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Cryptocurrency Modeling and Price Prediction Using Markov Switching Autoregressive Model

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Abstract

The emergence of cryptocurrency investment trends has brought the number of registered customers for crypto assets in Indonesia to surpass the number of investors in the capital market. Despite the continuous increase in the number of cryptocurrency investors, a different scenario is depicted by the declining transaction values. This decrease is attributed to the high volatile nature of cryptocurrency coins, which impacts investors' investment decisions. This research aims to obtain the best model and forecasts related to cryptocurrency prices in order to minimize concerns and potential losses experienced by investors. This research uses the closing price of the five largest market capitalized cryptocurrency coins. The research utilized the Markov Switching Autoregressive method to capture structural changes in the data, allowing it to be used for forecasting. The research findings indicate that the best model for BTC is MS(3)AR(1), the model for BNB is MS(3)AR(1), the model for ETH is MS(3)AR(1), the model for XRP is MS(3)AR(2), and the model for ADA is MS(3)AR(2). The RMSE values indicate that BTC is the coin with the most accurate price prediction compared to other coins.

Key words : Cryptocurrency, Markov Switching, Autoregressive, Investment, Forcasting

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INTRODUCTION

Economic is one of the most crucial sectors for a country's well being, there are various factors that can directly influence it, and one of these factors is investment. The Harrod-Domar model suggests that there is an impact of investment on the economic growth of a country, especially on a country's income and production capacity (Arsyad, 2010). There are various types of investment instruments include stocks, mutual funds, bonds, property, gold, or cryptocurrencies and the other instruments. Cryptocurrency itself is one of the instruments that has been widely discussed in recent years. Bitcoin was the first cryptocurrency introduced in 2008. Initially aimed at becoming a form of digital and alternative currency, today more people view cryptocurrency as an investment instrument.

In Indonesia, there is a prohibition on using cryptocurrency as a means of payment, but cryptocurrency falls into the category of commodities and can be used as an investment tool (BAPPEBTI, 2019). The Indonesian government, through the Commodity Futures Trading Regulatory Agency of the Ministry of Trade (BAPPEBTI), continues to work on strengthening the digital economy in Indonesia, including through the trading of cryptocurrency assets. The trading of cryptocurrency assets is expected to serve as a strategy to create, and accelerate the development of the digital economy in Indonesia (Viska, 2023).

Referring to Figure 1, based on the survey conducted by Tokenomy and Indodax, the official cryptocurrency exchange in Indonesia, it can be concluded that cryptocurrency asset purchases experienced a significant increase in 2021. The survey also revealed that 69% of respondents were prompted to buy cryptocurrency for the first time due to the abundance of news related to the booming cryptocurrency market during that period (Tokenomy, 2021).

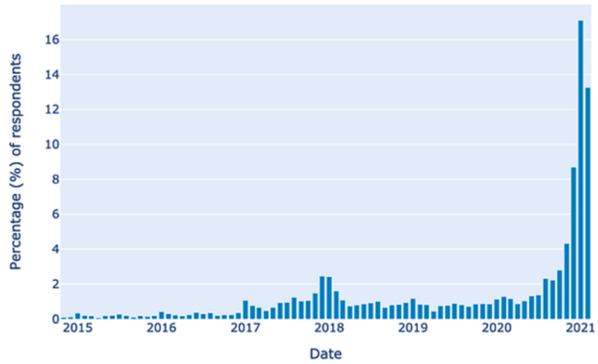

Figure 1. Year Survey Respondents Purchased Their First Crypto Asset
Sources: Medium-Tokenomy, 2021

The proliferation of cryptocurrency investments continues to be accompanied by a growing number of registered crypto asset customers, including in Indonesia. According to a report issued by BAPPEBTI on the development of crypto asset transactions and customers, it is found that the number of registered crypto asset customers in Indonesia continues to increase and it can be seen as shown in Figure 2.

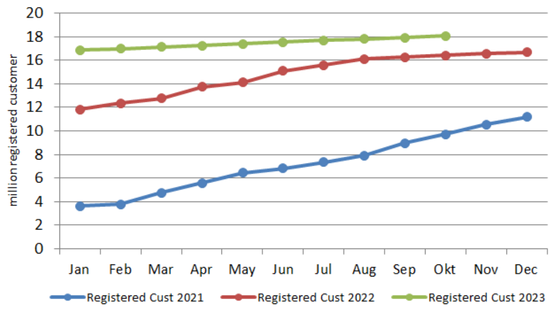

Figure 2. The Number of Registered Crypto Asset Customer in Indonesia
Sources: BAPPEBTI, 2023

This surge in registered crypto asset customers surpasses the number of investors in the stock market, despite the fact that the stock market has been operating in Indonesia for a much longer time than the crypto market. This can be clearly seen in Figure 3 that, in the month of October 2023, the number of cryptocurrency investors reached more than half times that of stock investors.

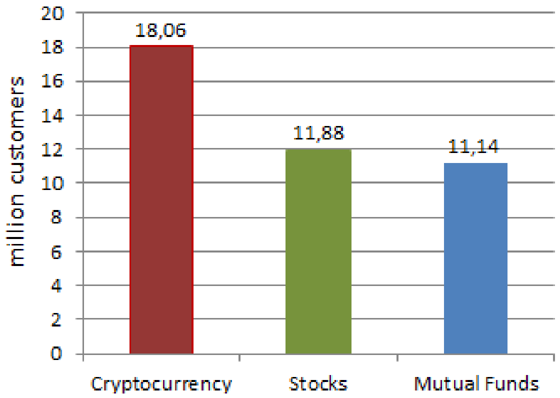

Figure 3. The Number of Investors in the Stock Market and Crypto Assets in Indonesia
Sources: Databoks, 2022

Although the number of registered crypto asset customers continues to rise, there is a very unique phenomenon: a decrease in the value of crypto asset transactions in Indonesia. This phenomenon does not align with the increasing number of customers. As seen in Figure 4, the value of crypto transactions in Indonesia steadily declined from December 2021 to December 2022. BAPPEBTI reported a 64.3% decrease in crypto transaction value in Indonesia from 2021 to 2022.

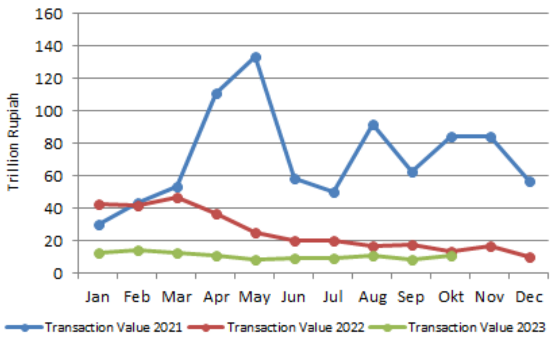

Figure 4. Cryptocurrency Transaction Value in Indonesia
Source: BAPPEBTI, 2023

Many factors can influence this decline in transaction value, one of which is the volatile and highly sensitive nature of cryptocurrencies to economic conditions and market circumstances (Bestari, 2023). Investor confidence or concern about their surrounding conditions have a significant impact on investor decisions, which can affect the transaction values (Nurbarani and Soepriyanto, 2022). This relates to behavioral finance theory where there are frame dependent biases (Shefrin, 2000). This can be in the form of loss aversion which refers to the tendency that investors have to avoid losses rather than gain profits. Loss aversion also makes investors much more precautionary and risk averse, so investors tend to be reluctant to enter the market if they think market conditions are not good enough (Alteza and Harsono, 2021). As it can be seen that cryptocurrency price movements are very volatile, investors must be very careful with the circumstances and situations that can affect the price of crypto because it provides the possibility of enormous risk with the option of large profits or large losses (Almeida and Gonçalves, 2023).

The impact of cryptocurrency asset investments has not yet yielded significant benefits for Indonesian economy, possibly due to the underutilization of cryptocurrency potential (Haji, 2022). However, the value of cryptocurrency investment transactions must still be monitored because one of the reasons cryptocurrency is classified as a commodity is its potential for future investment growth. Through regulation PMK 68/PMK.03/2022, the government has established tax regulations on value-added and income tax for cryptocurrency asset trading transactions. This demonstrates that cryptocurrency investment transactions in Indonesia can contribute to the revenue of the Indonesian government, particularly in the economic sector (Olavia, 2022).

The impact of Bitcoin on the Indonesian economy has been substantiated by research, which concluded statistically that Bitcoin has a significant positive effect on capital transactions in Indonesia, both in the short and long term (Samputra and Putra, 2020). Additionally, it has been noted that cryptocurrency prices have a positive influence on stock prices (Sihombing, Nawir and Mulyantini, 2020). Apart from its influence on tax revenue and the Indonesian stock market, it is also mentioned that fluctuations in cryptocurrency values have a strong connection to global economic activity (Conrad, Custovic and Ghysels, 2018). With supporting research indicating that cryptocurrency can impact the Indonesian economy through the stock market and given the promising future prospects of crypto assets, it is essential to safeguard cryptocurrency transaction values.

The fluctuating nature of cryptocurrency values leads to the emergence of specific structural changes in data for certain time periods. This necessitates the ability to understand potential structural changes or patterns in cryptocurrency price values in order to minimize potential losses and investor concerns. Given the structural changes in cryptocurrency data, a method is required to model and forecast the data, which is typically time series data. While Autoregressive models are commonly used for time series data, they are unable to capture structural changes. Therefore, the Markov Switching Autoregressive model is employed, designed for time series data with structural changes. Based on the previously outlined background, a more in-depth discussion is required to explain cryptocurrency price modeling with effective methods to alleviate investor concerns and promote the continued growth of the cryptocurrency investment landscape in Indonesia.

RESEARCH METHOD

The aim of this research is to analyze the best Markov Switching Autoregressive (MSAR) model for cryptocurrency prices to provide insights for crypto asset investors. This study employs a quantitative method because its objectives align with the fundamental assumptions of quantitative methods both epistemologically and axiologically. From an epistemological perspective, the issues within this research can be explored through existing theories and findings. On the other hand, from an axiological viewpoint, this research is conducted to provide explanations for the issues at hand using econometric analysis models (Priyono, 2008).

The variables in this study are the closing prices of five major cryptocurrencies. The five cryptocurrencies are Bitcoin (BTC), Ethereum (ETH), BinanceCoin (BNB), Ripple (XRP), and Cardano (ADA). The closing price for these five cryptocurrencies is the last price recorded when the exchange closed. Data collection was conducted using the documentation method, where the data is secondary data sourced from www.finance.yahoo.com. The data used consists of daily records from the first day up to August 31, 2023.

Autoregressive itself is based on the understanding that a dependent variable is influenced by independent variables at time 't' and by the same dependent variable at time 't - 1' (Gujarati, 2006). On the other hand, Markov Chain is an analytical method that examines the nature or structure of variables in the present based on the characteristics of those variables in the past (Manullang, 2018). Through this MSAR model, the researcher aims to obtain information about structural changes in the data, thereby indicating shifts in behavior within an economy.

The model of MSAR itself can be written using the following equation.

$$(y_t - \mu_{s_t}) = \sum \phi_p \left(y_{t-p} - \mu_{s_{t-p}}\right) + \varepsilon_t \qquad (1)$$

RESULT AND DISCUSSION

In Table 1, it can be observed that the highest average coin price is held by BTC with an average of $13,864 USD. Bitcoin itself still holds the record for the highest cryptocurrency price to date, which is $67,566 USD. Through the maximum values of these five cryptocurrencies, four out of the five cryptocurrencies with the highest market capitalization experienced their peak prices in 2021, except for XRP. This is supported by the fact that in 2021, several factors contributed to the rapid growth of cryptocurrencies. One of these factors was the booming Non-Fungible Token (NFT) market, where NFT buyers needed crypto wallets, leading to increased demand for cryptocurrencies. The increasing number of companies investing in cryptocurrencies also sparked interest in crypto investments. Another factor was the growth of the Decentralized Finance (DeFi) system, which is a financial infrastructure based on blockchain networks (Locke, 2021). These situations driving cryptocurrency growth have had a global impact on investment dynamics.

Table 1. Statistics Descriptive

Koin	Mean	Median	Max	Min	StDev
BTC	**13,864**	7,902	**67,566**	178.10	15,998
BNB	162.52	30.44	675.68	1.51	177.97
ETH	1,200	729.64	4,812	84.31	1,136
XRP	0.52	0.41	3.38	0.14	0.35
ADA	0.47	0.26	2.97	0.02	0.59

Source: RStudio (processed)

Another way to explore data is by examining data plot graphs. Figure 2 shows the movement of cryptocurrency prices up to August 2023. It can be understood that at a glance, ADA, BTC, and ETH have relatively similar movements, with a small increase in 2018 followed by stagnant values until reaching their peak in 2021. In contrast, XRP is quite different. XRP itself achieved its highest value record in 2018, driven by rumors about a new product to be developed and released by Ripple. These rumors gained the sympathy of investors and led to the highest XRP coin price in 2018 (Seth, 2018).

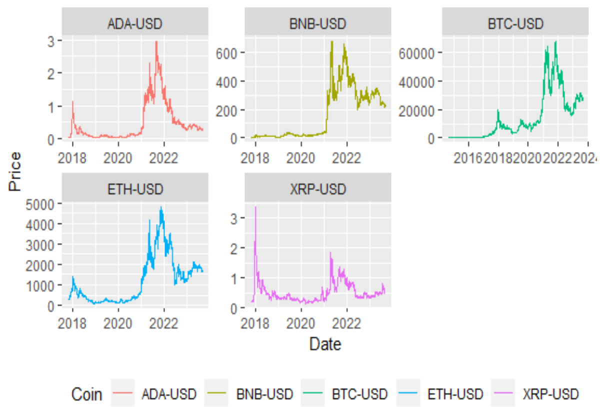

Figure 5. Cryptocurrency Price Data Plot

In the MSAR process, a stationarity test is mandatory; therefore, in this study, the Augmented Dickey Fuller (ADF) test is used to assess data stationarity. From Table 2, it can be seen that for all five coins used, the p-value > 5%. This indicates that the coin price data is non-stationary. Therefore, the next step will involve one of the methods to address non-stationarity, which is differencing. Non-stationarity in cryptocurrency data is caused by the fact that cryptocurrency prices tend to fluctuate over time, given that cryptocurrency prices are easily influenced by various factors.

Table 2. Stationarity test

Koin	ADF	*p-value*
BTC	-1.3998	0.4851
BNB	-2.3114	0.5117
ETH	-1.5968	0.6657
XRP	-2.9895	0.0287
ADA	-1.6383	0.6667

Source: RStudio (processed)

Table 3. Stationarity test on differenced data

Koin	ADF	*p-value*
BTC	-1.3962	0.01
BNB	-1.0300	0.01
ETH	-1.1723	0.01
XRP	-1.1967	0.01
ADA	-1.1594	0.01

Source: RStudio (processed)

Looking at Table 3, it can be observed that for all five coins with price data differenced at the first level, the p-value is < 5%. This indicates that the price data for the coins has become stationary at the first-level differencing. Therefore, the analysis can proceed to the next stage using the differenced data.

The goodness of fit of the model can be assessed by examining the resulting AIC values. The AIC value itself can provide the most suitable model for explaining the data at hand. This section will be used to demonstrate the model goodness of fit values for the five cryptocurrencies used. In this study, three states have been predetermined for each coin. The use of these three states is aimed at simplifying the identification of the formed structure, allowing the structure to be categorized into three conditions: bullish, bearish, and sideways. These trend conditions are a common part of technical analysis in the stock market, but they can also be applied in the cryptocurrency market. Bullish represents a condition where there is an upward price trend, while bearish signifies a downward price trend (Setiawan, 2021). On the other hand, sideways indicates a stagnant price condition, where the price movement remains within a relatively narrow range for an extended period.

Table 4. The Goodness of Fit of MSAR BTC

Model	AIC
MS(3)AR(1)	**-13499.99**
MS(3)AR(2)	-13490.16
MS(3)AR(3)	-13482.52
...	...
MS(3)AR(23)	-13435.69

Source: RStudio (processed)

Bitcoin was the first cryptocurrency introduced to the public and still holds its position as the cryptocurrency with the highest price. The Makov Switching (MS) value used in the model will indicate the number of states formed. In this case, BTC will have three states with the possible Autoregressive order for Bitcoin up to lag 23. The results of the goodness-of-fit model selection indicate that the chosen model is MS(3)AR(1), which means that the value of Bitcoin is influenced by the value from one period prior.

Table 5. The Goodness of Fit of MSAR BNB

Model	AIC
MS(3)AR(1)	**-7331.003**
MS(3)AR(2)	-7324.992
MS(3)AR(3)	-7319.397
...	...
MS(3)AR(11)	-7292.527

Source: RStudio (processed)

Table 6. The Goodness of Fit of MSAR ETH

Model	AIC
MS(3)AR(1)	**-7359.787**
MS(3)AR(2)	-7346.416
MS(3)AR(3)	-7339.051
...	...
MS(3)AR(33)	-7209.272

Source: RStudio (processed)

Table 5 and Table 6 show that the results obtained are similar to the BTC model. For BNB and ETH, based on the smallest AIC values, it indicates that the best model is the MS(3)AR(1) model. This suggests that for BTC, BNB, and ETH, their data values are influenced by values from one period prior.

Table 7. The Goodness of Fit of MSAR XRP

Model	AIC
MS(3)AR(1)	-7294.602
MS(3)AR(2)	**-7295.056**
MS(3)AR(3)	-7292.056
...	...
MS(3)AR(33)	-7051.836

Source: RStudio (processed)

Table 8. The Goodness of Fit of MSAR ADA

Model	AIC
MS(3)AR(1)	-6569.443
MS(3)AR(2)	**-6571.219**
MS(3)AR(3)	-6564.118
...	...
MS(3)AR(22)	-6508.263

Source: RStudio (processed)

It can be seen that in the goodness-of-fit test based on the AIC values, the best MSAR model for XRP and ADA coins is MS(3)AR(2), which means that for both of these coins, they are influenced by values from the previous 2 periods. The goodness-of-fit model calculation results can be seen in the appendix.

Based on the results from the best model table, it can be seen that each coin with a 3-state MS model has a low lag order of Autoregressive. For BTC, BNB, and ETH, it can be observed that the value of the previous period that influences them is only one period. Meanwhile, for XRP and ADA, they are influenced by the two previous periods.

Table 9. The Best MSAR Model

Model	AIC
BTC	MS(3)AR(1)
BNB	MS(3)AR(1)
ETH	MS(3)AR(1)
XRP	MS(3)AR(2)
ADA	MS(3)AR(2)

Source: RStudio (processed)

The low lag values obtained indicate that, in reality, cryptocurrency values are easily influenced by various events or short-term factors that are difficult to predict, considering that cryptocurrencies do not have underlying assets that can serve as fundamental price determinants. The low Autoregressive lag values indicate that these coins can move quickly.

Based on the best-selected model for each coin, parameter estimates can be obtained, which can be used to create model equations and market condition categorization. The parameter estimates provide an overview of how the observed data relates to the variables in the model. In this case, the parameter μ represents the average data in each state, while the parameter ϕ indicates the autoregressive behavior, showing how much the data from previous periods influences the current data.

The 3-state condition can categorize market conditions as bullish, bearish, and sideways. States can be categorized as market conditions by examining the values of μ and ϕ. If the μ value is positive, it can be indicated that in that state, the market tends to move upward or experience a price increase. Conversely, if the μ value is negative, it can be indicated that the market is experiencing a price decrease. Sideways conditions can be indicated if there is a value close to zero, indicating that the movements are not too significant compared to the other states. The categorization of each state into market conditions should also be accompanied by an understanding of the data movement, as seen in the data plot.

Table 10. Parameter Estimation of the BTC MS(3)AR(1) Model

Parameter	State 1	State 2	State 3
$\hat{\mu}$	0.0033	-0.0031	0.0006
$\hat{\phi}_1$	-0.0020	-0.0334	-0.1649

Source: RStudio (processed)

The results from Table 10 indicate that there are 3 states in the BTC MSAR model. State 1 shows a positive μ value, which is larger compared to state 3. This indicates that state 1 represents a bullish market condition. On the other hand, a negative value in state 2 suggests a bearish market condition. A positive value in state 3, which is closest to zero, characterizes state 3 as being in a sideways condition.

Table 11. Parameter Estimation of the BNB MS(3)AR(1) Model

Parameter	State 1	State 2	State 3
$\hat{\mu}$	0.0007	0.0028	0.0114
$\hat{\phi}_1$	-0.1550	-0.0473	0.0067

Source: RStudio (processed)

In Table 11, for the parameter estimation results of the BNB MSAR model, it can be observed that state 3 has both positive μ and ϕ parameter values. This indicates that the average data and the influence of past data lead to an increase in the current data. Therefore, state 3 is the appropriate state to categorize as a bullish condition. On the other hand, state 2, with a larger μ value compared to state 1, can be categorized as a sideways condition. Hence, state 1, with the lowest μ parameter, can be categorized as a bearish condition.

Table 12. Parameter Estimation of the ETH MS(3)AR(1) Model

Parameter	State 1	State 2	State 3
$\hat{\mu}$	-0.0011	-0.0145	0.0049
$\hat{\phi}_1$	-0.2543	-0.0850	0.0148

Source: RStudio (processed)

Table 12 provides the parameter estimation results for ETH. The categorization of conditions is done in the same manner, considering the values of the μ and ϕ parameters. Both positive parameter values are categorized as a bullish condition, which is found in state 3. Meanwhile, the state with the smallest μ value is categorized as a bearish condition; hence, state 2 represents a bearish condition. This also results in state 1 indicating a sideways condition.

Table 13. Parameter Estimation of the XRP MS(3)AR(2) Model

Parameter	State 1	State 2	State 3
$\hat{\mu}$	0.0270	-0.0033	-0.0009
$\hat{\phi}_1$	0.0605	-0.0711	-0.2534
$\hat{\phi}_2$	0.1021	-0.0021	-0.0673

Source: RStudio (processed)

The parameter estimation results provided by the MSAR model for XRP coin indicate that the positive values of μ and ϕ in state 1 categorize it as a bullish condition. As for state 2, with a smaller μ value compared to state 3, it is categorized as a bearish condition. Therefore, the μ value for state 3, which is closest to zero, classifies as sideways condition.

Table 14. Parameter Estimation of the ADA MS(3)AR(2) Model

Parameter	State 1	State 2	State 3
$\hat{\mu}$	0.0474	-0.0016	-0.0010
$\hat{\phi}_1$	0.6336	-0.1405	-0.0908
$\hat{\phi}_2$	0.7900	0.0083	0.0107

Source: RStudio (processed)

For ADA coin, it can be concluded that the positive parameter values categorize state 1 as a bullish condition. As for state 2, with a smaller value compared to state 3, it falls into a bearish condition, leaving state 3 in a sideways condition, which is further supported by the μ and ϕ values approaching zero. All the categorizations of market conditions in these states should be done by understanding and aligning them with the coin data plots and coin breakpoint graphs.

Based on the results of the parameter estimation test, it was found that each state recorded in the coin has different interpretations. This can be seen in Table 15 as a result of state categorization. Table 15 can be used to assist in interpreting the results of the transition matrix, allowing us to understand how the transition occurs from the current state to the state condition in the next period.

Table 15. Categorization of Market Conditions Based on State

Koin	State 1	State 2	State 3
BTC	Bullish	Bearish	Sideways
BNB	Bearish	Sideways	Bullish
ETH	Sideways	Bearish	Bullish
XRP	Bullish	Bearish	Sideways
ADA	Bullish	Bearish	Sideways

Source: RStudio (processed)

Table 16. MSAR Model Equation

Koin	State	Model Equation
	Model	$y_t - \mu_{s_t} = \phi_1(y_{t-1} - \mu_{s_t-1}) + \cdots + \phi_p(y_{t-p} - \mu_{s_t-p}) + \varepsilon_t$
BTC MS(3)AR(1)	State 1	$y_t - \mu_{s_t} = -0{,}0020(y_{t-1} - \mu_{s_t-1}) + \varepsilon_t$
	State 2	$y_t - \mu_{s_t} = -0{,}0334(y_{t-1} - \mu_{s_t-1}) + \varepsilon_t$
	State 3	$y_t - \mu_{s_t} = -0{,}1649(y_{t-1} - \mu_{s_t-1}) + \varepsilon_t$
BNB MS(3)AR(1)	State 1	$y_t - \mu_{s_t} = -0{,}1550(y_{t-1} - \mu_{s_t-1}) + \varepsilon_t$
	State 2	$y_t - \mu_{s_t} = -0{,}0473(y_{t-1} - \mu_{s_t-1}) + \varepsilon_t$
	State 3	$y_t - \mu_{s_t} = 0{,}0067(y_{t-1} - \mu_{s_t-1}) + \varepsilon_t$
ETH MS(3)AR(1)	State 1	$y_t - \mu_{s_t} = -0{,}2543(y_{t-1} - \mu_{s_t-1}) + \varepsilon_t$
	State 2	$y_t - \mu_{s_t} = -0{,}0850(y_{t-1} - \mu_{s_t-1}) + \varepsilon_t$
	State 3	$y_t - \mu_{s_t} = 0{,}0148(y_{t-1} - \mu_{s_t-1}) + \varepsilon_t$
XRP MS(3)AR(2)	State 1	$y_t - \mu_{s_t} = 0{,}0605(y_{t-1} - \mu_{s_t-1}) + 0{,}1021(y_{t-2} - \mu_{s_t-2}) + \varepsilon_t$
	State 2	$y_t - \mu_{s_t} = -0{,}0711(y_{t-1} - \mu_{s_t-1}) - 0{,}0021(y_{t-2} - \mu_{s_t-2}) + \varepsilon_t$
	State 3	$y_t - \mu_{s_t} = -0{,}2534(y_{t-1} - \mu_{s_t-1}) - 0{,}0673(y_{t-2} - \mu_{s_t-2}) + \varepsilon_t$
ADA MS(3)AR(2)	State 1	$y_t - \mu_{s_t} = 0{,}6336(y_{t-1} - \mu_{s_t-1}) + 0{,}7900(y_{t-2} - \mu_{s_t-2}) + \varepsilon_t$
	State 2	$y_t - \mu_{s_t} = -0{,}1405(y_{t-1} - \mu_{s_t-1}) + 0{,}0083(y_{t-2} - \mu_{s_t-2}) + \varepsilon_t$
	State 3	$y_t - \mu_{s_t} = -0{,}0908(y_{t-1} - \mu_{s_t-1}) + 0{,}0107(y_{t-2} - \mu_{s_t-2}) + \varepsilon_t$

Source: RStudio (processed)

From the results in the parameter estimation table, we can obtain the model equations for each cryptocurrency that has been formed. The values of the parameter ϕ can be included in the equations, resulting in a table of equations as shown in Table 16. The coefficient of autoregression in the equation is used to measure the extent to which the value of observations in the previous period influences the current observation.

After obtaining the best model and its equation, the next step is to find the transition probability matrix values. Fundamentally, the transition probability matrix is a matrix that contains information indicating the probability of transitioning between different states. Based on the state categorization results previously conducted, in the following steps, we can determine the probabilities of transitioning from one state to another.

The transition probability matrix tables are used to analyze changes in the states of data that can transition from one state to another. The results of the tables indicate the transition probabilities between states for the coins used in the study. In this case, the rows in the table represent the state at time 't', while the columns represent the state at time 't+1'.

From Table 17, we can conclude that if the current state for BTC is state 1 (bullish), the probability of staying in state 1 (bullish) in the next period is 0.8153. Similarly, if the current state is state 1, the probability of transitioning to state 2 (bearish) in the next period is 0.0642. The same method for reading and calculating transition probabilities applies to other coins as well.

Table 17. MSAR Model Matrix Transition Probabilities

Koin	**Matriks Transisi**			
	State	**State 1**	**State 2**	**State 3**
BTC	**State 1**	0.8153	0.1620	0.2463
	State 2	0.0642	0.8380	0.0000
	State 3	0.1205	0.0000	0.7537
	State	**State 1**	**State 2**	**State 3**
BNB	**State 1**	0.9122	0.0818	0.0000
	State 2	0.0878	0.8920	0.1979
	State 3	0.0000	0.0262	0.8021
	State	**State 1**	**State 2**	**State 3**
ETH	**State 1**	0.7715	0.0210	0.1027
	State 2	0.0089	0.7300	0.0553
	State 3	0.2196	0.2489	0.8420
	State	**State 1**	**State 2**	**State 3**
XRP	**State 1**	0.7051	0.0467	0.0000
	State 2	0.2948	0.8088	0.1729
	State 3	0.0000	0.1445	0.8271
	State	**State 1**	**State 2**	**State 3**
ADA	**State 1**	0.2549	0.0000	0.0550
	State 2	0.0000	0.9001	0.1002
	State 3	0.7451	0.0999	0.8448

Source: RStudio (processed)

After obtaining the best MSAR model, forecasting can be performed to provide estimates of data for the upcoming period, taking into consideration the probabilities of each state. It's important to note that in this study, differencing has been applied to the data, so the forecasted prices are also in differenced data. The results of the forecast can also be compared to the probabilities of states by referring to the transition probability matrix table established earlier. The forecasting in this stage extends up to 7 days from the last recorded data date used for forecasting, which is until September 7, 2023.

In table 18, the results of the BTC coin price forecast can be seen, and can be matched with the previously defined state categories. Based on the forecasted BTC prices, if the next period's state is predicted to be state 1, then the market will be in a bullish condition, supported by the positive forecasted values. On the other hand, state 2, with negative values, indicates a bearish condition.

The same process is applied to other data, where positive forecasted values are categorized as bullish conditions, and negative values, lower than others, indicate bearish conditions. Forecasted values close to zero are considered as sideways conditions. This can be cross-verified with the previously defined market categories in Table 15. By examining the transition probability matrix values and combining them with the forecasted results, investors are expected to gain additional information for understanding the market and making informed decisions.

To assess the accuracy of the developed MSAR model for the five cryptocurrencies, a test of model precision was conducted using the Root Mean Square Error (RMSE) value. From the results of the precision measure test that can be seen in Table 19, it can be observed that the RMSE values for the five cryptocurrencies, each using the best-fitted MSAR model, mostly approach zero.

This implies that the selected models can accurately depict the data movements. Based on the RMSE values, it is evident that BTC has the lowest RMSE, indicating that the BTC model tends to be the most accurate in predicting prices.

Table 19. MSAR Model Accuracy Measure

Model	RMSE
BTC MS(3)AR(1)	0,0235
BNB MS(3)AR(1)	0,0436
ETH MS(3)AR(1)	0,0402
XRP MS(3)AR(2)	0,0873
ADA MS(3)AR(2)	0,1932

Source: RStudio (processed)

Table 8. MSAR Model Price Forecasting

Tanggal	BTC			BNB			ETH			XRP			ADA		
	State 1	State 2	State 3	State 1	State 2	State 3	State 1	State 2	State 3	State 1	State 2	State 3	State 1	State 2	State 3
26/08/2023	-0,0015	-0,0015	-0,0015	-0,0091	-0,0091	-0,0091	-0,0040	-0,0040	-0,0040	-0,0053	-0,0053	-0,0053	-0,0005	-0,0005	-0,0005
27/08/2023	0,0031	0,0031	0,0031	0,0092	0,0092	0,0092	0,0068	0,0068	0,0068	0,0007	0,0007	0,0007	0,0095	0,0095	0,0095
28/08/2023	0,0006	0,0006	0,0006	0,0017	0,0017	0,0017	-0,0031	-0,0031	-0,0031	-0,0011	-0,0011	-0,0011	0,0150	0,0150	0,0150
29/08/2023	0,0603	0,0603	0,0603	0,0366	0,0366	0,0366	0,0457	0,0457	0,0457	0,0316	0,0316	0,0316	0,0186	0,0186	0,0186
30/08/2023	-0,0156	-0,0156	-0,0156	-0,0136	-0,0136	-0,0136	-0,0143	-0,0143	-0,0143	-0,0222	-0,0222	-0,0222	-0,0253	-0,0253	-0,0253
31/08/2023	-0,0513	-0,0513	-0,0513	-0,0327	-0,0327	-0,0327	-0,0355	-0,0355	-0,0355	-0,0335	-0,0335	-0,0335	-0,0395	-0,0395	-0,0395
01/09/2023	0,0034	-0,0014	0,0091	0,0058	0,0044	0,0112	0,0079	-0,0115	0,0044	0,0227	-0,0009	0,0091	0,0024	0,0037	0,0023
02/09/2023	0,0033	-0,0031	-0,0009	-0,0002	0,0026	0,0115	-0,0031	-0,0135	0,0050	0,0250	-0,0032	-0,0010	0,0178	-0,0025	-0,0016
03/09/2023	0,0033	-0,0030	0,0008	0,0007	0,0027	0,0115	-0,0003	-0,0134	0,0050	0,0308	-0,0031	-0,0013	0,0606	-0,0012	-0,0008
04/09/2023	0,0033	-0,0030	0,0005	0,0006	0,0027	0,0115	-0,0010	-0,0134	0,0050	0,0314	-0,0031	-0,0005	0,0998	-0,0015	-0,0009
05/09/2023	0,0033	-0,0030	0,0005	0,0006	0,0027	0,0115	-0,0008	-0,0134	0,0050	0,0321	-0,0031	-0,0007	0,1585	-0,0014	-0,0009

Source: RStudio (processed)

CONCLUSION

Based on the results of the conducted research, it is anticipated that investors can make more informed investment decisions regarding the cryptocurrency to be used as an investment instrument. This is particularly crucial considering the interconnection between the crypto market and the economic world, especially in the field of capital markets, as well as the future prospects related to the crypto investment world trusted by the government. The research findings also indicate that Bitcoin (BTC) can be the best choice among cryptocurrencies due to its positive outlook and forecasts showing an increase in the upcoming period. Additionally, BTC has the lowest RMSE value, signifying that BTC has the best forecasting accuracy.

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