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The Russian War in Ukraine and its Effect in the Bitcoin Market

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Abstract:

Purpose: *In this paper, we analyze the impact of the war in Ukraine on the price and volume volatility of bitcoin.*
Design/methodology/approach: *We apply a two-stage methodology, to explore whether bitcoin price and volume were affected by the Ukraine war event, and to analyze the magnitude of this effect.*
Findings: *Our results show that the Ukraine war affected more bitcoin volume, than bitcoin price.*
Practical implications: *We explore whether the effect of a major political event, such as the war in Ukraine, is differentiated between bitcoin price and volume respectively, and we show that volume is affected much more than price. This has important practical implications for traders and investors in the crypto-market, since bitcoin is gradually perceived as an asset that can bear portfolio diversifying features.*
Originality value: *Our results are surprizing since prior event literature shows that bitcoin price is heavily affected by major political and economic events, but is in line with the only to-date study of Bitcoin price and Ukraine war (Yatie, 2022).*

Keywords: *Insolvency Prediction Models, Bankruptcy, US firms.*

JEL Classification: *G00, O30.*

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1. Introduction

Bitcoin is the first cryptocurrency that 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 fields (e.g., statistics, econometrics, machine learning, forecasting techniques, 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.,* 2018; Elsayed *et al.,* 2022), while others investigate how it performs in comparison to equities, during certain periods (Ghosh *et al.*, 2022).

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) uses data from Bitcoin, Ethereum, and Gold prices, and finds 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.

In this paper, we apply event case methodology to explore whether and how, the major political event of the war in Ukraine has affected the price and volume of bitcoin. Specifically, we follow the bitcoin event literature developing the theoretical context of our approach, and we design a methodological approach to explore statistically significant abnormal volatility in price and volume of bitcoin, around the dates that the Ukraine war outbroke.

Our findings suggest that no significant abnormal price volatility was evidenced, but we do find significant volatility in the volume of bitcoin. We also show that volume predictability becomes lower during the war period, when compared with the pre-war period. To the best of our knowledge, no study has yet empirically examined the effect of the war in the Ukraine in the bitcoin's price and volume in an event case methodology context.

The remaining of the paper is structured as follows. Section 2 discusses the bitcoin event literature, section 3 presents the methodology employed, section 4 shows the data and variables used, plus the results of our empirical study, and section 5 concludes the paper.

2. Literature Review

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; 2019b) 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; 2019b; 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.

In this context, 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, the author applies 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.

3. Methodology and Data

3.1 Research Methods

As regards our methodology, we apply a two-stage analysis 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[3]:

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

$$DRR = \frac{Current\ Price - Previous\ Price}{Previous\ Price} \tag{1}$$

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

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:

$$RARR = Average(DRR_i) \tag{2}$$

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

$$ACRR = Average(RARR_i) \tag{3}$$

c. 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 $d_i = ACRR_i - Value_{Feb\_24}$ where *i* is the n-days window, and we apply the Wilcoxon signed rank test as follows:

$$T = \sum_{i=1}^{N} sign(d_i)R_i \tag{4}$$

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. Specifically, we construct a dummy variable that 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 and we also control for the effects of S&P500, crude oil, and gold future prices (Ahmed, 2022; Li *et al.*, 2022; Yaya *et al.*, 2022).

As regards the methodology, we use the time-varying parameter (TVP) modeling, and more precisely, the TVP regression, to allow changes in magnitude or even sign of the coefficients. Specifically, we know that the classical linear model is structured as follows:

$$Y_t = X_t^{\top}\beta + u_t\ , t = 1, \dots, T \tag{5}$$

Where:
Y_t = the dependent variable,
$X_t = (\boldsymbol{x_{1t}}, \boldsymbol{x_{2t}}, \dots, \boldsymbol{x_{dt}})^{\top}$ = a vector of independent variables (regressors),
β is the vector of coefficients, $\beta = (\boldsymbol{\beta_0}, \boldsymbol{\beta_1}, \dots, \boldsymbol{\beta_d})^{\top}$, and u_t the error term, satisfying the following: $E(u_t|x_t) = 0$ and similarly, $E(u_t^2|x_t) = \sigma^2$

Supposing that the coefficients are not constant, but they rather change with time, the coefficients are functions of the Z_t (smoothing) variable (Casas and Fernandez-

Casal, 2019). This renders the model as a time-varying parameter model, specified as follows:

$Y_t = X_t^{\top}\beta(Z_t) + u_t \,, t = 1, \dots, T$
Where $\beta(Z_t) = (\beta_0(Z_t), \beta_1(Z_t), \dots, \beta_d(Z_t)\,)^{\top}$ vary with time.

So, the model we estimate using TVP regression is the following:
$Y_t = X_t^{\top}\beta(Z_t) + u_t \,, t = 1, \dots, T$

In our case study, Y_t refers to bitcoin (price and volume), and $\beta(Z_t)$ represents a vector of coefficients of the following variables:

$\beta(Z_t) = (Intercept(Z_t), S\&P500(Z_t), Crude\ Oil(Z_t),\ Gold(Z_t), Dummy(Z_t)\,)^{\top}$, where the dummy variable captures the war in Ukraine. We run two similar models, one for the bitcoin price and the other for the bitcoin volume of transactions.

3.2 Data Sources and Data Collection

Our dataset consists of the bitcoin price (adjusted close) and volume of transactions, and cover the period 20 January 2022 to 01 April 2022. We use a relatively short period to avoid inherent price fluctuations evidenced in the crypto-market. All data were downloaded in daily frequency, from Yahoo.Finance.

4. Analysis of Findings

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 RARRs 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 1 below.

Table 1. *Wilcoxon signed rank test results*

Case of Comparison	P-value
Price	0.219
Volume	0.031

Source: *Own study.*

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 apply our econometric model to capture the magnitude of the effect of the war in Ukraine to the price and volume of Bitcoin respectively, controlling for S&P500, crude oil prices and gold futures prices (descriptive statistics in Tables 2A and 2B respectively).

Table 2A. *Descriptive statistics of the prices*

Variable	Mean	Std	Min	Max
S&P500	4413.719	118.678	4170.700	4631.600
Crude Oil	98.434	10.419	83.310	123.700
Gold	1895.167	63.164	1784.900	2040.100

Source: *Own study.*

Table 2B. *Descriptive statistics of the volume of transactions*

Variable	Mean	Std	Min	Max
S&P500	5176364313.725	858892289.385	4131390000.000	8278430000.000
Crude Oil	434406.804	153656.050	74247.000	872244.000
Gold	7740.078	32540.052	5.000	196036.000

Source: *Own study.*

The price and volume results (coefficients) are shown in Tables 3 and 4 respectively, accompanied with Figures 1 and 2 respectively, which depict the time-varying effect of each of the independent variables (i.e., S&P500, Crude Oil, Gold and Dummy) on the bitcoin price and volume.

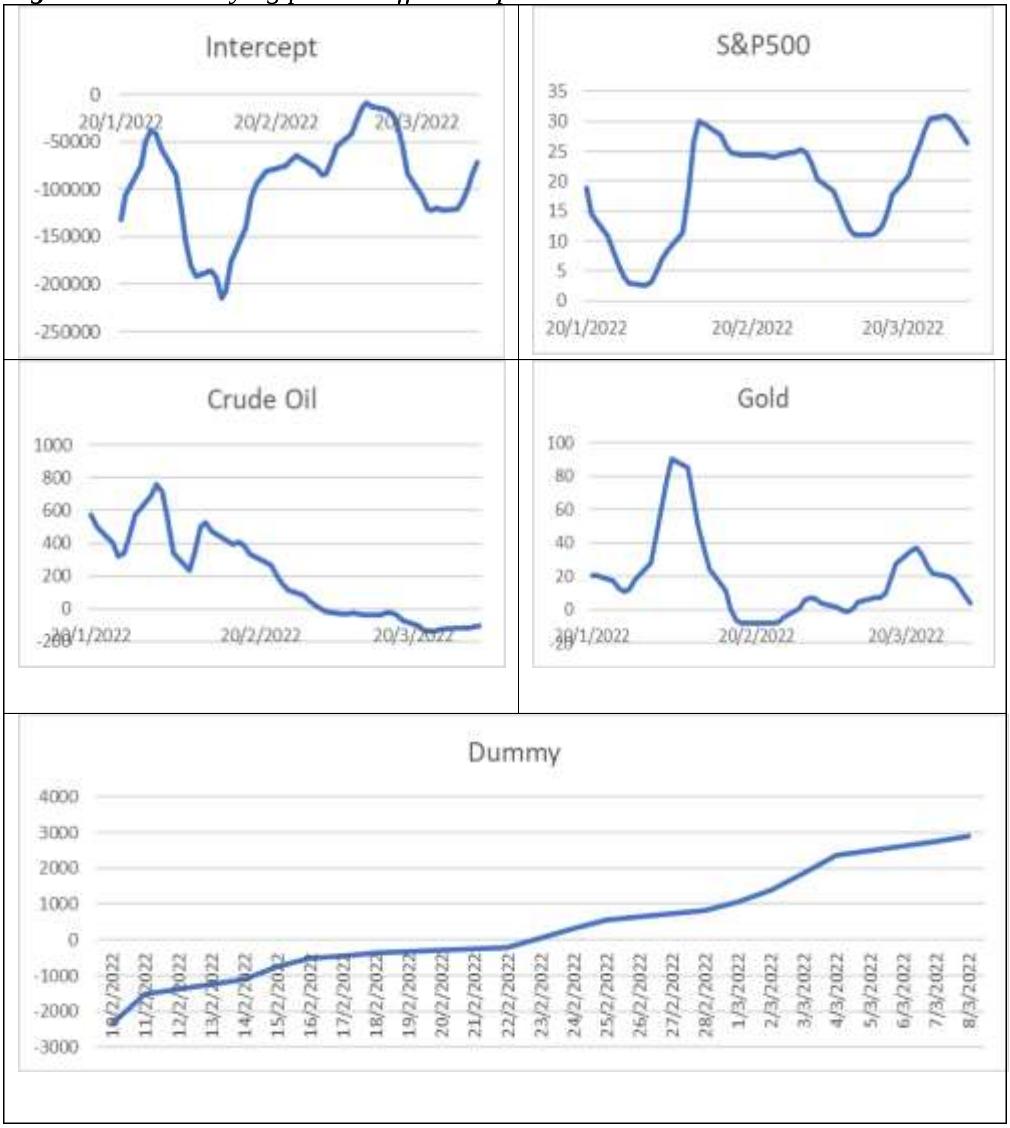
Table 3. *Summary of the price time-varying coefficients per variable*

Variable	Intercept	S&P500	Crude Oil	Gold	Dummy
Min	-214651.030	2.621	-139.376	-8.130	-2346.403
Max	-9127.740	30.989	762.101	90.162	2892.578
Mean	-92991.301	18.832	186.830	18.518	377.180
StDev	53465.338	8.670	271.545	23.860	1472.217

Pseudo R^2=0.8578

Source: *Own study.*

Figure 1. *Time-varying price coefficients per variable*



Source: *Own study.*

According to the results, the prices of S&P500, Crude oil, and gold futures, are positive during the period examined but demonstrate many deviations, in their effect on the price of bitcoin. The intercept is negative, also with many deviations, and finally, the dummy variable representing the war in Ukraine demonstrate a negative effect in the beginning of the war, and quickly becomes positive, with an upward trend. We should note that the dummy variable shows some algorithmic divergences, but this does not affect the validity of our results since we evidence a change in behavior with the start of the war, with the effect changing from negative to positive, capturing a continuous upward trend. Finally, the R^2 of the model is regarded very high, with a value greater than 85% or 0.85.

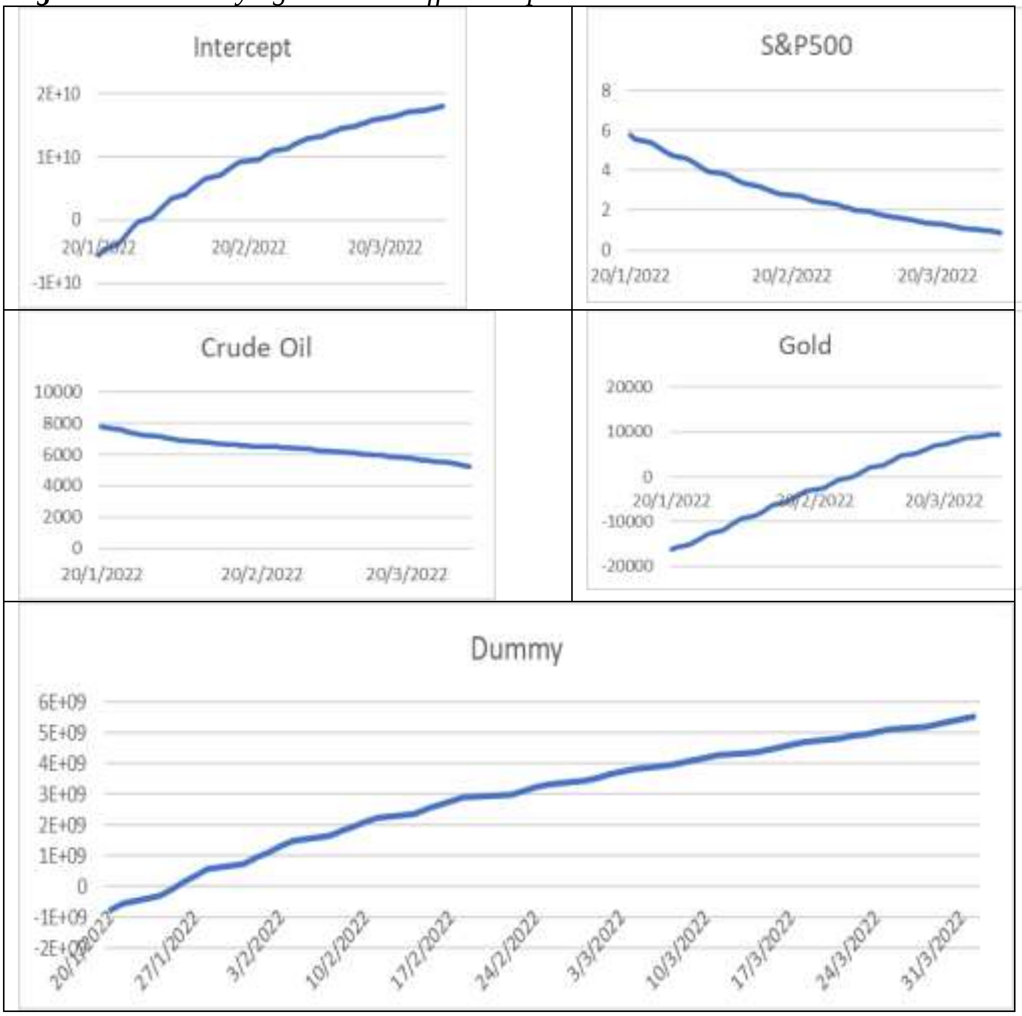
Table 4. *Summary of the volume time-varying coefficients per variable*

Variable	Intercept	S&P500	Crude Oil	Gold	Dummy
Min	-5627097811.000	0.875	5249.745	-16169.935	-761807137.000
Max	18098835348.000	5.763	7794.395	9469.527	5541417248.000
Mean	9365293757.137	2.723	6414.019	-1566.751	3020776187.843
StDev	6932064856.992	1.434	651.605	8176.407	1793859123.817

Pseudo R^2=0.4124

Source: *Own study.*

Figure 2. *Time-varying volume coefficients per variable*



Source: *Own study.*

According to the results, the coefficients of S&P500 and Crude oil, are positive during the period examined following a downward trend in their effect on the bitcoin volume. The intercept is positive, with an upward trend, while gold futures have an upward trend, starting from a negative effect in the beginning of the period, and moving to a positive effect from the middle of the period and onwards.

Finally, the dummy variable representing the war in Ukraine demonstrate a steadily positive upward trend, showing that the war in Ukraine affected positively and gradually more importantly bitcoin volumes of transaction. Finally, the R^2 of the model is 0.41 or 41%.

5. Conclusion

This paper investigates the impact of the war in Ukraine on bitcoin price and volume. We build our approach based on the bitcoin event literature in a policy uncertainty perspective and we apply a three-stage event analysis to explore a. how the market reacted in information prior to the event, in terms of price and volume volatility, and b. whether the event caused any significant change on the price and the volume of bitcoin, comparing price and volume before and after the event.

Our results indicate that bitcoin volume volatility seems to be heavier affected by the event, compared with 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.

Third, using dummies, we find that the Ukraine war event significantly affected the bitcoin price and volume after the event, since both (price and volume) dummies, demonstrate a steadily upward trend, showing that the war in Ukraine affected positively and gradually more importantly bitcoin price and volume.

Our results stand in between the findings of prior literature. Specifically, literature generally shows that bitcoin is affected by global political and economic events, and we do find support on this strand of literature, but the support is strong only for bitcoin volume. Second our results are also in line with the only, to date, paper to test bitcoin behaviour 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 seems to be affected by this specific event, but not as importantly as in the case of volume.

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 political events affect bitcoin price and volume differently.

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Appendix 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)

Appendix 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.