D214 Capstone

Modeling Inflation Adusted Recessionary Lumber Prices

Early 1990's Recession

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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[3938:4864]
```

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

Out[6]:

	Date	Trading Days	2022_Value	Value
3938	1988-07-06	3939	462.4340	194.30
3939	1988-07-07	3940	465.2900	195.50
3940	1988-07-08	3941	473.8580	199.10
3941	1988-07-11	3942	474.8100	199.50
3942	1988-07-12	3943	472.9060	198.70
...	...	...	...	...
4859	1992-02-26	4860	477.0428	239.72
4860	1992-02-27	4861	479.3910	240.90
4861	1992-02-28	4862	479.7492	241.08
4862	1992-03-02	4863	480.5850	241.50
4863	1992-03-03	4864	481.3810	241.90

926 rows × 4 columns

D1: Exploratory Data Analysis

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

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

Out[8]:

	Trading Days	2022_Value
3938	3939	462.4340
3939	3940	465.2900
3940	3941	473.8580
3941	3942	474.8100
3942	3943	472.9060
...	...	...
4859	4860	477.0428
4860	4861	479.3910
4861	4862	479.7492
4862	4863	480.5850
4863	4864	481.3810

926 rows × 2 columns

EDA

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

Out[9]:

	Trading Days	2022_Value
3938	3939	462.434
3939	3940	465.290
3940	3941	473.858
3941	3942	474.810
3942	3943	472.906

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

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 926 entries, 3938 to 4863
Data columns (total 2 columns):
 #   Column        Non-Null Count  Dtype  
---  ------        --------------  -----  
 0   Trading Days  926 non-null    int64  
 1   2022_Value    926 non-null    float64
dtypes: float64(1), int64(1)
memory usage: 14.6 KB
```

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

Out[11]:
```
(926, 2)
```

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

Out[12]:

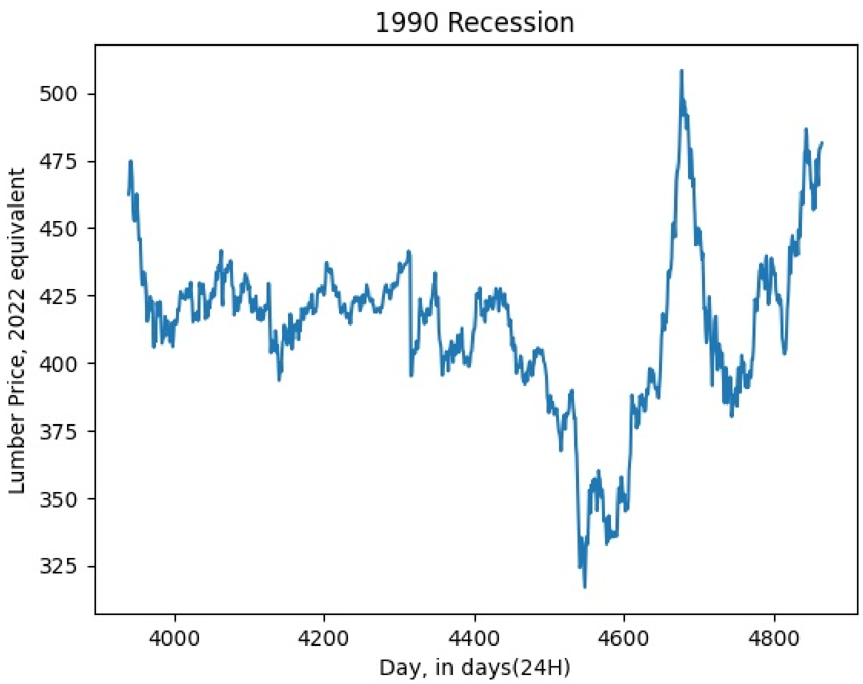
	Trading Days	2022_Value
count	926.000000	926.000000
mean	4401.500000	413.590309
std	267.457473	29.824984
min	3939.000000	316.917000
25%	4170.250000	400.136900
50%	4401.500000	418.709400
75%	4632.750000	427.207250
max	4864.000000	508.392000

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

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

Line Graph Visualization

In [14]:
```python
#-------
plt.plot(df['Trading Days'],df['2022_Value'])
plt.title('1990 Recession')
plt.xlabel('Day, in days(24H)')
plt.ylabel('Lumber Price, 2022 equivalent')
plt.show()
```



Data Cleaning

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

D2: Time Step Formatting, Indexing

Set df['Trading Days'] to Index

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

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

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 926 entries, 3938 to 4863
Data columns (total 2 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   Trading Days  926 non-null    datetime64[ns]
 1   2022_Value    926 non-null    float64
dtypes: datetime64[ns](1), float64(1)
memory usage: 21.7 KB
```

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

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

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 926 entries, 1980-10-14 to 1983-04-27
Data columns (total 1 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   2022_Value  926 non-null    float64
dtypes: float64(1)
memory usage: 14.5 KB
```

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

Out[20]:

Trading Days	2022_Value
1980-10-14	462.4340
1980-10-15	465.2900
1980-10-16	473.8580
1980-10-17	474.8100
1980-10-18	472.9060
...	...
1983-04-23	477.0428
1983-04-24	479.3910
1983-04-25	479.7492
1983-04-26	480.5850
1983-04-27	481.3810

926 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]:
```
(-2.312794090362915,
 0.16787481888011768,
 3,
 922,
 {'1%': -3.437462363899248,
  '5%': -2.8646798473884134,
  '10%': -2.568441851017076},
 5274.655766939205)
```

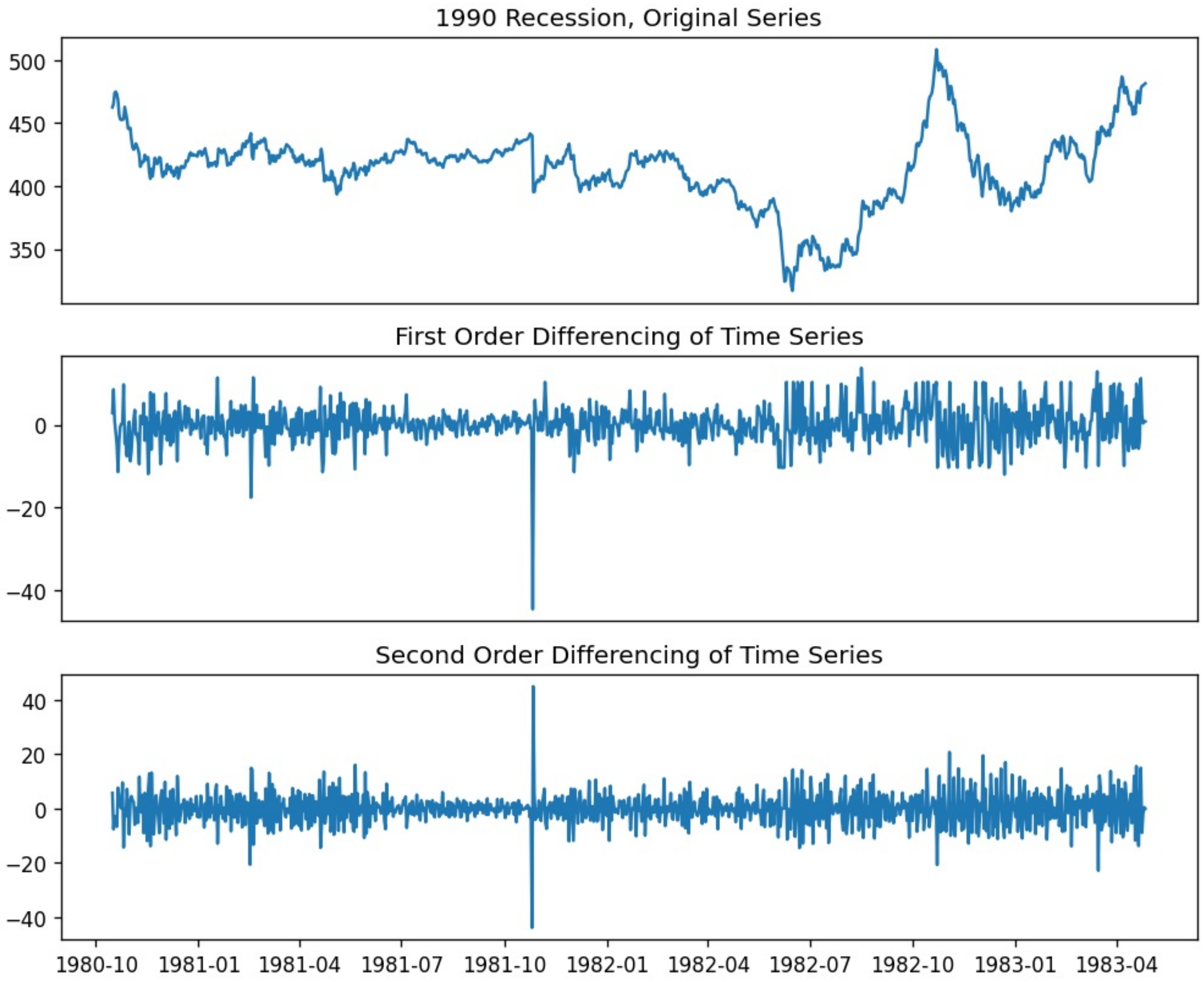
In [23]:
```
# Results show p = .16787
# Data does not reject null hypothesis at p < .05
# Therefore, Time series is determined to be non-stationary
```

D4 Differencing

1st and 2nd order Differencing

finding 'd' for ARIMA model

In [24]:
```
# 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('1990 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()
```



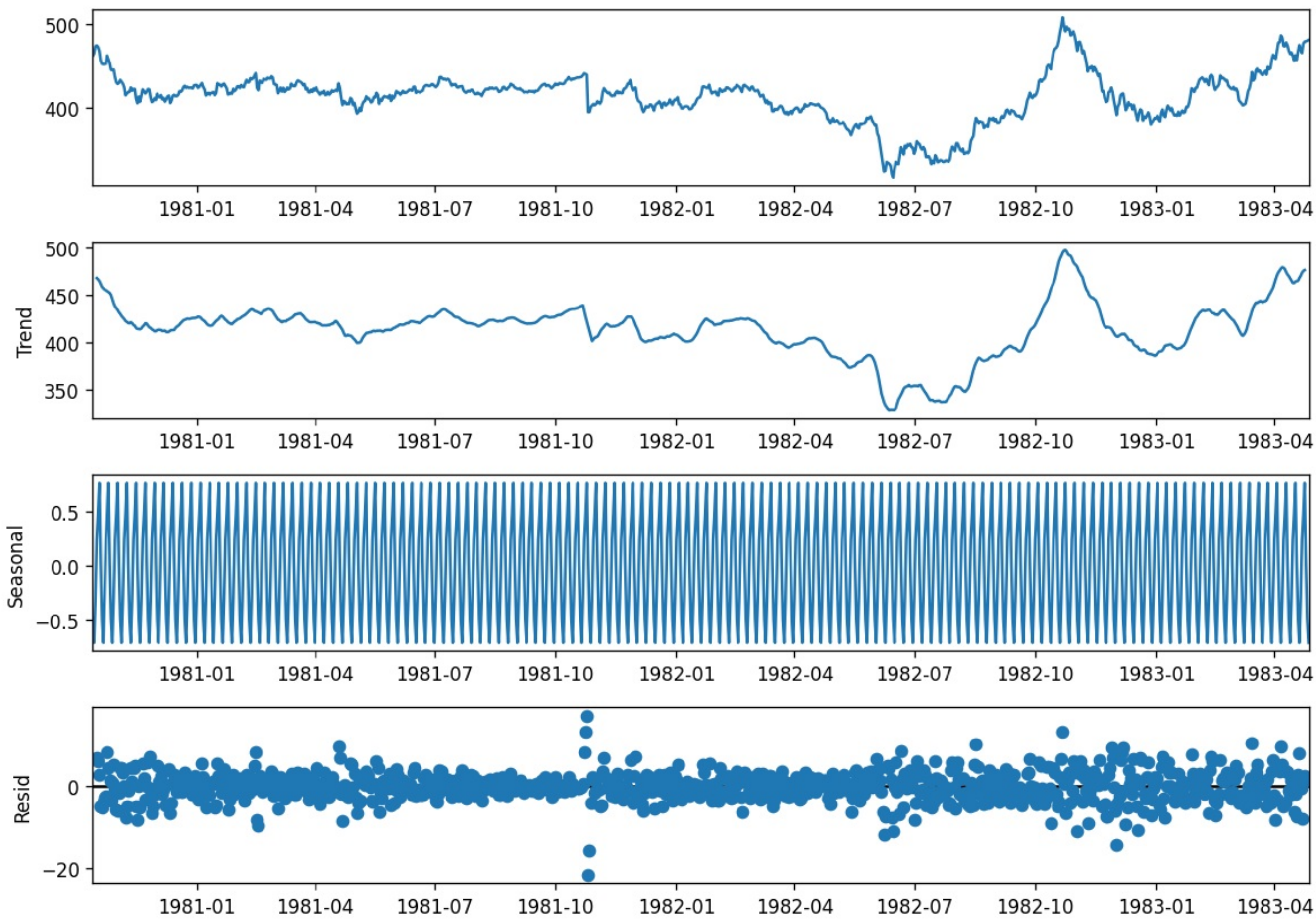
In [25]:
```
# Using pmdarima's ndiffs to find differencing term
# Code reference (Verma, 2021)

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]:
```
# Code Reference (Boston, 2020)
result = seasonal_decompose(df)
```

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

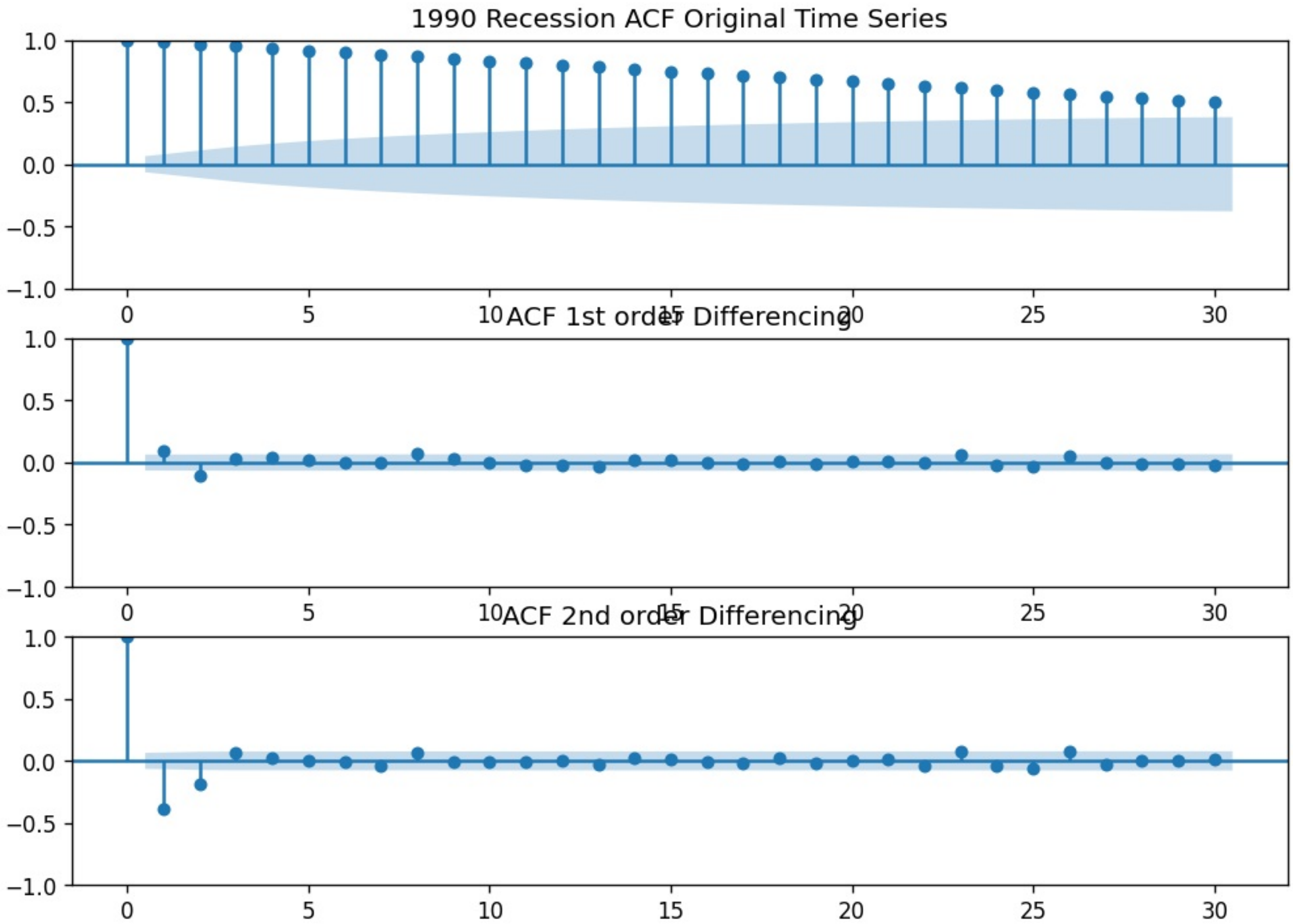


D6 ACF and PACF

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='1990 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');
```

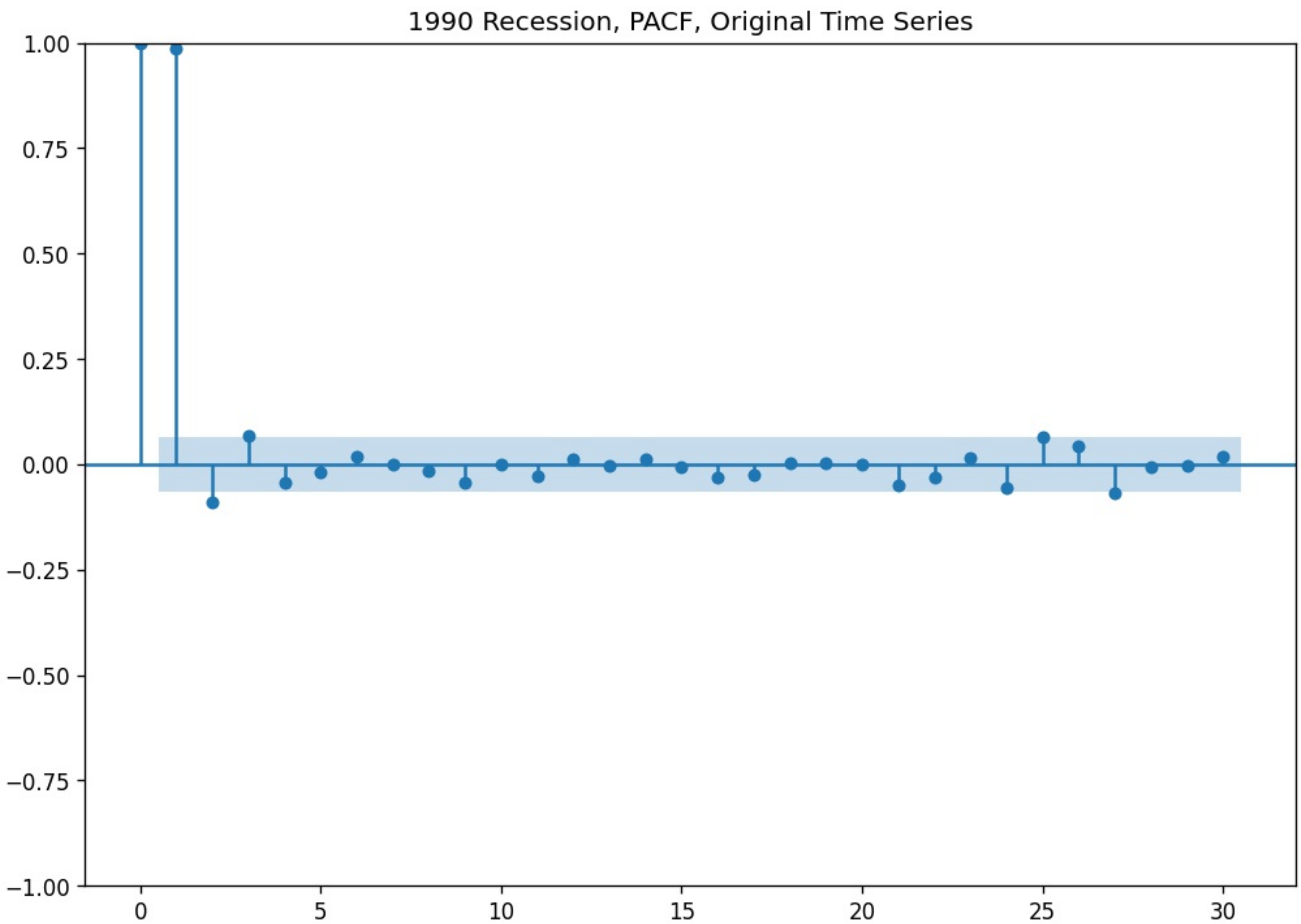


Finding order of AR term 'p'

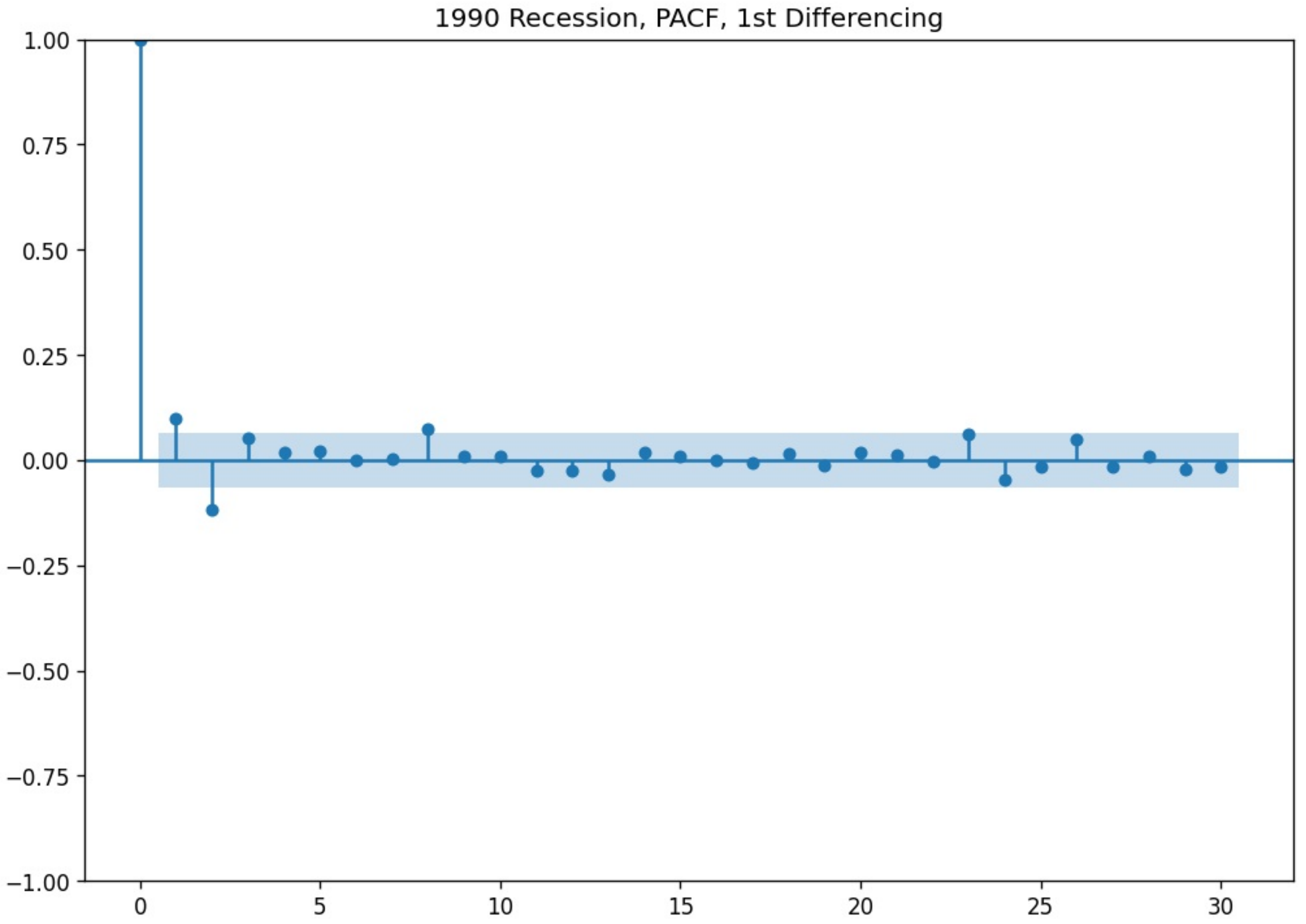
Using Partial autocorrelation (PACF)

In [29]:

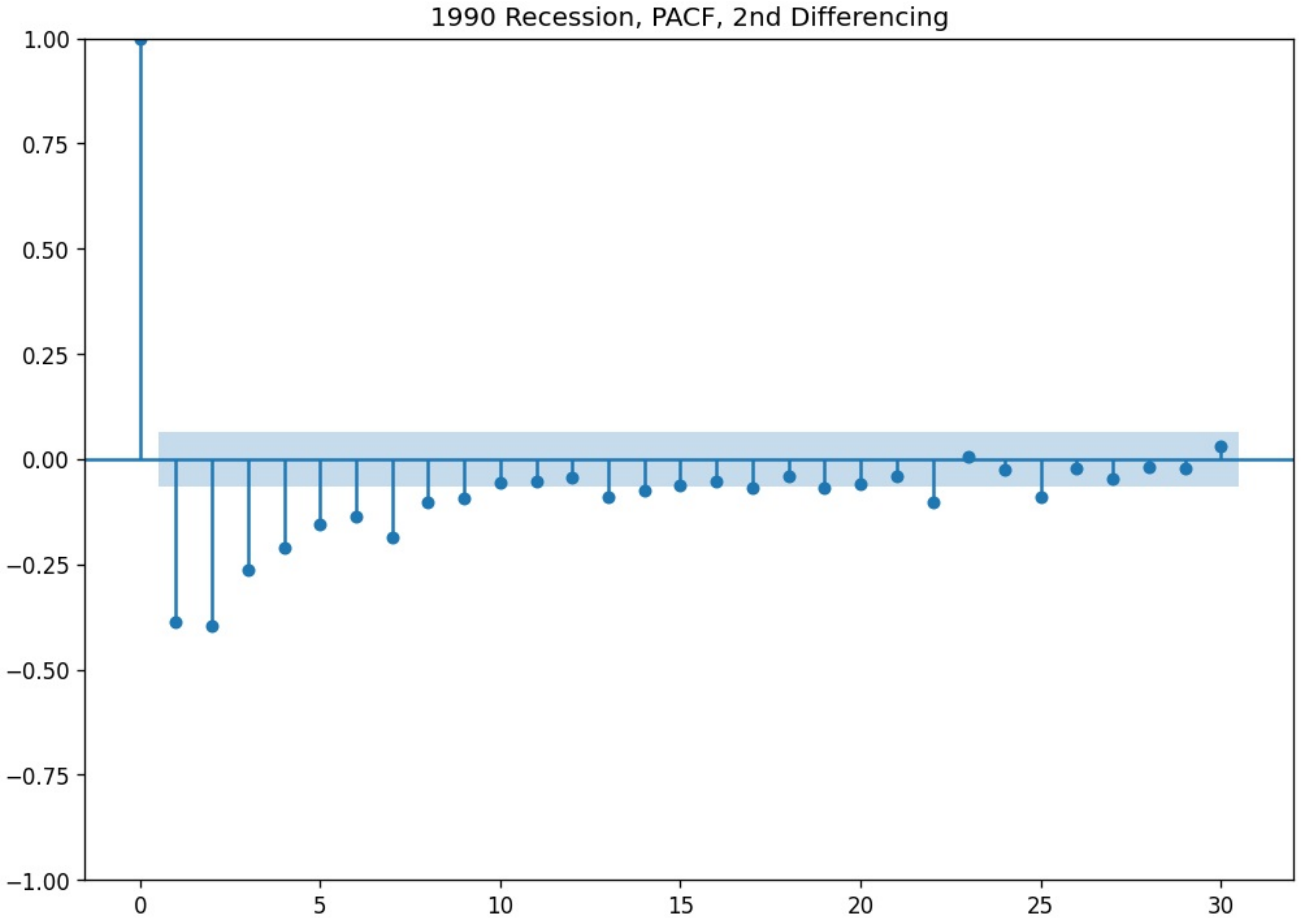
```
warnings.filterwarnings("ignore")
plot_pacf(df.dropna(), title='1990 Recession, PACF, Original Time Series');
```



In [30]:
```
plot_pacf(df.diff().dropna(), title='1990 Recession, PACF, 1st Differencing');
```

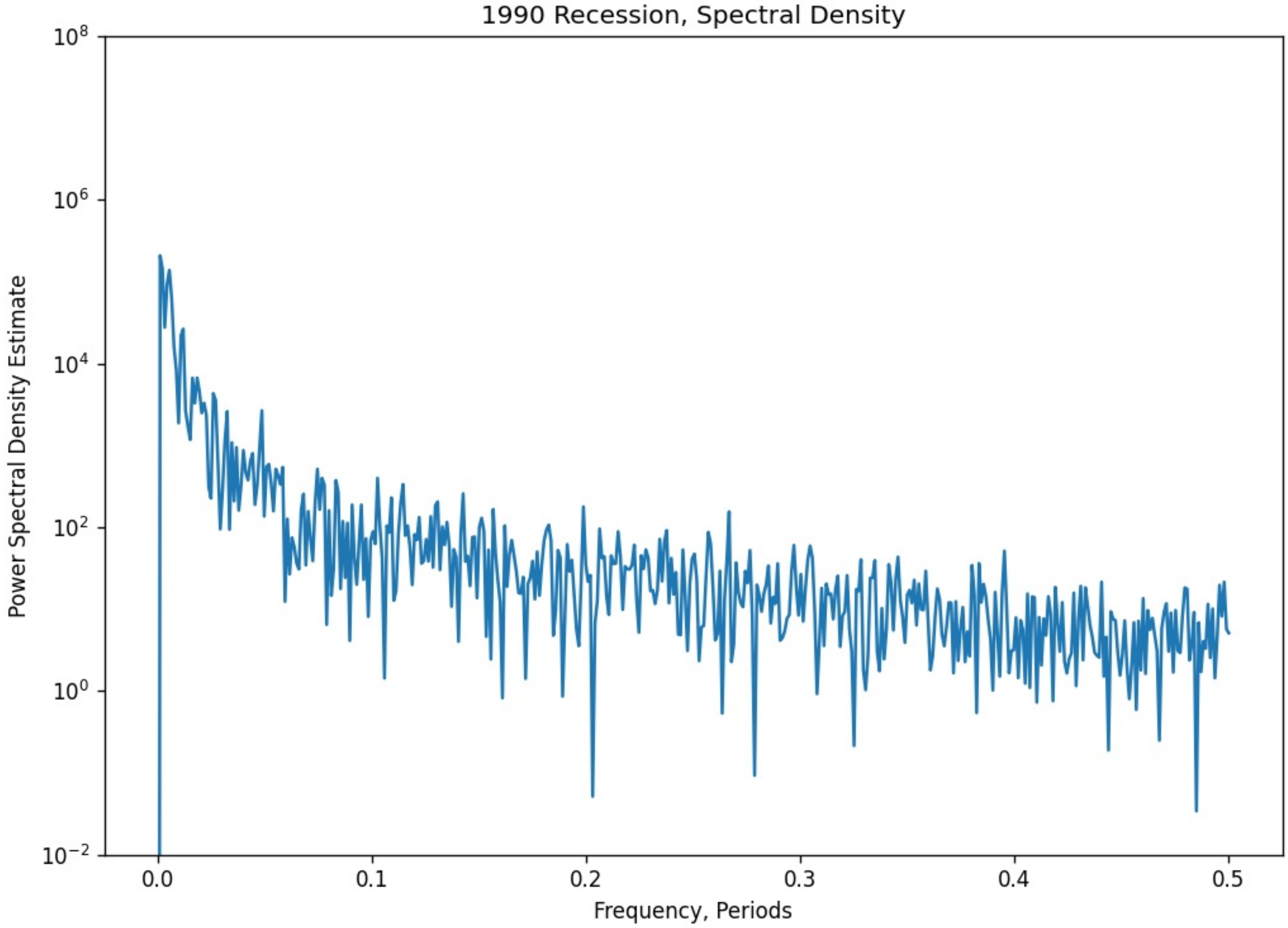


In [31]:
```
plot_pacf(df.diff().diff().dropna(), title='1990 Recession, PACF, 2nd Differencing');
```



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('1990 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 = 926 cases

80/20 Train/Test Split

Split is 741 / 185

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=741)
```

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

Out[34]:

	2022_Value
Trading Days	
1980-10-14	462.434
1980-10-15	465.290
1980-10-16	473.858
1980-10-17	474.810
1980-10-18	472.906
...	...
1982-10-20	490.383
1982-10-21	498.042
1982-10-22	508.392
1982-10-23	498.042
1982-10-24	491.625

741 rows × 1 columns

In [35]:

```
test
```

Out[35]:

	2022_Value
Trading Days	
1982-10-25	497.2140
1982-10-26	494.1090
1982-10-27	494.5230
1982-10-28	486.8640
1982-10-29	487.8990
...	...
1983-04-23	477.0428
1983-04-24	479.3910
1983-04-25	479.7492
1983-04-26	480.5850
1983-04-27	481.3810

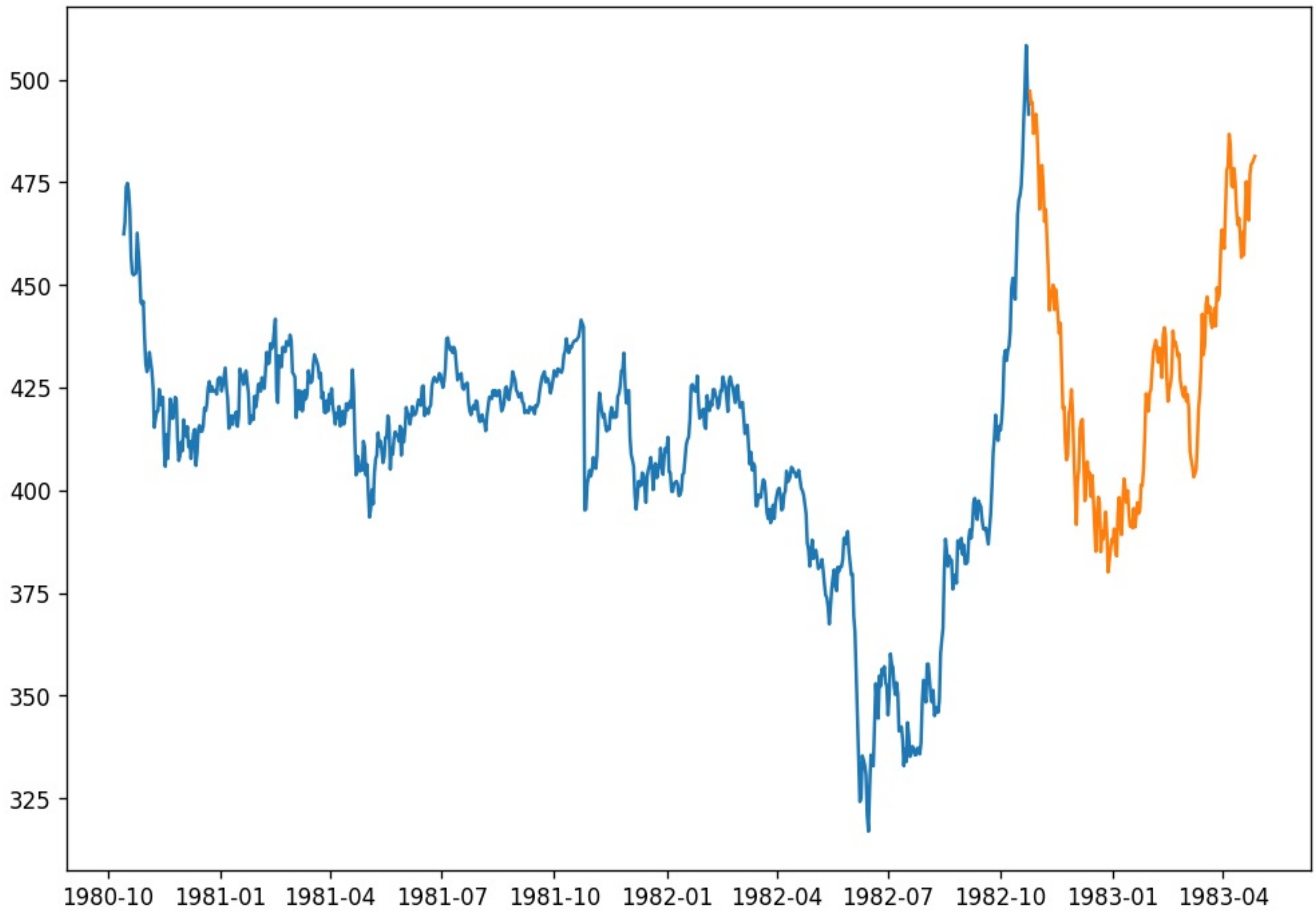
185 rows × 1 columns

In [36]:

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

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

Out[36]:

```
[<matplotlib.lines.Line2D at 0x1d31118f3c8>]
```



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

```
(741, 1)
(185, 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=4221.106, Time=0.23 sec
 ARIMA(0,1,0)(0,0,0)[0] intercept   : AIC=4235.930, Time=0.02 sec
 ARIMA(1,1,0)(0,0,0)[0] intercept   : AIC=4230.964, Time=0.07 sec
 ARIMA(0,1,1)(0,0,0)[0] intercept   : AIC=4229.001, Time=0.09 sec
 ARIMA(0,1,0)(0,0,0)[0]             : AIC=4235.930, Time=0.02 sec
 ARIMA(2,1,1)(0,0,0)[0] intercept   : AIC=4222.101, Time=0.25 sec
 ARIMA(1,1,2)(0,0,0)[0] intercept   : AIC=4222.076, Time=0.22 sec
 ARIMA(0,1,2)(0,0,0)[0] intercept   : AIC=4221.790, Time=0.13 sec
 ARIMA(2,1,0)(0,0,0)[0] intercept   : AIC=4223.970, Time=0.13 sec
 ARIMA(2,1,2)(0,0,0)[0] intercept   : AIC=4224.076, Time=0.56 sec
 ARIMA(1,1,1)(0,0,0)[0]             : AIC=4221.106, Time=0.14 sec

Best model:  ARIMA(1,1,1)(0,0,0)[0]
Total fit time: 1.887 seconds
                               SARIMAX Results
==============================================================================
Dep. Variable:                      y   No. Observations:                  741
Model:               SARIMAX(1, 1, 1)   Log Likelihood               -2106.553
Date:                Tue, 18 Oct 2022   AIC                           4221.106
Time:                        13:20:18   BIC                           4239.533
Sample:                    10-14-1980   HQIC                          4228.211
                         - 10-24-1982
Covariance Type:                  opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
intercept      0.0627      0.283      0.222      0.825      -0.492       0.618
ar.L1         -0.5745      0.148     -3.876      0.000      -0.865      -0.284
ma.L1          0.7059      0.132      5.346      0.000       0.447       0.965
sigma2        17.3822      0.309     56.320      0.000      16.777      17.987
===================================================================================
Ljung-Box (L1) (Q):                   0.15   Jarque-Bera (JB):             10487.22
Prob(Q):                              0.69   Prob(JB):                         0.00
Heteroskedasticity (H):               1.09   Skew:                            -1.69
Prob(H) (two-sided):                  0.48   Kurtosis:                        21.13
===================================================================================

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

In [68]:

```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=4224.076, Time=0.58 sec
 ARIMA(0,1,0)(0,0,0)[0] intercept   : AIC=4235.930, Time=0.02 sec
 ARIMA(1,1,0)(0,0,0)[0] intercept   : AIC=4230.964, Time=0.06 sec
 ARIMA(0,1,1)(0,0,0)[0] intercept   : AIC=4229.001, Time=0.09 sec
 ARIMA(0,1,0)(0,0,0)[0]             : AIC=4233.995, Time=0.02 sec
 ARIMA(1,1,2)(0,0,0)[0] intercept   : AIC=4222.076, Time=0.22 sec
 ARIMA(0,1,2)(0,0,0)[0] intercept   : AIC=4221.790, Time=0.12 sec
 ARIMA(0,1,3)(0,0,0)[0] intercept   : AIC=4222.109, Time=0.20 sec
 ARIMA(1,1,1)(0,0,0)[0] intercept   : AIC=4221.106, Time=0.14 sec
 ARIMA(2,1,1)(0,0,0)[0] intercept   : AIC=4222.101, Time=0.27 sec
 ARIMA(2,1,0)(0,0,0)[0] intercept   : AIC=4223.970, Time=0.12 sec
 ARIMA(1,1,1)(0,0,0)[0]             : AIC=4219.164, Time=0.08 sec
 ARIMA(0,1,1)(0,0,0)[0]             : AIC=4227.051, Time=0.05 sec
 ARIMA(1,1,0)(0,0,0)[0]             : AIC=4229.015, Time=0.03 sec
 ARIMA(2,1,1)(0,0,0)[0]             : AIC=4220.164, Time=0.11 sec
 ARIMA(1,1,2)(0,0,0)[0]             : AIC=4220.140, Time=0.11 sec
 ARIMA(0,1,2)(0,0,0)[0]             : AIC=4219.857, Time=0.06 sec
 ARIMA(2,1,0)(0,0,0)[0]             : AIC=4222.037, Time=0.05 sec
 ARIMA(2,1,2)(0,0,0)[0]             : AIC=4222.140, Time=0.26 sec

Best model:  ARIMA(1,1,1)(0,0,0)[0]
Total fit time: 2.600 seconds
                               SARIMAX Results
==============================================================================
Dep. Variable:                      y   No. Observations:                  741
Model:               SARIMAX(1, 1, 1)   Log Likelihood               -2106.582
Date:                Tue, 18 Oct 2022   AIC                           4219.164
Time:                        21:10:45   BIC                           4232.984
Sample:                    10-14-1980   HQIC                          4224.492
                         - 10-24-1982
Covariance Type:                  opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.L1         -0.5743      0.148     -3.878      0.000      -0.865      -0.284
ma.L1          0.7058      0.132      5.347      0.000       0.447       0.964
sigma2        17.3834      0.286     60.747      0.000      16.823      17.944
===================================================================================
Ljung-Box (L1) (Q):                   0.16   Jarque-Bera (JB):             10487.19
Prob(Q):                              0.69   Prob(JB):                         0.00
Heteroskedasticity (H):               1.10   Skew:                            -1.69
Prob(H) (two-sided):                  0.48   Kurtosis:                        21.13
===================================================================================

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

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

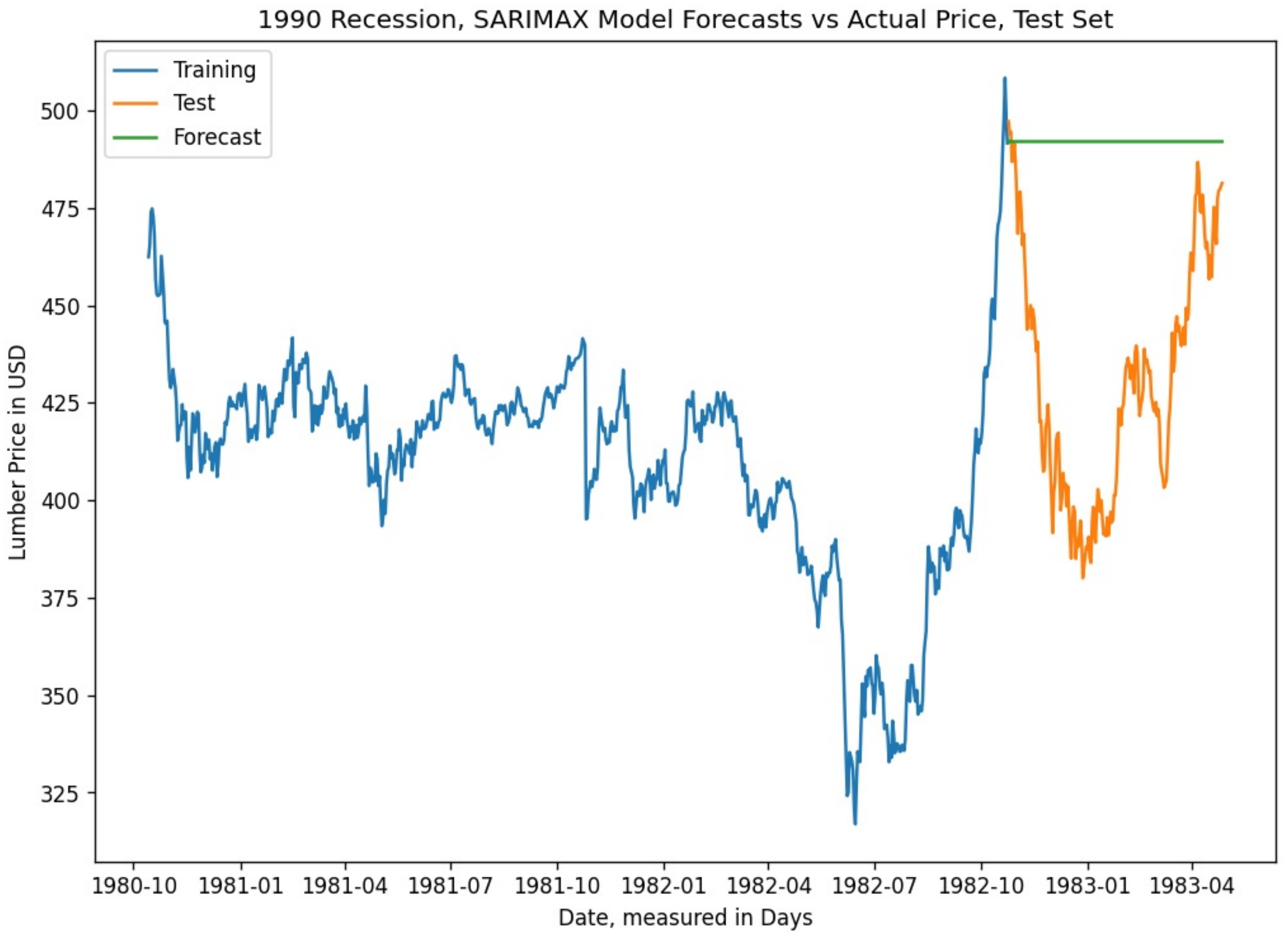
Out[40]:

	0	1
ar.L1	-0.864537	-0.284080
ma.L1	0.447082	0.964480
sigma2	16.822537	17.944259

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 = 185))

# 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('1990 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
1982-10-25	492.282685
1982-10-26	491.904971
1982-10-27	492.121895
1982-10-28	491.997314
1982-10-29	492.068862
...	...
1983-04-23	492.042761
1983-04-24	492.042761
1983-04-25	492.042761
1983-04-26	492.042761
1983-04-27	492.042761

185 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]:
```
(185, 1)
```

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

Out[46]:

	forecast_prices
1982-10-25	492.282685
1982-10-26	491.904971
1982-10-27	492.121895
1982-10-28	491.997314
1982-10-29	492.068862
...	...
1983-04-23	492.042761
1983-04-24	492.042761
1983-04-25	492.042761
1983-04-26	492.042761
1983-04-27	492.042761

185 rows × 1 columns

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

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

Out[48]:
```
(185, 1)
```

In [49]:
```
#RMSE Calculation

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

```
RMSE = 69.20596198874226
```

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))
```

```
62.12480063004482
```

D11 Visualizing Model Forecast Confidence Intervals at 20% CI# Visualizing Model Forecasts

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

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

```
ar.L1     0.148078
ma.L1     0.131992
sigma2    0.286159
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(185, return_conf_int=True, alpha=0.8)
print(conf_int)
```

```
[[491.22639477 493.33897531]
 [490.30992726 493.50001443]
 [490.17554048 494.06825026]
```

```
[489.73088261 494.26374487]
[489.53415865 494.60356544]
[489.24438258 494.8111599 ]
[489.04306442 495.05967566]
[488.81850775 495.25712634]
[488.62925039 495.46195091]
[488.43797806 495.64428286]
[488.26324742 495.82414804]
[488.09226856 495.99217808]
[487.93067808 496.15546209]
[487.77388343 496.31128414]
[487.62340583 496.46232031]
[487.47744946 496.60795589]
[487.33626804 496.74932154]
[487.19905573 496.88642805]
[487.06570771 497.01983683]
[486.93579267 497.14971697]
[486.80912895 497.27640074]
[486.68544336 497.40007482]
[486.56455866 497.52096613]
[486.44627927 497.63924172]
[486.33045144 497.75507173]
[486.2169243  497.86859761]
[486.10556855 497.97995409]
[485.99626267 498.08925955]
[485.88889832 498.19662414]
[485.78337508 498.30214724]
[485.67960165 498.40592075]
[485.5774936  498.50802876]
[485.47697333 498.60854905]
[485.37796894 498.70755342]
[485.28041389 498.80510849]
[485.18424631 498.90127606]
[485.08940864 498.99611374]
[484.99584718 499.0896752 ]
[484.90351176 499.18201062]
[484.8123554  499.27316697]
[484.72233407 499.3631883 ]
[484.63340639 499.45211599]
[484.54553344 499.53998894]
[484.45867856 499.62684381]
[484.37280717 499.71271521]
[484.28788659 499.79763578]
[484.20388592 499.88163645]
[484.12077591 499.96474647]
[484.0385288  500.04699358]
[483.95711826 500.12840411]
[483.87651928 500.20900309]
[483.79670806 500.28881432]
[483.71766193 500.36786044]
[483.63935932 500.44616306]
[483.56177962 500.52374275]
[483.48490318 500.6006192 ]
[483.40871121 500.67681117]
[483.33318574 500.75233663]
[483.25830959 500.82721278]
[483.1840663  500.90145608]
[483.11044007 500.9750823 ]
[483.03741578 501.04810659]
[482.9649789  501.12054348]
[482.89311548 501.1924069 ]
[482.8218121  501.26371027]
[482.75105589 501.33446649]
[482.68083442 501.40468795]
[482.61113576 501.47438661]
[482.54194841 501.54357397]
[482.47326126 501.61226111]
[482.40506363 501.68045875]
[482.33734519 501.74817718]
[482.27009599 501.81542638]
[482.20330641 501.88221597]
[482.13696714 501.94855523]
[482.0710692  502.01445317]
[482.0056039  502.07991848]
[481.94056282 502.14495955]
[481.87593783 502.20958454]
[481.81172104 502.27380134]
[481.74790481 502.33761757]
[481.68448173 502.40104064]
[481.62144464 502.46407774]
[481.55878656 502.52673582]
[481.49650074 502.58902163]
[481.43458063 502.65094175]
[481.37301985 502.71250252]
[481.31181223 502.77371014]
[481.25095175 502.83457062]
[481.19043258 502.8950898 ]
[481.13024903 502.95527334]
[481.07039558 503.01512679]
```

```
[481.01086686 503.07465551]
[480.95165765 503.13386473]
[480.89276284 503.19275953]
[480.83417749 503.25134488]
[480.77589677 503.3096256 ]
[480.71791597 503.3676064 ]
[480.66023051 503.42529186]
[480.60283593 503.48268644]
[480.54572786 503.53979451]
[480.48890206 503.59662031]
[480.43235439 503.65316798]
[480.37608079 503.70944158]
[480.32007733 503.76544504]
[480.26434015 503.82118222]
[480.20886548 503.87665689]
[480.15364966 503.93187271]
[480.09868909 503.98683328]
[480.04398027 504.04154211]
[479.98951976 504.09600262]
[479.93530421 504.15021816]
[479.88133036 504.20419201]
[479.827595   504.25792738]
[479.77409498 504.31142739]
[479.72082726 504.36469512]
[479.66778882 504.41773356]
[479.61497673 504.47054565]
[479.56238812 504.52313425]
[479.51002017 504.5755022 ]
[479.45787014 504.62765223]
[479.40593532 504.67958705]
[479.35421307 504.73130931]
[479.3027008  504.78282158]
[479.25139597 504.8341264 ]
[479.2002961  504.88522627]
[479.14939875 504.93612362]
[479.09870154 504.98682084]
[479.04820211 505.03732026]
[478.99789818 505.0876242 ]
[478.94778748 505.13773489]
[478.89786782 505.18765456]
[478.84813701 505.23738536]
[478.79859294 505.28692943]
[478.74923352 505.33628885]
[478.70005669 505.38546568]
[478.65106045 505.43446192]
[478.60224282 505.48327955]
[478.55360186 505.53192051]
[478.50513567 505.5803867 ]
[478.45684237 505.62868   ]
[478.40872014 505.67680224]
[478.36076715 505.72475522]
[478.31298165 505.77254072]
[478.26536189 505.82016049]
[478.21790615 505.86761623]
[478.17061275 505.91490962]
[478.12348004 505.96204233]
[478.07650639 506.00901598]
[478.02969021 506.05583217]
[477.98302991 506.10249247]
[477.93652395 506.14899843]
[477.89017081 506.19535157]
[477.84396899 506.24155338]
[477.79791703 506.28760535]
[477.75201346 506.33350891]
[477.70625687 506.3792655 ]
[477.66064586 506.42487651]
[477.61517904 506.47034334]
[477.56985505 506.51566732]
[477.52467256 506.56084981]
[477.47963025 506.60589213]
[477.43472682 506.65079556]
[477.38996099 506.69556138]
[477.34533152 506.74019086]
[477.30083715 506.78468522]
[477.25647668 506.8290457 ]
[477.21224889 506.87327348]
[477.16815261 506.91736976]
[477.12418667 506.96133571]
[477.08034992 507.00517246]
[477.03664122 507.04888115]
[476.99305947 507.0924629 ]
[476.94960356 507.13591881]
[476.90627241 507.17924997]
[476.86306495 507.22245743]
[476.81998012 507.26554225]
[476.7770169  507.30850547]
[476.73417425 507.35134812]
[476.69145117 507.39407121]
[476.64884665 507.43667572]
```

 [476.60635972 507.47916265]
 [476.56398942 507.52153296]
 [476.52173478 507.5637876]
 [476.47959486 507.60592752]]

In [54]:
```
# 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]:
```
# 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]:
```
#-----Load predictions, date column added

low_pred = pd.read_csv('C:/Users/ericy/Desktop/1990_Low_Prediction.csv')
high_pred = pd.read_csv('C:/Users/ericy/Desktop/1990_High_Prediction.csv')
```

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

Out[57]:

	Date	Low_Prediction
0	1982-10-25	491.226395
1	1982-10-26	490.309927
2	1982-10-27	490.175541
3	1982-10-28	489.730883
4	1982-10-29	489.534159
...	...	...
180	1983-04-23	476.648847
181	1983-04-24	476.606360
182	1983-04-25	476.563989
183	1983-04-26	476.521735
184	1983-04-27	476.479595

185 rows × 2 columns

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

Out[58]:

	Date	High_Prediction
0	1982-10-25	493.338975
1	1982-10-26	493.500014
2	1982-10-27	494.068250
3	1982-10-28	494.263745
4	1982-10-29	494.603565
...	...	...
180	1983-04-23	507.436676
181	1983-04-24	507.479163
182	1983-04-25	507.521533
183	1983-04-26	507.563788
184	1983-04-27	507.605928

185 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
1982-10-25	491.226395
1982-10-26	490.309927
1982-10-27	490.175541
1982-10-28	489.730883
1982-10-29	489.534159
...	...
1983-04-23	476.648847
1983-04-24	476.606360
1983-04-25	476.563989
1983-04-26	476.521735
1983-04-27	476.479595

185 rows × 1 columns

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

Out[64]:

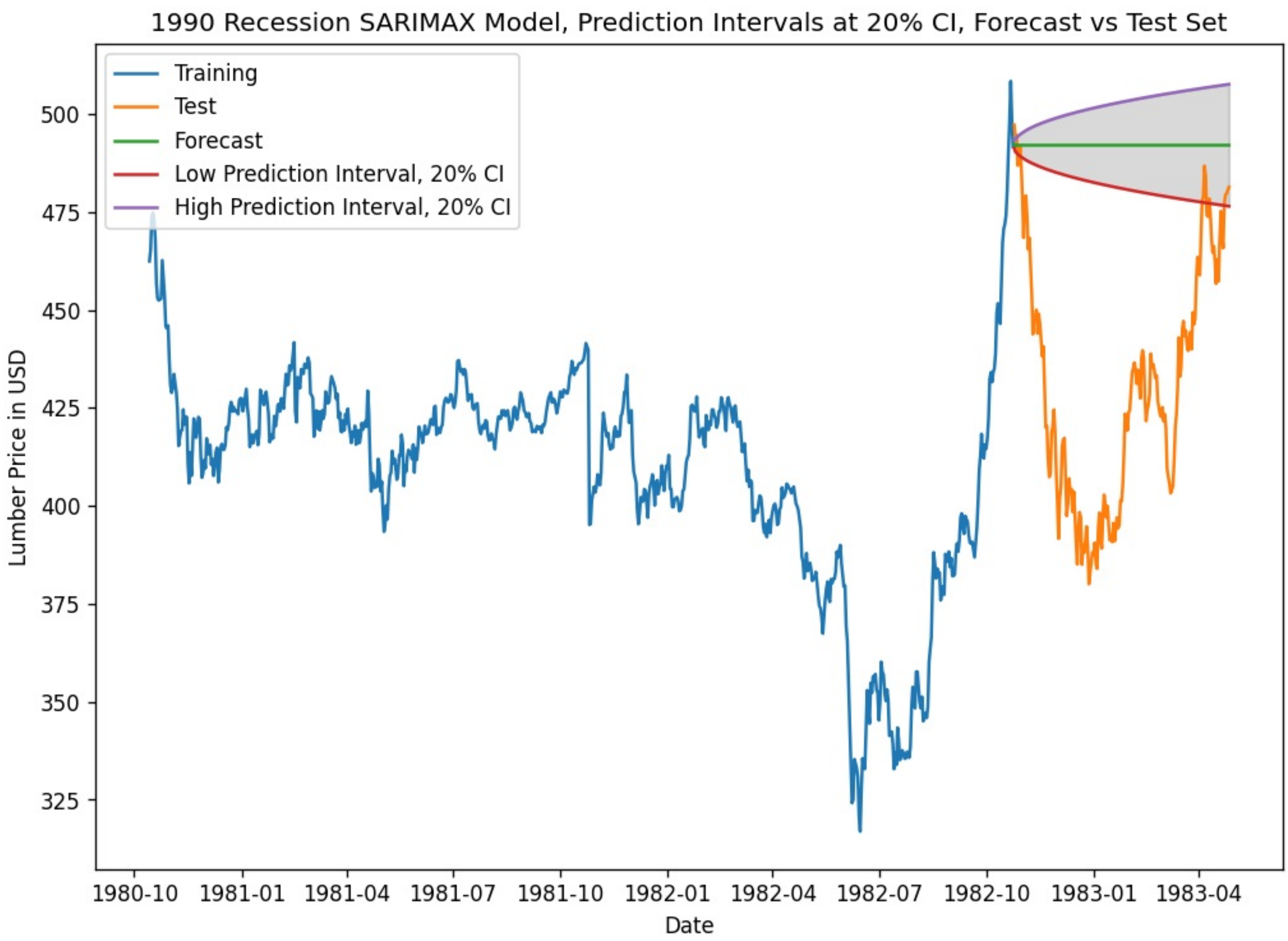
Date	High_Prediction
1982-10-25	493.338975
1982-10-26	493.500014
1982-10-27	494.068250
1982-10-28	494.263745
1982-10-29	494.603565
...	...
1983-04-23	507.436676
1983-04-24	507.479163
1983-04-25	507.521533
1983-04-26	507.563788
1983-04-27	507.605928

185 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 = 185),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))

# 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('1990 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]:
```
# Accept or reject the Null Hypothesis
# 1990 Recession we Accept the Null Hypothesis
```

In [ ]:

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