GROUP 1 PHASE 4 PROJECT

GRANDWILL REALTY SOLUTIONS

ZILLOW TIME SERIES ANALYSIS

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SUMMARY FOR TIME SERIES ANALYSIS

1. BUSINESS UNDERSTANDING

Real estate encompasses the land, plus any permanent man-made additions, such as houses and other buildings. Real estate investment entails the strategic allocation of capital into properties with the aim of generating income or capital appreciation.

In this time series forecasting project we're using data from Zillow Research, a trusted source for real estate information, to predict future property prices. With advanced techniques, we're helping **Grand Realty investment** firm find the best zip codes to invest in.

Our aim as consultants is to find valuable information, that will help us identify great places to invest in real estate and understand how the market works, including risks and expected returns. Our goal is to give our stakeholders the knowledge and resources to make smart decisions in the changing world of real estate investment.

2. DATA UNDERSTANDING

This data represents monthly housing sales prices for zip codes over the period of April 1996 to April 2018 as reported by Zillow.

Before conversion each row represents a unique home and its location(RegionName later renamed,ZipCode),Metro,city, State and CountyName and value(later renamed,Price).

- RegionID: Unique index, 58196 through 753844
- RegionName: Unique Zip Code, 1001 through 99901
- City: City in which the zip code is located
- State: State in which the zip code is located
- Metro: Metropolitan Area in which the zip code is located
- CountyName: County in which the zip code is located
- SizeRank: Numerical rank of size of zip code, ranked 1 through 14723
- 1996-04 through 2018-04: refers to the median housing sales values for April 1996 through April 2018, that is 265 data points of monthly data for each zip code

- Value: refers to the median housing price

3. DATA PREPARATION

We took the following data preparation steps

i. Dropping columns before 2008 The data starts from the year 1996 to 2018. These are 22 years. We decided we will consider data from 2008 to 2018 for the following reason:

- Relevance to current trends - Data before 2008 is less relevant to the current analysis due to significant changes in the underlying real estate market conditions. For example, the global financial crisis of 2008 resulted in substantial economic and financial changes worldwide, which may have rendered pre-crisis data less applicable to the post-crisis trends .

ii. Renaming Columns The zipcodes we needed are in the column 'RegionName'. For efficiency in working with the data, we renamed the RegionName to ZipCodes

iii. Filling in missing values - The following columns had missing values;

- Price - The price column is numeric and since it has missing values, we replaces the ones missing with 0.
- Metro - Which represents the metropolitan area, is a categorical column and therefore, could not fill missing values numerically. So we used the word 'unknown', to replace missing values.

iv. Converting data to Long Format - Data was in wide format, which is difficult to work with. So we performed melting to convert to long format so what we can have efficient rows and columns.

For time series specific pre-processing steps: i. Removing trends - We used the **dickey** fuller test to check for stationarity and used **Differencing to remove trends** so as to make the data stationary

4. MODELLING

Our modelling approach involved plotting the pacf and the acf so as to know the number of lags and the order(p,d,q) to use when using the ARIMA and SARIMAX models

We used the following models:

i. ARIMA - This was our baseline model

ii. Facebook Prophet

iii. SARIMAX Model

5. MAIN OBJECTIVE

To develop a time series model predicting the top five zip codes for real estate investment.

Specific Objectives

- To evaluate which county exhibits the most promising real estate investment opportunities.
- To understand the trend for the 5 best Zipcodes to invest in based on Return On Investment(ROI).
- To forecast property values over the short and long term, aiming to identify the most favourable zip codes for investment across various counties.

4. METRICS OF SUCCESS

1. Return On Investment - Used to evaluate how well an investment has performed by measuring the profitability and quantifying the benefit gained over a period of time. For this model, it is used to forecast which top 5 zip codes would have the best ROI so that the consultants can invest in them

2. Root Mean Squared Error - Measures the average magnitude of the errors between the actual and predicted values

6. LIBRARIES USED AND WHY WE USED THEM

- pandas - For data manipulation.
- numpy - For numerical operations such as square root. For example, to find RMSE, we find square root of MSE
- matplotlib and seaborn - For visualization
- scikit-learn - We've used this for tools such as train test split and perfomance metrics like mse and rmse.
- statsmodels - For time series operations such as plotting acf, pacf and time series models
- warnings - Efficient for filtering out warnings

Importing Libraries Needed

In [73]:
```
# Importing Libraries

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
import pmdarima as pm

from statsmodels.tsa.seasonal import seasonal_decompose
from statsmodels.tsa.stattools import adfuller
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
from sklearn.metrics import mean_squared_error as MSE
from pmdarima.model_selection import train_test_split
from statsmodels.tsa.statespace.sarimax import SARIMAXResults
from statsmodels.tsa.arima.model import ARIMA
import joblib
import warnings
warnings.filterwarnings('ignore')
warnings.simplefilter('ignore')
plt.style.use('ggplot')
```

In [74]:
```
#Loading the data

df = pd.read_csv("zillow_data.csv")
df.sample(5)
```

Out[74]:

	RegionID	RegionName	City	State	Metro	CountyName	SizeRank	1996-04	1996
6903	94979	85546	Safford	AZ	Safford	Graham	6904	61700.0	619
2963	97416	93705	Fresno	CA	Fresno	Fresno	2964	72300.0	721
1416	77984	46140	Greenfield	IN	Indianapolis	Hancock	1417	118600.0	1183
381	97748	94541	Hayward	CA	San Francisco	Alameda	382	161300.0	1611
3974	74278	37303	Athens	TN	Athens	McMinn	3975	52700.0	533

5 rows × 272 columns

As we can see above our data is in wide format.At some point we will change it to long format

In [75]:

```
# Investigating data type of each column

df.dtypes
```

Out[75]:

```
RegionID       int64
RegionName     int64
City          object
State         object
Metro         object
               ...
2017-12        int64
2018-01        int64
2018-02        int64
2018-03        int64
2018-04        int64
Length: 272, dtype: object
```

In [76]:

```
# Dropping years before 2008 as we stated the reason in the summary part

df.drop(columns = df.columns[7:148], inplace=True)
```

In [77]:

```
# Changing RegionName column to Zipcodes

df.rename(columns = {'RegionName': 'ZipCodes'}, inplace=True)
```

Calculating Return on Investment

In [78]:

```
"""
We've used the following formula:
ROI = Net Profit / Initial Cost of Investment
Net Profit - Years between 2018 and 2008
Initial investment - In the year 2008
"""
```

Out[78]:

```
" \nWe've used the following formula:\nROI = Net Profit / Initial Cost of Investment
\nNet Profit - Years between 2018 and 2008\nInitial investment - In the year 2008\n"
```

In [79]:

```
#Calculating the ROI(Return of Investment) for the last 10 years and the last 5 year

df['10_year_ROI(%)'] = round(((df['2018-04']-df['2008-01'])/df['2008-01'])*100,2)
df['5_year_ROI(%)'] = round(((df['2018-04']-df['2013-01'])/df['2013-01'])*100,2)
```

In [80]:

```
# Printing out df to see the new columns
df
```

Out[80]:

	RegionID	ZipCodes	City	State	Metro	CountyName	SizeRank	2008-01	2008-
0	84654	60657	Chicago	IL	Chicago	Cook	1	881700.0	87590
1	90668	75070	McKinney	TX	Dallas-Fort Worth	Collin	2	213900.0	21350
2	91982	77494	Katy	TX	Houston	Harris	3	254100.0	25270
3	84616	60614	Chicago	IL	Chicago	Cook	4	1163000.0	115700
4	93144	79936	El Paso	TX	El Paso	El Paso	5	131200.0	13030
...	...	...	...	...	...	...	...	...	
14718	58333	1338	Ashfield	MA	Greenfield Town	Franklin	14719	197300.0	19790
14719	59107	3293	Woodstock	NH	Claremont	Grafton	14720	229000.0	22840
14720	75672	40404	Berea	KY	Richmond	Madison	14721	104400.0	10360
14721	93733	81225	Mount Crested Butte	CO	NaN	Gunnison	14722	641200.0	64080
14722	95851	89155	Mesquite	NV	Las Vegas	Clark	14723	369400.0	35960

14723 rows × 133 columns

In [81]:

```
# Function to get the highest and lowest zip codes/ROI

def get_zip_ROI(dataframe):
    first_5_ROIs_10yrs = dataframe.sort_values('10_year_ROI(%)',ascending=False)[['Z
    last_5_ROIs_10yrs = dataframe.sort_values('10_year_ROI(%)',ascending=True)[['Zip

    first_5_ROIs_5yrs = dataframe.sort_values('10_year_ROI(%)',ascending=True)[['Zip
    last_5_ROIs_5_yrs = dataframe.sort_values('10_year_ROI(%)',ascending=True)[['Zip


    return first_5_ROIs_10yrs, last_5_ROIs_10yrs, first_5_ROIs_5yrs, last_5_ROIs_5_y
```

In [82]:

```
# Calling the ROI function ,passing in the zipcodes as parameters and assigning the

first_5_ROIs_10yrs, last_5_ROIs_10yrs, first_5_ROIs_5yrs, last_5_ROIs_5yrs = get_zip

print(f"10 years Top 5 ROIs: {first_5_ROIs_10yrs}")

print('\n')

print(f"10 years Bottom 5 ROIs: {last_5_ROIs_10yrs}")

print('\n')

print(f"5 years Top 5 ROIs: {first_5_ROIs_5yrs}")

print('\n')

print(f"5 years Bottom 5 ROIS: {last_5_ROIs_5yrs}")
```

```
10 years Top 5 ROIs:        ZipCodes  10_year_ROI(%)
6563       15201          176.01
```

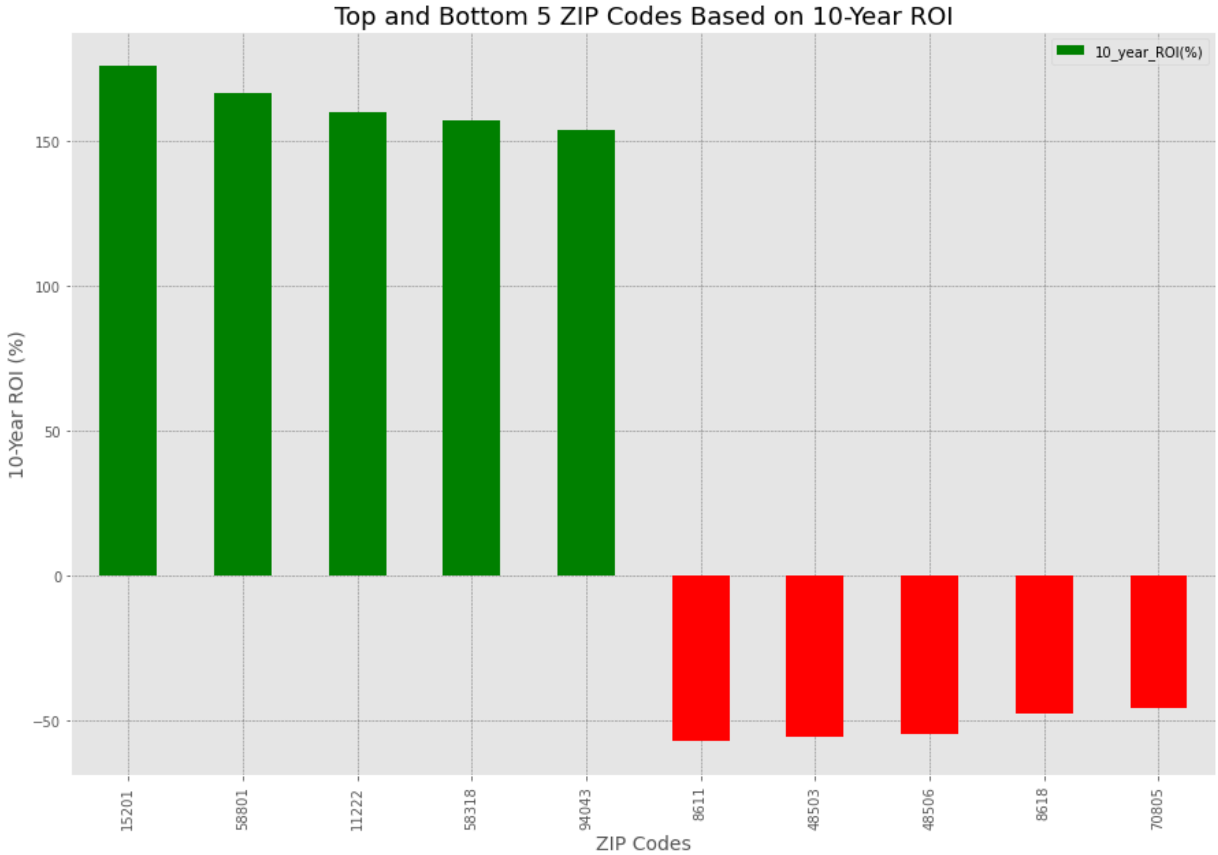
```
2452      58801          166.82
1155      11222          160.02
11167     58318          157.32
2580      94043          153.97


10 years Bottom 5 ROIs:       ZipCodes  10_year_ROI(%)
5278       8611         -56.98
4381      48503         -55.64
4149      48506         -54.74
2417       8618         -47.41
3894      70805         -45.79


5 years Top 5 ROIs:       ZipCodes  5_year_ROI(%)
5278       8611         20.47
4381      48503         35.71
4149      48506         20.79
2417       8618         14.71
3894      70805          0.71


5 years Bottom 5 ROIS:       ZipCodes  5_year_ROI(%)
5278       8611         20.47
4381      48503         35.71
4149      48506         20.79
2417       8618         14.71
3894      70805          0.71
```

Plotting the top 5 and bottom 5 zip codes for the last 10 years

In [83]:

```python
# Combine the first and last 5 ROIs
selected_ROIs_10yrs = first_5_ROIs_10yrs.append(last_5_ROIs_10yrs)

# Create a bar graph
plt.figure()
selected_ROIs_10yrs.plot(x = 'ZipCodes', y = '10_year_ROI(%)', kind='bar', figsize=(

# Add dark grid background
plt.grid(color='black', linestyle='--', linewidth=0.5, alpha=0.5)
plt.title('Top and Bottom 5 ZIP Codes Based on 10-Year ROI',fontsize=18)
plt.xlabel('ZIP Codes',fontsize=14)
plt.ylabel('10-Year ROI (%)',fontsize=14)
plt.show()
```

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



Plotting the top 5 and bottom 5 zip codes for the last 5 years

In [84]:
```
def get_zip_ROI(dataframe):
    first_5_ROIs = dataframe.sort_values('5_year_ROI(%)',ascending=False)[['ZipCodes
    last_5_ROIs = dataframe.sort_values('5_year_ROI(%)',ascending=True)[['ZipCodes',

    return first_5_ROIs, last_5_ROIs
```

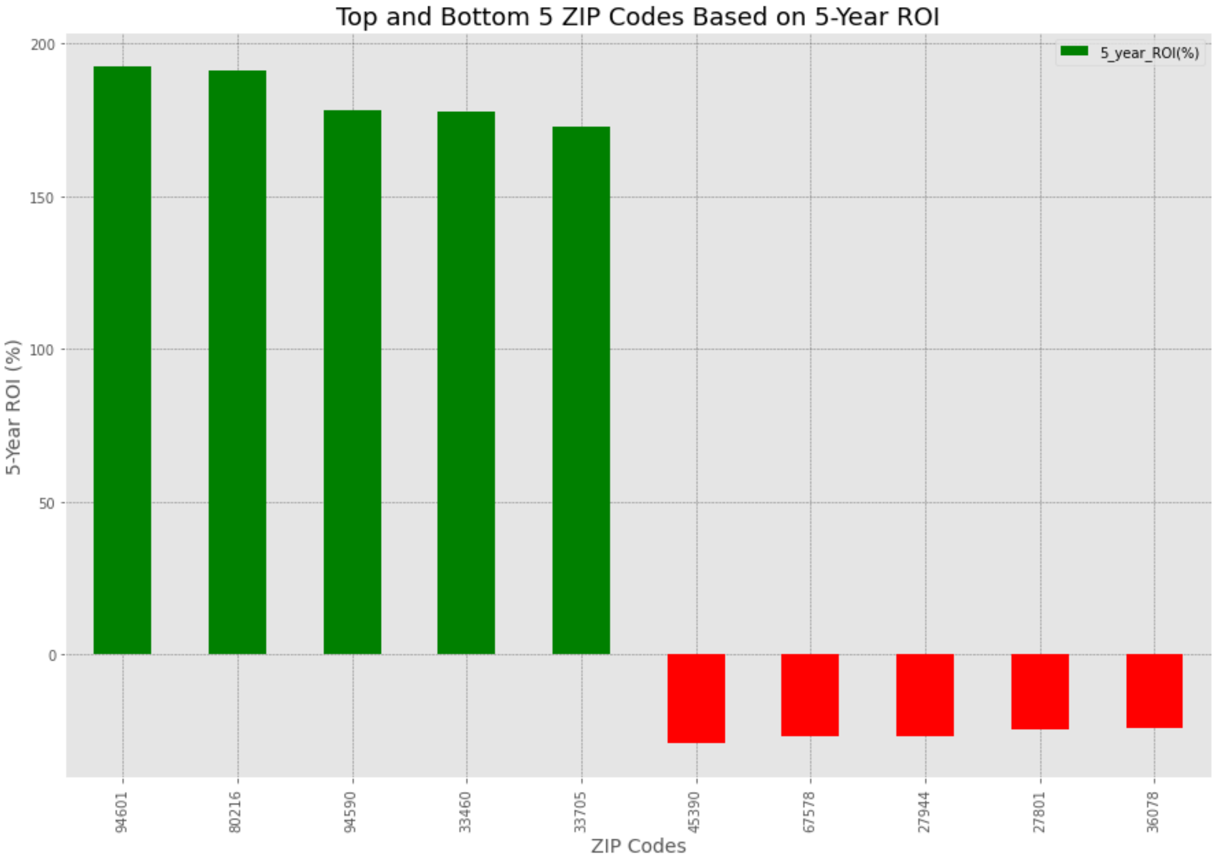
In [85]:
```
first_5_ROIs_5yrs, last_5_ROIs_5yrs = get_zip_ROI(df)

print("Top 5 ROIs:")
print(first_5_ROIs_5yrs)

print('\n')
print("\nBottom 5 ROIs:")
print(last_5_ROIs_5yrs)
```

```
Top 5 ROIs:
      ZipCodes  5_year_ROI(%)
1477     94601         192.57
7302     80216         191.18
1239     94590         178.39
2627     33460         177.84
2661     33705         172.77



Bottom 5 ROIs:
       ZipCodes  5_year_ROI(%)
12436     45390         -29.15
14300     67578         -26.88
7435      27944         -26.72
5690      27801         -24.66
6881      36078         -24.08
```

In [86]:
```
# Visualize the ROIs

selected_ROIs_5yrs = first_5_ROIs_5yrs.append(last_5_ROIs_5yrs)
```

```
# Bar graph for the top 5 zip codes
plt.figure()
selected_ROIs_5yrs.plot(x='ZipCodes', y='5_year_ROI(%)', figsize=(15,10), kind='bar'

# Add dark grid background
plt.grid(color='black', linestyle='--', linewidth=0.5, alpha=0.5)
plt.title('Top and Bottom 5 ZIP Codes Based on 5-Year ROI', fontsize=18)
plt.xlabel('ZIP Codes', fontsize=14)
plt.ylabel('5-Year ROI (%)', fontsize=14)
plt.show()
```

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



In [87]:
```
#Conversion to str
df['10_year_ROI(%)'] = df['10_year_ROI(%)'].astype('str')
```

Using a function to reshape data to long format

In [88]:
```
#Melting data
def reshape_data_to_long_format(dataframe):
    # Melting the df to long format
    melted_df = pd.melt(
        dataframe,
        id_vars=['ZipCodes', 'RegionID', 'SizeRank', 'City', 'State', 'Metro', 'Coun
        var_name='Date',
        value_name='Price'
    )

    # Filter out rows with invalid 'Date' values (e.g., '10_year_ROI', '5_year_ROI')
    invalid_date_conditions = melted_df['Date'].str.contains('10_year_ROI|5_year_ROI
    melted_df = melted_df[~invalid_date_conditions]

    # Convert the 'Date' column to datetime format
    melted_df['Date'] = pd.to_datetime(melted_df['Date'], infer_datetime_format=True

    # Sort by Date
```

```
    melted_df = melted_df.sort_values(by=['Date'])

    return melted_df
```

In [89]:
```
# Calling the function

data = reshape_data_to_long_format(df)
data.tail()
```

Out[89]:

	ZipCodes	RegionID	SizeRank	City	State	Metro	CountyName	Date	Price
1815840	22556	67309	4912	Stafford	VA	Washington	Stafford	2018-04-01	332700
1815841	33761	72802	4913	Clearwater	FL	Tampa	Pinellas	2018-04-01	334500
1815842	38242	74730	4914	Paris	TN	Paris	Henry	2018-04-01	90900
1815844	70785	88803	4916	Walker	LA	Baton Rouge	Livingston	2018-04-01	158400
1825651	89155	95851	14723	Mesquite	NV	Las Vegas	Clark	2018-04-01	357200

In [90]:
```
# Setting the Date column to index

data.set_index('Date', inplace=True)
```

In [91]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 1825652 entries, 2008-01-01 to 2018-04-01
Data columns (total 8 columns):
 #   Column      Dtype 
---  ------      ----- 
 0   ZipCodes    int64 
 1   RegionID    int64 
 2   SizeRank    int64 
 3   City        object
 4   State       object
 5   Metro       object
 6   CountyName  object
 7   Price       object
dtypes: int64(3), object(5)
memory usage: 125.4+ MB
```

Filling columns with missing values

In [92]:
```
# Dealing with missing values

data.isna().sum()
```

Out[92]:
```
ZipCodes           0
RegionID           0
SizeRank           0
City               0
State              0
Metro         129332
CountyName         0
Price          26266
dtype: int64
```

In [93]:
```
# Inspecting Metro

data[data['Metro'].isnull()].sample(10)
```

Out[93]:

Date	ZipCodes	RegionID	SizeRank	City	State	Metro	CountyName	Price
2016-02-01	38344	74776	8595	Huntingdon	TN	NaN	Carroll	72700
2009-06-01	59047	83904	6660	Livingston	MT	NaN	Park	178100
2018-02-01	74523	90434	9808	Antlers	OK	NaN	Pushmataha	44700
2013-07-01	67661	87710	12089	Phillipsburg	KS	NaN	Phillips	58700
2008-04-01	32696	72150	7453	Williston	FL	NaN	Levy	135200
2015-09-01	38860	75041	10141	Okolona	MS	NaN	Chickasaw	68100
2014-06-01	47634	78707	13484	Richland	IN	NaN	Spencer	80400
2008-07-01	59858	84226	13694	Philipsburg	MT	NaN	Granite	NaN
2009-03-01	63468	86076	12934	Shelbina	MO	NaN	Shelby	NaN
2017-06-01	67735	87727	9966	Goodland	KS	NaN	Sherman	102800

We can see that some rows of the Metro column are Not A Number, meaning null.

In [94]:
```
# Insepcting Price

print(data[data['Price'].isnull()].sample(10))
```

```
            ZipCodes  RegionID  SizeRank         City State          Metro  \
Date
2009-09-01     28526     70005     13042        Dover    NC       New Bern
2013-12-01     70431     88587     10454         Bush    LA    New Orleans
2011-10-01     74857     90561      8747       Norman    OK  Oklahoma City
2008-02-01     85607     94992      6912      Douglas    AZ   Sierra Vista
2011-11-01     89512     95940      4224         Reno    NV           Reno
2011-02-01     43450     76690     12188  Pemberville    OH         Toledo
2011-09-01     30168     70936      4325     Austell    GA        Atlanta
2012-12-01     43013     76460     14624     Hartford    OH       Columbus
2009-10-01     47564     78670     14371      Otwell    IN         Jasper
2012-09-01      2116     58630      3331       Boston    MA         Boston

                CountyName  Price
Date
2009-09-01          Craven    NaN
2013-12-01  Saint Tammany    NaN
2011-10-01       Cleveland    NaN
2008-02-01         Cochise    NaN
2011-11-01          Washoe    NaN
2011-02-01            Wood    NaN
2011-09-01            Cobb    NaN
2012-12-01         Licking    NaN
2009-10-01            Pike    NaN
2012-09-01         Suffolk    NaN
```

There are missing values in Price as seen above

In [95]:
```
# Filing the missig values in Price with '0'

data['Price'].fillna(value = 0, inplace=True)
```

In [96]:
```
# Confirming if there are missing values in price
data.isnull().sum()
```

Out[96]:
```
ZipCodes           0
RegionID           0
SizeRank           0
City               0
State              0
Metro         129332
CountyName         0
Price              0
dtype: int64
```

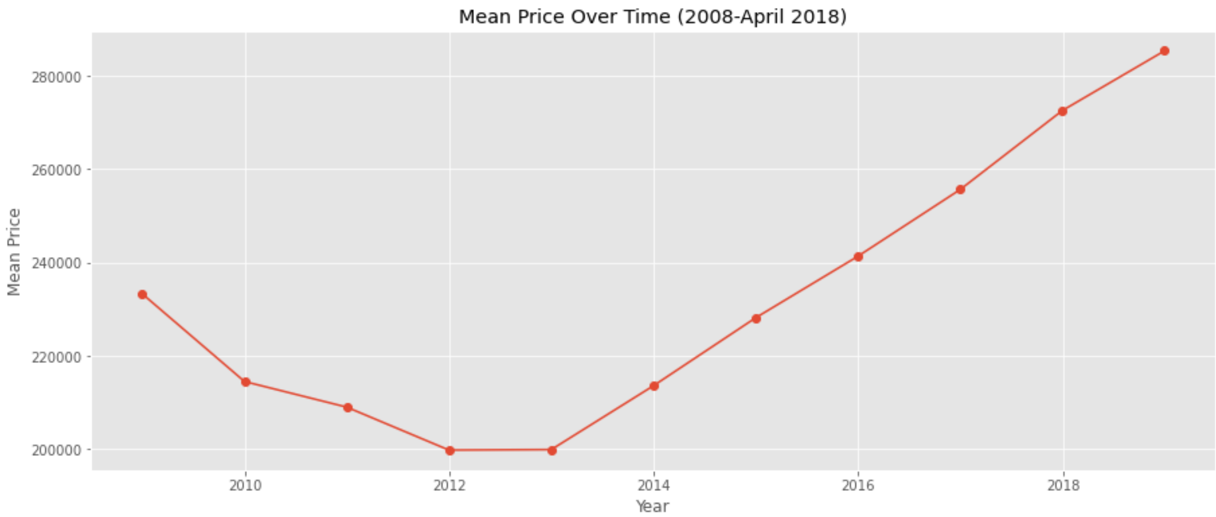
In [97]:
```
#Filling Metro Nan with Unknown

data['Metro'].fillna('Unknown', inplace=True)
```

In [98]:
```
# Confirming if there are missing values in Metro

data.isnull().sum()
```

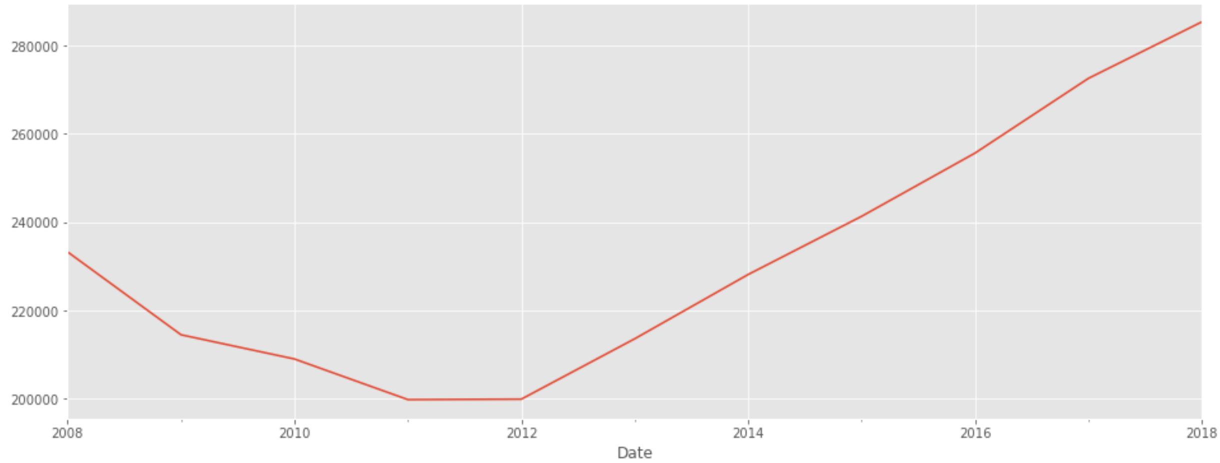
Out[98]:
```
ZipCodes      0
RegionID      0
SizeRank      0
City          0
State         0
Metro         0
CountyName    0
Price         0
dtype: int64
```

Plotting a visual to display the mean price over time

In [99]:
```
mean_price_by_year = data['Price'].resample('Y').mean()

# Plotting
plt.figure(figsize=(15, 6))
plt.plot(mean_price_by_year.index, mean_price_by_year.values, marker='o', linestyle=
plt.title('Mean Price Over Time (2008-April 2018)')
plt.xlabel('Year')
plt.ylabel('Mean Price')
plt.grid(True)
plt.show()
```



In [100…
```
mean_price_by_year.plot(figsize = (16,6));
```



In [101…

```
# Top Five Zipcode Analysis for the past five years (2013 to 2018)

first_5_ROIs_5yrs
```

Out[101…

	ZipCodes	5_year_ROI(%)
1477	94601	192.57
7302	80216	191.18
1239	94590	178.39
2627	33460	177.84
2661	33705	172.77

In [102…

```
"""
This line of code only selects the price value where the zip code value is among the
"""

data = data.loc[data['ZipCodes'].isin(first_5_ROIs_5yrs['ZipCodes'])][['ZipCodes', '
data
```

Out[102…

Date	ZipCodes	Price
2008-01-01	33705	150000.0
2008-01-01	33460	203800.0
2008-01-01	94601	420200.0
2008-01-01	94590	340000.0
2008-01-01	80216	0.0
...	...	...
2018-04-01	33705	177300.0
2018-04-01	33460	215600.0
2018-04-01	94601	566700.0
2018-04-01	94590	376100.0
2018-04-01	80216	267300.0

620 rows × 2 columns

In [103…

```
"""
This line of code creates a pivot table where the icolumns are zip codes, and each c
"""

data = data.pivot_table(index = 'Date', columns = 'ZipCodes', values = 'Price')
data
```

Out[103…

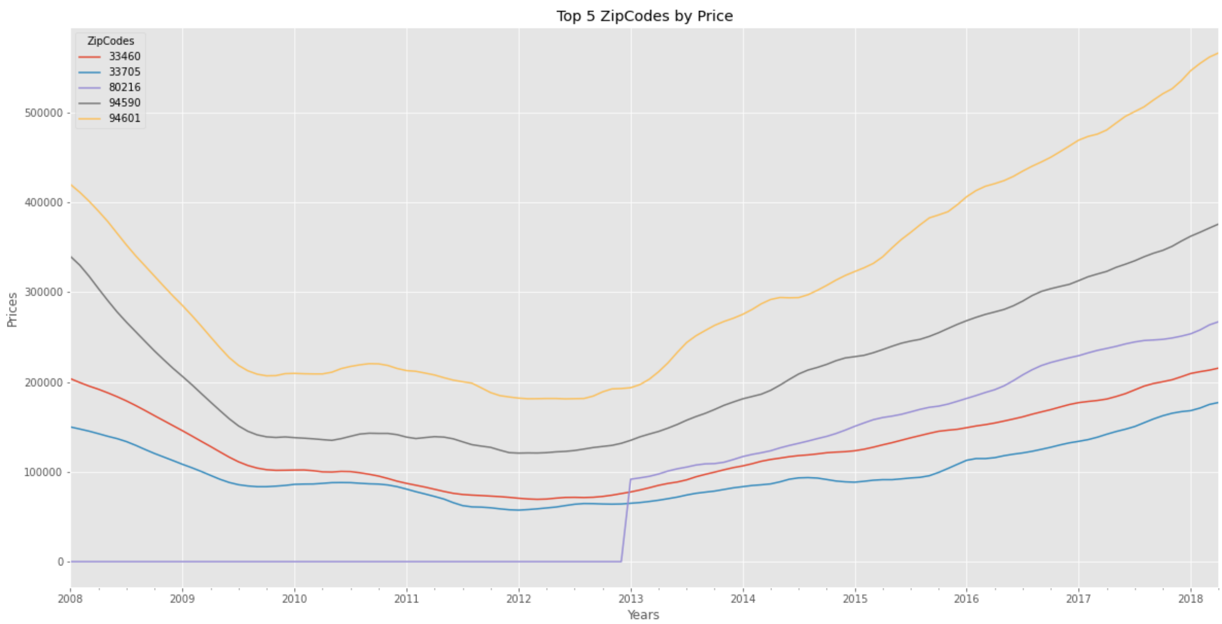
ZipCodes	33460	33705	80216	94590	94601
Date					
2008-01-01	203800.0	150000.0	0.0	340000.0	420200.0
2008-02-01	199500.0	147700.0	0.0	330200.0	411400.0
2008-03-01	195500.0	145300.0	0.0	317800.0	401400.0
2008-04-01	192000.0	142500.0	0.0	304100.0	390400.0
2008-05-01	188000.0	139600.0	0.0	290800.0	378800.0
...	...	...	...	...	...
2017-12-01	206000.0	167100.0	251200.0	357100.0	535800.0
2018-01-01	209600.0	168200.0	253800.0	362500.0	546900.0
2018-02-01	211600.0	171100.0	258100.0	366900.0	555000.0
2018-03-01	213300.0	175100.0	263700.0	371600.0	562000.0
2018-04-01	215600.0	177300.0	267300.0	376100.0	566700.0

124 rows × 5 columns

Plotting ZipCodes by Price

In [104…

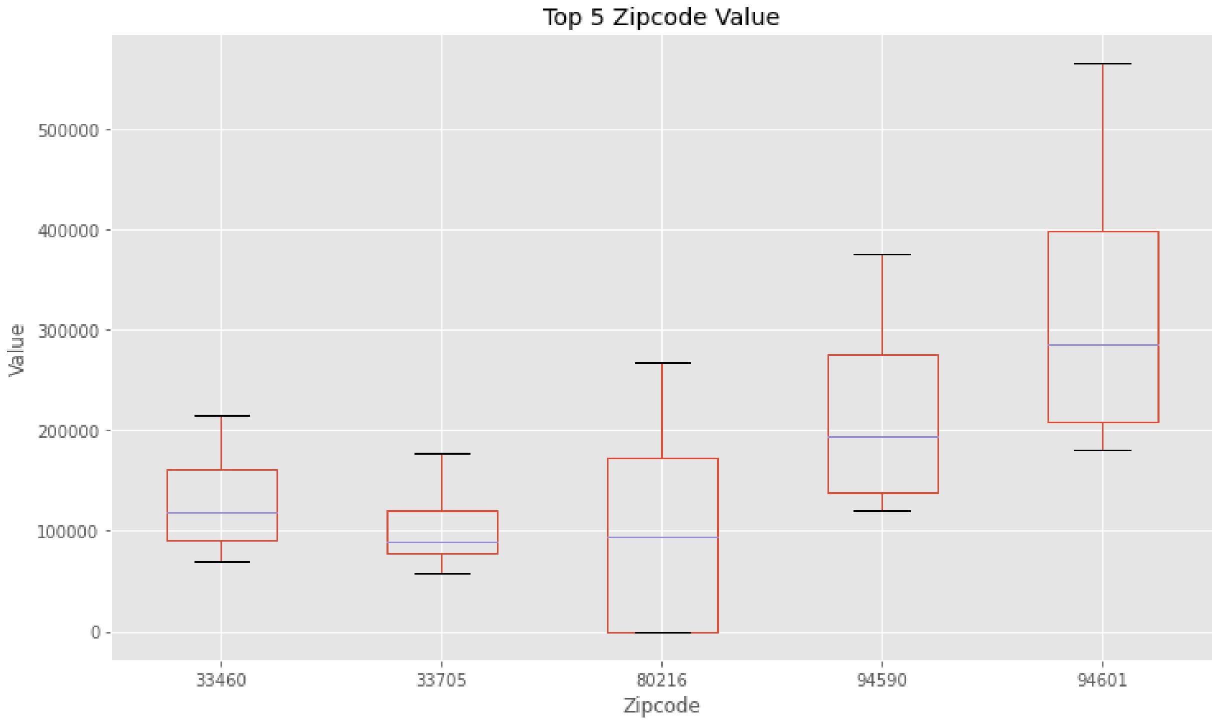
```
data.plot(figsize = (20,10))
plt.xlabel('Years')
plt.ylabel('Prices')
plt.title('Top 5 ZipCodes by Price')
plt.grid(True);
```



Generating a Box Plot for top 5 zipcodes

In [105…

```
box = data.boxplot(figsize = (12,7,));

box.plot()

# Title
plt.title('Top 5 Zipcode Value')
# xlabel
plt.xlabel('Zipcode')
# ylabel
plt.ylabel('Value');
```



Interpretation: We fail to reject the null hypothesis - the time series is non-stationary.

Checking for Stationarity

We've created a function to perform dickey fuller test for each zip code to check for stationarity

Null Hypothesis - The time series is not stationary. We're going to use the p-value and the significance level to either reject the null hypothesis or fail to reject the null hypothesis

In [106…

```
#Dickey Fuller Test

def adfullertestresults(column_name):
    print ('Results of Dickey-Fuller Test: \n')
    dftest = adfuller(data[column_name])

    # Extract and display test results
    dfoutput = pd.Series(dftest[0:4], index=['Test Statistic', 'p-value', '#Lags Use

    for key,value in dftest[4].items():
        dfoutput['Critical Value (%s)'%key] = value
    print(dfoutput)
```

In [107…

```
adfullertestresults(94590)
```

```
Results of Dickey-Fuller Test:

Test Statistic                 -0.501920
p-value                         0.891641
```

```
#Lags Used                       3.000000
Number of Observations Used    120.000000
Critical Value (1%)             -3.486056
Critical Value (5%)             -2.885943
Critical Value (10%)            -2.579785
dtype: float64
```

For zip code 94590, the p-value is greater than the significance level(0.05), so we **fail to reject the null hypothesis** Hence , the time series is **not stationary**

In [108…

```
adfullertestresults(94601)
```

```
Results of Dickey-Fuller Test:

Test Statistic                  -0.455479
p-value                          0.900416
#Lags Used                       5.000000
Number of Observations Used    118.000000
Critical Value (1%)             -3.487022
Critical Value (5%)             -2.886363
Critical Value (10%)            -2.580009
dtype: float64
```

For zip code 94601, the p-value is greater than the significance level(0.05), so we **fail to reject the null hypothesis** Hence , the time series is **not stationary**

In [109…

```
adfullertestresults(80216)
```

```
Results of Dickey-Fuller Test:

Test Statistic                   0.855678
p-value                          0.992484
#Lags Used                       0.000000
Number of Observations Used    123.000000
Critical Value (1%)             -3.484667
Critical Value (5%)             -2.885340
Critical Value (10%)            -2.579463
dtype: float64
```

For the above zip code we **fail to reject the null hypothesis**. Thus , the time series is **not stationary**

In [110…

```
adfullertestresults(33705)
```

```
Results of Dickey-Fuller Test:

Test Statistic                   0.201004
p-value                          0.972318
#Lags Used                      13.000000
Number of Observations Used    110.000000
Critical Value (1%)             -3.491245
Critical Value (5%)             -2.888195
Critical Value (10%)            -2.580988
dtype: float64
```

For zip code 33705 ,We also **fail to reject the null hypothesis**. Hence , the time series is **not stationary**

In [111…

```
adfullertestresults(33460)
```

```
Results of Dickey-Fuller Test:

Test Statistic                  -1.159221
p-value                          0.690887
#Lags Used                       5.000000
Number of Observations Used    118.000000
Critical Value (1%)             -3.487022
Critical Value (5%)             -2.886363
```

```
Critical Value (10%)           -2.580009
dtype: float64
```

For 33460 - **Fail to reject the null hypothesis**. Hence **not statinary**

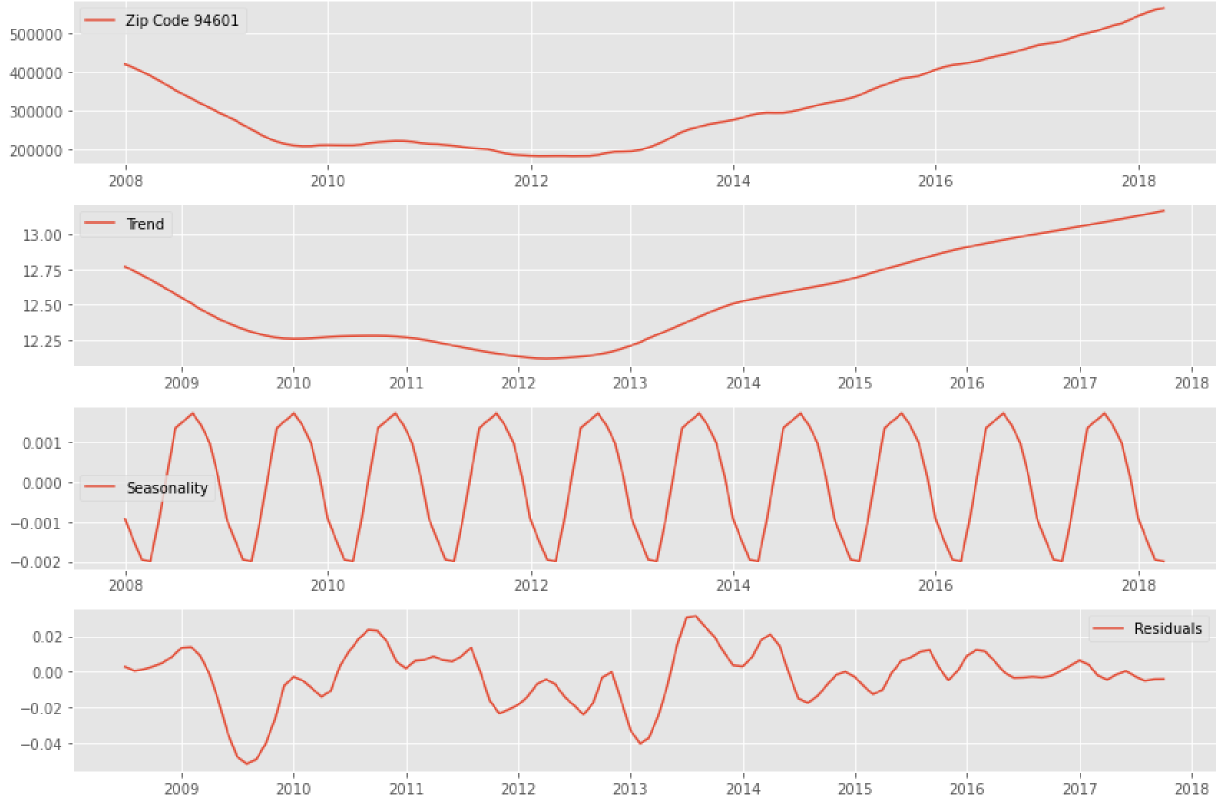
Checking for trends, seasonality and residuals using seasonal decompose

In [112…

```
# Function to plot decomposition

def plot_seasonal_decomposition(data, zipcode):

    # Assuming the DataFrame index needs to be converted to datetime
    data.index = pd.to_datetime(data.index)

    # Perform seasonal decomposition
    result = seasonal_decompose(np.log(data[zipcode]), model='additive')

    # Extract the trend, seasonal, and residual components
    trend = result.trend
    seasonal = result.seasonal
    residual = result.resid

    # Plot the components
    plt.figure(figsize=(12, 8))

    plt.subplot(411)
    plt.plot(data[zipcode], label=f'Zip Code {zipcode}')
    plt.legend(loc='best')

    plt.subplot(412)
    plt.plot(trend, label='Trend')
    plt.legend(loc='best')

    plt.subplot(413)
    plt.plot(seasonal, label='Seasonality')
    plt.legend(loc='best')

    plt.subplot(414)
    plt.plot(residual, label='Residuals')
    plt.legend(loc='best')

    plt.tight_layout()
    plt.show()
```

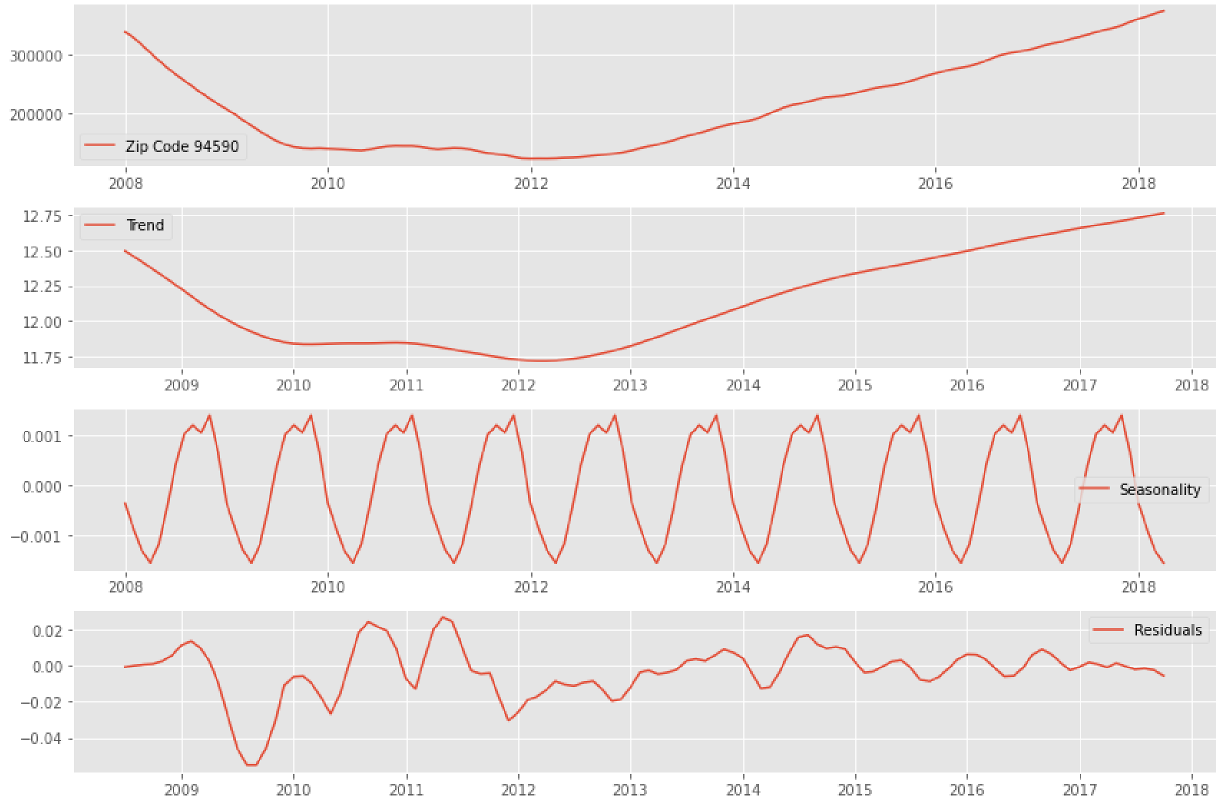
In [113…

```
zip_code_to_plot = 94601
plot_seasonal_decomposition(data, zip_code_to_plot)
```



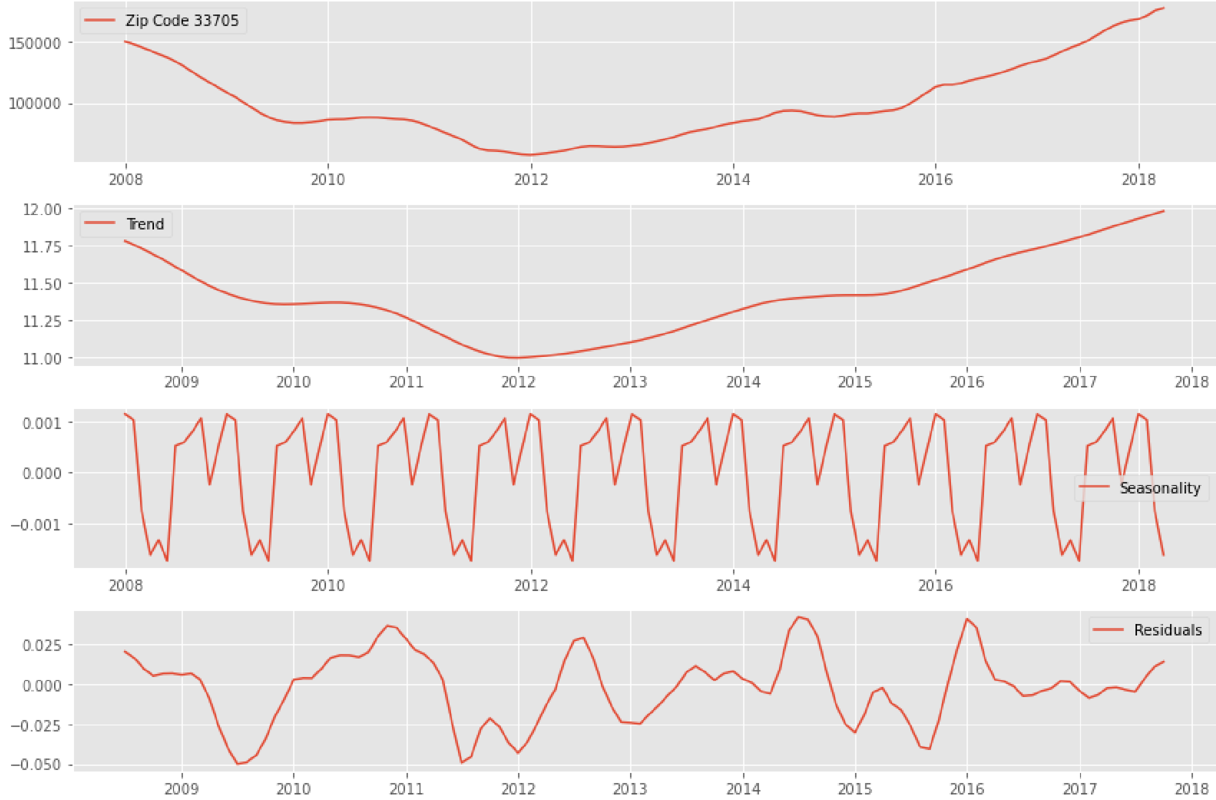
In [114…

```
zip_code_to_plot = 94590
plot_seasonal_decomposition(data, zip_code_to_plot)
```



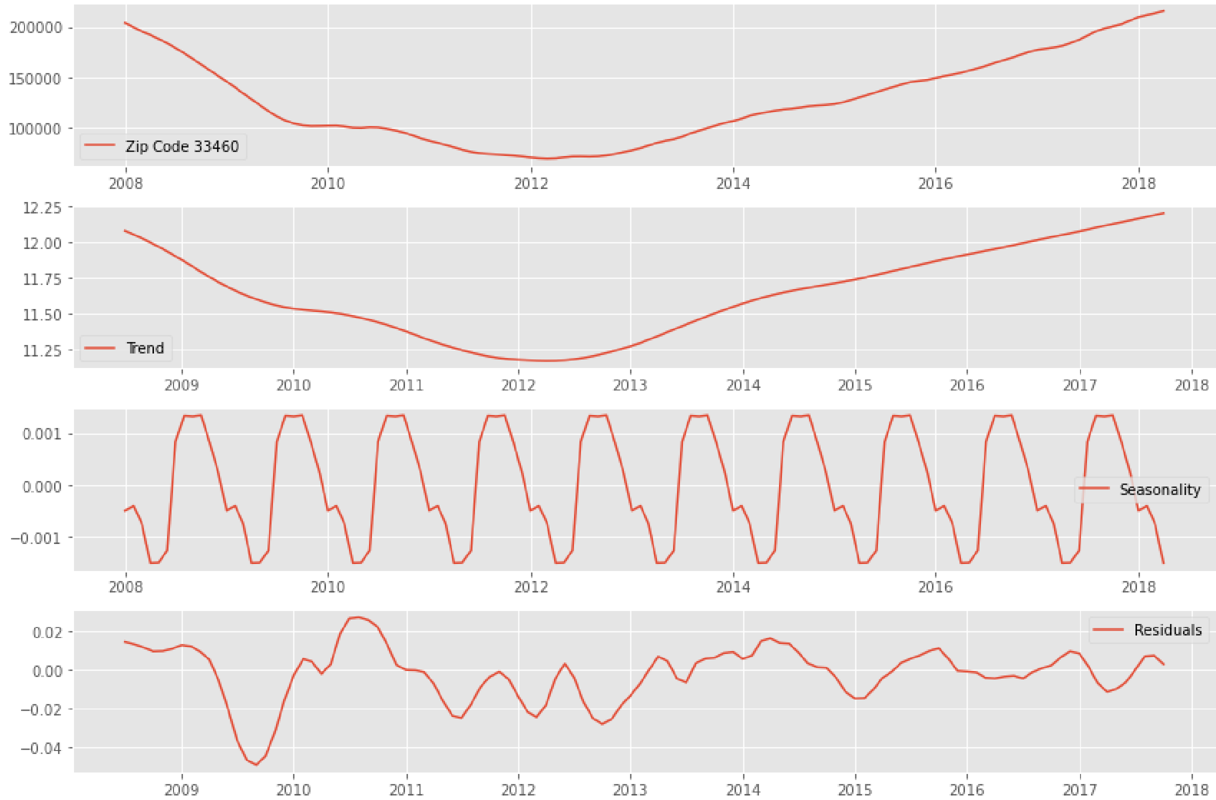
In [115…

```
zip_code_to_plot = 33705
plot_seasonal_decomposition(data, zip_code_to_plot)
```



In [116...

```
zip_code_to_plot = 33460
plot_seasonal_decomposition(data, zip_code_to_plot)
```



Performing Differencing to remove trends from each zip code

In [117...

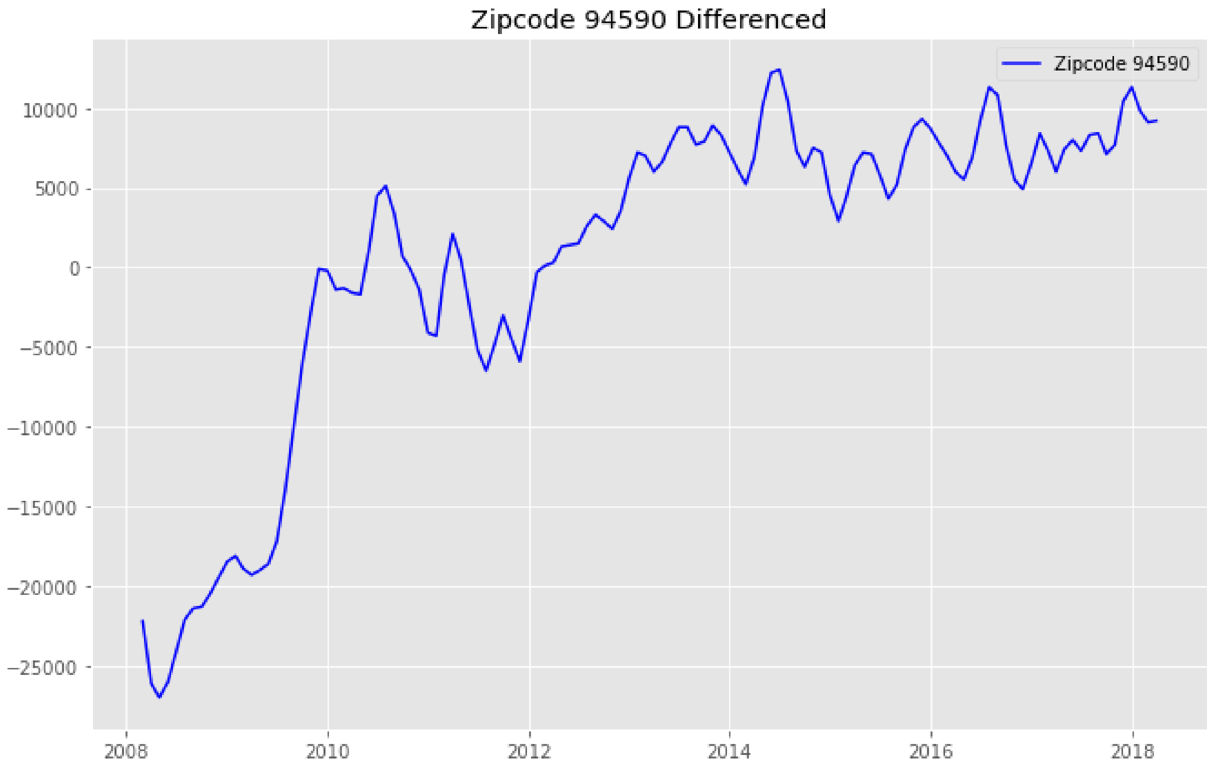
```
# Writing a function to perform differencing

def differencing_function(zipcode, data,periods):
    diff_data = data[zipcode].diff(periods=periods).dropna()  # Drop NaN values intr

    # Plotting differenced zipcodes
```

```
    fig, ax = plt.subplots(figsize=(11, 7))
    ax.plot(diff_data, color='blue', label=f'Zipcode {zipcode}')
    ax.legend(loc='best')
    ax.set_title(f'Zipcode {zipcode} Differenced')
    plt.show(block=False)

    return diff_data

# Function to print results
# ADF Test to check for stationarity
def adfuller_results(differenced_data):
    adf_result = adfuller(differenced_data)
    print("ADF Statistic:", adf_result[0])
    print("p-value:", adf_result[1])
    print("Critical Values:", adf_result[4])

    #Check for stationarity
    if adf_result[1] <= 0.05:
        print("The time series is likely stationary.")
    else:
        print("The time series is likely non-stationary.")
```

Calling the functions

In [118…

```
# Differencing for 94590, we'll use 2 periods

zip_code_to_difference = 94590
differenced_data_94590 = differencing_function(zip_code_to_difference,data,2)

print(adfuller_results(differenced_data_94590))
```

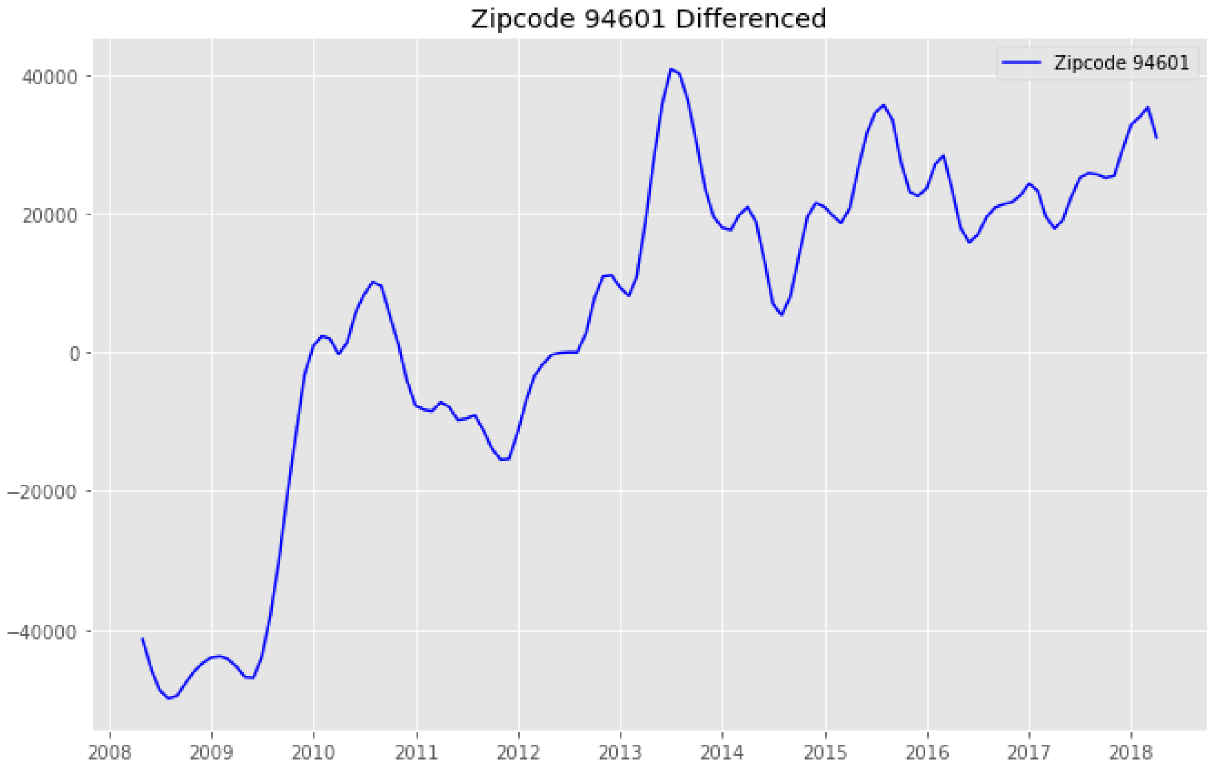



```
ADF Statistic: -2.9179016434479075
p-value: 0.043305532241847626
Critical Values: {'1%': -3.4885349695076844, '5%': -2.887019521656941, '10%': -2.5803
597920604915}
The time series is likely stationary.
None
```

In [119…

```
# Differencing for 94601, we'll use 4 periods
```

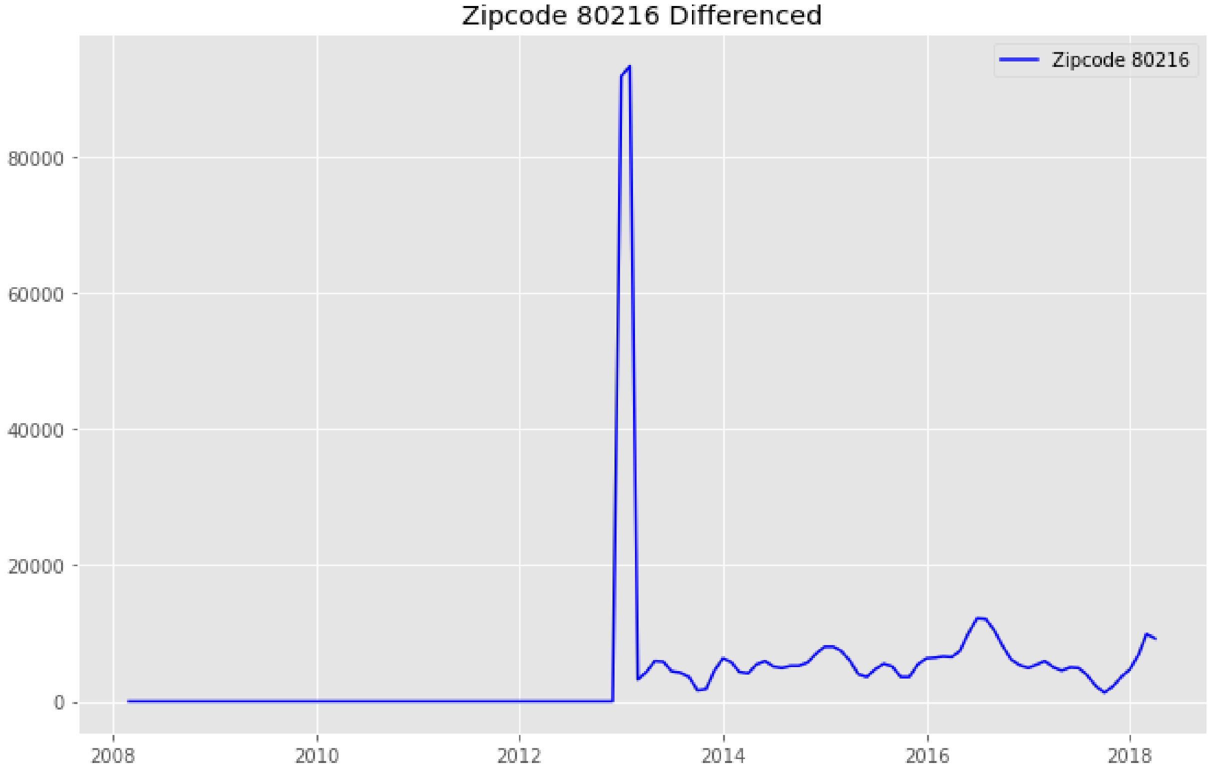
```
zip_code_to_difference = 94601
differenced_data_94601 = differencing_function(zip_code_to_difference,data,4)

# Adfuller results
print(adfuller_results(differenced_data_94601))
```




```
ADF Statistic: -2.898636019267401
p-value: 0.04550683993732019
Critical Values: {'1%': -3.4924012594942333, '5%': -2.8886968193364835, '10%': -2.581
2552709190673}
The time series is likely stationary.
None
```

In [120…

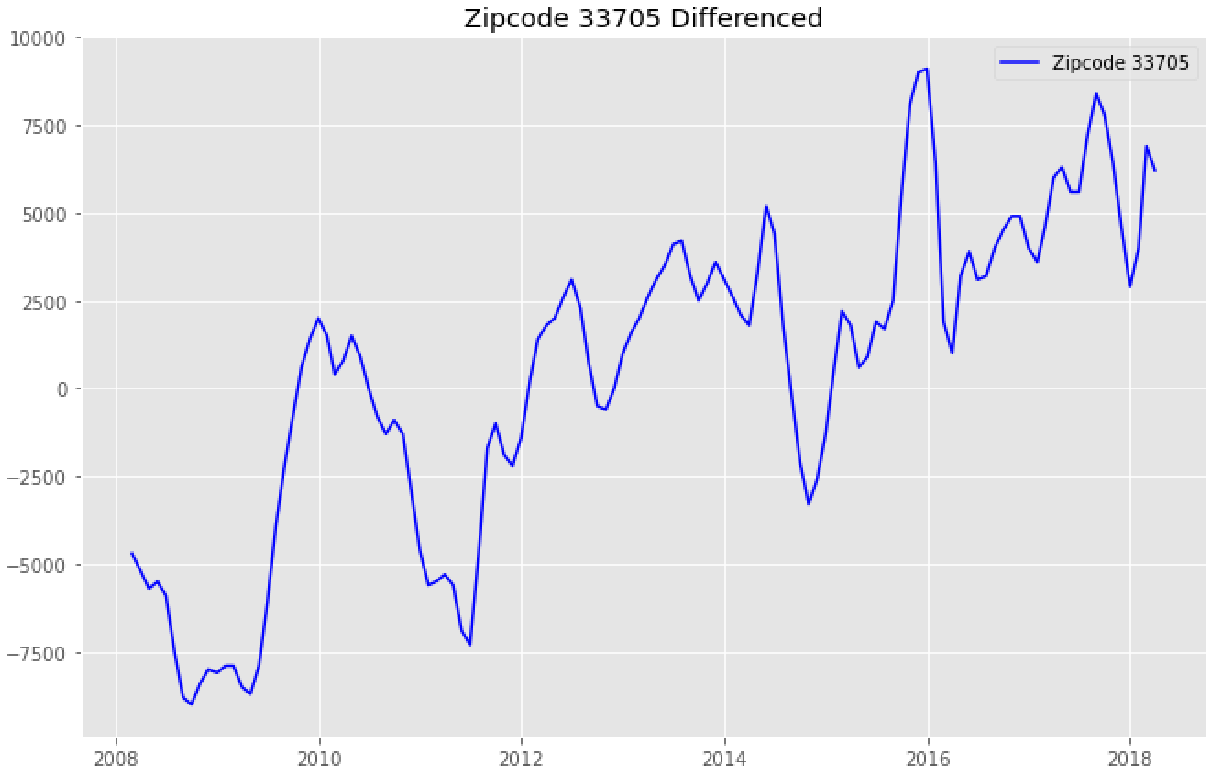
```
# Differencing for 80216,we'll use 2 periods

zip_code_to_difference = 80216
differenced_data_80216 = differencing_function(zip_code_to_difference,data,2)

# Adfuller results
print(adfuller_results(differenced_data_80216))
```




```
ADF Statistic: -4.0933861117205455
p-value: 0.0009931940007361381
Critical Values: {'1%': -3.4880216384691867, '5%': -2.8867966864160075, '10%': -2.580
2408234244947}
The time series is likely stationary.
None
```

In [121…

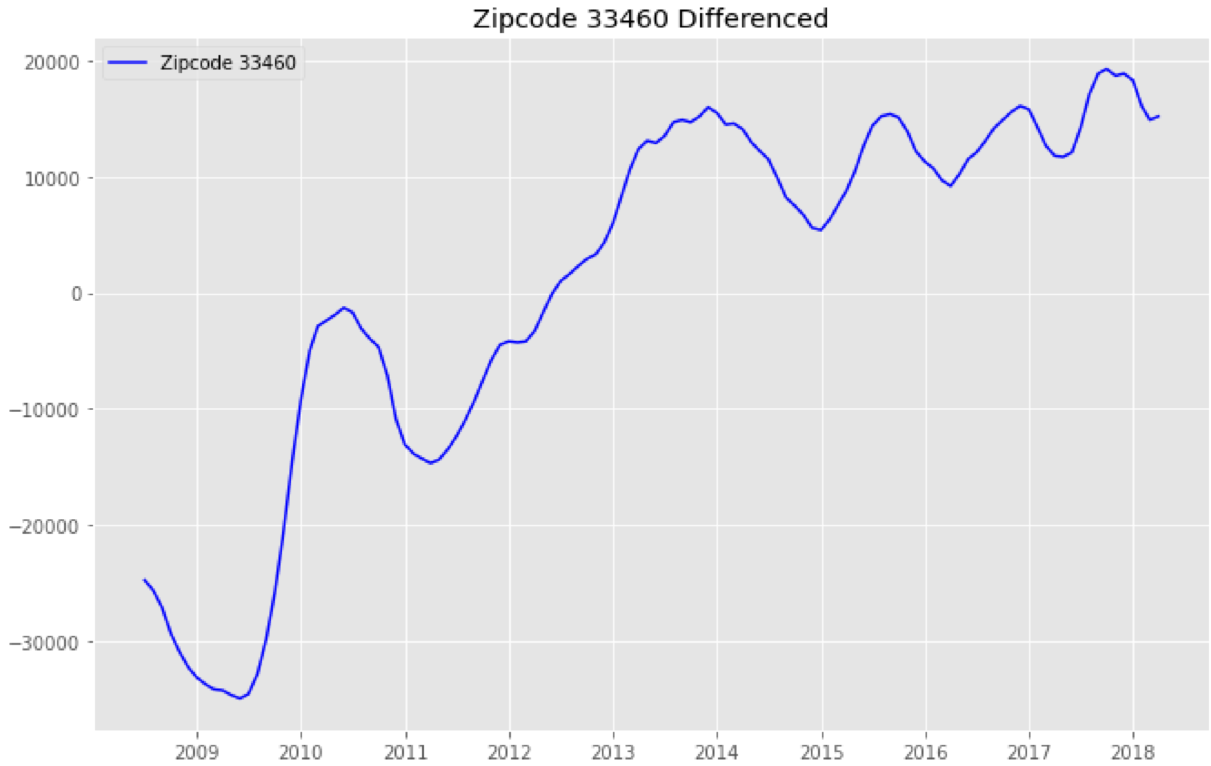
```python
# Differencing for 33705, we'll use 2 periods

zip_code_to_difference = 33705
differenced_data_33705 = differencing_function(zip_code_to_difference,data,2)

# Adfuller results
print(adfuller_results(differenced_data_33705))
```



```
ADF Statistic: -2.1672894973852217
p-value: 0.2183308967768836
Critical Values: {'1%': -3.49181775886872, '5%': -2.8884437992971588, '10%': -2.58112
01893779985}
The time series is likely non-stationary.
None
```

In [122…

```
# Differencing for 33460, we'll use 6 periods

zip_code_to_difference = 33460
differenced_data_33460 = differencing_function(zip_code_to_difference,data,6)

# Adfuller results
print(adfuller_results(differenced_data_33460))
```



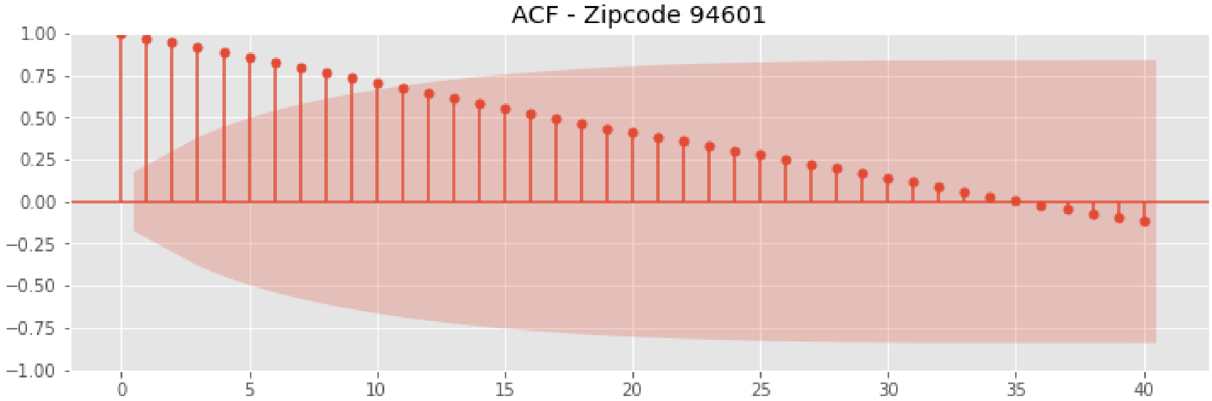

```
ADF Statistic: -3.0896344669963973
p-value: 0.027329855134247013
Critical Values: {'1%': -3.492995948509562, '5%': -2.888954648057252, '10%': -2.58139
291903223}
The time series is likely stationary.
None
```

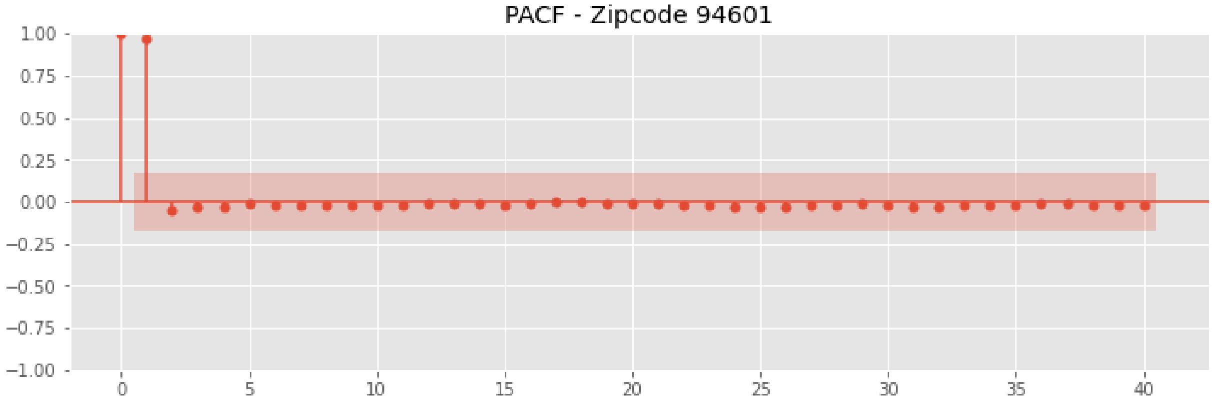
MODELLING

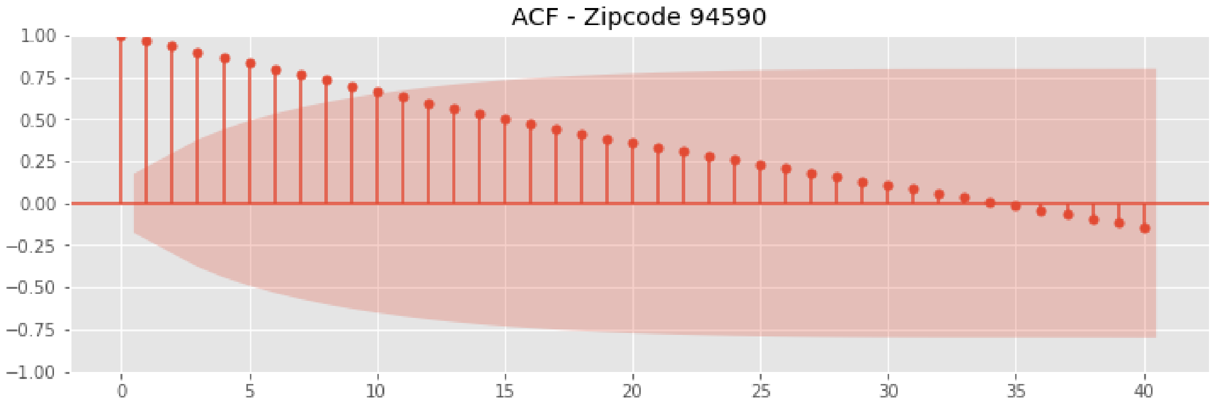
Plotting the pacf and acf plots of each zip code

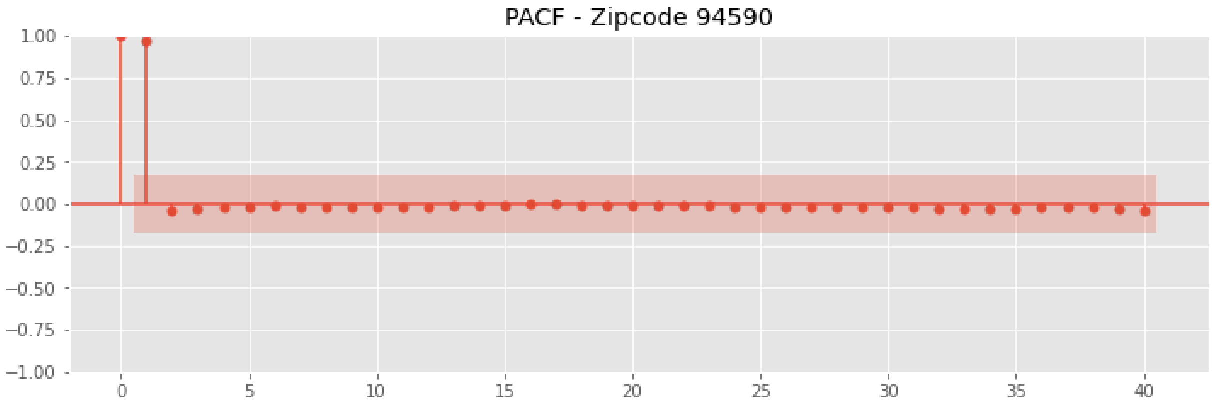
In [123…

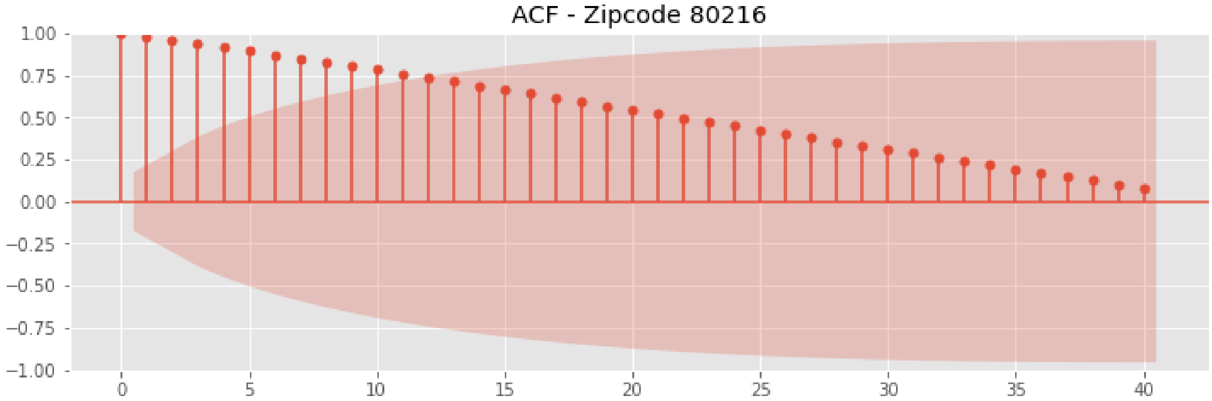
```
# ZipCodes to plot
#33705 will not be used since differencing did not work for this zipcode

zip_codes_to_plot = [94601,94590,80216,33460]


# Plot ACF and PACF for each zip code
for zipcode in zip_codes_to_plot:
    fig, (ax1, ax2) = plt.subplots(2, 1, figsize=(12, 8))
    plot_acf(data[zipcode], lags=40, ax=ax1, title=f'ACF - Zipcode {zipcode}')
    plot_pacf(data[zipcode], lags=40, ax=ax2, title=f'PACF - Zipcode {zipcode}')
    plt.show()
```

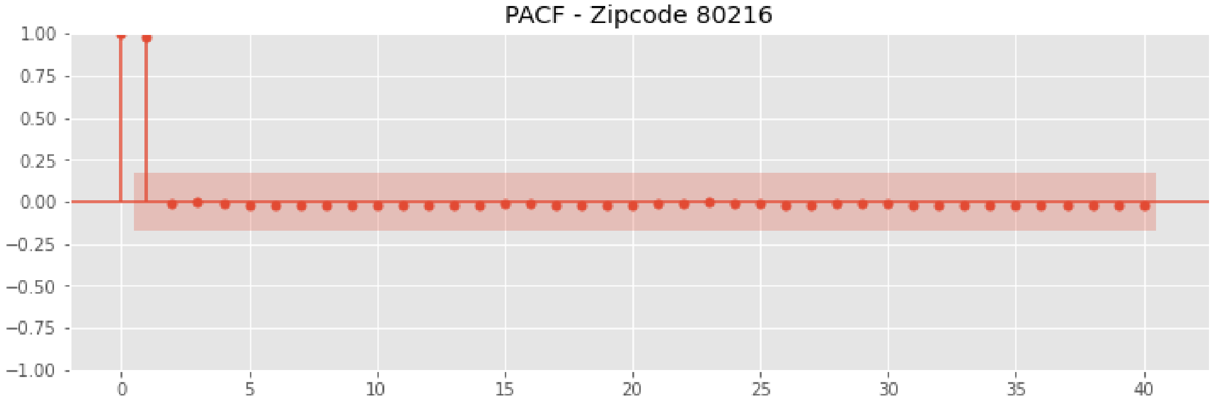

ACF - Zipcode 94601
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00
0
5
10
15
20
25
30
35
40

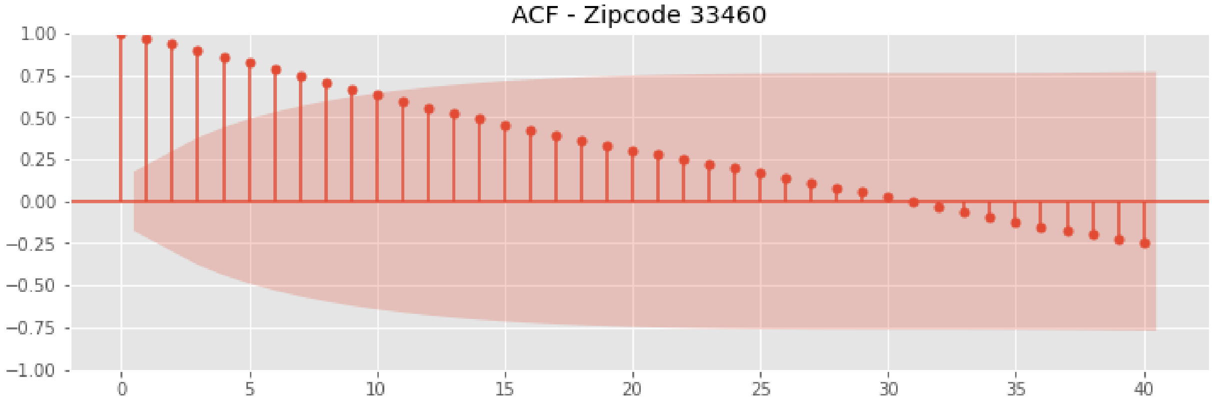

PACF - Zipcode 94601
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00
0
5
10
15
20
25
30
35
40

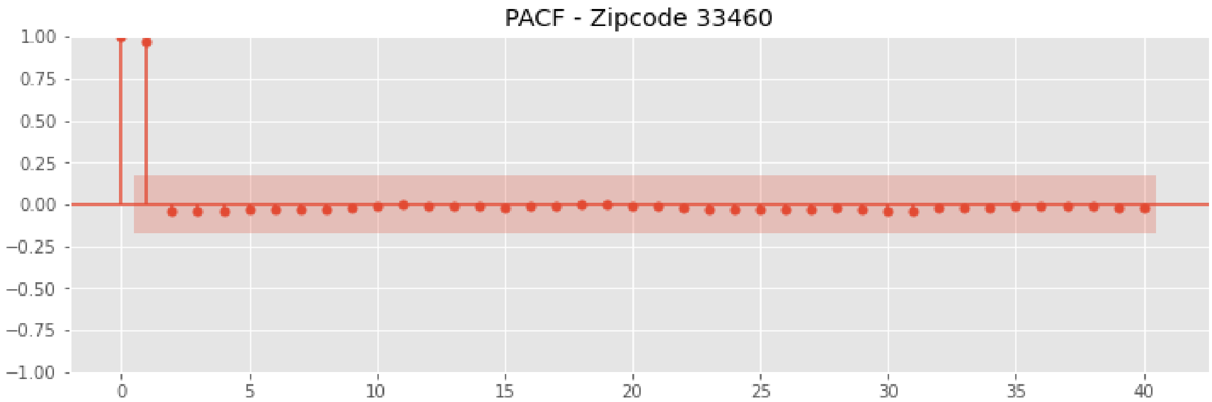

ACF - Zipcode 94590
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00
0
5
10
15
20
25
30
35
40


PACF - Zipcode 94590
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00
0
5
10
15
20
25
30
35
40









Performing a train test split. We've used train data from 2008 to 2016 and test data from 2018 onwards

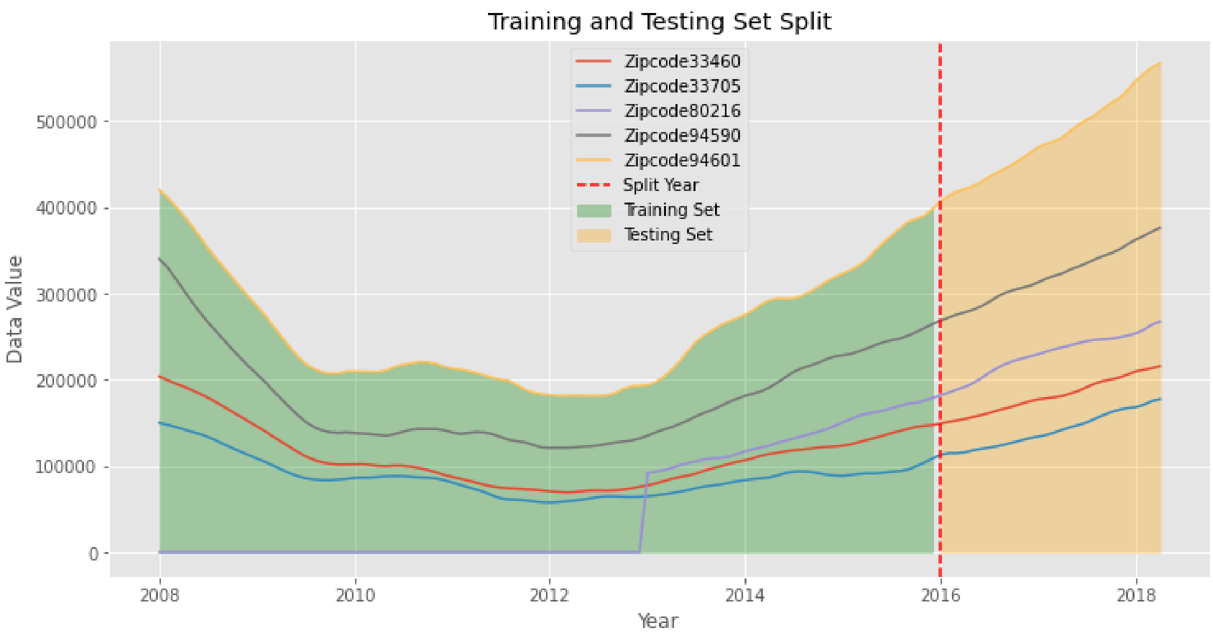
In [124…

```
# Define the split year

split_year = '2016-01'

# Split the data into training and testing sets
train = data[:split_year]
test = data[split_year:]
```

Plotting the train test split

In [125…

```
import matplotlib.pyplot as plt

# Plot the entire time series
plt.figure(figsize=(12, 6))
for zipcode in data.columns:
    plt.plot(data.index, data[zipcode], label = f'Zipcode{zipcode}')

# Add a vertical line to indicate the split point
plt.axvline(x=split_year, linestyle='--', color='red', label='Split Year')

# Highlight the training and testing sets
plt.fill_between(data.index, data[94601], where=(data.index < split_year), color='gr
plt.fill_between(data.index, data[94601], where=(data.index >= split_year), color='o

# Customize plot
plt.title('Training and Testing Set Split')
plt.xlabel('Year')
plt.ylabel('Data Value')
plt.legend()
plt.show()
```



1. ARIMA MODEL - BASELINE

In [126…

```
# ARIMA with an order of 2,1,2

endog_column = 94601
arima = ARIMA(data[endog_column], order=(2, 1, 2)).fit()

# predict and get summary
arima_pred = arima.predict(start= '2016-01-01')
arima.summary()
```

Out[126…

SARIMAX Results

Dep. Variable:	94601	**No. Observations:**	124
Model:	ARIMA(2, 1, 2)	**Log Likelihood**	-2285.394
Date:	Sat, 10 Feb 2024	**AIC**	4580.787
Time:	21:51:57	**BIC**	4594.848
Sample:	01-01-2008	**HQIC**	4586.499

	- 04-01-2018		
Covariance Type:	opg		

	coef	std err	z	P>|z|	[0.025	0.975]
ar.L1	0.0014	0.002	0.818	0.413	-0.002	0.005
ar.L2	0.9986	0.002	620.060	0.000	0.995	1.002
ma.L1	-0.0025	0.007	-0.373	0.709	-0.016	0.011
ma.L2	-0.9975	0.006	-159.772	0.000	-1.010	-0.985
sigma2	1.986e+06	6.36e-09	3.12e+14	0.000	1.99e+06	1.99e+06

Ljung-Box (L1) (Q):	113.65	**Jarque-Bera (JB):**	13.45
Prob(Q):	0.00	**Prob(JB):**	0.00
Heteroskedasticity (H):	0.68	**Skew:**	-0.80
Prob(H) (two-sided):	0.22	**Kurtosis:**	2.77

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).
[2] Covariance matrix is singular or near-singular, with condition number 2.46e+29. Standard errors may be unstable.

We'll use the AIC(Akaike Information Criterion) which gives us the goodness of fit.We have a value fo 4580 which is high. For the next models, we'll try to reduce that value for better fitting

In [127…
```
#RMSE for ARIMA
rmse = np.sqrt(MSE(test[94601],arima_pred))
rmse
```

Out[127…
```
6198.915793335476
```

We have an rmse of 6198 which is also high. We'll work towards reducing this value in the next models

The auto_arima function does a search and returns the best order to use.

2. FACEBOOK PROPHET

In [128…
```
# Importing FbPhrophet
from fbprophet import Prophet
```

In [129…
```
# Create and fit the Prophet model

prophet_data = data[94601].reset_index().rename(columns={data[94601].reset_index().c

fb_model = Prophet(changepoint_prior_scale=0.03,seasonality_prior_scale=12.0,)

fb_model.fit(prophet_data)
```

```
INFO:fbprophet:Disabling weekly seasonality. Run prophet with weekly_seasonality=True
to override this.
INFO:fbprophet:Disabling daily seasonality. Run prophet with daily_seasonality=True t
o override this.
```

Out[129… <fbprophet.forecaster.Prophet at 0x18c24c650d0>

In [130…
```
# Predicting values

future_data = fb_model.make_future_dataframe(periods=0, freq = 'm')
prophet_pred = fb_model.predict(future_data)
test_predictions = prophet_pred['yhat'][-len(test):]
```

Calculating rmse for the Facebook Prophet

In [131…
```
from sklearn.metrics import mean_squared_error as MSE

rmse_prophet= np.sqrt(MSE(test[94601],test_predictions))
rmse_prophet
```

Out[131… 4545.076833005094

The rmse for the Facebook Prophet is lower than the ARIMA Model but it is still high. It performs better than ARIMA but we're implementing SARIMAX as our 3rd model to see if there will be an improvement.

2. SARIMAX

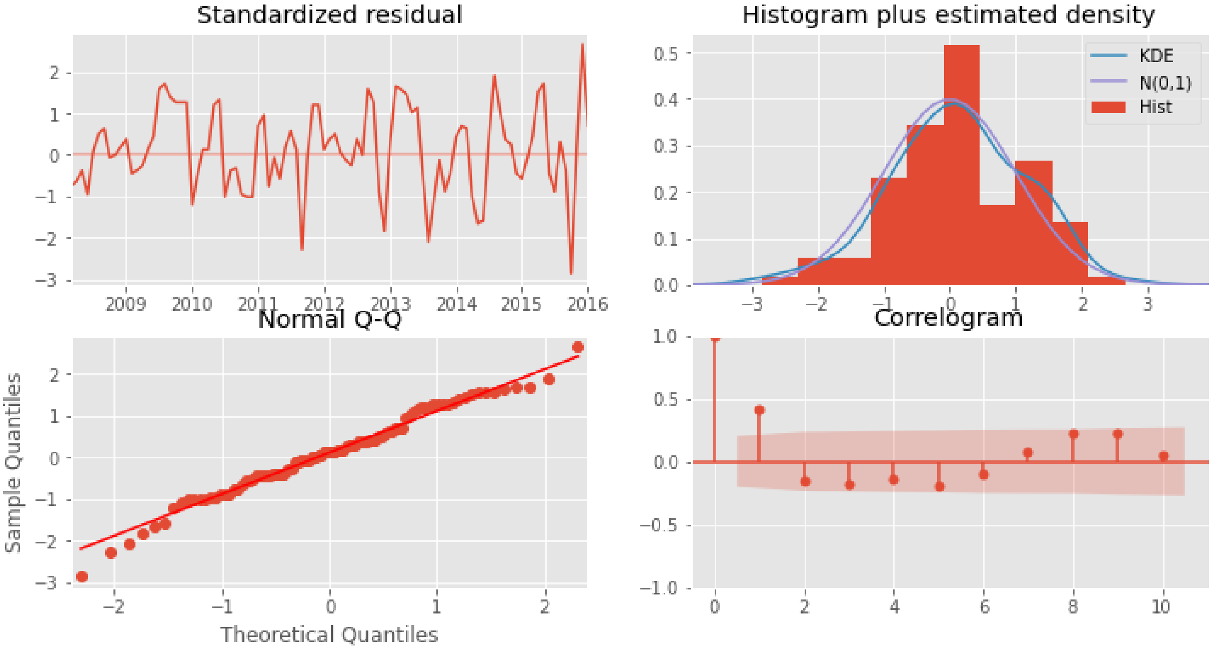
AUTO-ARIMA

In [57]:
```
# Running the auto_arima

auto_model = pm.auto_arima(y=train[94601], start_p=0, start_q=0, max_p=5,
                           max_q=5, start_P=0, start_Q=0, max_P=5,
                           max_Q=5, m=12, max_order=None,
                           trace=True)
```

```
Performing stepwise search to minimize aic
 ARIMA(0,2,0)(0,0,0)[12]             : AIC=1672.199, Time=0.03 sec
 ARIMA(1,2,0)(1,0,0)[12]             : AIC=1676.727, Time=0.12 sec
 ARIMA(0,2,1)(0,0,1)[12]             : AIC=1679.708, Time=0.06 sec
 ARIMA(0,2,0)(1,0,0)[12]             : AIC=1674.024, Time=0.08 sec
 ARIMA(0,2,0)(0,0,1)[12]             : AIC=1674.589, Time=0.05 sec
 ARIMA(0,2,0)(1,0,1)[12]             : AIC=1676.004, Time=0.05 sec
 ARIMA(1,2,0)(0,0,0)[12]             : AIC=1674.940, Time=0.05 sec
 ARIMA(0,2,1)(0,0,0)[12]             : AIC=1677.936, Time=0.03 sec
 ARIMA(1,2,1)(0,0,0)[12]             : AIC=1679.120, Time=0.08 sec
 ARIMA(0,2,0)(0,0,0)[12] intercept   : AIC=1672.876, Time=0.02 sec

Best model:  ARIMA(0,2,0)(0,0,0)[12]
Total fit time: 0.623 seconds
```

From the auto arima function, we've got the best order as (0,2,0) and the seasonal order which we will use for the SARIMAX model.

In [58]:
```
auto_model.plot_diagnostics(figsize=(12,6));
```



From the plot diagnostics:

Standardized Residuals: A time series plot of the standardized residuals to check for randomness and constant variance.

Histogram plus Kernel Density Estimate (KDE): This plot shows the distribution of the standardized residuals along with a kernel density estimate. It helps to assess whether the residuals are normally distributed.

Normal Q-Q (Quantile-Quantile) Plot: This plot compares the quantiles of the standardized residuals against the quantiles of a normal distribution. Deviations from the diagonal line suggest departures from normality.Our plot shows normality

Correlogram (ACF - AutoCorrelation Function): This plot displays the autocorrelation of the standardized residuals at different lags to identify any remaining autocorrelation.

Fitting SARIMAX Model

In [59]:

```
# Import SARIMAX model from statsmodels
from statsmodels.tsa.statespace.sarimax import SARIMAX

model = SARIMAX(endog=data[94601], order=(0,2,0), seasonal_order=(0, 0, 0, 12),
                enforce_stationarity=True, enforce_invertibility=True,)
results = model.fit(method='powell')
results.summary()
```

```
Optimization terminated successfully.
         Current function value: 8.670914
         Iterations: 1
         Function evaluations: 11
```

Out[59]:

SARIMAX Results

Dep. Variable:	94601	**No. Observations:**	124
Model:	SARIMAX(0, 2, 0)	**Log Likelihood**	-1075.193
Date:	Sat, 10 Feb 2024	**AIC**	2152.387
Time:	21:36:50	**BIC**	2155.191
Sample:	01-01-2008	**HQIC**	2153.526

- 04-01-2018

Covariance Type:	opg

	coef	std err	z	P>|z|	[0.025	0.975]
sigma2	2.645e+06	3.6e+05	7.353	0.000	1.94e+06	3.35e+06

Ljung-Box (L1) (Q):	16.24	**Jarque-Bera (JB):**	0.40
Prob(Q):	0.00	**Prob(JB):**	0.82
Heteroskedasticity (H):	2.04	**Skew:**	-0.10
Prob(H) (two-sided):	0.02	**Kurtosis:**	2.80

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

From the SARIMAX model, the AIC value is 2152 which is a drop from the ARIMA model. Hence our SARIMAX gives a good fit.

In [60]:

```
# Getting predicted value to use in finding rmse
y_predicted = results.predict(start = '2016-01-01', end = '2018-04-01')
y_predicted
```

Out[60]:

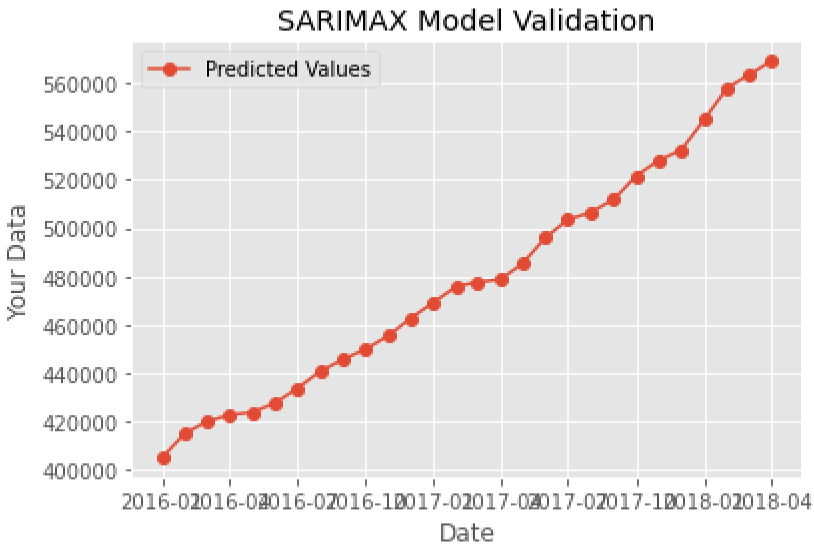
```
2016-01-01    405400.0
2016-02-01    415400.0
2016-03-01    420100.0
2016-04-01    422900.0
2016-05-01    423900.0
2016-06-01    427800.0
2016-07-01    433800.0
2016-08-01    440900.0
2016-09-01    445800.0
2016-10-01    450000.0
2016-11-01    455600.0
2016-12-01    462800.0
2017-01-01    469400.0
2017-02-01    476000.0
2017-03-01    477700.0
2017-04-01    478800.0
2017-05-01    485400.0
2017-06-01    496200.0
2017-07-01    503500.0
2017-08-01    506600.0
2017-09-01    511900.0
2017-10-01    521600.0
2017-11-01    528100.0
2017-12-01    532300.0
2018-01-01    544900.0
2018-02-01    558000.0
2018-03-01    563100.0
2018-04-01    569000.0
Freq: MS, Name: predicted_mean, dtype: float64
```

Plotting the predicted values

In [62]:

```
plt.plot(y_predicted.index, y_predicted, label='Predicted Values', marker='o')

# Adding labels and title
plt.xlabel('Date')
plt.ylabel('Your Data')
```

```
plt.title('SARIMAX Model Validation')
plt.legend()
plt.show()
```



In [63]:
```
#Mean squared error

from sklearn.metrics import mean_squared_error as MSE

rmse_sarimax = np.sqrt(MSE(test[94601],y_predicted))
rmse_sarimax
```

Out[63]: 1729.264914019001

Our RMSE score has also reduced, meaning that our SARIMAX model performs well.

In [67]:
```
# Saving sarimax model results

results.save('sarimax_model.pkl')
```

In [66]:
```
from statsmodels.tsa.statespace.sarimax import SARIMAXResults

# Load the saved SARIMAX model
loaded_model = SARIMAXResults.load('sarimax_model.pkl')
loaded_model
```

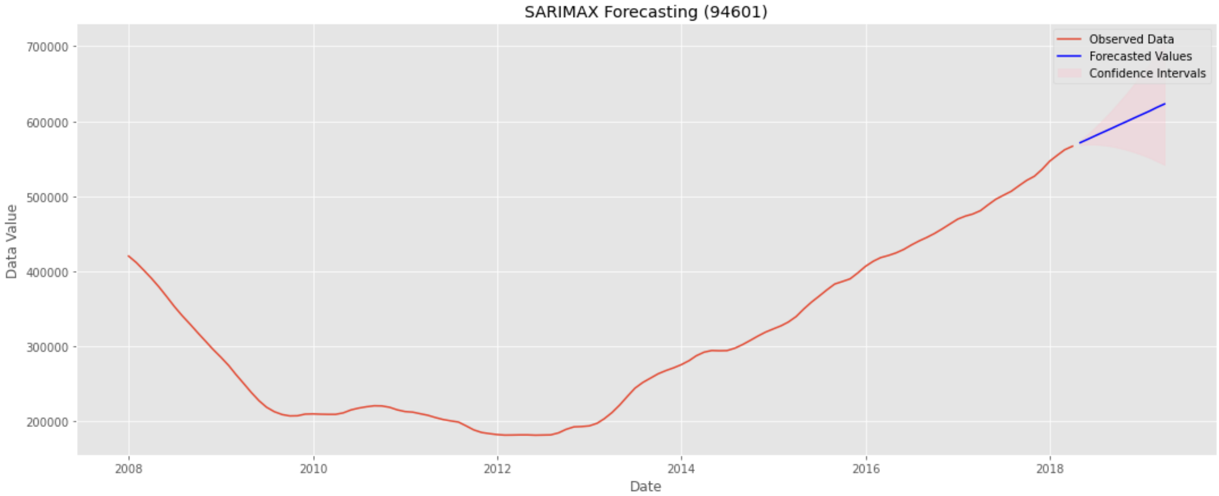
Out[66]: <statsmodels.tsa.statespace.sarimax.SARIMAXResultsWrapper at 0x18c24b4a6d0>

Forecasting

In [133…
```
forecast_periods= 12
```

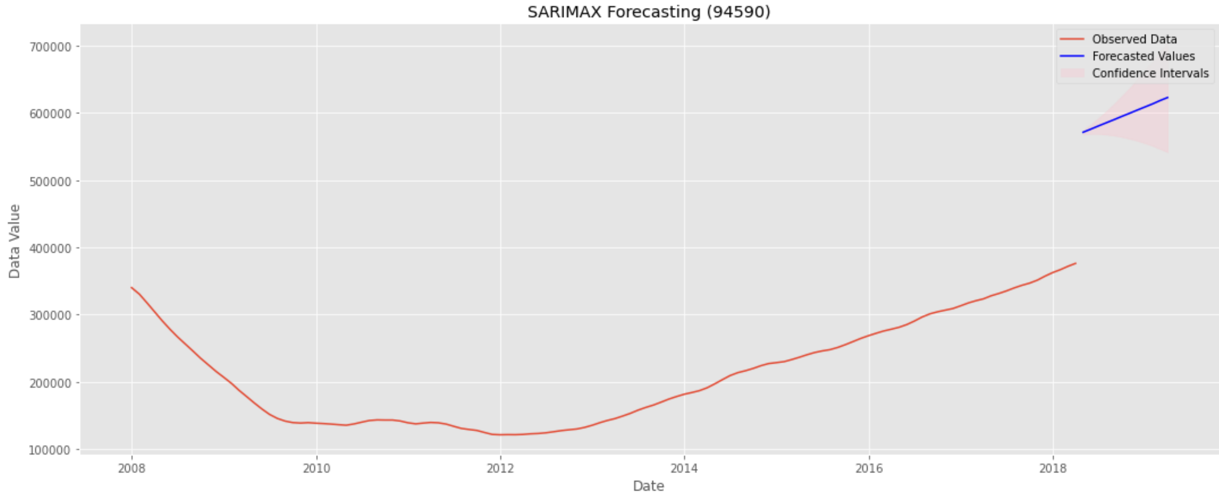
In [134…
```
# Get the forecast and confidence intervals
forecast = results.get_forecast(steps=forecast_periods)
forecast_ci = forecast.conf_int()

# Extract forecasted values, lower, and upper confidence intervals
forecast_values = forecast.predicted_mean
lower_ci = forecast_ci.iloc[:, 0]
upper_ci = forecast_ci.iloc[:, 1]

# Plotting
plt.figure(figsize=(18, 7))

# Plot observed data
```

```
plt.plot(data.index, data[94601], label='Observed Data')

# Plot forecasted values
plt.plot(forecast_values.index, forecast_values, color='blue', label='Forecasted Val

# Fill confidence intervals
plt.fill_between(forecast_values.index, lower_ci, upper_ci, color='pink', alpha=0.3,

# Add labels and title
plt.xlabel('Date')
plt.ylabel('Data Value')
plt.title('SARIMAX Forecasting (94601)')
plt.legend()
plt.show()
```



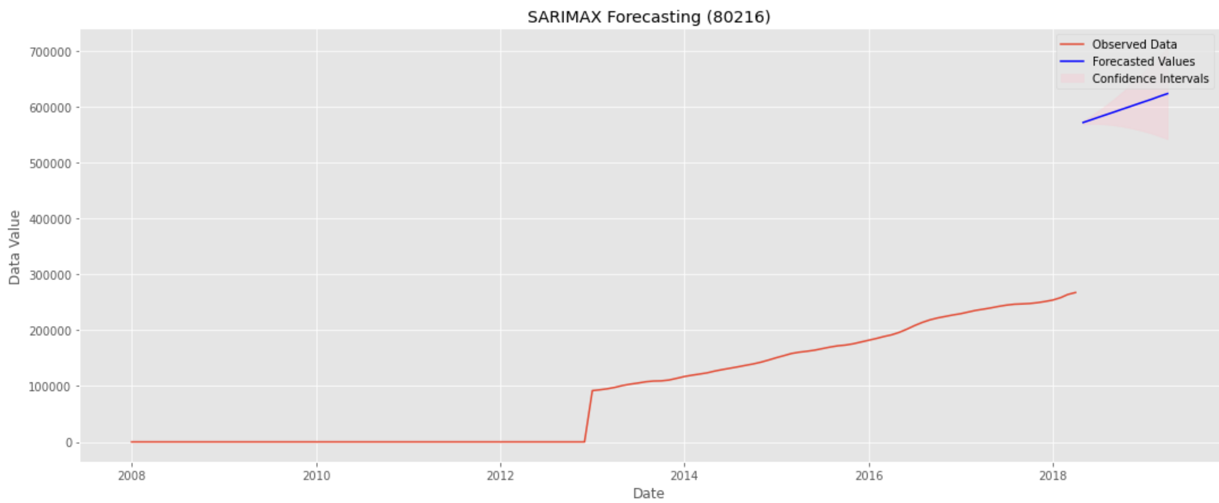
In [135…

```
# Get the forecast and confidence intervals
forecast = results.get_forecast(steps=forecast_periods)
forecast_ci = forecast.conf_int()

# Extract forecasted values, lower, and upper confidence intervals
forecast_values = forecast.predicted_mean
lower_ci = forecast_ci.iloc[:, 0]
upper_ci = forecast_ci.iloc[:, 1]

# Plotting
plt.figure(figsize=(18, 7))

# Plot observed data
plt.plot(data.index, data[94590], label='Observed Data')

# Plot forecasted values
plt.plot(forecast_values.index, forecast_values, color='blue', label='Forecasted Val

# Fill confidence intervals
plt.fill_between(forecast_values.index, lower_ci, upper_ci, color='pink', alpha=0.3,

# Add labels and title
plt.xlabel('Date')
plt.ylabel('Data Value')
plt.title('SARIMAX Forecasting (94590)')
plt.legend()
plt.show()
```



In [136…

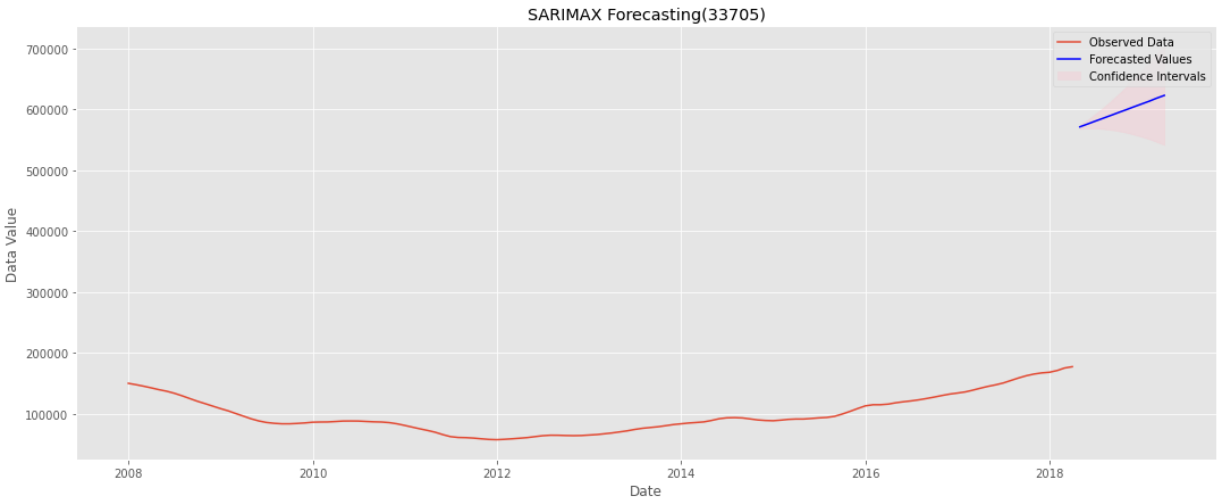
```
# Get the forecast and confidence intervals
forecast = results.get_forecast(steps=forecast_periods)
forecast_ci = forecast.conf_int()

# Extract forecasted values, lower, and upper confidence intervals
forecast_values = forecast.predicted_mean
lower_ci = forecast_ci.iloc[:, 0]
upper_ci = forecast_ci.iloc[:, 1]

# Plotting
plt.figure(figsize=(18, 7))

# Plot observed data
plt.plot(data.index, data[80216], label='Observed Data')

# Plot forecasted values
plt.plot(forecast_values.index, forecast_values, color='blue', label='Forecasted Val

# Fill confidence intervals
plt.fill_between(forecast_values.index, lower_ci, upper_ci, color='pink', alpha=0.3,

# Add labels and title
plt.xlabel('Date')
plt.ylabel('Data Value')
plt.title('SARIMAX Forecasting (80216)')
plt.legend()
plt.show()
```



In [137…

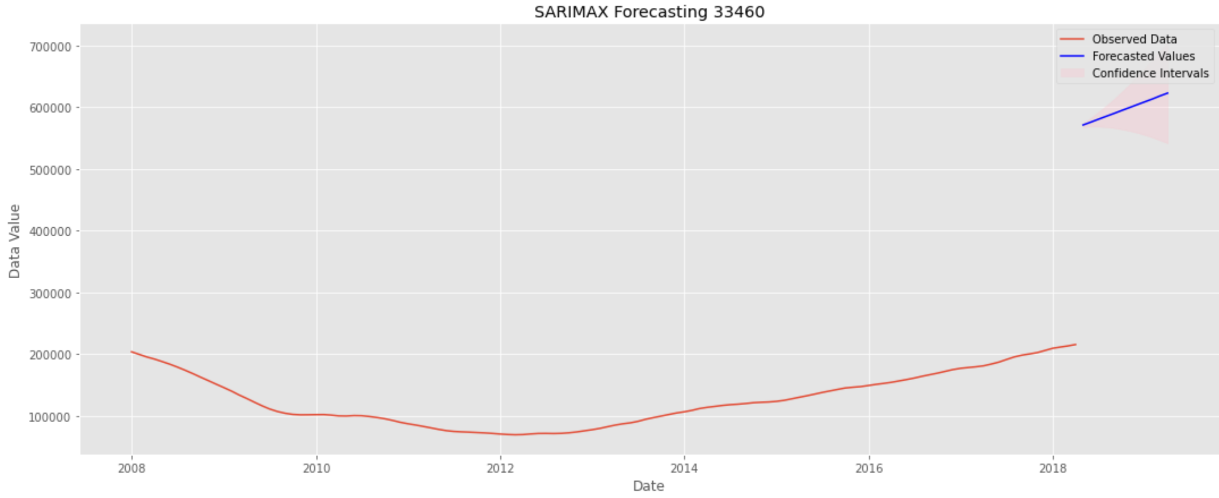
```
# The steps we've done apply to this too

forecast = results.get_forecast(steps=forecast_periods)
```

```
forecast_ci = forecast.conf_int()

forecast_values = forecast.predicted_mean
lower_ci = forecast_ci.iloc[:, 0]
upper_ci = forecast_ci.iloc[:, 1]

plt.figure(figsize=(18, 7))
plt.plot(data.index, data[33705], label='Observed Data')
plt.plot(forecast_values.index, forecast_values, color='blue', label='Forecasted Val
plt.fill_between(forecast_values.index, lower_ci, upper_ci, color='pink', alpha=0.3,

# Add labels and title
plt.xlabel('Date')
plt.ylabel('Data Value')
plt.title('SARIMAX Forecasting(33705)')
plt.legend()
plt.show()
```



In [138…

```
# Similar steps for forecasting apply to this zip code
forecast = results.get_forecast(steps=forecast_periods)
forecast_ci = forecast.conf_int()

forecast_values = forecast.predicted_mean
lower_ci = forecast_ci.iloc[:, 0]
upper_ci = forecast_ci.iloc[:, 1]

plt.figure(figsize=(18, 7))
plt.plot(data.index, data[33460], label='Observed Data')
plt.plot(forecast_values.index, forecast_values, color='blue', label='Forecasted Val
plt.fill_between(forecast_values.index, lower_ci, upper_ci, color='pink', alpha=0.3,

# Add labels and title
plt.xlabel('Date')
plt.ylabel('Data Value')
plt.title('SARIMAX Forecasting 33460')
plt.legend()
plt.show()
```



CONCLUSION

The study used the top 5 ZipCodes from a 5 year period with the highest Return of Investement for Real estate.The data at tghe end indincated a positve trend in the real estate market, no seasonality was observed.

The top 5 zipcodes chosen have shown to be still the best Zipcodes to invest in the area the ZipCodes are : 94590, 94601,33705,33460 with 94601 with the steadiest growth and 33705 with the best predicted ROI.

Best ZipCodes with their Counties:

- 94601 (Solano, Carlifonia)
- 94590 (Alameda, Carlifonia)
- 80216 (Denver, Colorado)
- 33705 (Pinellas, Florida)
- 33460 (Palm Beach, Florida)

RECOMMENDATIONS

1. Monitor Market Trends: Continuously monitor market trends and real estate indicators in the selected zip codes to stay informed about any changes or shifts in the market dynamics. This will help in making timely adjustments to investment strategies.

2. Consider Local Factors: Take into account local factors such as economic conditions, job growth, population demographics, and development projects in each zip code to assess the long-term sustainability of the real estate market in those areas.

Next Steps:

1. Implementation of Predictive Model: Integrate the predictive time series model into investment strategies, using it as a valuable tool for making informed decisions and optimizing portfolio performance.

2. Detailed Due Diligence: Conduct a comprehensive due diligence process, including property inspections, market analysis, and local economic factors, to further refine investment decisions and mitigate risks.

3. Diversification Strategies: Explore diversification strategies within the recommended zip codes and counties, spreading investments across different property types and neighborhoods to enhance portfolio resilience.

4. Continuous Monitoring: Stay abreast of market trends, economic indicators, and any emerging patterns to adapt investment strategies accordingly. Regularly update the predictive model with new data for improved forecasting accuracy.

By following these recommendations and next steps, investors can position themselves strategically in the real estate market, capitalize on identified opportunities, and navigate the dynamic landscape with confidence.

In [738…

```
import joblib
# Save the model using joblib
with open('sarimax_model.pkl', 'rb') as f:
    loaded_model = joblib.load(f)
```