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Mathematical Modeling and Regime Dynamics of Ammonium Chloride Imports in Indonesia Using Threshold Vector Autoregressive Integrated (TVARI) Approach

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Abstract

Ammonium chloride plays an important role in Indonesia as a key raw material for NPK fertilizers and chemical industries. Despite its importance, domestic production remains limited, and potential supply from by-product sources has not been utilized effectively. Consequently, Indonesia depends heavily on imports sourced mainly from a single country. This situation creates vulnerabilities in industrial supply chain and highlights the need for a clearer understanding of import volume and value dynamics. This study employs a Threshold Vector Autoregressive Integrated (TVARI) model to capture nonlinear and regime-dependent adjustments in the joint dynamics of import volume and value, with import volume growth as the threshold variable. The approach's novelty lies in its ability to accommodate structural changes that cannot be adequately represented by a single linear specification. Empirical results identify two statistically distinct regimes defined by whether import growth lies below or above an estimated threshold. In the first regime, where growth is below the threshold, short-run dynamics are primarily driven by changes in import value, indicating price-related adjustments. In the second regime, import volume exhibits stronger responses, reflecting quantity adjustments associated with supply-side conditions. These findings demonstrate that linear models are insufficient to capture asymmetric adjustment mechanisms in import behavior. By providing a formal mathematical description of regime-dependent dynamics, this study contributes to a deeper understanding of Indonesia's industrial import structure and offers insights for data-informed supply chain planning. The results support policy discussions related to Sustainable Development Goals 8 (economic stability), 9 (industry resilience), and 12 (responsible consumption and production).

Keywords: Ammonium chloride ; Import dynamics ; Regime analysis ; Threshold Vector Autoregressive Integrated ; Time series modeling

1. Introduction

Ammonium Chloride (NH4Cl) is an essential chemical compound widely used as a nitrogen source in NPK fertilizers, accounting for nearly 90% of its global consumption. It is also utilized in dry-cell batteries, pharmaceutical products, and ammonia derivatives, indicating its strategic importance in both agricultural and industrial sectors [1], [2], [3]. In Indonesia, the

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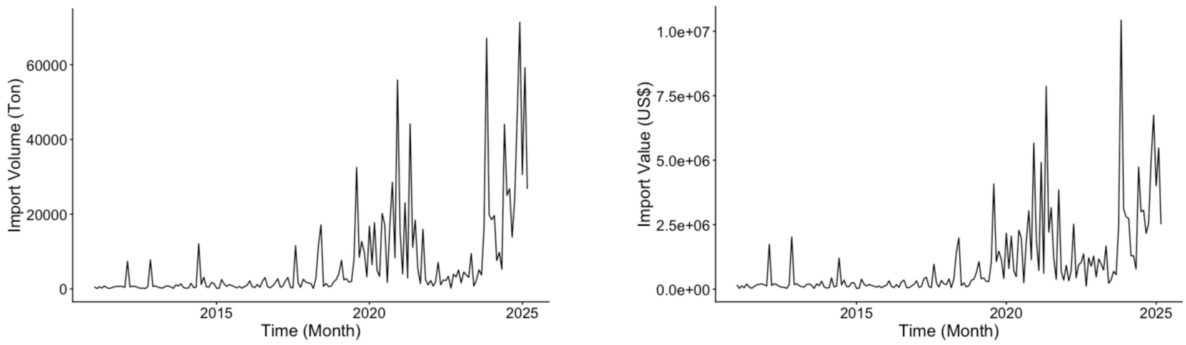
importance of ammonium chloride has increased in line with rising national fertilizer demand. In 2024, subsidized fertilizer allocation reached 9.55 million tons, while total national demand was estimated at 23 million tons, reflecting strong pressure on supporting raw materials such as ammonium chloride [1], [2].

Despite its growing importance, the domestic production of ammonium chloride in Indonesia remains very limited. Although several industries have the potential to produce ammonium chloride as a by-product, this capacity has not been commercially developed. Consequently, domestic demand is largely fulfilled through imports, making import dynamics a key indicator of industrial needs and supply vulnerability. This high dependency on imports creates structural risks for industrial continuity, particularly under conditions of global market uncertainty and supply chain disruptions.

Globally, ammonium chloride production is highly concentrated in China due to the application of the dual process in the soda ash industry, which allows the simultaneous production of ammonium chloride and sodium carbonate [4]. This has positioned China as the world's largest exporter and Indonesia's main supplier. In 2023, 99% of Indonesia's ammonium chloride imports originated from China [5], highlighting an extreme dependence on a single source and exposing the country to significant supply risk. Such concentration increases Indonesia's vulnerability to external shocks that are primarily transmitted through price adjustments, including production disruptions and international price volatility.



(a) Import volume **(b)** Import value (CIF)

Figure 1: Monthly dynamics of ammonium chloride imports in Indonesia: (a) import volume and (b) import value (CIF).

Fig. 1 shows that Indonesia's ammonium chloride import volume and Cost, Insurance, and Freight (CIF) value during the period January 2011–March 2025 exhibit strong and persistent fluctuations with similar movement patterns. Imports increased sharply during 2019–2021, declined in 2022, and rose again with higher volatility from 2023 to early 2025. This pattern indicates not only market instability but also a dynamic interaction between physical import volume and its corresponding economic value.

In international trade, import volume and import value (CIF) are the two main indicators used to describe the activity of a commodity. Import volume represents the physical quantity of goods entering the customs territory, while CIF value reflects the total monetary value of the transaction. From an economic perspective, imports represent demand for foreign goods; therefore, the relationship between import value and import volume can be explained by demand theory [6]. In general, when prices increase, the quantity imported tends to decrease, and vice versa. At the same time, changes in import volume can affect domestic supply conditions and contribute to price adjustments. This interaction indicates the existence of a bidirectional relationship between price and quantity. Previous studies have shown that changes in import prices can lead to adjustments in import quantities [7].

In econometric theory, price and quantity are jointly determined variables because they are simultaneously formed through the interaction of demand and supply [8], [9]. In this study, CIF value represents a transaction value (price proxy), while import volume represents the physical quantity of ammonium chloride. Consistent with demand–supply theory, both variables influence each other and are therefore treated as endogenous variables. Although macroeconomic factors such as exchange rates, global prices, and trade policies may affect import behavior, their influence is largely transmitted through transaction prices and is reflected in the CIF value. In addition, the extreme concentration of Indonesia's ammonium chloride imports in a single source country implies limited variation in supplier-specific trade conditions. Accordingly, a focused two-variable framework is sufficient to capture the core price–quantity adjustment mechanism, while broader macroeconomic determinants are beyond the scope of this study.

Despite Indonesia's high dependency on imports and the existence of untapped by-product production potential, quantitative studies on the trade dynamics and forecasting of ammonium chloride imports in Indonesia remain very limited. Previous studies have mainly focused on technical aspects such as plant design and production processes [2], [3], [10]. To the best of our understanding, no prior study specifically focused at the trade dynamics and forecasting of Indonesian imports of ammonium chloride.

Beyond its technical and economic relevance, the dynamics of ammonium chloride imports are closely linked to the broader agenda of sustainable industrial development. As a strategic industrial input, ensuring a stable and efficient supply of ammonium chloride is essential for strengthening industrial resilience, improving infrastructure reliability, and supporting data-driven supply chain management, which are core objectives of SDG 9 (Industry, Innovation, and Infrastructure) [11], [12].

In keeping with SDG 12 (Responsible Consumption and Production), more precise and effective import forecasting facilitates better planning of industrial raw materials, lowering the risks of excessive imports and supply interruptions while encouraging more efficient resource use. [13], [14], [15]. In this context, SDG 12 seeks to decouple economic growth from resource use and environmental degradation while emphasizing the shared responsibility of producing and consuming countries in achieving sustainable development [16].

Additionally, by promoting sustainable industrial growth and stable employment, the stability of essential industrial inputs supports SDG 8 (Decent Work and Economic Growth) and ensures production continuity. Promoting full and productive employment, decent work for all, and inclusive and sustainable economic growth are all highly prioritized in SDG 8 [17].

Therefore, this study addresses an important research gap by applying time series analysis to jointly model and forecast the volume and value of Indonesia's ammonium chloride imports. The results are expected to support government policymakers in evaluating import substitution strategies and to assist industries in long-term supply chain planning and risk mitigation.

2. Methods

This section outlines the methods employed in this study to analyze the behavior of ammonium chloride imports in Indonesia. It covers the data description, variable specification, and the statistical techniques applied to model the dynamic relationships among variables. Each analytical stage is presented systematically in the following subsections.

2.1. Data and Data Sources

Secondary data from the Central Bureau of Statistics (BPS), specifically the Indonesia Import Statistics Bulletin, are used in this study. The data consist of monthly observations of ammonium chloride imports (HS code 282710) from January 2011 to March 2025, totaling 171 observations. All variables are measured on a ratio scale, with a meaningful zero point, allowing for valid comparisons of magnitude and proportional differences.

Two main variables are analyzed: import volume and import value. Import volume is measured in tons and reflects the physical quantity of ammonium chloride entering Indonesia. Import value is measured in United States dollars (USD) based on the Cost, Insurance, and

Freight (CIF) scheme, which includes the cost of goods in the exporting country, insurance during shipment, and freight charges to the destination port in Indonesia.

2.2. Variance Stationarity

A time series is stationary in variance if its fluctuation or dispersion remains constant over time [18]. Variance stationarity is examined to ensure that the variability of the series remains constant over time, since non-constant variance may cause inefficiency in parameter estimates and bias in statistical inference. To stabilize the variance, the Box–Cox transformation is applied when necessary. A series is considered variance stationary when the estimated transformation parameter (λ) approaches one, indicating homoskedastic behavior. The Box–Cox transformation is defined as follows:

$$T(y_t) = y_t^{(\lambda)} = \begin{cases} \dfrac{y_t^{\lambda} - 1}{\lambda}, & \text{if } \lambda \neq 0, \\ \log(y_t), & \text{if } \lambda = 0. \end{cases} \tag{1}$$

2.3. Lag Optimum

To find the right number of delays to depict the dynamic relationship between the variables in the model, the ideal lag length is determined. The Akaike Information Criterion (AIC) is used to choose the lag order [19], [20], where the lag that produces the lowest AIC value is selected as the ideal lag since it offers the best trade-off between complexity and model fit [21], [22].

To maintain clarity, let k denote the candidate lag length and let n denote the number of estimated parameters. The general AIC form based on the residual sum of squares is written as:

$$AIC(k) = T \ln\left(\frac{SSR(k)}{T}\right) + 2n \tag{2}$$

2.4. Mean Stationarity

Mean stationarity describes a condition in which the expected value or mean remains stable across time [21], [23]. In other words, the data fluctuate around a constant mean rather than exhibiting a systematic upward or downward trend. The Augmented Dickey–Fuller (ADF) unit root test was applied to evaluate mean stationarity with the following hypotheses:

$$\begin{aligned} &H_0 : \beta = 1 \quad \text{(the series is non-stationary)}, \\ &H_1 : \beta < 1 \quad \text{(the series is stationary)}. \end{aligned}$$

The ADF test statistic is calculated using the following equation:

$$\tau = \frac{\hat{\beta}}{\text{se}(\hat{\beta})} \tag{3}$$

If the test statistic is less than the MacKinnon critical value, the null hypothesis fails to be rejected, indicating non-stationarity. Conversely, if the statistic exceeds the critical value, the null is rejected, and the series is considered stationary.

2.5. Cointegration Test

To test for the presence of cointegration among variables, the Trace Test developed by Johansen (1995) is employed [24]. This test aims to determine the cointegration rank in a system. The hypotheses are formulated as follows:

$$\begin{aligned} &H_0 : r_j = 0 \quad \text{(there is no cointegration vector)}, \\ &H_1 : r_j > 0 \quad \text{(the existence of at least one cointegration vector)}. \end{aligned}$$

The definition of the Trace test statistic is:

$$T_{\text{trace}}(r) = -n \sum_{i=r+1}^{m} \ln(1 - \lambda_i) \tag{4}$$

The decision rule is that if the calculated trace statistic T_{trace} exceeds the critical value at a given significance level, the null hypothesis (H_0) is rejected, indicating the presence of cointegration. Conversely, if the test statistic is smaller than the critical value, the null hypothesis cannot be rejected, suggesting that no cointegration exists.

2.6. Differencing

Differencing refers to the process of transforming a time series by computing the difference between consecutive observations, that is, by calculating the difference between the current value and its previous value, and it is applied to stabilize the mean by removing trend or seasonal patterns in the data[25], thereby producing a more stationary time series. Mathematically, first-order differencing can be seated as follows :

$$\Delta y_t = y_t - y_{t-1} \tag{5}$$

In practice, differencing may be performed more than once. If the series becomes stationary after first-order differencing, it is said to be integrated of order one, denoted as $I(1)$. If stationarity is achieved only after second-order differencing, the series is classified as $I(2)$, and so forth. Accordingly, the order of integration of a variable is expressed as $I(d)$, where d denotes the number of differencing operations required to render the data stationary. Although higher-order differencing may be required in some cases, this study applies only first-order differencing. After the differencing process is applied, the data are retested using the Augmented Dickey–Fuller (ADF) test to ensure that the transformation has achieved stationarity. The ADF test is widely used in empirical time-series analysis [26], [27], and is considered reliable in finite samples [27].

2.7. Vector Autoregressive Integrated (VARI)

When time series variables are non stationary but not cointegrated, the conventional VAR model is extended to create the Vector Autoregressive Integrated (VARI) model [28]. In such cases, differencing is required to achieve stationarity, and the model is specified in terms of changes $(\Delta Y_{t-1}, \Delta Y_{t-2}, \ldots)$ rather than in levels. Specifically, the VARI model with first differencing, denoted as VARI($p-1$), can be written as follows [29]:

$$\Delta \mathbf{y}_t = \mathbf{\Phi}_1 \Delta \mathbf{y}_{t-1} + \cdots + \mathbf{\Phi}_{p-1} \Delta \mathbf{y}_{t-p+1} + \boldsymbol{\varepsilon}_t \tag{6}$$

where $\Delta \mathbf{y}_t$ represents the differenced vector of endogenous variables, $\mathbf{\Phi}_1, \ldots, \mathbf{\Phi}_{p-1}$ are coefficient matrices capturing short-run dynamic interactions, and $\boldsymbol{\varepsilon}_t$ denotes the vector of error terms. In the absence of long-term equilibrium relationships, the VARI framework aims to capture short-term changes.

2.8. Linearity Test

A linear relationship between variables is assumed by the Vector Autoregressive Integrated (VARI) model. However, time series data may exhibit nonlinear behavior that cannot be fully captured by a linear model. Therefore, a linearity test is conducted using the Likelihood Ratio (LR) test [30], [31], by comparing the linear VARI model with the nonlinear Threshold Vector Autoregressive Integrated (TVARI). The hypotheses are:

H_0 : The linear VARI model is adequate (no threshold effect),

H_1 : The threshold model is more appropriate (threshold effect exists).

The LR statistic is defined as follows:

$$LR = -2\left(L_{\text{VARI}} - L_{\text{TVARI}}\right) \tag{7}$$

The decision rule is that if the p-value is smaller than the chosen significance level α, the null hypothesis is rejected, providing evidence of nonlinearity and supporting the use of the TVARI model. Conversely, if the p-value is greater than or equal to α, the null hypothesis cannot be rejected, indicating that the linear VARI specification is adequate.

2.9. Threshold Vector Autoregressive Integrated (TVARI)

The TVARI model allows for nonlinear analysis of data that are integrated of order one, $I(1)$. In other words, TVARI extends the VARI model by incorporating a threshold mechanism. While it retains the regime-switching concept of the TVAR, it operates on differenced data. The general form of a TVARI($p-1$) model with m regimes can be expressed as:

$$\boldsymbol{\Delta y}_t = \begin{cases} \boldsymbol{c}_1 + \sum_{k=1}^{p-1} \boldsymbol{A}_{1,k}\boldsymbol{\Delta y}_{t-k} + \boldsymbol{\varepsilon}_{1t}, & \text{if } q_{t-d} \le \gamma_1, \\ \boldsymbol{c}_2 + \sum_{k=1}^{p-1} \boldsymbol{A}_{2,k}\boldsymbol{\Delta y}_{t-k} + \boldsymbol{\varepsilon}_{2t}, & \text{if } \gamma_1 < q_{t-d} \le \gamma_2, \\ \vdots & \\ \boldsymbol{c}_m + \sum_{k=1}^{p-1} \boldsymbol{A}_{m,k}\boldsymbol{\Delta y}_{t-k} + \boldsymbol{\varepsilon}_{mt}, & \text{if } q_{t-d} > \gamma_{m-1}. \end{cases} \tag{8}$$

The threshold parameter (γ) represents the switching point that governs the transition from one linear regime to another within the piecewise linear framework [32]. The threshold variable serves as the regime separator in the TVARI model, whereby the system's behavior changes according to the conditions specified by this variable, allowing the dynamics of the system to differ across regimes.

2.10. Diagnostic Testing of the Threshold Vector Autoregressive Integrated (TVARI) Model

Diagnostic testing is conducted to ensure that the residuals of the Threshold Vector Autoregressive Integrated (TVARI) model satisfy the classical assumptions of a well-specified time series model. Three diagnostic tests are applied, namely the normality test, heteroskedasticity test, and autocorrelation test.

The normality of residuals is examined using the Mardia multivariate normality test [33] which evaluates the residual distribution based on multivariate skewness and kurtosis. The hypotheses are formulated as:

H_0 : Residuals are multivariate normally distributed

H_1 : Residuals do not follow a multivariate normal distribution

The test statistics are defined as:

$$b_{1,p} = \frac{1}{T^2}\sum_{i=1}^{T}\sum_{j=1}^{T}\left[(\mathbf{e}_i - \bar{\mathbf{e}})^\top \mathbf{S}^{-1}(\mathbf{e}_j - \bar{\mathbf{e}})\right]^3 \tag{9}$$

$$b_{2,p} = \frac{1}{T}\sum_{i=1}^{T}\left[(\mathbf{e}_i - \bar{\mathbf{e}})^\top \mathbf{S}^{-1}(\mathbf{e}_i - \bar{\mathbf{e}})\right]^2 \tag{10}$$

where T denotes the number of observations, $\mathbf{e}_i$ and $\mathbf{e}_j$ represent the residual vectors at the i-th and j-th observations, respectively, $\bar{\mathbf{e}}$ is the mean vector of residuals, and $\mathbf{S}^{-1}$ denotes the inverse of the covariance matrix. The statistic $b_{1,p}$ measures multivariate skewness, while $b_{2,p}$ measures multivariate kurtosis. The decision is based on the corresponding p-value. If the p-value is greater than or equal to the significance level α, the null hypothesis cannot be rejected, indicating that the residuals follow a multivariate normal distribution.

Heteroskedasticity is examined using the ARCH–LM test [34], [35] to assess whether the variance of the residuals remains constant over time. The hypotheses are formulated as follows:

$$H_0 : B_1 = B_2 = \cdots = B_q = 0 \quad \text{(no ARCH effect)},$$
$$H_1 : \text{at least one } B_i \neq 0 \quad \text{(ARCH effect exists)}.$$

The ARCH–LM test statistic is defined as

$$LM_{\text{ARCH}}(q) = \frac{1}{2}TM(M+1) - \text{Tr}\left(\hat{\boldsymbol{\Sigma}}_{\text{vech}}\hat{\boldsymbol{\Sigma}}_0^{-1}\right), \tag{11}$$

where T denotes the number of observations, M is the number of endogenous variables, $\hat{\Sigma}_0$ represents the theoretical covariance matrix under the null hypothesis, and $\hat{\Sigma}_{\text{vech}}$ is the empirical covariance matrix. The test statistic follows a chi-square distribution. The decision rule is based on the p-value: if the p-value is greater than or equal to the significance level α, the null hypothesis cannot be rejected, indicating homoskedastic residuals.

Residual autocorrelation is examined using the Portmanteau test [30], which evaluates whether the residuals are serially uncorrelated. The hypotheses are formulated as follows:

$$H_0 : \rho_1 = \rho_2 = \cdots = \rho_k = 0 \quad \text{(no autocorrelation)},$$
$$H_1 : \text{at least one } \rho_i \neq 0,\ i = 1, 2, \ldots, k \quad \text{(autocorrelation exists)}.$$

The Portmanteau test statistic is defined as

$$Q_p = T\sum_{i=1}^{p} \text{tr}\left(\boldsymbol{C}_i\boldsymbol{\Omega}^{-1}\boldsymbol{C}_i'\boldsymbol{\Omega}^{-1}\right), \tag{12}$$

with

$$\boldsymbol{C}_i = \frac{1}{T}\sum_{t=i+1}^{T} \boldsymbol{e}_t\boldsymbol{e}_{t-i}', \tag{13}$$

and

$$\boldsymbol{\Omega} = \frac{1}{T}\sum_{t=1}^{T} \boldsymbol{e}_t\boldsymbol{e}_t', \tag{14}$$

Here, T denotes the number of observations, $\boldsymbol{e}_t$ represents the residual vector at time t, k is the maximum lag considered, and p is the lag order used in the test statistic. Under the null hypothesis, the statistic Q_p asymptotically follows a chi-square distribution with degrees of freedom $M^2(k-p)$, where M is the number of endogenous variables. The decision rule is based on the p-value: if the p-value is greater than or equal to the significance level α, the null hypothesis cannot be rejected, indicating that the residuals are white noise.

2.11. Mean Absolute Percentage Error (MAPE)

Forecasting accuracy is assessed using the Mean Absolute Percentage Error (MAPE), which calculates the average percentage error between the expected and actual values [36]. A lower MAPE value indicates higher predictive accuracy of the model. It is defined as :

$$\text{MAPE} = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{y_t - \hat{y}_t}{y_t}\right| \times 100\%, \tag{15}$$

where Y_t denotes the actual observed value at time t, $\hat{Y}_t$ represents the corresponding forecasted value, and n is the number of observations in the evaluation sample. In this study, model validation is conducted using an out-of-sample approach, so the MAPE reflects the forecasting performance of the model on unseen data.

3. Results and Discussion

This section presents the empirical findings of the study and provides a discussion of their implications. The analysis begins with a descriptive overview of the data to illustrate general patterns and characteristics, followed by the results of subsequent statistical analyses and model estimation. The findings are then interpreted to explain the dynamics of ammonium chloride imports in Indonesia.

3.1. Descriptive Statistics

Descriptive statistics are provided to highlight the salient features of the data before the econometric analysis. Table 1 presents the summary statistics of ammonium chloride imports in Indonesia over the period January 2011 to March 2025, covering both import volume (in tons) and import value measured on a Cost, Insurance, and Freight (CIF) basis in United States dollars.

Table 1: Descriptive statistics of ammonium chloride import variables

Variable	Min	Q1	Median	Mean	Q3	Max
Import Volume (tons)	94.25	623.76	1797.97	6950.08	7493.15	71396.72
Import Value (USD)	27630	129306	339345	991255	1190096	10430505

The import volume ranges from 94.25 tons to 71,396.72 tons, with a mean of 6,950.08 tons and a median of 1,797.97 tons. The substantial difference between the mean and median indicates a right-skewed distribution, driven by periods of exceptionally high import volumes.

Similarly, import value exhibits considerable variability, ranging from USD 27,630 to USD 10,430,505. The average import value is USD 991,255, while the median is USD 339,345. The large gap between the mean and median reflects high volatility and the presence of extreme high-value import episodes.

3.2. Variance Stationarity

Variance stationarity refers to a condition in which the variability of a time series remains constant over time. If the variance changes systematically, the series is considered heteroskedastic and requires transformation prior to further time series modeling. In this study, variance stabilization is conducted using the Box–Cox transformation.

Table 2: Box–Cox transformation results

Stage	Variable	λ	Lower bound	Upper bound	Conclusion
Before transformation	Import Volume	-0.045498	-0.545498	0.454502	Not stationary
	Import Value	-0.067919	-0.567919	0.432081	Not stationary
After transformation	Import Volume	0.993260	0.493260	1.493260	Stationary
	Import Value	0.608257	0.108257	1.108257	Stationary

Based on the results presented in Table 2, both import volume and import value (CIF) are not variance stationary prior to transformation, as indicated by the estimated Box–Cox parameters (λ) that are not close to unity. After applying the Box–Cox transformation using a logarithmic specification, the estimated λ values approach one and fall within their respective confidence intervals. This indicates that both series achieve variance stationarity and are suitable for subsequent time series modeling.

3.3. Lag Length Selection

The Akaike Information Criterion (AIC), which is frequently employed in time series analysis, was utilized to determine the ideal lag duration. The optimal lag order is selected as the lag length that minimizes the AIC value, thereby achieving a balance between model goodness-of-fit and parsimony.

Table 3: Lag length selection using Akaike Information Criterion (AIC)

Lag (p)	AIC value	Lag (p)	AIC value
1	-2.82077588	6	-3.06893450
2	-2.90665673	7	-3.05335060
3	-3.02390234	8	-3.05863199
4	-3.04211830	9	-3.07123062
5	-3.05808635	10	-3.05422278

As reported in Table 3, the smallest AIC value is obtained at lag $p = 9$. Therefore, the optimal lag length used in the subsequent modeling process is set to nine.

3.4. Mean Stationarity

The mean stationary at the 5% significant level was examined using the Augmented Dickey-Fuller (ADF) test. Stationary series allow the direct application of the standard Vector Autoregressive (VAR) model. In contrast, non-stationary series require either a Vector Autoregressive Integrated (VARI) model or a Vector Error Correction Model (VECM), based on whether cointegration is present.

Table 4: ADF stationarity test results

Variable	p-value	Conclusion
Import volume of ammonium chloride	0.14470	Non-stationary
Import value of ammonium chloride	0.08163	Non-stationary

Based on the results presented in Table 4, both import volume and import value exhibit p-values greater than 0.05. This indicates that the two series are non-stationary in their mean. Consequently, further cointegration testing is required.

3.5. Cointegration Test

The Johansen cointegration test was used to determine whether import volume and import value (CIF) have a long-run equilibrium conjunction because the levels of both variables are non-stationary.

Table 5: Johansen cointegration test results (trace statistic)

Null hypothesis	Trace statistic	Critical value (5%)	Decision
$r = 0$	2.73	9.24	Fail to reject H_0
$r \leq 1$	8.88	19.96	Fail to reject H_0

As illustrated in Table 5, the trace statistics for both $r = 0$ and $r \leq 1$ are smaller than their corresponding critical values at the 5% significance level. Therefore, the null hypothesis of no cointegration cannot be rejected. This finding suggests that no long-term equilibrium relationship exists between import volume and import value. Hence, the Vector Autoregressive Integrated (VARI) model is an appropriate modeling framework for the data.

3.6. Differencing

Since both variables are non-stationary in their levels and no cointegration is detected, first-order differencing is applied to achieve stationarity. The Augmented Dickey–Fuller (ADF) test conducted on the differenced series yields p-values of 0.01 for both variables, as reported in Table 6.

These findings verify that both series are integrated of order one, $I(1)$, and become stationary following first differencing.

Table 6: ADF stationarity test results after differencing

Variable	p-value	Conclusion
Import volume of ammonium chloride	0.01	Stationary
Import value of ammonium chloride	0.01	Stationary

3.7. Vector Autoregressive Integrated (VARI)

Given the absence of cointegration and the $I(1)$ nature of both variables, the analysis proceeds using a Vector Autoregressive model estimated on first-differenced data, referred to as the Vector Autoregressive Integrated (VARI) model. From a theoretical perspective, a VAR(p) model in levels can be reparameterized into a Vector Error Correction Model (VECM) with $p-1$ lagged difference terms. When no cointegration is present, the error correction term is omitted, and the model reduces to a VAR expressed in first differences, i.e., a VARI($p-1$) model. Although the VARI model is estimated using first-differenced data, the reduction in the lag order is not driven by the loss of observations due to differencing, but rather follows from this standard VAR–VECM reparameterization. Since the optimal lag length selected from the level data is $p = 9$, a VARI(8) model is employed in this study.

The estimation results of the VARI(8) model indicate that most lagged coefficients are statistically insignificant at the 5% significance level in both equations, namely the import volume growth equation and the import value (CIF) growth equation. In the import volume equation, none of the lagged terms of either variable are statistically significant, suggesting that past growth in import volume and import value does not exert a meaningful short-run influence on current import volume growth. Similarly, the intercept term is insignificant, indicating the absence of a statistically constant growth tendency when past dynamics are excluded.

In the import value (CIF) equation, only the first lag of import value growth is statistically significant and exhibits a negative coefficient, reflecting a short-run adjustment mechanism or mean reversion behavior. Aside from this term, all remaining coefficients and the intercept are statistically insignificant, implying weak linear interdependencies among the variables in the short run.

Overall, the prevalence of insignificant coefficients suggests that the short-run dynamics captured by the linear VARI framework are relatively weak. In addition, the data exhibit periods of heightened and subdued volatility, pointing to potential regime-dependent behavior that may not be adequately represented by a linear specification. While the two-variable framework is theoretically justified, the absence of explicit external variables may limit the VARI model's ability to capture short-run shocks arising from abrupt policy changes, exchange rate movements, or global price disturbances, which may operate in a nonlinear or asymmetric manner and are not fully transmitted through transaction prices.

Consequently, the weak linear dynamics observed in the VARI(8) model may partly reflect aggregation bias, where heterogeneous adjustment processes are averaged within a linear structure. This limitation implies that policy interpretations based solely on the linear VARI results should be treated with caution, particularly for short-term policy or business applications. These findings therefore motivate the application of a nonlinear framework that allows for regime-dependent and asymmetric adjustments, as pursued in the subsequent TVARI analysis.

3.8. Linearity Test

In this study, the import volume of ammonium chloride is employed as the threshold variable. Import volume reflects the intensity of demand conditions in ammonium chloride trade, such that variations in import volume capture shifts between relatively low- and high-demand phases.

Using import volume as the threshold variable allows regime classification to be based on the level of import activity, thereby facilitating a clearer interpretation of regime-dependent dynamics within the system.

To examine whether a linear VARI model is sufficient to characterize the relationship between import volume and import value, a Likelihood Ratio (LR) linearity test is conducted. The test compares the linear VARI model against a Threshold VARI (TVARI) model with a single threshold.

Table 7: Likelihood Ratio Linearity Test Results

Test Comparison	LR Statistic	p-value	Decision
VARI vs. TVARI (one threshold)	83.19144	0.04800	Reject H_0

Based on Table 7, the LR test produces a p-value of 0.048, which is below the 5% significance level. Consequently, the null hypothesis of linearity is rejected, indicating the presence of nonlinear dynamics in the relationship between import volume and import value. This result provides formal statistical support for adopting the TVARI framework in subsequent analysis.

3.9. Parameter Threshold Vector Autoregressive Integrated (TVARI)

The selection of the Threshold Vector Autoregressive Integrated (TVARI) model parameters is conducted by fixing the lag length at 8, following the results of the Vector Autoregressive Integrated (VARI) model. The delay parameter is explored over the range of 1 to 8, while trimming values of 0.10 and 0.15 are considered under a single-threshold specification. A single-threshold TVARI specification is employed to capture a dominant regime shift in import dynamics, distinguishing periods of low and high import growth. This specification is sufficient to represent the key nonlinear adjustment mechanisms while maintaining model parsimony and interpretability. Introducing additional thresholds would increase model complexity without clear empirical evidence of further regime changes.

Table 8: Candidate TVARI model specifications based on AIC

Lag	Delay	Number of thresholds	Trim	AIC
8	4	1	0.10	-498.7649
8	5	1	0.10	-497.8140
8	7	1	0.10	-495.0006
8	6	1	0.10	-494.2942
8	6	1	0.15	-492.1169

As shown in Table 8, five candidate TVARI specifications yield the lowest AIC values among all combinations evaluated. All candidate models employ a lag length of 8 with one threshold, while differences across specifications are primarily driven by the delay parameter, which ranges from 4 to 7 in the selected models. These candidate models are subsequently subjected to diagnostic testing to determine the most appropriate TVARI specification for estimation and forecasting.

3.10. Diagnostic Testing of the Threshold Vector Autoregressive Integrated (TVARI)

To determine the most appropriate TVARI specification, the candidate models identified in the previous step are further evaluated using a set of diagnostic tests. These tests include residual normality, heteroskedasticity, and autocorrelation tests. A summary of the diagnostic test results for the candidate TVARI models is presented in Table 9.

Table 9: Summary of diagnostic test results for TVARI models

Model specification	Normality	Heteroskedasticity	Autocorrelation
TVARI(8), delay = 4, trim = 0.10	Not normal	No heteroskedasticity	No autocorrelation
TVARI(8), delay = 5, trim = 0.10	Not normal	Heteroskedasticity	No autocorrelation
TVARI(8), delay = 7, trim = 0.10	Normal	No heteroskedasticity	No autocorrelation
TVARI(8), delay = 6, trim = 0.10	Not normal	No heteroskedasticity	No autocorrelation
TVARI(8), delay = 6, trim = 0.15	Not normal	No heteroskedasticity	No autocorrelation

Based on the diagnostic test results reported in Table 9, most candidate TVARI specifications fail to satisfy at least one of the required statistical assumptions. Several models do not meet the residual normality assumption, while the specification with delay equal to 5 additionally exhibits heteroskedasticity. Among all candidates, only the TVARI(8) model with delay = 7 and trim = 0.10 satisfies all diagnostic criteria, namely normally distributed residuals, absence of heteroskedasticity, and no residual autocorrelation. Therefore, this specification is selected as the final TVARI model and is subsequently used for parameter estimation and forecasting.

3.11. Estimation of the Threshold Vector Autoregressive Integrated (TVARI) Model

The Threshold Vector Autoregressive Integrated (TVARI) model is estimated using the TVARI(8) specification with delay = 7 and trim = 0.10, which is selected based on parameter optimization and diagnostic testing. A single threshold is identified endogenously by minimizing the sum of squared residuals (SSR) under a trimming constraint. The estimated threshold value is $\hat{\gamma} = 0.1707489$, with the growth rate of import volume serving as the threshold variable. This threshold divides the system into two regimes, namely a low-import growth regime (55.6% of observations) and a high-import growth regime (44.4% of observations). Since the threshold is defined in terms of import growth, the regime classification reflects differences in growth dynamics rather than differences in absolute import levels.

The general estimated TVARI model can be expressed as:

$$\Delta \hat{\mathbf{y}}_t = \begin{cases} \hat{\mathbf{c}}_1 + \sum_{i=1}^{8} \hat{\mathbf{A}}_{1,i}\, \Delta \mathbf{y}_{t-i} + \hat{\boldsymbol{\varepsilon}}_{1,t}, & \text{if } \Delta \log y_{1,t-7} \le \hat{\gamma}, \\ \hat{\mathbf{c}}_2 + \sum_{i=1}^{8} \hat{\mathbf{A}}_{2,i}\, \Delta \mathbf{y}_{t-i} + \hat{\boldsymbol{\varepsilon}}_{2,t}, & \text{if } \Delta \log y_{1,t-7} > \hat{\gamma}, \end{cases} \tag{16}$$

where

$$\mathbf{y}_t = \begin{pmatrix} \log y_{1,t} \\ \log y_{2,t} \end{pmatrix},$$

with $y_{1,t}$ denoting import volume and $y_{2,t}$ denoting import value (CIF).

3.11.1. Low-import growth regime

For the low-import growth regime ($\Delta \log y_{1,t-7} \le \hat{\gamma}$), the estimated import volume equation with coefficients significant at the 5% level is given by:

$$\begin{aligned} \Delta \log \hat{y}_{1,t} = & -1.9288\, \Delta \log \hat{y}_{2,t-4} - 1.5381\, \Delta \log \hat{y}_{2,t-5} \\ & -1.4336\, \Delta \log \hat{y}_{2,t-6} - 2.0835\, \Delta \log \hat{y}_{2,t-7} \\ & -1.4215\, \Delta \log \hat{y}_{2,t-8} + \hat{\varepsilon}_{1,t}. \end{aligned} \tag{17}$$

Although the TVARI model in low-import growth for import volume equation is estimated with eight lags, coefficients associated with short-run dynamics (lags one to three) are statistically insignificant and therefore omitted from the reported equations. All lagged import value (CIF) coefficients are negative and statistically significant, indicating that increases in past CIF values significantly reduce current import growth. This suggests that, in this regime, import volume dynamics are predominantly price-driven, with delayed responses consistent with procurement contracts, shipping schedules, and inventory management practices.

The corresponding import value (CIF) equation in the low-import growth regime is:

$$\begin{aligned}\Delta \log \hat{y}_{2,t} = & -1.6691\,\Delta \log \hat{y}_{2,t-4} - 1.2706\,\Delta \log \hat{y}_{2,t-5} \\ & - 1.3408\,\Delta \log \hat{y}_{2,t-6} - 2.0721\,\Delta \log \hat{y}_{2,t-7} \\ & - 1.2199\,\Delta \log \hat{y}_{2,t-8} + 1.3703\,\Delta \log \hat{y}_{1,t-7} \\ & + \hat{\varepsilon}_{2,t}.\end{aligned} \tag{18}$$

Similarly, in the import value equation, coefficients at lags one to three are statistically insignificant and therefore omitted. The negative coefficients in lagged CIF indicate a strong price correction mechanism, while the positive and significant effect of lagged import growth reflects delayed transmission from higher import volumes to CIF values.

3.11.2. High-import growth regime

In contrast, under the high-import growth regime ($\Delta \log y_{1,t-7} > \hat{\gamma}$), the estimated import volume equation is:

$$\Delta \log \hat{y}_{1,t} = 0.7866 - 1.7181\,\Delta \log \hat{y}_{1,t-4} + \hat{\varepsilon}_{1,t}. \tag{19}$$

Although the model is estimated with eight lags, only lagged import growth at t-4 is statistically significant in this regime and therefore reported. The positive intercept indicates an inherent upward tendency in import growth, while the negative and significant coefficient on lagged import growth reflects an inventory adjustment mechanism. The absence of significant CIF terms implies that import volume in this regime is no longer sensitive to price fluctuations.

The corresponding import value (CIF) equation in the high-import growth regime is:

$$\Delta \log \hat{y}_{2,t} = 0.6390 - 1.3470\,\Delta \log \hat{y}_{1,t-4} + \hat{\varepsilon}_{2,t}. \tag{20}$$

Similarly, short-run dynamics and lagged CIF terms are statistically insignificant and therefore omitted from the reported equation. The negative and significant effect of lagged import growth indicates that higher past imports increase market supply and subsequently exert downward pressure on CIF values.

Overall, the estimation results reveal a clear regime-dependent asymmetry. The low-import growth regime is characterized by price-driven dynamics, with strong delayed price corrections and a dominant influence of CIF on import volume. In contrast, the high-import growth regime is supply-driven, where import dynamics are governed by inventory and volume adjustments, and CIF responds primarily to delayed supply pressures. These findings confirm that the TVARI framework based on thresholds effectively captures the nonlinear and state-dependent dynamics of ammonium chloride imports in Indonesia.

3.12. Out-of-Sample Forecast Evaluation

Forecast evaluation is conducted using the TVARI(8) model with one threshold, delay = 7, and trim = 0.10, employing an out-of-sample forecasting approach with a six-period forecasting horizon. This approach is used to assess the model's ability to predict observations that are not included in the estimation process. For benchmarking purposes, a linear VARI model with the same lag structure and data partition is also estimated.

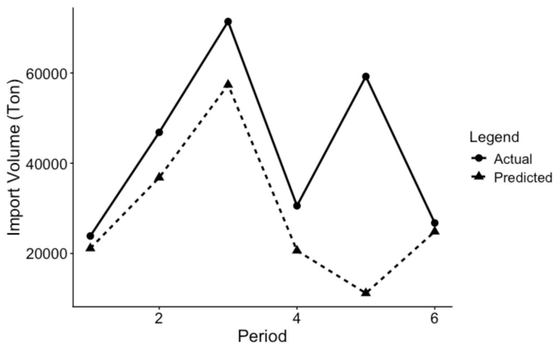
The dataset is divided into two subsets, namely a training set and a testing set. Specifically, the last six observations are reserved as the testing sample, while the remaining observations are used for model estimation. The TVARI model is estimated using the training sample and subsequently applied to generate forecasts of logarithmic changes (Δ log) in import volume and import value (CIF) of ammonium chloride over the testing period. The same data partition is applied to the benchmark VARI model to ensure comparability.

Since the forecasts are obtained in logarithmic change form, they do not directly represent import volume and CIF values in their original units. Therefore, to facilitate comparison with the actual data, the forecasted values are reconstructed back into level form using the actual value from the previous period as the starting point. The back-transformation is performed as follows:

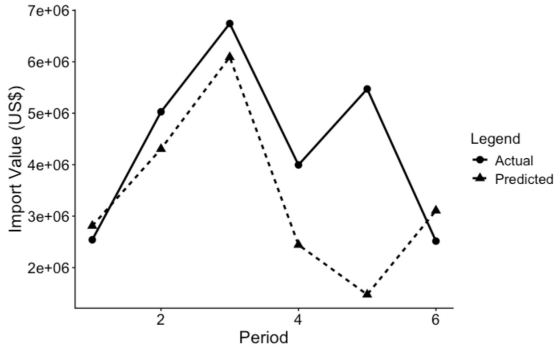
$$\hat{y}_t = y_{t-1}^{\text{actual}} \times \exp(\Delta \log \hat{y}_t)\,. \tag{21}$$

The out-of-sample evaluation indicates that the TVARI model achieves Mean Absolute Percentage Error (MAPE) values of 28.874% for import volume and 28.379% for import value (CIF), reflecting a moderate level of forecasting accuracy. Under the same forecasting scheme, the benchmark VARI model yields substantially higher MAPE values of 48.843% for import volume and 39.125% for import value (CIF). This difference suggests that incorporating regime-dependent dynamics improves predictive performance.

Based on this comparative evaluation, the graphical analysis focuses on the TVARI out-of-sample forecasts, as they provide a more informative representation of the model's forecasting capability. Fig. 2 presents the comparison between actual and predicted series for both variables.



(a) Import volume



(b) Import value (CIF)

Figure 2: Actual series (solid line) and out-of-sample forecasts (dashed line) of (a) import volume and (b) import value (CIF).

Fig. 2 shows that the TVARI forecasts broadly track the actual movements of import volume and CIF value, capturing the main directional trends while smoothing short-term volatility. Forecast deviations are more evident during periods of abrupt price adjustments, particularly in the CIF series, highlighting the inherent difficulty of predicting sudden market shifts in import-dependent commodities.

Although the MAPE values indicate that forecasting uncertainty remains non-negligible, with error levels that may limit the model's suitability for precise short-term policy or business planning, the consistently lower errors relative to the linear VARI model demonstrate the advantage of allowing for nonlinear, regime-dependent dynamics. The similar magnitude of MAPE across volume and value based indicators further suggests balanced forecasting performance across different dimensions of import activity. From a practical perspective, this level of accuracy implies that the TVARI model is better suited for strategic and medium-term analysis, where understanding directional movements, regime shifts, and relative changes is more relevant than generating highly precise point forecasts for operational decision-making.

Overall, the results indicate that the TVARI model performs well in capturing the general dynamics and regime-dependent behavior of ammonium chloride imports in Indonesia. The similar MAPE values obtained for both variables suggest balanced forecasting performance for real (volume-based) and monetary (value-based) trade indicators.

3.13. Real Forecast

Using the estimated TVARI(8) model with a single threshold, a real forecast is generated utilizing the entire sample with a 12-period forecast horizon, covering the period from April 2025 to March 2026. This forecasting exercise aims to project future movements of ammonium chloride import volume and import value (CIF) under the regime-dependent dynamics captured by the TVARI framework.

The forecasts generated by the TVARI model are obtained in the form of logarithmic differences ($\Delta \log$). To express the forecasts in their original units, the predicted log-differences are reconstructed into level values using the transformation defined in Eq. (21).

Table 10: TVARI-based forecasts of ammonium chloride imports and CIF values with 95% confidence intervals

Period	Import Volume (tons)			Import Value CIF (US$)		
	Point Forecast	Lower Bound	Upper Bound	Point Forecast	Lower Bound	Upper Bound
April 2025	30,495.96	4,773.23	176,282.80	2,978,884	592,188.13	14,815,662
May 2025	27,213.51	2,248.27	315,327.30	3,373,637	358,858.71	26,990,750
June 2025	37,220.00	1,813.29	747,736.00	3,941,601	293,169.91	49,164,492
July 2025	63,402.60	1,959.26	2,188,610.90	6,091,791	306,053.85	127,114,332
August 2025	243,552.44	5,340.79	14,082,318.70	18,117,741	725,514.98	646,018,701
September 2025	106,502.13	1,981.84	10,703,420.00	8,980,233	233,855.74	592,542,204
October 2025	83,524.83	1,056.40	8,012,004.10	7,450,047	169,286.99	475,973,010
November 2025	61,731.11	552.77	10,938,409.40	5,734,186	96,430.94	571,699,021
December 2025	38,627.44	213.32	7,071,944.30	3,493,106	40,450.99	308,351,082
January 2026	44,970.97	228.67	12,410,177.60	4,483,660	43,089.90	603,989,513
February 2026	55,580.52	139.26	17,361,964.00	5,660,201	33,934.94	753,318,580
March 2026	76,429.32	134.26	26,824,521.10	7,058,076	23,217.98	1,833,713,803

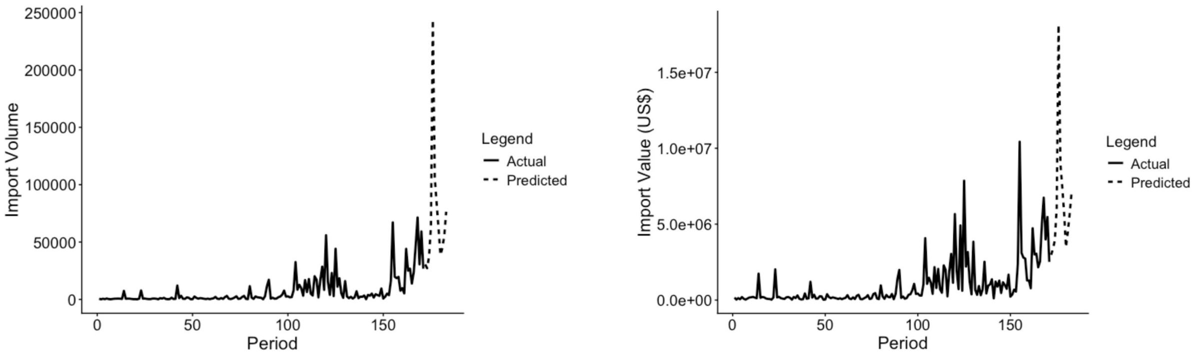
Table 10 presents the 12-period ahead real forecasts of ammonium chloride import volume and import value (CIF) generated from the TVARI(8) model with a single threshold. The forecasts reveal substantial variability over the forecast horizon, indicating pronounced short-term volatility in both import volume and import value.

A notable feature of the results is the sharp increase in the point forecast of import volume in August 2025, which reaches 243,552.44 tons. This surge is accompanied by an exceptionally wide 95% confidence interval, ranging from approximately 5,341 tons to over 14 million tons. Such a wide interval indicates a high degree of forecast uncertainty and suggests that the point forecast should not be interpreted as a precise prediction, but rather as a potential extreme outcome implied by the model dynamics.

The substantial width of the confidence interval reflects the nonlinear and regime-switching characteristics of the TVARI model. In particular, when the threshold variable crosses the estimated regime boundary, past large shocks can be amplified, resulting in explosive short-run responses in the forecast distribution. This behavior is especially evident in the mid-forecast horizon, where regime-dependent dynamics exert a stronger influence on projected outcomes.

A similar pattern is observed for the forecasted import value (CIF). The point forecast for CIF also increases markedly in August 2025, reaching approximately US$18.1 million, with the upper bound of the confidence interval extending beyond US$600 million. This further underscores the heightened uncertainty surrounding the forecast during periods associated with potential regime shifts.

Overall, the forecasting results indicate that future movements of ammonium chloride imports are characterized by high volatility and asymmetric risks, particularly in the presence of nonlinear adjustment mechanisms. The wide confidence intervals suggest that the TVARI model captures not only the central tendency of future imports but also the possibility of extreme fluctuations under adverse or high-growth regimes. Consequently, the forecasts should be interpreted as scenario-based projections rather than deterministic forecasts, providing valuable insights into the range of possible outcomes under changing market conditions.



(a) Import volume **(b)** Import value (CIF)

Figure 3: Actual series (solid line) and real forecasts (dashed line) of (a) import volume and (b) import value (CIF).

Fig. 3 illustrates the comparison between the historical series and the 12-period-ahead real forecasts generated by the TVARI model. Fig. 3a shows that the forecasted import volume broadly follows the general movement of the historical data, capturing the main upward and downward dynamics implied by the regime-dependent structure of the model.

However, the forecasted series appears smoother than the historical observations and does not fully replicate abrupt short-term spikes. This behavior reflects the model's reliance on past regime information and conditional expectations, rather than exact reproduction of extreme realizations. Similar patterns are observed in Fig. 3b, where the forecasted CIF values track the overall trend but exhibit dampened responses during periods of heightened volatility.

Overall, the graphical results indicate that the TVARI model is effective in capturing the underlying regime-dependent dynamics of ammonium chloride imports, while extreme fluctuations are reflected primarily through wider forecast uncertainty rather than sharp point forecasts.

4. Conclusion

This study aims to model and analyze the nonlinear dynamics between the import volume and the import value (CIF) of ammonium chloride in Indonesia using a Threshold Vector Autoregressive Integrated framework (TVARI). The results confirm that the TVARI(8) model with delay $= 7$ and trim $= 0.10$ is the most appropriate specification for capturing the regime-dependent behavior of the system.

The findings reveal that the relationship between import volume and import value is state-dependent, differing significantly across low and high import growth regimes. In the low-growth regime, import dynamics are predominantly price-driven, characterized by delayed price adjustments and a tendency toward mean reversion, where past import value exerts a strong corrective effect on import growth. In contrast, during the high-growth regime, import behavior becomes supply-driven, with past import volumes playing a dominant role and import value responding mainly to supply pressures rather than to its own past movements. These results highlight the importance of incorporating nonlinear and threshold effects when analyzing import dynamics, as linear models may fail to capture such asymmetric responses.

From a practical perspective, the proposed TVARI model serves as a valuable tool for understanding and forecasting ammonium chloride imports under different market conditions. By providing regime-specific insights into price and supply-driven dynamics, the model can assist policymakers and industry stakeholders in developing more effective import planning, inventory management, and price stabilization strategies. This study contributes to enhancing industrial resilience and data-driven supply chain management in line with the objectives of SDG 9 (Industry, Innovation, and Infrastructure), promotes more efficient and responsible use of industrial raw materials consistent with SDG 12 (Responsible Consumption and Production), and supports sustainable industrial activity and employment stability as emphasized in SDG 8 (Decent Work and Economic Growth).

This study is subject to several limitations, including the use of only two endogenous variables and the absence of external macroeconomic factors such as exchange rates or global price indices. Future research may extend this framework by incorporating additional explanatory variables, alternative nonlinear specifications, or higher-frequency data to further improve forecasting accuracy and policy relevance.

CRediT Authorship Contribution Statement

Carissa Egytia Widiantoro: Methodology, Formal Analysis, Writing–Original Draft, Software, Visualization.
Restu Arisanti: Supervision, Funding Acquisition.
Gumgum Darmawan: Supervision.

Declaration of Generative AI and AI-assisted technologies

During the research and manuscript preparation process, the author utilized AI-based tools in a limited and supportive capacity, primarily for checking code syntax and ensuring computational consistency. All analyses, interpretations, and the writing of the manuscript were conducted independently by the author, who has fully reviewed and verified the content and takes complete responsibility for the scientific accuracy and integrity of this work.

Declaration of Competing Interest

The authors declare no competing interest.

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Data and Code Availability

The dataset analysed during the current study is publicly available in the Central Bureau of Statistics (BPS).

References

[1] BPSI Serealia, *Berita bsip serealia: Kuantum pupuk tahun 2024 naik menjadi 9,55 juta ton*, https://serealia.bsip.pertanian.go.id/berita/kuantum-pupuk-tahun-2024-naik-menjadi-955-juta-ton, Diakses 1 Oktober 2025, 2024.

[2] S. S. Azzahra and R. A. Pradipta, *Pra rancangan pabrik amonium klorida dari amonium sulfat dan nacl kapasitas 200.000 ton/tahun*, https://dspace.uii.ac.id/bitstream/handle/123456789/50011/18521059.pdf?sequence=1&isAllowed=y, Skripsi, 2024.

[3] M. A. Qodhi, *Pra-rancangan pabrik amonium klorida (nh_4cl) dari amonium sulfat ($(nh_4)_2so_4$) dan sodium klorida (nacl) dengan kapasitas 91.000 ton/tahun*, Skripsi, Semarang, 2025. https://eprints2.undip.ac.id/id/eprint/35035/.

[4] M. Cichosz et al., "Influence of ammonia concentration on solvay soda process parameters and associated environmental and energetic effects," *Energies*, vol. 15, no. 22, p. 8370, 2022. DOI: 10.3390/en15228370.

[5] World Bank, *Indonesia ammonium chloride imports by country in 2023*, https://wits.worldbank.org/trade/comtrade/en/country/IDN/year/2023/tradeflow/Imports/partner/ALL/product/282710, World Integrated Trade Solution (WITS). Diakses 12 Juli 2025, 2023.

[6] R. Kamarullah, *Faktor-faktor yang mempengaruhi impor kentang indonesia dari australia periode 2000–2013*, Skripsi, Universitas Pasundan, Bandung, 2016. https://repository.unpas.ac.id/13279/.

[7] S.-I. Lee and B.-S. Yoon, "Dynamic causal relationships among import price, import quantity, and ocean freight rate index in the chemical pulp market," *Journal of Korea Technical Association of The Pulp and Paper Industry*, vol. 54, no. 4, pp. 94–102, 2022. DOI: 10.7584/JKTAPPI.2022.08.54.4.94.

[8] D. N. Gujarati, *Basic Econometrics*, 4th ed. New York: McGraw-Hill, 2003. https://books.google.co.id/books?id=xCq7AAAAIAAJ.

[9] A. MacKay and N. H. Miller, "Estimating models of supply and demand: Instruments and covariance restrictions," *American Economic Journal: Microeconomics*, vol. 17, no. 1, pp. 238–281, 2025. DOI: 10.1257/mic.20230024.

[10] S. P. Devina et al., "Pra rancangan pabrik amonium klorida dengan kapasitas 120.000 ton/tahun," *Jurnal Tugas Akhir Teknik Kimia*, vol. 7, no. 2, 2024, Diakses 20 Juli 2025. https://jtam.ulm.ac.id/index.php/jtatk/article/view/2726.

[11] S. Küfeoğlu, "SDG-9: Industry, innovation and infrastructure," in *Sustainable Development Goals*, Springer, 2022, pp. 349–369. DOI: 10.1007/978-3-031-07127-0_11.

[12] A. Hambali, "Komitmen atas SDGs-9, tingkat inovasi, dan dampaknya pada kinerja keberlanjutan perusahaan," *Jurnal Akuntansi*, vol. 24, 2024. DOI: 10.36452/akunukd.v24i1.3220.

[13] R. Castellano, G. De Bernardo, and G. Punzo, "Sustainable well-being and sustainable consumption and production: An efficiency analysis of Sustainable Development Goal 12," *Sustainability*, vol. 16, no. 17, p. 7535, 2024. DOI: 10.3390/su16177535.

[14] D. Gasper, A. Shah, and S. Tankha, "The framing of sustainable consumption and production in SDG 12," *Global Policy*, vol. 10, no. S1, pp. 83–95, 2019. DOI: 10.1111/1758-5899.12592.

[15] M. A. B. Omer and T. Noguchi, "A conceptual framework for understanding the contribution of building materials in the achievement of Sustainable Development Goals (SDGs)," *Sustainable Cities and Society*, vol. 52, p. 101 869, 2020. DOI: 10.1016/j.scs.2019.101869.

[16] S. Küfeoğlu, "SDG-12: Responsible consumption and production," in *Sustainable Development Goals*, Springer, 2022, pp. 409–428. DOI: 10.1007/978-3-031-07127-0_14.

[17] S. M. Rai, B. D. Brown, and K. N. Ruwanpura, "SDG 8: Decent work and economic growth – a gendered analysis," *World Development*, vol. 113, pp. 368–380, 2019. DOI: 10.1016/j.worlddev.2018.09.006.

[18] D. Santi, N. Nusyirwan, A. Dorrah, and F. Pandri, "Analisis model autoregressive integrated moving average data deret waktu dengan metode momen sebagai estimasi parameter," *Jurnal Siger Matematika*, vol. 2, no. 02, pp. 57–67, 2021. http://repository.lppm.unila.ac.id/39084/.

[19] A. Khair, S. Sarmanu, S. Martini, and B. W. Otok, "Vector autoregressive modeling on cases of malaria based on the tribal in tanah bumbu district," *CAUCHY: Jurnal Matematika Murni dan Aplikasi*, vol. 5, no. 3, pp. 150–160, 2018. DOI: 10.18860/ca.v5i3.5880.

[20] B. C. Thalita and I. Darti, "Pricing double barrier options with time-varying interest using standard, antithetic, and control variate monte carlo," *CAUCHY: Jurnal Matematika Murni dan Aplikasi*, vol. 10, no. 2, pp. 1176–1191, 2025. DOI: 10.18860/cauchy.v10i2.37010.

[21] D. R. Febrianti, M. A. Tiro, and S. Sudarmin, "Metode vector autoregressive (var) dalam menganalisis pengaruh kurs mata uang terhadap ekspor dan impor di indonesia," *VARIANSI: Journal of Statistics and Its Application on Teaching and Research*, vol. 3, no. 1, p. 23, 2021. DOI: 10.35580/variansiunm14645.

[22] R. Aditya Akbar and A. Rusgiyono, "Analisis integrasi pasar bawang merah menggunakan metode vector error correction model (vecm) (studi kasus: Harga bawang merah di provinsi jawa tengah)," *Jurnal Gaussian*, vol. 5, no. 4, pp. 811–820, 2016. http://ejournal-s1.undip.ac.id/index.php/gaussian.

[23] Z. Guo, "Research on the augmented dickey–fuller test for predicting stock prices and returns," *Advances in Economics, Management and Political Sciences*, vol. 44, no. 1, pp. 101–106, 2023. DOI: 10.54254/2754-1169/44/20232198.

[24] H. Lütkepohl and M. Krätzig, *Applied Time Series Econometrics*. Cambridge: Cambridge University Press, 2004. https://books.google.co.id/books/about/Applied_Time_Series_Econometrics.html?id=xe7NDY8leWwC&redir_esc=y.

[25] S. H. Prabuningrat, N. K. Salma, P. W. Muharamah, M. Al Haris, and M. S. Nur, "Peramalan indeks harga konsumen kota semarang dengan metode autoregressive integrated moving average," *Journal of Data Insights*, vol. 1, no. 1, pp. 1–9, 2023. http://journalnew.unimus.ac.id/index.php/jodi.

[26] D. A. Dickey and W. A. Fuller, "Distribution of the estimators for autoregressive time series with a unit root," *Journal of the American Statistical Association*, vol. 74, no. 366, pp. 427–431, 1979. DOI: 10.1080/01621459.1979.10482531.

[27] S. Maitra and D. N. Politis, "Prepivoted augmented dickey–fuller test with bootstrap-assisted lag length selection," *Stats*, vol. 7, no. 4, pp. 1226–1243, 2024. DOI: 10.3390/stats7040072.

[28] S. I. Maiyanti, M. Mahrudinda, A. F. W. Haq, and B. N. Ruchjana, "Model vector autoregressive integrated (vari) untuk peramalan banyaknya kasus terkonfirmasi dan kasus sembuh COVID-19 di indonesia," in *Pattimura Proceeding: Conference of Science and Technology*, 2022, pp. 523–532. DOI: 10.30598/PattimuraSci.2021.KNMXX.523-532.

[29] S. Wulandary, "Vector autoregressive integrated (vari) method for forecasting the number of international visitors in batam and jakarta," *Jurnal Matematika, Statistika dan Komputasi*, vol. 17, no. 1, pp. 94–108, 2020. DOI: 10.20956/jmsk.v17i1.10536.

[30] C. Oktavianita, *Penerapan model threshold vector autoregressive untuk memprediksi cadangan devisa indonesia (studi kasus: Cadangan devisa, ekspor, impor, dan inflasi periode januari 2010–juli 2019)*, Skripsi, UIN Syarif Hidayatullah Jakarta, 2021. https://repository.uinjkt.ac.id/dspace/bitstream/123456789/56386/1/CRUSITA%20OKTAVIANITA-FST.pdf.

[31] M. C. Lo and E. Zivot, "Threshold cointegration and nonlinear adjustment to the law of one price," *Macroeconomic Dynamics*, vol. 5, no. 4, pp. 533–576, 2001. DOI: 10.1017/S1365100501023057.

[32] P. D. Rahmaniah, "Aplikasi metode threshold vector autoregressive," *Jurnal Ekonomi Dan Statistik Indonesia*, vol. 4, no. 3, pp. 142–149, 2024. DOI: 10.11594/jesi.04.03.04.

[33] A. Kankainen, S. Taskinen, and H. Oja, "On Mardia's tests of multinormality," in *Theory and Applications of Recent Robust Methods*, Basel: Birkhäuser Basel, 2004, pp. 153–164. DOI: 10.1007/978-3-0348-7958-3_14.

[34] J. A. Doornik and D. F. Hendry, *Modelling Dynamic Systems Using PcFiml 9.0 for Windows*. London: International Thomson Business Press, 1997. https://www.abebooks.com/9781861520586/Modelling-Dynamic-Systems-Using-PcFiml-1861520581/plp.

[35] H. Lütkepohl, *New Introduction to Multiple Time Series Analysis*. Berlin, Heidelberg: Springer, 2005. DOI: 10.1007/978-3-540-27752-1.

[36] I. Nabillah and I. Ranggadara, "Mean absolute percentage error untuk evaluasi hasil prediksi komoditas laut," *JOINS (Journal of Information System)*, vol. 5, no. 2, pp. 250–255, Nov. 2020. DOI: 10.33633/joins.v5i2.3900.