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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 various chemical industries. Despite its importance, domestic production remains limited, and the potential supply from by-product sources has not been utilized in a meaningful way. As a result, Indonesia depends heavily on imports that come mainly from a single country. This situation creates vulnerabilities in the industrial supply chain and highlights the need for a clearer understanding of how import volume and import value behave over time. This study offers a mathematical model that examines the joint movement of these two variables by using the Threshold Vector Autoregressive Integrated approach, commonly known as TVARI. The novelty of the study lies in its use of a nonlinear threshold structure to show how the system shifts between different market conditions. The model reveals that import behavior changes across regimes. When import growth is low, movements are shaped mostly by changes in import value. When growth becomes higher, the pattern reflects the stronger influence of supply conditions. A single linear model cannot fully explain these shifts. By presenting a mathematical description of these regime movements, the study enhances the understanding of the underlying dynamics of Indonesia's industrial imports. The insights support data informed decisions in supply chain planning and relate to Sustainable Development Goal 9 (industry resilience) and Sustainable Development Goal 12 (efficient and responsible use of raw materials). Goal 8 of the Sustainable Development Agenda, which is to encourage stable and sustainable economic activity, is likewise aligned with the enhanced comprehension of market behavior.

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

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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, 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, including policy changes, production disruptions, and international price volatility.

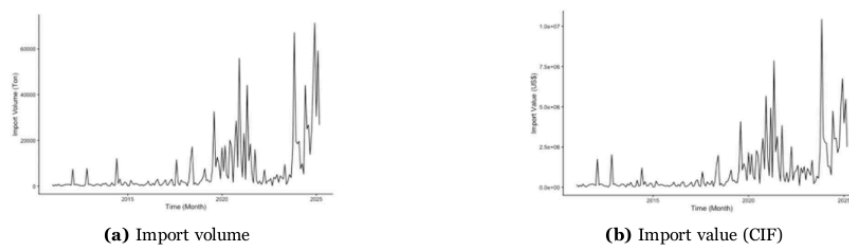


Figure 1: Monthly dynamics of ammonium chloride imports in Indonesia: (a) import volume and (b) import value (CIF).

Figure 1 shows that Indonesia's ammonium chloride import volume and 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 can therefore be treated as endogenous variables within a simultaneous dynamic system.

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

2.1 Data and Data Sources

Secondary data from the Central Bureau of Statistics (BPS) official publications is used in this study, specifically the Indonesia Import Statistics Bulletin. The dataset consists of monthly observations from January 2011 to March 2025, comprising a total of 171 data points. The variables are measured on a ratio scale.

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:

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

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:

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

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:

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

The ADF test statistic is calculated using the following equation:

$$\tau = \frac{\hat{\theta}}{se(\hat{\theta})} \quad (3)$$

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:

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

The definition of the Trace test statistic is:

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

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 :

$$\Delta y_t = y_t - y_{t-1} \quad (5)$$

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. 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.

2.7 Vector Autoregressive Integrated (VARI)

When time series variables are nont stationary but not cointegrated, the conventional VAR model is extended to create the Vector Autoregressive Integrated (VARI) model [26]. In such cases, differencing is required to achieve stationarity, and the model is specified in terms of changes ($\Delta Y_{t-1}, \Delta Y_{t-2}, \dots$) rather than in levels. Specifically, the VARI model with first differencing, denoted as $VARI(p-1)$, can be written as follows [27]:

$$\Delta \mathbf{y}_t = \Phi_1 \Delta \mathbf{y}_{t-1} + \dots + \Phi_{p-1} \Delta \mathbf{y}_{t-p+1} + \boldsymbol{\varepsilon}_t \quad (6)$$

where $\Delta \mathbf{y}_t$ represents the differenced vector of endogenous variables, $\Phi_1, \dots, \Phi_{p-1}$ 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 ¹⁵ 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 [28], [29], 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:

$$LR = -2(L_{VARI} - L_{TVARI}) \quad (7)$$

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:

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

The threshold parameter (γ) represents the switching point that governs the transition from one linear regime to another within the piecewise linear framework [30]. 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 [31] which evaluates the residual distribution based on multivariate skewness and kurtosis. The hypotheses are formulated as: The hypotheses are formulated as follows:

$$\begin{aligned} H_0 &: \text{Residuals are multivariate normally distributed} \\ H_1 &: \text{Residuals do not follow a multivariate normal distribution} \end{aligned}$$

The test statistics are defined as:

$$b_{1,p} = \frac{1}{T^2} \sum_{i=1}^T \sum_{j=1}^T \hat{\mathbf{e}}_i (\mathbf{e}_i - \bar{\mathbf{e}})^T \mathbf{S}^{-1} (\mathbf{e}_j - \bar{\mathbf{e}}) \hat{\mathbf{e}}_j \quad (9)$$

$$b_{2,p} = \frac{1}{T} \sum_{i=1}^T \hat{\mathbf{e}}_i (\mathbf{e}_i - \bar{\mathbf{e}})^T \mathbf{S}^{-1} (\mathbf{e}_i - \bar{\mathbf{e}}) \hat{\mathbf{e}}_i \quad (10)$$

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 [32], [33] to assess whether the variance of the residuals remains constant over time. The hypotheses are formulated as follows:

$$\begin{aligned} H_0 &: B_1 = B_2 = \dots = B_q = 0 \quad (\text{no ARCH effect}) \\ H_1 &: \text{at least one } B_i \neq 0 \quad (\text{ARCH effect exists}) \end{aligned}$$

The ARCH–LM test statistic is defined as

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

where T denotes the number of observations, M is the number of endogenous variables, $\hat{\Sigma}_o$ represents the theoretical covariance matrix under the null hypothesis, and $\hat{\Sigma}_{vech}$ 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 [28], which evaluates whether the residuals are serially uncorrelated. The hypotheses are formulated as follows:

$$H_0 : \rho_1 = \rho_2 = \dots = \rho_k = 0 \quad (\text{no autocorrelation}),$$

$$H_1 : \text{at least one } \rho_i \neq 0, i = 1, 2, \dots, k \quad (\text{autocorrelation exists}).$$

The Portmanteau test statistic is defined as

$$Q_p = T \sum_{i=1}^p \text{tr} \left(\mathbf{C}_i \boldsymbol{\Omega}^{-1} \mathbf{C}_i' \right)^2, \quad (12)$$

with

$$\mathbf{C}_i = \frac{1}{T} \sum_{t=i+1}^T \mathbf{e}_t \mathbf{e}_{t-i}', \quad (13)$$

and

$$\boldsymbol{\Omega} = \frac{1}{T} \sum_{t=1}^T \mathbf{e}_t \mathbf{e}_t'. \quad (14)$$

Here, T denotes the number of observations, $\mathbf{e}_t$ 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[34]. A lower MAPE value indicates higher predictive accuracy of the model. It is defined as :

$$MAPE = \frac{1}{n} \sum_{t=1}^n \frac{|Y_t - \hat{Y}_t|}{|Y_t|} \times 100\%, \quad (15)$$

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

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.

¹⁰
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

²⁹⁴ As reported in Table 3, the smallest AIC value is obtained at lag $p = 9$. Therefore, the
²⁹⁵ optimal lag length used in the subsequent modeling process is set to nine.

²⁹⁶ 3.4 Mean Stationarity

²⁹⁷ The mean stationary at the 5% significant level was examined ¹⁷using the Augmented Dickey-Fuller
²⁹⁸ (ADF) test. Stationary series allow the direct application of the standard Vector Autoregressive
²⁹⁹ (VAR) model. In contrast, non-stationary series require either a Vector Autoregressive Integrated
³⁰⁰ (VARI) model or a Vector Error Correction Model (VECM), based on whether cointegration is
³⁰¹ 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

³⁰² Based on the results presented in Table 4, both import volume and import value exhibit
³⁰³ p -values greater than 0.05. This indicates that the two series are non-stationary in their mean.
³⁰⁴ Consequently, further cointegration testing is required.

³⁰⁵ 3.5 Cointegration Test

³⁰⁶ The Johansen cointegration test was used to determine whether import volume and import
³⁰⁷ value (CIF) have a long-run equilibrium conjunction because the levels of both variables are
³⁰⁸ 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

³⁰⁹ As illustrated in Table 5, the trace statistics for both $r = 0$ and $r \leq 1$ are smaller than their
³¹⁰ corresponding critical values at the 5% significance level. Therefore, the null hypothesis of no
³¹¹ cointegration cannot be rejected. This finding suggests that no long-term equilibrium relationship
³¹² exists between import volume and import value. Hence, the Vector Autoregressive Integrated
³¹³ (VARI) model is an appropriate modeling framework for the data.

³¹⁴ 3.6 Differencing

³¹⁵ Since both variables are non-stationary in their levels and no cointegration is detected, first-
³¹⁶ order differencing is applied to achieve stationarity. The Augmented Dickey-Fuller (ADF) test
³¹⁷ 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 the Vector Autoregressive model applied to first-differenced data, known as the Vector Autoregressive Integrated (VARI) model. Since the optimal lag length selected from the level data is $p = 9$, the lag order is reduced by one after differencing. Accordingly, a VARI(8) model is employed in this study. The estimation results indicate that most coefficients in the linear VARI(8) model are statistically insignificant. This finding suggests that a purely linear specification may not adequately capture the dynamic relationship between import volume and import value. Consequently, a formal linearity test is required to assess the adequacy of the linear VARI model.

3.8 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. The Akaike Information Criterion (AIC) serves as a tool for model selection, and Table 7 enumerates the five specifications exhibiting the lowest AIC values. These candidate models are subsequently subjected to further diagnostic testing.

Table 7: 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 7, 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.

3.9 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 8.

Table 8: 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 8, 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.

3.10 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:

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

where

$$\mathbf{y}_t = \begin{matrix} \mathbf{A} & \mathbf{B} \\ \log y_{1,t} & \\ \log y_{2,t} & \end{matrix},$$

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

3.10.1 Low-import growth regime

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

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

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:

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

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.

3.10.2 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:

$$\Delta \log \hat{y}_{1,t} = 0.7866 - 1.7181 \Delta \log \hat{y}_{1,t-4} + \varepsilon_{1,t}.\quad (19)$$

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:

$$\Delta \log \hat{y}_{2,t} = 0.6390 - 1.3470 \Delta \log \hat{y}_{1,t-4} + \varepsilon_{2,t}.\quad (20)$$

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.

3.11 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.

The dataset is divided into two subsets, namely a training set and a testing set. The TVARI model is estimated using the training sample and subsequently applied to generate forecasts of logarithmic changes ($\Delta \log$) in import volume and import value (CIF) of ammonium chloride over the testing period.

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:

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

The out-of-sample evaluation results show that the Mean Absolute Percentage Error (MAPE) is 28.874% for import volume and 28.379% for import value (CIF), indicating a moderate level

of forecasting accuracy. The comparison between the actual and predicted series is illustrated in Figure 2.

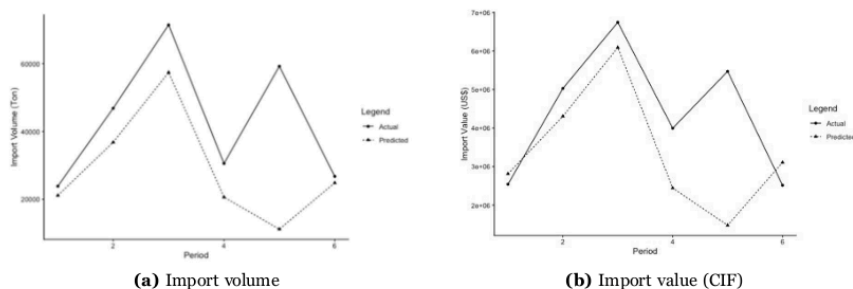


Figure 2: Actual series (solid line) and out-of-sample forecasts (dashed line) of (a) import volume and (b) import value (CIF).

Figure 2 shows that the predicted series generally follows the overall movement of the actual data for both import volume and CIF value. The model captures the main upward and downward trends reasonably well, although it tends to underestimate abrupt fluctuations during periods of high volatility. This limitation is more pronounced around sharp drops and rebounds in CIF values, reflecting the inherent difficulty of forecasting sudden market adjustments.

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.

3.12 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 Equation (21).

Table 9: Forecasted import volume and import value (CIF) of ammonium chloride

Period	Forecasted import volume (tons)	Forecasted import value (CIF, USD)
April 2025	30,495.96	2,978,884
May 2025	27,213.51	3,373,637
June 2025	37,220.00	3,941,601
July 2025	63,402.60	6,091,791
August 2025	243,552.44	18,117,741
September 2025	106,502.13	8,980,233
October 2025	83,524.83	7,450,047
November 2025	61,731.11	5,734,186
December 2025	38,627.11	3,493,106
January 2026	44,970.97	4,483,660
February 2026	55,580.52	5,660,201
March 2026	76,429.32	7,058,076

Table 9 shows that import volume is projected to increase dramatically in August 2025, reaching a peak of 243,552.44 tons, accompanied by a substantial increase in import value to approximately USD 18.12 million. Following this peak, both import volume and import value are expected to decline gradually toward the end of 2025, before exhibiting a moderate recovery in early 2026.

Overall, the forecast results indicate pronounced short-term volatility with a strong surge in mid-2025, reflecting persistent fluctuations in both physical import volume and import value under changing market conditions.

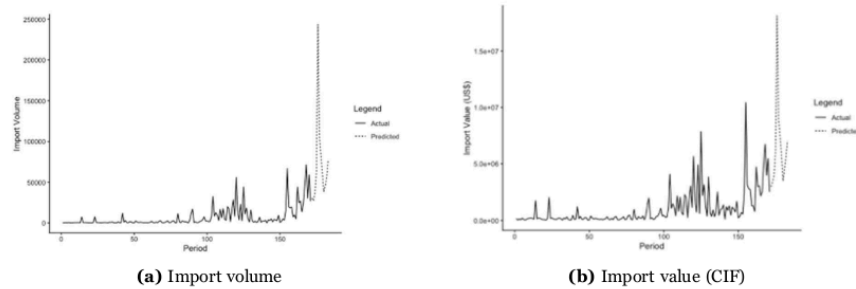


Figure 3: Actual series (solid line) and real forecasts (dashed line) of (a) import volume and (b) import value (CIF).

Figure 3 illustrates the comparison between actual observations and the 12-period-ahead forecasts generated by the TVARI model. Figure 3a shows that the forecasted import volume follows the general movement of the historical series, capturing the main upward and downward patterns, although extreme spikes are underestimated.

Similarly, Figure 3b indicates that the forecasted CIF values track the overall trend of the actual data but deviate during periods of high volatility. These results suggest that the TVARI model is effective in capturing the general dynamics and regime-dependent behavior of ammonium chloride imports, while its forecasting accuracy declines during abrupt market fluctuations.

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

Author One: Methodology, Formal Analysis, Writing–Original Draft, Software, Visualization.

Author Two: Supervision, Funding Acquisition.

Author Three: 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).

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