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Exploring Market Inefficiencies: Crypto Arbitrage

Evidence from various CEXs through 2017 - 2024

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ABSTRACT:

Cryptocurrencies have experienced rapid growth over the past decade, with Bitcoin consistently holding the highest market capitalisation. In early 2017, the total crypto market was valued at approximately $18 billion, surging to $500 billion by December. The market grew despite price fluctuations, reaching around $2.75 trillion in April 2025.

Market inefficiencies continue to play a central role in driving price discrepancies across exchanges. These discrepancies arise from various factors that cause prices to diverge from their intrinsic or benchmark value on different platforms. These deviations allow arbitrage traders to exploit exchange-based price differences to pursue risk-minimised profits. Understanding when and why arbitrage windows occur requires examining the market conditions that create them. This study applies Grey Correlation Analysis and the DCC GARCH model to evaluate the strength and dynamics of price relationships across exchanges.

Previous research has highlighted the presence of arbitrage in crypto markets, but few studies have explored the influence of multiple explanatory variables over an extended time frame. This research investigates the market drivers behind price divergences in the cryptocurrency space from 2017 to 2024. This study builds upon prior work while introducing new data with a similar scope of analysis. The seven-year sample includes 26,925 daily observations from 15 centralised exchanges. By applying the selected models across this dataset, the study assesses how each market variable contributes to changes in price correlation between Kraken and the comparison exchanges.

The results show that certain factors uniquely influence price divergences between Kraken and selected exchanges. Trading volume generally improves alignment, though effects vary across exchanges depending on liquidity. These findings suggest that arbitrage opportunities are not equally distributed but depend on each exchange's structural and behavioural conditions, highlighting the complex and evolving nature of crypto market inefficiencies.

This research helps explain cryptocurrency market behaviour. It identifies key factors that consistently drive arbitrage and exchange misalignments. The findings are helpful for traders building arbitrage strategies. They also offer value to researchers studying market efficiency and systemic risk in decentralised finance. This study adds depth and practical relevance to existing literature by presenting current empirical evidence over a multi-year period.

KEYWORDS: Arbitrage, Bitcoin, Market Inefficiency, Crypto Currency, Grey Correlation Analysis, DCC-GARCH Model, Trading, BTCUSD, Behavioural Finance

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TIIVISTELMÄ:

Kryptovaluutat ovat kasvaneet nopeasti viimeisen vuosikymmenen aikana, Bitcoinin säilyttäessä jatkuvasti korkeimman markkina-arvon. Vuoden 2017 alussa kryptomarkkinan arvo oli kokonaisuudessaan noin 18 miljardia dollaria, ja markkinan arvo nousi joulukuuhun mennessä 500 miljardiin. Markkina jatkoi kasvuaan vaihteluista huolimatta ja saavutti noin 2,75 biljoonan dollarin arvon huhtikuussa 2025.

Markkinoiden tehottomuus on keskeinen taustatekijä hintojen eroavaisuuksissa eri pörssien välillä. Eroavaisuudet johtuvat useista tekijöistä, jotka aiheuttavat hintojen poikkeamisen niiden luontaisesta tai vertailuarvosta eri alustoilla. Nämä poikkeamat antavat arbitraasi-kauppiaille mahdollisuuden hyödyntää pörssien hintaeroja tavoittelemalla vähäriskisiä voittoja. Arbitraasi-ikkunoiden syntymisen ja syyn ymmärtäminen edellyttää niitä luovien markkinaolosuhteiden tutkimista. Tässä tutkimuksessa käytetään Grey Correlation -analyysia ja DCC GARCH -mallia arvioimaan hintasuhteiden vahvuutta ja dynamiikkaa eri pörssien välillä.

Aiemmat tutkimukset ovat osoittaneet arbitraasin olemassaolon kryptomarkkinoilla, mutta harvat niistä ovat tarkastelleet useiden selittävien muuttujien vaikutusta pitkällä aikavälillä. Tämä tutkimus selvittää, mitkä markkinatekijät aiheuttavat hintapoikkeamia kryptovaluuttamarkkinoilla vuosina 2017–2024. Tutkimukseni pohjautuu aiempaan tutkimukseen, mutta tuo mukaan uutta dataa. Tutkimusaineisto koostuu 26 925 päivittäisestä havainnosta 15 keskitetystä pörssistä seitsemän vuoden ajalta. Mallit sovelletaan tähän aineistoon, jotta voidaan arvioida, miten kukin markkinamuuttuja vaikuttaa hintakorrelaation muutoksiin Krakenin ja muiden pörssien välillä.

Tulokset osoittavat, että tietyt tekijät vaikuttavat yksilöllisesti hintapoikkeamiin Krakenin ja muiden pörssien välillä. Kaupankäyntivolyymi yleensä parantaa hintojen yhdenmukaisuutta, mutta vaikutus vaihtelee likviditeetin mukaan. Tämä viittaa siihen, että arbitraasimahdollisuudet eivät jakaudu tasaisesti, vaan riippuvat kunkin pörssin rakenteellisista ja käyttäytymiseen liittyvistä tekijöistä. Tämä korostaa kryptomarkkinoiden tehottomuuden monimutkaista ja kehittyvää luonnetta.

Tämä tutkimus auttaa selittämään kryptovaluuttamarkkinoiden toimintaa. Se tunnistaa keskeiset tekijät, jotka johdonmukaisesti vaikuttavat arbitraasiin ja hintojen poikkeamiin. Tulokset ovat hyödyllisiä arbitraasistrategioita kehittäville kauppiaille sekä tutkijoille, jotka tarkastelevat markkinatehokkuutta ja systeemiriskiä hajautetussa rahoituksessa. Tämä tutkimus syventää aiempaa kirjallisuutta esittämällä ajankohtaista empiiristä näyttöä usean vuoden ajalta.

AVAINSANAT: Arbitraasi, Bitcoin, Markkinatehottomuus, Kryptovaluutta, Grey-korrelaatioanalyysi, DCC-GARCH-malli, BTCUSD

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Abbreviations

ADF	Augmented Dickey-Fuller Test
AMM	Automated Market Making
BTC	Bitcoin
BTCUSD	Bitcoin USD Currency Pair
CEX	Centralised Exchange
DCC	Dynamic Conditional Correlation
DEX	Decentralised Exchange
EMT	Efficient Market Hypothesis
GARCH	Generalised Autoregressive Conditional Heteroskedasticity
GRA	Grey Relational Analysis
IV	Instrumental Variable
LOOP	Law of One Price
NBBO	National Best Bid and Offer
PPP	Purchasing Power Parity
PP	Phillips-Perron Test
PP%	Price Premium in %
RWT	Random Walk Theory
SD	Standard Deviation
2SLS	Two-Stage Least Squares

1 Introduction

Behavioural finance views arbitrage as a process influenced by psychological biases and market inefficiencies. Investors take advantage of price differences to earn profits. These opportunities often arise from irrational behaviour or errors in judgment by other market participants.

The phenomenon of a 'free lunch', which means a risk-free return in the capital markets, shouldn't be possible based on the Efficient Market Theory (EMT) (Fama, 1970). The research emphasised that the markets are efficient. This means financial asset pricing fully reflects all available market information. Similarly, Fama (1965) stated stock market prices follow a random walk in capital markets. This meant that historical data of financial assets could not be used to predict future returns, nor could they consistently profit from the markets. The EMT and the Random Walk Theory (RWT) suggest that riskless profit should not be possible in financial markets. However, this does not mean that arbitrage opportunities do not exist.

Traditional arbitrage has proven consistently that opportunities to profit from market discrepancies to create riskless profit do exist (Shleifer & Vishny, 1997), therefore, criticising the previous models by Fama (1970). According to Brealey et al. (2011, p.57) "In well-functioning markets, where the costs of buying and selling are low, arbitrage opportunities are eliminated almost instantaneously by investors who try to take advantage of them". This research explores the nature of arbitrage opportunities in cryptocurrencies.

An example of crypto market inefficiencies and arbitrage trading was Alameda Research. During 2017, FTX made a foundation for itself through Alameda Research. They took advantage of the higher Bitcoin prices compared to those in America. They profited a total of 10 mil $ to 30 mil $ through this market inefficiency for years (Massa et al., 2022).

Cryptocurrency markets provide a wider arbitrage opportunity to capitalise on riskless profits than the traditional heavily regulated global equity markets (Makarov & Schoar, 2020). Since the release of Bitcoin (BTC) as a decentralised digital currency and the introduction of Blockchain technology in 2009 (Nakamoto, 2008), cryptocurrencies have grown tremendously over the past decade. Makarov & Schoar (2020) mentioned that 50 million active investors trade bitcoin on more than 100 exchanges globally. In 2024, nearly 600 crypto exchanges enabled the trading of BTC (Adams, 2024).

1.1 Purpose and motivation

Recent studies, including Makarov & Schoar (2020), Crépellière et al. (2023), Kristoufek & Bouri (2023), Hautsch et al. (2024) have shown evidence regarding the arbitrary nature of the cryptocurrency market. Significant returns can be created through arbitrage, highlighting the risks involved. Due to the quick rise in the popularity of cryptocurrency markets throughout the years, research into the field is still lacking in many aspects. These aspects are mostly the availability of reliable data and the number of scientific articles.

This thesis investigates arbitrage opportunities in the BTC and centralised cryptocurrency markets, analysing trends over time. BTCUSD was selected as it is currently the most liquid crypto-FIAT currency pair. As stated in Kissel et al. (2024) and Wüstenfeld & Geldner (2022) "BTC/EUR is the second most liquid market behind BTCUSD and has the lowest volatility. Furthermore, arbitrage opportunities in Bitcoin markets are not a new phenomenon; they persist due to underlying market inefficiencies”. This study conducts an empirical analysis of daily time series data to examine BTC price movements against the US dollar, incorporating a range of explanatory variables.

This thesis builds on earlier research by testing whether key market factors behind arbitrage still hold over a longer period. It also looks at how different exchanges behave, using a different exchange as a reference point, to see if specific exchange features help explain price gaps better. Arbitrage profits, considered risk-free in theory, arise when price discrepancies exist for the same asset across different trading locations. The motivation behind this research is understanding the structural and behavioural drivers of these inefficiencies, to answer the following central research question:

1. What are the sources behind statistical arbitrage opportunities among Bitcoin exchanges?

The research gap addressed in this study is the use of an extended timeframe compared to previous work, including the most recent data available at the time of analysis. This study uses Kraken as a baseline exchange to analyse how exchange-specific factors affect price differences and correlation patterns. The same explanatory variables are applied to Kraken to allow comparison with previous research. The selected explanatory variables will be further elaborated in Section 4, Data and Methodology. This approach adds depth to earlier findings. It also helps to test the persistence of ongoing arbitrage opportunities and evaluate whether previously observed patterns hold under a different baseline exchange.

1.2 Hypothesis development

To reach the objectives of this thesis, the following hypotheses were developed with reference to a similar research topic by Kristoufek & Bouri (2023):

H0: None of the selected explanatory variables (volatility, trading volume, on-chain transfers, network fees, momentum, search trends, lagged correlation, etc.) significantly explain the emergence of statistical arbitrage opportunities among Bitcoin CEXs.

The null hypothesis in this study states that the selected market variables have no significant effect on price discrepancies between exchanges. This provides a baseline for evaluating whether factors such as trading volume, volatility, and liquidity contribute meaningfully to observed divergences. Based on Kristoufek & Bouri (2023), higher trading volumes are often linked to reduced arbitrage opportunities due to increased market efficiency and faster price convergence. The study builds on this framework to assess each variable's contribution to the model's explanatory power. Kraken is used as the baseline exchange to test if these effects are consistent across platforms. The specific hypotheses are as follows:

H1: *Increased market volatility decreases price correlation between exchanges, resulting in increased statistical arbitrage opportunities.*
H2*: Increased trading volume increases price correlation between exchanges, resulting in decreased statistical arbitrage opportunities.*
H3: *Increased on-chain transfer activity increases price correlation between exchanges, resulting in decreased statistical arbitrage opportunities.*
H4: *Increased network fees decrease price correlation between exchanges, resulting in increased statistical arbitrage opportunities.*
H5: *Stronger price momentum decreases price correlation between exchanges, resulting in increased statistical arbitrage opportunities.*
H6: *Increased search trend activity does not significantly affect price correlation between exchanges and does not meaningfully impact arbitrage opportunities.*
H7: *Higher lagged correlation increases current price correlation between exchanges, resulting in decreased statistical arbitrage opportunities.*

The results of this study would help aid institutional traders and market makers involved in cross-exchange arbitrage. By identifying the market conditions and exchange-specific characteristics that lead to persistent price gaps, this research can help inform the timing, selection, and structure of real-time arbitrage strategies on a daily level. For example, recognising how volatility and momentum disrupt price alignment may help institutions better manage execution timing or capital allocation on a day-to-day basis.

Most importantly, the findings of this study confirm earlier conclusions by Makarov & Schoar (2020) regarding cross-exchange price inefficiencies but also suggest that these dynamics persist over a longer period than previously examined. Furthermore, the use of Kraken as a baseline reference point reveals that exchange-specific characteristics may play a larger role in arbitrage persistence than indicated in Kristoufek & Bouri (2023).

1.3 Structure of the study

This thesis is divided into both a theoretical and an empirical section. The study is structured as follows: After the introductory chapter, Chapter 2 explains the theoretical foundations regarding the topic. It begins with exploring the EMH, followed by the LOOP, PPP, and an overview of crypto markets and blockchain technology. The chapter concludes by examining arbitrage strategies and their limitations in the cryptocurrency market. This section aims to explain the foundational principles and market dynamics that affect price behaviour in the digital asset market.

Chapter 3 presents a comprehensive literature review, analysing key research on arbitrage and price discrepancies in the cryptocurrency market. It begins with well-known studies on market inefficiencies and arbitrage opportunities like Makarov & Schoar (2020), then expands into four main areas: market segmentation and inefficiencies; statistical arbitrage, volatility, and trading models; frictions and risks that limit arbitrage; and finally, exchange networks and decentralised arbitrage. This literature review structure helps establish the academic context for the study and highlights the contributions to the topic.

The empirical section begins with Chapter 4, explaining how the dataset is leveraged to address the main research question. It outlines the process for testing the hypotheses, describes the analytical approach, and discusses the key assumptions and potential challenges involved, especially regarding data quality.

Chapter 5 presents the analysis results, structured into sections based on the different methodologies covered in the study.

Chapter 6 concludes the thesis by summarising the main findings.

Lastly, Chapter 7 discusses the study's additional limitations and thoughts about how the research could be extended, improved or ideas for future work.

2 Theoretical Background

This section outlines the theoretical foundation supporting arbitrage strategies by reviewing key financial principles. It examines the EMH in its three forms: weak, semi-strong, and strong, highlighting their implications for arbitrage opportunities. The analysis also incorporates LOOP and PPP, emphasising their relevance in identifying market price discrepancies. A brief overview of BTC, blockchain technology, cryptocurrency market helps put those ideas into context. Crypto markets are defined by their technology, limitations, market development, and the role of exchanges is explained.

2.1 Efficient market hypothesis

As discussed earlier, a popular research about finance is the Efficient Market Hypothesis (EMH) by Fama (1970). The research mentioned highlights that publicly traded assets like stock prices price in all new information immediately. This means no information asymmetry could be utilised to create excess returns. The EMH fundamentally argues that investors cannot achieve returns beyond market averages by leveraging historical, public, or private information. All information is fully integrated into stock prices, leaving no opportunity to exploit it for abnormal returns.

In an efficient market, generating abnormal returns is impossible based on this theory by Fama (1970). Abnormal returns are calculated by subtracting the expected return of a publicly traded asset from its actual realised return. The formula is shown below:

$$Abnormal\ Return_{t+1} = R_{i,t+1} - E\left(R_{i,t+1}\right) = 0 \tag{1}$$

Where $E\left(R_{i,t+1}\right)$ represents the anticipated abnormal return for a publicly traded asset at time t + 1. It is determined by subtracting the expected return $E\left(R_{i,t+1}\right)$ from the actual realised return $R_{i,t+1}$ (Fama, 1970).

Fama (1970) further explained the various levels of market efficiency: strong form, semi-strong form, and weak form.

First, strong form tests address all possible information available to the market and priced in. This means that market players can't generate abnormal returns if the markets possess a strong form of efficiency. Summarised, the prices reflect all information, public and private.

Stock prices reflect all publicly available information about a company and its business in the semi-strong form of market efficiency. Prices adjust quickly to the release of new information. The only potential for generating abnormal returns lies in possessing private information. In this case, technical analysis and fundamental analysis cannot be utilised to generate excess returns in the market. An example of public information related to this level of efficiency is earnings reports of stocks or even crypto news.

Finally, weak form, where only historical price data is used as the information set. Based on Fama (1970), future prices cannot be predicted by analysing historical prices since they are all priced into the market. This means in the cryptocurrency market that price trends, volumes, as well as past volatilities, do not help with price predictions. These factors are unreliable when used to determine the direction cryptocurrency prices will take.

Within the EMH framework, the prospect of arbitrage should not result in excess or abnormal returns. Under weak-form market efficiency, which is grounded in historical stock data, the potential for successful arbitrage is theoretically impossible. Ultimately, such opportunities should not exist in an efficient market.

2.2 Law of one price (LOOP)

Following (Heijmans, 2018) and similarly to (Fil & Kristoufek, 2020), where testing the LOOP and contradicting the EMT is important regarding arbitrage in the cryptocurrency market. The basis of the LOOP dictates that all homogeneous primary goods should be traded at the same price across markets (Ardeni, 1989). Further mentioned in Kihn (2011), two main assumptions for the LOOP are zero or near-zero transaction costs and perfect substitutes. Based on the LOOP theory, we would assume, for example, that these relations hold:

$$LOOP: Price\ (BTC, USD, COINBASE) = Price\ (BTC, USD, BINANCE) \tag{2}$$

Based on the LOOP, we should assume that a cryptocurrency like Bitcoin should have the same price on every CEX.

2.3 Purchasing power parity (PPP)

Like the LOOP, PPP suggests that the exchange rate between two cryptocurrencies, such as Bitcoin and USD, should reflect the ratio of their purchasing power. It implies that the cost of one unit of Bitcoin in terms of goods or services should equal its cost in USD when adjusted for exchange rates. At its core, PPP states that changes in nominal exchange rates will balance differences in the future prices of goods between countries (Brealey et al., 2011).

Heijmans (2018) and Biais et al. (2023) also emphasised the importance of PPP. The theory assumes that the same amount of Bitcoin should be purchasable regardless of location. If that is not the case, PPP does not hold. The basic formula for PPP is:

$$PPP: Exchange\ Rate\ \left(\frac{BTC}{USD}\right) = \frac{Price\ Index\ in\ BTC}{Price\ Index\ in\ USD} \tag{3}$$

When evaluating the EMH by Fama (1970), the LOOP and PPP should hold, meaning Bitcoin prices should be consistent worldwide. However, significant price discrepancies often occur, even after adjusting for exchange rates. Particularly, South Korea has consistently shown a higher Bitcoin price compared to other countries, a phenomenon so pronounced it has been dubbed the "Kimchi premium” for two years (Nagy, 2018). From January 2016 to January 2020, Bitcoin prices in South Korea were, on average, 2.27% higher than in the United States (Jin Choi et al., 2019). Proposing evidence that is crypto market is inefficient, and arbitrage opportunities do exist.

2.4 Bitcoin and blockchain

Since the introduction of Bitcoin, financial markets have undergone rapid transformation. Bitcoin was launched in 2008 by Satoshi Nakamoto, whose identity remains unknown. In the white paper, Nakamoto (2008) An electronic coin is defined as " An electronic coin as a chain of digital signatures. Each owner transfers the coin to the next by digitally signing a hash of the previous transaction and the public key of the next owner and adding these to the end of the coin.” This innovation marked the first implementation of blockchain technology.

This created the first peer-to-peer virtual currency which can be transacted via an online exchange. Valuing a cryptocurrency like BTC has proved a challenge, since it can’t be valued similarly to traditional financial assets (stocks, bonds, etc.). BTC doesn’t yield notable cash flow, dividends or earnings as shown in the research by Polasik et al. (2015). This suggests that Bitcoin's value operates independently of any other currency or asset, possessing a unique and intrinsic value. Unlike the US dollar, which is heavily influenced by government policies and established monetary systems, Bitcoin does not follow the same principles. As a result, its value can change quickly and sharply, sometimes doubling or quadrupling quickly, or losing a significant portion of its value. If the US dollar showed this level of volatility, it would cause serious instability in the global economy, as reflected by Baur & Dimpfl (2021).

The market capitalisation of Bitcoin results from a multiplication of its price and the supply of coins in circulation. Several items influence the price, including supply, demand, hash rate, trading volume and market activity in general. These factors create the market value of Bitcoin.

The record of all Bitcoin transactions isn't stored in a centralised location, such as the US dollar and the US Treasury. Instead, a copy of this ledger is distributed across all computers in the network, with each copy continuously updated as new transactions occur. If anyone attempted to tamper with their Bitcoin, they would need to alter not just their transaction but every prior transaction on the Blockchain, across every computer in the network. This decentralised structure makes hacking Bitcoin virtually impossible for any single individual, as mentioned by Heijmans (2018) and Shrier (2020).

On-chain and off-chain refer to where and how blockchain-related data and transactions are processed. On-chain data is recorded directly on the blockchain, ensuring transparency, immutability, and decentralisation. In contrast, off-chain data is stored or processed outside the blockchain to improve efficiency and scalability. As based on Zheng et al. (2021), off-chain methods help reduce transaction costs and congestion, while on-chain mechanisms provide verifiable and permanent records essential for trust and auditability.

This sequence of transactions is known as the blockchain. To validate a transaction, a consensus is reached among the numerous computers in a large network, establishing what is considered true by all participating parties (Shrier, 2020). Once validated, a transaction is permanently recorded on the blockchain and cannot be changed. A timestamp ensures each transaction is unique and prevents double-spending (Heijmans, 2018).

2.5 Cryptocurrency exchanges

Hautsch, Scheuch, Voigt (2024) stated that most cryptocurrencies depend on fragmented and largely unregulated entities known as centralised exchanges (CEX). A CEX manages trades by operating an internal limit order book and settling transactions off-chain. An off-chain settlement allows CEXs to process transactions internally without using the blockchain, avoiding the need to pay validators. To make this possible, CEXs must securely manage and hold their customers' funds (Hautsch et al., 2024). Most importantly, Market fragmentation across multiple CEXs can lead to price differences for the same asset. The extent to which these price discrepancies continue depends on the risks and marginal costs faced by arbitrageurs moving between exchanges.

The opposite of a CEX is a decentralised exchange (DEX). DEXs naturally create arbitrage opportunities because they trade the same major cryptocurrencies with exchange rates that constantly change based on liquidity. This leads to frequent price differences that can be directly exploited for profit, as mentioned in Mazor & Rottenstreich (2024). Examples of DEXs are PancakeSwap and UniSwap. These exchanges operate through smart contracts, self-running pieces of code stored on a blockchain. Users connect their crypto wallets and select the tokens they want to trade. The DEX uses an automated market maker system to execute the transaction. This system relies on liquidity pools, which are collections of tokens provided by other users to facilitate trading (John et al., 2024; Lehar & Parlour, 2021; Mazor & Rottenstreich, 2024).

Figure 1 below shows the market share rankings of major cryptocurrency exchanges over time, highlighting shifts in dominance across the evolving crypto market. Each segment reflects a platform's percentage of market influence based on trading volume, user adoption, and trustworthiness, as sourced from Bitcoinity.org. Unfortunately, Binance is absent from the chart. The exchanges shown include Bitx (grey), Bitfinex (blue), Btce (yellow), Coinbase (red), Itbit (light blue), Kraken (pink), Mtgox (blue), Okcoin (orange), and others (green).

Initially, platforms such as Mt. Gox dominated the market, reflecting its early role as a pioneer in cryptocurrency trading. However, its sharp decline around 2014 highlights the impact of security breaches and loss of user trust, which led to its eventual collapse. Following this, exchanges like Bitfinex and Bitstamp rose significantly in market share, capitalising on Mt. Gox's downfall and establishing themselves as reliable alternatives. Nowadays, only a few dominant CEXs own most of the cryptocurrency trading market, while many smaller exchanges still exist globally.

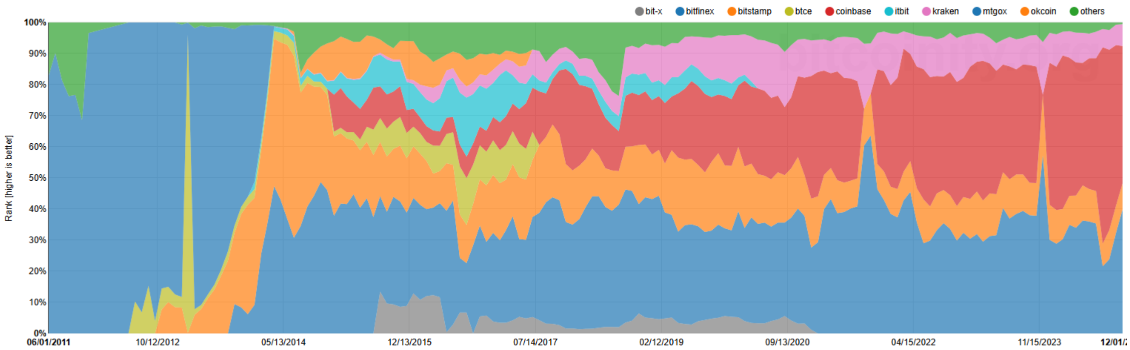

Figure 1. CEX Ranking 2011-2024 by Bitcoinity.org

The chart also reveals the emergence of new players, such as Coinbase and Kraken, which gained significant traction due to their focus on security, user experience, and compliance with US regulations. These platforms successfully captured substantial portions of the market, particularly during heightened regulatory scrutiny and increased demand for transparency. Smaller and niche exchanges, grouped under 'others' have maintained a presence but are gradually declining as users increasingly favour more secure and trusted mainstream platforms. This trend most probably reflects a growing preference for reliability and transparency, leading to reduced market share for lesser-known exchanges. Trusted mainstream CEXs like Coinbase have expanded significantly over the years.

The chart shows the development of Coinbase and Kraken becoming major players in the field. These platforms concentrated on security, user experience, as well as following US regulations. They obtained large market portions. This happened when regulations were examined more tightly, and transparency was wanted. Under 'others', smaller exchanges have remained, but their market share has reduced significantly. Users seem to prefer platforms that are secure plus trusted. This preference is a possible reason for the market share reduction in exchanges which are not well known. Mainstream centralised exchanges like Coinbase have grown a lot.

Overall, Figure 1 visualises the volatility and competitiveness of the cryptocurrency exchange landscape. It demonstrates how external events, such as security breaches, regulatory changes, and evolving user preferences, have shaped the rankings over time. The long-term sustainability of exchanges appears closely tied to their ability to adapt, innovate, and maintain user trust in a highly dynamic environment.

2.6 Arbitrage

When it comes to arbitrage, cryptocurrency arbitrage functions in a similar manner to traditional arbitrage. As mentioned in Crépellière et al. (2023)The inside bid at trading venue X exceeds the inside ask at venue Y, enabling investors to capitalise on cross-exchange price disparities, provided they have access to both trading platforms. The figure below illustrates this.

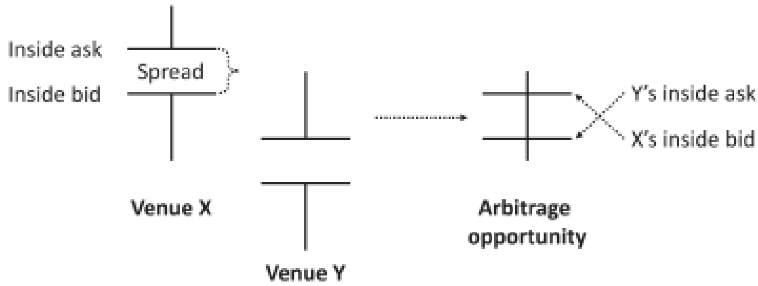

Figure 2. Arbitrage Opportunities Across Exchanges by Shkilko et al. (2008)

There are different types of arbitrage. Stobierski (2021) started with 'Pure Arbitrage' or 'Absolute Arbitrage', which takes advantage of current exchange price deviations. The other arbitrage types (merger and convertible arbitrage) are irrelevant to cryptos since company mergers and bonds are not directly linked to cryptocurrencies. Based on Brealey et al. (2011, p. 327), in an efficient market, arbitrageurs correct pricing disparities by purchasing undervalued securities, raising their prices, and selling overvalued ones, reducing their prices. They profit by exploiting these price differences until they align with the fundamental values. Even in the case of Bitcoin, the most actively traded cryptocurrency, arbitrage spreads between platforms can range from 8.67 % to 15.69 %. Stablecoins pegged to the US dollar, generally show much smaller arbitrage spreads than other cryptocurrencies (John et al., 2024).

Arbitrage opportunities are only possible if we assume the basic principle in economics called the 'Law of One Price' (LOOP) theory. Any identical good (or service) must have one price (Kihn, 2011). Likewise, this can be reflected in cryptocurrencies, where the BTC price should be the same on all digital currency exchanges. This is most similar to BTC trading on various exchanges to dual-listed companies. Kihn (2011) stated that any deviation from price parity is a deviation from the LOOP, and arbitrageurs are incentivised to eliminate violations of the LOOP through profits.

Last update:		bitfinex	bitstamp	cex.io	coinbase	exmo	gemini	kraken
		61243.00	61114.00	61900.00	61086.51	62364.38	61082.57	61140.70
bitfinex	61243.00	-	-0.21%	1.07%	-0.26%	1.83%	-0.26%	-0.17%
bitstamp	61114.00	0.21%	-	1.29%	-0.04%	2.05%	-0.05%	0.04%
cex.io	61900.00	-1.06%	-1.27%	-	-1.31%	0.75%	-1.32%	-1.23%
coinbase	61086.51	0.26%	0.05%	1.33%	-	2.09%	-0.01%	0.09%
exmo	62364.38	-1.80%	-2.00%	-0.74%	-2.05%	-	-2.06%	-1.96%
gemini	61082.57	0.26%	0.05%	1.34%	0.01%	2.10%	-	0.10%
kraken	61140.70	0.17%	-0.04%	1.24%	-0.09%	2.00%	-0.10%	-

Figure 3. Current BTCUSD Exchange Arbitrage by Bitcoinity.org

As shown in Figure 3, arbitrage opportunities still exist, and the possibility of capitalising on risk-free returns exists. However, it all comes down to arbitrage strategies, which are explained in the next section. Figure 3 shows arbitrage opportunities through the following CEXs: Bitfinex, Bitstamp, Cex.io, Coinbase, Exmo, Gemini, and Kraken.

In addition, efficient arbitrage plays an important role in all financial markets, even in the crypto markets. Based on Fama (1965), the paper stated that sophisticated traders can prevent stock price bubbles by selling overvalued stocks (and vice versa), expecting them to return to their true value, thus ensuring that price changes remain independent. This phenomenon might be even more apparent as interest in cryptos increases. Nevertheless, Makarov & Schoar (2020) argue that despite the presence of arbitrageurs, prices can still deviate from the LOOP. Traditional financial markets have mechanisms to ensure fair pricing. For example, the National Best Bid and Offer (NBBO) in the United States helps trades occur at the best available prices. Cryptocurrency markets do not have similar regulatory frameworks. As a result, price differences across platforms are more common. Missing these regulative frameworks can lead to significant price disparities across different exchanges, which can be exploited through arbitrage (Makarov & Schoar, 2020).

Evidence also shows that deviations from PPP are influenced by overall market volatility. In periods of heightened volatility, arbitrage becomes riskier, which can discourage traders from exploiting price differences across markets. This allows mispricing to persist for longer. On the other hand, higher levels of market liquidity tend to encourage arbitrage activity, thus improving market efficiency (Chordia et al., 2003, 2008; Gagnon & Andrew Karolyi, 2010; John et al., 2024).

2.6.1 arbitrage strategies

Hautsch, Scheuch, Voigt (2024) proposed two strategies to exploit price differences δ_t between two CEXs shown in Figure 1. The two strategies are the following: cross-exchange arbitrage and inventory arbitrage.

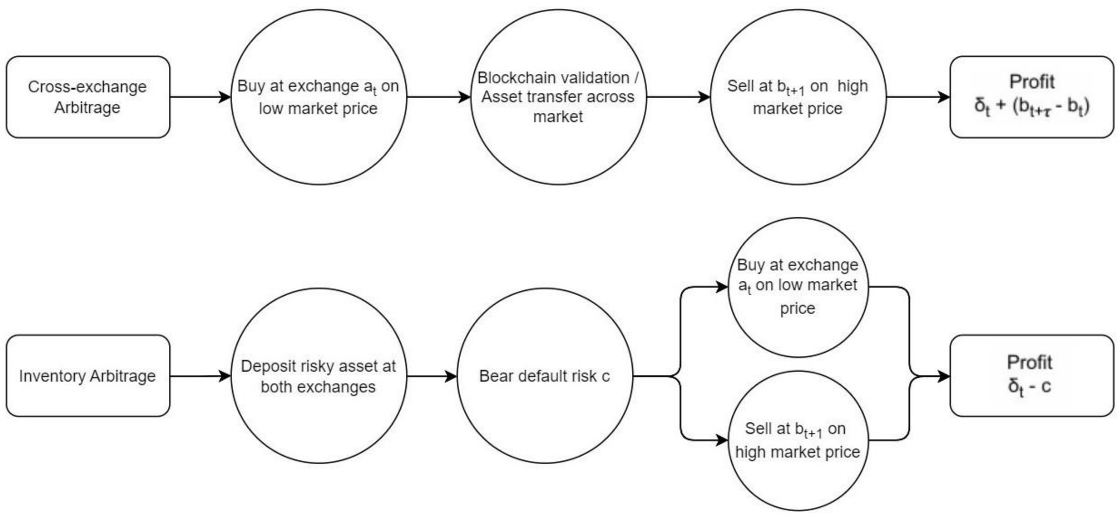

Figure 4. Illustration of Crypto Arbitrage by Hautsch et al. (2024)

Cross-exchange arbitrage involves buying a blockchain-based asset on a lower-priced centralised exchange (CEX) and transferring it to a higher-priced CEX to sell for profit. This process requires asset movement between exchanges and waiting for blockchain confirmation, assuming no default risk while the funds remain under CEX custody. This relationship helps understand arbitrage strategies used in blockchain environments. This means the arbitrageur assumes the price difference still exists when completing the trade at the final exchange. Without a clearinghouse, they must wait for transaction validation before closing the position. The model highlights the link between price fluctuations and transaction timing, providing insights into blockchain arbitrage strategies. When the asset is acquired on the low-price exchange at time *t* and subsequently transferred to the high-price exchange for settlement at *t+1 (t+τ)*, the arbitrageur is exposed to the log bid price $b^s_{t+\tau}, s \in \{i, j\}$ (Hautsch et al., 2024). The formula for cross-exchange arbitrage by Hautsch, Scheuch, Voigt (2024) is the following:

$$R(cross\ exchange - exchange\ arbitrage) = b^s_{t+\tau} - a^b_t = \delta_t + (b^s_{t+\tau} - b^s_t) \quad (4)$$

Where R is the total return, $b^s_{t+\tau}$ is the log bid price on the high-price exchange at time t+τ after the settlement delay, a^b_t is the log ask price on the low-price exchange at time *t* when the asset is initially bought. This would equal to instantaneous return δ_t, $(b^s_{t+\tau} - b^s_t)$ reflects the change in the log bid price on the high-price exchange between times t and *t+τ.*

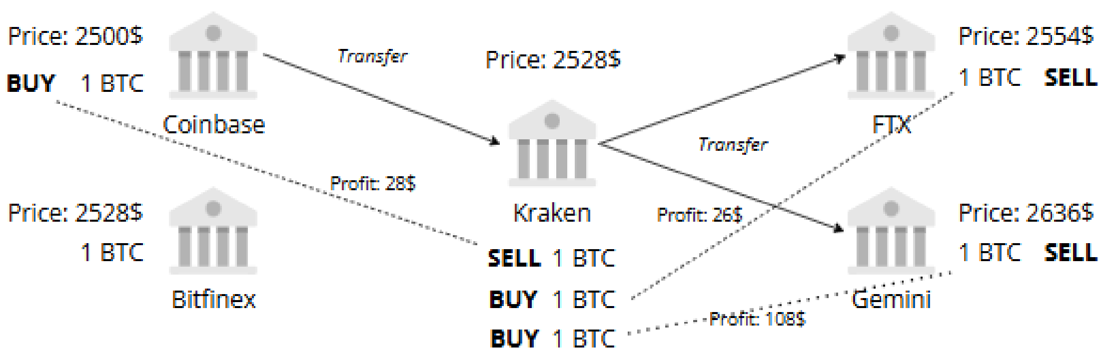

Figure 5. Inventory Arbitrage

Inventory arbitrage on centralised exchanges lets arbitrageurs get around settlement latency. They hold equal capital deposits and collateral at many exchanges. This method takes a lot of capital. It prevents exposure to settlement delays. When a price difference arises ($\delta_t > 0$), the arbitrageur buys a small amount on the low-price exchange and sells an equivalent amount from their inventory on the high-price exchange, yielding a return of δ_t (Hautsch et al., 2024). However, this strategy makes default risk more apparent than in cross-exchange arbitrage, which is 'c' in Figure 4.

Figure 5 shows a basic example with Kraken as the baseline exchange. Each exchange holds 1 BTC to avoid settlement delays. In this case, BTX is priced at 2500. Coinbase is the cheapest to buy from, while Kraken offers a higher selling price, creating a $28 profit. More trades follow by selling BTC on FTX and Gemini, then buying 2 BTC on Kraken to rebalance. These are transferred back to FTX and Gemini. This strategy earns a total profit of $162. Default risk should be considered in these scenarios.

2.6.2 arbitrage limitations

Makarov and Schoar (2019) specified important obstacles to arbitrage in cryptocurrency markets. A main concern is capital control, which limits fund transfers across borders and limits profit movement. Exchanges often function independently, they permit trading in local currencies. This prevents the integration of a global order book. Limited liquidity is another problem because low trading volume and wide bid-ask spreads hinder arbitrage execution. Transaction costs contribute to problems, even if they do not fully explain price differences. In addition, the paper pointed out that order flow imbalances can temporarily distort prices on some exchanges. Between cryptocurrencies, arbitrage spreads are smaller than they are between crypto and fiat. Fiat systems seem to cause considerable difficulties, which limit arbitrage efficiency. John et al. (2024) reached a similar conclusion.

Moreover, Hautsch et al. (2024) stated that there are only two major frictions when exploiting price differences through arbitrage in CEXs: the risk related to settlement latency and the risk due to the default of CEXs. Settlement latency makes arbitrage trades risky and expensive, forcing arbitrageurs to shoulder significant price risks. Without a trusted middleman, seizing price differences demands moving blockchain assets across centralised exchanges, dragging down profits with time-consuming blockchain validation (Hautsch et al., 2024). In a nutshell, Hautsch, Scheuch, Voigt (2024) presented an example of this. A trader buying from a lower-priced CEX faces price risk while waiting for blockchain validation before transferring the asset to a higher-priced CEX. Arbitrage opportunities can vanish due to settlement latency, and such trades are only profitable when price differences are large enough to offset potential losses. The best way to bypass settlement latency is to hold the same asset in both exchanges simultaneously, this is shown in Figure 5. This is capital-intensive and would put traders at great risk of exchange default risks. Biais et al. (2023) and Borri & Shakhnov (2023) documented over fifty hacks, thefts, and losses on BTC exchanges between 2011 and 2018. Their research shows that these risks influence the expected returns of cryptocurrency investors.

Following Hautsch et al. (2024), the model below displays frictionless trading, where the arbitrageur exploits price differences when his or her profits are positive:

$$\delta_t \coloneqq max\ b_t^i - a_t^i, b_t^j - a_t^i, 0 > 0 \tag{5}$$

Upon the arrival of a positive price difference between two different exchanges, we denote the resulting low-price exchange as $b \in \{i, j\}$ (for buy) and the high-price exchange as s (for sell) such that $\delta_t = b_t^s - a_t^b > 0$.

In conclusion, while crypto arbitrage offers profit potential, it is limited by key frictions such as capital controls, segmented exchanges, and liquidity gaps, as noted by Makarov and Schoar (2019). Hautsch et al. (2024) further highlight the risks of settlement latency and exchange default, which make arbitrage trades both capital-intensive and risky. Overcoming these challenges requires price gaps and careful management of volatility, execution speed, and counterparty risk.

3 Literature Review

The EMH, the LOOP, and PPP all suggest the same outcome. Identical assets should not have price differences. Markets should operate efficiently. Cryptocurrency market structure still creates difficulties for established financial theory. The markets continue to evolve, have little regulation and contain numerous disconnected exchanges. Price differences persist till today. This section will study important research on cryptocurrency arbitrage. The section looks at important research on cryptocurrency arbitrage, starting with early work on market segmentation and price disparities across countries, and moving into research on trading frictions, volatility, and the role of exchange networks. The section aims to review significant papers related to the current topic of research.

Early studies, such as Gandal and Halaburda (2014) highlighted the role of market inefficiencies in fostering arbitrage opportunities, particularly noting the competition between different exchanges and cryptocurrencies. As the market has matured, researchers have focused more on the factors behind inefficiencies. These include liquidity constraints, transaction costs, and network congestion. Recent studies highlight how crypto arbitrage has evolved. Over time, it has become more complex and sophisticated.

3.1 Market segmentation and inefficiencies

When discussing the ability of markets to accurately price assets, the EMH remains a key reference by Fama (1970). According to this theory, arbitrage opportunities should either not exist or be so limited that they are quickly eliminated. Research by Makarov & Schoar (2020), Eom (2021), Choi et al. (2019), Hautsch et al. (2024) Crépellière et al. (2023), Chen & Sarkar (2022) and Borri & Shakhnov (2023) show that this does not hold true in cryptocurrency markets. Persistent inefficiencies and arbitrage gaps continue to challenge the assumptions of market efficiency in this space.

One of the most influential contributions to the study of crypto market inefficiencies comes from Makarov & Schoar (2020). Their 2019 paper investigated sustained price variations across cryptocurrency exchanges. It showed that such variations are related to structural and geographic elements instead of being random. Their 2020 study greatly widened the scope based on the initial analysis. Data came from 34 exchanges located in 19 countries. Price differences show a pattern of being larger when they cross national borders instead of happening within the same nation. Such differences are greatly influenced by capital controls, limits on money transfers and varied national rules. In South Korea, the "Kimchi premium" is a noted example. Bitcoin repeatedly had higher prices there than it did in the United States. This should not be possible based on the EMT, the Kimchi premium would vanish as competition quickly corrects price differences (Eom, 2021; Francisco et al., 2024).

Choi et al. (2019) explored the previous phenomenon and demonstrated that, on average, Bitcoin was 2.27% more expensive in Korea during the study period, with spikes reaching over 50%. This was mostly due to strict capital controls and Bitcoin network frictions limiting the ability of arbitrageurs to profit from price differences between markets.

Chen & Sarkar (2022) built on the works of Makarov & Schoar (2020) and Choi et al. (2019), by further researching the dynamics of geographical market segmentation. They showed how Chinese citizens were able to bypass capital controls by purchasing Bitcoin with RMB and then offloading it for USD. This flow of capital led to persistent price differences and noticeable imbalances across foreign exchange markets in China. As a result, Bitcoin consistently traded at a premium on Chinese platforms, driven by intense buy-side demand within the country, while sell pressure built up abroad. Further emphasis is placed on the effects of market segmentation, and the role arbitrage plays in these markets. Their findings highlight how fragmented infrastructure and local demand shocks continue to create arbitrage opportunities. This challenges traditional finance concepts like the LOOP, suggesting that inefficiencies in crypto markets are not just random but shaped by market factors and proving wide-scale market inefficiencies.

Crépellière et al. (2023) confirmed that arbitrage opportunities still exist but have declined steadily since 2018. They used a broader dataset and a longer timeframe for analysis. The results show that market maturity, improved infrastructure, and greater involvement of professional traders are reducing the ability to exploit inefficiencies. A similar conclusion was made by Shynkevich (2023). This research examines how the market has matured over time and how arbitrage opportunities have decreased. These findings challenge the paper by Makarov & Schoar (2020), suggesting that market inefficiencies and arbitrage opportunities persist today despite more informed trading.

Borri and Shakhnov (2023) studied how BTC price differences, also known as discounts, remain across exchanges around the globe. The results show that price variances are significant in areas that have stricter rules about money movement and markets that trade at lower volumes. Discrepancies are more pronounced in countries with strict capital controls, which limit arbitrage opportunities. They also stated that regional supply and demand shocks, influenced by factors like local mining activity and investor interest, contribute to BTC price variability. Crypto-to-crypto arbitrage gaps are generally smaller and close quickly. Crypto-to-fiat gaps are larger and remain open for longer periods. This suggests that fiat currency systems are a significant source of market friction. They contributed to understanding the limits of arbitrage in segmented markets.

3.2 Statistical arbitrage, volatility, and trading models

Early research into statistical arbitrage in cryptocurrency markets focused on how inefficiencies could be captured using trading models across different timeframes. Fil & Kristoufek (2020) explored the application of pairs trading strategies across 26 liquid cryptocurrencies on Binance, emphasising high-frequency trading. Their findings showed that while pairs trading was ineffective at daily intervals, it produced significant returns at shorter windows such as 5-minute intervals. This highlighted how market inefficiencies, often driven by low liquidity and high volatility, were more pronounced at finer time scales.

Extending the current analysis, Kristoufek & Bouri (2023) examined the emergence of statistical arbitrage opportunities across five major Bitcoin exchanges: Binance, Bitfinex, Bitstamp, Coinbase, and Kraken. Their results revealed that arbitrage opportunities tend to emerge during high blockchain congestion and sharp volatility periods. However, the likelihood of such opportunities decreases with higher trading volume and active on-chain engagement. They applied Grey Relational Analysis and the DCC GARCH model to examine conditional correlations, showing that while the market remains highly volatile, it behaves in ways consistent with established financial theory.

Heijmans (2018) provides an in-depth examination of arbitrage opportunities within the Bitcoin market, specifically testing the Law of One Price (LOOP) using three distinct arbitrage techniques: Multiple Fiat Currency Triangular Arbitrage, Multiple Cryptocurrency Triangular Arbitrage, and Inter-Exchange Arbitrage. The paper focuses on identifying price discrepancies across different exchanges and currency pairs, using hourly closing prices over one year from July 2017 to July 2018. Heijmans (2018) finds that arbitrage opportunities are most prevalent during periods of heightened market activity, particularly in a bull market where volatility spikes. The results indicate that the largest arbitrage opportunities exist in the Multiple Fiat Currency Triangular Arbitrage technique, with price discrepancies exceeding 13%. In contrast, the other techniques show smaller but still significant opportunities. These findings suggest that arbitrage opportunities in the Bitcoin market depend highly on market conditions, and that volatility plays a key role in creating such opportunities.

Further supporting these findings, Fischer et al. (2019) applied a BEKK GARCH framework to assess statistical arbitrage strategies in crypto markets and found meaningful impulse responses in volatility following price shocks. Arbitraging at the minute level proved difficult due to low volumes and execution delay. Machine learning is feasible but is limited to the mentioned limitations. These findings underscore the frictions hindering full market efficiency in the crypto space.

3.3 Frictions and risks limiting arbitrage

Despite theoretical arbitrage possibilities in cryptocurrency markets, actual execution is often limited by practical frictions. A significant source of inefficiency comes from settlement latency, the time it takes for blockchain transactions to be validated and confirmed. Hautsch, Scheuch, Voigt (2024) showed that delays in settlement add considerable risk for arbitrageurs who must hold an asset while waiting for it to be processed. In contrast, the research found that settlement latency alone limits arbitrage, even without capital controls, challenging the focus of Makarov & Schoar (2020) and Choi et al. (2023). During trading periods, any price movements can quickly erase expected profits in DEXs. Their findings also pointed to high spot volatility and sudden spikes in network congestion as key contributors to these risks. Centralized exchanges allow faster trades but carry the risk of default, as explained in the theoretical background. The empirical analysis uses Bitcoin network and order book data, revealing that significant cross-exchange price differences are closely related to periods of high settlement latency and network congestion. Hautsch et al. (2024) also emphasised the need to analyse violations for the LOOP in line with past research, like Jin Choi et al. (2019), Borri & Shakhnov (2023), and Kroeger & Sarkar (2017).

Supporting the research on on-chain arbitrage, Guo et al. (2024) argued that Hautsch et al. (2024) overlooked the role of perceived exchange default risk in shaping arbitrage strategies. They showed that arbitrage opportunities between centralised exchanges become far less attractive once transaction fees, blockchain congestion, and the probability of exchange failure are considered. Even when price differences are observable, most traders cannot react fast enough without taking on significant risk. This aligns with the findings of Härdle et al. (2019) and Zimmerman (2019), who both emphasised how volatility clustering, latency uncertainty, and limited blockchain capacity contribute to execution frictions. These studies show that arbitrage seems simple in theory. However, in practice, it is more complex and riskier due to real-world obstacles.

The extreme price volatility of Bitcoin itself amplifies these risks. Baur & Dimpfl (2021) proved that Bitcoin's short-term price moves are highly volatile. It is more unstable than traditional currencies. This makes it hard to use as a reliable medium of exchange or store of value. In arbitrage, this volatility adds price risk. Settlement delays or execution lags make it worse. This risk discourages traders from acting on small price gaps.

3.4 Exchange networks and decentralised arbitrage

Decentralised exchanges (DEXs) and automated market makers (AMMs) have reshaped the landscape of arbitrage by removing intermediaries and relying on blockchain-based smart contracts (Hautsch et al., 2024). These platforms operate under different design rules than centralised exchanges, leading to new opportunities and limitations for arbitrage.

Decentralised arbitrages are further researched by the works of Lehar & Parlour (2021) and Harvey et al. (2021). Lehar & Parlour (2021) analysed Uniswap and its automated market maker model, finding that arbitrageurs play a vital role in correcting price deviations and ensuring efficiency, especially in markets with thinner liquidity. They argue that AMMs separate price discovery from liquidity provision, allowing for smoother performance under stress conditions. However, their findings also suggest that arbitrage profits are essential for incentivising traders to keep prices in check, and that the absence of persistent arbitrage opportunities signals improved efficiency over time.

Mazor & Rottenstreich (2024) extended the research scope by focusing on cross-chain arbitrage opportunities on platforms like PancakeSwap and QuickSwap, which operate on different blockchain networks such as BNB Chain and Polygon. Their research found significant price differences for the same tokens across different blockchains. These gaps could be used for profit. They also noted risks because trades cannot be completed simultaneously across blockchains. Since transactions are not instant or guaranteed on both sides, traders face issues like price slippage and failed trades. These risks grow during high volatility or network congestion. These challenges reflect the same market frictions discussed earlier.

Adding to this perspective, Barbon & Ranaldo (2022) looked at liquidity provider behaviour and found that providers on DEXs often face a trade-off between collecting fees and risking losses to better-informed traders. This structural inefficiency limits DEX performance under certain conditions. Similarly, Alexander et al. (2023) showed that although technical improvements in platforms like Uniswap-v3 have narrowed the gap with centralised exchanges in terms of price discovery, DEXs still lag in efficiency, largely due to persistent arbitrage opportunities and long-memory return patterns. Together, these findings highlight how both structural and technical frictions continue to shape the performance limits of decentralised markets.

Bruzgė & Šapkauskienė (2022) provided a different approach by applying network analysis to identify arbitrage routes across 13 cryptocurrency exchanges. While not focused on DEXs, their work highlights how certain exchanges act as hubs, shaping arbitrage pathways and influencing where liquidity is likely to move. Their research revealed that certain exchanges frequently act as hubs in the arbitrage network, facilitating the movement of capital and liquidity. These dynamics suggest that exchange-specific features, such as withdrawal speed and trading volume, play a key role in determining whether a market becomes an arbitrage hotspot.

To conclude the literature review, the most important literature concerning this thesis is from Kristoufek & Bouri (2023) and Crépellière et al. (2023). The former examines drivers of arbitrage opportunities using GRA and DCC-GARCH models, while the latter focuses on Kraken as the baseline exchange for their analysis.

4 Data and Methodology

This chapter outlines the data and methodologies employed to test the research hypotheses related to the research question. The data collection process is first outlined, covering the choice of data sources, the timeframe for analysis, and the reasoning behind selecting the BTCUSD currency pair. The chapter also presents relevant descriptive statistics to provide an overview of the data, such as trading volumes, price fluctuations, and volatility measures across the selected exchanges. These descriptive statistics help understand the overall market environment during the study period and offer context for the empirical analysis.

The research initially aimed to analyse both BTCUSD and BTCUSDT markets to ensure a comprehensive understanding of price movements and liquidity dynamics. However, due to the limited availability and quality of BTCUSDT data for the specified research period, the focus has shifted towards only incorporating BTCUSD. This approach ensured a more robust and reliable analysis while maintaining the integrity of the research findings. All BTCUSD datasets were assessed for anomalies to ensure data quality, with extreme outliers and instances of zero exchange volume removed. This process ensured that the dataset accurately reflected market conditions during the selected time frame.

4.1 Data

The datasets will include only the BTCUSD pair, which is currently the most popular and liquid crypto-FIAT currency pair globally (Wüstenfeld & Geldner, 2022). To ensure consistency and accuracy across the pricing data, all historical prices will follow the UTC time zone format, creating a unified and reliable framework for analysis. As mentioned in the introduction, the goal is to use the current available data and observe changes over time. The chosen sample period is from 01.01.2017 to 31.10.2024. This includes the most recent data available at the time of research. The average benchmark price used in this research is derived from firstratedata.com. Where the average price is extracted from 14 crypto exchanges on the daily level: Kraken, Bitfinex, Binance, Bitstamp, Coinbase, Bitthumb, Huobi, KuCoin, Coinone, bitFlyer, GDAX, BitBay, BTCMarkets, Cex.io, CoinFloor, Coinone, HitBTC, Wex. The average data has been backtested for reliability and accuracy by Firstratedata.com.

When selecting exchange data for this analysis, several critical factors were evaluated to ensure the dataset's suitability for investigating arbitrage opportunities across crypto-currency exchanges. These factors are the use of Unix timestamps, the completeness of data across the investigated period, and alignment with the UTC time zone. Unix timestamps, defined as the seconds elapsed since January 1, 1970 (termed the Unix epoch), were favoured for their standardised, machine-readable structure, crucial for aligning price data across globally operating exchanges (Mills, 1992). Data completeness was a key concern, focusing on accurate price, volume, and date information. The use of UTC ensured time consistency, as crypto markets operate globally and continuously. Mis-aligned time zones could otherwise distort price relationships. However, building a con-sistent dataset across all exchanges and the whole period was difficult. This required aggregating data from multiple sources.

The primary datasets include Bitcoin price and return time series from various exchanges. Several tests are applied to examine the properties of the data during processing. The Jarque-Bera test, developed by Jarque and Bera (1980), examines whether these da-tasets display normality and symmetry. A critical factor is that many statistical methods rely on normal distributions for valid outcomes. To complement this, excess kurtosis, first outlined by Pearson (1905) and elaborated by Westfall (2014), is assessed to detect pro-nounced tails in the return distributions, especially relevant given Bitcoin's volatility. Sta-tionarity is verified using the Augmented Dickey-Fuller (ADF) test (Said & Dickey, 1984) and the Phillips-Perron (PP) test (Phillips & Perron, 1988), ensuring consistent statistical properties over time. Consistent statistical properties over time are essential for model-ling reliable price relationships across exchanges, preventing false arbitrage signals from unstable trends. The ADF test adjusts for serial correlation, while the PP test addresses heteroskedasticity. For the secondary datasets, comprising correlation outputs from the

Grey Relation Analysis and DCC-GARCH models, the Wu-Hausman test, based on research by Durbin (1954), Wu (1973), and Hausman (1978), checks for endogeneity. This confirms that variables like trading volume or network activity affect correlations independently, preserving the model's accuracy and determining drivers of price disparities. Together, these tests assess the reliability and precision of the findings, aligning with analytical approaches in similar research by Mäki-Torkko (2024) and Runarsson (2024).

For the BTCUSD daily sample, the data has been mostly retrieved through 'www.CryptoDataDownload.com'. This site has been utilised in research by Kristoufek & Bouri (2023) and Heijmans (2018). Additional exchange data was gathered from data.bitcoinity.org and directly from centralised exchanges. The final dataset includes 15 BTCUSD exchanges and the market average. These exchanges are: Bitbay, Bitfinex, Bitstamp, Bittrex, Cex.io, Coinbase, Exmo, FTX, Gemini, HitBTC, Kraken, Kucoin, Okcoin, Poloniex, and Yobit. Each exchange is paired daily from 01.01.2017 to 31.10.2024, using the UTC time zone. Kraken's historical daily BTCUSD prices were sourced directly from support.kraken.com. This results in 15 centralised exchanges and 27,195 daily observations in the research sample.

Kraken is used as the baseline exchange for BTCUSD. It was chosen for its complete and reliable data over the whole period. Kraken is a well-regulated U.S.-based exchange. It often ranks in the top 10 globally by trading volume. Its market share has remained stable, as shown in Figure 1. Kraken's strong regulation and steady presence make it a reliable benchmark. Coinbase was excluded due to data issues for the baseline exchange. Binance was also excluded because it does not offer a direct BTCUSD pair for comparison.

Table 1 below presents the summary statistics of cryptocurrency exchanges, organised geographically, beginning with each exchange's price premium (PP%). Analysing the price premium of exchange is motivated by an earlier study by Crépellière et al. (2023). PP% shows how much an exchange's Bitcoin price differs from the overall market average. It is calculated as ((exchange price – total average) / total average) × 100. This measure helps compare price differences between local and global exchanges over the study period.

Summary Statistics of Exchanges

Price Premium %							
BTCUSD	Avg. Daily Volume	Mean	Median	Std. Deviation	Range	Count	Duration
Europe							
Bitbay (USD)	44222	-0.2112	0.0029	3.1693	53.4280	1307	02.06.2016 - 27.09.2020
Cex.io (USD)	3748811	-0.5935	-0.1408	1.6223	20.6325	2807	18.07.2014 - 22.10.2024
Exmo (USD)	3549713	-1.7510	-0.7914	3.1403	28.3685	2158	03.03.2016 - 29.11.2022
USA							
Bitstamp (USD)	80174212	0.1059	0.0096	0.7894	18.6797	2852	28.11.2014 - 23.10.2024
Bittrex (USD)	8377931	-0.1009	-0.0121	0.8424	17.8551	1270	13.06.2020 - 04.12.2023
Coinbase (USD)	390919001	0.0275	0.0443	1.1463	18.5724	2836	02.12.2014 - 19.01.2025
FTX (USD)	347186483	-0.0010	0.0071	0.2231	5.8294	1211	21.07.2019 - 12.11.2022
Kraken (USD)	81035687	0.0759	0.0071	1.1040	16.8477	2852	08.10.2013 - 19.01.2025
Gemini (USD)	37713767	0.0775	0.0150	1.1335	17.4419	2852	09.10.2015 - 22.10.2024
Asia							
Bitfinex (USD)	159442658	-0.1516	-0.0403	0.8703	14.5503	2852	09.02.2015 - 23.10.2024
Other							
Okcoin (USD)	4934574	-0.2291	0.0260	2.5445	45.3632	1166	24.07.2014 - 20.11.2020
HitBTC (USD)	40061243	-0.1682	-0.0116	1.2316	10.5135	382	26.05.2017 - 11.06.2018
Kucoin (USD)	491496	0.0085	0.0149	0.3722	4.3532	337	28.12.2021 - 29.11.2022
Poloniex (USD)	39737	-0.2027	-0.0055	1.6532	28.0741	1137	03.02.2021 - 15.03.2024
Yobit (USD)	410292	-3.2320	-3.0823	2.7691	22.1359	1176	26.05.2017 - 27.09.2024

Prices								
BTCUSD	Average	Bitbay	Bitfinex	Bitstamp	Bittrex	CEX	Coinbase	Exmo
Kurtosis	2.41	2.94	2.41	2.41	2.38	2.53	2.42	3.03
Ex. Kurtosis	-0.59	-0.06	-0.59	-0.59	-0.62	-0.47	-0.58	0.03
Skewness	0.8119	0.1933	0.8133	0.8117	0.4451	0.8506	0.8209	1.1532
Min	789.69	698.00	783.63	794.76	9043.73	801.45	790.43	794.31
Max	72323.62	18584.38	72198.50	72403.25	67318.38	72392.75	72745.88	67302.78
Q1	7285.96	3947.63	7285.41	7281.15	20144.72	7276.04	7257.22	6474.30
Q3	37984.99	9305.97	38006.50	37976.88	40802.03	36941.25	37961.52	25570.90
Jarque-Bera	354.88***	8.31**	355.64***	354.77***	62.18***	364.26***	358.42***	478.41***
	(0.00)	(0.02)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
	FTX	Gemini	HitBTC	Kraken	Kucoin	Okcoin	Poloniex	Yobit
Kurtosis	1.87	2.41	2.81	2.41	1.48	2.51	2.21	3.51
Ex. Kurtosis	-1.13	-0.59	-0.19	-0.59	-1.52	-0.49	-0.79	0.51
Skewness	0.4898	0.8129	0.6148	0.8126	0.3112	0.1665	0.4163	0.4535
Min	5040.50	789.61	788.57	1944.01	15937.93	767.48	15770.09	1949.28
Max	67357.75	72399.40	18942.27	72734.57	49038.45	17991.58	72940.54	19385.25
Q1	9834.69	7253.00	4000.13	7261.45	20120.50	3779.79	25876.35	5651.74
Q3	41559.25	37863.34	9466.94	38070.22	39680.95	9287.87	45906.94	9660.69
Jarque-Bera	113.15***	355.03***	24.64***	355.30***	38.06***	17.24***	62.30***	52.88***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

Note: *This table presents the primary summary statistics of the daily price premiums and price series across cryptocurrency exchanges, categorized by geographic region. The data spans the period from January 1, 2017, to October 31, 2024. Measures of skewness (Skew.), excess kurtosis (Ex. Kurt.), and the Jarque-Bera test are included to assess the normality of the distributions. In parentheses, the p-values are shown. The price premium (%) represents the percentage deviation of exchange prices from the market average. Statistical significance is indicated as follows: *** denotes significance at the 1% level, ** denotes significance at the 5% level, and * denotes significance at the 10% level.*

Table 1. Summary Statistics of Exchanges

Coinbase and FTX had the highest trading volumes over the period. FTX's data ends early due to its 2022 bankruptcy. Higher volume may explain the small positive premiums (0.0010% to 0.0775%), with medians close to zero. This means their prices usually follow the market average but are sometimes slightly higher. Exchanges like Exmo, Yobit, and Cex.io show larger negative premiums, possibly offering cheaper Bitcoin. US-based exchanges like Bitstamp and Kraken show small positive premiums, making them potential sell points. Still, with most premiums under 1%, factors like fees and transaction costs matter.

Bitbay shows the highest standard deviation at 3.1693, with a price premium range of 53.4280%. High variability is also seen in Exmo (3.1403, range 28.3685%) and Yobit (2.7691, range 22.1359%). These wide fluctuations suggest possible short-term arbitrage opportunities when prices move away from the market average. In comparison, exchanges like Bitfinex (0.8703, range 14.5503%), Coinbase (1.1463, range 18.5724%), and Gemini (1.1335, range 17.4419%) exhibit lower variability, reflecting more stable pricing relative to the market, which reduces arbitrage potential but also lowers the risk of sudden price shifts.

From a geographical perspective, European exchanges demonstrate larger negative premiums, such as Exmo's -1.7510% and Cex.io's -0.5935%. This suggests that there might be regional inefficiencies or regulatory differences. Notably, larger ranges and standard deviations tend to emerge in exchanges with lower trading volumes, such as Bitbay (44222 USD, range 53.4280%, SD 3.1693), Okcoin (4934574 USD, range 45.3632%, SD 2.5445), and Poloniex (39737 USD, range 28.0741%, SD 1.6532). This pattern is logical, as lower liquidity often leads to reduced price alignment with the market average, amplifying volatility and creating opportunities for price discrepancies that arbitrageurs might exploit.

The daily price series across the exchanges display positive skewness, reflecting distributions with extended right-hand tails. Exmo demonstrates the most pronounced skewness at 1.1532 compared to other exchanges, indicating that a significant number of elevated price premium observations shift the mean to the right, resulting in a highly asymmetrical distribution. Most exchanges exhibit relatively high kurtosis, with values like Coinbase (2.42), Bitbay (2.94), Yobit (3.51) and Exmo (3.03) suggesting that the BTCUSD price distributions feature sharper peaks and heavier tails compared to a normal distribution.

To evaluate the normality of the price distributions across the cryptocurrency exchanges, Jarque-Bera tests were conducted. The results for most exchanges, such as Coinbase (358.42***), Bitstamp (354.77***), and Kraken (355.30***), reveal a consistent pattern of non-normality to the market average of 354.88***, with p-values below 0.01, indicating significant deviation from a normal distribution. Notably, Exmo's Jarque-Bera test result is the highest at 478.41***, suggesting that its price premium distribution deviates more dramatically from normality compared to others, a finding consistent with its high skewness (1.1532) despite its low excess kurtosis (0.03). Bitbay reported a Jarque-Bera p-value of 0.02, which raises concerns about data quality regarding the exchange. These results align with the observed positive skewness and high kurtosis across most exchanges, confirming the non-normal nature of price premium distributions in cryptocurrency markets.

Excess kurtosis measures how much the distribution deviates from the kurtosis of a normal distribution (which is 0). Positive excess kurtosis values indicate a leptokurtic distribution (sharper peak, heavier tails) like Exmo and Yobit. Other exchanges follow the market average with negative values for excess kurtosis, highlighting flatter peaks and lighter tails compared to Exmo and Yobit values. For instance, the logarithmic return of Bitcoin from 2015 to 2022 resulted in a kurtosis of 9.292, as shown in the research by Mäki-Torkko (2024). This provides a broad perspective that crypto exchanges trading the BTCUSD pair are more prone to outliers than trading assets like gold or green bonds. The Jarque-Bera test also revealed Bitcoin having the highest result, emphasising the most significant deviation from normality in the research by (Mäki-Torkko, 2024).

Results of Stationarity Tests: Phillips-Perron and Augmented Dickey-Fuller

Price	Average	Bitbay	Bitfinex	Bitstamp	Bittrex	CEX	Coinbase	Exmo
Dickey-Fuller	-2.78	-2.52	-2.77	-2.78	-2.04	-2.79	-2.79	-1.88
	(0.25)	(0.36)	(0.25)	(0.25)	(0.56)	(0.24)	(0.24)	(0.63)
Philips-Perron	-8.74	-7.37	-8.78	-8.75	-4.74	-8.59	-8.94	-4.60
	(0.62)	(0.70)	(0.62)	(0.62)	(0.85)	(0.63)	(0.61)	(0.85)
	FTX	Gemini	HitBTC	Kraken	Kucoin	Okcoin	Poloniex	Yobit
Dickey-Fuller	-0.46	-2.76	-0.80	-2.78	-2.35	-2.47	-0.50	-2.44
	(0.98)	(0.26)	(0.96)	(0.25)	(0.43)	(0.38)	(0.98)	(0.39)
Philips-Perron	-0.99	-8.85	-8.76	-2.14	-11.64	-7.12	-1.15	-7.92
	(0.99)	(0.62)	(0.96)	(0.62)	(0.46)	(0.71)	(0.99)	(0.67)
Return	Average	Bitbay	Bitfinex	Bitstamp	Bittrex	CEX	Coinbase	Exmo
Dickey-Fuller	-12.69***	-10.45***	-12.84***	-12.69***	-9.62***	-12.31***	-12.75***	-11.54***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Philips-Perron	-1625.54***	-1399.81***	-1467.98***	-1474.58***	-694.00***	-1454.18***	-2148.77***	-1133.54***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
	FTX	Gemini	HitBTC	Kraken	Kucoin	Okcoin	Poloniex	Yobit
Dickey-Fuller	-9.92***	-12.58***	-6.59***	-12.66***	-7.12***	-9.99***	-10.73***	-9.19***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Philips-Perron	-664.30***	-1564.21***	-213.37***	-2168.89***	-176.52***	-695.10***	-846.79***	-586.69***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)

Note: *This table presents the logarithmic price and return series for all cryptocurrency exchanges. The results of the Augmented Dickey-Fuller (ADF) test and Phillips-Perron (PP) test for the full sample period are reported. P-values for each test are provided in parentheses. Statistical significance is denoted as follows: *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level.*

Table 2. Stationary Test Outcomes

Table 2 provides the outcomes of the augmented Dickey-Fuller and Phillips-Perron stationarity tests for the entire period. These tests aim to determine whether a time series exhibits stationarity or non-stationarity through unit root testing. Stationarity is essential for econometric analysis because it ensures that key statistical properties such as the mean and variance remain constant over time, which supports the validity of model estimation and inference. The stationarity test results from the Phillips-Perron (PP) and Augmented Dickey-Fuller (ADF) tests on the price and return series of 15 cryptocurrency exchanges reveal distinct patterns. Both ADF and PP tests consistently show non-stationarity for the price series across all exchanges. Test statistics like ADF: -2.78 and PP: 8.74 for the average failing to reject the null hypothesis of a unit root at any significance level (p-values ranging from 0.24 to 0.99). Both tests consistently indicate non-stationarity in the price series for all exchanges. Similarly, like in Mäki-Torkko (2024), the logarithmic return series through both tests proved the values to be stationary, and this can be realised from the significance at the 1% level for all exchanges. Stationarity in the logarithmic return series is critical, as it enables the GARCH model to produce accurate volatility forecasts and manage risk effectively, making its use in GARCH modelling and time series modelling strongly recommended.

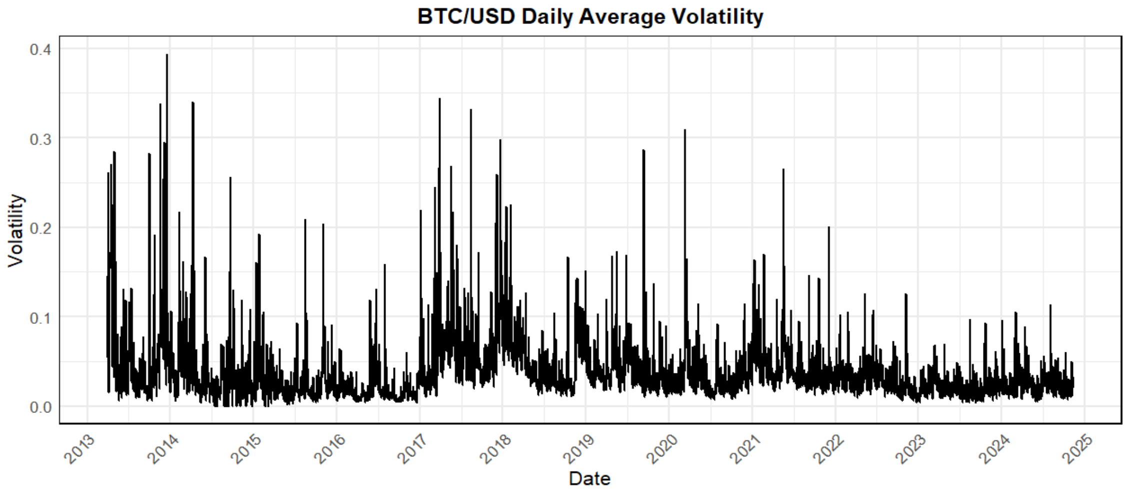

Figure 6. BTCUSD Volatility from 2013 to 2025

When it comes to volatility with the BTCUSD exchanges of the research sample, a non-parametric measure of volatility is used. The non-parametric measure of volatility would be the estimator of Garman & Klass (1980). The Garman & Klass (1980) estimator has been used in similar studies like Baur & Dimpfl (2021) and Kristoufek & Bouri (2023). This measure of volatility is shown below:

$$(i) \qquad variance = \sigma_t^2 = 0.5(h_t - l_t)^2 - (2\log(2) - 1)(c_t - o_t)^2,$$

$$(ii) \qquad standard\ deviation = \sigma_t = \sqrt{(0.5(h_t - l_t)^2 - (2\log(2) - 1)(c_t - o_t)^2},$$

Where h_t is the logarithm of the highest price, l_t is the logarithm of the lowest price, o_t is the logarithm of the opening price, and c_t is the logarithm of the closing price on day t. As stated in Baur & Dimpfl (2021), Bitcoin's price is far more volatile than FX rates, with its fluctuations being much more extreme. Using the square root of the estimated variance (σ_t^2) derived from the logarithmic high (h_t), low (l_t), open (o_t), and close (c_t) prices, the estimator reveals extreme fluctuations in the overall bitcoin market utilising market average prices.

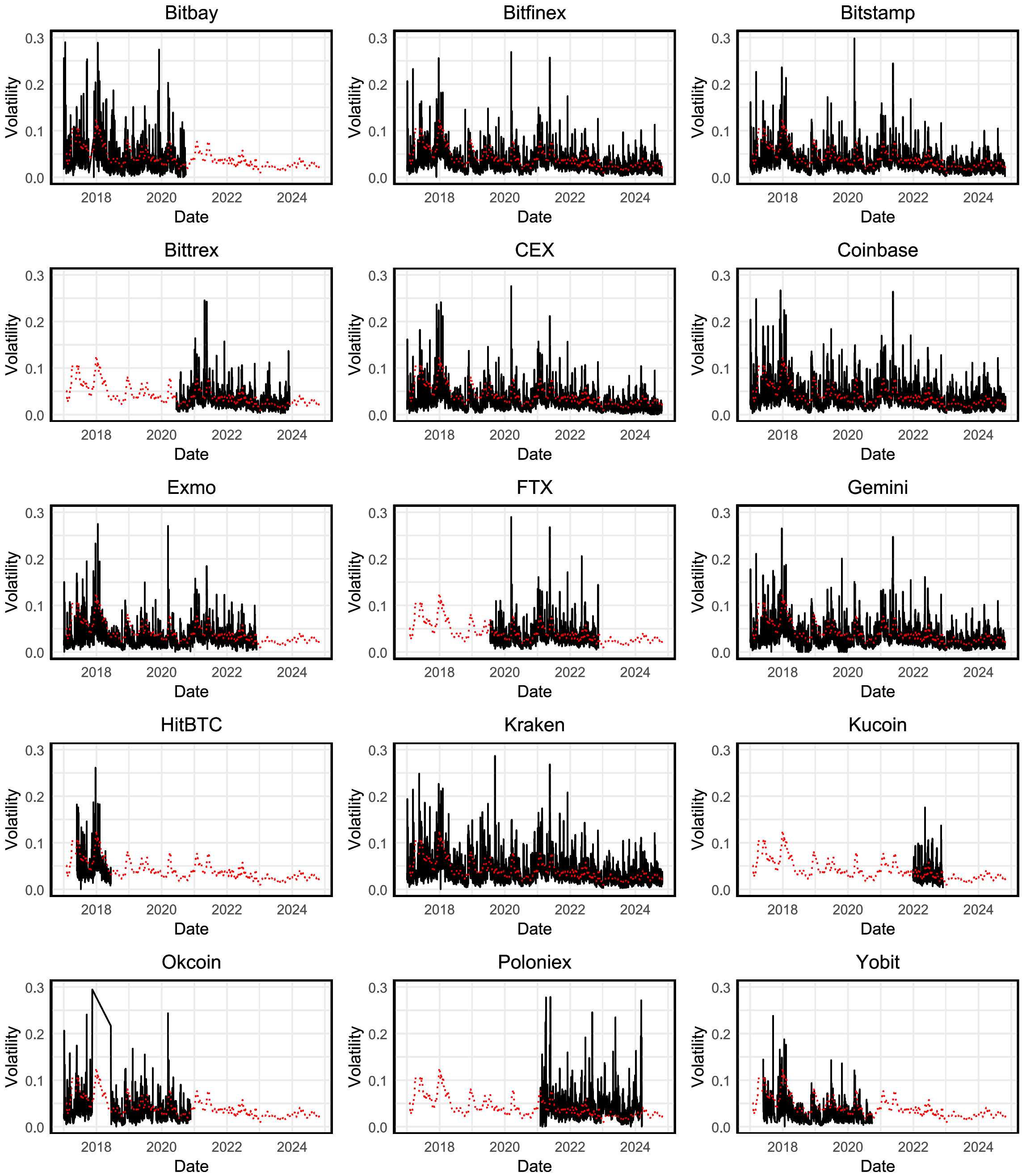

Figure 7. Volatility Time Series

The volatility time series offers a comprehensive overview of price variability across cryptocurrency exchanges from 2017 to 2024. Each panel illustrates the trends specific to individual exchanges. Furthermore, the red line in each plot represents the line of best fit, calculated using the average volatility across the 14 exchanges mentioned earlier, as shown in Figure 7. This would increase the comparability of these exchanges to the market average.

The level of volatility exhibits a significant decline over the years, as observed in Figure 6. A similar pattern is evident in Figure 7 and with the findings of Kristoufek & Bouri (2023), this shows the correlation between similar exchanges in different countries. It also highlights that price deviations became more stable after 2021. This matches the drop in volatility seen in the data. One reason for this could be the growing maturity of the crypto market. Liquidity has increased. Regulations have improved. More institutional investors have entered. Together, these changes help reduce the extreme price swings seen in earlier years (Baur & Dimpfl, 2021). This stabilisation suggests a shift toward more predictable market behaviour, potentially reducing arbitrage opportunities while enhancing the market's suitability for long-term investment strategies.

Many exchanges, such as Bitfinex and Bitstamp, exhibit consistent trends with sharp spikes corresponding to significant market events. For comparison, exchanges like HitBTC and Kucoin display unique patterns, likely driven by differing liquidity and trading activity. The average volatility highlights market-wide instability during key periods, such as 2017–2018 and 2021, aligning with major bull runs and regulatory shifts. Exchanges like CEX and Okcoin exhibit slightly lower volatility with fewer peaks, suggesting greater stability than others. Such differences show that it is important to understand the details of individual trades and general patterns in markets.

4.1.1 robustness checks

The analysis begins with a series of robustness checks to ensure the reliability of the datasets used in examining arbitrage opportunities across cryptocurrency exchanges. As shown in Tables 1 and 2, Jacque-Bera, Excess Kurtosis, and Stationarity tests have been conducted for the raw data. The Jarque-Bera test is applied first to the raw dataset, which includes daily Bitcoin prices from all 15 exchanges, including the market average. This test checks whether the price return distributions follow a regular pattern, which is essential for understanding if standard statistical methods will work well with the data.

Next, stationarity is assessed through the application of the Phillips-Perron and Augmented Dickey-Fuller tests to the same raw dataset of prices and returns, consistent with methodologies employed in prior studies such as Mäki-Torkko (2024) and Runarsson (2024). The Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests are widely used unit root tests that assess whether a time series is stationary or contains a unit root, indicating non-stationarity. The ADF test accounts for autocorrelation by incorporating lagged differences of the variable. On the other hand, the PP test adjusts for heteroskedasticity and autocorrelation in the error terms without adding lagged difference terms.

Autocorrelation means that residuals are correlated over time, which can bias standard errors and affect the reliability of statistical tests. Heteroscedasticity occurs when the variance of residuals is not constant, leading to inefficient estimates. Stationarity refers to a situation where statistical characteristics such as the mean and variance remain constant over time. If the data are non-stationary, model results can become distorted. Endogeneity happens when explanatory variables are correlated with the error term, which causes biased and inconsistent parameter estimates.

Applying these tests to the raw dataset of prices and returns is essential, as stationarity is a key requirement for time series modelling, including the DCC-GARCH model and Grey Correlation Analysis. For the DCC-GARCH model, which estimates time-varying correlations, stationarity ensures that volatility dynamics are properly captured without spurious trends. Similarly, for Grey Correlation Analysis, stationarity helps maintain consistency in the relationship patterns between variables, ensuring that trends or structural shifts in the data do not distort identified correlations. In short, stationarity matters because it ensures the studied price relationships are stable enough to draw meaningful conclusions about arbitrage potential.

To investigate the econometric issues from the tests conducted on the raw data sample more in-depth, the study needs to further investigate heteroscedasticity, autocorrelation, and endogeneity from the test results. Since Issues like heteroskedasticity, autocorrelation, and endogeneity arise within the regression model, not just in raw price/return data (Greene, 2003). The focus is then on whether these econometric issues arise from the regression model outputs used in the empirical analysis rather than the raw data. Identifying them within the regression framework helps assess the reliability of the results. So, the output result from the model will be adjusted accordingly if needed.

The Wu-Hausman test is used to check for endogeneity for the processed datasets, which involve the Grey Correlation Analysis and DCC-GARCH model outputs, with the variables part of this study. This test evaluates whether certain explanatory variables are correlated with the error term in the OLS regression results for both models. This determines whether the OLS regression results are biased or inefficient, indicating the potential need for the IV/2SLS model approach to address endogeneity and improve the reliability of the model's estimates.

On top of that, the Breusch-Pagan test will be used to detect heteroskedasticity and determine whether robust standard errors are necessary. The Durbin-Watson test will be conducted to assess the presence of autocorrelation. Based on the results, the appropriate adjustment method will be selected: HC robust errors (White standard errors by White (1980)) if only heteroskedasticity is present, or HAC robust errors (Newey-West standard errors by Newey & West (1987)) if both heteroskedasticity and autocorrelation are detected. This ensures that the model's estimates remain valid and reliable.

Final note: The processed datasets would possess stricter significance level thresholds to present more robust findings, avoid false positives, and increase the transparency of overall results. This means the following significance levels: *** 0.1%, ** 1%, * 5%,. 10%.

4.2 Methodology

As noted in the introduction of this research, this research fills a key gap by using a longer timeframe with updated data and analysing exchange relationships with a different baseline. This builds on the works of Kristoufek & Bouri (2023), expanding on the analysis to better reflect recent market developments and structural changes with a new baseline exchange. The same models are used in this study, the Grey Relational Analysis and the DCC GARCH model. This research also contributes to the findings of Crépellière et al. (2023), who document a significant decline in arbitrage opportunities since April 2018 with the same baseline exchange as in this research. Using an updated timeframe and a different exchange setup, this study tests whether similar trends hold under a different trading environment. While Crépellière et al. focus on cross-platform strategies using Kraken as a fixed trading point, this paper revisits that structure. It explores whether changes in exchange selection reveal any persistent inefficiencies with market factors.

Grey Relational Analysis helps identify which exchanges move most closely with the chosen baseline by ranking their price similarities using exchange pricing data. Using exchange return data, DCC-GARCH is used to track how the correlation between prices shifts over time, especially during periods of market volatility.

This study examines two separate models to explore the potential origins of statistical arbitrage opportunities in the BTCUSD pair within Bitcoin markets through various market factors. It mainly investigates the emergence of such opportunities by analysing conditional correlations between Kraken, one of the leading centralised crypto exchanges, and other prominent crypto exchanges for both pairs.

The baseline model for this research builds upon the foundational model (i) introduced by Kristoufek & Bouri (2023). The baseline regression model explains the variability in GRA correlations $\gamma(X_0, X_i)$ and DCC-GARCH correlations $(\rho_{ij,t})$ using explanatory variables that influence arbitrage opportunities:

$$(iii) \qquad \hat{\rho}_{i,t} = \beta_{i,0} + \beta_{i,1}\log(\sigma_t) + \beta_{i,2}\log(volume_t) + \beta_{i,3}\log(transfers_t) + \beta_{i,4}\log(fees) + \beta_{i,5}(momentum_t) + \beta_{i,6}(searches_t) + \beta_{i,7}\hat{\rho}_{i,t-1} + \varepsilon_{i,t}$$

Where σ represents the standard deviation of average Bitcoin returns, calculated using the robust range-based Garman & Klass (1980) estimator, leveraging open, close, high, and low prices sourced from firstratedata.com. Volume is the overall exchange-traded volume (in USD) during that particular time from FirstRateData. Transfers is the overall on-chain transfer volume in USD, obtained from coinmetrics.io (*TxTfrValAdjUSD*). Fees is the median fees for the given day in native BTC units paid to miners, obtained from coinmetrics.io (*FeeMedNtv*). Momentum is the logarithm of a ratio between the current and average prices of the previous seven days using FirstRateData closing prices. Search is Google Trends searches for queries “Bitcoin” and “BTC” on a daily basis. Daily data is extracted for overlapping three-month periods and chained together, with rescaling applied based on the mean search volume of the overlapping month. To minimise sampling bias from the Google algorithm, each segment is retrieved three times to enforce fresh sampling. The three samples are then averaged for consistency. Finally, a weighted average of the ‘Bitcoin’ and ‘BTC’ series is calculated, with weights determined by their overall search ratio, ensuring precise and reliable results regarding trend data. $\rho_{i,t-1}$ is the lagged value of the dependent variable, which in this case is the correlation ($\rho_{i,t}$) of BTCUSD prices between the baseline exchange and other exchanges.

Volume, transfers, and fees are considered endogenous variables because they are influenced by the dynamics of the Bitcoin market (Kristoufek & Bouri, 2023). This endogeneity arises due to the simultaneous relationship between these variables and market activity, making them likely correlated with the error term $\varepsilon_{i,t}$ in the regression model, which could lead to biased and inconsistent estimates. For example, an increase in arbitrage opportunities can lead to increased trade activity and movement of BTC among exchanges. This can lead to congested networks and create growing costs that can have an impact on how common these possibilities are.

An instrumental variables (IV) approach is utilised to address this issue. The selected factors are log of Bitcoin price ($\log(price)$), exchange ratio (volume divided by transfers), and log of the number of active Bitcoin addresses ($\log(addresses)$. Log(price) captures the broader market valuation of Bitcoin, independent of specific transaction costs or exchange activity. The exchange ratio is a proxy for market efficiency and trading intensity, while log(addresses) reflects network-wide user engagement and activity levels. By leveraging these instruments in the two-stage least squares (2SLS) regression, the analysis corrects for endogeneity, mitigates bias, and provides more reliable insights into the factors driving arbitrage opportunities in the Bitcoin market. As Kristoufek and Bouri (2023) discussed, these instruments are strongly correlated with the endogenous variables. Still, they are uncorrelated with the error term, ensuring unbiased and consistent estimates in the two-stage least squares (2SLS) regression.

IV: <u>Exchange ratio</u> is the ratio between the daily average USD volume and transfers
IV: <u>Addresses</u> is the number of active addresses for the given day, obtained from coinmetrics.io (*AdrActCnt*)
IV: <u>Price</u> is the average closing exchange price from firstratedata.com.

The study's coefficients are calculated through a regression analysis, which involves estimating the relationship between the dependent variables (Grey correlation and DCC-GARCH correlation) and the mentioned explanatory variables.

Given the fractured nature of the data, it is crucial to address missing data appropriately to ensure the accuracy and reliability of the analysis. For the baseline model, including Grey Relational Analysis and DCC-GARCH calculations, rows with missing values for any variable will be removed, and the dataset will be re-indexed to ensure continuity by aligning subsequent rows. This approach ensures the integrity of the time series and avoids biases introduced by interpolation or imputation, especially for models requiring complete data for accurate analysis.

4.2.1 GRA

The methods utilised in their research use the Grey Relational Analysis or Grey Correlation Analysis, which is based on Grey System Theory by Ju-long (1989). The Grey correlation detects non-linear relationships in return series without needing normal distribution, making it a more versatile and reliable measure compared to the traditional Pearson correlation (Li et al., 2015; Wang et al., 2022). GRA generally captures the non-linear relationship between returns, highlighting arbitrage possibilities. The grey correlation or grey relational analysis (GRA) (i) is determined below:

$$(iv) \quad \gamma\left(x_0(k), x_i(k)\right) = \frac{min_i\ min_k\ |x_0(k) - x_i(k)| + \varepsilon\ max_i\ max_k\ |x_0(k) - x_i(k)|}{|x_0(k) - x_i(k)| + \varepsilon\ max_i\ max_k |x_0(k) - x_i(k)|}$$

To conduct GRA for cryptocurrency exchanges, the first step involves identifying the sequences to be analysed. In this context, the reference sequence (X_0) represents the ideal or target data series, which is chosen as the data from the Kraken exchange. This reference sequence is denoted as $X_0 = \{x_0(1),\ x_0(2), \dots, x_0(n)\}$ and serves as the baseline or benchmark for comparison. The comparative sequences (X_i) are the data series from other exchanges, such as Bittrex, Cex.io, Okcoin, and others. The value will be compared against the reference sequence. These comparative sequences are expressed as $X_i = \{x_i(1), x_i(2), \dots, x_i(n)\}$, where $i = 1,2, \dots, m$ and m represents the total number of exchanges being analysed. By comparing the price data series from these exchanges with the Kraken price data, the analysis evaluates how closely the activity or behaviour of other exchanges aligns with Kraken. Where the alignment is quantified to understand the degree of similarity or correlation between the reference and comparative sequences in the GRA correlation model. The coefficient $\varepsilon \in\ [0,1]$ represents the adjustment parameter, which is set to $\varepsilon = 0.5$ based on Chang & Lin (1999) and in the research by Kristoufek & Bouri (2023).

The data used in this model consists of daily exchange prices, calculated as averages derived from the open, close, low, and high prices. This method of calculating prices ensures a comprehensive representation of daily price dynamics by incorporating intra-day volatility and capturing the full range of market activity. To address gaps in the data caused by missing periods for certain exchanges, the average minimum and maximum prices across all exchanges are utilised. This approach mitigates distortions and prevents the generation of artificially low or high normalised values due to incomplete data. By applying this method, the data remain representative of the overall market environment, ensuring that the Grey Relational Analysis (GRA) accurately reflects the relationships and dynamics among exchanges, while minimising the impact of inconsistencies in data availability.

Breaking down the methodology behind the Grey Correlation Analysis:

To ensure comparability, scaling all values to a similar range is important; this means values are transformed to a range between 0 and 1. Since the data has ‘the larger-the better’ characteristics, since we are seeking the highest arbitrary returns and exploring affecting factors, we utilise the normalisation method (ii) shown by Ertugrul (2016) for the GRA:

$$(v) \qquad x'_i(k) = \frac{x_i^{(0)}(k) - \min x_i^{(0)}(k)}{\max x_i^{(0)}(k) - \min x_i^{(0)}(k)},$$

Where $x_i(k)$ is the original value of the sequence at point k.

Next would be to calculate the absolute differences between the normalised reference sequence (Kraken) and each comparative sequence (other exchanges):

$$(vi) \qquad \Delta_i(k) = \|x'_0(k) - x'_i(k)\|,$$

Where $\Delta_i(k)$ is the absolute difference for the sequences i at data point k.

The Grey correlation coefficients will be computed for each point in the sequence:

$$(vii) \qquad \xi_i(k) = \frac{\Delta_{min} + \zeta\Delta_{max}}{\Delta_i(k) + \zeta\Delta_{max}},$$

Where Δ_{min} is the minimum difference across all sequences and points, Δ_{max} is the maximum difference across all sequences and points. ζ is the distinguishing coefficient, typically 0.5 and can be adjusted between 0 < ζ < 1 for sensitivity.

Finally, the last step is to compute the Grey Relational Grade. The Grey Relational Grade represents the similarity between a reference sequence and a comparative sequence. This similarity is calculated as the mean of all the GRA values:

$$(viii) \qquad \gamma_i = \frac{1}{n}\sum_{k=1}^{n} \xi_i(k),$$

Where n is the number of data points in the sequence.

4.2.2 DCC-GARCH

This research will add further depth to the data analysis by incorporating the DCC-GARCH model by Engle (2002), which stands for 'Dynamic Conditional Correlation Generalised Autoregressive Conditional Heteroskedasticity'. The model is utilised to examine the time-varying correlations in BTCUSD prices across several exchanges. Kraken serves as the baseline exchange, against which price movements on other exchanges are compared through the difference in return. The core objective is understanding how these return correlations evolve and the scale of arbitrage opportunities over time.

The DCC-GARCH framework enables the modelling of individual conditional volatilities and dynamic correlations among multiple time series. This is particularly relevant in high-frequency cryptocurrency markets where return volatility and cross-market relationships fluctuate significantly. Following prior research by Kung & Yu (2008), Kristoufek & Bouri (2023), and more recently Runarsson (2024) and Mäki-Torkko (2024). The model is implemented in two sections: (1) Univariate GARCH (1,1) is applied to each exchange's return series to model the time-varying variances, and (2) DCC Model is used to estimate the time-varying conditional correlations between Kraken and each of the selected exchanges. Through this methodology, it is possible to capture both the individual return volatility of each exchange and the evolving co-movement between exchange returns over time, providing clearer insights into arbitrage opportunities.

The data used in this model is similar to that used in Grey Relational Analysis. Instead of raw price data, it uses daily returns, which are calculated by subtracting the price of the previous day from the current day's price for both Kraken and the comparison exchange.

It starts with the return series. Let R_t represent the return vector at time t, which is the Kraken exchange and the other selected crypto exchanges, shown as:

$$(ix) \qquad R_t = \begin{pmatrix} Kraken \\ Exchange\ I \\ Exchange\ II \\ \dots \\ Exchange\ X \end{pmatrix}$$

The process begins by calculating the logarithmic price differences between Kraken and the selected exchanges:

$$(x) \qquad R_{i,t} = \ln\left(P_{i,t}\right) - \ln\left(P_{Kraken,t}\right),$$

Where $P_{i,t}$ is the BTCUSD price on the exchange of comparison, or exchange i. $P_{Kraken,t}$ is the price on Kraken. This creates a stationary return series suitable for modelling conditional variances.

Next is the mean equation. For each return series (e.g., Bittrex - Kraken and Bitstamp - Kraken), a conditional mean is modelled using a first-order autoregressive (AR (1)) process:

$$(xi) \qquad R_t = \mu + \phi R_{t-1} + \varepsilon_t,$$

$$(xii) \qquad \varepsilon_t = H_t^{1/2} \xi_t,$$

Where R_t represents a matrix capturing the price discrepancies between Kraken and other exchanges (e.g, FTX). μ is the constant term, ϕ captures autocorrelation, $\varepsilon_t$is the error term, and H_t is the conditional covariance matrix. The term ε_t represents unexpected shocks to the price differences or the so-called ‘shock component’. $H_t^{1/2}$ indicates the matrix of conditional volatilities of the return series. ξ_t signifies a matrix of independently and identically distributed innovations.

To add on, conditional variance estimation captures the clustering and persistence of volatility typical in crypto markets, which is critical to arbitrage timing. Utilising a univariate GARCH (1,1) model to estimate the conditional variance $h_{i,t}$ for each return series:

$$(xiii) \qquad R_{it} = \omega_i + \alpha_i \epsilon_{it-1}^2 + \beta_i h_{it-1},$$

The final step is to calculate the Dynamic Conditional Correlation (DCC). Once individual volatilities are estimated, the conditional covariance matrix H_t is modelled as:

$$(xiv) \qquad H_t = D_t R_t D_t,$$

$$(xv) \qquad D_t = diag\left(\sqrt{h_t^{Kraken}}, \sqrt{h_t^{Exchange\ I}}, \dots, \sqrt{h_t^{Exchange\ X}}\right),$$

Based on a similar approach by Runarsson (2024), where equation (xii) is a diagonal matrix containing the conditional standard deviations of the individual time series, and

R_t is the dynamic correlation matrix. The correlation dynamics follow the DCC (1,1) process:

$$(xvi) \qquad R_t = diag(Q_t)^{-1/2}\, Q_t diag(Q_t)^{-1/2},$$

$$(xvii) \qquad Q_t = (1 - \alpha - \beta)\bar{Q} + \alpha\varepsilon_{t-1}\varepsilon'_{t-1} + \beta Q_{t-1},$$

Where Q_t is the formation of the time-varying covariance matrix, and $\bar{Q}$ is the unconditional covariance matrix. The parameters α and β determine the persistence of shocks to correlation and must satisfy the $\alpha + \beta < 1$ condition, a requirement that ensures the model exhibits mean-reversion. The mean-reverting nature of the model suggests that, following a shock in returns, the dynamic correlation gradually converges back to its long-run average. When the condition $\alpha + \beta = 0$ holds, the model reduces to a constant conditional correlation specification, indicating that the correlation between exchange returns remains unchanged over time regardless of external disturbances. More specifically, the parameter α captures the immediate effect of recent shocks on current conditional correlations, while β represents the persistence of past conditional correlations in influencing present values.

5 Empirical Results

This chapter explores the findings from the selected methodologies exploring arbitrage sources across cryptocurrency exchanges. It is organised into three main sections: the Baseline model, the GRA, and the DCC-GARCH model. First, the baseline model is used to analyse the trends, effects, and characteristics of the variables. Also, looking at the instrument variables stated in the 4.2 Methodology section. Next, the GRA results show BTCUSD price alignment across these exchanges through the baseline model. The same is then executed with the DCC-GARCH model.

Further results will be presented based on the outcomes of the diagnostic tests discussed in Section 4.1.1, Data Quality and Robustness Checks. These findings establish a foundation for analysing price differences across exchanges and how the selected research variables contribute to arbitrage opportunities, as illustrated in Figure 2. This analysis aligns with the study's objective of understanding the emergence of arbitrage in the cryptocurrency market while building on previous research outlined in Section 4.2, Methodology.

5.1 Baseline model

The focus now shifts to the baseline model, which serves as the foundation of this research by emphasising the role of instrumental variables and their effects within the analytical framework. The analysis opens with a review of summary statistics for each exchange, providing key descriptive measures that outline the dataset's characteristics. The previously mentioned stationarity tests are followed to verify the time series' stability, reinforcing the validity of the econometric approach. The explanatory variables are then evaluated to determine their relationships with the dependent variables and their statistical significance, complemented by assessing the time series' volatility. It also investigates the identification and justification of instrumental variables, which address potential endogeneity concerns in the estimation process. These components form the foundation for constructing the baseline model, essential for understanding the interactions between the studied variables. As highlighted earlier, this research builds upon the framework outlined in Kristoufek & Bouri (2023) and Crépellière et al. (2023), incorporating their key findings, approach and methodologies.

First-stage equations - instrumental variables

	log(fees)	log(transfers)	log(volume)
Constant	-47.4701***	0.9087	-2.0446***
	(1.4098)	(0.5920)	(0.6535)
log(price)	-0.8891***	0.6588***	0.6114***
	(0.0211)	(0.0089)	(0.0098)
exchange ratio	0.7344***	-0.7754***	3.4955***
	(0.1297)	(0.0545)	(0.0601)
log(addresses)	3.3815***	1.0940***	1.1444***
	(0.1096)	(0.0460)	(0.0508)
R^2	0.4059	0.7969	0.7666
$\bar{R}^2$	0.4053	0.7966	0.7664
$F-test$	650.59***	3735.50***	3128.50***

Notes: *The table presents OLS regression estimates for the instrumental variables. Estimates are reported in the first row, with standard errors in parentheses. The F-test assesses the joint significance of the instruments. Statistical significance is indicated as follows: *** denotes significance at the 1% level, ** at the 5% level, and * at the 10% level.*

Table 3. Baseline Instrumental Variables

The findings from Table 3 summarise the first-stage regressions for the instrumental variables, focusing on $\log(fees)$, $\log(transfers)$, and $\log(volume)$ as the dependent variables. To run a separate regression for each endogenous variable, using the mentioned IVs as predictors. The coefficients and significance levels indicate the strength and direction of the relationships between the independent and instrumental variables. This is vital for implementing the IV approach in utilising the two-stage least squares (2SLS) regression model if the OLS model is inefficient and to improve the model's predictability.

As for Table 3, these findings align with or are at least similar to the results found in (Kristoufek & Bouri, 2023). The constant term is significant in two models, as indicated by (***), suggesting that the base fees and volume levels are significant even when all other variables are zero. For instance, the constant in the $\log(fees)$ regression is

−47.4701, which reflects a strong negative baseline effect on fees when other variables are held constant.

The $\log(price)$ variable is highly significant across all models, demonstrating its consistent influence on fees, transfers, and volume. For $\log(fees)$, the coefficient is −0.8891, suggesting that as Bitcoin's price increases, fees tend to decrease slightly. Conversely, the positive coefficients for $\log(transfers)$ 0.6588 and $\log(volume)$ 0.6114 indicates that higher Bitcoin prices are associated with increased transfers and trading volumes, reflecting the market's responsive behaviour to price changes.

The exchange ratio exhibits varying effects across the models. It has a positive and highly significant relationship with $\log(fees)$ 0.7344 and $\log(volume)$ 3.4955, implying that higher trading activity relative to transfers contributes to increased fees and volume. However, for $\log(transfers)$, the coefficient −0.7754 is negative and also highly significant, suggesting an inverse relationship between the exchange ratio and transfers.

The $\log(addresses)$ the variable is similarly highly significant across all regressions, emphasising the role of network activity in determining fees, transfers, and volume. Its positive coefficients across all three models show that as the number of active addresses increases, so do fees, transfers, and volume. For instance, in the $\log(fees)$ model, the coefficient 3.3815 reflects a substantial positive relationship between active network participants and fees.

The models also show strong explanatory power, as evidenced by the R^2 and adjusted $\bar{R}^2$ values in the table. For $\log(transfers)$, the R^2 of 0.7969 indicates that nearly 80% of the variation in transfers is explained by the IVs. Similarly, high R^2 values for $\log(fees)$and $\log(volume)$ suggest that the IVs strongly predict a large portion of the variation.

The highly significant F-test values confirm the IVs strong explanatory power, indicating they effectively predict the endogenous variables. For instance, the F-test for log(fees) (650.59) shows the predictors contribute meaningfully. This underscores the role of Bitcoin's price, market efficiency, and network activity in shaping fees, transfers, and volume. Ultimately, the IVs strongly reject the null hypothesis of weak instruments.

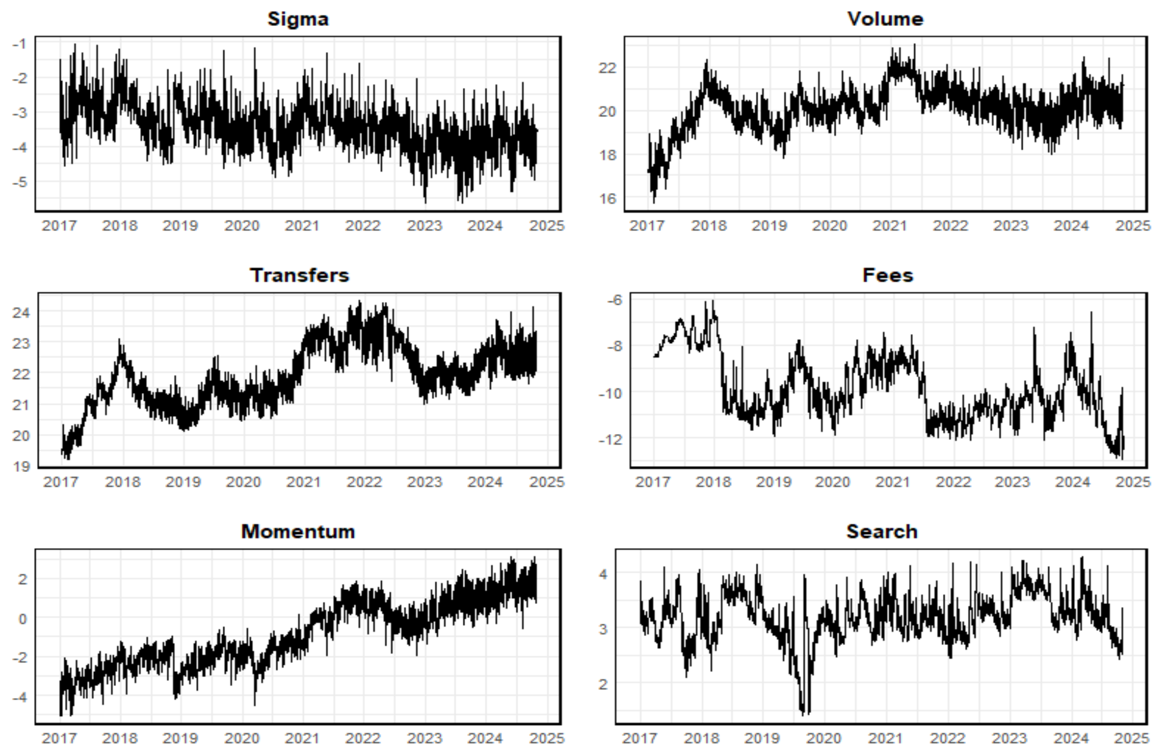

Figure 8. Explanatory Variables

When analysing the explanatory variables more in depth, it becomes more visible the overall trend and their role in the baseline model. Figure 8 shows the overall change in values of the explanatory variables throughout the research period. Sigma exhibits persistent fluctuations with a negative trend, indicating sustained market uncertainty. This can impact price correlation between exchanges and drive arbitrage opportunities. Volume remains relatively stable but shows periods of heightened activity, suggesting that liquidity dynamics may influence price efficiency across exchanges. Transfers demonstrate a long-term upward trend, highlighting increased blockchain activity, which could mean reduced arbitrage inefficiencies over time. In theory this means an active market participation. On the other hand, Fees vary a lot, with sudden spikes likely caused by network congestion, as in Kristoufek & Bouri (2023). Momentum shows a steady upward trend, suggesting that strong price moves may lead to market inefficiencies by affecting investor behaviour. Search interest rises and falls sharply, reflecting changes in public attention that can trigger bull or bear market trends. Together, these factors help explain how different forces shape the behaviour of cryptocurrency markets.

5.2 GRA correlations

Table 4 summarises the basic descriptive statistics of grey correlations between various cryptocurrency exchanges. The descriptive statistics include observations, mean, median, min, Q1, Q3, Max, Standard Deviation (SD), Skewness, and Kurtosis.

Descriptive Statistics of GRA

Exchange	Observations	Mean	Median	Min	Q1	Q3	Max	SD	Skewness	Kurtosis
Bitbay	1307	0.9160	0.9327	0.3333	0.9056	0.9508	1.0000	0.0714	-3.2898	18.2755
Bitfinex	2853	0.8577	0.8942	0.3333	0.8005	0.9441	1.0000	0.1181	-1.1909	4.0569
Bitstamp	2853	0.7655	0.8196	0.1179	0.6392	0.9293	1.0000	0.1966	-0.8475	2.7964
Bittrex	1270	0.8934	0.9199	0.2632	0.8534	0.9603	1.0000	0.0944	-2.0850	9.9752
CEX	2807	0.8840	0.9191	0.3333	0.8465	0.9606	1.0000	0.1139	-1.8202	6.6406
Coinbase	2846	0.9719	0.9871	0.2374	0.9739	0.9940	1.0000	0.0611	-6.4230	53.6405
Exmo	2158	0.8611	0.9351	0.3333	0.8201	0.9747	1.0000	0.1640	-1.4536	3.9235
FTX	1211	0.8815	0.9223	0.3334	0.8293	0.9599	1.0000	0.1090	-1.4871	5.1489
Gemini	2852	0.7904	0.8404	0.1265	0.6864	0.9372	1.0000	0.1802	-1.0146	3.3178
HitBTC	382	0.7987	0.8420	0.3334	0.6813	0.9351	1.0000	0.1613	-0.7476	2.5497
Kucoin	337	0.7976	0.8210	0.3345	0.7263	0.8963	1.0000	0.1362	-0.9050	3.6922
Okcoin	1164	0.9616	0.9683	0.7854	0.9503	0.9821	1.0000	0.0300	-1.7899	7.5183
Poloniex	1137	0.9169	0.9505	0.3334	0.9039	0.9761	1.0000	0.0971	-2.3288	8.9619
Yobit	1176	0.8151	0.8194	0.3334	0.7505	0.9086	1.0000	0.1193	-0.8812	4.3682

	Bitbay	Bitfinex	Bitstamp	Bittrex	CEX	Coinbase	Exmo
Jarque-Bera	15064.83***	807.22***	346.42***	3494.71***	3100.16***	323670.95***	836.68***
Ex. Kurtosis	15.28	1.06	-0.20	6.98	3.64	50.64	0.92

	FTX	Gemini	HitBTC	Kucoin	Okcoin	Poloniex	Yobit
Jarque-Bera	679.39***	501.31***	38.81***	52.73***	1611.62***	2711.67***	243.92***
Ex. Kurtosis	2.15	0.32	-0.45	0.69	4.52	5.96	1.37

Note: *This table presents the descriptive statistics of all cryptocurrency exchanges using the Grey Correlation Analysis model, with Kraken as the baseline exchange. The analysis is conducted over the research period from January 1, 2017, to October 31, 2024. Measures of skewness (Skew.), excess kurtosis (Ex. Kurt.), and the Jarque-Bera test are included to assess the normality of the distributions. Statistical significance is indicated as follows: *** denotes significance at the 1% level, ** at the 5% level, and * at the 10% level.*

Table 4. Descriptive Statistics - GRA

Mean grey correlations range from 0.9719 for Coinbase to 0.7655 for Bitstamp, showing strong alignment with Kraken across most exchanges. Median values follow a similar pattern, with Coinbase at the highest, 0.9871, and Bitstamp at the lowest, 0.8196.

Gemini and Bitstamp show the highest GRA variability with Kraken (SD: 0.1802, 0.1966), while Coinbase is the most stable (SD: 0.0611). This means that Coinbase and Kraken prices follow little variation from each other, limiting arbitrage opportunities. Correlations drop to as low as 0.1179 (Bitstamp) and 0.1265 (Gemini), but all exchanges reach a maximum of 1.0000, indicating some periods of perfect synchronisation. Most interestingly, the maximum of 1.0000 was often achieved mainly on 12.01.2017. This may be due to higher market efficiency from increased liquidity, regulatory news, or coordinated trading across major platforms. Nevertheless, no immediate surge of global trading volumes has been immediately apparent during this period, based on Figure 1 shown in the research by Wüstenfeld & Geldner (2022).

When it comes to skewness and kurtosis in Table 4, Coinbase (-6.4230), Poloniex (-2.3288), and Bitbay (-3.2898) exhibit strong negative skewness, indicating a longer left tail, which suggests instances of sudden and sharp deviations from Kraken. Kucoin (-0.9050) and Bitfinex (-1.1909) show milder negative skewness, implying relatively balanced distributions. Coinbase (53.6405) and Poloniex (8.9619) demonstrate extremely high kurtosis, indicative of highly peaked distributions with frequent extreme values. This leptokurtic behaviour suggests occasional large deviations in correlation, while Bitstamp (2.7964) and HitBTC (2.5497) show near-normal kurtosis, indicating more stable correlations.

The Jarque-Bera tests strongly reject normality across all exchanges, suggesting that correlation behaviours follow non-Gaussian distributions, which aligns with the assumption of the selected models. Coinbase (323670.95***) and Bitbay (15064.38***) exhibit the most extreme departures from normality, likely driven by heavy tails and high kurtosis.

Excess kurtosis values, with Coinbase at 50.64 and Bitbay at 15.28, confirm large deviations from normality, indicating fat tails and potential extreme correlation shifts.

OLS Regression Model: Grey Correlation Analysis

	Bitbay	Bitfinex	Bitstamp	Bittrex	Cex.io	Coinbase	Exmo
Constant	0.5707***	0.6097***	1.0208***	0.6311***	0.4617***	0.4043***	0.5724***
	(0.0984)	(0.0692)	(0.1119)	(0.1517)	(0.0735)	(0.0405)	(0.0792)
log(sigma)	-0.0148***	-0.0624***	-0.1076***	-0.0354***	-0.0602***	-0.0159***	-0.0161***
	(0.0040)	(0.0038)	(0.0060)	(0.0069)	(0.0040)	(0.0021)	(0.0032)
log(volume)	-0.0143***	-0.0132***	-0.0390***	-0.0199**	-0.0127***	-0.0004	0.0144***
	(0.0038)	(0.0028)	(0.0045)	(0.0065)	(0.0030)	(0.0016)	(0.0025)
log(transfers)	0.0043	0.0079*	0.0018	0.0124*	0.0040	-0.0024	-0.0299***
	(0.0064)	(0.0036)	(0.0058)	(0.0054)	(0.0038)	(0.0021)	(0.0041)
log(fees)	-0.0149***	0.0033*	-0.0040.	-0.0027	-0.0095***	-0.0064***	0.0094***
	(0.0018)	(0.0013)	(0.0022)	(0.0027)	(0.0014)	(0.0008)	(0.0013)
log(momentum)	-0.0190***	-0.0540***	-0.0896***	-0.0368***	-0.0363***	-0.0052***	-0.0004
	(0.0038)	(0.0022)	(0.0035)	(0.0035)	(0.0023)	(0.0011)	(0.0025)
log(search)	-0.0094**	0.0025	-0.0083	-0.0156*	-0.0021	-0.0007	0.0025
	(0.0035)	(0.0037)	(0.0060)	(0.0071)	(0.0039)	(0.0021)	(0.0034)
Pt-1	0.3636***	0.1154***	0.0352*	0.3189***	0.2958***	0.5228***	0.7924***
	(0.0231)	(0.0177)	(0.0179)	(0.0252)	(0.0170)	(0.0147)	(0.0124)
R^2	0.3984	0.5227	0.5547	0.3038	0.4446	0.4386	0.8582
$\bar{R}^2$	0.3952	0.5215	0.5536	0.2999	0.4432	0.4372	0.8578
F-test	122.89***	445.13***	506.26***	78.65***	320.11***	316.68***	1859.54***
No. Of Observations	*1307*	*2853*	*2853*	*1270*	*2807*	*2846*	*2158*

	FTX	Gemini	HitBTC	Kucoin	Okcoin	Poloniex	Yobit
Constant	1.4402***	1.2111***	0.8143*	1.9740***	0.8347***	0.2465.	0.3217**
	(0.1663)	(0.1119)	(0.3909)	(0.5781)	(0.0652)	(0.1343)	(0.1206)
log(sigma)	-0.0595***	-0.0795***	-0.1466***	-0.0864***	-0.0105***	-0.0270***	-0.0311***
	(0.0070)	(0.0059)	(0.0182)	(0.0221)	(0.0025)	(0.0059)	(0.0050)
log(volume)	-0.0507***	-0.0396***	-0.0233	-0.0790**	0.0017	-0.0078	-0.0069*
	(0.0069)	(0.0045)	(0.0159)	(0.0260)	(0.0023)	(0.0055)	(0.0042)
log(transfers)	0.0146*	-0.0034	-0.0026	0.0239	-0.0138***	0.0039	-0.0052
	(0.0059)	(0.0057)	(0.0251)	(0.0167)	(0.0040)	(0.0047)	(0.0069)
log(fees)	0.0051.	-0.0056**	0.0393***	0.0188	-0.0034**	-0.0143***	0.0062***
	(0.0029)	(0.0021)	(0.0062)	(0.0172)	(0.0011)	(0.0024)	(0.0019)
log(momentum)	-0.0490***	-0.0694***	-0.0636***	-0.0978***	-0.0070**	-0.0290***	-0.0204***
	(0.0042)	(0.0033)	(0.0140)	(0.0212)	(0.0023)	(0.0037)	(0.0043)
log(search)	-0.0032	0.0054	0.0266.	-0.0814*	-0.0059**	-0.0050	0.0075*
	(0.0064)	(0.0059)	(0.0137)	(0.0383)	(0.0023)	(0.0064)	(0.0037)
Pt-1	-0.0235	0.0518**	0.2203***	0.0523	0.3329***	0.5680***	0.7775***
	(0.0263)	(0.0184)	(0.0426)	(0.0507)	(0.0205)	(0.0228)	(0.0160)
R^2	0.4374	0.4831	0.5879	0.2629	0.2980	0.5574	0.7642
$\bar{R}^2$	0.4341	0.4818	0.5802	0.2472	0.2938	0.5546	0.7628
F-test	133.60***	379.67***	76.21***	16.76***	70.24***	203.11***	540.81***
No. Of Observations	*1211*	*2852*	*382*	*337*	*1166*	*1137*	*1176*

Note: *This table presents the estimated coefficients for the OLS Regression Model, incorporating the Grey Correlation Analysis with Kraken as the baseline exchange. The F-test evaluates the joint significance of the explanatory variables in the Ordinary Least Squares (OLS) regression. Standard errors are reported in parentheses. Significance levels: *** 0.1%, ** 1%, * 5%, . 10%.*

Table 5. OLS Results - GRA

At first glance of table 5, the coefficient for sigma is consistently negative and statistically significant across all exchanges, suggesting that higher volatility tends to weaken the correlation with Kraken. This pattern is most pronounced for HitBTC (-0.1466***), Bitstamp (-0.1076***), and Bitfinex (-0.0624***), implying that the increased market turbulence may lead to price divergences between these exchanges and Kraken. The impact is weaker for Coinbase (-0.0159***), possibly due to both exchanges being in the US market. These findings support H1. As shown in Table 5, higher volatility significantly decreases price correlation across exchanges, confirming volatility as a persistent driver of arbitrage. Increased trading volume negatively impacts correlation for most exchanges, including Bitbay (-0.0143***), Bitfinex (-0.0132***), and Bittrex (-0.0199**), while Exmo and Okcoin show positive coefficients, suggesting better alignment with Kraken. Mostly rejecting H2. Similarly, transfer activity has mixed effects across exchanges. Momentum consistently reduces correlation and shows strong acceptance of H5. Search interest is mainly insignificant, confirming H6. Lagged correlation remains highly persistent, indicating arbitrage frictions during strong price trends and stable price linkages over time.

Diagnostic Test Result

	Bitbay	Bitfinex	Bitstamp	Bittrex	Cex.io	Coinbase	Exmo
Breush-Pagan	167.91***	601.88***	589.74***	222.50***	666.07***	442.84***	185.80***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Durbin-Watson	2.0624	2.0446	1.9787	2.0109	2.0983	2.1018	2.4314
	(0.8392)	(0.8639)	(0.2539)	(0.5225)	(0.9939)	(0.9955)	(1.0000)
Wu-Hausman	64.4213 ***	-1.4983	-5.4909	0.3806	61.3840***	46.1788***	79.9584***
	(0.0000)	(1.0000)	(1.0000)	(1.0000)	(0.0000)	(0.0000)	(0.0000)
	FTX	Gemini	HitBTC	Kucoin	Okcoin	Poloniex	Yobit
Breush-Pagan	274.86***	523.55***	91.73***	58.01***	111.15***	217.97***	100.39***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Durbin-Watson	1.9514	1.9848	2.0346	2.0290	1.5464***	2.1096	2.1685
	(0.1645)	(0.3090)	(0.05368)	(0.5245)	(0.0000)	(0.9551)	(0.9969)
Wu-Hausman	1.2780	-90.8174	290.6666***	1.4270	97.0971***	39.2712***	9.1610
	(0.9958)	(1.0000)	(0.0000)	(0.9939)	(0.0000)	(0.0000)	(0.3289)

Note: *This table presents diagnostic test results for the baseline OLS estimates with the Kraken-Exchange X pairs. The Breusch-Pagan test checks for heteroscedasticity, the Durbin-Watson test detects autocorrelation, and the Wu-Hausman test assesses endogeneity. A significant Wu-Hausman test indicates that 2SLS should replace OLS due to bias or inefficiencies. P-values are in parentheses. Significance levels: *** 0.1%, ** 1%, * 5%, . 10%.*

Table 6. Robustness Check: Baseline GRA OLS

The Table 6 Durbin-Watson test for the GRA showed mostly no autocorrelation, as values close to 2.0 indicate that. However, significant heteroscedasticity was present across all exchanges through the Breusch-Pagan test, especially Cex.io. Okcoin was the only exchange exhibiting both autocorrelation and heteroscedasticity. Wu-Hausman tests indicated potential bias in Bitbay, Cex.io, Coinbase, Exmo, and HitBTC, though some insignificant negative values suggest weak evidence of endogeneity. To correct these issues, the model will be adjusted as mentioned in section 4.1.1, robustness checks.

OLS Regression Model: Robust Standard Errors

	Bitfinex	Bitstamp	Bittrex	FTX	Gemini	Kucoin	Yobit
Constant	0.6097***	1.0208***	0.6311***	1.4402***	1.2111***	1.9740***	0.3217.
	(0.0708)	(0.1145)	(0.1857)	(0.1730)	(0.1130)	(0.5753)	(0.1733)
log(sigma)	-0.0624***	-0.1076***	-0.0354***	-0.0595***	-0.0795***	-0.0864***	-0.0311***
	(0.0038)	(0.0056)	(0.0069)	(0.0073)	(0.0057)	(0.0245)	(0.0053)
log(volume)	-0.0132***	-0.0390***	-0.0199**	-0.0507***	-0.0396***	-0.0790**	-0.0069
	(0.0028)	(0.0045)	(0.0062)	(0.0071)	(0.0044)	(0.0277)	(0.0043)
log(transfers)	0.0079*	0.0018	0.0124**	0.0146*	-0.0034	0.0239	-0.0052
	(0.0040)	(0.0065)	(0.0046)	(0.0059)	(0.0062)	(0.0180)	(0.0075)
log(fees)	0.0033*	-0.0040.	-0.0027	0.0051.	-0.0056*	0.0188	0.0062*
	(0.0015)	(0.0022)	(0.0030)	(0.0030)	(0.0022)	(0.0165)	(0.0026)
log(momentum)	-0.0540***	-0.0896***	-0.0368***	-0.0490***	-0.0694***	-0.0978***	-0.0204***
	(0.0024)	(0.0038)	(0.0036)	(0.0045)	(0.0036)	(0.0225)	(0.0054)
log(search)	0.0025	-0.0083	-0.0156*	-0.0032	0.0054	-0.0814.	0.0075
	(0.0035)	(0.0056)	(0.0076)	(0.0051)	(0.0057)	(0.0414)	(0.0048)
Pt-1	0.1154***	0.0352	0.3189***	-0.0235	0.0518*	0.0523	0.7775***
	(0.0247)	(0.0221)	(0.0598)	(0.0331)	(0.0235)	(0.0554)	(0.0487)
R^2	0.5227	0.5547	0.3038	0.4374	0.4831	0.2629	0.7642
$\bar{R}^2$	0.5215	0.5536	0.2999	0.4341	0.4818	0.2472	0.7628
F-test	445.13***	506.26***	78.65***	133.60***	379.67***	16.76***	540.81***
No. Of Observations	*2853*	*2853*	*1270*	*1211*	*2852*	*337*	*1176*

*Note: This table presents the estimated improved coefficients for the Grey Correlation model applied to the Kraken–Exchange X pair, incorporating robust standard errors based on prior diagnostic test results. The model accounts for endogeneity and heteroskedasticity. HC robust standard used for all exchanges. Standard errors are reported in parentheses. Significance levels: *** 0.1%, ** 1%, * 5%, . 10%.*

Table 7. Baseline Model with Robust Standard Errors (GRA)

The OLS regression with robust standard errors gives more accurate coefficient estimates by fixing earlier problems. Heteroskedasticity has been corrected using heteroskedasticity-consistent (HC) standard errors, ensuring more reliable inference and reducing bias in parameter estimates. To account for endogeneity, an IV/2SLS regression will be conducted, and are currently not included in Table 7.

The same negative effect of sigma is found in Table 7 as in Table 6, with the strongest impact in exchanges like Kucoin (-0.0864***) and Bitstamp (-0.1076***), both highly significant and further supporting H1. The same can be said for trading volume, but continued partial acceptance of H2. While transfer activity (log(transfers)) shows mixed effects, with Bittrex (0.0124**) and FTX (0.0146*) experiencing stronger positive correlations. Hypothesis 3, which assumes that transfer activity increases correlation, remains inconclusive. Like in on-chain transfers, the impact on fees remains small, with negative and positive values, and mostly inconclusive for H4. Momentum consistently weakens correlation, with the most significant effects for Kucoin (-0.0978***) and Bitstamp (-0.0896***), further supporting H5. H7 is accepted, with strong lagged correlations and significant F-statistics confirming good explanatory power. About 50% of the variation is explained on average, while search remains mostly insignificant.

Estimated IV/2SLS Model: Grey Correlation Analysis

	Bitbay	Cex.io	Coinbase	Exmo	HitBTC	Okcoin	Poloniex
Constant	0.8220***	0.7266***	0.3196**	0.0618	2.4067***	0.8272***	0.9744**
	(0.1525)	(0.1259)	(0.1103)	(0.1173)	(0.6345)	(0.2322)	(0.3713)
log(sigma)	-0.0249***	-0.0642***	-0.0206***	-0.0178***	-0.1023***	-0.0119***	-0.0192**
	(0.0051)	(0.0040)	(0.0031)	(0.0033)	(0.0175)	(0.0024)	(0.0064)
log(volume) IV	-0.0041	-0.0100***	-0.0033.	0.0029	-0.0294*	-0.0004	-0.0170*
	(0.0025)	(0.0023)	(0.0019)	(0.0020)	(0.0123)	(0.0012)	(0.0066)
log(transfers) IV	-0.0195***	-0.0080.	0.0010	-0.0024	-0.0442.	-0.0102*	-0.0040
	(0.0054)	(0.0047)	(0.0032)	(0.0047)	(0.0247)	(0.0044)	(0.0105)
log(fees) IV	-0.0136***	-0.0012	-0.0089***	0.0008	0.0740***	0.0024	0.0189**
	(0.0036)	(0.0033)	(0.0019)	(0.0023)	(0.0134)	(0.0020)	(0.0073)
log(momentum)	-0.0122*	-0.0269***	-0.0075***	-0.0143***	-0.0084	-0.0026	-0.0119*
	(0.0054)	(0.0032)	(0.0020)	(0.0034)	(0.0222)	(0.0027)	(0.0052)
log(search)	-0.0066.	-0.0012	0.0008	-0.0025	0.0137	-0.0034	-0.0160*
	(0.0038)	(0.0035)	(0.0020)	(0.0028)	(0.0133)	(0.0027)	(0.0078)
Pt-1	0.4056***	0.3170***	0.5430***	0.8471	0.3093***	0.3583*	0.6114***
	(0.0729)	(0.0323)	(0.0779)	(0.0275)	(0.0595)	(0.1582)	(0.0541)
R^2	0.3789	0.4380	0.4322	0.8535	0.5468	0.2661	0.5441
$\bar{R}^2$	0.3755	0.4366	0.4308	0.8539	0.5383	0.2616	0.5413
Wald test	113.20***	311.70***	308.70***	1789.00***	64.46***	59.97***	192.50***
No. Of Observations	*1307*	*2807*	*2846*	*2158*	*382*	*1166*	*1137*

*Note: This table presents the estimated coefficients for the 2SLS Grey Correlation Analysis applied to the Kraken–Exchange X pair, correcting for potential bias in OLS estimates. The Wald test evaluates the joint significance of the explanatory variables in the instrumental variables (IV) regression. Based on the diagnostic test results, HC0 robust standard errors have been applied, while HAC robust errors were used exclusively for Okcoin. Standard errors are reported in parentheses. Significance levels: *** 0.1%, ** 1%, * 5%, . 10%.*

Table 8. IV/2SLS Results - GRA

To address endogeneity, the exchanges in Table 8 were analysed using the IV/2SLS model, which uses instrumental variables to produce more consistent and unbiased estimates than the OLS approach. The results remain mainly similar, with only minor value changes. The most notable shift is the reduced significance of variables like trading volume concerning GRA correlations, suggesting that volume alone may not consistently drive correlation fluctuations. This shows that the argument for H2 isn't particularly strong once the model for these exchanges is corrected. Increased trading volume exchanges still showed a significant decrease in correlation between Cex.io, HitBTC, and Poloniex with the baseline exchange, Kraken, further supporting the rejection of H2.

HitBTC sigma coefficient shows a reduced negative coefficient, from -0.1466*** to -0.1023***, but remains highly significant. Bitbay trading volume went from highly significant to insignificant. Bitbay (-0.0041) and Okcoin (-0.0004) now display near-zero effects. Transfers remain mostly insignificant for most exchanges, where the most notable change has been Bitbay's coefficient shift to high significance, vice versa for Exmo and Okcoin, partially supporting H3. Regarding fees, HitBTC significantly increased from 0.0393*** to 0.0740***, suggesting that its fee structure may encourage arbitrage rather than discourage it. Momentum remains significant for most exchanges, noticeably Cex.io (-0.0269***) and Exmo (-0.0143***) show larger negative effects. Even after correcting for endogeneity, lagged correlation is still a strong predictor of future correlation. The exception is Exmo, where this pattern does not hold. These results mostly support H5. There was no noticeable increase in R2 but a widespread increase in Wald test values, further confirming the joint significance of the explanatory variables in the instrumental variable regression.

To conclude the section on Grey Correlation Analysis, Figure 9 visualises the Grey Correlation values, illustrating the level of variation across exchanges as a static measure of similarity. Each plot covers the same period, ensuring a comprehensive overview of the data while highlighting potential gaps or missing periods.

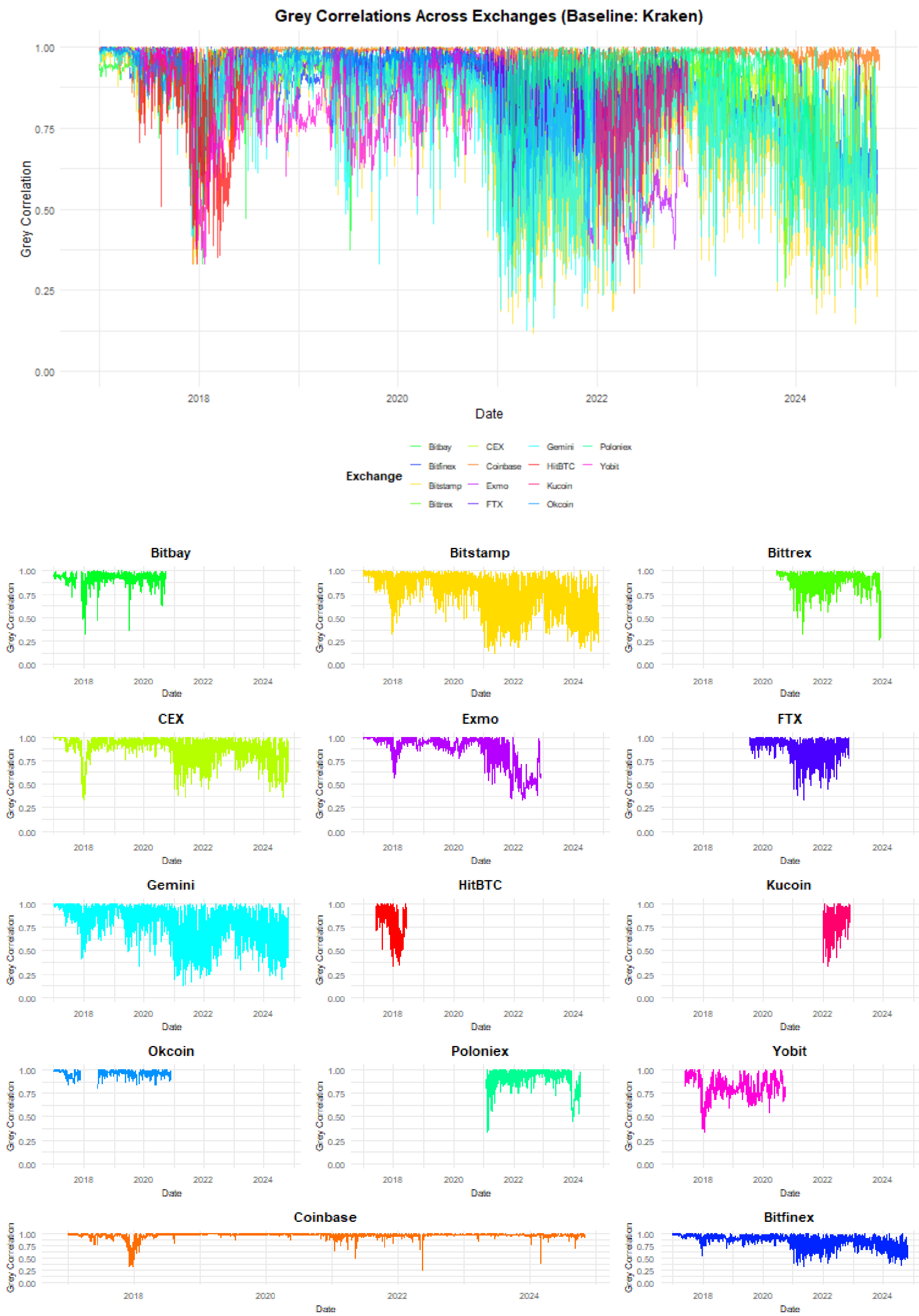

Figure 9. GRA Correlations

Among all analysed pairs in Figure 9, Kraken and Coinbase exhibit the most stable price co-movements, consistently maintaining high Grey Correlation values. This stability can be attributed to several key factors, including their high trading volumes, deep liquidity pools, and strong institutional presence. Both exchanges attract many professional traders and institutional investors, ensuring that large buy and sell orders have minimal impact on price fluctuations. Additionally, strict regulatory compliance on both platforms enhances market integrity by reducing the likelihood of manipulative trading practices and sudden price deviations. Similar patterns can also be found in Okcoin, Bitbay, and Poloniex exchanges. The relatively low volatility in their GRA values suggests that price discovery mechanisms function efficiently on these platforms, enabling seamless price adjustments that minimise the potential for statistical arbitrage opportunities.

Bitstamp and Gemini show greater volatility in their correlation with Kraken, suggesting potential inefficiencies for arbitrage traders to exploit. These fluctuations may result from differences in liquidity, market depth, and execution speed. Although the platforms generally maintain high correlations, occasional price gaps appear during periods of high volatility or low liquidity. Trading fees and withdrawal limits may further influence arbitrage opportunities, leading to brief price discrepancies across exchanges.

To sum up, the results support accepting H1, H5, H6, and H7, while partially accepting H3. H4 remains inconclusive due to mixed significant results in both directions, and H2 is rejected. The GRA results reject the null hypothesis, showing that certain factors help explain the presence of arbitrage opportunities across exchanges. Price synchronisation varies: Coinbase closely tracks Kraken, while Kucoin and Poloniex offer more arbitrage potential. IV/2SLS corrections identify volatility and momentum as key frictions affecting price alignment. Lagged correlations are good predictors of price movements, and strong Wald test results confirm the validity of IV methods. These findings reveal coordinated price behaviour and persistent inefficiencies within fragmented crypto markets through the GRA method.

5.3 DCC-GARCH correlations

The descriptive statistics regarding the DCC-GARCH correlations are presented in Table 9 below. Compared to Table 4, GRA had higher mean and median values across most exchanges than the DCC-GARCH correlations. Similarly, both models align with Kristoufek & Bouri (2023), where the GRA model exhibits greater variability than DCC-GARCH, despite differences in baseline exchange and research period.

Descriptive Statistics of DCC-GARCH

Exchange	Observations	Mean	Median	Min	Q1	Q3	Max	SD	Skewness	Kurtosis
Bitbay	1300	0.7255	0.7215	-0.3095	0.7124	0.7457	0.9598	0.0740	-4.9807	56.7887
Bitfinex	2852	0.9106	0.9117	0.7814	0.9071	0.9162	0.9746	0.0129	-2.5639	20.8355
Bitstamp	2852	0.9138	0.9139	0.7797	0.9117	0.9167	0.9776	0.0097	-2.8848	35.0362
Bittrex	1269	0.8693	0.8799	0.5712	0.8513	0.8960	0.9363	0.0443	-2.8393	17.1491
CEX	2776	0.9068	0.9079	0.7790	0.9030	0.9130	0.9726	0.0135	-2.2032	17.4163
Coinbase	2840	0.9978	0.9998	0.9123	0.9994	0.9998	1.0000	0.0072	-6.2705	52.4882
Exmo	2156	0.8965	0.8987	0.6455	0.8911	0.9058	0.9673	0.0199	-3.2543	27.8030
FTX	1210	0.9124	0.9135	0.7738	0.9097	0.9171	0.9546	0.0123	-3.4480	30.6701
Gemini	2851	0.8578	0.8630	0.6559	0.8465	0.8767	0.9565	0.0308	-1.7360	9.1694
HitBTC	381	0.9137	0.9144	0.7568	0.9119	0.9183	0.9533	0.0153	-5.2431	48.0038
Kucoin	381	0.9137	0.9144	0.7568	0.9119	0.9183	0.9533	0.0153	-5.2431	48.0038
Okcoin	901	0.6608	0.6608	0.6608	0.6608	0.6608	0.6608	0.0000	-5.7318	40.7837
Poloniex	1136	0.7953	0.8061	0.5680	0.7732	0.8304	0.8767	0.0511	-1.4696	5.8804
Yobit	1172	0.8893	0.8896	0.8482	0.8859	0.8932	0.9426	0.0083	-0.3679	9.6789

	Bitbay	Bitfinex	Bitstamp	Bittrex	CEX	Coinbase	Exmo
Jarque-Bera	15064.83***	807.22***	346.42***	3494.71***	3100.16***	323670.95***	836.68***
Ex. Kurtosis	53.79	17.84	32.04	14.15	14.42	49.49	24.80

	FTX	Gemini	HitBTC	Kucoin	Okcoin	Poloniex	Yobit
Jacque-Bera	679.39***	501.31***	38.81***	52.73***	1611.62***	2711.67***	243.92***
Ex. Kurtosis	27.67	6.17	45.00	45.00	37.78	2.88	6.68

Note: *This table presents the descriptive statistics of all cryptocurrency exchanges using the DCC-GARCH model, with Kraken as the baseline exchange. The analysis is conducted over the research period from January 1, 2017, to October 31, 2024. Measures of skewness (Skew.), excess kurtosis (Ex. Kurt.), and the Jarque-Bera test are included to assess the normality of the distributions. Statistical significance is indicated as follows: *** denotes significance at the 1% level, ** at the 5% level, and * at the 10% level.*

Table 9. Descriptive Statistics - DCC-GARCH

The mean correlation values indicate that Coinbase (0.9978) and Bitstamp (0.9139) exhibit the strongest price correlation with Kraken, suggesting a high degree of market integration. In contrast, Okcoin (0.6608) and Bitbay (0.7255) show the weakest mean correlations. Surprisingly, Okcoin shows almost no variation in the DCC-GARCH model, as seen in the SD in Table 9 and results in Table 10. This might be due to Okcoin's price movement, which has closely tracked Kraken. It may also be due to low-quality data. Both factors could limit the ability to capture time-varying correlations through the return series. Coinbase (0.0072) and Yobit (0.0083) exhibit the lowest SD values, indicating highly stable return correlations with Kraken and minimal fluctuations, disregarding Okcoin.

Skewness values indicate asymmetry in correlation distributions, with Bitbay (-4.9807) and Coinbase (-6.2075) showing extreme negative skewness, suggesting short extreme divergences from Kraken. Gemini, Poloniex, and Yobit exhibit more moderate skewness, implying fewer extreme deviations. The kurtosis of Bitbay, Bittrex, Coinbase, and Poloniex shows highly leptokurtic distributions, meaning their returns have heavy tails and a greater chance of extreme price movements, as explained in the GRA section.

The Jarque-Bera test strongly rejects normality across all exchanges, with Coinbase showing the most extreme value (323670.95***), followed by Bitbay and Poloniex. These high JB values highlight significant deviations from normality, underscoring the need for non-linear models like DCC-GARCH to capture dynamic correlations and volatility shifts.

The OLS DCC-GARCH results are shown in Table 10 below. Like the GRA result, the null hypothesis is rejected. The return series from the DCC-GARCH model exhibits minimal effects in explaining price correlations between exchanges compared to the GRA result. This suggests that the DCC-GARCH model, while capturing time-varying volatility, contributes little to the direct modelling of arbitrage opportunities in this context. Lower R^2 values also indicate reduced explainability compared to the Grey Correlation model for most exchanges.

Sigma fluctuates between negative and positive values, unlike the only negative sigma values in Table 5, meaning H1 is inconclusive. The most significant negative values regarding sigma are Kucoin (-0.0193***) and Coinbase (-0.0040***), indicating greater return correlation divergence when volatility increases. The opposite is true for Poloniex (0.0072***).

OLS Regression Model: DCC-GARCH Analysis

	Bitbay	Bitfinex	Bitstamp	Bittrex	Cex.io	Coinbase	Exmo
Constant	0.2313.	0.6545***	0.8181***	0.2066***	0.6279***	0.8537***	0.5423***
	(0.1275)	(0.0131)	(0.0113)	(0.0411)	(0.0135)	(0.0070)	(0.0214)
log(sigma)	-0.0086.	-0.0005	0.0002	-0.0012	-0.0008	-0.0040***	0.0002
	(0.0051)	(0.0005)	(0.0004)	(0.0020)	(0.0005)	(0.0003)	(0.0008)
log(volume)	0.0052	0.0005	0.0001	0.0004	-0.0007.	0.0037***	0.0020***
	(0.0048)	(0.0004)	(0.0003)	(0.0018)	(0.0004)	(0.0002)	(0.0006)
log(transfers)	0.0069	0.0008	0.0003	0.0008	0.0018**	-0.0020***	-0.0019*
	(0.0082)	(0.0005)	(0.0004)	(0.0016)	(0.0005)	(0.0003)	(0.0009)
log(fees)	-0.0034	0.0003.	0.0002	-0.0045***	0.0002	-0.0015***	0.0004
	(0.0021)	(0.0002)	(0.0002)	(0.0008)	(0.0002)	(0.0001)	(0.0003)
log(momentum)	-0.0220***	-0.0008**	-0.0004.	-0.0079***	-0.0014***	-0.0003*	-0.0004
	(0.0047)	(0.0003)	(0.0002)	(0.0010)	(0.0003)	(0.0001)	(0.0007)
log(search)	-0.0027	0.0001	0.0000	-0.0086***	0.0008	0.0001	0.0013
	(0.0045)	(0.0005)	(0.0004)	(0.0020)	(0.0005)	(0.0003)	(0.0009)
Pt-1	0.1997***	0.2509***	0.0972***	0.7068***	0.2763***	0.0841***	0.3964***
	(0.0260)	(0.0102)	(0.0090)	(0.0137)	(0.0104)	(0.0056)	(0.0128)
R^2	0.0730	0.1887	0.0472	0.7434	0.2180	0.3631	0.3265
$\bar{R}^2$	0.0680	0.1867	0.0449	0.7420	0.2160	0.3615	0.3243
F-test	14.53***	94.47***	20.14***	522.00***	110.20***	230.60***	148.80***
No. Of Observations	*1300*	*2852*	*2852*	*1269*	*2776*	*2840*	*2156*

	FTX	Gemini	HitBTC	Kucoin	Okcoin	Poloniex	Yobit
Constant	0.8256***	0.2478***	0.8773***	1.0333***	0.6608***	0.2294***	0.8024***
	(0.0249)	(0.0162)	(0.0569)	(0.0793)	(0.0000)	(0.0441)	(0.0170)
log(sigma)	0.0009	0.0003	-0.0043.	-0.0193***	0.0000	0.0072***	-0.0019**
	(0.0010)	(0.0008)	(0.0024)	(0.0031)	(0.0000)	(0.0020)	(0.0006)
log(volume)	-0.0003	-0.0028***	0.0071**	0.0055	0.0000**	-0.0071***	0.0028***
	(0.0010)	(0.0006)	(0.0023)	(0.0035)	(0.0000)	(0.0019)	(0.0006)
log(transfers)	-0.0003	0.0018*	-0.0056	-0.0176***	0.0000.	0.0053***	-0.0019*
	(0.0008)	(0.0007)	(0.0036)	(0.0023)	(0.0000)	(0.0016)	(0.0009)
log(fees)	0.0004	0.0007*	0.0011	0.0006	0.0000	-0.0067***	0.0008**
	(0.0004)	(0.0003)	(0.0009)	(0.0024)	(0.0000)	(0.0008)	(0.0002)
log(momentum)	0.0004	0.0001	0.0000	-0.0213***	0.0000.	-0.0013	-0.0032***
	(0.0006)	(0.0004)	(0.0019)	(0.0028)	(0.0000)	(0.0012)	(0.0006)
log(search)	0.0018*	0.0001	-0.0002	-0.0089.	0.0000	-0.0055**	0.0005
	(0.0009)	(0.0008)	(0.0020)	(0.0052)	(0.0000)	(0.0021)	(0.0005)
Pt-1	0.1102***	0.7374***	0.0129	0.0898***	0.0000	0.7123***	0.0711***
	(0.0118)	(0.0091)	(0.0161)	(0.0186)	(0.0000)	(0.0148)	(0.0083)
R^2	0.0758	0.7062	0.0488	0.6459	0.0189	0.8211	0.1479
$\bar{R}^2$	0.0704	0.7055	0.0309	0.6383	0.0113	0.8200	0.1428
F-test	14.08***	976.30***	2.73**	85.47***	2.46*	739.40***	28.86***
No. Of Observations	*1210*	*2851*	*381*	*336*	*901*	*1136*	*1172*

Note: *This table presents the estimated coefficients for the OLS Regression Model, incorporating the DCC-GARCH model with Kraken as the baseline exchange. The F-test evaluates the joint significance of the explanatory variables in the Ordinary Least Squares (OLS) regression. Standard errors are reported in parentheses. Significance levels: *** 0.1%, ** 1%, * 5%, . 10%.*

Table 10. OLS Results - DCC-GARCH

Even trading volume and transfers exhibit mixed effects across exchanges, so H2 and H3 are also inconclusive. Trading volume shows mixed effects. It has a positive and significant impact on HitBTC (0.0071**), but an adverse effect on Poloniex (-0.0071***). This suggests that higher trading volume can strengthen or weaken price co-movement, depending on the exchange. Similarly, on-chain transfers have mixed effects, meaning capital movements can help or disrupt price synchronisation. H4 is partially accepted, as fees significantly negatively affect some exchanges but not most. Exchanges like Bittrex and Poloniex show that increased network fees decrease correlation. Momentum and lagged correlation show greater significance in their effect on price divergences, accepting H5 and H7. Stronger momentum continues to decrease correlation even through the DCC-GARCH method, with exchanges like Bitbay (-0.0220***) and Kucoin (-0.0213***). Lagged correlation is also highly significant across most exchanges, confirming that past correlation levels strongly predict future price co-movement. The strongest effects are seen in Gemini (0.7374***), Bittrex (0.7068***), and Poloniex (0.7123***). This suggests that historical price relationships are highly stable, supporting market integration for these exchanges. Search remains mostly insignificant. The F-test values are significant for most exchanges, confirming the joint relevance of the explanatory variables.

Diagnostic Test Result

	Bitbay	Bitfinex	Bitstamp	Bittrex	Cex.io	Coinbase	Exmo
Breush-Pagan	17.80*	1712.60***	363.00***	410.52***	1712.90***	1610.30***	1108.30***
	(0.0129)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Durbin-Watson	1.9937	0.9473***	1.3258***	0.9198***	0.9066***	0.2512***	0.9706***
	(0.4029)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Wu-Hausman	-6.5801	4.9668	0.5585	6.4371	10.5977	198.0559***	1.6537
	(1.0000)	(0.7611)	(0.9998)	(0.5984)	(0.2255)	(0.0000)	(0.9899)
	FTX	Gemini	HitBTC	Kucoin	Okcoin	Poloniex	Yobit
Breush-Pagan	293.88***	660.27***	21.23**	222.05***	0.85	293.96***	399.06***
	(0.0000)	(0.0000)	(0.0035)	(0.0000)	(0.9969)	(0.0000)	(0.0000)
Durbin-Watson	0.8583***	1.0281***	1.5595***	0.5393***	0.2043***	0.8591***	0.5120***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Wu-Hausman	-0.5556	4.5359	1.9018	35.8069***	-1.8671	64.6075***	8.7389
	(1.0000)	(0.8058)	(0.9840)	(0.0000)	(1.0000)	(0.0000)	(0.3648)

Note: *This table presents diagnostic test results for the baseline OLS estimates with the Kraken-Exchange X pairs. The Breusch-Pagan test checks for heteroscedasticity, the Durbin-Watson test detects autocorrelation, and the Wu-Hausman test assesses endogeneity. A significant Wu-Hausman test indicates that 2SLS should replace OLS due to bias or inefficiencies. P-values are in parentheses. Significance levels: *** 0.1%, ** 1%, * 5%, . 10%.*

Table 11. Robustness Check: Baseline DCC-GARCH OLS

The OLS results of the DCC-GARCH model show significant heteroscedasticity and autocorrelation, unlike the GRA model, which showed none. Okcoin remains an outlier, with no detected heteroscedasticity, though data quality concerns persist. Exchanges like Bitfinex (0.9473***), Bittrex (0.9198**), and FTX (0.8583***) show strong autocorrelation.

The Wu-Hausman test confirms endogeneity for Coinbase (198.0559***), Poloniex (64.6075***), and Kucoin (35.8069***), necessitating an IV/2SLS approach for unbiased estimation. Thus, they have been entirely removed from Table 12. The baseline models need adjustments, like in the GRA model, using robust standard errors in OLS or an IV/2SLS approach to correct inefficiencies in Table 11.

Table 12 shows the improved OLS results with robust standard errors. The results in Table 11 provide a refined analysis of the factors affecting the time-varying correlation between cryptocurrency exchanges and Kraken. However, most variables' estimates remain near zero, indicating minimal impact on returns correlation dynamics. The coefficient estimates remain unchanged, but most notable are the changes in value for the standard error and significance of the baseline model.

The reduced significance of the constant for some exchanges in the improved OLS with robust standard errors suggests that previously observed baseline correlation may have been overstated due to heteroskedasticity or autocorrelation.

A similar trend for volatility, transfers, and fees is observed, making H1, H3, and H4 inconclusive. Sigma showed no significance in HitBTC from the 10% level after correcting for inefficiencies (-0.0040. to -0.0043). The most highly significant sigma values found to be endogenous were Coinbase, Kucoin and Poloniex. This means that their significance was influenced by correlations with the error term, leading to biased and unreliable estimates. Mixed results are observed for transfers, with Gemini showing a positive and significant effect, while HitBTC shows a negative and significant effect at the 10% level. The same can be seen for fees in the improved model.

OLS Regression Model: Robust Standard Errors

	Bitbay	Bitfinex	Bitstamp	Bittrex	Cex.io	Exmo	FTX
Constant	0.2313	0.6545***	0.8181***	0.2066	0.6279***	0.5423**	0.8256***
	(0.1818)	(0.1480)	(0.0723)	(0.1402)	(0.1550)	(0.1848)	(0.0945)
log(sigma)	-0.0086	-0.0005	0.0002	-0.0012	-0.0008	0.0002	0.0009
	(0.0070)	(0.0007)	(0.0004)	(0.0023)	(0.0007)	(0.0011)	(0.0011)
log(volume)	0.0052	0.0005	0.0001	0.0004	-0.0007	0.0020*	-0.0003
	(0.0048)	(0.0006)	(0.0004)	(0.0018)	(0.0006)	(0.0010)	(0.0011)
log(transfers)	0.0069	0.0008	0.0003	0.0008	0.0018*	-0.0019	-0.0003
	(0.0099)	(0.0007)	(0.0005)	(0.0016)	(0.0009)	(0.0014)	(0.0008)
log(fees)	-0.0034	0.0003	0.0002	-0.0045	0.0002	0.0004	0.0004
	(0.0024)	(0.0003)	(0.0002)	(0.0031)	(0.0004)	(0.0005)	(0.0006)
log(momentum)	-0.0220**	-0.0008*	-0.0004	-0.0079	-0.0014**	-0.0004	0.0004
	(0.0069)	(0.0004)	(0.0002)	(0.0050)	(0.0005)	(0.0008)	(0.0007)
log(search)	-0.0027	0.0001	0.0000	-0.0086	0.0008	0.0013	0.0018
	(0.0047)	(0.0009)	(0.0005)	(0.0062)	(0.0011)	(0.0014)	(0.0018)
Pt-1	0.1997***	0.2509	0.0972	0.7068***	0.2763	0.3964.	0.1102
	(0.0570)	(0.1669)	(0.0793)	(0.2044)	(0.1757)	(0.2042)	(0.1006)
R^2	0.0730	0.1887	0.0472	0.7434	0.2180	0.3265	0.0758
$\bar{R}^2$	0.0680	0.1867	0.0449	0.7420	0.2160	0.3243	0.0704
F-test	14.53***	94.47***	20.14***	522.00***	110.20***	148.80***	14.08***
No. Of Observations	*1300*	*2852*	*2852*	*1269*	*2776*	*2156*	*1210*

	Gemini	HitBTC	Okcoin	Yobit
Constant	0.2478	0.8773***	0.6608***	0.8024***
	(0.1568)	(0.0958)	(0.0000)	(0.0679)
log(sigma)	0.0003	-0.0043	0.0000	-0.0019
	(0.0008)	(0.0047)	(0.0000)	(0.0013)
log(volume)	-0.0028.	0.0071**	0.0000	0.0028**
	(0.0016)	(0.0023)	(0.0000)	(0.0010)
log(transfers)	0.0018.	-0.0056.	0.0000	-0.0019.
	(0.0011)	(0.0033)	(0.0000)	(0.0010)
log(fees)	0.0007	0.0011*	0.0000	0.0008.
	(0.0006)	(0.0005)	(0.0000)	(0.0004)
log(momentum)	0.0001	0.0000	0.0000	-0.0032**
	(0.0004)	(0.0028)	(0.0000)	(0.0011)
log(search)	0.0001	-0.0002	0.0000	0.0005
	(0.0009)	(0.0028)	(0.0000)	(0.0012)
Pt-1	0.7374***	0.0128	0.0000	0.0711
	(0.1629)	(0.0254)	(0.0000)	(0.0633)
R^2	0.7062	0.0488	0.0189	0.1479
$\bar{R}^2$	0.7055	0.0309	0.0113	0.1428
F-test	976.30***	2.73**	2.46*	28.86***
No. Of Observations	*2851*	*381*	*901*	*1172*

Note: *This table presents the estimated improved coefficients for the DCC-GARCH model applied to the Kraken–Exchange X pair, incorporating robust standard errors based on prior diagnostic test results. The model accounts for endogeneity, autocorrelation, and heteroskedasticity. HC robust standard errors are applied only to Bitbay, while HAC robust standard errors are used for all other exchanges. Standard errors are reported in parentheses. Significance levels: *** 0.1%, ** 1%, * 5%, . 10%.*

Table 12. Baseline Model with Robust Standard Errors (DCC-GARCH)

Trading volume showed more significant positive values, pushing for partial acceptance of H2, but it remains relatively weak. Only HitBTC, Yobit, and Exmo had significance at the 5% to 1% level. Most interestingly, trading volume shifts from a negative to a positive effect when comparing the GRA and DCC-GARCH results. This change may be due to using the return series in the DCC-GARCH model. Working with returns instead of prices can affect the direction of relationships between variables. For the DCC-GARCH result, volume reduces arbitrage opportunities for some exchanges. Continued partial acceptance to H5 and H7, due to weak effect and missing significance from multiple exchanges. Bitbay (-0.0220**) was most negatively affected by increased momentum, leading to a decrease in price correlation with Kraken. Lagged correlation produced highly significant results with only the following exchanges: Bitbay (0.1997***), Bittrex (0.7068***), and Gemini (0.7374***).

H6 is accepted as the exchanges showed insignificance with the search variable, as in the GRA result. As in Table 7, the R^2, $\bar{R}^2$ and the F-test remain the same for Table 12.

Lagged correlation has lost significance in several exchanges. After correcting for autocorrelation and endogeneity, it becomes insignificant for Bitfinex, Cex.io, and Yobit. Exmo and Yobit also show weaker significance in the adjusted model. Gemini's previously strong OLS results now show reduced significance.

This drop in significance and rise in standard errors suggest the original estimates were biased and inefficient. The revised model corrects these issues. It reveals that some relationships were overstated due to poor standard error handling.

Lagged correlation likely lost significance due to remaining dependencies in the residuals. The constant term also dropped for some exchanges, pointing to previously inflated baseline correlations. The larger standard errors now help filter out weak or unreliable relationships.

Only Coinbase, Kucoin, and Poloniex remained highly significant when testing for endogeneity. Therefore, the IV/2SLS model must be applied, as done previously for the GRA model. Table 13 below presents the results after correcting for endogeneity.

Significance levels dropped from 0.1% to 1% for most variables across the three exchanges, correcting previously inflated estimates due to endogeneity and heteroskedasticity. Poloniex saw the sharpest decline, with nearly all variables becoming insignificant, indicating prior inefficiencies in estimation. However, lagged correlation like (0.7656*) remained strongly significant, reinforcing persistent price co-movement.

Estimated IV/2SLS Models: DCC-GARCH Analysis

	Coinbase	Kucoin	Poloniex
Constant	0.7348***	1.1783**	0.4425
	(0.1248)	(0.3590)	(0.2996)
log(sigma)	-0.0053**	-0.0190***	0.0054
	(0.0017)	(0.0048)	(0.0033)
log(volume) IV	0.0019**	0.0134*	-0.0103
	(0.0007)	(0.0065)	(0.0065)
log(transfers) IV	0.0033**	-0.0246**	-0.0006
	(0.0012)	(0.0095)	(0.0031)
log(fees) IV	-0.0042**	0.0154**	-0.0018
	(0.0014)	(0.0055)	(0.0021)
log(momentum)	-0.0038**	-0.0174***	0.0015
	(0.0013)	(0.0046)	(0.0016)
log(search)	0.0007	-0.0156.	-0.0082
	(0.0006)	(0.0080)	(0.0061)
Pt-1	0.0885	0.1089	0.7656***
	(0.0951)	(0.1077)	(0.1678)
R^2	0.3312	0.6241	0.8122
$\bar{R}^2$	0.3295	0.6161	0.8111
Wald test	200.30***	77.81***	697.00***
No. Of Observations	*2840*	*336*	*1136*

Note: *This table presents the estimated coefficients for the 2SLS DCC-GARCH model applied to the Kraken–Exchange X pair, correcting for potential bias in OLS estimates. The Wald test evaluates the joint significance of the explanatory variables in the instrumental variables (IV) regression. Based on diagnostic test results, HAC robust standard errors are applied to all three exchanges. Standard errors are reported in parentheses. Significance levels: *** 0.1%, ** 1%, * 5%, . 10%.*

Table 13. IV/2SLS Results - DCC-GARCH

Coinbase's low explanatory power R^2 of 0.3312 suggests missing market factors. The variables still mainly remained significant at the 1% level. Volatility, volume, on-chain transfers, fees, and momentum showed significance for Coinbase and Kucoin, pushing for the partial acceptance of H1, H2, H3, H4, and H5. Nevertheless, when analysing the overall result, H1, H3 and H4 are still inconclusive since the DCC-GARCH results lack significance from most exchanges. H2 remains partially accepted, while H5 and H6 are accepted. The Wald test confirms a slight reduction in overall model significance, reflecting the impact of adjustments for bias and inefficiencies.

Figure 10. DCC-GARCH Correlations

To conclude, the DCC-GARCH model failed to capture much of the variation compared to the GRA result. Figure 10 visualises the DCC-GARCH values, illustrating the level of variation across exchanges as time-varying correlations. Each plot covers the same period, ensuring a comprehensive overview of the data while highlighting potential gaps or missing periods.

Coinbase (orange) stands out for its stable return correlation with Kraken. This relationship shows almost no variation over time. The consistency may result from domestic factors such as regulatory alignment, strong institutional trading, or liquidity. These conditions help reduce price differences and support a steady correlation structure.

As shown in Figure 9, most exchanges-maintained return correlations are around 0.90, closely mirroring Kraken's dynamics. However, Poloniex and Gemini experienced sharp volatility spikes, potentially signalling arbitrage opportunities. Despite this, correlation variability remained low across many exchanges compared to the Grey Correlation Analysis, suggesting a more rigid structure in the DCC-GARCH model. Generally, greater variability provides deeper insights into the relationships between variables, but here, the results appear more constrained, limiting the depth of interpretation.

Overall, the DCC-GARCH model produced mostly inconclusive to partial acceptance of the research hypotheses with weak effects. Where H1, H3, and H4 are inconclusive, H2 is partially accepted. Only H5, H6 and H7 are fully accepted, rejecting the null hypotheses. The model showed that volume, momentum, and lagged correlation are the main drivers of arbitrage opportunities in multiple exchanges through the return series.

6 Conclusion

The core of this study was to investigate further the works of Kristoufek & Bouri (2023) by adding a more extended research period with current data, different baseline exchange and further conclude trends previously mentioned in past research.

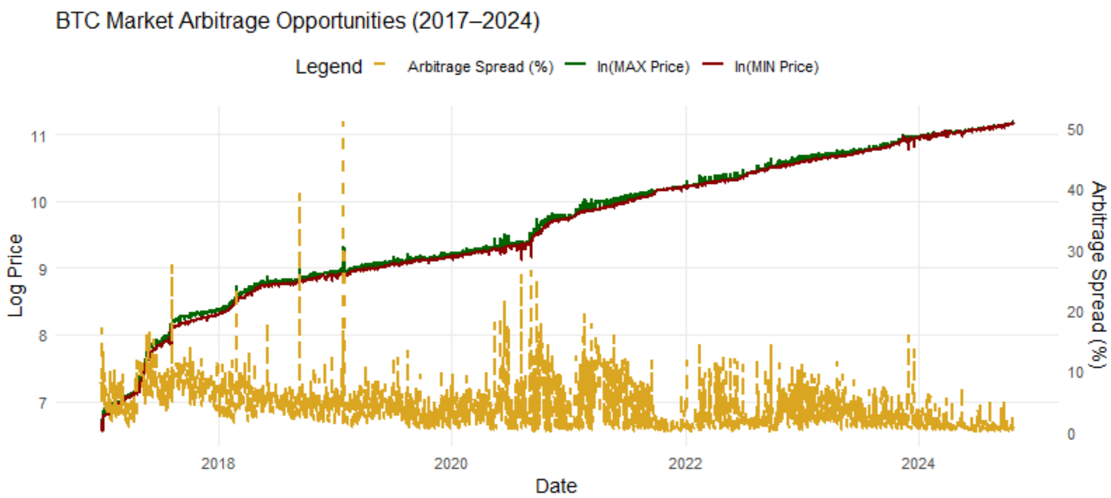

Figure 11. BTCUSD Arbitrage Development

The cryptocurrency market has evolved dramatically in recent years, with its popularity growing exponentially. Established financial institutions now include Bitcoin (BTC) in their portfolios, reflecting its growing acceptance. A clear indicator of this rise is Bitcoin's market capitalisation, which soared from $13 billion to nearly $2 trillion over the same research period (CoinMarketCap, 2025). As early studies highlight, cryptocurrency markets remain highly segmented, with persistent arbitrage opportunities across exchanges, particularly between countries, due to capital controls, regulatory restrictions, and liquidity constraints. Price deviations tend to co-move in regions with strict capital controls, and order flow accounts for up to 85% of price variation, underscoring the ongoing inefficiencies in the market. While institutional arbitrage has not fully eliminated these disparities, financial innovation and evolving regulations may gradually reduce arbitrage spreads over time (Makarov & Schoar, 2018). Recent studies by Crépellière et al. (2023), John et al. (2024), Hautsch et al. (2024), and Borri & Shakhnov (2023) add further depth to the understanding of market segmentation, arbitrage dynamics, and the evolving cryptocurrency landscape.

Adding to the current literature, this study revisits the topic of cryptocurrency arbitrage using a more extended timeframe and updated data, covering the period from 2017 to 2024. This extends the scope of earlier research, such as Kristoufek & Bouri (2023) , who focus on a narrower data window and use different baseline exchanges. This equates to an observation count of over 10,000 data points as specified in Table 1. A key contribution of this thesis is the selection of Kraken as the reference point for BTCUSD pricing, offering a widened benchmark of cross-exchange comparison from the Binance baseline exchange.

Although Crépellière et al. (2023) also used Kraken as a reference exchange, their study focuses on whether arbitrage can be carried out in practice by considering real-world limitations such as trading fees, transfer times, and liquidity conditions. Conversely, this research uses Kraken as a reference point to assess how prices on other exchanges align or diverge over time. The aim is to understand broader structural patterns in pricing differences between platforms rather than to evaluate the profitability or execution of specific trading strategies.

By utilising Grey Correlation Analysis and the DCC-GARCH model, it is possible to capture the complex, dynamic relationships between Bitcoin exchange markets and identify statistical arbitrage opportunities. Grey Correlation Analysis measures nonlinear dependencies between returns across exchanges without assuming a Gaussian distribution, making it more robust in detecting subtle market inefficiencies. The DCC-GARCH (1,1) model estimates time-varying correlations between exchanges, providing insights into how market volatility and liquidity conditions affect arbitrage opportunities. Both methods are employed solely to investigate the emergence of arbitrage opportunities and factors that contribute to it.

When analysing the results of both models, it is apparent that the GRA reveals greater variability in price synchronisation, emphasising exchange inefficiencies. The GRA method captured more variation because it works directly with price levels, while DCC-GARCH uses returns. Prices tend to show bigger and slower-moving differences between exchanges, while returns are small and fluctuate quickly. As a result, DCC-GARCH smoothed out most of the real variation, making correlations look almost constant. GRA visualised better real shifts in prices and reflected market dynamics. This made GRA more sensitive to differences and better at spotting potential arbitrage opportunities. GRA resulted in mean correlations ranging from 0.7655 to 0.9719. In comparison, the DCC-GARCH results indicate more rigid and stable correlations, reflecting reduced explanatory power for market frictions compared to GRA. While GRA is more sensitive to market anomalies, DCC-GARCH captures steadier trends over time, underlining the complementary strengths of both methodologies throughout the research period.

The results of this research thesis showed that the GRA method provided stronger evidence in support of the research hypotheses compared to the DCC-GARCH model. GRA results confirmed that momentum, lagged correlation, and volatility are key drivers of arbitrage opportunities, with Coinbase and Kraken showing tighter price alignment than, for example, Kucoin and Poloniex. The IV/2SLS corrections and Wald tests reinforced the robustness of these findings. By comparison, the DCC-GARCH model yielded mostly inconclusive or weak effects, with only H5, H6, and H7 fully supported. Both methods highlight persistent inefficiencies and fragmented price behaviour across crypto exchanges, rejecting the null hypothesis.

Moreover, the analysis reveals that pricing divergences are not random but are shaped by unique exchange-specific factors, as not all exchanges are affected by a particular variable. This research showed that high market volatility consistently reduces price correlation between exchanges, which is logical, as shown in the GRA and DCC-GARCH models. Exchanges like Bitstamp, HitBTC and Kucoin show more pronounced price divergences during volatile periods, which may lead to arbitrage opportunities with Kraken. This challenges the Efficient Market Hypothesis. Despite increased transparency and technological sophistication in crypto markets, persistent arbitrage windows suggest that prices do not always reflect all available information, as Heijmans (2018) mentioned. Similarly, the breakdown of the LOOP across centralised exchanges shows that, despite low transaction costs and the digital nature of Bitcoin, differences in market structure and behaviour still prevent prices from fully aligning.

The impact of trading volume fluctuates with each exchange, where exchanges like Exmo benefit from increased trading volume. This leads to greater price alignment with Kraken during high-volume periods. While the opposite effect was observed at the 5% significance level with HitBTC through the IV/2SLS method for the Grey Correlation Analysis. Most surprisingly, On-chain transfers didn't result in a similar highly significant result like in Kristoufek & Bouri (2023). On-chain transfers generally produced mixed results depending on the exchange. Fees also showed mixed results for each exchange in both models, where certain exchanges like Coinbase and Kucoin, had the opposite effect in Table 13. This suggests that fee optimisation could play a role in reducing inefficiencies. Momentum consistently showed a negative effect on price correlation across most exchanges. This was observed in both the Grey Relational Analysis and DCC-GARCH models. The results suggest that strong price trends can weaken price alignment between exchanges, creating arbitrage opportunities. The consistent result with momentum suggests it as a key driver for market inefficiencies. Search has remained largely insignificant and aligned with the results of Kristoufek & Bouri (2023). Like momentum, the lagged correlation variable emerges as a strong and consistent predictor of future price movements across most exchanges. This suggests a high level of stability in historical price relationships, particularly between Kraken and exchanges like Coinbase and Gemini, where long-term correlations remain robust.

A lot of regional and exchange-specific characteristics have been discussed. Most visible are regional disparities like US-based exchanges (e.g., Coinbase) demonstrating stronger alignment with Kraken due to shared market characteristics like regulatory frameworks and institutional participation, which can be seen in Figures 9 and 10. However, Gemini showed low correlation despite being situated in the US in Figure 9. Furthermore, the data reveals a clear long-term shift toward market stabilisation and integration, significantly limiting arbitrage opportunities. Due to exchanges being more connected and pricing becoming more efficient across regions, supporting Crépellière et al. (2023). The long-term diminishing of arbitrage opportunities can be witnessed in Figure 11.

In summary, the findings of this research complement the findings of Kristoufek & Bouri (2023), Makarov & Schoar (2020), Borri & Shakhnov (2023), Crépellière et al. (2023), and Baur & Dimpfl (2021) by reinforcing the complex nature of arbitrage in cryptocurrency markets. Like prior studies, this research confirms that some price inefficiencies arise due to volatility shocks, on-chain activity, fee structures, and regional fragmentation. The findings challenge key financial theories like EMH, LOOP and PPP. EMH suggests that prices reflect all available information, yet BTCUSD prices on platforms like Kraken, Bitstamp, and Binance often fail to converge, even in liquid markets. This contradicts LOOP, which assumes identical assets should trade at the same price after accounting for costs. Similarly, the results deviate from PPP, as Bitcoin does not maintain a consistent value across currencies. Instead, factors like liquidity, execution delays, and market behaviour contribute to persistent price differences across exchanges.

Although the models identify clear arbitrage signals linked to volatility, momentum, and structural inefficiencies, capturing these opportunities in real time remains difficult. Constraints such as latency, fees, transaction delays, and possible withdrawal limits often reduce or eliminate potential profits.

7 Limitations and Future Research

While the study offers further insights into arbitrage conditions in cryptocurrency markets, it is important to evaluate the research's limitations. This includes various aspects like the data used, methodology, and scope of the research. Addressing these constraints helps to highlight areas for improvement and future research developments related to the current topic.

One methodological limitation concerns how the two models respond to market disruptions. GRA is more flexible in detecting non-linear patterns and short-term pricing anomalies across exchanges. While the DCC-GARCH model produces smoother and more stable correlation estimates, it may underestimate the effect of sudden disruptions such as transaction delays, network congestion, or unexpected fee changes. This difference suggests that while DCC-GARCH helps identify long-term correlation trends, it may miss brief but relevant misalignments that GRA captures more effectively. Future research could search for models that keep the time-varying structure of DCC GARCH but can also capture sharp movements when they happen.

Another important limitation is regarding the frequency of the dataset used. The analysis relies on daily closing prices, which may overlook intraday arbitrage opportunities on much shorter time scales. Applying similar models to higher-frequency data, such as hourly or minute-level observations, could offer a more accurate view of arbitrage windows and the timing challenges associated with their execution.

The findings offer practical guidance for multiple stakeholders. Traders may identify higher potential returns on platforms where correlation to Kraken is consistently weak. Exchange operators could leverage this data to reduce inefficiencies by improving liquidity and latency. Finally, future research can use Kraken as a reference point to better identify structural mispricing in the market and build upon the current findings.

Additionally, the reliance on a single benchmark exchange, Kraken, may introduce limitations in terms of generalizability. While Kraken was selected for its regulatory stability and data quality, using multiple or rotating reference exchanges could help test the robustness of the correlation patterns observed in this study.

Regarding blockchain activity, while on-chain transfers were used as an explanatory variable for market integration, the thesis did not include network-specific variables such as gas fees or confirmation delays. Including these could improve the models' ability to detect when technical constraints affect price synchronisation between exchanges, as shown in Crépellière et al. (2023).

An interesting input for future research would be to include the Fear & Greed Index for cryptocurrencies to further investigate macro sentiments in the crypto market and the effects of market sentiment on arbitrage opportunities, meaning whether bull or bear markets create more arbitrage conditions.

All-in-all, most future research ideas come down to the availability and quality of cryptocurrency data. Since the beginning, data has been scarce, often requiring collecting and combining raw information from various sources to build coherent research datasets. One reason for this may be that many early centralised exchanges no longer exist, leading to the loss of historical data. As Chapter 4, Data and Methodology mentioned, the scope originally included plans to implement USDT into the analysis. However, sourcing USDT data with matching periods and consistent quality proved far more difficult than expected. This meant that the triangulation of the findings was difficult, and that could also be a future research topic.

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Note: This thesis used AI tools, such as Grammarly, to support and improve writing quality.

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