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IS THE CRYPTOCURRENCY POLICY UNCERTAINTY A DETERMINANT OF BITCOIN'S PRICE?

Yunus KARAÖMER*

Abstract

This study attempts to answer the question: "Is the Cryptocurrency Policy Uncertainty (UCRY Policy) a determinant of the Bitcoin's price (BTC)?". Besides, this study uses these factors as explanatory variables for the BTC movements alongside the UCRY Policy and control variables such as the velocity of the Bitcoin in circulation (BC), the computational power of Bitcoin (HR), popularity (PO), and exchange rate (EX). In the study, December 30, 2013-February 21, 2021, was determined as the term and weekly data were investigated. The ARDL bounds testing method was used to determine the relationship between the variables. According to empirical findings, this study suggests that the UCRY Policy is essential to the BTC. There is a negative relationship between UCRY Policy and BTC. When UCRY Policy increases, BTC decreases, holding other variables constant. Besides, this study shows that control variables can be used as determinants of BTC. In long run, BC and HR have a significant, positive relationship with BTC. The EX has a significant, negative relationship with BTC. The PO has a significant, positive relationship with BTC in the short run. In addition, this study demonstrates that UCRY Policy can be used as a type of uncertainty index for Bitcoin.

Keywords: *Bitcoin, Cryptocurrency Policy Uncertainty, Determinants of Bitcoin's Price.*

KRİPTO PARA POLİTİKASI BELİRSİZLİĞİ BİTCOİN'İN FİYATININ BİR BELİRLEYİCİSİ MİDİR?

Öz

Bu çalışma, "Kripto Para Birimi Politika Belirsizliği (UCRY Politikası) Bitcoin fiyatının (BTC) belirleyicisi midir?" sorusuna cevap bulmaya çalışmaktadır. Ayrıca, bu çalışma UCRY Politikasının yanı sıra Bitcoin'in dolaşımdaki hızı (BC), Bitcoin'in hesaplama gücü (HR), popülerlik (PO) ve döviz kuru (EX) gibi kontrol değişkenlerinin BTC hareketleri için açıklayıcı değişkenler olarak kullanmaktadır. Çalışmada, 30 Aralık 2013-21 Şubat 2021 dönem olarak belirlenmiş ve haftalık verilerle inceleme yapılmıştır. Değişkenler arasındaki ilişkiyi tespit etmek için ARDL sınır testi yöntemi kullanılmıştır. Ampirik bulgulara göre, bu çalışma UCRY Politikasının BTC için gerekli olduğunu göstermektedir. UCRY Politikası ile BTC arasında negatif bir ilişki vardır. Diğer değişkenler sabit tutulduğunda, UCRY Politikası arttığında BTC azalmaktadır. Ayrıca bu çalışma, kontrol değişkenlerinin BTC'nin belirleyicileri olarak kullanılabileceğini göstermektedir. Uzun vadede, BC ve HR, BTC ile önemli, pozitif bir ilişkisi vardır. EX'in BTC ile önemli, olumsuz bir ilişkisi vardır. PO'nun kısa vadede BTC ile önemli, pozitif bir ilişkisi vardır. Ayrıca bu çalışma, UCRY Politikasının Bitcoin için bir tür belirsizlik endeksi olarak kullanılabileceğini göstermektedir.

Anahtar Kelimeler: *Bitcoin, Kripto Para Politika Belirsizliği, Bitcoin Fiyatının Belirleyicileri.*

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1. INTRODUCTION

Cryptocurrency; in its most general definition, is a digital money type that is based on the internet system and is not connected to a central authority. Cryptocurrencies are based on a number of ciphers and are traded virtually. The fact that this system is in a development process that will replace the existing currencies and payment instruments and even replace the traditional monetary theory and practices increases the importance of this system day by day (Alpago, 2018: 411). While there has been an increasing interest in cryptocurrencies in recent years, Bitcoin is the most prominent (Kristoufek, 2015: 1). However, due to the fact that Bitcoin prices are constantly volatile, it is still not used in a significant amount of daily transactions. Among all the analyzed features of Bitcoin compared to existing currencies, extreme price volatility stands out most clearly (Ciaian et al, 2016: 883). Figure 1 displays the price development of Bitcoin from 15th August 2009 until 07th June 2021.

Figure 1: The Bitcoin price in USD, Coincodex

Source: Coincodex, 2021.

The BTC rose from zero at the beginning of 2009 to around $1,150 at the end of 2013. At the end of 2014, the BTC dropped to around $340. In 2016, the BTC rose from $400 to $1,190. In 2017, BTC pushed the $20,000 mark but fell to around $3,300 in the next 12 months. Then, in December 2020, BTC surpassed $20,000 and then reached an all-time record of $64,816 on April 14, 2021.

Bitcoin-related events affect the expectations of market participants. Bitcoin-related events have played an important role in triggering market price uncertainty. These events usually occur suddenly and are of very short duration, causing a particular channel to cause a ripple. Moreover, in times of economic unrest and weak confidence, Bitcoin's attractiveness for investors and practitioners increases, allowing it to shine. By focusing on Bitcoin-related information, investors will gain greater access to policy information and then adjust relevant strategies. Therefore, it is clear that policies play a decisive role in BTC volatility (Li, et al. 2021: 2). Colon et al. (2021) examine the effect of political and economic uncertainty on the cryptocurrency market. They find that the cryptocurrency market reacts to uncertainty differently, depending on the type of uncertainty and uncertainty is an essential determinant of cryptocurrency returns. Besides, Lucey et al. (2021) state that uncertainty is the main determinant of cryptocurrency volatility, and the UCRY Policy captures the uncertainty attributable to major events (for example, the Brexit vote, China banning ICOs, hacks of cryptocurrency exchanges, Covid-19 crisis).

Various uncertainty can have different effects and predictive power on cryptocurrency markets. The effects on cryptocurrencies have been examined by using various uncertainty measures in the literature. Some of the cryptocurrency literature analyzes how these uncertainties and risks affect cryptocurrency returns and price volatility. Akyildirim et al. (2020) analyze the relationship between the Volatility index (VIX) and cryptocurrency's volatility and results indicate that cryptocurrency markets experience an increase in volatility when investors' fears are increased. Fang et al. (2020) investigate the impact of the News-based Implied Volatility index (NVIX) on long-term cryptocurrency volatility. They find that the NVIX negatively affects long-term cryptocurrency volatility. Gozgor et al. (2019) investigate the relationship between Bitcoin returns and the Trade Policy Uncertainty (TPU) in the USA and results indicate that the TPU negatively affects Bitcoin returns. Shaikh (2020) investigate the effects of the Economic Policy Uncertainty (EPU) index on Bitcoin returns in the US, the UK, Japan, China, Hong Kong, and results indicate that uncertainty has a negative effect on the Bitcoin market in the US and Japan whereas in China it has a positive effect. Chen et al. (2021) investigate the relationship between Bitcoin returns and Chinese EPU and the result shows that Chinese EPU affects Bitcoin returns positively. Wu et al. (2020) investigate the effect of twitter-based EPU on the cryptocurrency market and results indicate that twitter-based EPU positively affects the returns of cryptocurrencies. A kind of new proxy of uncertainty is the Cryptocurrency Uncertainty Index (UCRY); it is an index developed in the study of Lucey et al. (2021) and based on the analysis of text content. UCRY captures two main types of uncertainty, UCRY Policy, and Cryptocurrency Price Uncertainty

(UCRY Price). They note that these indices could be used to assess how policy and regulatory debates affected cryptocurrency's price, return, or volatility, especially Bitcoin. They build UCRY Policy on the construct found in Baker et al. (2016). Hasan et al. (2021) analyze the UCRY Policy impact on Bitcoin, Sukuk, DJ Islamic Index, the US dollar, gold, and WTI returns and find that UCRY Policy negatively impacts Bitcoin, WTI returns, the US dollar. Hassan et al. (2021) investigate correlations between the top four precious metals (gold, platinum, silver, palladium) and UCRY. They find that gold shows a consistent positive correlation with UCRY among the precious metals.

There is rising interest in the literature by focusing on economic and financial determinants of the BTC. This study attempts to answer the question: “Is the UCRY Policy a determinant of the BTC?”. This study provides several contributions to previous literature. First, previous empirical studies focus on several determinants of the BTC: internal factors (supply and demand, Bitcoin in circulation, hash rate, trading volume, number of transactions) and external factors (popularity, macro-financial and political). This study differently investigated the determinants of the BTC using the UCRY Policy. Second, previous empirical studies comment on the relationship between various uncertainty measures (the VIX, NVIX, TPU, EPU, etc.) and Bitcoin price or return. This study comments on the relationship between the UCRY Policy and BTC. Third, due to the limited number of studies on the UCRY Policy in the finance literature, this study would be useful for new studies and fill a gap in finance literature.

The rest of this study is organized as follows: Section 2 introduces the literature review, section 3 explains the model, data, methodology. Empirical findings are discussed in section 4. Finally, section 5 is the conclusion.

2. LITERATURE REVIEW

There are many studies in the literature on the determinants of the BTC, which managed to attract the attention of all walks (of life) by showing a rapid rise with the first quarter of 2017 and hold approximately 54% of the cryptocurrency market. In this section, this study provides empirical studies on the determinants of the BTC. The empirical studies in the context of the determinants of the BTC are summarized in Table 1.

Table 1: Empirical studies

Study	Determinants	Methodologies	Results
Garcia et al. (2014)	Popularity, user volume	The VAR model	Popularity, user volume affect BTC positively.
Bouoiyour and Selmi (2015)	Popularity, hash rate, trading volume, gold price, Shanghai market index	The ARDL model	Popularity, hash rate, trading volume, gold price, Shanghai market index affect BTC positively.
Polasik et al. (2015)	News, popularity, Bitcoin in circulation, number of transactions	Ordinary and Tobit regressions	News, popularity, Bitcoin in circulation, number of transactions affect BTC positively.
Balcilar et al. (2017)	Number of trancations	A novel nonparametric causality-in-quantiles test	The number of transactions affects Bitcoin price positively.
Sukamulja and Sikora (2018)	Dow Jones Industrial Average (DJIA) index, gold price, Bitcoin supply and demand	The VAR model	Bitcoin supply affects BTC negatively (short-run). Bitcoin demand affects Bitcoin price positively (short-run and long-run). DJIA index and gold price affect Bitcoin price positively (long-run).
Sovbetov (2018)	Popularity, Standard & Poor's 500 index	The ARDL model	Popularity, Standard & Poor's 500 index affect BTC positively.
Panagiotidis et al. (2018)	European EPU, the NIKKEI index, popularity, exchange rates, interest rates, gold and oil returns.	The LASSO approach	European EPU, the NIKKEI index, popularity affect Bitcoin return negatively, while exchange rates, interest rates, gold and oil returns.
Ciaian et al. (2018)	Public interest, Bitcoin in circulation, number of transactions, exchange-rate	The ARDL model	Public interest, Bitcoin in circulation, number of transactions, exchange rate affect BTC positively.

3. MODEL, DATA, AND METHODOLOGY

In this part, weekly data is used for the model. The data time frame spans from December 30, 2013, to February 21, 2021. The reason why the weekly frequency is chosen is that it is impossible to obtain the data weekly for the UCRY Policy developed by Lucey et al. (2021). The model estimated in this study are given in the following equations:

$$\mathbf{BTC_t = \beta_0 + \beta_1 BC_t + \beta_2 HR_t + \beta_3 PO_t + \beta_4 EX_t + \beta_5 UCRY\ Policy_t + \varepsilon_t} \quad (1)$$

where the BTC is the price of Bitcoin versus the US Dollar (USD). The BC is the velocity of Bitcoin in circulation. The HR is the computational power of Bitcoin (Terahashes/Second). The PO is a popularity variable. The EX is the USD/EUR exchange rate. The UCRY Policy is a cryptocurrency policy uncertainty index developed by Lucey et al. (2021). All variables are in logarithmic form. A summary of data definitions and sources is given in Table 2.

Table 2: Variable definitions and sources

Variables	Definitions	Sources
BTC	Bitcoin's price (BTC/USD)	Investing.com (2021a)
BC	The velocity of Bitcoin in circulation	Bitcoin.com (2021)
HR	The estimated number of terahashes per second the Bitcoin network is performing in the last 24 hours.	Blockchain.com (2021)
PO	Numbers of "searches queries" including the keyword "bitcoin"	Google Trends (2021)
EX	USD/EUR exchange rate	Investing.com (2021b)
UCRY Policy	Cryptocurrency policy uncertainty	brianmlucey.wordpress.com (2021)

Figure 2 indicates the hypothesis of the research. It uses these factors as explanatory variables for the BTC movements alongside with the UCRY Policy and control variables such as the BC, HR, PO, and EX.

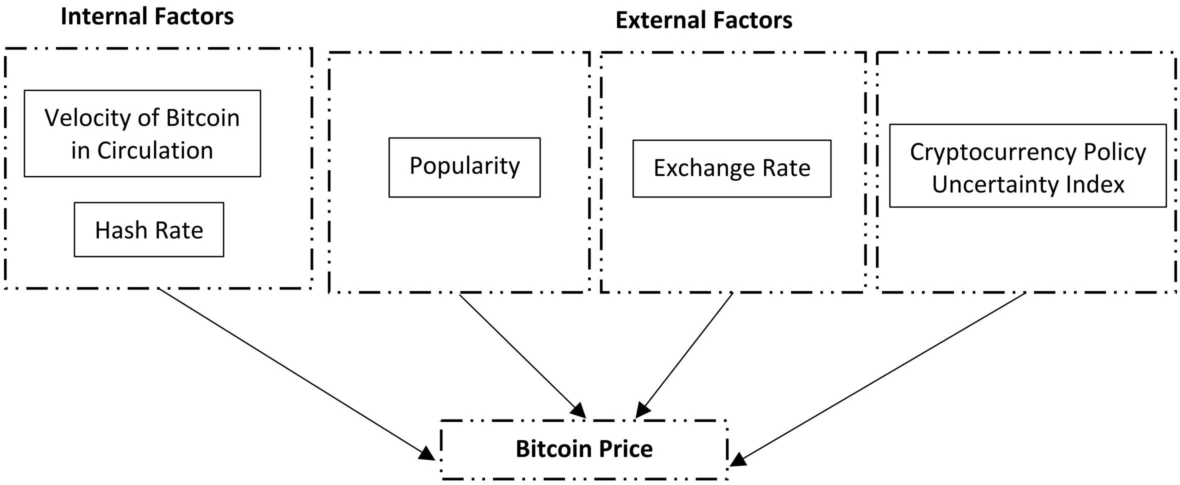

Figure 2: The hypothesis of the research

Poyser (2017) stated that types of BTC determinants were in two different ways, namely internal and external factors. Bitcoin's supply and demand, Bitcoin in circulation, hash rate, trading volume, number of transactions were the main internal factors that directly impacted the market price. On the other side, attractiveness (popularity), macro-financial, and political (adaptation, legalization, restrictions, bans, and others) factors were accepted as external factors. Based on this information, this study has the following five hypotheses for the determinants of BTC.

Hypothesis 1 (H_1): The BC has a positive impact on the BTC.

The BC is one of the factors affecting the BTC. Velocity measures the BC in the economy and is determined by the amount of spending on each transaction. In other words, velocity can be measured on a supply-demand basis because the more transactions made using Bitcoin, the faster the velocity. It is explained by the theory of the amount of money that the BTC, especially the BC, is positively correlated with the BTC, while the BTC has a negative relationship between the BTC and the quantity (Woo et al., 2019: 19).

Hypothesis 2 (H_2): The HR has a positive impact on the BTC.

The total number of Bitcoins in circulation is asymptotically given by a known algorithm until it reaches 21 million Bitcoins. The generation of new Bitcoins is driven and regulated by difficulties that reflect the computing power (hash rate) of Bitcoin miners. By solving computationally demanding tasks, Bitcoin miners confirm ongoing transactions and the uniqueness of Bitcoins and receive new Bitcoins as a reward. Awards and challenges are given with a known formula (Kristoufek, 2015: 4). It states that the greater the amount of computational power allocated to the mining process, the higher the price of Bitcoin. Because the higher the mining power, the more Bitcoin is accepted (Hayes, 2015: 2).

Hypothesis (H_3): The PO has a positive impact on the BTC.

If Bitcoin is spoken and heard by people, if their popularity increases due to mass media, the demand for Bitcoin is expected to increase (Nguyen et al., 2018: 114). Kristoufek (2013) stated that both Google Trends search queries and Wikipedia views for the keyword "Bitcoin" in the same time period had had a positive impact on the change in BTC.

Hypothesis 4 (H_4): The BTC reacts to the EX.

Many researchers have been trying to find the relationship between Bitcoin and macro-financial factors. Georgoula et al. (2015) examine the relationship between the BTC and basic economic variables using daily data between October 27, 2014, and January 12, 2015. They find that the BTC is negatively affected by the USD/EUR exchange rate and S&P 500 index. Jang and Lee (2017) find that the Dow Jones index, exchange rate, and WTI oil price affect the BTC in the long run.

Hypothesis 5 (H_5): The BTC reacts to the UCRY Policy.

Lucey et al. (2021) state that the UCRY Policy captures the uncertainty attributable to major events in the cryptocurrency more prominently compared to the Global EPU, EPU, and VIX indices.

In this study, the ARDL (Autoregressive Distributed Lag) test is applied to the series because it has the advantage of stationarity constraint to examine the relationship of variables. Cointegration tests are used to determine or examine the long or short-term relationships of various variables. In the literature, Engle-Granger (1987), Johansen (1988), and Johansen-Juselius (1990) cointegration tests are applied to variables that are integrated in the same order. It is not possible to use these tests if the series is integrated into a different order. However, the ARDL test developed by Pesaran and Shin (1998) and Pesaran et al. (2001) makes it possible to examine the relationship between different orders (I_0, I_1, or a combination of both) of integrated variables. The ARDL test also gives meaningful results when applied to small samples. The established ARDL model is as follows:

$$\Delta BTC_t = \psi + \eta_0 BTC_{t-1} + \eta_1 BC_{t-1} + \eta_2 HR_{t-1} + \eta_3 PI_{t-1} + \eta_4 EX_{t-1} + \eta_5 CPU_{t-1} \sum_{j=1}^{p} \beta_{1j}\, \Delta BTC_{t-j} + \sum_{j=0}^{q} \beta_{2j}\, \Delta BC_{t-j} + \sum_{j=0}^{q} \beta_{3j}\, \Delta HR_{t-j} + \sum_{j=0}^{q} \beta_{4j}\, \Delta PO_{t-j} + \sum_{j=0}^{q} \beta_{5j}\, \Delta EX_{t-j} + \sum_{j=0}^{q} \beta_{6j}\, \Delta UCRY\ Policy_{t-j} + \varepsilon_t \quad (2)$$

The ARDL model allows creating an error correction model to see in how many periods the variables will come to equilibrium. The error correction equation is as follows:

$$ECM_t = BTC_t - \beta_0 - \beta_1 BC_t - \beta_2 HR_t - \beta_3 PO_t - \beta_4 EX_t - \beta_5\ UCRY\ Policy_t \quad (3)$$

$$\Delta BTC_t = \gamma_0 + \sum_{i=1}^{n} \gamma_{1i}\, \Delta BTC_{t-1} + \sum_{i=0}^{q} \gamma_{2i}\, \Delta BC_{t-1} + \sum_{i=1}^{q} \gamma_{3i}\, \Delta HR_{t-1} + \sum_{i=1}^{q} \gamma_{4i}\, \Delta PO_{t-1} + \sum_{i=1}^{q} \gamma_{5i}\, \Delta EX_{t-1} + \sum_{i=1}^{q} \gamma_{1i}\, \Delta UCRY\ Policy_{t-1} + \delta ECM_{t-1} + \varepsilon_t \quad (4)$$

4. EMPIRICAL FINDINGS

Tablo 3 indicates results of Augmented Dickey-Fuller (1979) (ADF) and Kwiatkowski-Phillips-Schmidt-Shin (1992) (KPSS) unit root test for all variables both at the level and first difference.

Table 3: Unit root test results

		ADF		KPSS	
	Variable	**Intercept**	**Intercept and Trend**	**Intercept**	**Intercept and Trend**
Level	BTC	0.669370	-2.228837	2.177377	0.231791
	BC	-2.216113	-1.936832	2.315069	0.567493
	HR	-2.755292	-2.604011	2.407703	0.350598
	PO	-3.547474***	-3.502325***	0.183748***	0.137298***
	EX	-2.336777	-1.830856	0.878209	0.270067
	UCRY Policy	-0.318144	-1.293803	0.990058	0.080980***
	Variable	**Intercept**		**Intercept**	
1st Difference	BTC	-19.72655***		0.338380***	
	BC	-15.82198***		0.304027***	
	HR	-19.18647***		0.279407***	
	EX	-18.20194***		0.372044***	
	UCRY Policy	-21.04459***		-	

Note: "***,**, *" denote statistical significance at the 1%, 5%, 10% levels, respectively.

Findings from the ADF tests suggest that the BTC, BC, HR, EX, UCRY Policy exhibit non-stationarity and can be considered as an I_1 time series, while the PO exhibits stationarity and can be considered as an I_0 time series. Findings from the KPSS tests suggest that the BTC, BC, HR, EX exhibit non-stationarity and can be considered as an I_1 time series, while the PO and UCRY Policy exhibit stationarity and can be considered as an I_0 time series. According to both the ADF and KPSS unit root test findings, variables are integrated into different orders. Therefore, the ARDL model is appropriate for series with a mixture of I_0 and I_1 variables. The results of the ARDL model are as follows:

Table 4: ARDL (1, 1, 0, 2, 0, 0) estimation results

Model	**BTC = ƒ (BC, HR, PO, EX, UCRY Policy)**		
Variable	**Coefficient**	**t-Statistic**	**P value**
BTC(-1)	0.953810	57.26924	0.0000***
BC	-26.73694	-1.384144	0.1672
BC(-1)	27.55988	1.438607	0.1511
HR	0.013882	0.851227	0.3952
PO	-0.031932	-1.548987	0.1223
PO(-1)	-0.069023	2.511069	0.0125***
PO(-2)	0.045653	2.207036	0.0279***
EX	-0.540059	-2.256503	0.0246***
UCRY Policy	-1.371306	-1.675046	0.0948*
C	-18.87010	-2.897599	0.0040***
Diagnostic Tests		**Statistic**	**P value**
Serial correlation LM test		0.286	0.750
Heteroscedasticity test		1.926	0.166
Jarque Bera normality test		1.497	0.475
Ramsey Reset Test		0.959	0.328

Note: "***, **, and *" denote rejection of null hypothesis at 1%, 5%, and 10% significance levels, respectively.

The result of the ARDL (1, 1, 0, 2, 0, 0) model is shown in Table 4. The optimum lag levels are determined with Akaike Information Criterion (AIC). According to diagnostic test results, it is seen that ARDL (1, 1, 0, 2, 0, 0) model does not have autocorrelation, heteroscedasticity problems, and specification error. In addition, the error term is normally distributed. After the diagnostic tests, firstly, the "ARDL Bound Test" will be applied to variables in order to test whether there is a long-term relationship or not. In this step, the F-statistic value is needed to determine the long-term relationship of the series with each other. Table 5 indicates the results of the ARDL Bound Test.

Table 5: Result of ARDL bound test

Model	BTC = ƒ (BC, HR, PO, EX, UCRY Policy)	
F-statistic	3.674305	
Optimal lag	[1, 1, 0, 2, 0, 0]	
	Lower Bound	**Upper Bound**
5% significance	2.39	3.38

According to Table 5, the F-statistic value is exceeding the upper bound at a 5% significance level. This finding means that there is a long-term cointegration between variables.

Table 6: Long run coefficients

Model	BTC = ƒ (BC, HR, PO, EX, UCRY Policy)		
Variable	**Coefficient**	**t-Statistic**	**P value**
BC	17.816418	1.833574	0.0675*
HR	0.300545	0.731663	0.0848*
PO	0.185371	0.936939	0.3494
EX	-11.692082	-3.098829	0.0021***
UCRY Policy	-29.688285	-1.655352	0.0987*
C	-408.530963	-2.363710	0.0186**

Note: "***, **, and *" denote rejection of null hypothesis at 1%, 5%, and 10% significance levels, respectively.

In Table 6, it is seen that the EX, BC, HR, and UCRY Policy are statistically significant at the level of 1% and 10% in the long term, respectively. This means that there is a long-term cointegration relationship between the BTC and EX, BC, and UCRY Policy. In the long term, the BTC decreases as the EX, UCRY Policy increase, while the BTC increases as the BC, HR increase.

Table 7: Short run coefficients and error correction model results

Model	BTC = ƒ (BC, HR, PO, EX, UCRY Policy)		
Variable	**Coefficient**	**t-Statistic**	**P value**
D(BC)	18.37249	1.339671	0.1812
D(BC(-1))	-15.72739	-1.160294	0.2467
D(HR)	0.007807	0.166233	0.8681
D(PO)	0.044059	2.123991	0.0344**
D(PO(-1))	0.021272	2.208010	0.0243**
D(PO(-2))	0.051530	2.478858	0.0136**
D(EX)	-0.681566	-0.991779	0.3220
D(UCRY Policy)	-0.403445	-0.390120	0.6967
ECM(-1)	-0.046318	-2.630670	0.0089***

Note: "***, **, and *" denote rejection of null hypothesis at 1%, 5%, and 10% significance levels, respectively.

According to the error correction model (ECM) estimation results shown in Table 7, the coefficient of the ECM is negative and statistically significant at a 1% level, implying that 0.04% of the errors are correcting in a single time period. Besides, the PO has a significant impact on the BTC in the short run, and the impact is positive.

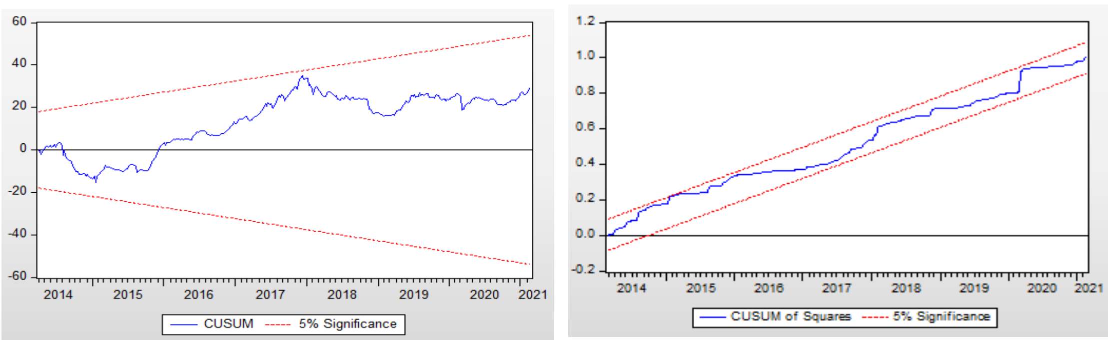

Figure 3: The plot of CUSUM and CUSUM of squares tests

The plot of CUSUM and CUSUM of Squares tests in Figure 3 shows that no misspecification and structural instability of long-run estimated parameters emerged in the sample period. Therefore, this means that the estimated parameter of the model constructs a reliable estimation.

The results from this empirical study can be summarized as follows: (i) This study regressed the BTC on the BC, HR, PO, EX, UCRY Policy using the ARDL Bounds testing method, the ADF, KPSS unit root test for weekly data covering the period from December 30, 2013, to February 21, 2021. The series is integrated into different orders according to the ADF, KPSS unit root test. Hence, the ARDL model and boundary testing method proposed by Pesaran and Shin (1998) and Pesaran et al. (2001) is suitable for this study. (ii) In the long run, regarding the BC, it is proved that the BC indicates a positive and significant coefficient in 10% significance, confirming H_1. When there is a 1% increase in the BC, the BTC would increase by 17.81%, holding other variables constant. It can be said that this result is consistent with the results of studies conducted by Polasik et al. (2015), Ciaian et al. (2018), Sukamulja and Sikora (2018). Regarding the HR, it is proved that the HR indicates a positive and significant coefficient in 10% significance, confirming H_2. When there is a 1% increase in the HR, the BTC would increase by 0.30%, holding other variables constant. It can be said that this result is consistent with the result of the study conducted by Bouoiyour and Selmi (2015). The EX shows a negative and significant relationship towards the BTC in the long-run relationship. When there is a 1% increase in the EX, the BTC would decrease by 11.69%, holding other variables constant. It can be said that this result is consistent with the result of the study conducted by Ciaian et al. (2018). Moreover, the UCRY Policy indicates a negative and significant relationship towards the BTC in the long-run relationship. When there is a 1% increase in the UCRY Policy, the BTC would decrease by 29.68%, holding other variables constant. It can be said that this result is consistent with the result of the study conducted by Hasan et al. (2021). (iii) In the short-run, regarding the PO, it is proved that the PO indicates a positive and significant coefficient in 5% significance, confirming H_3. When there is a 1% increase in the PO, the BTC would increase by 17.81 %, holding other variables constant. It can be said that this result is consistent with the results of studies conducted by Garcia et al. (2014), Bouoiyour and Selmi (2015), Polasik et al. (2015), Sovbetov (2018), Ciaian et al. (2018) but not Panagiotidis et al. (2018). (iv) According to error correction results, 0.04% of errors are correcting in a single time period and CUSUM and CUSUM of squares tests indicate consistency in coefficients at a 1% significance level.

5. CONCLUSION

This study attempts to answer the question: "Is the UCRY Policy a determinant of the BTC?". It uses these factors as explanatory variables for the BTC movements alongside the UCRY Policy and control variables such as the BC, HR, PO, and EX. According to empirical findings, this study suggests that the UCRY Policy is an essential determinant of the BTC. There is a negative relationship between the UCRY Policy and BTC. When the UCRY Policy increases, the BTC decreases, holding other variables constant. This result demonstrates that the UCRY Policy is used as a type of uncertainty index on Bitcoin. In addition, this result offers potential implication for policymakers. Policymakers should be aware that policy uncertainties can adversely impact BTC and thus take appropriate decisions.

The absence of a central, trusted authority means that the blockchain needs a "consensus mechanism" to maintain network-wide trust. In the case of Bitcoin, consensus is achieved through a method called "Proof of Work" (PoW), in which computers on the network - "miners" - compete with each other to solve a complex mathematical puzzle. Today, miners need to perform a (PoW) by spending a high level of energy in order to obtain a Bitcoin reward. Thus, the hash rate a miner makes per second would increase his energy expenditure (Kamiya, 2019). In this study, HR has a significant, positive relationship with BTC. According to this result, as the BTC increases, the hash rate would increase. Thus, it can be said that energy consumption would increase as the hash rate increases. Besides, this study shows that other control variables can be used as determinants of the BTC. In long run, the BC has a significant, positive relationship with the BTC. The EX has a significant, negative relationship with the BTC. This result offers potential implication for portfolio mangers, investors, and market participants. Bitcoin can be preferred by them as safe-haven or hedging assets. The PO has a significant, positive relationship with the BTC in the short run.

Furthermore, for further empirical investigations, it is recommended that researchers include additional independent variables suggested by previous empirical research to enhance and expand this research model.

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