Global Finance Journal 62 (2024) 101029

Contents lists available at ScienceDirect

Global Finance Journal

journal homepage: www.elsevier.com/locate/gfj

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

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A R T I C L E I N F O

*JEL classification:*
G14
C58
E32
E44

*Keywords:*
Cryptocurrency returns
Consumer confidence
Factor model
Cryptocurrency size
Momentum factors

A B S T R A C T

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

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https://doi.org/10.1016/j.gfj.2024.101029
Received 12 December 2023; Received in revised form 22 August 2024; Accepted 23 August 2024
Available online 24 August 2024

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) Mean | Median | High CCI (*N* = 336,354) Mean | Median | Sig. difference 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*):

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

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:

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

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:

$$R_{i,t} – R_{f,t} = \alpha + \beta_{t,1}\text{CMRT} + \varepsilon_t \tag{5}$$

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. $\alpha$ 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:

$$R_{i,t} – R_{f,t} = \alpha + \beta_1 \left(R_{m,t} – R_{f,t}\right) + \beta_2 \text{SMB}_t + \beta_{3,l}\text{HML}_t + \varepsilon_{i,t} \tag{6}$$

**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 $\varepsilon_t$ 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:

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

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 2SLS 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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