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Post-Pandemic Transformation of Zakat, Infaq, and Sadaqah (ZIS): Implications for Social Welfare and Economic Recovery

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ABSTRACT

This study examines how the collection and distribution of Zakat, Infaq, and Sadaqah (ZIS) transformed during the COVID-19 pandemic. It provides forecasts for 2024, with a particular focus on their implications for social welfare and economic recovery in the post-pandemic era. The study utilized secondary data obtained from BAZNAS monthly reports covering January 2020 to December 2023, a period that captures the initial peak of the COVID-19 crisis and the subsequent recovery phase. Due to the non-normal distribution of the data, the Wilcoxon signed-rank test was employed to assess differences in ZIS collection and distribution between the peak and recovery periods. Additionally, Seasonal Autoregressive Integrated Moving Average (SARIMA) models were applied to forecast future trends. The findings revealed statistically significant differences between the peak and recovery periods in both ZIS collection and distribution, indicating a structural shift in philanthropic behavior and institutional responsiveness after the pandemic. The SARIMA results demonstrated strong capability in capturing seasonal patterns and long-term trends, particularly the pronounced increase in ZIS activities during Ramadan. While the SARIMA model provided a robust foundation for understanding seasonal dynamics and short-term trends, incorporating additional data or hybrid forecasting approaches may enhance predictive accuracy.

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INTRODUCTION

Indonesia has been severely affected by the COVID-19 pandemic, which has caused major disruptions across several economic sectors. The pandemic caused a steep drop in export performance, a slowdown in economic growth, and a reduction in manufacturing output. Mobility limitations and lower occupancy rates have had a significant impact on other industries, like tourism and transportation. A declining currency exchange rate and inflationary pressures emerged, leading to a significant decline in the stock market. More than two million workers were also impacted by layoffs, which raised the unemployment rate and created economic instability. Additionally, the foreign debt-to-GDP ratio increased, making the difficulties the Indonesian economy faced during this historic period even more severe. (Arianto, 2021; Budastra, 2020; Nasution et al., 2020; Yamali & Putri, 2020).

The pandemic's significant social effects coincided with its economic ramifications, especially in shaping society's attitudes and habits. The administration of zakat was one area in Indonesia that saw significant changes. The economic downturn and public health measures implemented during the epidemic directly affected the collection and distribution of zakat, a vital part of Islamic social finance. According to studies, the economic slump and physical separation policies that impeded direct collection efforts led to a 20–50% decline in institutional zakat funds (Ridwan & Fadilah, 2022). On the other hand, conflicting data indicate that some institutions saw a rise in zakat collection, which was linked to increased public awareness of social solidarity during the crisis (Napitupulu et al., 2021). Zakat institutions used creative tactics to continue operating and helping the community, overcoming the obstacles posed by the pandemic. Promoting early zakat payments, improving digital collection techniques through mobile applications, and using online platforms to streamline transactions were among these activities. With strict adherence to health guidelines, traditional collection methods were preserved in areas less accustomed to digital technologies. Despite the limitations posed by the pandemic, targeted distribution methods were implemented to prioritize aid to the most vulnerable populations, ensuring that the social goals of zakat were fulfilled (Hidayanti Daulay & Nasution, 2022; Radiansyah, 2021).

The pandemic demonstrated the flexibility and resilience of Indonesia's zakat mechanisms. Many muzakki (zakat payers) persisted in fulfilling their responsibilities despite economic challenges, indicating their faith in the legitimacy and openness of the institutions.

This conduct reflects a long-standing religious and cultural commitment to social welfare, which is heightened in emergencies. Zakat institutions' crucial role in building community resilience and reducing the socioeconomic effects of the pandemic is highlighted by their capacity to uphold public trust and operational effectiveness (Harahap & , Harahap, Darwis, Aini, 2023; Napitupulu et al., 2021). An in-depth examination of these dynamics is necessary in light of the shifting patterns in zakat distribution and collection during the pandemic. With the pandemic starting in early 2020, reaching its height in 2021, and then progressively waning by 2022 before the official announcement of its conclusion in 2023, the years 2020–2023 offer a singular case study. This research aims to examine the differences in collection and distribution during that period.

Regarding forecasting, one method is the ARIMA (Autoregressive Integrated Moving Average) model. However, ARIMA cannot handle data with seasonal components well. To address this, the SARIMA (Seasonal ARIMA) model was developed to handle time series data with seasonal patterns (Montgomery et al., 2008). Previous research has also discussed the collection of zakat using that approach (Assakhiy et al., 2019). In the context of zakat, seasonal patterns can be observed in the spikes in collection and distribution that occur in certain months, such as Ramadan. This research aims to predict the collection and distribution of zakat for the year 2024.

METHOD, DATA, AND ANALYSIS

This research is an inferential quantitative study, a data analysis method that aims to draw conclusions and generalise from samples to populations (Siregar, 2021). Inferential data analysis consists of two types: parametric and non-parametric statistics (Syahroni, 2023). The analysis process involved preparing numerical data, using statistical programmes, reporting descriptive and inferential results, and interpreting findings. This study used a non-parametric approach because the data do not meet the normality assumption; therefore, the Wilcoxon test is used. The Wilcoxon signed-rank test is a widely used non-parametric statistical method for analyzing paired data in health research, particularly for ordinal-scale data, and it can be applied to both measurement and categorical data, with measurement data generally yielding better results (Budiono & Prasetia, 2022). The Wilcoxon test was conducted to determine whether there were differences in the collection and distribution of ZIS during the COVID-19 period.

The data used were secondary, derived from Baznas's monthly report. The monthly reports used cover the period from January 2020 to December 2023 and relate to ZIS collection and distribution. This time was taken to see how the collection and distribution during COVID-19 compares with the peak of 2020 to 2021 and the subsiding COVID-19 in 2022 to 2023. Montgomery et al. (2008) reported strong periodic patterns in several time series variables. The term "time series with seasonal characteristics" is frequently used to describe this. Seasonal time series are typically observed when variables are measured more precisely at monthly, weekly, or similar intervals. Seasonal ARIMA or SARIMA are terms frequently used to describe time series that show a seasonal pattern. Therefore, the fundamental ARIMA model is extended by the SARIMA model.

Data processing using the SARIMA model began by examining visualisation plots that exhibit seasonal patterns. The data's stationarity was then identified. It was done by analysing the original data through plots (time series) and using the Augmented Dickey-Fuller (ADF) to detect stationarity. If the data are not stationary, a differencing process is applied to both the non-seasonal (d) and seasonal (D) components until the data become stationary. Once the data were stationary, the next step was to identify the model parameters. Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots are used to determine the values of p (AR order), q (MA order), P (seasonal AR order), and Q (seasonal MA order). The seasonal period (m) must also be determined based on the data characteristics; for example, monthly data has m = 12. Next, the model parameters were estimated using the auto ARIMA function. The proposed models, such as SARIMA (p,d,q) (P, D, Q) [m], were tested using metrics such as the Akaike Information Criterion (AIC), the Bayesian Information Criterion (BIC), and other statistics.

After the model is built, residual diagnostics are performed to check whether the residuals are white noise (random) using the Ljung-Box test and residual plots. If the residuals are not white noise, the model needs to be adjusted. The final stage was forecasting using the calibrated SARIMA model. Data projections are made for future periods, and the forecasting results are visualised along with confidence intervals.

RESULTS AND DISCUSSION

Collecting

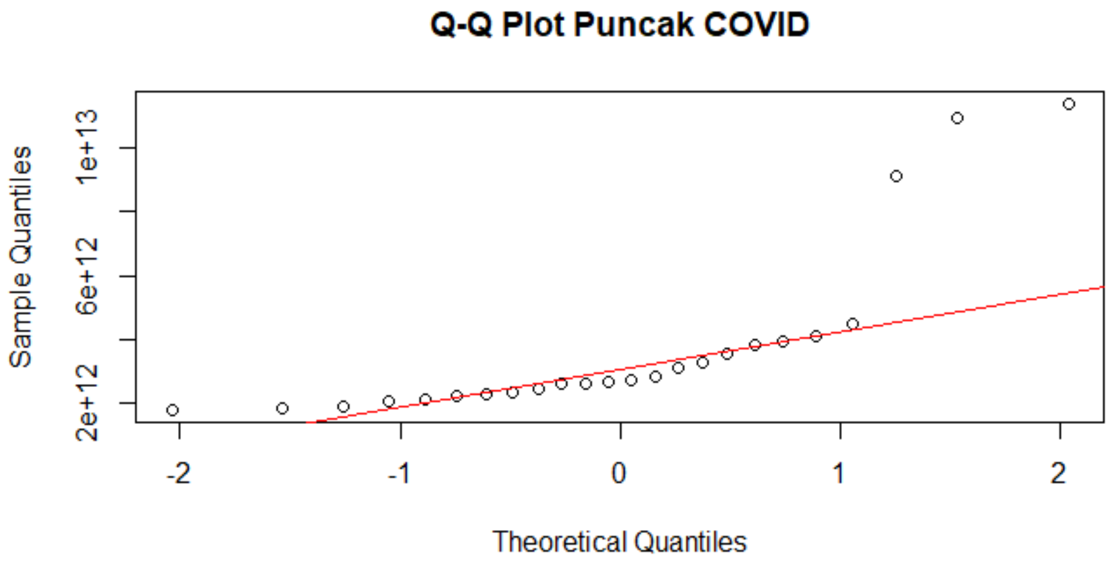
Based on data collected from January 2020 to December 2023, 48 data points will be split into 2 periods: 2020-2021, considered the peak of COVID, and 2022-2023, when COVID subsided. The data collected on the collection side is tested for assumptions, and using various tests, the following results are obtained.

Table 1. Normality Test during the Peak of COVID-19 Cases

Shapiro-Wilk Normality Test
Data: Data $Puncak_Covid
W = 0.65156, p-value = 2.456e-06

Source: Data Processed, 2025

Table 1 presents the results of the Shapiro–Wilk normality test conducted on the Zakat, Infaq, and Sadaqah (ZIS) data during the peak period of the COVID-19 pandemic. The test yields a Shapiro–Wilk statistic (W) of 0.65156 with a p-value of 2.456e−06, which is far below the conventional significance level of 0.05. This result indicated that the data significantly deviates from a normal distribution. Consequently, the assumption of normality is violated, justifying the use of non-parametric statistical methods in subsequent analyses. In this study, the Wilcoxon signed-rank test was therefore appropriately employed to examine differences in ZIS collection and distribution between the peak and recovery periods of the pandemic. From the results of the normality test above, the p-value is very small: 2.456e-06. It indicated that the data is not normally distributed. Furthermore, the non-normal distribution observed during the peak COVID-19 period reflects the high volatility and uncertainty affecting ZIS collection and distribution at that time. Disruptions in economic activity, mobility restrictions, and shifting donor behavior likely contributed to irregular fluctuations in the data. This condition underscores the exceptional nature of the pandemic period. It reinforces the methodological decision to apply robust non-parametric techniques, ensuring that the statistical conclusions remain valid despite the presence of extreme values and structural shocks in the dataset.



Graph 1. Q-Q Plot of Puncak Covid

Source: Data Processed, 2025

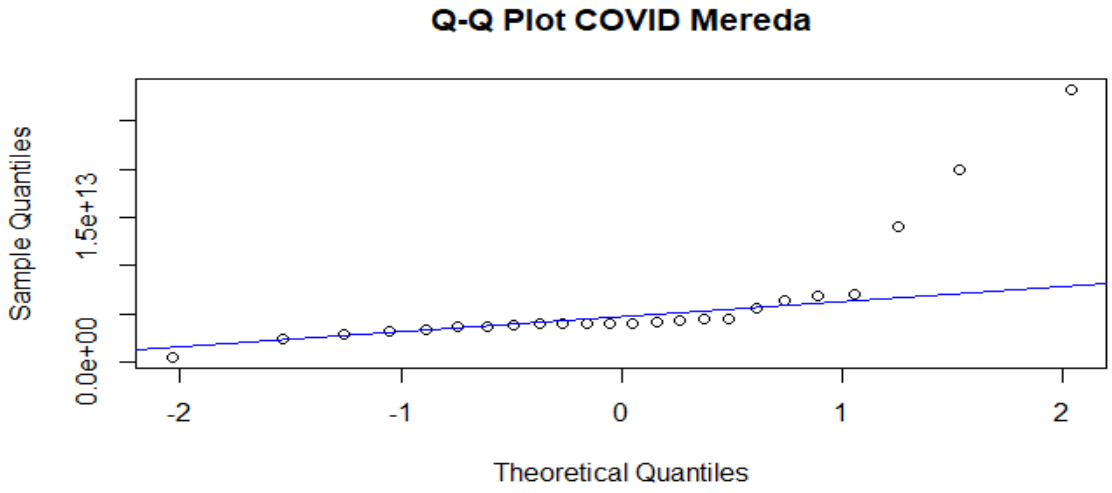
Graph 1 showed that the Q-Q plot indicates extreme outliers towards the right and some at the beginning of the graph.

Table 2. Normality Test during the Decline of COVID-19 Cases

Shapiro-Wilk Normality Test
Data: Data $Covid_Mereda
W = 0.60655, p-value = 7.316e-07

Source: Data Processed, 2025

From Table 2 above, the normality test showed a very small p-value (7.316e-07), indicating that the data are not normally distributed. The histogram shows that the data is unevenly distributed, with a dominant peak on one side. It indicated that this data is not normally distributed. This non-normality is further supported by the histogram pattern, which shows an uneven distribution with observations concentrated on one side. These findings confirm that parametric assumptions are violated during the recovery phase, thereby reinforcing the appropriateness of employing non-parametric analytical methods for comparative analysis in this study.



Graph 2. Q-Q Plot of Decline of COVID-19 Cases

Source: Data Processed, 2025

Graph 2 showed that the Q-Q plot also revealed extreme outliers to the right.

Table 3. Hypothesis Test during the Peak of COVID-19 Cases

Wilcoxon Signed Rank Exact Test
Data: Data Puncak $covid Covid and data $Covid Mereda
V = 67, p-value = 0.01641

Source: Data Processed, 2025

Based on Table 3, the p-value is 0.01641. It means there is a significant difference in collection between the peak of COVID and when COVID subsides. The higher median value in the COVID subsided period suggests that, after the pandemic, the amount of funds raised increased. Outliers in both periods indicated that some months saw fundraising much higher than others, perhaps due to special events or programmes that boosted donations. The COVID-19 pandemic has surprisingly led to an increase in zakat collection in some regions. Despite economic challenges, zakat funds in Indonesia rose by 30% due to a shift towards digital platforms, enabling easier donations from home (Zetira & Fatwa, 2021).

Similarly, Malaysia's *Pusat Pungutan* Zakat MAIWP experienced significant growth in business zakat collection during the pandemic (Anuaruddin et al., 2023). To optimize digital zakat collection, institutions have implemented effective management strategies based on James Stoner's theory (Zetira & Fatwa, 2021). Some organizations encouraged early zakat payments to provide immediate benefits during the crisis (Hidayanti Daulay & Nasution, 2022). The National Amil Zakat Agency in Indonesia reported a positive impact of the pandemic on online zakat collection, despite initial concerns of decreased donations (Ridwan & Fadilah, 2022).

Distribution

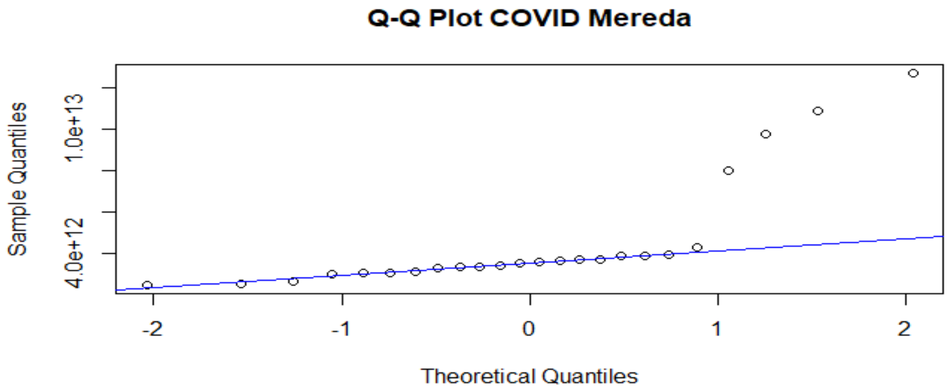
Based on data collected from January 2020 to December 2023, 48 data points will be split into two parts: 2020-2021, considered the peak of COVID, and 2022-2023, when COVID subsided. The data collected on the collection side is tested for assumptions, and using various tests, the following results are obtained.

Table 4. Normality Test during the Decline of COVID-19 Cases (2)

Shapiro-Wilk normality test
Data: Data$covid_mereda
W = 0.63696, p-value = 1.642e-06

Source: Data Processed, 2025

Based on Table 4, the normality test, the p-value is 1.642e-06, indicating the data are not normally distributed. From the histogram, it can also be seen that the data is not evenly distributed, with most values centred on one side.



Graph 3. Q-Q Plot of Decline of COVID-19 Cases (2)

Source: Data Processed, 2025

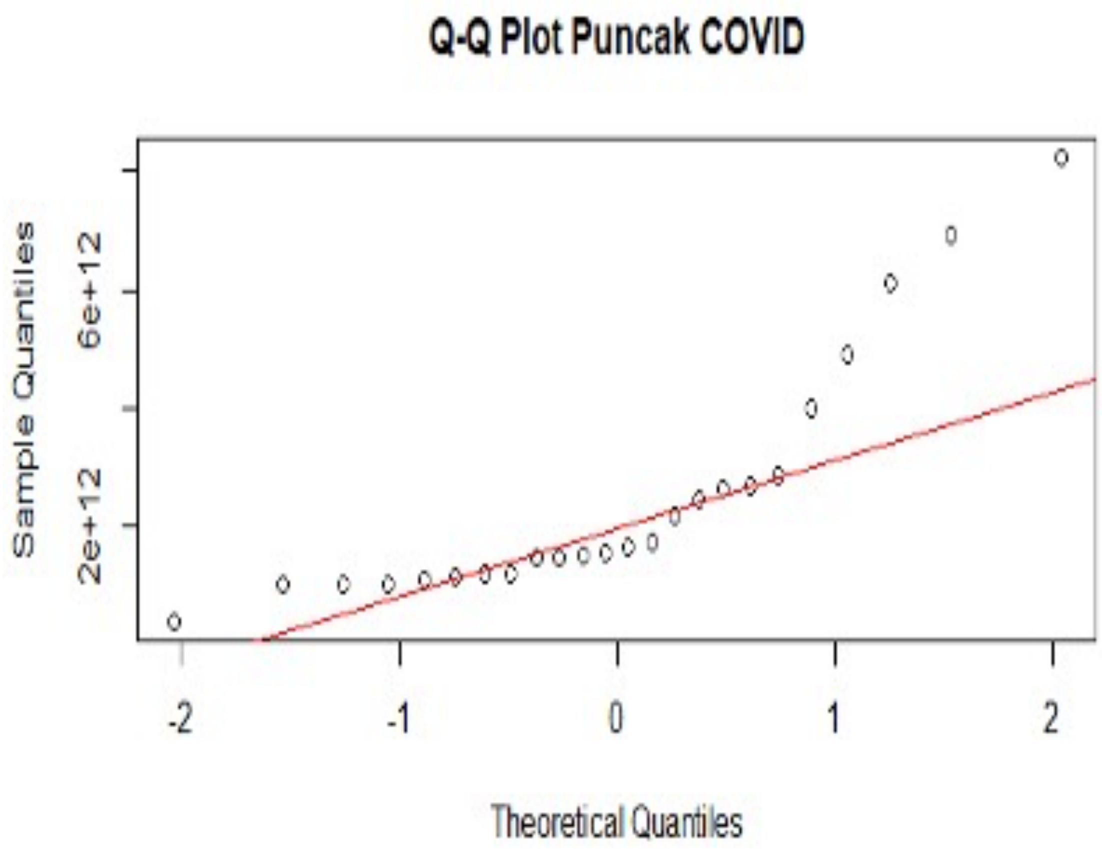
Graph 3 showed that the Q-Q plot revealed very extreme outliers, especially on the right. It showed that the distribution of data related to distribution during the COVID period is not normally distributed.

Table 5. Normality Test during the Peak of COVID-19 Cases (2)

Shapiro-Wilk normality test
Data: Data$Puncak_Covid
W = 0.78243, p-value = 0.0001541

Source: Data Processed, 2025

Table 5 from the normality test for the peak COVID period in channelling showed that the p-value of 0.0001541 is very small, indicating that the data are not normally distributed. The histogram also showed that the data distribution is uneven, with a strong skew towards one side.



Graph 4. Q-Q Plot of Peak of COVID-19 Cases (2)

Graph 4 showed that the Q-Q plot also revealed very extreme outlier values in this data, especially in the upper-right portion. It further indicated that the data is not normally distributed.

Table 6. Hypothesis Test of Peak COVID-19 Cases (2)

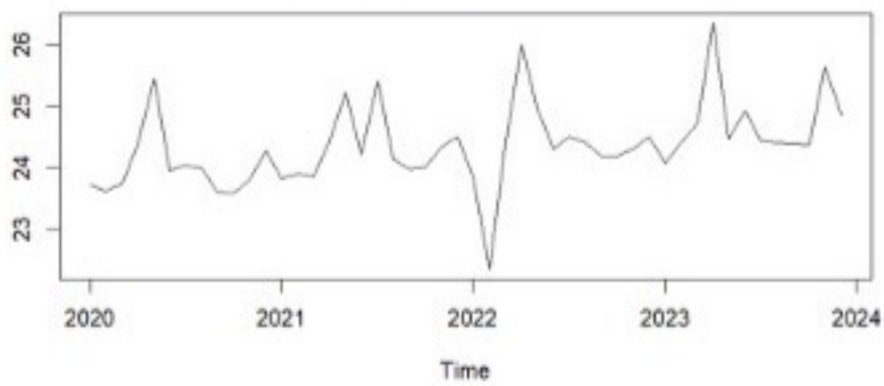
Wilcoxon Signed Rank Exact Test
Data: Data$puncak_covid and data$covid_mereda V = 31, p-value = 0.0002781

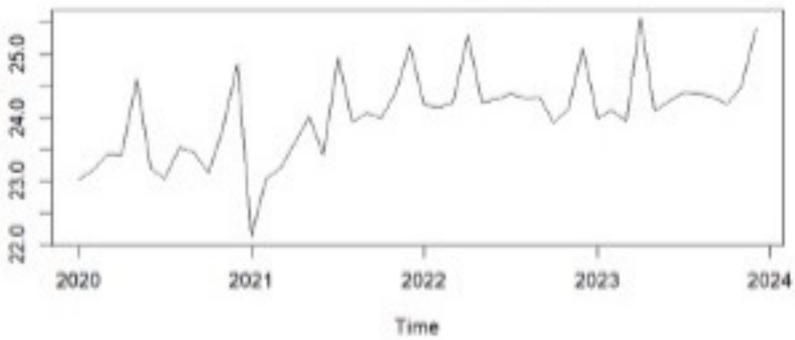
Source: Data Processed, 2025

Table 6 presents the Wilcoxon test results, yielding a p-value of 0.0002781. This value was so small that it showed a very significant difference between channeling at peak and when COVID subsided. From this boxplot and the previous Wilcoxon Signed Rank Test statistical result (p-value = 0.0002781), we can conclude that there is a significant difference in disbursements between the Peak COVID and Waning COVID periods. The higher median during the COVID-19 downturn suggests that, as the situation stabilised, disbursements increased significantly. Research indicates that zakat distribution increased during the COVID-19 pandemic, playing a crucial role in economic recovery and poverty alleviation. Zakat institutions in Indonesia showed positive collection trends despite economic challenges (Muhari, 2023). Distribution mechanisms adapted to prioritize the most vulnerable groups and address pandemic-related needs (Khumaini et al., 2022). BAZNAS and LAZNAS enhanced their roles in tackling poverty during the pandemic, with government support being crucial for effective implementation (Iswandi, 2021). Zakat distribution served as an economic solution during the pandemic, providing significant benefits to recipients affected by COVID-19. The distribution of zakat funds during this period was found to be in accordance with Islamic principles and played a vital role in supporting social welfare and economic stability (Sakinah & Maulana, 2021).

Forecasting

The first step is to create a visualisation plot of the distribution and collection of zakat data by Baznas. In this case, the data were presented in logarithmic form to facilitate a more proportional comparison. The forecasting process began with visualizing Zakat collection and distribution data from BAZNAS to identify underlying patterns, trends, and seasonal fluctuations. Transforming the data to logarithmic form is an essential step, as it stabilizes variance, reduces the impact of extreme values, and enables more proportional comparisons across periods with significantly different scales. This transformation is particularly useful in time-series analysis, where Zakat data tend to exhibit sharp increases during specific months, such as Ramadan. By examining the log-transformed plots, the study gains clearer insights into long-term movements and seasonal behavior, which subsequently support the selection and estimation of appropriate forecasting models, such as SARIMA, for more reliable and interpretable predictions.





Graph 5. Time Series of Zakat Collection and Distribution

Graph 5 explained that both graphs show a seasonal pattern that repeats each year, indicating a seasonal cycle in the collection and distribution of data. This pattern suggested that the SARIMA (Seasonal AutoRegressive Integrated Moving Average) model can be used, as it is designed to handle data with regularly recurring seasonal patterns. Identifying these seasonal patterns is important for understanding the periodic trends that consistently affect data fluctuations year to year.

In the graph of the collection, there is a rather stable trend with fairly clear seasonal fluctuations. However, there is a significant spike around the middle of 2022, which may be due to special events, such as a large zakat campaign or the momentum of Ramadan. Meanwhile, the distribution graph showed a more consistent seasonal pattern than the collection. However, large fluctuations were also recorded in early 2021. Several factors contribute to the increase in zakat payments, especially during Ramadan. Service quality, religious factors, social awareness, self-satisfaction, and improvements in the quality and transparency of zakat organizations can significantly Influence zakat payers' preferences during the month of Ramadan (Mukhlis & Beik, 2013).

Table 7. Augmented Dickey-Fuller Test of Collection

Augmented Dickey-Fuller Test
Data: Log_ Collection Dickey-Fuller = -3.8931, Lag order = 3, p-value = 0.02187 alternative hypothesis: stationary

Source: Data Processed, 2025

Table 8. Augmented Dickey-Fuller Test of Distribution

Augmented Dickey-Fuller Test
Data: Log_ Distribution Dickey-Fuller = -2.696, Lag order = 3, p-value = 0.2962 Alternative Hypothesis: Stationary

Source: Data Processed, 2025

From the Augmented Dickey-Fuller Test (ADF) results for collection and distribution, the log collection data is stationary because the p-value is less than 0.05. In contrast, the distribution log p-value is greater than 0.05, so differencing is required.

Table 9. Augmented Dickey-Fuller (ADF) Test Results for diff_log_distribution Data

Augmented Dickey-Fuller Test
Data: diff_Log_ Distribution Dickey-Fuller = -6.1647, Lag order = 3, p-value = 0.01 Alternative Hypothesis: Stationary

Source: Data Processed, 2025

Tables 7, 8, and 9 present the Augmented Dickey-Fuller Test (ADF) results for channeling, which indicate that the p-value is less than 0.05 (0.01), indicating that the channeling data meet the stationarity requirements. The Auto-Correlation Function (ACF) and Partial Auto-Correlation Function (PACF) are frequently employed as diagnostic tools to ascertain the parameters of the SARIMA model. ACF helps determine the "q" and "Q" terms of the model (connected to the moving-average components) by shedding light on the correlation between observations in a time series separated by lag intervals. In the meantime, PACF helps identify the "p" and "P" terms (associated with the autoregressive components) by separating the direct impact of historical lags on a current value. The model's setup is guided by the patterns shown in ACF and PACF plots, where spikes at particular lags suggest possible orders for these components. By taking a methodical approach, the SARIMA model's forecasting accuracy is increased, and it is guaranteed to match the data's underlying structure. To address this issue, first-order differencing was applied to the log distribution series. The results of the subsequent ADF test are presented in Table 9, where the differenced log distribution yields an ADF statistic of −6.1647 with a p-value of 0.01, indicating that the series is stationary after differencing.

Table 10. ARIMA Modeling Results (0,1,1) (1,0,0) [12] on Log_ Collection

Series: Log_ Collection
ARIMA (0,1,1) (1,0,0) [12]
Coefficients:
ma1 sar1
-0.9078 0.5188
s.e. 0.0542 0.1307
Sigma^2 = 0.3325: log likelihood = -42.36
AIC= 90.73 AICc= 91.28 BIC=96.28
Training set error measures:
ME RMSE MAE MPE MAPE MASE
Training set 0.1179642 0.5583081 0.3416909 0.4343837 1.387003 0.7702215
ACF1
Training set 0.05187389

Source: Data Processed, 2025

Table 10 showed that the SARIMA (0,1,1) (1,0,0) [12] model applied to the log collection data yields significant parameter estimates. The coefficient for the MA (1) non-seasonal component is -0.9078 with a standard error of 0.0542, while the coefficient for the AR (1) seasonal component is 0.5188 with a standard error of 0.1307. The sigma^2 value of 0.3325 indicates a fairly low level of residual variability, which reflects the model's ability to capture data patterns. The log-likelihood value of -42.36 indicates the model's fit to the data, with information criteria AIC, AICc, and BIC of 90.73, 91.28, and 96.28, respectively. Based on the error evaluation on the training data, the model achieved an RMSE of 0.5583, indicating the average error rate in predicting the log collection data. In addition, the MAE value of 0.3417 indicates a relatively small average absolute error, showing that the model is quite accurate in approximating the actual values. The MAPE value of 1.387% indicates that the average prediction error is only about 1.39% of the true value, which is a good indicator of model performance. The residual ACF1 value of 0.0519 is also close to zero, indicating that the model's residuals lack a significant pattern and that it has captured most of the data's patterns.

Table 11. ARIMA Modeling Results (0,1,1) (1,0,0) [12] on Log_ Distribution

Series: Log_ Distribution

```
ARIMA (0,1,1) (1,0,0) [12]
Coefficients:
 ma1    sar1
 -0.7461  0.4866
s.e.   0.1104  0.1460
sigma^2 = 0.2945:  log likelihood = -38.96
AIC=83.91   AICc=84.47   BIC=89.46
Training set error measures:
ME     RMSE      MAE      MPE    MAPE      MASE
Training set 0.08261392 0.5254902 0.3579758 0.3060797 1.479431 0.7334951
 ACF1
Training set -0.09565426
```

Source: Data Processed, 2025

Table 11: The SARIMA (0,1,1) (1,0,0) [12] model applied to the log channelling data successfully identified seasonal and non-seasonal patterns with significant parameter estimates. The coefficient for the non-seasonal component MA (1) is -0.7461 with a standard error of 0.1104, while the coefficient for the seasonal component AR (1) is 0.4866 with a standard error of 0.1460. The sigma^2 value of 0.2945 indicates low residual variability,

suggesting good performance in capturing the data pattern. The model's log-likelihood of -38.96 indicates a good fit, supported by AIC values of 83.91, AICc of 84.47, and BIC of 89.46, confirming that the model is efficient for the data.

Based on the error evaluation on the training data, the model yields an RMSE of 0.5255, indicating a small average error rate in predicting the log channelling data. In addition, the MAE value of 0.3580 reflects a relatively small average absolute error. At the same time, the MAPE of 1.479% indicates that the average model prediction error is only about 1.48% of the actual value. It indicated that the model can represent the data quite well. The residual ACF1 value of -0.0957, which is close to zero, indicates that no systematic pattern remains in the residuals, so the model captures important patterns in the data. Overall, the SARIMA (0,1,1) (1,0,0) [12] model gave satisfactory results for the log channelling data. The model successfully captures seasonal and non-seasonal patterns with significant parameters and good error evaluation performance. Next, a residual diagnostic test is conducted to ensure that the residuals are not autocorrelated and meet the white noise assumption, thereby improving the model's forecasting validity.

Table 12. Ljung-Box test Collection

Ljung-Box test Collection
Data: Residuals from ARIMA (0,1,1) (1,0,0) [12]
Q* = 7.9057, df = 8, p-value = 0.4427
Model df: 2. Total lags used: 10

Source: Data Processed, 2025

Table 12: the Ljung-Box test results for the residuals of the SARIMA (0,1,1) (1,0,0) [12] model on the log collection data showed a Q statistic value of 7.9057 with 8 degrees of freedom (df) and a p value of 0.4427. A p-value greater than the common significance level (i.e., 0.05) indicates insufficient evidence to reject the null hypothesis that the residuals do not exhibit significant autocorrelation at the tested lag. In other words, the residuals from this model can be considered white noise, indicating that the model has successfully captured the main patterns in the data without leaving systematic patterns in the residuals. It strengthens the model's validity for forward forecasting.

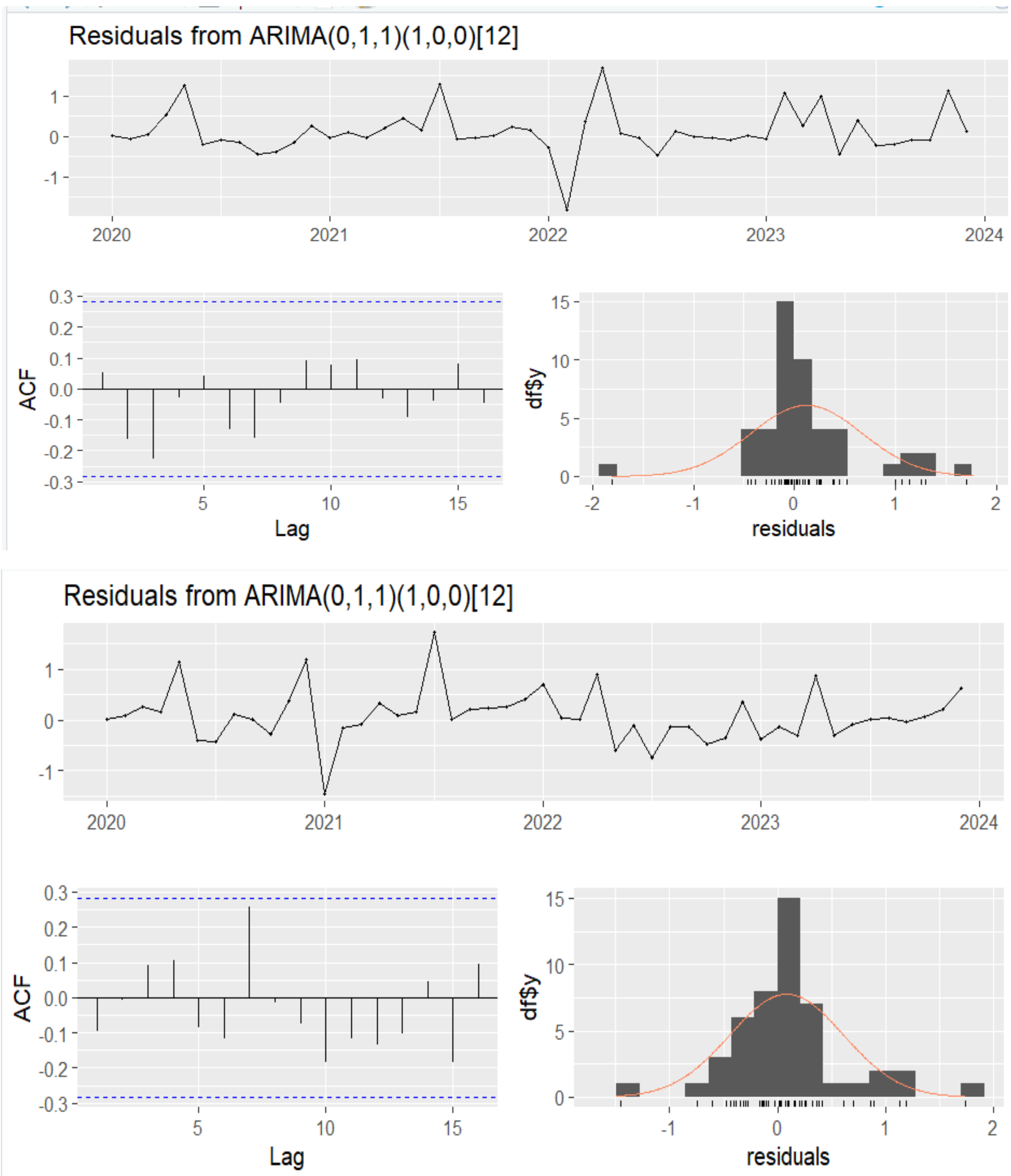
The Ljung–Box test results presented in Table 12 provide additional evidence regarding the adequacy of the SARIMA (0,1,1) (1,0,0) [12] model in modeling the log-transformed Zakat collection data. With a Q-statistic of 7.9057, 8 degrees of freedom, and a p-value of 0.4427, the test indicates that the null hypothesis of no autocorrelation among the residuals cannot be rejected. It is suggested that the residuals are independent and exhibit white noise characteristics, implying that the model has effectively captured the trend and seasonal components of the data. Consequently, the absence of significant autocorrelation in the residuals confirms the robustness of the selected SARIMA specification and supports its reliability for forecasting future Zakat collection patterns.

Table 13. Ljung-Box test Distribution

Ljung-Box test Distribution
Data: Residuals from ARIMA (0,1,1) (1,0,0) [12]
Q* = 9.0584, df = 8, p-value = 0.3374
Model df: 2. Total lags used: 10

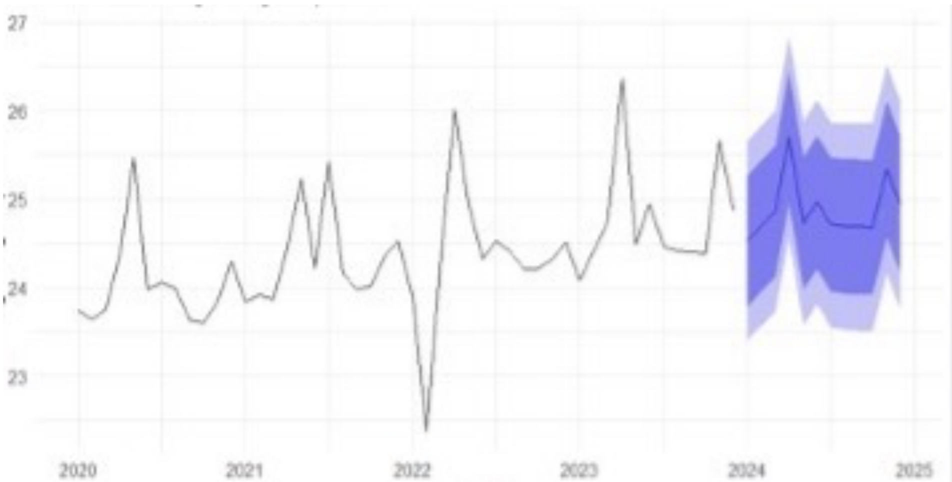
Source: Data Processed, 2025

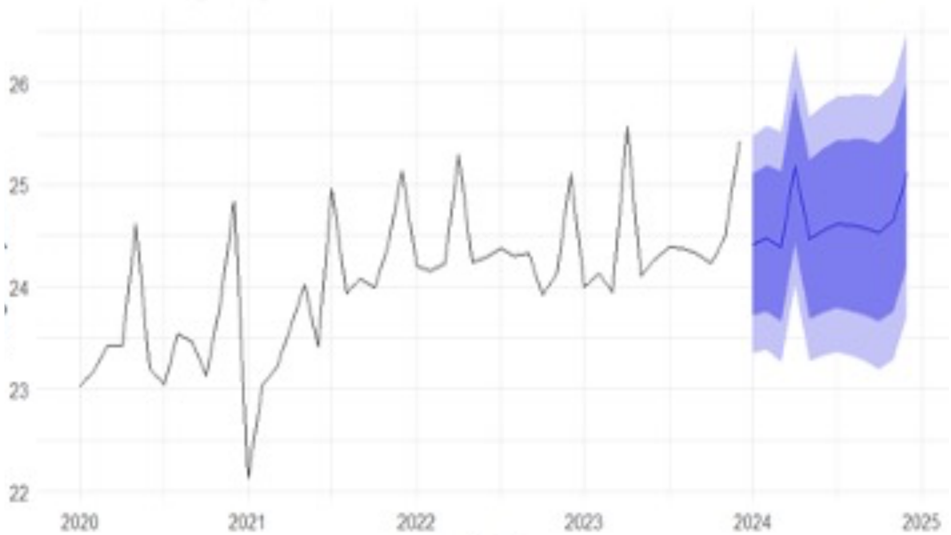
Table 13: the Ljung-Box test results for the SARIMA (0,1,1) (1,0,0) [12] model residuals on the log channelling data, with a Q statistic of 9.0584 on 8 degrees of freedom (df) and a p-value of 0.3374. A p-value greater than the common significance level (i.e., 0.05) indicated insufficient evidence to reject the null hypothesis that the residuals do not exhibit significant autocorrelation at the tested lag. This indicates that the model residuals are white noise. Thus, the model has successfully captured the main patterns in the data without leaving systematic patterns in the residuals, so this model can be considered valid and reliable for forecasting channelling data. Moreover, the white noise behavior of the residuals indicates that the model does not omit relevant systematic information, thereby minimizing the risk of biased or inefficient forecasts.



Graph 6. The residuals of the SARIMA (0,1,1) (1,0,0) model [12]

Graph 6 showed that the residuals of the SARIMA (0,1,1) (1,0,0) model [12] exhibited characteristics that support the model's validity. From the time-series plot of the residuals, the fluctuation pattern appears random around the zero line, suggesting that the model has successfully captured the main patterns in the data. In addition, the residual autocorrelation function (ACF) plot results showed that most of the autocorrelations are within significant limits, so there is no indication of significant autocorrelation in the residuals. This strengthens the assumption that the residuals are white noise. The distribution of the residuals also shows a tendency toward normality, with a symmetrical histogram and an average close to zero. The histogram shows a good fit between the residuals and the normal distribution. The normal distribution of residuals indicates that the model's normal error assumption is met. Overall, the residual analysis of the SARIMA model indicated that it is sufficient to describe the data patterns. The absence of systematic patterns in the residuals and the fit of the distribution to the normal distribution provide confidence that the model is suitable for forecasting log collection and log distribution data.





Graph 8. Results of Forecasting The Logarithm of Zakat Collection and Distribution

Graph 8 explained the graph above, which showed the results of forecasting the logarithm of zakat collection and distribution using the SARIMA time-series model. In the first graph, the forecast of the log of zakat collection shows a fluctuating pattern with a clear seasonal trend visible in the historical data (2020-2023). After the historical period, the blue-coloured area shows the model's prediction for 2024-2025, with the confidence interval (shaded area). The darker the blue colour, the higher the confidence level of the prediction. The model predicts a moderate increase in zakat collection, albeit with greater uncertainty over time. The second graph shows the forecast of the log of zakat distribution, with a similar pattern: seasonal fluctuations. Zakat distribution is also expected to increase slightly in the future, as seen in the slowly rising prediction line. However, the distribution's uncertainty range is also quite wide, indicating that the variability in the historical data poses a challenge for more accurate predictions.

Table 14. Forecasting Results 12 Months Ahead

Month	Collecting	Distribution
01/01/2024	44,700,780,695	40,236,776,277
01/02/2024	53,087,591,750	42,915,413,034
01/03/2024	62,773,525,168	39,302,683,337
01/04/2024	145,658,809,516	86,495,446,193
01/05/2024	54,939,069,059	42,458,334,134
01/06/2024	69,645,685,007	46,022,069,675
01/07/2024	54,164,008,617	48,897,448,984
01/08/2024	53,011,309,548	48,398,302,342
01/09/2024	52,619,310,839	47,420,164,864
01/10/2024	52,230,057,418	45,117,072,936
01/11/2024	101,155,804,389	50,847,220,279
01/12/2024	67,057,257,010	80,323,582,661

Source: Data Processed, 2025

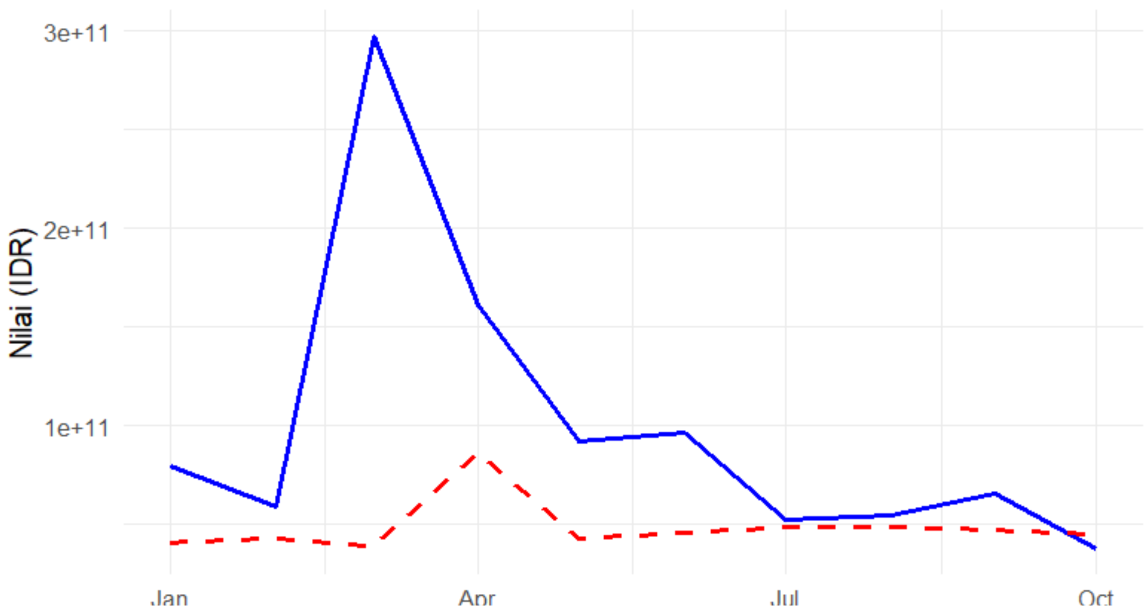
Table 14: after obtaining the forecast results, a comparison was made with the actual data on the collection and distribution of zakat from Baznas during 2024. Based on BAZNAS data, the collection and distribution amounts are only available for January-October 2024, so the forecast and actual values will be compared. After obtaining the forecast results, a comparison was made between the forecast values and actual data on zakat collection and distribution from BAZNAS in 2024. However, based on BAZNAS data availability, actual data was only available for the period from January to October 2024. Therefore, the comparative analysis between the forecast values and actual data was only conducted for that time period,

while the forecast results for November and December 2024 were used to project zakat performance at the end of the year.

Table 15. The Forecast and Actual Values of Collection and Distribution

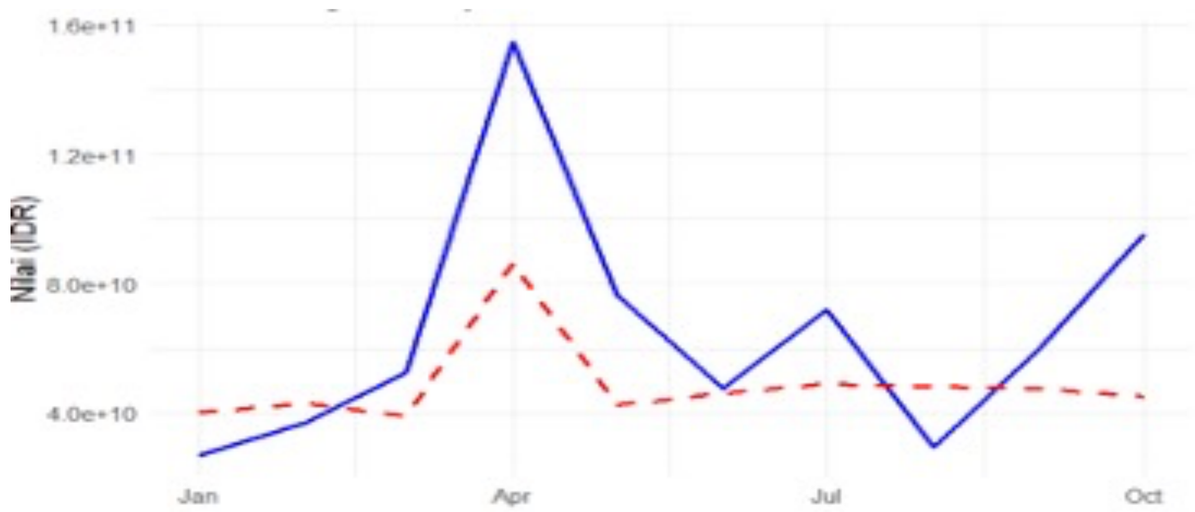
Month	Collection	Distribution
2024-01	79710031630.00	26816685613.00
2024-02	58687602332.00	37122990866.00
2024-03	297563294307.00	52673383819.00
2024-04	161072292105.00	154894363152.00
2024-05	92175682471.00	76642520733.00
2024-06	96491509158.00	47469546633.00
2024-07	52444042829.00	71987998085.00
2024-08	54441385637.00	29474110668.00
2024-09	65635548316.00	60200237896.00
2024-10	37449822840.00	95369968173.00

Source: Data Processed, 2025



Graph 9. The Comparison between the Actual Value and the Forecasted Value for Zakat Collection

Graph 9 compared the actual and forecast values for zakat collection and distribution over a given period. In the first graph, which shows zakat collection, the blue line represents the actual data, while the red dotted line shows the model's prediction. There are significant differences between the actual data and the forecasting results, especially in peak months such as April, which is expected to coincide with Ramadan. The model predictions are noticeably lower than the actual values, suggesting it may not have fully captured seasonal patterns or significant anomalies, such as the Ramadan spike.



Graph 10. The Comparison between The Actual Value and The Forecasted Value for Zakat Distribution

Source: Data Processed, 2025

Graph 10 showed zakat distribution, with a similar pattern: the actual data (blue line) shows a significant peak in the same month, while the predictions (red dashed line) tend to be lower and more stable. This difference indicates that the model has limitations in capturing sharp fluctuations that occur in historical data. Nevertheless, the predictions still provide an overview of the general trend and can serve as a guide for strategic planning, though further development is needed to improve the model's accuracy. SARIMA forecasting results that differ from actual values may occur due to several factors that affect the accuracy of the model. SARIMA is designed to accommodate seasonal and trend patterns. However, if seasonal patterns are dynamic or there are extreme spikes, as is often the case in financial or zakat data, SARIMA models may produce biased or undervalued predictions, especially when these seasonal events are irregular (Kwarteng & Andreevich, 2024). The accuracy of the

SARIMA model depends heavily on parameter selection (p, d, q, P, D, Q, m). Non-optimal parameter settings may lead to underfitting or overfitting, resulting in the model failing to predict patterns in the test data accurately. In addition, the use of historical data that does not reflect recent changes (such as the impact of policies or pandemics) can also affect prediction performance (Omar, MwanOmar, M. S., & Kawamukai, 2021).

CONCLUSION AND SUGGESTIONS

The research found a significant difference in distribution and collection between the peak and the waning of COVID. The results show an increase during the waning of COVID, both in collection and distribution. This shows that as the community's conditions improve, their ability to give zakat, infaq, and sadaqah also increases, which, in turn, drives greater distribution. Based on the SARIMA model analysis, the forecasting of zakat collection and distribution shows a fairly good ability to capture seasonal patterns and trends in historical data. The model successfully identifies regular patterns in the data, such as the significant increase in Ramadan, which is the main season for zakat activity. Overall, SARIMA provides a solid basis for understanding short-term trends and seasonal patterns, although forecasting accuracy can be further improved by considering additional data or using hybrid methods. It is recommended that policymakers and zakat management authorities optimally utilize forecasting results as a decision-support tool in formulating social welfare and poverty alleviation policies. Accurate forecasting enables better anticipation of zakat, infaq, and sadaqah fund availability, allowing for more targeted, timely, and sustainable distribution planning. Furthermore, the use of forecasting outcomes is essential for enhancing the resilience and effectiveness of zakat programs, particularly in the face of economic uncertainty and potential future crises.

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