D214 Capstone

Modeling Inflation Adusted Recessionary Lumber Prices

COVID 19 Recession

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Section C: Data Preparation

Import Packages

In [1]:
```
# Import Initial Libraries
import matplotlib.pyplot as plt
import pandas as pd
import numpy as np
from scipy import stats
from statsmodels.tsa.stattools import adfuller
import statsmodels
import datetime
import platform
from pmdarima.arima import ndiffs
from statsmodels.tsa.seasonal import seasonal_decompose
from pylab import rcParams
from statsmodels.graphics.tsaplots import plot_acf
from sklearn.metrics import mean_squared_error
from math import sqrt
from statsmodels.graphics.tsaplots import plot_pacf
import warnings
from scipy import signal
from pmdarima.arima import StepwiseContext
from pmdarima.arima import auto_arima
from pmdarima.model_selection import train_test_split
```

Environment

In [2]:
```
# Windows 10, Anaconda, JupyterLab, JupyterNotebook
# Jupyter environment version
!jupyter --version
```

```
Selected Jupyter core packages...
IPython          : 7.31.1
ipykernel        : 6.15.2
ipywidgets       : not installed
jupyter_client   : 7.3.5
jupyter_core     : 4.10.0
jupyter_server   : 1.18.1
jupyterlab       : 3.4.4
nbclient         : 0.5.13
nbconvert        : 6.4.4
nbformat         : 5.5.0
notebook         : 6.4.12
qtconsole        : not installed
traitlets        : 5.1.1
```

In [3]:
```
# Python Version
print(platform.python_version())
```

```
3.7.13
```

In [4]:
```
#Load Medical Dataset
df = pd.read_csv('C:/Users/ericy/Desktop/lumber_trading_days_adj.csv')
```

Data Selection for Analysis

In [5]:
```
#------ Select Data Set for Recession
df = df[11359:11941]
```

In [6]:
```
df
```

Out[6]:

	Date	Trading Days	2022_Value	Value
11359	2018-01-10	11360	511.3770	460.70
11360	2018-01-11	11361	514.8180	463.80
11361	2018-01-12	11362	517.3710	466.10
11362	2018-01-16	11363	526.9170	474.70
11363	2018-01-17	11364	528.8040	476.40
...	...	...	...	...
11936	2020-04-27	11937	333.0096	314.16
11937	2020-04-28	11938	343.0372	323.62
11938	2020-04-29	11939	333.5396	314.66
11939	2020-04-30	11940	340.4932	321.22
11940	2020-05-01	11941	348.2100	328.50

582 rows × 4 columns

D1: Exploratory Data Analysis

Select columns 'Trading Days' and '2022_Value' for time series modeling

In [7]:
```
df = df[['Trading Days','2022_Value']]
```

In [8]:
```
df
```

Out[8]:

	Trading Days	2022_Value
11359	11360	511.3770
11360	11361	514.8180
11361	11362	517.3710
11362	11363	526.9170
11363	11364	528.8040
...	...	...
11936	11937	333.0096
11937	11938	343.0372
11938	11939	333.5396
11939	11940	340.4932
11940	11941	348.2100

582 rows × 2 columns

In [9]:
```
df.head()
```

Out[9]:

	Trading Days	2022_Value
11359	11360	511.377
11360	11361	514.818
11361	11362	517.371
11362	11363	526.917
11363	11364	528.804

In [10]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 582 entries, 11359 to 11940
Data columns (total 2 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   Trading Days  582 non-null    int64
 1   2022_Value    582 non-null    float64
dtypes: float64(1), int64(1)
memory usage: 9.2 KB
```

Explore shape and descriptive statistics of dataset

In [11]:
```
df.shape
```

Out[11]: (582, 2)

In [12]:
```
df.describe()
```

Out[12]:

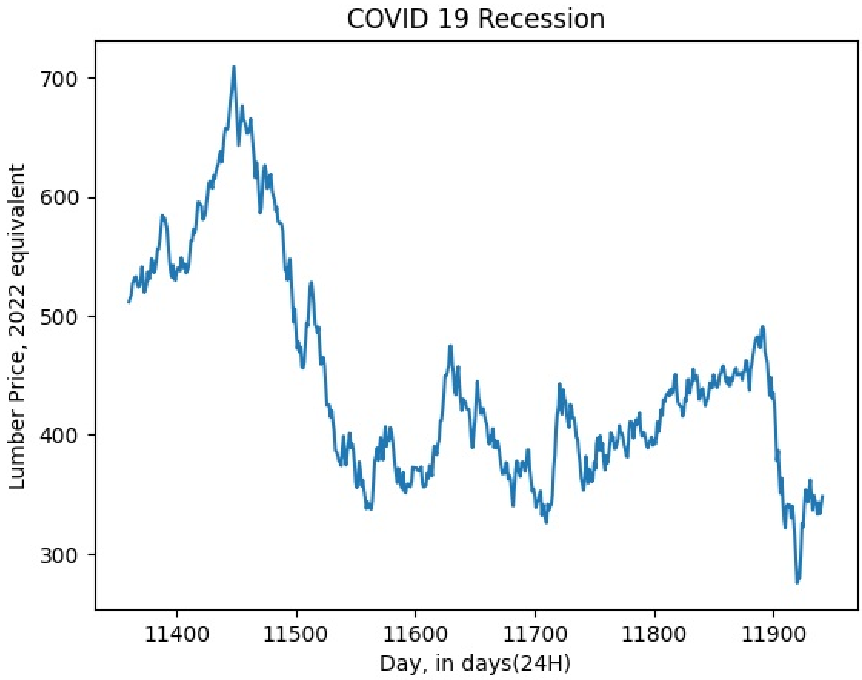
	Trading Days	2022_Value
count	582.000000	582.000000
mean	11650.500000	445.868714
std	168.153204	91.041451
min	11360.000000	275.388000
25%	11505.250000	377.255250
50%	11650.500000	422.064000
75%	11795.750000	493.478250
max	11941.000000	709.290000

In [13]:
```
df.isnull().any()
```

Out[13]:
```
Trading Days     False
2022_Value       False
dtype: bool
```

Line Graph Visualization

In [14]:
```
#-------
plt.plot(df['Trading Days'],df['2022_Value'])
plt.title('COVID 19 Recession')
plt.xlabel('Day, in days(24H)')
plt.ylabel('Lumber Price, 2022 equivalent')
plt.show()
```



Drop any null values, if there are any

In [15]:
```
# Drop any null columns
df = df.dropna()
```

D2: Time Step Formatting, Indexing

Set df['Trading Days'] to Index

In [16]:
```
# Day to datetime
df['Trading Days'] = pd.to_datetime(df['Trading Days'], unit='D')
```

In [17]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 582 entries, 11359 to 11940
Data columns (total 2 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   Trading Days  582 non-null    datetime64[ns]
 1   2022_Value    582 non-null    float64
dtypes: datetime64[ns](1), float64(1)
memory usage: 13.6 KB
```

In [18]:
```
# Set Day as Index
df.set_index('Trading Days',inplace=True)
```

In [19]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 582 entries, 2001-02-07 to 2002-09-11
Data columns (total 1 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   2022_Value  582 non-null    float64
dtypes: float64(1)
memory usage: 9.1 KB
```

In [20]:
```
df
```

Out[20]:

Trading Days	2022_Value
2001-02-07	511.3770
2001-02-08	514.8180
2001-02-09	517.3710
2001-02-10	526.9170
2001-02-11	528.8040
...	...
2002-09-07	333.0096
2002-09-08	343.0372
2002-09-09	333.5396
2002-09-10	340.4932
2002-09-11	348.2100

582 rows × 1 columns

D3: Stationarity Analysis

Augmented Dickey Fuller (ADF) Test

Assess stationarity of dataset

In [21]:
```
# Code Reference (Making time series stationary | Python, n.d.)
dicky_fuller_test = adfuller(df)
```

In [22]:
```
dicky_fuller_test
```

Out[22]:
```
(-1.364878377211528,
 0.5989933044250826,
 1,
 580,
 {'1%': -3.4416749612171467,
  '5%': -2.8665360672844318,
  '10%': -2.5694307639714626},
 4110.914790353596)
```

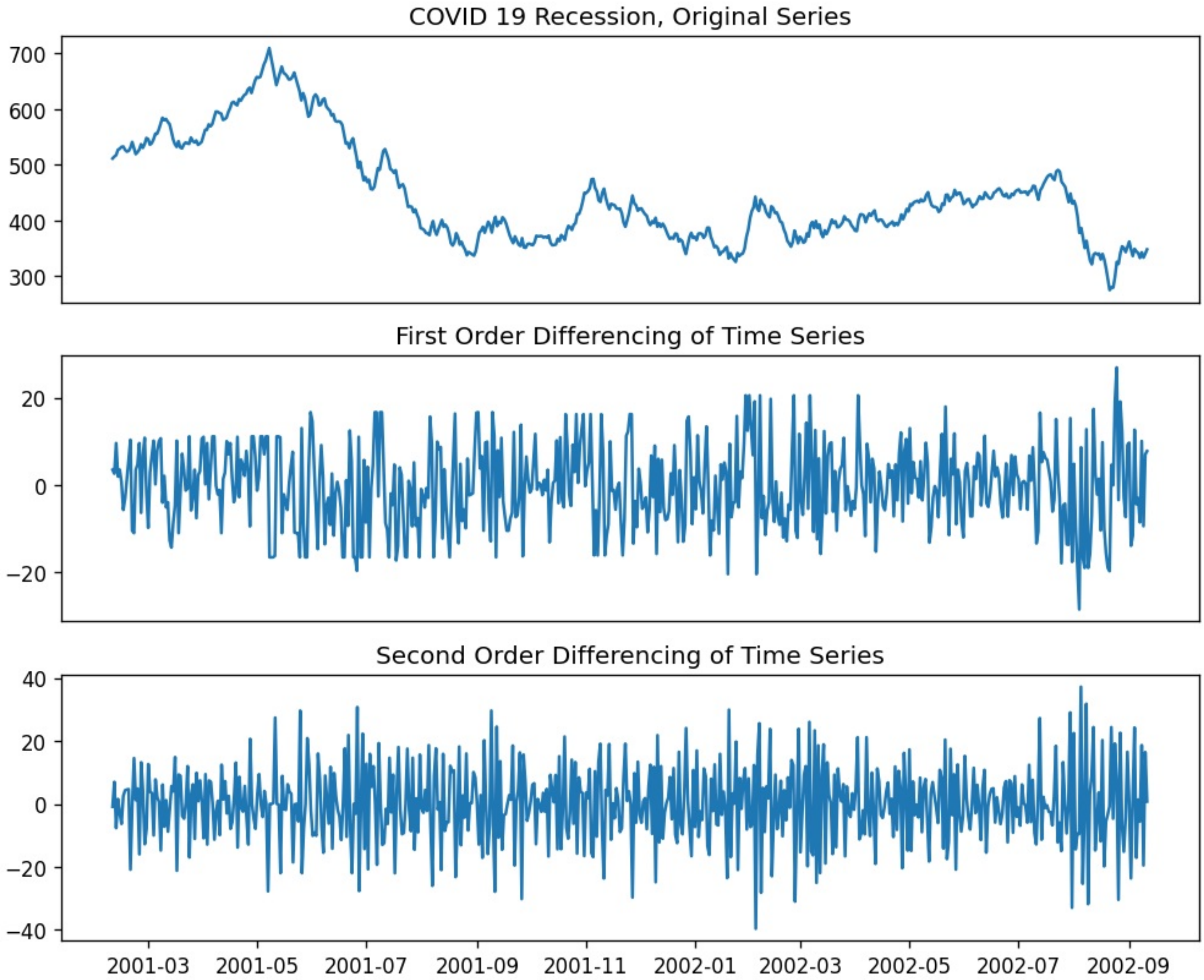
In [23]:
```
# Results show p = .55864
# Data does not reject null hypothesis at p < .05
# Therefore, Time series is determined to be non-stationary
```

D4 Differencing

1st and 2nd order Differencing

finding 'd' for ARIMA model

In [24]:
```python
# Set plot parameters for multi-ax subplots
plt.rcParams.update({'figure.figsize':(10,8), 'figure.dpi':120})

# Establish that there are three subplots
fig, (ax1, ax2, ax3) = plt.subplots(3)

# Plot the original dataset
ax1.plot(df); ax1.set_title('COVID 19 Recession, Original Series'); ax1.axes.xaxis.set_visible(False)

# First Order differencing of Time Series
ax2.plot(df.diff()); ax2.set_title('First Order Differencing of Time Series'); ax2.axes.xaxis.set_visible(False

# Second Order Differencing of Time Series
ax3.plot(df.diff().diff()); ax3.set_title('Second Order Differencing of Time Series')

# Plot all three graphs
plt.show()
```



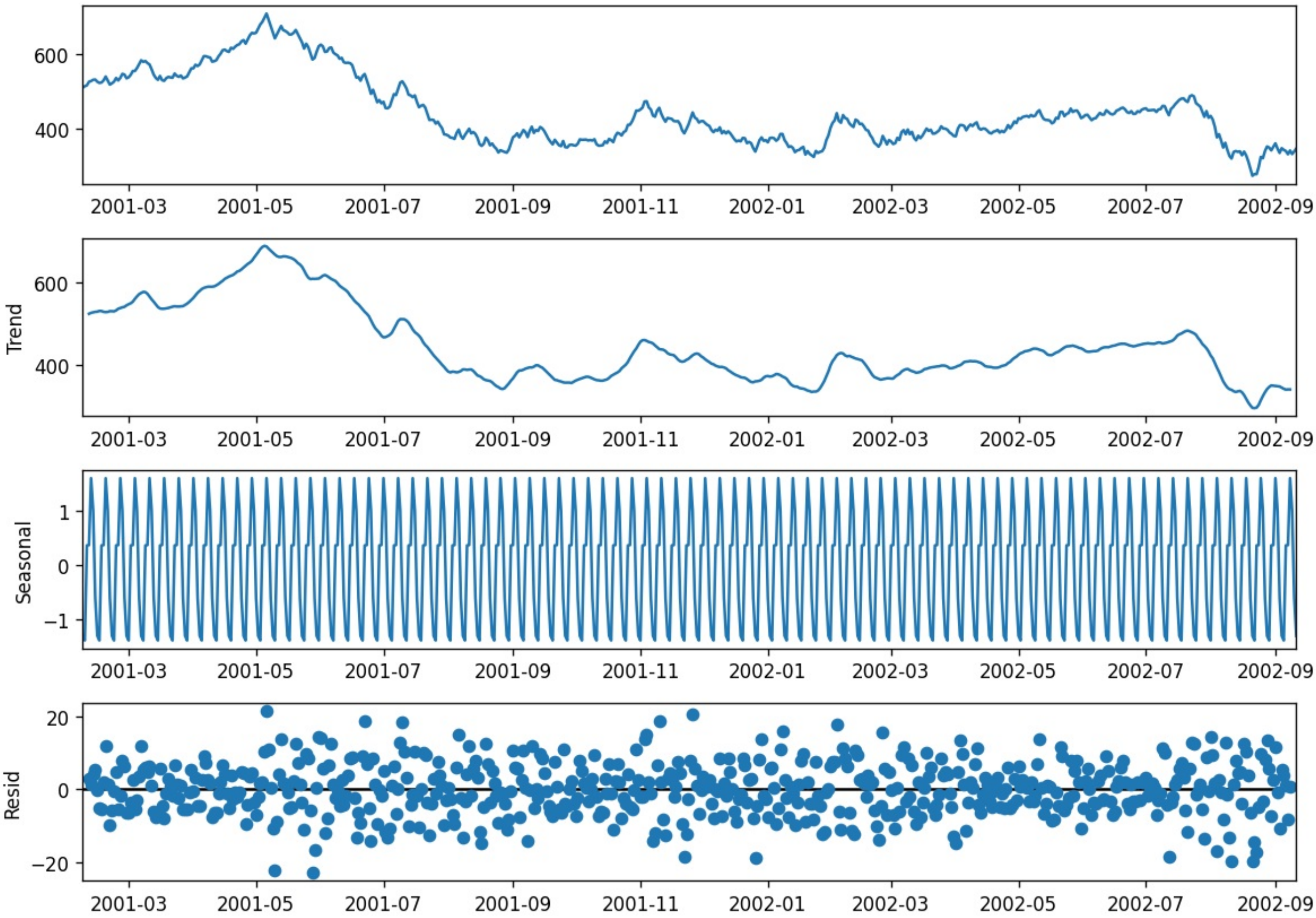
In [25]:
```python
# Using pmdarima's ndiffs to find differencing term
# Code reference (Verma, 2021)

kpss_diffs = ndiffs(df, alpha=0.05, test='kpss', max_d=6)
adf_diffs = ndiffs(df, alpha=0.05, test='adf', max_d=6)
n_diffs = max(adf_diffs, kpss_diffs)

print(f"Estimated differencing term: {n_diffs}")
```

```
Estimated differencing term: 1
```

D5: Seasonality Analysis

In [26]:
```python
# Code Reference (Boston, 2020)
result = seasonal_decompose(df)
```

In [27]:
```python
# plotting the result of our seasonal decomposition from the step above
rcParams['figure.figsize'] = 10,7
result.plot();
```



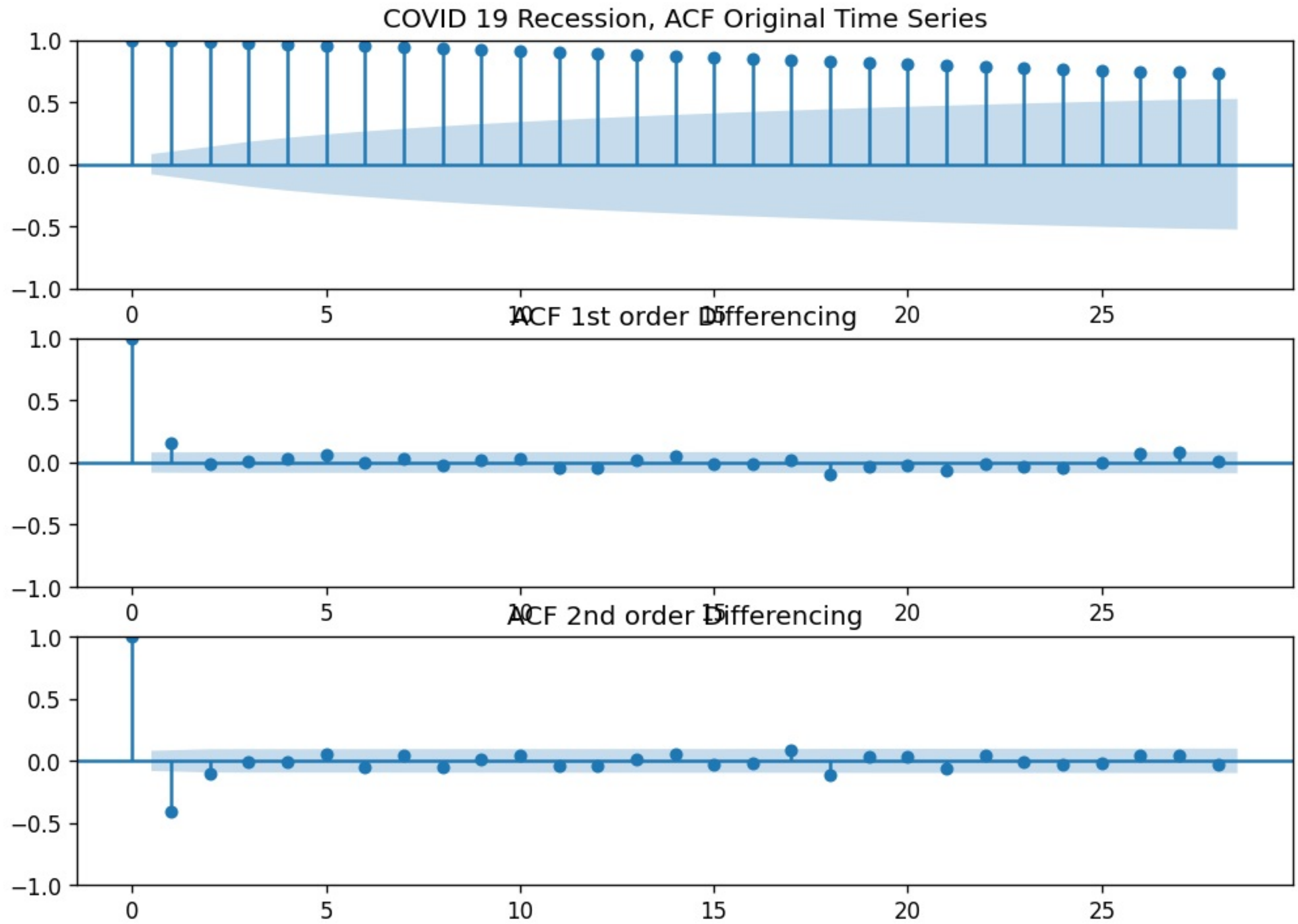
D6 ACF and PACF

Finding order of MA term 'q'

Using Autocorrelation function (ACF)

In [28]:

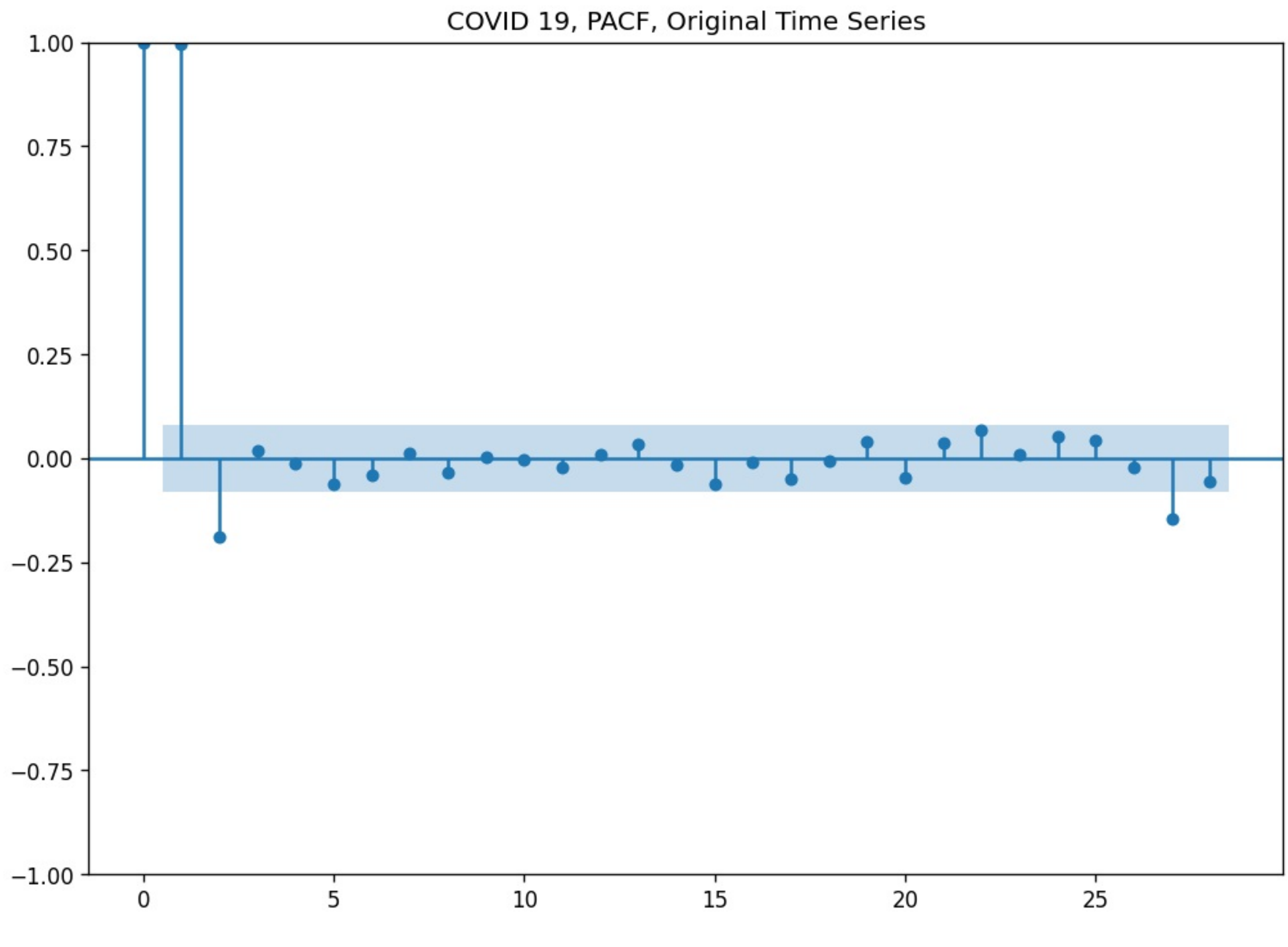
```
fig, (ax1, ax2, ax3) = plt.subplots(3)
plot_acf(df, ax=ax1, title='COVID 19 Recession, ACF Original Time Series');
plot_acf(df.diff().dropna(), ax=ax2, title='ACF 1st order Differencing');
plot_acf(df.diff().diff().dropna(), ax=ax3, title='ACF 2nd order Differencing');
```



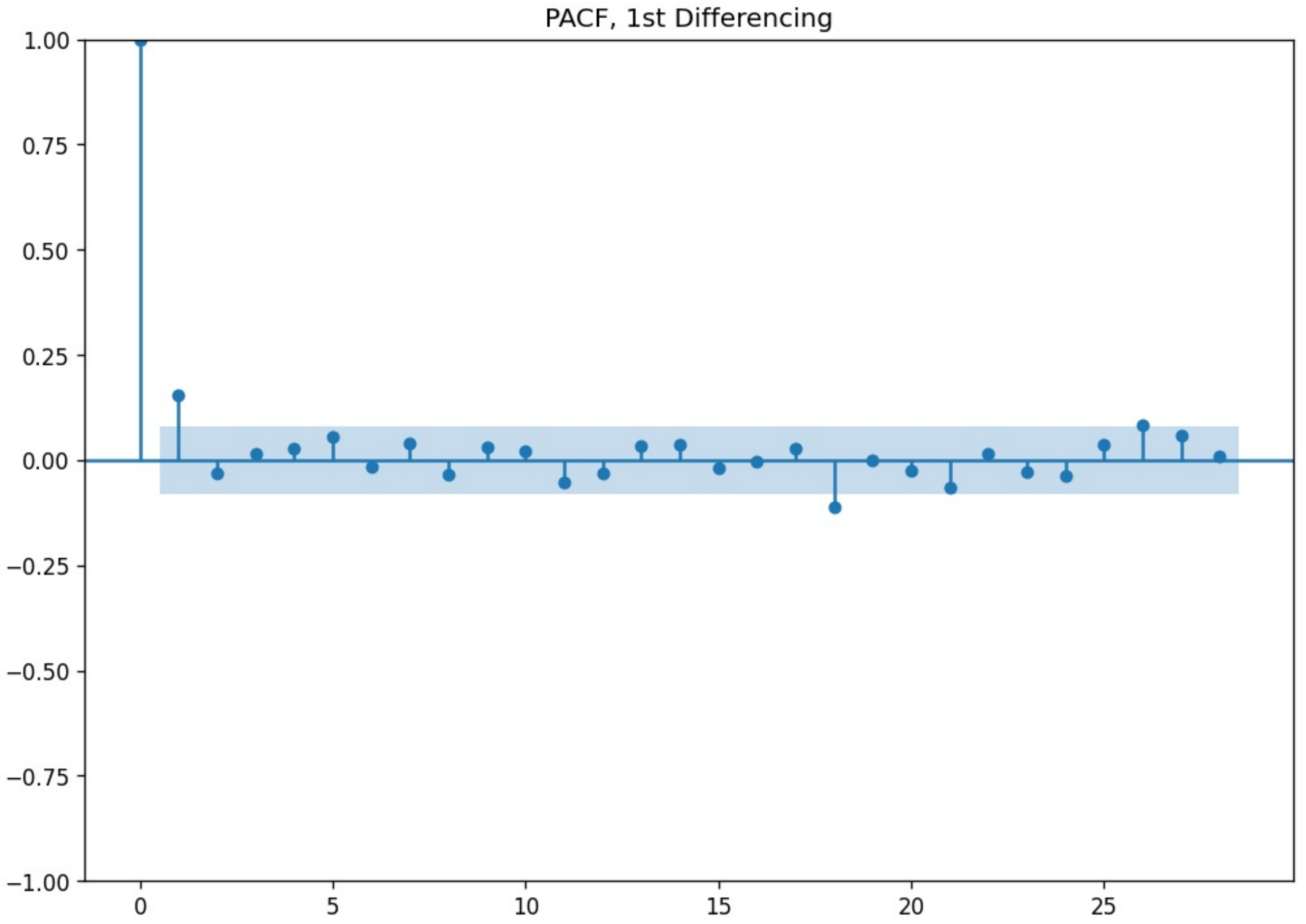
Finding order of AR term 'p'

Using Partial autocorrelation (PACF)

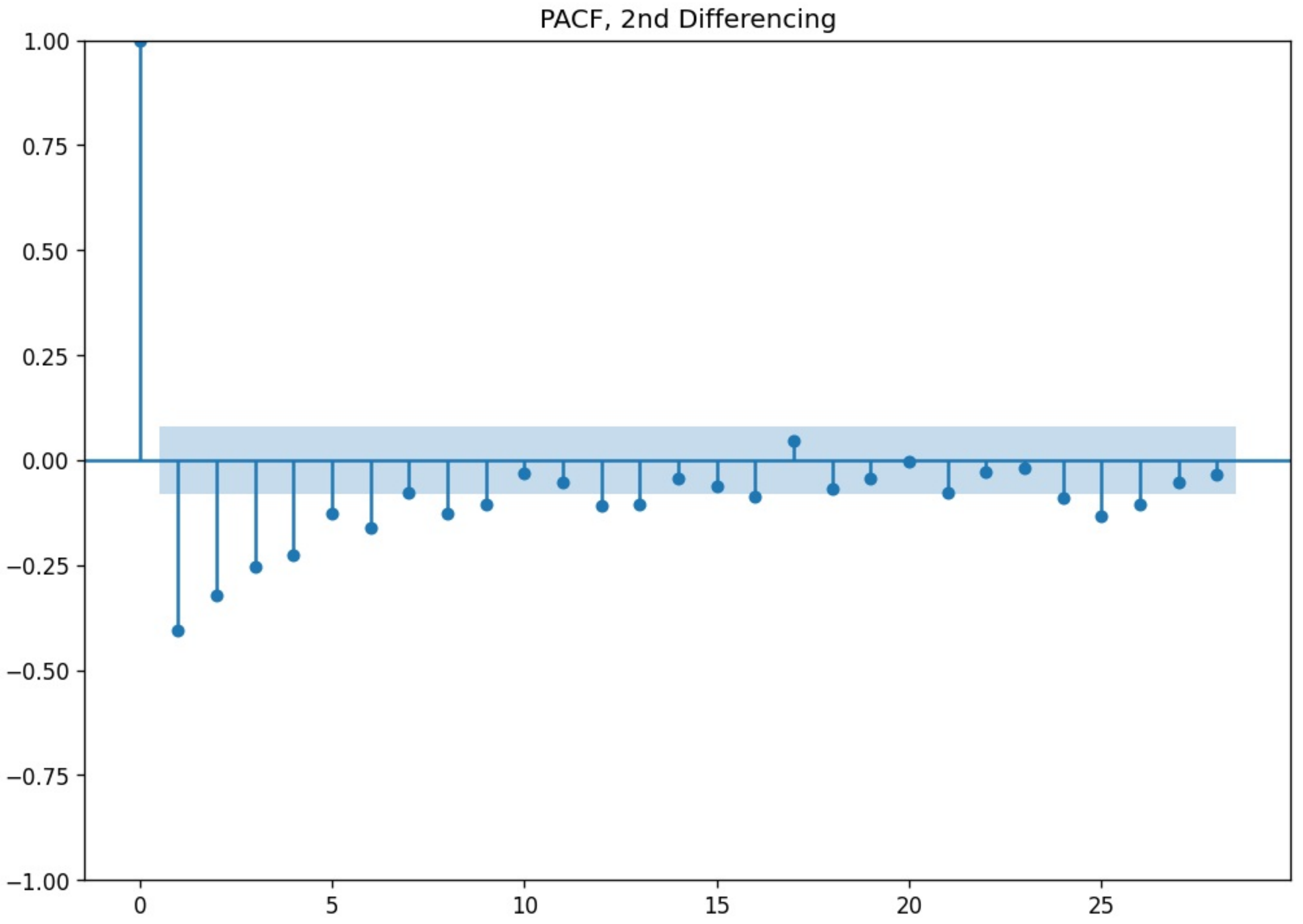
In [29]:
```
warnings.filterwarnings("ignore")
plot_pacf(df.dropna(), title='COVID 19, PACF, Original Time Series');
```



In [30]:
```
plot_pacf(df.diff().dropna(), title='PACF, 1st Differencing');
```

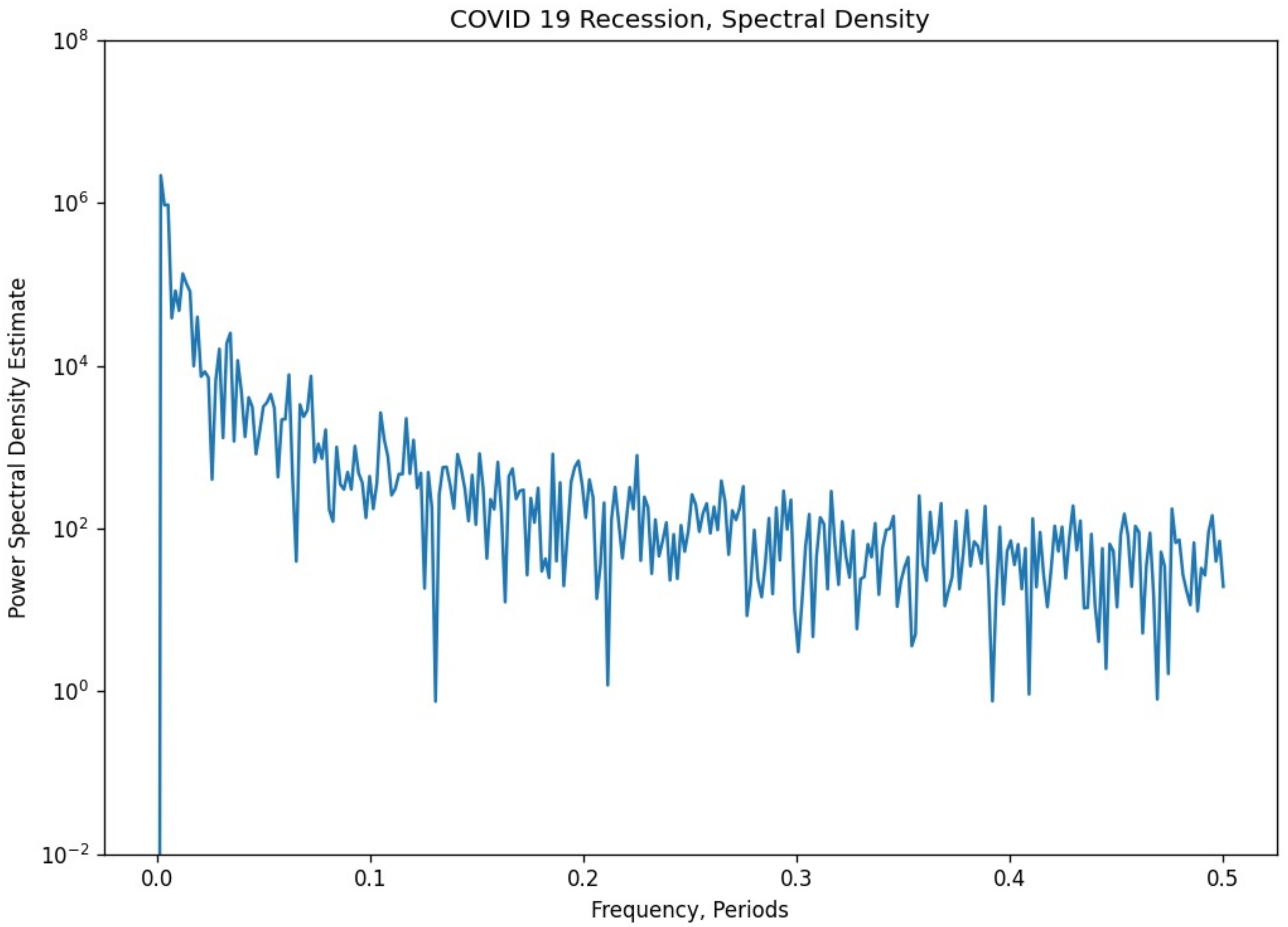


In [31]:
```
plot_pacf(df.diff().diff().dropna(), title='PACF, 2nd Differencing');
```



D7 Spectral Density

In [32]:
```
# Code Reference (Festus, 2022)

# signal periodogram
f, Pxx_den = signal.periodogram(df['2022_Value'])

# plotting semilogy - pyplot module used to make a plot with log scaling on the y-axis
plt.semilogy(f, Pxx_den)

# Setting coordinate values and titles for Spectral Density Graph
# setting y-axis min and max value
plt.ylim(1e-2, 1e8)

# Graph Title
plt.title('COVID 19 Recession, Spectral Density')

# X label for Periods
plt.xlabel('Frequency, Periods')

# Y Label for SD Estimate
plt.ylabel('Power Spectral Density Estimate')
plt.show()
```



D8 Create Train/Test Datasets

Dataset Size = 582 cases

80/20 Train/Test Split

Split is 465 / 113

In [33]:
```
# ------Splitting data into Test and Train sets using pmdarima's train_test_split
# code reference (Smith, 2019)

train, test = train_test_split(df, train_size=469)
```

In [34]:
```
train
```

Out[34]:

Trading Days	2022_Value
2001-02-07	511.377
2001-02-08	514.818
2001-02-09	517.371
2001-02-10	526.917
2001-02-11	528.804
...	...
2002-05-17	415.584
2002-05-18	418.932
2002-05-19	430.596
2002-05-20	428.112
2002-05-21	446.040

469 rows × 1 columns

In [35]:

```
test
```

Out[35]:

Trading Days	2022_Value
2002-05-22	446.4720
2002-05-23	434.9160
2002-05-24	440.8560
2002-05-25	443.2320
2002-05-26	455.0040
...	...
2002-09-07	333.0096
2002-09-08	343.0372
2002-09-09	333.5396
2002-09-10	340.4932
2002-09-11	348.2100

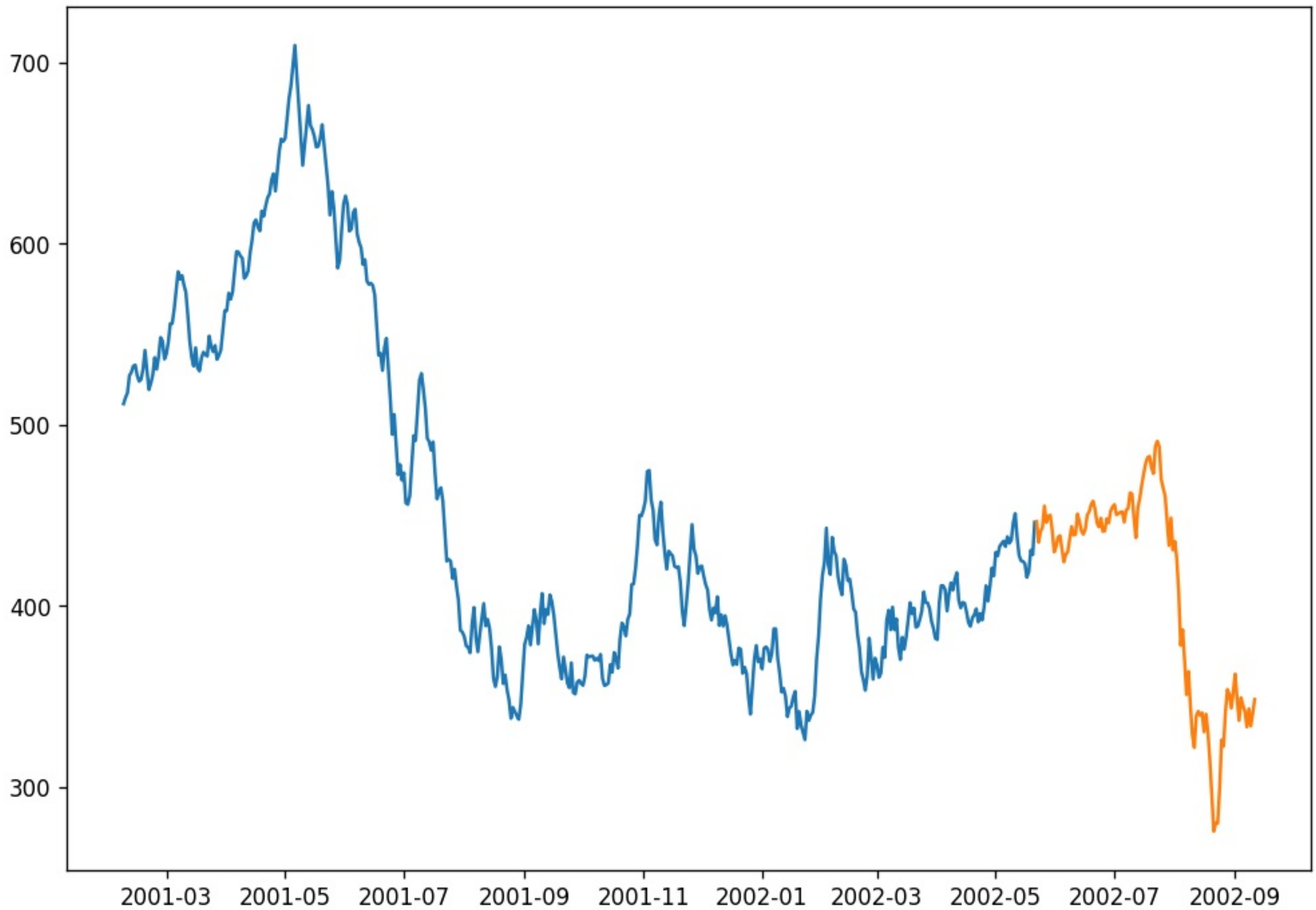
113 rows × 1 columns

In [36]:

```
# Plot training data
plt.plot(train)

# Plot Test Data
plt.plot(test)
```

Out[36]:

```
[<matplotlib.lines.Line2D at 0x1c27baf6808>]
```



In [37]:
```
print(train.shape)
print(test.shape)
```

```
(469, 1)
(113, 1)
```

D9 Auto-arima ARIMA Modeling

Using pmdarima's auto_arima

In [38]:
```
# Fit the model using auto_arima
# Auto-arima code reference (6. Tips to using auto_arima — pmdarima 2.0.1 documentation, n.d.)
# Additional code reference (Pmdarima.arima.AutoARIMA — pmdarima 2.0.1 documentation, n.d.)
# Auto-arima, initial parameter attempt
# Code Reference (Kosaka, 2021)
```

```python
# Establish auto_arima to run ARIMA and take into account
# Any Seasonality of the data, and any trends found.
model = auto_arima(train, start_p=1, start_q=1,
                   test='adf',
                   max_p=3,
                   max_q=3,
                   max_d=3,
                   seasonal=True,
                   stationarity=False,
                   seasonal_test='ocsb',
                   trace=True,
                   error_action='ignore',
                   suppress_warnings=True,
                   stepwise=True,
                  trend='c')

# Print Summary of Best AIC Minimized SARIMAX Model
print(model.summary())
```

```
Performing stepwise search to minimize aic
 ARIMA(1,1,1)(0,0,0)[0] intercept   : AIC=3404.640, Time=0.19 sec
 ARIMA(0,1,0)(0,0,0)[0] intercept   : AIC=3414.796, Time=0.02 sec
 ARIMA(1,1,0)(0,0,0)[0] intercept   : AIC=3403.209, Time=0.05 sec
 ARIMA(0,1,1)(0,0,0)[0] intercept   : AIC=3402.640, Time=0.06 sec
 ARIMA(0,1,0)(0,0,0)[0]             : AIC=3414.796, Time=0.01 sec
 ARIMA(0,1,2)(0,0,0)[0] intercept   : AIC=3404.639, Time=0.12 sec
 ARIMA(1,1,2)(0,0,0)[0] intercept   : AIC=3406.622, Time=0.36 sec
 ARIMA(0,1,1)(0,0,0)[0]             : AIC=3402.640, Time=0.07 sec

Best model:  ARIMA(0,1,1)(0,0,0)[0] intercept
Total fit time: 0.893 seconds
                               SARIMAX Results
==============================================================================
Dep. Variable:                      y   No. Observations:                  469
Model:               SARIMAX(0, 1, 1)   Log Likelihood               -1698.320
Date:                Tue, 18 Oct 2022   AIC                           3402.640
Time:                        13:37:45   BIC                           3415.085
Sample:                    02-07-2001   HQIC                          3407.537
                         - 05-21-2002
Covariance Type:                  opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
intercept     -0.1313      0.496     -0.264      0.791      -1.104       0.842
ma.L1          0.1761      0.045      3.903      0.000       0.088       0.265
sigma2        83.0825      6.640     12.512      0.000      70.068      96.097
===================================================================================
Ljung-Box (L1) (Q):                   0.00   Jarque-Bera (JB):                 8.24
Prob(Q):                              1.00   Prob(JB):                         0.02
Heteroskedasticity (H):               1.07   Skew:                             0.02
Prob(H) (two-sided):                  0.68   Kurtosis:                         2.35
===================================================================================

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

In [67]:
```python
model = auto_arima(train, trace=True)

# Print Summary of Best AIC Minimized SARIMAX Model
print(model.summary())
```

```
Performing stepwise search to minimize aic
 ARIMA(2,1,2)(0,0,0)[0] intercept   : AIC=3406.963, Time=0.66 sec
 ARIMA(0,1,0)(0,0,0)[0] intercept   : AIC=3414.796, Time=0.02 sec
 ARIMA(1,1,0)(0,0,0)[0] intercept   : AIC=3403.209, Time=0.05 sec
 ARIMA(0,1,1)(0,0,0)[0] intercept   : AIC=3402.640, Time=0.07 sec
 ARIMA(0,1,0)(0,0,0)[0]             : AIC=3412.903, Time=0.02 sec
 ARIMA(1,1,1)(0,0,0)[0] intercept   : AIC=3404.640, Time=0.13 sec
 ARIMA(0,1,2)(0,0,0)[0] intercept   : AIC=3404.639, Time=0.11 sec
 ARIMA(1,1,2)(0,0,0)[0] intercept   : AIC=3406.622, Time=0.37 sec
 ARIMA(0,1,1)(0,0,0)[0]             : AIC=3400.710, Time=0.03 sec
 ARIMA(1,1,1)(0,0,0)[0]             : AIC=3402.710, Time=0.05 sec
 ARIMA(0,1,2)(0,0,0)[0]             : AIC=3402.710, Time=0.05 sec
 ARIMA(1,1,0)(0,0,0)[0]             : AIC=3401.274, Time=0.03 sec
 ARIMA(1,1,2)(0,0,0)[0]             : AIC=3404.706, Time=0.07 sec

Best model:  ARIMA(0,1,1)(0,0,0)[0]
Total fit time: 1.708 seconds
                               SARIMAX Results
==============================================================================
Dep. Variable:                      y   No. Observations:                  469
Model:               SARIMAX(0, 1, 1)   Log Likelihood               -1698.355
Date:                Tue, 18 Oct 2022   AIC                           3400.710
Time:                        21:11:17   BIC                           3409.007
Sample:                    02-07-2001   HQIC                          3403.975
                         - 05-21-2002
Covariance Type:                  opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ma.L1          0.1763      0.045      3.914      0.000       0.088       0.265
sigma2        83.0924      6.642     12.510      0.000      70.074      96.111
===================================================================================
Ljung-Box (L1) (Q):                   0.00   Jarque-Bera (JB):                 8.23
Prob(Q):                              1.00   Prob(JB):                         0.02
Heteroskedasticity (H):               1.07   Skew:                             0.02
Prob(H) (two-sided):                  0.68   Kurtosis:                         2.35
===================================================================================

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

In [40]:
```
model.conf_int()
```

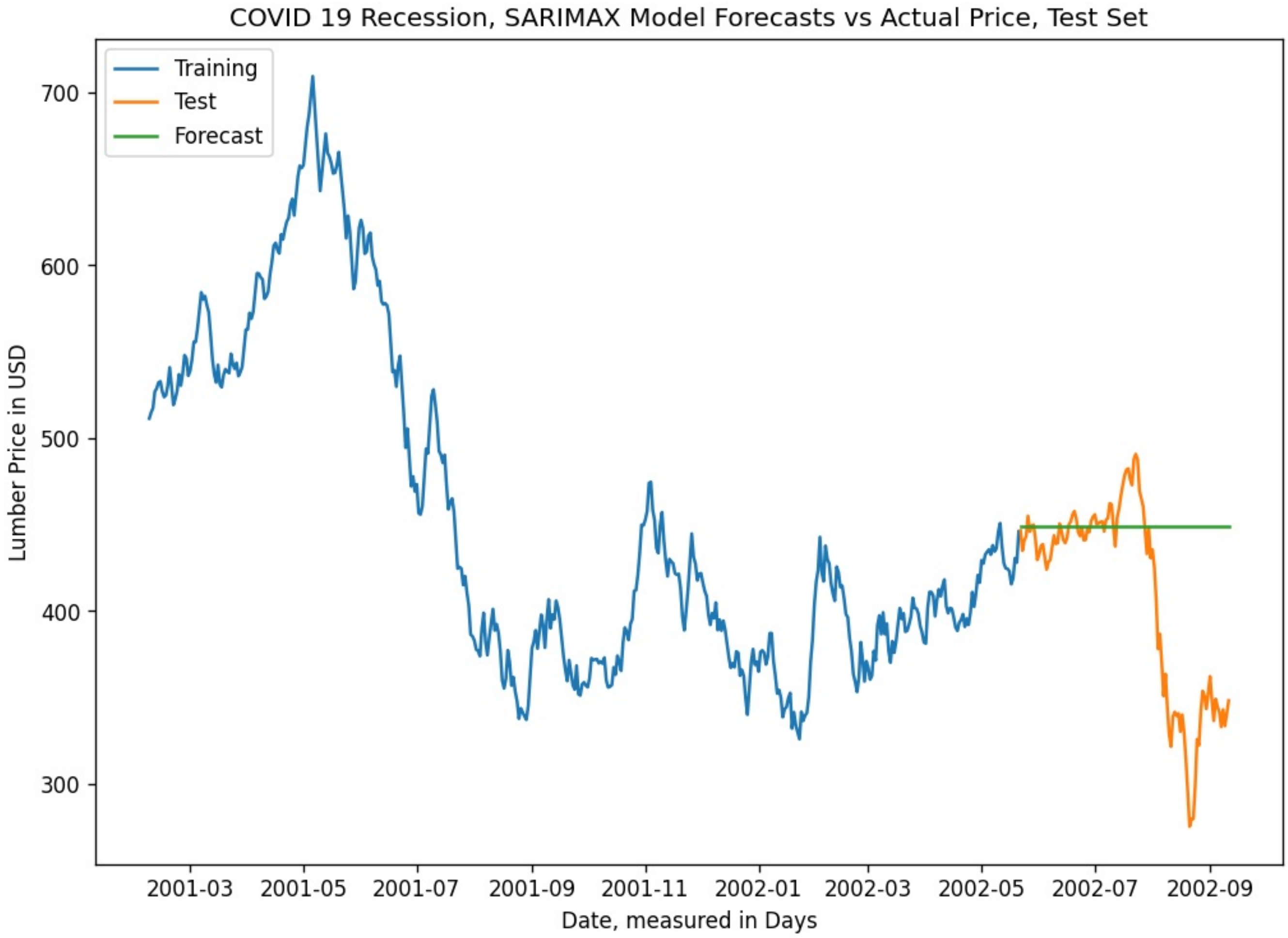
Out[40]:

	0	1
ma.L1	0.087989	0.264524
sigma2	70.074198	96.110677

Visualizing Model Results

In [41]:
```
# Prediction assignment, predicted revenue column named
# Training, Test, and Predicted data plotted together
# Code Reference (Matplotlib.pyplot.plot — Matplotlib 3.6.0 documentation, n.d.)

# ------Creating varible with forecast values
forecast = pd.DataFrame(model.predict(n_periods = 113))

# Naming forecast_revenue column in forecast variable
forecast.columns = ['forecast_prices']

# Establish plot parameters for Forecast

# Plot figure size
plt.figure(figsize=(10,7))

# Training data
plt.plot(train,label="Training")

# Annotate X-axis label
plt.xlabel('Date, measured in Days')

# Annotate Y-axis label
plt.ylabel('Lumber Price in USD')

# Annotate Plot Title
plt.title('COVID 19 Recession, SARIMAX Model Forecasts vs Actual Price, Test Set')

# Plot Test Data
plt.plot(test,label="Test")

# Plot Forecast Data
plt.plot(forecast,label="Forecast")

# Plot legend in upper lefthand corner
plt.legend(loc = 'upper left')
```

```
# Show Plot
plt.show()
```



In [42]:
```
forecast
```

Out[42]:

	forecast_prices
2002-05-22	449.336511
2002-05-23	449.336511
2002-05-24	449.336511
2002-05-25	449.336511
2002-05-26	449.336511
...	...
2002-09-07	449.336511
2002-09-08	449.336511
2002-09-09	449.336511
2002-09-10	449.336511
2002-09-11	449.336511

113 rows × 1 columns

D10 Accuracy Metrics for our forecast

In [43]:
```
# RMSE and MAE to test model accuracy
```

In [44]:
```
# Create array of actual Revenue values, stored in Test variable

test_array = test[['2022_Value']].to_numpy()
#test_array
```

In [45]:
```
test_array.shape
```

Out[45]:
```
(113, 1)
```

In [46]:
```
forecast
```

Out[46]:

	forecast_prices
2002-05-22	449.336511
2002-05-23	449.336511
2002-05-24	449.336511
2002-05-25	449.336511
2002-05-26	449.336511
...	...
2002-09-07	449.336511
2002-09-08	449.336511
2002-09-09	449.336511
2002-09-10	449.336511
2002-09-11	449.336511

113 rows × 1 columns

In [47]:
```
# Predictions to numpy array
predicted_array = forecast[['forecast_prices']].to_numpy()
```

In [48]:
```
predicted_array.shape
```

Out[48]:
```
(113, 1)
```

In [49]:
```
#RMSE Calculation

rmse = sqrt(mean_squared_error(test_array, predicted_array))
print ('RMSE = ' + str(rmse))
```

```
RMSE = 69.06287127867498
```

In [50]:
```
# MAE Calculation

def mae(y_true, predictions):
    y_true, predictions = np.array(y_true), np.array(predictions)
    return np.mean(np.abs(y_true - predictions))

true = test_array
predicted = predicted_array

print(mae(true, predicted))
```

```
46.66414833292884
```

D11 Visualizing Model Forecast Confidence Intervals at 20% CI

In [51]:
```
# Model Standard Error calculations, computed numerical Hessian

std_error = model.bse()
print(std_error)
```

```
ma.L1     0.045035
sigma2    6.642081
dtype: float64
```

In [52]:
```
# Generate Model confidence intervals

conf_int = model.conf_int()
```

In [53]:
```
# ------Generate Forecast Prediction Intervals at 90% Confidence

y_forec, conf_int = model.predict(113, return_conf_int=True, alpha=0.8)
print(conf_int)
```

```
[[447.02712386 451.64589761]
 [445.77108374 452.90193773]
 [444.85418193 453.81883954]
 [444.09530158 454.57771989]
 [443.43318325 455.23983822]
 [442.83818193 455.83483954]
 [442.29326722 456.37975425]
 [441.78758491 456.88543656]
 [441.31371303 457.35930844]
 [440.86631092 457.80671055]
 [440.4413836  458.23163787]
 [440.03585007 458.6371714 ]
 [439.64727492 459.02574655]
 [439.27369341 459.39932806]
 [438.9134932  459.75952827]
 [438.56533177 460.1076897 ]
```

```
[438.22807708 460.44494439]
[437.90076414 460.77225733]
[437.58256237 461.0904591 ]
[437.27275079 461.40027068]
[436.97069876 461.70232272]
[436.67585089 461.99717059]
[436.38771505 462.28530642]
[436.10585271 462.56716876]
[435.82987112 462.84315035]
[435.55941687 463.1136046 ]
[435.29417057 463.3788509 ]
[435.03384248 463.63917899]
[434.77816876 463.89485272]
[434.52690834 464.14611313]
[434.27984029 464.39318119]
[434.03676149 464.63625998]
[433.79748474 464.87553673]
[433.56183702 465.11118445]
[433.32965806 465.34336341]
[433.10079903 465.57222244]
[432.87512147 465.7979    ]
[432.65249628 466.02052519]
[432.43280285 466.24021862]
[432.21592832 466.45709315]
[432.00176689 466.67125458]
[431.79021922 466.88280225]
[431.58119187 467.0918296 ]
[431.37459687 467.29842461]
[431.17035121 467.50267026]
[430.96837654 467.70464493]
[430.76859875 467.90442272]
[430.57094766 468.10207381]
[430.37535678 468.29766469]
[430.18176299 468.49125848]
[429.99010633 468.68291514]
[429.80032981 468.87269166]
[429.61237914 469.06064233]
[429.42620263 469.24681884]
[429.24175095 469.43127052]
[429.05897704 469.61404443]
[428.87783593 469.79518554]
[428.69828463 469.97473684]
[428.52028201 470.15273946]
[428.34378865 470.32923282]
[428.16876682 470.50425465]
[427.99518031 470.67784116]
[427.82299438 470.8500271 ]
[427.65217565 471.02084582]
[427.48269208 471.19032939]
[427.31451283 471.35850864]
[427.14760824 471.52541323]
[426.98194978 471.6910717 ]
[426.81750992 471.85551155]
[426.65426218 472.01875929]
[426.49218099 472.18084048]
[426.3312417  472.34177977]
[426.17142051 472.50160096]
[426.01269443 472.66032704]
[425.85504125 472.81798022]
[425.69843952 472.97458196]
[425.54286846 473.13015301]
[425.38830799 473.28471348]
[425.23473867 473.4382828 ]
[425.08214167 473.5908798 ]
[424.93049876 473.74252271]
[424.77979226 473.89322921]
[424.63000503 474.04301644]
[424.48112045 474.19190102]
[424.3331224  474.33989907]
[424.18599523 474.48702624]
[424.03972375 474.63329773]
[423.89429318 474.77872829]
[423.74968921 474.92333226]
[423.60589788 475.06712359]
[423.46290566 475.21011581]
[423.32069936 475.35232211]
[423.17926617 475.4937553 ]
[423.03859361 475.63442787]
[422.89866954 475.77435193]
[422.75948214 475.91353934]
[422.62101989 476.05200158]
[422.48327158 476.18974989]
[422.34622628 476.32679519]
[422.20987333 476.46314814]
[422.07420235 476.59881913]
[421.93920319 476.73381828]
[421.80486599 476.86815548]
[421.67118109 477.00184038]
[421.53813909 477.13488239]
```

```
 [421.40573079 477.26729068]
 [421.27394724 477.39907424]
 [421.14277966 477.53024181]
 [421.0122195  477.66080197]
 [420.8822584  477.79076307]
 [420.75288819 477.92013328]
 [420.62410088 478.04892059]
 [420.49588866 478.17713281]]
```

In [54]:
```python
# Assign Predictions to pandas DataFrame

conf_pd = pd.DataFrame(conf_int, columns =['Low_Prediction','High_Prediction'])

#Assign Low predictions to variable
low_prediction = conf_pd['Low_Prediction']

#Assign High predictions to variable
high_prediction = conf_pd['High_Prediction']
```

In [ ]:

In [55]:
```python
# Read out Test and Train sets to csv file
# Open csv files in Google Sheets, Add Day Column
# Dates align with 'test' variable, which contains actual revenue figures

low_prediction.to_csv('C:/Users/ericy/Desktop/Low_Prediction.csv')
high_prediction.to_csv('C:/Users/ericy/Desktop/High_Prediction.csv')
```

In [56]:
```python
#-----Load predictions, date column added

low_pred = pd.read_csv('C:/Users/ericy/Desktop/COVID_Low_Prediction.csv')
high_pred = pd.read_csv('C:/Users/ericy/Desktop/COVID_High_Prediction.csv')
```

In [57]:
```python
# Variable exploration to ensure compatability with 'test' datetime timeframe
low_pred
```

Out[57]:

	Date	Low_Prediction
0	2002-05-22	447.002736
1	2002-05-23	445.734959
2	2002-05-24	444.809458
3	2002-05-25	444.043453
4	2002-05-26	443.375114
...	...	...
108	2002-09-07	420.743182
109	2002-09-08	420.611998
110	2002-09-09	420.481410
111	2002-09-10	420.351410
112	2002-09-11	420.221991

113 rows × 2 columns

In [58]:
```python
# Variable exploration to ensure compatability with 'test' datetime timeframe
high_pred
```

Out[58]:

	Date	High_Prediction
0	2002-05-22	451.665468
1	2002-05-23	452.933246
2	2002-05-24	453.858746
3	2002-05-25	454.624752
4	2002-05-26	455.293091
...	...	...
108	2002-09-07	477.925023
109	2002-09-08	478.056207
110	2002-09-09	478.186795
111	2002-09-10	478.316794
112	2002-09-11	478.446213

113 rows × 2 columns

Convert Low and High Prediction 'Day' column to datetime and index

In [59]:
```
# Lower Predictions, Set Day as Index
low_pred['Date'] = pd.to_datetime(low_pred['Date'])
```

In [60]:
```
low_pred.set_index('Date',inplace=True)
```

In [61]:
```
# High Predictions, Day to datetime
high_pred['Date'] = pd.to_datetime(high_pred['Date'])
```

In [62]:
```
# High Predictions, Set Day as Index
high_pred.set_index('Date',inplace=True)
```

In [63]:
```
low_pred
```

Out[63]:

Date	Low_Prediction
2002-05-22	447.002736
2002-05-23	445.734959
2002-05-24	444.809458
2002-05-25	444.043453
2002-05-26	443.375114
...	...
2002-09-07	420.743182
2002-09-08	420.611998
2002-09-09	420.481410
2002-09-10	420.351410
2002-09-11	420.221991

113 rows × 1 columns

In [64]:
```
high_pred
```

Out[64]:

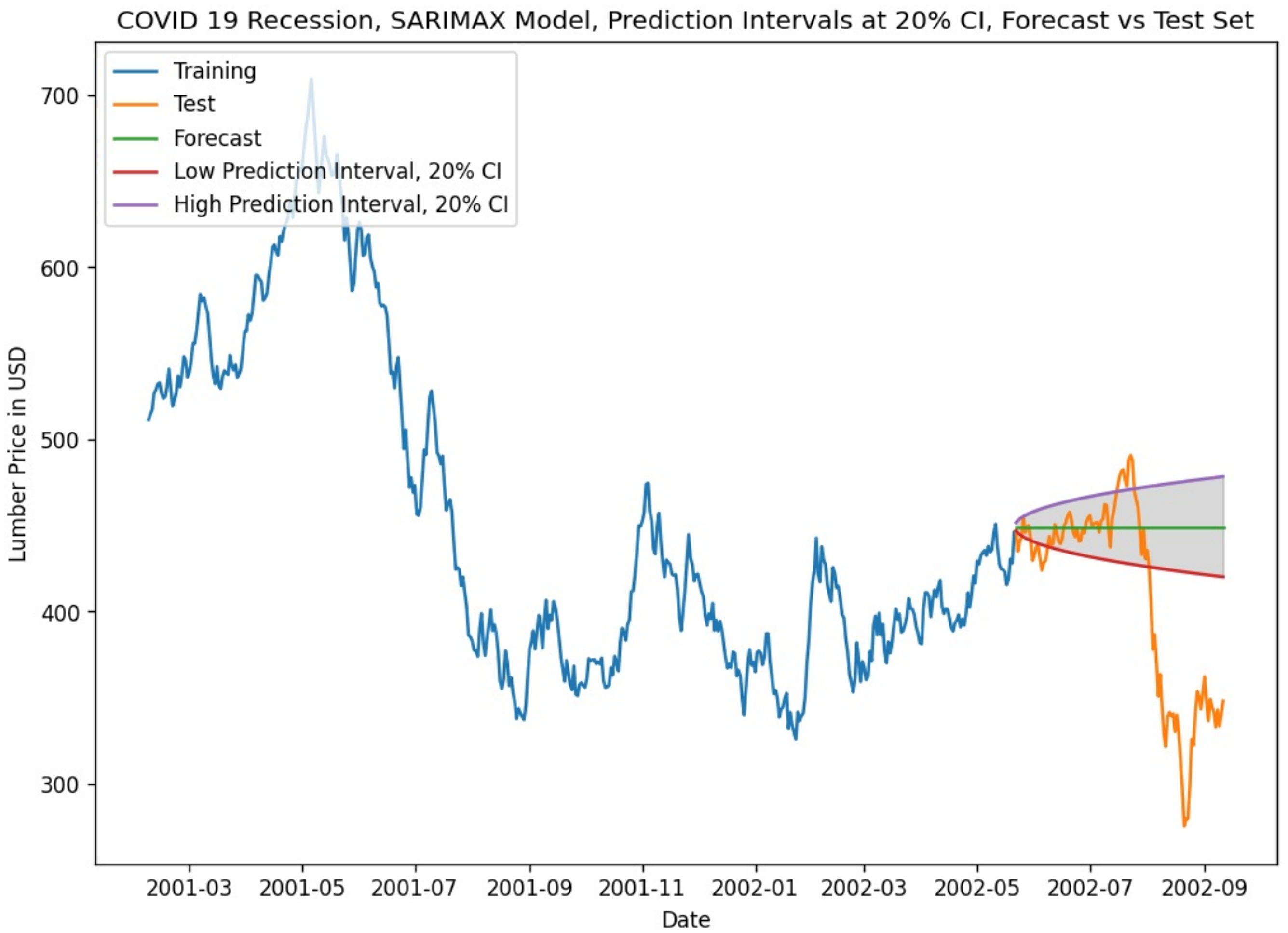
Date	High_Prediction
2002-05-22	451.665468
2002-05-23	452.933246
2002-05-24	453.858746
2002-05-25	454.624752
2002-05-26	455.293091
...	...
2002-09-07	477.925023
2002-09-08	478.056207
2002-09-09	478.186795
2002-09-10	478.316794
2002-09-11	478.446213

113 rows × 1 columns

SARIMAX Model Forecast, With Confidence Interval = 20%, Vs Test Set

In [65]:
```
# Prediction assignment, predicted revenue column named
# Training, Test, and Predicted data plotted together
# Code Reference (Matplotlib.pyplot.plot — Matplotlib 3.6.0 documentation, n.d.)

# -----Creating varible with forecast values
forecast = pd.DataFrame(model.predict(n_periods = 113),index=test.index)

# Naming forecast_revenue column in forecast variable
forecast.columns = ['forecast_prices']

# Establish plot parameters for Forecast

# Plot figure size
plt.figure(figsize=(10,7))
```

```python
# Training data
plt.plot(train,label="Training")

# Annotate X-axis label
plt.xlabel('Date')

# Annotate Y-axis label
plt.ylabel('Lumber Price in USD')

# Annotate Plot Title
plt.title('COVID 19 Recession, SARIMAX Model, Prediction Intervals at 20% CI, Forecast vs Test Set')

# Plot Test Data
plt.plot(test,label="Test")

# Plot Forecast Data
plt.plot(forecast,label="Forecast")

# Add Prediction Interval at 95% CI
plt.plot(low_pred,label='Low Prediction Interval, 20% CI')
plt.plot(high_pred,label='High Prediction Interval, 20% CI')
plt.fill_between(low_pred.index, low_pred['Low_Prediction'], high_pred['High_Prediction'], color='k', alpha=.15

# Plot legend in upper lefthand corner
plt.legend(loc = 'upper left')


# Show Plot
plt.show()
```



Is the null hypothesis Accepted or Rejected?

In [66]:
```python
# Accept or reject the Null Hypothesis
# COVID Recession we Accept the Null Hypothesis
```

In [ ]:

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