ETÜ SENTEZ
İKTİSADİ VE İDARİ BİLİMLER DERGİSİ
ETU SYNTHESIS JOURNAL OF ECONOMIC AND ADMINISTRATIVE SCIENCES

Sayı : 3 Yıl /Ay: 2021 / Mart Sayfa : 89-102

COVID-19 KORKUSU BITCOIN KORKUSUNU TETİKLER Mİ?

Ünal Gülhan
Dr. Öğr. Üyesi, Bayburt Üniversitesi, İktisadi ve İdari Bilimler Fakültesi, Maliye Bölümü,
e-mail: unalgulhan@bayburt.edu.tr
ORCİD: 0000-0002-8964-4018

DOI : 10.47358/sentez.2020.16
Makale Türü : Araştırma
Gönderim Tarihi: 11.01.2021
Düzeltme Tarihi: 10.03.2021
Kabul Tarihi: 19.03.2021

Bu makaleye atıfta bulunmak için:
Gülhan, Ü. (2021). COVID-19 Korkusu Bitcoin Korkusunu Tetikler mi?. ETÜ Sentez İktisadi ve İdari Bilimler Dergisi. Sayı: 3, 89-102.

iThenticate

Öz: Bitcoin fiyatlarının bağımlı değişken olarak kabul edildiği bu çalışmada, dünyadaki toplam Coronavirüs vaka sayısı, Ethereum Fiyatları, Altın Fiyatları, Koronavirüs Google Trend Endeksi ve Crypto Money Google Trend Endeksi bağımsız değişkenler olarak analize dahil edilmiştir. 21.01.2020 - 04.04.2020 tarihleri arasında günlük veri seti ARDL modeli kullanılarak analiz edilmiştir. Yapılan ARDL analiz sonuçlarına göre bağımsız değişkenler ile Bitcoin fiyatları arasında uzun dönemli ilişkili olduğu tespit edilmiştir. Bulgular çerçevesinde yatırımcıların korkuları Bitcoin fiyatları ve Covid-19 vaka sayıları ile ilişkilendirilerek yorumlanmıştır.

Anahtar Kelimeler: Covid-19, Bitcoin Fiyatları, ARDL
Jel Kodları: C58, I18, G15

ETÜ SENTEZ
İKTİSADİ VE İDARİ BİLİMLER DERGİSİ
ETU SYNTHESIS JOURNAL OF ECONOMIC AND ADMINISTRATIVE SCIENCES
Issue : 3 Year / Month: 2021 / March Paper : 89-102

DOES FEAR OF COVID-19 TRIGGER FEAR OF BITCOIN?

Unal Gulhan
Asist. Prof., Bayburt University,
Fakulty of Economics and
Administrative Science,
Depertmant of Finance,
e-mail: unalgulhan@bayburt.edu.tr
ORCİD: 0000-0002-8964-4018

DOI :10.47358/sentez.2020.16
Article Type : Research
Application Date: 01.11.2021
Revision Date: 03/10/2021
Admission Date: 03/19/2021

To cite this article:
Gulhan, U. (2021). Does Fear of Covid-19 Trigger Fear Of Bitcoin?. ETU Synthesis Journal of Economic and Administrative Sciences. Issue: 3, 89-102.

This article was checked by
iThenticate

Abstract: This study aims that Bitcoin prices are considered as dependent variables, and the total number of Coronavirus cases in the world, Ethereum Prices, Gold Prices, Coronavirus Google Trend Index, and Crypto Money Google Trend Index are considered as independent variables. Using the ARDL model, it was analyzed with a daily data set between 21.01.2020 - 04.04.2020. It is concluded that the relationship between the variables included in the analysis and Bitcoin prices exists co-integrated in the long term. Within the framework of the findings, investors' fears were interpreted by associating them with Bitcoin and Covid-19.

Keywords: Covid-19, Bitcoin Price, ARDL
JEL codes: C58, I18, G15

INTRODUCTION

Bitcoin can be defined as a digital currency or payment instrument with a decentralized, distributed settlement format that operates on the basis of Blockchain technology with a crypto algorithm. In this system, which allows users to make direct transfers with each other, transfers are carried out with a decentralized distributed record and reconciliation. Blockchain is the name of this registration and reconciliation system. The value unit realized using the Bitcoin (BTC) network is called Bitcoin. The currencies issued using this infrastructure due to the crypto algorithm of the blockchain are called cryptocurrencies.

Coronavirus, called COVID-19, still continues to affect the world after viruses such as SARS-CoV and MERS-CoV, which left their mark on the 19th century. After emerging in Wuhan province of China in December 2019, the number of cases in the world reached 1 million 276 thousand 302 on April 6, 2020. The world health organization declared the case of COVID-19 on 11 March 2020 as Pandemic. Covidien-19. Pandemic proves to humanity how vulnerable the world we live in and how helpless we can be. The results of this case affect the health sector as well as the financial markets. Pandemic seems to have negatively affected global financial markets and also financial instruments. As it is known, cryptocurrencies are now among these investment tools. Undoubtedly, Bitcoin and Ethereum are the most traded in cryptocurrencies which can be effected.

Determining how COVID-19 Pandemic reflects on BTC prices is a feature that distinguishes the study from other studies in the literature. For this purpose, the total number of pandemic cases and Coronavirus Google Trend Index variables are included in the analysis. Besides, Ethereum (ETH) prices, which are the alternative of BTC and have the highest transaction volume after BTC, are considered as independent variables. The study also included cryptocurrency Google Trend Index and Gold prices. The determination of the relationship between Google Trend Indices and BTC prices is another reason for the study. For these purposes, the study is composed of an introduction, data set and methodology, findings, and conclusion sections. As a result of the study, it was examined that there is a short and long-term relationship between BTC prices and independent variables.

LITERATURE REVIEW

International trade is not the only factor that increases its speed and volume with globalization but also international finance can be another factor on that. Apart from the increase in the international dimension of financial transactions and the decrease in transaction costs, the increase in fluidity in these markets is the result of an effect of globalization. Globalization has two different perspectives in terms of its effects on financial instruments in literature. First, the globalization of markets and hence the means of the widening of the effects of the global crises. Second, the effective pricing of the vehicles in the natural process with the free market mechanism. The study aims to examine the determinants of a global financial investment tool such as Bitcoin in the Covid-19 pandemic process. Bhuyan et al. (2010) examined the effects of the SARS pandemic, which started in China, in this context, and compared the pre-SARS period with the next period and examined the effects of the pandemic on the Asian Stock market. In the study, it is stated that commercially and financially closer countries follow a co-integrated relationship in the SARS process and therefore a pandemic such as SARS is more affected by the globalization dimension. Among the studies on cryptocurrencies, it is two-way that this system is more effective than traditional financial markets and vice versa. In this context, according to Koutmos (2018), traditional financial instruments in the markets have a weak relationship with cryptocurrencies. In this context, the cryptocurrency market is a more regular and homogeneous market, as it has investors with less global risk (Koutmos, 2018). In addition, Feng et al. (2018) states that the crypto money system, which cannot be separated from traditional markets, is possible to be affected by global high impact events, additionally, these two events cannot be considered independent of each other. In his studies, Baur and Hoang (2020) mentioned that the system of cryptocurrencies includes unexpected systematic crises that are different from traditional system because they are indeed independent from the authority. Jabotinsky, Sarel (2020) found a positive relationship between COVID-19 and Bitcoin in their modeling, which added variables to the number of deaths caught in Corona and deaths. He stated that the reason is why people want to stay in Bitcoin, they feel more secure than local currencies due to fear of pandemic processes. In addition, with the increase in demand for financial instruments, prices will increase, but at some point, a situation such as not finding someone to sell may be encountered. He stated that, contrary to traditional systems, the limited amount of Bitcoin on the market would lead to a more intense positive correlation. In this context, while determining the variables in the study; the hypothesis that pandemic and epidemic cases in the lithium are effective in traditional and crypto money markets is taken into consideration. Along with the assumption that the financial instruments of traditional markets and cryptocurrencies are in correlation with each other, Google trend data (Kristoufek, 2013; Aalborg et al., 2019) is also included in the model to measure the psychological effects of investors. Coronavirus had negative impact on stock market and cryptocurrency market by using GARCH process (Corbet et al., 2020).

DATA AND METHODOLOGY

Data

The study aims to reveal how the Coronavirus named Covid-19, which emerged in Wuhan, China and was declared a pandemic by the World Health Organization on 11.03.2020, affected the Bitcoin prices. For this purpose, Bitcoin prices are considered as dependent variables, and the total number of Coronavirus cases in the world, Ethereum Prices, Gold Prices, Coronavirus Google Trend Index and Crypto Money Google Trend Index are considered as independent variables. Using the ARDL model, it was analyzed with a daily data set between 21.01.2020 - 04.04.2020. Although there are many studies on BTC prices in the literature, it is the main target of the study to reveal the market effect of pandemic on bitcoin prices caused by the virus named COVID-19, which still continues even in the period we are in and affects the world. For this purpose, the variables given in Table 1 were selected which are considered to have an impact on BTC prices. Another feature that distinguishes this study from other studies in the literature is that the effect of Google Trend Indexes on variables has been tested in the model. Google Trend Indexes are created by the Google company on a topic searched on the Google search engine. Accordingly, Google Trend Coronavirus and Cryptocurrency indices are included in the analysis to test the effect of BTC prices. Table 1 contains the explanations of the variables and some descriptive statistics.

Table 1. Summary Statistics of Variables

Variables Names in Model	Definition	Data Source	Mean	Standard Deviation	Minimum	Maximum	Obs.
BTC	Bitcoin prices in US$	Investing.com database (2020)	8234,55	1619,19	4927,00	10339,00	74
LNCOVID	Logarithmic form of total number of Coronavirus cases	John Hopkins database (2020)	11,20	1,73	6,32	13,99	74
ETH	Ethereum prices in US$	Investing.com database (2020)	191,65	52,21	109,53	284,97	74
GTCI	Google trend index of Coronavirus	Google trend index (2020)	35,108	33,36	2,00	100,00	74
GTKPI	Google trend index of cryptocurrency	Google trend index (2020)	45,04	14,3,38	14,00	100,00	74
GOLD	Gold prices ounce in US$	Fred.stlouisfed.org database. (2020)	1595,19	47,62	1472,35	1687,00	74

Descriptive statistics about the variables selected for analysis and the source of the variables are given in Table 1 Accordingly, all variables other than the total number of cases of the COVID-19 virus were included in the model in linear form, but when the data set for the COVID variable was examined on the scatter diagram, it was included in the model logarithmically because it carries a logarithmic form.

Econometric Methodology

In the analysis about time series, the distribution of series, change structure, in other words, the character of the series is important. In this context, when selecting the method in time series, firstly, the mathematical equation, time composition and stationarity structure of the series are examined. In unit root tests developed for determination of stationarity, determination can be made about stationarity by checking at whether the series has unit root. Unit root test developed by Dickey-Fuller (1979) and later expanded into Augmented Dickey-Fuller (ADF) and later developed by Pesaran and Shin (1995),

$$\Delta y_t = \alpha + \beta t + \gamma y_{t-1} + \delta_1 \Delta y_{t-1} + \cdots + \delta_{p-1} \Delta y_{t-p+1} + \varepsilon_t \quad (1)$$

Equation (1) are also indicated. Accordingly, while t shows the time dimension of the series, p represents the correlation coefficient of the series in the autoregressive process estimation created by the lagged values. The constant α denotes the trend β. ADF uses not the t statistic, but the tau statistic created by Monte Carlo simulation and hypotheses, created.

$H_0: \delta \geq 0, series\ are\ not\ stationary\ and\ contain\ unit\ roots.$

$H_1: \delta < 0,$ *the series is stationary and the unit does not contain roots.*

For the series whose stability is decided, it is decided which time series model and method to choose. If the series are stationary at different levels, Auto Regressive Distributed Lag (ARDL) model based on OLS method can be applied. ARDL model contains lags of both autoregressive and independent variables. The process that allows the modeling of the series with stagnations at the I (0) and I (1) levels together first presents the model showing the short-term relationship. At the same time, the ARDL model shows the long-term relationships (if co-integrated) of the selected variables together with the error correction model. While the cointegration status of the series is all stationary, it can be tested with the Engle Granger Cointegration Test, if there is a degree of difference between the series by the Johansen Cointegration Test. However, the Bound Test which is developed instead of the weaknesses of the Johansen Cointegration Test is used. According to the result of the Bound Test, if there is a long term relationship, the correction coefficient obtained from the cointegration relationship gives the speed of catching the long term in the short relations. Since the ARDL model is based on the OLS method as the method, it will be subjected to basic assumption tests.

EMPIRICAL FINDINGS

In the ARDL modeling process, according to the results in Table 2, LNCOVID and GTKPI, are stationary in I (0) and BTC, ETH, GTCI and GOLD are stationary in I (1). Therefore, the ARDL model has been determined as the most effective model in the context of selected variables.

Table 2. Unit Root Test Results for Included Variables

Variables	Unit Root Test Results		The Level of Co-integration			
			I (0)		I (1)	
			t-Stats.	Prob.	t-Stats.	Prob.
BTC	ADF test stats.		-1,088668	0,7163	-10,14981	0.0000***
	Test critical values	1% level	-3,522887	-	-4,090602	-
		5% level	-2,901779	-	-3,473447	-
		10% level	-2,588280	-	-3,163967	-
LNCOVİD	ADF test stats.		-3,410095	0,0582*	-	-
	Test critical values	1% level	-4,094550	-	-	-
		5% level	-3,475305	-	-	-
		10% level	-3,165046	-	-	-
ETH	ADF test stats.		-1,085814	0,7174	-9,409528	0,0000***
	Test critical values	1% level	-3,522887	-	-3,524233	-
		5% level	-2,901779	-	-2,902358	-
		10% level	-2,588280	-	-2,588587	-
GTCI	ADF test stats.		-1,269097	0,6397	-4,893367	0,0001***
	Test critical values	1% level	-3,524233	-	-3,524233	-
		5% level	-2,902358	-	-2,902358	-
		10% level	-2,588587	-	-2,588587	-
GTKPI	ADF test stats.		-6,182938	0,0000***	-	-
	Test critical values	1% level	-3,522887	-	-	-
		5% level	-2,901779	-	-	-
		10% level	-2,588280	-	-	-
GOLD	ADF test stats.		-2,165987	0,2203	-8,316244	0,0000***
	Test critical values	1% level	-3,522887	-	-3,524233	-
		5% level	-2,901779	-	-2,902358	-
		10% level	-2,588280	-	-2,588587	-

Note: * *Statistical significance at 10% level. ** Statistical significance at 5% level.*** Statistical significance at 1% level*

Table 3. ARDL Short Run Model Results

Variables	Coefficient	Std. Error	t-Statistic
BTC(-1)	0,718323***	0,061323	11,713790
LNCOVID	-54,03684**	21,00891	-2,572092
ETH	25,31911***	1,56344	16,194520
ETH(-1)	-20,52374***	2,22835	-9,210282
GTCI	-16,99829***	4,79576	-3,544441
GTCI(-1)	12,00046**	5,15297	2,328844
GTKPI(-2)	-2,88731*	1,46821	-1,966551
ETH(-2)	3,51652**	1,70225	2,065808
ETH(-3)	-4,24702***	1,33901	-3,171771
C	2458,632***	526,60320	4,668850
R-squared	0,99271		
Adjusted R-squared	0,991635		
S.E. of regression	151,1278		
F-statistic	922,9970		
Durbin-Watson stat	1,9210		

Note: ** Statistical significance at 10% level. ** Statistical significance at 5% level.*** Statistical significance at 1% level.*

In ARDL modeling, information criteria are used to determine delay values. As stated in Table 4, Akaike Information Criteria (AIC) was determined as used in the study (1,0,1,1).

Table 4. Model Selection Summary

Model	LogL	AIC*	BIC	HQ	Adj. R-sq
ARDL (1,0,1,1)	-451,642450	13,004013*	13,322700	13,130745	0,991635
ARDL (1,1,1,1)	-451,447394	13,026687	13,377243	13,166092	0,991542
ARDL (2,0,1,1)	-451,632414	13,031899	13,382455	13,171304	0,991498
ARDL (3,0,1,1)	-451,212401	13,048237	13,430661	13,200315	0,991455
ARDL (2,1,1,1)	-451,411820	13,053854	13,436279	13,205932	0,991407

Lags found statistically insignificant in the short term relationship were excluded from the model and the results in Table 3 were obtained. Accordingly, it has been found appropriate to exclude the GOLD variable lags or level values from the model. In addition, it was found appropriate to exclude the level and first lag of the GTKPI variable from the model. In addition, testing for deviations from the basic assumption was performed for the predicted model. The model specification is shown in equation 2.

$$BTC_t = \alpha + \beta_1 BTC_{t-1} + \beta_2 LNCOVID_t + \beta_3 ETH_t + \beta_4 ETH_{t-1} + \beta_5 ETH_{t-2} + \beta_6 ETH_{t-3} + \beta_7 GTCI_t + \beta_8 GTCI_{t-1} + \beta_9 GTKPI_{t-2} + \varepsilon_t \quad (2)$$

One of the basic assumptions of the OLS method has been tested for normality testing (JB = 4.1624 <5.99). White Test was applied for the assumption of heteroskedasticity (Prob. Chi-Square (54) 0.2683). LM Test was used for testing autocorrelation (Probe. F (2,59) 0.8509). Moreover, with using Wald test, the significance of the parameters related to the variables in the model was tested (F-statistic 21851.29). Accordingly, the ARDL model has been found appropriate in terms of diagnostics. After the determination of the short-term relationship, it was concluded that the relationship was co-integrated as a result of testing whether the errors related to the pre-test model for the existence of the long-term relationship contain unit root. The Bound Test results developed for this are given in Table 5. According to the results in Table 5, the F statistical value of the model was found to be significant at 1% level because it is greater than I (1) values. In other words, it is concluded that there is a cointegrated relationship between the variables.

Table 5. Bound Test Results

	Critical Value Bounds	
Significance	**I (0) Bound**	**I (1) Bound**
10%	2,37	3,2
5%	2,79	3,67
2.5%	3,15	4,08
1%	3,65	4,66
F-statistic	6,606343***	
k	3	

Note: ** Statistical significance at 10% level. ** Statistical significance at 5% level.*** Statistical significance at 1% level.*

Long-term model specification,

$$\Delta BTC_t = \beta ECM + \delta_1 \Delta LNCOVID_t + \delta_2 \Delta ETH_t + \delta_3 \Delta ETH_{t-2} + \delta_4 \Delta ETH_{t-3} + \delta_5 \Delta GTCI_t + \delta_6 \Delta GTKPI_{t-2} + \varepsilon_t \quad (3)$$

The model containing error correction term estimation is shown in equation (3). Accordingly, the adjustment speed of the long term is 29 per cent transmission from the short term to the long term. It was observed that LNCOVID were statistically significant.

$$\Delta BTC_t = -0{,}292 ECM + 40{,}254 \Delta LNCOVID_t + 25{,}079 \Delta ETH_t + 3{,}391 \Delta ETH_{t-2} - 4{,}793 \Delta ETH_{t-3} - 17{,}192\, \Delta GTCI_t - 2{,}849 \Delta GTKPI_{t-2} + \varepsilon_t \quad (4)$$

When the long-term relationship after the error correction model (4) estimation is examined, the fact that the LNCOVID variable, which is statistically significant in the error correction model, cannot be rejected in the long term supports the hypothesis of the study.

$$BTC_t = 8728{,}540 - 191{,}839LNCOVID_t + 17{,}024ETH_t + 12{,}484ETH_{t-2} - 15{,}078ETH_{t-3} - 17{,}743GTCI_t - 10{,}250GTKPI_{t-2} \quad (5)$$

Table 6. ECM and Long Run Regression Results

Error Correction Form			
Variable	**Coefficient**	**Std. Error**	**t-Statistic**
D(LNCOVID)	40,254872	125,199004	0,321527
D(ETH)	25,079952	1,364968	18,374020
D(GTCI)	-17,192477	3,900306	-4,407981
D(GTKPI(-2))	-2,849343	1,072596	-2,656492
D(ETH(-2))	3,391644	1,223930	2,771108
D(ETH(-3))	-4,793925	1,216555	-3,940575
CointEq(-1)	-0,292863	0,056916	-5,145520
Long Run Regression			
Variable	**Coefficient**	**Std. Error**	**t-Statistic**
LNCOVID	-191,839561	75,030335	-2,556827
ETH	17,024344	5,681254	2,996582
GTCI	-17,743118	5,597042	-3,170088
GTKPI(-2)	-10,250430	5,509217	-1,860596
ETH(-2)	12,484225	6,968664	1,791480
ETH(-3)	-15,077618	4,904386	-3,074313
C	8728,540702	707,163861	12,343024

CONCLUSION

Economic and financial processes are affected not only by institutional crises, but also by global pandemic situations that affect the world. The COVID-19 pandemic that emerged in Wuhan, China in late 2019 caused not only psychological effects but also bypass effects on the free market economy as a result of the state's intervention in economic and social life. In other words, the pandemic not only affects the health sector, but also has negative effects on businesses and financial markets. Certainly, it is clear that financial instruments will also be heavily affected by this process. In addition to the increase in volatility in traditional financial instruments, the demand for cryptocurrencies from Bitcoin, and therefore their prices, is aimed at examining ARDL modeling, and Ethereum, Gold, Google Trends data and COVID-19 case numbers are included as independent variables. According to the results, it was concluded that the number of cases of pandemics had no effect on Bitcoin in the short term, but there was a long term relationship. It can be said that the existence of a negative relationship between COVID-19 and Bitcoin prices increases with the increase in the number of cases of individuals, so that they turn to traditional tools such as national currencies. Naturally, people prefer cash instead of digital money in pandemic settings.

When the directions of Google trend indexes with Bitcoin prices are analyzed, it is observed that both are negative. A negative relationship was found between the GTCI variable that we use as Coronavirus Google trend index and BTC both in the short and long term. This may express the fear dimension of the pandemic effect on investor behavior. In this context, GTCI's reverse relationship on BTC supports the hypothesis that the number of cases has negative effects on Bitcoin. A short and long-term negative relationship was found between Bitcoin prices and the cryptocurrency Google trend index. As it is known, Google trend indices can be defined as a recognition index since they are calculated based on search numbers. Therefore, as the awareness of cryptocurrencies in particular for Bitcoin increases, the demand for Bitcoin decreases as well as the prices.

REFERENCES

Aalborg, H. A., Molnár, P. and de Vries, J. E. (2019). What can explain the price, volatility and trading volume of Bitcoin?. *Finance Research Letters*, 29, 255-265.

Bhuyan, R., Lin, E. C. and Ricci, P. F. (2010). Asian stock markets and the Severe Acute Respiratory Syndrome (SARS) epidemic: implications for health risk management. *International Journal of Environment and Health*, 4(1), 40-56.

Corbet, S., Larkin, C. J. and Lucey, B. M. (2020). The Contagion Effects of the COVID-19 Pandemic: Evidence from Gold and Cryptocurrencies. *Available at SSRN 3564443*.

Baur, D. G. and Hoang, L. T. (2020). A Crypto Safe Haven Against Bitcoin, *Finance Research Letters*, 101431.

Feng, W., Wang, Y. and Zhang, Z. (2018). Informed Trading in the Bitcoin Market. *Finance Research Letters*, *26*, 63-70.

Jabotinsky, H. Y. and Sarel, R. (2020). How Crisis Affects Crypto: Coronavirus as a Test Case, *Available at SSRN 3557929*.

Koutmos, D. (2018). Return and Volatility Spillovers Among Cryptocurrencies, *Economics Letters,* 173, 122–27.

Kristoufek, L. (2013). Bitcoin meets Google Trends and Wikipedia: Quantifying the Relationship Between Phenomena of the Internet Era. *Scientific Reports*, *3*, 3415.

Pesaran, M.H. and Shin, Y. (1995). Autoregressive Distributed Lag Modelling Approach To Cointegration Analysis. *DAE Working Paper Series No 9514*. Department of Economics, University of Cambridge.

Appendix

Table 7. Autocorrelation test results

Breusch-Godfrey Serial Correlation LM Test:			
F-statistic	0,161898	Prob. F(2,59)	0,8509
Obs*R-squared	0,387527	Prob. Chi-Square(2)	0,8239

Table 8. Heteroskedasticity test results

Heteroskedasticity Test: White			
F-statistic	1,610252	Prob. F(54,16)	0,1472
Obs*R-squared	59,965900	Prob. Chi-Square(54)	0,2683
Scaled explained SS	63,770090	Prob. Chi-Square(54)	0,1705

Table 9. Walt test results

Wald Test			
Test Statistic	**Value**	**df**	**Probability**
F-statistic	21851.29	(10, 61)	0.0000
Chi-square	218512.9	10	0.0000

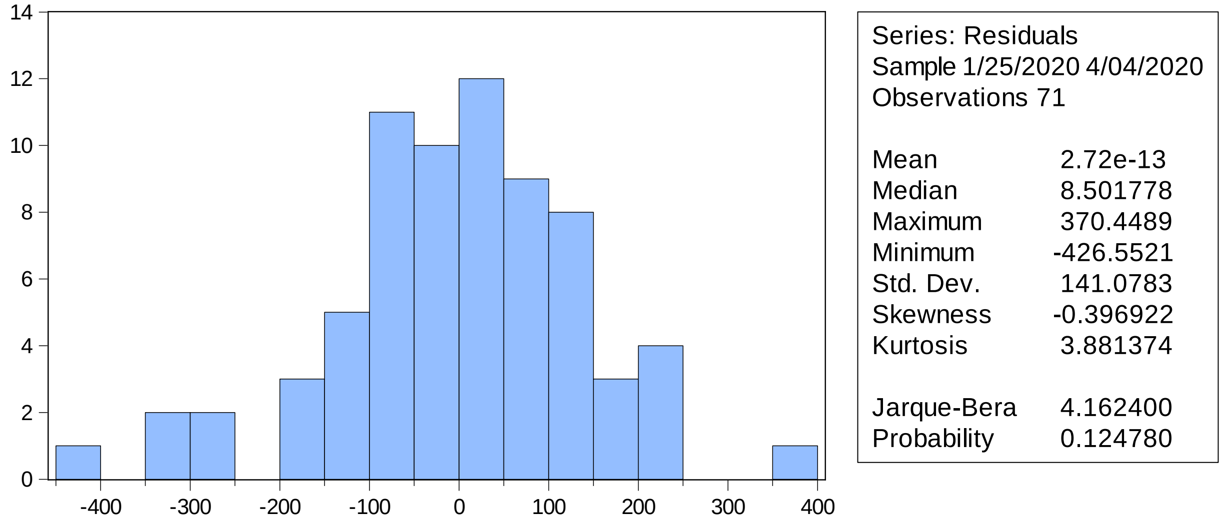

Figure 1. Normality test results

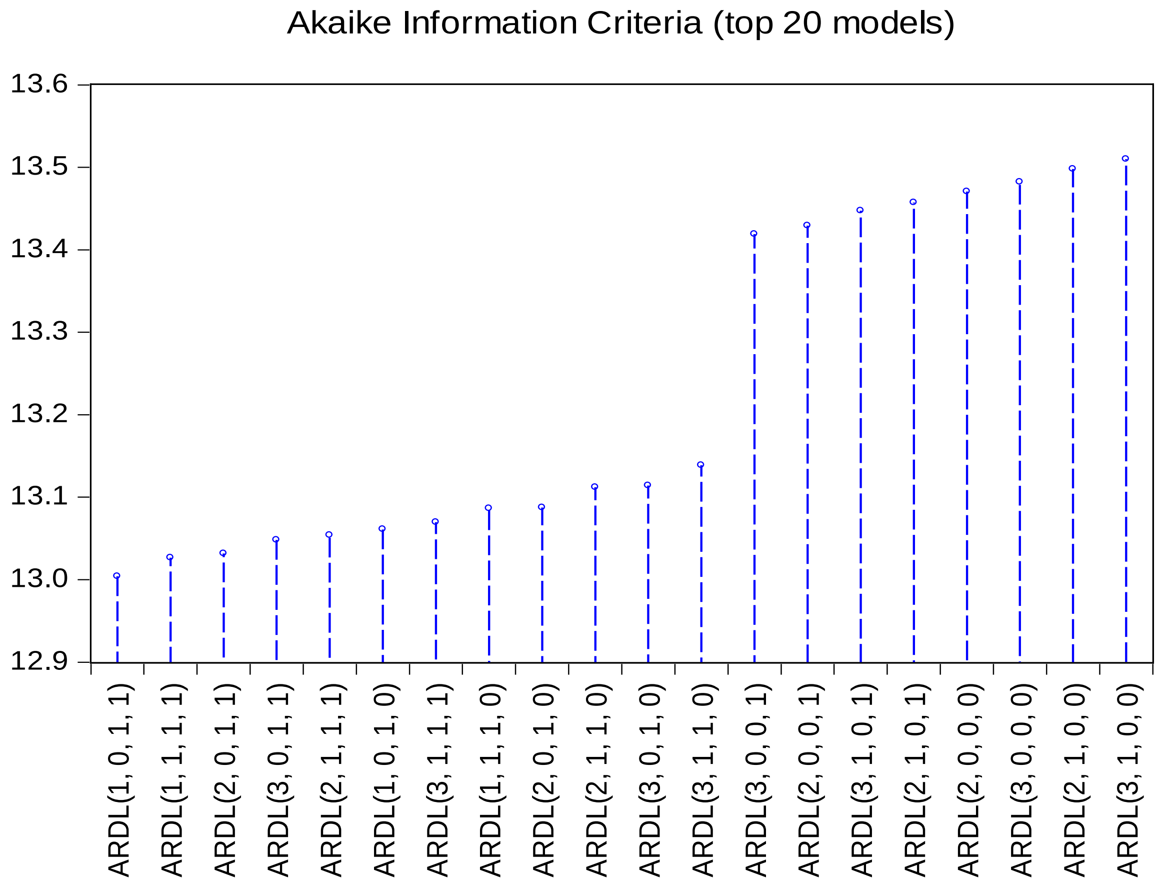

Figure 2. Model selection summary