

```
In [ ]: import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from pandas.plotting import register_matplotlib_converters
register_matplotlib_converters()
%matplotlib inline
```

```
In [ ]: data = pd.read_excel('Rice_Price_Inflation.xlsx')
data.head()
```

```
Out[ ]:
```

	DATE	PRICE	INFLATION	FOOD INFLATION	SECURITY INDEX
0	2012-05-15	14974.95	12.7	12.9	4.5
1	2012-06-15	14700.00	12.9	12.0	4.5
2	2012-07-15	16075.00	12.8	12.1	4.5
3	2012-08-15	16960.00	11.7	11.1	4.5
4	2012-09-15	15600.00	11.3	10.2	4.5

```
In [ ]: data.isna().sum()
```

```
Out[ ]:
```

DATE	0
PRICE	0
INFLATION	0
FOOD INFLATION	0
SECURITY INDEX	0

dtype: int64

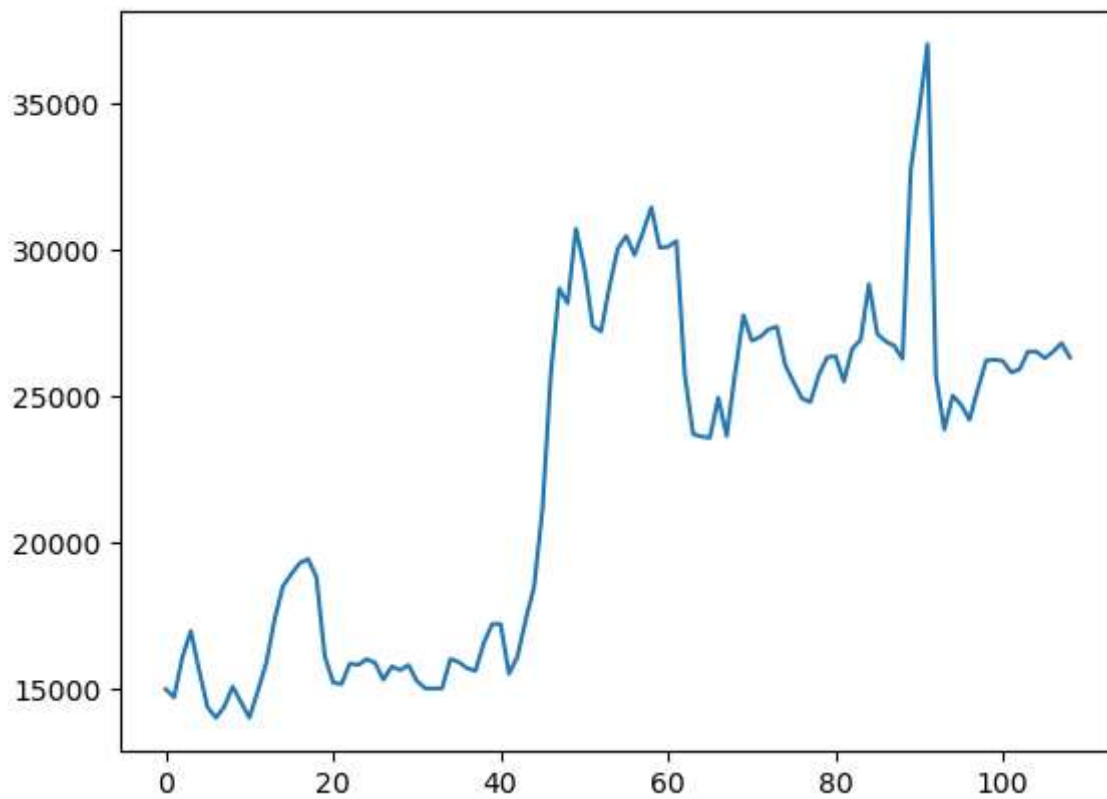
```
In [ ]: data.describe()
```

```
Out[ ]:
```

	PRICE	INFLATION	FOOD INFLATION	SECURITY INDEX
<b>count</b>	109.000000	109.000000	109.000000	109.000000
<b>mean</b>	22523.659633	12.378165	14.002110	8.695138
<b>std</b>	5905.227961	3.395078	4.058187	1.325293
<b>min</b>	14000.000000	7.700000	9.100000	4.500000
<b>25%</b>	15900.000000	9.200000	10.100000	8.700000
<b>50%</b>	24900.000000	11.700000	13.390000	9.000000
<b>75%</b>	26785.710000	15.750000	17.190000	9.500000
<b>max</b>	37000.000000	18.720000	22.950000	9.900000

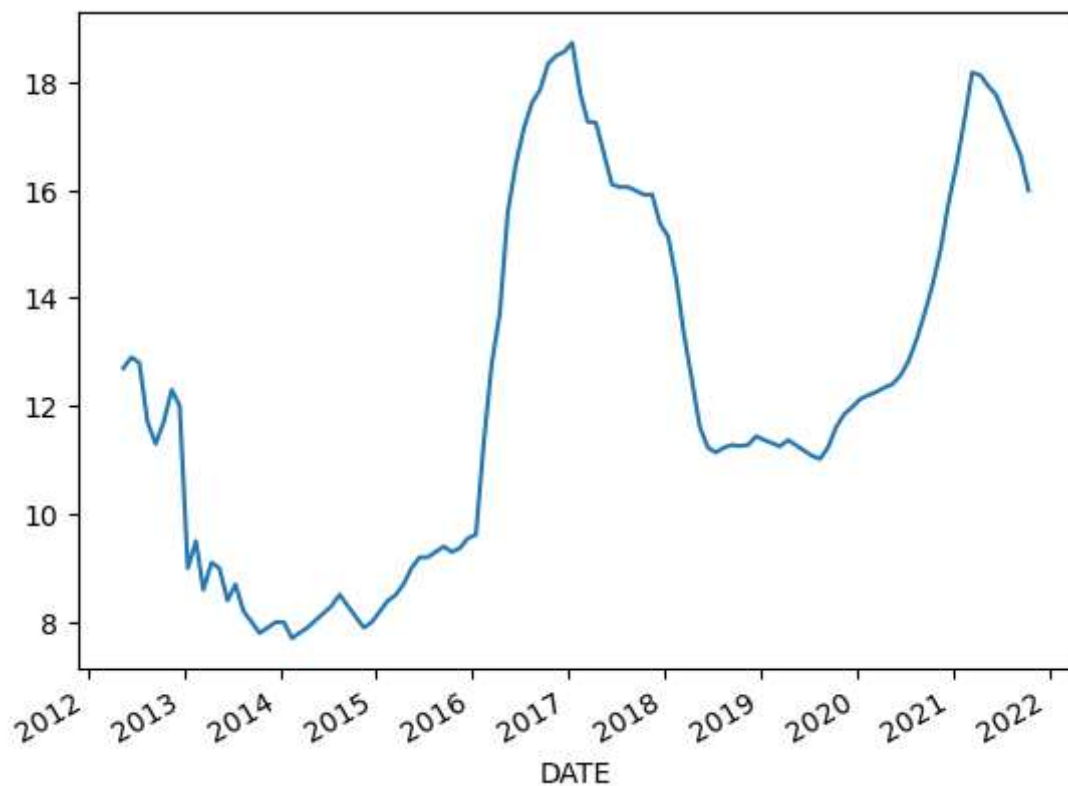
```
In [ ]: data['PRICE'].plot()
```

```
Out[ ]: <AxesSubplot:>
```



```
In [ ]: data['INFLATION'].plot()
```

```
Out[ ]: <AxesSubplot:xlabel='DATE'>
```



```
In [ ]: steps = -1  
dataset = data.copy()
```

```
dataset['Actual'] = dataset['PRICE'].shift(steps)
dataset.head()
```

```
Out[ ]:
```

	DATE	PRICE	INFLATION	FOOD INFLATION	SECURITY INDEX	Actual
0	2012-05-15	14974.95	12.7	12.9	4.5	14700.0
1	2012-06-15	14700.00	12.9	12.0	4.5	16075.0
2	2012-07-15	16075.00	12.8	12.1	4.5	16960.0
3	2012-08-15	16960.00	11.7	11.1	4.5	15600.0
4	2012-09-15	15600.00	11.3	10.2	4.5	14360.0

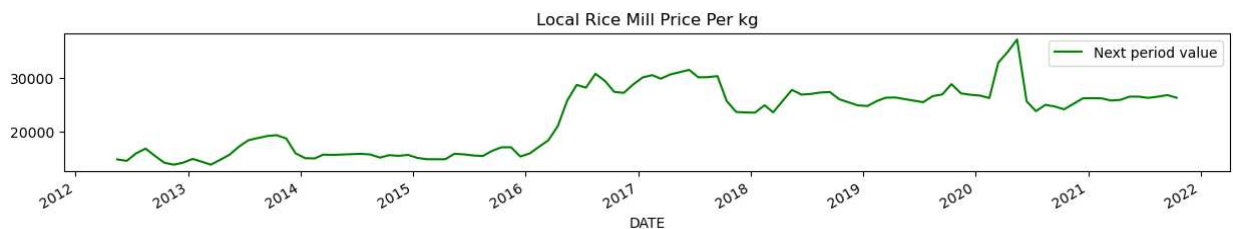
```
In [ ]: dataset['DATE'] = pd.to_datetime(dataset['DATE']) #freq='12M')
dataset.index = dataset['DATE']
dataset.drop(columns='DATE',inplace=True)
dataset.head(2)
```

```
Out[ ]:
```

	DATE	PRICE	INFLATION	FOOD INFLATION	SECURITY INDEX	Actual
	2012-05-15	14974.95	12.7	12.9	4.5	14700.0
	2012-06-15	14700.00	12.9	12.0	4.5	16075.0

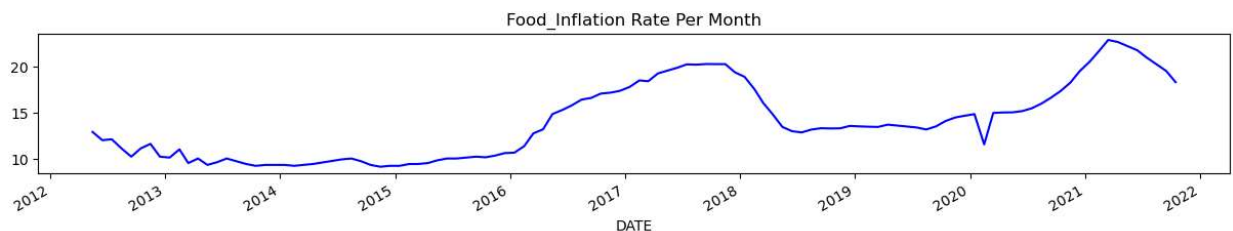
```
In [ ]: dataset['PRICE'].plot(color='green', figsize=(15,2))
plt.legend(['Next period value', 'prediction'])
plt.title("Local Rice Mill Price Per kg")
```

```
Out[ ]: Text(0.5, 1.0, 'Local Rice Mill Price Per kg')
```



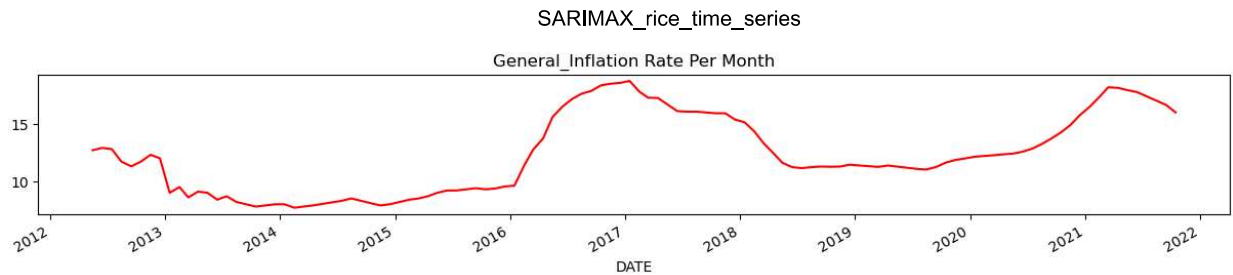
```
In [ ]: dataset['FOOD INFLATION'].plot(color='blue', figsize=(15,2))
plt.title("Food_Inflation Rate Per Month")
```

```
Out[ ]: Text(0.5, 1.0, 'Food_Inflation Rate Per Month')
```



```
In [ ]: dataset['INFLATION'].plot(color='red', figsize=(15,2))
plt.title("General_Inflation Rate Per Month")
```

```
Out[ ]: Text(0.5, 1.0, 'General_Inflation Rate Per Month')
```



```
In [ ]: from sklearn.preprocessing import MinMaxScaler
sc_in = MinMaxScaler(feature_range=(0, 1))

scaled_input = sc_in.fit_transform(dataset[['PRICE', 'INFLATION', 'FOOD INFLATION', 'SECURITY_INDEX']])

scaled_input = pd.DataFrame(scaled_input)

x = scaled_input
x.head(2)
```

```
Out[ ]:
```

	0	1	2	3
0	0.042389	0.453721	0.274368	0.0
1	0.030435	0.471869	0.209386	0.0

```
In [ ]: sc_out = MinMaxScaler(feature_range=(0, 1))
scaled_output = sc_out.fit_transform(dataset[['Actual']])

scaled_output = pd.DataFrame(scaled_output)

y = scaled_output
```

```
In [ ]: x.rename(columns={0:'Price', 1:'Inflation', 2:'Food_Inflation', 3:'Security_Index'}, inplace=True)
x.index = dataset.index
x.head()
```

```
Out[ ]:
```

	Price	Inflation	Food_Inflation	Security_Index
DATE				
2012-05-15	0.042389	0.453721	0.274368	0.0
2012-06-15	0.030435	0.471869	0.209386	0.0
2012-07-15	0.090217	0.462795	0.216606	0.0
2012-08-15	0.128696	0.362976	0.144404	0.0
2012-09-15	0.069565	0.326679	0.079422	0.0

```
In [ ]: y.rename(columns={0:'Price_prediction'}, inplace=True)
y.index = dataset.index
y.head(2)
```

Out [ ]:

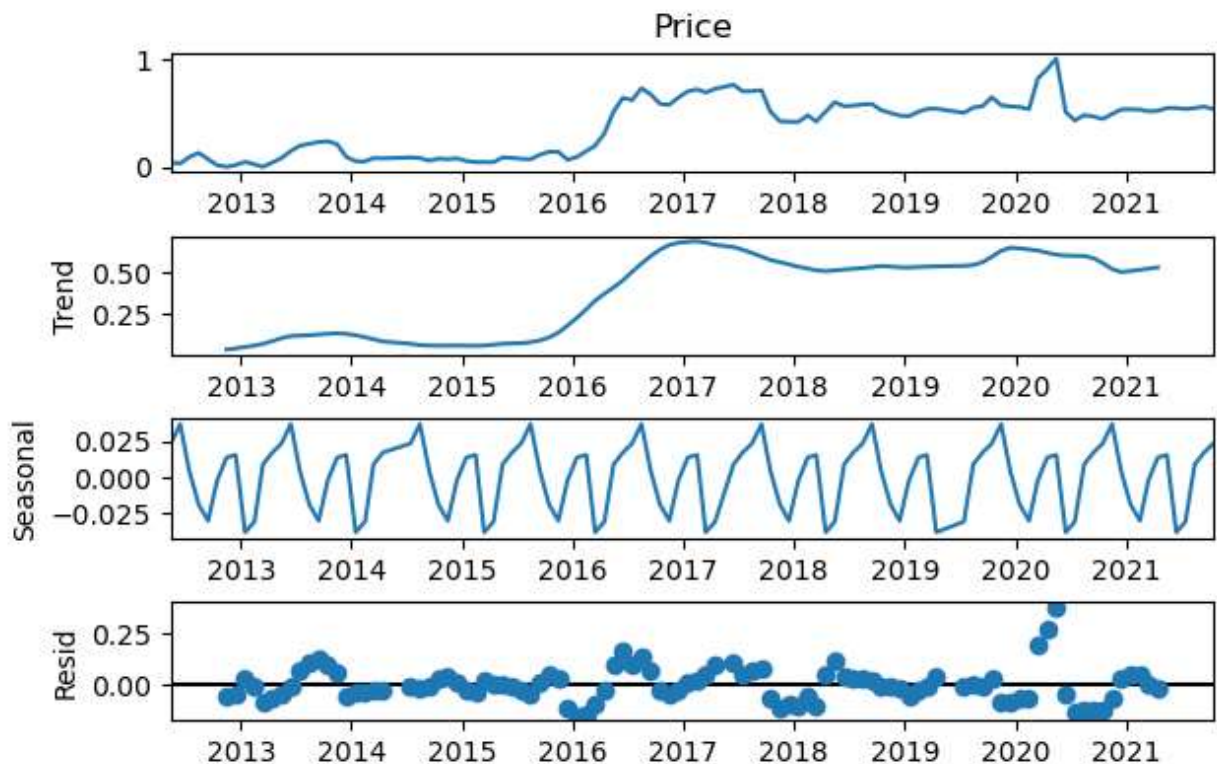
**Price\_prediction**

DATE	
2012-05-15	0.030435
2012-06-15	0.090217

```
In [ ]: train_size=int(len(dataset) *0.8)
test_size = int(len(dataset)) - train_size

train_x, train_y = x[:train_size-1].dropna(), y[:train_size-1].dropna()
test_x, test_y = x[train_size:].dropna(), y[train_size:].dropna()
```

```
In [ ]: import statsmodels.api as sm
seas_d=sm.tsa.seasonal_decompose(x['Price'], model='add', period=12);
fig=seas_d.plot()
fig.set_figheight(4)
plt.show()
```



Check for Data Stationarity using Augmented Dickey-Fuller(ADF) test.

If we make the data stationary, then the model can make predictions based on the fact that mean and variance will remain the same in the future. A stationarized series is easier to predict

To check if the data is stationary, we will use the Augmented Dickey-Fuller test. It is the most popular statistical method to find if the series is stationary or not. It is also called as Unit Root Test. If the value of  $p < 0.05$ , then the data is stationary.

```
In [ ]: from statsmodels.tsa.stattools import adfuller
def test_adf(series, title=''):

```

```
dfout={}
dftest=sm.tsa.adfuller(series.dropna(), autolag='AIC', regression='ct')
for key,val in dfctest[4].items():
    dfout[f'critical value ({key})']=val
if dfctest[1]<=0.05:
    print("Strong evidence against Null Hypothesis")
    print("Reject Null Hypothesis - Data is Stationary")
    print("Data is Stationary", title)
else:
    print("Strong evidence for Null Hypothesis")
    print("Accept Null Hypothesis - Data is not Stationary")
    print("Data is NOT Stationary for", title)
```

```
In [ ]: y_test=y['Price_prediction'][:train_size].dropna()
        test_adf(y_test, " Locally Milled Rice Price")
```

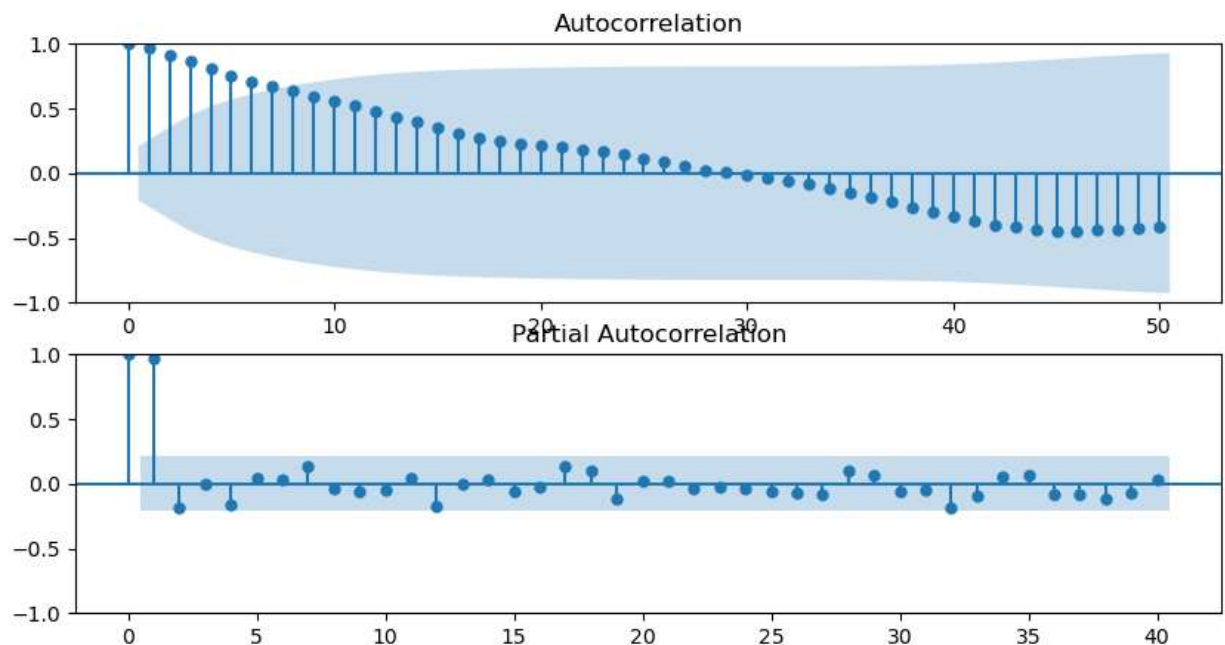
Strong evidence for Null Hypothesis  
Accept Null Hypothesis - Data is not Stationary  
Data is NOT Stationary for Locally Milled Rice Price

```
In [ ]: y_test_diff = test_adf(y_test.diff(), " -- Rice Price --")
```

Strong evidence against Null Hypothesis  
Reject Null Hypothesis - Data is Stationary  
Data is Stationary -- Rice Price --

We need to know the AR and MA terms to correct any autocorrelation in the differenced series  
ACF plot: is a bar chart of the coefficients of correlation between a time series and its lags. It helps determine the value of p or the AR term. PACF plot: a plot of the partial correlation coefficients between the series and lags of itself. Helps determine the value of q or the MA term

```
In [ ]: fig,ax= plt.subplots(2,1, figsize=(10,5))
        fig=sm.tsa.graphics.plot_acf(y_test, lags=50, ax=ax[0])
        fig=sm.tsa.graphics.plot_pacf(y_test, lags=40, ax=ax[1], method='ywm')
        plt.show()
```



We see that the PACF plot has a significant spike at lag 1 and lag 2, meaning that all the higher-order autocorrelations are effectively explained by the lag-1 and lag 2 autocorrelations

```
In [ ]: import pyramid as pm
step_wise=pm.auto_arima(train_y, exogenous= train_x, start_p=1, start_q=1,
max_p=7, max_q=7, d=1, max_d=7, trace=True, error_action='ignore',
suppress_warnings=True, stepwise=True)
```

```
-----
ModuleNotFoundError                                Traceback (most recent call last)
~\AppData\Local\Temp\ipykernel_7216\789207240.py in <module>
----> 1 import pyramid as pm
      2 step_wise=pm.auto_arima(train_y, exogenous= train_x, start_p=1, start_q=1,
      3 max_p=7, max_q=7, d=1, max_d=7, trace=True, error_action='ignore',
      4 suppress_warnings=True, stepwise=True)

ModuleNotFoundError: No module named 'pyramid'
```

```
In [ ]:
```

```
In [ ]: from statsmodels.tsa.statespace.sarimax import SARIMAX
model= SARIMAX(train_y, exog=train_x, order=(0,1,1),
enforce_invertibility=False, enforce_stationarity=False)
```

```
c:\ProgramData\Anaconda3\lib\site-packages\statsmodels\tsa\base\tsa_model.py:471: Val
ueWarning: A date index has been provided, but it has no associated frequency informa
tion and so will be ignored when e.g. forecasting.
  self._init_dates(dates, freq)
c:\ProgramData\Anaconda3\lib\site-packages\statsmodels\tsa\base\tsa_model.py:471: Val
ueWarning: A date index has been provided, but it has no associated frequency informa
tion and so will be ignored when e.g. forecasting.
  self._init_dates(dates, freq)
```

```
In [ ]: results = model.fit()
result_summary = results.summary()
```

```
In [ ]: result_summary
```



Out[ ]:

## SARIMAX Results

<b>Dep. Variable:</b>	Price_prediction	<b>No. Observations:</b>	86			
<b>Model:</b>	SARIMAX(0, 1, 1)	<b>Log Likelihood</b>	128.745			
<b>Date:</b>	Sun, 12 Feb 2023	<b>AIC</b>	-245.491			
<b>Time:</b>	15:17:26	<b>BIC</b>	-230.978			
<b>Sample:</b>	0	<b>HQIC</b>	-239.660			
	- 86					
<b>Covariance Type:</b>	opg					
	<b>coef</b>	<b>std err</b>	<b>z</b>	<b>P&gt; z </b>	<b>[0.025</b>	<b>0.975]</b>
<b>Price</b>	0.3856	0.236	1.633	0.102	-0.077	0.848
<b>Inflation</b>	0.3067	0.188	1.633	0.103	-0.061	0.675
<b>Food_Inflation</b>	-0.2115	0.213	-0.994	0.320	-0.628	0.205
<b>Security_Index</b>	0.0229	0.489	0.047	0.963	-0.935	0.981
<b>ma.L1</b>	-0.1315	0.262	-0.502	0.616	-0.645	0.382
<b>sigma2</b>	0.0026	0.000	8.537	0.000	0.002	0.003
<b>Ljung-Box (L1) (Q):</b>	0.01	<b>Jarque-Bera (JB):</b>	24.94			
<b>Prob(Q):</b>	0.94	<b>Prob(JB):</b>	0.00			
<b>Heteroskedasticity (H):</b>	2.96	<b>Skew:</b>	-0.64			
<b>Prob(H) (two-sided):</b>	0.01	<b>Kurtosis:</b>	5.36			

## Warnings:

[1] Covariance matrix calculated using the outer product of gradients (complex-step).

In [ ]: `predictions= results.predict(start =train_size, end=train_size+test_size+(steps)-1,ex`

```
c:\ProgramData\Anaconda3\lib\site-packages\statsmodels\tsa\base\tsa_model.py:834: ValueWarning: No supported index is available. Prediction results will be given with an integer index beginning at `start`.
    return get_prediction_index(
```

In [ ]: `act= pd.DataFrame(scaled_output.iloc[train_size:, 0])`

```
In [ ]: predictions=pd.DataFrame(predictions)
predictions.reset_index(drop=True, inplace=True)
predictions.index=test_x.index[1:]
predictions['Actual'] = act['Price_prediction']
predictions.rename(columns={0:'Pred'}, inplace=True)
```

In [ ]: `predictions.head(2)`



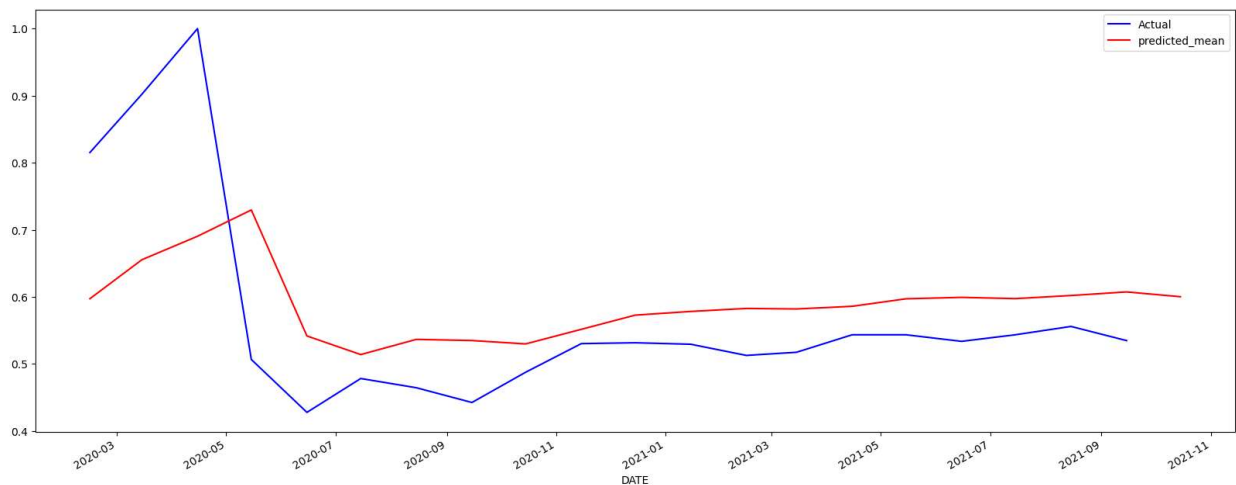
```
Out[ ]:

```

	predicted_mean	Actual
DATE		
2020-02-15	0.597266	0.815217
2020-03-15	0.655373	0.902174

```
In [ ]: predictions['Actual'].plot(figsize=(20,8), legend=True, color='blue')
predictions['predicted_mean'].plot(legend=True, color='red', figsize=(20,8))
```

```
Out[ ]: <AxesSubplot:xlabel='DATE'>
```



```
In [ ]: from statsmodels.tools.eval_measures import rmse
error=rmse(predictions['predicted_mean'], predictions['Actual'])
error
```

```
Out[ ]: nan
```

```
In [ ]: trainPredict = sc_out.inverse_transform(predictions[['predicted_mean']])
testPredict = sc_out.inverse_transform(predictions[['Actual']])
```

```
In [ ]: trainPredict.plot(figsize=(20,8), legend=True, color='blue')
testPredict.plot(legend=True, color='red', figsize=(20,8))
```

```
-----
AttributeError                                Traceback (most recent call last)
~\AppData\Local\Temp\ipykernel_7216\3649369440.py in <module>
----> 1 trainPredict.plot(figsize=(20,8), legend=True, color='blue')
      2 testPredict.plot(legend=True, color='red', figsize=(20,8))

AttributeError: 'numpy.ndarray' object has no attribute 'plot'
```

```
In [ ]: trainPredict
```

```
Out[ ]: array([[27737.11538133],
               [29073.5721988 ],
               [29878.33477372],
               [30780.72823982],
               [26458.81581969],
               [25820.73420125],
               [26341.94494212],
               [26301.77918815],
               [26186.78728508],
               [26686.9296076 ],
               [27172.9088113 ],
               [27300.10383618],
               [27402.66040124],
               [27385.2794759 ],
               [27475.80630076],
               [27733.61296097],
               [27782.80634754],
               [27739.80764137],
               [27846.34972505],
               [27969.58428183],
               [27804.52933757]])
```

```
In [ ]: len(testPredict)
```

```
Out[ ]: 21
```

```
In [ ]: testPredict
```

```
Out[ ]: array([[32750. ],
               [34750. ],
               [37000. ],
               [25652.17],
               [23838.71],
               [25000. ],
               [24683.33],
               [24177.42],
               [25216.67],
               [26196.77],
               [26225.81],
               [26175. ],
               [25791.67],
               [25900. ],
               [26500. ],
               [26500. ],
               [26274.19],
               [26500. ],
               [26785.71],
               [26300. ],
               [      nan]])
```