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What are The Financial and Technologic Determinants of Cryptocurrency Prices? The Case of Bitcoin

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Abstract: *Blockchain is distributed database provides encrypted transaction tracking. Similarly, Crypto money or cryptocurrency can be defined as digital currency or asset designed as alternative exchange tool, which uses cryptography to secure transactions based on blockchain database systematic is traded like cash. Moreover, without having central control system and authority, Bitcoin attracts investors more and more with this feature. In this context, the importance of this study may well explain factors affecting cryptocurrency prices in Bitcoin specific. It is used while choosing variables that determine Bitcoin prices, not only financial and economic factors, but also Bitcoin mining and Bitcoin Google Trend Index. While electricity unit costs from variables are included in model design; It is thought that electrical energy costs consumed by CPUs and GPUs of computers used by Bitcoin miners may have impact on Bitcoin prices In this study, bitcoin prices were modeled primarily with Box-Jenkins method with using between 2015-2020 daily data. In this study, it has been conducted with chosen control variables which are Gold unit prices, oil prices, Euro / Dollar parity, S&P 500 Index, LIBOR, Bitcoin Google Trend Index and electricity unit costs were determined as control variables and their effect on bitcoin prices was analyzed based on the Box-Jenkins model. Box-Jenkins modelling is chosen because this model has more power on forecasting future values with using AR and MA process together.*

Keywords: *Cryptocurrency, Threshold Models, Bitcoin*
Jel Codes: *G10, C32, G15*

Kripto Para Fiyatlarının Finansal ve Teknolojik Belirleyicileri Nelerdir? Bitcoin Örneği

Öz: *Blockchain dağıtılmış veritabanı şifreli işlem takibi sağlayan bir sistemdir. Benzer şekilde, Kripto para nakit gibi işlem gören blockchain veritabanı sistematiğine dayalı, işlemleri güvence altına almak için kriptografi kullanan ve alternatif takas aracı olarak tasarlanmış dijital para birimi olarak tanımlanabilir. Bitcoin'in merkezi kontrol sistemi olmayan bu özelliği yatırımcıları giderek daha çok cezbetmektedir. Bu bağlamda bu çalışma, Bitcoin özelinde kripto para fiyatlarını etkileyen faktörleri açıklayabilir. Bitcoin fiyatlarını belirleyen değişkenlerin seçiminde, finansal ve ekonomik faktörlerin yanı sıra, Bitcoin madenciliği ve Bitcoin Google Trend Endeksi gibi değişkenlerde kullanılmıştır. Model tasarımında değişkenlerden elektrik birim maliyetleri yer alırken; Bitcoin madencileri tarafından kullanılan bilgisayarların CPU'ları tarafından tüketilen elektrik enerjisi maliyetlerinin Bitcoin fiyatları üzerinde etkili olabileceği düşünülmektedir. Bu çalışmada 2015-2020 arası günlük veriler kullanılarak Bitcoin fiyatları öncelikle Box-Jenkins yöntemi ile modellenmiştir. Çalışmada, kontrol değişkenler olarak Altın fiyatları, petrol fiyatları,*

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Bu makale araştırma ve yayın etiğine uygun hazırlanmıştır iThenticate intihal incelemesinden geçirilmiştir.

Euro / Dolar paritesi, S&P 500 Endeksi, LIBOR, Bitcoin Google Trend Endeksi ve elektrik birim maliyetleri kullanılmıştır. Bu modelin seçilmesinin nedeni AR ve MA sürecini birlikte kullanarak gelecekteki değerleri tahmin etmede daha fazla güce sahip olmasıdır.

Anahtar Kelimeler: *Kripto Para, Threshold Modelleri, Bitcoin*
Jel Kodları: *G10, C32, G15*
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I. Introduction

Before talking about the importance of cryptocurrencies and their importance, it would be appropriate to give information about the infrastructure (blockchain), of course, which has a direct connection with the subject. Blockchain is a distributed database that provides briefly encrypted transaction tracking. The main purpose of blockchain-based systems is to spread the "trust" service provided by a central vehicle to the machines in the transactions between the two parties and thus to have a distributed (one decentralized) authority. Thus, by removing the need for this trust from the monopoly of a single vehicle, it will be possible to minimize or completely eliminate the negativities (cyber attack, legal restrictions, etc.) that may occur in one of the systems to be installed based on blockchain. In addition, it is possible to minimize transaction costs by eliminating the intermediary.

It seems possible that Blockchain can be applied in many areas from the supply chain to the health sector, from the travel sector to the financial markets. One of its important uses is the supply chain. For example, for a cooler traveling from Europe to East Africa, more than 30 people and institutions need approval and more than 200 information exchange. The reason for so many bureaucracies is the lack of trust between the parties. This is where the blockchain comes into play at this point, ensuring that all these transactions are made in a transparent and retrospective manner to all parties and are shared with the relevant parties instantly. Labor, time and cost savings achieved by reducing bureaucracy and errors reach significant amounts (Sert, 2019).

Blockchain is carefully followed today by many international companies and even some countries. For example, IBM and Maersk have partnered to create a platform that will appeal to the industry in this area (Sert, 2019). Mercedes-Benz decided to switch to blockchain infrastructure for the supply chain. Mercedes-Benz signed an agreement with US-based software company Icertis to take advantage of blockchain technology in complex supply chain steps. Thanks to this technology, the company claims that complex supply chain steps will be transformed into a more transparent and sustainable form. It is possible to increase the number of these samples.

Undoubtedly, one of the important sectors using blockchain technology is the financial sector. Cryptocurrencies are one of the new financial instruments that are now being seen as an investment instrument in financial markets. Cryptocurrency or cryptocurrency can be defined as a digital currency or asset designed as an alternative exchange tool, which uses cryptography to secure transactions based on the blockchain database, whose systematic is traded like cash and cash. Bitcoin, which was created in this sense and still has the most trading volume and popularity in the market, was created in 2009.

The use of Bitcoin as a settlement or payment instrument has also transformed this asset into a global financial instrument. Bitcoin, which is a central control system and not affiliated with authority, attracts more and more investors' attention day by day. In this sense, the determination of the factors affecting crypto money prices in Bitcoin is one of the reasons for this study. In addition, the volatility of Bitcoin prices compared to other investment instruments is another reason for the study to be conducted. While determining the variables that determine Bitcoin prices, not only financial and economic factors, but also Bitcoin mining and Bitcoin Google Trend Index have been used. For example, it is thought that the electrical energy costs consumed by processors such as CPU and GPU of computers used by Bitcoin miners may have an impact on Bitcoin prices. In this study, bitcoin prices were modeled primarily using the Box-Jenkins method using 2015-2020 daily data. Gold prices, oil prices, Euro / Dollar parity, S&P 500 Index, LIBOR, Bitcoin Google Trend Index and consumer electricity prices are determined as control variables.

For these purposes, the study is composed of introduction, literature, data set and methodology, empirical findings and conclusion sections.

II. Literature Review

Developed in 2009 by Satoshi Nakamoto, Bitcoin has become the cryptocurrency unit that has the most transaction volume in the financial flow. There are many different studies in the literature to examine the main determinants of cryptocurrencies. The financial terms of the literature in this context that studies addressing the relationship between the elements discussed in study after study as an argument related to Bitcoin ago will be examined in the literature section.

Dyhrberg (2016), he investigated how bitcoin can be used as a hedge against to traditional financial assets such as stock markets and also exchange rates. He concluded that Bitcoin, which is not connected to the central system, can be a strong hedge against the dollar euro and sterling. Bouri et al. (2017), in his study, he has found that bitcoin daily returns are negatively correlated with Asian stock market returns, addition to their study, Chan, Le and Wu (2019) indicated that bitcoin can be strong hedge against to stock market with using GARCH modelling between October 2019 and October 2017 daily data.

With his study of cryptocurrencies among themselves, Corbet et al. (2018) has researched bitcoin, Litecoin and ripple and expressed a strong commitment between them. In addition, the study has concluded that Bitcoin is more isolated than traditional financial assets by examining the isolation of bitcoin prices through volatility with traditional investment instruments.

Brandvold et al. (2015), in his study with the daily data set between April 2013 and February 2014, he investigated whether these variables are interdependent by examining seven different exchange rates from the classical financial assets in the context of correlation with Bitcoin price. In this context, they examined why Bitcoin could be an alternative tool from the investor's perspective, and with which factors they act when investing. Accordingly, there is a dependency between classic financial instruments and Bitcoin prices.

In another study, Ciaian and Rajcaniova (2018) examined their interdependence by comparing bitcoin prices with 16 different coins. In his study, he stated that cryptocurrencies are dependent on each other, although they are independent of external variables.

De Vires (2018) they state that the electricity consumed by an estimated 10000 connections spent in bitcoin mining is equal to the electricity consumed by 500,000 PlayStation per second. In the same time, considering the electricity costs that are valid not only in search but also in other cooling and transmission, it indicates that the growth of Bitcoin indicates further problems.

Hayes (2015) gives importance to cost production of Bitcoin and also, he concluded that technological progress brought down cost of mining. Moreover, it is stated that the marginal cost exceeding the marginal revenue will make the production demand of Bitcoin miners irrational and in this case, it will affect Bitcoin prices.

Parino et al. (2018), they examined how differs Bitcoin adaptation reasons and procedures by country with using socio-economic variables. They linked between socio economic determinants and technological drivers such as the number of download Bitcoin apps by IP-addresses and google trends index database. From their findings, development and freedom degrees of the chosen countries have significant importance and effects on Bitcoin demand.

III. Data and Methodology

In this context, the importance of this study may well explain factors affecting cryptocurrency prices in Bitcoin specific. It is used while choosing variables that determine Bitcoin prices, not only financial and economic factors, but also Bitcoin mining and Bitcoin Google Trend Index. While electricity unit costs from variables are included in model design; It is thought that electrical energy costs consumed by CPUs and GPUs of computers used by Bitcoin miners may have impact on Bitcoin prices In this study, bitcoin prices were modeled primarily with Box-Jenkins method with using between 2015-2020 daily data. In this study, it has been conducted with chosen control variables which are Gold unit prices, oil prices, Euro / Dollar parity, S&P 500 Index, LIBOR, Bitcoin Google Trend Index and electricity unit costs were determined as control variables and their effect on bitcoin prices was analyzed by using Engel Granger cointegration test and also threshold modelling approach.

Since we used bitcoin prices as a daily time series calculate and injunct to the model as return of Bitcoin (Figure 1.). Before applying any model and approach to the time series, unit root testing process should be used which is shown in Table 1.

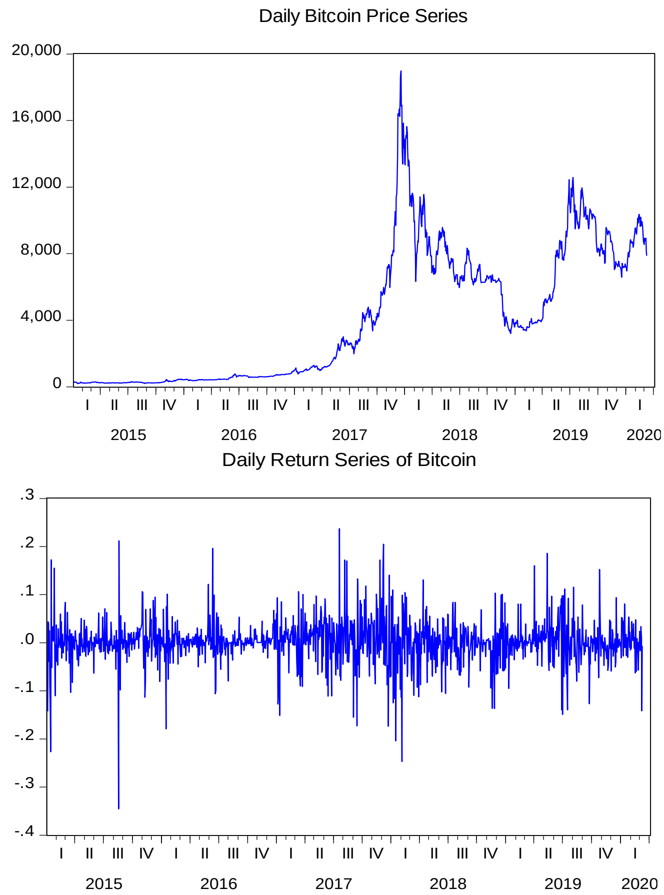

Figure 1. Bitcoin and Bitcoin Returns Scatter Graphs

According to the findings of ADF and KPSS unit root test, except electricity prices all variables are stationary at fist difference level. After unit root process to check cointegration process, Engle Granger cointegration test is used (Table 2.).

Table 1. ADF Unit Root and KPSS Stationarity Test Results

	ADF		***KPSS***		
Variables	**Level**	**First Difference**	**Level**	**First Difference**	**Integration degree**
btc	-0.87	-37.74	4.01	0.16	I(1)
ep	-3.07	-36.73	0.62	0.04	I(0), I(1)

gold	-0.42	-36.47	2.45	0.15	I(1)
gtw	-2.36	-36.70	2.87	0.04	I(1)
libor	-0.92	-9.06	3.35	1.07	I(1), I(2)
oil	-1.98	-38.49	1.81	0.15	I(1)
prt	-2.83	-37.30	0.77	0.09	I(1)
s&p500	-1.16	-37.15	4.18	0.05	I(1)
1%	-3.434	-3.434	0.739	0.739	
5%	-2.863	-2.863	0.463	0.463	
10%	-2.568	-2.568	0.347	0.347	

According to test results there are cointegration relationships among the considered variables. Engle Granger cointegration testing approach relies on the stationarity of error term taken from a cointegration equation. This requires to take a variable as dependent and others as independent. Thus, we conducted cointegration equations for every variable in which related variable is taken as dependent. All the results are given in Table 2.

Table 2. Engle Granger Cointegration Test Results

Variables	***tau-statistic***	***Prob.****	***z-statistic***	***Prob.****
L_BTC	-6.824795	0.0002	-94.37884	0.0001
L_EP	-3.484566	0.7604	-24.56358	0.7491
L_GOLD	-3.445198	0.7771	-23.23644	0.7924
L_GTW	-6.931562	0.0001	-95.22048	0.0000
L_LIBOR	-2.871884	0.9406	-22.38896	0.8182
L_OIL	-3.913163	0.5463	-33.86111	0.4159
L_PRT	-4.970853	0.0984	-45.67959	0.1282
L_SP	-6.288632	0.0016	-76.84136	0.0013

The nonlinear Enders and Siklos (2001) cointegration test assume that the long-term adaptation process between the variables is asymmetric. In this test, which can be seen as an expanded form of Engle and Granger (1987) cointegration test, the error terms are divided into two groups, large and small, from a certain threshold level. Enders and Siklos (2001) cointegration test where asymmetric adaptation process is added to the model with dummy variables. It can be explained by the following regression equation:

$$\Delta\mu_t = I_t\rho_t\mu_{t-1} + (1 - I_t)\rho_2\mu_{t-1} + \sum_{i=1}^{p}\gamma_i\,\Delta\mu_{t-i} + \varepsilon_t \quad (1)$$

Here, μ indicates the error terms obtained from the cointegration relationship between them, namely the error terms obtained from the cointegration equation, I dummy variables. For the determination of dummy variables, in TAR and MTAR models, respectively. The following two step functions are used:

$$I_t = \begin{cases} 1 \; if \; \mu_{t-1} \geq \tau \\ 0 \; if \; \mu_{t-1} < \tau \end{cases}, \quad (2)$$

$$I_t = \begin{cases} 1 \; if \; \mu_{t-1} \leq \tau \\ 0 \; if \; \mu_{t-1} < \tau \end{cases} \quad (3)$$

Adaptation coefficient number when μ_t is greater than 1 threshold value in TAR model ρ1 is the coefficient in the equation. Otherwise, this coefficient is ρ2. In the MTAR model, if Δμ_(t-1)is greater than the threshold value, the adaptation coefficient is ρ1 in equation 3. When Δμ_tküçük is less than 1 threshold value, the adaptation coefficient is ρ2. In this study, Chan (1993) method was used to determine the threshold values (τ). Accordingly, (τ) firstly values μ_tin TAR model and Δμt values in MTAR model are ranked from small to large. Then, in these rankings, 15% extreme values μ_t are subtracted from both sides. All other observations are used as threshold values μ_t and the model is estimated. The threshold value of the model that provides the smallest square of error terms among the predicted models is determined as the most appropriate threshold value.

Testing the cointegration relationship between the variables is done as follows. The coefficients of the variable of μt − 1 in equation 3 are statistically insignificant from zero, i.e. ρ1 = ρ2 = 0 F test. The rejection of the null hypothesis indicates the adaptation of error terms, that is, the cointegration relationship between the variables. It is. To test the presence of asymmetry in the cointegration relationship, Enders and Siklos (2001) in the hypothesis proposed by (2001), the coefficients of the variable μt − 1 are statistically different from each other. They are indifferent, that is, ρ1 = ρ2. The rejection of the null hypothesis, which states that the two coefficients are statistically the same, that the adaptation is symmetrical, will indicate the presence of an asymmetric cointegration relationship between the variables.

Table 3. Cointegrating equation estimation results for Bitcoin.

Variable	*Coefficient*	*Std. Error*	*t-Statistic*	*Prob.*
C	-34.45488	0.903713	-38.12593	0.0000
LOG(EP)	-0.387045	0.212123	-1.824626	0.0683
LOG(GOLD)	0.786693	0.115432	6.815197	0.0000
LOG(GTW)	0.571342	0.012027	47.50566	0.0000
LIBOR	0.397835	0.015017	26.49169	0.0000
LOG(OIL)	-0.535589	0.051710	-10.35747	0.0000
LOG(PRT)	2.885574	0.214481	13.45376	0.0000
LOG(SP500)	4.543513	0.120553	37.68883	0.0000
R-squared	0.976407	F-statistic		7951.839

The cointegration relationship tests that were examined over one and six delays were tested with Engle Granger. Accordingly, the existence of co-integrated relationships between the selected variables has been strongly demonstrated in Equation (4) and (5) respectively.

$BTC = -2.352EP - 1.165GOLD + 0.37LIBOR + 0.915GTW + 0.151OIL + 4.575PRT + 2.367SP$ (4)

$BTC = -1.892EP - 0.059GOLD + 0.323LIBOR + 0.873GTW + 0.102OIL + 2.834PRT + 3.138SP$ (5)

Table 4. Enders-Siklos Asymmetric Cointegration Test (TAR Adjustment)

Variable	*Coefficient*	*Std. Error*
Above Threshold	-0.065225	0.015048
Below Threshold	-0.070112	0.014058
Differenced Residuals(t-1)	-0.019456	0.027532
Differenced Residuals(t-2)	-0.011089	0.027441
Differenced Residuals(t-3)	0.028318	0.027310
Threshold value (tau):	**0.000000**	
F-equal:	**0.059456**	
T-max value:	**-4.334328**	
F-joint (Phi):	**20.751230**	

For T max value, the null hypothesis was rejected at -1.69, -1.89 and -2.29 levels at 10%, 5% and 1% confidence intervals for 500 or more observations, and asymmetric cointegration results were obtained. For F-joint statistics, the null hypothesis was rejected at 10%, 5% and 1% confidence intervals for 500 and above observations, at levels 5.21, 6.33 and 9.09 respectively, coefficients of positive and negative errors (ut) are significantly different (Table 4.).

Table 5. Enders-Siklos Asymmetric Cointegration Test (M-TAR Adjustment (Momentum TAR)

Variable	***Coefficient***	***Std. Error***
Above Threshold	-0.083879	0.014783
Below Threshold	-0.052947	0.014276
Differenced Residuals(t-1)	-0.019718	0.027507
Differenced Residuals(t-2)	-0.009419	0.027432
Differenced Residuals(t-3)	0.027286	0.027295
Threshold value (tau):	**0.000000**	
F-equal:	**2.388123**	
T-max value:	**-3.708870**	
F-joint (Phi):	**21.951460**	

For T max value, the null hypothesis was rejected at --1.75, -1,98 and -2.42 levels at 10%, 5% and 1% confidence intervals for 500 or more observations, and asymmetric cointegration results were obtained. For F-joint statistics, the null hypothesis was rejected at 10%, 5% and 1% confidence intervals for 500 and above observations, at levels 5.06, 6.05 and 8.31respectively, coefficients of positive and negative errors (ut) are significantly different (Table 5.).

Table 6. Threshold Regression Results

Variables	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
	U < -0.2122228 -- 202 obs			
C	-0.077843	0.006292	-12.3708	0.0000
U(-1)	-0.191070	0.017346	-11.0152	0.0000
	-0.2122228 <= U < -0.07372689 -- 281 obs			
C	-0.058142	0.004011	-14.4973	0.0000

U(-1)	-0.430004	0.026953	-15.9540	0.0000
	-0.07372689 <= U< 0.02686803 -- 247 obs			
C	-0.010019	0.002412	-4.15362	0.0000
U(-1)	-0.516357	0.030036	-17.1912	0.0000
	0.02686803 <= U< 0.1161037 -- 204 obs			
C	0.040711	0.003502	11.62347	0.0000
U(-1)	-0.541328	0.036169	-14.9664	0.0000
	0.1161037 <= U < 0.2149722 -- 212 obs			
C	0.088107	0.005750	15.32271	0.0000
U(-1)	-0.520614	0.034147	-15.2461	0.0000
	0.2149722 <= U -- 205 obs			
C	0.096812	0.006998	13.83380	0.0000
U(-1)	-0.278090	0.021613	-12.8666	0.0000
	Non-Threshold Variables			
DLOG(EP(-1))	-0.036170	0.188694	-0.19168	0.8480
DLOG(GOLD)	0.712726	0.132108	5.395023	0.0000
DLOG(GTW)	0.236396	0.011277	20.96283	0.0000
DLOG(LIBOR)	0.221289	0.074320	2.977542	0.0030
DLOG(OIL)	-0.294173	0.043284	-6.79641	0.0000
DLOG(PRT)	1.082703	0.197669	5.477343	0.0000
DLOG(SP500)	1.855444	0.127460	14.55703	0.0000
R-squared	**0.414587**	**F-statistic**		**52.40657**

Considering the long-term relationships, it is concluded that the estimated parameters with the threshold model are significant, but the electricity prices are statistically insignificant in the threshold modeling. In the time series examinations, the existence of a cointegrated relationship between the other variables selected symmetrically and asymmetrically, of the Bitcoin financial instrument, which was examined as demand and supply direction, was examined.

IV. Conclusion

Expectations on bitcoin prices have been the premise of research on which variables are so effective on bitcoin, a financial instrument. While the studies in the literature examine Bitcoin prices with other financial instruments and market variables, the study has been modeled by adding bitcoin prices and google trends search data and electricity prices to other financial instruments. Accordingly, it has been observed that Bitcoin prices, which are subjected to symmetrical and asymmetrical cointegration tests, have both asymmetrical and symmetrical cointegration. In the light of the findings obtained, it was found that while a negative but meaningless relationship was found with electricity prices, it was found that it had a positive and significant relationship with oil prices and other selected variables. On the other hand, in the symmetrical co-integrated model, it was concluded that all variables were significant, and electricity prices were negatively related and significant. While there is not a very effective cooperation relationship with electricity prices in the short term, a strong and positive action is observed in the long term. In this context, the effects of gold prices, libor, s & p 500 oil prices on bitcoin prices are significant and positive. however, it has been observed that bitcoin mining costs can be associated by changing the short-term negative impact in the long run. In addition, it can be said that the fact that google trends searches have a positive correlation with the bitcoin prices and the variable that reveals the demand side of the investors' demand is a fairly consistent finding.

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