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INFLATION FORECASTING USING AUTOREGRESSIVE DISTRIBUTED LAG (ARDL) MODELS

Abstract
This research aims at measuring and comparing the forecasting performance of various ARDL models against inflation. One particular type of ARDL is constructed formally, beginning with testing the stationarity, determining the lag length, and testing for cointegration. This formal construction of ARDL model resulted in ARDL(2,2). Besides, some other more arbitrarily chosen ARDL models were also included. The models were ARDL(1,1), ARDL(2,0), ARDL(1,0), ARDL(0,1), and ARDL(0,2). The forecasting object is inflation. The inflation data extended from January 2011 up to July 2022. They were monthly data. The data were divided into two categories namely training data and test data. Training data were from January 2011 until December 2021. Training data were used to generate parameters for each ARDL model. After obtaining the necessary parameters, the models were then employed to generate forecasts from January 2022 to July 2022. The forecasts generated were then compared to the test data which were the real data. From this comparisons, the accuracy was then measured. The results showed that ARDL (1,0) was the best model for forecasting inflation followed by ARDL(0,2). ARDL(2,2) which was formally developed came in the fourth place. This showed that for forecasting purpose, formally developed ARDL model is not the best method. Formally developed ARDL model was best used for testing influence of independent variables to dependent variable. Furthermore, ARDL models tend to generate more stable forecasts that have little volatility. This denotes the suitability of this model for stable economic condition.
Keywords: Forecasting; ARDL; Cointegration
JEL Classification: C32; C53; E4;

Introduction

Inflation denotes a general increase in goods and services. It carries cost that will affect the welfare of the society (Serletis & Xu, 2021). Inflation is often signified an incoming crisis or turbulence in the economy if it goes unchecked (Kusumatrisna, I, & Pasaribu, 2022). The economic crisis, in turn, will put the banking sector, stock market, or even the country's trading activities in jeopardy (Ahmed, Rostam, & Mohammed, 2020). Whereas economic growth is benefitted from low inflation, high inflation is proven detrimental to the economic growth (Atigala, Maduwanthi, Gunathilake, Sathsarani, & Jayathilaka, 2022). Raging inflation has been known to result in more unemployment and poverty (Sijabat, 2022). With mild to intermediate inflation, producer will increase their production in order to earn more profit in times of increasing prices. Thus, productivity will increase and so does general income (Kurniasih, 2019). Generally, inflation causes a deplete in customers' resource used to acquire the goods and services. Therefore, many parties keep an eye on the inflation rate. One of the party concern with inflation is central bank. In fact, it has become the main focus of central bank to control and curb inflation through monetary policy (Astuti & Udjianto, 2022). Central bank will construct its inflation targeting framework (ITF) to take steps to bring the inflation level within the acceptable range (Setiartiti & Hapsari, 2019) The more independent a central bank in enforcing its duties, the abler it becomes to limit the negative impact of inflation (Kunaedi & Darwanto, 2020). Therefore, in devising the right monetary policy, central bank must be able to forecast the inflation occurring in the economy. A wildly uncontrolled inflation has more probability to cause economic decline and crisis. Central bank must formulate the right monetary policy to keep increasing inflation from happening (Duong, 2022). Several variables have been known to have influence or relationship with inflation. These variables include interest rate, stock index, and exchange rate. These variables will be used as the predictors in forecasting the inflation rate.

One particular variable that affects inflation is interest rate. The interest rate is one of the main instrument for monetary policy conducted by central banks. Sulistiana, Hidayati, & Sumar (2017) found that the interest rate, proxied by BI rate (interest rate targeted by Indonesian central bank), is the most dominant factor that affects inflation. The relationship between these two variables are long-term, as indicated by the cointegrating relationship. Moreover, Granger Causality proves that inflation will move the interest rate, an evidence of monetary policy conducted by the central bank. In similar vein, Prieto & Lee (2019) found long-term relationship between interest rate and inflations. Yadav, Khera, & Mishra (2021) found that stock market and inflation are inherently cointegrated. It means the movement of both variables would be going on in the long-term.

Nghiem & Narayan (2021) found that interest rate has a positive influence toward inflation. This is reversely expected. This unusual result raises the question of monetary policy effectiveness in Vietnam. However, this result is likely in the case of Vietnam due to its high public debt and deeply ingrained inflation expectations. Stock index is also influential to the inflation rate. Pradhan, Filho, & Hall (2014) and Prieto & Lee (2019) found long-term relationship between stock index and inflation. Apparently, when the stock market index rises, the economic activity has increasing productivity. This in turn will drive the increase in general price of goods and services. Eldomiaty, Saeed, Hammam, & AboulSoud (2020) found that stock prices negatively correlated with inflation in a long-run equilibrium. Yadav, Khera, & Mishra (2021) found that stock market and inflation are inherently cointegrated. It means the movement of both variables would be going on in the long-term.

Inflation is also influenced by exchange rate. Sulistiana, Hidayati, & Sumar (2017) proved the existence of cointegration in the models involving exchange rate and inflation. This indicates long-term equilibrium between exchange rate and inflation. Sunal (2018) investigated how exchange rate and money supply affect inflation. He found that cointegration relationship exists in the model in which the inflation is the endogenous variable. This denotes a long-term effect of exchange rate against inflation. Besides, short-term effect from exchange rate occurs as well. Nghiem & Narayan (2021) found that depreciation in exchange rate brought about dampening in inflation and the strengthening of which causes hike in inflation. This could be caused by wealth effect or interest parity. Therefore, it is inconsistent with conventional thinking (Nghiem & Narayan, 2021). Yadav, Khera, & Mishra (2021) found that exchange rate and inflation form some cointegrated relationship. The long-run equilibrium exists within these variables. Based on the explanation above, this research will employ interest rate, stock index, and exchange rate as the predictors for forecasting inflation. In terms of methodology, forecasting using ARDL method is very scarce. Prior research mostly used Autoregressive Integrated Moving Average (ARIMA), Vector Autoregressive (VAR) and machine learning model to forecast inflation (Ozgur & Akkoc, 2021; Akbulut, 2022; Kelikume & Salami, 2014; Baybuza, 2018). Therefore, this research will fill in the gaps by providing forecast results on inflation using ARDL method.

Research Method

This research employs monthly data from January 2011 until July 2022. The data will be divided into training and test data. Training data span from January 2011 up to December 2021. Training data will be used to generate ARDL models. These models, in turn, will generate forecasts for January 2022 until July 2022. The forecast will be compared with the actual data, i.e. test data. From this comparison we can find out which model has the best forecast accuracy. The research variable of interest is inflation, since it is the object of the forecasting. It is posited that inflation is affected by interest rate, stock index, and exchange rate. Therefore, interest rate, stock index, and exchange rate will act as the independent variables. The following table lists the variables and the source.

Table 1 Research variables

No	Variable	Explanation	Source
1	INF	Inflation	Bank Indonesia
2	INT	Interest Rate	Bank Indonesia
3	IHSG	Stock Index	OJK/Otoritas Jasa Keuangan
4	EXR	IDR /USD Exchange Rate	Bank Indonesia

Source: Processed Data, 2022

Before jumping into constructing the ARDL model, we first have to test for the stationarity of the variable. ARDL model requires stationary variables. Test for stationarity will be using Dickey-Fuller test. This research will employ three kinds of Dickey-Fuller test, namely test without constant nor trend, test with a constant and no trend, and test with a constant and a trend. The Dickey-Fuller models are as follows:

$$\Delta y = \gamma y_{t-1} + v_t$$
$$\Delta y = \alpha + \gamma y_{t-1} + v_t$$
$$\Delta y = \alpha + \lambda t + \gamma y_{t-1} + v_t$$

The variable t denotes the trend. The variable y will be the all variables used in this research that consists of INF, INT, IHSG, and EXR. The variable will be declared stationary of the γ coefficient is statistically significant. If a variable is not stationary, the it will be first differenced and be retested again for stationarity. After all the variables are stationary, then we proceed by constructing the ARDL model. We propose some models of ARDL. The models are ARDL(1,0), ARDL(2,0), ARDL(3,0), ARDL(0,1), ARDL(0,2), ARDL(0,3). Besides these models, we will also search for the most optimal ARDL by choosing a certain lag length by way of Akaike Information Criterion (AIK). Also, we are going to include ARDL model with selected lag length accompanied by a cointegrating relationship. Therefore, a test for cointegration is necessary. The general model for ARDL(n,m) is as follows:

$$y_t = \delta + \sum_{i=i}^{n} \theta(i)\, y(t-i) + \sum_{i=i}^{m} \beta(i)\, x(t-i) + e_t$$

The expression t-i denotes the prior i period. The y variable will be the INF variable, our forecasting object while the x variables will be INT, IHSG, EXR. Hence inflation in a period will be affected by inflation in the prior periods together with the prior periods interest rate, stock index, and exchange rate. However, if the variables are not stationary then y will be replaced by Δy and x will be replaced by Δx The cointegrating relationship exists whenever the difference in residual in a certain period is affected by the residual of the prior period. The formal test of cointegration is as follows:

$$\Delta e_t = \beta e_{t-1} + v_t$$

The term e_t will be derived from the equation:

$$y_t = \alpha + \sum_{i=i}^{m} \beta(i)\, x(t) + e_t$$

As stated previously, y_t will be replaced by INF, our object of forecasting. While INT, IHSG, and EXR will be the x_t variables

If the coefficient β is statistically significant, then the ARDL model will also include a cointegrating relationship. The ARDL model with the cointegrating relationship is as follows:

$$y_t = -\rho(y_{t-1} - \alpha - \sum_{i=i}^{m} \beta(i)\, x(t)) + \sum_{i=i}^{n} \theta(i)\, y(t-i) + \sum_{i=i}^{m} \beta(i)\, x(t-i) + e_t$$

Forecasting accuracy will be measured using Mean Absolute Percentage Error (MAPE) and Root Mean Squared Error. The formula for MAPE and RMSE are as follow:

$$\textbf{MAPE} = 1/N \times (\sum_{n=1}^{t} \xi_n / y_n)$$

$$\textbf{RMSE} = (1/N \times (\sum_{n=1}^{t} \xi_n^2))^{0.5}.$$

The symbol ξ is forecast error derived from the difference between forecasts generated by the model and test data. N refers to the total amount of observations, while y_n is the value of the test data.

Result and Discussion

To have an idea of the behavior of the time-series, figure 1 below displays the plot of each variable based on the time reference.

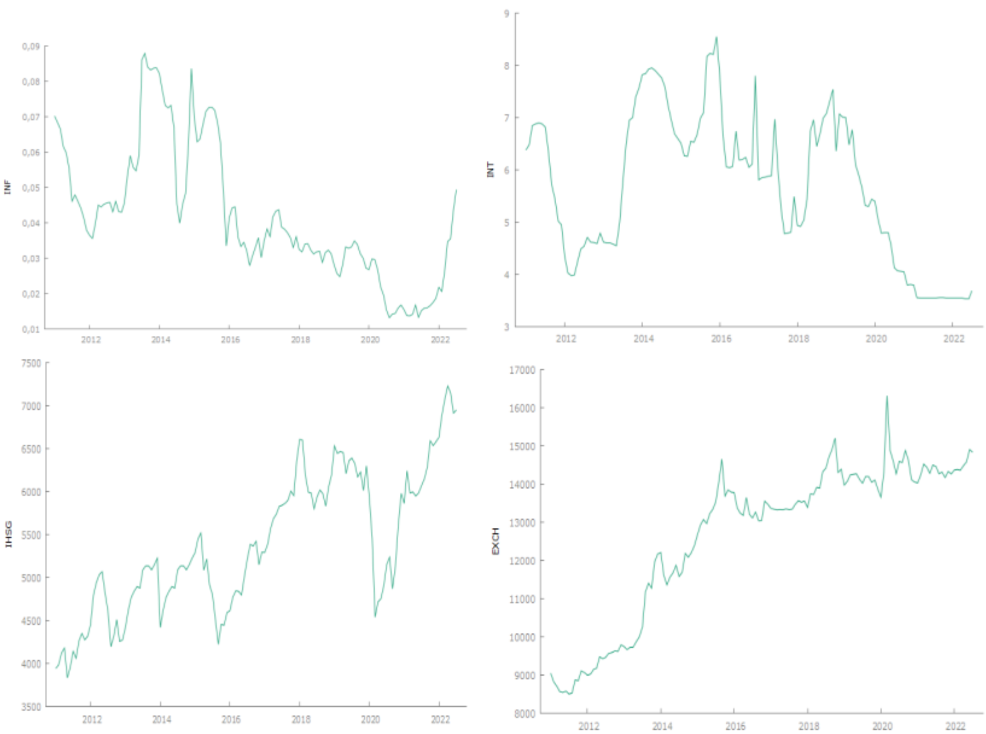

Figure 1 Time-Series Plot

Figure 1 above displays the movement of each variable over time. The top left hand corner figure plots the inflation series overtime. We can see that the volatility was high from 2012 leading up to 2016. In the beginning of the research period, the inflation was heading downward for a sharp decrease. Over a year period, there was more than 3% decrease in inflation, from 7% to around 3.5%. However, the inflation rate was starting to pick up from 2013 onwards. A huge increase was occurring in 2013 and 2015. In 2013, the inflation rate even reached 9% and gradually slowed down. In 2015, the inflation was surging again drastically to almost 9% and decreased when it approached 2016. This indicated a turbulence in the economy because there was a sharp increase in the general price of goods and services. From 2016 up until the beginning of 2021, the inflation showed a decreasing trend followed with a mild volatility. The inflation rate was ranging from 4% steeping down to slightly more than 1%. This was the time when Indonesia entered the pandemic. There was a slowdown in the economic activity as the government enforced the social distancing. The slowdown was due to decreasing demand in the goods and services generally. Although certain goods and services experienced increase in demand, it was not enough to make up for the loss demand in the other goods and services. Entering the 2022, the inflation began its way upward significantly. At the end of the research period, the inflation rate was almost 5%. The top right hand corner of figure 1 shows the interest rate series plot. There is some similarity between interest rate plot and inflation plot. This is due to the fact that government usually tries to control inflation by way of increasing or decreasing interest rate. When the inflation is high, government will rise interest rate. Similarly, when the inflation is low, government will decrease interest rate. Therefore, the movement of interest rate will lag behind the inflation, because government will act after the fact. When the inflation was high in 2013 and 2015, the rise in interest rate occurred in the mid of 2013 and approaching the end of 2015. A rise in interest rate was hope to tame the surging inflation. However, when the inflation started showing downward trend beginning in 2016 onwards, the interest rate was still high and only in 2018 did the interest rate start to decrease. Since then, the interest rate was maintained at a very low level. In 2022, the interest rate was around 3%. Nevertheless, we can expect the rise in interest rate since the inflation is showing signs of sharp increase. The bottom left hand corner of figure 1 shows the movement of IHSG over time. Some regular volatility can be seen. This denotes the seasonality component in the stock index. At certain times in a year, the stock index has a peak and a through. In other words, in certain times, stock index will rise and then they will decline. From 2011 until 2016, the pattern of seasonality is very obvious. Entering 2018, however, the pattern started to change. The stock index kept on rising until the end of 2019, although some seasonality is still present. In 2020, sharp decrease in stock index marked the commencement of the pandemic. Stock index plunged drastically. This represents the pessimistic expectation of the investors regarding the economy during the pandemic. However, stock index started to rise again approaching 2021. Since then, the upward trend continues up until the end of the research period. The right hand corner shows the movement of USD/IDR exchange rate. The exchange rate of US Dollar has a positive trend since the beginning of the research period. USD has a strong inclination to strengthen against IDR. The positive trend is markedly obvious. Nevertheless, some volatilities remain existent. In 2014, 2016, 2019, and 2020 we can see some sharp increase in the exchange rate. The sharp increase is immediately followed by sudden decrease. Overall, we can extrapolate the trend and expect the exchange rate to remain bullish for USD. Having plotted the time series for each variable, we turn to the stationarity check. Firstly, we plot the corrrelogram of each variable. This correlogram will give us visual representation of the stationarity of each variable. Figure 2 belows displays the correlogram.

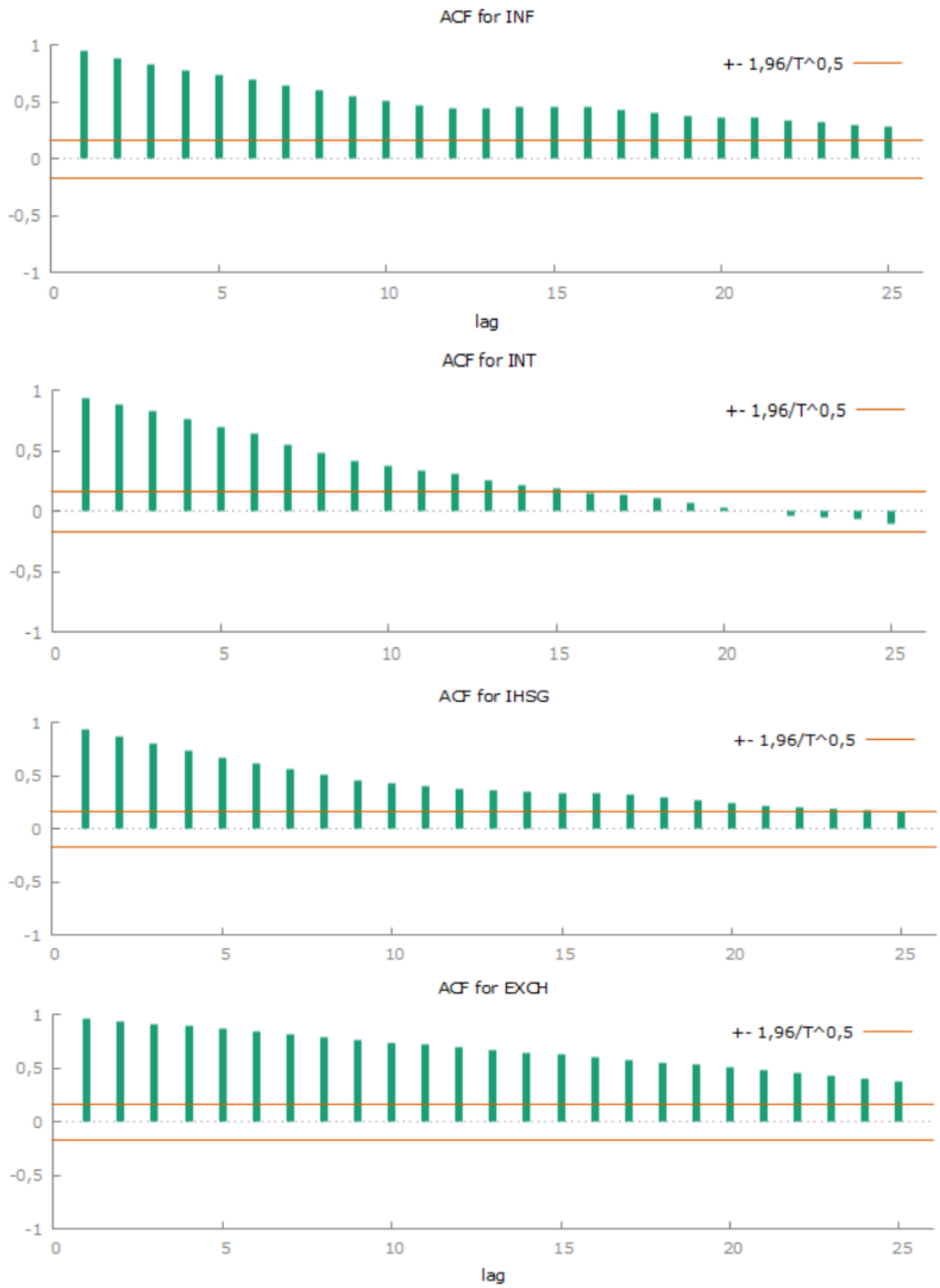

Figure 2 Correlograms of INF, INT, IHSG, and EXCH

Figure 2 above shows the correlation of a variable with its own series from previous periods. This will give us insights into the stationarity of the variables. All of the variables correlate significantly with its own prior periods series even after 10 period lags. For INF, lag 25 still has significant correlation with the current period series. For INF, the number is 15 lags. While for IHSG, the lag 22 still correlates significantly with current period. The correlation is even stronger of EXCH in which lag 25 is still positively significant. Overall, there is a gradual decline in all the variables along with time. The strongest correlation exists in lag 1. The further the lag, the weaker the correlation. If significant correlation still exists at longer lag, we might suspect that the data are not stationary. This can give rise to spurious regression if the data analysis still continues with nonstationary data. Therefore, we must conduct the formal test of stationarity to investigate this issue further.

Test of stationarity is conducted by employing Dickey Fuller testing procedure. The test involves testing without constant and trend, testing with a constant, and testing with a constant and a trend. The procedure is conducted against all the variables.

Table 2 Dickey Fuller Test of Stationarity at Level

Variable	Dickey-Fuller Test	Coefficient of γ	p-value
INF	Without a constant and a trend	-0,00655215	0.4291
	With a constant	-0,02925340	0.7174
	With a constant and a trend	-0,08648670	0.6922
INT	Without a constant and a trend	-0,00397397	0.4241
	With a constant	-0,04562600	0.4876
	With a constant and a trend	-0,06342460	0.5725
IHSG	Without a constant and a trend	0,00329844	0.9170
	With a constant	-0,03609200	0.4850
	With a constant and a trend	-0,11459500	0.1368
EXCH	Without a constant and a trend	0,00435012	0.9871
	With a constant	-0,02636600	0.3568
	With a constant and a trend	-0,06701080	0.5404

Source: Processed Data, 2022

Table 2 above shows the results of Dickey Fuller stationarity test. The null hypothesis for this test is that the variable is nonstationary. Hence, we seek to reject the null hypothesis by achieving a p-value that is smaller than 0.05. The testing results show that none of the variables is stationary. All the p-values are above 0.05. Therefore, we have to difference the variables once and redo the Dickey Fuller test. The result will be shows in the table 3 below.

Table 3 Dickey Fuller Test of Stationarity at First Difference

Variable	Dickey-Fuller Test	Coefficient of γ	p-value
INF	Without a constant and a trend	-1,37861	0.0000
	With a constant	-5,02871	0.0000
	With a constant and a trend	-1,38834	0.0001
INT	Without a constant and a trend	-0,905263	0.0000
	With a constant	-0,915963	0.0002
	With a constant and a trend	-1,16958	0.0105
IHSG	Without a constant and a trend	-0,887224	0.0000
	With a constant	-0,896728	0.0000
	With a constant and a trend	-0,896812	0.0000
EXCH	Without a constant and a trend	-1,08688	0.0000
	With a constant	-1,43798	0.0000
	With a constant and a trend	-1,46823	0.0000

Source: Processed Data, 2022

Table 3 above shows the result of stationarity test conducted at first difference. It shows that all the variables are stationary when differenced once. This is typical of time-series data. Just like before, the null hypothesis is the variable is not stationary. The p-values for all the tests are below 0.05. Hence, the null hypothesis is rejected. The data are stationary. Therefore, the forecasting process will be conducted in first difference. Having established the stationarity of the data, we continue to the determination of lag length. The following table shows the result of the test.

Table 4 Lag Length Determination

Lags	AIC	SIC	HQC
1	-7.4918720	-7.3478610	-7.4334260
2	-7.5221650	**-7.3541530***	**-7.4539780***
3	-7.5049550	-7.3129410	-7.4270270
4	-7.4878070	-7.2717910	-7.4001380
5	-7.4702840	-7.2302670	-7.3728740
6	-7.4592310	-7.1952120	-7.3520810
7	-7.4417990	-7.1537780	-7.3249070
8	-7.4242870	-7.1122650	-7.2976550
9	-7.4077440	-7.0717200	-7.2713710
10	-7.3909840	-7.0309580	-7.2448700
11	-7.3944990	-7.0104710	-7.2386430
12	-7.5325330	-7.1245030	-7.3669360
13	-7.5169740	-7.0849430	-7.3416370
14	-7.5152060	-7.0591720	-7.3301270
15	-7.5182430	-7.0382080	-7.3234230

Source: Processed Data, 2022

Table 4 above shows the lag length determination based on several criteria. AIC stands for Akaike Information Criterion. SIC is Schwarz Information Criterion, and HQC is Hannah Quinn Criterion. SIC and HQC determines the optimal lag length to be 2. We can see that at 2 lags, the criterion value is the lowest according to SIC and HQC. Length at Lag 1 is the second lowest criterion value. Surprisingly, AIC recommends the use of 25 lag length (not shown on the table). Based on the results above we will use 1 and 2 lag length in the forecasting process. The next step will be determining whether cointegration exists in the model. If cointegration exists, then we will inclide an ARDL with cointegration. The following equation indicates the result of cointegration test (without constant):

$$\Delta e_t = \underset{(0.042308)}{\underset{-0.1061427}{\beta e_{t-1}}} + v_t$$

The above equation shows that the β parameter is insignificant (p-value less than 0.05). This acts as a proof that the variables are not cointegrated. Therefore, we must include an ARDL model that excludes cointegration. The complete ARDL model will be:

$$\Delta INF_{t+1} = \alpha + \beta_1 \Delta INF_t + \beta_2 \Delta INF_t + \gamma_1 \Delta INT_t + \gamma_2 \Delta INT_{t-1} + \delta_1 \Delta IHSG_t + \delta_2 \Delta IHSG_{t-1} + \lambda_1 \Delta EXCH_t + \lambda_2 \Delta EXCH_{t-1}$$

The above model is ARDL (2,2). We posit that this model has the best forecasting performance. In order to have a robust results, we will also include ARDL(1,0), ARDL(2,0), ARDL(0,1), ARDL(0,2) and ARDL(1,1). The following table shows the results of forecasting and the measures of forecasts accuracy.

Table 5 Forecast Results

	REAL	ARDL(2,2)	ARDL(1,1)	ARDL(1,0)	ARDL(2.0)	ARDL(0,1)	ARDL(0,2)
January 2022	0.021800	0.01878	0.018708	0.020766	0.018700	0.018318	0.018806
February 2022	0.020600	0.01816	0.018526	0.021237	0.018503	0.017858	0.018361
March 2022	0.026400	0.01833	0.018599	0.021277	0.018162	0.017596	0.017986
April 2022	0.034700	0.01916	0.018589	0.021201	0.017760	0.017593	0.018217
May 2022	0.035500	0.01837	0.018596	0.021095	0.017371	0.017425	0.018709
June 2022	0.043500	0.01611	0.018185	0.020980	0.016999	0.017366	0.019036
July 2022	0.049400	0.01452	0.017534	0.020863	0.016629	0.016870	0.019094

Source: Processed Data, 2022

The above table shows the comparison of forecast results among the various ARDL models. We can see at the beginning of the forecast period. ARDL(1,0) results in the most result. It predicts that for January 2022, the inflation will be 2.0766%. This is most similar to the real inflation in January 2022 (the REAL column) which amounts to 2.18%. In contrast, ARDL(0,1) produces the least result. It predicts inflation to be 1.8318%. The real data shows that the real inflation has the inclination to always surge over the year. It begins with 2.18% which then increases to 2.06%. It finally winds up at 4.94%. The ARDL method is more likely than not to yield stable results. The forecasts are not really volatile and fluctuating. In times of turbulent economic condition, ARDL will likely result in inaccurate results. ARDL is powerful for forecasting in times of good economic condition. When the economy is conducive, the forecast results will show a gradual increase over time. Therefore, the values generated will tend to be smoothed. The following table shows the forecast accuracy of each method.

Table 6 Forecast Accuracy Measures

	ARDL(2,2)	ARDL(1,1)	ARDL(1,0)	ARDL(2.0)	ARDL(0,1)	ARDL(0,2)
Root Mean Squared Error (RMSE)	0.019202	0.018033	0.015761	0.018798	0.018737	0.017547
Mean Absolute Percentage Error (MAPE)	40.39%	38.65%	30.89%	40.39%	41.25%	38.41%

Source: Processed Data, 2022

The above table shows the parameter for forecast accuracy. The first parameter is RMSE. This shows the average squared error for each model. The higher the number, the less accurate the method. The method that generates the lowest value is ARDL(1,0). This signifies that the results from ARDL is most closely to the actual data. ARDL(0,2) is in the next place in terms of accuracy. ARDL(1,1) performs worse than ARDL(1,0) and ARDL(0,2). However, it still performs ARDL(2,0), ARDL(0,1), and ARDL(2,2). Hence, ARDL(2,2) makes the most forecast error among all the methods. Forecast accuracy is better understood when it is viewed from the error percentage. ARDL(1,0), ARDL(1,1), and ARDL(0,2) makes average error of around 30%. The rest of the methods, forecast error exceed 40%. These results show how much the ARDL forecast results deviate from the real data.

Conclusion

This research purports to compare the forecasting performance of various ARDL models. In this research, a specific ARDL model was constructed by following the usual formal procedure of ARDL testing. First, the variables were tested for stationarity. Once it was found out that the variables were not stationary, the variables were first differenced. This method proved successful in making the variables all stationary. Subsequently, we proceeded to lag length determination. After lag determination, we continued to cointegration test. There was no cointegration existed in the model. Hence, ARDL(1,1) was the result of formal construction of ARDL model. We posited that this model is the best model among other ARDL models for forecasting purpose. As comparisons, we include ARDL(1,0), ARDL(2,0), ARDL(0,1), AARDL(0,2), and ARDL(2,2). The forecast results showed that ARDL(1,0) has the best forecasting performance. The average mean error is 30.89%. ARDL(1,1) came third with the mean error of 38.65%. This proves that the ARDL which comes from the formal construction is not the best one for forecasting. Formal ARDL model is more frequently used for testing influence. Thus, it is not necessarily better for forecasting purpose. Secondly, ARDL model tends to produce stable forecasts. This works well in a stable economic condition. On the contrary, in a turbulent economic condition, ARDL model is unable to map the pattern of volatility and seasonality. The test data in this research were data right after the pandemic. The data have an apparent volatility. The surge in inflation after the pandemic is virtually drastic. In this case, ARDL models did not produce volatile results that mimic the turbulent economy. Future research could endeavor to use ARDL model that does not use first difference variables. This model has the potential to better capture the dynamic component existing in the data.

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