

CHAPTER V

DISCUSSION AND CONCLUSION

5.1 Discussion

5.1.1 Discussion of the ARIMA Model

The ARIMA model was used as the baseline model for comparison with the other models investigated in this study. The model development was conducted under different training and testing data ratios, namely 70:30, 75:25, and 80:20. In constructing the ARIMA model, it was necessary to examine the stationarity of the data beforehand, since the ARIMA model can only be developed under the condition that the data are stationary (Weak Stationarity). Therefore, the researcher tested the stationarity of the data using the Augmented Dickey–Fuller (ADF) Test. The results indicated that the gold price data at the original level were non-stationary under all data-splitting ratios. Consequently, the first-order differencing was applied, and the data were found to become stationary after this transformation.

The results of the model selection analysis for all data-splitting ratios showed that ARIMA(0,1,1) was the most appropriate model according to the selection criteria employed in this study. The residual diagnostic results further indicated that the ARIMA(0,1,1) model did not exhibit any autocorrelation problem in the error terms in all cases. However, when considering the forecasting errors, the values remained relatively high compared with those of the models developed in this research. This finding suggests that the use of only historical gold price data may not be sufficient to explain the long-term behavior of gold prices, which are influenced by economic factors and complex market conditions. Furthermore, the results also demonstrated that although ARIMA can effectively handle the non-stationarity problem of the data, a major limitation of the model is its inability to incorporate external variables that may influence gold prices into the forecasting process.

5.1.2 Discussion of the MIDAS Model

The MIDAS model was employed in this study because of its ability to incorporate data with different frequencies within a single model. Monthly gold prices were specified as the dependent variable, while the DXY index and weekly oil prices were used as independent variables. Three lag structures were considered, namely ($K = 4$), ($K = 8$), and ($K = 12$), under different training and testing data ratios.

The results of the AIC and BIC analyses indicated that the most appropriate model varied across different data-splitting ratios. For the Train:Test ratios of 70:30 and 75:25, the model with ($K = 12$) yielded the lowest information criteria values, whereas for the Train:Test ratio of 80:20, the model with ($K = 4$) produced the lowest information criteria values. This finding suggests that the optimal number of lags may vary according to the amount of data used for training. However, when considering the residual diagnostic results using the Ljung–Box Test, it was found that the residuals of the MIDAS model still exhibited autocorrelation problems in all cases. This indicates that although the model is capable of incorporating data with different frequencies, it is still unable to adequately explain the structure of gold price data. When considering forecasting performance, the MIDAS model produced relatively high forecasting errors in all cases and exhibited lower performance than the ARIMA(0,1,1) model. The RMSE values exceeded one thousand units for all data-splitting ratios, despite incorporating the DXY index and oil prices, which are factors related to gold prices, into the model.

These findings indicate that the inclusion of high-frequency data alone is not sufficient for forecasting gold prices. This is because gold prices are influenced not only by external factors but also by their own historical price movements. Therefore, although the MIDAS model can effectively address the problem of combining data with different frequencies, it still has limitations in explaining the temporal relationships within gold price data. This limitation is expected to be an important reason why its forecasting performance remains unsatisfactory.

5.1.3 Discussion of the MIDAS-AR Model

The MIDAS-AR model extends the MIDAS model by incorporating an autoregressive component into its structure in order to consider the effect of historical gold price data on forecasting. The results of the AIC and BIC analyses indicated that, for the Train:Test ratios of 70:30 and 75:25, the model with ($K = 4$) produced the lowest information criteria values, whereas for the Train:Test ratio of 80:20, the model with ($K = 12$) yielded the lowest AIC and BIC values. When considering the residual diagnostic results, it was found that the MIDAS-AR model passed the Ljung–Box test only in the case of Train:Test = 80:20 with ($K = 12$), indicating no autocorrelation problem in the residuals. In contrast, the other cases still exhibited such a problem. Regarding forecasting performance, the MIDAS-AR model showed substantially lower forecasting errors compared with the MIDAS model. In particular, the case of Train:Test = 80:20 with ($K = 12$) produced the lowest MAE and MAPE values. Under this data-splitting ratio, the MIDAS-AR model with ($K = 12$) was selected as the most appropriate model.

These findings indicate that incorporating historical gold price data into the forecasting process can significantly improve model performance. This suggests that gold prices are influenced not only by the DXY index and oil prices but also by their own historical price movements.

5.1.4 Discussion of the MIDAS-AR-Threshold Model

The MIDAS-AR-Threshold model is an extension of the MIDAS-AR model that incorporates a regime-switching mechanism through the threshold value of the gold price lagged by one period, Y_{t-1} , in order to investigate the effect of changes in market conditions on forecasting performance.

The results of the AIC and BIC analyses indicated that the model with ($K = 12$) produced the lowest information criteria values under all data-splitting ratios. This suggests that using a larger number of lags enables the model to better explain the data under a regime-switching structure. When considering the residual diagnostic results, it was found that the MIDAS-AR-Threshold model passed the Ljung–Box test in some cases,

particularly for $K = 4$ and $K = 8$ under the Train:Test ratios of 70:30 and 75:25, as well as for $K = 12$ under the Train:Test ratio of 80:20, where the p-values were greater than 0.05. This indicates that the residuals of the model in these cases did not exhibit statistically significant autocorrelation. However, some cases still produced p-values lower than 0.05, indicating that the MIDAS-AR-Threshold model did not pass the residual diagnostic test in all cases. Regarding forecasting performance, the MIDAS-AR-Threshold model produced relatively low forecasting errors, but overall the errors were slightly higher than those of the MIDAS-AR model. The most appropriate MIDAS-AR-Threshold model was the model with a Train:Test ratio of 80:20 and ($K = 12$), as it yielded the lowest AIC and BIC values under the same data-splitting ratio. Furthermore, no autocorrelation problem was detected in the residuals, and the forecasting errors remained at a relatively low level. Although, under the same data-splitting ratio, the model with ($K = 4$) produced slightly lower RMSE, MAE, and MAPE values, that model still suffered from an autocorrelation problem.

These findings indicate that dividing the data into regimes based on the level of gold prices enables the model to account for differences in data behavior under different market conditions. However, defining regimes using a single threshold value remains a fixed boundary approach, which may not fully capture actual changes in market conditions. Furthermore, when considering forecasting errors, the MIDAS-AR-Threshold model still produced higher RMSE, MAE, and MAPE values than the MIDAS-AR model in several experimental cases. This suggests that regime classification based solely on a threshold value may not be sufficient to explain complex market dynamics. Therefore, the application of a Hidden Markov Model for regime classification was investigated in the subsequent stage of the study.

5.1.5 Discussion of the MIDAS-AR-HMM Model

The MIDAS-AR-HMM model is an extension of the MIDAS-AR-Threshold model that employs a Hidden Markov Model (HMM) to classify market regimes instead of using a fixed threshold. The market regime classification was based on gold returns and the volatility of gold returns as observable variables, since these two variables can better reflect changes

in the gold market than the gold price level alone. Gold returns represent price changes over time, while volatility reflects the level of market fluctuations. Considering these two variables simultaneously enables the Hidden Markov Model to distinguish different market conditions more clearly, which is consistent with the concept of regime-switching that aims to explain changes in market behavior over time.

The results of the AIC and BIC analyses indicated that the model with ($K = 12$) produced the lowest information criteria values under all data-splitting ratios. This finding suggests that, within the MIDAS-AR-HMM framework, ($K = 12$) provides a better model fit according to the information criteria than $K = 4$ and $K = 8$. When considering the residual diagnostic results, it was found that the MIDAS-AR-HMM model passed the Ljung–Box test in almost all experimental cases. Autocorrelation was detected only in the case of Train:Test = 75:25 with ($K = 4$). This result indicates that the model was able to explain the underlying data structure more effectively than the MIDAS-AR-Threshold model. Regarding forecasting performance, the MIDAS-AR-HMM model produced lower forecasting errors than the MIDAS-AR-Threshold model. The model with a Train:Test ratio of 70:30 and ($K = 4$) provided the best overall forecasting performance, as it yielded the lowest RMSE, MAE, and MAPE values while exhibiting no autocorrelation problem in the residuals. Therefore, it was selected as the most appropriate MIDAS-AR-HMM model in this study.

These findings indicate that the Hidden Markov Model can classify market regimes more flexibly than a fixed-threshold approach. This is because the HMM can learn changes in market conditions directly from the data and takes into account the temporal continuity of regimes. Furthermore, the Transition Probability Matrix showed that each regime exhibited a relatively high degree of persistence over time, which is consistent with the behavior of the gold market, where market conditions tend to remain in the same state for a period before transitioning to a new state. However, although the MIDAS-AR-HMM model provided improved forecasting performance, regime classification was still based solely on the Hidden Markov Model. Therefore, the application of a Self-Organizing Map, which is a machine learning technique used for data clustering, in combination with the Hidden Markov Model may provide a more refined regime classification and may further

improve the forecasting performance of the model.

5.1.6 Discussion of the MIDAS-AR-HMM-SOM Model

The MIDAS-AR-HMM-SOM model is an extension of the MIDAS-AR-HMM model that integrates the Self-Organizing Map (SOM) technique with the Hidden Markov Model to assist in clustering the data prior to the classification of gold market regimes. In this study, logarithmic returns, volatility, and lagged returns of gold prices were used as variables for analysis because these three variables can reflect price changes, the level of volatility, and the influence of historical information, all of which are important factors affecting changes in market conditions.

The results of the AIC and BIC analyses indicated that the model with ($K = 8$) produced the lowest information criteria values under all data-splitting ratios. This finding suggests that the model provides the best ability to explain the data when compared with the other cases considered in this study. When considering the residual diagnostic results, it was found that the MIDAS-AR-HMM-SOM model passed the Ljung–Box test in almost all experimental cases. In particular, the cases of ($K = 8$) and ($K = 12$) passed the test under all data-splitting ratios, whereas the case of Train:Test = 75:25 with ($K = 4$) was the only case that produced a p-value lower than 0.05. Regarding forecasting performance, the MIDAS-AR-HMM-SOM model produced low forecasting errors in all experimental cases. The MAPE values were below 3% for all data-splitting ratios. Furthermore, when compared with the MIDAS-AR-HMM model, the forecasting errors were substantially reduced. In particular, the case of Train:Test = 70:30 with ($K = 4$) yielded an RMSE of 61.90, an MAE of 43.97, and a MAPE of 2.13, while also passing the Ljung–Box test. Therefore, this model was selected as the most appropriate model in this study.

The findings indicate that integrating SOM with HMM enables a more refined regime classification. This is because SOM can cluster data with similar characteristics before the learning process of the HMM, resulting in lower forecasting errors compared with the MIDAS-AR-HMM model. This improvement suggests that gold market data may possess a more complex structure than can be captured by regime classification using HMM alone, and that the inclusion of a data-clustering stage prior to regime classification helps the

model learn the underlying characteristics of the data more effectively. When considered together with the results of all models employed in this research, the MIDAS-AR-HMM-SOM model provided the best forecasting performance in this study, both in terms of forecasting accuracy and residual diagnostic results. This demonstrates that the integration of mixed-frequency data, the consideration of the influence of historical information, and regime classification through machine learning techniques can effectively enhance the forecasting performance of gold prices.

5.2 Conclusion

This study demonstrates that accurate forecasting of mixed-frequency financial time series requires more than the incorporation of high-frequency explanatory variables. The empirical findings indicate that forecasting performance depends critically on the ability of a model to account for both the temporal dependence embedded in historical observations and the dynamic changes in underlying market conditions. Consequently, the effectiveness of a forecasting framework is determined not only by the quantity or frequency of available information but also by its capacity to represent the structural characteristics of the data-generating process.

The results consistently show that regime-dependent modeling provides substantial benefits for forecasting gold prices. Financial markets are inherently characterized by periods of expansion, contraction, stability, and heightened uncertainty, and the relationships between explanatory variables and gold prices may vary across these market environments. Models that explicitly incorporate regime information were therefore able to capture changes in market behavior more effectively than models based solely on a single, fixed structure. In particular, probabilistic regime identification through the Hidden Markov Model proved more effective than deterministic threshold-based classification, suggesting that latent-state representations are better suited to describing the complex and evolving nature of financial markets.

A further contribution of this research is the integration of Self-Organizing Maps with the Hidden Markov Model within the MIDAS framework. The findings indicate that

combining unsupervised learning techniques with regime-switching methodologies enhances the identification of market states and improves the model's ability to distinguish between heterogeneous patterns in mixed-frequency data. This hybrid approach enables a more flexible representation of market dynamics and leads to superior forecasting performance across different experimental settings.

From a methodological perspective, the study extends the application of MIDAS models by incorporating autoregressive structures, latent regime-switching mechanisms, and machine-learning-based state classification into a unified forecasting framework. The superior performance of the MIDAS-AR-HMM-SOM model, supported by both forecasting accuracy measures and Diebold–Mariano statistical tests, demonstrates the value of integrating econometric and machine learning approaches for mixed-frequency financial forecasting.

Overall, the findings suggest that the combination of mixed-frequency information, temporal dependence, and adaptive regime identification provides a robust framework for forecasting gold prices under changing market conditions. The proposed MIDAS-AR-HMM-SOM model therefore offers a meaningful methodological contribution to the literature on mixed-frequency time series forecasting and provides a practical approach for improving predictive performance in complex financial environments.