1 Real Estate ROI Analysis- Time Series Modeling

1.1 Project Overview

This project will look into a Real Estate database to find valuable information about the value of homes and return on investment. My company, Xabios data international, has been hired to determind the change of prices in this market over time and to determine which areas have the most potential to increase. Thus, this project is aimed at two very targeted goal using Time Series Modeling :

Jupyter Notebook A brief note on this Jupyter notebook. This notebook presents story line following this structure:

- Part 1: Overview, Business Understanding & Objective
- Part 2 : EDA
- Part 3 : Modeling
- Part 4 : Conclusion

1.2 Business Understanding

As important as current prices are to Real Estate companies, so it is the ability to know where prices will go higher in the future to make investement decisions. The key metric of leaving knowing how much money will an investment property return is known as Return on Investment or "ROI" as it is commonly abbreviated and known in finance. From a business perspective, the business would like to understand exactly what factors and zip codes contribute to ROI, and most importantly, post identification of those factors, define precise strategic initiatives to aim funds disbursement for the purchase of Real Estate property. This project, therefore aims to help the business first in identifying the past, how prices change over time in the zone in which this analysis occurs, and in turn, build time-series models that can help the business predict future value of property, so that in fact strategic business initiatives can be outlined for solution.

1.2.1 Business Modeling Objectives

1. Understand Real Estate Prices - how they have changed overtime
2. Find out Real Estate Areas of Growth Measured by ROI

1.2.2 Important Data Modeling Success Considerations

We are conducting a Time Series Analysis over the Zillow Home Value Index (ZHVI):A data set that tracks a sample of real estate prices over time. In particular, a time series allows one to see what factors influence certain variables from period to period. Time series analysis can be useful to see how a given asset, in this case Real Estate, or economic variable, in this case ROI, changes over time.

1.3 EDA - Loading, Modifying and Understanding DataSet

In [1]:
```
import pandas as pd
from pandas import Series
import seaborn as sns
import matplotlib as mpl
import matplotlib.pyplot as plt

import plotly.express as px
import plotly.io as pio

%matplotlib inline
```

In [2]:
```
#Loading data
df= pd.read_csv ('zillow_data.csv')
```

In [3]:
```
#Seeing the shape of the
df.shape
```

Out[3]:
```
(14723, 272)
```

In [4]:
```
#Finding more key information of the data set
```

In [5]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 14723 entries, 0 to 14722
Columns: 272 entries, RegionID to 2018-04
dtypes: float64(219), int64(49), object(4)
memory usage: 30.6+ MB
```

In [6]:
```
#looking inside the data set
df.head()

```

Out[6]:

	RegionID	RegionName	City	State	Metro	CountyName	SizeRank	1996-04	1996-05
0	84654	60657	Chicago	IL	Chicago	Cook	1	334200.0	335400.0
1	90668	75070	McKinney	TX	Dallas-Fort Worth	Collin	2	235700.0	236900.0
2	91982	77494	Katy	TX	Houston	Harris	3	210400.0	212200.0
3	84616	60614	Chicago	IL	Chicago	Cook	4	498100.0	500900.0
4	93144	79936	El Paso	TX	El Paso	El Paso	5	77300.0	77300.0

5 rows × 272 columns

Basically, this is a national database, that's showing us there are 14,723 ZIP codes in total. We'd need to focus on one market area specifically. For the purpose of forecasting within

1.3.0.1 Selecting Market: State(s) & Indexing Columns

Focusing on getting an understanding of the Connecticut market zip codes since it is an area of interest to my client , and area of investement preference

In [7]:
```
#selecting zip codes within selected market
#making state Index and rename of RegionName and Zipcode
df_ct = df.loc[df['State']== 'CT'].reset_index()
df_ct.drop(['index', 'RegionID', 'City', 'State', 'CountyName'], axis
df_ct.rename(columns= {'RegionName' : 'Zipcode'}, inplace=True)
```

In [8]:
```
#finding unique vals
df_ct.Metro.unique()
```

Out[8]:
```
array(['Hartford', 'New Haven', 'Stamford', 'New London', 'Torrington',
       'Worcester'], dtype=object)
```

In [9]:
```
#understand how many zip codes
print(f'Number of CT zip codes : {len(df_ct)}')
```

```
Number of CT zip codes : 124
```

In [10]:
```
#looking at new data set df_ct head
df_ct.head()
```

Out[10]:

	Zipcode	Metro	SizeRank	1996-04	1996-05	1996-06	1996-07	1996-08	1996-09	199
0	6010	Hartford	113	120300.0	120000.0	119800.0	119400.0	119100.0	118800.0	1186
1	6516	New Haven	417	96500.0	96300.0	96100.0	95900.0	95600.0	95300.0	950
2	6511	New Haven	546	89800.0	90000.0	90200.0	90300.0	90500.0	90700.0	908
3	6810	Stamford	685	151100.0	150700.0	150200.0	149700.0	149100.0	148600.0	1482
4	6492	New Haven	899	146800.0	146600.0	146300.0	146100.0	145900.0	145700.0	1456

5 rows × 268 columns

1.3.1 Obtaining Return on Investment (ROI)

In [11]:
```
#Finding ROIs for 5 and 3 years
df_ct['ROI_5yr'] = round((df_ct['2018-04']- df_ct['2013-01'])/df_ct['
df_ct['ROI_3yr'] = round((df_ct['2018-04']- df_ct['2015-01'])/df_ct['

```

In [12]:
```
#Looking at the dataset to find ROI's were added correctly
df_ct.shape
df_ct.info()
df_ct.head()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 124 entries, 0 to 123
Columns: 270 entries, Zipcode to ROI_3yr
dtypes: float64(221), int64(48), object(1)
memory usage: 261.7+ KB
```

Out[12]:

	Zipcode	Metro	SizeRank	1996-04	1996-05	1996-06	1996-07	1996-08	1996-09	199
0	6010	Hartford	113	120300.0	120000.0	119800.0	119400.0	119100.0	118800.0	1186
1	6516	New Haven	417	96500.0	96300.0	96100.0	95900.0	95600.0	95300.0	950
2	6511	New Haven	546	89800.0	90000.0	90200.0	90300.0	90500.0	90700.0	908
3	6810	Stamford	685	151100.0	150700.0	150200.0	149700.0	149100.0	148600.0	1482
4	6492	New Haven	899	146800.0	146600.0	146300.0	146100.0	145900.0	145700.0	1456

5 rows × 270 columns

The formatted shape of this data set needs to be re-formatted to follow a long format, where the 268 columns are rows, and the rows are columns. We do this by re-shaping.

1.3.2 Reshaping data set to Long Format

In [13]:
```
def melt_data(df):

    melted = pd.melt(df, id_vars=['Zipcode', 'Metro', 'SizeRank', 'RO
    melted['Date'] = pd.to_datetime(melted['Date'], infer_datetime_fo
    melted = melted.dropna(subset=['value'])
    return melted

```

In [14]:
```
#passing the melt_data transformaiton into the dataset
melted_df=melt_data(df_ct)
```

In [15]:
```
#looking at the long format dataset
melted_df.head()
```

Out[15]:

	Zipcode	Metro	SizeRank	ROI_5yr	ROI_3yr	Date	value
0	6010	Hartford	113	0.1063	0.0982	1996-04-01	120300.0
1	6516	New Haven	417	0.0752	0.0970	1996-04-01	96500.0
2	6511	New Haven	546	0.1462	0.1839	1996-04-01	89800.0
3	6810	Stamford	685	0.2219	0.1839	1996-04-01	151100.0
4	6492	New Haven	899	0.1182	0.0410	1996-04-01	146800.0

In [16]:
```
melted_df.isna().value_counts()
```

Out[16]:
```
Zipcode  Metro  SizeRank  ROI_5yr  ROI_3yr  Date   value
False    False  False     False    False    False  False    32860
dtype: int64
```

A much better looking data set with ROI on a per Zip Code basis. However we want to look at its information and types of data that define the columns, and perhaps modify the setting a new index given that we are workin with a Time-Series analysis. So I'll do this next.

In [17]:
```
#Looking at the information
melted_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 32860 entries, 0 to 32859
Data columns (total 7 columns):
 #   Column     Non-Null Count  Dtype         
---  ------     --------------  -----         
 0   Zipcode    32860 non-null  int64         
 1   Metro      32860 non-null  object        
 2   SizeRank   32860 non-null  int64         
 3   ROI_5yr    32860 non-null  float64       
 4   ROI_3yr    32860 non-null  float64       
 5   Date       32860 non-null  datetime64[ns]
 6   value      32860 non-null  float64       
dtypes: datetime64[ns](1), float64(3), int64(2), object(1)
memory usage: 2.0+ MB
```

In [18]:
```
#Change Zipcode dtype to 'str'
melted_df['Zipcode'] = melted_df['Zipcode'].astype(str)

# Make sure the data type of the 'Date' column is datetime
melted_df['Date'] = pd.to_datetime(melted_df['Date'], format='%m/%y')

# Set the 'Date' column as index
melted_df.set_index('Date', inplace=True)
```

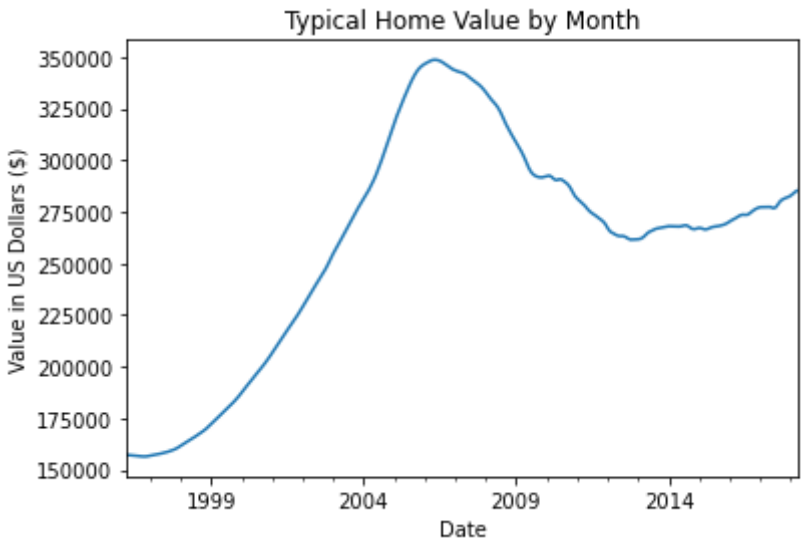
In [19]:
```
#checking for new date index
melted_df.index
```

Out[19]:
```
DatetimeIndex(['1996-04-01', '1996-04-01', '1996-04-01', '1996-04-01',
               '1996-04-01', '1996-04-01', '1996-04-01', '1996-04-01',
               '1996-04-01', '1996-04-01',
               ...
               '2018-04-01', '2018-04-01', '2018-04-01', '2018-04-01',
               '2018-04-01', '2018-04-01', '2018-04-01', '2018-04-01',
               '2018-04-01', '2018-04-01'],
              dtype='datetime64[ns]', name='Date', length=32860, freq=N
one)
```

Values are given from 1996. The focus of the analysis is on a 10 year window, starting in 2008 since there was a financial collapse during that time(**EXPLAINE BETTER_

Trend - Typical home value in the last 10 years

In [20]:
```
monthly_data = melted_df.resample('MS').mean()['value']
monthly_data.plot()
plt.title('Typical Home Value by Month')
plt.ylabel('Value in US Dollars ($)')
plt.show()
```



The 2008 crash dropped the values of home until 2013, when it started to pick up

1.3.3 Modifying and changing data types in long formatted data set (Para**graph below explaining to non-tech_

In [21]:
```
#looking only at the last 10 years
melted_df = melted_df['2008-01-01':'2018-04-01']
```

In [22]:
```
#resampling
melted_df.resample('MS').mean().index
```

Out[22]:
```
DatetimeIndex(['2008-01-01', '2008-02-01', '2008-03-01', '2008-04-01',
               '2008-05-01', '2008-06-01', '2008-07-01', '2008-08-01',
               '2008-09-01', '2008-10-01',
               ...
               '2017-07-01', '2017-08-01', '2017-09-01', '2017-10-01',
               '2017-11-01', '2017-12-01', '2018-01-01', '2018-02-01',
               '2018-03-01', '2018-04-01'],
              dtype='datetime64[ns]', name='Date', length=124, freq='M
S')
```

Resampling technique is used to gather more information about a sample.Retaking a sample or resampling often improves the overall accuracy and estimates any uncertainty within this picked population.

In [23]:
```
melted_df.info()
melted_df.head()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 15376 entries, 2008-01-01 to 2018-04-01
Data columns (total 6 columns):
 #   Column    Non-Null Count  Dtype  
---  ------    --------------  -----  
 0   Zipcode   15376 non-null  object 
 1   Metro     15376 non-null  object 
 2   SizeRank  15376 non-null  int64  
 3   ROI_5yr   15376 non-null  float64
 4   ROI_3yr   15376 non-null  float64
 5   value     15376 non-null  float64
dtypes: float64(3), int64(1), object(2)
memory usage: 840.9+ KB
```

Out[23]:

Date	Zipcode	Metro	SizeRank	ROI_5yr	ROI_3yr	value
2008-01-01	6010	Hartford	113	0.1063	0.0982	219300.0
2008-01-01	6516	New Haven	417	0.0752	0.0970	223900.0
2008-01-01	6511	New Haven	546	0.1462	0.1839	243500.0
2008-01-01	6810	Stamford	685	0.2219	0.1839	321900.0
2008-01-01	6492	New Haven	899	0.1182	0.0410	280200.0

1.3.4 Data Visualization & Stats to understand the data set

In [24]:
```
melted_df.Metro.unique()
```

Out[24]:
```
array(['Hartford', 'New Haven', 'Stamford', 'New London', 'Torrington',
       'Worcester'], dtype=object)
```

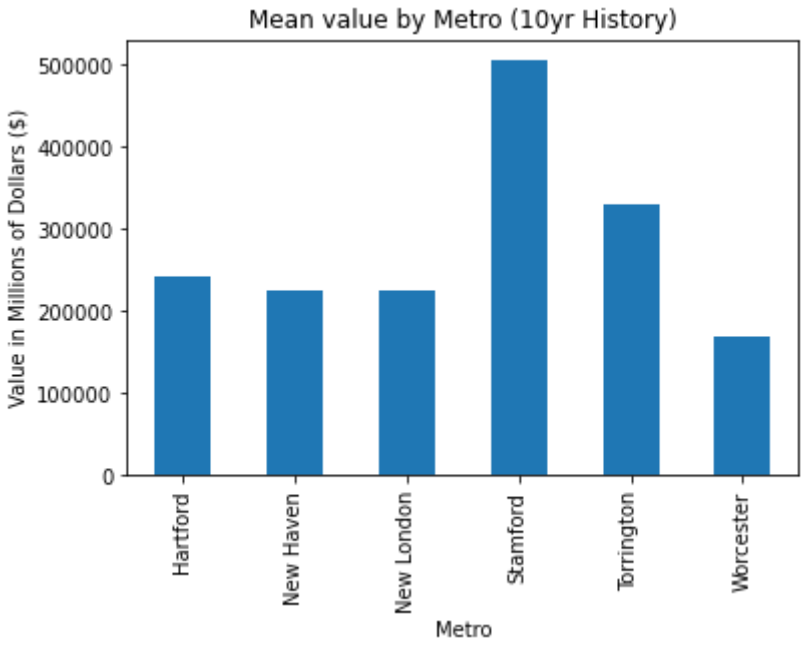
In [25]:
```
#Grouping by Metro
metro_grp = melted_df.groupby('Metro')
metro_grp = metro_grp.value.mean()
metro_grp = metro_grp.sort_values(ascending=False).head(10)
```

We have 5 different areas by Metro area. I have grouped them and this will help visualize data set

1.3.4.1 Metro Areas view

In [26]:
```
#looking at the values over time by Metro area
metro_area= melted_df.groupby('Metro')
metro_area= metro_area.value.mean()
metro_ara= metro_area.sort_values(ascending=False).head()
```

In [27]:
```
metro_area.plot(x="Name", y=["Age", "Height(in cm)"], kind="bar")
plt.title('Mean value by Metro (10yr History)')
plt.ylabel('Value in Millions of Dollars ($)')
plt.show()
plt.savefig('10yr-metro-mean-value')
```




```
<Figure size 432x288 with 0 Axes>
```

The top 3 with higuest mean values are Stamford, Torrington, and Hartford. Let's look at them.

In [28]:
```
#Stamford
stamford = melted_df.loc[melted_df['Metro']=='Stamford']
stamford.describe()
```

Out[28]:

	SizeRank	ROI_5yr	ROI_3yr	value
count	1984.000000	1984.000000	1984.000000	1.984000e+03
mean	5395.500000	0.117881	0.068744	5.050442e+05
std	2786.125208	0.108130	0.120613	3.820920e+05
min	685.000000	-0.019200	-0.076400	1.185000e+05
25%	3724.750000	0.040875	-0.000250	2.750750e+05
50%	5896.500000	0.090450	0.030600	3.450000e+05
75%	6677.500000	0.155375	0.109650	7.189750e+05
max	11245.000000	0.320200	0.316600	1.746000e+06

In [29]:
```
#Torringtong
torrington = melted_df.loc[melted_df['Metro']=='Torrington']
torrington.describe()
```

Out[29]:

	SizeRank	ROI_5yr	ROI_3yr	value
count	2480.000000	2480.000000	2480.000000	2480.000000
mean	11759.300000	0.150080	0.112490	331128.870968
std	2795.020029	0.099232	0.067996	123206.641312
min	3789.000000	0.015000	0.021000	135800.000000
25%	10302.250000	0.077700	0.062300	245900.000000
50%	13041.500000	0.146900	0.090500	307450.000000
75%	13663.000000	0.190975	0.168325	409825.000000
max	14552.000000	0.415800	0.248700	737800.000000

In [30]:
```
#Hartford
hartford = melted_df.loc[melted_df['Metro']=='Hartford']
hartford.describe()
```

Out[30]:

	SizeRank	ROI_5yr	ROI_3yr	value
count	4340.000000	4340.000000	4340.000000	4340.000000
mean	7921.885714	0.059234	0.071354	242469.493088
std	3897.308858	0.046046	0.042045	65698.245634
min	113.000000	-0.081200	-0.039600	103300.000000
25%	4011.000000	0.033900	0.040000	197475.000000
50%	8085.000000	0.063500	0.064900	242400.000000
75%	10809.000000	0.084400	0.096500	277900.000000
max	14655.000000	0.155800	0.158000	460500.000000

Size Rank

Looking at the population density

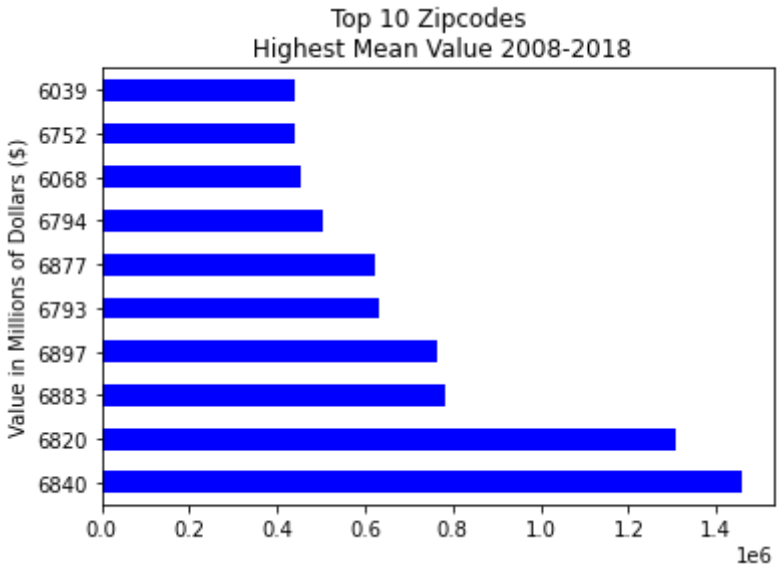
In [31]:
```
melted_df.SizeRank.unique()
```

Out[31]:
```
array([  113,   417,   546,   685,   899,  1145,  1332,  1362,  1599,
        1901,  2093,  2192,  2301,  2390,  2497,  3051,  3245,  3281,
        3368,  3532,  3565,  3581,  3696,  3760,  3778,  3789,  3978,
        4011,  4230,  4324,  4531,  4587,  4674,  4717,  5580,  5624,
        5687,  5756,  5852,  5870,  5941,  6037,  6063,  6084,  6176,
        6270,  6288,  6329,  6424,  6591,  6599,  6813,  6913,  7022,
        7031,  7144,  7259,  7317,  7382,  7471,  7496,  7595,  7704,
        7741,  7890,  8085,  8368,  8425,  8427,  8584,  8601,  8943,
        9032,  9136,  9160,  9275,  9298,  9457,  9577,  9681,  9715,
        9788,  9871,  9903,  9977, 10164, 10281, 10446, 10463, 10591,
       10651, 10663, 10786, 10809, 10893, 11245, 11629, 11907, 11929,
       12034, 12184, 12310, 12406, 12469, 12556, 12817, 12967, 13018,
       13065, 13214, 13215, 13266, 13465, 13564, 13567, 13646, 13714,
       13908, 13927, 14096, 14356, 14477, 14552, 14655])
```

It is noted that the areas range between mid high and low densily populated.

1.3.4.2 Top Zip Codes Mean Value of Homes View

In [32]:
```
#group zip code
zipcode_group= melted_df.groupby('Zipcode')

#top 10 values
zip_mean= zipcode_group.value.mean()
zip_mean= zip_mean.sort_values(ascending=False).head(10)

zip_mean.plot.barh(color='blue')
plt.title('Top 10 Zipcodes  \n Highest Mean Value 2008-2018')
plt.ylabel('Value in Millions of Dollars ($)')
plt.show()
plt.savefig('Zipcodes')
```




```
<Figure size 432x288 with 0 Axes>
```

In [33]:
```
#looking at the higest mean value zip_cove
melted_df.loc[melted_df['Zipcode']=='6840']

```

Out[33]:

Date	Zipcode	Metro	SizeRank	ROI_5yr	ROI_3yr	value
2008-01-01	6840	Stamford	5941	-0.0012	-0.0764	1746000.0
2008-02-01	6840	Stamford	5941	-0.0012	-0.0764	1736100.0
2008-03-01	6840	Stamford	5941	-0.0012	-0.0764	1729800.0
2008-04-01	6840	Stamford	5941	-0.0012	-0.0764	1728700.0
2008-05-01	6840	Stamford	5941	-0.0012	-0.0764	1727600.0
...	...	...	...	...	...	...
2017-12-01	6840	Stamford	5941	-0.0012	-0.0764	1355500.0
2018-01-01	6840	Stamford	5941	-0.0012	-0.0764	1361600.0
2018-02-01	6840	Stamford	5941	-0.0012	-0.0764	1374500.0
2018-03-01	6840	Stamford	5941	-0.0012	-0.0764	1381400.0
2018-04-01	6840	Stamford	5941	-0.0012	-0.0764	1379900.0

124 rows × 6 columns

In [34]:
```
#looking at the second higest mean value zip_cove
melted_df.loc[melted_df['Zipcode']=='6820']

```

Out[34]:

Date	Zipcode	Metro	SizeRank	ROI_5yr	ROI_3yr	value
2008-01-01	6820	Stamford	6037	0.1149	0.0045	1401500.0
2008-02-01	6820	Stamford	6037	0.1149	0.0045	1399200.0
2008-03-01	6820	Stamford	6037	0.1149	0.0045	1395800.0
2008-04-01	6820	Stamford	6037	0.1149	0.0045	1392500.0
2008-05-01	6820	Stamford	6037	0.1149	0.0045	1391200.0
...	...	...	...	...	...	...
2017-12-01	6820	Stamford	6037	0.1149	0.0045	1375600.0
2018-01-01	6820	Stamford	6037	0.1149	0.0045	1374700.0
2018-02-01	6820	Stamford	6037	0.1149	0.0045	1379100.0
2018-03-01	6820	Stamford	6037	0.1149	0.0045	1385800.0
2018-04-01	6820	Stamford	6037	0.1149	0.0045	1388100.0

124 rows × 6 columns

In [35]:
```
#further understanding the values in this data set
melted_df.value.describe()
```

Out[35]:
```
count    1.537600e+04
mean     2.802331e+05
std      1.840456e+05
min      8.010000e+04
25%      1.838000e+05
50%      2.419000e+05
75%      3.145250e+05
max      1.746000e+06
Name: value, dtype: float64
```

The Max value of all time and the Min Value of all times are:

In [36]:
```
melted_df.loc[melted_df['value']== 1746000]
```

Out[36]:

Date	Zipcode	Metro	SizeRank	ROI_5yr	ROI_3yr	value
2008-01-01	6840	Stamford	5941	-0.0012	-0.0764	1746000.0

In [37]:
```
melted_df.loc[melted_df['value']== 80100]
```

Out[37]:

Date	Zipcode	Metro	SizeRank	ROI_5yr	ROI_3yr	value
2015-04-01	6706	New Haven	7317	0.0274	0.3196	80100.0

1.3.5 Understanding 5 yr. ROI Homes & the Top 10% in this category

In [38]:
```
#There are 15,736 homes, we'll look at the top 10% in this set
melted_df['ROI_5yr'].describe()

```

Out[38]:
```
count    15376.000000
mean         0.098785
std          0.076585
min         -0.081200
25%          0.051025
50%          0.090000
75%          0.130150
max          0.415800
Name: ROI_5yr, dtype: float64
```

In [39]:
```
#getting the quantile .90 for the top 10%

#first getting 90% of these homes or the .90 quantile
ninety_perc_ROI_5yr = melted_df['ROI_5yr'].quantile(q=0.90)

#Now deriving the top 10% by taking the values greater than that 90th
top_10_percent = melted_df.loc[melted_df['ROI_5yr']>=ninety_perc_ROI_
```

In [40]:
```
#looking at the first 10 values of the top 10% with best 5yr ROI
top_10_percent.head(5)
```

Out[40]:

Date	Zipcode	Metro	SizeRank	ROI_5yr	ROI_3yr	value
2008-01-01	6810	Stamford	685	0.2219	0.1839	321900.0
2008-01-01	6606	Stamford	1332	0.3202	0.2165	252300.0
2008-01-01	6513	New Haven	2301	0.2725	0.1802	187600.0
2008-01-01	6604	Stamford	3778	0.3141	0.3166	274700.0
2008-01-01	6610	Stamford	4717	0.2999	0.3111	216600.0

In [41]:
```
top_10_percent.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 1612 entries, 2008-01-01 to 2018-04-01
Data columns (total 6 columns):
 #   Column    Non-Null Count  Dtype
---  ------    --------------  -----
 0   Zipcode   1612 non-null   object
 1   Metro     1612 non-null   object
 2   SizeRank  1612 non-null   int64
 3   ROI_5yr   1612 non-null   float64
 4   ROI_3yr   1612 non-null   float64
 5   value     1612 non-null   float64
dtypes: float64(3), int64(1), object(2)
memory usage: 88.2+ KB
```

1,612 homes are in that 10% with the best ROI.

Doing the same for the 3 yrs ROI

1.3.6 Top 10% Zip Codes 3 yr. ROI

In [42]:
```
#getting the quantile .90 for the top 10%
ninety_perc_ROI_3yr = melted_df['ROI_3yr'].quantile(q=0.90)
top_10_percent_3yr = melted_df.loc[melted_df['ROI_3yr']>=ninety_perc_
```

In [43]:
```
#looking at the first 10 values of the top 10% with best 3yr ROI
top_10_percent_3yr.info()
top_10_percent_3yr.head(5)
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 1612 entries, 2008-01-01 to 2018-04-01
Data columns (total 6 columns):
 #   Column    Non-Null Count  Dtype  
---  ------    --------------  -----  
 0   Zipcode   1612 non-null   object 
 1   Metro     1612 non-null   object 
 2   SizeRank  1612 non-null   int64  
 3   ROI_5yr   1612 non-null   float64
 4   ROI_3yr   1612 non-null   float64
 5   value     1612 non-null   float64
dtypes: float64(3), int64(1), object(2)
memory usage: 88.2+ KB
```

Out[43]:

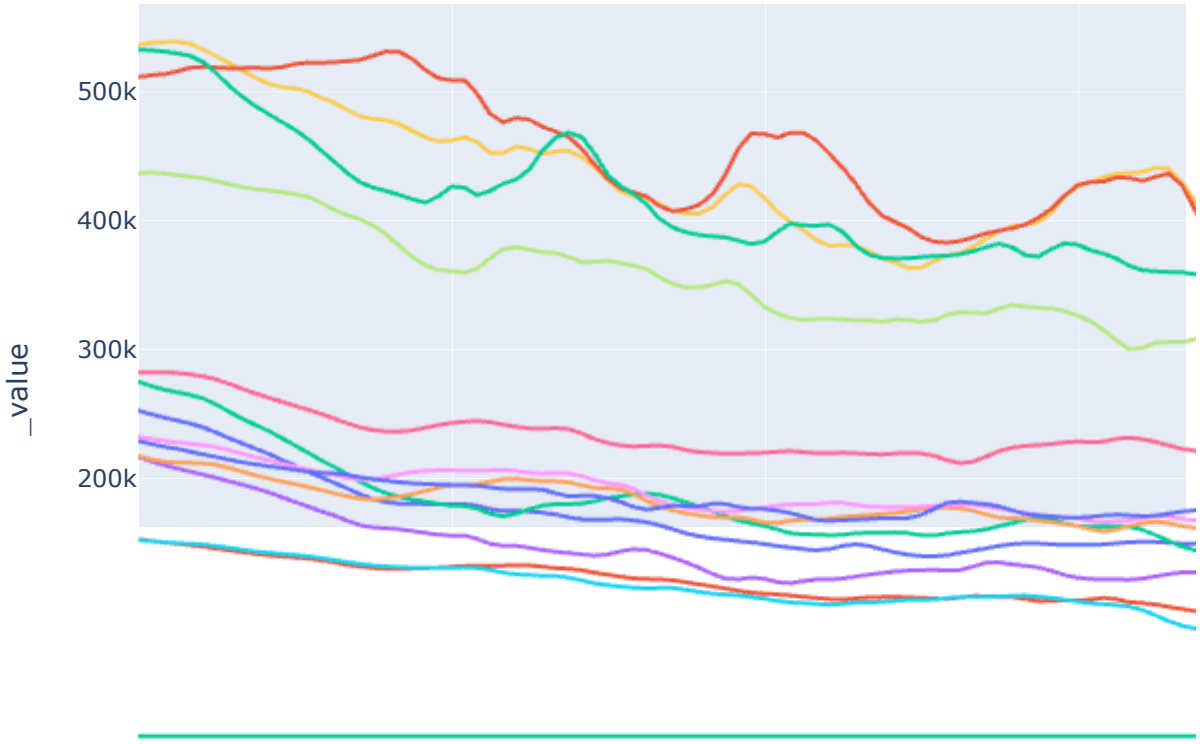
Date	Zipcode	Metro	SizeRank	ROI_5yr	ROI_3yr	value
2008-01-01	6606	Stamford	1332	0.3202	0.2165	252300.0
2008-01-01	6705	New Haven	3696	0.0056	0.1964	152500.0
2008-01-01	6604	Stamford	3778	0.3141	0.3166	274700.0
2008-01-01	6610	Stamford	4717	0.2999	0.3111	216600.0
2008-01-01	6351	New London	6591	0.1183	0.2234	217300.0

In [44]:
```
#New data set to drop the ROI 3yr data set Metro and SizeRank to prep
df = top_10_percent_3yr.drop(columns=['Metro', 'SizeRank'])

#Looking at it
df.head()
```

Out[44]:

Date	Zipcode	ROI_5yr	ROI_3yr	value
2008-01-01	6606	0.3202	0.2165	252300.0
2008-01-01	6705	0.0056	0.1964	152500.0
2008-01-01	6604	0.3141	0.3166	274700.0
2008-01-01	6610	0.2999	0.3111	216600.0
2008-01-01	6351	0.1183	0.2234	217300.0

In [45]:
```
#Showing the top 13 ZIP Codes ROI For the past 3yrs
px.line(df, color='Zipcode')
```



In [46]:
```
%store melted_df
```

```
Stored 'melted_df' (DataFrame)
```

In [47]:
```
%store df
```

```
Stored 'df' (DataFrame)
```

In [ ]:
```

```

1 ARIMA CODING

I'll be implementing and autoregressive integrated moving average model. An autoregressive integrated moving average mode, or ARIMA, is a statistical analysis model that uses time series data to either better understand the data set or to predict future trends. A statistical model is autoregressive if it predicts future values based on past values. I'll load the libraries and start the process of modeling. I'll build a base model and a second model choosing a best model. As the objective is to find the ZIP Codes in a particular market that predict the best ROI.

1.1 Loading data sets and libraries

In [4]:
```
#!pip install
%store -r df
%matplotlib inline
```

In [5]:
```
#importing libraries
import pandas as pd
import numpy as np
import matplotlib as mpl
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np


## Project Notebook Settings
pd.set_option('display.max_columns',0)

import warnings
warnings.filterwarnings('ignore')

plt.style.use('seaborn-notebook')
```

In [6]:
```
#checking the data set
df.head(5)
```

Out[6]:

Date	Zipcode	ROI_5yr	ROI_3yr	value
2008-01-01	6606	0.3202	0.2165	252300.0
2008-01-01	6705	0.0056	0.1964	152500.0
2008-01-01	6604	0.3141	0.3166	274700.0
2008-01-01	6610	0.2999	0.3111	216600.0
2008-01-01	6351	0.1183	0.2234	217300.0

1.1.1 Time Series Process

The data set has to be prepared to for modeling. The correct process for managing Time Series correctly includes:

1. Grouping the data set and creating a Time Series (TS)
2. Converting (Pandas Data Frame)
3. Understanding Differencing & Decomposition
4. Visualizing ACF & PACF and Detrending Transformation
5. Modeling - Predictions and Results

1.1.1.1 1. Grouping the data set

In [7]:
```
#Making a Zipcode list
zipcode_list = df['Zipcode'].unique().tolist()
```

In [8]:
```
#Creating a TS (time series) dictionary and loop
TS = {}
for zipcode in zipcode_list:
    temp_df = df.groupby('Zipcode').get_group(zipcode).sort_index()['
    TS[zipcode] = temp_df #df.loc[district]
```

In [9]:
```
#Looking at the keys
TS.keys()
```

Out[9]:
```
dict_keys(['6606', '6705', '6604', '6610', '6351', '6706', '6359', '606
9', '6330', '6039', '6235', '6068', '6796'])
```

In [10]:
```
#Looking at ZIP Code 6706
TS['6706']
```

Out[10]:
```
Date
2008-01-01    152200.0
2008-02-01    151200.0
2008-03-01    150300.0
2008-04-01    149600.0
2008-05-01    149200.0
                ...
2017-12-01    108900.0
2018-01-01    109800.0
2018-02-01    109500.0
2018-03-01    109000.0
2018-04-01    108600.0
Name: value, Length: 124, dtype: float64
```

1.1.1.2 Converting into a Pandas DataFrame

Now we are going to convert and visualize the TS dictionary created and put it into a Pandas

In [11]:
```
#Converting TS into Pandas DataFrame calling it ts_df
ts_df = pd.DataFrame(TS)
ts_df.head()
```

Out[11]:

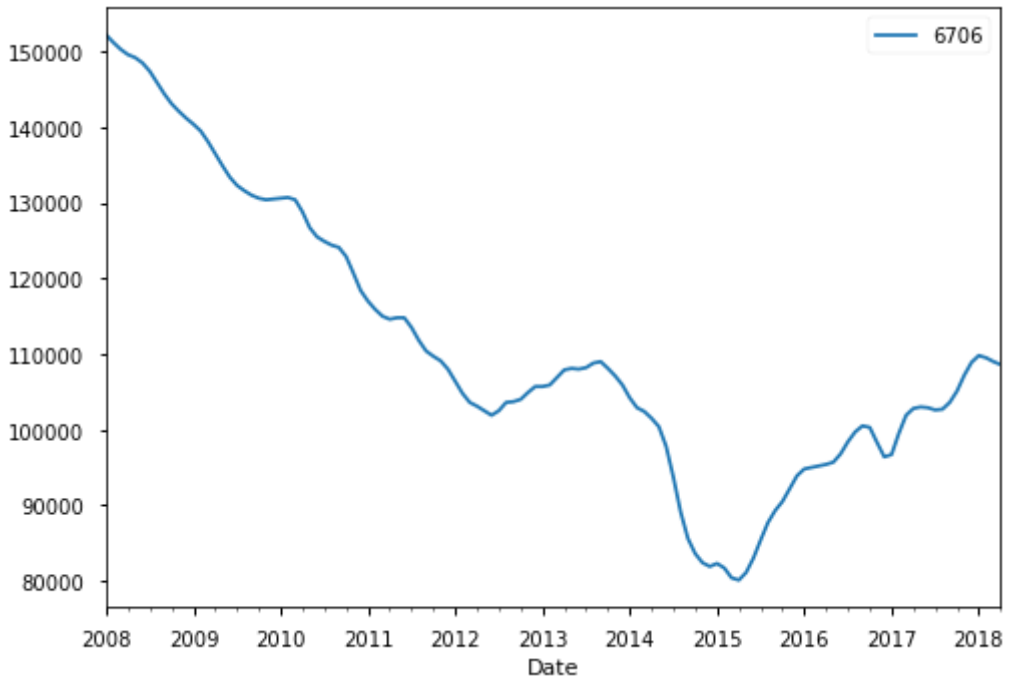
Date	6606	6705	6604	6610	6351	6706	6359	6069	6330
2008-01-01	252300.0	152500.0	274700.0	216600.0	217300.0	152200.0	282100.0	436300.0	232100.0
2008-02-01	249500.0	151300.0	271300.0	213100.0	214400.0	151200.0	282000.0	437000.0	230400.0
2008-03-01	247000.0	150200.0	268600.0	210100.0	212800.0	150300.0	282100.0	436300.0	228900.0
2008-04-01	244700.0	149100.0	266600.0	207500.0	212100.0	149600.0	281600.0	434900.0	227800.0
2008-05-01	242400.0	148100.0	264600.0	205100.0	211900.0	149200.0	280500.0	433700.0	226700.0

The above is a Pandas DataFrame for time series

1.1.1.3 Visualizing individual ZIP Code

In [12]:
```
#Zip Code # 6706
zipcode = '6706'
```

In [13]:
```
#Observing the Time Series now in Pandas DataFrame
ts = ts_df[zipcode].copy()
ax = ts.plot()
ax.legend()
plt.show()
```



1.1.1.4 Time Series- Decomposition, Differencing

Understanding Decomposition and Differencing

Time Series have major components that can affect the lags or how the lags are shown, such as:

- Trend component.
- Seasonal component.
- Cyclical component.
- Irregular component.

To make sure that these don't affect the model, the goal is make the trend on these lags more even. I can then difference the trend or transform the trend by differencing.

Time series data can exhibit a variety of patterns, and it is often helpful to split a time series into several components, each representing an underlying pattern category. To do this, we have to understand Auto Correlations and Partial Auto Correlations, and once we do, execute on decomposition. First, we'll be importing libraries that will help up to this effect followed by plotting and visualization to understand the time-series data.

Differencing is a technique to transform a non-stationary time series into a stationary one. It involves subtracting the current value of the series from the previous one, or from a lagged value. It can be used to remove the series dependence on time like trends and seasonality. This is an

important step in preparing the data used in ARIMA Modeling. To do this we can code a new plot showing the differencing applied. Let's also understand the sub-components of Auto Correlation and Partial Autocorrelation.

1.1.1.5 Understanding ACF & PACF and Lags

Autocorrelation is a measure of how much the data sets at one point in time influences data sets at a later point in time- thus I seek to identify how correlated the values in a time series are with each other. Autocorrelation is the correlation between a time series with a lagged version of itself. A lag is the period of time between one time series index and another one. The ACF starts at a lag of 0, which is the correlation of the time series with itself and therefore results in a correlation of 1. The ACF plots the correlation coefficient against the lag, which is measured in terms of a number of periods or units. In essence, its a measure of the link between the present and the past.

Partial Autocorrelation (PACF) is a plot of the partial correlation coefficients between the series and lags of itself. In general, the "partial" correlation between two variables is the amount of correlation between them which is not explained by their mutual correlations with a specified set of other variables.

Both, ACF and PACF can provide valuable insights into the behaviour of time series data. They are often used to decide the number of Autoregressive (AR) and Moving Average (MA) lags for the ARIMA models. Moreover, they can also help detect any seasonality within the data. The correct application and interpretation are essential in extracting useful information from the ACF and PACF plots.

The ACF plots the correlation coefficient against the lag, which is measured in terms of a number of periods or units. In essence, its a measure of the link between the present and the past.

The PACF plot is a plot of the partial correlation coefficients between the series and lags of itself. In general, the "partial" correlation between two variables is the amount of correlation between them which is not explained by their mutual correlations with a specified set of other variables.

Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) can provide valuable insights into the behaviour of time series data. They are often used to decide the number of Autoregressive (AR) and Moving Average (MA) lags for the ARIMA models. Moreover, they can also help detect any seasonality within the data. The correct application and interpretation are essential in extracting useful information from the ACF and PACF plots.

Understanding Lags

This is value of time gap being considered and is called the lag. A lag 1 autocorrelation is the correlation between values that are one time period apart. More generally, a lag k autocorrelation is the correlation between values that are k time periods apart

For the purpose of this project, my approach with annual data is 20 lags. The number of lags is typically small, 1 or 2 lags. With quarterly data, 1 to 8 lags is appropriate, and for monthly data, 6, 12 or 24 lags can be used given sufficient data points

1.1.1.6 Importing relevant libraries

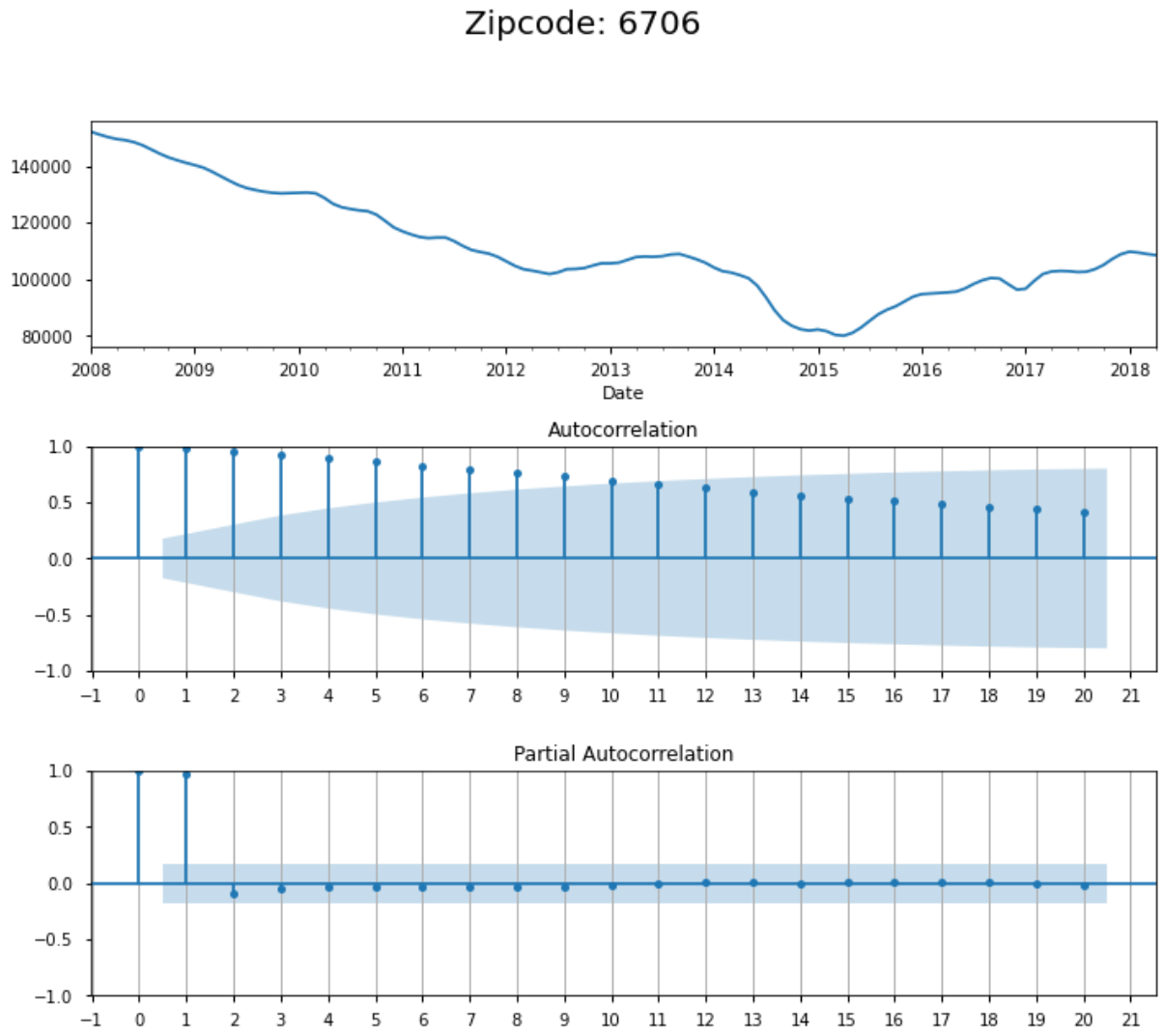
In [14]:
```
#For time series decomposition season decompose
from statsmodels.tsa.seasonal import seasonal_decompose
#Statsmodels for plotting the acf and pacf
from statsmodels.graphics.tsaplots import plot_acf,plot_pacf
#Pandas plotting import
from pandas.plotting import autocorrelation_plot,lag_plot
#Defining plot
def plot_acf_pacf(ts, figsize=(10,8),lags=24):

    fig,ax = plt.subplots(nrows=3,
                          figsize=figsize)

    ## Plot ts
    ts.plot(ax=ax[0])

    ## Plot acf, pavf
    plot_acf(ts,ax=ax[1],lags=lags)
    plot_pacf(ts, ax=ax[2],lags=lags)
    fig.tight_layout()

    fig.suptitle(f"Zipcode: {ts.name}",y=1.1,fontsize=20)

    for a in ax[1:]:
        a.xaxis.set_major_locator(mpl.ticker.MaxNLocator(min_n_ticks=
        a.xaxis.grid()
    return fig,ax
```

Lags

My approach with annual data is 20 lags. The number of lags is typically small, 1 or 2 lags. With quarterly data, 1 to 8 lags is appropriate, and for monthly data, 6, 12 or 24 lags can be used given sufficient data points

1.1.1.7 Plots ACF & PACF

In [15]:
```
1 plot_acf_pacf(ts,lags=20);
```



1.1.1.8 Differencing Transformation

Time Series have major components that can affect the lags or how the lags are shown, such as:

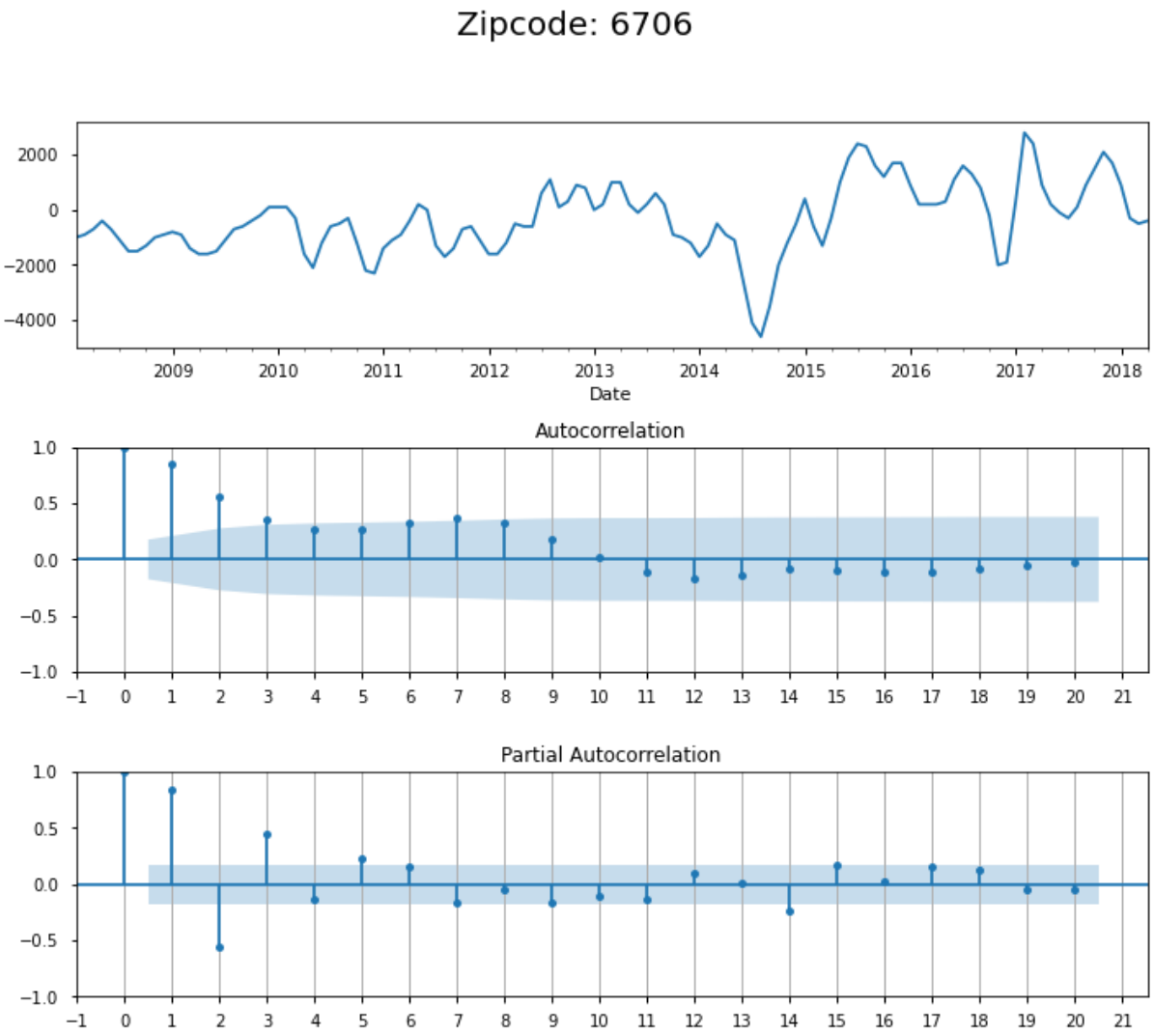
- Trend component.
- Seasonal component.
- Cyclical component.
- Irregular component.

To make sure that these don't affect the model, the goal is make the trend on these lags more even. I can then difference the trend or transform the trend by differencing.

Differencing is a method of transforming a time series dataset. It can be used to remove the series dependence on time like trends and seasonality. This is an important step in preparing the data used in ARIMA Modeling. To do this we can code a new plot showing the differencing applied.

d= 1 below, is a parameter that refers to the number of differencing transformations required by the time series to get stationary. By making the time series stationary I have basically made the mean and variance constant over time. It is easier to predict when the series is stationary.

In [16]:
```
#Coding ts.diff Differencing
d = 1
plot_acf_pacf(ts.diff(d).dropna(),lags=20);
```



Above we have detrended the series. I can now select parameters and run the first model.

Both of these functions (ACF and PACF) measure how correlated the data at time t is to its past values t-1,t-2,… There is one crucial difference, however. The ACF also measures indirect correlation up to the lag in question, while PCAF does not.

1.2 Modeling 1

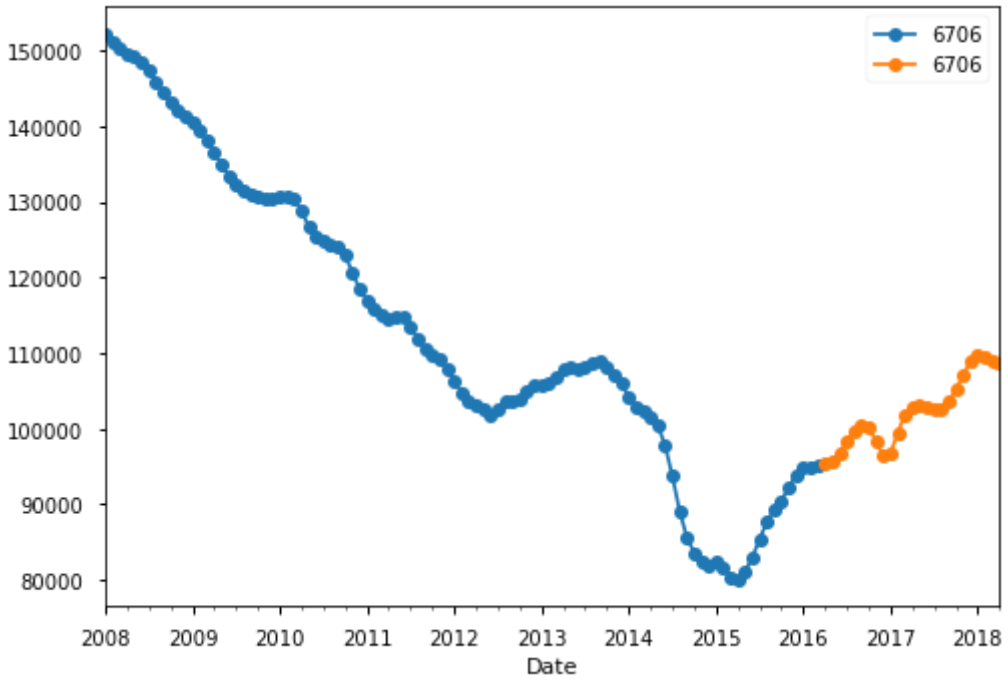
1.2.0.1 Selecting Parameters

ARIMA models are made up of three different parameters or terms:

- d: The degree of differencing.
- p: The order of the auto-regressive (AR) model (i.e., the number of lag observations). A time series is considered AR when previous values in the time series are very predictive of later values. An AR process will show a very gradual decrease in the ACF plot.
- q: The order of the moving average (MA) model. This is essentially the size of the “window” function over time series data.

In [17]:
```
# selected params
d = 1
p = 1
q = 1
```

In [18]:
```
#selecting a training size
train_size = 0.8
#multiply train size by len of ts
split_idx = round(len(ts)* train_size)
split_idx

## Split train/test for train 80% and test 20%
train = ts.iloc[:split_idx]
test = ts.iloc[split_idx:]

## Visualize split
fig,ax= plt.subplots()
kws = dict(ax=ax,marker='o')
train.plot(**kws)
test.plot(**kws)
ax.legend(bbox_to_anchor=[1,1])
plt.show()
```



Above, we see this ZIP Code's train test split

1.2.1 Using Statsmodels and SARIMAX

SARIMAX, is an extension of the ARIMA class of models. ARIMA models compose 2 parts: the autoregressive term (AR) and the moving-average term (MA). AR views the value at one time just as a weighted sum of past values. The MA model takes that same value also as a weighted sum but of past residuals. Overall, ARIMA is a very good model. However, it cannot handle seasonality, thus SARIMAX is used in this model.

In [19]:
```
#Using SARIMAX because it is better to use on seasonal data
from statsmodels.tsa.statespace.sarimax import SARIMAX

## Baseline model from eye-balled params
model = SARIMAX(train,order=(p,d,q),).fit()
display(model.summary())
model.plot_diagnostics();
plt.show()
```

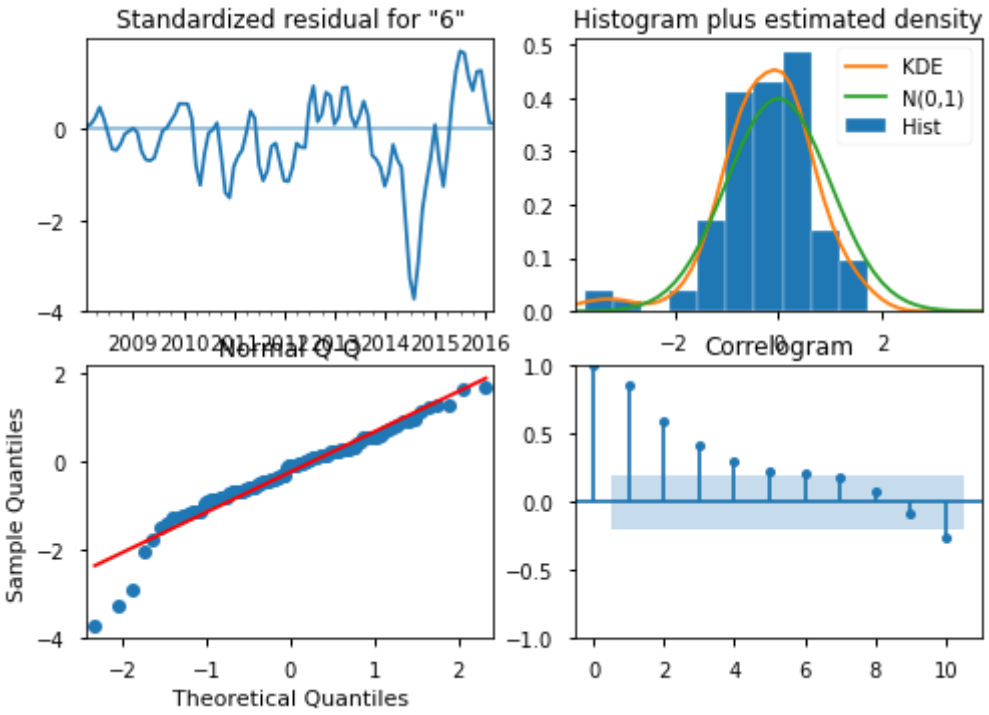
SARIMAX Results

Dep. Variable:	6706	**No. Observations:**	99
Model:	SARIMAX(1, 1, 1)	**Log Likelihood**	-833.096
Date:	Mon, 12 Jun 2023	**AIC**	1672.192
Time:	14:32:08	**BIC**	1679.947
Sample:	01-01-2008	**HQIC**	1675.329
	- 03-01-2016		
Covariance Type:	opg		

	coef	std err	z	P>|z|	[0.025	0.975]
ar.L1	0.9769	0.010	97.349	0.000	0.957	0.997
ma.L1	-0.9999	0.101	-9.903	0.000	-1.198	-0.802
sigma2	1.558e+06	6.13e-08	2.54e+13	0.000	1.56e+06	1.56e+06

Ljung-Box (L1) (Q):	74.21	**Jarque-Bera (JB):**	38.95
Prob(Q):	0.00	**Prob(JB):**	0.00
Heteroskedasticity (H):	9.74	**Skew:**	-0.95
Prob(H) (two-sided):	0.00	**Kurtosis:**	5.44

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).
[2] Covariance matrix is singular or near-singular, with condition number 1.99e+28. Standard errors may be unstable.



In [20]:
```
#Checking for the len of test
len(test)
```

Out[20]: 25

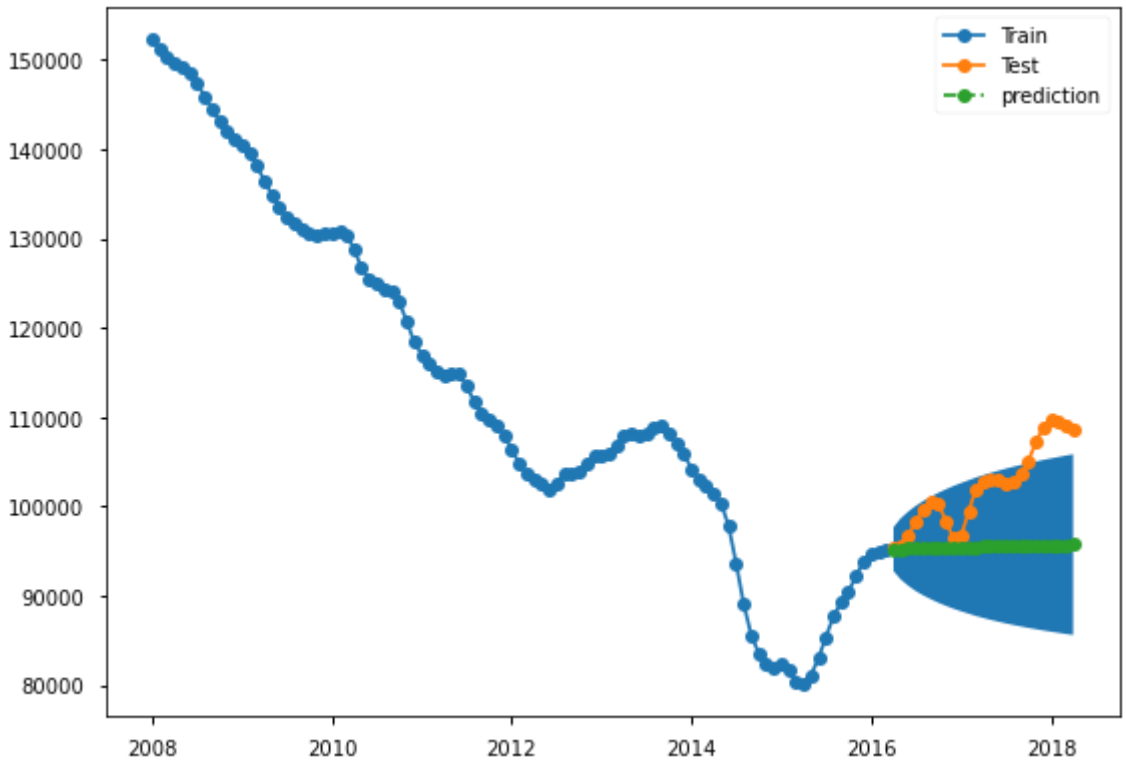
1.2.2 Forecasting

In [21]:
```
## Importing and obtaining forecast tools and set forecast code
from sklearn import metrics
forecast = model.get_forecast(steps=len(test))
```

In [22]:
```
#Defining Forecast
def forecast_to_df(forecast,zipcode):
    test_pred = forecast.conf_int()
    test_pred[zipcode] = forecast.predicted_mean
    test_pred.columns = ['lower','upper','prediction']
    return test_pred


pred_df = forecast_to_df(forecast,zipcode)
```

In [23]:
```
#Defining Plot
def plot_train_test_pred(train,test,pred_df):
    fig,ax = plt.subplots()
    kws = dict(marker='o')

    ax.plot(train,label='Train',**kws)
    ax.plot(test,label='Test',**kws)
    ax.plot(pred_df['prediction'],label='prediction',ls='--',**kws)

    ax.fill_between(x=pred_df.index,y1=pred_df['lower'],y2=pred_df['u
    ax.legend(bbox_to_anchor=[1,1])
    fig.tight_layout()
    return fig,ax
```

In [24]:
```
plot_train_test_pred(train,test,pred_df)
plt.show()
```



1.3 Model 2

I want to identify the optimal parameters for my model. Pmdarima's auto_arima function is very useful when building an ARIMA model as it helps us identify the most optimal p,d,q parameters and return a fitted model.

In [25]:
```
#@!pip install pmdarima
```

In [26]:

```
#importing libraries
from pmdarima.arima import auto_arima
```

In [27]:
```
auto_model = auto_arima(train,start_p=0,start_q=0)
display(auto_model.summary())
auto_model.plot_diagnostics();
```

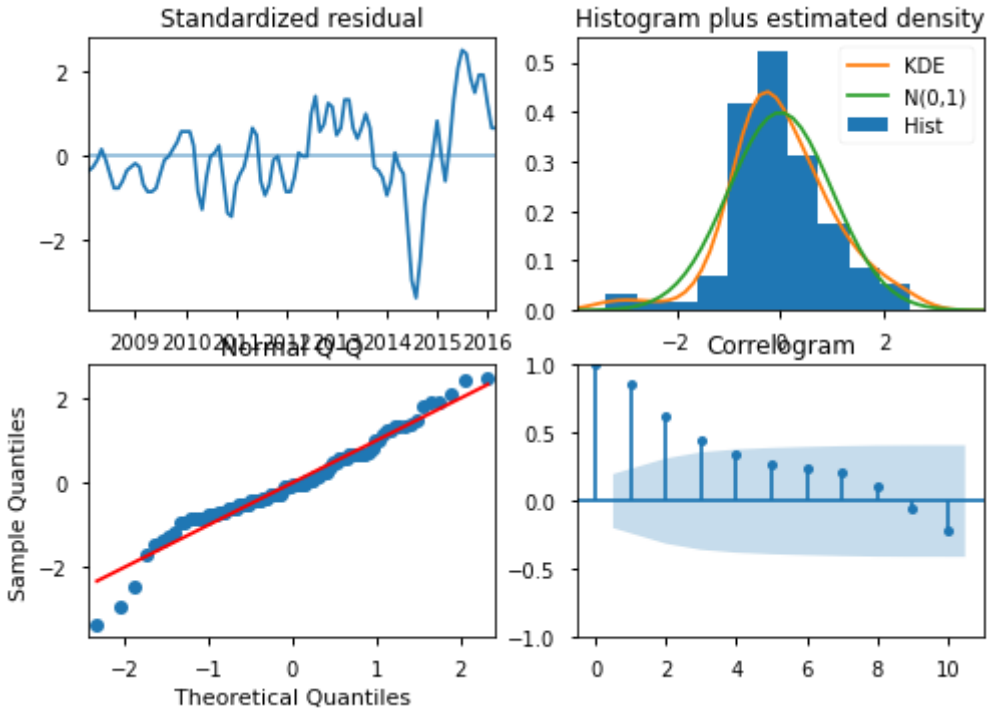
SARIMAX Results

Dep. Variable:	y	**No. Observations:**	99
Model:	SARIMAX(0, 1, 0)	**Log Likelihood**	-833.565
Date:	Mon, 12 Jun 2023	**AIC**	1671.131
Time:	14:32:14	**BIC**	1676.301
Sample:	01-01-2008	**HQIC**	1673.222
	- 03-01-2016		
Covariance Type:	opg		

	coef	std err	z	P>|z|	[0.025	0.975]
intercept	-581.6327	121.477	-4.788	0.000	-819.723	-343.542
sigma2	1.431e+06	1.6e+05	8.956	0.000	1.12e+06	1.74e+06

Ljung-Box (L1) (Q):	75.43	**Jarque-Bera (JB):**	7.58
Prob(Q):	0.00	**Prob(JB):**	0.02
Heteroskedasticity (H):	7.58	**Skew:**	-0.19
Prob(H) (two-sided):	0.00	**Kurtosis:**	4.31

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



In [28]:
```
#organize panda data frame into date range , with 10 periods, frequen
pd.date_range(train.index[-1], periods=10,freq='M')

```

Out[28]:
```
DatetimeIndex(['2016-03-31', '2016-04-30', '2016-05-31', '2016-06-30',
               '2016-07-31', '2016-08-31', '2016-09-30', '2016-10-31',
               '2016-11-30', '2016-12-31'],
              dtype='datetime64[ns]', freq='M')
```

Date ranges (pd.date_range) is like a "date ruler". You have a start and end time, the frequency if how I'd like to split the dates by.

In [29]:
```
#showing the index of train data
train.index
```

Out[29]:
```
DatetimeIndex(['2008-01-01', '2008-02-01', '2008-03-01', '2008-04-01',
               '2008-05-01', '2008-06-01', '2008-07-01', '2008-08-01',
               '2008-09-01', '2008-10-01', '2008-11-01', '2008-12-01',
               '2009-01-01', '2009-02-01', '2009-03-01', '2009-04-01',
               '2009-05-01', '2009-06-01', '2009-07-01', '2009-08-01',
               '2009-09-01', '2009-10-01', '2009-11-01', '2009-12-01',
               '2010-01-01', '2010-02-01', '2010-03-01', '2010-04-01',
               '2010-05-01', '2010-06-01', '2010-07-01', '2010-08-01',
               '2010-09-01', '2010-10-01', '2010-11-01', '2010-12-01',
               '2011-01-01', '2011-02-01', '2011-03-01', '2011-04-01',
               '2011-05-01', '2011-06-01', '2011-07-01', '2011-08-01',
               '2011-09-01', '2011-10-01', '2011-11-01', '2011-12-01',
               '2012-01-01', '2012-02-01', '2012-03-01', '2012-04-01',
               '2012-05-01', '2012-06-01', '2012-07-01', '2012-08-01',
               '2012-09-01', '2012-10-01', '2012-11-01', '2012-12-01',
               '2013-01-01', '2013-02-01', '2013-03-01', '2013-04-01',
               '2013-05-01', '2013-06-01', '2013-07-01', '2013-08-01',
               '2013-09-01', '2013-10-01', '2013-11-01', '2013-12-01',
               '2014-01-01', '2014-02-01', '2014-03-01', '2014-04-01',
               '2014-05-01', '2014-06-01', '2014-07-01', '2014-08-01',
               '2014-09-01', '2014-10-01', '2014-11-01', '2014-12-01',
               '2015-01-01', '2015-02-01', '2015-03-01', '2015-04-01',
               '2015-05-01', '2015-06-01', '2015-07-01', '2015-08-01',
               '2015-09-01', '2015-10-01', '2015-11-01', '2015-12-01',
               '2016-01-01', '2016-02-01', '2016-03-01'],
              dtype='datetime64[ns]', name='Date', freq=None)
```

In [30]:
```
#predictive models mean
pred_mean,pred_conf_int = auto_model.predict(return_conf_int=True)
pred_mean
```

Out[30]:
```
2016-04-01    94618.367347
2016-05-01    94036.734694
2016-06-01    93455.102041
2016-07-01    92873.469388
2016-08-01    92291.836735
2016-09-01    91710.204082
2016-10-01    91128.571429
2016-11-01    90546.938776
2016-12-01    89965.306122
2017-01-01    89383.673469
Freq: MS, dtype: float64
```

1.3.0.1 GridSearch Hyperparameter

Grid search The traditional way of performing hyperparameter optimization has been grid search, or a parameter sweep, which is simply an exhaustive searching through a manually specified subset of the hyperparameter space of a learning algorithm. A grid search algorithm must be guided by some performance metric, typically measured by cross-validation on the training set[4] or evaluation on a hold-out validation set.[5]

Since the parameter space of a machine learner may include real-valued or unbounded value spaces for certain parameters, manually set bounds and discretization may be necessary before applying grid search.

For example, a typical soft-margin SVM classifier equipped with an RBF kernel has at least two hyperparameters that need to be tuned for good performance on unseen data: a regularization constant C and a kernel hyperparameter γ. Both parameters are continuous, so to perform grid search, one selects a finite set of "reasonable" values for each, say

 ∈ { 10 , 100 , 1000 } C\in {10,100,1000} ∈ { 0.1 , 0.2 , 0.5 , 1.0 } \gamma \in {0.1,0.2,0.5,1.0} Grid search then trains an SVM with each pair (C, γ) in the Cartesian product of these two sets and evaluates their performance on a held-out validation set (or by internal cross-validation on the training set, in which case multiple SVMs are trained per pair). Finally, the grid search algorithm outputs the settings that achieved the highest score in the validation procedure.

Grid search suffers from the curse of dimensionality, but is often embarrassingly parallel because the hyperparameter settings it evaluates are typically independent of each other.[3]

In [31]:
```
#Grid Parameters
pred_df = pd.DataFrame({'pred':pred_mean,
                        'conf_int_lower':pred_conf_int[:,0],
                        'conf_int_upper':pred_conf_int[:,1]},
                        index= pd.date_range(test.index[0],
                                             periods=10,freq='M'
# auto_model.conf_int()
pred_df
```

Out[31]:

	pred	conf_int_lower	conf_int_upper
2016-04-30	NaN	92274.031616	96962.703077
2016-05-31	NaN	90721.343309	97352.126079
2016-06-30	NaN	89394.593446	97515.610636
2016-07-31	NaN	88184.797927	97562.140849
2016-08-31	NaN	87049.742679	97533.930790
2016-09-30	NaN	85967.777756	97452.630407
2016-10-31	NaN	84926.042096	97331.100761
2016-11-30	NaN	83916.156006	97177.721545
2016-12-31	NaN	82932.298931	96998.313314
2017-01-31	NaN	81970.232961	96797.113978

In [32]:
```
train.index[-1]
```

Out[32]:
```
Timestamp('2016-03-01 00:00:00')
```

In [33]:
```
auto_model.get_params()
```

Out[33]:
```
{'maxiter': 50,
 'method': 'lbfgs',
 'order': (0, 1, 0),
 'out_of_sample_size': 0,
 'scoring': 'mse',
 'scoring_args': {},
 'seasonal_order': (0, 0, 0, 0),
 'start_params': None,
 'suppress_warnings': True,
 'trend': None,
 'with_intercept': True}
```

1.4 Best Model Plot

In [34]:
```
best_model = SARIMAX(ts,order=auto_model.order,
                     seasonal_order=auto_model.seasonal_order).fit()
display(best_model.summary())
best_model.plot_diagnostics();
```

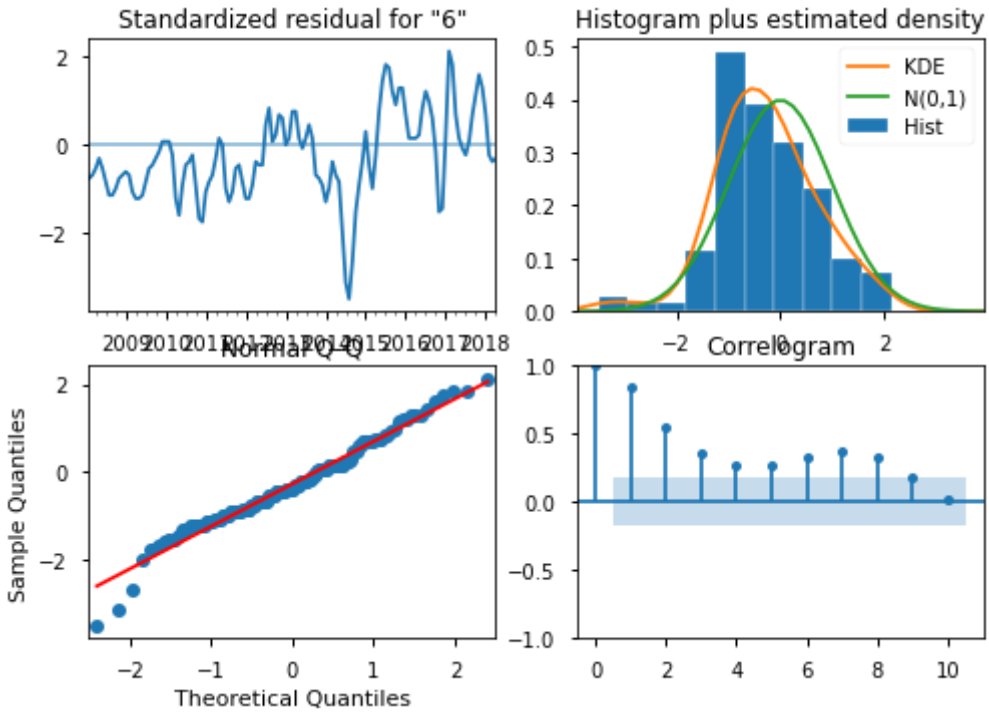
SARIMAX Results

Dep. Variable:	6706	**No. Observations:**	124
Model:	SARIMAX(0, 1, 0)	**Log Likelihood**	-1058.117
Date:	Mon, 12 Jun 2023	**AIC**	2118.234
Time:	14:32:21	**BIC**	2121.046
Sample:	01-01-2008	**HQIC**	2119.376
	- 04-01-2018		
Covariance Type:	opg		

	coef	std err	z	P>|z|	[0.025	0.975]
sigma2	1.722e+06	1.85e+05	9.330	0.000	1.36e+06	2.08e+06

Ljung-Box (L1) (Q):	90.11	**Jarque-Bera (JB):**	3.49
Prob(Q):	0.00	**Prob(JB):**	0.17
Heteroskedasticity (H):	1.38	**Skew:**	-0.12
Prob(H) (two-sided):	0.31	**Kurtosis:**	3.79

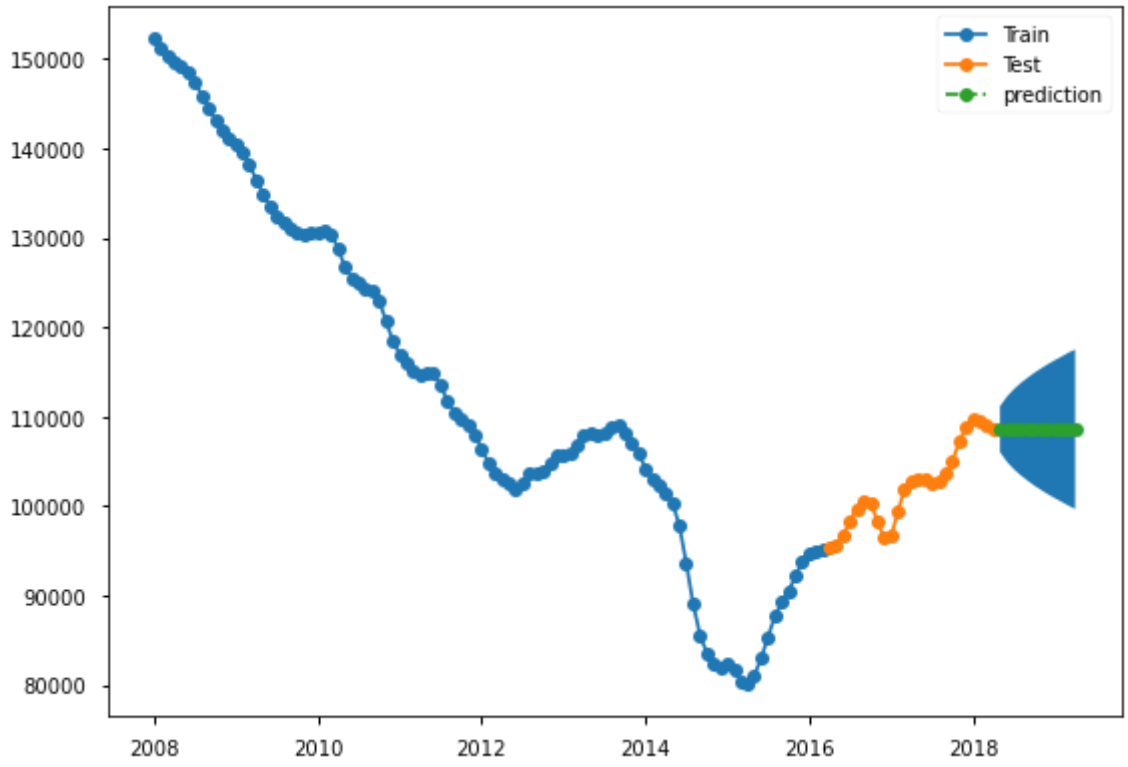
Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).



1.4.1 Forecast

In [35]:
```
1
2 pred = best_model.get_forecast(steps=12)#start=test.index[0],end=test
3 pred_df = forecast_to_df(pred,zipcode)
4 display(plot_train_test_pred(train,test,pred_df));
5 plt.show()
```

```
(<Figure size 576x396 with 1 Axes>, <AxesSubplot:>)
```



1.4.1.1 Loopin Best Model Forecast for the 13 best ROI ZIP Codes

In [36]:

```
RESULTS = {}

for zipcode in zipcode_list:
    print(zipcode)

    ## Make empty dict for district data
    zipcode_d = {}

    ## Copy Time Series
    ts = ts_df[zipcode].copy()


    ## Train Test Split Index
    train_size = 0.8
    split_idx = round(len(ts)* train_size)

    ## Split
    train = ts.iloc[:split_idx]
    test = ts.iloc[split_idx:]


    ## Get best params using auto_arima
    gridsearch_model = auto_arima(ts,start_p=0,start_q=0)
    best_model = SARIMAX(ts,order=gridsearch_model.order,
                         seasonal_order=gridsearch_model.seasonal_order).

    ## Get predictions
    pred  = best_model.get_forecast(steps=36)#start=test.index[0],end
    pred_df = forecast_to_df(pred,zipcode)

    ## Save info to dict
    zipcode_d['pred_df'] = pred_df
    zipcode_d['model'] = best_model
    zipcode_d['train'] = train
    zipcode_d['test'] = test

    ## Display Results
    display(best_model.summary())
    plot_train_test_pred(train,test,pred_df)
    plt.xlabel('Year')
    plt.ylabel('Value in US Dollars ($)')
    plt.show()


    ## Save district dict in RESULTS
    RESULTS[zipcode] = zipcode_d
    print('---'*20,end='\n\n')
```

```
6606
```

SARIMAX Results

Dep. Variable:	6606	**No. Observations:**	124
Model:	SARIMAX(0, 2, 0)	**Log Likelihood**	-981.444
Date:	Mon, 12 Jun 2023	**AIC**	1964.889
Time:	14:32:23	**BIC**	1967.693
Sample:	01-01-2008	**HQIC**	1966.028

1.5 Top 5 Zip Codes Recommendations

In [37]:
```
%store -r melted_df
```

Zip Code 6069

In [38]:
```
melted_df.loc[melted_df['Zipcode']=='6069']

```

Out[38]:

Date	Zipcode	Metro	SizeRank	ROI_5yr	ROI_3yr	value
2008-01-01	6069	Torrington	12310	0.2366	0.2412	436300.0
2008-02-01	6069	Torrington	12310	0.2366	0.2412	437000.0
2008-03-01	6069	Torrington	12310	0.2366	0.2412	436300.0
2008-04-01	6069	Torrington	12310	0.2366	0.2412	434900.0
2008-05-01	6069	Torrington	12310	0.2366	0.2412	433700.0
...	...	...	...	...	...	...
2017-12-01	6069	Torrington	12310	0.2366	0.2412	365800.0
2018-01-01	6069	Torrington	12310	0.2366	0.2412	370900.0
2018-02-01	6069	Torrington	12310	0.2366	0.2412	375900.0
2018-03-01	6069	Torrington	12310	0.2366	0.2412	386500.0
2018-04-01	6069	Torrington	12310	0.2366	0.2412	397200.0

124 rows × 6 columns

Zip Code 6610

In [39]:
```
melted_df.loc[melted_df['Zipcode']=='6610']
```

Out[39]:

Date	Zipcode	Metro	SizeRank	ROI_5yr	ROI_3yr	value
2008-01-01	6610	Stamford	4717	0.2999	0.3111	216600.0
2008-02-01	6610	Stamford	4717	0.2999	0.3111	213100.0
2008-03-01	6610	Stamford	4717	0.2999	0.3111	210100.0
2008-04-01	6610	Stamford	4717	0.2999	0.3111	207500.0
2008-05-01	6610	Stamford	4717	0.2999	0.3111	205100.0
...	...	...	...	...	...	...
2017-12-01	6610	Stamford	4717	0.2999	0.3111	160400.0
2018-01-01	6610	Stamford	4717	0.2999	0.3111	162200.0
2018-02-01	6610	Stamford	4717	0.2999	0.3111	163900.0
2018-03-01	6610	Stamford	4717	0.2999	0.3111	165900.0
2018-04-01	6610	Stamford	4717	0.2999	0.3111	167300.0

124 rows × 6 columns

Zip Code 6330

In [40]:
```
melted_df.loc[melted_df['Zipcode']=='6330']
```

Out[40]:

Date	Zipcode	Metro	SizeRank	ROI_5yr	ROI_3yr	value
2008-01-01	6330	New London	12817	0.1107	0.2078	232100.0
2008-02-01	6330	New London	12817	0.1107	0.2078	230400.0
2008-03-01	6330	New London	12817	0.1107	0.2078	228900.0
2008-04-01	6330	New London	12817	0.1107	0.2078	227800.0
2008-05-01	6330	New London	12817	0.1107	0.2078	226700.0
...	...	...	...	...	...	...
2017-12-01	6330	New London	12817	0.1107	0.2078	194700.0
2018-01-01	6330	New London	12817	0.1107	0.2078	195200.0
2018-02-01	6330	New London	12817	0.1107	0.2078	195800.0
2018-03-01	6330	New London	12817	0.1107	0.2078	197000.0
2018-04-01	6330	New London	12817	0.1107	0.2078	197600.0

124 rows × 6 columns

Zip Code 6039

In [41]:
```
melted_df.loc[melted_df['Zipcode']=='6039']
```

Out[41]:

Date	Zipcode	Metro	SizeRank	ROI_5yr	ROI_3yr	value
2008-01-01	6039	Torrington	13065	0.3212	0.1861	535900.0
2008-02-01	6039	Torrington	13065	0.3212	0.1861	537700.0
2008-03-01	6039	Torrington	13065	0.3212	0.1861	538100.0
2008-04-01	6039	Torrington	13065	0.3212	0.1861	538300.0
2008-05-01	6039	Torrington	13065	0.3212	0.1861	536700.0
...	...	...	...	...	...	...
2017-12-01	6039	Torrington	13065	0.3212	0.1861	468200.0
2018-01-01	6039	Torrington	13065	0.3212	0.1861	471500.0
2018-02-01	6039	Torrington	13065	0.3212	0.1861	473700.0
2018-03-01	6039	Torrington	13065	0.3212	0.1861	476000.0
2018-04-01	6039	Torrington	13065	0.3212	0.1861	480000.0

124 rows × 6 columns

Zip Code 6058

In [42]:
```
1 melted_df.loc[melted_df['Zipcode']=='6058']
```

Out[42]:

Date	Zipcode	Metro	SizeRank	ROI_5yr	ROI_3yr	value
2008-01-01	6058	Torrington	13564	0.4158	0.1849	350900.0
2008-02-01	6058	Torrington	13564	0.4158	0.1849	345200.0
2008-03-01	6058	Torrington	13564	0.4158	0.1849	340000.0
2008-04-01	6058	Torrington	13564	0.4158	0.1849	336800.0
2008-05-01	6058	Torrington	13564	0.4158	0.1849	336500.0
...	...	...	...	...	...	...
2017-12-01	6058	Torrington	13564	0.4158	0.1849	286500.0
2018-01-01	6058	Torrington	13564	0.4158	0.1849	292100.0
2018-02-01	6058	Torrington	13564	0.4158	0.1849	298900.0
2018-03-01	6058	Torrington	13564	0.4158	0.1849	307700.0
2018-04-01	6058	Torrington	13564	0.4158	0.1849	314600.0

124 rows × 6 columns

2 Conclusion - Top 5 ZIP Codes

to Invest in these ZIP Codes due to Higher ROI

Highest projected ROI:

- 6069 = 24.12%,
- 6610 = 31%,
- 6330 = 21%,
- 6039 = 19%,
- 6058 = 19%.

In [ ]:
```
1
```