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Unraveling the Drivers of Bitcoin Price Dynamics: An ARDL Bounds Testing Approach

Abstract

Research background and purpose: The rise of Bitcoin has prompted significant interest and debate, yet a comprehensive understanding of its pricing dynamics remains elusive. This study aims to address this gap by investigating the factors driving Bitcoin's price.
Methodology: Leveraging time-series data from December 19, 2016, to June 30, 2023, we employ the Auto-Regressive Distributed Lag (ARDL) model and cointegration test introduced by Pesaran et al. (2001) to analyze the impacts of various factors on Bitcoin's price.
Findings: Our findings highlight the influential roles of demand and supply metrics, such as the number of addresses and circulating stock, as well as technological factors related to the Blockchain, including transaction costs, hash rate, and mining difficulty. Interestingly, we find limited correlations between macroeconomic or financial developments and Bitcoin's price.
Value added and limitations: Our empirical findings validate the pivotal role of supply and demand dynamics in shaping Bitcoin prices, suggesting a degree of predictability corresponding to traditional currency pricing models. These findings underscore the complexity of Bitcoin's value dynamics and have implications for investors, policymakers, and researchers. Nevertheless, the study did not account for variables related to the appeal of Bitcoin as an asset class, nor did it explore the psychological aspects that could influence investor behavior. Therefore, it is likely that new determinants will arise in the future, demanding further exploration.

Keywords: *Bitcoin price, blockchain technology, ARDL model, cointegration test*

JEL Classifications: B27, C61, C82, G12

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1. Introduction

Emerging in the wake of the 2008 global financial crisis, Bitcoin stands as a pioneering digital currency, offering a decentralized alternative to traditional monetary systems. Devoid of government oversight or tangible assets like gold, Bitcoin operates on cryptographic protocols and a peer-to-peer network, revolutionizing the landscape of financial transactions (Bouri et al., 2020). This experiment in decentralized currency morphed in many ways into a new asset class during the past decade. By having the Blockchain as a decentralized, secure ledger, Bitcoin has baked in new notions of trust and transparency without requiring an intermediary; hence, transaction costs are minimized since funds are moved so effortlessly. In fact, at its core, Bitcoin addresses the challenge of double spending, a prevalent issue in electronic payment systems that undermines trust in centralized financial institutions. The solution lies in its innovative Blockchain technology, a distributed ledger that securely records all Bitcoin transactions across a network of computers (Bouri et al., 2017a). This decentralized architecture eliminates the need for intermediaries, ensuring the integrity and transparency of transactions while enhancing efficiency and resilience against tampering.

Bitcoin's emergence has sparked widespread interest among researchers, who have explored its multifaceted nature and potential applications. It has been lauded as both an investment vehicle and a hedge against global uncertainties, earning the moniker of "digital gold" for its perceived stability amidst economic turmoil (Popper, 2015; Kristoufek, 2015). Furthermore, Bitcoin's decentralized nature positions it as a potential instrument for diversification, offering lower correlations with traditional asset classes (Kristoufek, 2013; Pesaran & Shin, 1999). However, despite its promising attributes, Bitcoin's price remains a notable characteristic attributed to its dynamic price dynamics over time (Ciaian et al., 2016). Nevertheless, Bitcoin's resilience and potential for mitigating financial risks in emerging markets underscore its significance in the evolving landscape of global finance (Selmi et al., 2018).

This innovation opened new investment horizons, finally changing our perception and use of money. Investing in cryptocurrency opens the scope for investors to diversify from traditional investment options like stocks and bonds (Qureshi et al., 2020). This is all about investment opportunities and also enhances the independence of financial users. Cryptocurrencies have created a global financial ecosystem where every individual from any part of the world is able to participate, being a developer, investor, or user, and contribute to investment and more people participating in financial markets for the accrual of wealth (Shahzad et al., 2022). This rise in cryptocurrency investment has therefore affected the people greatly by bridging the gap in economic inequalities. It allows more and more people mostly those who are not allowed to take part in traditional financial systems to access world financial markets. By eliminating bank account requirements or minimum income stipulations, this heightened ease of access democratizes digital asset access (Fernandes et al., 2022). Where the capability to buy, sell, and hold cryptocurrencies is literally at every internet user's fingertip, that opens the door for many more people to seize investment opportunities and build some financial assets that can work toward equalizing gaps in wealth (Kakinaka & Umeno, 2022).

If we go deeply inside the market of cryptocurrencies, then it's full of all type of varieties, each carrying its peculiar characteristic and feature. It mainly comprises the leading cryptocurrencies like Bitcoin, Ethereum, Ripple, which are highly traded in the markets. Such digital assets come with better liquidity and greater acceptance, hence turning them as popular choices for investors and traders. With its very long time in the market and topping in terms of market capitalization, it is comparatively safer for assured returns. In contrast, there are a few other smaller, high potential cryptocurrencies that can afford greater gains, especially to those who take on higher risks (Bouoiyour & Selmi, 2019; Kristoufek, 2018).

Cryptocurrency values are influenced by a variety of factors, of which the price movement of Bitcoin holds a prominent place as the benchmark asset for other cryptocurrencies. However, there are many factors contributing to the price of these assets. The size of the cryptocurrency market is one of the most impactful factors (Naifar et al., 2023). At present, this market remains relatively small compared with fiat currencies and gold. As a result, the sale of a large quantity of cryptocurrency by a group of investors could be enough to cause its price to fall (Bouri et al., 2017b, 2020). What's more, the underlying technology, Blockchain, is still in its early stages of development. In the event of a technical problem that is not resolved immediately, this could have a negative impact on the value of the cryptocurrency concerned. It is important to stress that cryptocurrencies are virtual assets that are not backed by anything physical, such as a currency or commodity. As a result, their prices are determined entirely by the law of supply and demand. If investors lose confidence in the value of a cryptocurrency and anticipate a decline, they will be inclined to sell, leading to a significant reduction in prices. This may prompt others to sell as well, creating a downward spiral. Conversely, bullish situations can lead to excessive price rises and even speculative bubbles. Speculation plays a key role in the volatility of the cryptocurrency market (Poyser, 2019; Palombizio & Morris, 2012; Van Wijk, 2013; Dimitrova, 2005; Bouri et al., 2017c). Investors speculate on price fluctuations by buying and selling cryptocurrencies. Market volatility attracts speculative traders looking to make quick profits (Van Wijk, 2013; Bouoiyour & Selmi, 2019; Kristoufek, 2018). These speculative bets further amplify the volatility of an already unstable market. The media also plays a crucial role in influencing the price direction of these assets, as investors and speculators are constantly on the lookout for news that could impact the market. The profile of investors is also a determining factor in the cryptocurrency market. Given that anyone with a few dollars and an internet connection can start trading instantly, this attracts many amateur traders. However, institutional investors remain wary of this market, considering it too risky to invest significant capital in. This makes the cryptocurrency market vulnerable to manipulation and the spread of misleading information. Some researchers have examined the hypothesis that the costs associated with this asset play a significant role in its valuation (Chen et al., 2020; Lee et al., 2018). Others have highlighted the importance of computing power as a determining factor. In addition, empirical research has also highlighted the role of the Blockchain and its complexity in Bitcoin's price variations (Vujičić et al., 2018; Li et al., 2022).

Although numerous studies have explored the factors driving Bitcoin prices, there remains considerable uncertainty about which factors are the most influential. This is partly because the cryptocurrency market is still relatively new and not yet fully understood. Additionally, due to the complex nature of Bitcoin prices and the multitude of factors that may impact them, there is a clear need for a thorough study that employs advanced techniques to analyze the determinants of Bitcoin prices and enhance forecasting accuracy. This study seeks to address this gap by using an Auto-Regressive Distributed Lags (ARDL) model to explore the factors influencing Bitcoin prices and improve the precision of price predictions.

In this context, our research endeavors to uncover the determinants of Bitcoin price, examining the intricate interplay of market forces, technological advancements of Blockchain, difficulty of Bitcoin mining, and macroeconomic factors. By delving into these dynamics, we aim to enhance our comprehension of Bitcoin's role in the modern financial ecosystem and its implications for investors, policymakers, and researchers alike.

The remainder of the paper is structured as follows: Section 1 delves into a Literature Review and a Development of the Hypotheses, while Section 2 outlines the Methodology, and Section 3 presents the Experimental Results and Discussion. Finally, we will conclude with a summary of our main findings and recommendations for future research.

2. Literature Review and Development of Hypotheses

Deciphering the factors driving Bitcoin price necessitates a thorough examination of its underlying determinants. A burgeoning body of research has diligently explored the myriad influences shaping price fluctuations. This literature can be broadly classified into three overarching themes : market dynamics, encapsulating supply and demand dynamics, macroeconomic and financial factors, and the detailed technical aspects of Blockchain technology and mining complexities.

Financial markets are where buyers and sellers trade financial assets, such as stocks, bonds, commodities, and derivatives. They play a crucial role in the global economy by allowing businesses to raise capital, governments to borrow money, and investors to buy and sell assets to earn returns. They work on the basic principle of supply and demand. If more people want to buy a stock than sell it, its price goes up. Conversely, if more people want to sell a stock than buy it, the price drops. Markets provide a mechanism for determining the price of an asset based on the supply and demand dynamics. Also, the market dynamics of Bitcoin are fundamentally governed by the interplay of supply and demand, a cornerstone principle comparable to traditional financial assets. The supply of Bitcoin is dictated by its circulating quantity, while demand is shaped by its utility in transactions, reflected in metrics such as address usage and transaction volume. Buchholz et al. (2012) find that Bitcoin price variations are predominantly driven by fluctuations in supply and demand, with daily transaction volumes serving as a key indicator of price movements. Notably, they observe a positive correlation between the number of daily Bitcoin transactions and both the price and demand for Bitcoin. An increase in transactions leads to higher prices and demand for Bitcoin, while previous transactions significantly influence current Bitcoin prices, highlighting the impact of demand fluctuations, particularly amplified by Bitcoin's limited supply. Similarly, Bouoiyour and Selmi (2015) employ econometric approaches to demonstrate that Bitcoin prices respond to demand, driven by its perceived utility as a medium of exchange. Ciaian et al. (2016) further corroborate these findings. Their econometric model highlights the significant impact of market supply and demand forces on Bitcoin prices, with demand-side variables exerting a stronger influence than supply-side factors. Notably, an increase in Bitcoin supply puts downward pressure on its price, while an expansion of the Bitcoin economy results in price appreciation. Additionally, the study emphasizes that Bitcoin's demand stems from its perceived future exchange value, given its inherent lack of intrinsic value. Moreover, DeLeo and Stull (2014) show that Bitcoin transaction volumes have a significant positive effect on prices, underscoring the importance of user activity in driving market dynamics. Together, these studies underscore the complex correlation between supply, demand, and user behavior in determining Bitcoin's market value. Thus, our hypotheses are as follows:

H1.1: The demand has a positive impact on Bitcoin price.
H1.2: The offer has a negative effect on Bitcoin price.

In recent years, attention has increasingly turned to the technological aspects of Bitcoin, particularly the underlying Blockchain technology and the challenges associated with mining. Studies in this category delve into the technical intricacies of Blockchain protocols, analyzing their role in ensuring the security and efficiency of Bitcoin transactions. The speed at which computers can perform an operation within the Bitcoin code is known as the "Hash Rate" and is directly linked to the complexity of mining, referring to the level of difficulty posed by each block's mathematical problems. Li et al. (2022), Guizani and Nafti (2019) assert that Bitcoin mining can lead to increased associated costs, including those related to purchasing, maintaining, and powering the necessary equipment, such as computers, electricity, and human resources. Consequently, the complexity of Bitcoin mining can serve as a relevant indicator of Bitcoin production costs. While it's impossible to precisely quantify the actual costs incurred by miners, the complexity of Bitcoin mining offers a pertinent indication of these costs. Thus, Li et al. (2022) propose that the mining process influences Bitcoin price determination, suggesting that its value should increase in correlation with growing complexity. Moreover, Fantazzini and Kolodin (2020) note that the total transaction fees not only reflect individuals' interest in Bitcoin, but also the total amount of money users are willing to dedicate to miners to incentivize them to include more transactions in the blocks they mine. Therefore, as public interest in Bitcoin rises, Bitcoin users are more inclined to pay fees to conduct transactions with their Bitcoins, generating increased demand for Bitcoin, ultimately leading to a price increase for this cryptocurrency. Guizani and Nafti (2019), in their study analyzing the determinants of Bitcoin price using various approaches, including the ARDL model addressing mining difficulty factors through the hash rate variable, reveal that mining difficulty exerts a positive and significant short-term influence. In other words, when mining difficulty increases, the Bitcoin price tends to rise. However, this influence becomes less pronounced over time, as also noted by Li et al. (2022). Hash rate and mining complexity are intrinsically linked. As computing power increases, so does mining complexity, limiting the supply of Bitcoins to a predetermined quantity. Nonetheless, Guizani and Nafti (2019) point out that technological advancements enhance computing power over time. However, mining complexity decreases over time as it struggles to keep pace with these advancements. Thus, technological improvements mitigate the impact of mining and mining costs on Bitcoin prices. Conversely, according to Bouoiyour and Selmi (2015), it is the price of Bitcoin that influences the hash rate. This observation aligns with the principles of supply and demand economics, as an increase in the price of Bitcoin enhances the profitability of mining activity. This increased profitability attracts more participants to the mining sector, thereby encouraging existing miners to increase their computing power until profits reach balance. The hash rate, in contrast, represents an indicator of the Bitcoin network's processing capacity, essential for validating transactions and ensuring Blockchain stability. A higher hash rate signifies a strengthened network in terms of security, potentially prompting an increase in Bitcoin demand. This surge in demand can, in turn, influence the cryptocurrency's price. So, our hypotheses are written as follows:

H2.1: The difficulty of mining has a positive effect on the price of the Bitcoin.
H2.2: The impact of the mining difficulty on the Bitcoin price decreases over time.
H2.3: The mining costs has a positive effect on the Bitcoin price.

Also, the fluctuation of Bitcoin prices is influenced by various macroeconomic and financial indicators, particularly inflation and price indexes, which serve as vital barometers of economic health (Krugman & Obstfeld, 2003). These indicators play a significant role in shaping the demand and costs associated with Bitcoin (Wang et al., 2019). For instance, fluctuations in oil prices exert substantial pressure on both demand and costs, providing early signals of economic developments. Research by Palombizio and Morris (2012) suggests a correlation between oil prices and investors' behavior, with rising oil prices potentially leading to increased inflation. Consequently, investors may turn to Bitcoin as a hedge against impending inflation. However, an increase in oil prices tends to negatively impact Bitcoin prices, reflecting the potential adverse effects of rising oil prices on economic growth and investment demand for Bitcoin (Ciaian et al., 2016). Empirical studies, such as Van Wijk's (2013) research, have investigated the influence of inflation and oil prices on Bitcoin price formation. Findings reveal that various financial indicators, including the Dow Jones Index, Euro-Dollar exchange rate, and West Texas Intermediate oil prices, significantly affect Bitcoin's long-term value. Specifically, the Dow Jones Index positively impacts Bitcoin value, while the Euro-Dollar exchange rate and West Texas Intermediate oil prices exhibit significant negative effects. Additionally, Dimitrova (2005) examined the correlation between foreign exchange and stock markets, highlighting how a downturn in stock prices may prompt foreign investors to sell financial assets, potentially leading to currency depreciation but boosting Bitcoin prices as investors shift from stocks to Bitcoin. Moreover, the price of gold plays a crucial role in Bitcoin price dynamics. A decrease in gold prices, typically considered a safe haven against volatility, may prompt increased Bitcoin investments as traders and investors seek alternative protection. This shift in preference could further boost Bitcoin's perception as a hedge against economic turbulence (Ciaian et al., 2016). Studies by Dyhrberg (2016) have tested Bitcoin's hedging capabilities, revealing similarities with gold and its potential inclusion in portfolios to mitigate sudden shocks. However, conflicting perspectives exist within empirical literature, suggesting that Bitcoin price formation is influenced by factors unique to cryptocurrency. For instance, Panagiotidis et al. (2022) conducted an analysis considering various potential influencers on Bitcoin returns, such as gold returns, exchange rates, interest rates, oil prices, and stock indices like the Nikkei225. Their study found that Bitcoin returns are negatively affected by exchange rates with positive effects, while interest rates, gold, and oil prices have a positive impact on Bitcoin returns. Additionally, the effects of indices like SP350 and Nikkei225 are both negative. Based on the above, our hypotheses are written as follows:

H3.1: The Dow Jones index has a positive effect on the price of the Bitcoin.
H3.2: The Nikkei225 index negatively affects the price of the Bitcoin.

Also, political instability, economic crises, or regulatory changes can cause fluctuations in Bitcoin's price. Several researchers have demonstrated that Bitcoin has hedging capabilities against economic instability (Mokni et al., 2020) and can be used as a hedge and a safe haven among currencies. It can also serve as a hedge under certain market conditions. Appiah-Otoo (2023), in their study on the impact of the Russia-Ukraine war on Bitcoin trading volume and long-term returns, using panel data from twenty countries covering the period from January 23, 2022, to April 16, 2022, highlight a significant relationship. According to the results based on GMM and FEM estimates, the war has a negative impact on Bitcoin's trading volume. These findings show that the effect is particularly pronounced one week after the invasion, confirming earlier studies that uncertainties hinder Bitcoin's growth (Mokni et al., 2020). Therefore, the war between Russia and Ukraine leads to repercussions on both short-term and long-term Bitcoin returns (Appiah-Otoo, 2023). Furthermore, the study conducted by Boungou and Yatié (2022) highlighted the significant and negative impact of the tensions between Ukraine and Russia on the performance of global stock indices. These results emphasize the sensitivity of global markets to events related to the war in Ukraine, corroborating previous analyses that have established a negative relationship between conflicts and stock indices. Khalfaoui et al. (2022) explore the correlation between public attention to the Russia-Ukraine war and cryptocurrencies across different investment horizons and market conditions. Using the innovative quantile coherence analysis, which extends the work of Diebold and Yilmaz (2012), they observe a significant and negative co-movement between public attention and cryptocurrencies (BTC, XRP, ETC, and LTC) over various periods and market conditions. Numerous other studies examine the effects of geopolitical risk, political instability, and uncertainty on the performance of financial markets, including cryptocurrencies. These studies reveal the negative impact of political risk indicators on cryptocurrencies and stock markets. In summary, attention to the war has a short-term negative impact on all cryptocurrencies. However, in bullish market periods, attention to the war can have a positive impact on these cryptocurrencies. The results of the study conducted by Kumari et al. (2023) confirm that highly globalized economies are particularly vulnerable to international conflicts, with notable disparities. The authors conclude that the conflict in Ukraine will have significant and asymmetric effects on financial markets. In summary, this study sheds light on the complex interactions between conflicts, economic globalization, and financial markets, while offering insights into the factors influencing the vulnerability of globalized economies to geopolitical risks. Furthermore, the study finds that past returns have a significant impact on future returns during this event period. It employs an event study methodology to assess the impact of the Ukraine conflict on global stock markets, based on a sample of 42 global stock indices and utilizing both parametric and non-parametric tests. The authors also note that the event of February 24, 2022, had a marked negative impact on global stock indices during this event.

Also, the price of Bitcoin can be affected by other factors, including Bitcoin Exchange-Traded Funds (ETFs) and Bitcoin Halving. According to Catalini and Gans (2016), Bitcoin ETFs are financial products that allow investors to trade a basket of assets, such as stocks, bonds, commodities, or cryptocurrencies, on traditional stock exchanges. In the context of Bitcoin, an ETF would be a fund that holds Bitcoin as its underlying asset, offering investors a way to gain exposure to the cryptocurrency without needing to directly own or manage the Bitcoin themselves. They are particularly attractive to traditional investors who may be hesitant to directly purchase Bitcoin due to its complexity, security risks, or regulatory concerns. According to Foley et al. (2019), Bitcoin ETFs have gained popularity due to their ability to make exposure to Bitcoin more accessible to institutional investors. Bitcoin halving refers to an event that occurs approximately every four years, where the reward miners receive for verifying Bitcoin transactions is cut in half**.** This reduces the rate at which new Bitcoin is created and increases scarcity, which has historically led to price increases. In Foley et al. (2019)' study exploring the impact of cryptocurrencies on illegal activities, the authors provide an overview of developments in the Bitcoin market, including the growing interest in financial products such as ETFs. They state that Bitcoin ETFs are seen as a major step toward mainstream adoption of cryptocurrency, especially as more investors seek regulated, simple ways to gain exposure to the asset. With the Bitcoin halving events that reduce the cryptocurrency's supply, Bitcoin ETFs may be increasingly appealing as an investment vehicle during periods of heightened interest and price appreciation. Also, Easley et al. (2019) explore the impact of halving events on the Bitcoin market, suggesting that they can lead to increased volatility and influence investment strategies. **Bitcoin ETFs** influence price by driving demand and increasing market liquidity, especially from institutional investors (Foley et al., 2019; Catalini & Gans, 2016; Baur et al., 2018), while **Bitcoin halving** primarily affects the price by reducing the rate of new Bitcoin supply, which, if accompanied by constant or growing demand, leads to upward price pressure**.** Together, these factors can significantly shape the price dynamics of Bitcoin.

Researchers have identified other key factors that influence Bitcoin price fluctuations. Bouoiyour and Selmi (2017) highlighted the impact of investment attractiveness on Bitcoin's price. However, Kristoufek (2013) argues that Bitcoin's price cannot be fully explained by traditional economic and financial theories, such as the discounted cash flow model, purchasing power parity, and uncovered interest rate parity. According to Kristoufek (2013), the demand for Bitcoin depends on the expected profit users can gain by holding the currency and selling it later. As a result, the Bitcoin market is primarily composed of short-term investors, trend followers, noise traders, and speculators. Analyses conducted by Kristoufek in 2015, using continuous wavelet analysis, indicate that user attention and speculative behavior play a major role in Bitcoin's price dynamics. He suggests that investor attractiveness can positively influence Bitcoin's price during explosive upward periods, while having a negative impact during periods of rapid decline. Additionally, this study reveals a correlation between Bitcoin prices and search engine queries, emphasizing the relationship between public interest and price fluctuations. Kristoufek (2013) and Ciaian et al. (2016) used search queries on Google Trends and Wikipedia as proxy indicators to assess investor sentiment toward Bitcoin. These studies have highlighted a strong correlation between the price of the cryptocurrency and search queries on Google, as well as daily consultations of the Bitcoin Wikipedia page. Thus, interest in digital currencies can be assessed by monitoring the search volume for terms related to digital currencies (Kristoufek, 2015). Moreover, research by Panagiotidis et al. (2022) showed that the number of search queries on Wikipedia and the sentiment ratio on Twitter have a positive impact on the price of Bitcoin. However, it is important to note a major limitation in the use of these indicators, namely the difficulty in distinguishing whether the generated interest is due to positive or negative news. Studies, such as that of Lee et al. (2020), have demonstrated that Bitcoin's high price cycles are influenced by alternating positive and negative news. Therefore, the excitement generated around Bitcoin on social media can have a significant impact on its price dynamics, either positive or negative, depending on the type of prevailing news in the media at any given time. The study by Dyhrberg (2016), using the GARCH model, shows that Bitcoin reacts symmetrically to news, much like gold. Furthermore, Buchholz et al. (2012) examined the effects of media coverage on the Bitcoin market, finding that an increase in searches leads to an increase in Bitcoin's price, suggesting that publicity plays a role in stimulating demand for the currency. They also analyzed the dissemination of information about Bitcoin through news articles and blogs, finding that publicity has a significant impact on the Bitcoin market. Cinan (2016) observed that investment attractiveness has a significant impact on Bitcoin's price. «New messages» other than views on Wikipedia and new members were the variables most strongly associated with Bitcoin's price, reflecting increasing acceptance and growing confidence in the cryptocurrency, as measured by the intensity of Bitcoin user attention. This increase in investor interest may reflect a reduction in transaction costs and uncertainty, thereby increasing demand for investment in Bitcoin and, consequently, its price.

Other recent articles on Bitcoin have been reviewed and summarized in Table 1.

Table 1. **Previous studies using various approaches and main determinants for Bitcoin price prediction**

Author	Objective and Research Question	Period	Method and Objective of the Method	Main Results
Bouri et al. (2017a)	Evaluate the role of Bitcoin as a diversifier, hedge, or safe haven for commodities, especially energy commodities. Examine whether Bitcoin exhibits hedging and safe haven properties for commodities in general and energy commodities in particular.	From July 18, 2010, to December 28, 2015.	Daily data used to assess the relationship between Bitcoin and commodities. Analysis of Bitcoin's diversification, hedging, and safe haven properties compared to daily movements in commodity indices. Highlighting differences between pre-crash and post-crash periods of Bitcoin (December 2013). Examination of dynamic correlations between Bitcoin and commodities.	Bitcoin acts as a strong hedge and safe haven against movements in commodity indices, particularly energy commodities, for the entire studied period and the pre-crash period. After the December 2013 crash, Bitcoin loses these properties and simply becomes a diversifier for commodity indices. Results show a weak correlation between Bitcoin and energy commodities, non-energy commodities, or commodities in general. The dynamics between Bitcoin and commodities changed after the December 2013 crash, suggesting substantial changes in their relationships. Limitations related to the use of the Coindesk Bitcoin Price Index and the use of daily data are noted.
Bariviera et al. (2017)	Analyze the statistical properties of the Bitcoin market. The primary research question is to determine whether Bitcoin exhibits long-term memory characteristics in its time series of returns.	The study covers the period from 2011 to 2017.	The method used is Detrended Fluctuation Analysis to calculate the Hurst exponent, a measure of longterm memory. The method's objective is to measure long-term dependence in Bitcoin's return time series at different time scales.	Despite high volatility, Bitcoin shows a reduction in volatility over time. Long-term memory is not linked to market liquidity. The behavior of the Hurst exponent is essentially similar across different time scales, indicating a transition to short-term memory after 2014. Further research is needed to understand the reasons for the changing dynamics of Bitcoin over time.

Bouri et al. (2017b)	Determine if Bitcoin can act as a hedge and safe haven for major global stock indices, bonds, oil, gold, the general commodities index, and the US dollar index.	The daily and weekly data cover the period from July 2011 to December 2015.	Using a dynamic conditional correlation model to assess the hedging and safe haven properties of Bitcoin. The aim is to differentiate between Bitcoin's ability to diversify, hedge, and serve as a safe haven against price movements of a range of financial assets.	Bitcoin is a weak hedging instrument and is only suitable for diversification purposes. Conversely, Bitcoin can act as a strong safe haven against extreme weekly downward movements in Asian stocks. The hedging and safe haven properties of Bitcoin vary depending on time horizons.
Zhang et al. (2018)	Examine the stylized characteristics of eight cryptocurrencies representing nearly 70% of the cryptocurrency market capitalization. The underlying research question is to determine the important statistical properties of asset price random variations, particularly regarding heavy tails, autocorrelations, volatility clustering, leverage effect, etc.	The study covers the period from 2011 to 2017.	The method aims to fill the gap in the literature by examining the stylized features of the cryptocurrency market. The employed method involves investigating heavy tails, autocorrelations, volatility clustering, leverage effect, long-term dependence, and power-law correlation for eight cryptocurrencies.	The results indicate the presence of heavy tails for all cryptocurrency returns. Autocorrelations of returns decrease rapidly, while those of absolute returns decrease slowly. Cryptocurrency returns exhibit strong volatility clustering and leverage effects. The Hurst exponent for volatility is more volatile than that of returns, but all suggest the presence of long-term dependence. There is a power-law correlation between price and volume.
Baur and Dimpfl (2018)	Analyze the effects of asymmetric volatility for the top 20 cryptocurrencies and explain the reasons behind these effects. The underlying research question is to understand who trades cryptocurrencies and how it influences price volatility.	/	The method used is the asymmetric threshold GARCH (TGARCH) model by Glosten et al. (1993) and the indicator of asymmetric volatility based on Quantile Autoregression (QAR) by Baur and Dimpfl (2018a). The method's objective is to differentiate market conditions and identify who trades cryptocurrencies based on market situations.	Positive shocks increase cryptocurrency volatility more significantly than negative shocks, indicating an asymmetric volatility reaction. This asymmetry suggests a dominance of noise trading activity after positive shocks, while informed investors intervene more after negative shocks. The results are consistent with the presence of „fear of missing out" among noise traders and the existence of „pump and dump" strategies. There is also evidence of asymmetric volatility reaction for the majority of the 20 cryptocurrencies analyzed, although the two largest, Bitcoin and Ethereum, show weak evidence of this asymmetry.

Bouri et al. (2020)	Look at the persistence in the level and volatility of Bitcoin prices, taking into account the impact of structural breaks. This study seeks to answer whether the Bitcoin market is efficient by analyzing the presence of persistence in the level and volatility of Bitcoin prices.	The study analyzes the evolution of Bitcoin prices over an unspecified period, but including the period of both boom and crash in the Bitcoin market.	The methodology adopted relies on a combined approach of parametric and semiparametric methods to estimate the differentiation parameter d within the framework of fractional integration of time series. For parametric methods, the Whittle function in the frequency domain, proposed by Dahlhaus (1989), as well as the Lagrange multiplier test, are used. Regarding semiparametric methods, a local Whittle function in the frequency domain, with frequencies degenerating to zero (Robinson, 1995), is employed. The objective of the method is to determine if shocks are permanent and if there is mean-reverting behavior, as well as to identify structural breaks in the dynamics of Bitcoin.	The presence of permanent shocks and the absence of mean reversion in Bitcoin prices are observed. Evidence of structural changes in Bitcoin dynamics is revealed. Results indicate long memory in both measures of volatility (absolute and squared returns), while cases of short memory are also observed in the series of squared returns.
Qureshi et al. (2020)	Examine multiscale interdependence dynamics among five major cryptocurrencies. Research question: How do interdependencies evolve over time and frequency among Bitcoin, Ethereum, Ripple, Litecoin, and Bitcoin Cash?	The period covered in the study is from 2015 to 2018.	The method used is wavelet-based analyses to separate time series into different time and frequency scales. The objective of this method is analyzing interdependencies at various time and frequency scales to account for heterogeneous behavior among cryptocurrency market participants.	Strong volatility observed at daily time scales during the period 2015-2018. Ripple and Ethereum identified as major market contagion vectors. Short and long-term integration between certain cryptocurrency pairs confirmed by wavelet coherence. Unstable coherence at high frequencies but stable at lower frequencies. Alternating leadership and lag positions in cryptocurrency returns, suggesting fluctuating dependence over time and frequency.

Wu et al. (2021)	Study the effects of the COVID-19 pandemic on the Bitcoin market, with a particular focus on heavy tails and extreme events, while comparing these effects to those observed in other financial markets. Research question: How has the COVID-19 pandemic affected long memory, market efficiency, and the distribution of extreme events in the Bitcoin market compared to other assets (Ethereum, Binance Coin, S&P 500, and spot gold)?	The study period includes the onset and duration of the COVID-19 pandemic.	Sliding window approach: This method allows for the analysis of changing dynamics over time. Hurst exponent estimation: Used to measure persistence and long memory in the time series of Bitcoin and other financial assets. Objective: To assess Bitcoin's market efficiency during the COVID-19 pandemic and compare this efficiency with other markets (Ethereum, Binance Coin, S&P 500, and spot gold), and to identify changes in the distribution of heavy tails (probability of extreme events) before and after the start of the pandemic.	Bitcoin's market efficiency persisted during the COVID-19 pandemic. Heavy tails in the distribution of Bitcoin returns decreased after the start of the pandemic. Bitcoin proved to be as efficient as spot gold and more efficient than Ethereum, Binance Coin, and the S&P 500 during the pandemic.
Shahzad et al. (2022)	Detect episodes of price explosivity and collapse in Bitcoin and its competitor Dogecoin, as well as examine the relationship between these phenomena and Elon Musk's tweets. Research question: (1) Is there a bubble behavior in the prices of Bitcoin and Dogecoin? (2) Do Elon Musk's tweets influence the formation of bubbles in the prices of Bitcoin and Dogecoin?	/	The study utilizes price data at four-hour intervals and Phillips and Shi's (2019) model to detect episodes of price bubbles and collapses. It also employs logistic regressions to analyze the relationship between Elon Musk's tweets and the formation of bubbles in the prices of Bitcoin and Dogecoin. Method Objective: The aim is to identify episodes of price bubbles and collapses in Bitcoin and Dogecoin, as well as assess the impact of Elon Musk's tweets on these phenomena.	The study identifies several bubble episodes in Bitcoin and Dogecoin, with more frequent occurrences in Bitcoin. Collapse episodes are only observed in Bitcoin. The results show that Elon Musk's general tweets about cryptocurrencies contributed to the explosiveness of Bitcoin prices, while his specific tweets about Dogecoin contributed to the explosiveness of Dogecoin prices. These findings highlight the influential role of key personalities via social media in bubble formation, which is important for cryptocurrency traders' decision making and market efficiency.

Fernandes et al. (2022)	Investigate price disarray and informational efficiency of five cryptocurrencies (Bitcoin, BNB, Cardano, Ethereum, and XRP) before and during the COVID-19 pandemic. The underlying research question is whether the COVID-19 pandemic has had an impact on the informational efficiency and price disarray of these cryptocurrencies.	The study period spans from January 1, 2018, to December 31, 2021.	The researchers use complexity measures such as permutation entropy and Fisher information measure to assess price disarray and informational efficiency. They construct a Shannon-Fisher causality map to map cryptocurrencies in a two dimensional space. Then, they apply a sliding time window approach to study the temporal evolution of informational efficiency.	All cryptocurrencies exhibit high but slightly variable informational efficiency during both periods (before and during the COVID-19 pandemic), with Cardano being the most efficient cryptocurrency. During the COVID-19 crisis, Cardano is the most efficient cryptocurrency, followed by Bitcoin. The results suggest an increase in entropy and a decrease in price predictability during the COVID-19 pandemic, indicating an increase in market efficiency for some cryptocurrencies. Fluctuations in cryptocurrency market efficiency are low before and during the COVID-19 pandemic, suggesting their resilience to the global health crisis. The findings highlight the potential benefits of using cryptocurrencies in liquidity risk diversification strategies.
Kakinaka and Umeno (2022)	Analyze the scale-dependent structure of asymmetric volatility effect in six representative cryptocurrencies, namely Bitcoin, Ethereum, Ripple, Litecoin, Monero, and Dash. The underlying research question is to understand how cryptocurrency price volatility reacts to return shocks and whether this reaction varies depending on the time scale.	The study considers the period following two significant price bubbles in 2013 and 2017 up to January 2022.	The methodology relies on developing a dynamic approach to fractal regression analysis based on DFA (detrended fluctuation analysis). The objective of this method is to detect whether price change volatility is positively or negatively related to return shocks at different time scales.	The results reveal a structure of asymmetric volatility effect that varies depending on the time scale and the cryptocurrency analyzed. Unlike stock markets, lower cap cryptocurrencies exhibit a „reverse" asymmetric volatility effect at relatively large scales, where positive shocks have a greater impact on volatility than negative shocks. The implications of this asymmetric effect are discussed in relation to market participants and investor heterogeneity.

Source: own study

3. Methodology

When applied to the study of Bitcoin's price determinants, the theoretical background involves understanding the dynamic relationship between Bitcoin's price and its potential explanatory variables. In our investigation into the determinants of Bitcoin prices, we took into account market forces, macroeconomic and financial development, as well as Blockchain and difficulty of mining factors. We use Auto-Regressive Distributed Lags (ARDL) model, with its ability to handle mixed-order integration. This model is particularly well-suited for Bitcoin price studies, where different variables may exhibit non-stationary properties but still maintain a meaningful relationship. By using this approach, we aim to capture the **interactions between long-run equilibrium and short-run dynamics,** shedding light on the key drivers of Bitcoin's price movements.

3.1. Dataset and Experiments

Our dataset encompasses daily time series data spanning from December 2016 to June 2023, comprising a total of 2385 observations for each variable. During this timeframe, notable features include the heightened volatility observed in BTC/USD prices, coupled with the emergence of several speculative bubbles. Data aggregation for this study involved meticulous manual collection from diverse sources, including reputable platforms such as https://data.nasdaq.com and https://fr.investing.com.To assess Bitcoin's supply, we relied on the daily total number of Bitcoin currently in circulation, while demand was evaluated through Bitcoin's transactional activity, particularly the number of addresses using the Bitcoin Blockchain (NBR_ADR). In accordance with established research practices, we incorporated pivotal financial metrics, such as the Dow Jones Index (DJI) and the Nikkei225 Index, which serve as reliable proxies for macroeconomic and financial development. Furthermore, recognizing the technological nuances inherent in digital currencies, we integrated specific variables, such as Hash Rate (BTCHash) and BTCDIFF, which serve as indicators of Bockchain complexity, along with miner revenues denominated in USD per transaction (COSTTrans). A comprehensive overview of all indicators, along with their descriptions, can be found in Table 2.

Table 2. **Description of variables**

Dependent Variable	
BTCPrice	Bitcoin Price
Independent Variables	
TOTBTC	Total number of Bitcoin currently in circulation

NBR_ADR	Number of addresses utilizing the Bitcoin Blockchain
DJI	Dow Jones Index
Nikkei225	Nikkei225 Index
BTCHash	Estimated hash rate per second performed by the Bitcoin network
BTCDIFF	Difficulty in finding a valid block, serving as a relative measure of Blockchain complexity
COSTTrans	Miner revenues in USD divided by the number of transactions

Source: own study

3.2. Model

Prior to model estimation, an investigation into the integration properties of the variables in question is undertaken. Ensuring the stationarity of time series data is fundamental in conducting accurate analyses, as it mitigates the risk of spurious regression. To assess stationarity, we employed the Augmented Dickey-Fuller (ADF) test, a standard procedure in time series analysis.

To assess the short and long-term relationship between Bitcoin price and the independent variables, our study used the ARDL model. This model was chosen due to its numerous advantages over traditional statistical methods for evaluating cointegration and short and long-term relationships. While various cointegration methods exist in the literature (such as the Engle-Granger test in 2015, Johansen and Juselius methods in 1990, and Johansen in 1991), their application remains limited. For instance, the Engle-Granger test is only applicable to two variables that must be integrated at the same order, rendering it unsuitable for multivariate cases. The Johansen cointegration test (1988, 1991) is primarily used to assess cointegration among more than two series, specifically designed for multivariate situations. However, although the Johansen test, based on a Vector Error Correction Model (VECM), offers a solution to the limitations of the Engle-Granger test in multivariate contexts, it also imposes the condition that all series or variables involved must have the same order of integration, which is not always the case in practice.

Facing these limitations, we adopted the ARDL Bounds Testing approach proposed by Pesaran et al. (2001) to address these shortcomings and verify cointegration, which manifests itself as an error correction model. This approach tests a level relationship between variables that can be either I(0), I(1), or a combination of both. This allows us to avoid the pre-test issues associated with standard cointegration analysis, which requires classifying variables into I(0) or I(1). However, it's worth noting that ARDL cannot be used with non-stationary variables integrated of order two I(2). Additionally, the merits of ARDL have been highlighted by researchers, emphasizing its ability to produce robust results regardless of sample size. This method is also valuable for adjusting lags in models by providing solid estimations of statistics, particularly for long-term models. It stands out for its utility in small sample settings, where it enables reliable inferences even with limited data.

It's important to note that the power of ARDL also lies in its ability to capture the interaction between short and long-term dynamics of a given set of variables. This comprehensive approach reveals subtle links between variables, providing researchers with the means to explore the dynamics of the Unrestricted Error Correction Model (UECM), which plays a significant role in establishing long-term equilibriums associated with the short term. This method is also valuable in time series data analysis, providing guidance for establishing appropriate correlations and detecting endogeneity (Pesaran et al., 2001). To implement the bounds testing procedure, we estimated the following ARDL model (Model 1) to determine cointegration between TOTBTC, COSTTrans, NBR_ADR, BTCHash, BTCDIFF, DJI, Nikkei225, and Bitcoin price.

$$\Delta BTCPrice_{t} = \lambda_{0} + \theta_{1}\, lnBTCPrice_{t-1} + \theta_{2}\, lnTOTBTC_{t-1} + \theta_{3}\, ln\ NBR\_ADR_{t-1} + \theta_{4}\, lnBTCHash_{t-1} + \theta_{5}\, lnCOSTTrans_{t-1} + \theta_{6}\, lnBTCDIFF_{t-1} + \theta_{7}\, lnDJI_{t-1} + \theta_{8}\, lnNikkei225_{t-1} + \Sigma^{p}_{i=1}\alpha_{1i}\, \Delta lnBTCPrice_{t-i} + \Sigma^{q}_{i=0}\alpha_{2i}\, \Delta lnTOTBTC_{t-i} + \Sigma^{r}_{i=0}\alpha_{3i}\, \Delta lnNBR\_ADR_{t-i} + \Sigma^{v}_{i=0}\alpha_{4i}\, \Delta lnBTCHash_{t-i} + \Sigma^{t}_{i=0}\alpha_{5i}\, \Delta lnCOSTTrans_{t-i} + \Sigma^{u}_{i=0}\alpha_{6i}\, \Delta lnBTCDIFF_{t-i} + \Sigma^{v}_{i=0}\alpha_{7i}\, \Delta lnDJI_{t-i} + \Sigma^{w}_{i=0}\alpha_{8i}\, \Delta ln\ Nikkei225_{t-i} + \mathcal{E}_{t} \quad (1)$$

The variables have been previously defined (Table 2). The symbol Δ represents the first difference operator. λ_0 denotes the intercept, and $\mathcal{E}_t$ represents the stochastic error term. Summation signs indicate short-term dynamics, while θ_i stands for long-term coefficients. The variables p, q, r, s, t, u, v, and w represent the optimal lags. Following the estimation of equation (**1**), we proceed to determine the presence of a long-term relationship between the variables. This assessment relies on the ARDL bounds test approach, which utilizes F-test values with critical values for lower and upper bounds, labeled as I(0) and I(1) respectively, based on specific null and alternative hypotheses.

$$H_{\mathbf{0}}: \theta_1 = \theta_2 = \theta_3 = \theta_4 = \theta_5 = \theta_6 = \theta_7 = \theta_8 = 0 \textit{ (Absence of cointegration)}$$
$$H_{\mathbf{1}}: \theta_1 \neq \theta_2 \neq \theta_3 \neq \theta_4 \neq \theta_5 \neq \theta_6 \neq \theta_7 \neq \theta_8 \neq 0 \textit{ (Evidence of cointegration)}$$

The null hypothesis is rejected if the calculated F-statistic exceeds the upper critical bounds, indicating cointegration, while it's accepted if the F-statistic falls below the lower bounds, suggesting no cointegration. If the F-statistic falls between the upper and lower bounds, the decision is inconclusive. Therefore, it is imperative to gain a better understanding of the integration order of variables before drawing a definitive conclusion (Pesaran et al., 2001). Lastly, here is the formulation of the Error Correction Model, where Δ represents the first difference operator, and ECM_{t-1} and δ_1 respectively denote the error correction term and the long-term adjustment speed after short-term shocks (Model 2). The error correction term (ECT) must be negative and significant to confirm the existence of a long-term relationship between the variables.

$$\Delta \ln BTCPrice_t = \psi_0 + \delta_1 ECM_{t-1} + \sum^{p}_{i=1} \alpha_{1i} \Delta \ln BTCPrice_{t-i} + \sum^{q}_{i=0} \alpha_{2i} \Delta \ln TOTBTC_{t-i} + \sum^{r}_{i=0} \alpha_{3i} \Delta \ln NBR\_ADR_{t-i} + \sum^{s}_{i=0} \alpha_{4i} \Delta \ln BTChash_{t-i} + \sum^{t}_{i=0} \alpha_{5i} \Delta \ln COSTTrans_{t-i} + \sum^{u}_{i=0} \alpha_{6i} \Delta \ln BTCDiff_{t-i} + \sum^{v}_{i=0} \alpha_{7i} \Delta \ln DJI_{t-1} + \sum^{w}_{i=0} \alpha_{8i} \Delta \ln Nikkei225_{t-i} + \varepsilon_t \quad (2)$$

We will also employ the Box-Pierce correlation test to identify autocorrelation. Furthermore, we will utilize the ARCH LM heteroscedasticity test to examine its presence.

4. Results

Before beginning unit root tests, we conduct preliminary analyses on our data series. This involves conducting a thorough exploration and detailed analysis of the data, which includes calculating various measures of position and dispersion, as well as assessing their distribution for normality. The results of these calculations are documented in Table 3.

Table 3. **Descriptive statistics of the data**

	BTCPRICE	BTCHASH	BTCDIFF	COSTTrans	DJI	NBR_ADR	TOTBTC
Mean	9.349281	18.01378	29.84063	4.054302	6.019971	13.27191	16.70582
Median	9.241787	18.46662	30.30990	4.081638	5.996999	13.28877	16.72167
Maximum	11.12080	19.90391	31.58898	5.704817	6.363494	13.88584	16.78162
Minimum	6.660473	14.56326	26.64033	1.587192	5.606353	12.61530	16.59138
Std Dev	1.037177	1.303206	1.318983	0.809202	0.184880	0.199645	0.055465
Skewness	-0.41291	-0.99303	-1.00451	-0.58355	0.02141	-0.27620	-0.48407
Kurtosis	2.732927	3.050988	3.035896	3.330942	2.133037	2.753878	1.958468
Jarque-Bera	74.86103	392.2436	401.2273	146.2448	74.87504	36.34496	200.9462
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Sum	22298.04	42962.85	71169.91	9669.509	14357.63	31653.51	39843.39

Sum Sq Dev.	2564.557	4048.856	4147.486	1561.064	81.48626	95.02173	7.334119
Observations	2385	2385	2385	2385	2385	2385	2385

Source: Authors' estimations

After a thorough analysis of the variables, significant observations emerged. BTCPrice fluctuated between 6.66 and 11.12 during the examined period, while BTCHash ranged from 14.56 to 19.90. BTCDiff exhibited the highest average (29.84) and notable volatility, followed by BTCHash and Costtrans, with TOTBTC displaying the least volatility. The normality of the distributions varied across variables, as confirmed by the Jarque-Bera test, with some variables deviating from the normal distribution. Positive skewness was observed in DJI, while other variables showed right skewness. Furthermore, kurtosis coefficients indicated varying levels of dispersion, with DJI, NBR_ADR, TOTBTC, while the others displayed leptokurtic properties, indicating higher concentration around the mean. Figure 1 shows the daily trend series over the sample period. In Table 4, we showcase the correlation matrix among the considered variables. As illustrated in the table, the data offer insights into the associations among the variables being analyzed. One noteworthy finding is the robust positive

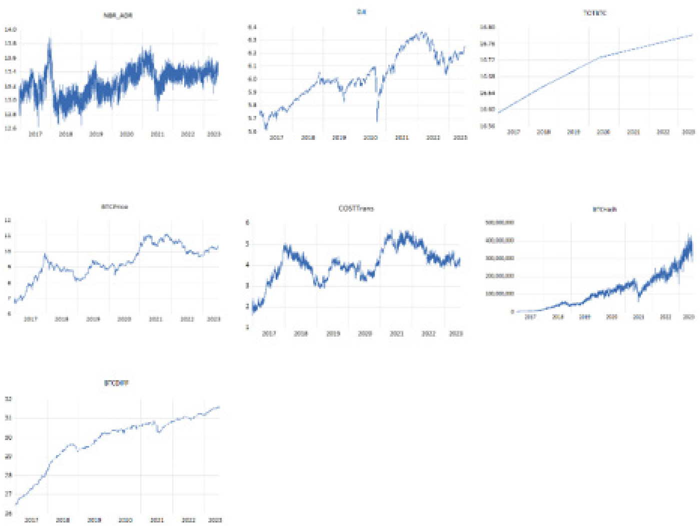

Figure 1. **Daily trend series over the sample period**

Source: own study

correlation observed between all variables and the price of Bitcoin, with correlation coefficients exceeding 0.5. Particularly notable is the variable COSTTrans, which demonstrates the strongest correlation, reaching a coefficient of 0.91, underscoring its considerable impact on Bitcoin pricing.

Table 4. **Correlation matrix**

	LBTCPrice	LTOTBTC	LNBR_ ADR	LBTCHash	LCOST Trans	LBTCDIFF	LDJI	LNikkei 225
LBTC-Price	1	0.835869	0.565683	0.824280	0.919713	0.822666	0.848485	0.805271
LTOT-BTC	0.835869	1	0.510293	0.968608	0.618869	0.971296	0.877367	0.900773
LNBR_ ADR	0.565683	0.510293	1	0.431520	0.351667	0.419281	0.339256	0.5209177
LBTC-Hash	0.824280	0.968608	0.431520	1	0.656084	0.996084	0.838865	0.862180
LCOST-Trans	0.919713	0.618869	0.351667	0.656084	1	0.645955	0.705611	0.641563
LBTC-DIFF	0.822666	0.971296	0.419281	0.996084	0.645955	1	0.842699	0.859698
LDJI	0.848485	0.877367	0.339256	0.838865	0.7011	0.842699	1	0.822366
LNikkei-225	0.805271	0.900773	0.520917	0.862180	0.641563	0.859698	0.822366	1

Source: Authors' estimations

This research employs the Augmented Dickey-Fuller (ADF) test to examine the stationarity of the variables under investigation, determining whether they are stationary at the level, after differencing, or both. The outcomes of these tests are presented in Table 5. The table presents findings indicating that the Nikkei225 series is stationary at a 5% significance level, suggesting it doesn't require differencing to achieve stationarity (order 0), while other related series become stationary after a first difference (order 1). This difference in integration orders complicates the application of multivariate cointegration tests like Engle-Granger and Johansen, which are unsuitable here. To address this, the bounds cointegration test is proposed by Pesaran et al. (2001) for a more accurate analysis of potential relationships between the series, considering their variable integration orders and enabling a robust evaluation of Bitcoin price formation.

Table 5. **The results of the unit root test**

Test/variables	Level		First difference		Order of integration
	ADF	Lag	ADF	Lag	
LBTCDIFF	-2.6251 (0.3137)	13	-11.888 (0.01)	13	I(1)
LBTCHash	-2.5515 (0.3448)	13	-17.68 (0.01)	13	I(1)
LBTCPrice	-2.1429 (0.5178)	13	-12.48 (0.01)	13	I(1)
LCOSTTrans	-1.8746 (0.6314)	13	-15.992 (0.01)	13	I(1)
LDJI	2.6783 (0.2912)	13	-12.412 (0.01)	13	I(1)
LNBR_ADR	-2.9798 (0.1635)	13	-17.457 (0.01)	13	I(1)
LTOTBTC	-1.0703 (0.9274)	13	-4.6519 (0.01)	13	I(1)
LNikkei225	-3.3743 0.05785	13	-	-	I(0)

NB: In this table, "L" denotes the logarithm of the variables

Source: Authors' estimations

With confirmation that none of the variables exhibit integration beyond I(2), we progress to the subsequent analysis stage to explore potential long-term relationships. Employing the bounds testing method by Pesaran et al. (2001), we test the null hypothesis of no long-term association. The decision rule dictates rejecting H_0 if the computed F-statistic exceeds the upper bound of the Pesaran test statistic table, indicating cointegration. Results from the ARDL bound test, as presented in Table 6, reveal that our model's F-statistic exceeds the upper bound of the Pesaran test statistic at the 1% significance level. Consequently, we decisively reject the hypothesis of no cointegration, confirming a long-term relationship between BTC/USD and the selected independent variables during the analyzed period.

Table 6. **Bound test for cointegration**

F-statistic	**4.2406**			
K	7			
Significance Level	**Lower Bound I(0)**	**Upper Bound I(1)**	**T-statistics**	**P-value**
10%	2.567033	4.229705	-4.560242	0.05052335

Source: Authors' estimations

Once a long-term relationship between the variables in the study is confirmed, our ARDL model can be estimated with both short-term and long-term dynamics. To do so, it is necessary to determine the optimal lag lengths for the model. As mentioned earlier, it is crucial to take into account the different orders of integration of our variables. Therefore, the appropriate approach is to opt for the bounds cointegration test developed by Pesaran et al. (2021). Before applying this test, several steps are necessary: determine the optimal lag length using criteria such as the Akaike Information Criterion (AIC) and use the Fisher test to evaluate the cointegration between the series. In adherence to the ARDL approach, determining suitable lag lengths for each variable is paramount. Utilizing the AIC lag length criterion, we established the (4,3,4,4,5,3,4,4) model to estimate the long-term relationship (Table 7).

Table 7. **Optimal shift according to AIC (Top 20 models)**

	lb-tcprice	**ltotbtc**	**lnbr_adr**	**lbt-chash**	**lcost-trans**	**lbtcdiff**	**ldji**	**lnik-kei225**	**AIC**
1	4	2	5	5	5	2	0	0	-9061.1006659512
2	4	2	5	5	5	3	0	0	-9060.72314734499
3	4	3	5	5	5	2	0	0	-9060.05820274625
4	4	2	5	5	5	2	0	1	-9059.45224550946
5	4	2	5	5	5	2	1	1	-9058.63294629675
6	4	2	5	5	5	3	1	1	-9058.27418116617
7	4	3	5	5	5	2	1	1	-9057.56058031834
8	4	2	5	5	5	2	1	2	-9056.63422499396
9	4	2	5	5	5	2	2	2	-9055.41685641689

10	4	2	5	5	5	3	2	2	-9055.02596605739
11	4	2	4	5	5	2	2	2	-9050.33516613548
12	4	3	4	5	5	2	2	2	-9049.18173400042
13	4	2	4	5	5	2	2	3	-9048.53618261414
14	4	2	4	5	5	2	3	3	-9046.58375037098
15	4	2	4	5	5	3	3	3	-9045.83946544545
16	4	2	4	4	5	3	3	3	-9044.90985276976
17	4	3	4	4	5	3	3	3	-9043.7796577905
18	4	2	5	4	5	3	3	3	-9043.69770341654
19	4	3	4	4	5	3	3	4	-9042.85414721536
20	4	3	4	4	5	3	4	4	-9041.02863355687

Source: Authors' estimations

5. Discussion

5.1. Long-Run Relationships

Since the variables exhibit a cointegrating connection, we can proceed to estimate the short and long-term dynamic associations among them. Table 8 illustrates the outcomes of the extended-term analysis. The analysis emphasizes the substantial impact of supply and demand dynamics on Bitcoin prices. Notably, demand-side factors, such as the number of addresses, exert a more significant influence on price compared to supply-side factors, like the number of Bitcoins. This result corroborates that found by Auer et al. (2022) and Koutmos (2018) who showed that the number of merchants accepting Bitcoin as a form of payment and the number of Bitcoin transactions are positively correlated with the price of Bitcoin. This means that an increase in the number of addresses leads to an increase in Bitcoin price. In other words, a large number of investors starts to accept payment in Bitcoin and is interested in buying it. This result corroborates that found by Guizani and Nafti (2019). Increasing the stock of Bitcoins leads to a notable reduction in price, with each increase in Bitcoin stock resulting in a decrease of approximately 7.2867% in its price. This suggests that as the quantity of stored Bitcoin rises, the price of this cryptocurrency declines. It's worth noting that Bitcoin's volume has been restricted and regulated since its inception, unlike traditional currencies. During periods of strong market performance, investors tend to gravitate towards Bitcoin, driving up its price.

This trend is particularly evident in the positive and significant correlation observed between the Dow Jones index and Bitcoin price (0,149), indicating that when the index rises, Bitcoin price tends to increase both in the short and long terms. This result confirms that found in Poyser's (2019) study which showed that the price of Bitcoin is positively correlated with stock market index, USD to Euro exchange rate. Conversely, the Japanese Nikkei225 index displays a negative and significant long-term correlation with Bitcoin (-0,42), suggesting a stronger association with the US economy than with Japan's. Sudies by Havidz et al. (2022) and Ciaian et al. (2016) do not support previous findings that macro-financial developments are driving Bitcoin price in the long run. The hash rate, reflecting the complexity of Bitcoin mining, contributes positively to long-term prices, but with a relatively modest impact. Each unit increase in the hash rate is associated with a 0.405% increase in the price of Bitcoin over the long term. However, this effect is not statistically significant in the long run. This result confirms that found by Kristoufek (2015) who showed a positive long-term correlation between the security of the network, measured by the network hashrate,

Table 8. **Long run coefficients of ARDL**

Term	Estimate	Std. Error	T value	Pr(>|t|)
(Intercept)	-117.3310467	48.9615641	-2.3963909	1.663518e-02
LTOTBTC	-7.2867276	3.2659531	2.2311183	2.576734e-02**
LNBR_ADR	0.9680780	0.2101100	4.6074812	4.293728e-06***
LBTChash	0.4052987	0.3965013	1.0221876	3.067974e-01
LCOSTtrans	0.7917486	0.0519880	15.2294487	5.099466e-50**
LBTCDIFF	-0.4926730	0.3990173	-1.2347159	2.170597e-01
LDJI	0.1494741	0.3385010	0.4415764	6.588364e-01**
LNikkei225	-0.4239133	0.2843966	-1.4905708	1.362085e-01***

(e.g., *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$)

Source: Authors' estimations

and the price of Bitcoin. Technological advancements are gradually decreasing the impact of mining costs on Bitcoin prices, aligning with previous research. While the difficulty of finding valid blocks (BTCDIFF)doesn't significantly affect long-term prices, transaction costs (COSTTrans) and the number of Bitcoin addresses using the Blockchain (NBR_ ADR) do. Each unit increase in transaction costs and the number of addresses leads to a respective long-term increase of approximately 0.791% and 0.968% in Bitcoin price. This indicates that an increase in these factors stimulates upward movement in Bitcoin prices.

5.2. Short-Run Relationships

After examining the long-term relationship between variables, the cointEq or ECM coefficient (-1) is noted as the lagged residual from the long-term balance equation, consistently negative and statistically significant, indicating cointegration between study variables. The ECT coefficient's value of -0.031334 suggests a moderate adjustment toward equilibrium, with approximately 3.13% of short-term imbalance resolving daily.

Insights from short-term analysis reveal significant dynamics in the Bitcoin market (Table 9).

Table 9. **Short run coefficients of ARDL (ECM Regression)**

Coefficients	Estimations	Std. Error	Tvalue	Pr(>|t|)
Intercept)	-3.67644	1.723640	-2.133	0.033032 *
L(lbtcprice,1)	0.031334	0.006871	-4.560	5.37e-06 ***
L(ltotbtc,1)	0.228832	0.110750	2.062	0.039355 *
L(lnbr_adr,1)	0.303343	0.009124	3.324	0.000900 ***
L(lbtchash,1)	0.012700	0.011400	1.114	0.0265389 **
L(lcosttrans,1)	0.024809	0.005912	4.196	2.81e-05 ***
L(lbtcdiff,1)	-0.015437	0.011267	-1.370	0.0170756 **
Ldji	0.004684	0.010841	0.432	0.665760
Lnikkei225	-0.013283	0.008972	-1.481	0.138868
D(L(lbtcprice,1))	-0.187554	0.021118	-8.881	< 2e-16 ***
D(L(lbtcprice,2))	-0.096889	0.021386	-4.530	6.18e-06 ***
D(L(lbtcprice,3))	-0.084912	0.020699	-4.102	4.23e-05 ***
D(ltotbtc)	-65.33886	22.55576	-2.897	0.003805 **
D(L(ltotbtc,1))	-65.21389	22.54798	-2.892	0.003860 **
D(lnbr_adr)	0.193017	0.011334	17.030	< 2e-16 ***
D(L(lnbr_adr,1))	0.173608	0.013582	12.783	< 2e-16 ***
D(L(lnbr_adr,2))	0.087883	0.013849	6.346	2.65e-10 ***
D(L(lnbr_adr,3))	0.044993	0.012878	3.494	0.000485 ***
D(L(lnbr_adr,4))	0.030983	0.011878	2.608	0.009153 **
D(lbtchash)	-0.134049	0.011208	11.960	< 2e-16 ***
D(L(lbtchash,1))	-0.157137	0.015277	-10.286	< 2e-16 ***
D(L(lbtchash,2))	-0.071475	0.015188	-4.706	2.67e-06 ***
D(L(lbtchash,3))	-0.041921	0.013919	-3.012	0.002625 **
D(L(lbtchash,4))	-0.035678	0.011751	-3.036	0.002422 **
D(lcosttrans)	0.210319	0.011046	19.039	< 2e-16 ***
D(L(lcosttrans,1))	0.202205	0.012567	16.091	< 2e-16 ***
D(L(lcosttrans,2))	0.110652	0.012919	8.565	< 2e-16 ***

D(L(lcosttrans,3))	0.062837	0.012384	5.074	4.20e-07 ***
D(L(lcosttrans,4))	0.057738	0.011287	5.115	3.39e-07 ***
D(lbtcdiff)	0.130989	0.048737	2.688	0.007246 **
D(L(lbtcdiff,1))	0.164434	0.047440	3.466	0.000537 ***
ECT	-0.031334	0.005063	-6.188	7.15e-10 ***

NB: Asterisks (***), (**), and (*) indicate statistical significance at the 1%, 5%, and 10% levels, respectively.
Residual standard error: 0.03581 on 2349 degrees of freedom.
Multiple R-squared: 0.218
Adjusted R-squared: 0.208
F-statistic: 21.83 on 30 and 2349 DF
P-value: < 2.2e-16

Residuals:
Min 1Q Median 3Q Max
-0.40751 -0.01756 0.00019 0.01863 0.15065

Source: Authors' estimations

Despite a negative impact from increased Bitcoin volume, the price decreases significantly, validating a 65% impact (Bouoiyour & Selmi, 2014; Ciaian et al., 2016). This reflects a common economic principle: supply increases drive price decreases. This result confirms that found by Guizani and Nafti (2019) who stipulated that the negative effect of the volume of Bitcoin on the short term can be explained by the fact that the volume of Bitcoin is limited and supervised since its creation in 2009. Accordingly, in this case, it is not possible to create new Bitcoin volumes as well as in the case of traditional currencies. Conversely, the number of addresses representing Bitcoin's size significantly impacts its price. An increase in addresses correlates with a substantial 0.193% price rise at the 0.1% boundary, indicating investor confidence and growing interest in Bitcoin. Hence, our hypotheses 1.1 and 1.2 are confirmed.

Stock indexes, reflecting global economic trends, can influence Bitcoin prices positively. The Dow Jones index, for instance, positively affects Bitcoin prices both short and long-term (0.0046%, 0.13%), indicating a prosperous US economy and investor profit from stock markets. Conversely, events like the Mt. Gox market collapse, in February 2014, disrupted Bitcoin transactions in Japan, reflected in the negative correlation between the Nikkei225 index and Bitcoin price (-0.0132%, -0.42%) (Van Wijk, 2013). Hence, our hypotheses 3.1 and 3.2 are confirmed.

In the short-term, the hash rate exhibits a negative coefficient, while the cost per transaction and Bitcoin difficulty remain significant and positive in the short-term, along with their lags (Bouoiyour et Selmi., 2019; Ciaian et al., 2016). In other words, tracking the actual costs incurred by miners is impossible; however, the difficulty of Bitcoin extraction serves as a reliable indicator of these costs. Consequently, this process has a positive impact on the price of Bitcoin (Li & Wang, 2017), meaning its value should rise alongside the increase in difficulty, thus supporting our hypothesis 2.1. However, over the long term, the mining difficulty coefficient diminishes. Therefore, advancements in technology reduce the influence of mining costs on the price of Bitcoin. This is supported by Bouoiyour & Selmi (2014). Likewise, Li and Wang (2017) suggest that the marginal impact of mining difficulty on Bitcoin price will lessen as mining technology advances. As a result, hypotheses H2.2 and H2.3 are confirmed.

Table 10. **Autocorrelation error test**

Test	X-squared	Probability
Box-Pierce test	0.38573	0.534

Source: Authors' estimations

Table 11. **Heteroscedasticity test**

Test	Chi-squared	Probability
ARCH LM-test	35.141	0.0004448

Source: Authors' estimations

In our research, we aimed to ensure the reliability and appropriateness of our model through the examination of serial correlation using the Box-Pierce test, as well as heteroscedasticity using the ARCH LM test. The findings from these assessments are presented in Table 10 and Table 11. Based on the test results, we can infer that the model is devoid of autocorrelation but exhibits heteroscedasticity. Finally, to check the stability of the long-term of the coefficient of the estimated variables in the model, the cumulative sum (CUSUM) and the cumulative sum of squares (CUSUMSQ) tests are used. The graphs of the CUSUM and CUSUMSQ (Figure 2) show that both plots lie within the 5% critical bound, indicating that the estimated coefficients of the model are stable for the period 2016-2023 at the 5% level of significance.

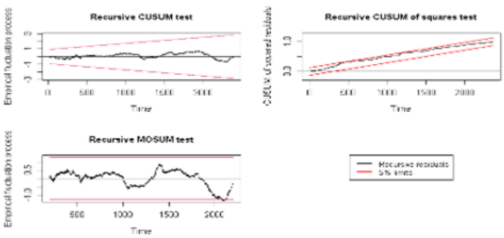

Figure 2. **CUSUM and CUSUMSQ plots**

Source: own study

6. Conclusions

Our study delves into the critical dynamics of price fluctuations within the cryptocurrency market, shedding light on its significance for users and traders. We focused our attention on a specific cryptocurrency, Bitcoin, owing to its dominant position in terms of market capitalization and renown. Our aim was to dissect the underlying factors driving its fluctuations.

Our research has a double contribution: Identify the key factors that determine the price of Bitcoin, including macroeconomic factors, technical indicators, and Blockchain-specific factors, and develop an ARDL model that can accurately predict the future price of Bitcoin. This approach has the merit to provide a more robust understanding of the factors driving Bitcoin prices. Our results offer valuable decision-making support for investors and serve as a reference for governments to develop more effective regulatory policies.

Through a comprehensive theoretical framework, we amalgamated traditional economic fundamentals with Bitcoin-specific variables, such as transaction costs, hash rate, and Blockchain validation complexity. Additionally, we incorporated significant global macroeconomic and financial indicators, notably the Dow Jones and Nikkei225 indexes. Our ARDL model analysis revealed compelling insights: demand, represented by the number of addresses using the Bitcoin Blockchain, emerged as a paramount driver of Bitcoin prices, exerting influence both in the short and long-term. Conversely, while Bitcoin supply wielded significance in the short-term, its impact waned over time due to the limited nature of Bitcoin issuance. Transaction costs emerged as a crucial determinant, with higher production costs leading to increased Bitcoin prices, underscoring a direct correlation between production costs and Bitcoin value. Moreover, the complexity associated with block validation displayed a short-term positive effect on Bitcoin prices, with decreasing marginal impact over time, reflecting technological advancements and investors comprehension. In contrast, macroeconomic and financial factors exhibited no significant influence on Bitcoin prices, challenging prior assertions regarding their impact on Bitcoin's value. In conclusion, our empirical findings validate the pivotal role of supply and demand dynamics in shaping Bitcoin prices, suggesting a degree of predictability corresponding to traditional currency pricing models.

While our study provides valuable insights into the determinants of Bitcoin price fluctuations, it's essential to acknowledge its limitations. The study did not account for variables related to the appeal of Bitcoin as an asset class, nor did it explore the psychological aspects that could influence investor behavior. Additionally, it is important to bear in mind that the realm of Bitcoin is still relatively in its early stages, and its ecosystem as a whole is constantly evolving. The Blockchain technology, the cornerstone of Bitcoin, continues to advance, with the continuous emergence of new features and applications. Therefore, it is likely that new determinants will arise in the future, demanding further exploration.

Despite these constraints, this research has contributed to enriching the existing literature review by providing a deeper understanding of various dimensions, particularly the technological aspect of this cryptocurrency, incorporating variables reflecting aspects of complexity, calculation speed, and costs, as well as the interconnection of these variables. Although these variables are interdependent, each reflects a distinct, the research contributes valuable insights into Bitcoin price formation mechanisms, calling for further exploration in this complex domain aspect. It can be renewed and is always subject to continuous modification. We are confident that the full potential of these determinants should be harnessed, and new techniques should be developed to effectively forecast cryptocurrency prices, like utilizing a machine learning or a deep learning approaches to investigate the factors that drive Bitcoin prices and improve the accuracy of price predictions. We hope that our findings have contributed not only a theoretical foundation for future researchers to explore additional variables, but also to broaden the understanding within the field of cryptocurrency research.

Authors' contribution

L.H.Z.: research methods applied, conducting the research, analysis and interpretation of results. **S.B.R.:** article conception, theoretical content of the article, conducting the research, analysis and interpretation of results, draft manuscript preparation.

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