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PRICE POLICY, AGRARIAN STRUCTURE, AND RURAL WELFARE: AN ARDL ANALYSIS OF RICE GOVERNANCE AND FARMER EXCHANGE RATES IN INDONESIA

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ABSTRACT

This study investigates the impact of the Government Purchase Price (HPP) policy and fertilizer subsidies on rice production and farmer welfare, measured by the Farmer Exchange Rate (NTP), within the framework of agrarian governance in Indonesia. It examines both short-run and long-run effects while situating these policies within broader state intervention dynamics. A quantitative approach is employed using the Autoregressive Distributed Lag (ARDL) model on monthly time-series data from January 2020 to December 2024, complemented by a qualitative review of policy regulations. The findings reveal that HPP significantly affects rice production in both the short and long term, albeit with a negative coefficient, indicating structural adjustment toward equilibrium. In contrast, fertilizer subsidies show no significant effect on production, reflecting implementation inefficiencies. Regarding welfare, HPP exerts a positive and significant influence on NTP, highlighting its role in enhancing farmers' purchasing power, whereas fertilizer subsidies remain insignificant. This study contributes by integrating production and welfare analysis within a single empirical framework and reinterpreting econometric findings through a state, society relations lens. It concludes that output price policies are more effective than input subsidies, although their impact remains constrained by institutional and governance challenges.

Keywords*: Agrarian Governance, ARDL, Farmer Exchange Rate, Fertilizer Subsidy, Government Purchase Price*

INTRODUCTION

Rice remains a strategic commodity within Indonesia's national food security architecture, not merely as a source of caloric intake but as a socio-economic and political anchor for millions of rural households (Mahadika & Wibowo, 2021; Nulhanuddin & Andriyani, 2020). The overwhelming dependence of the population on rice positions this commodity at the intersection of state policy, market dynamics, and agrarian livelihoods. Empirical evidence consistently shows that fluctuations in rice production have far-reaching implications, ranging from inflationary pressures to rural poverty dynamics (OECD, 2020; Rahmasari et al., 2019). Data from the Indonesian Central Statistics Agency indicate that variations in rice output are closely tied to seasonal cycles, input accessibility, and price volatility, often resulting in unstable farmer incomes and uneven welfare outcomes. These conditions underscore a persistent structural problem: while the state has long intervened through policy instruments such as output price controls and input subsidies, the extent to which these interventions effectively stabilize production and enhance farmer welfare remains contested.

Within the framework of agricultural production theory, output levels are shaped by a combination of land, labor, capital, technology, and policy interventions (Friman & Hyytiä, 2022; Peng et al., 2023). In the Indonesian context, rice production is particularly sensitive to harvested area, productivity rates, fertilizer utilization, and price incentives (Bai et al., 2022; Kamakaula, 2024). However, these determinants do not operate in isolation. Climate variability, pest outbreaks, and market imperfections frequently disrupt production stability, necessitating sustained government intervention (Y. Ma et al., 2022; Sujito & Ghofur, 2023). The Government Purchase Price policy for unhusked rice has historically functioned as a stabilizing mechanism, intended to provide a minimum price guarantee and protect farmers from adverse market fluctuations. By setting a floor price, the policy is expected to incentivize production while simultaneously safeguarding rural incomes (Haque et al., 2022; Zhang & Drury, 2024). Yet, its effectiveness is contingent upon institutional capacity, particularly the ability of state agencies to absorb output and maintain market equilibrium.

Parallel to output price interventions, fertilizer subsidies represent a central pillar of agricultural policy aimed at reducing production costs and enhancing land productivity. Fertilizer, as a critical input, directly influences yield outcomes, making subsidy schemes a potentially powerful tool for boosting agricultural performance (Jia et al., 2022; Räty et al., 2023). In Indonesia, the fertilizer subsidy program is designed to ensure affordability and accessibility for smallholder farmers. However, persistent issues such as distribution inefficiencies, leakage, and targeting inaccuracies have been widely documented (Mukhlis & Gürçam, 2022; Syahza et al., 2023). These challenges raise important questions about whether input-based interventions can deliver the intended productivity gains, particularly in a context characterized by structural inequalities and institutional constraints.

The relationship between production and farmer welfare further complicates the policy landscape. The Farmer Exchange Rate, widely used as an indicator of rural welfare, captures the relative purchasing power of farmers by comparing the prices they receive for their products with the prices they pay for consumption and production inputs (Khatri et al., 2023; Wang et al., 2023). While increased production is often assumed to enhance welfare, empirical realities suggest otherwise. In situations of oversupply or weak market absorption, rising production can lead to declining farm-gate prices, thereby eroding farmer incomes (Ammann et al., 2023; Moritz et al., 2022). This paradox highlights the importance of integrating price stability with production policies, as the absence of such alignment can undermine the very objectives of agricultural development.

A growing body of literature has attempted to examine the effectiveness of price policies and input subsidies in shaping agricultural outcomes. Studies by J. Ma et al. (2022) demonstrate that output price incentives can positively influence rice production, although their magnitude is often moderated by structural factors such as land availability. Similarly, research by Ilham et al. (2022) and Islam (2024) emphasizes the role of input subsidies in improving productivity, particularly in low-income agrarian settings. Other scholars, including Brooks (2023) and Sang et al. (2024), highlight the complex interplay between market conditions and policy interventions, noting that increased production does not automatically translate into improved welfare. In the Indonesian context, Eddy et al. (2023) and Zang et al. (2022) point to persistent inefficiencies in policy implementation, particularly in the distribution of subsidized inputs and the limited capacity of state agencies to stabilize markets.

Further empirical contributions reinforce these mixed findings. Indah et al. (2025) and Nurfajari (2024) argue that fertilizer subsidies often suffer from elite capture and administrative inefficiencies, reducing their overall impact on productivity. Hasan et al. (2025) and Vadilaksono et al. (2023) underscore the importance of price stabilization mechanisms in ensuring food security, yet also caution against over-reliance on state intervention without adequate institutional support. Farida et al. (2024) and Yusrin (2023) highlight the role of structural transformation in shaping agricultural outcomes, suggesting that policy effectiveness is deeply embedded in broader socio-economic processes. Meanwhile, Kharisma and Indrawan (2023) as well as Kusmiati and Prasetyo Ari Bowo (2024) emphasize the importance of technological and institutional innovation in driving agricultural growth, a perspective that remains highly relevant in contemporary policy debates.

Despite these extensive scholarly efforts, much of the existing literature tends to approach agricultural policy analysis through a fragmented lens, often focusing either on production outcomes or welfare indicators, and frequently within static analytical frameworks. Such approaches risk overlooking the dynamic interactions between policy instruments, market forces, and institutional arrangements. Moreover, the predominance of neoclassical economic perspectives has limited the incorporation of sociological dimensions, particularly those related to power relations, governance structures, and the uneven distribution of policy benefits across different groups of farmers.

Against this backdrop, a more integrated analytical approach becomes necessary—one that not only captures the dynamic relationships between output price policies, input subsidies, production, and welfare, but also situates these relationships within a broader governance framework. By employing an Autoregressive Distributed Lag model, this study seeks to unravel both short-term adjustments and long-term equilibria, offering a more nuanced understanding of policy effectiveness. At the same time, the interpretation of empirical findings is enriched by considering the relational dynamics between state institutions and agrarian actors, thereby moving beyond purely technocratic explanations.

In doing so, this study subtly advances a perspective that bridges econometric rigor with sociological insight, allowing for a more comprehensive reading of agricultural policy outcomes. It brings into conversation variables that are often analyzed separately, while also reinterpreting their interactions as reflections of institutional capacity and governance performance. This orientation not only deepens the analytical scope but also opens up new pathways for understanding how policy instruments operate within complex social systems.

The purpose of this study, therefore, is to empirically analyze the impact of the Government Purchase Price policy and fertilizer subsidies on rice production and the Farmer Exchange Rate in Indonesia, examining both short-term and long-term dynamics. At the same time, it seeks to interpret these relationships within the broader context of agrarian governance, thereby contributing to a more holistic understanding of how state interventions shape rural livelihoods. Through this approach, the study aims to provide insights that are not only relevant for policy formulation but also for the advancement of sociological inquiry into agricultural transformation and state–society relations.

RESEARCH METHOD

This study is designed within a quantitative research framework, grounded in the need to capture measurable, dynamic relationships between policy variables and agrarian outcomes in a systematic and empirically robust manner. The choice of a quantitative approach is particularly relevant given the nature of the research problem, which seeks to explain causal linkages between the Government Purchase Price policy, fertilizer subsidies, rice production, and farmer welfare over time. Quantitative methods enable the identification of patterns, trends, and statistical relationships that may not be immediately visible through qualitative observation alone, especially in the context of macro-level agricultural governance (Darma et al., 2025; Khumairoh et al., 2024). By employing time series data, this study is able to trace temporal dynamics and policy impacts across different periods, allowing for a more nuanced understanding of both short-term adjustments and long-term equilibria.

The research is conducted at the national level in Indonesia, which is purposively selected as the study area due to its relevance as a major rice-producing country with a long history of state intervention in the agricultural sector. The unit of analysis is not individual actors but aggregated macroeconomic indicators, making the concept of “informants” in the conventional qualitative sense less central. However, to enrich interpretation and ensure contextual validity, the study implicitly engages with institutional actors through documented policy outputs and statistical records produced by authoritative bodies such as the Central Statistics Agency and the Ministry of Agriculture. These institutions function as epistemic informants, as their datasets and policy documents represent validated and systematically collected information reflecting real-world conditions. The use of such sources ensures both reliability and credibility, as they are produced through standardized national statistical procedures (Purnamasari et al., 2023; Rachman et al., 2022).

Data collection relies entirely on secondary data, specifically monthly time series data spanning from January 2020 to December 2024. This period is selected to capture recent policy dynamics, including adjustments in price policies and subsidy mechanisms within a changing economic and environmental context. The data are obtained from official publications, including statistical reports, policy documents, and agricultural databases. The reliance on secondary data is methodologically justified, as it allows access to longitudinal datasets that would be difficult to generate through primary data collection, particularly at the national scale (Rahmasari et al., 2019; Nulhanuddin & Andryani, 2020). Furthermore, the use of official data enhances comparability and consistency, which are critical for econometric modeling.

The analytical method employed in this study is the Autoregressive Distributed Lag (ARDL) model, which is particularly suitable for analyzing time series data with mixed orders of integration. The ARDL approach allows for the estimation of both short-run and long-run relationships within a unified framework, making it highly relevant for policy analysis (Pesaran et al., 2001). The general form of the ARDL model used to analyze rice production is expressed as:

$$\Delta PROD_t = \alpha 0 + \sum_{i=1}^{p-1} \alpha_i \, \Delta PRODt_{-i} + \sum_{j=0}^{q-1} \beta_j \, \Delta HPPt_{-j} + \sum_{k=0}^{r-1} \delta_k \, \Delta UREA_{t-k} + \lambda ECT_{t-1} + \varepsilon_t \qquad \text{(i)}$$

The long-term specification is written as:

$$PROD_t = \beta_0 + \beta_1 HPP_t + \beta_2 UREA_t \varepsilon_t \qquad \text{(ii)}$$

The second objective of the ARDL model is as follows:

$$\Delta NTP_t = \alpha 0 + \sum_{i=1}^{p-1} \alpha_i \, \Delta NTP_{t-i} + \sum_{j=0}^{q-1} \beta_j \, \Delta HPP_{t-j} + \sum_{k=0}^{r-1} \delta_k \, \Delta UREA_{t-k} + \lambda(NTP_{t-1} - \beta_1 HPP_{t-1} - \beta_2 UREA_{t-1-}\beta_0) + \varepsilon_t \qquad \text{(iii)}$$

In these equations, Δ denotes first differences capturing short-term changes, while the Error Correction Term (ECT_{t-1}) reflects the speed of adjustment toward long-term equilibrium. A negative and statistically significant λ coefficient indicates model stability and convergence (Saleh et al., 2025).

The analytical process begins with descriptive analysis to observe trends and patterns in each variable. This is followed by stationarity testing using the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests, where the null hypothesis assumes the presence of a unit root (non-stationarity). If the p-value is less than 0.05, the data are considered stationary. Subsequently, the optimal lag length is determined using criteria such as the Akaike Information Criterion (AIC), Schwarz Criterion (SC), and Hannan-Quinn (HQ). The ARDL model is then estimated, followed by the Bounds Test for cointegration to assess the existence of long-term relationships. The decision rule is based on comparing the F-statistic with critical upper and lower bounds (Saleh et al., 2024).

To ensure the robustness of the model, classical assumption tests are conducted, including normality, autocorrelation, and heteroscedasticity tests, in line with the Best Linear Unbiased Estimator (BLUE) criteria (Sujianto et al., 2024). Model stability is further evaluated using CUSUM and CUSUM of Squares tests, which assess parameter consistency over time.

Although the study is primarily quantitative, triangulation is conducted through methodological and data source validation. This involves cross-checking statistical findings with policy documents and existing literature to ensure interpretive consistency. By integrating econometric results with institutional context, the study strengthens both internal and external validity. This layered approach reflects an awareness that numerical findings gain deeper meaning when situated within broader governance processes, thereby allowing the research to remain empirically rigorous while still socially grounded.

RESULTS AND DISCUSSION

Description of Research Variables

Study uses monthly data from January 2020 to December 2024 with dependent variables of rice production and Farmer Exchange Rate (NTP), and independent variables of Government Purchase Price (HPP) of rice and fertilizer subsidies, proxied by the Highest Retail Price (HET) of subsidized fertilizer. Rice production during the observation period shows a fluctuating pattern influenced by price policies and the use of production inputs. HPP plays a role in maintaining price stability at the farmer level, while fertilizer subsidies aim to reduce farming costs. NTP is used as an indicator of farmer welfare. Short-term and long-term relationships between variables are analyzed using the Autoregressive approach. Distributed Lag (ARDL).

HPP and Fertilizer Subsidy Policy on Rice Production

Stationarity Test (Unit Root Test)

Table 1 Unit Root Test Results Test Level Level I (0) Augmented Dickey Fuller Test

Variabel	ADF Statistik	Critical Value			Prob.	Keterangan
		1%	5%	10%		
Produksi	-8.021436	-3.565430	-2.919952	-2.597905	0.0000	Stasioner
HPP	-0.613891	-3.550396	-2.913549	-2.913549	0.8589	Tidak Stasioner
Urea	-2.153436	-3.546099	-2.911730	-2.593551	0.2252	Tidak Stasioner
NTP	0.933313	-3.546099	-2.911730	-2.593551	0.9953	Tidak Stasioner

Sources: Processed by the author (2026)

The stationarity test indicate that at the level level, only the production variable is stationary, while HPP, urea, and NTP are not stationary because the probability value is greater than 0.005. Therefore, testing is carried out on the first difference. ADF test results at the first level difference shows that all variables are stationary, indicated by a statistical ADF value that is smaller than the critical value and a probability of less than 0.005 (Massagony et al., 2023).

Table 2 Unit Root Test Results First Difference Level Test I (1) Augmented AugmentedDickey - Fuller Test

Variabel	ADF Statistik	Critical Value			Prob.	Keterangan
		1%	5%	10%		
HPP	-7.044897	-3.550396	-2.913549	-2.594521	0.0000	Stasioner
Urea	-7.615773	-3.548208	-2.912631	-2.594027	0.0000	Stasioner
NTP	-5.526858	-3.548208	-2.912631	-2.594027	0.0000	Stasioner

Sources: Processed by the author (2026)

Cointegration Test (Bound Test)

Table 3 Bound Test Results

Mark F-Statistic	Limitation Mark Critical		
	Significant	Lower Bound I (0)	Upper Bound I (1)
11.82485	10%	2.63	3.35
	5%	3.1	3.87
	2.5%	3.55	4.38
	1%	4.13	5

Sources: Processed by the author (2026)

The bounds test show an F-statistic value of 11.82485, which is higher than the critical value. The value at the 1% significance level is 5. Since the F-statistic value exceeds the upper limit, H_0 is rejected. Thus, it can be concluded that there is a long-term relationship between the independent and dependent variables in the model.

Determining Optimum Lag

Table 4 Results of the Optimal Lag Test (Lag Length Criteria)

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-1519,549	NA	6.21e+20	56.39070	56.50120*	56.43331
1	-1503.970	28.84974	4.87e+20	56.14704	56.58903	56.31750
2	-1490.883	22.78045	4.20e+20	55.99568	56.76917	56.29399*
3	-1479,512	18.53111*	3.88e+20*	55.90785*	57.01284	56.33400
4	-1471.771	11.75550	4.13e+20	55.95446	57.39095	56.50846
5	-1466.485	7.438737*	4.86e+20	56.09204	57.86003	56.77388

Sources: Processed by the author (2026)

The lag determination show that at lag 0 the LR statistical value cannot be calculated (NA), which is thought to be due to the limited number of observations. Based on the information criteria, the Akaike value Information The lowest AIC value is found at lag 3 and is marked as the best choice. The FPE criterion also supports lag 3, although SC and HQ recommend different lags.

Considering the limited sample size and prioritizing the smallest AIC value in time series analysis, the optimum lag used in this study is lag 3.

AIC value (Akaike Information Criterion) of the 20 Best ARDL (Autoregressive) Models Distributed Lag)

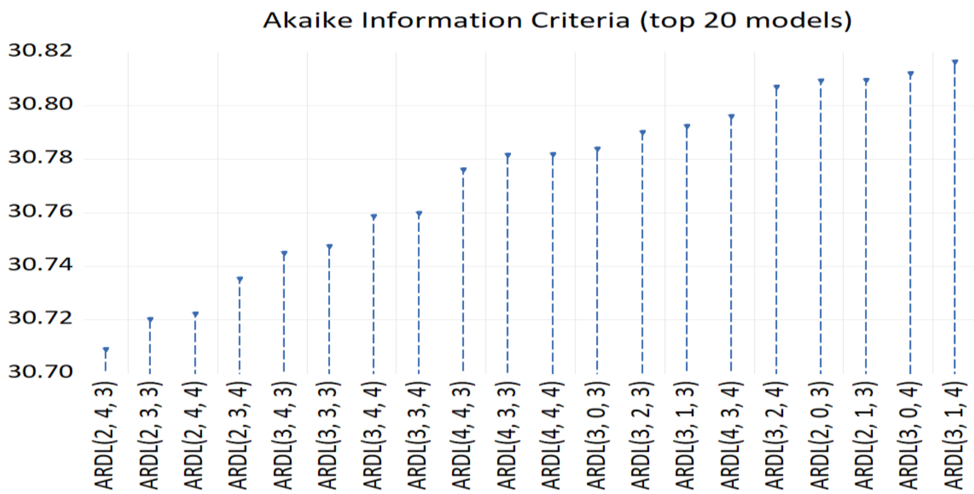

Figure 1 AIC Values of the 20 Best ARDL Models
Sources: Processed by the author (2026)

The ARDL model results were determined based on the AIC criteria to obtain the most efficient model. Of the 20 models tested, ARDL(2,4,3) had the lowest AIC value and was therefore selected as the best model. These results indicate that rice production is influenced by previous values, as well as by the cost of goods sold (HPP) and urea fertilizer prices over several periods, indicating a gradual adjustment process in the short and long term.

Error Correction Model

The Error-Correction Model (ECM) estimation results indicate a short-term influence and adjustment mechanism towards long-term equilibrium between production, COGS, and urea fertilizer prices. Production from the previous period significantly influences current production, reflecting the dynamics of adjustment over time. COGS has a significant effect, with a negative impact in the current period and a positive effect in the following period. Urea fertilizer prices are generally insignificant in the short term, except at certain lags. A negative and significant Error-Correction Term (ECT(-1)) value indicates an error correction process towards long-term equilibrium.

Table 5 *Error-Correction Test Results Coefficient*

Variables	Coefficient	Std.Error	t-Statistic	Prob.	Information
Production (-1)	1.994434	0.409520	4.870176	0.0000	Significant
Production (-2)	-1.574013	0.364689	-4.316041	0.0001	Significant
Production (-3)	0.771489	0.222873	3.461569	0.0013	Significant
Production (-4)	-0.263665	0.126910	-2.077574	0.0442	Significant
D(HPP)	-2555.959	735.3387	-3.475894	0.0012	Significant
D(HPP(-1))	4551.487	1371.198	3.319352	0.0019	Significant
D(HPP(-2))	-1982.991	884,0002	-2.243202	0.0305	Significant
D(Urea)	-4105.894	2352.040	-1.745673	0.0885	Not Significant
D(Urea(-1))	3634.016	2873.797	1.264535	0.2134	Not Significant
D(Urea(-2))	-571.8720	2417.438	-0.236561	0.8142	Not Significant
D(Urea(-3))	9220.939	2395.897	3.848638	0.0004	Significant
D(Urea(-4))	-12443.86	4263.683	-2.918570	0.0057	Significant
ECT(-1)	-1.270321	0.439637	-2.889478	0.0062	Significant
C	382576.1	1040295.	0.367757	0.7150	Not Significant

Sources: Processed by the author (2026)

Table 6 Results of Short-Term ARDL Model Estimation Test

Variables	Coefficient	Std.Error	t- Statistic	Prob.	Information
C	3763799.	647225.6	5.815281	0.0000	Significant
PRODUCTION(- 1)*	-0.796919	0.127509	-6.249923	0.0000	Significant
D(HPP(- 1))	-5738.539	1554.353	-3.691916	0.0006	Significant
D(UREA(- 1))	-1830.003	5386.880	-0.339715	0.7357	No Significant
D(PRODUCTION(- 1))	0.516795	0.117016	4.416450	0.0001	Significant
D(HPP(- 2))	-2990.749	674.2168	-4.435886	0.0001	Significant
(HPP(-1),2)	-3239.976	1205,358	2.687979	0.0102	Significant
D(HPP(-2),2)	2379.119	781.9231	3.042650	0.0040	Significant
D(HPP(-3),2)	927.9238	641.5461	1.446387	0.1553	No Significant
D(UREA,2)	-4407.961	2370.984	-1.859127	0.0699	No Significant
D(UREA(-1),2)	-4577.060	3613.273	-1.266735	0.2121	No Significant
D(UREA(-2),2)	-6989.318	2411.772	-2.898001	0.0599	No Significant

Note: one star (*) is significant at 5% confidence interval.

Sources: Processed by the author (2026)

The short-term ARDL estimation results show that the constant and lag -1 production significantly influence production, with the lag -1 coefficient being negative, reflecting the short-term adjustment process. The cost of goods sold (COGS) also significantly influences several lags, both in terms of differentiation and level, thus playing a role in influencing production. In contrast, the price of urea fertilizer is generally insignificant, indicating that changes in this input price do not directly impact production in the same period. Overall, short-term production is more responsive to previous production dynamics and the COGS policy than to the price of urea fertilizer.

Table 7 Results of Long-Term ARDL Model Estimation Test

Variables	Coefficient	Std.Error	t- Statistics	Prob.	Information
D(HPP)	- 7200.906	1554,319	- 4.632838	0.0000	Significant
D(UREA)	- 2296.347	6599.951	- 0.347934	0.7296	No Significant
C	4722938.	189958.9	24.86294	0.0000	Significant

Sources: Processed by the author (2026)

The long-term estimation results of the ARDL model show that the COGS variable has a negative and significant effect on production with a coefficient of -7200.906 at a 5 percent significance level. This finding indicates that in the long run, an increase in COGS is actually followed by a decrease in production, reflecting a structural adjustment or behavioral response of producers to government pricing policies. This result is in line with the findings of Supriatna et al. (2023) who stated that the effectiveness of COGS in encouraging production is limited by the implementation of policies and market mechanisms, and Yusiana et al. (2022) who emphasized that output pricing policies have the potential to cause incentive distortions if not supported by complementary policies, so that in the long run, production decisions are more determined by expectations of real profits.

Model Stability Test

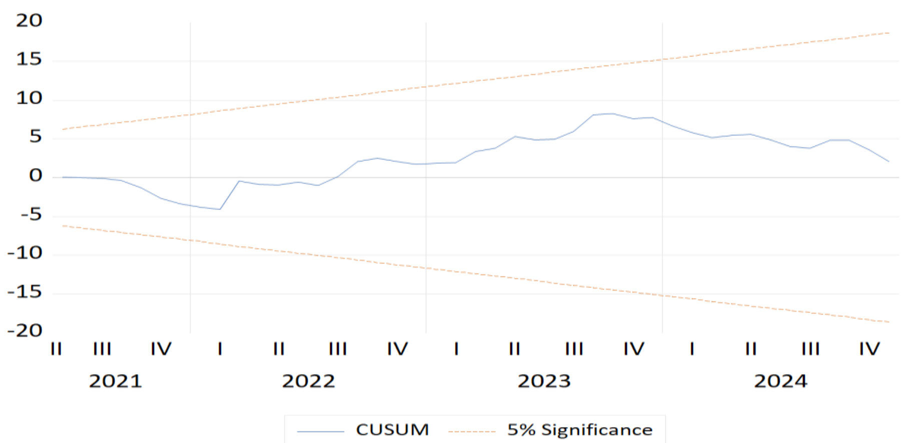

Figure 2 Results of the *Cusum Graph Test Test*
Sources: Processed by the author (2026)

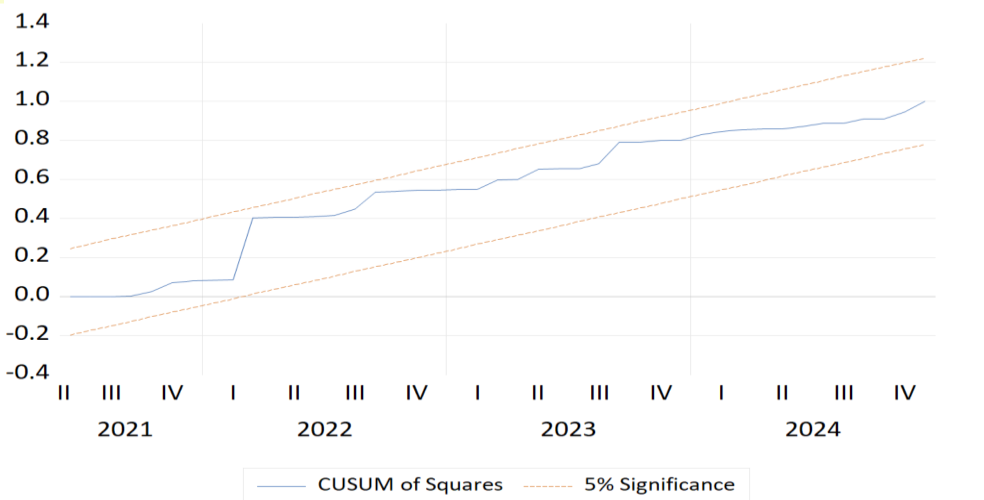

Figure 3 Results of the *Cusum Graph Test Of – Square*
Sources: Processed by the author (2026)

The results of the model stability test using CUSUM indicate that the model is in a stable condition and is suitable for analyzing long-term relationships between variables. This can be seen from the CUSUM line which is within the 5 percent significance limit. The CUSUM test of Squares also show the same pattern, so it can be concluded that the research model meets the stability criteria.

Classical Assumption Test

Normality

Table 8 Normality Test Results

Jarque - Bera	Probability
57.06375	0.000000

Sources: Processed by the author (2026)

Normality test results The Jarque –Bera test showed a statistical value of 57.06375 with a p- value of 0.000000, lower than the 0.05 significance level. This indicates that the data is not normally distributed, thus the assumption of normality is not met. Therefore, it is necessary to consider using methods that do not require normal distribution or data transformation before further analysis.

Multicollinearity

The multicollinearity test show that all variables have a Centered VIF value of less than 10, with the highest value of 2.992002 in the PRODUCTION (-2) variable. This indicates that the model does not experience multicollinearity problems, so that all independent variables are suitable for use in the research model.

Table 9 Multicollinearity Test Results

Variables	Coefficient Variance	Uncentered VIF	Centered VIF
PRODUCTION(- 1)	0.014182	17.97075	2.765913
PRODUCTION(- 2)	0.013693	18.46680	2.992002
D(HPP)	454568.3	1.557971	1.534302
D(HPP(- 1))	713349.1	2.443227	2.407437
D(HPP(- 2))	764566.9	2.690646	2.661439
D(HPP(- 3))	558266.7	1.993613	1.977259
D(HPP(- 4))	411581.4	1.472266	1.462874
D(UREA)	5621567	1.083108	1.063415
D(UREA(- 1))	5992442	1.154565	1.133573
D(UREA(- 2))	6047940	1.165258	1.144071
D(UREA(- 3))	5816644.	1.120694	1.100317
C	4.19E+11	21.92116	NA

Sources: Processed by the author (2026)

Autocorrelation

Table 10 Autocorrelation Test Results

R1	R2
1.943689	0.5510

Sources: Processed by the author (2026)

Autocorrelation test results show a Durbin - Watson value of 1.943689, which is close to 2, indicating no autocorrelation in the model. Furthermore, the Breusch - Godfrey Serial Correlation LM Test yields a Chi- Square Prob value of 0.5510, greater than the 5 percent significance level. Therefore, the null hypothesis is accepted, and it can be concluded that the model does not experience autocorrelation until the second lag.

Heteroscedasticity

Table 11 Heteroscedasticity Test Results

Prob. F	0.9699
F-Statistic	0.344460
F-Statistic	0.9547

Sources: Processed by the author (2026)

Heteroscedasticity test results The Breusch –Pagan– Godfrey test showed a Prob. F-statistic of 0.9699 and a Prob. Chi- Square of 0.9547, both greater than the 5 percent significance level. Thus, the null hypothesis stating that the model is homoscedastic is accepted. This means there are no symptoms of heteroscedasticity and the residual variance is constant, making the model suitable for further analysis.

HPP and Fertilizer Subsidy Policy on NTP Production

Cointegration Test (Bound Test)

Table 12 Cointegration Test Results *Bound Test*

Mark F-Statistic	Limitation Mark Critical		
	Significant	**Lower Bound I (0)**	**Upper Bound I (1)**
	10%	2.63	3.35
17.47853	5%	3.1	3.87
	2.5%	3.55	4.38
	1%	4.13	5

Sources: Processed by the author (2026)

The bounds test show an F-statistic value of 17.82485, which is higher than the critical value. The value at the 1 percent significance level is 5. Since the F-statistic value exceeds the critical limit, H_0 is rejected. Thus, it can be concluded that there is a long-term relationship between the independent and dependent variables in the model.

Determining Optimum Lag

Table 13 Results of the Optimal *Lag Test* (*Lag Length criteria)*

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-924.3036	NA	8.85e+10	33.72013	33.82962	33.76247
1	-742.4506	337.2547*	1.65e+08*	27.43457	27.87253*	27.60393*
2	-737.3743	8.860439	1.91e+08	27.57725	28.34368	27.87363
3	-730.1703	11.78826	2.06e+08	27.64256	28.73747	28.06597
4	-726.5793	5.484437	2.54e+08	27.83925	29.26263	28.38968
5	-721.3617	7.399516	2.99e+08	27.97679	29.72864	28.65425

Sources: Processed by the author (2026)

Lag Test indicate that the LR value at lag 0 is NA, which is suspected to be due to the limited amount of data. Based on the information criteria, lag 1 has the lowest AIC value and is supported by the LR, FPE, SC, and HQ criteria. Because the lag selection on the time data The series generally prioritizes the smallest AIC value and the support of the majority of criteria, so the optimum lag used in this study is lag 1.

AIC (Akaike value Information Criterion) of the 20 Best ARDL (Autoregressive Models Distributed Lag)

The ARDL(2,0,0) model shows that the dependent variable, NTP, is influenced by its own value up to two previous periods, reflecting dynamics and time dependence. Meanwhile, the independent variables HPP and urea fertilizer prices do not have a lag, so their influence on NTP occurs in the same period. This specification indicates that NTP adjustments to changes in output and input price policies occur relatively quickly, so the ARDL(2,0,0) model is considered capable of describing the dynamics of the relationship between rice policy and farmer welfare in the short and long term.

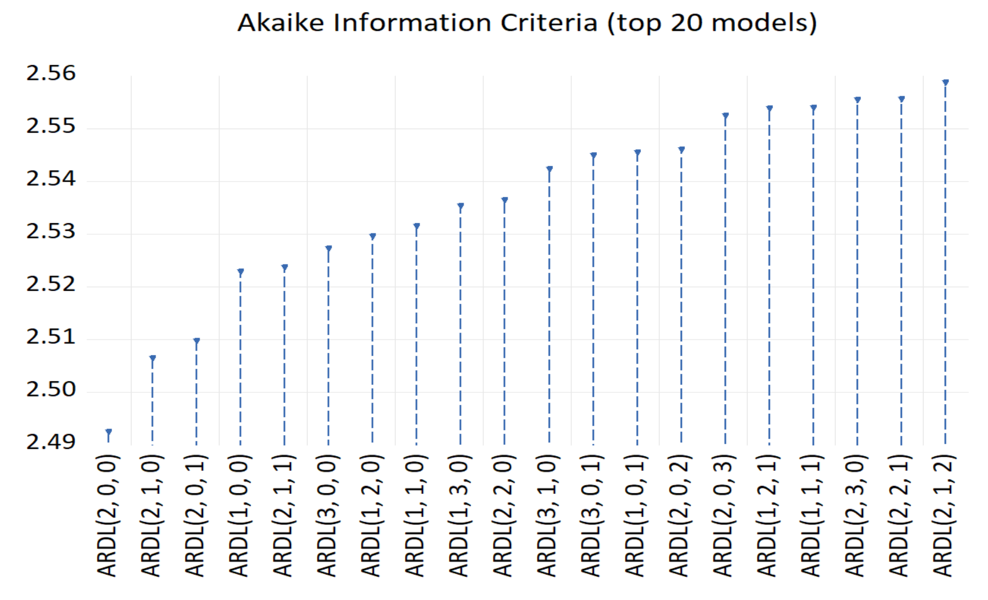

Figure 4 AIC Value Test Results of the 20 Best ARDL Models
Sources: Processed by the author (2026)

Error Correction Model

Table 14 *Error-Correction Test Results Coefficient*

Variables	Coefficient	Std.Error	t-Statistic	Prob.	Information
D(NTP(-1))	0.175863	0.101641	1.730235	0.0913	Not Significant
D(HPP)	0.002245	0.000429	5.232600	0.0000	Significant
D(UREA)	-0.001360	0.001640	-0.829361	0.4118	Not Significant
D(UREA(-1))	-0.002200	0.001634	-1.346575	0.1857	Not Significant
ECT(-1)	-7.36E-08	1.13E-07	-0.652026	0.5181	Not Significant
ECT(-2)	-3.00E-07	1.16E-07	-2.587677	0.0134	Significant
ECT(-3)	1.77E-07	1.19E-07	1.494179	0.1430	Not Significant
ECT(-4)	-2.53E-07	1.20E-07	-2.109953	0.0412	Significant
ECT(-5)	4.15E-07	1.20E-07	3.470355	0.0013	Significant
C	0.299339	0.110681	2.704517	0.0100	Significant

Sources: Processed by the author (2026)

The Error-Correction Model (ECM) estimation results show that in the short term, changes in the previous period's NTP have no significant effect on the dependent variable. Conversely, the HPP has a positive and significant effect in the current period, indicating that government pricing policies effectively influence the economic response in the short term. Urea fertilizer prices generally do not show a significant effect. A significant Error-Correction Term (ECT) component indicates the existence of an adjustment mechanism towards long-term equilibrium if deviations occur in the system.

Table 15 Results of Short-Term ARDL Model Estimation Test

Variables	Coefficient	Std.Error	t-Statistic	Prob.	Information
C	0.196270	0.114452	1.714861	0.0923	Not Significant
D(NTP(-1))*	-0.658665	0.125777	-5.236775	0.0000	Significant
D(HPP)**	0.002727	0.000450	6.062818	0.0000	Significant
D(UREA)**	-0.000352	0.001804	-0.195207	0.8460	Not Significant
D(NTP(-1),2)	-0.241351	0.111132	-2.171762	0.0345	Significant

Sources: Processed by the author (2026)

Short-term estimation results The ARDL model shows that in the short term, D(NTP(-1)) and D(NTP(-1,2) have a negative and significant effect, indicating a correction to the increase in NTP in the previous period. Conversely, D(HPP) has a positive and highly significant effect, so that the adjustment of HPP drives an increase in the dependent variable. Meanwhile, D(UREA) and the constant are insignificant, so the model dynamics are more influenced by changes in NTP and HPP.

Table 16 Results of the Long-Term ARDL Model Estimation Test

Variables	Coefficient	Std.Error	t-Statistic	Prob.	Information
D(HPP)	0.004140	0.001084	3.819622	0.0004	Significant
D(UREA)	-0.000535	0.002746	-0.194722	0.8464	Not Significant
C	0.297981	0.163814	1.819026	0.0747	Not Significant

Sources: Processed by the author (2026)

The long-term estimation results of the ARDL model show that HPP has a positive and significant effect on NTP (coefficient 0.004140; Prob. 0.0004), so that an increase in HPP drives an increase in NTP in the long run. Conversely, the urea price has a negative coefficient (-0.000535) but is not significant, so it has no real effect.
Long-term equation

Model Stability Test

The results of the CUSUM stability test indicate that the model is in a stable condition, indicated by the CUSUM line being within the 5% significance limit. The CUSUM test of Squares also yielded similar results. Thus, the model is stable and suitable for analyzing long-term relationships between variables.

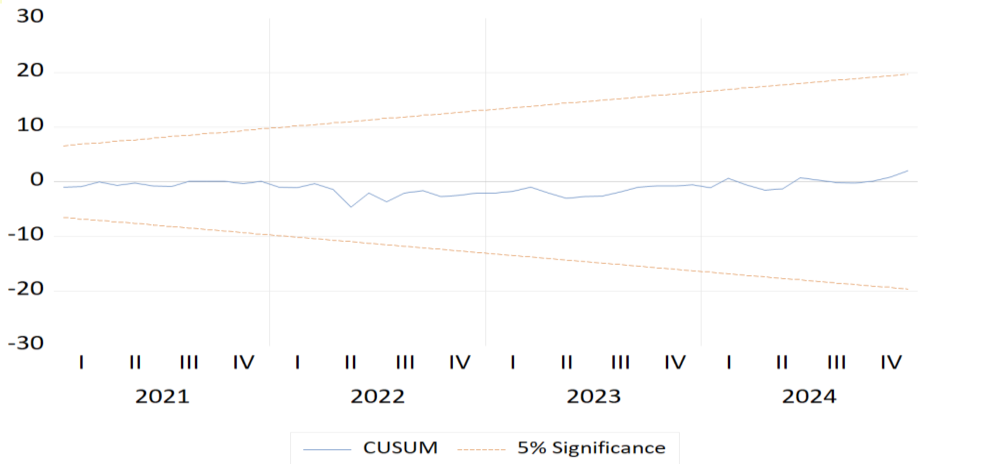

Figure 5 Results of the *Cusum Graph Test Test*
Sources: Processed by the author (2026)

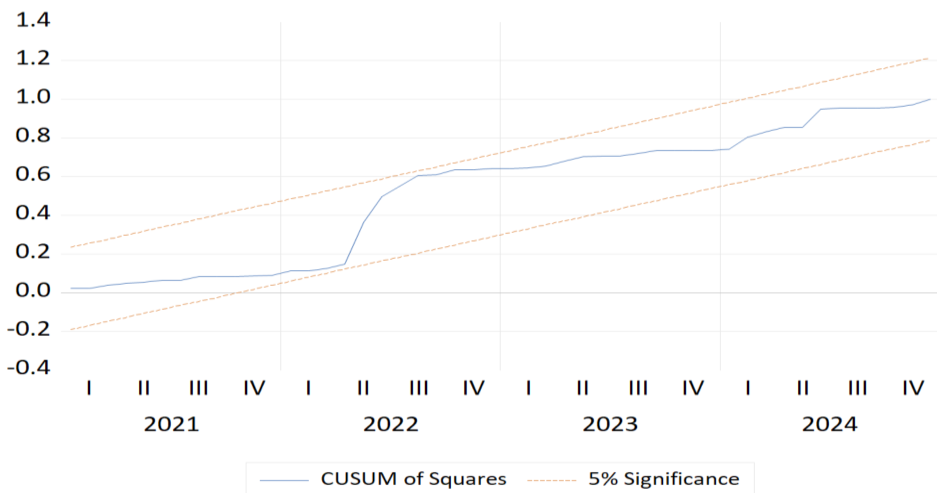

Figure 6 Results of the *Cusum* Graph Test *Of – Square*
Sources: Processed by the author (2026)

Classical Assumption Test

Normality

Table 17 Normality Test Results

Jarque - Bera	Probability
106.8785	0.000000

Sources: Processed by the author (2026)

The normality test show a probability value of 0.000000, which is smaller than the 5 percent significance level, so it can be concluded that the data is not normally distributed.

Multicollinearity

Table 18 Multicollinearity Test Results

Variables	Coefficient Variance	Uncentered VIF	Centered VIF
D(NTP(-1))	0.011923	1.270959	1.166735
D(NTP(-2))	0.012350	1.322426	1.230657
D(HPP)	2.02E-07	1.163768	1.152670
D(UREA)	3.26E-06	1.020520	1.002616
C	0.013099	1.155973	NA

Sources: Processed by the author (2026)

The multicollinearity test show that all independent variables, namely D(NTP(-1)), D(NTP(-2)), D(HPP), and D(UREA), have low Centered VIF values, with the highest value of 1.230657 at D(NTP(-2)). Since all VIF values are below 10, the model does not experience multicollinearity problems and all independent variables are suitable for use in the study.

Autocorrelation

Table 19 Autocorrelation Test Results

R1	R2
1.991270	0.2611

Sources: Processed by the author (2026)

Durbin – Watson value of 1.991270, which is close to 2, indicates that the model does not experience autocorrelation, either positive or negative. Furthermore, the Breusch – Godfrey test yields a Chi- Square Prob. value of 0.2611, which is greater than 5 percent, so the null hypothesis is accepted. Thus, the model is free from autocorrelation up to the second lag.

Development of HPP Policy and Fertilizer Subsidies in Indonesia

The development of the Government Purchase Price (HPP) for unhulled rice and fertilizer subsidies in Indonesia is closely linked to the dynamics of national food security, macroeconomic conditions, and efforts to improve farmer welfare. These two instruments are a crucial component of rice policy, which aims to protect farmers from price fluctuations while simultaneously promoting efficiency and increasing rice production, a strategic food commodity.

The price policy for unhusked rice and rice in Indonesia has been implemented since the issuance of Presidential Instruction (Inpres) Number 2 of 1973 concerning Domestic Rice Purchases and has continued consistently with various price level adjustments from year to year (Yusiana et al., 2022). In the initial period, this policy focused on domestic rice purchases, then developed with the affirmation of the role of the Logistics Affairs Agency (Bulog) as the implementer of price stabilization. Since Presidential Instruction No. 15 of 1980, the term “basic price” began to be used, which became the forerunner to the concept of Government Purchase Price (HPP). Clearer pricing of Harvested Dry Grain (GKP) at the farmer and mill levels only emerged in the early 2000s, and subsequently price regulation continued to be strengthened through various regulations up to the latest National Food Agency Regulation, reflecting the government's commitment to maintaining price stability and farmer welfare.

Several studies have shown that the HPP aims to maintain price stability and farmer incomes, particularly during peak harvest times. However, its effectiveness depends heavily on rice absorption capacity, post-harvest infrastructure, and trade efficiency. Challenges in rice quality, farmers' access to Bulog, and the length of the distribution chain often result in prices received by farmers not always being in line with the HPP. Therefore, the HPP policy needs to be continuously refined to ensure more equitable and sustainable benefits.

The Highest Retail Price (HET) policy for subsidized fertilizer is an important instrument in maintaining the stability of input costs. farming and ensuring farmers' access to affordable fertilizer. Since the Indonesian Ministry of Agriculture issued Regulation No. 69/2012, fertilizer prices such as urea, SP-36, and NPK have remained relatively stable until 2019, reflecting the government's priority of maintaining certainty in production costs.

Significant changes began in 2020, with price adjustments and the introduction of a special NPK formula, accompanied by an increase in the highest retail price (HET) for urea and SP-36. Entering the 2022–2025 period, the subsidy policy was simplified, focusing subsidies on strategic fertilizers such as urea and NPK, and implementing commodity segmentation, including cocoa NPK. This dynamic demonstrates the government's efforts to balance the fiscal burden of subsidies with protecting farmers' purchasing power.

Various studies confirm that fertilizer subsidies play a role in reducing production costs and maintaining the sustainability of agricultural businesses. However, their effectiveness depends heavily on accurate targeting and smooth distribution. Issues with quotas, distribution, and price monitoring at the retail level remain challenges, so the government continues to make improvements by strengthening governance and the e-RDKK system to ensure more targeted and effective subsidies.

CONCLUSION

This study demonstrates that the effectiveness of agricultural policy in Indonesia cannot be understood solely through its formal design, but must be interpreted through its empirical performance and institutional context. By examining the dynamic relationship between the Government Purchase Price policy, fertilizer subsidies, rice production, and the Farmer Exchange Rate, the findings confirm that output price policy plays a more consistent and meaningful role in shaping both production stability and farmer welfare compared to input-based interventions. While the Government Purchase Price functions as a stabilizing mechanism that supports farmers' purchasing power and mediates market uncertainty, fertilizer subsidies appear to be limited in their impact, reflecting deeper structural constraints in distribution, access, and governance. These results answer the core objective of the study by showing that policy effectiveness is uneven and contingent upon how directly it connects with farmers' economic realities. At the same time, the study advances an integrated perspective by linking production outcomes and welfare indicators within a single analytical framework, while also interpreting these relationships as part of broader state–society dynamics in the agrarian sector. In this sense, the contribution of this research lies in revealing that agricultural policy operates not merely as an economic instrument, but as a governance process shaped by institutional capacity, implementation mechanisms, and unequal access among rural actors.

ETHICAL STATEMENT AND DISCLOSURE

This article will be published without any ethical review and approval as there was no involvement of any vulnerable groups, such as children, the elderly, or survivors of any kind and pose no risk of harm to participants. All data were collected secondarily. Artificial intelligence (AI) tool is restricted only as a language editing assisstant and does not have any impact on the substance of the scintific research. The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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