

International Trade Price Index: A Leading Indicator for Indonesia's Inflation?

Wawan Kurniawan^{1⊠}, ²Kadir

^{1,2}Badan Pusat Statistik, Indonesia

Article Information Abstract

History of Article Received January 2023 Accepted March 2023 Pusblished May 2023

Keywords: Inflation, Leading Indicator, ITPI, PPI, WPI As one of essential indicators in economy, inflation rate can be determined by several factors. One of these factors is price index other than CPI, representing price change, other at consumer level. Many studies have examined the effect of price indices such as Producer Price Index (PPI) and Wholesale Price Index (WPI) on inflation, including in Indonesia. However, in an open economy, the level of openness, which can be approximated by International Trade Price Index (IHPI), may also influence changes in inflation. In Indonesia, no studies still examine the nexus between ITPI and inflationThis study aims to examine the effect of price indices variables other than at consumer level, particularly ITPI, on inflation and whether we can use it as one of the leading indicators of inflation in Indonesia. The analysis results of the ARDL-ECM model show that all price indices variables simultaneously influence inflation. However, the effect of each variable partially on inflation in the short and long run varies. The speed of adjustment to return to equilibrium is 4.67% per month after the shock happened. Nevertheless, the effect of ITPI on inflation is insignificant, both in the short and long run. Thus, we can conclude that ITPI is not yet able to be a leading indicator of inflation in Indonesia. However, the result of this study must be carefully concluded since the use of time series analysis depends on the lag length and the number of observations included.

^D Corresponding author :

Address: Badan Pusat Statistics, Indonesia E-mail: wawan.kurniawan@bps.go.id

INTRODUCTION

Inflation is one of the essential indicators in the economy (Kamber & Wong, 2020; Khan & Hanif, 2020; Chugunov et al., 2021; Agustina, Surjanto, and Apriliani, 2022; Nova, 2022). Inflation is measured by changes in Consumer Price Index (CPI) (Tjahjono et al., 2000; Suseno & Astiyah, 2009). CPI represents general changes in the prices of goods and services at the consumer level (Konny, 2020). In the chain of distribution activities, there are two distribution channels of goods and services from producers to consumers, i.e., both direct and indirect distribution (Burroughs & Burroughs, 2020; Đalić et al., 2020; Chaboud & Moustier, 2021; Ikbal, Saragi and Sitanggang, 2021; Haqberdievich, 2022; Sari, Sudarmiatin and Dhewi, 2022; Sun et al., 2022). Generally, countries implement an indirect distribution pattern (Vafaei et al., 2020; Hayu, Sulistiyawan, and Salim, 2021; Shankar & Kushwaha, 2021; Ismaya et al., 2022). It causes price differences and transmission between producers, intermediaries, and consumers (Deb, Dey, and Surathkal, 2022).

Producer Price Index (PPI) shows price changes at the producer level. Meanwhile, Wholesale Price Index (WPI) exhibits changes at the intermediary level. Changes in PPI and WPI are used as leading indicators of changes in CPI (Anggraeni & Irawan, 2018; Ghauri, 2020; Wei and Xie, 2022). According to the law of price conduction, price changes at the producer level will be transmitted to the consumer level (Ozturk, 2020; Andiojaya, 2021; Fitriani, Arifin, and Ismono, 2021; Gorter et al., 2021). Moreover, price changes at the consumer level will affect prices at the producer level (and vice versa). If illustrated, the two indices link upstream production to downstream consumption. PPI reflects upstream price changes, and CPI reflects downstream (Li et al., 2019). In practice, price transmission also occurs at an intermediate level. In international and domestic trade, the flow of distribution of goods and services from producers to consumers usually goes to intermediaries, i.e., wholesalers and retailers. An added value is at the intermediary level, transmitted to consumers (Artika, Firdaus, and Irawan, 2019).

Several studies have demonstrated the relationship between PPI and CPI. In the long run, PPI has an equilibrium cointegration relationship with CPI. It is supported by Li et al. (2019) using both vector autoregressive model (VAR) and vector error correction model (VECM) approaches. Kara and Keskin (2021), using the error correction model (ECM) approach, exhibited a long-run and short-run relationship between the PPI and the CPI. Anggraeni and Irawan (2018) also pointed out a one-way link between PPI and CPI. A two-way transmission mechanism between PPI and CPI has also been shown by Sun et al. (2021). Longrun and short-run cointegration relationships between PPI and CPI were demonstrated by Meyer and Habanabakize (2018). The study used an autoregressive distributed lag (ARDL) and ECM model approach at stationarity levels I(0) and I(1). Meanwhile, in the long run, WPI has a causal relationship with CPI (Tiwari, 2012; Ghauri, 2020; Mallick, Behera, and Dash, 2020).

Countries that implement an open economic system are characterized by international trade (Gräbner et al., 2021). One of the indicators used to measure international trade is the International Trade Price Index (ITPI). ITPI is an index that measures changes in the prices of goods and services in export and import activities (Gaulier et al., 2008; International Labour Office et al., 2009). As one of the macro indicators of a country that adheres to an open economy depending on export and import activities, it is necessary to review ITPI's role in CPI.

A previous study by Kurihara (2013) showed a significant correlation between economic openness and inflation. Meanwhile, a study conducted by Arora and Rakhyani (2020) using the ARDL model shows a significant relationship between exports and inflation but not between imports and inflation. A previous study for the Indonesian context conducted by Astuti and Udjianto (2022) using panel data and the VAR model showed that international trade positively affects inflation. This study fills the research gap by combining several indicators that affect inflation, whereas previous research only used one indicator. Additionally, the variable used to indicate economic openness in this study is the International Trade Price Index (ITPI). In previous studies, the variables used were exportimport volume, exchange rates, and GDP. (Ahmed et al., 2018; Sahu and Sharma, 2018).

Therefore, this study aims to investigate the relationship between ITPI and CPI in Indonesia. This study also examines whether ITPI can be used as the leading indicator of inflation in Indonesia. The authors believe that international trade can impact inflation in Indonesia. The effect can be positive and negative, depending on the circumstances. It is because, in Indonesia, inflation is calculated from changes in the price of a basket of commodities (goods and services) where some of the commodities are traded globally.

RESEARCH METHODS

The data used in this study is secondary data obtained from BPS-Statistics Indonesia. These data are monthly time series data from January 2010 to June 2022. Thus, the number of observations used in this study was 150 months. The data used are Consumer Price Index (CPI), Producer Price Index (PPI), Wholesale Price Index (WPI), and International Trade Price Index (ITPI). The CPI, WPI, and ITPI data use a base year of 2018=100, while the PPI data uses a base year of 2010=100. The base year of each index data series is then adjusted to the latest base year.

The dependent and independent variables used in the study are as follows: Consumer Price Index (CPI), which is an index that exhibits changes in the prices of goods and services at the consumer level. This index is used as a proxy to measure the inflation rate in Indonesia. Producer Price Index (PPI) is an index that describes the level of price change at the producer level. Wholesale Price Index (WPI) is a price index that describes price changes at the wholesaler or wholesaler level at a certain period in a region. International Trade Price Index (ITPI) is a price index that describes changes in the price of goods and services transactions carried out by one country with other countries. This price index reverses the level of openness in an economy.

Because the data is not normally distributed and non-linear, the four variables are first transformed into natural logarithm form. After the transformation, the variables are symbolized LN_CPI, LN_PPI, LN_WPI, and LN_ITPI.

This study uses two analytical methods, i.e., descriptive analysis and time series analysis. The descriptive analysis method is an analytical method used to provide a description or describe data but is not used to generalize or make conclusions from the data (Sugiyono, 2014). This study uses descriptive analysis to describe each variable's development from January 2010 to June 2022. In addition, this descriptive analysis is also used to determine the period in which the variables used in this study experienced the lowest point, the highest point, and the fluctuations.

Furthermore, this study uses an autoregressive distributed lag (ARDL) and error correction model (ECM) approach for time series analysis. This ARDL method determines whether there is a long-run relationship among time series variables. Operationally, this ARDL method has the advantage of not requiring the variables to be stationary at the same level. However, we cannot use this method to estimate variables at the second difference level (I(2)). In this study, we carried out several steps in estimation using the ARDL model following previous studies (Falianty, 2003; Enders, 2004; Nkoro & Uko, 2016). First, estimate and analyze the ARDL model, including model selection and perform diagnostic tests on whether or not there is an infraction of assumptions before proceeding to the following procedure. Second, make an error correction model (ECM) based on the selected model and test whether there is a longrun cointegration relationship (Johansen & Juselius, 1990). Third, analyze the output of the ECM to determine the short-run dynamics.

Fourth, analyze the long-run coefficient of the ARDL model.

Analyzing time series data is necessary to ensure that the data is stationary. In testing the stationary of the data in this study, we applied the Phillips-Perron (1988) test, which aimed to determine the existence of the unit root. The Philips-Perron test uses a non-parametric method to control the series higher-order serial correlation. The Phillips-Perron test is a process of AR (1) with the following equation:

Where y_t is a time series, t is a time period, α is constant, and e is a white noise error. The testing is done by looking at the stationarity of each time series included in the model at the level. If a time series is not stationary at the level, the stationarity test is carried out at the first difference level. If all variables are stationary at the first difference level, we can conduct the following analysis.

After we carried out the stationary test, the next step was to estimate the ARDL equation. Based on the Monte Carlo Experiment of Gerrard and Godfrey (1998), the ARDL model is considered better in estimating the long-run coefficient of the cointegration relationship. According to Pesaran and Shin (1999), the ARDL(p,q) model is as follows:

$$y_{t} = \alpha_{0} + \alpha_{1}t + \sum_{i=1}^{p} \phi_{i}y_{t-i} + \beta'x_{t} + \sum_{i=0}^{q-1} \beta_{i}^{*'} \Delta x_{t-i} + u_{t} \qquad (2)$$

$$\Delta x_t = P_1 \Delta x_{t-1} + P_2 \Delta x_{t-2} + \dots + P_s \Delta x_{t-s} + \varepsilon_t$$
(3)

Where x_t is k-dimensional, forcing variables I(1) that are not cointegrated among themselves. u_t and ε_t is a serially uncorrelated disturbance with zero mean and constant variance-covariance. Pi is k x k coefficient matrix, so the autoregressive process vector in Δx_t is stable. In the case of bivariate cointegration, we set k=1. By setting k=1, we avoided cointegration problems between forcing variables x_t .

In equations (2) and (3), α_0 , α_1 , β_1^* , ..., β_{q-i}^* , $\phi = (\phi_i, ..., \phi_p)$ are short-run parameters that are important in estimating long-run

coefficients defined by the ratio $\delta = \alpha_1/\phi(1)$ and $\theta = \beta/\phi(1)$, where $\phi(1)=1-\sum \phi(i)$. The ARDL model also assumes a stable long-run relationship between the variables X and Y. In the case where u_t dan ε_t is correlated, the ARDL specification is augmented by a lag of change in the regressor by enough lag. The degree of this addition depends on whether q>s+1 or not. This model becomes:

Where $m = \max(q, s + 1)$, $\pi_i = \beta_i^* - P'_i d$ where d is a 1x1 vector containing the contemporaneous correlation between u_t and ε_t . Thus, the ARDL model requires sufficient lag of forcing variable x_t to endogenize y_t . By doing it, we can correct endogenous regressor and serial autocorrelation problems simultaneously. The simpler ARDL model can be expressed as follows:

Where L is the log operator and w_t is vector sx1 of deterministic variables such as intercept, trend, dummy variable, and exogenous variable with fixed lag.

However, using the ARDL model is highly dependent on the optimal lag length used in the model. Therefore, selecting the optimal lag length plays a crucial role in determining the suitability of the ARDL model. Several measures, including the 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 (*) on the test results for each criterion can be used by the Eviews 10 program to conclude the ideal lag time. The more asterisks in a lag, the lag will be chosen to be the optimal lag for the ARDL model formed.

After the optimal lag length is known, it is necessary to determine the appropriate ARDL model. The criteria for determining the appropriate model are based on the AIC graph, one of the data processing outputs. The graph shows that the best ARDL model is the ARDL model that has the smallest AIC value among the other ARDL model alternatives.

The next test is the Bound Test, which is a test to determine whether there is a cointegration or long-run relationship between the variables used in the study. In the Bound Test, the test is carried out using the F test. We can conclude that there is a cointegration relationship between the variables if the resulting F test value is higher than the critical value in I(1). On the other hand, we can claim that the variables are not cointegrated if the resulting F test value is less than the critical value in I(1).

The next stage is estimating the short-run model using ECM once the long-run relationship between the variables has been determined. The short-run equation used is as follows:

$$EC_{t} = E_{t} = y_{t} - \sum_{i=1}^{k} \theta_{i} x_{it} - \psi' w_{t}$$
(6)

The elasticity of the short-run impact of the independent variable on the dependent variable may be observed in the created ECM. The cointEq1 coefficient (at the output of Eviews 10) or the error correction term (ECT) coefficient (from the ECM) will also be obtained. These terms describe the adjustment rate or residual speed in the prior period to correct changes in the dependent variable towards equilibrium in the subsequent period. According to the findings of the t-test, the model form is valid if the ECT coefficient value is negative and significant.

It is necessary to test the model's accuracy and stability in the final modeling step using the ARDL and ECM methods. The test was carried out through the classical assumption test to see whether there was autocorrelation in the residual model using the Breusch-Godfrey LM Test method and the model stability test using the CUSUM test. In the Breusch-Godfrey LM Test method, it is said that a model does not have autocorrelation if the resulting p-value is greater than the value used. Meanwhile, a model is considered stable if the CUSUM test chart shows that the CUSUM line (blue line) is between the significance line (red line).

RESULTS AND DISCUSSION

Figure 1 displays that from January 2010 to June 2022, the development of all price indices shows an increasing trend. However, WPI data experienced a slight decline around mid-2016 and 2017 and again showed a positive trend starting in 2018. Meanwhile, although ITPI data shows an increasing trend, the movement tends to fluctuate. In the mid-2013 to 2014 period, ITPI rose relatively high but decreased until 2016. The index then grew until mid-2018 and mid-2019 before declining again in the next period until 2020, when the Covid-19 epidemic started. The next trend of ITPI development continues to increase until June 2022. Meanwhile, Figure 1 also displays that inflation has increased relatively smoothly from January 2010 to June 2022.

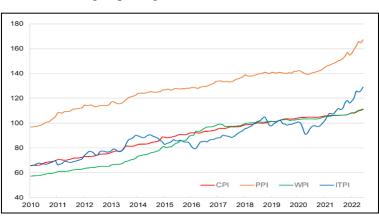


Figure 1. Development of the Price Index in Indonesia, January 2010 to June 2022 Source: CPI, PPI, WPI, and ITPI data from BPS (processed)

There have been many studies that discuss the relationship between price indices, especially PPI and WPI, with inflation rates, both nationally and internationally, such as studies from Anggraeni and Irawan (2018), Li et al. (2019), and Mallick et al. (2020). However, only a few studies discuss the role of ITPI on the inflation rate. Previous studies only looked at the relationship between ITPI and inflation and did not see the relationship between the two variables simultaneously with other price index variables. As a country that adheres to an open economy, Indonesia's inflation rate should be influenced by the domestic price index (PPI and WPI) and other price index variables that describe openness, such as ITPI. The autoregressive distributed lag (ARDL) model was used in this study's time series analysis to analyze the impact of the price index on Indonesia's inflation rate.

A stationary test was conducted before analyzing the ARDL model. In order to avoid the erroneous regression equation, this stationary test is meant to ascertain the order of integration and ensure that the input data are not stationary on the order of 2 or I(2). The findings of the Phillips-Perron test are displayed in the following table:

Table 1.	Unit Root Test Results with the Phillip-
	Perron Test Method

No.	Lev		1 st difference			
	Variable	Prob.	Variable	Prob.		
1.	LN_CPI	0.0297	D(LN_CPI)	0.0000		
2.	LN_PPI	0.8461	D(LN_PPI)	0.0000		
3.	LN_WPI	0.4154	D(LN_WPI)	0.0000		
4.	LN_ITPI	0.9672	D(LN_ITPI)	0.0000		
Source: Processed Data 2023						

Source: Processed Data, 2023

Table 1 displays that only the LN_CPI variable is stationary at the level, while for the LN_PPI, LN_WPI ,and LN_ITPI variables, none are stationary at the levels. Therefore, the stationary test of the data is continued to the following order, i.e., order 1. The Phillip-Perron test on the first difference provides a probability value of 0.0000, which is less than the crucial threshold of 0.05 and indicates that all variables are stationer at order 1.

The optimum lag employed significantly impacts the ARDL model's usability as an analytical tool. From Table 2, it can be inferred that 4 is the ideal lag length. The choice depends on how many asterisks (*) are in the lag 4 criteria value. Thus, lag 4 will be applied for additional analysis.

Lag	LogL	LR	FPE	AIC	SC	HQ
0	992.1114	NA	1.06e-11	-13.91706	-13.83380	-13.88323
1	2058.796	2058.251	3.97e-18	-28.71544	-28.29913*	-28.54627
2	2096.457	70.54667	2.93e-18	-29.02052	-28.27115	-28.71600
3	2119.902	42.59752	2.64e-18	-29.12538	-28.04296	-28.68553
4	2149.221	51.61808*	2.20e-18*	-29.31297*	-27.89750	-28.73778*
5	2161.833	21.49404	2.31e-18	-29.26525	-27.51674	-28.55473
6	2173.768	19.66733	2.46e-18	-29.20800	-27.12643	-28.36213
7	2187.846	22.40640	2.55e-18	-29.18093	-26.76631	-28.19973
8	2197.559	14.91117	2.82e-18	-29.09238	-26.34471	-27.97584

Table 2. Test Results for Optimal Lag Determination

Source: Processed Data, 2023

Next, the best ARDL model was selected using the AIC criteria. The best ARDL model is determined by comparing the AIC values of ARDL models formed automatically through Eviews 10 application according to the amount of lag used in each model. The results of determining the best ARDL model are shown in the following figure:

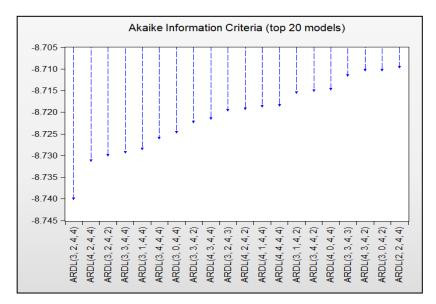


Figure 2. Results of Optimal Lag Length Determination Using AIC Criteria Source: Data Processed, 2023

In Figure 2, the horizontal axis shows the created ARDL models created, and its vertical axis displays the AIC value. The ARDL model proposed by Eviews10 is depicted in the figure. However, compared to other models based on the AIC value, the ARDL model (3,2,4,4) is the best because it has the smallest AIC value was (-8.740). The ARDL (3,2,4,4) model is utilized as a result. The LN_CPI variable has three lags, the LN_ITPI variable has two lags, and the LN_PPI and LN_WPI variables each have four lags according to the ARDL model (3,2,4,4).

The next step after selecting the optimal lag length is to determine whether the variables used in this study have a long-run equilibrium relationship (cointegration). The F-Bounds Test method is used to determine whether long-run equilibrium exists. The following table contains the cointegration test results of the combination of each variable as the dependent variable. Based on the test results using the F-Bounds Test method, only the LN_CPI variable has cointegration with the price index variables (LN_PPI, LN_WPI, and LN_ITPI). It can be seen from the F-statistics value, which is 5.415, it is more significant than the F-table value in the first difference I(1) for the 95% confidence level, which is 4.35.

No.	Dependent Variable	AIC Lag	F-stat	F-table I(1) (α = 5%)	Explanation
1	F _{CPI} (LN_CPI LN_ITPI, LN_PPI,	4	5.415	4.35	There is a
	LN_WPI)				cointegration
2	F _{ITPI} (LN_ITPI LN_CPI, LN_PPI,	4	2.805	4.35	No cointegration
	LN_WPI)				
3	F _{PPI} (LN_PPI LN_CPI, LN_ITPI,	4	1.753	4.35	No cointegration
	LN_WPI)				-
4	F _{WPI} (LN_WPI LN_CPI,	4	3.429	4.35	No cointegration
	LN_ITPI, LN_PPI)				C C
Source: Processed Data 2023					

Table 3. F-Bounds Cointegration Test Results

Source: Processed Data, 2023

These results indicate a long-run equilibrium relationship among the LN_CPI variable and the LN_PPI, LN_WPI, and

LN_ITPI variables. The equations of the longrun model formed are as follows: $LN_CPI = 0.061412 + 1.274795 LN_CPI(-1) -$ 0.517291 LN_CPI(-2) 0.190091 +LN_CPI(-3) + 0.002359 LN_ITPI -0.017465 0.034133 LN_ITPI(-1) + LN_ITPI(-2) + 0,101161 LN_PPI -0.122752 LN_PPI(-1) + 0.037998 LN_PPI(-2) - 0.197139 LN_PPI(-3) + 0.180403 LN_PPI(-4) + 0.414736 LN_WPI -0.093256 0.506372 LN_WPI(-1) + LN_WPI(-2) - 0.080669 LN_WPI(-3) + 0.100031 LN WPI(-4)(7)

From the long-run estimation model, the independent variables in the model together can explain 99.97% of the diversity that occurs in the dependent variable (LN CPI). In contrast, other factors outside the model influence the remaining 0.03. Furthermore, if the values of PPI, WPI, and ITPI are constant, then inflation in Indonesia will increase by 0.061412. From the model, if inflation in the previous month and the previous three months increased by 1%, ceteris paribus, there will be a change in the current month's inflation rate in Indonesia, which increased by 1.274795 and 0.190091, respectively. On the other hand, if inflation in the previous two months increased by 1%, it would reduce the inflation rate for the current year by 0.517291, assuming other variables remain constant.

The estimation results show that if the Producer Price Index (PPI) in the current month and the previous four months period has increased by 1%, then inflation in Indonesia will increase by 0.101161 and 0.180403, respectively, if other variables remain constant. However, if there is a 1% increase in the Producer Price Index (PPI) for the previous three months, it will reduce the inflation rate in Indonesia by 0.197139. Furthermore, there is a 1% increase in Wholesale Price Index (WPI) in the current period and the previous four months, ceteris paribus. In that case, it will cause inflation to increase by 0.414736 and 0.100031, respectively.

However, from the model, it appears that only the variables LN_CPI(-2), LN_CPI(-3), LN_PPI, LN_PPI(-3), LN_PPI(-4), LN_WPI, LN_WPI(-1), and LN_WPI(-4) which has a significant effect on changes in inflation. The results of this study support the results of the study from Li et al. (2019), Kara and Keskin (2021), Anggraeni and Irawan 2018), Meyer and Habanabakize (2018), Sun et al. (2021), (Tiwari, 2012), (Ghauri, 2020; Mallick, Behera and Dash, 2020).

While the variable LN_ITPI for the current period and the previous two months has a positive but insignificant effect, and LN_ITPI for the previous month period has a negative and insignificant effect. This result aligns with a study by Arora and Rakhyani (2020). However, it differs from the results of studies by Kurihara (2013) and Astuti and Udjianto (2022).

Selected Models: ARDL (3,2,4,4) Dependent Variable: D(LN_CPI)					
Independent Variable	Coefficient	Standard Error	t-statistics		
С	0.004204	0.00066	6.35768**		
D(LN_CPI(-1))	0.434434	0.11344	3.82978**		
D(LN_CPI(-2))	-0.385656	0.11354	-3.39654**		
D(LN_CPI(-3))	-0.119057	0.11359	-1.04812		
D(LN_CPI(-4))	0.056800	0.10528	0.53950		
D(LN_ITPI(-1))	-0.024694	0.02459	-1.00421		
D(LN_ITPI(-2))	-0.020855	0.02787	-0.74833		
D(LN_ITPI(-3))	0.009357	0.02821	0.33166		
D(LN_ITPI(-4))	-0.008214	0.02627	-0.31267		
D(LN_PPI(-1))	0.046445	0.06218	0.74692		
D(LN_PPI(-2))	0.064849	0.06279	1.03275		
D(LN_PPI(-3))	-0.200727	0.06474	-3.10048**		

Table 4 . Estimating the Coefficient of the Short-run 1	Model Based on the Selected ARDL Model
--	--

Wawan Kurniawan & Kadir	/ Economics Development	Analysis Journal Vol	. 12 No (2) (2023)

Independent Variable	Coefficient	Standard Error	t-statistics
D(LN_PPI(-4))	-0.051323	0.06707	-0.76524
D(LN_WPI(-1))	-0.047614	0.08074	-0.58972
D(LN_WPI(-2))	0.042090	0.07563	0.55654
D(LN_WPI(-3))	0.066165	0.07491	0.88325
D(LN_WPI(-4))	-0.047536	0.07910	-0.60096
CointEq1	-0.046675	0.01086	4.29818**
R-squared	0.425333		
Adj R-squared	0.348409		
F-statistic	5.529272		

Note: ****** significant at the level α =5%

Source: Processed Data, 2023

As explained in the previous section, the co-integration test results show that inflation (LN_CPI) has a long-run equilibrium relationship with other price indexes (LN_PPI, LN_WPI, and LN_ITPI). Therefore, it is necessary to further estimate the ARDL model by applying the ECM to form a short-run estimation model. The test results using the ARDL-ECM method are shown in Table 4.

From the resulting short-run model, it is generally known that about 42.53% of changes that occur in changes in the inflation rate variable in Indonesia are influenced by price index variables together in previous periods. Other variables influence the rest. However, if viewed more partially, the estimation results illustrate that only a few price index variables significantly affect changes in the inflation rate in Indonesia. These variables D(LN_CPI(-1)), D(LN_CPI(-2)), and D(LN_PPI(-3)), where these variables have a t-statistic value that is greater than the t-table value at 95% confidence level. If there is no increase in the price index variable, inflation will increase by 0.004204. In addition, from the equation, it can also be concluded that if last month's inflation increased by 1%, it would cause the inflation rate in the current period to increase by 0.434434. Meanwhile, if there is an increase of 1% in inflation for the previous two months, then inflation for the current period will decrease by 0.385656. Meanwhile, if there is a 1% increase in the producer price index for the previous three months, it will cause inflation in the current period to decrease by 0.200727.

On the other hand, the ITPI variable from the previous month to the previous four months partially influences changes in the inflation rate in Indonesia, but the effect is not significant. Table 4 also states that the value of CointEq1 is negative at -0.446675 and is significant at the 95% confidence level. It shows that the speed of adjustment to equilibrium after a shock or change occurs is 4.67% per month. The model form is valid and suitable for explaining the relationship between the inflation rate and the price index other than CPI in Indonesia because it has met the requirements to pass the classical assumption test (autocorrelation) and the stability test of the model, as shown in Table 5:

Table 5. Autoconclation Test Results							
Breusch-Godfrey Serial Correlation LM Test							
F-statistic 1.400238 Prob. F(4.125) 0.2378							
Obs*R-squared 6.261356 Prob. Chi-Square(4) 0.1805							
Source: Processed Data, 2023							

Table 5. Autocorrelation Test Results

The autocorrelation test using the Breusch-Godfrey LM Test method produces a p-value of 0.1805. This value indicates that at the

significance level of α =5%, it cannot reject the null hypothesis, or there is no autocorrelation in the residuals of the ARDL model formed.

Regarding model stability, it can be concluded that the model formed is stable at the 95% confidence level because the graph of the Cusum Test results in Figure 3 displays that the blue lines are between the significance lines (red lines).

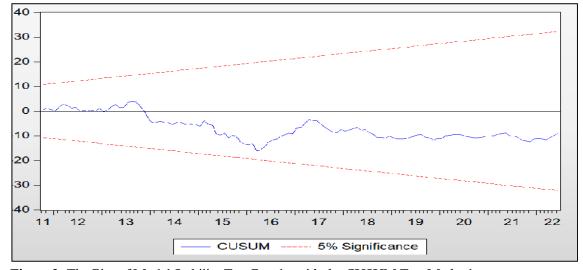


Figure 3. The Plot of Model Stability Test Results with the CUSUM Test Method Source: Processed Data, 2023

Thus far, according to several study results, the general price index that is the leading indicator for the inflation rate is the Wholesale Price Index (WPI). However, apart from WPI, several price index variables are considered leading indicators for inflation rates, especially in countries that adopt an open economic system. Therefore, this study examines whether the International Trade Price Index (LN_ITPI) variable is one of the variables that describe economic openness in Indonesia.

Based on the results of the analysis using the ARDL(3,2,4,4) model followed by ECM, it can be explained that at the 95% confidence level, the variable D(LN_ITPI) from the previous month period to the previous four-month period did not significantly affect changes in the inflation rate in Indonesia. It can be seen from the resulting t-statistics value, which is smaller than the t-table value. It means that the International Trade Price Index (ITPI), in general, influences changes in the inflation rate in Indonesia but has yet to become a leading indicator of inflation. Although the data used in this study, the ITPI and the inflation rate have shown the same trend. However, the finding from the test results in this study must be concluded very carefully because, in modeling using time series data, the flexibility of using the number of lags to form model specifications will affect the results obtained. In addition, modeling using time series data is strongly influenced by the amount of data used and the chosen analysis method.

This insignificant result illustrates that the commodities (goods and services) calculated in Indonesian inflation are mostly domestic commodities. In addition, price transmission from internationally traded commodities to domestic consumers has a long time lag.

CONCLUSION

This study aims to determine the leading indicators for inflation in Indonesia. This study limits the leading inflation indicators at PPI, WPI, and ITPI. In addition, this study also wants to know whether ITPI can be a leading indicator for inflation. The data used in this study is the monthly time series data of CPI, PPI, WPI, and ITPI from January 2010 to June 2022 sourced from BPS-Statistics Indonesia. The base year of each index data series has been rebased to the latest base year. The estimation technique used to answer the research objectives is the autoregressive distributed lag (ARDL), and error correction model (ECM) approaches.

From the long-run estimation model, the independent variables in the model together can explain 99.97% of the diversity that occurs in the CPI variable. Other factors outside the model influence the remaining 0.03%. Meanwhile, from the short-run model that was formed, around 42.53% of the changes that occurred in the changes in inflation rate variable in Indonesia were influenced by the price index variables together in the previous periods. Other variables influenced the rest. In general, the ITPI influences changes in the inflation rate in Indonesia, but it is still not enough to be a leading indicator of inflation.

REFERENCES

- Agustina, M.J.S., Surjanto, S.D. and Apriliani, E. (2022) [Estimasi Parameter Model Inflasi untuk Menganalisa Pengaruh Covid-19 Menggunakan GSTAR-Filter Kalman], Jurnal Sains dan Seni ITS, 11(2).
- Ahmed, R.R. et al. (2018) 'An Empirical Analysis of Export, Import, and Inflation: A Case of Pakistan', Article in Romanian Journal of Economic Forecasting, 9(3), pp. 117–130.
- Andiojaya, A. (2021) 'The Transmission of Paddy Grain Price to Rice Price: Review of Directions, Magnitude and Duration of Changes', *Journal of Social and Agricultural Economics*, 14(2), pp. 140– 154.
- Anggraeni, D. and Irawan, T. (2018) 'Causality Analysis of Producer Price Index (PPI) and Consumer Price Index (CPI) in Indonesia', *Jurnal Ekonomi dan Kebijakan Pembangunan*, 7(1), pp. 60–77.
- Artika, K., Firdaus, M. and Irawan, T. (2019) 'Volatility and Transmission of Shallot Commodity Prices in Indonesia', *International Journal of Scientific Research in Science, Engineering and Technology*, pp. 50–61.
- Burroughs, B. and Burroughs, W.J. (2020) 'Digital Logistics: Enchantment in Distribution Channels', *Technology in Society*, 62.
- Chaboud, G. and Moustier, P. (2021) 'The Role of Diverse Distribution Channels in Reducing Food Loss and Waste: The Case of the Cali Tomato Supply Chain in Colombia', *Food Policy*, 98.
- Chugunov, I. *et al.* (2021) 'Fiscal and Monetary Policy of Economic Development', *European Journal of Sustainable Development*, 10(1), p. 42.
- Đalić, I. et al. (2020) 'Selection of a Distribution Channel Using the Integrated FUCOM-MARCOS Model', International Review, (3–4), pp. 80–96.
- Deb, P., Dey, M.M. and Surathkal, P. (2022) 'Price Transmission and Market Integration of

Bangladesh Fish Markets', *Aquaculture*, 560, p. 738592.

- Enders, W. (2004) *Applied Econometric Time Series*. 4th edn. John Wiley & Sony, Inc.
- Falianty, T.A. (2003) [*Tinjauan terhadap Metode* Ekonometrika Lanjutan], Jurnal Ekonomi dan Pembangunan Indonesia, 4(1), pp. 59–74.
- Fitriani, F., Arifin, B. and Ismono, H. (2021) 'Indonesian Coffee Exports and its Relation to Global Market Integration', *Journal of Socioeconomics and Development*, 4(1), pp. 120– 133.
- Gaulier, G. et al. (2008) International Trade Price Indices. 10.
- Gerrard, W.J. and Godfrey, L.G. (1998) 'Diagnostic Checks for Single-Equation Error-Correction and Autoregressive Distributed Lag Models', *The Manchester School*, 66(2), pp. 222–237.
- Ghauri, S. (2020) 'Revisit the Relationship between Two Inflation Indicators: Case of Pakistan', *International Journal of Experiential Learning & Case Studies*, 5(2).
- Gorter, H. de *et al.* (2021) 'Analyzing the Economics of Food Loss and Waste Reductions in a Food Supply Chain', *Food Policy*, 98.
- Gräbner, C. *et al.* (2021) 'Understanding Economic Openness: a Review of Existing Measures', *Review of World Economics*, 157(1), pp. 87–120.
- Haqberdievich, K.D. (2022) 'Develop Criteria for Selecting Distribution Channels in Small Business', *Academic Journal of Digital Economics and Stability*, 16.
- Hayu, R.S., Sulistiyawan, E. and Salim, M. (2021) 'The Changes of Consumption Behavior in Bengkulu, Indonesia: Case of Purchasing Corona Prevention Products Through Indirect Ditribution Channel', *Journal of Distribution Science*, 19(11), pp. 27–36.
- Ikbal, M., Saragi, S. and Sitanggang, M.L. (2021) 'The Effect of Sales Distribution Channels and Promotion Policies on Consumer Buying Behavior and Its Impact on Sales Volume', *The International Journal of Business Review*, 4(1), pp. 23–32.
- International Labour Office. et al. (2009) Export and Import Price Index Manual: Theory and Practice. International Monetary Fund.
- Ismaya, S.B. et al. (2022) 'Optimization of Distribution Channels in The Marketing of Save and Environmentally Friendly Detergents (Deltamat) MSMEs in Cimanglid Village, Bogor Regency', International Journal of Economy, Education and Entrepreneurship, 2(1), pp. 128–134.
- Johansen, S. and Juselius, K. (1990) 'Maximum Likelihood Estimation and Inference on Cointegration-with Applications to the Demand for Money', *Oxford Bulletin of Economics and Statistics*, 52(2), pp. 169–210.
- Kamber, G. and Wong, B. (2020) 'Global Factors and Trend Inflation', *Journal of International Economics*, 122.

Wawan Kurniawan & Kadir / Economics Development Analysis Journal Vol. 12 No (2) (2023)

- Khan, M. and Hanif, W. (2020) 'Institutional Quality and the Relationship between Inflation and Economic Growth', *Empirical Economics*, 58(2), pp. 627–649.
- Konny, C. (2020) 'Modernizing Data Collection for the Consumer Price Index', Business Economics, 55(1), pp. 45–52.
- Li, S. *et al.* (2019) 'Research on the Relationship between CPI and PPI Based on VEC Model', *Open Journal of Statistics*, 09(02), pp. 218–229.
- Mallick, L., Behera, S.R. and Dash, D.P. (2020) 'Does CPI Granger Cause WPI? Empirical Evidence from Threshold Cointegration and Spectral Granger Causality Approach in India', *The Journal of Developing Areas*, 54(2), pp. 109–125.
- Meyer, D.F. and Habanabakize, T. (2018) 'Analysis of Relationships and Causality between Consumer Price Index (CPI), the Producer Price Index (PPI) and Purchasing Manager's Index (PMI) in South Africa', *Journal of Economics and Behavioral Studies*, 10(6), pp. 25–32.
- Nkoro, E. and Uko, A.K. (2016) 'Autoregressive Distributed Lag (ARDL) Cointegration Technique: Application and Interpretation', *Journal of Statistical and Econometric Methods*, 5(4), pp. 63–91.
- Nova, N. (2022) [Analisis Hubungan Kebijakan Moneter dengan Inflasi di Indonesia], Jurnal Ekonomika, 17(1).
- Ozturk, O. (2020) 'Market Integration and Spatial Price Transmission in Grain Markets of Turkey', *Applied Economics*, 52(18), pp. 1936–1948.
- Pesaran, M.H. and Shin, Y. (1999) 'An Autoregressive Distributed-Lag Modelling Approach to Cointegration Analysis', in Econometrics and Economic Theory in the 20th Century: The Ragnar Frisch Centennial Symposium. Cambridge University Press, pp. 371–413.
- Phillips, P.C.B. and Perron, P. (1988) 'Testing for a Unit Root in Time Series Regression', *Biometrika*, 75(2), pp. 335–346.
- Sahu, P. and Sharma, N.K. (2018) 'Impact of Trade Openness on Inflation in India: An Autoregressive Distributed Lag (ARDL) Approach', *The Empirical Economics Letters*, 17(1), pp. 21–32.
- Sari, F.R., Sudarmiatin, S. and Dhewi, T.S. (2022) 'Studying Distribution Channel Patterns in the Poultry Farming Industry', *Journal of Business* and Management Review, 3(4), pp. 306–322.
- Shankar, V. and Kushwaha, T. (2021) 'Omnichannel Marketing: Are Cross-Channel Effects Symmetric?', *International Journal of Research in Marketing*, 38(2), pp. 290–310.
- Sugiyono (2014) [Metode Penelitian Pendidikan Pendekatan Kuantitatif, Kualitatif, dan R&D]. Bandung: Alfabeta.
- Sun, J. et al. (2021) 'Dynamic Causality between PPI and CPI in China: A Rolling Window Bootstrap Approach', International Journal of Finance & Economics [Preprint].
- Sun, L. *et al.* (2022) 'Pricing Policies in Dual Distribution Channels: The Reference Effect of

Official Prices', *European Journal of Operational Research*, 296(1), pp. 146–157.

- Suseno and Astiyah, S. (2009) Inflasi. 22.
- Tiwari, A.K. (2012) 'Causality between Wholesale Price and Consumer Price Indices in India: An Empirical Investigation in the Frequency Domain', *Indian Growth and Development Review*, 5(2), pp. 151–172.
- Tjahjono, E.D. *et al.* (2000) 'Pengukuran Inflasi Inti (Core Inflation) di Indonesia', *Buletin Ekonomi Moneter dan Perbankan*, 2(4), pp. 1–34.
- Vafaei, A. *et al.* (2020) 'Designing a Sustainable Multichannel Supply Chain Distribution Network: A case study', *Journal of Cleaner Production*, 251.
- Wei, S.-J. and Xie, Y. (2022) Wedge Between the PPI and CPI Inflation Indicators. 5. Ontario.