D214 Capstone

Modeling Inflation Adusted Recessionary Lumber Prices

November 1973- March 1975 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')
```

November 16 1973 to March 31, 1975

42% of Trading Days are Pre-Recession, 58% are In-Recession

In [5]:
```
#------ Select Data Set for Recession
df = df[:591]
```

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

Out[6]:

	Date	Trading Days	2022_Value	Value
0	1972-11-16	1	865.416	128.4
1	1972-11-17	2	865.416	128.4
2	1972-11-20	3	865.416	128.4
3	1972-11-21	4	855.980	127.0
4	1972-11-27	5	856.654	127.1
...	...	...	...	...
586	1975-03-24	587	734.800	133.6
587	1975-03-25	588	746.900	135.8
588	1975-03-26	589	741.950	134.9
589	1975-03-27	590	755.150	137.3
590	1975-03-31	591	782.650	142.3

591 rows × 4 columns

D1: Exploratory Data Analysis

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

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

Out[8]:

	Trading Days	2022_Value
0	1	865.416
1	2	865.416
2	3	865.416
3	4	855.980
4	5	856.654
...	...	...
586	587	734.800
587	588	746.900
588	589	741.950
589	590	755.150
590	591	782.650

591 rows × 2 columns

EDA

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

Out[9]:

	Trading Days	2022_Value
0	1	865.416
1	2	865.416
2	3	865.416
3	4	855.980
4	5	856.654

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

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 591 entries, 0 to 590
Data columns (total 2 columns):
 #   Column        Non-Null Count  Dtype  
---  ------        --------------  -----  
 0   Trading Days  591 non-null    int64  
 1   2022_Value    591 non-null    float64
dtypes: float64(1), int64(1)
memory usage: 9.4 KB
```

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

Out[11]:
```
(591, 2)
```

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

Out[12]:

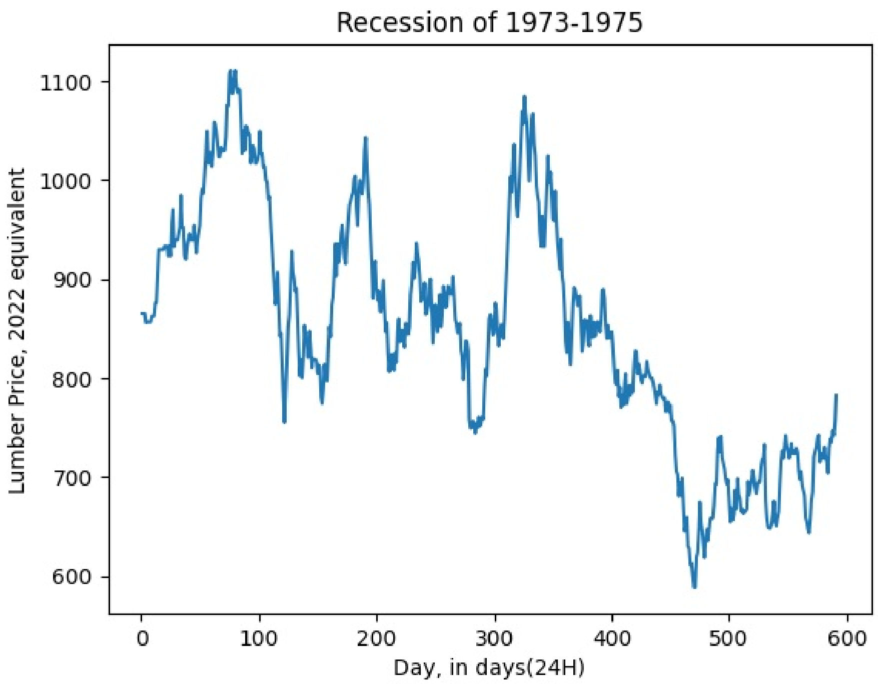
	Trading Days	2022_Value
count	591.000000	591.000000
mean	296.000000	848.870626
std	170.751281	119.660087
min	1.000000	588.650000
25%	148.500000	756.400000
50%	296.000000	852.170000
75%	443.500000	935.712000
max	591.000000	1111.320000

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('Recession of 1973-1975')
plt.xlabel('Day, in days(24H)')
plt.ylabel('Lumber Price, 2022 equivalent')
plt.show()
```



Data Cleaning

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: 591 entries, 0 to 590
Data columns (total 2 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   Trading Days  591 non-null    datetime64[ns]
 1   2022_Value    591 non-null    float64
dtypes: datetime64[ns](1), float64(1)
memory usage: 13.9 KB
```

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

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

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 591 entries, 1970-01-02 to 1971-08-15
Data columns (total 1 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   2022_Value  591 non-null    float64
dtypes: float64(1)
memory usage: 9.2 KB
```

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

Out[20]:

	2022_Value
Trading Days	
1970-01-02	865.416
1970-01-03	865.416
1970-01-04	865.416
1970-01-05	855.980
1970-01-06	856.654
...	...
1971-08-11	734.800
1971-08-12	746.900
1971-08-13	741.950
1971-08-14	755.150
1971-08-15	782.650

591 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]:
```
(-1.8272400283661347,
 0.3670240751916377,
 2,
 588,
 {'1%': -3.44152019959894,
  '5%': -2.8664679191981297,
  '10%': -2.569394451038919},
 4911.6844472068815)
```

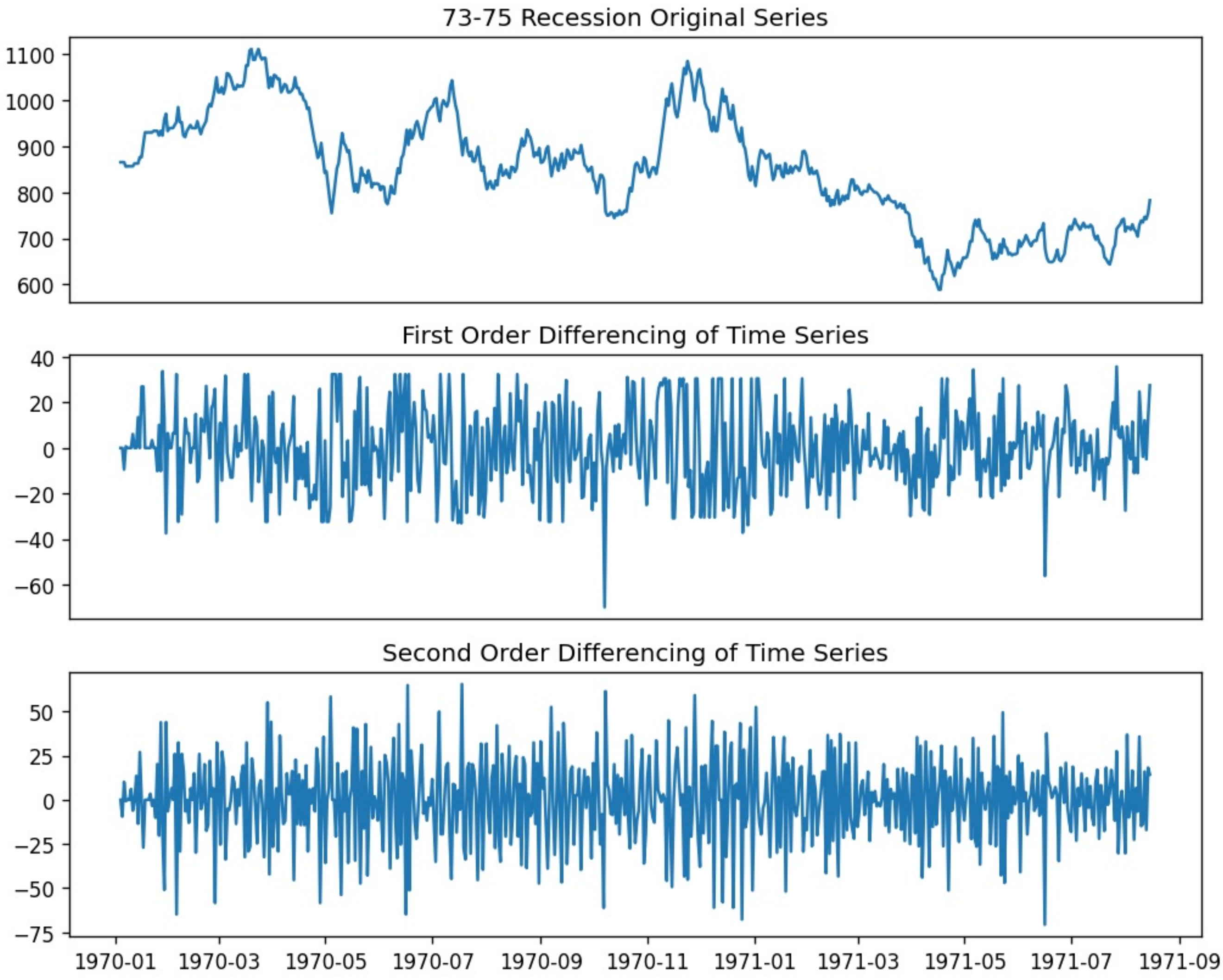
In [23]:
```
# Results show p = .36702
# Data does not reject null hypothesis at p < .05
# Therefore, Time series is determined to be non-stationary
```

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('73-75 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()
```



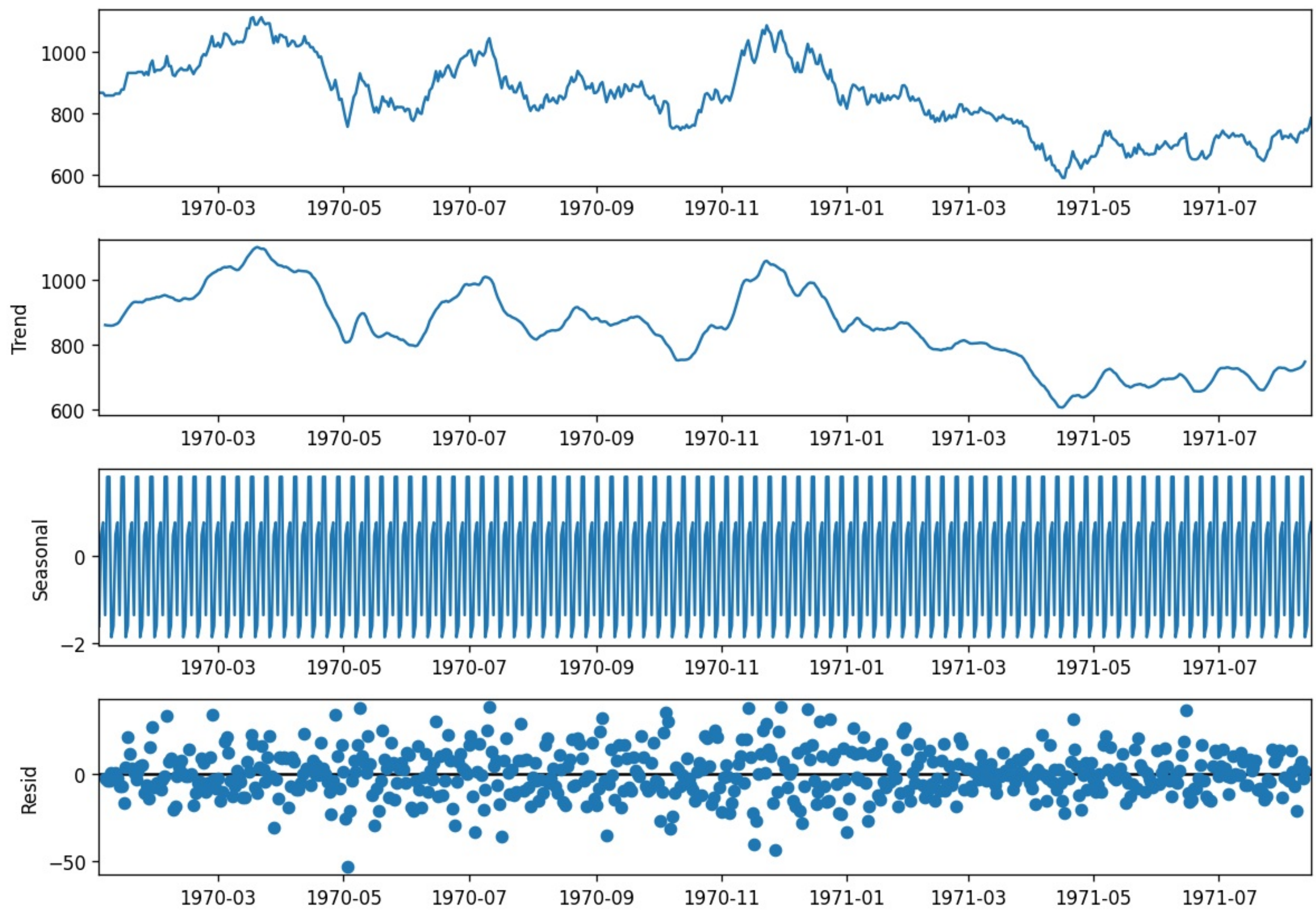
In [25]:
```
# Using pmdarima's ndiffs to find differencing term
# Code reference (Verma, 2021)

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();
```

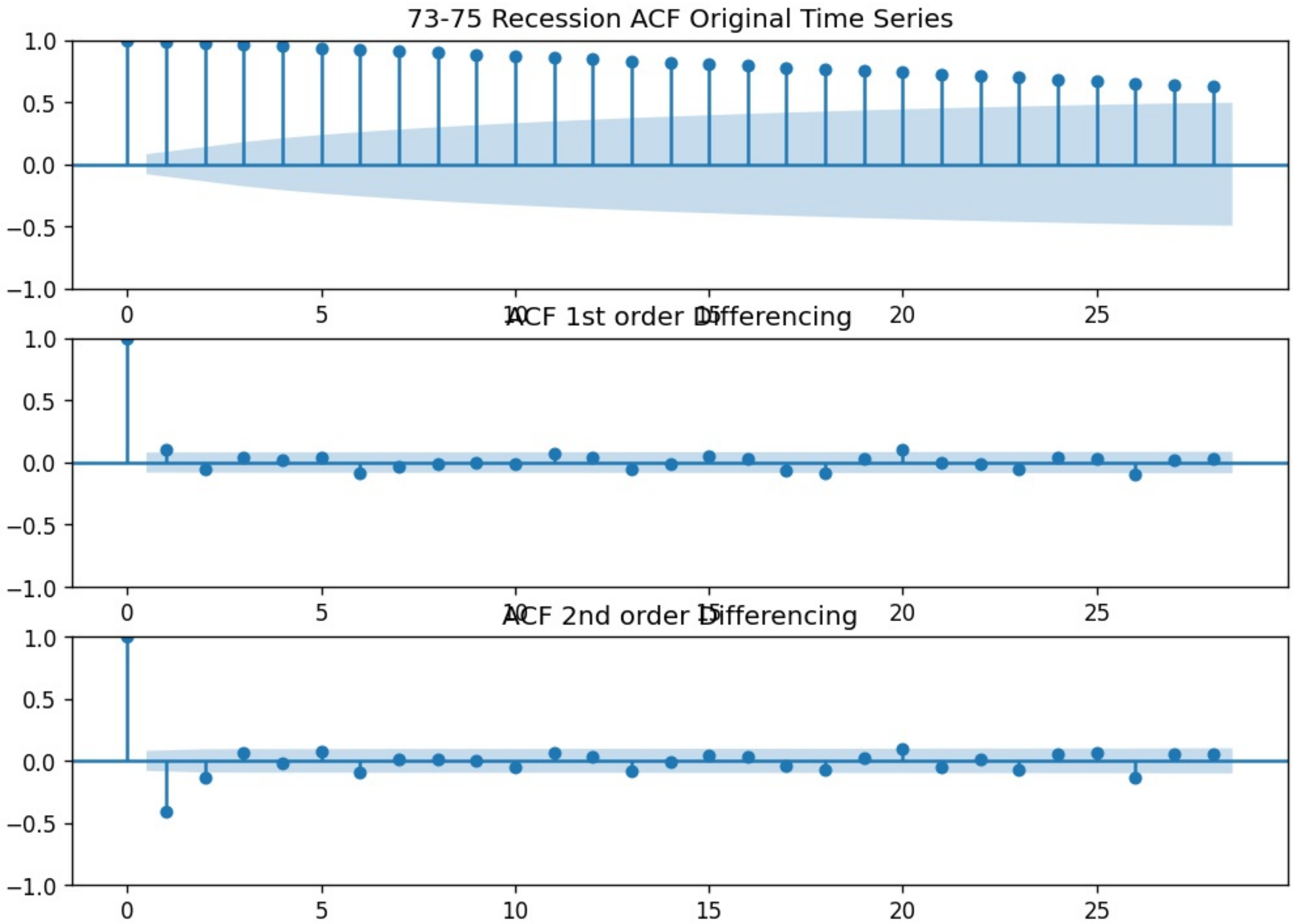


D6 ACF and PACF

Finding order of MA term 'q'

Using Autocorrelation function (ACF)

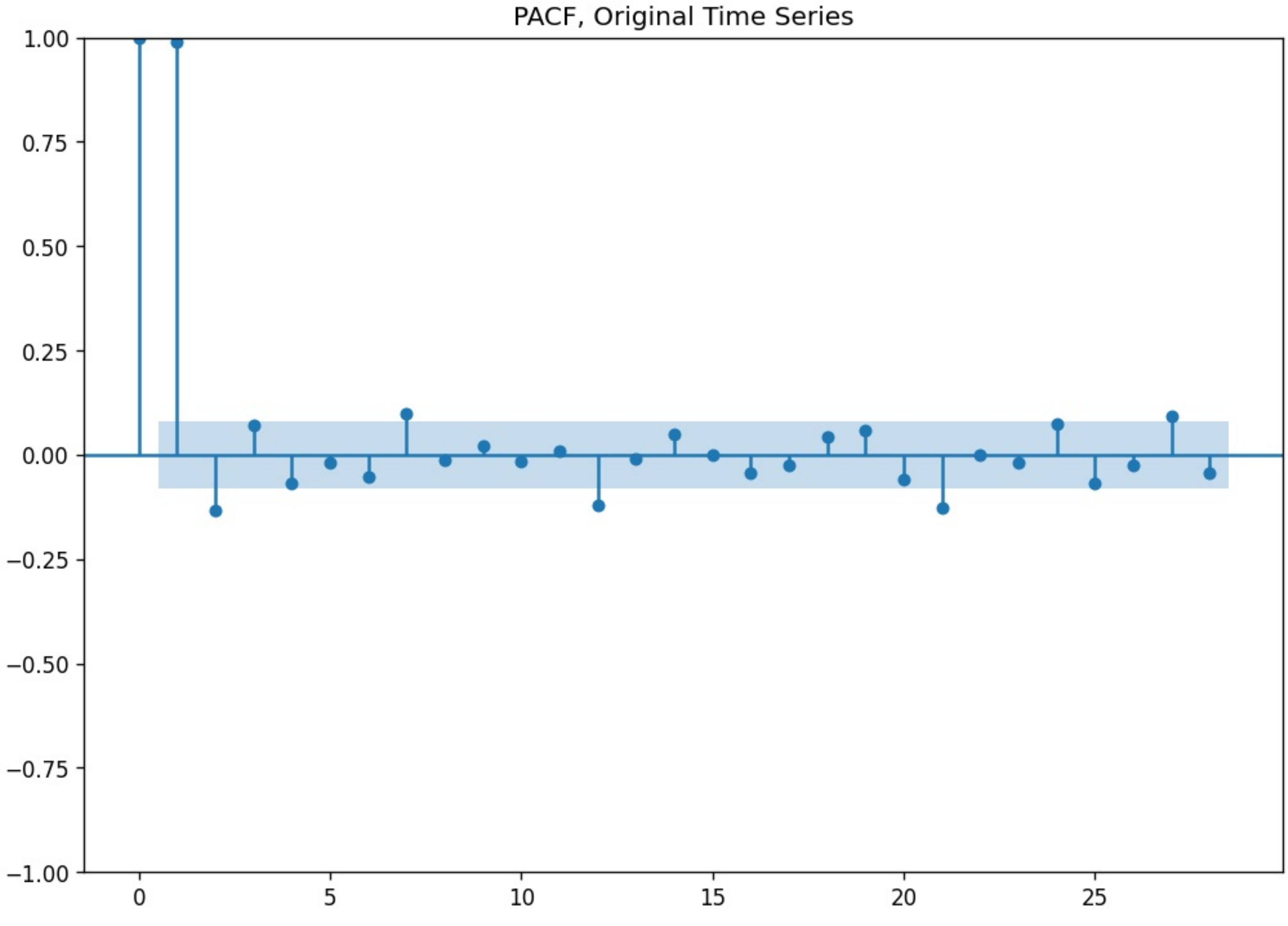
In [28]:
```
fig, (ax1, ax2, ax3) = plt.subplots(3)
plot_acf(df, ax=ax1, title='73-75 Recession ACF Original Time Series');
plot_acf(df.diff().dropna(), ax=ax2, title='ACF 1st order Differencing');
plot_acf(df.diff().diff().dropna(), ax=ax3, title='ACF 2nd order Differencing');
```



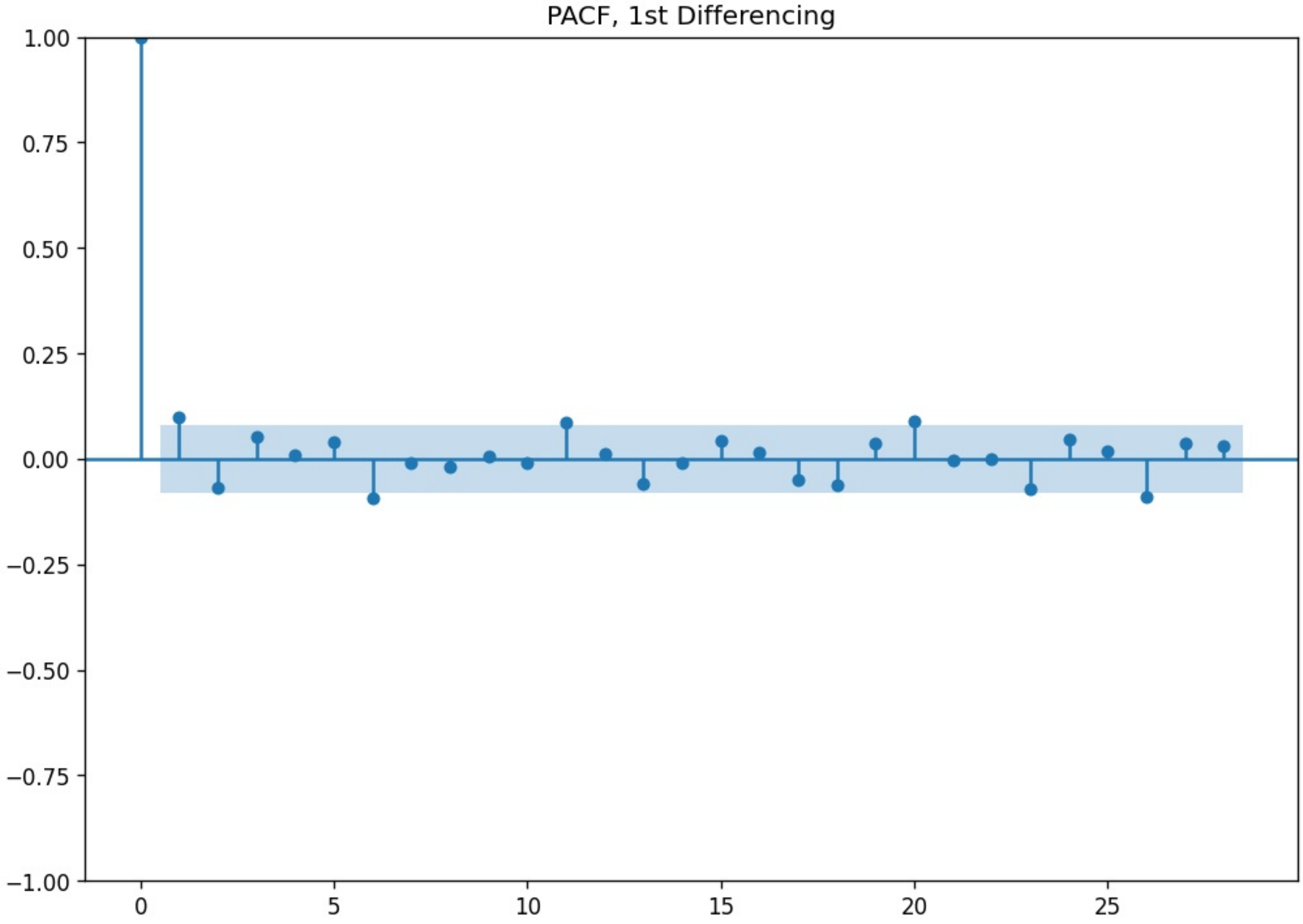
Finding order of AR term 'p'

Using Partial autocorrelation (PACF)

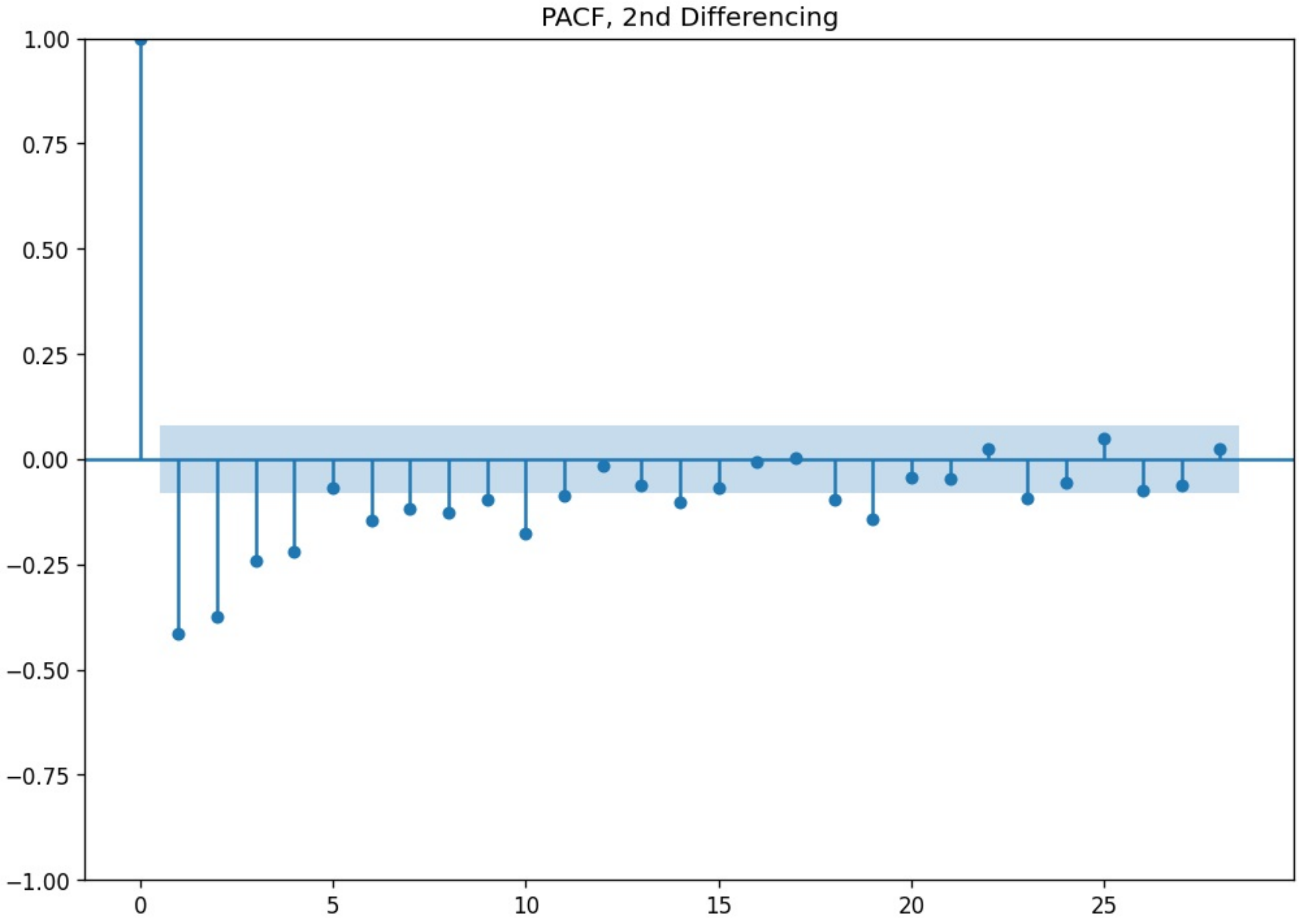
In [29]:
```
warnings.filterwarnings("ignore")
plot_pacf(df.dropna(), title='PACF, Original Time Series');
```



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

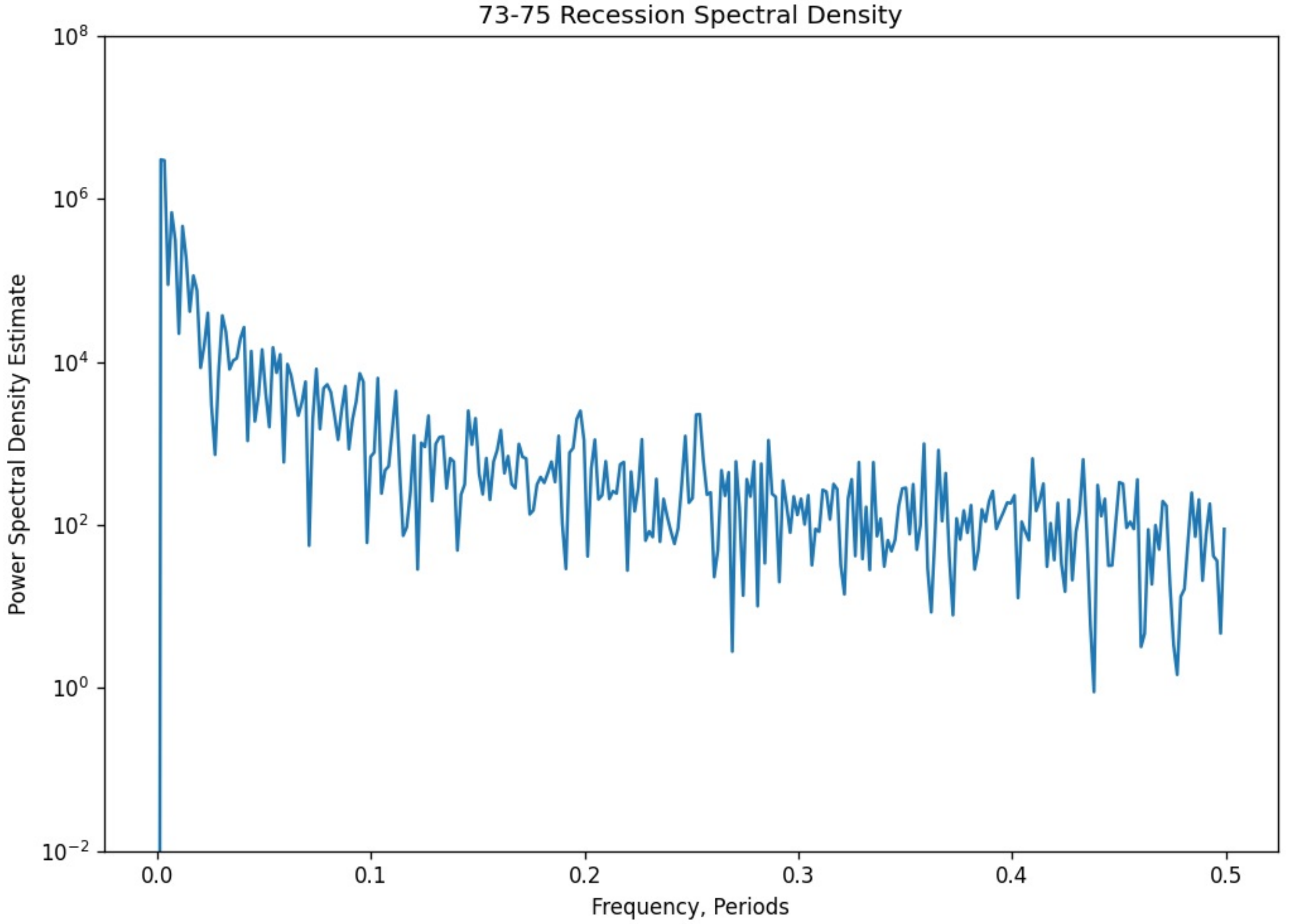


In [31]:
```
plot_pacf(df.diff().diff().dropna(), title='PACF, 2nd Differencing');
```



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('73-75 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 = 591 cases

80/20 Train/Test Split

Split is 472 / 119

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=472)
```

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

Out[34]:

Trading Days	2022_Value
1970-01-02	865.416
1970-01-03	865.416
1970-01-04	865.416
1970-01-05	855.980
1970-01-06	856.654
...	...
1971-04-14	612.440
1971-04-15	599.630
1971-04-16	588.650
1971-04-17	588.650
1971-04-18	619.150

472 rows × 1 columns

In [35]:

```
test
```

Out[35]:

Trading Days	2022_Value
1971-04-19	623.42
1971-04-20	644.16
1971-04-21	674.66
1971-04-22	653.92
1971-04-23	645.99
...	...
1971-08-11	734.80
1971-08-12	746.90
1971-08-13	741.95
1971-08-14	755.15
1971-08-15	782.65

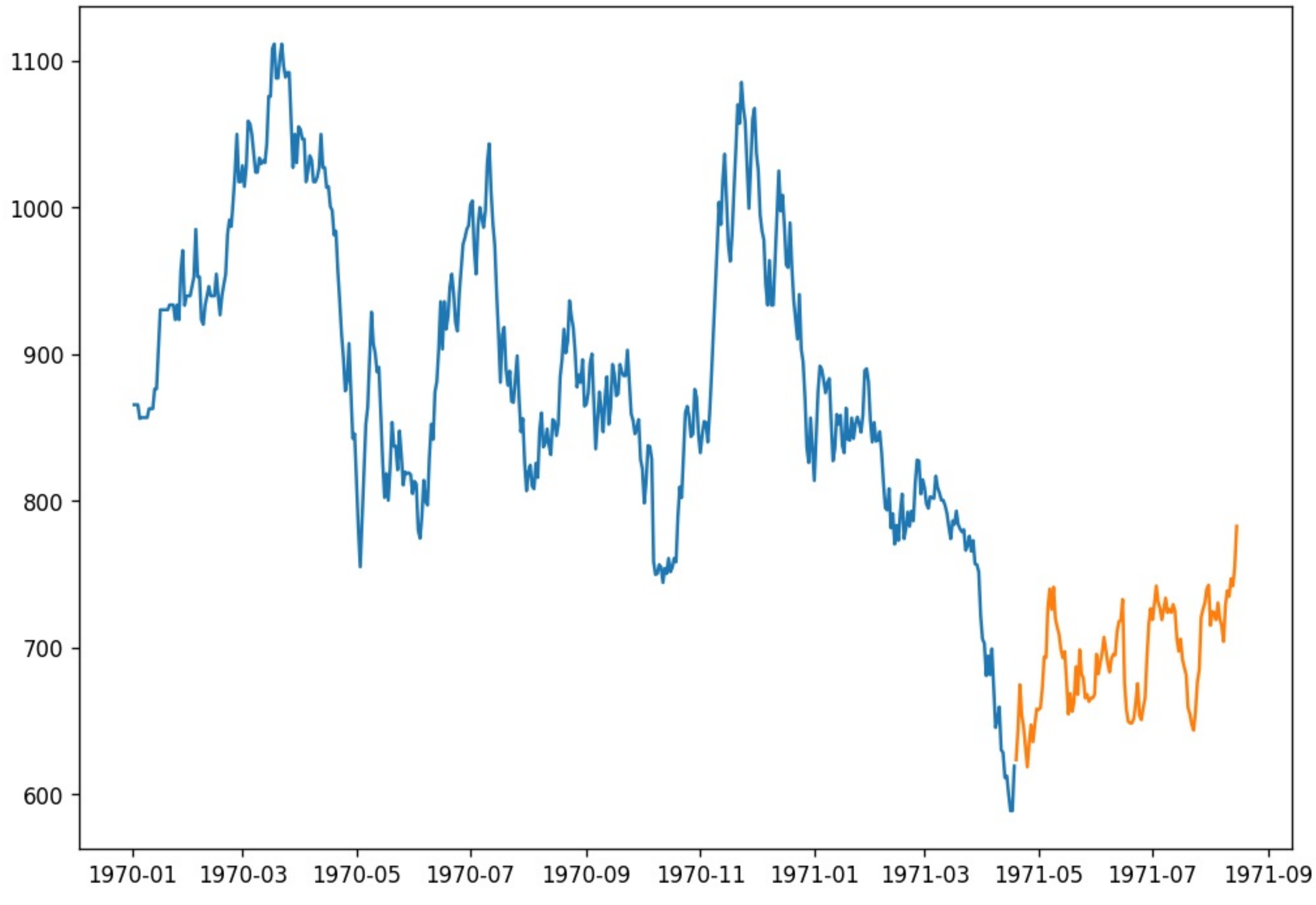
119 rows × 1 columns

In [36]:

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

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

Out[36]:

```
[<matplotlib.lines.Line2D at 0x1fc7adc3c48>]
```



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

```
(472, 1)
(119, 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)

# Establish auto_arima to run ARIMA and take into account
```

```python
# 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=4078.620, Time=0.24 sec
 ARIMA(0,1,0)(0,0,0)[0] intercept   : AIC=4085.328, Time=0.01 sec
 ARIMA(1,1,0)(0,0,0)[0] intercept   : AIC=4081.977, Time=0.05 sec
 ARIMA(0,1,1)(0,0,0)[0] intercept   : AIC=4080.759, Time=0.09 sec
 ARIMA(0,1,0)(0,0,0)[0]             : AIC=4085.328, Time=0.01 sec
 ARIMA(2,1,1)(0,0,0)[0] intercept   : AIC=4080.594, Time=0.26 sec
 ARIMA(1,1,2)(0,0,0)[0] intercept   : AIC=4080.588, Time=0.27 sec
 ARIMA(0,1,2)(0,0,0)[0] intercept   : AIC=4079.276, Time=0.10 sec
 ARIMA(2,1,0)(0,0,0)[0] intercept   : AIC=4079.655, Time=0.08 sec
 ARIMA(2,1,2)(0,0,0)[0] intercept   : AIC=4081.060, Time=0.51 sec
 ARIMA(1,1,1)(0,0,0)[0]             : AIC=4078.620, Time=0.13 sec

Best model:  ARIMA(1,1,1)(0,0,0)[0]
Total fit time: 1.780 seconds
                               SARIMAX Results
==============================================================================
Dep. Variable:                      y   No. Observations:                  472
Model:               SARIMAX(1, 1, 1)   Log Likelihood               -2035.310
Date:                Tue, 18 Oct 2022   AIC                           4078.620
Time:                        13:09:14   BIC                           4095.239
Sample:                    01-02-1970   HQIC                          4085.158
                         - 04-18-1971
Covariance Type:                  opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
intercept     -0.8371      1.466     -0.571      0.568      -3.709       2.035
ar.L1         -0.6178      0.159     -3.887      0.000      -0.929      -0.306
ma.L1          0.7375      0.136      5.409      0.000       0.470       1.005
sigma2       331.7774     24.702     13.431      0.000     283.362     380.193
===================================================================================
Ljung-Box (L1) (Q):                   0.01   Jarque-Bera (JB):                 4.20
Prob(Q):                              0.94   Prob(JB):                         0.12
Heteroskedasticity (H):               1.13   Skew:                            -0.07
Prob(H) (two-sided):                  0.43   Kurtosis:                         2.56
===================================================================================

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=4081.060, Time=0.54 sec
 ARIMA(0,1,0)(0,0,0)[0] intercept   : AIC=4085.328, Time=0.01 sec
 ARIMA(1,1,0)(0,0,0)[0] intercept   : AIC=4081.977, Time=0.05 sec
 ARIMA(0,1,1)(0,0,0)[0] intercept   : AIC=4080.759, Time=0.09 sec
 ARIMA(0,1,0)(0,0,0)[0]             : AIC=4083.707, Time=0.01 sec
 ARIMA(1,1,1)(0,0,0)[0] intercept   : AIC=4078.620, Time=0.16 sec
 ARIMA(2,1,1)(0,0,0)[0] intercept   : AIC=4080.594, Time=0.27 sec
 ARIMA(1,1,2)(0,0,0)[0] intercept   : AIC=4080.588, Time=0.28 sec
 ARIMA(0,1,2)(0,0,0)[0] intercept   : AIC=4079.276, Time=0.10 sec
 ARIMA(2,1,0)(0,0,0)[0] intercept   : AIC=4079.655, Time=0.08 sec
 ARIMA(1,1,1)(0,0,0)[0]             : AIC=4076.950, Time=0.06 sec
 ARIMA(0,1,1)(0,0,0)[0]             : AIC=4079.050, Time=0.04 sec
 ARIMA(1,1,0)(0,0,0)[0]             : AIC=4080.274, Time=0.03 sec
 ARIMA(2,1,1)(0,0,0)[0]             : AIC=4078.918, Time=0.11 sec
 ARIMA(1,1,2)(0,0,0)[0]             : AIC=4078.910, Time=0.14 sec
 ARIMA(0,1,2)(0,0,0)[0]             : AIC=4077.632, Time=0.06 sec
 ARIMA(2,1,0)(0,0,0)[0]             : AIC=4078.023, Time=0.05 sec
 ARIMA(2,1,2)(0,0,0)[0]             : AIC=4079.443, Time=0.18 sec

Best model:  ARIMA(1,1,1)(0,0,0)[0]
Total fit time: 2.267 seconds
                               SARIMAX Results
==============================================================================
Dep. Variable:                      y   No. Observations:                  472
Model:               SARIMAX(1, 1, 1)   Log Likelihood               -2035.475
Date:                Tue, 18 Oct 2022   AIC                           4076.950
Time:                        21:09:46   BIC                           4089.414
Sample:                    01-02-1970   HQIC                          4081.853
                         - 04-18-1971
Covariance Type:                  opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.L1         -0.6154      0.158     -3.892      0.000      -0.925      -0.306
ma.L1          0.7356      0.136      5.418      0.000       0.469       1.002
sigma2       331.8438     24.638     13.469      0.000     283.553     380.134
===================================================================================
Ljung-Box (L1) (Q):                   0.00   Jarque-Bera (JB):                 4.19
Prob(Q):                              0.95   Prob(JB):                         0.12
Heteroskedasticity (H):               1.14   Skew:                            -0.07
Prob(H) (two-sided):                  0.41   Kurtosis:                         2.56
===================================================================================

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

In [40]:

```python
model.conf_int()
```

Out[40]:

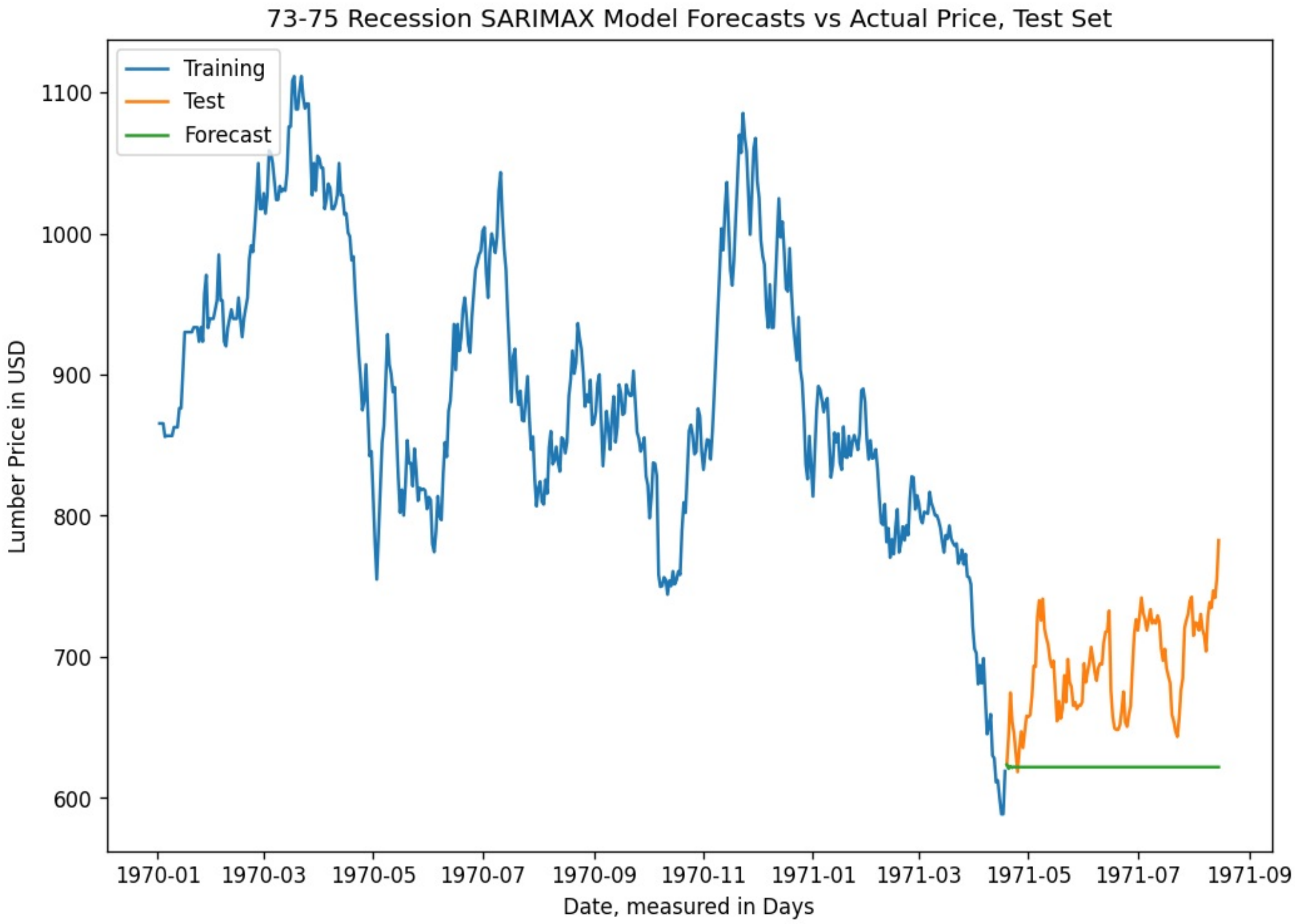
	0	1
ar.L1	-0.925237	-0.305514
ma.L1	0.469487	1.001738
sigma2	283.553386	380.134178

Visualizing Model Results

In [41]:

```python
# 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 = 119))

# 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('73-75 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
1971-04-19	623.707215
1971-04-20	620.902817
1971-04-21	622.628574
1971-04-22	621.566586
1971-04-23	622.220107
...	...
1971-08-11	621.971149
1971-08-12	621.971149
1971-08-13	621.971149
1971-08-14	621.971149
1971-08-15	621.971149

119 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]:
```
(119, 1)
```

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

	forecast_prices
1971-04-19	623.707215
1971-04-20	620.902817
1971-04-21	622.628574
1971-04-22	621.566586
1971-04-23	622.220107
...	...
1971-08-11	621.971149
1971-08-12	621.971149
1971-08-13	621.971149
1971-08-14	621.971149
1971-08-15	621.971149

119 rows × 1 columns

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

In [48]:
```
predicted_array.shape
```
Out[48]:
```
(119, 1)
```

In [49]:
```
#RMSE Calculation

rmse = sqrt(mean_squared_error(test_array, predicted_array))
print ('RMSE = ' + str(rmse))
```
```
RMSE = 78.186066504359
```

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))
```
```
70.57468763141186
```

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)
```
```
ar.L1      0.158096
ma.L1      0.135781
sigma2    24.638410
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(119, return_conf_int=True, alpha=0.8)
print(conf_int)
```
```
[[619.09209712 628.3223326 ]
 [613.97255839 627.83307539]
 [614.18207398 631.0750749 ]
 [611.73135695 631.40181441]
 [611.22767068 633.21254422]
 [609.74635657 633.88953588]
 [609.02216462 635.10868809]
 [607.9550276  635.87123874]
```

```
[607.19649082 636.81721048]
[606.32938584 637.56897259]
[605.59749461 638.37184299]
[604.84138486 639.0842739 ]
[604.15151433 639.80102331]
[603.46621182 640.46978523]
[602.81844449 641.12773123]
[602.18383057 641.75608144]
[601.5739085  642.36985804]
[600.97864361 642.96275095]
[600.40168378 643.54117044]
[599.83859857 644.10335741]
[599.29020351 644.65230523]
[598.7543177  645.18785089]
[598.23079661 645.7115813 ]
[597.7184065  646.22384259]
[597.21672299 646.72560537]
[596.72494339 647.21733619]
[596.24260106 647.69970854]
[595.76911244 648.17317869]
[595.30404433 648.63825817]
[594.84693993 649.09535557]
[594.39741776 649.54488204]
[593.95510387 649.98719328]
[593.5196676  650.42263118]
[593.09079446 650.85150333]
[592.66819836 651.27410004]
[592.25161026 651.69068776]
[591.84078173 652.10151652]
[591.43547982 652.50681828]
[591.03548762 652.90681058]
[590.64060157 653.30169658]
[590.25063108 653.6916671 ]
[589.86539697 654.07690119]
[589.48473078 654.45756739]
[589.10847375 654.83382441]
[588.73647614 655.20582203]
[588.36859648 655.57370169]
[588.00470097 655.9375972 ]
[587.64466291 656.29763526]
[587.28836216 656.65393601]
[586.9356847  657.00661347]
[586.58652219 657.35577598]
[586.24077158 657.70152658]
[585.89833477 658.04396339]
[585.55911827 658.3831799 ]
[585.22303289 658.71926528]
[584.8899935  659.05230467]
[584.55991875 659.38237942]
[584.23273084 659.70956732]
[583.90835535 660.03394282]
[583.58672095 660.35557721]
[583.26775933 660.67453884]
[582.95140492 660.99089324]
[582.63759483 661.30470333]
[582.32626863 661.61602953]
[582.01736826 661.9249299 ]
[581.71083789 662.23146028]
[581.40662378 662.53567439]
[581.1046742  662.83762396]
[580.80493934 663.13735883]
[580.50737115 663.43492702]
[580.21192332 663.73037485]
[579.91855116 664.02374701]
[579.62721152 664.31508664]
[579.33786275 664.60443542]
[579.05046456 664.8918336 ]
[578.76497805 665.17732012]
[578.48136556 665.46093261]
[578.19959066 665.74270751]
[577.91961809 666.02268007]
[577.64141371 666.30088446]
[577.36494442 666.57735374]
[577.09017817 666.85212   ]
[576.81708386 667.1252143 ]
[576.54563134 667.39666682]
[576.27579136 667.66650681]
[576.0075355  667.93476266]
[575.7408362  668.20146196]
[575.47566667 668.4666315 ]
[575.21200088 668.73029728]
[574.94981354 668.99248463]
[574.68908005 669.25321812]
[574.42977649 669.51252168]
[574.17187959 669.77041857]
[573.91536671 670.02693146]
[573.66021579 670.28208237]
[573.40640538 670.53589279]
[573.15391455 670.78838361]
```

```
 [572.90272295 671.03957521]
 [572.65281072 671.28948744]
 [572.40415851 671.53813965]
 [572.15674745 671.78555072]
 [571.91055913 672.03173903]
 [571.66557562 672.27672255]
 [571.42177938 672.52051879]
 [571.17915332 672.76314484]
 [570.93768076 673.00461741]
 [570.69734539 673.24495277]
 [570.4581313  673.48416686]
 [570.22002294 673.72227522]
 [569.98300512 673.95929304]
 [569.74706299 674.19523517]
 [569.51218203 674.43011613]
 [569.27834806 674.66395011]
 [569.04554719 674.89675097]
 [568.81376586 675.12853231]
 [568.58299078 675.35930739]
 [568.35320896 675.5890892 ]
 [568.12440769 675.81789047]
 [567.89657452 676.04572365]]
```

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 [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/7375_Low_Predictionz.csv')
high_pred = pd.read_csv('C:/Users/ericy/Desktop/7375_High_Predictionz.csv')
```

In [57]:

```
# Variable exploration to ensure compatability with 'test' datetime timeframe
low_pred
```

Out[57]:

	Date	Low_Prediction
0	1971-04-19	619.092097
1	1971-04-20	613.972558
2	1971-04-21	614.182074
3	1971-04-22	611.731357
4	1971-04-23	611.227671
...	...	...
114	1971-08-11	568.813766
115	1971-08-12	568.582991
116	1971-08-13	568.353209
117	1971-08-14	568.124408
118	1971-08-15	567.896575

119 rows × 2 columns

In [58]:

```
# Variable exploration to ensure compatability with 'test' datetime timeframe
high_pred
```

Out[58]:

	Date	High_Prediction
0	1971-04-19	628.322333
1	1971-04-20	627.833075
2	1971-04-21	631.075075
3	1971-04-22	631.401814
4	1971-04-23	633.212544
...	...	...
114	1971-08-11	675.128532
115	1971-08-12	675.359307
116	1971-08-13	675.589089
117	1971-08-14	675.817890
118	1971-08-15	676.045724

119 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	
1971-04-19	619.092097
1971-04-20	613.972558
1971-04-21	614.182074
1971-04-22	611.731357
1971-04-23	611.227671
...	...
1971-08-11	568.813766
1971-08-12	568.582991
1971-08-13	568.353209
1971-08-14	568.124408
1971-08-15	567.896575

119 rows × 1 columns

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

Out[64]:

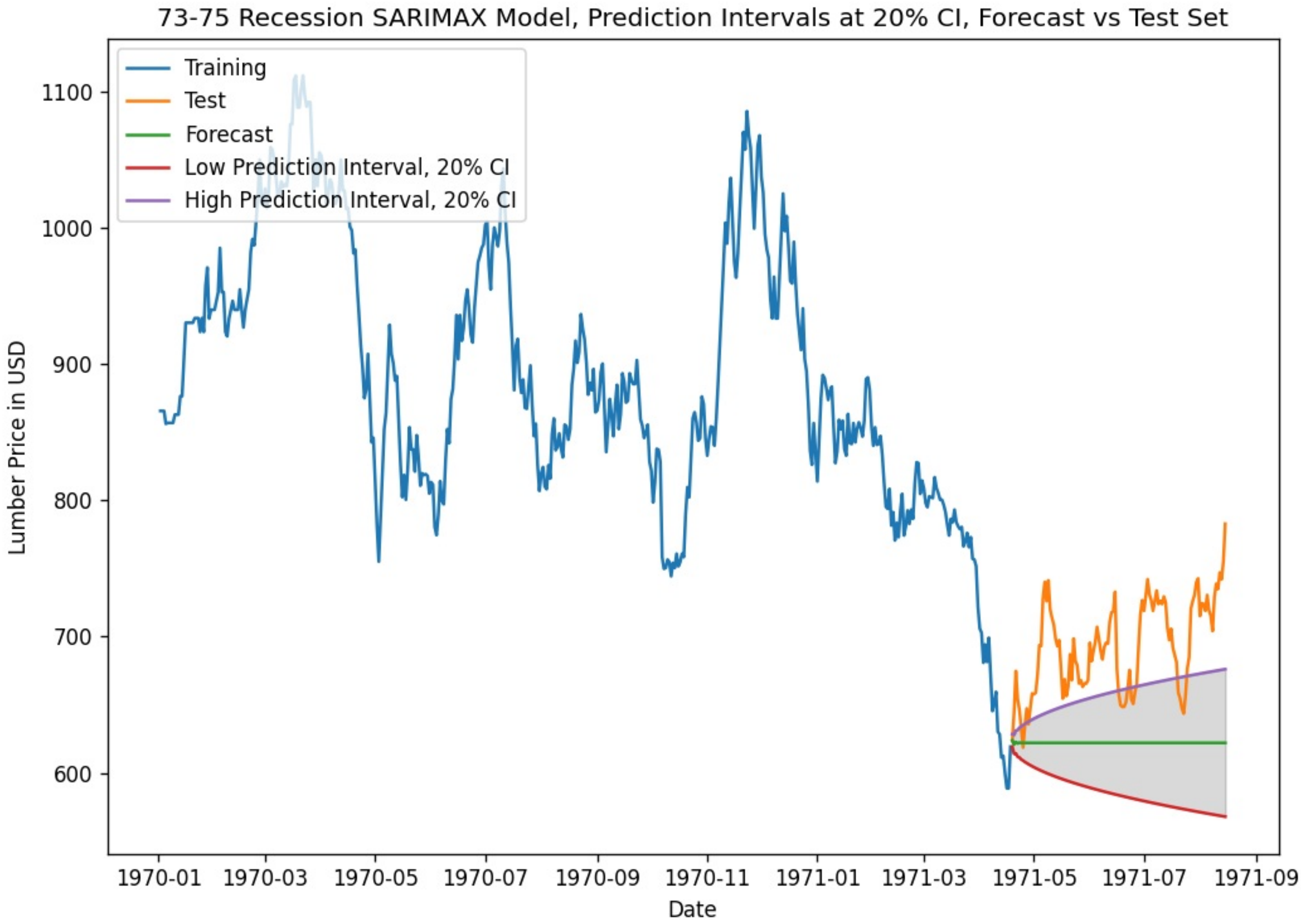
Date	High_Prediction
1971-04-19	628.322333
1971-04-20	627.833075
1971-04-21	631.075075
1971-04-22	631.401814
1971-04-23	633.212544
...	...
1971-08-11	675.128532
1971-08-12	675.359307
1971-08-13	675.589089
1971-08-14	675.817890
1971-08-15	676.045724

119 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 = 119),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('73-75 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
# 73-73 Recession we Accept the Null Hypothesis
```

In [ ]:

```
```

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