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Modelling and Forecasting the Trend in Cryptocurrency Prices

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ABSTRACT

The prediction of cryptocurrency prices is a hot topic among academics. Nevertheless, predicting the cryptocurrency price accurately can be challenging in the real world. Numerous studies have been undertaken to determine the best model for successful prediction. However, they lacked correct results because they avoided identifying the critical features. It is important to remember that trends are critical features in time series to obtain data information. A dearth of research demonstrates that the cryptocurrency trend comprises linear and nonlinear patterns. Therefore, this study attempted to fill this gap and focused on modelling and forecasting trends in cryptocurrency. This study examined the linear and nonlinear dependency trend patterns of the top five cryptocurrency closing prices. The weekly historical data of each cryptocurrency were taken at different periods due to the availability of data on the system. In achieving its goal, this study examined the results by plotting based on residual trend and diagnostic statistic checking using three deterministic methods: linear trend regression, quadratic trend, and exponential trend. Based on the minimum Akaike Information Criterion (AIC), the result showed that the top five cryptocurrency closing price data series contained nonlinear and linear trend patterns. The information of this study will assist traders and investors in comprehending the trend of the top five cryptocurrencies and choosing the suitable model to predict cryptocurrency prices. Additionally, accurately measuring the forecast will protect investors from losing their investment.

Keywords: Bitcoin, cryptocurrency, linear, nonlinear, trend.

INTRODUCTION

Cryptocurrency is a digital payment system that operates independently of a central monetary authority, such as a government or bank. Cryptocurrencies are created using cryptographic techniques that enable individuals to sell, buy, and trade them securely. It has been established and developed into a global phenomenon in the financial sector, and is widely accepted as a form of alternative currency exchange. It is also used in blockchain transactions. Throughout the previous few years, cryptocurrency has attracted the interest of the media, regulators, academics, and investors. Despite widespread scepticism in the financial sector, it is relevant academic research on cryptocurrencies (David et al., 2021). In addition, cryptocurrency is not merely among the most sophisticated and complex financial instruments. It is also seen as a puzzling financial problem because of its tremendous volatility (Hossain & Ismail, 2021; Zhu et al., 2021), noisy, non-stationary (Zhang et al., 2021), linear, and nonlinear data (Neslihanoglu, 2021).

In recent years, cryptocurrency, specifically the Bitcoin market, has steadily grown in popularity. Bitcoin is the most popular and the first one people think of when it comes to cryptocurrency. Bitcoin is the world's most valuable cryptocurrency. It was created under the pseudonym Satoshi Nakamoto by an unidentified person or group of people (Nakamoto, 2008). The network of nodes began in 2009, with the first node being established in 2009. Even though the system was launched in 2009, people started to use it in 2013. When Bitcoin began to get attention worldwide at the end of 2013, it saw a significant change in its value and the number of transactions. The price of Bitcoin frequently fluctuates dramatically, which causes many investors to rush into the market, oblivious to the risk. Indeed, many factors affect the Bitcoin price, whether internal or external (Khedr et al., 2021). Consequently, it is hard to predict the Bitcoin price accurately.

Ethereum is another popular and leading cryptocurrency on the market. It is a second-generation blockchain system that is intended to hold various data types in addition to transaction data (Antonopoulos & Wood, 2018). Unlike Bitcoin, Ethereum can store numerous types of data, including identity, health care, product, and transaction data. Furthermore, Ethereum's smart contract, which is a function for conducting trade under specific conditions, enhances its utility (Wang et al., 2021).

In a survey by Khedr et al. (2021), cryptocurrency price prediction is a hot topic among scholars, economists, financial analysts, investors, and traders. From their finding, numerous researchers focused their attention on projecting the future investment value of digital cryptocurrencies as their popularity grows. In other findings, some of the research focused on the best models for predicting price (Aditya Pai et al., 2022; Guo et al., 2018; Serrano, 2022; Zhang et al., 2021), return and volatility (Akyildirim et al., 2021; Loginova et al., 2021; Mahdi et al., 2021), and other factors that contribute to market bulling and bearishness (Cavalli & Amoretti, 2021; Huynh et al., 2020; Park & Chai, 2020). Furthermore, machine learning and traditional statistical algorithms for cryptocurrency price prediction are becoming more popular, and academics from various fields are showing interest. These techniques, such as linear regression (Aleksandra et al., 2021; Gandal et al., 2021; Levulytė & Šapkauskienė, 2021), logistic regression (Ibrahim, 2021; Trozze et al., 2022), Bayesian regression (Jalan et al., 2021; Koki et al., 2020), artificial neural network (Al-Ameer & Al-Sunni, 2021; Cahyani & Nuha, 2021; Serrano, 2022), and deep learning (Aditya Pai et al., 2022), are used in this field of research.

Numerous studies have been undertaken to determine the best model for successful prediction. Nevertheless, they lacked correct results because they avoided identifying the behaviour of the market. From the authors' survey, only a limited number of studies identified the behaviour of the market. Modelling the behaviour of the market system helps predict the price of cryptocurrency. It is parallel with the assumption of time series, the trend pattern of the past price behaviour that tends to repeat in the future (Fama, 1965). Therefore, one of the behaviours of the market is identifying the trend time series component in the history data, which will give an idea of what the price pattern will be in the future.

Other than that, to the best of the authors' knowledge, a dearth of research demonstrates that the cryptocurrency trend comprises linear and nonlinear patterns. However, most studies claimed and assumed that the Bitcoin trend data are nonlinear (Ahamed & Ravi, 2021; Fadil et al., 2021; Gao et al., 2021; Lahmiri & Bekiros, 2020) because they look at the graph pattern only without conducting the diagnostic to check the hidden pattern in the data before implementing the advanced analysis. Therefore, this study attempts to fill this gap and focus on modelling and forecasting trends in cryptocurrency. This study uses the linear regression, quadratic, and exponential trends modelling approaches to examine and determine whether the cryptocurrency closing price data contain a trend that is linear, nonlinear, and/or completely nonlinear. One of the study's constraints will be the deterministic trend model, wherein the trend develops in a completely foreseeable manner. In practice, deterministic trend models are very useful. This study focuses on the top five cryptocurrencies in market capitalisation.

This work makes a three-fold contribution: (1) this study illustrates the trend of the closing price for the top five cryptocurrencies based on a time series plot, and the modelling trend indirectly contributes to the current literature on cryptocurrency trend modelling; (2) demonstrates the trend by fitting and modelling a linear trend regression model, quadratic trend model, and exponential trend model; and (3) compares the performance of these three trend models for the closing price of the top five cryptocurrencies.

METHODOLOGY

Data Sources

This study illustrates the trend modelling in the time-varying of the top five cryptocurrencies with the highest market capitalisation identified in January 2022. The study examined the following sample of five cryptocurrencies deemed representative of more than 9,000 cryptocurrencies circulated, as the Yahoo Finance website reported in January 2022. The total of cryptocurrencies in the system will change from time to time. Therefore, this study utilised January 2022 as a benchmark for data collection. The timespan history data this study took of each cryptocurrency were different due to the availability of data on the system based on the existence of cryptocurrency mines. Bitcoin is the oldest cryptocurrency currently in existence and has the largest market capitalisation compared to other cryptocurrencies. The sample data of the top five cryptocurrencies vary in terms of the start and end dates for all cryptocurrencies on 24 January 2022. The detailed samples are as follows:

1. Bitcoin (BTC) – Bitcoin is the oldest cryptocurrency currently in existence. It has the largest market capitalisation with $660 billion of all cryptocurrencies and concerns the vast majority of scholarly research. The weekly closing price data coverage was from 5 January 2015 to 24 January 2011 (369 observations).

2. Ethereum (ETH) – Ethereum is the second most valuable cryptocurrency after Bitcoin in terms of market capitalisation, with $290 billion. The weekly closing price data coverage was from 6 November 2017 to 24 January 2022 (221 observations).

3. Tether (USDT) – Tether is the world's third largest cryptocurrency by market capitalisation, with $79 billion. The weekly closing price data coverage was from 6 November 2017 to 24 January 2022 (221 observations).

4. Binance Coin (BNB) – Binance is the fourth largest cryptocurrency, with around $60 billion in market capitalisation. The weekly closing price data coverage was from 6 November 2017 to 24 January 2022 (221 observations).

5. U.S. Dollar Coin (USDC) – USDC is the fifth largest market capitalisation with $50 billion. The weekly closing price data coverage was from 5 November 2018 to 24 January 2022 (169 observations).

The modelling and forecasting trend has been analysed using E-views version 12.0.

Estimation and Evaluation Procedure

Three stages were required to assess the forecasting performance of the models. Therefore, this study split the data into two portions in the first stage, namely model estimation and evaluation (holdout data part). An evaluation was conducted to identify the models' forecasting performance. This study divided all the cryptocurrency datasets by 70 percent observations as an estimation part and 30 percent as an evaluation part. All Bitcoin models were estimated using data from 5 January 2015 until 30 December 2019 (261 observations). The remaining observations from 6 January 2020 to 24 January 2022 (108 observations) were used to evaluate the models. The estimation period for ETH was from 6 November 2017 to 19 October 2020 (155 observations), and the evaluation period was 26 October 2020 to 24 January 2022 (66 observations). Other cryptocurrency details are shown in Table 1.

The models were estimated via quadratic, linear, and exponential trend regressions in the second stage. Finally, estimated models were assessed at the third stage by comparing their performance to other estimated models. Consequently, the best model was chosen. The findings of comparing their various error measures were used as the selection criterion. The best model needs to produce the smallest value of the error measure.

Table 1

Data Sample and Market Capitalisation

Cryptocurrency	Sample Period	Total Sample	Market Capitalisation
Bitcoin	5 January 2015 – 24 January 2022	369	$660 billion
	Estimation: 5 January 2015 – 30 December 2019	261	
	Evaluation: 6 January 2020 – 24 January 2022	108	
ETH	6 November 2017 – 24 January 2022	221	$290 billion
	Estimation: 6 November 2017 – 19 October 2020	155	
	Evaluation: 26 October 2020 – 24 January 2022	66	

(continued)

Cryptocurrency	Sample Period	Total Sample	Market Capitalisation
USDT	6 November 2017 – 24 January 2022	221	$79 billion
	Estimation: 6 November 2017 – 19 October 2020	155	
	Evaluation: 26 October 2020 – 24 January 2022	66	
BNB	6 November 2017 – 24 January 2022	221	$60 billion
	Estimation: 6 November 2017 – 19 October 2020	155	
	Evaluation: 26 October 2020 – 24 January 2022	66	
USDC	5 November 2018 – 24 January 2022	169	$50 billion
	Estimation: 5 November 2017 – 1 February 2021	118	
	Evaluation: 8 February 2021 – 24 January 2022	51	

Modelling Trends

It is empirically evident that there is a trend. Trends can be seen in numerous series in a wide range of disciplines. The trend looks generally linear, i.e., rises or falls in a straight line. The trend is well described by a simple linear function of time as given in Equation 1:

$$T_t = \beta_0 + \beta_1 TIME_t \tag{1}$$

where T_t is the linear trend and *TIME* denotes the time trend. *TIME* = (1, 2, 3, …, *T-1*, *T*), that is to say, $TIME_t = t$, while β_0 represents the regression intercept. It resembles the trend value at time t = 0, while β_1 denotes the regression slope. If the trend is increasing, it is positive. Nonetheless, if the trend is declining, it is negative. Therefore, the bigger the absolute value of β_1, the steeper the slope of the trend.

Sometimes trend appears nonlinear or curved. Quadratic trend models can potentially capture nonlinearities. These trends are quadratic rather than linear in nature, where the function of time is given by Equation 2:

$$T_t = \beta_0 + \beta_1 TIME_t + \beta_2 TIME_t^2 \tag{2}$$

where T_t is the quadratic trend and when $\beta_2 = 0$, a linear trend appears as a special case. Moreover, higher-order polynomial trends are occasionally considered, although maintaining smoothness necessitates the use of low-order polynomials. Based on the signs and magnitude of the coefficients, various of nonlinear quadratic trend shapes are available. In particular, if $\beta_1 > 0$ and $\beta_2 > 0$, the trend is monotonically, but nonlinearly, increasing. Conversely, if $\beta_1 < 0$ and $\beta_2 < 0$, the trend is monotonically decreasing. If $\beta_1 < 0$ and $\beta_2 > 0$, the trend has a U shape, and if $\beta_1 > 0$ and $\beta_2 < 0$, the trend has an inverted U shape. The diverse shapes or pattern curves depend on the signs and size of the parameters.

Other nonlinear trends, for instance, the logarithm of y, are sometimes appropriate. The phenomenon known as a log-linear trend or exponential trend occurs when a trend seems linear in logarithms but nonlinear in levels. It is particularly common in finance, business, and economics. Economic variables have a roughly constant growth rate. Therefore, if the trend is defined by constant growth at rate β_1, it can be expressed as in Equation 3:

$$T_t = \beta_0 e^{\beta_1 \mathrm{TIME}_t} \tag{3}$$

The exponential trends depend on parameters. The trend is a nonlinear (exponential) function of time at a level. However, in logarithms, it is expressed as in Equation 4:

$$\ln\left(T_t\right) = \ln\left(\beta_0\right) + \beta_1 \mathrm{TIME}_t \tag{4}$$

Therefore, (T_t) resembles a linear function of time.

Measuring the Models' Performance

In terms of estimation and evaluation samples, the goodness-of-fit of the estimated models was evaluated. The following measurements were used to evaluate the performance: mean square error (MSE), root mean square error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE), as expressed in Equations 5–8:

$$\mathrm{MSE} = \frac{\sum_t^n \left(y_t - \widehat{y}_t\right)^2}{} \tag{5}$$

$$\mathrm{RMSE}=\sqrt{\frac{\sum_{t}^{n}\left(y_t-\widehat{y}_t\right)^2}{n}}, \tag{6}$$

$$\mathrm{MAE}=\sum_{t=1}^{n}\frac{\left|\left(\frac{e_t}{y_t}\right)\right|}{n}, \tag{7}$$

$$\mathrm{MAPE}=\sum_{i=1}^{n}\frac{\left|\left(\frac{e_t}{y_t}\right)\times 100\right|}{n}, \tag{8}$$

y_t represents the actual observed value in time t

$\widehat{y}_t$ resembles the fitted value in time t

n is the effective data points

$e=y_t-\widehat{y}_t$

The models were then estimated and evaluated by analysing the estimated models' performance against one another. Finally, the benchmark model was used to compare the standard model to the benchmark model. As a result, the winning model would be chosen as the best model. The criterion for selection was based on the findings of a comparison of their various measures. A model needs to produce the lowest value of error measures to win.

Durbin-Watson Test for Serial Correlation

If the errors generated by a forecasting model are serially correlated, they are forecastable. Therefore, this study must enhance the forecasts by forecasting the forecast errors according to a popular test for serial correlation over time according to the Durbin-Watson (DW) statistic. The DW statistic's formula is as in Equation 9:

$$\mathrm{DW}=\frac{\sum_{i=2}^{n}\left(\varepsilon_t-\varepsilon_{t-1}\right)^2}{\sum_{t=1}^{n}\varepsilon_t^2}, \tag{9}$$

n which

$$\varepsilon_t = y_t - \widehat{y_t}$$

$\widehat{y}_t$ denotes the dependent variable's estimated or forecast value

y_t represents the dependent variable's actual value

When a positive error follows a positive error in one period in the next, this is known as a positive serial correlation. Conversely, a negative serial correlation occurs when negative errors in one period are linked to positive errors in the following period and vice versa. The DW value is between 0 and 4, and a value of 2 implies no first-order serial correlation, that is, when $\rho = 0$. The test results can be summarised as follows:

When DW < 2, there is a positive serial correlation.
When DW > 2, there is a negative serial correlation.
When DW is near 2, there is no first-order serial correlation.

The Akaike Information Criterion (AIC)

AIC is a mathematical test that determines how well a model fits the data it is supposed to represent. It penalises models with more independent variables (parameters) to avoid over-fitting. AIC is most commonly employed to analyse the relative goodness-of-fit of various models and then select the model that best fits the data. It is essentially a prediction of out-of-sample forecast variance. Nevertheless, it penalises the degree of freedom more severely. It is employed to choose between forecasting models that are competing, as represented in Equation 10:

$$\mathrm{AIC} = e^{\left(\frac{2k}{T}\right)} \frac{\sum_{t=1}^{T} e_t^2}{T}. \qquad (10)$$

The Schwarz Information Criterion (SIC)

SIC is similar to AIC but with a higher degree of freedom penalty and is calculated using Equation 11:

$$\mathrm{SIC} = T\left(\frac{k}{T}\right) \frac{\sum_{t=1}^{T} e_t^2}{T}. \qquad (11)$$

RESULTS AND DISCUSSION

The descriptive analysis of the cryptocurrency closing price of Bitcoin, ETH, USDT, BNB, and USDC is shown in Table 2. Bitcoin had the highest closing price of $65,466.84 with a standard deviation of $16,213.56 and an average of $11,608.63. Meanwhile, the lowest closing price was USDT and USDC, which had the same value of $1.02. USDT and USDC also had low risk and low return since they had the lowest value standard deviation compared to other cryptocurrencies. Additionally, all cryptocurrency closing price data were not normal and highly skewed with a skewness value of more than 1, except for USDT that had moderate skewness.

Table 2

Descriptive Analysis of Cryptocurrency Closing Price

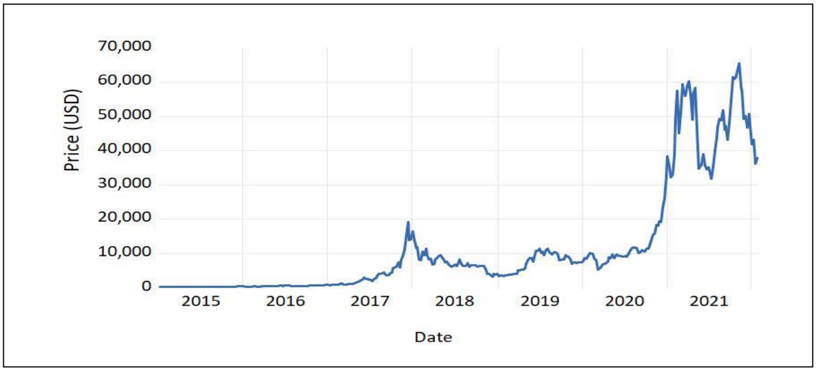
Cryptocurrency	Mean	Standard Deviation	Median	Min	Max	Mode	Skewness	Kurtosis
Bitcoin	11608.63	16213.56	6482.35	210.34	65466.84	458.55	1.85	2.26
ETH	970.02	1209.71	371.05	85.26	4626.35	N/A	1.57	1.23
USDT	1.00	0.005	1.00	0.98	1.02	0.99	0.83	4.25
BNB	111.26	181.37	19.49	1.52	662.23	12.12	1.65	1.25
USDC	1.00	0.006	1.00	0.97	1.02	1.00	1.44	4.63

The study illustrated a closing price plot of Bitcoin, ETH, USDT, BNB, and USDC, as depicted in Figure 1. This plot demonstrated Bitcoin, ETH, and BNB's distinct nonlinear trends while the other two showed stability. Bitcoin experienced tremendous growth. In January 2015, the price of a Bitcoin was about $200. In contrast, a single Bitcoin's price was over $50,000 as of January 2022, which was a growth of about $49,800. Furthermore, according to Knight (2021), the bell curve shape could be seen in the first major Bitcoin bull run in late December 2017, when the price rose from around $3,000 to almost $20,000. The Bitcoin price rose sharply from $11,000 to $63,000 in mid-2021 before falling back to $30,000. ETH also saw significant growth. Its price increased nearly 4,300 percent from November 2017 to January 2022, from about $300 to over $4,600. Unlike some other forms of cryptocurrency, USDT is a stable coin, which means that USDT's value is supposed to be more consistent than other cryptocurrencies. Therefore, it is favoured by investors who are wary of the extreme volatility of other coins. While BNB Coin was launched in 2017 with a closing price of $1, by 1 January 2022, it had risen to around $400, a gain of around 400 percent. USDC is also a stable coin that works similarly to USDT.

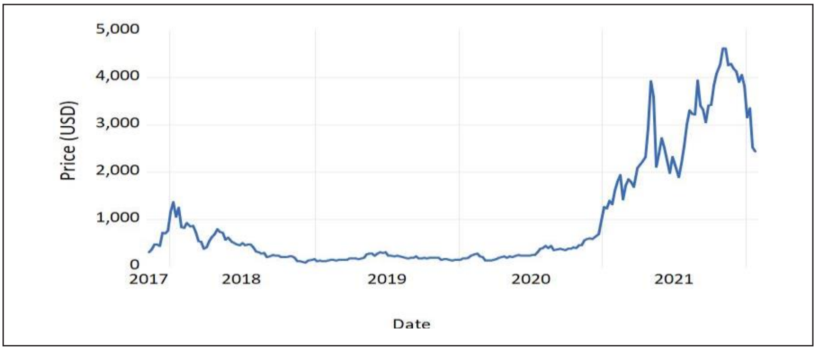
Table 3 shows the results of fitting a linear trend model using the closing price on a constant and a linear time trend. The time trend in Bitcoin, ETH, BNB, and USDC, appeared to be very significant, according to the *p*-value of the *t*-statistic on the time trend, except for USDT. According to the DW statistics, the disturbances were also positively serially correlated for all cryptocurrencies, indicating that each disturbance at time t was positively associated with the disturbance at time $t-1$. Nevertheless, it appeared that R^2 for Bitcoin was 0.60. The value showed that the variation of a time trend explained 60.0 percent of the total variation of Bitcoin's closing price. At the same time, the other 47.5 percent were contributed by other factors not accounted for in the model. This observation implied that R^2 for Bitcoin was moderate, while other cryptocurrencies showed weak linear relations. Nevertheless, the study used information criteria and error measurements instead of the R^2 value to answer the objective.

Figure 1

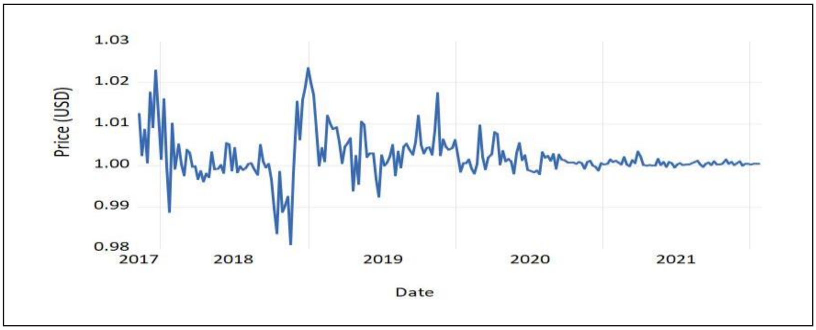
Closing Price



a) Bitcoin



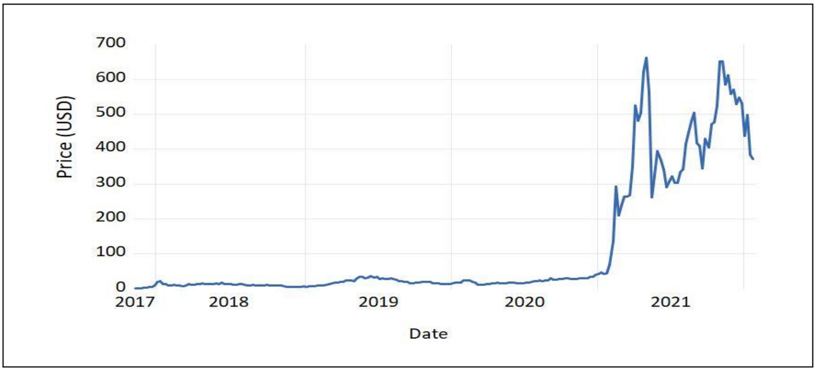
b) Ethereum



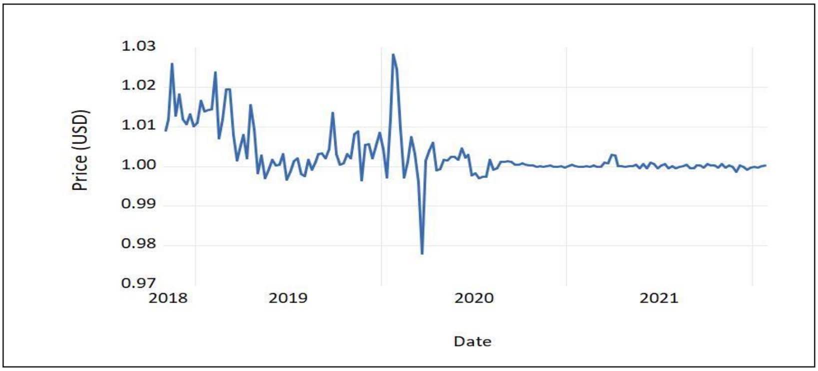
c) Tether

Figure 1

Closing Price (cont'd)



d) Binance



e) USD Coin

Table 3

Closing Price, Linear Trend Regression

Cryptocurrency	Variable	Coefficient	Std. Error	t-Statistic	Prob.
Bitcoin	c	-1350.26	315.82	-4.28	0.00
	TIME	40.78	2.09	19.51	0.00
	R-squared	0.60	Mean dependent var		3992.21
	Adjusted R-squared	0.59	SD dependent var		3990.43
	SE of regression	2543.77	Akaike info criterion		18.53
	Sum squared resid	1.68E+09	Schwarz info criterion		18.56
	Log-likelihood	-2415.95	F-statistic		380.82
	Durbin-Watson stat	0.10	Prob (F-statistic)		0.00
ETH	c	544.95	32.41	16.81	0.00
	TIME	-2.85	0.36	-7.90	0.00
	R-squared	0.29	Mean dependent var		322.81
	Adjusted R-squared	0.29	SD dependent var		237.48
	SE of regression	200.79	Akaike info criterion		13.46
	Sum squared resid	6168325.00	Schwarz info criterion		13.49

Table 3

Closing Price, Linear Trend Regression (cont'd)

Cryptocurrency	Variable	Coefficient	Std. Error	t-Statistic	Prob.
	Log-likelihood	-1040.78	F-statistic		62.43
	Durbin-Watson stat	0.14	Prob (F-statistic)		0.00
USDT	c	1.00	0.00	964.19	0.00
	TIME	-6.84E-06	1.16E-05	-0.59	0.56
	R-squared	1.0E-03	Mean dependent var		1.00
	Adjusted R-squared	-4.0E-03	SD dependent var		6.0E-03
	SE of regression	6.00E-03	Akaike info criterion		-7.24
	Sum squared resid	6.00E-03	Schwarz info criterion		-7.20
	Log-likelihood	562.95	F-statistic		0.35
	Durbin-Watson stat	0.96	Prob (F-statistic)		0.56
BNB	c	8.53	1.03	8.29	0.00
	TIME	0.10	0.01	8.54	0.00
	R-squared	0.32	Mean dependent var		16.15
	Adjusted R-squared	0.32	SD dependent var		7.72

Table 3

Closing Price, Linear Trend Regression (cont'd)

Cryptocurrency	Variable	Coefficient	Std. Error	t-Statistic	Prob.
	SE of regression	6.37	Akaike info criterion		6.56
	Sum squared resid	6215.19	Schwarz info criterion		6.59
	Log-likelihood	-506.01	F-statistic		72.94
	Durbin-Watson stat	0.14	Prob (F-statistic)		0.00
USDC	c	1.01	1.13E-03	894.93	0.00
	TIME	-1.1E-04	1.65E-05	-6.69	0.00
	R-squared	0.28	Mean dependent var		1.00
	Adjusted R-squared	0.27	SD dependent var		7.14E-03
	SE of regression	6.10E-03	Akaike info criterion		-7.35
	Sum squared resid	4.31E-03	Schwarz info criterion		-7.30
	Log-likelihood	435.41	F-statistic		44.74
	Durbin-Watson stat	0.99	Prob (F-statistic)		0.00

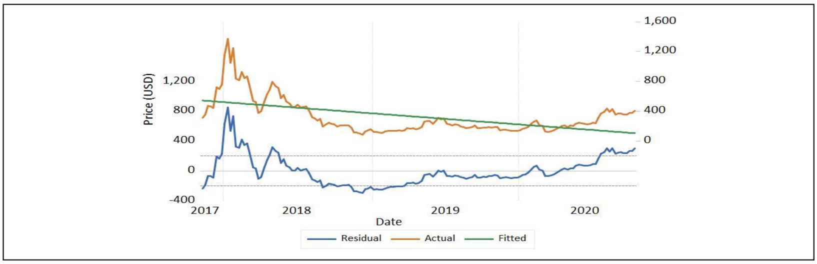
Figure 2 shows the residual plot. From the plot, all the cryptocurrencies had a non-random pattern. Since the actual trend was nonlinear, the linear trend was simply insufficient, causing the residual trend's high serial correlation. In addition, for Bitcoin, the closing price from 2015 to mid-2017 was below the trend line, while the closing price from mid-2017 to 2018 was above. Then, towards the end of 2018, the data began to decline gradually, while towards the middle of 2019, the data gradually increased the trend line. For ETH, the closing price from 2017–2018 was above the trend line, the closing price from mid-2018 to early 2019 was below the trend line, and then from mid-2019 to 2020, the closing price was around the trend line. While USDT showed no significant trend on the graph, it was proven by the p-value of the t-statistic in the linear trend regression model. Whereas for BNB, the closing price from early to mid-2019 was above the trend. For USDC, there was a negative trend line with a small coefficient of -0.000 110, indicating that the trend was more consistent than Bitcoin, ETH, and BNB.

This study exhibited a ±1 standard error of the regression alongside the residual for visual reference. The results of fitting a quadratic trend model are shown in Table 4. The quadratic and linear terms both appeared to be very important. Additionally, in ETH, BNB and USDC, the linear and quadratic time trends were very significant. At the same time, Bitcoin was insignificant on the quadratic trend, while USDT was insignificant in both trends.

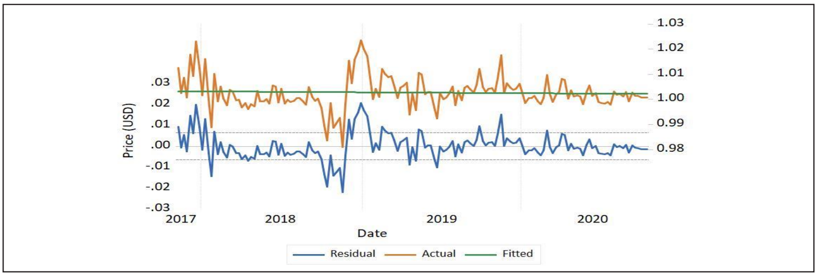
Figure 2

Closing Price, Linear Trend Residual Plot

a) Bitcoin



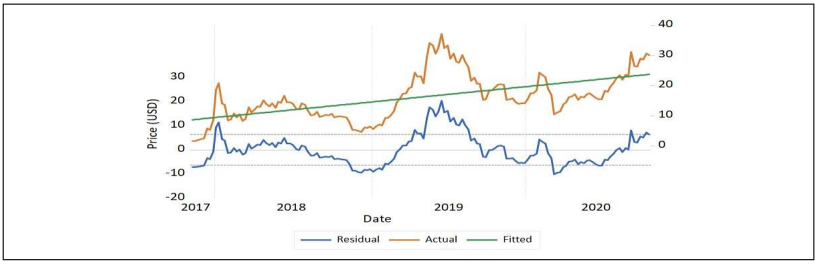
b) Ethereum



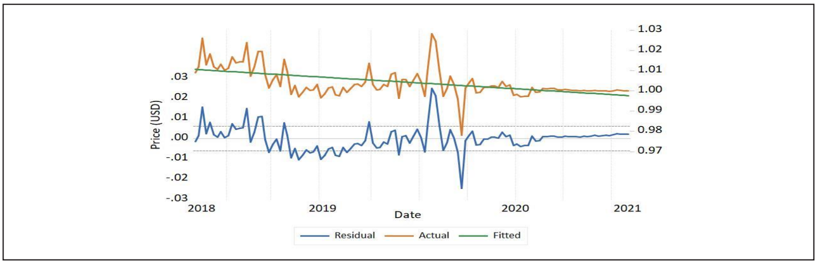
c) Tether

Figure 2

Closing Price, Linear Trend Residual Plot (cont'd)



c) Binance



c) USD Coin

Table 4

Closing Price, Quadratic Trend Regression

Cryptocurrency	Variable	Coefficient	Std. Error	t-Statistic	Prob.
Bitcoin	c	-1416.46	476.90	-2.97	0.00
	TIME	42.29	8.41	5.03	0.00
	TIME2	-5.77E-03	0.03	-0.19	0.85
	R-squared	0.60	Mean dependent var		3992.21
	Adjusted R-squared	0.59	SD dependent var		3990.43
	SE of regression	2548.52	Akaike info criterion		18.54
	Sum squared resid	1.68E+09	Schwarz info criterion		18.58
	Log-likelihood	-2415.93	F-statistic		189.72
	Durbin-Watson stat	0.10	Prob (F-statistic)		0.00
ETH	c	866.69	34.75	24.94	0.00
	TIME	-15.14	1.029	-14.72	0.00
	TIME2	0.08	6.39E-03	12.34	0.00
	R-squared	0.65	Mean dependent var		322.81
	Adjusted R-squared	0.64	SD dependent var		237.48

Table 4

Closing Price, Quadratic Trend Regression (cont'd)

Cryptocurrency	Variable	Coefficient	Std. Error	t-Statistic	Prob.
	SE of regression	142.37	Akaike info criterion		12.77
	Sum squared resid	3081058.00	Schwarz info criterion		12.83
	Log-likelihood	-986.98	F-statistic		138.23
	Durbin-Watson stat	0.30	Prob (F-statistic)		0.00
USDT	c	1.00	1.58E-03	635.45	0.00
	TIME	-3.74E-07	4.67E-05	-7.94E-03	0.99
	TIME2	-4.15E-08	2.90E-07	-1.43E-04	0.89
	R-squared	2.4E-03	Mean dependent var		1.00
	Adjusted R-squared	-0.01	SD dependent var		6.43E-03
	SE of regression	6.5E-03	Akaike info criterion		-7.22
	Sum squared resid	6.4E-03	Schwarz info criterion		-7.17
	Log-likelihood	562.96	F-statistic		0.18
	Durbin-Watson stat	0.96	Prob (F-statistic)		0.83
BNB	c	6.54	1.55	4.23	0.00

Table 4

Closing Price, Quadratic Trend Regression (cont'd)

Cryptocurrency	Variable	Coefficient	Std. Error	t-Statistic	Prob.
	TIME	0.17	0.05	3.79	0.0002
	TIME2	-4.87E-04	2.84E-03	-1.71	0.09
	R-squared	0.34	Mean dependent var		16.15
	Adjusted R-squared	0.33	SD dependent var		7.72
	SE of regression	6.33	Akaike info criterion		6.55
	Sum squared resid	6097.53	Schwarz info criterion		6.61
	Log-likelihood	-504.53	F-statistic		38.40
	Durbin-Watson stat	0.14	Prob (F-statistic)		0.00
USDC	c	1.04	1.66E-03	611.70	0.00
	TIME	-2.94E-04	6.43E-05	-4.57	0.00
	TIME2	1.54E-06	5.24E-07	2.94	3.90E-03
	R-squared	0.33	Mean dependent var		1.00
	Adjusted R-squared	0.32	SD dependent var		7.14E-03
	SE of regression	5.90E-03	Akaike info criterion		-7.40

Table 4

Closing Price, Quadratic Trend Regression (cont'd)

Cryptocurrency	Variable	Coefficient	Std. Error	t-Statistic	Prob.
	Sum squared resid	4.01E-03	Schwarz info criterion		-7.33
	Log-likelihood	439.70	F-statistic		28.19
	Durbin-Watson stat	1.07	Prob (F-statistic)		0.00

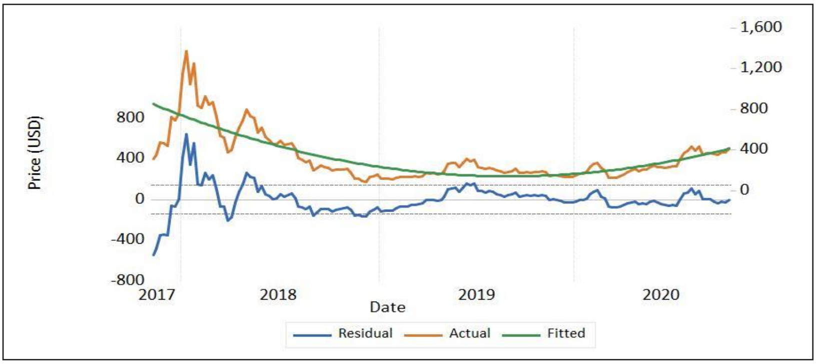
Figure 3 illustrates the quadratic trend residual plot. The residual still had persistent dynamics, as evidenced by the low DW statistic. Nevertheless, these dynamics are challenging to be described with the trend since they are tied to the market cycle rather than the growth trend. According to Knight (2021), the bell curve is a well-known technique to identify market cycle phases: accumulation, run-up (bull market), price plateau phase, and run-down phase (bear market), as well as the best tool to determine the time to enter and exit the market. The accumulation phase is when the market has bottomed out. This phase is the start of a new cycle. At this point in the cycle, the price is at its lowest. It is also a turning point in market sentiment, shifting from negative to positive. Then, when the market starts to move higher at a faster rate, it is said to be in a bull market. For example, the bull phase of Bitcoin in December 2017 was the most considerable price increase, when the price increased from \$3,000 to nearly \$20,000. Again, the same pattern occurred in 2021, with another significant price increase where the price increased from \$10,000 to \$63,000, as depicted in Figure 1. While it is possible to say that the cycle lasted around four years, there is no definitive time frame for a cycle. Then, the bear market began to move from highest to lowest, as can be seen when the ETH price graph started to decrease from \$700 to \$100.

This study then estimated an exponential trend, which is a distinct form of the nonlinear trend model. This study started with an ordinary least square (OLS) regression of the log of closing price on a linear and constant time trend variable. Table 5 and Figure 4 showed the estimated findings and residual plot. The results of fitting a linear trend to the closing price were low. Fitting a linear to the closing price log appeared to improve the results significantly for Bitcoin, but other cryptocurrency's price was still maintained. However, since the quadratic and linear models were in levels, not logs, it was difficult to compare the log-linear trend model. Consequently, diagnostic measures, such as R^2 and regression standard error, were incomparable. The exponential trend model could be directly estimated in level through nonlinear least squares, which was one way around this problem. The residual plot for the exponential trend model is shown in Table 4 and Figure 5. The residual plot and diagnostic statistics signified that the exponential trend was worse than the linear and quadratic for all cryptocurrencies except ETH.

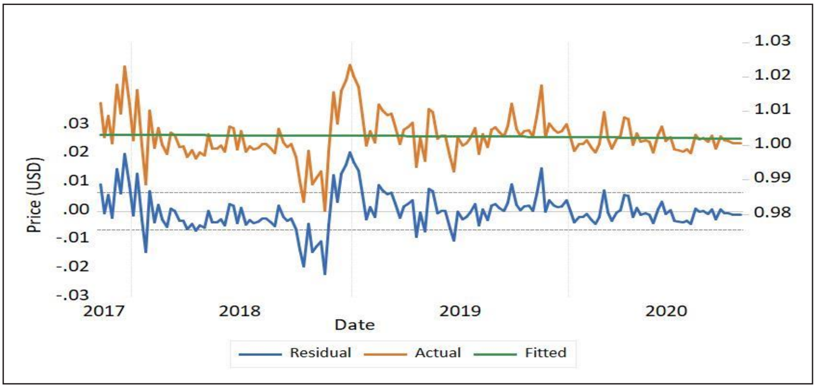
Figure 3

Closing Price, Quadratic Trend Residual Plot

a) Bitcoin



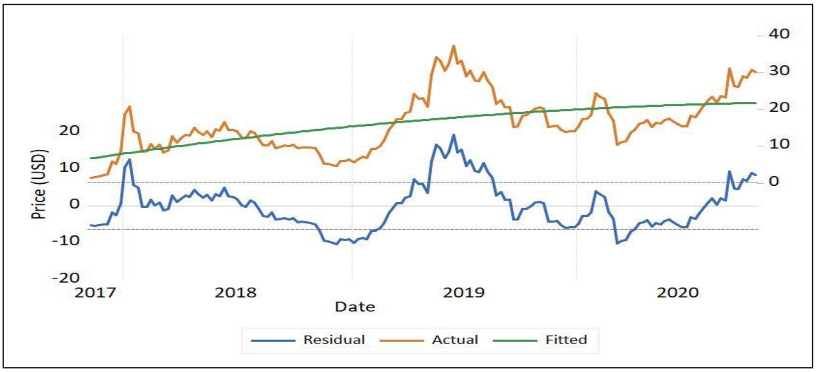
b) Ethereum



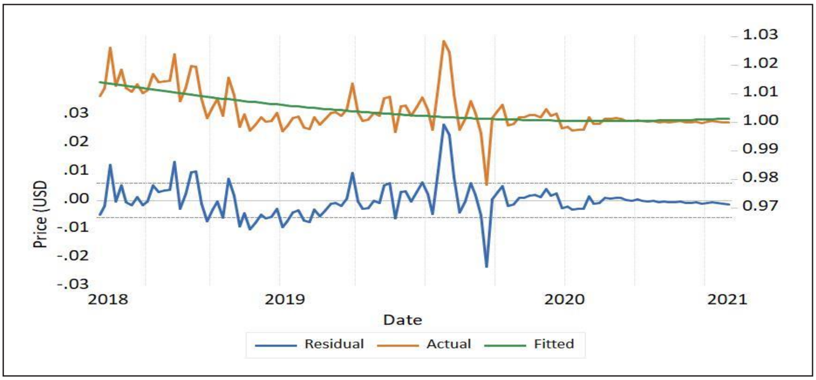
c) Tether

Figure 3

Closing Price, Quadratic Trend Residual Plot (cont'd)



d) Binance



e) USD Coin

Table 5

Closing Price, Log-Linear Trend Regression

Cryptocurrency	Variable	Coefficient	Std. Error	t-Statistic	Prob.
Bitcoin	c	5.26	0.07	76.56	0.00
	TIME	1.73E-02	4.54E-04	37.98	0.00
	R-squared	0.85	Mean dependent var		7.52
	Adjusted R-squared	0.85	SD dependent var		1.41
	SE of regression	0.55	Akaike info criterion		1.66
	Sum squared resid	79.23	Schwarz info criterion		1.69
	Log-likelihood	-214.77	F-statistic		1442.60
	Durbin-Watson stat	0.04	Prob (F-statistic)		0.00
ETH	c	6.07	32.41	16.81	0.00
	TIME	-6.36E-03	0.36	-7.90	0.00
	R-squared	0.22	Mean dependent var		5.58
	Adjusted R-squared	0.22	SD dependent var		0.60
	SE of regression	0.53	Akaike info criterion		1.59
	Sum squared resid	43.44	Schwarz info criterion		1.63

Table 5

Closing Price, Log-Linear Trend Regression (cont'd)

Cryptocurrency	Variable	Coefficient	Std. Error	t-Statistic	Prob.
	Log-likelihood	-121.36	F-statistic		44.15
	Durbin-Watson stat	0.08	Prob (F-statistic)		0.00
USDT	c	3.17E-03	1.04E-03	3.06	2.6E-03
	TIME	-6.84E-06	1.15E-05	-0.57	0.57
	R-squared	2.12E-03	Mean dependent var		2.70E-03
	Adjusted R-squared	-4.40E-03	SD dependent var		6.41E-03
	SE of regression	6.42E-03	Akaike info criterion		-7.25
	Sum squared resid	6.31E-03	Schwarz info criterion		-7.21
	Log-likelihood	563.56	F-statistic		0.33
	Durbin-Watson stat	0.96	Prob (F-statistic)		0.57
BNB	c	2.03	0.08	26.41	0.00
	TIME	7.85E-03	8.54E-04	9.19	0.00
	R-squared	0.36	Mean dependent var		2.64
	Adjusted R-squared	0.35	SD dependent var		0.59

Table 5

Closing Price, Log-Linear Trend Regression (cont'd)

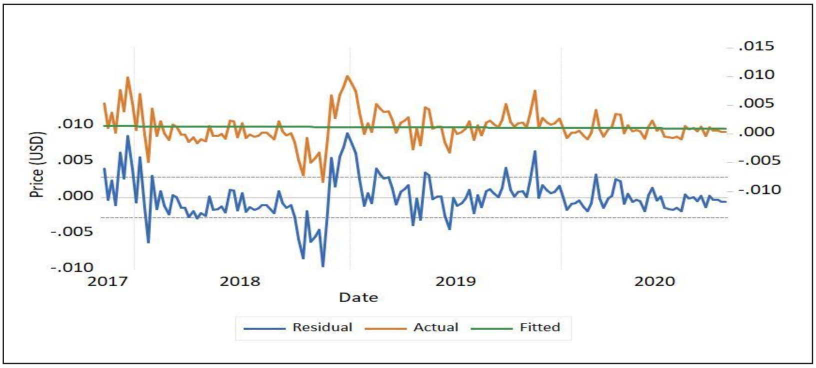
Cryptocurrency	Variable	Coefficient	Std. Error	t-Statistic	Prob.
	SE of regression	0.48	Akaike info criterion		1.37
	Sum squared resid	34.65	Schwarz info criterion		1.40
	Log-likelihood	-103.82	F-statistic		84.37
	Durbin-Watson stat	0.12	Prob (F-statistic)		0.00
USDC	c	0.01	1.12E-03	9.46	0.00
	TIME	-1.09E-04	1.64E-05	-6.69	0.00
	R-squared	0.28	Mean dependent var		4.10E-03
	Adjusted R-squared	0.27	SD dependent var		7.09E-03
	SE of regression	6.05E-032	Akaike info criterion		-7.36
	Sum squared resid	4.25E-03	Schwarz info criterion		-7.31
	Log-likelihood	436.25	F-statistic		44.74
	Durbin-Watson stat	0.99	Prob (F-statistic)		0.00

Figure 4

Closing Price, Log-Linear Trend Residual Plot

a) Bitcoin

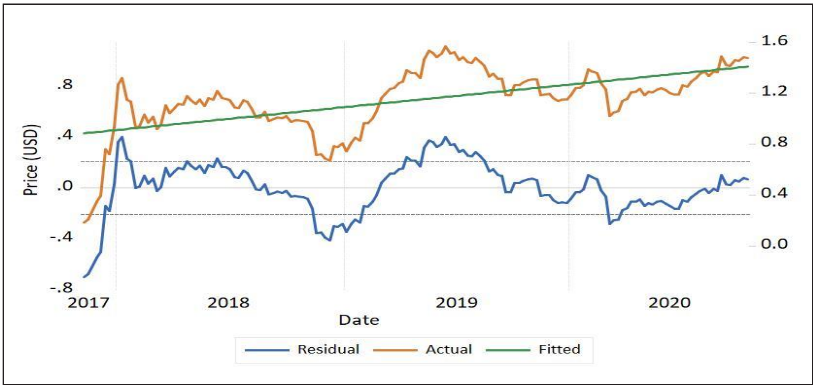
b) Ethereum



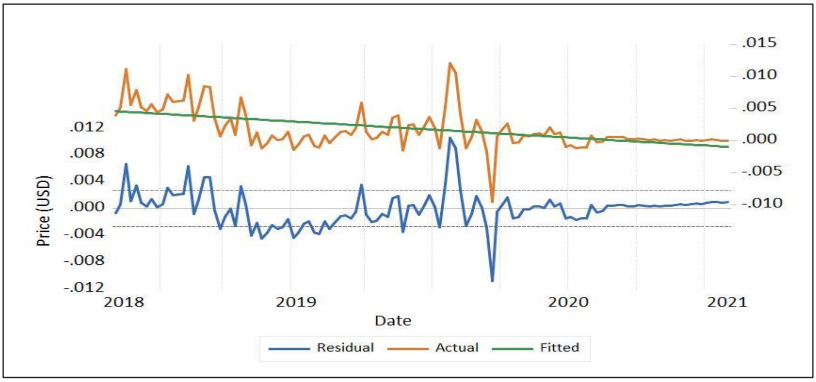
c) Tether

Figure 4

Closing Price, Log-Linear Trend Residual Plot (cont'd)



d) Binance



e) USD Coin

Table 6

Closing Price, Exponential Trend Regression

Cryptocurrency	Variable	Coefficient	Std. Error	t-Statistic	Prob.
Bitcoin	C(1)	1109.93	159.95	6.94	0.00
	C(2)	8.60E-03	6.78E-04	12.67	0.00
	R-squared	0.53	Mean dependent var		3992.21
	Adjusted R-squared	0.52	SD dependent var		3990.43
	SE of regression	2753.36	Akaike info criterion		18.69
	Sum squared resid	1.96E+09	Schwarz info criterion		18.71
	Log-likelihood	-2436.61	Durbin-Watson stat		0.09
ETH	C(1)	752.58	44.96	16.74	0.00
	C(2)	-0.01	1.28E-03	-10.75	0.00
	R-squared	0.44	Mean dependent var		322.81
	Adjusted R-squared	0.43	SD dependent var		237.48
	SE of regression	178.66	Akaike info criterion		13.22
	Sum squared resid	4883771.00	Schwarz info criterion		13.26
	Log-likelihood	-1022.68	Durbin-Watson stat		0.18

Table 6

Closing Price, Exponential Trend Regression (cont'd)

Cryptocurrency	Variable	Coefficient	Std. Error	t-Statistic	Prob.
USDT	C(1)	1.00	1.04E-03	963.93	0.00
	C(2)	-6.82E-06	1.15E-05	-0.59	0.56
	R-squared	2.28E-03	Mean dependent var		1.00
	Adjusted R-squared	-4.24E-03	SD dependent var		6.43E-03
	SE of regression	6.45E-03	Akaike info criterion		-7.24
	Sum squared resid	6.36E-03	Schwarz info criterion		-7.20
	Log-likelihood	562.95	Durbin-Watson stat		0.96
BNB	C(1)	10.04	0.08	26.41	0.00
	C(2)	5.70E-03	8.54E-04	9.19	0.00
	R-squared	0.30	Mean dependent var		16.15
	Adjusted R-squared	0.30	SD dependent var		7.72
	SE of regression	6.46	Akaike info criterion		6.58
	Sum squared resid	6383.48	Schwarz info criterion		6.62
	Log-likelihood	-508.08	Durbin-Watson stat		0.13

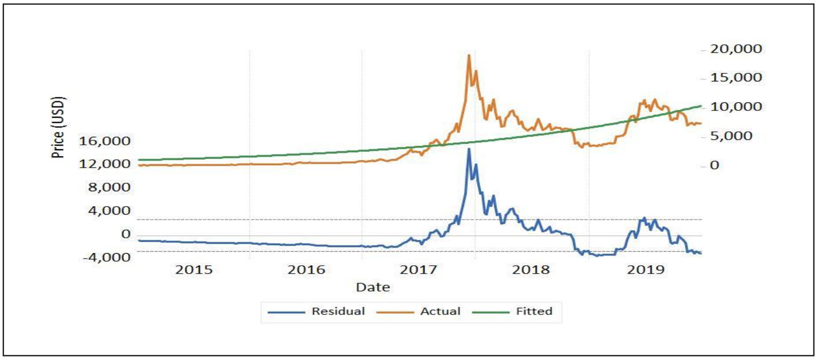
Table 6

Closing Price, Exponential Trend Regression (cont'd)

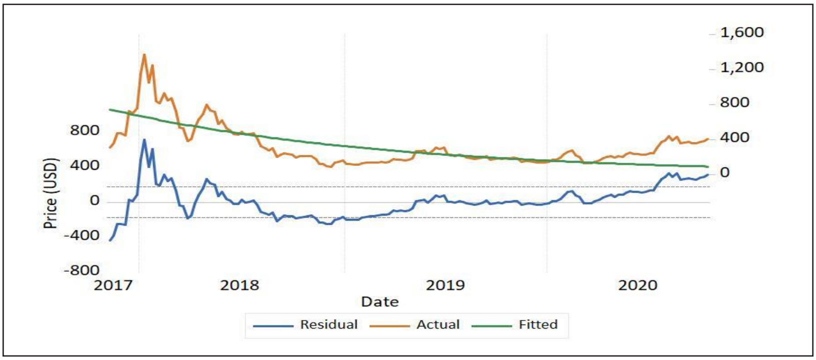
Cryptocurrency	Variable	Coefficient	Std. Error	t-Statistic	Prob.
USDC	C(1)	1.01	1.13E-03	892.24	0.00
	C(2)	-1.10E-04	1.64E-05	-6.70	0.00
	R-squared	0.28	Mean dependent var		1.00
	Adjusted R-squared	0.27	SD dependent var		7.14E-03
	SE of regression	6.09E-03	Akaike info criterion		-7.35
	Sum squared resid	4.31E-03	Schwarz info criterion		-7.30
	Log-likelihood	435.44	Durbin-Watson stat		0.99

Figure 5

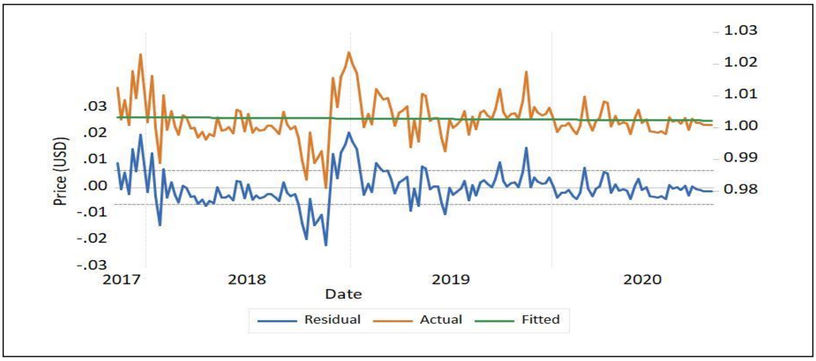
Closing Price, Exponential Trend Residual Plot



a) Bitcoin



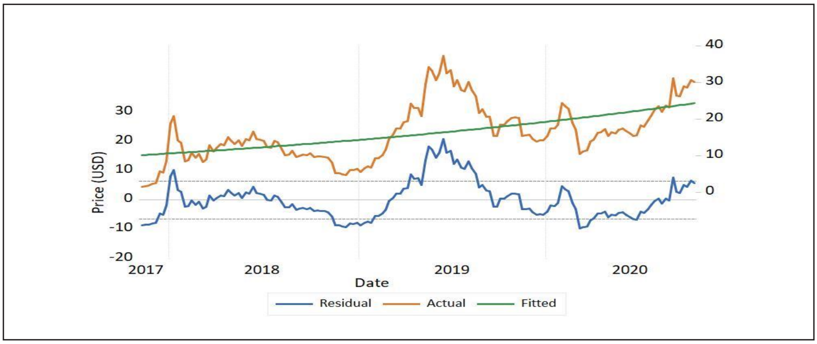
b) Ethereum



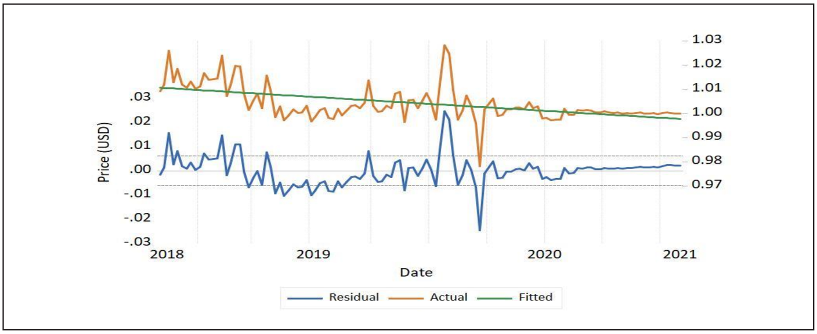
c) Tether

Figure 5

Closing Price, Exponential Trend Residual Plot (cont'd)



d) Binance



e) USD Coin

This study examined SIC, AIC, RMSE, MSE, MAE, and MAPE for the three trend models presented in Tables 7 and 8. For Bitcoin, there was a minor distinction number of decimal places between linear, quadratic, and exponential models on AIC and SIC. In that instance, both SIC and AIC implied that nonlinearity and linearity existed in the proximate price trend. Nevertheless, the best forecast model was the exponential trend model because the model had a minimum value of MSE, RMSE, MAE, and MAPE in the evaluation part compared to the linear and quadratic models. For ETH, this study examined SIC and AIC. Both indicated that the lowest values for quadratic trends meant that the nonlinearity was important compared to other models. Additionally, when this study checked the measurement errors, all showed the minimum error on the quadratic trend, followed by the exponential and linear models. This finding meant that ETH had a nonlinear trend on the closing price data. As for USDT, all models had negative SIC and AIC values.

The AIC value's absolute value was irrelevant. It could be both positive and negative. The lower the AIC value, the better the model fits. In this case, the linear and exponential trend models had the same SIC and AIC values and the lowest quadratic trend. This finding specified that the trends of closing prices were linear and nonlinear. Nevertheless, evaluating all measurement errors showed that the quadratic trend model was most suitable for USDT. Meanwhile, BNB shared the same pattern and model with Bitcoin since there was a minor distinction number of decimal places between linear, quadratic, and exponential models in AIC and SIC. In that instance, SIC and AIC implied that nonlinearity and linearity existed in the proximate price trend. Note that the best forecast model was also known as the exponential trend model. Lastly, USDC also shares the same pattern and model as USDT.

Table 7

Model Selection Criteria

Cryptocurrency	Linear Trend		Quadratic Trend	Exponential Trend
Bitcoin	AIC	18.53	18.54	18.69
	SIC	18.56	18.58	18.71
ETH	AIC	13.46	12.77	13.22
	SIC	13.50	12.83	13.26
USDT	AIC	-7.24	-7.22	-7.24
	SIC	-7.20	-7.17	-7.20
BNB	AIC	6.56	6.55	6.58
	SIC	6.60	6.61	6.62
USDC	AIC	-7.35	-7.40	-7.35
	SIC	-7.30	-7.33	-7.30

Table 8

Summary of Evaluation

Cryptocurrency	Measurement Error	Data Partition	Linear Trend	Quadratic Trend	Exponential Trend
Bitcoin	MSE	Estimation Period: 5 January 2015 – 30 December 2019 (261 observations)	6421166.14	**6420309.67**	7522869.56
		Evaluation Period: 6 January 2020 – 24 January 2022 (108 observations)	679645942.80	687971981.80	**410685221.20**
	RMSE	Estimation Period: 5 January 2015 – 30 December 2019 (261 observations)	2534.00	**2533.83**	2742.79
		Evaluation Period: 6 January 2020 – 24 January 2022 (108 observations)	26070.02	26229.22	**20265.37**

Table 8

Summary of Evaluation (cont'd)

Cryptocurrency	Measurement Error	Data Partition	Linear Trend	Quadratic Trend	Exponential Trend
	MAE	Estimation Period: 5 January 2015 – 30 December 2019 (261 observations)	**1739.31**	1747.26	2002.68
		Evaluation Period: 6 January 2020 – 24 January 2022 (108 observations)	19274.62	19391.76	**15266.26**
	MAPE	Estimation Period: 5 January 2015 – 30 December 2019 (261observations)	**125.91**	128.84	174.15
		Evaluation Period: 6 January 2020 – 24 January 2022 (108 observations)	47.38	47.52	**44.41**

Table 8

Summary of Evaluation (cont'd)

Cryptocurrency	Measurement Error	Data Partition	Linear Trend	Quadratic Trend	Exponential Trend
ETH	MSE	Estimation Period: 6 November 2017 – 19 October 2020 (155 observations)	39795.65	**19877.80**	31508.20
		Evaluation Period: 26 October 2020 – 24 January 2022 (66 observations)	7729795.62	**3673535.72**	7400989.67
	RMSE	Estimation Period: 6 November 2017 – 19 October 2020 (155 observations)	199.49	**141.00**	177.51
		Evaluation Period: 26 October 2020 – 24 January 2022 (66 observations).	2780.25	**1916.65**	2720.48

Table 8

Summary of Evaluation (cont'd)

Cryptocurrency	Measurement Error	Data Partition	Linear Trend	Quadratic Trend	Exponential Trend
	MAE	Estimation Period: 6 November 2017 – 19 October 2020 (155 observations)	151.45	**92.46**	129.96
		Evaluation Period: 26 October 2020 – 24 January 2022 (66 observations)	2481.88	**1649.45**	2432.26
	MAPE	Estimation Period: 6 November 2017 – 19 October 2020 (155 observations)	61.56	**33.21**	49.98
		Evaluation Period: 26 October 2020 – 24 January 2022 (66 observations)	97.28	**59.15**	95.79

Table 8

Summary of Evaluation (cont'd)

Cryptocurrency	Measurement Error	Data Partition	Linear Trend	Quadratic Trend	Exponential Trend
USDT	MSE	Estimation Period: 6 November 2017 – 19 October 2020 (155 observations)	4.10E-05	4.10E-05	4.16E-05
		Evaluation Period: 26 October 2020 – 24 January 2022 (66 observations)	2.44E-06	**1.47E-06**	2.44E-06
	RMSE	Estimation Period: 6 November 2017 – 19 October 2020 (155 observations)	6.40E-03	6.40E-03	6.40E-03
		Evaluation Period: 26 October 2020 – 24 January 2022 (66 observations)	1.56E-03	**1.21E-03**	1.56E-03

Table 8

Summary of Evaluation (cont'd)

Cryptocurrency	Measurement Error	Data Partition	Linear Trend	Quadratic Trend	Exponential Trend
	MAE	Estimation Period: 6 November 2017 – 19 October 2020 (155 observations)	4.47E-03	**4.46E-03**	4.47E-03
		Evaluation Period: 26 October 2020 – 24 January 2022 (66 observations)	1.45E-03	**1.05E-03**	1.45E-03
	MAPE	Estimation Period: 6 November 2017 – 19 October 2020 (155 observations)	4.46E- 03	**0.44**	0.45
		Evaluation Period: 26 October 2020 – 24 January 2022 (66 observations).	0.14	**0.11**	0.14

Table 8

Summary of Evaluation (cont'd)

Cryptocurrency	Measurement Error	Data Partition	Linear Trend	Quadratic Trend	Exponential Trend
BNB	MSE	Estimation Period: 6 November 2017 – 19 October 2020 (155 observations)	40.10	**39.34**	41.18
		Evaluation Period: 26 October 2020 – 24 January 2022 (66 observations)	132472.78	136289.37	**130447.74**
	RMSE	Estimation Period: 6 November 2017 – 19 October 2020 (155 observations)	6.33	**6.27**	6.42
		Evaluation Period: 26 October 2020 – 24 January 2022 (66 observations)	363.97	369.17	**361.18**

Table 8

Summary of Evaluation (cont'd)

Cryptocurrency	Measurement Error	Data Partition	Linear Trend	Quadratic Trend	Exponential Trend
	MAE	Estimation Period: 6 November 2017 – 19 October 2020 (155 observations)	**4.96**	4.97	4.99
		Evaluation Period: 26 October 2020 – 24 January 2022 (66 observations)	307.70	312.84	**305.05**
	MAPE	Estimation Period: 6 November 2017 – 19 October 2020 (155 observations)	46.32	**44.43**	48.55
		Evaluation Period: 26 October 2020 – 24 January 2022 (66 observations)	78.49	81.24	**77.28**

Table 8

Summary of Evaluation (cont'd)

Cryptocurrency	Measurement Error	Data Partition	Linear Trend	Quadratic Trend	Exponential Trend
USDC	MSE	Estimation Period: 5 November 2017 – 1 February 2021 (118 observations)	3.65E-05	4.00E-05	3.65E-05
		Evaluation Period: 8 February 2021 – 24 January 2022 (51 observations)	3.09E-05	**2.43E-05**	3.06E-05
	RMSE	Estimation Period: 5 November 2017 – 1 February 2021 (118 observations)	6.04E-03	**5.82E-03**	6.04E-03
		Evaluation Period: 8 February 2021 – 24 January 2022 (51 observations)	5.56E-03	**4.93E-03**	5.53E-03

Table 8

Summary of Evaluation (cont'd)

Cryptocurrency	Measurement Error	Data Partition	Linear Trend	Quadratic Trend	Exponential Trend
	MAE	Estimation Period: 5 November 2017 – 1 February 2021 (118 observations)	4.13E-03	**3.76E-03**	4.12E-03
		Evaluation Period: 8 February 2021 – 24 January 2022 (51 observations)	5.34E-03	**4.29E-03**	5.32E-03
	MAPE	Estimation Period: 5 November 2017 – 1 February 2021 (118 observations)	0.41	**0.37**	0.41
		Evaluation Period: 8 February 2021 – 24 January 2022 (51 observations)	0.53	**0.43**	0.53

CONCLUSION AND FUTURE RESEARCH

This study compared the quadratic, linear, and exponential trend models for the top five cryptocurrencies' closing prices in an informal way. For Bitcoin, the linear trend appeared to be the most appropriate. The linear trend model, in contrast, did an excellent job of fitting the training data, but it did not always predict accurately, as shown in Table 8 and the plot. In contrast, the linear trend model had one parameter compared to the other two models. Therefore, it is unexpected that historical data were a better bit. Nonetheless, there is no assurance that a better fit on historical data would transfer into better out-of-sample predicting performance. In conclusion, all cryptocurrency closing price data series contained both nonlinear and linear trend patterns. The findings of this study contradicted previous research that claimed Bitcoin's closing price and other cryptocurrency trends were nonlinear.

Therefore, this study suggests that before implementing the advanced analysis, researchers need to confirm the data trend pattern to make an accurate prediction. Once they understand the data pattern, researchers can select the best model to predict accurately and minimise errors. Nevertheless, this research needs to be expanded further. In this case, the traditional and single nonlinear or linear deterministic models are inadequate for modelling and predicting cryptocurrency prices. For future research, this study will compare the trend utilising the stochastic model and study the pattern behaviour. Then, this study also plans to design a novel hybridisation model to encounter linear and nonlinear problems. According to the findings, hybridisation is the most effective method for simulating the complicated properties of nonlinear and linear components and obtaining more accurate and optimum outcomes (Hossain & Ismail, 2020; Mohammed et al., 2020). Therefore, to correct the serial correlation problem, it is suggested to use the closing price lag as a dependent variable and/or the time lag as an independent variable in the model. Usually, lag 1 is enough to increase or reduce the DW value (MA Lazim, 2005).

It is important to remember that there are trends and cycles in every aspect of our lives. The moon, the sun, and the stock market all follow their own rhythms. When determining the best time to buy or sell, it is critical to understand the market trend and phase, especially in the highly volatile cryptocurrency markets. Knowing and applying this information will help cryptocurrency traders and investors reduce risk while increasing returns by choosing the model appropriately. In addition, the ability to measure and predict well will prevent investors from losing their investments.

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REFERENCES

Aditya Pai, B., Devareddy, L., Hegde, S., & Ramya, B. S. (2022). A time series cryptocurrency price prediction using LSTM. In N. R. Shetty, L. M. Patnaik, H. C. Nagaraj, P. N. Hamsavath, & N. Nalini (Eds.), *Emerging research in computing, information, communication and applications* (pp. 653–662). Springer. https://doi.org/10.1007/978-981-16-1342-5_50

Ahamed, S. A., & Ravi, C. (2021). Study of swarm intelligence algorithms for optimising deep neural network for bitcoin prediction. *International Journal of Swarm Intelligence Research (IJSIR)*, *12*(2), 22–38. https://doi.org/10.4018/IJSIR.2021040102

Akyildirim, E., Goncu, A., & Sensoy, A. (2021). Prediction of cryptocurrency returns using machine learning. *Annals of Operations Research*, *297*(1), 3–36. https://doi.org/10.1007/s10479-020-03575-y

Al to Ameer, A., & Al to Sunni, F. (2021). A methodology for securities and cryptocurrency trading using exploratory data analysis and artificial intelligence. In T. Saba (Ed.), *2021 1st International Conference on Artificial Intelligence and Data Analytics (CAIDA)* (pp. 54–61). IEEE. https://doi.org/10.1109/CAIDA51941.2021.9425223

Aleksandra, P., Dmitry, Z., & Vladimir, K. (2021). A study of uncertainty contribution to cryptocurrency investment dynamics. *International Journal of Technology*, *12*(7), 1529–1536. https://doi.org/10.14716/ijtech.v12i7.5348

Antonopoulos, A. M., & Wood, G. (2018). *Mastering Ethereum: Building smart contracts and dapps*. O'reilly Media, Inc.

Cahyani, N. D. W., & Nuha, H. H. (2021). Ransomware detection on Bitcoin transactions using artificial neural network methods. In W. Maharani (Ed.), *2021 9th International Conference on Information and Communication Technology (ICoICT)* (pp. 1–5). IEEE Indonesia Section. https://doi.org/10.1109/ICoICT52021.2021.9527414

Cavalli, S., & Amoretti, M. (2021). CNN to based multivariate data analysis for Bitcoin trend prediction. *Applied Soft Computing*, *101*, 107065. https://doi.org/10.1016/j.asoc.2020.107065

David, S. A., Inacio Jr, C. M. C., Nunes, R., & Machado, J. A. T. (2021). Fractional and fractal processes applied to cryptocurrencies price series. *Journal of Advanced Research, 32*, 85–98. https://doi.org/10.1016/j.jare.2020.12.012

Fadil, I., Helmiawan, M. A., & Sofiyan, Y. (2021). Optimisation parameters support vector regression using grid search method. In H. T. Sukmana & D. Khairani (Eds.), *2021 9th International Conference on Cyber and I.T. Service Management (CITSM)* (pp. 1–5). IEEE Indonesia Section. https://doi.org/10.1109/CITSM52892.2021.9589028

Fama, E. F. (1965). The behavior of stock to market prices. *The Journal of Business*, *38*(1), 34–105. http://www.jstor.org/stable/2350752

Gandal, N., Hamrick, J. T., Moore, T., & Vasek, M. (2021). The rise and fall of cryptocurrency coins and tokens. *Decisions in Economics and Finance*, *44*(2), 981–1014. https://doi.org/10.1007/s10203-021-00329-8

Gao, Z., He, Y., & Kuruoglu, E. E. (2021, October). A hybrid model integrating LSTM and GARCH for Bitcoin price prediction. In *2021 IEEE 31st International Workshop on Machine Learning for Signal Processing (MLSP)* (pp. 1–6). https://doi.org/10.1109/MLSP52302.2021.9596429

Guo, T., Bifet, A., & Antulov to Fantulin, N. (2018). Bitcoin volatility forecasting with a glimpse into buy and sell orders. In L. O'Conner (Ed.), *Proceedings to IEEE International Conference on Data Mining (ICDM)* (pp. 989–994). IEEE. https://doi.org/10.1109/ICDM.2018.00123

Hossain, M. J., & Ismail, M. T. (2021). Is there any influence of other cryptocurrencies on Bitcoin? *Asian Academy of Management Journal of Accounting and Finance*, *17*(1), 125–152. https://doi.org/10.21315/aamjaf2021.17.1.5

Hossain, M. R., & Ismail, M. T. (2020). Empirical mode decomposition based on Theta method for forecasting daily stock price. *Journal of Information and Communication Technology*, *4*(4), 533–558. https://doi.org/10.32890/jict2020.19.4.4

Huynh, T. L. D., Burggraf, T., & Wang, M. (2020). Gold, platinum, and expected Bitcoin returns. *Journal of Multinational Financial Management*, *56*, 100628. https://doi.org/10.1016/j.mulfin.2020.100628

Ibrahim, A. (2021). Forecasting the early market movement in bitcoin using Twitter's sentiment analysis: An ensemble to based prediction model. In S. Chakrabarti (Ed.), *2021 IEEE International IOT, Electronics and Mechatronics Conference (IEMTRONICS)* (pp. 1–5). IEEE. https://doi.org/10.1109/IEMTRONICS52119.2021.9422647

Jalan, A., Matkovskyy, R., & Urquhart, A. (2021). What effect did the introduction of Bitcoin futures have on the Bitcoin spot market? *The European Journal of Finance*, *27*(13), 1251–1281. https://doi.org/10.1080/1351847X.2020.1869992

Khedr, A. M., Arif, I., El-Bannany, M., Alhashmi, S. M., & Sreedharan, M. (2021). Cryptocurrency price prediction using traditional statistical and machine-learning techniques: A survey. *Intelligent Systems in Accounting, Finance and Management*, *28*(1), 3–34. https://doi.org/10.1002/isaf.1488

Knight, R. (2021, 07 Dec). *The 4 phases of a crypto market cycle*. Data Driven Investor. https://medium.datadriveninvestor.com/the-4-phases-of-a-crypto-market-cycle-6eb396097b9c

Koki, C., Leonardos, S., & Piliouras, G. (2020). Do cryptocurrency prices camouflage Latent economic effects? A Bayesian hidden Markov approach. *Future Internet*, *12*(3), 59. https://doi.org/10.3390/fi12030059

Lahmiri, S., & Bekiros, S. (2020). Intelligent forecasting with machine learning trading systems in chaotic intraday Bitcoin market. *Chaos, Solitons & Fractals*, *133*, 109641. https://doi.org/10.1016/j.chaos.2020.109641

Levulytė, L., & Šapkauskienė, A. (2021). Cryptocurrency in context of fiat money functions. *The Quarterly Review of Economics and Finance*, *82*, 44–54. https://doi.org/10.1016/j.qref.2021.07.003

Loginova, E., Tsang, W. K., van Heijningen, G., Kerkhove, L. P., & Benoit, D. F. (2021). Forecasting directional Bitcoin price returns using aspect to based sentiment analysis on online text data. *Machine Learning*, 1–24. https://doi.org/10.1007/s10994-021-06095-3

Mahdi, E., Leiva, V., Mara'Beh, S., & Martin to Barreiro, C. (2021). A new approach to predicting cryptocurrency returns based on the gold prices with support vector machines during the COVID to 19 pandemic using sensor to related data. *Sensors*, *21*(18), 6319. https://doi.org/10.3390/s21186319

Mohammed, A. J., Ghathwan, K. I., & Yusof, Y. (2020). A hybrid least squares support vector machine with bat and cuckoo search algorithms for time series forecasting. *Journal of Information and Communication Technology*, *19*(3), 351–379. https://doi.org/10.32890/jict2020.19.3.3

MA Lazim. (2005). *Introductory business forecasting*. Pusat Penerbitan UPENA Universiti Teknologi Mara.

Nakamoto, S. (2008). *Bitcoin: A peer-to-peer electronic cash system*. Bitcoin. https://bitcoin.org/bitcoin.pdf.

Neslihanoglu, S. (2021). Linearity extensions of the market model: A case of the top 10 cryptocurrency prices during the pre to COVID to 19 and COVID to 19 periods. *Financial Innovation*, *7*(1), 1–27. https://doi.org/10.1186/s40854-021-00247-z

Park, M., & Chai, S. (2020). The effect of information asymmetry on investment behavior in cryptocurrency market. In T. X. Bui (Ed.), *Proceedings of the 53rd Hawaii International Conference on System Sciences, HICSS 2020* (pp. 4043–4052). IEEE Computer Society. https://doi.org/10.24251/hicss.2020.494

Serrano, W. (2022). The random neural network in price predictions. *Neural Computing and Applications*, *34*(2), 855–873. https://doi.org/10.1007/s00521-021-05903-0

Trozze, A., Davies, T., & Kleinberg, B. (2022). Explaining prosecution outcomes for cryptocurrency to based financial crimes. *Journal of Money Laundering Control*, *26*(1), 172–188. https://doi.org/10.1108/JMLC-10-2021-0119

Wang, Z., Jin, H., Dai, W., Choo, K. K. R., & Zou, D. (2021). Ethereum smart contract security research: survey and future research opportunities. *Frontiers of Computer Science*, *15*(2). https://doi.org/10.1007/s11704-020-9284-9

Zhang, Z., Dai, H. N., Zhou, J., Mondal, S. K., García, M. M., & Wang, H. (2021). Forecasting cryptocurrency price using convolutional neural networks with weighted and attentive memory channels. *Expert Systems with Applications*, *183*, 115378. https://doi.org/10.1016/j.eswa.2021.115378

Zhu, P., Zhang, X., Wu, Y., Zheng, H., & Zhang, Y. (2021). Investor attention and cryptocurrency: Evidence from the Bitcoin market. *PLoS One*, *16*(2), e0246331. https://doi.org/10.1371/journal.pone.0246331