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THE CAUSAL RELATIONSHIP BETWEEN BITCOIN ENERGY CONSUMPTION AND CRYPTOCURRENCY UNCERTAINTY

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ABSTRACT
Purpose- Investigating the relationship between the energy consumption for Bitcoin and the price and policy uncertainties in the cryptocurrency markets.
Methodology- It was preferred for unit root tests of series the Zivot-Andrews Unit Root Test, which takes into account structural breaks. Depending on the stagnation of the variables at different levels, the Toda-Yamamoto (1995) causality test was applied by using weekly data in period 19.02.2017 and 07.02.2021.
Findings- One-way causality was found on the indices of cryptocurrency price uncertainty and cryptocurrency policy uncertainty from bitcoin energy consumption. In addition, it is understood from the Chi-Square Test Statistic (13.16980) coefficient that the change in bitcoin energy consumption is more dominant on the crypto money policy uncertainty. It was reached that changes in bitcoin energy consumption have an effect on both price and crypto money policies in all crypto markets.
Conclusion- In line with these results, it is concluded that the uncertainties in the crypto markets are under the influence of many external political factors. This study investigated the effect of price and political uncertainty on bitcoin energy consumption in the entire cryptocurrency market, but it was concluded that bitcoin energy consumption is not only linked to crypto markets, but also under the influence of government interventions, bans, ill-recognition, and developments and movements in other financial markets.

Keywords: Bitcoin energy consumption, bitcoin mining, cryptocurrencies, crypto money price uncertainty index.
JEL Codes: G00, G19, P43

1. INTRODUCTION

The way the real economy works has completely changed with the widespread use of the internet. The fact that all internet users can interact at the same time has reduced the costs of accessing information. Internet-based electronic marketplaces use information technology(IT) to match buyers and sellers with lower transaction costs. The internet age and developments in financial technology and innovations such as mobile payments, blockchain applications, the development of digital payment methods, and digital currencies have led to the emergence of new financial instruments. Cryptocurrencies, one of these new tools, allow real-time transactions, open algorithm and transaction history storage. With these features, it is among the investment instruments with high investor interest. Of course, this investor interest is heading in different directions with the uncertainties and risky movements in the financial markets.

Coins such as Bitcoin, which deviate from government or standard economic operations, were introduced in 2008. Cryptocurrencies are an innovation that emerged as a result of investors losing their trust in mainstream currencies due to excessive market uncertainty (Demir et al. 2018). Especially in times of high economic uncertainty, investors either restrict their investments, wait for the current conditions to settle, or try to find suitable strategies to reduce uncertainty around the world. Interestingly, the cryptocurrency market is emerging as a risk management tool for domestic and international investors of stock and commodity markets worldwide, during periods of high uncertainty in particular (Haq et al. 2021: 2).

However, when there is a significant level of uncertainty in the markets, a "wait and see" investment strategy is used by investors, which leads to an increase in the value of the cryptocurrency (Jiang and Ashworth, 2021: 1-2). While it is effective in crypto pricing and accordingly, it is thought that it may have possible effects on crypto energy consumption. In addition, attempts have been made to measure and evaluate the risks and uncertainties occurring in crypto markets. These indexes that Crypto Money Price Uncertainty Index and the Crypto Money Policy Uncertainty Index created by Lucey et al. (2021), are exised in this direction.

On the other hand, Bitcoin mining comes first among the methods used to obtain Bitcoin. In the Bitcoin mining process, a proof-of-work problem must be solved first. It should be ensured that the block header value of a certain length is passed through the SHA256 hash algorithm twice, and the resulting value is less than the target value provided by the system, thus preceding a certain amount of 0. There is a very serious competition among the miners in the network and a significant amount of electricity is consumed in the execution of this large number of transactions (Balcısoy, 2017: 2).

The process of producing Bitcoin, called Bitcoin mining, uses Blockchain technology and basically only needs hardware and electricity consumption. Possible changes in Bitcoin prices and crypto markets are thought to have an impact on the demand for Bitcoin mining. In addition, both the business world and researchers have started to discuss the energy consumption of Bitcoin mining. In this context, which factors are effective on bitcoin energy consumption has been the source of motivation for this study.

This study was designed to investigate the possible effects of price and policy uncertainties on bitcoin energy consumption in crypto markets, limited to preferred periods and variables. In this direction, following the introduction, in the second part, summaries of recent studies on the subject will be presented. Then, in Chapter 3, the econometric model to be used in the application part of the study will be introduced and the findings will be presented in the form of tables and graphics. In the last section, the findings obtained from the analysis will be interpreted in comparison with the literature studies. In addition, the benefits of the findings obtained from this study for investors and policy makers and those who will do academic studies in this field will be evaluated and suggestions will be made.

2.LITERATURE

In many studies which were taken into account macroeconomic factor efects on cryptocurrencies; Fang et al. (2020), Honak (2021); its relationship with capital markets; Shahzad et al. (2022), Dobrynskaya, V. (2021), Pillai et al. (2021), Huwaida and Hidajat (2020), Gürsoy and Tuncel (2020), Baur, Hong and Lee (2018); the relationship between bitcoin and other cryptocurrencies and commodities; Elsayed et al. (2022), Long et al. (2021), Singh (2021), Buğan (2021), Hassan et al. (2021), Ferreira and Pereira, (2019), Dyhrberg (2016); The relationship between energy consumption and environmental factor; Geels, (2022), Yan et al. (2021), Corbet et al. (2021), Badea and Mungpiu-Pupăzan (2021), Gallersdörfer et al. (2021), Jane et al. (2020), Egiyi and Ofoegbu, (2020 Stoll, (2019), Mora et al. (2018), ; Its relationship with global risks and uncertainties, investment risks; Sarkodie et.al (2022), Diaconaşu et al. (2022), Böyükaslan and Ecer (2021), Platt et al. (2021), Cheng and Yen (2020), (Çelik, 2020), Wu et al. (2019), Bouri et al. (2018), Hong et al. (2009) studies were observed in general. Most of these studies consider bitcoin, the most popular currency. In this study, an application made in which direct crypto currency uncertainty is selected as an independent variable. In the literature on cryptocurrency uncertainty, a very limited number of studies have found in the national literature, but it is seen that this number is higher in the international literature. Likewise, when the bitcoin energy consumption and literature are examined, it is seen that the studies have intensified in the last few years. Since this study will be the pioneer study examining the relationship between bitcoin energy consumption and cryptocurrency uncertainty, it is hoped that this aspect will contribute to the literature.

Although there are no directly similar studies on the subject, the most recent studies on Bitcoin energy consumption are as follows: Kristoufek (2020) investigated the relationship between Bitcoin mining costs, bitcoin price, Bitcoin hash-rate and Bitcoin electricity costs between in period of 2014M1- 2018M8. Bitcoin price and mining costs are closely linked. it was concluded from here that electricity costs play a primary role in Bitcoin mining efficiency. KıAytekin and Kaya (2022) found a relationship between Bitcoin and electrical energy consumption both in the short-term and in the long-term. Huynh et al. (2022) examined the relationship between bitcoin energy consumption and price, volume between 11.02.2017-18.09.2019. According to the results, Bitcoin trading volumes on energy consumption is higher than returns in the long run. Kılıç et.al. (2021) investigated the relationship between bitcoin energy consumption and energy companies. In the study using weekly data between 22.05.2017 - 10.02.2021, they tested the relationship between bitcoin energy consumption and the energy markets of the countries that produce the most bitcoin. Bitcoin electricity consumption affects energy company valuations of Russia and China; It has been observed that the USA and Russia are affected by the energy company valuations.

3.METHODOLOGY

The aim of this study is to reveal whether there is a causality between Bitcoin energy consumption and cryptocurrency uncertainty, and its direction. However, weekly Terawatt (TW) data were obtained on regarding bitcoin energy consumption

(BENRGY at digiconomist.net. For the represent crypto markets uncertainty, it was reached the Cryptocurrency price uncertainty index (UCRYPRI) and cryptocurrency policy uncertainty indices (UCRYPOL) created by (Lucey et al. 2021). Cryptocurrency uncertainty and indices data were created from weekly observation values and accessed from https://brianmlucey.wordpress.com/2021/03/16/cryptocurrency-uncertainty-index-dataset/. The application used weekly data consisting of 208 observations between 19 February 2017 and 7 February 2021. The optimal lag length was determined according to the Akaike information criterion-AIC after the series were recovered from the unit root, that is, after they were made stationary. It has been observed that the variables are stationary at different levels in the analyzes of the unit root tests. Toda-Yamamoto (1995) causality, which is a suitable method for this situation, was preferred. More than one equation has been established in the form of paired tests, in which each variable is included as both dependent and independent variables.

This method was introduced to take the Granger causality test to a higher level. Some problems in the Granger causality test were tried to be eliminated with this model. In order to apply the Granger causality test in time series analysis, the series must first become stationary and become stationary at the same level. After this condition is met, cointegration should also occur in order to demonstrate that there is a long-term relationship between the series that become stationary at the same level. Only the Granger causality test can be performed between the series that are stationary at the same level and have a cointegration relationship between them. However, the Toda-Yamamoto test revealed that there can be causality between time series that are stationary at different levels, and that the causality test can be performed without even the need for a stationarity test. This model can also be tested regardless of whether there is cointegration between the series without considering cointegration (Toda and Yamamoto, 1995).

In first stage of the test,that is to determining the lag length (k) in the model with the VAR model. Then, in the second stage of the model, the variable with the highest degree of integration (d_{max})) is added to the lag length (k) of the model. In the third step, the VAR model is estimated according to the latency with the level values of the series (k + d_{max}) In the last step, the coefficients from (d_{max})) are added to the constraints and the significance of the added constraints is tested using the modified Wald statistic. The VAR model developed by Toda-Yamamoto (1995) is as follows;

$$Y_t = a_0 + \sum_{i=1}^{k+d_{max}} a_{1i} Y_{t-i} + \sum_{i=1}^{k+d_{max}} a_{2i} X_{t-i} + u_t \qquad (1)$$

$$X_t = \beta_0 + \sum_{i=1}^{k+d_{max}} \beta_{1i} X_{t-i} + \sum_{i=1}^{k+d_{max}} \beta_{2i} Y_{t-i} + v_t \qquad (2)$$

The main hypothesis and alternative hypothesis are handled as follows

H0: Variable X is not Granger cause of variable Y.

H1: Variable X is the Granger cause of variable Y.

The success of the Toda-Yamamoto causality test is directly related to the correct determination of the (d_{max}) value of the series (k) in the model.

4. FINDINGS

In this section, presented the results of the tests applied to reveal the causal relationship between the BENRGY, UCRYPRI and UCRYPOL variables.

The main hypothesis of the research is as follows;

H0: There is no causal relationship between Bitcoin Energy Consumption (BENRGY), Cryptocurrency Price Uncertainty Index (UCRYPRI) and Cryptocurrency Policy Uncertainty Indices (UCRYPOL).

H1: There is a causal relationship between Bitcoin Energy Consumption (BENRGY), Cryptocurrency Price Uncertainty Index (UCRYPRI and Cryptocurrency Policy Uncertainty Indices (UCRYPOL).

The models consit of the BENRGY, UCRYPRI and UCRYPOL variables are as follows

The equations for BENRGY and UCRYPRI;

$$BENRGY_t = a_0 + \sum_{i=1}^{k+d_{max}} a_{1i} BENRGYc_{t-i} + \sum_{i=1}^{k+d_{max}} a_{2i} UCRYPRI\ x_{t-i} + u_t \qquad (3)$$

$$UCRYPRI_t = \beta_0 + \sum_{i=1}^{k+d_{max}} \beta_{1i} UCRYPRI_{t-i} + \sum_{i=1}^{k+d_{max}} \beta_{2i} BENRGY_{t-i} + v_t \tag{4}$$

In the Toda-Yamamoto test, the main hypothesis and alternative hypothesis are established as follows.

H0: The BENRGY variable is not the Granger cause of the UCRYPRI variable.

H1: The BENRGY variable is the Granger cause of the UCRYPRI variable.

The equations for BENRGY and UCRYPOL;

$$BENRGY_t = a_0 + \sum_{i=1}^{k+d_{max}} a_{1i} BENRGYc_{t-i} + \sum_{i=1}^{k+d_{max}} a_{2i} UCRYPOL\, x_{t-i} + u_t \tag{5}$$

$$UCRYPOL_t = \beta_0 + \sum_{i=1}^{k+d_{max}} \beta_{1i} UCRYPOL_{t-i} + \sum_{i=1}^{k+d_{max}} \beta_{2i} BENRGY_{t-i} + v_t \tag{6}$$

The main hypothesis and alternative hypothesis are established as follows.

H0: The BENRGY variable is not the Granger cause of the UCRYPOL variable.

H1: The BENRGY variable is the Granger cause of the UCRYPOL variable.

The equations for UCRYPRI and BENERGY;

$$UCRYPRI_t = a_0 + \sum_{i=1}^{k+d_{max}} a_{1i} UCRYPRIc_{t-i} + \sum_{i=1}^{k+d_{max}} a_{2i} BENERGY\, x_{t-i} + u_t \tag{7}$$

$$BENERGY_t = \beta_0 + \sum_{i=1}^{k+d_{max}} \beta_{1i} BENERGY_{t-i} + \sum_{i=1}^{k+d_{max}} \beta_{2i} UCRYPRI_{t-i} + v_t \tag{8}$$

The main hypothesis and alternative hypothesis are established as follows.

H0: UCRYPRI variable is not Granger cause of BENERGY variable.

H1: The UCRYPRI variable is the Granger cause of the BENERGY variable.

The equations for UCRYPOL and BENERGY ;

$$UCRYPOL_t = a_0 + \sum_{i=1}^{k+d_{max}} a_{1i} UCRYPOLc_{t-i} + \sum_{i=1}^{k+d_{max}} a_{2i} BENERGY\, x_{t-i} + u_t \tag{9}$$

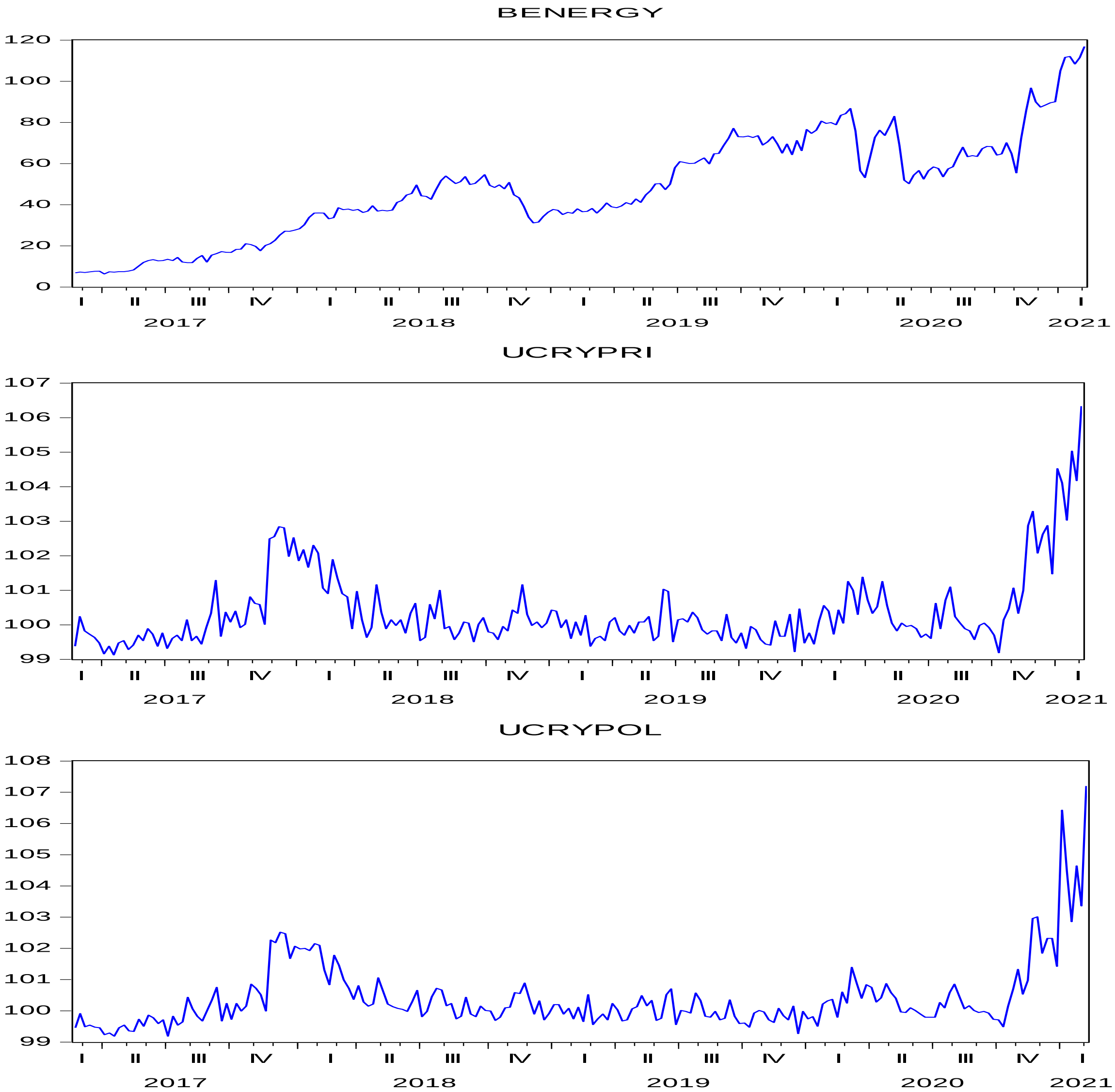
$$BENERGY_t = \beta_0 + \sum_{i=1}^{k+d_{max}} \beta_{1i} BENERGY_{t-i} + \sum_{i=1}^{k+d_{max}} \beta_{2i} UCRYPOL_{t-i} + v_t \tag{10}$$

The main hypothesis and alternative hypothesis are established as follows.

H0: UCRYPOL variable is not Granger cause of BENERGY variable.

H1: The UCRYPOL variable is the Granger cause of the BENERGY variable.

Figure 1: Price Series of Variables



4.1. Zivot-Andrews Unit Root Test Results

For the series, the C model was taken into account to determine the breaks of the series in the Zivot-Andrews test. The first difference of the non-stationary series at the level was taken and the Zivot-Andrews unit root test was applied again. findings are shown in Table 1.

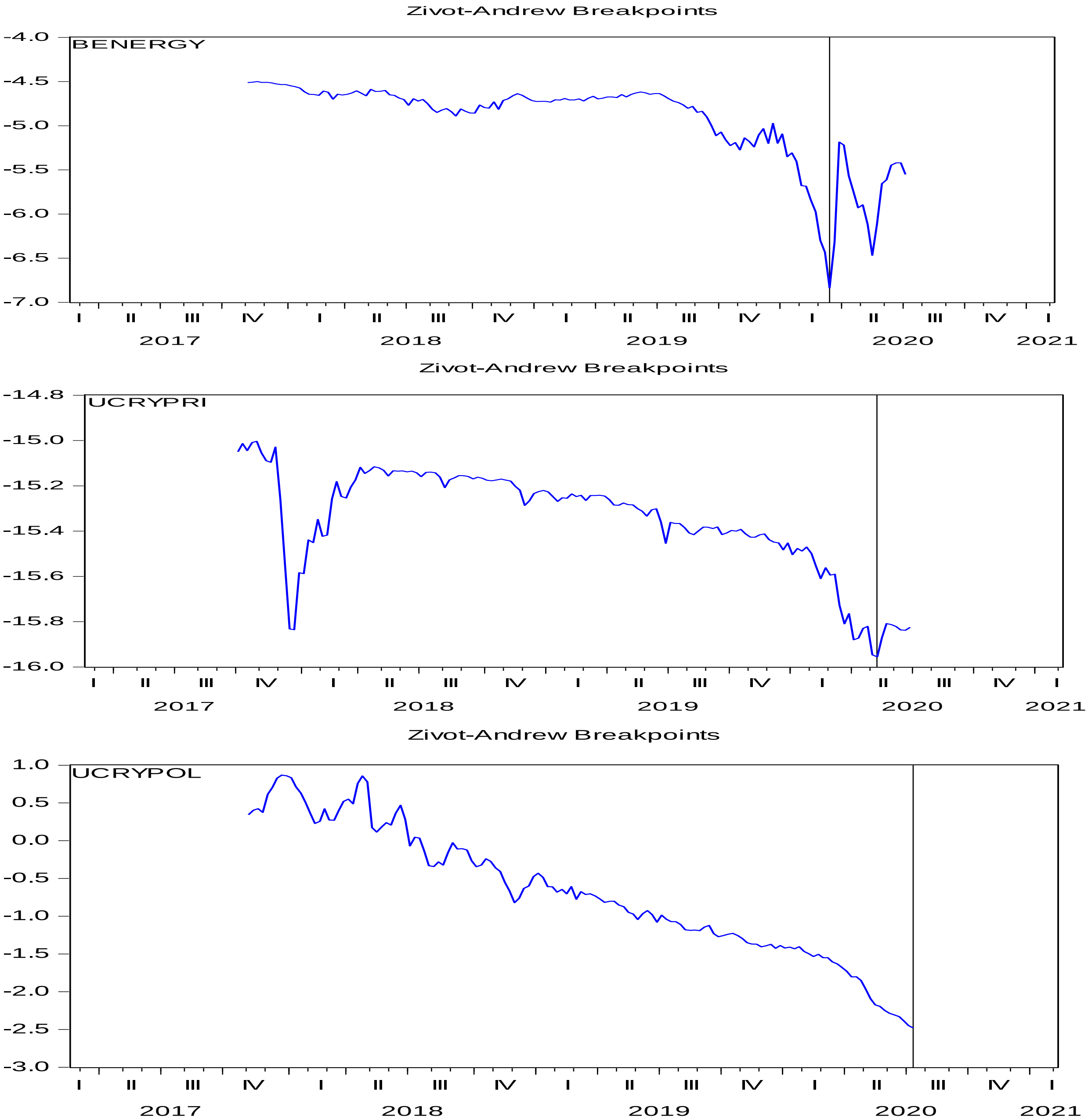
Table 1: Zivot-Andrews Unit Root Test Results

Zivot-Andrews (Model C)						
Variables	Level (T) Statistics	Level Break Date	Critical Values	1. Difference (T) Statistics	1.Difference Breaking Date	Critical Values
BENERGY	-3.21	17.05.2020	-5.08	-6.83*	15.03.2020	-5.08
UKRYPRI	-.2.69	07.05.2020	-5.08	-15.95	10.05.2020	-5.08
UKRYPOL	-7.47	12.05.2020	-5.08	-7.47	-	-5.08

*: it is significant at 5% level

According to the results obtained from the ZA unit root test, BENERGY and UCRYPRI were found to be stationary at I (0), that is, level, while the UCRYPOL variable became stationary at I (1), that is, at the first difference. In addition, there was no unusual situation in the said breaking dates, and the dynamism in political and economic policies caused them to break. Figure 2 shows the graph showing the breaking dates of the series below.

Figure 2: Breaking Dates of the Series



Looking at the results of the unit root tests applied, it was observed that the series became stationary at different levels. In addition, lag lengths were tested in the form of paired tests, and the model was constructed considering that the most appropriate lag length was according to the AIC criterion. Lag length tables are shared below.

Table 2: Lag length Graphs

VAR Lag Order Selection Criteria						
Endogenous variables: BENERGY UCRYPRI						
Exogenous variables: C						
Sample: 2/19/2017 2/07/2021						
Included observations: 196						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	-1182.171	NA	606.4489	12.08337	12.11682	12.09692
1	-752.4208	846.3441	7.871421	7.738988	7.839338	7.779615
2	-733.5173	36.84258	6.761057	7.586911	7.754162*	7.654622
3	-723.1854	19.92582	6.338274	7.522300	7.756451	7.617095*
4	-716.8254	12.13580*	6.187889*	7.498219*	7.799270	7.620099
5	-714.5968	4.207158	6.301425	7.516294	7.884245	7.665258
6	-712.1195	4.626031	6.401083	7.531831	7.966683	7.707880
7	-707.1881	9.107924	6.341867	7.522328	8.024080	7.725461
8	-705.6240	2.856944	6.503257	7.547183	8.115836	7.777401
9	-703.1541	4.460905	6.607888	7.562797	8.198350	7.820099
10	-702.0201	2.024980	6.806915	7.592042	8.294495	7.876428
11	-697.5720	7.852258	6.779394	7.587469	8.356823	7.898940
12	-694.0960	6.065284	6.819978	7.592816	8.429070	7.931372

Tablo 3: Lag length Graphs

VAR Lag Order Selection Criteria						
Endogenous variables: BENERGY UCRYPOL						
Exogenous variables: C						
Sample: 2/19/2017 2/07/2021						
Included observations: 196						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	-1177.877	NA	580.4519	12.03956	12.07301	12.05310
1	-757.3589	828.1631	8.278216	7.789377	7.889727	7.830004
2	-740.8873	32.10293	7.289122	7.662115	7.829366	7.729826
3	-729.2026	22.53464	6.739644	7.583700	7.817852	7.678496
4	-723.3536	11.16090	6.614128	7.564833	7.865884	7.686713
5	-711.2578	22.83395	6.090343	7.482222	7.850174	7.631187*
6	-708.5402	5.074708	6.171513	7.495308	7.930160	7.671357
7	-700.0975	15.59311	5.899221	7.449975	7.951727	7.653108
8	-696.0447	7.402654*	5.897657*	7.449435*	8.018088*	7.679653
9	-692.3223	6.722991	5.916446	7.452269	8.087821	7.709571
10	-691.1233	2.141130	6.090603	7.480850	8.183303	7.765237
11	-686.7604	7.701759	6.071258	7.477147	8.246501	7.788619
12	-683.0057	6.551644	6.090256	7.479650	8.315904	7.818206

4.2. Toda-Yamamoto Causality Test Results

Toda-Yamamoto causality test was used to see if there is any causality between the variables. The tests were performed one by one among the variables in the form of a double test. While performing the Toda-Yamamoto test, the lag length of the series was found according to the Akaike information criterion-AIC, and the maximum integration degree d_{max} was found according to the ZA unit root test. Then, by applying Wald statistics to the k-lagged values in this model, it was tried to determine whether there was a causal relationship. Test results are given below.

Tablo 4: Toda-Yamamoto Causality Test Results (Model 1)

Dependent Variable	Independent Variable	dmax	k	Chi-Square Test Statistic	Chi-Square P-value	Relationship
UCRYPRI	BENERGY	0	4	8.676757	0.0697	Yes
UCRYPOL		1	7	13.16980	0.0681	Yes

*: Statistically significant at the 5% level. The optimal lag length was determined according to the AIC criterion, dmax= the maximum stationarity level according to the Zivot-Andrews unit root test, k=VAR lag length.

According to the results of table 4, it was reached A causality relationship from the BENERGY to UCRYPRI at the 5% significance level. H0 hypothesis was rejected. H1 hypothesis could not be rejected. On the other hand, it was seen that the H1 hypothesis could not be rejected and the H0 hypothesis was rejected at the correct 5% significance level on UCRYPOL from BENERGY. Therefore, it was determined that there is a statistically significant causality relationship in BENERGY variable over other variables.

Tablo 5: Toda-Yamamoto Causality Test Results (Model 2)

Dependent Variable	Independent Variable	dmax	k	Chi-Square Test Statistic	Chi-Square P-value	Relationship
BENERGY	UCRYPRI	0	4	4.135214	0.3880	No
	UCRYPOL	1	7	7.824952	0.3483	No

*: Statistically significant at the 5% level. The optimal lag length was determined according to the AIC criterion, dmax= the maximum stationarity level according to the Zivot-Andrews unit root test, k=VAR lag length.

According to the findings in Table 5, the H0 hypothesis was accepted at the 5% significance level from UCRYPRI to BENERGY. H1 hypothesis was rejected. On the other hand, the H0 hypothesis was accepted at the correct 5% significance level on BENERGY from UCRYPOL. H1 hypothesis was rejected. lastly, it was found that there was no statistically significant causality relationship in the BENERGY variable over other variables.

5. CONCLUSION

The concept of energy has always been of vital importance in the progress of humanity. Undoubtedly, since it is not possible to have infinite energy, using it effectively is as important as reaching the source of energy. Accordingly, it is not only the results of crypto money mining, that is, crypto money energy consumption, but also what factors affect this energy consumption. In this context, in this study, unlike the literature, it is aimed to investigate the relationship between the energy consumption for crypto money and the uncertainties in these markets.

Considering the findings obtained from the analyzes; It has been seen that the changes in Bitcoin energy consumption have a one-way causality effect on the crypto money price uncertainties and crypto money policy uncertainties. It is understood from the Chi-Square Test Statistic (13.16980) that Bitcoin energy consumption has a more dominant effect on cryptocurrency policy uncertainty when compared to cryptocurrency price uncertainty. In addition, it has been found that cryptocurrency price uncertainties and policy uncertainties do not have an effect on the energy consumption of a bitcoin. While it can be interpreted that bitcoin energy consumption acts more independently from crypto currency uncertainties, it can also be interpreted that bitcoin mining is not the only factor affecting bitcoin prices in crypto money markets. Because there are cryptocurrencies such as ethereum, which are not limited in terms of supply in the crypto money markets. In this case, uncertainties in crypto markets and bitcoin did not have an effect on energy consumption. In addition, although it is not the same issue when compared with the literature studies, Demir et al. (2018) reached results in the same direction, and results in the opposite direction were obtained with Cheng and Yen (2020). However, in this study, it has been found that the change in bitcoin energy consumption is effective in crypto money markets, especially on crypto money policies.

This study has limitations in terms of both the variables it applies to and the observation interval, and it has searched for a relationship only by considering the relationship between selected variables. In this context, the empirical findings and interpretations were made based on these results. After that, for further studies in this area, models can be developed that include variables that have a direct impact on mining such as government sanctions and costs on bitcoin energy consumption.

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