Assessing the market efficiency of cryptocurrencies and its impact on portfolio performance

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PREFACE

A PhD thesis titled "*Assessing the market efficiency of cryptocurrencies and its impact on portfolio performance*" is presented here to fulfil the graduation requirements for the degree of Doctor of Philosophy in Economic and Management Sciences with Risk Management at the North-West University.

The thesis has been compiled and finalised in accordance with the full dissertation format. The theoretical work described in this dissertation was carried out whilst in the employment of Midlands State University (Gweru, Zimbabwe) and later at ING Risk Hubs (Warsaw, Poland). Some theoretical and practical work was carried out in collaboration with the Department of Risk Management, School of Economics, North-West University (South Africa) under the supervision of Prof André Heymans and co-supervision of Prof Chris van Heerden.

The work presented in this thesis is entirely my own, except where explicitly stated otherwise. I hereby affirm that this research has not been previously submitted to any institution or organisation for assessment, academic credit, or any other purpose. Additionally, I have made every effort to acknowledge all sources of information, data, and ideas utilised in this research, and these have been appropriately cited in the reference section.

My work on this thesis commenced in February 2020 and concluded in September 2025. This journey has been a profound and enlightening experience, both professionally and personally. Over this period, I have come to understand that struggle is an integral part of growth and that navigating through great disappointments often provides deeper insights than an unchallenged path. Hard work, discipline, and persistence have proven to be essential ingredients for success, and I firmly believe that failure only occurs when one concedes defeat.

This thesis has been a transformative teaching tool, instilling in me the confidence to venture into unfamiliar territory, the resilience to overcome obstacles, and the humility to appreciate that learning is a continuous and lifelong process. I am grateful for the opportunity to contribute to the academic discourse on cryptocurrencies and risk management, and I hope this research will be of value to others in this field.



Simiso Siziba

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DEDICATIONS AND ACKNOWLEDGEMENTS

To my committed professors, André Heymans and Chris van Heerden, whose wisdom and mentorship shaped every page of this thesis.

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My wife, Obvious, who believed in my dreams and endured all the lonely times.

For my daughters Bathandwa and Babalwa, who cheered me on.

To the persistent child within me, who undeterred by setbacks and disappointments continues to dream and persistently asks “why?” and to envision “what if?”; may your unwavering curiosity guide the pursuit of knowledge embodied in this work.

ABSTRACT

This study employs variance ratio tests to examine the efficiency of Bitcoin and Ethereum markets and evaluates their contribution to long-only equity, bond, and cash portfolios. Efficiency is analysed over 2015–2024 and across three crisis windows: the US–China trade tensions (2018), the Covid-19 shock (2020), and the Russia–Ukraine conflict (2022). Bitcoin displays comparatively stable weak-form efficiency, while Ethereum shows clear post-2019 improvement, consistent with evidence of evolving efficiency in major cryptocurrencies. Both Bitcoin and Ethereum experienced a marked efficiency breakdown in 2020, consistent with evidence that strong price appreciations attract noise traders and speculative flows, increasing return predictability. In contrast, the 2018 and 2022 drawdowns coincide with periods in which efficiency remains intact, aligning with studies showing that declining markets tend to be dominated by relatively informed trading, thereby preserving weak-form efficiency even under stress.

Employing both the Markowitz mean–variance and Black–Litterman optimisation frameworks, this study assesses the impact of time-varying efficiency in Bitcoin and Ethereum on their portfolio value across various crisis regimes. The findings indicate that during the trade and geopolitical disruptions of 2018 and 2022, both assets demonstrate relatively stable weak-form efficiency; however, their high volatility contributes to increased total and idiosyncratic portfolio risk, thereby limiting diversification benefits. Conversely, the Covid-19 shock in 2020 is associated with a significant decline in efficiency and increased return predictability. Portfolio analysis reveals that cryptocurrencies offer conditional enhancements in risk-adjusted performance, particularly within higher-risk allocations. Overall, the results suggest that Bitcoin and Ethereum function as context-dependent diversifiers, with their effectiveness varying according to prevailing market efficiency conditions (shaped by the type of market crisis) and investors' risk tolerance, rather than serving as universal hedging or safe-haven instruments.

Taken together, the results establish a testable link between time-varying return predictability and the conditional diversification benefits of cryptocurrencies. For investors, the evidence suggests that Bitcoin and Ethereum act primarily as context-dependent diversifiers rather than as true hedges or safe-haven assets, and their high volatility requires careful portfolio allocation. In the South African setting, the findings point to potential diversification gains in equity-heavy portfolios an insight that may be relevant given that regulatory frameworks such as Regulation 28 currently preclude cryptocurrency exposure.

Keywords: Bitcoin; cryptocurrencies; digital asset; diversification; economic crises; Ethereum; market efficiency; portfolio risk; risk-adjusted performance.

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List of Abbreviations

All Share Index - ALSI

AMH - Adaptive Market Hypothesis

AVR - Automatic Variance Ratio

AVR - Automatic VR

BL - Black Litterman

BPT - Behavioural portfolio theory

BTC - Bitcoin

BUSD - Binance USD

CAPE - Cyclically Adjusted Price-to-Earnings

CAPM - Capital Asset Pricing Model

CBDCs - Central Bank Digital Currencies

CEXs - centralised exchanges

CFTC - Commodity Futures Trading Commission

CVaR - Conditional Value at Risk

JS - Joint Sign

JSE - Johannesburg Stock Exchange

MiCA - Markets in Crypto-Assets

MPT - Modern Portfolio Theory

MVaR - Modified Value at Risk

MVO - Mean/Variance Optimisation

MVP - Minimum Variance Portfolio

NFTs - Non-Fungible Tokens

P2P - Peer-to-Peer

PoR - Proof of research

POS - Proof of Stake

POW - Proof of Work

dApps - Decentralised Applications

DeFi - Decentralised Finance

DEXs - Decentralised Exchanges

DLT - Distributed Ledger Technology

DNS - Domain Name System

EMH - Efficient Market Hypothesis

EPO - Enhanced Portfolio Optimisation

ETFs - Exchange Traded Funds

ETH - Ethereum

FinCEN - Financial Crimes Enforcement Network

FSB - Financial Stability Board

FSCA - Financial Sector Conduct Authority

ICO - Initial Coin Offering

IRS - Internal Revenue Service

JM - Wild Bootstrap

QE - Quantitative Easing

REITs - Real Estate Investment Trusts

RO - Robust Optimisation

SA - South Africa

SAA - Strategic Asset Allocation

SEC - Securities and Exchange Commission

SMEs - Small to Medium Enterprises

SOL - Solana

TAA - Tactical Asset Allocation

TEE - Test of Evolving Efficiency

UK - United Kingdom

US - United States

USD - United States Dollar

USDC - USD Coin

USDT - Tether

VaR - Value at Risk

VR - Variance Ratio

WSJ - Wall Street Journal

XRP - Ripple

CHAPTER ONE

INTRODUCTION

1.1 Background to the study

Cryptocurrencies have gained widespread attention from academia, investors, regulators and the public (Almeida & Gonçalves, 2023; Le Tran & Leirvik, 2020; Lee *et al.*, 2017; Mokni *et al.*, 2025). The heightened attention is attributable to several reasons related to remarkable returns (Corbet *et al.*, 2018; Liu & Tsyvinski, 2021), disruptive innovations (Makarov & Schoar, 2022; Qiu *et al.*, 2024), and regulatory ambiguity (Bjelajac & Bajac, 2022; Griffith & Clancey-Shang, 2023; Hughes, 2017; Nabilou, 2019). Originally designed to decentralise payment systems (Nakamoto, 2008), cryptocurrencies have dynamically evolved with varying applications in fintech investment strategies, financial services, supply chain management and healthcare applications (Radanliev, 2024; Soltani *et al.*, 2025). Makarov and Schoar (2022) classified them into two main types: stablecoins and non-stablecoins.

Stablecoins consists of cryptocurrencies collateralised by assets such as fiat currency or another cryptocurrency (Makarov & Schoar, 2022). Prominent examples include those backed by the United States Dollar (USD), such as Tether (USDT), USD Coin (USDC), and Binance USD (BUSD) (CoinMarketCap, 2025). Stablecoins are fundamentally different from Central Bank Digital Currencies (CBDCs) in the sense that they are privately issued while CBDCs are issued and regulated by central banks - making them an official digital representation of a country's currency (Makarov & Schoar, 2022). As of the end of 2024, 137 countries & currency unions, representing 98% of global GDP, were exploring a CBDC with three countries having officially launched CBDCs: Bahamas, Jamaica and Nigeria[1]. The other class of stablecoins comprises those collateralised by other cryptocurrencies, with DAI collateralised by a basket of cryptocurrencies being a notable example (Makarov & Schoar, 2022). At the end of December 2024, there were hundreds of stablecoins with a combined market capitalisation of approximately USD140 billion[2] - comparable to the total British Pound banknotes in circulation of about GBP82

[1] Central Bank Digital Currency tracker is obtained from Atlantic council (https://www.atlanticcouncil.org/cbdctracker/). 10 April 2025.

[2] Data relating to cryptocurrencies is obtained from CoinMarketCap (https://coinmarketcap.com/charts/). 10 April 2025.

billion[3] (about USD103 billion as of December 2024) and a substantial proportion of the USD2.3 trillion[4] notes in circulation.

Non-stablecoins encompass a broader and more diverse category within the cryptocurrency architecture. The leading non-stablecoins, such as Bitcoin (BTC), Ethereum (ETH), Ripple (XRP), and Solana (SOL), are defined by significant market-driven price volatility (Liu & Serletis, 2019; Sibande *et al.*, 2023), a feature that stablecoins aim to mitigate. Non-stablecoins function as stores of value, speculative instruments, and facilitate network fee payments or governance participation (Makarov & Schoar, 2022).

A substantial portion of cryptocurrencies are underpinned by Layer 1 blockchains - such as Bitcoin, Ethereum, Cardano, and Solana which function as the base infrastructure for decentralised transactions and smart contracts (Radanliev, 2024). However, Layer 1 blockchains have been found deficient in handling transaction loads comparable to those managed by traditional financial systems - such as transactions processing in banking, a realisation that Gudgeon *et al.* (2020) argued led to the development of Layer 2 blockchain protocols. The Layer 2 blockchain protocol are thus built on top of Layer 1 blockchains to optimise the Layer 1 network by reducing network congestion, improving transaction processing throughput while leveraging the base infrastructure of Layer 1 protocols (Gudgeon *et al.*, 2020; Jensen *et al.*, 2021). Layer 2 blockchain exemplified by Mantle, Arbitrum and Optimism (CoinMarketCap, 2025) aim to enhance scalability and efficiency by building on the Layer 1 blockchain protocols (Gudgeon *et al.*, 2020; Jensen *et al.*, 2021).

The non-stablecoin cryptocurrency ecosystem is further characterised by the development of decentralised applications (dApps), which primarily utilise Layer 1 blockchain protocols, though the importance of Layer 2 is also increasing across a wide range of sectors including finance, gaming, and social media (Fang *et al.*, 2025; Makarov & Schoar, 2022). Non-fungible tokens (NFTs) which provide unique digital ownership of assets are becoming more relevant especially among artists and collectors (Zhang, 2023). Moreover, the growing trend of asset tokenisation, the use of on-chain tokens such as ERC-20, and the rise of decentralised finance (DeFi) tokens, privacy coins, meme coins, governance tokens, and utility tokens all highlight the diverse ways in

[3] Volume of money in circulation in the UK is obtained from Banknote statistics Bank of England (https://www.bankofengland.co.uk/statistics/banknote). 10 April 2025.

[4] Volume of USD in circulation is obtained from Federal Reserve Board - Currency in Circulation: Volume (https://www.federalreserve.gov/paymentsystems/coin_currcircvolume.htm). 10 April 2025.

which cryptocurrencies continue to evolve, transforming economic, financial, and governance structures, marking a significant shift in how cryptocurrencies are viewed and what they represent (Makarov & Schoar, 2022).

Despite the diverse nature of cryptocurrencies, it is widely acknowledged that BTC and ETH are by far the most popular. As of December 2024, BTC and ETH recorded market capitalisations of approximately USD 1.83 trillion[5] and USD 0.40 trillion, respectively. Collectively, these two cryptocurrencies represented 70% of the total cryptocurrency market capitalisation, which was USD 3.2 trillion, with BTC accounting for 57% and ETH for 13%. The remaining market share of about 30% was comprised of hundreds of stablecoins (6%) and thousands of other cryptocurrencies (24%). Some of the high value cryptocurrencies included DeFi tokens with a market capitalisation of around USD 45 billion with tokens which include Chainlink, Hedera and Avalanche accounting for substantial values. NFTs had a considerable market capitalisation of over USD5 billion.

Cryptocurrencies, despite falling into various categories depending on their purpose and use, they share a fundamental characteristic: they are decentralised digital assets thereby facilitating global peer-to-peer (P2P) transactions (Jensen *et al.*, 2021; Makarov & Schoar, 2022; Nakamoto, 2008), employ cryptographic techniques to secure transactions and facilitate the transfer of value (Fang *et al.*, 2025; Gencer *et al.*, 2018). Unlike conventional fiat currencies, they are not associated with authorities' practices such as quantitative easing - QE (Afonso & Jalles, 2019; Christensen & Krogstrup, 2019), are highly divisible (Hayes, 2017; Urquhart & Zhang, 2019), have no physical representation (Low & Teo, 2018) and thus have no printing costs. The underlying principle of cryptocurrencies is that they are based on P2P communication instead of information being held and controlled by a central party. As a result, changes in how a cryptocurrency functions, require consensus among peers rather than any central policy-making authority (Klein *et al.*, 2018).

Since their introduction, cryptocurrencies have expanded at an extraordinary pace. The total market capitalisation grew from around USD10 billion at the beginning of 2014, when adoption began to accelerate to over USD3.2 trillion by December 2024. This expansion occurred despite major market disruptions including the Covid-19 crisis which generated substantial volatility across global financial markets (Corbet *et al.*, 2022; Lahmiri & Bekiros, 2020; Nguyen *et al.*, 2022). To contextualise this growth, by the end of 2024 the cryptocurrency market exceeded the size of

[5] All data relating to cryptocurrencies market capitalisation is obtained from CoinMarketCap (https://coinmarketcap.com/view/defi/). 10 April 2025.

South Africa's FTSE/JSE All Share Index, JSE ALSI (around ZAR19.3 trillion[6] or USD1.02 trillion) and was significantly larger than all other African equity markets. For example, Morocco's Casablanca Stock Exchange – the second largest on the continent had a market capitalisation of around USD74 billion[7] while Nigeria's NGX - Nigerian Exchange Group the third, stood at around USD41 billion.

By December 2024, the market capitalisation of cryptocurrencies had surpassed the equity market capitalisations of several major economies. Its size exceeded that of Brazil's Bolsa, Balcão exchange (USD 658 billion), the Australian Securities Exchange (ASX) (USD 1.7 trillion), and Switzerland's SIX Swiss Exchange (USD 1.6 trillion). It approached the scale of leading European markets such as the London Stock Exchange in the United Kingdom (USD 3.0 trillion) and France's Euronext Paris (USD 3.1 trillion). Only a handful of countries maintained equity markets that remained substantially larger than the cryptocurrency market capitalisation, including Japan with the Tokyo Stock Exchange (USD 6.3 trillion), India with the Bombay Stock Exchange (USD 5.1 trillion), and China with the combined value of the Shanghai and Shenzhen Stock Exchanges (USD 11.7 trillion) (Ceic, 2025). The US remained a global outlier with a combined market capitalisation of USD62.2[8] across the New York Stock Exchange, Nasdaq and the OTCQX substantially larger than cryptocurrency market capitalisation. Taken together, these comparisons highlight the remarkable scale achieved by cryptocurrencies within just over a decade. As of 2024, the total market capitalisation of the cryptocurrency sector exceeded that of most national equity markets worldwide, underscoring its growing relevance to global financial systems despite its relatively recent emergence.

As the cryptocurrency market continues to grow, its ecosystem has evolved, advancing from centralised exchanges (CEXs), such as Binance and Coinbase, to also include sophisticated decentralised exchanges (DEXs), like Uniswap and PancakeSwap, which leverage Ethereum's smart contract functionality allowing for P2P trading without intermediaries (Hägele, 2024). These platforms (CEXs and DEXs), while enabling continuous trading all the days (24/7) within themselves were as of December 2024 unable to facilitate direct trades between platforms due

[6] South Africa's stock market capitalisation levels are sourced from JSE Market Statistics - Weekly Trading Data (https://www.jse.co.za/services/market-data/market-statistics). 10 April 2025.

[7] All the other market capitalisation levels are sourced from Ceicdata (https://www.ceicdata.com/en/indicator/south-africa/market-capitalization). 10 April 2025.

[8] Stock market capitalist of US companies was obtained from Siblis research (https://siblisresearch.com/data/us-stock-market-value/?form=MG0AV3). 10 April 2025.

to a lack of direct pipelines for asset movement as they operated on separate blockchains (Hägele, 2024). Additionally, cryptocurrencies featured permissible trading pairs, such as BTC/USD, BTC/ZAR and ETH/BTC, which can lead to price variations across countries and exchanges (Hutton & van Vuuren, 2024). These discrepancies primarily arise from differences in market liquidity, trading activity compounded by time zone differences (Hutton & van Vuuren, 2024; Makarov & Schoar, 2022). For example, Hutton and van Vuuren (2024) found that the South African BTC market on Luno reflected the global BTC market, as its prices are predominantly driven by international demand and supply. Nonetheless, slight variations occurred due to market infrastructure factors, such as local currency exchange rates, regulatory environments, or liquidity differences.

The ongoing discussion on the market for cryptocurrencies gave rise to two prominent branches of literature. The first one explored cryptocurrencies' financial and non-financial riskiness in aspects which include legal ownership (Fry & Cheah, 2016; Low & Teo, 2018), moments of the distribution of returns (Lahmiri *et al.*, 2018; Zhang *et al.*, 2018) and teasing out cryptocurrencies from bubbles (Corbet, Lucey, *et al.*, 2019; Fry & Cheah, 2016; Kyriazis *et al.*, 2020). These elements contribute to a general understanding of price discovery process of cryptocurrencies, which was also discussed in various studies (Al-Yahyaee *et al.*, 2020; Bariviera, 2017; Noda, 2021; Urquhart, 2017; Wei, 2018) examining their market (informational) efficiency. By definition, informational efficiency reflects how accurately market prices reflect all available information about an asset's risk and return. This is fundamentally different from operational efficiency concerned with how easily investors can implement and adjust portfolios in practice, given trading costs, liquidity, regulation, and other market infrastructure (Lo, 2017). Throughout this study, "market efficiency" always refers to informational efficiency unless explicitly stated otherwise.

The second branch of the literature examined the value of cryptocurrencies as financial assets and their interaction with other markets. This included analyses of spillovers and connectedness with traditional asset classes (Bouri *et al.*, 2018; Ghorbel *et al.*, 2024), as well as assessments of their diversification potential, hedging capacity, and safe-haven characteristics (Almeida & Gonçalves, 2022; Brauneis & Mestel, 2019; Briere *et al.*, 2015; Corbet *et al.*, 2018; Didisheim *et al.*, 2024; Ehlers & Gauer, 2019). As cryptocurrencies increasingly came to be viewed as an alternative asset class (Bianchi, 2020; Krückeberg & Scholz, 2020; Lee *et al.*, 2017), discussions on their portfolio relevance gained prominence, particularly in relation to their behaviour under different monetary policy environments, including periods of quantitative easing - QE (Afonso & Jalles, 2019; Christensen & Krogstrup, 2019).

Numerous authors (Andrianto & Diputra, 2017; Dyhrberg, 2016; Klein *et al.*, 2018; Platanakis & Urquhart, 2020) explored their portfolio performance in terms of diversification, hedging, and safe-

haven properties compared to other assets such as gold, oil, silver and the USD. Other studies such as that of Fang *et al.* (2019) explored the impact of global economic uncertainty on the correlation between cryptocurrencies (BTC) and global equity (the MSCI world stock index), commodities (the S&P GSCI Commodity index), and bonds (PIMCO Investment-Grade Corporate Bonds index) to elucidate on diversification of cryptocurrencies in episodes of market uncertainty.

Despite substantial progress in understanding cryptocurrency behaviour, important gaps remain regarding the relationship between market efficiency and portfolio performance. Existing studies (Al-Yahyaee *et al*., 2020; Fry & Cheah, 2016; Khursheed *et al*., 2020; Urquhart, 2017) consistently show that the returns of major cryptocurrencies – including Bitcoin (BTC) and Ethereum (ETH), exhibit time-varying efficiency, rendering them occasionally predictable and thus capable of generating abnormal profits. Similar patterns of episodic efficiency have been documented in several equity markets across Africa (Smith & Dyakova, 2014), Asia (Kim & Shamsuddin, 2008; Lim *et al*., 2008), America, and Europe (Urquhart & McGroarty, 2016). However, it remains uncertain whether the periods of inefficiency (predictability) in cryptocurrency markets are significantly prolonged or related with episodes of inefficiency in other major markets, particularly during crisis periods. This uncertainty is notable given Urquhart and McGroarty's (2016) evidence that market efficiency evolves in response to changing market environments, and findings that cryptocurrencies tend to exhibit lower sensitivity to macroeconomic developments than traditional assets (Zhang & Wang, 2021), potentially positioning them as a strategic investment for diversification.

Regarding portfolio performance, a substantial body of research explored cryptocurrency portfolio benefits in the US market (Baur *et al.*, 2018; Bianchi, 2020; Bouri *et al.*, 2020; Briere *et al.*, 2015; Corbet *et al.*, 2018; Dyhrberg, 2016; Klein *et al.*, 2018). Literature on the portfolio performance of cryptocurrencies in other regionally popular markets such as China (Kajtazi & Moro, 2018; Pho *et al.*, 2021) and across several developed and developing countries in the Americas, Europe, Asia Middle East and Oceania (Colombo *et al.*, 2021; Demiralay & Bayracı, 2021) is growing. However, in the developing markets of Africa, this literature is sparse. Kumah and Odei-Mensah (2021) study the diversification benefits of cryptocurrencies in Nigeria, Egypt, Ghana, Kenya and Tunisia. However, these markets are relatively small (in terms of market capitalisations) thereby reducing the relevance of findings to other contexts. A few studies (Letho *et al.*, 2022; Robertson, 2018) have explored the diversification benefits of cryptocurrencies in Africa's largest equity market – South Africa (SA). Ozili (2024) argued that limited research on cryptocurrencies in many African countries is mostly driven by regulatory uncertainty which creates a challenging environment for researchers and investors to explore the value of cryptocurrencies.

SA stands out as one of the first African country to make strides towards cryptocurrency regulation – evidenced by Regulation 28[9], which prohibits retirement funds from investing in cryptocurrency assets. It follows other leading countries in financial regulation such as the UK (Huang, 2021; Pravdiuk, 2021), the European Union (Van Der Linden & Shirazi, 2023) and China (Xie, 2019) that have established regulatory positions. The US stands out as one of the forerunner countries in cryptocurrency regulation that has increasingly liberalised cryptocurrencies trading (Feinstein & Werbach, 2021; Griffith & Clancey-Shang, 2023). Therefore, analysing cryptocurrency portfolio performance in SA and the US offers significant insights due to their distinct regulatory frameworks and attention by academic researchers. SA, a developing market, has partial prohibition under Regulation 28, which precludes cryptocurrencies from being included in pension funds' investments, reflects a more restrictive regulatory approach. In contrast, the US' authorisation of cryptocurrency Exchange Traded Funds[10] (ETFs) represents a comparatively liberal regulatory environment, fostering institutional adoption. A comparative examination of these contrasting contexts provides a unique opportunity to critically evaluate policy decisions and their potential implications or impact on investment portfolio performance.

Furthermore, investment discussions in the cryptocurrency domain predominantly centre on BTC, given its prominence as the largest cryptocurrency (Dyhrberg, 2016; Fang *et al.*, 2019; Kajtazi & Moro, 2018; Urquhart, 2017). However, as the cryptocurrency market continues to evolve, it is imperative to expand the scope of research from the popular BTC to include other significant cryptocurrencies. ETH, which ranks (as of December 2024) as the second-largest cryptocurrency by market capitalisation, emerges as an important asset due to its multifaceted utility. While BTC primarily serves as a decentralised store of value (Makarov & Schoar, 2022), ETH's Layer 1 blockchain provides a robust infrastructure for several innovative applications including smart contracts, DeFi, dApps and NFTs (Radanliev, 2024; Zhang, 2023). This capability not only amplifies ETH's intrinsic value but also positions it as a dynamic asset within the cryptocurrency ecosystem. Including ETH in the analysis acknowledges its technological advantages and the expanding economic activity it enables, offering a broader perspective on cryptocurrencies.

Finally, periods of market crisis, such as the Covid-19 pandemic and the Russia-Ukraine conflict, underscore the need to reassess cryptocurrency portfolio performance to determine whether they

[9] SA National Treasury Publication of Regulation 28 (https://www.treasury.gov.za/publications/other/Reg28/). 9 March 2025.

[10] Securities and Exchange Commission Order Granting Accelerated Approval of Proposed Rule Changes, as Modified by Amendments Thereto, to List and Trade Bitcoin-Based Commodity-Based Trust Shares and Trust Units (https://www.sec.gov/files/rules/sro/nysearca/2024/34-99306.pdf). 9 March 2025

serve as a diversifier, hedge or safe haven. For context, Baur and Lucey (2010) described a diversifier as an asset with low correlation to others, a hedge as one that is either uncorrelated or negatively correlated, and a safe haven as an asset that maintains these characteristics specifically during crisis periods. Bhattarai *et al*. (2021) observed that QE, often implemented during economic stress, tends to fuel speculative interest in cryptocurrencies, thereby increasing their attractiveness. However, QE can also intensify correlations between asset classes, such as cryptocurrencies and equity (Aloui *et al.*, 2024; Corbet *et al.*, 2014; Zhao *et al.*, 2023), as both become reactive to macroeconomic factors. This heightened correlation may undermine cryptocurrencies' ability to act as a hedge or safe haven during crises, necessitating careful analysis of their performance during crisis periods to better understand their role in portfolios.

It is thus evident that the two leading branches of cryptocurrency research leave critical questions unanswered: Are cryptocurrencies becoming more efficient, even during crisis periods? Furthermore, what are the portfolio benefits of investing in cryptocurrencies and how are these benefits related to the cryptocurrency market efficiency? These gaps in the literature are particularly significant, as most existing discussions fall short in examining how cryptocurrency market efficiency evolves and in turn contributes to portfolio performance especially during periods of crisis. Consequently, the link between market efficiency and portfolio performance in the context of cryptocurrencies remains underexplored.

1.2 Problem statement

During economic crises, systemic risks permeate markets, heightening uncertainty and prompting synchronised trading behaviours among investors. This phenomenon results in a marked increase in asset correlations, thereby undermining diversification strategies precisely when they are most needed. Portfolio managers are thus confronted with the critical challenge of safeguarding investments during these turbulent periods. In this context, cryptocurrencies, as an emerging asset, have attracted attention for their potential role as diversification tools, primarily because they are not directly issued or controlled by central authorities. Despite extensive research, several crucial questions remain unresolved, particularly concerning their behaviour during crisis periods. A significant area of uncertainty is whether the market efficiency of cryptocurrencies deteriorates during crises, raising the possibility of exploitable price anomalies and challenging the informational efficiency of cryptocurrency prices. Furthermore, the academic literature provides limited insights into whether and how changes in market efficiency influence diversification benefits and portfolio performance. Due to these gaps, it remains unclear whether the market efficiency of cryptocurrencies weakens during crisis periods and how changes in efficiency affect cryptocurrency diversification capabilities and portfolio performance during such times.

1.3 Research question

How does the market efficiency of cryptocurrencies evolve during periods of crisis, and how does this evolution affect their diversification capabilities and risk-adjusted performance within investment portfolios?

1.4 Research objectives

Three related broad research objectives characterise the study:

1. To determine whether there is a breakdown in the efficiency of cryptocurrency markets over crisis periods;
2. To evaluate the impact of incorporating cryptocurrencies on portfolio diversification and risk-adjusted returns; and
3. To investigate the impact of variations in cryptocurrency market efficiency on the diversification benefits and risk-adjusted performance outcomes associated with the inclusion of cryptocurrencies.

1.5 Research hypothesis

The study utilises null hypothesis significance testing, wherein the null hypothesis denotes the absence of an effect or association, while the alternative hypothesis embodies the research proposition. Consequently, claims are articulated in terms of the strength of evidence against the null hypothesis, rather than as a "confirmation" of the hypothesis. To direct the empirical investigation, three hypotheses were formulated in accordance with the stated research objective.

Hypothesis 1:

H_0: Crisis periods do not exert a statistically significant impact on the weak-form market efficiency of cryptocurrencies.

H_1: Crisis periods significantly diminish the weak-form market efficiency of cryptocurrencies.

Hypothesis 2

H_0: The inclusion of cryptocurrencies in a bond-equity-cash multi-asset portfolio does not alter the diversification or performance outcomes within a multi-asset portfolio.

H_1: The inclusion of cryptocurrencies in a bond-equity-cash multi-asset portfolio enhances diversification outcomes or risk-adjusted performance.

Hypothesis 3

H_0: Crisis-induced fluctuations in the efficiency of cryptocurrency markets do not impact their diversification characteristics or their role in enhancing portfolio performance.

H_1: Crisis-induced fluctuations in cryptocurrency market efficiency do affect their diversification characteristics and their contribution to portfolio performance.

1.6 Theoretical perspective and framework

The theoretical framework for this study is grounded in the Adaptive Market Hypothesis (AMH), proposed by Lo (2004), as an alternative to the static perspective of market efficiency embodied in the Efficient Market Hypothesis (EMH), as detailed in Fama (1965) and Fama (1991). The EMH posits that asset prices fully and instantaneously incorporate all available information, thereby precluding investors from consistently outperforming the market. However, its application to young cryptocurrencies reveals certain limitations. Firstly, a substantial body of literature indicates the predictability of cryptocurrency prices, particularly in their nascent stages. Secondly, there are divergent findings regarding the market efficiency of cryptocurrencies, with some studies affirming it while others do not. Lastly, the literature on the behaviour of market efficiency in cryptocurrencies is expanding, with ongoing debates on how efficiency evolves during crisis periods.

Given the significance of these discussions, it was imperative to adopt the AMH, a more nuanced theoretical framework. The AMH suggests that market efficiency evolves, with periods where market prices are predictable followed by periods where they are not. The AMH bridges the traditional EMH with behavioural finance, proposing that market efficiency can coexist with anomalies that result in varying EMH findings. This is because the AMH provides a framework capable of interpreting conflicting market efficiency: investors are not always rational and utility maximisers but adapt to environments using heuristics (Lo, 2004; Pal, 2016). The AMH applies evolutionary concepts, such as adaptation and natural selection, to markets, arguing that survival, rather than utility maximisation, is the primary objective.

The major implications of the AMH are that, unlike in EMH, risk-return relationships and market efficiency fluctuate over time with changing market conditions (Pal, 2016). This approach allows for the segmentation of distinct market episodes, such as crisis periods, to inform this study's exploration of whether the market efficiency of cryptocurrencies deteriorates during crisis periods. Furthermore, this study leverages modern portfolio management theory of Markowitz (1952) and applies the mean-variance optimization (MVO) framework and the Black and Litterman (1990) - BL model to understand the diversification potential and risk-adjusted performance of

cryptocurrencies. The two models complement each other in that the MVO framework is theoretically robust and reflects rational decision-making, while the BL model aligns with industry practices, aiding in effectively assessing the diversification and portfolio performance of cryptocurrencies.

1.7 Research design and methodology

The conduct of research is shaped by both the research philosophy adopted and the research strategy employed to achieve fthe stated research objectives. Section 1.4 outlined these objectives. This section therefore highlights the research philosophy and outlines the strategy designed to accomplish them.

1.7.1 Study design and context

The study adopted a positivist philosophical paradigm. This philosophy postulates that real events can be observed empirically and can also be explained logically through analysis (Hume, 2016). Furthermore, positivist research focuses on experimentation, a key activity in attaining the objectives of this study. Through experimentation, reality can be observed and described from an objective viewpoint (Greenwood & Levin, 2006). Inferences are made based on the previously observed and explained realities and their inter-relationships. Accomplishing the research objectives thus requires: first, experimentation through statistical modelling based on multivariate analysis techniques and the statistical analysing of secondary data and second, making inferences based on previously observed and explained realities and their inter-relationships. Following Creswell's (2011) taxonomy of research methodologies, the quantitative research methodology best addresses the three research objectives of this study.

To evaluate whether cryptocurrency markets exhibit evolving efficiency, it is essential to assess whether the variance of multi-period returns scales linearly with time, as highlighted by Smith and Dyakova (2014). This approach involves quantifying the variance of returns and conducting statistical analyses to determine if this scaling relationship holds over different time horizons. Assessing the impact of adding cryptocurrencies to traditional portfolios requires measuring both portfolio risk and risk-adjusted returns before and after their inclusion. The analysis must focus on whether cryptocurrencies contribute to diversification and enhance risk-adjusted performance. To achieve these objectives, the study employs statistical tools and econometric models that ensure methodological rigour and allow for clarity of results. Quantitative analysis is thus justified as an ideal approach for attaining the research objectives set out in this thesis. It enables precise and objective evaluation of market efficiency and portfolio diversification by leveraging robust statistical methodologies.

Furthermore, quantitative research is premised on the generalisability of its findings, thereby supporting the use of sampling to draw inferences about the broader population. Accordingly, this study did not investigate every cryptocurrency in the market as there were over 10 000 cryptocurrencies by December 2024[11]. Instead, it utilised a purposive sample representing almost 70% of the cryptocurrency market capitalisation (as of December 2024) to inform its conclusions. While quantitative methods offer practical advantages, they are subject to limitations arising from the complexity and unpredictability of real-world phenomena, including the inherent uncertainty of future developments. Consequently, researchers cannot forecast future events with absolute certainty but can only outline possible scenarios and their impacts within specified confidence intervals (Leedy & Ormrod, 2015).

1.7.2 Literature review

The literature review comprises an in-depth review of cryptocurrencies, their origins, as well as their development as financial instruments. An overview of portfolio management is also given, highlighting the importance of market efficiency and its role in investment portfolio diversification. Finally, the literature review covers the development of the tests for market efficiency, current understanding of the evolving nature of market efficiency and its impact on portfolio diversification.

1.7.3 Empirical study

The study used secondary data and did not collect any primary data. The sections below highlight the nature of the data, how data were collected, the sources from where the data were collected, and the methods used to analyse the data. Further details on data are presented in the data section in Chapter 6.

1.7.3.1 Secondary data

To address the research questions, this study employed daily data of BTC and ETH – the largest cryptocurrencies representing a substantial part of the cryptocurrency market by market capitalisation. Three equity indices from developed markets, namely the S&P500 (US), FTSE 100 (UK) and NIKKEI 225 (Japan), and three equity indices from developing markets, namely the Shanghai Stock Exchange (SSE) Composite index (China), Bombay Stock Exchange (BSE) Sensex (India), and the FTSE/JSE All Share Index (South Africa) were included for contextualising the discussion of the relative market efficiency of cryptocurrencies. The equity markets were selected for their popularity and geographical locations around the world. This was

[11] Number of cryptocurrencies was sourced from Investing.com (https://www.investing.com/crypto/currencies). 10 April 2025.

important because when comparing the market efficiency of cryptocurrencies with the equity indices, the inclusion of geographically diverse indices is highly relevant. These indices represent major economic regions across different time zones, ensuring a comprehensive assessment of market behaviour. The geographic spread allows the analysis to account for variations in trading hours and cross-market influences, which are critical given that cryptocurrency markets operate 24/7. By covering multiple time zones, this approach captured global trading dynamics, ensuring robust and context-aware comparisons. All data from BTC and the six equity indices were synchronised with ETH (the youngest) for the same start date of the 500-day rolling window up to 31 December 2024 the end of the observation period. As a result, equity indices have varying start dates as the number of trading days in a year vary between countries.

To evaluate portfolio performance, the study also incorporated two bond indices: the FTSE/JSE All Bond Index (ALBI20) and 10-Year US Government Bond returns as well as proxies for money market (cash) rates, specifically the 91-day Treasury Bill (SA) and the USD 3-month Treasury Bill yields. Both the Treasury bills represent also the risk-free rate across the US and SA.

1.7.3.2 Econometric methods of analysis

The study utilised BTC and ETH and equities indices (comparators) time series to explore the evolvement of the market efficiency using the Adaptive Market Hypothesis (AMH) of Lo (2004). To capture evolving efficiency, the whole sample was divided into sub-samples, making use of a rolling window of 500 iterations as suggested by Smith and Dyakova (2014). By using rolling window variance ratio tests, it was possible to detect changes in efficiency and to rank the different equity indices and cryptocurrencies according to their return predictability. Because thin trading[12] (low volume of trade) is more likely to be present for daily return series (higher frequency) than lower frequency data (for example monthly data), the method of Miller *et al*. (1994a) was employed to tease out thin trading, such that returns would not be affected by infrequent trading. Thus, the AMH of Lo (2004) was adopted to test the evolving efficiency in the cryptocurrency market and equity markets. This was done by making use of the variance ratio (VR) tests of Lo and MacKinlay (1989). These tests include the joint sign (JS) test (Belaire-Franch & Contreras, 2004; Kim & Shamsuddin, 2008); the wild bootstrap (JM) test (Kim, 2006); and the automatic VR (AVR) test (Kim, 2009). These tests have good power and size properties (Smith & Dyakova, 2014), address different aspects of efficiency and account for potential data limitations and characteristics, such as non-normality (JS), heteroskedasticity (JM) and small sample sizes (AVR) thereby forming a comprehensive toolkit for assessing market efficiency. This multi-faceted

[12] Thin trading refers to when an asset is not traded in every successive interval. Its presence can result in spurious autocorrelation in returns (Smith & Dyakova, 2014).

approach enhances the robustness and reliability of results. These market efficiency tests were scripted and computed using the R programming language (R Foundation, 2025).

To examine the portfolio performance of cryptocurrencies, the study implemented a portfolio-based comparison with two steps. First, the study calculated the weights, w_t, of a baseline portfolio (e.g. bonds, equities and cash) by using the Minimum-Variance-Portfolio and maximum Sharpe ratio portfolio strategies of Markowitz (1952) and the Black and Litterman (1990) portfolio strategy. These strategies are supported by Platanakis and Urquhart (2020), who found that sophisticated portfolio management techniques (as contrasted to naïve equally-weighted portfolio management strategies) are preferred when managing cryptocurrency portfolios. Next, the study recomputed asset allocations when cryptocurrencies (BTC and ETH) were included in the already diversified baseline portfolio composed of bonds, equities and cash. Numerous risk metrics that include, standard deviation, value-at-risk (VaR), lower partial moments, tracking error were computed to parameterise risk. The study also utilised several risk-adjusted performance measures that include Calmar ratio (Young, 1991), the Sharpe ratio and its adjusted variants (Zsolt & Botond, 2021), as well as the Omega ratio, which captures the higher moments of the returns' distribution (van Dyk *et al.*, 2014a; Keating & Shadwick, 2002) to comprehensively assess risk-adjusted performance between portfolios that include cryptocurrencies and those that do not include cryptocurrencies across the three portfolio allocation strategies. All portfolio optimisations were performed in Microsoft Excel® (Microsoft Corporation, 2025) leveraging solver to optimally allocate capital.

1.8 Ethical considerations

The researcher sought approval from the North-West University ethical committee before commencing the study. This research is ethical in the sense that, it is methodologically sound and morally acceptable to the people and organisations who are involved.

Other ethical considerations of the study include,

1. Plagiarism;
2. Researcher's objectivity, honesty, and integrity;
3. Fabrication/falsification of data; and
4. Misleading or false reporting of research findings

This study, therefore, cites all sources using standard referencing practices throughout the research. Furthermore, it is the duty of the researcher not to fabricate any findings. The researcher has a responsibility to report all results honestly and truthfully. The researcher reports even results that refute previous research findings or are out of line with accepted theories.

1.9 Contribution of the study

This study contributes to the literature by integrating the AMH with portfolio diversification dynamics across distinct crisis regimes. While the AMH has been widely applied to explain time-varying efficiency in cryptocurrency markets, its implications for portfolio construction, particularly during crises remain underexplored. This research addresses this gap by examining how shifts in weak-form efficiency during crisis periods correspond to changes in diversification benefits and risk-adjusted performance. In doing so, the study evaluates whether the efficiency regimes predicted by the AMH are reflected in observable adjustments in portfolio outcomes, thereby clarifying how market adaptiveness and evolving behavioural conditions shape cryptocurrencies' diversification and risk-adjusted performance outcomes in multi asset portfolios.

By explicitly marking crisis episodes and analysing efficiency, diversification and risk adjusted performance interactions across these periods, the study challenges the traditional assumption of stable correlations and return distributions embedded in classical diversification theory. The findings demonstrate that efficiency breakdowns during systemic crises coincide with altered correlation structures and diversification benefits, highlighting the behavioural and regime-dependent nature of portfolio risk. These insights advance theoretical understanding by linking market efficiency dynamics to portfolio performance and by suggesting new avenues for research: namely, that shifts in efficiency under crisis regimes may serve as indicators of diversification and risk adjusted performance outcomes.

This study also contributes to the literature by providing a comparative assessment of cryptocurrency portfolio performance in the US and SA, two markets characterised by markedly different regulatory environments. SA's prudential framework – embodied by Regulation 28, which restricts cryptocurrency exposure in retirement portfolios reflects a risk-containment approach aimed at limiting concentration and downside risk rather than maximising returns. Consequently, the relevance of cryptocurrency allocations in the SA context must be evaluated primarily through their effects on risk management - volatility, VaR, and drawdown behaviour.

In contrast, the more permissive US regulatory stance, including the approval of cryptocurrency exchange-traded funds, illustrates a policy environment that facilitates broader investor access and signals a different regulatory perception of the asset. Consequently, the relevance of cryptocurrency allocations in the US context must be evaluated primarily through their effects on broader risk-adjusted performance. By juxtaposing these two regulatory regimes, the study highlights how policy choices shape the practical feasibility and portfolio impact of cryptocurrency exposure. The findings offer insights for policymakers in both jurisdictions by illustrating how regulatory constraints may either limit or protect portfolio outcomes, and by demonstrating the

conditions under which cryptocurrency allocations enhance or weaken diversification. This comparative perspective underscores the importance of aligning regulatory design with empirical evidence on risk and performance, thereby informing more balanced approaches that support innovation while safeguarding investor welfare.

1.10 Thesis structure

The thesis is assembled and completed under the full dissertation format and proceeds as follows: Chapter 2 presents the relevant literature on the current understanding of cryptocurrencies. It begins by detailing the evolution of cryptocurrencies and their development as investment assets. The chapter proceeds to look at some of the important aspects of cryptocurrencies from an investment viewpoint, mainly price dynamics, the regulatory dilemma and other risks related to cybersecurity. This section thus explores the potential benefits of cryptocurrencies as an investment asset. This directly leads to Chapter 3, which expands this discussion and begins with an overview of portfolio management, highlighting the importance of approaching investment from a portfolio context rather than a single asset investment point of view. Chapter 3 thus emphasises the importance of asset allocation in managing investments. It looks at the theoretical understanding of robust practices in the end-to-end process to portfolio management. The chapter is very important as it maps and justifies, from a theoretical viewpoint, the appropriate portfolio selection and performance measurement techniques that may be emphasised when managing portfolios that incorporate cryptocurrencies. However, much of portfolio management assumes that markets are efficient. Thus, Chapter 4 delves deeper into the subject of market efficiency and makes an extensive discussion and in-depth analysis of what market efficiency really means, how it is tested, and what the current understanding of market efficiency implies for portfolio management. Since the topic of market efficiency has far-reaching implications for portfolio management, Chapter 5 is dedicated to extensively discuss the various tests of market efficiency and maps the one more appropriate in the context of this study. Chapter 6 outlines the study's methodology to test market efficiency and assess its impact on diversification and portfolio performance. Chapter 7 applies the methodology and presents and discusses the results. Its thrust is assessing the evolving efficiency of BTC and ETH, comparing this efficiency to that of the popular equity indices in the US, UK, Japan, China, India and South Africa. The chapter is extended to survey the impact of including cryptocurrencies in a portfolio as it relates to risk and returns and how or if market efficiency potentially influences its portfolio performance. It thus formally presents findings on the effect of including cryptocurrencies on the performance of portfolios on a risk-adjusted basis. This presents a window of opportunity to assess how the evolving efficiency in the market of cryptocurrencies affects their portfolio performance. Chapter 8 concludes and sets out future possible research areas.

CHAPTER TWO

CRYPTOCURRENCIES: THEORY AND EMPIRICAL CONSIDERATION

2.1 Introduction

Since the launch of BTC in 2009, cryptocurrencies have transitioned from their initial concept as alternatives to traditional, institution-controlled payment systems (Chaum, 1983; Nakamoto, 2008) into technologies with increasing relevance across a diverse range of real-world applications. Makarov and Schoar (2022) documented that notable developments included decentralised finance (DeFi), which facilitates lending, borrowing, trading, and investing through decentralised platforms. The emergence of stablecoins and central bank digital currencies (CBDCs) demonstrated efforts to leverage cryptocurrency technology while seeking to mitigate the volatility characteristic of cryptocurrencies (Makarov & Schoar, 2022). Cryptocurrencies also underpin significant advancements in industry including digital identity verification, gaming and non-fungible tokens (NFTs) for digital ownership.

The developments in cryptocurrencies form important parts of discussions around technological innovation and applications of blockchain systems (Fang *et al.*, 2025; Radanliev, 2024). Challenges relating to cryptocurrency security, privacy and infrastructure(Gudgeon *et al.*, 2020; Makarov & Schoar, 2022), as well as regulation (Feinstein & Werbach, 2021; Griffith & Clancey-Shang, 2023; Nabilou, 2019; Ozili, 2024; Xie, 2019) inform various perspectives on risk. Within broader finance, a number of studies(Fry & Cheah, 2016; Le Tran & Leirvik, 2020; Lee *et al.*, 2017a; Moro-Visconti & Cesaretti, 2023) reported extraordinary returns in cryptocurrencies, informing research focusing on the fundamental value of cryptocurrencies (Caferra, 2022; Cheah & Fry, 2015; Huang *et al.*, 2019; Liu & Tsyvinski, 2021) and their diversification capabilities (Almeida & Gonçalves, 2022; Colombo *et al.*, 2021; Didisheim *et al.*, 2024; Letho *et al.*, 2022; Urquhart & Zhang, 2019).

Arguably, cryptocurrencies serve as both technology platforms and investment assets. Technological features – their essence – play a key role in how they are perceived and priced in financial markets and leveraged for risk sharing by investors. Consequently, it is important to understand cryptocurrency technology. By systematically analysing the current understanding of cryptocurrency technology, the discussion aims to elucidate their evolving function and how this shapes pricing processes and ultimately how cryptocurrencies are used for risk-sharing by investors.

To achieve this, the rest of the chapter proceeds as follows: Section 2.2 examines the technical definition of cryptocurrencies, while Section 2.3 explores the technology underpinning

cryptocurrencies. Section 2.4 explores the broader architecture of the market of cryptocurrencies. These sections are important to clarify what cryptocurrencies really are and the technological features that play a key role in shaping how they are allocated and priced. Section 2.5 assesses cryptocurrency price dynamics to gain insights into the behaviour of cryptocurrency returns, cross-correlations, especially with other assets and volatility dynamics. This was important for understanding the opportunities and challenges emanating from investing in cryptocurrency markets. Sections 2.6 and 2.7 highlight how regulation and cyber risks contribute to the broader discussion of risk in cryptocurrencies. The literature identified that besides regulation and cyber criminality market risks, crises also played an important role in pricing and risk-sharing mechanisms within financial markets. Section 2.8 was added to specifically discuss what crisis periods are, as there was no widely agreed conceptual definition for what constitutes a crisis. Section 2.9 concludes the chapter.

2.2 Regulatory and institutional definitions of cryptocurrencies

Cryptocurrencies are a subject of global intrigue among business, investors, researchers and regulators with their definitions reflecting the diverse perspectives and priorities of organisations and governments worldwide. From a global viewpoint, the Financial Stability Board (FSB) offered a broad characterisation, defining cryptocurrencies as private-sector digital assets reliant on cryptography[13] or distributed ledger technology[14] (DLT) or similar technology. The FSB's emphasis is on the technological foundations of cryptocurrencies and it does not make distinctions on utility or regulatory scope, making it a broadly applicable reference point for characterising cryptocurrencies based on technology.

[13] Cryptography refers to the use of advanced mathematical techniques and algorithms to secure and verify transactions, control the creation of new units, and protect user data. It ensures that sensitive information, such as private data and transaction details, remains confidential and tamper-proof. Definitions sourced from Financial Stability Board (https://www.fsb.org/work-of-the-fsb/financial-innovation-and-structural-change/crypto-assets-and-global-stablecoins/). 10 April 2025

[14] A repeated digital copy of data available at multiple locations.

SA, through its Financial Sector Conduct Authority (FSCA) aligns closely with the FSB's perspective but introduced a more detailed framework. According to the FSCA.[15], for an asset to qualify as a cryptocurrency, it must meet three criteria:

i) It should digitally represent value without being issued by a central bank.
ii) It should be tradable, transferable, and storable electronically by individuals and entities for purposes such as payment, investment, and utility.
iii) It must leverage cryptographic techniques and DLT.

The FSCA definition captured the key characteristics and functions of cryptocurrencies. This view also aligns closely with the EU's, guided by its Markets in Crypto-Assets (MiCA) regulation. The EU provides a more expansive and role-oriented approach to charactering cryptocurrencies. It describes them as digital representations of value or rights that can be stored and transferred electronically using DLT or similar systems. MiCA also emphasised the multifaceted roles cryptocurrencies play, such as:

i. facilitating capital raising;
ii. fostering competition and innovating inclusive financing mechanisms for consumers and small to medium enterprises (SMEs); and
iii. transforming payments, offering more efficient, cost-effective, and cross-border alternatives by reducing reliance on intermediaries.[16]

This definition mirrors the EU's ambition to balance cryptocurrency technology innovation with regulatory oversight, highlighting both entrepreneurial opportunities and regulatory risks.

In contrast, the US exhibits a fragmented regulatory landscape, with no single, unified definition of cryptocurrencies. Each regulatory body defines cryptocurrencies based on its specific jurisdiction and regulatory focus (Makarov & Schoar, 2022). For instance, the Securities and

[15] The definition of cryptocurrencies according to the FSCA was sourced from the press release on "Update on approved Cryptocurrency Asset Service Providers" https://www.fsca.co.za/News%20Documents/FSCA%20Press%20Release%20-%20FSCA%20update%20on%20approved%20Crypto%20Asset%20Service%20Providers%20%2002%20July%202024.pdf). 10 April 2025 (https://www.fsca.co.za/News%20Documents/FSCA%20Press%20Release%20-%20FSCA%20update%20on%20approved%20Crypto%20Asset%20Service%20Providers%20%2002%20July%202024.pdf). 10 April 2025.

[16] The European Commission categorisation of what constitutes cryptocurrencies is described in MiCA (https://finance.ec.europa.eu/digital-finance/crypto-assets_en). 10 April 2025.

Exchange Commission (SEC) classifies cryptocurrencies as securities, while the Commodity Futures Trading Commission (CFTC) views them as commodities. Meanwhile, the Internal Revenue Service (IRS) treats cryptocurrencies as property for tax purposes, and the Financial Crimes Enforcement Network (FinCEN) regards them as money equivalents under anti-money laundering laws. A broader conceptualisation is provided by the US Congress, which describes cryptocurrencies as digital financial instruments that operate on public blockchains, recorded on DL, and do not require central intermediaries like banks for clearance and settlements.[17]

The variability in definitions in the US underscores the complexity of characterising a multifaceted and rapidly evolving technology. The levels of details in the definitions of cryptocurrencies ranging from a more generic for example in the case of SA and the EU to a more fragment view in the US underscore the diverse economic, technological, and regulatory landscapes amidst the dynamic evolution of cryptocurrencies. Therefore, understanding the architecture of cryptocurrencies, how they evolved and their use cases is essential for comprehending their various forms and functions, which in turn shape distinct perspectives on their pricing, and risk-sharing mechanisms within financial markets.

2.3 The technological foundation of cryptocurrencies: from cryptographic theory to distributed ledger technology

The motivation behind cryptocurrencies can be traced back to Chaum (1983), who laid the groundwork for advancing knowledge in untraceable payment systems and the use of decentralised payment systems to transfer the benefits of transacting in cash (notes and coins) to online payments[18]. Historically, financial entities such as banks have been the key nodes in the financial systems, performing bookkeeping functions, settling accounts, ensuring accuracy of customer records and safeguarding accounts from unauthorised access (Duong *et al.*, 2020; Fanning & Centers, 2016; Qiu *et al.*, 2019). However, headway in cryptography technology enabled an alternative architecture that does not rely on financial entities for bookkeeping, settling accounts and protecting unauthorised access to financial data. Instead, multiple parties (known as validators and/or miners) hold their own copies of records and jointly decide which transactions are admissible through the DLT architecture (Makarov & Schoar, 2022; Wang *et al.*, 2022).

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[17] US Congress view on what cryptocurrencies represent (https://www.americanprogress.org/article/congress-must-not-provide-statutory-carveouts-for-crypto-assets/). 10 April 2025.

[18] Online payments are payments done over the internet using digital platforms and include bank credit/debit cards, bank transfers, digital wallets (Chaum, 1983).

According to El Ioini and Pahl (2018) and Soltani *et al*. (2022), DLT is based on three systems:

(i) public key cryptography,
(ii) distributed P2P networks and
(iii) consensus mechanisms.

Public key cryptography provides secure digital identities for participants, enabling transaction recording in the Distributed Ledger (DL) and enforcing ownership control (Soltani *et al.*, 2022). Distributed P2P network ensures scalability, prevents central points of failure and protects against domination by a single entity (Makarov & Schoar, 2022; Soltani *et al.*, 2022). Consensus mechanisms enable all nodes (validators and/or miners) in the DL to agree on a unified version of the truth without requiring a trusted third party (El Ioini & Pahl, 2018). The literature on DLT is broad and continues to evolve. However, Soltani *et al*. (2022) found that the prominent types include blockchain, hashgraph, tagle, holochain, sidechain and a hybrid of these models. Table 2.1 presents a brief description of the DLTs and their general applications.

Table 2.1: Types of distributed ledger technology

Types of DLTs					
Sidechains: Structure: Parallel blockchains that interact with a main blockchain. Key Features: Interoperability, experimentation without main chain risk. Applications: Scalability solutions, testing new features, and cross-chain transfers.	**Holochain**: Structure: Agent-centric, where participants maintain their own chains that interact with others. Key Features: Scalability, adaptability, and decentralization. Applications: dApps for social networks and collaboration.	**Tangle**: Structure: A Directed Acyclic Graph (DAG) where each transaction validates two previous ones. Key Features: Scalability, low resource consumption, no miners required. Applications: Internet of Things (IoT), lightweight and frequent microtransactions	**Hashgraph**: Structure: Uses a DAG for faster transaction processing. Key Features: High throughput, fairness, and efficiency. Applications: Financial markets, gaming platforms, high-speed microtransactions	**Blockchain**: Structure: A chain of blocks, each containing a batch of validated transactions. Key Features: Transparency, immutability, and security. Applications: Cryptocurrencies (e.g., Bitcoin, Ethereum), smart contracts, supply chain tracking	**Hybrid Models**: Structure: Combines elements of public and private DLTs. Key Features: Balances transparency and control. Applications: Healthcare, finance, and industries needing both privacy and collaboration.

Source: Adapted from Soltani et al. (2022)

Of these DLTs, blockchain is the most widely recognised due in part to its focus on trustless environments, transparency, and security which makes it foundational for numerous applications (El Ioini & Pahl, 2018; Fang *et al.*, 2025; Soltani *et al.*, 2022). Consequently, a comprehensive understanding of blockchain technology is essential, as it forms the foundation for both the functionality and the value proposition of cryptocurrencies.

A Giudici *et al*. (2020)described blockchain as a linking of records (blocks) to each other in such a way that each new record contains information about the previous records in the growing list

(chain) of digital records. Thus, a blockchain in its basic form is a chronological list of records. Fundamentally, it is a decentralised digital ledger composed of immutable record entries, each marked with a timestamp (Makarov & Schoar, 2022). These record entries are secured through cryptographic techniques and maintained collectively by a distributed (decentralised) network of computers, none of which are controlled by a single authority or entity to ensure decentralisation of decision making (Fang *et al.*, 2025). Blockchain ensures that every participant (node) in the network sees the same transaction history and a new block is accepted by agreement across the entire network thereby enabling the system to function decentralised with no requirement for a trusted third party (Nakamoto, 2008).

A simplified example of blockchain in operation is provided by Fang *et al*. (2025). The authors documented that in a transaction where a payor transfers X BTC to a payee:

> *the payor signs the transaction using their private key*[19] *to ensure authenticity and prevent tampering. The transaction is then broadcast to the blockchain network, where nodes verify the signature using the payor's public key. Once validated, the transaction is added to a block, which is appended to the chain of blocks (forming a blockchain). Subsequent blocks confirm the transaction, enhancing its security and immutability* (Fang *et al.*, 2025).

Most cryptocurrencies, including BTC and ETH, rely on blockchain technology to transfer value (Fang *et al.*, 2025; Soltani *et al.*, 2022). One of the main advantages of blockchain is that it eliminates a central point of failure (or control) by maintaining multiple record copies, ensuring security even if some participants are corrupted (Kerr *et al.*, 2023; Krause & Tolaymat, 2018). Moreover, by decentralising decision making, transactions are conducted P2P. The benefits of decentralisation include increased transaction speed (especially across borders) and enhanced privacy as users can maintain a degree of anonymity (Fang *et al.,* 2025).

The strength of blockchain technology - its decentralised architecture, paradoxically emerges as a limitation as the network scales. As the DL grows more decentralised with an increasing number of nodes (miners or validators), the blockchain network disseminates additional ledger copies resulting in the expenditure of substantial energy and computational resources to achieve protocol consensus and ensure security (Fang *et al*., 2025; Soltani *et al*., 2022). This intrinsic tension

[19] Private and public keys are cryptographic pairs generated using asymmetric encryption, mostly at the point of creating a wallet or registering for secure services. The private key is secret and allows the owner to sign transactions or access funds, while the public key is shared openly and enables others to verify the owner's signature or encrypt messages for them. If a private key is lost, access to the associated cryptocurrency or resources is irretrievable (Aydar, Cetin, Ayvaz & Aygun, 2019)

between decentralisation and resource efficiency has given rise to three distinct blockchain classifications: permissionless, permissioned, and private, each representing strategic adaptations to mitigate the scalability and resource demands inherent in decentralised systems (El Ioini & Pahl, 2018).

Permissionless blockchains, exemplified by BTC and ETH, permit universal access and transaction submission, fully embodying the ethos of decentralisation (Makarov & Schoar, 2022). In contrast, permissioned blockchains, such as XRP, are administered by a consortium of designated organisations with restricted access, while private blockchains such as Monero (XMR) fall under the exclusive governance of a single entity (El Ioini & Pahl, 2018). Arguably by design, permissioned and private blockchains compromise varying degrees of decentralisation to optimise resource utilisation and enhance scalability. This satisficing introduces a fundamental contradiction, as the primary objective of blockchain technology is to eliminate dependence on a central decision-making authority.

While permissionless blockchain represent the ideal decentralised decision making, they still have to contend with risks such as Sybil attacks, where adversaries exploit pseudonymous identities to disproportionately influence the consensus mechanism (Lai & Chuen, 2018; Soltani *et al*., 2022; Moro-Visconti & Cesaretti, 2023). To counter the challenges of Sybil attacks, consensus mechanisms - the most popular being Proof-of-Work (PoW) and Proof-of-Stake (PoS) were proposed (El Ioini & Pahl, 2018). PoW demands costly hardware and energy, concentrating mining in regions with cheaper resources, such as the US, and Russia.[20] Conversely, PoS requires significant capital for example 32 ETH[21] in the case of Ethereum potentially leading to validator oligarchies in wealthier, regulation-friendly regions. Thus, PoW risks centralisation through operational scale, while PoS poses a similar threat via wealth concentration (Soltani *et al*., 2022). Consensus algorithms (PoW or PoS) are key in decentralised blockchain systems as they drive the end-to-end processing of transactions whilst enabling security and agreement across a global network of participants (Soltani *et al*., 2022).

The literature (CoinMarketCap, 2025; Gudgeon *et al*., 2020) has given the nomenclature Layer 1 blockchain the underlying network that directly processes and validates transactions using its own DL. The most popular Layer 1 blockchains include Bitcoin, Ethereum, Solana, BNB Chain, Cardano, Dogecoin and Polkadot (CoinMarketCap, 2025). Layer 1 blockchains serve as the

[20] Top 10 Bitcoin Mining Countries of 2025 (https://hashrateindex.com/blog/top-10-bitcoin-mining-countries-of-2025/). 10 April 2025.

[21] Ethereum Proof-of-stake (https://ethereum.org/en/developers/docs/consensus-mechanisms/pos/). 10 April 2025.

foundational infrastructure for cryptocurrencies, are critical, as the cryptocurrencies with the highest market capitalisations are native to these networks. Despite its importance, Layer 1 blockchains are confronted with the trilemma of balancing the core principles of security, scalability and decentralisation (Gudgeon *et al*., 2020). As a result, a growing body of research emerged exploring alternative solutions, the prominent of which are commonly referred to as Layer 2 solutions (Gudgeon *et al*., 2020; Soltani *et al*., 2022).

Layer 2 solutions address the blockchain trilemma of optimising security, scalability and decentralisation by circumventing scalability challenges through enabling users to perform off-chain transactions (Gudgeon *et al*., 2020). Off-chain payments (as opposed to on-chain transaction in Layer 1 protocols) enable transactions to be executed through private and authenticated communication, rather than broadcasting all transactions on the base blockchain with just the net outcome being settled on the main DL (Gudgeon *et al*., 2020). While this alleviated network congestion and scaling up the amount of transaction load, double spend risk persist (El Ioini & Pahl, 2018; Gencer *et al.*, 2018; Radanliev, 2024). A body of literature has emerged proposing collateral, payment channel designs and delayed transaction to mitigate the double spend risk is growing (Gudgeon *et al*., 2020; Soltani *et al*., 2022).

For example, some off-chain transactions (such as those in Lighting Network) are secured through multi-signature channels where both parties must agree on the transaction outcome before it is settled on the base Layer 1 blockchain. If one party attempts to broadcast conflicting information to double spend, the protocol penalises them by forfeiting their collateral, thereby discouraging dishonest behaviour (Gudgeon *et al*., 2020; Soltani *et al*., 2022). Like all systems, off-chain transactions have vulnerabilities related to coding errors and implementation errors and attacks by malicious actors, or collusion. Regardless, off-chain payments symbolise an important innovation in blockchain architecture, towards resolving the trilemma for optimising security, scalability and decentralisation (Poon & Dryja, 2016). Some of the most popular Layer 2 cryptocurrencies as of December 2024 included Polygon with a market capitalisation USD9.8 billion, Immutable (USD4.6 billion) and Stacks (USD4.1 billion) (CoinMarketCap, 2025).

The overall point of the discussion on blockchain technology was to build an understanding of the broader mechanics behind cryptocurrencies to realise the novel transition from centralised decision-making control to a trustless system where security, transparency, and decentralisation are at the heart of every transaction. This was key especially for market participant who want to assess the fundamental potential of specific cryptocurrencies. An understanding of blockchain gives insights on how some cryptocurrencies leverage the principles of security, transparency, and decentralisation as they may be a determining factor that distinguishes sustainable

cryptocurrencies from fleeting trends on making investment decisions. The next section explores the various categories of cryptocurrencies highlighting variations in security, transparency, and decentralisation.

2.4 Cryptocurrency categories

Cryptocurrencies fall into several broad categories (sometimes often overlapping) reflecting their objectives and design philosophies. For example, BTC, a payment cryptocurrency prioritises security and scarcity, earning the nickname - digital gold (Baur *et al.*, 2024). Utility cryptocurrencies such as ETH grant access to the Ethereum network service and power decentralised applications and services (Makarov & Schoar, 2022). Stablecoins such as USDT prioritises decentralisation and have earned the nickname digital dollar (Arslanian, 2022). Governance tokens, meme coins, and other altcoins further diversify the ecosystem, each carving out unique roles and driving blockchain innovation forward. The following sections discussed some of the various categories of cryptocurrencies. Important to note that these categories are not entirely strict as cryptocurrencies serve multiple functions simultaneously. Additionally, the review was not meant to be exhaustive, instead it aimed to highlight the technological innovation within cryptocurrencies and capabilities. Makarov and Schoar (2022) provided an in-depth discussion of cryptocurrency categories

2.4.1 Non-stablecoins

Makarov and Schoar (2022) described non-stablecoins as coins that have no other function than being a cryptocurrency, either used for transaction purposes or as a store value. The authors argued that by construction, non-stablecoins, unlike stablecoins, their value is not backed by any external asset, such as fiat currency, commodities or any other reserves. Their value is determined by market supply and demand dynamics as driven by nondeterministic investor sentiments, making them inherently volatile (Anamika *et al.*, 2023; Arslanian, 2022).

Examples of popular non-stablecoins include BTC and ETH the largest cryptocurrencies by market capitalisation. Unlike stablecoins, which are designed to maintain a steady value, non-stablecoins have the potential for significant gains or losses based on market conditions and are therefore often used for investment and speculative trading (Makarov & Schoar, 2022). This section gives a brief overview of the development of non-stablecoins beginning with research focus that gave birth to BTC and how the core ideas that led to BTC have changed.

2.4.1.1 Tracing the history and the development of Bitcoin

Early development of cryptocurrencies is traced back to Chaum's (1983) work for advancing knowledge on balancing issues related to personal privacy and security in electronic payment systems. To this end, Chaum (1983) advocated for a cryptography-based system meeting three criteria: being untraceable by a third party, having the ability to provide proof of payment and having the ability to stop payment media reported as stolen. Two key studies advanced the idea of untraceable payments and cryptographic protocols. First, Chaum *et al*. (1988) explored the use of untraceable electronic cash, resulting in one of the first known online currencies - DigiCash. However, this online currency failed, partly due to scepticism about online transactions and concerns regarding its decentralisation (O'mahony *et al.*, 1997). Second, Law *et al*. (1996) advanced the use of a decentralised network in securing financial transactions, which resulted in two efforts at creating a cryptocurrency. Dai (1998) developed b-money, which outlined the fundamental principles and protocols employed by present-day cryptocurrencies. Szabo (2005) developed Bitgold, which uses smart digital contracts[22] that cut out the middleman using computer supervision (Popper, 2015). Despite these novel advancements, neither of these three attempts (DigiCash, b-money and Bitgold) was taken up by the broader market, primarily due to distrust about transacting online.

More than two decades after Chaum (1983) first laid the groundwork for untraceable payments, Nakamoto (2008) created Bitcoin - the first known operational cryptocurrency that runs on a permissionless blockchain (Geiregat, 2018). Bitcoin represents the culmination of decades of research in cryptography and distributed systems and includes four key innovations brought together in a unique combination: decentralised P2P network; a public transaction ledger (the blockchain); transaction validation and issuance rules (consensus rules); and mechanism for reaching global decentralised consensus (PoW algorithm) (Nakamoto, 2008).

Accordingly, Bitcoin is a collection of concepts and technologies that form the basis of a digital money ecosystem with its unit of currency, BTC used to store and transmit value among participants in the network (Hazlett & Luther, 2020). For the most part, network users interact within the Bitcoin protocol[23] over the internet, enabling users worldwide to communicate and

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[22] Smart digital contracts (or smart contracts) are self-executing agreements encoded as computer programs on a blockchain. They automatically carry out the terms of a contract when predetermined conditions are met (Makarov & Schoar, 2022).

[23] The Bitcoin protocol defines the rules and processes for creating, transferring, and verifying BTC transactions. The processes are detailed in Bitcoin (https://bitcoin.org/en/how-it-works). 10 April 2025

participate in the Bitcoin system (Segendorf, 2014). However, the protocol is not limited to operate exclusively on the internet. It can also function over alternative means such as mesh networks or satellite connections, allowing users to send and receive BTC even in areas with limited internet access (Segendorf, 2014). The Bitcoin software, which allows users to participate in the network, is available as open source[24], and can be run on a wide range of computing devices including smartphones and laptops making the technology accessible. Users can transfer BTC over the network as they would with conventional currencies (Segendorf, 2014). Additionally, BTC can be traded and exchanged for fiat currencies or other cryptocurrencies at specialised exchanges, such as Binance[25] or Coinbase[26] (Corbet *et al.*, 2018). Moreover, Bitcoin ATMs have become a convenient solution, enabling users to convert their holdings into fiat currency, spot, for withdrawal (Wyeth *et al.*, 2025). Unlike traditional currencies, BTC is entirely virtual[27], its users only own keys (passwords) that allow them to prove ownership in the Bitcoin network (Nakamoto, 2008; Fang *et al.*, 2025). Possession of the key that can sign a transaction is the only prerequisite to spending BTC, putting the control entirely in the hands of each user (Pillai *et al.*, 2019). Hence key management is one of the most important considerations for end users (Conti *et al.*, 2018). In-depth discussions on methods of securing keys are discussed in (Suratkar *et al.*, 2020).

The revolutionary aspect of the Bitcoin protocol lies in its operation as a distributed P2P system, which eradicates the reliance on a central server or point of control (Nakamoto, 2008). For instance, while central banks around the world adopt varying money creation processes influenced by their government policies, issuance rules for BTC remain predictable, pre-determined, and encoded within the Bitcoin protocol ensuring decentralised control over the creation of BTC, distinguishing it from traditional monetary systems (Nakamoto, 2008).

In practice, BTC is created through a process known as *mining*, which is a product of the PoW consensus mechanism. This process involved miners (individuals or entities using devices running the full Bitcoin protocol stack) competing to solve complex mathematical problems while simultaneously validating and processing BTC transactions (Geiregat, 2018; Gencer *et al.*, 2018). Miners in the Bitcoin network leveraged computational power to verify and record transactions on

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[24] Open-Sourced Bitcoin is available from Bitcoin Core (https://bitcoincore.org/?form=MG0AV3). 10 April 2025.

[25] Binance guide on how to buy Bitcoin (BTC) - Binance (https://www.binance.com/en/how-to-buy/bitcoin). 10 April 2025.

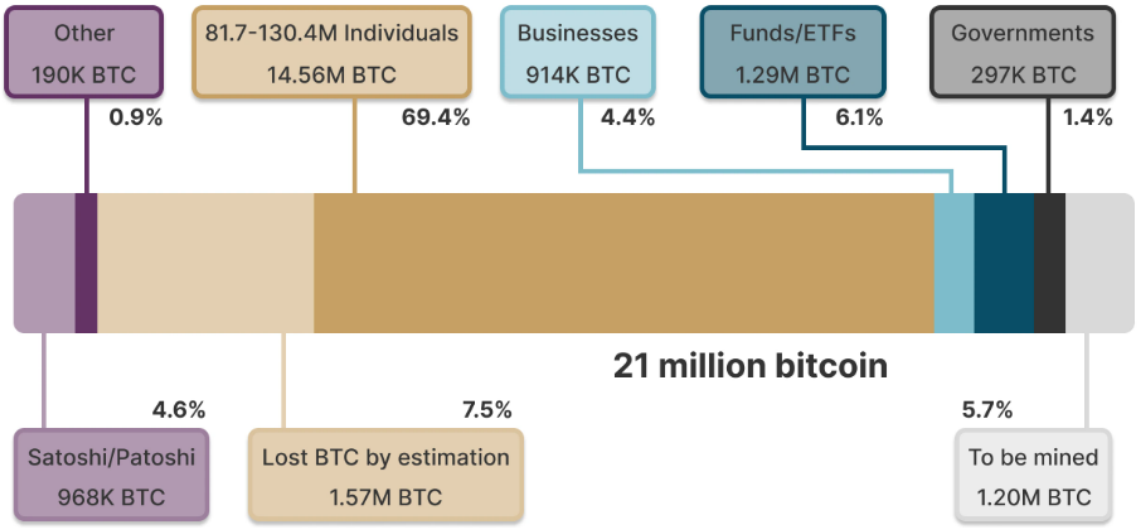
[26] Coinbase - Buy and Sell Bitcoin, Ethereum, and more from (https://www.coinbase.com/). 10 April 2025.

[27] BTC has no physical form and only exist on the Bitcoin network (Nakamoto, 2008)

the blockchain (Fang *et al.*, 2025). Miners with higher computational power possessed better chances of successfully solving the mathematical problems and simultaneously validating transactions to earn mining rewards (new BTC). As of December 2024, mining one block of BTC took approximately 10 minutes, with a successful miner rewarded 3.125[28] BTC (approximately USD 290 000). The protocol also halves the rate at which new BTC are created every 4 years (the approximate time it takes to reach a block of 210 000 given that 1 block takes 10 minutes to complete) and limits the total number of BTC that will be created to a fixed total supply of 21 million coins (Nakamoto, 2008). The result is that the number of BTC in circulation closely follows an easily predictable curve and its diminishing rate of issuance (because of halving mining rewards), over the long term, makes it deflationary (Geiregat, 2018).

The BTC market has continued to evolve rapidly, with its ownership[29] becoming increasingly diversified, as illustrated in Figure 2.1.

Figure 2.1: Bitcoin ownership distribution as of December 2024



Source: River (https://river.com/learn/who-owns-the-most-bitcoin/#companies-holding-the-most-bitcoin).

A substantial portion of BTC remains in the hands of individuals, including Satoshi Nakamoto, Bitcoin's pseudonymous creator, who is estimated to hold approximately 968 000 BTC. The bulk of individuals own a fraction of BTC, and a significant amount of has been lost, primarily due to misplaced private keys. Additionally, US-based public companies such as MicroStrategy and

[28] The Next Bitcoin Halving. From CoinMarketCap (https://coinmarketcap.com/events/bitcoin-halving/). 10 April 2025.

[29] Who Owns the Most Bitcoin in 2025? From River (https://river.com/learn/who-owns-the-most-bitcoin/#companies-holding-the-most-bitcoin). 10 April 2025.

Tesla, institutional investment firms like BlackRock, and various governments have also acquired BTC. Some governments have obtained BTC through legal seizures (China, the US, the UK, and Germany) as well as strategic purchases (Bhutan and El Salvador). Together, these diverse stakeholders exert a collective influence on the BTC market and its dynamics.

2.4.1.2 Alternative cryptocurrencies

The development of cryptocurrencies continued well after the launch of BTC, leading to numerous cryptocurrencies being launched. Most of the numerous alternative cryptocurrencies sought to build on the strengths of BTC and improve its shortcomings. On the positive side, some retailers were open to accepting BTC payments, thereby increasing payment flexibility by adding an alternative method of payment (Geiregat, 2018). On the negative side, some segments of the public (environmentalists) argued that PoW is not environmentally friendly due to its high computing power and excessive energy consumption (Kroll *et al.*, 2013; Lee *et al.*, 2017a; Makarov & Schoar, 2022). As a result, several alternative cryptocurrencies that use different mining techniques were proposed and launched to address the negative concerns of high computing power and intensive energy consumption. Other cryptocurrencies were launched to enhance the blockchain operational infrastructure by varying transaction processing time, transaction security, and means of rewarding stakeholders involved in the completing blocks. Namecoin (NMC) and Litecoin (LTC) were among the first alternative cryptocurrencies to launch in 2011 (Hamilton, 2021).

NMC, the first alternative cryptocurrency was created from modified BTC infrastructure and thus shared several foundational elements with Bitcoin. Its major contribution was to overcome the privacy issues that originated from traditional government and large corporation practices controlling Domain Name System (DNS) servers (Kalodner *et al.*, 2015). Thus, Namecoin branched out of Bitcoin and was developed with dual uses: a payment system and decentralised DNS (Haferkorn & Quintana Diaz, 2014). Its innovation thus laid the groundwork for later projects illustrating the broader potential of decentralised systems to enhance security, privacy, and resilience across various segments of business and commerce. In contrast Litecoin (LTC) was developed with the view of improving the operational efficiencies of BTC (Hamilton, 2021).

LTC sought to improve BTC infrastructure in four major ways – coin supply, transaction processing time, mining algorithm, and halving of mining rewards (Haferkorn & Quintana Diaz, 2014; Hamilton, 2021). Regarding coin supply, BTC has a coin supply limited to 21 million while LTC is limited to 84 million (Haferkorn & Quintana Diaz, 2014; Hamilton, 2021), potentially making LTC more accessible and tradable by users and investors. LTC can confirm transactions up to four times faster than BTC, which typically takes about 10 minutes to confirm a single transaction

(Haferkorn & Quintana Diaz, 2014; Hamilton, 2021). It can therefore be argued that LTC is relative to BTC is more attractive to retailers as a payment system/currency for everyday use because of the faster transaction processing speed. In terms of the mining algorithm, LTC requires less computing power, thereby making it possible for regular users to participate in the mining process. This potentially enhances decentralisation which is restrictive for BTC due to high computing power and energy resources. The final difference between BTC and LTC is that BTC's mining rewards halved every 210 000 blocks, while LTC block mining rewards halved every 840,000 blocks (Hamilton, 2021). Thus, Bitcoin's relative supply is constrained a lot quicker - a phenomenon that can potentially contribute to higher prices as supply is sticky upwards. Since BTC's inception and the development of alternative coins LTC and NMC, the cryptocurrency landscape began to expand at an increasing rate and by 31 December 2024, the market was made up of about 20 000 cryptocurrencies (CoinMarketCap, 2025).

Some of the numerous cryptocurrencies developed are not technology advancements offering a different use case such as NMC, instead they are modifications of existing cryptocurrencies aiming to rectify perceived infrastructure shortcomings, just like LTC. For example, in 2016, Bitcoin Classic was proposed to double the number of transactions that could be processed per second and to safeguard network security by reducing any possibility of third-party interference (Lee *et al.*, 2017). Bitcoin Classic, however, closed in 2017 due to a lack of following. Bitcoin Cash also branched out of Bitcoin in 2017 by altering the original Bitcoin code to reduce transaction costs and the time it took to confirm a transaction. Bitcoin Cash underwent another split in 2018 into Bitcoin Cash ABC (Adjustable Block size Cap) and Bitcoin Cash SV (Satoshi Vision), primarily because Bitcoin Cash followers could not agree on the scalability of the infrastructure (Kwon *et al.*, 2019). On one hand, Bitcoin ABC proponents wanted the block size to be maintained at 32MB, whereas the Bitcoin SV wanted the block size limit increased to 128 MB. Larger blocks would ultimately disadvantage individuals from running their full nodes, thereby supporting only large data centres to verify transactions, effectively centralising the network.

The different areas or technology enhancement in the alternative coins demonstrated the dynamism of the cryptocurrency market, suggesting that more currencies may still be launched, either from being developed ground up or by branching out from existing cryptocurrencies. Ethereum, the second largest cryptocurrency by market capitalisation at as 31 December 2024, is arguably one of the most important cryptocurrencies to have launched after Bitcoin and leveraged on smart contracts ideas of Szabo's (2005) defunct Bitgold. Ethereum, much like Bitcoin is a decentralised, permissionless blockchain platform that features its cryptocurrency, ETH. Ethereum aims to provide an alternative platform for building smart contracts and decentralised applications (dApps) with custom rules for ownership, transaction logic, and state

transitions (Buterin, 2014). It leverages a permissionless blockchain as its foundation, combined with the Solidity programming language enabling the creation of sophisticated computational logic, providing developers with the flexibility to create highly complex and innovative decentralised applications with a wide variety of application including finance, supply chain, voting and healthcare (Tikhomirov, 2017). The dApps therefore operate without a central authority, allowing for greater flexibility and innovation while the introduction of smart contracts enables programmable agreements that automatically execute when predefined conditions are met, broadening the scope of blockchain applications (Buterin, 2014). Thus, while Bitcoin is revolutionary in the sense that it fundamentally redefined the concept of money and financial systems, its scripting capabilities are less versatile than that of the Ethereum network which has the capabilities of enabling smart contracts and dApps with diverse applications including in decentralised finance (DeFi), identity verification, and autonomous organizations (Jensen *et al.*, 2021; Tikhomirov, 2017). The next section focuses on the differences between Ethereum and Bitcoin, the two most popular cryptocurrencies by market capitalisation.

2.4.1.3 Differences between Bitcoin and Ethereum

While Bitcoin was designed to be a global decentralised payment system, Ethereum is a smart contracts platform (Makarov & Schoar, 2022). At the core of its development, Ethereum features a decentralised platform that employs a transaction protocol to execute immutable contract agreements (smart contracts) between a buyer and a seller without the intervention of a third party (Buterin, 2014). The two platforms therefore differ in terms of use cases as is also reflected in their launch philosophies. Bitcoin adopted a decentralised grassroots model, relying solely on community-driven participation via mining. This approach aligned with Bitcoin's underlying philosophy of decentralisation and permissionless protocol, creating a widely distributed ownership base among early adopters who mined BTC without requiring financial investment (Nakamoto, 2008).

In contrast, Ethereum conducted an initial coin offering (ICO) - sells tokens for access or utility, not ownership to fund its development (Antonopoulos & Wood, 2018; Kapengut & Mizrach, 2023). While this structured fundraising enabled rapid innovation and scaling, it concentrated ownership among participants and developers during the early phases (Tikhomirov, 2018). These differences have profound implications: Bitcoin emphasises decentralisation and a permissionless protocol that prioritises security, while Ethereum exemplifies the use of structured fundraising to drive innovation - albeit with a potential risk of weakened decentralisation. Thus, from a risk management viewpoint, the Bitcoin philosophy minimises concerns of central control (because it started with minimum barriers to entry) while Ethereum's ICO demonstrates the trade-

offs involved in balancing inclusivity and operational risk (Sybil attacks). Successive ETH were generated through a mining process analogous to that of BTC (Antonopoulos & Wood, 2018). ETH mining rewards were initially set at a constant five (ETH) per block. This reward system varied from Bitcoin's payout of 3.125 BTC per block (as of December 2024) (Gencer *et al.*, 2018). Moreover, Ethereum originally had no fixed maximum supply, unlike Bitcoin's 21 million cap. However, it had an annual issuance limit of 18 million ETH (Antonopoulos & Wood, 2018; Gencer *et al.*, 2018). In 2022, Ethereum transitioned from a PoW to a PoS consensus mechanism, eliminating mining entirely. The ETH transition to a PoS model was expected to reduce the inflation rate of ETH to enhance its long-term value in financial markets (Binance, 2022). Under PoS, new ETH was issued to validators based on staking participation (the protocol required at least 16 384 validators each putting 32 ETH as capital) rather than miners (Kapengut & Mizrach, 2023). This transition significantly reduced Ethereum's issuance rate (inflation) from approximately 5 million ETH to around 0.6 million ETH annually, depending on network activity[30].

Additionally, the introduction of the Ethereum Improvement Proposal 1559 (EIP-1559) in 2021 implemented a mechanism to burn a portion of transaction fees, which offsets new issuance (Kapengut & Mizrach, 2023) While ETH does not have a fixed supply limit, the combination of capped issuance and fee burning often results in periods of deflation (Kapengut & Mizrach, 2023). This makes ETH scarcer, boosting its appeal as a long-term store of value (Félez-Viñas *et al.*, 2021). Investors perceive ETH (and BTC) as monetary assets with deflationary characteristics (Félez-Viñas *et al.*, 2021). Table 2.2 summarises the key differences between BTC and ETH.

Table 2.2: Differences between Bitcoin and Ethereum

	Bitcoin	**Ethereum**
Market capitalisation (as of December 2024)	USD 1.83 trillion	USD 0.4 trillion
Release date	2009	2015
Currency vs platform	A credible alternative to traditional fiat currencies (medium of exchange, store of value)	A platform for to run programmatic contracts (smart contracts) enabling dApps
Primary use cases	P2P transactions, store of value	DeFi, NFTs, dApps
Usages	Payment network	Smart contracts, blockchain platforms
Consensus algorithm	PoW	PoS (transitioned from PoW in 2022)
Block time	10 minutes on average	15 seconds on average
Transaction throughput	7 transactions per second	30 transactions per second
Supply	Finite supply-capped at 21 million BTC	Infinite supply
Monetary Policy	Fixed and predetermined issuance schedule	Flexible, with changes approved by community governance

Adapted from Cointelegraph (https://cointelegraph.com/learn/articles/bitcoin-vs-ethereum-key-differences-between-btc-and-eth). 10 April 2025.

[30] How The Merge impacted ETH supply from Ethereum (https://ethereum.org/en/roadmap/merge/issuance/). 10 April 2025.

Bitcoin focuses on being a decentralised payment network. Its fixed supply and decentralised nature challenge the traditional concept of fiat currencies controlled by central banks (Makarov & Schoar, 2022). Conversely, Ethereum goes beyond payment systems by introducing programmable smart contracts. This allows for dApps to operate without centralised control, further disrupting industries such as finance, gaming, and even supply chain management (Buterin, 2014; Mukherjee & Pradhan, 2021). Both cryptocurrencies present far-reaching disruptions to the financial markets landscape, reshaping how finance, services can be offered and presenting alternatives approaches to traditional monetary systems and financial intermediaries (Antonopoulos & Wood, 2018; Mukherjee & Pradhan, 2021; Tikhomirov, 2017).

The main point of this discussion is that while most cryptocurrencies leverage blockchain technology they have varying use cases. Investors with an appetite to participate in cryptocurrency risk-sharing must understand the technological infrastructure underlying their cryptocurrency of choice before committing to investing. This is consistent with all tenets of prudent investing which require due diligence on investment decisions. Within non-stablecoins, Bitcoin and Ethereum stand out as cornerstone with distinct yet complementary roles in shaping the finance and technology. Bitcoin's simplicity, combined with its robust security bolstered by an ever-growing network of participants, cements its position as an important payment system. This enduring reliability increases its appeal as an investment asset.

Ethereum's innovative platform has unlocked a wealth of possibilities, serving as the foundation for decentralised applications (dApps) and smart contracts. This opens significant opportunities for investors, positioning Ethereum within the broader Fintech scope where its technology informs its value opening up opportunities for investors seeking exposure to cutting-edge blockchain technologies. The next section explores what smart contracts and dApps are, following Makarov and Schoar (2022) who regarded them as a category of cryptocurrencies.

2.4.2 Smart contract-driven payments systems

Smart contract-driven payments systems represent a transformative application of blockchain technology, combining automation, decentralisation and security to reshape conventional industry and business processes (Khan *et al.*, 2021; Zheng *et al.*, 2020). A smart contract is an immutable self-executing agreement encoded on a public blockchain, programmed to execute specific actions, such as transferring funds, once predefined conditions are met (Makarov & Schoar, 2022).

Most smart contract driven payment systems run on permissionless blockchains, thereby eliminating third parties or the need of a central controlling entity (Zheng *et al.*, 2020). The concept

of smart contracts has been linked to Nick Szabo who defined it as a computerised transaction protocol that executes the terms of a contract.[31] The primary objectives of smart contract design are therefore to foster adherence to contract terms, reduce errors and reliance on intermediaries, and lower fraud, arbitration, and transaction costs (Makarov & Schoar, 2022). This technology is therefore disruptive to traditional contract enforcement and legal processes as contracts execute automatically and irreversibly (unless specific conditions for discontinuing the smart contract were included in the program ex ante), leaving little room for legal intervention, negotiation, or ex-post remediation (Werbach, 2018). Unlike traditional contracts, which rely on the legal system to address breaches, ambiguities, or unforeseen circumstances ex-post, smart contracts must be pre-emptively and completely specified ex-ante to eliminate disputes which in any case may be impractical to resolve due to the anonymity of transactions (Makarov & Schoar, 2022).

Despite smart contracts being an emerging innovation, they have gained a foothold in diverse scenarios such as escrow services, recurring subscriptions, and cross-border trading to minimise disputes and streamline the transaction process making them the backbone of dApps (Zheng *et al*., 2020). As a result, several types of smart contracts have emerged as popular including smart legal contracts (to create standard legal contracts enhanced with automated execution) and Decentralised Autonomous Organization (leaderless organizations governed by smart contracts) (Buterin, 2014; Geiregat, 2018).

It is therefore evident that smart contract platform systems like Ethereum do have an intrinsic economic value (related to network activity and subsequently transaction fees) other than the potential for capital appreciation with the value linked to the scope and the number of applications run on the platform (Makarov & Schoar, 2022). As of December 2024, the smart contract driven payment systems were substantial with market capitalisation of close US 600 billion dominated by ETH (USD 404 billion), BNB (USD 101 billion), and Cardano (USD 30 billion)[32] signalling their importance within the cryptocurrency market space.

It is important to note that smart contract platforms (which include Ethereum, Binance and Cardano amongst others) are not themselves smart contract, but the important blockchain platforms that power smart contract functionality (Buterin, 2014; Makarov & Schoar, 2022). The

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[31] Smart Contracts (https://www.fon.hum.uva.nl/rob/Courses/InformationInSpeech/CDROM/Literature/LOTwinterschool2006/szabo.best.vwh.net/smart.contracts.html). 10 April 2025.

[32] Top Smart Contracts Tokens by Market Capitalisation from CoinMarketCap (https://coinmarketcap.com/view/smart-contracts/?tagSlug=smart-contracts). 10 April 2025.

platforms allow developers to write and deploy smart contracts using their programming language and executed on their decentralised blockchain engine that enforces the terms encoded in the smart contract (Antonopoulos & Wood, 2018). The adoption of smart contract-driven payments aligns with the broader cryptocurrency discourse emphasising decentralisation and transparency whilst maintaining anonymity. However, several vulnerabilities remain within the smart contracts' domain. Buterin (2014) found that smart contract payment systems are susceptible to cyberattacks, coding errors, and regulatory disorientation. The authors emphasized the importance of thorough auditing, secure coding practices, and ongoing monitoring to reduce potential threats. Additionally, scalability remains an issue, as high transaction volumes can congest blockchain networks, leading to delays and increased fees (Makarov & Schoar, 2022). Despite these challenges, smart contract-driven payments are reshaping industries like real estate, supply chain management, and insurance by enabling secure, automated, and transparent transactions - demonstrating their transformative potential (Pranata & Tehrani, 2022). The next sections explore DeFi to illustrate how smart contract and blockchain technology is redefining the future of financial systems.

2.4.3 Decentralised Finance (DeFi)

DeFi marks a progressive development in the financial sector in utilising permissionless blockchain technology to facilitate automated and trustless P2P financial transactions. Within DeFi ecosystems, cryptocurrencies act as the medium of exchange, enabling seamless and transparent operations (Antonopoulos & Wood, 2018; Makarov & Schoar, 2022). Jensen *et al*. (2021) provided a clear characterisation of DeFi's role within the cryptocurrency space, framing it as a system of smart contracts deployed on a permissionless blockchain. Standardised smart contracts form the foundation for creating base assets, which are subsequently used to build more sophisticated financial instruments (Jensen *et al*., 2021).

DeFi applications, operating as advanced smart contracts, execute specific business logic deterministically, ensuring reliability and efficiency (Jensen *et al*., 2021). DeFi endeavour to democratise financial services beyond a central authority or institution's regulations in various niches including trading, lending and borrowing and yield farming. Regarding the latter, investors delegate tokens to validators for staking rewards, earning fees by providing liquidity to decentralised exchanges (DEXs), earning interest through lending protocols (Makarov & Schoar, 2022).

Arguably the prominent component of DeFi are dApps which through smart contracts allowing for automated and programmable monetary systems, and through blockchain, support immutable and seamless transactions without any third-party interference. Some of the most common dApps

include DEXs - a platform to exchange cryptocurrencies for a fiat currency or vice versa, and in some cases, exchange a cryptocurrency (Hägele, 2024). Individuals and corporations acquire DeFi tokens for several key purposes. These include trading on DEXs, gaining exposure to DeFi protocols, and participating in protocol governance, which is often carried out through proof-of-stake (PoS) mechanisms. Investors can opt to purchase tokens of specific DeFi protocols they believe will perform well, or they can invest in broad-based indices that track the overall performance of the DeFi sector. Binance allows users to purchase DeFi tokes. Some of the most popular ones like Uniswap (USD 8 billion market capitalisation as of 31 December 2024) and Sushiswap (USD 350 million).[33]. DeFi has also made it possible to allow users to directly use BTC on Ethereum-backed DeFi through wrapped bitcoin, lending it through the different platforms to earn interest (Makarov & Schoar, 2022).

The DeFi industry, though still in its growth phase, has experienced substantial expansion, increasing from approximately USD 1 billion in January 2020 to a market capitalisation exceeding USD 70 billion by the end of 2024. Notable cryptocurrencies dominating the DeFi space include Chainlink (LINK) with a market capitalisation of USD 12 billion, Avalanche (AVAX) at USD 14 billion, and Hedera (HBAR) at USD 10 billion. Additionally, the total value locked (TVL) in DeFi platforms has surpassed USD 20 billion. However, like all smart contracts driven innovations, the rapid growth of DeFi must contend with numerous risks, including vulnerabilities to cyber-attacks, regulatory gaps, and liquidity and funding challenges especially in leveraged positions (Makarov & Schoar, 2022).

As the blockchain-based cryptocurrency industry continues to grow, driven by the emergence of innovative products, it has begun to attract increasing interest from mainstream institutional investors. However, a significant challenge remains for risk-averse investors: the extreme volatility of the cryptocurrency market, characterised by frequent and unpredictable price swings. This inherent instability has made some participants hesitant to engage. Yet the technological innovativeness within the cryptocurrency space continues to evolve and widen its reach to even the arts sector. The next section introduces non-fungible tokens (NFTs) – systems better suited for tokenising artwork.

2.4.4 Non-fungible tokens (NFTs) systems

NFTs have emerged as a prominent asset within the cryptocurrency space, appealing to both cryptocurrency enthusiasts and collectors while expanding the scope of digital assets beyond

[33] Top DeFi Tokens by Market Capitalisation (https://coinmarketcap.com/view/defi/). Date of access: 25 March 2025.

BTC and ETH. Unlike fungible stable or non-stablecoins, NFTs are unique digital tokens that cannot be exchanged on a one-to-one basis (Makarov & Schoar, 2022; Zhang, 2023). They represent verified ownership of distinct assets or experiences, such as digital artwork, music, videos, or virtual real estate.

The NFT market has witnessed record-breaking sales in recent years, reflecting its growing significance and appeal. For instance, the renowned pseudonymous artist Pak's Merge achieved an unprecedented sale of USD 91.8 million on the NFT platform Nifty Gateway in December 2021[34]. The growth of the NFT market over the past two years has further drawn attention to its investment potential, as an increasing number of participants recognise the prospects of this innovative digital asset class.

The widespread use cases of cryptocurrencies have expanded beyond artwok and caught the attention of several Governments worldwide. This has led to the growing interest in Central Bank Digital Currencies (CBDCs) discussed next.

2.4.5 Central Bank Digital Currencies (CBDCs)

The exploration of Central Bank Digital Currencies (CBDCs) represents a significant development within the realm of digital payment systems. Arslanian (2022) provided an insightful overview of CBDCs, discussing what they are, how they operate and why central banks around the world are accelerating efforts roll out their own pilot projects. Arslanian (2022) argued that growing digitisation, and payment-system efficiency motivate central banks to pursue CBDCs (the digital form of a nation's fiat money) which could potentially help towards enhanced systemic resilience due in part to programmable payment functionalities. Yet risks that include commercial bank disintermediation, trading-off privacy and traceability and cybersecurity vulnerabilities remain (Arslanian, 2022).

CBDC projects such the Monetary Authority of Singapore's Project Ubin, Khokha in South Africa, China's digital yuan and the European Central Bank's digital euro, underscore the growing interest in this area (Shafranova *et al.*, 2024). Moreover, cryptocurrencies such as XRP launched CBDCs solution and are reported to have been working with several countries[35] to facilitate development of CBDCs.

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[34] Highest Price NFT Stats (https://coinmarketcap.com/nft/). Date of access: 25 March 2025.

[35] These include Russia, Japan, New Zealand, Hong Kong, UAE (https://finbold.com/ripple-reveals-8-countries-building-cbdcs-on-xrp-ledger/). Date of access: 31 March 2025.

The above discussion has demonstrated that the cryptocurrency landscape is expansive with numerous inventions such as smart contracts, DeFi, NFTs and CBDCs highlighting diversity. Yet one underlying criticism remains concerning most cryptocurrency categories: wild volatility. Consequently, another category of cryptocurrencies distinguishes itself from other cryptocurrencies by endeavouring to tease out the wild volatility that has become synonymous with cryptocurrencies. This category is commonly referred to as stablecoins and are discussed in the next section.

2.4.6 Stablecoins

Stablecoins represent a significant innovation within the cryptocurrency ecosystem, particularly in the context of permissionless blockchains. They are issued as tokens leveraging on existing networks such as Ethereum, Bitcoin, Tron, or Solana (Ante *et al.*, 2023; Lyons & Viswanath-Natraj, 2023). Stablecoins are designed to maintain a stable value, by benchmarking to a fiat currency or gold, or other financial asset to provide an alternative to the high volatility in cryptocurrencies making them more suitable for everyday transactions (Makarov & Schoar, 2022; Oefele *et al.*, 2024). This relative stability (lower volatility) is crucial for their use as a medium of exchange, bridging the gap between fiat currencies and popular cryptocurrencies BTC and ETH. As of December 2024, the stablecoin market had grown beyond USD140 billion and was dominated by fiat-backed stablecoins (97% of the market share by capitalisation) followed by cryptocurrency-backed stablecoins (2%). Algorithmic stablecoins as well as commodity-backed stablecoins account for a smaller share of the stablecoin market.[36]

The dominance of fiat-backed stablecoins, make them best classified as money. However, they can also be viewed as investment assets, particularly within the context of DeFi where users can lend them on platforms to earn interest, effectively treating them as investments (Ante *et al.*, 2023; Oefele *et al.*, 2024). Lyons & Viswanath-Natra (2023) revealed that despite the dominance of fiat-backed stablecoins, considerable research efforts, are channelled to make stablecoins less reliant on fiat currency assets, as it contradicts the core principle of decentralisation (since fiat money control is centralised). A popular idea is to tie stablecoins to the Consumer Price Index (CPI), which tracks the average cost of consumer goods and services (Makarov & Schoar, 2022). Future research may be able to establish whether these explorations materialise and reshape perception into what stablecoins represent.

[36] Top Stablecoins by Market Cap | CoinGecko (https://www.coingecko.com/en/categories/stablecoins#key-stats). Date of access: 15 March 2025.

The next section discusses Web3 payment systems that seek to expand the original spirit of BTC – to create autonomous payment system.

2.4.7 Web3 Payment Systems

Web3 payment systems represent a transformative approach to online transactions, leveraging blockchain technology to enabling P2P transactions breaking the monopoly of intermediaries like banks or traditional financial institutions (Arslanian, 2022; Chen *et al.*, 2022). Web3 payment systems are built on DLT and leverage blockchain protocols and smart contracts to reduces reliance on intermediaries, thereby lowering costs enabling faster secure, transparent, and immutable transactions (Arslanian, 2022). Wan *et al*. (2024) detailed examples of Web3 payment systems which include:

- Bitcoin network P2P payments using BTC for value transfer;
- Ethereum-based platforms such as Uniswap and DeFi protocols which include Aave and Compound enable payments and financial services via smart contracts;
- Stablecoins which include USDC payment transacted on networks such as Ethereum or Tron for stable, low volatility transactions;
- Payment-focused blockchains such as Solana, Ripple, or Stellar offer opportunities for quick and low-cost global payments; and
- Web3 payment gateway services such as Coinbase which integrate cryptocurrency payments for businesses.

The emergence of Web3 payment systems aligns with the broader evolution of a decentralised internet. For example, with a Web3 application, internet user's data is stored in their personal wallet rather than on a company's servers (such as Alphabet - formerly Google) (Wan *et al.*, 2024). Users decide who can access their data and are often rewarded for their participation (tokenisation). Web3 payment systems integrate cryptocurrencies into user-centric ecosystems, fostering trustless and secure interactions (Arslanian, 2022; Wan *et al.*, 2024).

The discussion in this section demonstrated that cryptocurrencies are dynamic pieces of technology (financial technology) infrastructure, tradeable assets and, in some contexts, a media of exchange. Their classification often depends on relevant use cases. Among the over 20 000 cryptocurrencies in circulation and actively traded as of December 2024 (CoinmarketCap, 2025), BTC and ETH stood as the top two largest by market capitalisation. BTC is regarded as an important payment system due to its robustness on transaction security, decentralised nature and privacy making it attractive to investors. ETH is regarded for its programmable blockchain platform that powers smart contracts, dApps, and other innovative technologies within its ecosystem. This

study is primarily focused on value of cryptocurrencies in general and BTC and ETH specifically, as investment because their decentralisation is unique and decouples from most of the financial assets. The next sections delve deeper into this view and explore price dynamics in cryptocurrencies, with emphasis on BTC and ETH. Elucidating price properties is important when characterising the value and risks associated with cryptocurrency investment.

2.5 Cryptocurrency price dynamics

The concurrent roles of cryptocurrencies, as pieces of payments technology infrastructure (Makarov & Schoar, 2022; Nakamoto, 2008; Szabo, 2005) tradeable assets (Bouri *et al.*, 2020; Van Der Linden & Shirazi, 2023) and, in certain circumstances, media of exchange (Davidson & Block, 2015; Oefele *et al.*, 2024) have substantially influenced the parameters that determine cryptocurrency valuation. This study did not find a universally agreed framework to cryptocurrency valuation. Traditional methods like discounted cash flow are inapplicable as cryptocurrencies do not produce regular cashflows as bonds. Additionally, commodity analogies have offered limited insights into the drivers of cryptocurrency prices, as they missed the unique traits. For example, Cheah and Fry (2015) applied stochastic processes techniques and found that the fundamental value of BTC was zero and motivated for alternative value frameworks. A growing branch of literature (Caferra, 2022; Fang *et al.*, 2025; Hayes, 2017) focused on a hybrid approach, combining network (on-chain) metrics, market sentiment, production-cost models, and tailored techniques to address questions of drivers of cryptocurrency prices.

A frequently referenced study in the discourse on factors impacting cryptocurrency prices is Corbet *et al*. (2019), which contends that, although speculation affects cryptocurrency valuations, fundamental elements such as on-chain metrics and protocol features play a significant role in shaping these prices. Liu and Tsyvinski (2021) and Nakagawa and Sakemoto (2022)confirmed that technology factors related to network metrics contributed to changes in cryptocurrency prices. The broad-based view that the interplay between intrinsic and extrinsic factors shape cryptocurrency prices has gathered widespread significance. Intrinsic factors included technology features that encompass mining costs (Kristoufek, 2015), halving (Ibrahim *et al.*, 2020) and network metrics (Chowdhury *et al.*, 2022). Some of the salient extrinsic factors included liquidity (Al-Yahyaee *et al.*, 2020), wider macroeconomic trends particularly equity prices (Ciaian *et al.*, 2018)), investor sentiment (Anamika *et al.*, 2023; Caferra, 2022; Sibande *et al.*, 2023) and regulation (Chokor & Alfieri, 2021; Feinstein & Werbach, 2021; Griffith & Clancey-Shang, 2023). The rest of this section delves deeper into highlighting how these factors, which often overlapped, are related with cryptocurrency prices.

Regarding intrinsic factors, the literature is littered with studies that explored the relationship between cryptocurrency prices and the fundamental value associated with producing them. This

literature is growing and builds on the novel work of Hayes (2017) who studied BTC's price formation. The author identified three ways of obtaining cryptocurrencies:

(i) buying them on an open exchange (using fiat currencies),
(ii) accepting them as payment for goods and services, and
(iii) mining them.

The latter case is the process by which *new* BTCs enter into circulation (as discussed in Section 2.4.1). BTC mining involves substantial energy consumption and costly computer hardware expended on processing the cryptographic computations needed to solve the PoW algorithms and complete blocks (Kroll *et al.*, 2013; Lee *et al.*, 2017). For this reason, practical BTC miners would only be in business if the marginal revenue from BTC mining exceeded the marginal costs of the mining process (Hayes, 2017). In light of this relationship, Hayes (2017) found a positive association between mining costs and the price for BTC, corroborating Kristoufek (2015). Chico-Frias (2021) confirmed a positive relationship between mining costs and BTC prices. However, several authors (Baldan & Zen, 2020; Kjærland *et al.*, 2018; Liu & Tsyvinski, 2021) found no evidence that BTC prices were related to the costs and earnings of the mining efforts, setting the stage for further debate. The lack of consensus on whether BTC prices where related to mining costs strengthen Dyhrberg's (2016) argument that cryptocurrencies are more like commodities such as oil and gold, whose prices are not determined by extraction costs, but rather by extrinsic factors such as supply and demand forces and market sentiments.

In terms of how supply and demand factors influence prices, the literature details that while supply affects price, demand exerts greater influence on prices with fluctuation in demand linked to price bubbles (Ciaian *et al.*, 2018; Peng *et al.*, 2024). Unlike demand, the supply of many cryptocurrencies like BTC is predictable and has less effect on prices, while demand is volatile and linked to price bubbles (Peng *et al.*, 2024). Price bubbles in the cryptocurrency market have been widely discussed, given their significant impact on investors. While such bubbles may present opportunities for substantial profits, they also underscore the considerable risks investors face during price reversals. Chen and Hafner (2019) argued that price bubbles are driven by exuberant sentiments, corroborating Lee Kuo Chuen (2015) who noted that two types of traders dominated the cryptocurrency market – speculators and tech-savvy investors. Speculators employed a momentum trading strategy when market volatility was high, pushing up prices and switched to a contrarian strategy when market volatility was low (Weber, 2014). It is, therefore, not unlikely that several cryptocurrencies experienced episodes of price bubbles primarily due to speculative activities that potentially amplified price gains or losses. Price corrections due mostly to the activities of informed tech-savvy investors led to price reversals, thereby exiting the bubble condition.

Understanding price bubbles is important for investors as it influences the balance of risk and returns. Fry and Cheah (2016) tested the existence of bubbles using data from 2011 to 2015. They found evidence of a negative bubble from 2014 to 2015 in the prices of BTC and XRP. Yet, Chaim and Laurini (2019) concluded that BTC prices had bubble behaviour as early as 2013 to mid-2014. The same BTC price bubble was confirmed by Corbet *et al*. (2018) who found that it was significant around the turn of the year 2013/2014 and from August 2017 to around November 2017. While these findings confirmed that cryptocurrencies undergo episodes of price bubbles, evidence from the literature suggested that bubbles are not unique to cryptocurrencies. US equities in 1932 and internet equity from 2002 to 2003 also experienced episode of bubbles (Siegel, 2003). Furthermore, Sornette and Woodard (2010) reported bubbles in several assets including derivatives, real estate and oil. More research is still necessary to understand how price bubbles in cryptocurrencies have evolved, by comparing different 'older' and 'newer' cryptocurrencies or other 'young' assets for example carbon credits discussed by Zhang *et al*. (2018).

It is important to note that speculation, often associated with price bubbles, does not occur randomly; rather, it reflects the ways in which certain market participants respond to and amplify prevailing market sentiment. Kjarland *et al.* (2018) found a strong relationship between cryptocurrency prices and investor sentiments reflected in Google searches. Optimistic sentiments were argued to lead to price increases (Anamika *et al.*, 2023; Garcia *et al.*, 2014) while negative sentiments negatively impacted prices (Huynh, 2021; Wang & Vergne, 2017). By focusing on sentiments on twitter and other social media, market participants may be able to assess whether prices could rise or fall, informing their trading strategies. In this regard, Bouri *et al*. (2019) found evidence of herding behaviour particularly in periods of uncertainty. Sibande *et al.* (2023) confirmed the herding behaviour and further showed that in periods of stress, strong sentiment swings and herding behaviour can be sources of cryptocurrency market instability and that extreme sentiment fuels price bubbles.

Several studies (Gkillas *et al.*, 2024; Patel *et al.*, 2020; Shahzad *et al.*, 2021; Smales, 2021) corroborated that market sentiments play an important role in cryptocurrency prices. Notably, Gaies *et al.* (2023) solidified the concept of the cryptocurrency fear and greed index – an indicator variable that reflects investor sentiments ranging from 0 (extreme fear) to 100 (extreme greed). When the index level is high (extreme greed), it means investors are more likely to buy or hold cryptocurrencies, pushing prices up, and the reverse is true for fear. Market participant can therefore utilise the fear/greed index related to market sentiments to anticipate how prices will change, informing their investment strategies.

The literature on factors influencing cryptocurrency prices is dynamic and continues to evolve. Table 2.3 summarises some of the studies on cryptocurrency price dynamics.

Table 2.3: Literature findings on price dynamics of cryptocurrencies

AUTHORS	KEY FINDINGS
Cheah and Fry (2015)	Bitcoin prices contain a considerable speculative component, are susceptible to bubbles and their fundamental value is zero.
Bouoiyour *et al.* (2015)	Bitcoin is a highly speculative asset, and there is no clear causality between Bitcoin price and trade transactions.
Fry and Cheah (2016)	Bitcoin and cryptocurrency markets contain a considerable speculative component and are extremely volatile. It's unclear how regulations affect Bitcoin prices.
Polasik *et al.* (2015)	Bitcoin prices are primarily driven by popularity, the sentiment expressed in newspaper reports on cryptocurrency, and the total number of transactions.
Hayes (2017)	Bitcoin price can be described by its cost of production.
Zhu *et al*. (2017)	US dollars, CPI and the Dow Jones are negatively related to BTC price
Corbet *et al.* (2018)	There are periods of clear bubble behaviour in cryptocurrency markets.
Gandal *et al.* (2018)	Trading volume on all exchanges increased greatly on days with suspicious activity. Suspicious trades on Bitcoin are linked to rises in the exchange rate.
Ciaian *et al.* (2018)	There is a strong relationship between Bitcoin and other coin prices in the short run. However, macro-financial developments (oil price, gold price, equity - NASDAQ Composite and treasuries) are a strong determinant of cryptocurrency prices in the long run.
Corbet *et al*. (2019)	Hacking events negatively affect the price of cryptocurrencies
Scaillet *et al*. (2020)	Cryptocurrency returns have a higher frequency of price jumps than US equities.
Anamika *et al*. (2023)	Equity market investors' sentiment is inversely related to cryptocurrency prices. Additionally, Bitcoin sentiment is positively associated with Bitcoin prices which in turn influences price of other cryptocurrencies.
Wang *et al*. (2022)	Economic Policy Uncertainty Index is negatively related to BTC prices while positive trading behaviours are positively related with BT prices
Shahzad *et al*. (2022)	There seems to be no evidence to suggest that the influential role of prominent individuals in society influences cryptocurrency prices
Corbet *et al*. (2022)	Market liquidity is interrelated with cryptocurrency prices
Caferra (2022)	Cryptocurrency prices emanated from complex interactions between speculative forces and fundamental factors anchored in on-chain metrics, economic indicators and cryptocurrency protocol-specific fundamentals.
Easley *et al*. (2024)	Market microstructure measures of liquidity and price discovery such as asymmetric information and auto-correlations significantly predict BTC and ETH returns and remain robust during periods of market downturns

Source: Compiled by Author.

The following observations can be made from Table 2.3:

1. Cryptocurrency prices are driven by a mix of sentiment, technical trends, on-chain activity and regulatory news.
2. Most of the research on price bubbles in cryptocurrencies refers to BTC. There is a dearth of studies exploring price bubbles in other cryptocurrencies.
3. Episodes of economic uncertainty and crisis such as the Covid-19 affect cryptocurrency prices.

Peng *et al*. (2024), along with the cited literature offered a comprehensive analysis of the multiple factors affecting cryptocurrency prices. The following factors were cited as key in shaping cryptocurrency prices:

(i) supply and demand factors;

(ii) technology factors underlying cryptocurrencies;

(iii) broader macroeconomic factors including interest rates, exchange rates, equity market indices and commodity prices; and

(iv) investor sentiments.

John *et al*. (2024) corroborated the findings of Peng *et al*. (2024) and pinpointed four influential drivers that underpin cryptocurrency price dynamics:

(i) technical metrics (for example momentum indicators and volatility measures)
(ii) blockchain features (on-chain activity)
(iii) market sentiments (mostly social media news)
(iv) legal and regulatory developments affecting market expectation.

There is therefore support in the literature that cryptocurrency prices are driven by a mix of sentiment, technical trends, network activity and regulatory news indicating the complexity in what determines cryptocurrency prices. Kukacka and Kristoufek (2023) made headway towards shaping an understanding of which factor among: fundamental factors or market sentiments played the foremost role in determining prices. The authors found that BTC's price is driven most by fundamentals such as network activity and broader equity (S&P 500) price dynamics. However, for other cryptocurrencies such as ETH, LTC, XRP and Dogecoin, market sentiments were the main speculative forces pushing prices changes. Although the authors cited complexity in separation between fundamental and speculative, their result contradicted the popular view that BTC, because of its decentralised governance, permissionless access and *global* liquidity was divorced from the traditional assets such as equity fundamentals. Kukacka and Kristoufek (2023) also noted that the complex interaction between price fundamental factors and market sentiments led to episodes of price bifurcations. This mean that while for example sentiments affected cryptocurrency prices, this effect was not the same across cryptocurrencies as they exhibited separate clusters of behaviour. Price bifurcations have far-reaching implications for risk-return relations within cryptocurrencies. Understanding them can aid investors and risk managers anticipate distinct performance paths for robust portfolio management especially when market changes regimes and enter crisis periods. The following sections examined the returns, risk profile, correlation, and diversification dynamics of cryptocurrencies. This analysis aimed to provide a comprehensive comparison with other commonly traded assets, thereby assessing the associated opportunities and risks for investors.

2.5.1 Returns dynamics

The literature documented a mix of factors associated with cryptocurrency prices. It also highlighted several instances of cryptocurrency price bubbles. This prompts analysis into whether

these originate from the complex interaction of factors involved in determining their price, a general lack of an agreed method to parameterise their fundamental value (Cheah & Fry, 2015), which may serve as reference points for investors thereby stabilising prices. Alternatively, these bubbles may be attributed to the pricing behaviour typically observed in young, rapidly evolving and sentiment driven assets (Anamika *et al.*, 2023; Kukacka & Kristoufek, 2023). Regardless of these unanswered questions, understanding cryptocurrency returns in comparison with those of other assets affords investors critical insights into portfolio performance and diversification potential.

In light of these considerations, Liu and Tsyvinski's (2021) study documented the risk-return profile of cryptocurrencies (BTC, XRP, and ETH) and compared them to those of equity (US and China), currencies (Australian Dollar, Canadian Dollar, Euro, Singaporean Dollar and British Pound), and commodities (gold, platinum, and silver). The results showed that the returns of cryptocurrencies were significantly higher and experienced higher probabilities of extreme events (disasters and successes). The high-risk, high-return characteristic of cryptocurrencies was corroborated by Jia *et al.* (2021) who argued that cryptocurrencies had lottery-type risk-return profiles, which make them more attractive to speculators and highly risk-tolerant investors less concerned about crash risk[37]. Higher returns in cryptocurrencies were also confirmed by Corbet *et al*. (2019) who found that cryptocurrency returns were considerably higher than those of any other publicly tradable asset (index) including commodities (MSC GSCI Total Returns Index), currencies (USD Broad Exchange Rate), equities (S&P500) precious metals (COMEX, gold) and fixed income products (Markit ITTR110). The realisation that cryptocurrency returns were higher than those of other assets found support in the literature (Corbet *et al.*, 2018; Leirvik, 2022; Liu & Tsyvinski, 2021). Moreover, recent empirical evidence reinforces the notion that BTC, the top performing cryptocurrency is unrivalled against six other major asset classes in the US as presented in Table 2.4.

[37] Crash risk refers to the potential for a sudden and significant decline in the value of an asset, dramatically eroding it market capitalisation and potentially impairing chances of continuity. Examples of cryptocurrencies that crashed include BitConnect (BCC), Terra Classic (LUNC) and Terra USD (UST) from CoinCodex (https://coincodex.com/article/22749/what-happened-to-luna/). 10 April 2025.

Table 2.4: Bitcoin returns for 2014-2024 compared with other selected major asset classes

2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024	Cumulative return	Annualized return
SPX 15%	BTC 36%	BTC 120%	BTC 1,375%	AGG 0.3%	BTC 95%	BTC 305%	BTC 60%	CMT 20%	BTC 157%	BTC 120%	BTC 11,836%	BTC 54%
AGG 6%	SPX 1%	HY 18%	EM 35%	HY -2%	SPX 31%	Gold 24%	SPX 31%	Gold 1%	SPX 27%	Gold 27%	SPX 293%	SPX 13%
HY 2%	AGG 0.3%	EM 15%	SPX 21%	Gold -3%	EM 21%	SPX 17%	CMT 30%	HY -11%	HY 13%	SPX 26%	Gold 114%	Gold 7%
EM 1%	HY -4%	CMT 14%	Gold 12%	SPX -5%	Gold 18%	EM 14%	HY 5%	AGG -12%	Gold 12%	EM 12%	HY 69%	HY 5%
Gold -3%	Gold -11%	SPX 14%	HY 7%	CMT -9%	HY 14%	AGG 7%	EM -0.4%	EM -18%	EM 9%	CMT 9%	EM 57%	EM 4%
CMT -18%	EM -14%	Gold 7%	CMT 6%	EM -15%	CMT 10%	HY 7%	AGG -1%	SPX -19%	AGG 5%	HY 9%	AGG 21%	AGG 2%
BTC -58%	CMT -25%	AGG 3%	AGG 4%	BTC -74%	AGG 9%	CMT -3%	Gold -6%	BTC -64%	CMT -2%	AGG 2%	CMT 15%	CMT 1%

*Source: Bloomberg and BlackRock calculations, as of 31 December 2024 (*https://www.ishares.com/us/literature/product-brief/ibit-product-brief.pdf*). BTC returns were calculated using Bloomberg Bitcoin Spot Price. SPX (S&P500 total return Index). EM (Dow Jones Emerging Markets Index -total return). AGG (Bloomberg US Aggregate Bond Index -total return. HY (Bloomberg US High Yield Corporate Bond Index -total return). Gold (spot exchange rate of gold against the US dollar index). CMT (Dow Jones Commodity Index -total return) represent other selected asset classes.*

The table reveals that, over the 11-year period ending December 2024, BTC exhibited extraordinary investment performance, delivering a cumulative return of 11,836%. To illustrate, a USD100 investment in BTC in 2014 which could buy about one-half of a metric ton of maize[38] would have grown to an astounding USD11,836 (equivalent to over 150 metric tons of maize) by December 2024. In comparison to other asset classes, BTC demonstrated far greater returns relative to US equities (293%) and Emerging Markets equities (57%). BTC also dwarfed the performance of US investment grade bonds (21%), US junk bonds (69%), precious metals gold (114%), and US commodities futures/derivatives (15%). This outperformance was evident both on a cumulative return basis and in terms of annualised performance.

BTC's performance underscores its potential to yield significantly high returns which could positively contribute to portfolio performance. However, the returns dynamic showed that during downturns in 2014, 2018 and 2022, BTC suffered annualised negative returns of 58%, 74% and 64%, respectively revealing its susceptibility to sizable crash risk. These losses far exceeded those observed in the next worst-performing asset classes of those years, such as commodities in 2014 (-18%), Emerging Markets equities in 2018 (-15%) and the S&P 500 in 2022 (-19%). Such

[38] IMF Data West Texas Intermediate crude (https://legacydata.imf.org/?sk=471dddf8-d8a7-499a-81ba-5b332c01f8b9). Date of access: 31 May 2025.

swings highlighted BTC's tendency to booms and busts as noted by Corbet *et al*. (2018) in their cautionary remarks to investors. Downturns in cryptocurrencies can result in substantial losses, particularly depending on the timing of investment entry and the duration of the investment horizon.

To elaborate more on the return dynamics of cryptocurrencies, Table 2.5 details some of the key findings.

Table 2.5: Literature findings on cryptocurrency returns

AUTHORS	KEY FINDINGS
Briere *et al.* (2015)	Bitcoin has high average returns.
Dwyer (2015)	The minimum and maximum daily returns in the market of cryptocurrencies overlap those of gold and currencies.
Fry (2018)	Bitcoin and cryptocurrency markets may generate heavy tails due in part to liquidity risk.
Lee *et al.* (2017)	The average daily return of most cryptocurrencies is higher than that of other asset classes.
Jia *et al.* (2020)	Only extreme positive returns significantly impact the predictability of cryptocurrency returns.
Long *et al.* (2020)	There is a significant seasonal pattern in the market of cryptocurrencies. Cryptocurrencies with high daily returns in the past outperformed cryptocurrencies with low daily returns.
González *et a*l. (2021)	The correlation between gold price returns and cryptocurrency returns tends to strengthen during periods of economic instability, such as the Covid-19 crisis
Gkillas *et al.* (2024)	Cryptocurrencies, have a higher tail risk than predicted under the assumption of normality.
Borri and Shakhnov (2022)	Bitcoin prices vary between exchanges or trading pairs.

Source: Compiled by Author.

The empirical literature in Table 2.5 and discussed above demonstrates that BTC and cryptocurrency returns are high compared with those of other assets and tend to be high in periods of economic policy uncertainty. Consequently, investors may leverage these dynamics to realising untold profits. A much less debated topic is cross-country comparison of returns in cryptocurrencies and how these differences evolve under varying conditions of economic policy uncertainty across countries. Meanwhile, the empirical evidence that cryptocurrency returns are highly skewed, have excess kurtosis and more susceptible crash risk speaks to the riskiness of cryptocurrencies. The next section delves deeper into exploring empirical literatures on the risk dynamic of cryptocurrency returns and compares the risk to those of other assets to understanding the differences in risk adjusted performance and inform investment strategy.

2.5.2 Volatility dynamics

The preceding section demonstrated that cryptocurrencies have historically delivered higher returns than traditional assets. However, the boom-bust nature of their returns and frequent occurrences of speculative bubbles indicate that they may present greater risks compared with other tradeable assets. This section provides a detailed empirical review of the risk profile associated with cryptocurrencies.

For the most past, finance literature (Bollerslev *et al.*, 2018; Chaim & Laurini, 2019; Engle, 2004) has relied on volatility, a measure of how much an asset's price or return fluctuates around its average level over a given period of time to parameterise risk. A more volatile cryptocurrency's prices (or returns) tend to swing wildly, whereas the price of a less volatile one moves in a steadier and less turbulent path. Volatility is a fundamental characteristic of financial assets and is inextricably linked to risk and uncertainty (Aven, 2012). This is because higher volatility indicates a wider spread of returns and a greater likelihood of substantial deviations from the average level, whereas lower volatility implies that returns will cluster more tightly around their average level, reflecting less uncertainty (Aven, 2012). By measuring volatility, investors can tailor asset allocations and diversification strategies to align with their individual risk tolerance and return objectives.

Numerous studies have examined the volatility of cryptocurrencies, providing valuable insights for comparing cryptocurrencies with traditional asset classes. Klein *et al.* (2018), for instance, compared the volatility of BTC with that of gold, silver, crude oil (WTI), US equity (S&P 500), and equity indices of developed and emerging markets (MSCI World and MSCI Emerging Markets 50 Index). Their analysis covered the period from July 2011 to December 2017. Klein *et al.* (2018) found that BTC was more volatile than the other assets (and indices) and therefore better suited for investors with a high-risk tolerance. Corbet *et al.* (2018) substantiated the analysis by Klein *et al.* (2018) further examining the evolution of volatility among major cryptocurrencies, namely BTC, XRP and LTC relative to other assets classes such as commodities (MSC GSCI Total Returns Index and COMEX), currencies (US$ Broad Exchange Rate[39]), US equities (S&P 500 Index), and derivatives (VIX and the Markit ITTR110 index related to credit default swaps) during the period from 2013 and 2017. Both studies consistently demonstrated that cryptocurrencies exhibited significantly higher volatility compared with other assets, a phenomenon confirmed by several studies (Gkillas *et al.*, 2024; Shahzad *et al.*, 2021; Smales, 2021). From an investment perspective, the high volatility of cryptocurrencies reflects both their potential for outsized gains and their vulnerability to substantial drawdowns. The elevated volatility is especially attractive to active traders as large price swings create opportunities to exploit short-term market movements.

Some of the key reasons explaining the high volatility in cryptocurrencies included an infant market or nascent asset (Balcilar *et al.*, 2017; Phillip *et al.*, 2019), low liquidity (Al-Yahyaee *et al.*, 2020; Wei, 2018), limited or the lack of regulation (Auer & Claessens, 2021; Chokor & Alfieri,

[39] The value of the USD relative to a diversified basket of major foreign currencies. Currency weights of the Index are available from Federal Reserve (http://www.federalreserve.gov/releases/H10/Weights). 10 April 2025.

2021; Griffith & Clancey-Shang, 2023; Huang, 2021; Hughes, 2017; Nabilou, 2019), spill over from other assets (Bouri *et al.*, 2018; Chowdhury *et al.*, 2022; Smales, 2021) and changing market sentiments (Caferra, 2022; Fry & Cheah, 2016; Katsiampa, 2019; Peng *et al.*, 2024). Of all the factors identified as contributing to high volatility, market sentiment, reflected through Google search trends, social media discussions concerning cryptocurrency market developments or sentiment indexes such as the fear/greed index has consistently garnered scholarly attention as was examined in detail in Section 2.5.

The literature has also made headway towards building an understanding of how volatility evolves following market shocks. Baur *et al*. (2018) argued that positive shocks increased volatility more than negative shocks - suggesting the presence of asymmetric volatility. The authors argued that higher volatility due to positive shocks was driven by the trading activity of uninformed traders, while the lower volatility resulting from negative shocks emanated from the trading activity of informed traders. The findings by Baur *et al.* (2018) supported Gandal and Halaburda's (2014) theory that cryptocurrencies are dominated by *inexperienced investors* with a fear of missing out (FOMO) on quick money to be made and the existence of pump and dump schemes[40]. The euphoria (optimistic sentiment) by inexperienced investors drives up prices and volatility to levels that were reversed and corrected by experienced investors, thereby establishing the asymmetric volatility effect. This asymmetric volatility effect was found to hold for a majority of cryptocurrencies, with the exceptions being the two largest, BTC and ETH (Baur *et al*, 2018), due in part because these two cryptocurrencies were found to be dominated by the *early* adopters who had acquired some experience investing in the cryptocurrency market. However, more recent findings by Aharon *et al*. (2023) revealed that even in major cryptocurrencies like BTC and ETH, positive news caused more volatility than negative news with the impact of especially positive news stronger in structural breaks (crisis periods). Yet, Sapkota's (2022) finding that BTC participants reacted more strongly to adverse information resulting in negative news disproportionately increasing volatility compared with positive news, introduce variation in the broader understanding of volatility resulting from positive or negative news to the asymmetric.

This variation implies that the news type matters more than whether it is positive or negative. For example, Rognone *et al*. (2020) argued that BTC is invariant to currency news but shows dampened volatility on account of cyber-attack news and fraud news reducing the exuberance in the market. This study noted that the divergent inquiries on how cryptocurrency volatility evolved following positive or negative checks was a thinly researched area. Future research could

[40] Entail spreading false or misleading positive information (pump), then quickly selling holdings at the inflated price (dump), causing a sharp decline in value that leaves later investors with losses. Date of access: 12 March 2025.

examine the heterogeneity in volatility asymmetry across distinct news categories such as the various intrinsic and extrinsic factors.

Meanwhile, some studies have focused on volatility connectedness within cryptocurrencies (Hasan *et al.*, 2021; Mensi *et al.*, 2021), while others explored the connections between cryptocurrencies and other asset markets (Ji *et al.*, 2019; Nguyen *et al.*, 2022). Within cryptocurrencies, Mensi *et al*. (2021) found that cryptocurrencies with higher market capitalisation such as BTC, ETH and LTC were net transmitters of volatility, potentially causing contagion. In contrast, cryptocurrencies like Dash, XRP, Monero and Stellar were net receivers of volatility. Hasan *et al*. (2021) found that BTC and LTC were net receivers of volatility shocks, while XRP and BNB emerged as net transmitters. While these studies vary on whether specific cryptocurrencies were transmitters or receivers of volatility there is general support that cryptocurrencies do transmit volatility among themselves. This interconnectedness in the volatility of cryptocurrencies was confirmed by Yi *et al.* (2018) who observed that volatility connectedness among cryptocurrencies exhibited periodic fluctuations with notable increases during times of market instability or in response to unforeseen external shocks. They further showed that volatility connectedness does not always depend on market capitalisation as was highlighted by Hasan *et al*. (2021) and Mensi *et al*. (2021). Yi *et al.* (2018) argued that typically, large-cap cryptocurrencies like BTC and ETH transmit major volatility shocks, while small-cap cryptocurrencies tend to absorb them. Certain smaller cryptocurrencies can also be significant sources of volatility. Taken together these results suggested that cryptocurrency in volatility connectedness is not essentially related to its market size (Ji *et al*., 2019).

Evidence of strong interconnectedness in volatility have important implications for investors who hold cryptocurrency portfolios as they indicate weakened diversification. More insights may be gained by exploring volatility connectedness in important cryptocurrency events that included the 2013 Silk Road, the 2017 CME Group planned launch of futures trading in the cryptocurrency (Conrad *et al.*, 2018), the 2018 US government emergency asset freeze against allegedly fraudulent ICOs (Zetzsche *et al.*, 2017), the 2018 surge in US Treasury yields resulting from the Federal Reserve announcement of future tapering of its policy of QE (Chari *et al.*, 2021), and the 2019 BTC futures launched by Bakkt (Deng *et al.*, 2021) all of which had sizable impact on BTC volatility – as it is the most dominant cryptocurrency.

Regarding the connectedness between cryptocurrencies and other assets, Ji *et al*. (2019) found a significant spillover effect from traditional financial equity markets to cryptocurrencies, indicating that cryptocurrencies were influenced by volatility in other markets. In contrast, Hung (2022) argued that traditional assets such as equity (S&P 500) were net receivers of volatility transmitted by BTC. Collectively, these studies suggested a bidirectional linkage between BTC and the S&P

500, in which investor sentiment and general market conditions drove cryptocurrency volatility, amplifying it especially in episodes of regimes when equity or cryptocurrencies underwent crises. Niyitegeka and Zhou (2023) found that during periods of downturn (such as the one caused by the Covid-19 pandemic) the volatility in US equities (S&P 500) and emerging market equities (MSCI emerging equity market) can be transferred to cryptocurrencies (BTC) substantially increasing interdependency between cryptocurrencies and equity. Nguyen *et al*. (2022) noted that investors trade especially the high market capitalisation cryptocurrencies during downturn conditions compared with normal or recovery times potentially explaining the increased interdependency between US equities and BTC in periods of heightened equity market volatility as discussed in Niyitegeka & Zhou (2023). Yet, Ghorbel and Jeribi (2021) argued that there was a relatively higher volatility spillover among cryptocurrencies than between cryptocurrencies and other assets and indices such as the S&P 500, Nasdaq, VIX, oil, and gold. The relatively lower interdependency between cryptocurrencies and other assets or indices suggests that investment portfolios with exposure to cryptocurrencies (along other asset classes such as equity, bonds and cash) can potentially experience some diversification benefits, especially in downturn periods, thereby urging forward investments in cryptocurrencies.

The extant literature consistently finds that cryptocurrencies demonstrate significantly greater volatility compared with traditional asset classes like equities and bonds, resulting in a higher risk profile. Borri (2019) confirmed their riskiness and argued that BTC, ETH, XRP and LTC are highly exposed to tail-risk[41], compared with US equities or gold. Lahmiri *et al.* (2018) corroborate the extreme risk in BTC and argued that it is because BTC returns distribution are positively skewed and have excess kurtosis. Overlooking the impact of skewness and kurtosis in cryptocurrency returns may inadvertently lead to misspecification of risk, thereby misleading investors. For this reason, investors need to utilise more rigorous risk metrics that better account for tail-risk when evaluating cryptocurrency investments. However, this not only relates to portfolios that include cryptocurrencies, since it is widely acknowledged that most financial returns including those of equities and bonds exhibited leptokurtic and skewed returns (Bekaert *et al.*, 1998; van Heerden, 2020; Sheikh & Qiao, 2010; Van Heerden, 2015).

Additionally, there is evidence that volatility fluctuates in response to shifts in investor sentiment and prevailing market conditions. Under certain circumstances, volatility in the cryptocurrency markets both influences and is influenced by volatility in traditional equity markets, such as the S&P 500. These complex volatility dynamics have significant implications for portfolio investors. The desirability of cryptocurrencies, considering their returns and volatility ultimately depend on

[41] Tail risk is the probability of an extreme loss due to events that occur infrequently but carry a very large impact.

the specific objectives and risk tolerance of individual investors. Individuals with a lower risk tolerance often avoid cryptocurrencies because of their significant volatility compared to other asset classes, while those with a greater appetite for risk may be attracted by the potential for considerable returns. As investors increasingly adopt cryptocurrencies to capture outsized returns and bolster diversification, it is essential to assess not only their volatility but also their correlations with other assets in shaping aggregate portfolio risk. Accordingly, the next section explores the correlation dynamics and diversification potential of cryptocurrencies within a conventional asset allocation framework.

2.5.3 Correlations dynamics and diversification

Diversification itself is extensively discussed in the literature (Alexeev & Dungey, 2015; Brands & Gallagher, 2005; Chua *et al.*, 2009; Didisheim *et al.*, 2024; Han *et al.*, 2024; Nguyen *et al.*, 2025; Statman, 2004), yet, its conceptual definition has mostly been based on heuristic approaches (Flint *et al.*, 2020; Fragkiskos, 2014). For example, with equities, these heuristic approaches designated specific indices such as the S&P 500 as the market portfolio[42], a baseline indicator of what a diversified portfolio reflects (Flint *et al*., 2020). Consequently, metrics such as number of assets in a portfolio (Zaimovic *et al.*, 2021), time varying correlations (Tse & Tsui, 2002), tail risk measures and risk contribution (Feng *et al.*, 2018; Gkillas *et al.*, 2024) as well as return (differences) gaps (Statman & Scheid, 2008)emerged as popular measures of diversification. Flint *et al*. (2020) argued that while the conceptual definition of diversification remains elusive, the essence of diversification was clear – that it served to mitigate specific risk within any single asset class and systemic risks across asset classes. From a portfolio management perspective, asset correlation[43] is one of the key metrics for constructing efficient portfolios – with combining negative or weakly correlated assets being the ideal situation as it leads to relatively reduced portfolio risk, a phenomenon widely regarded as enhanced diversification (Flint *et al.*, 2020; Markowitz, 1952).

Early studies on the correlation dynamics in cryptocurrencies found that including a small proportion of BTC radically improves the risk-return trade-off of well-diversified portfolios, suggesting a low correlation between BTC and other traditional asset classes such as equity, bonds and cash (Briere *et al.*, 2015). This was confirmed by Dyhrberg (2016), who found a low

[42] The market portfolio refers to all risky assets traded in the market (Lintner, 1965; Mossin, 1966; Fragkiskos, 2014),

[43] Correlation measures how two assets' returns move relative to each other. Mathematically, its scale ranges from -1 to +1. A value of +1 indicated that returns between two assets comove perfectly in tandem, indicates no linear relationship while -1 indicates returns comove exactly in opposite directions.

correlation between BTC and equity and currencies, and argued that BTC carried diversification properties like gold, and more commonly referred to as a safe haven.

Baur *et al.* (2018) built on the works of Dyhrberg (2016) and Briere *et al.* (2015) and analysed the statistical properties of BTC. The authors found that BTC was not correlated with other asset classes (equities, bonds and commodities), both in normal times and in crisis periods. The authors further found that BTC was, for the most part, used as a speculative asset. Therefore, it was unclear whether BTC, whose price constitutes speculative behaviours, can be as effective a safe haven as gold or a hedge, especially during market downturn when investors seek diversifiers the most. Bouri *et al.* (2018) made strides in exploring whether BTC is an effective hedge. The authors used a dynamic conditional correlation (DCC) analysis to compare the association between BTC and other assets (equity, bonds, commodities, and currencies). They found that BTC is a poor hedge and only suitable for diversification purposes, undermining the safe haven status against equities and currencies argued by Dyhrberg (2016). Bouri's *et al.* (2018) observation period (2011 to 2015) and Dyhrberg's (2016) observation period (2010 to 2015) were closely related yet their conclusion varied, setting the stage for further debate.

The literature also documented varying results on the correlation dynamics of cryptocurrencies during crisis periods such as the one induced by the Covid-19 pandemic. On the one hand, Conlon and McGee (2020) found a positive correlation between BTC and the S&P500 which substantially increased portfolio downside risk deprecating the safe haven properties in cryptocurrencies. The lack of safe have properties was also witnessed by Conlon *et al*. (2020) on several different international equity markets. On the other hand, Iqbal *et al*. (2021) contended that a number of cryptocurrencies including BTC and to some extent, ETH were able to absorb both large and small shocks of Covid-19 acting as a hedge against falling asset prices. Caferra and Vidal-Tom´(2021) confirmed the hedging quality of cryptocurrencies stating that although both cryptocurrency and equities' prices fell steeply in March 2020, cryptocurrencies quickly rebounded.

The literature also reported varying findings on the correlation dynamics of cryptocurrencies during the Russia–Ukraine crisis that started in 2022. Hampl *et al*. (2024) found that cryptocurrencies USDT (stablecoin) and SOL (utility token native to Solana, a Layer 1 blockchain) exhibited considerable safe haven traits for gold and the S&P 500. However, BTC and ETH did not effectively diversify equity portfolios. Hampl *et al.'s* (2024) findings contest the safe haven properties of BTC posited by Dyhrberg (2016) but indicate that the safe haven characteristics can also be possibly found in other types of cryptocurrencies. More research is, however, needed to confirm whether these safe haven properties are robust even through different crises or whether there are because of chance or coincidence.

Although much of the literature has explored correlation between cryptocurrencies and US equities, some studies have also explored other assets. Urquhart and Zhang (2019) studied the correlation between several cryptocurrencies and highly traded currencies. They found that BTC is a hedge for the CHF, EUR and GBP, a diversifier for the AUD, CAD and JPY and a safe haven for the CAD, CHF and GBP. Kang *et al*. (2020) supported the safe haven property of BTC against US equity (S&P 500), the USD, US Treasury bonds and gold futures. Corbet *et al.* (2018) also found that there are diversification benefits to investing in a portfolio of cryptocurrencies compared with investing in a single cryptocurrency. For instance, XRP was lowly correlated with both BTC and LTC. Thus, a portfolio containing BTC or LTC with XRP offered better risk-adjusted returns than either BTC or LTC, when considered independently. Klein *et al.* (2018) compared the correlation and portfolio performance of BTC with that of gold. The authors found that gold was a safe haven in times of market distress, while BTC was found to be positively correlated with equity in periods of stress and therefore not exhibiting hedging properties. The study by Klein *et al.* (2018) provided a window of opportunity to compare the performance of BTC with an established hedge asset, gold. However, the study was restricted to only BTC. Lee *et al.* (2017) extended the study on cryptocurrency performance and explored the correlation of the top ten cryptocurrencies by market capitalisation, including the cryptocurrency index, with six US traditional assets (S&P 500, treasuries, gold, oil, GSCI commodities index, real estate investment trusts, private equity). The authors found that cryptocurrencies were weakly correlated with other assets and therefore offered diversification benefits.

Robertson (2018) redirected focus to SA by examining the diversification benefits of BTC in the SA market. The author made four key findings. First, the inclusion of BTC in a typical investment portfolio enhances portfolio returns on a risk-adjusted basis (measured in terms of the Sortino ratio). Second, BTC outperformed gold in diversifying investment portfolios. Third, at optimal weighting of 5% or lower, the inclusion of BTC reduces the risk of the optimal portfolio. Fourth, BTC's inclusion in a portfolio increased the optimal weighting of SA bonds and SA cash (due to its negative correlation with these assets) and reduced the optimal allocation to global equity.

The review of literature discussing diversification capabilities of cryptocurrencies demonstrated that correlations between cryptocurrencies and other asset are regime-dependent and vary by cryptocurrency rather than generic and constant. In calm (or normal) market conditions, cryptocurrencies such as BTC exhibited low comovement with equities, currencies, and commodities, enhancing their potential diversification potential. Yet this sometimes breaks down during crisis periods. For example, amid the Covid-19 market turmoil, correlations between BTC and US equities rose markedly, reflecting a convergence in investor sentiment challenging the narrative of cryptocurrencies as reliable safe havens. At the same time, there is evidence that the

cryptocurrencies BTC and to some extent, ETH absorbed extreme price shocks and recovered swiftly during the Covid-19 pandemic, indicating that they possessed hedging capabilities but realising these may hinge on the investor's time horizon or performance measurement period. Additionally, the literature highlighted that there was evidence that SOL and USDT correlations with US equities remained weak amidst the market turmoil of 2022 also suggesting that even within the market of cryptocurrencies there is variation on how different cryptocurrencies comove with other assets including in different crisis periods. These insights underscore two intertwined research imperatives. First, assessing cryptocurrencies' diversification value requires a nuanced analysis of correlation dynamics across market regimes and assets. Second, the distinctive risk characteristics, particularly volatility and tail exposures must be better accounted for to wholly work out their diversification capabilities. This is because to establish diversification there is need to extend analysis beyond correlation and assess how much of a portfolio's total risk has been reduced because of combining uncorrelated assets in a portfolio

The extant literature overwhelmingly found that cryptocurrencies delivered both superior returns and elevated volatility relative to other tradeable assets. In some circumstances, large capitalisation cryptocurrencies notably BTC, exhibited negative correlations with equities and bonds, thereby serving as hedges or diversifiers. However, these protective dynamics have proved episodic. Consequently, critical questions remain as to whether incorporating cryptocurrencies into a diversified portfolios enhances overall diversification or improved risk-adjusted performance across varying market conditions. The remaining section turn focus towards understanding the cryptocurrency market conditions and explore regulation, cybersecurity and other emerging risks in cryptocurrencies. This is particularly important for investors seeking to understand non-financial risk in cryptocurrencies.

2.6 Cryptocurrency regulation

Several studies (Chohan, 2022; Hughes, 2017; Low & Teo, 2018; Vandezande, 2017) documented the regulatory ambiguity surrounding cryptocurrencies which arose from their state as nascent assets and their hybrid nature as payments technology, tradeable assets and media of exchange (Peng *et al.*, 2024; Radanliev, 2024). The absence of a central governing authority posed a distinct legal dilemma as there lacked a clear single entity to hold accountable, undermining effective enforcement of laws (Nabilou, 2019; Makarov & Schoar, 2022).

Al-Tawil (2023) extensively discussed the approaches of the various regulatory bodies in the US, Europe, UAE and other international bodies to regulate cryptocurrencies. The authors found that the blockchain technology underlying cryptocurrencies presented significant regulatory challenges, particularly in the implementation of anti-money laundering and counter-terrorist financing regulations. First, P2P transaction authentication bypassed institutions set up to detect

anti-money laundering and counter-terrorist financing in the broader financial markets. Second, transaction anonymity frustrated the Know-Your-Customer (KYC) and Customer Identification Procedures (CIP) on which then existing anti-money laundering and counter-terrorist financing regulations were dependent. Third, transaction immutability in blockchain technology prevented reversibility, even when an unlawful transaction has been identified. Finally, the absence of built-in geographic limitations made it difficult to resolve which jurisdiction, or jurisdictions, may potentially regulate each underlying activity.

However, in recent years, there has been a shift toward structured regulatory frameworks for cryptocurrencies (Nabilou, 2019). Regions such as the EU introduced MiCA, which created a standardised framework across EU member states, mandating the licensing of cryptocurrency issuers and service providers to enhance consumer protection and overall market integrity (Carata & Knottenbelt, 2024). However, MiCA though a positive stride was criticised for ineffectiveness in addressing money laundering concerns (Benson *et al.*, 2024). The EU also issued directive 2018/843[44] (the fifth anti-money laundering directive) which extended due diligence requirements, incorporated cryptocurrencies into its scope, and fostered greater cooperation and information exchange among the EU states' financial intelligence units and law enforcement agencies to address some of the money laundering concerns and terrorist financing risks in cryptocurrencies. Despite this directive, Haffke *et al.* (2020) noted that the cryptocurrency regulation remains unclear and inadequate in addressing gaps in anti-money laundering, because the EU directive's wording is unclear and thereby creates loopholes for some intermediaries in the cryptocurrency market to escape regulation.

South Korea advanced its regulatory landscape with the *Act on the Protection of Virtual Asset Users* of 2023[45], which sought to increase protection of cryptocurrency users and imposed strict KYC requirements on cryptocurrency exchanges. Switzerland enacted a law on DLTs that supported innovation while providing legal clarity for cryptocurrencies (Zellweger-Gutknecht *et al.*, 2021). The successful enactment of the law positioned Switzerland as one of the leading nations in cryptocurrency regulation. South Africa advanced its regulatory framework. It declared

[44] EU directive on anti-money laundering from (https://eur-lex.europa.eu/eli/dir/2018/843/oj/eng). 10 April 2025

[45] Act on the Protection of Virtual Asset Users from (https://elaw.klri.re.kr/eng_mobile/viewer.do?hseq=63752&type=part&key=23). 10 April 2025.

cryptocurrencies as a financial product under regulation of the Financial Advisory and Intermediary Services Act, 2002 (Act No. 37 of 2002)[46].

In the US, Federal legislative efforts, including the Financial Innovation and Technology for the 21st Century Act (FIT 21)[47] and the Blockchain Regulatory Certainty Act (H.R. 1747)[48], were (as of 2024) still undergoing their legislative journey discussion. Additionally, in 2024, the SEC approved BTC and ETH ETFs, signalling a positive step toward mainstream financial markets cryptocurrency integration[49]. However, as cryptocurrencies evolved and products like stablecoins, DeFi, NFTs become of significance, the US fragmented regulation due to overlapping agency jurisdictions posed some challenges. As discussed in Chapter 1, they are classified variously as securities (SEC), commodities (CFTC), property (IRS) and money equivalents under anti-money laundering laws (FinCEN). There are therefore variations on how cryptocurrencies are perceived and regulated by different regulatory authorities due to their distinct mandates.

Furthermore, many central banks globally approach cryptocurrencies with caution, citing concerns regarding their speculative nature, limited effectiveness as a payment method, and potential risks to financial stability and consumer protection (Nabilou & Prum, 2019). In contrast, tax authorities prioritise fiscal compliance, curb tax evasion and avoidance. Tax authorities concentrate on defining the taxable nature of cryptocurrencies, setting guidelines for valuation, and ensuring compliance for revenue purposes. Cryptocurrencies are often classified as property or capital assets for taxation (Mpanza *et al.*, 2025). This difference in focus creates a dual regulatory environment where monetary authorities (central banks) adapt to the innovative financial landscape while tax authorities develop frameworks to accurately capture taxable events in a rapidly evolving market.

These varying perspectives influencing cryptocurrency regulations create some uncertainty, for example in accounting. For instance, the international accounting standard (IAS) 38 - intangible assets, provides for the accounting of cryptocurrencies. However, invoking this standard may be

[46] https://www.fsca.co.za/Regulatory%20Frameworks/Regulatory%20Frameworks%20Documents/Policy%20Document%20supporting%20the%20Declaration%20of%20crypto%20assets%20as%20a%20financial%20product.pdf. Date of access: 31 March 2025

[47] https://www.sec.gov/newsroom/speeches-statements/gensler-21st-century-act-05222024. Date of access: 31 March 2025

[48] https://www.cbo.gov/publication/59576. Date of access: 31 March 2025.

[49] SEC Approval of Spot Bitcoin Exchange-Traded Products (https://www.sec.gov/newsroom/speeches-statements/gensler-statement-spot-bitcoin-011023). Date of access: 31 March 2025.

criticised as cryptocurrencies are not used in the operations of a business and therefore hardly qualify as any form of a non-current asset. IAS 2 - Inventories, also provides scope for accounting for cryptocurrencies. However, some investors do not hold cryptocurrencies for sale in the ordinary course of business, but hold them for longer periods, disqualifying them as inventory since they are a longer-term investment. Furthermore, cryptocurrencies are not cash equivalents under IAS7, because the value of the cryptocurrencies is currently subject to significant changes in value (high volatility). Accounting for cryptocurrencies as a financial asset as outlined in international financial reporting standards (IFRS) 9 also presents some challenges. Only three types of assets are recognised under IFRS 9 -debt, equity, and derivatives. Cryptocurrencies are far from the definition of debt or derivatives since they do not imply any future obligation to exchange cashflows. They are also not an equity instrument, because they do not provide ownership interest in any entity. It is, therefore, unclear what the appropriate accounting treatment of cryptocurrencies ought to be (Mosteanu & Faccia, 2020; Teh *et al.*, 2020). Despite regulatory hurdles, interest in cryptocurrency investments keeps rising (Han *et al.*, 2024; Le Tran & Leirvik, 2020; Mokni *et al.*, 2025; Smales, 2021). The next section explores the emerging risks and how they have shaped the cryptocurrency market landscape.

2.7 Cybersecurity risks and other emerging risks in cryptocurrencies

Cryptocurrencies have risen as an innovative element in the global financial technology. Their decentralisation, capacity to transact anonymously and P2P across borders expose them to significant cybersecurity risks that include distributed denial of service (DDoS) (Gandal *et al.*, 2018), transaction malleability (Apostolaki *et al.*, 2017; Rajput *et al.*, 2018), phishing and spoofing attacks (Pillai *et al.*, 2021; Scharfman, 2024; Xia *et al.*, 2020), ransomware (Zimba & Chishimba, 2019), hot wallet attacks (Lansky, 2018), and cryptojacking (Eskandari *et al.*, 2018). These incidents have resulted in substantial losses, for example USD1.5 billion in Bybit (happened in 2024), USD0.5 billion in Coincheck (2018), USD0.6 billion in Mt Gox (2011-2018), USD 0.4 billion in FTX (2022) amongst other losses.[50]

As cryptocurrencies have continued to gain market (Le Tran & Leirvik, 2020; Leirvik, 2022; Liu & Serletis, 2019), the increased interest attracted numerous participants to the space, including cybercriminals seeking to exploit the anonymity feature - mostly for sinister activities such as ransom payment, tax evasion, and money laundering (Scharfman, 2024; Xia *et al.*, 2020) as well as fraudulent ponzi schemes such as Russia's Finiko in 2021 and FTX in the Bahamas (and the US) in late 2022 (Kerr *et al.*, 2023; Scharfman, 2024).

[50] The Evolution of Cryptocurrency Exchange Breaches (2011-2025) from (https://forwardsecurity.com/the-evolution-of-crypto-exchange-breaches-2011-2025/). 10 April 2025.

Corbet *et al.* (2019) surveyed the effects of cybercriminality in cryptocurrency markets and found that hacking events increased the price volatility of the targeted cryptocurrency indicating heightened risk confirming Baur *et al*. (2018) in that negative shock exert substantial volatility to a cryptocurrency's return. Furthermore, Corbet *et al.* (2019) found that abnormal returns in the hours before the hacking event reverted to zero when the news was publicly announced and prices reacted adversely. As a result, many investors have incurred significant financial losses from cyber-attacks in the past, both directly, through the theft of cryptocurrencies, and when the value of their cryptocurrencies declined due to news of security incidents. Consequently, cybercriminality contributed to the negative view of cryptocurrency markets in someways and casted doubt on the safety and potential for cryptocurrencies to be fully integrated in financial markets (Nica *et al.*, 2017). As of December 2024, cryptocurrencies were illegal or banned in some countries (China, Nepal, Afghanistan, Bangladesh, Morrocco, Algeria, Egypt, and Bolivia). Meanwhile it has been adopted as legal tender in El Salvador and the Central African Republic with other countries (Panama, Paraguay the US) having made headway in integrating cryptocurrencies particularly BTC and ETH to the broader financial markets' architecture (O'Sullivan *et al.*, 2023).

Amidst the numerous incidents of cybercriminality, cryptocurrency holders must contend with varied threats of cyber-attacks that demand both heightened vigilance and the investment in advanced security measures. Pillai *et al.* (2019) underscored the trade-off holders confront when allocating funds among wallets: online "hot" wallets, and offline "cold" storage to mitigate hacking risks. The adverse reaction to security breaches, manifesting as immediate price declines, appeared intrinsic to digital assets. As industry participants strengthen cybersecurity protocols and regulators tighten know-your-customer (KYC) and anti-money-laundering requirements, it remains an open question whether strengthening cybersecurity protocols efforts will sustainably attenuate volatility and alter the correlation between cryptocurrencies and other investment assets. Future research should rigorously assess how enhanced security architectures and regulatory frameworks influence the resilience and stability of cryptocurrency markets.

2.8 What really are crisis periods

Up to this point, this study has employed the term "crisis periods" without an explicit definition. Given the importance of crises to the theoretical framework and empirical analysis, this section explored empirical literature to provide an operational definition and delineate the defining features that distinguish crisis episodes from routine market volatility thereby establishing clear criteria for identification.

The term "crisis" as it relates to the financial environment was broadly defined by Mishkin (1992) as market states which involved sharp declines in asset price, failures of large financial or

nonfinancial firms, deflation, disruptions in foreign exchange markets, or any combination of these events. Duprey *et al*. (2017), Claessens and Kose (2013) and Lo Duca *et al*. (2017) confirmed this definition underscoring that crisis periods were market states in which extreme financial market stress led to negative real economic outcome. This broader view of crises extended the monetarists view by some researchers (Allen & Gale, 2000; Kaminsky & Reinhart, 1999) who linked crises to bank panics. Following the broader view of crises, Lo Duca *et al*. (2017) supported the taxonomy of crises being divided into four often overlapping categories: currency, sovereign debt, asset prices and banking of which the most common crisis entailed banking failures and asset price crashes. The finance and economics literature extensively discussed several cases when these crises crystalised.

The 1997 Asian financial crisis was a major currency event, marked by Thailand abandoning its baht-USD peg. This led to rapid baht depreciation, capital flight, falling asset prices, and exposure to currency mismatch risks. The crisis quickly spread to other East and Southeast Asian countries, causing broader instability in global financial markets (Wyplosz, 1998). The Mexican default of its sovereign debt in 1982 marked a critical debt crisis that triggered real-economy downturn across several Latin American countries and deeply disrupted international financial markets especially in the US and the EU (Duprey *et al.*, 2017; Wyplosz, 1998). The Wall Street crash of 1987 widely referred to as Black Monday was a major crisis that plunged asset prices in the US and several parts of the world (Wyplosz, 1998). The 2008 US housing bubble sparked a banking crisis widely known as the 2008 Global Financial Crisis which also induced substantial negative impact on asset prices around the globe (Fry-McKibbin *et al.*, 2014).

Post the launch of BTC in 2009, financial markets the world over have experienced several crises including the European debt crisis of 2010–2013 triggered by Greece's sovereign debt deterioration in 2009–2010 which induced deep recessions within a number of EU countries (Duprey *et al*., 2017). In 2015, overleveraged retail investors and sudden regulatory changes plunged China's stock markets with the shocks transmitted to global financial markets (Han *et al.*, 2019). The Covid-19 health pandemic and lockdowns that halted economic activity plunged stock markets globally and oil prices momentarily turned negative (Nguyen *et al*., 2022). In 2023 the US also experienced substantial banking pressures triggered by interest rate hikes to combat inflation (which had surged due to pandemic-era stimulus) inadvertently exposing vulnerabilities especially in banks with high exposure to US long-term bonds (Omarova, 2024). Some of the affected banks also experienced a wave of withdrawals from cryptocurrency clients (as the collapse of FTX lingered) posing a systemic risk due to the interconnectedness amongst banks triggering regulatory interventions (Omarova, 2024).

The evidence in the literature suggested that much of the crises entailed bank failures and asset price crashes. However, how crises are classified often depends on whether the focus is placed on their triggering events (like Covid-19), transmission mechanisms (such as the Mexican debt crisis), or their ultimate consequences (for example, global or Asian financial crises). Consequently, careful operational definitions are important for empirical identification and comparisons. amidst this classification dilemma, what stands out in the literature is demarking 'systemic crises from non-systemic crises. Duprey *et al*. (2017) noted that systemic events are periods in which extreme financial stress is also associated with negative real economic outcomes. While their definition emphasises loss severity it remained unclear as losses are depended on the risk management approach of affected entities. However, Lo Duca *et al*. (2017) generalised the concept of systemic risk arguing that for a crisis to be 'systemic' it ought to entail

(i) the financial system acting as a shock originator or amplifier and/or
(ii) systemic financial intermediaries experiencing distress or going bankrupt and/or
(iii) substantial crisis management policy interventions.

That systemic crises entail policy management has implication for the broader efficiency of various markets. Mishkin (1992) singled out government policy interventions and argued that the lack of a rigorous theory of what characterises a crisis lends itself to being used too broadly as a justification for government interventions that might not be beneficial for the economy. This was because interventions can be harmful through excessive money growth or liquidity that stimulates inflation and debilitate efficient functioning of markets further destabilising asset prices (Mishkin, 1992).

However, this study found no universally agreed metrics and magnitudes for *what* constitutes a crisis. The lack of a universally agreed definition derives from Claessens and Kose (2013) who noted that crises are multi-dimensional and often overlap, hence a single label would miss important nuances. In practice, quantitative thresholds and expert judgment are commonly used to identify crises (Claessens & Kose, 2013). Yet, some scholars (Allen & Snyder, 2009; De Bonis & Silvestrini, 2014) emphasised conceptual models that focus on impacts on the real economy – such as bank failures, impacts on employment, and ultimately both micro (firm/household) and macro (government) default cycles. Meanwhile, Ang and Bekaert (2002), emphasised conceptual models that focused on low expected returns and high variance of asset prices. Guidolin and Timmermann (2007) characterised crises by simultaneous changes in asset price volatility and correlation. Chalkis *et al*. (2021) argued that crisis periods were market states marked by sudden, severe price drops and elevated volatility. This view was supported by Zhang *et al*. (2020) and Tabash *et al*. (2024), who also associated crisis periods with heightened volatility and negative mean returns. While the characterisation of crises as it related to asset prices often referenced

specific metrics related to evolution of prices: returns, variance, correlations - it is not always clear what '*heightened*' volatility and '*severe*' price drops actually mean in different markets (Claessens & Kose, 2013).

Sarkar and Patel (1998) adopted a threshold-based approach, defining a crisis as a market crash characterised by a decline of more than 20% from the historical peak for developed markets and more than 35% for more volatile emerging markets. Although the approach was straightforward and the thresholds were determined empirically, they remained largely ad hoc, and minor adjustments to these thresholds could alter which episodes are classified as crises. Meanwhile, Hollo *et al*. (2012) suggested a composite indicator of systemic stress (CISS) in the financial system which aggregated selected stress indicators in different markets including money markets, bonds markets, equity market, forex exchange and financial intermediaries. The CISS laid the foundation for several other model for identifying stress which included Oet's *et al*. (2015) Cleveland Financial Stress Index (CFSI) and Ishrakieh's *et al*. (2018) Institute of Financial Economics Financial Stress Index (IFEFSI). While the stress-index models are useful as real-time monitors of simultaneous financial stress across market segments, they have often showed limited out-of-sample predictive power for future stress episodes (Oet *et al*., 2015). Fry-McKibbin *et al*. (2014) employed regime-switching Markov techniques to detect crisis periods. While the approach provided a statistically robust method to crisis identification, the need to specify the number of regimes *a priori* and probabilistic inference of regime leaves the approach sensitive to parameter estimation and at the risk of overfitting which results in falsely identifying crises (Goutte, 2014). Though the stress index measures are robust, their use application and calibration can be complicated by data availability is some markets.

Claessens *et al*. (2012) suggested using business cycle approach, by identifying peaks and troughs in asset prices and focusing on the top and bottom quartiles of these changes to determine the booms, busts, or crunches (indicators of crisis periods). Their simplified approach mirrored that of Sarkar and Patel (1998) in the sense that both approaches aim to identify worst cases. The weaknesses on both approaches lie in the cut offs – quartiles in the case of Claessens *et al*. (2012) and the nominal rates in the case of Sarkar and Patel (1998).

Regardless, the differences in approaches and the absence of a universally agreed threshold for what constitutes a crisis, there is a clear underlying consensus – that the financial consequences of crises are negative and substantial, however a crisis is defined or measured. Consequently, crisis identification must be transparent, include quantitative thresholds to be unambiguous and be robust to alternative operationalisations.

2.9 Conclusions

Cryptocurrencies have reshaped the global financial ecosystem since the introduction of BTC in 2009, offering decentralised solutions as alternatives to traditional money. This innovation sparked the development of numerous alternative cryptocurrencies and blockchain platforms, broadening technological adoption and market participation. Continued innovations within the cryptocurrency space have shaped views of cryptocurrencies as dynamic pieces of financial technology infrastructure, tradeable assets and, in some contexts, a media of exchange.

As tradeable assets, they have delivered outstanding returns and pronounced volatility, influenced by several factors including market sentiment, speculative trading, network metrics, and developments in other markets – particularly equity. This high volatility of returns, combined with security vulnerabilities, lack of clear fundamental value and the potential for illicit use, continues to raise concerns among investors and policymakers. The absence of a comprehensive regulation in many regions intensifies these risks, although some countries are beginning to establish clearer regulatory frameworks. For instance, El Salvador and the Central African Republic have formally adopted cryptocurrencies, while regions such as the EU and the US are moving towards regulated trading environments. South Africa permits cryptocurrency trading, except within retirement funds, whereas China enforces a complete prohibition. Amidst this regulatory diversity, the cryptocurrency sector persists in growing, with BTC and ETH ETFs already having gained approval in the US market and some institutional investors including them in their portfolios.

Correlation between cryptocurrencies and traditional assets remain mostly modest, but has shown signs of strengthening, particularly during some periods of downturn, while in other periods correlations of returns have decoupled demonstrating capacity to absorb negative shocks. This complex relationship suggests that cryptocurrencies can act as a stabilising force in investment portfolios in some periods. Crisis episodes present a valuable opportunity to assess whether cryptocurrencies serve as effective diversifiers, hedges or safe havens, and whether they contribute to diversification and alter portfolio performance on a risk-adjusted basis. This underscores the importance of ongoing research and to further explore portfolio management and performance evaluation literature to build a framework for assessing the investment value of cryptocurrencies.

CHAPTER THREE

APPROACHES TO PORTFOLIO MANAGEMENT

3.1 Introduction

The previous chapter presented evidence that cryptocurrencies generally offer higher returns, elevated risk and typically weak correlation with traditional assets, though these relationships can become more complex and dynamic especially during periods of markets[51] stress (Almeida & Gonçalves, 2022; Bianchi, 2020; Liu & Tsyvinski, 2021; Zhang & Wang, 2021). The high returns and weak correlations with traditional assets such as equities and bonds make them a potentially valuable addition to an investment portfolio. However, it is still unclear whether incorporating cryptocurrencies into a diversified portfolios enhanced overall diversification or improves risk-adjusted performance across varying market conditions. This was because answering this question objectively necessitates first establishing the composition of a typical diversified baseline portfolio, measuring its performance and comparing how the performance of this baseline portfolio is altered by incorporating cryptocurrencies.

For this reason, this chapter revisits the portfolio management literature, and in Section 3.2 explores the importance of asset allocation in portfolio construction. It highlights the different asset allocation strategies practiced especially by institutional investors and reasons which ones are more appropriate when managing a portfolio incorporating cryptocurrencies, which are volatile. Section 3.3 explores asset allocation frameworks with emphasis on modern portfolio theory (MPT) and the mean-variance optimisation (MVO) and their implications when applied to establish the optimal allocations in a diversified portfolio, as well as its limitations and the modifications instituted to counter its shortcomings. This section is important as MPT is one of the key foundational theories that underpins asset allocation, guiding the process of choosing how much to invest in asset – a key component of establishing a baseline portfolio and determining the optimal allocation to cryptocurrencies. Section 3.4 details portfolio performance measurement techniques and suggests the appropriate techniques for assessing the impact of including cryptocurrencies in a portfolio. It recaps the concept of risk and how it is parameterised and highlights the most popular risk-adjusted measures used for measuring portfolio performance, their limitations, and the measures taken by this study to overcome the fundamental weaknesses of these measures. The section also leverages the conceptual definition of diversification highlighted in Section 2.5.3 and highlight discussions on portfolio rebalancing to reason the ideal

[51] Market stress: in this study equity prices are used as a real-time indicator of stress because they rapidly reflect new economic information and shifts in investor sentiment (Wyplosz, 1998)

rebalancing strategy to guide investors on when and how to restructure their investment holdings. Section 3.5 highlights empirical literature on portfolio allocations to cryptocurrencies. Section 3.6 concludes the chapter.

3.2 Asset allocation strategies

When investors implement their investment strategies[52], one of the top fundamental decisions they have to make is: selecting the appropriate asset classes, determining the optimal management approach for those investments. Investors must decide which asset classes to invest in to achieve the investment goals as outlined in an investment policy statement (IPS). The finance literature identifies numerous asset classes, the most common being equity, bonds, money market securities (cash and equivalents) and several alternative assets such as real estate, commodities, derivatives, hedge funds, private equity and now cryptocurrencies (Chen & Hafner, 2019; Conrad *et al.*, 2018). While there is no one-size-fits-all solution for selecting an asset class, investors typically select assets whose return profile matches their risk tolerance levels, investment horizon, liquidity needs, and income needs (Kritzman *et al.*, 2010).

The investment and finance literature classifies strategies for selecting investment assets into three broad approaches: strategic asset allocation (SAA), tactical asset allocation (TAA) and insured asset allocation (IAA) (Anson, 2005; Brennan *et al.*, 1998; Sharpe, 1987). SAA involves selecting an initial portfolio allocation that is consistent with the investor's objectives and constraints (Amenc & Martellini, 2002). As a result, it reflects the investor's desired exposure to risk and expected returns. This is because SAA is based on the belief that capital markets are generally efficient over long-term planning horizons and that hidden value is rarely waiting to be discovered by an astute investor.

Once suitable asset classes have been identified, investors must then decide how to allocate their capital among these assets using a defined investment strategy. This means that the portfolio is periodically rebalanced to maintain these predetermined proportions, ensuring that the investor's risk-return profile remains aligned with their overall financial goals. Strategic asset allocation (SAA) which sets a long-term target weight across asset classes, can be implemented via several approaches such as buy-and-hold, periodic rebalancing, threshold rebalancing, core satellite structure and constant-mix strategies (Perold & Sharpe, 1988). Although SAA frameworks have strong theoretical and empirical support (Cumming *et al.*, 2014), the literature lacks clear, universally accepted rules on precisely when and how often to rebalance an SAA portfolio strategy. This is because the evolution of market prices often leads to episodic deviations from

[52] An investment strategy is a set of rules or methods for choosing and managing a portfolio to achieve financial goals within a specific risk tolerance and time frame (Malkiel, 2003).

SAA limits, while at times presenting opportunities for investors to optimise portfolio performance by exploiting market mispricing (Corbet, Lucey, *et al.*, 2019; Hui *et al.*, 2014; Siegel, 2016) (Hui *et al.*, 2014; Siegel, 2016; Corbet *et al.*, 2019).

The realisation that there exist exploitable investment opportunities spurred the use of TAA, a strategy that overlays short-term adjustments onto a SAA baseline to exploit perceived market mispricing (Anson, 2005). TAA dynamically adjusts the SAA with the aim of taking advantage of prevailing market conditions (Amenc & Martellini, 2002; Anson, 2005; McCarthy & Tower, 2021) making it especially relevant in inefficient markets (Smith & Dyakova, 2014; Urquhart & McGroarty, 2016). Investors may leverage insights into the predictability of asset prices in inefficient markets to strive for higher returns or reduced risks. TAA flexibility enables investors to increase their exposure to risky assets during periods of high expected returns - market timing (Anson, 2005; Faber, 2017; Phillips & Lee, 1989) and decrease their exposure during periods of high volatility (volatility timing), thereby optimising risk-adjusted returns (Johannes *et al.*, 2011; Kandel & Stambaugh, 1996). This flexibility informs several well-known portfolio management approaches, such as momentum investing (De Bondt & Thaler, 1985), contrarian strategies (Jegadeesh & Titman, 1993), and market timing strategies (Merton, 1981).

SAA and TAA, therefore, represent related views of the asset allocation enigma. SAA is a translation of the IPS and dictates how assets should be divided across asset classes (Anson, 2005). It is ideal for long-term objectives and entails setting target allocations (or ranges) across various asset classes and rebalancing them regularly to minimise deviations from the target allocation through all market conditions (Ambachtsheer & Ezra, 1998). However, TAA characterises more active investing through its short-term, dynamic adjustments to exploit temporary mispricing among the different asset classes (mostly those prescribed by the SAA) by actively altering allocations across or within asset classes (Lumholdt, 2018). IAA combines the two approaches and takes the efficient market position that price changes are not predictable enough to form profitable market-beating systems (Sharpe, 1987). The IAA strategy sets a limit for the value of a portfolio and shifts an increasing portion of the investment to risk-free treasuries as the portfolio value approaches the floor. If the value falls to the floor value, the entire portfolio will be made up of treasury bills, limiting losses. In contrast, as the portfolio value rises above the floor, more funds are allocated to more risky investments such as equity (Sharpe, 1987).

The question of which asset allocation strategy among SAA, TAA, and IAA is best for a specific investment is determined by how well an allocation aligns with the investor objectives and circumstances (Sharpe, 1987). Investors in more efficient markets seeking stability and long-term growth are more likely to focus on SAA. Meanwhile those operating in relatively inefficient markets and seeking to maximise opportunities arising from episodic abnormal returns are more likely to

tilt a substantial part of their portfolio towards TAA with the caveat that it leads to more risk and costs (information gathering as well as dynamic trading). IAA blends the fundamentals of SAA and TAA strategies by locking in a floor value while seeking growth through dynamic asset allocation adjustments. Since SAA represents the baseline asset allocation, it is critical in establishing the systematic risk exposures that an investor tolerates (Brennan *et al.*, 1998; Clarke *et al.*, 2002). This makes it valuable when effectively budgeting risk (deciding how much of total risk is allocated to each asset) limits.

Brinson *et al*. (1986) confirmed this view and argued that the more passive management strategies (such as index investing) account for most of the variation in returns in pension plans, with more active strategies (security timing and security selection) accounting for minor variations. Brinson *et al*. (1986) further argued that the average contributions of security timing and security selection to active returns are negative, implying there is a realisation of losses on resources invested towards pursuing active investment strategies. Several authors (Bessler *et al.*, 2017; Brinson *et al.*, 1986; Ibbotson & Kaplan, 2012) reinforced the dominance of SAA strategies in explaining return variation particularly in equity markets.

For cryptocurrencies, the speculative nature of the market, driven by sentiments supports arguments for active trading (Bouoiyour *et al.*, 2015; Cheah & Fry, 2015). However, the high volatility makes it a challenge (Almeida & Gonçalves, 2022) leading to varying views. On the one hand, Wang *et al*. (2020) suggested a strategic allocation of a small percentage of the portfolio (such as 1% to 5%) to better position portfolios to hedge against systematic risks including declining equity and fiat currencies, geopolitical risks, and economic policy uncertainty (EPU). On the other hand, Nguyen and Chan (2024) emphasised IAA type strategies such as stop-loss orders, hedging and exposure caps to mitigate volatility. This view is supported by several authors (Han *et al.*, 2024; Johansson & Boyd, 2024; Petukhina *et al.*, 2021) who argued cryptocurrencies are best incorporated in portfolio of diversified assets as a dynamically managed component within a broadly diversified portfolio to control for the high volatility, while still benefiting from potential diversification and enhancing overall portfolio performance.

Taken broadly, the discussion indicates that there is no one correct asset allocation strategy suitable for all investors. This is because, in practice, investors have heterogeneous expectations, objectives and risk tolerances and market conditions changes. Through integrative reasoning, this study argues that, in the absence of insight-generating expectations different from the market, an investor should hold a passive fund (Lintner, 1965; Sharpe, 1964). The decision to embrace active management must be skewed by the supply of opportunities and aggregate transactional costs (Sharpe, 1991). Thus, a more prudent investor adopts a dynamic management approach. Where there are no clear opportunities, the investors will embrace passive management, else a

more active approach will be ideal. Furthermore, a decision to establish (or rebalance) asset allocation must balance both the return and risk objectives outlined in an IPS and match them with the available investment asset classes (Ibbotson & Kaplan, 2012; Masters, 2003). The balance between the resultant expected portfolio returns and aggregate portfolio risk is determined by the extent to which the asset allocation is diversified (varied) and therefore uncorrelated. The next section discusses some of the popular investments strategies that express the asset allocation strategies.

3.2.1 Investment strategies: tools to express strategic and tactical views when constructing portfolios

Investing has evolved from a few rules of thumb like those detailed in Graham and Dodd (1934) cited in Battisti *et al*. (2019) to more systematic approaches, such as fundamental analysis[53], which comprises trading based on dividend yields and earnings yields (Siegel, 2016), firm size (Reinganum, 1982; Schwert, 1983) and macroeconomic trends (Cochrane, 1991; Fama, 1990; Geske & Roll, 1983), as well as technical analysis[54], comprising trading based on seasonality in returns (Gultekin & Gultekin, 1983; Harris, 1986; Jaffe & Westerfield, 1985) and autocorrelation in equity returns (Lo & MacKinlay, 1989; McQueen & Thorley, 1991; Poterba & Summers, 1988). For the most part, these systematic approaches are utilised by investors to value assets and guide the buy (long) or sell (short) decisions, thereby supporting active trading to take advantage of the envisaged profit opportunities (Sharpe, 1991). As a result, active management is conceptualised as a bet against passive management (Grinold & Kahn, 2000) and promises superior market performance after fees through superior knowledge and asset selection (Rickens, 2020).

There is, however, debate on whether actively managed funds create more value for investors. A substantial body of research showed that actively managed funds do not create significant value above passively managed funds, especially after considering the fees associated with active fund management (Fahling *et al.*, 2019). This branch of the literature corroborates the view of some researchers (Carhart, 1997a; Fama & French, 2010; Jensen, 1968; Sharpe, 1991) who argued that active management does not create value for investors primarily because markets are efficient, and assets are correctly priced. Meanwhile, Sanchez (2020) argued that although there are some exceptions, at an aggregate level, a lower number of active funds outperform their

[53] Fundamental analysis refers to assessing an asset's intrinsic value by examining economic, industry, and asset-specific factors (Battisti *et al*., 2019).

[54] Technical analysis refers to forecasting future price movements by examining historical price trends, volume, and market indicators (Battisti *et al*., 2019).

benchmarks at varying rates from country to country and over different horizons. This is supported by the empirical evidence presented in Table 3.1.

Table 3.1: Percentage of large capital equity funds underperforming benchmarks

	1-year	3-years	5-years	10-years
US	34.76%	15.04%	23.74%	15.66%
EU	15.59%	5.64%	8.64%	7.93%
Japan	32.84%	21.48%	17.59%	20.59%
SA	58.21%	50.75%	53.40%	39.16%

Source: S&P Global (https://www.spglobal.com/spdji/en/research-insights/spiva/#us). Data as of 31 December 2024. Benchmark indexes are S&P 500 (US), S&P Europe 350 (EU), S&P Japan 500 (Japan), S&P South Africa DSW Capped (SA).

Active management faces a tougher battle particularly in developed markets and in the long-term (10-years), where only about 15.66% of US funds, 7.93% in the EU and 20.59% in Japan managed to beat their benchmarks. In the short-term (1-year), actively 34.76% of US funds, 15.59% in the EU, and 32.84% in Japan outperformed their benchmarks. In contrast, developing markets such as SA offer a seemingly more fertile ground, with 39.16% and 58.21% of funds outperforming the benchmark in the long-term (10-years) and short-term (1-year) respectively. This highlights the challenge of achieving alpha, especially in developed markets in the longer term than in developing markets particularly in the short-term.

Cremers *et al.* (2019) confirmed the differences between the value relevance of active and passive management and how they have evolved over the past two or so decades. The authors found that, while active management has become unfashionable in more developed markets such as the US, it still holds more promise for some investors around the world, particularly in less developed markets. In SA, early researchers (Gilbertson & Vermaak, 1982; Knight & Firer, 1989) found that managed funds performed better. The explanation for the outperformance was given as market inefficiency. However, several studies (Oldfield & Page, 1997; Oldham & Kroeger, 2005; Thobejane *et al.*, 2017; Toerien *et al.*, 2022) have refuted this while others still corroborate that managed funds do better (Kalima & Gopane, 2022; Wessels & Krige, 2005) setting the stage for debate on whether managed funds consistently improved fund performance.

Recently, Gopane and Ravhura (2024) found that actively managed funds outperformed passively managed funds both under downturn and normal market conditions, while passively managed funds outperformed the actively managed funds under bull market conditions. The results by Gopane and Ravhura (2024) suggested that the debate between active and passive management can be influence by the condition of the market confirming Knight and Firer (1989) who argued that managed funds performed better because of market inefficiency. Lim and Brooks (2011) and Baciu (2014) corroborated Knight and Firer (1989) and reasoned that less developed

markets have extended periods of market inefficiency which enhanced profit opportunities for active investors.

Meanwhile, extended periods of market inefficiency also give rise to sampled portfolios with a high tracking error[55] (Roll, 1992; Steyn, 2019). This is because when markets are inefficient, asset prices are not unbiased. Consequently, extended periods of market inefficiency potentially amplify deviations between passively managed realised portfolio returns and their benchmarks leading to higher tracking errors and indicating elevated risk in the sampled passively managed portfolios. Additionally, the incidence of low liquidity (Gopane & Ravhura, 2024; Steyn, 2019) and periodic regulatory frictions (Coetzee *et al.*, 2018) in developing markets such as in SA have been argued to make index replication and consequently passive investing relatively more difficult to operationalise than in developed markets.

Amidst the debate between passive and active management, smart beta investing has emerged as a midway that blends the systematic nature of passive management with factor-driven active management. Smart Beta-managed portfolios are constructed to outperform passive management portfolio by methodically tipping exposure toward factors (Kahn & Lemmon, 2016). The factors may be parameterised using several asset pricing models, including market systematic risk (Sharpe, 1964); the Fama and French (1993) three-factors comprising market factor, size (small minus big, SMB) and value (high minus low, HML); the Carhart (1997) four-factor model, which extended Fama and French's (1993) framework by incorporating momentum; the Fama and French (2015) five-factor model which further adds profitability and investment factors to the Fama and French's (1993) three-factors. Although the theoretical case for smart beta investing is compelling, the empirical evidence of its performance presents a complex picture. Some studies (Bowes & Ausloos, 2021; Glushkov, 2015; Rompotis, 2019) found no clear evidence to support the theory that smart beta portfolios outperform their risk-adjusted benchmarks while others (Hsu *et al.*, 2012; Mateus *et al.*, 2020) found that smart beta investing persistently outperformed their benchmarks providing the basis for debate.

The preceding analysis indicates that the distinction between passive, active, and smart beta management in terms of performance persistence is not always evident. This ambiguity may be attributed to varying market conditions, whether efficient or inefficient, or different market regimes, such as downturns, normal periods, or upturns. The perspective that adaptability is essential for optimising returns while managing risk is crucial in determining an appropriate investment

[55] Tracking error measures how closely a portfolio returns 'tracks' that of its benchmark. Mathematically it is the standard deviation of the difference between a portfolio's returns and that of its benchmark over a given period (Roll, 1992)

strategy. Consequently, the choice of asset allocation strategy is one of the important investment decisions made that affect whether a portfolio meets its performance objectives (Ibbotson & Kaplan, 2012). As a result, several strategies have emerged that describe how active, passive, or hybrid strategies such as smart beta can be implemented to build robust portfolios. The next section discusses the typical asset allocations and by extension how the investment strategies are implemented.

3.2.2 Typical asset allocation: empirical considerations

Section 3.2. highlighted that selecting the right asset classes and distributing an investor's wealth among them are key decisions in the investment process and have a significant impact on overall portfolio performance. Asset class selection decisions are mostly guided by a number of factors including investor objectives, liquidity needs expected returns and volatility, correlation and diversification, regulatory constraints and market infrastructure factors such as access barriers (Cumming *et al.*, 2014; Gupta & Sharma, 2022; Swensen, 2009).

A substantially body of research (Brinson *et al.*, 1986; Doeswijk *et al.*, 2014; Ibbotson & Kaplan, 2012) argued that equities, bonds and cash are important assets for most investors. In particular, equity and bonds received a lot of attention with one heuristic allocation, of 60% in equity and the remaining 40% in bonds cited in several studies (Anson, 2005; von Brandt & Costley, 2023; Perold & Sharpe, 1988) and also applied by some funds such as Vanguard Balanced Index Fund (VBAIX)[56] and American Funds Global Balanced Growth (GBLAX)[57]. In this allocation strategy, equity supports growth while bonds provide safety against market downturns. The heuristics-based 60/40 traditional model has historically been successful although it has also been questioned (Gupta & Somani, 2024). Questions rose from the realisation that it was founded on the view that bond investments provide capital protection, yield, liquidity and diversification, a function that the 60/40 portfolios[58] are increasingly unable to meet (Gupta & Somani, 2024). Brixton *et al*. (2023) emphasised the need to reexamine the view that bonds diversify especially equity portfolios and reduce overall risk in crisis periods especially considering increased market integration.

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[56] Vanguar from (https://investor.vanguard.com/investment-products/mutual-funds/profile/vbaix). 10 April 2025

[57] American Funds Global Balanced Growth from (https://www.capitalgroup.com/individual/investments/fund/gblax?msockid=133f78cb816261e031bd68828055600f). 10 April 2025.

[58] The Performance of the 60/40 US portfolio from (https://rpc.cfainstitute.org/research/reports/2025/performance-of-the-60-40-portfolio). 10 April 2025.

Moreover, Jarrow and Li's (2014) finding that increases in liquidity supply (though accommodative monetary policy or unprecedented QE by major central banks) destabilised bond markets have far-reaching implications on bond performance in a portfolio. Makin and Layton (2021) and Smales (2021) for example found that increased liquidity led to some bond returns worldwide falling close to zero, and in many cases becoming negative during the QE that followed the Covid-19 pandemic that peaked in 2020. Consequently, bonds could not provide safety nor achieve risk mitigation at low costs (Stamos, 2022). Thus, the equity/bond portfolio became less effective as the ability of bonds to provide safety in market downturns deteriorated in crisis periods such as during the Covid-19 pandemic of 2020 bond returns sharply declined (Cheema *et al.*, 2024; Jacobsen & Scheiber, 2022). This behoves investors to rethink asset allocation triggering a movement towards more diverse multi-asset allocation strategies (Fabozzi, 2022).

A multi-asset fund offers exposure to a diverse mix of asset classes in a single portfolio, combining traditional securities, such as equity, and bonds and cash with non-traditional ones, such as hedge funds, private equity, real estate investment trusts (REITs) and asset-backed securities (Petchrompo & Parlikad, 2019). Multi-asset investing began to pick up due to the enduring works of Brinson *et al.* (1986), who found that asset allocation (not security selection nor market timing) was the primary determinant of portfolio returns - a result that was discussed by several authors (Ang & Bekaert, 2002; Phillips & Lee, 1989; Sharpe, 1987).

Investing across a variety of asset classes is widely recognised for its ability to reduce portfolio risk by spreading investments among assets that do not move in perfect tandem (Bessler *et al.*, 2017; Petchrompo & Parlikad, 2019). Research provides various perspectives on how many asset classes should be included for effective diversification. Bekkers *et al*. (2009) found that expanding beyond traditional equity and bonds to include real estate and commodities can significantly enhance portfolio outcomes. Mundi and Kumar (2023) identified hedge funds, private equity, collectibles, commodities, and venture capital as increasingly important, noting the rising role of cryptocurrencies. Several studies (Briere *et al.*, 2015; Colombo *et al.*, 2021; Han *et al.*, 2024; Robertson, 2018) examining multi-asset portfolios have referenced six major asset classes: equity, bonds, cash, commodities, real estate, and currencies. Despite such expansion, consensus tends to centre on a smaller set of key classes. Nguyen *et al*. (2025) concluded that equities and bonds contribute most to the Sharpe ratio, with adding commodities, real estate, and foreign exchange further enhancing risk-adjusted returns. Nguyen *et al*. (2025) findings corroborate Idzorek & Kowara (2013) who suggested that the main benefits to volatility reduction come from holding equities and bonds with incorporating commodities, real estate, and other asset classes providing diminishing marginal improvements.

The global interests in the numerous asset classes are exhibited in the market portfolio - a representation of a portfolio that holds every available risky asset in the market (Sharpe, 1964). Although there is a dearth of studies detailing what the market portfolio is. Doeswijk *et al.* (2014) made strides in documenting the global multi-asset market portfolio. The authors argued that understanding the global market portfolio is important for two major reasons. First, to show the relative value of all asset classes according to the global financial investment community, which one could consider a natural benchmark for international investors. Second, to present a portfolio that may serve as a starting point for investors who use a passive investment management framework. The authors estimated the global market portfolio basing for the period 1990 - 2012 on key asset classes: equity, bonds (high-yield bonds, investment-grade credits, emerging-market debt, government bonds and inflation-linked bonds), private equity and real estate. They leveraged capitalisations of various indexes as shown on Appendix 1 to parametrise the global market portfolio which they found was about USD90.5 trillion as at the end of 2012. Doeswijk *et al.* (2014) found that between 1985 and 2012 the global market portfolio, on average constituted equity (51%), government bonds (30%), non-government bonds (15%), and real estate (commercial real estate available to financial investors) (4%). Equity and bonds collectively made up over (95%) of the global market portfolio, a finding that reiterated their importance to investors worldwide corroborating Bekkers *et al*. (2009) who found that equity and bonds made up the substantial part of the market portfolio.

Doeswijk and Swinkels (2025) also confirmed the global importance of equities and bond in investment portfolios. The authors constructed a comprehensive global market portfolio valued at US150 trillion as of 2022. The portfolio consisted of broad equity (included listed and private equity), real estate (investable commercial real estate), nongovernment bonds, government bonds broad, and commodities broad (those held for investment and cryptocurrencies). The authors found that equity (including private equity) (50%), government bonds (28%) and non-government bonds (15%), are the most popular asset classes among investors. Real estate (4%) and commodities (3%) were also significant. The implication of Doeswijk and Swinkels' (2025) analysis was that the market portfolio was heavily concentrated on equities and bonds and included alternative investments such as real estate and commodities. These empirical findings confirm the importance of bonds and equity in investment portfolios as corroborated in other studies (Bekkers *et al.*, 2009; Idzorek & Kowara, 2013; Nguyen *et al.*, 2025).

A comparative analysis of asset allocation ranges within the broader spectrum of asset allocation, represent equity and bonds as the core holdings for both institutional and individual portfolios in SA (Mahoney, 2014; Maré & Flint, 2019; Panulo, 2014) and in the US (Arnold *et al.*, 2024).

However, the optimal mix varies based on investor objectives, regulatory frameworks, risk tolerance, and economic conditions.

In SA, a growing body of academic work has sought to identify optimal asset allocation ranges for investors. Mahoney (2014) argued that regulatory constraints such as Regulation 28 shaped asset allocations leading to an optimal allocation of 65% equities, 25% property and 10% bonds. Higher allocations to equities were also supported by Maré and Flint (2019) who suggested that asset allocation is dependent on market regime. Under growth periods heavy (up to 80%) equity allocation were desirable, while shifting to bonds balanced funds in downturns. These results also corroborate Panulo (2014) who found that underweighting equities especially in volatile markets while favouring bonds and cash enhance portfolio performance, thereby supporting an adaptive allocation in South Africa's environment due to its heightened volatility. Yet, Auret (2014) documented that bonds outperformed equities over time, challenging the idea that equities should be overweighted for superior long-term performance setting the stage for debate.

The US boasts a diverse research tradition investigating optimal asset allocation, supported by an environment of greater market and regulatory flexibility than is typical in South Africa. Arnold *et al*. (2024) found that endowment funds typically allocate over 60% to equities and 10–30% to bonds, with allocations shifting based on risk, liquidity, and market conditions. Heavy allocations to equity are also corroborated by The National Association of State Retirement Administrators (NASRA) Public Fund Survey (2023/24)[59] that showed that public pension funds allocate equity ranges of 40–60% and bond allocations between 20–35% depending on fund risk profiles. However, empirical literature also mentions Warren Buffett's 90/10 Strategy which recommends 90% in the S&P 500 index fund and 10% in short-term government bonds for long-term investors comfortable with high equity exposure, though this approach is not suited for risk-averse or income-focused investors (Estrada, 2016).

The asset allocation across both SA and the US often result in portfolios that have considerable allocations to equity and bonds, underscoring their importance in portfolio investments. The allocation range for equities in optimal (institutional) portfolios typically range between 40 and 80%, with the Warren Buffets 90% signifying extreme circumstance. For most investors, investing especially in equities and bonds could be done through direct management, pooled funds or outsourcing the management – especially for wealthy individuals and institutional investors (Gadzinski *et al.*, 2021) While the processes for outsourcing available pooled funds can be standardised, it is always not clear how direct management may be approached.

[59] NASRA from (https://www.nasra.org/publicfundsurvey/). 10 April 2025.

Finance literature particularly on equity investment is littered with studies that have extensively explored the optimal number of assets needed to eliminate unsystematic risk in a portfolio. These studies have been carried out in both developed markets (Barber & Odean, 2000; Diyarbakırlıoğlu & Satman, 2013; O'neal, 1997; Oyenubi, 2019; Statman, 1987) and in less developed markets (Gupta *et al.*, 2001; Irala & Patil, 2007; Raju & Agarwalla, 2021; Stotz & Lu, 2014). Table 3.2 summarises some of the key findings regarding the number of assets needed to eliminate unsystematic risk (diversify the portfolio) and arguably the ideal number of assets to hold in an equity portfolio.

Table 3.2: Number of assets needed to eliminate systematic risk in a portfolio

Author(s) and Year	Market(s) and the Observed Period	Number of Assets or Other Information
Brands and Gallagher (2005)	Australia 1989 - 1999	6
Stotz and Lu (2014)	China, India, Korea, Taiwan, Hong-Kong, Malaysia, Singapore, Thailand, Indonesia, Philippines 2003 - 2013	8 (China) and 10 in the other countries
De Keyzer and De Schaepmeester (2014)	Europe	16
Irala and Patil (2007)	India 1999 - 2005	10 - 15
Murthy (2018)	India 2012 - 2016	14
Raju and Agarwalla (2021)	India 2014 - 2020	40 - 50
Norsiman *et al.* (2019)	Malaysia 2010 - 2014	35 - 45
Bradfield and Munro (2017)	SA 2002 - 2014	15 - 19 for equally-weighted and 33 - 60 for the Shareholder Weighted Indices (SWIX) weighting scheme
Barber and Odean (2000)	US 1991 - 1997	7 - 8
Statman (2004)	US 1926 - 2001	More than 300
Shawky and Smith (2005)	US 1992 - 2000	40 - 120
Domian *et al.* (2007)	US 1985 - 2004	More than 100
Benjelloun (2010)	US 1980 - 2000	40 - 50
Chong and Phillips (2013)	US 2003 - 2010	31
Zhou (2014)	US 2008 - 2013	10
Oyenubi (2019)	US 2005 - 2013	30 - 40
Haensly (2020)	US 2007 - 2016	300

Adapted from Zaimovic et al. (2021).

The outcomes illustrate that the literature on the number of assets needed to diversify an equity portfolio (and eliminate unsystematic risk) is vast, and the results have varied across markets and time. This is due mostly because portfolio sizes reflect changes in systematic risk and market conditions with crisis periods reducing the optimal number of assets in a portfolio. Zaimovic *et al.* (2021) contend that the general lack of consensus is convoluted by numerous factors including the heterogeneity relating to the way systematic risk is measured, investors' characteristics, evolving asset efficiency, the asset allocation model adopted to measure diversification (i.e., equally-weighted versus an optimal allocation), and the frequency of the data that is being used together with the time horizon. Eccles *et al*. (2021) support that for equity portfolios there is no one size fits all for ideal number of assets to hold in a portfolio as it depends on portfolio style.

Eccles *et al*. (2021) found that for large-cap portfolios about 15 equity assets were ideal in eliminating systematic risk while in small-cap portfolios and non-dividend portfolios around 26 equity assets were required. Dividend-paying equity assets requires fewer (about 5). Meanwhile, both growth and value portfolios need a greater number of assets (33–40) to optimally reduce volatility.

Another outcome from these results is that there seems to be a lower number of assets required to tease out unsystematic risk in dividend paying equity. Findings of lower volatility in dividend paying equity compared with, for example growth equity are corroborated in numerous studies (Rozeff, 1984; Shiller, 1981; Spaht & Rubin, 2016). This study thus reasoned that the number of assets required to eliminate unsystematic risk is also driven by market volatility – with more volatile markets requiring a higher number of assets to eliminate unsystematic risk.

Regarding bonds, to the best search of this study, the finance literature has not defined the ideal number that an investor needs to hold to optimise risk. However seminal research by Elton *et al*. (1995) suggested that 30–40 corporate bonds were required to diversify a corporate bond portfolio. Fabozzi (2022) disaggregated bonds by riskiness and found that 10–15 bonds were required to diversify a sovereign bond portfolio while 30–50 were required for corporate bonds. The findings of Fabozzi (2022) corroborated those of Elton *et al*. (1995) and clearly established that sovereign bond portfolios (which are less volatile) required fewer assets for diversification than corporate bonds (which are relatively more volatile). Moreover, the results of Fabozzi (2022) challenge general reasoning that bonds – which are less volatile than equities as established in various studies (Campbell & Taksler, 2003) seemingly required a greater number of assets to diversify than an equity portfolio (Eccles *et al.*, 2021). To the best of this study's search, it remains unclear how aligning bond duration and convexity, bond ratings, embedded options, among other determinants of bond selection with portfolio objectives, could impact the ideal number of bonds to be included in a bond portfolio.

This study also noted that the literature has not yet explicitly prescribed the number of real estate (Voicu & Seiler, 2013) hedge funds (Lhabitant & Vicin, 2004) and cryptocurrencies (Brauneis & Mestel, 2019) that may be held in these respective asset classes. There is, therefore, an opportunity for future studies to explore further the number of ideal assets that can be held under each of these asset classes. Thus, to the best of this study's knowledge, there is no definitive answer to how many assets must be in an asset class (equity, bonds, real estate). This is partly because markets undergo changing conditions which affect volatility and investors also have heterogeneous objectives, risk appetites, preferences and strategies which all affect the number of assets that can be held in a portfolio to achieve the desired objective.

Regardless of whether an investor adopts a passive or active management strategy, there is a need to systematically determine the amount of exposure they need in an asset (or asset class) given their expectations on an asset (or asset class) to achieve their performance or investment objective. The literature discusses several techniques that investors may use to allocate capital amongst several asset classes to leverage diversification benefits in an endeavour to achieve their desired objective. The following sections delve deeper and explore some of the most salient techniques that investors use to allocate capital to meet their unique needs and circumstances.

3.3 Establishing optimal capital allocations in a portfolio

Current strategies for optimal portfolio allocation predominantly emphasise diversification - distributing risk across various assets (and asset classes) to meet investment objectives. This perspective on investment is enunciated in modern portfolio theory (MPT) set out by Markowitz (1952). The MPT is a theoretical framework that explains how to combine assets to achieve an optimal risk-return trade-off. The MPT, while attributed to Markowitz (1952) following his seminal works on mean-variance optimisation (MVO), also benefitted from early investment studies and recent work critiquing the MVO framework.

Notably, Lowenfeld (1909) argued that investors' goals of maximising capital growth are inextricably linked with the size of the likelihood of suffering a loss. Graham and Dodd's (1934) [cited in Pratt (2008)] seminal works that differentiate investing from speculation following the US stock market crash of October 1929 also laid important groundwork for how investing is conceptualised. By proposing generic guidelines for real investing (as contrasted to speculation), which include buying assets upon careful examination that promise the safety of the principal (capital preservation) and a commendable return (security analysis), Graham and Dodd's work characterised the modern approach to investment management. However, criticism of the MVO framework in asset allocation birthed alternative theories and frameworks, including the capital asset pricing model (CAPM) discussed by Mossin (1966), multifactor investing or factor investing (Carhart, 1997a; Fama & French, 2015; Glushkov, 2015) and Black-Litterman and Bayesian approaches discussed by Lakhoo (2016).

The sections below discuss the MPT theory as expounded by Markowitz (1952) and investigate models that sought to address its shortcomings.

3.3.1 Mean-variance optimisation framework

Portfolio selection is the unifying process in the modern approach to portfolio management. Nevertheless, the best way to select portfolios (or assets) to invest in is a matter of intense debate. According to Markowitz (1952), the best way to choose securities for each portfolio (and by extension asset classes) is to build a set of efficient portfolios (maximising returns while

minimising risk) using quadratic programming and choosing an asset allocation that maximises the investor's risk-return trade-off given their risk aversion. Prior to Markowitz's work in 1952, investment strategies largely overlooked the systematic management of risk (Turnbull, 1977) and assets were selected on the belief that they provided some safety of the principal and growth as enunciated by Graham and Dodd (1934).

The MVO framework of Markowitz (1952) formalised the asset allocation enigma. It holds that the ideal (optimal) asset allocation is that which maximises returns per level of risk or minimises risk per level of return (Markowitz, 1952; Michaud & Michaud, 2007; Platanakis & Urquhart, 2020). Markowitz (1952) parameterised the risk of a portfolio with the variance of expected returns, inextricably connecting statistics and portfolio management. The MVO framework thus views investment decisions as a trade-off between expected return and investment risk[60], thereby placing the investment portfolio (rather than a single asset) at the forefront of discussions about investment management. It submits that investors' choices are a selection among several efficient portfolios (the ones with the lowest risk for a given level of expected return, or the ones with the highest expected return for a given level of risk). More risk-tolerant (risk-averse) investors select higher (lower) risk portfolios that also offer relatively higher (lower) expected returns. The MVO framework, therefore, requires knowledge of the expected returns and pairwise covariances of all assets under consideration to solve the optimisation problem (Markowitz, 1991; Vaclavik & Jablonsky, 2012).

In essence, the MVO hinges on the principle of diversification to manage and mitigate risk. As already discussed in Section 2.5.2, diversification involves leveraging on correlation dynamics (pairwise covariances) in spreading investments across a variety of assets to reduce the impact of any single asset's poor performance on the overall portfolio. By combining assets that are uncorrelated, investors can achieve a more stable return trajectory, reduce unsystematic risk (risk associated with individual assets) and in the process lower the overall risk of the portfolio. This helps in optimising the risk-reward trade-off, as it allows investors to achieve a higher expected return for a given level of risk, or conversely, minimise risk for a given expected return. Portfolio managers may take advantage of the framework's flexibility by tailoring it to individual investors through imposing constraints related to short-sale restrictions, minimum and maximum asset exposures, transaction costs, and the number of assets in a portfolio (Vaclavik & Jablonsky, 2012).

Despite its theoretical soundness which provides an intuitive framework for conceptualising risk and return trade-off, the MVO framework has attracted considerable criticism related to the

[60] Investment risk is the likelihood that the actual return from an investment will be different from the expected return.

performance of MVO portfolios (Lolic, 2024; Michaud, 1989; Michaud & Michaud, 2007). This is corroborated by Pedersen *et al*. (2021) who argued that, while the MVO framework benefits investors by logically guiding portfolio decisions, it works so poorly in practice that optimisation is sometimes abandoned in favour of naïve techniques, such as equally-weighted portfolios. As a result, the finance literature is littered with analysis from researchers (Elton & Gruber, 2013; Hasuike *et al.*, 2009; Konno & Yamazaki, 1991; Rom & Ferguson, 2001) on what weakens the framework as well as potential improvements (Lolic, 2024). The next section discusses some of the popular MVO weaknesses documented in the literature.

3.2.1.1 Weaknesses of the MVO framework

Haugh (2016) has thoroughly documented four major flaws in the MVO framework that limit its widespread application. First, the framework often results in portfolios characterised by extreme short and long positions. Second, the framework's portfolio allocations are extremely sensitive to very small changes in asset expected returns. A small increase in the expected return on one asset can drastically alter the optimal portfolio composition. Third, heavy-tailed return distributions often lead to substantial errors in covariance estimates, thereby misrepresenting diversification benefits. Finally, quadratic optimisation ignores higher-order moments of returns, reducing its reliability even further, especially when the portfolio consists of assets with non-normal returns (Van Heerden, 2015), a manifestation pronounced in cryptocurrencies (Ahmed & Al Mafrachi, 2021; Liu & Tsyvinski, 2021). According to Haugh's (2016) findings, the majority of the MVO framework's flaws stem from estimation errors in the mean return and asset pairwise covariances. These estimation errors are minimised in unpredictable (efficient) markets where historical returns serve as unbiased estimators of expected asset returns, thus enhancing the model's accuracy. However, when markets are predictable (inefficient), historical returns are biased estimators of true asset returns which undermine the model's accuracy. This reasoning is based on Lo's (2004) contention that an efficient market exists when the market price is an unbiased estimate of the true value of the investment.

The concerns in applying Markowitz's (1952) MVO framework have prompted several authors to question some of the model's assumptions. Fabozzi *et al*. (2007) summarised the key assumptions of the MVO framework as follows:

- *Assumption 1*: Investor decisions hinge exclusively on two factors - the anticipated return and the associated variance.
- *Assumption 2*: Investors are risk averse. They seek to maximise expected returns for any given level of risk (variance). In essence, when comparing investments with the same expected return, they favour those with lower variance.

- *Assumption 3*: All investors seek to achieve the highest expected return at a given level of risk.
- *Assumption 4*: All investors have homogeneous expectations regarding expected return, variance, and covariances for all risky assets.
- *Assumption 5*: Asset returns are normally distributed. The meaning (expected returns) and variance (risk) fully describe the return distribution.
- *Assumption 6*: All investors have a common one-period investment horizon with no changes in investor preferences, asset characteristics, or market conditions over time.

Changing or relaxing some of the framework's assumptions has enabled portfolio managers and researchers to gain new insights.

One of the most enduring assumptions that practitioners have overlooked is that of normality in the return distribution (assumption 5). According to Markowitz (1952), the expected returns on financial assets equal the mean value of their historical returns. Historical returns are used as an unbiased estimate of expected returns and in computing covariances (Vaclavik & Jablonsky, 2012). This assumption precludes the use of alternative methods for estimating expected returns and covariances, such as advanced mathematical and statistical methods such as the Capital Asset Pricing Model (CAPM) proposed by Mossin (1966), Monte Carlo Simulations or the popular Jensen *et al*. (1972) Black-Scholes asset pricing formulas or fundamental techniques such as Shiller's (1981) Cyclically Adjusted Price-to-Earnings (CAPE) ratio documented in Siegel (2016). Rom and Ferguson's (2001) Post-Modern Portfolio Theory studies advocated for breaking the normality assumption and utilising mathematical techniques to compute expected returns as the literature has documented that asset returns are non-normal (Sheikh & Qiao, 2010; Van Heerden, 2015).

Another assumption that authors are increasingly questioning is that of static single-period asset returns dynamics over time (Assumption 6). Some researchers (Guo & Zhou, 2021; Sheikh & Qiao, 2010) have shown that asset correlations tend to converge during crisis periods. Because the framework's estimation of correlations is a simple averaging over historical periods and assuming market conditions do not change, the model falters when expected diversification benefits fail to materialise at the most critical stage of the investment -during times of crisis. Some studies have suggested the use of time-varying correlations such as the vector error correction model (VECM) (Bollerslev *et al.*, 1988), the Baba-Engle-Kraft-Kroner (BEKK-GARCH) model (Engle & Kroner, 1995) and the dynamic conditional correlation (DCC) model (Klein *et al.*, 2018).

Overall, the weaknesses in the MVO framework resulted in maximising errors related to asset allocation, mostly due to misestimations in input parameters (returns and variance-covariance

estimates due to single period views and overlooking non-normality in returns). Securities with high estimated returns, low correlations, and low variances are overweighted (Michaud, 1989). This asset selection bias led to concentrated portfolios, a development contrary to the theory of diversification. In addition, the MVO framework produced unstable portfolios that were overly sensitive to small changes in input estimations (Best & Grauer, 1991; Britten-Jones, 1999). Thus, a minor change in the expected return dramatically changes portfolio asset allocation (Vaclavik & Jablonsky, 2012). This realisation made the MVO framework unintuitive, especially because expected returns are non-deterministic. Furthermore, there is a concern that the MVO framework does not consider liquidity and depth of assets and thus overstates risk-adjusted returns. Michaud and Michaud (2004) defined liquidity as the percentage of an asset's market capitalisation that a portfolio holds. When a portfolio holds a large part of the capitalisation of a less frequently traded asset, the price of the asset will be affected if a large part of the asset is traded. Despite these limitations, the MVO framework continues to attract a lot of interest from practitioners and academics alike. The next section discusses some modifications that have been suggested to counter the model's shortcomings.

3.2.1.2 Modifications of the MVO

There is substantial evidence in investment literature that some investors bypass optimisation in favour of passive asset allocation strategies such as the equal weighting, which in some circumstances have outperformed the MVO framework (DeMiguel *et al.*, 2009; Malladi & Fabozzi, 2017; Plyakha *et al.*, 2012). In other circumstances, investors also disregard optimisation and bet on fundamental characteristics such as value - HML[61], size - SMB[62], and momentum UMD[63] to construct portfolios without using optimisation (Fama & French, 1993, 2015). Thus, the MVO framework's flaws have given rise to other branches of literature seeking to confront the model's limitations and make improvements.

One of the most prominent lines of research examines how changes in expected returns affect asset allocation. This branch of the literature has made headway in countering asset return sensitivity in determining asset allocations (Best & Grauer, 1991). For example, to reduce the impact of return sensitivity in asset allocation, several techniques such as the re-sampled efficient

[61] High book-to-market ratio minus low book-to-market ratio.

[62] Small minus big.

[63] Up minus down.

frontier[64] (Michaud, 1989) and Monte Carlo simulation techniques (Cong & Oosterlee, 2016) are used. Other salient bodies of literature focus on ways to reduce concentrated portfolios by applying the CAPM-based equilibrium asset allocations suggested by Black and Litterman (1990) and incorporating changing correlations in asset allocations (Bollerslev *et al.*, 1988; Guidolin & Timmermann, 2007; Perold & Sharpe, 1988). Some researchers have also suggested a portfolio selection incorporating higher-order moments (Elton & Gruber, 2013; Konno & Yamazaki, 1991; Markowitz, 1991; Zsolt & Botond, 2021) to incorporate non-normality in returns distributions. Despite these modifications, there seems to be no consensus on whether these enhancements improve the MVO framework when allocating capital.

The lack of clarity is corroborated by Pedersen *et al.* (2021) who argue that the MVO framework is persistently let down by problematic portfolios - the ones whose estimated variances are likely to be too low for the safest portfolios and too high for the riskiest ones. The authors suggested enhanced portfolio optimisation techniques that address the estimated variance problem by shrinking the estimated variances toward their average. Pedersen *et al.*'s (2021) idea of shrinking variances builds from Ledoit and Wolf (2003) and Ledoit and Wolf (2004) some of the first authors who proffered alternative approaches to strengthening the Markowitz (1952) MVO framework. Pedersen *et al.* (2021) argued that shrinking the variance itself does not entirely eradicate the problem of significant errors in covariance estimates, which in turn leads to misrepresenting the benefits of diversification. This is because shrinking variance estimates does not incorporate the stylised facts (of heavy tails) in returns distributions and so it still led to understating risk.

Lakhoo (2016), in the discussions on the development and modification of the MVO framework, provided insights into how alternative models that offset the limitations of the MVO framework may be constructed. The author classified countering MVO weakness into approaches related to:

(i) improving the objective function formulation,
(ii) enhancing parameter estimates by methods such as covariance shrinkage, and
(iii) a combination of other methods.

The following sections synthesise these three categories and outline the robust methodologies for multi-asset portfolio selection.

3.2.1.2.1 **Enhancement of the objective function formulation**

The investment literature (Almeida & Gonçalves, 2022; Brands & Gallagher, 2005; Fragkiskos, 2014; Konno & Yamazaki, 1991; Michaud, 1989; Nguyen *et al.*, 2025; Pedersen *et al.*, 2021) has

[64] Efficient frontier refers to the set of portfolios that offer the highest expected return for a given level of risk (Markowitz, 1952).

extensively documented that there are benefits to portfolio diversification. As a result, several authors have revisited the MVO framework and made strides towards addressing the problem of concentrated portfolios.

Studies by Scherer (2011) and Yanushevsky and Yanushevsky (2015) suggested that prioritising low residual (unsystematic or specific) variance assets improve risk-adjusted returns. This is because residual risks are uncorrelated across assets and reducing them leads to more robust diversification (Michaud, 1989). Accounting for residual risks has gained support from the literature, with Choueifaty *et al*. (2013) and Jagannathan and Ma (2003) arguing that it limits specific risk concentration, while Yue *et al*., (2022) as well as Cesarone *et al*. (2025) argued that it enhanced portfolio stability.

King (2007) argued for adjusting the objective function of the MVO framework by including a nonparametric diversification preference parameter based on the Herfindahl-Hirshman Index (HHI). Rhoades (1993) defined the HHI as a measure of the weight of an individual asset in a portfolio. King (2007) reasoned that concentrated portfolios may be resolved by avoiding portfolios with a higher HHI to foster diversification in portfolio allocations. Incorporating diversification by modifying the investment objective function is a novel approach that is of growing significance. The traditional MVO framework has a single objective function of minimising risk per given level of return (or maximising return per given level of risk) and fosters diversification by introducing weight constraints to the optimisation problem. However, constraining an optimisation problem as a solution to avoid concentrated portfolios was challenged in numerous studies (Amenc & Martellini, 2002; Black & Litterman, 1990; Fabozzi *et al.*, 2007) as it was viewed as introducing bias in portfolio selection. As a result, King's (2007) method of improving the MVO framework objective function by including a diversification preference parameter presents promise for investors and portfolio managers (Scherer, 2011). This is corroborated by Lakhoo (2016), who found that King's (2007) model produces comparable results to Michaud's (1989) popular resampled efficiency optimisation (REO) methodology. The REO method uses Monte Carlo simulations to create numerous plausible scenarios for the efficient frontier based on estimated inputs (returns and variance-covariances). This is done to account for input uncertainty. The resampled efficient portfolio is created by averaging the simulated efficient frontiers (Michaud & Michaud, 2004), thereby causing a smoothing effect. Despite their stark differences, King's (2007) approach and Michaud's (1989) methodology yield comparable outcomes in terms of the efficient frontier and asset allocation recommendations (Lakhoo, 2016). This near convergence of their solutions to the optimisation dilemma suggests some validation of King's (2007) and Michaud's (1989) enhancement of the MVO framework.

Yet, the literature is littered with criticism of both approaches. Scherer (2002) found that the REO may force highly volatile and otherwise dominated assets into the solution. This is because highly volatile assets sometimes also exhibit very attractive mean returns. In addition, Scherer (2002) found that all re-samplings are derived from the same returns vector and covariance matrix and the true distribution is unknown. Thus, all the resampled portfolios suffer from a deviation of the parameters from their true distribution in much the same way. Hence, it can be argued that all REO portfolios inherit the same estimation error. King's (2007) methodology suggested that, at *suitable* levels of the diversification preference parameter, a single optimisation may be needed, unlike multiple optimisations with the REO. However, determining a *suitable* HHI index introduces bias to the optimisation. Furthermore, introducing the HHI to the objective function convolutes the optimisation process as the problem scales to a multi-objective optimisation, which does not always produce results (Anagnostopoulos & Mamanis, 2010).

Addressing these issues, Yanushevsky and Yanushevsky (2015) proposed an alternative model to address the drawbacks of King's (2007) model, which lacked a solution everywhere, and Michaud's (1989) model, whose solutions were unstable. Yanushevsky and Yanushevsky (2015) argued that, by incorporating the average trading volume indicator in the objective function, their model improved on Markowitz's (1952) MVO framework. This was because the average trading volume indicator added useful equity market information, making the optimisation problems less onerous, and was inherently a form of regularisation because it introduced fresh data that aided in the resolution of ill-posed problems. The ill-posed problems inferred are optimisations that do not have a solution everywhere, such as King's (2007) enhanced HHI optimisation framework and optimisation problems without unique or stable (continuous) solutions such as Michaud's (1989) REO and Markowitz's (1952) MVO framework. Despite its theoretical improvements over the traditional MVO framework, Yanushevsky and Yanushevsky's (2015) model has not seen widespread practical adoption. The literature has not extensively discussed why this is the case – a gap that future studies may fill.

Another model that has gained considerable attention in addressing concentrated portfolios by enhancing the objective function is that by Anagnostopoulos and Mamanis (2010). The authors modified the MVO framework of Markowitz (1952) to a tri-objective optimisation problem that strikes a balance among risk, return and the number of securities in the portfolio. The authors also argued for additional constraints to limit asset allocations in assets with common characteristics and to avoid very small holdings. Anagnostopoulos and Mamanis (2010) acknowledged that their model made it difficult to arrive at a solution, mostly because it simultaneously required integer decision variables (number of assets in a portfolio) and multiple (three) objectives. Thus, their model, although practicable, degenerates into an ill-posed problem

(does not have a solution everywhere). Despite this drawback, Anagnostopoulos and Mamanis (2010) argued that, even without an exact solution to the model, an approximation of the efficient surface provided investors with a diverse set of portfolios, thereby addressing the problem of a concentrated portfolio.

The above discussion illustrated that the literature aiming to improve the MVO framework's performance by enhancing its objective functions had made progress in handling particularly concentrated portfolios as several models have been mooted. This study notes that the quest to enhance model accuracy raises concerns about the resulting overly intricate systems. This highlights a critical challenge: balancing the pursuit of accuracy with the need for simplicity (computational resources), practicality, and broad applicability. For example, over and above the high input data requirements in the MVO framework, the suggested models required additional data on the diversification parameter in King's (2007) model, the average volume indicator in the case of Yanushevsky and Yanushevsky (2015) and the number of assets in a portfolio as suggested by Anagnostopoulos and Mamanis (2010). Generating such information may come at an additional cost and time delays for those seeking to use the model. Moreover, scaling the optimisation process to a multi-objective function such as that suggested by Anagnostopoulos and Mamanis (2010) may likely lead to model that do not produce results, thereby dissuading broad applicability.

The next section explores an alternative approach that addresses the MVO framework by only adjusting the input parameters without requiring additional data or changing the problem to a multi-objective optimisation function.

3.3.3.2.2 Enhancement through improved parameter inputs - Covariance Shrinkage

Following Chopra and Ziemba's (1993) findings that estimation errors in expected returns affect asset allocation more than errors in the covariance matrix, Fletcher (2009) teased out the impact of returns by assessing how the estimation errors in covariance impact the minimum variance portfolio (MVP) and the tracking error variance (TEV) portfolio[65]. Interest in the minimum variance portfolio stems from the realisation that the MVP has better out-of-sample performance than the sample MVO framework portfolios (DeMiguel *et al.*, 2009; Jagannathan & Ma, 2003; Jorion, 1991). Hence, Fletcher (2009) considered various models to estimate covariances, such as the constant correlation matrix (Elton & Gruber, 2013), the shrinkage approach (Ledoit & Wolf, 2003) and Sharpe's (1963) single index model to examine whether the MVP and TEV portfolios outperform passive benchmarks. Fletcher (2009) found that the choice of the covariance matrix

[65] A TEV portfolio is designed to minimize the variance in its returns when compared with those of a benchmark index (Fletcher, 2009).

model matters less when focusing on the MVP and that simpler covariance matrix models perform as well as more sophisticated models.

While these results have received widespread attention, leading to several scholars focusing on MVP optimisation, Ledoit and Wolf (2004) challenged using the sample covariance matrix (Elton and Gruber, 2013) in the MVO framework. They instead suggested an alternative technique for estimating the covariance matrix, based on shrinking extremes towards the centre. The authors found that the enhanced covariance matrix determined through shrinkage significantly improves the information ratio[66] of the portfolio manager. Munro and Bradfield (2017) corroborated Ledoit and Wolf's (2004) findings and argued that the use of systematic approaches such as Sharpe's (1963) single-index model and average covariance matrix results in lower risk portfolios (out of sample) than the sample covariance. The results of Fletcher (2009) and Ledoit and Wolf (2004) therefore suggested that the sample covariance may be applied when estimating allocation for an MVP. However, for riskier portfolio allocations, applying variance shrinkage estimators to the sample covariance can mitigate the issue of overly sensitive portfolios. This view is supported by the enhanced portfolio optimisation (EPO) model suggested by Pedersen *et al.* (2021).

The EPO also seeks to improve the performance of the MVO framework by shrinking the correlations of the assets toward zero, thereby addressing the problem of underestimated risk and overestimated returns. Pedersen *et al.* (2021) found that the EPO model outperforms the market, the equally weighted portfolio and the MVO framework model on a risk-adjusted basis. The authors further argued that the asset allocation solution arrived at through the EPO is equivalent to the popular Black and Litterman (1992) model, save that the EPO is simpler to apply and more transparent in how and why it works. The EPO has benefited from previous theories, such as robust optimisation (Fabozzi *et al.*, 2010; Kim *et al.*, 2018) and sampling errors in the MVO framework (Britten-Jones, 1999).

The next section explores more in depth some of these popular models (Black & Litterman, 1992; Fabozzi *et al.*, 2010) and other techniques applied to improve the MVO framework, which cannot be categorised purely as either enhancing the objective function or enhancing inputs.

3.3.3.2.3 Other techniques employed to improve the MVO framework

Most of the literature that has proposed modifications to address the shortfalls of the MVO framework has centred on enhancing the objective function or improving parameter estimates. However, there exists another branch of the literature that has proposed rather special

[66] The information ratio measures the excess return per unit of standard deviation of excess returns widely referred to as the tracking error (Ledoit & Wolf, 2004).

approaches. For example, Fabozzi *et al.* (2010) argued for the use of robust optimisation (RO) in place of the quadratic optimisation employed by Markowitz (1952) in the MVO framework. Robust optimisation has been extensively discussed in several portfolio management studies (Scherer, 2002; Kim *et al.*, 2018) and represents a relatively novel approach to solving optimisation problems by allowing for a solution (asset allocations) where some of the variables involved (expected returns and variance-covariances) are uncertain. Thus, RO, unlike quadratic optimisation, realises inputs are non-deterministic in both the objective and constraints functions of the optimisation problem. Fabozzi *et al.* (2010) therefore argue that, since RO acknowledges uncertainty in inputs, it is better positioned to give more realistic portfolio allocation decisions than the basic mean-variance quadratic optimisation. This is because the RO algorithm searches for a decision that is feasible, no matter what the constraints turn out to be, and is optimal for the worst-case objective function. Fabozzi *et al.* (2010) further proposed the mean-variance with box uncertainty (MVBU) to impose uncertainty in estimated returns and the mean-variance with ellipsoidal uncertainty (MVEU) to account for errors in the estimation of covariance of expected returns. In both the MVBU and MVEU, penalties for uncertainty in either return or covariance of returns are incorporated in the RO objective function. RO is of growing significance and has gained attention from several authors (Goldfarb & Iyengar, 2003; Kolbert & Wormald, 2010). Research conducted by Georgantas *et al*. (2024) and Salo *et al*. (2024) has examined the overall performance of RO in comparison to the MVO framework, particularly focusing on portfolio composition features such as diversification. The findings indicate that RO does not significantly differ from the MVO framework in these aspects. However, in terms of portfolio performance, RO results in more competitive portfolios, with its MVP outperforming the MVP derived through the MVO framework (Georgantas *et al*., 2021).

3.3.2 Alternative theories and frameworks

Other frameworks that seek to address the shortfalls of the MVO framework include that of Jorion (1985), who argued that the ex-post estimates of means, correlations and covariances are subject to estimation error, although the classic MVO framework makes use of them to guide capital allocation decisions. Jorion (1985) recognised that the literature is littered with models for estimating expected returns, such as the CAPM (Mossin, 1966; Sharpe, 1964), Sharpe's (1963) single index model and models for reducing the dimensionality of the variance-covariance matrix, such as principal component analysis. Jorion (1985) therefore argued that, by shrinking the ex-post sample means toward a common mean, the out-of-sample mean performance is enhanced, thereby substantially improving the out-of-sample optimal portfolio performance. This is because the classical MVO method maximises errors, leading to concentrated portfolios consisting of assets with higher expected returns, negative correlations and small variances.

Jorion (2012) expanded upon the notion that ex-post expected returns and covariances are subject to uncertainty, thereby undermining the decisions within the MVO framework. This is primarily because quadratic optimisation fails to account for estimation risk in its inputs. Consequently, the author proposed a simulation method that acknowledges the uncertainty of input parameters, thus maintaining optimal portfolio weights as point estimates with inherent variability. The use of simulations to improve asset allocation has also been investigated by Michaud and Michaud (2004), who employed numerous Monte Carlo simulations and averaged the results to derive recommended asset allocations. Nevertheless, the estimation risk associated with mean and variance-covariance inputs cannot be entirely mitigated through simulations (Lakhoo, 2016). Skylogiannis and Xu (2009) cited in Lakhoo (2016) introduced a Bayesian regularisation approach that incorporates Bayesian priors and Euler equations to address the uncertainty in inputs, specifically returns and the variance-covariance matrix. They proposed a Bayesian maximum a posteriori (MAP) estimator for these inputs. This methodology has been applied to regularise expected returns and variance-covariance matrices (Feng & Polson, 2020) and to estimate returns and covariances for large portfolios with limited historical data (Oya, 2022). The Bayesian MAP is posited to minimise portfolio losses, particularly during market downturns, in comparison to the MVO framework portfolio (Skylogiannis & Xu, 2009).

Another method that has been proposed to address estimation errors in ex-post returns and variance-covariance is that of Bouchaud *et al*. (1997). The authors proposed an optimisation framework with constraints on a diversification indicator that measures how concentrated the portfolio is. Bouchaud *et al.* (1997) were opposed to achieving portfolio diversification by assigning upper and lower weight bounds to restrict portfolio concentration. They argued that maximum and minimum bounds for asset weighting are akin to selecting a target portfolio, thereby impeding the optimisation process and disrupting diversification. They reasoned that a more prudent portfolio optimisation framework must account for the fact that ex-post returns are partial information and nondeterministic, as well as strive to maintain a minimum level of diversification. It is important to note that, although their model addresses the issue of concentrated portfolios, its main shortcoming is that its constraints of an effective level of diversification are based on some subjective minimum value of diversification. Moreover, it does not directly confront the problem of instability in the covariance matrix and average return vectors over time.

Most models that address portfolio allocation challenges do so by making assumptions about diversification preferences, shrinking the returns vector or variance-covariance matrix, or leveraging advanced optimisation algorithms. Black and Litterman (1990) took a different approach, focusing on the role that investor perspectives play in determining the fundamental trade-off between risk and expected return. Their argument was based on the work of Treynor

and Black (1973) who argued that combining a market portfolio with an active portfolio containing securities with an appraisal premium result in a robust and stable portfolio. Accordingly, Black and Litterman (1990) held that a robust MVO framework allows investors to incorporate their views on expected returns generated by the CAPM (the equilibrium market portfolio), while also allowing them to use historical returns to estimate risks. Thus, the Black and Litterman (1990) model has the advantage of allowing the investor to combine specific expected returns with the equilibrium returns. As a result, it enables investors to create portfolios that appear balanced and reflect their (subjective) views without resorting to arbitrary portfolio composition constraints. This significantly ameliorates the usual tendency of mean-variance models to map seemingly reasonable views into what appear to be extremely unbalanced portfolios.

When investor views are incorporated, the model produces posterior expected returns that reflect Bayesian updating. In the absence of explicit views, however, the posterior converges to the equilibrium prior. In such cases, the BL model functions primarily as an equilibrium-consistent and covariance-anchored portfolio construction framework rather than as a Bayesian information-integration mechanism. Adopting the equilibrium prior without introducing additional subjective views, emphasises structural allocation consistency rather than informational updating (Black & Litterman, 1990). This practicality has increased its popularity among investors and researchers (DeMiguel *et al.*, 2009; He & Litterman, 2002).

3.3.3 Implications of MPT Frameworks

The discussion on MVO framework modification suggests that the MVO framework of Markowitz (1952) is a theoretically sound method for guiding capital allocation decisions. However, its oversight in accounting for estimation risk is a let-down with far-reaching implications on the confidence in the framework's outputs. Practitioners find that the framework is an error maximiser, overly sensitive to input estimation risk, and produces portfolios that lie on extreme ends of the allocation spectra, either being concentrated in a few assets or consisting of extreme longs and extreme shorts, which is generally unintuitive (Lakhoo, 2016). In certain circumstances, imposing constraints related to short-sale restrictions, minimum and maximum asset exposures, and the number of assets in a portfolio improves the model's outputs (Vaclavik & Jablonsky, 2012).

Still, several modifications have been suggested to address some of these shortcomings. Most of these modifications approach the asset allocation problem from a purely statistical viewpoint, without regard to investor preferences and behaviour. They emphasise addressing the estimation error embedded in ex-post returns and variance-covariances. Different modification methodologies are suggested, ranging from enhancing the objective function to foster diversification, shrinking covariances to constrain estimation errors, and leveraging Bayesian statistics to incorporate investor views. Another modification endeavours to enhance the accuracy

or stability of the framework by utilising RO in place of quadratic optimisation and the introduction of diversification in the model through the objective function or constraints. Overall, these modifications, while leading to asset allocation that outperforms the MVO framework on a risk-adjusted basis, have not gained much attention in practice. Through integrative reasoning, this study conjectures that this is because the modifications are for the most part mathematically intensive and lead to black-box-type models with few investors understanding how they function. The MVO framework is critiqued for its naivety as are the modifications for their complexity. However, the enduring of the MVO suggests that given a choice between higher accuracy with low explainability and lower accuracy with high explainability, prioritising explainability offers the best practical compromise.

Meanwhile, the Black and Litterman (1990) model has been of growing significance, especially among institutional investors, in addressing the portfolio allocation enigma that remained unresolved with the challenges of the MVO model. The model takes the view that investors invest in the market portfolio and deviate from it based on their views on how assets will perform over some investment horizon. This method is in line with investment in practice and has thus gained popularity, especially amongst institutional investors who hold a diversity of asset classes within their portfolios.

This study viewed the MVP, the MVO framework of Markowitz (1952) and the Black and Litterman (1990) model as important frameworks in portfolio construction that include cryptocurrencies. The MVP with no short sales is robust since it does not make use of expected returns, which are prone to estimation risk, thereby minimising the estimation errors. The MVO framework is explainable, theoretically sound and reflects the decision making of economic agents. The BL model is an unbiased technique for portfolio allocation. It leverages MPT and holds that, in the absence of views of expected returns, investors hold the market portfolio. The model is arguably intuitive and aligns with industry practices as far as portfolio allocation is concerned.

The following section delves deeper into portfolio management, surveying for appropriate performance indicators to aid in measuring the impact of integrating cryptocurrency and investigating whether there is an optimal rebalancing frequency in best-practice portfolio management.

3.4 Portfolio performance evaluation and monitoring

Ex-post evaluation of investment performance is a prominent and ubiquitous feature of modern investment management practice (Bessler *et al.*, 2017; Clarke *et al.*, 2002; Jorion, 1992). This is because investing entails making decisions with quantifiable consequences that lend themselves to scrutiny. As a result, a large industry has developed to meet the demand for performance monitoring and risk attribution services at the institutional investor level, and to a lesser (but

growing) extent, at the individual investor level (Barber & Odean, 2000; Carhart, 1997a; Daniel *et al.*, 2002). Some researchers have posited that performance evaluation is often misapplied or cannot be achieved with a reasonable degree of statistical confidence (Ball *et al.*, 1995; Cooper *et al.*, 2001; Kerssens-van Drongelen & Fisscher, 2003). Nevertheless, this study builds upon other research (Chen & Knez, 1996; Conrad *et al.*, 2013; Grinblatt & Titman, 1989, 1994) that contends that robust portfolio performance evaluation techniques can yield valid insights into the sources of past returns, and such insights can provide valuable feedback for managing an investment program.

The goal of this section is to provide an overview of prominent performance evaluation metrics and techniques, as well as to identify those that are better suited to evaluating multi-asset portfolios that include cryptocurrencies.

3.4.1 Performance measurement techniques

Metrics for measuring portfolio performance are classified into two categories. First, traditional measures, which include holding period returns, arithmetic mean returns, geometric mean returns, and time-weighted returns (Chen & Knez, 1996). These indicators provide limited flexibility for rating performance due to their exclusion of risk, particularly when assessing the performance of multi-asset portfolios (Bessler *et al.*, 2017; van Dyk *et al.*, 2014; Lolic, 2024). The second category, which includes both classic and modern measurement techniques, comprises measures which incorporate risk and are thus widely used in evaluating multi-asset portfolios. The classic measures are mostly parametric techniques and include the Sharpe ratio (Sharpe, 1998), the M-squared ratio (Modigliani & Modigliani, 1997), the Treynor ratio (Treynor & Black, 1973), Jensen's alpha (Jensen, 1968) and the Information ratio (Gupta *et al.*, 2008). However, due to the realisation that asset returns are mostly non-normally[67] distributed (Bekaert *et al.*, 1998; Konno & Yamazaki, 1991; Sheikh & Qiao, 2010; Van Heerden, 2015), historical return patterns deviate from the symmetric bell curve of a normal distribution, which include lower partial moment measures such as Omega (Keating & Shadwick, 2002), the Sortino ratio (Sortino & Van Der Meer, 1991), and Kappa (Kaplan & Knowles, 2004), as well as drawdown measures such as the Calmar ratio (Young, 1991) as well as the Sterling ratio and the Burke ratio (Eling & Schuhmacher, 2007), are increasingly more popular. The investment literature is also littered with other performance metrics salient in the banking industry, which include value at risk (VaR), conditional VaR (CVaR) and modified VaR (MVaR) (van Heerden, 2020; Jorion, 2012; Klein *et al.*, 2018).

[67] Non normality refers to when the historical return patterns of an asset deviates from the normal distribution by exhibiting considerable skewness and/or excess kurtosis.

The various metrics employed to assess portfolio performance underscore the existence of multiple methodologies for evaluating risk in the context of portfolio performance (Bessler *et al.*, 2017; Chen & Knez, 1996; Grinblatt & Titman, 1989; Kerssens-van Drongelen & Fisscher, 2003). Consequently, there remains ambiguity regarding which measurement techniques, whether traditional or modern, are most effective in accurately accounting for risk-adjusted returns, particularly in portfolios that include cryptocurrencies, which often exhibit non-normal return distributions. Therefore, the subsequent section provides an overview of the concept of risk and the methods by which risk can be parameterised.

3.4.2 Parameterising portfolio risk

Risk is frequently mentioned in the finance literature, yet it lacks a universally accepted definition (Aven, 2012; Wood, 1964). As a result, it is difficult to determine which metrics amongst those used in key financial matters, such as investment theory (standard deviation), the hedge fund industry (Omega) and banking (VaR), reflect risk, especially since investment decisions rely on these metrics (Holton, 2004). Two branches of literature have emerged that document how risk is perceived and thus inform its parameterisation. The first branch is based on Knight's (1965) work and proposes that *a priori* statistical probabilities reflect measurable uncertainty (risk), whereas opinions represent unmeasurable uncertainty (uncertainty). This view of risk (as measurable uncertainty) is problematic in that it is based on an objectivist interpretation of probability, making it more applicable in some fields than in others (Holton, 2004). The second branch of the literature is based on Bridgman's (1954) argument that only what can be perceived can be defined. As a result, only perceived exposure, perceived uncertainty, and, by extension, perceived risk can be defined. This means that the actual risk may not really exist as a concrete fact. Financial experts usually deal with this by using their own judgments to estimate these uncertainties. Since risk can appear in various forms, it is challenging to define it precisely. To manage this, practitioners often focus on certain aspects of risk, like the variability of returns or potential maximum losses. The key practical question then becomes whether a chosen method for measuring risk is effective and if it leads to behaviour that aligns with what management desires (Holton, 2004).

These two strands of literature have led to risk being characterised severally as a concept based on events, consequences and uncertainties (Aven, 2012), a modelled quantifiable concept (Kaplan & Garrick, 1981) and phenomena with subjective descriptions (Campbell, 2005). The last characterisation of risk is more salient as it corroborates the broader view that risk is an uncertain consequence of an event or an activity concerning something that humans value (Rosa, 2010), or that it is exposure to a proposition of which one is uncertain (Holton, 2004). Since the overarching definition of risk is broad, the investment literature is littered with numerous metrics

that investors consider bringing about desirable behaviour. Table 3.3 shows some of the popular measures of risk, discussed in the finance literature and used by academics and practitioners as risk denominators in evaluating risk-adjusted investment performance.

Table 3.3: Risk-adjusted performance measures

Risk measure	Ratio / Measure	Source
Beta	Jensen's alpha, Treynor ratio	Jensen (1968), Treynor and Black (1973)
Standard deviation	Sharpe	Sharpe (1964)
Lower Partial Moments	Omega, Sortino, Kappa 3	Keating and Shadwick (2002), Sortino and Van der Meer (1991) and Kaplan and Knowles (2004)
Maximum drawdown	Calmar	Young (1991)
Value at risk (VaR) Conditional VaR (CVaR) Modified VaR (MVaR)	VaR, CVaR, MVaR	Dowd and Blake (2006), Rockafellar and Uryasev (2000) and Gregoriou and Gueyie (2003)
Tracking error	Modified Information	Israelsen (2005)
Modified standard deviation (adjustment for serial correlation skewness and kurtosis)	Modified Sharpe, Adjusted Sharpe	Israelsen (2005) and Pezier and White (2008)

Adapted from van Heerden (2020).

These multiple risk metrics support the view that investors' focus should be on achieving desirable behaviour or objectives rather than parameterising true risk (Holton, 2004). As a result, there has been a lot of discussion about whether investors and risk managers should prioritise metric accuracy over metric interpretation simplicity when it comes to risk metrics (Rockafeller & Uraysev, 2002). Extreme events, for example, may not be well accounted for in well-understood risk measures like the standard deviation, but they may be well accounted for in less-understood risk measures like the Omega measure, which allows for fatter tails. Thus, using more accurate but less understood risk measures may improve measurement accuracy, but at the expense of understanding ease (Aven, 2012).

This study corroborates the view that risk measurement is not one dimensional, and thus there is no one true portfolio performance measure. Instead, the relevance of a measure varies by context or market condition, type of fund and duration of investment (Chen & Knez, 1996; Cogneau & Hübner, 2009). Thus, in some instances, portfolio performance measures are subjective (Chen & Knez, 1996). There is, therefore, a need to revisit the portfolio performance measurement literature and select a combination of risk measures that otherwise explain the difference elements of risk that a portfolio faces, given that there is no unified approach to measuring risk.

The first and perhaps most popular performance measure is the Sharpe ratio, underpinned by the standard deviation as the risk denominator (Gregoriou & Gueyie, 2003; van Heerden, 2020; Israelsen, 2005; Ledoit & Wolf, 2004). Despite its widespread popularity, the Sharpe ratio is a metric fraught with intense criticism. Several authors (Gregoriou & Gueyie, 2003; van Heerden, 2020; Lakhoo, 2016; Lhabitant & Vicin, 2004; Van Heerden, 2015) have found that it is indifferent

to positive and negative variations from the mean in returns, leading to a misperception of risk. As a result, the risk of a fund may be overstated or understated. Konno and Yamazaki (1991) proposed a mean absolute deviation risk denominator which specifically considers returns below the average in computing risk. Significant criticism of the standard deviation, and consequently the Sharpe ratio, arises because these measures assume returns are normally distributed. However, in real market conditions, returns frequently exhibit skewness or kurtosis, altering the perceived risk profile. As the risk measure is independent of the higher-order moments of returns (mainly skewness and kurtosis), it is also unable to distinguish between erratic and continuous losses. Finally, the Sharpe ratio is based on the risk-free rate that is selected, which might change between markets and time frames and can potentially alter volatility in the portfolio. Thus, the standard deviation is not a reliable risk measure, especially when assessing a portfolio that includes cryptocurrencies whose returns experience significantly higher probabilities of extreme events than predicted by the normal distribution (Liu & Serletis, 2019; Liu & Tsyvinski, 2021; Takaishi, 2020). Despite these overwhelming reasons against the standard deviation, the Sharpe ratio is one of the most popular risk measures that investors understand and relate with. It is chosen for its simplicity in interpretation and general support in the literature (Cogneau & Hübner, 2009; Eling & Schuhmacher, 2007; Murthy, 2018; Platanakis & Urquhart, 2020).

To manage the problem of utilising noticeably suboptimal performance measures in standard deviation (in the Sharpe ratio), one strand of the literature (Rockafellar & Uryasev, 2002; Klein *et al.*, 2018) applies the historical CVaR, which can capture extreme events in a sample. CVaR is a non-parametric technique and is a coherent risk measure, meaning it satisfies some desirable properties such as subadditivity, monotonicity, translation invariance and positive homogeneity, crucial axioms in computing mean-CVaR efficient portfolios (Rockafellar & Uryasev, 2002). However, estimates of CVaR (and VaR) depend on a given level of value significance. This study followed Klein *et al.* (2018) and estimated the CVaR at 99% level as it accounts to the more extreme losses (1%).

Other strands of literature (van Heerden, 2020; Pedersen *et al.*, 2021) have applied the Sortino ratio (SR) of Sortino and Van der Meer (1991) to better account for excess performance by using a downside deviation measure. This downside deviation is related to the popular semi-deviation risk measure. The major difference between the two is that the semi-deviation deems the minimum acceptable return (MAR) threshold as the mean, yet the SR allows users to set a threshold for a minimum acceptable return. Other techniques that are suggested in the literature and popular amongst practitioners include the Calmar ratio of Young (1991), which demonstrates the amount of risk needed to obtain a positive return, as well as the Omega ratio, which captures the higher moments of the return's distribution (van Dyk *et al.*, 2014; Keating & Shadwick, 2002;

Young, 1991). van Heerden and van Heerden (2022) found that the Calmar ratio is the most robust portfolio performance measure and therefore should be considered by both passive and active investors. Regarding the Omega ratio, Van Dyk *et al.* (2014) found that the metric remains popular amongst hedge funds. Its risk denominator is the lower partial moments (LPM), which measures risk by negative deviations of the returns realised concerning a minimally acceptable return. Again, the risk-free rate is deemed a proxy for the minimally acceptable return in line with risk pricing, extensively discussed in the CAPM (Mossin, 1966; Sharpe, 1963; Treynor & Black, 1973). This, however, is subjective and a potential source of debate. Regardless of criticisms, the LPM[68] is arguably a more appropriate measure of risk as it does not include positive deviations from expected return (Sortino & Van Der Meer, 1991). The Omega measure is deemed robust as it is found to capture all the higher-order moments of returns distribution and incorporates sensitivity to return levels (Keating & Shadwick, 2002).

These discussions on performance measurement highlight the ongoing lack of consensus in the literature regarding the choice of ratio or set of ratios to use. Furthermore, the absence of a definitive and widely accepted agreement on defining risk led this study to advocate for a more cautious approach: consulting various risk-adjusted performance ratios to gain diverse perspectives on risk. In addition, to the question of how to evaluate portfolio performance, a plausible question is how frequently performance evaluation should take place. To the best knowledge of this study, there is no clear answer to this question as different investors have varying reporting preferences, objectives, and time horizons. It is clear, however, that actively managed portfolios are, at least in theory, more likely to utilise feedback on portfolio performance rather more frequently to inform their trading strategy. It is therefore important in the context of portfolio management to understand practices relating to portfolio monitoring. This stage of the portfolio management process is discussed extensively in the next section.

3.4.3 Monitoring portfolio performance

Portfolio monitoring is the ongoing process of tracking, evaluating, and adjusting an investment portfolio to ensure it remains aligned with the investor's financial goals, risk tolerance, and market conditions (Anson, 2005; Fabozzi, 2022; Lovell Jr & Arnott, 1989). The key components of monitoring include regularly assessing if returns, risks and allocations meet set objectives, regulatory requirements (for example Regulation 28 in SA prescribes asset allocations for some institutional investors). For most publicly traded assets, monitoring mostly leverages real-time market data allowing for quick decision making, while for other asset classes such as private equity it involves closely overseeing invested companies to ensure they are on track with their

[68] Lower partial moment

value creation plans which is a relatively lengthy process (Lovell & Arnott, 1989). Regardless of how quickly it can be done, portfolio monitoring is essential for maintaining alignment with investment objectives especially as market conditions (evolvement of asset prices) and investor circumstances (levels of wealth, time horizon, liquidity requirements, taxation and other regulations) change (Woodside-Oriakhi *et al.*, 2013). To maintain the alignment with objectives, over time, portfolios, almost always require to be rebalanced (Tokat & Wicas, 2007).

In its simplest form, portfolio rebalancing involves periodically adjusting the portfolio back to predetermined asset allocations. The finance literature (Eakins & Stansell, 2007; Mulvey & Simsek, 2002) documents three portfolio rebalancing strategies commonly practised in the industry that inform investors how and when best to rebalance portfolios. These are: (*i*) time-only, (*ii*) threshold-only and (*iii*) a combination of both. Time only specifies the period frequency that a portfolio may be rebalanced at (for example, monthly, quarterly, semi-annually or yearly), while threshold only triggers rebalancing when some thresholds are bridged (for example, the portfolio returns underperform the market by some prespecified margin) or both in the case of a hybrid strategy. There remains a notable dearth of empirical research that rigorously evaluates the optimal method or frequency for portfolio rebalancing. This gap is likely attributable to the fact that rebalancing outcomes are highly sensitive to a range of contextual factors, including prevailing market conditions, transaction costs, tax considerations, and investor-specific objectives. Consequently, the formulation of a universally applicable rebalancing strategy is inherently challenging.

Despite this, Zilbering *et al*. (2015) found that risk-adjusted returns do not differ significantly from one rebalancing strategy to another. Zilbering *et al.* (2015) argue that, for most broadly diversified equity and bond portfolios, a hybrid strategy of semi-annual or annual monitoring, with rebalancing at 5% thresholds, produces an optimal balance between risk control and cost minimisation for most investors. Other authors (Jia *et al.*, 2021; Smales, 2021) argue that when investing in assets such as cryptocurrencies, annual rebalancing is too long and may expose a portfolio to higher levels of risks especially considering that cryptocurrencies are highly volatile and susceptible to higher crash risks. As a result, there is a need for more adept portfolio monitoring which acknowledges that tactically rebalancing[69] asset holdings is key towards accomplishing portfolio objectives, which mostly entail minimising risk and maximising return (Zilbering *et al.*, 2015).

Such portfolio monitoring should be inextricably linked to the evolvement of asset prices, as they are best at determining the timing of when to rebalance (Bianchi, 2020). For example, indications

[69] Tactical rebalancing allows investors to temporarily deviate from their target allocations to capitalise on market trends (Zilbering *et al*., 2015).

that an asset is likely to outperform others within the near future may call for rebalancing towards increasing exposure to that asset and vice versa to enhance returns. Finance literature increasingly supports a more nuanced approach that determines the timing of rebalancing based on market signals and measured deviations rather than on a fixed calendar schedule. The traditional view, rooted in the MVO advocated by Markowitz (1952), implies that maintaining a constant asset allocation is critical to preserving a portfolio's risk-return trade-off. In practice, however, several studies have demonstrated that strictly periodic rebalancing can be suboptimal when compared with dynamic strategies that incorporate market conditions. For example, Guo and Ryan (2023) propose a hybrid strategy that uses time series momentum signals in tandem with downside risk controls to determine when a portfolio's allocation has significantly drifted from its target. Their approach termed the time series momentum controlling downside risk (TSMDR) strategy generates trading signals that trigger rebalancing only when the conditional value-at-risk (CVaR) exceeds a predetermined threshold, thereby enhancing risk-adjusted performance. Complementing this perspective, Dai *et al*. (2024) advocated for an adaptive rebalancing strategy, which follows market-driven triggers rather than fixed intervals. Dai *et al*. (2024) argued that that an adaptive strategy led to better performance compared to traditional periodic rebalancing approaches.

There are several other technical indicators ranging from classic approaches such as moving average crossovers (Pätäri & Vilska, 2014) and sophisticated approaches that include the Fibonacci retracements (Gaucan, 2011) and harmonic patterns (Hazan & Kale, 2015) which while generate trading signals may also be used as triggers to rebalance portfolios in a dynamic rebalancing strategy. Most of these technical signals are extensively discussed by Lukac *et al.* (1989), who found that at least 12 trading systems (moving average crossover, filter rule, channel breakout, volatility breakout, on-balance volume, relative strength index, stochastic oscillator, moving average convergence divergence, directional movement index, parabolic time/price system, commodity channel index and Bollinger bands) are the most applied in generating trading signals. Of these 12, the moving average crossover (5-day and 20-day), channel breakout (20-day) and volatility breakout (1-day range) tend to produce significant returns after adjusting for transaction costs (Lukac *et al.*, 1989). However, these strategies' duration is short and presents implementation challenges, given that market infrastructure weaknesses related to imperfect liquidity (Galariotis & Giouvris, 2015) lags in trade settlements (Bartolini *et al.*, 2010) and positive transaction costs (Benston & Smith, 1976; Dávila, 2023).

The key takeaway from the foregoing arguments is that optimal frequency of portfolio rebalancing depends on the diverse circumstances and objectives of each investor. Therefore, a suitable rebalancing strategy ought not be based on a specific metric but rather vary based on an

evaluation of the market opportunities given that most investors seek to buy low and sell high. Consequently, investors who participate in markets that offer relatively more chances for extraordinary profits will need to rebalance more often. This phenomenon is inextricably linked to market efficiency as discussed by Lo (2004), who argued that situations where markets are inefficient presented more possibilities for large gains (and losses) and demand more frequent rebalancing. Several researchers (DeMiguel *et al.*, 2009; Fama, 1965; Perold & Sharpe, 1988; Samuelson, 1965; Sharpe, 1964) corroborated this view and theorise that the degree of efficiency provides a general indication of the market condition. However, it is important to note that AMH requires regime-triggered rebalancing, which is beyond the scope of this thesis. The present study assesses informational efficiency within a static allocation evaluation necessity to rebalance portfolios. There is, therefore, a need to explore in depth what market efficiency means, how it is measured and its implications for portfolio management.

3.6 Empirical evidence on cryptocurrency allocations and portfolio performance

MPT posits that combining assets exhibiting low or negative return correlations optimises portfolio performance – placing diversification at the centre of portfolio management. Cryptocurrencies have emerged as prospective diversifiers due to their unique return characteristics and limited correlation with traditional assets such as bonds and equity. However, their diversification capabilities are a subject of debate. Empirical studies conducted within the US reported varying results. Brière *et al*. (2015) applied a spanning MVO framework on data from 2010–2013 and showed that the MVP of a portfolio of currencies, equity, bonds, commodities, hedge funds and real estate excluded BTC due to its inherent volatility. However, a slight increase in the investor's risk tolerance to 6% volatility resulted in a 3% allocation to BTC, which more than doubled annual returns from 8.8% to 17.6% and trimmed annualised semi-variance by almost half from 4.2% to 2.8%. At the 12% volatility level, including 6% of BTC in the portfolio enhanced the average return from 13.1% to 32.5%, while annualised semi-variance declined from 8.8% to 5.4%. However, the adjusted Sharpe ratio decreased from 0.7 to -1.1, indicating that, even for moderately risk-averse investors, BTC may lead to substantial financial gains, but simultaneously increase especially extreme risk. Meanwhile, Ang *et al*. (2023) argued that an allocation of approximately 10% to BTC, 25% to equity and 65% to bonds yielded the best risk-return trade-off. The asset allocations suggested by Brière *et al*. (2015) and Ang *et al*. (2023) were substantial. By contrast, the Blackrock investment institute contend that, in a hypothetical 60-40 equity-bond portfolio, a conservative 1% allocation to BTC resulted in a BTC carrying 2% risk share of the portfolio. A 2% allocation resulted in a risk share of 5%, while 4% resulted in a risk share of 14%. By comparison, an average 1–2% allocation to BTC carried the risk comparable to allocations to the "magnificent 7" stocks (Alphabet, Amazon, Apple, Meta, Microsoft, Nvidia and Tesla) of which their risk share

was 4%. Blackrock investment institute risk contribution was estimated using weekly returns between May 2012 and July 2024.

Conlon *et al*. (2020) opened a window of opportunity to appraise the diversification capabilities of cryptocurrencies in crisis periods. Their study focused on relative change in VaR and MVaR, when risk in an equity index was compared with risk in a mix containing an equity index and a cryptocurrency. They found that any allocation to BTC and ETH over the period 2010–2020 and 2015–2020, respectively, resulted in increased VaR and CvaR, indicating neither cryptocurrency was a hedge. However, allocation to USDT of 20–30% reduced downside risk, indicating hedging properties even during the Covid-19 periods. However, these allocations imply a greater acceptance of risk.

In the South African setting, Robertson (2018) demonstrated that a 12.74% allocation to BTC was most optimal from an MVO perspective within a typical Regulation 28 portfolio. This allocation resulted in optimal allocation to BTC, which increased the mean monthly return by a factor of four (from 1.05% to 3.97%), with a relatively low increase in semi-deviation (1.31% to 2.07%). An allocation as low as 5% significantly enhanced portfolio performance and was found most desirable. Letho *et al*., 2022 applied the MVO spanning tests of Brière *et al*. (2015) and found that, within a broad-based portfolio of SA equity, bonds commodities and currencies, an optimal allocation was 2% to cryptocurrencies. This allocation resulted in returns increasing from 8.64% to 11.64%, while volatility increased from 2.58% to 2.93%. Collectively, these findings indicate that integrating cryptocurrencies can enhance the performance of traditional portfolios, although diversification is still unclear, especially in crisis periods.

3.5 Conclusions

This chapter examined various aspects and approaches to portfolio management, including asset allocation, capital allocation frameworks, portfolio performance measurement and monitoring. It demonstrated that a robust portfolio management approach requires asset allocation strategies that are meticulously aligned with investors' objectives. Such alignment is achieved through a formal capital allocation framework that ensures consistency between the portfolio's structure and the investor's objectives. In the context of portfolios incorporating cryptocurrencies, the adoption of optimal allocation strategies, particularly those based on the MVO, MVP optimisation and the Black and Litterman (1992) framework are imperative. The MVP approach is particularly valued for its robustness, as it circumvents the pitfalls associated with estimating expected returns, which are error prone. Concurrently, the Black and Litterman (1992) model offers a systematic method for integrating diverse asset classes into a multi-asset portfolio, thereby aligning with prevailing industry practices. While the traditional MVO framework may exhibit suboptimal performance in

certain aspects, its widespread recognition and application underscore its continued relevance as a foundational tool in portfolio construction.

Moreover, this chapter underscored the necessity of employing multiple performance metrics when assessing the impact of cryptocurrencies on portfolio performance. Given the lack of consensus regarding an optimal single performance ratio, utilising a spectrum of measures facilitates a more comprehensive evaluation by capturing distinct facets of risk and return dynamics.

Finally, the determination of an appropriate rebalancing frequency emerges as a critical factor in sustaining a portfolio's intended risk profile over time. The literature indicates that while rebalancing can occur at regular intervals (monthly, quarterly, semi-annually, or annually) or be triggered by quantitative signals (thresholds), the optimal strategy remains context dependent. It is widely acknowledged that prevailing market conditions best understood through the lens of market efficiency play an important role in informing the rebalancing process. Considering these insights, the forthcoming chapter will explore market efficiency and its overarching implications for portfolio management, further enriching the understanding of portfolio management.

CHAPTER FOUR

MARKET EFFICIENCY THEORY AND EMPIRICAL CONSIDERATIONS

4.1 Introduction

Early researchers in the field of mathematics and financial markets (Regnault 1863, cited in Sewell 2012; Bachelier cited in Sewell 2012) were particularly interested in how fortunes may be made or lost by taking different positions on the securities exchanges and how prices of securities evolve. This part of the literature is based on the pioneering work of De Moivre (1756, cited in Schneider 2005) and Bayes (1763, cited in Bellhouse 2004). De Moivre published *Doctrine of Chance* – a foundational text that introduced key concepts and methods for calculating probabilities. Bayes extended De Moivre *Doctrine of Chance* by including theorems of conditional probability. Their research closely linked the process of pricing in financial markets to statistical methods. Early research on the pricing process in financial markets adopted a statistical perspective, investigating the forecasting of security prices (Schultz, 1925) and attempting to parametrise asset prices through statistical methods (Working, 1934). These studies found that fluctuations in the securities market resembled a chance curve, such as one obtained by rolling dice or drawing lottery numbers. He further observed that market prices exhibited characteristics akin to a random-difference series (Working, 1934). These findings are supported by Kendall and Hill (1953) and Harry (1959) who argued that market prices follow a random walk and investment professionals do not consistently beat the market (Cowles, 1944). This idea that fluctuations in financial markets follow a random walk and that investment professionals could not consistently outperform the market was formalised by Samuelson (1965) and operationalised by Fama (1965), coining this phenomenon as the EMH. The proposition under the EMH is that markets are efficient (Malkiel, 2003).

An [informationally] efficient market is one where prices fully incorporate the expectations of all the players in the market making the following price changes unpredictable (Lo, 2017). Efficient markets are thus driven by perfect information flow (no information asymmetry) and no consistent profit opportunities, with rational behaviour not strictly required if deviations from it are uncorrelated, for example if some investors overreact to news while others underreact (Lo, 2017). The immediate implications are that when markets are efficient, the expected value of information gathering (for example security research) is zero. It also means that low-cost portfolio execution strategies such as buy-and-hold and indexation are beneficial to investors.

As a result, the EMH (which hypothesises that markets are efficient) is contradictory and offers no explanation for why the investment management industry persists (Campbell, 2005). A growing branch of literature has confronted this paradox head on in an endeavour to offer answers to the

persistence of the investment management industry and profession. This branch includes behavioural finance scholars (Arrow, 1990a; Daniel *et al.*, 1998; Kahneman & Tversky, 1973; Shleifer, 2000) as well as proponents of the Adaptive Markets Hypothesis (AMH) (Lo, 2004).

This chapter explored in depth the EMH and other alternative theories that have emerged that characterise market efficiency and to profile the circumstances under which the theory provides pragmatic explanations of the behaviour of asset prices. Consequently, Section 4.2 explores the evolution of market efficiency theory and the implications that this theory has for investors and portfolio managers. Section 4.3 examines the criticisms of the EMH. Section 4.4 focuses on the developments leading to the behavioural finance view of market efficiency. Section 4.5 details the implication of behavioural finance to portfolio management. Section 4.6 reports the current findings on cryptocurrency market efficiency, and finally, Section 4.7 highlights the key risk measures to adopt in evaluating cryptocurrency portfolios.

4.2 The evolution of market efficiency theory

Much of modern finance literature (Lim & Brooks, 2011; Mlambo & Biekpe, 2007; Mokni *et al.*, 2025; Smith & Dyakova, 2014; Zhang *et al.*, 2018) cite Fama (1965) and Samuelson (1965) as the founding fathers of the EMH. However, there exists a large body of literature (Table 4.1) that detailed the behaviour of asset prices before operationalisation of the EMH by Fama (1965).

Table 4.1: Selected literature findings on the behaviour of asset prices

Source	Findings
Cardano 1564 cited in Bellhouse (2004)	The fundamental principle in gambling is equal opportunities.
Regnault 1863 cited in Sewell (2012)	The security price volatility is directly proportional to the square root of time. The longer you hold an asset, the more you can win or lose.
Gibson 1889 cited in Sewell (2012)	When assets become publicly known in an open market, the value that they acquire may be regarded as the judgement of the best intelligence concerning them.
Bachelier 1900 cited in Sewell (2012)	The mathematical expectation of the speculator is zero.
Mitchell 1915 cited in Mandelbrot (1963)	The distribution of price changes is too peaked to be relative to samples from Gaussian populations.
Taussig (1921)	Fluctuations in commodity prices are influenced by many speculators, most of whom are ill informed, are merely the gambling public, and for the most part, are outwitted by the professionals.
Working (1934)	Equity returns behave like numbers from a lottery.
Cowles (1944)	Investment professionals do not beat the market.
Kendall and Hill (1953)	Prices are random.
Schultz (1925)	Equity returns series follow a random walk.
Paetz (1972)	A scaled *t*-distribution produces a better fit to equity prices than the Brownian motion.
Larson (1960)	The distribution of price changes is close to normal for 80% of the data, but there is an excessive number of extreme values.
Alexander (1961)	The random walk model best fits the distribution of returns, but there is leptokurtosis in the distribution of returns.
Cootner (1962)	The stock market is not a random walk.
Granger and Morgenstern (1963)	Short-run movement of market prices obey the simple random walk hypothesis, but long-run movements do not.
Mandelbrot (1963)	Equity prices resemble stable Paretian distributions.
Steiger (1964)	Equity prices do not follow a random walk.

Source: Compiled by Author.

Across several decades of inquiry, the momentous studies converge on the insight that pricing dynamics in financial markets are shaped by a complex combination of random shocks, investor psychology and structural frictions, as opposed to fundamental valuation. Authors such as Godfrey *et al*. (1964) formalised the random walk hypothesis of security market behaviour, thereby supporting earlier findings by Bachelier (1900, cited in Sewell 2012), MacCauley (1925), Working (1934), Kendall and Hill (1953), Harry (1959) and Alexander (1961), which suggested that security prices follow a random process, while simultaneously challenging the conclusions of Cootner (1962) and Steiger (1964), who reported no evidence that security markets exhibit random walk behaviour.

The random walk hypothesis lay a foundation for further debate on whether security returns in markets are efficient or not. Samuelson (1965) formalised the idea of efficient markets wherein he argued that properly anticipated asset prices fluctuate randomly. In proving that prices fluctuate randomly, Samuelson (1965) focused on the concept of a martingale, unlike Fama (1965), who took the approach of a random walk process. The difference between a martingale and a random walk process is extensively discussed in Mandelbrot (1966a). The author holds that a martingale is a special case of random walk without drift. Fama (1965) explained how the idea of a random walk process presents challenges to both technical and fundamental analysts exploring developments in market prices. The formalisation of the idea of efficient markets by Samuelson (1965) also had a significant influence on both portfolio management and asset pricing literature as it set the stage for decades of debate and innovation on investment strategies, pricing models, and financial research.

One of the earliest researchers to leverage the idea of efficient markets is Mossin (1966) who integrated it to the developed of the Capital Asset Pricing Model (CAPM) from the pioneering works of Markowitz (1952), Sharpe (1964) and Lintner (1965). To date, the CAPM is one of the most popular models guiding investment asset allocation between a risky portfolio and a risk-free asset. Second, Mandelbrot (1966) confirmed Samuelson's conclusion (1965) and found that, in competitive markets with rational risk-neutral investors, returns are unpredictable, and security prices follow a martingale process (future price changes are independent of past changes), thereby cementing the notion of efficient markets. However, it was Roberts (1967, cited in Sewell 2012) who first introduced the nomenclature for the phenomenon of unpredictable price movements. He coined the term Efficient Market Hypothesis (EMH) and classified market efficiency into two forms: weak and strong. Fama (1991) reinforced the EMH as a research field that would remain a source of debate for decades and expanded its taxonomy from two forms to three: the weak form, the semi-strong form, and the strong form.

Fama (1991) delineated weak-form market efficiency as a condition in which all historical price information is wholly embedded in current asset prices. In such a market, the past offers no exploitable advantage, meaning that investors and portfolio managers cannot consistently generate abnormal returns using historical data alone (Lim & Brooks, 2011; Lo, 2017; Malkiel, 2003). In contrast, semi-strong market efficiency asserts that asset prices not only reflect past information, but also instantaneously incorporate all publicly available data ranging from news releases to macroeconomic indicators (Finnerty, 1976; Groenewold & Kang, 1993). Empirical investigations have applied the semi-strong framework across various asset classes, including equities and commodities (Mackey & Bacon, 2017) and cryptocurrencies (Vidal-Tomás & Ibañez, 2018). Crucially, a market that is semi-strong efficient also satisfies the conditions of weak-form efficiency, the converse is not necessarily true as the latter only requires that historical price data is reflected in current prices, without guaranteeing an immediate reaction to new public information. Extending this idea further, strong-form efficiency posits that market prices encapsulate all information historical, public as well as private, thereby eliminating any potential edge from insider or publicly sourced information (Fama, 1991). However, the literature (Finnerty, 1976; Lo, 2017; Rozeff & Zaman, 1988) showed that there are advantages of utilising private (insider) information. Regulators in numerous jurisdictions established laws designed to curb insider trading and ultimately protect market integrity and enhance investor confidence, boosting trust and increasing economic activity (Öberg, 2014).

In the cryptocurrency market, it is widely accepted that price changes are dominated by supply-demand mechanics and market sentiments (Liu & Tsyvinski, 2021; Peng *et al.*, 2024; Sibande *et al.*, 2023) as well as regulatory news (Auer & Claessens, 2021; Chokor & Alfieri, 2021; Feinstein & Werbach, 2021; John *et al.*, 2024) and security incidents (Apostolaki *et al.*, 2017; Scharfman, 2024; Xia *et al.*, 2020). Operationalising semi-strong form tests – which assess whether prices rapidly incorporate all publicly available information, including fundamental financial metrics – face several methodological challenges (John *et al.*, 2024; Mokni *et al.*, 2025). First, this study's search found no accepted *risk-free* rate in cryptocurrencies necessary to what can be regarded as abnormal returns (Mokni *et al*., 2025). Second, cryptocurrency events are widely popular on social media, making the process of accurately pinpointing price event dates and times challenging given the unstandardised nature in which 'news' in social media platforms is announced (John *et al*., 2024). Finally, with no clear and widely agreed fundamental indicators (John *et al*., 2024), for example earnings per share in equities instruments, as discussed in the literature (Shiller, 1981; Siegel, 2016), it is not always straightforward what to observe to assess how cryptocurrency markets digest new information. This is because most public information relating to cryptocurrencies is not fundamental in nature but mainly consists of event-based news such as regulatory announcements, security breaches, or technological upgrades (Auer &

Claessens, 2021; Rognone *et al.*, 2020; Sapkota, 2022). The market's reaction to these events tends to be driven more by sentiments and speculative behaviour (Anamika *et al.*, 2023; Gaies *et al.*, 2023). Consequently, observed price responses may reflect transitory shifts in sentiment rather than the rapid incorporation of objective, value-based information such as on-chain adoption.

Vidal-Tomás and Ibañez (2018) are among the limited number of scholars who have confronted these challenges and explored the semi-strong form efficiency of cryptocurrency markets. Employing an event-study framework, they analysed the responsiveness of Bitcoin prices to the dissemination of publicly available information. Their baseline model was predicated on a fixed, static model of expected returns. However, the two challenges are associated with testing for semi-strong form of market efficiency are evident in their approach. Firstly, cryptocurrency news is predominantly disseminated through various social media channels due to the decentralized nature of these markets, which lack a single entity responsible for communication. This decentralization complicates the process of timestamping news. Secondly, the static fixed returns model did not adequately capture the rapidly evolving structure, volatility dynamics, and informational complexity inherent in cryptocurrency markets. Notably, Vidal-Tomás and Ibañez (2018) acknowledge the broader dearth of research on semi-strong form market efficiency within the cryptocurrency domain. Beyond semi-strong form, strong-form efficiency necessitates that prices reflect all public information. This study posits that the decentralised architecture and anonymous nature of cryptocurrencies fundamentally complicate the empirical testing of strong-form efficiency, as the concept of "private information" becomes challenging to define, observe, or attribute within such systems.

Limited research in semi-strong (and strong-form) market efficiency introduces a gap in comprehending developments within cryptocurrency markets. When a market is weak-form efficient but semi-strong inefficient, past prices contain no exploitable information, yet publicly available information is not fully or rapidly incorporated into prices. This creates an environment where technical analysis is ineffective, but event-based strategies can yield abnormal returns, indicating incomplete information processing and persistent mispricing. This gap is exacerbated by the divergent perspectives on whether market efficiency should be assessed at an aggregated index level or at the disaggregated, individual asset level, with each perspective bearing distinct implications for investors and portfolio managers.

Furthermore, the evolving dynamics of market conditions continually challenge conventional efficiency paradigms, prompting further examination of how (evolution) can be incorporated into existing testing frameworks. The following section seeks to address these methodological gaps,

offering a comprehensive exploration of market efficiency testing and its consequential impact on investment strategies.

4.2.1 Testing Market Efficiency

One of the major implications of market efficiency is that investors and portfolio managers cannot consistently beat the market by using common investment strategies (Lo, 2004). As a result, testing whether a market can be beaten requires the specific evaluation of an investment strategy to determine if it results in excess returns (Loughran & Ritter, 2000). More rigorous tests incorporate transaction costs (emanating from both superior information gathering, sophisticated equity research and transaction settlement) and execution constraints (due to investor considerations) to explore whether any positive net returns accrue to profit-maximising investors (Gay & Jung, 1999).

Testing market efficiency may, therefore, be viewed as an assessment to invalidate the existence of positive excess returns (the difference between the actual and expected return on investment). Such an approach is predicated on the existence of a "true" model for parameterising expected returns. For this reason, testing of market efficiency is a joint test of market efficiency and the efficacy of the model used for expected returns (Jensen, 1978; Loughran & Ritter, 2000). Evidence of excess returns in such a test of market efficiency may give a false negative assessment, suggesting that markets are inefficient or that the model used to compute expected returns is wrong, or both. While this error presents a dilemma on the interpretation of results, when conclusions are insensitive to different return models, then it is likely that the results are being driven by true market inefficiencies and not just by model misspecifications (Loughran & Ritter, 2000). There are several other methods to test market efficiency which largely depend on the type of investment strategy being evaluated. For strategies based on trading information such as stock splits, earnings announcements, mergers and acquisition announcements, one common method is to use event studies, as described by Fama (1991). In event studies, returns around the event are analysed to detect any abnormal profits. For strategies that are based on firm-specific characteristics (like price-earnings ratios, price-book value ratios, or dividend yields), a ‘portfolio’ approach is often used. This involves creating and monitoring portfolios of assets that share these characteristics to see if they yield excess returns over time. Other approaches to test market efficiency are summarised in Table 4.2.

Table 4.2: Tests of market efficiency

Authors	Methodology utilised
Granger and Morgenstern (1963)	Spectral analysis
Alexander (1961)	Technical analysis
Ball and Brown (1968)	Abnormal returns
Shiller (1979)	Autocorrelation runs test
De Bondt and Thaler (1985)	Runs test
Fama and French (1988a)	Brownian motion
Lo and Mackinlay (1988)	Variance ratio
Choudhry (1994)	Augmented Dickey-Fuller, Kwiatkowski-Phillips-Schmidt-Shin (KPSS), cointegration
Al-Loughani (1995)	Serial correlation, Augmented Dickey-Fuller and Brock, Dechert, and Scheinkman (BDS) nonlinear test
Worthington and Higgs (2004)	Autocorrelation, Augmented Dickey-Fuller, Phillips-Peron (PP), Kwiatkowski-Phillips-Schmidt-Shin (KPSS) and Runs test
Jefferis and Smith (2005)	Test of evolving efficiency

Source: Compiled by Author.

Despite the wide range of approaches employed, the research remains divided on the most appropriate test methodology and whether tests should be performed on index or constituent asset level. This is because there are observed differences in efficiency between assets and the underlying index (Saha *et al.*, 2022). Differences in efficiency between an asset and the index (where that asset is also part of) presents some opportunities and challenges for investors, especially during portfolio construction. Investors selecting assets from markets deemed efficient (based on indices) may, for example, adopt more passive investment strategies, relying on broad market exposure to generate returns. However, individual assets within these indices may still exhibit inefficiencies and mispricing due to temporary disconnects from fair value. As a result, overvalued assets may face corrections, leading to potential losses, while undervalued securities present opportunities for active trading strategies to capitalise on these inefficiencies. Therefore, future studies need to explore in depth the appropriate portfolio management approaches of investing in a market, where the index is by and large efficient, yet significant constituents are inefficient. This is because several investors in equity markets seemingly invest in individual assets as opposed to indices - which are mostly tested for efficiency. The following section explores some of the relevant findings on market efficiency and assesses the levels at which efficiency has been measured using the different approaches cited in Table 4.2.

4.2.2 Evidence of market efficiency

Early financial market researchers (Black *et al.*, 1972; Fama, 1965; Jensen *et al.*, 1972) found evidence supporting the EMH. This is corroborated in several studies (Fama, 1991; Fama & French, 1988a; Lim & Brooks, 2011; Malkiel, 2003) despite overwhelming criticism. To this end, the EMH continues to be relevant in explaining asset price discovery processes (Fama, 1991) due to several justifications.

- First, the continued efficiency observed in financial markets is because, when anomalies are published, practitioners implement strategies implied by research and the anomalies subsequently weaken or disappear, implying that research findings cause the market to become more efficient (Schwert, 1990). This corroborates findings by Metcalf and Malkiel (1994) who found that investors do not consistently beat the market because markets self-correct from temporary mispricing. Haugen (1996) also noted that short-run overreaction (which causes momentum in prices) may lead to long-term reversals (when the market recognises its past error) and investors would not persistently achieve above-market returns.
- Second, financial markets are not always efficient because news (information) is not the only factor that adequately explains price movement. Instead, other factors, which include competition, liquidity, duration in transaction settlement and transaction costs also explain market movements (Lo, 2017; Shleifer, 2000). Thus, in practice (as opposed to theory) it is hard to profit from the observed predictability of returns, primarily because there are market frictions that include transaction costs, taxation and other related costs that eliminate the 'theoretical' profits, thereby confirming the EMH.

Despite these justifications, the literature detailing criticism of the EMH has grown to about as much as the literature supporting it. Criticisms of the EMH are widespread and include theoretical foundations of the hypothesis' weaknesses, bias in statistical tests of market efficiency and price behaviour not in line with the EMH.

- On theoretical foundations, the literature critiques the theoretical justification for Mandelbrot's (1966b)martingale property. Mandelbrot (1966) subsumed risk neutrality in formulating the martingale hypothesis, which underlies the formalisation of the EMH by Samuelson (1965). Several studies (Hood & Nofsinger, 2007; LeRoy, 1973; Tsaur, 2013) argued that, in practice, investors are risk averse and not risk neutral.
- Regarding statistical tests, Smidt (1968) argued that tests of efficiency bias the outcome towards acceptance of market efficiency as they are not directed toward a specific alternative hypothesis. Moreover, several statistical tests of market efficiency have been found to have low power, thereby making it difficult to reject market efficiency (Summers, 1986).
- On asset price behaviour, several branches of literature have emerged challenging various aspects of market efficiency including non-randomness of asset prices (Kemp & Reid, 1971), excess volatility (LeRoy & Porter, 1981), autocorrelations (Fama & French, 1988a; Lo & MacKinlay, 1989; Poterba & Summers, 1988) and predictability (Bekaert & Hodrick, 1992; Huang & Stoll, 1994; Jegadeesh, 1991; Kandel & Stambaugh, 1996;

McQueen & Thorley, 1991; Urquhart & McGroarty, 2016). All these factors point to the stationarity of asset prices, suggesting market inefficiency.

The debate on whether markets are efficient or not has not yielded any consensus due, in part, to the proof of certain anomalies that could not be explained by the EMH. Lo (2017) defined an anomaly as a reliable and regular (and therefore predictable) pattern in returns of an asset that is widely known. Understanding anomalies is important as they represent instances where asset prices deviate from (market efficiency) expected behaviour, potentially offering opportunities for excess returns. The sections that follow present some of the key studies that found market anomalies as they represent a turning point in the market efficiency debate. For a broader discussion on market anomalies, Moy and Lee (1991) detail a list of bibliographies that may be consulted. The next sections highlight key findings in selected studies from this vast literature.

4.2.2.1 Market anomalies

Market anomalies represent deviations from the predictions of the EMH, which posits that asset prices fully reflect all available information. These anomalies, often exemplified by seasonality in equity returns, the existence of earnings yields in equity returns, size-related anomalies, the impact of macroeconomic factors on equity returns, and the presence of autocorrelation in equity return, challenge the notion of perfectly efficient markets and provide avenues for excess returns. Empirical research has identified these persistent anomalies suggesting that informational dissemination is imperfect. Understanding these anomalies is crucial for realising that assets can be mispriced thereby fostering refining of investment strategies and advancing the theoretical foundations of finance and economics.

One of the most persistent anomalies that have been observed in the financial markets is seasonality in equity returns, which is generally distinguished between the January effect, and calendar effects such as holiday, weekend, and turn-of-the-month seasonality (Lakonishok & Smidt, 1988). The January effect (Constantinides, 1984; Haugen & Jorion, 1996; Keim, 1989; Reinganum & Gangopadhyay, 1991; Rogalski & Tinic, 1986; Thaler, 1987) and other calendar anomalies (Brooks & Kim, 1997; Jaffe & Westerfield, 1985; Kohers & Kohers, 1995; Lakonishok & Smidt, 1988; Smirlock & Starks, 1986) have attracted a lot of research leading to their extensive documentation in the literature. The literature indicates that the effects of seasonality are primarily attributable to price movements, with prices tending to align more closely with bid prices on exchange closing days (such as in December, on a Friday, or the last trading day preceding a holiday) and with ask prices when trading resumes (such as in January, on a Monday, or the next trading day following a holiday). Theoretically, investors may capitalise on these trends by purchasing at the lower bid price in December and selling at the higher ask price in January, thereby consistently achieving elevated profits in a manner that challenges the EMH.

While the presence of seasonality effects challenges the validity of the EMH, it remains arguable that the issue of whether investors can consistently derive profit from seasonality anomalies warrants more thorough examination. Theoretically, seasonality effects may present profit opportunities; however, in practice, several critical factors must be considered before these profits can be realised. These factors include transaction costs, liquidity constraints – particularly at the turn of the year and certain institutional rigidities (Lim & Brooks, 2011). Consequently, it is plausible that accounting for these costs may negate any potential profit opportunities, thereby supporting the EMH. Therefore, it is imperative to incorporate all practical considerations as comprehensively as possible when assessing the impact of anomalies.

Another leading anomaly salient in the literature is the existence of dividend yields and earnings yields in equity returns. Black and Scholes (1974) and Ball (1978) are some of the first authors to have researched this anomaly. While Black and Scholes (1974) explored whether expected returns on high-yield equity differ from the expected returns on low-yield equity after considering taxation, Ball (1978) surveyed anomalies in relationships between securities' yields and yield-surrogate and found that the earnings yield (earnings-to-price ratio) is a significant proxy for expected returns. Ball's (1978) survey revealed consistent excess returns after public announcements of firms' earnings. These studies laid the foundation for Basu (1977), who confirmed that equity with low price-to-earnings ratios earned higher risk-adjusted returns than equity with higher price-to-earnings ratios. However, after considering taxation, Basu (1977) concluded that tax effects hinder speculators from exploiting the price-to-earnings ratio. Other such tests were also done by Litzenberger and Ramaswamy (1979) [dividends], Shiller (1981) [dividends], Reinganum (1981) [earnings yield], Rozeff (1984) [dividends yields], Kormendi and Lipe, (1987) [earnings yield], Fama and French (1988) [dividends yields], Campbell and Shiller (1988) [equity prices, earnings and expected dividends]. These research studies confirm that both earnings yield and dividend yield may be leveraged to consistently beat the market. Additionally, Spaht and Rubin (2016) found that investing in a basket of dividend-paying equity outperforms indexing (and the market return), thereby confirming the dividend market anomaly.

Another anomaly, that is one of the most researched of all the anomalies, is size. Over the 1980s several researchers (Banz, 1981; Brown *et al.*, 1983; Cook & Rozeff, 1984) had explored the relationship between firm size and market return. It is, however, Fama and French's (1995) seminal paper that cemented the view that firm size and the book-to-market (B/M) ratio strongly predict future equity returns. Fama and French (1993) corroborate this idea and gave evidence that a three-factor model based on the size and book-to-market characteristics of firms explains average returns. Several studies (Agrawal & Tandon, 1994; Brennan *et al.*, 1998; Frankel & Lee, 1998; Naranjo *et al.*, 1998; Nelson & Kim, 1993) confirmed that investments based on size and

book-to-market value result in reward-to-risk ratios higher that obtained by investing in the market portfolio. Various studies (Brown *et al.*, 1983; Dowen & Bauman, 1986; Schwert, 1983) have found that the average returns of small firms exceed those of large firms and the market in general. The EMH and its proponents have not provided plausible explanations for why returns vary with size.

In addition to firm-specific metrics such as dividend yields, earnings yields, and size influencing equity returns, research has demonstrated that macroeconomic variables also affect equity returns. Nelson (1976) identified a negative relationship between equity returns and both anticipated and unanticipated changes in the rate of inflation. However, Nelson (1976) argued that this relationship does not inherently refute the EMH, primarily because it is not a testable hypothesis. Instead, the observation that predicted equity returns are sometimes lower than risk-free yields, and occasionally negative, suggests that the market may be inefficient at times. Several other scholars (Chen *et al.*, 1986; Fama, 1981; Geske & Roll, 1983; Gultekin, 1983; Schwert, 1990) have corroborated the negative relationship between inflation and equity returns. There is a consensus that rising inflation adversely affects real economic activity, which in turn leads to lower equity returns. While much of the focus on macroeconomic anomalies has been on examining the relationship between equity returns and inflation, two other macroeconomic metrics are significant in explaining equity returns. These metrics are the term structure of interest (Long Jr, 1974) and monetary policy decisions (Rozeff, 1974).

Finally, there is evidence of autocorrelation in equity returns – a condition that should not be possible under the EMH, since it violates the random walk processes. The years 1988 was very eventful concerning the autocorrelation anomaly. First, Fama and French (1988b) found significantly large and negative autocorrelations for equity portfolio return horizons beyond a year. This implies that past prices may be used to predict future prices. Moreover, they found that about 40% of three-to-five-year return variances for portfolios of small firms are predictable and that this percentage falls to around 25% for portfolios that consist of large firms only, reinforcing the size anomaly. Second, Lo and MacKinlay (1988) strongly rejected the random walk hypothesis for weekly equity market returns and did not find any evidence of mean-reverting. Third, Poterba and Summers (1988) found that equity returns have positive autocorrelation over short periods and negative autocorrelation over longer horizons. Their findings suggest some cyclicality and therefore predictability in equity returns. Kim *et al*. (1991) compared equity data before the Second World War to equity data after the war. They found equity returns to be mean converging before the war but mean diverging after the war, thus challenging the findings of Lo and MacKinlay (1988). However, the Lo and MacKinlay (1988) findings for post-war data were confirmed by McQueen and Thorley (1991), who used the Markov chains methodology and yearly returns,

whereas Lo and MacKinlay (1988) used the variance ratio test and weekly returns. McQueen and Thorley (1991) found that high (low) returns were followed by low (high) returns, thus proving predictability in equity returns. The literature on mean reversion also benefitted from the work of Bessembinder *et al*. (1995) who found evidence of mean reversion in various futures markets, and several other researcher (Balvers *et al.*, 2000; Jorion & Sweeney, 1996; Malliaropulos & Priestley, 1999; Sloan, 1996) who found mean reversion in various equity markets around the globe.

So far, this section discussed the most salient anomalies in the EMH literature. The persistence of these anomalies is proof that the EMH (which holds that asset prices fully reflect information and investors cannot consistently beat the market) does not always hold true. However, proponents of the EMH insist that such anomalies persist because they cannot be exploited profitably due to, for example, transaction costs. As a result, the question of whether investors can profit from market anomalies continues to attract research, incorporating several aspects of investment considerations including transaction costs, investor's liquidity needs, and institutional rigidities as governed by investment policy statements. Even then, reasonable efforts still need to be made to separate cases of superior investment performance from luck (Lo, 2008). Luck tends to play a significant role in finding and interpreting market anomalies, particularly when numerous interrogations are done on the same data set. Lo and MacKinlay (1989) argue that, when data-snooping[70] is heightened, small biases can translate into substantial anomalies such as superior investment returns or the size effect. The arguments concerning transaction costs and data snooping do not invalidate the existence of legitimate violations of EMH. Instead, they highlight potential biases and limitations that must be considered in empirical analysis. Table 4.3 lists popular anomalies documented in the academic.

[70] Data-snooping is the excessive and repeated analysis of a dataset to identify patterns or relationships that may not be genuinely present but arise due to chance (Lo & MacKinlay,1989).

Table 4.3: Market anomalies

Market Anomaly	Author(s)	Findings
Seasonality in equity returns	Aggarwal and Rivoli (1989)	Equity markets exhibit a weekend effect with low Mondy returns.
	Ariel (1987)	Equity returns are positive immediately before and during the first half of calendar months and indistinguishable from zero for days.
	Lakonishok and Maberly (1990)	Higher sell transactions relative to buy transactions on Mondays potentially explain cyclicality returns.
	Ogden (1990)	Equity returns are higher following the month of December.
Dividend yields, earnings yields and equity returns	Ball (1978)	The are excess returns following public announcements of firms' earnings.
	Basu (1983)	Equity returns of high earnings/price firms are significantly higher than returns low earnings/price firms.
Size related anomalies	Banz (1981)	Smaller firms have higher returns than larger firms.
	Cook and Rozeff (1984)	Equity returns are related to firm size, the earnings/price ratio and the month of January.
	Roll (1983)	Small firms' returns are higher than large firms.
Macroeconomic factors and equity returns	Balvers *et al*. (1990)	Equity returns can be predicted based on gross national product.
	Chen *et al*. (1986)	Equity returns are related to developments in macroeconomic factors that include interest rates, inflation and bond prices.
	Cochrane (1991)	Industrial production, interest yields and changes in inflation affect equity prices.
	Fama (1981)	Equity returns are determined by real economic activity.
	Geske and Roll (1983)	Equity returns are negatively related to changes in expected inflation.
Autocorrelation in equity returns	Fama and French (1988b)	A slow mean-reverting component of equity prices induces negative autocorrelation in returns.
	Kim *et al*. (1991)	Weakening mean reverting behaviour of equity prices.
	Lo and MacKinlay (1988)	Weekly equity returns are autocorrelated
	Porterba and Summers (1988)	Evidence of positive autocorrelation in returns over short horizons and negative autocorrelation over longer horizons.
Value line's rankings and equity returns	Copeland and Mayers (1982)	Investments based on value line ranking and forecasts result in abnormal performance.
	Holloway (1981)	Value line investment strategies yield abnormal returns.
	Stickel (1985)	The value line investment survey rank changes affect common equity prices.

Source: Compiled by Author.

Market anomalies pose a significant challenge to the assumptions of the EMH, revealing persistent inefficiencies that contradict the notion of informational efficiency. Empirical research has demonstrated that several factors contribute to deviations from theoretical EMH predictions. These include seasonality in returns, macroeconomic fundamentals, fundamental information such as dividend announcements, and autocorrelation in asset prices. The identification and analysis of these anomalies inform investment strategies aimed at exploiting predictable patterns. While some anomalies diminish over time due to arbitrage, others persist due to market frictions, such as information asymmetry and the irrationality of some market participants. The subsequent section explores biases that lead to markets incorrectly, or irrationally, adjusting to information, resulting in overreaction and underreaction. Understanding underreaction and overreaction is crucial as it provides an opportunity to explore how real-world investor behaviour deviates from rationality, thereby consistently presenting both opportunities and risks in the market.

4.2.2.2 Market overreaction and underreaction

The EMH assumes that investors process information rationally (Lo, 2017) and that prices adjust immediately to reflect all available data. However, behavioural research (De Bondt & Thaler, 1985; Kahneman & Tversky, 1973; Kahnemann & Tversky, 1979) has shown that investors do not have homogeneous expectations and do not always react proportionately to new information (Lo, 2017). De Bondt and Thaler (1985) were among the authors to document that asset prices sometimes overreact, thereby evidencing weak-form market inefficiencies. DeBondt and Thaler (1985) surveyed counters listed on the New York Stock Exchange (NYSE) from 1926 to 1982 and found evidence of price reversal and opportunities to realise above-market returns by employing contrarian investment strategies. The authors found that price reversal occurred over a three-year horizon and that most of the reversals occurred in January, thereby validating the January seasonality effect. Findings by De Bondt and Thaler (1985) elicited research aimed at understanding the behaviour of market participants and whether there were any trading strategies that investors could gainfully employ, considering that market participants oftentimes overreact.

Lehmann (1990) followed the novel works of De Bondt and Thaler (1985) and used the NYSE equity returns data from 1962 to 1985 to show that, when long positions in losers are financed by short positions in gainers (a zero-net-investment strategy), the result almost always yields positive monthly returns. These results are confirmed by Chopra *et al*. (1992), who, even after correcting for the size effect, showed that equity prices overreacted. The implication of overreaction and price reversals is that investors formulating *contrarian* investment strategies[71] – on the premise that markets overreact, so winners are overvalued and therefore must be sold while losers are undervalued and therefore must be purchased (Jegadeesh & Titman, 1993). However, Bernard and Thomas (1990) noted that, even if investors sometimes underreact to news about future earnings - thereby creating opportunities for momentum profits, the true economic impact of such reactions remains uncertain. Bernard and Thomas (1990) argued that, while such behaviours theoretically challenge the EMH, the slightest market frictions (for example trading costs and taxes) could wipe out any profits from strategies that try to capitalise on these inefficiencies.

The question of whether one can benefit from market underreaction, or overreaction remains open for debate, but what has been clear in this line of research, is that there are several different theories as to how markets come to overreact and underreact.

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[71] A contrarian investment strategy is an approach in which investors deliberately go against prevailing market trends by buying assets that are currently out of favour and selling those that are widely popular (Jegadeesh & Titman, 1993).

- First, Daniel *et al.* (1998, 2002) found that overconfidence about private signals[72] causes an overreaction in equity returns, giving rise to phenomena like the book-to-market effect and long-run reversals. In these cases, self-attribution (attributing one's success to competence but ascribing failures to bad luck) maintains overconfidence, allowing prices to continue this path of overreaction, and in doing so creating momentum. These overstated prices then lead to reversals in the long run as prices revert to their fundamental value.
- Second, Barberis *et al*. (2000) stated that extrapolation from random sequences - wherein agents expect patterns in small samples to continue, creates overreaction that eventually leads to a reversal of the asset price. Conservatism - the opposite of extrapolation, leads to agents underreacting, creating momentum in this way.
- A third view was offered by Hong and Stein (1999a), who suggested that news is transmitted gradually into the market, thereby causing momentum. This creates a feedback loop wherein market participants who buy based on past returns create overreaction. In doing so, market participants attribute the actions of past momentum trades to news and, in doing so, they end up over purchasing assets. Once these positions are reversed, momentum is caused. Following this reasoning, Hong *et al.* (2005) suggested a model in which market participants 'dumb down' market behaviour and make use of overly simplified models to evaluate assets. In doing so, they ignore the true, more complex market model. They then use their overly simplified models to explain a variety of phenomena, 'forcing' these phenomena to fit their models. This then leads to price reversals.
- Grossman and Stiglitz (1980) confronted the inherent contradiction within the EMH from a logical viewpoint. The authors argued that if markets were completely efficient and all available information was already reflected in asset prices, there would be no incentive for investors to gather information, as they would not expect to earn any extra returns. Consequently, without the effort of information gathering, markets would cease to function effectively, as new information would not be incorporated into prices. This implied that some degree of market inefficiency is necessary to motivate investors to collect and act on information, allowing markets to remain dynamic and functional. As a result, Grossman and Stiglitz's (1980) finding suggest that the view that markets ought to stay efficient is inconsistent.

[72] Private signals are non-publicly available pieces of information about an asset's value that are known by selected individuals, mostly insiders and sophisticated investors/analysts (Daniel *et al*., 1998).

- On a related, but different strand of research, several authors showed how the mood of investors influenced asset prices. Saunders (1993), for example, found that positive returns on sunny days while documenting mediocre returns on cloudy days on the NYSE. Hirshleifer and Shumway (2003) corroborated these findings. Similar effects linked to weather patterns were recorded by Kamstra *et al.* (2000) who document that returns around the weekend of the switch to standard time from daylight savings time were very negative and suggested that induced depression from the switch amongst investors submersed with seasonal affective disorder causes the negative return. There are, however, also other events that change the mood of market participants in such a manner that it impacts asset prices. The outcomes of sporting events involving a country were proven to impact the equity markets of the country (Edmans *et al.*, 2007), while a study by Bollen *et al.* (2011) found that the accuracy of Dow Jones Industrial Average predictions can be improved significantly by the inclusion of specific public mood dimensions.

The broader point of this discussion is that market participants do not have access to all and equal information at the same time, and even if they do, they may have different sentiments and exuberance about the information, leading to overreaction or underreaction to news. As a result, asset prices sometimes deviate from their *unbiased* value predicted by the EMH. Moreover, market participants are heterogeneous in terms of their risk tolerance to given returns, and as a result, the EMH's assumption of homogeneous behaviour when confronted with risks is unrealistic. There is a need to acknowledge that market participants are heterogeneous. Shleifer (2000) questioned the assumptions of the EMH – investor rationality and perfect arbitrage, an inquiry which led to the rise of behavioural critiques and the establishment of behavioural finance, an alternative world view to market efficiency, which seeks to incorporate how differences in human behaviour contribute to asset price volatility.

The next section explores some of the most salient studies strengthening the behavioural view of market efficiency.

4.2.2.3 Behavioural critiques

The EMH has served as a cornerstone in financial theory, positing that asset prices fully reflect all available information. However, an emerging body of research has critically challenged this notion by highlighting the role of psychological biases and cognitive limitations in investment decision-making. Empirical evidence such as those presented by Moy and Lee (1991) on several market anomalies including market overreaction and underreaction presented by De Bondt and Thaler (1985) suggested that investors sometimes deviate from the rational behaviour assumed by EMH. This discussion aims to examine these behavioural criticisms and explore how

incorporating insights from psychology and cognitive processes enrich the understanding of market dynamics and inform investment strategy.

Moy and Lee's (1991) research resulted in significant headway in integrating human behaviour and psychology in explaining asset prices. Rook (2006) characterised the role of herd behaviour and crowd psychology in individual behaviour and contributed to formalising the idea that movements in asset prices are the result of the mental attitude of investors in equity markets, a proposition confirmed by Burrell (1951). Other influential studies include Festinger (1957) and Kahneman and Tversky (1973; 1979). Festinger (1957) introduced the theory of cognitive dissonance (inconsistent thoughts relating to decisions and attitudes), while Kahneman and Tversky (1973; 1979) inextricably linked human behaviour and financial markets by formalising the concepts of heuristics. These rules of thumb in investment can be summarised as two distinct behaviours:

(i) mental accounting - where market participants separate decisions that should, in principle, be combined leading to suboptimal decisions, and
(ii) framing - which distorts the presentation of information to individuals that in turn affects their purchasing behaviour.

Since then, there has been widely scattered evidence suggesting that human behaviour has an impact on asset pricing. Over time, this line of reasoning grew due, in part, to the inconclusiveness of the EMH in explaining why market anomalies occur and the rather self-justifying feat of simply attributing evidence of overreaction and underreaction to chance (Michaely *et al.*, 1995).

Specifically, in explaining why anomalies occur, behavioural critiques delved deeper into the psychology of market participants, exploring why and if market participants seem to act irrationally when confronted with decisions on buying and selling financial assets. This field continues to be of growing significance in the attempt to explain market movements based on market participants' perceptions. Its key difference from the market efficiency of Samuelson (1965) and Fama (1965) is that, unlike the EMH, which suggests that asset prices depend on the information, behavioural critiques argue that the price depends on the reaction of the market participants to the available information (Fakhry, 2016). In this regard, behavioural critiques offer an alternative to market efficiency and built on the behavioural decision theory of Kahneman and Tversky (1982), predicting that markets sometimes overreact (Loughran & Ritter, 2000) or underreact (Desai & Jain, 1997) to news. As a result, behavioural critiques have, with the benefit of human psychology (Kahneman & Tversky, 1973) and human behaviour (DeBondt & Thaler, 1995) literature suggested two key behavioural models that offer more plausible explanations on how investor perceptions lead to market overreaction in some circumstances and underreaction on others.

The first model was proposed by Daniel *et al.* (1998) and holds that the financial markets are dominated by uninformed and informed investors, with the latter determining asset prices. Uninformed investors are free from judgement biases, whereas informed investors are subject to overconfidence and self-attribution (Fama, 1998). Overconfidence leads investors to exaggerate the precision of their private signals about asset values. Signals that are associated with confidence include investments in corporate social responsibility and decreasing cost of capital (Bassen *et al.*, 2006; El Ghoul *et al.*, 2011). By contrast, biased self-attribution causes investors to down weigh public signals about value, especially when the public signals contradict their private signals (Fama, 1998). Overreaction to private information (non-public confidential data accessible by authorised individuals) mostly due to overconfidence and underreaction to public information (freely accessible information), due to self-attribution, tend to produce a short-term continuation of asset returns, but as public information eventually overwhelms the behavioural biases of the informed investors, long-term asset return reversals begin to kick in (Fama, 1998). This interplay leads to short-term momentum and long-term reversals, thereby challenging the view of perfectly efficient markets.

The second model is that of Barberis *et al.* (1998) and is cognisant of both the representative judgement bias of Kahneman and Tversky (1979) and the conservative judgement bias of Edwards (1968). These two judgement biases are extensively discussed in Fama (1998) and Ritter (2003). Fama (1998) refers to when investors are underweighting long-term averages and give weight to most recent events. Investors leaning on the representative judgment bias of Kahneman and Tversky (1979) tend to overweight recent information relative to long-term statistical averages. This bias can create short-term momentum effects in asset prices (Fama, 1998). The Barberis *et al.* (1998) model holds that asset prices follow a random walk process, but investors, because of their judgement bias, erroneously perceive two pricing regimes.

(i) The first regime assumed that asset prices are mean reverting (Fama, 1998) and therefore underreacted to changes in asset price as it believes all changes are more likely to be temporary. These predictions were motivated by the evidence of short-term momentum in asset returns (Jegadeesh & Titman, 1993) and delayed short-term responses of asset prices to earnings announcements (Ball & Brown, 1968; Bernard & Thomas, 1990).

(ii) The second regime assumed that when consecutive prices changed with the same sign, then an asset is trending, leading to overreaction. Yet, since prices follow a random walk, overreactions are revealed by future prices, which eventually lead to long-term price reversals. This regime corroborated the long-term return reversals of

DeBondt and Thaler (1985) and the superior returns realised by contrarian investment strategies of Lakonishok *et al.* (1994).

Both the representative judgement bias of Barberis *et al.* (1998) and the conservative judgement bias discussed in Daniel *et al.* (1998) affected investor behaviour helping to explain the interplay of short-term momentum (overreaction) and long-term reversals in financial markets. Behavioural critiques, therefore, drew on ideas of EMH, psychology, and neuroeconomics and emphasise how individuals behave and make decisions (Barberis & Thaler, 2003; Sewell, 2012). Neuroeconomics has been used to assess decision making under uncertainty, drawing on studies of brain chemistry to understand how decision making utilises both rational and emotional areas of the brain (Levallois *et al.*, 2012). This branch of the literature is premised on the recognition that framing (the way information is presented) can affect decision making leading to both emotional and cognitive biases (Redelmeier & Tversky, 1992). Consequently, individuals sometimes act in different ways from those predicted by the risk-averse utility maximisation theory, grounded on the works of von Neumann and Morgenstern (Fishburn, 1989).

The evidence that investors oftentimes violate the expected utility theory when choosing among risky investments ignited research leading to the development of other theories, most notably the weighted utility theory (Chew & MacCrimmon, 1979; Hong & Waller, 1986), the disappointment aversion (Gul, 1991), the rank-dependent utility theory (Quiggin, 1991; Segal, 1990) and the regret theory (Loomes & Sugden, 1987; Quiggin, 1991). These alternative theories corroborate that decisions by investors are sometimes suboptimal from an expected utility maximisation standpoint, and this suboptimality leads to markets that temporarily or continually deviate from efficiency. Behavioural critiques, notably Lo (2017) advocated for a model that challenges the traditional assumptions to explaining the behaviour of asset prices. Specifically, Lo (2017) advocated that such models do not presume individuals behave as rational economic men (REM), are consistently risk averse, invariably act in their self-interest, or possess perfect information. Lo (2017) argued that a model explaining the behaviour of asset prices ought to be grounded on the understanding that, at times, individual behaviour, which in turn influences market movements, is better explained by human psychology than rationality (Lo, 2008).

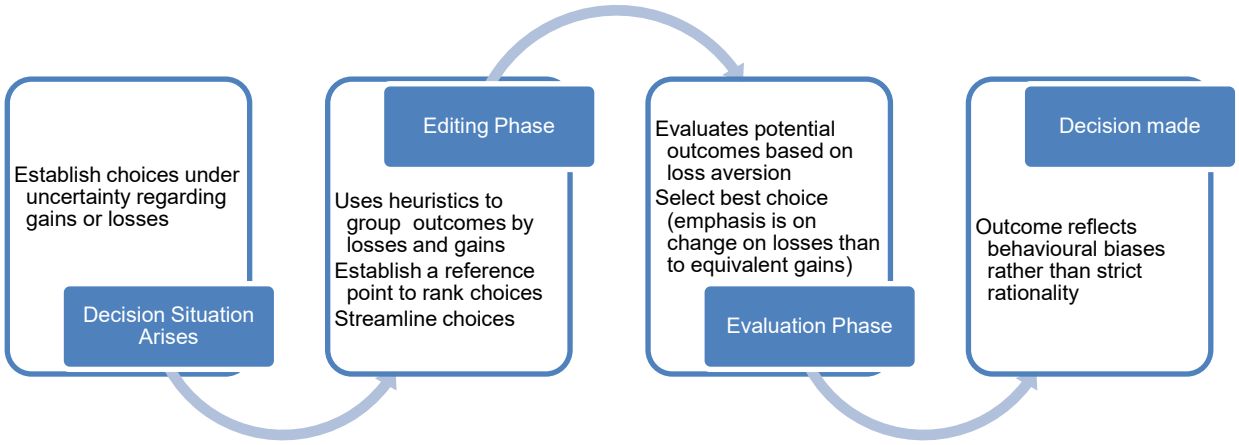
The behavioural finance literature details several challenges of assuming market participants are REM. These challenges are extensively discussed by Blume and Durlauf (2015) and include:

(i) The evidence that decision making can be flawed by lack of information or flaws in the decision-making process;
(ii) The persistence of personal inner conflicts that prioritise short-term (spending) goals over long-term (saving) goals can lead to poor prioritisation; and
(iii) The general lack of perfect knowledge.

These challenges of assuming REM are also confirmed in the bounded rationality theory and the prospect theory. The bounded rationality theory (Sargent, 1993) posits that knowledge capacity limits and removes the assumptions of perfect information, fully rational decision making, and consistent utility maximisation, thereby directly confronting the validity of the EMH. Accordingly, individuals do not always maximise utility per se, instead, they strive for outcomes that offer sufficient satisfaction, but not optimal utility (Sargent, 1993). This is primarily because individuals suffer from some cognitive limitations that emanate from a lack of resources (mental or physical) to accurately interpret information (Hong & Stein, 1999). Market participants are, therefore, susceptible to knowledge limitations. As a result, it was impractical for the EMH to assume perfect information and expect utility maximisation since they are contradictory realities.

Moreover, prospect theory argues that individuals are not risk averse per se but are loss-averse (Kahnemann & Tversky, 1979; Redelmeier & Tversky, 1992). The theory focuses on the framing of decisions as either gains or losses and weighting uncertain outcomes. Kahneman and Tversky (1979) formulated the prospect theory and established that choices are made in two phases. In the first (editing) phase, proposals are framed or edited using simple heuristics (decision rules) to make a preliminary analysis before the second (evaluation) phase. In the editing phase, economically identical outcomes are grouped, and a reference point is established to rank the proposals. The goal of the editing phase is to simplify the number of choices that must be made before making the final evaluation and decision. Doing so addresses the cognitive limitations individuals face in evaluating large amounts of information. The risk is that the selection of the reference point frames the proposal as a gain or loss and affects the subsequent evaluation or decision step. In the evaluation phase, investors focus on loss aversion rather than risk aversion. The difference is subtle, but the implication is that investors are more concerned with the change in wealth than they are with the resulting level of wealth, per se. In addition, investors are assumed to place a greater value in change on a loss than on a gain of the same amount. Given a potential loss and gain of equal sizes, the increase in utility associated with the potential gain is smaller than the disutility associated with the potential loss. Investors tend to fear losses and can become risk seeking to avoid them, thereby defying rationality (Isen & Geva, 1987; Lo, 2004). Figure 4.1 illustrates the decision-making process advocated by the prospect theory

Figure 4.1: Prospect theory and decision making



The flow diagram illustrates how prospect theory separates investor decision making into two main phases—editing (framing and reference point selection) and evaluation (loss aversion) highlighting the cognitive limitations and tendency towards loss avoidance that diverge from traditional rational models. *Source: Compiled by Author*.

The above discussion demonstrated that the EMH has been a source of many debates since it was formalised by Samuelson (1965) and that it is still in controversy. Researchers' views on the EMH have changed during the past 50 years or so, primarily due to arguments of market anomalies brought forward by behavioural critiques. Fama (1970) summarised that, in early research, several studies supported the EMH, but Fama (1991) modified this view because of a lot of anomalies reported after their earlier study (Fama, 1970). The EMH continues to be a subject of intense debate as it faces criticism from behavioural finance perspectives, which offer an alternative approach to explaining market price behaviour. The next section highlights the behavioural view on market efficiency and its implications for portfolio management.

4.3 The behavioural finance perspective

The EMH assumes markets are efficient, prices reflect fundamental value, and that new information is quickly and accurately assimilated in market prices. As a result, portfolio managers can focus on identifying efficient portfolios on the efficient frontier that meet the client's objectives of risk and return, while also observing the investor's constraints. Moreover, the EMH is grounded on models that assume market participants are rational, implying that they are efficient and unbiased processors of all relevant information and that their decisions are consistent with utility maximisation (Fama, 1965; Samuelson, 1965). The benefit of the rationality framework (and utility maximisation) lies in its simplicity and scalability (Brooks & Byrne, 2008). However, some studies show that markets and the trading behaviour of market participants may not always be characterised by the rationality framework (Barberis & Thaler, 2003). Consequently, market prices are not correctly reflecting asset intrinsic values, or at least providing the best indication possible which suggest the market efficiency approach to portfolio management is flawed.

An alternative approach called behavioural finance emerged from the cognitive psychology literature (Shefrin, 2006; Statman, 1995), reconciles the views of psychology and sociology and applied these fields in a financial context. Ricciardi and Simon (2000) defined behavioural finance as the field of study that explores the cognitive and emotional processes influencing investors' decision making, aiming to elucidate the reasoning patterns and emotional factors that impact their financial choices.

Behavioural finance concedes that some market participants are subject to behavioural biases and therefore their financial decisions are not always fully rational, nor do they always conform to the utility maximisation theory (Arrow, 1990b; Quinn, 2016). The behavioural finance literature (Brooks & Byrne, 2008; Mankuroane, 2021; Ritter, 2003; Shleifer, 2000) discusses a number of these biases that lead to deviations from rationality expectations. Some of these have been discussed in Section 4.2.2.3 and include:

(i) Overconfidence and overoptimism which lead market participants to misjudge their ability and the accuracy of the information they have (Tversky & Kahneman, 1974);
(ii) Representative bias which entails analysing situations based on sentiments and not their probabilities (Jain *et al.*, 2022);
(iii) Conservatism which entails holding on to prior beliefs even in the face of new information (Hoppe & Kusterer, 2011; Ritter, 2003);
(iv) Availability bias manifested by market participants through overweighting the probabilities of more recent events simply because the memory of those experiences is still fresh (Shefrin, 2006);
(v) Frame dependence and anchoring which asserts that the way information is packaged and disseminated affects investment decisions (Lowies *et al.*, 2016);
(vi) Mental accounting asserts that individuals assign investment and wealth to separate mental partitions and ignore correlation effects (Ritter, 2003; Mankuroane, 2021); and
(vii) Regret aversion refers to circumstances where market participants make decisions in a way that allows them to avoid feeling emotional pain in the event of an adverse outcome (Brooks & Byrne, 2008; Mankuroane, 2021).

Behavioural finance is a growing research field and has not yet been able to propose a unified and widely acceptable alternative theory to market efficiency. However a number of studies (Barberis & Thaler, 2003; Brooks & Byrne, 2008; Kahnemann & Tversky, 1979; Ricciardi & Simon, 2000; Ritter, 2003; Sewell, 2012; Tversky & Kahneman, 1974) provided a comprehensive introduction to the behaviouralist view of market behaviour. This comprehensive introduction has so far given birth to four models that seeks to characterise how market participants' behaviour

affects pricing processes in financial markets, what market efficiency means and its implications to investors.

These models include (1) consumption and savings, (2) behavioural asset pricing, (3) behavioural portfolio theory, and (4) the adaptive markets hypothesis (AMH). Among these four models, the AMH is the most widely recognised by finance professionals and academics, and it is the most pertinent to this study. The subsequent sections will elaborate on the theses of these models.

4.3.1 Consumption and savings

The literature (Goyal & Kumar, 2021; Jappelli & Padula, 2013) argued that rational investors save and invest in the earlier stages of life to fund retirement. Rationality, therefore, requires investors to exercise restraint by foregoing immediate consumption and saving to meet future (long-term) need and goals. This characterisation of consumption and savings is informed by the lifecycle models (Modigliani & Brumberg, 2013) and the permanent income theory (Friedman, 1957). However, individuals often struggle to exercise the self-control expected of rational economic actors. Instead, investors are prone to mental accounting and framing biases (Thaler, 1987). Statman (1995) argued that investors mentally account for and frame wealth as either current income or capital, which is different from the rational view of Modigliani and Miller (2013) that all forms of wealth are interchangeable. Thus, for example being paid a cash dividend in place of an equity dividend moves such a payment from the capital (mental) account to an income (mental) account and allows consumption without violating the rule of "do not consume capital". Accordingly, mental accounting for wealth by source makes individuals more likely to spend from current assets and this may impact how they build self-control to save some of what they will need to meet long-term needs and goals.

Mental accounting also makes investors subject to framing bias. For example, if individuals perceive a bonus as current income, they are more likely to spend it. However, if they perceive it as future income, they are more likely to save it. Under a consumption-driven model, most of the market price volatility emanates from changes in consumption levels (Campbell & Cochrane, 1999) and, therefore, asset returns and consumption are significantly correlated (Barberis *et al.*, 2021).

Although the consumption model offers an alternative explanation to market price behaviour, it does not attempt to confront the EMH anomalies or integrate investor sentiments in asset pricing.

4.3.2 Behavioural asset pricing

One of the shortcomings of the consumption and savings model described above is that it does not account for market players' behaviour when calculating asset returns (and thus prices). This phenomenon is addressed by the behavioural asset pricing model, which modifies the CAPM

(Lintner, 1965; Mossin, 1966; Sharpe, 1964) by incorporating behavioural biases into the calculation of expected returns and risk. This is because investors are deemed not always rational and influenced by their emotions, preferences, and beliefs, which explains the numerous market anomalies including the winner-loser effect[73] and the size effect[74] (Chandra & Thenmozhi, 2017). The behavioural asset pricing model assumes that investors are not fully rational as a result, the expected return on an asset is made up of the risk-free rate, fundamental risk premium (as in the CAPM) and sentiment premium (Brav & Heaton, 2002). Sakariyahu *et al*. (2024) incorporated the sentiment proxy into the Cahart's (1997) four factor model and present it as in Equation 4.1.

$$R_{pt} - R_{ft} = R_{ft} + \beta[\mathrm{RFV_t}] + \beta_{p,RSI} RSI_t + \in_{pt} \text{ [75]} \quad (4.1)$$

Where R_{pt} is the return on portfolio p for time t, R_{ft} the risk-free rate of return for time t, RFV_t are Cahart's (1997) four factors $RM_t + SMB_t + HML_t + UMD_t$, RSI_t is the raw sentiment index as time t and $\in_t$ is the residual term.

The sentiment premium is measured by using survey data or experimental approaches to assess investors' perceived risk and return, as well as how they are influenced by factors such as overconfidence or loss aversion (Brooks & Byrne, 2008). However, there are several problems with including behavioural bias in the model, emanating from the complexity of testing and validating the models, as well as a lack of consensus on the definition and measurement of biases.

The behavioural asset pricing model integrates investor sentiments, which is one of the most common behavioural biases affecting asset prices (Baker & Wurgler, 2006; Kumar & Lee, 2006; Smales, 2017). A high level of sentiment, characterised by excessive optimism, often drives asset prices above their intrinsic values, resulting in relatively low subsequent returns, and vice versa (Chue & Mian, 2022). Some studies have explored the cause, role, and impact of investor sentiment on market prices and returns, and found that a variety of factors such as the weather (Hirshleifer & Shumway, 2003), social media feeds (Duz Tan & Tas, 2021) and news on macroeconomic indicators (Chen & Lien, 2017) influence investor sentiments. However, metrics used to gauge 'investor sentiments' that are published in investment newsletters have been argued to not influence returns, not translate into additional predictive power for future returns

[73] The winner-loser effect refers to when assets that have recently performed well (the "winners") tend to continue performing well in the short to medium term, while those that have lagged (the "losers") tend to keep underperforming over a similar horizon (Chandra & Thenmozhi, 2017).

[74] The size effect refers to the tendency of assets (mainly equities) with low market capitalisation to have higher returns than assets with high market capitalisation (Chandra & Thenmozhi, 2017) .

[75] Cahart's (1997) four factors: $RM, SMB + HML$ and UMD represent Market Risk (RM), Size (SMB - Small Minus Big, Value (HML - High Minus Low) and Momentum (UMD - Up Minus Down)

and their reactive nature means they simply confirm what has already occurred rather than forecasting what will come next (Clarke & Statman, 1998).

Behavioural asset pricing, therefore, directly confronts the EMH given that it does not provide scope for investor sentiment in asset pricing. The idea of integrating investor sentiment in understanding market pricing processes is corroborated by various studies. For instance, Gemmill and Thomas (2002) showed that noise trader sentiment, as proxied by retail investor fund flows, leads to fluctuations in the discount of closed-end funds. Da *et al*. (2015) constructed a sentiment index based on internet search volume on recession, unemployment, and bankruptcy and found that the index predicts short-term return reversals, temporary increases in volatility, and mutual fund outflows from equity funds to bond funds. Meier *et al*. (2021) used a sample of US firms from 1927 to 2019 and found that positive investor sentiment is positively associated with the profitability of momentum strategies and Fama and French's (1993) small minus big factor, providing empirical evidence in line with prominent behavioural models. Sibande *et al*. (2023) analysed daily data for nine developed market currencies[76] between 2003 and 2019 and found that the effect of sentiment on anti-herding is generally stronger in extreme bullish sentiment states, while average sentiment is associated with less severe anti-herding. The findings lend support to the behavioural factors for asset pricing models and suggest that real-time investor sentiment signals can be utilised to monitor potential speculative activities.

Another important bias affecting equity prices is the extent to which investors underreact or overreact to information in pricing securities. The literature provides evidence of short-term (up to 12 months) return momentum (Jegadeesh & Titman 1993), but longer-term (three to five-year) reversals (Lakonishok *et al.*, 1994). This evidence of momentum followed by reversals presents a challenge for behavioural finance scholars to come up with a theory that explains underreaction followed by overreaction and at the same time counter Fama's (1998) contention that consistent market overreaction and underreaction cancel out, leading to a broadly efficient market. Barberis *et al.* (2006) provided a model based on representative heuristic and conservatism bias to counter Fama (1998). In this context, representative heuristic means that individuals assess the probability of an event or situation based on superficial characteristics and similar experiences they have had, rather than on the underlying probabilities (Grether, 1980). This approach can mean that investors, seeing patterns in random data, could extrapolate a company's recent positive earnings announcements further into the future than is warranted, creating overreaction. Conservatism means that individuals are slow to change their beliefs in the face of new evidence and can explain why investors fail to take full account of the implications of an earnings surge,

[76] The developed markets currencies analysed by Sibande *et al*. (2023) included the Australian dollar, Canadian dollar, Euro, Japanese yen, New Zealand dollar, Norwegian krone, Swedish krona, Swiss franc, and British pound.

leading to underreaction (Ritter, 2003). Barberis *et al.*, (2006) found that the interaction of the investor's belief process with the model for earnings can generate price series showing underreaction and overreaction to news. However, this model by Barberis *et al.*, (2006) has not been employed on a large scale in practice.

Daniel *et al.* (1998) proposed another model to counter Fama (1998) based on overconfidence and biased self-attribution. Overconfidence leads investors to overweigh their private information in assessing the value of securities, causing the equity price to overreact (Ritter, 2003). When public information arrives, mispricing is only partially corrected, giving rise to underreaction. Market overreaction and underreaction have been confirmed in several developed and developing markets (Lasfer *et al.*, 2003), including the US (Fabozzi *et al.*, 2013), SA (Page & Way, 1992) as well as in REITs (Ngene *et al.*, 2020), bonds (Wang, 2021) and currencies (Larson & Madura, 2001). Daniel *et al.* (1998) noted that events for which no announcements are made are associated with a stronger tendency toward overreaction than those events for which an explanation is given, suggesting that investors overreact more when the source of the extreme fluctuation is unknown. Further evidence shows that political events are associated with a stronger tendency toward overreaction than economic events (Larson & Madura, 2001). This is because political events (such as civil uprising) are more difficult to parameterise than economic events (such as the release of an inflation report). A growing body of research has also shown evidence of overreaction in the BTC and ETH market, and an underreaction effect in XRP (Caporale & Plastun, 2019), although it is still unclear why that is.

This section introduced behavioural asset pricing and explained that deviations from expected returns under traditional models such as CAPM (that assume rationality) can be partly explained by the sentiment premium investors demand or discount due to biases such as overconfidence or herd behaviour. Essentially, the model endeavours to provide explanations as to why assets with similar risks may be priced (in terms of expected returns) differently. Further to understanding how behavioural biases impact market pricing mechanism there is a need to explore how these biases affect investment decision-making. The next section explores how investors allocate their wealth among various assets, not merely by optimising risk and return, as suggested by MPT, but integrating human behaviour to asset allocation.

4.3.3 Behavioural portfolio theory (BPT)

As was discussed in Chapter 3, MPT assumes that investors are fully rational and that their sole objective is to optimise risk and returns. The evidence of behavioural biases challenging the assumption of rationality led to an alternation approach, Behavioural Portfolio Theory (BPT) that recognises the human imperfections in decision making. This section explores what BPT means and its importance in portfolio contraction and how this potentially alters MPT portfolios.

BPT can be traced back to Shefrin and Statman (2000) who argued that investors set apart their portfolios into different layers (portfolio segments) each aligned with different financial goals, levels of risk tolerance and emotional considerations (Oehler & Horn, 2021). Allocation of capital to each layer (portfolio segment) largely depends on its importance (weight attached to the respective financial goal of that segment) to the investor (Shefrim & Thaler, 1988). If, for example, a high-return goal is desired, then funds will be allocated to the high-return (leading to high-risk) portfolio segment (layer). Conversely, if a low risk is the desired objective, then capital will be allocated to the low-risk (resulting in a low-return) layer. The number of assets in a layer reflect the investor's risk aversion. Risk-averse investors will hold a larger number of assets in each layer (Oehler & Horn, 2021). If an investor is loss averse, the investor will hold larger cash positions to avoid the possible need to sell assets at a loss to meet liquidity needs. The resulting overall portfolio may appear to be diversified but is likely to be suboptimal because the layers were constructed without regard to their correlations (Oehler & Horn, 2021).

Understanding BPT is important for several reasons including:

(i) Proffering more plausible investor behaviour that for example, investors prioritise portfolio segments over covariance considerations (Oehler & Horn, 2021; Shefrin & Statman, 2000).

(ii) Imparting an understanding of decision-making processes for aligning the parameterisation of outcomes with actual behaviour. For example, Kahneman and Tversky's (1979) prospect theory, which underpins BPT and Thaler's (1999) work on loss aversion demonstrated that investors evaluate gains and losses asymmetrically - an insight critical to how risk measures are defined.

(iii) Insights into some of the reasons for market inefficiencies. For example, segmenting investment into layers and ultimately a few or individual assets for high return portfolio segments (rather than the entire portfolio as in MPT) leads to pricing anomalies (Barberis & Huang, 2001; Domowitza & Madhavan, 1997).

Overall, BPT's relevance lies in its ability to integrate behaviour and offering insights into market inefficiencies and goal-based portfolio construction. While the BPT presents an alternative view to the question of how portfolios are built it does not explain how these biases influence the broader market and evolve with learning. The next section explores the Adaptive Market Hypothesis (AMH), a model that sought to fill these gaps and challenged the EMH.

4.3.4 Adaptive markets hypothesis (AMH)

Given the stark differences between the underlying principles of the EMH and those of behavioural critiques, the finance literature has seen the emergence of an increasingly popular

school of thought - the AMH, as outlined by Lo (2004). Under the AMH, market efficiency and other rationality-based models of modern finance such as CAPM can coexist with behavioural models (Pal, 2016). Under the AMH behavioural biases resulting in market anomalies reflect human behaviour - learning and adapting to a changing environment using simple heuristics (Lo, 2004; Pal, 2016). Moreover, Lo (2004) contended that the AMH reconciles market efficiency with behavioural alternatives in that it applies the principles of evolution, competition, adaptation, and natural selection to financial interactions. Thus, the AMH holds that success in the market is an evolutionary process and market participants who do not evolve to adapt do not survive (Lo, 2004). Thus, investors do not consistently pursue maximum utility, rather they satisfice by meeting the minimum requirements necessary to survive changing market conditions. In this fashion, they do not necessarily maximise utility, but through trial and error, they apply heuristic rules and those that work come to be adopted by more participants until they are reflected in market pricing and then no longer work. Consequently, the AMH holds that markets evolve which leads to several conclusions with far-reaching consequences as discussed by (Pal, 2016).

(i) First, the relationship between risk and return should not be stable and, as a result, the market risk premium changes over time as the competitive environment changes.
(ii) Second, active portfolio management can find opportunities to exploit arbitrage and add value.
(iii) Third, no investment strategy should result in profitability all the time.
(iv) Fourth, the primary objective in markets is survival. Profit and utility maximisation are secondary.
(v) Finally, market participants who survive financial markets change and adapt to changing market conditions (Pal, 2016).

Since Lo's (2004) seminal work on the AMH, several studies have been added to this field. Lo (2005), for example, showed how the traditional models of modern financial economics (the principles of efficient markets) can coexist alongside the models underlying behavioural finance. Todea *et al.* (2009) confirmed a varying degree of market efficiency through time in a cyclical fashion for six Asia-pacific stock market indices located in Australia, Hong Kong, India, Malaysia, Singapore and Japan. Ghazani and Araghi (2014) studied the evolution of prices on the Tehran stock exchange between 1999 and 2013 and found that the index returns oscillate in a manner consistent with the AMH. The AMH was also confirmed in some popular stock markets, including the US, UK, Europe and Japan (Urquhart & McGroarty, 2016), China (Xiong *et al.*, 2019) and South Africa (Seetharam, 2016; Smith & Dyakova, 2014). These results are supported by Tripathi *et al*. (2020), who surveyed 21 major stock exchanges and found evidence that market efficiency is time-varying in a manner consistent with the AMH. Other studies have confirmed the AMH in

other asset class markets, including foreign currency markets (Neely *et al.*, 2009) oil markets (Ghazani & Ebrahimi, 2019), and REITs (Zhou & Lee, 2013).

The broader thesis of these findings supporting the AMH is that they do not necessarily lead to a conclusion that the EMH is wrong (Lo, 2012), but that the EMH is incomplete. This leads to the understanding that market participants are not always rational in all situations, but that they are intelligent enough to adapt to changes in the market. If those changes are within the expected bounds - when comparing them to historical data - market participants will act rationally, and market efficiency prevails. If market changes are abrupt and course-changing, market participants might overreact, leading to conditions that cannot be reconciled with the EMH. An example of this is where sudden increases in price volatility cause investors to shift their money from equity to "safer" asset classes such as bonds. This puts downward pressure on equity prices while boosting the prices of safer asset classes. This temporarily distorts the positive relationship between risk and return, which transgresses the assumptions of the EMH. These effects do, however, seem to be temporary, leading to the conclusion that market efficiency is not fixed. Markets seem to be efficient most of the time, but there are times when efficiency breaks down, and market participants act irrationally.

The AMH implies that market efficiency is not an all-or-nothing condition but a continuum. This continuum of market efficiency depends on the relative proportion of market participants who are making rational investment decisions versus the proportion of market participants who act irrationally (Lo, 2004). Markets will, therefore, behave according to the extent to which a given set of market participants has adapted to the environment in which the market has developed. Therefore, it is expected that a relatively young market, such as cryptocurrency, will be less efficient than a more established market, such as the equity market (Lo, 2012). This study will have the opportunity to assess these *a priori* expectations. The older markets can, however, still exhibit inefficiency if the environment shifts dramatically, or the population of investors changes materially. Markets may thus become efficient (or inefficient) as market conditions and investor populations change. The AMH is essentially the EMH with bounded rationality, satisficing, heuristics, and evolution. In the AMH, the degree to which the market is efficient will depend on the degree of competition in the market, the availability of profit, and the flexibility of participants to exploit opportunities (Lo, 2004, 2012).

The following section examines empirical evidence on how the literature has assessed market efficiency in cryptocurrencies using either of the three primary methodologies (the EMH, behavioural finance, and the AMH), as well as their findings. This is essential because it enables investors to understand the pricing process and make informed decisions, such as exploiting

market anomalies, avoiding the pump-and-dumb schemes[77] that are common in cryptocurrency markets.

4.4 Empirical evidence on the market efficiency of cryptocurrencies

Research by Urquhart and McGroarty (2016) showed that different financial markets exhibit varying degrees of efficiency that are influenced by market conditions, confirming the AMH. This points to the need to further examine the efficiency of various cryptocurrencies, particularly those most popular among market participants and across different market conditions.

Lui and Tsyvinski (2021) investigated how cryptocurrency returns can be predicted by factors that are specific to cryptocurrency markets. These factors included excess market return, size factor, momentum factor as in the Fama and French (1993). By doing so Lui and Tsyvinski (2021) evaluated whether cryptocurrency returns may be explained by the EMH as they overlook how evolving changes in the relationships between cryptocurrency returns and factors over time. Lui and Tsyvinski (2021) found that a strong time-series momentum effect and proxies for investor attention strongly forecast cryptocurrency returns. In relation to the momentum effect, their findings indicate that a one-standard-deviation increase in BTC's return on a given day predicts a 0.33% increase in the following day's return. With respect to investor attention, their findings suggest that an increase in Google search activity predicts higher future returns over a 1- to 2-week horizon for BTC, a 1-week horizon for XRP, and 1-, 3-, and 6-week horizons for ETH. While the predictability of these cryptocurrencies renders their pricing inefficient it is not always clear whether this predictability extends across time.

The inefficiency in cryptocurrencies is corroborated by Huang *et al.* (2019), who explored the predictability of BTC returns based on technical analysis. The authors developed a model for return prediction using 124 technical indicators. They found that technical analysis can help predict BTC returns, thereby suggesting cryptocurrency market inefficiency. The inefficiency of cryptocurrencies is also documented by Cheah *et al.* (2018), who found long memory in BTC prices. However, Dimitrova *et al.* (2019) applied a 512-day sliding window, and then repeated the analysis with 64, 128, 256, and 1024-day windows to confirm robustness and found that while BTC looks inefficient at first glance, once one control for its wild distribution, it behaves much like a random, efficient market with occasional short-term reversals, corroborating Urquhart (2016) and Nadarajah and Chu (2017) who found no evidence of predictability of BTC returns.

[77] Pump-and-dumb schemes refer to a price manipulation chicanery that entails artificially inflating an asset's price before selling the cheaply purchased asset at a higher price to maximise profits before price reverse (Li *et al*., 2021).

Consequently, the variation in findings regarding the market efficiency of cryptocurrencies sets the stage for further debate.

Several studies on cryptocurrency efficiency have adopted the AMH view and examined whether various cryptocurrencies markets are becoming efficient, recognising that efficiency varies over time. BTC, so far, the largest and most popular cryptocurrency by market capitalisation, was found to be time-varying efficient (Khuntia & Pattanayak, 2018), meaning it experienced both episodes of market efficiency as well as episodes of inefficiency. Khuntiya and Pattanayak's (2018) findings were supported by Catania and Sandholdt (2019), who observed that, on sample frequencies of above one day, there was no evidence suggesting predictability of BTC returns. However, higher frequency data of up to 6 hours showed some evidence of predictability for returns. This study reasoned that, because thin trading is more salient in high-frequency data, market efficiency tests are more likely to detect predictability of returns in high frequency data due to 'flatter' prices than in non-thinly traded asset as was noted by Smith and Dyakova (2014).

Time-varying efficiency of cryptocurrencies was also reported by Le Tran and Leirvik (2020), who found that the level of market efficiency in the five largest cryptocurrencies[78] was highly time-varying. The authors found that these cryptocurrencies were mostly inefficient before 2017 but became more efficient between 2017 and 2019 (Le Tran & Leirvik, 2020). Similarly, Noda (2021) examined whether the efficiency of cryptocurrency markets (BTC and ETH) evolves with time. The author measured the degree of market efficiency using a generalised least squares-based time-varying model. The empirical results showed that the degree of market efficiency varied with time in these markets and that BTC was more efficient than ETH over most periods. Since then, other authors have expanded the market efficiency study to many cryptocurrencies. Khursheed *et al.* (2020) investigated the dynamic market efficiency of four cryptocurrencies: BTC (launched in 2009), Monero - XMR (2013), LTC (2011) and Stellar - XLM (2014) during the period from 2014 to 2018. Their analysis revealed that BTC, XMR, and LTC experienced the longest periods of market efficiency. In contrast, XMR demonstrated the most extended duration of market inefficiency due in part to lower liquidity and smaller user base as at was new and gaining market acceptance.

The varying results of market efficiency across cryptocurrencies confirm that cryptocurrencies experience changing levels of efficiency per the AMH. Consequently, when assessing cryptocurrency market efficiency, it is prudent to analyse it at individual cryptocurrency level such

[78] The five largest cryptocurrencies assessed by Le Tran and Leirvik (2020) where measured as of 28 February 2019 and included Bitcoin (BTC), Ethereum (ETH), Ripple (XRP), Litecoin (LTC) and EOS (EOS).

as BTC, ETH or USDT rather than at the aggregated market or index level such as the *CryptoCurrency Index 30* (CCi30)[79]. This is important for several reasons, including:

(i) Cryptocurrencies have widely varying levels of liquidity and volatility (Leirvik, 2022; Noda, 2021; Takaishi, 2020), dynamic technological development (Makarov & Schoar, 2022), sensitive to investor sentiment (Liu & Tsyvinski, 2021; Sibande *et al.*, 2023) and changing economic indicators varies (Peng *et al.*, 2024) which in turn impact their levels of market efficiency (Al-Yahyaee *et al.*, 2020). Analysing an aggregated index masks these factors.

(ii) The unique characteristics such as technological features affect the type of investors within a cryptocurrency which in terms of the AMH dramatically impact levels of market efficiency (Mokni *et al.*, 2025). Given the wider differences in cryptocurrency technological features as discussed in Chapter 2, there is reason to assess cryptocurrencies market efficiency individually than in an aggregated index which could potentially smooth out price patterns.

(iii) Following the SEC approval of BTC and ETH ETFs in the US, cryptocurrencies like BTC and ETH are attracting a broader range of investors, each with distinct strategies and behaviours which could potentially influence their price discovery processes (Krause, 2024).

By focusing on individual cryptocurrencies, researchers are providing actionable insights for investors, policymakers and the broader market participants. However, literature on whether episodes of efficiency (or inefficiency) in one cryptocurrency are linked to episodes of efficiency (or inefficiency) in another cryptocurrency or other markets remain sparce. This inquiry is important as extant research has shown that there are return linkages across cryptocurrencies (Ji *et al.*, 2019; Mensi *et al.*, 2021), volatility spillover from some cryptocurrency to major equity markets in the US, Germany, the UK and Japan (Liu & Serletis, 2019) which affect the portfolio diversification potential of cryptocurrencies. Determining whether periods of inefficiency in one cryptocurrency market coincide with periods of efficiency in another can offer nuanced insights for developing robust portfolio management strategies. In cases where episodes of market inefficiency occur independently across different cryptocurrencies, adopting a more active management approach may prove beneficial.

[79] The CCi30 Index is a market capitalisation-weighted index that tracks the performance of the top 30 cryptocurrencies (excluding stablecoins) by market capitalisation. The capitalisation tracked by the index represented 90% of the total cryptocurrency market capitalisation as of December 2024. The index was created in 2017, and its start value is set on January 2015. The index is available from CCi30 (https://cci30.com/). 10 April 2025.

4.5 Distinguishing market inefficiency from market microstructure-induced serial dependence

Market (informational) inefficiency occurs when asset prices fail to fully and instantaneously reflect available information, leading to predictable return patterns that contravene the EMH and may be exploited for abnormal profits (Fama, 1970; Lo, 2005; Malkiel, 2003). Nevertheless, return predictability is not exclusively attributed to informationally inefficiencies. It can be induced by market microstructure frictions such as bid-ask spreads, liquidity, and execution delays – which create short-term autocorrelations in returns even when the underlying price process is informationally efficient (Easley *et al.*, 2024; Huang & Stoll, 1994; Roll, 1983; Wei, 2018). Under the EMH, such predictability is regarded as transient noise attributable to market frictions and does not, in itself, signify inefficiency unless it results in economically significant predictability (Fama, 1970; Lehmann, 1990; Samuelson, 1965). The AMH offers a broader framework, suggesting that market efficiency evolves as participants adapt to changing environments, thereby accommodating episodes of serial dependence (predictability) as a reflection of learning and behavioural biases (Lo, 2004, 2012).

Empirical studies utilising high-frequency data demonstrate that distinguishing between these sources is essential for accurate volatility measurement (Andersen *et al.*, 2017; Hansen & Lunde, 2006). Market (informational) efficiency pertains to the absence of predictable return patterns arising from information asymmetry and does not encompass mechanical price delays resulting from thin trading or exchange fragmentation (Fama, 1998; Lim & Brooks, 2011; Malkiel, 2003; Mlambo & Biekpe, 2007). Consequently, adjustments are applied to mitigate microstructure effects that would otherwise contaminate the informational efficiency proxy (Al-Loughani, 1995; Cohen *et al.*, 1983; Mlambo & Biekpe, 2007; Smith & Dyakova, 2014). The thin-trading adjustment is thus intended to isolate informational persistence from liquidity and other microstructure related distortions.

The discussions above demonstrate that, from a purely EMH viewpoint, cryptocurrencies are by and large informationally inefficient (Cheah *et al.*, 2018; Huang *et al.*, 2019; Long *et al.*, 2020). However, from a behavioural finance and AMH perspective, cryptocurrencies and indeed other currencies and several equity markets undergo episodes of efficiency as well as episodes of inefficiency (Khursheed *et al.*, 2020; Le Tran & Leirvik, 2020; Selmi *et al.*, 2018). This emphasises the significant role of human behaviour and psychological factors as determinants of investment decisions (Al-Mansour, 2020; Liu & Tsyvinski, 2021). It is, therefore, important that market participants in the cryptocurrency space gain an understanding of the market efficiency dynamics of the cryptocurrency market to enhance their ability to make informed investment decisions. Doing so will equip especially uninformed investors to navigate the turbulence within the

cryptocurrency market and develop their abilities (through heuristics) on sound risk choices. Episodes of high price volatility, price bubbles and inefficiency driven by the fear of missing out (FOMO) should dissipate with time as the proportion of informed investors increases compared with uninformed investors. This should lead to a relatively more efficient cryptocurrency market with fewer and shorter episodes of inefficiency. Since cryptocurrencies are a young asset, models emanating from the EMH are not best suited to parameterise risks and, therefore, develop trading strategies or determine the market efficiency of cryptocurrencies, given a substantial behavioural portion in the cryptocurrency market. Moreover, the literature has made strides in documenting that some cryptocurrencies are time-varying efficient, although it remains unclear how the market efficiency of cryptocurrencies evolves through economic crises such as the one induced by Covid-19 restrictions.

The key takeaway from the different findings regarding cryptocurrencies' market efficiency is that the cryptocurrencies go through episodes of efficiency as well as episodes of inefficiency influenced by prevailing market conditions. Thus, market efficiency tests based on the EMH may specify the market as inefficient, yet that is not always the case. However, going by behavioural finance and, specifically, the AMH approach, the efficiency of cryptocurrencies evolves in a manner resembling the efficiency of other established developed equity markets (Urquhart & McGroarty, 2016) and developing equity markets (Smith and Dyakova, 2014). What, however, has not been established is:

(i) Whether the episodes of inefficiency in cryptocurrencies are more extended than those of other more established markets such as equity markets; and

(ii) It is unclear how cryptocurrency market efficiency evolves through crisis periods such as the one induced by Covid-19.

Examining whether extreme market conditions erode market efficiency is essential to assess cryptocurrencies' resilience and reliability as investment instruments during crises.

An in-depth understanding of how market efficiency evolves carries significant implications for the movement of asset prices. When a market or asset exhibits inefficiency, this can result in price predictability, which may be leveraged to improve portfolio diversification and performance; an aspect that becomes especially critical during periods of crisis when the need for diversification is heightened. Recognising shifts in market efficiency enables investors and portfolio managers to identify and exploit these periods of inefficiency. Such awareness supports more strategic diversification and risk management, ultimately assisting investors in navigating turbulent market phases with greater resilience. The next section delves deeper exploring the ways in which the evolution of market efficiency has influenced portfolio management practices.

4.6 Impact of market efficiency on portfolio management

The EMH suggests that no group of investors can consistently outperform the market by employing a single investing strategy (Fama, 1970). This concept has various implications for investment strategy, as explained by Malkiel (2003). The most enduring implication of the EMH is that it suggests that investment research and valuation would become expensive *excursions* with no tangible returns (Malkiel, 2003). The chances of finding an undervalued equity are as great as the chances of not finding one, reflecting the randomness of prices. That prices were always random called into doubt the value relevance of data driven investment practices as random diversification or low-cost indexing would be superior to any other strategy with higher information and execution costs. Therefore, it is unsurprising that the concept of market efficiency evokes strong reactions from portfolio managers and analysts, who see it as a challenge to their value proposition of judicious investment management.

Lo (2004) made tremendous strides with the AMH presented in Section 4.4.5 to proffer pragmatic implications of market efficiency. Lo (2004) argued that because markets are time-varying efficient (and not time-invariant efficient per the EMH), the relationship between risk and return of an asset is unlikely to be consistent over time. This is because market participants and their behaviours, as well as the regulatory interventions and legislation change over time and in the process influencing the risk-reward relationship – arguments drawn from Simon (1984). As a result, portfolio managers may need to periodically rebalance their portfolios to maintain their desired balance between risk and return. Lo's (2004) arguments refuted the view that indexation or random diversification produces at the minimum, market returns and supported the view of prudent portfolio management to achieve desired results. In addition, Lo (2004) also argued that arbitrage opportunities do arise in the market from time to time and without such opportunities, there would be no incentive to gather information, and the price-discovery aspect of financial markets would collapse, corroborating the findings of Grossman (1995).

Lo's (2004) findings suggest that asset prices are shaped by evolutionary forces – competition, adaptation, natural selection – leading to alternating periods of rational efficiency and behaviour-driven inefficiency, which opens the door for strategic active management (Charles *et al.*, 2012; Kim *et al.*, 2011; Lim & Brooks, 2011; Neely *et al.*, 2009; Urquhart & McGroarty, 2016). The ability to achieve above-market returns can be particularly valuable during crisis periods when diversification benefits are needed the most. Consequently, a deeper evaluation of how the efficiency of cryptocurrencies evolves during crisis periods and how investments in cryptocurrencies impact portfolio diversification and performance is essential to assess their potential as safe havens, hedges or diversifiers during crises. This is because deviations from market efficiency (mispricing) translate into changes in diversification benefits and portfolio risk–

return trade-offs. Since market efficiency is more plausible in weak form and semi-strong form, their respective implications for portfolio management are critical. Semi-strong efficiency concerns the rapid incorporation of public fundamental information, which is typically the basis for long-horizon strategic asset allocation (Groenewold & Kang, 1993; Mackey & Bacon, 2017; Vidal-Tomás & Ibañez, 2018). In contrast, weak-form efficiency pertains to the informational content of historical prices, which is more relevant for tactical allocation or timing strategies (Borges, 2010a; Jefferis & Smith, 2005; Lim & Brooks, 2011; Worthington & Higgs, 2004). This study evaluates weak-form efficiency, and the interpretation of results are grounded in how short-term predictability interacts with portfolio construction.

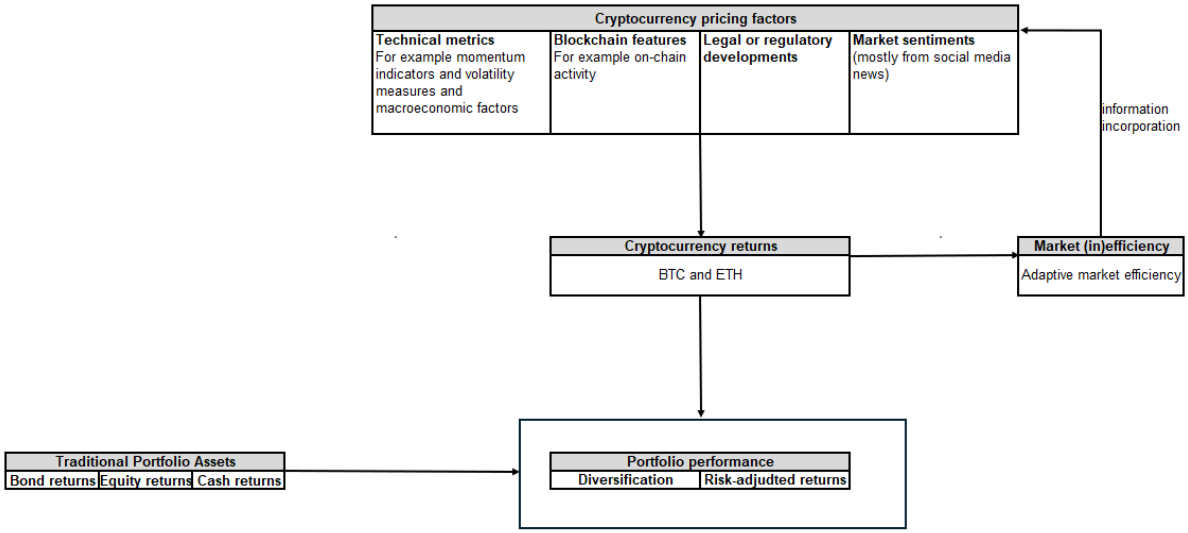
Weak-form inefficiency suggests that technical signals such as trend persistence or mean reversion, may, temporarily enhance or diminish diversification benefits depending on whether predictable movements amplify or dampen co-movement with traditional assets (Khursheed *et al.*, 2020; Nguyen & Parsons, 2022; Noda, 2021). This distinction is central to understanding why efficiency states matter for portfolio outcomes. Moreover, weak-form inefficiency implies that past price information contains predictive content, allowing short-term return patterns such as momentum, reversals, or volatility clustering to persist (Zalewska-Mitura & Hall, 1999).

These predictable components alter the covariance structure of returns because assets experiencing mispricing (inefficiency) tend to exhibit co-movement driven not by fundamentals but by behavioural trading, liquidity shocks, or noise-driven order flow (John *et al.*, 2024; Peng *et al.*, 2024). As a result, correlations deviate from their long-run equilibrium levels, either converging during periods of herding or diverging when assets respond asymmetrically to information. Consequently, when markets are weak-form inefficient, the predictability of returns reshape the joint distribution of asset returns, thereby influencing the extent to which portfolio risk can be reduced through asset combination.

The practical relevance of weak-form efficiency also depends on the investment horizon and decision framework of portfolio managers. Short-horizon traders, quantitative funds, and tactical allocators may actively exploit weak-form inefficiencies by adjusting cryptocurrency exposure in response to predictable return patterns. However, long-horizon or passive investors typically rely on macroeconomic and fundamental signals aligned with semi-strong efficiency. For these investors, weak-form inefficiency matters indirectly: predictable price dynamics influence correlations, volatility, and tail-risk behaviour, which in turn affect the strategic role of cryptocurrencies as diversifiers, hedges, or safe-haven assets. Clarifying this distinction ensures that the study's findings are interpreted appropriately: weak-form inefficiency does not imply that long-horizon investors will trade on technical signals, but rather that efficiency states shape the

diversification benefits and portfolio risk–return trade-offs within which long-term allocation decisions are made. Figure 4.2 present the study's conceptual framework outlining how market mispricing is transmitted to portfolio performance.

Figure 4.2: Conceptual framework depicting how market efficiency states shape cryptocurrency returns behaviour and influence diversification and portfolio performance



Moderators: Crisis Periods: Crisis periods are determined through equity returns movements Source: Authors own compilation

The theoretical link between the AMH and diversification performance lies in the proposition that evolving efficiency states directly influence asset co-movement and correlation structure and ultimately portfolio performance. The AMH posits that markets adapt to changing conditions such as macroeconomic stress, regulatory shocks, market sentiments or behavioural responses to news. In periods of low efficiency (and mispricing), marked by increased noise trading, behavioural biases and uncertainty, investors tend to herd, leading to higher asset correlations and diminished diversification benefits. Conversely, in high-efficiency regimes, where information is processed more rationally, market segmentation increases, and correlations weaken, enabling portfolio diversification to improve. This dynamic suggests that time-varying efficiency is not merely a background condition, but a determinant of how portfolio components interact.

Although the AMH provides the theoretical foundation for interpreting time-varying informational conditions, the empirical strategy adopted in this thesis does not employ regime-responsive or high-frequency rebalancing mechanisms. Instead, the analysis is situated within a weak-form EMH testing framework and uses conventional mean–variance portfolio optimisation. The choice of static annual rebalancing is deliberate: it mirrors institutional asset-allocation practices, reduces turnover-related distortions, and avoids conflating efficiency-driven changes in return dynamics with tactical market-timing effects. This design ensures that any differences in portfolio outcomes

across crisis and non-crisis periods can be attributed to shifts in correlation structures and risk metrics.

The conceptual framework advances this theoretical link indicating that AMH shapes the impact of cryptocurrencies on portfolio diversification and risk-adjusted performance as moderated by crisis periods. Under the tenets of the AMH, in episodes of informational efficiency, prices rapidly incorporate new information, thereby narrowing opportunities for abnormal returns and reducing mispricing-driven volatility. Price discrepancies are brief, correlations tend to be closer to long-run averages, and the scope for non-systematic risk reduction via diversification increases as markets segment and cryptocurrency returns decouple. Consequently, the benefit of adding cryptocurrencies with historically low correlation to a traditional equity-bond-cash mix materialises. Under crisis induced episodes of lower degrees of informational efficiency mispricing endures for longer horizons. Mispricing and behavioural biases such as herding lead to return correlations deviating from long-run averages, thereby altering diversification and risk adjusted performance for longer horizon investors. In essence, when markets enter a crisis, and efficiency remains high, diversification and risk-adjusted performance flatten, whilst when efficiency wanes during a crisis, diversification and risk-adjusted performance improve. Based on this premise, this study advanced the following hypothesis:

Hypothesis 1:

H_0: Crisis periods do not exert a statistically significant impact on the weak-form market efficiency of cryptocurrencies.

H_1: Crisis periods significantly diminish the weak-form market efficiency of cryptocurrencies.

Hypothesis 2

H_0: The inclusion of cryptocurrencies in a bond-equity-cash multi-asset portfolio does not alter the diversification or performance outcomes within a multi-asset portfolio.

H_1: The inclusion of cryptocurrencies in a bond-equity-cash multi-asset portfolio enhances diversification outcomes or risk-adjusted performance.

Hypothesis 3

H_0: Crisis-induced fluctuations in the efficiency of cryptocurrency markets do not impact their diversification characteristics or their role in enhancing portfolio performance.

H_1: Crisis-induced fluctuations in cryptocurrency market efficiency do affect their diversification characteristics and their contribution to portfolio performance.

By embedding market efficiency as a dynamic variable shaped by crisis periods, the framework unifies divergent outcomes and underscores the importance of 'market condition' adaptive allocation strategies.

4.7 Summary

This chapter explored the literature on market efficiency, beginning with an account of the evolution of the theory of market efficiency and its importance in academia and practice. A market is regarded as efficient if prices fluctuate randomly and cannot be forecasted, thereby making it almost impossible for any investor to consistently outperform it. The concept of market efficiency is well established in the finance literature and draws on insights from statistics and financial market researchers, including Working (1934), Cowles (1944), Kendall and Hill (1953) and Alexander (1961). Market efficiency was formally defined by Samuelson (1965), operationalised by Fama (1965, 1970) and later coined the Efficient Market Hypothesis (EMH) by Roberts (1967 cited in Sewell 2012). Since its popularisation, the theory has provided valuable insights – particularly that market prices reflect all available and relevant information – while also sparking significant controversy in asset pricing and equity selection processes. Researchers testing the EMH have faced two key challenges: first, the unrealistic assumption that market participants are rational, and second, the joint hypothesis problem, which involves simultaneously testing the EMH and an asset pricing model to confirm the presence of abnormal returns. Despite these challenges and over half a century of research, there is still no consensus on the efficiency of markets. However, an increasing body of research seeks to relax the assumption of rationality, as human behaviour has been shown to be prone to numerous biases. This has fostered the development and growth of behavioural finance as an alternative perspective on market efficiency. Nevertheless, this field remains in its developmental stages, with no unified theory yet established to challenge the EMH.

In response to the shortcomings of the EMH, the Adaptive Market Hypothesis (AMH) was born from the behavioural finance literature, which itself evolved from the study of market anomalies. The AMH views the EMH as an idealised construct that is economically unfeasible but remains a valuable benchmark for assessing relative market efficiency (Pal, 2016). In this regard, market efficiency is viewed not as a binary phenomenon as in the case of EMH, but as an evolving phenomenon that is adaptable to changing dynamics of the market, thereby suggesting that investors are capable of an optimal dynamic asset allocation. The AMH thus reconciles the EMH with behavioural alternatives by applying principles of evolution, competition, adaptation, and

natural selection to financial interactions. The theory is of growing significance and has been applied by several researchers to assess market efficiency across various assets including equity (Urquhart & McGroarty, 2016), foreign currency markets (Neely *et al.*, 2009), oil markets (Ghazani & Ebrahimi, 2019), and REITs (Zhou & Lee, 2013) and cryptocurrencies (Khursheed *et al.*, 2020). The next chapter explores in depth the various methods available for testing market efficiency.

CHAPTER FIVE

TESTING MARKET EFFICIENCY

5.1 Introduction

The previous chapter discussed how efficient financial markets offer the best asset price discovery mechanism and unbiased estimates of 'true' asset values. Theoretically, markets that are said to be (informationally) efficient cannot be consistently exploited by any market participant to make superior returns, primarily because the market error expectations value is zero. By contrast, inefficient market prices are biased estimate of asset values, potentially offering profit opportunities. Consequently, the question of whether financial markets are efficient or not has far-reaching implications for investors and portfolio managers. More adept and active market participants may exploit inefficient market errors by instantly identifying mispriced assets and trading them accordingly to make superior returns. Profit-maximising investors will prefer inefficient markets over more efficient ones. The previous chapter also reviewed empirical evidence supporting three distinct perspectives on the efficiency of cryptocurrencies: that they are inefficient (Cheah *et al.*, 2018; Huang *et al.*, 2019; Liu & Tsyvinski, 2021), efficient (Nadarajah & Chu, 2017; Urquhart, 2016) and time-varying efficient (Catania & Sandholdt, 2019; Khuntia & Pattanayak, 2018; Le Tran & Leirvik, 2020; Mokni *et al.*, 2025; Selmi *et al.*, 2018). This chapter extends discussion on market efficiency by focusing on how it is measured.

The tests were classified into three broad categories, namely: (i) tests that take a static view, (ii) rolling window tests, and (iii) tests for evolving efficiency (TEE). While these three broad categories of tests make up the typical approach to testing market efficiency, other financial theory phenomena such as volatility (Takaishi, 2020) and price bubbles (Chaim & Laurini, 2019; Cheah & Fry, 2015; Kyriazis *et al.*, 2020) are also related to the theory of market efficiency and have been applied in supporting or rejecting efficiency in financial markets. Methodologically, the wide range of tests for market efficiency makes it unclear which are most appropriate, as markets and assets differ in efficiency levels and changing market conditions (Urquhart & McGroarty, 2016).

This chapter, therefore, confronts the methodological dilemma in testing market efficiency by ascertaining the circumstances under which each of the three categories of market efficiency tests is suitable. Its primary focus is to identify the conditions under which a specific category can be applied in evaluating market efficiency. Emphasis is placed on how the tests are sensitive to evolving price dynamics and whether the tests allow for a longitudinal analysis of how efficiency changes over time. This was particularly important because this study aimed to ascertain how efficiency in the market of cryptocurrencies, changes overtime through crisis periods such as the one induced by the Covid-19 pandemic. Furthermore, the study sought to ascertain how changes

in the market efficiency of cryptocurrencies affected portfolio performance. Therefore, it was crucial to conduct a comprehensive review of prominent market efficiency tests to select those best suited to achieve the set research objectives. To achieve the objective selection of suitable market efficiency tests, Section 5.2 presents tests that take a static view to market efficiency and provided an overview of their robustness in tracking changes in efficiency. Section 5.3 explores rolling window tests, while Section 5.4 explores TEE. Section 5.5 concludes the chapter by applying inductive reasoning and presenting more appropriate tests for real-world situations where assets can be infant or mature.

5.2 Static view tests of market efficiency

Early investigations into market efficiency examined whether specific investment strategies or investment professionals could achieve excess returns (Cowles, 1944; Jensen, 1968). This line of inquiry was supported by Loughran and Ritter (2000), who argued that assessing market efficiency necessitates a detailed evaluation of an investment strategy to ascertain whether it yields excess returns. The analysis of excess returns poses a joint hypothesis problem in assessing market efficiency and validating the effectiveness of the model employed to calculate expected returns (Fama, 1970, 1991; Hogan *et al.*, 2004; Jensen, 1978). Yet, several researchers have conducted joint tests of market efficiency with the capital asset pricing model - CAPM (Ball, 1978; Banz, 1981; Schwert, 1983), while some have relied on the rational expectations model (Hakkio, 1981). Irrespective of the model employed to calculate expected returns, the presence of excess returns in joint tests indicates either market inefficiency or inadequacy in the model used for computing expected returns. Such indeterminate criteria reduce the specificity of the test, allowing findings to be subject to the researcher's interpretation, thereby diminishing overall confidence in the method's approach to assessing market efficiency. For instance, some researchers (Dimson & Mussavian, 1998; Jensen, 1978; Loughran & Ritter, 2000) who employed joint tests and identified significant excess returns attributed these findings to irregularities in asset pricing models rather than a deficiency in evidence supporting market efficiency. This inherent bias in joint test methodologies presents certain inexplicable challenges when assessing market efficiency. Nevertheless, Black (1986) posited that the joint hypothesis dilemma can be circumvented by defining market efficiency as the predictability of returns based on historical prices. Consequently, Black's (1986) findings enable the evaluation of market efficiency through statistical (time series) analysis to ascertain whether asset prices are predictable, with unpredictability indicating efficiency. These tests are numerous but can be categorized into three broad types: (i) linear, (ii) non-linear, and (iii) conditional variance models.

Linear models encompass autocorrelation tests (Box & Pierce, 1970; Escanciano & Lobato, 2009), unit root tests (Dickey & Fuller, 1979a; Phillips, 1987), long memory (Cajueiro & Tabak,

2004; Hurst, 1951), autoregressive (AR), moving average (MA), autoregressive moving average processes (ARMA) (Cortez *et al.*, 2004), as well as seasonal models and regression models with time series errors (Brooks *et al.*, 2005; Tsay, 2005). Non-linear models include the nonparametric runs (Wald & Wolfowitz, 1943) and rank (Bartels, 1982) tests for the independence of asset returns, bispectral tests for randomness in asset prices (Durlauf, 1991; Hinich, 1982) and the Brock-Dechert-Scheinkman (BDS) test for independent and identically distributed (iid) returns (Brock *et al.*, 1996; Kim *et al.*, 2003), in addition to the parametric reset test (Ramsey, 1969), the F-test (Tsay, 1986), and the Threshold test (Chan, 1991). Conditional variance models include the autoregressive conditional heteroskedasticity (ARCH) model of Engle (1982) and its variants, the generalized ARCH (GARCH) model (Engle & Bollerslev, 1986) the conditional heteroscedastic ARMA (CHARMA) model (Tsay, 1987), stochastic volatility (SV) models (Melino & Turnbull, 1990), and long-memory stochastic volatility (LMSV) models (Ray & Tsay, 2000). The subsequent subsections explored the most prominent of these techniques and assessed their robustness in predicting asset returns, thereby inferring market efficiency. An extensive review of these models is also provided by Tsay (2005).

5.2.1 Autocorrelation tests

Autocorrelation, also known as serial correlation, is one of the early techniques utilised by numerous researchers (Fama, 1965; Samuelson, 1965; Sewell, 2012; Taylor, 1984) to investigate the predictability of asset prices. This method assesses the relationship between an asset's current value and its values in preceding periods (Fama, 1965). When a series of asset returns exhibit no autocorrelation, their autocorrelation coefficient is zero (Tsay, 2005). Consequently, the absence of autocorrelation implies that prices fluctuate randomly, following a Gaussian process, and historical prices cannot be used to forecast future prices. In practical applications, Tsay (2005) argued that it was advisable to test the hypothesis that multiple autocorrelations are simultaneously zero. To achieve this, two principal approaches for estimating autocorrelation were proposed: the standard error test (Sun *et al.*, 2008) and the portmanteau statistic (Box & Pierce, 1970), along with its modifications by Ljung and Box (1978) and subsequently by Escanciano and Lobato (2009), who introduced the automatic portmanteau test.

The standard error test evaluates the autocorrelation coefficient for individual lags and identifies the significant one through a correlogram ([autocorrelation function (ACF)]) test, which assesses the correlation between current returns and several lagged observations in the time series of equity returns (Tsay, 2005). The portmanteau test presumes that asset returns constitute an independent and identically distributed (iid) sequence, with its asymptotic null distribution being a chi-squared random variable with a specific number of degrees of freedom that the user must define (Box & Pierce, 1970). Modifications by Ljung and Box (1978) are attempts to improve the

accuracy of the test statistic. However, the selection of degrees of freedom in the chi-square test statistic is not always clear and therefore affects the accuracy of the test (Tsay, 2005). Accordingly, the automatic portmanteau test redresses these challenges in two ways. First, the test automatically chooses the order of the autocorrelation tested and thus by design generates chi-square critical values. Second, the test is robust in the presence of conditional heteroskedasticity (Escanciano & Lobato, 2009).

Regardless of the test method chosen, autocorrelation can be positive or negative. A positive autocorrelation implies that an increase in returns is likely to be followed by a subsequent increase, and a decrease in returns is likely to be followed by a subsequent decrease. A negative serial correlation indicates that an increase in returns is more likely to be followed by a decrease in returns, and conversely, a decrease in returns is likely to be followed by an increase (Borges, 2010). This sequence points to some level of predictability that can be exploited by market participants, but some authors (Lo & MacKinlay, 1988; Mlambo & Biekpe, 2007) argue that the presence of autocorrelation must not be taken to indicate market inefficiency, since the tests do not demonstrate how the serial correlation may be exploited to earn excess returns. Furthermore, there is the likelihood that the way index returns are calculated potentially introduces autocorrelations in observed return series, particularly in the analysis of high-frequency financial data (Tsay, 2005). These criticisms are significant and signal caution in the use of autocorrelation to infer market efficiency, especially when high-frequency data is being analysed.

5.2.2 Unit root test

Numerous financial time series, including asset prices, commodity prices, and foreign exchange rates, demonstrate trending behaviour, or non-stationarity, in their mean (Bekaert *et al.*, 2009, 1998; Gumbo & Siziba, 2016; Tsay, 2005). Non-stationarity in a time series essentially indicates that the distribution's shape evolves over time, thereby diminishing the series' predictability (Tsay, 2005). Consequently, the unpredictability or non-stationarity of a time series is intrinsically associated with random walks. Thus, the terms non-stationarity, random walk, and unit root are often used interchangeably (Brooks *et al.*, 2005; Escanciano & Lobato, 2009; Tsay, 2005). The literature (Choi, 2001; Phillips & Perron, 1988; Phillips & Xiao, 1998) extensively explored various methodologies for unit-root testing, partly because no single approach is universally recognised as the most powerful. These methodologies include the Dickey-Fuller (DF) test (Dickey & Fuller, 1979), which was extended to the Augmented Dickey-Fuller (ADF) test (Said & Dickey, 1984), the Elliott-Rothenberg-Stock (ERS) test (Elliott *et al.*, 1996), the Schmidt-Phillips test (Schmidt & Phillips, 1992), the Phillips-Perron (PP) test (Phillips & Perron, 1988), the Zivot-Andrews test (Zivot & Andrews, 2002) and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test (Kwiatkowski *et al.*, 1992).

The DF test is based on regression and is set up either as a driftless random walk against a stationary first order (one-lagged) autoregression, or a random walk with drift against an unknown linear trend with stationary first-order autoregressive errors. Its null hypothesis is that there is a unit root in the data, implying asset returns are non-stationary (price unpredictable) and the alternative hypothesis varies depending on the version of the test being used (Dickey & Fuller, 1979). A major drawback associated with the DF test is that the regression error term is unlikely to be white noise, in which case the DF model is augmented to capture higher-order autocorrelation, which is popularly known as the Augmented Dickey-Fuller (ADF) test (Brooks *et al.*, 2005; Maddala & Kim, 1998). Several authors (Leybourne, 1995; Pantula *et al.*, 1994) have proposed modifications to enhance the accuracy of the ADF, whose major weakness is a high Type 1 error[80].

Elliott *et al*. (1996) introduced the Elliott-Rothenberg-Stock (ERS) test, which is a modification of the Augmented Dickey-Fuller (ADF) test. The ERS test assesses the presence of a unit root in a detrended series, rather than the original data series, by employing the generalised least squares (GLS) method to derive the detrended version of the original series. Harvey and Leybourne (2005) demonstrated that the ERS tests surpass the ADF models in terms of both sensitivity and specificity. Consequently, several studies have utilised the ERS test to evaluate market efficiency in equity markets of several countries including Asia (Cooray & Wickremasinghe, 2007a), Asian and American equity markets (Nguyen & Parsons, 2022) as well as cryptocurrencies (Alam, 2017). Another model proposed to address the low power of the ADF is that of Schmidt and Phillips (1992), who employed Lagrange Multipliers (LM) to establish a deterministic trend of the respective assets' trends. However, a significant limitation of this model is error autocorrelation (Lee & Strazicich, 2003). This limitation is mitigated by the Phillips and Perron test (Phillips & Perron, 1988), which is a direct modification of the Dickey-Fuller (DF) that seeks to correct for autocorrelation and heteroscedasticity in the errors.

Nevertheless, the Phillips and Perron test (Phillips & Perron, 1988) also exhibits certain limitations. Notably, Ng and Perron (2001) and Nguyen and Parsons (2022) have demonstrated that it is subject to significant size distortions when errors possess large autoregressive and moving average roots. Ng and Perron (2001) recommended employing the Akaike information criterion (AIC) for lag selection to enhance the test’s power. Despite these shortfall, the Phillips and Perron has garnered attention among researchers evidences by widespread use in several studies exploring market efficiency in various equity markets located in European (Worthington &

[80] A Type 1 error refers to incorrectly rejecting a true null hypothesis of unpredictability, thereby, concluding that the market is inefficient when it is efficient (Leybourne, 1995).

Higgs, 2004), Asia (Narayan & Narayan, 2007) the US and Latin America (Escobari *et al.*, 2017) South Africa (Grater & Struweg, 2015) and Asia (Cooray & Wickremasinghe, 2007).

Another variation of the ADF is that as modified by Kwiatkowski *et al.* (1992) that is widely referred to as the KPSS[81] test. The KPSS test tests the null hypothesis of stationarity against the alternative of a unit root (non-stationarity) (Kwiatkowski *et al.*, 1992). It also addresses the critique that the ADF and PP tests lack power relative to relevant alternative tests. This is because the method of testing the null hypothesis in the ADF and PP tests does not provide much insight into the presence of a unit root (Kwiatkowski *et al.,* 1992). The KPSS test is specifically designed to test the null hypothesis of stationarity (market efficiency) against a unit root (market inefficiency) as the alternative hypothesis (Maddala & Kim, 1998). The KPSS tests have been applied to test for market efficiency in several asset classes including equity (Worthington & Higgs, 2004), currencies (Firoj & Khanom, 2018), derivatives (Lee & Ryu, 2014), commodities (Maslyuk & Smyth, 2008) and cryptocurrencies (Alam, 2017).

5.2.3 Spectral-based tests

The spectral analysis tests use Fourier transformation to express a time-domain representation of data (time series) to a spectrum-domain representation by summing up trigonometrical functions (sines and cosines) with different amplitudes to get artificial time series that resemble actual time series (Hinich, 1982). This allows for the analysis of variance in which the population variance is broken up across different frequencies, thereby making it possible to test for the non-randomness of a time-dependent variable (Durlauf, 1991). Spectral analysis has a long history in econometrics (Granger & Hatanaka, 2015) and its applications include business cycle analysis (Baxter & King, 1999), option valuation (Carr & Madan, 1999), as well as the volatility and correlation of assets (Chaudhuri & Lo, 2015). Granger and Morgenstern (1963) are some of the first authors to apply spectral analysis in finance to test the weak-form EMH. One strand of the literature (Deo, 2000; Durlauf, 1991; Escanciano & Lobato, 2009) has utilised spectral analysis to test whether a given time series is a martingale difference. Another strand of the literature (Bertoneche, 1979; McPherson & Palardy, 2007) has extensively applied spectral analysis to test for deviations from randomness.

Despite its widespread use, some authors have criticised the tests, arguing that price randomness in the time domain does not allow one to reach the more general conclusion that the market is efficient in a broad economic sense (Logue & Sweeney, 1977). This finding is supported by Bertoneche (1979), who analysed selected European equity markets and discovered that, while spectral analysis initially suggests that market prices are random (indicating market efficiency),

[81] Kwiatkowski-Phillips-Schmidt-Shin (1992)

further examination of the data reveals discernible above-market profits. These conflicting findings, therefore, render spectral analysis unreliable for testing market efficiency. Moreover, Smidt (1968) noted that spectral analysis is not a particularly powerful test of market efficiency, due in part because these tests are not directed against specific alternative hypotheses.

5.2.4 Runs test

The runs test developed by Wald and Wolfowitz (1940) and operationalised by Bartels (1982) is a non-parametric test, whereby the number of sequences of consecutive positive and negative returns is tabulated and compared against its sampling distribution under the random walk hypothesis (Chen, 2010; Hentati-Kaffel & De Peretti, 2015). The runs test is based on the premise that if price changes (returns) are random, the actual number of runs should be close to the expected number of runs computed by a standard normal distribution, since for large sample sizes, the test statistic is approximately normally distributed (Guidi & Gupta, 2013; Mood, 1940). A run (sequence of consecutive price changes with the same sign) can therefore take any of three forms - an upward run (prices go up), a downward run (prices go down) and a flat run (prices do not change). Numerous studies (Borges, 2010a; Hentati-Kaffel & De Peretti, 2015; Nadarajah & Chu, 2017; Sukmana & Khairani, 2024; Urquhart, 2016; Worthington & Higgs, 2004) Brauneis & Mestel, 2019) have employed runs tests to assess market efficiency. Moreover, the efficacy of runs tests is extensively supported in the literature and authors argue that they are more appropriate than the parametric autocorrelation test, since observed returns are not assumed to follow the normal distribution (Gujarati, 2003). However, there is strong criticism against the runs test, emanating from observations that the number of runs for pre-crisis and post-crisis periods is similar, thereby rendering it insensitive to changing economic environments (Huitema *et al.*, 1996). Furthermore, Yen and Lee (2008) argue that runs tests refute random behaviour relatively infrequently, because they are not designed to be powerful when there are trends.

5.2.5 Long memory

Numerous definitions of long memory are detailed in Beran *et al.* (2013). However, a more recent and integrative definition is provided by Saha *et al.* (2022), who reasoned that long memory (or persistence) is a trending process where a positive or negative price movement is more likely to be followed by another price move in the same direction. For an anti-persistent (mean reversion) process, a positive price movement is more likely to be followed by a move in the opposite direction. The presence of long memory, therefore, suggests some predictability in asset prices, a condition associated with market inefficiency. Three methods are commonly used in determining whether a series has a short memory, anti-persistence, or long memory. These three methods are: Hurst's (1951) rescaled range (R/S) analysis, the modified R/S analysis and Generalised Autoregressive Conditional Heteroscedastic (GARCH) type models.

The Hurst exponent (H), typically calculated through Hurst's (1951) rescaled range (R/S) analysis ranges from 0 to 1 and is used to classify a time series into three types based on its value, H (Qian & Rasheed, 2004). If H equals 0.5, the series is random. When $0 < H < 0.5$, the series is mean reverting[82] and the strength of mean reversion increases as the Hurst exponent (H) approaches 0. When $0.5 < H < 1$, the series is persistent[83] (or trending) and becomes more predictable as H approaches 1 (Qian & Rasheed, 2004). To compute H, Hurst (1951) compared the minimum and maximum values of cumulative deviations from the sample mean, renormalised by the sample standard deviation. For persistent (long-memory) processes, the deviations are larger than for random (short-memory[84]) processes (Saha *et al.*, 2022).

Lo (1991) argued that the classical Hurst's (1951) R/S test has been proven to be weak, as it tends to indicate a time series has a long memory even when it not present. As a result, the modified R/S was suggested to improve the weaknesses of the R/S in estimating H (Lo, 991). The motivation for this modification was to account for autocovariances especially in the case of dependent random variables (Clark, 2005). Nevertheless, Teverovsky and Taqqu (1997) and Teverovsky *et al*. (1999) contended that Lo's (1991) modified R/S test cannot reject the null hypothesis of short memory either.

GARCH type models including the Fractionally Integrated Generalised Autoregressive Conditional Heteroscedastic (FIGARCH) models by Baillie *et al*. (1996) and its derivatives such as the Fractionally Integrated Exponential Generalised Autoregressive Conditional Heteroskedastic (FIEGARCH) model by Bollerslev and Mikkelsen (1996) also are of significance in explaining long memory in asset prices. Additionally, the use of fractional Brownian noise and the Autoregressive Fractionally Integrated Moving Average (ARFIMA) process by Chung (1996) have also been applied to explore long memory in asset prices (Saha *et al.,* 2022).

The finance literature provides evidence of long memory in several assets including bonds (Backus & Zin, 1993), equities (Bollerslev & Mikkelsen, 1996; Hiemstra & Jones, 1997; Hull & McGroarty, 2014), currencies (Cheung, 1993), commodities(Elder & Serletis, 2008; Ghorbel &

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82 Mean reversion suggests that increases in values of a series are likely to be followed by decrease, and vice versa, thereby sustaining the long-term average (mean) (Hurst, 1951).

83 Persistence suggests past values of a series exert influence on future values over long horizons, (Hurst, 1951).

84 The differences among short memory, anti-persistence, or long memory are here summarised:
Persistent (long memory): $0.5 < H < 1$. The series shows long-term trends (high values follow high values).
Random (short memory): $H \approx 0.5$. The series has no long-term correlation, behaving like a random walk.
Anti-Persistent: $0 < H < 0.5$. The series frequently reverts to the mean.

Souissi, 2016), futures (Barkoulas *et al.*, 1999) and cryptocurrencies (Cheah *et al.*, 2018; Khuntia & Pattanayak, 2018; Phillip *et al.*, 2019; Takaishi, 2020), suggesting some inefficiency in these assets. Therefore, Saha *et al.* (2022) noted that this is because there are multiple factors, such as structural breaks, temporal and cross-sectional aggregation, and bias in the estimation process which can manifest as spurious long memory. Researchers, investors and policy makers, therefore, need to exercise caution when utilising long memory tests to profile the market efficiency of assets as it may be misleading.

5.2.6 Other static tests of market efficiency

The finance literature mentions other alternative statistical tests that have been applied to assess market efficiency. These alternative approaches often gain plausibility when certain market conditions or assumptions regarding pricing processes are relaxed. Among the most prominent are methods based on non-linear processes. Furthermore, given that market efficiency, by definition, implies that investors cannot consistently outperform the market, alternative lines of inquiry have focused on identifying the existence of arbitrage opportunities. This section introduces these two types of tests, beginning with non-linear models. Its aim is to illustrate that the list of market efficiency tests is broad and what has been presented in this study is not exhaustive.

Regarding non-liner tests, Hinich and Patterson (1985) found that several researchers test random walk using the correlation structure, consequently ignoring possible nonlinear relationships between consecutive price changes. From a statistical perspective, (linear) autocorrelation-based tests have no power against nonlinear processes (Granger & Andersen, 1978). Hence, the use of linear processes may mislead users to conclude no autocorrelation, inferring market efficiency when prices are non-linearly correlated. Consequently, a number of studies (Jiménez-Rodríguez, 2015; Lim & Brooks, 2011; McPherson & Palardy, 2007; Scheinkman & LeBaron, 1989) endeavoured to capture nonlinearity in testing for randomness in asset prices.

Following Lim and Brooks (2011), nonlinear stationarity tests may be grouped into two categories: (i) those that do not specify a nonlinear alternative and (ii) those that do. The former includes the bi-spectrum test (Hinich, 1982), the third-order moment test (Hsieh, 1991), the BDS test (Brock *et al.*, 1996) and the bicorrelation test (Brooks & Hinich, 2001; Hinich, 1996). Kumar and Kamaiah (2016) explored nonlinearity in the nominal exchange rates of BRICS countries using the BDS test, bi-spectrum test, and neural network test to backtest the variance ratio (VR) test results, which found market inefficiency. All three tests confirmed the presence of nonlinearity dependence in the five series studied. Despite their usefulness as general tests for nonlinearity, they do not suggest the actual type of nonlinear dynamics. The second category of tests (those

that specify a nonlinear alternative) is more popular than the first and involves testing linearity against specified nonlinear models (Lim & Brooks, 2011). Common nonlinear alternatives are considered in the literature by McLeod and Li (1983), Engle (1982) and Tsay, (1986).

Another test that is increasingly used as a tool to investigate market efficiency is statistical arbitrage. This technique aims to bypass the joint hypothesis problem by implementing strategies that exploit persistent anomalies, without requiring the specification of an equilibrium model (Hogan *et al.*, 2004). Consequently, the presence of statistical arbitrage suggests a deviation from market equilibrium and, by extension, challenges the notion of market efficiency. The major drawback of this group of models is that they view efficiency as a static phenomenon, a conjecture at variance with the current understanding of market dynamics as presented by Lo (2004).

5.2.7 Summary of static view tests of market efficiency

The foregoing discussion on static view tests demonstrated that numerous techniques have been applied to measure market efficiency. Some of the techniques, such as autocorrelation tests, are more popular than others due to their simplicity in terms of both implementation and interpretation of results. Other tests, such as the unit root and long memory tests, have undergone several transformations to enhance test accuracy. Yet, their major weakness - that they measure market efficiency on an absolute basis, remains. Therefore, when static view tests are applied, it remains unclear whether a market is becoming (relatively) efficient. Understanding whether a market is becoming (more) efficient is particularly important for portfolio managers who take appropriate positions to exploit anomalies by betting that markets will become more inefficient to unlock profit opportunities. In addition, most new markets are rarely born efficient. Thus, a method that does not tell if a market is becoming more efficient or less efficient is not fully informative, as it does not shed light on whether an asset demands more passive or active trading to benefit from it. Overlooking changes in efficiency in new markets may result in aggregating inefficiency during the early days of a market, thereby biasing the results of the test and erroneously leading to the conclusion that there are profit opportunities simply because of past inefficiencies ((Emerson *et al.*, 1997).

Therefore, while the above static view test models to market efficiency continue to evolve in line with calls to enhance their accuracy, much of the emphasis has shifted towards enhancing a model's responsiveness to changing market conditions. This focus has necessitated the development of rolling window tests that capture changes in efficiency across time (Lim & Brooks, 2011).

Section 5.3 discusses the main rolling window tests that have been used to measure market efficiency.

5.3 Rolling Window Tests of market efficiency

The finance literature documents several rolling window methods for testing market efficiency, including variance ratio (VR) tests and their modifications (Belaire-Franch & Contreras, 2004; Kim, 2006, 2009; Kim & Shamsuddin, 2008; Smith & Dyakova, 2014), GARCH-in-mean (GARCH-M) models (Charfeddine & Khediri, 2016), the Generalised Spectral (GS) test (Escanciano & Velasco, 2006), and the Dominguez-Lobato (DL) test (Domínguez & Lobato, 2003). Of these tests, the VR test is the most popular methodology applied to test market efficiency of several asset classes such as equities (Urquhart & McGroarty, 2016), currencies (Cialenco & Protopapadakis, 2011), commodities (Roubaud & Arouri, 2018) and cryptocurrencies (Brauneis & Mestel, 2019). The VR tests are seen as valuable for their robust statistical powers, and robustness to non-normality. The following section discusses VR tests greater detail.

5.3.1 Variance Ratio Test

Ever since the pathbreaking works of Poterba and Summers (1988) and Lo and MacKinlay (1988), the variance ratio (VR) test has emerged as a key tool in examining whether asset returns are serially uncorrelated and, by inference, whether they are market informationally efficient (Charles & Darné, 2009; Smith & Dyakova, 2014; Urquhart & McGroarty, 2016). The power of the VR test is corroborated by Lo and MacKinlay (1989), who benchmarked its performance against common unit root and serial correlation tests and found that the VR test is more powerful and outperforms the DF unit root test and the Box-Pierce serial correlation test in detecting serial correlation. As a result, the VR test has become one of the most popular techniques for testing market efficiency (Kim & Shamsuddin, 2008; Charles & Darné, 2009). The VR method assesses whether returns are serially uncorrelated by exploiting the understanding that the variance of a random walk increases linearly in all sampling intervals (Poterba & Summers, 1988; Lo & MacKinlay, 1988). This means that, if an asset with price p_t follows a random walk, then the variance of its ***k-period*** return, $r_{t,k}$ $[Var(r_{t,k})]$ is equal to k times the variance of the one-period r_t return[85] $Var(r_t)$ (Urquhart & McGroaty, 2016)

$$VR(k) = \frac{Var(r_{t,k})}{kVar(r_t)}. \tag{5.1}$$

[85] Lo and MacKinlay (1988) showed that the random walk model assumes $r_t = p_t - p_{t-1} = \varepsilon_t$. The random error term ε_t is independent and identically distributed (iid) with $E(\varepsilon_t) = 0$ and $Var(\varepsilon_t) = \sigma^2$. Therefore, the variance of the one-period return is σ^2 while the variance of the k-period (from t to k) return, $Var(r_{t,k}) = \sum_{i=1}^{k} Var(\varepsilon_t + i) = k\sigma^2$.

Mathematically, the VR is the variance of returns sampled at a higher frequency divided by the variance of returns sampled at a lower frequency (Lo & MacKinlay, 1988). This makes it better positioned to capture linear serial correlation. The value of the higher frequency sampled variance and that of the lower frequency sampled variance in theory are equivalent. Thus, the ratio of the variances is an *a priori* one.

Smith and Dyakova (2014) illustrated that, given a one-period return, a_t, and an arbitrary drift parameter μ, for $t = 1,\ldots,T$, the unpredictable characteristic of returns in weak-form efficient markets may be modelled by a martingale model as in Equation 5.2:

$$a_t = \mu + \varepsilon_t, \tag{5.2}$$

where $a_t = p_t - p_{t-1}$, and p_t is the natural logarithm of an asset's price (cryptocurrency price or equity index level). The series p_t is a martingale if,

$$E[p_{t+1}|\{p_t, p_{t-1}, \ldots\}] = p_t. \tag{5.3}$$

Since forecasts of p_{t+1}cannot be improved by past information of p_t, returns a_t are unpredictable and form a martingale difference sequence (MDS) i.e., $E|a_t| < \infty$, $E[a_t|\{a_{t-1}, a_{t-2}, \ldots\}] = 0$. Accordingly, under the martingale hypothesis, asset returns are uncorrelated. Lo and MacKinlay (1988) showed that the VR of an MDS scales linearly across holding period frequencies, as shown in Equation 5.4:

$$VR(q) = \frac{\frac{1}{q}\, var\big(a_t(q)\big)}{var(a_t)} = 1 + \sum_{j=1}^{q-1}\left(1 - \frac{j}{q}\right)\rho_j, \tag{5.4}$$

where $a_t(q)$ is the q-period continuously compounded return ($a_t(q) \equiv a_t + a_{t-1} + \cdots a_{t-q+1} = p_t - p_{t-q}$), and ρ_j is the jth order autocorrelation coefficient of $\{a_t\}$.

Lo and MacKinlay (1988) showed that $VR(q) = 1$ for all q if the series is a martingale[86]. However, if the returns are serially correlated[87], $VR(q) \neq 1$, with significantly higher values suggesting positive serial correlation (trending), while those significantly lower than one suggest negative serial correlation mean reversion (Charles & Darné, 2009).

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[86] When VR = 1 then returns are a martingale implying that price changes are entirely random because all available information is already reflected in the price and any price changes are driven only by new information.

[87] Serial correlation refers to the degree to which past returns influence future returns. If market returns show strong serial correlation, it suggests patterns or trends that investors might exploit (Charles & Darné, 2009).

The VR test statistic proposed by Lo and MacKinlay (1989) is given by Equation 5.5:

$$Z(q) = \frac{VR(q) - 1}{\phi(q)} \tag{5.5}$$

where $VR(q)$ is the variance ratio for a given q period return. $\phi(q)$ represents the asymptotic standard error of the VR defined as in Equation 5.6:

$$\phi(q) = \begin{cases} \sqrt{\dfrac{2(2q-1)(q-1)}{3qT}} \; conditional\ homoscedasticity \\ \qquad\qquad or \\ \sqrt{\displaystyle\sum_{j=1}^{q-1} \left[\frac{2(q-j)}{q}\right]^2 \rho(j)} \; conditional\ \ Heteroscedasticity \end{cases} \tag{5.6}$$

where T is the total number of observations, j is an index used for changing variance and $\rho(j)$ accounts for autocorrelation as defined in Equation 5.4.

The VR test uses fixed-length rolling windows of data to re-estimate variance over the out-of-sample period on successive periods, thereby capturing evolving serial correlation (price predictability) changes with the magnitude of the difference highlighting the relative predictability of markets (Kim, 2009; Lim & Brooks, 2011; Smith & Dyakova, 2014). This makes VR tests robust for testing market efficiency, exploring how efficiency is changing and comparing the levels of efficiency in different markets or periods. However, the VR test has received some criticism.

Notably, bias and skewness in finite samples[88] occurred because the test followed a standard normal distribution asymptotically (Charles & Darné, 2009). The normality assumption presented challenges, especially in parameterising variance in smaller samples, and where asset returns are highly volatility and returns deviate significantly from the normality assumption.

Additionally, for a series to be deemed a pure random walk (serially uncorrelated), strictly all VRs for that series, regardless of the holding period, must be equal to one. Hence, the test for serially uncorrelated returns should be conducted as a joint test for all VRs, a phenomenon that is not provided for in the Lo and MacKinlay (1988) VR test. This criticism is, however, addressed by Chow and Denning (1993), who suggested the use of multiple VR tests where only the maximum absolute VR value in a set is considered since it is pragmatic to employ multiple VR tests rather than individual VR tests. Yet, the modifications to the VR test set out by Lo and MacKinlay (1988)

[88] Bias and skewness in finite samples emanate from that variance estimators especially in small sample sizes, deviate from the normality distribution assumption (Charles & Darné, 2009).

suggested by Chow and Denning (1993) are asymptotic tests with low power and poor size properties in finite samples resulting in misleading statistical inference (Wright, 2000).

Consequently, Wright (2000) proposed a non-parametric alternative to asymptotic VR tests using ranks. Wright's (2000) tests have two advantages. First, as the rank tests have exact sampling distribution, there is no need to resort to asymptotic distribution approximation. Second, the tests may be more powerful against a wide range of models displaying serial correlation since the tests based on ranks are exact under the *iid* assumption (Charles & Darne, 2009). Belaire-Franch and Contreras (2004) followed the approach of Chow and Denning (1993) and instead suggested a multiple-rank VR test based on Wright's tests (2000) to counter the low power of VR tests emanating from the need for joint tests and redressing asymptotic testing. The resulting method, which is popularly known as the Joint Sign test, is corroborated by Kim and Shamsuddin (2008) and is widely applied in testing market efficiency.

Although Wright (2000) suggested utilising rank tests to address the drawbacks related to asymptotic theory, it does not address the problem of unreliability of VR tests in small samples (Deo & Richardson, 2003). To redress this, Kim (2006) proposed a wild bootstrap method for the Chow and Denning (1993) modified VR test to improve the performance of the VR test on small samples. The wild bootstrap method/approach by Kim (2006) involves computing the individual and joint VR test statistics on samples of T observations formed by weighting the original data by mean 0 and variance 1 and using the results to form bootstrap distributions of the test statistics (Charles & Darné, 2009; Smith & Dyakova, 2014). This wild bootstrap method is, therefore, a resampling method that approximates the sampling distribution of the VR test statistic and applies to data with unknown forms of conditional and unconditional heteroscedasticity (Davidson & Flachaire, 2008).

However, when using joint variance ratio tests, including the joint sign and wild bootstrap tests, a set of holding periods must be chosen. The set of values selected can affect the power of the tests. To avoid this problem, Choi (1999) proposed an automatic VR (AVR) test to implement joint VR tests. The automatic variance ratio, AVR, test is corroborated by Kim (2009).

Finally, and perhaps the lasting criticism of VR tests, thin (or infrequent) trading, which is not uncommon in developing markets or young assets, causes bias when VRs are applied in testing the evolvement of a market's efficiency (Miller *et al.*, 1994). This is because the absence of a price change between moments may be interpreted as being caused by the absence of a price reaction and consequently as a sign that the market is inefficient, when it may simply be caused by the absence of any trade due to trading taking place infrequently (Mlambo & Biekpe, 2007). To deal with the problem of thin trading, Miller *et al.* (1994) suggested that a moving average model that reflects the number of non-trading days be estimated, after which returns are adjusted

accordingly. While the moving average method addresses issues related to infrequent trading, it also tends to smooth out asset volatility and can create new trends that may not accurately reflect the actual evolution of an asset's price changes.

Smith and Dyakova (2014) applied a recursive least square (RLS) smoothing approach to tease out the impact of thin trading on asset returns. Smith and Dyakova's (2014) method proceeded with observed returns modelled as in Equation 5.7.

$$a_t = \vartheta_0 + \vartheta_1 a_{t-1} + \varepsilon_t, \tag{5.7}$$

where a_t is one-period observed returns. The regression coefficients ϑ_0, ϑ_1 and the residual disturbance ε_t are estimated by the RLS method. This approach varies from Miller *et al.'s* (1994), who relied on ordinary least squares (OLS) to estimate the regression residual disturbance and the regression coefficients. Smith and Dyakova (2014) reasoned that the OLS generate a non-trading adjustment that is constant through the observation period, which is unrealistic, especially for emerging markets. Therefore, Smith and Dyakova (2014) argued that the RLS approach, instead of OLS, is ideal to adjust for non-trading as it entails repeatedly applying the regression equation to subsets of data to estimate the parameters of the regression model (5.2). This procedure is carried out (recursively) until convergence is attained. RLS is therefore more robust than the OLS, since the latter is more static. The RLS method estimated residuals, ε_t, and regression coefficient, ϑ_1, are then used to obtain corrected returns (a_t^{CR}) as shown in Equation 5.8.

$$a_t^{CR} = \frac{\varepsilon_t}{1 - \vartheta_1}. \tag{5.8}$$

Overall, this section presented the VR test as a useful tool rooted in the iid nature of price innovations. This property is tested empirically, with deviations indicating potential market inefficiencies. Its major weaknesses include assuming constant correlations, finite samples, and length of rolling windows. Users should ideally support it with additional tests or models that account for these limitations. The next section explores other rolling windows tests with primary focus on their strengths and weaknesses in parameterising evolving market efficiency.

5.3.2 Other rolling window tests of market efficiency

A substantial branch of the literature discussed in Section 5.2 comprised static view tests which view market efficiency as an all-or-nothing condition, overlooking the AMH view that market efficiency evolves with periods of inefficiency alternating with those of efficiency. This led some authors to estimate the static view tests in rolling windows to detect changes in market efficiency. For example, Cajueiro and Tabak (2004) estimated the time-varying Hurst exponent (defined in Hurst, 1951) in rolling windows to detect changes in the long-range dependence, given that long-

range dependence (or long memory) invalidates the random walk hypothesis and therefore contradicts market efficiency.

Another rolling window test is that of Hull and McGroarty (2014), who examined the changing behaviour of calendar anomalies[89] over time through a GARCH analysis. The authors took a five-year window and calculated GARCH (1,1)[90] statistics. The authors argued that the five-year window provided enough observations to generate reliable results while also providing enough results to analyse how the calendar anomalies have behaved over time.

5.3.3 Rolling-window horizon and estimator reliability

There are notable differences between the rolling windows applied in several VR studies (Belaire-Franch & Contreras, 2004; Kim & Shamsuddin, 2008; Lim *et al.*, 2008; Smith & Dyakova, 2014), the four-year window applied by Cajueiro and Tabak (2004) and the five-year window applied by Hull and McGroarty (2014). These differences leave users of rolling window test with a delicate balancing act. A shorter window is more sensitive to identifying temporary changes in the predictability patterns, which may be missed by a longer time window. Yet, statistically, the window length should be sufficiently long so that subsequent statistical tests do not suffer size distortion or inadequate power(Zivot & Wang, 2003).

The rolling-window choice reflects the standard bias–variance trade-off inherent in estimating long-memory measures. VR estimates are sensitive to short sample lengths and can become unstable when windows are too short, especially in high-volatility assets. The study therefore prioritises estimator reliability and interpretability over high-frequency responsiveness. This is consistent with the portfolio design, which applies static annual rebalancing; a highly reactive efficiency series would create a horizon mismatch between a daily regime proxy and an annually implemented allocation rule. The efficiency proxy is estimated using a rolling horizon that is intentionally aligned with the strategic allocation horizon of the study. Because portfolio weights are rebalanced on an annual schedule, the purpose of the efficiency estimate is not to generate short-term trading signals, but to characterise the prevailing informational environment over a strategic horizon. A longer rolling window therefore provides an efficiency measure that is commensurate with the investment horizon under investigation.

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89 Calendar anomalies explored by Hull and McGroarty (2014) include: the Monday effect, January effect, time of the month and Halloween effect.

90 The GARCH (1.1) model estimated by Hull and McGroarty (2014) was, $\sigma_t^2 = \omega + \alpha\epsilon_{t-1}^2 + \beta\sigma_{t-1}^2$. The (1,1) specifically indicated that the model used one lag of the squared error term (ϵ_{t-1}^2) and one lag of the conditional variance (σ_{t-1}^2) to forecast the t period's variance, σ_t^2

A short rolling window may risk conflating volatility dynamics induced by crises with genuine informational inefficiency. Extreme market events lead to volatility clustering, heavy-tailed return distributions, and structural breaks, all of which mechanically distort efficiency estimators. When the window is excessively short, these transient turbulence effects are misclassified as persistent deviations from weak-form efficiency, implying that the estimator captures the statistical artifacts of crises rather than the underlying informational structure of the market. Utilising a longer rolling window mitigates this mechanical endogeneity by smoothing episodic shocks and allowing efficiency estimates to reflect more enduring properties of the return-generating process rather than short-lived volatility spikes.

5.3.4 Summary of rolling-window tests of market efficiency

Rolling window tests provide a dynamic, time-sensitive framework for assessing the evolution of market efficiency. Their effectiveness depends critically on several methodological choices, such as selecting appropriate window sizes, adjusting for non-normality in financial time series, and addressing issues like thin trading in less liquid markets. Furthermore, ensuring that model assumptions realistically reflect the underlying data is crucial, as reliance on historical data may limit the tests' predictive power regarding future efficiency trends. Judicious parameter selection is essential, as an incorrect choice in window length can lead to model overfitting or underfitting, thereby increasing the risk of Type 1 and Type 2 errors[91]. Nevertheless, rolling window tests, particularly when applied through VR tests represent a significant step forward in transitioning from a static to a more nuanced, dynamic understanding of market efficiency. Rolling window tests are however not the only tests that explore changes in market efficiency. Test of Evolving Efficiency (TEE) represent an alternative approach. The next section delves deeper and explores what TEE are and how they differ from rolling window tests.

5.4 Tests of Evolving Efficiency

TEE include various multifactor models such as the Adjusted Market Inefficiency Magnitude (AMIM) model by Le Tran and Leirvik (2019), the Market Inefficiency Magnitude (MIM) from Noda (2021), and the multi-factor model with time-varying coefficients of Emerson *et al.* (1997). These tests are found to be of growing significance among researchers (Ito *et al.*, 2016; Jefferis & Smith, 2005; Lim & Brooks, 2011; Noda, 2016). The TEE is a time-varying AR process with GARCH errors (Hall & (Hall & Miles, 1992), and it has been widely applied to detect changes in efficiency through time (Lim & Brooks, 2011; Noda, 2016). This technique is unique in the sense that it is

[91] Type 1 error (false positive) occurs when the null hypothesis of market efficiency is rejected even though the market is truly efficient. Type 2 error (false negative) happens when the null hypothesis of market efficient is not rejected when the market is inefficient (Leybourne, 1995).

cognisant of the view that new markets are rarely born fully efficient, but become more efficient with time due in part because new markets have a short history, and therefore agents do not have much information on which to base their expectations (or predictions) of asset prices (Zalewska-Mitura & Hall, 1999). In new markets it is common to observe wild swings in asset prices and erratic trades. Emerson *et al.* (1997) reason that this is because, when new markets first start trading, market players would not know how the price discovery mechanism works. As the market matures, players learn how prices move. Consequently, the learning of the market players is time-varying towards steady state values over time (Emerson *et al.*, 1997). Thus, TEE does not test whether a market is efficient or not per se. Rather it delves deeper and explores whether and how a market is becoming more efficient. This helps separate bias in concluding that a market, especially new markets, is inefficient based on inefficiencies at the early stages of a market. As a result, the TEE model fulfils two criteria. First, it evaluates existing market efficiency and presents whether there are profit opportunities. Second, it measures how quickly markets move towards efficiency. This is achieved by developing a serial correlation AR model that explicitly allows for the changing parameters that may be present (Emerson *et al.*, 1997).

Since its development, the TEE has been applied extensively in several markets, including those located in Central and Eastern European countries (Rockinger & Urga, 2000; Zalewska-Mitura & Hall, 2000), Chinese Shanghai and Shenzhen Stock Exchanges (Li, 2003), some African stock exchanges (Jefferis & Smith, 2005), some Arab stock markets (Abdmoulah, 2010), as well as in South Africa (Heymans & Santana, 2018). There is also evidence that the TEE model outperforms the fixed coefficient model (static view models) in characterising market efficiency (Bonga-Bonga, 2012). This finding indicates that the time-varying parameter model adds a benefit in testing the weak-form efficiency and changes in the market microstructure may be detected more easily in high-frequency data (Rockinger & Urga, 2000).

The tests are only limited to assessing whether there is any significant change in market behaviour across time, i.e., whether there are different patterns of autocorrelation of returns. This makes it difficult to compare or rank assets in terms of relative efficiency. Other weaknesses have to do with the methodology. For the most part, TEE is estimated using parametric GARCH processes with time-varying coefficients (Emerson *et al.*, 1997; Zalewska-Mitura & Hall, 1999, 2000). The weaknesses of parametric GARCH processes are that they tend to be mis-specified when the true conditional variance function is nonlinear or nonstationary. This, in turn, leads to a model that does not capture the true distribution of the error terms, weakening the modelling of autocorrelation. In addition, erroneously applying a parametric GARCH model causes overfitting or underfitting the model (depending on the choice of the lag orders) thereby increasing the likelihood of false conclusions (Engle & Kroner, 1995).

By comparison, the TEE and Rolling window tests are different in terms of approaches. A rolling window test involves looking at a fixed period (say a 500-day window) and moving this window through the data to help determine if a relationship remains stable over different time periods and identifying shifts in market conditions (Kim & Shamsuddin, 2008). On the other hand, TEE focuses on the dynamic nature of market efficiency by using models such as GARCH that adapt to new information. Instead of fixed periods, TEE uses time-varying parameters that adjust as more data becomes available. This helps build an understanding why market efficiency changes over time (Neely et al., 2009). Thus, while both methods study evolving market efficiency, rolling window tests check for stability using fixed periods, while TEE captures changes in efficiency using flexible models. This makes Rolling windows examine if efficiency changes over time, while TEE ideal for analysing why efficiency changes over time.

5.5 Summary

This chapter explored the various tests for market efficiency. It presented that, for the most part, these tests explore whether asset prices follow a random walk or are predictable tests in line with weak-form efficiency. Three broad categories of the test are available in testing whether a market is efficient or not, namely: static views tests, rolling window tests, and TEE.

Static view tests of market efficiency explore whether the market is efficient or not. The most popular of these include serial-correlation tests, unit-root tests, runs tests, long-memory tests and spectral tests. Their major weakness is that they do not explore how efficiency changes. This makes them more suitable for developed and mature markets with steady and less dramatic changes in pricing processes. A more flexible category of tests, TEE, which allows for assessing whether a market is becoming (more) efficient has been proposed to address the shortcomings of static view tests. TEE capture gradual changes in efficiency, making them ideal to capture evolving efficiency in all markets, infant and mature, developed and less developed across time. This category of tests is of growing significant among researchers. By contrast, rolling window tests and in particular VR tests are becoming more popular among academics and practitioners. This is because they resonate with investors and are seen as bridging the gap between the popular views of EMH proponents and behavioural finance advocates. Another advantage of utilising the VR tests is that, unlike statistic view tests and TEE, VR tests can incorporate gradual changes in efficiency, especially in infant markets characterised by thin trading. The VR method is therefore found robust and appropriate to assess changes in efficiency in infant or nascent asset classes such as cryptocurrencies and other less developed markets where thin trading is common. The next chapter therefore applied VR tests to assess the market efficiency of cryptocurrencies.

CHAPTER SIX

DATA AND METHODOLOGY

6.1 Introduction

The foundation of scientific research lies in the guiding philosophy that shapes its approach and the methodology that drives its execution. Understanding how research unfolds requires an exploration of both the philosophical lens through which inquiries are framed and the strategy that leads to meaningful discoveries.

This chapter presents the research philosophy and outlines the research strategy and data used to attain the research objectives outlined in Section 1.4. It builds on Chapter 2 which presented what cryptocurrencies are, how they have evolved. Chapter 2 highlighted a mix of huge potential for untold returns, evidence of diversification potential and high levels of risk – evidenced by wild volatility. Chapter 3 then explored the numerous portfolio management methodologies to build an understanding of leveraging the performance and diversification potential of cryptocurrencies. The chapter discussed that sophisticated capital allocation methods such as the minimum variance portfolio (MVP) and Black-Litterman (BL) model are appropriate for cryptocurrency portfolios because they better position investors to optimise their risk-adjusted performance, enhance diversification and exploit emerging profit opportunities. Chapter 3 also examined the continued popularity of the Mean Variance Optimisation (MVO) as a key tool in portfolio management. Furthermore, a range of metrics, including beta, standard deviation, lower partial moments, maximum drawdown, Value at Risk (VaR), tracking error, and modified standard deviation (adjusted for serial correlation, skewness, and kurtosis), were identified as key measures for assessing risk-adjusted performance in portfolios that include cryptocurrencies. These numerous measures complement each other since it was discussed that there was no universally accepted and unified measure of risk that can be used as risk denominator in assessing risk-adjusted performance. Chapter 3 also highlighted that the frequency to rebalance portfolios that include cryptocurrencies is at best informed by market condition.

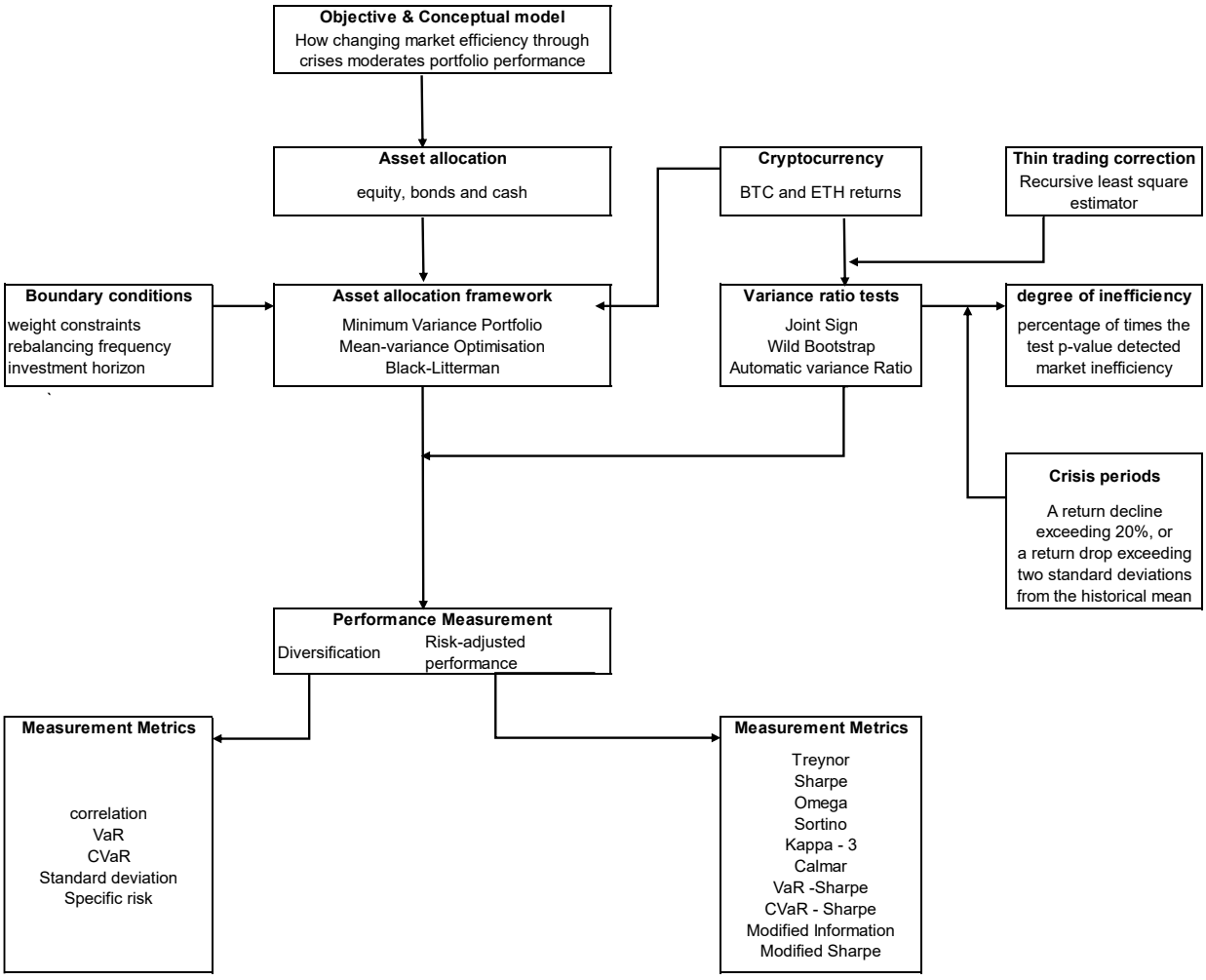
Chapter 4 then focused on the concept of market efficiency, a broad-based indicator of market condition. Chapter 5 reviewed the salient approaches to measuring market efficiency. It established that variance ratio (VR) tests first proposed by Lo and MacKinlay (1988) are instrumental in assessing market efficiency, due mostly because they are aligned with the AMH – a pragmatic characterisation of market efficiency and also because they have high power and minimal size distortions (Lim & Brooks, 2011).

This chapter integrates insights from the previous chapters and present this study's methodological framework to attain the research objectives.

6.2 Study design and context

This study adopted a positivist philosophical paradigm. This philosophy postulates that real events can be observed empirically and can also be explained logically through analysis (Hume, 2016). Furthermore, positivist research focuses on experimentation, a key activity in attaining the objectives of this study. Through experimentation, reality can be observed and described from an objective viewpoint (Creswell, 2011; Greenwood & Levin, 2006; Leedy & Ormrod, 2015). Inferences are made based on the previously observed and explained realities and their inter-relationships. Accomplishing the research objectives requires, first, experimentation through statistical modelling based on multivariate analysis techniques and the statistical analysing of secondary data. Second, making inferences based on previously observed and explained realities and their inter-relationships. Following Creswell's (2011) taxonomy of research methodologies, the quantitative research methodology best addresses the three research objectives of this study.

Figure 6.1: Analytical framework



Source: Author's own compilation

The core principle underlying all quantitative research is the generalisability of its findings. This principle justifies the use of sampling and allows researchers to draw inferences about the broader population. Despite its practical advantages, quantitative research encounters challenges due to the complexity of real-world phenomena, such as the inherent unpredictability of future changes. Consequently, researchers cannot predict future events with absolute certainty; rather, they can only construct scenarios of potential future occurrences (Leedy & Ormrod, 2015). The remainder of this chapter elaborates on the methodology employed in this experimentation. As a reference, Figure 6.1 presents the framework. To facilitate comprehension of this guide, the chapter is organized as follows: Section 6.3 describes the data; Section 6.4 discusses the process of assessing market efficiency, beginning with thin trading correction; Section 6.5 delineates the asset allocation framework; Section 6.6 specifies the constraints (boundary conditions) applied in executing the asset allocation; Section 6.7 outlines the metrics for measuring diversification and risk-adjusted performance; and Section 6.8 provides a summary of the chapter.

6.3 Data

This study employed a diverse array of carefully selected data; each chosen to align with the research objectives and facilitate a comprehensive analysis. To address the question of cryptocurrency market efficiency, this study employed daily data of BTC and ETH the largest cryptocurrencies by market capitalisation. Additionally, daily data for three equity indices from developed markets, namely the S&P500 (US), FTSE 100 (UK) and NIKKEI 225 (Japan), and three equity indices from developing markets, namely the Shanghai Stock Exchange (SSE) Composite index (China), Bombay Stock Exchange (BSE) Sensex (India), and the FTSE/JSE All Share Index (South Africa) were included for contextualising the discussion of the relative market efficiency of cryptocurrencies. To evaluate the portfolio performance of cryptocurrencies - further to the S&P 500 and the FTSE/JSE All Share Index, this study incorporated daily data of two bond indices: the FTSE/JSE All Bond Index (ALBI20) and 10-Year US Government Bonds returns, as well as daily data of proxies for money market (cash) rates: the 91-day Treasury Bill (SA) and the USD 3-month Treasury Bill. Treasury bills also represented the risk-free rates across SA and the US. Data for the ALBI20 and the 91-day Treasury Bill were sourced from the IRESS (2025) while data for the US 10-year Treasuries and the US 3-month Treasury Bill were sourced from the US Treasury. All other data were sourced from Investing.com (2025). Table 6.1 summarises the data used, its source, frequency and range.

Table 6.1: Data attributes

Market/Index[92]	Asset/Category	Source	Frequency	Date range of data collected*
BTC	Cryptocurrency	Investing.com	Daily	01.01.2015 to 31.12.2024
ETH	Cryptocurrency	Investing.com	Daily	01.09.2015 to 31.12.2024
BSE Sensex	Equity	Investing.com	Daily	01.01.2015 to 31.12.2024
FTSE 100	Equity	Investing.com	Daily	01.01.2015 to 31.12.2024
JSE ALSI	Equity	Investing.com	Daily	01.01.2015 to 31.12.2024
Nikkei 225	Equity	Investing.com	Daily	01.01.2015 to 31.12.2024
S&P 500	Equity	Investing.com	Daily	01.01.2015 to 31.12.2024
SSE	Equity	Investing.com	Daily	01.01.2015 to 31.12.2024
ALBI	Bond	IRESS	Daily	01.09.2015 to 31.12.2024
10-Year US Government Bonds	Bond	US Treasury	Daily	01.09.2015 to 31.12.2024
SA 91-day Treasury bill	Cash/Risk free proxy	IRESS	Daily	01.09.2015 to 31.12.2024
US 3-month Treasury bill	Cash/Risk free proxy	US Treasury	Daily	01.09.2015 to 31.12.2024
South African Rand (USD/ZAR)	Exchange rate	IRESS	Daily	01.09.2015 to 31.12.2024

**The actual start date used in market efficiency tests differed from the stated range, as it was calculated retrospectively from the 500th trading day of ETH (the youngest asset in the sample) return. Source: Authors literature review*

The justification for choosing BTC and ETH among the numerous cryptocurrencies are summarised in Table 6.2.

Table 6.2: Key factors supporting the selection of BTC and ETH.

Cryptocurrency	Launched	Market capitalisation Rank	Market capitalisation (USD billion)	Market share	Blockchain type	Approved ETF?	Additional functionality
BTC	2009	1	1 834	56%	Permissionless	Yes	Store of value, payment network
ETH	2015	2	404	12%	Permissionless	Yes	Smart contracts, DeFi, NFTs

Launch year represents the year the cryptocurrency was launched. Market dominance represents the percentage of market capitalisation as a total of the cryptocurrency market. Only BTC and ETH ETFs had been approved in the US. All details were as of 31 Dec 2024. Source: CoinMartCap (2024).

The details in the table illustrates that:

(i) Market dominance. BTC and ETH were the largest cryptocurrencies by market capitalisation. Studying them provides insights into the most influential cryptocurrencies.

(ii) Established use cases. BTC is widely regarded as a store of value while ETH powers smart contracts and dApps. Their maturity makes them valuable study subjects.

[92] For all equity indices, this study used price returns indices as opposed to total return indices. This was important to align with previous research on market efficiency and also that price return indices are directly observable on trading days. By contrast, total-return data entails adjustment for dividend payment which potentially would conflate return dynamics with yield distributions.

(iii) Regulatory interest. BTC and ETH have garnered significant institutional adoption and regulatory attention such as approval of ETFs in the US. Researching them helps understand mainstream adoption and policy developments.

(iv) Embodiment of the ethos of cryptocurrency. BTC and ETH are permissionless systems. Researching them is essential to understanding the core philosophy of cryptocurrencies and their role in reshaping global finance.

The equity indices were selected for their popularity and diverse geographical locations around the world. The indices represent major economic regions across the globe, ensuring a comprehensive assessment of market behaviour. By covering different regions and economies, this approach captured global trading dynamics, ensuring robust and context-aware comparisons.

The sample period is anchored to the introduction of ETH. ETH was launched in August 2015, and its first full month of trading was September 2015, which defines the start of the observation window; the end of the sample is December 2024, the most recent year-end available at the time of thesis compilation. Because ETH is relatively young, its observation window was treated as the baseline and other asset price series were back-propagated to align with that window, ensuring all series share a common start date and a consistent 500-day look-back period for comparative analysis. Daily frequency was used as it provided the maximum statistical power (resulting from the number of observations) to test market efficiency. However, using higher frequency data such as daily data presents the challenge of conflating autocorrelation in returns with thin trading, more so in young markets (Smith & Dyakova, 2014). Consequently, a thin trading correction (discussed in Section 6.4) was applied.

In addition to the JSE ALSI and the S&P 500, the ALBI and US 10-Year Treasuries were included as representative benchmarks for bond market returns, while the 91-day Treasury Bill and the 3-month US Treasury Bill were selected as proxies for cash and risk-free rates in the South African and US markets, respectively. The selection of these asset classes (equities, bonds and cash) aligned with established academic literature, which consistently identifies equities and bonds as core components of diversified investment portfolios. By constructing a baseline portfolio that includes these major asset classes, the study ensured coverage of the principal sources of systematic risk and return relevant to both institutional and individual investors. This approach supports comprehensive and contextually relevant analysis, enabling robust comparison of portfolio performance before and after incorporating cryptocurrencies across different (South African and US) environments.

The next section details how this data was processed and analysed to meet the research objectives of this study.

6.4 Correcting for thin trading and assessing evolving efficiency

When assets are introduced to the market and begin trading, their price discovery processes do not immediately exhibit informational efficiency (Emerson *et al.*, 1997; Jefferis & Smith, 2005; Lim & Brooks, 2011). This is because the early stages of an asset are characterised by fewer participants, making it easier for some individuals to influence prices. Sudden changes in the order-flow balance, especially when sell pressure outpaces available buy-side depth, can induce significant price dislocations and impair execution efficiency. Such market microstructure driven frictions have been observed in the nascent cryptocurrency markets (Easley *et al.*, 2024) and in some developing equity markets (Hansen & Lunde, 2006; Huang & Stoll, 1994; Mlambo & Biekpe, 2007) where transient sell-side imbalances disrupted transaction completion. The presence of thin trading suggests that returns in young assets can sometimes be misunderstood as those exhibiting positive autocorrelation, since a small number of market players leads to infrequent trading (thin trading), especially when using high-frequency data.

This study followed the approach of Smith and Dyakova (2014) and applied their smoothing approach to tease out the impact of thin trading on asset returns.

Equation 6.1 presents Smith and Dyakova's (2014) model for observed returns

$$a_t = \vartheta_0 + \vartheta_1 a_{t-1} + \varepsilon_t, \tag{6.1}$$

where a_t is one-period observed returns. The regression coefficients ϑ_0, ϑ_1 and the residual disturbance ε_t are estimated by the recursive least squares (RLS) method. This procedure is carried out (recursively) until convergence is attained. The RLS method estimated residuals, ε_t, and regression coefficient, ϑ_1, are then used to obtain corrected returns (a_t^{CR}) as shown in Equation 6.2.

$$a_t^{CR} = \frac{\varepsilon_t}{1 - \vartheta_1}. \tag{6.2}$$

After correcting for thin trading, the new returns series, a_t^{CR} was tested for market efficiency using variance ratio tests. The observed returns, a_t, were also tested and the results were used as comparators. It is important to underscore that the thin trading adjustment are not intended to eliminate genuine inefficiency signals. Rather, it mitigates measurement distortions arising from infrequent or clustered trading. It is acknowledged that any preprocessing may influence estimated persistence metrics; however, the adjustment is conceptually justified (as a correction for non-informational artefacts rather than as an efficiency-enhancing transformation.

The following sections outline the structure of these tests and how they were applied by this study.

6.4.1 Variance ratio

Building on the methodology of Smith and Dyakova (2014), this study applied VR tests to examine the market efficiency and predictability of cryptocurrencies and selected equity indices. As highlighted in Chapter 5, VR tests are in line with the AMH, which holds a significant importance for market participants, acting as a point of convergence between the perspectives of the EMH and those of behavioural finance. Unlike alternative static approaches and TEE, VR tests are well suited to capture gradual shifts in efficiency, particularly relevant for young markets (or assets) that experience thin trading. This robustness makes VR tests ideal for assessing the evolving market efficiency of cryptocurrencies. This is because VR tests are adapted to detecting changing (predictability) conditions of returns, an important consideration for cryptocurrencies which are less understood and have been known to be susceptible to episodes of price bubbles (Cheah & Fry, 2015; Chowdhury *et al.*, 2022) and herding behaviour (Almeida & Gonçalves, 2023; Anamika *et al.*, 2023; Sibande *et al.*, 2023).

In addition, several modifications to the VR test addressed challenges commonly encountered in financial data analysis and of significance in cryptocurrency returns. These include the JS test, which confronts the non-normality of asset returns, the JM test, which considers the asymptotic properties of VR, and the AVR test, which optimises the selection of lag length in VR calculations. The sections that follow describe the implementation of these three tests.

6.4.1.1 Joint Sign Test

The JS test is a nonparametric rank and sign-based test which counters Lo and MacKinlay's (1988) parametric assumption weaknesses (Wright, 2000). The test improves the statistical power of the VR test of Lo and MacKinlay (1988), because it is based on ranks that are exact under the iid assumption. The signs are also exact, even under conditional heteroscedasticity and their use (as opposed to returns) counters the influence of return outliers (Charles & Darné, 2009).

The JS test assumed that a_t (or a_t^{CR} after correcting for thin trading) is generated from an MDS and uses ranks and signs of a time series to test the null hypothesis that the series is an MDS. The test defines s_t as a sign of the first difference of returns at time t, which is an iid sequence with zero mean and unit variance taking values of +1 and −1 (the signs), each with a probability of 0.5. If the difference of returns is positive, s_t = 1; else s_t = −1. For the individual test that $VR(q) = 1$, Wright (2000) proposed an individual test statistic shown in Equation 6.1:

$$S(q) = \left[\frac{\frac{1}{Tq}\sum_{t=q}^{T}\left(s_t + s_{t-1} + \cdots + s_{t-q+1}\right)^2}{\frac{1}{T}\sum_{t=1}^{T} s_t^2} - 1\right] x \left[\frac{2(2q-1)(q-1)}{3qT}\right]^{-\frac{1}{2}}, \quad (6.1)$$

where T, is the total number of observations, q is the length of the period return.

This study applied the approach of Smith and Dyakova (2014), who computed $S(q_i)$ for $m = 2{,}000$ values of $q = 500$, and the test statistic with the maximum absolute value was selected. The values for m=2,000 replications were argued to be sufficient for stable estimates of standard errors, while $q = 500$ was argued to be long enough to ensure statistical veracity and short enough to capture short term deviations from efficiency.

Thus,

$$JS = \max_{1 \leq i \leq m} |S(q_i)|, \tag{6.2}$$

where m represents the number of comparisons or groups being tested. The idea of multiple comparisons in VR testing largely derivers from Chow and Denning (1993) who argued that in a rolling window, the decision regarding the null hypothesis ought to be made based on the maximum absolute value of individual VR statistics.

The selection of rolling-window parameters is crucial, as inappropriate window lengths may result in overfitting or underfitting, potentially biasing test statistics and increasing the risk of both Type I and Type II errors. Despite this sensitivity, rolling-window analysis utilised in the JS test (and other VR tests) provided a significant improvement over static, full-sample approaches by capturing time-varying deviations from the random-walk hypothesis and enabling efficiency evaluations that reflect changing market dynamics.

For this study, a 500-day rolling window was selected based on empirical support (Belaire-Franch & Opong, 2005; Kim & Shamsuddin, 2008; Lim *et al.*, 2013; Shawky & Smith, 2005), as it effectively balances competing objectives: it is short enough to detect short-term predictability and transient inefficiencies, yet sufficiently long to ensure adequate statistical power for JS, JM, and AVR tests. This approach mitigated the trade-off between detection sensitivity and estimator precision and aligned the empirical design with the study's emphasis on dynamic efficiency.

The primary limitation of the chosen window length is its reliance on specific sample characteristics; alternative market regimes or sampling frequencies may necessitate different window lengths, and findings could be sensitive to these choices. Consequently, results should be interpreted with consideration of the selected window specification.

6.4.1.2 Wild Bootstrap test

While Wright (2000) confronted biases of Lo and MacKinlay (1989) VR tests with sign-based tests, Kim (2006) suggested using a bootstrap to confront biases arising from subsuming the normal asymptotic distribution. Bootstrapping is a distribution-free randomisation technique which

can be used to estimate the sampling distribution of the VR statistic when the distribution of the original population is unknown (Charles & Darné, 2009). Kim's (2006) wild bootstrap is a resampling method that approximates the sampling distribution of the VR statistic and applies it to data with unknown forms of conditional and unconditional heteroscedasticity.

Kim (2006) held that, under a martingale null hypothesis, which allows for general forms of heteroskedasticity including GARCH processes, the test statistic is:

$$M(a;q) = \left[\frac{\frac{1}{Tq}\sum_{t=q}^{T}(a_t + a_{t-1} + \cdots + a_{t-q+1} - q\hat{\mu})^2}{\frac{1}{T}\sum_{t=1}^{T}(a_t - \hat{\mu})_t^2}\right] - 1\left[4\sum_{j=1}^{q-1}\left(1 - \frac{j}{q}\right)\delta_j\right]^{-\frac{1}{2}}, \quad (6.3)$$

where $\hat{\mu} = T^{-1}\sum_{t=1}^{T} a_t$, and q is the holding period.

$$\delta_j = \frac{\left\{\sum_{t=j+1}^{T}(a_t - \mu)^2\left(a_{t-j} - \mu\right)^2\right\}}{\{[\sum_{t=1}^{T}(a_t - \mu)^2]^2\}}, \quad (6.4)$$

is asymptotically distributed as standard normal.

The Kim (2006) wild bootstrap test derived and used in this study uses the test statistic in Chow and Denning's (1993) joint test. The test statistic in Kim's (2006) wild bootstrap test is

$$JM = \max_{1 \le i \le m} |M(a;\, q_i)|, \quad (6.5)$$

where m 2000 represents the number of comparisons or groups being tested for a $q = 500$ period return as in the JS test.

Kim's (2006) wild bootstrap test uses the test statistic in Equation (6.5) with p-values obtained through a wild bootstrap, which proceeds as below:

(i) Form a bootstrap sample $a_t^* = \eta_t a_t (t = 1, \ldots T)$, where $\eta_t$is a normally distributed random variable having zero mean and unit variance, a_t is one-period return and T is the total number of observations. Any non-normality and heteroskedasticity in a_t, the original returns series, is preserved in a_t^*;

(ii) Use a_t^* to obtain a value, JM^*, for the test statistic JM in Equation (6.5); and

(iii) Repeat (i) and (ii) many times to create the bootstrap distribution of the test statistic, $\{JM^*(j)\}_{j=1}^{m}$. The implementation of the bootstrap followed Kim and Shamsuddin (2008) and Smith and Dyakova (2014) and used m = 2,000 to ensure stable distribution of the test statistic and enhancing approximation of the true distribution effectively. Several studies (Davison & Hinkley, 1997; Tibshirani & Efron, 1993) show that around 1,000–2,000 bootstrap replications are generally sufficient for stable estimates of standard errors.

The wild bootstrap test is denoted by JM^*. The p-value of the test is obtained as the proportion of $\{JM^*(j)\}_{j=1}^{m}$ greater than the sample value of $M(a; q_i)$ as documented in the literature (Chow & Denning, 1993; Kim & Shamsuddin, 2008; Smith & Dyakova, 2014).

6.4.1.3 Automatic Variance Ratio Test

Although the JS and the JM tests, confront the weakness of VR tests of Lo and MacKinlay (1988) related to the distribution of returns, they do not address that, q, the holding period must be set. A shorter q, increases volatility and randomness, potentially reducing statistical power of the tests. By contrast, a longer holding period, q, smooths out short-term fluctuations, potentially masking some episodes of inefficiency. This effect occurs because extended holding periods reduce the impact of temporary price movements, making it harder to detect deviations from a random walk. Consequently, balancing between a 'long' and a 'short' holding period is a delicate choice.

Choi (1999) proposed an AVR test that employs a data-dependent method to select the optimal value of the holding period, q. Choi (1999) showed that under a null hypothesis of no serial correlation (market efficiency), the test statistic for the AVR for holding period q is

$$AVR(q) = \frac{\sqrt{\left(\frac{T}{q}\right)[VR(q) - 1]}}{\sqrt{2}} \sim N(0,1), \tag{6.6}$$

where T is the total number of observations, q is the length of the holding period, $VR(q)$ is the variance ratio for the q-period return as defined in Equation 5.4 and $N(0,1)$ is the standard normal distribution with mean zero and unit variance.

However, Kim (2009) argued that most financial time series are not homoscedastic and when asset returns are conditional heteroscedastic, Choi's (1999) approach leads to the following challenges:

- The presence of heteroscedasticity inflates the $AVR(q)$ test statistic leading to low statistical power of the tests. This distortion does not diminish as the sample size increases as in the VR test of Lo and MacKinlay (1989) reliant on asymptotic normal tests (Kim, 2009).
- The test statistic exhibits right-skewness further distorting the statistical power of the tests (Kim, 2009).
- Reliance on asymptotic approximations result in unstable critical values, making the test unreliable in finite samples.

Kim (2009) showed that wild bootstrapping Choi's (1999) AVR test improves performance in small samples. Wild bootstrapping $AVR(q)$ is essentially the same as that for the JM test.

The wild bootstrap version of the AVR test is denoted AVR^*, the estimated two-tail p-value is the proportion of the absolute values of the bootstrap distribution $AVR^*\ (q^*;\ j)_{j=1}^{n}$ that is greater than the absolute value of $AVR(q)$ calculated from the returns series a_t. A unique advantage about Kim's (2009) AVR^* is that unlike the other VR methods that only focus on identifying market inefficiencies linked to linear relationships, the AVR^* test is robust across both linear and non-linear market structures, making them more effective in evaluating efficiency under complex financial dynamics (Charles *et al.*, 2012).

6.4.2 Interpretation of variance ratio test results

To capture evolving efficiency (predictability of returns), this study applied the three tests: joint sign (JS) test (Belaire-Franch & Contreras, 2004; Kim & Shamsuddin, 2008) the wild bootstrap (JM) test of Kim (2006); and the Automatic VR (AVR) test by Kim (2009). The three tests were scripted and computed using the R programming language (R Foundation, 2025).

The test results were interpreted as follows:

(i) JS test: When the computed p-value exceeded the critical value, the test indicated dependence (predictability) in asset returns. In simpler terms, values above the critical threshold signify times when the market was predictable, leading to rejecting market efficiency.

(ii) JM and AVR tests: values falling below the 5% critical level indicated dependence in asset returns and consequently predictability of equity returns leading to rejection of the market efficiency hypothesis.

(iii) The frequency with which the three tests (JS, JM and AVR) rejected the martingale hypothesis was used to construct an efficiency ranking as defined by Smith and Dyakova (2014). The efficiency ranking was calculated by averaging the percentages of each of the three test statistics where the efficiency hypothesis was rejected at the 5% level.

To evaluate Hypothesis 1, this study examined the progression of average inefficiency levels, as measured by VR test p-values, during crisis periods as defined in Section 6.6.4. A decrease in the average p-values of the JM and AVR tests indicated a decline in efficiency. Conversely, for the JS test, p-values exceeding the average observed during non-crisis periods suggested diminishing efficiency. The tests were conducted at significance levels of 95%, 97.5%, and 99% to detect significant deviations from the random walk hypothesis. P-values were compared

against critical values, and significant deviations led to the rejection of the null hypothesis. This analysis was preceded by time-series plots illustrating the evolution of efficiency levels, with shaded areas indicating crisis periods to depict changes in efficiency over time and to illustrate whether there were instances of null hypothesis rejection during a crisis.

It is important to emphasise that market efficiency tests are for estimating a *latent* efficiency state. A long window acts as a stabiliser and protects against overinterpreting transient volatility booms and busts. For this reason, the test results presented in this study were all based on variance ratios obtained with a 500-observation rolling window. Several studies (Belaire-Franch & Opong, 2005; Kim & Shamsuddin, 2008; Lim *et al.*, 2013; Smith & Dyakova, 2014) support the use of 500 observations and find them short enough to detect short-horizon predictability, while also being long enough for JS, JM, and the AVR tests to have good statistical power properties. This study thus contends that rolling-window length is chosen to estimate informational efficiency as a structural property of the return-generating process rather than as an event-detection device. Short-lived crises can induce temporary volatility bursts and microstructure noise that may distort VR estimates and produce spurious regime conditions. A longer window reduces this estimation noise and yields a more stable proxy for the underlying efficiency state, consistent with the thesis objective of comparing regime-conditioned portfolio outcomes under a static annual rebalancing framework outlined in Section 6.6.3. The chosen rolling-window horizon emphasises stability over high-frequency responsiveness. Consequently, the efficiency proxy is designed to characterise medium- to long-horizon informational conditions rather than to detect abrupt short-lived dislocations. This is consistent with the study's static annual rebalancing framework, but it implies that very short crisis-phase inefficiencies may be smoothed in the efficiency series.

6.5 Portfolio management strategy with cryptocurrencies

As already highlighted in Chapter 2, the increasing popularity of cryptocurrencies has sparked considerable interest among investors. Their unique characteristics and price dynamics present opportunities and challenges for investment portfolios. This section outlines the methodology used to assess the impact of incorporating cryptocurrencies into a diversified investment portfolio. Specifically, the section presents how the inclusion of cryptocurrencies influences risk-return dynamics and diversification. The approach involved quantitative analysis, including asset allocation models and statistical measures, to evaluate portfolio performance across different market conditions.

This section also presents the portfolio parameters: the composition of the default portfolio, the weight restrictions, and the investment objectives along with their justifications. Additionally, it outlines the rebalancing frequency and explains the rationale behind it. The hypothesise is that the addition of cryptocurrencies to a portfolio of equity, bonds and cash enhances overall portfolio

performance by offering improved risk-adjusted metrics. Additionally, the section examines the potential safe haven benefits that cryptocurrencies may provide due to low correlation with traditional asset classes through crisis periods. By analysing historical data and portfolio management techniques, this research seeks to provide insights into the viability of cryptocurrencies as strategic investment components.

6.5 Asset allocation strategies for cryptocurrency integration into traditional portfolios

Chapter 3 presented asset allocation techniques and highlighted that the minimum variance portfolio (MVP) framework and the Black and Litterman (1990) (BL) methodology are key in determining strategic asset allocation. The MVP framework's robustness emanates from relatively lower estimation risk as it only utilises variances and covariances (and not expected returns, which are more prone to estimation risk), thereby minimising the estimation errors. Moreover, it is motivated by the view that the objective of asset allocation is to minimise risk (or equivalently, to maximise return for a given level of risk), as in Klein *et al.* (2018). The Black and Litterman (1990) model is robust in deciding strategic asset allocation among multi-asset portfolios and in line with standard industry practices. This study also incorporated the mean variance optimisation (MVO) because it continues to be a cornerstone of theoretical portfolio management and informs many practical strategies. The next sections give an overview of the MVO, MVP and BL method and how they were implemented in this study.

6.5.1 Mean variance optimisation and minimum variance portfolio frameworks

Markowitz (1952) theorised that investors face a trade-off between return and risk, the latter measured by the variance of returns. While higher returns are desired, higher variance is mostly undesirable. Therefore, the emphasis of MVO framework is to minimise risk (variance) for a given level of return, or equivalently maximising return for a given level of risk (Jorion, 2012). Darolles and Gourieroux (2010) documented that MVO framework which proceeds as follows:

Given a portfolio consisting of n risky assets, a $1\ x\ n$ vector of expected returns μ and square matrix of order n where the leading diagonal represents variance of asset i denoted σ_{ii} and the other elements, σ_{ij} represent covariance between two assets i, j, where $j \neq i$. Thus, the matrix is referred to as the variance-covariance matrix, denoted Σ.

Each of the n assets have a weight ω_i, such that $\sum_{i=1}^{n} \omega_i = 1$. Accordingly, the portfolio variance, σ_p^2 and expected return, $E(r_p)$ are computed as $\omega^T \sum \omega$ and $\omega^T \mu$ respectively. Where ω is the vector of asset weights in a portfolio, ω^T represents the transpose of the weights vector and μ is the vector of expected returns. Darolles and Gourieroux (2010) and van Heerden (2020) detailed that, in the MVO framework, optimal capital allocations may be reached by solving this problem:

$$\max_{w} \omega^T \mu - \frac{\lambda}{2}\ \omega^T \sum \omega, subject\ to\ \sum \omega_i = 1, \quad (6.7)$$

Where λ represents the risk aversion parameter. Varying λ from 0 to ∞ while solving Equation 6.7 produces all the efficient portfolios. On the one extreme end, risk tolerant investors $(\lambda = 0)$ invest in the maximum return portfolio, while extremely risk-averse investors $(\lambda \to \infty)$ invest in a minimum variance portfolio. All other (rational) investors will invest in a portfolio with combination of low risk and high return, depending on their risk tolerance.

As investors' risk aversion varies, this study defined the optimal portfolio as the one with the highest return-to-risk ratio. Equation 6.8 outlines the optimisation problem that MVO investors solve to achieve such a portfolio:

$$\max_{w} \frac{\omega^T \mu}{\sqrt{\omega^T \sum \omega}}\ subject\ to\ \sum \omega_i = 1. \quad (6.8)$$

The solution to the optimisation problem in Equation 6.13, as well as the sub problems of maximising $E(r_p)$ or minimising σ_p^2 may be arrived at through quadratic programming. By the same reasoning, the minimum variance portfolio (MVP) may be obtained by solving Equation 6.9

$$\min_{w} \omega^T \sum \omega\ subject\ to\ \sum \omega_i = 1. \quad (6.9)$$

The reference maximum portfolio return may be arrived at by solving Equation 6.10

$$\max\ \omega^T \mu\ subject\ to\ \sum \omega_i = 1. \quad (6.10)$$

This study applied Microsoft Excel® (Microsoft Corporation, 2025) to solve the optimisation problems in Equations, 6.8 (MVO) and 6.9 (MVP). The resulting MVP (Equation 6.9) is widely supported as a robust portfolio, since it does not make use of returns which are more prone to estimation risk (McLeod & van Vuuren, 2004). Meanwhile, the maximum return-to-risk portfolio, Equation 6.8, is widely accepted as a rational approach to constructing portfolios since it integrates risk. These two portfolios encompass a rational view on how portfolios ought to be constructed. However, another much more salient view is investing in the market portfolio. Thus, to allocate capital following this view, the study leveraged the Black Litterman (BL) optimisation model whose implementation is discussed in the next section.

6.5.2 Black Litterman model

The BL model offers a balanced and flexible method for portfolio construction by merging market data with subjective views, thereby producing allocation recommendations that are both theoretically robust and practically appealing (Black & Litterman, 1990). By integrating subjective views, the BL is an attractive tool for investors seeking to include cryptocurrencies in their portfolios is it allows investors to temper the inherent volatility of cryptocurrencies by creating

allocations that align with an investor's outlook and risk tolerance (Palmquist & Mednis, 2022; Platanakis & Urquhart, 2020). The BL model proceeds as follows:

Given daily returns, r_i of the asset i computed as $\frac{P_{xi}}{P_{xi-1}} - 1$, where P_{xi} is the price of the asset i, an assumption is made for the risk-free rate needed to compute the CAPM expected returns and the tangency[93] portfolios. In the context of South Africa, the 91-day Treasury Bill rate is held as the risk-free rate, while the 3 months treasury bill rate is the risk-free rate for the US.

The following steps are based on Idzorek (2007), which outlines the procedure for computing - BL optimal portfolios:

i. Compute annualised expected returns A as $\left(\frac{P_N}{P_0}\right)^{\frac{1}{N}} - 1$,

where P_0 and P_N are the beginning and end prices/indices of the assets. N is the length of the observation period in years.

ii. Compute beta, β, the sensitivity of an asset's daily returns, r_i, to those of the market, r_m (S&P 500 or JSE All Share index) by estimating Equation 6.11 below through ordinary least squares (OLS) regression:

$$r_i = \alpha_i + \beta_i(r_m) + u_i, \tag{6.11}$$

where α_i is the intercept or "alpha" for asset i which captures the asset-specific return component not explained by the market's performance and μ_i is the error term (or residual) for asset i which accounts for the portion of asset i return that is not explained by the market return.

iii. Compute CAPM returns, R_i, the starting point for BL portfolio optimisation, as follows:

$$R_i = r_f + \beta_i(r_m - r_f), \tag{6.12}$$

where r_f is the risk-free rate of return.

iv. Compute the variance-covariance matrix, Σ based on historical daily returns r_i.The matrix is scaled linearly by multiplying it by 252, the number of trading days to annualise the volatility.

v. Compute the matrix inverse, C^{-1}, as the inverse of Σ .

[93] The Tangency portfolio represent the portfolio with the highest Sharpe ratio (Black & Litterman, 1992). All investors in the CAPM framework will hold the same tangency portfolio in different proportions based on their risk references (Black & Litterman, 1992).

vi. Define a unit vector as e with elements equal to i, the number of assets.

vii. Define r as the vector of CAPM expected as computed in 6.12 (not to be confused with daily returns).

viii. Compute the risk vector $h = \mathrm{e}C^{-1}$.

ix. Compute the returns vector as $g = \mathrm{r}C^{-1}$.

Next, compute optimisation constants for the investable universe that are necessary to compute the optimal (tangency) portfolio as per equation in xiv.

x. Alpha (not to be confused with asset specific return), $\alpha = eh^T$.

xi. Beta (not to be confused with market beta), $\beta = eg^T$.

xii. Gamma, $\gamma = rg^T$.

xiii. Delta, $\Delta = \alpha\gamma - \beta^2$.

xiv. The tangency portfolio, r_t maybe defined as follows:

$$r_t = \frac{\gamma - \beta r_f}{\beta - \alpha r_f}. \tag{6.13}$$

After computing the tangency portfolio, the next step is to compute the weights required to achieve the tangency portfolio and assess how these correspond to the market capitalisation weightings. This is because, at equilibrium, all investors are assumed to be investing in proportions of the risk-free rate and the tangency portfolio (Idzorek, 2007).

Thus, the risk and return vectors h and g are weighed according to λ and μ to obtain tangency weights:

xv. λ - the weight of the $MVP = \frac{\gamma - \beta R}{\Delta}$, where R is the target return - the tangency return.

xvi. μ - the value of the tangency portfolio at zero risk free rate, $= \frac{\alpha R - \beta}{\Delta}$.

xvii. The tangency portfolio weights, $w^* = \lambda h + \mu g$.

The tangency portfolio weights w^* are compared to value (market capitalisation) weights w. Therefore, the BL objective is:

$$\min_r \sum(\omega^* - w)^2. \tag{6.14}$$

Investor views are incorporated by adjusting the returns, r, producing a portfolio that started off at market equilibrium and was adjusted to reflect the market/investment views and beliefs of an analyst or portfolio manager.

In the implementation adopted in this study, no explicit investor views were imposed on expected returns. Consequently, the posterior expected return vector corresponds closely to the equilibrium-implied return vector derived from reverse optimisation. The Black–Litterman model therefore operates as a stabilised mean–variance framework anchored to market equilibrium rather than as a Bayesian updating mechanism incorporating subjective information. Performance differences between Black–Litterman and alternative optimisation methods should therefore be interpreted as arising from equilibrium anchoring and constraint interaction rather than from informational advantages. Any observed differences in allocation or performance relative to traditional mean–variance optimisation are attributable to the equilibrium prior, the covariance structure, and the imposed portfolio constraints, including cryptocurrency exposure caps, rather than to view-driven posterior shifts.

6.6 Portfolio configuration: composition and constraints for cryptocurrency integration

This section outlines the portfolio configuration framework adopted to evaluate the integration of cryptocurrencies into a traditional asset portfolio. It details the composition of the default portfolio, specifies weight constraints, and clarifies the investment objectives and their justifications. Additionally, the section describes the rebalancing frequency strategy, ensuring that the approach remains robust in the face of cryptocurrency market efficiency and volatility.

6.6.1 The default portfolio

To assess whether and incorporating cryptocurrencies impact portfolios diversification and risk-adjusted performance, this study first established a default baseline portfolio. Consistent with the popular asset classes delineated in Doeswijk and Swinkels (2025), the baseline portfolio comprised bonds, equity, and cash. For the SA market, this baseline allocation included exposure the JSE ALSI (equity), the ALBI (bonds), and the 91-day Treasury Bills (cash). For the US market, the baseline portfolio was constructed with the S&P 500 (equity), US 10-year Treasuries (bonds), and the 3-month Treasury Bill (cash). Subsequently, BTC and ETH were added to the diversified portfolio resulting in an adjusted asset allocation. Constructing a baseline portfolio that included equity and bonds – the major asset classes, the study ensured examination of the primary sources of systematic risk and return relevant to both institutional and individual investors.

The asset allocation before and after incorporating the cryptocurrencies were arrived at by using the three asset allocation strategies: MVP, BL portfolio and the MVO (maximum Sharpe ratio portfolio). This multifaceted methodology enabled a robust investigation into how cryptocurrencies influence diversification and risk-adjusted returns across varying investment strategies as reflected by the portfolio allocation model. Table 6.3 illustrates how the portfolio allocation models were aligned with common investment.

Table 6.3: Aligning portfolio allocation models with common investment strategies

Portfolio allocation model	Investment strategies
Minimum Variance Portfolio	Minimise overall portfolio risk
Mean-Variance Optimisation	Optimise the risk-return trade-off
Black-Litterman Model	Neutral views, yields equilibrium (market) weights / Invest in the market portfolio

Source: Compiled by Author.

6.6.2 Calibration of asset allocation weights

Asset weight restrictions represent a critical parameter in portfolio construction. Since cryptocurrencies are a young asset of growing significance, an important question is what the optimal allocation to cryptocurrency in a well-diversified portfolio is. This question has attracted varying views. Andrianto and Dutra (2017) suggested that an optimal cryptocurrency allocation ranges between 5% and 20% depending on investor risk tolerance. Robertson (2018) demonstrated that even a 5% allocation can significantly influence portfolio performance. A survey by Kher (2023) on 250 US institutional investors found that 35% percent of respondents noted allocating 1%-5% to cryptocurrencies, with 60% of respondents indicating they allocate more than 1% of their portfolio. It was noteworthy that 45% of institutions with more than $500 billion in AUM responded that they allocate more than 1% of their portfolio, suggesting a large amount of capital invested in the cryptocurrency space by traditional institutional investors. Shalett *et al*. (2025) argues that optimal asset allocation varies by risk profile with 0% suitable for wealth conservation, up to 2% for balanced growth, and a maxim of 4% for opportunistic growth. Ang *et al*. (2023) confronted this asset allocation dilemma head-on. They made numerous inquiries and found that

(i) A risk averse investor with a 20–80 equity-bond portfolio allocations led to a 12.5% BTC allocation.

(ii) A 60–40 equity-bond portfolio, lead to an optimal BTC allocation of 84.9% BTC.

(iii) A risk tolerant investor with an 80–20 equity-bond portfolio desires a levered position in BTC of 106.6%.

Ang *et al*. (2023) considered that individual are not always rational but are influenced by some behavioural preferences which include preferences for positively skewed payoffs and overweighting events with small probability while underweighting events that occur more frequently. Integrating these behavioural biases lead to a 28%-72% equity-bond portfolio and adding BTC resulted in a 9.5% allocation to BTC. This resulted in an allocation of approximately 10% BTC, 25% equity and 65% bonds as yielding the best risk-return trade-off. Based on these insights and the discussion is Chapter 3, this study sets the following asset allocation weight limits of each asset class.

Table 6.4: Asset allocation weight restrictions

Asset class	Minimum weight allocation	Maximum weight allocation
Equity	40%	80%
Bonds	10%	50%
Cash	5%	10%
Cryptocurrency	1%	10%

Source: Compiled by Author.

The allocation caps implemented in the optimisation framework are designed to simulate prudential constraint environments analogous to those considered in regulatory calibration discussions. These caps allow evaluation of the marginal risk contribution of cryptocurrency exposure within an institutional-style portfolio context discussed in Section 3.2.2.

The study imposed a no-short-selling constraint for both theoretical and practical grounds necessary in evaluating the diversification role of a nascent asset such as cryptocurrencies. Short positions introduce leverage, borrowing requirements, and margin dynamics that fundamentally alter the risk profile of a portfolio, making it difficult to isolate the true contribution of an asset to diversification and risk-adjusted performance (Haugh, 2016). Moreover, unconstrained optimisation often produces extreme negative weights that are artefacts of the mathematical solution (Michaud, 1989) rather than economically meaningful allocations, especially when assets exhibit unstable correlations or high volatility, as is typical for cryptocurrencies (Hampl *et al.*, 2024). Preventing short-selling ensures that portfolio weights remain interpretable, stable, and aligned with realistic investment practice, allowing the analysis to focus on the genuine diversification properties of cryptocurrencies rather than on leveraged or synthetic exposures that would not be feasible for most market participants.

6.6.3 Portfolio rebalancing strategy

Due to the limited consensus in the literature regarding the optimal rebalancing method and frequency, this study derives its rebalancing protocol from established strategies documented by Mulvey and Simsek (2002) and Eakins and Stansell (2007), which include time-only, threshold-only, and combined time-threshold approaches. Building on the findings of Zilbering *et al*. (2015), who observed that diversified equity and bond funds generally benefit from annual or semi-annual monitoring with a 5% rebalancing threshold to balance risk control and minimize costs, this study opted for an annual rebalancing scheme. To avoid potential bias from selectively tuning the threshold parameter, the 5% threshold is disregarded, and portfolios are rebalanced exclusively at the end of each calendar year).

The study underscores that the efficiency regimes are descriptive conditioning variables and not rebalancing triggers. The investment weights are set according to optimisation constraints at

annual rebalancing dates. Market efficiency regimes are used to interpret results, not to generate trading signals. Moreover, because the portfolio framework operates on an annual rebalancing horizon, the objective is to measure whether and how structural informational efficiency rather than short-lived noise influences the diversification role of cryptocurrencies. The adjustment reduces the influence of transient liquidity effects that are unlikely to affect strategic asset allocation decisions.

6.6.4 Investment horizon and crisis periods

To evaluate the impact of cryptocurrencies on investment portfolios, the entire investment horizon spanning January 2015 to December 2024 was analysed. During this period, both optimal baseline portfolios and portfolios that included cryptocurrencies were constructed using proxies for cash, bonds, and equity, based on the portfolio allocation models presented in Table 6.3. These portfolios were rebalanced annually over the investment horizon to ensure consistency and comparability.

However, a key aspect of the study involved assessing the impact of cryptocurrencies on portfolio performance through crisis periods. The literature offered various methodologies to parameterise crises, providing a robust foundation for this analysis. Fry-McKibbin *et al*. (2014) employed regime-switching Markov techniques to detect crisis periods. In contrast, Patel and Sarkar (1998) adopted a threshold-based approach, defining a crisis as a market crash characterised by a decline of more than 20% from the historical peak for developed markets and more than 35% for emerging markets. While the specific thresholds and the use of regional indices may be open to debate, the essence of crisis identification in Patel and Sarkar's (1998) approach was tied to drawdowns in returns. This study adopted a crisis definition inspired by Patel and Sarkar (1998) while incorporating additional criteria. Specifically, a crisis was empirically identified as a period during which equity indices experienced:

(i) a decline exceeding 20% from the historical maximum (the conservative threshold established by Patel and Sarkar (1998)), or

(ii) a return drop exceeding two standard deviations from the historical mean, in line with the approach of Fry and Cheah (2016), who used this criterion to investigate whether BTC exhibits bubble characteristics.

The rationality behind using declines in equity indices as a signal for a crisis period derives from the behaviour of equity prices relative to bonds or cash. Equity prices tend to experience wild volatility during episodes of economic or political shocks (Bartram & Bodnar, 2009). However, bonds and cash tend to react differently even due during episodes of crisis. Bonds, particularly government bonds are often regarded as a "flight-to-quality" asset, and they usually experience prices rises (and falling yields) as investors seek protection. Cash, remains relatively stable due

to its inherent low volatility. This differing behaviour can obscure the onset of systemic stress. By focusing on the equity market, which records the most pronounced response to a shock, this study captured unfolding of broader market disruptions.

Consequently, for the purpose of this study, a crisis periods were defined as a significant market disruption characterised by abnormal returns, increased volatility, and altered investor behaviour, consistent with the literature on financial crises (Claessens *et al.*, 2012; Lo Duca *et al.*, 2017). The classification of crises was based on both their origin and transmission dynamics, following the frameworks established in the literature (Forbes & Rigobon, 2002; Kaminsky & Reinhart, 1999).

This study adopted a two-staged analysis to provide a comprehensive assessment of including cryptocurrencies in portfolio performance. First, the impact of cryptocurrencies was evaluated over the full historical period (2015–2024). This long-term analysis, which spans both stable market conditions and crisis periods, established a baseline for understanding the overall risk-return dynamics and diversification benefits. Subsequently, the methodology was refined by isolating crisis periods. Focusing exclusively on these crisis windows enabled the study to extensively assess the resilience of cryptocurrencies in enhancing diversification and improving portfolio performance during periods of market crises, serving as potential safe havens.

By employing this two-stage approach, the analysis captured the average performance over a broad horizon and the behaviour of cryptocurrencies in periods when their diversification properties might be most valuable. This robust methodology provided deeper insights into how cryptocurrencies perform under varying market conditions.

6.6.5 Scope of performance evaluation and trading frictions

Portfolio performance is evaluated on a gross-return basis. The study adopted a static annual rebalancing framework consistent with strategic asset allocation practice rather than tactical trading. Given the low rebalancing frequency and allocation caps applied, turnover is structurally constrained. The analysis therefore focuses on structural diversification and regime-conditioned allocation properties, with transaction costs treated as an implementation consideration beyond the scope of the present structural investigation.

Including these factors (transaction costs and taxes) would introduce institution and market-specific implementation variability, thereby complicating the relationship between allocation rules and performance outcomes. By omitting such frictions, the analysis achieves a clearer understanding of how efficiency regimes influence diversification and risk-adjusted performance outcomes.

6.7 Evaluating portfolio performance

The study evaluated the impact on portfolio performance of including cryptocurrencies in a portfolio from two perspectives: effect on diversification and on risk-adjusted performance. To understand whether adding cryptocurrencies to a default portfolio consisting of equity, bonds and cash enhanced portfolio diversification, the following analysis were undertaken:

(i) Assessed the time-varying correlation between BTC returns r_{BTC} and ETH returns, r_{ETH} and the returns of the individual assets (r_{equity}, r_{bonds}, r_{cash}) to gain insights on correlation dynamics between cryptocurrency and equity, bonds and cash in the local (SA) market and in the global (US) market. Weak correlations indicate stronger diversification potential benefits with perfectly negative correlations (-1) yielding the maximum diversification and therefore risk reduction (Markowitz, 1952).

(ii) Assessed the evolution of one-year (rebalancing time) time-varying correlation between the optimal baseline portfolio in SA and in the US with cryptocurrency returns.

(iii) Evaluated how portfolio risk metrics and risk-adjusted returns in the SA and the US baseline portfolios were altered by including cryptocurrencies.

Regarding risk measures, the study leveraged complementary insights from multiple risk measures to develop a more comprehensive risk assessment of how adding cryptocurrencies to a baseline portfolio (in SA and in the US) impacts a portfolio. Specifically:

(i) Standard deviation: Captured the total volatility or overall risk.

(ii) VaR provided estimates of the maximum potential losses over a defined time horizon (one year) at given confidence level (95%) as in Klein *et al*. (2018)

(iii) CVaR evaluated the expected loss beyond the VaR threshold, thereby incorporating the impact of extreme losses.

(iv) Unsystematic risk assessed how the proportion of diversifiable risk in the portfolio shifted with the inclusion of cryptocurrencies.

Overall, lower risk metrics (standard deviation, VaR, CVaR and unsystematic risk) signal improved diversification benefits. These metrics are defined and computed as in Equations 6.15 to 6.18.

The first metric considered to give insights on diversification was correlation. Letting r_{ct} and r_{pt} be two time series of cryptocurrency returns and returns of the default portfolio (or individual

assets - equity, bonds and cash) in the local and in the global market. The one-year rolling (or time-varying) correlation at time t (with $t \geq 252$) is ρ_t and is given by.

$$\rho_t = \frac{\sum_{i=t-252}^{t}(r_{ci} - \mu_{c,t})(r_{pi} - \mu_{p,t})}{\sqrt{\sum_{i=t-252}^{t}(r_{ci} - \mu_{c,t})^2}\sqrt{\sum_{i=t-252}^{t}(r_{pi} - \mu_{c,t})^2}} \quad (6.15)$$

where $\mu_{c,t} = \frac{1}{252}\sum_{i=t-252}^{t}(r_{ci})$ and $\mu_{p,t} = \frac{1}{252}\sum_{i=t-252}^{t}(r_{pi})$ are mean returns in a cryptocurrency, c, and the default portfolio, p, (and assets making up the default portfolio in the case of single asset comparison with cryptocurrencies.

In both the local market and the global market, the standard deviation, σ_p of the portfolios[94] was computed following Jorion (2012) as follows:

$$\sigma_p = \sqrt{\sum_{i=1}^{n}\sum_{j=1}^{n} w_i w_j \sigma_{ij}} \quad (6.16)$$

where w_i is the weight of asset i in the portfolio, σ_{ij} is the covariance of returns of asset i and of asset j.

VaR is computed for the portfolios (Darolles & Gourieroux, 2010) as:

$$VaR_\alpha = r_p + \sigma_p\left(\Phi^{-1}(\alpha)\right), \quad (6.17)$$

where r_p is the annualised portfolio return, σ_p is the annualised standard deviation of the returns, Φ^{-1} is the inverse of the cumulative distribution function of the standard normal distribution at α, the probability of confidence level, assumed as 99% in this study as in van Heerden (2020). This study purposefully selected a 99% confidence level rather than a popular 95% to provide estimate that focuses on extreme events given the focus of assessing portfolio performance through crisis periods. Since VaR does not account for losses beyond the VaR (Jorion, 2012) the CVaR was computed adapting van Heerden (2020) to capture losses beyond VaR as follows:

$$CVaR_\alpha = r_p - \sigma_p\left[\frac{\phi\left(\Phi^{-1}(\alpha)\right)}{1 - \alpha}\right], \quad (6.18)$$

where ϕ is the probability density function of the standard normal distribution.

[94] Both the optimised default portfolio consisting equity, bonds and cash and the optimised portfolio that includes equity, bonds, cash and cryptocurrencies.

Finally, the study explored how the impact of including cryptocurrencies alters portfolio diversification by assessing unsystematic risk (Agarwal *et al.*, 2013) computed as

$$Unsystematic\ risk = \sqrt[2]{\sigma_p^2 - \beta_p^2\sigma_M^2}, \tag{6.19}$$

where σ_p^2 is the annual portfolio variance and $\beta_p^2\sigma_M^2$ reflects the systematic (market-driven) risk, thus $\sigma_p^2 - \beta_p^2\sigma_M^2$ *is the idiosyncratic (diversifiable) risk.*

To determine whether cryptocurrencies enhanced risk-adjusted performance, the study compared the risk-adjusted measures of the SA and US default portfolio with the respective ones which includes cryptocurrencies. Superior risk-adjusted returns (measures/metrics) indicated enhanced performance. The risk-adjusted measures were computed as per Equations 6.20 to 6.30.

These included Treynor's (1962) ratio computed as follows:

$$Treynor\ ratio = \frac{r_p - r_f}{\beta}, \tag{6.20}$$

where r_p is the portfolio return, r_f is the risk-free rate proxied by the 3-month Treasury bill rate tracked by the TB3MS in IS and INTGSTZAM193N for SA. β is market risk and was defined as the slope between market returns (JSE All share index or S&P500) and the portfolio.

The study also leveraged Sharpe's (1966) ratio computed as

$$Sharpe\ ratio = \frac{r_p - r_f}{\sigma_p}, \tag{6.21}$$

where σ_p is the annualised portfolio standard deviation. Still, r_p is the portfolio return, r_f is the risk-free rate. Sharpe's (1998) ratio emphasises mean and standard deviation overlooking higher order moments of return distribution. However, it is widely understood that financial time series in general and cryptocurrency returns in particular are non-normally distributed (Zsolt & Botond, 2021). Ignoring higher order moments of non-normal returns leads to risk understatement (Jorion, 2012). This study employed Shadwick and Keating's (2002) Omega ration to incorporate the effects of skewness and kurtosis in the distribution of returns. According to van Heerden (2020), the Omega ration maybe computed as follows:

$$Omega = \frac{\sum_{r_p > r_T}(r_p - r_T)}{\sum_{r_p < r_T}(r_T - r_p)}, \tag{6.22}$$

where r_T is the minimum target portfolio return (set to zero) and r_p is the portfolio return. A larger Omega ratio indicates that the portfolio is more likely to produce positive returns, reflecting a more favourable risk-reward profile.

Another way of seeing risk is concentrating on downside risk. Sortino and Van der Meer (1991) used this approach quantifying variability below a target return.

metric

$$Sortino\ ratio = \frac{r_p - r_f}{\sqrt{LPM_2(r_T)}}\ , \tag{6.23}$$

where $LPM_2\ (r_T) = \frac{1}{T}\sum_{i=1}^{T}\left[\max(\mathrm{r_i} - \mathrm{r_p}, 0)\right]^2$.

Where r_i is the return at time i, r_p is the portfolio return and r_f in the risk-free rate and T is the number of observations. The denominator in the Sortino ratio, the Lower partial moment of order $n\ =\ 2$ measures the variability of portfolio returns relative to the set target (Van Heerden, 2020). Again, given that financial time series is nonnormal, it is important to incorporate higher order of moments of distribution of returns. This study extended the second order LPM to the third order, Kappa, to capture skewness as in Van Heerden (2020).

$$Kappa\ 3\ ratio = \frac{(r_p - r_f)}{\sqrt[3]{LPM_3(r_T)}}, \tag{6.24}$$

where $LPM_3\ (r_T) = \frac{1}{T}\sum_{i=1}^{T}\left[\max(\mathrm{r_i} - \mathrm{r_p}, 0)\right]^3$.

To enhance the insight on risk adjusted performance measure, the study applied Young's (1991) Calmar ratio to contextualise the excess return per unit of drawdown risk as show below:

$$Calmar\ ratio = \frac{(r_p - r_f)}{MD}. \tag{6.25}$$

For simplicity, the study defined maximum drawdown (MD) over t observations with peak returns $P(u)$, trough returns $T(u)$ as $MD = \max_{u\in[0,t]}[P(u) - T(u)]$.

This study also made use of the following variants of VaR type risk measures as denominators in Sharpe ratios:

$$VaR\ -\ Sharpe\ = \frac{r_p - r_f}{VaR}, \tag{6.26}$$

$$CVaR\ -\ Sharpe\ = \frac{r_p - r_f}{CVaR}, \tag{6.27}$$

Moreover, this study applied the modified information ratio to add the perspective of risk as deviations from market returns. Israelsen (2005) annualised variance of market excess returns is applied as the risk denominator as below:

$$Modified\ Information\ = \frac{r_p - r_f}{\sqrt[2]{\sigma_{pm}^2}}, \tag{6.29}$$

where σ_{pm}^2 is the annualised volatility of the market excess return $(r_p - r_m)$.

The study also applied the modified Sharpe as in Van Heerden (2020) to enhance the performance of Sharpe's (1966) ration when excess returns are negative:

$$Modified\ Sharpe\ = \frac{(r_p - r_f)}{\sigma_p\left(\frac{r_p - r_f}{abs(r_p - r_f)}\right)}, \tag{6.30}$$

Where r_p is the portfolio return, r_f is the risk-free rate, σ_p is the portfolio standard deviation.

The risk and risk-adjusted performance measures were estimated using frequency-consistent inputs. Daily portfolio returns were annualised using the exponential transformation which follows directly from modelling asset prices as a process with continuously compounded returns. Letting T denote the number of observed trading days and N the notional number of trading days in a year (252 for other assets); then the annualised return is $r_{annual} = \exp\left(\frac{N}{T}\sum_{t=1}^{T} r_{daily}\right) - 1$. The annualised risk, σ_{annual} was obtained as $\sigma_{daily} * \sqrt{N}$. The annual risk-free rate was applied to the annualised return series to compute annual excess returns in the numerator of risk adjusted rations such as the Sharpe, Sortino and Kappa ratios. This ensures dimensional consistency between return, risk and the risk-free benchmark.

To evaluate Hypothesis 2, the study examines whether incorporating cryptocurrencies into an optimised baseline portfolio of bonds, equities, and cash alters diversification outcomes – measured through standard risk metrics and risk-adjusted performance. The analysis first uses the full-sample period to establish a long-term reference point. Because investor objectives and benchmark preferences vary widely, the assessment focuses on the direction of change rather than the magnitude. Economically meaningful reductions (increases) in portfolio risk or improvements (deteriorations) in risk-adjusted performance are interpreted as evidence against the null hypothesis, indicating that cryptocurrency inclusion modifies diversification characteristics or performance relative to the baseline allocation.

To evaluate Hypothesis 3, the same portfolio-based approach is applied within the pre-identified crisis windows. VR *p*-values serve as indicators of market efficiency conditions during each crisis.

The analysis then examines how portfolio outcomes differ when cryptocurrencies are added under these crisis-specific efficiency states, relative to the full-sample baseline. Evidence that diversification properties or performance contributions shift systematically with crisis-driven changes in efficiency is taken as grounds to reject the null hypothesis, supporting the view that variations in cryptocurrency market efficiency influence their diversification role and portfolio performance during periods of market stress.

A qualification of the current approach is that it does not separate between estimation and investment windows (also called training and testing windows) as advocated by Brooks (2014). However, this study follows Baur and Lucey (2010), Dyhrberg (2016) and Bouri *et al*. (2020), where in the separation of estimation and testing windows was not implemented. This is because the portfolio analysis focuses specifically on crisis periods, which are both infrequent and short-lived. Across the full sample from 2015 to 2024, only three (Section 7.2) distinct crisis episodes were identified. Partitioning these already limited periods into separate estimation and testing samples would leave insufficient data to produce statistically credible portfolio results. In this context, applying a conventional rolling or split-sample design would compromise, rather than strengthen, the validity of the analysis. The chosen approach therefore reflects the empirical reality of rare crisis events and ensures that the portfolio results remain based on the full information available for each crisis period.

The next Chapter implements the metrics presented above and assessed whether the inclusion of cryptocurrencies enhances portfolio diversification and risk-adjusted performance.

6.8 Summary

This chapter presented three variance ratio tests to assess the market efficiency of the two largest cryptocurrencies, BTC and ETH, which together accounted for close to 70% of the total cryptocurrency market capitalisation as of December 2024. The tests used daily data for the observation period 1 September 2015 to December 2024 for ETH with a 500-day fixed-length rolling subperiod window to capture evolving efficiency. Data for BTC and three developed equity indices (S&P 500, FTSE 100, and Nikkei 225) and three developing markets (JSE ALSI, SSE, and Sensex) were synchronised for the same start date as the ETH 500-day rolling window. The tests were performed on both observed returns and returns corrected for thin trading, as thin trading may bias efficiency results, particularly in relatively newer and less frequently traded assets.

This chapter also presented methods for assessing how the inclusion of BTC and ETH in a diversified portfolio impacts diversification and risk-adjusted performance. This study examined the impact over a long period from September 2015 to December 2024 and during selected crisis

periods. The study selected two distinct investment universes – South Africa and the US – to evaluate how incorporating cryptocurrencies affects portfolio outcomes. In each environment (South Africa and the US), a default portfolio consisting of equity, bonds and cash was defined as the baseline. Three asset allocation strategies: MVP, MVO, and the BL model were used to compute portfolio allocations before and after – including cryptocurrencies. Correlation analysis and various risk metrics and risk-adjusted performance were presented as methods to assess overall diversification capabilities. The next chapter presents the results.

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CHAPTER SEVEN

MARKET EFFICIENCY EMPIRICAL FINDINGS AND PORTFOLIO ANALYSIS

7.1 Introduction

This chapter presents the empirical results from the analysis of cryptocurrency market efficiency and their portfolio performance through crisis periods. It is based on market efficiency and portfolio optimisation theories discussed in earlier chapters and supported by the methodological rigour detailed in Chapter 6. The findings address two core issues: how market efficiency of cryptocurrencies evolves and how this evolution impacts diversification and risk-adjusted performance benefits during crisis periods.

To this end, Section 7.2 identifies episodes when the S&P 500 and the JSE ALSI experienced dramatic losses at times when the US and SA markets where in crisis. Section 7.3 draws on extensive datasets that span diverse periods of market activity from nascent development to periods of growing institutional involvement to assess market efficiency of cryptocurrencies. The analysis was guided by the AMH and employed modifications of the VR tests of Lo and MacKinlay (1989). Specifically, it applied the JS test (Belaire-Franch & Contreras, 2004; Kim & Shamsuddin, 2008) the JM test (Kim, 2006) and the AVR test (Kim, 2009). This empirical approach evaluated whether returns series exhibited patterns (or autocorrelation) that could be exploited based solely on historical returns. The evidence presented sought to confront existing questions of whether cryptocurrencies were evolving into efficient markets and whether there is a breakdown in the efficiency of cryptocurrency markets over crisis periods. The levels of market efficiency exhibited by cryptocurrencies were compared with those of popular equity indices to provide context on the levels of market efficiency of cryptocurrencies.

Following the market efficiency analysis, the focus of Section 7.4 shifts to the evaluation of portfolio performance when cryptocurrencies were added to a traditional diversified portfolio of equity, bonds and cash. The analysis was restricted to the US and SA cases. Robust risk metrics such as the standard deviation, VaR, CVaR and unsystematic risk were used to assess the diversification benefits of cryptocurrencies. Numerous performance measurement metrics such as the Sharpe ratio (and its variants), Omega ratio, Sortino ratio, and maximum drawdown were applied to assess how the inclusion of cryptocurrencies in a portfolio impact performance. By comparing the risk metrics as well as risk-adjusted performance indicators between baseline portfolios and the respective portfolios that included cryptocurrencies, this section critically examines the impact cryptocurrencies offer, especially considering their return, correlation and volatility dynamics. Moreover, by repeating the analysis during crisis periods, this study sought to

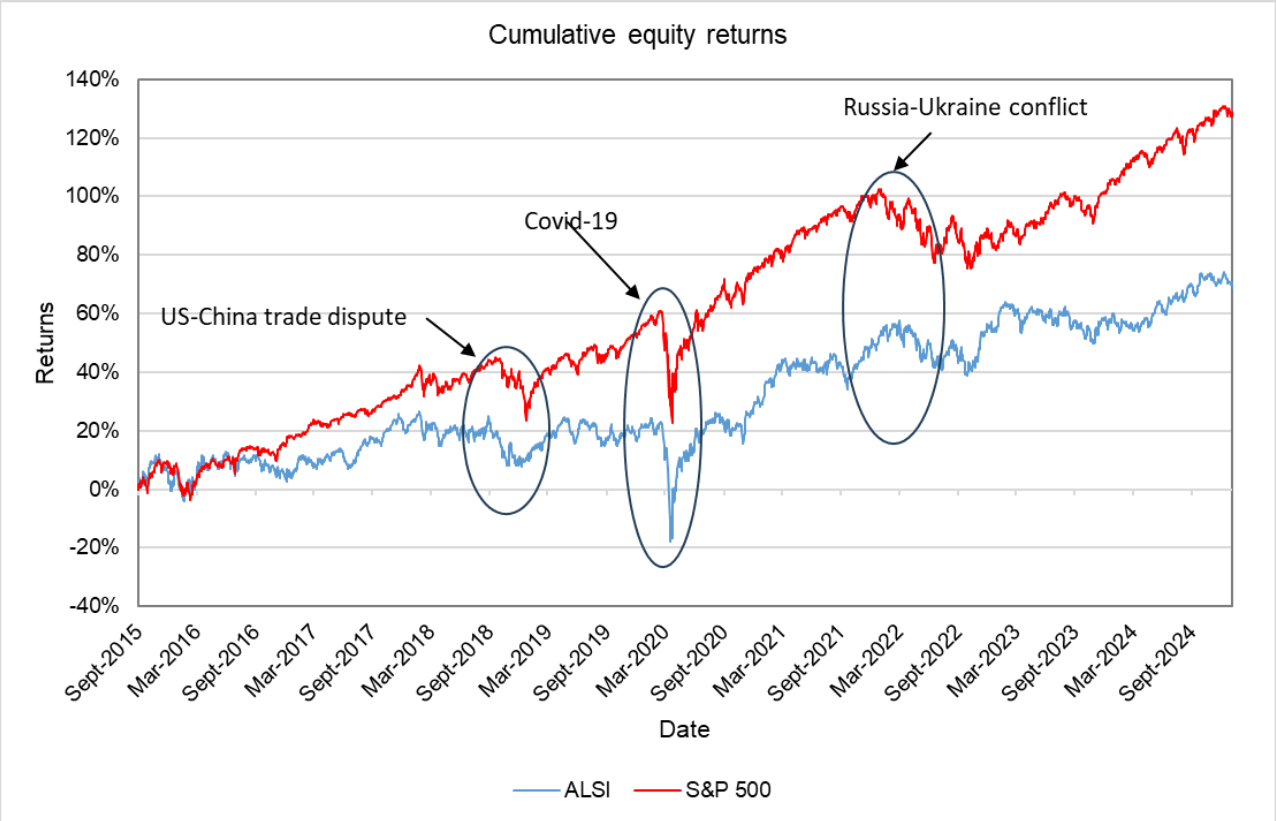
shed more light on unanswered questions relating to the diversification capabilities and risk-adjusted performance of cryptocurrencies during crisis periods.

In synthesising these insights, this chapter serves as the cornerstone for forging an understanding of how market efficiency manifests in an environment as fluid and disruptive as the cryptocurrency sector, and how these dynamics influence portfolio management even more in crisis periods.

7.2 Investment horizon and crisis periods

Following the delineation of the observation period as 1 September 2015 to 31 December 2024, this study adapted Patel and Sarkar's (1998) definition of crisis to identify crisis intervals within that window. The resulting episodes, which differ in severity, are presented in Figure 7.1.

Figure 7.1: Cumulative returns and crisis periods in the S&P 500 and JSE All Share Index



Source: Author's computations from investing.com (2024).

The identified crises are in line with Wyplosz's (1998) and Claessens and Kose (2013) reasoning that while there is not generally agrees definition of 'what' constitutes a crisis, the broader financial consequences of crises are negative and substantial, however a crisis is defined or measured.

The three crises were classified according to their origins and transmission as follows:

(i) US–China trade tensions are considered a policy or trade-induced crisis. These unfolded gradually, affecting investor sentiment and market pricing through expectations about global supply chains, tariffs and economic nationalism.
(ii) Covid-19 was classified as a systemic crisis. It originated outside the financial system but had broad, global impact, causing widespread panic, sharp drawdowns, and liquidity constraints and resulted in widespread governments policies.
(iii) Russia–Ukraine war is classified as a geopolitical crisis. It generated substantial uncertainty and market disruption primarily through regional instability, energy market volatility, and inflation spillovers.

These classifications allow for a more rigorous interpretation of results. For instance, according to the AMH, market efficiency is expected to decline during systemic crises due to government policy disruptions. Similarly, portfolio diversification is expected to weaken during such periods as cross-asset correlations increase, consistent with contagion and co-movement literature.

To ensure that these crises were not artifacts of the identification approach utilised in this study, relevant finance literature was reviewed to verify whether existing research identified crises during similar periods. The first crisis coincided with the escalation of trade tensions between the US and China in 2018, particularly during the latter half of the year and was corroborated by Liao *et al*. (2019). During 2018, escalating disputes and tariff wars heightened concerns regarding potential disruptions to global supply chains (Bown, 2019). Empirical evidence indicates significant impacts in both US and Chinese equity markets, with indices reflecting increased volatility (Chen & Pantelous, 2022). Notably, this crisis also precipitated a measurable reduction in business activity and industrial output, prompting firms to reconfigure their supply networks (Bown, 2019).

The second crisis emerged from the global market downturn instigated by the Covid-19 pandemic. The most pronounced decline occurred between 19 February 2020 and 23 March 2020, during which the S&P500 and the JSE ALSI experienced one of their fastest declines of the observation period with losses exceeding one-third of their value within about a single month. Several studies (Caferra & Vidal-Tomás, 2021; Iqbal *et al.*, 2021; Saha *et al.*, 2022; Zhang *et al.*, 2020) confirmed the widespread impact of the pandemic. Ali et al. (2020) further noted that rapidly falling commodity prices and the emergence of negative interest rates exacerbated instability in financial markets in the months following Covid-19 shocks.

The third crisis period coincided with the Russia-Ukraine conflict, which began in February 2022. This event shocked global food, fertilizer, and fuel supply chains, with far-reaching implications for inflation, particularly within the EU and other close trading partners of Russia and Ukraine including the US and SA (Maurya *et al.*, 2023). On February 21, 2022, when Russia recognised some Ukrainian republics as autonomous entities, European equities experienced a significant

negative abnormal return, with the impact spilling over to other global markets (Maurya *et al*., 2023). Comparing the severity of the three crises shows that the Covid-19 systemic market disruption in 2020 led to one of the most damaging and fasted declines for both the US and SA equity markets. In SA, the effect was especially severe, wiping out all cumulative returns since September 2015. The crisis coinciding with the Russia-Ukraine conflict also had substantial and longer-lasting impact particularly on US equities which continued to be on a declining trend for most of 2022. The 2018 crisis coinciding with the US-China trade tensions also affected both the US and SA equities substantially as they declined considerably during the calendar year 2018.

Market efficiency as well as impact of cryptocurrencies on portfolio performance and diversification was analysed over the period 1 September 2015 - 31 December 2024 and during the years of the three crises: the US-China trade tensions (January 2018 to December 2018), the Covid-19 pandemic (January 2020 to December 2020), and the Russia-Ukraine conflict (January 2022 to December 2022). It is important to note that these periods do not necessarily indicate the exact beginning or end of each crisis. Instead, the intervals were defined according to annual rebalancing strategies.

The following section examines the market efficiency of cryptocurrencies. It focuses on how efficiency evolves during crisis periods and explores whether cryptocurrencies are as efficiently priced as widely traded equities.

7.3 Changing efficiency of cryptocurrencies

Before delving into market efficiency tests, it was essential to provide an overview of the datasets through descriptive statistics. This was key to lay the groundwork for subsequent assessment of market behaviour. The summary statistics offer critical insights into the distributional characteristics of cryptocurrencies. By examining measures such as the first four moments of distribution of returns, this study built an understanding of the overall properties and variability inherent in cryptocurrencies and contextualised them with popular equity indices. These descriptive measures were invaluable for identifying features such as non-normality or significant volatility clustering that influence the interpretation of the market efficiency tests and necessitate emphasis on non-normal and bootstrapping tests. Insights gained enabled a more informed and contextually robust interpretation of market efficiency tests, ensuring that conclusions drawn were well-grounded in the underlying statistical properties of the observed financial series statistics presented in Table 7.1 below.

Table 7.1: Descriptive summary statistics

	Start date	Mean	Standard deviation	Skewness	Kurtosis	JB**	ARCH*
BTC	01-09-2015	0.17%	3.65%	-0.79	13.29	26327.55	64.56
ETH	01-09-2015	0.20%	5.33%	-0.07	6.02	5320.02	298.54
BSE Sensex	09-01-2015	0.04%	1.05%	-1.36	21.06	47931.34	463.54
FTSE 100	26-01-2015	0.01%	0.99%	-0.93	13.18	19131.78	442.01
JSE ALSI	16-01-2015	0.02%	1.12%	-0.41	8.47	7759.44	779.93
Nikkei 225	05-01-2015	0.03%	1.33%	-0.39	9.44	9433.91	465.75
S&P 500	24-02-2015	0.04%	1.15%	-0.66	15.68	26438.97	778.72
SSE	05-01-2015	0.00%	1.31%	-1.05	8.37	7793.29	331.21

The start date was chosen to coincide with the 500th day of recorded ETH returns. The computations were based on daily log returns. $JB \sim \chi^2_{0.95}(2) = 5.99$. *In all cases normality is rejected;* $*ARCH \sim \chi^2_{0.95}(5) = 11.07$. *In all cases ARCH effects are detected. Source: Author's computations from investing.com (2025).*

In terms of returns, ETH boasted the highest mean daily return of 0.20%, followed by BTC's 0.17%. The mean daily returns for cryptocurrencies were notably higher than those observed in equities indices. Specifically, the BSE Sensex (0.04%), S&P 500 (0.04%), Nikkei 225 (0.03%), JSE ALSI (0.02%) and FTSE 100 (0.01%). These results are corroborated by numerous authors (Corbet *et al.*, 2018; Demiralay & Bayracı, 2021; Liu & Tsyvinski, 2021; Zsolt & Botond, 2021) who found that cryptocurrency returns were considerably higher than in equities. SSE had the lowest mean daily returns of less than one basis point. The SSE's weak performance has been attributed to institutional deficiencies in listing and delisting processes, as well as inadequate corporate governance related to insider dealing (Allen *et al.*, 2024).

A further analysis of returns indicated that, in the beginning of 2015, cryptocurrencies consistently delivered the highest holding period returns during years characterised by market gains. However, they also experienced the most severe declines during periods of market crises, notably in 2018 and 2022, which were marked by crises associated with the US–China trade tensions and the Russia–Ukraine conflict, as illustrated in Table 7.2.

Table 7.2: Annualised holding period returns

Year	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024
BTC	38%	129%	1251%	-72%	89%	308%	63%	-65%	166%	114%
ETH*	-32%	791%	9132%	-82%	-4%	455%	414%	-68%	94%	44%
BSE Sensex	-5%	2%	27%	7%	14%	16%	24%	3%	18%	9%
FTSE 100	-7%	18%	7%	-12%	13%	-14%	14%	1%	2%	7%
JSE ALSI	0%	3%	17%	-14%	13%	5%	22%	1%	2%	12%
Nikkei 225	6%	6%	20%	-17%	19%	17%	7%	-12%	29%	18%
S&P 500	-2%	12%	19%	-7%	30%	14%	30%	-20%	24%	24%
SSE	-2%	-5%	7%	-26%	25%	14%	4%	-14%	-5%	10%

**From 01-09-2015. Source: Author's computations from investing.com (2025).*

Descriptive summary statistics also showed that ETH (5.56%) and BTC (3.7%) were the most volatile assets compared with the most volatile equities indices – the Nikkei 225 (1,33%) and SSE (1,31%) corroborating other researchers (Gkillas *et al.*, 2024; Shahzad *et al.*, 2021; Smales, 2021). Several other studies (Balcilar *et al.*, 2017; Phillip *et al.*, 2019; Urquhart, 2017) argued that the wild swings in ETH (the youngest asset) and BTC were due in part because of an erratic infant market or nascent asset and changing market liquidity. Assessing whether the volatility of cryptocurrencies was decreasing was outside the scope of this research. An important question was assessing and understanding whether cryptocurrency volatility was rewarded in the markets. To this end, this study utilised the coefficient of variation (CV)[95], to shed light in comparing volatility per unit of mean return across cryptocurrencies and equity indices. The descriptive summary statistics indicated that BTC exhibited the lowest CV at 21, followed by the BSE Sensex at 25, ETH at 26, and the S&P 500 at 30. In contrast, the FTSE 100 and the SSE reported much higher CVs of 118 and 956 respectively, suggesting a markedly higher risk per unit of return. These findings illustrate that the high volatility in BTC and ETH is better compensated for than the apparently modest volatility in popular equity indexes.

The summary statistics also illustrated that cryptocurrency returns, like returns for equity indices were skewed and had excess kurtosis leading to significant deviations from the normality assumptions as evidenced by the JB statics that are significantly larger than the critical value of 5.99. The non-normality of returns in cryptocurrencies and in equity indices is corroborated in numerous studies (Aharon *et al.*, 2023; Liu & Tsyvinski, 2021; Zhang *et al.*, 2018; Zsolt & Botond, 2021) and suggests that nonparametric techniques are better suited for assessing cryptocurrency returns dynamics. This lends support for the JS test because it does not make any distributional assumptions.

The ARCH test indicated that the volatility in the returns on cryptocurrencies as well as the returns on equity indices was not constant, but clustered through time, supporting assessing market efficiency with the AMH tests that allow for changing aggregate risk. Approaches such as the JM test that accommodates heteroskedasticity were instrumental. Smith and Dyakova (2014) made similar findings and argued that the presence of conditional heteroskedasticity necessitates the use of VR tests, which are robust to heteroskedasticity. Models that do not accommodate changing volatility might falsely detect inefficiency when there is a shift in market risk levels (Katsiampa, 2019; Khursheed *et al.*, 2020; Le Tran & Leirvik, 2019; Takaishi, 2020).

The summary of statistics reinforces that cryptocurrencies are high-return assets and, historically, have outperformed equities in terms of holding period gains. However, during market crises in

[95] $CV = \frac{standard\ deviation}{mean}$

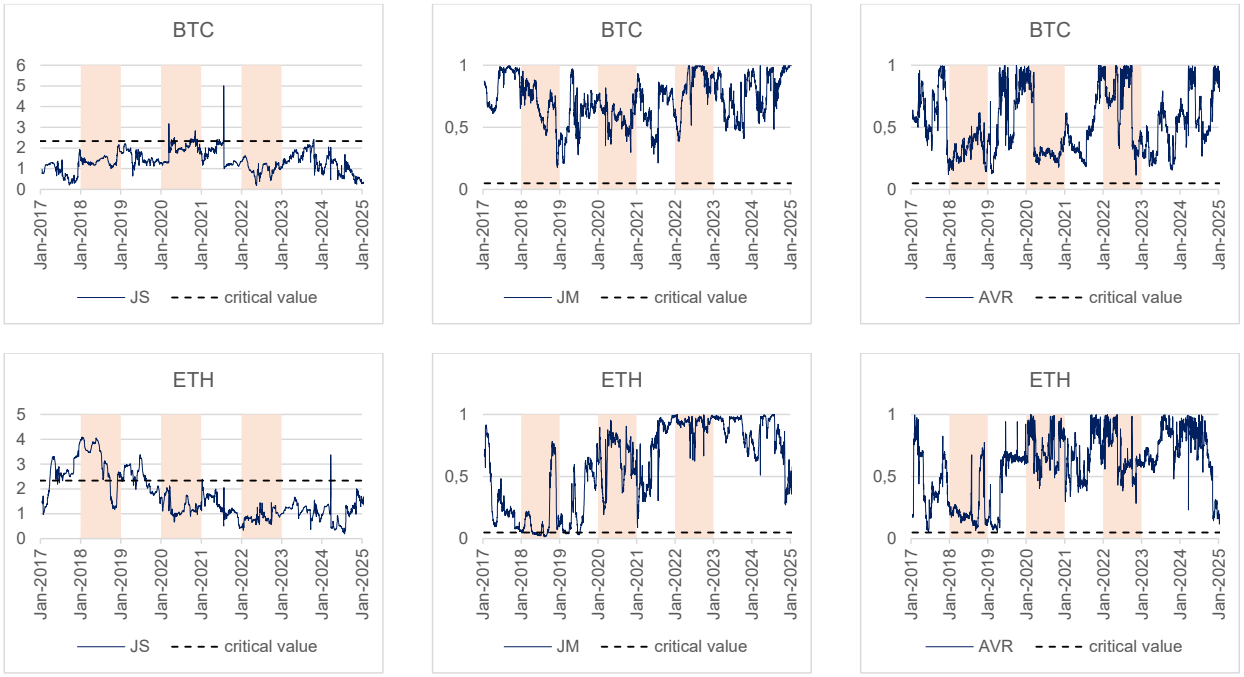
2018 and 2022, their performance was severely affected. Further evaluation revealed that the return distributions for both cryptocurrencies and equity indices deviated significantly from normality, as evidenced by the results of the JB test. In addition, these returns exhibited marked heteroskedasticity, indicating that volatility was not constant over time. To address these characteristics, this study adopted the AMH and employed non-parametric JS tests and bootstrapped versions of the JM and AVR tests in assessing market efficiency. By aligning statistical methods with the underlying distributional properties of the data, the analysis mitigated the risk of test misspecification and ensured the robustness of the results.

7.3.1 Assessing the market efficiency of cryptocurrencies through crisis conditions

The analysis of market efficiency was based on tests applied to successive subsamples derived from a rolling window of 500 observations. The 500-day rolling window size has been applied by several researchers (Belaire-Franch & Opong, 2005; Hung, 2009; Lim *et al.*, 2013; Smith, 2012; Smith & Dyakova, 2014) who argued it is *short* enough to capture short-term market inefficiency, yet *long* enough for the tests to maintain accurate size properties which were identified as one of the major challenges with the VR of Lo and McKinlay (1988). Kim and Shamsuddin (2008), Kim (2009), and Charles *et al*. (2012) corroborate that with 500 observations, the JS, JM, and AVR tests are robust and do not suffer from size distortions. More recently, Karaömer and Acaravci (2023) applied the 500-day rolling window to test the market efficiency of cryptocurrencies.

Figure 7.2 presents the VR test results using thin trading-corrected returns for the three distinct tests: JS, JM and AVR. Each row corresponds to a specific cryptocurrency or equity index denoted in the figure heading. The first column displays the JS test results, followed by the JM test and the AVR results. In all three tests, the dotted line marks the 5% critical value. For the JS test, when the p-value (solid line) rises above the 5% critical value, the result indicated significant autocorrelation in returns and, consequently, market inefficiency. By contrast, in the JM and AVR tests, values that fell below the 5% critical value signalled periods of market inefficiency. Shaded regions highlight the calendar years 2018, 2020, and 2022, intervals when the US and South African equity markets entered crises.

Figure 7.2: Cryptocurrency variance ratio tests



Source: Author's computations from WSJ (2024).

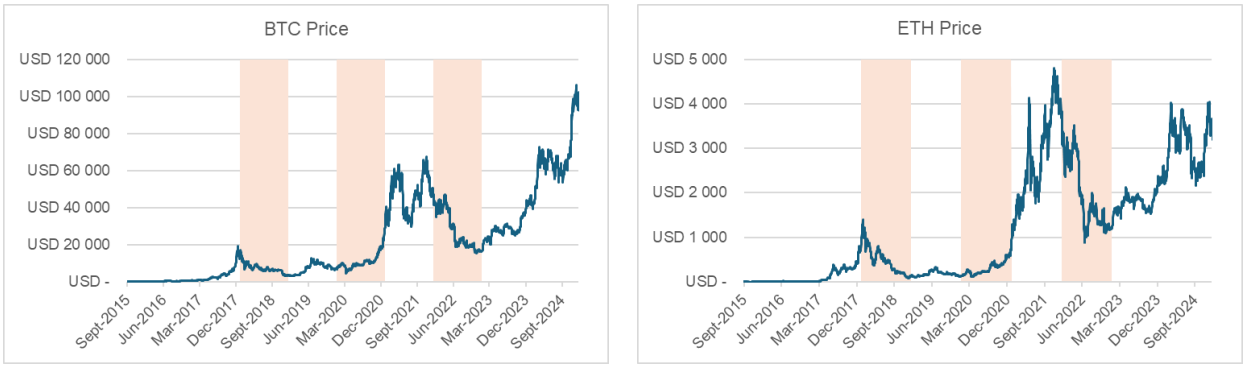
The empirical examination revealed distinctive patterns in the market efficiency of BTC and ETH returns over the investigated period. Both the JM and AVR tests indicate that BTC returns exhibit time-varying efficiency, marked by alternating periods of robust efficiency and episodes of diminished efficiency.

BTC was mostly efficient throughout the observation period with transient deviations from efficiency coinciding with the Covid-19 market crisis period. ETH on the other hand, exhibited market inefficiency over early periods from 2017 to 2019. This inefficiency in ETH was expected, consistent with Lo's (2004) assertion that assets do not suddenly emerge in the market as efficient but rather they develop towards efficiency over time. The results of the JS test for ETH provided a compelling narrative that over approximately four years, from its inception in September 2015, ETH transitioned toward market efficiency in 2019. Since mid-2019, the JS test showed that ETH returns were marked by alternating periods of robust efficiency and episodes of diminished efficiency, albeit with spikes towards market inefficiency in 2021 and 2024. These results were also confirmed through the JM and the AVR tests, which showed that from 2019, ETH also exhibited time-varying efficiency, marked by alternating periods of robust efficiency and episodes of diminished efficiency. The market efficiency tests for ETH, unlike those for BTC, do not show a shift in trends towards market inefficiency during the turbulent Covid-19-induced market crisis in 2020, nor any significant signs of debilitation towards inefficiency as markets entered crisis periods related to the US–China trade dispute in 2018 and the Russia–Ukraine conflict in 2022.

Collectively, the market efficiency of BTC and ETH varied over time according to the AMH, confirming Le Tran and Leirvik (2020) and Noda (2021). Moreover, this study's results corroborate Khursheed *et al*. (2020), who found that BTC had the longest periods of market efficiency among cryptocurrencies. Additionally, the findings partly match those of Naeem *et al*. (2021), who reported that the Covid-19 crisis greatly affected the efficiency of both BTC and ETH. This study revealed that BTC's market efficiency during Covid-19 (2020) was more negatively affected than ETH, as shown by the JS test. The other two crisis periods did not have a major impact on the market efficiency of either BTC or ETH.

When comparing the market efficiency results across crises, the results showed that, while both BTC and ETH were maturing in efficiency, their changing levels of efficiency varied by crisis and tracked the evolution of prices. During geopolitical tensions such as the US–China trade disputes (2018) or the Russia–Ukraine conflict (2022), cryptocurrency prices were in a declining trend, albeit without a corresponding breakdown in market efficiency. Meanwhile, during the market-wide crisis induced by Covid-19 (2020), cryptocurrency prices rallied amidst waning market efficiency. Figure 7.3 shows the evolution of prices through crisis periods.

Figure 7.3: Evolution of BTC and ETH prices



The observation period is from 1 September 2015 to 31 December 2024. The highlighted background represents the years 2018, 2020 and 2022 when markets entered into crisis. Author's computations from investing.com (2025).

The 2020 price surge in cryptocurrencies generated strong momentum and attendant positive narratives that produced predictable trading patterns, thereby weakening weak-form efficiency. Mokni *et al*. (2025) attributed the weakening efficiency to changing liquidity conditions, a process that reconciles with momentum-driven news developments. Rapid inflow of speculative liquidity increased demand-side pressure. This elevated demand created temporary information-processing frictions in which prices reflected sentiment and demand-side persistence more than newly available information, producing measurable VR deviations. This study's results differed from Khuntia and Pattanayak (2018), who argued that positive news events increased market efficiency. The evidence suggests that momentum trades can paradoxically induce market

efficiency when rising liquidity limits immediate arbitrage. In 2018 and 2022, the downward price trends built negative news which, for the most part, was more informative than the upbeat narratives driving rallies. Aharon *et al*. (2023) argued that trades driven by negative information were largely emanating from informed individuals, explaining why prices adjusted more fully and quickly, reducing predictable residuals.

The results suggests that during episodes such as the US–China trade disputes (2018) and the Russia–Ukraine crisis (2022), cryptocurrency prices declined and trading was dominated by waning demand flows, which supported rapid information incorporation and preserved weak-form efficiency particularly for BTC. By contrast, the 2020 rebound following the Covid-19 shock was characterised by larger demand-side inflows and elevated market liquidity that amplified momentum and demand-flow persistence, producing measurable short-horizon predictability and a temporary breakdown in efficiency. Collectively, these findings imply that some crises produce exploitable, transient opportunities for above-average returns when positive news-driven trades (or speculation) and market-structure frictions dominate, whereas crises dominated by informed trading constrain abnormal return opportunities and require investors to rely on disciplined risk management and diversification. There is therefore evidence to suggest rejection of hypothesis (H1) which states that extreme market conditions do not reduce market efficiency in cryptocurrency markets.

To contextualise the market efficiency of cryptocurrencies results, this study compared them with the market efficiency of selected equity indices. As with cryptocurrencies, the results indicated that market efficiency of the equity indices fluctuated over time, with periods of inefficiency followed by intervals of efficiency, confirming the AMH as shown in Figure 7.4.

Figure 7.4: Equity indices variance ratio tests

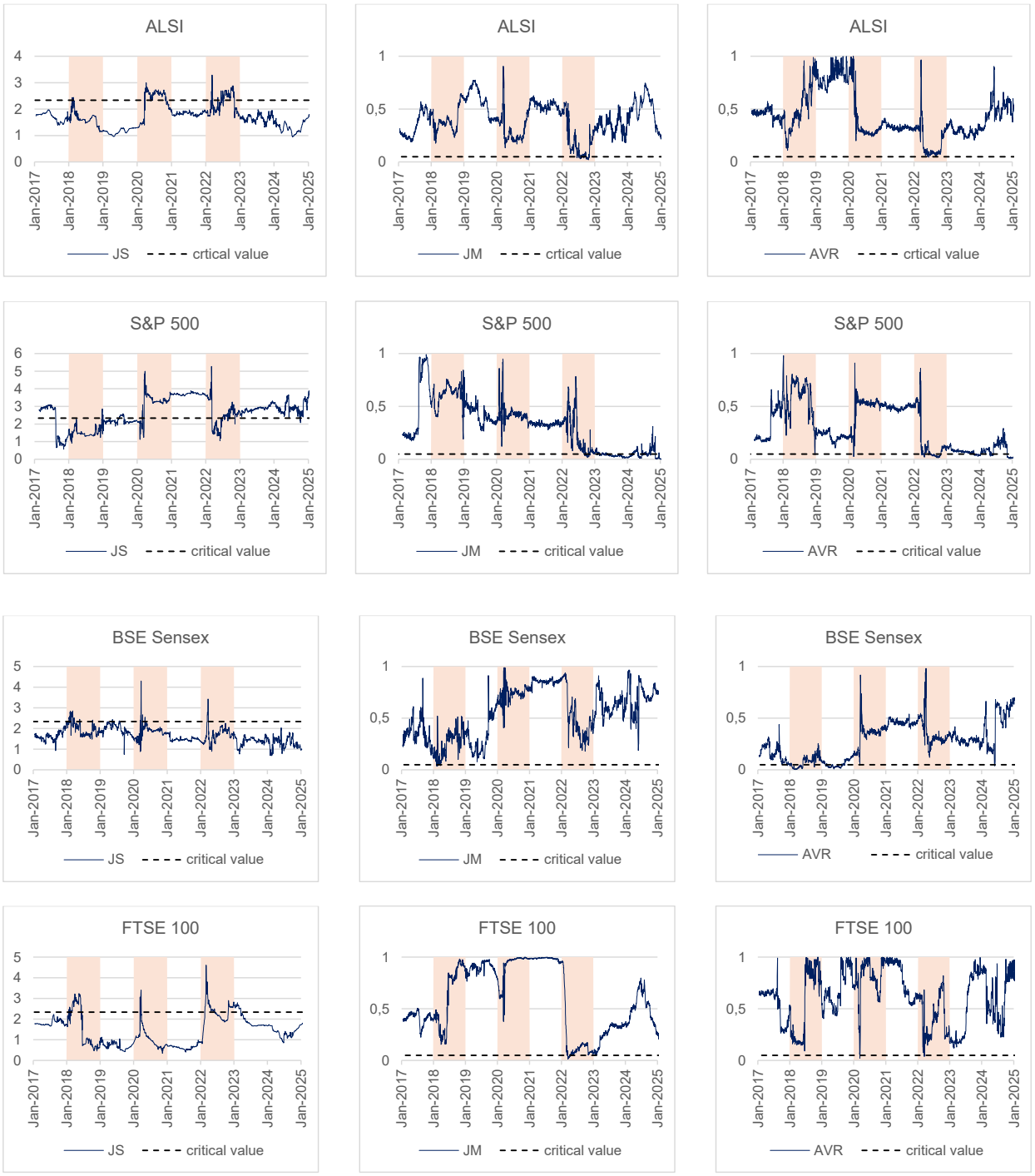


Figure 7.4: Equity indices variance ratio tests *continued*



Source: Author's computations from Investing.com (2025).

The VR test results showed that different markets undergo different levels of efficiency related to market condition, confirming the AMH in equities. The ALSI and S&P 500, BSE Sensex, FTSE 100, demonstrated considerable inefficiencies during the three crisis periods. The Nikkei 225 demonstrated inefficiency subsequent to the Covid-19 crisis, persisting until the start of 2022, when it returned to efficiency levels comparable to those observed prior to the crisis. Similarly, the SSE exhibited marked reductions in market efficiency during the US–China trade crisis, suggesting that the bilateral trade disruptions propagated to the China and US equity markets, weakening market efficiency. For the SSE, it appears the US–China trade dispute was more impactful on market efficiency than either Covid-19 or the Russia-Ukraine conflict.

In all the equity markets, the S&P 500's market efficiency was the worst affected, highlighting the vulnerability of US markets to geopolitical tensions and systematic crises. The disturbances that have persisted from 2022 through the end of 2024 prompt further examination of the S&P 500's efficiency, as the JS test suggested continued market inefficiency. Sharpe and Gil de Rubio Cruz (2024) offer additional insight, contending that heightened autocorrelation in returns resulted from anticipated announcements regarding Federal Reserve tightening, as well as spillover effects related to increased inflation following Covid-19 and continuing geopolitical events such as the Russia–Ukraine conflict, which have continued to influence US equity markets.

The outcomes from this analysis are indicative that cryptocurrencies are a dynamic yet resilient market. Like equities, cryptocurrencies also undergo levels of efficiency related to market condition. Yet, despite the occurrence of momentary deviations from market efficiency, notably during the Covid-19 crisis, the infrequency of significant inefficiency episodes underscores the maturity of especially of BTC. Since its inception in 2009, BTC appears to have evolved toward greater efficiency. This evolution is noteworthy, as it addresses the longstanding debate regarding the robustness of cryptocurrencies in the context of market efficiency. The application of robust econometric techniques, including bootstrapped JM and AVR critical values to enhance statistical power, substantiated that BTC and ETH have attained an efficient market status comparable to that of popular equity markets. Specifically, ETH was becoming largely efficient since mid-2019. These observations advanced the understanding of cryptocurrency market dynamics and offer valuable insights into the behaviour of young assets through crisis, thus contributing to the broader discourse on market efficiency and financial stability.

Discrepancies among the JS, JM, and AVR test results were anticipated, given each test's unique methodology, as detailed in Section 6.4. These differences arise from varying underlying assumptions and distinct statistical properties across the tests. Consequently, an unbiased synthesis of these three tests' results yields a more comprehensive insight into the evolution of market efficiency and enables the comparison and ranking of markets based on their efficiency (Smith & Dyakova, 2014). The next section presents an aggregated average metric derived from these tests, which was employed to compare and rank the levels of market efficiency of cryptocurrencies relative to the equity indices.

7.3.2 Relative predictability of cryptocurrencies

The frequency with which the JS, JM and AVR tests detected significant inefficiency episodes was used to construct an efficiency ranking as supported by various studies (Lim, 2007; Lim & Brooks, 2011; Smith & Dyakova, 2014). The efficiency ranking was calculated by averaging the percentages of each of the three test statistics where market efficiency was rejected at the 5% level. Table 7.3 provides insights into the predictability of BTC and ETH when compared with popular equity indices.

Table 7.3: Predictability of cryptocurrencies

	Thin trading corrected returns					Observed returns				
	JS	JM	AVR	Ave*	Rank	JS	JM	AVR	Ave	Rank
BTC	1.49%	0.00%	0.00%	0.50%	8	16.39%	0.03%	0.03%	5.49%	4
ETH	26.12%	5.75%	0.00%	10.63%	2	19.11%	0.73%	0.00%	6.61%	3
BSE Sensex	3.22%	0.44%	11.07%	4.91%	4	8.78%	0.00%	2.78%	3.85%	6
FTSE 100	12.43%	0.96%	0.14%	4.51%	6	12.24%	1.63%	0.19%	4.68%	5
JSE ALSI	12.28%	2.03%	0.19%	4.84%	5	19.97%	0.00%	0.00%	6.66%	2
Nikkei 225	23.86%	0.15%	1.28%	8.43%	3	5.88%	0.00%	0.00%	1.96%	7
S&P 500	66.13%	20.96%	12.66%	33.25%	1	25.33%	3.06%	0.00%	9.46%	1
SSE	5.52%	4.53%	2.49%	4.18%	7	3.28%	0.60%	0.15%	1.34%	8

Observed returns are the daily returns and thin trading corrected returns represents the returns after correcting for thin trading. JS, JM, AVR are the frequency with which the respective test detected significant inefficiency. Ave is the arithmetic average of the frequency with which tests detected significant inefficiency. Rank is in descending order of Ave. Higher ranking denotes the least number of times returns were market inefficient. Source: Author's computations with data from Investing.com (2025).

Based on thin trading corrected returns, BTC emerged as the least predictable and therefore the most informationally efficient with an average of 0.5% of returns predictable. In contrast, ETH (10.63%) was substantially predictable, confirming that BTC had the longest period of unpredictability. Meanwhile the S&P 500 (33.25%) was the most predictable, with close to a third of returns being regarded as inefficient compared with ETH (10.63%) and BTC (0.50%). The observation that BTC was relatively less predictable than other equity indices is not inherently paradoxical but reflects the market's microstructure and sampling arguments. Lim and Brooks (2011) documented that predictability is dependent on asset class and sampling frequency. This study confirmed that cryptocurrencies' continuous trade at daily intervals tend to reduce detection of short-horizon predictability more than equities with non-synchronous trading and discrete market hours with overnight gaps which inflate apparent predictability.

When plain observed returns were utilised without adjusting for thin trading, the SSE (1.34%) was the least predictable, followed by the Nikkei 225 (1.96%), the BSE Sensex (3.85%), FTSE 100 (4.68%), BTC (5.49%) and ETH (6.61%). The S&P 500 (9.46%) remained the most predictable followed by the ALSI (6.66%). The evidence showed that, while adjusting for thin trading adjusts for illiquidity in cryptocurrencies, it also adjusts especially for weekend, holiday and overnight gaps which inflate equity predictability.

The continued observation that the S&P500 was more predictable than other equity indices and cryptocurrencies challenged the widespread view that the S&P 500 was relatively more efficient than developing equity indices, especially in SA, China and India and cryptocurrencies. This study, however, reconciled this outcome with arguments in the literature that the dominant retail and mostly speculative base in cryptocurrencies can create rapid high-frequency predictability, but is less persistent in daily autocorrelation as demand flows are volatile and often reversed quickly (Al-Yahyaee *et al*., 2020). However, equity markets especially the S&P500, exhibit

institutional-investor-dominance and tend to exhibit greater predictability because institutional flows (index rebalancing, benchmark tracking, mechanical allocation rules) generate systematic, forecastable return pattern components (Griffin *et al.*, 2003; Huang & Stoll, 1994).

The average predictability results thus indicated that, after accounting for thin trading, BTC and ETH were less efficient than the popular SSE, Nikkei 225, BSE Sensex, and FTSE 100, but were evolving toward higher levels of informational efficiency compared with the mature S&P 500 and the ALSI. These results are striking in the sense that they showed that the S&P 500, arguably the world's most mature and diversified equity index, exhibited lower efficiency than BTC and the young ETH. The differences were potentially explained by varying market structure and participant composition, of which the S&P 500 exhibits dominance of institutional investors with predictable trades. Cryptocurrency return dynamics are primarily driven by investor sentiment, leading to increased randomness and lowering predictability as contrasted to the S&P 500's predictability that is reinforced by institutional maturity, regulatory oversight, and macroeconomic anchoring; factors that, paradoxically, contribute to greater market inefficiency by making returns more forecastable. Further inquiries on why the S&P 500 was the least efficient among the equity indices investigated was beyond the scope of the study.

Meanwhile, the relatively infrequent predictability of BTC and ETH illustrate that cryptocurrencies are emerging as robust, time-varying efficient assets. BTC and increasingly ETH prices efficiently reflect available information, making them more suitable for strategic allocation within investors' risk appetites. The next section highlights the implications, especially for diversification and risk adjusted performance.

7.3.1 Implications for market efficiency of cryptocurrencies

Changing market efficiency dynamics have material implications for investors considering exposure to cryptocurrencies especially across crisis periods. The evidence indicated that strategic asset allocation is generally preferable to active trading, since persistent opportunities to outperform the market are limited and episodic. Temporary inefficiencies such as those observed in BTC during the Covid-19 episode and in ETH at its early stages can produce exploitable short-term gains. However, these episodes are transient and subject to high implementation risk. Consequently, the key decision for investors is the determination of an appropriate allocation weight to cryptocurrencies that balances expected return against risk.

An important outcome is that cryptocurrency investors should adopt a long-term investment horizon. Short term unpredictability and episodic inefficiencies mean that successful outcomes are more likely to arise from disciplined exposure through strategic allocations rather than from attempts to time transient mispricings. This approach mitigates the behavioural hazards of

reacting to market euphoria and permits investors to capture potential secular appreciation as market structure and participation mature.

These findings refine and extend earlier work. Consistent with Urquhart (2016), both BTC and ETH exhibited a trend toward greater efficiency despite their relative youth. Aligning with Noda (2021), BTC remained more susceptible to efficiency disruptions during acute crises (for example Covid-19) yet showed greater market quality attributes than ETH, which appeared to have attained more persistent efficiency since 2019. The magnitude of observed efficiency metrics now lies within ranges comparable to those of mainstream equity indices, indicating that labelling cryptocurrencies purely as inefficient or as speculative bubbles is empirically unwarranted.

Although the results support the view that cryptocurrency pricing is becoming more efficient, the implications for portfolio performance and diversification remain insufficiently resolved. In particular, it is unclear how time varying efficiency alters risk return trade-offs and diversification benefits during crisis periods. The next section addresses this gap by empirically examining the relationship between cryptocurrency market efficiency and portfolio performance, with an emphasis on long run and crisis periods stress testing.

7.4 Assessing the link between cryptocurrency market efficiency and portfolio performance through crisis periods

Crises have historically been associated with significant breakdowns in portfolio diversification. A large body of literature shows that during periods of systemic financial stress, asset correlations tend to spike, often nullifying diversification benefits (Ang & Bekaert, 2002; Bartram & Bodnar, 2009; Chalkis *et al.*, 2021; Fry-McKibbin *et al.*, 2014). This phenomenon is linked to contagion effects, where volatility shocks transmit across markets, and to herding behaviour among investors (Forbes & Rigobon, 2002).

Liquidity spirals and market-wide deleveraging also play a role in elevating cross-asset correlations (Brunnermeier & Pedersen, 2009; Galariotis & Giouvris, 2015). In response to panic and uncertainty, investors tend to crowd into safe-haven assets such as gold or cash-equivalents, while riskier assets experience outflows, exacerbating co-movement and undermining diversification (Baur & Lucey, 2010).

This dynamic has been observed in both traditional markets and in cryptocurrency markets. While crypto assets were initially promoted for their diversification benefits due to low correlation with traditional assets, studies suggest that this correlation may increase during global stress events (Bouri *et al.*, 2020; Corbet *et al.*, 2018; Klein *et al.*, 2018). Such shifts challenge their role as effective diversifiers in crisis periods.

Building on this literature, the selected crisis periods in this study, namely, the US–China trade war, the Covid-19 pandemic, and the Russia–Ukraine conflict are evaluated through the lens of expected diversification breakdowns. The analysis explores whether cryptocurrencies offered consistent diversification benefits across these episodes, and how observed correlation dynamics aligned with or deviated from patterns found in the literature.

Evaluating the relationship between cryptocurrency market efficiency and portfolio performance and diversification under crisis periods, this section implemented the study's two-step analytical framework. The first step built from markets efficiency tests in Section 7.3. These tests established that BTC had become efficient while ETH was becoming efficient. This first step established a long-run baseline of the impact of cryptocurrencies on portfolio outcomes across the observation window 1 September 2015 to 31 Dec 2024. This served as an essential reference point, benchmarking following analyses within a contextualised framework. Building on this foundation, the second step conducted a focused, event-driven analysis during identified crisis windows. By isolating these periods, the study was able to gauge short-term portfolio responses and efficiency dynamics, offering a nuanced understanding of how the inclusion of cryptocurrencies impacts portfolio diversification and risk-adjusted performance under adverse conditions.

The analyses proceeded as follows. Section 7.4.1 presents the portfolio summary of statistics to gain insights on how returns and risk evolved over the observation period. Section 7.4.2 analyses the correlation dynamics between cryptocurrencies and portfolio constituents. This was important because the correlation dynamics gave a window of opportunity to assess the association of cryptocurrency returns with those of the other assets to detect their diversification value. In Sections 7.4.3 and 7.4.4, starting with the full horizon window and then during crisis periods, evaluate the asset allocation, risk metrics and risk adjusted performance to assess how cryptocurrencies contribute to portfolio diversification in SA and in the US, respectively. The assessment offered critical insights into the extent to which cryptocurrencies impact portfolio on diversification and risk-adjusted performance. By zooming in on episodes of market crisis to provide a detailed examination of the link between market efficiency and portfolio performance, this study elucidated the potential of cryptocurrencies to serve as diversification instruments, hedging mechanisms, or haven assets within investment strategies.

7.4.1 Data and descriptive statistics

This study analysed two investment universes: The SA market (local) and the US market (global). The asset categories considered included equities, bonds and cash. These categories were selected based on the findings of Doeswijk and Swinkels (2025), who identified them as comprising the bulk of global investment assets, making them crucial for analysing the portfolio performance and diversification of cryptocurrencies. For the SA market, the FTSE/JSE All Share

Index (JSE ALSI), the FTSE/JSE All Bond Index (ALBI) and the SA 91-day Treasury Bill (SA 91-day T-bill) served as proxies for equities, bonds and cash. For the US market, the S&P 500, US 10-Year Treasuries (US 10-year Treasuries) and the US 3-month Treasury Bill (US 3-Month T-bill) were proxies for equities, bonds and cash. In both the SA and US markets, BTC and ETH cryptocurrencies were evaluated for their impact on portfolio diversification and risk-adjusted returns. Table 7.4 presents the descriptive statistics for the returns from 1 September 2015 to 31 December 2024.

Table 7.4: Descriptive statistics of BTC, ETH and SA and US equities, bonds and cash

	JSE ALSI	ALBI	SA 91-day T-bill	S&P 500	US 10-year Treasuries	US 3-Month T-bill	BTC	ETH*
Return	6.12%	9.03%	5.33%	12.80%	0.02%	1.94%	90.49%	130.93%
Risk	17.95%	9.30%	1.61%	18.02%	7.41%	1.95%	62.78%	89.86%
Return / Risk	0.34	0.97	3.31	0.71	0.00	0.99	1.44	1.46
Skewness	-0.21	-1.03	-0.83	-0.54	0.12	0.77	-0.15	0.59
Kurtosis	8.38	17.95	-0.31	14.84	2.77	-0.88	7.58	5.84

Computations are based on daily data for the period 1 September 2015 to 31 December 2024. Return is defined as the annualised total return. Risk is defined as standard deviation calculated using daily values and annualised. JSE ALSI, JSE ALBI and the SA 91-day T-Bill are denominated in ZAR while the rest are in USD. Source: Author's computations using data sourced from Investing.com (2025) and Iress (2025).

Within the local market, the ALBI delivered the highest returns[96] of 9.03%, followed by the ALSI (6.12%) and the SA 91-day T-bill (5.33%). The ALSI had the highest risk at 17.95%, even though it was outperformed by the ALBI, which had a considerably lower risk of 9.30%. The SA 91-day T-bill retained the least amount of risk (1.61%) despite the strong returns. As a result, the ALSI delivered the lowest returns per unit of risk (0.34) followed by the ALBI (0.97), with the SA 91-day T-bill (3.31) outperforming them. This suggested that SA cash investors enjoyed the best risk-return trade-off while ALSI investors faced the worst. The ALBI was positioned midway between these two. The strong performance of SA cash and bonds versus SA equity continues to be a topic of discussion among researchers, particularly considering market volatility and crises in 2018, 2020 and 2022. Several authors (Auret, 2014; Cloete, 2023; Fanta & Makina, 2017; Firer & McLeod, 1999) made headway in comparing asset performance and profiled cash and bonds as better performers than equity.

In the US, the S&P 500 delivered annualised returns of 12.80%, higher than the JSE ALSI's 6.12%. Several studies suggest that emerging market specific risks, including higher country risk premium, higher interest rates and liquidity premium require expected returns in emerging

[96] Returns are annualised and were compute as $\left(\frac{P_{end\ date}}{P_{start\ date}}\right)^{\frac{1}{Time}} - 1$. Where P is the price or value, and T is the time in years between 1 September 2015 and 31 December 2024

markets like SA to be higher than in more developed markets such as the US (Bekaert & Harvey, 2003). These further highlight the relatively constrained performance of the JSE ALSI. The US 10-year Treasury bill's annualised return of 0.02% was lower than the US 3-month T-bill's annualised return of 1.94%, even though the former had a considerably higher risk of 7.41% compared with the US 3-month T-bill's risk of 1.95%. This suggested that the US 10-year Treasury bill had a very low return for high risk emphasising its underperformance.

BTC and ETH far outperformed other assets in both SA and the US markets during the observed period. ETH delivered annualised returns of 130.93%, while BTC achieved 90.49%, substantially surpassing equities, bonds and cash in both SA and the US. This remarkable outperformance by cryptocurrencies has been documented in several studies (Almeida & Gonçalves, 2022, 2023; Andrianto & Diputra, 2017; Liu & Tsyvinski, 2021). The extraordinary gains have contributed to heightened interest from both investors and regulators, who are increasingly considering the implications of including cryptocurrencies in portfolios (Ang *et al.*, 2023; Feng *et al.*, 2018; Shalett *et al.*, 2025). However, these returns are accompanied by wild volatility. ETH and BTC had the highest risks of 89.86% and 62.78%, respectively. The high risk of cryptocurrencies is well-documented in the literature with studies by Cheah and Fry (2015), Chaim and Laurini (2019) and and Liu and Tsyvinski (2021) highlighting their wild volatility. Contextualisation of risk showed that the volatility in cryptocurrency returns is compensated by substantial returns. The Returns/Volatility analysis indicated that in SA, only cash has higher returns per unit of risk than BTC and ETH, while in the US, cryptocurrencies rewarded the highest returns per unit risk. The sturdy risk per unit of return in BTC and ETH supports the view that cryptocurrencies, hold promise when added to portfolios of equities, bonds and cash.

Finally, the third and fourth moments of returns (distributions) indicated that all returns had varying levels of skewness and excess kurtosis, confirming several studies (Conrad *et al.*, 2013; Sheikh & Qiao, 2010; Zhang *et al.*, 2018; Zsolt & Botond, 2021) on the presence of stylised facts in financial time series. This suggested that performance measures incorporating non-normality better account for risk.

Overall, the descriptive statistics in Table 7.4 characterised BTC and ETH as high-risk high-return cryptocurrencies. The high returns compensate more for risk than bonds and equities do in SA and US. In the following sections, this study explored how these returns have evolved and whether they demonstrate diversification capabilities through crisis periods.

7.4.1.1 Evolution of BTC, ETH and SA and US equities, bonds and cash returns

The outstanding returns of BTC and ETH, which have outperformed US equities, bonds and cash prompts the question whether these returns are episodic or persistent enough for investors to

consider allocating a portion of their portfolios to cryptocurrencies for diversification. Table 7.5 presents how BTC and ETH annualised returns compared to SA and US equities, bonds and cash. For each year, data are sorted in descending order of returns. The years 2018, 2020 and 2022 are the years in which SA and US equities entered crisis.

Table 7.5: Annualised returns for BTC, ETH, SA and US equities, bonds and cash returns from September 2015 to December 2024

2016*	2017	2018	2019	2020	2021	2022	2023	2024
194.62% BTC	9030.25% ETH	7.66% ALBI	93.65% BTC	472.64% ETH	396.77% ETH	4.94% 91-day T-Bill	154.96% BTC	120.36% BTC
152.24% ETH	1327.23% BTC	6.91% 91-day T-Bill	28.75% S&P500	299.24% BTC	59.45% BTC	4.25% ALBI	89.99% ETH	46.20% ETH
12.44% S&P500	19.42% S&P500	1.97% 3-month T-Bill	10.29% ALBI	16.12% S&P500	26.77% S&P500	2.07% 3-month T-Bill	7.64% 91-day T-Bill	23.21% S&P500
6.65% 91-day T-Bill	17.63% ALSI	0.08% 10-year Treasuries	8.75% 10-year Treasuries	10.69% 10-year Treasuries	24.18% ALSI	-0.90% ALSI	24.34% S&P500	17.08% ALBI
6.28% ALBI	10.19% ALBI	-6.24% S&P500	8.31% ALSI	8.61% ALBI	8.38% ALBI	-16.59% US 10-year Treasuries	9.67% ALBI	9.41% ALSI
3.31% ALSI	7.05% 91-day T-Bill	-11.42% ALSI	6.85% 91-day T-Bill	4.42% 91-day T-Bill	3.71% 91-day T-Bill	-19.44% S&P500	5.61% ALSI	7.96% 91-day T-Bill
0.26% 3-month T-Bill	2.27% 10-year Treasuries	-73.12% BTC	2.11% 3-month T-Bill	4.06% ALSI	0.05% 3-month T-Bill	-64.12% BTC	5.27% 3-month T-Bill	5.18% 3-month T-Bill
-0.49% 10-year Treasuries	0.95% 3-month T-Bill	-82.57% ETH	-1.18% ETH	0.36% 3-month T-Bill	-4.44% 10-year Treasuries	-67.37% ETH	3.55% 10-year Treasuries	-1.68% 10-year Treasuries

**Computations are based on daily data for the period 1 September 2015 to 31 December 2024. Year 2016 starts from 1 September 2015. The rest of the years represent calendar years. Returns are the annualised total return. JSE ALSI, JSE ALBI and the SA 91-day T-Bill are denominated in ZAR while the rest are in USD. Source: Author's computations using data sourced from Investing.com (2025) and Iress (2025).*

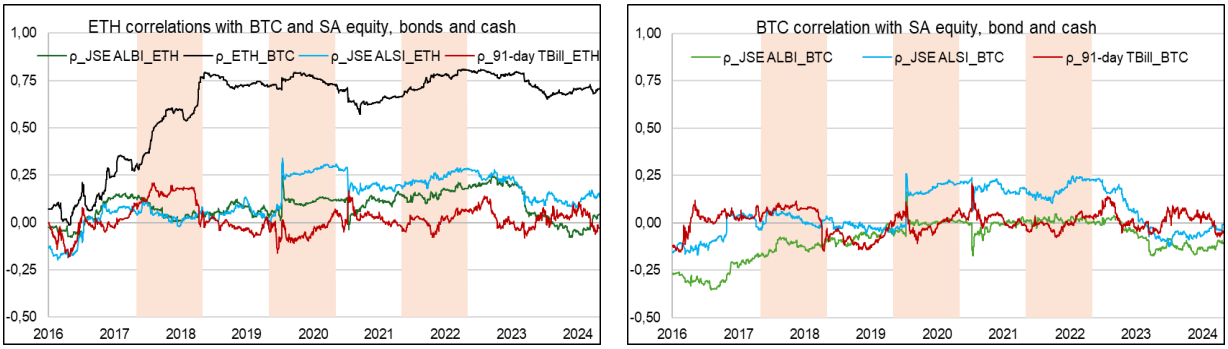
When benchmarking with equity markets, this result shows that in 2018 and 2022, when the SA equity and US equity markets experienced losses under the backdrop of geopolitical crises, cryptocurrencies were the worst affected. BTC and ETH experienced losses of 73.12% and 82.57% in 2018 and 64.12% and 67.37% in 2022. These large drawdowns reinforce the extreme risk in cryptocurrencies capable of wiping away substantial value in a year. In 2020, when the Covid-19 pandemic dominated markets, BTC and ETH quickly recovered and by end of the year, they rewarded substantial returns of 299.24% and 472.64%, respectively. Moreover, the results showed that BTC and/or ETH were the top performing assets in non-crises years. The evolution of returns indicated that cryptocurrencies behave as boom-bust assets, performing extremely well in 'normal' market conditions and collapsing under crises where equities also decline.

To further gain insight into the evolution of returns, this study evaluated their one-year rolling-window Pearsons's correlations with bonds, equities and cash using a rebalancing period of one year.

7.4.1.2 BTC and ETH correlations with SA equities, bonds and cash

The evolution of correlations between BTC and ETH with SA equities, bonds and cash are presented in Figure 7.5. The first figure to the left depicts correlations between ETH and the ALBI (green line), ETH and BTC (black line), ETH and the JSE ALSI (blue line), and ETH and the 91-day T-bill (red line). The figure on the right depicts correlations between BTC and the ALBI (green line), BTC and the JSE ALSI (blue line), and BTC and the 91-day T-bill (red line). In both figures, the highlighted background indicates the calendar years in which the three crises lie: 2018, 2020 and 2022.

Figure 7.5: One-year rolling correlations between cryptocurrencies and local equity, bonds and cash



The background represents the calendar years when markets entered crises. The length of the rolling window for the correlations is one year. Source: Author's computations using data sourced from Investing.com (2025) and Iress (2025).

The Pearson rolling window correlations results showed that BTC and ETH became increasingly correlated from close to 0 in 2016 to about 0.75 by the end of 2019. For example, in December 2016 the correlation was within the ±0.02 range indicating minimal comovement. By end of 2019, this had increased to about 0.75, reflecting a significant increase in comovement between BTC and ETH. The increased correlation indicated growing comovement between BTC and ETH, a development that potentially reduced diversification benefits when holding both ETH and BTC in the same portfolio. The upward surge in correlation coincided with ETH's transition toward market efficiency as shown in Figure 7.2. ETH remained largely inefficient until early 2019, whereas BTC had already achieved efficiency as shown in Figure 7.2. As ETH's market efficiency improved mid-2019, the BTC-ETH correlation stabilised, fluctuating around 0.75. The results demonstrate that, during ETH's early market phase, its specific noise dominated its price dynamics. As ETH's market efficiency improved, this resulted in stronger returns co-movement with BTC.

ETH also exhibited minimal co-movement with SA 91-day T-bills, with correlation coefficients confined to a narrow ±0,10 interval. Correlation between ETH also remained weak. Although their trend showed modest increases since 2020, the correlation coefficients barely reached 0.25 at its maximum in 2023. This relationship demonstrated remarkable stability, displaying no structural alterations even during periods when the SA equity market entered crises in 2018, 2020, and 2022.

In contrast, correlations between BTC and the JSE ALSI started off at minimal levels fluctuating around zero – demonstrating considerable diversification potential between BTC and SA equities until early 2020. Thereafter correlations increased. In 2020 the correlations coefficient averages 0.22 and remained modest averaging 0.22 and slowly decreasing to about 0.12 in 2021 to 2024. Correlations between ETH and the also notably rose since the 2020 but through the observation period they remain and low ranges of 0 - 0.20 demonstrating strong diversification potential.

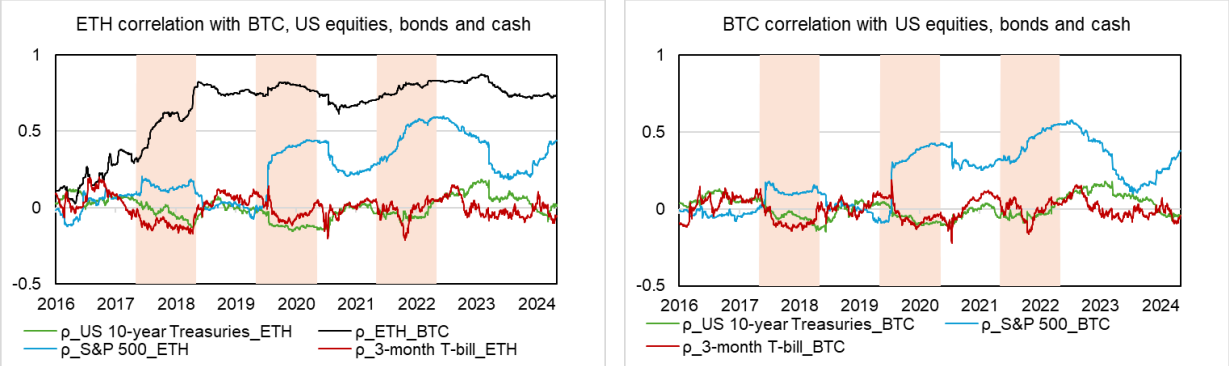
Correlations between BTC and SA 91-day T-bill mirrored those of ETH, showing remarkable stability. Over the period September 2016 to December 2024, correlations coefficients remained tightly confined to the ±0.10, indicating limited comovement between returns. BTC's correlation with the JSE ALBI was mostly weakly negative. From 2016 to 2019, the average correlation was -0.20. Since 2020, however, the correlation fluctuated narrowly around zero, reflecting a loss of the early negative linkage between BTC and the JSE ALBI. Correlations between BTC and the JSE ALSI returns showed some behaviour changes in time. From 2016 to 2020, they BTC and JSE ALSI returns moved mostly independent of each other with correlation coefficient fluctuating around zero. The shock of the Covid-19 pandemic drove both assets into temporary inefficiency (Figure 7.2), pushing their correlation modestly higher albeit below 0.25. This elevated level persisted through 2023, before beginning to ease in 2024.

Overall, the magnitudes of correlations remained modest, even during the crises of 2018, 2020, and 2022. The correlations of BTC with the JSE ALSI, JSE ALBI, and SA 91-day T-bill were slightly lower than those of ETH, indicating BTC's relative robustness. Further analysis revealed that the correlation coefficient between BTC and the JSE ALSI barely exceeded 0.25, while the correlation between BTC and the ALBI remained tightly within the ±0.10 range, demonstrating a higher potential for diversification within South African bonds and cash. These correlation results underscore the potential for BTC, in particular, to contribute to the diversification of South African investment portfolios, especially in bond dominated portfolio where correlations were the lowest. The subsequent section presents the correlation dynamics between BTC and ETH and US equities, bonds, and cash.

7.4.1.3 BTC and ETH correlations with US equities, bonds and cash

To situate the portfolio performance of BTC and ETH within the US market, this study also estimated one-year, rolling-window Pearson's correlations between BTC and ETH and US bonds (US 10-year Treasuries), equities (S&P 500) and cash (US 3-month T-bill). The resulting time-series of correlation coefficients appears in Figure 7.6. The left panel of Figure 7.6 illustrates four correlation series: ETH and BTC[97] (ρ_ETH_BTC), ETH and the S&P 500 ($\rho\_S\&P\ 500\_ETH$), ETH and US 10-year Treasuries ($\rho\_10-year\ Treasuries\_ETH$) and ETH and the US 3-month T-bill ($\rho\_3-month\ T-bill\_ETH$). The right panel depicts the analogous correlations for BTC: BTC and the S&P 500 ($\rho\_S\&P\ 500\_BTC$), BTC and the US 10-year Treasuries ($\rho\_10-year\ Treasuries\_BTC$) and BTC and the US 3-month T-bill ($\rho\_3-month\ T-bill\_BTC$). These plots enable a direct comparison of how BTC and ETH co-move with equity, bonds, and cash benchmarks over time.

Figure 7.6: One-year rolling correlations between cryptocurrencies and US equity, bonds and cash



The background represents the calendar years when markets entered crisis. The length of the rolling window for the correlations is one year. Source: Author's computations using data sourced from Investing.com (2025) and Iress (2025).

The rolling-window correlation coefficients revealed that BTC and ETH became increasingly correlated between 2016 and 2019, with coefficients rising steadily from 0.1 to 0,8, indicating growing co-movement. From 2019 to 2024, the correlation stabilised at elevated levels, remaining within the 0,60-0,90 range; this development undermines the diversification benefits of holding both cryptocurrencies within the same portfolio. Further analysis indicated that both ETH and BTC exhibited minimal co-movement with the US 3-month T-bills as well as the US 10-year Treasuries, with correlation coefficients confined to a narrow ±0,20 interval. These low correlations demonstrated remarkable stability, showing no structural changes during the period in which ETH was becoming market efficient (up to mid-2019, as presented in Figure 7.2) and through crisis

[97] BTC and ETH returns in the US are expressed in USD and therefore are not exactly as the same as in SA where they are converted to ZAR.

periods in 2018, 2020 and 2022. In contrast, correlations between ETH/BTC and the S&P 500 spiked in 2018, 2020 and 2022, indicating that cryptocurrencies' diversification benefits with US equities weaken during crisis periods. However, even at their highest (0.55 in 2022-2023), these correlations remained moderate, underscoring independent return movements relative to the S&P 500.

The broader result from the descriptive summary statistics and the rolling window correlation statistics were that BTC and ETH are high-risk, high-return assets characterised by intense boom-bust cycles, which further amplify their risk profile. However, their correlations with SA and US bonds and cash have remained remarkably low and stable, even during equity market crises and following ETH's transition to becoming market efficient, suggesting that return drivers in BTC and ETH are considerably divorced from those in the bonds and cash in SA and the US. Meanwhile, correlations with especially the S&P 500 rose modestly in crisis years, underscoring potentially limited cryptocurrency diversification potential against US equity. The subsequent sections investigated how including BTC and ETH in a portfolio of equities, bonds, and cash affected asset allocation as it is fundamental for meaningful performance assessment.

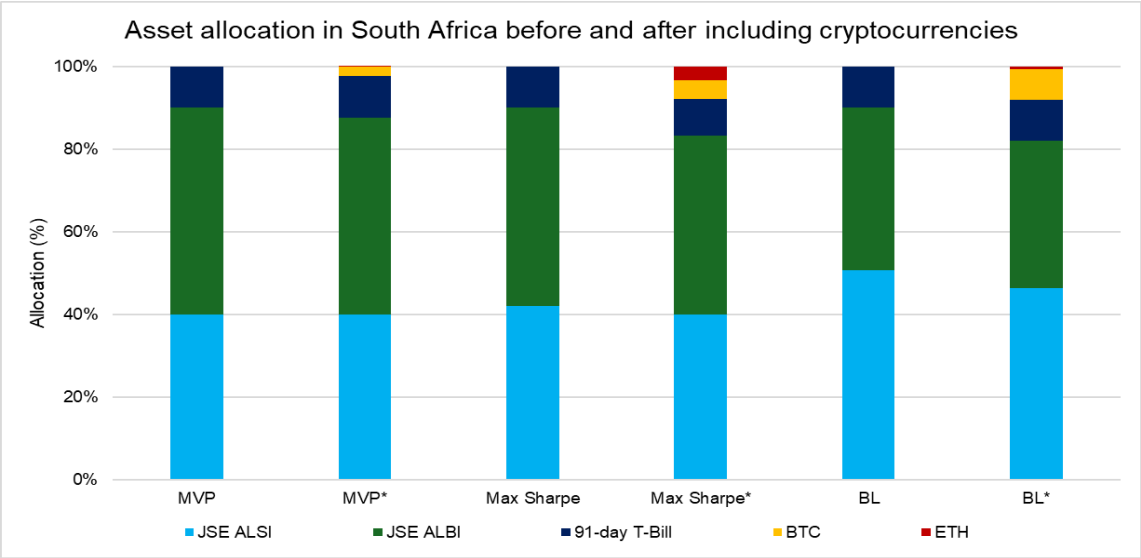
7.4.2 Long run baseline portfolio allocations and cryptocurrency tilts

To evaluate the impact of BTC and ETH on portfolio performance, two portfolios were constructed: a baseline portfolio and a revised portfolio incorporating the cryptocurrencies. Three asset-allocation frameworks: minimum-variance portfolio (MVP), maximum-Sharpe ratio (max Sharpe) portfolio, and the Black Litterman (BL) portfolio were used to determine allocation weights for the period 1 September 2015 to 31 December 2024. In constructing asset allocations, portfolios were rebalanced annually at calendar-year end, beginning on 31 December 2016. Asset allocations were achieved under no short-selling restrictions and within allocation constraints of 40–80% for equity, 10–50% for bonds, 5–10% for cash and 1–10% for cryptocurrencies. The following sections present the baseline portfolios and cryptocurrency tilts in the SA and US markets.

7.4.2.1 Long run average portfolio allocations in the SA market

The baseline portfolio comprised the JSE ALSI (equities), the ALBI (bonds), and SA 91-day Treasury bills (cash). Figure 7.7 illustrates the average portfolio weights before and after adding BTC and ETH

Figure 7.7: SA asset allocation pre- and post-inclusion of cryptocurrencies



The columns "MVP", "Max Sharpe" and "BL" refer, respectively, to the asset allocation achieved using the minimum-variance portfolio, maximum-Sharpe ratio portfolio and the Black-Litterman portfolio models. Names marked with asterisks (*) indicate that the portfolio also includes cryptocurrencies. Source: Author's computations using data sourced from investing.com (2025).

The empirical results demonstrated that the three asset allocation frameworks: MVP, Max Sharpe and BL converged to a related baseline composition. Equities accounted for 40–50%, bonds for 35–50% and cash for 8–10%. The results showed that allocation to equity was at the lower end of its floor limit of 40%, while bonds and cash were on the higher ceiling end of their limits of 50% and 10%, respectively. This challenges the long-standing assumption that equities invariably outperform bonds (and cash), as posited by Firer and McLeod (1999). The robust annual returns and relatively lower volatility associated with the SA 91-day T-bills and the ALBI resulted in allocating a substantial part of the baseline portfolio to bonds and cash. Given the restrained performance of equities, investors may be compelled to explore other assets, cryptocurrencies among them, to bolster portfolio diversification.

The inclusion of cryptocurrencies in the baseline portfolio resulted in modest shifts in asset allocation. Under the MVP framework, the optimal allocation to BTC averaged 2.27%, while ETH received 0.1% due to its relatively higher risk. In contrast, the maximum Sharpe portfolio supported higher allocations, averaging 4.5% for BTC and 3.4% for ETH, driven primarily by the strong risk-return profiles as evidenced in Table 7.4, which ranked the return per unit of risk in cryptocurrencies higher than in SA bonds and equities. The BL model recommended even greater exposure, with average allocations of 7.36% to BTC and below 1% to ETH, largely influenced by higher cryptocurrency returns, one of the key drivers for asset weighting in the BL framework.

Appendix 2 presents a detailed, year-on-year breakdown of asset allocations at each rebalancing point. Over the full observation period (1 September 2015 to 31 December 2024), both the MVP

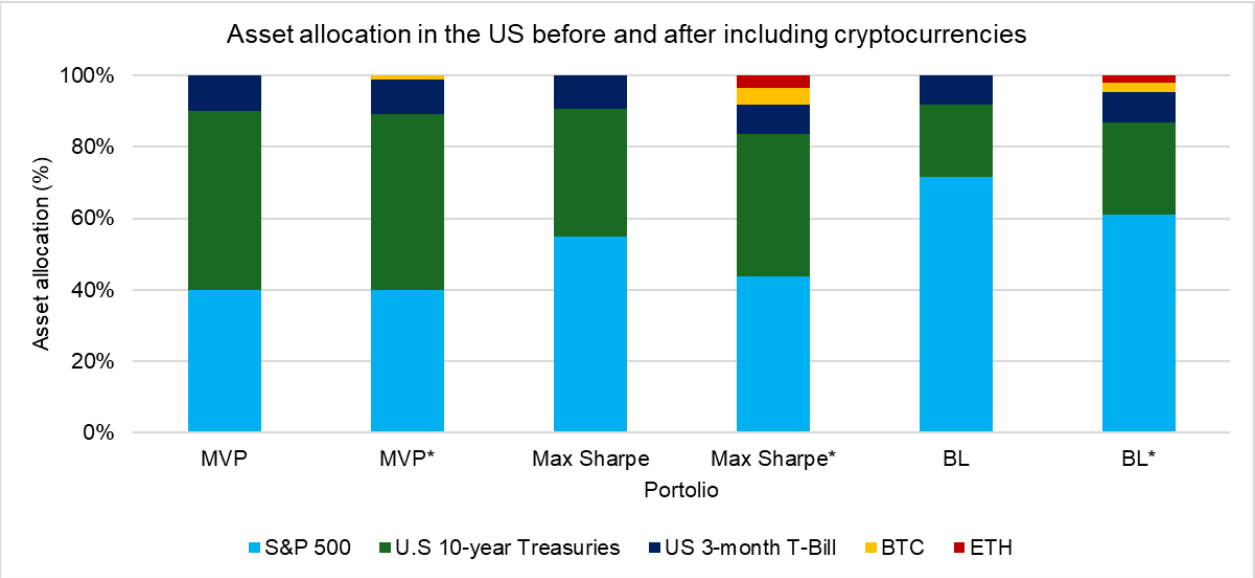
and BL models consistently assigned a larger share of cryptocurrency exposure to BTC than to ETH. Under MVP, BTC allocations typically ranged from 1% to 2%, with a pronounced spike to 7,04% at the end of 2016. This outlier aligns with BTC's 324% price appreciation from USD 227,20 to USD 963.40 between 1 September 2015 and 31 December 2016. The low allocation to cryptocurrencies underscores that investors with low risk tolerances should maintain minimal exposure to highly volatile ETH and BTC. By contrast, the max Sharpe portfolio framework alternated its allocations between ETH and BTC during periods of extraordinary performance: ETH in 2017, 2020, and 2021; BTC in 2016, 2019, 2023, and 2024. Higher correlations between the two cryptocurrencies limited simultaneously including them in the same portfolio, especially after 2019, when ETH became efficient and increasingly highly correlated with BTC. In the downturns of 2018 and 2022, both cryptocurrencies were assigned the 1% allocation floor due to their excessive losses, which enervated performance. Overall, the max Sharpe portfolio framework recommended substantially higher allocations to BTC and ETH than the MVP on the back of robust return/risk in cryptocurrencies. The BL model yielded the most stable cryptocurrency weights — generally between 6% and 10% but also reacted to crisis periods, with allocations collapsing towards the 1% floor in 2022 following severe drawdowns. Across all three optimisation regimes, there was no clear indication that ETH's changing market efficiency influenced its portfolio weighting.

The results on cryptocurrency allocations aligned with research findings that found that allocation of 1-10% of the portfolio to cryptocurrencies enhanced portfolio performance in investment portfolios (Letho *et al.*, 2022; Ntare *et al.*, 2025; Robertson, 2018).

7.4.2.2 Long run portfolio allocations in the US market

In the US market, the baseline portfolio also comprised equities (S&P 500), bonds (US 10-year Treasuries) and cash (US 3-month T-bills). Figure 7.8 illustrates the average asset allocations before and after the addition of BTC and ETH to the baseline portfolio over the period 1 September 2015 to 31 December 2024. Full periodic allocation results are detailed in Appendix 3.

Figure 7.8: US asset allocation pre- and post-inclusion of cryptocurrencies



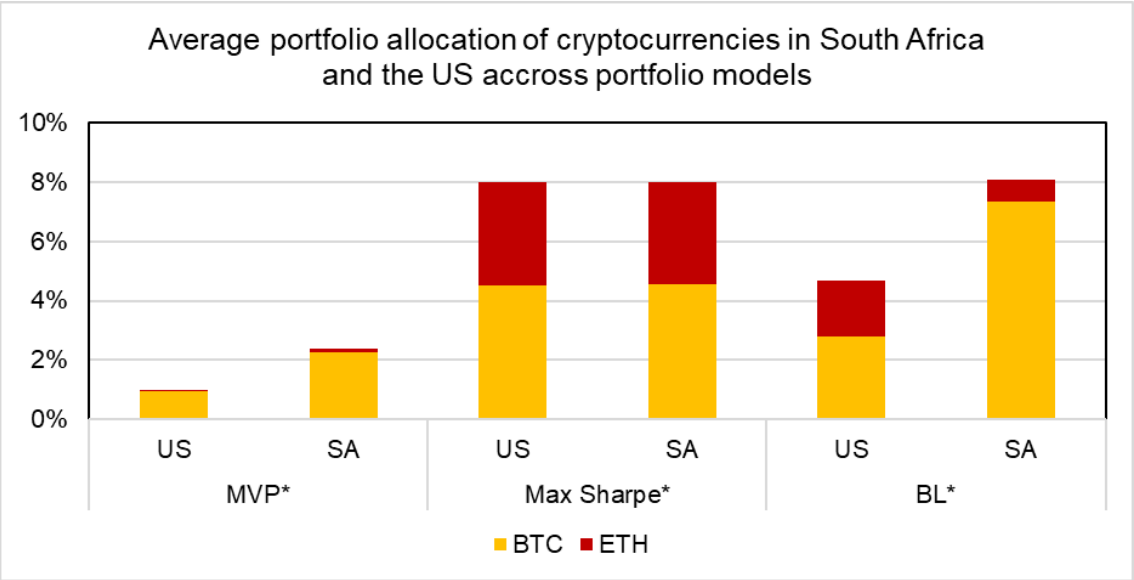
Column headings "MVP", "Max Sharpe" and "BL" refer, respectively, to the minimum-variance portfolio, maximum-Sharpe portfolio and the Black-Litterman portfolio. Asterisks (*) indicate that the corresponding portfolio includes cryptocurrencies. Source: Author's computations using data sourced from investing.com (2025).

The results indicated that, under the MVP framework, the optimal allocation to cryptocurrencies averaged 1%, with BTC accounting for 0.95% while ETH received 0.05% — suggesting peripheral importance of cryptocurrencies to US risk-averse portfolios. The max Sharpe portfolio resulted in comparatively higher allocations, averaging 4.5% for BTC and 3.5% for ETH, driven primarily by the higher returns per unit of risk exhibited by cryptocurrencies (Table 7.4). Investors who seek to optimise their risk/return relations may leverage a higher portion of their portfolio to cryptocurrencies compared with those who seek minimum risk. The BL model recommended a midway allocation with average allocations of 2.8% to BTC and below 1.9% to ETH. All the allocation models consistently assigned a larger share of cryptocurrency exposure to BTC, despite ETH being the highest rewarding cryptocurrency. This was due mostly to the higher volatility in ETH, especially during the period up to 2019, when it was becoming efficient.

7.4.2.3 Comparisons of portfolio allocation to BTC and ETH between SA and the US

Comparisons of portfolio allocation to BTC and ETH between SA and the US market indicated that the US portfolio allocations were more conservative than the SA allocations for the MVP and BL portfolio allocation frameworks, as presented in Figure 7.9.

Figure 7.9: BTC and ETH asset allocations among US and SA portfolios



Headings "MVP", "Max Sharpe" and "BL" refer, respectively, to the minimum-variance portfolio, maximum-Sharpe portfolio and the Black-Litterman portfolio. Asterisks (*) indicate that the allocations were extracted from a optimal portfolio with cryptocurrencies. US and SA refer, respectively, to the United States of America and South Africa Source: Author's computations using data sourced from investing.com (2025).

The prominence of cryptocurrencies within the South African portfolios can be attributed to several factors. While bonds and cash exhibit no correlation with cryptocurrencies in either SA or the US, the correlation between cryptocurrencies and equities is comparatively lower in SA than in the US, thereby justifying the inclusion of cryptocurrencies in the SA minimum variance portfolio. In the context of SA, there appears to be a similarity between proportion of cryptocurrency allocations under the max Sharpe and the BL optimisation frameworks. However, in the US, there are reduced allocations to cryptocurrencies, as per BL allocations, reflecting equilibrium-consistent expected returns and risk balancing based on covariance. The observed differences relative to the Max Sharpe portfolio seem to stem from the stabilising effect of equilibrium anchoring and the interaction with allocation constraints, rather than from the incorporation of subjective views.

The higher allocation of cryptocurrencies per the BL in SA than in the US suggests that in equilibrium, cryptocurrencies provide better diversification benefits in SA due to lower correlation with equities and make them a comparatively better contributor to risk-adjusted returns. Section 7.5 further emphasises this distinction highlighting that US portfolios with higher Sharpe ratios tend to incorporate fewer cryptocurrencies than SA portfolios, which are characterised by comparatively lower Sharpe ratios. The next section quantifies the impact that the asset allocations discussed above had on portfolio diversification and risk-adjusted performance.

7.4.3 Impact of adding BTC and ETH in a SA equity-bond-cash portfolio on diversification and risk-adjusted performance

For diversification assessment, this study appraised the correlation between baseline portfolio returns and those of cryptocurrencies. This was important to anticipate how adding them would affect outcomes. Afterward, the study evaluated how adding cryptocurrencies to the baseline portfolios altered the baseline portfolio's risk metrics. These risk metrics included standard deviation, which served as a proxy for overall volatility. VaR_{95}, and $CVaR_{95}$, which captured potential maximum losses under adverse conditions. Idiosyncratic (unsystematic) risk which measures the residual risk unique to the pre- and post-inclusion portfolios. A reduction in unsystematic risk post-inclusion of cryptocurrencies suggested enhanced diversification. In terms of risk-adjusted performance metrics, this study examined how including cryptocurrencies altered the Treynor, Sharpe, Omega, Sortino, Kappa 3, Calmar, VaR-Sharpe, CVaR-Sharpe, modified information and modified Sharpe ratios of the baseline portfolio. Excess return was the numerator in the risk-adjusted performance measures[98]. An increase in the value of any ratio after the inclusion of cryptocurrencies signified an enhancement in the portfolio's risk-adjusted efficacy.

Table 7.6 Panel A restates the market efficiency of BTC, ETH and the ALSI – extracted from Table 7.3. This is important as it helps build an understanding of portfolio performance within the framework of market efficiency. Panel B presents the correlations between BTC and ETH and the baseline portfolios, risk and risk-adjusted performance metrics pre- and post-inclusion of BTC and ETH. The JSE ALSI's performance is included alongside performance pre- and post-inclusion of BTC and ETH index to provide a widely recognised benchmark, enabling comparison against a fundamental market standard.

The Panel A results show that, over the observation period 1 September 2015 to 31 December 2024, BTC and ETH demonstrated strong efficiency levels in terms of observed daily returns. After adjusting for thin trading, BTC drifted towards greater market efficiency, with only 0.5% of p-values having detected inefficiency. Meanwhile, ETH showed signs of becoming efficient, with 10.63% of p-values indicating market inefficiency. The ALSI (6.66%) was midway through, being relatively more efficient than ETH but less efficient than BTC.

[98] The risk-adjusted performance measures that is an exception to the rule of excess return as the numerator in the Omega ratio - which measures the ratio of upside returns (positive) to downside (negative) returns. However, this did not impact the general interpretation that; a higher Omega indicates more favourable risk adjusted performance.

Table 7.6: Market efficiency and impact of including cryptocurrencies on portfolio performance in South Africa (2015-2024).

Panel A: The number of times variance ratio tests p-values detected market inefficiency in BTC, ETB and the ALSI

	Observed returns				Thin trading corrected returns			
	AVR	**JM**	**JS**	**Ave**	**AVR**	**JM**	**JS**	**Ave**
BTC	0.03%	0.03%	16.39%	5.49%	0.00%	0.00%	1.49%	0.50%
ETH	0.00%	0.73%	19.11%	6.61%	0.00%	5.75%	26.12%	10.63%
ALSI	0.19%	2.03%	12.28%	4.84%	0.00%	0.00%	19.97%	6.66%

Observed returns are the daily returns and thin trading corrected returns represents the returns after correcting for thin trading. JS, JM, AVR are the frequency with which the tests detected significant inefficiency using the Joint-Sign test, the Wild Bootstrap Test and the Automatic Variance Ratio test. Ave is the arithmetic average of the frequency with which tests detected significant inefficiency. Source: Extract from Table 7.3

Panel B: Diversification and risk-adjusted performance

Metric/Ratio	MVP	MVP*	Max Sharpe	Max Sharpe*	BL portfolio	BL portfolio*	JSE ALSI
Correlation with BTC	0.01	-	0.01	-	0.03	-	0.07
Correlation with ETH	0.11	-	0.11	-	0.11	-	0.10
Standard Dev	9.54%	9.42%	9.60%	11.55%	10.76%	11.31%	17.95%
VaR_{95}	-12.93%	-12.56%	-13.08%	-14.92%	-15.05%	-15.54%	-26.99%
$CVaR_{95}$	-21.38%	-20.93%	-21.33%	-24.09%	-24.12%	-24.20%	-39.83%
Specific risk	4.40%	4.31%	4.29%	7.49%	3.42%	6.11%	NA
Treynor	0.02	0.12	0.03	0.95	0.02	0.52	-0.00
Sharpe	0.12	0.60	0.13	4.04	0.08	2.45	-0.02
Omega	1.36	1.42	1.36	1.49	1.32	1.45	1.07
Sortino	0.17	0.88	0.19	6.15	0.12	3.62	-0.03
Kappa - 3	0.10	0.50	0.11	3.44	0.07	2.00	-0.02
Calmar	0.05	0.25	0.06	1.96	0.04	1.28	-0.01
VaR - Sharpe	0.09	0.45	0.10	3.13	0.06	1.78	-0.01
CVaR - Sharpe	0.05	0.27	0.06	1.94	0.04	1.14	-0.01
Modified Information	0.11	0.54	0.12	3.96	0.10	2.65	NA
Modified Sharpe	0.12	0.60	0.13	4.04	0.08	2.45	-0.00

The JSE ALSI is regarded as the market and therefore metrics such as specific risk and modified information are not applicable. Daily data from 1 September 2015 to 31 December 2024 were used. MVP, Max Sharpe and BL refer to the Minimum variance portfolio, maximum Sharpe portfolio and the Black Litterman portfolio. Asterisk (*) means that the portfolio includes cryptocurrency. Source: Author's computations from data sourced from Investing.com (2025) and Iress (2025).

The results in Panel B show weak correlation coefficients between BTC and the baseline portfolios, ranging from 0.01 to 0.03. These low values indicate that BTC's returns (and therefore price movements) were largely independent of those in the baseline portfolios. Correlation between BTC and the JSE ALSI (0.07) was also weak, indicating that both had high levels of efficiency and the price drivers in BTC were fundamentally unlinked to the ALSI. ETH was marginally more correlated with both the baseline portfolios and the ALSI (0.10), although the correlations coefficients were also weak. The weak correlation in BTC and in ETH indicated their potential diversification capabilities because assets with low or negative correlation can reduce

overall portfolio risk when included in a portfolio. To assess that potential, this study further evaluated the impact of including cryptocurrencies on several risk metrics and risk-adjusted performance.

Regarding how cryptocurrencies impacted risk under the MVP framework, which aims to create a portfolio with the lowest risk for a given level of expected return, the inclusion of a combined average 2.37% in BTC and ETH led to a modest reduction in overall portfolio risk. Standard deviation declined from 9.54% to 9.42%, indicating lower volatility. At the 95% confidence level, historical value-at-risk (VaR_{95}), which measures the annualised maximum expected loss over one year, improved markedly. The one-year loss threshold tightened from 12.93% to 12.56%. Conditional Value-at-risk ($CVaR_{95}$), which provides an average of losses that occur beyond the VaR_{95} threshold, likewise decreased from 21.38% to 20.93%, implying that in the worst 5% of scenarios, the expected loss beyond VaR_{95} dropped from 21.38% to 20.93%. Unsystematic risk decreased marginally from 4.40% to 4.31%. Although this reduction is small in absolute terms, it confirmed that adding cryptocurrencies can trim idiosyncratic risk. For investors, portfolio managers and regulators, this suggests that including a small allocation of cryptocurrencies could enhance portfolio diversification and reduce overall risk for risk averse portfolios.

Under the max Sharpe portfolio framework, the inclusion of a combined average of 8% in BTC and ETH led to a notable increase in overall portfolio risk. The standard deviation increased from 9.60% to 11.55%, indicating heightened volatility. Historical VaR_{95} increased from 13.08% to 14.92%. This means that there was 95% confidence that adding cryptocurrencies could increase portfolio losses from 13.08% to 14.92% in a bad year. The $CVaR_{95}$ showed that the average losses in extreme downside scenarios became more severe, increasing from 21.33% to 24.09%. Unsystematic risk, or diversifiable volatility, increased notably from 4.29% to 7.49%. The rise in unsystematic risk indicated that adding cryptocurrencies introduced substantial diversifiable risks. This was mainly because cryptocurrencies possessed high standalone volatility and because their weak (or no correlation) structure did not offset idiosyncratic swings within the baseline max Sharpe portfolio. The BL portfolio, like the max Sharpe portfolio, resulted in an increase in risk when an average of 8.08% of the portfolio was allocated to cryptocurrencies. The portfolio standard deviation increased from 10.76% to 11.31%. VaR_{95} and $CVaR_{95}$ marginally increased from 15.05% to 15.54% and from 24.12% to 24.20%, respectively. Specific risk almost doubled from 3,42% to 6,11% after including cryptocurrencies.

Despite the increased risk both within the max Sharpe and BL portfolios, their risk levels remained considerably lower than the levels projected by the ALSI, which is a benchmark index representing the performance of several investments in SA. The total risk of the ALSI was the highest at 17,95% compared with the max Sharpe* (11.55%) and the BL* portfolio (11.31%). The

ALSI's historical VaR_{95} and $CVaR_{95}$ of 26.99% and 39.83% signalled high risk compared with the BL* portfolio (15.54% and 24.20%) as well as the max Sharpe* (14.92% and 24.09%). These results suggest that at low levels (averaging 2.37%) including cryptocurrencies results in modest risk reduction. However, at relatively higher allocation (8%), it leads to weakened diversification and increases overall portfolio risk – although the risk remains still lower than that of the ALSI.

Regarding the impact of cryptocurrencies on performance, the results under the MVP framework indicated that the addition of cryptocurrencies improved all risk-adjusted performance metrics. This was due in part to the enhanced returns which rose from 7.56% to 12.09% and the marginal decreases in risk. The Treynor ratio rose from 0.02 to 0.12 - exceeding the ALSI Treynor of 0.00 indicating that including cryptocurrencies earned greater excess return per unit of systematic risk. The ALSI underperformed cash leading to negative excess returns. The ZAR index increased from 48515.13 on 1 September 2015 to 84095.14 on 31 December 2024, representing annualised return of 6.12% in the 9.25 years. In contrast cash performed better. On 1 September 2016 the 91-day T-bill yields stood at 6.19% and increasing marginally reaching 7.64% as of December 2016. They experienced a significant deep reaching a record low of 3.43% in April 2020, coinciding with accommodative monetary policy responses to the Covid-19 pandemic. Yield rebounded reaching 8.72% as of November 2023 and were recorded at 7.71% as of 31 December 2024.

Under both the max Sharpe and BL frameworks, adding cryptocurrencies improved every risk-adjusted metric. Portfolio volatility rose from 9.60% to 11.55% in the max Sharpe case and from 10.76% to 11.31% under Black-Litterman, both remaining below the ALSI benchmark of 17.95%. Annualised returns increased from 7.73% percent to 53.14% and from 7.32% to 34.10%, respectively, outperforming the ALSI's 8.99%.

Sharpe ratios advanced from 0.13 to 4.04 and from 0.08 to 2.45 and Omega ratios rose from 1,36 to 1.49 and from 1.32 to 1.45 (versus the ALSI's 1,07). Sortino and Kappa-3 ratios demonstrated similar gains. Calmar ratios increased from 0.06 to 1.96 (maximum Sharpe) and from 0.04 to 1.28 (Black-Litterman), indicating that excess returns exceeded maximum drawdowns of 22.53% and 24.35% in March 2020, compared with the JSE ALSI's 33.92 percent drawdown (Calmar 0.07).

Tail-risk measures (VaR-Sharpe and CVaR-Sharpe) also strengthened, and modified information ratios rose from 0.12 to 3.96 and from 0.10 to 2.65 – reflecting greater excess return per unit of tracking risk.

In summary, all three the portfolios included cryptocurrencies, albeit at varying levels. Despite this, adding cryptocurrencies led to superior risk-adjusted returns compared with the baseline portfolio and the benchmark ALSI. Allocating a small percentage (averaging 2.37%) to

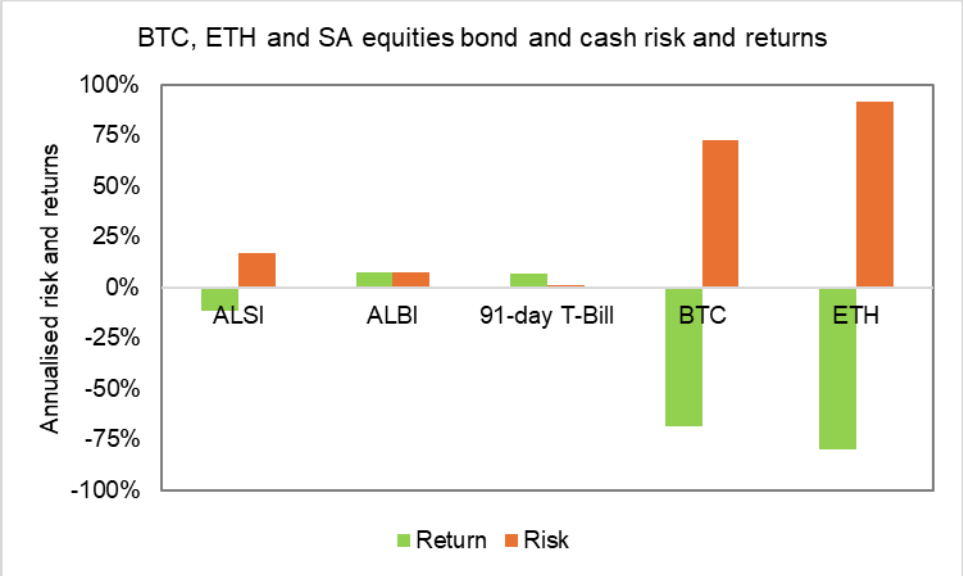
cryptocurrencies through the MVP trimmed overall volatility, tightened tail-risk and marginally reduced diversifiable risk while boosting Treynor, Sharpe, Omega, Sortino, Kappa-3, Calmar, and modified information ratios. At higher allocations averaging 8%, the max Sharpe portfolios and the BL portfolio increased overall volatility and diversifiable risk. Moreover, higher allocations substantially increased portfolio returns, resulting in improved Treynor, Sharpe, Omega, Sortino, Kappa-3, Calmar, VaR-Sharpe, CVaR-Sharpe and modified information ratios.

However, cryptocurrencies had a boom-bust behaviour experiencing severe losses during some crisis periods. The following sections therefore zoom into the crisis periods analysing how incorporating BTC and ETH affected diversification and risk-adjusted performance.

7.4.3.1 Impact during the 2018 market crisis US-China trade dispute

In 2018, escalating trade disputes between the US and China manifested in successive tit-for-tat rounds of reciprocal tariffs which sent shockwaves in several equity markets around the world (Bown, 2019; Chen & Pantelous, 2022). In SA, this was compounded by other domestic factors including political uncertainty, slow GDP growth and depressed commodity prices which culminated in the ALSI's marked underperformance (van der Merwe *et al.*, 2023). Figure 7.10 illustrates the risk and returns for the ALSI, ALBI and SA 91-day T-bill and for BTC and ETH and during January 2018 to December 2018.

Figure 7.10: Risk and returns of BTC, ETH and SA equities, bonds and cash in 2018 US-China trade tensions



*Computations were based on daily data from 1 January 2018 to 31December 2018. * ETH and BTC returns are converted to ZAR. Risk is defined as annualise standard deviation. Return refers to annualised return. Source: Author's computations with data sourced from Investing.com (2025) and Iress (2025).*

The ALBI and SA 91-day T-bill were a haven, delivering positive annualised returns of 7.66% and 6.91%. These returns were also stable, with volatilities of 7.25% and 1.15%, respectively compared with their volatilities over the entire period[99] of Sept 2015 – December 2024, which were of 9.3% and 1.61%, respectively. Therefore, the risk levels in SA bonds and cash were not dramatically affected by the US–China trade disputes. In contrast, the ALSI suffered a sharp downturn, resulting in negative annualised returns of 11.42%, inflicting substantial losses on SA equity investors. 2018 proved particularly damaging for holders of BTC and ETH, as both cryptocurrencies experienced some of their worst losses. BTC recorded an annualised return of -68.81%, while ETH recorded -79.75%, effectively eroding most of their market values. These substantial losses were accompanied by pronounced fluctuations in returns, resulting in exceptionally high annualised volatilities of 72.93% for BTC and 91.57% for ETH, underscoring the extreme risk inherent in cryptocurrency markets. Importantly, these elevated levels of volatility were not unusual; they were broadly consistent with the long-term volatility of 62.78% for BTC and 89.86% for ETH (Table 7.4). The year 2018 proved a stark reminder that, when the risks in cryptocurrencies materialise, the consequences for investors can be severe.

The results for how BTC and ETH impacted diversification and risk-adjusted portfolio performance during 2018 are presented in Table 7.7. Panel A built on the analysis presented in Section 7.3. and illustrates the percentage of times BTC, ETH and the ALSI tested inefficient. Zooming into 2018 is important as it helped contextualise portfolio performance within the framework of market efficiency under a period when markets (equity) were stressed. Panel B presents the correlations between BTC, ETH and the baseline portfolios, alongside their risk and risk-adjusted performance metrics before and after the inclusion of BTC and ETH. The performance of the ALSI over the same periods were also reported for comparison.

Table 7.7: Impact of including BTC and ETH in a SA equity-bond-cash portfolio during 2018 when equity markets were reeling under the US–China trade tensions

Panel A: The number of times variance ratio tests detected market inefficiency in BTC, ETH and the ALSI

	Observed Returns				Corrected Returns			
	JS	JM	AVR	Ave	JS	JM	AVR	Ave
BTC	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
ETH	69.77%	6.04%	0.00%	25.27%	81.32%	32.42%	0.00%	37.91%
ALSI	0.00%	0.00%	0.00%	0.00%	2.00%	0.00%	0.00%	0.67%

Observed returns are the daily returns and corrected returns represent the returns after correcting for thin trading. JS, JM, AVR are the frequency with which the tests detected significant inefficiency using the Joint-Sign test, the Wild Bootstrap Test and the Automatic Variance Ratio test. Ave is the arithmetic average of the frequency with which tests detected significant inefficiency. Source: Author's computations with data sourced from Investing.com (2025)

[99] The entire period (1 September 2015 to 31December 2024) descriptive statistics are presented in Table 7.4.

Panel B: Diversification and risk-adjusted performance

Metric/Ratio	MVP	MVP*	Max Sharpe	Max Sharpe*	BL portfolio	BL portfolio*	JSE ALSI
Correlation with BTC	-0.01		-0.01		0.01		-0.01
Correlation with ETH	0.09		0.09		0.09		0.08
Standard Dev	8.57%	8.55%	8.57%	8.60%	9.87%	10.40%	17.16%
VaR_{95}	-13.98%	-13.64%	-13.98%	-13.84%	-15.93%	-16.99%	-29.24%
$CVaR_{95}$	-16.38%	-16.47%	-16.38%	-16.62%	-19.15%	-21.44%	-36.08%
Specific risk	3.47%	3.41%	3.47%	3.47%	2.71%	5.16%	NA
Treynor	-0.15	-0.17	-0.15	-0.17	-0.16	-0.25	-0.18
Sharpe	-0.81	-0.90	-0.81	-0.90	-0.91	-1.29	-1.07
Omega	1.19	1.18	1.19	1.15	1.14	1.03	0.90
Sortino	-1.24	-1.37	-1.24	-1.35	-1.37	-1.87	-1.48
Kappa - 3	-0.94	-1.04	-0.94	-1.03	-1.04	-1.39	-1.12
Calmar	-1.18	-1.31	-1.18	-1.26	-1.24	-1.49	-1.00
VaR -Sharpe	-0.50	-0.57	-0.50	-0.56	-0.57	-0.79	-0.63
CVaR - Sharpe	-0.42	-0.47	-0.42	-0.46	-0.47	-0.63	-0.51
Modified Information	-0.70	-0.78	-0.70	-0.78	-1.11	-1.39	NA
Modified Sharpe	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.03

*The ALSI is regarded as the market and therefore metrics such as specific risk and modified information are not applicable. Daily data from January - December 2018 was used. MVP, Max Sharpe and BL refer to the Minimum variance portfolio, maximum Sharpe portfolio and the Black Litterman portfolio. * Means that the portfolio includes cryptocurrency. Source: Author's computations with data sourced from Investing.com (2025) and Iress (2025).*

Panel A results exhibited varying levels of market efficiency during the year 2018, as equity and cryptocurrency markets entered a crisis. On the one hand, BTC maintained strong levels of efficiency with none of the tests detecting market inefficiency. The ALSI index also exhibited strong levels of efficiency and was more efficient than its long run average of 6.66% of returns showing market inefficiency. On the other hand, ETH was relatively inefficient with the JS and JM test detecting inefficiency in 81.32% and 32.42% of ETH returns.

Pane B results indicate diverse outcomes ranging from correlation, risk measures and risk-adjusted performance. Regarding correlation, the results indicated that ETH and BTC returns were weakly correlated with the default portfolios. BTC correlations ranged between ±0.01, while ETH correlations were slightly higher, with correlation coefficients of 0.09 demonstrating modest diversification potential. However, the elevated risks and large drawdowns in cryptocurrencies resulted in losses when cryptocurrencies were added to portfolios.

Regarding risk, under the MVP, adding 1%[100] of BTC, marginally reduced total risk, VaR_{95} and specific risk from 8.57%, 13.98% and 3.47% to 8.55% and 13.64% and 3.41% respectively due mostly to a robust correlation of -0.01. However, $CVaR_{95}$ increased modestly from 16.38% to

[100] All asset allocations for the South African portfolio are detailed in Appendix 2.

16.47%, indicating higher losses due to a greater frequency of extreme losses in BTC. Similar results were also observed under the max Sharpe portfolio with 1% allocation to BTC. With higher allocation of 6% to BTC as suggested by the BL portfolio, risk as measured by the standard deviation, VaR_{95}, $CVaR_{95}$ and specific risk all increased from 9.87%, -15.93%, -19.15% and 2.71% to 10.40%, -16.99%, -21.44% and 5.16%, respectively. This increase was because BTC experienced higher levels of volatility and the weak correlation of 0.01 with the baseline portfolio did not lead to portfolio risk reduction. However, the elevated risk levels after adding BTC to a bond-equity-cash portfolio still produced a portfolio with risk levels lower than that of the ALSI.

Regarding risk adjusted performance, the bloodbath faced by equities and cryptocurrencies further worsened portfolios. Adding, BTC further worsened portfolio returns leading to lower excess returns. All the risk-adjusted performance measure in Table 7.7 indicated worse performance after including BTC particularly in the BL portfolio which had a higher exposure (6%) than the MVP and the max Sharpe (1%) portfolios. Allocating 6% of the portfolio to BTC even resulted in portfolio risk adjusted performance lower than the ALSI's risk adjusted performance.

The overall results indicated, that during 2018 when equity markets entered a crisis induced by the US-China trade dispute, BTC maintained strong levels of efficiency while ETH was becoming efficient. However, both BTC and ETH experienced severe declines leading to large negative returns. Adding small portion of BTC to an equity-bond-cash MVP and max Sharpe ratio portfolio while marginally lowering portfolio risk levels due to low correlation, it degraded risk-adjusted performance due to outsized negative returns. Increasing exposure to cryptocurrencies led to higher risk and worsened risk-adjusted performance.

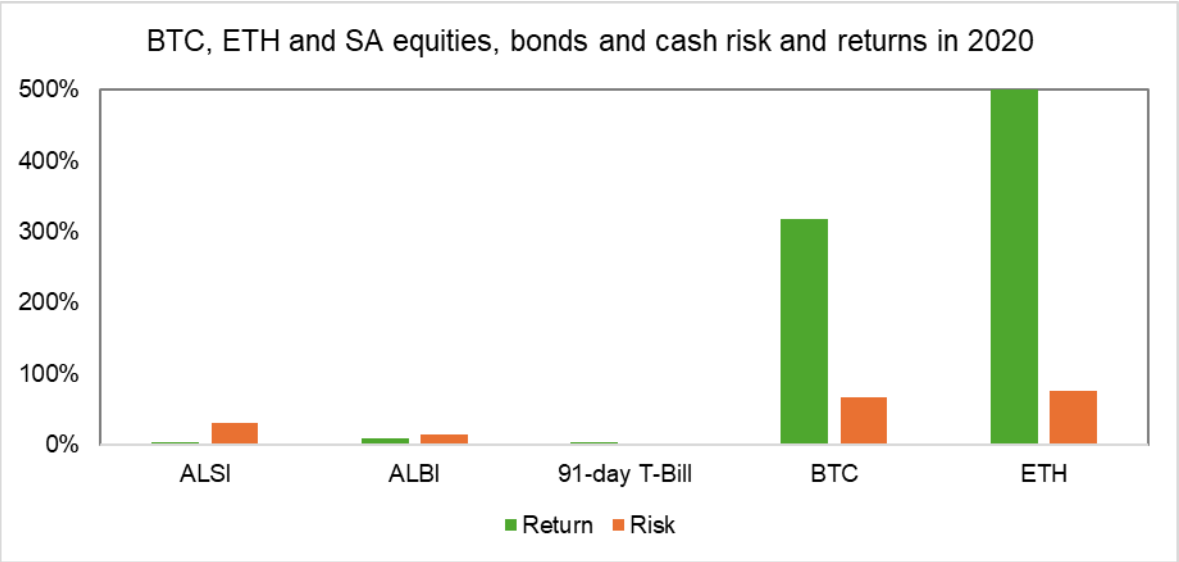
The next section explores performance during 2020, the year markets entered crisis induced by the Covid-19

7.4.3.2 Impact during the 2020 Covid-19 induced market crisis

The Covid-19 pandemic and lockdowns that followed around the globe to manage the spread of the disease induced substantial market stress, particularly for equities and cryptocurrencies. For example, the ALSI experienced a significant decline of 33% during the period from February 18, 2020, to March 18, 2020, when the index plummeted from 57,715 to 38,604 (index points). However, by the end of the year 2020, it had fully recovered, and its year-on-year annualised returns were 4.06%. BTC and ETH, which had suffered substantial drawdowns - losing more than half of their value between February and March 2020 - also staged remarkable recoveries. BTC's price surged, bouncing back from one of the crises lows of approximately USD4 970 on 12 March 2020, to end the year (2020) at over USD29 000. Similarly, ETH experienced an impressive recovery over the same period soaring from USD 109 on 16 March 2020 to over USD 739 on 31

December 2020. Thus, the Covid-19-induced market crisis had a shock-like impact on both SA equities and cryptocurrencies BTC and ETH within the first half of 2020. Figure 7.11 illustrates the risk and returns experience by BTC and ETH and SA equities, bonds and cash during 2020.

Figure 7.11: Risk and returns of BTC, ETH and SA equities, bonds and cash in 2020 when markets entered a crisis induces by the Covid-19 pandemic



*Computations were based on daily data from 1 January 2020 to 31December 2020. * ETH and BTC returns are converted to ZAR. Risk is defined as annualised standard deviation. Return refers to annualised return. Source: Author's computations with data sourced from Investing.com (2025) and Iress (2025).*

BTC and ETH had the highest annualised returns of 319% and 500%, respectively. By contrast the ALSI (4.06%), ALBI (8.61%) and SA 91-day T-bills (4.42%) had relatively lower returns. Notwithstanding the high risk in BTC (67.96%) and ETH (75.82%) compared to the ALSI (30.38%), ALBI (14.05%) and SA 91-day T-bills (1.21%) the two cryptocurrencies had higher returns per unit of risk. Their higher returns per unit of risk made them an attractive investment option with an attractive payoff for relatively more risk tolerant investors.

The results for how BTC and ETH impacted diversification and risk-adjusted portfolio performance during 2020 are presented in Table 7.8. Panel A presents the percentage of times BTC, ETH and the ALSI tested inefficient. This is important as it helps contextualise portfolio performance within the framework of market efficiency under a period when markets (equity) were stressed. Panel B presents the correlations between BTC, ETH and the baseline portfolios, alongside their risk and risk-adjusted performance metrics before and after the inclusion of BTC and ETH. The performance of the ALSI over the same periods were also reported as a widely recognised benchmark, enabling valuable comparison against a fundamental market standard.

Table 7.8: Impact of including BTC and ETH in a SA equity-bond-cash portfolio during the Covid-19 market downturn in 2020

Panel A: The number of times variance ratio tests detected market inefficiency in BTC, ETH and the ALSI metric

	Observed returns				Thin trading corrected returns			
	JS	JM	AVR	Ave	JS	JM	AVR	Ave
BTC	80.55%	0.00%	0.00%	26.85%	9.04%	0.00%	0.00%	3.01%
ETH	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
ALSI	76.98%	0.00%	0.00%	25.66%	59.13%	0.00%	0.00%	19.71%

Observed returns are the daily returns and thin trading corrected returns represents the returns after correcting for thin trading. JS, JM, AVR are the frequency with which tests detected significant inefficiency. Ave is the arithmetic average of the frequency with which tests detected significant inefficiency. Source: Author's computations with data from investing.com (2025).

Panel B: Diversification and risk-adjusted performance

Metric/Ratio	MVP	MVP*	Max Sharpe	Max Sharpe*	BL portfolio	BL portfolio*	JSE ALSI
Correlation with BTC	0.16		0.16		0.18		0.21
Correlation with ETH	0.27		0.27		0.28		0.30
Standard Dev	16.71%	16.72%	16.71%	19.16%	18.84%	18.97%	30.38%
VaR_{95}	-22.89%	-22.23%	-22.89%	-22.35%	-24.80%	-21.98%	-39.46%
$CVaR_{95}$	-44.80%	-44.64%	-44.80%	-49.14%	-50.20%	-48.96%	-78.45%
Specific risk	6.15%	5.99%	6.15%	8.68%	4.74%	7.56%	0.00%
Treynor	0.04	0.10	0.04	0.91	0.02	0.57	-0.00
Sharpe	0.12	0.30	0.12	2.67	0.08	1.73	-0.01
Omega	1.18	1.20	1.18	1.36	1.16	1.36	1.05
Sortino	0.35	0.90	0.35	8.95	0.22	4.58	-0.03
Kappa - 3	0.09	0.24	0.09	2.00	0.06	1.24	-0.01
Calmar	0.09	0.23	0.09	2.14	0.06	1.52	-0.01
VaR -Sharpe	0.09	0.23	0.09	2.29	0.06	1.49	-0.01
CVaR - Sharpe	0.04	0.11	0.04	1.04	0.03	0.67	-0.00
Modified Information	0.12	0.32	0.12	3.22	0.11	2.18	NA
Modified Sharpe	0.12	0.30	0.12	2.67	0.08	1.73	-0.00

The JSE ALSI is regarded as the market and therefore metrics such as specific risk and modified information are not applicable. Daily data from 1 January 2020 to 31 December 2020 was used. MVP, Max Sharpe and BL refer to the Minimum variance portfolio, maximum Sharpe portfolio and the Black Litterman portfolio. Asterisks (*) means that the portfolio includes cryptocurrency. Source: Author's computations from data sourced from Investing.com (2025) and Iress (2025).

The results showed that, in 2020 when the Covid-19 crisis affected financial markets, BTC was becoming less efficient (compared with its long-term average). The JS tests showed that more than 80% of BTC observed returns were inefficient However, after adjusting for thin trading, 9.04% of BTC returns were inefficient. These results suggested that the Covid-19 period had a notable impact on the efficiency of BTC. By contrast, ETH remained efficient throughout the year 2020, with all the market efficiency tests not detecting inefficiency. These results suggest that the crisis affected BTC's efficiency more than ETH's.

BTC, which was experiencing weakening efficiency, was modestly correlated with the baseline portfolio.[101] Its correlation with the MVP and max Sharpe was 0.16 while with the BL portfolio it was 0.18. In contrast, ETH though efficient was relatively highly correlated with the MVP and max Sharpe portfolio (0.27) and the BL portfolio (0.28).

These weak correlations improved overall portfolio risk profiles across all three portfolio allocation strategies. Under the MVP, a 1% allocation to BTC had a negligible effect on total risk, yet specific risk fell from 6.15% to 5.99%, reflecting a slight reduction in idiosyncratic exposure. In the BL portfolio, increasing BTC's weight to 10% raised total risk marginally from 18.84% to 19.87%, while VaR_{95} and $CVaR_{95}$ declined from 24.80% and 50.20% to 21.98% and 48.96%, respectively, indicating improved downside protection. However, specific risk rose markedly from 4.74% to 7.56%, implying diminished diversification benefits when BTC was becoming market inefficient. By contrast, the max Sharpe-ratio portfolio with a 10% allocation to ETH exhibited more pronounced risk changes. The portfolio's standard deviation increased from 16.71% to 19.16%, and $CVaR_{95}$ rose from 44.80% to 49.14%. Specific risk also climbed from 6.15% to 8.68%. Regardless of these increases, the portfolio risks after including cryptocurrencies were till lower than the ALSI risks. These results therefore suggested that higher exposures to cryptocurrencies, while they elevated both total and specific risk, driven by their heightened volatility and only modest correlation with traditional asset classes, still resulted in risk levels lower than the ALSI.

Moreover, the inclusion of cryptocurrencies in portfolios had a positive impact on all risk-adjusted performance measures across the different portfolios. For example, the max-Sharpe ratio portfolio's Sharpe increase from 0.12 to 2.67 indicating higher returns per unit of risk. Under the BL portfolio the Sharpe ration also increased from 0.058 to 1.73. This was because cryptocurrencies had higher returns per unit of risk thereby positively enhancing Sharpe ratios. Another benefit of including cryptocurrencies is reflected by in the Calmar ratios. While in all the three portfolio allocations, Calmar ratios increased, increases in the max-Sharpe ratio portfolio and the BL portfolio surpassed one - demonstrating that the annualised gains after including cryptocurrencies outpaced the maximum drawdowns the portfolio suffered - demonstrating resilience.

The overall results therefore suggested that during 2020, when markets entered a crisis induced by the Covid-19 pandemic, BTC market efficiency was weakening while ETH remained largely efficient. ETH and BTC remained modestly correlated with baseline equity-bond-cash portfolios. This correlation was lower than with the ALSI, suggesting potential diversification opportunities.

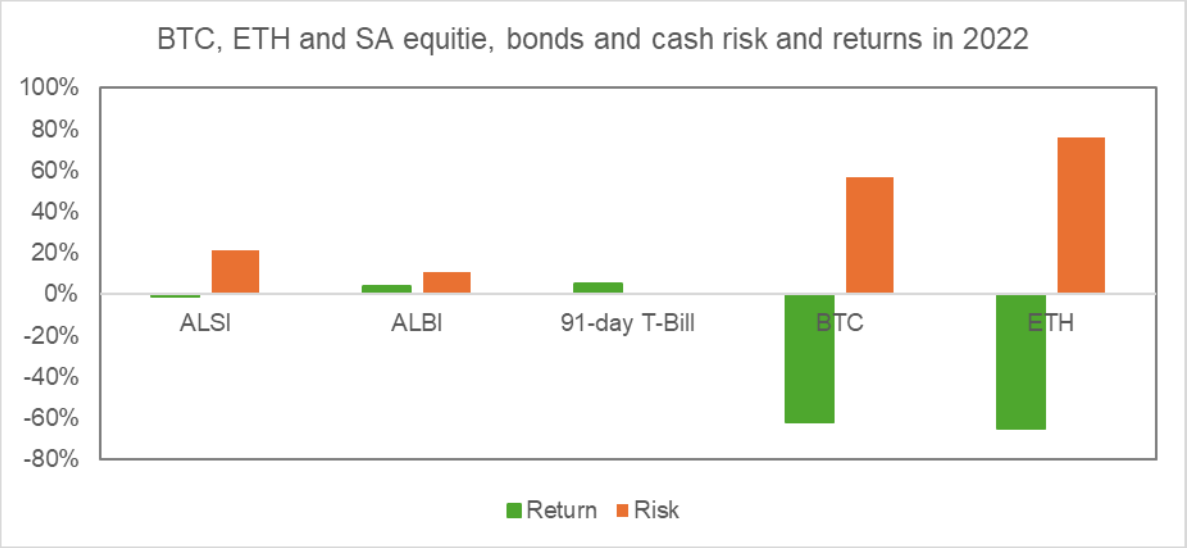
[101] Baseline MVP and max Sharpe allocations were ALSI (40%), ALBI (50%) and SA 91-day T-Bill (10%). For the BL portfolio the baseline allocations were ALSI (51.5%), ALBI (38.5%) and SA 91-day T-Bill (10%)

The results showed that, for risk-averse investors (MVP), small (1%) portfolio allocations to cryptocurrencies (BTC) in a SA equity-bond-cash modestly reduced risk and enhanced risk-adjusted performance. Higher allocations (10%) for max-Sharpe ratio (ETH) and BL portfolio investors (BTC) increased risk levels and dramatically enhanced risk-adjusted performance. These enhanced risk-adjusted returns emanated from outsized cryptocurrency returns despite the shock-like drawdowns observed between February and March 2020.

7.4.3.3 Impact during 2022 at the start of the Russia-Ukraine conflict

When Russia commenced its military operation in Ukraine in February 2022, South African equity markets responded sharply. The JSE ALSI experienced significant losses and increased volatility as investors shifted their holdings towards safe-haven assets (Oyadeyi *et al.*, 2024). In tandem, rising prices for food, fuel, and fertiliser exerted upward pressure on inflation expectations, with the ALSI being a net recipient of these systemic shocks — underscoring its vulnerability to global crises (Anyikwa & Phiri, 2023). By the end of 2024, the Russia–Ukraine war continued, with the ALSI recovering moderately and offsetting most of the losses sustained by the end of 2022. Figure 7.12 illustrates the annual risk and return profiles for ALSI, ALBI, SA 91-day T-bills, BTC, and ETH throughout 2022.

Figure 7.12: Risk and returns of BTC, ETH and SA equities, bonds and cash in 2022 when markets fell amidst the Russia-Ukraine conflict



Computations were based on daily data from 1 January 2022 to 31 December 2022. ETH and BTC returns are converted to ZAR. Risk is defined as annualised standard deviation. Return refers to annualised return. Source: Author's computations with data sourced from Investing.com (2025) and Iress (2025).

During the market crisis triggered by the Russia–Ukraine conflict in 2022, similar to the US–China trade tensions in 2018, the ALBI and South African 91-day Treasury bills served as stable investment options. The SA 91-day T-bills achieved annualised returns of 4.94% with a low risk profile of 1.2%, while the ALBI provided returns of 4.25% alongside a moderate annualised risk of 10.65%. The ALSI returned -0.9% annually, nearly breaking even, but experienced elevated volatility at 21.09%. In contrast, BTC and ETH experienced substantial underperformances, with annualised returns of -61.85% and -65.20% and volatility levels of 56.97% and 76.30%, respectively. These results indicate that the Russia–Ukraine crisis had a pronounced impact on BTC and ETH, which faced substantial drawdowns.

To provide a comprehensive understanding of how adding BTC and ETH to a SA equity-bond-cash portfolio influenced diversification and risk-adjusted performance amidst the market turmoil of 2022, Table 7.9 is introduced below. Panel A details the proportion of instances in which BTC, ETH, and the JSE ALSI exhibited market inefficiency throughout the year. These findings are integral for situating subsequent portfolio analyses within the broader context of market efficiency, especially during periods of pronounced stress in equity markets. Panel B reports the correlations between BTC, ETH, and the baseline portfolios, as well as the associated risk and risk-adjusted performance measures before and after including BTC and ETH. This panel also presents comparative metrics for the ALSI over identical periods, which serves as a key benchmark for evaluating the impact of cryptocurrency inclusion relative to a traditional market standard. This structured presentation allows for clear comparison and contextualisation of portfolio outcomes against the background of market efficiency and benchmark performance, deepening the analysis of diversification and risk management during crisis conditions.

Table 7.9: Impact of including BTC and ETH in a SA equity-bond-cash portfolio during the Russia-Ukraine induced market crisis during 2022

Panel A: The number of times variance ratio tests detected market inefficiency in BTC, ETH and the ALSI.

	Observed returns				Thin trading corrected returns			
	JS	JM	AVR	Ave	JS	JM	AVR	Ave
BTC	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
ETH	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
ALSI	21,60%	0,00%	0,00%	7,20%	40,00%	16,80%	1,60%	19,47%

Observed returns are the daily returns and thin trading corrected returns represents the returns after correcting for thin trading. JS, JM, AVR are the frequency with which the tests detected significant inefficiency using the Joint-Sign test, the Wild Bootstrap Test and the Automatic Variance Ratio test. Ave is the arithmetic average of the frequency with which tests detected significant inefficiency.

Panel B: Diversification and risk-adjusted performance

Metric/Ratio	MVP	MVP*	Max Sharpe	Max Sharpe*	BL portfolio	BL portfolio*	JSE ALSI
Correlation with BTC	0,17		0,16		0,18		0,23
Correlation with ETH	0,30		0,30		0,31		0,29
Standard Dev	11,12%	11,16%	11,12%	11,38%	12,52%	11,92%	21,09%
VaR	-20,57%	-20,09%	-20,57%	-20,89%	-22,03%	-21,59%	-31,40%
$CVaR_{95}$	-24,41%	-24,28%	-24,41%	-24,70%	-26,49%	-25,29%	-42,77%
Specific risk	5,14%	5,04%	5,14%	5,27%	4,02%	4,68%	0,00%
Treynor	-0,06	-0,07	-0,06	-0,07	-0,06	-0,07	-0,06
Sharpe	-0,24	-0,30	-0,24	-0,30	-0,26	-0,31	-0,28
Omega	1,16	1,15	1,16	1,13	1,14	1,13	1,01
Sortino	-0,36	-0,44	-0,36	-0,44	-0,39	-0,46	-0,41
Kappa - 3	-0,26	-0,32	-0,26	-0,32	-0,29	-0,34	-0,31
Calmar	-0,34	-0,41	-0,34	-0,38	-0,37	-0,41	-0,32
VaR -Sharpe	-0,13	-0,17	-0,13	-0,16	-0,15	-0,17	-0,19
CVaR - Sharpe	-0,11	-0,14	-0,11	-0,14	-0,12	-0,14	-0,14
Modified Information	-0,22	-0,27	-0,22	-0,28	-0,32	-0,33	N/A
Modified Sharpe	0,00	0,00	0,00	0,00	0,00	0,00	-0,01

*Note: minimum variance portfolio (Min VAR), maximum Sharpe (Max R/SD), and the minimum deviation from the market equilibrium (Min Mkt Dev). *The portfolio includes cryptocurrency. Source: Author's computations from data sourced from Investing.com (2025) and Iress (2025).*

Panel A shows that, during the Russia-Ukraine crisis of 2022, both BTC and ETH maintained strong levels of market efficiency, even though their returns were substantially negative. In contrast, the ALSI experienced a decline in efficiency but managed to deliver comparatively better returns, almost remaining unchanged. Analysing the two geopolitical crises revealed that BTC consistently exhibited strong market efficiency, regardless of experiencing largely negative returns. ETH, however, showed distinct patterns: it was relatively inefficient in its early stages and during the US–China trade conflict in 2018, but its efficiency improved noticeably by the time the Russia–Ukraine crisis started in 2022. Despite this improvement, ETH also recorded negative returns during 2022. By contrast, during the Covid-19 crisis in 2020, ETH maintained strong efficiency and produced outsized returns. BTC, on the other hand, showed relatively weakened efficiency, but still managed to deliver untold returns. These results highlight that the prices of BTC and ETH can undergo substantial declines or appreciation while still retaining differing strengths of efficiency in the market.

Further to the high levels of efficiency, Panel B results showed that BTC and ETH were modestly correlated with the baseline portfolio, with correlation coefficients ranging between 0.16–0.18 and 0.3–0.31, respectively.

Panel B presented the results of adding BTC to a MVP composed of ALSI (40%), ALBI (50%), and cash (10%). Introducing a 1% allocation to BTC led to subtle shifts in the portfolio's risk characteristics. Specifically, the portfolio's standard deviation edged upward from 11.12% to 11.16%. Meanwhile, the VaR_{95} and $CVaR_{95}$ experienced minor decreases, moving from 20.57% and 24.14% to 20.09% and 24.28%, respectively. Specific risk also declined slightly, from 5.14% to 5.04%. These findings indicate that, despite BTC's inherently higher risk, a small allocation (1%) brought modest improvements to the risk profile of an equity-bond-cash portfolio. This outcome was primarily due to the weak correlation between BTC and the traditional asset classes within the portfolio

Incorporating a 1% allocation to ETH into a max-Sharpe ratio portfolio consisting of ALSI (40%), ALBI (50%), and cash (10%) resulted in modest increases across several risk metrics. The portfolio's standard deviation rose from 11.12% to 11.38%, while VaR_{95} and $CVaR_{95}$ grew from 20.57% and 24.41% to 20.89% and 24.70%, respectively. Specific risk also increased from 5.14% to 5.27%. These results suggest that even a minimal exposure to ETH introduces higher volatility to the overall portfolio given ETH's inherently elevated risk profile.

Incorporating ETH into a BL portfolio with increased equity exposure - comprising ALSI (50%), ALBI (10%), and cash (10%) yielded notable risk management improvements. The standard deviation declined from 12.52% to 11.92%, while both VaR_{95} and $CVaR_{95}$ decreased from 22.03% and 26.49% to 21.59% and 25.29%, respectively. However, specific risk rose from 4.02% to 4.68%, attributable to a stronger correlation in returns between ETH and the baseline portfolio. These results suggested that in portfolios with higher exposure to ALSI because it is considerable risky, ETH can introduce modest risk improvements to the risk profile of the portfolio.

7.4.3.4 Summary of the impact of cryptocurrencies on SA equity-bond-cash portfolios

This section explored the impact of adding BTC and ETH across three baseline portfolios MVP, max-Sharpe ratio portfolio and the BL portfolio representing diverse investor attributes. The analysis was split into two: the long-term covering the observation window 1 September 2015t 31 December 2024 and in specific windows (years) when equity markets entered a crisis: 2018, 2020 and 2022. The resulted showed that in the full observation window (long-term), both BTC and ETH became more efficient, with BTC being relatively more efficient. Adding the two cryptocurrencies to an equity-bond-cash portfolio impacted both the risk and risk adjusted performance or portfolios in nuanced ways. For risk averse MVP investors. a small allocation (averaging 2.37%) modestly trimmed overall MVP volatility, tightened tail-risk and marginally reduced diversifiable risk while boosting Treynor, Sharpe, Omega, Sortino, Kappa-3, Calmar, and modified information ratios. For risk optimising (max-Sharpe ratio portfolio) and equilibrium market

investors (BL portfolio) optimal allocations to BTC and/or ETH were higher, averaging 8%. These relatively higher allocations led to increased portfolio standard deviation and diversifiable risk due to the inherently high risk in BTC and ETH and the positive correlation with the baseline portfolios. However, the increased risk was associated with higher portfolio returns thereby improving Treynor, Sharpe, Omega, Sortino, Kappa-3, Calmar, VaR-Sharpe, CVaR-Sharpe and modified information ratios. Thus, over the period from September 2015 to December 2024, which when ETH matured becoming more efficient and BTC remained relatively more efficient going through episodes of strong efficiency followed by weakened efficiency, adding then to an equity-bond-cash portfolio delivered modest diversification benefits and improved risk-adjusted returns due to their high returns and modest correlations.

However, diversification is needed the most in crisis periods. In 2018, SA equity markets entered a crisis compounded by the US–China trade dispute, while BTC maintained strong levels of efficiency ETH was experienced weakened levels of market efficiency following its launch in 2015. Both BTC and ETH experienced severe declines leading to large negative returns. Adding small portion (1%) of BTC to equity-bond-cash portfolios while marginally lowering portfolio risk levels due to low correlation, it degraded risk-adjusted performance due to outsized negative returns. Increasing exposure to cryptocurrencies led to higher risk and worsened levels of risk adjusted performance.

In 2022, at the onset of the Russia-Ukraine conflict SA equity markets also entered a crisis. Both BTC and ETH remained strongly efficient through 2022. Adding a small (1%) allocation to BTC modestly lowered risk in MVP. However, adding an equally small (1%) allocation ETH to the max-Sharpe ratio and the BL portfolio increased risk marginally due to the inherently higher volatility. Since in both the geopolitical crisis, BTC and ETH experienced outsized negative losses, adding them to portfolios worsened risk adjusted performances.

By contrast, during the global crisis induced by the Covid-19, BTC was experiencing weakening efficiency while ETH remained largely efficient. For risk averse (MVP) investors, lower (1%) portfolio allocations to BTC in a equity-bond-cash modestly reduced risk and enhanced risk adjusted performance. Higher allocations of up to 10% for max-Sharpe ratio (ETH) and BL portfolio investors (BTC) increased risk levels and dramatically enhanced risk-adjusted performance.

The portfolio allocations results were skewed toward BTC which had become more matured, mostly due to its relatively weaker correlations with equities, bonds and cash and also due to relatively lower volatility compared with ETH.

7.4.4 Impact of adding BTC and ETH in a US equity-bond-cash portfolio on diversification and risk adjusted performance

As in the case of SA, to assess the impact on diversification and risk-adjusted performance of BTC and ETH in a US portfolio, this study appraised the correlation, risk and risk-adjusted performance between BTC and ETH and three baseline equity-bond-cash portfolio returns. These three baseline portfolios are the MVP, max-Sharpe ratio and the BL portfolio reflecting the risk appetites of risk-averse investors, investors willing to accept moderate risk in pursuit of the best risk-return trade-off and neutral market equilibrium investors (this study did not incorporate investor's specific views about expected returns). These three portfolios were important to give a broader view on how adding BTC and ETH affected different investors given that investors objectives are heterogeneous.

Table 7.10 Panel A restates the market efficiency of BTC, ETH and the S&P 500 - already presented in Table 7.4. This was important as it helped build an understanding of portfolio performance within the framework of market efficiency. Panel B presents the correlations between BTC and ETH and the baseline US portfolios, risk metrics and risk-adjusted performance metrics before and after adding BTC and ETH. The S&P 500 performance was included alongside portfolio performance before and after inclusion of BTC and ETH to provide a widely recognised benchmark, enabling comparison against a fundamental US market standard.

Table 7.10: Market efficiency and impact of including cryptocurrencies on portfolio performance in the US (2015-2024).

Panel A: The number of times variance ratio tests p-values detected market inefficiency in BTC, ETH and the S&P 500

	Observed returns				Thin trading corrected returns			
	AVR	**JM**	**JS**	**Ave**	**AVR**	**JM**	**JS**	**Ave**
BTC	0.03%	0.03%	16.39%	5.49%	0.00%	0.00%	1.49%	0.50%
ETH	0.00%	5.75%	26.12%	10.63%	0.00%	0.73%	19.11%	6.61%
S&P 500	66,13%	20,96%	12,66%	33,25%	25,33%	3,06%	0,00%	9,46%

Observed returns are the daily returns and thin trading corrected returns represents the returns after correcting for thin trading. JS, JM, AVR are the frequency with which the tests detected significant inefficiency using the Joint-Sign test, the Wild Bootstrap Test and the Automatic Variance Ratio test. Ave is the arithmetic average of the frequency with which the three tests detected significant inefficiency. Source: Extract from Table 7.4

Panel B: Diversification and risk-adjusted performance

Metric/Ratio	MVP	MVP*	Max Sharpe	Max Sharpe*	BL	Metric/Ratio	S&P 500
Correlation with BTC	0,23		0,22		0,24		0,24
Correlation with ETH	0,21		0,20		0,22		0,21
Standard Dev	8,12%	8,23%	9,75%	11,31%	13,46%	12,85%	18,12%
VaR_{95}	-11,13%	-11,26%	-13,97%	-15,72%	-18,31%	-17,83%	-27,12%
$CVaR_{95}$	-17,52%	-17,90%	-21,35%	-23,32%	-31,12%	-29,27%	-43,95%
Specific risk	4,80%	4,79%	5,28%	7,79%	4,11%	5,71%	0,00%
Treynor	0,18	0,25	0,21	1,19	0,15	0,23	0,12
Sharpe	0,81	1,10	0,98	4,76	0,77	1,15	0,68
Omega	1,24	1,25	1,26	1,40	1,22	1,23	1,15
Sortino	1,26	1,71	1,52	7,53	1,11	1,68	0,95
Kappa - 3	0,78	1,05	0,96	4,50	0,62	0,95	0,56
Calmar	0,47	0,65	0,61	3,09	0,37	0,66	0,36
VaR -Sharpe	0,59	0,81	0,68	3,43	0,56	0,83	0,45
CVaR - Sharpe	0,37	0,51	0,45	2,31	0,33	0,50	0,28
Modified Information	0,54	0,76	0,89	4,43	1,73	1,81	N/A
Modified Sharpe	0,81	1,10	0,98	4,76	0,77	1,15	0,68

*The S&P 500 is regarded as the market and therefore metrics such as specific risk and modified information are not applicable. Daily data from 1 September 2015 to 31 December was used. MVP, Max Sharpe and BL refer to the Minimum variance portfolio, maximum Sharpe ratio portfolio and the Black Litterman portfolio. * Means that the portfolio includes BTC and/or ETH. Source: Author's computations from data sourced from Investing.com (2025) and US Treasury (2025).*

Panel A, together with Figure 7.2, details the efficiency dynamics for BTC and ETH as well as the S&P 500 for the observation period 1 September 2015 to 31 December 2024. During this period, both cryptocurrencies exhibited strong levels of market efficiency based on daily return data. BTC, after accounting for thin trading effects, exhibited a pronounced shift towards greater market efficiency. Only 0.5% of its p-values indicated inefficiency, highlighting its robust efficiency profile. ETH also showed noteworthy progress towards efficiency, although to a lesser degree than BTC as 6.61% of its p-values flagged inefficiency. While less efficient than BTC, ETH's performance in this regard was still compelling. By comparison, the S&P 500 registered 9.46% of p-values with inefficiency, situating it below BTC and ETH. Overall, these findings suggested that the investment value of BTC and ETH should not be judged solely on their market efficiency. In several respects, BTC and ETH's efficiency levels were comparable and even stronger than those of the S&P 500.

Panel B reveals modest correlations between BTC and ETH and the US baseline MVP, max-Sharpe ratio, and BL portfolios[102], ranging from 0.20 to 0.24. These correlation coefficients were

[102] The MVP, max-Sharpe ratio, and BL portfolio allocations are detailed in Appendix 2. On average, the baseline MVP held 40% in the S&P 500, 50% in 10-year US Treasuries, and 10 % in 3-month T bills. By comparison, the

slightly higher than those observed between BTC and the baseline SA portfolios (0.01 to 0.03) and between ETH and the baseline SA portfolios (0.09 to 0.10). The results suggested that, while BTC and ETH retained some diversification potential within US portfolios, their impact was comparatively less pronounced than in SA portfolios.

Regarding how BTC and ETH impacted risk under the MVP framework, the inclusion of an average of 1% in cryptocurrencies split (0.95% BTC and 0.05% ETH) led to a modest increase in portfolio risk. Standard deviation increased from 8.12% to 8.23%, indicating higher volatility. At the 95% confidence level, historical VaR_{95}, which measured the annualised maximum expected loss over one year, marginally worsened from 11.13% to 11.26%. $CVaR_{95}$ increased from 17.52% to 17.90%, implying that in the worst 5% of scenarios the expected loss beyond VaR_{95} marginally worsened because of including BTC and ETH. Unsystematic risk modestly dropped from 4.80% to 4.79%. Although this reduction is small in absolute terms, it confirmed that adding cryptocurrencies can trim idiosyncratic risk. For investors, portfolio managers and regulators, this suggests that including a small allocation of BTC and ETH to US risk-averse portfolios could amplify overall risk — a realisation at odds with the SA case wherein an average of 2.37% allocation to BTC and ETH (split 2.27% BTC and 0.1% ETH) led to overall risk reduction for arisk-averse MVP. Some of the major reasons why BTC and cryptocurrencies positively contribute to lower portfolio risk are that they are lowly correlated with the SA baseline portfolios and that, on average, the SA baseline portfolios were riskier (have higher standard deviation) than the US portfolios.

Under the max Sharpe ratio portfolio, the inclusion of about 8% cryptocurrency (split between 4.51% BTC and 3.49% ETH) led to increases in portfolio risk. Standard deviation increased from 9.75% to 11.31%, indicating heightened volatility. Historical VaR_{95} increased from 13.97% to 15.72%, suggesting that there was 95% confidence that adding a combined 8% in BTC and ETH would increase portfolio losses from 13.97% to 15.72% in a bad year. The $CVaR_{95}$ showed that the average losses in extreme downside scenarios became more severe, increasing from 21.35% to 23.32%. Unsystematic risk, or diversifiable volatility, increased notably from 5.28% to 7.79%, which indicated that adding BTC and ETH introduced substantial diversifiable risks. Despite these overall increases, the risk levels of the max Sharpe ratio portfolio after including cryptocurrencies remained markedly lower than the risk levels of the S&P 500. For example, the standard deviation of the S&P 500 was 18.12% compared with 11.31% of the max Sharpe ratio portfolio after

maximum Sharpe ratio portfolio allocated 55% to the S&P 500, 36% to 10-year Treasuries, and 9% to 3-month T-bills, while the Black-Litterman portfolio invested 72% in the S&P 500, 20% in 10-year Treasuries, and 8 % in 3-month T-bills. Section 7.4.2 discussed the asset allocation and made comparisons with the SA case.

including cryptocurrencies. Additionally, The VaR_{95} and $CVaR_{95}$ of 15.42% and 23.32% were lower than those of the S&P 500, which measured 27.12% and 43.95% respectively. These findings mirror those observed in the SA case, demonstrating that incorporating a moderate allocation (8%) of BTC and ETH into an equity-bond-cash portfolio in both the US and South Africa resulted in a portfolio that exhibited lower risk than the corresponding equity indices – mostly due to weak correlations between cryptocurrencies and bonds and cash.

Analysis of the BL portfolio revealed further nuances regarding the impact of BTC and ETH on US-based portfolios. A moderate allocation of 4.7% (comprising 2.8% BTC and 1.9% ETH) resulted in a slight reduction in portfolio risk. Specifically, the standard deviation, VaR_{95}, and $CVaR_{95}$ decreased from 13.46%, 18.31%, and 31.12% to 12.85%, 17.83%, and 29.27%, respectively. This outcome was noteworthy because, in contrast, the MVP exhibited a minor risk increase with a much smaller (1%) allocation to cryptocurrencies. In the BL context, however, a larger allocation led to modest risk reductions. A closer examination suggested that the composition of the portfolio played a pivotal role in determining how cryptocurrencies influence diversification. The BL portfolio featured a heavier weighting toward equities, which were riskier compared with bonds in the MVP. This higher equity exposure appears to support the inclusion of cryptocurrencies, indicating that they may be more advantageous for portfolios geared toward higher risk appetites rather than those designed for risk-averse investors. These results indicated that BTC and ETH can provide meaningful diversification benefits, particularly within portfolios that emphasize higher-risk assets.

Regarding the impact of cryptocurrencies on performance, the results under the MVP framework showed that the addition of BTC and ETH improved all risk-adjusted performance metrics. This was due mostly to enhanced returns, which rose from 6.58% to 9.09% in spite the marginal increases in risk. The Treynor ratio rose from 0.13 to 0.19, exceeding the S&P Treynor of 0.10, indicating that including BTC and ETH earned greater excess return per unit of systematic risk. Sharpe ratios advanced from 0.57 to 0.87, outperforming the S&P 500's 0.57. Omega ratios remained almost flat, marginally increasing from 1.24 to 1.25, indicating sustained potential for positive returns rather than negative returns. Sortino and Kappa-3 ratios demonstrated similar gains. The Calmar ratio increased from 0.33 to 0.51, but remained less than one, indicating that the enhanced returns after adding cryptocurrencies still did not outpace the largest drawdown of the portfolio, cautioning that, even although adding cryptocurrencies to a US equity-bond-cash portfolio enhanced its performance, the resulted portfolio remained vulnerable to drawdowns. Tail-risk measures (VaR-Sharpe and CVaR-Sharpe) also strengthened. Modified information ratios rose from 0.38 to 0.60, reflecting substantially greater excess return per unit of tracking risk.

Adding cryptocurrencies also had dramatic improvements in risk-adjusted performance on the max Sharpe ratio portfolio. What stands out is that the Sharpe ratio surged from 0.78 to 4.59, far higher than one, indicating an investable portfolio with greater excess returns compared with risk. Similarly, the Calmar ratio jumped from 0.48 to 2.98, well above one, - indicating that the returns after adding BTC and ETH outpaced the maximum drawdown.

The BL portfolio results also showed notable improvement in risk-adjusted performance resulting from including BTC and ETH. Turning points were on the Sharpe ratio, which increased from 0.62 to 1, demonstrating a robust and investable portfolio with balance between excess returns and risk. Similarly, the Sortino ratio increased from 0.91 to 1.46, above one, indicating greater upside relative to downside risk because of adding BTC and ETH. However, the Calmar ratio, although it increased from 0.30 to 0.57, remained less that one, also highlighting the fragility of the portfolio to substantial risk of drawdowns due to the high drawdowns observed in equities[103] which made a substantial part of the portfolio

To summarise, across all three portfolio types, cryptocurrencies were included at varying allocations. The integration of BTC and ETH consistently led to improved risk-adjusted returns compared with both the baseline portfolios (without cryptocurrencies) and the benchmark S&P 500.

(i) MVP: A small allocation (1%) to BTC and ETH resulted in a slight increase in overall portfolio risk but also produced moderate gains across key risk-adjusted performance metrics including the Treynor, Sharpe, Omega, Sortino, Kappa-3, Calmar, and modified information ratios.
(ii) Maximum Sharpe ratio portfolio: Raising the allocation to an average of 8% further increased portfolio risk, yet risk-adjusted returns improved more substantially, largely due to higher returns from cryptocurrencies.
(iii) Black-Litterman (BL) Portfolio: Allocating a moderate 4.7% to BTC and ETH within an equity-heavy portfolio produced a modest reduction in overall risk, while returns and risk-adjusted metrics also increased.

In all cases, BTC received a higher allocation than ETH. Over the period from September 2015 to December 2024 which included both stable and crisis periods BTC continued to dominate ETH in portfolio allocations, despite improvements in ETH's market efficiency. These findings set the

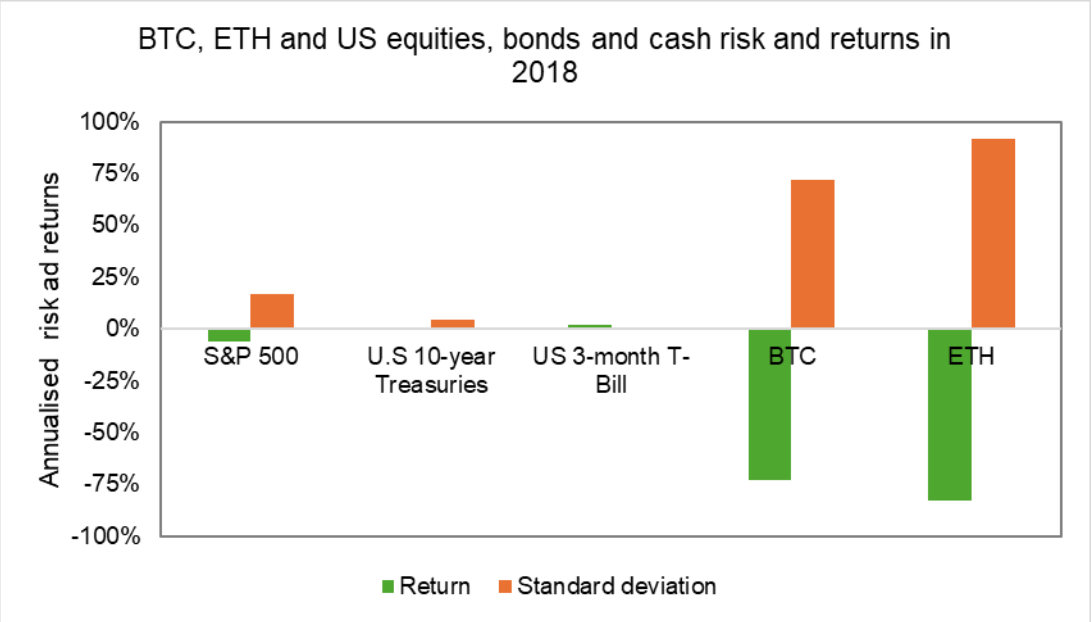
[103] US equities (S&P 500), at the peak of the Covid-19 crisis experienced drawdowns of 34% in March 2020

stage for the following sections, which examine how BTC and ETH performed during market crises and assess their roles in diversification and risk-adjusted performance.

7.4.4.1 Impact during the 2018 market crisis US-China trade dispute

In 2018, escalating trade disputes between the US and China culminated to poor performance of the S&P 500 as illustrated in Figure 7.13.

Figure 7.13: Risk and returns of BTC, ETH and US equities, bonds and cash in 2018 amidst US-China trade tensions



Computations were based on daily data from 1 January 2018 to 31December 2018. All returns are denominated in USD. Risk is defined as annualised standard deviation. Return refers to annualised return. Source: Author's computations with data sourced from Investing.com (2025) and US Treasury (2025).

The S&P 500 recorded annualised returns of -6.24% and volatility of 17.02%, signalling depressed performance. In the same year, the US 3-month T-bills was a haven, delivering positive annualised returns of 1.97%. The US 10-year Treasuries also managed to preserve value, delivering returns of 0.08% although its volatility remained higher at 4.66%, emphasising higher risk over returns. As a result, both MVP and max Sharpe ratio portfolios converged to the same asset allocation of S&P 500 (40%), bonds (50%) and cash (10%). Equity maintained its dominance in the US BL portfolio, with allocation of 66% (equity), 25% (bonds) and 9% (cash) in the baseline portfolios (asset allocation are detailed in Appendix 3).

In 2018, BTC and ETH had steep losses, with annualized returns of -73.12% and -82.57% respectively, wiping out much of their market value. Volatility was high, BTC at 72.02% and ETH at 91.57% highlighting the significant risks in cryptocurrencies. Holding these assets led to negative outcomes.

Table 7.11 details how BTC and ETH affected diversification and risk-adjusted portfolio performance in 2018. Panel A shows the frequency of inefficiency tests for BTC, ETH, and the S&P 500, highlighting the importance of diversification during this period. Panel B reports correlations between BTC, ETH, and three baseline portfolios, as well as risk and performance metrics before and after adding BTC and ETH. The S&P 500's performance is included as a standard benchmark for US portfolios.

Table 7.11: Impact of including BTC and ETH in a US equity-bond-cash portfolio during 2018 when equity markets were reeling under the US-China trade tensions

Panel A: The number of times variance ratio tests detected market inefficiency in BTC, ETH and the S&P500.

	Observed Returns				Corrected Returns			
	JS	JM	AVR	Ave	JS	JM	AVR	Ave
BTC	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
ETH	69.77%	6.04%	0.00%	25.27%	81.32%	32.42%	0.00%	37.91%
S&P 500	1.59%	0.00%	0.00%	0.53%	2.38%	0.00%	0.40%	0.93%

Observed returns are the daily returns and thin trading corrected returns represents the returns after correcting for thin trading. JS, JM, AVR are the frequency with which the tests detected significant inefficiency using the Joint-Sign test, the Wild Bootstrap Test and the Automatic Variance Ratio test. Ave is the arithmetic average of the frequency with which tests detected significant inefficiency. Source: Author's computations with data sourced from Investing.com (2025) and US Treasury (2025).

Panel B: Diversification and risk-adjusted performance

Metric/Ratio	MVP	MVP*	Max Sharpe	Max Sharpe*	BL	Metric/Ratio	S&P 500
Correlation with BTC	0,06		0,06		0,09		0,11
Correlation with ETH	0,07		0,07		0,08		0,09
Standard Dev	6,93%	7,03%	6,93%	7,03%	11,20%	12,07%	17,02%
VaR_{95}	-11,56%	-12,23%	-11,56%	-12,21%	-20,45%	-20,88%	-32,81%
$CVaR_{95}$	-15,13%	-15,34%	-15,13%	-15,32%	-27,37%	-28,22%	-43,64%
Specific risk	3,65%	3,72%	3,65%	3,73%	3,14%	8,27%	0,00%
Treynor	-0,08	-0,10	-0,08	-0,10	-0,08	-0,23	-0,08
Sharpe	-0,41	-0,51	-0,41	-0,51	-0,46	-0,98	-0,48
Omega	1,03	0,99	1,03	1,00	0,99	0,82	0,94
Sortino	-0,61	-0,76	-0,61	-0,76	-0,64	-1,33	-0,63
Kappa - 3	-0,43	-0,54	-0,43	-0,54	-0,44	-0,94	-0,44
Calmar	-0,20	-0,26	-0,18	-0,20	-0,19	-0,53	-0,41
VaR -Sharpe	-0,24	-0,29	-0,24	-0,29	-0,25	-0,57	-0,25
CVaR - Sharpe	-0,19	-0,23	-0,19	-0,23	-0,19	-0,42	-0,19
Modified Information	-0,25	-0,32	-0,25	-0,32	-0,81	-1,05	N?A
Modified Sharpe	-0,42	-0,53	-0,42	-0,53	-0,48	-1,06	-0,50

*The S&P is regarded as the market and therefore specific risk and modified information are not applicable. Daily data from January - December 2018 was used. MVP, Max Sharpe and BL refer to the Minimum variance portfolio, maximum Sharpe portfolio and the Black Litterman portfolio. * Means that the portfolio includes cryptocurrency. Source: Author's computations with data sourced from Investing.com (2025) and Iress (2025).*

Panel A results exhibited varying levels of market efficiency during the year 2018 as markets entered a crisis. BTC maintained strong levels of efficiency with none of the tests detecting market inefficiency. The S&P 500 also exhibited strong levels of efficiency with less than a percentage of returns showing market inefficiency. ETH market efficiency was weak with the JS and JM test detecting inefficiency in 81.32% and 32.42% of thin trading corrected returns.

Pane B results indicate diverse results ranging from correlation, risk measures and risk-adjusted performance. Regarding correlation, the results indicated that ETH and BTC returns were weakly correlated with the default portfolios. Correlations coefficient ranged between 0.06 and 0.09, suggesting modest diversification potential. This study found that as this crisis unravelled there were no material differences in diversification potential between BTC and ETH and across the three portfolios despite ETH showing signs of weak market efficiency.

The large drawdowns and high volatility of cryptocurrencies had negative ramifications on diversification and risk-adjusted performance of BTC and ETH across the MVP, max Sharpe ratio and the BL portfolios.

Adding 1% of BTC and ETH in the MVP (0.84% BTC and 0.16% ETH) as well as the max-Sharpe ratio (1% BTC) resulted in modest increases in all risk measures. Notably, specific risk also increased from 3.65% to 3.72% in the MVP and 3.73% in the max-Sharpe ratio portfolio, indicating weakened diversification. Risk increases were much higher in the BL portfolio, which allocated close to 10% to cryptocurrencies, resulting in substantial increases in portfolio risk. The standard deviation, VaR_{95}, and $CVaR_{95}$ all increased from 11.20%, 20.45% and 27.37% to 12.07%, 20.88% and 28.22%, respectively. Yet, even at these levels, the risk remained below the S&P 500 risk measured by the standard deviation (17.02%), VaR_{95} (32.81%) and $CVaR_{95}$ (43.64%).

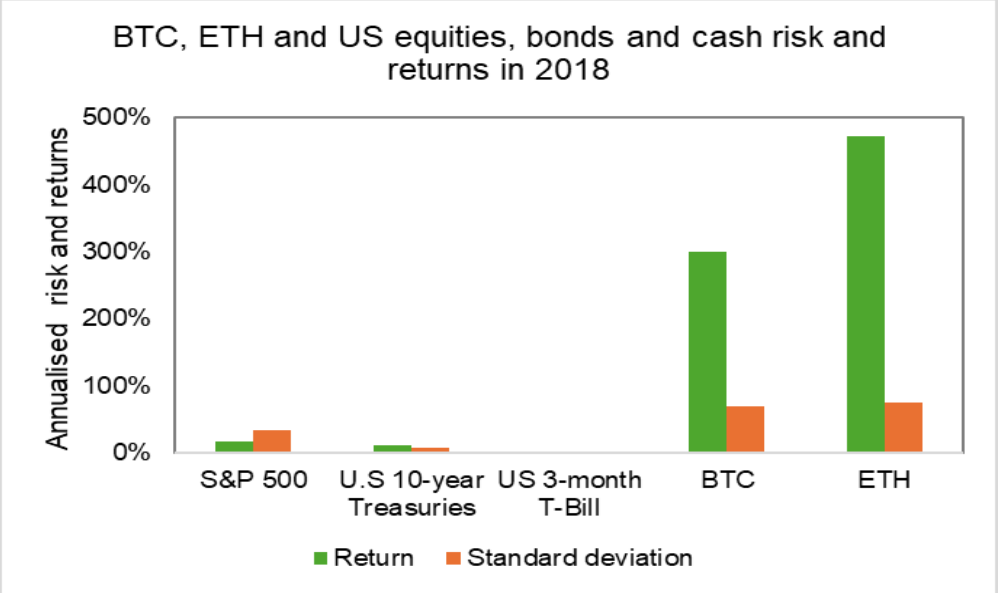
Regarding risk adjusted performance, the bloodbath faced by equities and cryptocurrencies further worsened portfolio performance. All the risk-adjusted performance measure in Table 7.11 indicated worse performance after including BTC particularly in the BL portfolio which had a higher exposure to equities and bonds which performed badly.

The overall results indicated that, during 2018, when US equity markets entered a crisis amidst the US-China trade dispute, although BTC maintained strong levels of efficiency while ETH efficiency was weakened their severe decline enervated portfolio performance. Adding a small BTC and ETH to an equity-bond-cash modestly increased portfolio risk levels due to high risk levels and degraded risk-adjusted performance due to outsized negative returns. The next section explores performance during 2020, the year markets entered crisis induced by the Covid-19.

7.4.4.2 Impact during the 2020 Covid-19 induced market crisis

The onset of the Covid-19 pandemic triggered profound volatility in US equity markets. At the height of the crisis, the S&P 500 index experienced a dramatic decline of 33.93%, falling from 3,386.2 points on 19 February 2020 to 2,237.4 points on 20 March 2020. However, the market began to recover over the subsequent months, and by 18 August 2020, the S&P 500 had rebounded to 3,389.80 points. By the close of 2020, the index had fully recuperated, posting an impressive, annualised return of 16.12% for the year. This sequence of events demonstrated that the market shock-like behaviour induced by the Covid-19 crisis was abrupt yet temporary, with a rapid recovery occurring within the same calendar year. Figure 7.14 presents the risk and return profiles of BTC, ETH, US equities, bonds, and cash during 2020.

Figure 7.14: Risk and returns of BTC, ETH and US equities, bonds and cash in 2020 when markets entered a crisis induced by the Covid-19 pandemic



Computations were based on daily data from 1 January 2020 to 31December 2020. All returns are in USD. Risk is defined as annualised standard deviation. Return refers to annualised return. Source: Author's computations with data sourced from Investing.com (2025) and US Treasury (2025).

In 2020, BTC and ETH recorded high annualised returns at 299% and 472%, respectively. In contrast, the S&P 500 (16.12%), 10-year Treasuries (10.69%), and the 3-month T-Bill (0.36%) delivered comparatively lower returns. Despite elevated risk levels associated with BTC (68.47%) and ETH (75.37%) versus the S&P 500 (34.36%), 10-year Treasuries (8.38%), and SA 910-day T-bills (0.53%), both cryptocurrencies provided superior returns per unit of risk. Consequently, they emerged as compelling investment options for individuals seeking to optimise risk and returns.

Table 7.12 presents the impact of adding BTC and ETH on investment portfolios' diversification and risk-adjusted performance. First, Panel A details the frequency with which BTC, ETH, and the S&P 500 were identified as inefficient, offering context for portfolio outcomes within the market efficiency framework under stressed equity conditions. Panel B outlines the correlations among BTC, ETH, and the baseline portfolios, along with risk and risk-adjusted performance metrics for including BTC and ETH in three investment portfolio; MVP, max Sharpe ratio and the BL portfolio. For benchmarking purposes, the S&P 500 performance during the same periods was also included, facilitating meaningful comparisons against a recognised market standard.

Table 7.12: Impact of including BTC and ETH in a SA equity-bond-cash portfolio during the Covid-19 market downturn in 2020

Panel A: The number of times variance ratio tests detected market inefficiency in BTC, ETH and the ALSI metric

	Observed returns				**Thin trading corrected returns**			
	JS	JM	AVR	Ave	JS	JM	AVR	Ave
BTC	80.55%	0.00%	0.00%	26.85%	9.04%	0.00%	0.00%	3.01%
ETH	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
S&P 500	82,14%	2,38%	0,00%	28,17%	81,35%	0,00%	0,79%	27,38%

Observed returns are the daily returns and thin trading corrected returns represents the returns after correcting for thin trading. JS, JM, AVR are the frequency with which tests detected significant inefficiency. Ave is the arithmetic average of the frequency with which tests detected significant inefficiency. Source: Author's computations with data from Investing.com (2025).

Panel B: Diversification and risk-adjusted performance

Metric/Ratio	**MVP**	**MVP***	**Max Sharpe**	**Max Sharpe***	**BL portfolio**	**BL portfolio***	**JSE ALSI**
Correlation with BTC	0.16		0.16		0.18		0.21
Correlation with ETH	0.27		0.27		0.28		0.30
Standard Dev	16.71%	16.72%	16.71%	19.16%	18.84%	18.97%	30.38%
VaR_{95}	-22.89%	-22.23%	-22.89%	-22.35%	-24.80%	-21.98%	-39.46%
$CVaR_{95}$	-44.80%	-44.64%	-44.80%	-49.14%	-50.20%	-48.96%	-78.45%
Specific risk	6.15%	5.99%	6.15%	8.68%	4.74%	7.56%	0.00%
Treynor	0.04	0.10	0.04	0.91	0.02	0.57	-0.00
Sharpe	0.12	0.30	0.12	2.67	0.08	1.73	-0.01
Omega	1.18	1.20	1.18	1.36	1.16	1.36	1.05
Sortino	0.35	0.90	0.35	8.95	0.22	4.58	-0.03
Kappa - 3	0.09	0.24	0.09	2.00	0.06	1.24	-0.01
Calmar	0.09	0.23	0.09	2.14	0.06	1.52	-0.01
VaR -Sharpe	0.09	0.23	0.09	2.29	0.06	1.49	-0.01
CVaR - Sharpe	0.04	0.11	0.04	1.04	0.03	0.67	-0.00
Modified Information	0.12	0.32	0.12	3.22	0.11	2.18	NA
Modified Sharpe	0.12	0.30	0.12	2.67	0.08	1.73	-0.00

The JSE ALSI is regarded as the market and therefore metrics such as specific risk and modified information are not applicable. Daily data from 1 January 2020 to 31 December 2020 was used. MVP, Max Sharpe and BL refer to the Minimum variance portfolio, maximum Sharpe portfolio and the Black Litterman portfolio. Asterisks (*) means that the portfolio includes cryptocurrency. Source: Author's computations from data sourced from Investing.com (2025) and US Treasury (2025).

The findings indicated that in 2020, during the Covid-19 crisis, BTC exhibited decreased market efficiency, with an average of 3.01% of returns deemed inefficient, contrasting with no detected inefficiency in prior years such as 2018 and 2019 (see Figure 7.2). The JS tests revealed that over 80% of BTC observed returns were inefficient; however, after adjusting for thin trading, only 9.04% remained inefficient. These results suggested that the pandemic period had a considerable impact on BTC's efficiency. In contrast, ETH maintained its efficiency throughout 2020, with all three market efficiency tests indicating no inefficiency. The existing literature does not provide a clear explanation for ETH's resilience. Based on the change in BTC's efficiency after accounting for thin trading, it is conjectured that ETH's stability may be partially attributed to increased traction from the rise of decentralised finance (DeFi), which could have supported its efficiency during the crisis.

In terms of diversification, BTC, which was becoming inefficient, was moderately correlated with the baseline portfolios. Its correlation with the MVP, max Sharpe ratio portfolio and the BL portfolio was between 0.42 and 0.45. ETH, which maintained strong levels of efficiency, was also correlated with the three portfolios within a similar range of 0.42 to 0.46, showing no material differences. These correlations were comparable to the correlation between BTC and ETH and the S&P 500 of 0.41.

These moderate correlations led to modest increase portfolio risk across all three portfolio allocation strategies when relatively more risky cryptocurrencies were added in portfolios. Under the MVP, a 1% allocation to BTC resulted in minor increases in risk. Standard deviation, VaR_{95}, $CVaR_{95}$ and specific risk all increased from 14.17%, 15.61%, 31.15% and 8.35% to 14.44%, 15.85%, 31.90% and 8.42%, respectively. Risk increases were much higher in the max Sharpe ratio, which allocated 10% to ETH. The BL portfolio, which allocated substantial portfolio to BTC (5.29%) and ETH (4.71%), experienced notable risk decreases. Total risk dropped from 27.48% to 23.80%, while VaR_{95} and $CVaR_{95}$ declined from 40.86% and 69.25% to 31.30% and 57.96%, respectively, indicating improved downside protection. These risk reductions were mainly because, unlike the baseline MVP and the max Sharpe ratio portfolios, the BL portfolio had a greater equity weighting.[104] Regardless of portfolio allocation to cryptocurrencies, all the portfolios had lower risk than the S&P500, whose standard deviation (34.36%), VaR_{95} (53.31%), $CVaR_{95}$ (87.95%) of the S&P 500 were higher than for all baseline portfolios, including after adding BTC

[104] The MVP and max Sharpe ratio allocations were 40%, 50%, and 10% to the S&P 500, US 10-year Treasuries, and the US 3-month T-Bill, respectively Meanwhile the BL portfolio allocations were 80%, 10%, and 10% to the S&P 500, US 10-year Treasuries, and the US 3-month T-Bill, respectively.

and ETH. This demonstrated that, although adding cryptocurrency increased risk, the risk levels remained lower than that of the S&P 500 the market benchmark.

The results underscore that the introduction of cryptocurrencies into investment portfolios yielded varied impacts on risk levels, largely dependent on the underlying portfolio structure. In portfolios oriented towards risk aversion and notably composed of lower-risk assets like bonds, the addition of BTC and ETH resulted in an increase in overall risk, with higher allocations amplifying this effect. Conversely, for portfolios heavily weighted towards equities, incorporating BTC and ETH can reduce total portfolio risk, especially during periods marked by heightened equity market volatility, such as the Covid-19 crisis. This highlights the context-dependent nature of diversification benefits when integrating cryptocurrencies into traditional investment strategies.

During 2020, BTC and ETH experienced outsized gains even after adjusting for risk. Thus, including them dramatically enhanced risk-adjusted returns across all three portfolios. Notable improvements were the Sharpe ratios and Calmar ratios. Under the MVP, allocating 1% of BTC to the portfolio, although improving the risk-adjusted performance, still left the portfolio fragile. The Sharpe ratio increased from 0.46 to 0.66 — higher than the S&P 500's 0.46 but still lower than 1, implying that risk was still larger than returns. Similar observations were noted based on the Calmar ratio.

By contrast, adding 10% ETH in the max Sharpe ratio portfolio and a combined 10% in BTC and ETH in the BL portfolio had far-reaching performance implications. Under the max Sharpe ratio portfolio, the Sharpe improved from 0.46 to 2.88, while the Calmar also increased from 0.47 to 3.08. This demonstrated that higher allocation to BTC, while introducing elevated risks, still resulted in a much more robust portfolio, emphasising better returns than risk, which has outpaced the maximum drawdown the portfolio suffered during the year. Similar results we also noted under the BL portfolio as the Sharpe and Calmar ratios both increased from 0.46 to 1.99 and 2.12, respectively.

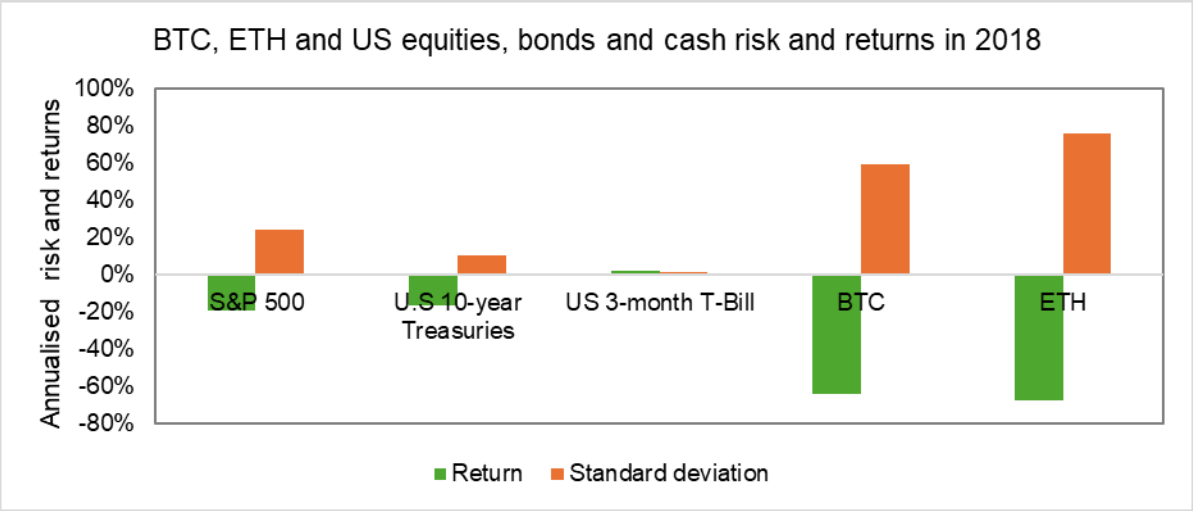
The overall results illustrated that, in 2020, US equity markets faced a Covid-19-induced crisis during which BTC' efficiency was weakening while ETH stayed largely efficient. BTC had modest correlations with US portfolios composed of equity-bonds-cash, offering limited diversification. For risk-averse MVP investors, a small allocation (1%) to BTC increased overall risk due to BTC's volatility, but improved risk-adjusted returns on account of higher BTC returns. Larger allocations (10%) in the max Sharpe ratio portfolio elevated risk, but enhanced risk-adjusted performance. Adding 10% in an equity-heavy portfolio modestly reduced risk and improved risk-adjusted results.

7.4.4.3 Impact during 2022 at the start of the Russia-Ukraine conflict

When Russia initiated its military action in Ukraine on 24 February 2022, US equity markets initially experienced a modest uptick. On 24 February 2022, the S&P 500 stood at 4,288.7 points, rising to 4,384.65 points the very next day. However, in the ensuing months, the index steadily declined, closing the year at 3,839.50 points. This downward trend was driven by several factors, some directly related to the conflict, such as disruptions in supply chains, rising energy prices, and increased geopolitical uncertainty causing broader macroeconomic impacts that weighed on the market — and others tied to economic measures following the 2020 Covid-19 crisis, like interest rate cuts (Maurya *et al*., 2023).

Though the Russia–Ukraine conflict continued beyond 2024, its immediate effects on the S&P 500 diminished, with the index recording annualised returns of 24% in 2023. Figure 7.15 presents the annual risk and return profiles for US equities, bonds, cash, and cryptocurrencies (BTC and ETH) in 2022, a period marked by significant strain on the US equity market due to the ongoing conflict.

Figure 7.15: Risk and returns of BTC, ETH and US equities, bonds and cash in 2022 when markets fell amidst the Russia-Ukraine conflict



Computations were based on daily data from 1 January 2022 to 31 December 2022. All returns are in USD. Risk is defined as annualised standard deviation. Return refers to annualised return. Source: Author's computations with data sourced from Investing.com (2025) and US Treasury (2025).

During the equity market crisis of 2022, the US 3-month Treasury bills stood out as a stable investment choice, yielding modest annualised returns of 2.07% and carrying a relatively low annualised risk of 1.53%. By contrast, US Treasuries underperformed, posting negative returns of -16.59%. This decline was driven by rising yields, which increased from 1.63% at the beginning of 2022 to 3.88% at year-end, reflecting efforts to counter inflationary pressures that followed the

Covid-19 crisis. The S&P 500 experienced one of its worst performances in years, recording annualised returns of -19.44%. This significant decline was indicative of the broader market struggles during the onset of the Russia–Ukraine conflict. The environment was even more challenging for major cryptocurrencies. Both BTC and ETH suffered substantial losses, with annualised returns of -64.12% and -67.37%, respectively. These pronounced negative returns highlighted the heightened sensitivity and risk exposure of cryptocurrencies during periods of geopolitical crises and macroeconomic stress.

In sum, the year 2022, marked by the beginning of the Russia–Ukraine conflict, exerted a profound impact on US equities and bonds, and resulted in considerable underperformance for BTC and ETH. The observed trends underscore the vulnerability of both traditional and cryptocurrencies to external shocks and crisis conditions.

To provide a comprehensive understanding of how adding BTC and ETH to a US equity-bond-cash portfolio influenced diversification and risk-adjusted performance amidst the market crisis of 2022, Table 7.13 is presented below. Panel A details the proportion of instances in which BTC, ETH, and the S&P 500 exhibited market inefficiency throughout the year. Understanding market efficiency is integral for situating subsequent portfolio analyses within the broader context of portfolio performance, especially during periods of market crisis. Panel B first reports the correlations between BTC, ETH and the baseline portfolios. Second, it provides a comprehensive view of how adding BTC and ETH in a portfolio alters the risk profile. Finally, Panel B explores how risk-adjusted performance measures before and after including BTC and ETH change. This panel also presents comparative metrics for the S&P 500, as the index serves as a key benchmark for evaluating portfolio performance. This comprehensive presentation allows to clearly compare and contextualise portfolio outcomes against the background of market efficiency.

Table 7.13: Impact of including BTC and ETH in a US equity-bond-cash portfolio during the Russia-Ukraine induced market crisis during 2022

Panel A: The number of times variance ratio tests detected market inefficiency in BTC, ETH and the S&P 500.

	Observed returns				**Thin trading corrected returns**			
	JS	JM	AVR	Ave	JS	JM	AVR	Ave
BTC	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
ETH	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
S&P 500	21,43%	9,92%	0,00%	10,45%	67,86%	14,29%	36,11%	39,42%

Observed returns are the daily returns and corrected returns represents the returns after correcting for thin trading. JS, JM, AVR are the frequency with which the tests detected significant inefficiency using the Joint-Sign test, the Wild Bootstrap Test and the Automatic Variance Ratio test. Ave is the arithmetic average of the frequency with which tests detected significant inefficiency. . Source: Author's computations from data sourced from Investing.com (2025)

Panel B: Diversification and risk-adjusted performance

Metric/Ratio	MVP	MVP*	Max Sharpe	Max Sharpe*	BL	BL*	S&P 500
Correlation with BTC	0,48		0,48		0,54		0,55
Correlation with ETH	0,50		0,50		0,58		0,59
Standard Dev	12,68%	12,79%	12,68%	12,97%	16,88%	17,54%	24,13%
VaR_{95}	-18,83%	-18,84%	-18,83%	-18,78%	-27,05%	-28,16%	-41,65%
$CVaR_{95}$	-24,22%	-24,92%	-24,22%	-24,88%	-35,96%	-38,18%	-53,13%
MVaR	55,91%	64,63%	54,61%	116,90%	48,60%	99,22%	47,65%
Specific risk	6,99%	6,67%	6,99%	6,85%	3,79%	3,24%	0,00%
Treynor	-0,19	-0,20	-0,19	-0,20	-0,21	-0,22	-0,2151
Sharpe	-0,65	-0,70	-0,65	-0,69	-0,84	-0,89	-0,8915
Omega	0,84	0,83	0,84	0,83	0,88	0,86	0,8811
Sortino	-0,96	-1,01	-0,96	-1,02	-1,18	-1,23	-1,2285
Kappa - 3	-0,74	-0,77	-0,74	-0,78	-0,89	-0,93	-0,9294
Calmar	-0,60	-0,64	-0,53	-0,52	-0,51	-0,70	-0,8460
VaR -Sharpe	-0,44	-0,47	-0,44	-0,48	-0,52	-0,55	-0,5165
CVaR - Sharpe	-0,34	-0,36	-0,34	-0,36	-0,39	-0,41	-0,4048
Modified Information	-0,57	-0,63	-0,57	-0,64	-1,74	-2,11	N/A
Modified Sharpe	-0,65	-0,70	-0,65	-0,69	-0,88	-0,94	-0,9621

*Minimum variance portfolio (MVP), maximum Sharpe ratio portfolio (Max Sharpe), and the Black-Litterman portfolio allocation (BL portfolio). *The portfolio includes BTC and/or ETH. Source: Author's computations from data sourced from Investing.com (2025) and Iress (2025).*

Panel A shows that, during the Russia–Ukraine crisis of 2022, both BTC and ETH maintained strong levels of market efficiency, even though their returns were substantially negative. In contrast, the S&P 500 experienced enervated efficiency as detected by all three VR tests. These results highlighted that the returns of BTC and ETH can undergo substantial declines while still retaining differing strengths of efficiency in the market. Similarly, the S&P 500, although not maintaining comparably strong levels of efficiency, still let its performance (in terms of returns) edge BTC and ETH, despite their stronger levels of efficiency. This result serves as a reminder not to misconstrue market efficiency with better returns.

In addition to the observed high levels of efficiency, Panel B indicates that BTC and ETH exhibited substantial correlations with the baseline portfolio, with correlation coefficients ranging from 0.48–0.54 for BTC and 0.50–0.58 for ETH. These findings suggest that, in 2022, the inclusion of BTC and ETH in a portfolio may have offered limited diversification benefits compared with historical levels (Figure 7.4).

Further analysis of the impact on the baseline portfolio[105] performance results showed that allocating 1% of the MVP to BTC modestly increased portfolio risk. Portfolio standard deviation edged upward from 12.68% to 12.69%. Meanwhile, the VaR_{95} and $CVaR_{95}$ saw minor increases, moving from 18.33% and 24.22% to 18.34% and 24.92%, respectively. Specific risk, however, declined slightly from 6.99% to 6.67%. Allocating 1% of the max Sharpe ratio portfolio led to similar results of modest increases in portfolio risk and minor decline in specific risk. These findings indicated that, despite BTC's inherently high risk, a small allocation brought modest improvements to the risk profile of a risk-averse MVP and risk-optimising max Sharpe ratio portfolio.

Incorporating modestly higher allocation to BTC (1.50%) and ETH (0.66%) into a BL portfolio with heightened equity exposure yielded higher portfolio risk. The standard deviation declined from 16.88% to 17.54%, while both VaR_{95} and $CVaR_{95}$ increased from 27.05% and 35.96% to 28.16% and 38.18%, respectively. However, specific risk declined modestly from 3.79% to 3.24%, attributable to higher market risk and lower Beta between the market and the BL portfolio returns. These results suggested that, in portfolios with higher exposure to risky equities (S&P 500), a small allocation (1–2%) to BTC and ETH, while it caused modest risk to increase, especially during episodes of heightened correlations, diversifiable risk decreased, suggesting some improvements in diversification.

Given the large negative returns produced by BTC and ETH, incorporating the two cryptocurrencies to a portfolio of equity-bonds-cash resulted in worse risk-adjusted performances, especially because correlations were generally higher, leading to higher risk and thus poor risk-adjusted performance across all three portfolios. The next section summarises the results for the impact of BTC and ETH on US portfolios.

7.4.4.4 Summary of the impact of cryptocurrencies on US equity-bond-cash portfolios

This section explored the impact of adding BTC and ETH across three US equity-bond-cash baseline portfolios. The baseline portfolios were constructed using the MVP, max Sharpe ratio and the BL portfolio allocation strategies representing diverse investor attributes. The analysis was split into two; the long-term horizon covering the full observation window 2015–2024, and secondly, in specific windows (calendar years) when US equity markets entered a crisis: 2018, 2020 and 2022. The results showed that, in the long term (full observation window), BTC

[105] The baseline portfolio was structured as follows: MVP and max Sharpe ratio allocations - 40% (S&P 500), 50% (US 10-year Treasuries), and 10% (US 3-month T-Bill). Meanwhile, the BL portfolio allocations were 66% (S&P 500), 24% (US 10-year Treasuries), and 10% (US 3-month T-Bill).

remained strongly efficient, experiencing intermittent disturbances in efficiency, notably during 2020 when the Covid-19 crisis was felt through most major markets. By contrast, ETH became more efficient, especially after 2019, when it remained efficient, albeit fluctuating, showing periods of strong efficiency followed by periods of weakening market efficiency.

In all three portfolios, BTC, which remained relatively more efficient, accounted for a larger allocation than ETH. For the MVP, BTC accounted for 95% of the allocation, 60% for the BL portfolio and 56% for the max-Sharpe ratio. This showed that, although ETH has become efficient, BTC continues to be a robust choice to a diverse range of investors and is particularly a 'less risky' choice for risk-averse investors.

The MVP results showed that allocating a small portion (1%) of the portfolio to BTC and ETH modestly trimmed overall portfolio volatility, tightened tail-risk and marginally reduced diversifiable risk while boosting Treynor, Sharpe, Omega, Sortino, Kappa-3, Calmar, and modified information ratios. In contrast, the max-Sharpe ratio portfolio suggested higher allocation averaging 8%, while the BL portfolio suggested allocations of 4.8% - midway between the MVP and the max Sharpe ratio portfolio allocations. The relatively higher allocations to BTC and ETH of the max-Sharpe ratio and the BL portfolios led to increased portfolio standard deviation and diversifiable risk due to the inherently high risk in BTC and ETH. However, the increased exposure to cryptocurrencies, while it led to increased risk, it also enhanced portfolio returns due to outsized cryptocurrency returns resulting in higher Treynor, Sharpe, Omega, Sortino, Kappa-3, Calmar, VaR-Sharpe, CVaR-Sharpe and modified information ratios than for baseline portfolios and for the S&P 500.

In 2018, US equity markets entered a crisis compounded by the US–China trade dispute. While BTC maintained strong levels of efficiency, ETH was becoming efficient following its launch in 2015. Both BTC and ETH experienced severe declines leading to large negative returns. Allocating a small portion (1%) of an equity-bond-cash portfolio to BTC and ETH, while marginally lowering portfolio risk levels due to low correlation, degraded risk-adjusted performance due to outsized negative returns. Increased exposure to cryptocurrencies led to higher risk and worsened levels of risk-adjusted performance. Similarly, in 2022, at the onset of the Russia–Ukraine conflict, US equity markets also entered a crisis. Both BTC and ETH remained strongly efficient through 2022. However, allocating a small (1%) portion of the portfolio to BTC and ETH modestly increased risk due to the inherently higher volatility. In both geopolitical crises, BTC and ETH experienced outsized negative losses, therefore adding them to equity-bond-cash portfolios worsened risk-adjusted performances. By contrast, during the crisis induced by the Covid-19 health pandemic, BTC was becoming inefficient, while ETH remained largely efficient. For risk-averse (MVP) investors, a small (1%) portfolio allocation to BTC in an equity-bond-cash modestly reduced risk and enhanced risk-adjusted performance. Higher allocations of up to 10% for max

Sharpe ratio (ETH) and BL portfolio investors (BTC) increased risk levels and dramatically enhanced risk-adjusted performance.

7.5 Implications for portfolio management

The results showed that cryptocurrencies can play a significant role in investment portfolios, though their effects vary across portfolios composition, market conditions, crises and optimisation. In long-term horizons that span both upturns and downturns, the inclusion of cryptocurrencies increases portfolio volatility. The increased volatility is often accompanied by higher returns, which tends to improve risk-adjusted performance over the long term across diverse investment objectives. In this study, the impact of cryptocurrencies on portfolio dynamics was notable even at modest allocations of 1-2% for MVP, and more hefty allocation of averaging 5-8% for MVO and BL portfolios indicating that they can meaningfully alter returns and risks. MVO methods led to the highest exposures to cryptocurrencies and considerably better risk-adjusted returns compared with MVP and BL portfolios. The higher cryptocurrency exposure in the MVO and BL portfolios resulted in significantly elevated risks, particularly for the BL portfolios, because of their higher equity exposures. Investors should be mindful of these nuanced effects. While cryptocurrencies enhance risk-adjusted returns by augmenting returns potential, they also add considerable risk especially in high equity exposure portfolios, resulting in higher, but less stable (more volatile) portfolio returns.

Evidence indicates that while the inclusion of cryptocurrencies consistently increased risk, particularly for MVP, its impact on risk for MVO and BL portfolios was more nuanced. In certain scenarios, it reduced risks, especially in portfolios heavily weighted with equities, thereby demonstrating diversification benefits. Furthermore, due to their typically higher returns per unit of risk, incorporating a small proportion of cryptocurrencies enhanced the risk-adjusted performance across portfolios. This evidence supports the rejection of Hypothesis 2, concluding that under specific conditions, the inclusion of cryptocurrencies in a bond-equity-cash multi-asset portfolio improved diversification outcomes and risk-adjusted performance.

The performance of cryptocurrencies also varied distinctly across different crises considered in this study, particularly in response to geopolitical or economic crises versus systemic market shocks. During geopolitical or economic crises, such as the China-US trade tensions and the Russia-Ukraine conflict, cryptocurrencies seem to become more efficient, as prices quickly reflect new information related to these political and economic developments. This heightened efficiency limits pricing anomalies and reduced the opportunity for abnormal returns. Moreover, during these crises, correlations between cryptocurrencies and both SA and US equities generally increase as both assets react to shared macroeconomic pressures, which reduces cryptocurrencies' value as portfolio diversifiers and undermines their suitability as safe haven assets. The combination of

higher efficiency and elevated correlations results in lower risk-adjusted performance, as there are fewer opportunities for gains, and the heightened volatility further constrains risk-adjusted returns relative to traditional assets.

It appears that during systemic market shocks, such as the Covid-19 crisis, expansive monetary policies like Quantitative Easing (QE) may alter the behaviour of cryptocurrencies. Central banks responded to the Covid-19 crisis with aggressive QE programmes that injected liquidity into financial systems, lowered borrowing costs, and boosted speculative interest in high-growth assets, including cryptocurrencies. This liquidity-driven environment led to greater inefficiency, as speculative trading and rapid capital influx generated more price anomalies and mispricing opportunities, which investors could exploit for abnormal returns. Initially (during the investigated crisis period), correlations between cryptocurrencies and equities spiked as both suffered significant negative returns. However, as the effects of QE took hold and markets began to recover, cryptocurrencies diverged from equities. This decoupling allowed investors to capitalise on the higher risk-adjusted performance of cryptocurrencies, especially during the recovery phase.

The unique behaviour of cryptocurrencies during the Covid-19 crisis highlights the influence of QE on markets, as the liquidity injection initially pushed all asset prices upward, driving correlations with equities higher. However, as liquidity became ample and markets stabilised, cryptocurrencies began to decouple from equities. Further research is, however, needed to determine if this behaviour holds consistently in similar types of systemic market shocks, as this relationship may vary across various geographical markets depending on the specific nature and scale of central bank interventions.

When focusing on the distinct behaviours of cryptocurrencies during crisis periods, the patterns suggest that, while they can enhance returns during certain crises, their inherent volatility and varying correlations with traditional assets (predominantly equities) prevent them from serving as reliable safe-haven assets across all crises. During the geopolitical US–China trade dispute and the Russia–Ukraine conflict that were evaluated, cryptocurrencies, especially BTC, exhibited high efficiency and stronger correlations with equities, which can limit their portfolio diversification value. By contrast, in systemic shocks like the Covid-19 crisis, expansive monetary policies such as QE seem to alter cryptocurrency behaviour (specifically BTC and ETH), leading to inefficiencies and increased return potential as liquidity boosts speculative interest in high-growth assets.

The evidence regarding the influence of cryptocurrencies on diversification and portfolio performance during crises challenges Hypothesis 3, which posits that crisis-induced variations in cryptocurrency market efficiency do not affect their diversification properties or their contribution

to portfolio performance. It appears that during crises, when market efficiency remains unaltered, opportunities for superior returns are limited, as trades are predominantly driven by informed investors. Under these circumstances, cryptocurrencies do not provide diversification value nor enhance risk-adjusted returns. Instead, price crashes diminish performance, highlighting their inherent riskiness. However, in crises where efficiency breaks down, there are opportunities to achieve abnormal profits and alter diversification and risk-adjusted performance, particularly in portfolios with less equity exposure, such as the MVO and BL portfolios, which allow for greater risk tolerance than the MVP. The evidence suggests rejecting Hypothesis 3 and concluding that crisis-driven variations in cryptocurrency market efficiency do influence their diversification properties and their contribution to portfolio performance.

As a result, approvals of cryptocurrency trading, especially for regulated entities or in banned jurisdiction could open new possibilities for enhancing risk-adjusted performance, particularly in long-term investments. For SA investors, the inclusion of cryptocurrencies could offer alternative investment options that would be especially valuable to investors seeking exposures beyond equity, bonds and cash to improve potential returns options. US investors, likewise, could benefit from incorporating cryptocurrencies in strategic allocations, especially as regulatory frameworks become more accommodating to their inclusion. However, it is important to note that, in this study, BTC and ETH always exhibited inherent high risk and some level of correlation with other assets and were susceptible to increasing overall risk in equity-bond-cash portfolios at higher allocations; as such, they are a less reliable hedge or safe haven tool.

In summary, while cryptocurrencies provide a dynamic asset class that can enhance returns potential under certain conditions, their impact on portfolio risk and limited diversification benefit require careful consideration within an investment portfolio, particularly during crisis periods.

7.6 Summary

This chapter utilised three variance ratio tests to assess the market efficiency of the two largest cryptocurrencies, Bitcoin (BTC) and Ethereum (ETH), which combined, account for 70% of the total cryptocurrency market capitalisation by December 2024. The tests used daily data from January 2015 to December 2024, with a 500-day fixed-length rolling subperiod window to capture how cryptocurrency efficiency evolved over the timeframe. Equity indices from three developed markets, namely, US (S&P 500), UK (FTSE 100) and Japan (Nikkei 225) and three developing markets SA (FTSE/JSE ALSI), China (SSE), and Indica (BSE Sensex) contextualised the analysis, providing efficiency benchmarks. The tests were performed on both observed returns and returns corrected for thin trading (corrected returns) as thin trading may bias efficiency results, particularly in relatively newer and less frequently traded assets. The results revealed that BTC and ETH, like most major/established financial markets, experienced cycles of predictability (an

indicator and or characteristic of market inefficiency) followed by periods of non-predictability (an indicator and or characteristic of market efficiency), consistent with Lo's (2004) AMH. The S&P 500 was the most predictable index (as measured by average percentage of predictable returns), followed by ETH, while the least predictable (and therefore relatively more efficient) were BTC, followed by the SSE, FTSE 100, JSE ALSI, BSE Sensex and the Nikkei 225. The results demonstrate that from 2015 to 2024, the market efficiency of BTC and ETH was comparable to that of other equity indices and notably surpassed the efficiency levels observed in equity indices within SA and the US. The time-varying efficiency of BTC and ETH has significant implications for investment decision-making, demonstrating that these assets merit systematic investor attention. Their price-discovery processes exhibit adaptive efficiency dynamics comparable to those documented in major equity indices, reinforcing the view that cryptocurrencies increasingly operate as information-responsive markets.

This chapter further investigated the diversification capabilities of cryptocurrencies by examining their impact on portfolio performance and risk-adjusted returns both over a long period from September 2015 to December 2024 and during crisis periods. The study selected two distinct investment universes – local (SA) and global (US) – to evaluate how incorporating cryptocurrencies affects portfolio outcomes. Three portfolio strategies were considered: (i) a minimum variance portfolio, (ii) maximum Sharpe portfolio, and (iii) the market equilibrium portfolio. The cryptocurrencies BTC and ETH were added to baseline portfolios comprising equities, bonds and cash (using the three different portfolio strategies), in the two investment universes (SA and US). Correlation analysis between cryptocurrencies and the default portfolios as well as specific risk metrics were used to assess BTC and ETH's diversification capabilities. Additionally, selected risk-adjusted performance indicators were evaluated to assess the effect of adding cryptocurrencies to a default portfolio of equities, bonds, and cash. These default assets were represented by the FTSE/JSE All-Share Index, the FTSE/JSE All Bond Index and the 91-day Treasury Bills in the case of South Africa. For the US, the defaults assets were S&P 500 (equity), 10-year Treasuries (bonds) and 3-month Treasury-bills (cash).

The analysis was divided into two main sections, assessing cryptocurrency performance both in the long-term period from September 2015 to December 2024 and across three identified crisis periods: (i) the US-China trade dispute in 2018, (ii) the Covid-19-induced market crisis in 2020, and (iii) the Russia-Ukraine conflict in 2022. On over the long term, results showed that cryptocurrencies are becoming more efficient. Adding them in investment portfolios contributes to increased portfolio volatility, leading to less stable returns. However, this heightened volatility is generally accompanied by even higher returns leading to improved returns per unit of risk. As cryptocurrency markets continue to mature and exhibit greater efficiency, investors might view

them as valuable strategic assets to take advantage of is growth potential. In contrast, during crisis periods, the study revealed that the role of cryptocurrencies in investment portfolios changes depending on how their market efficiency and market conditions evolve. During crises when markets become less efficient, such as during the Covid-19 crisis, adding cryptocurrencies can increase portfolio risk but also improve risk-adjusted return performance - due to a more substantial increase in returns relative to the increase in risk. However, when market efficiency is restored during crises, as seen during the US-China trade tensions of 2018 and the Russia-Ukraine conflict (in 2022), incorporating cryptocurrencies into investment portfolios often results in lower risk-adjusted returns. In these cases, cryptocurrencies tended to underperform in terms of returns while maintaining high volatility, thereby increasing portfolio risk without the corresponding returns compensating increased risk. This outcome underscores the need for investors to monitor shifts in market efficiency closely, especially during crisis periods, to inform strategic decisions on inclusion of and allocation to cryptocurrencies.

In summary, while cryptocurrencies offer potential for enhanced returns, their role as a reliable diversification tool and safe-haven asset is limited. They consistently show some level of correlation especially with equity and bonds and increase portfolio risk in an equity-bond-cash portfolio, though they can improve risk-adjusted performance under specific conditions. Findings reveal distinct patterns based on crisis type: during geopolitical/economic crises like the China-US trade tensions of 2018 and Russia-Ukraine conflict (in 2022), cryptocurrencies exhibited higher efficiency and correlation with both SA and US equities, resulting in lower risk-adjusted performance and reducing their diversification value. In contrast, systemic shocks like Covid-19 led to lower efficiency, initially high but diverging correlations, and improved risk-adjusted performance due to exploitable mispricing and recovery-driven returns.

These patterns underscore that, while cryptocurrencies can be a dynamic addition to portfolios, they lack the consistency needed to act as reliable safe-haven assets across crisis types. Regulatory developments may may make it possible for various investors to gain exposure to cryptocurrencies and leverage on dynamic patterns to enhance risk adjusted performance. However, investors should monitor efficiency trends and market conditions closely, particularly during crises, to make informed and suitable/most appropriate investment portfolio decisions. The next chapter presents the study’s conclusions and recommendations.

CHAPTER EIGHT

CONCLUSIONS AND RECOMMENDATIONS

8.1 Summary and conclusions

This chapter summarises the key findings of the study, presents the resulting conclusions, and identifies potential avenues for further research emerging from the analysis.

The preceding chapters sought to address unresolved inquiries concerning the market efficiency of cryptocurrencies, their potential for diversification, and their influence on portfolio performance, particularly during periods of crisis. This investigation was motivated by the growing interest and discourse surrounding cryptocurrency investments, driven by their potential for high returns and diversification opportunities. Consequently, several strands of literature have emerged that characterise the properties of cryptocurrencies and the inherent risks, aiming to enhance understanding of their value as a unique and alternative investment asset. Despite the expansion of the literature, a gap persisted regarding the comparison of cryptocurrency market efficiency with that of other financial markets. Specifically, it remained unclear whether inefficiency periods in cryptocurrency markets were significantly prolonged or correlated with inefficiency episodes in other financial markets, and whether crisis periods materially affected the efficiency of cryptocurrency markets. Understanding the market efficiency of cryptocurrencies is crucial, as it offers insight into the conditions under which informed trading can enhance investment strategies, including the optimisation of asset allocations to improve overall portfolio performance.

To empirically assess the investment value of cryptocurrencies, it was imperative to conduct experimental evaluations of their impact on the performance and diversification of a conventional investment portfolio. This analysis was particularly crucial during periods of financial crisis, as asset correlations typically intensify during market distress, presenting a significant challenge for portfolio managers who must diversify their portfolios at critical junctures in the investment lifecycle. The uncertainty persisted regarding whether cryptocurrencies can sustain market efficiency under severe economic conditions and whether they can function as effective portfolio diversifiers during crisis periods. Consequently, this study aimed to address these unresolved questions and enhance the understanding of how the inclusion of cryptocurrencies in investment portfolios affects portfolio performance and diversification during times of market distress.

To answer these questions, the study, in Chapter 2, revisited the literature and explored what cryptocurrencies are, how they evolved and, importantly, explored their price dynamics and the risk associated with them. This contribution added to the broader discourse by emphasising that, although cryptocurrencies have gained significant attention over the past decade, their origins trace back to the 1980s. Early pioneers like Chaum (1983) advanced the field with innovations in

untraceable payment systems and cryptographic protocols, laying the groundwork for decentralised payment systems – the foundation of modern cryptocurrencies. It was established that there is no clear fundamental value of cryptocurrencies beyond the *value* of the security of an algorithm that records and verifies the validity of payments. The literature reviewed in Chapter 2 indicates that cryptocurrencies exhibit pronounced volatility, driven in part by sentiment-based trading, the relative immaturity of these markets, the concentration of holdings among large investors ("whales"), regulatory uncertainty, and vulnerabilities associated with cybercriminal activity. The high volatility is, however, often overlooked because of the exceptional returns that cryptocurrencies have generated in recent years. The study further noted that strong connectedness within cryptocurrency markets, with the largest assets by market capitalisation – BTC and ETH – more likely to transmit volatility shocks to others, thereby reducing the scope for effective hedging and diversification within the cryptocurrency ecosystem. Nonetheless, evidence of low correlation with traditional asset classes such as cash and bonds suggests that cryptocurrencies may still offer diversification benefits at the broader multi asset portfolio level.

This led Chapter 3 to examine a range of portfolio-management approaches to identify suitable strategies for integrating cryptocurrencies into investment portfolios. Chapter 3 reasoned that when constructing portfolios that include cryptocurrencies, optimal allocation frameworks—such as the minimum-variance portfolio (MVP) and the Black–Litterman (1990) methodology—are essential for determining asset weights. The maximum Sharpe ratio framework, although limited by issues such as allocation concentration, remains relevant because it directly operationalises the fundamental risk–return trade-off and continues to be widely adopted in both academic and practitioner settings. The chapter also reviewed risk and performance measurement techniques to identify metrics capable of assessing, without bias, whether cryptocurrency inclusion materially alters portfolio performance on a risk-adjusted basis. As the literature offers no consensus on a single preferred performance metric – owing to differing investment objectives, risk tolerances, and evaluative perspectives, the chapter selected three investment strategies (MVP, maximum Sharpe ratio, and Black–Litterman) to reflect diverse investor profiles, alongside a suite of performance measures capturing multiple dimensions of risk. Finally, the chapter noted that while the optimal rebalancing strategy remains context-dependent, there is broad agreement that prevailing market conditions play a critical role in guiding rebalancing decisions.

Since market conditions are most effectively understood through an assessment of a market's underlying efficiency, Chapter 4 was devoted to developing a deeper theoretical foundation for evaluating efficiency in cryptocurrency markets. The chapter identified the Adaptive Market Hypothesis (AMH) as an appropriate conceptual framework, offering a balanced position between the traditional Efficient Market Hypothesis (EMH) and the behavioural finance perspective. This

theoretical grounding was essential, as it established the lens through which the efficiency dynamics of cryptocurrencies could be meaningfully examined.

Chapter 5 explored various methodologies for evaluating market efficiency, with a particular emphasis on VR tests, which align with the AMH theory. Chapter 6 elaborated on the research methodology employed to systematically determine whether inefficiency episodes in cryptocurrency markets were significantly prolonged or related with inefficiency episodes observed in selected prominent equity indices across developed markets (the US, UK, and Japan) and developing markets (SA, China, and India). Additionally, it examined whether market efficiency deteriorates during crisis periods. Furthermore, Chapter 6 outlined the methodology used to assess the impact of evolving cryptocurrency market efficiency on portfolio performance and diversification capabilities during crisis periods. Chapter 7 applied this methodology to evaluate the evolving efficiency of cryptocurrencies and examined the effects of including them in a portfolio on diversification and risk-adjusted performance, both in the long term and during crisis periods.

Overall, the study does not claim to provide evidence of exploitable trading opportunities, and it does not test regime-triggered adaptive allocation. It instead provides evidence about how diversification benefits and risk exposures behave across informational regimes under institutional rebalancing constraints.

8.1.1 Findings and Conclusions: The market efficiency for cryptocurrencies

To understand the changing efficiency of cryptocurrencies, this study applied three approaches to variance ratio testing. These included: (i) the joint sign (JS) test (Belaire-Franch & Contreras, 2004; Kim & Shamsuddin, 2008), (ii) the wild bootstrap (JM) test (Kim, 2006), and (iii) the automatic variance ratio (AVR) test (Kim, 2009). The efficiency of the cryptocurrency market was assessed through successive subsamples derived from a 500-day rolling observation window, with data spanning January 2015 to December 2024. The findings revealed that both BTC and ETH exhibited time-varying efficiency patterns consistent with Lo's (2004) Adaptive Market Hypothesis (AMH). Initially, ETH demonstrated greater predictability; however, it transitioned to being less predictable by the final quarter of 2019. This progression in efficiency corroborates the assertions of Lo (2004), who posited that assets do not immediately attain efficiency. Since August 2019, the predictability of ETH returns has remained minimal. Notably, ETH has been relatively less predictable than the S&P 500, despite its status as a comparatively young asset.

BTC exhibited prolonged periods of unpredictability – indicative of higher efficiency – with a marked shift toward greater predictability around 2020, coinciding with the market disruptions associated with the Covid-19 pandemic. Such spikes in inefficiency were not unique to

cryptocurrencies; well-established equity indices, including the FTSE 100, Nikkei 225, JSE ALSI and BSE Sensex, also experienced varying degrees of inefficiency during 2020 as global financial markets reacted to the pandemic. Overall, the efficiency results showed that Bitcoin was generally less predictable than major equity indices such as the S&P 500 and JSE ALSI. Despite their relative youth, both BTC and ETH displayed efficiency levels comparable to – and in the case of Bitcoin, often exceeding those observed in several mature equity markets.

The analysis further demonstrated that although cryptocurrencies have become more efficient over time, their efficiency varies across crisis types. Cryptocurrencies tended to maintain efficiency during geopolitical crises that produced market drawdowns yet exhibited deteriorating efficiency during systemic crises such as Covid-19, which were associated with sharp price increases. These inefficiencies, however, are neither uniform nor pervasive; rather, they depend on the specific characteristics and transmission mechanisms of each crisis. Consequently, academics, investors and regulators should not dismiss cryptocurrencies as inherently inefficient assets, as their market behaviour reflects increasingly robust price-discovery processes. Moreover, as cryptocurrencies continue to mature and exhibit improving efficiency, investors and fund managers may find greater justification for adopting less active investment strategies when managing cryptocurrency exposures.

8.1.2 Findings and Conclusions: Portfolio performance of cryptocurrency

Given the evidence that cryptocurrencies – specifically BTC and ETH – exhibit time-varying efficiency similar to major equity indices, it became essential to evaluate how their contribution to portfolio performance is conditioned by prevailing efficiency regimes. Focusing on South Africa (local) and the United States (global), the study assessed how diversification benefits and portfolio outcomes change when cryptocurrencies are added to a traditional equity–bond–cash baseline. This assessment was conducted across three allocation strategies – MVP, maximum-Sharpe ratio, and Black–Litterman (BL) – to ensure robustness across distinct optimisation philosophies.

Importantly, the BL framework was implemented without subjective views, allowing expected returns to be anchored solely to market equilibrium. This provided a stabilised benchmark against which the diversification effects of emerging assets could be evaluated. The resulting insight is noteworthy: the BL findings reveal how equilibrium-based optimisation interacts with the inclusion of cryptocurrencies, demonstrating that their portfolio impact shaped not by Bayesian information-integration advantages, but by how these assets alter risk–return relationships.

The findings revealed that, over the long term (2015-2024), cryptocurrencies became more efficient and exhibited a low, but consistent, correlation with equity, bonds and cash. Adding them to a baseline portfolio of equity-bonds-cash increased total portfolio risk (as measured by standard

deviation), and unsystematic risk, suggesting a potential reduction in diversification benefits. However, this elevated risk was often accompanied by higher returns, improving risk-adjusted performance over the long term. The higher risk-adjusted returns when cryptocurrencies are included in a portfolio stemmed from the superior return-to-risk ratio cryptocurrencies possessed compared especially to equity and bonds. These findings were robust for MVP at modest allocations of up to 1-2% and maximum-Sharpe as well as BL portfolio allocations averaging 8% and 5–8%, respectively.

BTC constituted the majority of allocations, while allocations to ETH were generally lower for all portfolio strategies; demonstrating the robustness of BTC which had become more mature and had a relatively (to ETH) stable price volatility and lower correlations with equity, bonds and cash. Furthermore, cryptocurrency allocation to US portfolios were lower than the allocations to SA portfolios, demonstrating that BTC and ETH had a relatively more impactful role in SA portfolios than in the US. This was primarily because cryptocurrencies were less correlated with SA assets than they were with US assets.

Thus, in the South African context, these results, illustrate that adding cryptocurrencies enhanced risk-adjusted performance measures, present a case for reassessing Regulation 28, which currently restricts institutional investment in cryptocurrencies. Allowing for limited, regulated cryptocurrency exposure could give SA institutional equity-bond-cash investors opportunities to enhance their portfolio performance and earn higher risk-adjusted returns. In the US, evidence that adding cryptocurrencies to an equity-bond-cash portfolio improves its risk-adjusted performance underpins the SEC's approval of cryptocurrency ETFs, providing institutional investors with direct, regulated access to cryptocurrencies in a wide range of investment plans and helping them build more robust portfolios. Nonetheless, investing in cryptocurrencies carries the caveat of higher portfolio risk, and investors must be prepared to manage substantial losses when these risks materialise.

8.1.3 Findings and Conclusions: Cryptocurrency diversification capabilities in crisis periods

Cryptocurrencies offer nuanced diversification potential, as their inclusion in investment portfolios often increases both unsystematic and overall risk across time periods. While cryptocurrencies may enhance risk-adjusted performance, they do not offer consistent diversification benefits to equity-bond-cash portfolios, especially during crises.

In geopolitical and economic crises such as the China–US trade tensions (of 2018) or the Russia–Ukraine conflict (2022), cryptocurrencies exhibited heightened market efficiency. This efficiency was characterised by the ability of cryptocurrency prices to swiftly assimilate new information, demonstrating a rapid adjustment in market valuations.

However, the integration of cryptocurrencies into investment portfolios during these periods led to an increase in overall portfolio risk. The elevated risk was primarily a result of the inherent volatility of cryptocurrencies and their modest correlations with equities. This limited correlation undermined their capacity to provide effective diversification, a cornerstone of sound portfolio management. Moreover, cryptocurrencies experienced some of their worst drawdowns in terms of returns during these crises. Under such conditions, their persistent correlation with equities further reduced their potential as diversification tools. Consequently, investment portfolios that included cryptocurrencies during these periods tended to deliver diminished risk-adjusted performance, challenging the assumption that they could reliably enhance portfolio stability in the face of geopolitical and economic crises.

Conversely, during systemic shocks like the Covid-19 pandemic, cryptocurrencies exhibited lower efficiency, characterised by frequent mispricing and price anomalies. Initially, cryptocurrencies correlated strongly with equities as both assets experienced sharp declines, but as markets began to recover, cryptocurrencies diverged more from equities. This divergence and increased inefficiency can create opportunities for abnormal returns, which can in turn enhance risk-adjusted performance. However, the overall risk (as measured by portfolio standard deviation) associated with cryptocurrencies remains high, and they do not effectively mitigate unsystematic risk, highlighting the complex relationship between their risk and return when incorporated into portfolios.

The observed patterns can be interpreted in light of the broader literature on quantitative easing (QE) and global liquidity conditions. During systemic crises such as the Covid-19 pandemic, extensive QE programmes expanded liquidity and supported a rapid rebound in risk-asset valuations, including major cryptocurrencies. This liquidity backdrop coincided with elevated volatility and strong price recoveries, which in turn reduced the short-term co-movement between cryptocurrencies and equities, although the overall diversification benefits remained modest. By contrast, in geopolitical or economic crises where QE was absent, cryptocurrencies experienced deeper and more prolonged drawdowns and behaved in a manner consistent with greater information efficiency, with prices adjusting more rapidly to new information and offering fewer opportunities for mispricing. In these episodes, cryptocurrencies remained closely correlated with equity markets, limiting abnormal returns and providing little scope for diversification.

In summary, while cryptocurrencies may enhance returns during specific systemic disruptions, their modest correlation with equities, and inherently high volatility constrain their effectiveness as a reliable diversification tool. The inclusion of cryptocurrencies in investment portfolios, regardless of efficiency shifts, raised both unsystematic and overall risk, as cryptocurrencies lacked a stable inverse correlation with equities, bonds and cash assets. Ultimately, although they

may yield attractive returns under particular conditions, cryptocurrencies tend to elevate risk and offer limited diversification capacity, behaving more like equities than like a distinct asset class.

8.2 Contributions of the study

The contribution of this study is grounded in empirical evidence and contingent upon the specific empirical design employed. The thesis does not imply to demonstrate universal or causal enhancements in performance resulting from the inclusion of cryptocurrencies, nor does it assert the establishment of exploitable trading opportunities. Rather, it offers empirical evidence indicating that, within a static annual rebalancing framework and under the tested allocation constraints, diversification and risk-adjusted performance outcomes vary across estimated informational efficiency states, as examined under specific conditions of lag length. The findings are interpreted as regime-conditioned structural allocation effects rather than as evidence of tactical adaptation. Consequently, the study contributes to the literature by demonstrating that market efficiency is associated with the role of cryptocurrencies in portfolio diversification and risk-adjusted performance. This relationship coincides with market conditions in crisis or non-crisis periods. The present study offers multiple contributions to the field of finance and its sub-fields, including investment management, risk management, and portfolio theory, particularly in relation to cryptocurrencies:

(i) Theoretical Contribution

This study contributes to the finance literature by introducing a regime-dependent market efficiency framework that associates time-varying predictability with portfolio diversification benefits and risk-adjusted performance, thereby refining existing theories on market efficiency and portfolio theory. The proposed model reconciles previous conflicting findings by demonstrating that periods of market inefficiency enhance diversification gains during episodes of crisis. Additionally, it developed testable propositions to inform future theoretical advancements.

(ii) Methodological Contribution

This research applies and validates the AMH within cryptocurrency markets, demonstrating how market efficiency evolves during various crisis periods. By extending the AMH framework to emerging cryptocurrencies, this study not only broadens its application but also affirms its relevance in analysing the distinctive dynamics of cryptocurrency markets, thereby contributing to both theoretical understanding and practical application.

(iii) Empirical Contribution

Using a bi-country series of equity, bonds and cash returns spanning three major crises, the study provides systematic evidence that crisis-detected market inefficiency is a practically useful signal

for improving portfolio diversification and risk-adjusted performance. At best cryptocurrencies are diversifiers and they do not show any safe have or hedging benefits.

(iv) Practical Contribution

The findings deliver actionable guidance for investors and portfolio managers by presenting a regime-aware asset allocation rule that enhances diversification and risk-adjusted performance. The rule is implementable with standard data inputs and requires only moderate increases in monitoring frequency.

(v) Contribution to Policy and Regulation

The study informs regulators that the inclusion of a modest allocation of cryptocurrencies in investment portfolios may enhance diversification and improve risk-adjusted returns. It suggests that regulatory asset allocation frameworks should consider incorporating cryptocurrencies as an alternative asset, particularly to diversify the investment mix during periods of market dislocations. However, the high risk associated with cryptocurrencies necessitates cautious integration into institutional portfolios. The empirical results demonstrate that, under certain conditions, a cryptocurrency exposure of between 1-2% in South Africa reduces downside risk metrics, whereas in the United States, even a 1% allocation may increase portfolio risk and weaken diversification. Within the evaluated sample and under annual rebalancing constraints, an intermediate allocation level of up to 1-5% in the United States and 2-8% in South Africa is likely to enhance risk-adjusted performance under specific conditions, balancing risk and returns for investors who can tolerate risk. These findings are contingent upon the estimation period and modelling assumptions and are presented as empirical input to regulatory discussions rather than prescriptive policy directives.

8.3 Limitations of the study

This study had several limitations that affected the generalisability and widespread applicability of the findings. These are detailed below:

(i) Data source variability

Variations in data sources pose a risk of bias, as different data providers can yield inconsistent price and market data. Different data providers may apply distinct timestamp conventions, data-cleaning rules, smoothing algorithms and sampling intervals, which may result in different price data. This discrepancy may affect the precision of the assessments regarding cryptocurrency performance and efficiency.

(ii) Narrow Asset Scope

This research primarily examined the major cryptocurrencies BTC and ETH. Focusing on these restricted the study's scope and might have overlooked the risk and diversification characteristics in other less popular cryptocurrencies or emerging cryptocurrency categories such as L2 solutions, DeFi and Stablecoins.

(iii) Approaches to measuring efficiency

This study adopted the 500-day rolling windows and averaging approach of Smith and Dyakova (2014) to derive a measure of market efficiency for the JS, JM and AVR tests, reflecting the current absence of a single, universally endorsed efficiency metric. While these strategies are grounded in established literature, it may introduce some measurement uncertainty. Additionally, the averaging methodology has not yet been evaluated via comprehensive out-of-sample backtests, nor sensitivity checks performed on the 500-day rolling windows, leaving their behaviour under alternative market conditions to be fully ascertained.

(iv) Using only the US as a proxy for the global market.

This study used the US market as a proxy for the global market which may overlook cross-country differences in asset performance, thereby limiting the external validity of the study's conclusions.

(v) Exclusion of transaction costs

The performance results are evaluated before transaction costs. While trading frictions would reduce realised net returns, particularly for higher-volatility assets, the study's primary contribution lies in identifying structural diversification patterns and regime-conditioned allocation behaviour rather than in demonstrating cost-adjusted tactical superiority. Incorporating explicit trading cost models would refine implementability assessment but would not alter the diversification-driven mechanism central to the thesis.

(vi) Absence of robustness checks

The study does not include comprehensive robustness checks or sensitivity analyses; while this limitation does not undermine the principal findings, it indicates that their durability under alternative specifications remains to be confirmed. Performing a targeted set of additional assessments such as varying crisis regime definitions, adjusting rolling window lengths and implementing out-of-sample validations would strengthen confidence in the outcomes and clarify their applicability. Pending these supplementary analyses, interpretations and recommendations for implementation should be considered provisional and dependent on

further corroboration, although the central empirical observations presented can serve as an informative foundation for subsequent testing and refinement.

8.4 Suggestions for future work

Based on this study, several suggestions for future research can enhance the understanding of cryptocurrency market efficiency and the role of cryptocurrencies in investment portfolios.

(i) Robustness and sensitivity battery

Future research can implement a comprehensive robustness suite by systematically varying key modelling parameters, such as rolling-window lengths or estimating market efficiency with a challenger model such as the TEE. Crisis threshold criteria can also be varied, as well as portfolio weighting methods (value-weighted versus equally weighted versus constant weighting). Presenting a succinct robustness table that summarises effect sizes and statistical significance across these model specifications will enhance transparency regarding the stability of the main findings.

(ii) Transaction-cost and implementation analysis

Gross empirical gains can be converted to net gains by accounting for realistic transaction costs and varying rebalancing frequencies. By incorporating transaction costs, results can be validated for rigor, especially because the EMH posits that there are no meaningful gains after incorporating transaction costs.

(iii) Alternative crisis period detection methods and model comparison

The current approach to detecting crises can be compared with alternative methods such as Markov models, regime-switching vector autoregressions, and supervised machine-learning classifiers.

(iv) Cross-market and asset-class generalisability

The sample can be extended to additional countries, asset classes, other cryptocurrency categories such as stablecoins and crisis episodes to assess heterogeneity in crises effects.

(v) Efficiency ranked portfolio

Future research can construct and tracks portfolios sorted by asset efficiency rankings with regular rebalancing to assess whether efficiency measures translate into superior risk-adjusted returns.

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APPENDICES

Appendix 1: Global market portfolio as of 2012

Index name or source	Thomson Reuters Datastream mnemonic	USD billion		USD billion
Equities				32 920
MSCI AC World Index	MSACWF$	29474	+	
MSCI AC World Small Cap Index	MSSAWF$	4300	+	
MSCI AC World REITs Index	M3AFRL$	558	-	
MSCI AC World Small Cap REITs Index	C3AFRL$	296	-	
Private equity				3 270
Preqin	*	3270	+	
Real estate				4 612
GPR General PSI Global Index (2012)	GPRGLES	1310		
GPR General PSI Global Index (2011)	GPRGLES	1039	./.	
Real estate estimate 2011	**	3659	+	
High yield bonds				1 523
Barclays Capital Global Corporate High Yield Index	LHGHYCO	1523	+	
Emerging market debt				2 681
JPM Government Bond Index - Emerging Markets Global Composite	JGE$GCM	953	+	
JPM Emerging Markets Bond Index Global Composite	JPMGTOT	579	+	
JPM Corporate Emerging Markets Bond Index Broad		620	+	
Barclays Capital Emerging Markets Government Inflation-Linked Index	BCEMALL	530	+	
Investment-grade credits				16 761
Barclays Capital Multiverse Index	LHMVALL	45022	+	
Barclays Capital Multiverse Government Index	LHMVGVT	26739	-	
Barclays Capital Global Corporate High Yield Index	LHGHYCO	1523	-	
Government bonds				26 739
Barclays Capital Multiverse Government Index	LHMVGVT	26739	+	
Inflation-linked bonds				2 062
Barclays Capital Global Aggregate Inflation-Linked Index	LHGREAL	2062	+	
Global invested multi-asset market portfolio				**90 568**

*Source: adapted from Doeswijk et al. (2014). *Not available on Thomson Reuters and authors reported they sourced from Preqin (https://www.preqin.com/). ** Not available on Thomson Reuters and authors sourced from JP Morgan.*

Appendix 2: Asset allocations in the South African market

Date	Asset/Index	Min VAR	Min VAR*	Max R/SD	Max R/SD*	Mkt Dev	Mkt Dev*
Dec-16	JSE ALSI	40,0%	40,00%	40,0%	40,0%	52,64%	50,67%
Dec-16	JSE ALBI	50,0%	42,02%	50,0%	40,0%	37,36%	34,23%
Dec-16	91-day T-Bill	10,0%	10,00%	10,0%	10,0%	10,00%	10,00%
Dec-16	BTC	0,0%	7,04%	0,0%	10,0%	0,00%	3,72%
Dec-16	ETH	0,0%	0,94%	0,0%	0,0%	0,00%	1,37%
Dec-17	JSE ALSI	40,0%	40,0%	58,6%	40,0%	46,10%	53,0%
Dec-17	JSE ALBI	50,0%	48,7%	31,4%	40,0%	43,91%	27,0%
Dec-17	91-day T-Bill	10,0%	10,0%	10,0%	10,0%	9,99%	10,0%
Dec-17	BTC		1,3%		0,0%		6,6%
Dec-17	ETH		0,0%		10,0%		3,4%
Dec-18	JSE ALSI	40,0%	40,0%	40,0%	40,0%	50,84%	47,6%
Dec-18	JSE ALBI	50,0%	49,0%	50,0%	50,0%	39,18%	35,9%
Dec-18	91-day T-Bill	10,0%	10,0%	10,0%	9,0%	9,98%	10,0%
Dec-18	BTC		1,0%		1,0%		6,6%
Dec-18	ETH		0,0%		0,0%		0,0%
Dec-19	JSE ALSI	40,0%	40,0%	40,0%	40,00%	53,2%	47,6%

Dec-19	JSE ALBI	50,0%	48,6%	50,0%	45,00%	36,8%	32,4%
Dec-19	91-day T-Bill	10,0%	10,0%	10,0%	5,00%	10,0%	10,0%
Dec-19	BTC		1,4%		10,00%		9,4%
Dec-19	ETH		0,0%		0,00%		0,6%
Dec-20	JSE ALSI	40,0%	40,0%	40,0%	40,0%	51,5%	44,8%
Dec-20	JSE ALBI	50,0%	49,0%	50,0%	40,0%	38,5%	35,2%
Dec-20	91-day T-Bill	10,0%	10,0%	10,0%	10,0%	10,0%	10,0%
Dec-20	BTC		1,0%		0,0%		10,0%
Dec-20	ETH		0,0%		10,0%		0,0%
Dec-21	JSE ALSI	40,0%	40,0%	40,0%	40,0%	54,88%	44,6%
Dec-21	JSE ALBI	50,0%	49,0%	50,0%	40,0%	35,56%	35,4%
Dec-21	91-day T-Bill	10,0%	10,0%	10,0%	10,0%	9,56%	10,0%
Dec-21	BTC		1,0%		0,0%		10,0%
Dec-21	ETH		0,0%		10,0%		0,0%
Dec-22	JSE ALSI	40,0%	40,0%	40,0%	40,0%	50,93%	44,9%
Dec-22	JSE ALBI	50,0%	49,0%	50,0%	50,0%	39,08%	44,0%
Dec-22	91-day T-Bill	10,0%	10,0%	10,0%	9,0%	9,99%	10,0%
Dec-22	BTC		1,0%		0,0%		0,0%
Dec-22	ETH		0,0%		1,0%		1,0%
Dec-23	JSE ALSI	40,0%	40,0%	40,0%	40,0%	49,2%	43,0%
Dec-23	JSE ALBI	50,0%	45,4%	50,0%	40,0%	40,8%	37,0%
Dec-23	91-day T-Bill	10,0%	10,0%	10,0%	10,0%	10,0%	10,0%
Dec-23	BTC		4,6%		10,0%		10,0%
Dec-23	ETH		0,0%		0,0%		0,0%
Dec-24	JSE ALSI	40,0%	40,0%	40,0%	40,0%	46,8%	40,9%
Dec-24	JSE ALBI	50,0%	48,0%	50,0%	45,0%	43,2%	39,1%
Dec-24	91-day T-Bill	10,0%	10,0%	10,0%	5,0%	10,0%	10,0%
Dec-24	BTC		2,0%		10,0%		10,0%
Dec-24	ETH		0,0%		0,0%		0,0%

Appendix 3: Asset allocations in the United Sates of America market

Date	Asset//Index	Min VAR	Min VAR	Max R/SD	Max R/SD	Mkt Dev	Mkt Dev
Dec-16	S&P 500	40,00%	40,00%	40,00%	40,00%	44,67%	49,46%
Dec-16	U.S 10-year Treasuries	50,00%	49,00%	50,00%	40,00%	50,00%	44,34%
Dec-16	US 3-month T-Bill	10,00%	10,00%	10,00%	10,00%	5,33%	5,00%
Dec-16	BTC		0,73%		9,57%		1,01%
Dec-16	ETH		0,27%		0,43%		0,19%
Dec-17	S&P 500	40,00%	40,00%	44,66%	40,00%	80,00%	44,00%
Dec-17	U.S 10-year Treasuries	50,00%	49,00%	47,73%	40,00%	15,00%	50,00%
Dec-17	US 3-month T-Bill	10,00%	10,00%	7,61%	10,00%	5,00%	5,00%
Dec-17	BTC		0,94%		0,00%		0,98%
Dec-17	ETH		0,06%		10,00%		0,02%
Dec-18	S&P 500	40,00%	40,00%	40,00%	40,00%	66%	50,22%
Dec-18	U.S 10-year Treasuries	50,00%	50,00%	50,00%	50,00%	25%	29,78%
Dec-18	US 3-month T-Bill	10,00%	9,00%	10,00%	9,00%	9%	10,00%
Dec-18	BTC		0,84%		1,00%		5,21%
Dec-18	ETH		0,16%		0,00%		4,79%
Dec-19	S&P 500	40,00%	40,00%	80,00%	75,00%	80,00%	59,20%
Dec-19	U.S 10-year Treasuries			10,00%	10,00%	10,00%	20,80%
Dec-19	US 3-month T-Bill			10,00%	5,00%	10,00%	10,00%

Dec-19	BTC		1,00%		10,00%		5,12%
Dec-19	ETH		0,00%		0,00%		4,88%
Dec-20	S&P 500	40,00%	40,00%	45,00%	40,00%	80,00%	57,91%
Dec-20	U.S 10-year Treasuries	50,00%	50,00%	50,00%	45,00%	10,00%	22,09%
Dec-20	US 3-month T-Bill	10,00%	9,00%	5,00%	5,00%	10,00%	10,00%
Dec-20	BTC		1,00%		0,00%		5,29%
Dec-20	ETH		0,00%		10,00%		4,71%
Dec-21	S&P 500	40,00%	40,00%	45,67%	40,00%	67,44%	66,35%
Dec-21	U.S 10-year Treasuries	50,00%	49,00%	44,33%	45,00%	27,56%	23,74%
Dec-21	US 3-month T-Bill	10,00%	10,00%	10,00%	5,00%	5,00%	7,75%
Dec-21	BTC		1,00%		0,00%		1,50%
Dec-21	ETH		0,00%		10,00%		0,66%
Dec-22	S&P 500	40,00%	40,00%	40,00%	40,00%	66%	66,35%
Dec-22	U.S 10-year Treasuries	50,00%	50,00%	50,00%	49,00%	24%	23,74%
Dec-22	US 3-month T-Bill	10,00%	9,00%	10,00%	10,00%	9%	7,75%
Dec-22	BTC		1,00%		0,00%		1,50%
Dec-22	ETH		0,00%		1,00%		0,66%
Dec-23	S&P 500	40,00%	40,00%	80,00%	40,00%	80,00%	78,23%
Dec-23	U.S 10-year Treasuries	50,00%	49,00%	10,00%	40,00%	10,00%	8,51%
Dec-23	US 3-month T-Bill	10,00%	10,00%	10,00%	10,00%	10,00%	11,09%
Dec-23	BTC		1,00%		10,00%		1,63%
Dec-23	ETH		0,00%		0,00%		0,54%
Dec-24	S&P 500	40,00%	40,00%	80,00%	40,00%	80,00%	79,01%
Dec-24	U.S 10-year Treasuries	50,00%	49,00%	10,00%	40,00%	10,00%	7,63%
Dec-24	US 3-month T-Bill	10,00%	10,00%	10,00%	10,00%	10,00%	9,81%
Dec-24	BTC		1,00%		10,00%		2,90%
Dec-24	ETH		0,00%		0,00%		0,64%

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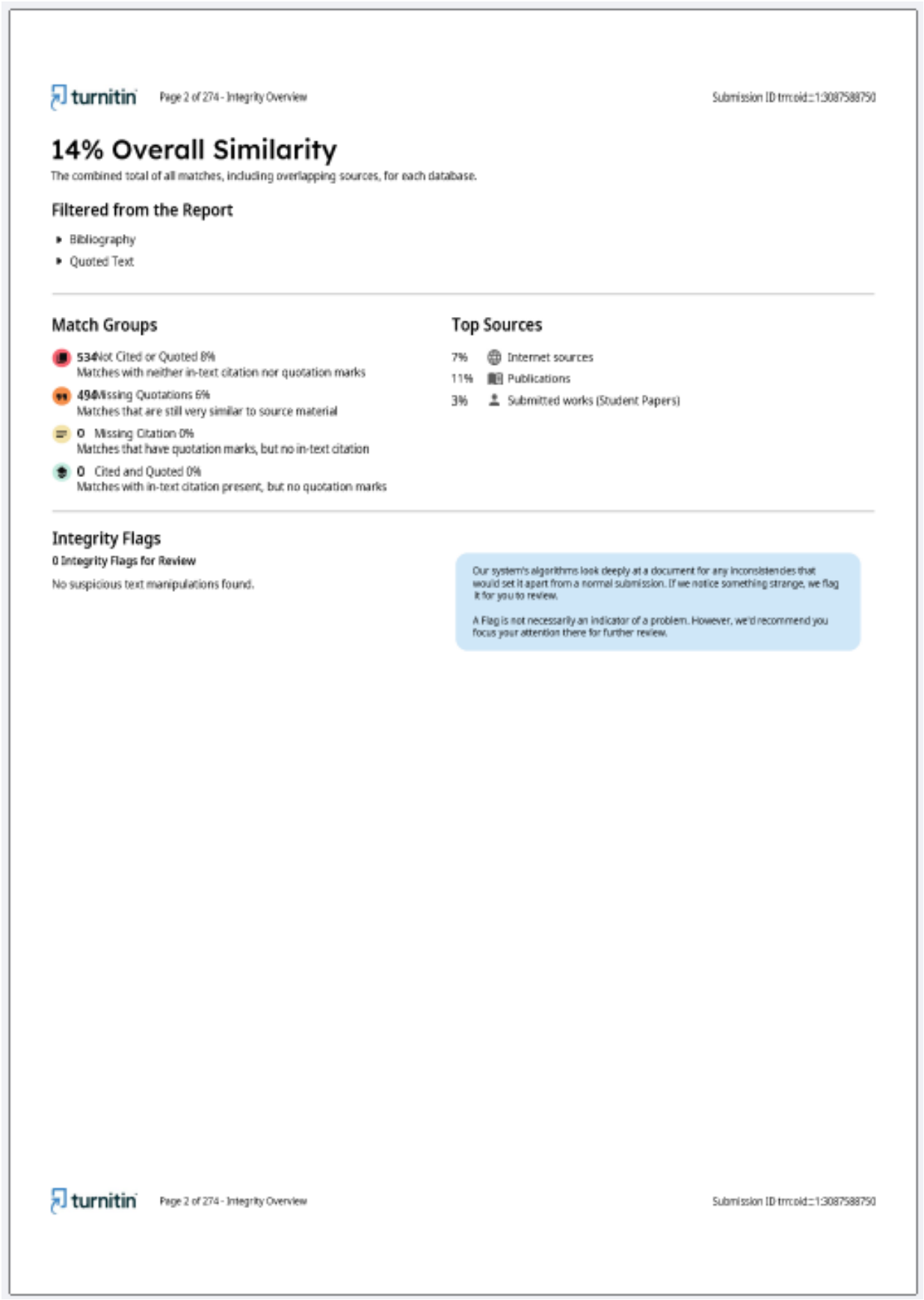
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