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Forecasting the Export Value of ASEAN Goods using the ARIMA–GARCH Hybrid Model

Hoang Thi Thu Ha
Department of Digital Economy, Faculty of Mathematical Economics, Thuongmai University
Email address: hoangha.math@tmu.edu.vn

***Abstract*–** *This study aims to forecast the export value of ASEAN goods amid ongoing global economic and trade fluctuations. It utilizes monthly time series data on ASEAN's export values from January 2015 to October 2024. To perform the forecast, the study applies the ARIMA(1,1,1) model to capture the linear patterns in the data, combined with the GARCH(1,1) model to address time-varying variance (heteroskedasticity). The results indicate that the combined ARIMA–GARCH model provides higher forecasting accuracy than individual models and effectively captures both the trend and volatility of export values during the study period.*

***Keywords*–** *Time series forecasting, goods exports, ARIMA-GARCH.*

I. INTRODUCTION

Export activities play a crucial role in the economic growth of nations, particularly in developing economies. Exports not only serve as a vital source of foreign exchange but also stimulate domestic production, generate employment, and enhance global competitiveness. According to Bhagwati and Srinivasan (1979), international trade—especially exports—is a powerful engine of growth for developing countries by expanding markets, improving production efficiency, and fostering technological innovation.

In Southeast Asia, the member states of the Association of Southeast Asian Nations (ASEAN) have been playing an increasingly significant role in the regional and global economy. With more than 670 million people living together and a prime location, ASEAN is becoming a major hub for trade and production worldwide. According to the ASEAN Secretariat (2023), the region has sustained stable export growth, which has positively contributed to GDP expansion and strengthened both intra-regional cooperation and global economic integration.

Several ASEAN countries—such as Vietnam, Thailand, Indonesia, and Malaysia—have made notable contributions to export activities. Vietnam, for instance, has become a major exporter of electronics and textiles; Thailand is prominent in automobile and processed food exports; while Indonesia and Malaysia have strengths in natural resources and petrochemical products. These contributions not only promote domestic economic growth but also help solidify ASEAN's trade position in global markets (World Bank, 2022).

In the context of a global market that is constantly fluctuating due to factors such as the pandemic, geopolitical conflicts, and climate change, forecasting the export value of ASEAN goods has become extremely urgent. Accurate forecasts enable governments to formulate effective trade policies, optimize production and investment decisions, and proactively respond to external shocks (Zhou et al., 2021).

Although numerous studies have focused on international trade and exports in individual ASEAN member states, there remains a significant gap in developing high-accuracy export forecasting models for the ASEAN bloc as a whole. The application of the combined ARIMA-GARCH model to ASEAN export data represents a novel contribution. This approach offers enhanced forecasting accuracy and aligns well with the volatility and complexity of today's globalized market. The model not only forecasts export value trends but also facilitates the analysis and management of export volatility—an aspect often inadequately addressed by traditional models. By utilizing recent ASEAN export data, this study broadens the analytical scope and offers high practical value, particularly in informing regional economic policymaking and trade strategy development.

Therefore, the objective of this study is to develop and evaluate a forecasting model for ASEAN export values by combining the ARIMA and GARCH models. Specifically, the study addresses the following two research questions:
RQ1: Does the combined ARIMA-GARCH model improve the accuracy of forecasting ASEAN countries' export values compared to the use of each model individually?
RQ2: What useful insights can the application of the ARIMA-GARCH model offer for economic policymaking and trade strategy in the ASEAN region?

This paper is structured into five sections: (1) Introduction; (2) Literature Review; (3) Data and Research Methods; (4) Results and Discussion; and (5) Conclusion and Policy Implications.

II. LITERATURE OVERVIEW

Time series forecasting, particularly for import and export values, has garnered increasing attention from researchers in recent years. Classical forecasting methods commonly employed include the ARIMA (AutoRegressive Integrated Moving Average) model, GARCH (Generalized Autoregressive Conditional Heteroskedasticity), and artificial neural networks (ANNs).

2.1 Empirical studies using ARIMA models

Farooqi (2014) is one of the case studies that applied the ARIMA model to forecast export and import values. The study uses annual data on Pakistan's exports and imports from 1947 to 2013. The results indicate that the ARIMA(2,2,2) model is most suitable for forecasting import values, while the ARIMA(1,2,2) model performs better for export values. Similarly, Ahmar et al. (2023) employed the ARIMA(0,1,1) model to forecast Indonesia's oil and gas export values, using monthly data from January 2010 to March 2022. More recently, Quang et al. (2024) applied the ARIMA model to forecast Vietnam's black pepper export prices from January 2019 to February 2024. However, a common limitation of these studies is that they did not test for the presence of ARCH effects, even though the residual plots suggest potential heteroskedasticity over time.

2.2 Empirical Studies Using GARCH Models

While the ARIMA model is widely used, GARCH family models are more suitable when the data exhibits time-varying variance (heteroskedasticity). For example, Wudu and Ayalew (2022) applied GARCH models to assess the volatility of Tana Flora's flower export values in Ethiopia between January 2012 and December 2017. The results indicate that the EGARCH(1,2) model with a GED distribution best captures the asymmetric volatility of flower export values, due to its lower forecast error and superior performance in modeling and forecasting export sales.

Similarly, Rakhmawan et al. (2015) analyzed Indonesia's crude palm oil (CPO) export data from 1996 to 2013 using time series forecasting methods. The study considered both ARIMA and GARCH models, concluding that ARIMA is appropriate for series with constant variance, whereas GARCH models perform better when heteroskedasticity is present. However, the results also suggest that with certain modifications, the ARIMA model can address variance instability without necessarily relying on GARCH-type models. This suggests that, with appropriate adjustments, the ARIMA model can still provide reliable forecasts despite variance fluctuations.

2.3 Empirical studies combining ARIMA and neural networks

A growing research trend in time series forecasting is the integration of ARIMA models with artificial neural networks (ANNs). For instance, Dave et al. (2021) combined the ARIMA model with a long short-term memory (LSTM) neural network to forecast Indonesia's export values, using monthly data from January 1998 to December 2019. In this hybrid model, the linear component of the time series is captured by ARIMA, while the nonlinear patterns are modeled using LSTM. The experimental results indicate that the ARIMA–LSTM model outperforms individual models, achieving the highest forecast accuracy with a MAPE of 7.38% and an RMSE of 1.66×10^{13}.

Similarly, Pannakkong et al. (2019) developed a hybrid model combining ARIMA and artificial neural networks (ANNs), incorporating a moving average component and an annual crop index. The model was used to forecast Thailand's cassava export values based on monthly data from 2001 to 2013. The proposed model was evaluated against ARIMA, ANN, and the Khashei–Bijari hybrid models using standard error metrics, including MSE, MAE, and MAPE. The results demonstrate that the proposed model achieves the highest accuracy in forecasting the export of pure and modified starch—which account for 98% of total cassava exports—while the Khashei–Bijari model performs better in forecasting sago exports.

2.4 Empirical studies combining ARIMA and GARCH models

To address the problem of time-varying error variance, some studies have employed a combination of ARIMA and GARCH models. For example, Suryatin et al. (2024) developed a model to forecast the value of Indonesia's non-oil and gas exports using data from January 2004 to December 2020. The results indicate that the ARIMA(1,1,1)–EGARCH(1,1) hybrid model is the most suitable, with a MAPE of 9.35%. This hybrid model demonstrates superior forecasting performance compared to individual models, particularly in capturing asymmetries and large fluctuations in export data.

In addition, Asim et al. (2022) compared the forecasting performance of two approaches: the ARIMA model combined with GARCH variants (both symmetric and asymmetric), and the ARIMA model with Markov regime-switching (MRS-ARIMA). Their analysis was based on industrial output price chain data in Pakistan from 2005 to 2020. The results indicate that the MRS-ARIMA model effectively captures heteroskedasticity and structural changes, while the ARMA(2,1)–PARCH(1,1) model offers the best predictive performance among the GARCH-type models. Overall, asymmetric GARCH models tend to provide more accurate forecasts than their symmetric counterparts.

From the overview of the above studies, it is evident that the ARIMA model is effective in capturing the linear patterns and trends in time series data, particularly when the series becomes stationary after differencing. However, ARIMA is not well-suited for handling time-varying variance—a common characteristic of economic time series such as export values. In contrast, GARCH family models are capable of flexibly modeling the volatility of forecast errors, especially in series exhibiting asymmetry or high fluctuations.

Recent studies have also proposed hybrid ARIMA–LSTM models to leverage neural networks' capacity for capturing long-term dependencies and learning nonlinear patterns. Nevertheless, these models require large datasets, involve complex training procedures, and often lack interpretability from an economic standpoint. Meanwhile, the ARIMA–GARCH hybrid model retains a traditional statistical framework that is easier to validate, interpret, and still proves effective in modeling volatile series such as exports.

Thus, the ARIMA–GARCH hybrid model, which combines the power of GARCH to account for heteroskedasticity with the strength of ARIMA in modeling linear components, is used in this research. This approach is well-aligned with the goal of forecasting the export values of ASEAN countries—data typically marked by strong volatility and sensitivity to macroeconomic conditions.

III. Research Methodology

3.1 Data collection

This study employs monthly time series data on ASEAN's export values, denoted as Export (measured in million USD), from January 2015 to October 2024. The dataset was obtained from the General Statistics Office of Vietnam via publicly

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available reports on its official website (https://www.gso.gov.vn). Fig. 1 illustrates the fluctuations of the Export series over the observed period.

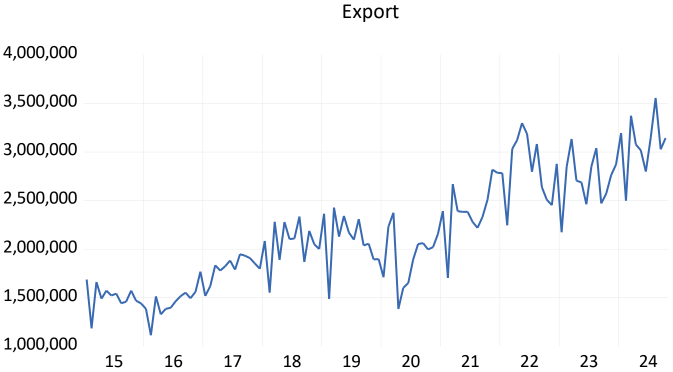

Fig. 1. Export value of ASEAN goods from 2015 to 2024

Fig. 1 clearly illustrates a steady upward trend in the export value of ASEAN goods over the observed period. However, the series also exhibits evident seasonality, with regular fluctuations recurring on an annual basis. Additionally, the amplitude of these fluctuations appears to be increasing over time, suggesting rising volatility and an unstable pattern in export growth.

3.2 Forecasting approach using ARIMA–GARCH model

This study aims to forecast the export value of ASEAN goods by employing a hybrid ARIMA–GARCH model. The forecasting procedure is outlined as follows.

Step 1: Test for stationarity of the time series

The Augmented Dickey-Fuller (ADF) test is commonly used to determine whether a time series is stationary. If the series is non-stationary, it must be differenced to achieve stationarity, which is a necessary condition for the ARIMA model to perform effectively.

Step 2: Identify the parameters of the ARIMA model

The ARIMA(p,d,q) model for forecasting the time series $\{Y_t\}$ is expressed as follows:

$$\Delta^d Y_t = c + \phi_1 \Delta^d Y_{t-1} + \phi_2 \Delta^d Y_{t-2} + \cdots + \phi_p \Delta^d Y_{t-p} + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \cdots + \theta_q \varepsilon_{t-q}. \quad (1)$$

Where:

- Y_t: the original value at the time,
- $\Delta^d Y_t$: the differenced series of order d ,
- c: constant term,
- ϕ_i: autoregressive (AR) coefficients,
- θ_j: moving average (MA) coefficients,
- ε_t: white noise at the time t.

The forecasting performance of the model depends on the parameters p, d, and q. The parameter d is determined as the minimum number of differencing operations required to make the series stationary. The values of p and q are identified through the analysis of the partial autocorrelation function (PACF) and the autocorrelation function (ACF), respectively. Various combinations of parameters may be considered. The optimal set is selected based on estimation and diagnostic testing results, as described in the subsequent steps.

Step 3: Estimate the ARIMA model

In this step, the ARIMA(p, d, q) model is estimated to forecast the export value of goods. The optimal parameters are selected based on the following criteria:

- Ensure that regression coefficients are statistically significant (p-value < 0.05);
- Maximize the adjusted R-squared;
- Minimize the values of AIC and BIC.

Step 4: Validate the ARIMA model

The following diagnostic checks are performed on the residuals to validate the ARIMA(p, d, q) model:

- Residual independence: tested using ACF and PACF plots.
- Normality of residuals: assessed using the Jarque-Bera test, histogram, or Q-Q plot.
- Homoscedasticity: tested using the ARCH test. If heteroscedasticity is detected, the ARIMA model is combined with a GARCH model

Step 5: Modeling volatility variance with GARCH

The GARCH model was developed by Bollerslev (1986). This model is based on the idea that time series volatility depends not only on past forecast errors but also on its own past variances. Stated differently, the autoregressive moving average (ARMA) process governs the conditional variance of the error term in the GARCH model.

Consider the mean equation:

$$Y_t = \mu_t + \varepsilon_t \quad (2)$$

where, $\mu_t = E(Y_t | \varepsilon_t)$ and ε_t is the random error estimated from the ARIMA(p,d,qp,d,qp,d,q) model. The error term εt\varepsilon_tεt is typically assumed to follow one of three standard distributions: Gaussian (normal), Student's t, or Generalized Error Distribution (GED).

$$\varepsilon_t = \sigma_t . u_t$$

where $\sigma_t^2 = Var(\varepsilon_t | I_{t-1})$, and I_{t-1} represents the information set up to time $t-1$. The variable u_t is a white noise process that is independent and identically distributed with mean zero and variance one, i.e., $u_t \sim i.i.d.(0,1)$.

The GARCH(m, s) model is defined as:

$$\sigma_t^2 = \omega + \sum_{i=1}^{m} \alpha_i \sigma_{t-i}^2 + \sum_{j=1}^{s} \beta_i \varepsilon_{t-j}^2 \quad (3)$$

where $\omega > 0, \alpha_i \geq 0, \beta_j \geq 0$ for all $i = 1, \ldots, m$ and $j = 1, \ldots, s$. In addition, to ensure stationarity, the condition $\sum_{i=1}^{m} \alpha_i + \sum_{j=1}^{s} \beta_j \leq 1$ must be satisfied.

The selection of the m and s parameters in the GARCH model is similar to the selection of the two parameters p and q in the ARMA model and typically relies on information criteria such as AIC and BIC.

Step 6: Combine ARIMA and GARCH

The combined ARIMA(p,d,q)–GARCH(m,s) model simultaneously forecasts the conditional mean of the time series using the ARIMA model (see Equation (1)) and models the conditional variance of the residuals using the GARCH model (see Equation (3)).

Step 7: Validate the ARIMA – GARCH model

The residual diagnostics outlined in Step 4 must be revisited to ensure that the ARIMA–GARCH model satisfies the key assumptions, including uncorrelated, normally distributed, and homoscedastic residuals.

Step 8: Forecast and evaluation of forecast error

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After estimating and validating the ARIMA–GARCH model, forecasting is performed and its accuracy is assessed using the following performance metrics:

- RMSE (Root Mean Squared Error), MAE (Mean Absolute Error), and MAPE (Mean Absolute Percentage Error): These indicators measure the magnitude of deviation between the actual and forecasted values. Lower values indicate better forecasting accuracy.
- Theil's U inequality coefficient: This figure contrasts the model's predicting accuracy with a naïve prediction. A Theil U value less than 1 indicates that the ARIMA–GARCH model performs better than the benchmark.
- Bias Proportion: This component of Theil's U decomposition measures the extent of systematic error in the forecasts. A value close to 0 indicates minimal bias, meaning the model's predictions are not consistently over- or under-estimated.

IV. Results And Discussion

4.1 Test for Stationarity

The article first analyzes the export value time series' stationarity using the ADF test.

TABLE 1. Results of ADF test for export value time series

Null Hypothesis: EXPORT has a unit root				
Exogenous: Constant				
Lag Length: 4 (Automatic - based on SIC, maxlag=12)				
			t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic			-0.309977	0.9188
Test critical values:	1% level		-3.489117	
	5% level		-2.887190	
	10% level		-2.580525	

Since the ADF test statistic (-0.309977) is higher than all critical values and the p-value (0.9188) is greater than 0.05, we fail to reject the null hypothesis. Therefore, the export value time series is non-stationary at level and must be differenced to achieve stationarity.

After taking the first-order difference of the Export series, the resulting Dexport series is obtained, as illustrated in Fig. 2.

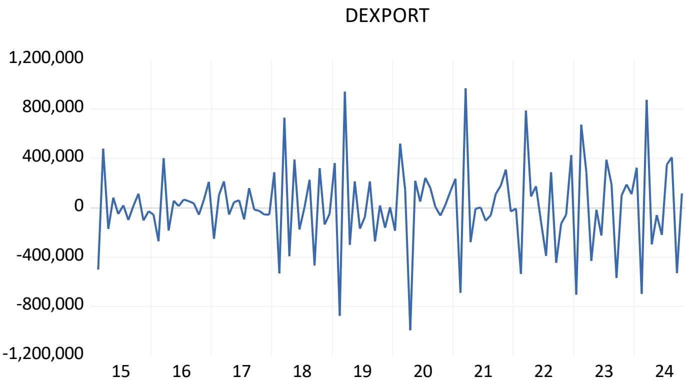


Fig. 2. First-order differenced series of ASEAN export value during the period 2015–2024

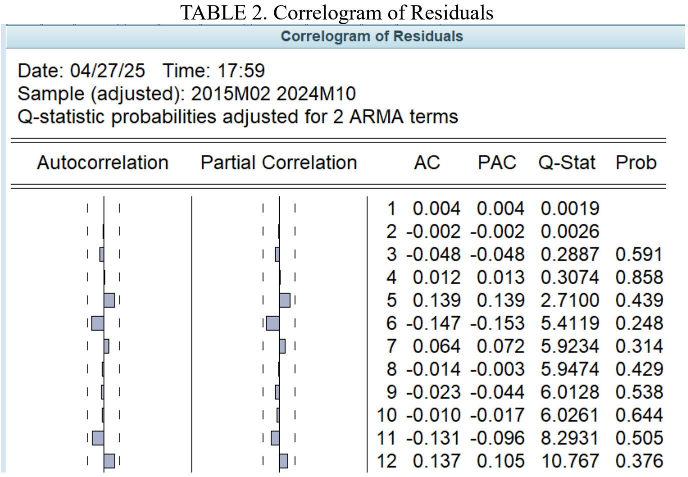
The graph shows that the first-order differenced series appears stationary in mean, though the variance fluctuates over time, suggesting the presence of heteroskedasticity. This observation is supported by the ADF test, which yields a test statistic of approximately $t \approx -9.18$ with a very small p-value, confirming the stationarity of the Dexport series after first differencing.

4.2 ARIMA model estimation

To determine the appropriate structure of the ARIMA model, this study utilizes ACF and PACF plots in conjunction with model suggestions provided by the statistical software based on AIC and BIC criteria. Although the ARIMA(2,1,3) model was identified as optimal according to these information criteria, several of its coefficients were found to be statistically insignificant. In contrast, the ARIMA(1,1,1) model—identified based on the ACF and PACF plots—has all of its coefficients statistically significant at the 5% and 10% levels, while its AIC and BIC values are not substantially higher. Following the principle of model parsimony, the ARIMA(1,1,1) model was selected to ensure interpretability and satisfactory forecasting accuracy.

Subsequently, the residual assumptions of the ARIMA(1,1,1) model were examined using a series of diagnostic tests. According to the residual correlogram results (Table 2), all p-values exceed the 0.05 threshold, indicating no evidence of autocorrelation in the residuals.

TABLE 2. Correlogram of Residuals



Correlogram of Residuals

Date: 04/27/25 Time: 17:59
Sample (adjusted): 2015M02 2024M10
Q-statistic probabilities adjusted for 2 ARMA terms

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.004	0.004	0.0019	
		2	-0.002	-0.002	0.0026	
		3	-0.048	-0.048	0.2887	0.591
		4	0.012	0.013	0.3074	0.858
		5	0.139	0.139	2.7100	0.439
		6	-0.147	-0.153	5.4119	0.248
		7	0.064	0.072	5.9234	0.314
		8	-0.014	-0.003	5.9474	0.429
		9	-0.023	-0.044	6.0128	0.538
		10	-0.010	-0.017	6.0261	0.644
		11	-0.131	-0.096	8.2931	0.505
		12	0.137	0.105	10.767	0.376

The results of the residual normality test are illustrated using the histogram and the Jarque–Bera test (Fig. 3).

The Jarque–Bera statistic was 1.447, with a corresponding p-value of 0.485, which is greater than the 5% significance level. This suggests that the residuals of the ARIMA(1,1,1) model are roughly normally distributed, further validating the model's adequacy and appropriateness.

However, the results of the ARCH test for the residuals indicate that the F-statistic is 8.912 with a corresponding p-value of 0.0035, which is less than the 5% significance level. This suggests that the residuals exhibit heteroskedasticity, violating the constant variance assumption. Therefore, to address this issue and enhance the accuracy of the forecasts, this

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study proceeds with the application of a combined ARIMA–GARCH model.

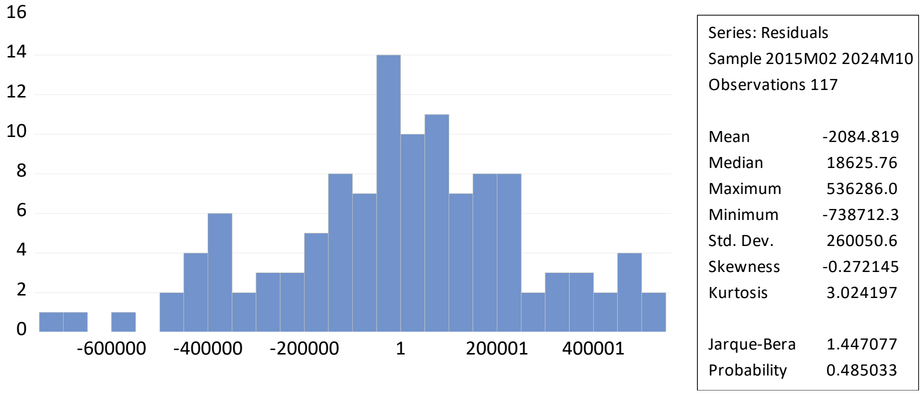

Fig. 3. Residual Normality Test

4.3 ARIMA – GARCH model estimation

Numerous studies have demonstrated that the GARCH(1,1) model is highly effective in modeling and forecasting variance. Therefore, this article employs the ARIMA(1,1,1)–GARCH(1,1) model to forecast the export value of ASEAN goods. The estimation results of the model are presented in Table 3.

TABLE 3. Estimation results of the ARIMA(1,1,1) – GARCH(1,1) model

Variable	Coefficient	z-Statistic	Prob.
C	11101.62	1.277504	0.2014
AR(1)	-0.411253	-2.794415	0.0052
MA(1)	-0.305215	-2.008259	0.0446
Variance Equation			
C	7.66E+09	1.616914	0.1059
RESID (−1)^2	0.629093	2.827714	0.0047
GARCH(-1)	0.346019	2.534707	0.0113

In the ARIMA(1,1,1)–GARCH(1,1) model, the estimated coefficients are statistically significant at the 5% level, indicating a strong influence of past values and errors on the dependent variable. Specifically, the negative AR(1) coefficient (−0.356) suggests that the current export value of goods is negatively affected by its lagged value. Similarly, the negative MA(1) coefficient (−0.499) implies that previous error terms have a dampening effect on the current value.

In the variance equation, both the coefficients of the lagged squared residual (RESID$(-1)^2$) and the lagged conditional variance (GARCH(−1)) are positive, and their sum is less than one. This result satisfies the stationarity condition and reflects the persistence of volatility, indicating that current conditional variance is influenced by past shocks and volatility levels.

Furthermore, the adjusted R-squared value stands at 0. 373, signifying that the model accounts for roughly 37. 3% of the variation in the first-order differenced series. In the context of empirical time series data, this explanatory power is considered acceptable. The Durbin–Watson statistic is 2. 088, implying that there is no indication of autocorrelation in the model's residuals.

Finally, the results of the ARCH effect test on the residuals yield an F-statistic of 0.008 with a corresponding p-value of 0.927, which is greater than the 5% significance level. This indicates that the residuals no longer exhibit ARCH effects, thereby confirming the adequacy of the variance specification in the ARIMA(1,1,1)–GARCH(1,1) model.

Based on the above results, the forecasting of ASEAN goods export value is carried out using two components:

- Mean equation:

$$D(\widehat{EXPORT})_t = 11101.62 - 0.411253 \times D(EXPORT)_{t-1} - 0.305215 \times \varepsilon_{t-1}$$

it implies that

$$\widehat{EXPORT}_t = EXPORT_{t-1} + D(\widehat{EXPORT})_t$$

- Variance equation:

$$\sigma_t^2 = 7.66\text{E} + 09 + 0.346019\,\sigma_{t-1}^2 + 0.629093\,\varepsilon_{t-1}^2$$

4.4 Evaluation of the forecasting performance of the ARIMA–GARCH model

4.4.1 Comparison of model fit

Table 4 presents the AIC and BIC values for the ARIMA(1,1,1)-GARCH(1,1) model, as well as the ARIMA(1,1,1) and GARCH(1,1) models.

TABLE 4. Synthesis of indicators to assess the suitability of models

Model	AIC	BIC
ARIMA(1,1,1)	27.84188	27.93631
GARCH(1,1)	28.12465	28.21908
ARIMA(1,1,1)-GARCH(1,1)	27.73324	27.87567

From the above table, the AIC and BIC values of the ARIMA(1,1,1)-GARCH(1,1) model are the smallest. Therefore, it can be concluded that this combined model outperforms the individual ARIMA(1,1,1) and GARCH(1,1) models in terms of suitability.

4.4.2 Evaluation of the forecasting ability of models

Table 5 reports the values of RMSE, MAE, and MAPE for the ARIMA(1,1,1), GARCH(1,1), and combined ARIMA(1,1,1)-GARCH(1,1) models.

TABLE 5. Summary of indicators for evaluating predictability

Model	RMSE	MAE	MAPE
ARIMA(1,1,1)	334268.2	238000.3	108.333
GARCH(1,1)	340024.5	244893.6	116.489
ARIMA(1,1,1)-GARCH(1,1)	311370.4	201541.6	93.304

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The comparison results indicate that the ARIMA(1,1,1)-GARCH(1,1) model provides superior forecasting performance. This is evidenced by its lower error metrics compared to the other two models. Specifically, the model yields an RMSE of 311370.4, an MAE of 201541.6, and a MAPE of 93.304% — all lower than the corresponding values from the ARIMA(1,1,1) and GARCH(1,1) models. These findings suggest that integrating ARIMA and GARCH models improves forecasting accuracy, especially for data characterized by time-varying volatility.

In addition, the actual and forecasted ASEAN's export value for the period 2015–2024 are presented in Fig. 4.

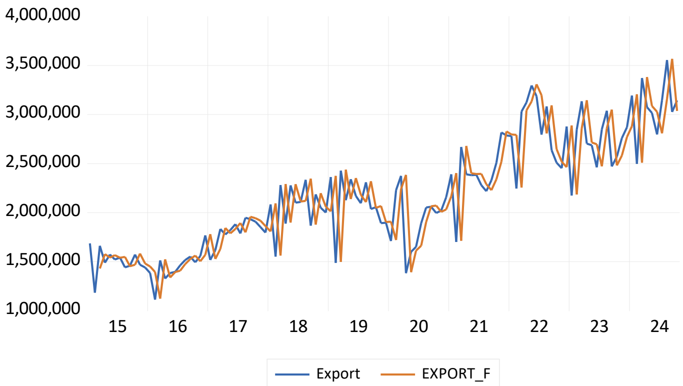

Fig. 4. Actual and forecasted ASEAN export values from 2015 to 2024

From the graph above, it can be observed that the two lines representing the actual and forecasted values are closely aligned throughout the entire research period, indicating the model's strong forecasting capability. Both the actual and forecasted values display a gradual upward trend over time, accompanied by notable seasonal fluctuations, particularly in the years 2020–2024. The variation between the actual and predicted values is usually minor, indicating a low forecasting error. This confirms that the ARIMA-GARCH model used in the study can accurately capture both the trends and fluctuations in export value during the analysis period.

V. Conclusions and Recommendations

The research findings indicate that the combined ARIMA(1,1,1) – GARCH(1,1) model is the most suitable for modeling and forecasting the export value of ASEAN goods for the period 2015–2024. This conclusion is supported by evaluation metrics such as AIC, BIC, RMSE, and MAE, where the combined model consistently yields the lowest values compared to the individual ARIMA and GARCH models. Moreover, the close alignment between actual and forecasted values throughout the study period—particularly the model's ability to capture trends and seasonal fluctuations—highlights the reliability of the ARIMA-GARCH model in the context of highly volatile time series data. Based on these findings, several policy recommendations can be proposed:From the above findings, some policy recommendations can be made:

Firstly, the application of the ARIMA-GARCH model in economic forecasting—particularly in the export sector—should be further promoted. This model has proven highly effective in handling data with significant volatility and time-dependent changes. Therefore, statistical agencies, policy-makers, and exporters can utilize it to enhance forecasting accuracy and improve their capacity for production planning and trade management.

Second, it is advisable to develop and implement early warning systems based on integrated time series models, such as ARIMA–GARCH, to support decision-making amid increasingly volatile market conditions. Such systems can help detect abnormal trends or potential risks in export activities at an early stage, thereby minimizing losses and enhancing proactive operational responses.

Third, policymakers should promote more in-depth research into the characteristics of seasonal fluctuations and shock factors that may impact the region's export performance. A better understanding of seasonal patterns and uncertainties—such as epidemics, supply chain disruptions, or shifts in global trade policy—will support the development of flexible operational policies and enable timely responses to unforeseen events.

Finally, ASEAN countries should strengthen collaboration to establish a unified and regularly updated database on export values. Such a database would not only enhance the accuracy of forecasting models but also improve the effectiveness of economic cooperation within the region. It would facilitate more systematic and evidence-based analysis, planning, and adjustment of regional trade policies.

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Disclosure

Declaration of AI Assistance in Language Editing: The authors used ChatGPT to improve language clarity and correct minor errors in grammar and style. They reviewed all suggestions and are fully responsible for the content of this publication.

Conflicts of Interest

The authors declare no conflicts of interest.

References

[1] Ahmar, A. S., Rahman, A., Anatolievich, P. V., Rusli, R., & Meliyana R., S. M. (2023). Forecasting the export value of oil and gas in Indonesia using autoregressive integrated moving average (ARIMA). *Quantitative Economics and Management Studies, 4*(5), 1036–1044. https://doi.org/10.35877/454RI.daengku1040

[2] ASEAN Secretariat. (2023). *ASEAN statistical yearbook 2023*. Jakarta: ASEAN Secretariat.

[3] Bhagwati, J., & Srinivasan, T. N. (1979). Trade policy and development. In *International economic policy: Theory and evidence*.

[4] Dave, R., Pradhan, P., & Sharma, A. (2021). Forecasting Indonesia exports using a hybrid model ARIMA-LSTM. *Procedia Computer Science, 179*, 480–487. https://doi.org/10.1016/j.procs.2021.01.031

[5] Farooqi, A. (2014). ARIMA model building and forecasting on imports and exports of Pakistan. *Pakistan Journal of Statistics and Operation Research, 10*(2), 157–168. https://doi.org/10.18187/pjsor.v10i2.732

[6] Pannakkong, W., Huynh, V. N., & Sriboonchitta, S. (2019). A novel hybrid autoregressive integrated moving average and artificial neural network model for cassava export forecasting. *International Journal of Computational Intelligence Systems, 12*(2), 1047–1058. https://doi.org/10.2991/ijcis.d.190909.001

[7] Quang, P. D., Mai, P. N., & Quyen, H. N. (2024). Application of ARIMA model in forecasting Vietnam's black pepper export price to the U.S.

market. *International Journal of Statistics and Applied Mathematics, 9*(3), 40–47. https://doi.org/10.22271/maths.2024.v9.i3a.1729

[8] Rakhmawan, S., Notodiputro, K. A., & Sumertajaya, I. M. (2015). A study of ARIMA and GARCH models to forecast crude palm oil (CPO) export in Indonesia. In *Proceedings of the International Conference on Research, Implementation and Education of Mathematics and Sciences (ICRIEMS 2015)* (pp. M-33–M-40). Yogyakarta State University.

[9] Suryatin, E., Hadijati, M., & Baskara, Z. W. (2024). Hybrid ARIMA modeling with stochastic volatility for forecasting the value of non-oil and gas exports in Indonesia. *International Journal of Computing Science and Applied Mathematics, 10*(1), 27–36.

[10] World Bank. (2022). *ASEAN economic integration brief*.

[11] Wudu, T. K., & Ayalew, S. (2022). Time series modeling using export data of Tana Flora: Application of GARCH family models. *Academy of Accounting and Financial Studies Journal, 26*(6), 1–14. Retrieved from https://www.researchgate.net/publication/371856101

[12] Zhou, Y., Liu, B., & Lin, H. (2021). Forecasting international trade flows using deep learning models. *Economic Modelling, 98*, 50–65.