THE DETERMINANTS INFLUENCING CRYPTOCURRENCY RETURNS

A Thesis submitted by

Sanshao Peng

(BSBF, MSF)

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ABSTRACT

The cryptocurrency market has been volatile in terms of pricing and investment returns. Very few studies have attempted to understand the dynamics of the factors influencing cryptocurrency returns. The studies documented in this thesis aim to explore these factors and examine how each factor accounts for the market return. To address this aim, three studies are undertaken, comprising a systematic literature review and empirical research. The first study employs a systematic literature review to identify the factors influencing cryptocurrency pricing and the potential gaps in this area of research. The second study draws on a three-factor model and examines the relationship between consumer confidence and cryptocurrency excess returns through empirical analytics. The third study investigates the association between the composite leading indicator and cryptocurrency returns. The latter two studies draw on a sample of 3,318 cryptocurrencies from 1 January 2014–31 December 2022. The first study's results reveal the influential factors for cryptocurrency pricing, with these categorised as supply and demand, technology, economics, market volatility, investors' attributes, and social media. The results of the second study show a significant negative relationship between the Consumer Confidence Index and cryptocurrency excess returns, with this finding reinforced by further robustness testing. The findings from the third paper suggest that short-term changes in the composite leading indicator are negatively associated with cryptocurrency returns. This relationship is validated by a series of additional tests and robustness tests. The studies in this thesis are the first to identify the pricing factors of cryptocurrency through the systematic literature review and by investigating the association between consumer confidence/composite leading indicator and cryptocurrency returns. The studies in this thesis contribute to consumer behaviour research and the financial market literature, as well as having important implications for regulators, policy makers, investors, portfolio managers, researchers, and firms.

CERTIFICATION OF THESIS

I, Sanshao Peng, declare that the PhD Thesis entitled "THE DETERMINANTS INFLUENCING CRYPTOCURRENCY RETURNS" is not more than 100,000 words in length including quotes and exclusive of tables, figures, appendices, bibliography, references, and footnotes.

This Thesis is the work of Sanshao Peng except where otherwise acknowledged, with the student undertaking most of the contribution to the papers presented in this Thesis by Publication. The work is original and has not previously been submitted for any other award, except where acknowledged.

Date: 13/01/2024

Endorsed by:

Associate Professor Syed Shams

Principal Supervisor

Professor Tapan Sarker

Associate Supervisor

Professor Catherine Prentice

Associate Supervisor

The student's and supervisors' signatures of endorsement are held at the university.

STATEMENT OF CONTRIBUTION

Three papers produced from the studies in this thesis are joint works by the authors identified below. The details of the co-authors' contributions are as follows:

First paper:

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This paper was published in *China Accounting and Finance Review* in 2023.Ranking A.

Sanshao Peng contributed 70% to this paper. Collectively, Syed Shams, Tapan Sarker and Catherine Prentice contributed the remainder.

Second paper:

Peng, S., Shams, S., Prentice, C., & Sarker, T. (2024). Consumer confidence and cryptocurrency excess returns: A three-factor model. *Global Finance Journal*, 101029.

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Sanshao Peng contributed 70% to this paper. Collectively, Syed Shams, Tapan Sarker and Catherine Prentice contributed the remainder.

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This paper is under review by *European Journal of Finance*. ABDC Ranking A.

Sanshao Peng contributed 70% to this paper. Collectively, Syed Shams, Tapan Sarker and Catherine Prentice contributed the remainder.

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LIST OF ABBREVIATIONS

2SLS	two-stage least squares
CBOE	Chicago Board of Exchange
CC	control of corruption
CCI	Consumer Confidence Index
CLI	composite leading indicator
CMRT	cryptocurrency market returns
COVID-19	COVID-19 pandemic
CPI	Consumer Price Index
CRYPTO	cryptocurrency returns
DJIA	Dow Jones Industrial Average
EPU	economic policy uncertainty
EPUI	Economic Policy Uncertainty Index
EXCHANGE	exchange rate
FEDRATE	Federal rate
GDP	gross domestic product
GE	government effectiveness
GFC	Global Financial Crisis
GOLD	gold price
GPIAC	Global Price Index of All Commodities
H1	Hypothesis 1
H2	Hypothesis 2
HML	high minus low
LAG_CLI	lagged value of composite leading indicator
NYSE	New York Stock Exchange
OECD	Organisation for Economic Co-operation and Development
OIL	oil price
PRISMA	preferred reporting items for systematic reviews and meta-analysis (approach)
RL	rule of law
Rm-Rf	cryptocurrency excess returns
RQ	regulatory quality
S&P500	Standard & Poor's 500 Index
SENTIMENT	consumer sentiment
SMB	small minus big
TREND_BTC	Google Trends Index for Bitcoin
UNEMPLOY	unemployment rate
US/USA	United States/United States of America
VIX	Volatility Index

WIKI_BTC	Wikipedia search Bitcoin

CHAPTER 1: INTRODUCTION

1.1. Background and motivation

A cryptocurrency serves as a virtual currency system, mirroring the functionality of traditional currencies. It empowers users to conduct virtual transactions for goods and services independently of conventional financial institutions, potentially diminishing intermediary transaction costs (Kim, Bock, et al., 2021). Cryptocurrencies have garnered considerable attention, reaching unprecedented market capitalisation (Bouri, Lau, et al., 2019; Fry, 2018). The decentralisation offered through cryptocurrencies plays a pivotal role in safeguarding users' privacy and affording varying levels of anonymity (Sarwar et al., 2019). Unlike traditional financial assets, the value of cryptocurrency is not tied to tangible assets but is determined by a specific algorithm capable of recording all transactions (Corbet et al., 2019). Consequently, its value lacks a fundamental underpinning (Yermack, 2015). Moreover, the cryptocurrency market operates in a completely decentralised manner, contributing to price volatility and the emergence of a substantial speculative bubble (Yermack, 2015). Tong et al. (2022) further supported this by suggesting that the lack of effective supervision in the cryptocurrency market allows prices to rise rapidly and to fluctuate significantly due to the arbitrage behaviour of speculators.

Bitcoin, initially introduced by (Nakamoto, 2008), stands out as one of the foremost blockchain-based cryptocurrencies. The blockchain technology inherent in cryptocurrencies is widely acknowledged as a groundbreaking innovation with significant implications for the future of finance (Liu et al., 2022a). Van Wijk (2013) highlights Bitcoin's extensive influence on financial development, affecting stock market indices, exchange rates, and oil prices. Polasik et al. (2015) noted a significant surge in Bitcoin returns, driven by increased trading demand against the US dollar in July 2010. Similarly, Bouoiyour and Selmi (2015) argue that the rising demand for Bitcoin trading and exchange transactions plays a crucial role in its long-term returns. Li and Wang (2017) emphasised the role of technological factors as crucial determinants influencing Bitcoin prices in its early market. Kristoufek (2013) suggested a correlation between increased interest in Bitcoin searches on platforms like Google and Wikipedia and a corresponding rise in its price. Examining the relationship between Bitcoin returns and mining based on daily trading data, Rehman and Kang (2021) found a significant impact of energy commodities, including oil, coal and gas, due to the energy-intensive nature of Bitcoin mining. Furthermore, Bitcoin's success has spurred the creation of numerous altcoins, such as Litecoin, Dogecoin, Ethereum, etc. (Ammous, 2018). Sovbetov (2018) underscored the influence of crypto-market-related factors, attractiveness of individual cryptocurrencies and the S&P 500 Index on the prices of major cryptocurrencies, like Bitcoin, Ethereum, Dash, Litecoin and Monero. Despite Bitcoin's prominence, thousands of other viable cryptocurrencies are available (Corbet et al., 2021), fuelling growing interest among users, investors, regulators and economists in obtaining a comprehensive understanding of the cryptocurrency market and the key determinants shaping cryptocurrency returns.

Previous research has established that cryptocurrency returns are influenced by various attributes of investors. Agosto et al. (2022) affirmed that investor sentiment plays a crucial role in predicting speculative bubbles and significantly impacts cryptocurrency returns. This finding was reinforced by Anamika et al. (2023), employing a direct survey-based measurement, who emphasised that investor sentiment affects cryptocurrency returns. Additionally, Anamika et al. (2021) and Bartolucci et al. (2020) demonstrated that investor sentiment and emotional factors, particularly those expressed on social media, are primary drivers of cryptocurrency returns. The underlying principle is that comments and opinions circulated on social media platforms can shape investors' perceptions and decisions regarding cryptocurrencies (Huynh, 2021). Moreover, Hollanders and Vliegenthart (2011) validated the view that consumer sentiment derived from social media, in the context of economic activities, correlates with consumer confidence. Notably, an abundance of negative news tends to lead to a decrease in consumer confidence. Shayaa et al. (2017) asserted that consumer sentiment, as gauged through social media, serves as a reflection of consumer confidence within a broader population. Given that consumer confidence, which represents the level of optimism or pessimism regarding the current state of the economy (James, 2021), can influence saving and spending behaviours. The raises the question: can consumer confidence also serve as an indicator of current economic conditions or impact investment decisions? Motivated by this inquiry, this study aims to explore whether consumer confidence can act as a proxy for consumer behaviour in the cryptocurrency market, thereby shedding light on its role in explaining the volatility of cryptocurrency returns.

Empirical studies have highlighted the significant impact of macroeconomic factors on cryptocurrency returns. For instance, Heikal et al. (2022) found a positive correlation between global oil price fluctuations and cryptocurrency returns. Corbet, Larkin, et al. (2020a) contributed empirical evidence indicating that interest rates set by the United States (US) Federal Fund impact the returns of cryptocurrencies. Yen and Cheng (2021) proposed that alterations in China's Economic Policy Uncertainty Index (EPUI) could forecast cryptocurrency volatility, revealing a negative association between the EPUI and future cryptocurrency volatility. Notably, changes in the Economic Policy Uncertainty Indices (EPUIs) of the US, Japan or Korea were found to have no significant effect on cryptocurrency volatility. Furthermore, Long, Demir, et al. (2022) highlighted the significant impact of geopolitical risk on the cross-section of cryptocurrency returns. This is attributed to risk-averse investors seeking additional compensation for holding cryptocurrencies that exhibit low or negative geopolitical betas. Naeem et al. (2022), employing a time-varying parameters vector autoregression approach, delved into the relationship between financial volatility and the risk of cryptocurrency indices. The findings indicated distinct spill-over patterns from uncertainties in stock, oil, gold and currency markets to cryptocurrency indices.

Ciner et al. (2022) revealed that government bond indices and small-cap stock returns significantly influence the tail behaviour of cryptocurrency returns. Additionally, Leirvik (2022) emphasised the positive association of cryptocurrency market volatility and liquidity with the large capitalisation of cryptocurrencies. The rationale behind this is that investors demand a higher price premium to account for the variation in liquidity volatility. Moreover, Zhang, Dai, et al. (2021) identified a positive cross-sectional relationship between downside risk and future returns in the cryptocurrency market. Investors were found to earn higher returns by holding cryptocurrencies with greater downside risk, highlighting the complex dynamics of risk and returns in the cryptocurrency landscape.

The affluent economic landscape, coupled with the spill-over effects of volatility, renders financial markets more susceptible to external influences (Li, Liang, et al., 2020; Mei et al., 2020). Previous studies have underscored the unreliability of relying on a single economic indicator for short-term forecasting, as it may generate false signals (Atabek et al., 2005). Recognising this, the composite leading indicator (CLI) amalgamates various individual leading indicators that have proven statistically relevant for analysing and forecasting significant macroeconomic indicators, such as gross domestic product (GDP) and industrial production (Kľúčik & Haluška, 2008). Notably, empirical evidence has supported the notion that changes in the CLI offer a more promising approach to forecasting economic activities compared to the averaging of multiple single indicators (Jansen et al., 2016). Consequently, the principal objective of this study is to investigate whether the CLI can furnish pertinent and reliable information for predicting cryptocurrency returns.

1.2. Research objectives and questions

Cryptocurrency has emerged as a fascinating phenomenon in financial markets, largely due to its decentralized nature, which has stirred considerable debate. Despite numerous studies identifying various determinants of cryptocurrency pricing, the research remains fragmented. To address this, the present study systematically reviews the existing literature, identifying and synthesizing the factors that influence cryptocurrency pricing. By integrating these findings, this review offers a comprehensive and unified perspective on cryptocurrency pricing, mapping out the key factors that significantly impact it.

Empirical studies have highlighted the significance of consumer confidence in the traditional financial market. Chen (2012) demonstrated that consumer confidence can be an important priced factor in stock market. Dees and Brinca (2013) found that the Consumer Confidence Index (CCI) effectively predicts household consumption, even when considering economic fundamentals. Islam and Mumtaz (2016) established a long-term relationship between the CCI and economic growth, especially in European countries. Kilic and Cankaya (2016) reported a strong association between the CCI and variables such as industrial production, inventories, personal consumption expenditure and the housing market. Mazurek and Mielcová (2017) highlighted the CCI's reliability as a predictor of GDP in the United States (US). Similarly, Acuña et al. (2020) showed a positive correlation between the CCI and subsequent consumption growth. Additionally, Koy and Akkaya (2017) demonstrated that consumer confidence significantly influences investment-related judgments in decision-making.

Numerous empirical studies have investigated the impact of Composite Leading Indicator (CLI) on economic activities. Castro (2010) found that the duration of economic expansions is positively related to CLI variables. Korte (2012) demonstrated that both the Organisation for Economic Co-operation and Development (OECD)'s CLI and its business confidence indicator performed best in terms of information criterion and forecasting accuracy. Jansen et al. (2016) showed that changes in the CLI offer more promising GDP forecasts compared to averaging multiple single indicators. Mo et al. (2018) explored the CLI's relationship with commodity futures across various countries, finding a significant negative relationship between the CLI and commodity futures volatility, suggesting that declining future business cycle expectations increase commodity futures fluctuations in

China. Celebi and Hönig (2019) noted that the CLI has delayed effects on stock returns. Ojo et al. (2023) identified the CLI as a valuable leading indicator of the Industrial Production Index and a potential tool for forecasting the unemployment rate. However, the CLI showed poor performance in forecasting GDP growth. Additionally, Larch et al. (2021) highlighted a negative association between the nature of discretionary fiscal policy and change in the composite leading indicator (CLI).

The above points have motivated this research to focus on empirically examining the factors that influence cryptocurrency returns by examining, specifically, the impact of consumer confidence and CLI on cryptocurrency returns. This research fills a gap in the previous literature on factors influencing cryptocurrency returns, on consumer confidence and the CLI by answering the following research questions:

1. What are the factors that influence cryptocurrency returns?
2. Does consumer confidence influence cryptocurrency returns?
3. Do Composite Leading Indicators (CLIs) influence cryptocurrency returns?

1.3. Conceptual framework and underlying hypotheses

The first paper employs a systematic literature review to reveal factors identified in previous literature as influencing cryptocurrency pricing and defines the main gaps for future research. The systematic literature review used the preferred reporting items for systematic reviews and meta-analysis (PRISMA) approach. This approach has played an important role in assisting researchers with appropriate summarising of previous studies (Liberati et al., 2009; Sarkis-Onofre et al., 2021).

Figure 1.1 presents the flow chart of the first paper's systematic literature review. In this paper, a predetermined search strategy was followed using the terms ("cryptocurrency" OR "encryption currency" OR "digital money" OR "digital currency") AND ("factor" OR "determine") AND ("price"). Three databases, namely, Scopus, Web of Science and

EBSCOhost were used as most relevant studies can be sourced from these databases (Akyildirim et al., 2021; Liu et al., 2022b; Mohamed, 2021). To maintain a consistent standard for analysis and to ensure high-quality findings, this review only considered peer-reviewed journal articles which provided reliable and accurate data (Li, 2019). Only articles published in English were chosen. This review included all relevant studies published before August 2022 when the search was conducted. The review followed the procedure described in the PRISMA checklist (Tricco et al., 2018).

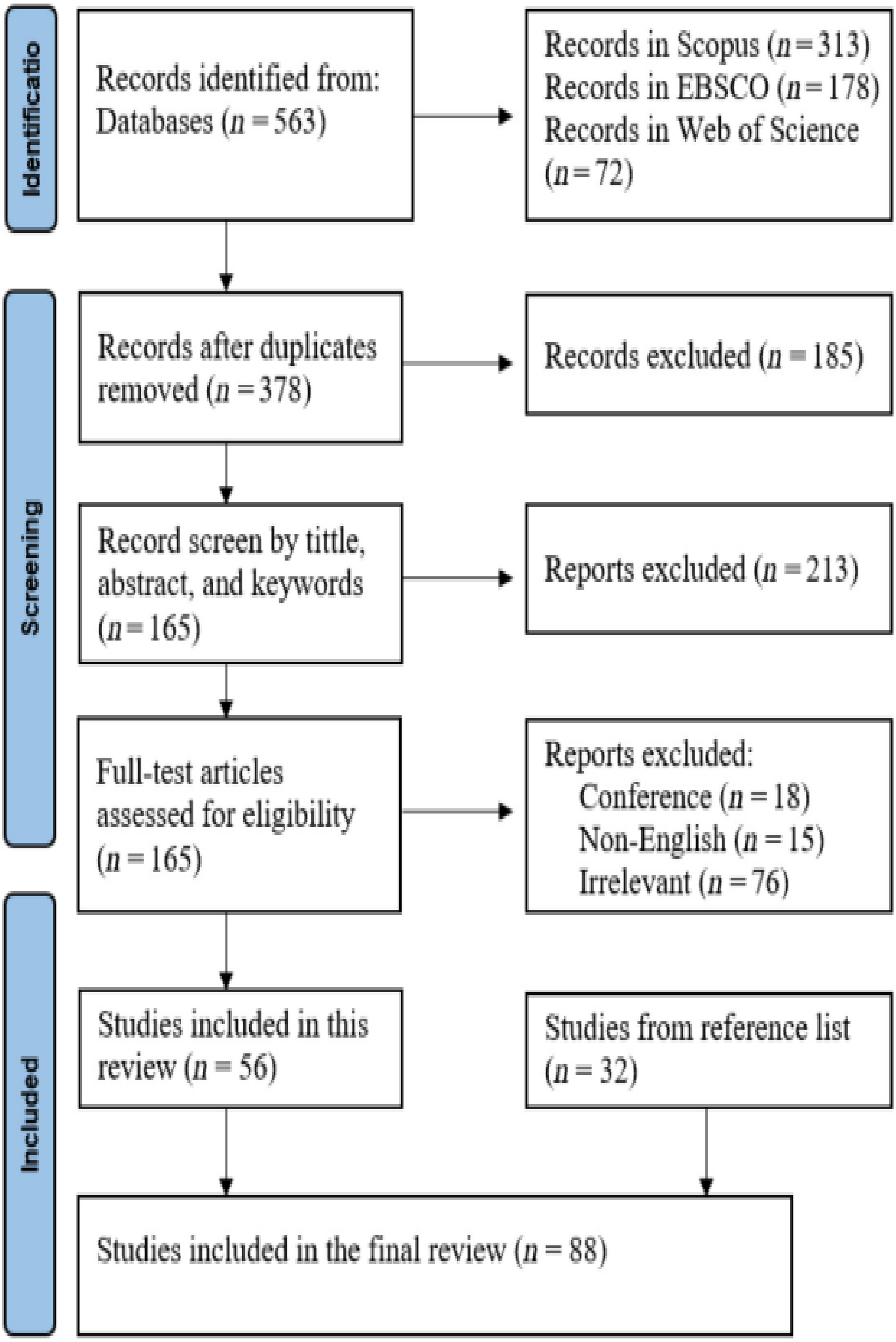

Figure 1.1. Flow chart of systematic literature review

The second paper discusses the arguments and presents a detailed view of the hypothesis development for that study. Figure 1.2 shows the conceptual framework and hypotheses of the study documented in the second paper. The independent variable is the Consumer Confidence Index (CCI), sourced from the Organisation for Economic Co-operation and Development (OECD). The study uses cryptocurrency excess returns as the dependent variable. Hypothesis 1 (H1) examines the positive relationship between the CCI and cryptocurrency excess returns through the three-factor model. Hypothesis 2 (H2) examines the negative relationship between the CCI and cryptocurrency excess returns through the three-factor model.

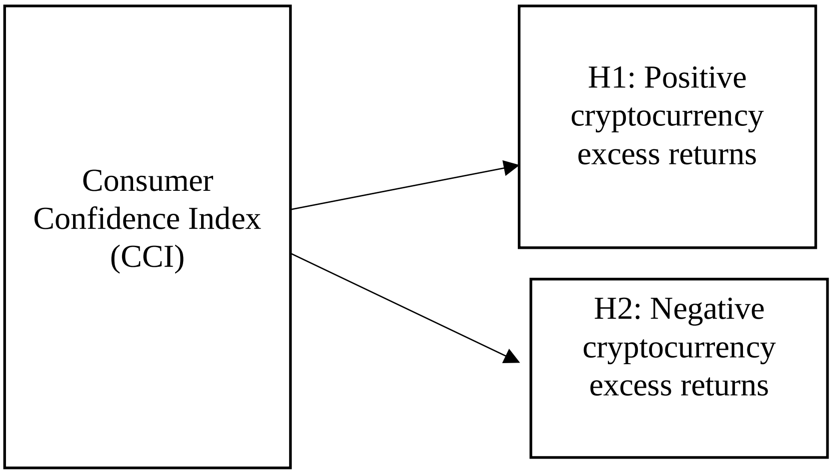

Figure 1.2. Conceptual framework and underlying hypotheses for the second paper
Source: developed by the author

The third paper discusses the arguments and presents a detailed view of the hypothesis development for that study. Figure 1.3 illustrates the conceptual framework and hypotheses of the study presented in the third paper. The independent variable is the Composite Leading Indicator (CLI) from the Organisation for Economic Co-operation and Development (OECD), while cryptocurrency returns serve as the dependent variable. Hypothesis 1 explores the positive relationship between the CLI and cryptocurrency returns using the three-factor model. Conversely, Hypothesis 2 (H2) investigates the potential negative relationship between the CLI and cryptocurrency returns through the same model.

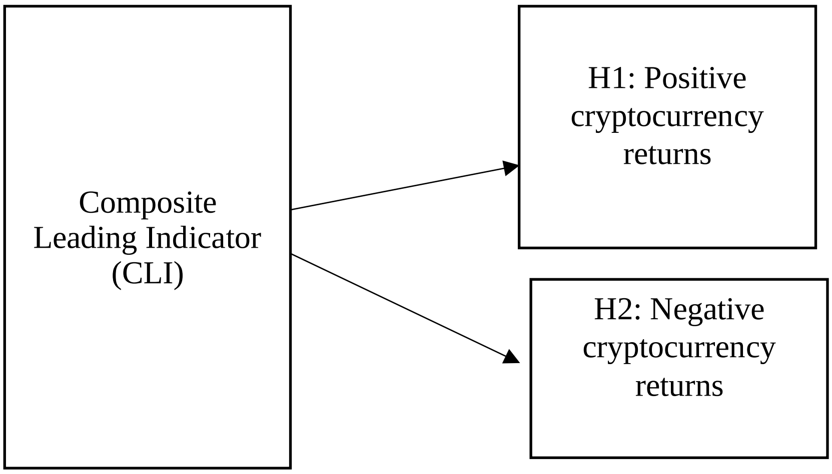

Figure 1.3. Conceptual framework and underlying hypotheses for the third paper
Source: developed by the author

For their theoretical framework, the studies documented in the thesis adopted the perspective of the behavioural finance theory (Yazdipour & Howard, 2010) which is derived from the pioneering work of psychologists Daniel Kahneman and Amos Tversky (1974). This theory emphasises the crucial role played by different types of psychological bias in investor decision making and how this bias, when translated into specific behaviours, subsequently influences the financial market's dynamics (Adam, 2022). To be specific, the behavioural finance theory posits that asset prices are influenced by the reaction of investors to relevant information and provides explanations for reasons why investors make irrational financial decisions (Hirshleifer, 2015).

1.4. Overview of findings

1.4.1. Findings of the first paper

This study is conducted by employing a systematic literature review, based on three databases. The study provides a comprehensive and consolidated view of the literature on cryptocurrency pricing and maps the significant influential factors. In addition, the influential factors are identified and categorised as follows: supply and demand, technology, economics, market volatility, investors' attributes, and social media. This study is the first to review the relevant literature systematically and comprehensively on cryptocurrency to identify pricing fluctuation factors. This study contributes to the literature on cryptocurrency and, more broadly, to studies on consumer behaviour and the marketing discipline.

1.4.2. Findings of the second paper

This study examines the association between the Consumer Confidence Index (CCI) and cryptocurrency excess returns through a three-factor model, using the following factors: market, size and momentum. Using the daily returns of a sample of 3,318 cryptocurrencies in the period 1 January 2014–31 December 2022, the baseline results suggest that the CCI is negatively associated with cryptocurrency excess returns. The predictions of cryptocurrency excess returns by the one-factor model and the three-factor model are firstly compared through Jensen's alpha coefficient analysis. The results show that the three-factor model performs better in predicting cryptocurrency excess returns. The entropy balancing approach and the two-stage least (2SLS) approach is then used to address potential endogeneity, such as omitted variables bias, selection bias and the reverse causality problem. A series of additional tests, including tests for robustness, are also conducted. These results are consistent with the main findings. This study contributes to the research on consumer behaviour and financial management within the cryptocurrency market. It also provides valuable insights for investors to improve their investment portfolio and for relevant authorities seeking to formulate effective policies for monitoring the cryptocurrency market with greater precision.

1.4.3. Findings of the third paper

This study investigates the relationship between the Composite Leading Indicator (CLI) and cryptocurrency returns using a three-factor model that includes cryptocurrency market, size and momentum factors. The analysis utilizes a dataset of 3,318 cryptocurrencies spanning from 1 January 2014 to December 31, 2022. The baseline results indicate a negative association between short-term changes in the United States (US) CLI and cryptocurrency returns. To address potential endogeneity issues, such as omitted variables bias, selection bias and reverse causality, the study employs an entropy balancing approach. Additional robustness tests further confirm this negative relationship. The findings suggest that incorporating CLI information can enhance investment portfolios and cryptocurrency prediction models. Additionally, policymakers can use these insights to better understand future economic conditions and their potential impact on the cryptocurrency market.

1.5. Research contributions and significance

The studies in the current thesis make several contributions to the literature. Firstly, the first study provides a comprehensive overview of the existing literature and categorises the significant factors that influence cryptocurrency pricing. The review provides evidence that cryptocurrency can be considered as an alternative currency that complements the existing financial industry. Prior studies have shown that cryptocurrency usage in transactions, its supply and its price levels are consistent with monetary economics and the quantity theory of money (Wang & Vergne, 2017). Moreover, cryptocurrency offers low transaction costs, decentralisation and a peer-to-peer system (Kim, Bock, et al., 2021). This makes it possible for users to access a cost-effective remittance system in developing countries where banking systems are underdeveloped or insecure (Ciaian et al., 2016a). Therefore, cryptocurrency has the potential to serve as a medium of exchange for the global economy (Ciaian et al., 2016b).

Secondly, the studies in this thesis contribute to the existing literature by providing evidence of the impact of consumers' emotions (or sentiment) on their decision making in the cryptocurrency market, as consumers' decision making can be affected by their incidental emotion and integral emotion (Han et al., 2007). In their study, Lansdall-Welfare et al. (2012) highlighted that consumer confidence is greatly affected by consumer incidental emotion, the rationale being that some consumers from the population that responded to the survey on which the CCI is based may reflect incidental emotion. In addition, the studies in this thesis contribute to the existing literature by providing empirical evidence of the impact of the CLI on cryptocurrency returns. The OECD's CLI effectively provides early signals of the business cycle turning points, with these signals' reliability tending to increase considerably when the sub-index obtained from the time scale components correspond to minor cycles (Gallegati, 2014). To the best of the author's knowledge, these studies are the first to assess the association between the monthly change of the CLI and cryptocurrency returns.

Thirdly, the studies in this thesis provide evidence that the behavioural finance theory can be used as the theoretical framework when assessing the relationship between the CCI and cryptocurrency returns. This theory emphasises the crucial role played by different types of psychological bias in investor decision making and how these types of bias, when translated into specific behaviours, subsequently influence the financial market's dynamics (Adam, 2022). To be specific, the behavioural finance theory posits that asset prices are influenced by the reaction of investors to relevant information and provides explanations for reasons why investors make irrational financial decisions (Hirshleifer, 2015). Thus, investors may consider the CCI and the CLI as relevant determinants influencing cryptocurrency returns.

Fourthly, by considering a broad range of macroeconomic indicators, the studies in this thesis contribute to the literature on predicting cryptocurrency returns. Evidence on how the CCI and the CLI influence cryptocurrency returns is markedly absent, with previous studies concentrating on variables such as the Consumer Price Index (CPI) (Wang et al., 2022); Federal funds rate (Havidz et al., 2021); Economic Policy Uncertainty Index (KaraÖMer, 2022); Chicago Board of Exchange (CBOE) Volatility Index (VIX) (Kim, Trimborn, et al., 2021); the exchange rate of US$ to euros (Polasik et al., 2015); and the Dow Jones Industrial Average (DJIA) (Zhu et al., 2017). In addition, the US CLI series is based on seven components including the work started for dwellings, net new orders for durable goods, and consumer and industrial confidence indicators (Gulen et al., 2011). Empirical evidence has supported the view that changes in the CLI can provide more promising forecasts of economic activities than can be achieved by averaging many single indicators (Jansen et al., 2016).

Fifthly, the studies in this thesis provide evidence that the three-factor model comprising cryptocurrency market, size and momentum performs better than the one-factor model in predicting cryptocurrency returns. This is consistent with the study by Jia et al. (2022) which found that the three-factor model showed better explanatory power than the quasi-cryptocurrency one-factor model. Finally, the studies in this thesis contribute to research on the COVID-19 pandemic and institutional factors by showing the CLIs' important mediating role. This indicates that the COVID-19 pandemic and institutional factors have a significant effect on cryptocurrency returns and in moderating the CCI–CLI association with cryptocurrency returns through the three-factor model.

Taken together, findings from these studies have important implications for investors. As they are seeking to diversify their portfolios with cryptocurrencies or by designing better trading strategies, the findings offer a consolidated discussion of the determinants of cryptocurrency prices and assist investors to construct cryptocurrency price prediction models. Investors can effectively trace cryptocurrency price movements, thus avoiding large change events in cryptocurrency prices, which may have a significant effect on the risk and return of individual risky assets. Policy makers can obtain a comprehensive view of the cryptocurrency market, gaining an understanding of the potential factors that would induce economic crisis, expressed as factors that are influential on cryptocurrency returns. Thus, the findings contribute to effective formulation of monetary policy in response to the challenges posed by cryptocurrencies. These findings also have important implications for companies that are considering cryptocurrency as a means of payment in cross-border transactions. This may especially be the case between countries without a coherent and reliable payment infrastructure. Cryptocurrency offers characteristics such as low transaction costs and decentralisation as well as a peer-to-peer payment system. In addition, the information from this systematic literature review may enable individuals to access international business when they lack access to traditional financial institutions or when they have less access to credit from within the banking system.

1.6. Structure of the thesis

The remainder of the thesis is organised as follow. Chapter 2 presents a summary of the relevant literature. Chapter 3 presents the first paper, titled “A systematic literature review on the determinants of cryptocurrency pricing”. Chapter 4 presents the second paper, titled “Consumer confidence and cryptocurrency excess returns: A three-factor model”. Chapter 5 presents the third paper, titled “Does composite leading indicators predict cryptocurrency returns?”.

Finally, Chapter 6 presents a summary of the overall findings. It highlights the significant implications for regulators, policy makers, researchers, investors and asset analysts, as well as offering a comprehensive view of the cryptocurrency market and the potential determinants influencing cryptocurrency returns. Additionally, it presents the limitations of all three studies and provides insights for future research.

CHAPTER 2: LITERATURE REVIEW

2.1. Chapter overview

This chapter begins with an overview (Section 2.1), followed by an introduction summarising the current study's literature review process (Section 2.2). Section 2.3 discusses the literature on the determinants of cryptocurrency returns and pricing. Section 2.4 demonstrates the impact of consumer confidence on financial markets. Section 2.5 presents the influence of the CLI on financial markets, while the chapter concludes with Section 2.6.

2.2. Introduction

This section summarises the literature related to the current research. Figure 2.1 presents a summary of the literature review process. Previous studies are reviewed to identify scholarly articles that discuss the influence of determinants on cryptocurrency returns and the research gaps for future study. Articles are identified that focus on the impact of consumer confidence on financial markets. The impact of the CLI on financial markets is next examined, with the relevant literature that helped in the development of hypotheses reviewed.

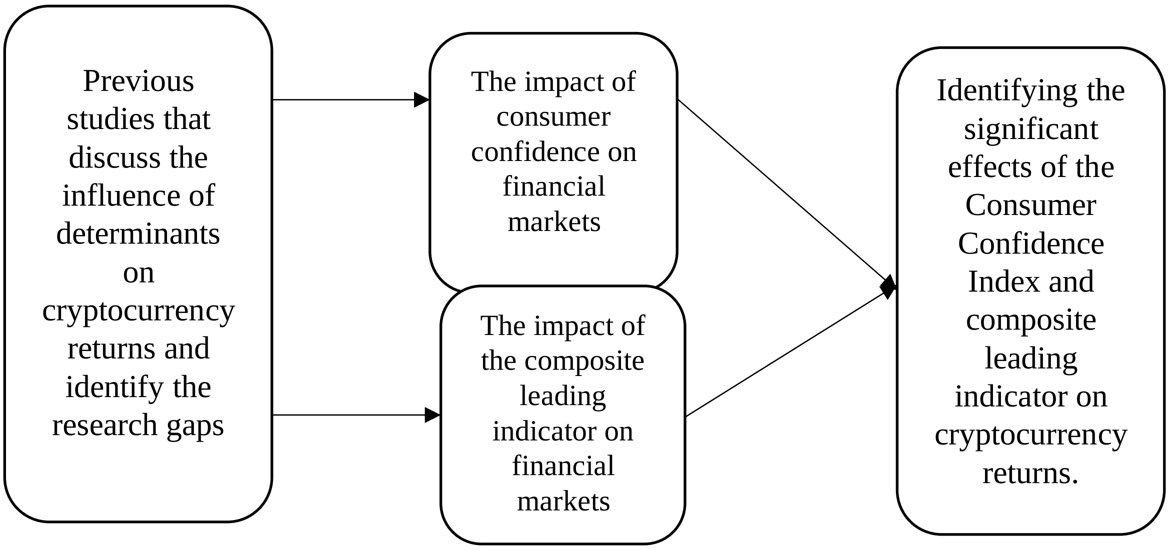

Figure 2.1. Process of reviewing relevant literature and identifying a knowledge gap
Source: developed by the author

2.3. Determinants influencing cryptocurrency returns

The theoretical literature has proposed several cryptocurrencies and specific factors as drivers of cryptocurrency returns. Sockin and Xiong (2023) argued that cryptocurrency returns are intimately linked to the marginal cost of mining, as the cost of mining is essential for cryptocurrency infrastructure and security. Cryptocurrencies' mining cost is related to production factors which are not exposed to cryptocurrency returns. In contrast, cryptocurrency returns are sensitive to cryptocurrency network factors that capture the user adoption of cryptocurrencies (Liu & Tsyvinski, 2021). This is consistent with Cong et al. (2021) who stated that cryptocurrency adoption is the main driver of their returns. Ciner et al. (2022) considered a large set of predictors and examined their impact on cryptocurrency returns at different quantiles. The results showed that government bond indices and small company stock returns significantly impacted the tail behaviour of cryptocurrency returns. In addition, (Leirvik, 2022) highlighted that the cryptocurrency market volatility and liquidity are, in general, positively associated with large capitalisation of cryptocurrencies, the rationale being that investors require a high price premium for the variation in liquidity volatility. Zhang, Li, et al. (2021) found that investors could achieve higher returns by holding cryptocurrencies with greater downside risk, revealing a positive cross-sectional relationship between downside risk and future returns in the cryptocurrency market. Furthermore, online investor sentiment was found to have predictive ability for cryptocurrency returns, for example, the Happiness Sentiment Index significantly predicted cryptocurrency returns (Naeem et al., 2021). While previous studies have identified numerous determinants of cryptocurrency pricing and returns in existing financial markets, research on cryptocurrency pricing remains fragmented.

2.4. Impact of consumer confidence on financial markets

Consumer confidence is a measure of the degree of optimism or pessimism expressed by consumers regarding the current state of the economy, with this reflected in their saving and spending activities which influence changes in the economy (James, 2021). Hollanders and Vliegenthart (2011) highlighted that consumer sentiment regarding economic activities, as derived from the media, is associated with consumer confidence, with negative news having a dampening effect. As demonstrated by Lymperopoulos et al. (2010), the level of consumer confidence regarding the overall economic situation can exert a significant influence on consumer purchase intentions. Han et al. (2022) confirmed a positive correlation between consumer confidence and the intention to make environmentally friendly purchases. The connection arises as consumers with a positive view of the current economy are more motivated to engage in green consumption.

Many studies have considered the monthly CCI score as the measure of consumer confidence (Islam & Mumtaz, 2016; Mazurek & Mielcová, 2017). The Conference Board's CCI is based on the Consumer Confidence Survey which measures consumer attitudes and confidence regarding their financial prospects (Ganti, 2023).

This index serves as a predictor of future household consumption and saving, based on survey responses from households regarding their expectations about various aspects, including their anticipated financial situation, general economic sentiment, unemployment outlook, and ability to save (OECD, 2023b).

2.4.1. Association between consumer confidence and stock market

Jansen and Nahuis (2003) explored the short-run relationship between stock market returns and consumer confidence across 11 European countries from 1986 to 2001. Their findings indicated a positive relationship between stock market returns and consumer confidence in most of these countries. Similarly, Lemmon and Portniaguina (2006) demonstrated that consumer confidence is a significant predictor of returns on small stocks and stocks with low institutional ownership during their 25-year study period. They attributed this to the impact of changes in consumer sentiment on spending behaviour, which in turn affects expectations of corporate profits. In addition, Chen (2011) confirmed a positive and significant relationship between consumer confidence and contemporaneous stock returns. This relationship is explained by the fact that when investors anticipate an economic downturn, they tend to become more cautious about the future performance of the stock market. Hence, they sell their stocks, causing the market to fall (Whaley, 2009). This view was supported by Sum (2014), who demonstrated that both business and consumer confidence positively impact stock market returns.

While previous studies have confirmed a positive association between consumer confidence and stock returns, the relationship is not universally positive. Ciner (2014) identified a time-varying relationship, where high consumer confidence was associated with higher short-term returns but negative returns in the medium term. Additionally, Ferrer et al. (2016) examined the correlation between the CCI and stock market returns using data from Europe and US, focusing on the post-dotcom bubble correction of 2000–2002 and the 2007–2009 Global Financial Crisis. Their findings indicated that the relationship between consumer confidence and stock returns was not consistently positive. Similarly, Koy and Akkaya (2017) proposed an inverse correlation between the CCI and capital market returns during both recession and economic expansion.

2.4.2. Association between Consumer Confidence Index and economic activities

Dees and Brinca (2013) revealed that the CCI effectively predicts household consumption, even when taking into account economic fundamentals. Islam and Mumtaz (2016) confirmed the presence of a long-term relationship between the CCI and economic growth, particularly within European countries. Kilic and Cankaya (2016) reported a robust association between the CCI and factors such as industrial production, inventories, personal consumption expenditure and housing market variables. Additionally, Mazurek and Mielcová (2017) asserted that the CCI could serve as a reliable predictor of GDP in the United States

(US). Similarly, Acuña et al. (2020) demonstrated a positive correlation between the CCI and subsequent consumption growth.

2.4.3. Importance of Consumer Confidence Index in cryptocurrency market

Firstly, the Consumer Confidence Index (CCI) serves as a pre-eminent indicator of aggregate demand and overall economic well-being (Mazurek & Mielcová, 2017). Prior studies have demonstrated that the CCI has a close correlation with economic fundamentals, such as the unemployment rate (Mandal & McCollum, 2013); GDP growth (Islam & Mumtaz, 2016); stock market performance (Chen, 2012); and consumer growth (Malovaná et al., 2021). Thus, it is reasonable to assume that investors regard the CCI as a key proxy for investment in the cryptocurrency market. Secondly, the CCI offers insights into consumers' perceptions of their personal financial situations which often transcend the realm of economic fundamentals (Acuña et al., 2020). Empirical studies have suggested that cryptocurrency returns can be driven by investor sentiment (Akyildirim et al., 2021; Naeem et al., 2021). Thirdly, Koy and Akkaya (2017) suggested that consumer confidence plays an important role in shaping the individual's investment-related judgements when making investment decisions. This suggests that consumer confidence could potentially shape the investment choices of individuals in the cryptocurrency market.

2.5. Impact of Composite Leading Indicator on financial markets

The OECD constructs the CLI using economic time series that exhibit leading relationships with the business cycle, particularly at turning points (Cevik, Dibooglu, & Kutan, 2013). The CLI combines several individual leading indicators that have proven to be statistically relevant for analysing and forecasting significant macroeconomic indicators such as GDP and industrial production (Kľúčik & Haluška, 2008). Furthermore, previous studies have suggested that it is not reliable to use only one economic indicator for short-term forecasting as it may produce false signals (Atabek et al., 2005). The changes in the CLI can provide more promising forecasting for economic activities than would be the case for averaging many single indicators (Jansen et al., 2016).

2.5.1. Relationship between Composite Leading Indicator and stock market

Gulen et al. (2011) investigated the time variation of the expected value premium using a two-stage Markov switching model. They found that the monthly change of the US CLI could serve as an alternative instrument with a significant impact on time-varying expected stock returns. Topcu and Unlu (2013) examined the association between the CLIs and share prices in emerging markets. The results highlighted the importance of the component structure of the CLI in determining its effectiveness in investors' decisions. Prasetyo and Asianto (2020) investigated the impact of many indicators on the Indonesia Stock Exchange. Their analysis showed that the OECD's CLI moved ahead of movement in the main index. In addition, indicators from the Nasdaq stock market, New York Stock Exchange (NYSE) and German Stock Index were the most optimal CLIs in the Indonesia Stock Exchange, in comparison to the miscellaneous industry sectors. In addition, Long, Demir, et al. (2022) examined whether investors adequately accounted for changes in leading economic indicators within the stock market. Their results revealed that monthly changes in the CLI were positively associated with future stock returns, based on six decades of data from 39 countries. This finding highlights the significant role of leading economic indicators in forecasting future business conditions. Gulen et al. (2011) investigated time variations of the expected value premium using a two-state Markov switching model. The findings revealed that the monthly index for the US CLI could be an alternative instrument with a significant effect on time-varying expected stock returns. In terms of cryptocurrencies, previous studies have highlighted that cryptocurrencies could be considered as alternative assets in financial markets (Bianchi, 2020; Pele et al., 2023).

2.5.2. Relationship between Composite Leading Indicator and economic activities

Korte (2012) assessed the forecasting power of confidence indicators for the Russian economy and found that both the CLI and business confidence indicator performed best in terms of information criterion and forecasting accuracy. Cevik, Dibooglu and Kenc (2013) developed a Financial Stress Index for the Turkish economy from 1997 to 2010 and compared it to the CLI. Their results showed that a decrease in the CLI preceded significant slowdowns in economic activity. Jansen et al. (2016) conducted a systematic comparison of the short-term forecasting abilities of 12 statistical models using three CLI from the OECD, finding that changes in the CLI were more effective in forecasting GDP than averaging multiple single indicators. Corsetti et al. (2012) explored how government spending effect varied with the economic environment in a panel of OECD countries and found a significant correlation between the CLI and fiscal policy. Ojo et al. (2023) evaluated the OECD's CLI using the continuous wavelet transform and found it to be a useful leading indicator for the Industrial Production Index and forecasting the unemployment rate, though it performed poorly in forecasting GDP growth. Lastly, Larch et al. (2021) identified a negative association between discretionary fiscal policy and changes in the CLI.

2.5.3. Importance of Composite Leading Indicator in cryptocurrency market

The current research draws on existing literature to underscore the CLI's role as a leading indicator for economic performance. The CLI has been shown to be more effective in forecasting GDP changes compared to individual indicators (Jansen et al., 2016). Ojo et al. (2023) demonstrated the CLI's utility as a leading indicator for the Industrial Production Index and its applicability in forecasting unemployment rates. Notable findings included a positive correlation between the CLI and the duration of economic expansion and that a decrease in CLI values served as a precursor indicator of economic slowdown (Cevik, Dibooglu, & Kutan, 2013). Investors tend to invest more money in the financial market when the economy is in an expansionary phase than when it is not (Campiglio, 2016). Hence, investors may consider the CLI as the driver of economic activities including investment in the cryptocurrency market. Cryptocurrencies, deemed alternative assets, are subject to the influence of investor perceptions, as indicated in research by Fang et al. (2020). Furthermore, the CLI is published monthly and produced in a narrow time frame, performing well in both tracking and forecasting economic activities (Long, Zaremba, et al., 2022). Investors can adjust their portfolios in the cryptocurrency market according to this leading economic indicator. The lead time of the CLI allows policy makers time in which to react and formulate efficient policies for the cryptocurrency market.

Numerous studies have emphasised the significant relationship between the CLI and financial markets. Mo et al. (2018) highlighted a noteworthy negative association between the CLI and the volatility of commodity futures. Larch et al. (2021) demonstrated a negative connection between change in the CLI and discretionary fiscal policy. Chung et al. (2012) found evidence of a significantly negative relationship between changes in the CLI and stock returns, suggesting predictive power. Similarly, Celebi and Hönig (2019) indicated delayed impacts of the CLI on stock returns, aligning with the notion that various economic indicators influenced stock returns. Based on the above discussion, the CLI was negatively correlated with financial assets.

Empirical studies have demonstrated that if a financial market is not fully efficient, underreaction to macroeconomic news may skew its asset's returns. Hafner (2020) posited that cryptocurrencies serve as alternative assets, with their market behaviour characterised by volatility, with this challenging the efficient market hypothesis (Li, Zhang, et al., 2020). Similarly, Brauneis and Mestel (2018) demonstrated that cryptocurrencies become less efficient as liquidity increases, supporting the notion of inefficiency in the cryptocurrency market. Although the CLI, being a leading indicator, may offer valuable information regarding potential shifts in market sentiment and risk appetite from the traditional financial market, the cryptocurrency market may not adequately reflect the information embedded in the CLI, potentially leading to negative cryptocurrency returns.

Previous literature has highlighted that the post-GFC period has been marked by a shortage of safe assets such as gold (Klein, 2017). Cryptocurrencies, with their hedging and safe-haven properties, have been likened to digital gold (Henriques & Sadorsky, 2018; Som & Kayal, 2022). Jiang et al. (2021) found that cryptocurrencies serve as effective hedging assets during extreme financial market crises, such as the COVID-19 pandemic. Similarly, Bouri et al. (2020) evaluated the hedging and safe-haven properties of cryptocurrencies and found that they effectively mitigated fluctuations in the S&P 500 Index and across 10 equity sectors, helping investors offset equity losses. Regarding the CLI, Castro (2010) proposed that changes in the CLI could predict economic expansions or contractors, demonstrating a positive correlation between the CLI and economic activities. This view is further supported by Cevik, Dibooglu and Kutan (2013), who noted that a decrease in the CLI value signals an economic slowdown.

2.6. Chapter conclusion

In summary, while previous research has identified numerous determinants of cryptocurrency pricing and returns in existing financial markets, this area remains fragmented. This study aims to address this gap by systematically reviewing and synthesizing the factors that influence cryptocurrency pricing and returns. Additionally, although the impacts of consumer confidence and the CLI on economic activities have been explored, no study, to the best of the author’s knowledge, has examined their effects specifically on the cryptocurrency market and cryptocurrency returns. This thesis seeks to fill this gap by investigating the influence of consumer confidence and the CLI on cryptocurrency returns.

CHAPTER 3: PAPER 1 – A SYSTEMATIC LITERATURE REVIEW ON THE DETERMINANTS OF CRYPTOCURRENCY PRICING

This chapter has been published as:

Peng, S., Prentice, C., Shams, S., & Sarker, T. (2023). A systematic literature review on the determinants of cryptocurrency pricing. *China Accounting and Finance Review*, ahead-of-print. https://doi.org/10.1108/CAFR-05-2023-0053. (ABDC Ranking: A).

3.1. Introduction

This chapter introduces the first paper of the current thesis, which is "A systematic literature review on the determinants of cryptocurrency pricing". The chapter provides an overview of its contents in Section 3.1. Following the University of Southern Queensland guidelines, each page of the article is uploaded as a photo, beginning with the title and abstract page and ending with Appendix 1. The article itself starts with an introduction in Section 1, followed by Section 2, which is the method. Section 3 presents the research results, while Section 4 discusses the study and its results. The study's implications are presented in Section 5, while Section 6 presents the study's limitations and future research directions.

3.2 Published paper

The current issue and full text archive of this journal is available on Emerald Insight at:
https://www.emerald.com/insight/1029-807X.htm

A systematic literature review on the determinants of cryptocurrency pricing

Sanshao Peng, Catherine Prentice, Syed Shams and Tapan Sarker
School of Business, University of Southern Queensland – Springfield Campus, Springfield Central, Australia

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Abstract

Purpose – Given the cryptocurrency market boom in recent years, this study aims to identify the factors influencing cryptocurrency pricing and the major gaps for future research.

Design/methodology/approach – A systematic literature review was undertaken. Three databases, Scopus, Web of Science and EBSCOhost, were used for this review. The final analysis comprised 88 articles that met the eligibility criteria.

Findings – The influential factors were identified and categorized as supply and demand, technology, economics, market volatility, investors' attributes and social media. This review provides a comprehensive and consolidated view of cryptocurrency pricing and maps the significant influential factors.

Originality/value – This paper is the first to systematically and comprehensively review the relevant literature on cryptocurrency to identify the factors of pricing fluctuation. This research contributes to cryptocurrency research as well as to consumer behaviors and marketing discipline in broad.

Keywords Cryptocurrency, Systematic literature review, Influential factors

Paper type Literature review

Introduction

In recent years, cryptocurrencies have attracted more attention in the wider community, with market capitalization reaching a high level (Bouri, Shahzad, & Roubaud, 2019; Fry, 2018). Cryptocurrency refers to a digital payment system that operates similarly to the standard monetary currency system and allows users to send and receive virtual payments outside of traditional financial institutions. These virtual payments offer low transaction costs and a peer-to-peer system (Kim, Bock, & Lee, 2021). The decentralization of cryptocurrencies has been a key factor in the enhancement of user privacy and provides various levels of anonymity (Sarwar, Nisar, & Khan, 2019). Bitcoin was the first decentralized blockchain-based cryptocurrency and continues to be the most well-known and widely used cryptocurrency in the market (Li & Wang, 2017). A blockchain is a distributed ledger technology that allows data to be recorded and shared across a network of computers or nodes. Each block in the blockchain contains a list of transactions, and once a block is added to the chain, it cannot be altered. The immutability of records is a key feature of blockchain technology and provides a high level of trust and security (Ferguson, 2018). Blockchain provides users with the promise of transaction trust and transparency. Blockchain technology, as demonstrated by cryptocurrency, is also widely considered to be a significant innovation with profound implications for the future of finance (Liu, Tsyvinski, & Wu, 2022).

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While cryptocurrency innovation brings benefits and potential advantages, it also poses significant challenges and issues for traditional financial systems. This is because cryptocurrencies diverge from traditional financial assets in their value determination. Instead of being reliant on tangible assets or governments, the value of cryptocurrencies is based on specific algorithms that record transactions within the underlying blockchain networks (Corbet, Lucey, Urquhart, & Yarovaya, 2019). Yermack (2015) highlighted the prevalence of speculative price bubbles in the cryptocurrency market. These bubbles arise from swift and sometimes irrational increases in cryptocurrency prices, often not supported by underlying fundamentals. Thus, the unique nature of cryptocurrencies, their decentralized structure and the influence of speculative factors pose distinct challenges for investors and policymakers. Understanding these characteristics is crucial when assessing the value and potential risks associated with cryptocurrency market investment.

Studies have shed light on the factors influencing the price of Bitcoin and other more notable cryptocurrencies. In the case of Bitcoin, its decentralized system and a unique combination of anonymous miners and profit-driven incentives have been the primary drivers of innovation. This innovation has encouraged investors to participate freely in the Bitcoin market and has motivated researchers to identify the various factors that affect returns (Leshno & Strack, 2020). Van Wijk (2013) investigated the influence of macroeconomic factors on bitcoin price and suggested that factors such as the stock market index, exchange rates and oil prices impacted Bitcoin's value. Polasik, Piotrowska, Wisniewski, Kotkowski, and Lightfoot (2015) observed that the Bitcoin price experienced exponential growth in July 2010, which was attributed to increased trading against the US dollar. Bouoiyour and Selmi (2015) found that the long-term price increase in Bitcoin was influenced by a growing demand for Bitcoin trading and exchange transactions. Kristoufek (2013) indicated that the increased interest, as measured by the number of Google searches for Bitcoin, had a positive impact on Bitcoin's price. The prices of common cryptocurrencies such as Bitcoin, Ethereum, Dash, Litecoin and Monero were significantly affected by factors related to the overall crypto market, the attractiveness of individual cryptocurrencies and movement in the S&P 500 Index (Sovbetov, 2018). Technological factors were also an important determinant influencing Bitcoin price in the early market (Li & Wang, 2017).

Studies have provided many determinants of cryptocurrency pricing within the existing financial market; however, research on cryptocurrency pricing is rather fragmented. This study systematically reviews the literature and identifies and synthesizes the factors that influence cryptocurrency pricing. This review contributes to the literature by providing a consolidated view of cryptocurrency pricing and systematically maps significant influential factors. This review also highlights the different research methods used in cryptocurrency pricing studies and identifies those commonly applied. This review provides a depth of understanding and a more comprehensive discussion of the determinants of cryptocurrency prices. This consolidation of the literature will inform investors and investment managers about the market dynamics of cryptocurrencies. Thus, it will guide the construction of more comprehensive cryptocurrency price prediction models and trading decisions within the cryptocurrency market.

The following presents the methodology, including the procedure used to conduct the systematic literature review, followed by the results of the review. The study highlights research gaps and offers direction for future research. The conclusion presents the implications of the study, and limitations are acknowledged.

Method

To identify the influential factors of cryptocurrency pricing, this systematic literature review utilized the Preferred Reporting Items for Systematic Review and Meta-Analyses (PRISMA) approach. PRISMA is an evidence-based approach for reporting and evaluating the literature

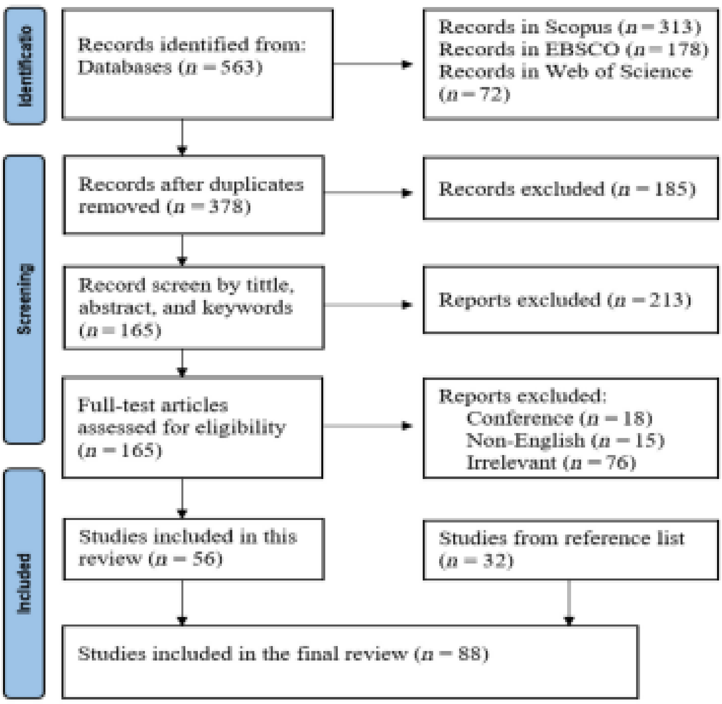
(Saeed, Paolo, & Sarah NR, 2019) and is regarded as an appropriate methodology for reproducing data, especially when compared to narrative literature reviews (Rother, 2007).

Keywords and databases

This review followed a predetermined search strategy using the terms ("cryptocurrency" OR "encryption currency" OR "digital money" OR "digital currency") AND ("factor" OR "determine") AND "(price)". Three databases, Scopus, Web of Science and EBSCOhost, were used as most relevant studies can be sourced from these databases (Akyildirim, Aysan, Cepni, & Darendeli, 2021; Liu *et al.*, 2022; Mohamed, 2021). To maintain a consistent standard for analysis and to ensure high-quality findings, this review only considered peer-reviewed journal articles which provided reliable and accurate data (Li *et al.*, 2019). Articles published in English were chosen. This review included all relevant studies published before August 2022 when the search was conducted. The review followed the procedure described in the PRISMA checklist (Tricco *et al.*, 2018).

Screening

Figure 1 presents the flow chart of the systematic literature review using the PRISMA approach. The initial search yielded a total of 563 articles: Scopus (313), Web of Science (72) and EBSCOhost (178). EndNote X9 software was utilized to screen the articles for duplication, with 185 articles discarded as duplicates. A further 213 articles were taken out after initial screening based on a comprehensive review of titles and abstracts. The remaining 165 articles were assessed for eligibility. In this assessment, 76 articles did not explicitly examine the factors of cryptocurrency pricing and were excluded. A further 18 peer-reviewed journal articles were removed as they were conference papers, and 15 articles were excluded as they were not in English. A total of 56 articles met the eligibility criteria for final analysis. The review conducted a thorough examination of the reference lists, which resulted in the inclusion of an additional 32



Source(s): Figure created by the authors

Figure 1. Flow chart of systematic literature review

articles. This resulted in 88 articles being selected for the review. This approach ensured the inclusion of a diverse and relevant body of literature for the review.

Results

Publishing trends and currency focus

Much of the literature focused on Bitcoin, suggesting that it remains the most popular and widely researched cryptocurrency. As a pioneer and the first cryptocurrency, Bitcoin has received significant attention from researchers, investors and the general public (Wang & Vergne, 2017). The earliest article on cryptocurrency pricing was published in 2014, indicating that research remains in the early stages of development. As cryptocurrencies gained traction and public attention over the last decade, academic interest in pricing dynamics also grew. The upward trend in the number of published studies on cryptocurrency pricing reflects increasing interest and recognition of the importance of this research topic. The development of the research is presented in Figure 2.

Journal outlets

Studies of cryptocurrency pricing have been published in journals across a wide range of disciplines, with a primary focus on finance. Table 1 highlights the 54 different journals that have published cryptocurrency pricing studies. The spread of interest indicates recognition of the importance of this research area. *Finance Research Letters* published a total of 27 articles, followed by the *PLoS One* journal (4), *Financial Innovation* (2), *Journal of Risk and Financial Management* (2), *Journal of Behavioural Finance* (2), *Studies in Economics and Finance* (2) and *International Review of Financial Analysis* (2). The distribution of the remaining 47 articles across journals from various disciplines highlights the wide-ranging interest and the multi-faceted nature of cryptocurrencies. The journals covered disciplines such as electrical energy, technological innovation, social media, investor sentiment and macroeconomic policy.

Countries

Geographic analysis considered the location of data collection of the studies included in the review. An understanding of the geographic distribution of research and how different regions

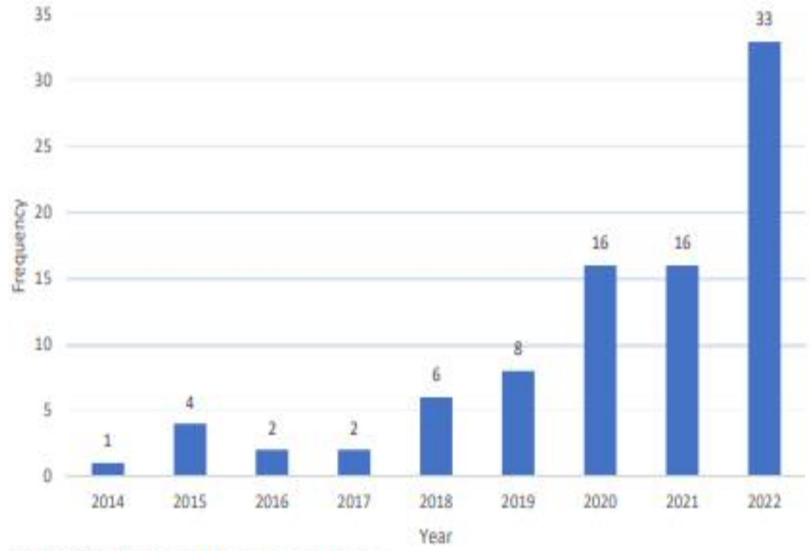


Figure 2. Number of articles published between 2014 and August 2022

Source(s): Figure created by the authors

Table 1. Article distribution by journal and date of publication

Journal	Number of articles	2014	2015	2016	2017	2018	2019	2020	2021	Jan-Aug 2022
Finance Research Letters	*27*					*1*		*1*	*1*	*24*
Journal of Finance	*1*									*1*
PLoS One	4		1		1	1			1	
Journal of Network Theory in Finance	1						1			
International Review of Economics and Finance	1								1	
The Quarterly Review of Economics and Finance	1								1	
Mathematical Social Science	1									1
American Economic Review: Insight	1							1		
The North American Journal of Economics and Finance	1								1	
Economic Modelling	1							1		
Journal of The Royal Society Interface	1	1								
International Journal of Electronic Commerce	1		1							
Applied Economics	1		1							
Information Systems and e-Commerce Management	1			1						
Decision Support Systems	1			1						
Financial Innovation	2				1			1		
Journal of Risk and Financial Management	2					1		1		
Procedia Computer Science	1						1			
Malaysian Journal of Economic Studies	1						1			
Investment Management and Financial Innovations	1						1			
Eurasian Economic Review	1					1				
ACM SIGMETRICS Performance Evaluation Review	1					1				
International Journal of Scientific and Technology Research	1							1		
Frontiers in Artificial Intelligence	1							1		
Journal of Management Analytics	1							1		
EPJ Data Science	1							1		

(continued)

Table 1.

Journal	Number of articles	2014	2015	2016	2017	2018	2019	2020	2021	Jan-Aug 2022
Financial Studies	1									
								1		
The European Journal of Finance	1									
								1		
Journal of Industrial and Business Economics	1						1			
Resources Policy	1									
								1		
Economic Letters	1						1			
Annals of Operations Research	1						1			
Mathematics	1									
								1		
Research in International Business and Finance	1						1			
Journal of Information Security and Applications	1									
								1		
Journal of Energy Markets	1						1			
Journal of Behavioural Finance	2								1	
								1		
Entropy	1								1	
Journal of Economics and Finance	1								1	
DLSU Business and Economic Reviews	1								1	
Organizations and Markets in Emerging Economies	1					1				
Journal of Behavioural and Experimental Finance	1					1				
Expert Systems with Applications	1					1				
Studies in Economics and Finance	2					1	1			
Journal of Business Research	1						1			
Review of Behavioural Finance	1						1			
Applied Economics Letters	1						1			
Pamukkale University Journal of Social Sciences Institute	1									1
International Review of Financial Analysis	2						1			1
Journal of Computer Information Systems	1						1			
Computational Economics	1						1			
Journal of Risk and Financial Management	1									
								1		
Annals of Economics and Finance	1		1							
Journal of Banking and Finance	1									
									1	

Source(s): Table created by the authors or countries contribute to the body of knowledge of cryptocurrency pricing is also included. The 88 studies were conducted in 18 different regions, with Europe accounting for 29 studies; followed by the United Kingdom (12), China (12), the United States (9), United Arab Emirates (4), Russia (3), India (3), Canada (3), Australia (3) and South Korea (2) (see Table 2). The imposition of restrictions on cryptocurrency trading by the Chinese government in September 2017 had an impact on cryptocurrency pricing research (Chen & Liu, 2022). However, despite the regulatory challenges, 12 studies were conducted in China and contributed to the literature.

Research methods

Table 3 presents the research methods used to analyze the determinants of cryptocurrency pricing. The most used model was the vector autoregression model (9), followed by the autoregressive distributed lag model (6), generalized autoregressive conditional heteroskedasticity model (5), three-factor model (4), the fixed-effect model (3), the wavelet coherence analysis (3), the ordinary least squares (L.S.) regression (2), the vector error correlation (2), the asset pricing model (2), the cost of production model (2) and the text analytic approach (2). The vector autoregression model is a statistical model used to reveal correlations between variables as they change over time (Garcia, Tessone, Mavrodiev, & Perony, 2014) and generates a vector error correction model (Hakim das Neves, 2020). This model has achieved better performance in simulating past Bitcoin trading prices, in contrast to traditional autoregression models and Bayesian regression models (Ibrahim, Kashef, Li, Valencia, & Huang, 2020).

Cryptocurrency pricing factors

The current review identified and categorized the factors that influence cryptocurrency pricing. These factors include (i) supply and demand, (ii) technology, (iii) economics, (iv) market volatility, (v) investors' attributes and (vi) social media, where the categories are not mutually exclusive. The following subsections present a discussion of each category.

Location	Number of articles	2014	2015	2016	2017	2018	2019	2020	2021	Jan-Aug 2022
USA	9						1	2	2	4
Europe	29	1	2	1		4	1	6	2	11
UK	12		1			2	3	1	1	4
Canada	3				1			1	1	
China	12			1	1			1	3	6
South Korea	2							1	1	
Taiwan	1									1
UAE	4						1	1	1	1
Russia	3						1	1		1
Brazil	1							1		
India	3							1	1	1
Philippines	1								1	
Indonesia	1								1	
Australia	3								1	2
Tunisia	1						1			
Japan	1									1
Bangladesh	1									1
Lebanon	1								1	

Source(s): Table created by the authors

Table 2. Article distribution by country and date of publication

Theory/Model	Number of articles	2014	2015	2016	2017	2018	2019	2020	2021	2022
Vector autoregression analysis	9	*		*			*	***	*	**
Wavelet coherence analysis	3		*			*				*
Autoregressive distributed lag model	6		*	*		*	*			**
Ordinary least squares regression	2		*						*	*
Long short-term memory model	3					*		*		*
Vector error correlation	2				*				*	
Text analytic approach	2							*	*	
Tobit estimation approach	1		*							
Modular Integrated Distributed Analysis System	1									*
Least Absolute Shrinkage and Selection Operator	2					*				*
Generalized AutoRegressive Conditional Heteroskedasticity	5								*	****
Dynamics Equi-correlation Model	2								**	
Overlapping generations model	1									*
Axiomatic approach	1							*		
Impossibility theorem	1							*		
Machine learning approach	1									*
Dynamic Bayesian model	1									*
Smooth Transition Conditional Correlation Model	1									*
Quantile regression	1									*
Quantile-on-quantile regression	2									**
Rolling window estimations	1									*
Augmented version of Barro's model	1		*							
Comparative analysis	1						*			
Artificial recurrent neural network model	1							*		
Bayesian structural time series approach	1					*				
Autoregressive integrated moving average model	2							*	*	

Table 3.
Main theories or models in studies

(*continued*)

Theory/Model	Number of articles	2014	2015	2016	2017	2018	2019	2020	2021	2022
Fourier KPSS unit root test	1							*		
Asymmetric nonlinear cointegration approach	1							*		
Negative coefficient of skewness analysis	1						*			
Markov regime-switching model	1						*			
Asset pricing model	2						*			*
Robust least squares (L.S.) method	1								*	
Sentiment index model	1							*		
Corpus linguistics approach	1							*		
Value-at-risk analysis	1								*	
Garman–Klass analysis	1								*	
Systematic review	1					*				
Quantile regression approach	1									*
Linear discriminant analysis	1								*	
Autoregressive conditional jump intensity model	1									*
Structural break analysis	1									*
Heterogeneous autoregressive model	1									*
Random-effect analysis	2				*					*
Deep learning integration method	1									*
Portfolio analysis	2						*		*	
Cost of production model	2							*	*	
Fixed-effect analysis	3				*				*	*
Three-factor model	4							*	*	**

Source(s): Table created by the authors

Table 3.

Supply and demand

Studies in Table 4 have shown that the basic principles of supply and demand are fundamental factors which play a crucial role in determining cryptocurrency prices (Ciaian, Rajcaniova, & Kancs, 2016; Lamothe-Fernández, Alaminos, Lamothe-López, & Fernández-Gámez, 2020). Bitcoin was the most cited currency. The supply of Bitcoins has been asymptotically capped at 21 million (Polasik *et al.*, 2015) and is governed by a special cryptographic algorithm that determines the frequency, time and amount of Bitcoin supply (Ibrahim *et al.*, 2020; Sauer, 2016). While the supply of Bitcoin works as a standard supply, the growth of supply leads to downtrend pressures being exerted on its price. This means that a negative relationship exists between the supply of Bitcoin and its price (Ciaian *et al.*, 2016; Dubey, 2022; Kristoufek, 2015). However, it has been argued that growth in the cryptocurrency supply can drive up the price, based on a random-effect and fixed-effect analysis (Wang & Vergne, 2017), the rationale being that new cryptocurrencies appear to be more attractive than older competitors.

Although the literature provides evidence that the supply of cryptocurrency has a significant effect on the price, demand-side drivers have a stronger impact on cryptocurrency prices (Ciaian *et al.*, 2016, Ciaian, Rajcaniova, & Kancs, 2016). An increase in the number of Bitcoins available for

No	Authors	Location	Methodology	Influential factor	Relationship	Currency types
1	Kristoufek (2015)	UK	Wavelet coherence analysis	Bitcoin supply	Negative	Bitcoin price
2	Ciaian *et al.* (2016)	Europe	Vector autoregressive model	Bitcoin supply	Negative	Bitcoin price
3	Dubey (2022)	India	Random-effect regression model	Bitcoin supply	Negative	Bitcoin price
4	Wang and Vergne (2017)	Canada	Random-effect and fixed-effect analysis	Cryptocurrency supply	Positive	Cryptocurrency returns
5	Polasik *et al.* (2015)	Europe	Ordinary least squares and tobit estimation approaches	Transaction demand	Positive	Bitcoin price
6	Ciaian *et al.* (2016)	Europe	Augmented version of Barro's model	Transaction demand	Positive	Bitcoin price
7	KaraÖMer (2022)	Europe	Autoregressive distributed lag model	Transaction demand	Positive	Bitcoin price
8	Polasik *et al.* (2015)	Europe	Ordinary least squares and tobit estimation approaches	Bitcoin payment	Positive	Bitcoin price
9	Będowska-Sójka *et al.* (2021)	Europe	Garman–Klass analysis	Other cryptocurrencies	Positive	Bitcoin returns
10	Bouri *et al.* (2021)	Lebanon	The dynamic equi-corelation model	Transaction demand	Positive	Cryptocurrency returns
11	Nakagawa and Sakemoto (2022)	Japan	The machine learning approach	Transaction demand	Positive	Cryptocurrency returns
12	Liu and Tsyvinski (2021)	USA	The Capital Asset Pricing Model and Fama–French three-factor model	Transaction demand	Positive	Cryptocurrency returns

Source(s): Table created by the authors

Table 4.
Fundamental factors

transactions may result in Bitcoin price volatility and a massive speculative price bubble (Ciaian *et al.*, 2016). The growth of a transactional need for Bitcoin leads to an increase in price (KaraÖMer, 2022). For example, Bitcoin trading against the US dollar has increased exponentially since July 2010 (Polasik *et al.*, 2015). Additionally, Bitcoin as a payment method has had a positive effect on Bitcoin price (Polasik *et al.*, 2015) as many people in developing countries have limited access to traditional bank transfer systems (Schuh & Stavins, 2011). Network factors including wallet users, payment accounts and transaction accounts were the main demand for cryptocurrencies and contributed to the volatility of their returns (Liu & Tsyvinski, 2021; Nakagawa & Sakemoto, 2022). Bouri, Vo, and Saeed (2021) highlighted the importance of trading volume in shaping the dynamics of the cryptocurrency market and its impact on returns and correlations. A Garman–Klass analysis also demonstrated that the emergence of other cryptocurrencies positively affected Bitcoin returns (Będowska-Sójka, Kliber, & Rutkowska, 2021). Although Bitcoin is governed by a cryptographic algorithm, its usage in transactions, supply and price level are consistent with standard economic theory, especially the quantity theory of money (Kristoufek, 2015).

Technology

As can be seen in Table 5, the literature suggests that Bitcoin mining is one of the main factors driving the supply and pricing of Bitcoin (Bouoiyour & Selmi, 2016; Garcia *et al.*, 2014; Ibrahim *et al.*, 2020). Bitcoin supply is determined by a mathematical algorithm for blockchain hashing (Ibrahim *et al.*, 2020), where any attempt to modify the amount of issuance is rejected

No	Authors	Location	Methodology	Influential factor	Relationship	Currency type
1	KaraÖMer (2022)	Europe	Autoregressive distributed lag model	Hash rate	Positive	Bitcoin returns
2	Kjaerland *et al.* (2018)	Europe	Autoregressive distributed lag model	Hash rate	N/A	Bitcoin returns
3	Fantazzini and Kolodin (2020)	Russia	Cost of production model	Hash rate	N/A	Bitcoin price
4	Li and Wang (2017)	China	Autoregressive distributed lag model	Mining difficulty	Positive	Bitcoin price
5	Kristoufek (2015)	UK	Wavelet coherence analysis	Mining difficulty	Positive	Bitcoin price
6	Guizani and Nafti (2019)	Tunisia	Autoregressive distributed lag model	Mining difficulty	Positive	Bitcoin price
7	Meynkhard (2019)	Russia	Comparative analysis	Halving	Positive	Cryptocurrency price
8	Ibrahim *et al.* (2020)	Canada	Vector autoregression model	Halving	Positive	Bitcoin price
9	Fantazzini and Kolodin (2020)	Russia	Cost of production model	Halving	Positive	Bitcoin price
10	Sapkota and Grobys (2020)	Europe	Portfolio analysis	Mining cost	Positive	Cryptocurrency price
11	Chico-Frias (2021)	Philippines	Cost of production model	Mining cost	Positive	Cryptocurrency price
12	Baldan and Zen (2020)	Europe	Vector autoregression model	Mining cost	N/A	Bitcoin price
13	Chen (2021)	USA	Vector error correction model	Blockchain technology	Positive	Bitcoin price
14	Kim *et al.* (2021)	South Korea	Autoregressive integrated moving average model	Blockchain information	Positive	Ethereum price
15	Wang and Vergne (2017)	Canada	Random-effect and fixed-effect analysis	Other technological factors	Positive	Cryptocurrency returns
16	Chowdhury *et al.* (2022)	USA	Quantile vector autoregressive model	The consensus protocol technologies	Positive	Cryptocurrency returns

Source(s): Table created by the authors

Table 5.
Technological factors

(Nelson, 2018). The term hash rate refers to the speed of computer processing power in the Bitcoin network (Lopatin, 2019). There are indications that growth in the hash rate has a significant and positive effect on Bitcoin returns (KaraÖMer, 2022). However, Kjaerland, Khazal, Krogstad, Nordstrom, and Oust (2018) argued that the hash rate is an irrelevant technological factor for modeling Bitcoin return dynamics, the reason being that the underlying code makes the supply of Bitcoins deterministic, which contrasts with previous studies. This finding was supported by Fantazzini and Kolodin (2020) who demonstrated that the hash rate had no direct effect on the Bitcoin price from the energy efficiency effect of Bitcoin mining equipment, based on the cost of production model.

Mining difficulty is also an important determinant influencing the supply and pricing of Bitcoin (Kristoufek, 2015). The term "mining difficulty" refers to a measurement unit used in the process of Bitcoin mining to maintain the speed of block generation and the hash rate criterion (Zhang, Qin, Yuan, & Wang, 2018). The unique Bitcoin mining process has a significant effect on the Bitcoin price (Kristoufek, 2015). In other words, an increase in mining difficulty leads to an increase in the Bitcoin price (Guizani & Nafti, 2019). This is in line with Li and Wang (2017) who used the autoregressive distributed lag model to confirm that the growth of mining difficulty would increase the Bitcoin price in the early market. The rationale for this is that the short-term adjustment in the Bitcoin price is the response to the growth of mining difficulty, although mining difficulty has a weak impact on the Bitcoin price in the long term (Guizani & Nafti, 2019).

Halving is another technical factor that influences the supply and pricing of Bitcoin (Ibrahim *et al.*, 2020; Meynkhard, 2019). The term Bitcoin halving refers to a process in which the reward for mining Bitcoin transactions is reduced by half (Ramos & Zanko, 2020). Miners can earn new Bitcoins as remuneration for their work, but the block subsidy will decrease by 50% every four years. Reducing the supply of Bitcoins every four years leads to the growth of Bitcoin capitalization (Fantazzini & Kolodin, 2020). Ramos and Zanko (2020) demonstrated that the first halving occurrence caused increases in the Bitcoin price, market capitalization and average transaction fees. Meynkhard (2019) utilized comparative analysis to show that halving positively affected the cryptocurrency price.

The theoretical literature has considered the cost of cryptocurrency mining as a crucial factor that influences cryptocurrency pricing. Sapkota and Grobys (2020) employed portfolio analysis to explore the relationship between mining cost and cryptocurrency pricing. Results indicated that the mining cost from an energy aspect positively impacted cryptocurrency pricing. Chico-Frias (2021) confirmed this impact by demonstrating that mining costs were positively related to cryptocurrency pricing, as Bitcoin mining consumes electricity (Lamothe-Fernández *et al.*, 2020). Nevertheless, Baldan and Zen (2020) argued that profits and costs were not the factors driving Bitcoin pricing. One possible explanation is that there is insufficient evidence to support the association between Bitcoin price and mining costs. Liu and Tsyvinski (2021) confirmed that electricity and computing costs (mining costs) did not drive cryptocurrency returns. However, transaction costs can be an important determinant driving cryptocurrency pricing (Crettez & Morhaim, 2022) because the impact of volatility in cryptocurrency pricing can be driven by the transaction costs that individuals incur when purchasing cryptocurrency.

Empirical studies indicate that other technologies may also contribute to the volatility of the cryptocurrency price. Chen (2021) argued that blockchain technology factors only demonstrated a small impact on the Bitcoin price. Kim *et al.* (2021) showed that blockchain information was an important determinant influencing Ethereum prices. Wang and Vergne (2017) found that the drivers of cryptocurrency returns were the number of unique collaborators and proposals emerging. Chowdhury, Damianov, and Elsayed (2022) indicated that the price dynamics of cryptocurrencies, particularly Rapple, were influenced by the technologies related to the consensus protocol used in these cryptocurrencies. However, Vo *et al.* (2022) showed that cryptocurrency pricing, while changeable in the short term, may be less sensitive to technological factors and more responsive to underlying economic factors in the long term.

Economic factors. This study shows that economic factors significantly affect cryptocurrency pricing. For example, Van Wijk (2013) examined the impact of Bitcoin price on macroeconomic factors, such as the stock market index, exchange rates and oil prices. Polasik *et al.* (2015) showed an exponential increase in the Bitcoin price due to increased trading against the US dollar in July 2010. Similarly, Bouoiyour and Selmi (2015) found that demand for Bitcoin trading and exchange transactions will drive up prices. The correlation between variables is shown in Table 6. The economic factors most commonly examined in this research are now discussed.

Exchange rates. Exchange rates appear to have a significant effect on cryptocurrency pricing. Previous studies have demonstrated that the exchange rate has a significant and negative relationship with the Bitcoin price (KaraÖMer, 2022; Zhu, Dickinson, & Li, 2017). Polasik *et al.* (2015) demonstrated that both the US dollar and the Euro had a strong negative relationship with the Bitcoin price. These findings were consistent with Poyser (2019) who suggested that the exchange rate of the Chinese yuan was negatively associated with the Bitcoin price. Panagiotidis, Stengos, and Vravosinos (2018), through a Least Absolute Shrinkage and Selection Operator (LASSO) approach, revealed that the exchange rates including JPY/USD, CNY/USD, USD/EUR, and GBP/USD positively affected Bitcoin returns in order to have a positive impact. This was supported by Huang, Gau, and Wu (2022) who found that the exchange rates of EUR/USD, GBP/USD and JPY/USD affected Bitcoin returns. However, it has also been argued that Bitcoin returns are not significantly affected by exchange rates USD/JPY, USD/GBP, USD/GBP and USD/AU when confidence was measured at a 95% level (Almansour, Almansour, & In'airat, 2020). When the confidence level was 90%, however, the exchange rate of the GBP was found to be significant.

Interest rates. Studies indicate that interest rates are also an important determinant of cryptocurrency pricing. Nguyen, Nguyen, Nguyen, Pham, and Nguyen (2022) investigated the Federal rate of the US and the Chinese interbank rate on the stablecoins and cryptocurrencies, based on the Generalized AutoRegressive Conditional Heteroskedasticity (GARCH), EGARCH and the fixed-effect model. The results suggested that higher federal fund rates and Chinese interbank rates had a significant impact on both stablecoins and cryptocurrencies, leading to increased price volatility in these markets. Havidz, Karman, and Mambea (2021) also found that the Federal Reserve interest rate negatively affected the price of Bitcoin, with the negative relationship being that a higher Federal Reserve interest rate discouraged investors from investing in Bitcoin as a speculative asset. This finding was consistent with Zhu *et al.* (2017) who stated that an increased interest rate may result in reduced speculative investment by investors. In addition, an increase in interest rates was found to reduce the demand for Bitcoin as well as its returns (Jareño, González, Tolentino, & Sierra, 2020). However, Panagiotidis *et al.* (2018) found a positive effect on Bitcoin returns from interest rates through a LASSO approach.

Consumer price index (CPI). Studies have indicated that the consumer price index (CPI) is an important determinant influencing the Bitcoin price. Empirical results have suggested that the CPI had a long-term negative influence on the Bitcoin price (Zhu *et al.*, 2017). In contrast with previous findings, Wang, Sarker, and Bouri (2022) argued that the CPI had a positive correlation with Bitcoin in the short term as Bitcoin can be a hedging asset. However, Corbet, Larkin, Lucey, Meegan, and Yarovaya (2020) utilized a sentiment index to explore the relationship between macroeconomic news regarding the CPI and Bitcoin pricing. The results indicated that CPI news had no significant relationship with the Bitcoin price.

Gold and oil. Several studies have demonstrated that gold, as a macro-financial factor, has a significant and positive effect on the Bitcoin price. Based on deep learning methods,

No	Authors	Location	Methodology	Influential factor	Relationship	Currency type
1	Polasik *et al.* (2015)	Europe	Ordinary least squares and tobit estimation approaches	US dollars	Negative	Bitcoin price
2	Zhu *et al.* (2017)	China	Vector error correction model	US dollars	Negative	Bitcoin price
3	KaraÖMer (2022)	Europe	Autoregressive distributed lag model	Exchange rate	Negative	Bitcoin price
4	Poyser (2019)	Europe	Bayesian structural time series approach	Exchange rate	Negative	Bitcoin price
5	Panagiotidis *et al.* (2018)	Europe	Least Absolute Shrinkage and Selection Operator approach	Exchange rate	Positive	Bitcoin returns
6	Huang *et al.* (2022)	China	The lens of empirical asset pricing analysis	Exchange rate	Positive	Bitcoin returns
7	Nguyen *et al.* (2022)	UK	Fixed-effect model, Generalized AutoRegressive Conditional Heteroskedasticity	Federal rate and Chinese interbank rate	N/A	Cryptocurrency prices
8	Panagiotidis *et al.* (2018)	Europe	Least Absolute Shrinkage and Selection Operator approach	Interest rate	Positive	Bitcoin returns
9	Zhu *et al.* (2017)	China	Vector error correction model	Interest rate	Negative	Bitcoin price
10	Havidz *et al.* (2021)	Indonesia	Fixed-effect model and generalized method of moments	Interest rate	Negative	Bitcoin price
11	Zhu *et al.* (2017)	China	Vector error correction model	Consumer Price Index	Negative	Bitcoin price
12	Wang *et al.* (2022)	China	Wavelet-based methods	Consumer Price Index	Positive	Bitcoin price
13	Corbet *et al.* (2020)	Europe	Sentiment Index	News related to Consumer Price Index	N/A	Bitcoin price
14	Jareño *et al.* (2020)	Europe	Asymmetric nonlinear cointegration approach	Gold	Positive	Bitcoin price
15	Lamothe-Fernández *et al.* (2020)	Europe	Deep learning methods	Gold	Positive	Bitcoin price
16	Pogudin *et al.* (2019)	UK	Wavelet coherence analysis	Gold and oil	Positive	Bitcoin price
17	Ciaian *et al.* (2016)	Europe	Augmented version of Barro's model	Gold and oil	Positive	Bitcoin price
18	Panagiotidis *et al.* (2018)	Europe	Least Absolute Shrinkage and Selection Operator approach	Gold and oil	Positive	Bitcoin returns
19	Jareño *et al.* (2020)	Europe	Asymmetric nonlinear cointegration approach	Oil price	Negative	Bitcoin price
20	Ciaian *et al.* (2016)	Europe	Vector autoregressive model	Oil price	Negative	Bitcoin price
21	Ciaian *et al.* (2016)	Europe	Vector autoregressive model	Dow Jones Index	Positive	Bitcoin price
22	Lamothe-Fernández *et al.* (2020)	Europe	Deep learning methods	Dow Jones Index	Positive	Bitcoin price
23	Zhu *et al.* (2017)	China	Vector error correction model	Dow Jones Index	Negative	Bitcoin price

Table 6.
Economic factors

(continued)

No	Authors	Location	Methodology	Influential factor	Relationship	Currency type
24	Jareño *et al.* (2020)	Europe	Asymmetric nonlinear cointegration approach	S&P Index and Chinese Stock Index	Positive	Bitcoin price
25	Bouoiyour and Selmi (2015)	Europe	Autoregressive distributed lag model	S&P Index and Chinese Stock Index	Positive	Bitcoin price
26	Vo *et al.* (2022)	USA	Ordinary least squares regression	S&P 500 Index	Positive	Bitcoin price
27	Panagiotidis *et al.* (2018)	Europe	Least Absolute Shrinkage and Selection Operator approach	Nikkei Index	Positive	Bitcoin returns
28	Havidz *et al.* (2021)	Indonesia	Fixed-effect model and generalized method of moments	Stock Market Index	Negative	Bitcoin price
29	KaraÖMer (2022)	Europe	Autoregressive distributed lag model	Economic Policy Uncertainty Index	Negative	Bitcoin price
30	Wang *et al.* (2022)	China	Wavelet-based methods	Economic Policy Uncertainty Index	Negative	Bitcoin price
31	Hasan *et al.* (2022)	Bangladesh	Ordinary least square, quantile regression and quantile-on-quantile regression approaches	Cryptocurrency Policy Uncertainty Index	Negative	Bitcoin returns
32	Wu *et al.* (2022)	China	Modular Integrated Distributed Analysis System	Economic Policy Uncertainty Index	N/A	Bitcoin returns
33	Panagiotidis *et al.* (2018)	Europe	Least Absolute Shrinkage and Selection Operator approach	European Economic Policy Uncertainty Index	Negative	Bitcoin returns
34	Kalyvas *et al.* (2020)	UK	Negative coefficient of skewness analysis	Economic Policy Uncertainty Index	Negative	Bitcoin price
35	Jareño *et al.* (2020)	Europe	Asymmetric nonlinear cointegration approach	Economic Policy Uncertainty Index	Negative	Bitcoin price
36	Anamika *et al.* (2021)	India	Robust least squares method	Fear in the equity market	Positive	Bitcoin, Ethereum and Litecoin returns
37	Scharnowski (2022)	UK	The fixed-effect model	Central bank digital currency policies	Positive	Cryptocurrency returns

Source(s): Table created by the authors

Table 6.

Lamothe-Fernández *et al.* (2020) showed that gold positively affected Bitcoin pricing. This finding was supported by Ciaian *et al.* (2016) and Pogudin, Chakrabati, and Di Matteo (2019) where it was found that gold and oil were positively correlated with the Bitcoin price. Panagiotidis *et al.* (2018) utilizing a LASSO framework, also supported that Bitcoin returns were positively affected by gold and oil. Nevertheless, Jareño *et al.* (2020) used the asymmetric nonlinear cointegration approach and Ciaian *et al.* (2016) utilized the vector autoregressive model to reveal a negative relationship between oil price and the Bitcoin price. It was considered that as oil prices increase, available budgets (consumer and company) decrease, resulting in less expenditure on investment assets, including Bitcoin.

Stock market. Many studies in Table 6 suggest that economic indicators have a significant impact on cryptocurrency pricing. For example, the Dow Jones Index was found to be positively associated with the Bitcoin price (Ciaian *et al.*, 2016; Lamothe-Fernández *et al.*, 2020). However, Zhu *et al.* (2017) demonstrated that the Dow Jones Index had a long-term negative effect on the price of Bitcoin. The S&P 500 Index was found to have a significant and positive effect on the price of Bitcoin (Bakas, Magkonis, & Oh, 2022; Francisco. Jareño *et al.*, 2020; Nguyen, 2022), while it also moved in tandem with Bitcoin returns (Vo *et al.*, 2022). The Chinese Stock Market Index also had a positive and significant effect on the Bitcoin price (Bouoiyour & Selmi, 2015). This was also consistent with Panagiotidis *et al.* (2018), who showed that the Nikkei index emerged as a determinant that positively affected Bitcoin returns. Anamika, Chakraborty, and Subramaniam (2021) also indicated that fear in the equity market had a positive correlation with Bitcoin, Ethereum and Litecoin returns. When the equity market was experiencing bearish sentiment, this may lead investors to consider cryptocurrency as an alternative asset as a result of the increase in cryptocurrency prices. These findings were supported by Dyhrberg (2016) who studied which stock markets had an impact on the Bitcoin price. However, Havidz *et al.* (2021) argued that the Stock Market Index had a negative but insignificant effect on the Bitcoin price, which contrasted with previous findings. Other factors such as government bond indices and small company stock returns significantly impacted the cryptocurrency returns (Ciner, Lucey, & Yarovaya, 2022).

Empirical studies have provided evidence that the cryptocurrency price may also be affected by the Economic Uncertainty Index. A number of studies conducted by Hasan, Hassan, Karim, and Rashid (2022) and Wu, Ho, and Wu (2022) showed a negative relationship between the Cryptocurrency Policy Uncertainty Index and the Bitcoin price. This means that when the cryptocurrency policy uncertainty increases, the Bitcoin price will decrease, when all other variables are kept constant (KaraÖMer, 2022). Similarly, the Economic Uncertainty Index displayed the same negative and significant association with the Bitcoin price (Kalyvas, Papakyriakou, Sakkas, & Urquhart, 2020; Wang, Sarker, & Bouri, 2022). These results were consistent with Jareño *et al.* (2020), who demonstrated that fear in the Financial Market Index and the St Louis Fed's Financial Stress Index had a negative and significant effect on Bitcoin returns. European economic policy uncertainty was the most important variable for Bitcoin returns (Panagiotidis *et al.*, 2018). The possible explanation is that when the economy has suffered a crisis or was under stress, cryptocurrency was more likely to be considered by investors as a hedging asset (Nakagawa & Sakemoto, 2022). Scharnowski (2022) indicated that economic policies related to central bank digital currencies (CBDC) have had a positive effect on cryptocurrency prices, the rationale being that the introduction and development of CBDC can be perceived as a favorable signal for other forms of digital currencies, including cryptocurrencies.

Market volatility

Table 7 presents that the systematic risk of cryptocurrencies is an important factor driving returns. Zhang, Li, Xiong, and Wang (2021) showed a positive cross-sectional relationship existed between downside risk and future returns in the cryptocurrency market. Liu, Liang, and Cui (2020) demonstrated that cryptocurrency returns were driven by three common risk factors: cryptocurrency market returns, market capitalization (size) and the momentum of cryptocurrencies. These findings were supported by Liu *et al.* (2022) who found that cryptocurrency returns were captured by the cryptocurrency market, size and momentum. Similarly, size, momentum and the value to the growth of cryptocurrency also affected cryptocurrency returns (Wang & Chong, 2021). The combined effect of size and momentum factors can effectively capture the cross-sectional variation observed in cryptocurrency returns (Liu *et al.*, 2020). Other factors specific to the cryptocurrency market, such as MAX momentum (Li, Urquhart, Wang, & Zhang, 2021), reversal factors (Jia, Goodell, & Shen, 2022), idiosyncratic volatility (Leirvik, 2022; Liu & Tsyvinski, 2021) and liquidity (Zhang & Li, 2020), were also important for predicting cryptocurrency returns. Furthermore, Ciaian *et al.* (2016) showed that risk and uncertainty related to the Bitcoin system negatively affected the Bitcoin price. Nadler and Guo (2020) added that specific risk associated with blockchain had a stronger effect on cryptocurrency pricing.

No	Authors	Location	Methodology	Influential factor	Relationship	Currency type
1	Zhang *et al.* (2021)	China	Univariate portfolio analysis	Downside risk	Positive	Cryptocurrency returns
2	Liu *et al.* (2022)	USA	Three-factor model	Cryptocurrency market return	Positive	Cryptocurrency returns
3	Liu *et al.* (2022)	USA	Three-factor model	Market capitalisation	Positive	Cryptocurrency returns
4	Liu *et al.* (2022)	USA	Three-factor model	Momentum	Positive	Cryptocurrency returns
5	Wang and Chong (2021)	China	Fama–French three factor model	Risk factor	N/A	Cryptocurrency prices
6	Liu *et al.* (2020)	China	Fama–MacBeth method	Common risk factor	Negative	Cryptocurrency returns
7	Jia *et al.* (2022)	China	Market, size and momentum factors (MSM three-factors model	Reversal factors	N/A	Cryptocurrency returns
8	Ciaian *et al.* (2016)	Europe	Vector autoregressive model	Risk and uncertainty of bitcoin system	Negative	Bitcoin price
9	Nadler and Guo (2020)	UK	Asset pricing model	Blockchain risk	Positive	Cryptocurrency price
10	Koutmos (2020)	USA	Markov regime-switching model	Asset pricing risk	Positive	Bitcoin returns
11	ÇElik *et al.* (2020)	Europe	Fourier KPSS unit root test and Fourier–SHIN cointegration test	COVID-19 pandemic	Positive	Bitcoin price
12	Lee *et al.* (2022)	USA	Structural break analysis	COVID-19 pandemic	Positive	Bitcoin price
13	Corbet *et al.* (2022)	Europe	Vector autoregression analysis and Generalized AutoRegressive Conditional Heteroskedasticity	COVID-19 pandemic	Positive	Cryptocurrency price
14	Sarkodie *et al.* (2022)	Europe	A polynomial regression	COVID-19 pandemic	Positive	Cryptocurrency returns
15	Burke, Fry, Kemp, and Woodhouse (2022)	UK	A time-series regression	COVID-19 pandemic	Positive	Cryptocurrency returns
16	Nguyen (2022)	Australia	A VAR-GARCH model	COVID-19 pandemic	Positive	Bitcoin returns
17	Apergis (2022)	Europe	An asymmetric GARCH modeling	COVID-19 pandemic	Positive	Cryptocurrency returns
18	Demiralay and Golitsis (2021)	UK	Dynamic Equicorrelation GARCH (DECO-GARCH) model	Hacker attacks and COVID-19	N/A	Cryptocurrency trading volume
19	Almaqableh *et al.* (2022)	Australia	Asset pricing model and ARCH model	Terrorist attack	Positive	Cryptocurrency returns
20	Corbet *et al.* (2019)	Europe	Systematic review	Hacking events	Negative	Cryptocurrency price
21	Zhu *et al.* (2017)	China	Vector error correction model	Exchange platform	Negative	Bitcoin price

Source(s): Table created by the authors

Table 7.
Market volatility

Studies have also provided evidence that unsystematic risk can be a determinant of cryptocurrency price. Koutmos (2020), unitizing the Markov regime switching model, stated that other asset pricing risk factors were important determinants of Bitcoin returns. Corbet *et al.* (2019) found that hacking events are drivers of price volatility in cryptocurrencies. Almaqableh *et al.* (2022) indicated that terrorist attacks positively affected cryptocurrency returns, while these attacks also resulted in short-term risk shifting behavior for different cryptocurrencies. The COVID-19 pandemic has had a positive and significant effect on the Bitcoin price in the short term (ÇElik, Yilmaz, Emir, & Sak, 2020; Lee, Vo, & Chapman, 2022). The pandemic had a notable impact on the conditional volatility of cryptocurrency returns (Apergis, 2022; Nguyen, 2022; Sarkodie, Ahmed, & Owusu, 2022). The heightened uncertainty and market disruptions caused by the pandemic have led to increased cryptocurrency price fluctuations and volatility. Additionally, increased COVID-19 cases/deaths were positively linked to cryptocurrency returns. Demiralay and Golitsis (2021) also found that cryptocurrency returns exhibit time-varying patterns and were highly correlated with major events such as hacker attacks and the COVID-19 pandemic. These events can significantly affect investor sentiment and market dynamics as a result of cryptocurrency price fluctuation (Corbet *et al.*, 2022). Zhu *et al.* (2017) further indicated that cryptocurrency exchange platforms are a potential risk that could influence cryptocurrency pricing. For example, Mt. Gox, a Bitcoin exchange platform, saw both the website and trading engine disappear without official comment, leading to a decline in the Bitcoin price.

Investors' attributes

Investors' attention has been argued to be an important determinant of cryptocurrency pricing. Smales (2021) showed that investors' attention had a positive relationship with the cryptocurrency price. Similarly, others have highlighted that investors' attention had the potential to improve prediction accuracy for Bitcoin returns. Zhu, Zhang, Wu, Zheng, and Zhang (2021) and Mohamed (2021) also confirmed that investor attention predicts future cryptocurrency volatility through a vector autoregression framework. Attractiveness indicators were also found to be important determinants of Bitcoin pricing, with variations over time (Guizani & Nafti, 2019). These findings suggest that a strong relationship exists between investors' interest and the Bitcoin price (Hakim das Neves, 2020). Cryptocurrency popularity is one of the main factors that determine returns. KaraÖMer (2022) demonstrated that popularity had a significant and positive relationship with Bitcoin in the short term. The growth of Bitcoin's popularity has been predicted to exert upward pressure on the Bitcoin price (Garcia *et al.*, 2014; Nepp & Karpeko, 2022). With cryptocurrency's growing popularity leading to higher search volume and social media activity, the implications are that there is increasing investor interest in cryptocurrencies, which drives higher prices.

The literature has demonstrated evidence of a wide range of volatility within cryptocurrency prices (see Table 8), which is significantly affected by investors' sentiment. Positive investor opinion or sentiment has a positive correlation with pricing (Kjaerland *et al.*, 2018; Patel, Tanwar, Gupta, & Kumar, 2020). Social media as a platform where investors can express psychological and financial sentiments plays a significant role in Bitcoin volatility (Gurrib & Kamalov, 2022; Sapkota, 2022). These findings were consistent with those of Garcia *et al.* (2014) who stated that positive word of mouth contributes to Bitcoin price bubbles. Positive feedback associated with Bitcoin trading behavior also increased its volatility (Wang, Lee, Liu, & Lee, 2022). Huynh (2021) also showed that negative sentiment had a significant impact on Bitcoin return and trading volume. This was supported by Wang and Vergne (2017) who demonstrated that the "buzz" surrounding cryptocurrencies was negatively associated with returns. Shahzad, Anas, and Bouri (2022) emphasized the influential role of key individuals, such as Elon Musk, and social media tweets that led

No	Authors	Location	Methodology	Influential factor	Relationship	Currency type
1	Smales (2021)	Australia	Quantile regression approach	Attention	Positive	Cryptocurrency price
2	Zhu *et al.* (2021)	China	Value-at-risk analysis	Attention	Positive	Cryptocurrency price
3	Al Guindy (2021)	Canada	Vector autoregression framework	Investor attention	Positive	Cryptocurrency returns
4	Guizani and Nafti (2019)	Tunisia	Autoregressive distributed lag model	Attractiveness	Positive	Bitcoin price
5	KaraOMer (2022)	Europe	Autoregressive distributed lag model	Popularity	Positive	Bitcoin returns
6	Polasik *et al.* (2015)	Europe	Ordinary least squares and tobit estimation approaches	Popularity	Positive	Bitcoin return
7	Garcia *et al.* (2014)	Europe	Vector autoregression model	Popularity	Positive	Bitcoin return
8	Nepp and Karpeko (2022)	Russia	Autoregressive distributed lag model and generalized autoregressive conditional heteroscedasticity model	Popularity	Positive	Bitcoin return
9	Patel *et al.* (2020)	India	Long short-term memory model and gated recurrent unit model	Investors' sentiment	Positive	Cryptocurrency price
10	Sapkota (2022)	Europe	Heterogeneous autoregressive model	Investors' sentiment	Positive	Cryptocurrency price
11	Gurrib and Kamalov (2022)	UAE	Linear discriminant analysis and sentiment analysis	Investors' sentiment	Positive	Cryptocurrency price
12	Garcia *et al.* (2014)	Europe	Vector autoregression model	Investors' sentiment	Positive	Cryptocurrency price
13	Huynh (2021)	Europe	Textual analysis	Negative sentiment	Negative	Cryptocurrency returns
14	Wang and Vergne (2017)	Canada	Random-effect and fixed-effect analysis	Negative sentiment	Negative	Cryptocurrency returns
15	Wang *et al.* (2022)	China	Combining rolling window estimations with regression analysis	Positive trading behaviors	Positive	Bitcoin returns
16	Barth *et al.* (2020)	USA	Text analytic approach	Unethical discussion	Negative	Bitcoin price
17	Shahzad *et al.* (2022)	Europe	A crisis-dating and a timely cautionary alert method	Influential role of key individuals	N/A	Cryptocurrency price
18	Rubbaniy *et al.* (2022)	UAE	A quantile-on-quantile regression	Investors' mood	N/A	Cryptocurrency price
19	Bartolucci *et al.* (2020)	UK	Artificial recurrent neural network model	Developers' emotions	Positive	Bitcoin price and Ethereum price
20	Ahn and Kim (2021)	Korea	Corpus linguistics approach	Emotional factors	Positive	Bitcoin return

Source(s): Table created by the authors

Table 8.
Investors' attributes

to the formation of bubbles, which significantly affected cryptocurrency prices. Similarly, Gerritsen, Lugtigheid, and Walther (2022) revealed that crypto experts have had a significant effect on Bitcoin returns. Barth, Herath, Herath, and Xu (2020) highlighted a negative association between the frequency of discussions of unethical practices related to Bitcoin and its price. Bartolucci *et al.* (2020) showed that developers' emotions were also the drivers of the price volatility within Bitcoin and Ethereum. Ahn and Kim (2021) agreed that emotional factors played a significant role in predicting Bitcoin trading volume and return volatility. Rubbaniy, Tee, Iren, and Abdennadher (2022) also supported the notion that investors' mood is linked to the volatility of the cryptomarket.

Social media

Empirical evidence has demonstrated that cryptocurrency pricing was significantly affected by online activities (see Table 9). Wikipedia views, which represented online information queries, had a positive and statistically significant effect on the Bitcoin price (Figà-Talamanca & Patacca, 2020). Ciaian *et al.* (2016) also suggested that Wikipedia exercised a strong impact on the Bitcoin price. Growth in the volume of Google Trends or Google Search also led to high Bitcoin returns (Polasik *et al.*, 2015). Aslanidis, Bariviera and López (2022) suggested a positive relationship between cryptocurrency returns and the attention received on Google Trends, particularly when measuring attention specific to the cryptomarket. Additionally, Panagiotidis *et al.* (2018) identified Google Search as the most important variable for explaining Bitcoin returns, and it was found to be a good predictor of cryptocurrency prices (Chuffart, 2022). This indicated that increased interest and search

No	Authors	Location	Methodology	Influential factor	Relationship	Currency type
1	Ciaian *et al.* (2016)	Europe	Augmented version of Barro's model	Wikipedia	Positive	Bitcoin price
2	Phillips and Gorse (2018)	UK	Wavelet coherence analysis	Wikipedia	Positive	Bitcoin price
3	Phillips and Gorse (2018)	UK	Wavelet coherence analysis	Google Search	Positive	Bitcoin returns
4	Panagiotidis *et al.* (2018)	Europe	Least Absolute Shrinkage and Selection Operator approach	Google Search	Positive	Bitcoin returns
5	Chuffart (2022)	Europe	Smooth transition conditional correlation model	Google Search	Positive	Cryptocurrency price
6	Bakas *et al.* (2022)	UK	A dynamic Bayesian model	Google Search	Positive	Cryptocurrency returns
7	Ciaian *et al.* (2016)	Europe	Augmented version of Barro's model	Google Search	Positive	Bitcoin returns
8	Polasik *et al.* (2015)	Europe	Ordinary least squares and tobit estimation approaches	Google Search	Positive	Bitcoin returns
9	Smuts (2019)	UK	Long short-term memory model	Google Trends	Negative	Bitcoin price and Ethereum price
10	Aslanidis *et al.* (2022)	Europe	Shannon transfer entropy approach	Google Trends	Positive	Cryptocurrency returns

Source(s): Table created by the authors

Table 9.
Social media

volume for cryptocurrencies on Google can be associated with higher cryptocurrency returns (Bakas *et al.*, 2022). Increased investors' curiosity and attention imply that demand for Bitcoin will also likely increase (Kjaerland *et al.*, 2018). Online factors, such as online activities, social media, Google Search and Wikipedia, have had a long-term positive relationship with the cryptocurrency price (Phillips & Gorse, 2018). However, it has also been reported that Bitcoin and Ethereum price movements were negatively affected by search volume obtained via Google Trends (Smuts, 2019).

Discussion

This study employs a systematic literature review to identify the influential factors of cryptocurrency pricing and to determine the major gaps for future research. This review included all peer-reviewed journal articles that met the selection criteria and were published before September 2022. The final analysis included a total of 88 articles, 56 articles that met the eligibility criteria and 32 articles from reference lists of the eligible articles. The earliest article was published in 2014, with most articles being published in 2022, indicating that the field of cryptocurrency pricing is still emerging. The overall upward trend in the number of published studies on cryptocurrency pricing reflects increasing interest and recognition of the importance of this research topic. Empirical cryptocurrency pricing studies focused on Bitcoin, suggesting that it remains the most popular and widely researched cryptocurrency in the market. As a pioneer and the first cryptocurrency, Bitcoin has received significant attention from researchers, investors and the public (Wang & Vergne, 2017). Future studies could explore factors that influence other cryptocurrencies, such as Dogecoin or Litecoin, to offer a comprehensive overview of cryptocurrency pricing.

The peer-reviewed articles on the influential factors of cryptocurrency pricing were published in 54 different journals. The majority of articles (27) were published in *Finance Research Letters*. The remaining 47 articles were distributed across journals from various disciplines and highlight the wide-ranging interest and multi-faceted nature of cryptocurrencies. *Finance Research Letters* presents as the leading journal in cryptocurrency pricing research. Thus, future studies may consider other high-quality journals to allow investors or policymakers to obtain a more comprehensive understanding of cryptocurrency pricing. Future studies could also research the connections between traditional finance and the cryptocurrency market to improve the depth of research.

The geographic analysis conducted in this review offered another layer of insight into the research on cryptocurrency pricing. A total of 88 studies were conducted in 18 different regions, with Europe accounting for 29 studies. Cryptocurrency pricing research appears to be more active in Europe than in other locations, suggesting significant academic interest in the region. Extending the geographic coverage by encouraging research to focus on developing countries and perhaps exploring the development of financial technologies and their effect on the cryptocurrency market could be useful for the field.

A total of 48 different research methods were applied across the research to analyze the determinants of cryptocurrency pricing. The most used model was the vector autoregression model (9), followed by the autoregressive distributed lag model (6), generalized autoregressive conditional heteroskedasticity (5), three-factor model (4), the fixed-effect model (3) and the wavelet coherence analysis (3). Ordinary least squares regression, vector error correlation, the asset pricing model, the cost of production model, fixed-effect analysis and the text analytic approach were applied twice each. Future studies could apply other methods or combine existing research methods in the construction of cryptocurrency pricing models to improve their predictions.

This review has revealed the factors that influence cryptocurrency pricing and has been classified into six categories: (i) fundamental factors, (ii) technological factors, (iii) economic factors, (iv) market volatility, (v) investors' attributes and (vi) social media. Although studies have mentioned that cryptocurrency pricing can be explained by many factors, Bitcoin continues to be the most studied. Future studies could examine the impact of other coins on cryptocurrency pricing. As cryptocurrency is the result of financial innovation, future research could also consider the technological dimensions of cryptocurrency. This exploration might include whether it is more explicit and dynamic than traditional currency. The rationale for this focus is that cryptocurrency needs to continually update its underlying software to maintain its technological advantage (Wang & Vergne, 2017). Cryptocurrency could be an alternative way to reshape the existing financial system. Research could consider cryptocurrency connection with the existing financial market and examine the impact of economic policies on the cryptocurrency market. The role of financial technologies is evolving within existing financial systems. These technologies can improve efficiency and service quality but may also lead to new challenges for the financial market. Research that examines the potential challenges faced by cryptocurrency pricing or value would be of value. The research selected for this study has provided evidence to suggest that investors' sentiment is a key factor influencing cryptocurrency pricing. Future studies could quantify these sentiment factors or examine the potential factors affecting investors' sentiment towards cryptocurrency. Although many determinants have been identified in this review, several important factors continue to be neglected in the literature, such as cultural and political factors, and the development of financial technologies. These research gaps are areas of interest to the field.

Implications

This systematic literature review identified factors influencing cryptocurrency pricing and highlighted major gaps in the research. The findings generated from this research offer important contributions to the literature and practitioners.

Theoretical implications

This study contributes to the cryptocurrency literature in several ways. Firstly, this research provides a comprehensive overview of the existing literature and categorizes the significant factors that influence cryptocurrency pricing. Within this field, there has been a lack of systematic reviews that may guide future research by identifying factors that may affect the determinants of cryptocurrency pricing.

The review also highlights the varying research methods used to identify the determinants of cryptocurrency pricing. In total, 48 different research methods have been employed to analyze the determinants of cryptocurrency pricing. The most common research methods applied were the vector autoregression model and the autoregressive distributed lag model, with other types of models used in various studies. This study therefore informs future studies of the commonly used methods and theories that could be considered for theoretical frameworks to underpin cryptocurrency pricing research.

This review provides evidence that cryptocurrency can be considered an alternative currency that complements the existing financial industry. Prior studies have shown that cryptocurrency usage in transactions, its supply and price levels are consistent with monetary economics and the quantity theory of money (Wang & Vergne, 2017). Moreover, cryptocurrency offers a low transaction cost, decentralization and a peer-to-peer system (Kim *et al.*, 2021). This makes it possible for users to use a cost-effective remittance system in developing countries where banking systems are underdeveloped or unsecure (Ciaian *et al.*, 2016). Therefore, cryptocurrency has the potential to serve as a medium of exchange for the global economy (Ciaian *et al.*, 2016). In addition, Kristoufek (2015) has stated that although the

Bitcoin price was mainly driven by speculative opportunities due to its high volatility and decentralization, its unique asset-possessing property is that it is both a standard financial asset and a speculative asset. Jareño *et al.* (2020) also revealed a positive connection between Bitcoin and gold price returns during times of economic turmoil. Bitcoin was found to have the properties similar to gold in that it could serve as a financial haven during periods of high economic uncertainty. Kjaerland *et al.* (2018) suggested that Bitcoin price volatility could be explained by investment theories such as the greater fool theory and momentum theory. Therefore, it can be concluded that cryptocurrencies have the potential to complement the existing financial industry, with this information having significance for practical applications.

Practical implications

This research has implications for multiple stakeholders. Firstly, this study brings together the literature and synthesizes multiple elements of the cryptocurrency market. The systematic review of this literature adds a depth of understanding through a discussion of the determinants of cryptocurrency prices. This information is useful for investors and investment managers when making trading decisions in relation to the cryptocurrency market. A large number of Bitcoin users are considered to be young and inexperienced (Baur, Dimpfl, & Kuck, 2018) and are more likely to require potential indicators of cryptocurrency pricing to make appropriate investment decisions. Thus, investors will benefit from this review when seeking to diversify their portfolios with cryptocurrencies or by designing better trading strategies. The review may also benefit more experienced investors, such as investment managers. This study provides a consolidated discussion of the determinants of cryptocurrency prices and may assist investors to construct cryptocurrency price prediction models. Portfolio managers can effectively trace cryptocurrency price movements, thus avoiding large change events in cryptocurrency prices, which may have a significant effect on the risk and return of individual risky assets.

Secondly, the review has a series of policy implications. From the consolidated technological aspects, regulators may utilize cryptocurrency technologies to update their financial systems, thus being able to offer lower costs, higher efficiency and greater convenience for their consumers, as per their profiles and needs. Given the safe haven characteristics of cryptocurrencies, many investors are more likely to buy cryptocurrency to minimize financial risk during times of economic stress or crisis (Jareño *et al.*, 2020). Thus, policymakers could monitor these financial activities or establish alternatives to avoid the depreciation of their currencies. The review also assists regulatory bodies in assessing the determinants of cryptocurrency returns as an alternative investment, thus enriching their knowledge (Gurrib, Kweh, Nourani, & Ting, 2019). It is well known that the cryptocurrency market is unregulated and highly speculative (Hameed & Farooq, 2017). If private cryptocurrencies widely enter the market as public forms of currency, this will likely encourage money laundering and financial crimes that will significantly affect monetary policy and financial stability (Baldan & Zen, 2020). Therefore, regulators have a requirement to understand the potential factors that would induce economic crisis, expressed as the influential factors of cryptocurrency pricing. The understanding of these factors may assist regulators to effectively formulate monetary policy in response to these challenges.

Thirdly, this review also has important implications for companies that consider cryptocurrency as a means of payment in cross-border transactions. This may especially be the case between countries without a coherent and reliable payment infrastructure. Cryptocurrency offers characteristics such as low transaction costs and decentralization and offers a peer-to-peer payment system. In addition, the information from this review may allow individuals to access international business when there is a lack of access to traditional financial institutions or when they have less access to credit from within the banking system.

Limitations of the study and future research

Several limitations are acknowledged within this study. Firstly, this review only considered peer-reviewed articles. Future studies could consider other sources in the literature such as conference papers, government reports and theses to review a larger number of studies. Secondly, this review used only three databases to collect the selected articles. Studies not written in English and published in other databases may provide further insights. Future research that draws on more databases and other relevant search items may provide a more comprehensive review. Thirdly, some relevant articles may have been missed given the arbitrary nature of inclusion and exclusion criteria in the keywords, title and abstract. Future research could adjust the search strategies, the intervals and reading sources to collect relevant studies. Studies that included the design of a measurement scale of the influential factors with statistical validation would also improve insights into the literature.

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About the authors

Sanshao Peng is Ph.D. candidate in the Business School at the University of Southern Queensland. His research interests include financial technologies and cryptocurrency pricing. Sanshao has published few papers, including two conference papers and a paper under review in Q1 Journal, since she began her Ph.D.

Dr Catherine Prentice is Professor of Marketing at the University of Southern Queensland and Director of Asia Pacific Association for Gambling Studies. She currently serves as Associate Editor for three journals, including *Service Industries Journal* (Q1), *Tourism Review* (Q1) and *Journal of Global Scholars of Marketing Science* (B-ABDC). Catherine has published extensively in marketing and management journals as the first or solo author. She is one of the world-leading experts in emotional intelligence and artificial intelligence and has chaired several international conferences as well as delivering keynote speeches for various conferences. Her main research interests include artificial intelligence, emotional intelligence, service research, consumer psychology, consumer behavior, services and relationship marketing and gambling studies. Catherine Prentice is the corresponding author and can be contacted at: cathyjournalarticles@gmail.com

Syed Shams has more than 15 years of corporate and academic leadership in various finance and academic roles. He is former Associate Head of Research at the School of Business. He is the guest editor of the *Sustainability* (Q1) journal. Shams has extensively published articles in prestigious finance journals relating to climate finance, mergers and acquisitions, especially concentrating on corporate climate finance disclosures, such as Economics and Finance, Accounting and Finance Journal, *Australian Journal of Management*, *Pacific Basin Finance Journal*, *Journal of Contemporary Accounting and Economics*, *International Journal of Managerial Finance*, *Journal of Behavioral and Experimental Finance* and *International Review of Financial Analysis*.

Dr Tapan Sarker has more than 20 years of teaching and training, research, administrative and consulting experience. Within the industry, he has been Consultant for leading MNCs such as BHP Billiton, Rio Tinto and Mahindra and Mahindra Ltd, India. His interdisciplinary research expertise is in the areas of sustainable and green finance, public financial management, financing for the SDGs, business responses to climate change and circular economy. His research has been published in leading journals including *Finance Research Letters*, *International Review of Economics and Finance*, *Australian Tax Forum*, *Global Finance Journal*, *Economic Modelling*, among others.

3.3. Links and implications

This study employs a systematic literature review to identify the factors influencing cryptocurrency pricing and potential gaps within the research. Three databases, namely, Scopus, Web of Science and EBSCOhost were used for this review. Influential factors were identified and categorised as follows: supply and demand, technology, economics, market volatility, investors' attributes and social media. This review provides a consolidated view of cryptocurrency pricing and maps significant influential factors. Furthermore, it highlights research gaps for future research.

Building on these research gaps, the study documented in the second paper examines the relationship between consumer confidence and cryptocurrency excess returns through a three-factor model, comprising market, size and momentum. This was based on a data set comprising 3,318 cryptocurrencies spanning from 1 January 2014–31 December 2022 from the CoinMarketCap website.

In addition, the study documented in the third paper explores the moderating influence of the COVID-19 pandemic on the relationship between the CCI and cryptocurrency returns. This investigation sheds further light on the mechanism underlying the influence of consumer confidence on cryptocurrency returns and provides insights into the moderation role of the COVID-19 pandemic in the cryptocurrency market.

Overall, this research aims to contribute to research on consumer behaviour and financial management within the cryptocurrency market.

CHAPTER 4: PAPER 2 – CONSUMER CONFIDENCE AND CRYPTOCURRENCY EXCESS RETURNS: A THREE-FACTOR MODEL

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4.1. Introduction

This chapter presents the second paper of the thesis, which investigates the relationship between consumer confidence and cryptocurrency excess returns through a three-factor model.

The article itself starts with an introduction in Section 1, which is an introduction into the article and its key objectives. Section 2 reviews the relevant literature and forms the hypotheses for the study. Section 3 describes the research methodology, including data and sample period, instrument and model specifications in the study. Section 4 presents descriptive statistics for variables and Pearson's correlation.

Section 5 shows the empirical results of the study, with results of post-hoc analysis and robustness testing also provided to reinforce the study's findings. Section 6 provides additional analysis of the results to further investigate the relationship between the variables. Section 7 provides the conclusion of the findings and the implications.

4.2. Published Paper

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Consumer confidence and cryptocurrency excess returns: A three-factor model

Sanshao Peng *, Syed Shams, Catherine Prentice, Tapan Sarker

The School of Business, The University of Southern Queensland, Australia

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ABSTRACT

This study examined the relation between consumer confidence and cryptocurrency excess returns using a three-factor model of market, size and momentum. We analysed a dataset comprising 3318 cryptocurrencies from 1 January 2014 to 31 December 2022 based on the CoinMarketCap website. Results indicate a significant negative relation between the United States Consumer Confidence Index and cryptocurrency excess returns. The findings were reinforced based on robustness tests. This study contributes to consumer behaviour research and financial management within the cryptocurrency market. It also provides valuable insights for investors to strengthen their investment portfolios and for relevant authorities seeking to formulate effective policies for monitoring the cryptocurrency market.

1. Introduction

Cryptocurrency has received significant attention over the past decade. Bitcoin's market capitalisation has experienced a notable upsurge since its emergence in 2008 (Albrecht et al., 2019). Cryptocurrencies' decentralised properties have enabled online transactions to be achieved without reliance on financial intermediaries (e.g. banks), thus creating more peer-to-peer interactions (Nabilou, 2019). Rather than relying on traditional fundamental values, the value of cryptocurrencies is determined through specific algorithms that record transactions within underlying blockchain networks (Corbet et al., 2019). However, the decentralisation of cryptocurrencies presents challenges for regulators and investors, particularly in achieving a balance between the potential benefits of financial innovation and the associated risks posed by innovative approaches (Arner et al., 2015). As such, cryptocurrencies have become increasingly volatile investment assets, attracting individual and institutional investors (Sun et al., 2021). Reflecting the sentiment and beliefs of investors, consumer confidence plays a significant role in driving cryptocurrency market trends and asset prices (Chung et al., 2012). This results in highly volatile cryptocurrency prices and returns, thereby providing investors with unprecedented speculative opportunities (Agosto et al., 2022). Recently, social media significantly impacted cryptocurrency returns, illustrating that it can influence individual investors' perceptions and confidence regarding cryptocurrency assets. For instance, Elon Musk, one of the wealthiest individuals worldwide and a significant influencer on social media and the cryptocurrency market, frequently the context of X about cryptocurrencies several times in a day. This behaviour can be interpreted as short-term noise within the market (Shahzad et al., 2022). In other words, Musk's activity on X has been shown to impact investor sentiment regarding short-term cryptocurrency returns and trade volume (Ante, 2023). This circumstance has motivated us to investigate whether investor

* Corresponding author.
E-mail addresses: Sanshao.peng.academic@gmail.com (S. Peng), Syed.Shams@usq.edu.au (S. Shams), Tapan.Sarker@usq.edu.au (T. Sarker).

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psychological factors and behaviours influence investment decisions, consequently impacting cryptocurrency returns.

Past research suggests that cryptocurrency returns can be driven by multiple factors. González et al. (2021) found that the connectedness between gold prices and cryptocurrency returns increases during economic turmoil, such as during the COVID-19 pandemic. This finding indicates that cryptocurrencies and gold can be considered alternative assets, offering avenues for effective risk management and dynamic hedging strategies during economic uncertainty and market downturn (Gkillas & Longin, 2019; Hsu et al., 2021). For investors, Philippas et al. (2019) considered Twitter and Google Trends as proxies for investor sentiment for cryptocurrency prices. Their findings indicate that investors' sentiments on social media are highly associated with cryptocurrency prices. This finding aligns with Shen et al. (2019), who incorporated various Tweets as a proxy for investor attention, suggesting that investor attention significantly affects future realised volatility and trade volume. The rationale is that investors can easily obtain cryptocurrency information via social media. Comments and opinions on social media may induce investors' perceptions or decisions regarding cryptocurrencies as a result, thus changing trade volume and subsequent returns (Huynh, 2021). This supposition is supported by Shayaa et al. (2017) who asserted that consumer sentiment derived from social media can illustrate consumer confidence within a large population.

Regarding economic activities, investor/consumer sentiment derived from social media is associated with consumer confidence, while more negative news can often lead to a decrease in consumer confidence (Hollanders & Vliegenthart, 2011). Past research indicates that consumer confidence affects green purchase intention, indicating that environmental and status consciousness impact consumers' purchase behaviour (Han et al., 2022). This aligns with James (2021), who highlighted that consumers with high confidence in the current economy are more likely to increase spending and saving. In contrast, when consumers exhibit low confidence in the economy due to economic slowdown or negative changes in economic growth, they may reduce spending and saving (Islam & Mumtaz, 2016). Therefore, consumer confidence, reflecting the sentiments and beliefs of investors, plays a significant role in driving market trends and asset prices (Chung et al., 2012). Investors can make more informed investment decisions, manage risks effectively and potentially capitalise on market opportunities when they understand how consumer confidence changes affect cryptocurrency excess returns. As such, examining the relationship between consumer confidence and cryptocurrency excess returns is timely amid the increasing need for research addressing cryptocurrency market volatility.

Empirical studies have highlighted the significance of consumer confidence in the traditional financial market. Many studies have confirmed that consumer confidence can be a critical priced factor in various markets, including the stock market (Chen, 2012), unemployment rates (Mandal & McCollum, 2013), gross domestic product (GDP) and growth (Islam & Mumtaz, 2016). Thus, consumer confidence significantly affects an individual's judgements when making investment decisions (Koy & Akkaya, 2017). Although past studies have explored the impact of consumer confidence on traditional financial market activities, to our knowledge, no study has identified the association between consumer confidence and cryptocurrency returns. To fill this research gap, the present study investigated the relationship between consumer confidence and cryptocurrency returns based on a three-factor model.

We analysed the daily returns of a sample of 3318 cryptocurrencies from 1 January 2014 to 31 December 2022 as the study period. We utilised the Consumer Confidence Index (*CCI*) as a proxy for consumer confidence in cryptocurrency excess returns (*Rm-Rf*). First, we compared the one-factor and three-factor models to predict cryptocurrency excess returns through Jensen's alpha coefficient. The findings indicate that the three-factor model performed better in predicting cryptocurrency excess returns. This finding aligns with (Jia et al., 2022), who revealed that the three-factor model outperformed the quasi-cryptocurrency one-factor model; the three-factor model exhibited a larger explanatory power than the one-factor model. Second, we conducted the baseline analysis to determine the association between *CCI* and *Rm-Rf*, which controlled for all control variables, the year fixed effects and crypto fixed effects across all models. The empirical results indicate that the *CCI* coefficient was negative and statistically significant regarding the cryptocurrency excess returns. Third, we utilised the entropy balancing approach to address potential endogeneity between *CCI* and *Rm-Rf* due to potential omitted variables bias, selection bias and reverse causality. The entropy balancing approach findings were mainly compatible with the main findings regarding a significantly negative association between *CCI* and *Rm-Rf*. The negative association between *CCI* and *Rm-Rf* was further confirmed through an additional endogeneity test based on the two-stage least (2SLS) approach.

Fourth, we considered COVID-19 as a moderator for conducting the interaction analysis. The results in Panel B of Table 8 suggest that *CCI* was negatively associated with *Rm-Rf* in the medium-sized sample. This indicates that COVID-19 had a stronger impact on cryptocurrencies with medium market capitalisation. This is because cryptocurrencies with smaller market capitalisation are inefficient (Brauneis & Mestel, 2018) while cryptocurrencies with larger market capitalisation are more mature (Bakhtiar et al., 2023). Finally, we conducted a series of additional analyses and robustness tests across all models. This included assessing the impact of cryptocurrency market capitalisation, cryptocurrency trade volume, specific coins and additional control variables concerning cryptocurrency excess returns. The results from these tests are consistent with the main findings.

The study contributions are as follows. First, we provide empirical evidence of the relationship between consumer confidence and cryptocurrency excess returns. The findings augment the growing research on consumer confidence in the cryptocurrency market. The findings also enhance the understanding of the impact of consumers' incidental emotions on their confidence within this market. Second, identifying the relationship between consumer confidence and cryptocurrency returns has implications for portfolio diversification, leading to the effective construction of prediction models and policies. Third, we provide empirical evidence that cryptocurrency can be a hedge asset for traditional investors and portfolio managers during pandemics or other times of economic uncertainty.

The remainder of the paper is organised as follows. Section 2 reviews the relevant literature and hypotheses development, followed by Section 3, which is a detailed presentation of the methodology used to test the hypotheses. Section 4 presents the descriptive statistics. Section 5 presents the data analysis and results. Post-hoc analysis and robustness testing are provided in Section 6 to reinforce the study's findings, and Section 7 concludes the paper with a discussion of the findings and their implications.

2. Literature review and hypotheses development

2.1. Theoretical framework

This study adopted behavioural finance theory (Yazdipour & Howard, 2010) derived from the pioneering work of psychologists Danie Kahneman and Amos Tversky (1974) as the theoretical framework. This theory emphasises the crucial role played by differing types of psychological bias in investor decision-making and how bias subsequently influences the financial market's dynamics when translated into certain behaviours (Adam, 2022). Specifically, the behavioural finance theory posits that asset prices are influenced by the reaction of investors to relevant information, thereby providing explanations for why investors make irrational financial decisions (Hirshleifer, 2015). This notion is supported by Ainia and Lutfi (2019), who stated that individual investment decisions are not always driven by rational considerations but can be affected by irrational aspects related to an investor's psychology.

Previous studies indicate the importance of behavioural finance theory in the financial market. Behavioural finance theory focuses on the cognitive psychology underlying individuals' financial decisions. This theory has developed in response to conventional economic theory, which assumes that individuals are rational, risk-averse and seek to maximise profits (Charles & Kasilingam, 2016). However, investors' behaviour is significantly impacted by various types of bias highlighted within the developing discipline of behavioural finance (Madaan & Singh, 2019). Behavioural finance theory provides behavioural explanations for anomalies in decisions regarding real-world investors affected by their personal psychological biases (Kapoor & Prosad, 2017). This notion aligns with Charles and Kasilingam (2016) who suggested that investors' behavioural bias significantly affects their investment decisions. Furthermore, investor psychology, including risk perception, risk tolerance and confidence, are crucial factors in explaining asset price bubbles and crashes (Ainia & Lutfi, 2019; Kourtidis et al., 2011). This is consistent with the suggestion of Fakhry (2016) regarding the presence of asset price bubbles and investors' overreactions, indicating a significant impact on behavioural asset prices and volatility, particularly regarding the potential for asset price increases to surpass their underlying fundamental value. In contrast, cryptocurrency market capitalisation is determined by specific algorithms that record transactions within underlying blockchain networks (Corbet et al., 2019). Thus, behavioural finance theory was adopted to underpin the theoretical framework of this study.

Ballis and Verousis (2022) conducted a systematic literature review on the behavioural aspects of cryptocurrencies. Their findings indicate that prevalent phenomena such as herding behaviour among cryptocurrencies, momentum effects, overreaction, contagion effects, investor sentiment and uncertainty are associated with investment decision-making. This finding is consistent with behavioural finance theory, which examines how various psychological traits and types of bias impact investment decisions made by investors. The theory further investigates the impact of emotions, cognitive bias and other psychological factors on financial choices and market outcomes (Sattar et al., 2020). For instance, the CCI scores define the degree of optimism consumers express regarding the state of the economy, as indicated in their saving and spending activities. These scores represent consumers' perceptions of their sentiments regarding economic conditions. Moreover, investors' decisions in the cryptocurrency market are significantly affected by their sentiment and psychological factors. This is because as cryptocurrency emerges as an alternative currency in the financial market, it can elicit both uncertainty and volatility (Kjaerland et al., 2018; Patel et al., 2020). Based on the above, we chose behavioural finance theory to underpin the current study's theoretical framework in exploring the association between consumer confidence and cryptocurrency returns.

2.2. Consumer confidence and investment returns

Consumer confidence measures of the degree of optimism or pessimism expressed by consumers regarding the current state of the economy. This is reflected in their saving and spending activities, which leads to changes in the economy (James, 2021). In other words, consumers with high confidence in the current economy are more likely to engage in increased spending and investment, thus leading to positive changes in a country's economic growth. In contrast, when consumers exhibit low confidence in the economy, they may reduce spending and investment, potentially contributing to economic slowdown or negative changes in economic growth (Islam & Mumtaz, 2016). Furthermore, Hollanders and Vliegenthart (2011) highlighted that consumer sentiment that is derived from the media regarding economic activities is associated with consumer confidence, while negative news has a dampening effect. Lymperopoulos et al. (2010) demonstrated that the level of consumer confidence regarding the overall economic situation can significantly affect consumer purchase intentions. Han et al. (2022) confirmed a positive correlation between consumer confidence and the intention to make environmentally friendly purchases. The connection arises from consumers who have a positive view of the current economy and are more motivated to engage in green consumption.

Several studies have considered monthly CCI scores as the measure of consumer confidence (Islam & Mumtaz, 2016; Mazurek & Mielcová, 2017). The Conference Board's CCI is based on the Consumer Confidence Survey, which measures consumer attitudes and confidence regarding their financial prospects (Ganti, 2023). This index provides an indicator regarding the future development of household consumption and savings. It is derived from households' answers regarding their expectations about various aspects, including their anticipated financial situation, sentiment about the general economic situation, unemployment prospects and ability to save (OECD, 2023).

Empirical studies have demonstrated that CCI scores are significantly correlated with economic activities. Dees and Brinca (2013) indicate that the CCI can be used to effectively predict household consumption, even when considering economic fundamentals. Islam and Mumtaz (2016) confirmed the presence of a long-term relationship between the CCI and economic growth, particularly within European countries. Kilic and Cankaya (2016) reported a strong association between CCI scores and factors such as industrial production, inventories, personal consumption expenditure and housing market variables. Furthermore, Mazurek and Mielcová (2017) found that the CCI can serve as a reliable predictor of GDP in the United States (US). Similarly, Acuña et al. (2020) demonstrated a positive correlation between the CCI and subsequent consumption growth.

2.3. Cryptocurrency returns

Previous research indicates that several factors impact cryptocurrency returns, referring to gains or losses from investments in the cryptocurrency market. Bitcoin was the first cryptocurrency introduced by Nakamoto (2008). Rehman and Kang (2021) examined the association between Bitcoin returns and mining based on daily trade data. Their results indicate that energy commodities, including oil, coal and gas, significantly affected Bitcoin returns. The rationale for this relationship was that Bitcoin mining consumes energy for the complexity of computation. Liu et al. (2020) reported that the most common risk factors, namely, the cryptocurrency market, size and momentum, significantly affected cryptocurrency returns. Phillips and Gorse (2018) confirmed that online activities, including Google searches and Wikipedia queries, have a long-term positive association with cryptocurrency returns. The reason is that increased interest and the number of searches for cryptocurrency have generated the growth of cryptocurrency demand, including purchasing, methods of payment and transaction needs (Bakas et al., 2022). Similarly, Aslanidis et al. (2022) documented that growth in the volume of Google searches was positively associated with cryptocurrency returns, representing a direct way in which investors could obtain relevant information (Kjaerland et al., 2018). Furthermore, Smales (2021) identified a positive relationship between investor attention and cryptocurrency returns while suggesting that their association could enhance the predictive accuracy of future cryptocurrency volatility. Rubbaniy et al. (2022) found that various comments, opinions, news and information related to cryptocurrencies were linked to cryptocurrency return volatility.

Daas and Puts (2014) highlighted the connection between changes in consumer confidence and social media sentiment, uncovering common underlying and driving factors. This aligns with the appraisal–tendency framework developed by Han et al. (2007), who claimed that consumer decision-making is influenced by two types of emotions: incidental and integral. Lansdall-Welfare et al. (2012) suggested that consumer confidence is likely to be affected by incidental emotion. This is because sentiment derived from social media often reflects the incidental emotions among those who are active on social media platforms. This finding was supported by Shayaa et al. (2017) who stated that sentiment obtained from social media can represent consumer confidence sentiment within a large population. Shayaa et al. (2018) further demonstrated the significance of the relationship between the CCI and sentiment derived from social media, emphasising the wealth of data that social media platforms can provide regarding consumer confidence. These findings have motivated the present study to investigate the relationship between the CCI and cryptocurrency returns. As such, we explored whether incidental emotions expressed by consumers in consumer confidence surveys can effectively describe their behaviour in the cryptocurrency market while illustrating the dynamics of cryptocurrency returns.

Several theoretical underpinnings support this study in exploring the relationship between the CCI and an excess in cryptocurrency returns. First, the CCI is a pre-eminent indicator of aggregate demand and overall economic well-being (Mazurek & Mielcová, 2017). Prior studies indicate that the CCI has a strong correlation with economic fundamentals, such as unemployment rates (Mandal & McCollum, 2013), GDP growth (Islam & Mumtaz, 2016), stock market performance (Chen, 2012) and consumer growth (Malovaná et al., 2021). Thus, it is reasonable to assume that investors regard the CCI as a key proxy for investment in cryptocurrency. Second, the CCI provides insights into consumers' perceptions of their personal financial situations, which often transcend the realm of economic fundamentals (Acuña et al., 2020). Empirical studies indicate that investor sentiment can drive cryptocurrency returns (Akyildirim et al., 2021; Naeem et al., 2021). Third, Koy and Akkaya (2017) indicate that consumer confidence is essential in shaping individual investment-related judgements when making investment decisions. This is because CCI scores refer to consumers' perceptions of their sentiment regarding economic conditions (James, 2021). Moreover, investor psychology factors such as risk perception, risk tolerance and confidence contribute to investment decision-making (Ainia & Lutfi, 2019). This aligns with Charles and Kasilingam (2016), who suggested that investors' behavioural bias factors significantly affect investors' investment decisions. Thus, the CCI can be an essential factor in shaping individual investment choices in the cryptocurrency market.

Considering these theoretical foundations, we investigated whether consumer confidence, particularly consumers' saving and spending behaviours, could effectively induce them to invest in cryptocurrency, thus providing insights into the dynamics of cryptocurrency returns. This exploration contributes to a deeper understanding of the role of consumer confidence in the context of cryptocurrency investment, which is significant for investors and market analysis.

2.4. Hypotheses development

In a traditional financial market, consumer confidence is a significant economic indicator of the stock market. Jansen and Nahuis (2003) examined the short-run relationship between stock market returns and consumer confidence across 11 European countries from 1986 to 2001. Their findings indicate that a positive relationship exists between stock market returns and consumer confidence in the stock markets of most of these countries. Lemmon and Portniaguina (2006) confirmed that consumer confidence can be an essential predictor of returns on smaller stocks and stocks with low institutional ownership during their 25-year study period. Their rationale was that consumer sentiment changes affect consumer spending, leading to changes in expected corporate profits. Similarly, Chen (2011) confirmed a significantly positive relationship between consumer confidence and contemporaneous stock returns. The rationale was that when investors believe that the economy is heading for a downturn, they often become apprehensive about the stock market's future performance. Hence, they may sell their stocks, causing the market to fall (Whaley, 2009). This perspective is supported by Sum (2014), who found that business and consumer confidence positively affect stock market returns. Consumers with high confidence in the current economy are likelier to increase spending and investment (James, 2021). In contrast, when consumers

Table 1
Normal yearly distribution of cryptocurrency.

Panel A: Yearly distribution					
Year	Total coins	New coins	%	Discontinued coins	%
2014	111	0	0	0	0
2015	157	50	1.54	4	0.4
2016	223	72	2.22	6	0.61
2017	581	363	11.19	5	0.51
2018	1512	939	28.95	8	0.81
2019	1979	561	17.30	94	9.51
2020	2416	623	19.21	186	18.83
2021	2748	590	18.19	258	26.11
2022	2366	45	1.39	427	43.22
Total	3318	3243	100 %	988	100 %

Panel B Size and volume distribution							
		Market cap (mil)			Volume (thous)		
Year	Number	Mean	Median	SD	Mean	Median	SD
2014	111	1103.22	2.91	8764.54	5231.77	19.84	40,909.64
2015	157	455.13	1.14	4741.96	4052.16	3.18	52,773.38
2016	223	873.37	2.42	10,001.75	9940.99	6.07	114,296.26
2017	581	5403.67	33.24	76,129.50	238,950.74	275.35	3,715,754.28
2018	1512	3960.26	53.87	61,807.23	233,632.38	556.24	3,358,500.52
2019	1979	2122.58	17.15	54,416.17	541,790.63	235.18	10,653,984.34
2020	2416	257,000.00	24.43	1,400,000.00	1,200,443.87	452.43	24,855,139.78
2021	2748	14,043.62	77.59	323,000.00	1,870,203.67	2257.19	39,018,321.17
2022	2366	12,144.82	54.55	239,000.00	1,314,371.52	1553.85	29,804,705.29
Full	3318	290,011.90	34.74	241,984.60	1,074,038.79	679.46	26,177,582.12

Note: This table presents the number of coins, new coins and discontinued coins by year in Panel A. Panel B presents the number of coins, the mean, the median of market capitalisation and the mean and median of daily trading price volume by year.

exhibit lower confidence in the economy due to economic slowdown or negative changes in economic growth, they may reduce spending and investment (Islam & Mumtaz, 2016). Reflecting the sentiment and beliefs of investors, consumer confidence plays a significant role in driving market trends and asset prices (Chung et al., 2012). Furthermore, investors' psychological factors, such as risk perception, risk tolerance and confidence, contribute to investment decision-making (Ainia & Lutfi, 2019; Charles & Kasilingam, 2016). These findings indicate that prevalent phenomena such as herding behaviour among cryptocurrencies, momentum effects, overreaction, contagion effects, investor sentiment and uncertainty are associated with investment decision-making. Therefore, we expect that an increase in the CCI can incentivise consumers to invest more money in cryptocurrency to obtain positive returns.

While previous studies have confirmed the positive association between consumer confidence and stock returns, the relationship between consumer confidence and financial asset returns is not universally positive. Ciner (2014) confirmed a time-varying relationship between consumer confidence and stock market returns. Specifically, a high level of consumer confidence indicates a higher return in the short term but a negative return in the medium term. Additionally, Ferrer et al. (2016) examined the correlation between the CCI and stock market returns through European and United States (US) data, based on post-dotcom bubble correction of 2000–2002 stock meltdowns and the 2007–2009 Global Financial Crisis stock meltdowns. Their results indicate that the association between consumer confidence and stock returns was not always positive. In contrast to previous findings, Koy and Akkaya (2017) proposed an inverse correlation between the CCI and capital market returns during periods of recession or economic expansion. While previous studies have illustrated the impact of the CCI on asset returns in the traditional financial market, the index has not been utilised in the cryptocurrency market context. Furthermore, a growing number of individual investors have considered cryptocurrencies as an alternative investment due to the potential for substantial profits (Ji et al., 2019). Hence, we expect that the CCI may negatively impact cryptocurrency returns owing to their volatility (Yi et al., 2018). To explore this notion, we proposed the following competing hypotheses:

Hypothesis 1 (H1). The CCI is positively associated with cryptocurrency excess returns through the three-factor model.

Hypothesis 2 (H2). The CCI is negatively associated with cryptocurrency excess returns through the three-factor model.

3. Methodology

3.1. Data and sample period

This study obtained daily cryptocurrency trade data from the cryptocurrency market website <https://coinmarketcap.com/>. This website serves as a prominent source of cryptocurrency price and volume, as noted by Liu et al. (2022). It compiles information from

Table 2
Descriptive statistics.

Variables	Low CCI (N = 338,613)		High CCI (N = 336,354)		Sig. difference	
	Mean	Median	Mean	Median	Mean	Median
Panel A Independent variable						
CCI	1.9904	1.9911	2.0036	2.0051	***	***
Panel B Dependent variable						
R_m - R_f	−0.0020	−0.0087	−0.0050	−0.0161	***	***
Panel C Three-factor model						
CMRT	−0.0054	−0.0050	−0.0100	−0.0113	***	***
SMB	0.0364	0.0158	0.0282	0.0160	***	***
HML	0.2390	0.1888	0.2813	0.2410	***	***
Panel D Control variables						
FEDRATE	−0.6490	−1.0458	−0.1478	0.1903	***	***
OIL	1.8224	1.8807	1.7506	1.7643	***	***
GDP	4.3684	4.3865	4.3250	4.3331	***	***
EPUI	2.2128	2.1800	2.0126	2.0138	***	***
VIX	1.3788	1.3758	1.2269	1.2033	***	***
EXCHANGE	1.1144	1.1296	1.1497	1.1364	***	***
CPI	2.4432	2.4452	2.4072	2.4077	***	***
DJIA	4.4983	4.5161	4.4187	4.4191	***	***
SENTMENT	1.8269	1.8470	1.9691	1.9818	***	***
Gtrend_BTC	1.4199	1.4771	1.2175	1.1139	***	***
Wiki_BTC	3.6894	3.6672	3.7378	3.6796	***	***

Note: This table compares the mean and median of the study variables, comparing the low-value and high-value CCI. Panel A provides the descriptive statistics for the independent variable, the dependent variable is in Panel B, the three-factor model variables are in Panel C and the control variables are in Panel D. We provide the definitions of the variables in Appendix A.

over 200 major cryptocurrency exchanges, providing daily data on metrics, such as opening and closing prices, high and low prices, trade volume and market capitalisation (in US dollars [US$]) for active and discontinued cryptocurrencies. We obtained data for all cryptocurrencies using the application programming interface (API) provided by the website <https://coinmarketcap.com/>. The interface reports the last traded price and trade volume for the past 24 h. Subsequently, all historical cryptocurrency data was cleaned and processed using Python software. This process led to the exclusion of cryptocurrencies, which lack available data on trade volume and market capitalisation.

Data were collected from 1 January 2014 to 31 December 2022. This period was based on the rationale that Liu et al. (2022) highlighted the availability of cryptocurrency trade volume data during the last week of 2013, with a sample period starting at the beginning of 2014. Another reason is the remarkable expansion of the cryptocurrency market beginning in 2018, along with the onset of the COVID-19 pandemic in March 2020 and the regulatory actions taken by the Chinese government in May 2022 (Yang et al., 2023). Bitcoin-halving events occurred in 2016 and 2020, marking two complete Bitcoin cycles from 2014 to 2022. These events have had a significant impact on the cryptocurrency market (Singla et al., 2023). Furthermore, the selected sample period ensures sufficient data for this study's empirical analysis.

The CCI data were obtained from the OECD database. The CCI generated from this database is sourced directly from The Conference Board, thus distinguishing it from other consumer confidence indices commonly used in practice (Mazurek & Mielcová, 2017). When the index value surpasses 100, it signifies a rise in consumer confidence regarding future economic prospects. This often results in reduced saving tendencies and a greater willingness to make substantial purchases over the subsequent 12 months. In contrast, values below 100 indicate a pessimistic outlook on the economy, which potentially prompts individuals to increase savings and reduce consumption (OECD, 2023). The control variable data were derived from the US Federal Reserve Bank of St Louis, Google Trends and the Wikipedia database. We merged the control variable and CCI data to align with cryptocurrency dates.

3.2. *Instruments*

3.2.1. *Consumer confidence index*

This used monthly CCI scores to measure consumer confidence. The index is updated monthly by the Conference Board and obtained from OECD.org at <https://data.oecd.org/leadind/consumer-confidence-index-cci.htm>. CCI scores are typically calculated by surveying a representative sample of consumers (i.e. households) while asking a series of questions related to their economic outlook (Van den Brakel et al., 2017). Administered by the Conference Board, CCI scores measure the level of optimism or pessimism among consumers regarding their anticipated financial situation (James, 2021). To maintain consistency with the cryptocurrency data, we downloaded CCI data from January 2014 to December 2022.

3.2.2. *Cryptocurrency returns*

This study used cryptocurrency's daily close prices to construct daily returns. We considered the one-month Treasury Bill (T-Bill) rate (risk-free [Rf]), generated from the US Treasury Department, as the risk-free benchmark rate to align with previous studies (Chen

Table 3
Pairwise correlations.

Variables	V1	V2	V3	V4	V5	V6	V7	V8	V9	V10	V11	V12
V1: Rm - Rf	1.000											
V2: CCI	0.002*	1.000										
V3: CMRT	0.146***	−0.004***	1.000									
V4: SMB	0.006***	−0.083***	−0.036***	1.000								
V5: HML	0.039***	0.134***	0.115***	0.515***	1.000							
V6: FEDRATE	−0.079***	0.252***	−0.307***	−0.067***	−0.114***	1.000						
V7: OIL	−0.033***	−0.467***	−0.130***	0.117***	−0.064***	0.249***	1.000					
V8: GDP	−0.008***	−0.301***	−0.015***	0.054***	−0.030***	−0.022***	0.278***	1.000				
V9: EPUI	0.036***	−0.267***	0.140***	−0.038***	−0.030***	−0.402***	−0.405***	−0.004***	1.000			
V10: VIX	0.009***	−0.565***	0.041***	−0.008***	−0.103***	−0.322***	−0.186***	0.118***	0.551***	1.000		
V11: EXCHANGE	0.043***	0.378***	0.172***	−0.005***	0.140***	−0.429***	−0.198***	−0.132***	−0.008***	−0.215***	1.000	
V12: CPI	−0.028***	−0.887***	−0.084***	0.104***	−0.144***	0.000	0.663***	0.365***	0.085***	0.394***	−0.435***	1.000
V13: DJIA	−0.002	−0.603***	0.021***	0.126***	−0.038***	−0.270***	0.573***	0.340***	0.057***	0.131***	−0.029***	0.790***
V14: SENTIMENT	0.007***	0.985***	0.015***	−0.076***	0.141***	0.189***	−0.477***	−0.294***	−0.253***	−0.544***	0.407***	−0.879***
V15: Gtrend_BTC	0.023***	−0.424***	0.096***	0.090***	0.038***	−0.383***	0.338***	0.246***	0.169***	0.223***	0.187***	0.528***
V16: Wiki_BTC	0.023***	0.058***	0.081***	0.077***	0.135***	−0.229***	0.266***	0.028***	−0.266***	−0.278***	0.381***	−0.026***
Variables	V13	V14	V15	V16								
V13: DJIA	1.000											
V14: SENTIMENT	−0.567***	1.000										
V15: Gtrend_BTC	0.755***	−0.412***	1.000									
V16: Wiki_BTC	0.170***	0.053***	0.466***	1.000								

Note: This table presents the Pearson's correlation coefficients between the variables employed in the primary regression analysis. ***, ** and * indicate significance at the 1 %, 5 % and 10 % levels, respectively. We present the variable definitions in Appendix A.

Table 4
Jensen's alpha for one- and three-factor model on cryptocurrency excess returns.

Panel A One-factor model

	Full size	Small size	Medium size	Large size
	Model 1	Model 2	Model 3	Model 4
α	0.0012***	−0.0024***	0.0034***	0.0003
	(6.12)	(−4.75)	(12.81)	(1.33)
CMRT	0.6133***	0.5798***	0.6003***	0.6721***
	(122.91)	(42.70)	(88.20)	(112.66)
F	15,106.51	1823.51	7779.28	12,692.67
Prob>F	0.0000	0.0000	0.0000	0.0000
N	692,888	173,222	346,336	173,330
R-squared	0.0213	0.0104	0.0220	0.0682

Panel B Three-factor model

	Full size	Small size	Medium size	Large size
	Model 1	Model 2	Model 3	Model 4
α	−0.0043***	−0.0053***	−0.0022***	−0.0081***
	(−11.80)	(−5.60)	(−4.38)	(−18.75)
CMRT	0.6022***	0.5925***	0.5866***	0.6413***
	(119.17)	(43.14)	(85.12)	(106.34)
SMB	−0.0017	0.1129***	−0.0215***	−0.0906***
	(−0.67)	(17.76)	(−6.09)	(−29.39)
HML	0.0210***	−0.0016	0.0239***	0.0440***
	(16.15)	(−0.47)	(13.09)	(28.06)
F	5152.61	745.12	2651.67	4608.01
Prob>F	0.0000	0.0000	0.0000	0.0000
N	692,888	173,222	346,336	173,330
R-squared	0.0218	0.0127	0.0225	0.0739

Note: This table presents the coefficient estimates for the modified one-factor model and three-factor model together with the *t*-value (in brackets). This model was estimated for the small, medium, large size and full size. ***, ** and * indicate significance at the 1 %, 5 % and 10 % levels, respectively.

et al., 2022; Liu et al., 2022). Hence, cryptocurrency excess returns were constructed as the difference between cryptocurrency returns and the T-Bill rate (Rf).

3.2.3. *Control variable data*

We considered a wide range of possible indicators as control variables that significantly influence cryptocurrency returns following previous literature. The selected control variables comprised the following: consumer price index (*CPI*) (Wang et al., 2022), federal funds rate (*FEDRATE*) (Havidz et al., 2021), crude oil (*OIL*) (Pogudin et al., 2019), economic policy uncertainty index (*EPUI*) (Yen & Cheng, 2021), the Chicago Board of Exchange and the volatility index (*VIX*) (Kim et al., 2021), the exchange rate of US$ to Euro (*EXCHANGE*) (Polasik et al., 2015), the Dow Jones industrial average (*DJIA*) (Zhu et al., 2017) and consumer sentiment (*SENTIMENT*) (Salhin et al., 2016). Data for these variables was obtained from the US Federal Reserve Bank of St Louis. Google Trends for Bitcoin (*Gtrend_BTC*) (Aslanidis et al., 2022) was generated from Google Trends, while the trend for Wikipedia Bitcoin (*Wiki_BTC*) (Stolarski et al., 2020) was obtained from the Wikipedia homepage. The definitions of relevant variables are presented in Appendix A.

3.3. *Fama–French three-factor model*

The three-factor model is a financial model illustrating asset returns while assessing portfolio risk and expected returns. It was developed by Eugene Fama and Kenneth French in the early 1990s as an extension of the traditional capital asset pricing model (CAPM) (Fama & French, 1993). The three-factor model introduces additional factors, namely, small-minus-big size (SMB) portfolios and high-minus-low book (HML) to market value to determine size and book-to-market value effects, respectively.

Several studies employ the three-factor model to examine cryptocurrency returns. Shen et al. (2020) employed the three-factor pricing model, comprising cryptocurrency market, size and reversal factors, to assess cryptocurrency excess returns. The findings indicate that the three-factor pricing model provides significantly better explanatory power compared to cryptocurrency's CAPM. Jia et al., 2022 developed a three-factor pricing model comprising market, size and momentum factors that outperformed the cryptocurrency CAPM, illustrating greater explanatory power than Shen et al. (2020) findings. This finding is also supported by Liu et al. (2020), who documented that the three-factor model based on market, size and momentum factors can explain average cryptocurrency returns effectively. Moreover, Liu et al. (2022) highlighted that size and momentum variables are among the most studied effects in

Table 5
CCI and cryptocurrency excess returns: baseline analysis.

Variables	Full size	Small size	Medium size	Large size
	Model 1	Model 2	Model 3	Model 4
Constant	2.9810***	1.3744*	2.7114***	4.0579***
	(9.36)	(1.68)	(6.20)	(10.18)
CCI	−0.6268***	−0.0326	−0.5430***	−1.1897***
	(−5.65)	(−0.12)	(−3.55)	(−8.52)
CMRT	0.5468***	0.5381***	0.5278***	0.5860***
	(102.61)	(37.10)	(72.99)	(93.27)
SMB	0.0019	0.1217***	−0.0207***	−0.0878***
	(0.72)	(18.76)	(−5.75)	(−27.93)
HML	0.0133***	−0.0102***	0.0158***	0.0348***
	(9.83)	(−2.96)	(8.36)	(21.40)
FEDRATE	−0.0038***	−0.0046*	−0.0050***	−0.0036***
	(−4.22)	(−1.94)	(−3.98)	(−3.27)
OIL	0.0227***	0.0159*	0.0209***	0.0243***
	(6.51)	(1.83)	(4.32)	(5.57)
GDP	−0.0032	0.0006	−0.0059**	−0.0028
	(−1.53)	(0.11)	(−1.98)	(−1.15)
EPUI	0.0064***	0.0076***	0.0064***	0.0041***
	(6.31)	(2.85)	(4.69)	(3.25)
VIX	−0.0023	−0.0084	0.0004	−0.0024
	(−0.75)	(−1.02)	(0.09)	(−0.63)
EXCHANGE	−0.0080*	0.0019	−0.0168***	−0.0041
	(−1.95)	(0.15)	(−3.14)	(−0.86)
CPI	−0.6901***	−0.4362***	−0.6080***	−0.7322***
	(−11.07)	(−2.63)	(−7.10)	(−9.65)
DJIA	−0.0292*	−0.0723*	−0.0481**	0.0029
	(−1.94)	(−1.84)	(−2.33)	(0.16)
Year fixed effects	Yes	Yes	Yes	Yes
Crypto fixed effects	Yes	Yes	Yes	Yes
F	28.02	10.88	23.40	47.43
Prob>F	0.0000	0.0000	0.0000	0.0000
N	692,888	173,075	346,141	173,269
R-squared	0.0256	0.0213	0.0377	0.0971

Note: This table presents the regression results of the CCI on cryptocurrency excess returns with the control variables. ***, ** and * indicate significance at the 1 %, 5 % and 10 % levels, respectively. The low adjusted R-squared value reported in our baseline results in Table 5 was expected given that several prior studies also reported similar low adjusted R-squared values (Zhang et al., 2021; Zhang & Li, 2023). The un-tabulated additional analysis indicates that the adjusted R-squared ranged between 13.62 % to 27.58 % for the top 10 % and 1 % market capitalisations of cryptocurrencies, respectively. For brevity, we do not report these findings in our manuscript. The data is available upon request.

both traditional and cryptocurrency asset pricing. Hence, the present study employed the three-factor model using cryptocurrency market, size and momentum as the factors to assess the relationship between CCI scores and cryptocurrency excess returns.

Based on the above, this study constructed a cryptocurrency market return based on the value-weighted return of all underlying available coins. Cryptocurrency excess market return (*CMRT*) represented the difference between cryptocurrency market return and the T-Bill rate (*Rf*):

$$R_{m,t} = \sum_{i=1}^{n} R_{i,t} \times \frac{Capi, t}{TotalCapt} \tag{1}$$

where $R_{m,t}$ depicts the cryptocurrency market return of coins on day t and $R_{i,t}$, Cap_t indicates the returns and capitalisation of the i_{th} cryptocurrency on day t and $TotalCap_t$. The cryptocurrency market factor is proxied by excess market return (*CMRT*), constructed as follows:

$$\mathrm{CMRT} = R_{m,t} - R_{f,t} \tag{2}$$

where $R_{m,t}$ is the cryptocurrency market return of coins on day t and $R_{f,t}$ is the risk-free rate proxied by the T-Bill rate.

We constructed the cryptocurrency market factors for the Fama–French three-factor model based on market, size and momentum to account for a broader range of influences on cryptocurrency excess return (Jia et al. (2022).

3.4. Size factors

This study defined the top 30 % of cryptocurrency market capitalisation as large portfolios, the bottom 30 % as small portfolios and the middle 40 % as medium portfolios, consistent with (Fama & French, 2012). Therefore, the size factor *SMB* (small minus big) represented the difference between the returns of small and large portfolios.

Table 6
CCI and cryptocurrency excess returns: entropy balancing analysis.

Panel A Mean value of variables for treatment and control groups

	Treatment group			Control group		
	Mean	Treat variance	Skewness	Mean	Treat variance	Skewness
CMRT	−0.0100	0.0017	0.1454	−0.0054	0.0012	0.0315
SMB	0.0282	0.0072	1.5190	0.03644	0.0085	2.4860
HML	0.2814	0.0252	3.8590	0.2391	0.0336	3.6300
FEDRATE	−0.1491	0.3840	−0.8208	−0.6483	0.4245	0.9005
OIL	1.7510	0.0082	−1.7230	1.8220	0.0357	−1.0630
GDP	4.3250	0.0006	−0.9120	4.3690	0.0173	−26.5200
EPUI	2.0120	0.0662	−0.1922	2.2120	0.0637	0.37270
VIX	1.2270	0.0230	1.5420	1.3790	0.0102	0.21310
EXCHANGE	1.1500	0.0055	98.6000	1.1140	0.0047	−0.3739
CPI	2.4070	0.0002	−0.3929	2.4430	0.0005	−0.1272
DJIA	4.4180	0.0055	−0.6202	4.4980	0.0027	−0.9878

Panel B Entropy balancing regression results

Variables	Full size	Small size	Medium size	Large size
Constant	1.4483***	1.2674***	1.4058***	1.2428***
	(13.65)	(4.35)	(9.67)	(9.89)
High_CCI	−0.0026***	0.0003	−0.0025**	−0.0057***
	(−3.53)	(0.13)	(−2.51)	(−6.68)
CMRT	0.5465***	0.5381***	0.5275***	0.5859***
	(102.55)	(37.10)	(72.94)	(93.24)
SMB	0.0016	0.1217***	−0.0209***	−0.0883***
	(0.60)	(18.76)	(−5.81)	(−28.10)
HML	0.0134***	−0.0102***	0.0158***	0.0350***
	(9.89)	(−2.97)	(8.39)	(21.57)
FEDRATE	−0.0056***	−0.0049**	−0.0064***	−0.0062***
	(−6.77)	(−2.26)	(−5.63)	(−6.13)
OIL	0.0253***	0.0160*	0.0231***	0.0300***
	(7.30)	(1.84)	(4.79)	(6.91)
GDP	−0.0032	0.0006	−0.0059*	−0.0026
	(−1.50)	(0.10)	(−1.96)	(−1.06)
EPUI	0.0067***	0.0077***	0.0067***	0.0047***
	(6.64)	(2.88)	(4.87)	(3.73)
VIX	−0.0024	−0.0086	0.0004	−0.0030
	(−0.79)	(−1.04)	(0.10)	(−0.79)
EXCHANGE	−0.0071*	0.0020	−0.0162***	−0.0033
	(−1.73)	(0.16)	(−3.03)	(−0.69)
CPI	−0.5279***	−0.4148***	−0.4785***	−0.4608***
	(−10.45)	(−3.01)	(−6.89)	(−7.73)
DJIA	−0.0556***	−0.0745**	−0.0699***	−0.0487***
	(−3.95)	(−2.02)	(−3.62)	(−2.78)
Year fixed effects	Yes	Yes	Yes	Yes
Crypto fixed effects	Yes	Yes	Yes	Yes
N	692,485	173,075	346,141	173,269
R-squared	0.0255	0.0213	0.0377	0.0970

Note: This table presents the entropy balancing results of the impact of the CCI on cryptocurrency excess returns with other control variables. Panel A presents the mean differences of dependent and independent variables between the control and matched groups. Panel B presents the regression estimates using these two groups. ***, ** and * indicate significance at the 1 %, 5 % and 10 % levels, respectively. We present the variable definitions in Appendix A.

3.5. *Momentum factors*

This study's analysis involved six value-weighted portfolios based on cryptocurrency market capitalisation and performance on the previous trading day. These portfolios were designed to capture momentum factors, representing the intersections of two portfolios categorised by size and three portfolios categorised by returns from the previous day (prior returns).

The breakpoints of prior returns were defined as the 30th and 70th percentiles. Within this framework, cryptocurrencies in the top 30 % of market capitalisation were categorised as large (size). Cryptocurrencies in the bottom 30 % were considered small (size). This classification elicited six distinct portfolios, each formed independently and denoted as BH, BM, BL, SH, SM and SL. Further, B signifies large portfolios, and S represents small portfolios. Moreover, H, M and L correspond to high, medium and low prior returns, respectively (Jia et al. (2022) as follows:

Table 7
CCI and cryptocurrency excess returns: 2SLS.

Variables	First stage	Second stage
	Model 1	Model 2
Intercept	2.1441***	2.5550***
	(2925.34)	(6.76)
Pred_CCI		−0.4719***
		(−3.54)
SENTIMENT	0.0604***	
	(1247.75)	
CMRT	0.0001***	0.5468***
	(2.92)	(102.65)
SMB	0.0002***	0.0017
	(10.69)	(0.67)
HML	0.0001***	0.0133***
	(10.01)	(9.83)
FEDRATE	0.0015***	−0.0046***
	(295.79)	(−4.70)
OIL	−0.0015***	0.0232***
	(−71.98)	(6.65)
GDP	−0.0000**	−0.0033
	(−2.38)	(−1.53)
EPUI	−0.0000**	0.0066***
	(−2.07)	(6.45)
VIX	−0.0016***	−0.0026
	(−85.39)	(−0.86)
EXCHANGE	0.0003***	−0.0077*
	(12.10)	(−1.89)
CPI	−0.1145***	−0.6278***
	(−328.23)	(−9.09)
DJIA	0.0040***	−0.0371**
	(43.35)	(−2.39)
Year fixed effects	Yes	Yes
Crypto fixed effects	Yes	Yes
N	692,485	692,485
R-squared	0.9849	0.0256
Endogeneity test of endogenous regressors:		
Chi-sq	18,157.37***	
p-value	0.00	
Ramsey RESET test:		
F -statistic	71.17***	
P-value	0.00	
Durbin–Wu–Hausman Test		
Durbin (score) Chi-sq	0.654059	
Wu-Hausman F-statistic	0.654046	

Note: This table presents the 2SLS regression results of the impact of the CCI on cryptocurrency excess returns with other control variables. We used an instrument and presented the first stage in Column 1 based on CCI as the dependent variable. Column 2 presents the results of the impact of the predicted *CCI* on *Rm-Rf* as the dependent variable. ***, ** and * indicate significance at the 1 %, 5 % and 10 % levels, respectively. We present the variable definitions in Appendix A.

$$\text{SMB} = \text{Returns of small portfolios–Returns of big portfolios} \tag{3}$$

$$\text{HML} = 1/2(\text{Small High [SH]} + \text{Big High [BH]}) - 1/2(\text{Small Low [SL]} + \text{Big Low [BL]}) \tag{4}$$

3.6. Model specifications

To simplify assumptions and parsimony, we specified the one-factor CAPM to capture cryptocurrency excess returns as follows:

$$\text{R}_{i,t} - \text{R}_{f,t} = \alpha + \beta_{i,1}\text{CMRT} + \varepsilon_t \tag{5}$$

where $R_{m,t}$ is the cryptocurrency market return of coins on day t. $R_{f,t}$ is the risk-free rate proxied by the T-Bill rate. $CMRT = R_{m,t} - R_{f,t}$ is the cryptocurrency excess market returns. α is the cryptocurrency excess return after controlling for the effect of all explanatory variables.

To assess the impact of the cryptocurrency market, size and momentum on cryptocurrency excess returns, we utilised the three-factor model as follows:

$$\text{R}_{i,t} - \text{R}_{f,t} = \alpha + \beta_1(\text{R}_{m,t} - \text{R}_{f,t}) + \beta_2\text{SMB}_t + \beta_{3,i}\text{HML}_t + \varepsilon_{i,t} \tag{6}$$

Table 8
CCI and cryptocurrency excess returns: additional analysis.

Panel A Change over different periods

	Before COVID-19 (2014–2019)	COVID-19 (2020–2022)
CCI	−0.6437*	−0.2056*
	(−1.78)	(−1.84)
Constant	1.6358*	1.3235***
	(1.89)	(4.33)
Baseline controls	Yes	Yes
Crypto fixed effects	Yes	Yes
N	237,165	455,320
R-squared	0.0263	0.0245

Panel B The impact of COVID-19 on cryptocurrency excess returns

Variables	COVID-19 full size	COVID-19 small size	COVID-19 med size	COVID-19 large size
	Model 1	Model 2	Model 3	Model 4
CCI	−0.2198**	−0.0035	−0.1102	−0.7941***
	(−2.09)	(−0.01)	(−0.76)	(−5.99)
COVID-19	0.0043***	0.0101***	0.0059***	0.0032**
	(3.73)	(3.59)	(3.78)	(2.00)
Constant	0.9898***	0.6286	0.4608	2.3791***
	(3.47)	(0.86)	(1.17)	(6.63)
Baseline controls	Yes	Yes	Yes	Yes
Crypto fixed effects	Yes	Yes	Yes	Yes
N	692,485	173,075	346,141	173,269
R-squared	0.0251	0.0210	0.0369	0.0958

Panel C Interaction analysis

Variables	COVID-19 full size	COVID-19 small size	COVID-19 med size	COVID-19 big size
	Model 1	Model 2	Model 3	Model 4
CCI	−0.2972	−0.7724	−2.3749***	−0.3935
	(−1.05)	(−1.11)	(−5.96)	(−0.89)
COVID-19	−0.1611	−1.6767	−4.8686***	0.8379
	(−0.29)	(−1.18)	(−6.09)	(0.96)
CCI x COVID-19	0.0825	0.8410	2.4306***	−0.4162
	(0.29)	(1.19)	(6.10)	(−0.95)
Constant	1.1416*	2.1198	4.9018***	1.5839*
	(1.93)	(1.46)	(5.92)	(1.75)
Baseline controls	Yes	Yes	Yes	Yes
Crypto fixed effects	Yes	Yes	Yes	Yes
N	692,485	173,075	346,141	173,269
R-squared	0.0251	0.0210	0.0370	0.0958

Note: This table presents the results of the impact of COVID-19 on the relationship between CCI and Rm-Rf with other control variables. ***, ** and * indicate significance at the 1 %, 5 % and 10 % levels, respectively. We present the variable definitions in Appendix A.

where SMB_t and HML_t indicate cryptocurrency size and momentum factors, respectively, while ε_t is the residual term.

To obtain a comprehensive analysis of the association between the CCI and cryptocurrency excess returns, we considered additional control variables to capture their effect on cryptocurrency excess returns as follows:

$$\begin{aligned} R_{i,t}-R_{f,t} = {} & \alpha+\beta_1\left(R_{m,t-1}-R_{f,t-1}\right)+\beta_2 SMB_{t-1}+\beta_3 HML_{t-1}+\beta_4 CCI_{i,t-1}+\beta_5 FEDRATE_{i,t-1}+\beta_6 OIL_{i,t-1}+\beta_7 GDP_{i,t-1}+\beta_8 EPUI_{i,t-1} \\ & +\beta_9 VIX_{i,t-1}+\beta_{10} EXCHNGE_{i,t-1}+\beta_{11} CPI_{i,t-1}+\beta_{12} DJIA_{i,t-1}+\sum YEAR_{i,t-1}+\sum Crypto_{i,t-1}+\varepsilon_{i,t-1} \end{aligned} \tag{7}$$

The control variables were entered into the equation as lag factors. We winsorised cryptocurrency variables at the 99th percentile to mitigate the impact of outliers.

Table 9
CCI and cryptocurrency excess returns: robustness tests.

Panel A The impact of cryptocurrency market capitalisation		
Variables	Low Market Cap	High Market Cap
CCI	−0.2068	−1.0736***
	(−1.11)	(−9.28)
CMRT	0.5351***	0.5557***
	(57.21)	(105.16)
SMB	0.0711***	−0.0702***
	(16.24)	(−26.47)
HML	0.0002	0.0275***
	(0.09)	(19.90)
Constant	1.9022***	4.0759***
	(3.54)	(12.31)
Test of coefficient difference	15.95***	
Baseline controls	Yes	Yes
Year and crypto fixed effects	Yes	Yes
N	346,193	346,292
R-squared	0.0182	0.0658

Panel B The impact of cryptocurrency trade volume		
Variables	Low Volume	High Volume
CCI	−0.2807	−0.9754***
	(−1.47)	(−8.78)
CMRT	0.5354***	0.5562***
	(56.77)	(107.78)
SMB	0.0618***	−0.0629***
	(14.04)	(−24.20)
HML	0.0033	0.0250***
	(1.42)	(18.57)
Constant	1.9899***	3.9589***
	(3.62)	(12.41)
Test of coefficient difference	9.98***	
Baseline controls	Yes	Yes
Year and crypto fixed effects	Yes	Yes
N	346,207	346,278
R-squared	0.0169	0.0624

Note: Panel A in this table presents the regression results of cryptocurrency market capitalisation's effect on excess returns with all control variables. Panel B presents the regression results of the effect of cryptocurrency trade volume on cryptocurrency excess returns with all control variables. ***, ** and * indicate significance at the 1 %, 5 % and 10 % levels, respectively. We present the variable definitions in Appendix A.

4. Descriptive analyses

4.1. Cryptocurrency distribution

We removed all cryptocurrencies without data on trade volume and market capitalisation from the analysis. Overall, 3318 cryptocurrencies survived the initial screening. Notably, the number of coins meeting the inclusion criteria increased from 111 in 2014 to 2748 in 2021. The number decreased to 2366 in 2022 (Panel A in Table 1). This result suggests that the total supply of cryptocurrencies increased over time while the cryptocurrency market has received increasing attention. A significant increase in the generation of new cryptocurrencies since around 2016 indicates a pronounced cryptocurrency market trend. A rise in the number of discontinued coins in the cryptocurrency market paralleled the expansion of new coins. The results in Panel B indicate that the mean (median) market capitalisation in the sample was US $290,011.90 million (US $34.74 million). The mean (median) daily price volume of the sample was US $1074.04 million (US $6.79 million). Therefore, the cryptocurrency market has witnessed significant growth and appreciation regarding the value of various cryptocurrencies during the study period. While the cryptocurrency market creates trade opportunities for speculators seeking to obtain excess returns from price fluctuations, it also elicits risks within this market, as illustrated by the high number of standard errors.

4.2. Variable descriptive statistics

We classified the CCI values into two groups: low-value and high-value CCI. These were based on the median CCI value. Then, we tested the differences between low-value CCI and high-value CCI, as shown in Table 2. The results suggest significant differences in mean/median values between these two groups across all variables. Panel A presents the statistical mean and median for the independent variable. Panel B presents the mean and median value of dependent variable. The three-factor model variables are presented

Table 10
CCI and cryptocurrency excess returns: robustness tests.

Panel A Conditional sample: excluding Bitcoin (BTC)

Variables	Model 1
CCI	−0.6304***
	(−5.66)
CMRT	0.5463***
	(102.04)
SMB	0.0017
	(0.67)
HML	0.0134***
	(9.84)
Cons	3.0038***
	(9.38)
Baseline controls	Yes
Year and crypto fixed effects	Yes
N	689,200
R-squared	0.0255

Panel B Conditional sample: excluding the top 10 coins

Variables	Model 1
CCI	−0.6349***
	(−5.62)
CMRT	0.5439***
	(100.06)
SMB	0.0033
	(1.27)
HML	0.0131***
	(9.49)
Constant	3.0271***
	(9.31)
Baseline controls	Yes
Year and crypto fixed effects	Yes
N	667,842
R-squared	0.0250

Panel C Conditional sample: excluding the bottom 10 coins

Variables	Model 1
CCI	−0.6314***
	(−5.70)
CMRT	0.5476***
	(102.64)
SMB	−0.0033
	(−1.25)
HML	0.0136***
	(10.01)
Constant	2.9775***
	(9.36)
Baseline controls	Yes
Year and crypto fixed effects	Yes
N	671,338
R-squared	0.0264

Note: Panel A in this table presents the regression results of the effect of excluding Bitcoin on cryptocurrency excess returns with all control variables. Panel B presents the regression results of the effect of excluding the top 10 cryptocurrencies on its excess returns with all control variables. Panel C presents the regression results of the effect of excluding the bottom 10 cryptocurrencies on its excess returns with all control variables. ***, ** and * indicate significance at the 1 %, 5 % and 10 % levels, respectively. We present the variable definitions in Appendix A.

in Panel C and the control variables are shown in Panel D. The results indicate that cryptocurrencies with high value of CCI (*high_CCI*) showed a significant lower cryptocurrency excess returns score.

4.3. Pearson's correlation

Table 3 presents the Pearson's correlation coefficient for each pair of variables. The results indicate that the correlation between *CCI* and *Rm-Rf* impact proxies was positive and statistically significant. Cryptocurrency excess returns were positive and statistically

Table 11
CCI and cryptocurrency excess returns: robustness tests/additional control variables.

Variables	Full size	Small size	Medium size	Large size
	Model 1	Model 2	Model 3	Model 4
Cons	2.9729***	1.3063	2.7735***	4.1234***
	(9.31)	(1.60)	(6.33)	(10.28)
CCI	−0.5936***	0.0408	−0.5092***	−1.1779***
	(−5.34)	(0.14)	(−3.33)	(−8.42)
CMRT	0.5467***	0.5387***	0.5283***	0.5855***
	(102.56)	(37.11)	(73.03)	(93.18)
SMB	0.0018	0.1210***	−0.0213***	−0.0878***
	(0.68)	(18.64)	(−5.91)	(−27.90)
HML	0.0135***	−0.0096***	0.0162***	0.0349***
	(9.97)	(−2.81)	(8.59)	(21.45)
FEDRATE	−0.0040***	−0.0050**	−0.0052***	−0.0036***
	(−4.45)	(−2.11)	(−4.10)	(−3.25)
OIL	0.0233***	0.0164*	0.0210***	0.0247***
	(6.68)	(1.87)	(4.33)	(5.67)
GDP	−0.0031	0.0009	−0.0057*	−0.0026
	(−1.47)	(0.16)	(−1.89)	(−1.09)
EPUI	0.0059***	0.0070**	0.0063***	0.0036***
	(5.71)	(2.57)	(4.55)	(2.85)
VIX	−0.0033	−0.0092	0.0010	−0.0021
	(−1.07)	(−1.10)	(0.25)	(−0.54)
EXCHANGE	−0.0050	0.0085	−0.0114**	−0.0008
	(−1.19)	(0.65)	(−2.10)	(−0.17)
CPI	−0.7036***	−0.4577***	−0.6703***	−0.7699***
	(−11.04)	(−2.73)	(−7.68)	(−9.81)
DJIA	−0.0299*	−0.0717*	−0.0394*	0.0080
	(−1.96)	(−1.81)	(−1.88)	(0.42)
Gtrend_BTC	0.0023	0.0005	−0.0037	0.0008
	(1.44)	(0.10)	(−1.64)	(0.40)
Wiki_BTC	−0.0072***	−0.0100***	−0.0064***	−0.0067***
	(−5.43)	(−2.89)	(−3.57)	(−4.10)
Year fixed effects	Yes	Yes	Yes	Yes
Crypto fixed effects	Yes	Yes	Yes	Yes
F	27.99	10.85	23.36	47.25
Prob>F	0.0000	0.0000	0.0000	0.0000
N	692,888	173,075	346,141	173,269
R-squared	0.0256	0.0213	0.0378	0.0972

Note: This table presents the CCI regression results on cryptocurrency excess returns with additional control variables. ***, ** and * indicate significance at the 1 %, 5 % and 10 % levels, respectively. We present the variable definitions in Appendix A.

significant in their association with the three factors of *CMRT*, *SMB* and *HML*. The findings indicate that cryptocurrencies with small market capitalisation (high momentum) outperformed cryptocurrencies with large market capitalisation (small momentum). Hence, investors may re-design their portfolios according to the market capitalisation and trade momentum of cryptocurrency. However, the independent variable *CCI* negatively correlated with *CMRT* and the cryptocurrency size factor, *SMB*. In contrast, *CCI* had a positive relationship with the cryptocurrency momentum factor, *HML*. Notably, the correlation between *CCI* and *SENTIMENT* indicated a positive and significant coefficient (0.985), which was the strongest correlation in our sample. Moreover, all control variables, including the three factors, had a statistically significant correlation with *CCI*. These findings suggest that consumer confidence is an essential determinant for investors regarding portfolio design.

5. Analysis and results

The study employed different models to examine the relationships between CCI and cryptocurrency excess returns through the one-factor and three-factor models. We also conducted additional analysis and robustness checks to ensure that the findings remained consistent while not being overly reliant on the study's specific measurement techniques and models. These additional tests and assessments contributed to the robustness and reliability of our research results and are outlined below.

5.1. Jensen's alpha analysis

Table 4 shows the estimations for Jensen's alpha coefficients for the small, medium, large and full samples through the one-factor and three-factor models. Panel A (1) and (3) showed significantly positive Jensen's alpha coefficients. The large size (4) had a positive Jensen's alpha coefficient, but it was not significant. In contrast, the small size (2) had a significantly negative Jensen's alpha coefficient. The findings suggest that the one-factor model with a different sample produced a different Jensen's alpha coefficient and that this model may not be a good predictor of cryptocurrency returns. The Jensen's alpha coefficients in the three-factor model are presented in Panel B; they were negative and significant at the 1 % level across all models. The value exhibited low volatility, ranging from −0.0081 to −0.0022. Additionally, the *R*-squared (R^2) value in the three-factor model was higher than in the one-factor model. These findings indicate that the three-factor model achieved better performance than the one-factor model in predicting cryptocurrency excess returns. This result is supported by Jia et al. (2022), who found that the three-factor model exhibited greater explanatory power in cryptocurrency returns than the one-factor model. Similarly, Blanco (2012) confirmed that the three-factor model outperformed the one-factor model in explaining stock returns in the traditional financial market.

5.2. Baseline analysis

We employed the three-factor model including year and crypto (i.e. cryptocurrency) fixed effects to test the study hypotheses by assessing the association between the CCI and cryptocurrency excess returns. Table 5 shows the regression results in Columns (1)–(4), which indicate that the main explanatory variable *CCI* was negative and statistically significant in (1) ($\beta = -0.6268, p < 0.05$), (3) ($\beta = -0.5430$, $p < 0.05$) and (4) ($\beta = -1.1897$, $p < 0.05$). This finding indicates that *CCI* was negatively associated with changes in cryptocurrency excess returns using samples of various sizes. The *CCI* coefficient (2) was negative but not significant concerning *Rm-Rf*. This suggests that *CCI* and *Rm-Rf* had a negative relationship. However, the relationship in (2) was not strong enough to be statistically valid. The rationale behind the relationship is that cryptocurrencies with smaller market capitalisation demonstrate stronger future performance. This supports the existing body of literature that underscores the inefficiencies within the cryptocurrency market. This finding also challenges the efficient market hypothesis (Li et al., 2020). Notably, *CCI* had the largest coefficients in (2) ($\beta = -0.0326$) followed by (3) ($\beta = -0.5430$), (1) ($\beta = -0.6268$) and (4) ($\beta = -1.1897$). Cryptocurrencies with small market capitalisation are supported by the literature on cryptocurrency's inefficiency (Brauneis & Mestel, 2018), challenging the efficient market hypothesis (Li et al., 2020). Another explanation is that cryptocurrencies with large market value are likely to be mature (Bakhtiar et al., 2023). In other words, cryptocurrencies with small market capitalisation can generate higher returns than cryptocurrencies with larger market capitalisation (Liu et al., 2022). As such, investors can construct investment portfolios based on risk aversion. Furthermore, the *CCI* coefficient was not only negative and insignificant in (2), but it was also negative across all models. This finding suggests that the CCI was negatively associated with cryptocurrency excess returns through the three-factor model. Hence, H2 is supported.

Notably, the three-factor coefficients were statistically significant across all models at the 1 % level, except for *SMB* in (1). This result suggests that the three-factor model can provide a significant prediction of cryptocurrency returns. Regarding the control variables, the *FEDRATE* and *CPI* coefficients were negative and statistically significant in their association with cryptocurrency excess returns. This indicates that a higher federal funds rate or CCI score induces lower cryptocurrency excess returns. The control variables in the regression models align with variables most commonly considered in past studies concerning the federal funds rate (Havidz et al., 2021). In contrast, the *OIL* and *EPUI* coefficients were positive and statistically significant, indicating that higher oil prices and EPU index scores contribute to greater cryptocurrency excess returns. The *R*-squared (R^2) values in the research models varied from 0.0213 to 0.0971. This suggests that the independent variable collectively captured between 2.13 % and 9.71 % of the variance in cryptocurrency excess returns. Regarding economic significance, moving from the 25th percentile (1.9911) to the 75th percentile (2.0050), the *CCI* coefficient estimates showed a reduction in cryptocurrency returns by 87 basis points ([2.0050–1.9911] x [−0.6268] = −0.0087). The *CCI* mean and median values were 1.9971 and 0.2190, respectively, implying that the CCI value can indicate an economically significant reduction in cryptocurrency excess returns.

5.3. Entropy balancing analysis

Although the baseline regression provides empirical evidence that the CCI was negatively associated with cryptocurrency excess returns, the possible endogeneity from omitted variables biases, selection bias and reverse causality problem still needs to be considered. The entropy balancing method can be used to mitigate potential selection bias and adjust for variations in characteristics across treatment and control groups (Hainmueller, 2012). This approach assigns weights to observations on a continuous scale, facilitating an optimal weighted match with a treatment sample. Therefore, it can achieve covariate balance while retaining the original sample size and improving efficiency (Wilde, 2017). An increasing number of studies have employed the entropy balancing method, highlighting its advantages (Jia & Li, 2022).

To address the covariate imbalance between the treatment and control groups when estimating causal effects, we divided cryptocurrency market capitalisation into a treatment group (*High_CCI*) and a control group (*Low_CCI*). The treatment group was generated based on those with a greater cryptocurrency market value than the median market value. The control group comprised those with a lower cryptocurrency market value than the median market value. We also controlled for the year and crypto fixed effects across all models. We re-ran the baseline models using the entropy balancing method. Panel A in Table 6 presents the descriptive statistics for the entropy-balanced samples when balancing *High_CCI* with *Low_CCI* for the treatment and control groups, respectively. Panel B in Table 6 presents the second-stage regression results for the entropy-balanced samples. The results indicate that the *CCI* coefficients were consistently negative and statistically significant across all models except for (2). Evidently, the CCI was negatively associated with cryptocurrency excess returns based on the three-factor model.

5.4. Two-stage least squares (2SLS)

We applied the 2SLS model to address possible endogeneity issues related to reverse causality and omitted variables (Sarkodie et al., 2022; Wang et al., 2021). This approach is crucial for estimation when the error term of the dependent variable correlates with the independent variables, as utilised in this study. Overlooking this circumstance could lead to biased estimation outcomes, further challenging the exogeneity assumption (Shittu et al., 2021).

To validate the regression models and confirm H2 based on the baseline model, we addressed potential endogeneity through 2SLS estimation using an instrument variable approach (Cheung, 2016). We incorporated consumer sentiment (*SENTIMENT*) as the instrumental variable. The rationale behind the choice of consumer sentiment is that the correlation between *CCI* and *SENTIMENT* was positive and significant. This correlation coefficient (0.985) was the strongest correlation (Table 3). We also controlled for year and crypto to reduce the year and cryptocurrency fixed effects on cryptocurrency returns.

Table 7 presents the results of the 2SLS. Model (1) reports the first-stage results where *CCI* was the dependent variable. The Column (1) results illustrate that *SENTIMENT* was positive with a coefficient of 0.0604 and significant at the 1 % level. The R^2 value in (1) was 98.49 %, suggesting that *SENTIMENT* effectively explained the *CCI* in (1).

We used this study's regression model *SENTIMENT* from the first stage to replace the endogenous variable to perform the second stage. Column (2) reports the second-stage regression results with *SENTIMENT*, the instrumental variable from the first stage. The predicted value of *CCI* (*Pred_CCI*) was negative and statistically significant ($\beta = -0.4719$, $p < 0.01$) at the 1 % level of the total sample size related to *Rm-Rf*, aligning with the previous findings. Furthermore, we conducted the Wald Chi-squared test to assess the significance of individual coefficients. The Chi-squared statistic and *p*-value from endogeneity testing revealed that the regression model had a significant endogeneity issue. This result was supported by Ramsey's regression equation specification error test (RESET) and the Durbin–Wu–Hausman test for endogeneity. Hence, the *SENTIMENT* variable was considered a valid and reliable measure in our study. Thus, our main findings retained their strength and reliability after addressing the issue of endogeneity caused by potential reverse causality.

6. Additional and robustness tests

6.1. The COVID-19 pandemic and cryptocurrency return analysis

Cryptocurrencies are considered highly volatile financial assets (Sahoo, 2020), and they have better hedging capabilities than other financial assets, such as stocks and US dollars (USD) (Dyhrberg, 2016). During the COVID-19 pandemic, many investors attempted to diversify their portfolios towards cryptocurrencies to make short-term gains (Sahoo, 2021). Caferra and Vidal-Tomás (2021) examined the behaviour of cryptocurrencies and stock markets during the COVID-19 pandemic. The results indicate that, although both cryptocurrency and stock prices fell steeply during financial contagion, cryptocurrencies promptly rebounded. In contrast, stock markets were trapped in the bear phase. In other words, the dynamics of financial asset prices during the pandemic depended on market type. These findings are significant for investors as hedging properties are apparent in the cryptocurrency response to such a drastic event. For instance, Gkillas and Longin (2019) investigated the potential benefits of Bitcoin during extremely volatile periods. They found a low extreme correlation between Bitcoin and gold, which implies that both assets can be used concurrently in times of turbulence in financial markets to protect equity positions. Similarly, Baur et al. (2018) replicated the relationship between Bitcoin, gold and the US dollar. Their results indicate that Bitcoin exhibited distinctively different returns, volatility and correlation characteristics than other assets, including gold and the US dollar.

To examine whether the association between *CCI* and *Rm-Rf* might change in different time periods, we divided the sample period into the pre-COVID-19 pandemic (2014–2019) and the COVID-19 pandemic (2020−2022) groups. The baseline results illustrate that the *CCI* coefficient (−0.6437) was negatively associated with cryptocurrency excess returns before the COVID-19 pandemic. Similarly, the *CCI* coefficient was −0.2056, which was significant and statistically negative in its association with cryptocurrency excess returns (Panel A, Table 8). This finding suggests the relationship between the *CCI* and cryptocurrency excess returns was not affected by changes in different time periods.

We re-estimated the regression model with an additional control variable to examine whether the association between *CCI* and *Rm-Rf* was influenced by the COVID-19 pandemic from 2020 to 2022. We created an indicator variable for COVID-19, which was equal to 1 if the year was 2020 or above, and 0 otherwise, considering all other things being equal. Panel B in Table 8 shows that the *CCI* coefficient was negatively associated with *Rm-Rf* across all models. Moreover, in (1) and (4), the *CCI* coefficients were not only negative but also statistically significant in terms of *Rm-Rf*. Notably, the *COVID-19* coefficients were positive and statistically significant in terms of *Rm-Rf* across all models. This finding suggests that the COVID-19 pandemic positively impacted *Rm-Rf*. These findings corroborate those of previous studies (Corbet et al., 2020). For instance, Corbet et al. (2020) reported that investors earned significant and positive cryptocurrency returns during the COVID-19 pandemic. Therefore, cryptocurrency can be considered a safe haven in a similar manner to gold during a period of economic uncertainty, such as the COVID-19 pandemic (González et al., 2021).

To further examine the association between *CCI* and *Rm-Rf*, we considered the *COVID-19* variable as a moderator to conduct the interaction analysis. Panel C illustrates that the *CCI* coefficients were negatively associated with *Rm-Rf* but were statistically significant only in (3), i.e. the medium size. This finding suggests that the COVID-19 pandemic significantly impacted cryptocurrencies with medium market capitalisation. The rationale for medium-sized market capitalisation is that cryptocurrencies with small market capitalisation are inefficient (Brauneis & Mestel, 2018), thus challenging the efficient market hypothesis (Li et al., 2020). In contrast, cryptocurrencies with large market capitalisation are more mature (Bakhtiar et al., 2023). Hence, cryptocurrencies with medium market value were more sensitive to the COVID-19 pandemic crisis.

6.2. Cryptocurrency market capitalisation and trade volume analysis

Empirical studies indicate that cryptocurrency market capitalisation and trade volume significantly impact cryptocurrency returns (Bouri et al., 2019; Li et al., 2020). This study assessed whether the relationship between *CCI* and *Rm-Rf* was influenced by cryptocurrency market capitalisation and trade volume. Based on (1) (i.e. the full sample) from the baseline analysis, we divided all cryptocurrencies into high and low market capitalisation. We created the indicator variable *High market cap*, which was equal to 1 if the cryptocurrency market capitalisation was at or above the median and 0 otherwise. Similarly, we created the indicator variables as *high* and *low trade volumes*.

Table 9 in Panel A indicates that the association between *CCI* and *Rm-Rf* was driven by cryptocurrency market capitalisation. Regarding low cryptocurrency market capitalisation, this study found that the *CCI* coefficient had a negative and non-significant association with *Rm-Rf* (i.e. cryptocurrency excess returns). Regarding high market capitalisation, we found that *CCI* had a negative and statistically significant association with *Rm-Rf*, with the *CCI* coefficient being −1.0736. This result indicates a stronger association between *CCI* and *Rm-Rf* than *CCI*'s association with other variables in this model. In other words, a change of one unit in the CCI was associated with a cryptocurrency change in excess returns greater than one unit. Our study also tested the coefficient differences to determine whether *CCI* in the regression model varied significantly across the treatment and control groups. The coefficient differences test statistics were 15.95 and significant at the 1 % level. This suggests that the test statistic provided enough information to determine its significance. Therefore, the association between *CCI* and *Rm-Rf* was affected by cryptocurrency market capitalisation.

Panel B in Table 9 indicates that the cryptocurrency trade volume also affected the relationship between *CCI* and *Rm-Rf* in the study sample. The regression results indicate that *CCI* had a negative effect on *Rm-Rf* if these cryptocurrencies had low trade volume, but the effect was not significant. With high trade volume, *CCI* (−0.9754) had a negative and statistically significant effect on *Rm-Rf*. This suggests that the association between *CCI* and *Rm-Rf* was significantly affected by cryptocurrencies with a high trade volume. The test result of the coefficient difference (9.98) was significant at the 1 % level. Hence, cryptocurrency trade volume affects the association between *CCI* and *Rm-Rf*.

6.3. Robustness tests

This section reports the results of additional analysis and robustness tests conducted to enable more holistic insights into the relationship between *CCI* and *Rm-Rf*. To address the impact of cryptocurrencies with either the largest or smallest market capitalisation on cryptocurrency returns, we assessed the association between *CCI* and *Rm-Rf* by excluding the largest and smallest coins. We also considered additional control variables to remove the effect of control variables on cryptocurrency returns.

6.3.1. Excluding specific cryptocurrencies

Previous studies indicate that cryptocurrency returns are driven by cryptocurrency market capitalisation (Liu et al., 2022). Bitcoin holds the largest share of market capitalisation while exceeding all other cryptocurrencies in the market (Oosthoek & Doerr, 2020). Additionally, Colon et al. (2021) highlighted that the top 25 cryptocurrencies comprise almost 95 % of the total market capitalisation. This raises the question of whether excluding the largest or smallest coins will affect the association between *CCI* and *Rm-Rf*. Thus, we segmented the cryptocurrencies based on the top 1, top 10 and bottom 10 coins to examine this relationship through (1). We also controlled for the year and crypto fixed effects in the regression model.

Panel A in Table 10 shows the findings when we re-ran the three-factor model for all cryptocurrency returns while excluding Bitcoin. We also controlled for the variables listed in Table 6 and for the year and crypto fixed effects. The findings indicate that the *CCI* coefficient was −0.8552, indicating that the CCI scores were negative and significantly associated with cryptocurrency excess returns (*Rm-Rf*) at the 1 % level. This finding is consistent with the study's main findings.

Panel B in Table 10 shows the findings from when we also ran the three-factor model for all cryptocurrency returns, excluding the top 10 coins. The *CCI* coefficient was still negative and significantly associated with *Rm-Rf*. This suggests that the results presented in Panel B align with the study's main findings. Thus, excluding the top 10 coins did not affect the association between *CCI* and *Rm-Rf*.

Panel C in Table 10 shows the findings when we excluded the bottom 10 coins and ran the regression model for cryptocurrency excess returns. The *CCI* was −0.8706 in this model, indicating that although we excluded the bottom 10 coins, the negative and significant association between *CCI* and *Rm-Rf* was unaffected. Thus, the results in Table 10 remained qualitatively similar to the study's previous findings in Table 5 after controlling for the variables mentioned above.

6.3.2. Additional control variables

We considered a Google trend Bitcoin (*GTrend_BTC*) and a Wikipedia search Bitcoin (*Wiki_BTC*) as the control variables to examine whether additional variables affected the association between *CCI* and *Rm-Rf* in the regression model to re-run our baseline regression model. The rationale for selecting these two variables is that they have been used in several previous studies as independent variables (Ciaian et al., 2016; Smuts, 2019). Table 11 presents the results, where Columns (1)–(4) indicate that the *CCI* was negative and significantly associated with *Rm-Rf*. Thus, the regression results strongly support the main findings. Our findings regarding the negative association between *CCI* and *Rm-Rf* remained robust.

7. Conclusion

This study investigated whether consumer confidence was associated with cryptocurrency excess returns. We followed existing literature and adopted the CCI as a proxy variable for consumer confidence. To examine the relationship between the CCI and cryptocurrency excess returns, we employed a three-factor model and controlled for year and crypto fixed effects. The baseline results indicate that the *CCI* coefficient was negatively associated with cryptocurrency excess returns, confirming H2. Moreover, we found that cryptocurrencies with small market capitalisation supported the literature regarding the inefficiency of cryptocurrency (Brauneis & Mestel, 2018), thereby challenging the efficient market hypothesis (Li et al., 2020). The rationale is that cryptocurrencies with large market capitalisation are more likely to be mature (Bakhtiar et al., 2023). We employed the entropy balancing approach and a 2*SLS* model to address possible endogeneity from omitted variables bias, selection bias and reverse causality. The empirical results of these analyses were consistent with our baseline results presented in Table 5. Furthermore, the negative relationship between the CCI and cryptocurrency excess returns was reinforced by a series of additional analysis and robustness tests, including the COVID-19 pandemic, the impact of cryptocurrency market capitalisation and trade volume, the impact of specific coins and new control variables. These results provide empirical evidence to support the main findings reported in the baseline analysis, thus supporting the negative association between the CCI and cryptocurrency excess returns.

The findings from this study provide critical theoretical contributions. First, our study contributes to the existing literature by providing evidence of the impact of consumer emotions on consumer decision-making in the cryptocurrency market in that consumer decision-making can be affected by consumer incidental emotion and consumer integral emotions (Han et al., 2007). Lansdall-Welfare et al. (2012) highlighted that consumer confidence is significantly affected by consumer incidental emotion, the rationale being that some consumers responding to the survey on which the CCI is based may reflect incidental emotion. Similarly, consumer/investor sentiment derived from social media can reflect confidence that is representative of a large sample population. Furthermore, the present study evinces that behavioural finance theory can serve as the theoretical framework to examine the relationship between the CCI and cryptocurrency excess returns. Future research can explore other psychological factors that may affect cryptocurrency markets. Second, this study confirms that macroeconomic factors originating from the US significantly impact the cryptocurrency market. The rationale for this conclusion is supported by the statistically significant coefficients of the control variables in this study's baseline model. Specifically, the findings indicate that the US determinants significantly affected cryptocurrency excess returns. This observation implies the cryptocurrency market is evolving, illustrating heightened responsiveness to macroeconomic factors. Third, this study provides empirical evidence that the three-factor model outperforms the one-factor CAPM model. The support for this finding is that the Jensen's alpha coefficient exhibited low volatility in the three-factor model (Table 4). These findings align with Jia et al. (2022), who demonstrated that the three-factor model surpasses the quasi-cryptocurrency one-factor model; the three-factor model exhibited greater explanatory power than the one-factor model. Future research should compare the four- and five-factor models regarding explanatory power with the three-factor model.

Our study's findings have practical implications. First, by highlighting consumer confidence as a significant influencer of cryptocurrency excess returns, investors and portfolio managers should closely monitor consumer confidence for better predictions and risk mitigation in the cryptocurrency market. Future research should examine how changes in consumer confidence interact with other market factors, such as regulatory developments and macroeconomic trends, contributing to understanding cryptocurrency market behaviour. Second, we offer insights for policymakers to develop more effective monetary policies in response to challenges posed by cryptocurrencies, strengthening their ability to forecast market developments. The decentralisation of cryptocurrency has emerged as a significant phenomenon in financial markets. However, cryptocurrency remains controversial without a central authority issuing this currency. Future studies should explore additional factors influencing the cryptocurrency market, such as technological advancements and various regulatory environments, thereby providing policymakers with a comprehensive understanding of market dynamics. Integrating these insights into the policymaking process can enhance policymakers' ability to address the evolving landscape of digital assets while promoting sustainable economic growth. Third, empirical evidence from this study suggests that the COVID-19 pandemic moderated the relationship between the CCI and cryptocurrency excess returns. This finding points to cryptocurrencies' potential as an alternative asset for hedging risks and diversification amid pandemic-related uncertainty. This finding aligns with past research advocating for cryptocurrencies to enhance portfolio diversification and mitigate downturn risk during economic uncertainty (Dunbar & Owusu-Amoako, 2022; Mayer, 2018).

The study limitations are as follows. First, we focused on US-specific variables, potentially limiting the applicability to the global cryptocurrency market. Second, exploring consumer confidence and cryptocurrency returns was confined to one-factor and three-factor models. We suggest a need for future research with alternative models. Third, while attempts to address endogeneity through the entropy balancing approach and the 2SLS model were made, complete elimination of this issue remained challenging. Fourth, this study has not considered relationships that may be affected by changes in different regulatory environments. Despite these limitations, this study contributes valuable insights into consumer confidence and cryptocurrency excess returns literature.

CRediT authorship contribution statement

Sanshao Peng: Writing – original draft, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Syed Shams:** Supervision, Methodology, Formal analysis, Data curation. **Catherine Prentice:** Writing – review & editing, Validation, Supervision, Methodology, Investigation, Formal analysis, Conceptualization. **Tapan Sarker:** Supervision, Methodology.

Declaration of competing interest

There is no conflict of interest identified in this research.

Data availability

Data will be made available on request.

Appendix A. Definitions of variables

Variable name	Definition
Independent variable	
Rm-Rf	Refers to the difference between the daily cryptocurrency returns and the overall US Treasury bills (T-bills) yield in the United States.
Dependent variable	
CCI	Defines the degree of optimism on the current state of the economy that consumers express through their saving and spending activities, which leads to economic growth in the country.
Three-factor model	
CMRT	Cryptocurrency market return is the value-weighted return on all underlying available coins.
SMB	Small minus large refers to the return difference between the small coin's portfolio and the large coin's portfolio.
HML	High minus low refers to the return difference between high and low-momentum portfolios.
Control variables	
FEDRATE	The federal funds rate is the interest rate at which depository institutions trade federal funds with each other overnight.
OIL	Oil refers to the current fossil fuel price, and crude oil is a fundamental commodity in the global economy.
GDP	It represents the Gross Domestic Product in the US. It is a key economic indicator that measures the total value of all goods and services produced within the US during a quarter period.
EPUI	The daily news based EPUI is based on newspapers in the US.
VIX	The Chicago Board of Exchange Volatility Index (VIX) measures market expectations of near-term volatility conveyed by stock index option prices.
EXCHANGE	It refers to the exchange rate between the US dollar and Euro.
CPI	It is a price index of a basket of goods and services paid by urban consumers.
DJIA	The Dow Jones Industrial Average provides a view of the US stock market and economy.
SENTIMENT	Sentiment refers to consumer sentiment; it measures the confidence and expectations of consumers regarding the current and future economic conditions.
GTBTC	Google Trend index is based on the volume of searches using the term 'Bitcoin'.
WIKIBTC	Wikipedia refers to the relevant information or articles on Bitcoin.

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4.3 Links and implications

The current study provides important insights into the influence of consumer confidence on cryptocurrency excess returns through the three-factor model. The next study aims to examine the association between the CLI and cryptocurrency returns. This research contributes to the literature on the change of CLI by providing a more comprehensive understanding of the factors that influence cryptocurrency returns.

CHAPTER 5: PAPER 3 – DOES COMPOSITE LEADING INDICATORS PREDICT CRYPTOCURRENCY RETURNS

5.1. Introduction

This chapter presents the third paper of the thesis, which investigates the impact of Composite Leading Indicator on cryptocurrency returns. It begins with an overview of the chapter's contents in Section 5.1.

Section 1 introduces the article and outlines its research objectives.

Section 2 reviews relevant literature and formulates the hypotheses.

Section 3 describes the research methodology, including data and sample period, instrument and model specifications used in the study.

Section 4 presents the distribution of cryptocurrency, descriptive statistics for variables and Pearson's correlation.

Section 5 details the empirical results of the study, including post-hoc analysis and robustness tests to reinforce the findings.

Section 6 offers additional analysis to further explore the relationship between the variables.
Section 7 concludes with a summary of the findings and their implications.

5.2. Paper Under Review

Does composite leading indicators forecast cryptocurrency returns?

Abstract

This study investigates the relationship between the Composite Leading Indicator (CLI) and cryptocurrency returns using a three-factor model that includes cryptocurrency market, size and momentum factors. The analysis utilizes a dataset of 3,318 cryptocurrencies spanning from 1 January 2014 to December 31, 2022. The baseline results indicate a negative association between short-term changes in the United States (US) CLI and cryptocurrency returns. To address potential endogeneity issues, such as omitted variables bias, selection bias and reverse causality, the study employs an entropy balancing approach. Additional robustness tests further confirm this negative relationship. The findings suggest that incorporating CLI information can enhance investment portfolios and cryptocurrency prediction models. Additionally, policymakers can use these insights to better understand future economic conditions and their potential impact on the cryptocurrency market.

Keywords: cryptocurrency returns; composite leading indicator; three-factor model; endogeneity; entropy balancing.

Does composite leading indicators and cryptocurrency returns?

1. Introduction

Since the emergence of cryptocurrency a decade ago, it has gained substantial attention from academic researchers and witnessed a surge in popularity among investors (Yousaf & Yarovaya, 2022). The first cryptocurrency, introduced by Nakamoto (2008), is Bitcoin which dominated the market, accounting for over 85% from 2010 most of 2015. Bitcoin's price experienced a remarkable 122% increase in 2016 and an astounding 1360% surge in 2017 (Bouri, Shahzad, et al., 2019). In 2020, Bitcoin recorded a gain of more than 300%, closing near $30,000 by the year-end. The rationale behind the soaring prices lies in the cryptocurrency market's lack of effective supervision, leading to rapid and substantial price fluctuations due to the arbitrage behaviour of speculators (Tong et al., 2022).

Bitcoin's success has inspired the launch of numerous altcoins with diverse features and economic properties, including Litecoin, Dogecoin, Ethereum and others (Ammous, 2018). Based on the CoinMarketCap website, the total estimated market capitalization exceeded $990 billion in January 2021 (Gkillas et al., 2022). While Bitcoin remains the most renowned cryptocurrency, thousands of other viable cryptocurrencies exist (Corbet et al., 2021). A multitude of studies has delved into the determinants influencing cryptocurrency returns, contributing to a comprehensive understanding of the cryptocurrency market.

A substantial body of empirical literature has examined the impact of various determinants on cryptocurrency returns. For instance, Anamika et al. (2023) confirmed the critical role of investor sentiment, utilising direct survey-based measurements. Additionally, Heikal et al. (2022) identified a positive correlation between fluctuations in world oil prices and cryptocurrency returns. Corbet, Larkin, et al. (2020a) have provided empirical evidence indicating that changes in the US Federal Fund interest rates directly affect cryptocurrency returns. Yen and Cheng (2021) propose that alterations in China's Economic Policy

Uncertainty Index (EPUI) can predict cryptocurrency volatility, revealing a negative association between EPUI and future cryptocurrency volatility. Conversely, changes in the EPUIs of the US, Japan or Korea show no significant impact on cryptocurrency volatility. Additionally, Naeem et al. (2022) investigated the relationship between financial volatilities and the risk associated with cryptocurrency indices, revealing distinct spill-over patterns through time-varying parameters vector autoregression. In contrast, Lojka et al. (2016) suggested that fluctuations in financial assets are closely correlated with economic or business cycles. McLean and Zhao (2014) further emphasised that investor sentiment in financial markets is influenced by the business cycle. Previous research has shown that the CLIs are effective in predicting economic cycles and identifying turning points (Castro, 2010; Mazur, 2017).

Empirical literature consistently underscores the crucial role played by the CLI in the financial market. Topcu and Unlu (2013) examined the relationship between the CLI and share prices in emerging markets, highlighting the importance of the CLI's component structure in shaping investor decisions. Similarly, Celebi and Hönig (2019) demonstrated that various economic indicators significantly impact stock returns, noting that the CLI has a delayed effect on these returns. Prasetyo and Asianto (2020) observed that the OECD's CLI anticipated movements in the main index, with indicators from the Nasdaq stock market, New York Stock Exchange and German Stock Index proving to be the most optimal CLI for the Indonesia Stock Exchange.

In the context of the evolving financial landscape, Iyer (2022) argued for an increasing interconnection between cryptocurrencies and equities compared to other assets such as bonds and gold. Sami and Abdallah (2021) examined the significant relationship between cryptocurrency market performance and stock market performance in the Middle East and North Africa region (MENA). Their findings revealed that a 1% increase in cryptocurrency returns led to a 0.15% decrease in stock market performance in the MENA region, while in other countries, the same increase in cryptocurrency returns resulted in a 0.13% rise in stock market performance. This raises questions about whether investors view crypto assets as traditional assets in relation to economic changes signal by the CLI. Therefore, the primary objective of this study is to investigate the association between the CLI and cryptocurrency returns.

To assess the relationship between the CLI and cryptocurrency returns, our initial analysis compared the performance of a one-factor model with a three-factor model. The results indicate that the three-factor model significantly outperforms the one-factor model in predicting cryptocurrency returns, suggesting that additional factors improve the model's predictive accuracy and provide deeper insights into the dynamics affecting cryptocurrency returns. This finding is consistent with Jia et al. (2022), who highlight that the three-factor model offers a more robust and significant explanation of cryptocurrency returns compared to the one-factor model. The next step in our analysis involves a comprehensive baseline evaluation, which includes all relevant control variables, year fixed effects, and cryptocurrency fixed effects across all models.

The results illuminate the relationship between the lagged Composite Leading Indicator *(LAG_CLI)* and cryptocurrency returns within the three-factor model framework. The negative coefficient for *LAG_CLI* is both statistically significant and consistent with our study's main findings, highlighting a notable association between changes in the CLI and cryptocurrency returns. To enhance the robustness of our results and address potential endogeneity issues—such as omitted variable bias, selection bias, and reverse causality—we employ both the entropy balancing approach and the two-stage least squares (2SLS) method. The outcomes from these alternative models further substantiate our primary findings, reinforcing the negative association between *LAG_CLI* and cryptocurrency returns. This comprehensive approach strengthens the validity and reliability of our conclusions.

In addition to our primary analysis, we conduct supplementary tests and robustness checks to further validate the association between the CLI and cryptocurrency returns. First, we examine the impact of COVID-19 as a moderator. The results consistently show a positive and statistically significant relationship between COVID-19 and cryptocurrency returns across all models. This supports the findings of González et al. (2021), which suggest that cryptocurrencies can act as alternative assets during economic uncertainties, including crises like the COVID-19 pandemic. Additionally, we investigate the role of institutional factors as moderators in the relationship between the CLI and cryptocurrency returns. Our results reveal significant correlations between four institutional factors and cryptocurrency returns, indicating that these factors can indeed influence the association between the CLI and cryptocurrency returns. This interaction analysis further reinforces our primary findings.

To ensure the robustness of our conclusions, we perform additional tests. First, we assess the impact of cryptocurrency market capitalization and trading volume on returns. Second, we exclude specific cryptocurrencies to evaluate the relationship more broadly. Third, we introduce variations in the lagged CLI over one, three, and six-month periods. These robustness tests consistently confirm the negative association between the CLI and cryptocurrency returns, supporting Hypothesis 2 (H2). Overall, these comprehensive tests enhance the reliability and validity of our study's core findings.

This paper makes several significant contributions to the empirical literature on cryptocurrency returns. Firstly, it provides empirical evidence on the impact of the CLI on cryptocurrency returns, offering a novel assessment of the monthly changes in the CLI and their effects on these returns. This innovation enhances our understanding of the underlying dynamics in the cryptocurrency market. Secondly, the study expands the literature on predicting cryptocurrency returns by integrating a comprehensive set of macroeconomic indicators from the United States. The CLI series used includes seven components, such as work started for dwellings, net new orders for durable goods, and consumer and industrial confidence indicators (Gulen et al., 2011). This broader analysis contributes to a more nuanced understanding of the factors influencing cryptocurrency returns. Thirdly, the research examines the moderating effect of the COVID-19 pandemic on the relationship between the CLI and cryptocurrency returns. The study finds positive returns for cryptocurrencies during the pandemic, suggesting their potential as alternative assets for risk hedging and diversification in times of economic uncertainty, consistent with Dunbar and Owusu-Amoako (2022). Finally, the paper explores the role of institutional factors in the cryptocurrency market. It not only provides empirical evidence of the correlation between institutional factors and cryptocurrency returns but also highlights how these factors moderate the relationship between the CLI and cryptocurrency returns. This multi-faceted approach enriches the literature and offers valuable insights for both researchers and practitioners seeking to understand the complexities of cryptocurrency market dynamics.

The remainder of the paper is organized as follows. The next section reviews the relevant literature and develops the hypotheses. This is followed by a detailed presentation of the methodology used to test these hypotheses. Data analysis and results are then presented, including additional and robustness tests to reinforce the study's findings. The paper concludes with a discussion of the findings and their implications.

2. Literature review and hypothesis development

2.1. Literature review

The theoretical literature on cryptocurrency returns has put forth various perspectives, identifying specific factors as key drivers. Sockin and Xiong (2023) contend that cryptocurrency returns are intricately tied to the marginal cost of mining. The cost of mining, essential for cryptocurrency infrastructure and security, is not directly exposed to cryptocurrency returns. Instead, cryptocurrency returns are seen as sensitive to network factors capturing user adoption, as noted by (Liu & Tsyvinski, 2021). This aligns with Cong et al. (2021), who assert that cryptocurrency adoption is a primary driver of returns. Ciner et al. (2022) explore a diverse set of predictors and their impact on cryptocurrency returns across different quantiles. Their findings highlight the significant influence of government bond indices and small company stock returns on the tail behaviour of cryptocurrency returns. Leirvik (2022) emphasises a positive association between cryptocurrency market volatility and liquidity with large capitalisation cryptocurrencies. This positive relationship is attributed to investors requiring a higher price premium for variations in liquidity volatility.

Recognizing that investors often consider a range of macroeconomic indicators for their investment decisions is crucial, as relying on only a few indicators may not fully capture changes in economic states (Nakagawa & Sakemoto, 2021). This recognition motivates our investigation into the impact of the CLI on the financial market. The CLI, used to assess how current expectations influence future economic behaviour, has proven to be a valuable tool in economic analysis (Mazur, 2017). Constructed by the OECD from economic time series, CLI indices show the leading relationships to the business cycle at turning points (Cevik, Dibooglu, & Kutan, 2013). Particularly noteworthy is the CLI's ability to amalgamate various individual leading indicators, proving statistically relevant for analysing and forecasting significant macroeconomic indicators such as GDP and industrial production (Kľúčik & Haluška, 2008). Prior studies underscore the unreliability of relying solely on a single economic indicator for short-term forecasting, which may result in false signals. The CLI, by combining multiple leading indicators, enables governments to track economic performance and forecast near-term economic trajectories (Atabek et al., 2005). In essence, the CLI serves as a comprehensive tool for anticipating economic shifts, providing a more accurate and reliable gauge of economic conditions for investors and policy makers alike.

Numerous empirical studies have investigated the impact of Composite Leading Indicator (CLI) on economic activities. Castro (2010) found that the duration of economic expansions is positively related to CLI variables. Korte (2012) demonstrated that both the Organisation for Economic Co-operation and Development (OECD)'s CLI and its business confidence indicator performed best in terms of information criterion and forecasting accuracy. Jansen et al. (2016) showed that changes in the CLI offer more promising GDP forecasts compared to averaging multiple single indicators. Mo et al. (2018) explored the CLI's relationship with commodity futures across various countries, finding a significant negative relationship between the CLI and commodity futures volatility, suggesting that declining future business cycle expectations increase commodity futures fluctuations in China. Celebi and Hönig (2019) noted that the CLI has delayed effects on stock returns. Ojo et al. (2023) identified the CLI as a valuable leading indicator of the Industrial Production Index and a potential tool for forecasting the unemployment rate. However, the CLI showed poor performance in forecasting GDP growth. Additionally, Larch et al. (2021) highlighted a negative association between the nature of discretionary fiscal policy and change in the composite leading indicator (CLI).

A significant body of research has explored the relationship between the CLI and financial markets. Cevik, Dibooglu and Kutan (2013) investigated the impact of CLI on the financial stress index across various countries. Their findings revealed a negative association between the financial stress index and CLI, with notable effects observed with up to nine-month lags and up to four-month leads in Hungary and Poland. In Russia, significant correlations were found at all lags and up to four-month leads. The Czech Republic, however, showed no significant correlations at lags, though a significant negative relationship emerged with four-month leads. Additionally, Mo et al. (2018) examined the relationship between CLI and commodity futures across countries, identifying a significant negative relationship between the CLI and the volatility of commodity futures. This indicates that a decline in future business cycle expectations leads to increased fluctuations in Chinese commodity futures. Although the CLI fluctuations may have relatively small economic significance compared to other macroeconomic volatilities, they play a crucial role in influencing commodity futures prices in emerging countries.

Previous studies have consistently emphasized the critical role of the CLI in understanding stock market dynamics and volatility. Gulen et al. (2011) used a two-stage Markov switching model to examine the time variation of the expected value premium, finding that the monthly change in the US CLI can act as a significant alternative instrument for predicting time-varying expected stock returns. Topcu and Unlu (2013) investigated the relationship between the CLI and share prices in emerging markets, highlighting the importance of the component structure of CLI in influencing investor decisions. Celebi and Hönig (2019) analysed the effect of macroeconomic factors and leading indicators on German stock index, revealing that the CLI impacts stock returns with a delay. Attig et al. (2021) explored the influence of economic policy uncertainty on dividend policy across 19 countries, finding a positive correlation between high economic policy uncertainty and increased dividend payouts. They also noted that a high CLI value typically signals more favourable market expectations for future economic conditions. Long, Zaremba, et al. (2022) assessed whether investors fully consider changes in leading economic indicators in the stock market. Their results demonstrated a positive association between monthly CLI changes and future stock returns across 39 countries over six decades, highlighting the significance of leading economic indicators in forecasting future business conditions.

Motivated by the extensive literature on the CLI's impact on traditional financial markets, our study aims to investigate the influence of the CLI on the cryptocurrency market and evaluate whether the CLI can be used to predict cryptocurrency returns. This research aligns with the increasing recognition of cryptocurrencies as alternative assets within the financial market, as noted in recent studies (Bianchi, 2020; Pele et al., 2023). By exploring the CLI's effect on the cryptocurrency market, our study introduces a novel perspective to the existing literature on economic indicators and financial asset returns.

2.3 Hypotheses development

The study draws on existing literature to underscore the CLI's role as a leading indicator for economic performance. The CLI's effectiveness in forecasting GDP changes compared to individual indicators (Jansen et al., 2016). Ojo et al. (2023) demonstrate the CLI's utility as a leading indicator for the Industrial Production Index and its applicability in forecasting unemployment rates. Notable findings include a positive correlation between the CLI and the duration of economic expansion (Castro, 2010), a precursor indicator of economic slowdown following a decrease in CLI values (Cevik, Dibooglu, & Kenc, 2013). It is likely that the business cycle affects investor sentiment in the financial markets (McLean & Zhao, 2014). Investors tend to invest more money into the financial market when the economy is in an expansionary phase and when it is not (Campiglio, 2016). In addition, Iyer (2022) argue that cryptocurrencies and equities have become increasingly interconnected compared to other assets, such as bonds and gold. It is presumed that investors are more likely to buy crypto asset as conventional asset according to the change of the CLI in the economy. When investors purchase more (less) cryptocurrency during the stage of expansions based on the change of CLI, this will increase (decrease) cryptocurrency returns.

Hypothesis 1 (H1): The CLI is positively associated with cryptocurrency returns through the three-factor model.

The existing body of research indicates several mechanisms through which the CLI may contribute to negative cryptocurrency returns. Firstly, economic downturns tend to increase uncertainty and induce risk aversion among investors. Cryptocurrencies, characterized by their high volatility and speculative nature, are often perceived as riskier assets in terms of uncertainty (Antonakakis et al., 2019). As a result, the option value of deferring investment increases under heightened uncertainty, leading investors to opt for safer investment such as government bonds or traditional safe-haven assets like gold (Ren et al., 2023). Second, economic downturns, exemplified by the ongoing COVID-19 pandemic, can lead to liquidity shortages in financial markets (Simon et al., 2021). Cryptocurrencies, which may experience liquidity issues during period of market stress, could be perceived as illiquid assets. Furthermore, Zhang and Li (2023) highlighted a negative relationship between liquidity and cryptocurrency returns. Hence, investors may prioritize assets with greater liquidity to ensure ease of buying and selling, especially in turbulent market conditions. Third, despite growing interest from institutional investors, cryptocurrencies continue to face challenges related to uncertainty and infrastructure development. Since most cryptocurrencies are decentralized digital currencies without centralized organisational support, addressing these challenges remains complex (Sun et al., 2021). Hence, during economic downturns, investors may gravitate towards assets with strong institutional support and regulatory oversight, which cryptocurrencies may currently lack to some extent. Considering above these perspectives, we posit that the change of CLI can be negatively correlated with cryptocurrency returns.

Hypothesis 2 (H2): The CLI is negatively associated with cryptocurrency returns through the three-factor model.

3. Data and variables

3.1. Sample preparation and data sources

This study obtained all available daily cryptocurrency trading data from the cryptocurrency market website <https://coinmarketcap.com/>. This website stands out as a significant reference for cryptocurrency price and volume, as highlighted by Liu et al. (2022a). Drawing data from more than 200 major cryptocurrency exchanges, the platform offers comprehensive daily information on key metrics. These metrics encompass opening and closing prices, high and low prices, trading volume and market capitalisation (in US dollars [US$]). The coverage extends to a diverse array of both active and discontinued cryptocurrencies.

The data collection spans the timeframe from January 1, 2014, to December 31, 2022. This chosen period aligns with the insights provided by Liu et al. (2022a) who emphasised the availability of cryptocurrency trading volume data from the concluding week of 2013, initiating their sample period at the commencement of 2014. Several pivotal factors influenced the selection of this time frame, including the notable expansion of the cryptocurrency market, particularly commencing in 2018. Additionally, the chosen period encapsulates significant events such as the onset of the COVID-19 pandemic in March 2020 and regulatory actions implemented by the Chinese government in May 2022, as elucidated by Yang et al. (2023). Importantly, this sample period is designed to ensure an ample and robust data set for the empirical analysis conducted in our study.

3.2. Composite Leading Indicator

Our independent variable is the fluctuation in the Organisation for Economic Co-operation and Development (OECD)'s Composite Leading Indicator (CLI), sourced from OECD (2023a). The CLI, originally designed to provide early signals of business cycle turning points and depict economic activity fluctuations around its long-term potential level (Gallegati, 2014), is a valuable tool for economic analysis. According to the OECD's guidelines, the CLI is expected to anticipate actual changes in economic activity by approximately six to nine months (Long, Zaremba, et al., 2022).

3.3. Control variables

We consider a standard set of control variables commonly utilised in prior research. The chosen control variables encompass the following: consumer price index (*CPI*) (Wang et al., 2022), federal funds rate (*FEDRATE*) (Havidz et al., 2021), economic policy uncertainty index (*EPUI*) (Yen & Cheng, 2021), the Chicago Board of Exchange (CBOE) Volatility Index (*VIX*) (Kim, Trimborn, et al., 2021), the exchange rate US$ to euro (*EXCHANGE*) (Polasik et al., 2015), the Dow Jones industrial average (*DJIA*) (Zhu et al., 2017), Google Trend for Bitcoin (*TREND_BTC*) (Aslanidis et al., 2022), Wikipedia Bitcoin (*WIKI_BTC*) (Stolarski et al., 2020), gold price (GOLD) (Elsayed et al., 2022), Global price Index of all commodities (GPIAC) (Yin et al., 2021), unemployment rate (*UNEMPLOY*) (Corbet, Larkin, et al., 2020b), four institutional factors (Nguyen et al., 2019): Control of Corruption (CC), Government effectiveness (GE), Regulatory quality (RQ) and Rule of law (RL). The definitions of these variables can be found in Appendix 1.

3.4. Fama-French three-factor model

The three-factor model is a financial model illustrating asset returns while assessing portfolio risk and expected returns. It was developed by Eugene Fama and Kenneth French in the early 1990s as an extension of the traditional capital asset pricing model (CAPM) (Fama & French, 1993). The three-factor model introduces additional factors, namely, small-minus-big size (SMB) portfolios and high-minus-low book (HML) to market value to determine size and book-to-market value effects, respectively.

Several studies have utilised the three-factor model to analyse cryptocurrency returns. Shen et al. (2020) applied a three-factor pricing model, including cryptocurrency market, size and reversal factors, to assess cryptocurrency excess returns. Their findings indicate that this model significantly outperforms the CAPM for cryptocurrency. Jia et al. (2022) developed a similar three-factor pricing model, incorporating market, size and momentum factors, which demonstrated even greater explanatory power than the model proposed by Shen et al. (2020). Liu et al. (2020) also confirmed that the three-factor model, encompassing market, size and momentum factors, effectively explains average cryptocurrency returns. Furthermore, Liu et al. (2022a) noted that size and momentum variables are among the most extensively studied effects in both traditional and cryptocurrency asset pricing. Therefore, this study employs the three-factor model – based on cryptocurrency market, size and momentum factors - to examine the relationship between the CLI scores and cryptocurrency returns.

Based on the above, this study constructed a cryptocurrency market return based on the value-weighted return of all underlying available coins. Cryptocurrency excess market return (*CMRT*) represented the difference between cryptocurrency market return and the T-Bill rate (*Rf*):

$$R_{m,t} = \sum_{i=1}^{n} R_{i,t} \text{ x } \frac{Capi,t}{TotalCapt} \quad (1)$$

where $R_{m,t}$ is the cryptocurrency market return of coins on day t and $R_{i,t}$ and Cap_t are the returns and capitalisation of the i_{th} cryptocurrency on day t and $TotalCap_t$. The cryptocurrency market factor, proxied by excess market return (*CMRT*), is constructed as follows:

$$CMRT = R_{m,t} - R_{f,t} \quad (2)$$

where $R_{m,t}$ is the cryptocurrency market return of coins on day t and $R_{f,t}$ is the risk-free rate proxied by the T-Bill rate.

We construct the cryptocurrency market factors for the Fama–French three-factor model, based on market, size and momentum, to account for a broader range of influences on cryptocurrency excess return, which is consistent with Jia et al. (2022).

Size factors

This study defined the top 30% of cryptocurrency market capitalisation as large portfolios, the bottom 30% as small portfolios and the middle 40% as medium portfolios, consistent with (Fama & French, 2012). Therefore, the size factor *SMB* (small minus big) represented the difference between the returns of small and large portfolios.

Momentum factors

This study's analysis involved six value-weighted portfolios based on cryptocurrency market capitalisation and performance on the previous trading day. These portfolios were designed to capture momentum factors, representing the intersections of two portfolios categorised by size and three portfolios categorised by returns from the previous day (prior returns).

The breakpoints of prior returns were defined as the 30^{th} and 70^{th} percentiles. Within this framework, cryptocurrencies in the top 30% of market capitalisation were categorised as large (size). Cryptocurrencies in the bottom 30% were considered small (size). This classification elicited six distinct portfolios, each formed independently and denoted as BH, BM, BL, SH, SM and SL. Further, B signifies large portfolios, and S represents small portfolios. Moreover, H, M and L correspond to high, medium and low prior returns, respectively (Jia et al. (2022) as follows:

$$SMB = \text{Returns of small portfolios} - \text{Returns of big portfolios} \quad (3)$$

$$HML = 1/2(\text{Small High [SH]} + \text{Big High [BH]}) - 1/2(\text{Small Low [SL]} + \text{Big Low [BL]}) \quad (4)$$

3.5. Model specifications

To simplify assumptions and parsimony, we specified the one-factor CAPM to capture cryptocurrency excess returns as follows:

$$CRYPTO_{i,\,t} = \alpha + \beta_t \, CMRT + \varepsilon_t \quad (5)$$

where $CRYPTO_{i,\,t}$ is the cryptocurrency market return of coins on day t; $R_{f,t}$ is the risk-free rate proxied by the T-Bill rate; $CMRT = R_{m,t} - R_{f,t}$ is the cryptocurrency excess market returns; and α is the cryptocurrency excess return after controlling for the effect of all explanatory variables.

To assess the impact of cryptocurrency market, size and momentum on cryptocurrency excess returns, we also utilise the three-factor model as follows:

$$CRYPTO_{i,t} = \alpha + \beta_1(R_{m,t} - R_{f,t}) + \beta_2 SMB_t + \beta_{3,I} HML_t + \varepsilon_{i,t} \quad (6)$$

where SMB_t and HML_t represent cryptocurrency size factors and momentum factors, respectively, while ε_t is the residual.

To obtain a comprehensive analysis the association between the CLI and cryptocurrency excess returns, we consider additional control variables to capture their effect on cryptocurrency excess returns as follow:

$$CRYPTO_{i,t} = \alpha + \beta_1(R_{m,t} - R_{f,t}) + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 LAG\_CLI_{i,t-1} + \beta_5 FEDRATE_{i,t} + \beta_6 GOLD_{i,t} + \beta_7 GDP_{i,t} + \beta_8 EPUI_{i,t} + \beta_9 VIX_{i,t} + \beta_{10} EXCHNGE_{i,t} + \beta_{11} CPI_{i,t} + \beta_{12} DJIA_{i,t} + + \beta_{13} UNEMPLOY_{i,t} + \beta_{14} GPIAC_{i,t} + \beta_{15} TREND\_BTC_{i,t} + \beta_{16} WIKI\_BTC_{i,t} + \sum YEAR_{i,t} + \sum Crypto_{i,t} + \varepsilon_{i,t} \quad (7)$$

All the control variables enter the equation as lagging factors. To mitigate the impact of outliers, cryptocurrency variables were winsorised at the 99th percentile.

4. Descriptive analyses

4.1. Cryptocurrency distribution

We exclude all cryptocurrencies lacking data on trading volume and market capitalisation from our analysis. Following this initial screening, a total of 3,318 cryptocurrencies remains for examination. Notably, the number of coins meeting the inclusion criteria has surged from 111 in 2014 to 2,748 in 2021 but experiences a slight decline to 2,366 in 2022 (refer to Table 1, Panel A). This observed trend indicates a consistent increase in the overall supply of cryptocurrencies, underscoring the growing attention garnered by the cryptocurrency market. The substantial uptick in the creation of new cryptocurrencies, particularly since around 2016, has emerged as a noteworthy trend in the cryptocurrency market. Simultaneously, the increase in discontinued coins has mirrored the expansion of new coins within this market. Panel B presents results indicating that the mean (median) market capitalisation in our sample stands at US$290,011.90 million (US$34.74 million), while the mean (median) daily price volume is US$1,074.04 million (US$6.79 million). This underscores the significant growth and appreciation in the value of various cryptocurrencies over the years. While this market offers trading opportunities for speculators aiming to capitalise on price fluctuations, it also introduces risks, as evidenced by the elevated number of standard errors.

Chapter 5, Table 1: Normal yearly distribution of cryptocurrency

Panel A: Yearly Distribution

Year	Total coins	New coins	%	Discontinued coins	%
2014	111	0	0	0	0
2015	157	50	1.54	4	0.4
2016	223	72	2.22	6	0.61
2017	581	363	11.19	5	0.51
2018	1512	939	28.95	8	0.81
2019	1979	561	17.30	94	9.51
2020	2416	623	19.21	186	18.83
2021	2748	590	18.19	258	26.11
2022	2366	45	1.39	427	43.22
Total	3318	3243	100%	988	100%

Panel B: Size and Volume Distribution

		Market Cap (mil)			Volume (thous)		
Year	Number	Mean	Median	SD	Mean	Median	SD
2014	111	1103.22	2.91	8764.54	5231.77	19.84	40909.64
2015	157	455.13	1.14	4741.96	4052.16	3.18	52773.38
2016	223	873.37	2.42	10001.75	9940.99	6.07	114296.26

2017	581	5403.67	33.24	76129.50	238950.74	275.35	3715754.28
2018	1512	3960.26	53.87	61807.23	233632.38	556.24	3358500.52
2019	1979	2122.58	17.15	54416.17	541790.63	235.18	10653984.34
2020	2416	257000.00	24.43	1400000.00	1200443.87	452.43	24855139.78
2021	2748	14043.62	77.59	323000.00	1870203.67	2257.19	39018321.17
2022	2366	12144.82	54.55	239000.00	1314371.52	1553.85	29804705.29
Full	3318	290011.90	34.74	241984.60	1074038.79	679.46	26177582.12

Notes: This table reports the number of coins, new coins and discontinued coins by year in Panel A. Panel B reports the number of coins, the mean, the median of market capitalisation, and the mean and median of daily trading price volume by year.

4.2. Descriptive statistics for variables

We begin by categorising the CLI values into two groups, distinguishing between low-value of CLI and high-value of CLI, based on the median CLI value. Subsequently, we analyse the disparities between these two groups in Table 2. The findings indicate significant differences in mean and median values across all variables. Panel A displays the statistical mean and median for the independent variable, *LAG_CLI* represents the log value of Composite Leading Indicator, *REAL_CLI* is the real value of Composite Leading Indicator. Panel B illustrates the mean and median values of the dependent variable, Panel C presents the three-factor model variables, while Panel D depicts the control variables. In addition, it is noteworthy that cryptocurrencies with a high value of CLI (High_CLI) exhibit significantly higher cryptocurrency return scores in comparison to those with Low_CLI, in Panel A.

Chapter 5, Table 2. Descriptive statistics

	Low LAG_CLI (N=338,613)		High LAG_CLI (N=336,354)		Sig. Difference	
Variables	Mean	Median	Mean	Median	Mean	Median
Panel A: Independent Variable						
LAG_CLI	1.9943	1.9963	2.0028	2.0031	***	***
REAL_CLI	7.3471	7.3618	7.4098	7.4116	***	***
Panel B: Dependent Variable						
CRYPTO	-0.0080	-0.0165	0.0007	-0.0075	***	***
Panel C: Three Factor Model						
CMRT	-0.0103	-0.0116	-0.0052	-0.0048	***	***
SMB	0.0233	0.0137	0.0409	0.0190	***	***
HML	0.2456	0.2129	0.2746	0.2247	***	***
Panel D: Control Variables						
CPI	2.4226	2.4121	2.4272	2.4289	***	***
FEDRATE	-0.1805	0.1987	-0.6026	-1.0000	***	***
GOLD	3.2046	3.2199	3.2101	3.2510	***	***
VIX	1.3231	1.3365	1.2815	1.2751	***	***
GPIAC	2.1016	2.0612	2.1979	2.1900	***	***
EXCHANGE	1.1045	1.1115	1.1589	1.1632	***	***
DJIA	4.4345	4.4367	4.4800	4.5193	***	***
GDP	4.3382	4.3332	4.3542	4.3626	***	***
UNEMPLOY	5.5315	3.7000	4.6283	4.2000	***	***

TREND_BTC	1.1775	1.2041	1.4494	1.5315	***	***
WIKI_BTC	3.5471	3.5344	3.8739	3.8480	***	***
CC	1.1152	1.1043	1.1250	1.1043	***	***
GE	1.3377	1.2751	1.3576	1.2995	***	***
RQ	1.3233	1.3346	1.4695	1.4410	***	***
RL	1.3861	1.3717	1.4210	1.3906	***	***
EPUI	2.1750	2.1426	2.0503	2.0524	***	***

Notes: This table compares means and medians of variables analysed in the study between low-value of CLI and high-value of CLI. Panel A provide the descriptive statistics for independent variable, dependent variable in Panel B, three-factor model variables in Panel C and control variables in Panel D. Definitions of variables are provided in Appendix 1.

4.3. Pearson's correlation coefficients

Table 3 presents Pearson's correlation coefficients for each pair of variables. The results indicate a negative and statistically significant correlation between *LAG_CLI* and *CRYPTO* impact proxies. Cryptocurrency returns show a positive and statistically significant association with the three factors: *CMRT*, *SMB* and *HML*. *LAG_CLI* exhibits a positive correlation with the three-factor variables. Notably, it demonstrates the strongest correlation with *DJIA* and *S&P500*, displaying a positive and significant coefficient of 0.979. Regarding all control variables, including the three factors, they exhibit statistically significant correlations with *LAG_CLI*, except for *CMRT*, which shows a positive but non-significant correlation with *LAG_CLI*. These findings underscore the significance of the CLI as a factor associated with the financial market.

Chapter 5, Table 3. Pairwise correlations

Notes: This table presents Pearson's correlation coefficients between the variables employed in the main regression analysis. Superscript ***, ** and * correspond to statistical significance at the

Variables	V1	V2	V3	V4	V5	V6	V7	V8	V9	V10	V11	V12
V1: *CRYPTO*	1.000											
V2: *LAG_CLI*	-0.002*	1.000										
V3: *CMRT*	0.146***	0.001	1.000									
V4: *SMB*	0.006***	0.112***	-0.036***	1.000								
V5: *HML*	0.039***	0.080***	0.115***	0.515***	1.000							
V6: *GOLD*	0.029***	-0.030***	0.140***	0.083***	-0.039***	1.000						
V7: *FEDRATE*	-0.079***	-0.004***	-0.307***	-0.067***	-0.114***	-0.592***	1.000					
V8: *GDP*	-0.008***	0.159***	-0.014***	0.054***	-0.029***	0.253***	-0.023***	1.000				
V9: *UNEMPLOY*	0.050***	-0.637***	0.192***	-0.052***	0.008***	0.302***	-0.618***	-0.144***	1.000			
V10: *VIX*	0.009***	-0.303***	0.042***	-0.008***	-0.102***	0.536***	-0.323***	0.116***	0.405***	1.000		
V11: *EXCHANGE*	0.045***	0.256***	0.179***	-0.004***	0.148***	-0.004***	-0.448***	-0.137***	0.204***	-0.224***	1.000	
V12: *CPI*	-0.028***	0.224***	-0.084***	0.104***	-0.144***	0.671***	-0.001	0.363***	-0.251***	0.392***	-0.454***	1.000
V13: *DJIA*	-0.002	0.384***	0.022***	0.126***	-0.037***	0.747***	-0.274***	0.338***	-0.177***	0.128***	-0.025***	0.788***
V14: *EPUI*	0.036***	-0.453***	0.141***	-0.039***	-0.030***	0.448***	-0.403***	-0.006***	0.588***	0.551***	-0.007***	0.082***
V15: *GPIAC*	-0.022***	0.529***	-0.076***	0.129***	-0.092***	0.458***	0.029***	0.344***	-0.476***	0.121***	-0.291***	0.879***
V16: *TREND_BTC*	0.023***	0.344***	0.097***	0.091***	0.039***	0.621***	-0.388***	0.244***	0.013***	0.221***	0.200***	0.525***
V17: *WIKI_BTC*	0.023***	0.544***	0.081***	0.078***	0.136***	-0.026***	-0.229***	0.029***	-0.153***	-0.277***	0.396***	-0.023***
V18: *CC*	-0.033***	0.098***	-0.155***	-0.072***	0.001	-0.875***	0.594***	-0.212***	-0.378***	-0.493***	-0.047***	-0.510***
V19: *GE*	-0.024***	0.120***	-0.117***	-0.081***	0.063***	-0.904***	0.511***	-0.247***	-0.303***	-0.624***	0.208***	-0.708***
V20: *RQ*	-0.019***	0.588***	-0.099***	0.051***	0.025***	-0.348***	0.259***	0.040***	-0.456***	-0.353***	0.084***	0.057***
V21: *RL*	-0.003**	0.290***	-0.057***	-0.020***	0.104***	-0.786***	0.320***	-0.205***	-0.333***	-0.607***	0.137***	-0.540***
V22: *S&P500*	0.010***	0.361***	0.064***	0.137***	-0.030***	0.821***	-0.400***	0.344***	-0.096***	0.221***	-0.034***	0.811***

Variables	V13	V14	V15	V16	V17	V18	V19	V20	V21	V22
V13: *DJIA*	1.000									
V14: *EPUI*	0.053***	1.000								
V15: *GPIAC*	0.722***	-0.179***	1.000							
V16: *TREND_BTC*	0.753***	0.165***	0.498***	1.000						
V17: *WIKI_BTC*	0.175***	-0.265***	0.233***	0.471***	1.000					
V18: *CC*	-0.703***	-0.466***	-0.237***	-0.584***	0.097***	1.000				
V19: *GE*	-0.627***	-0.448***	-0.453***	-0.467***	0.136***	0.857***	1.000			
V20: *RQ*	0.066***	-0.436***	0.353***	0.224***	0.565***	0.489***	0.466***	1.000		
V21: *RL*	-0.600***	-0.508***	-0.199***	-0.408***	0.365***	0.870***	0.795***	0.596***	1.000	
V22: *S&P500*	0.979***	0.116***	0.743***	0.746***	0.176***	-0.749***	-0.724***	0.022***	-0.614***	1.000

1%, 5% and 10% levels, respectively. Definitions of variables are presented in Appendix 1.

5. Analysis and results

We assess the association between the Composite Leading Indicator and cryptocurrency returns using both a one-factor model and a three-factor model. To ensure the robustness and reliability of our findings, we conduct additional analyses and robustness checks. These supplementary tests help verify that our results are consistent and not influenced by the specific measurement techniques and models used in our study.

5.1. Jensen's alpha coefficient analysis

As can be seen in Table 4, we first conduct the one factor model to assess the association between *LAG_CLI* and cryptocurrency returns without any control variables. Panel A results show that Jensen's alpha coefficient is positive and significant at the 5% level (0.1285). Additionally, the coefficient of *LAG_CLI* is negatively and significantly associated with cryptocurrency returns, at the 5% of levels. The *R*-squared value for one-factor model is 0.0221.

Panel B presents the results from the three-factor model, which assesses the association between *LAG_CLI* and cryptocurrency returns without any control variables. Here, Jensen's alpha coefficient is positive and significant (0.2118), and it is higher than in the one-factor model. Furthermore, the coefficient of *LAG_CLI* remains negatively and significantly related to cryptocurrency returns. The *R*-squared value in the three-factor model is 0.0226, surpassing that of the one-factor model. This indicates that the three-factor model performs better in predicting cryptocurrency returns compared to the one-factor model. This finding aligns with Jia et al. (2022), who demonstrate that the three-factor model offers stronger and more significant explanatory power for cryptocurrency returns compared to the one-factor model. Therefore, this study employs the three-factor model to analyse the association between the CLI and cryptocurrency returns.

Chapter 5, Table 4. Jensen's alpha coefficients for one-factor model and three-factor model

Panel A: One-Factor Model	Model 1
A	0.1285**
	(2.08)
LAG_CLI	-0.0636**
	(-2.05)
CMRT	0.6293***
	(123.31)
F	7605.01
Prob>F	0.0000
N	671710
R-squared	0.0221
Adj *R*-squared	0.0221
Panel B: Three-Factor Model	**Model 1**
A	0.2118***
	(3.40)
LAG_CLI	-0.1082***
	(-3.47)
CMRT	0.6178***
	(119.50)
SMB	-0.0021
	(-0.82)
HML	0.0216***
	(16.28)
F	3890.94
Prob>F	0.0000
N	671710
R-squared	0.0226
Adj *R*-squared	0.0226

Notes: This table reports coefficient estimates for the modified one-factor model and three-factor model, along with *t*-value (in brackets). Superscript ***, ** and * correspond to statistical significance at the 1%, 5% and 10% levels, respectively.

5.2. Baseline analysis

To examine the hypotheses and assess the relationship between the CLI and cryptocurrency returns, we expand our models by incorporating additional control variables from previous literature. Furthermore, we introduce year and crypto fixed effects to account for unobserved variations across different years and cryptocurrencies in our analyses. As outlined in Table 5, the regression outcomes consistently highlight *LAG_CLI* as the primary explanatory variable in all models, displaying a consistently negative and statistically significant association with cryptocurrency returns. It is noteworthy that the model with the most substantial coefficient value for *LAG_CLI* is Model (2) (β = -0.0470), followed by Model (4) (β = -0.1813), Model (1) (β = -0.2370) and Model (3) (β = -0.3742). Regarding significance, Model (1) (β = -0.2370, $p < 0.01$), Model (3) (β = -0.3742, $p < 0.01$) and Model (4) (β = -0.1813, $p < 0.1$) exhibit statistically significant negative associations between *LAG_CLI* and cryptocurrency returns, indicating the robustness of the findings across different sample sizes. However, in Model (2), the negative correlation between *LAG_CLI* and cryptocurrency returns is not statistically significant, suggesting that this association may not be strong enough to be considered statistically valid. This observation could be attributed to cryptocurrencies with small market values, highlighting inefficiencies within the cryptocurrency market (Brauneis & Mestel, 2018). This aligns with Li, Zhang, et al. (2020) assertion that cryptocurrencies with small values challenge the efficient market hypothesis. In conclusion, our results consistently support Hypothesis 2 (H2), indicating a negative association between the CLI and cryptocurrency returns across all models in the three-factor framework.

The coefficients of the three factors consistently exhibit statistical significance across all models at the 1% level, except for *SMB* in Model (1). This indicates that the three-factor model effectively predicts cryptocurrency returns. Regarding the control variables in Table 5, the coefficients of *CMRT*, *EPUI*, *GOLD* and *GPIAC* are positively related to cryptocurrency returns across all models, suggesting that higher values of these variables contribute to higher cryptocurrency returns. Conversely, the coefficients of *FEDRATE*, *UNEMPLOY*, *VIX*, *EXCHANGE*, *CPI*, *DJIA* and *WIKI_BTC* are negatively associated with cryptocurrency returns across all models, implying that lower values of these variables contribute to higher cryptocurrency returns. Examining the *R*-squared values across all models, they range from 0.0216 to 0.0999. These values indicate that the *LAG_CLI* collectively explains between 2.16% and 9.99% of the variation in cryptocurrency returns. While the explanatory power is modest, it suggests that the CLI contributes significantly to understanding changes in cryptocurrency returns in conjunction with other factors considered in the models.

To account for various factors influencing cryptocurrency returns, we utilize panel regressions with both year fixed effects and crypto fixed effects based on the three-factor model. Initially, we estimate Equation (7) with three-factor variables (Appendix 2, Column 1). In subsequent columns (Columns 2–12), we progressively include all control variables. The results consistently demonstrate that the coefficient on *LAG_CLI* remains negative and statistically significant at the 1% level, even after accounting for a comprehensive set of factors known to have predictive power in cryptocurrency returns. These findings provide strong and robust support for Hypothesis 2 (H2).

Chapter 5, Table 5. CLI and cryptocurrency returns: baseline analysis

	Full Size	Small Size	Medium Size	Big Size
	Model 1	Model 2	Model 3	Model 4
LAG_CLI	-0.2370***	-0.0470	-0.3742***	-0.1813*
	(-3.32)	(-0.27)	(-3.82)	(-1.89)

CMRT	0.5617***	0.5440***	0.5484***	0.6001***
	(103.00)	(37.05)	(73.72)	(94.05)
SMB	0.0004	0.1166***	-0.0215***	-0.0894***
	(0.15)	(17.85)	(-5.88)	(-28.18)
HML	0.0141***	-0.0085**	0.0164***	0.0356***
	(10.24)	(-2.44)	(8.53)	(21.65)
EPUI	0.0055***	0.0068**	0.0057***	0.0035***
	(5.31)	(2.46)	(4.05)	(2.72)
GOLD	0.0333***	0.0806***	0.0375**	0.0319**
	(2.86)	(2.72)	(2.37)	(2.03)
FEDRATE	-0.0055***	-0.0036	-0.0077***	-0.0069***
	(-5.53)	(-1.41)	(-5.57)	(-5.76)
GDP	-0.0034	0.0008	-0.0064**	-0.0027
	(-1.60)	(0.15)	(-2.13)	(-1.12)
UNEMPLOY	-0.0005**	-0.0006	-0.0011***	-0.0002
	(-2.32)	(-1.06)	(-3.51)	(-0.80)
VIX	-0.0062*	-0.0165*	-0.0012	-0.0081*
	(-1.79)	(-1.77)	(-0.24)	(-1.92)
EXCHANGE	-0.0209**	-0.0127	-0.0467***	-0.0142
	(-2.13)	(-0.53)	(-3.43)	(-1.09)
CPI	-0.6980***	-0.6122***	-0.7319***	-0.5407***
	(-11.60)	(-3.95)	(-8.66)	(-7.39)
DJIA	-0.0486***	-0.0965**	-0.0481**	-0.0433**
	(-2.96)	(-2.29)	(-2.12)	(-2.08)
GPIAC	0.0517***	0.0128	0.0443***	0.0632***
	(6.46)	(0.62)	(3.92)	(6.54)
TREND_BTC	0.0020	-0.0015	-0.0028	0.0008
	(1.18)	(-0.33)	(-1.20)	(0.38)
WIKI_BTC	-0.0078***	-0.0095***	-0.0062***	-0.0080***
	(-5.62)	(-2.64)	(-3.28)	(-4.77)
Constant	2.1844***	1.7470***	2.5723***	1.6415***
	(11.83)	(3.83)	(10.12)	(6.79)
Year Fixed Effect	Yes	Yes	Yes	Yes
Crypto Fixed Effect	Yes	Yes	Yes	Yes
Adj *R*-squared	0.0255	0.0196	0.0376	0.0978
R-squared	0.0264	0.0216	0.0392	0.0999
F	28.27	10.99	23.66	47.75
Prob > F	0.0000	0.0000	0.0000	0.0000
N	674929	170114	336153	168662

Notes: This table presents the regression results of the CLI on cryptocurrency returns with control variables. Superscript ***, ** and * correspond to statistical significance at the 1%, 5% and 10% levels, respectively. Definitions of variables are presented in Appendix 1.

5.3. Entropy balancing analysis

While the baseline regression has offered empirical support for the negative association between the CLI and cryptocurrency returns, it is essential to address potential endogeneity concerns stemming from omitted variables, selection bias and the reverse causality problem. To mitigate these issues, we adopt an entropy balancing approach, aiming to reduce selection bias and enhance the comparability of groups, especially in the context of estimating causal effects (Jia & Li, 2022).

To address the issue of covariate imbalance between the treatment and control groups when estimating causal effects, we partition cryptocurrency market capitalisation into a treatment group (*HIGH_LAG_CLI*) and a control group (*LOW_LAG_CLI*). The treatment group consist of cryptocurrencies with market values greater than the median, while the control group comprises those with values lower than the median. We incorporate year and crypto fixed effects in all models to control for potential confounding factors. The baseline research models are then re-executed using the entropy balancing method.

In Table 6, Panel A, descriptive statistics for the entropy-balanced samples are presented, balancing *HIGH_LAG_CLI* with *LOW_LAG_CLI* for the treatment and control groups. Table 6, Panel B, displays the second-stage regression results for the entropy-balanced samples. The findings indicate that the coefficients of *HIGH_LAG_CLI* consistently exhibit a negative and statistically significant association across all models, except for Model (2). Therefore, the results from the entropy balancing approach generally align with our main findings from the baseline analysis.

Chapter 5, Table 6. CLI and cryptocurrency returns: entropy balancing analysis

Panel A: Mean value of variables for treatment and control groups

	Treatment group			Control group		
	Mean	Treat Variance	Skewness	Mean	Treat Variance	Skewness
CMRT	-0.0104	0.0012	0.2488	-0.0104	0.0009	-0.1474
SMB	0.0233	0.0059	1.9190	0.0233	0.0067	1.2020
HML	0.2449	0.0257	4.1930	0.2449	0.0276	3.9510
EPUI	2.1760	0.0935	-0.0021	2.1760	0.0794	0.1541
GOLD	3.2050	0.0037	-0.5355	3.2050	0.0036	-0.7969

FEDRATE	-0.1808	0.4673	-0.5185	-0.1809	0.3822	-0.7345
GDP	4.3380	0.0175	-25.7700	4.3380	0.0020	0.4806
UNEMPLOY	5.5360	9.3730	1.6080	5.5360	11.5600	1.6410
VIX	1.3240	0.0277	0.5047	1.3240	0.0336	0.3282
EXCHANGE	1.1050	0.0035	-0.3665	1.1050	0.0704	46.3000
CPI	2.4230	0.0008	1.0330	2.4230	0.0008	0.7777
DJIA	4.4350	0.0039	-1.2090	4.4350	0.0051	-0.8788
GPIAC	2.1020	0.0155	1.0880	2.1020	0.0186	0.9176
TREND_BTC	1.1790	0.0425	-1.3370	1.1790	0.0616	-0.6168
WIKI_BTC	3.5460	0.0227	1.0590	3.5460	0.0297	1.3000

Notes: This table presents the entropy balancing results of the impact of the composite leading Indicator (CLI) on cryptocurrency returns with other control variables. Panel A repots the mean differences of dependent and independent variables between control group and matched group. Panel B reports the regression estimates using these two groups. Superscript ***, ** and * correspond to statistical significance at the 1%, 5% and 10% levels, respectively. Definitions of variables are presented in Appendix 1.

Chapter 5, Table 6. CLI and cryptocurrency returns: entropy balancing analysis

Panel B: Entropy balancing regression results				
Variables	Full Size	Small Size	Medium Size	Big Size
HIGH_LAG_CLI	-0.0063***	-0.0025	-0.0066***	-0.0096***
	(-7.15)	(-1.11)	(-5.52)	(-8.61)
CMRT	0.5463***	0.5392***	0.5282***	0.5858***
	(102.19)	(37.05)	(72.82)	(92.95)
SMB	0.0012	0.1215***	-0.0218***	-0.0889***
	(0.47)	(18.72)	(-6.06)	(-28.27)
HML	0.0137***	-0.0096***	0.0163***	0.0351***
	(10.09)	(-2.78)	(8.61)	(21.57)
EPUI	0.0061***	0.0061**	0.0066***	0.0047***
	(5.92)	(2.25)	(4.72)	(3.70)

GOLD	0.0298***	0.0679**	0.0288**	0.0320**
	(2.82)	(2.47)	(2.01)	(2.34)
FEDRATE	-0.0033***	-0.0025	-0.0054***	-0.0030**
	(-3.32)	(-1.00)	(-3.91)	(-2.44)
GDP	-0.0032	0.0010	-0.0059**	-0.0024
	(-1.48)	(0.18)	(-1.96)	(-0.99)
UNEMPLOY	0.0001	-0.0003	-0.0003	0.0005*
	(0.57)	(-0.55)	(-0.99)	(1.80)
VIX	-0.0101***	-0.0162*	-0.0082*	-0.0095**
	(-2.96)	(-1.75)	(-1.78)	(-2.29)
EXCHANGE	-0.0064	0.0002	-0.0133**	-0.0019
	(-1.50)	(0.02)	(-2.39)	(-0.38)
CPI	-0.4805***	-0.5005***	-0.4179***	-0.3083***
	(-8.26)	(-3.20)	(-5.17)	(-4.44)
DJIA	-0.0671***	-0.0950**	-0.0846***	-0.0594***
	(-4.24)	(-2.30)	(-3.91)	(-2.99)
GPIAC	0.0336***	0.0078	0.0191*	0.0427***
	(4.08)	(0.37)	(1.65)	(4.32)
TREND_BTC	0.0023	-0.0003	-0.0036	0.0011
	(1.40)	(-0.07)	(-1.60)	(0.55)
WIKI_BTC	-0.0084***	-0.0099***	-0.0077***	-0.0077***
	(-6.31)	(-2.86)	(-4.24)	(-4.70)
Constant	1.3070***	1.4164***	1.2763***	0.8204***
	(11.54)	(4.58)	(8.11)	(6.07)
Year Fixed Effect	Yes	Yes	Yes	Yes
Crypto Fixed Effect	Yes	Yes	Yes	Yes
N	692850	173196	346325	173329
R-squared	0.0257	0.0213	0.0378	0.0973
Adj *R*-squared	0.0247	0.0194	0.0362	0.0952

Notes: This table presents the entropy balancing results of the impact of the composite leading Indicator (CLI) on cryptocurrency returns with other control variables. Panel A repots the mean differences of dependent and independent variables between control group and matched group. Panel B reports the regression estimates using these two groups. Superscript ***, ** and * correspond to statistical significance at the 1%, 5% and 10% levels, respectively. Definitions of variables are presented in Appendix 1.

6. Additional tests and robustness tests

In this section, we present the outcomes of various additional analyses and robustness tests to provide a comprehensive understanding of the relationship between *LAG_CLI* and *CRYPTO* using the three-factor model. These analyses include an interaction analysis examining the influence of the COVID-19 pandemic and institutional factors, an assessment of the impact of cryptocurrency market capitalisation and trading volume on cryptocurrency returns, the creation of the change in different months of *LAG_CLI* and an analysis excluding specific coins to further evaluate the association between the *LAG_CLI* and cryptocurrency returns.

6.1. Interaction analysis for COVID-19 pandemic

To evaluate the influence of the COVID-19 pandemic on the relationship between *LAG_CLI* and *CRYPTO*, we introduced COVID-19 as a control variable in our regression model. The years were categorized into two periods: pre-COVID-19 (2014–2019) and COVID-19 (2020–2022), with the indicator variable *COVID-19*, equal to 1 for the years 2020 and above and 0 otherwise. As shown in Table 7, Panel A, the coefficient of *LAG_CLI* maintains a consistent negative associated with *CRYPTO* across all models. Notably, the coefficients for *COVID-19* are both positive and statistically significant, suggesting that the COVID-19 pandemic had a positive impact on cryptocurrency returns. This finding is consistent with previous studies, such as those by Corbet, Hou, et al. (2020), which reported significant positive returns from cryptocurrencies during the pandemic. The perception of cryptocurrencies as alternative assets, similar to gold, during period of economic uncertainty, further explains their resilience throughout the pandemic crisis (González et al., 2021).

To further investigate the relationship between *LAG_CLI* and *CRYPTO*, we performed an interaction analysis with *COVID-19* as a moderating variable. The results in Panel B demonstrate that *LAG_CLI's* coefficients continue to show a negative association with *CRYPTO* in Models (1) – (3), with statistically significant results in Models (2) and (3). However, in Model (4), the coefficient of *LAG_CLI* becomes positively and significantly associated with *CRYPTO*. This change suggests that the COVID-19 pandemic's impact varied depending on the market capitalization of different cryptocurrencies. Specifically, cryptocurrencies with smaller market capitalisations tend to be less efficient, as noted by Brauneis and Mestel (2018), while those with larger market capitalisation are generally more mature and stable, as discussed by Bakhtiar et al. (2023). Consequently, cryptocurrencies with different market values responded differently to the economic disruptions caused by the COVID-19 pandemic.

Chapter 5, Table 7. CLI and cryptocurrency returns: additional tests

Panel A: The impact of COVID-19 pandemic on cryptocurrency excess returns				
Variables	COVID_19 full size	COVID-19 small size	COVID-19 medium size	COVID-19 big size
	Model 1	Model 2	Model 3	Model 4
LAG_CLI	-0.2370***	-0.0470	-0.3742***	-0.1813*
	(-3.32)	(-0.27)	(-3.82)	(-1.89)
COVID-19	0.0492***	0.0335**	0.0582***	0.0439***
	(8.03)	(2.17)	(6.57)	(5.16)
CMRT	0.5617***	0.5440***	0.5484***	0.6001***
	(103.00)	(37.05)	(73.72)	(94.05)
SMB	0.0004	0.1166***	-0.0215***	-0.0894***
	(0.15)	(17.85)	(-5.88)	(-28.18)
HML	0.0141***	-0.0085**	0.0164***	0.0356***
	(10.24)	(-2.44)	(8.53)	(21.65)
Constant	2.1844***	1.7470***	2.5723***	1.6415***
	(11.83)	(3.83)	(10.12)	(6.79)

Baseline controls	Yes	Yes	Yes	Yes
Crypto Fixed Effect	Yes	Yes	Yes	Yes
N	674929	170114	345977	173168
R-squared	0.0264	0.0216	336153	168662
Adj *R*-squared	0.0255	0.0196	0.0376	0.0978

Panel B: Interaction analysis				
Variables	COVID_19 full size	COVID-19 small size	COVID-19 median size	COVID-19 big size
	Model 1	Model 2	Model 3	Model 4
LAG_CLI	-0.2518	-2.1170**	-1.9556***	2.0801***
	(-0.62)	(-2.18)	(-3.48)	(3.57)
LAG_COVID-19	0.0189	-4.1986**	-3.1568***	4.6269***
	(0.02)	(-2.15)	(-2.81)	(3.97)
LAG_CLI x COVID-19	0.0152	2.1204**	1.6121***	-2.2950***
	(0.04)	(2.17)	(2.86)	(-3.93)
CMRT	0.5617***	0.5425***	0.5475***	0.6009***
	(102.90)	(36.91)	(73.52)	(94.13)
SMB	0.0004	0.1166***	-0.0215***	-0.0893***
	(0.15)	(17.86)	(-5.86)	(-28.14)
HML	0.0141***	-0.0088**	0.0162***	0.0357***
	(10.23)	(-2.54)	(8.43)	(21.68)
Constant	2.2149***	6.0443***	5.8278***	-2.9444**
	(2.63)	(2.97)	(4.99)	(-2.47)
Baseline controls	Yes	Yes	Yes	Yes
Crypto Fixed Effect	Yes	Yes	Yes	Yes
N	674929	170114	336153	168662
R-squared	0.0264	0.0216	0.0392	0.1000
Adj *R*-squared	0.0255	0.0197	0.0376	0.0979

Notes: This table presents the results of the impact of COVID-19 on the relationship between CLI and cryptocurrency returns with other control variables. Superscript ***, ** and * correspond to statistical significance at the 1%, 5% and 10% levels, respectively. Definitions of variables are presented in Appendix 1.

6.2. Interaction analysis for institutional factors

The previous study shows that the quality of institutions plays a crucial role in shaping the interactions within the inter-country financial markets (Nguyen et al., 2019). This motivates us to examine whether the institutions contribute to cryptocurrency returns. Thus, we conduct the interaction analysis using four institutional quality indicators: government effectiveness *(GE)*, regulatory quality *(RQ)*, rule of law *(RL)* and control of corruption *(CC)*.

The results presented in Table 8 demonstrate that the coefficient of *LAG_CLI* is negatively associated with cryptocurrency returns across all the models. Additionally, the institutional factors, including *CC*, *RQ* and *RL*, exhibit a negative and statistically significant relationship with cryptocurrency returns. These findings suggest that the institutional indicators consistently show a negative correlation with cryptocurrency returns, indicating that institutional factors can effectively moderate the association between the CLI and cryptocurrency returns. These conclusions align with and reinforce the consistency of our baseline findings.

Chapter 5, Table 8. CLI and cryptocurrency returns: additional tests

Variables	Model 1	Model 2	Model 3	Model 4
LAG_CLI	-5.0318***	-0.9748	-8.7245***	-11.6603***
	(-2.78)	(-0.39)	(-7.32)	(-3.73)
CMRT	0.5623***	0.5621***	0.5627***	0.5627***
	(103.09)	(103.00)	(103.17)	(103.12)
SMB	-0.0001	-0.0000	-0.0006	-0.0002
	(-0.02)	(-0.00)	(-0.22)	(-0.06)
HML	0.0143***	0.0142***	0.0148***	0.0145***
	(10.39)	(10.30)	(10.76)	(10.51)
CC	-9.3782***			
	(-2.71)			
CC_LAG_CLI	4.5996***			
	(2.66)			
GE		-1.4059		
		(-0.36)		
GE_LAG_CLI		0.5811		
		(0.30)		
RQ			-13.2052***	
			(-6.95)	
RQ_LAG_CLI			6.7496***	

			(7.14)	
RL				-17.2569***
				(-3.71)
RL_LAG_CLI				8.5147***
				(3.66)
Constant	12.0150***	4.1622	18.7601***	25.5069***
	(3.38)	(0.84)	(7.91)	(4.08)
Baseline Controls	Yes	Yes	Yes	Yes
Year & Crypto Fixed Effects	Yes	Yes	Yes	Yes
N	674929	674929	674929	674929
R-squared	0.0264	0.0264	0.0265	0.0264
Adj *R*-squared	0.0251	0.0251	0.0251	0.0252

Notes: This table presents the results of the impact of institutional factors on the relationship between CLI and cryptocurrency returns with other control variables. Superscript ***, ** and * correspond to statistical significance at the 1%, 5% and 10% levels, respectively. Definitions of variables are presented in Appendix 1.

6.3. Cryptocurrency market capitalization and trading volume analysis: robustness tests

Empirical studies have established that both cryptocurrency market capitalisation and trading volume significantly influence cryptocurrency returns (Bouri, Lau, et al., 2019; Li, Zhang, et al., 2020). In this study, we investigate whether the association between *LAG_CLI* and *CRYPTO* is moderated by these two factors. We begin by categorizing all cryptocurrencies into high and low market capitalization groups. An indicator variable, *High-market cap*, equal to 1 if the cryptocurrency's market capitalisation is at or above the median and 0 otherwise. Similarly, we define indicator variables for *High trading volume* and *Low trading volume*.

In Table 9, Panel A, the findings suggest that cryptocurrency market capitalization affects the relationship between *LAG_CLI* and *CRYPTO*. Specially, for cryptocurrencies with low market capitalization, the coefficient of *LAG_CLI* shows a negative but statistically insignificant. However, for those with high market capitalization, *LAG_CLI* exhibits a negative and statistically significant association with *CRYPTO*, with a coefficient of -0.3618. This result indicates a stronger association, where a one-unit change in CLI corresponds to a 36.18% decrease in cryptocurrency returns. Additionally, the test for coefficient difference reveals a statistically significant variation in the *LAG_CLI* coefficient between treatment and control groups, with a test statistic of 2.71, significant at the 10% level. Therefore, cryptocurrency market capitalization is a crucial factor influencing the relationship between the CLI and cryptocurrency returns.

Table 9, Panel B presents results indicating that cryptocurrency trading volume also significantly impacts the relationship between the *LAG_CLI* and *CRYPTO*. The regression analysis shows that the coefficient of *LAG_CLI* is negative and significant correlated with *CRYPTO* in both *High* and *Low trading volume* groups. However, the coefficient difference test yields a non-significant statistic of 0.19, suggesting that while trading volume does affect the relationship between *LAG_CLI* and *CRYPTO*, the difference between the high and low trading volume groups is not statistically significant.

Chapter 5, Table 9. CLI and cryptocurrency returns: robustness tests

Panel A: The impact of cryptocurrency market capitalisation		
Variables	Low Market Cap	High Market Cap
LAG_CLI	-0.1329 (-1.13)	-0.3618*** (-4.75)
CMRT	0.5447*** (57.09)	0.5760*** (105.93)
SMB	0.0677*** (15.31)	-0.0726*** (-26.81)
HML	0.0012 (0.53)	0.0297*** (21.04)
Constant	2.1471*** (7.00)	2.4157*** (12.42)
Test of Coefficient difference	2.71*	
Baseline Controls	Yes	Yes
Year & Crypto Fixed Effects	Yes	Yes
N	338868	336061
R-squared	0.0157	0.0545
Adj *R*-squared	0.0156	0.0545

Panel B:The impact of cryptocurrency trading volume		
Variables	Low Volume	High Volume
LAG_CLI	-0.2056*	-0.2665***
	(-1.71)	(-3.67)
CMRT	0.5452***	0.5770***
	(56.80)	(109.55)
SMB	0.0588***	-0.0641***
	(13.24)	(-24.36)
HML	0.0040*	0.0261***
	(1.70)	(19.13)
Constant	2.0307***	2.3417***
	(6.44)	(12.60)
Test of Coefficient difference	0.19	
Baseline Controls	Yes	Yes
Year & Crypto Fixed Effects	Yes	Yes
N	339708	335221
R-squared	0.0172	0.0655
Adj *R*-squared	0.0156	0.0638

Notes: Panel A presents the regression results of the effect of cryptocurrency market capitalisation on cryptocurrency returns with all control variables. Panel B presents the regression results of the effect of cryptocurrency trading volume on cryptocurrency returns with all control variables. Superscript ***, ** and * correspond to statistical significance at the 1%, 5% and 10% levels, respectively. Definitions of variables are presented in Appendix 1.

6.4. Excluding specific cryptocurrencies: robustness tests

Previous studies have revealed that cryptocurrency returns are significantly influenced by market capitalisation, with larger coins like Bitcoin holding a dominant position in the market (Liu et al., 2022a; Oosthoek & Doerr, 2020). Notably, Colon et al. (2021) found that the top 25 cryptocurrencies account for nearly 95% of the total market capitalisation. This raised the question of whether the exclusion of the largest or smallest coins might affect the relationship between *LAG_CLI* and *CRYPTO*. Thus, we segment the cryptocurrencies based on the top 1, top 10 and bottom 10 coins to examine this relationship through full sample size. We also control for the year and crypto fixed effects in our regression model.

Table 10, Panel A presents the results of re-estimating the three-factor model for all cryptocurrency returns, excluding Bitcoin. The results show that the coefficient value of *LAG_CLI* is -0.2367, indicating that *LAG_CLI* is negative and statistically significant in association with *CRYPTO* at the 1% level. This results align with the study's main findings, suggesting that Bitcoin's exclusion does not alter the observed relationship.

Table 10, Panel B shows the regression results after excluding the top 10 coins. The coefficient of *LAG_CLI* remains negative and statistically significant, consistent with our primary findings. This suggests that excluding the top 10 coins does not impact the relationship between *LAG_CLI* and *CRYPTO.*

Table 10, Panel C examines the results after excluding the bottom 10 coins. The coefficient for *LAG_CLI* is -0.2358, indicating a negative and significant association with *CRYPTO*. This result confirms that even without the smallest coins, the negative relationship between *LAG_CLI* and *CRYPTO* persists. Overall, the robustness tests in Table 10 consistently support our baseline findings, affirming that the relationship between *LAG_CLI* and *CRYPTO* is robust across different segments of the cryptocurrency market. These results provide additional support for Hypothesis 2 (H2).

Chapter 5, Table 10. CLI and cryptocurrency returns: robustness tests

Panel A: Conditional sample - excluding Bitcoin (BTC)	
Variables	Model 1
LAG_CLI	-0.2367***
	(-3.30)
CMRT	0.5612***
	(102.24)
SMB	0.0003
	(0.10)
HML	0.0141***
	(10.24)
Cons	2.1878***
	(11.81)
Baseline Controls	Yes
Year & Crypto Fixed Effects	Yes
N	671673
R-squared	0.0263
Adj *R*-squared	0.0254
Panel B: Conditional sample – excluding the top 10 coins	
Variables	Model 1
LAG_CLI	-0.2357***
	(-3.24)
CMRT	0.5587***
	(100.47)
SMB	0.0018
	(0.66)

HML	0.0139***
	(9.90)
Constant	2.1997***
	(11.70)
Baseline Controls	Yes
Year & Crypto Fixed Effects	Yes
N	661038
R-squared	0.0258
Adj *R*-squared	0.0249

Notes: Panel A presents the regression results of the effect of excluding Bitcoin on cryptocurrency excess returns with all control variables. Panel B presents the regression results of the effect of excluding the top 10 cryptocurrencies on its excess returns with all control variables. Panel C presents the regression results of the effect of excluding the bottom 10 cryptocurrencies on its excess returns with all control variables. Superscript ***, ** and * correspond to statistical significance at the 1%, 5% and 10% levels, respectively. Definitions of variables are presented in Appendix 1.

Chapter 5, Table 10. CLI and cryptocurrency returns: robustness tests

Panel C: Conditional sample – excluding the bottom 10 coins	
Variables	Model 1
LAG_CLI	-0.2358***
	(-3.31)
CMRT	0.5631***
	(103.08)
SMB	-0.0046*
	(-1.73)
HML	0.0143***
	(10.37)
Constant	2.1631***
	(11.74)
Baseline Controls	Yes
Year & Crypto Fixed Effects	Yes
N	654072
R-squared	0.0272
Adj *R*-squared	0.0263

Notes: Panel A presents the regression results of the effect of excluding Bitcoin on cryptocurrency excess returns with all control variables. Panel B presents the regression results of the effect of excluding the top 10 cryptocurrencies on its excess returns with all control variables. Panel C presents the regression results of the effect of excluding the bottom 10 cryptocurrencies on its excess returns with all control variables. Superscript ***, ** and * correspond to statistical significance at the 1%, 5% and 10% levels, respectively. Definitions of variables are presented in Appendix 1.

6.5. Monthly change in LAG_CLI: robustness tests

Based on the OECD's guidance, the CLI is anticipated to signal changes in economic activity approximately six to nine months in advance (Long, Zaremba, et al., 2022). Earlier research has explored how monthly changes in the CLI impact stock returns (Chung et al., 2012; Long, Zaremba, et al., 2022), economic activity (Cevik, Dibooglu, & Kutan, 2013), economic news (Damstra & Boukes, 2021), unemployment rate or GDP (Soroka et al., 2015). Therefore, we assess the impact of the one-month change, three-month and six-month of *LAG_CLI* on cryptocurrency returns.

Table 11, Panel A provides evidence that one-month changes of *LAG_CLI* is negative associated with cryptocurrency returns. Additionally, the results indicate that the coefficient of *LAG_CLI* is statistically significant in Models (1), (3) and (4), demonstrating a consistent negative association with cryptocurrency returns. The three-month change in *LAG_CLI* shows a statistical negative relationship with cryptocurrency returns across all models.

Similarly, the six-month change in *LAG_CLI* also reveals a negative association, with coefficients in Models (1), (3) and (4) being negative and statistically significant.

These findings align with the baseline results, confirming that the monthly change in *LAG_CLI* maintains a negative association with cryptocurrency returns. This supports Hypothesis 2, reinforcing the argument that fluctuations in the CLI are predictive of changes in cryptocurrency returns.

Chapter 5, Table 11. CLI and cryptocurrency returns: robustness tests

Panel A: One-month change in *LAG_CLI*				
Variables	Full Size	Small Size	Median Size	Big Size
	Model 1	Model 2	Model 3	Model 4
LAG_CLI_MONTH	-0.1483**	-0.0771	-0.2287**	-0.2093**
	(-2.15)	(-0.46)	(-2.42)	(-2.28)
CMRT	0.5574***	0.5381***	0.5454***	0.5959***
	(100.48)	(36.52)	(72.24)	(91.29)
SMB	-0.0015	0.1079***	-0.0218***	-0.0915***
	(-0.56)	(16.39)	(-5.87)	(-27.92)
HML	0.0142***	-0.0073**	0.0164***	0.0360***
	(10.14)	(-2.09)	(8.43)	(21.25)
Constant	1.7159***	1.6735***	1.8236***	1.2904***
	(14.77)	(5.52)	(11.23)	(9.16)
Baseline Controls	Yes	Yes	Yes	Yes
Year & Crypto Fixed Effects	Yes	Yes	Yes	Yes
N	653905	167138	326378	160389
R-squared	0.0262	0.0214	0.0399	0.1016
Adj *R*-squared	0.0253	0.0194	0.0383	0.0995
Panel B: Three-month change in *LAG_CLI*				
Variables	Full Size	Small Size	Medium Size	Big Size
	Model 1	Model 2	Model 3	Model 4
LAG_CLI_THREE_MONTH	-0.2633***	-0.1818*	-0.3236***	-0.3478***
	(-5.78)	(-1.68)	(-5.11)	(-5.87)
CMRT	0.5479***	0.5330***	0.5339***	0.5875***
	(95.60)	(35.75)	(68.09)	(87.21)
SMB	-0.0011	0.0995***	-0.0189***	-0.0888***
	(-0.40)	(14.91)	(-4.94)	(-26.38)
HML	0.0133***	-0.0087**	0.0160***	0.0357***
	(9.30)	(-2.49)	(7.97)	(20.57)
Constant	1.6776***	1.6094***	1.7217***	1.3129***
	(14.06)	(5.25)	(10.28)	(9.10)
Baseline Controls	Yes	Yes	Yes	Yes

Year & Crypto Fixed Effects	Yes	Yes	Yes	Yes
N	618694	160728	307660	150306
R-squared	0.0258	0.0211	0.0403	0.1038
Adj *R*-squared	0.0248	0.0191	0.0386	0.1016

Notes: Panel A presents the regression results of the effect of month-on-month change lagging value of CLI on cryptocurrency returns with all control variables. Panel B presents the regression results of the effect of three-month-on-month change lagging value of CLI on cryptocurrency returns with all control variables. Panel C presents the regression results of the effect of six-month-on-month change lagging value of CLI on cryptocurrency returns with all control variables. Superscript ***, ** and * correspond to statistical significance at the 1%, 5% and 10% levels, respectively. Definitions of variables are presented in Appendix 1.

Chapter 5, Table 11. CLI and cryptocurrency returns: robustness tests

Panel C: Six-month change in *LAG_CLI*				
Variables	Full Size	Small Size	Medium Size	Big Size
	Model 1	Model 2	Model 3	Model 4
LAG_CLI_SIX_MONTH	-0.2355***	-0.0929	-0.2162***	-0.3200***
	(-5.92)	(-0.98)	(-3.92)	(-6.16)
CMRT	0.5404***	0.5259***	0.5284***	0.5768***
	(89.68)	(34.54)	(63.69)	(81.79)
SMB	-0.0036	0.0834***	-0.0176***	-0.0862***
	(-1.25)	(12.15)	(-4.39)	(-24.60)
HML	0.0131***	-0.0078**	0.0155***	0.0348***
	(8.81)	(-2.17)	(7.41)	(19.33)
Constant	1.7835***	1.7901***	1.8423***	1.3901***
	(14.52)	(5.80)	(10.65)	(8.78)
Baseline Controls	Yes	Yes	Yes	Yes
Year & Crypto Fixed Effects	Yes	Yes	Yes	Yes
N	567002	150848	280488	135666
R-squared	0.0255	0.0213	0.0412	0.1067
Adj *R*-squared	0.0245	0.0193	0.0393	0.1044

Notes: Panel A presents the regression results of the effect of month-on-month change lagging value of CLI on cryptocurrency returns with all control variables. Panel B presents the regression results of the effect of three-month-on-month change lagging value of CLI on cryptocurrency returns with all control variables. Panel C presents the regression results of the effect of six-month-on-month change lagging value of CLI on cryptocurrency returns with all control variables. Superscript ***, ** and * correspond to statistical significance at the 1%, 5% and 10% levels, respectively. Definitions of variables are presented in Appendix 1.

7. Conclusion

In this study, we assess the association between the CLI and cryptocurrency returns, using the monthly changes in the OECD's CLI. To examine this association, we employ a three-factor model and control for year and crypto fixed effects in our models. The baseline results reveal that the coefficient of *LAG_CLI* is negatively associated with cryptocurrency returns, supporting Hypothesis 2 (H2). To address the possible endogeneity such as omitted variables bias, selection bias and the reverse causality problem, we employ the entropy balancing approach. The empirical findings are consistent with our baseline findings presented in Table 5. We also conduct a series of additional tests and robustness tests to assess the association between the CLI and cryptocurrency returns. These results provide empirical evidence to support the main findings as demonstrated in baseline analysis. Furthermore, the change of *LAG_CLI* can play an important role in predicting future cryptocurrency returns, which is in line with Long, Zaremba, et al. (2022) who state that the short-term changes in the CLI is related to future stock returns in the cross-section. Therefore, this study supporting the negative association between the CLI and cryptocurrency returns through the three-factor model.

The findings of this study contribute significantly to the existing literature in several ways. First, it presents empirical evidence on the impact of the CLI on cryptocurrency returns. The CLI, known for providing early signals of business cycle turning points, demonstrates increased reliability when considering sub-indices corresponding to minor cycles (Gallegati, 2014). Notably, this study is the first to investigate the relationship between the monthly change in the CLI and cryptocurrency returns. Second, this study extends the literature on predicting cryptocurrency returns by incorporating a diverse set of macroeconomic indicators from the United States. The US CLI series, which includes components such as work started for dwellings, net new orders for durable goods, and consumer and industrial confidence indicators (Gulen et al., 2011), provides a comprehensive view of economic conditions. By evaluating the effectiveness of these leading economic indicators and exploring their impact on cryptocurrency returns, the study adds valuable insights into the dynamics of how macroeconomic factors influence the cryptocurrency market. Third, the study provides evidence supporting the superiority of the three-factor model—comprising crypto market, size and momentum—over the one-factor model. This is evident in the comparison of Jensen's alpha coefficients and the *R*-squared values, as outlined in Table 4. The findings align with Jia et al. (2022), emphasising the superior explanatory power of the three-factor model compared to the quasi-cryptocurrency one-factor model.

The practical implications derived from our findings are noteworthy. Firstly, this study identifies a significant indicator that holds potential for constructing prediction models beneficial for cryptocurrency investors. Investors can leverage the CLI to enhance their decision-making processes in the cryptocurrency market. Secondly, the study provides empirical evidence indicating that the COVID-19 pandemic moderates the relationship between the CLI and cryptocurrency returns. The observed positive returns of cryptocurrencies during the COVID-19 period highlight their potential as alternative assets for risk hedging and diversification amid pandemic-related uncertainty (Dunbar & Owusu-

Amoako, 2022). This finding offers valuable guidance for investors navigating the challenges introduced by the pandemic. Thirdly, the study explores the role of institutional factors in cryptocurrency returns. It finds that institutional factors can moderate the association between the CLI and cryptocurrency returns, underscoring the significance of institutional dynamics in market analysis. This adds depth to investment strategies by highlighting the importance of considering institutional influences in the cryptocurrency market.

This study acknowledges certain limitations. Firstly, its focus on US-specific variables may limit the generalisability of the findings to the global cryptocurrency market. Future research could expand the scope by incorporating a more extensive data set to provide insights that are more broadly applicable to cryptocurrency returns on a global scale. Secondly, the examination of the association between the CLI and cryptocurrency returns is confined to the one-factor and three-factor models. Future research could explore alternative models to gain a more comprehensive understanding of the dynamics shaping this association. These considerations emphasise the potential for further refinement and expansion in future investigations.

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Appendix 1: Definitions of variables

Variable name	Definition
Dependent variable	
CRYPTO	It refers to the difference between the daily cryptocurrencies returns on the overall the yield on US Treasury bills (T-bills) in the United States
Independent variable	
LAG_CLI	Moving average of the monthly composite leading indicator (CLI) of turning points in business cycles over the 12 months ending in the month of the fiscal year-end. The index shows a fluctuation of economic activity around its long-term potential level. It indicates short-term economic movements in qualitative rather than quantitative terms.
Three-Factor Model	
CMRT	Cryptocurrency market return is the value-weighted return on of all underlying available coins
SMB	Small minus Big refers to the return difference between the small coin's portfolio and the large coin's portfolio
HML	High minus low refers to the return difference between high momentum portfolios and the low momentum portfolios
Control variables	
GPIAC	Global Price Index of All commodities represent the commodity's benchmark prices which are representative of the global market
S&P 500	It is one of the most commonly use benchmarks for the overall performance of the US stock market and a key indicator of the health of the US economy.
CPI	It is a price index of a basket of goods and services paid by urban consumers
GOLD	It refers to the price at which gold is being traded in the financial market
FEDRATE	The federal funds rate is the interest rate at which depository institutions trade federal funds with each other overnight
GDP	It represents the gross domestic product (GDP) in the United States (US). It is a key economic indicator that measures the total value of all goods and services produced within the US during a quarter period
UNEMPLOY	It is the percentage of people in the labour force who are unemployed.
EPUI	The daily news-based Economic Policy Uncertainty Index is based on newspapers in the United States
VIX	The Chicago Board of Exchange Volatility Index (VIX) measures market expectation of near-term volatility conveyed by stock index option prices
EXCHANGE	It refers to the exchange rate between the US dollar and Euro
DJIA	The Dow Jones Industrial Average provides a view of the US stock market and economy
TREND_BTC	Google Trend index is based on the volume of search on the term "Bitcoin"
WIKI_BTC	Wikipedia refers to the relevant information or articles of Bitcoin
CC	It refers to control of corruption, which captures perceptions of the extent to which public power is exercised for private gain, including both petty and grand forms of corruption, as well as "capture" of the state by elites and private interests.
GE	It refers to government effectiveness, which captures perceptions of the quality of public services; the quality of the civil service and the degree of its independence from political pressures; the quality of policy formulation and implementation; and the credibility of the government's commitment to such policies.
RQ	It refers to regulatory quality, which captures perceptions of the ability of the government to formulate and implement sound policies and regulations that permit and promote private sector development.
RL	It refers to rule of law, which captures perceptions of the extent to which agents have confidence in and abide by the rules of society and, in particular, the quality of contract enforcement, property rights, the police and the courts, as well as the likelihood of crime and violence.

Appendix 2: Panel analysis: Association between CLI and cryptocurrency returns

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
LAG_CLI	-0.2056***	-0.1889***	-0.1941***	-0.1941***	-0.1897***	-0.3049***	-0.3021***	-0.2098***	-0.1997***	-0.2580***	-0.2607***	-0.2391***
	(-4.40)	(-4.04)	(-4.14)	(-4.14)	(-4.03)	(-4.51)	(-4.47)	(-2.98)	(-2.83)	(-3.63)	(-3.66)	(-3.35)
CMRT	0.5684***	0.5660***	0.5661***	0.5661***	0.5661***	0.5661***	0.5663***	0.5663***	0.5650***	0.5632***	0.5633***	0.5626***
	(104.78)	(104.29)	(104.29)	(104.29)	(104.30)	(104.29)	(104.29)	(104.27)	(103.87)	(103.39)	(103.37)	(103.23)
SMB	-0.0013	0.0004	0.0005	0.0005	0.0005	0.0006	0.0007	0.0005	0.0005	0.0001	0.0001	0.0001
	(-0.49)	(0.16)	(0.19)	(0.19)	(0.19)	(0.22)	(0.26)	(0.19)	(0.19)	(0.05)	(0.02)	(0.05)
HML	0.0155***	0.0141***	0.0141***	0.0141***	0.0141***	0.0140***	0.0139***	0.0140***	0.0140***	0.0140***	0.0140***	0.0142***
	(11.39)	(10.34)	(10.31)	(10.31)	(10.32)	(10.18)	(10.13)	(10.19)	(10.21)	(10.19)	(10.20)	(10.32)
CPI		-0.4622***	-0.4760***	-0.4760***	-0.4728***	-0.4857***	-0.4858***	-0.6005***	-0.4987***	-0.6681***	-0.6719***	-0.6739***
		(-12.73)	(-12.64)	(-12.64)	(-12.53)	(-12.74)	(-12.74)	(-13.25)	(-9.56)	(-11.19)	(-11.20)	(-11.23)
GOLD			0.0133	0.0133	0.0131	0.0113	0.0133	0.0412***	0.0485***	0.0455***	0.0453***	0.0391***
			(1.38)	(1.38)	(1.36)	(1.18)	(1.36)	(3.61)	(4.19)	(3.93)	(3.92)	(3.37)
FEDRATE				-0.0050***	-0.0050***	-0.0059***	-0.0058***	-0.0065***	-0.0081***	-0.0063***	-0.0062***	-0.0061***
				(-7.07)	(-7.10)	(-7.37)	(-7.15)	(-7.89)	(-8.82)	(-6.43)	(-6.38)	(-6.27)
GDP					-0.0026	-0.0029	-0.0029	-0.0035	-0.0034	-0.0038*	-0.0038*	-0.0036*
					(-1.25)	(-1.35)	(-1.35)	(-1.64)	(-1.58)	(-1.80)	(-1.78)	(-1.70)
UNEMPLOY						-0.0005**	-0.0005**	-0.0006***	-0.0009***	-0.0005**	-0.0005**	-0.0004*
						(-2.38)	(-2.54)	(-3.01)	(-4.13)	(-2.16)	(-2.14)	(-1.95)
VIX							0.0029	0.0006	-0.0098***	-0.0046	-0.0043	-0.0060*
							(1.45)	(0.28)	(-2.94)	(-1.33)	(-1.23)	(-1.71)
EXCHANGE								-0.0415***	-0.0324***	-0.0337***	-0.0318***	-0.0217**
								(-4.69)	(-3.54)	(-3.69)	(-3.30)	(-2.21)
DJIA									-0.0638***	-0.0591***	-0.0585***	-0.0616***
									(-3.93)	(-3.64)	(-3.59)	(-3.78)
GPIAC										0.0466***	0.0465***	0.0493***
										(5.84)	(5.83)	(6.17)
GTBTC											-0.0010	0.0030*
											(-0.60)	(1.76)
WIKIBTC												-0.0086***
												(-6.27)
Year Fixed Effect	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Crypto Fixed Effect	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
R-squared	0.0260	0.0262	0.0262	0.0262	0.0262	0.0262	0.0262	0.0262	0.0263	0.0263	0.0263	0.0264
N	674967	674967	674967	674967	674967	674967	674929	674929	674929	674929	674929	674929

This table reports estimates of panel regressions with year and crypto fixed effect and a varying set of controls. Superscript ***, ** and * correspond to statistical significance at the 1%, 5% and 10% levels, respectively. Definitions of the variables are presented in Appendix 1

5.3 Links and implications

The current study provides important insights into the impact of composite leading indicator on cryptocurrency returns through the three-factor model. The next study aims to discuss the research findings, implications, limitations and direction for future research.

CHAPTER 6: DISCUSSION AND CONCLUSIONS

6.1. Chapter overview

This chapter concludes the thesis by discussing the research findings, implications, limitations and direction for future research. The current chapter consist of the following sections: Section 6.2 that presents a summary of the research findings and robustness checks of each article. Section 6.3 provides the limitations of this research. finally, section 6.4 presents the limitations of the current study and some direction for future research.

6.2. Summary of findings

This section provides a short summary of the research questions, research design and methodology used in the study. Furthermore, it presents the key findings and the outcomes of the robustness tests. The text three subsections separately present a synopsis of each article of this thesis.

6.2.1. Findings of the first paper

The first paper employs a systematic litereture review to identify the factors influencing cryptocurrency pricing and map the potential gaps. The influential factors were identified and categorised as supply and demand, technology, economics, market volatility, investors' attributes and social media. This review provides a consolidated view of cryptocurrency pricing and contributes to cryptocurrency research and consumer behaviours.

6.2.2. Findings of the second paper

The second paper reports on the determinants of consumer confidence on cryptocurrency returns through a three-factor model, that is, market, size and momentum. The paper uses a data set comprising 3,318 cryptocurrencies spanning from 1 January 2014–31 December 2022 from the CoinMarketCap website.

This study uses descriptive statistics to provide some insights into the cryptocurrency distribtution. Using the median of the CCI as the cut-off point and comparing mean/median values, the study's sample is spilt into two groups: one of those with high-value CCI and one of those with low-value CCI. Table 4.2, Panel A reports that cryptocurrencies with high-value CCI (*high_CCI*) report significant lower cryptocurrency excess returns scores.

This study employs the three-factor model to test H1 and H2. The results of the second paper presents a negative coefficient for *CCI* across all the models in Table 5.5, indicating that the CCI is negatively associated with cryptocurrency excess returns through the three-factor model. These findings provide strong support for H2. In addition, the study uses entropy balancing analysis and two-stage least squares (2SLS) to address potential endogeneity, such as omitted variable bias, selection bias and the reverse causality problem. The coefficient of the variables of interest suggest that the results remain robust and are in support of the baseline regression model and proposed hypothesis. Additional test suggest that the study's findings are robust. Furthermore, the COVID-19 pandemic plays an important mediating role in the relationship between the CCI and cryptocurrency excess returns.

6.2.3. Findings of the third paper

The third paper aims to explore the relationship between the CLI and cryptocurrency returns through a three-factor model that includes factors related to cryptocurrency market, size and momentum. The analysis is based on a data set comprising 3,318 cryptocurrencies, covering the period from 1 January 2014–31 December 2022.

This study uses descriptive statistics to provide some insights into sample varibles and cryptocurrency distribtution. Using the median of the CLI as the cut-off point and comparing mean/median values, the study's sample is spilt into two groups: those with high-value CCI and those with low-value CCI. Table 5.2, Panel A reports that cryptocurrencies with high-value CLI (*high_CLI*) report significant higher cryptocurrency returns score.

This study employs the three-factor model to test H1 and H2. The results of the third paper presents a negative coefficient for *LAG_CLI* across all the models in Table 5, indicating that CLI is negatively associated with cryptocurrency returns through the three-factor model. These findings provide strong support for H2. In addition, the study uses entropy balancing analysis to address potential endogeneity, such as omitted variable bias, selection bias and the reverse causality problem. The coefficient of the variables of interest suggest that the results remain robust and are in support of the baseline regression model and proposed hypothesis. The results of this study remain robust using a battery of additional tests and robustness tests including excluding specific coins, the impact of cryptocurrency market value and trading volume. Furthermore, COVID-19 pandemic and institutional factors significantly influence cryptocurrency returns and can be a modirator for the association between CLI and cryptocurrency returns.

6.3. Implications

This section presents the implications of the thesis; however, the implications of each research question are discussed separately in each article. This research provides significant theoretical/academic and practionner/policy implication. The results of the first paper show that it provides a comprehensive overview of the existing literature and categorises the significant factors that influence cryptocurrency pricing. This review highlights the varying research methods used to identify the determinants of cryptocurrency pricing, informing future studies of the commonly used methods and theories. The reseach also provide evidence that cryptocurrency can be considered an alternative currency that complements the existing financial industry. This research has implications for multiple stakeholders. such as providing relevant information for investors and assisting policy makers to update financial systems, monitor financial activities and formulate monetary policy in response to these challenges.

Furthermore, the resutls of the second paper contributes to the existing literature by providing evidence of the impact of consumer emotions on consumer decision making in the cryptocurrency market. this paper confirms evidence that macroeconomic factors originating in the US exert a significant influence on the cryptocurrency market. This paper has practical implications for investors to keep a close eye on consumer confidence for better predictions and risk mitigation in the cryptocurrency market, offers insights for policy makers to formulate more effective monetary policies in response to cryptocurrency challenges. The paper provide empirical evidence that the COVID-19 pandemic moderates the relationship between the CCI and cryptocurrency excess returns.

Finally, the results of the third paper provide important theoretical and practical implications. Theoretically, this study contributes to the existing literature by providing emprical evidence of the impact of the CLI on cryptocurrency returns. The change of CLI provides the signal for investors in the cryptocurrency market. The paper add to the literature on predicting cryptocurrency returns considering a broad range of macroeconomic indicators from the US. In addition, this paper provides evidence that the three-factor model with cryptocurrency market, size and momentum outperform the one-factor model. Practically, this paper highlighs an influential indicator that can be used to constuct the prediction model for cryptocurrency investors. The paper provides empirical evidence that COVID-19 pandemic moderates the association between the CLI and cryptocurrency returns. Additionally, cryptocurrencies achieve the positive returns during the period of COVID-19, which indicate that cryptocurrencies can be considered as alternative asset for hedging risk and diversification. Furthermore, the institutional factors can play an important role in moderating in the association between the CLI and cryptocurrency returns.

6.4. Limitations and future research

Several limitations are acknowledged within this study. First, some relevant articles may have been missed given the arbitrary nature of inclusion and exclusion, in the keywords, title and abstract in the first paper. Future research could adjust the search strategies, the intervals and reading sources to collect relevant studies. Second, the second and third papers only focus on the US-specific variables potentially limiting its applicability to the global cryptocurrency market. Future research should explore the broader data set to obtain insight for cryptocurrency returns. Third, the exploration of the CLI and cryptocurrency returns is confined to the one-factor model and the three-factor model, indicating that future research may consider alternative models to assess the association. Finally, while attempts to address endogeneity through the entropy balancing approach and the two-stage least squares (2SLS) model, complete elimination this issue entirely remains challenging. Despite these limitations, this study contributes valuable insights to the literature on consumer confidence and cryptocurrency excess returns.

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