

## Article

# Study of Inflation using Stationary Test with Augmented Dickey Fuller & Phillips-Peron Unit Root Test (Case in Bukittinggi City Inflation for 2014-2019)

### Article Info

#### Article history :

Received Januray 14, 2022  
Revised March 10, 2022  
Accepted March 21, 2022  
Published June 30, 2022

#### Keywords :

Stationary, non autocorrelation, phillips-peron test, augmented dickey, fuller test, inflation

Afnita Roza<sup>1\*</sup>, Evony Silvino Violita<sup>2</sup>, Sherly Aktivani<sup>3</sup>

<sup>1</sup>Fuctional Youth Statistics, Statistics of Padang Municipality, Padang, Indonesia

<sup>2</sup>Islamic Business, Faculty of Economics and Business, Universitas Indonesia, Depok, Indonesia

<sup>3</sup>BPS Young Expert Statistician Padang City, Indonesia

**Abstract.** This classical regression model is designed to handle the relationship between stationary variables and should not be applied to non-stationary series. A time series data is said to be stationary if the mean, variance, and covariance remain constant over time. The problem associated with non-stationary variables, and often encountered by researchers when dealing with time series data, is spurious regression. A clear indicator of false regression is the low Durbin-Watson statistic but has a higher coefficient of determination (R<sup>2</sup>). Therefore, before doing modeling or forecasting using time series data, it is very important to do a stationary test. In this study, we use inflation data in the City of Bukittinggi from January 2014 to December 2019 as a case study. The data shows an uptrend and correlated error terms. Empirical results show that inflation data in Bukittinggi City is a stationary series.

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#### Corresponding Author :

Afnita Roza  
Statistician, Statistics of Padang Municipality, Padang, Indonesia  
Email : [afnita@bps.go.id](mailto:afnita@bps.go.id)

## 1. Introduction

In everyday life, observation data about a phenomenon dependent on time is frequently encountered. Time series data, according to Rosidi (2004), is a set of data formed from the outcomes of regular observations made throughout time. According to Mulyana (2004), the time series data model is used to evaluate data by taking into account the effect of time in order to forecast the future using past data that may be considered as a function of time.

One of the assumptions of data analysis with time series data is that the data must be stationary. Stationary data does not have a large diversity as long as the observational data does not have a tendency to approach the mean value [1,2,3]. Inflation is the occurrence of a trend where the prices of goods and services increase continuously. The increase in the price of goods and services will cause the value of the currency to fall so that the purchasing power of the currency will decrease. In addition, with inflation, it will make planning for the business world difficult and will have a negative impact on the economy [4,5,6,7].

The city of Bukittinggi is one of the cities in West Sumatra Province that is experiencing inflation. The Bukittinggi city government uses inflation data to determine the direction of policy and planning that will be carried out. If the inflation data utilized is not stationary, the policy decisions made on the basis of the inflation statistics are invalid. As a result, the stationarity test of inflation data in Bukittinggi City will be examined in this study from January 2004 to December 2019.

The issue of inflation is an important focus for the government at a time of recent unstable economic conditions. Inflation is the tendency of prices to rise in general and continuously. To find out the high and low prices or the rate of inflation, the price index is often used. One method that is often used is to use the value of the consumer price index. The consumer price index (CPI) is the relative comparison of a package of commodities compared to the prices of these commodities at a certain time which is used in a base year [8,9,10,11,12,13]. With changes in people's consumption patterns, starting from January 2014, the CPI is presented using the base year 2012 = 100, so the researcher uses inflation data for the period of January 2014 - December 2019. The data collection is in the form of secondary data processed by the Central Statistics Agency (BPS) and obtained from the table dynamic website of the Central Statistics Agency of West Sumatra Province (<https://sumbar.bps.go.id/>) [14].

## 2. Research Methodology

Many studies use time series data as an attempt to get an accurate picture of the development or of a phenomenon. Time series data is a collection of regularly observed data from time to time [15,16,17]. The time series data model is basically used to perform data analysis that considers the effect of time to predict the future using historical data so that the data is considered a function of time [18,19,20].

A time series data  $\{Y\}$  is said to be stationary if the shared distribution of  $(Y_{t1}, \dots, Y_{tk})$  is identical to  $(Y_{t1+t}, \dots, Y_{tk+t})$  for all  $t$ , where  $k$  is any positive integer. In other words, in the stationary state the joint distribution  $(Y_{t1}, \dots, Y_{tk})$  is the same at one time. Time series data is said to be stationary if the mean, variance, and covariance in each lag are the same at all times. If the time series data does not meet these criteria, then the data is said to be non-stationary. Time data is said

to be non-stationary if the mean and variance are not constant, changing over time (time varying mean and variance). Stationarity test can be done by various methods, namely:

### 2.1. Graphic Method

Plots or graphs of observational data against time can be used to visually detect whether a time series data is stationary or not [6]. If the data is stationary, the graph will have a constant tendency around the average value with a relatively constant amplitude or no up or down trend is seen.

### 2.2. Correlogram Test

Correlogram test is performed using autocorrelation (autocorrelation function), abbreviated as ACF, which is formed by the set of autocorrelation between lag  $k$  or correlation between  $Z_t$  and  $Z_{t+k}$ . The relationship between autocorrelation and the lag is called the Autocorrelation Function (ACF). While the Partial Autocorrelation Function (PACF) is defined as the correlation between  $t$  and  $t+k$  after eliminating the effect between  $Y$  and lies between  $t$  and  $t+k$ . so that  $t$  is considered as a constant. Just as autocorrelation is a function of the lag, whose relationship is called the autocorrelation function (ACF), partial autocorrelation is also a function of the lag, and the relationship is called the Partial Autocorrelation Function (PACF).

Correlogram is a visualization of ACF and PACF which can then be used to examine the significance of autocorrelation and stationary data. If the ACF coefficient value in each lag is the same or close to zero, then the data is said to be stationary, otherwise, the ACF coefficient value is relatively high, then the data is not stationary. If the ACF image forms a decreasing histogram (exponential pattern), then the autocorrelation is significant or the data is autocorrelated, and if it is followed by a PACF image whose histogram is immediately truncated at lag 2, then the data is not stationary and can be stationary through the differencing process.

However, because checking with ACF and PACF is done visually, the results can be different for each person, in other words there is an element of subjectivity. So to produce a more accurate decision, it is necessary to do statistical testing for stationarity.

### 2.3. Unit root test

The unit root test was originally developed by D.A. Dickey and W.A. Fuller, so it is often known as the Dickey-Fuller unit root test. The Dickey-Fuller unit root test assumes that the residual  $\epsilon_t$  is an independent residual with a mean of zero, constant variance, and unrelated (non-autocorrelation). However, in many cases, the residuals  $\epsilon_t$  are often interconnected or contain elements of autocorrelation. So it is necessary to develop a unit root test for data containing autocorrelation in the residual  $\epsilon_t$ .

In its development, the most widely used stationary data at this time is the Augmented Dickey Fuller Test (ADF Test) which is a development of the Dickey-Fuller unit root test on the grounds that the ADF Test has considered the possibility of autocorrelation in the error term if the series used is non-stationary. The steps for testing unit roots using the ADF Test method are as follows:

1. Suppose there is an equation as follows:

$$Y_t = \rho Y_{t-1} + \mu_t \quad (1)$$

Where is  $\rho$  the autoregressive coefficient,  $\mu_t$  is the white noise error term which has an average = 0 and constant variance and does not contain autocorrelation. If  $\rho = 1$ , then it can be stated that the

variable  $Y_t$  has a unit root. In econometric terms, a series that has a unit root is called a random walk. In the form of a hypothesis becomes:

$H_0 : \rho = 1$ , or the series contains unit roots

$H_a : \rho < 1$ , or series does not contain unit roots

The equation is then translated to obtain an equation in the form of differencing:

$$Y_t = \rho Y_{t-1} + \mu_t \quad (2)$$

$$Y_t - Y_{t-1} = \rho Y_{t-1} - Y_{t-1} + \mu_t \quad (3)$$

$$\Delta Y_t = (\rho - 1) Y_{t-1} + \mu_t \quad (4)$$

Where  $\delta = (\rho - 1)$  and  $\Delta Y_t$  is the first difference (first difference) or easily expressed in the form  $\Delta Y_t = (Y_t - Y_{t-1})$ . So the form of the hypothesis becomes:

$H_0$  : or series contains unit root

$H_a$  : or series does not contain unit root

If  $\delta$ , then the above equation can be written:

$$\Delta Y_t = (Y_t - Y_{t-1}) = \mu_t \quad (5)$$

Equation (5) shows that the first derivative of a random walk  $\mu_t$  series is a stationary series assuming that  $\mu_t$  is truly random.

After obtaining the equation, the test procedure is to first calculate the ADF statistical value, where the ADF test is known as  $T$  (tau statistic). The formula can be written as follows:

$$\tau = \frac{\delta}{Se(\delta)}$$

$Se(\delta)$  is the standard error of the coefficient or the standard error of  $\delta$ . Furthermore, the value of tau statistics is compared with the critical value of the Mac Kinnon table. If the absolute value or statistic from the ADF test  $>$  the critical value of the ADF table, then  $H_0$  is rejected and the series is said to be stationary.

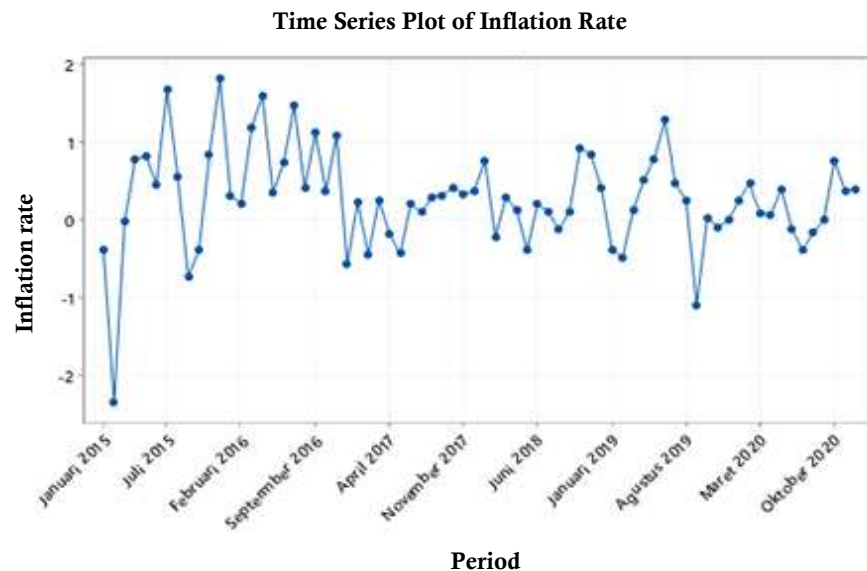
If it is not stationary, then differencing must be carried out until the data is stationary. Differencing is calculating the change or difference in the value of the observation. The value of the difference obtained is checked again whether it is stationary or not. If it is not stationary then differencing must be done again. If the original data from a series are integrated with each other or the data is stationary, then the data is integrated on order 0 or denoted by  $I(0)$ . Furthermore, if the new data is stationary and integrated with each other in the first derivative, then the data is integrated in order 1 or  $I(1)$ . And so on until the data is stationary on order  $d$  or  $I(d)$ . Unit root testing in this study uses the help of software e-views 9 to facilitate testing.

The problem that can arise in the ADF test is the discovery of lags that are included in the model. If the lag is too long, it will reduce the ability of the null hypothesis because the other lags will be longer which will cause a decrease in the estimation parameters and loss of degrees of

freedom. On the other hand, a lag that is too short causes the inability to reveal the actual error process, as a result, the standard error cannot be estimated.

### 3. Results and Discussion

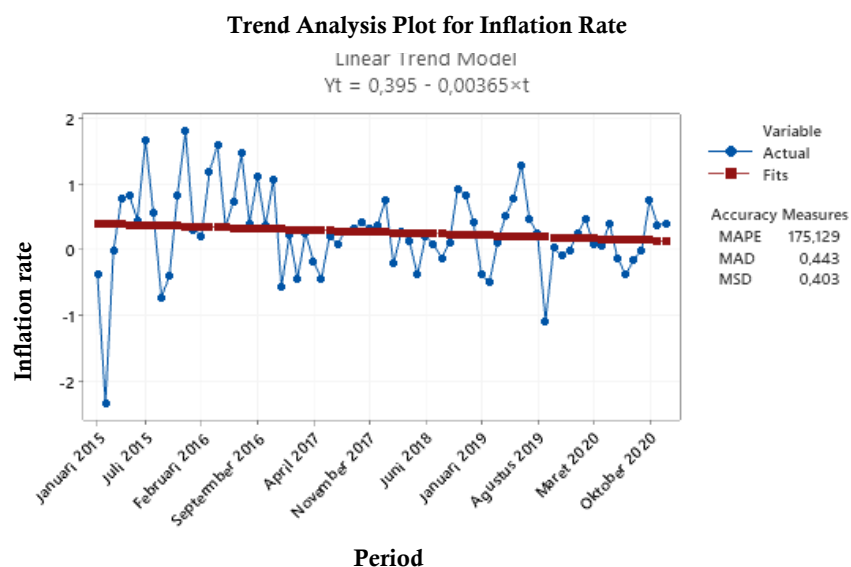
In this study, inflation data for the City of Bukittinggi was used as a case study for stationarity testing from January 2014 to December 2019. Several approaches, including the way of assessing the inflation plot graph, Correlogram Plot ACF and PACF, and the Unit Root Test utilizing the Augmented Dickey Fuller Test and the Phillips-Peron Test, were used to test the stationarity of the inflation data for Bukittinggi. Minitab 19 and E-Views 9 were used to process time series data.



**Figure 1.** Plot of Bukittinggi City Inflation Data Period January 2014 – December 2019

The graph above shows the rate of inflation in the City of Bukittinggi from January 2014 to December 2019. The inflation value of the City of Bukittinggi changed from time to time over the study period, as can be seen. The greatest inflation rate of 2.03 was recorded in November 2014, and the lowest rate of -2.35 was recorded in February 2015.

The presence of stationary signs in the generated graph can be visually noticed. Figure 1 illustrates that data in the 2014-2015 period as a whole has rather extreme variations around the average, or in other words, the time series data on inflation in Bukittinggi City appears to have a constant average value but has a non-constant variance.



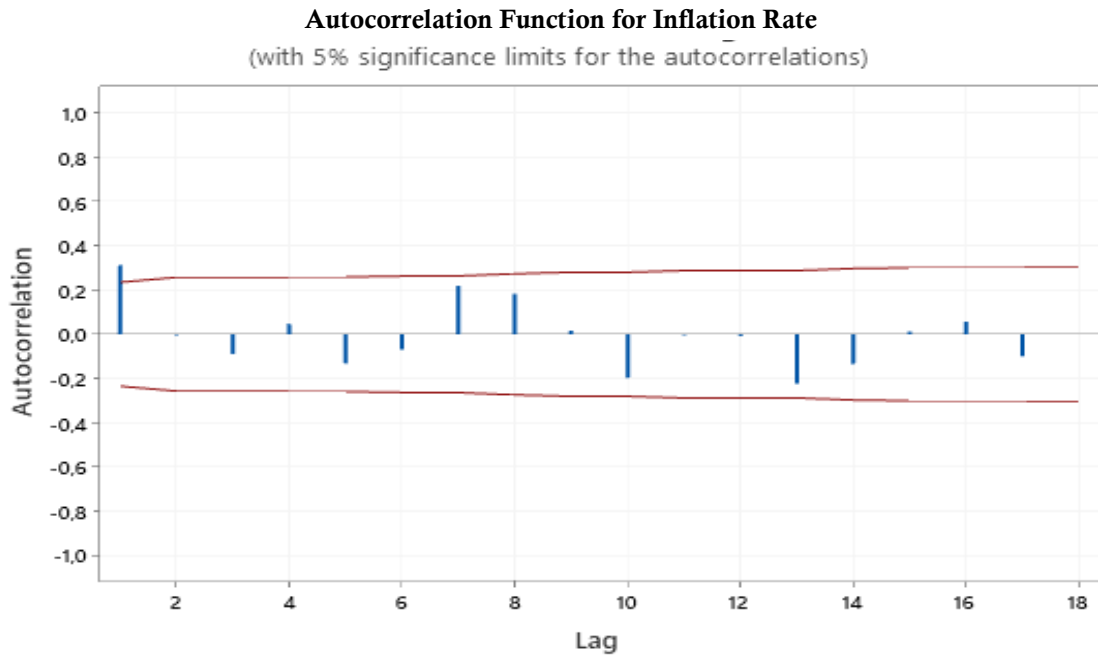
**Figure 2.** Trend analysis of inflation in Bukittinggi

However, a more thorough examination of time series data trends, based on plots and analysis of the existence of time series data trends as shown in Figure 2, cannot conclusively determine whether or not the time series data for Bukittinggi City inflation is stationary. The graph shows that the inflation time series data supplied shows a downward tendency, but this trend is not very noticeable when seen visually.

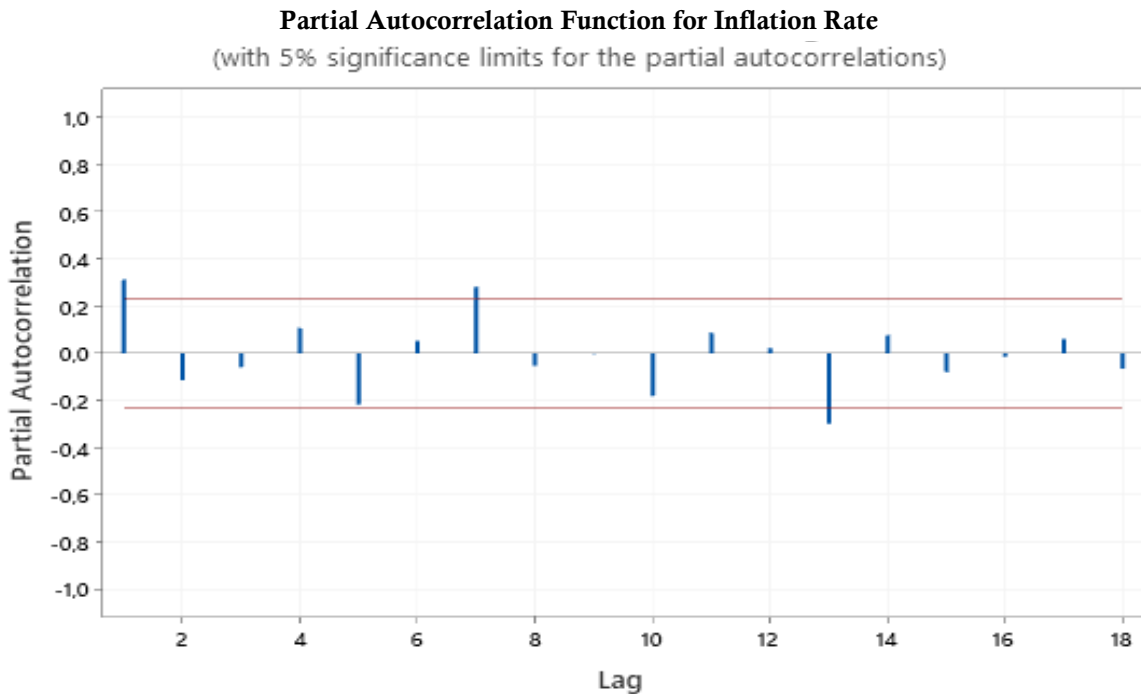
Therefore, the level of validity of the stationary test using this graphical method cannot be determined because the check is solely based on graphics and visuals, so additional checks must be conducted using a formal test, such as the correlogram and the Unit Root Test using a formal test, such as the Augmented Dickey Fuller (ADF. Test) and the Phillips-Peron Test.

### 3.1. Correlogram

It can be shown that the time series data is not stationary based on the value of the Autocorrelation Function (ACF). When a series is not stationary, the autocorrelation value slowly decreases or drops. Meanwhile, autocorrelation values on positive and negative autocorrelation values will decline or drop rapidly/dramatically, forming an up and down pattern on stationary data.



**Figure 3.** Autocorrelation Function (ACF) Bukittinggi City Inflation.



**Figure 4.** Partial Autocorrelation Function (PACF) Bukittinggi City Inflation

The values for the ACF and PACF values from the correlogram data at the level are shown in Figures 3 and 4. The figure shows that the ACF coefficient value is high at lag 1 and then gradually decreases at lags 2 and 3. This value is also shown in the dotted line. As a result, it is possible to conclude that the data is stationary at the level and does not require differencing. However, because

the results of checking ACF and PACF are done visually, further checking is done with the Unit Root Test for more precise and accurate results.

### 3.2. Unit Root Test

The results of the Unit Root Test utilizing the Augmented Dickey Fuller (ADF Test) and the Phillips-Peron Test on inflation data for the City of Bukittinggi using the E-Views 9 program for the period January 2014 to December 2019 are presented below.

The results of the E-Views output for the Augmented Dickey Fuller and Phillips-Peron Test results at the level with the equation including the intercept and trend constants indicate that with a 95 percent confidence level, it was decided to reject  $H_0$  because the probability value is less than 0.05. In other words, it can be concluded that the inflation data for the City of Bukittinggi from January 2014 to December 2019 with a base year CPI calculation of 2012=100 was stationary at the level.

#### 3.2.1. Augmented Dickey Fuller Test (ADF Test)

##### a) At Level Intercept & Trend

Null Hypothesis: INFLASI has a unit root Exogenous: Constant, Linear Trend Lag Length: 0 (Automatic - based on SIC, maxlag=11)		
	t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic	-6.118761	0.0000
Test critical values:		
1% level	-4.092547	
5% level	-3.474363	
10% level	-3.164499	
*Mackinnon (1996) one-sided p-values.		

##### b) At Level Intercept

Null Hypothesis: INFLASI has a unit root Exogenous: Constant Lag Length: 0 (Automatic - based on SIC, maxlag=11)		
	t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic	-6.051852	0.0000
Test critical values:		
1% level	-3.525618	
5% level	-2.902953	
10% level	-2.588902	
*Mackinnon (1996) one-sided p-values.		



### 3.2.2. Phillip-Peron Test

#### a) At Level Intercept & Trend

Null Hypothesis: INFLASI has a unit root Exogenous: Constant, Linear Trend Bandwidth: 9 (Newey-West automatic) using Bartlett kernel		
	Adj. t-Stat	Prob.*
Phillips-Perron test statistic	-5.861447	0.0000
Test critical values:		
1% level	-4.092547	
5% level	-3.474363	
10% level	-3.164499	
*Mackinnon (1996) one-sided p-values.		
Residual variance (no correction)		0.362499
HAC corrected variance (Bartlett kernel)		0.233533

#### b) At Level Intercept

Null Hypothesis: INFLASI has a unit root Exogenous: Constant Bandwidth: 6 (Newey-West automatic) using Bartlett kernel		
	Adj. t-Stat	Prob.*
Phillips-Perron test statistic	-5.835849	0.0000
Test critical values:		
1% level	-3.525618	
5% level	-2.902953	
10% level	-2.588902	
*Mackinnon (1996) one-sided p-values.		
Residual variance (no correction)		0.367293
HAC corrected variance (Bartlett kernel)		0.271983

## 4. Conclusion

After using the graph method, correlogram, and the Augmented Dickey Fuller and Phillips Platform test unit root test to test the inflation data for the City of Bukittinggi from January 2014 to December 2019, it was determined that the data was stationary at a level and that no further tests with differencing on the data were required. The results of the data being stationary at the level lead to the conclusion that the time series inflation data for the City of Bukittinggi meets good stationarity requirements for further testing in the form of forecasting time series data, which can then be useful for the government and researchers in making decisions and determining policies in planning. The results of this study can be used as a reference for further research on inflation data in the City of Bukittinggi, but the follow-up data period from January 2020 cannot be directly compared to the previous period because the Consumer Price Index (CPI) calculation has changed the base year, namely the base year 2018 = 100. As a result, future study using the same variables should begin in January 2020.

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