BITCOIN PRICE PREDICTION BY BOX-JENKINS MODEL

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Abstract: *Bitcoin (BTC) and other cryptocurrencies have seen an explosion in popular notoriety. Indeed, the price of Bitcoin is known to vary widely. Meanwhile, as Bitcoin's use cases grow, mature, and grow, hype and controversy have swirled. As with any design or commodity on the market, bitcoin trading and financial instruments have quickly followed the public adoption of bitcoin and continue to grow. We will carry out a detailed analysis of Bitcoin prices using time series of the Box-Jenkins model, in particular the closing price. Which Traders will then use.*
Keywords: Bitcoin; Time Series; Box-Jenkins Model; VAR.
JEL Code : C55, E66, C22.

1. INTRODUCTION

Crypto-currencies is the most effective category in the virtual context whose exchange rate analysis is too volatile. The Bitcoin (BTC) price variation as a best-known example in the global Stock Exchange system. In recent years this new currency has appeared on the internet. A strange currency that is not governed by anyone, a currency that is self-regulated by an algorithm and which is moreover anonymous. The virtual currency “Bitcoin” represents the digitization of an anonymous aspect which is characterized by its decentralization, i.e. the fact that no State or banking entity controls it. Moreover, Bitcoin is not backed by any precious metal like gold. Virtual currency is qualified but is really just a simple computer program. In this sense, Bitcoin has its own characteristics, the true identity of which remains unknown until today; we therefore refer to the pseudonym that has been left to the public “Satoshi Nakamoto”, creator of Bitcoin constant.

Also, we attempts to simulate the Bitcoin price based on supply and demand. He explores the possibility of using a double logarithmic time model for supply and demand and rejects it due to serious heteroscedasticity. Then using the Auto program. ARIMA, he finds a fairly productive autoregressive integrated moving average model. After that, it uses the supply and demand forecasts built with ARIMA (Box-Jenkins Model) to model the future price of Bitcoin, taking into account that its supply volume is known.

2. LITERATURE REVIEW

2.1. Bitcoin price volatility by different non-parametric methods

In this work, Auestad et al. (1994) investigated the possibility of identifying nonlinear time series patterns using nonparametric methods.

Hardle et al. (1995) present a selective review of procedure-based approaches to nonparametric model building in time series analysis. They point out that nonlinear, nonparametric time series analysis is useful in dealing with the limitations of constant-mean ARIMA models. Hardle et al. (1997) review some developments in modern non parametric techniques for time series analysis.

Although, manu studies investigate the performance of the stock market. Faff and McKenziet's (2007) study concluded that low or even negative return autocorrelations are more likely in situations where: return volatility is high; the price drops significantly; volumes of shares traded are high; and the economy is in a recession, Abu Bakar and Rosbi (2017) investigate the reliability of the Box-Jenkins statistical method for predicting stock price performance for the oil and gas sector in Malaysia, Stock found that the performance of Gas Malaysia Berhad can be accurately predicted using the Autoregressive Integrated

Moving Average (ARIMA) Model of (5,1,5). Like in Malaysia. The importance of the forecasting method in the stock market is also presented by Stevenson (2007), discusses issues relating to the application of the forecasting method.

Although the study by Jadevicius and Huston (2015) suggests that ARIMA is a useful technique for assessing general changes in market prices, the results highlight the limitations of using the conventional approach to identify the pattern ARIMA best specified in the sample, when the purpose of the analysis is to provide forecasts. The results show that ARIMA models can be useful in anticipating major market trends; there are substantial differences in the predictions obtained using alternative specifications.

In total, our work is subdivided into two phases, the first phase consisting in finding if our Bitcoin price time series can support the Box-Jenkins ARIMA model, through a series of stationarity tests since the latter is a necessary condition for the application of this model, then in a second phase we will select the best coefficients of our ARIMA model, in particular through several iterations via the choice table of the ARIMA model according to the Akaike information criterion (AIC) work is subdivided into two phases, the first phase consisting in finding if our time series of Bitcoin prices can support an ARIMA model, through a series of tests, then in the second phase we will select the best coefficients of our ARIMA model, in particular a through multiple iterations through the ARIMA Model Choice Table according to the Akaike Information Criterion (AIC).

2.2. Time Series: Modeling and Prediction

Volatility can be defined as a measure of the price dispersion of a financial asset. Market participants and investors are therefore interested in an accurate estimate of volatility in the cryptocurrency market. This is the result of the correlation between volatility and investment returns. It should be noted that volatility is not directly observable and therefore there is a growing need for an efficient model that can capture price volatility in the cryptocurrency market. As bitcoin has gradually had a place in financial markets and portfolio management, time series analysis is a useful tool for studying the characteristics of bitcoin prices and returns, and extracting meaningful statistics to predict future values. from the Serie.

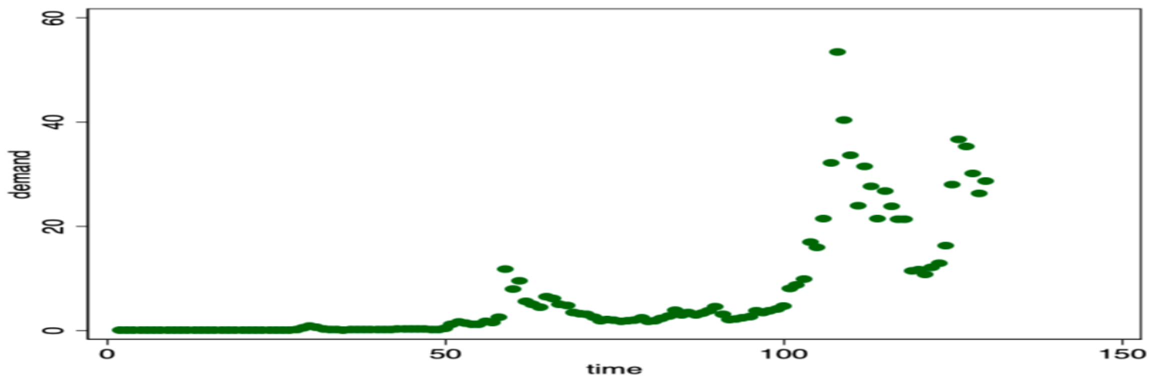
Virtual currency market: According to Bitcoin supply and demand on date T

We add the condition that the demand is modeled by a function of time:

F (t) = Demand = ßt.

This regular least squares (OLS) regression is a method for finding a linear relationship between two or more variables. To start, let's define a linear model as a function X, which equals Y with an error: Y = ßX + ε ; where Y is a dependent variable, X is an independent variable, ε is the magnitude of the error, and ß is multiplier X. The OLS task is to print the value ß in order to minimize ε.

Figure 1: The relationship of demand to time seems potentially exponential [1].



2.3. The ARMA Model

The stationarity of a series (Z_t) would normally follow an autoregressive moving average pattern of orders p and q, normally with the designation ARMA (p, q) which is deemed to be formed by two headings namely:

[1] https://newdaycrypto.com/fr/supply-and-demand-model-for-bitcoin-price/

- *Autoregressive models **(AR)***

It is one of the methods used to model univariate time series data, where the current observed value is assumed to be a function of past values plus a random shock. The process $\{X_t\}$ is said to be autoregressive of order p, denoted AR (p) if,

$$X_t = \varphi_1 X_{t-1} + \varphi_2 X_{t-2} + \quad \dots\dots\dots.. \varphi_p X_{t-p} + \varepsilon_t, \{\varepsilon_t\} \sim N(0, \sigma^2) \qquad \mathbf{(1)}$$

$$X_t - \varphi_1 X_{t-1} - \varphi_2 X_{t-2} - \quad \dots\dots\dots.. \varphi_p X_{t-p} = \varepsilon_t$$

Or $(1 - \varphi_1 L^1 - \dots - \varphi_P L^p)\, X_t = \varepsilon_t$

So an autoregressive model is simply a linear regression of the current value in the series against one or more previous values in the series. Therefore, we can easily determine current production, but the weakness of the autoregressive model is that past disturbances are not taken into account.

- *Moving average **(MA)***

Another approach used in univariate time series modeling is the autoregressive model, in which the observed time series depends on the weighted linear sum of past random shocks. Therefore, the process$\{Y_t\}$ is said to be a moving average MA (q) d of order q si $Y_t = \zeta_t - \theta_1 \zeta_{t-1} - \theta_k \zeta_{t-2} - \dots - \theta_q \zeta_{t-q}, \{\zeta_t\} \sim N(0, \sigma^2)$ $\mathbf{(2)}$

Or $(1 - \theta_1 L^1 - \dots - \theta_q L^q)\, \zeta_t = Y_t$

- ***ARMA (p, q)* models:** Another useful time series model is formed by combining the MA(q) and AR(p) processes. An ARMA (p,q) model comprises according to its name two components: the weighted sum of past values (autoregressive component) and the weighted sum of past errors (moving average component).

Then, the process Z_t is an ARMA process (p, q) if: $(1 - \varphi_1 L^1 - \dots - \varphi_P L^p)\, X_t = (1 - \theta_1 L1 - \dots - \theta_q Lq)\, \zeta_t$ (3) is said to be a sequence of random variables, with zero mean and constant variance, normally called the white noise process (α and ß being constant).

This means that with p = 0, relation (3) becomes a moving average model of order q and with a designated MA (q). With q = 0, the process will then become an autoregressive process of order p, denoted by AR (q). A time series ζ_t is said to be a sequence of random variables, with zero mean and constant variance, normally called a white noise process (α and ß being constant).

This means that with p = 0, relation (3) becomes a moving average model of order q and with a designated MA (q). With q = 0, the process will then become an autoregressive process of order p, denoted by AR (q). A time series (Zt) is called an ARIMA model of order (p, d, q), it is the average of the autoregressive integrated moving average:

$$\Phi(\beta)\partial^d X_t = \theta(\beta)\zeta_t \qquad (3)$$

The ARIMA process is characterized by three important values: p: is the order of the autoregressive component, d: the number of differences needed to transform the not stationary series into a stationary ARMA process (p,q) and q: the order of moving average.

3. METHODOLOGY AND MODELING OF A TIME SERIES

3.1. *Box & Jenkins Model (1976)*

The Box & Jenkins (1976) model is used to determine an adequate methodology for showing a chronicle for the purpose of predicting nearby eventual values. Indeed, the objective of this methodology is the modeling of a time series according to its past and present values in order to determine the appropriate ARIMA process by principle of parsimony. This methodology suggests model identification with a three-step procedure including model estimation and model validation. Then, the three steps are identified as the sequences:

3.2. Data

The data used are the daily closing prices of bitcoin from 1-hour intervals from 01/01/2018 00:00 to 04/03/2021 08:30:00, corresponding to a total of 27801 observations. released in US dollars. We calculate the returns by taking the natural logarithm of the ratio of two consecutive prices, as a good approximation of the daily percentage price changes.

The data is titled: Starter Bitcoin Intraday OHLCV Data 266aba01-6, is an open-high-low-close chart (also OHLC) a type of chart typically used to illustrate movements in the price of a financial instrument over time.
Source: https://www.kaggle.com/kerneler/starter-bitcoin-intraday-ohlcv-data-266aba01-6/data

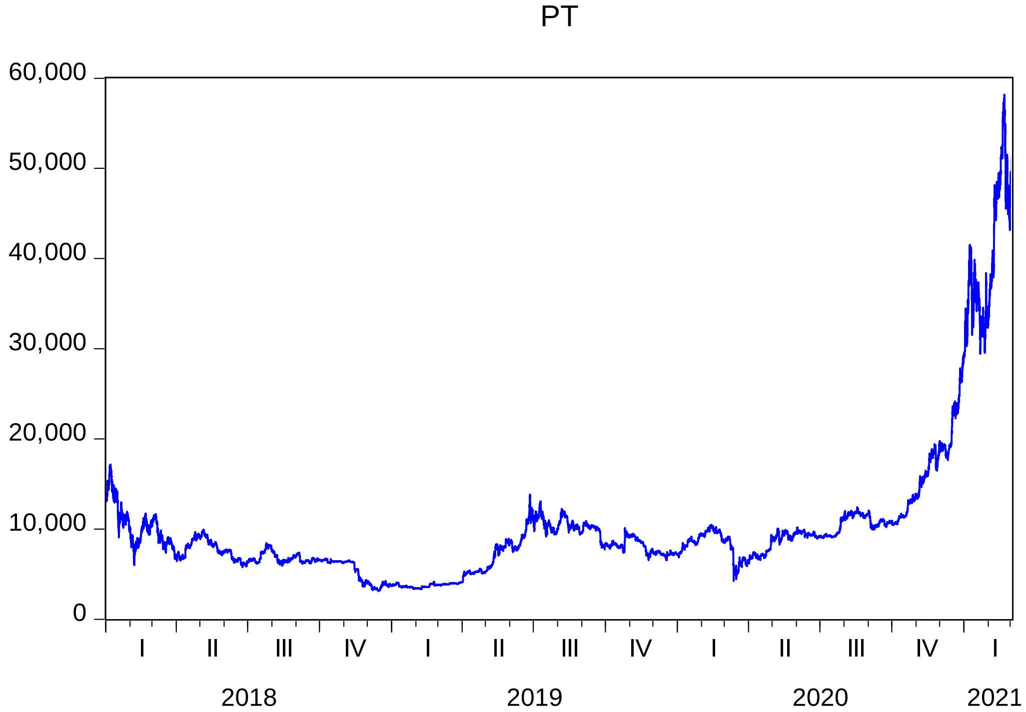


Figure 2: Bitcoin prices

Figure 2 shows the dynamic behavior of Bitcoin exchange rate. The observation data are selected from January 2018 until march 2021. The total number of observations is 27801. .

3.3. Model identification

The first state is to determine the number of differences needed to render the time series over a long period. To do this, we will test the stationarity of the series by a simple or augmented unit root test (ADF) to determine the type of stationarity process, namely DS or TS.

Then, if the data is stationary, then we determine the order of the autoregressive process AR (p) and the moving average MA (q) by creating the graph of the partial correlation function (PACF) and the autocorrelation function (ACF) So that we can get the ARIMA model.

3.4. Unit root test

Whether the time series is stationary or not is a very important concept before drawing conclusions in time series analyses. Therefore, Augmented Dickey Fuller (ADF), Phillips Perron (PP), and Kwiathowsky-Phillips-Schmidt-Shin (KPSS) tests were used to verify the stationery of the series. The test is based on the assumption that a series of time data Y_t follows a random movement: $Y_t = \rho\ Y_{t-1} + e_t$

Where ρ is the characteristic root of an AR polynomial and e_t is a purely random process with mean zero and variance Var (e_t) equal to zero..

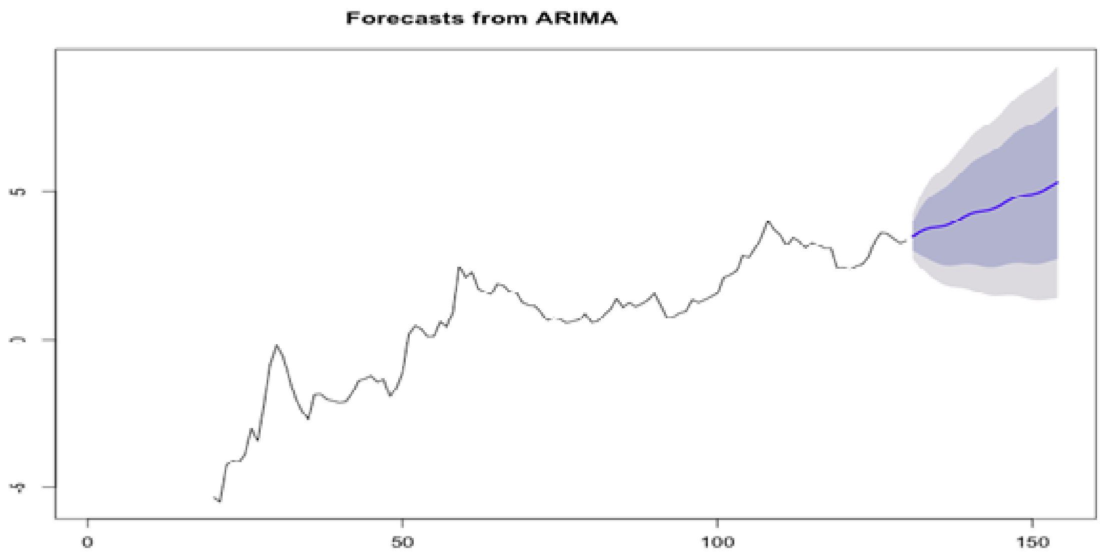
3.4.1 Augmented Dickey Fuller Test (ADF)

The Augmented Dickey Fuller test (1979) is a root test of the ADF unit, which therefore tests the acceptance, or rejection of one of the following two hypotheses:

H0: ρ = 1 non stationary or else H1: ρ ≠ 1 stationary.

The ARIMA model is the course of the Box and Jenkins method which makes it possible to determine a time series according to its characteristics. It consists of several steps:

Figure 3: The process of creating a dynamic forecast from ARIMA[2]

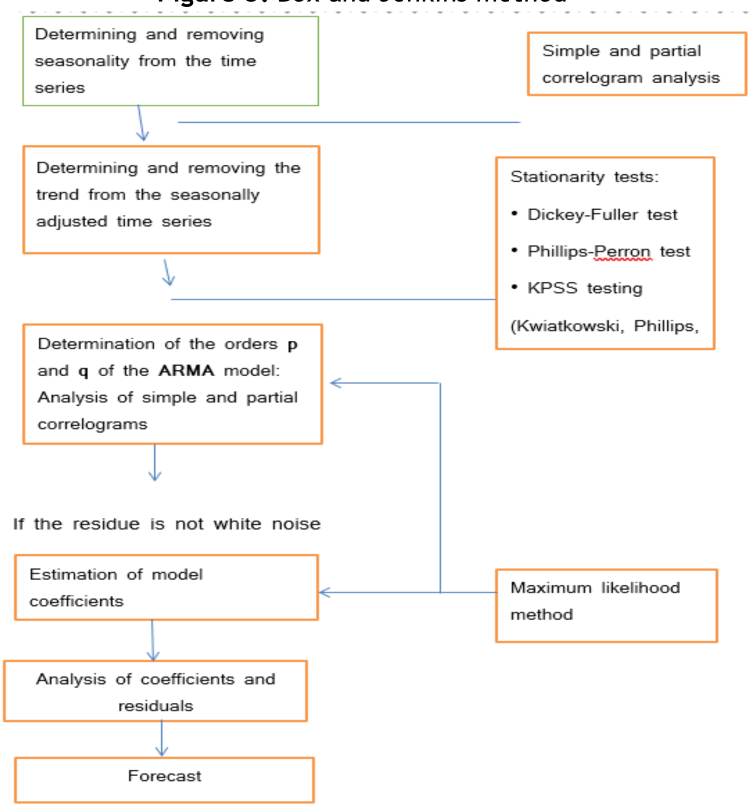


In order to derive a reliable calculated value β, it is necessary to observe some basic conditions:

- The presence of a linear relationship between the dependent and independent variables
- Homoscedasticity (i.e. constant dispersion) of errors
- The mean value of the error distribution is usually zero
- Absence of autocorrelation of errors (i.e. they are not correlated with the sequence of errors taken with a time shift)

In total, we can calculate demand using the model MCO; F(t)= β t

Figure 3: *Box and Jenkins method* [3]



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2 https://newdaycrypto.com/fr/supply-and-demand-model-for-bitcoin-price

3 Hélène Hamisultane (2002). 'Time series econometrics'. *Licence. Frensh. 2002. ffcel01261174f*

3.4.2. Other stationarity tests

- Phillips Perron Test

Phillips and Perron (1988) is perhaps the most frequently used alternative to the Augmented Dickey Fuller (ADF) test.

They modify the statistical test so that no additional delay of the dependent variable is needed in the presence of serial errors. The advantage of this test is that it does not assume any functional form during the first process of the variable which is applicable to a very large number of problems.

Test de Kwiathowsky-Phillips-Schmidt-Shin

Kwiathowsky-Phillips-Schmidt-Shin (KPSS) (1992) is a test where the null hypothesis is the reverse. These are tests to see if the test can reject stationary. This is the PP and ADF test reserve.

- ***Identification***

A series that exhibits an AR (p) process whose ACF bounds exponentially and whose PACF increases in one or more cases.

➢ *The number of spikes only the command p.*

Series that exhibit an MA(q) process whose PACP declines exponentially and ACFs have peaks in the former are more lodges.

➢ *The number of spikes only the command q.*

The series exhibits an ARMA (p,q) process if the PCA and PACF bound exponentially. The number of spikes includes only p and q orders.

- *Estimation*

This involves estimating the parameters of the appropriate ARIMA model identified in the previous step by the conditional least squares method.

➢ *Diagnostic test*

In this step, it is necessary to validate the adequate model which minimizes the information criteria: Akaike Information Criterion (AIC), Modified Akaike Information Criterion (AICC), Boyesion Information Criterion (BIC), then verification of the model by analyzing the residual must be white noise.

➢ *Akaike Information Criterion (AIC)*

The AIC says to select the ARIMA (p, d, q) model that maximizes

$AIC = -2Ln\ L + 2k$

➢ *Modified Akaike Information Criterion (AICC)*

The problem arises in the sense that the AIC whose statistical alternative corrected for this bias becomes:

$$AICC = AIC + \frac{2\,(K+1)+(K+2)}{n-k-2}$$

➢ *Boyesion Information Criterion (BIC)*

The BIC says to select the ARIMA(p,d,q) model that maximizes.

BIC = -2Ln L + 2k Ln (n);

Where Ln L is the natural logarithm of the estimated likelihood function and k = p + q is the number of parameters in the model and n observations.

Both *AIC* and *BIC* require the maximization of the log likelihood function when we compared AICC to BIC, resulting in a more severe penalty for parameterized models.

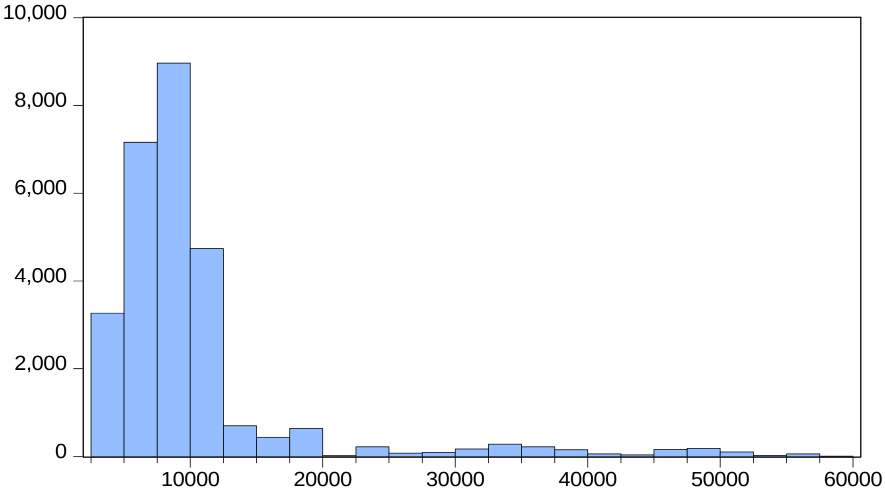
Results and discussion

4. RESULTS

This section describes the result for autoregressive integrated moving average (ARIMA) model for forecasting the Bitcoin prices.

4.1. Descriptive statistics:

Figure 4: Descriptive statistics

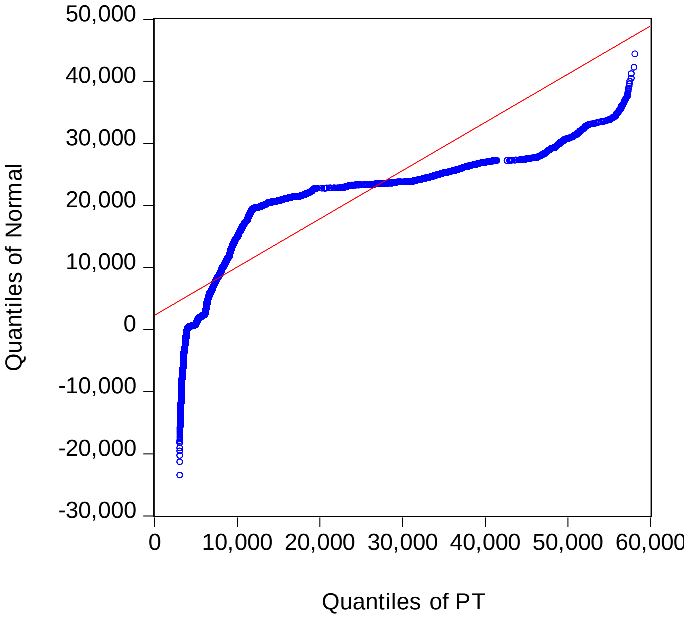


Series: PT
Sample 1/01/2018 00:00 3/04/2021 08:00
Observations 27778

Mean	10371.57
Median	8558.150
Maximum	58179.70
Minimum	3141.400
Std. Dev.	8208.034
Skewness	3.212474
Kurtosis	14.14600
Jarque-Bera	191567.7
Probability	0.000000

Source : Made by the authors

Figure 5 : QQ-plot



- We reject the null hypothesis of the Jarque bera test, our series does not follow a normal law,
- the QQplot graph clearly confirms the non-normality of our series

Table 1: Empirical distribution Test

Empirical Distribution Test for PT				
Hypothesis: Normal				
Date: 09/23/22 Time: 15:59				
Sample: 1/01/2018 00:00 3/04/2021 08:00				
Included observations: 27778				
Method	Value	Adj. Value	Probability	
Lilliefors (D)	0.287544	NA	0.0000	
Cramer-von Mises (W2)	644.6179	644.6295	0.0000	
Watson (U2)	571.2420	571.2522	0.0000	
Anderson-Darling (A2)	3453.828	3453.922	0.0000	
Method: Maximum Likelihood - d.f. corrected (Exact Solution)				
Parameter	Value	Std. Error	z-Statistic	Prob.
MU	10371.57	49.24800	210.5989	0.0000
SIGMA	8208.034	34.82422	235.6990	0.0000
Log likelihood	-289774.2	Mean dependent var.		10371.57
No. of Coefficients	2	S.D. dependent var.		8208.034

4.2. Unit root test

➢ Augmented DICKEY-FULLER

➢ Table 2 : ADF for PT

Null Hypothesis: PT has a unit root			
Exogenous: Constant			
Lag Length: 17 (Automatic - based on SIC, maxlag=20)			
		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		2.533249	1.0000
Test critical values:	1% level	-3.430416	
	5% level	-2.861453	
	10% level	-2.566764	

❖ the ADF's null hypothesis that a unit root is present in our time series is accepted. there is a unit root,

❖ so we proceed to the differentiation of our series.

Table 3 : ADF for D(PT)

Null Hypothesis: D(PT) has a unit root			
Exogenous: Constant			
Lag Length: 16 (Automatic - based on SIC, maxlag=20)			
		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-37.79887	0.0000
Test critical values:	1% level	-3.430416	

	5% level	-2.861453
	10% level	-2.566764

❖ the ADF's null hypothesis that a unit root is present in our time series is rejected. there is no unit root.

➢ PHILIP PERRON :

Table 4 : PHILIP PERRON for PT

Null Hypothesis: PT has a unit root Exogenous: Constant Bandwidth: 58 (Newey-West automatic) using Bartlett kernel			
		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		3.132504	1.0000
Test critical values:	1% level	-3.430415	
	5% level	-2.861453	
	10% level	-2.566764	

- the ADF's null hypothesis that a unit root is present in our time series is accepted. there is a unit root,

- so we proceed to the differentiation of our series.

Table 5 : PHILIP PERRON for D(PT)

Null Hypothesis: D(PT) has a unit root Exogenous: Constant Bandwidth: 59 (Newey-West automatic) using Bartlett kernel			
		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-175.2545	0.0001
Test critical values:	1% level	-3.430415	
	5% level	-2.861453	
	10% level	-2.566764	

❖ the ADF's null hypothesis that a unit root is present in our time series is rejected. there is no unit root.

4.3. Autocorrelation function (ACF) and partial autocorrelation function (PACF) analysis:

Table 4: Correlogram for Bitcoin Prices

Date: 09/23/22 Time: 15:40
Sample: 1/01/2018 00:00 3/04/2021 08:00
Included observations: 27778

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.999	0.999	27747.	0.000
		2	0.999	0.026	55462.	0.000
		3	0.998	0.011	83146.	0.000
		4	0.998	-0.002	110799	0.000
		5	0.997	0.017	138423	0.000
		6	0.997	-0.006	166017	0.000
		7	0.996	-0.025	193578	0.000
		8	0.995	-0.007	221108	0.000
		9	0.995	0.002	248606	0.000
		10	0.994	0.010	276073	0.000
		11	0.994	-0.008	303507	0.000
		12	0.993	-0.007	330910	0.000
		13	0.992	-0.000	358281	0.000
		14	0.992	-0.018	385618	0.000
		15	0.991	-0.004	412922	0.000
		16	0.991	0.014	440193	0.000
		17	0.990	-0.000	467432	0.000
		18	0.989	0.016	494640	0.000
		19	0.989	0.002	521816	0.000
		20	0.988	-0.012	548960	0.000
		21	0.988	-0.017	576071	0.000
		22	0.987	0.011	603149	0.000
		23	0.986	0.006	630196	0.000
		24	0.986	-0.000	657211	0.000

This study performed the autocorrelation function (ACF) and partial autocorrelation function (PACF) analysis. There is slow decay in autocorrelation analysis. Therefore, exchange rate data is a non-stationary data.

Then, this study evaluated the stationarity characteristics or the first bitcoin exchange rate difference. Table 4 shows autocorrelation function (ACF) and partial autocorrelation function (PACF) analysis for the first bitcoin exchange rate difference.

Autocorrelation function (ACF) shows strong autocorrelation in a way that does not let us conclude from its order. At the same time, partial autocorrelation function (PACF) shows a significant peak at second order. This indicates the the autoregressive part can be represented by order two. Consequently, we cannot conclude for our ARIMA model and we move on to differentiation.

Table 5 : Correlogram for first difference of Bitcoin exchange rate

Date: 09/23/22 Time: 15:47
Sample: 1/01/2018 00:00 3/04/2021 08:00
Included observations: 27772

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.049	-0.049	66.357	0.000
		2	-0.023	-0.026	81.465	0.000
		3	0.021	0.019	93.751	0.000
		4	-0.030	-0.028	117.94	0.000
		5	-0.013	-0.015	122.41	0.000
		6	0.008	0.005	124.18	0.000
		7	-0.025	-0.024	141.45	0.000
		8	0.034	0.032	173.43	0.000
		9	-0.007	-0.006	174.83	0.000
		10	0.018	0.020	183.35	0.000
		11	0.007	0.006	184.52	0.000
		12	0.030	0.033	209.77	0.000
		13	0.054	0.058	291.24	0.000
		14	-0.020	-0.013	302.17	0.000
		15	0.014	0.016	307.33	0.000
		16	0.019	0.018	316.87	0.000
		17	-0.040	-0.032	360.50	0.000
		18	-0.004	-0.008	361.04	0.000
		19	-0.002	-0.004	361.17	0.000
		20	-0.005	-0.003	361.90	0.000
		21	0.012	0.006	366.20	0.000
		22	-0.018	-0.018	374.97	0.000
		23	-0.001	-0.005	374.99	0.000
		24	-0.043	-0.050	427.16	0.000

The Table 5 shows the first bitcoin price difference lack. this allow us to conclude that our series is stationary in first difference.

- ARIMA

So to conclude for our ARIMA model, the best way is to use an adequate selection criterion based on iterations, the ARIMA model selection table according to the Akaike Information Criterion (AIC)

Table N°. 5 ARIMA model selection table according to the Akaike Information Criterion (AIC)

AR / MA	0.000000	1.000000	2.000000	3.000000	4.000000	5.000000	6.000000	7.000000	8.000000	9.000000	10.00000
0.000000	12.75193	12.74954	12.74909	12.74888	12.74808	12.74795	12.74795	12.74752	12.74619	12.74626	12.74607
1.000000	12.74966	12.74923	12.74874	12.74870	12.74802	12.74709	12.74705	12.74665	12.74626	12.74633	12.74461
2.000000	12.74904	12.74865	12.74817	12.74536	12.74805	12.74537	12.74678	12.74499	12.74513	12.74517	12.74021
3.000000	12.74878	12.74860	12.74879	12.74579	12.74548	12.74523	12.74550	12.74500	12.74083	12.73996	12.74283
4.000000	12.74802	12.74791	12.74797	12.74539	12.74069	12.73921	12.73883	12.73886	12.73941	12.73883	12.73866
5.000000	12.74788	12.74712	12.74541	12.74525	12.73914	12.73892	12.73899	12.73886	12.73890	12.73929	12.73857
6.000000	12.74793	12.74713	12.74701	12.74553	12.73885	12.73899	12.73887	12.74156	12.73729	12.73733	12.73837
7.000000	12.74741	12.74657	12.74708	12.74421	12.74323	12.74415	12.74161	12.73793	12.73798	12.73776	12.73634
8.000000	12.74651	12.74642	12.74646	12.74453	12.73938	12.73891	12.73616	12.73622	12.73686	12.73628	12.73616
9.000000	12.74654	12.74662	12.74565	12.74002	12.73930	12.73852	12.73832	12.73670	12.73518	12.73375	12.73382
10.00000	12.74624	12.74624	12.74041	12.74321	12.73937	12.74604	12.73744	12.73782	12.73396	12.73494	12.73521

after iterations, by the powerful calculation tool, the ARIMA model selection table according to the Akaike Information Criterion (AIC), our model turns out to be an ARIMA(9,1,9).

- **Forecating of price bitcoin ARIMA model**

Dependent variable: PT
Method: ARMA Maximum Likelihood (BFGS)
Date: 09/23/22 Time: 21:31
Sample: 1/01/2018 10:00 3/04/2021 08:00
Included observations: 27763
Convergence achieved after 267 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
PT	0.000298	2.52E-05	11.85158	0.0000
AR(1)	-0.115929	0.020501	-5.654911	0.0000
AR(2)	0.235511	0.012078	19.49970	0.0000
AR(3)	0.517362	0.007232	71.53956	0.0000
AR(4)	-0.368164	0.014635	-25.15708	0.0000
AR(5)	-0.059557	0.018867	-3.156611	0.0016
AR(6)	0.484219	0.014050	34.46321	0.0000
AR(7)	0.408901	0.006376	64.12685	0.0000
AR(8)	-0.456808	0.012427	-36.75858	0.0000
AR(9)	-0.622783	0.017782	-35.02403	0.0000
MA(1)	0.062045	0.021099	2.940647	0.0033
MA(2)	-0.268745	0.013064	-20.57168	0.0000
MA(3)	-0.496816	0.007330	-67.77743	0.0000
MA(4)	0.370494	0.014786	25.05668	0.0000
MA(5)	0.037241	0.019158	1.943891	0.0519
MA(6)	-0.478208	0.014420	-33.16256	0.0000
MA(7)	-0.371487	0.006621	-56.10958	0.0000
MA(8)	0.523433	0.012054	43.42247	0.0000

MA(9)	0.598033	0.018888	31.66240	0.0000
SIGMASQ	19818.53	28.94291	684.7454	0.0000

R-squared	0.020085	Mean dependent var	1.325927
Adjusted R-squared	0.019413	S.D. dependent var	142.2162
S.E. of regression	140.8290	Akaike info criterion	12.73375
Sum squared resid	5.50E+08	Schwarz criterion	12.73968
Log likelihood	-176743.6	Hannan-Quinn criter.	12.73566
Durbin-Watson stat	1.999190		

Inverted AR Roots	.94-.24i	.94+.24i	.53+.84i	.53-.84i
	-.41-.91i	-.41+.91i	-.73-.58i	-.73+.58i
	-.78			
Inverted MA Roots	.95-.25i	.95+.25i	.53+.84i	.53-.84i
	-.41+.90i	-.41-.90i	-.73+.56i	-.73-.56i
	-.75			

Source : Made by the authors

5. INTERPRETATIONS AND DISCUSSIONS

The Augmented Dickey-Fuller (ADF) test is applied to the Bitcoin daily closing price time series and it can be observed that the ADF did not reject the null hypothesis and has a p-value greater than the significance level value of 0.05; thus indicating non-stationarity. Therefore, it is necessary to difference the series to obtain stationarity (Brockwell and Davis, 2012).

Therefore, series became stationary with first difference. (Table 5): Differenced Time Series for Bitcoin Daily Closing Price With stationarity confirmed, the process for ARIMA modelling of the Bitcoin daily closing price time series was carried out.

As a starting point, ARIMA(1,1,0) (Table 3) was conditionally selected based on highest number of significant coefficients and lowest values of volatility and AIC; but must be confirmed by running residual diagnostics to ensure that all its coefficients are within the significance interval.

Running Residual ACF (Table 4: Correlogram for Bitcoin Prices) on ARIMA(1,1,0) showed that there were outliers at lags 1 to 24 which indicates that not all information of the time series has been captured in the model and there was therefore a need for model re-estimation.

Re-estimation involved taking the outliers mentioned above into consideration and re-running residual diagnostics. ARIMA (9,1,9) model was found to present a better performance and its residual diagnostics showed that it has all coefficients located within the confidence interval, this calculation was on (Table 5), with the tool ARIMA model selection table according to the Akaike Information Criterion (AIC).

6. CONCLUSION

In this paper, we have conducted the forecast of Bitcoin daily closing price using the ARIMA model in order to assist investors in their investment decisions. This is because price forecast of Bitcoin constantly attracts attention due to its direct monetary advantage.

Eviews was used for model identification, parameter estimation, diagnostics and forecasting and ARIMA (9,1,9) model was selected as the most suitable based on number of significant coefficients, values of volatility, AIC and BIC, and having all coefficients within the significance interval for residual diagnostics. ARIMA (9,1,9) model gave very close forecast values for the first seven days of forecast with a prediction accuracy of 99 %. Thus, this reinforces the ease of application and suitability of ARIMA models for short - term forecast only; as against more complex models such as artificial neural network models.

From the perspective of BTC investors or users, these results can be useful in understanding BTC price movements and could help in understanding the influence of historical data on BTC price. This elaborate model will precisely help investors in this market to make a decision according to the forecasts obtained.

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