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Unraveling The Interplay Among Inflation, Rice Prices, And Farmers Terms of Trade in Central Java, Indonesia

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ABSTRACT

Farmers' Terms of Trade is an essential variable for measuring welfare and is also affected by other factors, such as inflation and rice prices. Therefore, this study aimed to investigate the interplay among inflation, rice prices, and farmers' Terms of Trade in food crop farming in Central Java Province, in short and long term using a dynamic model. A quantitative method employing Autoregressive distributed lags (ARDL) model was used with monthly data from January 2018 to March 2023. The results showed that rice prices and inflation partially had a significant and positive influence on farmers' Terms of Trade in long term. According to short term estimation, the dependent variable was significantly and positively influenced by farmers' Terms of Trade from the previous 1-2 months. Inflation rate was also shown to have a positive influence on the variable in short term. In addition, rice prices had a positive and significant impact in the previous 3 months, but had no significant influence in recent months. Based on the results, inflation could positively influence farmers' Terms of Trade in short and long term. However, the recent rice prices had no impact due to the requirement of time lags. The assessment findings showed that recent rice prices could significantly increase farmers' Terms of Trade in the next 3 months and long term period.

INTRODUCTION

Rice is the most important food commodity in Indonesia (McCulloch & Timmer, 2008; Windarto & Wanto, 2018), holding an essential position as a staple food for more than 90% of the population. In addition, the significance of this commodity in agricultural sector is evident through the constant assessment of its consumption patterns, price dynamics, and production levels. According to previous studies, Indonesia is the world's third-largest rice producer, with an anticipated increase in production to 31.54 million tons in 2022.

In the context of agricultural

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production, the majority of farmers engage in the cultivation of rice as the primary crop (Hermawan et al., 2017). This increased cultivation is primarily due to the role of the commodity in facilitating national food security (Mariyono, 2014). Previous reports also showed that its production was predominantly concentrated on Java Island, which serves as Indonesian primary agricultural center, contributing approximately 55% to the nation output. These results are consistent with the study conducted by Widiyanti (2015), demonstrating the importance of Java in meeting food demand. Despite the potential of the area, several challenges affecting production have been identified, including increased food demand, climate change, and land scarcity. Consequently, farmers are required to increase cultivation productivity and efficiency (Setiyowati et al., 2018; Setiawan et al., 2022) in an effort to maintain food security and welfare as well as reduce reliance on rice imports.

In Indonesia, the number of farmers is reported at 40.69 million individuals (BPS: 2023), with approximately 250 million Indonesians consuming rice daily (Wulandari et al., 2020). However, farmers who play an essential role in meeting this high demand have been identified as a vulnerable group experiencing poverty, indicating the need to prioritize their welfare (Anindita & Setiawan, 2014; Setiawan & Adzim, 2017). Several factors contribute to the low level of welfare among this demographic, such as limited land ownership, fluctuations in agricultural production, and unpredictability of agricultural product selling prices. Limited land ownership has been reported to impede farmers' income potential, while fluctuations in production and selling prices can lead to income uncertainty (Setiyowati et al., 2018).

According to previous studies, price fluctuations are caused by insufficient production and a reduction in output (McCalla, 2009). These fluctuations can lead to volatile food inflation when production is halted due to reasons, such as a shortage of raw materials, a lack of knowledge, or logistical issues. In addition, McCulloch (2008) stated that food price inflation was primarily caused by information asymmetry and market distortions. Consequently, domestic market prices deviate from actual prices, leading to various detrimental effects on farmers, particularly their welfare. Variations in rice prices have also been shown to exert a significant impact on farmers' Terms of Trade (Makbul et al., 2021).

As a primary staple food commodity, fluctuations in rice prices are closely monitored due to their significant influence on inflation. According to Cameron (1980), food inflation can significantly affect the overall or "real" inflation in a country due to its prominent role in the consumer price index (CPI), which is a key indicator. Furthermore, the consumer price index reflects the average change over time in the prices paid by urban consumers for a market basket of goods and services. Given the fundamental nature of food as a necessity, changes in prices have a direct and immediate impact on household budgets and consumer behavior (Woertz et al., 2014), necessitating government intervention to stabilize the market condition (Annisa et al., 2022). Recent data showed that the year-on-year inflation in Indonesia until September 2023 was approximately 2.56%, coinciding with an 18.44% increase in rice price accumulation in 2023 (BPS, 2023).

Inflation and fluctuations in rice prices have been shown to have a direct impact on grain selling prices at the farm level. According to Ramadhanu et al. (2021), an increase in inflation has effects on the price level of domestic rice, which in turn influences the supply and demand, leading to price level volatility. In addition, these fluctuations are known to have a significant impact on farmers' Terms of Trade. Tupamahu et al. (2021) and Bafada (2020) also stated that an increase in inflation could reduce farmers' Terms of Trade. The result was inconsistent with Aulia & Wibowo (2021) and Lee (1980), which reported the positive effect of increased inflation on the variable.

The income of farmers is largely determined by the production levels and prices received from crops. However, an increase 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 increment and the actual income gains experienced can lead to an imbalance in the overall welfare.

Previous studies investigated the impact of both inflation rates and rice prices on farmers' welfare. However, there are inconsistencies in results concerning the effect of inflation on farmers' Terms of Trade. Tupamahu et al. (2021) stated that a decrease in the parameter could increase farmers' Terms of Trade. Meanwhile, Lee (1980) reported that an increment in inflation could increase the prices of goods and services, particularly agricultural products, leading to enhanced welfare. These studies used the consumer price index for calculating inflation. Based on the results, there are limited studies employing dynamic models to address the research question. In an attempt to bridge the gap, this current study adopts a time series data approach to obtain more empirical results on farmers' welfare in Indonesia. Previous results also not fully elucidated short and long term impact on farmers' Terms of Trade. Therefore, this study aims to fill the gap using a dynamic model to assess the time lag effect of inflation and rice prices on Terms of Trade.

METHODS

This quantitative study was carried out using an econometric method and comprised analyzing populations or samples using report tools providing numerical data to test predetermined hypotheses. In addition, the study aimed to determine the influence of inflation and rice

Table 1. Operational Definition of Variables

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

Source: Data Processed (2023)

prices in Indonesia on farmers' Terms of Trade. In this investigation, Autoregressive distributed Lags (ARDL) method was applied, and the data used was obtained through secondary data sourced from Central Statistics Agency (BPS) and hargajateng.org. Central Java Province time-series data from January 2018 to March 2023 were utilized, leading to a total of 63 months of observations.

Terms of Trade of food crop farmers served as the dependent variable, while inflation and Central Java rice prices were used as independent variables. Table 1 showed the operational definitions for the variables used in this study. Based on the 3 factors identified, the hypothesis was that farmers' Terms of Trade were a function of 2 other factors, namely inflation and rice prices.

NTP = F (INF, RP) .... (1)

Where NTP is farmers' Terms of Trade, INF is the value of inflation and the consumer price index, and RP is rice prices in Central Java. This study used 63 months of Central Java Province time series data from January 2018 to March 2023 obtained from BPS and hargajateng.org reports. Farmers' Terms of Trade were calculated using an index, and rice prices were converted to natural logarithmic (LN) form. However, inflation was not converted to natural logarithmic because it was already a percentage unit, indicating that it could be interpreted as an elasticity. Based on the results, the obtained coefficient value could be decoded as an elasticity value.

The ARDL method was employed for conducting time series analysis to ascertain whether a long-term relationship exists between the variables. Unlike some methods, ARDL doesn't necessitate all variables to be stationary at the same level, as noted by Enders (2004). However, it's not suitable for estimating variables at the second level of difference (I(2)). This report follows the steps outlined in a prior study by Nkoro & Uko (2016). Initially, the ARDL model was estimated and analyzed, involving model selection and diagnostic tests to identify any assumption violations. Subsequently, an error correction model (ECM) was constructed based on the chosen ARDL model, and tests were conducted to ascertain long-term cointegration relationships as per Johansen & Juselius (1990). The third step involved assessing short-term dynamics from the output, while the final step focused on analyzing the long-term coefficients of the ARDL model.

In the analysis of time series data, ensuring data stationarity is crucial. The Augmented Dickey-Fuller (ADF) test, devised by Hassler & Wolters (2006), was utilized in this study to test data stationarity and detect the presence of a unit root. The ADF test can be described as an AR(1) process with a specific equation.

$$\Delta y_t = \alpha + \beta y_{t-1} + e_t \quad \text{.....................} (2)$$

The ADF test evaluates the stationarity of each time series, denoted as yt, over time (t). Here, α represents the constant term, and e signifies the error term. Initially, each time series' stationarity was assessed at a particular level. If a time series did not exhibit stationarity at that level, a stationarity test was subsequently conducted at the first difference. Once all variables attained stationarity at the first difference, further analysis was carried out.

After conducting the stationarity tests, the next step was to estimate the ARDL equation. Based on Monte Carlo experiments by Gerrard & Godfrey (1998), the ARDL model was found to be superior in estimating coefficients related to long-term cointegrating relationships. According to Pesaran & Shin (1995), the ARDL model is typically represented by the following equation:

$$Y = \beta_0 X_t + \beta_1 X_{t-1} + \beta_2 X_{t-2} + \ldots + \mu_t \quad \text{...} (3)$$

ARDL model in this study was transformed into a semi-logarithmic form and the lag was as follows:

$$NTP_t = \alpha + \beta_1 INF_{t-i} + \beta_2 LnRP_{t-i} + \mu_t \quad \text{.......................................} (4)$$

Where NTP is farmers' Terms of Trade, INF is inflation rate according to the consumer price index, RP is rice prices in rupiah, Ln is the natural logarithm, α is a constant, β1 and β2 are the coefficients of the independent variables, t-i is the time I, and μt is the residual/error. This equation belonged to the semi-logarithmic model, and Inflation and NTP were not converted to natural logarithmic due to the percentage and index unit nature.

The selection of the optimal lag length was crucial for employing the ARDL model effectively, as it directly influenced its suitability. Various measures, including Sequential Modified LR Test Statistics (LR), Final Prediction Error (FPE), Akaike Information Criterion (AIC), Schwarz Information Criterion (SC), and Hannan-Quinn Information Criterion (HQ), were utilized to identify the ideal lag length. The number of asterisks (*) in the test results of each criterion indicated the significance level of the lag. A higher number of asterisks in a lag suggested a higher probability of it being selected as the optimal lag for the model. Once the optimal length was determined, the appropriate ARDL model was selected based on criteria such as the AIC graph, which depicted the model with the smallest AIC value as the best fit among others.

Subsequently, the Bound Test was employed to assess whether there existed cointegration or a long-term relationship among the variables under study. The Bound Test, as described by Hunter (2019), utilized an F-test for evaluation. Cointegration between variables was established if the F-test value exceeded the critical value at I(1). Conversely, when the F-test value was lower than the critical value at I(1), it indicated the absence of cointegration among the variables..

Estimation of short term model using ECM was carried out after long term relationship between the variables had been determined. Short term equation used was as follows:

$$\mathrm{EC_t} = \mathcal{E}_t = y_t - \sum_{i=1}^{k} \theta_i x_{it} - \psi' \mathrm{w}_t \quad \text{......................(5)}$$

The short-term impact elasticity of independent variables on dependent variables could be observed through the error correction model (ECM). Specifically, the cointEq1 coefficient (as labeled in Eviews 12 output) or the error correction term (ECT) coefficient represents the speed of adjustment or the level of correction of residuals from the previous period towards equilibrium in the subsequent time frame.

In the context of interpreting the ECM, a negative and statistically significant ECT coefficient, validated through t-test results, indicates that the model is robust. This signifies that the dependent variables adjust towards their equilibrium levels in response to changes in the independent variables. Essentially, a significant negative ECT coefficient implies that any deviations from the long-term equilibrium are corrected in the short term.

In the final stage of modeling using ARDL and ECM, it was essential to conduct accuracy and stability testing of the model. This involved performing classic assumption tests to detect autocorrelation in the residual model using the Breusch-Godfrey LM Test method. Additionally, stability assessment was carried out using the CUSUM test method, as outlined by Cho et al. (2015). According to Pesaran (2004), in the Breusch-Godfrey LM Test method, a model was deemed to have no autocorrelation when the resulting p-value exceeded the threshold value. Similarly, the stability of the model was assessed by examining the CUSUM test graph, where the CUSUM line (blue line) falling between the significance lines (red line) indicated model stability.

RESULTS AND DISCUSSION

The initial step in analyzing the ARDL model involved conducting a stationarity test. This was crucial to prevent spurious regression by ensuring the order of integration and verifying that the input data was not stationary at order 1, denoted as I(1). If any variables were found to be stationary in the first difference, ARDL would not be appropriate for analysis. In this study, the stationarity test utilized the Augmented Dickey-Fuller (ADF) test, specifically examining the results for the study variables. As presented in Table 2, all variables exhibited stationarity at the first difference, indicated by probability values (α) less than 0.05, suggesting

Table 2. Unit Root Test Results with ADF Test Method

Level		1st difference	
Variable	**Prob.**	**Variable**	**Prob.**
NTP	0.0323	D(NTPTP)	0.0003
INF	0.5572	D(INFIHK)	0.0000
RP	0.0000	D(HARBER)	0.0000

Source: Data Processed (2023)

non- stationarity at level I(0) with probability values (α) greater than 0.05. Moreover, the selection of the optimal lag was deemed highly significant in the ARDL model.

According to Table 2, the pre-differenced probability values of NTP and RP were lower compared to the alpha value at a 95% confidence level (0.0003< α 0.05 and 0.0000< α 0.05), while the probability value of the variable INF was higher than the alpha at a 5% (0.5572> α 0.05). The results of the ADF test for these 3 variables indicated that 1 variable had non-stationary data. Furthermore, the presence of non-stationary data could lead to spurious regression or spurious correlation, requiring differentiation at distinct levels. The results revealed that the probability values for these 3 variables were lower than the alpha (5%), indicating data stationarity.

Based on the results, it was necessary to select the optimum lag criteria, which were specifically shown in Table 3. The ideal lag to be used in ARDL model was (-3). Lag (-3) was selected because there were many asterisks (*) in the criteria value, specifically at lag 3, which was the optimum for most criteria, including FPE, AIC, and HQ. Therefore, lag (-4) could be used for additional analysis.

The subsequent step involved identifying the best ARDL model using the Akaike Information Criterion (AIC) criteria. This process entailed comparing the AIC values of various ARDL models generated automatically by the analysis software, in this case, Eviews 12 application, based on the different numbers of lags used for each model. The results of determining the best ARDL model in this study are presented in Figure 1.

In Figure 1, the horizontal axis represents the ARDL models created, while the vertical axis displays the corresponding AIC values. The optimal ARDL model, ARDL(1,3,0), is identified

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)

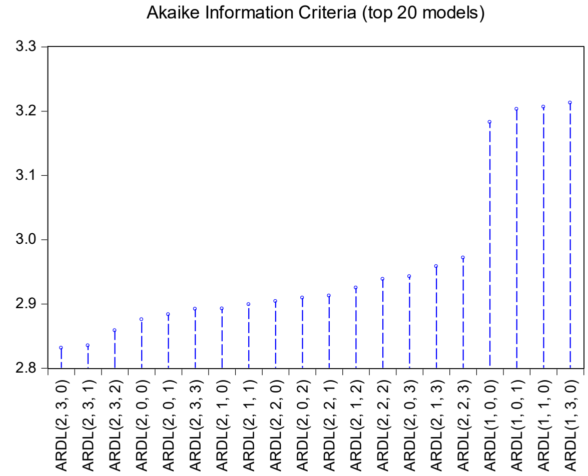

Figure 1. Results of Optimal Lag Length (Best Model) Determination Using AIC Criteria

Source: Data Processed (2023)

as having the highest AIC value, which is recorded at 3.210.

For the assessment, the next step was to assess whether the variables used in this study had long term equilibrium relationship (cointegration) using the F-Bound test. The results of the cointegration test using the F-Bound test are presented in Table 4 below. In the cointegration bound testing, the calculated F-statistic value of 5.8733 surpassed the upper limit value for I(1) at the 5% significance level, which was 4.85. This suggests that all variables exhibit a long-term equilibrium relationship, indicating that the three variables move together over the long term. Furthermore, the results from model testing using the Akaike Information Criterion (AIC) method indicated that the ARDL model with lags (2,3,0), as depicted in Figure 1, performed the best among the models considered.

The study procedures continued the evaluation of long term estimation model. Based on the estimation results in Table 6, the CointEq coefficient value was used to explain the

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)

Table 5. Long Run Estimation Model, Dynamic Cointegration and Speed of Adjustment

Cointegrating Form			
Variable	**Coefficient**	**t-Statistic**	**Probability**
CointEq(-1)	-0.37203	3.441798	0.0011***

Cointeq = NTP - (0.0008*LnRP + 0.1186*INF + 78.4882)

Long Run Coefficients			
Variable	**Coefficient**	**t-Statistic**	**Probability**
LnRP	0.018045	1.527767	0.0326**
INF	0.118586	2.783868	0.0075**
C	78.48821	9.337319	0.0000***

Note: ***Significance at p-value ≤0,01; **Significance at p-value ≤0,05
Source: Data Processed (2023)

speed of adjustment in response to changes. The CointEq value in the above estimation results was -0.37203 with a probability value of 0.0011, which was significant at α<5%. This indicated that ARDL model had short term cointegration. In addition, the CointEq value of -0.37203 was negative and the model was heading towards equilibrium at a rate of 0.37% per year. Table 5 showed the results of ARDL long term estimation model in this study.

Based on ARDL model estimation results, in long term, when all independent variables had a value of 0 or unchanged, the value of farmers' Terms of Trade was 78.48821. In addition, rice prices had a

Table 6. ARDL Short Run Estimation Results

Selected Model: ARDL(2,3,0)			
Dependent Variable: NTP			
Variable	**Coefficient**	**t-Statistic**	**Probability**
NTP(-1)	1.343571	12.17786	0.0000***
NTP(-2)	-0.564904	-5.169171	0.0000***
LnRP	3.68E-05	0.561697	0.5767
LnRP(-1)	7.30E-05	1.107630	0.2731
LnRP(-2)	-7.20E-05	-1.091891	0.2799
LnRP(-3)	0.000149	2.409105	0.0196**
INF	0.026247	2.492759	0.0159**
C	17.37203	3.441798	0.0011***
R-Square	0.886346		
Adjusted R-Squared	0.871046		
F-Statistics	57.93246*		
Prob(F-Statistics)	0.000000		

Note: *Significance at p-value ≤0,05
Source: Data Processed (2023)

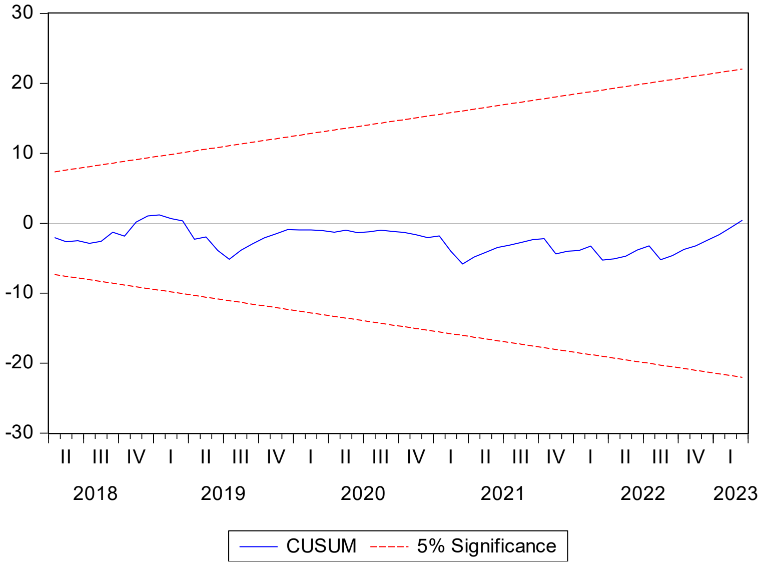

Figure 2. The Plot of Model Stability Test Results with the CUSUM Test Method
Source: Data Processed, 2023

positive and significant effect on increasing farmers' Terms of Trade. Every 1% increase in rice prices caused an increment in the variable by 0.00018 points. The results also revealed that inflation rate had a positive and significant effect, where every 1% increase in inflation caused an increment in farmers' Terms of Trade by 0.1185 points. According to the cointegration, these variables had long term influence.

The partial estimation results revealed that when all variables were at 0, farmers' Terms of Trade was 17.37 points in short term. Short term partial estimation showed that farmers' Terms of Trade in the previous month also significantly increased. A 1% increase in rice prices in the previous 3 months caused an increment in farmers' Terms of Trade by 0,00000149 points in a certain month. However, the increase in rice prices in the last 1, or 2 months did not significantly influence the variable in a certain month. Inflation rate also proved to have a significant and positive influence, where every 1% increase caused an increment in Terms of Trade by 0.026 points in short term. Short term ARDL model had an R-Square value of 0.886346. This indicated that it already explained 88.63% variance effect of farmers' welfare, and the other 13.37% were explained by factors outside this study.

The subsequent step in this analysis involved conducting a stability test of the ARDL model using the CUSUM test. As depicted in Figure 2, the CUSUM test exhibited a blue line positioned between the significance lines (red lines). Based on the results of the CUSUM test, it is evident that the blue line remained within the two red lines at a significance level of 5%. This signifies that the model is stable and can effectively elucidate long-term cointegration among the variables. Following the determination of long-term cointegration in the bound test,

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)

the estimation of the long-term model could be pursued with confidence.

To ensure that ARDL model used in this study was valid and the best, classical assumption assessments were carried out, consisting of normality, autocorrelation, and heteroscedasticity tests. The results showed ARDL model used in this study was free from all classical assumption problems, as shown in Table 7.

Indonesia as agricultural country had a very high amount of food crop production and was one of the world's food crop centers. According to the Ministry of Agriculture (2021), the production of food crops in Indonesia reached 153.06 million tons, presenting an increase of 1.15% compared to the previous year. The main food commodities produced were rice, corn, soybeans, and cassava. Rice production in 2021 reached 63.4 million tons, an increase of 0.73% compared to the previous year. Meanwhile, corn production reached 29.88 million tons, exhibiting a 0.57% increment, Soybean and cassava production reached 11.88 million tons and 23.15 million tons, respectively, with an increase of 3.97%, 1.88%. The Central Java Province served as a major contributor to agricultural production in Indonesia, also called "*Lumbung Padi Nasional*" due to approximately 40% of it being produced on Java Island (Prabayanti, 2022).

The market distortions, macroeconomic volatility, and market information asymmetry led to the low price of food crops in several conditions (Anindita & Setiawan, 2014). This study aimed to identify 2 factors that played an important role in farmers' welfare, namely inflation and domestic rice prices.

This report succeeded in proving that inflation both in long and short term could increase farmers' Terms of Trade, which represented farmers' welfare. This result was inconsistent with Tupamahu et al. (2021), which discovered that increased inflation reduced farmers' Terms of Trade by using a panel of data from 12 Indonesian provinces. Wibowo (2019) stated that an increase in inflation did not necessarily enhance welfare, and the relationship between both variables was complex. The investigation found that Inflation could lead to higher prices for agricultural commodities. This could benefit farmers by increasing the revenue earned from selling their produce. Farmers could also receive more money for the crops, leading to increased income and profitability. Inflation was reported to exert an influence on debt relief. Monke et al., (2022) asserted when farmers had procured loans at fixed interest rates that inflation could gradually diminish the actual value of the debt. This had the practical effect of lessening the weight of debt carried by farmers, thereby simplifying the ability to settle loans and potentially enhancing overall financial stability.

Ramadhanu et al. (2021) further stated that inflation had a terrible and massive impact on farmers' trade prices. Hermawan et al. (2017) also stated that the increase in inflation led to an increment in the production costs of domestic products in Indonesia. Simultaneously, this facilitated the enhancement of household income for farmers and overall welfare. Yasin & Amin (2021) discovered that farmers' Terms of Trade could boost inflation rates due to COVID-19 outbreaks. The COVID-19 pandemic reduced incentives to do farming, leading to a significant increase in production costs that ultimately led to uncontrollable escalation of agricultural commodity prices in the domestic market.

This study found that every 1% increase in rice prices only increased farmers' Terms of Trade by 0.02%. Based on these results, an increase in rice prices did not have a significant impact on the improvement of farmers' welfare represented by Terms of Trade. According to Hani et al., (2023), this phenomenon occurred because farmers' welfare was an indicator influenced by various factors, and not limited solely to the income earned. Girik et al., (2019) also stated that several external factors outside the market mechanism led to minimal benefits received by farmers from the increment in rice prices, such as government policy intervention and market monopolies by middlemen. In line with this result, Ruspayandi et al., (2022) suggested that the effect of rising rice prices on farmers' welfare was complex and depended on various factors, including the size and type of farming operation, government policies, and the overall economic context. Although higher rice prices could potentially provide benefits by increasing income and reducing debt burdens. However, it was essential to consider the broader socioeconomic implications and potential disparities in the farming community and among consumers.

The increased value of farmers' Terms of Trade had a significant impact on national economic growth. According to the study by Nurhab (2022), an increase was able to accelerate the pace of economic growth in Indonesia, which was agricultural country with a high production of food crops. Setiyowati et al., (2018) discovered empirically through path analysis that inflation had a negative effect. Maintaining stable inflation volatility in Indonesia was important in the formation of agricultural output prices, supply, and demand, including rice, which was the commodity with the highest consumption (McCulloch, 2008). Increased farmers' Terms of Trade was one of the efforts in poverty alleviation for low-income community (Jayadi, 2012).

This study was successful in demonstrating that price was a critical component with a significant impact on farmers' welfare both in long and short term, as it was an endogenous factor in the formation of income (Anindita & Setiawan, 2014). This result was consistent with a report by Ramadhan (2023) using regional panel data, which discovered that prices and income had a positive and significant influence on Terms of Trade in Medan Krio Village.

According to Barrett & Dorosh (1996), economic theory provided clear guidance on how to model welfare effects of food price increases. The theoretical framework examined a household that consumed and possibly produced a staple food commodity as well as engaged in other economic activities. Hari (2009) stated that welfare was also affected by price variability, and economists often referenced the Arrow-Pratt income risk aversion. This assumption posited that utility was concave in income, implying the reduction of household welfare by income variability.

Domestic rice prices were empirically determined by supply and demand in the domestic rice market (Mariyono, 2017). In addition, rice was the primary staple product in Indonesia, and it was a critical component of community welfare. Several studies showed that it was consumed by approximately 250 million Indonesians daily, creating a high demand to be fulfilled (Wulandari et al., 2020). The increase in population and demand for the commodity caused fluctuations in product availability and prices. Rice also contributed to food security, poverty reduction, macroeconomic stability, and the country's economic growth (Setiartiti, 2021). In this situation, the government must manage and secure the prices to provide food price stability for the entire community (Sayeed & Yunus, 2018).

Price regulation ostensibly ensured balanced value, ensuring that farmers produced rice in sufficient quantities and community could obtain the commodity at affordable prices (Makbul et al., 2020). A stable crop price promoted national food security goals while also increasing social welfare. Furthermore, it could also clearly protect farmers and reduce poverty. Hani et al. (2023) reported that agricultural sector employed the majority of poor rural citizens. In another study, Makbul et al. (2021) added that when consumption patterns were concentrated locally, price increases had a positive spillover effect on rural economies, leading to the circulation of value local community and promoting the growth of small businesses. Barrett & Dorosh (1996) conducted a report in Madagascar, bolstering the notion that gross farm income had a significant impact on rice production. Cororaton (2004) also conducted a study in the Philippines and concluded that the exportation of premium rice affected domestic prices and farmers' income. McCalla, (2009) showed that high rice prices influenced farmers' income and larger firm production.

CONCLUSION

In conclusion, this study was successful in demonstrating that inflation rate and domestic rice prices had a positive and significant effect on food crop farmers' Terms of Trade both in short and long term. According to short term ARDL model, farmers were also influenced by Terms of Trade from the previous 1-2 years. In addition, inflation rate had a direct effect on farmers' Terms of Trade in short term. The results showed that rice prices had a significant impact in the previous 3 years, indicating long term impact on trade in Indonesia. This study was also successful in filling in the gaps in the literature and reporting inconsistencies that occurred in previous studies regarding the effect of inflation on farmers' Terms of Trade in both short and long term. The different significant levels and signs showed that inflation and rice prices had a different impact in short and long term.

The results explained the essential role of these variables in influencing farmers' welfare in . Indonesia. This report suggested that the government compiled price regulations ostensibly to ensure balanced value, where farmers produced rice of reasonable quality in sufficient quantities and community could obtain the commodity at affordable prices. In addition, the government should ensure that the market operated in a balanced and perfect competition environment. This could be achieved through the elimination of information asymmetry with the potential to lead to price discrimination, thereby harming farmers and disrupting the supply chain of rice commodities because this current study was limited to rice commodity and the report scope was regional. Future studies were expected to provide a more in-depth analysis using more advanced methods and analytical tools, as well as a broader report scope, to obtain more empirical results.

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