3. BÖLÜM / CHAPTER 3

INVESTIGATION INTO THE RELATIONSHIP BETWEEN THE SUPPLY AND DEMAND AND PRICE OF ETHEREUM: AN ARDL BOUNDS TEST APPROACH

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ABSTRACT

The purpose of this article is to examine the relationship between supply, demand and price fundamentals of Ethereum. In the paper, daily data covering the period 20.05.2017- 31.01.2019 was used. Hypotheses were explained using the Classical Unit Root and ARDL Test. Respectively, the supply of Ethereum is explained by the "Ethereum Energy Consumption Index" and the demand of Ethereum is explained by "Transaction Fee". As a control variable, "Hashrate" is included in the model. Hashrate also expresses a technology used. Ethereum price is considered in Ether/USD. First, stationarity of the variables was determined using the Augmented Dickey-Fuller (ADF) test. The long-term dynamics are characterized using the Autoregressive Distributed Lag (ARDL) Bounds Test. As a result of the analysis, it was found that there is a long-term relationship between Ethereum's supply, demand, price, and Hashrate. Additionally, Ethereum price and Hashrate affect the supply of Ethereum positively in the long-term.

Keywords: ARDL test, Stationary, Cointegration, Ethereum, Supply, Demand, Price

1. Introduction

Ethereum was first introduced by Vitalik Buterin in the article "Ethereum: A Next-Generation Smart Contract & Decentralized Application Platform". It is a process-based state machine that tries to create generalized technology. Processes start with a genesis block and are carried out in stages. Blocks include information that can be represented by a computer, such as account balances, reputation, trust arrangements, and data from the physical world. (Wood, 2014, s. 1–2) In 2014, with the publication of the "Ethereum White Book" and the implementation of the Ethereum platform, Blockchain technology was moved to the second generation. New and Blockchain-based programmable software for decentralized applications has been created. This software initially uses Blockchain features to automatically enforce restrictions that the two parties can agree upon when they sign a contract in an unreliable environment. (Pinna, Ibba, Baralla, Tonelli, and Marchesi, 2016,s. 1–3)

Written in Turing's complete language, which includes seven different programming languages, Ethereum provides an abstract layer that allows everyone to create their own rules for ownership, transactional forms, and state transition functions. This is done only by including smart contracts with a set of cryptographic rules that are executed if certain conditions are met. (Vujičić, Jagodić, and Randić, 2018, s. 1–6; Harm, Obregon, and Stubbendick, 2016) Smart Contracts are small computer programs that are stored in the Ethereum ledger or in another blockchain and are associated with a specific blockchain address that references the Smart Contract software code. (Pinna, 2016, s. 3)

Ethereum supports the External Property account controlled by private keys and Contract Accounts controlled by contract codes. (Buterin, 2014, s. 1–36) The Ethereum account consists of 4 fields, such as "Nonce", "Ether Balance", "Contract Code Hash" and "Storage Root", which represent the number of transactions sent from a particular address or the number of contract creations by an account and are used to guarantee that each transaction can be performed only once. (Vujičić, 2018, s. 6) In Ethereum, there are two different processes for those who create messages and new accounts. A transaction is defined as a signed data packet sent from an externally owned account. Each transaction includes the recipient of the message, a signature identifying the sender, the amount of Ether to be sent, an optional data field, the STARTGAS and GASPRICE values. (Chinchilla, 2019; G. Wood, 2014, s. 1–32)

The differences between an Ethereum blockchain and a Bitcoin blockchain are that Ethereum includes a list of transactions and the latest status, in addition to the number of blocks and difficulty. The new state is created by applying the previous state for each transaction in the transaction list. The Ethereum network has successfully managed over one million unique transactions in an average of 24 hours with approximately 11 transactions per second. (Filiba, 2017)

Ethereum is used in areas such as token systems financial derivatives, identity and reputation systems, file storage, insurance, cloud computing, forecasting markets. (Buterin, 2014, s. 1–36) However, Ethereum's most important usage areas are decentralized applications (dAPPs) such as Golem, Augur, Civic, OmiseGO, Storj, and ICOs. (Moskov, 2018) Andrew Phillip, Jennifer S.K. Chan and Shelton Peiris (2018) tested the generalized long memory, stochastic volatility, and leverage effect of cryptocurrencies such as Bitcoin, Ethereum, Ripples, NEM, Dash with the Taylor (1986) Volatility Model. According to empirical data analysis, Cryptocurrencies show long memory, leverage effect, stochastic volatility and heavy queuing. Ethereum and Dash have a lower liquidity risk than Bitcoin, and error distributions are closer to the Gaussian distribution.

Konstantinos Gkillas and Paraskevi Katsiampa (2018) investigated the tail behavior of the top 5 cryptographic currencies (Bitcoin Coindesk Index, Ethereum, Ripple, Bitcoin Cash and Litecoin) using "Extreme Value Theory". As a result of this study, Bitcoin Cash has the highest potential gains and losses. Therefore, it is the riskiest cryptocurrency. In contrast, Bitcoin and Litecoin are safer than the other cryptocurrencies discussed in this study.

Shaen Corbet, Brian Lucey and Larisa Yarovya (2018) aimed to test the fundamental principles of Bitcoin and Ethereum. As a result of the study, Bitcoin is currently in a balloon stage and the price of it has increased above $1000. However, there is no clear evidence for a permanent price bubble in the market for both Bitcoin and Ethereum.

Walid Mensi, Khamis Hamed Al-Yahyaee and Sang Hoon Kang (2018) aimed to test the effect of dual long memory and structural breaks on the conditional volatility of the Bitcoin and Ethereum markets. As a result, Bitcoin and Ethereum show dual long memory, which is opposed to market efficiency and the random walking hypothesis. The FIGARCH model provides better predictive accuracy.

Guglielmo Maria Caporale and Timur Zekokh (2018) aimed to find the best model or model set to model the variability of the most popular cryptocurrency using the daily closing prices of Bitcoin, Ethereum, Ripple and Litecoin cryptocurrencies. The findings show that cryptocurrencies have high volatility and leverage effects. The use of single regime GARCH models can give false estimates of VaR and ES.

The study of Pavel Ciaian, Miroslava Rajcaniova and d'Artis Kancs (2017), investigated whether the similarities between Bitcoin and Altcoin price formation mechanisms strengthen the cointegration between markets and whether Bitcoin price development affects Altcoin prices using the ARDL Cointegration test. According to the estimation results, Subcoins that are more similar to the Bitcoin in price formation mechanism (procurement, transaction verification) follow Bitcoin price dynamics more closely. Only Ethereum, Namecoin, NxT and SuperNET altcoins' prices were affected by the Bitcoin price. In terms of total coin supply, only NxT, Namecoin and SuperNET altcoins apply the maximum limit for coin supply.

The study of David Lee Kuo Chuen, Li Guo and Yu Wang (2018), using a cryptocurrency portfolio represented by the Cryptocurrency Index (CRIX), tried to discover the risk and return characteristics of crypto assets such as Bitcoin, Ethereum, Litecoin, Dash, Dogecoin, Monero, BitShares, MaidSafeCoin, Nxt, Bytecoin (BCN), Ethereum Classic, Factom, NEM, Ripple, ZCash. According to the result of this paper, the CRIX index and cryptocurrencies may be a good option to help diversify portfolio risks.

Yukun Liu and Aleh Tsyvinski (2018) aimed to find out whether large cryptocurrencies such as Bitcoin, Ethereum, Ripple will act together with stocks, currencies, commodities, macroeconomic factors, and factors specific to the cryptocurrency market. According to the findings of the study, the returns of crypto assets can be estimated by two factors such as momentum and investors' interest. Supply factors such as mining costs, price/dividend ratio, or actual volatility are useful in predicting return behavior in the crypto asset unit. Blockchain technology in the cryptocurrency system has the potential to affect important industries such as consumer products, health care, restaurants, hotels, motels.

Bruno Biais, Christophe Bisière, Matthieu Bouvard and Catherine Casamatta (2019) sought answers to questions like "Can public blockages be expected to provide a stable consensus?", "Is this consensus a by-product of the blockchain protocol?" or "Can the Blockchain protocol lead to different, competing versions of the notebook?". As a result, it was seen that coordination effects can lead to forks and diversity of balance, information delays and double-spending initiatives may play a role in triggering forks.

The purpose of this article is to examine the relationship between supply, demand and price fundamentals of Ethereum. This article consists of five parts. In the first part, ARDL Bounds test is examined. In the second part, the variables used in the study are introduced and information about the data set is given. In the third part, the empirical results obtained are shown. In the fourth part, the findings are evaluated and then interpreted in the "Conclusion" section. In the fifth part, references are shown.

2. Methodology

Economic time series usually have non-stationary processes (Johansen, and Juselius, 1990, s. 170). Spurious regression problems may arise as a result of analyses using non-stationary time series (Granger, 1974, s. 111–120). To engage stationarity, the difference in variables is taken. However, this process may cause loss of information in the series, while eliminating the existing relationship between the series (Tari, and Yıldırım, 2009, s. 100). According to the article by Pesaran et al. (2001), the boundary test approach eliminates this problem and enables the investigation of the existence of the cointegration relationship between the series regardless of whether the series is I(0) or I(1). (Pesaran, and Smith, 2001, s. 290). In addition, the bounds test approach yields convenient results with data containing a low number of observations. (Narayan, and Narayan, 2005, s. 423–438).

The ARDL bounds testing approach consists of three stages. In the first step, it is tested whether there is a long-term relationship between the variables included in the analysis. In case there is a cointegration relationship between these variables, long and short term elasticities are obtained respectively in the following stages. (Narayan, and Smyth, 2006, s. 337).

The ARDL (1,1) model is the simplest version of the ARDL test. The ARDL (1,1) model equation is shown as follows:

$$Y_t = \alpha + \beta_1 X_t + \beta_2 X_{t-1} + \beta_3 Y_{t-1} + \varepsilon_{yt} \tag{1}$$

The ARDL (1, 1) model has some important limitations:

1. $\beta 2 = \beta 3 = 0$ Static regression,
2. $\beta 1 = \beta 2 = 0$ First order autoregressive process,
3. $\beta 3 = 1, \beta 1 = -\beta 2$ Equation in the first difference,
4. $\beta 2 = 0$ Partial correction equation.

Since the ARDL test considers delay structure, it can give better results than other conventional cointegration tests. (Ahmed, 2018, s. 1–31).

The model shown in Equation 1 is first estimated by the OLS method. Information criteria such as AIC, SIC, FPE, and HQ are used to determine the lag lengths. After determining the lag length in ARDL boundary test approach, the basic hypothesis is tested using the F- test to investigate the presence of the cointegration relationship between the variables included in the analysis (Narayan, 2005, s. 1981). The calculated F statistical value is compared with the lower and upper critical values given in Pesaran, Shin and Smith's (2001) study. According to the variables I (0) and I (1), critical values were determined for upper and lower limits. If the calculated F statistical value is greater than the upper limit of the critical value, the basic hypothesis that there is no long-term relationship between the variables is rejected. The basic hypothesis cannot be rejected if the calculated F statistical value is lower than the lower limit of the critical value. If the calculated F statistical value is between the upper and lower limits, no decision can be made and other cointegration tests that take into account the stationarity of the variables are recommended. If there is a cointegration relationship between variables, long and short term coefficients are obtained respectively. Once these coefficients have been determined, the diagnostic tests of the model are examined and it is decided whether the model is appropriate. (Yılancı, 2012, s. 70)

3. Data

In the study, while explaining the relationship between supply, demand, and price, “proxy” variables are used for all variables except Ethereum price. The price of Ethereum is in ETHER/USD. “Ethereum Energy Consumption Index” represents the supply of Ethereum. “Transaction Fee” is used as a measure of Ethereum demand. “Hashrate” (a term which expresses the technology used in Ethereum), is included in the model as a control variable. Respectively, data for variables are obtained from https://digiconomist.net/bitcoin-energy-consumption, https://www.quandl.com/, and “finans/yahoo.com”. The long term relationship between variables was identified using the ARDL Bound test. Daily data are used in the study. The data for all variables covers the period from 20.05.2017 to 31.01.2019. Natural logarithms of the variables were taken.

4. Empirical Results

Table 1
Unit Root Test Results

Variables	ADF		ADF First diff.	
	Trend+Constant	Constant	Trend+Constant	Constant
LnEnergy	-0.573591 (0.9798)	-2.443623 (0.1302)	-10.94963 (0.000)	-11.57513 (0.000)
LnHashrate	-1.165747 (0.9155)	-4.176104 (0.0008)	-7.514497 (0.000)	-
LnPrice	-1.912902 (0.6465)	-1.212208 (0.6708)	-8.423245 (0.000)	-8.210523 (0.000)
LnTrans Fee	-3.686899 (0.0239)	-3.737333 (0.0038)	-	-

In the study, ADF test was used to determine the degree of stationarity of the variables. As a result of the ADF test, the stationarity of the variables was found to be different from each other. Therefore, the long-run equilibrium relationship between the variables was examined with ARDL Bounds test.

The first step of the ARDL model is to determine the appropriate lag length. At this stage, the variables are tested with different lag combinations and the model that gives the lowest value of the information criteria (AIC, SIC or HQ) is selected as the best model. In this study, the optimal lag length was determined as 8, considering the minimum AIC value. Thus the ARDL (8,0,0) model selected as the best model.

Table 2

ARDL Bounds Test Result

I(0) Bound	I(1) Bound	Significant Level	F Statistics	k lag number
4.29	5.61	1%	5.9794	3
3.23	4.35	5%		
2.72	3.77	10%		

In order to perform the ARDL test, the F statistical value must first be determined. According to Table 2, the statistical value of F test is greater than I(1) bound value at the 5% significance level. We don't accept zero hypotheses. There is a cointegration relationship between variables.

Table 3

Estimation Result of ARDL (8,0,0)

Dependent Variable: Energy Consumption Index			
Variables	**Coefficient**	**t-stat.**	**Prob.**
LNENERGY(-1)	0.112808	2.772289	0.0057
LNENERGY(-2)	0.103694	2.54253	0.0113
LNENERGY(-3)	0.09481	2.315166	0.0209
LNENERGY(-4)	0.088329	2.158252	0.0313
LNENERGY(-5)	0.080763	1.97075	0.0492
LNENERGY(-6)	0.074386	1.814443	0.0701
LNENERGY(-7)	0.072488	1.77075	0.0771
LNENERGY(-8)	0.079308	1.944466	0.0523
LNHASH	0.273207	3.766299	0.0002
LNPRICE	0.054212	2.394272	0.017
LNTRANS	-0.021948	-0.907639	0.3644
C	-1.849171	-1.477849	0.14
Selected Model	ARDL(8,0,0)		
R Square	0.7839		
Adjusted R Square	0.77999		
F stat.	198.5723 (0.000)		
Breush -Godfrey LM Test	17.59295 (0.1286)		
Breusch - Pagan - Godfrey	5.834742 (0.8842)		

Table 3 also includes the diagnostic test results of the estimated ARDL (8,0,0) model. It is understood that there is no autocorrelation, heteroskedasticity problem in the predicted model and there is no error of model building. The long-term estimation results or elasticity coefficients calculated as a result of ARDL model are shown in Table 4.

Table 4
ARDL Long Term Estimation Result

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LNHASH	0.931129	0.085362	10.908062	0.0000
LNPRICE	0.184762	0.081717	2.260996	0.0241
LNTRANS	-0.074803	0.083664	-0.894088	0.3716
C	-6.302244	3.722558	-1.692987	0.0910

According to Table 4, the long-term estimation results or elasticity coefficients of Hashrate, Ethereum Price and Transaction Fee variables are 0.93, 0.1847 and -0.0748, respectively. However, the transaction fee coefficient is not statistically significant. There is a positive relationship between the control variable Hashrate and the Energy Consumption Index. Similarly, there is a positive relationship between the Ethereum Price and Energy Consumption Index. Short-term estimation results are also shown in Table 5.

Table 5
ARDL Short Term Estimation Result

Cointegrating Form				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
D(LNENERGY(-1))	-0.593777	0.069801	-8.506715	0.000
D(LNENERGY(-2))	-0.490083	0.071485	-6.85576	0.000
D(LNENERGY(-3))	-0.395273	0.070731	-5.588393	0.000
D(LNENERGY(-4))	-0.306944	0.068131	-4.505171	0.000
D(LNENERGY(-5))	-0.226181	0.062984	-3.591094	0.0004
D(LNENERGY(-6))	-0.151795	0.054554	-2.782465	0.0056
D(LNENERGY(-7))	-0.079308	0.040786	-1.944466	0.0523
D(LNHASH)	0.273207	0.07254	3.766299	0.0002
D(LNPRICE)	0.054212	0.022642	2.394272	0.017
D(LNTRANS)	-0.021948	0.024182	-0.907639	0.3644
EC(-1)	-0.293415	0.06567	-4.46804	0.000

The variable ECt-1 in Table 5 is a period-delayed value of the series of error terms obtained from the long-term relationship. The coefficient of this variable shows how much of the imbalance in the short term will be corrected in the long term. According to Table 5, the error correction term is negative, less than 1, and statistically significant as expected. Therefore, short-term deviations between long-run series disappear and the series converge again to the long-run equilibrium value.

5. Conclusion

Ethereum is the largest blockchain platform supporting large volume transactions, accounts, blocks, smart contracts, and the largest market value. This paper investigates the relationship between supply, demand and price movements for the period 20.05.2017-31.01.2019. For this purpose, the ARDL Bounds test developed by Pesaran et al. (2001) was used. In the first step, long term relationships between variables were examined using the ARDL bounds test approach, and in the second step, the error correction model was used to obtain short term relationships between variables.

The results of the unit root test indicated the variables under study were both I(0) and I(1) processes and the Error Correction Model was consequently employed. With diagnostic tests performed, there are no problems such as autocorrelation, heteroskedasticity and model building error. The ARDL (8,0,0) model is the appropriate cointegration model. According to the cointegration results, there is a long-run relationship between the dependent variable and the independent variable, which implies that some of the variables move together in the long term. According to long term estimation results, there is a positive relationship between supply – the price of Ethereum and Hashrate - Supply of Ethereum.

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