

Analysis of MNC36 Index Movements Using the Autoregressive Integrated Moving Average (ARIMA) Method During and After the COVID-19 Pandemic

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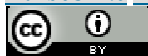
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ABSTRACT

This study analyzes the movement of the MNC36 index during the COVID-19 pandemic (2020–2022) and after the pandemic (2023–2025) using the Autoregressive Integrated Moving Average (ARIMA) method. Daily closing-price observations were obtained from Investing.com for the period 2 January 2020 to 30 December 2025, comprising 1,449 observations, and were processed using EViews 12. The analysis followed the Box–Jenkins procedure, including descriptive analysis, Augmented Dickey–Fuller (ADF) stationarity testing, model identification using ACF and PACF, parameter estimation, information criteria comparison, and residual diagnostics. The results show that MNC36 was more volatile during the pandemic, with a mean of 314 and standard deviation of 31, compared with a mean of 343 and standard deviation of 24 after the pandemic. The series in both periods was non-stationary at level and became stationary after first differencing. Based on AIC and SIC, ARIMA (3,1,3) was selected for the pandemic period, while ARIMA (2,1,13) was selected for the post-pandemic period. The latter produced lower AIC and SIC values and a Durbin–Watson statistic closer to 2, indicating relatively better fit and milder residual autocorrelation. However, residuals from both selected models did not fully satisfy the white-noise criterion. The findings indicate that ARIMA remains useful for modeling MNC36, but its performance depends on market conditions and the model should be interpreted alongside residual diagnostics.

INTRODUCTION

The capital market performs an important economic and financial function by connecting parties with excess funds and parties requiring funds for business expansion. In Indonesia, the capital market is also an important transmission mechanism through which investor expectations, macroeconomic conditions, and global shocks are reflected in security prices. Consequently, stock indices are not merely measuring of market performance; they also provide information about changing investor sentiment and perceived economic prospects.

The COVID-19 pandemic created an exceptional shock to the global economy and financial markets. Restrictions on mobility, disruptions to production and consumption, uncertainty about corporate earnings, and changes in investor confidence generated sharp movements in stock prices. Evidence summarized in the underlying thesis indicates that Indonesian stock-market conditions were substantially disturbed during the pandemic and that the shock was associated with significant fluctuations in market indices. The MNC36 Index is particularly relevant for examination because it represents 36 selected Indonesian stocks characterized by high liquidity and large market capitalization and is therefore a focused indicator of selected leading equities.

Descriptive evidence in the thesis shows a clear difference between the two study periods. During 2020–2022, the MNC36 Index had a mean of approximately 314, a median of 319, a maximum of 371, a minimum of 205, and a standard deviation of 31. During 2023–2025, its mean increased to approximately 343, the median to 347, the maximum to 388, the minimum to 265, while the standard deviation declined to 24. The lower dispersion after the pandemic suggests relatively more stable index movements, although the index still experienced meaningful fluctuations.

Forecasting a financial time series requires a method that can accommodate temporal dependence and non-stationarity. ARIMA is a widely used univariate time-series framework that combines autoregressive, differencing, and moving-average components. The Box–Jenkins approach provides a systematic sequence of identification, estimation, and diagnostic evaluation. Previous studies cited in the thesis have applied ARIMA to stock prices and other economic variables, while comparative studies have also shown that more flexible machine-learning models can outperform ARIMA when nonlinear patterns become dominant.

A research gap therefore remains. Much of the previous Indonesian literature reviewed in the thesis concentrates on the IHSG, individual stocks, IDX30, or other established indices. The specific application of ARIMA to MNC36 and the direct comparison of its model structure between the pandemic and post-pandemic periods remain limited. The present study addresses this gap by examining whether the best ARIMA structure changes across the two market regimes and whether the resulting models differ in their relative fit and residual behavior. The study aims to analyze the best ARIMA specification for MNC36 during 2020–2022, determine the best specification for 2023–2025, and compare the characteristics and relative performance of the two models.

LITERATURE REVIEW

Time Series Analysis

Time-series analysis examines observations arranged chronologically to identify temporal dependence, trends, and patterns that can be used for forecasting. In a univariate framework, the information used to model the current observation comes primarily from the historical values of the same variable and, depending on the model, from past error terms. This makes the approach appropriate when the objective is to study the internal temporal structure of an index without introducing external explanatory variables (Box et al., 2016; Wibowo, 2016).

Autoregressive Integrated Moving Average (ARIMA)

ARIMA combines three elements: autoregression (AR), integration through differencing (I), and moving average (MA). The model is conventionally represented as $ARIMA(p,d,q)$, where p is the autoregressive order, d is the number of differences required to obtain stationarity, and q is the moving-average order. The Box-Jenkins procedure begins with identification, including stationarity assessment and inspection of autocorrelation and partial autocorrelation patterns, followed by parameter estimation and residual diagnostics (Box et al., 2016; Hyndman & Athanasopoulos, 2021).

For financial-price series, non-stationarity at the level is common. Differencing is therefore used to stabilize the mean before AR and MA terms are identified. The diagnostic stage is essential because a model with attractive information criteria should not automatically be accepted if its residuals retain systematic autocorrelation. A satisfactory residual process should approximate white noise, indicating that the systematic temporal information has been adequately captured by the model.

MNC36 Index and COVID-19

The MNC36 Index was launched in 2013 and measures the performance of 36 selected stocks with high liquidity and large market capitalization. Its constituents are periodically evaluated using quantitative trading characteristics and qualitative considerations concerning fundamentals and growth prospects. Because it represents selected leading equities, changes in its dynamics provide a useful case for examining how a market shock can alter the temporal structure of an index.

The literature reviewed in the thesis indicates that COVID-19 was associated with higher stock-market volatility in several emerging and Asia-Pacific markets. In Indonesia, the pandemic was linked to substantial movements in stock indices, while comparative studies in other markets found that nonlinear or machine-learning approaches could outperform conventional ARIMA in certain post-pandemic settings. These findings support the need to examine ARIMA performance separately across market conditions rather than assuming that a single specification remains appropriate throughout different regimes.

Research Gap and Hypothesis

The reviewed evidence suggests three relevant gaps. First, relatively little work has focused specifically on MNC36 using ARIMA. Second, studies that compare ARIMA structures during and after COVID-19 within an Indonesian stock-index setting are limited. Third, a model should be evaluated not only

through information criteria but also through residual diagnostics. Accordingly, the study proposes the following research hypothesis: ARIMA can identify a best-fitting model for the MNC36 Index in both periods, but the model structure and relative adequacy differ between the pandemic and post-pandemic periods.

Table 1. Conceptual Framework

Stage	Process	Output
Input	Daily MNC36 closing prices, 2 January 2020–30 December 2025	Two periods: 2020–2022 and 2023–2025
Identification	Descriptive analysis, ADF, differencing, ACF and PACF	Stationary series and candidate p, d, q
Estimation	Estimate alternative ARIMA specifications in EViews 12	Candidate models and information criteria
Diagnosis	Residual correlogram / Q-statistic and model statistics	Adequate or inadequate residual behavior
Comparison	Compare best models across the two periods	Differences in structure and relative performance

METHODOLOGY

This study uses a descriptive quantitative design with a univariate time-series approach. The observation period runs from 2 January 2020 to 30 December 2025. Secondary daily closing-price data for the MNC36 Index were obtained from Investing.com. The thesis reports 1,449 daily observations. The sample is divided into two periods: the pandemic period from January 2020 through December 2022 and the post-pandemic period from January 2023 through December 2025.

Data were downloaded in CSV format and processed using Microsoft Excel and EViews 12. Data cleaning included checking chronological order, duplicates, missing observations, anomalous entries, and inconsistent date formats. The dependent series is the daily closing value of MNC36; no external explanatory variables are included because the study is designed as a univariate ARIMA analysis.

The analysis follows the Box–Jenkins sequence. First, descriptive statistics are used to summarize the central tendency and dispersion of each period. Second, stationarity is assessed using the Augmented Dickey–Fuller test and correlogram inspection at the level and after differencing. Third, candidate ARIMA models are estimated using alternative p and q combinations with d determined by the differencing requirement. Fourth, model selection considers AIC, SIC, adjusted R-squared, parameter significance, and model diagnostics. Finally, residual correlograms and Q-statistics are examined to determine whether residual autocorrelation remains.

The general ARIMA notation is:

$$\text{ARIMA}(p,d,q)$$

where p denotes the autoregressive order, d denotes the number of differences, and q denotes the moving-average order. In the empirical analysis, the final candidate selected for the pandemic period is ARIMA (3,1,3), while the

post-pandemic period selects ARIMA(2,1,13) on the basis of the reported information criteria.

RESEARCH RESULT

Descriptive Statistics

Table 2. Descriptive Statistics of MNC36

Statistic	COVID-19 Period (2020–2022)	Post-COVID-19 Period (2023–2025)
Mean	314	343
Median	319	347
Maximum	371	388
Minimum	205	265
Standard deviation	31	24

The descriptive results show that the average MNC36 level increased from approximately 314 during the pandemic to 343 after the pandemic. The maximum also increased from 371 to 388, while the minimum increased from 205 to 265. At the same time, the standard deviation declined from 31 to 24. Taken together, the results indicate a higher average index level and lower dispersion after the pandemic, suggesting a relatively more stable market environment in the later period.

Stationarity Testing

The thesis reports that the MNC36 series was not stationary at the level and required first differencing before ARIMA estimation. After first differencing, the correlogram patterns no longer displayed the persistent slow decay characteristic of a non-stationary series, supporting the use of $d = 1$ in both periods. The same differencing order across the two periods is important because it indicates that the principal difference between the two models lies in the autoregressive and moving-average structures rather than in the order required to achieve stationarity.

Table 3. Summary of Stationarity Identification

Period	Level	First Difference	Integrated Order (d)
2020–2022	Non-stationary	Stationary	1
2023–2025	Non-stationary	Stationary	1

ARIMA Model Selection During the COVID-19 Pandemic

Table 4. Candidate ARIMA Models During 2020–2022

Model	AIC	SIC	Adjusted R ²
ARIMA(3,1,3)	6.787	6.812	0.947
ARIMA(3,1,9)	6.796	6.821	0.948
ARIMA(9,1,3)	7.562	7.587	0.887
ARIMA(9,1,9)	8.070	9.095	0.813

ARIMA(15,1,15)	8.520	8.545	0.708
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Among the candidate models, ARIMA(3,1,3) has the lowest AIC and SIC values, 6.787 and 6.812, respectively. Its adjusted R-squared is 0.947, indicating a high degree of in-sample explanatory performance according to the reported model statistics. The estimated coefficients for the constant, AR(3), and MA(3) are statistically significant in the EViews output.

Table 5. Estimated ARIMA(3,1,3) During 2020–2022

Variable	Coefficient	Std. Error	t-Statistic	Probability
C	322.3808	10.22596	31.52572	0.0000
AR(3)	0.969083	0.007912	122.4831	0.0000
MA(3)	0.109086	0.023431	4.655724	0.0000
SIGMASQ	50.71535	1.366443	37.11488	0.0000

The diagnostic stage, however, qualifies the interpretation of this model. The residual correlogram indicates remaining serial dependence, and the reported Durbin–Watson statistic is 0.673194. Thus, although ARIMA(3,1,3) is the best candidate according to the information criteria used in the thesis, the residuals do not fully satisfy the desired white-noise condition. This means that the model is useful for describing the pandemic-period series but should not be treated as fully adequate without qualification.

ARIMA Model Selection After the COVID-19 Pandemic

Table 6. Candidate ARIMA Models During 2023–2025

Model	AIC	SIC	Adjusted R ²
ARIMA(2,1,2)	6.057	6.083	0.961
ARIMA(2,1,13)	6.054	6.079	0.960
ARIMA(2,1,35)	6.054	6.080	0.960
ARIMA(13,1,2)	7.063	7.089	0.892
ARIMA(13,1,35)	7.736	7.762	0.790

For 2023–2025, ARIMA(2,1,13) records the lowest SIC at 6.079 and the lowest reported AIC at 6.054, tied closely with ARIMA(2,1,35). ARIMA(2,1,2) has a marginally higher adjusted R-squared of 0.961, while ARIMA(2,1,13) has 0.960. Because the information criteria favor the more parsimonious ARIMA(2,1,13) over the much higher-order alternative and the reported selection procedure identifies it as the best model, ARIMA(2,1,13) is retained for comparison.

Table 7. Estimated ARIMA(2,1,13) During 2023–2025

Variable	Coefficient	Std. Error	t-Statistic	Probability
C	344.9081	9.017383	38.24924	0.0000
AR(2)	0.973682	0.006911	140.8917	0.0000
MA(13)	0.106157	0.034192	3.104714	0.0020
SIGMASQ	24.44661	0.891976	27.40726	0.0000

The estimated coefficients are statistically significant. The model has an R-squared of 0.960265 and an adjusted R-squared of 0.960097. Its standard error of regression is 4.958259 and the reported log likelihood is -2157.293. Nevertheless, residual diagnostics again reveal remaining autocorrelation: the first residual autocorrelation is reported at approximately 0.439 and the Q-statistic probabilities from lag 3 onward are below 0.05. The Durbin-Watson statistic is 1.121537. Therefore, the post-pandemic model is relatively better behaved than the pandemic-period model, but it does not completely satisfy the white-noise criterion.

Comparison of the Two Periods

Table 8. Comparison of Selected ARIMA Models

Indicator	COVID-19 (2020–2022)	Post-COVID-19 (2023–2025)
Selected model	ARIMA(3,1,3)	ARIMA(2,1,13)
AR component	AR(3)	AR(2)
MA component	MA(3)	MA(13)
Differencing	1	1
AIC	6.787315	6.054042
SIC	6.812375	6.079649
Durbin-Watson	0.673194	1.121537
Standard deviation	31	24

The two periods share the same integrated order, $d = 1$, but differ substantially in their AR and MA structures. During the pandemic, the selected specification relies on three autoregressive lags and three moving-average lags. After the pandemic, the autoregressive component falls to two lags while the moving-average component extends to lag 13. This indicates that the temporal dependence captured by the preferred model changed across the two market regimes.

The information criteria are lower in the post-pandemic period: AIC falls from 6.787315 to 6.054042 and SIC falls from 6.812375 to 6.079649. The Durbin-Watson statistic also moves closer to the conventional benchmark of two, from 0.673194 to 1.121537, although it remains below two. In combination with the lower standard deviation, these results support the conclusion that the post-pandemic market was relatively more stable and that the ARIMA specification performed comparatively better in that environment.

DISCUSSION

Different Temporal Structures Across Market Conditions

The most important empirical finding is that the best ARIMA structure is not constant across the two periods. Both models require one difference, indicating that non-stationarity is a common characteristic of the MNC36 level series. However, the pandemic period is represented by AR(3) and MA(3), whereas the post-pandemic period is represented by AR(2) and MA(13). The change in the moving-average order is particularly notable because it suggests

that the model needs to accommodate a longer residual-memory structure after the pandemic than during the pandemic.

This result should not be interpreted as evidence that the pandemic itself mechanically caused a specific ARIMA order. Rather, the result shows that the statistical dependence structure of the observed index differs between the two samples. The pandemic was characterized by rapid information transmission, abrupt repricing, policy uncertainty, and strong market reactions. Under such conditions, the historical relationship among observations can change quickly. In the later period, the lower dispersion and higher average index level suggest a different environment in which persistence and residual effects can be represented differently.

The finding is consistent with the broader literature reviewed in the thesis. Studies of COVID-19 and stock markets have reported significant increases in volatility followed by moderation, while comparative forecasting studies have shown that model performance can vary according to the complexity and nonlinearity of market patterns. Consequently, model selection should remain sample-specific rather than relying on a fixed ARIMA specification across all periods.

Information Criteria versus Residual Adequacy

A second important finding is the distinction between selecting a model and validating a model. ARIMA(3,1,3) and ARIMA(2,1,13) are the selected specifications according to the reported information criteria, but neither residual series fully satisfies the white-noise requirement. The pandemic-period model has stronger evidence of residual autocorrelation, reflected in its low Durbin-Watson statistic. The post-pandemic model improves on this aspect, but significant Q-statistics remain at multiple lags.

This result reinforces the Box-Jenkins principle that a model with the lowest AIC or SIC should not automatically be considered the final forecasting model if diagnostic tests show systematic residual dependence. Information criteria evaluate the trade-off between fit and complexity, whereas residual diagnostics evaluate whether relevant temporal information remains unexplained. In practical forecasting work, these criteria should be considered jointly.

The results also explain why the study should describe the post-pandemic ARIMA(2,1,13) as relatively better rather than perfectly adequate. Its lower AIC and SIC and improved Durbin-Watson statistic indicate better relative performance within the study design, but the residual autocorrelation means that additional model development could still be justified. The thesis itself emphasizes the potential value of alternative specifications such as ARIMA with exogenous variables or other time-series methods when volatility is high.

Comparison with Previous Research

The findings are broadly consistent with studies showing that ARIMA can be useful for stock-price forecasting when the data are transformed appropriately. Diharjo and Arief (2022), for example, reported the use of ARIMA for IDX30 during the pandemic, while Faisal (2021) applied ARIMA to Telkom shares. Kurnia et al. (2025) likewise used ARIMA for BCA stock-price prediction.

These studies support the continuing relevance of conventional time-series methods in financial forecasting.

At the same time, the present findings are consistent with studies that identify limitations of ARIMA under complex market conditions. Ho et al. (2021) and comparative research summarized by Zhang et al. (2023) report that neural-network approaches can outperform ARIMA in some stock-price forecasting settings. The evidence from the current MNC36 study is complementary: ARIMA remains informative, but its residual diagnostics show that a linear univariate structure may not capture all of the dynamics present in the data.

The lower post-pandemic dispersion and better relative information criteria also align with the broader observation in the thesis that market volatility moderated after the pandemic. Vo et al. (2022) reported that Asia-Pacific stock-market volatility increased substantially during COVID-19 and subsequently moderated. Insaiddoo et al. (2023) also documented a negative relationship between the pandemic and stock-market performance in emerging economies. These findings provide contextual support for interpreting the different MNC36 model structures as a reflection of changing market conditions.

Theoretical and Practical Implications

Theoretically, the study supports the application of the Box-Jenkins framework to a focused Indonesian stock index. It demonstrates that stationarity transformation, model identification, estimation, and residual diagnostics are necessary stages rather than optional steps. The evidence also reinforces the principle that the usefulness of an ARIMA model is conditional on the temporal characteristics of the sample.

For investors, the findings suggest that ARIMA can be used as a supporting tool for understanding the historical dynamics of MNC36, but it should not be treated as a stand-alone decision rule. During periods of extreme uncertainty, residual dependence can remain substantial, so ARIMA forecasts should be complemented with fundamental analysis, market indicators, and risk assessment. For managers and market participants, the comparison highlights the importance of adapting analytical models when market regimes change.

CONCLUSIONS AND RECOMMENDATIONS

The study concludes that ARIMA can model the MNC36 Index in both the COVID-19 and post-COVID-19 periods, but the preferred model structures differ. For 2020–2022, ARIMA(3,1,3) is selected because it provides the lowest AIC and SIC among the candidate models. For 2023–2025, ARIMA(2,1,13) is selected because it provides the lowest reported AIC and SIC. Both periods require first differencing, confirming that $d = 1$ is sufficient to transform the series into a stationary form.

The post-pandemic model demonstrates relatively better performance. Its AIC and SIC are lower than those of the pandemic-period model, its Durbin-Watson statistic is closer to two, and the descriptive standard deviation falls from 31 to 24. Nevertheless, neither selected model produces residuals that are completely white noise. The pandemic-period residuals show stronger evidence of autocorrelation, while the post-pandemic residuals show improvement but still contain statistically significant serial dependence.

For investors, ARIMA results should be used as an analytical supplement rather than as the sole basis for trading or investment decisions, particularly during high-volatility periods. For future researchers, the MNC36 series can be analyzed using ARIMAX, ARIMA-GARCH, SARIMA, regime-switching models, or nonlinear machine-learning methods. Future studies should also consider out-of-sample forecasting accuracy using measures such as MAE, RMSE, and MAPE and should test whether alternative models can remove the residual autocorrelation identified in this study.

ADVANCED RESEARCH

This study is limited by its univariate design, its reliance on daily closing prices, and its use of information criteria and residual diagnostics within a single modeling framework. Because the residuals of the selected models remain autocorrelated, future research should investigate alternative lag structures and models that can explicitly address conditional heteroskedasticity or nonlinear dependence. Comparative research could also evaluate ARIMA against ARIMA-GARCH, ARIMAX, LSTM, support-vector regression, or hybrid forecasting approaches using consistent in-sample and out-of-sample evaluation periods.

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