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PERFORMANCE EVALUATION OF CRYPTOCURRENCIES: COMPARING CRYPTOCURRENCY AND STOCK MARKET PERFORMANCE

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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 do Professor Doutor Filipe Miguel Pereira Rodrigues da Costa

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Resumo

Este estudo analisa o desempenho das dez criptomoedas com maior capitalização até ao final de 2022 e compara-as com estratégias de investimento alternativas, no período de 1 de janeiro de 2016 a 31 de dezembro de 2022. Os resultados mostram que as criptomoedas têm características únicas em termos de rendibilidade e de risco, oferecendo níveis de rendibilidade sem precedentes, mas também níveis de risco elevados em comparação com os ativos tradicionais. O MATIC, o BNB e o BTC apresentam um desempenho superior ao de outras classes de ativos financeiros em termos de rácios ajustados ao risco, enquanto o ADA e o LTC são as criptomoedas com pior desempenho.

O estudo conclui também que as criptomoedas geram consistentemente rendibilidades anormais, com coeficientes alfa positivos e significativos em diferentes modelos de regressão. Os resultados também indicam que este desempenho superior depende do contexto, uma vez que os alfas estimados perdem a sua significância estatística em condições de mercado em baixa.

O estudo sugere que os investidores devem estar consientes dos riscos associados às criptomoedas e utilizar modelos de desempenho que ajustem a rendibilidade às fontes de risco relevantes.

Palavras chave: Criptomoeda, Ajustado ao risco, Desempenho, Descentralisado.

Abstract

This study examines the performance of ten cryptocurrencies with the highest capitalisation by the end of 2022 and compares them with alternative investment strategies, over the period January 1, 2016, to December 31, 2022. The results show that cryptocurrencies have unique characteristics in terms of returns and risks, offering unprecedented levels of returns but also elevated levels of risk compared to traditional assets. MATIC, BNB, and BTC outperform other financial asset classes in risk-adjusted ratios, while ADA and LTC are the worst performing cryptocurrencies.

The study also finds that cryptocurrencies consistently generate abnormal returns, with positive and significant alpha coefficients across different regression models. The results also suggest that this outperformance is state-dependent, as the estimated alphas lose their statistical significance under bear market states.

The study suggests that investors should be aware of the risks associated with cryptocurrencies and use performance models that adjust return for relevant sources of risk.

Key words: Cryptocurrency, Risk-adjusted, Performance, Decentralised.

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List of Abbreviations

ADA – Cardano

BNB – Binance

BTC – Bitcoin

CAR4 – Carhart four factor model

CMA – Conservative Minus Aggressive

DOGE – Doge Coin

DpoS – Delegated Proof of Stake

ETF – Exchange Traded Fund

ETH – Ethereum

FF3F – Fama and French three factor

FF5F – Fama and French five factor

FF5F+ - Fama and French five factor plus

HML – High Minus Low

LSE – London Stock Exchange

LTC – Litecoin

MATIC – Polygon

MKT – Market

PoS – Proof of Stake

PoW – Proof of Work

RMW – Robust Minus Weak

SMB – Small Minus Big

SOL – Solana

TRX – Tron

WML – Winner Minus Loser

XRP – Ripple

Chapter - Introduction

Bitcoin is a cryptocurrency that can be traded all over the world. Cryptocurrency is stored as a string code and can be accessed via a digital wallet, which can be installed on a smartphone or computer. The most remarkable aspect is the complete absence of involvement by any government or financial institution in the cryptocurrency's transactions. Bitcoin, the first decentralised blockchain-based digital currency, is the most recognised between all the cryptocurrency market. Cryptocurrencies pose significant challenges and issues for traditional financial systems because their value is based on specific algorithms that record transactions within the blockchain networks. On the one hand it is based on a fundamentally new technology, called Blockchain, which is not fully understood by investors. On the other hand, at least in the current forms, it fulfils similar function as other traditional assets. In recent years, cryptocurrencies have attracted more attention in the wider community with market capitalisation reaching a high level. In 2013, the total market capitalisation for all cryptocurrencies combined was approximately 1.5 billion USD. By 2017, it had exceeded 600 billion USD and in 2021, the market capitalisation surpassed 2 trillion USD, marking a historic all-time high.

Satoshi Nakamoto the creator of Bitcoin used history to justify the creation of Bitcoin in 2009: "*The root problem with conventional currency is all the trust that's required to make it work. The central bank must be trusted not to debase the currency, but the history of fiat currencies is full of breaches of that trust. Banks must be trusted to hold our money and transfer it electronically, but they lend it out in waves of credit bubbles with barely a fraction in reserve. We must trust them with our privacy, trust them not to let identity thieves drain our accounts. Their massive overhead costs make micropayments impossible.*"

Cryptocurrencies are a new phenomenon worthy that deserves attention in economic and financial research. Our study aims to contribute to this research by evaluating the performance of a representative group of cryptocurrencies, defining performance as the return on investment adjusted for the level of risk involved.

Our main objectives are to assess if: (i) cryptocurrencies outperform broad stock market investments, (ii) their outperformance persists when accounting for systematic risk, and (iii) cryptocurrencies generate superior performance during both bull and bear markets.

In order to accomplish these objectives, we evaluate the performance of the ten cryptocurrencies with the largest capitalisation by the end of 2022: Bitcoin (BTC), Ethereum

(ETH), Ripple (XRP), Dogecoin (DOGE), Litecoin (LTC), Binance (BNB), Cardano (ADA), Tron (TRX), Polygon (MATIC) and Solana (SOL) and compare them with alternative investment strategies, over the period January 1, 2016, to December, 31, 2022. We start by calculating simple performance measures including the Sharpe and Sortino ratios. Then we estimate benchmark-adjusted alphas, using alternative passive benchmarks strategies that mirror real investment opportunities available to investors. These alternative strategies are represented by exchange-traded funds of stocks, gold, commodities, and bonds.

Additionally, we estimate risk-adjusted alphas using three of the most common risk-factor models in the finance literature: the single-factor Capital Asset Pricing Model (CAPM), the Fama-French (1992) three-factor model, and a six-factor model that extends the Fama-French five-factor model (Fama and French, 2015) to incorporate momentum (Carhart, 1997). The resemblance of cryptocurrencies to common stocks provides a rationale for employing Fama and French stock models to assess cryptocurrency performance (see, among others, Alfieri et al., 2019).

Finally, in order to assess whether the cryptocurrency performance is influenced by market conditions, we estimate risk-adjusted alphas with dummies for bull and bear periods in stock markets.

This study makes several unique contributions to the literature. Unlike much of the previous research, we analyse not just one cryptocurrency individually but a set of ten, enabling us to examine potential differences among them. Furthermore, our extended time span allows us to investigate more recent and significant altcoins, such as ETH, BNB, and SOL. Lastly, we assess whether cryptocurrency performance is influenced by bull and bear periods in stock markets.

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

1 Cyptocurrencies : background context

The aim of this section is to enhance our comprehension of cryptocurrency. We start by contrasting cryptocurrency with virtual currency. Whilst both are types of digital currency, the have distinct characteristics. Secondly, we explore the history of cryptocurrency development to better frame its evolution and role. Then, we highlight its key merits and drawbacks. Finally, we categorise cryptocurrency according to its nature between currency, commodity, or financial speculative asset.

1.1 Cryptocurrency vs. Virtualcurrency

Cryptocurrency is a type of currency that functions independently of a central bank and uses encryption for protection. It is a decentralised system that secures transactions and controls the generation of new units using powerful cryptographic techniques. The demand for a secure, digital method of payment that is not controlled or regulated by any centralised authority gave rise to the concept of bitcoin (Giudici et. al., 2020). Cryptocurrency is a type of currency that only exists electronically or digitally. Digital currencies, unlike traditional forms of money including coins or banknotes, have no physical substance. They are generated and stored electronically using modern cryptography techniques (Sitthipon et. al., 2023; Urquhart & Lucey, 2022). Individuals often use digital wallets to store and handle cryptocurrencies. These wallets are software tools that provide a safe place to store and manage. To transmit and receive cryptocurrencies, digital wallets enable users to generate unique addresses, which function similarly to digital bank account numbers (Urquhart & Lucey, 2022). Cryptographic keys, including a public key and a private key, are used by digital wallets to offer safe access to and control over cryptocurrency. The public key is used to receive funds, while the private key is kept private and is used to sign transactions, establishing ownership and approving funds transfers. It is critical to protect the private key because it is the key that gives access to the wallet and its related cash (Jørgensen & Beck, 2022). Cryptocurrency uses blockchain technology to function on decentralised networks. A distributed ledger called blockchain keeps track of all cryptocurrency transactions; by making all transactions immutable and publicly visible, it ensures openness and security (Cretarola et. al., 2021).

Several advantages exist between digital cryptocurrency and traditional types of money. They provide improved security since blockchain transactions are particularly resistant to alteration and fraud. Furthermore, cryptocurrencies allow for faster and more efficient cross-border transactions, eliminating the need for intermediaries including banks or financial organisations. Furthermore, they provide greater financial inclusion because everyone with internet access, regardless of geography or socioeconomic position, can engage in crypto transactions (Bunjaku et. al., 2017). Despite these benefits, digital currency is not without hurdles and criticism. Price volatility, regulatory uncertainty, scalability limitations, and worries about energy consumption and environmental effect are just a few of the issues that the bitcoin business is addressing. (Liu et. al., 2022).

Virtual currencies in virtual settings have grown in popularity in recent years, particularly in the world of online gaming. They improve the gaming experience by letting gamers to buy virtual objects, costumes, accessories, or even in-game bonuses that can improve gameplay or give them a competitive advantage (Asadi & Hemedi, 2018). Virtual currency is a sort of digital currency that is used in virtual environments like video games or virtual worlds. These currencies differ from cryptocurrencies, they often have no value outside of the virtual environment in which they are used (Frick, 2019). Virtual currencies are developed by the virtual environment's developers or operators and are frequently designed to assist in-game transactions or purchases. They function as a medium of trade within the virtual economy, allowing players to get virtual goods, services, or experiences within the game (Asadi & Hemedi, 2018). While virtual currencies have no real-world value, some collectors participate in secondary marketplaces where virtual products or currencies can be swapped for real money. These marketplaces operate outside of the virtual world and must comply with a variety of legal and regulatory requirements (Giudici et. al., 2020).

It is vital to highlight that virtual currencies and cryptocurrencies operate on separate platforms and serve different functions. Cryptocurrencies seek to replace traditional fiat currencies by enabling decentralised, secure, and transparent financial transactions. They are not limited to a single virtual environment and are intended for use in the real world (Kumar, 2022; Perez, 2019). Virtual currencies, on the other hand, are exclusive to virtual environments and are largely utilised for transactions and experiences within such virtual spaces. They have no value outside of the virtual ecosystem and are controlled by the virtual environment's developers or operators (Guo et. al., 2019; Perez, 2019).

1.2 Brief history of the cryptocurrencies

As technological breakthroughs prepared the door for new possibilities in the financial environment in the late twentieth century, the concept of digital currency began to gain traction. David Chaum, an American cryptographer, and computer scientist, is a key figure in this field (Chaum et. al., 2021). Chaum made seminal contributions to the development of digital currency in the 1980s with the introduction of eCash, a cryptographic electronic money. Many of the concepts and principles present in modern cryptocurrencies may be traced back to Chaum's work. While Chaum's eCash system was important and seen as a big development in digital currency at the time, it did not achieve widespread adoption. Barriers to entrance, like limited internet usage and a lack of technological infrastructure, have hindered digital currencies from being widely implemented and accepted (Baddeley, 2004; Ebringer & Thorne, 1999; Prasad, 1998). Chaum's work, on the other hand, set the groundwork for future breakthroughs in the field of cryptocurrency. His emphasis on anonymity and security established a precedent for the basic qualities that modern cryptocurrencies respect.

However, the world was not introduced to the first decentralised cryptocurrency Bitcoin until 2008. Under the alias Satoshi Nakamoto, an unknown individual or group produced the Bitcoin whitepaper titled "Bitcoin: A Peer-to-Peer Electronic Cash System." In this whitepaper, a revolutionary cryptocurrency based on decentralised blockchain technology is proposed (Bonneau et. al., 2015; Nakamoto, 2008).

The primary goal of Bitcoin was to create a peer-to-peer electronic cash system that would eliminate the need for intermediaries including banks or financial organisations. Because Bitcoin is decentralised, individuals can conduct secure and transparent transactions with one another without the requirement for a central authority to oversee or validate the transactions (Nakamoto, 2008; Nakamoto, 2009). The introduction of Bitcoin in January 2009 signaled the beginning of the cryptocurrency age. Bitcoin pioneered a new way of thinking about money and established an alternative financial ecosystem independent of existing banking systems. It gave consumers the opportunity to digitally store and transfer value, piqued the interest and curiosity of engineers, financial experts, and early adopters (Marzo et. al., 2022). A blockchain is a distributed and decentralised digital ledger that transparently, securely, and immutably records and preserves a sequence of transactions or data. It is the fundamental technology for most cryptocurrencies. The name "blockchain" alludes to the idea of a series of blocks, each of which contains a collection of transactions (Michael et. al., 2018). A blockchain's blocks contain transaction information including the sender, the receiver, the amount transferred, and a timestamp. Furthermore, each block carries a unique identification known as a cryptographic hash that links it to the previous block in the chain. This connection protects the blockchain's integrity and immutability (Treiblmaier, 2020). The primary feature of a blockchain is decentralisation. The blockchain is maintained and validated by a distributed network of computers known as nodes, rather than a single authority or middleman. Each node has a copy of the complete blockchain that is constantly updated as new blocks are added (Zarrin et. al., 2021). Various consensus processes are utilised to ensure the security of the blockchain. Proof-of-Work (PoW) is the most well-known consensus technique. Miners compete in PoW to solve mathematical puzzles, as previously indicated, to validate and add new blocks to the blockchain. However, there are alternative consensus processes that use different techniques of block validation, including Proof-of-Stake (PoS) and Delegated Proof-of-Stake (DPoS) (Harper, 2018). Miners are critical members in blockchain networks who undertake critical duties like as transaction validation and security. They give processing power and resources to the network, maintaining the blockchain's integrity and functionality. The name "miners" comes from the concept of digging for valuable materials and being rewarded for their work (Xu et. al., 2021). Miners are critical in ensuring consensus among network participants in the context of blockchain. They accomplish this by mining, which entails solving difficult mathematical riddles or algorithms. Miners validate transactions and add them to the blockchain by successfully solving these challenges (Xu et. al., 2021). Miners' primary task is to check the legitimacy of new transactions. They confirm that the sender has enough funds and authority to complete the transaction. This mechanism eliminates double-spending and guarantees that only valid transactions are posted to the blockchain (Komalavalli et. al., 2020). Miners compete to solve mathematical riddles, and the first miner to find the correct solution broadcasts it to the network. This miner is then rewarded and is appointed as the temporary leader in charge of adding a new block to the network. The process of solving these problems needs a significant amount of computer power, and miners frequently employ specialised hardware to boost their chances of success (Nilsen et. al., 2022).

The world of cryptocurrencies is vast and diversified, stretching far beyond the pioneering Bitcoin. Alternative coins, sometimes known as altcoins, have entered the cryptocurrency market. These are all cryptocurrencies other than Bitcoin. Some are similar to Bitcoin, seeking to improve on the original idea, while others have broken free totally. They aim to perform a variety of roles, including supporting smart contracts, strengthening privacy safeguards, and catering to specific industries including social media and gaming (Martynov, 2020; Spurr & Ausloos, 2021).

Bitcoin uses a proof-of-work (PoW) consensus mechanism to ensure transaction confirmation and successful addition to the blockchain. Alternatively, cryptocurrencies, while based on identical technological foundations, frequently inject their own distinct twists into the mix. Different consensus procedures, including proof-of-stake (PoS) or delegated proof-of-stake (DPoS), may be used. These methods avoid the energy-intensive practice of mining, perhaps producing a more sustainable paradigm. At the same time, numerous altcoins have added new features to their blockchains to provide greater functionality (Ciaian & Rajcaniova, 2018).

Bitcoin is unquestionably the supreme cryptocurrency in terms of market valuation and acceptability. With the highest market capitalisation of any cryptocurrency, Bitcoin has attracted the interest of institutional investors and has been acknowledged as a form of payment by businesses worldwide (Kayal & Rohilla, 2021). Altcoins, on the other hand, have diverse market capitalisation, with some predicting exponential increase over time. However, in terms of overall recognition and usage, altcoins frequently lag Bitcoin. Nonetheless, famous altcoins including Ethereum, Ripple, and Litecoin have garnered significant attention and are widely traded (Dumitrescu, 2017).

The inherent volatility of all cryptocurrencies is an important factor to consider. Despite its status, BTC is no exception, and its value has fluctuated significantly since its inception. Because of its scarcity and limited supply, many people regard it as a high-risk, high-reward investment, or even a potential inflation hedge. Because of their lower market capitalisation and liquidity, altcoins frequently outperform Bitcoin in terms of price volatility, offering investors with both opportunities and hazards (Gupta & Chaudhary, 2022).

Bitcoin heralded the arrival of cryptocurrency in 2009. It was the field's first and only player by then. During its earliest stages, BTC was worthless, and its market capitalisation was close to zero. Its first notable price was recorded in 2010, when BTC traded around $0.003 (Chohan, 2022). With the advent of additional cryptocurrencies in the years since, this subject has gained increased interest. By 2011, various additional cryptocurrencies or Altcoins (alternatives to Bitcoin) have emerged, including Namecoin, SwiftCoin, and

Litecoin. These began to include additional features like as faster block generation times and more efficient mining operations (Pistunov & Nikolaenko, 2023).

The word market capitalisation refers to the entire dollar worth of a cryptocurrency's outstanding units; in traditional equity terms, it is similar to the share price multiplied by the number of shares outstanding. In 2013, the total cryptocurrency market cap was roughly 1.5 billion USD (Taskinsoy, 2020). More cryptocurrencies entered the market between 2014 and 2016. The biggest breakthrough, however, occurred in 2015, with the introduction of Ethereum. Unlike Bitcoin, Ethereum introduced "Smart Contracts" and the concept of "Decentralised Applications," making blockchain more than just a financial transaction medium (Cai et. al., 2018). By early 2017, the number of cryptocurrencies had surpassed 700, and the crypto market cap had surpassed $18 billion. The cryptocurrency industry had an unparalleled rise at the end of 2017, with Bitcoin reaching about $20,000 in value and the whole market worth rising to around 600 billion USD. This period saw a surge in the number of new investors entering the cryptocurrency market (Corral et. al., 2022). According to the currency market tracking website CoinMarketCap, it was expected over 10,000 distinct cryptocurrencies in 2021. The global cryptocurrency market cap was around $750 billion at the start of the year, and by April 2021, it had crossed $2 trillion for the first time (Pessa et. al., 2023). As a result, the evolution of cryptocurrencies has been characterised by exponential expansion, both in terms of the quantity of cryptocurrencies and their market valuation. Despite instability and governmental attention, the area continues to evolve, demonstrating considerable future promise. Since its inception with Bitcoin in 2009, the cryptocurrency sector has experienced fast growth and evolution. In comparison to traditional investment vehicles including ETFs, gold, and stock markets, the cryptocurrency industry has grown tremendously but continues to be smaller. To begin, according to EPFR, the worldwide assets under management in the ETF market, which consists of a collection of securities that are exchanged, often on major exchanges, exceeded $10 trillion by the end of 2021. This market value still far eclipses that of all cryptocurrencies (PWC, 2022). Consider the gold market, which has served as a safe haven for thousands of years. The total market capitalisation of all gold ever mined was expected to be around $10 trillion in 2021. This is about five times the total market capitalisation of all cryptocurrencies (Stevens, 2021). The overall global stock market was worth approximately $95 trillion as of 2021. This dwarfs the cryptocurrency market, demonstrating that bitcoin, despite its rapid rise, has still a minor role in the global financial system (Jeris et. al., 2022; Price, 2023). Finally, the commodities market is big and diverse, since it comprises a wide range of products including oil, natural gas, wheat, among others. While an exact figure is difficult to calculate, the annual market size for the oil business alone is roughly $1.7 trillion (Ji et. al., 2019). The cryptocurrency industry began with Bitcoin and had since grown to encompass over 10,000 distinct types of cryptocurrencies. The exponential growth tend of this sector has seen its market cap expand from $10 billion in 2013 to $2 trillion in 2021, demonstrating a phenomenal expansion in less than a decade. The cryptocurrency market still represents a fraction of other more established financial markets, but the crypto market's growth rate and potential cannot be overlooked. However, the bitcoin market's limited size does not reflect its significance or potential. Its impact on financial systems, transaction procedures, and the whole concept of money has been revolutionary. As the market evolves and matures, it is expected to command a larger portion of the global financial landscape (Feng, 2023).

In the table below, different cryptocurrencies are compared to Bitcoin (BTC), because it was the first and most well-known cryptocurrency. Ethereum (ETH), Ripple (XRP), Dogecoin (DOGE), Litecoin (LTC), Binance Coin (BNB), Cardano (ADA), TRON (TRX), Polygon (MATIC), and Solana (SOL).

The key characteristics or functions of each cryptocurrency are highlighted in the "Main Characteristics" column. Their functionalities and targeted use cases are briefly described in this section. While Ripple (XRP) focuses on digital payments for banks (Crawley, 2021), Ethereum is a smart contract framework made to support decentralised applications (dApps) (Kushwaha et. al., 2022). Due to similarities with other cryptocurrencies, Litecoin (LTC) is frequently referred to as the "silver" to Bitcoin's "gold" (Yu et. al., 2023), and Dogecoin (DOGE) is known for being a humorous cryptocurrency based on a meme (Chohan, 2021). Three unique characteristics of each cryptocurrency are stated under "Differences from Bitcoin (BTC)" in the table. These traits help set them apart from Bitcoin and emphasise their distinctive value propositions. For instance, compared to Bitcoin, Ethereum has programmable blockchain capability outside of money use, uses a different consensus mechanism (Proof-of-Stake), and confirms blocks more quickly (Rankhambe & Khanuja, 2019). With a pre-mined quantity that differs from Bitcoin's, Ripple (XRP) primarily targets financial institutions and employs a distinct consensus protocol (XRP Ledger)(Chase & MacBrough, 2018).

Similar to how Bitcoin differs from the other cryptocurrencies in the table, each of them has its unique use cases, consensus mechanisms, transaction rates, community-centeredness, and ecosystem-specific uses.

TABLE 1 – MAIN DIFFERENCES FROM BITCOIN

Cryptocurrency	Main Characteristics	Differences from Bitcoin (BTC)
BTC	First and most well-known cryptocurrency	- Serves as the benchmark for other cryptocurrencies. - High market capitalization and widespread recognition.
ETH	Smart contract platform, powering decentralised applications (dApps).	- Offers programmable blockchain functionality beyond currency use - Utilizes a more advanced consensus algorithm (Proof-of-Stake) - Faster block confirmation times.
XRP	Digital payment protocol and cryptocurrency for banks	- Primarily targets financial institutions, providing faster, low-cost international payment settlement. - Utilizes a different consensus protocol (XRP Ledger) with validators instead of miners. - Pre-mined supply, coins not obtained through mining.
DOGE	Initially created as a meme, gained popularity for tipping and fun purposes	- Emphasizes a lighthearted, community-driven approach, lacking distinct functionality compared to BTC. - Higher coin supply and faster block generation times. - Known for its active and passionate online community
LTC	Often considered as "silver" to Bitcoin's "gold."	- Provides faster block confirmation times and uses a different hashing algorithm (Scrypt) compared to BTC. - Has a larger maximum supply (84 million coins). - Early adoption of Segregated Witness (SegWit) technology.

Table 1 (continued)

BNB	Native cryptocurrency of the Binance exchange	- Primarily used within the Binance ecosystem for discounted trading fees and participation in token sales. - Powers the Binance Smart Chain, offering smart contract functionality. - Offers utility for various applications such as staking and governance on the Binance platform.
ADA	Utilizes a proof-of-stake consensus algorithm (Ouroboros).	- Employs a different consensus mechanism emphasizing energy efficiency, distinct from Bitcoin's proof-of-work. - Focuses on scalable and sustainable decentralised applications. - Designed with a strong focus on security and formal verification
TRX	Aims to build a decentralised entertainment content sharing platform	- Focuses on creating a decentralised digital entertainment ecosystem, offering different use cases than BTC. - Utilizes delegated proof-of-stake (DPoS) consensus, enabling faster transaction confirmation. - Designed to handle high transaction volumes
MATIC	Scalable layer 2 solution for the Ethereum network	- Aims to improve scalability and transaction speeds on the Ethereum network using sidechains. - Implements a proof-of-stake (PoS) consensus mechanism. - Offers interoperability and compatibility with Ethereum.
SOL	Native cryptocurrency of the Solana blockchain platform	- Utilizes a unique consensus mechanism (Proof-of-History) to achieve high transaction throughput and scalability. - Focuses on ultra-fast transaction speeds and low fees. - Designed for decentralised applications and DeFi on the Solana network

Source: Author's own elaboration

1.3 Advantages and disadvantages of the cryptocurrencies

By providing a substitute for existing currencies and presenting a variety of distinctive benefits, cryptocurrencies have completely changed the financial landscape. But it's important to go into further depth about both the advantages and disadvantages.

The decentralisation of cryptocurrencies is one of its most notable features. Cryptocurrencies run on decentralised blockchain networks, in contrast to conventional fiat currencies, which are managed by central banks and subject to government regulation. Since there in no longer a middleman, users have more power over their money thanks to decentralisation. Additionally, it shields cryptocurrencies from manipulation or meddling by the government, providing some degree of financial independence and security (Makarov & Schoar, 2022). Additionally, the availability of financial transactions for people all over the world has been made possible by cryptocurrencies like Bitcoin and Ethereum. Cryptocurrencies promote financial inclusion by requiring only an internet connection and a digital wallet, especially in areas with little or no access to traditional banking services. Individuals are now more able to take part in international financial transactions and explore previously unavailable business prospects (Carmona, 2022). Also, the quickness and effectiveness of cryptocurrency transactions are praised. Cryptocurrencies rely on decentralised networks that allow for almost instantaneous transactions, in contrast to traditional banking systems that may include time-consuming procedures like clearinghouses and intermediaries. For a variety of use situations, like cross-border payments and remittances, where conventional techniques can be time-consuming and expensive, this speed and efficiency is useful (Gowda & Chakravorty, 2021). The privacy that bitcoins provide is yet another important benefit. While record-keeping and the need for personal identification are common in traditional banking systems, cryptocurrency users can conduct transactions with some degree of anonymity. Users are often not identifiable by their real names during transactions and are instead identified by cryptographic addresses. With the use of this privacy feature, users can have more control over their personal data and avoid having their financial information compromised (Yu et. al., 2022). Finally, the high return on investment is another benefit of cryptocurrencies. Dramatic price swings in the cryptocurrency market have produced huge profits for astute investors. Since its launch, Bitcoin's value has increased dramatically, garnering attention from a wide audience and demonstrating the possibility of substantial gains. However, it should also be noted that if not handled with prudence and effective risk management, this volatility can also result in substantial losses (Liu & Tsyvinski, 2021).

Although cryptocurrencies have numerous benefits, it is important to understand their drawbacks and hazards as well. The price volatility of cryptocurrencies is the main source of worry. The cryptocurrency market is extremely vulnerable to jarring price shifts brought on by changes in market sentiment, legislation, or technological advancements. Investors should therefore be ready for both the risk of big losses and the possibility of sizable returns

(Al-Yahyaee et. al., 2020). Additionally, the absence of a central regulatory body in charge of regulating the cryptocurrency market is another matter of concern. Although decentralisation is a key component of cryptocurrencies, it also makes the market susceptible to fraud and manipulation. Additionally, customers might have no recourse if they run across problems like lost property or fraudulent activity in the absence of centralised monitoring (Kutera, 2022). The scalability of cryptocurrency is another issue. Transaction speed and processing costs may change as additional users join the network. For instance, Bitcoin has experienced scaling problems that cause delays and excessive fees during periods of increasing network congestion. To overcome these issues and increase scalability, actions are being taken like the creation of layer-two solutions like the Lightning Network (Zhou et. al., 2020). In addition, the potential for cryptocurrencies to facilitate illegal activity has drawn criticism. There are worries that cryptocurrencies can be used for money laundering, tax evasion, and other illegal activities due to the anonymity and pseudonymity connected with transactions. It is important to underline that genuine bitcoin transactions greatly exceed any illegal ones, but this problem shows the necessity for stronger security safeguards and regulatory frameworks (Baek et. al., 2019). Finally, there is discussion on how cryptocurrencies will affect the environment. Due to its carbon footprint, the energy usage incurred when mining cryptocurrencies, especially Bitcoin, has received attention. Blockchain networks need a lot of computing power to validate and record transactions, which is an energy-intensive operation (Martynov, 2020).

1.4 The nature of the cryptocurrencies: currency, commodity or financial speculative asset?

Cryptocurrencies have distinctive qualities that make it difficult to categorise them. Depending on the context and viewpoint, they can be viewed as a hybrid of a money, a commodity, and a financial speculative asset.

First, cryptocurrencies were initially imagined as digital money. They permit peer-to-peer exchanges and can be applied to the acquisition of products and services. For instance, Bitcoin was created with the goal of being a decentralised digital currency. Certain cryptocurrencies aspire to replace fiat money by providing speedier cross-border transactions and obviating the need for middlemen. It's crucial to remember that just a small number of people are now using cryptocurrency for regular transactions (Faturahman et. al., 2021).

Second, some aspects of cryptocurrencies are similar to those of commodities. Since they are scarce, their value may be impacted by their restricted supply, with some cryptocurrencies having a predetermined maximum issuance. Moreover, cryptocurrency mining requires energy and processing capacity, much like the extraction and manufacturing processes that are involved in the manufacture of commodities. Additionally, cryptocurrency exchanges frequently trade them, much like commodity futures markets do (Vejačka, 2014). Nonetheless, due to of disagreements over definitions and authority between regulators, developers, traders, investors, and judges, the framework for classifying digital commodities and other assets remains unclear (Frankenfield, 2023).

Finally, it is impossible to overlook the speculative nature of cryptocurrencies. Numerous investors looking for speculative possibilities have been drawn to the volatility and possibility for big gains or losses. The price of cryptocurrencies has fluctuated noticeably due to market sentiment, legislative changes, technological improvements, and investor activity. This element of speculation has given rise to a brand-new asset class that is susceptible to fluctuations in investor sentiment and market dynamics (Almeida & Gonçalves, 2022). However, there seems to be a potential for illicit use through its anonymity within a young, underdeveloped exchange system, and infrastructural breaches influenced by the growth of cyber criminality (Corbet et. al., 2018).

It's crucial to note, though, that different regulatory agencies, nations, and financial institutions may have different classifications for cryptocurrencies. While some organisations might see them primarily as currencies, others might see them more as commodities or financial speculative assets. The classification of these digital assets is still a subject of debate and legislation given the dynamic nature of cryptocurrencies and their expanding acceptance across numerous industries.

2 Review of empirical literature

In this section, we discuss the empirical findings of previous work measuring the performance of crypto assets and review the methodologies employed in a broader literature on performance measurement.

Alfieri et al., (2019) conducted an empirical study on the financial performance of Bitcoin (BTC) over the period from 22/Sep/2010 to 30/Dec/2016. The study employs quantitative methodologies to assess BTC's performance, primarily focusing on risk-adjusted return. To achieve this, the researchers estimate the alpha from the FF3F model and the alpha from the FF5F model. The central finding of the study is that BTC shows low correlation with traditional financial indices, indicating potential diversification benefits. Furthermore, BTC exhibits a positive and statistically significant alpha, suggesting it outperforms conventional assets within the study's timeframe.

Bianchi and Babiak (2022) present a comprehensive analysis of the performance of cryptocurrency funds in an unregulated market. They utilise a dataset comprising over 200 actively managed funds spanning from March 2015 to June 2021. The study examines both aggregate and individual fund performance through various regression analyses. The primary focus is on cryptocurrency-focused funds, and the study's main empirical findings reveal that these funds consistently generate significantly positive alphas in comparison to passive benchmarks and conventional risk-factors. The authors validate this by comparing actual fund alphas with simulated values derived from a panel semi-parametric bootstrap approach. While the study's results suggest that this notable outperformance is not merely a matter of luck, the statistical significance of these alphas weakens when accounting for cross-sectional correlation among fund returns. Empirically, the study examines the performance of 250 cryptocurrency-focused funds actively managed. The analysis begins with an assessment of aggregate fund performance in contrast to alternative passive investment strategies, including a buy-and-hold investment in Bitcoin, an equal-weighted portfolio of top cryptocurrencies, a value-weighted average of tokens listed on Coinbase, and a buy-and-hold investment in Ethereum. The study calculates alphas for equal-weighted portfolios of all funds as well as specific fund types and investment strategies.

Chokor and Alfieri (2021) delve into the influence of regulatory developments on cryptocurrency market performance. The study explores how cryptocurrency traders perceive market regulation and employs an event study methodology using daily data spanning from 2015 to 2019. The research uncovers that regulatory news and events have a significant impact on cryptocurrency markets, particularly in terms of returns. Cryptocurrencies characterised by greater illiquidity and higher information asymmetry risk exhibit fewer negative reactions. Furthermore, the study extends its analysis to assess the long-term effects of regulatory events on cryptocurrency performance. To achieve this, the researchers employ traditional performance measures, including the Sharpe Ratio, Fama and French three-factor model, and Carhart four-factor model. Two distinct periods are considered: the pre-event period, from 24/Jun/2016 to 24/Jun/2017, and the post-event period, from 21/Oct/2018 to 21/Oct/2019. The chosen sample for the study comprises the top thirty cryptocurrencies based on market capitalisation as of July 2019.

Gregoriou (2019) investigates the impact of trading cryptocurrencies on the London Stock Exchange (LSE). The primary focus of the study is to determine whether investors can achieve abnormal returns by daily trading cryptocurrencies and the implications of these returns on asset pricing models. The research reveals that investors do obtain abnormal returns through daily trading of cryptocurrencies on the LSE. Even after accounting for systematic risk, size, value, momentum, profitability, and investment, excess returns persist. This persistence of abnormal returns implies inefficiency in the cryptocurrency market. The study examines the impact of cryptocurrency returns on asset pricing models and conducts empirical research on all stocks listed on the LSE over the 2014-2017 period. To assess abnormal time series performance of portfolios generated based on cryptocurrency returns, the study estimates the alpha from the FF3F model, the CAR4 model, and the alpha from the FF5F model. The data collection focuses on the ten largest cryptocurrencies by trading volume within the given dataset. The study constructs decile portfolios based on statistical measures, with Portfolio 1 (P1) comprising shares with the lowest cryptocurrency returns, and Portfolio 10 (P10) containing shares with the highest cryptocurrency returns. The findings provide strong evidence that individuals can achieve excess returns on the LSE by investing in cryptocurrencies, and that these abnormal returns persist even when considering established risk-factors in asset pricing, including systematic risk, size, value, momentum, profitability, and investment. This highlights the significant impact of cryptocurrencies on asset pricing models and suggests an inefficiency in the cryptocurrency market.

Bouri et al., (2018) investigates the relationships between Bitcoin and traditional asset classes, specifically equities, stocks, commodities, currencies, and bonds, in both bear and bull market conditions. The analysis covers daily data from 19/Jul/2010 to 31/Oct/2017. The authors utilised a methodological framework that employed a bivariate GARCH-in-mean (BTGARCH-M) model with a Dynamic Conditional Correlation (DCC) approach to model volatility. They also employed a smooth transition vector autoregressive (STVAR) specification, allowing for market condition switches and asymmetry in conditional variance based on market situations. The "in-mean" component of the model explicitly captures the effects of different volatility spillovers on returns. They tested various hypotheses of asymmetric spillovers of returns and volatility using the Wald test. The dataset included Bitcoin prices and proxies for four asset classes: MSCI World, MSCI Emerging Markets, MSCI China, S&P GSCI Commodity, S&P GSCI Energy, gold, US dollar index, and US 10-year Treasury yields. The research revealed significant evidence of return spillovers between Bitcoin and the four asset classes studied. These spillovers were often asymmetric and varied depending on market conditions. The study also found significant volatility spillovers to the Bitcoin market, with minimal feedback effects to other markets. The study observed differences in spillover significance and direction in bear and bull market conditions. These results challenge the notion that Bitcoin operates in complete isolation from traditional financial systems and economic factors. The study's findings suggest that Bitcoin's behaviour is more intertwined with traditional asset classes and is sensitive to economic fundamentals.

Van Wijk (2013) conducted an extensive study, where the relationship between Bitcoin and various stock indices, including Dow Jones, FTSE 100, and Nikkei 225, spanning from 2010 to 2013, was analysed. Using Ordinary Least Squares (OLS) regression and the Error Correction Model (ECM), this study revealed that the variables examined had a significant impact on Bitcoin's value, both in the short and long term. Of note, the variable with the most profound influence was linked to the United States' economy, notably the Dow Jones stock index, which exhibited a clear and positive correlation with Bitcoin. This relationship underscored the substantial role that economic conditions in the United States played in shaping Bitcoin's value.

Šafka (2014) delved into the relationship between Bitcoin's returns and prominent stock indices, including NASDAQ, Nikkei 225, and SSE Composite, within the time frame of 2010 to 2014. This investigation employed OLS models to scrutinise the connections. The findings presented in this study indicated a marked degree of independence between Bitcoin and the stock indices. Specifically, no significant relationships were identified, suggesting that Bitcoin operated somewhat autonomously from the broader stock market, especially during the observed period.

Matkovskyy and Jalan (2019) investigated the relationship between Bitcoin and an array of stock indices, which included NASDAQ 100, S&P 500, Euronext 100, FTSE 100, and Nikkei 225. The examination spanned from 2015 to 2018. Their study presented results that elucidated a significant contagion effect from traditional financial markets to Bitcoin. During periods of low Bitcoin prices, risk-averse investors were observed to shift their investments toward less volatile markets, exemplified by stock indices. This underscored the risk-on, risk-off dynamics in financial markets, which played a pivotal role in influencing Bitcoin's performance during various market conditions.

Ciaian et al., (2017) examined the intricate interplay between Bitcoin and Altcoin markets, both in the short and long term, during the period spanning 2013 to 2016. Their findings shed light on the interdependence between these two forms of cryptocurrency, with a more pronounced price relationship observed in the short term compared to the long term. This observation highlighted the intricate dynamics of cryptocurrency markets, which were influenced by a myriad of factors, including investor sentiment, technological developments, and broader economic conditions.

Liu and Tsyvinski (2021) investigate the complex dynamics of risk and return of cryptocurrencies compared with other traditional assets. Focusing on the years 2011 to 2018 and three key cryptocurrencies, Bitcoin, Ripple, Ethereum. The authors conclude that cryptocurrency returns are characterised by significantly higher volatility and returns compared to traditional assets. These cryptocurrencies exhibit minimal exposure to conventional stock market risk-factors, with ETH being notably sensitive to the HML factor. The authors studied CAPM betas for cryptocurrencies, they conclude significant alphas. This implies that while cryptocurrencies carry risk in line with the CAPM model, their returns remain notably significant. This observation highlights the distinct risk-return trade-off offered by cryptocurrencies compared to traditional assets including stocks, currencies, and precious metals.

Liu et al., (2022) conducted a thorough empirical analysis of the factors influencing cryptocurrency returns over the period 2014 to July 2020. They construct a single-factor model CAPM. This model falls short in explaining the cross-sectional variations in cryptocurrency returns, emphasising the need for more nuanced models. To address this, the authors introduce a three-factor model, comprising the Cryptocurrency Market Factor (CMKT), Cryptocurrency Size Factor (CSMB), and Cryptocurrency Momentum Factor (CMOM). This model successfully captures the cross-sectional variations in cryptocurrency returns. It also nullifies the statistical significance of alphas associated with various cryptocurrency portfolio investment strategies. The authors explore commonalities between the cryptocurrency market and the traditional currency market, uncovering shared level factors and momentum effects. However, traditional stock market factor models prove insufficient in explaining cryptocurrency returns. The study concludes the empirical challenge of a concentrated momentum effect among large cryptocurrencies, posing a challenge to underreaction-based explanations.

Wang et al., (2016) employed the Vector Error Correction Model (VECM) methodology to explore the dynamic relationship between Bitcoin's price and the Dow Jones stock index from 2011 to 2016. Their research unearthed a significant relationship. Interestingly, it was found that changes in the Dow Jones index had a noteworthy impact on Bitcoin's price. Bitcoin displayed a negative correlation with the Dow Jones index, meaning that when the stock market was thriving during economic prosperity, Bitcoin's price tended to decrease. However, a positive correlation was observed between Bitcoin's price and its transaction volume, signifying that when the economy faced a downturn or a stock market crisis, Bitcoin's price tended to rise. This observation underlined the dynamic and complex relationship between Bitcoin and stock markets in varying economic conditions.

Tripathi and Bhandari (2016) evaluates the performance of socially responsible companies (ESG Index), general companies (NIFTY Index), market portfolio (CNX 500 Equity Index) and the various sectors of ESG index over the period 1996 to 2013. The authors decided to include different periods of boom and recession in India as identified by Federal Reserve Bank of St. Louis. To assess the performance of various sectors during identified boom and recession periods, the authors used for performance evaluation, Sharpe Ratio, Single factor alpha, three factor alpha based on Fama-French and others.

TABLE 2 – FINDINGS OF THE REVIEWED EMPIRICAL SOURCES

AUTHORS	PERIOD	METHODOLOGY	RESULTS	COMMENTS
Alfieri, E., Burlacu, R., & Enjolras G. (2019)	22/Sep/2010 to 30/Dec/2016	Quantitative methodologies, Alpha estimation	BTC exhibited low correlation with traditional financial indices, a high annualised return of 568.82%, a standard deviation of 111.69%, positive skewness and a high Sharpe Ratio	BTC demonstrated unique performance characteristics
Bianchi, D., & Babiak, M. (2022)	March 2015 to June 2021	Regression analyses, Alpha estimation	Cryptocurrency funds consistently generate significantly positive alphas compared to passive benchmarks and conventional risk-factors.	Notable outperformance of cryptocurrency funds, but statistical significance weakens when considering cross-sectional correlation among fund returns
Bouri, E., Das, M., Gupta, R., & Roubaud, D. (2018).	July 2010 to October 2017	Bivariate GARCH-in-mean (BTGARCH-M) model with dynamic conditional correlation (DDC) approach and smooth transition vector autoregressive (STVAR) specification	Significant return spillovers between BTC and traditional asset classes. These spillovers are often asymmetric and vary in different market conditions	BTC operates in complete isolation from traditional financial systems and sensitivity to economic fundamentals.
Chokor, A., & Alfieri, E. (2021)	2015 to 2019	Event study methodology, Traditional performance measures (Sharpe Ratio, FF3F model, CAR4 model)	Regulatory news and events significantly impact cryptocurrency in terms of returns. Different cryptocurrencies exhibit varying return reactions to regulatory events.	Regulatory events have a significant short and long-term impact on cryptocurrency market performance
Ciaian, P., Rajcaniova, M., & Kancs, D. (2017)	2013 to 2016	Autoregressive Distributed Lag (ARDL)	Relationship between BTC and ALT coins. They found stronger relationship in the short term.	BTC and ALT coins relationship varies over different timeframes.
Gregoriou, A. (2019)	2014 to 2017	Alpha estimation (FF3F model, CAR4 model, FF5F model)	Investors obtain abnormal returns through daily trading of cryptocurrencies on the LSE. Abnormal returns persist even after accounting for risk-factors.	Cryptocurrency trading on the LSE generates significant and persistent excess returns, indicating market inefficiency and its impact on asset pricing models.
Liu, Y., & Tsyvinski, A. (2021)..	2011 to 2018	FF5F model	Cryptocurrencies showed minimal exposure to stock market risk-factors, ETH being the exception. The study found significant alphas.	The distinct risk returns profile of cryptocurrencies in contrast to traditional assets.

Table 2 (continued)

Liu, Y., Tsyvinski, A., & Wu, X. (2022).	2014 to July 2020	Cryptocurrency Three factor model (CMKT, CSMB, CMOM)	It revealed shared factors and momentum effects between cryptocurrency and traditional currency markets	Large cryptocurrencies showed strong momentum effect.
Matkovskyy, R., & Jalan, A. (2019).	2015 to 2018	Regime switching skew-normal model of crisis and contagion	Significant effect from traditional financial markets to BTC. During low BTC price periods, risk-averse investors shifted investments to less volatile markets. Highlights the role of risk dynamics in influencing Bitcoin's performance	BTC's dual role as a speculative asset and a safe haven for risk-averse investors during market instability.
Šafka, J. (2014).	2010 to 2014	Ordinary Least Squares (OLS) models	There was a marked degree of independence between BTC and stock indices, suggesting that BTC operated autonomously from the broader stock market.	There is no significant long-term relationship between the price of BTC and the tangible economy. Bitcoin's independency.
Tripathi, V., & Bhandari, V. (2016).	1996 to 2013	Analyse performance under boom and recession periods, using Sharpe Ratio and FF3F model	They find that Information Technology (IT) and Fast-moving consumer goods (FMCG) sector portfolios are well rewarding during different boom and recession period by generating significantly higher returns and outperforming general companies in terms of risk-adjusted measures.	Analyse financial asset during boom and recession periods.
Van Wijk, D. (2013).	2010 to 2013	Ordinary Least Squares (OLS) regression and Error Correction Model (ECM)	The variables examined had a significant impact on BTC's value, in the short and long term. The variable with the most influence was Dow Jones stock index exhibited positive correlation with BTC.	Most influencing variables are related to the U.S. economy and therefore the economic performance and growth should be watched most closely when investing in the BTC.
Wang, J., Xue, Y., & Liu, M. (2016).	2011 to 2016	Vector Error Correction Model (VECM)	Significant relationship between Bitcoin's price and the Dow Jones stock index. Positive correlation between Bitcoin's price and its transaction volume, during economic crises, BTC's price tended to rise.	Bitcoin's price responding differently to economic upturns and downturns.

Source: Author's own elaboration

3 Methodology and Data

3.1 Methodology

This section presents the methodology employed to evaluate the performance of a representative group cryptocurrencies. Performance can be defined as the return on an investment that has been adjusted to account for the level of risk involved. To assess the performance of cryptocurrencies and compare them with alternative investment strategies, we start by calculating simple performance measures including the Sharpe and Sortino ratios, which are widely used in related literature. Our next step involves estimating abnormal performance for cryptocurrencies by employing the CAPM (Treynor, 1961, 1962; Sharpe, 1964; Lintner, 1965a, b; Mossin, 1966) and multifactor models. For robustness, we use two different multifactor models, the Fama-French three-factor model (Fama & French 1992, 1993), and the Fama-French five-factor model (Fama & French 2015)

Subsequent sections will provide the details of these alternative performance measures: risk-adjusted return ratios and risk-adjusted alpha models.

3.1.1 Risk-adjusted return ratios

We employ two risk-adjusted returns: the Sharpe Ratio, a statistic developed by William F. Sharpe, which is widely used for evaluating the risk-adjusted returns of an investment (Chokor & Alfieri, 2021, p. 166), and the Sortino Ratio. The Sortino Ratio is an extension of the Sharpe ratio that places particular emphasis on the measurement of downside risk and was developed by Dr. Frank A. Sortino (Martin and Simin, 2003).

The Sharpe ratio is calculated using the following formula:

$$S_p = \frac{\overline{R}_p - \overline{R}_f}{\sigma_p} \qquad (1)$$

where $\overline{R}_p$ is the average return on the cryptocurrency or ETF portfolio, $\overline{R}_f$ is the average return on the risk-free asset and σ_p is the standard deviation of the portfolio considered. Lintner (1965) emphasised the significance of the Sharpe ratio in encapsulating the underlying idea of current portfolio theory, which revolves around the inherent trade-off between risk and return.

The Sortino ratio is a modification of the Sharpe ratio that employs downward deviation as a measure of risk, as opposed to using standard deviation. In other words, it only considers returns that fall below a predefined threshold when measuring risk.

The Sortino ratio is calculated by substituting the standard deviation σ_p of the Sharpe ratio by the standard deviation of downward deviations. According to Martin and Simin (2003), the Sortino ratio holds significant value for investors that prioritise the mitigation of losses. The approach offers a specific perspective on returns that have been adjusted for risk, with a particular emphasis on mitigating downside risk. This ratio will enable us to evaluate the effectiveness of cryptocurrencies in mitigating downside risk.

3.1.2 Risk-adjusted and benchmark-adjusted alpha models

Many authors argue that the nature of cryptocurrencies is akin to that of common stocks. For instance, Alfieri et al. (2019, p. 114-115) posit that while Bitcoin shares some common characteristics with currencies and gold, it possesses specific economic and legal profiles, risk-return characteristics, and liquidity that align it more closely with common stocks. The resemblance of cryptocurrencies to common stocks provides a rationale for employing Fama and French stock models to assess cryptocurrency performance. Following, among others, the work of Alfieri et al. (2019), Chokor and Alfieri (2021), and Gregoriou (2019), we will utilise the Fama and French risk-factor models to estimate cryptocurrency outperformance relative to the market.

We estimate three risk-factor models: the single-factor CAPM, the FF3F model, and a FF5F+ model that expands the FF5F model to capture momentum CAR4.

In their empirical form, the models are expressed as follows:

CAPM:

$$R_{it} - R_{ft} = \alpha_i + \beta_{i1}\left(R_{mt} - R_{ft}\right) + \varepsilon_{it} \qquad (2)$$

FF3F:

$$R_{it} - R_{ft} = \alpha_i + \beta_{i1}\left(R_{mt} - R_{ft}\right) + \beta_{i2}SMB_t + \beta_{i3}HML_t + \varepsilon_{it} \qquad (3)$$

FF5F+:

$$R_{it} - R_{ft} = \alpha_i + \beta_{i1}\left(R_{mt} - R_{ft}\right) + \beta_{i2}SMB_t + \beta_{i3}HML_t + \beta_{i4}RMW_t + \beta_{i5}CMA_t + \beta_{i6}WML_t + \varepsilon_{it} \qquad (4)$$

In the above equations, Rit is the return on cryptocurrency i for day t, Rft is the risk-free rate, Rmt is the return on the market portfolio, SMBt is the return on diversified portfolios of small stocks minus big stocks, HMLt is the difference between the returns on diversified portfolios of high and low B/M stocks, RMWt is the difference between the returns on diversified portfolios of stocks with robust and weak profitability, CMAt is the difference between the returns on diversified portfolios of the stocks of low (conservative) and high (aggressive) investment firms, WMLt denotes the momentum risk-factor, and εit is a zero-mean error term. The coefficients β_{i1}, β_{i2}, β_{i3}, β_{i4}, β_{i5} and β_{i6} capture the exposure of cryptocurrency i to each risk-factor.

The risk-adjusted return generated by the different cryptocurrencies is measured by the constant coefficient (α_i) from estimating these three models. We consider global factors because cryptocurrencies are used across the world and are not linked to a special country.

According to Gregoriou (2019), these models play a vital role in evaluating whether cryptocurrencies produce higher returns than anticipated based on their level of systematic risk. The methodology facilitates the assessment of the risk-adjusted performance of cryptocurrencies and offers valuable perspectives on their viability as investment assets.

Within the framework of our study, risk-adjusted alpha models assume a crucial role in the assessment and interpretation of the performance of cryptocurrencies. The purpose of these models is to offer a comprehension of whether cryptocurrencies yield alpha, indicating greater risk-adjusted returns in comparison to the systematic risk they assume.

A positive statistically significant alpha indicates that cryptocurrencies offer abnormal returns, after accounting for systematic risk, size, value, profitability, investment, and momentum.

However, some authors argue that it is relatively difficult to invest in long-short portfolios that are part of risk-factors. Factor portfolios are not practical investment strategies because retailers would incur significant investment frictions and costs when taking short positions (Bianchi & Babiak, 2022). To address this issue, we additionally consider passive benchmark strategies consisting of buy-and-hold investments in some broad-based indexes. Following Bianchi and Babiak (2022), we use exchange-traded funds (ETFs) to track broad indexes instead of the indexes themselves, because it could be argued that the indexes are not investable, making them unsuitable for passive investment strategies. Therefore, we also employ the returns from passive investment strategies on benchmark indices to estimate the

CAPM. We calculate the benchmark-adjusted alphas for cryptocurrencies using three exchange-traded funds (ETFs) as benchmarks for stocks, gold, and bonds.

To assess whether the cryptocurrency performance is influenced by market conditions, we estimate risk-adjusted alphas with dichotomous variables for bull and bear periods in stock markets.

In this paper we use the Pagan and Sossounov (2003) algorithm to define bull and bear periods for the stock market, which is a modified version of Bry & Boschan (1971) algorithm, originally aimed at detecting peaks and throughs for the business cycle. Pagan and Sossounov (2003) adapted the original algorithm to better fit stock market data. We identify bull and bear periods for the S&P 500 index sing a window of eight periods, a censor of six periods, a cycle of 16 periods and a maximum change of 20%[1]

All the models estimated using ordinary least squares (OLS), with Newey-West heteroscedasticity and autocorrelation (HAC) robust standard errors.

3.2 Data

We obtain daily data for cryptocurrencies from the CoinMarketCap website, a widely used source of cryptocurrencies market data in academic research. (Bouri, 2019; Cheah, 2015; Fry, 2016). Our sample comprises the ten cryptocurrencies with the highest market capitalisation, as determined by the market conditions in January 2023. These cryptocurrencies include Bitcoin (BTC), Ethereum (ETH), Ripple (XRP), Dogecoin (DOGE), Litecoin (LTC), Binance Coin (BNB), Cardano (ADA), Tron (TRX), Polygon (MATIC), and Solana (SOL). For robustness and to capture mean performance, we also include an equal-weighted portfolio built from the data collected for the ten cryptocurrencies in our study. This technique entails allocating an equal portion of our investment money to each of the ten cryptocurrencies in our portfolio. The efficacy of a cryptocurrency portfolio is discernible through two distinct avenues. First and foremost, it serves to decrease the standard deviation, thereby mitigating the overall level of risk. Furthermore, the expansion of allocation possibilities provides investors with a wider range of choices, enhancing their flexibility to optimise their portfolios (Andrianto & Diputra, 2017).

[1] We use the bbdetection package in R with standard values for window, censor, cycle and maximum change to estimate the bull and bear periods.

We collect daily data for all other assets in our research from Yahoo Finance. We select ten exchange-traded funds (ETFs) as proxies for stocks, one gold ETF, one commodities ETF and one fixed income ETF. We include in our research the following ETFs: Vanguard Total World Stock ETF (VT), Vanguard Total Stock Market ETF (VTI), Vanguard S&P500 ETF (VOO), Invesco QQQ ETF (QQQ), iShares MSCI China ETF (MCHI), Vanguard FTSE Europe ETF (VGK), Vanguard FTSE Pacific ETF (VPL), Vanguard FTSE Developed Markets ETF (VEA), Vanguard FTSE Emerging Markets ETF (VWO), SPDR Gold Shares (GLD), Invesco DB Commodity Index Tracking Fund (DBC), and Vanguard Total Bond Market ETF (BND).

To estimate the three risk-factor models, we need to collect daily data for the six global risk-factors: Market (MKT), Size Small Minus Big (SMB), Value High Minus Low (HML), Profitability Robust Minus Weak (RMW), Investment Conservative Minus Aggressive (CMA), and Momentum Winner Minus Loser (WML). We obtain data for the Global factors size, value, operating profitability, investment, and momentum from Kenneth French's website at Dartmouth College[2].

The sample period chosen for our study spans from 01/Jan/2016 to 31/Dec/2022. This timeframe was picked due to its relevance in capturing the recent and current market dynamics, characterised by substantial development and transformation. Notably, this period encompasses the birth of novel cryptocurrencies and notable shifts in market structure. One notable distinction between cryptocurrencies and ETFs is the concept of trading days, which is imperative to acknowledge. Cryptocurrencies are traded continuously throughout the week, operating 24 hours a day. In contrast, stock markets are only accessible on weekdays. The time discrepancy gives rise to a lack of coherence in the data pertaining to cryptocurrencies and ETFs. This implies that although currencies are exchanged over the entire year, the trading of all financial independent variables typically occurs within approximately 250 days. The time discontinuity between consecutive trading days introduces a discrepancy in the data pertaining to the dependent and independent variables when conducting daily data analysis.

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[2] Retrieved 27 April 2023, from Kenneth R. French - Data Library (dartmouth.edu)

The choice of daily data facilitates a more accurate comprehension of transient price variations and the dynamics of the market. According to Naeem et al. (2021), this approach offers a more comprehensive depiction of intraday price fluctuations and incorporates the influence of news, events, and market mood daily. To better capture market dynamics, we use daily data in this study. The data presented in Table 3 reveals that BTC, ETH, XRP, DOGE, and LTC, along with all ETFs, started in the year 2016. However, a notable disparity is observed in the number of observations, with cryptocurrencies exhibiting a greater frequency of observations compared to ETFs. There are certain deviations within the dataset pertaining to cryptocurrency. BNB, ADA, TRX, MATIC, and SOL are cryptocurrencies that emerged in the years 2017, 2019, and 2020, respectively. These digital assets are very new in the cryptocurrency market and have a smaller number of recorded observations compared to other cryptocurrencies and exchange-traded funds (ETFs).

The data on cryptocurrencies need to be transformed to calculate daily returns and daily excess returns. In this study, we use excess returns unless otherwise stated. Excess returns subtract the risk-free rate from an asset return, to better reflect the return investors get for bearing risk. The modification holds significant importance in the context of asset comparison, portfolio performance evaluation, the use of financial models including the Capital Asset Pricing Model (CAPM), and the computation of risk-adjusted performance measures like the Sharpe ratio (Cooper, 2006). The risk-free rate is commonly employed as a standard for assessing the anticipated yield of an investment. The yield on short-term US government debt is often used as risk-free rate, as Treasury Bills are widely recognised for bearing no default risk (Garcia & Luger, 2011).

Return (5)

$$R_a = \frac{P_t - P_{t-1}}{P_{t-1}}$$

Where, R_i represent the daily return of the cryptocurrency i, P_t = is its price at time t, P_{t-1} represents the price at time $t - 1$.

Excess Return (6)

$$ER_i = R_i - R_f$$

Where, ER_i is the Excess Return of the cryptocurrency i, R_i represents the return of the asset i, R_f is the risk-free rate.

TABLE 3 – ASSET LIST

Name / ***CRYPTOCURRENCY***	**Acronym**	**Period**	**Observations**	***Source***
Bitcoin	*BTC*	*2016 – 2022*	*1826*	*Bitcoin price today, BTC to USD live price, marketcap and chart | CoinMarketCap*
Etherum	*ETH*	*2016 – 2022*	*1826*	*Ethereum price today, ETH to USD live price, marketcap and chart | CoinMarketCap*
Ripple	*XRP*	*2016 – 2022*	*1826*	*XRP price today, XRP to USD live price, marketcap and chart | CoinMarketCap*
Doge Coin	*DOGE*	*2016 – 2022*	*1826*	*Dogecoin price today, DOGE to USD live price, marketcap and chart | CoinMarketCap*
Lite Coin	*LTC*	*2016 – 2022*	*1826*	*Litecoin price today, LTC to USD live price, marketcap and chart | CoinMarketCap*
Binance	*BNB*	*2017 – 2022*	*1418*	*BNB price today, BNB to USD live price, marketcap and chart | CoinMarketCap*
Cardano	*ADA*	*2017 – 2022*	*1369*	*Cardano price today, ADA to USD live price, marketcap and chart | CoinMarketCap*
Tron	*TRX*	*2017 – 2022*	*1382*	*TRON price today, TRX to USD live price, marketcap and chart | CoinMarketCap*
Polygon	*MATIC*	*2019 – 2022*	*959*	*Polygon price today, MATIC to USD live price, marketcap and chart | CoinMarketCap*
Solana	*SOL*	*2020 – 2022*	*710*	*Solana price today, SOL to USD live price, marketcap and chart | CoinMarketCap*

Source: Author's own elaboration

RISK-FACTOR	**Acronym**	**Period**	**Observations**	***Source***
Market	*MKT*	*2016 – 2022*	*1826*	*Kenneth R. French - Data Library (dartmouth.edu)*
Size	*SMB*	*2016 – 2022*	*1826*	
Value	*HML*	*2016 – 2022*	*1826*	
Profitability	*RMW*	*2016 – 2022*	*1826*	
Investment	*CMA*	*2016 – 2022*	*1826*	
Momentum	*WML*	*2016 - 2022*	*1826*	

Source: Author's own elaboration

Table 3 (continued)

ETFs	Acronym	Period	Observations	*Source*
Vanguard Total World Stock ETF	*VT*	*2016 – 2022*	*1762*	*Vanguard Total World Stock Index Fund (VT) Stock Price, News, Quote & History - Yahoo Finance*
Vanguard Total Stock Market ETF	*VTI*	*2016 – 2022*	*1762*	*Vanguard Total Stock Market Index Fund (VTI) Stock Price, News, Quote & History - Yahoo Finance*
Vanguard S&P500 ETF	*VOO*	*2016 - 2022*	*1762*	*Vanguard 500 Index Fund (VOO) Stock Price, News, Quote & History - Yahoo Finance*
Invesco QQQ ETF	*QQQ*	*2016 – 2022*	*1762*	*Invesco QQQ Trust (QQQ) Stock Price, News, Quote & History - Yahoo Finance*
iShares MSCI China ETF	*MCHI*	*2016 – 2022*	*1762*	*iShares MSCI China ETF (MCHI) Stock Price, News, Quote & History - Yahoo Finance*
Vanguard FTSE Europe ETF	*VGK*	*2016 – 2022*	*1762*	*Vanguard FTSE Europe ETF (VGK) Stock Price, News, Quote & History - Yahoo Finance*
Vanguard FTSE Pacific ETF	*VPL*	*2016 – 2022*	*1762*	*Vanguard Pacific Stock Index Fund (VPL) Stock Price, News, Quote & History - Yahoo Finance*
Vanguard FTSE Developed Markets ETF	*VEA*	*2016 – 2022*	*1762*	*Vanguard Developed Markets Index Fund (VEA) Stock Price, News, Quote & History - Yahoo Finance*
Vanguard FTSE Emerging Markets	*VWO*	*2016 – 2022*	*1762*	*Vanguard Emerging Markets Stock Index Fund (VWO) Stock Price, News, Quote & History - Yahoo Finance*
SPDR Gold Shares	*GLD*	*2016 – 2022*	*1762*	*SPDR Gold Shares (GLD) Stock Price, News, Quote & History - Yahoo Finance*
Invesco DB Commoditi y Index Tracking Fund	*DBC*	*2016 – 2022*	*1762*	*Invesco DB Commodity Index Tracking Fund (DBC) Stock Price, News, Quote & History - Yahoo Finance*
Vanguard Total Bond Market ETF	*BND*	*2016 – 2022*	*1762*	*Vanguard Total Bond Market Index Fund (BND) Stock Price, News, Quote & History - Yahoo Finance*

Source: Author's own elaboration

4 Results

In this section, we report our empirical results. We start by describing our dataset, providing the key descriptive statistics. We then report the results for risk-adjusted return ratios (Sharpe and Sortino), risk and benchmark – adjusted alphas, and risk-adjusted alphas during bull and bear markets.

4.1 Descriptive statistics

Table 4 reports descriptive statistics for cryptocurrencies and an equally weighted portfolio of cryptocurrencies (Panel A) and for global ETFs for Stocks, Gold, Commodities and Bonds (Panel B), over the period 01/Jan/2016 to 31/Dec/2022. It also presents, in Panel C, descriptive statistics for the factors that are used on the estimations of the risk-adjusted alphas: market risk (MKT), size effect (SMB), value effect (HML), profitability (RMW), investment (CMA) and momentum (WML). As aforementioned, the first price date varies with cryptocurrency, leading to a varying number of observations across assets.

TABLE 4 – DESCRIPTIVE STATISTICS

PANEL A. CRYPTO	OBSERVATIONS	MEAN (%)	SD (%)	SKEWNESS	KURTOSIS
PORTFOLIO	*1826*	*451,226*	*93,791*	*0,865*	*13,794*
BTC	*1826*	*112,835*	*72,035*	*-0,059*	*9,262*
ETH	*1826*	*377,915*	*110,534*	*1,184*	*13,063*
XRP	*1826*	*265,987*	*131,417*	*3,806*	*40,308*
DOGE	*1826*	*644,490*	*196,066*	*14,604*	*385,981*
LTC	*1826*	*154,235*	*105,923*	*1,766*	*20,695*
BNB	*1418*	*920,020*	*159,332*	*9,152*	*198,838*
ADA	*1369*	*275,476*	*151,111*	*5,649*	*76,141*
TRX	*1382*	*411,601*	*160,094*	*5,104*	*61,674*
MATIC	*959*	*1429,385*	*173,969*	*3,095*	*33,357*
SOL	*710*	*599,465*	*153,745*	*1,248*	*11,755*

Table 4 (continued)

PANEL B. ETFs	OBSERVATIONS	MEAN (%)	SD (%)	SKEWNESS	KURTOSIS
VT	*1762*	*9,147*	*18,538*	*-0,882*	*18,625*
VTI	*1762*	*12,045*	*19,468*	*-0,580*	*16,460*
VOO	*1762*	*12,482*	*19,270*	*-0,537*	*17,846*
QQQ	*1762*	*16,119*	*23,291*	*-0,409*	*9,574*
MCHI	*1762*	*5,296*	*27,434*	*0,772*	*16,869*
VGK	*1762*	*6,140*	*20,411*	*-1,258*	*18,103*
VPL	*1762*	*5,249*	*17,519*	*-0,734*	*15,490*
VEA	*1762*	*5,790*	*18,406*	*-1,123*	*18,762*
VWO	*1762*	*6,791*	*20,892*	*-0,768*	*12,223*
GLD	*1762*	*7,662*	*14,091*	*-0,116*	*6,553*
DBC	*1762*	*10,552*	*18,583*	*-0,754*	*7,529*
BND	*1762*	*0,111*	*5,344*	*-1,527*	*60,858*

PANEL C. RISK-FACTORS	OBSERVATIONS	MEAN (%)	SD (%)	SKEWNESS	KURTOSIS
MKT	*1826*	*8,588*	*15,822*	*-0,915*	*18,038*
SMB	*1826*	*-2,296*	*6,720*	*-1,200*	*18,184*
HML	*1826*	*-0,077*	*9,901*	*0,269*	*6,737*
RMW	*1826*	*3,635*	*4,658*	*0,005*	*4,591*
CMA	*1826*	*1,453*	*6,110*	*0,142*	*6,003*
WML	*1826*	*3,460*	*12,417*	*-1,504*	*18,150*

Source: Table 4 presents summary statistics (annualised mean, annualised volatility, skewness and kurtosis) based on daily excess returns for Bitcoin (BTC), Etherum (ETH), Ripple (XRP), Doge Coin (DOGE), Lite Coin (LTC), Binance (BNB), Cardano (ADA), Tron (TRX), Polygon (MATIC), Solana (SOL), equally weighted portfolio of ten cryptocurrencies, also ETFs of stock (Vanguard Total World Stock ETF (VT), Vanguard Total Stocl Market ETF (VTI), Vanguard S&P 500 ETF (VOO), Invesco QQQ ETF (QQQ), iShares MSCI China ETF (MCHI), Vanguard FTSE Europe ETF (VGK), Vanguard FTSE Pacific ETF (VPL), Vanguard FTSE developed Markets ETF (VEA), Vanguard FTSE Developed Markets ETF (VEA), Vanguard FTSE Emerging Markets (VWO), ETF of Gold (SPDR Gold Shares (GLD), ETF of Commodities (Invesco DB Commodity Index Tracking Fund (DBC), ETFs of Bonds (Vanguard Total Bond Market ETF (BND) and also the risk-factors, namely Market (MKT), Size- Small Minus Big (SMB), Value- High Minus Low (HML), Profitability- Robust Minus Weak (RMW), Investment-Conservative Minus Aggressive (CMA), and Momentum- Winner Minus Loser (WML). Database is over the period 01/Jan/2016 to 31/Dec/2022

The equally weighted ten cryptocurrencies portfolio has a mean annualised excess return of 451,226% and a standard deviation of 92,791%, exceeding by large the mean and standard deviation for all the ETFs. For comparison, the Invesco QQQ ETF, the ETF with highest average return, exhibits an annual return of 16,119% and a standard deviation of 23,291%.

Among the ten cryptocurrencies, Matic is the cryptocurrency with the highest average value, followed by BNB. In contrast, the cryptocurrencies with the lowest average return are BTC and LTC. In terms of standard deviation, the highest values appear in DOGE, while the lowest values correspond to BTC. In this way, DOGE emerges as the cryptocurrency with the highest volatility, according to observation. In summary, the Bitcoin (BTC), the first and more popular cryptocurrency, exhibits both the lowest average annual return (112,835%) and the lowest annualised standard (72,035%).

The ALT Coins exhibit higher average return and greater volatility. For example, Ethereum (ETH) presents an intertwined story with greater complexity, demonstrating an average annual return of 377,915%, paired with a significant annual standard deviation of 110,534%. The remarkable rise of Dogecoin (DOGE) is reflected by its average annual return of 644,490% and its significant annual standard deviation of 196,066%. Binance Coin (BNB) stands out for being closely linked to the Binance platform, presenting an average annual return of 920,020% with an annual standard deviation of 159,332%.

Apart from BTC, all cryptocurrencies present positive skewness, meaning that their returns are right-skewed and that lower return values predominate compared to higher ones. Most cryptocurrencies indicate that there are more outliers or extreme values on the upside, as in Bianchi & Babiak (2022). In turn, as referred by Alfieri et al. (2019), the existing empirical literature found that the BTC has a positive or a negative skewness.

In turn, almost all the ETFs exhibit a negative skewness, corroborating the results from the previous literature (e.g., Bianchi and Babiak, 2022, and Alfieri et al., 2019).

In terms of kurtosis, all values are much larger than 3, meaning that the data distribution does not appear flat, being called leptokurtic. This is valid not only for cryptocurrencies returns but also for all the ETFs returns.

In summary, cryptocurrencies offer higher average returns compared to traditional global ETFs. However, it is important to note that cryptocurrencies also exhibit significantly greater volatility, which consequently translates into higher levels of risk when compared to ETFs. Therefore, to obtain a reliable performance measure, it is necessary to adjust the average return by the corresponding risk.

Table 5 presents the Pearson correlation coefficients between the returns of cryptocurrencies and the returns of global ETFs from stocks, bond, and gold.

TABLE 5 – MATRIX CORRELATION

VARIABLES	ETFs										
	ETF STOCKS									ETF GOLD	ETF BOND
	VT	VTI	VOO	QQQ	MCHI	VGK	VPL	VEA	VWO	GLD	BND
PORTFOLIO	*0,252*	*0,243*	*0,239*	*0,240*	*0,172*	*0,241*	*0,232*	*0,248*	*0,216*	*0,101*	*0,117*
BTC	*0,241*	*0,237*	*0,231*	*0,237*	*0,140*	*0,229*	*0,208*	*0,233*	*0,191*	*0,112*	*0,134*
ETH	*0,209*	*0,202*	*0,198*	*0,206*	*0,147*	*0,202*	*0,194*	*0,207*	*0,184*	*0,105*	*0,106*
XRP	*0,162*	*0,157*	*0,156*	*0,158*	*0,129*	*0,148*	*0,157*	*0,157*	*0,152*	*0,041*	*0,069*
DOGE	*0,117*	*0,112*	*0,110*	*0,106*	*0,071*	*0,115*	*0,103*	*0,116*	*0,094*	*0,058***	*0,053***
LTC	*0,205*	*0,198*	*0,194*	*0,203*	*0,150*	*0,195*	*0,186*	*0,200*	*0,180*	*0,076*	*0,100*
BNB	*0,180*	*0,174*	*0,169*	*0,169*	*0,136*	*0,171*	*0,165*	*0,175*	*0,169*	*0,067*	*0,076*
ADA	*0,218*	*0,205*	*0,201*	*0,198*	*0,140*	*0,218*	*0,207*	*0,221*	*0,193*	*0,085*	*0,096*
TRX	*0,160*	*0,149*	*0,145*	*0,143*	*0,115*	*0,162*	*0,159*	*0,168*	*0,151*	*0,052***	*0,068***
MATIC	*0,240*	*0,228*	*0,222*	*0,221*	*0,159*	*0,244*	*0,226*	*0,246*	*0,216*	*0,103*	*0,117*
SOL	*0,304*	*0,286*	*0,286*	*0,281*	*0,169*	*0,295*	*0,280*	*0,303*	*0,246*	*0,106*	*0,083*

Source: This table presents Pearson correlation coefficients between Bitcoin (BTC), Etherum (ETH), Ripple (XRP), Doge Coin (DOGE), Lite Coin (LTC), Binance (BNB), Cardano (ADA), Tron (TRX), Polygon (MATIC), Solana (SOL),, equally weighted portfolio of ten cryptocurrencies, also ETFs of stock (Vanguard Total World Stock ETF (VT), Vanguard Total Stocl Market ETF (VTI), Vanguard S&P 500 ETF (VOO), Invesco QQQ ETF (QQQ), iShares MSCI China ETF (MCHI), Vanguard FTSE Europe ETF (VGK), Vanguard FTSE Pacific ETF (VPL), Vanguard FTSE developed Markets ETF (VEA), Vanguard FTSE Developed Markets ETF (VEA), Vanguard FTSE Emerging Markets (VWO), ETF of Gold (SPDR Gold Shares (GLD), ETFs of Bonds (Vanguard Total Bond Market ETF (BND). Database is over the period 01/Jan/2016 to 31/Dec/2022. All the coefficients are significant at 1% level, except the ones marked with (a) which are significant at 5%.

The correlation coefficients between the returns of cryptocurrencies and global ETFs based on stocks are positive and statistically significant at the 1% level. They range from 0.1 to 0.3, indicating relatively low correlation. The correlations between the returns of cryptocurrencies and gold and bond ETFs are even lower, suggesting opportunities for portfolio diversification.

4.2 Risk-adjusted return ratios

4.2.1 Sharpe Ratio

Table 6 presents the annualised Sharpe ratios for cryptocurrencies and the equally weighted cryptocurrencies portfolio. It also reports the Sharpe ratios for stocks, bonds, commodities, and gold ETFs over the period from 2016 to 2022, providing data for both the entire period and each individual year. As aforementioned, the Sharpe ratio is a measure of performance that adjusts excess returns for total (systematic and diversifiable) risk.

TABLE 6 – SHARPE RATIO

VARIABLES	2016	2017	2018	2019	2020	2021	2022	2016 - 2022
CRYPTO OBSERVATIONS	*261*	*260*	*261*	*261*	*262*	*261*	*260*	*1826*
PORTFOLIO	*1,941*	*4,595*	*-1,187*	*0,642*	*1,226*	*2,609*	*-1,288*	*1,381*
BTC	*1,603*	*2,976*	*-1,730*	*0,908*	*1,773*	*0,579*	*-1,562*	*0,681*
ETH	*1,590*	*3,303*	*-1,598*	*-0,071*	*1,667*	*1,467*	*-1,250*	*0,907*
XRP	*0,091*	*3,057*	*-1,455*	*-0,912*	*0,095*	*0,967*	*-1,039*	*0,459*
DOGE	*0,441*	*1,997*	*-1,062*	*-0,259*	*0,843*	*1,426*	*-0,855*	*0,588*
LTC	*0,405*	*2,505*	*-2,143*	*0,318*	*1,058*	*0,141*	*-0,880*	*0,391*
BNB			*-0,293*	*0,938*	*0,988*	*1,930*	*-0,968*	*1,023*
ADA			*-1,913*	*-0,296*	*1,457*	*1,545*	*-1,773*	*0,306*
TRX			*-0,373*	*-0,423*	*0,639*	*0,817*	*-0,495*	*0,423*
MATIC				*0,897*	*0,177*	*2,699*	*-1,008*	*0,878*
SOL					*0,355*	*3,000*	*-2,288*	*0,554*
ETFs OBSERVATIONS	*252*	*251*	*251*	*252*	*253*	*252*	*251*	*1762*
VT	*0,532*	*3,195*	*-0,817*	*1,814*	*0,444*	*1,311*	*-0,933*	*0,377*
VTI	*0,893*	*2,765*	*-0,459*	*1,919*	*0,533*	*1,677*	*-0,927*	*0,484*
VOO	*0,876*	*2,970*	*-0,406*	*1,986*	*0,466*	*1,955*	*-0,886*	*0,512*
QQQ	*0,423*	*2,748*	*-0,106*	*1,874*	*1,078*	*1,329*	*-1,270*	*0,523*
MCHI	*-0,014*	*3,002*	*-0,931*	*0,941*	*0,766*	*-0,900*	*-0,661*	*0,052*
VGK	*-0,020*	*2,642*	*-1,211*	*1,634*	*0,152*	*1,135*	*-0,726*	*0,187*
VPL	*0,305*	*3,259*	*-1,173*	*1,199*	*0,500*	*0,080*	*-0,911*	*0,203*
VEA	*0,144*	*3,060*	*-1,276*	*1,597*	*0,269*	*0,846*	*-0,813*	*0,211*
VWO	*0,536*	*2,418*	*-0,917*	*1,123*	*0,407*	*0,073*	*-0,945*	*0,208*
GLD	*0,479*	*1,223*	*-0,439*	*1,194*	*1,099*	*-0,309*	*-0,135*	*0,453*
DBC	*0,954*	*0,384*	*-1,012*	*0,644*	*-0,400*	*1,755*	*0,620*	*0,444*
BND	*0,762*	*1,398*	*-0,831*	*1,765*	*0,730*	*-0,509*	*-1,936*	*-0,006*

Source: This table presents Sharpe ratios per year for Bitcoin (BTC), Etherum (ETH), Ripple (XRP), Doge Coin (DOGE), Lite Coin (LTC), Binance (BNB), Cardano (ADA), Tron (TRX), Polygon (MATIC), Solana (SOL),, equally weighted portfolio of ten cryptocurrencies, also ETFs of stock (Vanguard Total World Stock ETF (VT), Vanguard Total Stocl Market ETF (VTI), Vanguard S&P 500 ETF (VOO), Invesco QQQ ETF (QQQ), iShares MSCI China ETF (MCHI), Vanguard FTSE Europe ETF (VGK), Vanguard FTSE Pacific ETF (VPL), Vanguard FTSE developed Markets ETF (VEA), Vanguard FTSE Developed Markets ETF (VEA), Vanguard FTSE Emerging Markets (VWO), ETF of Gold (SPDR Gold Shares (GLD), ETF of Commodities (Invesco DB Commodity Index Tracking Fund (DBC), ETFs of Bonds (Vanguard Total Bond Market ETF (BND). The period 01/Jan/2016 to 31/Dec/2022.

Based on the annualised Sharpe ratio for the period 2016-2022, cryptocurrencies outperform both bond and stock ETFs, except for XRP, TRX, LTC, and ADA, which underperform the US stock ETFs (QQQ, VOO, and VTI). This better performance of cryptocurrencies also holds against gold and commodities ETFs, except for the three cryptocurrencies TRX, LTC, and ADA. In this period, the top-performing three cryptocurrencies were BNB, ETH, and MATIC. As expected, the equally weighted cryptocurrency portfolio outperforms individual cryptocurrencies due to its lower volatility and risk.

These results, which demonstrate the outperformance of cryptocurrencies over other classes of financial assets, are generally consistent with those found by Alfieri et al. (2019) and Bianchi & Babiak (2022).

From the analysis of Table 3, it is worth noting that, for individual years within the period of 2016-2022, both 2018 and 2022 exhibit negative values for the Sharpe ratios across all classes of financial assets. These overall negative performance results can be attributed to the financial/stock market crisis in 2018 (see Younis et al., 2023, for a documentation of financial crisis episodes) and the market reactions to Russia's invasion of Ukraine in 2022 (cf. Silva et al., 2023). These results also raise the suspicion that cryptocurrency performance may change with market conditions. In section chapter 2, we investigate this issue further, setting a model explaining performance in bull and bear markets.

In turn, from Table 6, there is no evidence that cryptocurrencies outperform stocks in individual years, including 2017 and 2019, where the performance of all ETFs is positive.

4.2.2 Sortino Ratio

While the Sharpe ratio measures risk-adjusted returns by penalising both upside and downside volatility equally, the Sortino ratio only penalises returns that fall below the risk-free rate of return. Therefore, the Sortino ratio is a variation of the Sharpe ratio that specifically considers downside risk.

Table 7 corresponds to Table 6 but reporting the annualised Sortino ratios instead of the Sharpe ratios.

TABLE 7 - SORTINO RATIO

VARIABLES	2016	2017	2018	2019	2020	2021	2022	2016 - 2022
CRYPTO OBSERVATIONS	*261*	*260*	*261*	*261*	*262*	*261*	*260*	*1826*
PORTFOLIO	*2,990*	*6,627*	*-1,597*	*0,936*	*1,234*	*3,449*	*-1,489*	*1,783*
BTC	*1,900*	*4,243*	*-2,127*	*1,293*	*1,711*	*0,846*	*-1,766*	*0,681*
ETH	*2,614*	*5,495*	*-2,182*	*-0,095*	*1,755*	*2,010*	*-1,534*	*0,907*
XRP	*0,180*	*7,596*	*-2,082*	*-1,358*	*0,108*	*1,376*	*-1,352*	*0,459*
DOGE	*0,728*	*3,132*	*-1,619*	*-0,400*	*1,072*	*2,896*	*-1,098*	*0,588*
LTC	*0,496*	*4,363*	*-3,292*	*0,499*	*1,195*	*0,156*	*-1,112*	*0,391*
BNB			*-0,410*	*1,504*	*0,958*	*2,899*	*-1,106*	*1,023*
ADA			*-3,163*	*-0,431*	*1,752*	*2,533*	*-2,416*	*0,306*
TRX			*-0,614*	*-0,612*	*0,677*	*1,106*	*-0,577*	*0,423*
MATIC				*1,455*	*0,188*	*4,824*	*-1,383*	*0,878*
SOL					*0,616*	*4,588*	*-2,622*	*0,554*
ETFs OBSERVATIONS	*252*	*251*	*251*	*252*	*253*	*252*	*251*	*1762*
VT	*0,670*	*4,586*	*-1,038*	*2,275*	*0,463*	*1,851*	*-1,537*	*0,430*
VTI	*1,149*	*3,705*	*-0,553*	*2,370*	*0,572*	*2,377*	*-1,477*	*0,556*
VOO	*1,132*	*3,957*	*-0,493*	*2,419*	*0,506*	*2,775*	*-1,393*	*0,586*
QQQ	*0,534*	*3,248*	*-0,136*	*2,404*	*1,193*	*1,863*	*-2,053*	*0,633*
MCHI	*-0,021*	*4,378*	*-1,442*	*1,257*	*0,951*	*-1,357*	*-1,141*	*0,074*
VGK	*-0,021*	*4,600*	*-1,634*	*2,133*	*0,158*	*1,659*	*-1,252*	*0,211*
VPL	*0,426*	*5,634*	*-1,519*	*1,640*	*0,539*	*0,108*	*-1,605*	*0,249*
VEA	*0,169*	*5,329*	*-1,688*	*2,103*	*0,277*	*1,189*	*-1,442*	*0,244*
VWO	*0,755*	*3,768*	*-1,396*	*1,475*	*0,428*	*0,106*	*-1,646*	*0,261*
GLD	*0,757*	*2,115*	*-0,698*	*1,799*	*1,332*	*-0,392*	*-0,221*	*0,631*
DBC	*1,622*	*0,571*	*-1,300*	*0,960*	*-0,455*	*2,157*	*0,789*	*0,563*
BND	*1,087*	*2,464*	*-1,307*	*2,749*	*0,644*	*-0,792*	*-3,223*	*-0,007*

Note: This table presents Sortino ratios per year for Bitcoin (BTC), Etherum (ETH), Ripple (XRP), Doge Coin (DOGE), Lite Coin (LTC), Binance (BNB), Cardano (ADA), Tron (TRX), Polygon (MATIC), Solana (SOL),, equally weighted portfolio of ten cryptocurrencies, also ETFs of stock (Vanguard Total World Stock ETF (VT), Vanguard Total Stocl Market ETF (VTI), Vanguard S&P 500 ETF (VOO), Invesco QQQ ETF (QQQ), iShares MSCI China ETF (MCHI), Vanguard FTSE Europe ETF (VGK), Vanguard FTSE Pacific ETF (VPL), Vanguard FTSE developed Markets ETF (VEA), Vanguard FTSE Developed Markets ETF (VEA), Vanguard FTSE Emerging Markets (VWO), ETF of Gold (SPDR Gold Shares (GLD), ETF of Commodities (Invesco DB Commodity Index Tracking Fund (DBC), ETFs of Bonds (Vanguard Total Bond Market ETF (BND). The period 01/Jan/2016 to 31/Dec/2022.

From the comparison of Table 6 and Table 7, it is evident that Sortino ratios are higher than Sharpe. For the period 2016-2022, the Sortino ratios reinforce the outperformance of cryptocurrencies over bond and stock ETFs, as positive values dominate negative, when considering individual years. Notwithstanding, the same qualitative results hold for this period.

The best performing cryptocurrencies are still BNB, ETH and MATIC. The order is not the same as recorded in the Sharpe ratio, but the same three continue to perform better. On the other hand, the cryptocurrencies that perform the worst are ADA and LTC, which is identical in the Sharpe ratio and Sortino ratio. The best performing ETFs are GLD, VPL and DBC. This conclusion is different from that obtained from the Sharpe ratio. On the other hand, the worst performing ETFs are VEA, BND and QQQ.

4.3 Risk and benchmark – adjusted alphas

This section estimates the performance of cryptocurrencies based on the alpha, which accounts for risk-adjusted and benchmark-adjusted returns, using six regression models. The first three models (models 1A, 1B, and 1C) are CAPM models employed to estimate the alphas of cryptocurrencies, using as benchmarks three exchange-traded funds (ETFs) - QQQ, GLD, and BND - as proxies for stocks, gold, and bonds. The other three models (models 2, 3 and 4) are used to estimate risk-adjusted alphas for cryptocurrencies, using the Fama and French factors. Model 2 is single-factor CAPM, model 3 is the FF3F model, and model 4 is FF5F+ model that expands the FF5F to capture momentum (CAR4).

Table 4 shows the descriptive statistics for the dependent and independent variables. Cryptocurrencies have higher average return and higher risk than the global market portfolio and the Fama–French factor-mimicking portfolios.

Table 8 presents the OLS estimation results of all these models, with Newey-West heteroscedasticity and autocorrelation (HAC) robust standard errors.

TABLE 8 – ESTIMATION RESULTS

VARIABLES	MODEL	ALPHA (%)	STOCKS (QQQ)	GOLD (GLD)	BONDS (BND)	MKT	SMB	HML	RMW	CMA	WML	R^2	ANNUAL ALPHA (%)
	1A	*0,649****	*0,964****									*0,058*	*410,487*
	1B	*0,685****		*0,67****								*0,010*	*458,629*
PORTFOLIO	1C	*0,704****			*2,037***							*0,014*	*485,833*
(2016-2022)	2	*0,632****				*1,469****						*0,061*	*389,213*
	3	*0,634****				*1,529****	*0,514*	*-0,461***				*0,064*	*391,670*
	4	*0,651****				*1,418****	*0,312*	*0,137*	*-1,031***	*-1,094*	*0,444***	*0,071*	*413,050*
	1A	*0,253***	*0,732****									*0,056*	*89,034*
	1B	*0,28***		*0,569****								*0,012*	*102,307*
BTC	1C	*0,296****			*1,803***							*0,018*	*110,606*
(2016 - 2022)	2	*0,264***				*1,093****						*0,058*	*94,333*
	3	*0,266***				*1,126****	*0,334*	*-0,415****				*0,061*	*95,312*
	4	*0,287****				*0,982****	*0,099*	*0,067*	*-1,094****	*-1,037***	*0,27***	*0,070*	*105,897*
	1A	*0,567****	*0,975****									*0,043*	*315,705*
	1B	*0,6****		*0,821****								*0,011*	*351,535*
ETH	1C	*0,624****			*2,188***							*0,011*	*379,510*
(2016-2022)	2	*0,576****				*1,43****						*0,042*	*325,186*
	3	*0,579****				*1,491****	*0,593*	*-0,697***				*0,046*	*328,394*
	4	*0,591****				*1,456****	*0,453*	*-0,523*	*-1,062*	*-0,302*	*0,387**	*0,049*	*341,468*
	1A	*0,512***	*0,897****									*0,025*	*262,172*
	1B	*0,554***		*0,382**								*0,002*	*302,380*
XRP	1C	*0,564***			*1,695***							*0,005*	*312,591*
(2016-2022)	2	*0,472**				*1,337****						*0,026*	*227,606*
	3	*0,475**				*1,4****	*0,494*	*-0,326*				*0,027*	*230,080*
	4	*0,499***				*1,265****	*0,213*	*-0,041*	*-1,605***	*-0,735*	*0,328*	*0,031*	*250,557*
	1A	*0,791***	*0,898****									*0,011*	*628,253*
	1B	*0,82***		*0,816****								*0,003*	*683,009*
DOGE	1C	*0,843****			*1,949****							*0,003*	*729,337*
(2016-2022)	2	*0,754***				*1,394****						*0,013*	*563,894*
	3	*0,753***				*1,352****	*-0,229*	*-0,098*				*0,013*	*562,236*
	4	*0,806***				*0,82*	*-0,831*	*2,205*	*-1,451**	*-4,618*	*0,484**	*0,021*	*656,081*
	1A	*0,297**	*0,921****									*0,041*	*111,136*
	1B	*0,335**		*0,573****								*0,006*	*132,284*
LTC	1C	*0,351***			*1,98***							*0,010*	*141,807*
(2016-2022)	2	*0,327***				*1,353****						*0,041*	*127,663*
	3	*0,328***				*1,362****	*0,21*	*-0,492***				*0,043*	*128,235*
	4	*0,352***				*1,214****	*-0,066*	*0,133*	*-1,451***	*-1,229**	*0,488***	*0,051*	*142,415*
	1A	*0,929****	*1,055****									*0,029*	*928,074*
	1B	*0,969****		*0,748****								*0,004*	*1036,030*
BNB	1C	*0,994****			*2,07***							*0,006*	*1109,162*
(2017-2022)	2	*0,882***				*1,639****						*0,031*	*814,215*
	3	*0,888****				*1,714****	*0,708*	*-0,577***				*0,033*	*828,020*
	4	*0,898****				*1,661****	*0,496*	*0,187*	*-1,2*	*-1,101*	*0,767***	*0,037*	*851,491*
	1A	*0,457*	*1,163****									*0,039*	*215,509*
	1B	*0,501**		*0,907****								*0,007*	*252,319*
ADA	1C	*0,533**			*2,454****							*0,009*	*281,749*
(2017-2022)	2	*0,478**				*1,87****						*0,046*	*232,573*
	3	*0,489**				*2****	*0,974**	*-0,416*				*0,048*	*241,876*
	4	*0,512**				*1,81****	*0,674*	*0,622*	*-0,848*	*-1,899**	*0,372**	*0,051*	*262,172*
	1A	*0,656***	*0,898****									*0,021*	*419,513*
	1B	*0,693***		*0,594**								*0,003*	*469,926*
TRX	1C	*0,713***			*1,848**							*0,005*	*499,176*
(2017-2022)	2	*0,612**				*1,446****						*0,024*	*365,313*
	3	*0,617**				*1,512****	*0,471*	*-0,157*				*0,025*	*371,177*
	4	*0,629**				*1,501****	*0,235*	*-0,074*	*-1,576**	*-0,046*	*0,521***	*0,028*	*385,552*
	1A	*1,094****	*1,396****									*0,049*	*1451,658*
	1B	*1,12****		*1,151****								*0,011*	*1555,539*
MATIC	1C	*1,181****			*3,005****							*0,014*	*1827,258*
(2019-2022)	2	*1,026****				*2,208****						*0,060*	*1209,652*
	3	*1,044****				*2,438****	*1,655***	*-0,609*				*0,066*	*1269,789*
	4	*1,052****				*2,413****	*1,39***	*-0,064*	*-1,178*	*-0,727*	*0,675*	*0,070*	*1297,392*
	1A	*0,632**	*1,67****									*0,079*	*389,213*
	1B	*0,71**		*1,065***								*0,011*	*494,695*
SOL	1C	*0,771***			*2,296***							*0,007*	*592,729*
(2020-2022)	2	*0,639**				*2,696****						*0,089*	*397,864*
	3	*0,66**				*2,669****	*0,593*	*-0,584*				*0,092*	*424,741*
	4	*0,644**				*2,77****	*0,747*	*-1,103*	*0,143*	*0,947*	*-0,093*	*0,092*	*404,136*

*Source: This table presents regression estimates for the 4 models in equations 1,2,3 and 4, over the period 01/ Jan/2016 to 31/Dec/2022. ***,** and * indicate that the coefficient is significant at 1%, 5% and 10% level respectively.*

The alpha coefficients in the regressions are positive and statistically significant for all cryptocurrencies, with daily values between 0.253% and 1.181% across models and cryptocurrencies (corresponding to annualised values between 89.034% and 1827.258%).

We begin to consider passive benchmark strategies, which involve buy-and-hold investments in broad-based stock indexes, equivalent to one-factor risk-adjusted models using ETFs that track these indexes3.

When controlling just for benchmarks passive investment strategies (models 1A, 1B and 1C), the equal-weighted portfolio of cryptocurrencies generates significant alphas with values between 0.649% and 0.704% daily. As expected, this outperformance is more pronounced when compared to more defensive investment strategies, including bond ETFs. These abnormal returns are quite heterogeneous across different cryptocurrencies. For instance, when controlling for stock ETFs, MATIC generates a daily alpha of 1.094%, which is more than four times the alpha of BTC (0.253%). Relative to a simple measure of performance, including the Sharpe ratio, there are some noticeable differences. For instance, BTC is now the cryptocurrency that generates the lowest excess performance, even though, according to the Sharpe ratio, it was the fourth cryptocurrency with higher performance.

Common stock characteristics of cryptocurrencies, as argued by Glaser et al. (2014), Baur et al. (2018), Alfieri et al. (2019), and Chokor & Alfieri (2021), validate the use of Fama-French factor models to measure cryptocurrency performance. Next, we will discuss cryptocurrency performance in relation to the CAPM (Model 2), the FF3F (Model 3), and the FF5F augmented by momentum (FF5F+, Model 4) models, due to the popularity of these common stock risk-factor models and their widespread use in the literature.

The equal-weighted portfolio of cryptocurrencies generates a significant excess performance of 0.632% per day under the single-factor CAPM, 0.634% per day under the FF3 model, which includes size and value as additional risk-factors in the CAPM, and 0.651% per day under the FF5F+ model, which includes size, value, profitability, investment, and momentum as additional risk-factors in the CAPM. Therefore, the abnormal returns continue to persist once we account for commonly used risk-factors in asset pricing including market risk, size, value, profitability, investment, and momentum. In turn, the market beta estimates are highly positive and significant in all three models, indicating a

[3] It could be argued that the indexes are not investable, making them unsuitable for passive investment strategies. For more on the topic, see Bianchi & Babiak (2022).

strong exposure of the cryptocurrency portfolio to market risk. However, the estimates of the other risk-factor loadings are less expressive: in the FF5F+ model, in addition to the market factor, only the betas for the profitability and momentum factors are statistically significant. The coefficient of determination (R2) allows to check which of the models explains a greater percentage of the portfolio's variation. It is concluded that the best model is model 4, as it explains 7.1% of the variations in the portfolio.

The excess returns under the factor models are still quite heterogeneous across different cryptocurrencies. When controlling for the six risk-factors (Model 4), MATIC generates a daily alpha of 1.052%, which is more than three times the alpha of BTC (0.287%). The best performing cryptocurrencies are MATIC, BNB and DOGE, while the bottom-3 are BTC, LTC and XRP. The BTC and LTC lowest performance is at odds with the findings of Gregoriou (2019). According to the estimations of this author, BTC and LTC exhibit the highest annualised returns among all the cryptocurrencies. However, it is worth noting that neither our sample periods nor the 10 largest cryptocurrencies are the same. Our data covers the period from 2016 to 2022, while Gregoriou's (2019) data covers the period from 2014 to 2017, with only four cryptocurrencies coinciding in both datasets.

In summary, cryptocurrencies consistently generate abnormal returns. These findings remain robust across various regression model specifications, including CAPM models with stock, gold, and bond ETFs, as well as the traditional market factor risk, the FF3 model, and the FF5F+ model.

In the next section, we assess whether these excess returns are influenced by market conditions, specifically, whether they differ during bull and bear periods in stock markets.

4.4 Risk adjusted alphas under bull and bear periods

Table 9 presents the estimates for bull and bear alphas, derived from the estimation of Model 4, which includes dichotomous variables to differentiate performance during bear and bull periods.

The results suggest that, except for MATIC, the outperformance of cryptocurrencies is smaller during bear markets compared to bull markets. During bear markets, the alphas are not statistically significant for 9 out of 10 cryptocurrencies, indicating no outperformance. Conversely, in bull markets, the alphas remain positive and significant, except for XRP and

TRX. For these two cryptocurrencies, the alphas are not statistically significant, whereas the alpha estimated without distinguishing between bear and bull periods was significant at only the 10% level (see Table 8).

Both MATIC and the equal-weighted portfolio of cryptocurrencies show positive and significant alphas in both bull and bear markets. The Wald test did not reject the null hypothesis of the equality of these two alphas.4

Therefore, our results suggest that the excess returns of some cryptocurrencies are influenced by market conditions, as they cease to be significant during bear markets.

TABLE 9 – ESTIMATION UNDER BULL AND BEAR PERIOD

VARIABLES	BULL MARKET (%)	BEAR MARKET (%)
PORTFOLIO	*0,684****	*0,568***
BTC	*0,332***	*0,184*
ETH	*0,643****	*0,471*
XRP	*0,433*	*0,651*
DOGE	*1,15***	*0,024*
LTC	*0,445***	*0,138*
BNB	*0,611***	*1,506*
ADA	*0,774***	*-0,034*
TRX	*0,696*	*0,487*
MATIC	*0,948***	*1,253**
SOL	*0,927**	*0,109*

*Source: This table presents regressions estimates for the Model 4 adding Bull market and Bear market over the period 01/Jan/2016 to 31/Dec/2022. ***,** and * indicate that the coefficient is significant at 1%, 5% and 10% level respectively.*

[4] The pvalues of the Wald test for the equality of the two alphas were 0.886 for the portfolio and 0.723 for the MATIC. Wald tests for the other cryptocurrencies are not presented, because the alpha bear is statistically non-significant while the alpha bull is positive and statistically significant.

5. Conclusion

We assessed the performance of 10 cryptocurrencies and a portfolio from 2016 to 2022 using daily data. We employed various performance measures, including simple measures like the Sharpe and Sortino ratios, as well as benchmark- and risk-adjusted returns. These returns were calculated by estimating the alphas of three of the most common asset pricing models in the finance literature: the single-factor Capital Asset Pricing Model (CAPM), the Fama and French (1992) three-factor model, and a six-factor model that extends the Fama-French five-factor model (Fama and French, 2015) to incorporate momentum (Carhart, 1997).

Our study has revealed significant insight into cryptocurrencies by using descriptive statistics and risk-adjusted ratios analysis offered informative results, showing the unique characteristics of cryptocurrencies and in terms of returns and risks. They emerge as a tool to access unprecedented levels of returns which would be impossible for an investor to have imagined previously. However, these high returns come with elevated levels of risk in comparison to traditional assets. Several authors have highlighted this phenomenon ((Liu et al. (2021), Enoksen et al. (2020), Liu and Tsyvinski (2018), Papadopoulos (2015), Brière et al. (2015)). Out of all cryptocurrencies, MATIC have the highest average value, followed by BNB. On the other hand, BTC and LTC have lowest average returns. BTC, the initial and most renowned cryptocurrency, displays the lowest annualized return and annualised standard deviation. Our correlation analysis implies that cryptocurrencies have a very low correlation with traditional assets. The correlations between cryptocurrency returns and ETFs of gold and bonds are even lower. Suggesting opportunities for portfolio diversification. Low correlations have been reported by several authors ((Brière et al. (2015), Bouri et al. (2017), Liu and Tsyvinski (2018)) and these findings support our results in the literature.

The results from Sharpe and Sortino ratios suggest already that cryptocurrencies outperform a broad stock market investment. According to Alfieri et al., (2019) and Bianchi & Babiak (2022), these findings are generally in line with previous studies. This outperformance persists when accounting for systematic risk, as our results also suggest that cryptocurrencies deliver risk-adjusted abnormal returns, as measured by the alphas in our models. They confirm their outperformance, by consistently delivering statistically significant positive alphas irrespective of the risk factors and benchmarks used.

However, this outperformance is not homogeneous across markets states. We find that this outperformance is state-dependent, that is, when we consider bull and bear market states, the bear alphas estimated in our models lose their statistical significance.

Therefore, regarding the three main questions addressed in this dissertation, we can answer that: (i) cryptocurrencies demonstrate superior performance; (ii) their outperformance persists when accounting for systematic risk; (iii) and, this outperformance is state-dependent, becoming non-significant during bear markets.

Moreover, we also find that the outperformance of bitcoin is lower than for other more recent cryptocurrencies, suggesting that the outperformance may decline over time. This is an avenue for future work.

In turn, the general finding that cryptocurrencies risk-adjusted returns are superior to those obtained by other financial assets is at odds with the efficient market hypothesis (EMH). However, the finding that this outperformance may be state-dependent, and age-dependent suggests that this result may be largely explained by cryptocurrencies markets being at the earliest ages. As the market matures, and when there are significant risk events, investors seek for fundamentals.

In our opinion, an investor should still learn about cryptocurrency and the risks associated with them. Investors should be aware of this. There are significant risks associated with them and it is only by being aware of them that they can be managed.

6. Bibliography

Alfieri, E., Burlacu, R., & Enjolras, G. (2019). On the nature and financial performance of bitcoin. *The Journal of Risk Finance*, *20*, 2.

Almeida, J., & Gonçalves, T. C. (2022). A systematic literature review of volatility and risk management on cryptocurrency investment: A methodological point of view. *Risks*, *10*, 5. https://www.mdpi.com/2227-9091/10/5/107.

Al-Yahyaee, K. H., Mensi, W., Ko, H. U., Yoon, S. M., & Kang, S. H. (2020). Why cryptocurrency markets are inefficient: The impact of liquidity and volatility. *The North American Journal of Economics and Finance*, *52*, 101168. https://www.sciencedirect.com/science/article/pii/S1062940820300656?casa_token=HV8eEv_s1uwAAAAA:kzkBqZJZZjcn62diTbBOjs72auGNVRTS_8yFUmTesBWPmYTMWAyYmH98kGmQeBXxqHOoKSJLpBI.

Andrianto, Y., & Diputra, Y. (2020). The effect of cryptocurrency on investment portfolio effectiveness. *Journal of Finance and Accounting*, *5*, 6.

Asadi, A. R., & Hemadi, R. (2018). *Understanding virtual currencies in video games: A review*. 109–117. https://arxiv.org/ftp/arxiv/papers/2203/2203.14253.pdf.

Baddeley, M. (2004). Using e-cash in the new economy: An economic analysis of micro-payment systems. *Journal of Electronic Commerce Research*, *5*, 4. http://ojs.jecr.org/jecr/sites/default/files/05_4_p03_0.pdf.

Baek, H., Oh, J., Kim, C. Y., & Lee, K. (2019). *A model for detecting cryptocurrency transactions with discernible purpose*. 713–717. https://ieeexplore.ieee.org/stamp/stamp.jsp?arnumber=8806126&casa_token=XjQMIItzIxAAAAAA:4xhhpw1dBkk6FT-MfzN_dMntj6n9ycUpFy6HSmH15aS7KRmHNyDHigpl6PkoqI4Rd5fkWZVgR64&tag=1.

Baur, D. G., Hong, K., & Lee, A. D. (2018). Virtual currencies: media of exchange or speculative asset?”. *Journal of International Financial Markets, Institutions and Money*, *54*, 177–189.

Bianchi, D., & Babiak, M. (2022). On the performance of cryptocurrency funds. *Journal of Banking & Finance*, *138*, 106467.

Bonneau, J., Miller, A., Clark, J., Narayanan, A., Kroll, J. A., & Felten, E. W. (2015). *Sok: Research perspectives and challenges for bitcoin and cryptocurrencies*. 104–121. https://spia.princeton.edu/system/files/research/documents/Felten_SoK.pdf.

Bouri, E., Das, M., Gupta, R., & Roubaud, D. (2018). Spillovers between Bitcoin and other assets during bear and bull markets. *Applied Economics*, *50*, 55.

Bouri, E., Gupta, R., & Roubaud, D. (2019). Herding behaviour in cryptocurrencies. *Finance Research Letters*, *29*, 216–221.

Bouri, E., Jalkh, N., Molnár, P., & Roubaud, D. (2017). Bitcoin for energy commodities before and after the December 2013 crash: diversifier, hedge or safe haven? *Applied Economics*, 1–11. https://doi.org/10.1080/00036846.2017.1299102

Briere, M., Oosterlinck, K., & Szafarz, A. (2015). Virtual currency, tangible return: Portfolio diversification with bitcoin. *Journal of Asset Management*, *16*, 365–373.

Bry, G., & Boschan, C. (1971). *Front matter to" Cyclical Analysis of Time Series: Selected Procedures and Computer Programs"* (pp. 13–12).

Bunjaku, F., Gjorgieva-Trajkovska, O., & Miteva-Kacarski, E. (2017). Cryptocurrencies–advantages and disadvantages. *Journal of Economics*, *2*, 1. https://js.ugd.edu.mk/index.php/JE/article/download/1933/1706.

Cai, W., Wang, Z., Ernst, J. B., Hong, Z., Feng, C., & Leung, V. C. (2018). Decentralised applications: The blockchain-empowered software system. *IEEE Access*, *6*, 53019–53033. https://ieeexplore.ieee.org/abstract/document/8466786.

Carhart, M. M. (1997). On persistence in mutual fund performance. *The Journal of Finance*, *52*, 1.

Carmona, T. (2022). *Debunking the narratives about cryptocurrency and financial inclusion*. https://www.brookings.edu/articles/debunking-the-narratives-about-cryptocurrency-and-financial-inclusion

Chase, B., & MacBrough, E. (2018). *Analysis of the XRP ledger consensus protocol*. https://arxiv.org/pdf/1802.07242.pdf.

Chaum, D., Grothoff, C., & Moser, T. (2021). *How to issue a central bank digital currency*. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3965032.

Cheah, P. (2015). *What is a world?: on postcolonial literature as world literature*. Duke University Press.

Chohan, U. W. (2022). *A history of bitcoin*. https://www.zbw.eu/econis-archiv/bitstream/11159/343037/1/EBP07563001X_0.pdf.

Chokor, A., & Alfieri, E. (2021). Long and short-term impacts of regulation in the cryptocurrency market. *The Quarterly Review of Economics and Finance*, *81*, 157–173.

Ciaian, P., & Rajcaniova, M. (2018). Virtual relationships: Short-and long-run evidence from BitCoin and altcoin markets. *Journal of International Financial Markets, Institutions and Money*, *52*, 173–195. https://www.sciencedirect.com/science/article/pii/S1042443117302858.

Ciaian, P., Rajcaniova, M., & Kancs, D. (2017). Virtual relationships: Short- and longrun evidence from BitCoin and altcoin markets. *Journal of International Financial Markets, Institutions and Money*, *52*, 173–195,. https://doi.org/10.1016/j.intfin.2017.11.001.

Cooper, I. (2006). Asset pricing implications of nonconvex adjustment costs and irreversibility of investment. *The Journal of Finance*, *61*, 1.

Corbet, S., Lucey, B., Urquhart, A., & Yarovaya, L. (2019). Cryptocurrencies as a financial asset: A systematic analysis. *International Review of Financial Analysis*, *62*, 182–199. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3143122.

Corral, F. J. G., García, J. A. C., Valenciano, J. P., & Toril, J. U. (2022). A bibliometric review of cryptocurrencies: how have they grown? *Financial Innovation*, *8*, 1. https://jfin-swufe.springeropen.com/articles/10.1186/s40854-021-00306-5.

Crawley, J. (2021). *Ripple touts role for XRP in central bank digital currency white paper*. https://www.coindesk.com/tech/2021/03/23/ripple-touts-role-for-xrp-in-central-bank-digital-currency-white-paper

Cretarola, A., Figà-Talamanca, G., & Grunspan, C. (2021). *Blockchain and cryptocurrencies: economic and financial research*. Decisions in Economics and Finance. https://link.springer.com/article/10.1007/s10203-021-00366-3.

Dumitrescu, G. C. (2017). Bitcoin–a brief analysis of the advantages and disadvantages. *Global Economic Observer*, *5*, 2. http://www.globeco.ro/wp-content/uploads/vol/GEO_Vol_5_No_2.pdf#page=63.

Ebringer, T., & Thorne, P. (1999). *Engineering an eCash system*. *32-36*. https://link.springer.com/content/pdf/10.1007/3-540-47790-X.pdf#page=42.

Enoksen, F. A., Landsnes, C. J., Lučivjanská, K., & Molnár, P. (2020). Understanding risk of bubbles in cryptocurrencies. *Journal of Economic Behavior & Organization*, *176*, 129–144.

Fama, E. F., & French, K. R. (1992). The cross-section of expected stock returns. *The Journal of Finance*, *47*, 2.

Fama, E. F., & French, K. R. (2015). A five-factor asset pricing model. *Journal of Financial Economics*, *116*, 1.

Fama, E. F., French, K. R., Booth, D. G., & Sinquefield, R. (1993). Differences in the risks and returns of NYSE and NASD stocks. *Financial Analysts Journal*, *49*, 1.

Faturahman, A., Agarwal, V., & Lukita, C. (2021). Blockchain technology-the use of cryptocurrencies in digital revolution. *IAIC Transactions on Sustainable Digital Innovation (ITSDI*, *3*, 1. https://aptikom-journal.id/itsdi/article/view/523.

Feng, R. (2023). The future prospects of cryptocurrencies and their impact on financial markets. *Highlights in Business, Economics and Management*, *17*, 28–31. https://drpress.org/ojs/index.php/HBEM/article/view/11020.

Frankenfield, J. (2023a). *Cryptocurrency explained with pros and cons for investment*. https://www.investopedia.com/terms/c/cryptocurrency.asp.

Frankenfield, J. (2023b). *Is crypto a commodity? What it means, examples*. https://www.investopedia.com/terms/c/crypto-commodity.asp.

Frick, T. A. (2019). Virtual and cryptocurrencies—regulatory and anti-money laundering approaches in the European Union and in Switzerland. *Era Forum*, *20*, 1. https://link.springer.com/article/10.1007/s12027-019-00561-1.

Fry, R. (2016). Millennials overtake baby boomers as america's largest generation. *Pew Research Center*, *25*, 1–36.

García-Álvarez, L., & Luger, R. (2011). *Dynamic correlations, estimation risk, and portfolio management during the financial crisis*.

Giudici, G., Milne, A., & Vinogradov, D. (2020). Cryptocurrencies: market analysis and perspectives. *Journal of Industrial and Business Economics*, *47*, 1–18. https://link.springer.com/article/10.1007/s40812-019-00138-6

Glaser, F., Zimmermann, K., Haferkorn, M., Weber, M. C., & Siering, M. (2014). Bitcoin-asset or currency? revealing users' hidden intentions. In *Revealing Users' Hidden Intentions*. ECIS.

Gowda, N., & Chakravorty, C. (2021). Comparative study on cryptocurrency transaction and banking transaction. *Global Transitions Proceedings*, *2*, 2. https://www.sciencedirect.com/science/article/pii/S2666285X21000923.

Gregoriou, A. (2019). Cryptocurrencies and asset pricing. *Applied Economics Letters*, *26*, 12.

Guo, H., Hao, L., Mukhopadhyay, T., & Sun, D. (2019). Selling virtual currency in digital games: Implications for gameplay and social welfare. *Information Systems Research*, *30*, 2. https://pubsonline.informs.org/doi/abs/10.1287/isre.2018.0812.

Gupta, H., & Chaudhary, R. (2022). An empirical study of volatility in cryptocurrency market. *Journal of Risk and Financial Management*, *15*, 11.

https://www.mdpi.com/1911-8074/15/11/513.

Harper, C. (2018). *Making sense of proof of work vs. Proof of stake*. https://coincentral.com/making-sense-of-proof-of-work-vs-proof-of-stake

Jeris, S. S., Chowdhury, A. N. U. R., Akter, M. T., Frances, S., & Roy, M. H. (2022). *Cryptocurrency and stock market: bibliometric and content analysis*. https://www.sciencedirect.com/science/article/pii/S2405844022018023.

Ji, Q., Bouri, E., Roubaud, D., & Kristoufek, L. (2019). Information interdependence among energy, cryptocurrency and major commodity markets. *Energy Economics*, *81*, 1042–1055. https://www.sciencedirect.com/science/article/pii/S0140988319301896?casa_token=MFuGOPOoGv4AAAAA:gUsbzLtDlq-p6DR28yjQV_x4f28H383tSgmN1DfJ7NZbnftGUf-X_SPrHyyiFYvzhgeW61o3_w.

Jørgensen, K. P., & Beck, R. (2022). *Universal wallets*. Business & Information Systems Engineering. https://link.springer.com/article/10.1007/s12599-021-00736-6.

Kayal, P., & Rohilla, P. (2021). Bitcoin in the economics and finance literature: a survey. *SN Business & Economics*, *1*, 7. https://link.springer.com/article/10.1007/s43546-021-00090-5.

Komalavalli, C., Saxena, D., & Laroiya, C. (2020). *Overview of blockchain technology concepts* (pp. 349–371). Academic Press. https://www.researchgate.net/profile/Vibha-Nehra/publication/339591585_Blockchain_Implementation_for_Internet_of_Things_Applications/links/603ddce94585154e8c6e19e2/Blockchain-Implementation-for-Internet-of-Things-Applications.pdf#page=382.

Kozak, S., & Gajdek, S. (2021). Risk of investment in cryptocurrencies. *Economic and Regional Studies/Studia Ekonomiczne I Regionalne*, *14*, 3.

Kushwaha, S. S., Joshi, S., Singh, D., Kaur, M., & Lee, H. N. (2022). Ethereum smart contract analysis tools: A systematic review. *IEEE Access*, *10*, 57037–57062. https://ieeexplore.ieee.org/abstract/document/9762279.

Kutera, M. (2022). Cryptocurrencies as a subject of financial fraud. *Journal of Entrepreneurship, Management and Innovation*, *18*, 4. https://ruj.uj.edu.pl/xmlui/bitstream/handle/item/304717/kutera_cryptocurrencies%20_as_a_subject_of_financial_fraud_2022.pdf?sequence=1&isAllowed=y.

Lintner, J. (1965). Security prices, risk, and maximal gains from diversification. *The Journal* *of Finance*, *20*, 4.

Liu, Y., & Tsyvinski, A. (2018). *Risks and returns of cryptocurrency* (Issue w24877)).

Liu, Y., & Tsyvinski, A. (2021). Risks and returns of cryptocurrency. *The Review of Financial Studies*, *34*, 6. https://academic.oup.com/rfs/article/34/6/2689/5912024?login=false.

Liu, Y., Tsyvinski, A., & Wu, X. (2022). Common risk factors in cryptocurrency. *The Journal of Finance*, *77*, 2. https://onlinelibrary.wiley.com/doi/pdfdirect/10.1111/jofi.13119?casa_token=ZJuxDoklFxcAAAAA:wWzOYkNingaPy_meI9viKj_kFkCjzoavWeu74fBBWjf2d59kxE6ifnEwFxuILba5wIs7V3ILxQr9csI

Makarov, I., & Schoar, A. (2022). *Cryptocurrencies and decentralised finance (DeFi* (No. w30006)). National Bureau of Economic Research. https://www.nber.org/system/files/working_papers/w30006/w30006.pdf.

Martin Martin, R. D., & Simin, T. T. (2003). Outlier-resistant estimates of beta. *Financial Analysts Journal*, *59*, 5.

Martynov, O. (2020). *Sustainability analysis of cryptocurrencies based on projected return on investment and environmental impact*. https://dash.harvard.edu/bitstream/handle/1/37365412/martynov-document-2020.pdf?sequence=1.

Marzo, G. D., Pandolfelli, F., & Servedio, V. D. (2022). Modeling innovation in the cryptocurrency ecosystem. *Scientific Reports*, *12*, 1. https://www.nature.com/articles/s41598-022-16924-7.

Matkovskyy, R., & Jalan, A. (2019). From financial markets to Bitcoin markets: A fresh look at the contagion effect. *Finance Research Letters*, *31*, 93–97,. https://doi.org/10.1016/j.frl.2019.04.007.

Mossin, J. (1966). Equilibrium in a capital asset market. In *Econometrica: Journal of the econometric society* (pp. 768–783).

Naeem, M. A., & Karim, S. (2021). Tail dependence between bitcoin and green financial assets. *Economics Letters*, *208*, 110068.

Nakamoto, S. (2008). *Bitcoin: A peer-to-peer electronic cash system Bitcoin: A Peer-to-Peer Electronic Cash System*. https://bitcoin.

Nakamoto, S. (2009). *Bitcoin: A peer-to-peer electronic cash system. Decentralised business review*. https://bitcoin.org/bitcoin.pdf.

Nilsen, J. M., Park, J. H., Yun, S., Kang, J. M., & Jung, H. (2022). Competing miners: A synergetic solution for combining blockchain and edge computing in unmanned aerial vehicle networks. *Applied Sciences*, *12*, 5. https://www.mdpi.com/2076-3417/12/5/2581.

P.W.C. (2022). *ETFs 2026: The next big leap*. https://www.pwc.com/gx/en/financial-services/publications/assets/ETF_2026_PwC.pdf.

Pagan, A. R., & Sossounov, K. A. (2003). A simple framework for analysing bull and bear markets. *Journal of Applied Econometrics*, *18*, 1.

Papadopoulos, G. (2015). *Blockchain and digital payments* (pp. 153–172). https://doi.org/10.1016/B978-0-12-802117-0.00007-2

Pessa, A. A., Perc, M., & Ribeiro, H. V. (2023). Age and market capitalization drive large price variations of cryptocurrencies. *Scientific Reports*, *13*, 1. https://www.nature.com/articles/s41598-023-30431-3.

Pistunov, I. M., & Nikolaenko, A. O. (2023). *The emergence of deflationary cryptocurrencies: a new era of digital assets*. https://ir.nmu.org.ua/handle/123456789/163543.

Prasad, S. (1998). *Study of electronic cash: Its impact on the economy and society, and its future*. https://digitalcommons.law.uga.edu/stu_llm/218

Price, A. (2023). *Stock market vs cryptocurrency: Full comparison*. https://tectum.io/blog/stock-market-vs-cryptocurrency/#Stock_Market_vs_Cryptocurrency_Is_the_stock_market_bigger_than_crypto.

Rankhambe, B. P., & Khanuja, H. K. (2019). *A comparative analysis of blockchain platforms–Bitcoin and Ethereum*. 1–7. https://ieeexplore.ieee.org/abstract/document/9129332?casa_token=tyLbSjAhITwAAAAA:0xHCwGW-k69KI5Cn3MdXy-b-TrR08fDNZ5y68x54KLzzjefTmymlY_XSCikGaGKRda7KVr8xNA.

Šafka, J. (2014). *Virtual currencies in real economy: Bitcoin (charles university in prague*. Charles University in Prague.

Sharpe, W. F. (1964). Capital asset prices: A theory of market equilibrium under conditions of risk. *The Journal of Finance*, *19*, 3.

Silva, T. C., Wilhelm, P. V. B., & Tabak, B. M. (2023). Trade matters except to war neighbors: The international stock market reaction to 2022 Russia’s invasion of Ukraine. *Research in International Business and Finance*, *65*(101935), 101935. https://doi.org/10.1016/j.ribaf.2023.101935

Sitthipon, T., Kaewpuang, P., Auttawechasakoon, P., Sitthipon, T., Kaewpuang, P., & Auttawechasakoon, P. (2023). A review of cryptocurrency in the digital economy. *International Journal of Computing Sciences Research*, *7*, 1152–1161. https://www.researchgate.net/profile/Tamonwan-Sitthipon/publication/365128937_A_Review_of_Cryptocurrency_in_the_Digital_Economy/links/6365bf7237878b3e878286da/A-Review-of-Cryptocurrency-in-the-Digital-Economy.pdf.

Spurr, A., & Ausloos, M. (2021). Challenging practical features of Bitcoin by the main altcoins. *Quality & Quantity*, *55*, 5. https://link.springer.com/article/10.1007/s11135-020-01062-x.

Stevens, P. (2021). *Cryptocurrencies are close to reaching a big milestone versus gold by one Wall Street firm's count*. CNBC. https://www.cnbc.com/2021/05/18/cryptocurrencies-are-close-to-reaching-a-big-milestone-versus-gold-by-one-wall-street-firms-count.html.

Taskinsoy, J. (2020). *Bitcoin could be the first cryptocurrency to reach a market capitalization of one trillion dollars*. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3693765.

Treiblmaier, H. (2020). *Toward more rigorous blockchain research: Recommendations for writing blockchain case studies. Blockchain and distributed ledger technology use cases*. Applications and Lessons Learned. https://www.frontiersin.org/articles/10.3389/fbloc.2019.00003/full.

Treynor, J. L. (1961). Market value, time, and risk. In *Time, and Risk*.

Treynor, J. L. (1962). *Jack treynor's' toward a theory of market value of risky assets'*.

Tripathi, V., & Bhandari, V. (2016). Performance evaluation of socially responsible stocks portfolios across sectors during different economic conditions. *Journal of Management Research*, *16*, 02.

Urquhart, A., & Lucey, B. (2022). Crypto and digital currencies—nine research priorities. *Nature*, *604*, 7904. https://www.nature.com/articles/d41586-022-00927-5.

Vejačka, M. (2014). Basic aspects of cryptocurrencies. *Journal of Economy, Business and Financing, 2,* 2. https://www.researchgate.net/profile/Martin-Vejacka/publication/292586903_Basic_Aspects_of_Cryptocurrencies/links/56af544c08ae19a38517479e/Basic-Aspects-of-Cryptocurrencies.pdf.

Wang, J., Xue, Y., & Liu, M. (2016). *An analysis of bitcoin price based on VEC model*. 146–152,. https://doi.org/10.2991/icemi-16.2016.36.

Wijk, D. (2013). *What can be expected from the bitcoin?* Universiteit Rotterdam). Universiteit Rotterdam.

Xu, J., Bai, W., Hu, M., Tian, H., & Wu, D. (2021). Bitcoin miners: Exploring a covert community in the Bitcoin ecosystem. *Peer-To-Peer Networking and Applications, 14,* 644–654. https://link.springer.com/article/10.1007/s12083-020-01021-1.

Younis, I., Shah, W. U., & Yousaf, I. (2023). Static and dynamic linkages between oil, gold and global equity markets in various crisis episodes: Evidence from the Wavelet TVP-VAR. *Resources Policy*, *80*(103199), 103199. https://doi.org/10.1016/j.resourpol.2022.103199

Yu, C., Yang, W., Xie, F., & He, J. (2022). *Technology and security analysis of cryptocurrency based on Blockchain*. Complexity. https://www.hindawi.com/journals/complexity/2022/5835457

Yu, H., Sun, Y., Liu, Y., & Zhang, L. (2023). *Bitcoin gold, litecoin silver: An introduction to cryptocurrency's valuation and trading strategy*. https://arxiv.org/pdf/2308.00013.pdf.

Zarrin, J., Phang, W., Babu Saheer, L, & Zarrin, B. (2021). Blockchain for decentralization of internet: prospects, trends, and challenges. *Cluster Computing*, *24,* 4. https://link.springer.com/article/10.1007/s10586-021-03301-8.

Zhou, Q., Huang, H., Zheng, Z., & Bian, J. (2020). Solutions to scalability of blockchain: A survey. *Ieee Access, 8,* 16440–16455. https://ieeexplore.ieee.org/abstract/document/8962150