**Unraveling the Interplay among Inflation, Rice Prices, and Farmers Exchange Rate in Indonesia**

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**ABSTRACT**

Farmers exchange rate is an important variable to measure the farmers welfare. However, previous research finds that it affected by another variables such inflation and rice price. this paper try to investigates the interplay among inflation, rice price towards farmers exchange rate in a short-term and long-term. the novelty in this research is the using of short-term and long-term analysis to explain how farmers welfare influenced by the regressors in each period. The research method is quantitative analysis using the Auto regression and distributed lags model. this method perceived suitable to explain the result in a short and long term. the research shows that the inflation rate and domestic rice prices have a positive and significant effect on food crop farmers' exchange rates both in the short and long term. According to the short-term ARDL model, farmer exchange rates are also influenced by farmer exchange rates from the previous 1-2 years. The inflation rate has also been shown to have a direct effect on farmer exchange rates in the short term. Furthermore, rice prices had a significant impact on farmer exchange rates in the previous three years, indicating that rice prices had a long-term impact on farmer exchange rates in Indonesia.

Keywords: farmers exchange rate, inflation, rice price, ARDL

**INTRODUCTION**

Rice is the most important food commodity in Indonesia (McCulloch & Timmer, 2008; Perdana Windarto & Wanto, 2018). It is a staple food for more than 90% of the population. Rice is the most important agricultural commodity due to its high consumption, and price movements and production are constantly monitored. Indonesia is the world's third largest rice producer, with production expected to reach 31.54 million tons in 2022.

Most of farmers cultivate paddy for their primary crop (Hermawan et al., 2017). The commodity plays a critical role in national food security (Mariyono, 2014). It production is primarily concentrated on the island of Java, which serves as Indonesia's primary agricultural center. Java Island contributes approximately 55% of national production. In line with Widiyanti (2015) research, this demonstrates how important Java is in meeting the food demand. Farmers are attempting to increase cultivation productivity and efficiency in order to meet existing challenges such as rising food demand, climate change, and land scarcity (Setiyowati et al., 2018; Setiawan et al., 2022). This effort became critical in maintaining food security and farmer welfare while reducing reliance on rice imports.

The majority of Indonesia's population earns a living as farmers, and approximately 250 million Indonesians consume rice every day, which must be fulfilled (Wulandari et al., 2020). Given that these farmers welfare are a vulnerable group experiencing poverty, their well-being is a major concern (Anindita & Setiawan, 2014; Setiawan & Adzim, 2017). Several factors contribute to farmers' low level of welfare in Indonesia, including limited land ownership, fluctuations in agricultural production, and fluctuations in agricultural product selling prices. Farmers' income potential is limited by limited land ownership, and fluctuations in production and selling prices can lead to income uncertainty (Setiyowati et al., 2018).

Price fluctuations are caused by insufficient production and a reduction in output (McCalla, 2009). This causes volatile food inflation if production is halted for any reason, such as a lack of raw materials, a lack of knowledge, or a problem with the logistics system. According to McCulloch (2008) states that food price inflation is primarily caused by information asymmetry and market distortions, resulting in domestic market prices that are not actual prices, which is also harmful to farmers and ultimately reduces farmer welfare. Meanwhile, if the price of rice fluctuates, it will have an effect on the farmer's exchange rate (Makbul et al., 2021).

As a primary staple food commodity, rice price fluctuations is closely monitored. Fluctuations in rice prices undoubtedly have an impact on inflation. Considering that food inflation contributes the most to overall inflation, changes in rice prices become a crucial factor that affects the inflation.

Inflation and rice price fluctuations have a direct impact on grain selling prices at the farm level. According to Ramadhanu et al., (2021) an increase in inflation will affect the price level of domestic rice, which in turn will affect supply and demand for domestic rice, resulting in price level volatility. Farmers' exchange rates are affected by fluctuations in rice prices. found that food inflation has a positive and significant effect on farmers' income in the long run. Tupamahu et al., (2021) and Bafada (2020) discovered that an increase in inflation would reduce farmers' exchange rated. In contrast, Aulia & Wibowo (2021) and Lee (1980) found that inflation could increase the farmers exchange rate.

The income farmers is largely determined by production and prices that received for the crops. However, it is often the case that the rise in rice prices does not necessarily translate into higher incomes for farmers, as the surplus profits tend to be captured by middlemen and traders. This discrepancy between the impact of price increases and the actual income gains experienced by farmers can lead to an imbalance in their overall welfare.

Previous studies have investigated the impact of the inflation rate and rice prices on farmer welfare. However, there are inconsistencies in research findings concerning the effect of inflation on farmer welfare. Tupamahu et al., (2021) discovered that a decrease in the inflation rate would increase farmer welfare, in contrast to Lee (1980) who discovered that an increase in inflation would increase the prices of goods and services, particularly agricultural products, thus encouraging farmer welfare. Furthermore, by employing a time series data approach to obtain more empirical findings, this study attempts to fill a gap in the literature regarding studies on the level of welfare of farmers in Indonesia. Therefore, previous findings did not answer the short-term and long-term impact towards farmers welfare. This study also try to investigate the impact of inflation and rice price on farmers welfare in a short-term and long-term. The period need to investigates because we will get an information whether variables have a time sensitivity or not.

**METHOD**

This research is a quantitative study that utilizes an econometric method. Quantitative research involves analyzing populations or samples using research tools that provide numerical data to test predetermined hypotheses. The study aims to determine the effect between the variables of farmers welfare, consumer price inflation and rice price in Indonesia. In this study, the Auto Regression and Distributed Lags (ARDL) method was applied. The data used in the study was obtained through an observational process and consisted of secondary data sourced from the BPS and hargajateng.org. The study specifically utilized time-series data for Indonesia from Januari 2018 until Maret 2023, resulting in a total of 63 monts of observations.

The variables used in this study are the exchange rate of food crop farmers as the dependent variable, and 2 independent variables including consumer price index inflation, and Central Java rice prices. Specifically, Table 1 shows the operational definitions for the variables used in this study. Based on the three variables that have been identified, the hypothesis is that the farmer's exchange rate variable is a function of two other variables, namely the inflation variable and the rice price variable.

NTP = F (INF, RP) ..……………………… (1)

Whereas NTP denotes the exchange rate for food crop farmers, INF denotes the value of inflation and the consumer price index, and rp denotes the price of rice in Central Java. The sample used 63 months of observational data and Indonesian time series data from January 2018 to March 2023 obtained from Central Statistics Agency (BPS) and hargajateng.org reports. The three variables' data are calculated in percentage units. For time series data, all data is then converted into a logarithmic equation. As a result, the obtained coefficient value can be interpreted as an elasticity value.

**Table 1.** Operational Definition of Variables

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Variables** | **Code** | **Descriptions** | **Unit** | **Source** |
| Farmer Exchange Rate | NTP | Crop Farmer Exchange Rate that represented farmer welfare | Index | BPS. |
| Inflation Rate | INF | Inflation rate based on consumer price index  | Index | BPS. |
| Rice Price | RP | Price of Rice in Central Java | Rupiahs | Hargajateng.org |

Source: Data Processed (2023)

This study uses the Autoregressive Distributed Lag (ARDL) approaches for time series analysis. This ARDL method determines whether there is a long-term relationship between time series variables. Operationally, the ARDL method has the advantage of not requiring the variables used to be stationary at the same level (Enders, 2004). However, we cannot use this method to estimate variables at the second level of difference (I(2)). In this study, we carried out several estimation steps using the ARDL model following previous research (Nkoro & Uko, 2016). First, is estimating and analyzing the ARDL model, which includes: model selection and conducting diagnostic tests whether there are assumption violations or not before proceeding to the next procedure. Second, compiling an error correction model (ECM) based on the selected model and conducting tests to find out the long-term cointegration relationship (Johansen & Juselius, 1990). Third, analyze the output to determine short-run dynamics. And the final step is to analyze the long-term coefficient of the ARDL model.

Analyzing time series data requires ensuring that the data is stationary. In testing the stationarity of data in this study, the Augmented Dickey-Fuller (ADF) test designed by Hassler & Wolters (2006) was used, which aims to determine the presence of a unit root. The ADF test is an AR(1) process with the following equation.

$∆y\_{t}=α+βy\_{t-1}+e\_{t}$ ………………..…. (2)

Where yt is the time series, t is the time period, α is the constant, and e is error term. The test is conducted by checking the stationarity of each time series included in the model at that level. If a time series is not stationary at the level, a stationarity test is performed at the first difference. If all variables are stationary at the first difference, then further analysis can be conducted.

After conducting the stationarity test, the next step is to estimate the ARDL equation. Based on the Monte Carlo experiments by (Gerrard & Godfrey, 1998), the ARDL model is considered better in estimating the coefficients of long-run cointegrating relationships. According to Pesaran & Shin (1995) the ARDL model is generally represented by the following equation:

Y = $β\_{0}X\_{t}+β\_{1}X\_{t-1}+β\_{2}X\_{t-2}+...+µ\_{t}$

….………………………………..…………….. (3)

While the ARDL model in this study is transformed into a logarithmic form and the lag is as follows:

$LnNTP\_{t}=β\_{1}INF\_{t-i}+β\_{2}LnRP\_{t-i}+µ\_{t}$ ………………………………………………….. (4)

Where NTP represents the exchange rate of food crop farmers, INF represents the inflation rate according to the consumer price index, RP is the price of rice in rupiah, Ln is the natural logarithm, α is a constant, β1, β2, β3, β4, β5 are the coefficients of the independent variables, t-i represents the time period i, and µt represents the residual/error.

The use of the ARDL model depends on the optimal lag length used in the model. Therefore, the selection of the optimal lag length plays a very important role in determining the suitability of the ARDL model. Several measures, such as Sequential Modified LR Test Statistics (LR), Final Prediction Error (FPE), Akaike Information Criterion (AIC), Schwarz Information Criterion (SC), and Hannan-Quinn Information Criterion (HQ), can be used to identify the ideal lag length. The number of asterisks (\*) in the test results of each criterion can be used to conclude the ideal lag length (Pesaran, 2006). The more asterisks in a lag, the lag will be selected as the optimal lag for the formed ARDL model. After the optimal lag length is known, it is necessary to determine the appropriate ARDL model. The criteria for determining a suitable model are based on the AIC graph, one of the outputs of data processing. The graph shows that the best ARDL model is the ARDL model that has the smallest AIC value among other alternative ARDL models.

The next testing is the Bound Test, which is a test to determine whether there is cointegration or a long-term relationship between the variables used in the study (Hunter, 2019). In the Bound Test, testing is done using an F-test. It can be concluded that there is a cointegration relationship between variables if the F-test value generated is higher than the critical value at I(1). On the other hand, we can claim that the variables are not cointegrated if the F-test value generated is less than the critical value at I(1).

The next step is to estimate the short-term model using ECM after the long-term relationship between variables has been determined. The short-term equation used is as follows:

$EC\_{t}=Ԑ\_{t} =y\_{t}-\sum\_{i=1}^{k}θ\_{i}x\_{it}-ψ^{'}w\_{t}$ (5)

Short-term impact elasticity of independent variables on dependent variables can be observed in the ECM created. The cointEq1 coefficient (in Eviews 12 output) or the error correction term (ECT) coefficient of the ECM model will also be obtained. These terms describe the level of adjustment or speed of residuals in the previous period to correct the dependent variable towards equilibrium in the next period. According to the t-test findings, the model is valid if the ECT coefficient is negative and significant.

Therefore, accuracy and stability testing of the model is needed in the final stage of modeling using the ARDL and ECM methods. Testing is performed through classic assumption tests to see if there is autocorrelation in the residual model using the Breusch-Godfrey LM Test method, and stability testing using the CUSUM test method (Cho et al., 2015). According to Pesaran (2004), in the Breusch-Godfrey LM Test method, a model is said to have no autocorrelation if the resulting p-value is larger than the threshold value. On the other hand, a model is considered stable if the CUSUM test graph shows that the cusum line (blue line) is between the significance lines (red line).

**RESULT AND DISCUSSION**

The first step in analyzing the ARDL model is the stationarity test. This is intended to determine whether the data is stationary or not. To avoid spurious regression, this stationarity test is intended to ensure the order of integration and ensure that the input data is not stationary at order 1 or I(1). Because if there are variables that are stationary in first difference, the ARDL method is not suitable for use. The stationarity test in this study uses Augmentet Dickey-Fuller (ADF) Test, specifically the results of the stationarity test for the research variables are shown in table 2 below:

|  |  |  |
| --- | --- | --- |
| **No.** | **Level** | **1st difference** |
| **Variable**  | **Prob.** | **Variable** | **Prob.** |
| 1. | NTP | 0.0323 | D(NTPTP) | 0.0003 |
| 2. | INF | 0.5572 | D(INFIHK) | 0.0000 |
| 3. | RP | 0.0000 | D(HARBER) | 0.0000 |

**Table 2.** Unit Root Test Results with ADF Test Method

Source: Data Processed (2023)

Table 2 shows that all variables used in this study are stationary at first difference I(1) as indicated by the probability values α<0.05, and not stationary at level I(0) as indicated by the probability values α>0.05. The selection of optimum lag is very significant in the ARDL model. Therefore, it is necessary to select the optimum lag criteria, which are specifically shown in Table 3.

From the table above, it can be observed that the pre-differenced probability values of NTP and RP are lower than the alpha value at a 5% confidence level (0.0003<0.05 and 0.0000<0.05), while the probability value of the variable INF is higher than the alpha value at a 5% confidence level (0.0000>0.05). The results of the Augmented Dickey-Fuller test for these three variables indicate that one variable has non-stationary data. The presence of non-stationary data can lead to spurious regression or spurious correlation, thus requiring differentiation at different levels. The results reveal that the probability values for these three variables are lower than the alpha value at a 5% confidence level, indicating that the data is stationary.

**Table 3.** Test Results for Optimal Lag Determination

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Lag** | **LogL** | **LR** | **FPE** | **AIC** | **SC** | **HQ** |
| 0 | -914.8945 | NA  |  3.89e+09 |  30.59648 |  30.70120 |  30.63744 |
| 1 | -801.5341 |  211.6059 |  1.20e+08 |  27.11780 |  28.53667 |  27.28165\* |
| 2 | -789.5464 |  21.17831\* |  1.28e+08 |  27.10821 |  27.75123 |  27.30494 |
| 3 | -785.2012 |  7.242094 |  1.09e+08\* |  27.01337\* |  27.22054\* |  27.58298 |

Note: \* indicates lag order selected by the criterion

Source: Data Processed (2023)

Based on table 3, it can be seen that the ideal lag to be used in this ARDL model is (-3). Lag (-3) is chosen as the ideal lag because there are many asterisks (\*) in the lag (-3) criteria value, specifically at lag 3 which is the lag optimum for most criteria including Final Prediction Error (FPE), Akaike Information Criterion (AIC), and Hannan-Quinn (HQ). Therefore, lag (-4) will be used for additional analysis.

The next step is to determine the best ARDL model using the AIC criteria. The best ARDL model is determined by comparing the AIC values of the automatically generated ARDL models through the analysis software used in this study, which is Eviews 12 application, based on the number of lags used for each model. The results of determining the best ARDL model in this study are shown in figure 1 below



**Figure 1.** Results of Optimal Lag Length (Best Model) Determination Using AIC Criteria

Source: Data Processed (2023)

In the Figure 1, the horizontal axis represents the ARDL models created, and the vertical axis represents the AIC value. The optimal ARDL model is the one with the highest AIC value, so according to the table above, the best model is ARDL(1,3,0) with an AIC value of 3.210.

The next step is to test whether the variables used in this study have a long-run equilibrium relationship (cointegration). In conducting the cointegration test of variables, this study uses the F-Bound Test. The results of the cointegration test using the F-Bound Test are shown in Table 4 below:

**Table 4**. Bound-Testing Cointegration Test (F-Bounds test)

|  |  |  |
| --- | --- | --- |
| **Test Statistic** | **Value** | **K** |
|  |  |  |
|  |  |  |
| F-statistic | 5.873379 | 2 |
|  |  |  |
|  |  |  |
| Critical Value Bounds |
|  |  |  |
|  |  |  |
| Significance | I0 Bound | I1 Bound |
|  |  |  |
|  |  |  |
| 10% | 3.17 | 4.14 |
| 5% | 3.79 | 4.85 |
| 2.5% | 4.41 | 5.52 |
| 1% | 5.15 | 6.36 |
|  |  |  |
|  |  |  |

Source: Data Processed (2022)

In the cointegration bound-testing, the F-statistic value of 5.8733 is greater than the upper limit value of I(1) at the 5% level which is 4.85. This indicates that all variables have a long-run equilibrium relationship or can be said that the three variables move together in the long run. The results of the model testing using the Akaike Information Criterion (AIC) method show that the Autoregressive Distributed Lag (ARDL) model with lags (2,3,0) (see figure 1) is the best model. Thus, the long-run model estimation is obtained as follows:

**Table 5.** ARDL Short Run Estimation Results

|  |
| --- |
| Selected Model: ARDL(2,3,0) |
| Dependent Variable: LnNTP |
| **Variable** | **Coefficient** | **t-Statistic** | **Prob.\*** | **Explanation** |
| LnNTP(-1) | 1.343571 | 12.17786 | 0.0000\* | Significant |
| LnNTP(-2) | -0.564904 | -5.169171 | 0.0000\* | Significant |
| LnRP | 3.68E-05 | 0.561697 | 0.5767 | Not Significant |
| LnRP(-1) | 7.30E-05 | 1.107630 | 0.2731 | Not Significant |
| LnRP(-2) | -7.20E-05 | -1.091891 | 0.2799 | Not Significant |
| LnRP(-3) | 0.000149 | 2.409105 | 0.0196\* | Significant |
| INF | 0.026247 | 2.492759 | 0.0159\* | Significant |
| C | 17.37203 | 3.441798 | 0.0011\* | Significant |
| R-Square | 0.886346 |  |  |  |
| Adjusted R-Squared | 0.871046 |  |  |  |
| F-Statistics | 57.93246 |  |  |  |
| Prob(F-Statistics) | 0.000000 |  |  |  |

Source: Data Processed (2023)

Further examination of the partial estimation results reveals that if all variables are at 0, the farmer welfare will increase by 17,37. The farmer welfare in the previous year also significantly increases the farmer welfare in the following year, with a 1% increase in the food production index leading to a 1,34 increase in the farmer exchange rate in the next year. Furthermore, an increase in rice price also will stimulate farmer exchange in 1-3 year prior by 7,30 and 0,01 respectively. The inflation rate also proved has significant and positive effect on farmer welfare, every 1% increase of inflation rate will increase farmer welfare by 0,03 in the short term. This short term ARDL model has R-Square value 0,886346, which means this model already explain 88,63% variance effect of farmer welfare, and the other 13,37% are explain in outside models.

The next step in this analysis is the stability test of the Autoregressive Distributed Lag (ARDL) model, which in this study uses the CUSUM test. This test is used to determine whether the model is stable or not. Figure 2 shows the CUSUM test which displays a blue line between the significance lines (red lines).



**Figure 2.** The Plot of Model Stability Test Results with the CUSUM Test Method

Source: Data Processed, 2023

Based on the CUSUM test results, it is evident that the blue line is still between the two red lines with a significance of 5%, indicating that the model in this study is stable and can be used to explain long-term cointegration. After it was determined that the model has long-term cointegration in the bound-test, the long-term model estimation can be obtained. Table 6 below shows the results of the ARDL long-term estimation model in this study:

**Table 6.** Long Run Estimation Model, Dynamic Cointegration and Speed of Adjustment

|  |
| --- |
| **Cointegrating Form** |
| **Variable** | **Coefficient** | **t-Statistic** | **Prob.** | **Explanation** |
|  |  |  |  |  |
| CointEq(-1) | -0.37203 | 3.441798 | 0.0011\* | Significant |
|  |  |  |  |  |
|  |  |  |  |  |
| Cointeq = LnNTP - (0.0008\*LnRP + 0.1186\*INF + 78.4882)  |
|  |  |  |  |  |
|  |  |  |  |  |
| **Long Run Coefficients** |
| **Variable** | **Coefficient** | **t-Statistic** | **Prob.** | **Explanation** |
| LnRP | 0.018045 | 1.527767 | 0.0326\* | Significant |
| INF | 0.118586 | 2.783868 | 0.0075\* | Significant |
| C | 78.48821 | 9.337319 | 0.0000\* | Significant |
|  |  |  |  |  |

Source: Data Processed (2023)

 Based on the long-term estimation results of the ARDL model in Table 6 above, it can be seen that the CointEq coefficient value will be used to explain the speed of adjustment or the speed of adjustment in response to changes. The CointEq value in the above estimation results is -0.37203with a probability value of 0.0011, which can be said to be significant at α<5%. This means that the ARDL model has short term cointegration. In addition, the CointEq value of -0.37203 is a negative value indicating that the model will head towards equilibrium at a rate of 0.37% per year.

Based on the ARDL model estimation results above, it is known that in the long run, when all independent variables have a value of 0, the value of the food production index is 78.48821. In the long run rice prices have been shown to have a positive and significant effect on increasing farmer welfare, every 1% increase in rice prices will result in an increase in farmer welfare of 0.02. Furthermore, the inflation rate has also been shown to have a positive and significant effect, meaning that every 1% increase in inflation will encourage farmers' welfare by 0.11.

To ensure that the ARDL model used in this study is valid and best model, classical assumption tests were carried out, consisting of normality, autocorrelation, and heteroscedasticity tests. Table 7 shows the results of the classical assumption tests, and it is known that the ARDL model used in this study is free from all classical assumption problems.

**Table 7.** Classical Assumption Test

|  |  |  |  |
| --- | --- | --- | --- |
| **Classical Assumption** | **Type of Test** | **Result Score** | **Description** |
| Normality | Jarque Bera Value | 0.0436 < α 0.05 | Data normally distributed |
| Autocorrelation | Breusch-Godfrey Serial Correlation LM Test | 0.1024> α 0.05 | No Autocorrelation |
| Heterokedasticity | Harvey Test | 0.6175> α 0.05 | No Heterokedasticity |

Source: Data Processed (2023)

Indonesia as an agricultural country has a very high amount of food crop production and is one of the world's food crop centers. However, market distortions, variable macroeconomic volatility, and market information asymmetry have resulted in the price of food crops in Indonesia being very low in several conditions(Anindita & Setiawan, 2014). This study tries to identify 2 factors that play an important role in the welfare of farmers, namely inflation and domestic rice prices.

This research succeeded in proving that inflation both in the long and short term can increase the farmer exchange rate which represents farmer welfare. This finding is consistent with research conducted by Tupamahu et al., (2021), who discovered that increasing inflation will reduce farmer exchange rates by using a panel of data from 12 Indonesian provinces. Ramadhanu et al., (2021) further states that inflation has a terrible and massive impact on farmers' trade prices. Hermawan et al., (2017) asserts that rising inflation will raise the cost of domestic goods in Indonesia, thereby improving farmer welfare through increased farmer household income. Surprisingly, Yasin & Amin (2021) discovered that farmer exchange rates could boost inflation rates due to Covid-19 outbreaks in Indonesia.

Furthermore, increasing the value of farmer exchange rate determined to have a significant impact on national economic growth. According to research from Nurhab (2022), an increase in farmer exchange rates has been shown to be able to accelerate the pace of economic growth in Indonesia, which is an agricultural country with a high production of food crops. Setiyowati et al., (2018) discovered empirically through path analysis that inflation has a terrible and enormous effect on farmers' trade prices. Inflation volatility is important in the formation of agricultural output prices, supply and demand, including rice, which is the commodity with the highest consumption in Indonesia (McCulloch, 2008). Increased inflation and farmer exchange rates have also been shown to be one of the efforts in poverty alleviation for low-income communities (Jayadi, 2012).

This study was successful in demonstrating that price is a critical component that has a significant impact on farmer welfare both in the long and short term, as it is an endogenous factor in the formation of farmer income (Anindita & Setiawan, 2014). This finding is consistent with research by Ramadhan (2023) using regional panel data, which discovered that farmer prices and incomes had a positive and significant influence on farmer exchange rates in Medan Krio Village. According to Barrett & Dorosh (1996), economic theory provides clear guidance on how to model the welfare effects of food price increases. Consider a household that consumes and possibly produces a staple food commodity as well as engages in other economic activities. Hari (2009) added to the previous statement by stating that welfare is also affected by price variability, economists are familiar with Arrow-Pratt income risk aversion. This is the assumption that utility is concave in income, implying that income variability reduces household welfare.

Domestic rice prices are empirically determined by supply and demand in the domestic rice market (Mariyono, 2017). Rice is the primary staple product in Indonesia, and it is a critical component for community welfare; approximately 250 million Indonesians consume rice every day, and this demand must be fulfilled (Wulandari et al., 2020). The increase in population and demand for the main commodity cause fluctuations in product availability and prices. Furthermore, rice contributes to food security, poverty reduction, macroeconomic stability, and the country's economic growth (Setiartiti, 2021). In this regard, the government should manage and secure the rice price in order to provide food price stability for the entire community (Sayeed & Yunus, 2018).

Price regulation ostensibly ensures balanced value, so that farmers can produce rice of reasonable quality in sufficient quantities and the community can obtain rice products at affordable prices (Makbul et al., 2020). A Stable crop price promotes national food security goals while also increasing social welfare. It can also clearly protect farmers and reduce poverty. Hani et al., (2023) contended that the agricultural sector employed the majority of poor rural citizens. In another study, Makbul et al., (2021) added that if consumption patterns were concentrated locally, price increases would have a positive spillover effect on rural economies. As a result, value would circulate among local communities, promoting the growth of small businesses. Barrett & Dorosh (1996) conducted research in Madagascar, bolstering the notion that gross farm income had a significant impact on rice production. Cororaton (2004) conducted research in the Philippines and concluded that the exportation of premium rice affected domestic rice prices and farm income. McCalla, (2009) showed the impact of rice prices on farm incomes, finding that the consequences of high rice prices influenced farm income and larger firm production.

**CONCLUSION**

This study was successful in demonstrating that the inflation rate and domestic rice prices have a positive and significant effect on food crop farmers' exchange rates both in the short and long term. According to the short-term ARDL model, farmer exchange rates are also influenced by farmer exchange rates from the previous 1-2 years. The inflation rate has also been shown to have a direct effect on farmer exchange rates in the short term. Furthermore, rice prices had a significant impact on farmer exchange rates in the previous three years, indicating that rice prices had a long-term impact on farmer exchange rates in Indonesia. This research was also successful in filling in the gaps in the literature and research inconsistencies that occurred in previous studies regarding the effect of inflation on farmers' exchange rates.

The results of this study explain the crucial role of inflation and the price level of rice in explaining the welfare of farmers in Indonesia. This research suggests the government to compile price regulations ostensibly ensuring balanced value, so that farmers can produce rice of reasonable quality in sufficient quantities and the community can obtain rice products at affordable prices. F Furthermore, the government must ensure that the market operates in a balanced and perfect competition environment, which means that there should be no information asymmetry that could lead to price discrimination, thereby harming farmers and disrupting the supply chain of rice commodities. Because this study is limited to the rice commodity and the research scope is national, it is hoped that future studies will provide a more in-depth analysis using more advanced approaches and analytical tools, as well as a broader research scope, to obtain more empirical findings.

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