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An inquiry of Bitcoin price formation: Evidence from Linear and Nonlinear ARDL Frameworks, 2017-2018

Clément Landormy*

Abstract: This study comprehensively analyses Bitcoin's price dynamics amidst the volatility of 2017-2018, considering various influencing factors. Drawing from Fisher's Equation of Exchange (1911), Keynes' liquidity preference theory (1936), and prior research insights, we formulate an Equation of Bitcoin Exchange, setting the stage for empirical testing. Employing autoregressive distributed lag models in both linear (ARDL) and nonlinear (NARDL) frameworks, we scrutinise daily data from 2017 to 2018. Our findings underscore the predominant impact of internal factors, driven by market dynamics and technological advancements, on Bitcoin prices, with investment attractiveness following closely behind. Surprisingly, macroeconomic and financial variables demonstrate relatively less influence. While Bitcoin may not serve as a direct store of value like gold or offer complete hedging against US dollar fluctuations, its potential as a diversification tool in stock markets becomes apparent, barring short-term disruptions associated with Bitcoin price crashes. Moreover, factors related to investment attractiveness frequently exert downward pressure on Bitcoin prices, emphasising the speculative nature inherent in cryptocurrencies. Noteworthy is the positive short-term connection between Bitcoin prices and tether transactions, coupled with the positive long-term interaction between Bitcoin prices and crypto fundraising efforts at the peak of the ICO boom, signalling a pre-crash surge in 2017. Conversely, the long-term negative relationship between Bitcoin prices and Tether transactions suggests that Tether acts as a hedge against Bitcoin price crashes.

Keywords: Bitcoin, NARDL, Market forces, Safe haven, Tether.

JEL Classification: C32, E42, E44, G11, G12, G15.

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1 Introduction

Bitcoin is a digital currency that operates on a decentralised peer-to-peer network, the Bitcoin Blockchain, representing a distributed ledger recording all Bitcoin transactions. These transactions are cryptographically verified by a network of nodes (computers) and secured by miners (dedicated nodes) following a specific consensus algorithm, the proof-of-work (PoW). Unlike traditional currencies, Bitcoin does not rely on a central bank to emit and control its supply. Instead, the bitcoins are emitted automatically at a predetermined and disinflationary rate until Bitcoin's supply cap of 21 Million is reached. Since its inception in 2009, Bitcoin has progressively piqued investors' interest (Clarke 2023) as a financial asset in occidental countries, a store of value, and an intermediary of exchange in countries suffering from hyperinflation (Landormy 2022). Following requests from their clients (Shevlin 2021b), some major financial institutions, such as Morgan Stanley (Helms 2021; Morrell and Ramaswamy 2021), began to embrace the asset by proposing Bitcoin investment services (mostly limited to wealthy clients) and gaining indirect exposure through investments in companies owning bitcoins, like MicroStrategy (Sinclair 2021; Cirrone 2023). Bitcoin has gradually been integrated into traditional financial markets with the introduction of Bitcoin futures contracts in December 2017, their associated Exchange-Traded funds (ETFs) in October 2021, and the approval of 11 Bitcoin spot ETFs (Mitchelhill 2024) in the United-States on January 10, 2024. In parallel with this widespread adoption, Bitcoin has exhibited a remarkable yet highly fluctuating Bitcoin price growth. The Bitcoin price oscillation has never been as wild as during the 2017-2018 timeline. From Bitcoin's 2017 low on January 11, 2017, to its remarkable peak on December 16, 2017, the cryptocurrency yielded a staggering 2,341.98% return. Conversely, investors faced a devastating 83.45% loss on December 15, 2018, compared to Bitcoin's previous all-time high in December 2017[1]. These extreme levels of price volatility result from Bitcoin's largely unregulated environment, lack of an intrinsic value in the production chain, and speculative nature due to a floating exchange rate system with fiat currencies (Aglietta et al. 2014). Beyond causing the financial ruin of some investors, Bitcoin's volatility becomes a systemic risk susceptible to triggering financial crises as its widespread adoption and usage in crypto shadow banking progress. In the face of such danger and due to the ripple effect caused by the FTX collapse (DiCamillo 2022), U.S. regulators began dissociating the banking system from the cryptoasset sector (Coppola 2023; Yueqi Yang and Nicolle 2023) without providing a comprehensive regulatory framework for digital assets. Bitcoin's remarkable price swings have sparked numerous researchers' interest, prompting investigations into its price formation, potential applications and risks. To gain deeper insights into the mechanisms governing Bitcoin's price evolution, researchers have explored a range of factors that influence Bitcoin's price, including (i) internal factors, (ii) macroeconomic and financial developments, and (iii) attractiveness factors for investors and users.

The studies addressing the internal factors intend to show that Bitcoin's value is not solely a product of speculative fervour and media hype but is impacted by tangible and solid elements. Hayes (2019; 2017) suggests that the cost of Bitcoin production drives its value, with reductions in production costs negatively influencing the price. Buchholz et al. (2012) emphasise the significance of Bitcoin supply and demand in explaining its price movements.

Several others have examined the impact of macroeconomic and financial developments on Bitcoin to show the degree of integration of Bitcoin with the global economy. Van Wijk (2013)

[1] Bitcoin price data sourced from coinmetrics website

revealed a close connection between Bitcoin and financial indicators, notably the euro-dollar exchange rate, the Dow Jones and the oil price. Some suggest (G. Wang et al. 2019) that Bitcoin can serve as a haven, a hedging option, or a diversifier, while others (Ji et al. 2018) argue that Bitcoin remains relatively isolated from traditional financial assets.

Bitcoin will have value if acknowledged and trusted as a medium of exchange and a store of value by an ever-growing user base. Any shift in perceived acceptance, often driven by actions or statements from states, companies, or influential individuals, can result in significant volatility, hindering Bitcoin's evolution into a mainstream currency (Cheo 2017). The Bitcoin price was observed to react to publicly disclosed information, whether positive or negative events of various kinds, consistent with the efficient markets hypothesis. Generally, the Bitcoin price tends to be higher during positive events and lower during adverse events than in periods without significant events (Jakub 2015). Burnie and Yilmaz (2019) demonstrated that Bitcoin is influenced by shifts in user interest, as measured by the appearance of specific words on platforms like Reddit[2], which can be associated with government or corporate decisions affecting Bitcoin users' interests. We follow subsequent studies by employing attractiveness factors for users and investors as a proxy for speculation since the Bitcoin price cycles can be partially explained by interest in the currency (Kristoufek 2013). Garcia et al. (2014) noticed that preceding drastic price declines were upsurges in information searches (Wikipedia and Google Trends) linked to external events. Kristoufek (2013; 2015) and Panagiotidis et al. (2018) found that investor sentiment proxied by Google Trends and Wikipedia exerts varying effects on the Bitcoin price depending on the specific trend[3]. When these variables surpass (fall below) their trend, the increasing investor sentiment pushes (pulls) the price further up (down). These studies on Bitcoin price and social dynamics suggest that the market is dominated by short-term investors, trend chasers, noise traders and speculators relying on the expected profits of holding the currency and selling it later (Kristoufek 2013). These buyers have been primarily attracted by the cryptocurrency's remarkable price performance and influenced by news and social media, characteristics commonly associated with previous financial bubbles. Gerlach et al. (2019) argued that Bitcoin behaved as a highly speculative asset exhibiting intense bubble activity from January 2012 to February 2018.

Ciaian et al. (2016) criticized previous studies for examining various determinants of Bitcoin separately without considering their interactions. They conducted a comprehensive analysis by considering three critical categories of Bitcoin determinants: market forces of Bitcoin supply and demand, investment attractiveness, and global macroeconomic and financial developments. Using vector autoregression (VAR) models, vector error correction models (VECMs) and autoregressive distributed lags (ARDL) models on daily data, they uncovered the short- and long-term determinants of Bitcoin from a first regime (November 2009 to September 2013) and a second regime (October 4^{th}, 2013 to May 2015). Their findings indicated that the supply and demand forces had a crucial impact on Bitcoin, mainly during the second regime when Bitcoin was more established. Since the supply is exogenous and fixed over time, the demand has and will have more impact on the market price of Bitcoin. In terms of attractiveness factors, they found that they positively impacted Bitcoin. Specifically, Wikipedia had a more pronounced effect on Bitcoin during the first

[2] Reedit was significantly correlated with Google searches and their contextual information, making their results analogous to Google Trends

[3] A dummy variable is adopted by Kristoufek, taking 1 when the Bitcoin price is above its trend and 0 otherwise. An internet trend variable (Wikipedia, Google Trends) is constructed by Panagiotidis et al., taking 1 when it exceeds its 7-day simple moving average and 0 otherwise.

regime compared to the second regime in the short run, and it had no significant long-term impact. Additionally, they could not reject the hypothesis that investor speculation affects Bitcoin's price movements, as they found that Wikipedia and new posts were statistically significant in the short run. However, they did not identify a long-term influence of global macro-financial development variables on Bitcoin, even though they detected a short-run relationship (Ciaian et al. 2016). Similarly, Bouoiyour and Selmi (2014) resorted to a mix of variables from the three major classifications of Bitcoin determinants using the ARDL bounds testing approach on daily data from December 2010 to June 2014. Unlike Ciaian et al. (2016), they acknowledged the importance of including variables describing China's financial market and the Bitcoin network's processing power.

These previous papers' main shortcomings are that they wholly or partially (in the case of Ciaian et al.) overlooked possible nonlinear relationships between the Bitcoin price and its determinants. To our knowledge, only some studies have fixed this issue. One survey led by Bouri et al. (2018) employed NARDL, QARDL, and QNARDL models on daily data from July 17^{th}, 2010, to February 2^{nd}, 2017. They found asymmetric and nonlinear relations between Bitcoin and gold and between Bitcoin and aggregate commodities, emphasising the need to proceed with non-standard cointegration models to reflect the intricacy and hidden relations between Bitcoin and these variables. However, a substantial flaw of this paper and subsequent studies (Jareño et al. 2020; Long et al. 2021) is that they exclusively studied the relation between Bitcoin and macro-financial variables without considering the influences that may exert internal variables and attractiveness factors on the price of Bitcoin.

Our paper aims to fill these gaps in the literature by providing a deeper understanding of Bitcoin's status and price behaviour, shedding light on the mechanisms behind its abnormal price fluctuations and potential implications for the future. In order to accomplish this task, our study is based on three central pillars. The first pillar is to develop a theoretical framework, the equation of Bitcoin exchange, inspired by Fisher's Equation of Exchange (1911), the liquidity preference theory of Keynes (1936) and Ciaian et al.'s study (2016), from which we derived our testable hypotheses. This equation accounts for the diverging views on Bitcoin's status and the most influential variables inspired by the literature and our knowledge of Bitcoin. The combination of well- and lesser-known Bitcoin determinants with unprecedented significant variables depicting Bitcoin's liquidity in centralised exchange platforms (SPREAD) and the Tether economy (TETHER) constitutes our second pillar. The purpose is to capture a complete picture of the interactions between these variables and the market price of Bitcoin and deduce the evolution of Bitcoin's status during such turbulent periods as the 2017 Boom and its subsequent crashes. The adoption of Bitcoin spot Exchange-Traded funds (ETFs) makes today's actors (Javorská and Vojtko 2024; Knight and Godbole 2024; Hecht 2024) ponder their potential impact on the Bitcoin price while drawing comparisons with this 2017-2018 period marked by the introduction of Bitcoin futures contracts. The presence of at least five structural breaks revealed by the Bai and Perron multiple breakpoint tests indicates that the whole period cannot be adequately analysed when treated uniformly. Hence, it should be divided into six periods with inherent dynamics and drivers (Figure 1). Lastly, the third pillar is to insert asymmetries for the three categories of Bitcoin determinants in our autoregressive distributed lags (ARDL) models to construct our nonlinear autoregressive distributed lags (NARDL) models. It will enable us to discover the hidden short and long-run relations that may not be seen by employing classical symmetric models. It would also fix the potential biases from not accounting for relevant asymmetrical relationships in the time series. Once these pillars are estab-

Figure 1: Bitcoin price evolution, 2017-2018

lished, we provide recommendations to improve the Bitcoin Blockchain and ease the detrimental impact of a future crash.

Our empirical results yield three crucial insights. First, internal factors exert the most significant influence on Bitcoin's price, followed by attractiveness factors and occasionally macro-financial factors. The significance and magnitude of these variables' impact on the Bitcoin price and Bitcoin's perceived role evolve throughout different periods, with Bitcoin primarily seen as a store of value in the long term and equally as a medium of exchange in the short term. Second, the main drivers of the 2017 Bitcoin price boom were the appealing status of Bitcoin (store of value, medium of exchange) perceived by investors, particularly Chinese investors (alternative to the Shanghai Stock Exchange) who used Tether as a gateway, improvements in its technological aspects (FEE, HASH), and the appeal of crypto fundraising events boosting its demand. Speculation was a less critical Bitcoin price driver than during the succeeding crash periods. While speculation via Bitcoin futures contracts and negative news triggered the first crash, the second was instigated by miners' and long-term holders' massive selling of bitcoins. Third, internal factors exhibit the most pronounced asymmetric impacts on the Bitcoin price, with some discernible asymmetries within attractiveness factors. Unlike previous studies, hardly any asymmetric relationships are identified with macro-financial factors. In sum, Bitcoin is a speculative and technological asset, almost entirely detached from traditional macroeconomic and financial systems, that is essentially and progressively employed as a store of value but would gain to remain a viable medium of exchange.

The remainder of the paper is structured as follows. Section 2 provides a conceptual framework and testable hypotheses. Section 3 presents the econometric approach, and Section 4 discusses the results. Section 5 concludes and derives policy implications.

2 Conceptual framework and testable hypotheses

When confronted with the unique characteristics of Bitcoin, analysts often encounter challenges in ascertaining its intrinsic value. Traditional comparisons with established international currencies like the Dollar, Yen, or Euro prove inadequate due to Bitcoin's inherent volatility, a trust based on the technology and not on the credibility of a central bank managing a sovereign currency (Aglietta et al. 2014) and its limited transaction processing capabilities. As such, measurements like the real effective exchange rate, the interest rate parity, or the Big Mac index are not appropriate to determine the actual value of Bitcoin. Likewise, traditional approaches to evaluating the intrinsic value of shares of publicly listed companies, which rely on well-established tools such as balance sheets and cash flows, do not apply to Bitcoin and other cryptoassets. Being intangible and belonging to a new asset class, Bitcoin lacks established measurements for its intrinsic value. Some have drawn parallels with speculative bubbles or likened it to Gold as a store of value. However, despite various comparisons, the true nature of Bitcoin and its intrinsic value still need to be identified. The absence of widely accepted metrics for gauging Bitcoin's intrinsic value has spurred the development of an original model: the equation of Bitcoin exchange.

2.1 Equation of Bitcoin Exchange

The elaboration of the equation of Bitcoin exchange is based on Fisher's Equation of Exchange (Fisher 1911) supporting the Quantity Theory of Money and Ciaian et al.'s Bitcoin model (2016), which represents one of the earliest attempts to model Bitcoin's behaviour and is an extension of Barro's model for the gold standard. However, we recognize a crucial limitation in Fisher's Equation of Exchange, as it assumes that a currency is primarily a medium of exchange and does not account for its speculative or store-of-value aspects. While this assumption may hold for fiat currencies since the transactions and precautionary demand for money are generally much higher than those for speculative purposes, it falls short for cryptocurrencies such as Bitcoin. Admittedly, Bitcoin serves as a means of exchange but significantly less than a fiat currency and much more as a speculative asset and store of value, evidenced by Bitcoin price expansion, its high volatility, and the investment products (Bitcoin futures contracts) built upon it. Despite Bitcoin lacking the liquidity of fiat currencies and incurring some foreign exchange risks, its low-cost and fast transfers compete with international payment processors, making it a relevant medium for cross-border transactions (Coppola 2019). Ciaian et al. made a Bitcoin model considering the impact of market forces, investment attractiveness, and global macroeconomic and financial developments. However, they failed to integrate the constantly evolving status of Bitcoin, its technological aspect, other significant variables, and the asymmetric impacts of Bitcoin price determinants. Nevertheless, they failed to integrate the constantly evolving status of Bitcoin, its technological aspect, major Bitcoin determinants and their asymmetric impacts on the Bitcoin price.

To begin with, our equation of the total supply of Bitcoin is identical to that in Ciaian et al.'s study (2016). We assume that users need to convert bitcoins into dollars or other traditional currencies since most goods and services cannot be purchased using bitcoins. The Bitcoin price is denominated in US dollars, as the dollar has been the predominant currency in global Bitcoin trading since February 2017[4]. Suppose B describes the total volume of Bitcoins in circulation, and P^b designates the Bitcoin price in dollars. The product of both gives the total supply of Bitcoin expressed in US dollars as follows:

$$M^s = B * P^b \tag{1}$$

Assume the total demand for Bitcoin, M^d, to be a function of the classical factors from a typical equation of exchange, namely the general price level of goods and services, P, the size of the Bitcoin economy, G, and the velocity of Bitcoin, V. After that, the equation is supplemented by Bitcoin's technological factors, namely the transaction fees, F, and the Bitcoin hash rate, H. The velocity and the fees are broken down into two, with V^s and V^m for velocity and F^s and F^m for fees. The subscripts m and s indicate that Bitcoin is seen for the former as a medium of exchange and the latter as a speculative asset or store of value by investors. We drew this dichotomy from Keynesian theory by assuming that Bitcoin serves transactional and speculative purposes. Bitcoin attracts holders due to liquidity preference and expectations of substantial returns. When Bitcoin's expected returns and liquidity get lower than other assets', speculators will sell their bitcoins and vice-versa (V^s). Bitcoin's lower maturity and broader user base compared to fiat currencies and predictable supply suggest that increased adoption as a medium of exchange could boost its price (V^m). Transaction fees are less significant for speculators (F^s) as a cost than remuneration for miners guaranteeing Bitcoin's integrity since they prefer holding bitcoins rather than conducting frequent transactions. When they eventually exchange bitcoins, these transactions occur on exchange platforms unaffected by Bitcoin transaction fees. However, speculators typically transfer their bitcoins to private wallets for security, resulting in smaller transaction sizes and lower fees. On the other hand, transactional users (F^m) engage in frequent, low-value transactions, generating numerous small UTXOs across multiple addresses. These transactions involve various inputs and outputs, increasing transaction weight and fees. Transactional users are more sensitive to fees as a cost rather than an incentive for miners to maintain Blockchain security and sustainability. Lastly, the size of the tether economy, T, completes the subsequent equation since tether constitutes a gateway to trade Bitcoin and a hedge against a Bitcoin price decline (see further).

$$M^d = \frac{P * G * V^m}{V^s} * \frac{F^s * H}{F^m} * \frac{1}{T} \tag{2}$$

The equilibrium between the total supply of Bitcoin and the total demand for Bitcoin gives the following equilibrium price relationship:

$$P^b = \frac{P * G * V^m}{B * V^s} * \frac{F^s * H}{F^m} * \frac{1}{T} \tag{3}$$

When Bitcoin is seen entirely as a medium of exchange by all investors, V^s and F^s's impact becomes negligible while V^m exerts a negative impact on the Bitcoin price, transforming the equation (3) into (4).

$$P^b = \frac{P * G}{B * V^m} * \frac{H}{F^m} * \frac{1}{T} \tag{4}$$

[4]https://data.bitcoinity.org/markets/volume/5y?c=c&t=b

Here, it is implied that the Bitcoin price decreases with the velocity and the fees. If Bitcoin stops being a store of value, it becomes similar to a utility token that suffers from the velocity problem. In other words, the cryptoasset circulates rapidly between users as it provides no compelling reason for its holders to store it for more than the time necessary to proceed to the transaction and convert this cryptoasset with another cryptoasset or fiat currency. Even if the platform supporting it becomes widely used, this cryptoasset's price will not appreciate significantly since the underlying token mechanics were not structured to make this cryptoasset retain value over time.

Conversely, when it is regarded entirely as a speculative asset or store of value by all investors, V^m and F^m's effect disappears, turning the equation (3) into (5).

$$P^b = \frac{P * G}{B * V^s} * (F^s * H) * \frac{1}{T} \tag{5}$$

Suppose Bitcoin evolves as a fully-fledged store of value that is unusable as a means of exchange. In that case, it becomes comparable to non-fungible tokens (NFTs) that have a typically low-velocity level because the value of these tokens is not derived from their transactional usage but exclusively from their store of value and speculative aspect. A velocity surge indicates that investors sell several of their tokens promptly, generating a plunge in these tokens' prices. It implies that the Bitcoin price will fall with the velocity and rise with the fees.

Equations (4) and (5) describe extreme cases whereby investors see Bitcoin either as a medium of exchange or a speculative asset and store of value. In reality, the genuine relationship lies in between and is represented by equation (3). The effect of Bitcoin's velocity and fees on its price depends on the relative weight of each category of investors, their respective velocity levels for the former and their associated amount of fees for the latter. Suppose that the overall velocity and transaction fees are dominated by the velocity from and transaction fees paid by those seeing Bitcoin as a medium of exchange over those using it as a store of value. It implies the effect of V^m and F^m would be higher than that of V^s and F^s, resulting in V being positively and F negatively associated with the Bitcoin price and vice versa. This impact might evolve throughout the periods since the number and economic importance of investors from each category are not fixed, and investors' views may change over time.

In any case, the Bitcoin price goes up with the general price level of goods and services, the size of the Bitcoin economy and the hash rate and diminishes with the total volume of bitcoins in circulation and the size of the Tether economy independently of how Bitcoin is perceived.

It is worth mentioning that from the market equilibrium in equation (3), some variables, such as the Bitcoin price, P^b, the general price level of goods and services, P, the size of the Bitcoin economy, G, the bitcoin hash rate, H and the fees, F^s and F^m, adjust simultaneously provoking a possible endogeneity bias when one estimates the Bitcoin price econometrically. This violation of the exogeneity assumption makes the OLS estimation produce biased and inconsistent parameters, while hypothesis tests can be misleading. In order to address this problem, we shall employ the ARDL approach to cointegration (See further).

2.2 Testable hypotheses

Based on the hypotheses formed by Ciaian et al. (2016) and insights from previous empirical studies (Li and C. A. Wang 2017; Kristoufek 2015; Bouoiyour and Selmi 2014; Bouoiyour and

Selmi 2017; Panagiotidis et al. 2018; Baur and Hoang 2021; Wei 2018), we derived the testable hypotheses of Bitcoin price formation and incorporated them into the following equation.

$$p_t^b = f_{H1}(\overset{+}{g_t}, \overset{-}{b_t}, \overset{-}{v_t^s}, \overset{+}{v_t^m}, \overset{+}{f_t^s}, \overset{-}{f_t^m}, \overset{+}{h_t}, \overset{-}{t_t}) + f_{H2}(\overset{-}{p_t}, \overset{+-}{m_t}) + f_{H3}(\overset{+-}{a_t}, \overset{+-}{d}) \tag{6}$$

In equation (6), the Bitcoin price, p_t^b, is a function of internal factors, $f_{H1}(g_t, b_t, v_t^m, f_t^s, f_t^m, h_t, t_t)$, global macroeconomic and financial developments, $f_{H2}(p_t, m_t)$, and attractiveness factors for investors and users, $f_{H3}(a_t, d)$.

Hypothesis 1: Internal factors

Our first category, $f_{H1}(g_t, b_t, v_t^m, f_t^s, f_t^m, h_t, t_t)$, comprises all the factors interacting within the Bitcoin Blockchain and the cryptoasset ecosystem. These factors are drawn from equation (3) except for the general price level of goods and services, p_t, which is outside of the cryptoasset sphere

The size of the Bitcoin economy, g_t, is proxied by variables of demand accounting for the transactions (TRANS) and the number of addresses (ACT) as in Ciaian et al.'s inquiry (2016) and one liquidity measurement in centralized exchanges (SPREAD). TRANS expresses the median value, in US dollars, of bitcoins exchanged per transaction between distinct addresses. Utilizing the median value instead of the total sum of bitcoins traded in distinct addresses, as commonly used in the literature, reduces the influence of large transactions from major investors or whales. We anticipate a positive relationship between TRANS and the Bitcoin price, as a higher value of bitcoins traded for cryptocurrencies, goods, and services within the Bitcoin network indicates a broader and more appealing Bitcoin economy to investors and users. ACT represents the daily count of unique Bitcoin addresses, which provides insights into the number of participants in the Bitcoin network. More unique addresses imply greater network participation and liquidity, which, in turn, should positively impact the Bitcoin price. SPREAD is the bid-ask spread on cryptocurrency exchange platforms. It reflects the discrepancy between the highest price a buyer is willing to pay and the lowest price a seller is willing to accept for a bitcoin. A narrower Bitcoin spread signifies higher liquidity and lower hidden transaction costs for investors, making Bitcoin more attractive and potentially increasing its price. Thus, we expect a negative relationship between SPREAD and the Bitcoin price.

To proxy the total volume of bitcoins in circulation, b_t, we align with Polasik et al. (2015)'s approach by considering the daily emission of bitcoins (ISSUANCE) instead of the total number of bitcoins in circulation employed in other studies (Ciaian et al. 2016; Kristoufek 2015; Li and C. A. Wang 2017; Georgoula et al. 2015) to mitigate multicollinearity, while its effect on Bitcoin price remains essentially unchanged. Although this emission indirectly impacts investors by reducing the scarcity value of their bitcoins, it maintains blockchain performance and security, making the sign of ISSUANCE contingent on the balance between these forces. Moreover, given the public knowledge of Bitcoin's fixed supply and emission schedule, its influence on the Bitcoin price is likely minimal or statistically insignificant.

To gauge velocity (VELOCITY), we adopt the Token_Age_Consumed metric utilised by Matonis (2012) and Ciaian et al. (2016), which quantifies the movement of Bitcoin by considering the amount transferred and the time since its last transaction. While neoclassical and monetarist economists like Fisher (1911) and Friedman (1959) assume stable and predictable fiat currency velocity, Keynesian theory (1936) suggests that velocity varies with money supply and interest rates. From our Bitcoin exchange equation, we assumed that Bitcoin is employed for transactional and speculative intents, mirroring fiat currencies' velocity in the Keynesian theory. Whether velocity positively or negatively affects Bitcoin price depends on its role for investors. If speculative use dominates ($v^s > v^m$), velocity may depress prices; if it is primarily a medium of exchange ($v^s < v^m$), velocity could enhance prices.

Bitcoin is a currency and a decentralized payment and data storage system, necessitating speed, scalability, decentralization, and security. We incorporated two mining-related variables to assess their impact on Bitcoin's price within its PoW consensus algorithm. The first variable, FEE, represents the total fees paid to miners in US dollars, essential to the Bitcoin Blockchain's sustainability and miner revenue (Kaskaloglu 2014; Easley et al. 2019), especially given the shrinking block reward every four years. Like velocity, FEE's impact on the Bitcoin price depends on the category of investors dominating Bitcoin transactions. If speculators are more fee-sensitive ($f^s > f^m$), Bitcoin prices benefit; otherwise, if transactional users are more impacted ($f^s < f^m$), fees can harm Bitcoin prices. The second variable, HASH, measures the Bitcoin network's processing power, representing miners' average costs and overall computing power dedicated to securing the Blockchain. While prior research (Kristoufek 2015; Li and C. A. Wang 2017) employed variables like mean difficulty, HASH proved superior in determining Bitcoin prices in our dataset due to the difficulty's adjustment lag to the hash rate. HASH influences Bitcoin prices through its dual role: increasing coin supply and enhancing Blockchain security. A higher hash rate puts more bitcoins into circulation, potentially causing inflation and lowering bitcoin value. However, it also enhances Blockchain security, which generally outweighs the former due to the system's adaptive difficulty target. A higher hash rate should drive Bitcoin prices upward (Bouoiyour and Selmi 2014; Georgoula et al. 2015; Kristoufek 2015).

To proxy the size of the tether economy, t_t, one employs a variable, TETHER, measuring the US dollar value of tethers traded between distinct addresses. Tether (USDT) is a stablecoin operating on its decentralized Blockchain and is issued by Tether Limited, which is closely linked to the Bitfinex exchange. Official statements released by Tether Limited[5] and outlined in the Tether Whitepaper[6] claim that each USDT is backed by a one-to-one reserve of traditional currencies, cash equivalents, other assets, and receivables from loans provided to third parties. This backing is designed to maintain USDT's value at parity with the US dollar, allowing holders to redeem them for dollars at any time. However, scepticism about these claims has arisen, most notably from Griffin and Shams[7], casting doubt on Tether's claims' veracity and questioning its role in the 2017 Bitcoin price surges. Tether is a stablecoin bridging the fiat financial system and the cryptocurrency market. Investors frequently use Tether to enter or exit the cryptocurrency space, seeking a relatively stable store of value amid the high volatility of other cryptocurrencies. Tether's role as a gateway has become particularly significant, especially after regulatory actions against cryptocurrency exchanges in China in September 2017. Additionally, Tether is considered a speculative

[5] https://tether.to/tether-issuance-primer/

[6] https://whitepaper.io/coin/tether

[7] Griffin and Shams (2020) stated that the 2017 Bitcoin price boom was driven by the supply of tethers mainly due to one entity on Bitfinex that used Tether to purchase large amounts of bitcoins when its price was falling and following the printing of tethers. They concluded that the link between Tether and Bitcoin is more likely driven by the Tether supply than the demand from investors, implying that the Bitcoin price was purposefully inflated to manipulate the market. Moreover, it suggests that the tethers were sometimes printed without being fully backed by dollars.

hedge against extreme price fluctuations in the broader cryptocurrency market. Among stablecoins, Tether has displayed characteristics of a safe haven asset, especially during severe adverse movements in Bitcoin prices (Baur and Hoang 2021). Fluctuations in the Tether premium have been identified as potential indicators of market tension within the cryptoasset space, reflecting the growing adoption of Tether as a safe haven asset during times of heightened cryptoasset market uncertainty (M. Shen 2021; Cavicchioli 2021). Overall, Tether's value is expected to rise when concerns of a Bitcoin price drop loom, potentially leading to a Bitcoin price decline. Conversely, a decreasing Tether's value might signal investor confidence in a future Bitcoin price increase, prompting them to convert USDT holdings into bitcoins.

Hypothesis 2: Global macroeconomic and financial developments

Our second hypothesis, $f_{H2}(p_t, m_t)$, encompasses five macro-financial variables capturing the dynamics of the global economy, one of which proxies p_t, while the other four embody m_t.

The general price level of goods and services, p_t, is regarded as a global macroeconomic and financial development variable rather than an internal factor despite being part of the equation of Bitcoin exchange. Unlike fiat currencies, Bitcoin is not widely recognised as a unit of account on a national level due to its lack of legal recognition and limited use in everyday transactions of goods and services. Thus, Bitcoin's influence on the price level of goods and services within developed or developing countries with established and stable national currencies is typically negligible. While Bitcoin may face challenges in becoming a national unit of account and replacing fiat currencies, it has the potential to serve as an international unit of account for multinational corporations engaged in frequent international trade. Bitcoin offers advantages over fiat currencies in global trade, particularly in mitigating exchange rate risks from fluctuations in national currencies. Therefore, we use an exchange rate indicator, USDEUR, representing the exchange rate between the US dollar and the Euro (USD/EUR) to account for the general price level of goods and services. The US dollar is uniquely positioned as the world's predominant global currency, backed by the most prominent economy. It is the most traded currency in the foreign exchange market, with nearly 40% of the world's debt denominated in dollars, and it constitutes over 60% of all central bank foreign exchange reserves as of 2019[8]. These factors favour the dollar's stability, making transactions in dollars easier and less risky. Initially, the yuan was a significant currency in Bitcoin trading volume from 2014 to early 2017. However, it lost its dominance in the Bitcoin trading volume in February 2017, ceding its position to the US dollar. As a result, the US dollar to Chinese renminbi exchange rate, used in previous studies to determine the Bitcoin price (Kristoufek 2015; Van Wijk 2013), has become less relevant. Furthermore, the yuan's depreciation contributed to the increase in Bitcoin prices from 2014 to 2016, while the dollar's decline may have played a crucial role in the 2017 Bitcoin boom. Despite the Federal Reserve's increase in the federal fund rate, the dollar depreciated due to factors such as inflationary pressure, challenging trade negotiations with China, and substantial deficit spending (Haber 2018; Monge-Naranjo 2018). Another contributing factor to the dollar's depreciation and Bitcoin's surge may have been a declining confidence in the American government and institutions (Rolph 2017). During this period of dollar depreciation, investors sought alternative assets to preserve their relative purchasing power, including traditional safe-haven assets like Gold and Silver and more unconventional options such as Bitcoin. Hence,

[8] https://data.imf.org/?sk=E6A5F467-C14B-4AA8-9F6D-5A09EC4E62A4

we concur with Ciaian et al.'s study (2016) by hypothesising that USDEUR is negatively linked with Bitcoin since a depreciation or a devaluation of the US dollar could trigger a flow of funds from dollars to Bitcoin, intensifying the dollar's depreciation and swelling the Bitcoin price.

The impact of global macroeconomic and financial development variables, m_t, on the Bitcoin price is assumed to be heterogeneous, operating through various channels. In particular, we consider the impact of global stock markets, characterized by their indexes and volatilities, which can exert divergent effects on Bitcoin prices due to the interplay of wealth and substitution effects. When the wealth effect prevails, these variables positively impact the Bitcoin price while negatively influencing the latter when the substitution effect dominates. For instance, the Dow Jones Industrial Average (DJIA), an index representing 30 major American companies, is often used as a proxy for the overall economic situation in the United States (Ciaian et al. 2016; Van Wijk 2013). However, the omnipresent influence of the big tech companies known as the FAAMG (Facebook et al.) on the index may drive it in the opposite direction of the American economy. Still, these technological companies, born from the dot-com bubble, experienced the same challenging commencement as Bitcoin, having to survive the implosion of the dot-com bubble in 2001 before becoming widely accepted and essential for the world. As such, they are still more likely to follow the sustained trajectory of Bitcoin and invest in it than any other company. Despite the engagement of numerous large American firms and financial institutions with the Bitcoin blockchain (Castillo 2018), this level of adoption is less widespread among smaller enterprises and the general population. Overall, we foresee a positive influence of the DOW JONES on the price of Bitcoin. However, the relationship with the Shanghai Stock Exchange Composite Index (SSE), tracking the performance of all A-shares and B-shares listed on the Shanghai Stock Exchange, is more complex. While many large Chinese corporations are involved in Blockchain technology (Castillo 2018), Chinese investors, both small enterprises and individuals, have shown a greater propensity to use and invest in Bitcoin due to various factors peculiar to China. The SSE's impact on Bitcoin prices may be influenced by two opposing factors: its connection to China's macroeconomic conditions and heavy dependence on its major public companies on one side and its role as an alternative investment for Chinese investors disposing of a small pool of investments and looking to hedge their equity portfolios on the other. Nevertheless, the literature suggests a positive impact (Bouoiyour and Selmi 2014; Panagiotidis et al. 2018) on the Bitcoin price, making the first factor the dominant influence. To account for market uncertainty's impact on Bitcoin price dynamics, we incorporate the CBOE DJIA Volatility Index (CBOEDJIA), reflecting expected volatility for options on the DJIA. This index is employed by market participants for risk management, with higher VIX values indicating a more considerable market uncertainty. Thomas (2015) noted that a rise of VIX, by and large, leads to "flights to safety". Consequently, one should anticipate a positive effect of CBOEDJIA on the price of Bitcoin. Given Bitcoin's recognized safe-haven characteristics during times of global uncertainty (Bouri, Gupta, Tiwari, et al. 2017), we anticipate that both DJIA and CBOEDJIA will positively affect Bitcoin prices. Following Kristoufek (2015), we consider the Gold Fixing Price in the London Bullion Market, GLD, denominated in US dollars. Given that Bitcoin shares specific characteristics with gold, notably its limited supply, it is reasonable to assume that Bitcoin may also possess safe-haven qualities. Dyhrberg (2016) has already discovered that Bitcoin's ability to act as a hedge is similar to that of gold. She justified this similarity by highlighting their shared traits, including limited and scarce supplies, lack of nationality, and generation through a "mining" process. Consequently, we expect a positive effect of GLD on the Bitcoin price. Specifically, during times of uncertainty that drive investors toward gold (GLD), we expect a similar movement toward Bitcoin, resulting in simultaneous price increases.

Hypothesis 3: Attractiveness factors for investors and users

Our last premise, $f_{H3}(a_t, d)$, embodies the attractiveness factors for investors and users, a_t, and the dummy variables, d, capturing critical events.

To grasp the effect of attractiveness factors, a_t, we drew data from three distinct social media platforms. Social media content varies due to their unique features, user behaviours, and contribution frequencies, which can differentially affect the Bitcoin price (Mai et al. 2015). Inspired by the studies of Kristoufek (2013; 2015) and Panagiotidis et al. (2018), we introduced two variables: BGT and WIKI. The former represents the global number of Google searches for the term "Bitcoin." Google is used by individuals with diverse motivations and backgrounds. A fundamental limitation is that all searches related to Bitcoin are treated equally and cannot be distinguished from one another. Nevertheless, BGT provides valuable insights into the relationship between Bitcoin's price and general interest in the cryptocurrency. The latter is based on the number of views of the Wikipedia page dedicated to Bitcoin. Wikipedia serves as a primary source of basic information on Bitcoin, primarily accessed by newcomers seeking to understand its fundamentals (Ciaian et al. 2016). These newcomers often own minimal or no Bitcoin holdings and typically have less influence than scholars, developers, miners, or regulators who rely on more precise, advanced, and reputable sources of information. Following Garcia et al. (2014), Mai et al. (2015), and Shen et al. (2019), we included the variable TWTS, representing the sum of all tweets mentioning Bitcoin worldwide. Twitter is used by more informed but less numerous investors compared to the broader user base of Google. It is a media platform favoured by well-integrated participants of the crypto sphere (D. Shen et al. 2019). While Google users may be more reactive to news outside the crypto sphere, Twitter users are often more attuned to events within the Bitcoin community. Twitter users may also be influenced by hype generated by influential figures with large followings, who sometimes use their positions to manipulate the Bitcoin price (Shevlin 2021a). Based on previous studies (Burnie and Yilmaz 2019; Jakub 2015) and our knowledge, we expect these factors to have positively impacted the Bitcoin price during boom periods when positive sentiment dominated. Conversely, during crash periods when negative sentiment predominated, these factors might have had a negative effect. In consolidation periods, when positive and negative sentiments are roughly balanced, the relative impact of these sentiments will determine the sign of their coefficients.

Fundraising efforts, although not directly associated with social media platforms, are also considered attractiveness factors. The variable FUNDRAISING measures the cumulative funds raised by crypto projects through various methods such as Initial Coin Offerings (ICOs), Security Token Offerings (STOs), Initial Exchange Offerings (IEOs), private token sales, and other, albeit less prevalent, traditional methods, encompassing all funding rounds. During the ICO boom, which peaked in 2017, numerous high-profile projects raised substantial sums, predominantly in bitcoins and ethers, indicating a robust market appetite for new crypto ventures. ICOs allowed projects to issue tokens directly to investors in exchange for cryptoassets (mostly bitcoins), linking fundraising efforts and Bitcoin demand (Fisch 2019; Gan et al. 2021). STOs and IEOs emerged later in 2018 as more regulated and structured alternatives to ICOs. STOs comply with securities regulations and offer higher investor protection, often accepting both fiat currencies and cryptoassets. This broadens their appeal but can dilute the direct impact on Bitcoin prices. IEOs, conducted on cryptocurrency exchanges, typically require participants to hold cryptoassets like Bitcoin to purchase new tokens, maintaining a more direct influence on Bitcoin demand similar to ICOs. Private token sales typically involve projects selling tokens to a select group of private investors in exchange for fiat currencies and, more rarely, bitcoins before opening up to the broader public through an ICO. Fundraising efforts such as ICOs, STOs, and IEOs signal market confidence, innovation, and the potential for significant returns, attracting more investors and increasing demand for Bitcoin. This increased demand stems from the necessity of holding or using Bitcoin to participate in these fundraising events, linking it to the attractiveness of Bitcoin as an investment vehicle. Consequently, the funds raised by crypto projects should drive the Bitcoin price upward.

Concerning the events, d, we hypothesise that the adoption and hacking events positively and negatively affected the Bitcoin price, respectively. In contrast, the tax, regulatory and internal events could have had a positive or a negative impact.

2.3 Data

To build our dependent variable, p_t^b, we obtained Bitcoin price data in US dollars from Coinmetrics and referred to as PRICE. Table A1 presents a descriptive analysis of the six periods from the Bitcoin price used in our study, followed by a brief discussion of the results. All internal factors were also drawn from Coinmetrics apart from VELOCITY and SPREAD. The former originates from Santiment, while the latter was calculated based on the bid-ask spread in percentage from the three cryptocurrency exchange platforms with the highest Bitcoin trading volume at the time[9]: Coinbase, Bitfinex, and Bitstamp. We employed principal component analysis to extract the first principal component as a representative measure of Bitcoin's bid-ask spread, thereby abstracting from the nuances of individual exchange platforms. The macro-financial variables were extracted from the Federal Reserve Bank of St. Louis Database, except for SSE, which was gathered from Yahoo Finance. BGT is an adjusted value corresponding to the global number of Google searches for the term "BITCOIN" from Google Trends. WIKI and TWTS were retrieved from Wikishark and Bitinfocharts, respectively. FUNDRAISING measures the cumulative funds raised by crypto projects, based on data from CryptoRank. The definitions and sources of all these variables are summarised in Table A2.

Supplementary dummy variables, d, associated with events of significant impact on the Bitcoin price were introduced to mitigate the instability from the structural breaks found in Subsection 3.4. We recorded two tax events (TAXBILLS, TAXPAID), three hacking events (MEWHACK, COINRAILHACK, BITHUMBHACK), five regulatory events (CHINESEBAN, FEARSKBAN, FEARINDIABAN, BANKINGBAN, SECDELAY), two adoption events (BTCFUTURES, GEMINI), and three internal and technological events (FEARBTCSPLIT, CAPITULATION, BIP91). The location of all those dummy variables within the six separate periods of the Bitcoin History 2017-2018 timeline is illustrated in Figure A1. The data stretches from January 1st, 2017, to December 31st, 2018, and is divided into six periods due to structural changes in the evolution of the Bitcoin price seen in Subsection 3.3. The data is daily, and missing days due to closing days for the indices and velocity of stock markets, EU / U.S. Foreign Exchange Rate and the Gold Fixing Price were dealt with using linear interpolation. Each variable was log-transformed except for SPREAD.

[9]https://data.bitcoinity.org/markets/volume/5y?c=e&t=b

3 Econometric approach

This section provides a condensed review of the linear and nonlinear ARDL models before presenting the Bai-Perron multiple structural break tests and the unit root tests performed during this study. We let p_t^b denote the fixed closing price of Bitcoin as of the timestamp set by the block's mine on day t. We aim to model the Bitcoin price as a function of all significant variables previously listed across the multiple periods indicated by the multiple structural break tests.

3.1 ARDL model

Pesaran's linear autoregressive distributed lag (ARDL) model (1998) captures the long- and short-term impacts of explanatory variables on a dependent variable. It relies on the bounds-testing approach (M Hashem Pesaran, Shin, and R. J. Smith 2001), which unlike other cointegration techniques such as Johansen Cointegration (Johansen and Juselius 1990) or Engle-Granger tests (Engle and Granger 1987), enables the identification of cointegrated variables with different orders of integration before incorporating them in an error-correction model (ECM). The ARDL model is autoregressive because it includes lagged values of the dependent variable, p_t^b, to explain its current value. In this context, a single lagged value of p^b proved adequate for addressing autocorrelation and partial correlation issues. Additionally, it is distributed as it incorporates successive lags of our explanatory variables, denoted as X. The ARDL procedure can also be extended to detect cointegration among endogenous independent variables. As we suspected the possible presence of endogeneity between our variables, we performed an unrestricted ECM estimator, a method estimating the coefficients of the ECM without imposing restrictions on them. This technique yields accurate long-term parameter estimates and valid t-values, even in the presence of endogenous explanatory variables (Ang 2008; Inder 1993). When applying unrestricted ECM to mitigate endogeneity issues, determining the optimal and sufficient lag structure in ARDL models is essential (M Hashem Pesaran and R. P. Smith 1998). Besides, excessive lags can inflate coefficient estimate standard errors, a phenomenon referred to as overfitting, whereas too few lags may introduce estimation bias. Generally, five types of ARDL models can be considered. We selected a model with an unrestricted constant and no trend, which yielded the most satisfactory results.

In our framework, the specification of our linear ARDL$(1,\underbrace{n,\ldots,n}_{m})$ model is as follows

$$\Delta p_t^b = \alpha + \phi p_{t-1}^b + \sum_{j=1}^{m}\sum_{i=0}^{n-1} \psi_{j,i}\Delta X_{j,t-i} + \sum_{v=1}^{k}\eta_v D_v + \sum_{j=1}^{m}\rho_j X_{j,t-1} + u_t \tag{7}$$

Where: Δ is the first difference operator; t represents the time subscript; p^b is the dependent variable; α denotes an intercept; ϕ is the speed of adjustment parameter of the error correction term, p_{t-1}^b; X contains our (m) independent variables associated with their (n) lags; D constitutes our (k) dummy variables; ρ_j designates the long-run coefficients; $\psi_{j,i}$ and η_v are the short-term coefficients; and u is our random disturbance term. These coefficients can be combined to obtain the long-run multipliers[10]. $\beta_j := -\rho_j/\phi, \forall j \in [1, m]$.

[10] By gathering the terms in levels, one can use that definition of the multipliers to express the specification in the usual ECM form: $\Delta p_t^b = \alpha + \phi(p_{t-1}^b - \sum_{j=1}^{m} \rho_j X_{j,t-1}) + \sum_{j=1}^{m}\sum_{i=0}^{n-1} \psi_{j,i}\Delta X_{j,t-i} + \sum_{v=1}^{k}\eta_v D_v + u_t$

The bounds-testing approach (M Hashem Pesaran, Shin, and R. J. Smith 2001) is employed to examine the existence of a long-run (i.e., cointegration) relationship among series integrated of different orders, provided these orders remain below 2. It is built around two bound tests designed to assess cointegration in long-term relationships among variables integrated of order zero (I(0) for short) and one (I(1) for short). The first test, an F-test, examines the null hypothesis $H_0 : (\phi = \rho_1 = \rho_2 = \ldots = \rho_m = 0)$ against the alternative that rejects H_0. The rejection of the null indicates the existence of a long-run relationship. The test statistic is compared to two asymptotic critical values, representing cases with purely I(0) and purely I(1) variables. If the test statistic falls below the lower critical bound, the null is not rejected, suggesting the absence of cointegration. Conversely, if the test statistic exceeds the upper critical value, the null is rejected, implying probable cointegration. Further investigation into the cointegration rank is warranted when the test statistic lies between the lower and upper bounds. The second test is a t-test, assessing the hypothesis $H_0 : (\phi = 0)$ against $H_1 : (\phi < 0)$. Like the F-test, it has lower and upper bounds. If the test statistic is below the lower bound, the series is considered stationary, while exceeding the upper bound indicates a long-term relationship among variables. Results of these tests are presented in Table 1 and Table A13, where most models exhibit test statistics exceeding the upper bounds at the 1% significance level in both bounds tests, confirming the presence of long-run relationships in our ARDL and NARDL models.

Table 1: F-Bounds and t-Bounds Tests (NARDL models)

Estimated models	**F-Bounds Test**				**t-Bounds Test**			
	Signif. F-statistic	Signif. bounds	Lower I(0)	Upper I(1)	Signif. t-statistic	Signif. bounds	Lower I(0)	Upper I(1)
NARDL1	9.3459	1%	2.650	3.970	-6.3817	1%	-3.430	-5.540
NARDL2	8.6769	1%	2.960	4.100	-6.4132	1%	-3.430	-5.370
NARDL3	5.4217	1%	2.540	3.860	-5.9767	1%	-3.430	-5.680
NARDL4	5.0889	1%	3.150	4.430	-4.8107	5%	-2.860	-4.380
NARDL5	9.5328	1%	2.790	4.100	-5.9301	1%	-3.430	-5.370
NARDL6	8.3031	1%	2.540	3.860	-8.4947	1%	-3.430	-5.680

Notes: Signif. stands for level of significance, solely the lowest significance level satisfying the rejection of the null hypothesis of no long-run relationship is displayed

3.2 NARDL model

Linear ARDL models must be revised to capture the complexities of the relationship between variables in the context of nonlinearity and asymmetry. To account for asymmetries in the presence of variables that are stationary in level $I(0)$ and in first difference $I(1)$, the nonlinear autoregressive distributed lag (NARDL) model proposed by Shin et al. (2014) offers a valuable solution. The NARDL model extends the ARDL framework by introducing long- and short-run asymmetries through the decomposition of some explanatory variables, denoted as $\sum_{g=1}^{f} x_g \in \sum_{j=1}^{m} X_j$, into its positive ($x^+_{g,t}$) and negative ($x^-_{g,t}$) partial sums of increases and decreases, respectively. Mathematically, these partial sums are defined as follows:

$$
\begin{aligned}
x^+_{g,t} &= \sum_{t=1}^{T} \Delta x^+_{g,t} = \sum_{t=1}^{T} \max(\Delta x_{g,t}, 0), \\
x^-_{g,t} &= \sum_{t=1}^{T} \Delta x^-_{g,t} = \sum_{t=1}^{T} \min(\Delta x_{g,t}, 0), \\
&\sum_{g=1}^{h} x_g \in \sum_{j=1}^{m} X_j, \forall g \in [1, m]
\end{aligned}
\tag{8}
$$

By incorporating these partial sums into the ARDL equation (Equation (7)), we obtain the NARDL equation as follows:

$$
\begin{aligned}
\Delta p^b_t = \alpha + \phi p^b_{t-1} &+ \sum_{j=1, j\neq g}^{m} \sum_{i=0}^{n-1} \psi_{j,i} \Delta X_{j,t-i} + \sum_{g=1}^{f} \sum_{i=0}^{n-1} \psi^+_{g,i} \Delta x^+_{g,t-i} + \sum_{g=1}^{f} \sum_{i=0}^{n-1} \psi^-_{g,i} \Delta x^-_{g,t-i} \\
&+ \sum_{v=1}^{k} \eta_v D_v + \sum_{j=1, j\neq g}^{m} \rho_j X_{j,t-1} + \sum_{g=1}^{f} \rho^+_g x^+_{g,t-1} + \sum_{g=1}^{f} \rho^-_g x^-_{g,t-1} + u_t
\end{aligned}
\tag{9}
$$

Where the superscripts (+) and (-) in equations (8) and (9) represent the positive and the negative partial sum decompositions, respectively. To obtain the real positive θ^+_g and negative θ^-_g long-term coefficients, the following calculations are performed: $\theta^+_g = -\rho^+_g/\phi$ and $\theta^-_g = -\rho^-_g/\phi$. Notice that the equation integrates multiple asymmetric regressors designated by the subscript (g) in x_g with long-term, short-term or both long- and short-term asymmetries.

When asymmetry is detected, the response of the dependent variable to positive and negative shocks from one asymmetric predictor is captured by the positive and negative cumulative dynamic multipliers ($w^+_{g,h}$ and $w^-_{g,h}$, respectively).

$$
w^+_{g,h} = \sum_{j=1}^{h} \frac{\delta p_{g,t+j}}{\delta x^+_{g,t}}, \quad w^-_{g,h} = \sum_{j=1}^{h} \frac{\delta p_{g,t+j}}{\delta x^-_{g,t}}, \quad h = 0, 1, 2 \ldots \tag{10}
$$

Where $h \to \infty$, $w^+_{g,h} \to \theta^+_g$, and $w^-_{g,h} \to \theta^-_g$ by construction. These multipliers provide insights into the dynamic adjustment of the response variable from its initial equilibrium to a new equilibrium following a shock from one asymmetric regressor.

Within the framework of NARDL models, the bounds testing is still valid to test the presence of a long-run relationship. More specifically, the null hypothesis becomes $H_0 : (\phi = \rho_1 = \rho_2 = \ldots = \rho_m = \rho^+_1 = \rho^-_1 = \rho^+_2 = \rho^-_2 = \ldots = \rho^+_f = \rho^-_f = 0)$

By design, the NARDL specification accommodates three particular cases: (i) an asymmetric long-term relationship through the rejection of $H_0 : (\theta^+_g = \theta^-_g)$; (ii) an asymmetric short-term relationship via the rejection of $H_0 : (\psi^+_{g,i} = \psi^-_{g,i})$; and (iii) the joint presence of long- and short-run asymmetries with the rejection of previous null hypotheses. These three specificities are tested using standard Wald tests.

3.3 Bai-Perron multiple structural breaks tests

Given Bitcoin prices' rapid and substantial reactions to publicly disclosed information (Jakub 2015), it is reasonable to anticipate that the relationships between the variables in our models will evolve in response to external factors. Structural models are designed to account for these changes by incorporating sudden and enduring shifts in model parameters. Ignoring these structural changes can result in inaccurate forecasts, flawed economic relationship inferences, and the unreliability of the model. We conducted Bai-Perron multiple breakpoint tests and followed Bai and Perron's strategy (Bai and Perron 2003) to identify potential multiple and unidentified structural breaks within our time series data. We complemented the results from these tests with findings from global information criteria, such as the Bayesian Information Criterion (BIC) introduced by Yao (1988), and the modified Schwarz criterion (LWZ) proposed by Liu et al. (1997).

The outcomes of the Bai-Perron multiple structural breaks tests are summarized as follows: The initial sequential procedure, presented in the first row of Table A7, suggests an absence of breaks in the time series. Subsequently, we proceeded with the UD and WD max tests that indicate at least five breakpoints (Table A8). This finding prompted us to perform a sequential examination, comparing l+1 breakpoints against l breakpoints, and consider global information criteria for determining the number of breakpoints. The results presented in Table A7 reveal two breakpoints, with the null hypotheses of zero and one breakpoint being rejected in favour of the alternatives of one and two breakpoints, respectively, while the test comparing three versus two breakpoints did not yield a rejection. Additionally, the Schwarz and LWZ values presented in Table A9 are at their lowest when the number of breakpoints is set at five. Given the suspicion of multiple breaks in our time series data, we opted to rely on the results from global information criteria rather than the sequential examination comparing l+1 against l breakpoints. Consequently, we partitioned our time series into six distinct periods (Figure 1), each corresponding to one of the five break dates estimated by the global information criteria: {4/21/2017, 8/08/2017, 11/25/2017, 3/14/2018, 9/14/2018}.

3.4 Unit root tests

In assessing the stationarity of our variables, we conducted four unit-root tests, namely the augmented Dickey-Fuller (ADF) test, Phillips-Perron (PP) test, Perron unit root test with a breakpoint, and Zivot-Andrews (ZA) unit root test. Nevertheless, the ADF and PP unit root tests suffer from a power reduction due to omitting exogenous and endogenous shocks that may lead to biased test statistics towards not rejecting a false unit root null hypothesis (Perron 1989). To address this, we employed the Perron unit root test with a breakpoint and the ZA test (Zivot and Andrews 2002), both capable of identifying structural breaks in intercept, trend, or both. The former assesses exogenous shocks, while the latter scrutinizes endogenous shocks. These tests mitigate bias in test results and pinpoint the periods when structural breaks occurred (Perron 1989).

The classical unit root tests[11] (ADF and PP) and structural break tests (Table 2) indicate that no variable is integrated beyond order one, as the unit root hypothesis is rejected for all series in first difference.

Having ascertained that our variables comprise a mix of I(0) and I(1) components, we can now construct our ARDL and NARDL models. It involves the combination of various variables into

[11] The methodology and results of these unit root tests are available upon request

Table 2: Order of integration

	The regulatory consolidation		The technological boom		The irresistible boom		The bubble burst		The eventful consolidation		The hash war crash	
Variable	**PPU**	**ZA**	**PPU**	**ZA**	**PPU**	**ZA**	**PPU**	**ZA**	**PPU**	**ZA**	**PPU**	**ZA**
PRICE	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)
TRANS	I(0)	I(0)	I(0)	I(0)	–	–	I(1)	I(0)	I(1)	I(0)	I(0)	I(0)
ACT	I(0)	I(0)	–	–	I(0)	I(0)	–	–	I(0)	I(0)	I(0)	I(0)
SPREAD	I(0)	I(0)	I(0)	I(0)	I(1)	I(0)	I(0)	I(0)	I(0)	I(0)	I(1)	I(0)
ISSUANCE	–	–	–	–	–	–	–	–	I(0)	I(0)	–	–
VELOCITY	–	–	I(1)	I(1)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)
FEE	I(1)	I(1)	I(1)	I(1)	I(1)	I(0)	–	–	I(1)	I(1)	I(0)	I(0)
HASH	–	–	I(0)	I(0)	–	–	–	–	–	–	I(1)	I(1)
TETHER	–	–	I(0)	I(0)	I(1)	I(1)	I(1)	I(0)	–	–	I(0)	I(0)
DJIA	–	–	–	–	–	–	I(0)	I(0)	I(1)	I(1)	–	–
SSE	–	–	–	–	I(1)	I(1)	–	–	–	–	I(1)	I(1)
CBOEDJIA	I(1)	I(0)	–	–	I(1)	I(1)	–	–	–	–	–	–
GLD	–	–	I(1)	I(1)	–	–	–	–	–	–	I(1)	I(1)
USDEUR	I(1)	I(1)	–	–	–	–	–	–	–	–	–	–
BGT	I(1)	I(1)	–	–	–	–	–	–	I(0)	I(0)	I(1)	I(0)
TWTS	I(0)	I(0)	–	–	–	–	–	–	–	–	–	–
WIKI	–	–	I(1)	I(0)	I(0)	I(0)	I(0)	I(0)	–	–	–	–
FUNDRAISING	–	–	–	–	I(0)	I(0)	–	–	–	–	–	–

"Notes: The results from the Perron Unit Root Test with Break (PPU) in and the Zivot-Andrews unit root test (ZA) from Table A3 to Table A6, allow us to determine whether a variable is integrated of order zero (I(0)), one (I(1)), or higher based on the presence of a constant, a trend, or both in the time series of the variable. The symbol '–' refers to the absence of a variable in the reference period."

diverse models, the determination of appropriate lag lengths, and the subsequent assessment of long-term relationships using bound testing.

3.5 Diagnostic Tests and Model Evaluation

We performed diagnostic tests on our models, including assessments for normality, serial correlation, heteroskedasticity, autoregressive conditional heteroskedasticity, and instability, with results presented in Table A15. The Jarque-Bera normality test (J-B) indicates that our models' errors follow a normal distribution, as we fail to reject the null hypothesis of error normality at a 10% significance level for all models. Furthermore, serial correlation is absent, as affirmed by the Breusch-Godfrey serial correlation test, which rejects the null hypothesis at a 10% significance level for all models. Heteroskedasticity is absent in our models, with the Breusch-Pagan and White heteroskedasticity tests rejecting the null hypothesis at a 10% significance level. The ARCH heteroskedasticity test found no ARCH effect at a 5% significance level in our NARDL models. We conducted the Ramsey RESET test to evaluate model stability and examined CUSUM and CUSUM-SQ plots. The Ramsey RESET test results indicate that our models display stability at a 10% significance level, except for ARDL1, NARDL5, and NARDL6, which exhibited stability at a 5% significance level. We followed the approach proposed by H. Pesaran and B. Pesaran (Mohammad Hashem Pesaran and B. Pesaran 1997) for testing the stability of long-run coefficients using CUSUM and CUSUM-SQ tests. None of our models exhibited CUSUM and CUSUM-SQ statistics exceeding critical boundaries, affirming the stability of their coefficients. Additionally, we scrutinized potential multicollinearity among our independent variables via correlation coefficients and the Variance Inflation Factor (VIF). Our aim was to gauge the extent of multicollinearity in our models. Typically, multicollinearity arises when correlated independent variables are included in the same model. Variables displaying high multicollinearity (VIF $>$ 10) and strong correlations (r $>$ 0.7) with other explanatory variables can introduce bias into coefficient estimates and inflate standard errors, leading to erroneous inferences and inappropriate policy recommendations. Given that our NARDL models incorporate positive and negative partial sum decompositions of asymmetric variables, which are naturally highly correlated, it was crucial to address this issue adequately. To mitigate this concern, we transformed the asymmetric variables back to their original symmetric form before calculating their VIFs. The VIFs for the ARDL and NARDL models are reported in Table A16 and Table A17. Most VIFs in our models fall below five, with a few ranging between five and ten, indicating moderate multicollinearity, generally considered acceptable. Moreover, the correlation matrices in Table A18 reveal moderate correlations among the variables, suggesting no significant multicollinearity issues.

4 Results and discussions

Following the chronological subdivisions, we estimated both linear and nonlinear models for each period: ARDL1-NARDL1 for regulatory consolidation, ARDL2-NARDL2 for technological boom, ARDL3-NARDL3 for irresistible boom, ARDL4-NARDL4 for bubble burst, ARDL5-NARDL5 for eventful consolidation, and ARDL6-NARDL6 for hash war crash. NARDL models extend their linear counterparts, incorporating variables that attain significance under a nonlinear framework while discarding insignificant ones. This strategic adjustment aims to prevent overfitting and multicollinearity while unveiling nonlinear interactions. Our ARDL and NARDL model compositions are detailed in Table A10. It should be noted that in order to select the final ARDL specification, we adopted the general-to-specific approach. The preferred specification is chosen by imposing a maximum lag order on each first-differenced variable based on the Likelihood Ratio (LR), employing Akaike's Information Criterion (AIC) to select the optimum lags and dropping all insignificant regressors. Results of lag selections for our NARDL (ARDL) models are presented in Table 3 (Table A13), providing the optimal maximum lag order for all variables.

Table 3: Max lag order selection (NARDL models)

	0	1	2	3	4
NARDL1	NA	1456.915	135.327	100.555	104.110*
NARDL2	NA	920.189	85.048	78.268*	52.491
NARDL3	NA	1790.269	220.6660*	127.8386	123.2771
NARDL4	NA	1541.581	109.574*	68.170	80.921
NARDL5	NA	2656.710	186.846	127.238	152.895*
NARDL6	NA	1717.790	183.805*	141.991	146.318

*Notes: * indicates lag order selected by the sequential modified Likelihood Ratio (LR) test statistic*

Diagnostic tests were performed to check eventual problems of non-normality, serial correlation, heteroskedasticity, autoregressive conditional heteroskedasticity, instability and multicollinearity. The test results indicate that the models are correctly specified[12]. From the Wald statistics reported in Table 4, we notice that the null hypothesis of a fully symmetric ARDL model is rejected for all periods at a 1 or 5% significance level (except for the fifth period, which is mildly rejected at a 10% significance level).

It implies that the asymmetric relationships between the Bitcoin price and its determinants are unstable and more critical during specific periods. The long-term and short-term results of NARDL (ARDL) models are reported in Table 5 (Table A11) and Table 6 (Table A12), respectively.

Hypothesis 1: Internal factors

The first significant observation from the models (Table 5, Table 6) is that the supply side of Bitcoin (ISSUANCE) exhibited weaker repercussions on its price compared to the demand side (TRANS, ACT, SPREAD). ISSUANCE's only significant impact occurred during the eventful consolidation, when it positively influenced Bitcoin prices in both the short and long term, suggesting that improvements in the performance and security of the Bitcoin Blockchain outweighed the indirect costs to Bitcoin owners from new Bitcoin issuance. The median value of bitcoins transferred across the Blockchain (TRANS) positively influenced Bitcoin prices in the long term during all studied periods except the irresistible boom. Its short-term influence appeared negligible, as indicated by insignificant coefficients in all linear models. However, incorporating asymmetries revealed a positive short-term impact of TRANS during the irresistible boom and crash periods. Specifically, a

[12] The outcomes and conclusions of these diagnostic tests are available upon request

Table 4: Wald tests for long-run and short-run asymmetry

	Long-run asymmetry (W_{LR})				Short-run asymmetry (W_{SR})				
Variable	NARDL1	NARDL2	NARDL3	NARDL6	NARDL1	NARDL3	NARDL4	NARDL5	NARDL6
SPREAD	11.9822***	–	–	–	–	–	–	–	–
	[0.000]	–	–	–	–	–	–	–	–
USDEUR	11.6454***	–	–	–	–	–	–	–	–
	[0.001]	–	–	–	–	–	–	–	–
TWTS	–	–	–	–	5.1599**	–	–	–	–
	–	–	–	–	[0.026]	–	–	–	–
FEE	–	18.546***	11.696***	–	–	6.741**	–	3.161*	8.872***
	–	[0.000]	[0.000]	–	–	[0.011]	–	[0.077]	[0.000]
HASH	–	11.395***	–	20.816***	–	–	–	–	16.549***
	–	[0.000]	–	[0.000]	–	–	–	–	[0.000]
VELOCITY	–	–	11.029***	4.458**	–	6.583**	4.969**	–	–
	–	–	[0.000]	[0.038]	–	[0.011]	[0.03]	–	–
TRANS	–	–	–	–	–	–	5.611**	–	7.462***
	–	–	–	–	–	–	[0.02]	–	[0.000]
BGT	–	–	–	21.124***	–	–	–	–	–
	–	–	–	[0.000]	–	–	–	–	–

*Notes: This table reports the Wald F-statistics of the long- and short-run symmetry tests for the effect of each asymmetric variable on the bitcoin price from each NARDL model. W_{LR} denotes the Wald statistic for the long-run symmetry, which tests the null hypothesis of each explanatory variable in Eq. (8). W_{SR} corresponds to the Wald statistic for the short-run asymmetry, which tests the null hypothesis that for each explanatory variable in Eq. (8). The numbers in brackets are the associated p-values. *, ** and *** indicate a rejection of the null hypothesis of symmetry at the 10%, 5% and 1% levels, respectively.*

1% rise in TRANS led to a 0.1666% and a 0.1587% short-term increase in Bitcoin prices during the bubble burst and hash war crash, respectively. This asymmetric relationship indicates that, in contrast to increasing transacted Bitcoin values, decreases in transacted Bitcoin values did not affect short-term Bitcoin prices during crash periods. The dynamic multipliers of every asymmetric variable starting with this one and their interpretation can be examined in Appendix B. The number of unique Bitcoin addresses (ACT) positively impacted Bitcoin prices in the long run during the irresistible boom and eventful consolidation. The negative long-term impact during the hash war crash became irrelevant once asymmetries were included. In the short run, ACT negatively impacted Bitcoin prices during consolidation periods but had a positive effect during the irresistible boom. Overall, the network effect of unique addresses was limited to specific periods with beneficial long-term impacts on Bitcoin prices and some negative short-term impacts, likely due to massive short-term sell-offs from regulatory crackdowns and large-scale security hacks. The final proxy for the size of the Bitcoin economy, SPREAD, had a consistently negative and significant long-term impact on Bitcoin prices across all periods except the boom periods. The lack of depth in the Bitcoin market (Smales 2019) explains liquidity's strong influence on prices. In the short run, the current value in the first difference of SPREAD negatively influenced prices across all periods except for the hash war crash in the nonlinear case and the eventful consolidation when it had no significant impact. The first lagged value in the first difference had a positive and significant impact during the irresistible boom, which exceeded the influence of the current value. Additionally, SPREAD showed an asymmetric impact during regulatory consolidation, where a one-unit increase in SPREAD would have caused a 0.0352% long-term decrease in Bitcoin prices.

Table 5: Long-run effects on Bitcoin price (NARDL models)

	NARDL1	NARDL2	NARDL3	NARDL4	NARDL5	NARDL6
TRANS	0.0905***	0.1143**	–	0.3376***	0.8001***	0.1773***
ACT	0.0754	–	0.3758***	–	0.7217***	–
SPREAD	–	-0.0020	-0.0157	-0.1181**	-0.1928***	-0.0632***
SPREAD_P	-0.0352***	–	–	–	–	–
SPREAD_N	-0.0087	–	–	–	–	–
ISSUANCE	–	–	–	–	0.5897***	–
VELOCITY	–	–	–	0.2666	0.2471***	–
VELOCITY_P	–	–	-0.0839	–	–	-0.0497***
VELOCITY_N	–	–	-0.1554**	–	–	-0.0213
FEE	0.1764***	–	–	–	-0.0683	0.0934***
FEE_P	–	0.5167**	0.0640**	–	–	–
FEE_N	–	0.3038***	0.1353***	–	–	–
HASH_P	–	0.5877***	–	–	–	0.3103***
HASH_N	–	0.8468***	–	–	–	-0.0376
TETHER	–	-0.1031***	-0.0500	-0.1936***	–	–
DJIA	–	–	–	0.0741	-1.5952**	–
SSE	–	–	-1.7623*	–	–	0.0453
CBOEDJIA	0.3832***	–	-0.2590*	–	–	–
GLD	–	-0.8206	–	–	–	–
USDEUR	–	–	–	–	–	–
USDEUR_P	2.0719	–	–	–	–	–
USDEUR_N	-6.1250***	–	–	–	–	–
BGT	–	–	–	–	-0.1028*	–
BGT_P	–	–	–	–	–	-0.2068***
BGT_N	–	–	–	–	–	0.0533
TWTS	-0.2031***	–	–	–	–	–
WIKI	–	–	–	0.1006	–	–
FUNDRAISING	–	–	1.1682**	–	–	–

*Notes: (1) Dependent variable: Bitcoin price. (2) *** significant at 1% level, ** significant at 5% level, and * significant at 10% level. (3) "–" designates the absence of a variable in the respective model or its non-significance.*

Table 6: Short-run effects on Bitcoin price (NARDL models)

	NARDL1	NARDL2	NARDL3	NARDL4	NARDL5	NARDL6
D(TRANS)	–	0.0736***	–	–	–	–
D(TRANS(-1))	–	0.0556***	–	–	–	–
D(TRANS(-2))	–	0.0332**	–	–	–	–
D(TRANS_P)	–	–	–	0.1666***	–	0.1587***
D(ACT)	–	–	0.0779***	–	–	–
D(ACT(-1))	0.0292	–	–	–	-0.1710***	–
D(ACT(-2))	-0.0352	–	–	–	-0.1106***	–
D(ACT(-3))	-0.0770***	–	–	–	-0.0830***	–
D(SPREAD)	-0.0271***	-0.0189***	-0.0221***	-0.0473***	–	-0.0066
D(SPREAD(-1))	-0.0043**	–	0.0282***	–	–	–
D(SPREAD(-2))	0.0035	–	–	–	–	–
D(SPREAD(-3))	-0.0074***	–	–	–	–	–
D(ISSUANCE)	–	–	–	–	0.0477**	–
D(ISSUANCE(-2))	–	–	–	–	0.0473**	–
D(VELOCITY(-1))	–	–	–	–	-0.0412***	–
D(VELOCITY(-2))	–	–	–	–	-0.0238***	–
D(VELOCITY_P)	–	–	0.0256*	-0.0402*	–	–
D(VELOCITY_N)	–	–	-0.0705***	0.0843***	–	–
D(FEE(-1))	–	-0.0545***	–	–	–	–
D(FEE_P)	–	–	-0.0170	–	0.0302***	0.0655***
D(FEE_P(-1))	–	–	0.0634***	–	–	–
D(FEE_N)	–	–	0.0215*	–	–	–
D(FEE_N(-1))	–	–	-0.0618***	–	–	-0.0709***
D(HASH)	–	0.1155***	–	–	–	–
D(HASH_P)	–	–	–	–	–	0.1645***
D(HASH_N)	–	–	–	–	–	-0.1265***
D(TETHER)	–	-0.0093*	0.0110**	–	–	–
D(TETHER(-1))	–	0.0216***	0.0144***	–	–	–
D(TETHER(-2))	–	0.0140**	–	–	–	–
D(DJIA)	–	–	–	1.2552**	–	–
D(SSE)	–	–	-2.0735***	–	–	0.6767***
D(CBOEDJIA)	-0.0471	–	-0.2415***	–	–	–
D(CBOEDJIA(-1))	-0.1821***	–	–	–	–	–
D(CBOEDJIA(-2))	-0.0834**	–	–	–	–	–
D(GLD(-2))	–	-2.9825***	–	–	–	–
D(USDEUR)	1.5219**	–	–	–	–	–
D(BGT)	–	–	–	–	-0.0445**	–
D(TWTS_P(-1))	-0.0856***	–	–	–	–	–
D(WIKI)	–	–	–	0.0255	–	–
D(WIKI(-1))	–	–	–	-0.0827***	–	–
D(FUNDRAISING(-1))	–	–	-0.5037**	–	–	–
Constant	2.1226***	5.4402***	-2.1690***	1.4116***	1.1510***	4.2078***
ECM	-0.4534***	-0.3861***	-0.3623***	-0.1869***	-0.1739***	-0.6506***
Adjusted R-squared	0.7160	0.6749	0.6473	0.5649	0.5351	0.6095
Akaike crit.	-4.7435	-4.1294	-4.2397	-3.2507	-4.4953	-4.4925
Schwarz crit.	-4.3688	-3.7344	-3.7706	-2.9050	-4.0760	-4.1449
Hannan-Quinn crit.	-4.5916	-3.9692	-4.0495	-3.1105	-4.3254	-4.3516
Durbin-Watson stat	2.1715	2.1112	1.7601	2.1748	2.1312	2.1732

*Notes: (1) Dependent variable: Bitcoin price. (2) *** significant at 1% level, ** significant at 5% level, and * significant at 10% level. (3) "–" designates the absence of a variable in the respective model or its non-significance.*

This suggests that the decreased liquidity from fears of a potential cryptocurrency crackdown in China negatively impacted Bitcoin prices during regulatory consolidation. In contrast, a surge in liquidity was likely driven by the cryptocurrency craze following Bitcoin's acceptance as a legally recognized form of payment and property in Japan during the technological boom.

Contrary to the neutrality of money theory, the relationship between Bitcoin's velocity (VELOCITY) and its price is more complex than that of a traditional currency. On the one hand, its long-term negative and asymmetric impact on Bitcoin's price during the irresistible boom and the hash war crash suggests that traders regarded Bitcoin primarily as a store of value during these periods. During the irresistible boom, a 1% decrease in VELOCITY led to a 0.1554% long-term increase in Bitcoin's price. Conversely, a 1% increase in VELOCITY resulted in a 0.0497% long-term decline in Bitcoin's price during the hash war crash. On the other hand, during the eventful consolidation, VELOCITY exhibited a positive long-term effect on Bitcoin's price, indicating that users viewed Bitcoin as a means of exchange. In the short term, VELOCITY had varied effects: during the irresistible boom, a 1% rise (fall) in VELOCITY caused a 0.0256% (0.0705%) increase in Bitcoin's price, while during the bubble burst, a 1% rise (fall) in VELOCITY led to a 0.0402% (0.0843%) decrease in Bitcoin's price. This indicates that Bitcoin's short-term use as both a medium of exchange and a store of value benefited its price during the irresistible boom. In contrast, its reduced usage and the selling by those treating it as a store of wealth during the bubble burst negatively impacted its price. Furthermore, VELOCITY negatively affected Bitcoin's price in the short term during the eventful consolidation, confirming its role as a value reserve. Thus, the analysis of VELOCITY suggests that Bitcoin's utilisation and its impact on price depend on the reference period and the prevailing investor sentiment. Investors may view Bitcoin as a store of value, a medium of exchange, or both, and these perceptions influence its price effects in both the short and long term.

The first variable representing Bitcoin's technological aspects, FEE, demonstrated a significant positive long-term effect on Bitcoin's price across all periods except the bubble burst and the eventful consolidation when its impact was negligible. Furthermore, FEE exhibited a notable long-term asymmetric effect, with a 1% increase (decrease) in FEE resulting in a Bitcoin price rise (fall) of 0.5167% (0.3038%) during the technological boom and 0.0640% (0.1353%) during the irresistible boom. This suggests that the benefits of enhanced security and transaction confirmation speed provided by higher fees consistently outweigh user transaction costs in the long term. As transaction volumes increased, miners required higher fees to maintain Blockchain security and speed. Consequently, in the long term, Bitcoin's transaction fees indicate a preference for its role as a store of value and a speculative asset rather than a medium of exchange for inexpensive and rapid transactions. In the short term, however, the impact of FEE varied depending on the period. Transaction costs might outweigh the benefits of enhanced security and transaction speed for users who primarily view Bitcoin as a medium of exchange. Conversely, for those who see Bitcoin as a store of value, the benefits of higher security and faster confirmation times will likely outweigh the transaction costs.

The Bitcoin cost-of-production, HASH, demonstrated a significantly positive asymmetric long-term impact on Bitcoin prices during both the technological boom and the hash war crash. Specifically, a 1% increase in the hash rate led to a 0.5877% rise in Bitcoin's price during the technological boom and a 0.3103% increase during the hash war crash. In the short term, a 1% growth in the hash rate resulted in a 0.1645% increase in Bitcoin's price, whereas a 1% contraction led to a 0.1265% decrease during the hash war crash. Notably, the hash rate's evolution mitigated some of the downward pressure on Bitcoin's price, even amid miner capitulation, underscoring the efficacy of Bitcoin's proof-of-work (PoW) consensus algorithm in maintaining security. HASH also had a positive short-term effect on Bitcoin prices during the technological boom. Overall, the impact of the hash rate on Bitcoin's price is significant, mainly during periods of substantial technical changes or miner capitulation. Outside these periods, the hash rate's influence on the Bitcoin price is minimal, reflecting its tendency to follow Bitcoin price trends, as noted by Fantazzini et al. (2020), who observed a unilateral causality from Bitcoin prices to the hash rate. A surge in Bitcoin prices increases miners' revenues through fees and Coinbase rewards, prompting additional mining hardware deployment and raising the hash rate. However, as Kristoufek (2020) highlights, hardware shortages can delay hash rate adjustments, causing it to lag behind Bitcoin price fluctuations.

The most widely used stablecoin, Tether (USDT), had a detrimental impact on Bitcoin prices in the long run during the technological boom, the irresistible boom (in the linear model), and the bubble burst. This indicates that investors likely used Tether as a hedge against potential declines in Bitcoin prices. However, Tether had a positive short-term effect on Bitcoin prices during the technological and irresistible booms, suggesting that it functioned as a gateway to Bitcoin investment. This was particularly relevant in China, where Bitcoin trading has been restricted since the crackdown in September 2017. Chinese investors would acquire Tether with Yuan through over-the-counter transactions and then exchange Tether for Bitcoin, leading to a surge in Tether transactions and highlighting its role in facilitating Bitcoin trading. After the bubble burst, Tether experienced a temporary loss of its peg to the US dollar (Harper 2018), which rendered its influence on Bitcoin prices insignificant in subsequent analysis periods. This dual role of Tether—serving both as a long-term hedging tool and a short-term trading intermediary—illustrates its complex impact on Bitcoin markets.

We observed notable asymmetric impacts of internal factors on Bitcoin prices. Specifically, velocity and transaction fees emerged as the most asymmetric determinants of Bitcoin's price, highlighting the evolving dynamics of Bitcoin's market behaviour.

Hypothesis 2: Global macroeconomic and financial developments

Bitcoin acted as a hedge against the declining value of the U.S. dollar, particularly evident in the exchange rate between the U.S. dollar and the Euro (USDEUR), which had a notable positive long-term effect on Bitcoin prices during the regulatory consolidation period. Specifically, a 1% depreciation of the U.S. dollar against the Euro was associated with a significant 6.1250% appreciation in Bitcoin prices. This correlation was influenced by U.S. dollar depreciation and rising inflation, driven by surges in crude oil prices and the Federal Reserve's struggle to manage inflation through interest rate adjustments. Despite this, the exchange rate's impact on Bitcoin prices diminished in subsequent periods, suggesting that Bitcoin may not consistently serve as an effective hedge against U.S. inflation. This trend was particularly evident in the short term, where the exchange rate positively influenced Bitcoin prices during the regulatory consolidation.

The robust performance of the American economy in 2017, as indicated by the Dow Jones Industrial Average (DJIA), did not profoundly drive Bitcoin's short-term or long-term growth. The DJIA's only significant short-term impact on Bitcoin prices was observed during the bubble burst when Bitcoin's price decline was exacerbated by a severe correction in the DJIA in February. Conversely, the subsequent recovery in the DJIA negatively influenced Bitcoin prices during the eventful consolidation period in the long run. In contrast, despite solid growth in the Chinese economy, the Shanghai Stock Exchange Index (SSE) negatively affected Bitcoin prices in both the long and short terms during the irresistible boom. This suggests that Chinese investors may have sought Bitcoin as an alternative investment due to the SSE's underperformance. The SSE had a notable positive short-term impact on Bitcoin prices during the hash war crash, reflecting a period of declining SSE due to the U.S.-China trade war, seemingly boosting Bitcoin prices. Bitcoin acted as a diversification tool relative to American and Chinese stock markets, particularly in the long run and, with some exceptions during crash periods, in the short term.

The rising levels of fear, risk, and stress in the U.S. stock market, as indicated by the CBOEDJIA index, prompted investors to use Bitcoin as a long-term hedging instrument during the regulatory consolidation. However, it is essential to note that Bitcoin exhibited a negative correlation with the CBOEDJIA index in the short term during this period, as well as in both the short and long terms during the irresistible boom. This suggests that Bitcoin was not uniformly resilient to stock market volatility. Consequently, it cannot be definitively asserted that Bitcoin consistently served as a dependable hedge against uncertainty in the American stock market.

Ultimately, Gold (GLD) did not positively affect Bitcoin prices, either in the short term or long term, indicating that Bitcoin does not exhibit the same characteristics as gold in terms of serving as an inflation hedge or store of value. Notably, gold negatively influenced Bitcoin prices in the short term during the technological boom, suggesting that Bitcoin functioned as a competing asset to gold. The absence of a significant correlation between these assets highlights Bitcoin's distinct qualities, such as its role as a medium of exchange, technological currency, online payment system, and decentralised data storage solution.

Contrary to previous research (Bouri, Gupta, Lahiani, et al. 2018; Jareño et al. 2020; Long et al. 2021), our analysis found no asymmetric effects of macro-financial variables on Bitcoin prices, with the sole exception of the USD/EUR exchange rate. This underscores the importance of incorporating internal and attractiveness factors when evaluating the presence of asymmetries with macro-financial variables.

Hypothesis 3: Attractiveness factors for investors and users

The number of tweets (TWTS) negatively impacted Bitcoin prices both in the short and long term during the regulatory consolidation. The significant asymmetric short-term effect indicates that a 1% increase in TWTS would have led to a 0.0856% decline in Bitcoin prices during this time. These adverse effects may be attributed to the uncertainty surrounding potential cryptocurrency crackdowns, particularly in China and the US. In contrast to Ciaian et al. (2016), who found the long-term impact of WIKI to be insignificant, our analysis reveals that WIKI had a notable positive effect on Bitcoin prices during the irresistible boom and the bubble burst (linear case). However, during the bubble burst, WIKI negatively impacted Bitcoin prices in the short run, likely due to the influx of information regarding Bitcoin's price collapse, which may have discouraged new entrants or prompted existing investors to exit the market. The Bitcoin Google Trend (BGT) also showed a detrimental impact on Bitcoin prices, both in the short and long terms, during the eventful consolidation. The increase in negative sentiment associated with regulatory tensions from March to June 2018 likely contributed to this adverse relationship. Similarly, BGT had a significant long-term negative effect during the hash war crash, where a 1% increase in BGT corresponded to a 0.2068% contraction in Bitcoin prices. This negative impact was driven by heightened internal tensions within the cryptoasset market, particularly the hash civil war and miner capitulation.

Crypto fundraising efforts (FUNDRAISING) exhibited a positive long-term and a negative short-term impact on Bitcoin prices during the irresistible boom. These efforts significantly affected Bitcoin prices at the peak of the ICO boom, when numerous prominent projects raised substantial funds through ICOs with minimal regulatory oversight. The positive long-term impact was driven by increased demand for Bitcoin, fueled by speculative investments in these fundraising projects and heightened confidence in the crypto market due to the success of early ICOs. Conversely, the short-term negative impact emerged when project teams converted their received bitcoins into fiat currency or other cryptocurrencies to fund development, coupled with the speculative trading that intensified price volatility during this period. Outside of this timeframe, the influence of crypto fundraising on Bitcoin prices was minimal, even when considering other fundraising methods like STOs and IEOs.

In general, attractiveness factors tend to negatively impact Bitcoin prices during consolidation and crash periods, while their positive effects during boom periods are associated mainly with the ICO hype captured by FUNDRAISING. This observation is consistent with Jakub (2015) and Philippas et al. (2019), who highlight that negative news and media attention often lead to more pronounced adverse price fluctuations during periods of uncertainty compared to the effects of positive news.

The asymmetric effects of attractiveness factors on Bitcoin prices during specific periods align with prior research (Kristoufek 2013; Kristoufek 2015; Panagiotidis et al. 2018), which demonstrates that these factors exert asymmetric impacts on Bitcoin prices across various periods depending on prevailing trends.

Lastly, detailed results and discussions on the key events are provided in Appendix C.

Exploring the Bitcoin price boom and subsequent price crashes

Our overall findings and the resultant classification of Bitcoin's status for investors in Table 7 enable us to explain for the Bitcoin price boom and subsequent price crashes.

During the 2017 boom, Bitcoin was viewed by many investors as a store of value, leading to short-term and long-term hoarding behaviour, while others employed it as a short-term medium of exchange. Notably, Chinese investors turned to Bitcoin as an alternative to the sluggish Shanghai Stock Exchange (SSE), continuing their trading activities despite regulatory crackdowns by using Tether to enter the crypto market. The surge in demand for Bitcoin was further driven by the need to convert Bitcoin into newly issued tokens for participation in crypto projects. Concurrently, Bitcoin's price benefited from reduced uncertainty in the U.S. market and brief declines in gold prices in the short term, positioning it as a lucrative investment and resulting in increased transaction volumes, deeper liquidity pools, and more unique addresses. Despite rising fees, Bitcoin's price growth persisted, suggesting that most users treated it as a store of value or speculative asset rather than a medium of exchange. Speculation played a more pronounced role in the subsequent price downturn than during the boom, exacerbated by negative news, deteriorating investor sentiment, and the introduction of Bitcoin futures contracts, which artificially inflated prices. This bubble burst as investors bet against Bitcoin, further compounded by scams, hacks, and the failure of many ICO tokens, undermining market confidence. Additionally, the decline in transaction value and liquidity, driven by the selling of Bitcoin for more secure assets, aggravated the crash. Tether emerged as a hedge against the price decline. Remarkably, the impact of Bitcoin's use as a medium

Table 7: Classification of Bitcoin's Role for Owners

	NARDL1	NARDL2	NARDL3	NARDL4	NARDL5	NARDL6
Long Term	Store of Value (FEE)	Store of Value (VELOCITY)	Store of Value (VELOCITY, FEE)	N/A	Medium of Exchange (VELOCITY)	Store of Value (VELOCITY, FEE)
Short Term	N/A	Medium of Exchange (FEE)	Medium of Exchange (VELOCITY_P, FEE_N), Store of Value (VELOCITY_N, FEE_P)	Medium of Exchange (VELOCITY_N), Store of Value (VELOCITY_P)	Store of Value (VELOCITY, FEE_P)	Medium of Exchange (FEE_N), Store of Value (FEE_P)

Notes: (1) Bitcoin exhibits store-of-value characteristics when the variables FEE, FEE_P, and VELOCITY_N positively affect its price. (2) Bitcoin demonstrates medium of exchange properties when the variables VELOCITY, VELOCITY_P, and FEE_N negatively influence its price. (3) "Not Applicable" (N/A) denotes the lack of statistical significance of the variables and implies that Bitcoin has neither of the aforementioned features.

of exchange was more detrimental to its price than the actions of long-term holders. Technological factors, such as fees and hash rates, had minimal impact on the crash, indicating no inherent blockchain issues. The Dow Jones collapse also contributed to the downturn by reducing available funds for Bitcoin investments. In the subsequent period, Bitcoin's price stabilized as trading volumes from those using it as a currency remained steady, despite intermittent selling by long-term holders and short-term shifts of funds to the U.S. stock market. Although speculation decreased, it continued to influence the price, especially in the short term. During the hash war crash, technological factors gained prominence, with miners and investors involved in the Bitcoin Cash civil war driving Bitcoin's second significant downturn. The loss of mining profitability and difficulty adjustments led to a capitulation among small to medium-sized miners, who sold their Bitcoin holdings, triggering price and hash rate declines. This capitulation was exacerbated by larger mining operations and long-term investors reallocating assets to competing blockchains from the Bitcoin Cash hard fork. The SSE downturn and trade tensions between the U.S. and China further accelerated the Bitcoin price drop. Despite this, the resilience of Bitcoin's transaction verification and security via the PoW reassured its users, while shrinking fees favoured those regarding Bitcoin as a means of payment, thus attenuating the Bitcoin price crash. Despite this, Bitcoin's resilience through proof-of-work and reduced fees reassured users and supported Bitcoin's use as a means of payment, thus attenuating the extent of the crash.

5 Conclusions and policy implications

Due to its rapid market capitalisation growth, enticing returns, and notable price volatility, Bitcoin has captured the attention of investors, legislators, and scholars alike. A particularly tumultuous and intriguing phase in Bitcoin's history unfolded during the 2017 market boom and subsequent crashes in 2018. . Despite the significance of this period, an econometric study has yet to be conducted to elucidate the determinants of Bitcoin's price movements during this timeframe. Moreover, only a few inquiries have explored potential asymmetric relationships between Bitcoin and its underlying factors. Therefore, the primary objective of this research endeavour is to address these critical gaps in the existing literature.

This study employed structural break tests, including the Bai and Perron multiple breakpoint test, to identify six distinct periods with unique dynamics. Additional structural discontinuities were detected via dedicated structural break tests and accommodated with dummy variables, capturing significant events. The research also provided a comprehensive overview of Bitcoin's operational framework and evolution, establishing the groundwork for our Bitcoin exchange equation and hypotheses based on Fisher's Equation of Exchange (1911) and insights from Ciaian et al.'s study (2016). Ultimately, ARDL cointegration techniques were applied to variables in levels and first differences, supplemented by a NARDL framework to incorporate nonlinearities. Rigorous diagnostic tests were conducted to ensure the robustness and validity of our models.

Our empirical findings strongly indicate that during the 2017-2018 period, internal factors predominantly influenced the Bitcoin price, with attractiveness factors playing a secondary role. Conversely, macroeconomic and financial development factors had minimal impact, except in rare instances, such as when stock markets positively influenced Bitcoin prices in the short term during crash periods and negatively in the preceding periods. Consequently, a Bitcoin investment can diversify a stock portfolio in the long run, albeit with heightened short-term risk during Bitcoin price crashes.

Secondly, the study on fees and velocity provides valuable insights into investor behaviour and Bitcoin's dual role as both a store of value and a medium of exchange. These internal factors suggest that Bitcoin primarily functions as a store of value over the long term, whereas in the short term, it serves both purposes. The current structure of the Bitcoin Blockchain promotes higher transaction fees, which benefit those who perceive Bitcoin as a store of value or a speculative asset. Importantly, these fees are expected to constitute a significant and growing portion of miners' revenue as they progressively replace Bitcoin supply, which, unlike fiat currencies, exerts minimal impact on Bitcoin prices due to its exogeneity. This perspective suggests that Bitcoin is more likely to evolve into digital gold rather than a feasible digital medium of exchange capable of supplanting the US dollar as a global currency in the future.

Thirdly, our estimates demonstrate that the 2017 boom was mainly sparked by Bitcoin's appealing technological advancements and the ICO hype. In contrast, speculation played a pivotal role in the 2017 bubble burst, while the 2018 hash war crash was primarily instigated by investors involved in the civil war and miner capitulation. Although the factors directly triggering the 2018 crash differed from those of the 2017 bubble burst, miner capitulation was exacerbated by reduced mining profitability from the lingering effects of the previous crash.

Fourthly, our investigation into the asymmetric effects of Bitcoin's price determinants revealed that the internal factors exhibit the highest degree of asymmetry, followed by attractiveness factors. In contrast, macro-financial factors generally manifest no asymmetry, unlike earlier research findings (Bouri, Gupta, Lahiani, et al. 2018; Jareño et al. 2020; Long et al. 2021). It proves the relevance of including additional asymmetric variables alongside macro-financial factors when analysing Bitcoin price formation.

An important insight from this study is that Bitcoin represents the precursor of a new asset class known as cryptoassets, a superclass of cryptocurrencies that necessitates a distinct regulatory approach. Bitcoin exhibits unique characteristics that differentiate it from conventional asset classes and is particularly susceptible to speculation—a common trait of innovative financial products. Given these unique and intricate attributes, investors and regulators must monitor Bitcoin's evolution closely. Concurrently, scholars and practitioners should aim to comprehensively understand, elucidate, and disseminate knowledge about the intricacies of Bitcoin and the broader cryptoasset realm.

To mitigate the potential risks associated with integrating financial products into the cryptoasset ecosystem, lessons drawn from the 2017 Bitcoin crash provide valuable policy insights. While it may not have been entirely possible to avoid the excessive speculation from the ICO hype and the introduction of Bitcoin futures contracts, several measures could have been implemented to mitigate this speculation and alleviate the subsequent price downfall. A crucial step is the implementation of explicit legislation governing Bitcoin and the cryptoasset market, aimed at reducing uncertainty over potential bans and safeguarding investors against scams and custodial risks, as exemplified by the Markets in Crypto Assets (MiCA) Regulation[13] effective from June 29th, 2023. MiCA clarifies EU market rules for cryptoassets and introduces tailored regulations reflecting their unique characteristics. Centralised exchanges, influential in Bitcoin pricing and susceptible to irregular practices (e.g., Mt. Gox, FTX), warrant enhanced oversight. Stablecoins, particularly Tether, require stringent regulatory scrutiny to prevent failures and persistent de-pegging that could severely impact investors and market stability. Promoting stablecoin development is crucial in the cryptoasset ecosystem, offering investors a hedge against market volatility. While these regulatory measures could reduce the magnitude of speculative crashes like that of 2017, they might not address crashes stemming from miner capitulation, such as the 2018 crash. Policymakers could consider fiscal and regulatory incentives to promote non-mineable cryptoassets and support Proof-of-Work (PoW) systems transitioning to energy-efficient algorithms like Proof-of-Stake (PoS). These modifications would reduce energy consumption and prevent miner capitulation by lowering operational costs and ensuring sustainable rewards. However, transitioning from PoW to new consensus algorithms must ensure comparable security to Bitcoin's established PoW system. Bitcoin's evolution towards a store of value and speculative asset rather than a medium of exchange challenges its original vision as a decentralised cash system. Enhancing the Bitcoin Lightning Network and exploring alternative technologies to reduce transaction fees and improve scalability is critical to maintaining its utility and appeal as a means of exchange. Once again, transitioning from PoW to a more efficient consensus algorithm not reliant on mining could achieve these objectives, benefiting Bitcoin's long-term viability and utility. Balancing these dual roles can sustain Bitcoin's global recognition and adoption, preserving its foundational principles amid evolving market dynamics.

Future studies could delve deeper into the facets of Bitcoin illuminated by this research. Such investigations could examine diverse cryptoassets and countries over varying timeframes to identify which cryptoassets serve as media of exchange or stores of value in specific regions and peri-

[13]https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:52020PC0593

ods. Other studies could explore the impact of cryptoassets' technological features on their price and transaction volume. Cryptoassets with more advanced and efficient consensus protocols should be more valuable and less volatile. Furthermore, as this study focused on Bitcoin, researchers could adapt and extend this framework to better understand price formation in other public cryptocurrencies like Litecoin, Bitcoin Cash, Bitcoin SV, and Dogecoin, capturing their unique characteristics. Lastly, while our study incorporated a specific type of nonlinearity via the NARDL model, it would be intriguing to investigate whether other nonlinearities influence the relationships between Bitcoin and its determinants. For instance, exploring the nonlinear effects of variables such as hash rate, transaction fees, and velocity could offer valuable insights into the cryptoasset ecosystem.

Data availability statement

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

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Declaration of competing interest

The author declares that he owns cryptocurrencies, including Bitcoin. However, he asserts that these holdings do not present any conflicts of interest relevant to the research presented in the paper.

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appendix A. Additional Figures and Tables

Table A1: Descriptive statistics of the logarithm of the Bitcoin price in line with its particular time span

	Regulatory Consolidation (1/1/2017 - 4/21/2017)	Technological Boom (4/22/2017 - 8/8/2017)	Irresistible Boom (8/9/2017 - 11/25/2017)	Bubble Burst (11/26/2017 - 3/14/2018)	Eventful Consolidation (3/15/2018 - 9/14/2018)	Hash War Crash (9/15/2018 - 12/31/2018)
Mean	6.961	7.713	18.527	39.375	8.902	28.551
	($1063.104)	($2301.886)	($5222.767)	($12136.79)	($7412.528)	($5347.023)
Median	6.951	7.801	18.434	39.326	8.896	18.742
	($1045.163)	($2443.824)	($4600.457)	($11225.90)	($7303.631)	($6265.490)
Maximum	7.161	8.139	9.078	9.885	39.189	78.816
	($1289.363)	($3425.677)	($8760.165)	($19640.51)	($9795.626)	($6741.143)
Minimum	6.669	7.125	8.085	8.831	9.675	78.066
	($788.3147)	($1243.550)	($3247.469)	($6849.543)	($5858.636)	($3185.074)
Std. Dev.	0.124	0.248	0.255	0.240	0.131	0.264
Skewness	-0.295	-0.875	0.494	0.192	0.386	-0.521
Kurtosis	2.133	2.828	2.056	2.147	2.020	1.510
Growth Rate* (%)	63.554%	175.4756%	169.7536%	-65.1254%	-40.1913%	-52.7517%
Jarque-Bera	5.177805	514.06	48.48	63.9768	11.9320	14.8805
Probability (JB)	0.0751	0.0009	0.0144	0.1369	0.0026	0.0006
Observations	111	109	109	109	184	108

Notes: The corresponding Bitcoin market price in U.S. dollar between parentheses, "" The growth rate and the daily growth rate were computed according to the maximum and minimum value of the period.*

Interpretation of the above table: The kurtosis of each period is consistently below 3. Consequently, all periods exhibit a leptokurtic deviation from the normal distribution, indicating that these distributions contain fewer extreme outliers than a normal distribution. The distribution associated with the technological boom contains the most significant extreme outliers, while the hash war crash distribution has the fewest. The third, fourth, and fifth periods display a positively skewed, long right tail, whereas the others demonstrate a negatively skewed, long left tail. The regulatory consolidation and the irresistible boom exhibit the lowest and highest absolute skewness values, respectively. It implies that the bubble burst distribution is relatively symmetric, while the technological boom distribution is the most asymmetric. Applying the Jarque-Bera test, we fail to reject the null hypothesis that the price dataset of the bubble burst follows a normal distribution at a significance level of 10%. The same holds for the price dataset of the regulatory consolidation at a 5% significance level and the irresistible boom at a 1% significance level. However, we reject the null hypothesis at a 1% significance level for the other three periods, suggesting that their price datasets are likely not normally distributed. Furthermore, the standard deviations of the regulatory and eventful consolidation are the smallest, whereas those of the other four periods are twice as large. It illustrates that the Bitcoin price was relatively more stable during these two periods compared to the other periods. The growth rate between their maximum and minimum values supports this relative stability. On the one hand, the Bitcoin price experienced the slowest growth during the regulatory consolidation among the three expansion periods. On the other hand, the Bitcoin price suffered its smallest decline during the eventful consolidation among the three contraction periods. Interestingly, the technological and irresistible boom had nearly identical growth rates, indicating that the Bitcoin price increase was similar during both booms. Meanwhile, the Bitcoin price decrease was more significant during the hash war crash. However, this does not imply that the decline was more severe during the hash war crash than during the bubble burst. Indeed, the Bitcoin price lost approximately 50% of its value from November 11^{th} to December 15^{th} 2018, over 36 days during the former, compared to a 60% price decline from December 16^{th} 2017, to February 5^{th} 2018, equivalent to 52 days during the latter.

Table A2: List of Variables

	Variable	Definition	Source
Dependent variable	PRICE	Price USD of bitcoin	Coinmetrics
Internal Factors	TRANS	The median value transferred per transaction in US dollar (the median size in US dollar of a transfer)	Coinmetrics
	ACT	Sum count of unique addresses active in the network	Coinmetrics
	SPREAD	The bid/ask spread is the difference between the highest price a buyer is willing to pay for a Bitcoin and the lowest price a seller is disposed to accept in exchange for its bitcoin. Principal component analysis was used to calculate an approximated value of the market spread. One employed the spreads of the exchange platforms (Coinbase, Bitfinex, Bitstamp) with the highest trading volumes during the period of reference	Data.bitcoinity
	ISSUANCE	Total number of Bitcoins mined per day	Coinmetrics
	VELOCITY	Token_Age_Consumed metric reflects the amount of Bitcoin changing hand multiplied by the time since they last moved	Santiment
	FEE	The sum of all fees paid to miners in USD	Coinmetrics
	HASH	The mean rate at which miners are solving hashes (computational power)	Coinmetrics
	TETHER	The value in US dollar of the sum of all tethers being traded between distinct addresses while removing noise and some artefacts	Coinmetrics
	USDEUR	EUR/USD Foreign Exchange Rate	Federal Reserve Bank of St. Louis

Continued on the next page

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	Variable	Definition	Source
Macroeconomic Factors	DJIA	Dow Jones Industrial Average	Federal Reserve Bank of St. Louis
	SSE	Shanghai Stock Exchange Composite Index	Yahoo Finance
	CBOEDJIA	CBOE DJIA Volatility Index	Federal Reserve Bank of St. Louis
	GLD	Gold Fixing Price in London Bullion Market, based in U.S. Dollars	Federal Reserve Bank of St. Louis
Attractiveness Factors	BGT	Adjusted value corresponding to the global number of searches of BITCOIN on the web	Google Trends
	TWTS	Sum of all tweets mentioning Bitcoin worldwide	Bitinfocharts
	WIKI	Number of views of the Bitcoin page in English on Wikipedia	Wikishark
	FUNDRAISING	The cumulative sum of the funds in USD raised through Crypto Investments and Fundraising Rounds since January 1^{st}, 2017	Cryptorank

Table A3: Perron Unit Root Test with break (PPU-Root)

	The regulatory consolidation			The technological boom			The irresistible boom			The bubble burst		
Variable	**Constant**	**Trend**	**Constant & Trend**	**Constant**	**Trend**	**Constant & Trend**	**Constant**	**Trend**	**Constant & Trend**	**Constant**	**Trend**	**Constant & Trend**
PRICE	-4.6044 (3/15/2017)	-3.0189 (3/01/2017)	-4.5928 (3/15/2017)	-3.3016 (6/26/2017)	-2.6904 (5/28/2017)	-3.3066 (6/11/2017)	-4.2124 (9/07/2017)	-3.9082 (9/24/2017)	-4.5374 (9/12/2017)	-3.3256 (1/13/2018)	-2.9031 (2/09/2018)	-3.0733 (2/13/2018)
TRANS	-8.5775*** (3/17/2017)	-8.4137*** (3/05/2017)	-8.5361*** (2/23/2017)	-7.1620*** (5/08/2017)	-7.3723*** (5/16/2017)	-7.5582*** (5/25/2017)	–	–	–	-3.4749 (1/17/2018)	-3.6028 (12/29/2017)	-3.9431 (1/17/2018)
ACT	-6.9909*** (3/24/2017)	-6.0927*** (3/04/2017)	-6.9531*** (1/23/2017)	–	–	–	-7.6123*** (10/09/2017)	-5.6801*** (9/23/2017)	-6.0323*** (10/08/2017)	–	–	–
SPREAD	-4.6622 (1/18/2017)	-5.6510*** (1/20/2017)	-5.5940** (1/23/2017)	-5.8455** (5/27/2017)	-5.1975** (5/27/2017)	-6.9232*** (5/27/2017)	-5.1496* (9/15/2017)	-4.1652 (10/20/2017)	-5.1888 (9/15/2017)	-6.5028*** (12/19/2017)	-5.4916*** (12/26/2017)	-6.3579*** (12/19/2017)
ISSUANCE	–	–	–	–	–	–	–	–	–	–	–	–
VELOCITY	–	–	–	-5.2727** (7/23/2017)	-4.8813** (7/19/2017)	-4.5543 (7/07/2017)	-9.0642*** (9/04/2017)	-9.1637*** (9/14/2017)	-9.4720*** (9/24/2017)	-10.2409*** (2/08/2018)	-9.9622*** (2/06/2018)	-10.2158*** (2/06/2018)
FEE	-4.8816 (3/23/2017)	-4.6618* (3/08/2017)	-5.2748 (2/20/2017)	-3.2793 (5/17/2017)	-5.4821*** (6/04/2017)	-5.5224* (6/03/2017)	-5.1177* (9/08/2017)	-4.1917 (9/24/2017)	-5.1232 (9/09/2017)	–	–	–
HASH	–	–	–	-10.9159*** (6/10/2017)	-10.2101*** (5/29/2017)	-11.0816*** (6/10/2017)	–	–	–	–	–	–
TETHER	–	–	–	-7.5335*** (5/21/2017)	-6.5930*** (6/26/2017)	-7.5492*** (5/21/2017)	-4.9875* (9/15/2017)	-3.7416 (10/11/2017)	-5.0768 (9/15/2017)	-4.4178 (2/08/2018)	-4.0717 (1/19/2018)	-4.4287 (2/06/2018)
DJIA	–	–	–	–	–	–	–	–	–	-5.0108* (2/01/2018)	-3.3287 (1/20/2018)	-5.8869** (2/01/2018)
SSE	–	–	–	–	–	–	-2.7679 (8/25/2017)	-3.9154 (8/30/2017)	-4.0356 (9/06/2017)	–	–	–
CBOEDJIA	-5.1070* (3/15/2017)	-4.2103 (3/23/2017)	-5.1710 (3/15/2017)	–	–	–	-4.5316 (10/16/2017)	-4.6171* (9/17/2017)	-4.9366 (9/08/2017)	–	–	–
GLD	–	–	–	-2.7723 (6/14/2017)	-1.8050 (7/14/2017)	-2.9828 (6/28/2017)	–	–	–	–	–	–
USDEUR	-3.2755 (3/08/2017)	-2.7097 (3/02/2017)	-3.4246 (3/15/2017)	–	–	–	–	–	–	–	–	–
BGT	–	–	–	–	–	–	–	–	–	–	–	–
TWTS	-7.2706*** (3/23/2017)	-6.6098*** (3/21/2017)	-7.0920*** (3/23/2017)	–	–	–	–	–	–	–	–	–
WIKI	–	–	–	-2.8970 (5/12/2017)	-2.9984 (5/12/2017)	-4.6971 (5/26/2017)	-3.9170 (9/15/2017)	-4.0210 (9/30/2017)	-6.8057*** (10/10/2017)	-6.6415*** (12/26/2017)	-6.7257*** (2/26/2018)	-6.7257*** (2/20/2018)
FUNDRAISING	–	–	–	–	–	–	-5.5686** (10/08/2017)	-2.5580 (9/21/2017)	-5.2368** (10/09/2017)	–	–	–
						1^{st} **difference**						
PRICE	-11.0599*** (3/18/2017)	-10.6978*** (1/19/2017)	-10.9935*** (3/18/2017)	-12.3323*** (7/15/2017)	-11.8039*** (7/12/2017)	-12.3686*** (7/20/2017)	-11.7952*** (9/14/2017)	-10.5819*** (9/04/2017)	-12.2494*** (9/14/2017)	-11.2635*** (2/05/2018)	-10.2853*** (12/22/2017)	-11.2787*** (2/05/2018)
TRANS	-11.8017*** (4/02/2017)	-11.6244*** (4/04/2017)	-12.0135*** (4/04/2017)	-9.3751*** (7/10/2017)	-8.8469*** (5/28/2017)	-9.3944*** (6/04/2017)	–	–	–	-8.5532*** (12/22/2017)	-8.3054*** (1/20/2018)	-8.8180*** (2/02/2018)
ACT	-9.3365*** (3/10/2017)	-9.3385*** (3/10/2017)	-9.3385*** (3/10/2017)	–	–	–	-9.5994*** (10/28/2017)	-9.1299*** (8/30/2017)	-9.5020*** (10/28/2017)	–	–	–
SPREAD	-9.6656*** (3/18/2017)	-7.7649*** (3/08/2017)	-9.5777*** (3/18/2017)	-12.1265*** (5/27/2017)	-11.1397*** (7/23/2017)	-12.1161*** (5/27/2017)	-8.3900*** (9/04/2017)	-7.9092*** (11/09/2017)	-8.4295*** (9/04/2017)	-8.5258*** (12/22/2017)	-6.7473*** (2/26/2018)	-8.3171*** (12/22/2017)
ISSUANCE	–	–	–	–	–	–	–	–	–	–	–	–
VELOCITY	–	–	–	-7.3017*** (7/23/2017)	-6.9256*** (5/13/2017)	-8.0753*** (7/23/2017)	-10.3478*** (11/01/2017)	-9.9900*** (11/09/2017)	-10.3132*** (9/29/2017)	-9.5264*** (2/22/2018)	-8.4717*** (2/10/2018)	-9.4925*** (2/22/2018)
FEE	-10.4545*** (3/08/2017)	-10.0296*** (1/21/2017)	-10.3662*** (3/08/2017)	-9.3940*** (7/16/2017)	-8.6318*** (7/04/2017)	-9.3538*** (7/16/2017)	-11.3393*** (9/16/2017)	-7.9460*** (9/03/2017)	-11.7438*** (9/16/2017)	–	–	–
HASH	–	–	–	-8.9743*** (7/02/2017)	-8.5304*** (6/13/2017)	-8.9420*** (7/02/2017)	–	–	–	–	–	–
TETHER	–	–	–	-10.7580*** (6/06/2017)	-10.3659*** (5/11/2017)	-10.7146*** (6/06/2017)	-7.7479*** (9/15/2017)	-7.2021*** (11/07/2017)	-7.7919*** (9/04/2017)	-8.9083*** (2/22/2018)	-7.8650*** (2/12/2018)	-8.9257*** (2/22/2018)
DJIA	–	–	–	–	–	–	–	–	–	-10.4091*** (2/08/2018)	-8.8258*** (2/04/2018)	-10.3988*** (2/08/2018)
SSE	–	–	–	–	–	–	-10.3371*** (8/25/2017)	-10.5136*** (11/09/2017)	-10.7886*** (8/27/2017)	–	–	–
CBOEDJIA	-19.8087*** (3/15/2017)	-16.5190*** (1/18/2017)	-20.1710*** (3/15/2017)	–	–	–	-6.4644*** (10/24/2017)	-5.4279** (10/18/2017)	-6.3666*** (10/24/2017)	–	–	–
GLD	–	–	–	-10.6270*** (6/07/2017)	-9.9228*** (5/17/2017)	-10.7268*** (6/07/2017)	–	–	–	–	–	–
USDEUR	-11.6356*** (3/29/2017)	-11.5039*** (2/08/2017)	-11.7562*** (3/29/2017)	–	–	–	–	–	–	–	–	–
BGT	–	–	–	–	–	–	–	–	–	–	–	–
TWTS	-10.0191*** (2/24/2017)	-8.8613*** (3/30/2017)	-9.9752*** (2/24/2017)	–	–	–	–	–	–	–	–	–
WIKI	–	–	–	-9.5794*** (5/15/2017)	-8.1006*** (5/31/2017)	-9.8850*** (5/15/2017)	-8.4195*** (10/12/2017)	-7.6384*** (11/03/2017)	-8.4257*** (10/12/2017)	-8.7863*** (12/31/2017)	-7.9080*** (12/15/2017)	-8.7895*** (12/31/2017)
FUNDRAISING	–	–	–	–	–	–	-14.2085*** (10/17/2017)	-11.2145*** (10/18/2017)	-14.1641*** (10/17/2017)	–	–	–

*Notes: *** significant at 1% level, ** significant at 5% level, * significant at 10% level. The null hypothesis of this test is that the time series has a unit root with a structural break in the intercept/trend/both. Date of break in parenthesis. '–' refers to the absence of variable in the reference period.*

Table A4: Perron Unit Root Test with break (PPU-Root)

Variable	The eventful consolidation			The hash war crash		
	Constant	**Trend**	**Constant & Trend**	**Constant**	**Trend**	**Constant & Trend**
PRICE	-3.0935 (5/21/2018)	-2.6910 (4/25/2018)	-3.2058 (5/21/2018)	-5.2992** (11/18/2018)	-1.9618 (12/15/2018)	-4.6887 (11/18/2018)
TRANS	-4.7883 (5/24/2018)	-4.0358 (8/15/2018)	-5.0199 (5/24/2018)	-8.9158*** (10/07/2018)	-7.5625*** (11/09/2018)	-8.8859*** (10/07/2018)
ACT	-7.7978*** (4/15/2018)	-7.5212*** (4/23/20018)	-7.9969*** (5/11/2018)	-7.8966*** (10/14/2018)	-8.1403*** (11/05/2018)	-8.3264*** (10/28/2018)
SPREAD	-6.1473*** (7/01/2018)	-5.4207** (6/08/2018)	-6.2387** (7/01/2018)	-4.5757 (11/18/2018)	-2.2278 (12/04/2018)	-4.5401 (11/18/2018)
ISSUANCE	-12.0211*** (7/16/2018)	-11.6186*** (8/17/2018)	-12.3755*** (7/16/2018)	–	–	–
VELOCITY	-11.6341*** (5/17/2018)	-10.7316*** (7/15/2018)	-11.6028*** (5/17/2018)	-5.1354* (12/03/2018)	-4.5708* (12/05/2018)	-5.8296** (11/28/2018)
FEE	-4.0688 (4/19/2018)	-3.9716 (4/27/2018)	-4.6937 (5/19/2018)	-4.0538 (12/08/2018)	-3.9436 (11/27/2018)	-5.3785* (11/14/2018)
HASH	–	–	–	-4.7317 (11/17/2018)	-4.0303 (12/15/2018)	-5.0718 (11/28/2018)
TETHER	–	–	–	-7.9774*** (10/06/2018)	-7.3043*** (10/15/2018)	-7.9552*** (10/11/2018)
DJIA	-4.6396 (6/17/2018)	-3.5247 (7/16/2018)	-5.1458 (6/18/2018)	–	–	–
SSE	–	–	–	-3.3642 (10/29/2018)	-2.8645 (10/16/2018)	-3.8193 (10/29/2018)
CBOEDJIA	-4.1246 (4/12/2018)	-4.2434 (5/20/2018)	-4.6523 (6/18/2018)	–	–	–
GLD	–	–	–	–	–	–
USDEUR	–	–	–	–	–	–
BGT	-6.2865*** (7/14/2018)	-5.5138*** (6/06/2018)	-6.2650*** (7/14/2018)	-4.5450 (11/13/2018)	-2.070 (12/15/2018)	-4.0323 (11/13/2018)
TWTS	–	–	–	–	–	–
WIKI	–	–	–	–	–	–
			1^{st} **difference**			
PRICE	-14.8176*** (4/12/2018)	-14.2627*** (4/13/2018)	-14.7731*** (4/12/2018)	-11.8598*** (11/28/2018)	-11.4923*** (11/22/2018)	-12.1294*** (11/28/2018)
TRANS	-12.0598*** (5/03/2018)	-11.5655*** (4/15/2018)	-12.0892*** (5/03/2018)	-9.7135*** (10/07/2018)	-8.0760*** (12/15/2018)	-9.7444*** (10/07/2018)
ACT	-14.4132*** (7/12/2018)	-14.1454*** (4/16/2018)	-14.3588*** (7/12/2018)	-10.6383*** (12/02/2018)	-10.0694*** (12/15/2018)	-10.6169*** (12/02/2018)
SPREAD	-10.9540*** (6/13/2018)	-10.5471*** (8/14/2018)	-10.9436*** (6/13/2018)	-10.2116*** (11/25/2018)	-8.8584*** (11/18/2018)	-10.1349*** (11/25/2018)
ISSUANCE	-10.2039*** (6/27/2018)	-9.8370*** (4/26/2018)	-10.1768*** (6/27/2018)	–	–	–
VELOCITY	-11.8916*** (5/20/2018)	-11.0673*** (4/28/2018)	-11.8606*** (5/20/2018)	-9.5302*** (12/09/2018)	-8.5491*** (11/17/2018)	-9.4772*** (12/04/2018)
FEE	-11.8923*** (6/21/2018)	-10.6898*** (8/18/2018)	-11.8877*** (6/21/2018)	-9.3545*** (11/21/2018)	-8.6704*** (11/14/2018)	-9.2844*** (11/21/2018)
HASH	–	–	–	-13.2129*** (10/14/2018)	-13.0094*** (11/20/2018)	-13.3577*** (11/24/2018)
TETHER	–	–	–	-9.3472*** (10/21/2018)	-8.7470*** (12/15/2018)	-9.2922*** (10/21/2018)
DJIA	-5.4140*** (4/24/2018)	-6.43070*** (6/22/2018)	-5.6932** (4/17/2018)	–	–	–
SSE	–	–	–	-12.5552*** (10/11/2018)	-11.4603*** (10/03/2018)	-12.7133*** (10/11/2018)
CBOEDJIA	-14.7327*** (6/19/2018)	-14.9254*** (4/12/2018)	-14.8776*** (4/17/2018)	–	–	–
GLD	–	–	–	–	–	–
USDEUR	–	–	–	–	–	–
BGT	-9.7257*** (6/10/2018)	-9.1431*** (7/21/2018)	-9.6976*** (6/10/2018)	-9.5776*** (11/14/2018)	-8.8060*** (11/19/2018)	-9.7824*** (11/14/2018)
TWTS	–	–	–	–	–	–
WIKI	–	–	–	–	–	–

*Notes: *** significant at 1% level, ** significant at 5% level, * significant at 10% level. The null hypothesis of this test is that the time series has a unit root with a structural break in the intercept/trend/both. Date of break in parenthesis. '–' refers to the absence of variable in the reference period.*

Table A5: Zivot-Andrews unit root test

	The regulatory consolidation			The technological boom			The irresistible boom			The bubble burst		
Variable	**Constant**	**Trend**	**Constant & Trend**	**Constant**	**Trend**	**Constant & Trend**	**Constant**	**Trend**	**Constant & Trend**	**Constant**	**Trend**	**Constant & Trend**
PRICE	-4.6275* (3/16/2017)	-3.0591 (2/24/2017)	-4.6144 (3/16/2017)	-3.2993 (6/24/2017)	-2.88605 (5/24/2017)	-3.3218 (6/12/2017)	-4.1953 (9/08/2017)	-4.1088 (9/22/2017)	-4.5104 (9/13/2017)	-3.3506 (1/14/2018)	-2.9431 (2/06/2018)	-3.0641 (2/14/2018)
TRANS	-6.9390*** (2/06/2017)	-7.0720*** (3/04/2017)	-7.2140*** (2/21/2017)	-6.962*** (5/08/2017)	-7.2631*** (5/17/2017)	-7.5796*** (5/27/2017)	–	–	–	-4.916** (12/12/2017)	-5.273*** (12/20/2017)	-5.358** (1/18/2018)
ACT	-10.1170*** (1/24/2017)	-9.7380*** (3/08/2017)	-10.2310*** (1/24/2017)	–	–	–	-7.694*** (10/09/2017)	-7.586*** (9/23/2017)	-7.799*** (10/02/2017)	–	–	–
SPREAD	-4.679* (1/18/2017)	-5.759*** (1/18/2017)	-5.6017*** (1/22/2017)	-5.2735** (5/21/2017)	-5.1667*** (5/27/2017)	-5.8173*** (6/01/2017)	-5.0384** (9/23/2017)	-4.1192* (10/18/2017)	-5.0625* (9/17/2017)	-6.5078*** (12/20/2017)	-5.6857*** (12/23/2017)	-6.4219*** (12/20/2017)
ISSUANCE	–	–	–	–	–	–	–	–	–	–	–	–
VELOCITY	–	–	–	-4.4987 (7/23/2017)	-4.5041** (7/20/2017)	-4.6065 (7/08/2017)	-9.1227*** (9/05/2017)	-9.0387*** (9/13/2017)	-9.3229*** (9/25/2017)	-10.3196*** (2/09/2018)	-9.9622*** (2/06/2018)	-10.2612*** (2/09/2018)
FEE	-4.0190 (3/24/2017)	-3.8970 (3/07/2017)	-4.4600 (2/21/2017)	-3.1970 (5/18/2017)	-5.8048*** (6/05/2017)	-5.4791** (6/04/2017)	-5.3728*** (9/02/2017)	-4.8079*** (9/13/2017)	-5.4564** (9/25/2017)	–	–	–
HASH	–	–	–	-7.3020*** (6/13/2017)	-6.1365*** (7/07/2017)	-7.3984*** (6/10/2017)	–	–	–	–	–	–
TETHER	–	–	–	-7.4249*** (5/22/017)	-6.5016*** (6/16/2017)	-7.5206*** (5/22/2017)	-4.8694* (9/17/2017)	-3.8261 (10/08/2017)	-4.9926* (9/16/2017)	-6.2737*** (2/09/2018)	-5.9432*** (1/18/2018)	-6.2329*** (2/09/2018)
DJIA	–	–	–	–	–	–	–	–	–	-5.068** (2/02/2018)	-3.506 (1/18/2018)	-5.932*** (2/02/2018)
SSE	–	–	–	–	–	–	-4.118 (8/25/2017)	-4.2526* (8/27/2017)	-4.517 (8/25/2017)	–	–	–
CBOEDJIA	-3.9996 (4/04/2017)	-4.2842* (3/16/2017)	-4.8895* (3/11/2017)	–	–	–	-4.5479 (10/17/2017)	-4.6504** (9/15/2017)	-4.8739* (9/09/2017)	–	–	–
GLD	–	–	–	-2.7943 (6/15/2017)	-2.01446 (7/09/2017)	-3.0011 (6/29/2017)	–	–	–	–	–	–
USDEUR	-3.2439 (3/09/2017)	-2.6923 (3/22/2017)	-3.4447 (3/16/2017)	–	–	–	–	–	–	–	–	–
BGT	–	–	–	–	–	–	–	–	–	–	–	–
TWTS	-7.0863*** (3/26/2017)	-6.5655*** (3/21/2017°	-7.0620*** (3/26/2017)	–	–	–	–	–	–	–	–	–
WIKI	–	–	–	-4.182 (5/11/2017)	-3.6183 (5/14/2017)	-4.6972 (5/27/2017)	-3.9557 (9/16/2017)	-4.2513* (9/30/2017)	-5.0180* (10/11/2017)	-6.3376*** (12/27/2017)	-6.0769*** (2/26/2018)	-6.7634*** (12/27/2017)
FUNDRAISING	–	–	–	–	–	–	-5.5692*** (10/09/2017)	-2.4726 (9/11/2017)	-5.2516** (10/09/2017)	–	–	–
						1^{st} **difference**						
PRICE	-6.0971*** (3/07/2017)	-5.4164*** (3/12/2017)	-6.07173*** (3/07/2017)	-12.3089*** (7/17/2017)	-11.6426*** (7/11/2017)	-12.2704*** (7/14/2017)	-10.4385*** (9/02/2017)	-10.4387*** (9/05/2017)	-11.2463*** (9/15/2017)	-10.8821*** (2/06/2018)	-10.1384*** (12/22/2017)	-10.8682*** (2/06/2018)
TRANS	-8.5370*** (3/04/2017)	-8.5700*** (4/05/2017)	-8.8090*** (4/01/2017)	-9.2880*** (7/11/2017)	-8.9208*** (5/31/2017)	-9.2255*** (7/11/2017)	–	–	–	-8.862*** (12/23/2017)	-8.704*** (1/21/2018)	-8.843*** (12/23/2017)
ACT	-10.8700*** (3/28/2017)	-10.8490*** (4/05/2017)	-10.8720*** (3/25/2017)	–	–	–	-9.300*** (9/25/2017)	-9.188*** (8/30/2017)	-9.256*** (9/25/2017)	–	–	–
SPREAD	-9.728*** (1/21/2017)	-9.0836*** (2/09/2017)	-9.3635*** (3/25/2017)	-9.5153*** (5/28/2017)	-8.7778*** (6/03/2017)	-9.7206*** (5/28/2017)	-7.9238*** (9/17/2017)	-7.5255*** (9/24/2017)	-7.8779*** (9/17/2017)	-7.4446*** (12/26/2017)	-7.2206*** (2/25/2018)	-7.6568*** (12/26/2017)
ISSUANCE	–	–	–	–	–	–	–	–	–	–	–	–
VELOCITY	–	–	–	-7.0158*** (5/26/2017)	-6.8264*** (6/21/2017)	-7.1855*** (7/23/2017)	-10.1049*** (9/25/2017)	-10.0167*** (11/09/2017)	-10.1813*** (10/30/2017)	-7.7080*** (2/07/2018)	-7.3468*** (2/11/2018)	-7.8017*** (2/07/2018)
FEE	-8.7600*** (3/05/2017)	-8.4920*** (1/28/2017)	-8.7190*** (3/05/2017)	-9.3186*** (6/09/2017)	-8.7353*** (7/07/2017)	-9.2752*** (6/09/2017)	-9.3095*** (9/18/2017)	-8.4218*** (10/12/2017)	-9.4311*** (9/18/2017)	–	–	–
HASH	–	–	–	-7.6449*** (6/3/2017)	-7.3937*** (6/14/2017)	-7.6187*** (6/30/2017)	–	–	–	–	–	–
TETHER	–	–	–	-7.6536*** (5/22/2017)	-7.4690*** (5/26/2017)	-7.7342*** (5/28/2017)	-7.7302*** (10/12/2017)	-7.3667*** (11/09/2017)	-7.8065*** (9/06/2017)	-8.3715*** (1/20/2018)	-8.0997*** (2/14/2018)	-8.3297*** (1/20/2018)
DJIA	–	–	–	–	–	–	–	–	–	-6.018*** (2/09/2018)	-5.323*** (2/03/2018)	-5.861*** (2/09/2018)
SSE	–	–	–	–	–	–	-10.252*** (8/25/2017)	-10.3658*** (11/09/2017)	-10.8000*** (8/27/2017)	–	–	–
CBOEDJIA	-16.6852*** (3/16/2017)	-16.291*** (1/18/2017)	-16.7375*** (3/16/2017)	–	–	–	-11.6006*** (10/25/2017)	-11.641*** (8/25/2017)	-11.737*** (9/12/2017)	–	–	–
GLD	–	–	–	-10.6771*** (6/08/2017)	-9.7847*** (5/18/2017)	-10.7897*** (6/08/2017)	–	–	–	–	–	–
USDEUR	-11.5192*** (3/03/2017)	-11.3505*** (2/08/2017)	-11.7705*** (3/28/2017)	–	–	–	–	–	–	–	–	–
BGT	–	–	–	–	–	–	–	–	–	–	–	–
TWTS	-9.4766*** (3/24/2017)	-9.2673*** (2/04/2017)	-9.6725*** (3/26/2017)	–	–	–	–	–	–	–	–	–
WIKI	–	–	–	-9.0000*** (5/18/2017)	-8.2159*** (6/02/2017)	-9.8803*** (5/17/2017)	-8.3689*** (10/01/2017)	-7.9392*** (11/03/2017)	-8.3625*** (10/08/2017)	-7.7297*** (2/25/2018)	-8.6775*** (2/22/2018)	-8.0831*** (1/02/2018)
FUNDRAISING	–	–	–	–	–	–	-11.3560*** (10/19/2017)	-11.2088*** (10/18/2017)	-11.6412*** (10/09/2017)	–	–	–

*Notes: *** significant at 1% level, ** significant at 5% level, * significant at 10% level. The null hypothesis of this test is that the time series has a unit root with a structural break in the intercept/trend/both. Date of break in parenthesis. '–' refers to the absence of variable in the reference period.*

Table A6: Zivot-Andrews unit root test

Variable	The eventful consolidation			The hash war crash		
	Constant	**Trend**	**Constant & Trend**	**Constant**	**Trend**	**Constant & Trend**
PRICE	-3.1079 (5/22/2018)	-2.6038 (4/21/2018)	-3.2097 (5/21/2018)	-5.3123** (11/19/2018)	-2.0270 (12/14/2018)	-4.7340 (11/19/2018)
TRANS	-7.863*** (5/25/2018)	-7.198*** (8/17/2018)	-8.010*** (5/25/2018)	-7.1351*** (11/21/2018)	-6.4977*** (11/09/2018)	-7.0988*** (11/21/2018)
ACT	-7.8724*** (4/15/2018)	-7.5004*** (4/25/2018)	-7.9965*** (5/12/2018)	-8.8671*** (11/23/2018)	-9.1757*** (11/06/2018)	-9.3588*** (11/17/2018)
SPREAD	-7.9243*** (7/02/2018)	-7.0098*** (6/11/2018)	-7.9961*** (7/02/2018)	-6.422*** (11/19/2018)	-4.481** (10/06/2018)	-6.538*** (11/19/2018)
ISSUANCE	-11.7763*** (7/17/2018)	-11.5175*** (8/17/2018)	-12.0816*** (7/17/2018)	–	–	–
VELOCITY	-11.3418*** (5/18/2018)	-10.6410*** (7/15/2018)	-11.4829*** (8/13/2018)	-5.0227*** (12/07/2018)	-4.6846** (12/05/2018)	-5.7991*** (11/29/2018)
FEE	-4.1183 (4/24/2018)	-3.9720 (4/26/2018)	-4.7283 (5/20/2018)	-4.0463 (12/08/2018)	-3.9513 (11/24/2018)	-5.4177** (11/15/2018)
HASH	–	–	–	-4.0601 (11/18/2018)	-3.6709 (12/12/2018)	-4.3882 (11/28/2018)
TETHER	–	–	–	-7.8881*** (10/11/2018)	-7.4837*** (10/16/2018)	-7.9850*** (10/09/2018)
DJIA	-4.253 (6/15/2018)	-3.733 (7/01/2018)	-4.801 (6/19/2018)	–	–	–
SSE	–	–	–	-3.3769 (10/31/2018)	-2.9402 (10/14/2018)	-3.8305 (10/30/2018)
CBOEDJIA	-4.235 (4/12/2018)	-4.078 (5/17/2018)	-4.414 (6/19/2018)	–	–	–
GLD	–	–	–	–	–	–
USDEUR	–	–	–	–	–	–
BGT	-6.7137*** (7/1/2018)	-6.0745*** (6/04/2018)	-6.8309*** (7/15/2018)	-4.6258* (11/14/2018)	-1.9336 (12/15/2017)	-4.0718 (11/14/2018)
TWTS	–	–	–	–	–	–
WIKI	–	–	–	–	–	–
			1^{st} **difference**			
PRICE	-8.8634*** (5/06/2018)	-8.891*** (4/13/2018)	-9.0717*** (4/25/2018)	-11.5868*** (12/15/2018)	-11.3293*** (11/21/2018)	-11.8218*** (11/14/2018)
TRANS	-11.7382*** (5/08/2018)	-13.002*** (5/27/2018)	-11.8687*** (4/26/2018)	-8.4166*** (10/08/2018)	-8.0804*** (12/15/2018)	-8.8517*** (10/08/2018)
ACT	-14.2158*** (7/15/2018)	-10.223*** (8/13/2018)	-14.2085*** (7/15/2018)	-10.4514*** (12/03/2018)	-10.3196*** (12/15/2018)	-10.4201*** (12/03/2018)
SPREAD	-10.7841*** (6/15/2018)	-10.054*** (4/15/2018)	-10.8835*** (5/21/2018)	-9.9621*** (11/26/2018)	-8.9408*** (11/21/2018)	-9.8537*** (11/26/2018)
ISSUANCE	-10.0009*** (7/17/2018)	-9.8855*** (7/23/2018)	-10.0863*** (7/17/2018)	–	–	–
VELOCITY	-11.2184*** (5/18/2018)	-11.1194*** (8/18/2018)	-11.3312*** (4/22/2018)	-9.050*** (12/05/2018)	-8.5027*** (12/15/2018)	-9.5473*** (12/07/2018)
FEE	-11.0857*** (6/24/2018)	-10.822*** (4/15/2018)	-11.3023*** (4/28/2018)	-9.2343*** (11/23/2018)	-8.8075*** (11/17/2018)	-9.1804*** (11/23/2018)
HASH	–	–	–	-8.5311*** (12/13/2018)	-8.4053*** (11/22/2018)	-8.6111*** (11/04/2018)
TETHER	–	–	–	-8.8374*** (10/17/2018)	-8.6214*** (10/21/2018)	-8.8693*** (10/17/2018)
DJIA	-9.849*** (6/11/2018)	-9.905*** (4/14/2018)	-10.256*** (4/18/2018)	–	–	–
SSE	–	–	–	-11.7586*** (10/19/2018)	-11.3073*** (10/03/2018)	-12.3759*** (10/19/2018)
CBOEDJIA	-14.650*** (4/12/2018)	-14.842*** (4/12/2018)	-14.9284*** (4/18/2018)	–	–	–
GLD	–	–	–	–	–	–
USDEUR	–	–	–	–	–	–
BGT	-9.3896*** (6/10/2018)	-9.1568*** (7/19/2018)	-9.3625*** (6/10/2018)	-9.2823*** (11/11/2018)	-8.7791*** (11/20/2018)	-9.5322*** (11/11/2018)
TWTS	–	–	–	–	–	–
WIKI	–	–	–	–	–	–

*Notes: *** significant at 1% level, ** significant at 5% level, * significant at 10% level. The null hypothesis of this test is that the time series has a unit root with a structural break in the intercept/trend/both. Date of break in parenthesis. '–' refers to the absence of variable in the reference period.*

Table A7: Bai-Perron tests of L+1 vs. L globally determined breaks

Sequential F-statistic determined breaks:	0
Significant F-statistic largest breaks:	2

Break Test	F-statistic	Scaled F-statistic	Critical Value**
0 vs. 1	0.189887	0.189887	8.58
1 vs. 2*	20.68585	20.68585	10.13
2 vs. 3	0.278719	0.278719	11.14
3 vs. 4	0.381863	0.381863	11.83
4 vs. 5	0.245147	0.245147	12.25

** Significant at the 0.05 level*

*** Bai-Perron (Econometric Journal, 2003) critical values.*

Estimated break dates:

1: 8/07/2017

2: 5/18/2017, 10/12/2017

3: 5/18/2017, 10/13/2017, 6/10/2018

4: 4/21/2017, 8/08/2017, 11/25/2017, 5/23/2018

5: 4/21/2017, 8/08/2017, 11/25/2017, 3/14/2018, 9/14/2018

Notes: The number of maximum breaks is 5 and the trimming option was set at 15. HAC covariances were used along with a prewhitening including a single lag, a Quadratic-Spectral Kernel and an Andrews bandwidth. Heterogeneous error distributions across breaks were allowed.

Table A8: Bai-Perron tests of 1 to M globally determined breaks

Sequential F-statistic determined breaks:	0
Significant F-statistic largest breaks:	5
UDmax determined breaks:	5
WDmax determined breaks:	5

Number of Breaks	F-statistic	Scaled F-statistic	Weighted F-statistic	Critical Value
1	0.189887	0.189887	0.189887	8.58
2	1.730567	1.730567	2.056547	7.22
3	4.478765	4.478765	6.447619	5.96
4*	33.56842	33.56842	57.71885	4.99
5*	78.54258	78.54258	172.3517	3.91
UDMax statistic*	78.54258		UDMax critical value**	8.88
WDMax statistic*	172.3517		WDMax critical value**	9.91

** Significant at the 0.05 level.*

*** Bai-Perron (Econometric Journal, 2003) critical values.*

Estimated break dates:

1: 8/07/2017

2: 5/18/2017, 10/12/2017

3: 5/18/2017, 10/13/2017, 6/10/2018

4: 4/21/2017, 8/08/2017, 11/25/2017, 5/23/2018

5: 4/21/2017, 8/08/2017, 11/25/2017, 3/14/2018, 9/14/2018

Notes: The number of maximum breaks is 5 and the trimming option was set at 15. HAC covariances were used along with a prewhitening including a single lag, a Quadratic-Spectral Kernel and an Andrews bandwidth. Heterogeneous error distributions across breaks were allowed.

Table A9: Global information criteria for 0 to M globally determined breaks

Schwarz criterion selected breaks:	5
LWZ criterion selected breaks:	5

Number of Breaks	Sum of Sq. Resids.	Log-L	Schwarz* Criterion	LWZ* Criterion
0	467.6724	-873.2992	-0.436245	-0.422406
1	114.5980	-359.9858	-1.824520	-1.782998
2	71.54248	-188.0202	-2.277595	-2.208383
3	48.52672	-46.33566	-2.647709	-2.550798
4	40.45406	20.07515	-2.811593	-2.686976
5	32.24376	102.8727	-3.020373	-2.868042

* *Minimum information criterion values displayed with shading*

Estimated break dates:

1: 8/07/2017

2: 5/18/2017, 10/12/2017

3: 5/18/2017, 10/13/2017, 6/10/2018

4: 4/21/2017, 8/08/2017, 11/25/2017, 5/23/2018

5: 4/21/2017, 8/08/2017, 11/25/2017, 3/14/2018, 9/14/2018

Notes: The number of maximum breaks is 5 and the trimming option was set at 15. HAC covariances were used along with a prewhitening including a single lag, a Quadratic-Spectral Kernel and an Andrews bandwidth.

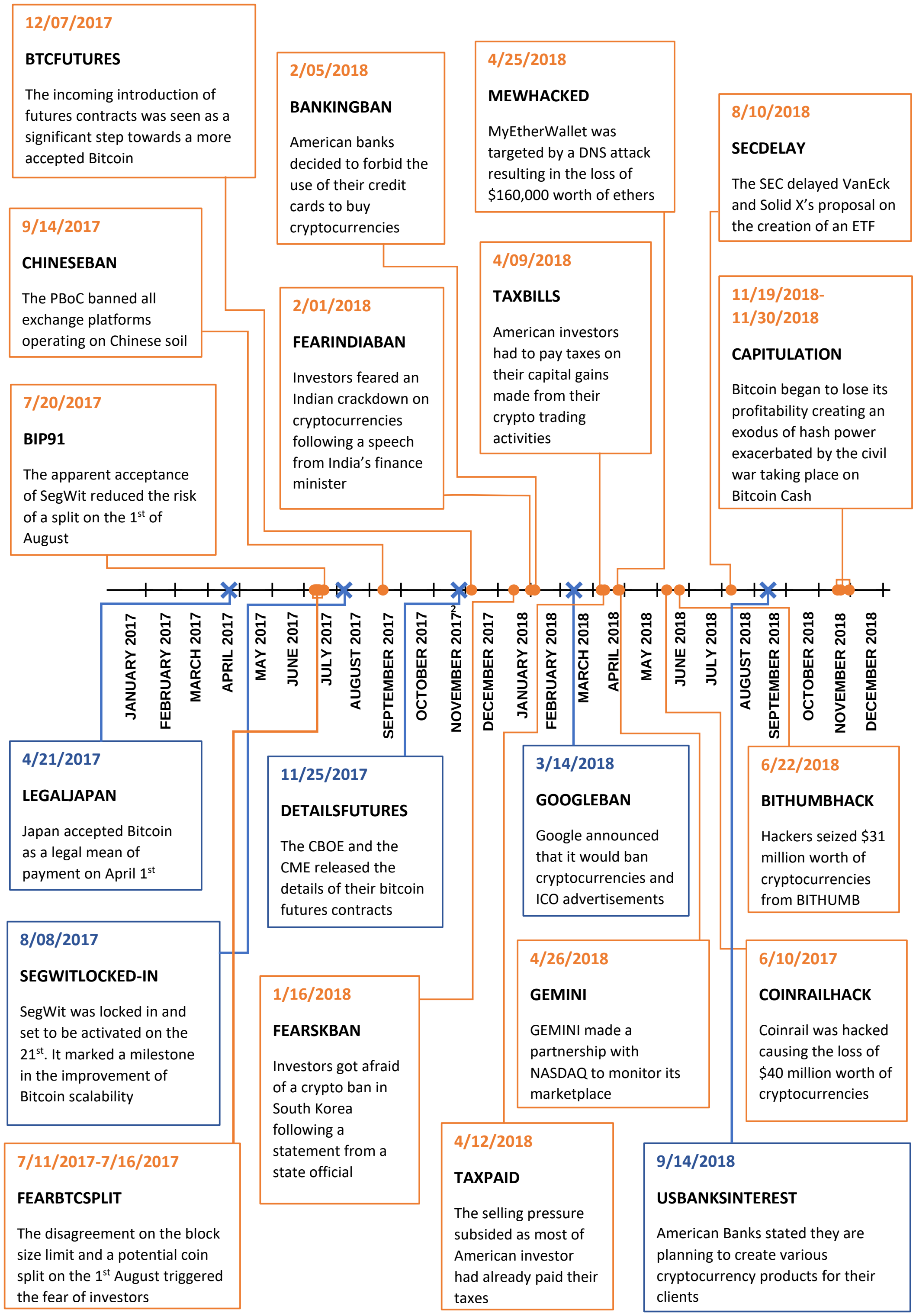

Figure A1: Bitcoin history 2017-2018 Timeline

Table A10: Linear and nonlinear autoregressive distributed lag models along with their respective variables

	The regulatory consolidation		The technological boom		The irresistible boom		The bubble burst		The eventful consolidation		The hash war crash	
	ARDL1	NARDL1	ARDL2	NARDL2	ARDL3	NARDL3	ARDL4	NARDL4	ARDL5	NARDL5	ARDL6	NARDL6
Dependant variable												
PRICE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Internal Factors												
TRANS	✓	✓	✓	✓			✓	✓	✓	✓	✓	✓
ACT	✓	✓			✓	✓			✓	✓	✓	
SPREAD	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
ISSUANCE									✓	✓		
VELOCITY			✓		✓	✓		✓	✓	✓	✓	✓
FEE	✓	✓	✓	✓	✓	✓			✓	✓	✓	✓
HASH			✓	✓							✓	✓
TETHER				✓	✓	✓	✓	✓			✓	
Global macroeconomic and financial developments												
DJIA							✓	✓	✓	✓		
SSE					✓	✓					✓	✓
CBOEDJIA	✓	✓			✓	✓						
GLD			✓	✓								
USDEUR	✓	✓										
Bitcoin Attractiveness for investors and users												
BGT									✓	✓		✓
TWTS	✓	✓										
WIKI			✓		✓		✓	✓				
FUNDRAISING					✓	✓						
Pivotal events												
BANKINGBAN							✓	✓				
BIP91				✓								
BITHUMBHACK										✓		
BTCFUTURES							✓	✓				
CAPITULATION											✓	✓
CHINESEBAN					✓	✓						
COINRAILHACK									✓	✓		
FEARBTCSPLIT			✓									
FEARINDIABAN							✓	✓				
FEARSKBAN							✓	✓				
GEMINI									✓	✓		
MEWHACK									✓	✓		
TAXBILLS									✓	✓		
TAXPAID									✓	✓		
SECDELAY									✓	✓		

Table A11: Long-run effects on Bitcoin price (ARDL models)

	ARDL1	**ARDL2**	**ARDL3**	**ARDL4**	**ARDL5**	**ARDL6**
TRANS	0.1204***	0.3323***	–	0.3238***	0.7975***	0.2548**
ACT	-0.0312	–	0.2154**	–	0.6889***	-0.4290**
SPREAD	-0.0433***	-0.0512**	-0.0369	-0.1072**	-0.1833***	-0.3028***
ISSUANCE	–	–	–	–	0.5927***	–
VELOCITY	–	0.0805	0.0572	–	0.2396***	-0.1534***
FEE	0.2403***	0.1289**	0.1193***	–	-0.0621	0.2558***
HASH	–	1.0926***	–	–	–	0.5713***
TETHER	–	–	-0.0516*	-0.1895***	–	0.0761**
DJIA	–	–	–	0.2872	-1.4272**	–
SSE	–	–	-0.7545	–	–	-0.5537
CBOEDJIA	0.2780***	–	-0.2943**	–	–	–
GLD	–	0.2941	–	–	–	–
USDEUR	-3.4284***	–	–	–	–	–
BGT	–	–	–	–	-0.1031**	–
TWTS	-0.1233	–	–	–	–	–
WIKI	–	0.0425	0.2035***	0.1804***	–	–
FUNDRAISING	–	–	0.9872***	–	–	–

*Notes: (1) Dependent variable: Bitcoin price. (2) *** significant at 1% level, ** significant at 5% level, and * significant at 10% level. (3) "–" designates the absence of a variable in the respective model or its non-significance.*

Table A12: Short-run effects on Bitcoin price (ARDL models)

	ARDL1	ARDL2	ARDL3	ARDL4	ARDL5	ARDL6
D(ACT(-1))	-0.0249	–	–	–	-0.1802***	–
D(ACT(-2))	-0.0782**	–	–	–	-0.1104***	–
D(ACT(-3))	–	–	–	–	-0.0864***	–
D(SPREAD)	-0.0295***	-0.0229***	-0.0267***	-0.0512***	–	-0.0459***
D(SPREAD(-1))	-0.0026	–	0.0331***	–	–	–
D(SPREAD(-2))	0.0087***	–	0.0129**	–	–	–
D(SPREAD(-3))	0.0107***	–	–	–	–	–
D(ISSUANCE)	–	–	–	–	0.0488**	–
D(ISSUANCE(-2))	–	–	–	–	0.0458**	–
D(VELOCITY)	–	-0.0022	-0.0142	–	-0.0024	-0.0244***
D(VELOCITY(-1))	–	-0.0157	-0.0671***	–	-0.0455***	0.0238**
D(VELOCITY(-2))	–	-0.0321**	-0.0534***	–	-0.0272***	–
D(VELOCITY(-3))	–	–	-0.0291**	–	–	–
D(FEE)	–	-0.0066	0.0215***	–	0.0196***	0.0048
D(FEE(-2))	–	0.0006	-0.0306***	–	–	–
D(FEE(-3))	–	-0.0731***	–	–	–	–
D(HASH(-1))	–	0.0960***	–	–	–	-0.0722**
D(HASH(-2))	–	–	–	–	–	-0.0877***
D(DJIA)	–	–	–	1.1839**	-0.9619***	–
D(SSE)	–	–	-1.5117**	–	–	0.9124***
D(SSE(-1))	–	–	-1.4797**	–	–	–
D(SSE(-2))	–	–	-2.1620***	–	–	–
D(CBOEDJIA(-1))	-0.1328***	–	–	–	–	–
D(GLD(-2))	–	-2.3469***	–	–	–	–
D(BGT)	–	–	–	–	-0.0414**	–
D(TWTS(-1))	-0.0487**	–	–	–	–	–
D(TWTS(-2))	-0.0389*	–	–	–	–	–
D(WIKI)	–	-0.0231	–	0.0442*	–	–
D(WIKI(-1))	–	-0.0279*	–	-0.0668***	–	–
D(WIKI(-3))	–	-0.0545***	–	–	–	–
D(FUNDRAISING(-1))	–	–	-0.6965**	–	–	–
Constant	2.0546***	-3.4520***	-4.2587***	1.2653***	0.9550***	0.9853***
ECM	-0.4154***	-0.2270***	-0.3545***	-0.1978***	-0.1784***	-0.2631***
Adjusted R-squared	0.6732	0.5695	0.6154	0.5338	0.5255	0.4844
Akaike crit.	-4.5953	-3.8292	-4.1530	-3.2137	-4.4842	-4.2389
Schwarz crit.	-4.1957	-3.3572	-3.6838	-2.9668	-4.0998	-3.9657
Hannan-Quinn crit.	-4.4333	-3.6361	-3.9627	-3.1135	-4.3284	-4.1281
Durbin-Watson stat	2.2381	2.0414	2.0540	2.2491	2.1500	2.0745

*Notes: (1) Dependent variable: Bitcoin price. (2) *** significant at 1% level, ** significant at 5% level, and * significant at 10% level. (3) "–" designates the absence of a variable in the respective model or its non-significance.*

Table A13: Max lag order selection (ARDL models)

	0	1	2	3	4
ARDL1	NA	827.646	128.126	80.066	101.996*
ARDL2	NA	968.276	119.3952	76.893	90.521*
ARDL3	NA	1264.464	161.2771	126.5295	125.7094*
ARDL4	NA	879.440	54.686*	41.935	33.159
ARDL5	NA	1646.768	135.567	108.0323	142.0968*
ARDL6	NA	915.103	126.537*	84.087**	98.710

*Notes: * and ** indicates lag order selected by the sequential modified Likelihood Ratio (LR) test statistic and by the modeler to ensure the normality of the model, respectively.*

Table A14: F-Bounds and t-Bounds Tests (ARDL models)

Estimated models	**F-Bounds Test**				**t-Bounds Test**			
	Signif. F-statistic	Signif. bounds	Lower I(0)	Upper I(1)	Signif. F-statistic	Signif. bounds	Lower I(0)	Upper I(1)
ARDL1	10.5645	1%	2.960	4.260	-5.7001	1%	-3.430	-5.190
ARDL2	5.8621	1%	2.960	4.260	-5.1027	5%	-2.860	-4.570
ARDL3	5.2847	1%	2.650	3.970	-5.7201	1%	-3.430	-5.540
ARDL4	5.9654	1%	3.410	4.680	-5.3611	1%	-3.430	-4.790
ARDL5	9.7523	1%	2.790	4.100	-6.1947	1%	-3.430	-5.370
ARDL6	6.5149	1%	2.790	4.100	-6.3162	1%	-3.430	-5.370

Notes: Signif. stands for level of significance, solely the lowest significance level satisfying the rejection of the null hypothesis of no long-run relationship is displayed

Table A15: Diagnostic Tests for Model Evaluation

	LM(1)		**LM(2)**		**BPH/ARCH(1)**		**WHITE***		**JBN**		**RESET(1)**		**Recursive Estimations**	
Model	**F-stat**	**Prob F**	**F-stat**	**Prob F**	**F-stat**	**Prob F**	**F-stat**	**Prob F**	**Stat χ^2**	**Prob**	**F-stat**	**Prob F**	**CUSUM**	**CUSUM-SQ**
ARDL1	1.7575	0.1886	0.8689	0.4232	0.8487	0.6582	0.8309	0.6799	1.2263	0.5416	2.8800	0.0934	S	S
ARDL2	0.1056	0.7460	0.7983	0.4536	1.0907	0.3716	1.1110	0.3499	3.6581	0.1606	1.22E-0.5	0.9972	S	S
ARDL3	0.1927	0.6618	0.4627	0.6312	1.2408	0.2274	0.9966	0.4833	1.7350	0.4200	0.0010	0.9742	S	S
ARDL4	2.6315	0.1081	1.5465	0.2145	0.6834	0.7851	0.6547	0.8118	0.6616	0.7183	0.0627	0.8029	S	S
ARDL5	1.1533	0.2845	0.8673	0.4221	0.9815	0.4998	1.0130	0.4560	1.2456	0.5364	2.6804	0.1036	S	S
ARDL6	0.2535	0.6159	0.2288	0.7960	1.3069	0.2031	1.7750	0.1308	4.1387	0.1263	0.0776	0.7813	S	S
NARDL1	0.9653	0.3287	0.5346	0.5879	0.1143	0.7360	0.8073	0.7131	0.1393	0.9327	1.5562	0.2158	S	S
NARDL2	0.5063	0.4787	0.3182	0.7284	2.9663	0.0879	0.5101	0.9655	0.0756	0.9629	0.4709	0.4945	S	S
NARDL3	1.1014	0.2972	0.5603	0.5733	0.0842	0.7722	0.7756	0.7724	0.1923	0.9083	3.4610	0.0666	S	S
NARDL4	1.4144	0.2375	0.6992	0.4998	2.3602	0.1274	0.7177	0.7916	1.0455	0.5929	0.7721	0.3820	S	S
NARDL5	0.9861	0.3223	1.0173	0.3641	0.1426	0.7062	1.2319	0.2049	2.2668	0.3219	3.4085	0.0668	S	S
NARDL6	1.4246	0.2361	1.1906	0.3092	0.5925	0.4432	1.2510	0.2277	4.1728	0.1241	2.8226	0.0967	S	S

*Notes: LM(n): Breusch-Godfrey serial correlation LM test up to n lags, BPH/ARCH(1): Breusch-Pagan heteroskedasticity test applied to ARDL models / ARCH heteroskedasticity test with 1 lag applied to NARDL models, WHITE: White heteroskedasticity test, JBN: Jarque-Bera Normality, RESET(1)= Ramsey RESET test with 1 lag, VIF: Variance inflation factor, * depicts the non-inclusion of white cross terms due to an insufficient number of observations, thus heteroskedasticity is checked but not the specification bias. The BPH test is not fitted to test heteroskedasticity in the presence of non-linearity, so the ARCH heteroskedasticity test was carried out in its stead for NARDL models.*

Table A16: VIF estimations of ARDL models

	ARDL1	ARDL2	ARDL3	ARDL4	ARDL5	ARDL6
TRANS	2.45	2.48	–	2.54	2.75	1.99
D(TRANS)	–	–	–	–	–	–
ACT	8.08	–	2.47	–	5.20	2.22
D(ACT)	8.15	–	–	–	5.27	–
D(ACT(-1))	4.64	–	–	–	4.49	–
D(ACT(-2))	2.31	–	–	–	2.22	–
D(ACT(-3))	–	–	–	–	1.84	–
SPREAD	2.19	2.38	4.55	2.66	1.74	4.42
D(SPREAD)	1.72	1.56	1.56	1.65	–	1.49
D(SPREAD(-1))	1.67	–	1.53	–	–	–
D(SPREAD(-2))	1.55	–	1.49	–	–	–
D(SPREAD(-3))	1.39	–	–	–	–	–
ISSUANCE	–	–	–	–	3.39	–
D(ISSUANCE)	–	–	–	–	4.71	–
D(ISSUANCE(-1))	–	–	–	–	3.28	–
D(ISSUANCE(-2))	–	–	–	–	1.90	–
VELOCITY	–	4.11	5.91	–	3.16	3.26
D(VELOCITY)	–	3.49	7.74	–	4.27	2.44
D(VELOCITY(-1))	–	3.03	5.82	–	3.55	2.09
D(VELOCITY(-2))	–	2.05	3.68	–	2.18	–
D(VELOCITY(-3))	–	–	2.12	–	–	–
FEE	2.82	2.42	3.34	–	2.29	2.21
D(FEE)	–	2.09	1.81	–	2.12	2.09
D(FEE(-1)))	–	2.41	1.88	–	–	–
D(FEE(-2)))	–	2.10	1.49	–	–	–
D(FEE(-3))	–	1.77	–	–	–	–
HASH	–	3.24	–	–	–	6.20

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	ARDL1	ARDL2	ARDL3	ARDL4	ARDL5	ARDL6
D(HASH)	–	1.42	–	–	–	3.69
D(HASH)	–	–	–	–	–	3.69
D(HASH)	–	–	–	–	–	3.14
TETHER	–	–	4.09	1.74	–	1.86
D(TETHER)	–	–	2.29	–	–	–
DJIA	–	–	–	1.97	2.14	–
D(DJIA)	–	–	–	1.09	1.21	–
SSE	–	–	3.87	–	–	1.82
D(SSE)	–	–	1.27	–	–	1.14
D(SSE(-1))	–	–	1.36	–	–	–
D(SSE(-2))	–	–	1.29	–	–	–
CBOEDJIA	1.49	–	1.86	–	–	–
D(CBOEDJIA)	1.80	–	–	–	–	–
D(CBOEDJIA(-1))	1.83	–	–	–	–	–
D(CBOEDJIA(-2))	1.39	–	–	–	–	–
GLD	–	1.81	–	–	–	–
D(GLD)	–	1.63	–	–	–	–
D(GLD(-1))	–	1.46	–	–	–	–
D(GLD(-2))	–	1.39	–	–	–	–
USDEUR	1.11	–	–	–	–	–
D(USDEUR)	1.30	–	–	–	–	–
BGT	–	–	–	–	1.87	–
D(BGT)	–	–	–	–	1.77	–
D(BGT(-1))	–	–	–	–	1.57	–
TWTS	4.30	–	–	–	–	–
D(TWTS)	3.32	–	–	–	–	–
D(TWTS(-2))	2.62	–	–	–	–	–
D(TWTS(-3))	1.86	–	–	–	–	–

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	ARDL1	ARDL2	ARDL3	ARDL4	ARDL5	ARDL6
WIKI	–	3.83	3.54	4.11	–	–
D(WIKI)	–	1.68	–	1.38	–	–
D(WIKI(-1))	–	1.68	–	1.07	–	–
D(WIKI(-2))	–	1.65	–	–	–	–
D(WIKI(-3))	–	1.64	–	–	–	–
FUNDRAISING	–	–	7.35	–	–	–
D(FUNDRAISING)	–	–	1.44	–	–	–
D(FUNDRAISING(-1))	–	–	1.25	–	–	–
BANKINGBAN	–	–	–	1.13	–	–
BTCFUTURES	–	–	–	1.24	–	–
CAPITULATION	–	–	–	–	–	1.19
CHINESEBAN	–	–	1.16	–	–	–
COINRAILHACK	–	–	–	–	1.29	–
FEARBTCSPLIT	–	1.47	–	–	–	–
FEARINDIABAN	–	–	–	1.04	–	–
FEARSKBAN	–	–	–	1.06	–	–
GEMINI	–	–	–	–	1.20	–
MEWHACK	–	–	–	–	1.18	–
SECDELAY	–	–	–	–	1.15	–
TAXBILLS	–	–	–	–	1.14	–
TAXPAID	–	–	–	–	1.15	–
VIF Mean	2.30	2.29	2.93	1.70	2.49	2.55

Notes: Dependent variable: Bitcoin price. "–" designates the absence of a variable in the respective model. A value of variance inflation factors (VIF) lower than 2 indicates a low correlation, a VIF between 2 and 5 corresponds to a moderate correlation while a VIF between 5 and 10 suggests a high though acceptable correlation. A VIF higher than 10 demonstrates a multicollinearity problem.

Table A17: VIF estimations of NARDL models

	NARDL1	NARDL2	NARDL3	NARDL4	NARDL5	NARDL6
TRANS	2.34	3.62	–	2.90	2.97	3.39
D(TRANS)	–	3.37	–	1.54	–	2.46
D(TRANS(-1))	–	3.10	–	–	–	–
D(TRANS(-2))	–	2.35	–	–	–	–
ACT	7.96	–	3.52	–	5.26	–
D(ACT)	7.75	–	2.44	–	5.39	–
D(ACT(-1))	4.09	–	–	–	4.67	–
D(ACT(-2))	2.09	–	–	–	2.25	–
D(ACT(-3))	–	–	–	–	1.86	–
SPREAD	2.02	2.25	4.71	3.00	1.75	5.07
D(SPREAD)	1.64	1.53	1.50	1.68	–	1.48
D(SPREAD(-1))	1.60	–	1.40	–	–	–
D(SPREAD(-2))	1.49	–	–	–	–	–
D(SPREAD(-3))	1.38	–	–	–	–	–
ISSUANCE	–	–	–	–	3.40	–
D(ISSUANCE)	–	–	–	–	4.75	–
D(ISSUANCE(-1))	–	–	–	–	3.29	–
D(ISSUANCE(-2))	–	–	–	–	1.90	–
VELOCITY	–	–	2.46	4.14	3.20	1.81
D(VELOCITY)	–	–	2.12	2.51	4.30	–
D(VELOCITY(-1))	–	–	–	–	3.73	–
D(VELOCITY(-2))	–	–	–	–	2.25	–
FEE	2.63	2.52	2.68	–	2.78	2.42
D(FEE)	–	2.42	1.75	–	2.56	1.78
D(FEE(-1)))	–	1.84	1.43	–	–	1.60
D(FEE(-2)))	–	–	–	–	–	–
D(FEE(-3))	–	–	–	–	–	–

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	NARDL1	NARDL2	NARDL3	NARDL4	NARDL5	NARDL6
HASH	–	3.77	–	–	–	4.09
D(HASH)	–	1.62	–	–	–	1.68
D(HASH)	–	–	–	–	–	–
D(HASH)	–	–	–	–	–	–
TETHER	–	4.58	5.51	1.79	–	–
D(TETHER)	–	2.62	4.40	–	–	–
D(TETHER(-1))	–	1.96	2.18	–	–	–
D(TETHER(-2))	–	1.63	–	–	–	–
DJIA	–	–	–	2.08	2.14	–
D(DJIA)	–	–	–	1.11	1.23	–
SSE	–	–	3.01	–	–	2.01
D(SSE)	–	–	1.26	–	–	1.24
D(SSE(-1))	–	–	–	–	–	1.21
D(SSE(-2))	–	–	–	–	–	–
CBOEDJIA	1.49	–	2.10	–	–	–
D(CBOEDJIA)	1.78	–	1.50	–	–	–
D(CBOEDJIA(-1))	1.83	–	1.46	–	–	–
D(CBOEDJIA(-2))	1.37	–	–	–	–	–
D(CBOEDJIA(-3))	–	–	–	–	–	–
GLD	–	1.18	–	–	–	–
D(GLD)	–	1.17	–	–	–	–
D(GLD(-1))	–	1.21	–	–	–	–
D(GLD(-2))	–	1.23	–	–	–	–
USDEUR	1.08	–	–	–	–	–
D(USDEUR)	1.27	–	–	–	–	–
BGT	–	–	–	–	1.87	2.68
D(BGT)	–	–	–	–	1.83	–
D(BGT(-1))	–	–	–	–	1.58	–

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	NARDL1	NARDL2	NARDL3	NARDL4	NARDL5	NARDL6
TWTS	2.73	–	–	–	–	–
D(TWTS)	1.81	–	–	–	–	–
D(TWTS(-2))	–	–	–	–	–	–
D(TWTS(-3))	–	–	–	–	–	–
WIKI	–	–	–	4.95	–	–
D(WIKI)	–	–	–	1.53	–	–
D(WIKI(-1))	–	–	–	1.11	–	–
D(WIKI(-2))	–	–	–	–	–	–
D(WIKI(-3))	–	–	–	–	–	–
FUNDRAISING	–	–	5.90	–	–	–
D(FUNDRAISING)	–	–	1.38	–	–	–
D(FUNDRAISING(-1))	–	–	1.31	–	–	–
BANKINGBAN	–	–	–	1.38	–	–
BIP91	–	1.13	–	–	–	–
BITHUMBHACK	–	–	–	–	–	1.52
BTCFUTURES	–	–	–	1.27	–	–
CAPITULATION	–	–	–	–	–	1.22
CHINESEBAN	–	–	1.19	–	–	–
COINRAILHACK	–	–	–	–	1.29	–
FEARBTCSPLIT	–	–	–	–	–	–
FEARINDIABAN	–	–	–	1.07	–	–
FEARSKBAN	–	–	–	1.08	–	–
GEMINI	–	–	–	–	1.21	–
MEWHACK	–	–	–	–	1.19	–
SECDELAY	–	–	–	–	1.16	–
TAXBILLS	–	–	–	–	1.15	–
TAXPAID	–	–	–	–	1.15	–

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	NARDL1	NARDL2	NARDL3	NARDL4	NARDL5	NARDL6
VIF Mean	2.61	2.25	2.51	2.07	2.53	2.27

Notes: Dependent variable: Bitcoin price. "–" designates the absence of a variable in the respective model. A value of variance inflation factors (VIF) lower than 2 indicates a low correlation, a VIF between 2 and 5 corresponds to a moderate correlation, while a VIF between 5 and 10 suggests a high though acceptable correlation. A VIF higher than 10 demonstrates a multicollinearity problem. The asymmetric variables were treated as symmetric ones to be able to estimate an approximate value of VIF, which wouldn't be distorted by the evident correlation that exists between the partial sum of positive change in one's explanatory variable and its negative counterpart.

Table A18: Correlation Matrices of ARDL and NARDL Models

(a) Correlation Matrix of ARDL1-NARDL1

	PRICE	TRANS	FEE	CBOEDJIA	ACT	SPREAD	USDEUR	TWTS
PRICE	1.00	0.46	0.83	0.11	0.35	−0.30	−0.19	0.23
TRANS		1.00	0.54	−0.05	0.49	−0.16	0.16	0.52
FEE			1.00	−0.02	0.44	−0.05	0.09	0.38
CBOEDJIA				1.00	−0.07	0.06	−0.14	0.01
ACT					1.00	−0.05	0.07	0.43
SPREAD						1.00	−0.08	0.23
USDEUR							1.00	0.05
TWTS								1.00

(b) Correlation Matrix of ARDL2-NARDL2

	PRICE	GLD	SPREAD	FEE	TRANS	HASH	WIKI	VELOCITY	TETHER
PRICE	1.00	0.10	−0.03	0.43	0.19	0.76	0.38	0.38	0.62
GLD		1.00	0.20	0.22	0.18	−0.05	0.00	0.22	−0.05
SPREAD			1.00	0.41	0.27	−0.15	0.36	0.04	0.18
FEE				1.00	0.43	0.00	0.36	−0.06	0.25
TRANS					1.00	−0.18	0.53	0.34	0.05
HASH						1.00	0.17	0.29	0.60
WIKI							1.00	0.27	0.16
VELOCITY								1.00	0.20
TETHER									1.00

(c) Correlation Matrix of ARDL3-NARDL3

	PRICE	FEE	SPREAD	ACT	SSE	WIKI	CBOEDJIA	VELOCITY	TETHER	FUNDRAISING
PRICE	1.00	0.68	−0.56	0.64	0.57	0.65	0.13	0.17	0.39	0.92
FEE		1.00	−0.24	0.45	0.27	0.60	0.39	0.25	0.34	0.49
SPREAD			1.00	−0.40	−0.36	−0.01	0.06	0.09	0.17	−0.59
ACT				1.00	0.32	0.56	0.18	0.21	0.43	0.60
SSE					1.00	0.26	−0.29	−0.03	0.28	0.68
WIKI						1.00	0.21	0.28	0.56	0.54
CBOEDJIA							1.00	0.20	0.08	0.05
VELOCITY								1.00	0.11	0.13
TETHER									1.00	0.33
FUNDRAISING										1.00

(d) Correlation Matrix of ARDL4-NARDL4

	PRICE	SPREAD	TRANS	TETHER	DJIA	WIKI	VELOCITY
PRICE	1.00	0.31	0.74	−0.03	−0.05	0.65	0.33
SPREAD		1.00	0.50	0.14	−0.15	0.67	0.51
TRANS			1.00	0.35	0.16	0.61	0.43
TETHER				1.00	0.52	−0.09	0.09
DJIA					1.00	−0.37	−0.24
WIKI						1.00	0.62
VELOCITY							1.00

(e) Correlation Matrix of ARDL5-NARDL5

	PRICE	SPREAD	VELOCITY	ACT	ISSUANCE	FEE	BGT	TRANS	DJIA
PRICE	1.00	0.13	0.04	0.11	−0.02	0.57	0.39	0.75	−0.37
SPREAD		1.00	−0.14	−0.41	0.02	0.24	0.19	0.28	−0.42
VELOCITY			1.00	0.23	−0.03	0.10	0.09	0.12	0.10
ACT				1.00	−0.11	0.06	0.01	0.15	0.16
ISSUANCE					1.00	0.01	0.00	−0.12	0.06
FEE						1.00	0.27	0.50	−0.37
BGT							1.00	0.59	−0.43
TRANS								1.00	−0.55
DJIA									1.00

(f) Correlation Matrix of ARDL6-NARDL6

	PRICE	SPREAD	TRANS	VELOCITY	TETHER	SSE	FEE	HASH	ACT	BGT
PRICE	1.00	−0.82	0.47	−0.37	0.21	0.54	0.32	0.82	0.23	−0.66
SPREAD		1.00	−0.47	0.31	−0.13	−0.46	−0.05	−0.67	−0.35	0.68
TRANS			1.00	0.14	0.45	0.31	0.12	0.33	0.48	−0.19
VELOCITY				1.00	0.19	−0.08	0.17	−0.39	0.29	0.47
TETHER					1.00	0.00	0.15	0.23	0.57	0.21
SSE						1.00	0.39	0.44	0.12	−0.23
FEE							1.00	0.15	0.16	0.04
HASH								1.00	0.24	−0.55
ACT									1.00	−0.03
BGT										1.00

Appendix B. Dynamic multipliers and their interpretation

SPREAD's dynamic multipliers

In Figure B1.a, the analysis of the dynamic multiplier reveals that the adverse impact on the Bitcoin price, resulting from a positive shock (green curve) on SPREAD, surpasses the overall effect arising from a negative shock (red curve) on SPREAD of equal magnitude during the period of regulatory consolidation. The influence of positive shocks exhibits an increasing trend until the second day, followed by a decline from the second to the fourth day and a subsequent surge from the fourth day onward, ultimately reaching its long-run equilibrium (indicated by the green dashed line) on the 12^{th} day. Conversely, the impact of negative shocks declines until the fourth day, experiences a slight intensification after that, and ultimately attains its long-run equilibrium (indicated by the red dashed line) on the 11^{th} day. The asymmetric difference (blue curve) steadily grows in favour of positive shocks, gradually establishing dominance over negative shocks. Notably, the 95% confidence interval (blue stripe) never encompasses the zero line, indicating that SPREAD exhibits a consistently significant asymmetric response at a 5% significance level.

TWTS's dynamic multiplier

In Figure B1.b, the examination of the dynamic multiplier illustrates that the adverse effect on the Bitcoin price attributable to a positive shock (green curve) on TWTS exceeds the beneficial impact of a negative shock (red curve) on SPREAD of equal magnitude during the period of regulatory consolidation until the ninth day. The detrimental effect of positive shocks and the salutary effect of negative shocks escalate until they both reach their long-run equilibrium (indicated by the red dashed line) on the 11^{th} day. The negative shocks adversely affected the Bitcoin price until the second day, while the positive shocks consistently and increasingly had a detrimental impact. The asymmetric difference (blue curve) diminishes until it becomes null on the ninth day. Significantly, the 95% confidence interval (blue stripe) encompasses the zero line from the seventh day onward, suggesting that TWTS's asymmetric response becomes statistically insignificant at a 5% significance level in the long term.

USDEUR's dynamic multiplier

Regarding the cumulative dynamic multiplier in Figure B1.c, it is evident that both negative (red curve) and positive shocks (green curve) on USDEUR confer benefits to the Bitcoin price during the regulatory consolidation period. The favourable impact of the positive shock (green line) on the Bitcoin price steadily increases, swiftly reaching its long-term equilibrium (indicated by the green dashed line) on the sixth day. Initially, the negative shock (red line) adversely affected the Bitcoin price until the second day, after which it positively affected the price until it achieved its long-term equilibrium (indicated by the red dashed line) on the 10^{th} day. Both shocks contributed to the growth of the asymmetric difference (blue curve), with positive and negative shocks having the dominant influence in the short and long term, respectively. Notably, the 95% confidence interval (blue stripe) consistently excludes the zero line, indicating that USDEUR exhibits a persistent and statistically significant asymmetric response at a 5% significance level.

FEE's dynamic multipliers

When analyzing the cumulative dynamic multiplier (CDM) throughout the technological boom in Figure B2.a, one notices that shocks on FEE initially had a symmetric short-term impact on the Bitcoin price. Subsequently, the benefit of a positive shock (green curve) on FEE for the Bitcoin price became more prominent than the detrimental effect of its negative counterpart (red curve). Both shocks displayed an increasing impact on the Bitcoin price until reaching their long-term equilibrium (indicated by the green dashed line) on the 13^{th} day, with the positive shock exhibiting the highest effect. The asymmetric difference (blue curve) increased until the 10^{th} day, primarily due to the more substantial impact of positive shocks. Notably, the 95% confidence interval (blue stripe) consistently excluded the zero line, signifying that FEE maintained a persistent and statistically significant asymmetric response at a 5% significance level.

Meanwhile, in the CDM during the irresistible boom in Figure B3.a, it is observed that a positive (negative) shock on FEE initially detrimentally impacted the Bitcoin price until approximately the first (third) day. Subsequently, the impact of a positive (negative) shock on FEE became increasingly (un)favourable for the Bitcoin price until reaching its long-term equilibrium on the ninth (13^{th}) day. The asymmetric difference (blue curve) surged due to the dominance of the positive shock's influence over its counterpart until the third day. At that point, it started plummeting and became increasingly negative from the fourth day onwards.

In the CDM during the eventful consolidation in Figure B5.a, both shocks initially had an advantageous impact on FEE until the third day. Afterwards, the positive shock's impact on FEE became increasingly pernicious, while the negative shock's beneficial effect grew slower. The 90% confidence interval did not encompass the zero line until the 12^{th} day, suggesting that FEE's asymmetric response is statistically significant at a 10% significance level in the short and medium term.

Ultimately, in the CDM during the hash war crash in Figure B6.e, both shocks initially had a positive impact on FEE. However, the negative shock's effect turned detrimental to the Bitcoin price from the third day and equalled the positive shock's impact in absolute value around the seventh day. Concurrently, the positive shock's beneficial impact on the Bitcoin price increased until the fifth day and swiftly reached its long-run equilibrium on the seventh day. The asymmetric difference intensified until the third day and then decreased until reaching the zero line on the sixth day. Notably, the 95% confidence interval consistently excluded the zero line around the same time, suggesting that FEE was no longer statistically significant as an asymmetric response at a 5% significance level at this point.

HASH's dynamic multipliers

Like the dynamic multiplier for FEE during the same period, the cumulative dynamic multiplier (CDM) for HASH during the technological boom depicted in Figure B2.b exhibits a short-term symmetric impact. Subsequently, both shocks escalate, with the detrimental effect of the negative shock (red curve) increasingly surpassing the salutary impact of the positive shock (green curve) until they reach their respective long-term equilibrium (indicated by the green and red dashed lines) on the 12^{th} day. The asymmetric difference (blue curve) increasingly favours the negative shock, gradually dominating the positive shock. HASH maintains a consistent and statistically significant asymmetric response at a 5% significance level, as evidenced by the 95% confidence interval (blue stripe) consistently excluding the zero line.

Meanwhile, HASH's CDM during the hash war crash from Figure B6.a indicates that both shocks beneficially impact the Bitcoin price. The positive (negative) shock's impact rises (falls) until it reaches its long-term equilibrium on the fifth day. The negative shock's effect consistently lags behind that of the positive shock. The asymmetric difference surges until the third day due to both shocks exhibiting a positive impact. The 95% confidence interval consistently excludes the zero line, indicating that HASH maintains a persistent and statistically significant asymmetric response at a 5% significance level.

VELOCITY's dynamic multipliers

One can observe the impact trajectory of VELOCITY on the Bitcoin price during three distinct phases: the irresistible boom, the bubble burst, and the hash war crash, as depicted by the dynamic multipliers in Figure B3.b, Figure B4.b, and Figure B6.c, respectively.

In the initial period, the negative shock (red curve)'s beneficial effect exceeds the positive shock's detrimental impact (green curve). The positive shock had a favourable impact until the second day when its impact turned increasingly adverse. Conversely, the negative shock's impact remained consistently favourable and became even more so. Both shocks eventually reached their long-term equilibrium (indicated by the red and green dashed lines) around the 10^{th} day. Although the difference (blue curve) between the two effects initially favoured the positive shock, it stabilized on the 8^{th} day onward. The 95% confidence interval (blue stripe) consistently excluded the zero line, indicating that VELOCITY has a persistent and statistically significant asymmetric impact on the Bitcoin price in both the short and long term at a 5% significance level.

During the second period, the negative shock's detrimental effect surpassed the positive shock's impact from the short to medium term. While the positive shock initially had a deleterious impact, it began to affect the Bitcoin price on the third day beneficially. In contrast, the negative shock's impact remained consistently detrimental, but it was eventually surpassed by the positive shock, resulting in a negative asymmetric difference that became null on the 13^{th} day. Indeed, VELOCITY exhibited a short-term asymmetric impact and a long-term symmetric impact, as evidenced by the 95% confidence interval beginning to include the zero line on the 12^{th} day.

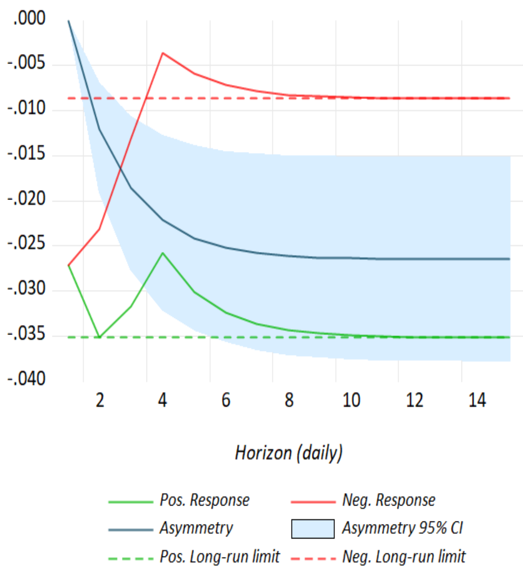
In the final period, the positive shock's detrimental impact exceeded the negative shock's beneficial effect. The difference between the influence of these shocks widened in favour of the positive shock until the sixth day, when both long-run equilibriums were reached, resulting in a stabilized difference.

TRANS's dynamic multipliers

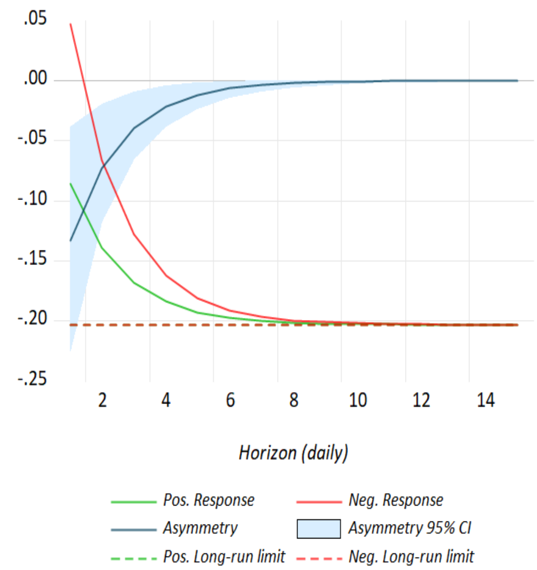
Analyzing its dynamic multiplier during the bubble burst in Figure B4.a and the hash war crash in Figure B6.d, it becomes evident that the beneficial impact of the positive shock (green curve) initially surpasses the detrimental effect of the negative shock (red curve). However, the difference (blue line) between these two effects diminishes as the negative shock starts to exert a prominent impact from the first day. The negative shock catches up with its counterpart on the seventh day during the bubble burst and the 22^{nd} day during the hash war crash, respectively. Consequently, the difference becomes null, and the 95% confidence interval (blue stripe) begins to include the zero line, suggesting that TRANS has a long-term symmetric impact on the Bitcoin price during both periods.

BGT's dynamic multiplier

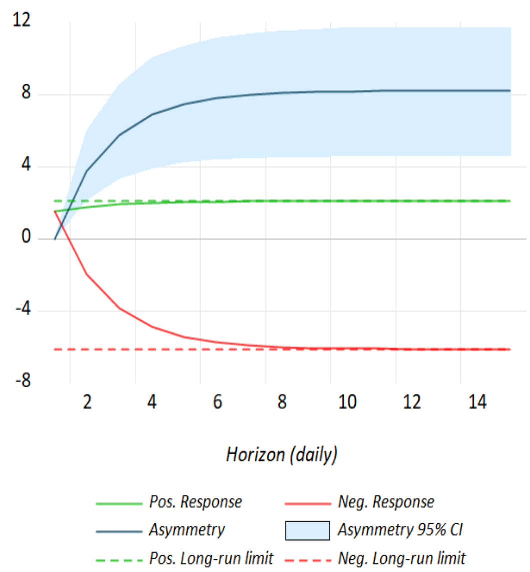
The dynamic multiplier during the hash war crash in Figure B6.b reveals that both shocks on BGT have a detrimental impact on the Bitcoin price, with the positive shock (green curve) exhibiting the most pronounced influence. These shocks gather momentum until they reach their long-run equilibrium on the fourth day for the negative shock (red curve) and the fifth day for the positive shock. The asymmetric difference (blue curve) widens as the pernicious effects of both shocks on the Bitcoin price intensify until the fifth day. Remarkably, BGT maintains a continuous and statistically significant asymmetric response at a 5% significance level, as evidenced by the 95% confidence interval (blue stripe) consistently excluding the zero line.



(a) Cumulative Dynamic Multiplier: SPREAD on PRICE

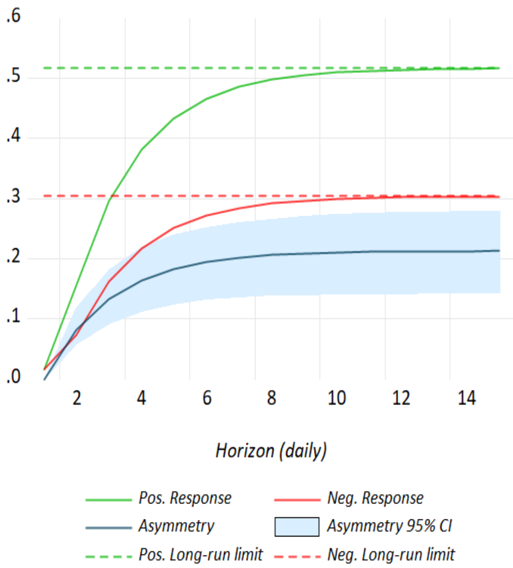


(b) Cumulative Dynamic Multiplier: TWTS on PRICE

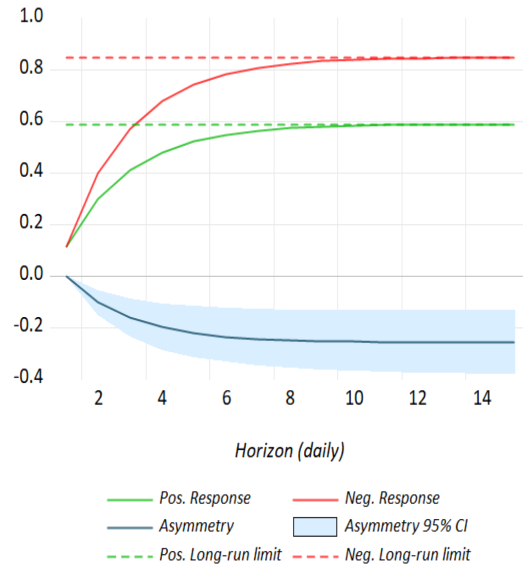


(c) Cumulative Dynamic Multiplier: USDEUR on PRICE

Figure B1: Multipliers during the regulatory consolidation

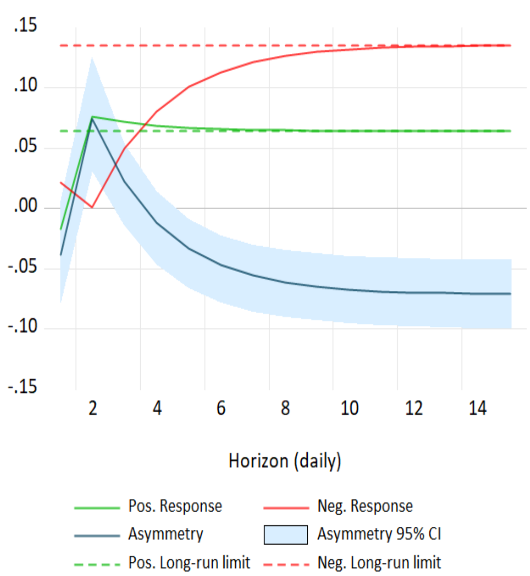


(a) Cumulative Dynamic Multiplier: FEE on PRICE

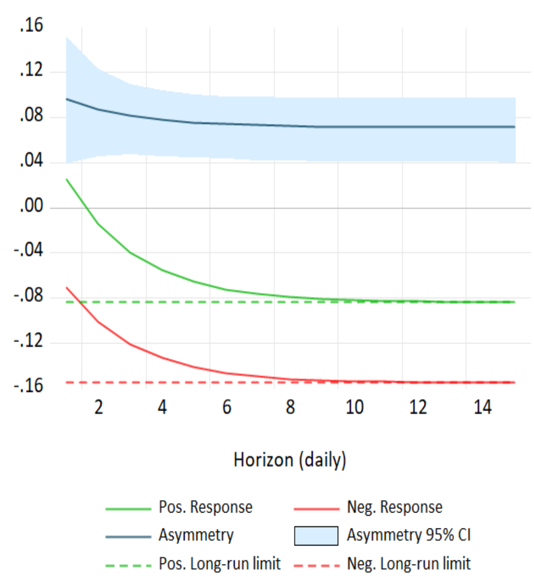


(b) Cumulative Dynamic Multiplier: HASH on PRICE

Figure B2: Multipliers during the technological boom

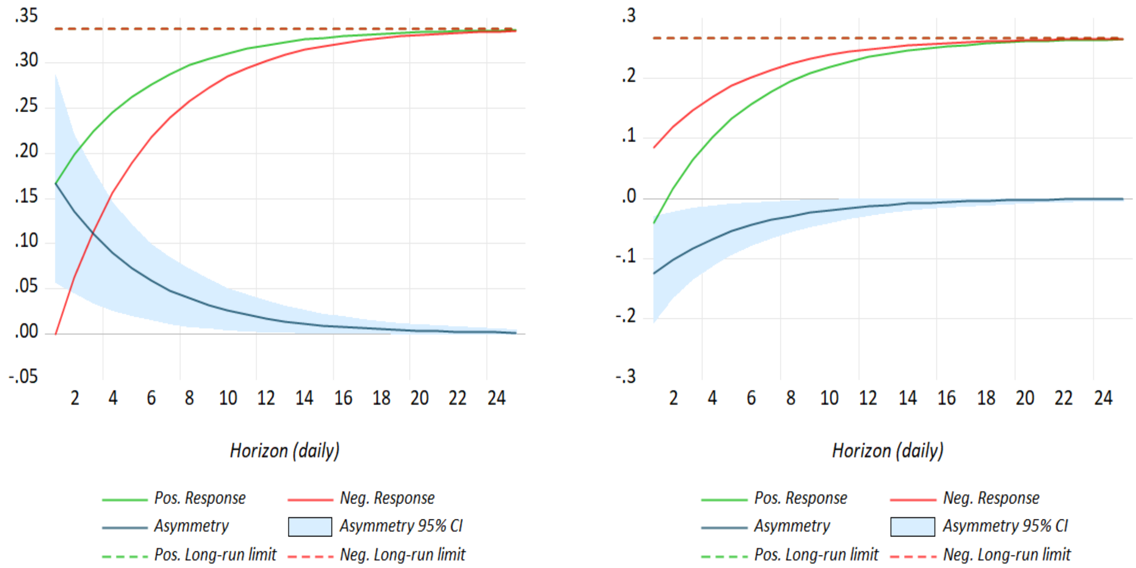


(a) Cumulative Dynamic Multiplier: FEE on PRICE



(b) Cumulative Dynamic Multiplier: VELOCITY on PRICE

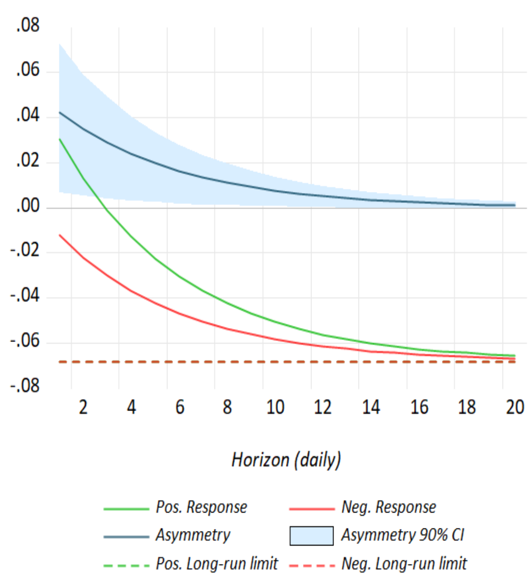
Figure B3: Multipliers during the irresistible boom



(a) Cumulative Dynamic Multiplier: TRANS on PRICE

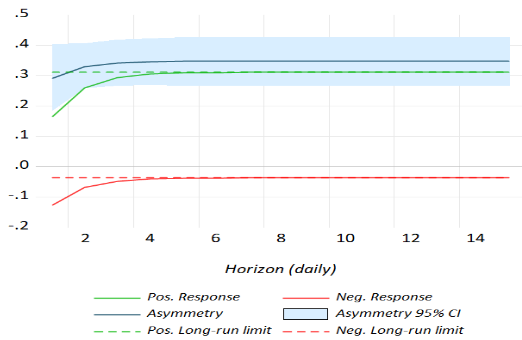
(b) Cumulative Dynamic Multiplier: VELOCITY on PRICE

Figure B4: Multipliers during the bubble burst

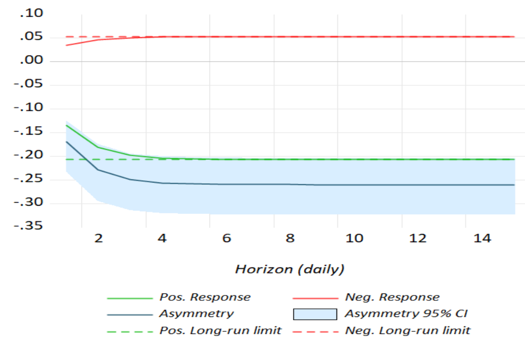


(a) Cumulative Dynamic Multiplier: FEE on PRICE

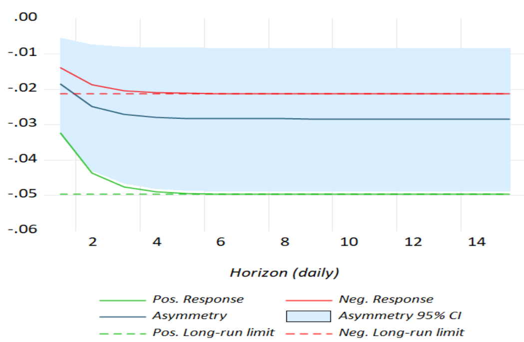
Figure B5: Multipliers during the eventful consolidation



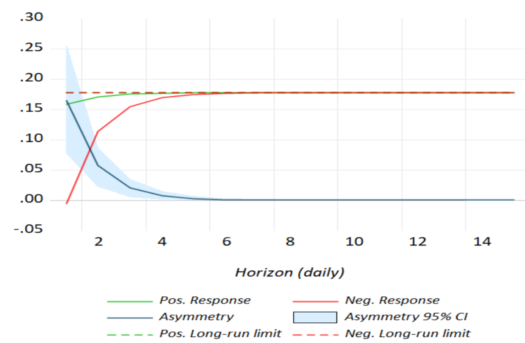
(a) Cumulative Dynamic Multiplier: HASH on PRICE



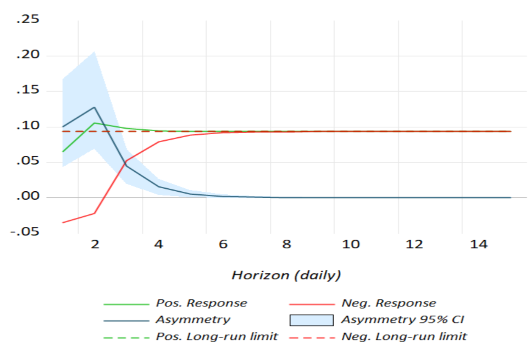
(b) Cumulative Dynamic Multiplier: BGT on PRICE



(c) Cumulative Dynamic Multiplier: VELOCITY on PRICE



(d) Cumulative Dynamic Multiplier: TRANS on PRICE



(e) Cumulative Dynamic Multiplier: FEE on PRICE

Figure B6: Multipliers during the hash war crash

Appendix C. Results and discussions on critical events

Table C1: Dummy variables' effects on Bitcoin price (ARDL and NARDL models)

	ARDL1	NARDL1	ARDL2	NARDL2	ARDL3	NARDL3	ARDL4	NARDL4	ARDL5	NARDL5	ARDL6	NARDL6
BANKINGBAN	–	–	–	–	–	–	-0.1661***	-0.2107***	–	–	–	–
BIP91	–	–	–	0.1721***	–	–	–	–	–	-0.0562*	–	–
BITHUMBHACK	–	–	–	–	–	–	–	–	–	–	–	–
BTCFUTURES	–	–	–	–	–	–	–	0.2210***	–	–	–	–
CAPITULATION	–	–	–	–	–	–	–	–	–	–	-0.0680***	-0.0373***
CHINESEBAN	–	–	–	–	-0.2104***	-0.1976***	–	–	–	–	–	–
COINRAILHACK	–	–	–	–	–	–	–	–	-0.0648**	-0.0563**	–	–
FEARBTCSPLIT	–	–	-0.0468***	–	–	–	–	–	–	–	–	–
FEARINDIABAN	–	–	–	–	–	–	-0.1279***	-0.1304***	–	–	–	–
FEARSKBAN	–	–	–	–	–	–	-0.1102**	-0.0900*	–	–	–	–
GEMINI	–	–	–	–	–	–	–	–	0.0593**	0.0594**	–	–
MEWHACK	–	–	–	–	–	–	–	–	-0.0993***	-0.1080***	–	–
TAXBILLS	–	–	–	–	–	–	–	–	-0.0653**	-0.0672***	–	–
TAXPAID	–	–	–	–	–	–	–	–	0.1087***	0.1106***	–	–
SECDELAY	–	–	–	–	–	–	–	–	-0.0469*	-0.0439*	–	–

Notes: (1) Dependent variable: Bitcoin price. (2) *** significant at 1% level, ** significant at 5% level, and * significant at 10% level. (3) "–" designates the absence of a variable in the respective model or its non-significance.

In analysing the outcomes illustrated in Table C1, it becomes evident that our hypotheses are affirmed. The adverse impact of hacking events (MEWHACK, COINRAILHACK, BITHUMBHACK) on the Bitcoin price aligns with expectations, while the positive influence of adoption events (BTCFUTURES, GEMINI) corroborates prior assertions. Also, we correctly predicted the disparate influence of tax and internal events. Indeed, TAXBILLS had a detrimental impact and TAXPAID a beneficial one on the Bitcoin price for the former. Those two tax events emphasise that tax returns hurt the Bitcoin price before they are filled and paid, but once investors have settled their taxes, they invest the remaining funds after taxes back to Bitcoin. For the latter, FEARBTCSPLIT and CAPITULATION were detrimental to the Bitcoin price and spread for an extended period, stressing the damaging repercussions on Bitcoin from the community division and the scalability problem. On the other hand, all the regulatory events (CHINESEBAN, FEARSKBAN, FEARINDIABAN, BANKINGBAN, SECDELAY) negatively affected the Bitcoin price, contrary to our expectations. The non-presence of a regulatory event positively affecting Bitcoin can be explained by the fact that those events were solely outright bans or refusals to grant permissions to integrate the cryptocurrency market into the financial markets. Finally, the price was positively impacted by the technological advancements fixing Bitcoin's scalability problem and healing community divisions like BIP91.