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A Comparative Study of Investment Strategies in the Cryptocurrency Market

Master in Corporate Finance

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Leiria, September of 2025

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Originality and Copyright

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Abstract

The aim of this dissertation is to test the applicability of two strategies – Dollar Cost Average (DCA) and Lump-Sum (LS) – in the context of the crypto market.

We tested these strategies on three assets, namely Bitcoin, Ethereum and Ripple. We developed a simulation using daily historical data recorded over a period of nine years. We then calculated performance ratios and created an AR-GARCH model to analyse their properties and predictive capacity more effectively.

Our empirical results show that all assets are highly volatile and exhibit heavy tails and asymmetry. Additionally, they are moderately to highly correlated with each other. We also presented proof of higher Sharpe and Sortino ratios for DCA strategies, with Bitcoin performing better than the other two assets. The results also show that Bitcoin has low-to-moderate shock sensitivity and high persistence; Ethereum has low shock sensitivity and high persistence; and Ripple has both high shock sensitivity and persistence. Furthermore, we observed the impact of strategy choice on volatility. When compared to DCA, LS lowered shock sensitivity in Bitcoin and Ripple, enhancing persistence, while having an insignificant effect on Ethereum. Finally, we demonstrate that our model exhibits superior predictive capacity with regard to Ripple compared to Bitcoin and Ethereum, and that all three assets are inefficient.

These findings contribute to previous literature by providing novel empirical data and attesting to the attributes of cryptocurrencies. Furthermore, this thesis improves financial awareness and provides investors with valuable information.

Keywords: Dollar cost average, lump-sum, cryptocurrency, AR-GARCH model, volatility, investing.

Resumo

Esta dissertação tem como objetivo testar a aplicabilidade das estratégias *Dollar Cost Average* (DCA) e *Lump-Sum* (LS) no contexto do mercado de criptomoedas.

Testámos estas estratégias em três ativos, nomeadamente Bitcoin, Ethereum e Ripple. Desenvolvemos uma simulação utilizando dados históricos diários registados ao longo de nove anos. Em seguida, calculámos rácios de retorno ajustado ao risco e criámos um modelo AR-GARCH para melhor avaliar as suas propriedades e capacidade preditiva.

Os nossos resultados empíricos mostram que todos os ativos têm alta volatilidade, assimetria e "caudas-pesadas", além de serem bastante correlacionados entre si. Apresentamos provas de índices de Sharpe e Sortino mais elevados para estratégias DCA, com a Bitcoin a destacar-se dos três ativos em causa. Os resultados também indicam que a Bitcoin tem uma sensibilidade ao choque baixa-moderada em contrapartida de uma alta persistência, o Ethereum tem baixa sensibilidade ao choque e alta persistência, e o Ripple apresenta elevada sensibilidade ao choque e elevada persistência. Além disso, observamos o impacto da escolha da estratégia na volatilidade, com a LS, quando comparada com a DCA, a reduzir a sensibilidade ao choque na Bitcoin e no Ripple e aumentando a sua persistência, por sua vez, o efeito da escolha de estratégia é insignificante no Ethereum. Por fim, mostramos que o nosso modelo tem melhor capacidade preditiva para o Ripple do que para o Bitcoin ou o Ethereum e que os três ativos são mercados ineficientes.

Essas descobertas não apenas contribuem para a literatura anterior, adicionando novos dados empíricos, mas também atestam os atributos das criptomoedas. Adicionalmente, esta tese promove a conscientização financeira e adiciona não só informação como valor ao investidor.

Palavras-chave: *Dollar cost average*, *lump-sum*, criptomoedas, modelo AR-GARCH, volatilidade, investimentos.

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List of Acronyms

AML	Anti-money laundering
BTC	Bitcoin
DCA	Dollar Cost Average
Defi	Decentralized Finance
DTB	Daily Treasure Bills
ESTG	*Escola Superior de Tecnologia e Gestão*
ETH	Ethereum
FA	Fundamental Analysis
FOMO	Fear of Missing Out
LS	Lump-sum
MiCa	Market in Crypto-Assets Regulation
PoS	Proof-of-Stake
PoW	Proof-of-Work
TA	Technical Analysis
XRP	Ripple

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1. Introduction

Once considered to be a technological niche, cryptocurrencies have increasingly attracted attention from users, enthusiasts and investors alike. Since the publishing of Nakamoto's article about Bitcoin (Nakamoto, 2008), the cryptocurrency market (hereafter referred to as the crypto market) has transcended an experimental concept into a financial ecosystem with a market capitalization of over three trillion dollars (CoinmarketCap, 2025).

Consequently, this remarkable growth has created a necessity of understanding this new asset class, how it functions and its inherent characteristics. A thorough understanding of these assets has now become an essential attribute to any investor.

Due to their recent emergence, cryptocurrencies are perceived by many as purely speculative assets (Cheah & Fry, 2015), characterised by high volatility and unpredictable market behaviour. There is no consensus on whether these crypto assets should be defined as speculative or as a currency. However, being used as an investment and store of value, they have created a market of their own. Consequently, as in any other market, a structured and deliberate strategy is essential in the investment process, not only to mitigate risks but also to maximise potential returns.

Unlike traditional financial markets, where investment strategies have been extensively studied and analysed over many decades (Brennan et al., 2005; Isynuwardhana & Aslam, 2024; Kirkby et al., 2020; Merlone & Pilotto, 2014; Payne & Bredthauer, 2013; Rozeff, 1994; Thorley, 1995; Trainor, 2005), research in the crypto market still contains significant gaps. Much about this market remains unclear, patterns and unique characteristics are not yet fully understood, which poses considerable challenges for investors.

Consequently, there is a need for novel studies with up-to-date information on this topic not only to fill the existing gaps in the literature, but also to advance the knowledge and understanding of investors seeking to capitalise on this market.

The motivation for this study is to deepen knowledge of the cryptocurrency market by providing novel and up-to-date empirical evidence. Although research in this area is growing rapidly, as evidenced by the increasing number of papers published between 2013 and 2018

(Corbet et al., 2019), it remains a relatively recent and largely unexplored field. Consequently, new and updated studies are essential in this rapidly evolving area.

Our approach is to apply strategies already implemented in traditional markets to the crypto market, in order to assess their viability, the patterns they generate and potentially adapt them to better suit this emerging class. This framework facilitates a deeper understanding of both the market, and the strategies themselves.

Building on financial market theory, this study compares two of the most well-known investment strategies. Although simple, both are a strong choice for investors. Moreover, the two selected approaches seem to be the most reliable strategies for novice investors, depending on their risk aversion (Habsjah & Permana, 2023; Lu et al., 2021; Panyagometh & Zhu, 2016). Therefore, both the Dollar Cost Average (DCA), primarily used for retirement and pension plans, and the Lump-Sum (LS), commonly applied in real estate and stocks with a long-term perspective, appear well suited for adaptation from traditional markets to the cryptocurrency market.

Although the primary objective is to assess their viability in this market, this comparative study also aims to identify which of the selected strategies provides the highest profitability under the study's conditions, while highlighting their inherent strengths and weaknesses and how these manifest in the specific environment of the cryptocurrency market.

Ultimately, the study seeks to raise awareness among investors and help them make better informed decisions about this market, which differs characteristically from other financial markets. It provides useful insights that can be add value for investors, guiding them on how to approach the crypto market and which strategies may be best suited to each individual.

The remainder of this dissertation is structured as follows. Section 2 reviews the literature on the cryptocurrency market and the selected investment strategies. Section 3 provides the hypothesis derived from the literature. Section 4 outlines the methodology used and describes the data. Section 5 reports the empirical results. Finally, section 6 provides the conclusions.

2. Literature Review

2.1. Cryptocurrencies

2.1.1. Background and Context

Nakamoto (2008) exposed the potential of Bitcoin and cryptocurrencies in general to everyone. Cryptocurrencies are digital assets that use cryptographic methods and decentralized technology to promote peer-to-peer transactions without the need of any third party (Corbet et al., 2019; Giudici et al., 2020; Härdle et al., 2019; Murugappan et al., 2023; Wątorek et al., 2021). The first cryptocurrency to obtain some notoriety was Bitcoin.

As of January 2025, and according to Coingecko, Bitcoin has reached a peak of around 106.074 USD. The "white paper" of Nakamoto (2008), published in the global financial crisis, enlightened the inefficiencies of the traditional system used in financial institutions and proposed a technological reform mechanism, a decentralized monetary system that stems from mathematical cryptography.

Since then, attention in the crypto world has grown stronger, with many users and investors being attracted by the minimal regulatory mechanisms (Colon et al., 2021; Corbet et al., 2019; Giudici et al., 2019; Hairudin et al., 2020) and the anonymity factor inherent to this system, as well as the potential for large profitability.

To this day many cryptocurrencies have surfaced with the same purpose, to provide alternatives to the centralized monetary system, each of them relies on their own different technological attributes as well as their consensus mechanisms (ElBahrawy et al., 2017; Li & Whinston, 2019; Trimborn & Härdle, 2018).

2.1.2. Blockchain Technology

The underlined quality of cryptocurrencies is their foundation on a decentralized theory enabled by blockchain technology. Blockchain is a public ledger that validates and records every transaction in blocks of information interconnected with one another (Huynh-The et al., 2023). The use of this technology ensures that cryptocurrencies are decentralized (Balcilar et al., 2017; Corbet et al., 2019), in the sense that there is no single device storing the data, as it is distributed in the network in real time. Simultaneously, there is no central authority (Huynh-The et al., 2023) approving actions; rather, the system operates through a computer program, meaning that, when a set of predefined requirements are met, the transaction is registered. This way, Blockchain provides not only decentralization but also facilitates security and transparency, while maintaining a level of anonymity of its users (Bariviera et al., 2017; Baur et al., 2018).

2.1.3. Regulatory and Measures and Frameworks

Due to the growth of these currencies as well as their decentralized behaviour, governments are aiming to establish regulatory measures to protect, regulate and restrict the usage of these assets, whether in the form of currencies or investment assets.

Crypto regulatory frameworks are not uniform across the globe with some countries such as Singapore and Switzerland implementing innovation-friendly regulations while others, such as China and India, impose stricter restrictions (Arima, 2022; Blandin et al., 2019; Karisma, 2022; Mohsin, 2021; Sufian et al., 2024; Ukwueze, 2021). In Europe, the objective is to fight this heterogeneous regulation, with the Market in Crypto-Assets Regulation (MiCA) playing a huge role in harmonizing the rules, striving for investor protection, market integrity and anti-money laundering (AML) (Frick, 2019; Linden & Shiraz, 2023; Nastri, 2025; Zhelekhovska, 2024). Nonetheless, MiCA still presents gaps, namely in not fully addressing new innovations, like Decentralized Finance (Defi) and Non-Fungible Tokens (NFTs), showing that there is still a long way to uniformization.

The literature argues that although significant progress has been made in developing and implementing new regulations, the fragmented and inconsistent jurisdictional behaviour across countries remains a challenge in the regulation of these assets (Dhali et al., 2023; Iris Ng, 2025; Xiong & Luo, 2024).

2.1.4. Currency or Speculative Asset?

Even though the article by Nakamoto was published in 2008, the topic of cryptocurrency is still relevant (Angerer et al 2021; Li et al., 2021) and of growing importance (Bialkowski, 2020), being one of the fastest growing markets (Bialkowski, 2020; Fang et al., 2021). Among the literature, this subject is still understudied and presents polarized positions. For instance, ambiguity in cryptocurrency's definition has been observed in previous research (Katsiampa, 2017; Pieters & Vivanco, 2017).

Patel et al. (2020) define cryptocurrencies as "virtual currencies that can be exchanged between individuals or groups… a network-based exchange medium that uses cryptographic algorithms to secure transactions" (p. 1). Although accurate in terms of operating method, describing these assets as currencies is not unanimously agreed upon by previous researchers.

Hence, the literature is divided, with some researchers focusing on the financial attributes of crypto market by analysing its relationships with other financial markets, such as the stocks, bonds, and energy markets (Corbet et al., 2018; Ji et al., 2019), as well as by comparing it to gold (Klein et al., 2018; Selmi et al., 2018).

On the other hand, some authors focus on the currency attributes of these assets, studying their potential as a store of value (Ammous, 2018) and legal constraints associated with their use (Foley et al., 2019).

Traditionally, a currency is defined by three core functions: (1) serving as a medium of exchange, (2) functioning as a unit of account and (3) functioning as a store of value (Bariviera et al., 2017).

Until now, every form of currency has followed these rules. However, in the case of cryptocurrencies, authors such as Bariviera et al. (2017) note that cryptocurrencies barely possess the qualities of a monetary system. Some authors even categorize Bitcoin and cryptocurrencies in general as purely speculative assets (Chea & Fry, 2015; Dyhrberg, 2016), arguing that although they are occasionally used as payment methods (Almeida & Gonçalves, 2023), thereby slightly fulfilling the condition of being a medium of exchange, their volatility and price fluctuations do not provide evidence of constant fundamental value. Moreover, the lack of regulation and the low adoption for everyday transactions further limit their role as a medium of exchange, making them more similar to financial assets than to currencies (Yermack, 2024).

Additionally, although not homogeneous as shown before, most regulatory bodies and accounting standards do not recognize cryptocurrencies as currency. Instead, they often classify them as speculative assets and subject them to capital gains tax and other regulations applicable to investments rather than to currencies (White et al., 2020; Țegledi & Straoanu, 2021)

In this context, Blau (2017) states that the use of these assets in speculative trading is the reason they fail to meet the criteria of currency. This hypothesis is based on the premises that speculation leads to the destabilization of asset prices, as demonstrated by earlier authors

(Hart & Kreps, 1986; Stein, 1987). Nevertheless, while cryptocurrencies are used as speculative investments, their behaviour is distinct from that of stocks, bonds, or even commodities (Baur et al., 2018).

Some authors even describe cryptocurrencies as a unique asset class, exhibiting qualities of both currency and speculative assets (Corbet et al., 2018; Kristoufek, 2015). Specifically, Selgin (2015) defines crypto not as a speculative asset - fundamentally because of its lack of intrinsic value - but as a "synthetic commodity money", lacking non-monetary value and being characteristically scarce.

Regardless of how cryptocurrencies are defined, their high volatility, investor-driven price movements, and limited use as a stable medium of exchange currently position them primarily as speculative assets.

2.1.5. The Valuation Problem

The discussion on classification presents a new challenge for cryptocurrency assets. The inherent speculative nature of this new class, disputed in previous studies, raises the question of valuation. For cryptocurrencies to be used as a speculative asset, the investor will only invest if they expect a return from it, meaning the price of the asset (in this case cryptocurrencies) is at that moment lower than the perceived value of that asset.

2.1.5.1. Consensus Algorithms

While some authors argue that cryptocurrencies lack intrinsic value (Chea & Fry, 2015; Yermack, 2024), others contend that the existence of a consensus algorithm mechanism on which each blockchain is built provides them with value (Hayes, 2017; Huynh-The et al., 2023).

Within the cryptocurrencies selected for this study, three different consensus algorithms are implemented. While Bitcoin utilizes Proof-of-Work (PoW), Ethereum implements Proof-of-Stake (PoS), and Ripple uses its own consensus protocol (Zheng et al., 2017).

The first consensus approach, PoW consists of a mechanism that requires a certain amount of computing effort to solve a mathematical puzzle to obtain the "hash", which in turn is used to verify the originality and quality of the information going into the blockchain (Huynh-The et al., 2023). This process, known as mining, not only ensures security but according to Hayes (2017), also provides intrinsic value to the currency. Additionally, the mining difficulty is increased every 2016 blocks (Alangot et al., 2021) ensuring that the time required to mine a block remains within the expected period.

In comparison, PoS serves as a more energy-efficient option, where miners are required to prove ownership of the respective currency (Alangot et al., 2021). This process does not require specialized hardware to solve a mathematical puzzle, as the generation of new blocks is based on stake. In other words, individuals with greater ownership of the coin have a higher chance of being selected as a leader to validate transactions and add additional blocks to the chain (Nguyen et al., 2019).

Finally, Ripple employs a consensus mechanism that relies on querying information. Withing the network, existing nodes are consulted, once an agreement of over 80% is reached, the information is accepted and recorded in the ledger (Alangot et al., 2021; Ma et al., 2022).

2.1.5.2. Fundamental vs Technical Analysis

The literature has also sought to value cryptocurrencies using approaches applied in other markets, namely Fundamental Analysis (FA) and Technical Analysis (TA).

Fundamental Analysis has been used to determine whether the price of an asset is below or above its true value. In essence, it attempts to identify the intrinsic value of given cryptocurrency.

Technical analysis focuses on price and volume data to predict price movements. It relies solely on market behaviour and statistical trends, rather than trying to uncover the underlying fundamentals of the crypto-asset.

This type of analysis is based on the principles that not all the information available in the market is reflected in prices, and that these prices move in trends (Akgül et al., 2022; Jain et al., 2022), and therefore, are able to be predicted.

Nevertheless, both methods have limitations. Specifically in the crypto market, TA may provide contradictory or delayed information, which in turn affect profitability (Jain et al., 2022). FA, on the other hand, is difficult to apply, as there is no real consensus on a consistent fundamental value of the cryptocurrencies.

Although these two approaches can complement each other, the literature tends to focus on Technical Analysis (Bazán-Palomino & Svogun, 2023; Filippou et al., 2023), namely for price prediction, since the fundamentals of cryptocurrencies are inherently difficult to value (Detzel et al., 2021).

Whether or not the existence of an intrinsic value of cryptocurrency is agreed upon, the growing appeal of this asset class as an investment asset to both retail and institutional investors is undeniable (Almeida & Gonçalves, 2023, De la Horra et al., 2019; Gandal et al., 2018). This attractiveness stems from its detachment from economic fundamentals (Brière et al., 2015), along with the potential for high returns (Corbet et al., 2018).

The usage of both analytical approaches might help investors to choose appropriate strategies to implement and allow them to make better-informed decisions about their investments.

2.1.6. Volatility, a Defining Characteristic

The high returns observed in crypto result from the high volatility that characterises this emerging market (Katsiampa, 2017; Vandezande, 2017). Given that the crypto market is defined by its inherent volatility, it logically follows that it also entails high risks (Gkillas & Katsiampa, 2018), creating both opportunities for significant profits, as well as practical challenges for investors and traders.

Past authors have focused on this defining characteristic and its implications. The main results indicate that this market exhibits high and persistent volatility (Abakah et al., 2020; Baur & Dimpfl, 2019; Baur & Dimpfl, 2021; Caporale & Zekokh, 2019; Katsiampa, 2018; Katsiampa et al., 2019a; Katsiampa et al., 2019b; Liu & Serletis, 2019). Moreover, this volatility has been shown asymmetric, with positive shocks increasing it more than negative ones (Aharon et al., 2023; Baur & Dimpfl, 2019; Cheikh et al., 2020; Kakinaka & Umeno, 2022a; Karim et al., 2023), from which it can be inferred that investors and traders tend to ignore negative new information. Additionally, although asymmetric, volatility is strongly impacted by events, news and sentiment as well as macroeconomic events (Akyildirim et al., 2021; López-Cabarcos et al., 2021; Lyócsa et al., 2020; Rognone et al., 2020; Salisu & Ogbonna, 2022; Sapkota, 2022; Yen & Cheng, 2021) which not only makes it unpredictable but also creates opportunities for investors.

Volatility spillover is an effect often observed in various asset classes (Coudert et al 2015; Katsiampa, 2019a), and the same can be seen in the crypto market (Katsiampa, 2019a; Chea & Fry, 2015), however, Corbet et al. (2018) argues that although cryptocurrencies are highly interconnected, they are disconnected from other assets. This view is challenged by Mensi et al. (2019b) who provide evidence of significant volatility spillover between Bitcoin and precious metals.

The consensus on spillovers in the crypto market seems to be that Bitcoin is the dominant contributor, meaning that shocks to Bitcoin's returns and volatility tend to impact other cryptocurrencies as well (Katsiampa et al., 2019a; Koutmos, 2018; Li, 2022). In conclusion, the existence of volatility spillovers and interdependencies in cryptocurrencies can be verified (Katsiampa et al., 2018; Katsiampa et al., 2019a; Liu & Serletis, 2019; Özdemir, 2022; Shi et al., 2020).

2.1.7. Efficiency in the Cryptocurrency Market

Based on Markowitz's Portfolio Theory (Markowitz, 1952), the duality of return and risk in the crypto market which stems not solely but largely from its volatility, should in theory be observable. However, since this is not the case, previous authors agree that cryptocurrency markets are inefficient (Barivieira et al., 2017; Nadarajah & Chu, 2017; Urquhart, 2016), with this inefficiency being attributed to the market's immaturity.

According to past studies, the efficiency of this market is both dynamic and time-varying (Al-Yahyaee et al., 2020; Aslam et al., 2023; Kakinaka & Umeno, 2022b; Mensi et al., 2019a; Naeem et al., 2021; Sigaki et al., 2019; Tran & Leirvik, 2020; Urquhart, 2016) meaning it varies over time, sometimes appearing more efficient than at other moments. Despite this, it is noted that Bitcoin and other major cryptocurrencies have exhibited overall increasing market efficiency over time (Diaconaşu et al., 2022; Naeem et al., 2021; Noda, 2020; Sigaki et al., 2019; Tran & Leirvik, 2020; Urquhart, 2016).

As stated before, news and events cause shocks in market volatility, but they also affect market efficiency. The literature seems to agree that crises negatively affect market efficiency, with multiple studies showing increased inefficiency during crises, followed by steady recovery (Asthana, 2024; Fernandes et al., 2022; Kakinaka & Umeno, 2022b; Mnif et al., 2020; Montasser et al., 2022; Naeem et al., 2021; Wang & Wang, 2021). Additionally, it has also been noted that the degree of informational efficiency varies across different cryptocurrencies (Urquhart, 2016).

Although inefficient, results from past studies show that both liquidity and regulatory compliance improve market efficiency (Al-Yahyaee et al., 2020; Dong et al., 2022; Mokni et al., 2024; Nimalendran et al., 2024).

The bottom line is that this market is not yet fully efficient, with added information not being instantly reflected on the asset prices right away. This provides arbitrage opportunities, especially in the cryptocurrencies that show less efficiency (Al-Yahyaee et al., 2020; Aslam et al., 2023; Sigaki et al., 2019; Tran & Leirvik, 2020; Vidal-Tomás et al., 2019).

2.1.8. What Drives Crypto Returns

Upon the consensus of this market's inefficiency, studies analysing the impact of many factors on returns have emerged, specifically studies on the effects of news (Corbet et al., 2020b; Gkillas & Katsiampa, 2018; Rognone et al., 2020). These studies are motivated by the concept of market efficiency, because if it were an efficient market, new information would have an instant impact on prices.

In these studies, some find that positive news influence returns, while negative news are usually ignored by investors (Rognone et al., 2020). Others argue that various news can have both positive and negative effects (Gkillas & Katsiampa, 2018).

The relationship between liquidity, volatility and efficiency has also been a focus of research in crypto. It has been stated that there is a positive correlation between liquidity and efficiency (Brauneis & Mestel, 2018; Wei, 2018). Related results from other studies indicate that higher liquidity improves market efficiency, while higher volatility weakens it (Al-Yahyaee et al., 2020).

This evidence indicates that crypto returns are driven by both investor sentiment (Anamika et al., 2021; Banerjee et al., 2022; Bouteska et al., 2022; Liu & Tsyvinski, 2018) and macroeconomic factors (Corbet et al., 2020a; Naifar et al., 2023; Zhang et al., 2024).

The subsequent Table 1 systematically summarises all the key information presented in this section. It is a chronological representation of cryptocurrencies studies and synthetises the principal findings and contributions discussed so far.

Table 1
Summary of Previous Cryptocurrencies Research

Authors	Objective	Results
Cheah and Fry (2015)	Assesses the Bitcoin market for the existence of speculative bubbles.	Bitcoin prices are prone to speculative bubbles. The bubble component is substantial. The fundamental value of Bitcoin is zero.
Urquhart (2016)	Evaluates the efficiency of the Bitcoin market.	Bitcoin is an inefficient market but becomes more efficient over time.
Blau (2017)	This paper examines the relationship between speculative trading and Bitcoin's volatility and provides explanation for Bitcoin value and volatility across time.	Speculative trading does not drive excess volatility.
Bariviera et al. (2017)	Investigates statistical properties of the Bitcoin market.	Bitcoin shows large but decreasing overtime volatility. Long-range memory is unrelated to market liquidity. Behaviour is consistent across time scales in long-term memory range.
Zheng et al. (2017)	Explores blockchain and consensus methods used in cryptocurrencies.	Bitcoin, Ethereum, and Ripple use distinct blockchain-based consensus methods.
Corbet et al. (2018)	Analyses the relationship between three cryptocurrencies and other financial assets.	Cryptocurrencies are a new investment asset class. They are highly interconnected but disconnected from traditional assets. They offer diversification benefits for investors.
Corbet et al. (2019)	Conducts a systematic review of empirical literature on the major topics related to cryptocurrencies.	Literature remains fragmented, with numerous gaps.
Katsiampa (2019b)	Examines volatility dynamics in five major cryptocurrencies.	Volatility is responsive to news. Cryptocurrencies are interlinked.
Al-Yahyaee et al. (2020)	Analyses the impact of liquidity and volatility on cryptocurrency market efficiency.	Inefficiency is time-varying. Markets exhibit long memory and multifractality. Liquidity enhances efficiency, while volatility weakens it.

Table 1 (Continuation)
Summary of Previous Cryptocurrencies Research

Authors	Objective	Results
Rognone et al. (2020)	Studies the relationship between major forex markets and Bitcoin.	Bitcoin reacts differently than forex to news, positive news affects returns, while negative ones are mostly ignored by investors.
Naeem et al. (2021)	Examines the effect of COVID-19 on the efficiency of leading cryptocurrencies.	COVID-19 negatively affected efficiency. Market efficiency is time-varying.
Detzel et al. (2021)	Utilizes technical analysis to predict cryptocurrency returns.	Technical analysis is effective in assets with hard to value fundamentals.
Nastri (2025)	Evaluates the regulations on crypto assets.	Regulation is fragmented. The European Union is moving toward harmonization, control, and anti-money laundering.

Note. Source: Author's own elaboration

2.2.Investment Strategies

Investing is the process of allocating resources in expectation of future profitable returns, or as defined by Maharani and Saputra (2021), it is the sacrifice of something (usually capital) to leverage for future gains or benefits. In every investment, the investor must accommodate the risk involved according to the potential profitability.

Markowitz (1952) explained this duality, stating that if an asset offers a higher risk when compared to a similar asset, it should also provide higher profitability. Thus, an asset with lower risk but the same possible profitability can be described as a more efficient choice than an asset with a lower risk/return ratio. Based on this theory, investors must base their investments on a strategy that fits not only the market in which the investment will take place (whether it is stocks, crypto or any other) but also the investor's own profile.

Two of the most well-known investment strategies used by investors are the DCA and LS (Lu et al., 2021). However, to our knowledge, this research has not yet focused on cryptocurrencies. While the implementation of these two strategies in traditional markets has been extensively reviewed (Brennan et al., 2005; Isynuwardhana & Aslam, 2024; Kirkby et al., 2020; Merlone & Pilotto, 2014; Payne & Bredthauer, 2013; Rozeff, 1994; Thorley, 1995;

Trainor, 2005), the question of whether the knowledge derived from these studies is applicable to this new market remains.

Hence, the need arises to explore the applicability of these strategies in this new market. For that, we first need to analyse and break down their strengths and weaknesses when applied in established markets, namely the traditional ones.

2.2.1. Dollar Cost Average

Shen (2022) defines DCA as a strategy that relies on allocating a constant amount of money into the same investment for a certain period at regular intervals. In this approach, when the price is low, more shares are acquired; conversely, when the price of the asset is higher, the number of shares acquired is lower. The objective of this strategy is to achieve a lower average cost basis on the asset.

Overall, the available literature labels this strategy as inefficient, mainly because it does not adapt over time, nor does it incorporate current market information (Constantinides, 1979; Kapalczynski & Lien, 2021). Also, if the investor has the entirety of the capital that will be partitioned in regular intervals at the initial moment, it would be suboptimal not to invest it immediately (Bierman & Hass, 2004), and therefore it is not recommended. In essence, this strategy (according to the literature) is neither efficient in terms of information nor in terms of capital allocation.

Despite these disadvantages, DCA has some upsides, most of them pointed out by behavioural finance. The most notable one being the removal of emotional bias from the equation (Lu et al., 2021) such as Fear of Missing Out (FOMO), self-control, or loss aversion. It is generally agreed that DCA presents a lower inherent risk when compared to other strategies like LS (Anantanasuwong & Chaivisuttangkun, 2019; Isynuwardhana & Aslam, 2024; Zein & Darma, 2023), being considered a “protective measure” against market uncertainties. Additionally, it provides a form of diversification in investment, namely, time diversification (Constantinides, 1979). Overall, this method is considered a beginner friendly approach to investing (Isynuwardhana & Aslam, 2024).

2.2.2. Lump-sum

In contrast with the previous strategy, Lump-sum (LS) is defined as committing a single large sum of money at a predetermined moment (Lu et al., 2021). The main objective of this strategy is to maximise the amount of money in the market.

According to Bierman and Hass (2004), it is the optimal strategy because if one possesses a certain amount of money and is considering an investment from which a higher return is expected compared to not investing, delaying purchases will reduce those returns.

This strategy has benefits as well as disadvantages in its implementation. The main advantages for the investor are the low level of involvement required (Choudhari & Borgaon, 2020), due to only needing to actively interact at the moment of purchase or sale, as well as the fact that the total amount is being invested, which in a bullish market will provide maximum returns (Habsjah & Permana, 2023).

Nonetheless, this strategy is not without its limitations. According to Habsjah and Permana (2023) a major downside of LS is the high "entry barrier", represented by the necessity of possessing the whole sum of capital at the start of the investment process. Furthermore, this approach requires research given that investing at an unfavourable moment decisively determines the viability of the strategy. Finally, a crucial disadvantage noted by previous literature is the risk associated with it (Anantanasuwong & Chaivisuttangkun, 2019).

2.2.3. Contrast Between the Strategies in Traditional Markets

As mentioned before, these two strategies have been extensively examined by academics in the context of other markets, such as stocks (Anantanasuwong & Chaivisuttangkun 2019; Isynuwardhana & Aslam, 2024) and funds (Merlone & Pilotto, 2014; Gajera et al., 2020).

The literature frequently shows that the LS strategy yields better returns when compared to its competitor, namely the DCA strategy (Choudhari & Borgaon, 2021; Gajera et al., 2020; Habsjah & Permana, 2023; Isynuwardhana & Aslam, 2024; Kirkby et al., 2020); however, these higher potential returns come at the cost of higher risk (Kirkby et al., 2010; Lu et al., 2021; Panyagometh & Zhu, 2016). Even though this statement is widely accepted in previous studies, a definitive conclusion on the superiority of one strategy has not been established, with different authors advocating different strategies according to their results on risk-return ratios.

As a result, the viewpoints of previous authors are contradictory. Some early experts defend the LS strategy (Constantinides, 1979; Knight & Mandel, 1992; Rozeff, 1994; Thorley, 1995; Leggio & Lien, 2003) and are supported by more recent research (Choudhari & Borgaon, 2021; Gajera et al., 2021; Habsjah & Permana, 2023; Isynuwardhana & Aslam, 2024; Merlone & Pilotto, 2014; Panyagometh & Zhu, 2016).

In contrast, some early studies advocate for DCA strategies (Brennan et al., 2005; Milevsky & Posner, 2003; Statman, 1995; Trainor, 2005), with some more recent studies supporting those results (Kapalczynski & Lien, 2021; Kirkby et al., 2020; Lu et al., 2021; Payne & Bredthauer, 2013).

Finally, there are authors who dismiss this comparison, sustaining that while LS strategy is ideal for some investors, the DCA strategy is a better fit for others (Anantanasuwong & Chaivisuttangkun, 2019; Panyagometh & Zhu, 2016).

Interestingly, when predicting the success of these two strategies in more volatile environments, authors seem confident that DCA is better suited than LS, (Choudhari & Borgaon, 2020; Habsjah & Permana, 2023; Kapalczynski & Lien, 2021; Lu et al., 2021; Merlone & Pilotto, 2014; Milevsky & Posner, 2003).

Table 2 provides a compilation of the most crucial topics developed in this section, highlighting the results and conclusions of some of the authors cited in this discussion.

Table 2
Summary of Previous Investment Strategies Research

Authors	Objective	Results
Constantinides (1979)	Examines the efficiency of the DCA strategy.	DCA is a flawed and inefficient strategy of investment.
Rozeff (1994)	Compares DCA and LS.	DCA is mean-variance inefficient compared to LS.
Milevsky and Posner (2003)	Examines DCA using continuous financial mathematics.	DCA may be a good option if the market is driven by Brownian bridges instead of Brownian motions.
Panyagometh and Zhu (2016)	Analyses both DCA and LS.	Compares DCA and LS to AA strategies where DCA allocates 50–65% in risky assets, while LS allocates 100%, so they are not directly comparable.

Table 2 (Continuation)
Summary of Previous Investment Strategies Research

Authors	Objective	Results
Lu et al. (2019)	Uses both Sharpe Ratio and Economic Performance Measure to compare DCA and LS in uptrend situations.	DCA outperforms LS in almost all situations.
Kirkby et al. (2020)	Creates a rigorous mathematical framework for analysing DCA and studies the impact of investment frequency.	The frequency of DCA investment fundamentally impacts risk, return, and risk-return trade-offs.
Kapalczynski and Lien (2021)	Studies the effectiveness of Augmented DCA.	Augmented DCA outperforms both DCA and LS.
Habsjah and Permana (2023)	Compares DCA and LS in the S&P 500 index.	The LS strategy provides higher returns than DCA.
Isynuwardhana and Aslam (2024)	Compares DCA and LS in Indonesian stock investment.	The LS method is optimal and provides better returns compared to DCA.

Note. Source: Author's own elaboration

2.3. Literature Review Conclusions

As a summary, we ascertain some coherences in past literature. Past authors present cryptocurrencies as a recent and emerging market, which is based on blockchain technology each with their own consensus method.

The literature shows that regulatory frameworks are still fragmented, not uniform over the globe and present various gaps. Additionally, the literature does not reach a consensus on the classification of cryptocurrencies as speculative asset or as currencies, with many authors defending one or the other and other authors going as far as describing them as a new asset class altogether.

What the literature does agree upon is the inherent volatility of these assets, with volatility clustering and spillovers as well as their hard-to-value fundamentals. For this reason, most articles that focus on price analysis chose Technical Analysis methods to valuate cryptocurrencies. Some studies also show that news and macroeconomic factors tend to impact these cryptocurrencies.

Additionally, cryptocurrencies are inefficient markets, the reason given by past authors is that of the immaturity of this market. Many studies show that overtime cryptocurrencies are becoming more efficient, with Bitcoin displaying enhanced efficiency when compared to other cryptocurrencies.

As for investment strategies, past literature reveals differences in the DCA and the LS strategies, with the DCA strategy usually reducing risk at the cost of return, and the LS strategy displaying higher risk but also higher returns. Overall, the DCA strategy usually shows better risk-return ratios. Also, an augmented DCA strategy in some cases shows better risk-return than both the normal DCA and the LS strategy. However, the superiority of each strategy depends on each study conditions, with a consensus on which strategy is best not existing.

Finally, the literature shows confidence that the DCA strategy is better for more volatile scenarios and therefore may be a better fit for the crypto market.

3. Hypotheses Development

From the literature review, we can establish that previous authors, although sometimes contradictory in their conclusions, are based on the same underlying premises.

We ascertain, based on studies conducted in other markets, firstly that DCA and LS are different approaches to the market; secondly, that DCA yields lower risk than its counterpart; thirdly, that LS is usually optimal in terms of return when compared to DCA; and finally, that DCA seems better suited than LS in more volatile environments.

Additionally, since in this study we intend to evaluate these strategies in terms of their potential return and risk-return performance, we must also conduct this analysis based on certain assumptions.

1) The investor is a rational one, focusing on maximizing expected utility rather than being affected by heuristics and cognitive biases.
2) In this simulation, both transaction costs and taxes are not considered.
3) Investors using both strategies are homogeneous in terms of information, meaning they possess the same amount of information at the same time.
4) The investment horizon is predetermined before the moment of investment.

Based on both our literature review and these assumptions, we theorise four main hypotheses for analysis.

***Hypothesis 1*:** DCA will yield higher Sharpe-Ratios than LS in all three cryptocurrencies.

The first hypothesis is made considering the fact that although LS usually yields higher returns than DCA, many authors defend that DCA is better suited for more volatile markets (Choudhari & Borgaon, 2020; Habsjah & Permana, 2023; Kapalczynski & Lien, 2021; Lu et al., 2021; Merlone & Pilotto, 2014; Milevsky & Posner, 2003).

Therefore, since the crypto market is characterized by its inherent volatility, we theorise that DCA will prove to be better suited in terms of risk-adjusted returns.

***Hypothesis 2*:** Extending the Dollar-Cost Averaging (DCA) investment period from 12 to 24 or 36 months is associated with a decrease in overall portfolio profitability but an increase in risk-return ratios.

The second hypothesis is drawn from the results of Kirkby et al. (2020), where the authors established, for the S&P 500 index, that the frequency of investment in DCA impacts various risk-return metrics, including the reduced final wealth in longer investment periods.

We theorise that the same conclusions will be achieved in the cryptocurrency markets.

***Hypothesis 3*: **Returns observed in Bitcoin will be positively correlated with those of Ethereum and Ripple.

This third hypothesis is based on the fact that many authors have demonstrated the existence of spillovers in the crypto market (Katsiampa et al., 2019a; Koutmos, 2018; Li, 2022), namely one-directional spillovers, meaning that when Bitcoin's returns increase, others tend to increase as well, and if it decreases, the same happens in other cryptocurrencies. This effect generates positive correlation between assets.

Therefore, we theorise that Bitcoin will show correlation with the other two assets when applying these specific strategies.

***Hypothesis 4*: **All scenarios contain predictive power and therefore the market is not efficient ($\phi \neq 0$).

Our final hypothesis was formulated since past authors agree on the inefficiency of cryptocurrencies (Barivieira et al., 2017; Nadarajah & Chu, 2017; Urquhart, 2016), more particularly Bitcoin, even though it appears to be more efficient over time. We aim to corroborate this assumption by implementing an AR-GARCH model to assess efficiency.

4. Methodology

This section outlines the methodology implemented in this thesis. In essence, this study is based on an investing simulation conducted using daily real historical data over a period of nine years (2016 – 2024). Three major cryptocurrencies were selected as the underlying asset: Bitcoin (BTC), Ethereum (ETH) and Ripple (XRP). For each currency, two strategies were evaluated, DCA and LS.

To effectively understand the impact that the investment period has on profitability, the DCA strategy was also divided into three different investment period horizons, namely 12 months, 24 months, and 36 months, totalling four strategies for each currency.

Following the execution of the simulation, standard statistical calculations were performed, and relevant ratios were calculated to address the previously formulated hypotheses as well as to ascertain the performance of the strategies. Additionally, Liu and Chen (2020) model was implemented to test predictability in these three assets.

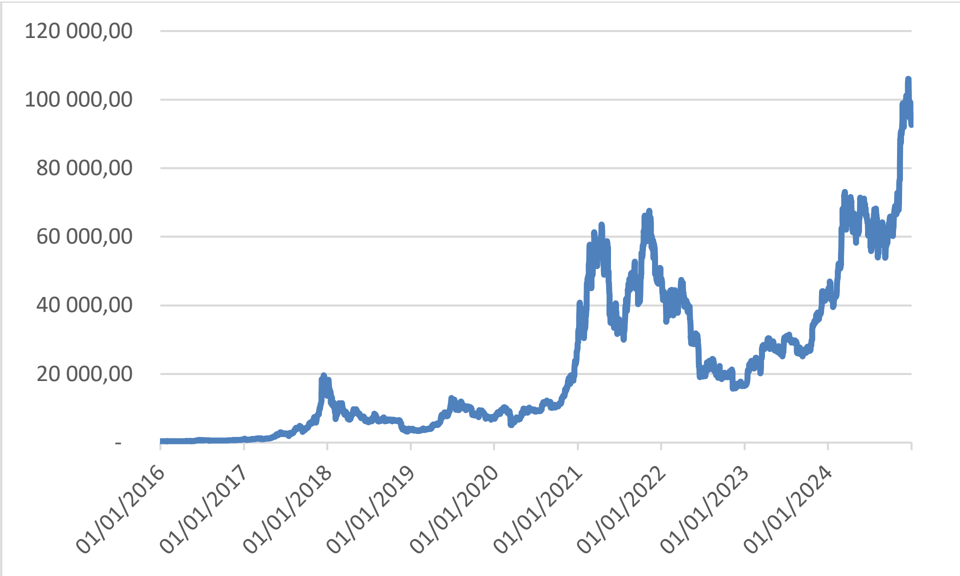
4.1. Data

All the data on cryptocurrencies used in this study was extracted from Coingecko, which, according to the literature is one of the best sources of reliable crypto data (Vidal-Tomás, 2022). As previously explained, the data set consists of daily historical data on the three major cryptocurrencies, over a period of nine years. The behaviour of the assets in question over the defined time period is visualized in the Figures 1, 2 and 3 (in USD).

Overall, it can be seen that we are working in a bull market scenario for every chosen asset. The tendency of market growth can be seen. When compared to the others, XRP seems to be the asset with the least growth, although it has experienced extreme peaks.

It should also be noted that the initial period shows small imbalances which may impact our DCA strategies.

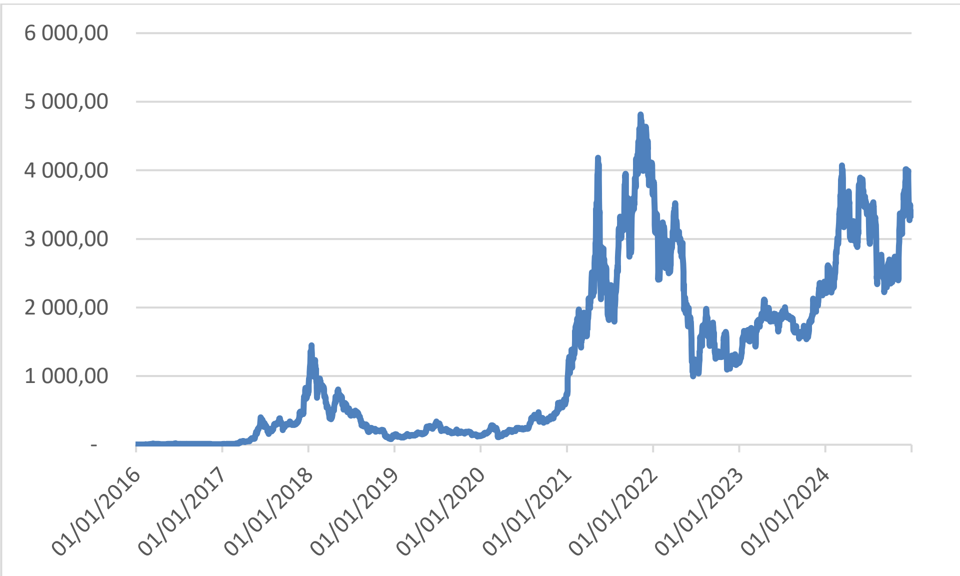
Figure 1
BTC Historical Data.



Source: Author's own elaboration adapted from coingecko

As with BTC, ETH experienced exponential growth followed by a decline between the years of 2017 and 2018, which may once again influence future results of DCA strategies implemented during this period.

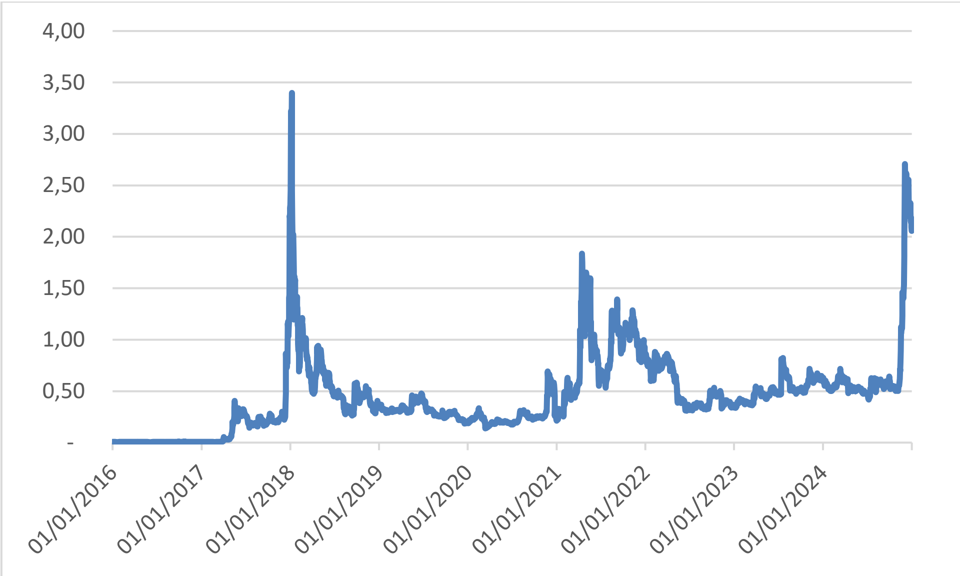
Figure 2
ETH Historical Data.



Source: Author's own elaboration adapted from coingecko

Similarly, XRP also experienced this growth during the same period, reaching its peak price.

Figure 3
XRP Historical Data.



Source: Author's own elaboration adapted from coingecko

4.2. Analysis Model

As stated before, the simulation and construction of our database were carried out using historical daily prices for each of the selected cryptocurrencies. To simulate our investment strategies, four different scenarios were created for each cryptocurrency, to each scenario were implemented an amount of 1 000 000 USD.

1. DCA_12: the amount of money to be invested was divided into twelve equal monthly instalments, to be incorporated into the portfolio on the first day of each month for the first year.
2. DCA_24: the amount of money to be invested was divided into twenty-four equal monthly instalments, to be incorporated into the portfolio on the first day of each month for the first two years.
3. DCA_36: the amount of money to be invested was divided into thirty-six equal monthly instalments, to be incorporated into the portfolio on the first day of the month for the first three years.
4. LS: the total amount of capital was allocated to the asset in a single investment at the initial moment.

With this implementation we created 12 different combinations of asset-strategy, which will be addressed as BTC_DCA12, ETH_DCA12, XRP_DCA12, BTC_DCA24, ETH_DCA24,

XRP_DCA24, BTC_DCA36, ETH_DCA36, XRP_DCA36, BTC_LS, ETH_LS, and XRP_LS.

To analyse patterns in our data, we must first calculate the daily returns of each asset-strategy pair. There are many methods to determine them. According to the literature, the market model proposed by Sharpe (1963) would have been an appropriate methodological choice. However, in the crypto market a reliable benchmark for the horizon period of the data is, to our knowledge, non-existent.

Appropriate crypto indexes have been created only recently which precludes their use, as they do not cover the required time period. Additionally, using bitcoin itself as a benchmark would defeat the purpose, since this asset is included among the study's data. Although it would be a reasonable choice as a benchmark for ETH and XRP, it would be redundant to be compared it to itself and is therefore also not ideal.

For this reason, we selected a simpler approach. We calculated the logarithm daily returns of our collected data, to be compared among the strategies used and the selected assets, rather than effectively testing a duality with the market itself. In this scenario, instead of calculating an index return, we work with observed returns.

$$R_{i,t} = Ln(P_{i,t}/P_{i,t-1}) \tag{1}$$

Where:

$R_{i,t}$: Return of strategy-asset *i* on day *t*.

$P_{i,t}$: Value of strategy-asset *i* on day *t*.

$P_{i,t-1}$: Value of strategy-asset *i* on day *t-1*.

4.3. Statistical Testing and Data Treatment

After finalizing our dataset, we began by ascertaining the normality of our distributions through the program Gretl. In this instance, we applied the Shapiro-Wilk and Lilliefors tests, which are the recommended tests for continuous data, and are usually used in logarithmic returns.

Subsequently we conducted a series of descriptive statistical analysis to summarize and characterise our data. This analysis was then enhanced by statistical testing of correlations between the strategies and assets. Finally, we used our data to calculate two ratios to assess the duality of risk-return between the strategies implemented, namely the Sharpe ratio and the Sortino ratio.

$$Sharpe\ Ratio = \frac{(R_i - R_f)}{\sigma_i}$$

(2)

Where:

R_i : Return of the combination i.

R_f : Risk-Free rate.

σ_i: Standard deviation of the combination's excess return.

We then annualise our ratio for better comparison with future work, as well as to ensure the uniformity of the data.

$$Sharpe\ Ratio_{Annual} = Sharpe\ Ratio \times \sqrt{365}$$

(3)

The Sharpe ratio assumes however that the distribution of the data set is normal, proving to be limited with asymmetric distributions. Additionally, it presumes the risk-free rate to be known and constant. In our case, we selected the rate of Daily Treasury Bills (DTBs) of the USA, to be in accordance with the data that was extracted in USD. Given this premise this ratio alone may prove to be insufficient to completely appraise the performance of these strategies, so we decided to also incorporate the Sortino ratio.

$$Sortino\ Ratio = \frac{(R_i - R_f)}{downside\ \sigma_i}$$

(4)

Where:

R_i : Return of the combination i.

R_f : Risk-Free rate.

σ_i: Standard deviation of the negative combination's return.

And in accordance with the Sharpe Ratio, this ratio too was annualized.

$$Sortino\ Ratio_{Annual} = Sortino\ Ratio \times \sqrt{365}$$

(5)

Unlike the Sharpe ratio, this ratio focusses exclusively on the downside risk. It provides a more conservative and, in non-normal distributions, more accurate assessment of risk.

Additionally, to address our previous ***Hypothesis 3***, we also tested all the combinations for existing correlation between them.

4.4. AR-GARCH Model

To further extend our study we also analysed our data considering non-constant volatility. In essence, the methodology used so far is based on the premise of constant volatility calculated from the means of returns. However, the AR(1)-GARCH(1,1) model integrates a conditional mean and variance; the objective of this model is to capture the predictable components of both return and risk.

Since financial return series, especially those of cryptocurrencies, exhibit time-varying variance, this model is a good fit (Katsiampa, 2017; Kirkby et al, 2020). Using this method, we aim to ascertain the efficiency or inefficiency of this market.

This method is divided into two stages. Firstly, we start by calculating our conditional mean equation.

$$R_t = \mu + \phi R_{t-1} + \varepsilon_t$$

(6)

$$\varepsilon_t = \sigma_t z_t$$

(7)

Where:

R_t: Return of the combination at time *t*.

μ: Constant mean.

ϕ: Autoregressive coefficient.

R_{t-1}: Return of the combination at time *t-1*.

ε_t: Error term.

σ_t: Conditional variance.

z_t: Standardized white noise process.

Secondly, we construct the model equation for obtaining conditional volatility.

$$\sigma_t^2 = \omega + \alpha \mathcal{E}_{t-1}^2 + \beta \sigma_{t-1}^2$$

(8)

Where:

σ_t^2: conditional variance at time *t*.

ω: constant variance component.

α: ARCH coefficient capturing short reaction of volatility.

$\mathcal{E}_{t-1}^2$: past squared error term.

β: GARCH coefficient capturing persistent effect of volatility.

σ_{t-1}^2: lagged condition variance.

The AR-GARCH model provides a flexible framework for assessing both expected returns and time-varying volatility, which is essential for evaluating risk-adjusted performance metrics. Furthermore, setting the order of AR to one allows us to evaluate the predictability of returns. It has also been proven that the Sharpe ratio can be calculated through the AR(1) process without the impact of GARCH components (Liu & Chen, 2020).

Using this model enables us to understand future risk and dynamically adjust the selected performance ratios. The model assesses the continuity of risk and evaluates whether the volatility is static or explosive.

In conclusion, we calculated the Sharpe ratio using these new variables to draw more accurate conclusions about the tendency of these assets and quantify predictability through our model specifications.

5. Empirical Results

The present section details the empirical findings obtained through the aforementioned simulation. The results serve as a response to our initial hypothesis and are presented as follows. The section is divided into subsections to enable a clearer analysis of our results. We begin by presenting the portfolio returns obtained for each combination.

We then present the descriptive statistics, in which a summary of statistical results is provided and explained. The measures obtained include central tendencies (means and medians), indicators of dispersion (standard deviation as well as downside deviation) and distributional measures (skewness and kurtosis).

Subsequently, performance ratios outlining the relationship between risk and return in each strategy-cryptocurrencies combination are evaluated, namely the Sharpe and Sortino ratios. Although we are working with daily data, these ratios are presented in annualised form to facilitate comparison, not only among themselves but also with future work.

The next subsection presents evidence regarding the existence of correlation between the two strategies and cryptocurrencies; these results are derived from a non-parametric correlation test (the Spearman test).

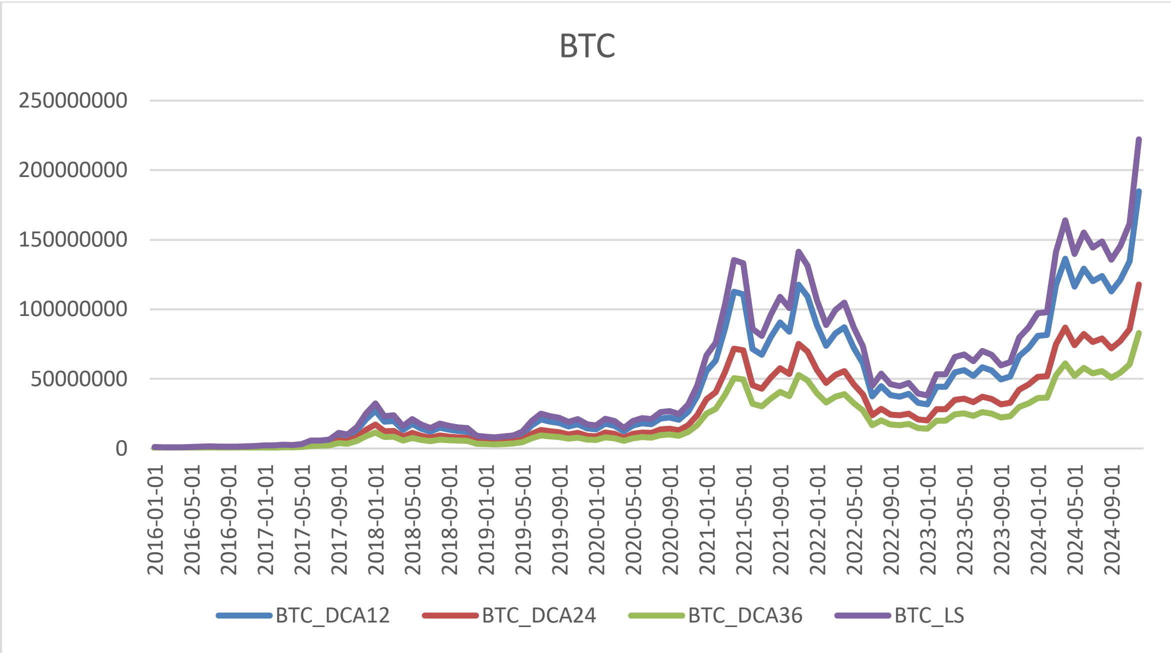
Subsequent statistical tests are presented to further demonstrate the significance of the observed differences in performance between combinations. The results of paired t-tests are displayed to enhance robustness of our results.

Subsequently, the AR-GARCH model's results are presented and analysed, providing a model to obtain conditional volatility. Finally, a new set of Sharpe ratios is calculated to quantify the predictive power of our model.

5.1. Portfolio Results

In terms of our nominal portfolio values, the trend observed is that LS presents greater profitability. As expected, the scenarios with the LS strategy mimic the graphical patterns of the cryptocurrency in each case. For all scenarios, the order of pure profitability in terms of strategy remains unchanged, with the LS strategy as the most profitable, followed by DCA12, DCA24 and DCA36, implying that delaying the initial investment may be prejudicial to overall profitability, which corroborates the work of Kirkby et al. (2020).

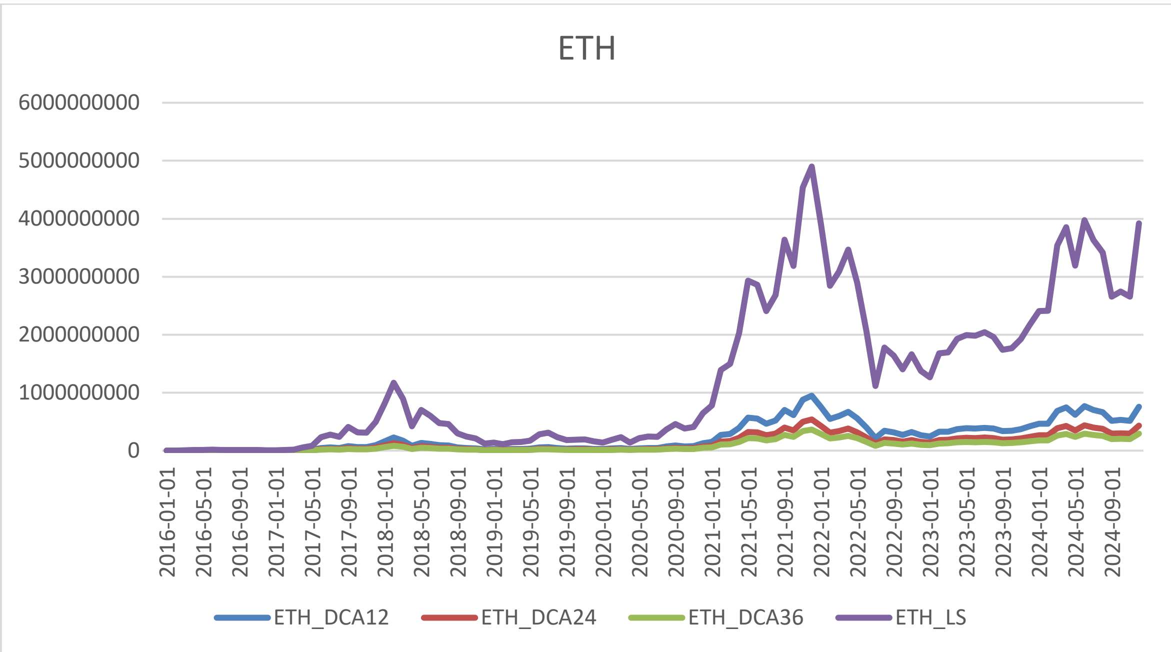
Figure 4
BTC Combination's Returns.



Source: Author's own elaboration

Specifically for ETH, the changes in prices during the first year were very noticeable, and as theorised earlier, had a significant impact on our results, as shown by the dramatic difference between the LS and DCA strategies.

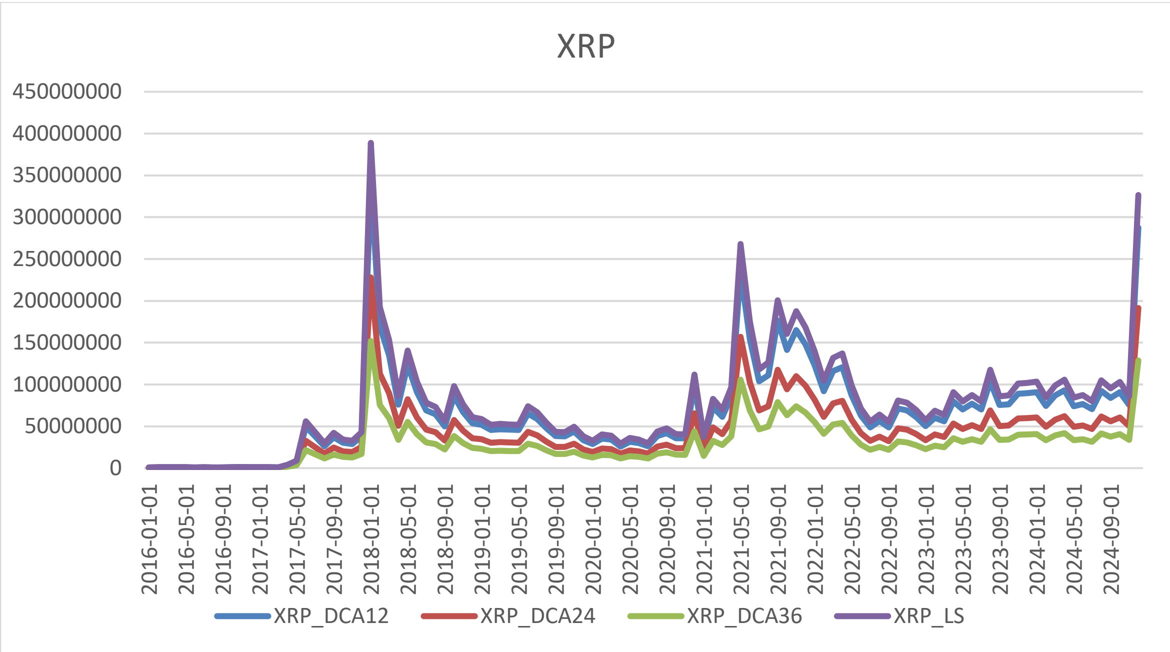
Figure 5
ETH Combination's Returns.



Source: Author's own elaboration

For XRP the extreme upwards movement in 2017 and 2018, which greatly affected investments in DCA24 and DCA36, is the main reason for this discrepancy in obtained profitability. Nonetheless, since the absolute growth during this period differs from that of ETH, the overall difference between strategies at the end of the simulation is not as significant.

Figure 6
XRP Combination's Returns.



Source: Author's own elaboration

Nonetheless, analysing results solely from a graphical perspective is not only insufficient but also potentially misleading. Therefore, the only reliable conclusion that we can draw is that, overall, all the markets within the chosen time horizon, are bull markets and that all strategies have provided positive returns, with LS granting higher profits in every asset-strategy combination.

In Table 3 we report the final portfolio value for each combination. If we were to evaluate based solely on final profitability, the LS strategy would be the clear winner, having achieved a higher final value than its counterpart. Furthermore, within each strategy, we note that ETH is the asset that generated the highest profitability.

Table 3
Final Portfolio Values

	Final Value (USD)
BTC_DCA12	177 401 304.17
ETH_DCA12	686 597 152.55
XRP_DCA12	304 726 674.04
BTC_DCA24	113 103 422.51
ETH_DCA24	389 874 453.88
XRP_DCA24	202 966 187.30
BTC_DCA36	79 618 304.25
ETH_DCA36	263 218 720.11
XRP_DCA36	136 527 577.60
BTC_LS	**213 217 139.20**
ETH_LS	**3 550 107 336.37**
XRP_LS	**346 250 920.50**

Note. Source: Author's own elaboration

5.2.Descriptive Statistics

Before obtaining any statistics, all the paired cryptocurrency-strategy data were tested for normality to categorise their distributions. For this purpose, two tests were employed to enhance the robustness of their results, namely the Shapiro-Wilk and the Lilliefors tests.

$\boldsymbol{H_0}$: The data follows a normal distribution.

$\boldsymbol{H_1}$: The data does not follow a normal distribution.

After applying both tests at a standard significance level of 5% (α = 0.05), our results yielded p-values approaching zero; therefore, we reject the null hypothesis (H_0) at a significance level of 5%. The observed deviations reflect asymmetry, and for this reason, the subsequent tests selected are non-parametric, as they prove more reliable in non-normal distributions.

The distribution results were expected. According to the literature, returns in crypto markets usually follow a non-normal distribution, characterized by asymmetry and fat tails typically caused by the heightened volatility for which this market is known (Chan et al, 2017; Corbet et al, 2019; Fry, 2018).

In Table 4 all the descriptive statistics are reported; additionally, all the metrics shown are daily results.

Table 4
Summary of Descriptive Statistics

	Mean	Median	Standard Deviation	Skewness	Kurtosis	Downside Standard Deviation	Coefficient of Variation
BTC_DCA12	0.0023	0.0016	0.0403	2.2245	54.369	0.0294	17.3110
ETH_DCA12	0.0027	0.0010	0.0525	-0.3044	8.911	0.0396	19.1430
XRP_DCA12	0.0025	-0.0005	0.0634	2.1150	28.683	0.0419	25.4180
BTC_DCA24	0.0024	0.0016	0.0404	2.2152	54.019	0.0294	16.8040
ETH_DCA24	0.0028	0.0010	0.0525	-0.3043	8.895	0.0396	18.8850
XRP_DCA24	0.0026	-0.0005	0.0635	2.1090	28.580	0.0419	24.5790
BTC_DCA36	0.0024	0.0016	0.0404	2.2157	54.044	0.0294	16.6870
ETH_DCA36	0.0028	0.0010	0.0525	-0.3044	8.896	0.0396	18.8580
XRP_DCA36	0.0026	-0.0005	0.0635	2.1089	28.581	0.0419	24.5530
BTC_LS	0.0016	0.0016	0.0366	-0.5976	10.668	0.0294	22.4120
ETH_LS	0.0025	0.0008	0.0521	-0.3973	8.708	0.0396	20.9490
XRP_LS	0.0018	-0.0007	0.0615	1.8535	28.257	0.0418	34.5800

Note. Source: Author's own elaboration

We can observe that all scenarios present positive and similar means. However, we cannot compare this mean with a cumulative mean, as a higher mean does not necessarily imply higher profitability. Nonetheless, we can conclude that, on average, all the combinations provided positive daily mean returns.

As for standard deviation, we note that BTC has the lowest values across all strategies, followed by ETH and XRP, which displays the highest values. Nonetheless all assets present high daily values of volatility. Specifically, in the DCA strategy, it seems that the investment horizon does not affect volatility, since all values are approximately equal within the same asset. Additionally, the coefficient of variation shows higher values for XRP and lower for BTC. Taken together, these metrics suggest that, based on this data, BTC seems to be the most stable asset of the three.

In contrast, the downside standard deviation quantifies the variability of negative returns, it highlights potential losses rather than overall volatility. In essence, the higher the value of this metric the larger or more frequent the negative returns are relative to the average performance of the assets. In this case, it shows that XRP presents higher downside risk, complementing the analysis on volatility.

All results imply that XRP has the worst risk metrics of all examined assets.

As for skewness and kurtosis, the obtained results complement the conclusions on non-normal distribution, with all assets being asymmetric and fat-tailed. Specifically, BTC shows the highest asymmetry and the fattest tails. By contrast, ETH has the lowest values with smaller asymmetry and less heavy tails.

5.3. Risk-Return Results

After acquiring the data displayed in Table 4, we calculated the performance ratios of these asset-strategy combinations and the conclusions drawn are presented in Table 5.

Table 5
Performance Ratios

	Sharpe Ratio	***Sortino Ratio***
BTC_DCA12	**1.0487811**	**1.4394327**
ETH_DCA12	0.9558573	1.2673318
XRP_DCA12	0.7167030	1.0856490
BTC_DCA24	**1.0821655**	**1.4875425**
ETH_DCA24	0.9695169	1.2860559
XRP_DCA24	0.7423960	1.1247992
BTC_DCA36	**1.0901493**	**1.4988760**
ETH_DCA36	0.9709178	1.2878864
XRP_DCA36	0.7432505	1.1259432
BTC_LS	0.7918924	0.9853254
ETH_LS	**0.8694598**	**1.1441691**
XRP_LS	0.5164650	0.7591969

Note. Source: Author's own elaboration

For each strategy we have highlighted the combination with the highest performance ratio to facilitate analysis.

When comparing strategies, the Sharpe ratio takes higher values in all DCA combinations, meaning that DCA presents a better risk-return trade-off than its counterpart, implying that this strategy is better suited in terms of the balance between risk and return.

In all DCA combinations we can also observe that BTC is the asset with the highest risk-return ratio. Furthermore, we can also infer that delaying the investment period has a positive impact on balancing returns with risk, due to slight growth across all assets, when delaying the investment from 12 to 24 or 36 months.

As for the LS strategy, the outlook shifts, with ETH proving to be more efficient in this ratio.

In every scenario, XRP is the asset that presents the lowest Sharpe ratios. Aligning this finding with the previous obtained risk result, we can infer that, even though it presented profitability, the other assets not only achieved higher returns but also exhibited lower risk. According to Markowitz (1952), and under the assumptions of our study, this asset is an inefficient investment.

After assessing the non-normality of the distributions, we note that this ratio alone is insufficient to fully capture the context of these scenarios, as the Sharpe ratio relies on the assumption of normality, which as stated before, is not the case. For this reason, we further employed another ratio to better understand our results.

The Sortino ratio, however, yielded the same conclusions, with BTC outperforming every other asset in DCA strategies while ETH has a higher ratio in the LS strategy. When comparing both strategies for the same asset, DCA achieves better Sortino ratios, meaning that this strategy represents a better risk-return balance.

With these results, we can now validate our ***Hypothesis 1***. We conclude that our findings corroborate those of past studies in other markets (Choudhari & Borgaon, 2020; Habsjah & Permana, 2023; Kapalczynski & Lien, 2021; Lu et al., 2021; Merlone & Pilotto, 2014; Milevsky & Posner, 2003), and DCA indeed presents better performance ratios.

As stated above, our data is characterised by high volatility. Moreover, the risk-adjusted returns obtained in this simulation appear to favour the DCA strategy as the winner, even though, as demonstrated in previous sections, it was LS that provided higher profitability.

In the same way we do not reject ***Hypothesis 2***, as our data show that, although delaying the investment period does reduce overall profitability (in our case), it slightly improves our ratios in every combination of DCA strategies.

In any case, we can state that all values of both the Sharpe ratio and the Sortino ratio are either above 1 or close to it, apart from the XRP_LS combination, meaning that these strategies seem to provide higher returns relative to the given risk. It should be noted that these conclusions are drawn from our period in analysis, extending or shortening it may significantly alter our conclusions.

We further examined these values from a statistical point of view. We assessed the normality of the distributions of both the Sharpe ratio and the Sortino ratio and subsequently conducted t-tests. As can be observed in Table 6, we concluded that both ratios are significantly positive at the 1% level, indicating that the strategies present statistically significant positive risk-adjusted returns.

Table 6
Statistical Significance of Performance Ratios

	t-test	*p-value*
Sharpe Ratio	17.248	<0.001
Sortino Ratio	19.316	<0.001

Note. Source: Author's own elaboration

5.4. Correlation Between Strategies

With the objective of addressing our ***Hypothesis 3***, we created a correlation table (the Table 7) using a Spearman test. We selected this test specifically because our data distribution is non-normal. We also determined p-values to infer the validity of our results. For every correlation metric obtained, the associated p-value is close to zero, signifying strong significance at any level, which in this case was the usual 5%.

Table 7
Levels of Correlation Between Combinations

	BTC_DCA12	ETH_DCA12	XRP_DCA12	BTC_DCA24	ETH_DCA24	XRP_DCA24	BTC_DCA36	ETH_DCA36	XRP_DCA36	BTC_LS	ETH_LS	XRP_LS
BTC_DCA12	1.000	0.659	0.575	**0.999**	0.659	0.576	**0.999**	0.659	0.576	**0.996**	0.653	0.568
ETH_DCA12		1.000	0.606	0.658	**0.999**	0.607	0.658	**0.999**	0.607	0.658	**0.997**	0.603
XRP_DCA12			1.000	0.575	0.606	**0.998**	0.575	0.606	**0.998**	0.569	0.601	**0.996**
BTC_DCA24				1.000	0.659	0.577	**0.999**	0.659	0.577	**0.996**	0.653	0.568
ETH_DCA24					1.000	0.608	0.659	**1.000**	0.608	0.658	**0.996**	0.603
XRP_DCA24						1.000	0.577	0.608	**1.000**	0.571	0.602	**0.994**
BTC_DCA36							1.000	0.659	0.577	**0.995**	0.652	0.568
ETH_DCA36								1.000	0.608	0.658	**0.996**	0.603
XRP_DCA36									1.000	0.571	0.602	**0.994**
BTC_LS										1.000	0.656	0.570
ETH_LS											1.000	0.604
XRP_LS												1.000

Note. Source: Author's own elaboration

The results were to be expected. In each combination of cryptocurrency-strategy, the highest level of correlation is highlighted to facilitate understanding of our results. We concluded that all combinations are positively correlated with one another.

Furthermore, for the same cryptocurrency, regardless of the strategy, the level of correlation is close to its maximum. In contrast, when comparing different assets with the same strategy, the level of correlation is medium-high, with values of relationship between 0.5 and 0.7.

This metric indicates how closely the returns of our assets behave, with the high values suggesting strong co-movement among certain combinations.

Although our high values of correlation do not necessarily indicate volatility spillovers between our assets, we can state that all three assets exhibit positive co-movements throughout our investment horizon, which corroborates the patterns observed in the previously displayed graphs as well as previous studies (Katsiampa, 2019b).

The evidence presented in Table 7 provides strong support for the ***Hypothesis 3***, that returns observed in Bitcoin will be positively correlated with those of Ethereum and Ripple. We further show that, not only are they correlated with each other, but their levels of correlation are medium to high.

Furthermore, this implies that investing in all three assets may prove to be inefficient in terms of diversification, as the assets, by showing these levels of correlation, our results show that they move together and seem to react similarly to market conditions. Moreover, investing in two or more at the same time presents little risk reduction by the attempt of portfolio diversification.

5.5. AR-GARCH Model

Our subsequent phase in this study consisted of creating our AR(1)-GARCH(1,1) model to better understand not only our historical data but also to enable us to assess its predictive capacity.

After completing the model, we can now observe the results of our data more accurately. The variables of our model are displayed in Table 8, with their significance levels categorised as 1%, 5% or 10%.

Table 8
AR(1)-GARCH(1,1) Model

	μ	ϕ	ω	α	β
BTC_DCA12	0.00156616 ***	-0.05245350 ***	0.00014436 *	0.37127300 **	0.83577100 ***
ETH_DCA12	0.00123446 **	-0.07685720 ***	0.00007290 *	0.16580500 ***	0.86273400 ***
XRP_DCA12	-0.00124600 ***	-0.10685900 ***	0.00065000 *	0.90686900 *	0.72665400 ***
BTC_DCA24	0.00152882 ***	-0.05111290 ***	0.00014179	0.38186100 **	0.83981900 ***
ETH_DCA24	0.00125896 **	-0.07587410 ***	0.00007200 *	0.16280400 ***	0.86409700 ***
XRP_DCA24	-0.00119535 ***	-0.10638200 ***	0.00071893	0.96005700	0.72591700 ***
BTC_DCA36	0.00155226 ***	-0.05120270 ***	0.00014144	0.37634800 **	0.83931300 ***
ETH_DCA36	0.00126285 **	-0.07583090 ***	0.00007204 *	0.16275600 ***	0.86409500 ***
XRP_DCA36	-0.00119368 ***	-0.10634600 ***	0.00071780	0.95839800	0.72587200 ***
BTC_LS	0.00144420 ***	-0.05525660 ***	0.00001329	0.16646400 ***	0.90910300 ***
ETH_LS	0.00115357 **	-0.07881850 ***	0.00007687 *	0.17197700 ***	0.85768900 ***
XRP_LS	-0.00139032 ***	-0.10561100 ***	0.00021564 **	0.46717400 ***	0.78426500 ***

Note. Source: Author's own elaboration

The means obtained through this process are different from those previously presented in the descriptive statistics. It is important to note that these values are conditional means and can be used to evaluate serial correlations.

When compared to the means calculated earlier it is evident that they all diminished, with the divergence being more pronounced in combinations involving the asset XRP, which show negative means for every XRP combination. Although these negative values might look paradoxical given the positive returns previously shown, this mean is calculated controlling for the autoregressive (AR) effect. For this reason, the means must be analysed alongside the AR metric (ϕ).

All assets show negative values of this metric, indicating that every asset exhibits some level of mean reversion. That is, for every day that the mean is negative, the subsequent day it is positive, and vice-versa. This effect is more apparent in XRP, which exhibits the lowest value. This metric also reflects the predictability of the model; the greater the absolute value, the higher the predictive capability. Since XRP has the highest values of the three assets and BTC the lowest, it follows that BTC has lower predictability under this model while XRP shows the highest.

For our ARCH coefficient (α), in BTC specifically in DCA strategies, it is around 0.37 while the GARCH coefficient (β) is 0.83. These results imply that these asset-strategy combinations are moderately shock-sensitive ($\alpha \approx 0.37$) meaning shocks have an eventual rather than an immediate effect on volatility. However, the effect is highly persistent ($\beta \approx$

0.83). By contrast, the LS strategy produces weaker volatility shocks ($\alpha \approx 0.16$), which disperse slowly, meaning a higher persistence ($\beta \approx 0.91$). Additionally, DCA12, DCA24 and DCA36 have similar values, suggesting that the time horizon of investment does not have a significant impact on volatility clustering.

For ETH, the DCA strategies are similar too, once again confirming the unchanged effect of the investment horizon. When compared to BTC, ETH has lower sensitivity to shocks ($\alpha \approx 0.16$) however it is also characterized by high persistence ($\beta \approx 0.86$). In the LS strategy, the pattern is maintained, with a slight increase in shock-sensitivity and a slight decrease in volatility persistence.

Finally, XRP has the highest values of shock-sensitivity coefficient ($\alpha \approx 0.95$) and the lowest volatility persistence ($\beta \approx 0.72$). This means that XRP reacts strongly to new shocks, although the effects dissipate more quickly in comparison with the other assets, noting that the values of β are still high. Once again, the pattern in investment horizons of DCA appears, with all values showing minor differences. In the LS strategy, however, shock sensitivity changes significantly, reducing from around 0.95 in the DCA strategies to 0.46, showing that LS impacts the shock sensitivity, diminishing its effect.

In conclusion, for BTC, the strategy seems to affect our results, with DCA stabilising short-term shocks while keeping volatility persistent and LS reducing shocks at the cost of slower reversion.

ETH shows little difference indicating that strategy choice and investment horizon do not drastically change volatility dynamics.

As for XRP, the strategy highly affects the shock reaction, significantly lowering its sensitivity while maintaining the same level of persistence across the scenarios.

After obtaining our models we then computed the variables into Sharpe ratios according to the equations of Liu and Chen (2020). The model-based ratios are illustrated in Table 9. They describe the risk-adjusted exploitable return, serving as predictors of return. As shown mathematically, these Sharpe ratios do not stem from the GARCH components of the model; thus, they simply represent a forecast based on the model (AR values) and not raw historical returns. The objective of these Sharpe ratios is different from before as they do not reflect the return-risk duality for the future but rather they denote the efficiency of the market.

Table 9
Predictability Levels of AR(1)-GARCH(1,1) Model

	Sharpe ratio
BTC_DCA12	0.80027942
ETH_DCA12	1.17378669
XRP_DCA12	**1.63486505**
BTC_DCA24	0.77979146
ETH_DCA24	1.15871690
XRP_DCA24	**1.62751421**
BTC_DCA36	0.78116376
ETH_DCA36	1.15805474
XRP_DCA36	**1.62695946**
BTC_LS	0.84312730
ETH_LS	1.20385771
XRP_LS	**1.61563420**

Note. Source: Author's own elaboration

Of our three assets, BTC is the one that shows the lowest Sharpe ratio in every strategy, followed by ETH and then XRP, which has the highest values.

Additionally, the LS strategy seems to benefit this metric when compared to DCA. It is also observable that the increase of the investment period has an impact on our ratios, with the greatest Sharpe ratio among BTC_DCA strategies being the 12 months scenario.

The asset ETH seems to display a similar pattern with LS providing a higher Sharpe ratio, and among DCA strategies, the longer the investment horizon the smaller the Sharpe ratio.

In XRP, however, the paradigm shifts, with the LS strategy providing the smallest of Sharpe ratios, although, once again, the increase in investment period does not have a positive consequence on this ratio.

Although, as stated before, we cannot directly compare these Sharpe ratios with the previously calculated ones because these show predictable risk-return values rather than historical ones, we can ascertain that the closer to zero the AR(1) coefficient is, the weaker the predictability factor.

It is measurable that the strategy-asset combinations with the highest absolute values of AR (ϕ), consequently present the highest Sharpe ratios. This predictability stems from the dependence on yesterday's results, and thus, what this model presents indirectly is market efficiency in each asset under study. An efficient market would incorporate all information into its prices instantly, meaning that past results would not be relied upon or considered.

Therefore, these results corroborate past literature, which ascertains the inefficiency of cryptocurrencies market, although the literature also classifies Bitcoin market as being more efficient when compared to other cryptocurrencies.

These results show evidence of significant predictability in all scenarios leading us not to reject ***Hypothesis 4***, meaning inefficiency in this market, which corroborates past literature (Barivieira et al., 2017; Nadarajah & Chu, 2017; Urquhart, 2016).

In conclusion, all our hypotheses were corroborated by the obtained results. ***Hypothesis 1*** which theorized that the DCA strategy would present better ratios, was corroborated after obtaining both the Sharpe and Sortino ratios that gave us the same conclusion. Additionally, ***Hypothesis 2*** which said that delaying the investment period would result in better risk-return ratios at the cost of reducing return has also been corroborated, with the reduction of portfolio value in each case with a slight enhancement of both ratios. ***Hypothesis 3*** that theorized the existence of positive correlation between Bitcoin and the other two cryptocurrencies, to test this hypothesis we have shown evidence of medium to high correlation between all cryptocurrency-strategy combination. Finally, we have also corroborated ***Hypothesis 4***, with resource to our model where we show that all combinations have some degree of predictive capacity and therefore are not efficient. All our results were robust since all were validated by strong p-values.

5.6. Limitations and Future Work

Although we were able to obtain results supporting our initially proposed hypothesis, this study is not without its limitations.

First, we assumed a time period of nine years which we deemed to be appropriate for our analysis. However, even a slight reduction or extension of this horizon can drastically alter our results. Similarly, changing the starting point of investment is critical and any other starting moment would yield different metrics. Hence, we propose testing our combinations over shorter time periods, categorized as “normal” and “eventful” to better analyse trends and study the impact of significant events, such as wars or the COVID-19 pandemic.

Second, this study was conducted during an overall bullish market period. Future research could explore the performance of these strategies in both a bullish and bearish market conditions.

Third, we found that incorporating transaction costs could significantly influence results, specifically in DCA strategies where the number of transactions is higher. We thus, suggest analysing the impact of including such costs into our model.

Another limitation was the absence of a reliable benchmark in this market. Future work may incorporate more recent data to better utilize new crypto indexes as benchmarks.

We also propose the introduction of an augmented DCA strategy in future works, as referenced in the literature review, as to better compare these strategies and analyse their application in the crypto market.

6. Conclusions

The objective of this study was to evaluate two different strategies (DCA and LS) in a 9-year simulation to assess for profitability, performance, and risk. All objectives were achieved, and all hypotheses were duly examined, and the robustness of the results was confirmed.

The empirical results revealed firstly that all of our asset-strategy combinations generated overall profitability demonstrating their ability to generate returns and underscoring the role of structured investment strategies.

Subsequently, we confirmed that all assets in this study inherently exhibit high volatility, asymmetry, and fat-tails, which in the case of BTC, could be mitigated through investment strategy selection.

Additionally, we found that DCA was the strategy delivering the most favourable risk-return profile with higher values for both the Sharpe and the Sortino ratios. Moreover, BTC was the asset that exhibited the strongest ratios within the DCA strategy.

Correlation analysis indicated that all three assets are moderately to highly positively correlated. We also inferred that strategy and investment period have little to no effect on the correlations between these assets.

In developing our AR(1)-GARCH(1,1) model, we identified that BTC exhibits low to moderate shock sensitivity while displaying high persistence; ETH shows lower shock sensitivity and high persistence; and XRP exhibits both high shock sensitivity and high persistence. Additionally, we observed that strategy choice affects both sensitivity and persistence in BTC and XRP, while having an insignificant effect on ETH, with LS reducing shock sensitivity and enhancing persistence.

Finally, we ascertained that our model has greater predictive capacity for XRP compared with the other assets. However, it was observed that all cryptocurrencies are inefficient with the model exhibiting some short-term predictive power.

We also identified certain limitations not only in the overall study but also in the results obtained and their treatment. These limitations, consequently, provided opportunity to propose future work stemming from this paper, as well as potential improvements.

Overall, the analysis conducted provide relevant insights, as were the benefits of employing both strategies in the cryptocurrencies market. Taken together, these findings highlight both the opportunities and risks of applying traditional investment strategies to cryptocurrencies. While DCA appears more effective in balancing profitability and risk, the persistence and volatility of crypto assets underline the need for careful strategy selection. These findings carry important implications for both investors and researchers, encouraging further investigation, namely extend this analysis across broader datasets and market conditions, to further refine investment approaches in this emerging asset class.

References

Abakah, E. J., Gil-Alana, L. A., Madigu, G., & Romero-Rojo, F. (2020). Volatility persistence in cryptocurrency markets under structural breaks. *International Review of Economics & Finance, 69*, 680–691. doi:https://doi.org/10.1016/j.iref.2020.06.035

Aharon, D. Y., Butt, H. A., Jaffri, A., & Nichols, B. (2023). Asymmetric volatility in the cryptocurrency market: New evidence from models with structural breaks. *International Review of Financial Analysis, 87*, 102651. doi:https://doi.org/10.1016/j.irfa.2023.102651

Akgül, A., Şahin, E. E., & Şenol, F. Y. (2022). Blockchain-based cryptocurrency price prediction with chaos theory, onchain analysis, sentiment analysis, and fundamental-technical analysis. *Chaos Theory and Applications, 4*(3), 157–168. doi:https://doi.org/10.51537/chaos.1199241

Akyildirim, E., Corbet, S., Lucey, B. M., Sensoy, A., & Yarovaya, L. (2020). The relationship between implied volatility and cryptocurrency returns. *Finance Research Letters, 33*, 101212. doi:https://doi.org/10.1016/j.frl.2019.06.010

Alangot, B., Reijsbergen, D., Venugopalan, S., Szalachowski, P., & Yeo, K. S. (2021). Decentralized and lightweight approach to detect eclipse attacks on proof of work blockchains. *IEEE Transactions on Network and Service Management, 18*(2), 1659–1672. doi:https://doi.org/10.1109/TNSM.2021.3069502

Almeida, J., & Gonçalves, T. C. (2023). A decade of cryptocurrency investment literature: A cluster-based systematic analysis. *International Journal of Financial Studies, 11*(2), 71. doi:https://doi.org/10.3390/ijfs11020071

Al-Yahyaee, K. H., Mensi, W., Ko, H. U., Yoon, S. M., & Kang, S. H. (2020). Why cryptocurrency markets are inefficient: The impact of liquidity and volatility. *The North American Journal of Economics and Finance, 52*, 101168. doi:https://doi.org/10.1016/j.najef.2020.101168

Ammous, S. (2018). Can cryptocurrencies fulfil the functions of money? *The Quarterly Review of Economics and Finance, 70*, 38–51. doi:https://doi.org/10.1016/j.qref.2018.05.010

Anamika, Chakraborty, M., & Subramaniam, S. (2023). Does sentiment impact cryptocurrency? *Journal of Behavioral Finance, 24*(2), 202–218. doi:https://doi.org/10.1080/15427560.2021.1950723

Anantanasuwong, K., & Chaivisuttangkun, S. (2019). Do investors benefit from DCA? Evidence from the stock exchange of Thailand. *Creative Business and Sustainability Journal, 41*(2), 84–101. https://so01.tci-thaijo.org/index.php/CBSReview/article/view/198086

Angerer, M., Hoffmann, C. H., Neitzert, F., & Kraus, S. (2021). Objective and subjective risks of investing into cryptocurrencies: A systematic literature analysis. *Finance Research Letters, 38,* 101737. doi:https://doi.org/10.1016/j.frl.2020.101737

Aslam, F., Memon, B. A., Hunjra, A. I., & Bouri, E. (2023). The dynamics of market efficiency of major cryptocurrencies. *Global Finance Journal, 58*, 100899. doi:https://doi.org/10.1016/j.gfj.2023.100899

Asthana, V. (2024). The inefficiency of Bitcoin and the COVID-19 pandemic. *Review of Applied Socio-Economic Research, 27*, 50-60. doi:https://doi.org/10.54609/reaser.v27i1.409

Balcilar, M., Bouri, E., Gupta, R., & Roubaud, D. (2017). Can volume predict Bitcoin returns and volatility? A quantiles-based approach. *Economic Modelling, 64*, 74–81. doi:https://doi.org/10.1016/j.econmod.2017.03.019

Banerjee, A. K., Akhtaruzzaman, M., Dionisio, A., Almeida, D., & Sensoy, A. (2022). Nonlinear nexus between cryptocurrency returns and COVID–19 news sentiment. *Journal of Behavioral and Experimental Finance, 36*, 100747. doi:https://doi.org/10.1016/j.jbef.2022.100747

Bariviera, A. F., Basgall, M. J., Hasperué, W., & Naiouf, M. (2017). Some stylized facts of the Bitcoin market. *Physica A: Statistical Mechanics and its Applications, 484*, 82–90. doi:https://doi.org/10.1016/j.physa.2017.04.159

Baur, D. G., & Dimpfl, T. (2018). Asymmetric volatility in cryptocurrencies. *Economics Letters, 173*(C), 148–151. doi:https://doi.org/10.1016/j.econlet.2018.10.008

Baur, D. G., & Dimpfl, T. (2021). The volatility of Bitcoin and its role as a medium of exchange and a store of value. *Empirical Economics, 61*(5), 2663–2683. doi:https://doi.org/10.1007/s00181-020-01990-5

Baur, D. G., Hong, K. H., & Lee, A. D. (2018). Bitcoin: Medium of exchange or speculative assets? *Journal of International Financial Markets, Institutions and Money, 54*, 177–189. doi:https://doi.org/10.1016/j.intfin.2017.12.004

Bazán-Palomino, W., & Svogun, D. (2023). On the drivers of technical analysis profits in cryptocurrency markets: A distributed lag approach. *International Review of Financial Analysis, 86*, 102516. doi:https://doi.org/10.1016/j.irfa.2023.102516

Białkowski, J. (2020). Cryptocurrencies in institutional investors' portfolios: Evidence from industry stop-loss rules. *Economics Letters, 191*, 108834. doi:https://doi.org/10.1016/j.econlet.2019.108834

Bierman, H. J., & Hass, J. E. (2004). Dollar-Cost Averaging. *The Journal of Investing, 13*(4), 21–24. doi:https://doi.org/10.3905/joi.2004.450752

Blandin, A., Cloots, A. S., Hussain, H., Rauchs, M., Saleuddin, R., Allen, J., . . . Allen, J. (2019). Global cryptoasset regulatory landscape study. *University of Cambridge Faculty of Law Research,* Paper No. 23/2019. doi:http://dx.doi.org/10.2139/ssrn.3379219

Blau, B. M. (2017). Price dynamics and speculative trading in Bitcoin. *Research in International Business and Finance, 41*, 493–499. doi:https://doi.org/10.1016/j.ribaf.2017.05.010

Bouteska, A., Mefteh-Wali, S., & Dang, T. A. (2022). Predictive power of investor sentiment for Bitcoin returns: Evidence from COVID-19 pandemic. *Technological Forecasting and Social Change, 184*, 121999. doi:https://doi.org/10.1016/j.techfore.2022.121999

Brauneis, A., & Mestel, R. (2018). Price discovery of cryptocurrencies: Bitcoin and beyond. *Economics Letters, 165*, 58–61. doi:https://doi.org/10.1016/j.econlet.2018.02.001

Brennan, M. J., Li, F., & Torous, W. N. (2005). Dollar Cost Averaging. *Review of Finance, 9*(4), 509–535. doi:https://doi.org/10.1007/s10679-005-4999-x

Brière, M., Oosterlinck, K., & Szafarz, A. (2015). Virtual currency, tangible return: Portfolio diversification with bitcoin. *Journal of Asset Management, 16*(6), 365–373. doi:https://doi.org/10.1057/jam.2015.5

Caporale, G. M., & Zekokh, T. (2019). Modelling volatility of cryptocurrencies using Markov-Switching GARCH models. *Research in International Business and Finance, 48*, 143-155. doi:https://doi.org/10.1016/j.ribaf.2018.12.009

Cheah, E.-T., & Fry, J. (2015). Speculative bubbles in Bitcoin markets? An empirical investigation into the fundamental value of Bitcoin. *Economics Letters, 130*, 32–36. doi:https://doi.org/10.1016/j.econlet.2015.02.029

Cheikh, N. B., Zaied, Y. B., & Chevallier, J. (2020). Asymmetric volatility in cryptocurrency markets: New evidence from smooth transition GARCH models. *Finance Research Letters, 35*, 101293. doi:https://doi.org/10.1016/j.frl.2019.09.008

Choudhari, S. R., & Borgaon, H. (2020). The Comparative Study on Systematic Investment Plan and One Time Investment Plan in Mutual Fund. *GBS Impact: Journal of Multi Disciplinary Research, 6*(1), 25-30. https://www.journalpressindia.com/gbs-impact-journal-of-multi-disciplinary-research/doi/v6i1.07

CoinGecko. (n.d.). Retrieved January, 2025, from https://www.coingecko.com

CoinMarketCap. (n.d.). Retrieved November, 2024, from https://coinmarketcap.com/

Colon, F., Kim, C., Kim, H., & Kim, W. (2021). The effect of political and economic uncertainty on the cryptocurrency market. *Finance Research Letters, 39*, 101621. doi:https://doi.org/10.1016/j.frl.2020.101621

Constantinides, G. M. (1979). A Note on the suboptimality of Dollar-Cost Averaging as an investment policy. *The Journal of Financial and Quantitative Analysis, 14*(2), 443–450. doi:https://doi.org/10.2307/2330513

Corbet, S., Larkin, C., Lucey, B. M., Meegan, A., & Yarovaya, L. (2020a). The impact of macroeconomic news on Bitcoin returns. *The European Journal of Finance, 26*(14), 1396–1416. doi:https://doi.org/10.1080/1351847X.2020.1737168

Corbet, S., Larkin, C., Lucey, B., Meegan, A., & Yarovaya, L. (2020b). Cryptocurrency reaction to FOMC announcements: Evidence of heterogeneity based on blockchain stack position. *Journal of Financial Stability, 46*, 100706. doi:https://doi.org/10.1016/j.jfs.2019.100706

Corbet, S., Lucey, B., Urquhart, A., & Yarovaya, L. (2019). Cryptocurrencies as a financial asset: A systematic analysis. *International Review of Financial Analysis, 62*, 182–199. doi:https://doi.org/10.1016/j.irfa.2018.09.003

Corbet, S., Meegan, A., Larkin, C., Lucey, B., & Yarovaya, L. (2018). Exploring the dynamic relationships between cryptocurrencies and other financial assets. *Economics Letters, 165*, 28–34. doi:https://doi.org/10.1016/j.econlet.2018.01.004

Coudert, V., Hervé, K., & Mabille, P. (2015). Internationalization versus regionalization in the integration of emerging markets. *International Journal of Finance & Economics, 20*(1), 16–27. doi:https://doi.org/10.1002/ijfe.1501

De la Horra, L. P., de la Fuente, G., & Perote, J. (2019). The drivers of Bitcoin demand: A short and long-run analysis. *International Review of Financial Analysis, 62*, 21–34. doi:https://doi.org/10.1016/j.irfa.2019.01.006

Detzel, A., Liu, H., Strauss, J., Zhou, G., & Zhu, Y. (2021). Learning and predictability via technical analysis: Evidence from bitcoin and stocks with hard-to-value fundamentals. *Financial Management, 50*, 107-137. doi:https://doi.org/10.1111/fima.12310

Dhali, M., Hassan, S., Mehar, S. M., Shahzad, K., & Zaman, F. (2023). Cryptocurrency in the darknet: Sustainability of the current national legislation. *International Journal of Law and Management, 65*(3), 261–282. doi:https://doi.org/10.1108/IJLMA-09-2022-0206

Diaconaşu, D. E., Mehdian, S., & Stoica, O. (2022). An analysis of investors' behavior in Bitcoin market. *PLOS ONE, 17*(3). doi:https://doi.org/10.1371/journal.pone.0264522

Dong, B., Jiang, L., Liu, J., & Zhu, Y. (2022). Liquidity in the cryptocurrency market and commonalities across anomalies. *International Review of Financial Analysis, 81*, 102097. doi:https://doi.org/10.1016/j.irfa.2022.102097

Dyhrberg, A. H. (2016). Bitcoin, gold and the dollar – A GARCH volatility analysis. *Finance Research Letters, 16*, 85–92. doi:https://doi.org/10.1016/j.frl.2015.10.008

El Montasser, G., Charfeddine, L., & Benhamed, A. (2022). COVID-19, cryptocurrencies bubbles and digital market efficiency: Sensitivity and similarity analysis. *Finance Research Letters, 46*, 102362. doi:https://doi.org/10.1016/j.frl.2021.102362

ElBahrawy, A., Alessandretti, L., Kandler, A., Pastor-Satorras, R., & Baronchelli, A. (2017). Evolutionary dynamics of the cryptocurrency market. *Royal Society Open Science, 4*(11). doi:https://doi.org/10.1098/rsos.170623

Fang, F., Chung, W., Ventre, C., Basios, M., Kanthan, L., Li, L., & Wu, F. (2021). Ascertaining price formation in cryptocurrency markets with machine learning. *European Journal of Finance, 30*(2), 1–23. doi:https://doi.org/10.1080/1351847X.2021.1908390

Fernandes, L. H., Bouri, E., Silva, J. W., Bejan, L., & de Araujo, F. H. (2022). The resilience of cryptocurrency market efficiency to COVID-19 shock. *Physica A: Statistical Mechanics and its Applications, 607*, 128218. doi:https://doi.org/10.1016/j.physa.2022.128218

Filippou, I., Nguyen, M. T., & Viswanath-Natraj, G. (2023). Fundamental sentiment and cryptocurrency risk premia. doi:http://dx.doi.org/10.2139/ssrn.4402365

Foley, S., Karlsen, J. R., & Putniņš, T. J. (2019). Sex, drugs, and Bitcoin: How much illegal activity is financed through cryptocurrencies? *Review of Financial Studies, 32*(5), 1798–1853. doi:https://doi.org/10.1093/rfs/hhz015

Frick, T. A. (2019). Virtual and cryptocurrencies—regulatory and anti-money laundering approaches in the European Union and in Switzerland. *ERA Forum, 20*(1), 99–112. doi:https://doi.org/10.1007/s12027-019-00561-1

Fry, J. (2018). Booms, busts and heavy-tails: The story of Bitcoin and cryptocurrency markets? *Economics Letters, 171*, 225-229. doi:https://doi.org/10.1016/j.econlet.2018.08.008

Gajera, A., Raval, N., & & Mandaviya, M. (2020). An empirical study on risk and return analysis of SIP V/S lump sum investment w.r.t. ELSS mutual fund scheme.

International Journal of Management, 11(12), 2848–2855. doi:https://doi.org/10.34218/IJM.11.12.2020.266

Gandal, N., Hamrick, J., Moore, T., & Oberman, T. (2018). Price manipulation in the Bitcoin ecosystem. *Journal of Monetary Economics, 95*, 86–96. doi:https://doi.org/10.1016/j.jmoneco.2017.12.004

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

Gkillas, K., & Katsiampa, P. (2018). An application of extreme value theory to cryptocurrencies. *Economics Letters, 164*, 109-111. doi:https://doi.org/10.1016/j.econlet.2018.01.020

Habsjah, M. E., & Permana, I. S. (2023). Comparison of long-term investment strategies: DCA vs lump-sum investing in the S&P 500 Index. *International Journal of Management Science and Application, 2*(2), 19-25. doi:https://doi.org/10.58291/ijmsa.v2i2.126

Hairudin, A., Sifat, I. M., Mohamad, A., & Yusof, Y. (2022). Cryptocurrencies: A survey on acceptance, governance, and valuation. *International Journal of Finance & Economics, 27*(4), 5030–5052. doi: https://doi.org/10.1002/ijfe.2392

Härdle, W. K., Harvey, C. R., & Reule, R. C. (2020). Understanding cryptocurrencies. *Journal of Financial Econometrics, 18*(2), 181–208. doi:https://doi.org/10.1093/jjfinec/nbz033

Hart, O. D., & Kreps, D. M. (1986). Price Destabilizing Speculation. *Journal of Political Economy, 94*(5), 927–952. doi:https://doi.org/10.1086/261418

Hayes, A. S. (2017). Cryptocurrency value formation: An empirical study leading to a cost of production model for valuing Bitcoin. *Telematics and Informatics, 34*(7), 1308–1321. doi:https://doi.org/10.1016/j.tele.2016.05.005

Huynh-The, T., Gadekallu, T. R., Wang, W., Yenduri, G., Ranaweera, P., Pham, Q. V., . . . Liyanage, M. (2023). Blockchain for the metaverse: A Review. *Future Generation Computer Systems, 143*, 401–419. doi:https://doi.org/10.1016/j.future.2023.02.008

Isynuwardhana, D., & Aslam, A. N. (2024). Optimization of stock investments in Indonesia Stock Exchange: Comparing the method of dollar cost averaging (DCA) and lump sum (LS). *International Journal of Religion, 5*(7), 839-848. doi:https://doi.org/10.61707/w3vk5149

Jain, R., Bhardwaj, P., & Soni, P. (2022). Can the market of cryptocurrency be followed with the technical analysis? *International Journal for Research in Applied Science & Engineering Technology (IJRASET), 10*(IV), 2425–2445. doi:https://doi.org/10.22214/ijraset.2022.41760

Ji, Q., Bouri, E., Roubaud, D., & Kristoufek, L. (2019). Information interdependence among energy, cryptocurrency and major commodity markets. *Energy Economics, 81*, 1042–1055. doi:https://doi.org/10.1016/j.eneco.2019.06.005

Kakinaka, S., & Umeno, K. (2022a). Asymmetric volatility dynamics in cryptocurrency markets on multi-time scales. *Research in International Business and Finance, 62*, 101754. doi:https://doi.org/10.1016/j.ribaf.2022.101754

Kakinaka, S., & Umeno, K. (2022b). Cryptocurrency market efficiency in short- and long-term horizons during COVID-19: An asymmetric multifractal analysis approach. *Finance Research Letters, 46*, 102319. doi:https://doi.org/10.1016/j.frl.2021.102319

Kapalczynski, A., & Lien, D. (2021). Effectiveness of augmented dollar-cost averaging. *The North American Journal of Economics and Finance, 56* 101370. doi:https://doi.org/10.1016/j.najef.2021.101370

Karim, M. M., Ali, M. H., Yarovaya, L., Uddin, M. H., & Hammoudeh, S. (2023). Return-volatility relationships in cryptocurrency markets: Evidence from asymmetric quantiles and non-linear ARDL approach. *International Review of Financial Analysis, 90*, 102894. doi:https://doi.org/10.1016/j.irfa.2023.102894

Karisma, K. (2022). Comparative Review of the Regulatory Framework of Cryptocurrency in Selected Jurisdictions. Em *Regulatory Aspects of Artificial Intelligence on Blockchain*, 82–111. doi:https://doi.org/10.4018/978-1-7998-7927-5.ch005

Katsiampa, P. (2017). Volatility estimation for Bitcoin: A comparison of GARCH models. *Economics Letters, 158*, 3-6. doi:https://doi.org/10.1016/j.econlet.2017.06.023

Katsiampa, P. (2019). An empirical investigation of volatility dynamics in the cryptocurrency market. *Research in International Business and Finance, 50*, 322–335. doi:https://doi.org/10.1016/j.ribaf.2019.06.004

Katsiampa, P., Corbet, S., & Lucey, B. (2019a). Volatility spillover effects in leading cryptocurrencies: A BEKK-MGARCH analysis. *Finance Research Letters, 29*, 68–74. doi:https://doi.org/10.1016/j.frl.2019.03.009

Katsiampa, P., Corbet, S., & Lucey, B. (2019b). High frequency volatility co-movements in cryptocurrency markets. *Journal of International Financial Markets, Institutions and Money, 62*, 35-52. doi:https://doi.org/10.1016/j.intfin.2019.05.003

Kirkby, J. L., Mitra, S., & & Nguyen, D. (2020). An analysis of dollar cost averaging and market timing investment strategies. *European Journal of Operational Research, 286*(3), 1168–1186. doi:https://doi.org/10.1016/j.ejor.2020.04.055

Klein, T., Pham Thu, H., & Walther, T. (2018). Bitcoin is not the New Gold – A comparison of volatility, correlation, and portfolio performance. *International Review of Financial Analysis, 59*, 105–116. doi: https://doi.org/10.1016/j.irfa.2018.07.010

Knight, J. R., & Mandell, L. (1992). Nobody gains from dollar cost averaging: Analytical, numerical, and empirical results. *Financial Services Review, 2*(1), 51–61. doi:https://doi.org/10.1016/1057-0810(92)90015-5

Koutmos, D. (2018). Return and volatility spillovers among cryptocurrencies. *Economics Letters, 173*, 122–127. doi:https://doi.org/10.1016/j.econlet.2018.10.004

Kristoufek, L. (2015). What are the main drivers of the bitcoin price? Evidence from wavelet coherence analysis. *PLOS ONE, 10*(4). doi:https://doi.org/10.1371/journal.pone.0123923

Leggio, K. B., & Lien, D. (2003). An empirical examination of the effectiveness of dollar-cost averaging using downside risk performance measures. *Journal of Economics and Finance, 27*(2), 211–223. doi:https://doi.org/10.1007/BF02827219

Li, R., Li, S., Yuan, D., & Zhu, H. (2021). Investor attention and cryptocurrency: Evidence from wavelet-based quantile Granger causality analysis. *Research in International Business and Finance, 56*, 101389. doi:https://doi.org/10.1016/j.ribaf.2021.101389

Li, S. (2022). Spillovers between Bitcoin and Meme stocks. *Finance Research Letters, 50*. doi:https://doi.org/10.1016/j.frl.2022.103218

Li, X., & Whinston, A. B. (2020). Analyzing cryptocurrencies. *Information Systems Frontiers, 22*(1), 17–22. doi:https://doi.org/10.1007/s10796-019-09966-2

Liu, J., & Serletis, A. (2019). Volatility in the cryptocurrency market. *Open Economies Review, 30*(4), 779–811. doi:https://doi.org/10.1007/s11079-019-09547-5

Liu, L., & Chen, Q. (2020). How to compare market efficiency? The Sharpe ratio based on the ARMA-GARCH forecast. *Financial Innovation, 6*(1), 1-21. doi:https://doi.org/10.1186/s40854-020-00200-6

Liu, Y., & Tsyvinski, A. (2021). Risks and returns of cryptocurrency. *The Review of Financial Studies, 34*(6), 2689–2727. doi:https://doi.org/10.1093/rfs/hhaa113

López-Cabarcos, M. Á., Pérez-Pico, A. M., Piñeiro-Chousa, J., & Šević, A. (2021). Bitcoin volatility, stock market and investor sentiment. Are they connected? *Finance Research Letters, 38*, 101399. doi:https://doi.org/10.1016/j.frl.2019.101399

Lu, R., Hoang, V. T., & Wong, W.-K. (2021, July 27). Do lump-sum investing strategies really outperform dollar-cost averaging strategies? *Studies in Economics and Finance, 38*(3), 675-691. doi:https://doi.org/10.1108/SEF-04-2018-0107

Lyócsa, Š., Molnár, P., Plíhal, T., & Širaňová, M. (2020). Impact of macroeconomic news, regulation and hacking exchange markets on the volatility of bitcoin. *Journal of Economic Dynamics and Control, 119*, 103980. doi:https://doi.org/10.1016/j.jedc.2020.103980

Ma, C., Zhang, Y., Fang, B., Zhang, H., Jin, Y., & Zhou, D. (2022). Ripple+: An improved scheme of Ripple consensus protocol in deployability, liveness and timing assumption. *Computer Modeling in Engineering & Sciences, 130*(1), 463–481. doi:https://doi.org/10.32604/cmes.2022.016838

Maharani, A., & Saputra, F. (2021). Relationship of investment motivation, investment knowledge and minimum capital to investment interest. *Journal of Law, Politic and Humanities, 2*(1), 23-32. doi:https://doi.org/10.38035/jlph.v2i1.84

Markowitz, H. (1952). Portfolio selection. *The Journal of Finance, 7*(1), 77–91. doi:https://doi.org/10.2307/2975974

Martz, C. (2022). The U.S. regulatory framework on cryptocurrency: Risks and solutions. doi:http://dx.doi.org/10.2139/ssrn.4106927

Mensi, W., Lee, Y. J., Al-Yahyaee, K. H., Sensoy, A., & Yoon, S. M. (2019a). Intraday downward/upward multifractality and long memory in Bitcoin and Ethereum markets: An asymmetric multifractal detrended fluctuation analysis. *Finance Research Letters, 31*, 19–25. doi:https://doi.org/10.1016/j.frl.2019.03.029

Mensi, W., Sensoy, A., Aslan, A., & Kang, S. H. (2019b). High-frequency asymmetric volatility connectedness between Bitcoin and major precious metals markets. *The North American Journal of Economics and Finance, 50*, 101031. doi:https://doi.org/10.1016/j.najef.2019.101031

Merlone, U., & Pilotto, D. (2014). Dollar cost averaging vs lump sum: Evidence from investing simulations on real data. *Proceedings of the Winter Simulation Conference 2014,* USA, 962–973. doi:https://www.doi.org/10.1109/WSC.2014.7019956

Milevsky, M. A., & Posner, S. E. (2003). A continuous-time reexamination of dollar-cost averaging. *International Journal of Theoretical and Applied Finance, 6*(2), 173–194. doi:https://doi.org/10.1142/S0219024903001888

Mnif, E., Jarboui, A., & Mouakhar, K. (2020). How the cryptocurrency market has performed during COVID-19? A multifractal analysis. *Finance Research Letters, 36*, 101647. doi:https://doi.org/10.1016/j.frl.2020.101647

Mohsin, K. (2022). Cryptocurrency legality and regulations – An international scenario. *International Journal of Cryptocurrency Research, 2*(1), 19–29. doi:https://doi.org/10.51483/IJCCR.2.1.2022.19-29

Mokni, K., El Montasser, G., Ajmi, A. N., & Bouri, E. (2024). On the efficiency and its drivers in the cryptocurrency market: the case of Bitcoin and Ethereum. *Financial Innovation, 10*(1), 39. doi:https://doi.org/10.1186/s40854-023-00566-3

Murugappan, M., Nair, R., & Krishnan, S. (2023). Global market perceptions of cryptocurrency and the use of cryptocurrency by consumers: A pilot study. *Journal* *of Theoretical and Applied Electronic Commerce Research, 18*(4), 1955–1970. doi: https://doi.org/10.3390/jtaer18040098

Nadarajah, S., & Chu, J. (2017). On the inefficiency of Bitcoin. *Economics Letters, 150*, 6–9. doi:https://doi.org/10.1016/j.econlet.2016.10.033

Naeem, M. A., Bouri, E., Peng, Z., Shahzad, S. J., & Vo, X. V. (2021). Asymmetric efficiency of cryptocurrencies during COVID-19. *Physica A: Statistical Mechanics and its Applications, 565*, 125562. doi:https://doi.org/10.1016/j.physa.2020.125562

Naifar, N., Altamimi, S., Alshahrani, F., & Alhashim, M. (2023). How media coverage news and global uncertainties drive forecast of cryptocurrencies returns? *Heliyon, 9*(6). doi:https://doi.org/10.1016/j.heliyon.2023.e16502

Nakamoto, S. (2008). A peer-to-peer electronic cash system. https://bitcoin.org/bitcoin.pdf

Nastri, M. (2025). A look at the new developments in the european union's regulation on crypto-assets and anti-money laundering. *International Journal of Criminology and Sociology, 14*(5), 48-55. doi:https://doi.org/10.6000/1929-4409.2025.14.05

Ng, Y. K. (2025). The legal recognition and regulation of digital assets. *Highlights in Business, Economics and Management, 52*, 52–61. doi:https://doi.org/10.54097/ybywwm42

Nguyen, C. T., Hoang, D. T., Nguyen, D. N., Niyato, D., Nguyen, H. T., & Dutkiewicz, E. (2019). Proof-of-stake consensus mechanisms for future blockchain networks: fundamentals, applications and opportunities. *IEEE Access, 7*, 85727-85745. doi:https://doi.org/10.1109/ACCESS.2019.2925010

Nimalendran, M., Pathak, P., Petryk, M., & Qiu, L. (2025). Informational efficiency of cryptocurrency markets. *Journal of Financial and Quantitative Analysis, 60*(3), 1439–1461. doi:https://doi.org/10.1017/S0022109024000310

Noda, A. (2021). On the evolution of cryptocurrency market efficiency. *Applied Economics Letters, 28*(6), 433–439. doi:https://doi.org/10.1080/13504851.2020.1758617

Özdemir, O. (2022). Cue the volatility spillover in the cryptocurrency markets during the COVID-19 pandemic: evidence from DCC-GARCH and wavelet analysis. *Financial Innovation, 8*(12). doi:https://doi.org/10.1186/s40854-021-00319-0

Panyagometh, K., & Zhu, K. X. (2016). Dollar-cost averaging, asset allocation, and lump sum investing. *Journal of Wealth Management, 18*(4), 75–89. doi:https://doi.org/10.3905/jwm.2016.18.4.075

Patel, M. M., Tanwar, S., Gupta, R., & Kumar, N. (2020). A deep learning-based cryptocurrency price prediction scheme for financial institutions. *Journal of Information Security and Applications, 55*, 102583. doi:https://doi.org/10.1016/j.jisa.2020.102583

Payne, B. C., & Bredthauer, J. (2013). The LSI or DCA decision: investing strategies for the lump sum averse. *International Journal of Financial Services Management, 6*(4), 263–272. doi:https://doi.org/10.1504/IJFSM.2013.059603

Pieters, G., & Vivanco, S. (2017). Financial regulations and price inconsistencies across Bitcoin markets. *Information Economics and Policy, 39*, 1–14. doi:https://doi.org/10.1016/j.infoecopol.2017.02.002

Rognone, L., Hyde, S., & Zhang, S. S. (2020). News sentiment in the cryptocurrency market: An empirical comparison with Forex. *International Review of Financial Analysis, 69*, 101462. doi:https://doi.org/10.1016/j.irfa.2020.101462

Rozeff, M. S. (1994). Lump-sum investing versus dollar-averaging. *The Journal of Portfolio Management, 20*(2), 45–50. doi:https://doi.org/10.3905/jpm.1994.409474

Salisu, A. A., & Ogbonna, A. E. (2022). The return volatility of cryptocurrencies during the COVID-19 pandemic: Assessing the news effect. *Global Finance Journal, 54*, 100641. doi:https://doi.org/10.1016/j.gfj.2021.100641

Sapkota, N. (2022). News-based sentiment and bitcoin volatility. *International Review of Financial Analysis, 82*, 102183. doi:https://doi.org/10.1016/j.irfa.2022.102183

Selgin, G. (2015). Synthetic commodity money. *Journal of Financial Stability, 17*, 92–99. doi:https://doi.org/10.1016/j.jfs.2014.07.002

Selmi, R., Mensi, W., Hammoudeh, S., & Bouoiyour, J. (2018). Is Bitcoin a hedge, a safe haven or a diversifier for oil price movements? A comparison with gold. *Energy Economics, 74*, 787–801. doi:https://doi.org/10.1016/j.eneco.2018.07.007

Sharpe, W. F. (1963). A simplified model for portfolio analysis. *Management Science, 9*(2), 277-293. http://www.jstor.org/stable/2627407

Shen, J. (2022). A general framework for enhancing the return of dollar cost averaging investing. doi:http://dx.doi.org/10.2139/ssrn.4235766

Shi, Y., Tiwari, A. K., Gozgor, G., & Lu, Z. (2020). Correlations among cryptocurrencies: Evidence from multivariate factor stochastic volatility model. *Research in International Business and Finance, 53*, 101231. doi:https://doi.org/10.1016/j.ribaf.2020.101231

Sigaki, H. Y., Perc, M., & Ribeiro, H. V. (2019). Clustering patterns in efficiency and the coming-of-age of the cryptocurrency market. *Scientific Reports, 9*(1). doi:https://doi.org/10.1038/s41598-018-37773-3

Statman, M. (1995). A behavioral framework for dollar-cost averaging. *The Journal of Portfolio Management, 22*(1), 70–78. doi:https://doi.org/10.3905/jpm.1995.409537

Stein, J. C. (1987). Informational externalities and welfare-reducing speculation. *Journal of Political Economy, 95*(6), 1123–1145. doi:https://doi.org/10.1086/261508

Sufian, M. H., Sutan Syahril, N. A., & Ghapa, N. (2024). Regulatory framework for cryptocurrency: A comparative analysis of Malaysia, Indonesia and Singapore. *Malaysian Journal of Social Sciences and Humanities (MJSSH), 9*(11), 003113. doi:https://doi.org/10.47405/mjssh.v9i11.3113

Ţegledi, A. M., & Straoanu, B. M. (2022). Cryptocurrency (virtual coins): Accounting aspects and tax regulations. *LUMEN Proceedings, 17*, 650–657. doi:https://doi.org/10.18662/wlc2021/64

Thorley, S. R. (1995). The time-diversification controversy. *Financial Analysts Journal, 51*(3), 68-76. doi:https://doi.org/10.2469/faj.v51.n3.1907

Trainor, W. J. (2005). Within-horizon exposure to loss for dollar cost averaging and lump sum investing. *Financial Services Review, 14*(4), 319-330. https://api.semanticscholar.org/CorpusID:17550853

Tran, V. L., & Leirvik, T. (2020). Efficiency in the markets of crypto-currencies. *Finance Research Letters, 35*, 101382. doi:https://doi.org/10.1016/j.frl.2019.101382

Trimborn, S., & Härdle, W. K. (2018). CRIX: An index for cryptocurrencies. *Journal of Empirical Finance, 49*, 107–122. doi:https://doi.org/10.1016/j.jempfin.2018.08.004

Ukwueze, F. (2021). Cryptocurrency: Towards regulating the unruly enigma of fintech in Nigeria and South Africa. *Potchefstroom Electronic Law Journal, 24*, 1–38. doi:https://doi.org/10.17159/1727-3781/2021/v24i0a10743

Urquhart, A. (2016). The inefficiency of Bitcoin. *Economics Letters, 148*, 80–82. doi:https://doi.org/10.1016/j.econlet.2016.09.019

U.S. Department of the Treasury. (2025, January). Daily trasure bill rates. U.S. Department of Treasury. https://home.treasury.gov/resource-center/data-chart-center/interest-rates/TextView?type=daily_treasury_bill_rates&field_tdr_date_value=2025

Van der Linden, T., & Shirazi, T. (2023). Markets in crypto-assets regulation: Does it provide legal certainty and increase adoption of crypto-assets? *Financial Innovation, 9*(1), 22. doi:https://doi.org/10.1186/s40854-022-00432-8

Vandezande, N. (2017). Virtual currencies under EU anti-money laundering law. *Computers & Security, 33*(3), 341–353. doi:https://doi.org/10.1016/j.clsr.2017.03.011

Vidal-Tomás, D. (2022). Which cryptocurrency data sources should scholars use? *International Review of Financial Analysis, 81*, 102061. doi:https://doi.org/10.1016/j.irfa.2022.102061

Vidal-Tomás, D., García, J. A., & García, J. A. (2022). Which cryptocurrency data sources should scholars use? *Journal of Risk and Financial Management, 10*(2), 12. doi:https://doi.org/10.3390/jrfm10020012

Vidal-Tomás, D., Ibáñez, A. M., & Farinós, J. E. (2019). Weak efficiency of the cryptocurrency market: A market portfolio approach. *Applied Economics Letters, 26*(19), 1627–1633. doi:https://doi.org/10.1080/13504851.2019.1591583

Wang, J., & Wang, X. (2021). COVID-19 and financial market efficiency: Evidence from an entropy-based analysis. *Finance Research Letters, 42*, 101888. doi:https://doi.org/10.1016/j.frl.2020.101888

Wątorek, M., Drożdż, S., Kwapień, J., Minati, L., Oświęcimka, P., & Stanuszek, M. (2021). Multiscale characteristics of the emerging global cryptocurrency market. *Physics Reports, 901*, 1–82. doi:https://doi.org/10.1016/j.physrep.2020.10.005

Wei, W. C. (2018). Liquidity and market efficiency in cryptocurrencies. *Economics Letters, 168*, 21–24. doi:https://doi.org/10.1016/j.econlet.2018.04.003

White, R., Marinakis, Y., Islam, N., & Walsh, S. (2020). Is Bitcoin a currency, a technology-based product, or something else? *Technological Forecasting and Social Change, 151*,119877. doi:https://doi.org/10.1016/j.techfore.2019.119877

Xiong, X., & Luo, J. (2024). Global Trends in Cryptocurrency Regulation: An Overview. doi: https://doi.org/10.48550/arXiv.2404.15895

Yen, K. C., & Cheng, H. P. (2020). Economic policy uncertainty and cryptocurrency volatility. *Finance Research Letters, 38*, 101428. doi:https://doi.org/10.1016/j.frl.2020.101428

Yermack, D. (2024). Is Bitcoin a real currency? An economic appraisal. In Chuen, D. L. K. (Eds.) *Handbook of Digital Currency* (pp. 29-40). doi:https://doi.org/10.1016/B978-0-323-98973-2.00014-9

Zein, M. M., & Darma, G. S. (2023). The dollar cost averaging, lump sum, and value averaging strategies in mutual fund investments. *Quantitative Economics and Management Studies, 4*(6), 1123–1140. doi:https://doi.org/10.35877/454RI.qems2068

Zhang, P., Kong, D., Xu, K., & Qi, J. (2024). Global economic policy uncertainty and the stability of cryptocurrency returns: The role of liquidity volatility. *Research in International Business and Finance, 67*, 102165. doi:https://doi.org/10.1016/j.ribaf.2023.102165

Zhelekhovska, T. (2024). Legal regulation of cryptocurrency and cryptocurrency operations in the European Union. *Visegrad Journal on Human Rights, 6*, 201-207. doi:https://doi.org/10.61345/1339-7915.2023.6.31

Zheng, Z., Xie, S., Dai, H., Chen, X., & Wang, H. (2017). An Overview of Blockchain Technology: Architecture, Consensus, and Future Trends. *2017 IEEE International*

Congress on Big Data (BigData Congress), USA, 557–56). doi:https://doi.org/10.1109/BigDataCongress.2017.85