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RESEARCH ARTICLE / ARAŞTIRMA MAKALESİ

On the Predictability of Bitcoin Price Movements: A Short-term Price Prediction with ARIMA*

Bitcoin Fiyat Hareketleri Üzerine: ARIMA ile Kısa Vadeli Bir Fiyat Tahmini

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ABSTRACT

Daily transactions in cryptocurrencies have long been following an ascending tendency, with Bitcoin leading the charge. Daily transactions recorded in the system increased from 7000 trade per day in 2012to more than 1 million nowadays. The study aims to examine the utility of cryptocurrencies specific to Bitcoin and diagnose how predictable its price fluctuations and the volatility of the crypto market. Because the dilemma between risk aversion and return maximization became evident for investors with high yielded digital assets in a zero-lower bound environment. Hence the predictability of its price movements in the short run may shed some light on the price formation of Bitcoin. Using an ARIMA model in forecasting Bitcoin price due to its response to short-term data, the study revealed that ARIMA (1,1,0) is efficient in forecasting quarterly price movements for the last two quarters of 2020, and the deviation of its price in this period might suggest a change in its perceived investment value to investors as a digital asset after the outbreak of COVID-19.

Keywords: Volatility Forecasting, Crypto Market, Market Microstructure, Asset Pricing, Bitcoin Jel Code: G170, G150, G120

ÖΖ

Kripto paraların günlük işlem hacmi Bitcoin öncülüğündeki artış eğilimini uzun zamandır sürdürürken 2012'den bugüne, günlük işlem miktarı 7 binden 1 milyona ulaşmıştır. Bu çalışma Bitcoin özelinde kripto paralardan beklenen faydanın ne olduğunu inceleyip, fiyat dalgalanmaları ve volatilitenin öngörülebilirlik derecesini tespit etmeyi amaçlamaktadır. Çünkü yüksek getiri vaadeden bu piyasaya dönük risk iştahı ve getiri maksimizasyonu ikilemi, kurumsal yatırımcılar için özellikle sıfır alt sınırı ve negatif getiri ortamında belirginleşmiştir. Dolayısıyla Bitcoin'in kısa



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vadeli fiyat hareketlerinin öngörülebilirliği, fiyat formasyonuna da ışık tutacaktır. Çalışmada ARIMA yaklaşımının tercih edilme nedeni kısa vadeli tahminlerdeki duyarlılığıdır. ARIMA (1,1,0) Bitcoin'in 2020Q3 ve 2020Q4 dönemlerindeki fiyat hareketlerini istatistiki olarak isabetli tahmin etmiş ve modelde görülen sapmalar, yatırımcıların Bitcoin için dijital bir varlık olması yönünde değişen, yatırım değeri algıları ile ilişkilendirilmiştir.

Anahtar Kelimeler: Volatilite Tahmini, Kripto Piyasası, Piyasa Mikro Yapısı, Varlık Fiyatlaması, Bitcoin Jel Kodları: G170, G150, G120

1. Introduction

Compared to a total market value of \$15,72 billion on January 1 in 2017, which incremental upwards movements have reached in 8 years after its birth, the total market value of all Bitcoins in circulation at the end of May was \$647 billion after reaching its top on April 9 as \$1,185 trillion in 2021. As of May 2021, the daily transaction volume has approximately reached 205,000 BTC (blockchain.com, May 2021), where its market capitalization briefly reached \$1 trillion U.S. Dollars in March 2021. Market capitalization is computed by multiplying the total number of Bitcoins in circulation by the Bitcoin price, and Bitcoin sustained this path until May 11, which was followed by a sharp fall (Best, 2021; Statistica, 2021). Right afterward: 1)

The People's Bank of China (PBOC) Digital Currency Research Institute and the China Academy of Information and Communications Technology (CAICT) announced their cooperation for developing two Blockchain standards for performance assessment of distributed ledger technology platforms, 2) the three financial industry associations -the National Internet Finance Association of China, the China Banking Association, and the Payment & Clearing Association of China- issued a statement to forbid financial institutions in their offerings with cryptocurrencies, 3) China's top financial regulatory authority, the Financial Stability and Development Committee (FSDC), called for a ban on BTC operations, 4) large institutional investors shifted their assets from BTC to gold following the regulations in China (CBN, 2021; Manoukian, 2021). The development paths of the cryptocurrency market and the BTC transactions call attention to the leverage of erratic movements, including the price movements, regulations, and market sentiments. This discontinuity which has long been transforming the market to a more complex structure, might have been affiliated with the risks driven by the system design of the cryptocurrency market and may spread to traditional market sentiments. Therefore divergent risk factors of the crypto markets can be listed as the structural backdrop of Bitcoin price volatility, investor positioning, and the composition of investors' profiles over time. On the other hand, global monetary order, symbiosis of monetary and fiscal policies, and motions in the traditional markets can be categorized as the macroeconomic backdrops of volatilities over time in the crypto markets.

Due to their system design, the risks associated with cryptocurrencies heavily differ from fiat money and other forms of financial assets. The market risk of cryptocurrencies and BTC is the shallow market problem in which trading in more significant amounts cannot be done unless heavy price fluctuations. Besides, a massive volume of BTC exchanges was observed as ceased operations, meaning the intermediary does not reimburse its client after leaving the cryptocurrency. This intermediary is so often a bank in which the user converts a currency to BTC. If the crypto is not held in exchange after closing the transaction, this may increase cybersecurity concerns for the digital wallets and generate a counterparty risk. Irreversibility of the transactions is another disadvantage that results in increased transaction costs, including ill-gotten cryptos that might have been on the blacklist. Furthermore, the protocol design has operational risks in nature, such as "%51 attacks" and security issues like double-spending in fast payments. Privacy is another risk that is similar to traditional banking risks. Because a user's registry information is revealed by intermediaries where third parties can retrieve personal informations through the system to further associate them with the user's future transactions. Lastly, the volume of legal concerns and regularity risks is much more than the others. The system facilitates financial crimes; as a result, money laundering is more welcomed to the system due to the lack of regulations that comes by the decentralized and half anonymous-half pseudonymous structures of the transactions. Also, the tax treatment of cryptocurrencies is uncertain for similar reasons (Böhme, Christin, Edelman, & Moore, 2015). Besides, the uncertainty in the tax treatment towards cryptocurrencies is much more likely to be related to their unidentified classification in the Money market, which draws attention to their volatility again.

It was not before the outbreak of COVID19 when BTC and the crypto-market have drawn the great attention of institutional investors as a hedging instrument. The number of mutual funds has increased over time. Hence, the market became more volatile, and its assetlike function became more prominent. There might be a point where the market sentiments turned positive for the crypto-market and exceeded investors' concerns related to the risk factors. Therefore, macroeconomic backdrops of all the volatilities in the crypto market over time are as crucial as risk factors.

The interest rates reaching the zero-lower bond, inflation expectations due to a twin demand and supply shock, unparalleled levels of quantitative easing, and fiscal stimulus opposed to the old monetary and fiscal orders aftermath of the COVID-19 might be the first-order components to the macroeconomic backdrop of the changing investor profile, price volatilities and investor positioning in the crypto markets and BTC transactions (Bhutoria, 2021). All these factors deteriorated returns on equities, fixed income, fiat currencies, and commodity prices as opposed to BTC because the utility function of crypto assets is not dependent on money supply, total output, or profitability ratios due to their system design. Besides, they have driven the interest in BTC as an alternative investment for corporates and

institutional investors to hedge market-driven interest rates, inflation, foreign exchange, liquidity, and credit risks, as shown in Table 1 (Bhutoria, 2020).

Risk	Description	BTC as a Potential Solution		
Interest Rate Risk	Makes the cash unproductive, and traditional hedging methods less functional and efficient.	Under the zero lower bound or negative yield environment policy, a non-yielding asset with asymmetric upside potential may serve as an alternate for hedging.		
Inflation Risk	Undermines the purchasing power of a company's cash position relative to the purchases of goods-services and investments that could be done.	BTC's price formation, its inelasticity to the money supply, and crypto-market formation may preserve business capital.		
Foreign Exchange Rate Risk	Exchange rate volatility could hurt the revenues and costs of corporations.	It can be used as a tactical tool for arbitrage, and when used as a bridge currency to move in and out of different currencies may lower the cost of transacting.		
Liquidity Risk	Inability to fulfill debt obligations to creditors due to illiquid assets. A prolonged reduction may cause the sale of illiquid assets at a less than favorable price to meet debt service.	Provides a dual efficiency to capital because BTC holder's borrow of cash against BTC collateral may increase liquidity while maintaining a tactical investment advantage through BTC holding.		
Credit Risk	The default risk of borrowers or fixed income securities issuers.	When used as collateral, it could reduce credit risk as a 24/7/365 operating asset.		
Source: Bhutoria & McCurdy, 2020.				

The study investigates the price movements in the crypto markets and their predictability because, often criticized for being over volatile, the price formation in the crypto market has started to become integral to investing decisions. The rest of the paper is organized into four sections. The first section introduces the price formation of Bitcoin. The literature review will be given in the second section, while the methodology, data descriptions, and model estimation will take part in the third section. Lastly, the paper will be finalized after conveying the study findings in conclusion.

1.1. Price Formation and Price Movements in Bitcoin

Bitcoin, a Proof-of-Work (PoW) based currency, operates a Peer-to-Peer (P2P) network ensuring its users to generate cryptocurrencies by the execution of payments with their digital signatures over transactions, in which a distributed time-stamping service prevents the users from double-spending the coins and makes their execution available to the public (Androulaki, Karame, Roeschlin, Scherer, & Capkun, 2013; Nakamoto, 2008). Therefore it is a cryptocurrency that is neither controlled nor regulated by a central bank or financial institution and capable of drawing its price movements (Nakamoto, 2009). The idea of removing central authority's control away from the system has been the most controversial issue since the inception of Bitcoin transactions. As a result, its price had followed a constant path from the first public use till the end of 2012 when the prices noticed some volatility in the crypto markets. As shown in Graph 1, the volatility shows enormous fluctuations in prices from 120\$ in 2013 up to more than 16.000\$ in the middle of 2020.



Graph 1. BTC Price Fluctuations from 2013 to 2020

Observable in Graph 1, the volatility of BTC has been increasing in the very last few years following 2017, with a peak after the outbreak of COVID-19. Approximately reaching \$20,000 in 2020, its price reached an average of \$40.000 in the aftermath of COVID-19, which was followed by an all-time high record of \$60.000 in April 2021 and experienced a quick rebound to its pandemic average of \$35.000-\$40.000 (blockchain.com, 2021).

The price formation of Bitcoin is primarily determined by the supply-demand mechanism. However, the price responds heavily to shifts in demand in which investors accept any change in demand. This causes the demand curve to be horizontal since its supply is exogenous and disconnected from demand and price to a large extent. User consideration on BTC or a cryptocurrency about to what extent it substitutes the functions of fiat money is the determinant for its demand and price movements aside from a function responding to the combination of benefit received, costs of adoption, industry or social environment, uncertainty, and information. There was no coincidence when the early investor profile was coming from a tech-savvy population (Buchholz, Delaney, Warren, & Parker, 2012; Kristoufe, 2013). Nevertheless, the investor profiles in transactions have long reached institutional investors and corporates.

Being capable of determining its price aside from traditional markets, however, the volatility in the crypto market and BTC draws attention to investor sentiments which are exposed to risk factors and macroeconomic backdrops. Bitcoin price volatility and predictability of its price movements have become more prominent after corporates, and institutional investors increased in the crypto market.

Source: Blockchain.com data, (retrieved from) https://www.blockchain.com/explorer, April 2020.

MassMutual, Tudor Investment, Ruffer Investment, ARK Invest, Horizon Kinetic, and Blackrock are examples of institutional investors in BTC aside from the MicroStrategy and Square Public companies. Furthermore, NYDIG, SkyBridge Capital, and Osprey Bitcoin Trust have emerged as Bitcoin investment funds, and Bitcoin futures were started to be traded while these institutional investors were increasing their BTC allocation in their portfolios (Bhutoria, 2021).

On the other hand, price stability is recognized as a significant challenge for cryptocurrencies due to their inability to substitute fiat money with three functions. Therefore, stable coins were devised to lower the volatility in the cryptomarket. Stablecoin is when a cryptocurrency pegs its market value to another cryptocurrency, fiat money, or commodity. However, Blockchain can be a leverage for cryptocurrencies to answer the functions of fiat money in the long run (Senner & Sornette, 2019; Variankaval, Junek, Saperia, Richards, & Moy, 2018; Bhutoria, 2020). Even there is a remarkable consensus that cryptocurrencies may serve as a store of value, their functions as a medium of exchange and as a unit of account are controversial (Senner & Sornette, 2019; Variankaval et al., 2018; Ciaian, Rajcaniova, & Kancs, 2016; Bhutoria, 2020). In the medium to long run, the potential impact expected from Blockchain is the monetization of digital and crypto coins, which may serve them to better comply with the medium of exchange function (Variankaval et al., 2018; Bhutoria, 2020). As it should be, the desired condition for a property is to have a steady and foreseeable value over short to medium terms, and it is less likely for BTC to alter large price movements in the short run. Therefore, huge volatility and dispersed prices in BTC cause firms and users to lose purchasing power with increased risks and costs when used as a medium of exchange in transactions (Ciaian et al., 2016). On the other hand, Blockchain and coin-base solutions have the potential to integrate traditional markets with crypto and digital-based systems in the long run. Nevertheless, for today, the reasons for corporates and institutional investors to make a Bitcoin or crypto-asset allocation highlight three points. According to Bhutoria (2021, p. 58) the primary reasons for the increased Bitcoin allocations are: 1) the properties that may allow bitcoin to function and gain share as a store of value, 2) the maturation of the bitcoin market and infrastructure, and 3) bitcoin's potential to improve diversification in a multi-asset portfolio.

There is increasing literature on the predictability of Bitcoin price movements, and it is for all these reasons, Bitcoin's price predictability is an integral part of the discussions about its ability to substitute fiat currencies. This study aims to contribute to this literature by following an ARIMA process to test the short-term predictability of BTC prices. The model will be specified for quarterly BTC data in the third section after summarizing the developing literature.

2. Literature Review

Even there is increasing literature about Bitcoin price forecast models, Autoregressive Integrated Moving Average (ARIMA) models are still on top of the short and medium-term analysis. According to Roche & Caton (2018) Recurrent Neural Network (RNN) and Long Short Term Memory (LSTM) network models both outperform ARIMA models only in forecasting the long-term tendencies in Bitcoin prices. In a similar vein, Azari (2019) investigates the ARIMA model accuracy for a time series of a 3-years-long time and reveals the model's efficiency for short-term predictions as opposed to long-term predictions. The study suggests that the longer the predictions introduce, the more prediction errors due to Bitcoin's price vulnerability to sudden jumps or drops.

Munim, Shakil, & Alon (2019) examine the performance of ARIMA and Neural Network Autoregression (NNAR) models in bitcoin price prediction on daily prices under two time periods as from January 1 of 2012 to May 14, 2013 (for 500 days) and to June 25 of 2017 (for 2000 days). Their study emphasizes that ARIMA models better perform than NNAR models during volatile periods besides their accuracy in future forecasts. However, due to the NNAR model's superiority over ARIMA in the first training sample, one can suggest that less volatility increases the performance of NNAR models in future forecasts. Twarakavi & Bansal (2020), moreover, test the prediction accuracy of ARIMA and Deep Learning (DL) Models as per Mean Squared Error (MSE) values. The result suggests that the ARIMA model outperforms DL Models in performance. Dyhrberg (2016), on the other hand, investigates the financial asset capabilities of Bitcoin against Gold and the Dollar by following a Generalized Autoregressive Conditionally Heteroscedastic (GARCH) model for the volatility analysis and suggests that Bitcoin can be placed somewhere between the Dollar and Gold in terms of its medium of exchange and store of value offerings.

There is also literature emphasizing the importance of stationary data and structural breaks for the Bitcoin market. According to Balcilar, Bourid, Guptac, & Roubaud (2016), there is a causality-in-quantiles from volume to returns even the volume does not predict the volatility of Bitcoin returns in quantiles. Ji, Kim, & Im (2019) depict a comparative analysis method among various combinations of DL models, including Deep Neural Network (DNN), LSTM, Convolutional Neural Network (CNN), and Deep Residual Network (ResNet) models to detect their distinguishing features. The study claims that LSTM-based prediction models best perform for Bitcoin price prediction while DNN-based models perform best for upward and downward price trends. Yen & Cheng (2021) searches for the predictability of the cryptocurrency volatility in the context of the policy uncertainty index (EPU) against a change in the EPU of the U.S., Japan, and Korea, which all do not predict any

volatility such EPU of China does. By modifying a Stochastic Volatility (SV) model, the study also observes the tendency to act as a hedging instrument due to the negative correlation between the EPU of China and cryptocurrency volatility.

Instead of ARIMA and GARCH models, the applicability of Heterogeneous Autoregressive (HAR-type) models has also been questioned for the coin markets. Pichl & Kaizoji (2017) not only captures the daily realized volatility of Bitcoin with the HAR-type Models for realized volatility (HAR-RVJ) but also interrelates the price volatility with the arbitrage opportunities for USD, EUR, and CNY currency pairs. The study finds the HAR-RVJ model for BTCUSD more favorable amongst other currency pairs where the arbitrage spread for the USD-CNY and EUR-CNY is superior to the EUR-USD. Consistent with Pichl & Kaizoji (2017), Shen, Urquhart, & Wang (2019) estimate the forecasting ability of HAR-type models with 5-minute high-frequency Bitcoin data. Based on their study, the inclusion of structural breaks increases the accuracy of HAR models in forecasting. In a similar vein, Aalborg, Molnár, & Erik de Vries (2019) study the predictability of Bitcoin return, its volatility, results show that the HAR model predictability can further be improved by the trading volume even though Bitcoin returns have no legitimate relationship with others.

Following the asymmetric-GARCH models, Bouri, Azzi, & Dyhrberg (2017) find an inverse relationship between the US VIX and the Bitcoin volatility as opposed to equities as proof of its safe-haven property before the price crash of 2013. The study indicates that it is the price-crash of 2013 altering the safe-haven property of Bitcoin but sustaining it as a proper risk allocation method for equity portfolios. Another approach to Bitcoin volatility is searching for the level of price clustering in cryptocurrencies and Bitcoin. Baig, Blau, & Sabah (2019) claim the positive correlation between price clustering and market sentiments towards Bitcoin concerning the uneven level of price clustering. Their study findings reveal that one point upward movement in the standard deviation is capable of qualifying from %2.5 to %5 of the uneven clusterings in Bitcoin and equities follow a common pattern.

Autoregressive (AR) models are also capable of searching for the relationship between volatility and sentiments in the context of Bitcoin. Bukovina & Marticek (2016) find that positive sentiments tend to be more robust than negative sentiments, and negative sentiments explain only a negligible amount of the volatilities. In this sense, the price of Bitcoin is exposed to fewer rationale factors aside from the supply-demand relationship, which has been recognized as the major determinant of its price due to its mixed crypto-asset characteristics. Following a GARCH model, Fang, Bourib, Guptac, & Roubaud (2019) examine Bitcoin's volatility and its hedging ability relative to other conventional assets

under uncertainty. The study findings demonstrate that the economic policy uncertainty has a significant impact on the long-term volatility of Bitcoin and conventional assets. However, findings support the assertion that Bitcoin acts as a hedging tool since its volatility performs likewise equities instead of bonds. Implementing a BEKK-GARCH model, Klein, Thu, & Walter (2018) find the time-varying conditional correlations of Bitcoin and gold relative to a set of assets. Because the correlations differ from one another, the study finds no evidence for hedging capability of Bitcoin as a portfolio component as opposed to gold.

3. Methodology, Data Description, and Model Estimation

3.1. Methodology

The Autoregressive Integrated Moving Average (ARIMA) model was first introduced by Box and Jenkins (Box & Jenkins, 1976). This univariate model involves three parts, the Autoregressive (AR) model, Order of Integration I(d) and, the Moving Average (MA) model. While the initial AR model only sheds light on the previous lags of a variable, the ARIMA model can incorporate the MA process, representing the linear combination of regressions residuals. The order of integration points towards the existence of the unit root in the data, which is a significant sign of non-stationarity. The order of integration represents the differencing process level required to eliminate the unit root in the data and transform the nonstationary time series into stationary. According to the Box-Jenkins methodology, the ARIMA model works with stationary data, and non-stationarity leads to misspecification in the model. Thus, the I(d) in the ARIMA model represents the level of differencing process to eliminate the unit root and make the series stationary in terms of mean and variance. We demonstrate the mathematical representation of the ARIMA process as:

$$y_t = c + \phi_1 y_{(t-1)} + \dots + \phi_p y_{(t-p)} + \theta_1 \varepsilon_{(t-1)} + \dots + \theta_q \varepsilon_{(t-q)} + \varepsilon_t$$
(1)

In this formula, ϕ determines the coefficient of the AR process, and θ shows the coefficient for the MA process. As in the literature, the ARIMA model is determined by ARIMA (p, d, q). The "p" refers to the order of the AR process, which means how many previous lags of the variable are included in the model. The "d" represents the level of differencing is needed to transform the series into stationary. Finally, the "q" shows the level of the regression residuals' previous residuals that are included in the model.

To define the orders of AR and MA processes, Box and Jenkins suggested investigating the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) patterns to identify the right order. However, due to inherent error in visual methods, Hyndman and Athanasopoulos advise the use of Akaike's Information Criterion (AIC) and Bayesian Information Criterion (BIC) for selection of the right order (Hyndman & Athanasopoulos, 2018). In this case, the best model is selected by minimizing the information criterion, and the ARIMA model answers to short-term forecasts efficiently because medium and long-term horizons affect the dependent variable instead of the records of the target variable.

3.2. Data Description

The quarterly data used for Bitcoin price in this study have been retrieved from the "Coinmarketcap." We selected this time interval because it was the most volatile time for Bitcoin. Thus it could be a challenge to test our forecast model. The data was divided into two sections to perform an out-of-sample forecast. The first part includes the timeframe from 2014Q1 to 2020Q2, which is used to make our model. The second set of data was structured from 2020Q3 to 2020Q4 to test the model afterward. The price movements for the entire timeframe are shown in Graph 2.



Graph 2. Price Movements (BTC)

As Graph 2 illustrates, the Bitcoin price was raised sharply in the middle of 2017 after a long consolidation period from 2014 to 2017. However, this rise was followed by a steep decline in the middle of 2018, which kept the uptrend through 2020. Therefore, the time series are log-transformed and used in logarithms (logs) to stabilize the variance of the series. A demonstration of the descriptive statistics for the data processed is available in Table 2.

	1
	Bitcoin Price
Mean	4474.327
Median	2682.915
Maximum	16629.39
Minimum	236.1466
Std. Dev.	4575.851
Observations	28

Table 2: Descriptive Statistics

3.3. Autocorrelation Function

As shown in Graph 3, ACF and PACF graphs have been plotted to assess the potential trend, seasonality and, stationarity detection by visual means. From the slight decay of ACF to the baseline with decreasing significance, it is observable that the data has a trend. Due to the gradual decrease to the baseline with no spikes, we can conclude that the data are not seasonal as expected due to the cryptocurrency market's unresponsiveness to seasonality in nature. The ACF function for the first six lags is significant, which is strong proof that the data is not stationary, and the Augmented Dickey-Fuller (ADF) test might better perform for further investigation.





3.4. Augmented Dickey-Fuller Test

After ACF and PACF graphs revealed the stationarity in the data, the ADF test may provide better concrete for the stationarity of the times series (Dickey & Fuller, 1979). In search for the unit root, the null hypothesis favors unit root existence as a strong sign of non-stationarity in the data, and rejection of the null hypothesis concludes the stationarity of the data. As demonstrated in Table 3, the ADF test was calculated under %5 significance level to test if the original data were stationary.

	Table 5: ADF Test Results				
Variables	t-stat	Prob.	∆ Variables	t-stat	Prob.
BTCP	-3.595026	0.2054	Δ BTCP	-3.622033	0.0211

Fable 3	3:	ADF	Test	Results
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Notes: $\Delta =$ first difference, the Significance level is 5%

While the ADF test revealed that the original data were nonstationary, it became stationary after first differencing the time series. Therefore, the unit root has been removed as the null hypothesis was rejected after the differencing process by 0.0211 probability at 0.05 significance level, and the model can be demonstrated by the log-transformed and first differenced series.

3.5. Selecting ARIMA Order

Time series were log-transformed and first differenced. The ACF and PACF graphs seen in Graph 4 can give a clue about the order of the ARIMA (p, d, q) model regarding the Box-Jenkins methodology. The sharp fall in ACF after the first lag suggests ARIMA (1, 1, 0). However, for statistical inference reasons, ARIMA (0, 1, 1) and (2, 1, 0) combinations were also tested to view which combination minimizes the AIC values.



Graph 4. ACF and PACF for ARIMA

3.6. ARIMA Model Specification

AIC values being compared, ARIMA (1, 1, 0) indicated a better-fit model as it has outperformed the other combinations with a lower AIC value equivalent to 0.69. The results for ARIMA (1, 1, 0) are presented in Table 4. AR coefficient is 0,5059 for ARIMA (1, 1, 0), which lies inside the unit circle. The inverted root of 0.51 with the p-value of 0.0018 confirms that the model is statistically significant at the 0.05 level. The results indicate that the stationarity and invertibility conditions are satisfied. R² suggests forecasting approximately 21% of the price movement behavior based on its past values. The Durbin-Watson test statistics (DW=1.85) enacts that the model satisfies the assumption that there is no serial-autocorrelation or pattern in the error term and the residuals are stationary. The statistical test results assure that the ARIMA (1, 1, 0) is the best fit model for the data.

Estimated Coefficients::	t-Statistics	P-Values	
$\phi_1 = 0.505839$	3.536153	0.0018	
Model Fit:			
R ² : 0.210232	DW: 1.853567	AIC: 0.697198	
Inverted AR Roots: 0.51			

Table 4: ARIMA (1,1,0) Model Estimations for BTCP

Notes: DW: Durbin-Watson statistics

The forecast model runs for the price movements of 2020Q3 and 2020Q4 to compare the ARIMA (1, 1, 0) forecast with the real market values of BTC. Being tested, Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE) were used to test forecast accuracy. Because MAPE is recognized as an effective accuracy measure for data with positive and large values (Hyndman & Koehler, 2006) and RMSE suits to test the accuracy of a forecast which complies with the analyses using a single model, not two different models (Armstrong & Collopy, 1992).

Table 5: Forecast Accuracy Measures for BTCP			
MAPE	4.24%		
RMSE 0.463037452			
MAPE: Mean Absolute			
Percentage Error			
RMSE: Root Mean Square			
Error			

Interpreting the forecast accuracy, a MAPE result less than %10 refers to a highly accurate forecast, while measures from 11% to 20%, 21% to 50%, and a value higher than 51% are respectively recognized as good, reasonable, and inaccurate forecasts. Besides MAPE, an RMSE measure of less than 0.5 considers the model proper for forecasting (Lewis, 1982; Makridakis, Hibon, & Moser, 1979; Kim & Kim, 2016; Moreno, Pol, Abad, & Blasco, 2013). Accuracy results are shown in Table 5 recognize the ARIMA (1, 1, 0) as a highly accurate forecast with 4.24% MAPE and 0.46 RMSE measures.

Graph 5. Model Forecast



As shown in Graph 5 and Table 5, the results show that ARIMA (1, 1, 0) is an effective forecast for the last two quarters of 2020 based on quarterly data and provided an accurate forecast for short-term price predictions of Bitcoin. However, forecast values follow the previous trend while we have a sharp increase from the second quarter of 2020. The average market prices of Bitcoin for the 2020Q3 and 2020Q4 were approximately 9.27 and 9.71, while ARIMA (1, 1, 0) predictions were 9.08 and 9.09, respectively. Compared to 2020Q4, model accuracy has better performed for the 2020Q3 as expected due to its short-term sensitivity. Because the majority of the institutional investors increased their Bitcoin allocation in the second half of 2020, this was an unanticipated time for the shallow market similar to a structural change leveraged with corporates and institutional investors. The findings highlight that not only previous values of price but also exogenous factors are determinants in the price formation of Bitcoin due to the crypto market's shallow characteristics. The output fall-off driven by COVID-19 lockdowns has pulled down the productivity levels and employment ratios, and forced authorities for unconventional policy responses might be the reasons for the increased Bitcoin allocations of the institutional investors during COVID-19.

4. Conclusion

The timeframe predicted in the ARIMA model was when the COVID-19 cases were reached their second peak, fiscal stimuli and quantitative easing were continued by governments to combat the output gap in the economy. As a result, supply chain disruptions and tightened demand with increased debt service ratios were contributed to a twin supply-demand shock in the global markets. On the other hand, the new normal of COVID-19 caused a dual formation in the global markets in which high-tech industries gained power and commodity markets weakened.

Drastic prices were sustained in the last two quarters of 2020 after the historic %300 drops on WTI crude oil in April when it was traded at around negative \$37 per barrel. This might be the fork in the road for corporates and institutional investors to change their asset allocation in favor of digital assets leading with Bitcoin. Because after that, the institutional investors in the crypto market sharply increased with their coin-based offerings.

Moreover, the use of crypto market operations by mutual funds as an effective hedging policy in the zero-lower bound environment suggests that, at this point, the returns offered by the macroeconomic backdrops in favor of digital assets and Bitcoin exceeded the potential loss from the risk factors of the crypto market. However, the security concerns and regulatory needs have drawn the public interest when China announced a state declaration forbidding the financial institutions in their use of coin-based offerings in the middle of May 2021. After that, the price of Bitcoin has fallen drastically as a response to potential implications that might arise, such as tax regulations, financial cryptocurrency investigations, freezing accounts, or account suspensions. Even so, this policy environment did not put back J.P. Morgan to enrich its coin-base offerings with Bitcoin futures in a particular market where the fund was not existing before.

It is likely for trade wars and currency manipulations to turn into new jargon as long as crypto and coin markets give policy responses to investors as a hedging tool. In conclusion, even provided an accurate prediction, the ARIMA results also revealed the prominent role of institutional investors in leveraging Bitcoin's digital asset characteristics and highlighted the significant role of the macroeconomic backdrops in favor of Bitcoin aftermath of COVID-19 in explaining the deviations for the last two quarters of 2020.

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