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Do bitcoin shocks truly Cointegrate with financial and commodity markets?

Mustafa Özer [a], Michael Frömmel [b,*], Melik Kamişli [c], Darko B. Vuković [d,e]

[a] Anadolu University, Faculty of Economics and Administrative Sciences, Department of Economics, Eskişehir, Turkey
[b] Department of Economics, Ghent University, Sint-Pietersplein 5, Ghent 9000, Belgium
[c] Bilecik Seyh Edebali University, Faculty of Applied Sciences, Department of Finance and Banking, Bilecik, Turkey
[d] Graduate School of Management, Saint Petersburg State University, Volkhovskiy Pereulok 3, Saint Petersburg 199004, Russia
[e] Geographical Institute "Jovan Cvijic" SASA, Djure Jaksica 9, Belgrade 11000, Serbia

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ABSTRACT

This study examines the long-run relationships between Bitcoin and various financial and commodity markets. Utilizing a novel methodology termed the Implicit Asymmetric Combined Cointegration Test (IACC), an augmented variant of the Bayer Hanck combined cointegration method (BH), this research applies ten-minute frequency time series data to test asymmetric shocks associated with Bitcoin, stock markets, futures indices, sectoral stock indices, Islamic stocks, commodities, and foreign exchange markets. The principal finding reveals a hidden cointegration between negative Bitcoin shocks and both negative and positive shocks in almost all examined financial instruments, indicating an absence of decoupling in the connections between Bitcoin shocks and other financial instrument shocks. The study demonstrates Bitcoin's centrality in financial investments and establishes long-run relationships between Bitcoin price shocks and those of other financial instruments. The findings suggest caution for participants in both financial and commodity markets, as Bitcoin emerges as a major source of the recent volatility observed in these instruments' prices.

1. Introduction

Diversification, and consequently the interrelations among financial instruments, holds significant importance for investors. Particularly in volatile markets, investors endeavor to mitigate portfolio risk by diversifying their investments across various asset classes (Vukovic et al., 2017, 2019). Concurrently, policymakers require accurate insights into the nature and direction of market relationships to devise and enact effective economic policies. Consequently, governments, academia, and investors actively engage in identifying patterns within market relationships. These relationships can be short-term or long-term and may exhibit either symmetrical or asymmetrical characteristics.

The analysis of the relationships between Bitcoin and financial markets and/or instruments emerges as a prominently researched area in financial literature. These studies predominantly concentrate on spillovers, contagion, and connectedness between markets, employing methodologies such as MGARCH, Cointegration, causality, VAR/VECM framework, and connectedness measures like the Diebold Yılmaz method. Notable contributions in this field include works by Bouri et al. (2017), Guesmi et al. (2019), Urquhart and Zhang (2019), Bouri et al. (2020), Keilbar and Zhang (2021), Moussa et al. (2021), Qarni and Gulzar (2021), Sami and Abdallah (2021), Thaker and Mand (2021), Wu et al. (2021), Cui and Maghyereh (2022), Özdemir (2022), and Cagli and Mandaci (2023).

The exploration of cryptocurrencies' hedging and safe-haven properties against traditional financial markets has attracted considerable academic interest, especially in the context of their performance during market downturns. Bouri et al. (2020) embark on this inquiry by assessing the behavior of eight cryptocurrencies against the S&P 500 and its ten equity sectors. Through the application of the cross-quantilogram approach, their research concludes that Bitcoin, along with Ripple and Stellar, serves as a safe haven across all U.S. equity indices, demonstrating its resilience and potential as a diversification tool during times of market stress. In the context of energy commodities and Bitcoin nexus, Bouri et al. (2017) find Bitcoin's strong hedging capabilities and its safe-haven status against movements in commodity indices. Importantly, the research delves into the time-varying role of Bitcoin, noting significant differences in the dynamics of its correlations

* Corresponding author at: Department of Economics, Ghent University, Sint-Pietersplein 5, 9000 Ghent, Belgium.
E-mail addresses: muozer@anadolu.edu.tr (M. Özer), michael.froemmel@UGent.be (M. Frömmel), melik.kamisli@bilecik.edu.tr (M. Kamişli), vdarko@hotmail.rs (D.B. Vuković).

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with traditional markets during periods of extreme upward and downward movements. This nuanced view underscores the complexity of Bitcoin's relationship with traditional financial assets, suggesting that its behavior as a hedge or safe haven is not static but varies over time and across different market conditions.

The academic discourse extends into the domain of other econometric models to analyze the intricate relationships between cryptocurrencies and traditional markets. Keilbar and Zhang (2021) utilize an augmented nonlinear version of the error correction model, named the COINtensity VECM, which considers nonstationary effects. Their study validates the cointegration among the top ten cryptocurrencies, as listed on Coinmarketcap.com, shedding light on the interconnectedness within the cryptocurrency market itself. Moussa et al. (2021) contribute to this conversation by applying the Smooth Transition Error Correction Model (STECM) to investigate Bitcoin's relationship with the commodity market, particularly energy commodities and gold. Their analysis reveals a nonlinear and asymmetric relationship, highlighting the complex adjustment process of Bitcoin towards long-run equilibrium with these markets. This finding is in line with Thaker and Mand (2021), who also employ the Vector Error Correction Model (VECM) to examine Bitcoin's dynamics with various financial and commodity markets.

The use of the Vector Autoregressive (VAR) model, specifically the fractional cointegrated vector autoregressive (FCVAR) model by Wu et al. (2021), examines the relationship between Bitcoin and futures markets. Their research indicates that these assets exhibit long memory properties and are fractionally cointegrated, offering insights into the deep-rooted connections between Bitcoin and futures markets. In addition, GARCH models, particularly the EGARCH and DCC-GARCH models, alongside wavelet analyses as utilized by Özdemir (2022), provide a lens through which to view the volatility spillovers across major cryptocurrency returns, including Bitcoin, Ethereum, and Litecoin. The study reveals a mutual dependency within these markets, where shocks in one market incite similar reactions in others, leading to volatility spillovers. Lastly, the time and frequency connectedness measures proposed by Diebold and Yilmaz (2012) (one more popular model) offer a framework for evaluating the uncertainty connectedness between cryptocurrencies and other markets. Cagli and Mandaci (2023) employ this model to analyze the relationship between the cryptocurrency market and various financial and commodity markets, finding a relatively low degree of uncertainty connectedness, which suggests a certain level of isolation of the cryptocurrency market from traditional financial fluctuations.

A common element across these studies is their exploration of the overt relationships between markets and/or assets. However, as argued by Granger and Yoon (2002), Hatemi (2012), and Hatemi-J and Irandoust (2012), in instances lacking explicit relations or even in cases where explicit connections are acknowledged, there remains a potential for overlooking the true relationships or connections due to the limitations of the methods used.

In the recent studies especially related to crypto currencies and financial, and commodity markets, there is a growing number of studies that used the high frequency data (Albrecht & Kočenda, 2024; Alam et al., 2019; Ameur et al., 2021; Cui and Maghyereh, 2022; Égert and Kočenda, 2011; Ftiti et al., 2021; Katsiampa et al., 2022; Lu et al., 2019; Luo and Ji, 2018; Mensi et al., 2022; Naeem et al., 2022; Tse and Zhao, 2011; Yousaf and Ali, 2020). In this study, we also use the ten-minutes frequency data, because of its following advantages. The ten minute-frequency data provides a range of advantages over traditional lower frequency data. First and foremost, the ten minute-frequency data enables more accurate tracking of rapidly changing market conditions, allowing traders and investors to make informed decisions in real-time. Additionally, such frequency data can provide more comprehensive and granular insights into market behavior, as well as the ability to identify emerging trends and patterns before they become widely apparent to those who are relying solely on lower-frequency data. Moreover, ten minute-frequency data can also be used to test and refine trading models and algorithms in a shorter time frame than lower frequency data, allowing traders to adapt their strategies quickly to changing market conditions and potentially gain a competitive edge. In summary, the advantages of the ten minute-frequency data make it an invaluable resource for investors and traders looking to stay ahead of the curve in today's rapidly changing financial markets. By leveraging high-quality, the ten minute-frequency data, traders and investors can make informed decisions in real-time, gain more comprehensive insights into market behavior, identify emerging trends before they become widely apparent, and ultimately adapt their strategies quickly to changing market conditions.

This study aims to examine the long-term and hidden relationship between Bitcoin and diverse financial and commodity markets through an advanced the Implicit Asymmetric Combined Cointegration Test (hereafter referred to as the IACC method). This IACC is an augmentation of the conventional Bayer and Hanck (2013) cointegration method (hereafter referred to as the BH method), which investigates the asymmetric impacts linked to Bitcoin across various financial instruments. Utilizing data at a ten-minute frequency, this research attempts to identify hidden cointegrations between Bitcoin's negative shocks and both negative and positive shocks across a wide array of financial instruments. The research is motivated by the imperative to deepen our comprehension of the interplay between Bitcoin and other financial and commodity markets, especially considering the rising prominence of cryptocurrencies in financial portfolios and their noted influence on market volatility. As Shahzad et al. (2017) claim that the rationale for investigating hidden cointegration between two time series stems from the failure of traditional cointegration methods to provide evidence for cointegration. In cases of hidden cointegration, long-run relationships exist between the positive and negative components of the two series. In essence, this research endeavors to provide empirical evidence to address the question: Can Bitcoin be considered a major source of recent fluctuations in financial and commodity markets? The methodology encompasses a tripartite analytical framework. Initially, the integration level of all variables is assessed using standard unit root tests. Following this, the study probes for cointegration using the BH method. In instances where the BH method does not ascertain evidence of cointegration, the IACC method is deployed. This innovative approach allows the study to uncover hidden long-term relationships that traditional methodologies might miss, thereby significantly augmenting the literature on financial market dynamics.

Pursuing the objectives of this study, we attempt to address the following research questions: Firstly, does explicit or hidden cointegration exist between Bitcoin and other financial instruments? Secondly, what are the characteristics of these hidden long-run relationships between Bitcoin and other financial instruments? Thirdly, do these hidden long-run relationships exhibit uniformity across different financial instruments? Fourthly, is there a decoupling in these hidden relations considering the market's developmental level, geographic region, and type of financial instrument?

In addition to employing a novel method, IACC, for analyzing the relationship between Bitcoin, financial, and commodity markets, this study contributes significantly to the existing literature in two major ways. Firstly, by applying the BH method to our data, we initially do not find evidence of cointegration between Bitcoin and other financial instruments. However, using the IACC method, we consistently detect cointegration across almost all cases (in the most cases at 1% significance level). Our results reveal that the relationship between Bitcoin, other financial instruments, and commodities is asymmetric rather than symmetric. This finding underscores the importance of selecting an appropriate method to uncover hidden and previously unidentified effects, with this study serving as a prime example. Secondly, our findings also suggest that, in most instances, negative Bitcoin shocks correlate with both negative and positive shocks in other assets over the long term, even at a one-percent significance level. Such findings alert market participants, including investors and policymakers, to the necessity of considering Bitcoin's volatility in their strategic planning and policy formulation. By revealing these obscured connections, the research not only contributes valuable insights to academic discussions on financial market interrelations but also aids market participants in navigating the complex interactions between cryptocurrency and traditional financial markets.

The structure of this paper is organized as follows: Section 2 details the data utilized in this study. Section 3 introduces and elucidates the novel method employed in our research. Section 4 exhibits the empirical results obtained. Section 5 tests robustness of obtained data. Section 6 delves into the implications of these empirical findings, particularly in relation to the study's research questions. The final section provides the conclusion.

2. Data

To investigate the long-term connections between Bitcoin and various financial instruments, this study employs the ten minute-frequency[1] interval time series data for Bitcoin and six different markets: stock markets, Index Futures, Sector Indices, Islamic Indices, Foreign Exchange, and Commodities. Given the 24-h availability of Bitcoin data, we align the data for other variables to match the Bitcoin data timeline. Notably, there are discrepancies in the opening and closing times of some markets. The sample data spans from the first business day of January 2023 to March 17th, 2023, ending at 05:10:00 (the indicated time is as provided by the data provider). All data is sourced from the Thomson Reuters Refinitiv database. Table 1 in the paper provides a detailed description of the variables, markets, countries, and abbreviations used throughout.

3. Research framework

To investigate the connections between Bitcoin and other financial instruments, this study employs a three-step procedure. Initially, our study tests the degree of integration of all variables utilized in the research by using the traditional unit root tests of Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) (please see Appendix 1). This step is crucial since cointegration necessitates that a series be integrated of order one, I (Afshan et al., 2018). Then, the study examines the presence of cointegration between variables, using the BH method. The unique aspect of the BH test lies in its amalgamation of the results from four distinct cointegration tests (Engle and Granger, 1987 – the EG test; (Johansen, 1988) – Johansen test; (Boswijk, 1994) – BO test; and Banerjee et al., 1998 – BDM test), yielding a singular outcome. For more details on these tests, please refer to Appendix 2. Its widespread application is evidenced in works such as Polat et al. (2014), Kyophilavong et al. (2015), Sahoo et al. (2016), Ahad (2017), Afshan et al. (2018), Türsoy and Faisal (2018), Apergis and Apergis (2019), Churchill et al. (2019), Sahoo et al. (2019), Kirikkaleli and Adebayo (2020), Nathaniel and Khan (2020), Sethi et al. (2020), Alam et al. (2021), Athari et al. (2022), and Xu and Zhao (2023).

Even though these studies have proven that the symmetric version of the test is commonly used and welcomed, they also failed to provide results on whether the relationships are indeed asymmetric by nature. Therefore, our study should be considered a new direction in this framework, taking into account hidden cointegration. Furthermore, it offers a combined analysis of both the EG and Johansen tests, as well as an integrated result encompassing all four tests. This comprehensive approach enhances the robustness and reliability of the cointegration analysis, offering a more nuanced understanding of the interrelationships among the studied variables.

In this study (in the third step), we develop the IACC method to the cases where we fail to find evidence of the presence of cointegration by using the BH method. To do this, we first decompose each series, for example, X and Y, into positive and negative shocks based on the following definitions:

$$X_t = X_{t-1} + e_t = Z_0 + \sum_{i=1}^{t} e_i \tag{1}$$

$$Y_t = Y_{t-1} + \varepsilon_t = W_0 + \sum_{i=1}^{t} \varepsilon_i \tag{2}$$

Where X_t and Y_t are variables that explore a cointegration between them; $t = 1,2,3\ldots$, T. The eqs. 10 and 11 consider non-stationary time series data. They express the accumulative sum of shocks that affect the series Xt and Yt over time, starting from initial values Z_0 and W_0 respectively. Here, e_i and ε_i are white noise error terms, which represent the new information or shocks that impact the variables at each time period.

In the subsequent step, as per the augmentation, we decompose these shocks into their positive and negative components. One can define the positive and negative shocks as:

$$e_i^+ = max(e_i, 0), e_i^- = min(e_i, 0) \tag{3}$$

$$\varepsilon_i^+ = max(\varepsilon_i, 0), \varepsilon_i^- = min(\varepsilon_i, 0) \tag{4}$$

Since $e_i = e_i^+ + e_i^-$ and $\varepsilon_i = \varepsilon_i^+ + \varepsilon_i^-$, we express the Eq. (1) and (2) as follow:

$$X_t = Z_0 + \sum_{i=1}^{t} e_i^+ + \sum_{i=1}^{t} e_i^- \tag{5}$$

$$Y_t = W_0 + \sum_{i=1}^{t} \varepsilon_i^+ + \sum_{i=1}^{t} \varepsilon_i^- \tag{6}$$

Both equations (Ameur et al., 2021; Apergis and Apergis, 2019) demonstrate that each series is the summation of initial values and the accumulation of both positive and negative shocks over time. After decomposing series into positive and negative shocks, we carry out the IACC test. For this purpose, we particularly test the existence of the following pairs of cointegration relations:

I. Positive Bitcoin (BTC) shocks and positive shocks of financial instrument (FI).

$$P_{FI} = f(P_{BTC}) \tag{7}$$

II. Positive Bitcoin (BTC) shocks and negative shocks of financial instrument (FI).

$$N_{FI} = f(P_{BTC}) \tag{8}$$

III. Negative Bitcoin (BTC) shocks and positive shocks of financial instrument (FI).

$$P_{FI} = f(N_{BTC}) \tag{9}$$

IV. Negative Bitcoin (BTC) shocks and negative shocks of financial instrument (FI).

$$N_{FI} = f(N_{BTC}) \tag{10}$$

The function f represents a cointegrating regression, which is estimated using an error correction model. The error correction term from these estimations would reveal the adjustment dynamics towards the long-run equilibrium after accounting for different types of shocks. To

[1] Bitcoin, 10-min intervals can provide a granular view of its price movements and trading activity, making it valuable for traders and analysts focusing on short-term strategies or studying intraday market behaviors. Several studies support this situation, like Zargar and Kumar (2019), and Chen et al. (2019).

Table 1
Data Description.

Panel A. Stock Markets

Americas (4.01.2023 09:20:00–17.03.2023 05:10)

Argentina - ARG, Brazil - BRA, Chile - CHL, Colombia - COL, Mexico - MEX, Nasdaq - NSQ, Peru - PER, United States of America - USA, Venezuela - VEN

Asia (4.01.2023 09:20:00–17.03.2023 05:10)

China - CHN, Hong Kong - HKG, India - IDN, Indonesia - IND, South Korea - KOR, Sri Lanka - LKA, Malaysia - MYS, New Zealand - NZL, Pakistan - PAK, Philippines - PHL, Singapore - SGP, Thailand - THA, Taiwan - TWN, Vietnam - VNM

Europe (4.01.2023 09:20:00–17.03.2023 05:10)

Australia - AUS, Belgium - BEL, Bulgaria - BGR, Bosnia and Herzegovina - BIH, Switzerland - CHE, Cyprus - CYP, Czechia - CZE, Germany - DEU, Denmark - DNK, Spain - ESP, Estonia - EST, Finland - FIN, France - FRA, United Kingdom - GBR, Greece - GRC, Croatia - HRV, Hungary - HUN, Ireland - IRL, Iceland - ISL, Italy - ITA, Lithuania - LTU, Luxembourg - LUX, Latvia - LVA, Republic of North Macedonia - MKD, Netherlands - NLD, Norway - NOR, Poland - POL, Portugal - PRT, Romania - ROU, Slovakia - SVK, Slovenia - SVN, Sweden - SWE, Turkey - TUR

Middle East Africa (4.01.2023 09:20:00–17.03.2023 05:10)

Bahrain - BHR, Egypt - EGY, Kuwait - KWT, Mauritius - MUS, Morocco - MAR, Nigeria - NGA, Oman - OMN, Qatar - QAT, Saudi Arabia - SAU, South Africa - ZAF, Tanzania - TZA, Tunisia - TUN, Uganda – UGA

Panel *B. index* Futures (4.01.2023 10:00:00–17.03.2023 05:10)

Brazil - F_BRA, Switzerland - F_CHE, China - F_CHN, Germany - F_DEU, Spain - F_ESP, France - F_FRA, United Kingdom - F_GBR, Greece - F_GRC, Hong Kong - F_HKG, India - F_IND, Italy - F_ITA, Japan - F_JPN, South Korea - F_KOR, Netherlands - F_NLD, Norway - F_NOR, Nasdaq - F_NSQ, Poland - F_POL, Sweden - F_SWE, Turkey - F_TUR, United States of America - F_USA

Panel C. Sector Indices (4.01.2023 09:20:00–17.03.2023 05:10)

Consumer Cyclicals - CYC, Consumer Non-Cyclicals - NCYC, Energy - ENE, Financials - FIN, Healthcare - HLC, Industrials - IND, Materials - BMAT, Technology - TEC, Utilities – UTL

Panel D. Islamic Indices (4.01.2023 09:20:00–17.03.2023 05:10)

United Arab Emirates - IS_ARE, Australia - IS_AUT, Bahrain - IS_BHR, Egypt - IS_EGY, Global - IS_GLBL, Indonesia - IS_IDN, Kuwait - IS_KWT, Malaysia - IS_MYS, Qatar - IS_QAT, Turkey - IS_TUR

Panel E. Foreign Exchange (4.01.2023 09:20:00–17.03.2023 05:10)

AUD - AUD/USD, CAD - USD/CAD, CHF - USD/CHF, EUR - EUR/USD, GBP - GBP/USD, JPY - USD/JPY

Panel F. Commodities (4.01.2023 09:20:00–17.03.2023 05:10)

Brent Crude Oil (OIL), Natural Gas (NG)

Base Metal

Aluminum - AL, Copper - CU, Zinc - ZN

Ferrous metal

Iron - IRON, Steel - STL

Fibres

Cotton - CO

Grains

Corn - CORN, Rough Rice - RICE, wheat - WHT

Oilseeds

Soybean - SYBN

Precious metal

Gold - AU, Palladium - PD, Platinum - PT, Silver – AG

Softs

Cocoa - CCA, Coffee - COE, Rubber - RBR, Sugar – SUG

Source: Thomson Reuters Refinitiv database. Note: Despite China's strict anti-cryptocurrency stance, Bitcoin and Chinese financial instruments may show cointegration due to several factors. Firstly, global market dynamics affect Bitcoin's value, as it's part of the worldwide digital currency market. Changes in global markets, including those linked to Chinese financial assets, can impact Bitcoin. Secondly, Chinese investors might still access the Bitcoin market through international platforms, despite the ban. Thirdly, Bitcoin's price is sensitive to market sentiment and speculation, which can be influenced by news or perceptions about China's economy or regulations. Fourthly, as a major global economic player, China's technological and economic developments can affect various markets, including cryptocurrencies. Lastly, cryptocurrencies like Bitcoin are used to maneuver around strict capital controls like those in China, potentially linking Bitcoin's movements to Chinese financial market changes, especially during shifts in capital control policies. Due to these reasons, we did not exclude the Chinese market.

test these relationships, we employ an augmented version of BH method adapted for positive and negative shock decomposition. The statistical significance of the estimated coefficients in these relations provides evidence of cointegration between Bitcoin and the financial instrument in question, conditional on the type of shocks.

The combined test statistic for corresponding equations () are expressed as follows:

$$\chi^2_{X_t} = -2(ln(p_{e^+}) + ln(p_{e^-})) \tag{11}$$

$$\chi^2_{Y_t} = -2(ln(p_{\varepsilon^+}) + ln(p_{\varepsilon^-})) \tag{12}$$

Let's denote p_{e^+} as the p-value from the test for significance of positive shocks (e_i^+) and p_{e^-} as the p-value for negative shocks (e_i^-) in X_t. And let's denote p_{ε^+} as the p-value from the test for significance of positive shocks (ε_i^+) and p_{ε^-} as the p-value for negative shocks (ε_i^-) in Y_t.

These combined chi-square statistics for X_t and Y_t will allow us to evaluate the significance of both positive and negative shocks in each time series separately. The chi-square values can be compared against critical values from the chi-squared distribution with 4 degrees of freedom. If these chi-square statistics are significant, it implies that the corresponding shocks (positive or negative) are significantly influencing the behavior of the time series. Such an approach enhances the understanding of how different types of shocks (positive or negative) contribute to the dynamics of each time series, providing a more nuanced view of their behaviors and potential cointegration relationships when compared to other variables or series.

For the objective of this study, we initially examine the presence of cointegration between Bitcoin and various financial instruments employing the BH method. This approach is recognized as a symmetric combined cointegration test. Then we apply the IACC method. In most of the cases where BH methods fail to find significant cointegration between series, the IACC method provides evidence about the presence of cointegration. That constitutes the major advantage of using the IACC method. By using the IACC method, one can accomplish two important goals. Considering asymmetric effects, the researcher will be able to test the presence of hidden cointegration between variables. By doing this, the researcher will be able to find evidence of cointegration in cases where other methods fail.

Second, and most importantly, we provide evidence for hidden long-run relationships between variables that other methods ignore. In the case of the time series X_t and Y_t, the long-run relationships are implied in the eqs. 5 and 6. The cumulative sums of the positive shocks $(e_i^+$and $\varepsilon_i^+)$ and negative shocks (e_i^- and ε_i^-) represent the integration of short-term variations (or shocks) over time. The long-run relationship between the variables X_t and Y_t is then inferred by analyzing the accumulated impact of these shocks. If the IACC test finds that there is a significant and consistent relationship between the accumulated shocks of X_t and Y_t, it suggests the existence of a long-run equilibrium relationship between these variables. This is because the test essentially investigates whether the variables, when subjected to different types of shocks, converge or diverge from each other over time, indicative of their long-term dynamics and interdependencies.

4. Empirical results

In this section, we present the results of the IACC method along with the BH method results. Since we try to explore the existence of long-run relations between Bitcoin and stock markets, Bitcoin and Index futures, Bitcoin and sectoral stocks, Bitcoin and Islamic stocks, Bitcoin and foreign exchange rates, and Bitcoin and commodity markets, we present the results of each pair of variables in each subsection. In the execution of both methods, we use maximum lag length as 24. Our study excluded variables that had integration order zero. Also, we implement unit root tests of ADF and PP to determine the degree of integration of variables, which is a precondition for implementing our suggested method (Appendix 1).

4.1. Stock markets

To investigate the existence of hidden combined cointegration between Bitcoin and stock markets, we divide stock markets into four regions. These regions are the Americas, Asia, Europe, the Middle East, and Africa. Tables 1–4 (Appendix 3) display the results of these tests across the regions. According to the results in Table 1 (Appendix 3), based on the BH method, we fail to provide evidence for cointegration. However, when we apply our method, we produce significant results in every case. Except for Venezuela, there is a cointegration between negative Bitcoin shocks and both positive and negative stock market shocks. In Venezuela, in addition to these results, there are long-term relationships between positive Bitcoin shocks and positive stock market shocks.

Contrary to the study of Qarni and Gulzar (2021), we fail to provide any evidence of cointegration between Bitcoin and Asian stock markets by using the BH methodology (Table 2, Appendix 3). But when we use the IACC method, we produce significant results for each market. There is evidence of hidden combined cointegration between negative Bitcoin shocks and both positive and negative stock market shocks except for Indonesia and Pakistan. In addition to these findings, for example, for New Zealand and Thailand, there are significant long-run relations in all forms of asymmetric relations between Bitcoin and stock markets. Also, for Sri Lanka and Singapura, there is long-run relations between positive Bitcoin shocks and positive stock market shocks. For India, besides the above results, there is a cointegration between positive Bitcoin shocks and negative stock market shocks. For Indonesia, there is only cointegration between negative Bitcoin shocks and negative stock market shocks. Finally, for Pakistan, there is only a long-run relationship between negative Bitcoin shocks and positive stock market shocks.

According to the results in Table 3 (Appendix 3), by using the BH method, we only produce significant results for Latvia. Other than

Table 2
Summary of cointegration test results.

Cointegration tests	BH	Extracted variables	AICC
Panel A. BTC Stock Markets			
Americas	8(0)	CHL, PER	–
Positive BTC shocks and positive shocks of stock markets	-		6(1)
Positive BTC shocks and negative shocks of stock markets	-		6(0)
Negative BTC shocks and positive shocks of stock markets	-		6(6)
Negative BTC shocks and negative shocks of stock markets	-		6(6)
Asia	14 (0)	KOR	–
Positive BTC shocks and positive shocks of stock markets	-		13(4)
Positive BTC shocks and negative shocks of stock markets	-		13(3)
Negative BTC shocks and positive shocks of stock markets	-		13 (12)
Negative BTC shocks and negative shocks of stock markets	-		13 (12)
Europe	33 (1)	LVA, POL, SVN	–
Positive BTC shocks and positive shocks of stock markets	-		30(3)
Positive BTC shocks and negative shocks of stock markets	-		30 (15)
Negative BTC shocks and positive shocks of stock markets	-		30 (28)
Negative BTC shocks and negative shocks of stock markets	-		30 (28)
Middle East Africa	13 (1)	MAR, NGA, TUN, TZA, ZAF	–
Positive BTC shocks and positive shocks of stock markets	-		8(1)
Positive BTC shocks and negative shocks of stock markets	-		8(3)
Negative BTC shocks and positive shocks of stock markets	-		8(5)
Negative BTC shocks and negative shocks of stock markets	-		8(7)
Panel B. BTC Index Futures	20 (0)	F_BRA, F_KOR	–
Positive BTC shocks and positive shocks of index futures	-		18(0)
Positive BTC shocks and negative shocks of index futures	-		18(2)
Negative BTC shocks and positive shocks of index futures	-		18 (17)
Negative BTC shocks and negative shocks of index futures	-		18 (17)
Panel C. BTC Sector Indices	9 (0)	–	–
Positive BTC shocks and positive shocks of sector indices	-		9(0)
Positive BTC shocks and negative shocks of sector indices	-		9(2)
Negative BTC shocks and positive shocks of sector indices			9(9)
Negative BTC shocks and negative shocks of sector indices	-		9(8)
Panel D. BTC Islamic Indices	10 (0)	IS_IDN	–
Positive BTC shocks and positive shocks of sector indices	-		9(0)
Positive BTC shocks and negative shocks of sector indices	-		9(1)
Negative BTC shocks and positive shocks of sector indices	-		9(8)
Negative BTC shocks and negative shocks of sector indices	-		9(8)
Panel E. BTC Foreign Exchange	6(0)	GBP	–
Positive BTC shocks and positive shocks of foreign exchange	-		5(1)
Positive BTC shocks and negative shocks of foreign exchange	-		5(1)

(continued on next page)

Table 2 (*continued*)

Cointegration tests	BH	Extracted variables	AICC
Negative BTC shocks and positive shocks of foreign exchange	-		5(5)
Negative BTC shocks and negative shocks of foreign exchange	-		5(5)
Panel F. BTC Commodities	18 (0)	CCA, COE, RBR	–
Positive BTC shocks and positive shocks of commodities	-		15(4)
Positive BTC shocks and negative shocks of commodities	-		15(3)
Negative BTC shocks and positive shocks of commodities	-		15 (15)
Negative BTC shocks and negative shocks of commodities	-		15 (13)

Note: The first number in the second and fourth columns in each panel gives the number of variables that were used for testing the existence of long-run relationships, and the number in parenthesis presents the number of significant cases. The difference in the number of variables included in BH and IACC results from the fact that, as we indicated above, we didn't consider the variables that are stationary. Obviously, those cases where we found significant long-run relationships between variables by varying out the BH test automatically excluded from our main analysis which uses IACC test.

Latvia, we have similar results regarding the existence of cointegration between negative Bitcoin shocks and both positive and negative stock market shocks for the sample countries. In addition to these results, in Bulgaria and Ireland, there is cointegration in all forms of asymmetric shocks. But, in countries like Austria, Czechia, Spain, Finland, UK, Greece, Italy, Lithuania, Portugal, Romania and Sweden there is an evidence of long run relations between positive Bitcoin shocks and negative stock market shocks. In Bosnia-Herzegovina, there is a cointegration between positive Bitcoin shocks and positive stock market shocks. In Denmark and Estonia, there is a long-run relationship between negative Bitcoin shocks and negative stock market shocks. Along with Macedonia, in Turkey, there is cointegration between negative Bitcoin shocks and positive stock market shocks.

For Tasmania, the results of BH tests show that there is cointegration between Bitcoin and stock prices (Table 4, Appendix 3). Also, except for Mauritius, there is evidence of cointegration between negative Bitcoin shocks and both positive and negative stock market shocks. In addition to this, in Bahrein, there is cointegration between positive Bitcoin shocks and positive stock market shocks. For Kuwait, Oman, and Saudi Arabia, there is a long-run relationship between positive Bitcoin and negative stock market shocks. Finally, for Qatar, there is a cointegration between negative Bitcoin shocks and negative stock market shocks.

4.2. Index futures

As is the case in stock market cases (Table 5, Appendix 3) we fail to provide any evidence showing the long-run relations between Bitcoin and Index futures when we use the BH method. However, we found significant long-run relationships when we used the IACC method, except for Turkey. According to the results in Table 5, there is a cointegration between negative Bitcoin shocks and both positive and negative Index future shocks. Besides these common results, for Greece and Norway, there are evidence of cointegration between positive Bitcoin shock and negative Index future shocks.

4.3. Sector indices

With the implementation of the BH test, we failed to provide any evidence for cointegration between Bitcoin and sector indices (Table 6, Appendix 3). But when we use IACC, in contrast to earlier findings by Bouri et al. (2020), there is evidence of hidden cointegration between Bitcoin and all sector indices. From Table 6, it can be noted that particularly, there is long-run relation between negative Bitcoin shocks and both positive and negative sectoral indices' shocks. In addition to these results, for Basic Materials and Financial sector indices, there is cointegration between positive Bitcoin shocks and negative sector indices' shocks. Finally, for only the Energy sector, we found further evidence of cointegration between negative Bitcoin shocks and positive energy sector shocks.

4.4. Islamic indices

According to results in Table 7 (Appendix 3), again we fail to produce significant results which support the existence of cointegration by using BH tests. On the other hand, the IACC method produces significant results showing that there is cointegration between negative bitcoin shocks and both negative and positive Islamic stock market shocks, except for the United Arab Emirates, Kuwait, and Qatar. The results are in line with Sami and Abdallah (2021). For Kuwait, there is only long-run relations between negative Bitcoin shocks and negative Islamic stock market shocks; there is long-run relations between negative Bitcoin shocks and positive Qatar stock market shocks. For the UAE, there is cointegration between positive Bitcoin shocks and negative Islamic stock market shocks.

4.5. Foreign exchange

Table 8 (Appendix 3) displays the results of combined cointegration tests between Bitcoin and foreign exchange markets. In this case also, we fail to derive significant results by using the BH methodology. But we received significant results when we used the IACC method except for Japanese Yen regarding the cointegration between negative Bitcoin shocks and both negative and positive foreign exchange market shocks. Also, according to the results in Table 9, there is evidence of cointegration between Bitcoin and the Japanese foreign exchange rate market in all forms of shock. In contrast to earlier findings by Urquhart Zhang (2019) and Qarni and Gulzar (2021), these results suggest that due to the long-run relationship between bitcoin and exchange rates, it is not suitable for portfolio diversification.

4.6. Commodities

Table 9 (Appendix 3) presents the results of combined cointegration tests between Bitcoin shocks and commodity price shocks. The study fails to derive significant results by using the BH methodology. Like Moussa et al. (2021), we got significant results when we used the IACC method except for platinum, rice, wheat, aluminum, sugar, and copper regarding the cointegration between negative Bitcoin shocks and both negative and positive foreign exchange market shocks. As can be seen in Table 10, for platinum, rice, and wheat, there is evidence of cointegration between Bitcoin shocks and these commodity price shocks in all forms. For copper, there is evidence of cointegration between positive Bitcoin shocks and positive copper shocks. For aluminum and sugar, there is a cointegration between positive Bitcoin shocks and positive aluminum and sugar price shocks.

5. Robustness checking

In the next step, we utilize the Fully Modified Ordinary Least Squares (FMOLS)[2] model to estimate the long-run coefficients between variables that we found the cointegration relationships. The FMOLS technique is particularly proficient at adjusting for serial dependencies and potential

[2] We also estimate pairwise long-run relationships between variables by using DOLS and CCR cointegration regressions. Since all regression yield almost identical results, we only include the results of FMOLS estimates. We can provide the results of these cointegrated regressions upon request as well.

reciprocal influences between independent variables and error terms (Hansen, 1996; Phillips and Hansen, 1990). This adjustment is crucial in non-parametric contexts, where FMOLS ensures the generation of asymptotically neutral and efficient estimations in scenarios characterized by cointegration (Hansen, 1996). Given that our study focuses on asymmetric effects within cointegrated variables, the FMOLS's ability to provide accurate long-run estimates even in the presence of nonlinearity and asymmetry is particularly beneficial.

The application of FMOLS in our analysis substantiates the considerable influence of Bitcoin on a broad spectrum of financial instruments and markets (Tables 1–9, Appendix 4), with a significant confidence level of 1%. This evidence not only confirms our study's research questions, but also confirms the methodological soundness of our analysis. The dynamics identified within our study may be indicative of the evolving efficiencies and the degree of synchronization of various markets with overarching financial trends, including those in the cryptocurrency domain. The sensitivity of certain markets to the volatilites of Bitcoin underscores the growing nexus of cryptocurrencies with global financial dynamics. This is particularly relevant when market efficiency might lead to simultaneous feedback loops between Bitcoin and other financial instruments. According to our results (Appendix 4), the estimated coefficients are unbiased and consistent, providing reliable insights into the true nature of these long-run relationships.

6. Empirical discussion

In this section, we delve into the empirical findings of our study within the framework of addressing the research questions posed. Through this examination, we aim to demonstrate the pertinence of our findings in relation to both the research questions and the objectives of our study.

RQ1: *Is there a hidden cointegration between Bitcoin and other financial instruments?*

As is seen in Table 2, in many cases, the BH cointegration method fail to provide evidence for the existence of cointegration between Bitcoin and other financial instruments. On the other hand, the IACC method provided highly significant evidence about the hidden combined cointegration between Bitcoin shocks and other financial instruments' shocks. The major contribution of our proposed method is that it provides evidence for cointegration where the BH fails to do so. In this case, without using the IACC method, we could have failed to provide these very important results on the relations between Bitcoin and other financial instruments.

RQ2: *What are the forms of these hidden long-run relations between Bitcoin and other financial instruments?*

Based on the results of the IACC method, we find the highly significant evidence of hidden combined long-run relations between Bitcoin and other financial instruments except for Mauritius between Bitcoin and stock market and for Turkey Bitcoin and Index future. These two exemptions shouldn't be seen as a weakness of the method we propose, instead they must be treated as a country specific result. As we indicated above, most of our findings about the hidden cointegration is about the negative Bitcoin shocks and both negative and positive other instruments shocks. Furthermore, a notable strength of our method lies in its capacity to uncover evidence of long-term relationships between Bitcoin and various financial instruments, where the BH method may not. Utilizing our approach, we have identified numerous highly significant findings regarding hidden cointegration between Bitcoin shocks and commodities such as platinum, rice, and wheat, as well as the USD/JPY foreign exchange rate and the stock markets of New Zealand, Thailand, Bulgaria, and Ireland.

RQ3: *Are these hidden long-run relations similar across financial instruments?*

Our empirical results show that, with a few exceptions, there are similar long-run relationships between Bitcoin shocks and other instruments' shocks, particularly hidden cointegration between negative Bitcoin shocks and both negative and positive other instrument shocks. Therefore, it is fair to conclude that using the appropriate method will benefit exploring the hidden and unidentified effects. This study can be considered a prime example of this.

RQ4: *Is there decoupling in these hidden relations across the developmental level of the market, region, and type of financial instrument?*

Our study results do not show any evidence of decoupling between Bitcoin shocks and other instruments' shocks across region, market and developmental level of particular markets, and types of any commodity and instruments. In other words, there is almost a unique long-run connection between Bitcoin shocks and shocks associated with each financial instrument. Therefore, these findings should be seen as new evidence explaining the recent turmoil in Bitcoin, financial, and commodity markets.

Overall, we can highlight that our study's results have the potential to create new research lines, especially in applied research. There are many reasons why we reach this conclusion. First, the findings of the study can be used to explain the recent fluctuations in Bitcoin, financial, and commodity markets across the globe. As mentioned in Vukovic et al. (2022) and Maiti et al. (2022), there is radical shift in investment perception of considering the effects of economic crises, COVID-19 type of global pandemic and policies implemented to decrease adverse effects of these global events. Following this argument and other evidence provided by the studies of Lammer et al. (2019), Saiedi et al. (2020), and Li et al. (2021), crypto currencies in general, but Bitcoin in particular, have been becoming the major financial instrument in the portfolios of not only institutional investors but also individual investors. However, based on the findings of our study, it is fair to conclude that, unlike the conclusions drawn from earlier studies related to our topic, such as Bouri et al. (2017), Stensås et al. (2019), Urquhart and Zhang (2019), Wang et al. (2019) and Paule-Vianez et al. (2020), Bitcoin cannot be considered a safe haven; instead, it should be treated as one of the major sources of not only volatility in financial markets but also major causes of the uncertainties in these markets. As indicated in Özdemir (2022), this could be one of the reasons why we have witnessed increasing volatility in the Bitcoin market and other financial markets recently. Also, it seems that negative Bitcoin price shocks do have more potential to drive a long-run path than other instruments' shocks. Based on this evidence, what we can suggest is that the negative Bitcoin shocks should be taken as one of the major drivers of the contagion seen recently in almost all financial and commodity markets; thus, portfolios aiming to reduce the systemic risk of each market should take this fact into account. Moreover, monetary authorities should be aware of this fact as well, since increasing the amount of money in circulation for the purposes of decreasing the adverse effects of financial crises and/or pandemics will stimulate erratic behavior in almost all markets since rising money supply has been the major driving force behind the speculative investments in Bitcoin (Zer et al. 2022).

7. Conclusion

This study explores the long-run relationships between Bitcoin and various financial instruments using a novel approach, the IACC method, an extension of the BH method. Our research spanned multiple dimensions, assessing connections with stocks, futures, exchange rates, commodities, and more, across different markets and commodities. We discovered significant long-run relations and the impact of hidden effects, emphasizing the importance of advanced methodologies like IACC for uncovering intricate financial linkages. The findings underscore the critical need for meticulous research in identifying fundamental dynamics and hidden shocks within financial systems. Traditional methods may overlook asymmetric shocks crucial for understanding contagion effects, highlighting the utility of innovative approaches in financial research.

Moreover, the study has practical implications for investors, policymakers, and regulators. By revealing hidden long-run relations and asymmetric connections, it aids in informed decision-making concerning portfolio management, risk mitigation, and market regulation. The research particularly points to the necessity of regulating the Bitcoin market, given its potential to influence global financial stability negatively. Recent market turmoil and its contagious effects underscore the urgency of policy action to protect investors and maintain the integrity of the financial system. Our study advocates for a proactive regulatory stance to safeguard against future disruptions and ensure the financial ecosystem's resilience.

Declaration of competing interest

The authors declare that they have no competing interests.

Data availability

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.irfa.2024.103354.

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