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The Bitcoin cycles and the effect of the war in Ukraine

MSC Thesis

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To my beloved wife and mother for being next to me, and to my professors for the inspiration!

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Abstract

In this work we investigate the cycles of bitcoin based on its price and volume. To do so, we define the cycles' starting point based on the local minimum before its ascending phase, and the ending point being the local minimum after its descending phase. This methodological framework can be derived among other disciplines, by solar physics in the high-speed solar wind streams identification. In this way, we can argue at which point of a probable cycle we currently are, and characterize the Bitcoin's performance, i.e., smooth, or extreme volatility. We also analyze the impact of the war in Ukraine on the price and volume of Bitcoin. We apply a two-stage event-analysis methodology, to explore whether Bitcoin price and volume were affected by the Ukraine war event, and to investigate the magnitude of this effect. The results indicate that the cycles differ in their number based on price and volume, and we currently are in a smooth period not profound if another cycle has already started. Moreover, based on the results, the war in Ukraine significantly affected Bitcoin volume, but not its price.

Keywords: Bitcoin; price; volume; cycles; war in Ukraine

1. Introduction

As a response to the financial crisis of 2008, new technology was applied to perform a decentralized network, namely blockchain. In this technological advancement, all nodes, representing users, have equal rights and obligations, and in this framework, for an action to be performed, e.g., a transaction, must be validated by the majority of the users. With the validation of the action, the information is stored in all users' computers, rendering this information transparent, and irreversible. However, to retain the anonymity of the users, every user has also his private key, known only by him. The concept of this technology is to construct a decentralized system in which an intermediary is not necessary. The first cryptocurrency that was launched, having these features, was bitcoin.

In this context, bitcoin is the first cryptocurrency that was launched, the most dominant to date in terms of market capitalization and the one that is perceived as the leader of the cryptocurrency market (Corbet et al., 2019). It is known to present unique characteristics in many aspects, displaying a very high volatility (Wang et al., 2021), serving as hedge, and also as a safe haven (Wustenfeld and Geldner, 2022), and simultaneously possessing properties of both a standard financial asset and a speculative one (Kristoufek, 2015). This unique combination of characteristics renders BTC one of a kind, and a very interesting case for research, combining theories from many disciplines (economics, finance, etc), utilizing also methods from many technical domains (e.g statistics, econometrics, machine learning, forecasting, etc).

It is thus no wonder that academia and industry try to investigate and predict Bitcoin's dynamics. There are many factors that have been known to play an important role in the price and volume of Bitcoin. Most studies explore Bitcoin's price volatility and volume characteristics (Glaser et al. 2014, Dowling et al. 2016, Katsiampa, 2017). Others look at possible relationships with equity markets (Kostika and Laopodis, 2020) and financial assets in general (Corbet et al. 2019, Elsayed et al., 2022).

The BTC among many financial stocks and futures, serves as a volatility spillover transmitter (Jiang et al., 2022), implying that its role in the financial system is very important, rendering its analysis imperative. The fact that BTC is perceived the most important cryptocurrency, since it was the first to be launched, can be also derived from empirical evidence, since BTC affects many other cryptocurrencies (Yi et al., 2021).

Moreover, BTC is known to have specific cycle characteristics, with its price fluctuations having cyclical trends and inherent long-term unpredictability, and fractal characteristics (Tong et al., 2022). A cycle analysis, especially for a dominant cryptocurrency as BTC, is a very important subject for investigation for the academia and industry, as well, since such an analysis can give insights in the dynamics and various characteristics that emerge many times, rendering also at some point its forecasting feasible. Based on the current literature, many factors play an important role in the BTC price and volume, and similarly, the BTC affects many factors, however, no study, based on the authors' current knowledge, examines the cycles of the BTC in an endogenous manner, which can be inferred as a core approach. Although there are many studies investigating the economic and business cycles in general, such an analysis does not exist in the current literature for the BTC.

Last, there is a strand of literature that explores how significant events affect Bitcoin performance, ranging from political events (Qin et al. 2021), to even the COVID-19 pandemic (Raza et al., 2022). We build on this context, by exploring whether and how the Ukraine war has affected the price and the volume of Bitcoin. To date, there is only one paper that explores how Bitcoin and the war in Ukraine are linked to each other; Yatie (2022) use data from Bitcoin, Ethereum, and Gold price, and find that all of these assets failed as safe havens during this war. This finding is interesting, since most academic literature that will be discussed in the following section tends to conclude that Bitcoin can act as a safe haven in a global economic policy uncertainty context.

Based on the aforementioned, the present thesis fills these gaps in the literature, since it provides a unique approach, detecting, examining, and comparing the cycles of the BTC based on both its price and volume. Moreover, the present paper examines empirically the impact of the war in Ukraine on the Bitcoin's price and volume performance. The remaining of the paper is structure as follows: section 2 presents the theoretical framework of the bitcoin, section 3 states the review of the literature, section 4 presents the methodology employed, section 5 presents the data and variables used and the results of the present work, and section 6 concludes the paper.

2. Theoretical Framework

The traditional definition of the financial system includes mainly, activities, services, and agents, that facilitate and also promote, the flow of funds from certain agents that seem to stagnate them, to other agents that require these funds for personal and/or investing reasons. This is the point at which, the financial infrastructure, in classical terms, intervenes, in order to promote the flow of these funds. Based on the literature, the financial system consists of the financial markets, also known as direct finance, and also the financial intermediaries, known as indirect finance (Daskalakis and Georgitseas, 2020). According to the authors, in the first one, borrowers get the funds directly from the lenders, while in the second one, there is an agent that plays the role of the intermediary to decide the allocation of the money to specific borrowers, money that is captured from lenders.

Back in 2008, under the nickname of Satoshi Nakamoto, a white paper was published, regarding the invention of bitcoin, the first cryptocurrency (Nakamoto, 2008). Based on this whitepaper, the author(s) stated that the aim of the launch of bitcoin was mainly the transaction between individuals, without the intervention of intermediaries, enabling the trust in the system through its functioning properties. The functions of this ecosystem, based on cryptographic algorithms, enable the anonymity ensuring the privacy of participants. Since an important factor that is known to play a significant role in the proper functioning of the financial system, in general, is trust, through the bitcoin ecosystem, this trust can be empowered, without the need for well-known intermediaries.

The BTC was based on a specific technological framework, known as the blockchain. The emergence of this technology, introduced in the BTC cryptocurrency paved the way for a new era in finance. However, even though it is widely known and accepted that there are significant differences between crypto and financial assets, the nature of cryptocurrencies has inherent difficulty in their definition, leading to difficulties also in their valuation. To be more precise, there is not currently any valuation technique that can be applied appropriately to the valuation of cryptocurrencies (Daskalakis and Georgitseas, 2020), and many researchers are trying to solve this problem by analyzing and proposing alternative ways of these assets' evaluation.

In what follows, the present chapter introduces the basic concepts regarding blockchain technology and why specific characteristics of this technology are important for the field of finance. We then provide a presentation of the importance of this technology for the performance of the BTC cryptocurrency, and the value that is obtained from its adaptation. Finally, we present the difficulties in the investigation of the BTC, due to its nature, and we propose a different approach in the bitcoin's research, as derived from the field of solar physics, contributing to the literature, in this way.

2.1 Blockchain Technology

In a specific network, the way the various nodes are interconnected characterizes the network as centralized, decentralized, and other characterizations (Sueur et al., 2012). In a centralized network, an authority, or in other words, a central node, is present, retaining full control over all other nodes. To give an example from the field of finance, in the conventional financial networks, digital payments require an intermediary that keeps continuous track of the transaction, to avoid double-spending. This agent can be regarded as the central node that has full control of the whole financial network, by supervising the financial system itself. On the other hand, the decentralized system is different. In a decentralized system, all nodes have the same participation, and thus, demonstrate the same weight and significance in the network. In this context, blockchain technology presents decentralized characteristics, and this is the reason why it has been adapted from the BTC ecosystem. More analytically, in this network, all nodes, representing each user, have the same rights and obligations, being all together connected. In this way, no user is disconnected from the others, and no information can be channeled only through specific routes. In this ecosystem, all users can create entries, and for the system to validate these entries, at least the majority of the users must validate these entries. This is why this system is also known as distributed ledger technology (Daskalakis and Georgitseas, 2020). Through its function, the blockchain infrastructure makes good use of this specific utility, so that the intermediary that is required in the conventional financial system, now is not needed.

In the scope of blockchain technology, when a user creates a query, for instance, to perform a transaction with another user, the transaction is represented online as a block, containing specific information, always with encryption (Rajasekaran et al., 2022). The users (in their majority) must confirm and validate the block, approving the query of the user. When the query is validated, it is added to the chain of all up-to-now records of blocks. Finally, the query is executed, for instance, the transaction takes place.

We should highlight that the aforementioned system demonstrates certain characteristics. The most important are related to safety, irreversibility, and transparency (Rajasekaran et al., 2022). To be more precise, regarding safety, the information is stored in all user’s computers, rendering hacking extremely difficult, if not inevitable, since information should change on all computers. The irreversibility is derived from the fact that a transaction that has been added to the block, cannot be deleted. Finally, the transparency is also a feature of this specific network, since all users that participate in the network have equal rights and obligations, as stated above, the information is publicly stored, displayed, and validated by all the users of the network so that no intermediary is required (Daskalakis and Georgitseas, 2020).

Blockchain technology can be utilized by many fields, some of them being healthcare, distribution, finance, supply chains, and many others (Rajasekaran et al., 2022; Mollah et al., 2021; Arasan et al., 2021; Iqbal et al., 2021; Subramani et al., 2021; Subramani et al., 2022; Yousefi and Tosarkani, 2022; Corte-Real et al., 2022).

2.2 Mining in the Blockchain Ecosystem

As stated above, the transactions in the blockchain ecosystem are performed through peers, without any involvement of intermediaries, and always online. A very common practice for the verification of transactions in the blockchain ecosystem is through mining. The so-called miners are individuals that utilize their hardware to perform cryptographic calculations, to solve complex algorithms generated by the blockchain system. When the algorithm is solved, the network is informed, and all the nodes verify the solution. With the verification of the majority, and more precisely, 51% of the miners, this new block is added to the chain. The miners receive a certain amount of the cryptocurrency, as a reward for their effort, utilizing their computers to solve the algorithm (Daskalakis and Georgitseas, 2020).

We should mention here that with the increase in the users' multitude, and with the increase in the transactions, in the blockchain ecosystem, the mining process has become very demanding, leading to the emergence of mining farms. These are rooms concentrating a huge number of computers, with extreme computational power, and servers that can validate mining quicker than conventional computers. This makes the mining process a rally for whom will be the first to solve the algorithm and be rewarded with a coin from the system. Finally, the energy consumption to solve the algorithm has become very high, with many researchers highlighting the pollution of the environment due to energy consumption, and increasing the co2 emissions (Köhler and Pizzol, 2019).

2.3 Cryptocurrencies

The launch of blockchain technology paved the way for the creation of networks with unique features, and also for the emergence of various assets. There are specific assets whose definition is not concrete. To begin with, digital currencies are the currencies that mainly represent value in a digital form, however, there is no strict definition, and although they demonstrate some monetary characteristics, they are neither connected to a sovereign currency nor backed by any authority (Daskalakis and Georgitseas, 2020). On the other hand, virtual currencies are assets that have been developed by individuals, demonstrating their unit of account. These can be used for the exchange of the virtual currency with fiat currency, or to perform payments in the real economy, and in some cases can operate in a self-contained virtual environment (Daskalakis and Georgitseas, 2020). Finally, cryptocurrencies are virtual currencies that make use of cryptography, to operate in a decentralized, secure environment. We should also mention the definition of tokens, which are assets like cryptocurrencies, however, tokens can operate more functions than cryptocurrencies.

Cryptocurrencies are assets that can operate transactions. These assets can operate in networks of peers, using open-source protocols. Such a network is decentralized. Since cryptocurrencies are digital assets and do not exist in a physical form, a digital wallet is required to store the cryptocurrencies. A digital wallet is software that is capable of storing, sending, and receiving digital codes that represent the value of cryptocurrencies (Daskalakis and Georgitseas, 2020). A digital wallet has two keys, a private, one that is known only by the owner, and a public key, that is known by everyone in the system.

Cryptocurrencies utilize blockchain technology to merit from its properties that were referred to and discussed above, which are safety, irreversibility, and transparency. The system is decentralized and transparent with all users sharing the same information, equaling all in power, the system demonstrates encryption properties, rendering the system safe, and finally, when a block is created, this action cannot be undone, giving validity to the systems irreversibility.

2.4 Bitcoin (BTC)

Bitcoin is the first cryptocurrency that was launched, with the largest market share. This is probably why all other cryptocurrencies are known as altcoins, separating them from bitcoin. Apart from its common characteristics with other cryptocurrencies, for instance, transparency, irreversibility, and safety, however, it has also some unique features. To avoid inflation due to excessive and finite supply, the amount of the bitcoin cryptocurrency that is given as a reward to miners with the solution of the algorithmic problem, is divided into half after a certain period. This means that around every four years, the reward given to miners breaks in half. This is known as the halving of bitcoin. The aforementioned reward with a specific number of bitcoins given to the miners will stop at around 2140. In this way, the total amount of BTC supply is fixed, being 21 million in multitude, confronting a probable inflation effect in this specific cryptocurrency. To give some numbers, in 2009, the reward for each block in the chain mined was 50 bitcoins, while after the first halving, it was 25, and then 12.5. In May 2020, it became 6.25 bitcoins per block. In this context, if its value is based on its scarcity, then a "halving" of the BTC every four years will theoretically drive its price higher.

Even though BTC is a powerful cryptocurrency with many positive aspects, some implications also emerge, since no adequate regulation and policies have been structured in all countries, rendering BTC vulnerable to malpractices. Some of these may be money-laundering, distribution of money for unethical reasons or purchases, some of them being drugs, cybercrimes, and many others (Karim et al., 2021). This is probably one of the most important concerns that have been posed by many researchers, organizations, institutions, and users, as well. Furthermore, the halving of the BTC reduces the rate at which new coins are created decreasing the supply, even though demand may increase. This fact has some implications for investors as other assets with a low or finite supply, can have high demand, affecting this ecosystem, pushing them to a higher level. Finally, the need for processing power is increasing, leading to a need for more energy to solve the algorithm. This may lead to more environmental pollution, increasing the co2 emissions (Köhler and Pizzol, 2019).

3. Literature review

In what follows, we illustrate the review in the literature regarding both the cycle detection of the price and volume of transactions of the bitcoin and also the event case study. In this context, we divide the literature review into two subsections. More analytically, the first one describes the efforts related to the cycle detection, and the second one presents the findings and methodologies performed regarding the events studies.

3.1 BTC cycles literature

The fact that many governments, e.g., China, have stated their interest in creating cryptocurrencies as national currency (Allen et al., 2022), show the amount of penetration of the blockchain technology in the global economy. There are many studies trying to interpret the bitcoin's performance, its interconnectedness with other financial assets, the probable spillover effects, trying also to forecast its value. To begin with, Chevallier et al. (2021) use numerous machine learning approaches to forecast the value of Bitcoin, examining also its interactions with other cryptocurrencies.

Alternative approaches investigate the effect of various factors in cryptocurrencies. To give an example, Tandon et al. (2021) use data derived from social media to investigate its effect in cryptocurrencies. Similarly, Garcia et al. (2014) investigate the social interactions and socio-economic signals that create or affect the price bubbles, regarding the Bitcoin. According to Ullah et al. (2022) positive tweets by celebrities, and also positive government endorsements are related to a positive change in the BTC's price.

Furthermore, many studies unveil the interconnectedness of BTC and other cryptocurrencies with the financial market assets. More precisely, Huynh et al. (2020) investigate the predictive power of the ratio gold to platinum prices on Bitcoin, and based on the authors, the ratio predicts the prices of BTC. Moreover, Tang and Wang (2022) argue that market and funding liquidity is important in the forecasting of BTC's price volatility.

Moreover, stablecoin transfers have been found to play an important role in the BTC price and volume of transactions (Ante et al., 2021). More analytically, around stablecoin transfers, abnormal increase in the trading volume and also abnormal returns in the BTC are evidenced. It has been also shown that the volume of the BTC has an impact on its returns distribution (Balcilar et al., 2017). In the same context, Marthinsen and Gordon (2022) argue that the BTC mining cost is related to its price. The authors state that the mining costs follow price movements of the BTC, rather than precede them, as one would imagine.

On the other hand, the halving of the BTC leads to an increase in the market value of BTC (Meynkhard, 2019). This fact shows the importance of the halving in the BTC price. Masiak et al. (2019) analyze the effect and duration of shocks in the initial coin offerings, the Bitcoin and the Ethereum cryptocurrencies.

As for the cycle detection and analysis, there are many researchers trying to unveil the dynamics enfolded behind economic and business cycles. Such was the work of Krolzig and Toro (2005), in which, a Markov-switching vector autoregressive model was employed to investigate the dynamics of cycles in Europe. Furthermore, Tong et al. (2022) show that the fluctuation of the price of cryptocurrencies, represented by BTC, do not follow a random walk, and the fluctuation is positively correlated with time. The price fluctuations have cyclical trends and inherent long-term unpredictability, and fractal characteristics. The aforementioned studies show the importance of cyclic behavior enfolded in the business, economic, and financial markets, including BTC which demonstrates also a cyclic behavior, as shown by the literature.

Based on the current knowledge, BTC is found to be affected and it also affects many other variables, see among many others Masiak et al. (2019), Meynkhard (2019), Ullah et al. (2022). According to Baldan and Zen (2020) there aren't ultimate drivers for Bitcoin price, so, one should take into consideration many variables or different approaches. There seems to be an interaction between volume and returns, indicating a positive and significant correlation (Bianchi and Dickerson, 2019). This means that the price and the volume are both important for the BTC evaluation and thus, they should both be examined, and not as most studies investigating only the price of BTC. Elsayed et al. (2022) examined the volatility interconnectedness among many financial assets, and based on the authors, BTC plays the role of a net transmitter of volatility spillovers to all the other markets examined, especially during the COVID-19 era. This fact shows that there are shocks and external events that can promote certain characteristics of the BTC, affecting the whole financial world. In this way, the investigation of the BTC properties, especially during certain events of great importance, is imperative.

Although some researchers have found a link between BTC and conventional financial assets, see among others Zeng et al. (2020), however, the BTC is affected by many financial and non-financial variables, rendering its analysis and prediction a complicated theme. In this context, it is imperative to examine in an endogenous way the different cycles that are structured, based on the BTC price, and the BTC volume, respectively. The present paper aims to fill this gap in the literature, since there is not any study examining the BTC cycles in an endogenous way. The present paper is a first of its kind approach, motivating the utilization of different approaches from different fields and disciplines.

3.2 Bitcoin event literature

Qin et al. (2021) provide an interesting context of exploring how Bitcoin and global economic policy uncertainty interreact. Specifically, they apply the bootstrap sub-sample rolling-window causality test (Balcilar et al. 2010, Su et al., 2019a,b) on monthly data during 2010-2019, to explore the non-constant interaction between global economic policy uncertainty and the Bitcoin price. Their results show that the Bitcoin market contains useful information to forecast global economic policy uncertainty and that global economic policy uncertainty also contains valuable information to improve the prediction of returns and volatility in the Bitcoin market.

In the context discussed above, a series of studies have shown that individual political events interact with Bitcoin. The main focus of literature is to explore whether Bitcoin can act as a hedge under specific economic policy uncertainty conditions (Demir et al., 2018; Wu et al., 2019; Su et al., 2019a,b; Fang et al., 2019). For example, Bouoiyour and Selmi (2017) explored the surge of Bitcoin price just after Trump‘s election win in 2016, in a safe haven context. Specifically, their research question was whether Bitcoin can serve a hedge or safe haven for U.S. stock index, over the uncertainty surrounding Trump’s victory in the U.S. presidential elections. They found that the Bitcoin‘s safe-haven property is time-varying and that it has primarily been a weak safe haven in the short- and long-term. Umar et al. (2021) reach similar conclusions; they investigate whether Bitcoin can be considered as a safe haven asset amid political and economic uncertainty in the U.S. during mid-2010 – late-2010 and also find that although Bitcoin appears to be a safe haven asset when uncertainties are on the rise, however, this relationship tends to change during the short- to long-run.

Furthermore, many other important events are shown to have been linked with Bitcoin. For example, Qin et al. (2021) denote that uncertain events, such as the Brexit, the economic crisis in Brazil and the Cyprus and Turkey debt crises also lead the price of Bitcoin to increase. Similarly, Wustenfeld and Geldner (2022) show that local and global shocks affect local Bitcoin activities and trading volatilities. Raza et al. (2022) argue that dynamic spillover effects were evidenced due to COVID-19 among some of the most important cryptocurrencies. Even terrorist attacks are found to affect Bitcoin use (Almaqableh et al., 2022). All the aforementioned evidence, shows that many events of political and economic nature affect significantly Bitcoin.

This general conclusion that implies that Bitcoin price seems to be affected by various political events is questioned by the only study to date that explores how Bitcoin behaved in the Ukraine war context, that of Yatie (2022), who argues that Bitcoin, Ethereum, and other assets failed to serve as safe haven during this war. Using daily data from Bitcoin, Ethereum and Gold prices and S&P VIX and Russian VIX and covering the time period during from 1 November 2021 to 15 March 2022, they apply a DCC-GARCH methodology to capture the interactions among assets by allowing correlations to change over time. Yatie (2022) shows that Bitcoin, Ethereum and Gold failed as safe havens during this war.

Summing up, prior to the Ukraine war, Bitcoin is found to be affected by global or local, economic, and political uncertainty, and especially by specific important events. This implies that there are shocks and external events that can promote certain characteristics of Bitcoin, affecting the entire financial world. Following the afore-mentioned literature, in this paper we explore whether and how the major event of the war in Ukraine that outbroke on 24 February 2022 has affected Bitcoin price and volume, having in mind the findings of Yatie (2022) that are not in line with previous literature. In this way, the present paper contributes to the literature by examining the impact of the war in Ukraine on the BTC price and volume, using both statistical and event-study approaches.

4. Methodology

In this work, we examine the cycles of the BTC based on both its price and its volume. To do so, we use an approach used by many researchers in the detection of a one-cycle happening. We then investigate the impact of the war in Ukraine on the price and the volume of BTC, using an event-analysis.

4.1 Cycle detection analysis

As stated above, we use an approach for the detection of a one-cycle happening. This approach has been used also by *solar physics*, as a method-detection for high-speed solar wind streams (Xystouris et al., 2018; Gerontidou et al., 2019). A solar wind stream is an extreme event with a long duration, which could be parallelized in our case as a cycle of the Bitcoin. In our case, the minimum before the ascending phase is the starting point of the present cycle, while the minimum after the descending phase is the ending point of the cycle. We capture the cycles based on the price of BTC, and the cycles based on the volume of BTC.

4.2 Event study examination

As regards our methodology, we apply a two-stage event-analysis approach as follows. At stage one, we test whether there was a significant change on the price and the volume of Bitcoin at the date of the event (war in Ukraine), comparing them with the pre-war period. We capture a 3-day, 5-day, 7-day, 9-day, 11-day, and 13-day, starting half the days before the event, to half the remaining days after the event, where the event day is February 24. Specifically, we follow Brown and Douglass (2020), and design our methodology in the following four (4) steps[1]:

a. first we compute the daily rate of return (DRR) for the entire period of 20 January to 1 April:

[1] Detailed information on the calculations are provided in the Appendix.

$$DRR = \frac{Current\ Price - Previous\ Price}{Previous\ Price} \quad (4.1)$$

b. we then capture the rolling average rate of return (RARR) simply by calculating the average rates of return for the rolling n-days, according to the respective rolling window:

$$RARR = Average(DRR_i) \quad (4.2)$$

c. we then compute the average cumulative rate of return (ACRR), for all values of i, as follows:

$$ACRR = Average(CRR_i) \quad (4.3)$$

d. we finally compare the results from the ACRR for all the values before the event (war in Ukraine), with the respective derived around the event, for all n-day windows. We capture these values for all n-day windows examined and we then employ a Wilcoxon sign rank test for paired couples to test whether the price and the volume of Bitcoin around the event differed with statistical significance from the corresponding before the event. Specifically, we set $d_i = ACRR_i - RARR_i$ where *i* is the n-days window, and we apply the Wilcoxon signed rank test as follows:

$$T = \sum_{i=1}^{N} sign(d_i) R_i \quad (4.4)$$

At stage two, we formulate an econometric model, to capture the sign and the magnitude of the impact of the war in Ukraine on both price and volume of Bitcoin. We first test the stationary characteristics of price and volume, and we implement the first differences transformation in case we get non-stationary variables. To do so, we utilize the Phillips and Perron unit root test (1988). The null hypothesis of this specific test is that the time series has a unit root, and thus, it is non-stationary. We then use a dummy variable for the war in Ukraine, using the following formula:

$$Dummy\ variable = \begin{cases} 0, period\ before\ the\ war \\ 1, period\ during\ the\ war \end{cases} \quad (4.5)$$

The dummy variable takes the value of zero during 20 January until 23 February of 2022, and the value of 1 during 24 February until 01 April of 2022. We then apply regression analysis, setting the Bitcoin price (3.6) and the Bitcoin volume (3.7) as the dependent variables respectively, and the dummy variable as the independent variable for both equations .

$$Bitcoin\ Price = a + b * Dummy \ (4.6)$$

$$Bitcoin\ Volume = c + d * Dummy \ (4.7)$$

5. Result analysis

We first present the data and variables used in the present work. Then, we illustrate the results, explaining their meaning.

5.1 Data and Variables

The data used in the present paper where the price (adjusted close) and the volume of transactions (volume) of the Bitcoin. All data were downloaded in daily frequency, from Yahoo.Finance, spanning the period 17 September of the year 2014 until 01 April of the year 2022. We present the descriptive statistics of the variables in Table 1.

Table 1: Descriptive statistics of the variables.

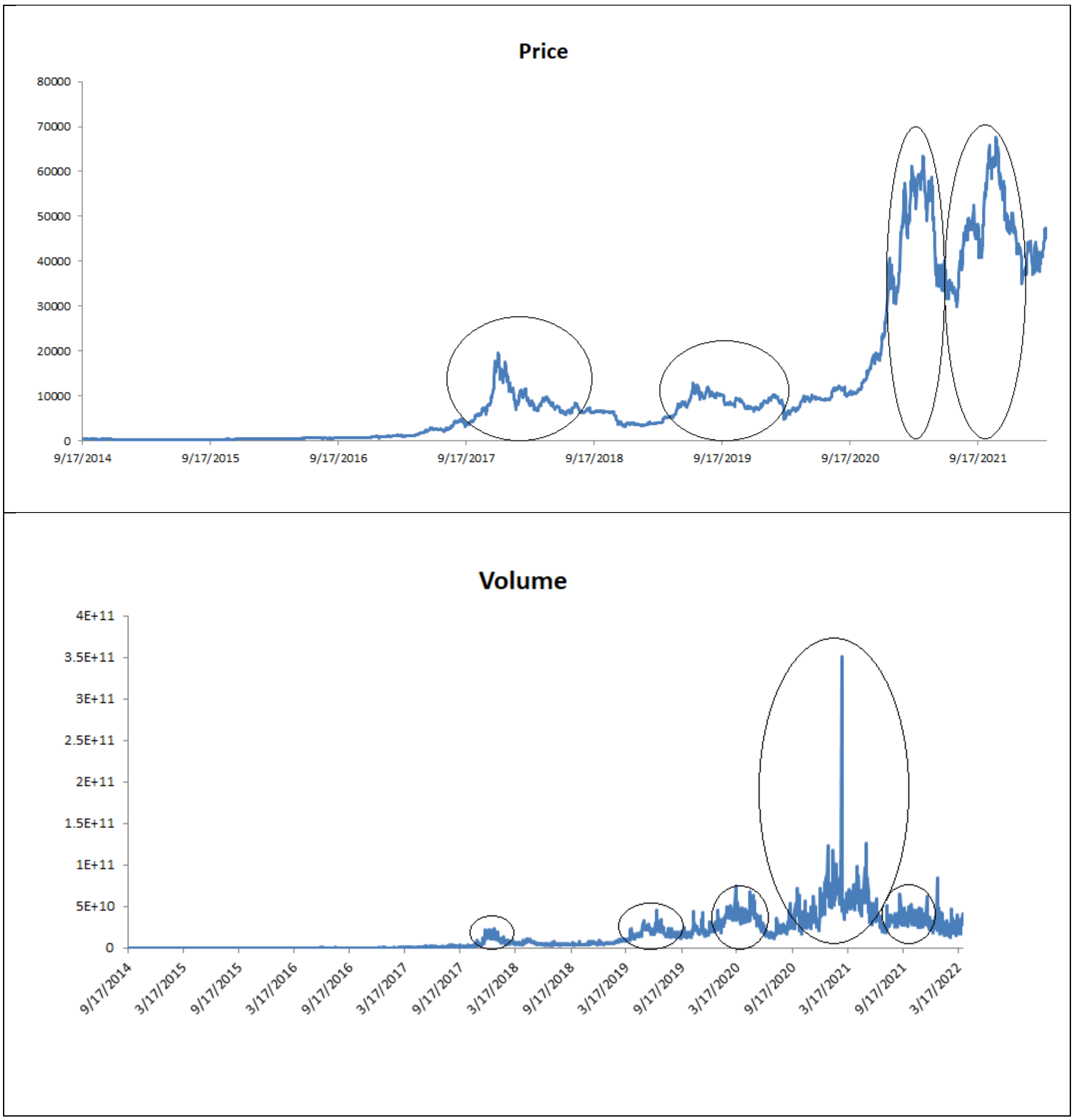
Variable	Mean	Standard Deviation	Min	Max
Price	11770.70	16402.03	178.10	67566.83
Volume	14888142525.56	19942643417.22	5914570.00	350967941479.00

5.2 Result analysis

5.2.1 Cycle analysis results

In this section, we present and comment on the results. At first, we present the cycle-analysis. As illustrated in Figure 1, there are 4 cycles of the BTC based on its price, while 5 based on its volume.

Figure 1: The cycles of BTC based on its price and volume.



From Figure 1 we may infer that it is not apparent in which part of the current cycle we are, or whether the 5th cycle (based on the price) or the 6th cycle (based on the volume) of the BTC has begun. The current period of the Bitcoin's price and volume seem to be rather calm and smooth, from 20th of January of the year 2022. This will be a point of reference for the event-analysis.

Based on Figure 1, we depict in Table 2 below, the starting and ending point of each cycle of the BTC, based on its price. We then present in Table 3 the descriptive statistics of each cycle of the BTC, based on its price.

Table 2: Period of each BTC cycle based on its price.

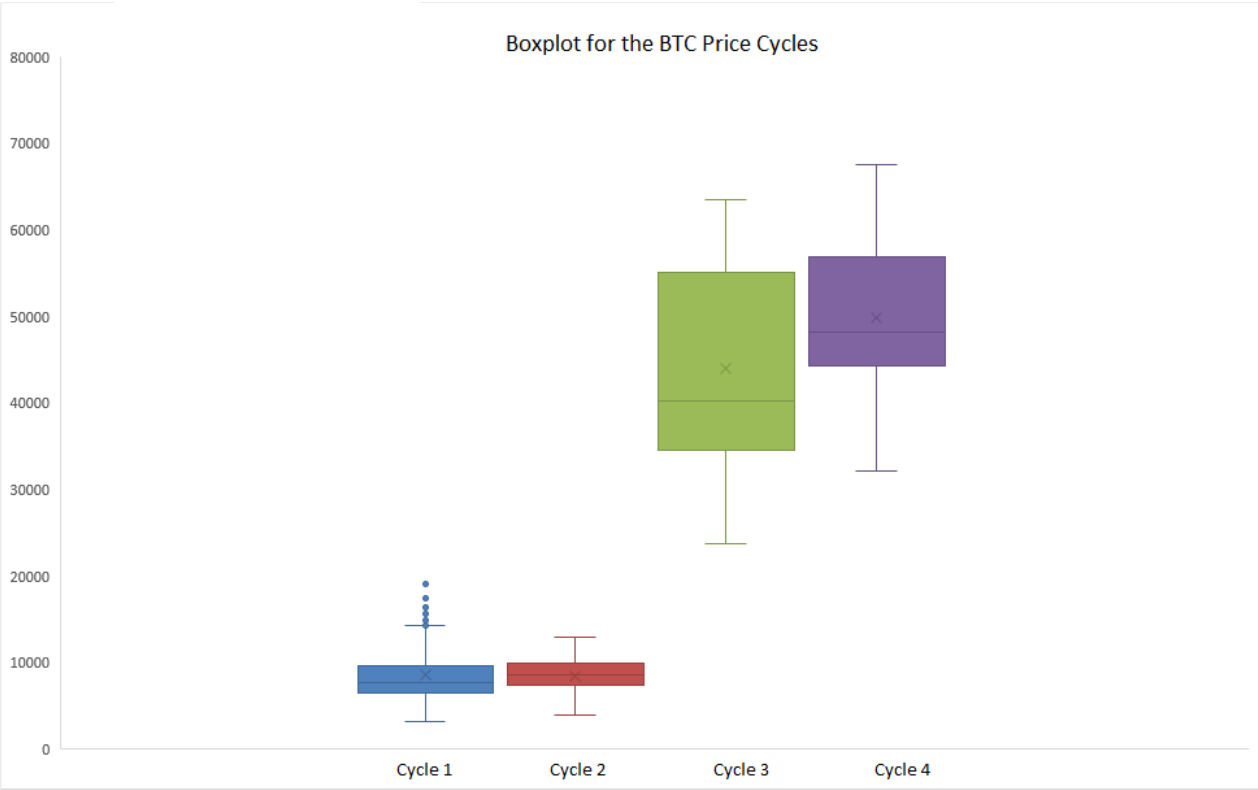
Cycle	1	2	3	4
Starting Date	9/13/2017	3/25/2019	12/24/2020	7/21/2021
Ending Date	9/8/2018	3/16/2020	7/20/2021	1/22/2022

Table 3: Descriptive statistics of the cycles of BTC based on its price.

Cycle	1	2	3	4
Mean	8548.901853	8506.087237	43939.58645	49907.82244
StDev	3175.33367	1862.642129	10649.68692	7967.599079
Min	3154.949951	3963.070557	23735.94922	32110.69336
Max	19497.40039	13016.23145	63503.45703	67566.82813

In the same context, we illustrate the boxplots of the cycles based on their price in Figure 2.

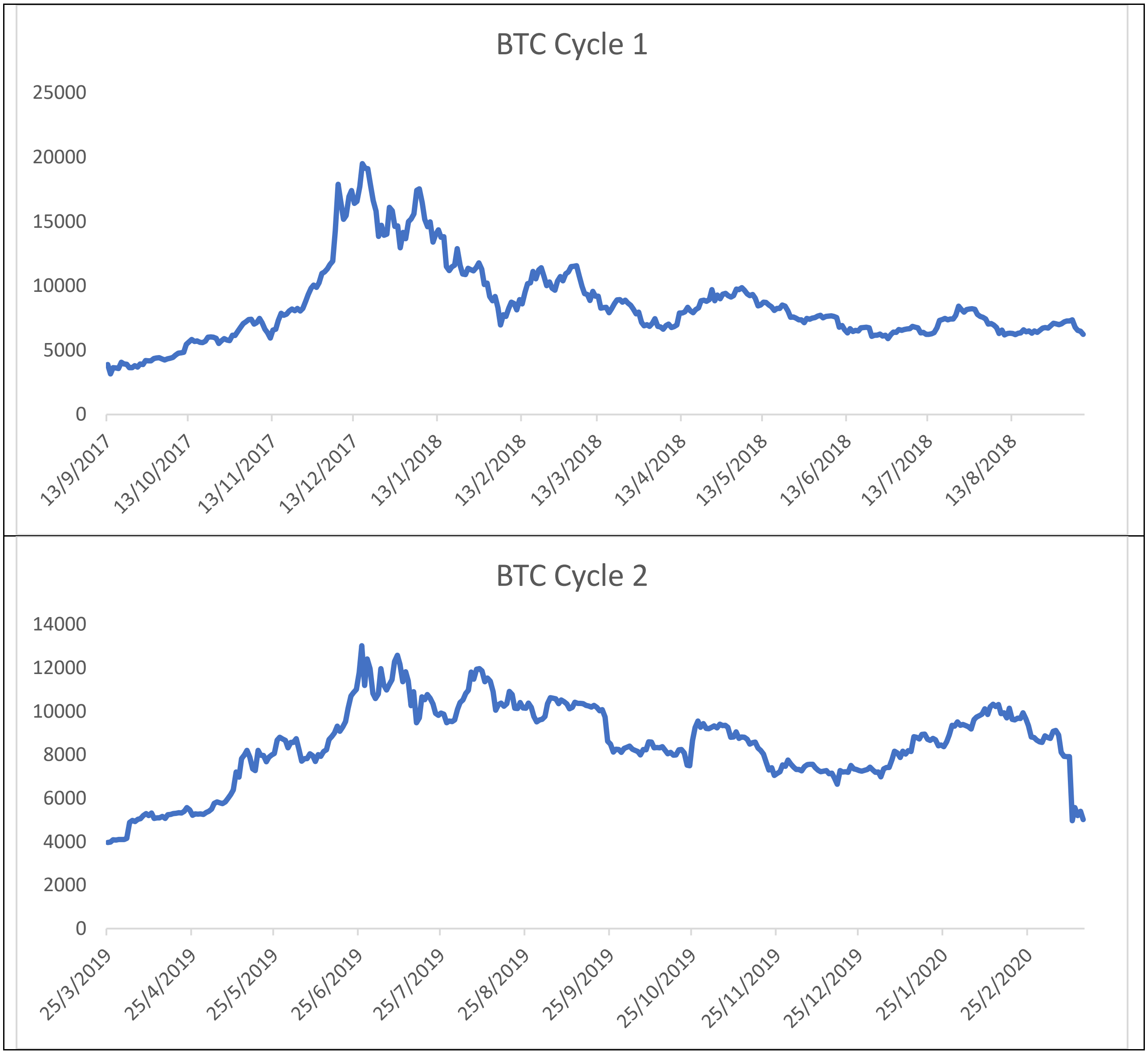
Figure 2: Boxplot for the BTC cycles based on their price.

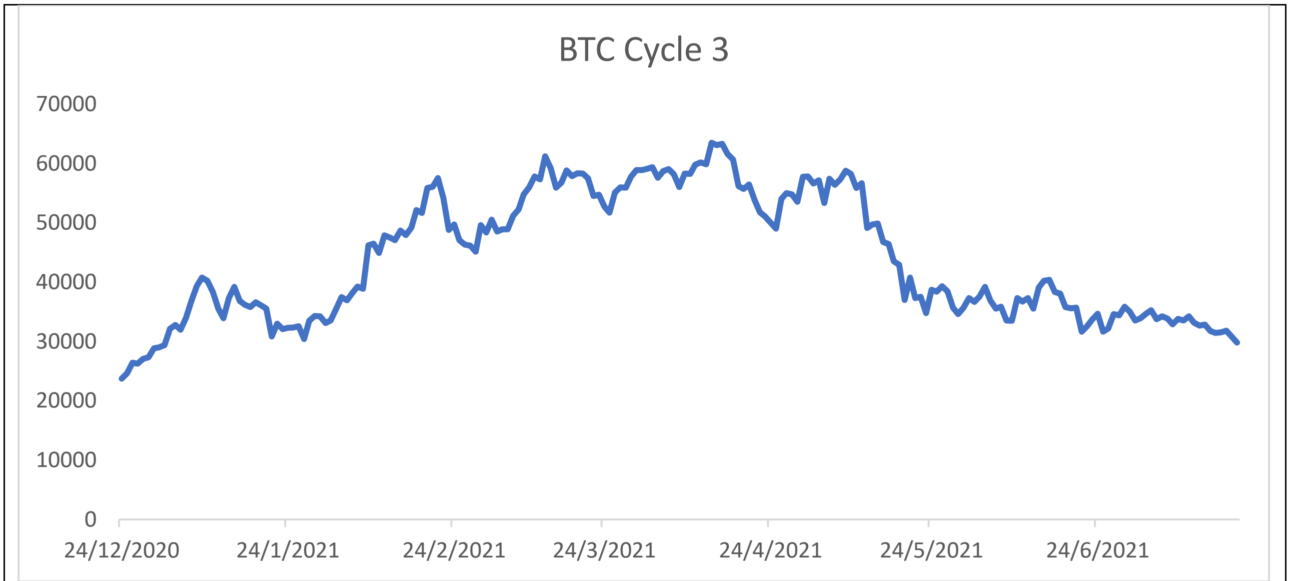


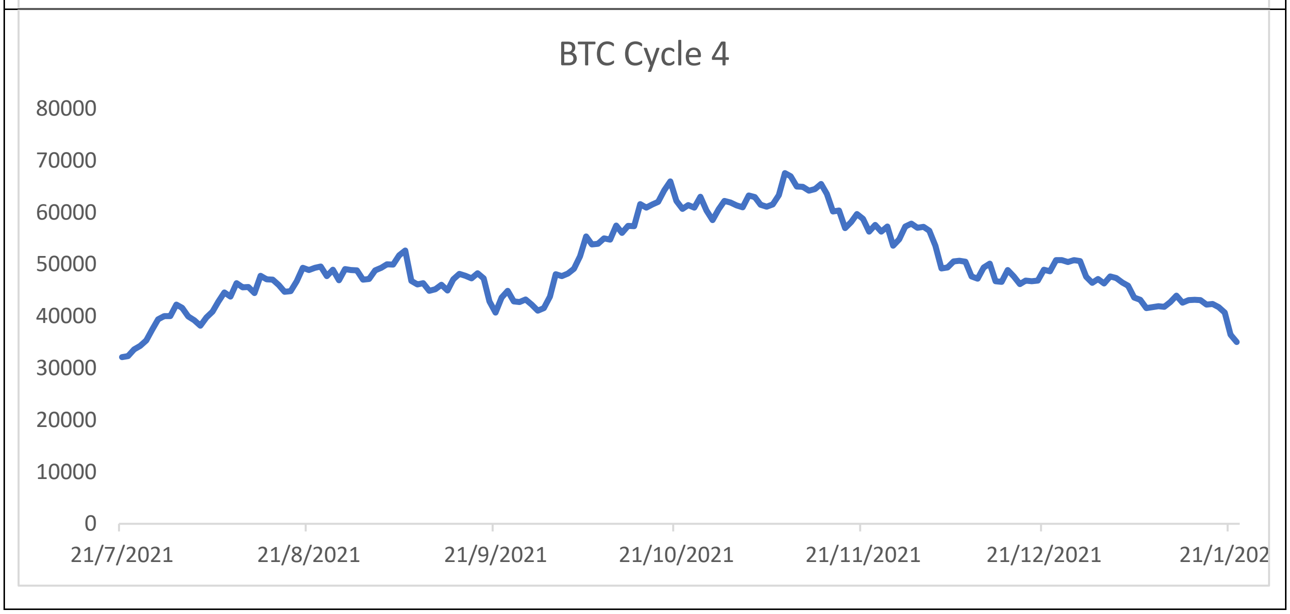
From Figure 2 we may derive that the cycle 3 and 4 have very higher values than the respective cycles 1 and 2. Moreover, the first and the second cycle have short volatility, while the price span of the third and fourth cycle are huge, with the third cycle having the greatest volatility in its prices. Finally, the first cycle has some outliers.

We then illustrate in Figure 3 the plot of the BTC cycles based on their price.

Figure 3: BTC cycles plot based on their price.







We then follow the same procedure for the volume of BTC. Based on Figure 1, we depict in Table 4 below, the starting and ending point of each cycle of the BTC, based on its volume. We then present in Table 5 the descriptive statistics of each cycle of the BTC, based on its volume.

Table 4: Period of each BTC cycle based on its volume.

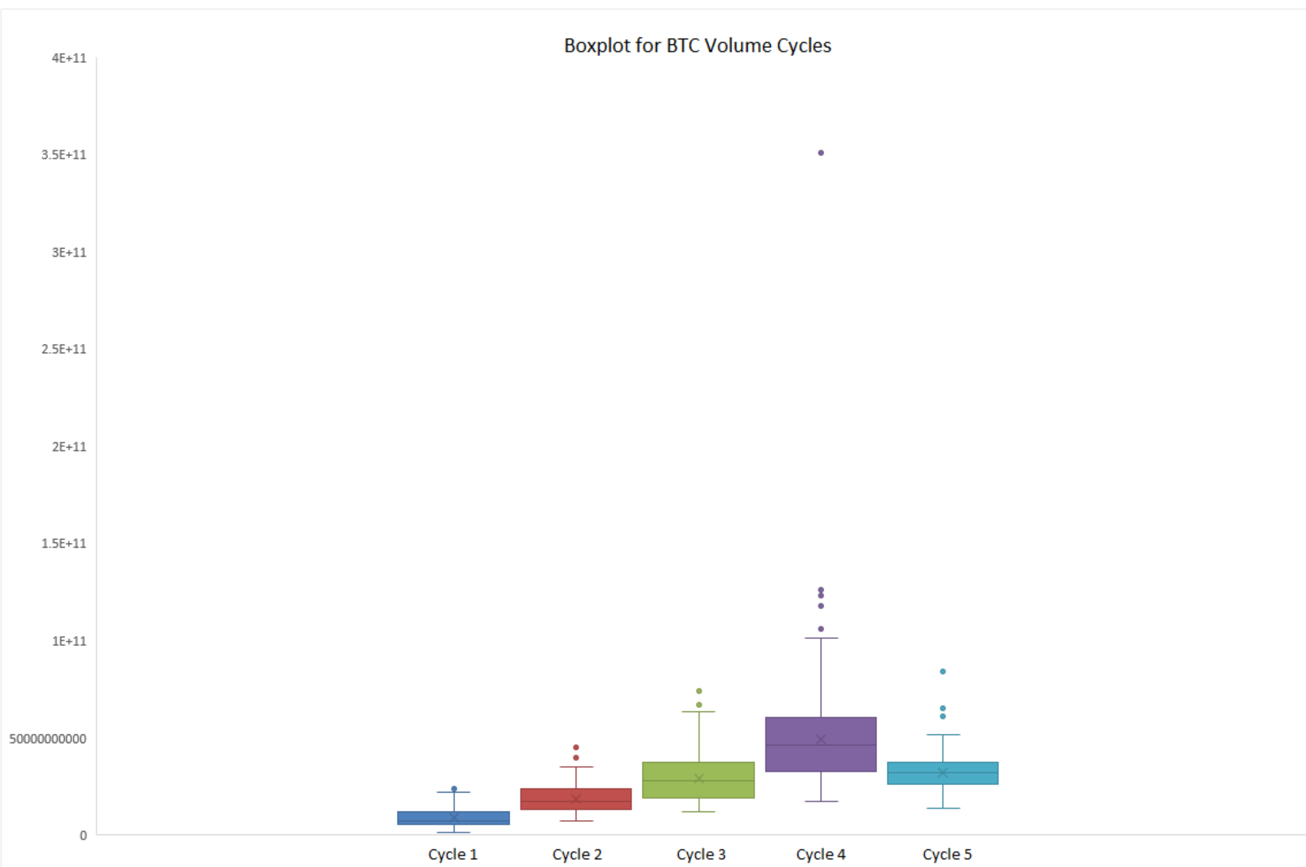
Cycle	1	2	3	4	5
Starting Date	10/28/2017	3/3/2019	9/15/2019	8/23/2020	7/18/2021
Ending Date	4/8/2018	7/28/2019	7/4/2020	7/18/2021	2/19/2022

Table 5: Descriptive statistics of the cycles of BTC based on its volume.

Cycle	1	2	3	4	5
Mean	8806575606	18650365665	29338501926	49051808486	32336826571
StDev	4798465456	7263982563	11861885296	25807167844	8976383374
Min	1403920000	7253558152	12043433567	17485597759	13736557863
Max	23840899072	45105733173	74156772075	3.50968E+11	84196607520

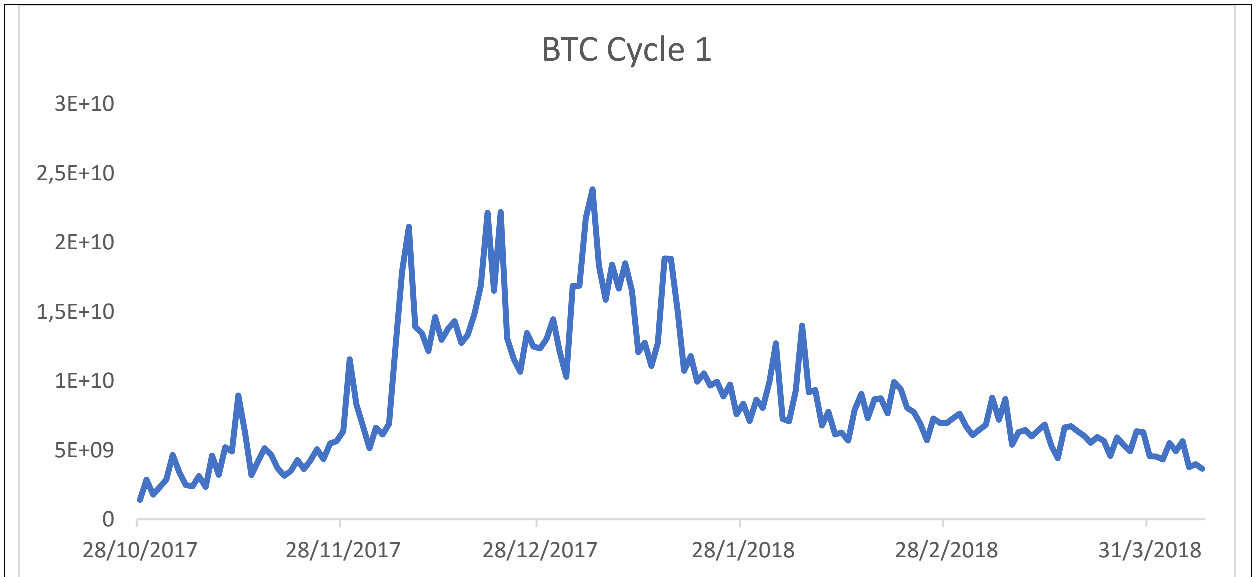
We then illustrate in Figure 4 the boxplots of the cycles of the BTC based on its volume.

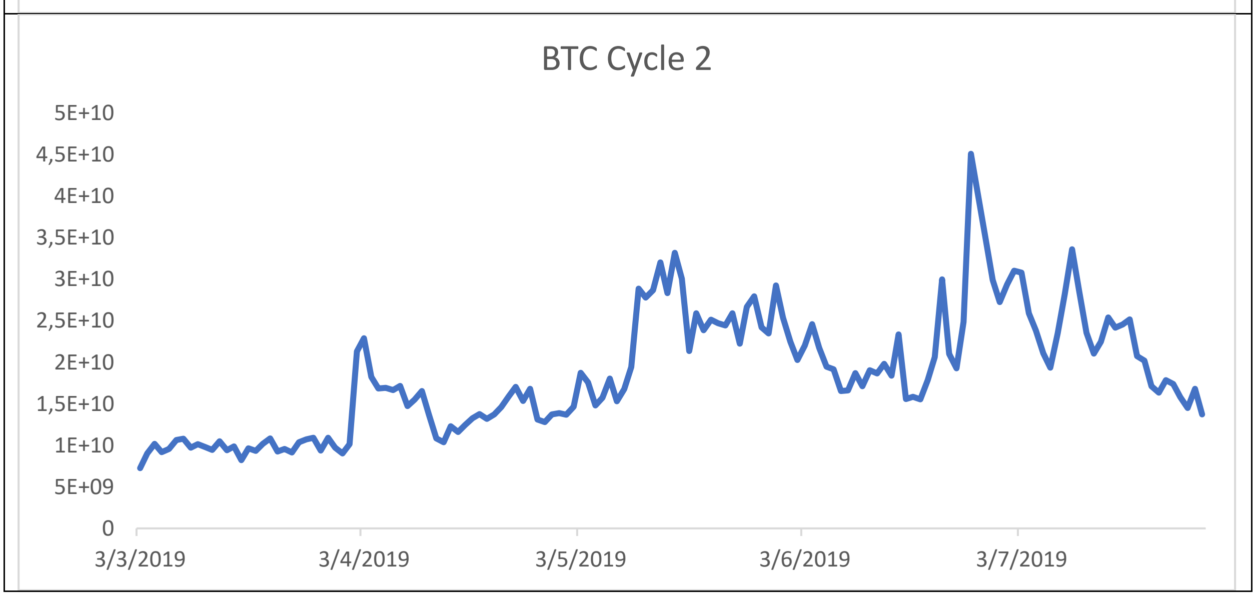
Figure 4: Boxplot for the BTC cycles based on their volume.

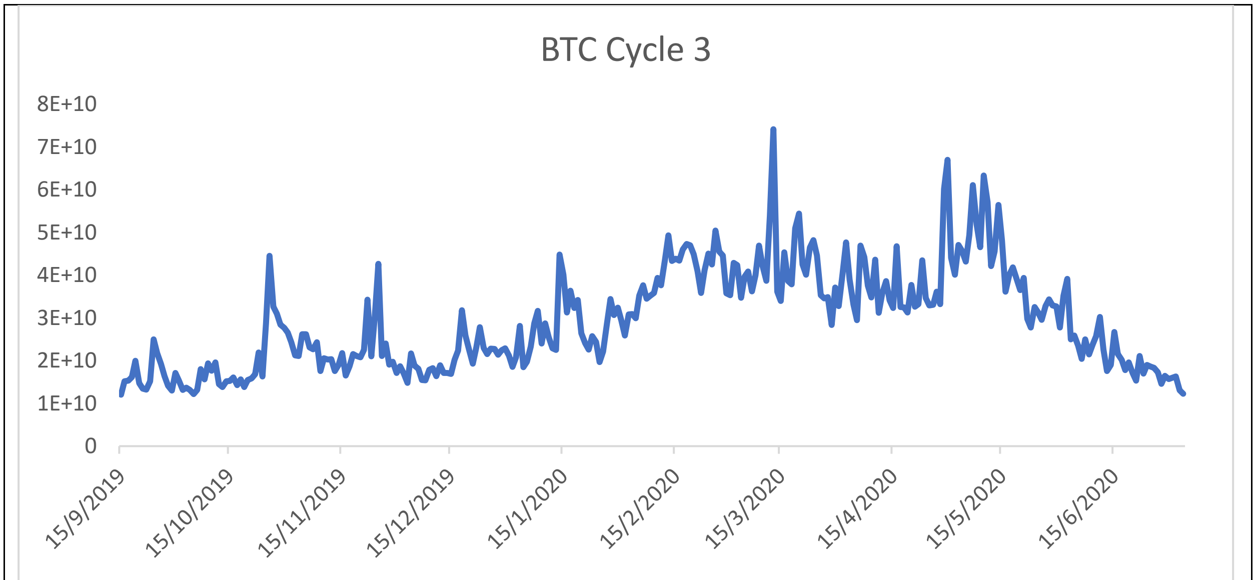


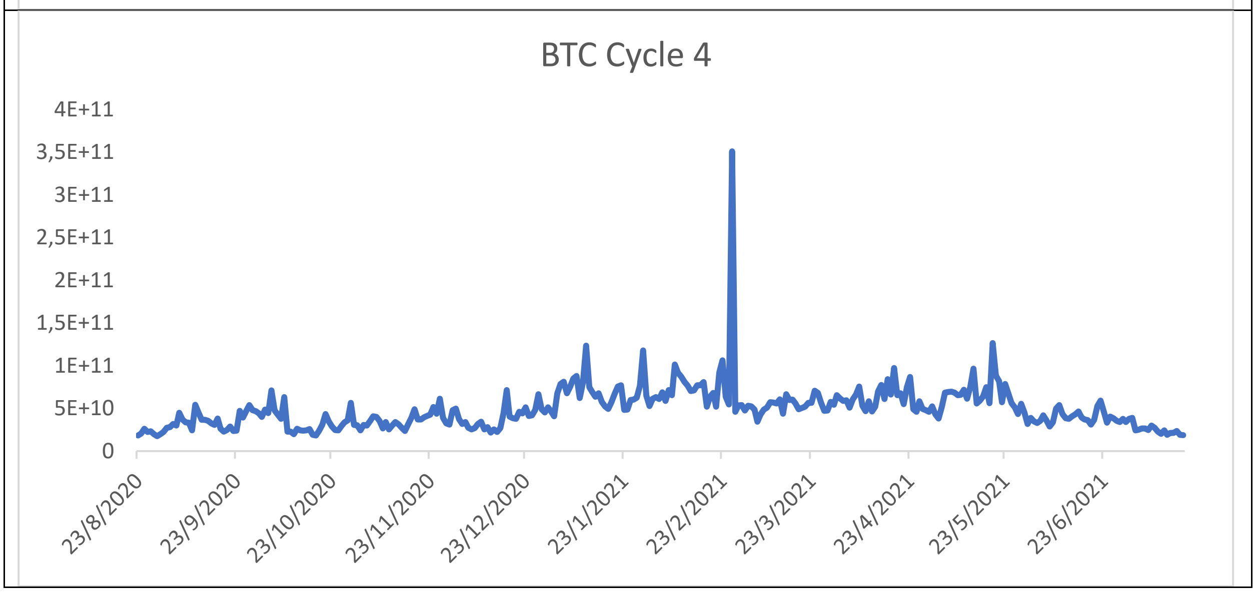
Finally, we illustrate in Figure 5 the plot of the BTC cycles based on their volume. All cycles demonstrate some outliers, and also a short volatility, with cycle 3 and mainly cycle 4, demonstrating the biggest volatility of all cycles.

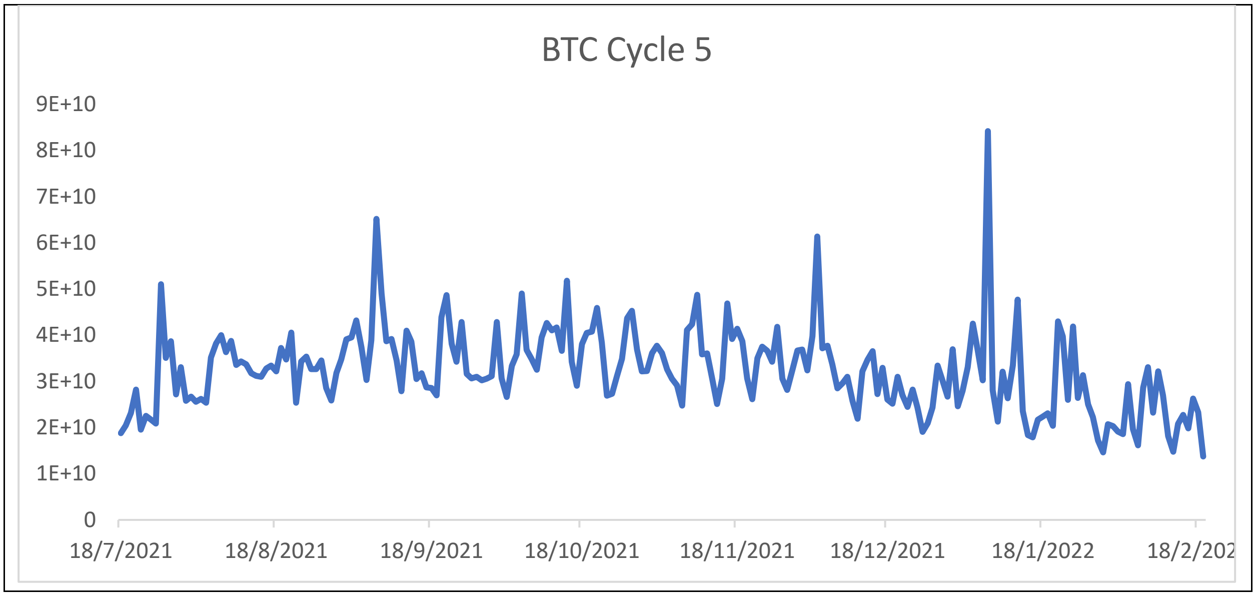
Figure 5: BTC cycles plot based on their volume.






BTC Cycle 3
8E+10
7E+10
6E+10
5E+10
4E+10
3E+10
2E+10
1E+10
0
15/9/2019
15/10/2019
15/11/2019
15/12/2019
15/1/2020
15/2/2020
15/3/2020
15/4/2020
15/5/2020
15/6/2020


BTC Cycle 4
4E+11
3,5E+11
3E+11
2,5E+11
2E+11
1,5E+11
1E+11
5E+10
0
23/8/2020
23/9/2020
23/10/2020
23/11/2020
23/12/2020
23/1/2021
23/2/2021
23/3/2021
23/4/2021
23/5/2021
23/6/2021



Based on the aforementioned results, the cycles of the BTC can be categorized according to both its price and volume, with the volume of BTC giving more cycles than the price. However, it is not profound in which part of a probable following cycle we currently are, but we may argue that from 20 of January of the year 2022 we are in a relatively smooth period. That will be our point of reference, in order to compare the near the war in Ukraine period, with the pre-war period, starting from 20 of January of the year 2022.

5.2.2 Case study event analysis

As a final step of our analysis, we present the event study of the war in Ukraine. In this context, we test the statistical significance of a differentiation of the price and volume of the BTC due to the war in Ukraine. On 24 of February of the year 2022, which was the initial war combat of Russia to Ukraine, the BTC price increased about 3%, while its volume 112%. This evidence shows that there was a significant increase in the volume of BTC transaction during this day.

We start by examining the event day Bitcoin price and volume fluctuations. Specifically, at the event day (24 February), the Bitcoin price increased by about 3%, while its volume also increased by a staggering 112%. Thus, the price does not seem to have been affected at the event day, but the volume seems to have been affected significantly.

We next turn to our first-stage methodology, where we perform event analysis for different windows of observations. Specifically, we test for statistically significant differences between the corresponding (window-based) average price and volume volatility, and the price and volume volatility of the Bitcoin before and around the event day. We first calculate DRRs for each day during January 20 to February 24. We then calculate the CCRs for each n-days window respectively, and we last compare the ACRR of each n-day window with the n-day data around the day of the event. Applying this process for all n-days windows we derive pairs that we then compare via the non-parametric Wilcoxon ranked test (since calculations do not follow the normal distribution). Data and respective calculations appear at Tables A.1 and A.2 in the Appendix, for Bitcoin price and Bitcoin volume respectively. The Wilcoxon test results are shown in Table 6 below.

Table 6: Wilcoxon signed rank test results.

Case of Comparison	P-value
Price	0.219
Volume	0.031

Our results show that the volatility of the volume of Bitcoin around the day of the event, differ with statistical significance from the corresponding average value for n-day at the pre-war period, while the volatility of the price of Bitcoin around the day of the event, does not differ with statistical significance; this implies that the war in Ukraine affected the volume volatility of Bitcoin, but not its price.

Next, we construct a statistical model to capture the magnitude of the effect of the war in Ukraine to the price and volume of Bitcoin respectively. We first test the stationary characteristics of Bitcoin price and volume, for the entire sample period (20/01/2022 – 01/04/2022). The results are shown in Table 7.

Table 7: Phillips and Perron unit root test.

Variable	Test	P-Value
Price	-2.8929	0.212
Volume	-6.3663	0.010

As regards the Bitcoin price, our data are non-stationary, so that we perform a first differences transformation in the data. As regards the Bitcoin volume, our data are stationary, so that we proceed our analysis without any data transformation. We then construct the dummy variable to test the effect of the war in Ukraine to the Bitcoin price and volume. The results are shown in Tables 8A&B and 9A&B, respectively.

Table 8A: Regression results for the price of Bitcoin (in first differences).

	Coefficients	Standard Error	t-test	P-Value
Constant	-99.525	261.379	-0.381	0.705
Dummy (war)	311.008	362.075	0.859	0.393

Table 8B: Statistics of the Regression Model for the price of Bitcoin (in first differences).

Statistics of the Regression Model	
R squared	0.011
Multiple R squared	0.103
F stat	0.738

Table 9A: Regression results for the volume of Bitcoin (in levels).

	Coefficients	Standard Error	t-test	P-Value
Constant	24,296,784,255	1236484159	19,6499	<0,001
Dummy (War)	3,321,605,916	1724860366	1,925725	0,06

Table 9B: Statistics of the Regression Model for the volume of Bitcoin.

Statistics of the Regression Model	
R squared	0.050
Multiple R squared	0.224
F stat	3.708

The results show that no specific change in the magnitude of the Bitcoin price can be determined, while volume seems to be significantly affected by the event. Specifically, we get that, the Ukraine war event significantly increased the Bitcoin volume by 3,321,605,916, which is the coefficient derived from the regression model.

6. Conclusions

In this work, we examine the cycles of the BTC in an endogenous investigation, since there is evidence that BTC is unique in its properties and is affected by many factors, also affecting many other variables. In this way, an endogenous investigation of the cyclic behavior is imperative and the first step of a cycle analysis. To do so, we adopted an approach followed by many disciplines, also used by solar physics, for the detection of high-speed solar wind streams, incorporating it to BTC cycles detection. The period examined is the 17 September of the year 2014 until 01 April of the year 2022, due to data availability. We then examine the effect of the war in Ukraine, in the Bitcoin's price and volume, using event-analysis.

The present paper highlights the cyclic characteristics of the BTC, identifying 4 cycles based on the Bitcoin's price, while 5 cycles based on the Bitcoin's volume. The fact that price and volume give different number of cycles is an important finding, since they provide different information, that is overseen from many approaches that examine only the price of the BTC. The present paper is in accordance with past approaches, since a cyclic behavior of BTC has already been stated by Tong et al. (2022).

Furthermore, the present paper investigates the impact of the war in Ukraine on the Bitcoin's price and volume. Since we cannot infer in which phase of a probable cycle the Bitcoin's price and volume are, according to the cycle detection, we detect a smooth period, starting from 20 January of the year 2022 and having this date as a point of reference, we analyze the effect of the war in the BTC. To do so, we followed an event-analysis and the results show that the impact of the war in Ukraine on the Bitcoin is statistically significant in its volume but not in its price, as shown by the Wilcoxon sign paired test. Finally, we implemented a statistical regression model to examine the coefficient of the effect of the war in Ukraine, and based on the results, the war affected significantly the increase of the Bitcoin's volume, while the statistical model does not provide statistically significant results for the price of the BTC. Our results indicate that Bitcoin volume volatility seems to be affected by the event, but not Bitcoin price. First, there is a staggering daily volume increase of 112% at the date of the event. Second, we find statistically significant differences across different time windows before the event, implying that the market is unrest prior to and around the event. Last, using dummies, we find that the Ukraine war event significantly increased the Bitcoin volume after the event.

We should note that the aforementioned finding should not be surprising, since, based on the literature, there are many significant events that affect the cryptocurrencies' performance, especially Bitcoin's. Such an event was the COVID-19 pandemic (Raza et al., 2022). Additionally, it has already been stated that the BTC can be used by investors as an investment strategy in cases of high geopolitical risks (Su et al., 2020). Moreover, regarding the war in Ukraine, our results stand in between the findings of prior literature, since literature generally shows that Bitcoin is affected by global political and economic events, and we do find support on this strand of literature, but only for Bitcoin volume. Second, our results are also in line with the only, to date, paper testing Bitcoin's behavior on the specific event of Ukraine war (Yatie, 2022), which provides results that are not in line with the prior Bitcoin-as-safe-haven literature, and we also find that Bitcoin price does not seem to be affected by this specific event. This is an interesting finding that future research could explore more in depth, namely either whether this specific event carries characteristics that differentiate it from prior events, or whether the crypto market has entered a new era, where exogenous political events do not affect Bitcoin's specific characteristics.

The present paper contributes in many ways to the literature. First, by providing a unique approach for the detection, examination, and comparison of the cycles of the BTC based on both its price and volume. Secodn, the present paper empirically examines the impact of the war in Ukraine on the Bitcoin's price and volume performance. In this context, we should note that we took into account in our analysis both price and volume of the BTC, differing by many past studies that were mainly limited to the Bitcoin's price investigation, with volume being disregarded.

We should also note that there are some limitations in our work since data are available from 2014 and Bitcoin was launched in 2008. This could exclude a cycle (or even more) of the BTC from our analysis.

Finally, from the present paper's analysis many probable future works emerge, for instance, an endogenous cycle analysis with simultaneous consideration of other variables (futures, stock indices, etc), econometrical models could also be employed, and finally other cryptocurrencies could be investigated.

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Appendix

Table A.1: Bitcoin Price – Stage 1 calculations

Date	Price	DRR	RARR_1	RARR _3	RARR _5	RARR _7	RARR _9	RARR _11	RARR _13
20/01/2022	40,680.42	NA	NA	NA	NA	NA	NA	NA	NA
21/01/2022	36,457.32	-0.10381	-0.10381	NA	NA	NA	NA	NA	NA
22/01/2022	35,030.25	-0.03914	-0.03914	NA	NA	NA	NA	NA	NA
23/01/2022	36,276.80	0.03559	0.03559	-0.03579	NA	NA	NA	NA	NA
24/01/2022	36,654.33	0.01041	0.01041	0.00228	NA	NA	NA	NA	NA
25/01/2022	36,954.00	0.00818	0.00818	0.01806	-0.01776	NA	NA	NA	NA
26/01/2022	36,852.12	-0.00276	-0.00276	0.00528	0.00245	NA	NA	NA	NA
27/01/2022	37,138.23	0.00776	0.00776	0.00439	0.01183	-0.01197	NA	NA	NA
28/01/2022	37,784.33	0.01740	0.01740	0.00747	0.00820	0.00535	NA	NA	NA
29/01/2022	38,138.18	0.00936	0.00936	0.01151	0.00799	0.01228	-0.00634	NA	NA
30/01/2022	37,917.60	-0.00578	-0.00578	0.00699	0.00520	0.00637	0.00456	NA	NA
31/01/2022	38,483.13	0.01491	0.01491	0.00617	0.00873	0.00701	0.01056	-0.00435	NA
01/02/2022	38,743.27	0.00676	0.00676	0.00530	0.00853	0.00681	0.00736	0.00570	NA
02/02/2022	36,952.98	-0.04621	-0.04621	-0.00818	-0.00419	0.00060	0.00107	0.00506	-0.0067
03/02/2022	37,154.60	0.00546	0.00546	-0.01133	-0.00497	0.00027	0.00077	0.00232	0.0017
04/02/2022	41,500.88	0.11698	0.11698	0.02541	0.01958	0.01450	0.01407	0.01201	0.0137
05/02/2022	41,441.16	-0.00144	-0.00144	0.04033	0.01631	0.01295	0.01305	0.01113	0.0108
06/02/2022	42,412.43	0.02344	0.02344	0.04633	0.01964	0.01713	0.01372	0.01351	0.0119
07/02/2022	43,840.29	0.03367	0.03367	0.01855	0.03562	0.01981	0.01642	0.01587	0.0138
08/02/2022	44,118.45	0.00634	0.00634	0.02115	0.03580	0.01975	0.01777	0.01486	0.0145
09/02/2022	44,338.80	0.00499	0.00499	0.01500	0.01340	0.02706	0.01667	0.01447	0.0143
10/02/2022	43,565.11	-0.01745	-0.01745	-0.00204	0.01020	0.02379	0.01398	0.01340	0.0116
11/02/2022	42,407.94	-0.02656	-0.02656	-0.01301	0.00020	0.00328	0.01616	0.00963	0.0089
12/02/2022	42,244.47	-0.00385	-0.00385	-0.01596	-0.00731	0.00294	0.01512	0.00867	0.0090
13/02/2022	42,197.52	-0.00111	-0.00111	-0.01051	-0.00880	-0.00057	0.00200	0.01277	0.0078
14/02/2022	42,586.92	0.00923	0.00923	0.00142	-0.00795	-0.00406	0.00319	0.01311	0.0080
15/02/2022	44,575.20	0.04669	0.04669	0.01827	0.00488	0.00170	0.00577	0.00672	0.0151
16/02/2022	43,961.86	-0.01376	-0.01376	0.01405	0.00744	-0.00097	0.00050	0.00560	0.0136
17/02/2022	40,538.01	-0.07788	-0.07788	-0.01498	-0.00737	-0.00961	-0.00886	-0.00361	-0.0014
18/02/2022	40,030.98	-0.01251	-0.01251	-0.03472	-0.00965	-0.00760	-0.01080	-0.00781	-0.0022
19/02/2022	40,122.16	0.00228	0.00228	-0.02937	-0.01104	-0.00672	-0.00861	-0.00818	-0.0038
20/02/2022	38,431.38	-0.04214	-0.04214	-0.01746	-0.02880	-0.01259	-0.01034	-0.01246	-0.0097
21/02/2022	37,075.28	-0.03529	-0.03529	-0.02505	-0.03311	-0.01894	-0.01383	-0.01408	-0.0129
22/02/2022	38,286.03	0.03266	0.03266	-0.01492	-0.01100	-0.02095	-0.01008	-0.00870	-0.0107
23/02/2022	37,296.57	-0.02584	-0.02584	-0.00949	-0.01367	-0.02268	-0.01398	-0.01070	-0.0114
24/02/2022	**38,332.61**	**0.02778**	**0.02778**	**0.01153**	**-0.00857**	**-0.00758**	**-0.01608**	**-0.00807**	**-0.0072**
25/02/2022	39,214.22	0.02300	0.02300	0.00831	0.00446	-0.00251	-0.01199	-0.00682	-0.0051
26/02/2022	39,105.15	-0.00278	-0.00278	0.01600	0.01096	-0.00323	-0.00365	-0.01132	-0.0053
27/02/2022	37,709.79	-0.03568	-0.03568	-0.00515	-0.00271	-0.00231	-0.00622	-0.01331	-0.0087

28/02/2022	43,193.23	0.14541	0.14541	0.03565	0.03155	0.02351	0.00968	0.00699	-0.0011
01/03/2022	44,354.64	0.02689	0.02689	0.04554	0.03137	0.02268	0.01735	0.01057	0.0020
02/03/2022	43,924.12	-0.00971	-0.00971	0.05420	0.02483	0.02499	0.02019	0.00948	0.0072

ACRR_1	**24 Feb_1**
-0.0019	0.0278
ACRR_3	**24 Feb_3**
0.0011	0.0083
ACRR_5	**24 Feb_5**
0.0027	0.0110
ACRR_7	**24 Feb_7**
0.0051	-0.0023
ACRR_9	**24 Feb_9**
0.0063	0.0097
ACRR_11	**24 Feb_11**
0.0078	0.0106
ACRR_13	**24 Feb_13**
0.0092	0.0072

RARR_1 coincides with DRR_i
RARR_3 is the rolling average of DRR for the three respecting days before (and including) the date in which it is calculated.
RARR_5 is the rolling average of DRR for the five respecting days before (and including) the date in which it is calculated.
RARR_n is the rolling average of DRR for the n respecting days before (and including) the date in which it is calculated.

ACRR_1 is the average of all daily data of RARR_1
ACRR_3 is the average of all daily data of RARR_3
ACRR_n is the average of all daily data of RARR_n

24 Feb_1 is the DRR for 24 Februrary
24 Feb_3 is the average DRR for the three days around the event (in this case, 1 day before the event, the event date, and 1 day after the event)
24 Feb_5 is the average DRR for the five days around the event (in this case, 2 days before the event, the event date, and 2 days after the event)
24 Feb_n is the average DRR for the n days around the event (in this case, n-3 days before the event, the event date, and n-2 days after the event)

Table A.2: Bitcoin Volume – Stage 1 calculations

Date	Volume	DRR	RARR_1	RARR_3	RARR_5	RARR_7	RARR_9	RARR_11	RARR_13
20/1/2022	20382033940	NA	NA	NA	NA	NA	NA	NA	NA
21/1/2022	43011992031	1,11029	1,11029	NA	NA	NA	NA	NA	NA
22/1/2022	39714385405	-0,07667	-0,07667	NA	NA	NA	NA	NA	NA
23/1/2022	26017975951	-0,34487	-0,34487	0,22958	NA	NA	NA	NA	NA
24/1/2022	41856658597	0,60876	0,60876	0,06241	NA	NA	NA	NA	NA
25/1/2022	26428189594	-0,36860	-0,36860	-0,03491	0,18578	NA	NA	NA	NA
26/1/2022	31324598034	0,18527	0,18527	0,14181	0,00078	NA	NA	NA	NA
27/1/2022	25041426629	-0,20058	-0,20058	-0,12797	-0,02401	0,13051	NA	NA	NA
28/1/2022	22238830523	-0,11192	-0,11192	-0,04241	0,02259	-0,04409	NA	NA	NA
29/1/2022	17194183075	-0,22684	-0,22684	-0,17978	-0,14453	-0,06554	0,06387	NA	NA
30/1/2022	14643548444	-0,14834	-0,14834	-0,16237	-0,10048	-0,03746	-0,07598	NA	NA
31/1/2022	20734730465	0,41596	0,41596	0,01359	-0,05434	-0,06501	-0,02124	0,07659	NA
1/2/2022	20288500328	-0,02152	-0,02152	0,08203	-0,01853	-0,01542	0,01469	-0,02630	NA
2/2/2022	19155189416	-0,05586	-0,05586	0,11286	-0,00732	-0,04987	-0,05916	-0,02441	0,05885
3/2/2022	18591534769	-0,02943	-0,02943	-0,03560	0,03216	-0,02542	-0,02147	0,00426	-0,02882
4/2/2022	29412210792	0,58202	0,58202	0,16558	0,17824	0,07371	0,02261	0,00183	0,02185
5/2/2022	19652846215	-0,33181	-0,33181	0,07359	0,02868	0,05872	0,00803	0,00518	0,02285
6/2/2022	16142097334	-0,17864	-0,17864	0,02386	-0,00274	0,05439	0,00062	-0,02791	-0,03771
7/2/2022	28641855926	0,77436	0,77436	0,08797	0,16330	0,10559	0,11186	0,06073	0,05021
8/2/2022	33079398868	0,15493	0,15493	0,25022	0,20017	0,13080	0,14556	0,08498	0,04787
9/2/2022	23245887300	-0,29727	-0,29727	0,21067	0,02431	0,09631	0,06631	0,07858	0,04043
10/2/2022	32142048537	0,38270	0,38270	0,08012	0,16722	0,15518	0,11122	0,12686	0,07848
11/2/2022	26954925781	-0,16138	-0,16138	-0,02532	0,17067	0,04898	0,09950	0,07437	0,08352
12/2/2022	18152390304	-0,32657	-0,32657	-0,03508	-0,04952	0,04973	0,06648	0,04664	0,06981
13/2/2022	14741589015	-0,18790	-0,18790	-0,22528	-0,11808	0,04841	-0,01906	0,03464	0,02336
14/2/2022	20827783012	0,41286	0,41286	-0,03387	0,02394	-0,00323	0,06368	0,07485	0,05677
15/2/2022	22721659051	0,09093	0,09093	0,10530	-0,03441	-0,01238	0,09363	0,03020	0,06806
16/2/2022	19792547657	-0,12891	-0,12891	0,12496	-0,02792	0,01168	-0,00673	0,04865	0,06041
17/2/2022	26246662813	0,32609	0,32609	0,09604	0,10261	0,00359	0,01228	0,09453	0,04072
18/2/2022	23310007704	-0,11189	-0,11189	0,02843	0,11782	0,01066	0,03288	0,01396	0,05764
19/2/2022	13736557863	-0,41070	-0,41070	-0,06550	-0,04690	-0,00136	-0,05527	-0,03746	0,03979
20/2/2022	18340576452	0,33517	0,33517	-0,06247	0,00195	0,07336	-0,00010	0,02004	0,00600
21/2/2022	29280402798	0,59648	0,59648	0,17365	0,14703	0,09960	0,10246	0,03947	0,03997
22/2/2022	25493150450	-0,12934	-0,12934	0,26743	0,05594	0,06813	0,10896	0,04238	0,05289
23/2/2022	21849073843	-0,14294	-0,14294	0,10806	0,04973	0,06612	0,04721	0,05908	0,01245
24/2/2022	**46383802093**	**1,12292**	**1,12292**	**0,28354**	**0,35646**	**0,17996**	**0,16187**	**0,17824**	**0,11125**
25/2/2022	26545599159	-0,42770	-0,42770	0,18409	0,20388	0,13484	0,12868	0,10183	0,10347
26/2/2022	17467554129	-0,34198	-0,34198	0,11775	0,01619	0,14466	0,05445	0,06247	0,09161
27/2/2022	23450127612	0,34250	0,34250	-0,14239	0,11056	0,14570	0,10493	0,10533	0,08620
28/2/2022	35690014104	0,52195	0,52195	0,17416	0,24354	0,13506	0,20856	0,12313	0,11936
1/3/2022	32479047645	-0,08997	-0,08997	0,25816	0,00096	0,14068	0,16132	0,12513	0,12235
2/3/2022	29183112630	-0,10148	-0,10148	0,11017	0,06620	0,14661	0,08377	0,15324	0,08946

ACCRR_1	**24 Feb_1**
0.0583	1.1229
ACCRR_3	**24 Feb_3**
0.0419	0.1841
ACCRR_5	**24 Feb_5**
0.0335	0.0162
ACCRR_7	**24 Feb_7**
0.0293	0.1457
ACCRR_9	**24 Feb_9**
0.0297	0.2086
ACCRR_11	**24 Feb_11**
0.0410	0.1251
ACCRR_13	**24 Feb_13**
0.0410	0.0895

Methodological explanations are the same as in the Bitcoin price case.