D214 Capstone

Modeling Inflation Adusted Recessionary Lumber Prices

Early 2000'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[6630:7324]
```

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

Out[6]:

	Date	Trading Days	2022_Value	Value
6630	1999-03-03	6631	562.408	338.8
6631	1999-03-04	6632	558.590	336.5
6632	1999-03-05	6633	566.392	341.2
6633	1999-03-08	6634	567.222	341.7
6634	1999-03-09	6635	557.096	335.6
...	...	...	...	...
7319	2001-11-27	7320	348.226	221.8
7320	2001-11-28	7321	355.448	226.4
7321	2001-11-29	7322	356.390	227.0
7322	2001-11-30	7323	349.953	222.9
7323	2001-12-03	7324	342.731	218.3

694 rows × 4 columns

D1: Exploratory Data Analysis

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

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

Out[8]:

	Trading Days	2022_Value
6630	6631	562.408
6631	6632	558.590
6632	6633	566.392
6633	6634	567.222
6634	6635	557.096
...	...	...
7319	7320	348.226
7320	7321	355.448
7321	7322	356.390
7322	7323	349.953
7323	7324	342.731

694 rows × 2 columns

EDA

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

Out[9]:

	Trading Days	2022_Value
6630	6631	562.408
6631	6632	558.590
6632	6633	566.392
6633	6634	567.222
6634	6635	557.096

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

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 694 entries, 6630 to 7323
Data columns (total 2 columns):
 #   Column        Non-Null Count  Dtype  
---  ------        --------------  -----  
 0   Trading Days  694 non-null    int64  
 1   2022_Value    694 non-null    float64
dtypes: float64(1), int64(1)
memory usage: 11.0 KB
```

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

Out[11]:
```
(694, 2)
```

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

Out[12]:

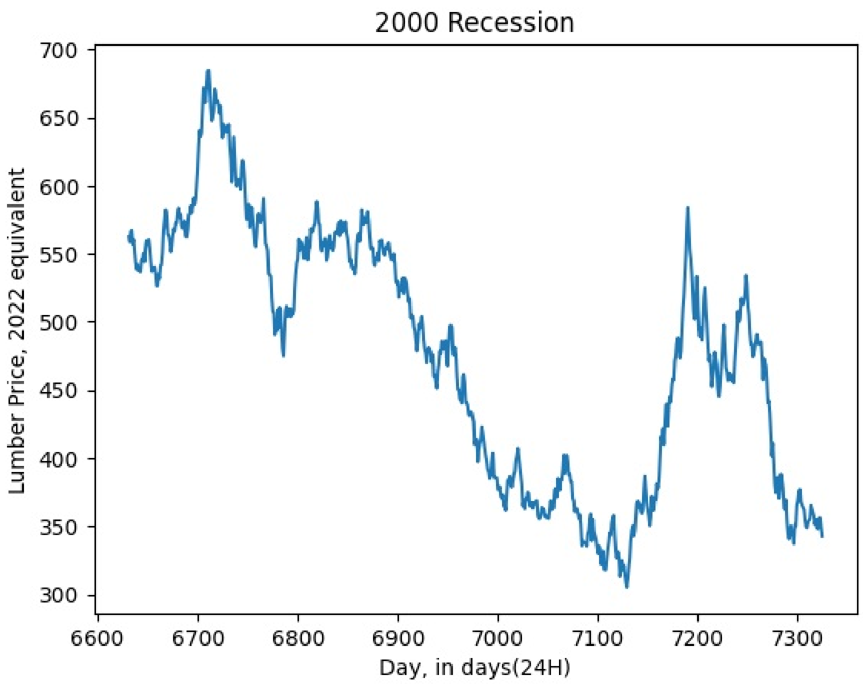
	Trading Days	2022_Value
count	694.000000	694.000000
mean	6977.500000	475.437570
std	200.484829	93.310951
min	6631.000000	305.365000
25%	6804.250000	380.024750
50%	6977.500000	484.454900
75%	7150.750000	554.772000
max	7324.000000	684.517600

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('2000 Recession')
plt.xlabel('Day, in days(24H)')
plt.ylabel('Lumber Price, 2022 equivalent')
plt.show()
```



Data Cleaning

In [ ]:

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: 694 entries, 6630 to 7323
Data columns (total 2 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   Trading Days  694 non-null    datetime64[ns]
 1   2022_Value    694 non-null    float64
dtypes: datetime64[ns](1), float64(1)
memory usage: 16.3 KB
```

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

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

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 694 entries, 1988-02-27 to 1990-01-20
Data columns (total 1 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   2022_Value  694 non-null    float64
dtypes: float64(1)
memory usage: 10.8 KB
```

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

Out[20]:

	2022_Value
Trading Days	
1988-02-27	562.408
1988-02-28	558.590
1988-02-29	566.392
1988-03-01	567.222
1988-03-02	557.096
...	...
1990-01-16	348.226
1990-01-17	355.448
1990-01-18	356.390
1990-01-19	349.953
1990-01-20	342.731

694 rows × 1 columns

D3 Stationarity Analysis

Augmented Dickey Fuller (ADF) Test

Assess stationarity of dataset

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

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

Out[22]:
```
(-1.108102894290722,
 0.7118297706953935,
 2,
 691,
 {'1%': -3.4398489271901713,
  '5%': -2.8657317673059395,
  '10%': -2.569002221596252},
 4756.26141939622)
```

In [23]:
```python
# Results show p = .71183
# 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('2000 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()
```

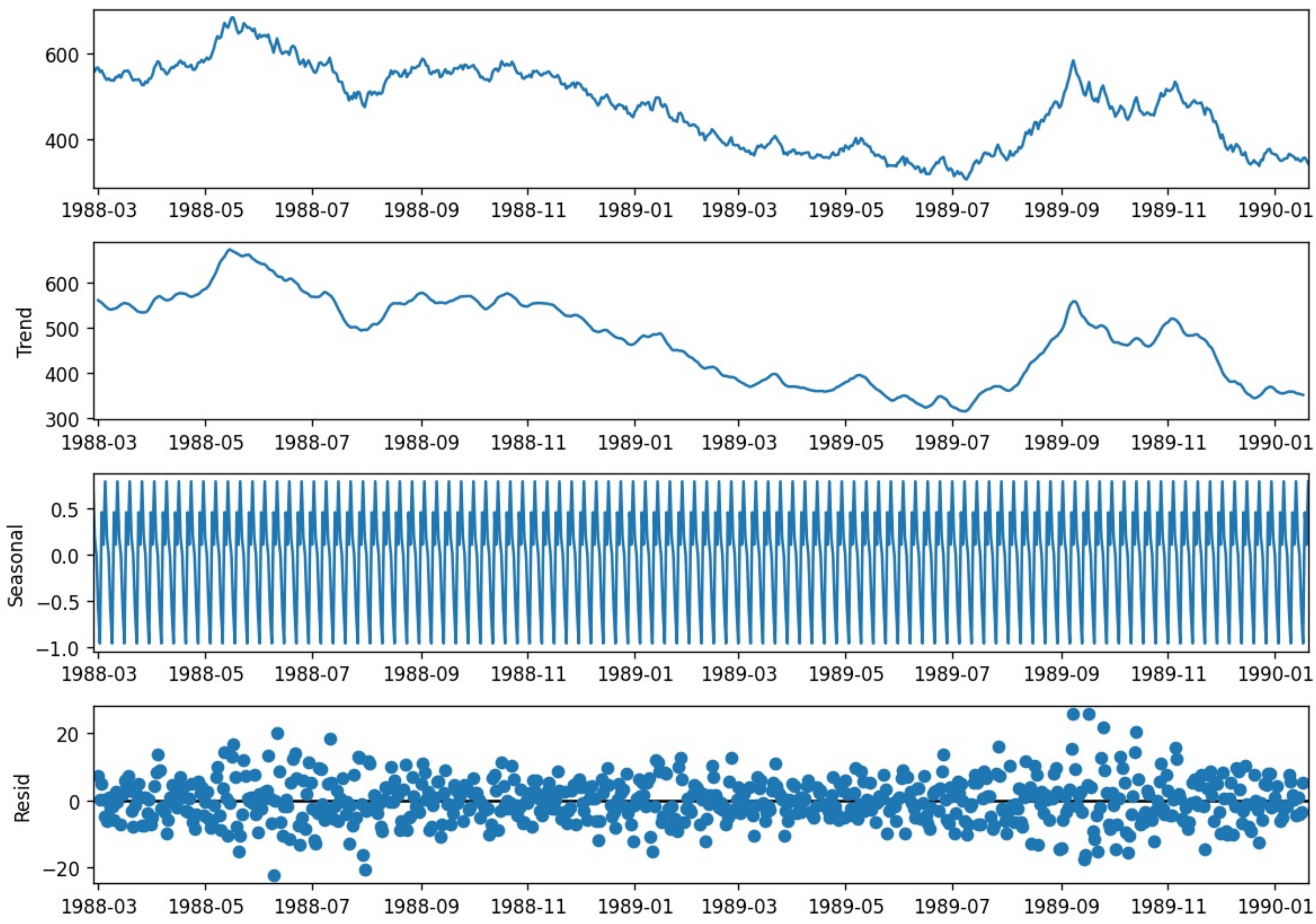
In [25]:
```
# Using pmdarima's ndiffs to find differencing term
# Code reference (Verma, 2021)

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();
```

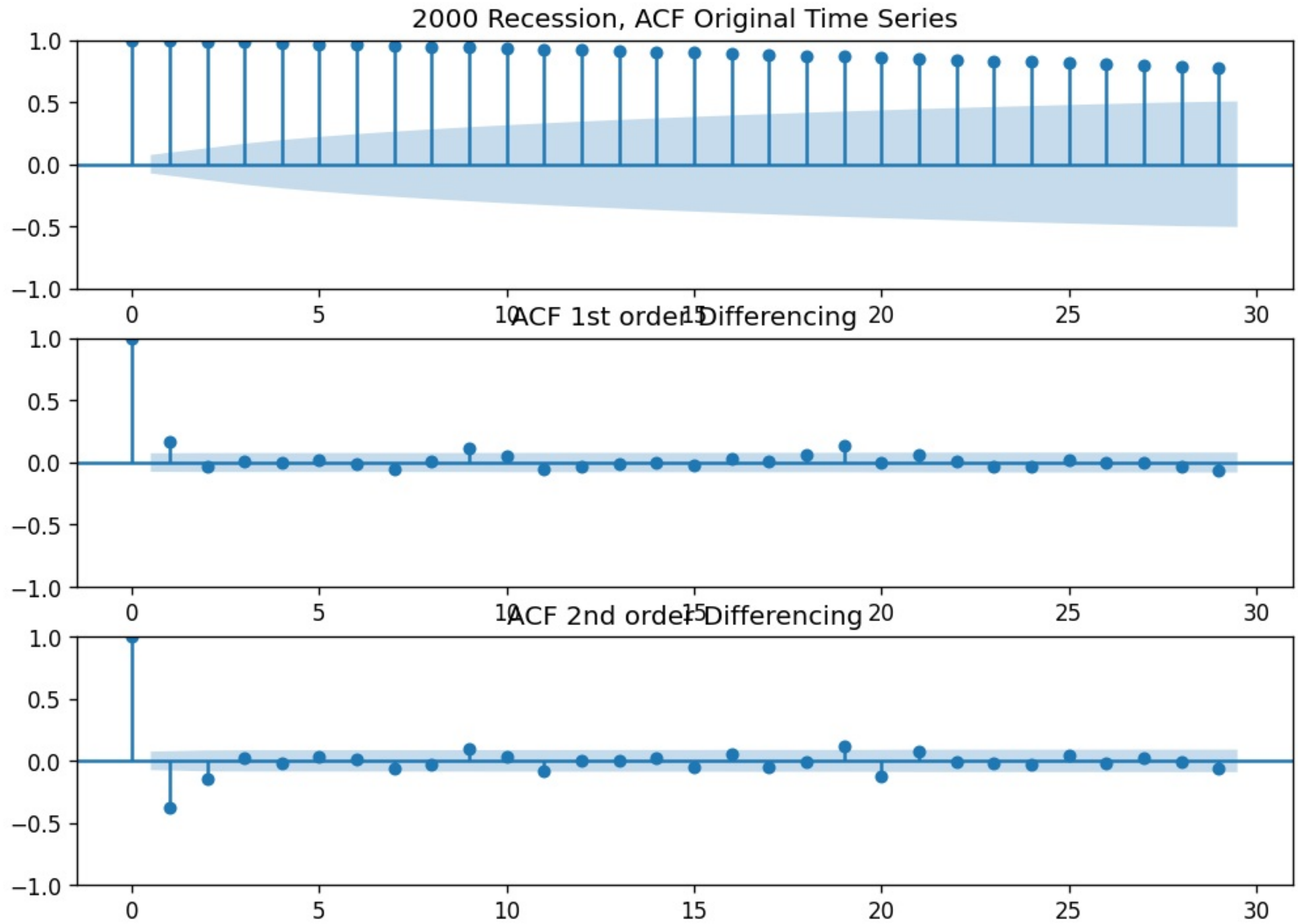


D6 ACF and PACF

Finding order of MA term 'q'

Using Autocorrelation function (ACF)

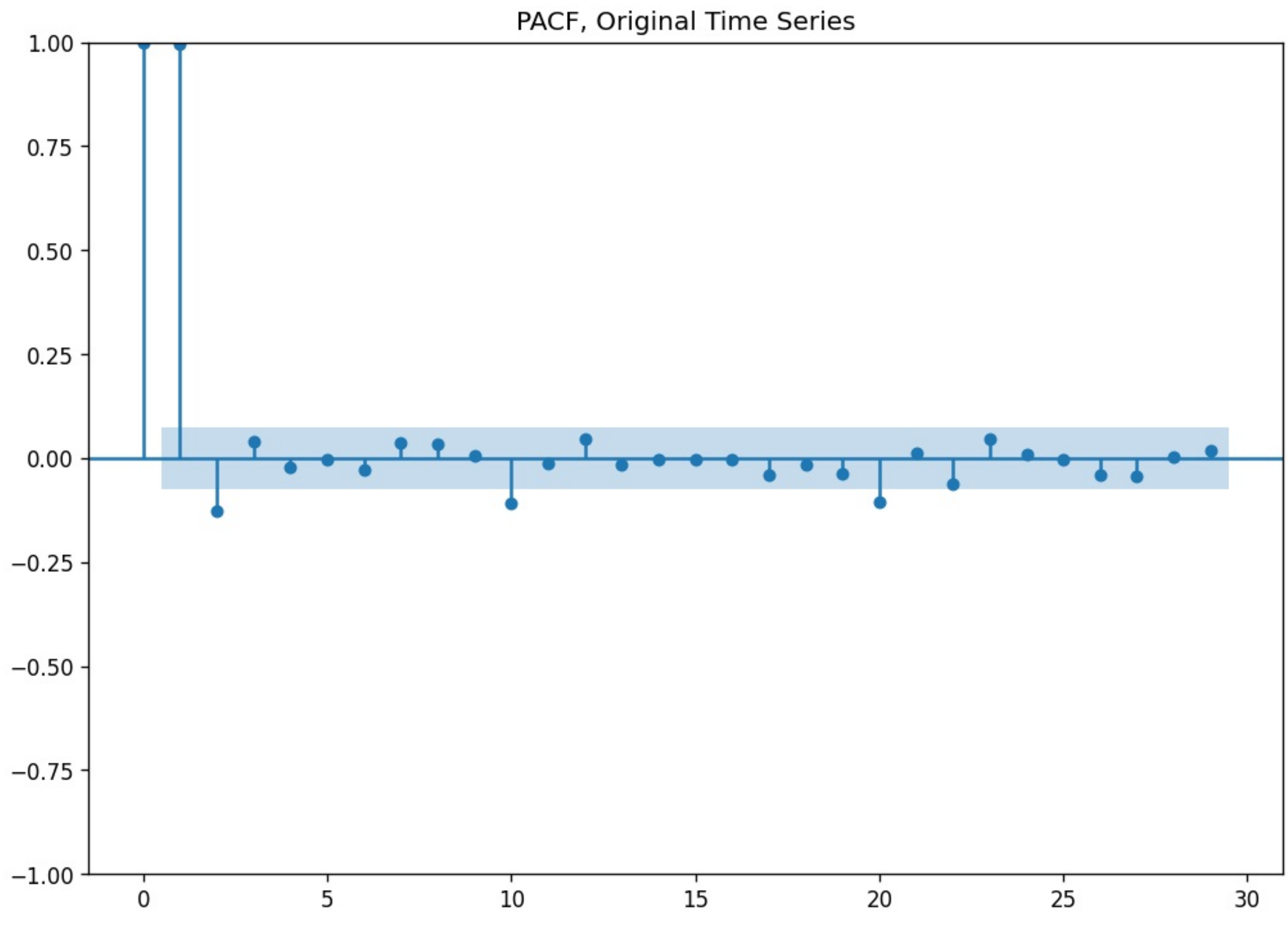
In [28]:
```
fig, (ax1, ax2, ax3) = plt.subplots(3)
plot_acf(df, ax=ax1, title='2000 Recession, ACF Original Time Series');
plot_acf(df.diff().dropna(), ax=ax2, title='ACF 1st order Differencing');
plot_acf(df.diff().diff().dropna(), ax=ax3, title='ACF 2nd order Differencing');
```



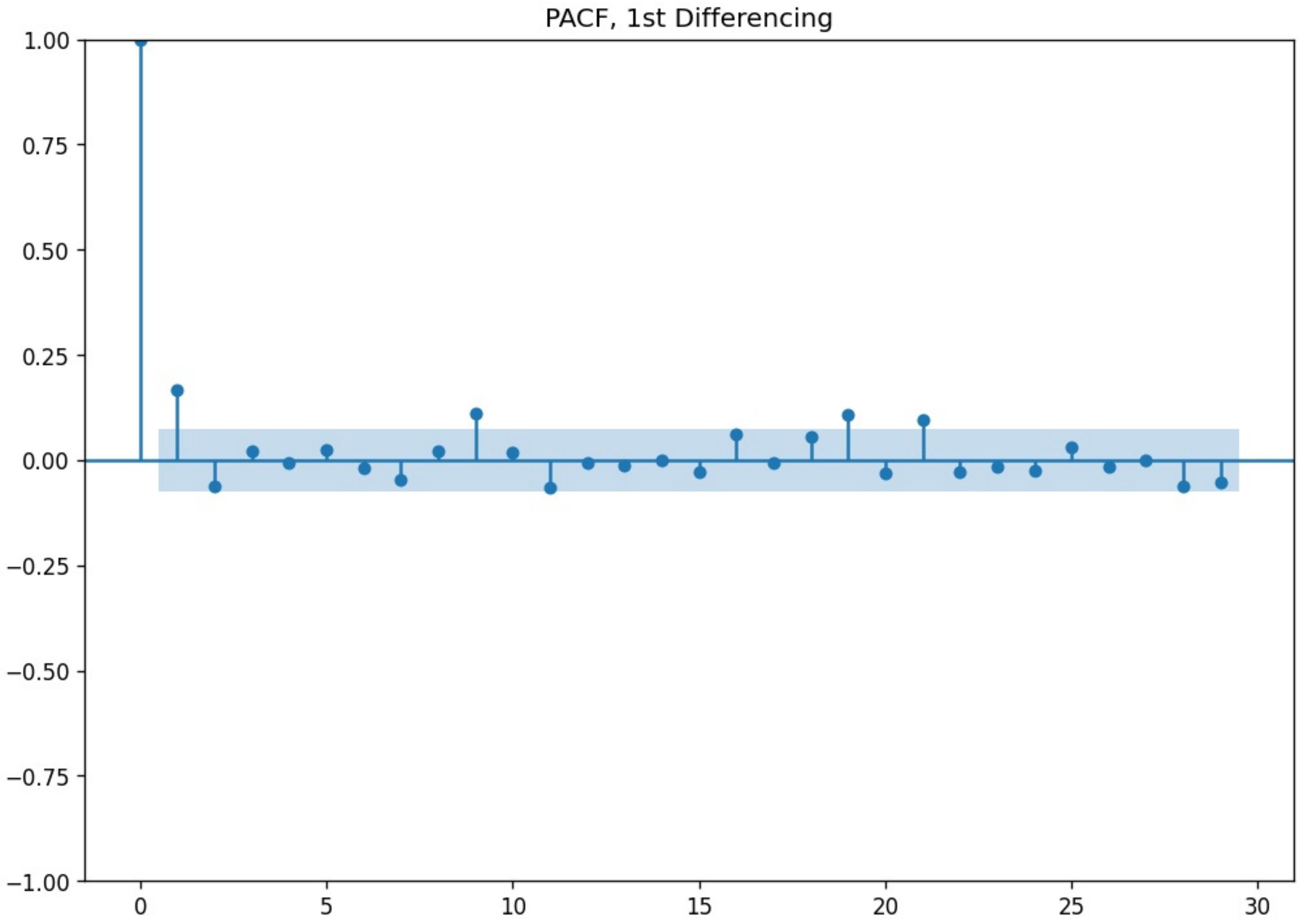
Finding order of AR term 'p'

Using Partial autocorrelation (PACF)

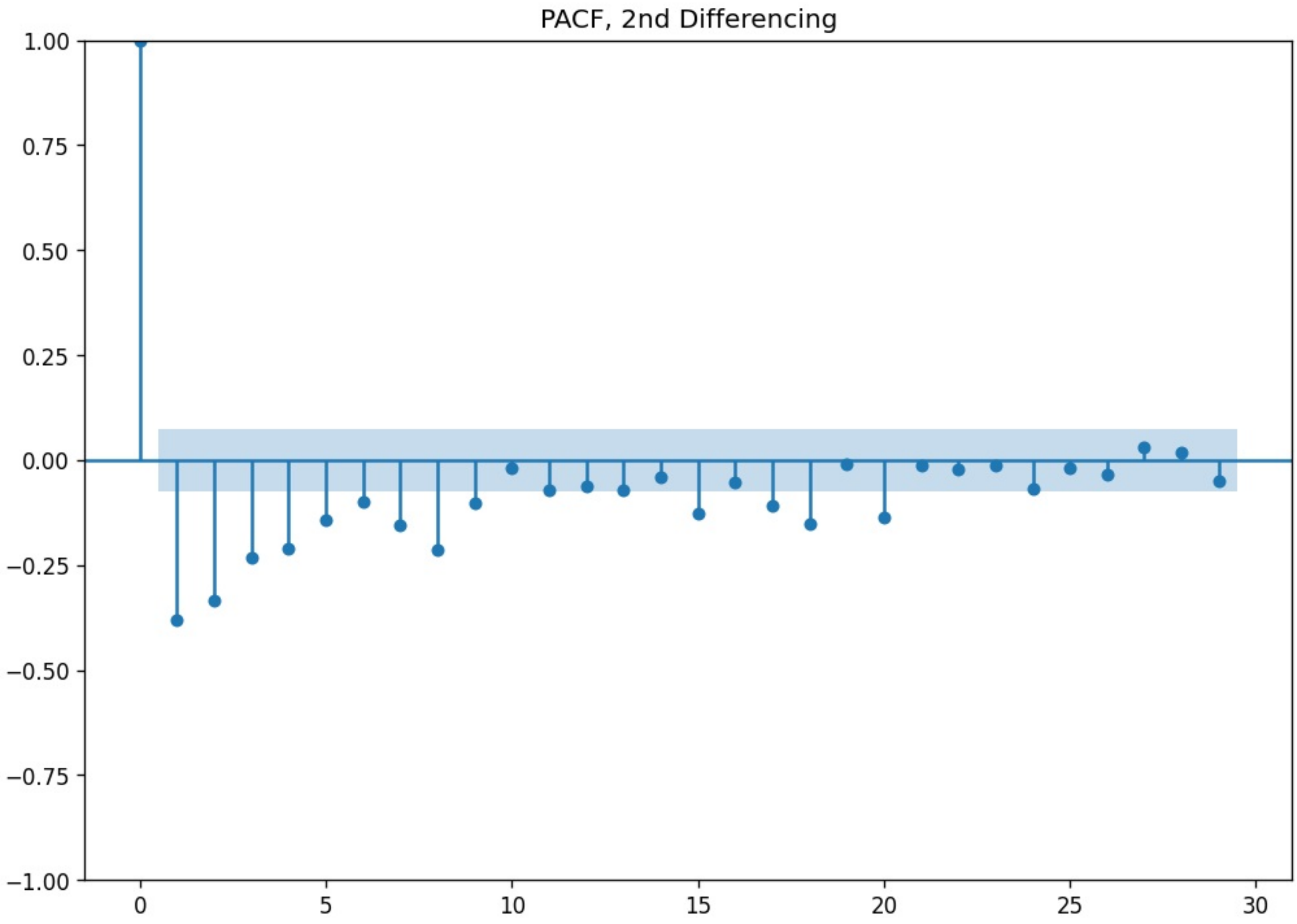
In [29]:
```
warnings.filterwarnings("ignore")
plot_pacf(df.dropna(), title='PACF, Original Time Series');
```



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

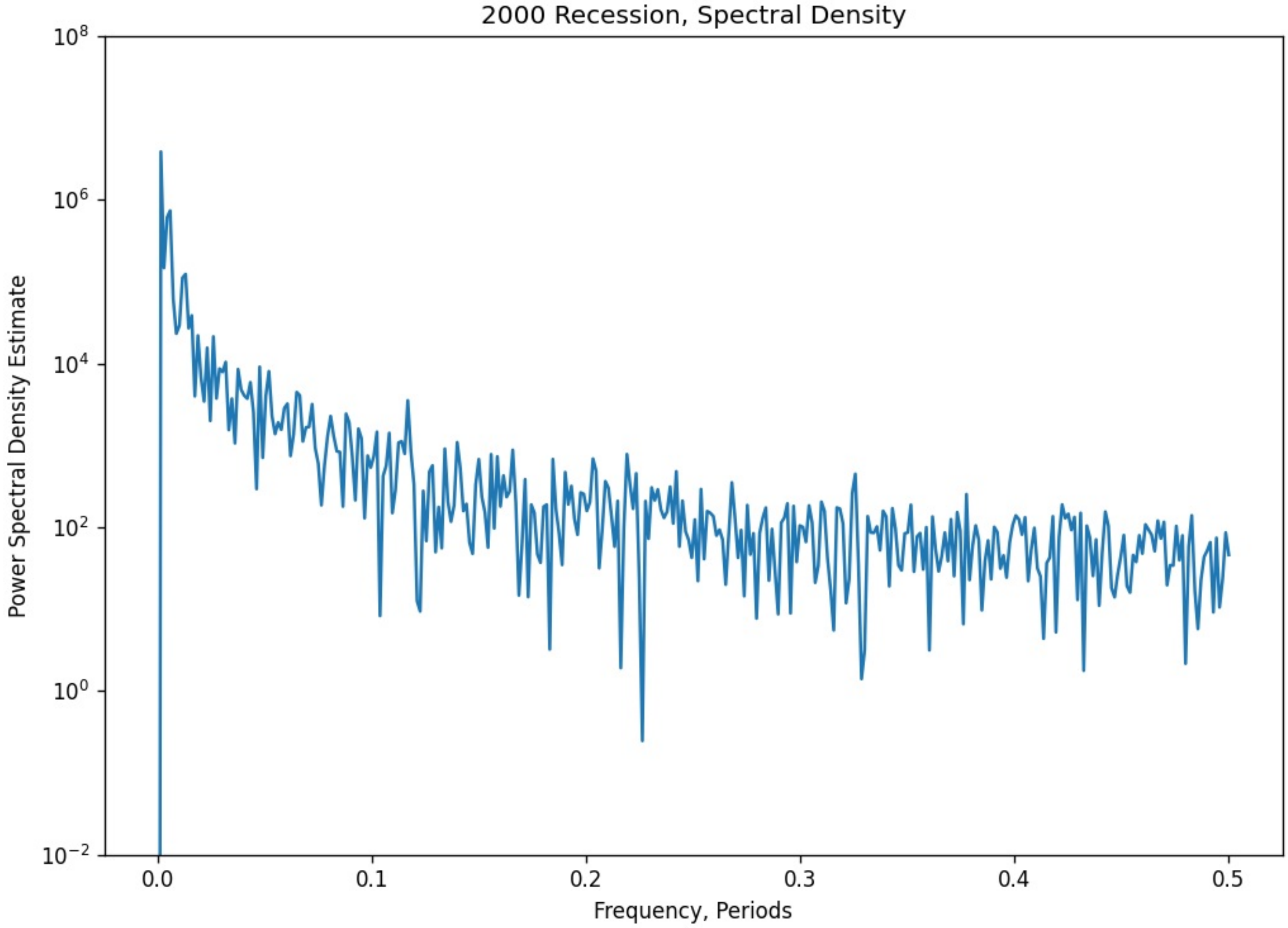


In [31]:
```
plot_pacf(df.diff().diff().dropna(), title='PACF, 2nd Differencing');
```



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('2000 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 = 694 cases

80/20 Train/Test Split

Split is 555 / 139

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=555)
```

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

Out[34]:

Trading Days	2022_Value
1988-02-27	562.408
1988-02-28	558.590
1988-02-29	566.392
1988-03-01	567.222
1988-03-02	557.096
...	...
1989-08-30	484.188
1989-08-31	473.355
1989-09-01	478.536
1989-09-02	494.236
1989-09-03	509.936

555 rows × 1 columns

In [35]:
```
test
```

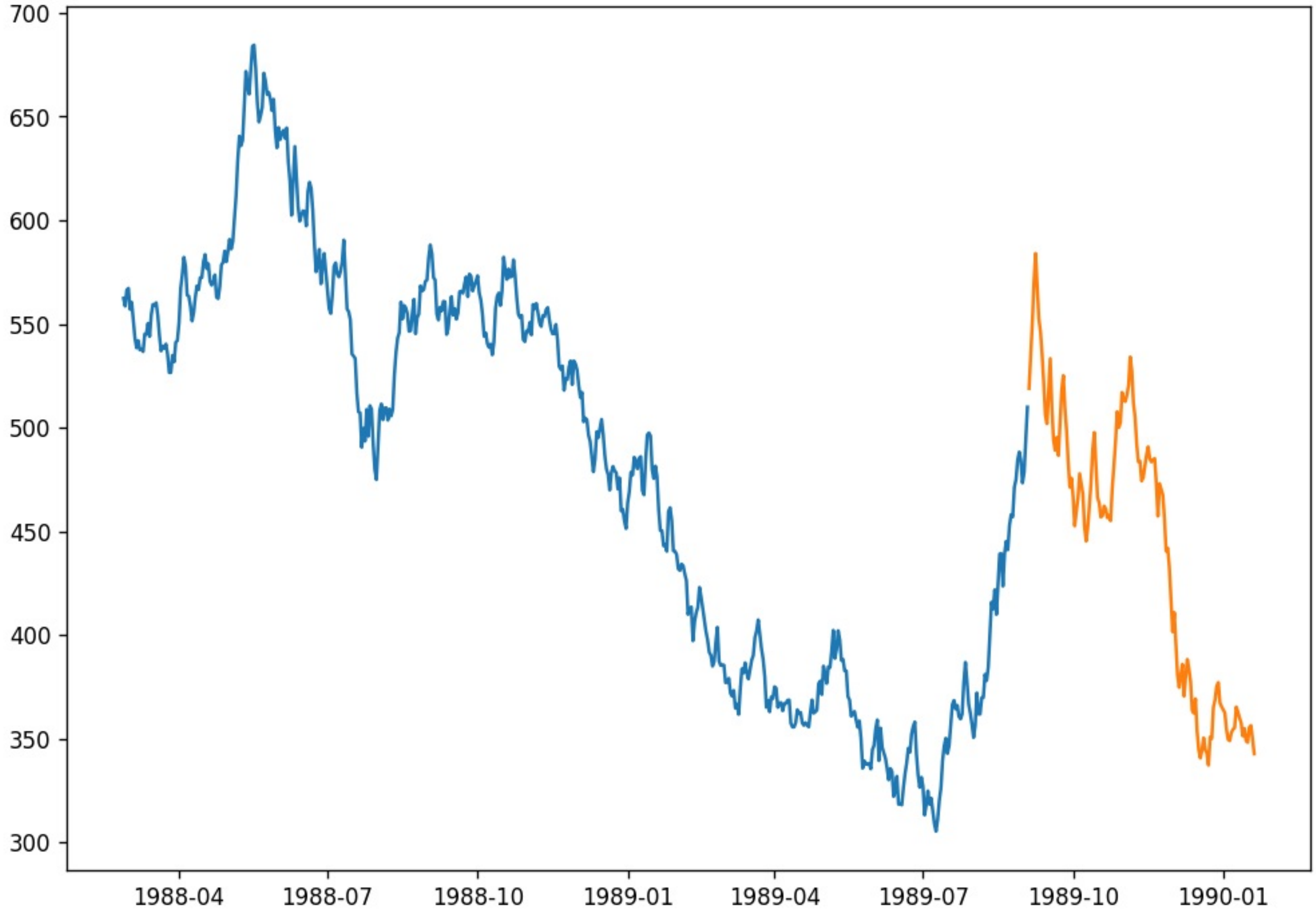
Out[35]:

Trading Days	2022_Value
1989-09-04	518.885
1989-09-05	534.585
1989-09-06	550.285
1989-09-07	569.910
1989-09-08	584.040
...	...
1990-01-16	348.226
1990-01-17	355.448
1990-01-18	356.390
1990-01-19	349.953
1990-01-20	342.731

139 rows × 1 columns

In [36]:
```
# Plot training data
plt.plot(train)

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

Out[36]:
```
[<matplotlib.lines.Line2D at 0x2a7e2eb9348>]
```



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

```
(555, 1)
(139, 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=3862.344, Time=0.20 sec
 ARIMA(0,1,0)(0,0,0)[0] intercept   : AIC=3866.355, Time=0.02 sec
 ARIMA(1,1,0)(0,0,0)[0] intercept   : AIC=3862.726, Time=0.05 sec
 ARIMA(0,1,1)(0,0,0)[0] intercept   : AIC=3861.975, Time=0.07 sec
 ARIMA(0,1,0)(0,0,0)[0]             : AIC=3866.355, Time=0.02 sec
 ARIMA(0,1,2)(0,0,0)[0] intercept   : AIC=3862.305, Time=0.12 sec
 ARIMA(1,1,2)(0,0,0)[0] intercept   : AIC=3864.237, Time=0.23 sec
 ARIMA(0,1,1)(0,0,0)[0]             : AIC=3861.975, Time=0.06 sec

Best model:  ARIMA(0,1,1)(0,0,0)[0]
Total fit time: 0.765 seconds
                               SARIMAX Results
==============================================================================
Dep. Variable:                      y   No. Observations:                  555
Model:               SARIMAX(0, 1, 1)   Log Likelihood               -1927.988
Date:                Tue, 18 Oct 2022   AIC                           3861.975
Time:                        13:18:03   BIC                           3874.927
Sample:                    02-27-1988   HQIC                          3867.035
                         - 09-03-1989
Covariance Type:                  opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
intercept     -0.0918      0.372     -0.247      0.805      -0.821       0.637
ma.L1          0.1143      0.039      2.914      0.004       0.037       0.191
sigma2        61.7015      4.037     15.284      0.000      53.789      69.614
===================================================================================
Ljung-Box (L1) (Q):                   0.02   Jarque-Bera (JB):                 2.21
Prob(Q):                              0.89   Prob(JB):                         0.33
Heteroskedasticity (H):               0.76   Skew:                            -0.01
Prob(H) (two-sided):                  0.06   Kurtosis:                         2.69
===================================================================================

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=3866.240, Time=0.32 sec
 ARIMA(0,1,0)(0,0,0)[0] intercept   : AIC=3866.355, Time=0.02 sec
 ARIMA(1,1,0)(0,0,0)[0] intercept   : AIC=3862.726, Time=0.05 sec
 ARIMA(0,1,1)(0,0,0)[0] intercept   : AIC=3861.975, Time=0.06 sec
 ARIMA(0,1,0)(0,0,0)[0]             : AIC=3864.435, Time=0.01 sec
 ARIMA(1,1,1)(0,0,0)[0] intercept   : AIC=3862.344, Time=0.13 sec
 ARIMA(0,1,2)(0,0,0)[0] intercept   : AIC=3862.305, Time=0.11 sec
 ARIMA(1,1,2)(0,0,0)[0] intercept   : AIC=3864.237, Time=0.20 sec
 ARIMA(0,1,1)(0,0,0)[0]             : AIC=3860.037, Time=0.04 sec
 ARIMA(1,1,1)(0,0,0)[0]             : AIC=3860.412, Time=0.06 sec
 ARIMA(0,1,2)(0,0,0)[0]             : AIC=3860.380, Time=0.05 sec
 ARIMA(1,1,0)(0,0,0)[0]             : AIC=3860.788, Time=0.03 sec
 ARIMA(1,1,2)(0,0,0)[0]             : AIC=3862.309, Time=0.10 sec

Best model:  ARIMA(0,1,1)(0,0,0)[0]
Total fit time: 1.186 seconds
                               SARIMAX Results
==============================================================================
Dep. Variable:                      y   No. Observations:                  555
Model:               SARIMAX(0, 1, 1)   Log Likelihood               -1928.019
Date:                Tue, 18 Oct 2022   AIC                           3860.037
Time:                        21:10:52   BIC                           3868.672
Sample:                    02-27-1988   HQIC                          3863.410
                         - 09-03-1989
Covariance Type:                  opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ma.L1          0.1144      0.039      2.914      0.004       0.037       0.191
sigma2        61.7100      4.037     15.286      0.000      53.797      69.623
===================================================================================
Ljung-Box (L1) (Q):                   0.02   Jarque-Bera (JB):                 2.21
Prob(Q):                              0.88   Prob(JB):                         0.33
Heteroskedasticity (H):               0.76   Skew:                            -0.01
Prob(H) (two-sided):                  0.06   Kurtosis:                         2.69
===================================================================================

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

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

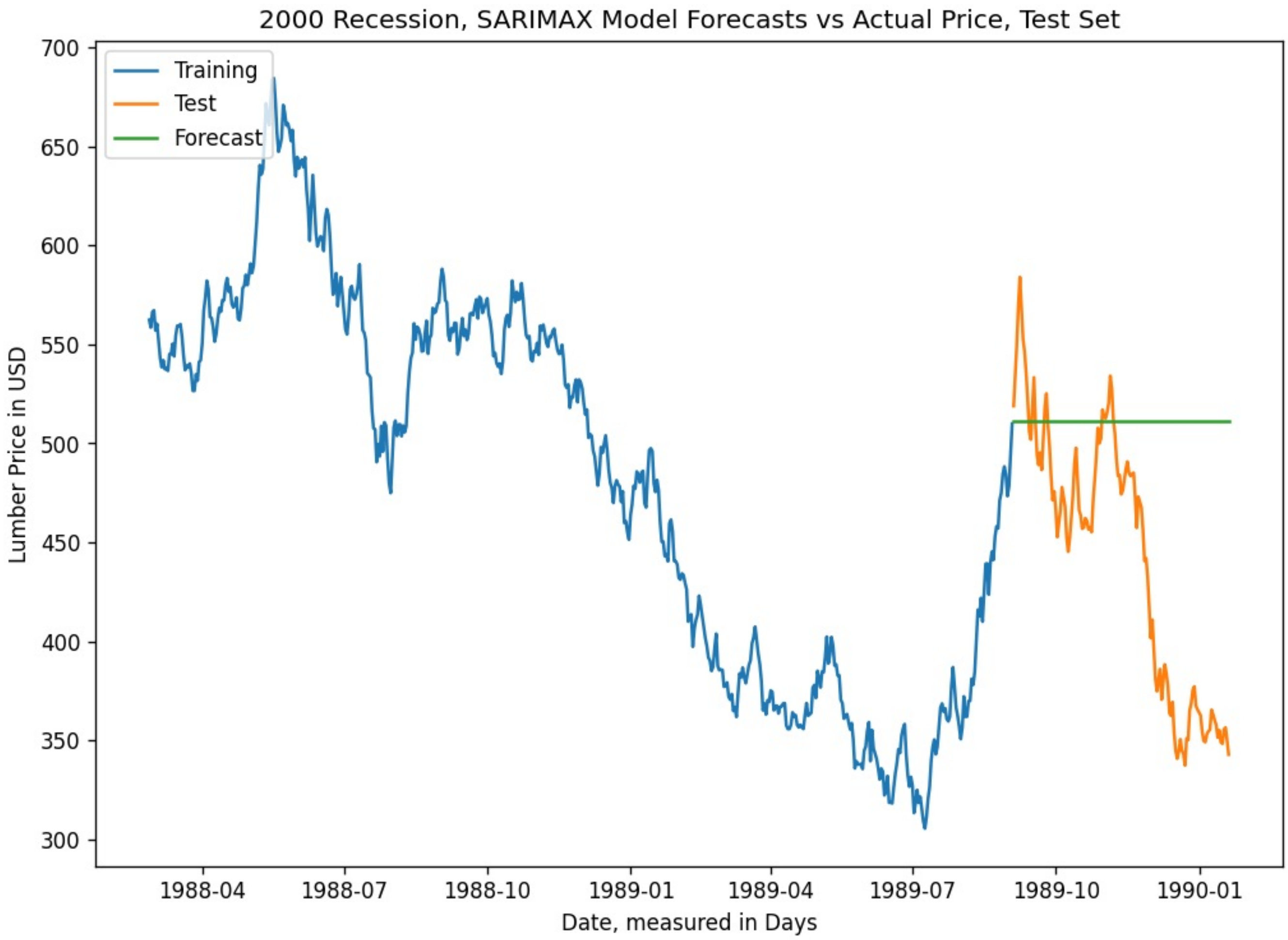
Out[40]:

	0	1
ma.L1	0.037453	0.191373
sigma2	53.797337	69.622658

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 = 139))

# 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('2000 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')
```

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



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

Out[42]:

	forecast_prices
1989-09-04	511.536298
1989-09-05	511.536298
1989-09-06	511.536298
1989-09-07	511.536298
1989-09-08	511.536298
...	...
1990-01-16	511.536298
1990-01-17	511.536298
1990-01-18	511.536298
1990-01-19	511.536298
1990-01-20	511.536298

139 rows × 1 columns

D10 Accuracy Metrics for our forecast

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

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

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

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

Out[45]:
```
(139, 1)
```

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

Out[46]:

	forecast_prices
1989-09-04	511.536298
1989-09-05	511.536298
1989-09-06	511.536298
1989-09-07	511.536298
1989-09-08	511.536298
...	...
1990-01-16	511.536298
1990-01-17	511.536298
1990-01-18	511.536298
1990-01-19	511.536298
1990-01-20	511.536298

139 rows × 1 columns

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

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

Out[48]:
```
(139, 1)
```

In [49]:
```
#RMSE Calculation

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

```
RMSE = 95.71276638539831
```

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))
```

```
75.1690398533788
```

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     0.039266
sigma2    4.037146
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(139, return_conf_int=True, alpha=0.8)
print(conf_int)
```

```
[[509.54611213 513.52648449]
 [508.55638617 514.51621045]
 [507.82160967 515.25098695]
 [507.20987404 515.86272259]
 [506.67451034 516.39808629]
 [506.19251523 516.8800814 ]
 [505.75053536 517.32206127]
 [505.34000198 517.73259465]
 [504.95502764 518.11756898]
 [504.59136066 518.48123596]
 [504.24581175 518.82678487]
 [503.9159158  519.15668082]
 [503.59972065 519.47287597]
 [503.29564905 519.77694757]
 [503.00240497 520.07019165]
 [502.71890806 520.35368856]
```

```
[502.4442465  520.62835013]
[502.17764234 520.89495428]
[501.91842553 521.15417109]
[501.66601401 521.40658261]
[501.41989838 521.65269824]
[501.17962979 521.89296683]
[500.94481031 522.12778632]
[500.71508519 522.35751144]
[500.49013659 522.58246003]
[500.26967841 522.80291822]
[500.053452   523.01914462]
[499.84122265 523.23137397]
[499.63277656 523.43982006]
[499.42791835 523.64467828]
[499.22646888 523.84612775]
[499.02826345 524.04433317]
[498.83315022 524.2394464 ]
[498.64098883 524.4316078 ]
[498.45164921 524.62094741]
[498.26501061 524.80758602]
[498.08096061 524.99163601]
[497.89939441 525.17320221]
[497.72021409 525.35238254]
[497.54332798 525.52926864]
[497.36865017 525.70394646]
[497.19609994 525.87649668]
[497.02560141 526.04699521]
[496.85708308 526.21551355]
[496.69047751 526.38211911]
[496.52572102 526.5468756 ]
[496.36275338 526.70984325]
[496.20151754 526.87107908]
[496.04195946 527.03063717]
[495.88402781 527.18856881]
[495.72767386 527.34492277]
[495.57285124 527.49974539]
[495.41951582 527.6530808 ]
[495.26762556 527.80497107]
[495.11714034 527.95545628]
[494.96802188 528.10457474]
[494.82023361 528.25236301]
[494.67374054 528.39885608]
[494.52850922 528.5440874 ]
[494.38450759 528.68808904]
[494.24170492 528.8308917 ]
[494.10007178 528.97252485]
[493.95957987 529.11301675]
[493.82020206 529.25239456]
[493.68191225 529.39068438]
[493.54468535 529.52791128]
[493.40849722 529.6640994 ]
[493.27332463 529.79927199]
[493.13914519 529.93345143]
[493.00593732 530.0666593 ]
[492.87368023 530.19891639]
[492.74235384 530.33024279]
[492.61193876 530.46065786]
[492.4824163  530.59018032]
[492.35376837 530.71882825]
[492.22597749 530.84661913]
[492.09902675 530.97356987]
[491.97289981 531.09969681]
[491.84758083 531.2250158 ]
[491.72305447 531.34954215]
[491.59930589 531.47329074]
[491.47632069 531.59627593]
[491.35408492 531.71851171]
[491.23258503 531.84001159]
[491.11180791 531.96078871]
[490.9917408  532.08085583]
[490.87237132 532.20022531]
[490.75368745 532.31890917]
[490.63567752 532.4369191 ]
[490.51833017 532.55426645]
[490.40163437 532.67096226]
[490.28557937 532.78701725]
[490.17015475 532.90244188]
[490.05535033 533.01724629]
[489.94115623 533.13144039]
[489.82756282 533.24503381]
[489.71456071 533.35803592]
[489.60214076 533.47045586]
[489.49029408 533.58230255]
[489.37901197 533.69358465]
[489.26828598 533.80431065]
[489.15810784 533.91448878]
[489.04846951 534.02412711]
[488.93936314 534.13323349]
[488.83078104 534.24181559]
```

```
 [488.72271573 534.34988089]
 [488.61515992 534.45743671]
 [488.50810645 534.56449018]
 [488.40154835 534.67104828]
 [488.29547881 534.77711782]
 [488.18989117 534.88270546]
 [488.08477892 534.98781771]
 [487.98013569 535.09246093]
 [487.87595528 535.19664135]
 [487.77223157 535.30036505]
 [487.66895864 535.40363799]
 [487.56613063 535.50646599]
 [487.46374187 535.60885476]
 [487.36178675 535.71080987]
 [487.26025983 535.8123368 ]
 [487.15915574 535.91344088]
 [487.05846926 536.01412737]
 [486.95819524 536.11440138]
 [486.85832867 536.21426796]
 [486.7588646  536.31373202]
 [486.65979823 536.4127984 ]
 [486.5611248  536.51147182]
 [486.46283969 536.60975693]
 [486.36493835 536.70765828]
 [486.26741631 536.80518032]
 [486.1702692  536.90232743]
 [486.07349272 536.9991039 ]
 [485.97708268 537.09551394]
 [485.88103493 537.19156169]
 [485.78534543 537.28725119]
 [485.69001019 537.38258643]
 [485.59502531 537.47757131]
 [485.50038695 537.57220967]
 [485.40609135 537.66650527]]
```

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/2000_Low_Prediction.csv')
high_pred = pd.read_csv('C:/Users/ericy/Desktop/2000_High_Prediction.csv')
```

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

Out[57]:

	Date	Low_Prediction
0	1989-09-04	509.546112
1	1989-09-05	508.556386
2	1989-09-06	507.821610
3	1989-09-07	507.209874
4	1989-09-08	506.674510
...	...	...
134	1990-01-16	485.785345
135	1990-01-17	485.690010
136	1990-01-18	485.595025
137	1990-01-19	485.500387
138	1990-01-20	485.406091

139 rows × 2 columns

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

Out[58]:

	Date	High_Prediction
0	1989-09-04	513.526485
1	1989-09-05	514.516210
2	1989-09-06	515.250987
3	1989-09-07	515.862723
4	1989-09-08	516.398086
...	...	...
134	1990-01-16	537.287251
135	1990-01-17	537.382586
136	1990-01-18	537.477571
137	1990-01-19	537.572210
138	1990-01-20	537.666505

139 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]:

	Low_Prediction
Date	
1989-09-04	509.546112
1989-09-05	508.556386
1989-09-06	507.821610
1989-09-07	507.209874
1989-09-08	506.674510
...	...
1990-01-16	485.785345
1990-01-17	485.690010
1990-01-18	485.595025
1990-01-19	485.500387
1990-01-20	485.406091

139 rows × 1 columns

In [64]:

```
high_pred
```

Out[64]:

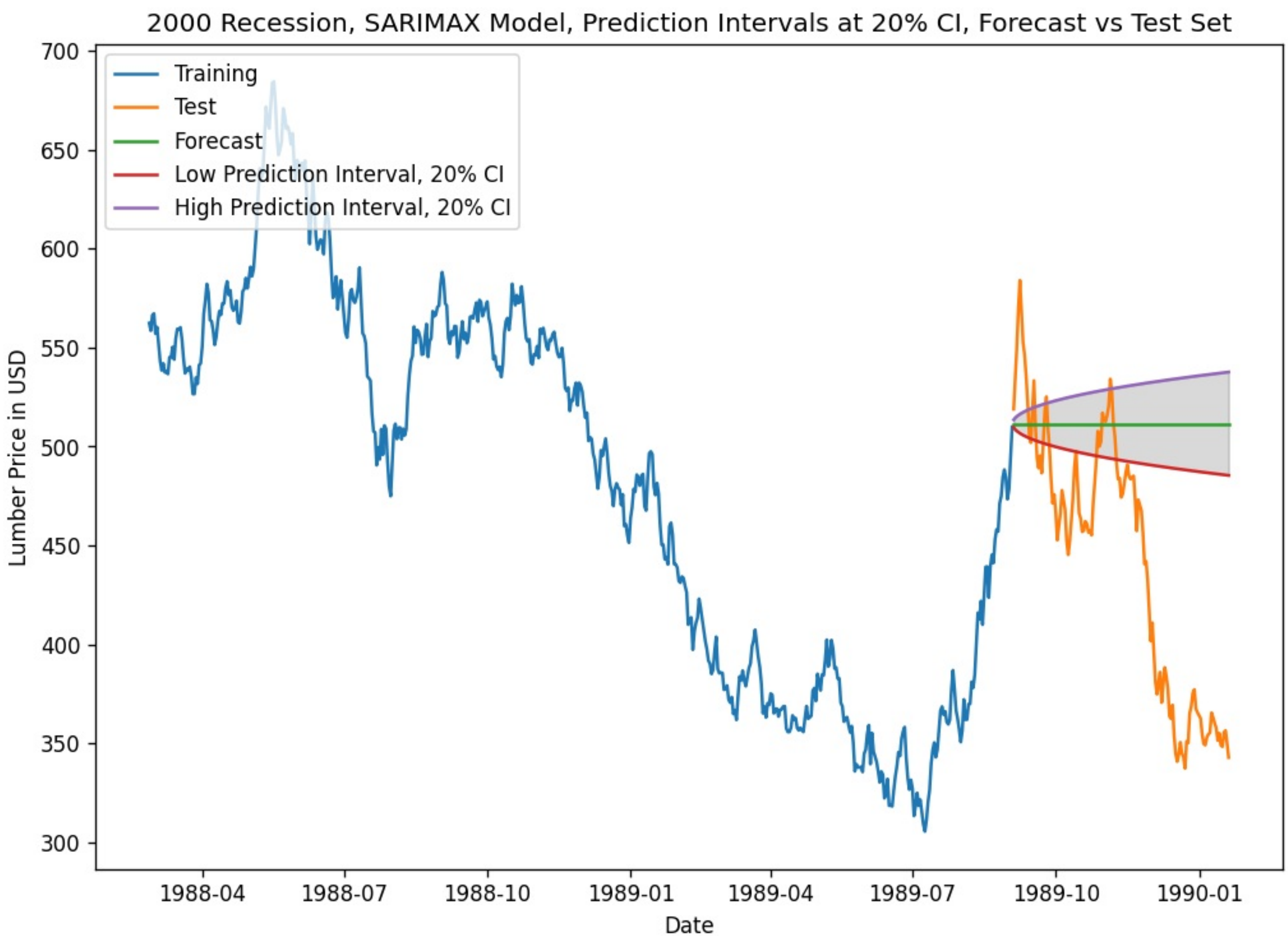
Date	High_Prediction
1989-09-04	513.526485
1989-09-05	514.516210
1989-09-06	515.250987
1989-09-07	515.862723
1989-09-08	516.398086
...	...
1990-01-16	537.287251
1990-01-17	537.382586
1990-01-18	537.477571
1990-01-19	537.572210
1990-01-20	537.666505

139 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 = 139),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('2000 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
# 2000 Recession we Accept the Null Hypothesis
```

In [ ]:

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