returns of BTC to commodities, energy, gold and bonds, as well as positive spillovers in the returns of the US dollar to BTC.

Iyer and Popescu (2023) found that in 2017, the price of BTC increased exponentially, but the interconnectedness between cryptocurrencies remained relatively low. At the end of 2017 and the beginning of 2018, the financial and cryptocurrency markets recorded price increases driven by bullish sentiment. However, towards the end of 2017, spillovers began to increase consistently, reflecting greater interconnectedness during the market downturn in January 2018. The stock market crash in 2018 had a significant impact on interconnectedness, with return and volatility spillover indices remaining high. During the pandemics, uncertainty led to a stock market crash, with spillovers reaching high levels. The MSCI World Equity Index and the S&P 500 are the largest senders of return and volatility spillovers, while the crypto market and emerging equity markets are net recipients of spillovers.

TABLE 1 - FINDINGS OF THE REVIEWED EMPIRICAL SOURCES

AUTHORS	MARKETS' SAMPLE	METHODOLOGY	RESULTS
Aydogan, Vardar and Taçoğlu (2021)	The stock indices of the Group of Seven (G7) includes S&P 500 (the US), FTSE100 (the UK), CAC40 (France), DAX (Germany), Nikkei 400 (Japan), FTS-MIB (Italy) and TSX (Canada), Emerging 7 (E7), includes Bovespa (Brazil), Shanghai SEE (China), BSE Sensex (India), S&P/BMV (Mexico), RTS (Russia), JKSE (Indonesia) and BIST100 (Turkey) Two major cryptocurrencies, namely, Bitcoin and Ethereum. Period: Bitcoin and G7 – E7 stock markets: 2013 - 2021; Ethereum: 2015 - 2021	Multivariate GARCH (MGARCH) models; the BEKK and DCC models	In the E7 countries, there are bidirectional spillovers between Ethereum, Bitcoin and the Indian stock indices. Unidirectional spillovers for Ethereum occur in Indonesia and Brazil, and for Bitcoin in Indonesia and Russia. In the G7 countries, there are bidirectional spillovers between cryptocurrencies and stock markets, with the FTSE 100 influencing cryptocurrencies in the UK. The volatility of cryptocurrencies and stock markets is influenced by past shocks, with significant spillovers between Ethereum and stock markets in Brazil, and between Bitcoin and stock markets in India and China.
Baur and Dimpfl (2018)	20 cryptocurrencies (BTC, ETH, XRP, BCH, EOS, XLM, LTC, ADA, USDT, MIOTA, TRX, XMR, ETC, DASH, NEO, BNB, XEM, XTZ, ZEC, OMG). Period: 2013 - 2018.	Asymmetric GARCH model	For most cryptocurrencies negative shocks increase volatility less than positive shocks. Positive asymmetric volatility is predominant, except for Bitcoin and Ethereum. The study highlighted strong interdependencies between cryptocurrencies, with Bitcoin not being a dominant player despite its shocks having a longer duration.
Bouri, Das, Gupta and Rouband (2018)	Bitcoin and 4 asset classes (stocks, commodities, currencies and bonds): MSCI World, MSCI Emerging markets, MSCI China, S&P GSCI Commodity, S&P GSCI energy, one ounce of gold, U.S. dollar index and U.S. 10-year treasury yields. Period: 2010 - 2017	DCC – GARCH	In bullish markets, there are positive return spillovers from global and emerging markets to BTC, while negative returns from BTC affect equities, energy, gold and bonds. In bear markets, return spillovers from global and emerging markets to BTC become negative, with positive spillovers from BTC to global, emerging and Chinese markets.
Bouteska, Sharif and Abedin (2023)	4 cryptocurrencies (Bitcoin, Dash, Monero, and Stellar) and US energy and bond market indices (VXXLE and VXTLT). Period: 2016 -2021, covering the first, second, and third waves of the pandemics COVID-19	General autoregressive conditional heteroskedastic (GARCH) models.	Bitcoin and Dash show negative asymmetry and high kurtosis, indicating non-normal returns and leptokurtic distribution. Cryptocurrencies are not connected to the energy market and act as hedges. There is bidirectional spillover from BTC to ETH, LTC and XMR, showing that smaller cryptocurrencies are significant, challenging the idea that BTC is the main player in the market.
Corbet, Meegan, Larkin, Lucey and Yarovaya (2018)	Bitcoin and Ethereum Period: 2009 to 2017	The generalized variance decomposition methodology (Diebold and Yilmaz, 2012)	The analysis reveals strong interconnections between Ripple, Litecoin, and Bitcoin, with Litecoin exerting notable influence on both Bitcoin and Ripple's volatility. However, Bitcoin's volatility spillovers to other assets exhibit erratic patterns, indicating time-dependent and unstable dynamics.
Elsayed, Gozgor and Lau (2020)	3 cryptocurrencies: Bitcoin (BTC), Ripple (XRP), and Litecoin (LTC) 9 traditional currencies: AUD, the GBP, the Canadian Dollar (CAD), the Euro (EUR), the Japanese Yen (JPY), the NZD, the Swedish Krona (SEK), the Swiss Franc (CHF), and the Chinese Renminbi (Yuan) (CNY) Period: 2013 to 2018	vector autoregressive (VAR)	Bitcoin and select currencies act as net transmitters of return spillover. The Euro stands out as a major transmitter, with Bitcoin leading in volatility spillover.

Ismail and Basah (2021)	3 cryptocurrencies (Bitcoin, Monero, Stellar) Stock price indexes (Dow Jones and Nikkei) Brent Oil and WTI Australian Dollar, Euro and Pound Sterling Period: 2016 - 2020	Vector error correction model (VECM).	It was found that the JP225 (Nikkei) and the WTI (West Texas Intermediate) have a negative and significant relationship with Bitcoin in the long term. In addition, the results show a positive correlation between the Dow Jones and Bitcoin price movements.
Iyer (2022)	2 cryptocurrencies (Bitcoin, Tether) US equity indices (S&P 500, Russell 2000) Period: 2017 - 2021	vector autoregressive (VAR)	Study reveals reciprocal volatility spillovers between Bitcoin and S&P 500 during stress. Bitcoin's volatility correlates highest with U.S. stocks, with post-pandemic increases noted. Equities emit more volatility spillovers to crypto markets.
Iyer (2023)	23 crypto assets: Bitcoin (BTC), Bitcoin Cash (BCH), Binance Coin (BNB), Dash (DASH), Decred (DCR), DigiByte (DGB), Dogecoin (DOGE), Ethereum (ETH), Ethereum Classic (ETC), Gnosis(GNO), Golem (GNT), Litecoin (LTC), MaidSafeCoin (MAID), Neo (NEO), OMG Network (OMG), Augur (REP), Status (SNP), Vertcoin (VTC), NEM (XEM), Stellar (XLM), Monero (XMR), Ripple (XRP) and Zcash (ZEC) Period: 2015 - 2023	VAR	Crypto assets show significant return and volatility spillovers, notably during market downturns and the pandemic, with major contributions from MSCI World Equity Index and S&P 500. Connections between crypto and financial assets remain strong, especially with emerging markets and gold, indicating robust market integration.
Jiang, Li, Lu, Wang and Wei (2022)	Six commodities of emerging and major market: Bitcoin (BTC), WTI crude oil (WTI), gold index (XAU), S&P 500 ETF (SPY), US Dollar index (FX) and natural gas (NG) Period: 2014 to 2020	TVP-VAR	Markets with positive Net Spillovers, such as Bitcoin, gold, foreign exchange and natural gas, spread more volatility than they receive. Markets with negative Net Spillovers, such as stocks and crude oil, act as volatility receivers, with the stock market being the biggest receiver due to its sensitivity to external turbulence.
Khalfaoui, Jabeur and Dogan (2022)	10 green commodity markets (S&P 500, XBT, BTC, The S&P 500 ESG, IHS Markit Global Carbon, Global Wind Energy, Global Water, NASDAQ OMX Global Water, Ardour Solar Energy, World Solar Energy, Wilderhill Clean Energy, NASDAQ OMX Green Economy Global and Solactive Clean Energy) Two cryptocurrencies (BTC and XBT) Period: 2014 - 2021	Quantile VAR	In bull markets, all markets contribute and receive greater information spillovers. The S&P 500 stock market transfers risks to green commodities, Bitcoin and uncertainty markets in extreme circumstances and steady states. Markets such as BTC, S&P 500 Global Clean Energy, NASDAQ OMX Green Economy Global, World Solar Energy and Global Water show strong connectivity of volatility spillovers.
Kumar and Anandarao (2019)	4 cryptocurrencies (Bitcoin, Ethereum, Ripple and Litecoin) Period: 2015 - 2018	DCC – GARCH model	There is significant spillover in cryptocurrency returns, especially between Bitcoin, Litecoin and Ripple. Volatility is persistent, with a negative correlation between Bitcoin and Ethereum during turbulence. After 2017, the volatility spillover between Bitcoin, Ethereum and Ripple became significant. Volatility in the cryptocurrency market has increased with greater demand for these assets.
Koutmos (2018)	18 cryptocurrencies (Bitcoin, Ethereum, XRP, Litecoin, Dash, Stellar, NEM, Monero, Tether, Bytecoin, BitShares, Verge,	Vector Autoregressive (VAR)	In returns, BTC transmits more shocks than it receives. In volatility, BTC is the main contributor of shocks to other cryptocurrencies but receives few. The return and volatility spillovers are similar in magnitude and move together, maintaining a narrow distribution.

	Dogecoin, DigiByte, MaidSafeCoin, MonaCoin, ReddCoin, Emercoin). Period: 2015 - 2018		
Malhotra and Gupta (2019)	5 Asian stock indices ((S&PBSE (India stock exchange), PSE (Philippines stock exchange), SGX (Singapore stock exchange), HNX (Vietnam stock exchange), BUR (Malaysia stock exchange)) Four cryptocurrencies (BTC (Bitcoin), LTC (Litecoin), DASH, XMR (Monero)) Period: 2014 - 2018	EGARCH model, Diagonal BEKK and Dynamic Conditional Correlation	The own volatility spillover effects are positive and significant for five Asian exchange markets and four cryptocurrencies. Cross-volatility spillovers are greater than own volatility spillovers in all markets. Bitcoin has the greatest impact on Asian markets, but has no significant connection with emerging markets, showing almost zero values.
Omri (2023)	Bitcoin and stock market indexes from 15 developed markets (USA (S&P 500), Canada (SPTSX), UK (FTSE100), France (CAC40), Finland (OMXH25), Spain (IBX 35), Switzerland (SMI), Ireland (ISEQ), Sweden (OMX Stockholm 30), Belgium (BEL20), Germany (DAX), New Zealand (NZD), Japan (Nikkei225), South Korea (KOSPI), Hong Kong (HSI) and 15 emerging markets (Brazil (BOVESPA), Argentina (S&P Merval), Mexico (S&P/BMV IPC), Chile (S&P IPSA), Croatia (CROBEX) Bangladesh, (DSEX), Indonesia (JKSE), Tunisia (Tunindex), Morocco (Moroccan All Shares MASI), South Africa (JSE Top 40), Ivory Coast (BRVM10), Egypt (EGX30), Saudi Arabia (Tadawul All Share TASI), Qatar (QE Index), Bahrain (Bahrain All Share BAX)). Period: 2017 to 2021	Vector Autoregressive (VAR)	Bitcoin's high returns contrast with developed markets' low ones. VAR ties stock indices, especially from developing nations, to short-term Bitcoin returns. Granger test confirms Bitcoin as a net receiver of shocks from developing, not developed, markets.
Qarni, Gulzar, Fatima, Khan and Shafi (2019)	Bitcoin price index and financial markets (U.S. 10 years notes futures, USD index futures, Thomson Reuters Core commodity CRB excess return and S&P 500 index) Period: 2010 - 2017	Vector Autoregressive (VAR)	They found that the US BTC market receives and transmits the lowest volatility spillover among selected US markets. During calm periods, the volatility spillover in financial markets is lower, but during turbulent periods, it gradually increases. Both stock and currency markets exhibit the most reactive behaviour to global financial events, with high volatility spillovers. BTC is considered the lowest recipient of volatility spillover among all other US financial markets during the sample period.
Trabelsi (2018)	4 cryptocurrencies: Bitcoin (BTC), Ethereum (ETH), Ripple (XRP) and Litecoin (LTC) Five popular stock indexes (i.e., SP500, NASDAQ, FTSE100, Hang Seng and Nikkei225) Five major Forex currencies (i.e., EUR/USD, GBP/USD, USD/JPY, USD/CHF and USD/CAD) Period: 2010 to 2018	Vector Autoregressive (VAR)	There is limited interconnection between cryptocurrencies and traditional stocks. Bitcoin has minimal impact on the wider financial markets, acting as a minor transmitter and receiver of shocks.
Uzonwanne (2021)	Bitcoin and stock index prices for five major stock markets (FTSE 100,	VARMA-AGARCH model	It was found negative average returns for Bitcoin and CAC40, but positive ones for DAX30, FTSE100, NIKKEI225 and S&P500. There was high volatility in

	S&P 500, CAC 40, DAX 30, and Nikkei 225) Period: 2013 - 2018		Bitcoin and CAC40. In the short term, the spillover of returns from Bitcoin to the S&P500 was significant, but not the other way round. In the long term, the spillover from the S&P500 to Bitcoin was negative and significant, while the reverse was positive and significant.
Wang , Wei , Wang and Liu (2022)	3 assets (bitcoin, gold, commodities) and the stock market indices of world. Period: 2010 - 2021	Time-varying parameter vector autoregressive model (TVP-VAR)	Bitcoin and emerging stock markets are net receivers of spillovers, while world and developed stock markets are net transmitters. The world stock market is the largest transmitter of spillovers, leading globally, while emerging markets have less impact. Spillovers "from" are greater than "to" in Bitcoin are making them net receivers. The spillover from other markets to Bitcoin is increasing rapidly.
Zhang and He (2021)	Assets of cybercurrency, gold, oil stock index, including CME Group bitcoin futures (BC), international gold price (GD), Brent crude oil future price (BO), and 7 stock indexes (S&P, Dow Jones, and Nasdaq, Shanghai Composite Index, Nikkei 225, DAX and the FTSE Index and British Brent crude oil future. No period	DC-GC-MSV Model	They found that Bitcoin volatility has Granger causality from the Dow Jones stock market, but the spillover effect is almost zero and insignificant. Bitcoin's volatility is significantly higher than that of the stock market. The study suggests that Bitcoin has a lower risk compared to the Dow Jones, which has greater volatility persistence. Thus, there are no significant spillover effects between Bitcoin and the Dow Jones index.

Source: Author's own elaboration

CHAPTER III – METHODOLOGY AND DATA

3.1 Methodology

This section presents the methodology used to evaluate return and volatility spillovers, as well as the methods applied to analyse bull and bear markets. Two hypotheses were explored: in the first, we use three types of cryptocurrencies (BTC, ETH, and XRP), three ETF indices (S&P 500, VT, and MCHI), and two other indices (BCO and TNX). In the second hypothesis, we use three cryptocurrencies (BTC, ETH, and XRP), three different ETF indices (VT, VWO, and VEA), and two other indices (BCO and TNX).

To assess the spillovers of the hypotheses, we first calculate the returns and then the volatility. The next step is to determine which has the best connection in both hypotheses using the VAR model (Diebold and Yilmaz, 2012) applied to the results of returns and volatility to check the direction and connectivity of the spillovers. To compare with the VAR model, we will use the LASSO study (Annex). For greater robustness, we used the Lunde and Timmermann algorithm (2004) (Zakamulin, 2017) to identify bull and bear moments.

Next, dummies were created for the bull and bear markets of the S&P 500, and the returns and volatilities of all the variables were analysed. The VAR model (Diebold and Yilmaz, 2012) was then used again to understand connectivity and verify the linkage of spillovers. This method it was used to LASSO study too.

The following sections will present the details of these alternative performance measures: the return and volatility ratios of each hypothesis, the return and volatility spillovers of each hypothesis, and the relationship between returns and volatility with bull and bear market spillovers.

3.1.1 The return and volatility spillovers of each hypothesis

According by Diebold and Yilmaz (2023), the first step is the embryonic idea (2009), here they obtain the variance using a VAR model with a small data and no network theory. In a second step in 2012, they consider not only “total connectedness” but also “directional” aspects, so that $i \rightarrow j$ connectedness need not match $j \rightarrow i$ connectedness. The term “connectedness” is still never used, however, and network perspectives are absent. The last step in 2014, they maintain the same things from the last analysis, and they can stile introduce a network framework for the first time, and some network graphics.

We utilize the VAR-based connectedness methodology originally introduced by Diebold and Yilmaz (2012). This approach relies on forecast error variance decompositions

obtained from vector autoregressions (VARs) to construct measures of spillover and assess the degree of interconnections among assets. To implement this methodology, we model both the returns and the volatilities of crypto assets and financial variables as VARs. By decomposing the forecast error variance of each variable, we determine the proportion of variance attributable to shocks in each individual variable. This enables us to analyse the impact of each variable on the transmission and reception of shocks across different variables in the system, from which various metrics of spillovers, alternatively called connectedness, can be derived.

Drawing on the methodologies established by Diebold and Yilmaz (2012, 2014), we utilize the generalized VAR framework developed by Lyer (2022) and Lyer and Popescu (2023). This framework is robust and invariant to the ordering of variables in the VAR model. In this approach, let θ_{ij}^H represent the normalized contribution of variable j to the forecast error variance of variable i at horizon H . These contributions are typically presented in a connectedness table (matrix), which also allows for the summarization of cumulative impacts as follows.

The off-diagonal column and row sums of the table are contributions "To" others and contributions "From" others, respectively. More specifically, the directional spillover transmitted from all assets j TO assets i as:

$$C_{* \leftarrow i} = \sum_{i=1, i \neq j}^N \tilde{\theta}_{ij}^H \quad (1)$$

while the directional spillover transmitted FROM asset i to all other assets j is:

$$C_{i \leftarrow *} = \sum_{i=1, i \neq j}^N \tilde{\theta}_{ij}^H \quad (2)$$

The column of contributions "From" others measure the share of volatility shocks received from other assets in the total variance of the forecast error for each asset. By definition, it is equal to 100% minus the own share of the total forecast error variance. Similarly, the column sum of all pairwise spillovers results in the corresponding assets' total directional contribution "To".

On the basis of the "From" and "To" connectedness, one can estimate the "Net" spillover from crypto i to all other cryptos as the difference between the two, namely: $C_i^H = C_{*\leftarrow i} - C_{i\leftarrow*}$.

To calculate the net pairwise directional connectedness between variable i^{th} and variable j^{th} is: $C_{ij}^H = C_{j\leftarrow i}^H - C_{i\leftarrow j}^H$. If the variable i is positive (negative), it means that variable i is a net transmitter (receiver) of shocks or that variable i is driving (driven by) the network according with Gabauer, D. (2020).

The sum of the contributions to others (including own) is 100%. The total connectedness or spillovers index (TCI or TSI) is the share of contributions to others relative to the entire forecast error variance of the system, namely:

$$TCI^H = \frac{\sum_{i,j=1, i \neq j}^N \tilde{\theta}_{ij}^H}{\sum_{i,j=1}^N \tilde{\theta}_{ij}^H} \quad (3)$$

The index represents the off-diagonal column sum (or row sum) divided by the column sum including diagonal elements (or row sum including diagonal elements). Intuitively, it captures the average spillovers in the entire system from all other variables to any given variable, while ignoring the effects due to its own lags.

3.1.2 The return and volatility spillovers of each hypothesis, and the relationship between returns and volatility with bull and bear market spillovers

We analyse the relationship between bull and bear markets using the `bbdetection` package, which implements two algorithms for detecting bull and bear phases in stock prices (Zakamulin, V.). The algorithms used are the Bry and Boschan (1971) algorithm and the Lunde and Timmermann (2004) algorithm.

This Algorithm is based on imposing a minimum on the price change since the last peak or trough. This dating rule is implemented in the following manner.

The Lunde and Timmermann Algorithm (2004) is used to identify change points between bull and bear market states based on significant movements in share prices. The algorithm is initially defined by setting λ_1 and λ_2 . The λ_1 defines the change from a bear market to a bull market. It represents the minimum change in share price required to declare the start of a bull market. λ_2 defines the change from a bull market to a bear market. It represents the minimum change in share price needed to declare the start of a bear market. Denote by P_t the stock market price at time t and suppose that a trough in P has been detected at time $t_0 < t$. Therefore, the algorithm knows that a Bull state begins from time $t_0 + 1$. The algorithm first finds the maximum value of P on the time interval $[t_0, t]$

$$P_{t_0,t}^{max} = \max \{P_{t_0}, P_{t_0+1}, \dots, P_t\}$$

and then computes the (inverse of the) relative change in P where the maximum value serves as the reference value

$$\delta_t = \frac{P_{t_0,t}^{max} - P_t}{P_{t_0,t}^{max}} \quad (4)$$

If $\delta_t > \lambda_2$ then a new peak is detected at time t_{peak} at which P attains maximum on $[t_0, t]$. The period $[t_0 + 1, t_{peak}]$ is labelled as a Bull state. A Bear state begins from $t_{peak} + 1$.

If, on the other hand, a peak in P has been detected at time $t_0 < t$, then the algorithm finds the minimum value of P on the time interval $[t_0, t]$

$$P_{t_0,t}^{min} = \min \{P_{t_0}, P_{t_0+1}, \dots, P_t\}$$

and computes the relative change in P from the minimum value

$$\delta_t = \frac{P_t - P_{t_0,t}^{min}}{P_{t_0,t}^{min}} \quad (5)$$

If $\delta_t > \lambda_1$, then a new trough is detected at time t_{trough} at which P attains minimum on $[t_0, t]$. The period $[t_0 + 1, t_{trough}]$ is labelled as the Bear state. A Bull state begins from $t_{trough} + 1$.

In this study, we use the algorithm of Lunde and Timmermann (2004) to define bull and bear periods for the stock market. This algorithm will be adapted to our sample to have a better understanding of both hypotheses. We opted by the filtering Algorithm. We identify bull and bear periods for the S&P 500 index using a bull parameter (λ_1) of fifteen and a bear parameter (λ_2) of fifteen.

According to Zakamulin (2017), there is a consensus among financial analysts that a Bull market is characterized by a period of rising prices, while a Bear market is marked by a period of falling prices. However, opinions differ when it comes to precisely defining these phases. One group of analysts asserts that for a period to be classified as a Bull (or Bear) market, there must be a significant increase (or decrease) in stock prices. Conversely, the other group contends that the defining criterion should be the duration over which the stock market prices rise (or fall), rather than the magnitude of the price change.

The Lunde and Timmermann (2004) algorithm is robust but has difficulty accurately identifying the initial state of the market and only difficulty is the right identification of the first state of the market. Conversely, the Bry and Boschan (1971) algorithm employs pattern recognition techniques, but its outcomes are not always reliable due to the arbitrary choice

of parameters, which can sometimes lead to incorrect identification of bull and bear market states (Zakamulin (2017)).

Within the framework of our study, this algorithm aims to identify where the volatility and returns of both hypotheses have peaks and troughs, and to determine the connectedness between them. The purpose of this model is to identify the inflection points robustly and accurately between the bull and bear phases of the stock market.

3.2 Data

We obtain daily data for cryptocurrencies from the CoinMarketCap website. Our sample comprises the 3 cryptocurrencies with the highest market capitalization, as determined by the market conditions in April 2024. These cryptocurrencies include Bitcoin (BTC), Ethereum (ETH), Ripple (XRP).

We collect daily data for all other assets in our research from Yahoo Finance. We select five exchange-traded funds (ETFs) as proxies for stocks, one S&P 500 index, one US treasury Bond Rate and one fixed income. We include in our research the following ETFs: Vanguard Total World Stock ETF (VT), iShares MSCI China ETF (MCHI), Vanguard FTSE Developed Markets ETF (VEA), Vanguard FTSE Emerging Markets ETF (VWO), CBOE Interest Rate 10 Year T No (TNX), Brent Crude Oil Last Day Financ (BCO).

To estimate the VAR model, we need to collect daily data to calculate the return, the volatility and after that the annualized volatility. Our data we be the same from behind.

The sample period for our study spans from January 1, 2016, to April 30, 2024. This timeframe was selected for its ability to capture recent and current market dynamics, characterized by significant development and transformation. Notably, this period includes the emergence of new cryptocurrencies and notable changes in market structure.

A key distinction between cryptocurrencies and ETFs is their trading schedules. Cryptocurrencies are traded continuously throughout the week, 24 hours a day, whereas stock markets are only open on weekdays. This discrepancy results in a lack of coherence in the data between cryptocurrencies and ETFs. While cryptocurrencies are traded year-round, financial independent variables typically have around 252 trading days per year. The discontinuity between consecutive trading days introduces a discrepancy in the data for dependent variables when conducting daily data analysis.

The choice of daily data facilitates a more accurate comprehension of transient price variations and the dynamics of the market. To better capture market dynamics, we used daily data in this study. The data presented in Table 3 reveals that BTC, ETH, XRP, along with all the other markets, started in the year 2016. However, there was some difference between markets in the observations, where it was possible to identify that the cryptocurrency market had more observations than the other markets. Following this reasoning, the decision was made that we would work according to the observations of the stock markets, thus making all the observations the same. The same approach was applied to both the VAR and LASSO studies.

The analysis in this paper examines both asset returns and volatilities. This dual approach is necessary because returns and volatilities capture asset comovement differently. For instance, a positive comovement of returns indicates a positive correlation between prices. However, this does not necessarily apply to volatilities, as positive comovement between volatilities can occur even when asset prices move in opposite directions with large magnitude changes. Additionally, as a second moment, volatilities tend to show more significant "spikes," which help identify moments of substantial price swings and the timing of specific shocks.

Return

$$r_{i,t} = 100 \times [\ln(P_{i,t}) - \ln(P_{i,t-1})] \quad (6)$$

where P denotes the closing price. Volatilities, on the other hand, are calculated in two steps. First, inter-day variance is calculated for series i on day t:

Volatility

$$\sigma_{i,t}^2 = 0.361 \times [\ln(High P_{i,t}) - \ln(Low P_{i,t})]^2 \quad (7)$$

Annualized Volatility

Next, daily return volatility is then converted to annualized volatility. Since volatilities tend to be skewed, log-volatilities are generally preferred as they approximate a normal distribution. However, to control for observations where volatility is zero, the inverse hyperbolic sine function is used, namely:

$$\tilde{\sigma}_{i,t} = \sin^{-1}(\sqrt{252 \times \sigma_{i,t}^2}) \quad (8)$$

The same transformation are applied for financial assets as well.

TABLE 2 - ASSET LIST

Name	Acronym	Period	Observations	Source
Bitcoin	BTC	2016-2024	2095	Bitcoin price today, BTC to USD live price, marketcap and chart CoinMarketCap
Ethereum	ETH	2016-2024	2095	Ethereum price today, ETH to USD live price, marketcap and chart CoinMarketCap
Ripple	XRP	2016-2024	2095	XRP price today, XRP to USD live price, marketcap and chart CoinMarketCap
S&P 500	GSPC	2016-2024	2095	S&P500 (GSPC) Stock Price, News, Quote & History – Yahoo Finance
Vanguard Total World Stock ETF	VT	2016-2024	2095	Vanguard Total World Stock Index Fund (VT) Stock Price, News, Quote & History - Yahoo Finance
iShares MSCI China ETF	MCHI	2016-2024	2095	iShares MSCI China ETF (MCHI) Stock Price, News, Quote & History - Yahoo Finance
Vanguard FTSE Emerging Markets	VWO	2016-2024	2095	Vanguard Emerging Markets Stock Index Fund (VWO) Stock Price, News, Quote & History - Yahoo Finance
Vanguard FTSE Developed Markets ETF	VEA	2016-2024	2095	Vanguard Developed Markets Index Fund (VEA) Stock Price, News, Quote & History - Yahoo Finance
CBOE 10 Year Treasury Note Yield Index	TNX	2016-2024	2095	CBOE Interest Rate 10 Year T No (TNX) Stock Price, News, Quote & History - Yahoo Finance
Brent Crude Oil Last Day Financ	BZ=F (BCO)	2016-2024	2095	Brent Crude Oil Last Day Financ (BZ=F) Stock Price, News, Quote & History - Yahoo Finance

Source: Author's own elaboration

In this section, we report our empirical results. We start by describing our dataset, providing the key descriptive statistics. Then we estimate the VAR model using returns and volatilities of the selected variables and, finally, we repeat the process for bull and bear markets.

4.1 Descriptive Statistics

Table 3 shows the descriptive statistics for the daily returns of the three largest cryptocurrencies by market capitalization, stock market ETFs (H1 and H2), US Treasury yield (TNS) and Brent crude oil (BCO), over the period from 01/Jan/2016 to 30/Apr/2024. The number of observations is balanced only to consider data in working days.

TABLE 3 – DESCRIPTIVE STATISTICS ON RETURNS

	Observations	Mean (%)	SD (%)	skew	kurtosis
BTC	2094	0.236	4.445	-0.620	9.380
ETH	2094	0.385	6.525	0.273	8.606
XRP	2094	0.212	7.351	1.636	19.729
SP500 (H1)	2094	0.044	1.164	-0.845	16.352
MCHI (H1)	2094	0.005	1.700	0.410	9.292
VWO (H2)	2094	0.025	1.262	-0.959	10.957
VEA (H2)	2094	0.026	1.121	-1.363	17.681
VT	2094	0.039	1.120	-1.163	17.717
TNX	2094	0.001	0.054	-0.073	2.644
BCO	2094	0.041	2.620	-0.663	20.589

Source: Table 3 presents summary statistics (mean, volatility, skewness and kurtosis) based on daily returns for Bitcoin (BTC), Ethereum (ETH), Ripple (XRP), equally weighted portfolio of three cryptocurrencies, also ETFs of stock (Vanguard Total World Stock ETF (VT), iShares MSCI China ETF (MCHI), Vanguard FTSE developed Markets ETF (VEA), Vanguard FTSE Emerging Markets (VWO), The S&500 Index (GSPC), one treasury Yield, CBOE 10 Year Treasury Note Yield Index (TNX) and the Brent Crude Oil Last Day Financ (BCO). Database is over the period 01/Jan/2016 to 30/Apr/2024

All assets recorded positive mean returns. Cryptocurrencies (BTC_RT, ETH_RT, XRP_RT) exhibit higher mean returns than other assets, with ETH_RT showing the highest mean daily return at 0.385%. Among the ETFs tracking stock market indices, those from emerging economies display the lowest mean returns (0.005% for MCHI_RT and 0.025% for VWO). As expected, the risk-free asset, the US Treasury bond, has the lowest mean daily return (0.001%). Cryptocurrencies offer higher mean returns but also exhibit significantly

higher variability than other assets, with much higher standard deviations. This confirms the findings of, *inter alia*, Baur & Dimpfl (2018), Bouri et al. (2018) and Antonopoulos (2014).

The presence of high asymmetry and kurtosis in cryptocurrencies indicates that the returns of these assets do not follow a normal distribution, presenting long tails and peaks, which suggests the possibility of more frequent extreme events (Dwyer, 2015, Corbet et al., 2018). Dwyer (2015) argues that the volatility and distribution characteristics of cryptocurrencies limit their viability as a stable currency, while Corbet et al. (2018) highlight the speculative nature and risks associated with cryptocurrencies. Corroborating the results from the literature (e.g., Iyer and Popescu, 2023), apart from BTC, the return distributions for cryptocurrencies are positively skewed, while most asset returns exhibit negative skewness. With the exception of US Treasury bonds, all assets have return distributions with kurtosis greater than three, indicating that the data distribution is leptokurtic.

4.2 Return and volatility spillovers

The estimations in this research were carried out in a programming program called R. To carry out these estimations, a data frame corresponding to each calculation was used and transformed into a zoo data matrix, after which the VAR model was estimated using the connectedness approach from the study by Diebold and Yilmaz (2012). The model was estimated with a Rolling-window size of 150, a Lag length of 1 and an H-step ahead forecast horizon of 10. The type of connection is over time.

4.2.1 Return spillovers

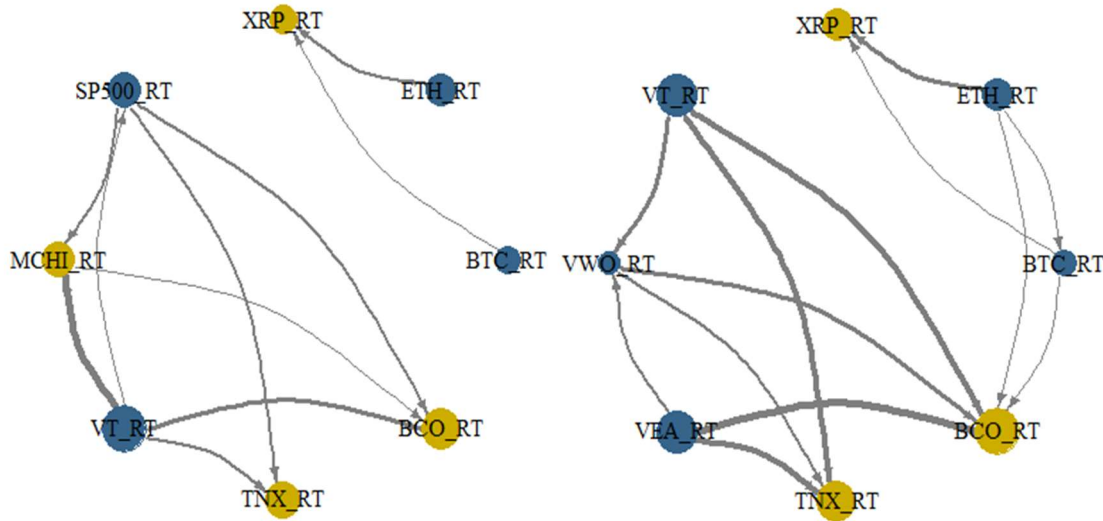
Table 4 presents the VAR return connectedness heat map for cryptocurrencies, ETFs, Treasuries and one type of oil price (H1) and, for the other hypothesis, the same but with including alternative ETFs (H2). The table shows where the connection goes, in columns (To), where the connection comes from, in lines (From), whether connections are balanced or dominant between two variables ($net=To-From$) and check how large is the ratio of the connection between all the variables (TCI). Diagonal green-shadowed cells are variable own connectivity, within markets (intra-crypto and intra-stocks), higher (lower) connectedness are painted dark (light) blue, whereas larger (smaller) spillovers across markets (inter crypto and stocks) are shadowed orange (yellow).

TABLE 4 – AVERAGE RETURN CONNECTEDNESS MATRIX

H1	BTC	ETH	XRP	S&P 500	MCHI	VT	TNX	BCO	FROM
BTC	51,08	24,63	13,82	3,28	1,92	3,46	1,07	0,74	48,92
ETH	23,67	49,71	16,05	3,17	2,03	3,64	0,81	0,91	50,29
XRP	15,38	18,58	55,98	2,84	2,11	3,28	1,06	0,77	44,02
S&P 500	3,24	3,26	2,45	36,95	13,31	34,07	3,94	2,77	63,05
MCHI	2,52	2,94	2,43	16,47	48,22	22,05	3,10	2,27	51,78
VT	3,23	3,46	2,58	32,16	16,68	34,83	3,78	3,29	65,17
TNX	1,64	1,52	1,17	7,02	4,14	6,90	73,38	3,23	26,62
BCO	1,97	2,05	1,50	5,39	4,12	6,79	3,44	74,75	25,25
TO	51,65	56,43	40,01	70,33	44,32	80,19	17,21	13,97	374,10
INC. OWN	102,74	106,13	95,99	107,28	92,54	115,01	91,59	88,72	cTCI/TCI
NET	2,74	6,13	-4,01	7,28	-7,46	15,01	-8,41	-11,28	53,44/46,76
NPT	4,00	6,00	3,00	5,00	2,00	7,00	1,00	0,00	
H2	BTC	ETH	XRP	VEA	VWO	VT	TNX	BCO	FROM
BTC	51,06	24,50	13,65	2,98	2,68	3,33	1,05	0,75	48,94
ETH	23,36	49,16	15,79	3,51	2,96	3,49	0,82	0,91	50,84
XRP	15,02	18,25	55,65	3,17	2,95	3,15	1,04	0,77	44,35
VEA	2,70	3,18	2,41	33,36	21,81	29,30	3,94	3,54	66,64
VWO	2,71	3,05	2,47	23,93	36,96	25,02	2,74	3,11	63,04
VT	3,00	3,21	2,32	29,03	22,52	33,04	3,79	3,16	66,96
TNX	1,60	1,53	1,16	6,98	4,53	6,80	74,16	3,25	25,84
BCO	1,92	1,96	1,44	7,15	5,86	6,47	3,34	71,86	28,14
TO	50,32	55,68	39,25	76,75	63,31	77,55	17,41	15,49	394,76
INC. OWN	101,38	104,84	94,90	110,29	100,27	110,59	90,57	87,35	cTCI/TCI
NET	1,38	4,84	-5,10	10,11	0,27	10,59	-9,43	-12,65	56,39/49,34
NPT	4,00	5,00	2,00	7,00	3,00	6,00	1,00	0,00	

Notes: Table 4 information under the form of network mapping. It depicts the net pairwise relationship between all assets, with the arrows indicating the direction of the bilateral net spillover flow, while the width of the arrow is proportional to the magnitude of the spillover. The size of the node captures total spillovers (the sum of "to" and "from") for each asset, while the colour of the node indicates whether the asset is a net sender (blue) or a net receiver (yellow). Only the top 75% percentile of bilateral spillovers are shown.

FIGURE 2 - VAR NET RETURN SPILLOVERS, H1 (left-hand side) AND H2 (right-hand side), 75% threshold



Notes: We show the most important directional connections among the pairs of crypto assets. Node size indicates the size of the total spillovers (sum of to and from) for each asset. The colour of the node indicates whether the asset is a net sender (blue) or a net receiver (yellow). The thickness of the arrows represents the strength of the spillovers (normalized to improve visibility), with only the top 75% percentile of bilateral spillovers shown

Some relevant findings emerge from analysis of Table 4. First, the values of the total connectedness index (TCI) indicate that the interconnectedness in the network cause 46.76% (49.34%) of the total forecast error variance on average under sample H1 (H2)¹. These values are relatively lower than those estimated by Iyer and Popescu (2023) for larger samples of crypto and financial assets. Zhang and He (2021) state that low overall connectivity reflects segmentation between markets, which can be seen as positive for portfolio diversification, but also indicates insufficient market integration.

Second, the connectedness within a class asset (intra-market) is, on average, much larger than across asset classes (inter-market). In particular, the pairwise connectedness between cryptocurrencies and stocks ranges between 2.46% and 3.64%, while among stocks and among cryptocurrencies, it ranges between 13.31% and 34.07%.

Third, the directional return spillovers between cryptocurrencies and stocks are small, with no evidence of dominant return spillovers between the two asset markets. Consequently, net return spillovers are not significant, as evident from Figure 1, which shows no arrows linking cryptocurrencies and stock indices. These results align with the findings of Iyer (2022). Similarly, Aydogan and Vardar (2021) are skeptical about the

significant influence between cryptocurrencies and traditional markets, suggesting that cryptocurrencies operate largely independently of traditional financial markets. Elsayed, Gozgor, and Lau (2020) support this view, highlighting the low connectivity between these markets.

Fourth, among cryptocurrencies, in both hypotheses, ETH is the best transmitter (H1- 56.43%; H2- 55.48%) and the best receiver (H1- 50.29%; H2- 50.84%). In this market, the returns of the cryptocurrencies with the highest market capitalization (BTC and ETH) are transmitted, in net terms (blue circles in Figure 2), to the returns of the least representative, XRP. However, the bilateral connectivity between the most representatives (ETH and BTC) is, of course, larger (Table 4, dark blue cells). Bouri et al. (2018) also recognizes the importance of ETH as the main return transmitter, while Jiang, Nie and Ruan (2022) highlight the growing influence of the more representative cryptocurrencies on the less representative ones.

Fifth, under the stock market, advanced economies (S&P500 and VEA) and worldwide (VT) return indices are stronger transmitter than receivers. Under H1 (H2), the world index (VT) has the highest transmission, with a value of 70.98% (69.74%), indicating that it has the greatest influence on the market. In both samples, bilateral directional return connectivity is always higher between the stock indices of developed economies and those of global worldwide indices (dark blue cells in Table 4) than between those of emerging economies and global indices (light blue cells in Table 4). Return spillovers from developed economies/ S&P500 indices to emerging economies/MCHI indices are dominant (arrow from developed to emerging countries indices, in Figure 1). Corbet, Lucey and Yarovaya (2018) see the influence of developed markets as a confirmation of their dominance and resilience.

To check the robustness of our results, we follow Yang and Feng (2023) and estimate the VAR model using the LASSO method to accommodate the high-dimensional network resulting from the consideration of bull and bear markets in the following analysis. Table C1 and Figure C1 in the Annex C summarize the main results of this estimation. The qualitative results are the same when comparing the VAR and LASSO estimates reported in Tables 1 and C1, respectively. Intra-market return linkages still dominate inter-market linkages, and the latter remain weak. Return pairwise directional dominance, producing non-negligible net return linkages, is not observed across cryptocurrencies and stocks (cf. Figures 2 and C1).

Across cryptocurrencies, ETH remains the highest transmitter, the highest receiver, and net sender, while XRP is the lowest transmitter, the lowest receiver, and net receiver. Across stock indices, return spillovers are stronger between developed economies and worldwide than between emerging economies and worldwide. Stock market returns of developed economies remain net transmitter to stock market returns of emerging economies.

Compared to Figure 2, Figure B1 presents a less conservative network of pairwise directional connectedness, showing the top 90th percentile of pairwise net return spillovers, in contrast to the 75th percentile in Figure 2. As expected, the significant inter-linkages increase, but the net return spillovers between cryptocurrencies and stock markets remain weak. We identify only weak spillovers from BTC and ETH to MCHI, and from VT, VWO, and VEA to XRP (Figure 2). Jiang, Nie and Ruan (2022) see these spillovers as indicative of a growing integration between global markets and cryptocurrencies, while Bouri et al. (2018) emphasizes that although there are interactions, they are still limited and have a modest impact.

4.2.2 Volatility spillovers

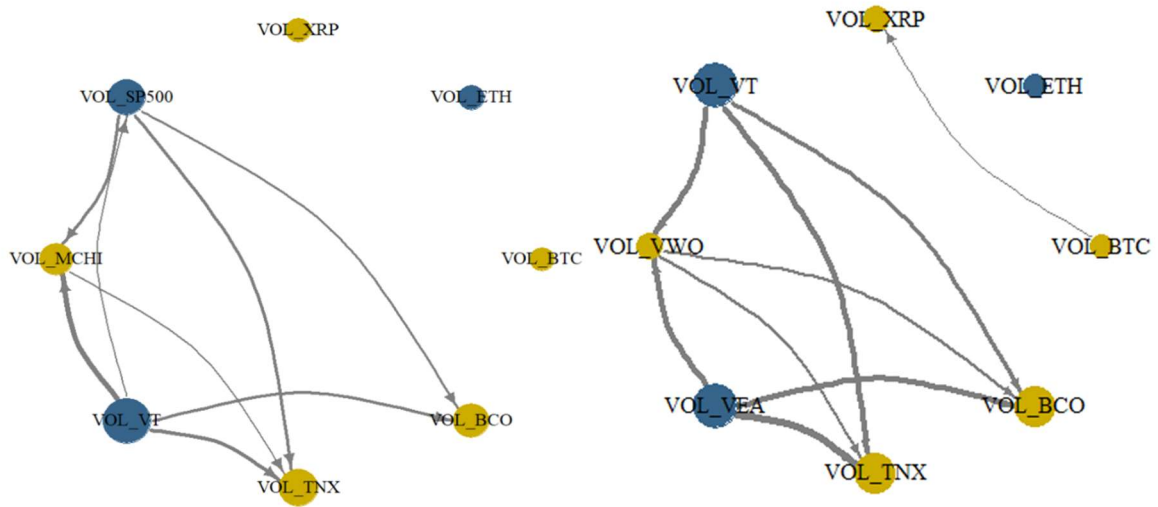
Table 5 presents the VAR volatility connectedness heat map for cryptocurrencies, ETFs, Treasuries and one type of oil price (H1) and, for the other hypothesis, the same but with including alternative ETFs (H2). These samples are taken over the period 2016 to 2024, providing data for the entire period. The table cells and their colours have the same meaning as in Table 1.

TABLE 5 – AVERAGE VOLATILITY CONNECTEDNESS MATRIX

H1	BTC	ETH	XRP	S&P 500	MCHI	VT	TNX	BCO	FROM
BTC	57,34	23,45	12,08	1,60	1,37	1,62	1,35	1,18	42,66
ETH	22,45	55,68	15,79	1,41	1,27	1,30	1,10	1,01	44,32
XRP	13,05	16,00	65,01	1,25	0,92	1,20	1,40	1,16	34,99
S&P 500	1,23	1,28	0,92	42,48	11,82	35,34	3,67	3,26	57,52
MCHI	1,34	1,26	1,05	14,70	57,45	18,33	2,82	3,04	42,55
VT	1,18	1,20	0,82	34,11	13,87	41,58	3,88	3,35	58,42
TNX	1,14	1,16	1,93	6,16	3,92	7,07	74,87	3,74	25,13
BCO	1,75	1,33	1,28	5,58	3,75	6,11	3,56	76,64	23,36
TO	42,14	45,69	33,88	64,82	36,92	70,98	17,79	16,73	328,95
INC. OWN	99,48	101,37	98,90	107,30	94,37	112,56	92,66	93,37	cTCI/TCI
NET	-0,52	1,37	-1,10	7,30	-5,63	12,56	-7,34	-6,63	46,99/41,12
NPT	2,00	4,00	3,00	6,00	4,00	7,00	1,00	1,00	
H2	BTC	ETH	XRP	VEA	VWO	VT	TNX	BCO	FROM
BTC	57,28	23,29	11,99	1,54	1,84	1,62	1,34	1,11	42,72
ETH	22,34	55,81	15,65	1,27	1,53	1,31	1,10	0,98	44,19
XRP	12,96	15,82	64,93	1,26	1,29	1,18	1,36	1,19	35,07
VEA	1,14	1,13	0,82	41,76	18,83	29,57	3,83	2,92	58,24
VWO	1,38	1,26	0,77	22,49	45,35	23,31	3,02	2,41	54,65
VT	1,14	1,13	0,75	29,02	19,95	41,11	3,73	3,17	58,89
TNX	1,12	1,16	1,89	7,63	4,90	6,79	73,03	3,49	26,97
BCO	1,71	1,30	1,30	5,98	4,25	5,97	3,38	76,12	23,88
TO	41,79	45,08	33,18	69,18	52,60	69,74	17,76	15,27	344,61
INC. OWN	99,08	100,89	98,12	110,94	97,95	110,85	90,79	91,39	cTCI/TCI
NET	-0,92	0,89	-1,88	10,94	-2,05	10,85	-9,21	-8,61	49,23/43,08
NPT	2,00	4,00	2,00	6,00	5,00	7,00	1,00	1,00	

Notes: Table 5 information under the form of network mapping. It depicts the net pairwise relationship between all assets, with the arrows indicating the direction of the bilateral net spillover flow, while the width of the arrow is proportional to the magnitude of the spillover. The size of the node captures total spillovers (the sum of "to" and "from") for each asset, while the colour of the node indicates whether the asset is a net sender (blue) or a net receiver (yellow). Only the top 75% percentile of bilateral spillovers are shown.

FIGURE 3 - VAR NET VOLATILITY SPILLOVERS, H1 (left-hand side) AND H2 (right-hand side), 75% threshold



Notes: We show the most important directional connections among the pairs of crypto assets. Node size indicates the size of the total spillovers (sum of to and from) for each asset. The colour of the node indicates whether the asset is a net sender (blue) or a net receiver (yellow). The thickness of the arrows represents the strength of the spillovers (normalized to improve visibility), with only the top 75% percentile of bilateral spillovers shown

Regarding volatility spillovers, the findings are largely like return spillovers, with some interesting nuances. Own connectivity increases, while cross-asset connectivity generally diminishes, causing the total connectedness index (TCI) to become slightly lower. Specifically, under H1, it is 41.12% for volatilities, whereas for returns, it reaches 46.76% (cf. Tables 4 and 5).

The directional volatility spillovers between cryptocurrencies and stocks became even smaller, still with no evidence of dominant volatility spillovers between the two asset markets. Net pairwise volatility spillovers are not significant, as evident from Figure 3. (as supported by Zhang & He, 2021, Basah & Ismail, 2021).

Among cryptocurrencies, in both hypotheses, ETH remains the best transmitter (H1- 45.69%; H2- 45.08%), the best receiver (H1- 44.32%; H2- 44.19%) and net sender, while BTC becomes net receiver. Antonopoulos (2014) highlighted the role of ETH in leading the cryptocurrency market, while Baur and Dimpfl (2018) emphasize the high volatility and risks associated with this connectivity.

For stock market volatility connectedness, we observe the same qualitative results as return connectedness. Namely, the stock market indices of advanced economies (S&P500

and VEA) and global worldwide (VT) are net senders in terms of volatility and return, while those of emerging economies (MCHI and VWO) are net receiver. Volatility spillovers to and from stock market indices of advanced economies are higher than those of emerging economies.

Main volatility spillover results remain robust to Lasso estimation methodology (cf. Tables 5 and C2). From comparison of Figures 3 and C3, we observe the same net connections within financial markets and the lack of linkages between cryptocurrencies and stocks. However, relative to VAR, under Lasso there are net volatility connections from ETH to XRP (H1 and H2) and from BTC to XRP (H2).

4.3 Return and Volatility spillovers in Bull and Bear Market

In this subsection, we assess whether there is any asymmetry in return and volatility spillovers. Specifically, we examine if their magnitudes differ under bull and bear markets and if there are any changes in net pairwise connectedness.

As described above, we first estimated the periods of bull and bear markets using the S&P 500 index. Then, we tested connectedness asymmetry using dichotomous variables for these bull and bear periods.

Tables 6 and 7 provide the return and volatility static connectedness matrices for bull and bear markets, respectively. Each connectedness matrix is decomposed into four submatrices: 1) the bull intra-layer network, corresponding to the submatrix in the upper left corner; 2) the bear intra-layer network, corresponding to the submatrix in the lower right corner; 3) the bidirectional inter-layer network, corresponding to the submatrix in the lower left corner (from bull to bear) and the submatrix in the upper right corner (from bear to bull). Cells and colours have the same meaning as above.

4.3.1 Return spillovers in Bull and Bear Market

The examination of return connectedness estimates in Table 6 and net pairwise connections in Figure 4 suggests that:

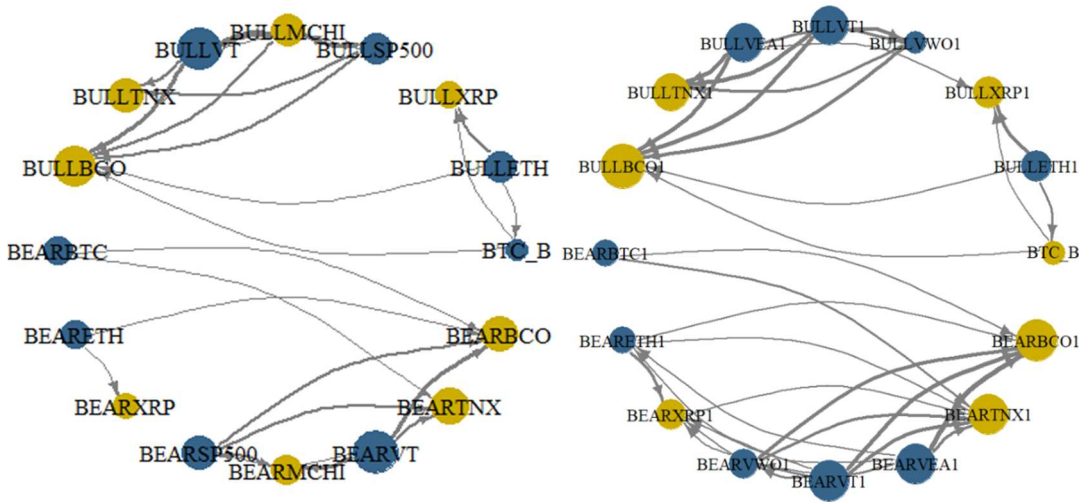
TABLE 6 – RETURN SPILLOVERS, H1 AND H2, BULL AND BEAR

H1	BULL								BEAR									
	BTC	ETH	XRP	S&P 500	MCHI	VT	TNX	BCO	BTC	ETH	XRP	S&P 500	MCHI	VT	TNX	BCO	FROM	
BULL	BTC	49,29	25,54	12,71	2,89	2,00	3,14	1,41	1,38	0,22	0,18	0,18	0,22	0,15	0,21	0,33	0,15	50,71
	ETH	23,92	46,84	16,22	3,03	1,85	3,45	1,23	1,79	0,27	0,25	0,19	0,21	0,16	0,21	0,26	0,13	53,16
	XRP	14,21	19,17	54,38	2,64	2,09	3,05	1,73	1,54	0,20	0,17	0,16	0,17	0,15	0,17	0,08	0,08	45,62
	S&P 500	2,52	3,27	2,25	36,71	13,03	33,60	4,35	2,86	0,23	0,21	0,18	0,19	0,17	0,20	0,13	0,11	63,29
	MCHI	2,53	2,71	2,19	16,20	47,74	21,60	3,94	2,15	0,16	0,16	0,12	0,11	0,11	0,11	0,09	0,08	52,26
	VT	2,62	3,37	2,29	31,82	16,40	34,62	4,41	3,28	0,20	0,18	0,15	0,15	0,15	0,16	0,11	0,10	65,38
	TNX	1,77	2,07	1,87	7,23	5,23	7,37	69,93	3,44	0,15	0,12	0,12	0,17	0,13	0,16	0,15	0,08	30,07
	BCO	2,81	3,15	2,41	5,55	4,25	6,59	4,09	69,95	0,13	0,12	0,11	0,23	0,16	0,21	0,14	0,10	30,05
BEAR	BTC	0,11	0,10	0,24	0,06	0,06	0,06	0,06	0,06	41,94	21,00	16,22	5,24	3,95	5,46	2,45	2,99	58,06
	ETH	0,19	0,09	0,26	0,05	0,06	0,05	0,06	0,08	20,09	41,52	16,59	5,49	4,43	6,22	1,95	2,88	58,48
	XRP	0,13	0,19	0,63	0,07	0,06	0,09	0,10	0,11	17,17	18,58	43,86	4,76	3,99	5,27	1,91	3,09	56,14
	S&P 500	0,05	0,04	0,03	0,02	0,03	0,02	0,03	0,03	5,30	5,03	4,13	32,21	12,96	29,86	5,40	4,87	67,79
	MCHI	0,06	0,05	0,09	0,04	0,04	0,04	0,07	0,05	4,75	4,76	4,23	15,20	41,44	19,99	4,29	4,92	58,56
	VT	0,04	0,04	0,04	0,03	0,02	0,02	0,03	0,03	5,08	5,18	4,12	28,49	15,91	30,74	5,96	5,26	69,26
	TNX	0,10	0,10	0,11	0,05	0,05	0,05	0,06	0,07	4,24	3,23	3,07	7,80	4,93	7,22	61,82	7,10	38,18
	BCO	0,16	0,13	0,20	0,06	0,05	0,06	0,07	0,08	4,42	4,20	3,80	7,33	6,03	8,40	6,11	58,90	41,10
	TO	51,21	60,01	41,52	69,75	45,22	79,19	21,65	16,95	62,62	63,35	53,36	75,76	53,38	83,82	28,37	31,93	838,09
	INC. OWN	100,50	106,85	95,90	106,46	92,97	113,81	91,58	86,90	104,57	104,87	97,23	107,97	94,81	114,56	90,19	90,83	cTCI/TCI
NET	0,50	6,85	-4,10	6,46	-7,03	13,81	-8,42	-	4,57	4,87	-2,77	7,97	-5,19	14,56	-9,81	-9,17	55,87/52,38	
NPT	6,00	6,00	8,00	5,00	2,00	7,00	1,00	0,00	12,00	11,00	10,00	13,00	10,00	15,00	7,00	7,00		

H2	BULL								BEAR									
	BTC	ETH	XRP	VEA	VWO	VT	TNX	BCO	BTC	ETH	XRP	VEA	VWO	VT	TNX	BCO	FROM	
BULL	BTC	49,28	25,32	12,65	2,80	2,53	3,09	1,43	1,37	0,22	0,17	0,18	0,17	0,16	0,20	0,30	0,14	50,72
	ETH	23,46	46,42	16,03	3,40	2,70	3,35	1,29	1,76	0,27	0,24	0,19	0,18	0,16	0,19	0,23	0,12	53,58
	XRP	13,96	18,94	53,92	3,21	2,62	2,99	1,73	1,54	0,18	0,16	0,16	0,14	0,14	0,15	0,08	0,08	46,08
	VEA	2,25	3,07	2,07	33,03	21,46	28,66	4,75	3,71	0,18	0,16	0,14	0,12	0,12	0,12	0,09	0,08	66,97
	VWO	2,27	2,65	1,90	23,58	36,90	24,78	3,80	3,04	0,19	0,17	0,15	0,13	0,14	0,13	0,09	0,08	63,10
	VT	2,49	3,15	2,18	28,41	22,19	32,88	4,38	3,19	0,20	0,18	0,16	0,14	0,14	0,14	0,10	0,09	67,12
	TNX	1,76	2,06	1,82	7,89	5,83	7,36	68,80	3,48	0,16	0,12	0,12	0,13	0,14	0,15	0,14	0,07	31,20
	BCO	2,73	3,00	2,27	7,11	5,63	6,43	4,07	67,65	0,14	0,13	0,12	0,16	0,17	0,20	0,13	0,08	32,35
BEAR	BTC	0,10	0,09	0,23	0,06	0,06	0,06	0,06	0,06	41,66	20,80	16,18	5,10	4,97	5,39	2,34	2,84	58,34
	ETH	0,15	0,08	0,26	0,05	0,06	0,05	0,05	0,08	20,02	40,98	16,25	5,83	5,47	5,83	2,01	2,85	59,02
	XRP	0,12	0,17	0,61	0,15	0,09	0,10	0,09	0,11	17,05	18,28	43,21	4,95	5,16	5,02	2,10	2,82	56,79
	VEA	0,04	0,04	0,06	0,02	0,03	0,02	0,05	0,03	4,72	4,52	3,58	29,68	20,61	26,51	4,53	5,54	70,32
	VWO	0,04	0,04	0,06	0,03	0,03	0,03	0,05	0,03	4,73	4,60	3,95	22,22	32,92	22,74	3,49	5,03	67,08
	VT	0,04	0,04	0,04	0,02	0,02	0,02	0,03	0,03	4,93	4,83	3,82	26,25	21,04	29,30	4,62	4,97	70,70
	TNX	0,08	0,09	0,10	0,05	0,06	0,05	0,06	0,07	4,05	3,33	3,46	6,58	5,46	7,17	62,68	6,71	37,32
	BCO	0,15	0,12	0,19	0,06	0,05	0,06	0,06	0,07	4,06	4,00	3,68	9,24	7,61	8,31	5,66	56,66	43,34
TO	49,65	58,86	40,47	76,83	63,34	77,03	21,91	18,58	61,11	61,67	52,13	81,36	71,47	82,25	25,90	31,51	874,05	
INC. OWN	98,93	105,28	94,38	109,86	100,24	109,91	90,70	86,23	102,77	102,64	95,34	111,04	104,39	111,54	88,57	88,17	cTCI/TCI	
NET	-1,07	5,28	-5,62	9,86	0,24	9,91	-9,30	-	2,77	2,64	-4,66	11,04	4,39	11,54	-11,43	-	58,27/54,63	
NPT	4,00	4,00	7,00	7,00	5,00	7,00	1,00	0,00	10,00	11,00	8,00	14,00	13,00	15,00	7,00	7,00		

Notes: This table shows the static spillovers between the volatilities of the cryptoassets and financial assets analysed over the period from 1 January 2016 to 30 April 2024. Each (i,j)-th value represents the contribution of innovation in the volatility of asset j to the variance of the forecast error in asset i. The column headed 'From' aggregates the cumulative contributions to asset i of all other assets, while the row headed 'To' summarizes the impact of asset j on all other assets. The row labelled 'Net' captures the net pass-through transmitted by each asset to all other assets. Positive (negative) values indicate that the asset in question acts as a net transmitter (receiver) of spillovers to other assets. To facilitate interpretation, colour scales are used. The minimum value is highlighted in yellow for values between the crypto market and in light blue between the financial market, the maximum value for values between the crypto market is in dark blue and for the financial market is orange. Diagonal elements are not included in the colour scale (green).

FIGURE 4 - VAR NET RETURN SPILLOVERS IN BULL AND BEAR MARKET, H1 (left-hand side) AND H2 (right-hand side), 75% threshold



Notes: We show the most important directional connections among the pairs of crypto assets. Node size indicates the size of the total spillovers (sum of to and from) for each asset. The colour of the node indicates whether the asset is a net sender (blue) or a net receiver (yellow). The thickness of the arrows represents the strength of the spillovers (normalized to improve visibility), with only the top 75% percentile of bilateral spillovers shown

In the cryptocurrency market, during the BULL moment, the most relevant link is between BTC and ETH, with the ETH-BTC relationship being the strongest. ETH is the best sender and receiver. In the BEAR moment, the spillovers are the same, but with less intensity, except for the increase in spillover between BTC and XRP. Compared to Table 4, the values and spillovers remain consistent at both times (Aydogan & Vardar, 2021; Corbet, Lucey & Yarovaya, 2018).

In the financial market, in Hypothesis 1, the strongest spillovers in the BULL and BEAR moments are between the S&P 500 and VT, while in Hypothesis 2, they are between VT and VEA. In both hypotheses, return spillovers are strongest at the BULL moment. VT is the best receiver and transmitter in Hypothesis 1, while in Hypothesis 2, the spillover between VT and VEA is bilateral and strong. S&P 500 is also a significant transmitter. Comparison with Table 4 shows a continuing trend of a strong connection between the world index and developed countries (Aydogan & Vardar, 2021; Corbet, Lucey & Yarovaya, 2018).

The magnitudes of inter-layer (bull-to-bear and bear-to bull) bilateral connections are insignificant in comparison with intra-layer connections (bull-to-bull and bear-to-bear).

In the intra-layer network, bilateral connectedness between cryptocurrencies and stock market indices are much stronger under bear markets than under bull. The existence of asymmetric return spillovers between cryptocurrencies and stocks in bull and bear markets is supported by Bouri et al. (2018), using a different methodology. Using a smooth transition VAR GARCH-in-mean model, they found that return spillovers from world and emerging stock market indices to Bitcoin are positive in bull markets and negative in bear markets, while the return spillovers from Bitcoin are positive in bear markets. The lack of arrows between cryptocurrencies and stocks in Figure 4 demonstrates the non-significance of net bilateral spillovers in bull and bear markets in the top 75th percentile.

In the intra-layer network, there is also some asymmetry in return spillovers across stock market indices in bull and bear markets, but here they are stronger in bull markets than in bear markets. Similar pattern is observed within cryptocurrencies, except for bilateral connections with XRP. As well, Figure 4 suggests that net bilateral connections within stock markets and within cryptocurrencies are stronger under bull markets than under bear markets.

Checking these results obtained previously (table 6), now compared with LASSO, and analysing table C3, both hypotheses have the same direction and the same connectivity in relation to cryptocurrencies and financial markets independently. What was obtained earlier in the VAR applies here only to the BULL and BEAR moments. Regarding the connection between markets where BULL and BEAR intersect, there is no analysis because there are no significant results.

In the stock market, the connections are stronger and there are more links between them, as can be seen in figures B1 and C6. In these two hypotheses, bilateral connectivity is always greater between the returns associated with the stock market indices of developed economies and those of global (world) indices than between emerging indices and global indices. Bilateral connectivity is greater between the returns associated with the stock market indices of developed economies and those of emerging indices than between the specific indices, the SP500 and the MCHI. The spillovers of returns from

developed economy/SP500 indices to emerging economy/MCHI indices are dominant (arrow from developed to emerging in figure B1) (Aydogan & Vardar, 2021; Corbet, Lucey & Yarovaya, 2018).

Between markets we observe (figures B1 and C6) a greater relationship, i.e. the spillovers that exist are between VT, VEA and VWO with BTC and XRP. These are only represented as unilateral spillovers, with BTC and XRP being the recipients (Zhang & He, 2021). There is no connection between the BULL and BEAR markets, further intensifying the connections that exist in the stock markets, which have found limited interactions between the stock markets and cryptocurrencies, cryptocurrencies still operate very much on their own and without having links to the stock market on the way to becoming more connected to that market (Basah & Ismail, 2021).

4.3.2 VAR Volatility in Bull and Bear Market

In turn, the volatility link estimates in Table 7 and the net links between pairs in Figure 5 suggest that:

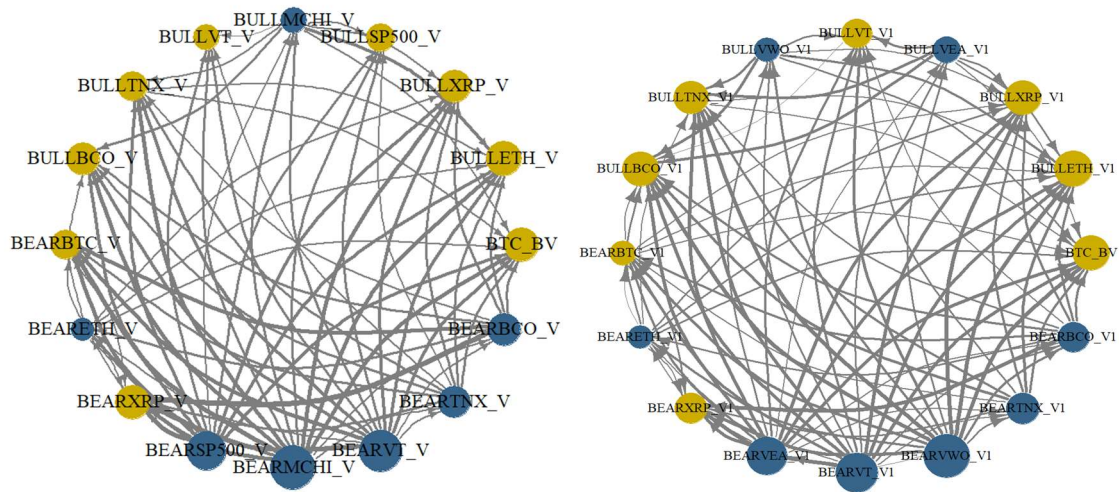
TABLE 7 – VOLATILITY SPILLOVERS, H1 AND H2, BULL AND BEAR

H1		BULL								BEAR								
		BTC	ETH	XRP	S&P 500	MCHI	VT	TNX	BCO	BTC	ETH	XRP	S&P 500	MCHI	VT	TNX	BCO	FROM
BULL	BTC	26,64	12,12	9,01	2,90	4,77	3,00	4,29	3,27	3,06	3,47	2,59	4,74	5,71	4,99	4,70	4,74	73,36
	ETH	11,72	24,53	9,99	3,13	5,26	3,07	4,03	3,59	3,16	3,58	2,63	4,84	5,82	5,05	4,78	4,81	75,47
	XRP	8,57	9,89	28,96	2,90	4,37	3,11	3,45	3,38	3,18	3,59	2,73	4,86	5,96	5,16	4,86	5,03	71,04
	S&P 500	2,69	2,78	2,71	18,21	10,97	16,37	5,60	5,38	3,04	3,59	2,54	5,09	5,93	5,33	4,97	4,81	81,79
	MCHI	3,16	2,89	2,82	9,37	18,93	10,25	5,74	5,35	3,57	4,21	3,07	5,90	6,98	6,17	5,79	5,79	81,07
	VT	2,75	2,73	2,72	15,44	11,38	17,71	5,73	5,58	3,10	3,65	2,61	5,17	6,05	5,40	5,06	4,93	82,29
	TNX	3,30	2,90	3,22	5,87	7,30	6,40	21,15	6,13	3,75	4,39	3,23	6,17	7,25	6,49	6,30	6,14	78,85
	BCO	3,19	2,80	3,01	5,98	7,33	6,63	5,95	25,72	3,43	3,95	2,92	5,67	6,63	5,76	5,52	5,50	74,28
BEAR	BTC	2,23	2,26	2,40	3,00	4,00	3,11	3,31	2,91	18,70	12,70	9,03	7,42	7,81	7,33	5,88	7,90	81,30
	ETH	2,16	2,19	2,36	2,99	3,96	3,09	3,27	2,81	11,39	20,80	10,29	6,53	7,49	6,65	6,06	7,94	79,20
	XRP	2,10	2,13	2,31	2,82	3,85	2,96	3,17	2,69	10,29	11,55	21,28	7,03	6,88	6,95	5,74	8,25	78,72
	S&P 500	2,25	2,18	2,43	3,16	4,23	3,34	3,36	2,95	4,16	5,12	3,25	17,19	12,14	16,58	9,17	8,50	82,81
	MCHI	2,76	2,70	2,94	3,65	5,05	3,85	3,98	3,47	4,32	5,22	3,69	11,21	17,30	12,41	8,94	8,51	82,70
	VT	2,29	2,22	2,47	3,19	4,00	3,37	3,41	2,98	4,15	5,16	3,26	15,68	12,83	17,07	9,10	8,51	82,93
	TNX	2,85	2,72	3,00	3,76	5,22	3,99	4,16	3,55	4,18	5,33	3,90	10,25	10,70	10,81	17,19	8,40	82,81
	BCO	2,81	2,69	3,02	3,80	5,16	4,00	4,17	3,70	4,95	5,94	4,19	9,51	9,78	9,92	8,77	17,60	82,40
	TO	54,83	55,21	54,42	71,96	87,14	76,54	63,61	57,76	69,73	81,46	59,95	110,07	117,96	114,99	95,65	99,74	1271,03
	INC. OWN	81,46	79,74	83,38	90,17	106,08	94,25	84,76	83,49	88,43	102,26	81,23	127,26	135,26	132,06	112,84	117,34	cTCI/TCI
NET	-18,54	-20,26	-16,62	-9,83	6,08	-5,75	-15,24	-16,51	-11,57	2,26	-18,77	27,26	35,26	32,06	12,84	17,34	84,74/79,44	
NPT	0,00	1,00	2,00	6,00	9,00	8,00	3,00	4,00	7,00	10,00	5,00	13,00	15,00	14,00	12,00	11,00		

H2		BULL								BEAR								
		BTC	ETH	XRP	VEA	VWO	VT	TNX	BCO	BTC	ETH	XRP	VEA	VWO	VT	TNX	BCO	FROM
BULL	BTC	25,69	11,70	8,76	4,02	4,21	2,92	3,96	3,17	3,36	3,61	2,86	5,19	5,93	5,07	4,82	4,76	74,31
	ETH	11,28	23,93	9,63	4,25	4,64	3,03	3,75	3,47	3,50	3,69	2,91	5,24	5,93	5,10	4,85	4,80	76,07
	XRP	8,35	9,45	27,61	4,03	3,87	2,93	3,26	3,32	3,59	3,72	3,04	5,43	6,14	5,29	4,94	5,04	72,39
	VEA	2,79	2,63	2,57	17,66	11,75	13,31	5,24	5,39	3,47	3,82	2,96	5,70	6,44	5,62	5,46	5,21	82,34
	VWO	2,83	2,77	2,55	12,31	16,88	11,08	5,10	4,96	3,76	4,13	3,21	6,10	6,88	6,02	5,78	5,64	83,12
	VT	2,66	2,63	2,54	15,41	12,86	16,97	5,21	5,19	3,28	3,62	2,77	5,40	6,09	5,33	5,15	4,91	83,03
	TNX	3,15	2,82	3,06	7,75	7,18	5,92	19,58	5,61	4,15	4,45	3,52	6,53	7,44	6,47	6,29	6,08	80,42
	BCO	3,04	2,69	2,91	8,10	7,30	6,14	5,38	24,43	3,68	3,99	3,14	5,91	6,62	5,70	5,57	5,38	75,57
BEAR	BTC	2,17	2,20	2,32	3,80	4,04	2,92	3,09	2,74	19,14	12,83	9,41	7,00	7,51	7,42	5,89	7,53	80,86
	ETH	2,10	2,13	2,28	3,73	3,94	2,87	3,03	2,61	11,92	20,61	10,52	6,58	7,37	6,81	6,00	7,52	79,39
	XRP	2,04	2,06	2,22	3,61	3,87	2,76	2,96	2,52	10,77	11,54	21,20	6,61	7,10	7,19	5,77	7,77	78,80
	VEA	2,37	2,24	2,49	4,37	4,45	3,31	3,39	3,00	4,83	5,36	3,87	15,45	13,22	14,55	9,05	8,05	84,55
	VWO	2,58	2,48	2,73	4,63	4,78	3,51	3,65	3,19	5,09	5,48	4,23	12,36	15,65	12,61	8,92	8,13	84,35
	VT	2,24	2,14	2,40	4,13	4,20	3,15	3,18	2,82	4,93	5,50	3,78	14,24	13,16	16,66	9,13	8,34	83,34
	TNX	2,74	2,61	2,87	4,89	5,03	3,72	3,85	3,33	4,88	5,37	4,15	10,33	10,79	10,55	16,85	8,04	83,15
	BCO	2,74	2,60	2,92	4,97	5,06	3,77	3,89	3,49	5,44	5,97	4,51	9,36	10,13	9,94	8,56	16,68	83,32
	TO	53,07	53,14	52,24	89,99	87,16	71,34	58,96	54,79	76,64	83,06	64,87	111,98	120,73	113,65	96,19	97,21	1285,03
	INC. OWN	78,75	77,08	79,85	107,64	104,04	88,31	78,54	79,23	95,78	103,67	86,07	127,43	136,38	130,31	113,04	113,88	cTCI/TCI
	NET	-21,25	-22,92	-20,15	7,64	4,04	-11,69	-21,46	-20,77	-4,22	3,67	-13,93	27,43	36,38	30,31	13,04	13,88	85,67/80,31
	NPT	0,00	1,00	2,00	9,00	8,00	5,00	3,00	4,00	7,00	10,00	6,00	13,00	15,00	14,00	12,00	11,00	

Notes: This table shows the static spillovers between the volatilities of cryptoassets and financial assets in the Bull and Bear markets analysed over the period from 1 January 2016 to 30 April 2024. Each (i,j)-th value represents the contribution of innovation in the volatility of asset j to the variance of the forecast error in asset i. The column headed 'From' aggregates the cumulative contributions to asset i of all other assets, while the row headed 'To' summarizes the impact of asset j on all other assets. The row labelled 'Net' captures the net pass-through transmitted by each asset to all other assets. Positive (negative) values indicate that the asset in question acts as a net transmitter (receiver) of spillovers to other assets. To facilitate interpretation, colour scales are used. The minimum value is highlighted in yellow for values between the crypto market and in light blue between the financial market, the maximum value for values between the crypto market is in dark blue and for the financial market is orange. Diagonal elements are not included in the colour scale (green).

FIGURE 5 - VAR NET VOLATILITY SPILLOVERS IN BULL AND BEAR MARKET, H1 (left-hand side) AND H2 (right-hand side), 75% threshold



Notes: We show the most important directional connections among the pairs of crypto assets. Node size indicates the size of the total spillovers (sum of to and from) for each asset. The colour of the node indicates whether the asset is a net sender (blue) or a net receiver (yellow). The thickness of the arrows represents the strength of the spillovers (normalized to improve visibility), with only the top 75% percentile of bilateral spillovers shown spillovers

In Table 7, the results obtained for the cryptocurrency market indicate an increase in connections. At the BULL moment, in both hypotheses, we can see (dark blue) a strong spillover between BTC and ETH. This connection is bilateral with almost the same strength, with ETH being a stronger transmitter in the market than BTC. The rest of the connections are very close, and there is little evidence of who is transmitting or who is receiving. At the BEAR moment, in Hypothesis 1, we see two distinct links: ETH with BTC and ETH with XRP, these being considered the most important (dark blue) and realizing that there is unilateralism in these spillovers. In Hypothesis 2, we see stronger spillovers between ETH and BTC, again obtaining a bilateral spillover. The strongest link is when ETH transmits to BTC.

In the financial market, we obtained strong results between VT and the S&P 500. It can be seen in both hypotheses at both times (BULL and BEAR) that these spillovers are the strongest in the market and present a bilateral link, where both transmit to each other, but the strongest is from VT to the S&P 500 in H1, and from VT to the SEE in H2.

Asymmetric volatility spillovers are also observed between cryptocurrencies and stock market indices. Like return spillovers, volatility spillovers between cryptocurrencies

and stock markets are more higher in bear markets than in bull markets. Bouri et al. (2018) also supports the existence of asymmetric volatility spillovers between Bitcoin and stock market indices.

However, in contrast to returns, there are significant net bilateral volatility spillovers between cryptocurrencies and stocks in both bull and bear markets (cf. Figure B4). In general, and in relation to shares, cryptocurrencies are net receivers. In the intra-layer network, volatility spillovers between cryptocurrencies and stocks are generally smaller in bull markets than in bear markets, in contrast to return spillovers.

In short, the estimates suggest the existence of asymmetry in return and volatility spillovers between the cryptocurrency and stock markets in different market states. Spillovers are stronger in both directions in bear markets than in bull markets. Net spillovers only become significant for volatilities in both bearish and bullish markets and, in general, cryptocurrencies are net receivers.

The results of the Lasso estimation, presented in Table C4 and Figure C4 in the Appendix, provide the same qualitative results. After analyzing the VAR, a comparison was made with the LASSO study. The result obtained in this study was very similar to the VAR, i.e., checking Table 10, it is possible to see that at the BULL moment and at the BEAR moment, the most relevant spillovers are the same as in the VAR study in both hypotheses.

CHAPTER V - CONCLUSION

There is a growing body of empirical literature on the connectivity between cryptocurrencies and stock markets. However, there is still limited research on potential asymmetries in their linkages. Specifically, it remains unclear whether these linkages are sensitive to stock market states (bull and bear markets) and the nature of the stock markets (advanced and emerging economies).

This dissertation aims to fill this gap in the empirical literature by estimating return and volatility spillovers between cryptocurrencies and stock market indices under bull and bear markets, and for advanced and emerging economies stock market indices.

Following Diebold and Yilmaz's connectedness methodology, we assessed the return and volatility spillovers between the top three most historic cryptocurrencies (Bitcoin, Ethereum, and Ripple), a worldwide stock market index (VT), selected indices for advanced (S&P 500 and VEA) and emerging (MCHI and VWO) markets, a risk-free bond (TNX), and a commodity (BCO), covering daily data from 2016 to 2024. We expanded Diebold and Yilmaz's approach to include potential spillover differences in bull and bear market periods, estimated using Lunde and Timmermann's (2004) algorithm.

Overall, our findings indicate that, as expected, cryptocurrencies and stocks are less interconnected across them than within their respective classes of assets. Furthermore, the directional pairwise return and volatility spillovers between cryptocurrencies and stocks are small, and there is no evidence of net directional dominance. Therefore, net return and volatility spillovers are not significant. These results, common to advanced and emerging economies, suggest that cryptocurrencies operate independently from stock markets.

When considering bull and bear market states, and consistent with previous literature (e.g., Iyer and Popescu, 2023 and Bouri et al., 2018), our estimations suggest the existence of asymmetry in both return and volatility spillovers between crypto and stock markets under different market states. The magnitude of these spillovers is much higher in both directions under bear markets than under bull markets. This tendency suggests that cryptocurrencies may not effectively serve as diversifiers during bearish periods. Moreover, net spillovers become significant for volatilities and in, general, cryptocurrencies are net receivers. The nature of stock markets, whether from emerging or advanced economies, does not add any relevant asymmetry to the spillovers between crypto and stock markets.

Overall, the findings of this study, indicate that cryptocurrencies and stocks maintain characteristics of separate asset classes, but there is evidence of closer interconnection during bearish periods. This analysis is relevant for investors aiming to diversify their portfolios, as

well as for policymakers seeking to understand the role of cryptocurrencies for the stability of the financial system. For instance, given the stronger connection during bearish periods, it is important to reinforce regulation in cryptocurrency market.

In future research, it may be interesting to assess the robustness of the results by including more cryptocurrencies and adopting other methodologies that explore causality and provide tests to assess the statistical significance of the connections and the differences across them.

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ANNEX A – DESCRIPTIVE STATISTICS

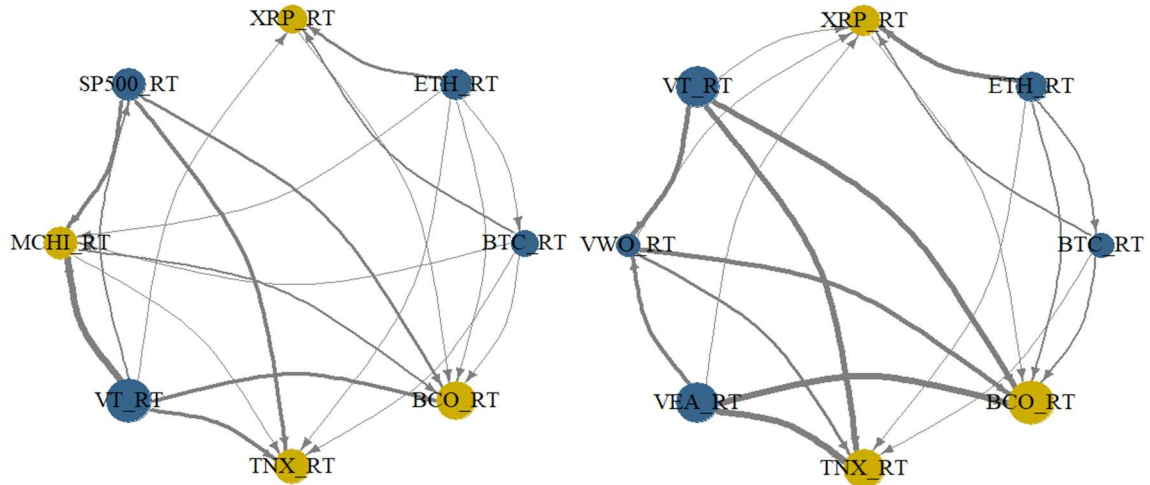
TABLE A1 – DESCRIPTIVE STATISTICS OF VOLATILITY

	Observations	Mean (%)	SD (%)	skew	kurtosis
BTC	2094	3.837	3.889	3.240	15.316
ETH	2094	2.301	1.747	1.916	6.043
XRP	2094	2.709	2.641	3.359	19.091
SP500 (H1)	2094	14.256	9.248	1.511	3.445
MCHI (H1)	2094	10.174	5.167	1.175	1.821
VWO (H2)	2094	13.194	6.291	0.978	1.213
VEA (H2)	2094	16.635	9.124	1.069	1.294
VT	2094	15.666	9.679	1.416	3.212
TNX	2094	2.414	1.360	1.093	2.034
BCO	2094	4.121	6.024	36.848	1563.677

Source: Table A1 presents summary statistics (mean, volatility, skewness and kurtosis) based on daily returns for Bitcoin (BTC), Ethereum (ETH), Ripple (XRP), equally weighted portfolio of three cryptocurrencies, also ETFs of stock (Vanguard Total World Stock ETF (VT), iShares MSCI China ETF (MCHI), Vanguard FTSE developed Markets ETF (VEA), Vanguard FTSE Emerging Markets (VWO), The S&500 Index (GSPC), one treasury Yield, CBOE 10 Year Treasury Note Yield Index (TNX) and the Brent Crude Oil Last Day Financ (BCO). Database is over the period 01/Jan/2016 to 30/Apr/2024

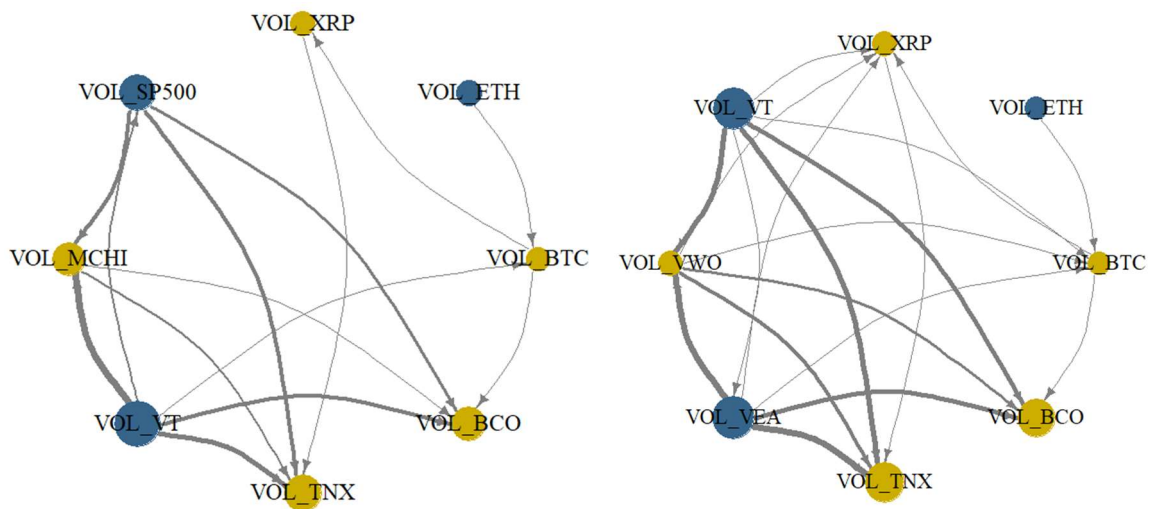
ANNEX B - VAR STUDY

FIGURE B1 - VAR NET RETURN SPILLOVERS H1 (left-hand side) AND H2 (right-hand side), 90% threshold



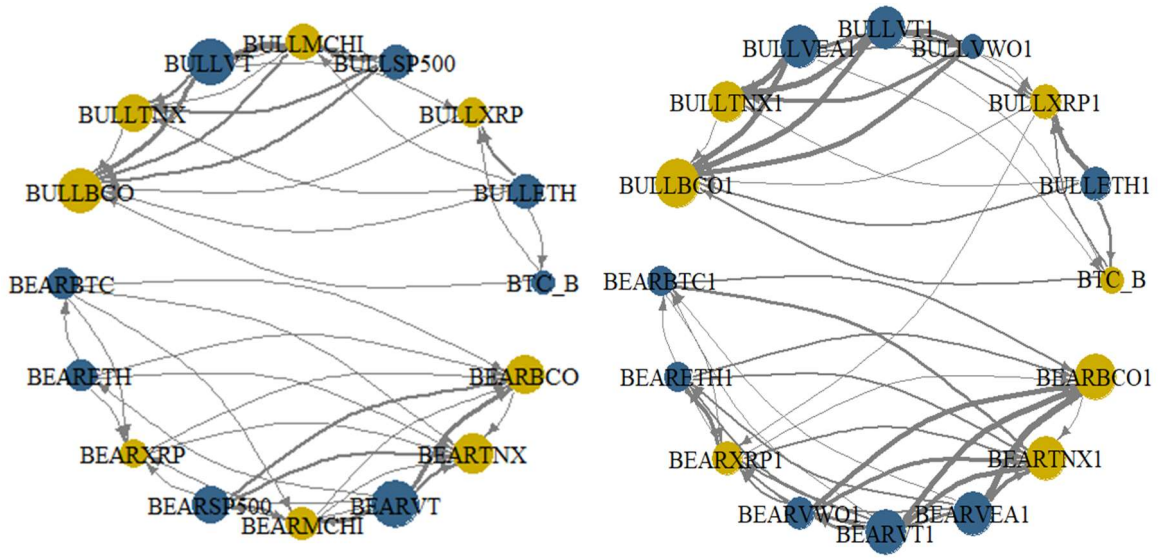
Notes: We show the most important directional connections among the pairs of crypto assets. Node size indicates the size of the total spillovers (sum of to and from) for each asset. The colour of the node indicates whether the asset is a net sender (blue) or a net receiver (yellow). The thickness of the arrows represents the strength of the spillovers (normalized to improve visibility), with only the top 90% percentile of bilateral spillovers shown

FIGURE B2 - VAR NET VOLATILITY SPILLOVERS, H1 (left-hand side) AND H2 (right-hand side), 90% threshold



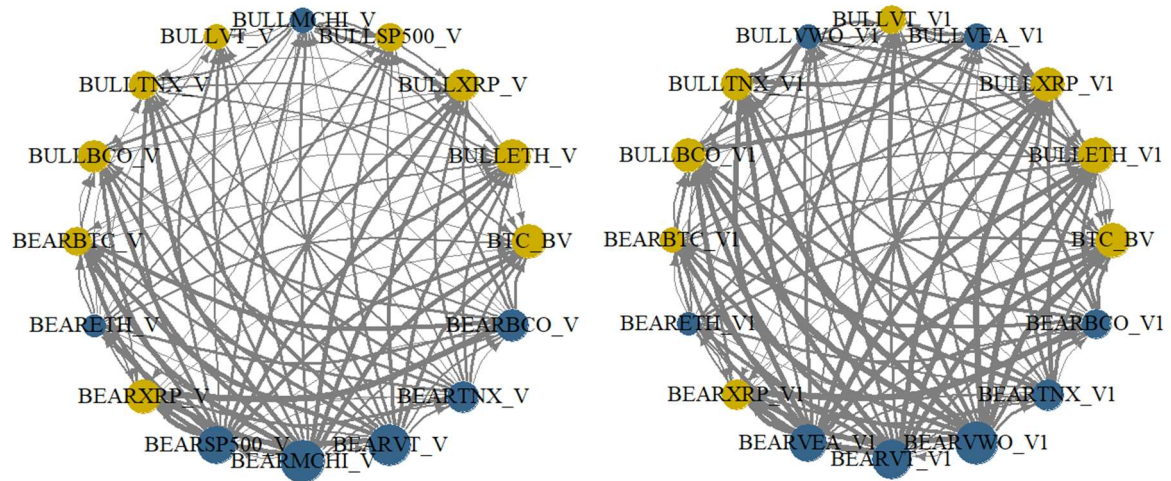
Notes: We show the most important directional connections among the pairs of crypto assets. Node size indicates the size of the total spillovers (sum of to and from) for each asset. The colour of the node indicates whether the asset is a net sender (blue) or a net receiver (yellow). The thickness of the arrows represents the strength of the spillovers (normalized to improve visibility), with only the top 90% percentile of bilateral spillovers shown

FIGURE B3 - VAR NET RETURN SPILLOVERS IN BULL AND BEAR MARKET, H1 (left-hand side) AND H2 (right-hand side), 90% threshold



Notes: We show the most important directional connections among the pairs of crypto assets. Node size indicates the size of the total spillovers (sum of to and from) for each asset. The colour of the node indicates whether the asset is a net sender (blue) or a net receiver (yellow). The thickness of the arrows represents the strength of the spillovers (normalized to improve visibility), with only the top 75 percentile of bilateral spillovers shown

FIGURE B4 - VAR NET VOLATILITY SPILLOVERS IN BULL AND BEAR MARKET, H1 (left-hand side) AND H2 (right-hand side), 90% threshold



Notes: We show the most important directional connections among the pairs of crypto assets. Node size indicates the size of the total spillovers (sum of to and from) for each asset. The colour of the node indicates whether the asset is a net sender (blue) or a net receiver (yellow). The thickness of the arrows represents the strength of the spillovers (normalized to improve visibility), with only the top 90% percentile of bilateral spillovers shown

ANNEX C - LASSO STUDY

TABLE C1 – LASSO RETURN

H1	BTC	ETH	XRP	S&P 500	MCHI	VT	TNX	BCO	FROM
BTC	52,44	24,87	13,76	3,00	1,64	3,25	0,49	0,53	47,56
ETH	23,82	50,66	16,03	3,02	1,91	3,55	0,43	0,58	49,34
XRP	15,09	18,48	58,45	2,58	1,76	2,92	0,33	0,40	41,55
S&P 500	2,80	2,88	2,09	37,77	13,44	34,82	3,60	2,61	62,23
MCHI	2,10	2,45	1,95	16,58	49,81	22,51	2,54	2,05	50,19
VT	2,86	3,13	2,24	32,80	16,97	35,58	3,31	3,11	64,42
TNX	0,79	0,75	0,52	6,87	3,85	6,61	77,82	2,79	22,18
BCO	1,00	1,02	0,66	5,02	3,33	6,34	2,74	79,89	20,11
TO	48,46	53,58	37,25	69,87	42,91	80,00	13,44	12,08	357,58
INC. OWN	100,90	104,25	95,71	107,63	92,72	115,57	91,26	91,96	cTCI/TCI
NET	0,90	4,25	-4,29	7,63	-7,28	15,57	-8,74	-8,04	51,08/44,7
NPT	4,00	5,00	3,00	6,00	2,00	7,00	0,00	1,00	
H2	BTC	ETH	XRP	VEA	VWO	VT	TNX	BCO	FROM
BTC	52,17	24,65	13,61	3,18	2,48	2,90	0,49	0,52	47,83
ETH	23,47	49,94	15,79	3,45	2,86	3,51	0,42	0,57	50,06
XRP	14,85	18,22	58,10	2,85	2,58	2,67	0,32	0,39	41,90
VEA	2,67	2,93	2,10	33,71	22,82	29,63	3,18	2,96	66,29
VWO	2,34	2,72	2,14	25,43	37,78	24,48	2,24	2,86	62,22
VT	2,43	2,91	2,02	29,90	22,15	34,04	3,24	3,31	65,96
TNX	0,79	0,74	0,51	6,56	4,14	6,68	77,80	3,78	22,20
BCO	0,96	0,98	0,63	6,01	5,26	6,72	2,62	76,84	23,16
TO	47,50	53,16	36,79	77,40	62,29	76,58	12,51	13,39	379,61
INC. OWN	99,67	103,10	94,90	111,11	100,07	110,62	90,32	90,22	cTCI/TCI
NET	-0,33	3,10	-5,10	11,11	0,07	10,62	-9,68	-9,78	54,23/47,45
NPT	3,00	4,00	2,00	7,00	5,00	6,00	0,00	1,00	

Notes: This table shows the static spillovers between the returns of the cryptoassets and financial assets analysed over the period from 1 January 2016 to 30 April 2024. Each (i,j)-th value represents the contribution of the innovation in the return of asset j to the variance of the forecast error in asset i. The column headed 'From' aggregates the cumulative contributions to asset i of all other assets, while the row headed 'To' summarises the impact of asset j on all other assets. The row labelled 'Net' captures the net pass-through transmitted by each asset to all other assets. Positive (negative) values indicate that the asset in question acts as a net transmitter (receiver) of spillovers to other assets. To facilitate interpretation, colour scales are used. The minimum value is highlighted in yellow for values between the crypto market and in light blue between the financial market, the maximum value for values between the crypto market is in dark blue and for the financial market it is orange. Diagonal elements are not included in the colour scale (green).

TABLE C2 – LASSO VOLATILITY

H1	BTC	ETH	XRP	S&P 500	MCHI	VT	TNX	BCO	FROM
BTC	60,38	24,02	11,79	0,86	0,60	0,99	0,59	0,77	39,62
ETH	23,24	58,69	14,79	0,73	0,70	0,73	0,55	0,58	41,31
XRP	13,08	16,70	66,51	0,78	0,53	0,79	0,92	0,68	33,49
S&P 500	0,73	0,62	0,57	44,60	11,31	36,29	3,58	2,30	55,40
MCHI	0,62	0,71	0,51	14,32	60,33	18,82	2,75	1,94	39,67
VT	0,78	0,61	0,55	34,76	13,94	43,04	3,88	2,45	56,96
TNX	0,77	0,69	1,06	5,91	3,71	6,71	78,40	2,75	21,60
BCO	1,07	0,86	0,81	4,13	2,67	4,47	2,95	83,03	16,97
TO	40,30	44,20	30,07	61,48	33,46	68,81	15,22	11,46	305,01
INC. OWN	100,68	102,90	96,59	106,08	93,79	111,85	93,62	94,49	cTCI/TCI
NET	0,68	2,90	-3,41	6,08	-6,21	11,85	-6,38	-5,51	43,57/38,13
NPT	4,00	5,00	2,00	6,00	3,00	7,00	1,00	0,00	
H2	BTC	ETH	XRP	VEA	VWO	VT	TNX	BCO	FROM
BTC	60,19	23,94	11,75	0,85	0,90	1,01	0,59	0,76	39,81
ETH	23,13	58,67	14,75	0,77	0,83	0,73	0,55	0,57	41,33
XRP	13,03	16,65	66,37	0,94	0,63	0,78	0,93	0,68	33,63
VEA	0,64	0,61	0,63	42,68	19,43	29,43	4,26	2,30	57,32
VWO	0,75	0,73	0,49	22,13	47,71	23,15	3,24	1,81	52,29
VT	0,77	0,59	0,53	29,32	20,24	42,37	3,76	2,40	57,63
TNX	0,76	0,67	1,03	7,34	4,86	6,35	76,31	2,67	23,69
BCO	1,05	0,83	0,81	4,33	2,97	4,38	2,83	82,70	17,30
TO	40,13	44,03	30,00	65,68	49,87	65,84	16,25	11,20	323,01
INC. OWN	100,32	102,70	96,37	108,36	97,58	108,21	92,56	93,90	cTCI/TCI
NET	0,32	2,70	-3,63	8,36	-2,42	8,21	-7,44	-6,10	46,14/40,38
NPT	3,00	4,00	2,00	6,00	5,00	7,00	1,00	0,00	

Notes: This table shows the static spillovers between the volatilities of the cryptoassets and financial assets analysed over the period from 1 January 2016 to 30 April 2024. Each (i,j)-th value represents the contribution of innovation in the volatility of asset j to the variance of the forecast error in asset i. The column headed 'From' aggregates the cumulative contributions to asset i of all other assets, while the row headed 'To' summarizes the impact of asset j on all other assets. The row labelled 'Net' captures the net pass-through transmitted by each asset to all other assets. Positive (negative) values indicate that the asset in question acts as a net transmitter (receiver) of spillovers to other assets. To facilitate interpretation, colour scales are used. The minimum value is highlighted in yellow for values between the crypto market and in light blue between the financial market, the maximum value for values between the crypto market is in dark blue and for the financial market is orange. Diagonal elements are not included in the colour scale (green).

TABLE C3 – LASSO RETURN BULL AND BEAR MARKET

H1	BULL								BEAR									
	BTC	ETH	XRP	S&P 500	MCHI	VT	TNX	BCO	BTC	ETH	XRP	S&P 500	MCHI	VT	TNX	BCO	FROM	
BULL	BTC	52,43	26,18	12,97	2,49	1,33	2,74	0,67	0,94	0,09	0,04	0,06	0,01	0,02	0,02	0,01	0,02	47,57
	ETH	24,63	49,52	17,09	2,49	1,50	2,87	0,69	1,04	0,06	0,03	0,04	0,01	0,01	0,01	0,01	0,01	50,48
	XRP	13,88	19,55	58,24	2,58	1,74	2,79	0,58	0,54	0,03	0,02	0,02	0,01	0,01	0,01	0,00	0,00	41,76
	S&P 500	2,19	2,35	1,94	38,59	13,26	35,30	3,60	2,69	0,02	0,01	0,02	0,00	0,01	0,01	0,00	0,00	61,41
	MCHI	1,65	1,93	1,72	16,17	50,98	22,28	3,21	2,02	0,01	0,01	0,01	0,00	0,00	0,00	0,00	0,00	49,02
	VT	2,27	2,53	2,01	33,19	16,95	36,26	3,55	3,15	0,02	0,01	0,01	0,00	0,01	0,01	0,00	0,00	63,74
	TNX	1,02	1,10	0,81	6,49	4,70	6,64	76,50	2,66	0,02	0,01	0,02	0,00	0,01	0,01	0,00	0,00	24,50
	BCO	1,61	1,75	0,78	5,16	3,28	6,36	2,70	78,31	0,02	0,01	0,01	0,00	0,00	0,00	0,00	0,00	21,69
BEAR	BTC	0,06	0,05	0,02	0,02	0,01	0,03	0,01	0,01	45,87	21,86	16,95	4,45	2,89	4,76	1,32	1,70	54,13
	ETH	0,03	0,03	0,01	0,01	0,01	0,01	0,01	0,00	21,46	44,50	17,32	4,66	3,76	5,37	0,93	1,88	55,50
	XRP	0,04	0,03	0,02	0,02	0,01	0,02	0,01	0,01	18,16	18,80	48,78	3,82	3,36	4,39	1,15	1,40	51,22
	S&P 500	0,01	0,01	0,00	0,00	0,00	0,00	0,00	0,00	4,20	4,35	3,47	34,78	13,45	32,17	3,82	3,75	65,22
	MCHI	0,02	0,01	0,01	0,01	0,00	0,01	0,00	0,00	3,46	4,26	3,70	16,23	44,55	21,41	2,69	3,64	55,45
	VT	0,01	0,01	0,00	0,00	0,00	0,00	0,00	0,00	4,26	4,65	3,74	30,35	16,54	32,82	3,41	4,20	67,18
	TNX	0,02	0,01	0,01	0,01	0,00	0,01	0,00	0,00	2,11	1,51	1,46	7,00	3,87	6,43	71,51	5,06	27,49
	BCO	0,02	0,01	0,01	0,01	0,00	0,01	0,00	0,00	2,77	2,96	2,15	6,20	5,27	7,50	4,28	68,79	31,21
	TO	47,45	55,54	37,41	68,66	42,81	79,07	15,03	13,07	56,67	58,52	48,97	72,76	49,20	82,08	17,64	21,70	766,58
	INC. OWN	99,88	105,06	95,65	107,25	93,79	115,33	91,53	91,38	102,54	103,01	97,75	107,54	93,75	114,90	90,15	90,49	cTCI/TCI
NET	-0,12	5,06	-4,35	7,25	-6,21	15,33	-8,47	-8,62	2,54	3,01	-2,25	7,54	-6,25	14,90	-9,85	-9,51	51,11/47,91	
NPT	6,00	8,00	4,00	11,00	8,00	13,00	2,00	1,00	10,00	10,00	8,00	14,00	7,00	15,00	0,00	3,00		

H2		BULL								BEAR								
		BTC	ETH	XRP	VEA	VWO	VT	TNX	BCO	BTC	ETH	XRP	VEA	VWO	VT	TNX	BCO	FROM
BULL	BTC	52,24	26,07	12,90	2,34	1,91	2,69	0,67	0,92	0,09	0,04	0,06	0,02	0,02	0,01	0,01	0,02	47,76
	ETH	24,40	49,05	16,94	2,71	2,20	2,80	0,69	1,03	0,06	0,03	0,04	0,01	0,01	0,01	0,01	0,01	50,95
	XRP	13,76	19,44	58,17	2,52	2,13	2,76	0,58	0,54	0,03	0,02	0,02	0,01	0,01	0,01	0,00	0,00	41,83
	VEA	1,84	2,25	1,75	34,66	22,30	30,00	3,81	3,35	0,02	0,01	0,01	0,00	0,00	0,00	0,00	0,00	65,34
	VWO	1,71	2,06	1,63	24,70	38,69	25,49	2,85	2,82	0,01	0,01	0,01	0,00	0,00	0,00	0,00	0,00	61,31
	VT	2,11	2,36	1,88	29,80	22,88	34,44	3,44	3,02	0,02	0,01	0,01	0,01	0,00	0,00	0,00	0,00	65,56
	TNX	1,02	1,10	0,81	7,27	4,85	6,52	75,72	2,62	0,02	0,01	0,02	0,01	0,01	0,01	0,00	0,00	24,28
	BCO	1,53	1,68	0,76	6,74	5,13	6,10	2,60	75,42	0,01	0,01	0,01	0,00	0,00	0,00	0,00	0,00	24,58
BEAR	BTC	0,06	0,04	0,02	0,02	0,01	0,02	0,01	0,01	45,56	21,58	16,72	4,42	3,86	4,67	1,32	1,68	54,44
	ETH	0,03	0,02	0,01	0,01	0,01	0,01	0,00	0,00	21,18	43,80	17,12	5,12	4,65	5,25	0,92	1,86	56,20
	XRP	0,04	0,03	0,02	0,01	0,01	0,02	0,01	0,01	17,87	18,50	48,33	4,14	4,21	4,28	1,14	1,38	51,67
	VEA	0,01	0,01	0,00	0,00	0,00	0,01	0,00	0,00	3,89	4,30	3,57	31,67	21,05	28,08	3,02	4,40	68,33
	VWO	0,01	0,01	0,00	0,00	0,00	0,00	0,00	0,00	3,71	4,32	3,87	22,99	34,82	23,88	2,18	4,19	65,18
	VT	0,01	0,01	0,00	0,00	0,00	0,00	0,00	0,00	4,07	4,46	3,63	27,70	21,57	31,21	3,29	4,04	68,79
	TNX	0,01	0,01	0,01	0,01	0,00	0,01	0,00	0,00	2,13	1,52	1,46	5,78	3,86	6,47	73,68	5,05	26,32
	BCO	0,02	0,01	0,01	0,01	0,01	0,01	0,00	0,00	2,67	2,89	2,09	8,00	6,95	7,17	4,05	66,12	33,88
	TO	46,58	55,12	36,74	76,15	61,44	76,45	14,66	14,33	55,78	57,69	48,62	78,20	66,19	79,86	15,96	22,66	806,44
	INC. OWN	98,82	104,17	94,92	110,81	100,13	110,89	90,38	89,75	101,33	101,49	96,95	109,87	101,01	111,06	89,64	88,78	cTCI/TCI
	NET	-1,18	4,17	-5,08	10,81	0,13	10,89	-9,62	-10,25	1,33	1,49	-3,05	9,87	1,01	11,06	-10,36	-11,22	53,76/50,40
	NPT	5,00	6,00	4,00	11,00	10,00	12,00	1,00	2,00	8,00	9,00	7,00	14,00	13,00	15,00	0,00	3,00	

Notes: This table shows the static spillovers between the returns of the cryptoassets and financial assets analysed over the period from 1 January 2016 to 30 April 2024. Each (i,j)-th value represents the contribution of innovation in the return of asset j to the variance of the forecast error in asset i. The column headed 'From' aggregates the cumulative contributions to asset i of all other assets, while the row headed 'To' summarizes the impact of asset j on all other assets. The row labelled 'Net' captures the net pass-through transmitted by each asset to all other assets. Positive (negative) values indicate that the asset in question acts as a net transmitter (receiver) of spillovers to other assets. To facilitate interpretation, colour scales are used. The minimum value is highlighted in yellow for values between the crypto market and in light blue between the financial market, the maximum value for values between the crypto market is in dark blue and for the financial market is orange. Diagonal elements are not included in the colour scale (green).

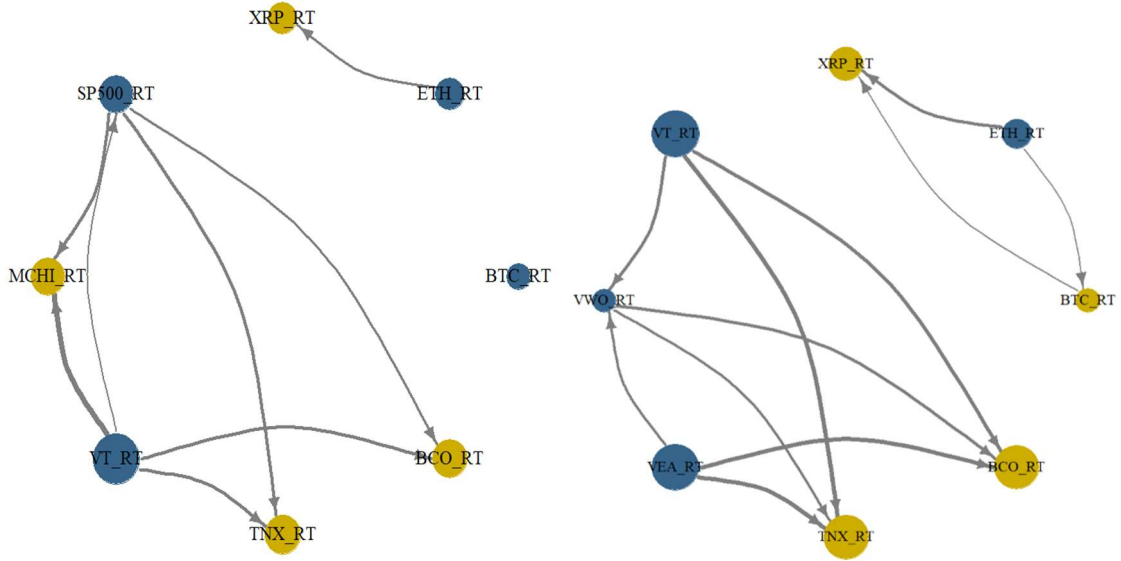
TABLE C4 – LASSO VOLATILITY BULL AND BEAR MARKET

H1		BULL								BEAR								
		BTC	ETH	XRP	S&P 500	MCHI	VT	TNX	BCO	BTC	ETH	XRP	S&P 500	MCHI	VT	TNX	BCO	FROM
BULL	BTC	33.87	15.06	10,00	2.79	4.48	2.95	3.93	2.68	2.56	2.62	2.22	3.1	3.91	3.29	3.48	3.06	66.13
	ETH	14.25	31.6	11.11	3.12	4.69	3.22	3.74	2.81	2.67	2.76	2.37	3.28	4.09	3.48	3.58	3.22	68.4
	XRP	10.14	11.92	35.3	2.82	3.93	2.97	3.25	2.62	2.79	2.89	2.56	3.43	4.36	3.68	3.78	3.56	64.7
	S&P 500	2.57	2.6	2.31	22.86	11.82	20.18	6.19	4.79	2.48	2.69	2.24	3.65	4.35	3.87	3.94	3.46	77.14
	MCHI	3.13	3.15	2.64	10.93	22.67	12.42	6.36	5.04	3.24	3.47	2.92	4.53	5.5	4.8	4.87	4.34	77.33
	VT	2.64	2.64	2.39	18.92	12.6	21.99	6.4	5.05	2.56	2.75	2.31	3.74	4.46	3.95	4.03	3.56	78.01
	TNX	3.33	3.03	2.98	6.91	7.65	7.47	27.16	5.79	3.45	3.68	3.07	4.77	5.77	5.03	5.3	4.63	72.84
	BCO	2.98	2.92	2.63	6.46	7.1	7.04	6.45	32.57	3,00	3.14	2.69	4.33	5.19	4.55	4.68	4.27	67.43
BEAR	BTC	1.98	2,00	2.03	2.55	3.26	2.67	2.93	2.24	25.42	14.29	10.91	6.02	6.35	6.21	5.1	6.04	74.58
	ETH	1.92	1.98	2,00	2.58	3.28	2.7	2.89	2.2	13.72	25.5	11.74	5.76	6.25	5.84	5.46	6.17	74.5
	XRP	1.83	1.94	1.99	2.47	3.16	2.61	2.78	2.13	12.18	12.68	27.45	5.94	5.76	5.89	5.07	6.13	72.55
	S&P 500	1.86	1.91	1.97	2.96	3.69	3.11	3.1	2.52	4.49	4.8	3.7	19.67	11.88	18.41	8.83	7.09	80.33
	MCHI	2.43	2.49	2.52	3.53	4.54	3.73	3.86	3.06	4.73	5,00	4.02	11.55	19.69	13.15	8.66	7.05	80.31
	VT	1.89	1.95	2.01	3.01	3.76	3.16	3.14	2.55	4.57	4.84	3.73	17.44	12.77	19.28	8.84	7.07	80.72
	TNX	2.48	2.48	2.52	3.58	4.65	3.8	4.11	3.12	4.48	5.23	4.1	9.94	10.07	10.58	21.47	7.39	78.53
	BCO	2.43	2.44	2.55	3.58	4.61	3.78	3.95	3.17	5.38	6.11	4.78	8.75	8.89	9.31	8.73	21.53	78.47
	TO	55.85	58.53	51.65	76.21	83.23	81.79	63.08	49.77	72.29	76.94	63.36	96.24	99.6	102.03	84.35	77.03	1191.96
	INC. OWN	89.72	90.13	86.94	99.07	105.91	103.78	90.24	82.34	97.71	102.45	90.81	115.91	119.29	121.31	105.81	98.57	cTCI/TCI
NET	-10.28	-9.87	-13.06	-0.93	5.91	3.78	-9.76	-17.66	-2.29	2.45	-9.19	15.91	19.29	21.31	5.81	-1.43	79.46/74.50	
NPT	2,00	3,00	1,00	8,00	10,00	9,00	4,00	0,00	6,00	10,00	5,00	13,00	14,00	15,00	12,00	8,00		

H2		BULL								BEAR								
		BTC	ETH	XRP	VEA	VWO	VT	TNX	BCO	BTC	ETH	XRP	VEA	VWO	VT	TNX	BCO	FROM
BULL	BTC	33.37	14.8	9.83	3.75	3.85	3.02	3.76	2.65	2.56	2.64	2.21	3.66	4.03	3.34	3.48	3.04	66.63
	ETH	14.02	31.36	10.92	3.86	4.2	3.18	3.6	2.78	2.67	2.79	2.37	3.8	4.18	3.5	3.6	3.19	68.64
	XRP	10.03	11.76	34.77	3.65	3.37	2.99	3.16	2.56	2.78	2.91	2.55	4.03	4.43	3.72	3.79	3.5	65.23
	VEA	2.68	2.68	2.44	21.09	13.6	16.37	6.21	5.25	2.73	2.92	2.43	4.51	4.84	4.18	4.33	3.75	78.91
	VWO	2.71	2.9	2.29	14.24	20.73	13.83	5.96	4.72	3.07	3.31	2.75	4.91	5.27	4.55	4.66	4.11	79.27
	VT	2.54	2.6	2.28	17.99	14.85	21.47	6.01	4.81	2.51	2.7	2.25	4.17	4.48	3.87	3.99	3.48	78.53
	TNX	3.15	2.93	2.84	8.61	7.85	7.3	26.09	5.78	3.39	3.61	3.01	5.31	5.82	4.94	5.2	4.46	73.91
	BCO	2.87	2.86	2.53	8.21	7.23	6.84	6.04	31.66	2.94	3.08	2.61	4.83	5.19	4.45	4.55	4.1	68.34
BEAR	BTC	1.94	1.98	1.97	3.11	3.37	2.69	2.82	2.18	24.84	14.14	10.9	6.25	6.6	6.14	5.05	6.01	75.16
	ETH	1.89	1.97	1.95	3.11	3.38	2.7	2.79	2.13	13.7	25.14	11.52	5.93	6.56	5.73	5.34	6.17	74.86
	XRP	1.82	1.93	1.96	3.00	3.27	2.61	2.71	2.08	12.21	12.58	27.18	5.67	6.14	5.78	5.03	6.03	72.82
	VEA	2.00	2.04	2.06	3.87	4.06	3.31	3.26	2.65	4.63	4.89	3.73	18.08	14.08	15.93	8.79	6.61	81.92
	VWO	2.24	2.28	2.3	4.16	4.39	3.55	3.57	2.85	4.8	5.16	4.14	13.84	17.87	13.43	8.61	6.81	82.13
	VT	1.85	1.92	1.95	3.64	3.82	3.12	3.03	2.49	4.72	4.95	3.77	16.3	13.96	18.84	8.79	6.84	81.16
	TNX	2.39	2.43	2.44	4.43	4.67	3.77	3.9	3.00	4.46	5.15	3.96	10.58	10.44	10.3	20.95	7.14	79.05
	BCO	2.36	2.41	2.47	4.42	4.67	3.78	3.79	3.07	5.37	6.04	4.71	9.05	9.47	9.13	8.56	20.7	79.3
	TO	54.49	57.47	50.25	90.03	86.6	79.05	60.61	48.7	72.53	76.88	62.91	102.85	105.49	99.00	83.76	75.25	1205.86
	INC. OWN	87.87	88.83	85.02	111.12	107.33	100.52	86.7	80.35	97.36	102.02	90.08	120.93	123.36	117.84	104.72	95.95	cTCI/TCI
	NET	-12.13	-11.17	-14.98	11.12	7.33	0.52	-13.3	-19.65	-2.64	2.02	-9.92	20.93	23.36	17.84	4.72	-4.05	80.39/75.37
	NPT	2,00	3,00	0,00	12,00	11,00	8,00	4,00	1,00	6,00	8,00	5,00	14,00	15,00	13,00	10,00	8,00	

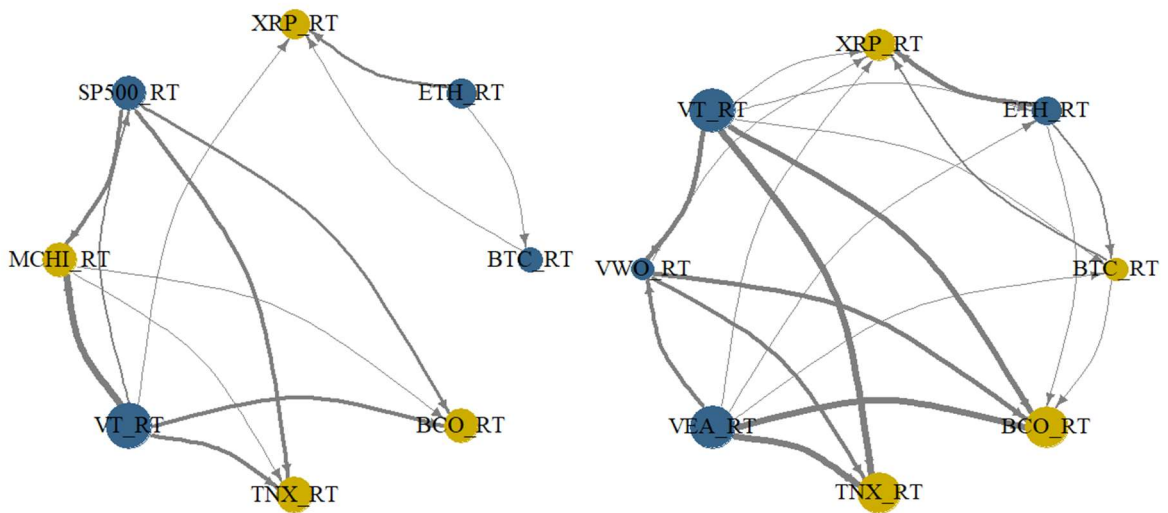
Notes: This table shows the static spillovers between the volatilities of cryptoassets and financial assets in the Bull and Bear markets analysed over the period from 1 January 2016 to 30 April 2024. Each (i,j)-th value represents the contribution of innovation in the volatility of asset j to the variance of the forecast error in asset i. The column headed 'From' aggregates the cumulative contributions to asset i of all other assets, while the row headed 'To' summarizes the impact of asset j on all other assets. The row labelled 'Net' captures the net pass-through transmitted by each asset to all other assets. Positive (negative) values indicate that the asset in question acts as a net transmitter (receiver) of spillovers to other assets. To facilitate interpretation, colour scales are used. The minimum value is highlighted in yellow for values between the crypto market and in light blue between the financial market, the maximum value for values between the crypto market is in dark blue and for the financial market is orange. Diagonal elements are not included in the colour scale (green)

FIGURE C1 - LASSO NET RETURN SPILLOVERS, H1 (left-hand side) AND H2 (right-hand side), 75% threshold



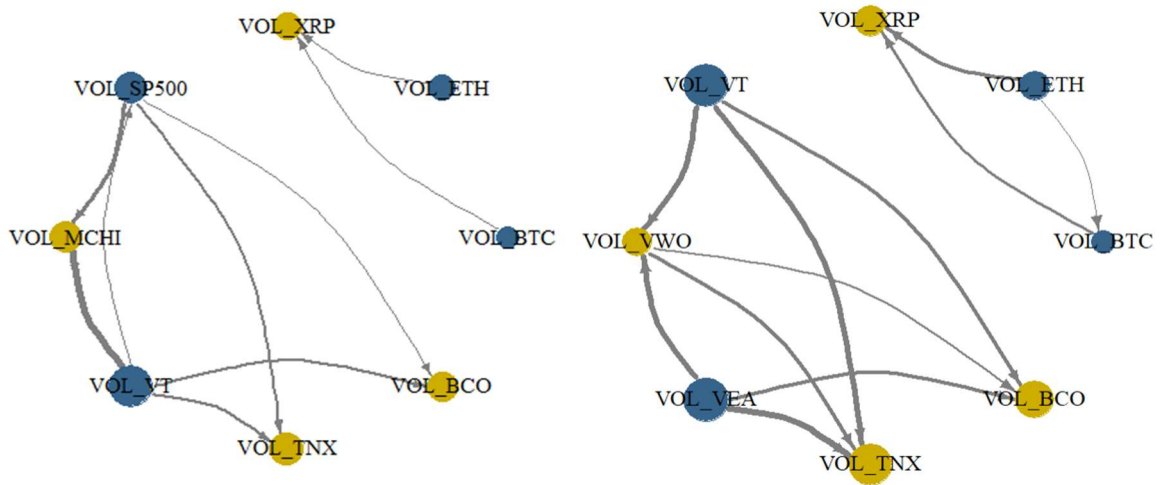
Notes: We show the most important directional connections among the pairs of crypto assets. Node size indicates the size of the total spillovers (sum of to and from) for each asset. The colour of the node indicates whether the asset is a net sender (blue) or a net receiver (yellow). The thickness of the arrows represents the strength of the spillovers (normalized to improve visibility), with only the top 75% percentile of bilateral spillovers shown

FIGURE C2 - LASSO NET RETURN SPILLOVERS, H1 (left-hand side) AND H2 (right-hand side), 90% threshold



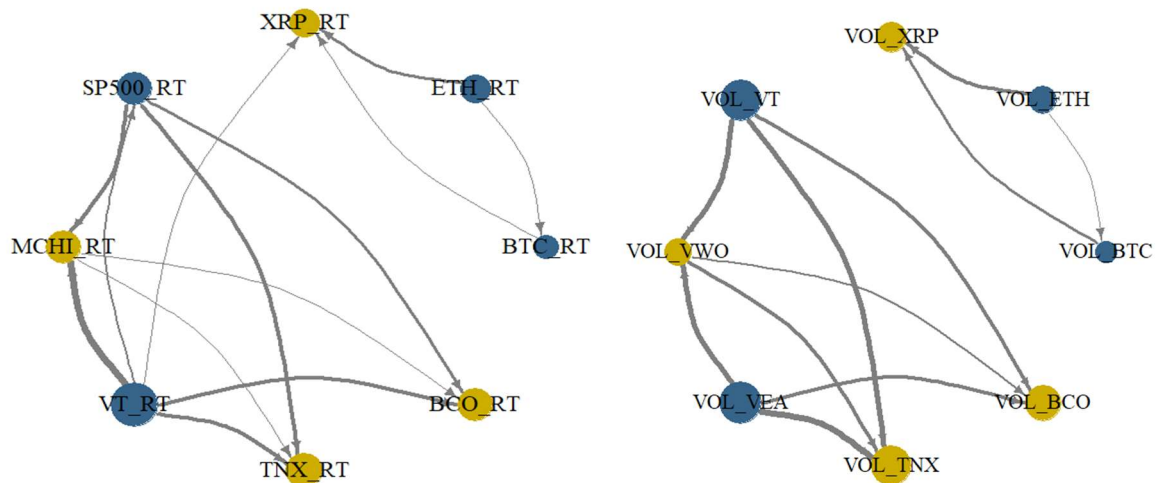
Notes: We show the most important directional connections among the pairs of crypto assets. Node size indicates the size of the total spillovers (sum of to and from) for each asset. The colour of the node indicates whether the asset is a net sender (blue) or a net receiver (yellow). The thickness of the arrows represents the strength of the spillovers (normalized to improve visibility), with only the top 90% percentile of bilateral spillovers shown

FIGURE C3 - LASSO NET VOLATILITY SPILLOVERS, H1 (left-hand side) AND H2 (right-hand side), 75% threshold



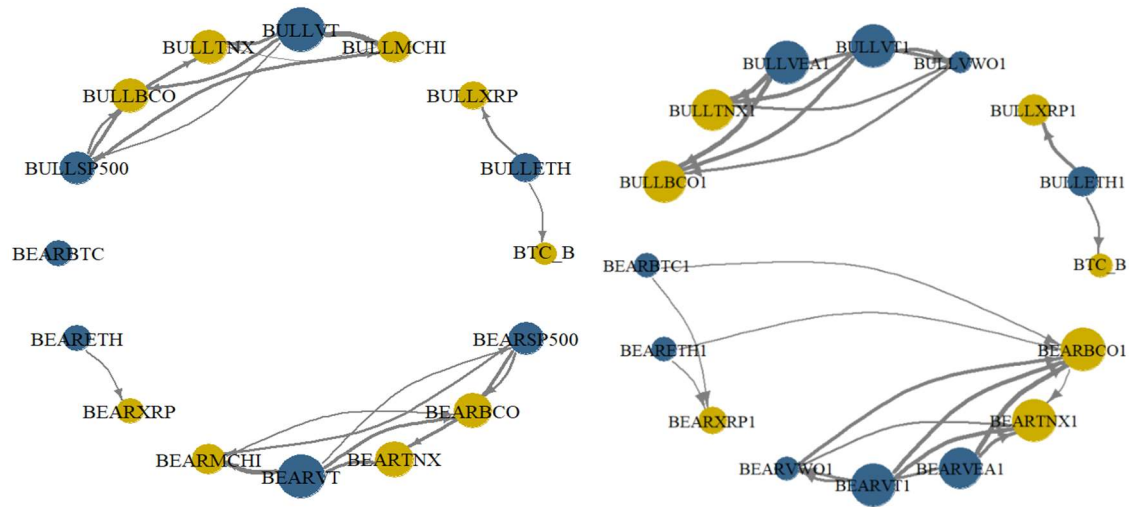
Notes: We show the most important directional connections among the pairs of crypto assets. Node size indicates the size of the total spillovers (sum of to and from) for each asset. The colour of the node indicates whether the asset is a net sender (blue) or a net receiver (yellow). The thickness of the arrows represents the strength of the spillovers (normalized to improve visibility), with only the top 75% percentile of bilateral spillovers shown

FIGURE C4 - LASSO NET VOLATILITY SPILLOVERS, H1 (left-hand side) AND H2 (right-hand side), 90% threshold



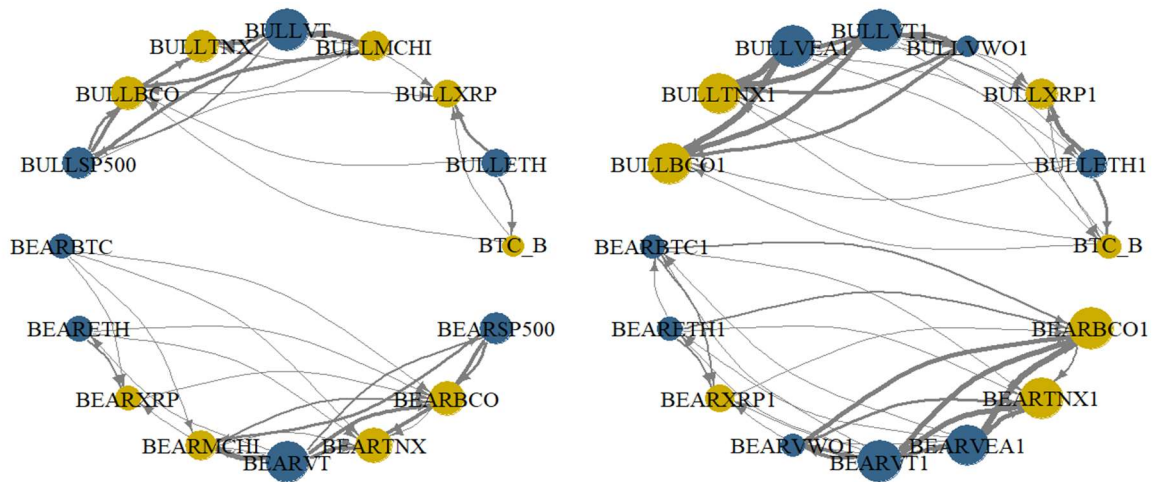
Notes: We show the most important directional connections among the pairs of crypto assets. Node size indicates the size of the total spillovers (sum of to and from) for each asset. The colour of the node indicates whether the asset is a net sender (blue) or a net receiver (yellow). The thickness of the arrows represents the strength of the spillovers (normalized to improve visibility), with only the top 90% percentile of bilateral spillovers shown

FIGURE C5 - LASSO NET RETURN SPILLOVERS IN BULL AND BEAR MARKET, H1 (left-hand side) AND H2 (right-hand side), 75% threshold



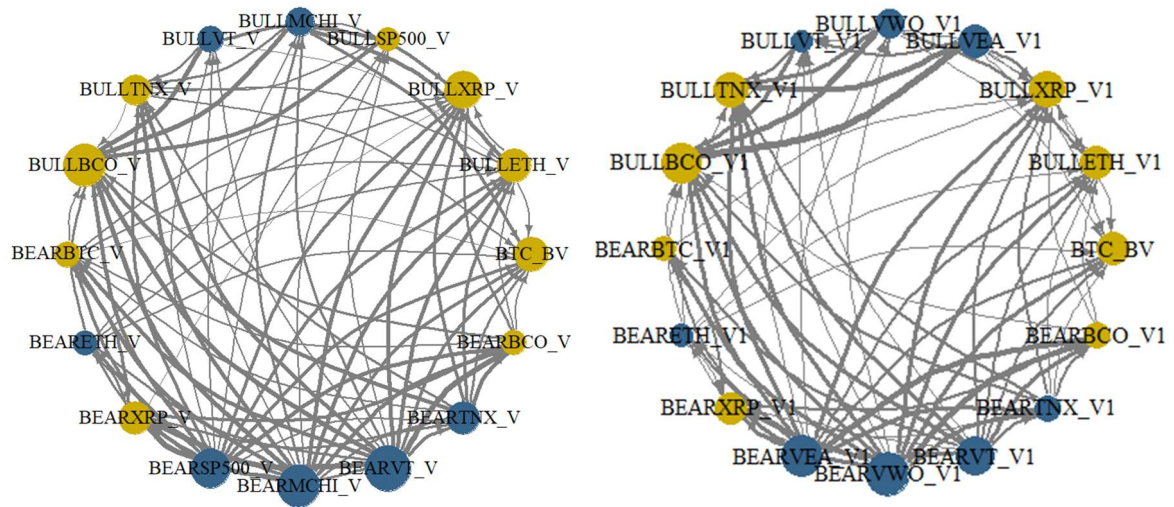
Notes: We show the most important directional connections among the pairs of crypto assets. Node size indicates the size of the total spillovers (sum of to and from) for each asset. The colour of the node indicates whether the asset is a net sender (blue) or a net receiver (yellow). The thickness of the arrows represents the strength of the spillovers (normalized to improve visibility), with only the top 75% percentile of bilateral spillovers shown

FIGURE C6 - LASSO NET RETURN SPILLOVERS IN BULL AND BEAR MARKETS, H1 (left-hand side) AND H2 (right-hand side), 90% threshold



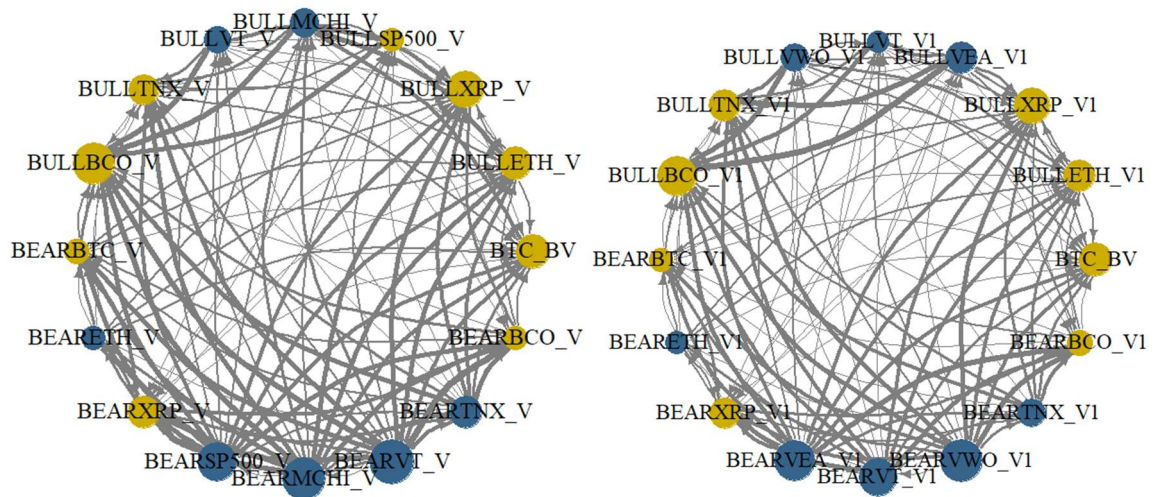
Notes: We show the most important directional connections among the pairs of crypto assets. Node size indicates the size of the total spillovers (sum of to and from) for each asset. The colour of the node indicates whether the asset is a net sender (blue) or a net receiver (yellow). The thickness of the arrows represents the strength of the spillovers (normalized to improve visibility), with only the top 90% percentile of bilateral spillovers shown

FIGURE C7 - LASSO NET VOLATILITY SPILLOVERS IN BULL AND BEAR MARKET, H1 (left-hand side) AND H2 (right-hand side), 75% threshold



Notes: We show the most important directional connections among the pairs of crypto assets. Node size indicates the size of the total spillovers (sum of to and from) for each asset. The colour of the node indicates whether the asset is a net sender (blue) or a net receiver (yellow). The thickness of the arrows represents the strength of the spillovers (normalized to improve visibility), with only the top 75% percentile of bilateral spillovers shown

FIGURE C8 - LASSO NET VOLATILITY SPILLOVERS IN BULL AND BEAR MARKETS, H1 (left-hand side) AND H2 (right-hand side), 90% threshold



Notes: We show the most important directional connections among the pairs of crypto assets. Node size indicates the size of the total spillovers (sum of to and from) for each asset. The colour of the node indicates whether the asset is a net sender (blue) or a net receiver (yellow). The thickness of the arrows represents the strength of the spillovers (normalized to improve visibility), with only the top 90% percentile of bilateral spillovers shown