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AUTOREGRESSIVE DISTRIBUTED LAG MODELING FOR RICE PRICE PREDICTOR ANALYSIS IN BOJONEGORO REGENCY

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ABSTRACT

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Rice price fluctuations in Bojonegoro Regency are driven by complex interactions of economic, social, and environmental elements. These dynamics have a direct impact on the welfare of low-income households, making it essential to understand the underlying factors to support effective price stabilization efforts. Addressing this issue requires a comprehensive econometric model capable of capturing both immediate and lagged effects of relevant variables. This study analyzes the main drivers of rice price changes in Bojonegoro Regency by applying the Autoregressive Distributed Lag (ARDL) model. It focuses on how variables such as dried corn prices, rice consumption, harvest area, rice production, and money exchange rates contribute to rice price volatility.

The ARDL model is employed to explore both short-term and long-term relationships between selected variables and rice prices. Model selection is guided by performance indicators including the Akaike Information Criterion (AIC), Root Mean Square Error (RMSE), R-Square, as well as results from stationarity, cointegration, and classical assumption tests. The study utilizes secondary data sourced from the Bojonegoro Regency Food Security and Agriculture Office and the Bojonegoro Statistics Agency. The optimal model, identified as ARDL (3,4,4,4,4,0), produces an R-Square of 97.13% and the lowest AIC among alternatives. The analysis reveals that dried corn prices, rice consumption, harvest area, and rice production significantly influence rice prices, each with distinct lag structures. The money exchange rate, however, is found to have no significant effect.

This study does not account for policy-specific variables or broader external factors such as global climate change or international trade regulations, which may also impact rice prices. Additionally, the availability and quality of secondary data may affect the model's predictive accuracy. By incorporating lag structures and localized economic factors, this research offers a robust predictive framework tailored to Bojonegoro Regency. It provides practical insights for policymakers aiming to enhance rice price stability and protect household purchasing power.

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1. INTRODUCTION

Indonesia is an agricultural country with diverse natural resources and vast agricultural land. Agriculture is the primary sector and is very important for fulfilling basic needs in an agricultural country. In addition, agriculture plays a significant role in the national economy [1]. One of the countries with the most significant rice production in the world is Indonesia. As most of Indonesia's population depends on rice, which is considered the main factor causing inflation, the availability of rice is crucial. A shortage of rice can cause Indonesia's food security to be compromised [2]. The area harvested after the crop is old enough is referred to as the harvest area. Harvest failure or the lack of suitable harvest areas can occur in a large planting area, thereby underscoring the importance of adequate harvest areas.

Rice production is dry grain milled from rice fields or fields in an area [3]. Human needs are met by creating goods or services that are realized in production. The value of rice can be produced from grain through rice production [4]. Rice consumption is the amount of rice consumed by the population from year to year, calculated in kilograms. Another factor that can affect the price of rice is the price of corn. Historically, corn was widely consumed as a staple food; however, over time, it was replaced by rice as a staple food, such as in the Eastern Indonesia region. In addition, the money exchange rate also affects the price of rice. The money exchange rate is the value individuals use to exchange national goods and services for international goods and services [5].

For rice supply in Indonesia, it is necessary to strengthen the position of the community and local government in maintaining domestic rice supply. One way to increase the role of the community in maintaining the availability of rice is by planting rice and increasing production; it can be applied at the regional and rural levels while maintaining the availability of supporting materials to carry out rice production, which is the role of the government. Factors affecting rice prices are rice consumption, prices of other goods, and government policies. However, based on the Malian philosophy, the factors that affect the price of rice are harvest area, rice production, and rice availability [6].

The Indonesian government is constantly working to improve food security to recognize rice's great need and influence. Most Indonesians want rice prices to be stable, affordable, available anytime, and fairly distributed. One of the food agencies in Indonesia assigned by the government to handle post-production issues, especially in pricing, marketing, and distribution of foodstuffs, is the Badan Urusan Logistik (BULOG) [7].

East Java Province was the most significant contributor of rice in Indonesia in 2020, with Central Java Province ranked second and West Java Province ranked third. Lamongan and Ngawi are the most significant contributors to rice production in East Java Province, while in third place is Bojonegoro Regency, with rice production equal to 412,970 tons [8]. Rice production can still be increased to meet national rice needs, even though Bojonegoro Regency has a rice surplus.

As a staple food, rice is inelastic for price transformation. Market conditions affect rice price fluctuations in Bojonegoro. The demand for rice will also affect the increase or decrease of rice prices. People will not significantly reduce or increase rice consumption despite price fluctuations. Based on facts from the community, rice prices often experience significant increases in global, regional, and local markets. Most poor households that have to spend their income to buy this rice may experience more significant economic pressure [4].

Based on data from the Bojonegoro News Tribun 2023 [9], the price of rice in Bojonegoro Regency has increased significantly, where rice has risen to Rp. 16,000. The price of rice was previously around Rp. 13,000, and now it has increased to Rp. 16,000. Like other regions in Indonesia, Bojonegoro Regency has a relevant number of poor households. One of the causes of economic hardship and the more significant economic condition of low-income families is the increase in rice prices. Other factors that affect the welfare of poor households, including economics, are cultural and social, as well as other influential factors [10]. In addition, fluctuations in rice prices can also impact on the welfare of the entire household.

Previous research on rice prices has also been conducted in various regions of Indonesia, such as analyzing factors affecting rice prices in South Kalimantan province [3]. In this study, the factors influencing rice prices are population, demand, corn prices, and rice production. The study's results jointly show that these variables influence the demand for rice in South Kalimantan Province. In a study entitled Economic factors that affect rice price fluctuations in North Sumatra [11], two factors affect the price of rice, namely 60% production, which means that the price of rice will decrease if rice production increases and if rice production is low. The second factor is inflation at 38%, which occurs when rice prices continue to rise. Inflation is one of the short-term factors affecting rice prices in North Sumatra.

Furthermore, research with the title Analysis of Factors Affecting the Increase in Rice Prices in Kolaka Regency [4] shows that rice prices are influenced by production, distribution, government policy, and rice prices. The results of the t-test research show that the production and government policy variables, when analyzed individually, have a significant effect on the increase in rice prices in Kolaka Regency; on the other hand, those that do not have a substantial impact on the rise in rice prices in Kolaka Regency are the distribution and government policy variables. Previous research entitled Autoregressive Distributed Lag Rate and Crumb Rubber Exports on Rice Prices in Indonesia [12] shows that the money exchange rate is a component that affects the price of rice in Indonesia. The short-term equation model shows that the money exchange rate variable affects Indonesian rice prices significantly and negatively. In contrast, in the long-term equation model, it is known that the money exchange rate variable affects rice price growth negatively but not significantly.

For this problem, it is necessary to conduct research using regression modeling that affects rice prices to support the improvement of community welfare in Bojonegoro Regency. The purpose of this study is to identify variables that affect the price of rice in Bojonegoro Regency from 2020 to 2022 and to produce descriptive statistics of rice price, dried small corn price, rice consumption, harvest area, rice production, and money exchange rate in Bojonegoro Regency. Rice price modeling was conducted using the Autoregressive Distributed Lag (ARDL) model. The ARDL method combines Autoregressive (AR) and Distributed Lag (DL). Autoregressive is defined as a model that describes the response variable as being influenced by itself in the previous period. Distributed Lag is a regression model influenced by the current predictor variable and the last predictor variable of the response. The advantage of this method is that the ARDL model offers various lag procedures to select the most optimal model based on AIC criteria. To determine the lag order parameter using this criterion, choose the lowest Lag AIC. So, if the AIC value is smaller, the value is better.

In previous studies, determining whether the predictor variables significantly affect the response variable has been the standard method to study the causal relationship in ARDL equations or models. Linear regression models are still used to model several cases in data mining studies. One example is research that models the number of dengue hemorrhagic fever cases in Bojonegoro Regency using the Autoregressive Distributed Lag model [13]. This modeling has been applied in previous studies, namely to analyze the factors that affect rice imports in Indonesia [10], investigate the factors that significantly affect the volume of palm oil exports in Indonesia [14], and model with autoregressive distributed lag modeling the effect of inflation and the exchange rate of American money on stock prices in 2014-2018 [15].

This research was conducted in the hope of providing benefits to the Bojonegoro Regency Food Security and Agriculture Office, namely providing information in the form of statistical models related to rice prices to create more efficient and effective food security and agricultural policies and programs to reduce fluctuations in rice prices in Bojonegoro Regency and help the Bojonegoro Regency Food Security and Agriculture Office of the Bojonegoro Regency Government related to making activity plans and managing household and national rice. Thus, proposing research entitled “Autoregressive Distributed Lag Modeling for Predictor Analysis of Rice Prices in Bojonegoro Regency” is necessary.

2. METHODS

Material and Data

This study uses three years of data, with the price of rice as the response variable and the price of dry corn as the predictor variable, as well as rice consumption, harvest area, rice production, and the exchange rate. Secondary data from the Bojonegoro District Food Security and Agriculture Office, the Bojonegoro District Central Bureau of Statistics [16], and Satu Data Bojonegoro are used as monthly data from January 2020 to December 2022.

Research Method

This study uses two variables, namely response variables and predictor variables. The response variable (Y) is rice price, while the predictor variables (X) are factors that affect rice price, such as the price of dry-shelled corn (X_1), rice consumption (X_2), harvest area (X_3), rice production (X_4), and money exchange rate (X_5). Each predictor variable has a ratio measurement scale. The following definition of the research variables can be seen in Table 1.

Table 1. Summary of Descriptive Statistics

Number	Variable	Variable Definition	Measurement Scale
1	Rice Price (Y)	The amount of money paid by the population for each Kilogram of premium rice in rupiah (IDR).	Ratio
2	Price of Dry-Shelled Corn (X_1)	The amount of money residents pays for each Kilogram of corn in rupiah (IDR).	Ratio
3	Rice Consumption (X_2)	The amount of rice consumed by Bojonegoro residents from 2020 to 2022 is calculated in kilograms (Kg).	Ratio
4	Harvest Area (X_3)	The area of a crop harvested after it has reached a sufficient age in hectares (Ha).	Ratio
5	Rice Production (X_4)	Milled dry grain (paddy or field) in Bojonegoro Regency in kilograms (Kg).	Ratio
6	Money Exchange Rate (X_5)	The medium of exchange for national and international goods and services in units of dollars (USD).	Ratio

This research outlines the implementation process from beginning to end through the following stages:

1. Perform descriptive statistical analysis.
2. Modelling rice prices using the Autoregressive Distributed Lag (ARDL) model in the following way:
   2.1 Testing stationarity for all series with Dickey-Fuller testing at level conditions. This assumption can be tested using the Augmented Dickey-Fuller test in EViews software with the null hypothesis (H_0) that the series is not stationary. The assumption of stationarity is not met if the p-value is less than α (reject H_0) and α is a significant level determined at 5%.
   2.2 Perform the differencing process at lag-1 if there is one series that is concluded to be non-stationary for all series.
   2.3 Conduct a cointegration test using the Engle-Granger Cointegration Test. This cointegration test is used in the EViews program to test the cointegration assumption by rejecting the null

hypothesis (H_0) that the series has cointegration properties. In other words, the belief in cointegration is fulfilled if the p-value > α (Accept H_0) with α is the significant level set at 5%.

2.4 If the response and predictor variables show cointegration, the Autoregressive Distributed Lag (ARDL) model is used. However, if the results show no cointegration, the Error Correction Model (ECM) model is used.

2.5 Assessing AIC, RMSE, and R-Square. A more considerable R-Square value indicates that is the best result of the regression model. In addition, other measures of regression model goodness, such as Root Mean Square Error (RMSE), are used, and these are expected to be small.

2.6 Get the best regression model results based on the best criteria testing.

2.7 Conducting classical hypothesis tests, namely the Breusch-Godfrey serial correlation LM test to test the autocorrelation hypothesis, the Breusch-Godfrey heteroscedasticity test to test heteroscedasticity, the Jarque-Bera normality test to test normality, and checking the VIF value for the multicollinearity test.

i. The normality hypothesis test uses the Jarque-Bera test with the null hypothesis (H_0), indicating that the residual model is normally distributed. In this test, it is expected that H_0 is accepted so that the test concludes that the residual model is usually distributed. The null hypothesis (H_0) is accepted if the p-value > α. In this study, the value of α is determined. In this study, the α value was set at 5%.

ii. The autocorrelation hypothesis test is performed on EViews software using the Breusch-Godfrey serial correlation LM test with the null hypothesis (H_0), which states no serial correlation in the residual model. In other words, the autocorrelation assumption still needs to be met. If the p-value > α (Accept H0), where α is the significance level determined at the 5% level, then the regression model shows no autocorrelation.

iii. The heteroscedasticity hypothesis test is performed on E-Views software using the Breusch-Godfrey heteroscedasticity test. The null hypothesis test (H_0) indicates that homoscedasticity is the residual variance of the model. Therefore, the heteroscedasticity hypothesis still needs to be met. If the p-value > α with α set at 5% (H0 is accepted), the regression model is not heterogeneous.

iv. The multicollinearity hypothesis test in E-Views software checks the VIF (variance inflation factors) value. It is expected that there is no multicollinearity phenomenon in the regression model. The regression model is multicollinear if the VIF value is greater than ten.

2.8 Determine the factors that affect rice prices by conducting parameter significance tests using the F-test and t-test. In testing the significance of the regression model parameters, the following test conditions are given:

i. Testing parameters or regression coefficients simultaneously with the F test. The null hypothesis test (H_0) shows that the effect is insignificant. Therefore, this hypothesis is not met if the p-value $\leq \alpha$ with α set at 5% (H0 is rejected) so that the effect of the predictor variables simultaneously is said to affect the response variable significantly.

ii. Testing parameters or regression coefficients individually with the t-test. The null hypothesis test (H_0) shows that the effect is insignificant. Therefore, this hypothesis is not met if the p-value $\leq \alpha$ with α set at 5% (H0 is rejected) so that the influence of the predictor variables is said to partially affect the response variable significantly.

3. Interpret the ARDL model to find out what factors significantly affect the price of rice in Bojonegoro in 2020-2022.

3. RESULTS

The results and discussion in this study are in the form of monthly data on rice prices from January 2020 to December 2022 and data on the price of dry corn, rice consumption, harvest area, rice production, and money exchange rate. Matters related to the answers to the problem formulations contained in this study will be presented, including descriptive statistics of rice prices and their predictor variables, modeling rice prices with the Autoregressive Distributed Lag (ARDL) Model, and factors that affect rice prices in Bojonegoro Regency.

Before further analysis is carried out with the Autoregressive Distributed Lag (ARDL) method, descriptive statistical analysis is carried out first to see the general description of the data of each variable to be studied. The number of observational data involved in the study is 36 observations, where the data is in the form of data on the price of dry-shelled corn (X_1), rice consumption (X_2), harvest area (X_3), rice production (X_4), money exchange rate (X_5), and rice prices (Y) for 3 years in monthly in Bojonegoro Regency from 2020 to 2022. The details of the observation data can be seen in Appendix 1. In this study, the tool used to conduct descriptive statistical analysis is EViews 9 software. The following Table 2 presents a summary of the descriptive statistical results of each research variable.

Table 2. Summary of Descriptive Statistics

	Y	X_1	X_2	X_3	X_4	X_5
Mean	12,391	5,805	11,260	11,220	33,798	14,629
Median	12,500	5,714	11,313	5,904	18,996	14,480
Maximum	13,000	7,000	11,353	49,075	163,435	16,367
Minimum	12,000	5,071	10,574	1,602	4,231	13,662
Standard Deviation	226,040	559,722	170,404	11,426	35,703	546,449

Table 2 shows that the average price of rice in Bojonegoro Regency from 2020 to 2022 is IDR 12,391 per kilogram, with the lowest value of IDR 12,000 per kilogram from June to December 2021 and the highest value of IDR 13,000 per kilogram in November 2022, where the median value is IDR 12,500 per kilogram and the standard deviation is IDR 226,040. In addition, information was obtained that the average value of the price of dried unhusked corn in Bojonegoro District was IDR 5,805 per kilogram, with the lowest value of IDR 5,071 per kilogram in February 2020 and the highest value of IDR 7,000 per kilogram in July 2022 where the median value was IDR 5. Other information that can be obtained from Table 4.1 is related to rice consumption in the Bojonegoro Regency area, which shows that the average value of rice consumption is 11,260 tons, with the lowest value of 10,574 tons found in February 2020. In 2022, it is known that the harvest area with the highest value of 49,075 hectares is seen in March, where the median value obtained is 5,904 hectares and a variance of 11,426. Meanwhile, information related to rice production in Bojonegoro Regency can also be seen in Table 1, which shows that the average value of rice production is 33,798 tons, with the highest value in 2020. In 2022, it is known that the harvest area with the highest value of 49,075 hectares is found in March, where the median value obtained is 5,904 hectares and a variance of 11,426.

In modeling rice prices, the ARDL model will be estimated with the help of EViews software. Model testing is done by testing stationarity, cointegration, classical assumptions, and parameter significance and assessing the model's goodness, namely R-square, RMSE, and AIC. The first step is the stationarity test, which determines to what degree the data will be stationary. There are two methods to conduct stationarity tests: correlogram and unit root test. This research used the ADF (Augmented Dickey-Fuller) test to observe the unit root test. The results of the unit root test at the level and the difference at the first level on the Premium Rice Price (PRP) response variable are presented in Table 3.

Table 3. Unit Root Test Results at the Level Degree

Variable	Symbol	Statistic *t*	*p*-value
Response	*PRP*	-2.453466	0.1360
Predictor	*DSCP*	-1.799199	0.3748
	RC	-6.964756	0.0000*
	HA	-7.180370	0.0000*
	RP	-6.607707	0.0000*
	TU	-3.558270	0.0120*

*Significant for α of 5%

From Table 3, it can be seen that the ADF value of each variable with a significance level α of 5% shows that the stationary variables seen from the p-value using the Dickey-Fuller test are variables *RC* (Rice Consumption), *HA* (Harvest Area), *RP* (Rice Production), and *MER* (Money Exchange Rate). Meanwhile, the variables of premium rice price (PRP) and dried small corn price (DSCP) are not stationary. So further stationary is done at the differencing level at lag 1 for all series, as in Table 4.

Table 4. EViews command to perform differencing process at lag-1

EViews Commands
genr dprp=prp-prp(-1)
genr ddscp=dscp-dscp(-1)
genr drc=rc-rc(-1)
genr dha=ha-ha(-1)
genr drp=rp-rp(-1)
genr dmer=mer-mer(-1)

Table 4 shows the differencing process in a series, namely $dZ_t = Z_t - Z_{t-1}$, which is interpreted as a difference or difference that shows a decrease if the value is negative and an increase if the value is positive. The following results of the unit root test at the first level of difference are given in Table 5.

Table 5. Unit Root Test Results at the First Level of Differences

Variable	Symbol	Statistic *t*	*p*-value
Response	*dPRP*	-3.926371	0.0053*
Predictor	*dDSCP*	-6.189178	0.0000*
	dRC	-6.964756	0.0000*
	dHA	-7.180370	0.0000*
	dRP	-6.607707	0.0000*
	dMER	-3.558270	0.0120*

*Significant for α of 5%

Based on Table 5, it can be seen that at the first level of differencing, the ADF value of each variable is stationary, and there is no single variable whose degree of freedom exceeds differencing 2. After the differencing process, integrity testing is carried out using the Engle-Granger cointegration test together (group) for all series whose summary is given in Table 6.

Table 6. Cointegration Test Results for PRP Response Variable

Variable	Symbol	Statistic *z*	*p*-value
Response	*dPRP*	-23.04793	0.2745
Predictor	*dDSCP*	-20.19093	0.4284
	dRC	-53.93355	0.0000*
	dHA	-22.20824	0.3163
	dRP	-22.29077	0.3120
	dMER	-23.06483	0.2737

*Significant for α of 5%

From Table 6, it can be seen from the test results that there is only one series that has cointegration properties, namely the *dRC* series. Thus, rice price modeling is used with the ARDL model, where the lag distribution is only given to the *dRC* variable. Stationary tests and cointegration tests have been carried out; the results show that there are stationary at the level unit root test, while at differencing 1 and differencing 2, there are no stationary variables. Then in the cointegration test, it is obtained that there is cointegration in the data, so the procedure is in accordance with the ARDL model, that if cointegration occurs and Y_t and X_t are not stationary, the right model to use is the ARDL model. The next stage is determining the optimum lag and calculating parameter estimates. The following lag optimum test results are given in Figure 1.

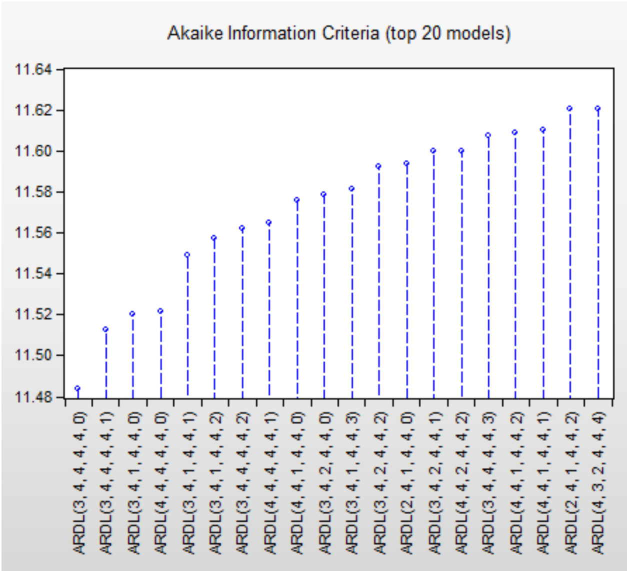

Figure 1. Criteria for selecting the best model based on minimal AIC

Based on Figure 1, there are 20 top models. However, the suitable model for the ARDL method in this study is ARDL (3,4,4,4,4,0) because it has a smaller AIC value than other ARDL models. Furthermore, model goodness testing is carried out, namely the assessment of AIC, RMSE, and R-Square in Table 7.

Table 7. Model Goodness Measure

AIC	RMSE	R-Square
11.4836	32.549	0.9713

Based on Table 7, the goodness of the model is obtained with an R-square value of 0.9713, meaning that the diversity of the *dPRP* variable that can be explained by the predictor variables *dDSCP*, *dRC*, *dHA*, *dRP*, and *dMER* together is 97.13%. The remaining 2.87% is described by the residual variable representing the other variables not included in the regression model. The RMSE value obtained a value of 32.549 obtained from the calculation of the sum squared error value divided by the amount of data compared to the MSE value, which is still relatively small, and received an AIC value of 11.4836 relatively small compared to other AIC values at the optimum lag length based on the ARDL modeling results obtained a value that is still relatively small so that it is the best model of this criterion and the ARDL model formed is still simple.

After the ARDL model estimation process and the model's goodness, the resulting classical assumption test must be met before interpreting and concluding the regression model results. Table 8 summarizes the classical assumption testing, which includes testing the assumptions of Normality, Autocorrelation, Heteroscedasticity, and Multicollinearity.

Table 8. Summary of Classical Assumption Test Results

Classical Assumption	Test	Statistic	*p*-Value
Normality	**Jarque-Bera**	5.209	0.074
Autocorrelation	**Bruesch-Godfrey**	0.000	0.651
Heteroscedasticity	**Bruesch-Godfrey**	0.769	0.707

Multicollinearity	VIF
dPRP(-1)	2.47487
dDSCP	1.87417
dRC	3.60730
dHA	1.04359
dRP	7.03317
dMER	2.39473

From Table 8, the test results show that the regression model formed has passed the classical assumption test. The regression model residuals do not have Autocorrelation and Heteroscedasticity properties because the starting p-value is above 5%. The regression model residuals fulfill the Normal distribution so that the Normality assumption is met because the starting p-value is above 5%. The multicollinearity test does not contain any cases of multicollinearity because the VIF values are all below 10 for each predictor. Thus, the regression model estimation results can be interpreted and concluded with the regression model results.

Furthermore, to determine the factors that affect the price of rice, the simultaneous test (F-test) and partial test (t-test) are used. The test results for the simultaneous test are in Table 9.

Table 9. Simultaneous Test

F-Statistic	*p*-value
9.900227	0.002235*

*Significant for α of 5%

With an alpha significance level of 5%, the p-value is obtained at 0.002235, and it is known that the critical area (reject H_0) is if the p-value < α with α of 0.05. Thus, the decision to reject H_0 is given, which indicates that the predictor variables and the response variable have a simultaneous influence. Other results on testing the significance of the regression model related to the t-test are summarized in Table 10.

Table 10. Partial Test

Variable	Coefficient	Standard Error	*t*-Statistic	*p*-value
dPRP(-1)	0.521550	0.320057	1.629552	0.1472
dPRP(-2)	-0.068116	0.483650	-0.140837	0.0420*
dPRP(-3)	-0.747028	0.488433	-1.529436	0.1700
dDSCP	-0.021975	0.099003	-0.221961	0.8307
dDSCP(-1)	0.149276	0.115735	1.289811	0.2381
dDSCP(-2)	-0.348244	0.131944	-2.639327	0.0335*
dDSCP(-3)	-0.235105	0.141641	-1.659868	0.1409
dDSCP(-4)	0.194686	0.089120	2.184530	0.0652
dRC	0.416092	0.228448	1.821385	0.1113
dRC(-1)	0.459204	0.279397	2.287798	0.0460*
dRC(-2)	-0.047805	0.287234	-0.166433	0.8725
dRC(-3)	0.045882	0.225920	0.203088	0.8448
dRC(-4)	0.259236	0.199402	1.300071	0.2347

Variable	Coefficient	Standard Error	*t*-Statistic	*p*-value
dHA	0.073441	0.038899	1.888001	0.1010
dHA(-1)	-0.039546	0.032909	-1.201699	0.2686
dHA(-2)	-0.022614	0.026097	-0.866553	0.4149
dHA(-3)	0.038579	0.021657	1.781379	0.1181
dHA(-4)	0.031289	0.019447	2.123185	0.0314*
dRP	-0.022407	0.011896	-1.883510	0.1016
dRP(-1)	0.011038	0.010095	1.093445	0.3104
dRP(-2)	0.005524	0.007891	0.700009	0.5065
dRP(-3)	-0.035393	0.007697	-2.000032	0.0356*
dRP(-4)	-0.013185	0.006671	-1.976503	0.0886
dMER	0.019989	0.039684	0.503704	0.6299
C	2628.899	3662.989	0.717692	0.4962

*Significant for α of 5%

Based on Table 10, the partial parameter testing results are as follows:

1. The coefficient value of the variable $dDSCP_{t-2}$ is -0.348244, which means that an increase in *DSCP* (Dry Small Corn Price) of 1 unit in this month will significantly affect the decrease in *PRP* (Premium Rice Price) in Bojonegoro in the next 2 months by 0.348244.
2. The coefficient value of the variable dRC_{t-1} is 0.459204, which means that an increase in *RC* (Rice Consumption) of 1 unit this month will significantly affect the rise in *PRP* (Premium Rice Price) in Bojonegoro in the next 1 month by 0.459204.
3. The variable coefficient value dHA_{t-4} is 0.031289, which means that an increase in *HA* (Harvest Area) of 1 unit in this month will significantly affect the rise in *PRP* (Premium Rice Price) in Bojonegoro in the next 4 months by 0.031289.
4. The coefficient value of the variable dRP_{t-3} is -0.035393, which means that an increase in *RP* (Rice Production) of 1 unit in this month will significantly affect the decrease in *PRP* (Premium Rice Price) in Bojonegoro in the next 3 months by 0.035393.
5. The coefficient value of the *dMER* (Money Exchange Rate) variable is 0.019989, which means that this month is statistically insignificant and does not affect the increase in *PRP* (Premium Rice Price) in Bojonegoro currently and several months ahead.

4. DISCUSSIONS

Meanwhile, information related to rice production in Bojonegoro Regency can also be seen in Table 1, which shows that the average value of rice production is 33,798 tons, with the lowest value of 4,231 tons found in August 2021 and the highest value of 163,435 tons, where the median value obtained is 18,996 tons and a variance of 35,703. In addition, Table 1 also shows the money exchange rate, where the standard deviation value is 546,449 USD, with a median value of 14,480 USD. Based on Table 1, the standard deviation value for each observation variable is significant, meaning that the data from each variable is quite diverse.

The results of the stationarity and cointegration tests confirm that the ARDL model is suitable for modeling rice prices in Bojonegoro Regency. Initial stationarity tests revealed that some variables were not stationary at the level, necessitating differencing at lag 1, after which all variables became stationary. The cointegration test indicated that only rice consumption (dRC) exhibited long-term equilibrium, justifying the use of the ARDL model with lag distribution for this variable. The optimal ARDL (3,4,4,4,4,0) model was selected based on the lowest AIC value and demonstrated strong explanatory power with an R-square of 97.13%. The model's goodness-of-fit, assessed through AIC, RMSE, and R-square, confirmed its robustness. Additionally, classical assumption tests verified that the model met normality, autocorrelation, heteroscedasticity, and multicollinearity assumptions, ensuring the validity of the regression results. The simultaneous F-test confirmed the joint significance of the predictor variables, while the t-test further evaluated their individual impact on rice price fluctuations. Overall, the study successfully identifies the key determinants of rice prices, providing valuable insights for policymakers in stabilizing local rice markets.

The analysis results using the ARDL model show a significant relationship between several variables and the price of premium rice (*PRP*) in Bojonegoro, with the impact varying by the time lag. The negative coefficient for the small dry maize price variable (*dDSCP*) at lag 2 (-0.348244) indicates that an increase in the price of small dry maize will cause a decrease in the price of premium rice in the next two months. It is consistent with previous research showing that the price of substitute food can affect rice prices [3]. In contrast, rice consumption (*dRC*) at lag 1 has a positive coefficient (0.459204), indicating that an increase in rice consumption significantly increases the price of premium rice in the following month, consistent with demand theory [11]. The positive coefficient for harvested area (*dHA*) at lag 4 (0.031289) indicates that an increase in rice harvested area contributes to the increase in premium rice prices in the longer term, which can be attributed to structural changes in supply [11]. In contrast, rice production (*dRP*) with a negative coefficient in the third lag (-0.035393) indicates that an increase in rice production reduces the price of premium rice in the next three months by the law of supply and demand [4]. However, the money exchange rate variable (*dMER*) shows a slight positive coefficient (0.019989). It is insignificant, which suggests that the increase in rice production reduces the price of premium rice in the next three months [17].

5. CONCLUSION

The conclusions obtained from the results of this study are given. The premium rice price fluctuates and shows an increase in price from 2020 to 2022. This price change is also followed by its predictor variables, such as dry small corn price, rice consumption, harvest area, and money exchange rate, which has an average premium rice price of IDR 12,391, the highest premium rice price of IDR 13,000, and the lowest premium rice price of IDR 12,000. Some series are not stationary, so it is necessary to do a differencing process, and then the premium rice price series has cointegration properties (long-term influence). Thus, the best regression model is the ARDL(3,4,4,4,4,0) model, which has passed the classical assumptions and obtained a measure of the goodness of the ARDL model, namely R-square of 97.13%. The RMSE is still significant, but the regression model is parsimony based on the AIC measures. In Bojonegoro Regency, the premium rice price has a long-term influence that needs to be prevented and anticipated in the following months. Individually, the percentage of the money exchange rate does not significantly affect the premium rice price. On the other hand, the dry small corn price, rice consumption, harvest area, and rice production significantly affect the decrease and increase of premium rice prices in Bojonegoro District. One of the main advantages of the ARDL method, as shown in this study, is its ability to handle variables with different integration orders (I(0) and I(1)) without requiring all variables to be stationary at the same level. It also allows for simultaneous estimation of short-term and long-term relationships and is suitable for small samples, making it ideal for regional economic analysis. However, the ARDL model also has some limitations, such as the risk of overfitting due to multiple lag terms and its sensitivity to lag selection, which can affect the accuracy and interpretability of the model. Furthermore, ARDL does not capture structural breaks or nonlinear patterns unless extended through additional techniques.

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