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Time Series Analysis of the San Antonio Metro Area

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1 Overview

San Antonio is the seventh-most populous city in the United States. According to Wikipedia, it was the fastest-growing city among those in the top ten, at roughly 2% growth per year. [1] (https://en.wikipedia.org/wiki/San_Antonio) According to recent data from DCInno.com, San Antonio, over the last 4 years, was among the nation's fastest-growing cities for college-educated Millennials, and was tops in Texas. [2] (https://www.forbes.com/sites/scottbeyer/2016/04/30/when-it-comes-to-millennial-appeal-san-antonio-is-creeping-on-austin/?sh=6d8c68727c57)

San Antonio has been one of the hottest real estate markets in the country for many years. It is one of the best places to visit and has one of the fastest-growing economies in the country, driven by sectors such as military, tourism, health care, and insurance. The U.S. Armed Forces have numerous facilities in and around San Antonio; including Fort Sam Houston, Lackland Air Force Base, Randolph Air Force Base, Kelly Air Force Base, Camp Bullis, and Camp Stanley. [1] (https://en.wikipedia.org/wiki/San_Antonio)

The aim of this project is to provide a detailed analysis of the real estate market in the San Antonio metropolitan area using time series modeling and price forecasting. Utilizing median monthly home sales prices contained in this dataset (./data/zillow_2022.csv) prepared by Zillow, I will recommend the top 5 San Antonio metro zip codes to invest in to my client based on their specific needs.

2 Business Problem

A new real estate investment firm has hired me to identify the top 5 neighborhoods in the SA metro area that would give them the highest return on investment upon selling in 3 - 5 years.

They want to start with short term investments in one of the most lucrative real estate markets in the country. The company is most interested in safe investments to ensure they will have cash flow to reinvest when the time comes.

3 Data Understanding

The dataset used for this analysis contains median monthly housing sales prices for 265 zip codes over the period of January 2000 through June 2022 as reported by Zillow and can be found here (./data/zillow_2022.csv). This is the most up to date information that is available on Zillow (https://www.zillow.com/research/data/).

Each row represents a unique zip code. Each record contains location info and median housing sales prices for each month.

There are 27280 rows and 277 variables:

- *RegionID* - Unique index
- *RegionName* - Unique Zip Code
- *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 34430
- *2000-01-31* through *2022-06-30* - median monthly housing sales prices from January 2000 through June 2022, that is 269 data points of monthly data for each zip code

Our business case is based solely in the San Antonio metro area, so I will filter the dataset down to only include the zip codes contained in the SA metro area.

In [1]:

```
# Basics
import pandas as pd
import numpy as np
import itertools

# Visualization
import matplotlib.pyplot as plt
import plotly.express as px
import seaborn as sns
import matplotlib.patches as mpatches
from matplotlib.pylab import rcParams
import time

# Modeling
import statsmodels.api as sm
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
from statsmodels.tsa.statespace.sarimax import SARIMAX
from sklearn.metrics import mean_squared_error
from statsmodels.tsa.seasonal import seasonal_decompose
from statsmodels.tsa.arima.model import ARIMA
from statsmodels.tsa.stattools import acf, pacf, adfuller
from sklearn.linear_model import LassoLarsCV

# Warnings
import warnings
from statsmodels.tools.sm_exceptions import ConvergenceWarning
warnings.simplefilter('ignore', ConvergenceWarning)
warnings.filterwarnings('ignore')
```

In [2]:
```
# load in zillow home price data as df
df = pd.read_csv('data/zillow_2022.csv')
df = df.drop(columns = ['RegionType', 'StateName'], axis=1)
df.head()
```

Out[2]:

	RegionID	SizeRank	RegionName	State	City	Metro	CountyName	2000-01-31	2000-02-29
0	61639	0	10025	NY	New York	New York-Newark-Jersey City	New York County	NaN	NaN
1	84654	1	60657	IL	Chicago	Chicago-Naperville-Elgin	Cook County	378936.0	380056.0
2	61637	2	10023	NY	New York	New York-Newark-Jersey City	New York County	NaN	NaN
3	91982	3	77494	TX	Katy	Houston-The Woodlands-Sugar Land	Harris County	225068.0	225385.0
4	84616	4	60614	IL	Chicago	Chicago-Naperville-Elgin	Cook County	497125.0	498166.0

5 rows × 277 columns

In [3]:
```
# pd.set_option('display.max_rows', 1000)
df['Metro'].value_counts()
```

Out[3]:
```
New York-Newark-Jersey City        894
Chicago-Naperville-Elgin           377
Los Angeles-Long Beach-Anaheim     357
Philadelphia-Camden-Wilmington     339
Washington-Arlington-Alexandria    309
                                  ...
Ketchikan                            1
Gallup                               1
Connersville                         1
Portales                             1
Clovis                               1
Name: Metro, Length: 857, dtype: int64
```

In [4]:
```
#Dataframe containing only zips from San Antonio metro
sa_df = df[df['Metro']=='San Antonio-New Braunfels']
sa_df.head()
```

Out[4]:

	RegionID	SizeRank	RegionName	State	City	Metro	CountyName	2000-01-31	2000-02-29
21	92271	23	78130	TX	New Braunfels	San Antonio-New Braunfels	Comal County	NaN	NaN
44	92341	47	78245	TX	San Antonio	San Antonio-New Braunfels	Bexar County	116692.0	116770.0
150	92336	153	78240	TX	San Antonio	San Antonio-New Braunfels	Bexar County	114140.0	114360.0
378	92345	382	78249	TX	San Antonio	San Antonio-New Braunfels	Bexar County	130419.0	130549.0
386	92350	390	78254	TX	San Antonio	San Antonio-New Braunfels	Bexar County	140116.0	140318.0

5 rows × 277 columns

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

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 105 entries, 21 to 26415
Columns: 277 entries, RegionID to 2022-06-30
dtypes: float64(270), int64(3), object(4)
memory usage: 228.0+ KB
```

In [6]:
```
1 sa_df.describe()
```

Out[6]:

	RegionID	SizeRank	RegionName	2000-01-31	2000-02-29	2000-03-31	
count	105.000000	105.000000	105.000000	69.000000	69.000000	69.000000	
mean	92308.304762	8461.390476	78193.685714	130346.579710	130606.971014	130841.608696	13
std	93.859564	7199.818934	156.834143	68273.344025	68513.528089	68645.817295	6
min	92192.000000	23.000000	78002.000000	52991.000000	53036.000000	53262.000000	5
25%	92255.000000	2025.000000	78108.000000	85073.000000	85130.000000	85117.000000	8
50%	92307.000000	7824.000000	78211.000000	106068.000000	105880.000000	106357.000000	10
75%	92336.000000	12186.000000	78240.000000	160421.000000	160555.000000	160815.000000	16
max	92727.000000	29964.000000	78886.000000	427022.000000	429011.000000	430687.000000	43

8 rows × 273 columns

In [7]:
```
1 sa_df.isna().sum()
```

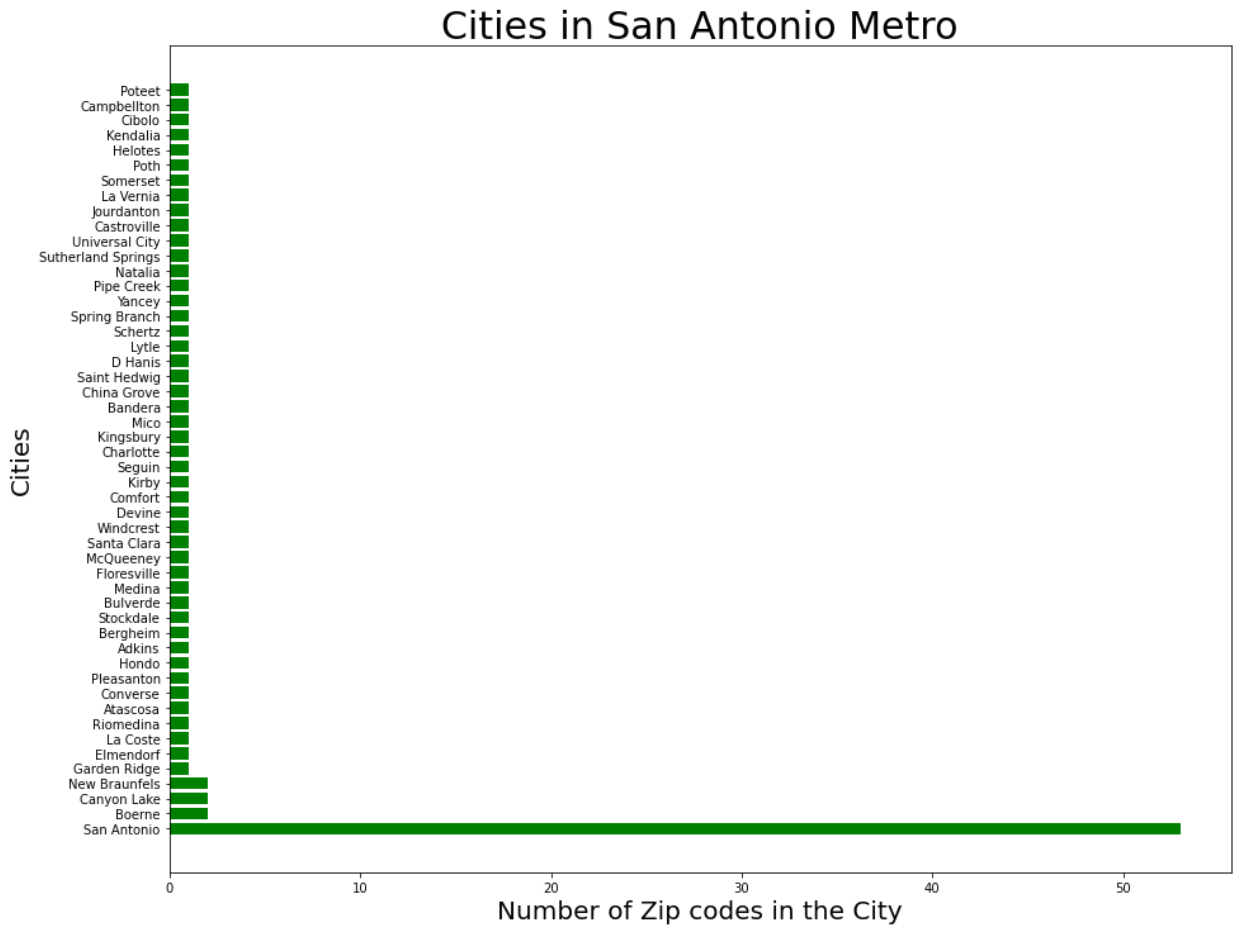
Out[7]:
```
RegionID      0
SizeRank      0
RegionName    0
State         0
City          0
             ..
2022-02-28    0
2022-03-31    0
2022-04-30    0
2022-05-31    0
2022-06-30    0
Length: 277, dtype: int64
```

Our filtered dataset contains a wide range of median home values, from a starting range of 53k to 427k for 105 zip codes in the SA metro area with several null values. The null values are mostly contained in the early years of the data, but due to the massive growth of the area, there is data in the later years of the dataset.

4 EDA

4.1 Number of Zip Codes per City in SA Metro

In [8]:
```
#Visualizing the value counts of zipcodes in each city in the San Anto

fig, ax = plt.subplots(figsize=(15,12))

y = [a for a in sa_df['City'].value_counts()]

x = [a for a in sa_df['City'].value_counts().keys()]

ax.barh(x,y,color='green')
ax.set_title('Cities in San Antonio Metro',fontsize=30)
ax.set_ylabel('Cities',fontsize=20)
ax.set_xlabel('Number of Zip codes in the City',fontsize=20)
fig.savefig('./images/zip_per_city.jpeg');
```



There are several small cities in the SA metro area that only have 1 zip code, while San Antonio itself contains 55 zip codes.

4.2 Reshape from Wide to Long Format

The data needs to be melted from wide to long format in order to proceed with visualization and modeling. Let's go ahead and do that now!

In [9]:
```
def melt_data(df):
    """
    Takes the zillow_data dataset in wide form or a subset of the zil
    Returns a long-form datetime dataframe
    with the datetime column names as the index and the values as the

    If more than one row is passes in the wide-form dataset, the value
    will be the mean of the values from the datetime columns in all o
    """

    melted = pd.melt(df, id_vars=['RegionName', 'RegionID', 'SizeRank
    melted['time'] = pd.to_datetime(melted['time'], format = '%Y-%m')
    melted = melted.dropna(subset=['value'])
    return melted.groupby('time').aggregate({'value':'mean'})
```

In [10]:
```
# Get average of San Antonio metro zipcodes
satx_df_melted = melt_data(sa_df)
satx_df_melted.tail()
```

Out[10]:

time	value
2022-02-28	326126.866667
2022-03-31	331758.419048
2022-04-30	337743.838095
2022-05-31	343256.361905
2022-06-30	347860.333333

In [11]:
```
# Get average of all US zipcodes
df_melted = melt_data(df)
df_melted.head()
```

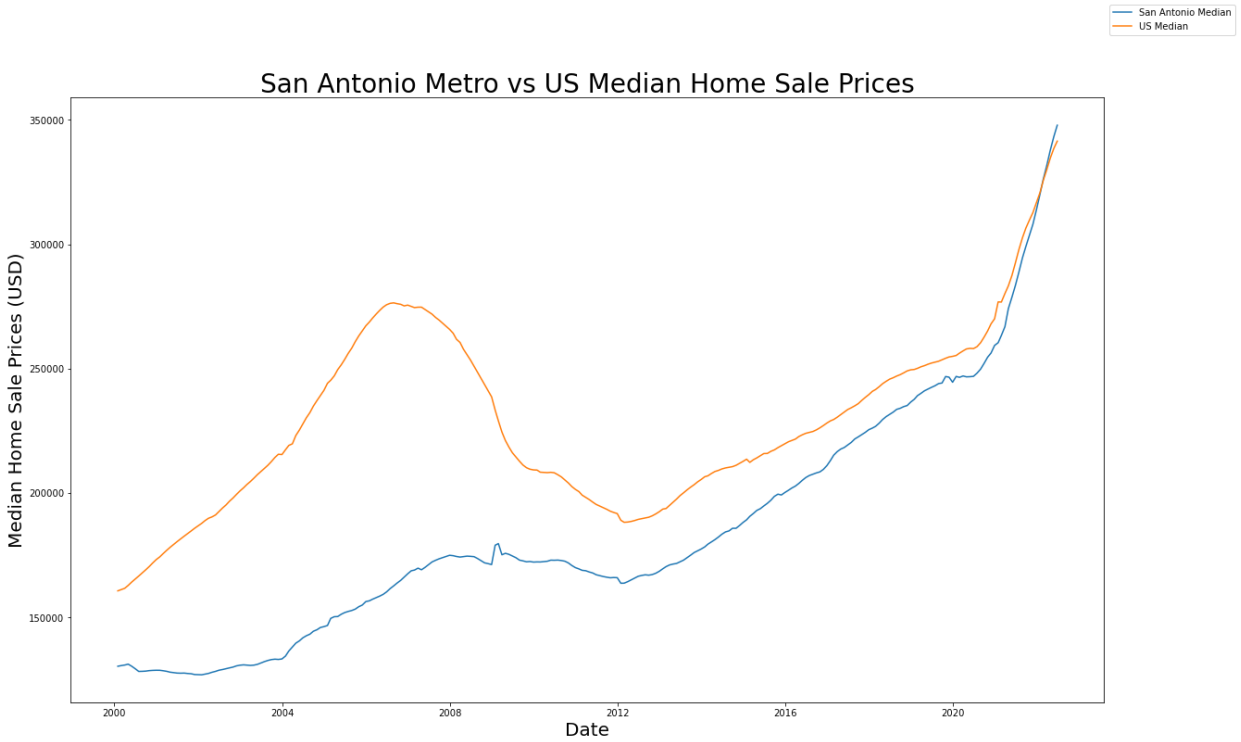
Out[11]:

time	value
2000-01-31	160670.656547
2000-02-29	161164.847325
2000-03-31	161690.402760
2000-04-30	162842.504295
2000-05-31	164204.550578

4.3 San Antonio vs US Median Home Prices

In order to compare how San Antonio home prices stack up the the US Median home price, I created a time series for the average median prices of the San Antonio area and a time series for the average median price of the US. Plotted together, we can see the differences.

In [12]:
```
# Plot home value time series for all zip codes averaged

# Define figure
ax = plt.figure(figsize=(20,12))

# Plot
plt.plot(satx_df_melted, label = 'San Antonio Median')
plt.plot(df_melted, label = 'US Median')

# Title, x & y labels
plt.title('San Antonio Metro vs US Median Home Sale Prices', fontsize=
plt.ylabel('Median Home Sale Prices (USD)', fontsize=20)
plt.xlabel('Date', fontsize=20)
ax.legend()
plt.savefig('./images/sa_vs_us.jpeg')

plt.show()
```



The median home value in San Antonio metro used to be much lower than the national average, but has actually surpassed it this year! This is due to the massive growth in the area and the low inventory of homes that are available for sale. We can also see that the housing market in San Antonio was not as affected by the crash in 2008. I will leave all of the data in the model to provide my client with a more conservative model to forecast housing prices.

Next, I will create another time series that will contain all the location info in long format.

In [13]:
```
#Create dataframe for new melted data
def melt_df(df):
    merged = []
    for zipcode in df.RegionName:
        melted = melt_data(df.loc[df['RegionName'] == zipcode])
        row = df.loc[df['RegionName'] == zipcode].iloc[:,:6]
        rows = pd.concat([row]*len(melted), ignore_index=True)
        merge = pd.concat([rows, melted.reset_index()], axis= 1)
        merged.append(merge)
    melted_df = pd.concat(merged)
    return melted_df
```

In [14]:
```
satx_df = melt_df(sa_df)
satx_df.head()
```

Out[14]:

	RegionID	SizeRank	RegionName	State	City	Metro	time	value
0	92271	23	78130	TX	New Braunfels	San Antonio-New Braunfels	2007-01-31	167985.0
1	92271	23	78130	TX	New Braunfels	San Antonio-New Braunfels	2007-02-28	168585.0
2	92271	23	78130	TX	New Braunfels	San Antonio-New Braunfels	2007-03-31	169390.0
3	92271	23	78130	TX	New Braunfels	San Antonio-New Braunfels	2007-04-30	170118.0
4	92271	23	78130	TX	New Braunfels	San Antonio-New Braunfels	2007-05-31	170191.0

In [15]:
```
# Drop columns no longer needed
model_df = satx_df.drop(['RegionID','City','State','Metro','SizeRank'
model_df.head()
```

Out[15]:

	RegionName	value
time		
2007-01-31	78130	167985.0
2007-02-28	78130	168585.0
2007-03-31	78130	169390.0
2007-04-30	78130	170118.0
2007-05-31	78130	170191.0

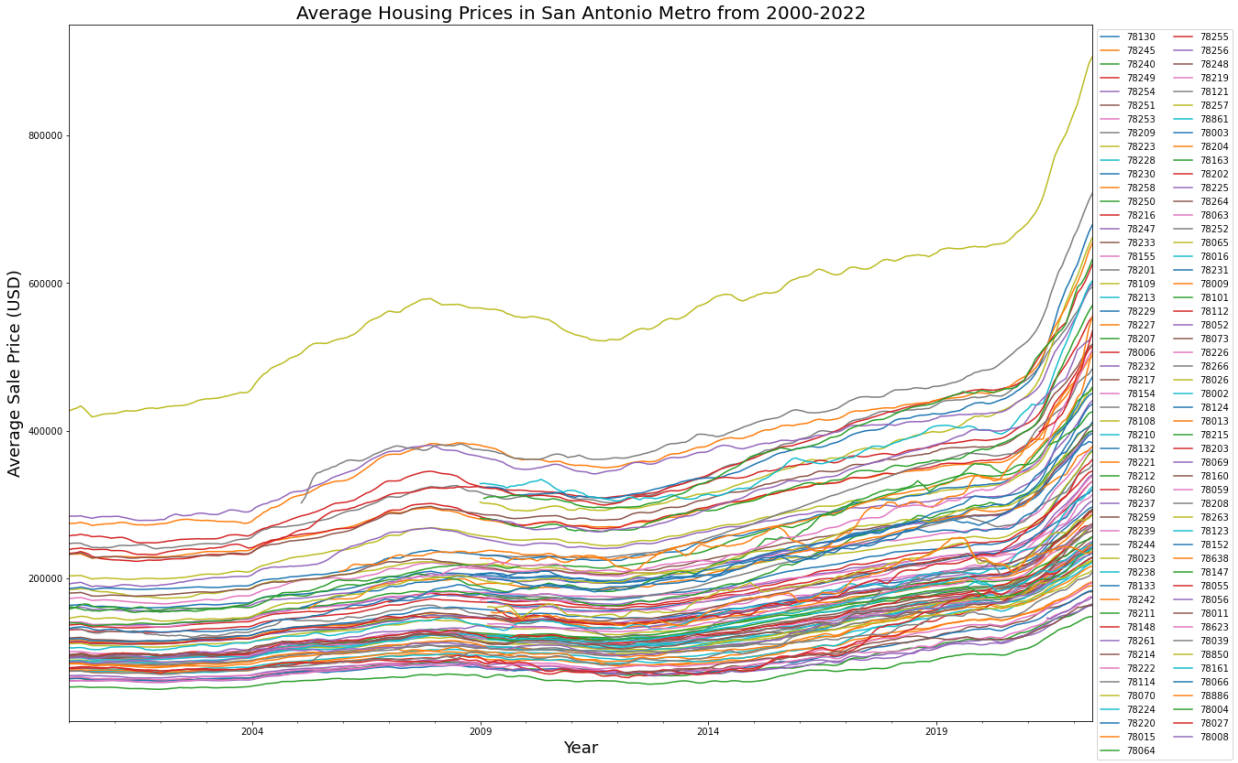
In [16]:
```
1 model_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 24245 entries, 2007-01-31 to 2022-06-30
Data columns (total 2 columns):
 #   Column      Non-Null Count  Dtype  
---  ------      --------------  -----  
 0   RegionName  24245 non-null  int64  
 1   value       24245 non-null  float64
dtypes: float64(1), int64(1)
memory usage: 568.2 KB
```

4.4 Average Housing Prices In San Antonio Metro Over Time

Let's take a look at the time series plotted for all 105 zip codes. We will be able to see the overall trend, but will be very dense on the plot.

In [17]:
```
#plot the values grouped by zipcode
plt.figure(figsize=(20,14))
for zipcode in model_df.RegionName.unique():
    model_df.loc[model_df['RegionName'] == zipcode].value.plot(label=
plt.legend(bbox_to_anchor=(1,1), loc='upper left', ncol=2)

plt.xlabel("Year", fontsize = 18)
plt.ylabel("Average Sale Price (USD)", fontsize=18)
plt.title('Average Housing Prices in San Antonio Metro from 2000-2022
plt.savefig('./images/all_sa_prices.jpeg')
plt.show();

```



In [18]:
```
# Which zipcode is the one with the highest median value?
model_df.loc[model_df['value'] >= 800000]
```

Out[18]:

time	RegionName	value
2021-11-30	78257	802164.0
2021-12-31	78257	815748.0
2022-01-31	78257	829571.0
2022-02-28	78257	842365.0
2022-03-31	78257	860608.0
2022-04-30	78257	878970.0
2022-05-31	78257	897059.0
2022-06-30	78257	907023.0

Much to my surprise, 78257 is outside of the main city loop. These must be a development of custom luxury homes in Leon Springs.

4.5 Zipcodes with Highest 5 Year ROI

In order to narrow down our focus before modeling, we will only keep 10 zip codes with highest ROI based on our last 5 years of historical data.

In [19]:
```
# Create copy of df to calculate ROIs
roi_df = sa_df.copy()
roi_df.head()
```

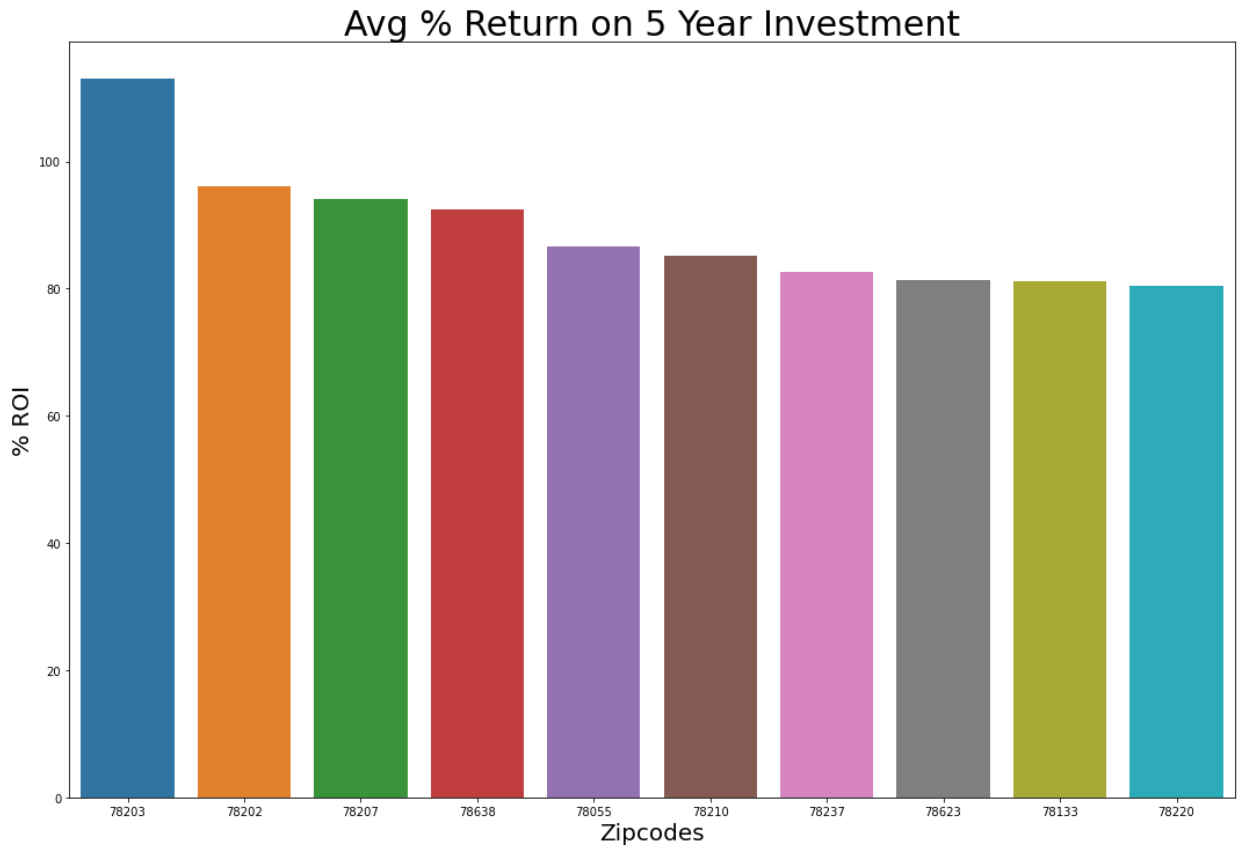
Out[19]:

	RegionID	SizeRank	RegionName	State	City	Metro	CountyName	2000-01-31	2000-02-29
21	92271	23	78130	TX	New Braunfels	San Antonio-New Braunfels	Comal County	NaN	NaN
44	92341	47	78245	TX	San Antonio	San Antonio-New Braunfels	Bexar County	116692.0	116770.0
150	92336	153	78240	TX	San Antonio	San Antonio-New Braunfels	Bexar County	114140.0	114360.0
378	92345	382	78249	TX	San Antonio	San Antonio-New Braunfels	Bexar County	130419.0	130549.0
386	92350	390	78254	TX	San Antonio	San Antonio-New Braunfels	Bexar County	140116.0	140318.0

5 rows × 277 columns

In [20]:

```
# Calculate 5 year ROI and keep top 10
roi_df['roi_5_year'] = ((roi_df['2022-06-30'] - roi_df['2017-06-30']),
sa_5_year_roi = roi_df.sort_values('roi_5_year',ascending=False).head
sa_5_year_roi['RegionName'] = sa_5_year_roi['RegionName'].astype(str)

#Plot
fig,ax=plt.subplots(figsize=(18,12))
sns.barplot('RegionName', 'roi_5_year', data = sa_5_year_roi)

ax.set_ylabel('% ROI',fontsize='20')
ax.set_xlabel('Zipcodes',fontsize='20')
ax.set_title('Avg % Return on 5 Year Investment',fontsize='30')
plt.savefig('./images/roi_5_year.jpeg');
```



78203 contains the Arena District, which is the area surrounding the AT&T Center. The other zip codes with highest ROI are spread all around the city in every direction. While most are around the downtown area, there are several suburbs like Canyon Lake and Medina that have taken the top ROI spots!

4.6 Zip Codes with Highest 22 Year ROI

Out of curiosity, are the zip codes with the highest ROI over 22 years the same as the top 10 zip codes over the last 5 years?

In [21]:
```
# Calculate 22 year ROI and keep top 10
roi_df['roi_22year'] = ((roi_df['2022-06-30'] - roi_df['2000-01-31']),
sa_22_year_roi = roi_df.sort_values('roi_22year',ascending=False).hea
sa_22_year_roi['RegionName'] = sa_22_year_roi['RegionName'].astype(st

#Plot
fig,ax=plt.subplots(figsize=(18,12))
sns.barplot('RegionName', 'roi_22year', data = sa_22_year_roi)

ax.set_ylabel('% ROI',fontsize='20')
ax.set_xlabel('Zipcodes',fontsize='20')
ax.set_title('Avg % Return on 22 Year Investment',fontsize='30');
```

Only 3 zip codes that have the highest ROI on a 5 year investment are in the highest ROI over a 22 year investment. This is once again due to new developments in the suburban areas, as well as gentrification of areas that were once undesirable.

4.7 Discussion on EDA

There is a similar trend amongst all of our neighborhoods in the SA metro area. There is also a very wide range of median housing values, where the more affluent neighborhoods have a a much higher value than others.

We can also cleary see the housing bubble and 2008 crash in the data. Values increased rapidly starting in 2004 and took a dip through 2009, plateaued, and begin rising again in 2012. All zip codes in the San Antonio metro were mildly affected by this crash in comparison to the rest of the US. A number of reasons contributed to this crash outside of the typical housing market highs and lows, and while they are rare, they do occur and are unpredictable. I am going to leave this data in for our model to create a more conservative forecast for my client.

According to the National Association of Realtors, the number of home sales increases significantly in the spring, with home sales increasing by 34% in February and March. Sales continue upward with the busiest home selling months being May through August, accounting for 40% of United States annual home sales volume. The slowest months are November through February. Prices of homes slightly increase during surge months when the demand in the market is higher. Therefore, selling homes during these peak times could prove to be advantageous for maximizing profits.[4] (https://www.nar.realtor/blogs/economists-outlook/seasonality-in-the-housing-market) Knowing that there is going to be seasonality in our data, I will use SARIMAX for my time series model.

5 SARIMAX Modeling

5.1 Create Time Series for Each Zip Code in Our Top 10

In [22]:
```
# Define function to create individual time series for each zipcode
def zipcode_ts(df, zipcode):
    '''
    Input:
        df : dataframe of Zillow housing data.
        zipcode : list of zip codes to iterate through.
    '''
    zipcode_df = df[df['RegionName'] == zipcode]
    zipcode_df = zipcode_df.drop(columns = 'RegionName', axis=1)
    return zipcode_df
```

In [23]:
```
# Empty list
zip_df = []

#Zipcodes with highest 5 year ROI
zip_list = [78203,78202,78207,78638,78055,78210,78237,78623,78133,782

# Return list of time series for each zipcode in our zip_list
for z in model_df['RegionName'].unique():
    for z in zip_list:
        training_data = zipcode_ts(model_df, z)
        zip_df.append(training_data)
    else:
        continue
```

In [24]:
```
# Sanity check
zip_df[0]
```

Out[24]:

time	value
2000-01-31	77799.0
2000-02-29	77923.0
2000-03-31	78250.0
2000-04-30	78620.0
2000-05-31	78765.0
...	...
2022-02-28	227521.0
2022-03-31	231757.0
2022-04-30	235924.0
2022-05-31	239372.0
2022-06-30	241568.0

270 rows × 1 columns

Our zip_df now contains a list of 10 time series for each of our 10 zipcodes of interest.

5.2 Seasonal Decomposition

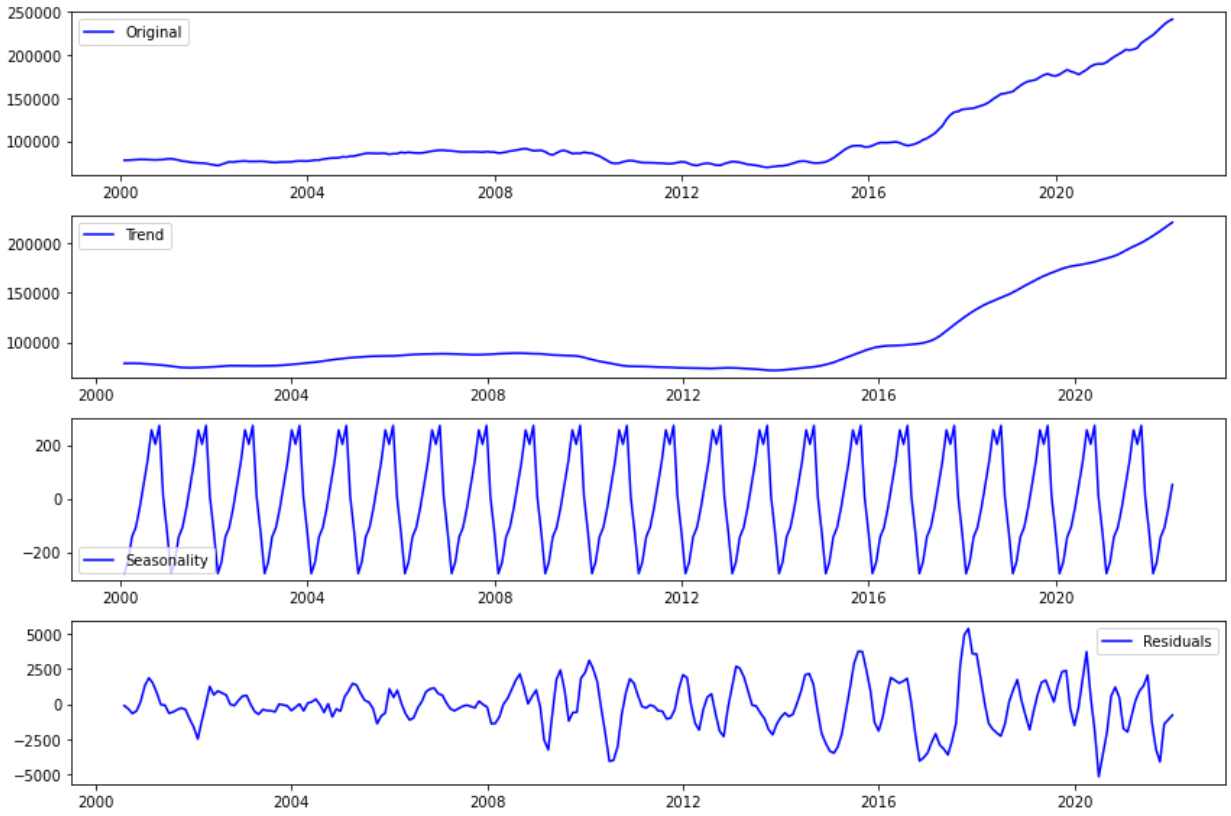
We can also decompose our time series to look for trend and seasonality.

Let's start by looking at our top ROI zip code - 78203 (Arena District), and 78133 (Canyon Lake), which has had huge ROI gains in the last 2 years compared to all data in the dataset.

In [25]:
```
def decomposition_plot(ts):
    decomposition = sm.tsa.seasonal_decompose(ts, model='additive')

    #Gather the trend, seasonality, and residuals
    trend = decomposition.trend
    seasonal = decomposition.seasonal
    residual = decomposition.resid

    # Plot gathered statistics
    plt.figure(figsize=(12,8))
    plt.subplot(411)
    plt.plot(ts, label='Original', color='blue')
    plt.legend(loc='best')
    plt.subplot(412)
    plt.plot(trend, label='Trend', color='blue')
    plt.legend(loc='best')
    plt.subplot(413)
    plt.plot(seasonal,label='Seasonality', color='blue')
    plt.legend(loc='best')
    plt.subplot(414)
    plt.plot(residual, label='Residuals', color='blue')
    plt.legend(loc='best')
    plt.tight_layout();
    return decomposition_plot
```

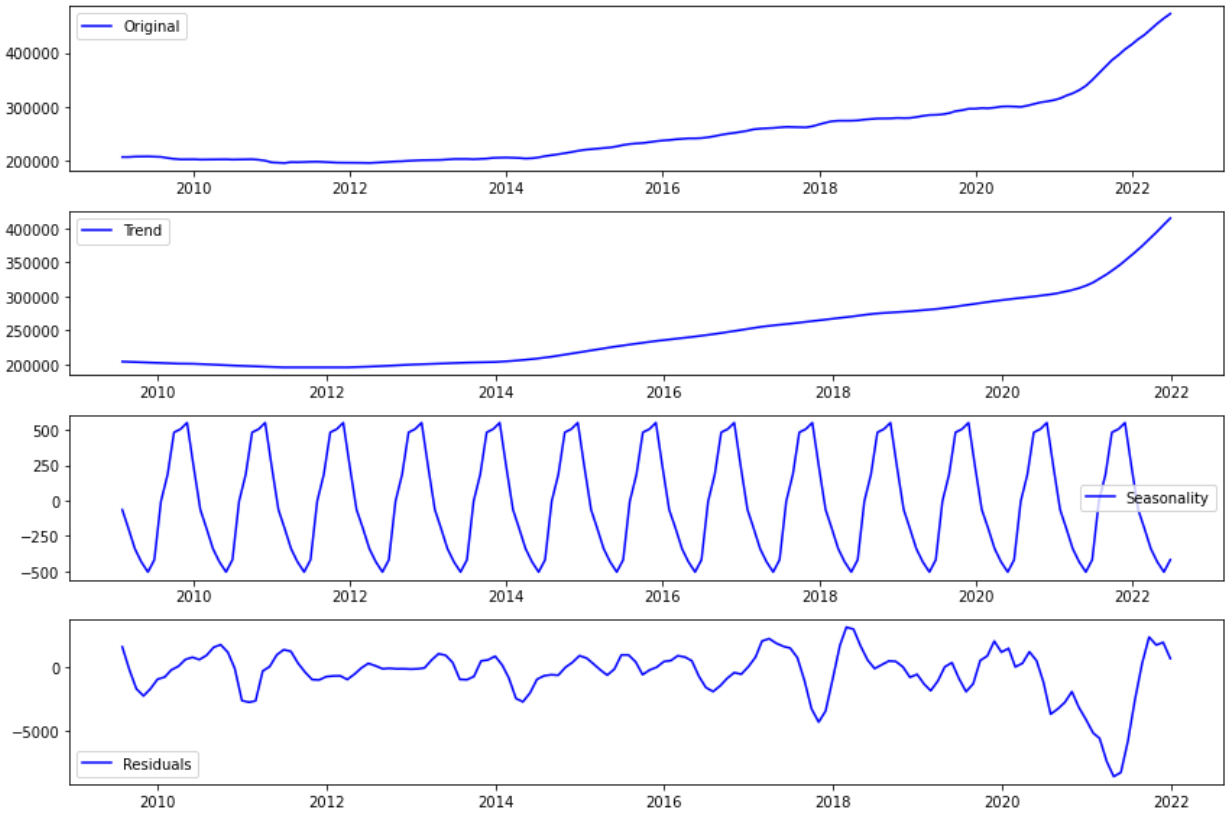
In [26]:
```
#Decomposition plot of the Arena District
decomposition_plot(zip_df[0])
```

Out[26]: <function __main__.decomposition_plot(ts)>



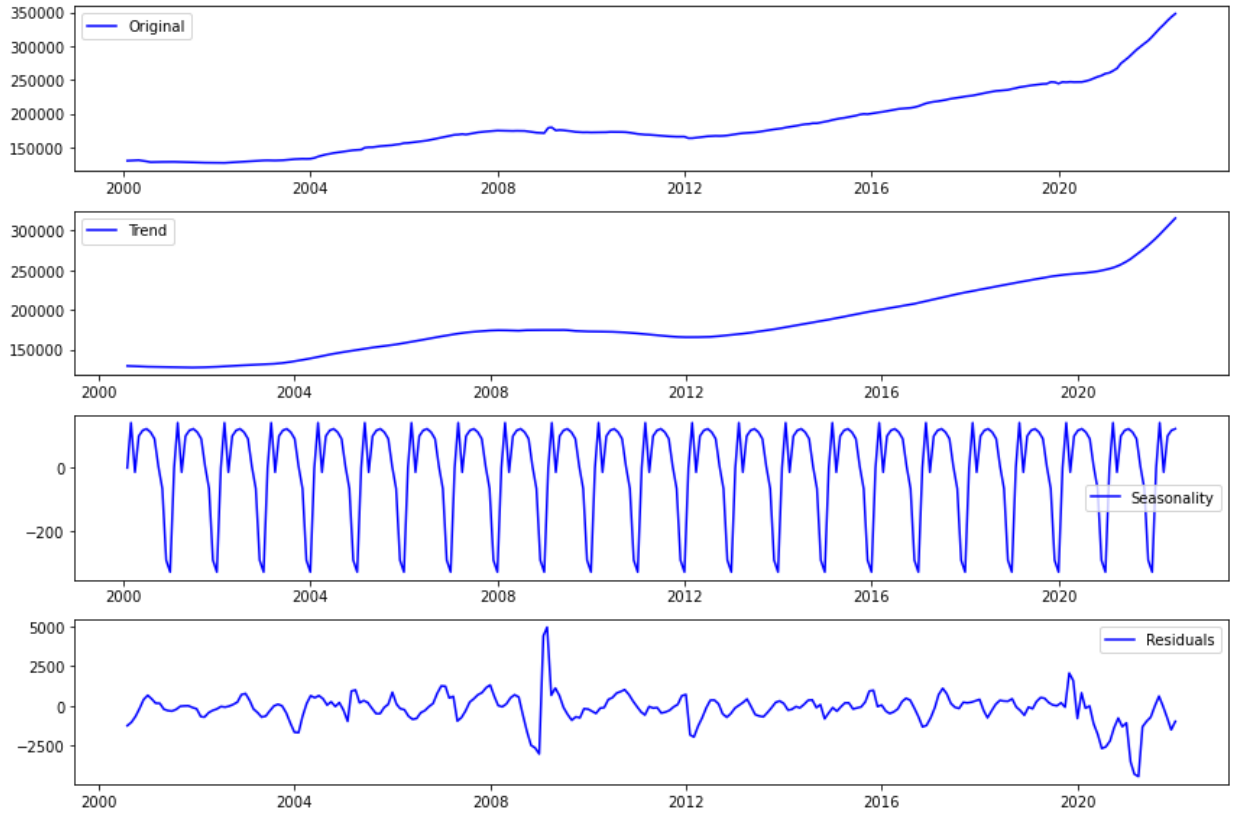
In [27]:
```
# #Decomposition plot of Canyon Lake
decomposition_plot(zip_df[8])
```

Out[27]:
```
<function __main__.decomposition_plot(ts)>
```



In [28]:
```
# Decomposition plot of the SA Metro area averaged
decomposition_plot(satx_df_melted)
```

Out[28]:
```
<function __main__.decomposition_plot(ts)>
```



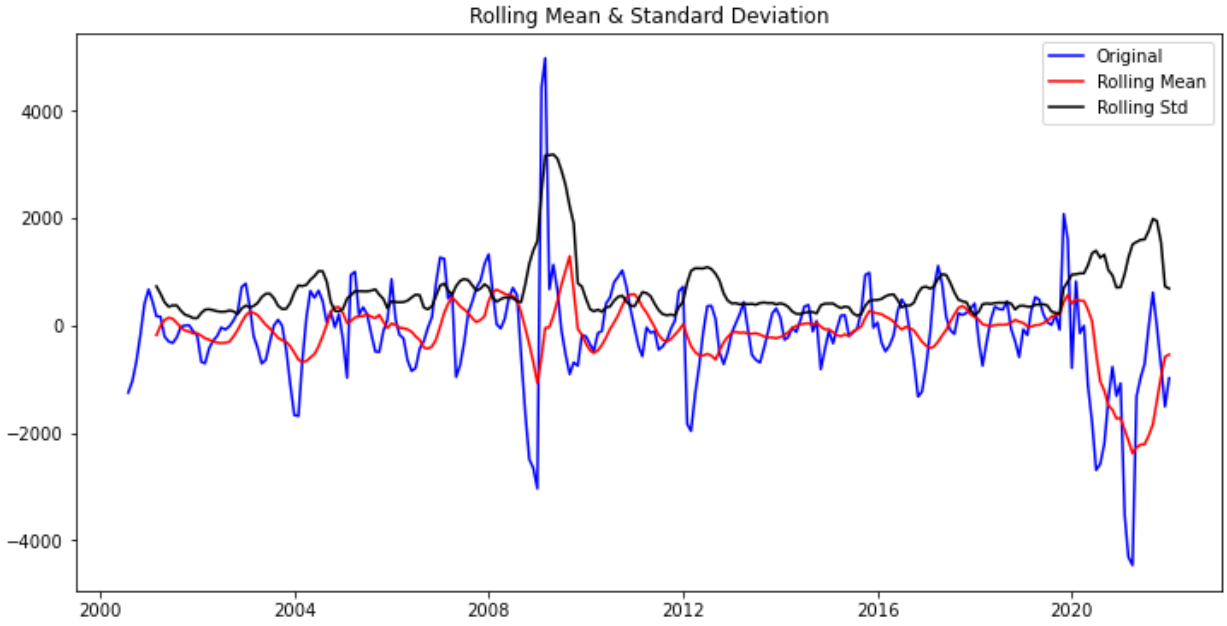
We can clearly see the seasonality in the individual zip codes and the SA Median average. There is also an overall upwards trend after the small dip after the housing bubble popped, with a steep increase over the last 2 years.

5.3 Stationarity Check

In [29]:
```
def stationarity_check(TS):

    # Calculate rolling statistics
    roll_mean = TS.rolling(window=8, center=False).mean()
    roll_std = TS.rolling(window=8, center=False).std()

    # Perform the Dickey Fuller test
    dftest = adfuller(TS)

    # Plot rolling statistics:
    fig = plt.figure(figsize=(12,6))
    orig = plt.plot(TS, color='blue',label='Original')
    mean = plt.plot(roll_mean, color='red', label='Rolling Mean')
    std = plt.plot(roll_std, color='black', label = 'Rolling Std')
    plt.legend(loc='best')
    plt.title('Rolling Mean & Standard Deviation')
    plt.show(block=False)

    # Print Dickey-Fuller test results
    print('Results of Dickey-Fuller Test: \n')

    dfoutput = pd.Series(dftest[0:4], index=['Test Statistic', 'p-valu
                                             '#Lags Used', 'Number of
    for key, value in dftest[4].items():
        dfoutput['Critical Value (%s)'%key] = value
    print(dfoutput)

    return None
```

In [30]:
```
# Get decomposition for stationarity check
decomposition = sm.tsa.seasonal_decompose(satx_df_melted, model='addit
residual = decomposition.resid
ts_log_decompose = residual
ts_log_decompose.dropna(inplace=True)
```

In [31]:
```
1 stationarity_check(ts_log_decompose)
```

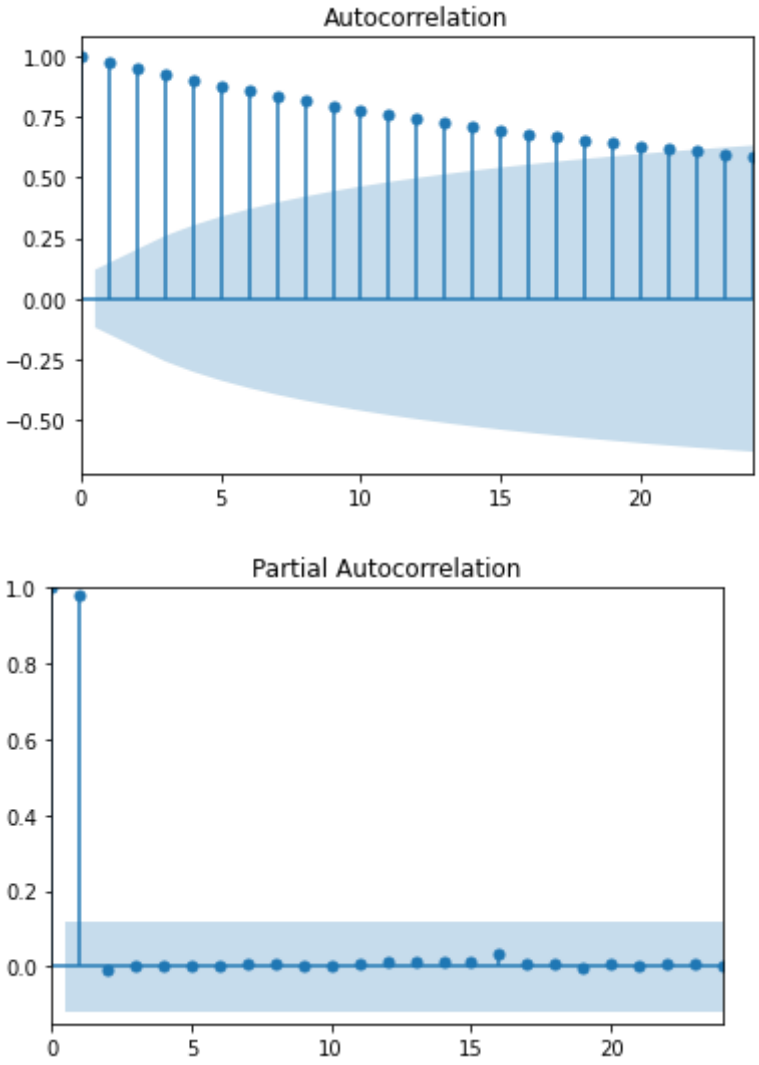



```
Results of Dickey-Fuller Test:

Test Statistic                  -4.393976
p-value                          0.000304
#Lags Used                       6.000000
Number of Observations Used    251.000000
Critical Value (1%)             -3.456674
Critical Value (5%)             -2.873125
Critical Value (10%)            -2.572944
dtype: float64
```

The p-value is <0.05, which means we accept the null hypothesis that the residuals are stationary. We can move on to check our autocorrelation and partial autocorrelation plots.

5.4 Autocorrelation and Partial Autocorrelation

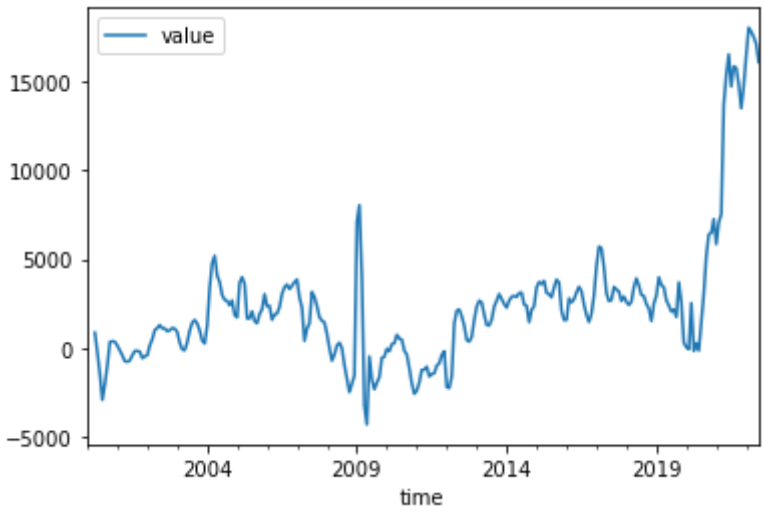
In [32]:
```
plot_acf(satx_df_melted); plt.xlim(0,24); plt.show()
plot_pacf(satx_df_melted); plt.xlim(0,24); plt.ylim(-0.15,1);plt.show
```



There is a slow decline in our autocorrelation plot, while the partial autocorrelation drops off right away. This means we should use an Autoregressive model for out data, but we are going to run gridsearch anyway to find best parameters. We can try to plot again with a lag of 3, which would make sense for different seasons of the year.

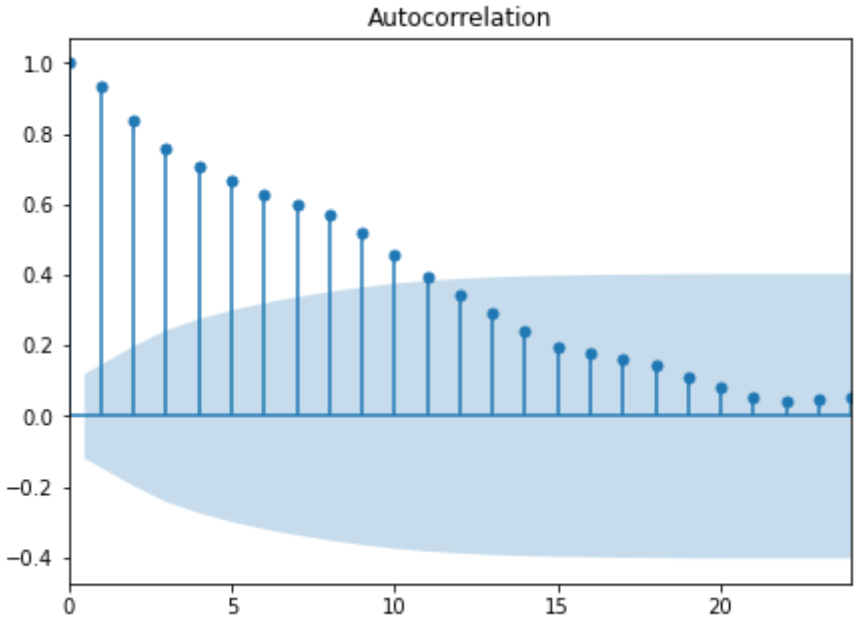
In [33]:
```
1 satx_df_melted.diff(periods=3).plot()
```

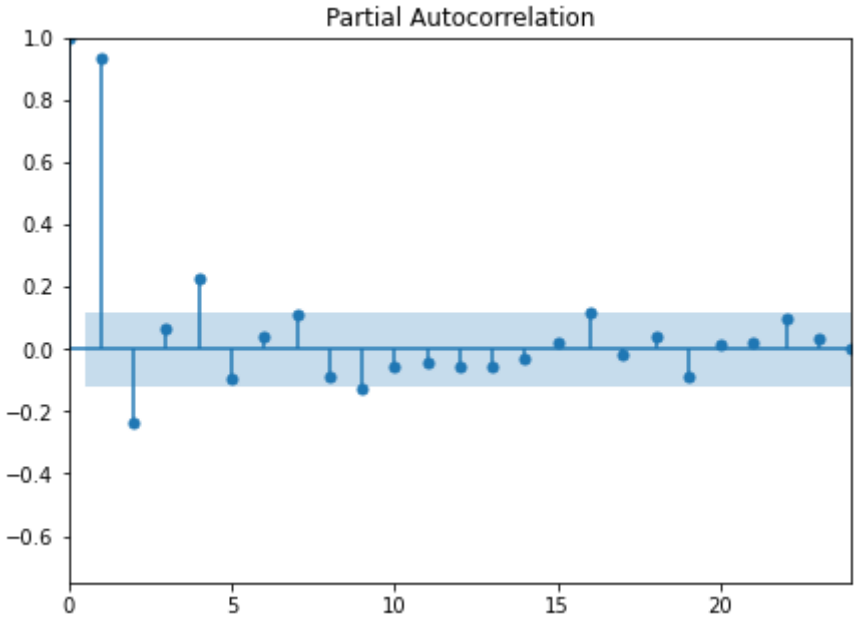
Out[33]: <AxesSubplot:xlabel='time'>



We can see some autocorrelation at a lag of 3.

In [34]:
```
rcParams['figure.figsize']=7,5
plot_acf(satx_df_melted.diff(periods=3).bfill()); plt.xlim(0,24); plt
plot_pacf(satx_df_melted.diff(periods=3).bfill()); plt.xlim(0,24); plt
```





In [35]:
```
1 model_df
```

Out[35]:

time	RegionName	value
2007-01-31	78130	167985.0
2007-02-28	78130	168585.0
2007-03-31	78130	169390.0
2007-04-30	78130	170118.0
2007-05-31	78130	170191.0
...	...	...
2022-02-28	78008	165845.0
2022-03-31	78008	167301.0
2022-04-30	78008	169326.0
2022-05-31	78008	171558.0
2022-06-30	78008	174902.0

24245 rows × 2 columns

5.5 Gridsearch for SARIMAX Model

Next, I am going to conduct gridsearch to find optimal values for (p,d,q) and (P,D,Q,s) ranked by lowest AIC. This will provide optimal paramets for each of my 10 zip codes of interest.

In [36]:
```
1 # Define the p, d and q parameters to take any value between 0 and 2
2 p = d = q = range(0, 2)
3
4 # Generate all different combinations of p, q and q triplets
5 pdq = list(itertools.product(p, d, q))
6
7 # Generate all different combinations of seasonal p, q and q triplets
8 pdqs = [(x[0], x[1], x[2], 12) for x in list(itertools.product(p, d, q
```

In [37]:
```
# Run a grid with pdq and seasonal pdq parameters calculated above an
ans = []
for df, name in zip(zip_df, zip_list):
    for comb in pdq:
        for combs in pdqs:
            try:
                mod = sm.tsa.statespace.SARIMAX(df,
                                                order=comb,
                                                seasonal_order=combs,
                                                enforce_stationarity=
                                                enforce_invertibility=

                output = mod.fit()
                ans.append([name, comb, combs, output.aic])
                print('Result for {}'.format(name) + ' ARIMA {} x {}1
            except:
                continue

```

```
Result for 78203 ARIMA (0, 0, 0) x (0, 0, 0, 12)12 : AIC Calculated = 701
9.4166327271905
Result for 78203 ARIMA (0, 0, 0) x (0, 0, 1, 12)12 : AIC Calculated = 840
09.30465452891
Result for 78203 ARIMA (0, 0, 0) x (0, 1, 0, 12)12 : AIC Calculated = 562
2.870386243331
Result for 78203 ARIMA (0, 0, 0) x (0, 1, 1, 12)12 : AIC Calculated = 537
1.74710460903
Result for 78203 ARIMA (0, 0, 0) x (1, 0, 0, 12)12 : AIC Calculated = 550
0.263984338111
Result for 78203 ARIMA (0, 0, 0) x (1, 0, 1, 12)12 : AIC Calculated = 548
1.179697261492
Result for 78203 ARIMA (0, 0, 0) x (1, 1, 0, 12)12 : AIC Calculated = 523
8.3061736622185
Result for 78203 ARIMA (0, 0, 0) x (1, 1, 1, 12)12 : AIC Calculated = 646
1.6577264304215
Result for 78203 ARIMA (0, 0, 1) x (0, 0, 0, 12)12 : AIC Calculated = 679
9.994138687387
Result for 78203 ARIMA (0, 0, 1) x (0, 0, 1, 12)12 : AIC Calculated = 777
```

In [38]:
```
# Find the parameters with minimal AIC value
ans_df = pd.DataFrame(ans, columns=['name', 'pdq', 'pdqs', 'aic'])
ans_df
```

Out[38]:

	name	pdq	pdqs	aic
0	78203	(0, 0, 0)	(0, 0, 0, 12)	7019.416633
1	78203	(0, 0, 0)	(0, 0, 1, 12)	84009.304655
2	78203	(0, 0, 0)	(0, 1, 0, 12)	5622.870386
3	78203	(0, 0, 0)	(0, 1, 1, 12)	5371.747105
4	78203	(0, 0, 0)	(1, 0, 0, 12)	5500.263984
...	...	...	...	...
635	78220	(1, 1, 1)	(0, 1, 1, 12)	3807.534751
636	78220	(1, 1, 1)	(1, 0, 0, 12)	3942.412763
637	78220	(1, 1, 1)	(1, 0, 1, 12)	3929.565653
638	78220	(1, 1, 1)	(1, 1, 0, 12)	3830.610297
639	78220	(1, 1, 1)	(1, 1, 1, 12)	3812.442178

640 rows × 4 columns

In [39]:
```
#Return the best set of parameters based on AIC
best_para = ans_df.loc[ans_df.groupby("name")["aic"].idxmin()]
best_para
```

Out[39]:

	name	pdq	pdqs	aic
319	78055	(1, 1, 1)	(1, 1, 1, 12)	2318.584674
575	78133	(1, 1, 1)	(1, 1, 1, 12)	2308.113622
123	78202	(1, 1, 1)	(0, 1, 1, 12)	4068.244419
63	78203	(1, 1, 1)	(1, 1, 1, 12)	4144.531317
187	78207	(1, 1, 1)	(0, 1, 1, 12)	3833.302485
383	78210	(1, 1, 1)	(1, 1, 1, 12)	3868.587565
635	78220	(1, 1, 1)	(0, 1, 1, 12)	3807.534751
443	78237	(1, 1, 1)	(0, 1, 1, 12)	3843.766288
511	78623	(1, 1, 1)	(1, 1, 1, 12)	2765.827273
255	78638	(1, 1, 1)	(1, 1, 1, 12)	2641.330470

5.6 Best Parameters SARIMAX Model

Now that we have our optimal parameters for each zip code from our gridsearch, we will use the to

build a sarimax model for each zip code. Following are 3 functions we will use to build, evaluate and test each model, and forecast predictions for each of our top 10 zip codes.

In [40]:

```
# Define function to build SARIMAX model, print summary and output di
def sarimax(ts, order=(1, 1, 1), seasonal_order=(1, 1, 1, 12)):
    '''
    Input:
    ts : Time series data.
    order : (p, d, q) values for ARIMA. Default = (1, 1, 1)
    seasonal_order : Seasonal (P, D, Q, s) values for SARIMA.
        Default = (1, 1, 1, 12).

    Output:
    Prints model output summary.
    Plots model diagnostics.

    Returns: Model output.
    '''

    # Sarimax model
    SARIMAX = sm.tsa.statespace.SARIMAX(ts,
                                        order=order,
                                        seasonal_order=seasonal_order
                                        enforce_stationarity=False,
                                        enforce_invertibility=False)

    # Fit the model and print results
    output = SARIMAX.fit()

    # Print output summary
    print(output.summary().tables[1])
    output.plot_diagnostics(figsize=(15,18));

    return output
```

In [41]:

```
def ose_forecast(ts, output, neighborhood =''):
    '''
    Plot forecast with real and predicted data.

    Input:
        ts : Time series.
        output : SARIMAX model output.
        neighborhood : Name of city for plot title.

    Output:
        Prints RMSE.
        Plots real vs. model predicted plot.
    '''

    # Get predictions starting from 2019-06-30 and calculate confiden

    pred = output.get_prediction(start=pd.to_datetime('2019-06-30'), 

    # Get the real and predicted values
    ts_forecasted = pred.predicted_mean
    ts_truth = ts['2019-06-30':].value

    # Calc RMSE
    mse = mean_squared_error(ts_truth, ts_forecasted)
    rmse = np.sqrt(mse)

    # Print RMSE
    print('The RMSE of our forecasts is {}'.format(round(rmse, 2)))

    # Confidence Intervals
    pred_conf = pred.conf_int()

    ### Plot real vs predicted w/ confidence intervals ###

    rcParams['figure.figsize'] = 15, 6

    # Plot observed values
    ax = ts['2017-06-30':].plot(label='observed')

    # Plot predicted values

    ts_forecasted.plot(ax=ax, label='one-step ahead forecast', alpha=

    # Plot the range for confidence intervals
    ax.fill_between(pred_conf.index,
                    pred_conf.iloc[:, 0],
                    pred_conf.iloc[:, 1], color='g', alpha=.3)

    # Title
    ax.set_title(neighborhood)

    # Set axes labels
    ax.set_xlabel('Date')
    ax.set_ylabel('Median Home Value (USD)')
    plt.legend()

```

```
    return plt.show()
```

In [42]:

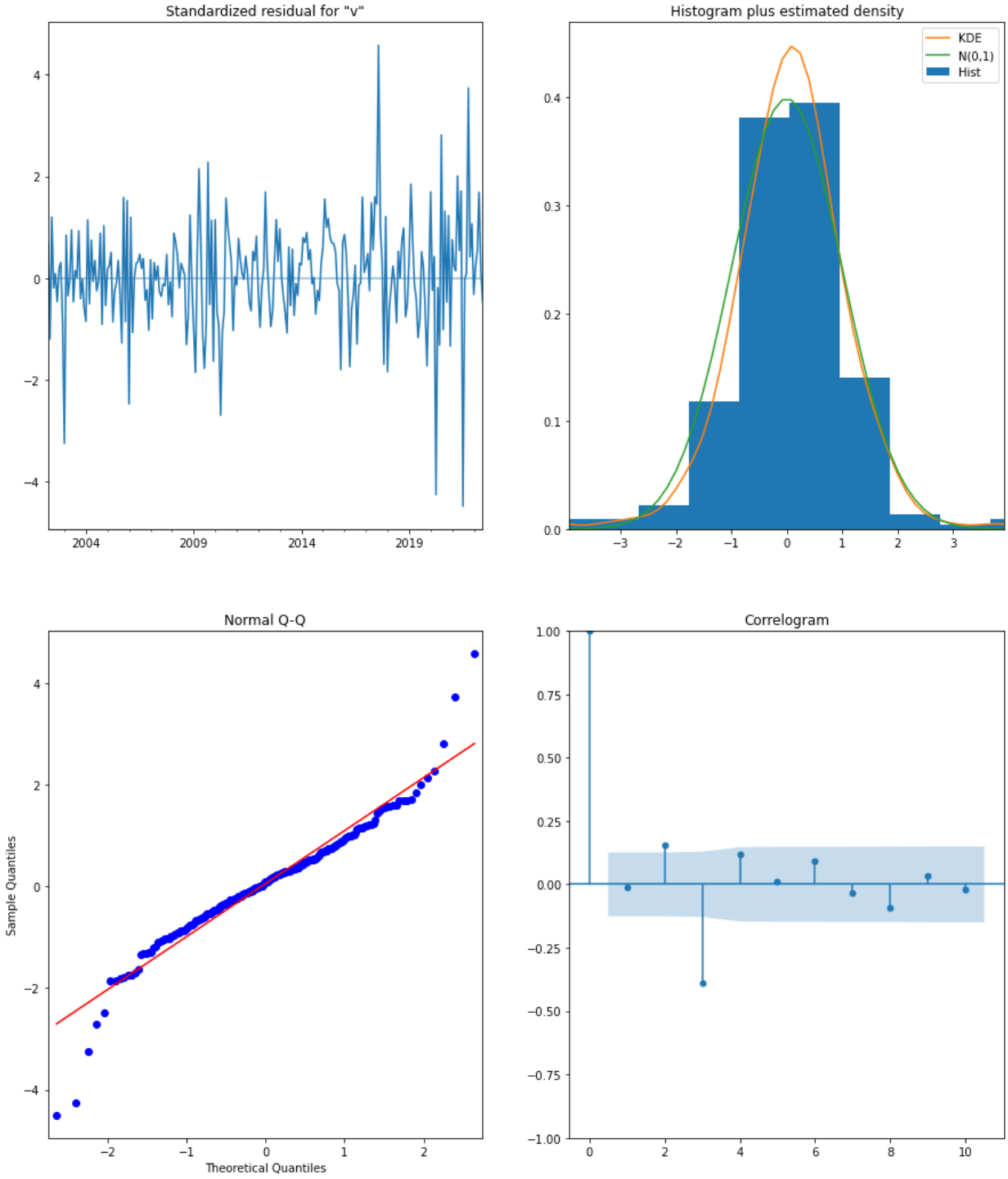
```
# Forecast 5 year predictions - Home Sale Values #

def dynamic_forecast(ts, model_output, years=5, neighborhood='', save_
    '''
    Plots dynamic forecast for specified time into the future.

    Inputs:
        ts : Time series data.
        model_output : Output results from our model.
        years : n-years to forcast into the future.
        neighborhood: Name of neighborhood for plots

    Outputs:
        Prints : Time series plot with one step ahead forecast.
        Returns : Dictionary of predictions.

    '''

    # Calcualte steps
    steps = years*12

    # Get forecast and confidence interval for steps ahead in future
    future = model_output.get_forecast(steps=steps, dynamic=True, ful
    future_conf = future.conf_int()

    ### Plot forecast ###

    # Observed
    ax = ts.plot(label='Observed', figsize=(12, 6))
    # Predicted
    future.predicted_mean.plot(ax=ax, label='dynamic forecast', alpha=

    # Confidence Intervals
    ax.fill_between(future_conf.index,
                    future_conf.iloc[:, 0],
                    future_conf.iloc[:, 1], color='k', alpha=.25)

    # Title
    ax.set_title(f"5-Year Forecast for {neighborhood}")

    # x & y-labels
    ax.set_xlabel('Date')
    ax.set_ylabel('Median Home Sale Value (USD)')

    # Legend
    ax.legend()

    if save_fig:
        plt.savefig(f'./images/dynamic_forecast_{neighborhood}.jpeg')

    # Print plot
    plt.show()

    # Forecast prediction for n-years into the future
    forecast = future.predicted_mean[-1]
    maximum = future_conf.iloc[-1,1]
```

```
    minimum = future_conf.iloc[-1,0]

    # Create dictionary of predictions
    predictions = {}
    predictions['forecast'] = forecast.round()
    predictions['minimum'] = minimum.round()
    predictions['maximum'] = maximum.round()

    return predictions
```

5.6.1 Arena District

In [43]:
```
arena_district = zip_df[0]
output_arena_district = sarimax(arena_district, order=(1, 1, 1), seas
```

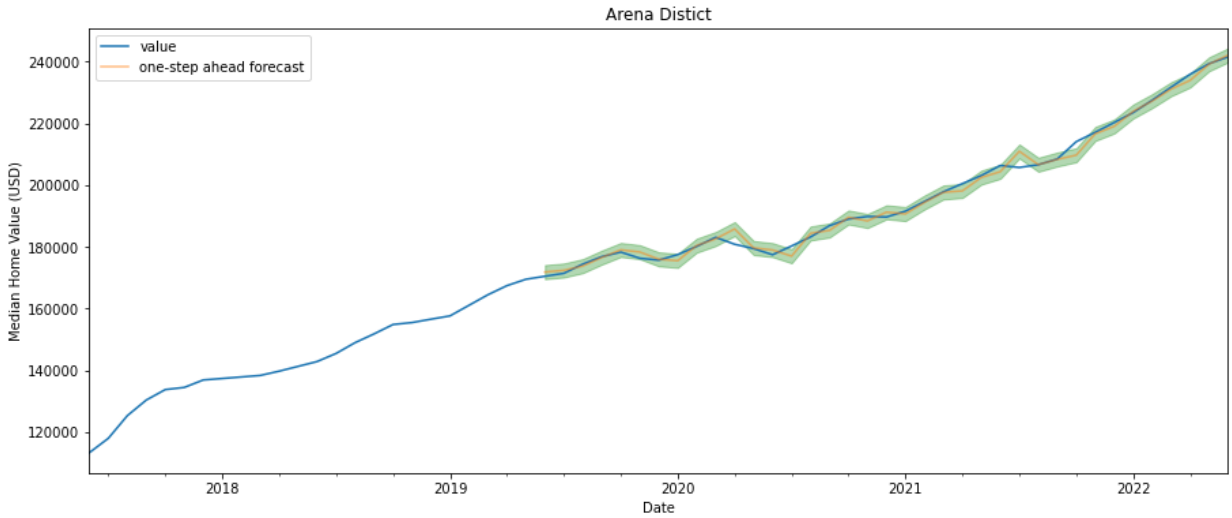
```
==============================================================================
=====
                 coef    std err          z      P>|z|      [0.025
0.975]
------------------------------------------------------------------------------
-----
ar.L1          0.6052      0.063      9.657      0.000       0.482
0.728
ma.L1          0.0708      0.099      0.715      0.475      -0.123
0.265
ma.S.L12      -0.4880      0.025    -19.377      0.000      -0.537      -
0.439
sigma2      1.354e+06   7.35e+04     18.427      0.000    1.21e+06     1.
5e+06
==============================================================================
=====
```



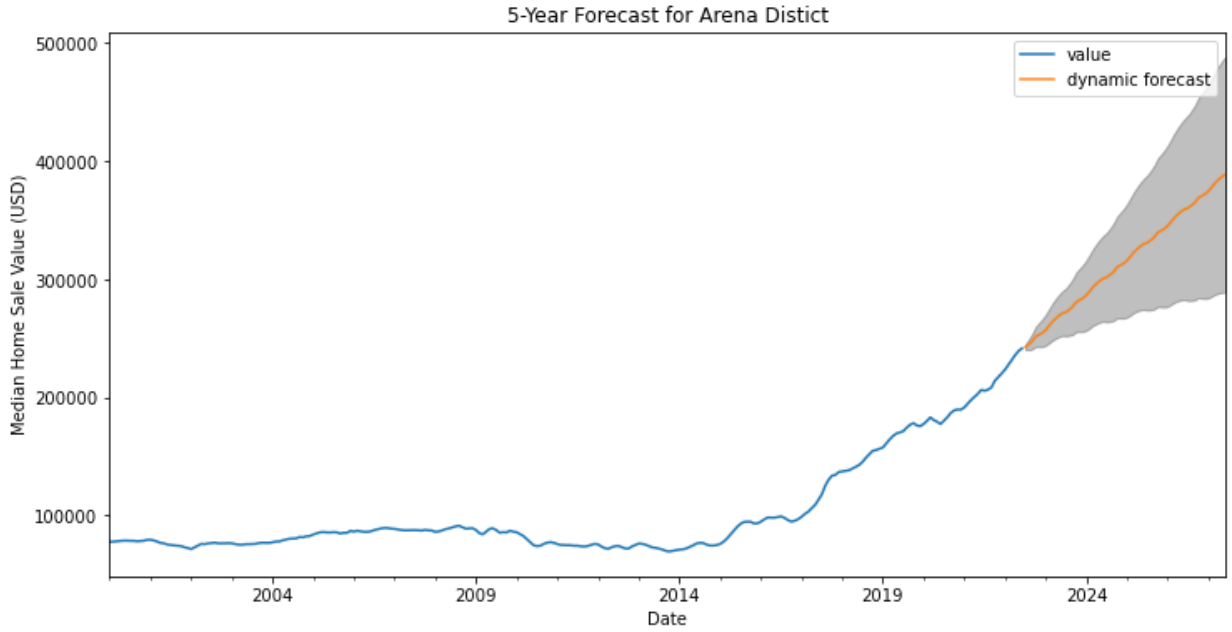
The residuals look normally distributed, even though there are some heavy outliers presence in the tails of the Q-Q plot. We are likely going to see this in several of our following models. This is due to the model being "confused" over the dip after the housing bubble, and the huge increases that have taken place in this area over the last few years. We can see negative correlation in the correlogram at a month 3. This makes sense knowing that we have seasonality in our data. The ma.L1 has a p-value that is >0.05, and we will likely see this in all of our following zipcodes. I am going to leave the model as is since I ran gridsearch to find optimal parameters.

In [44]:
```
1 ose_forecast(arena_district, output_arena_district, neighborhood='Are
```

```
The RMSE of our forecasts is 1816.45
```



In [45]:
```
1 dynamic_forecast(arena_district, output_arena_district, neighborhood=
```



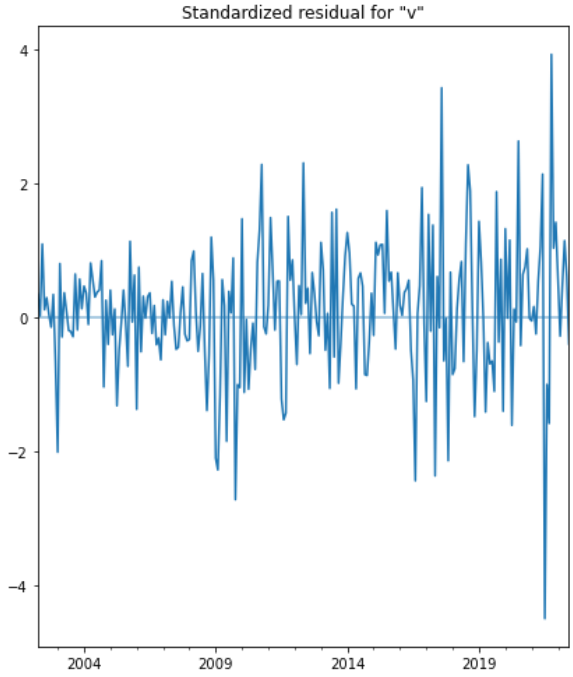
Out[45]:
```
{'forecast': 388893.0, 'minimum': 289050.0, 'maximum': 488735.0}
```

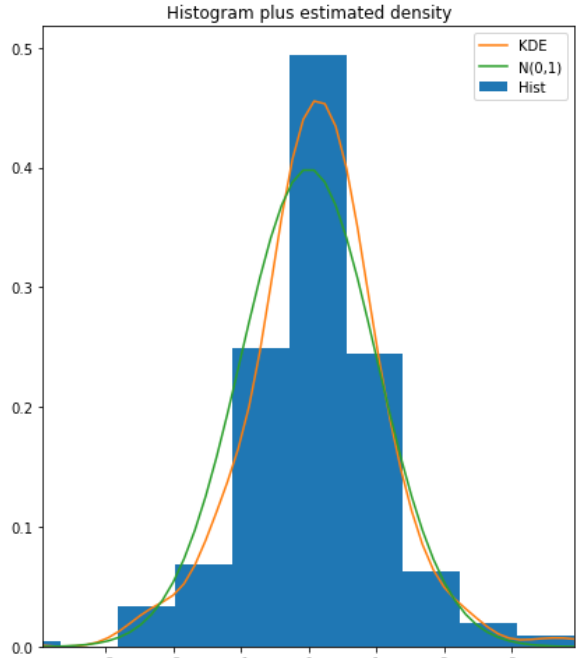
The RMSE of our one step ahead forecast for the Arena District look great at $1,816! The confidence interval is small and the ROI of our minimum bounds are higher than the current value, which guarantees a positive ROI.

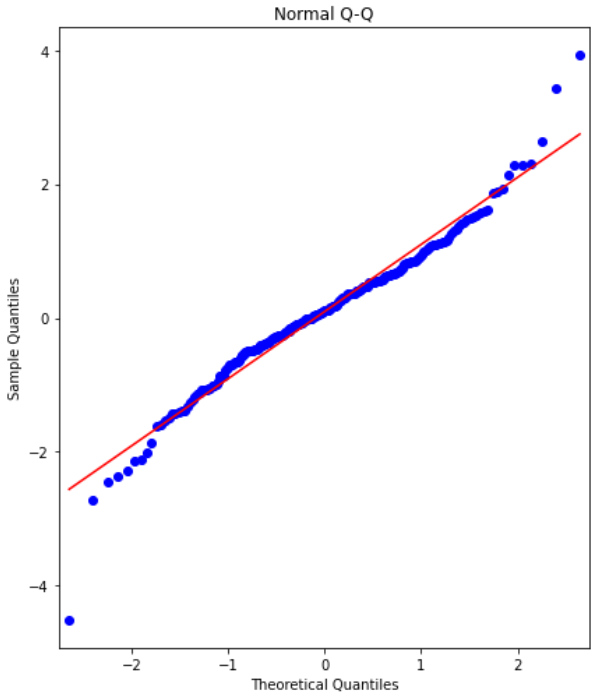
5.6.2 Dignowity Hill

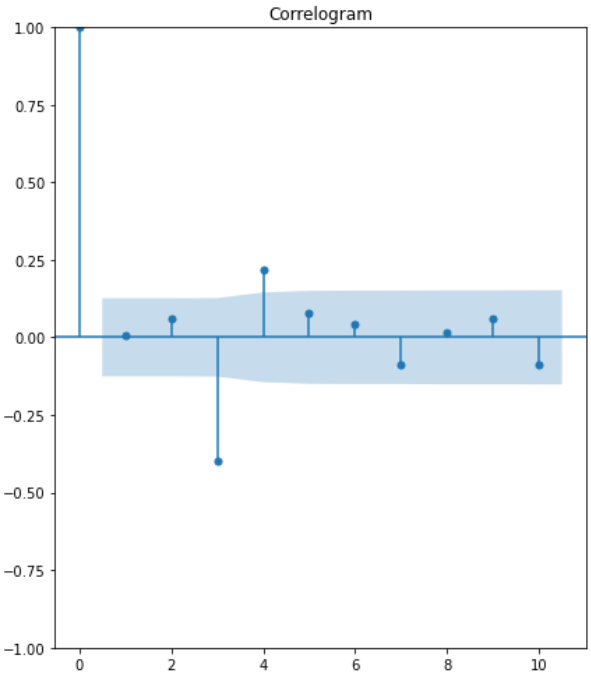
In [46]:
```
dig_hill = zip_df[1]
output_dig_hill = sarimax(dig_hill, order=(1, 1, 1), seasonal_order=(
```

```
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.L1          0.4494      0.109      4.136      0.000       0.236       0.662
ma.L1          0.1275      0.130      0.981      0.326      -0.127       0.382
ar.S.L12      -0.3287      0.071     -4.651      0.000      -0.467      -0.190
ma.S.L12      -0.1885      0.049     -3.876      0.000      -0.284      -0.093
sigma2      1.045e+06    7.6e+04     13.747      0.000    8.96e+05    1.19e+06
==============================================================================
```


Standardized residual for "v"
4
2
0
−2
−4
2004
2009
2014
2019

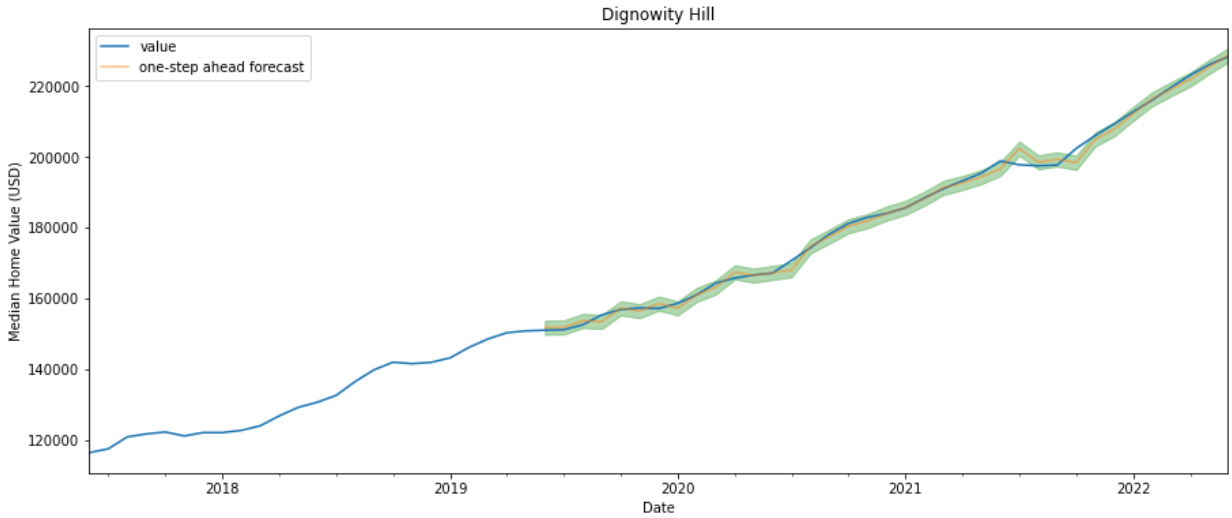

Histogram plus estimated density
KDE
N(0,1)
Hist
0.5
0.4
0.3
0.2
0.1
0.0
−3
−2
−1
0
1
2
3


Normal Q-Q
Sample Quantiles
Theoretical Quantiles
4
2
0
−2
−4
−2
−1
0
1
2

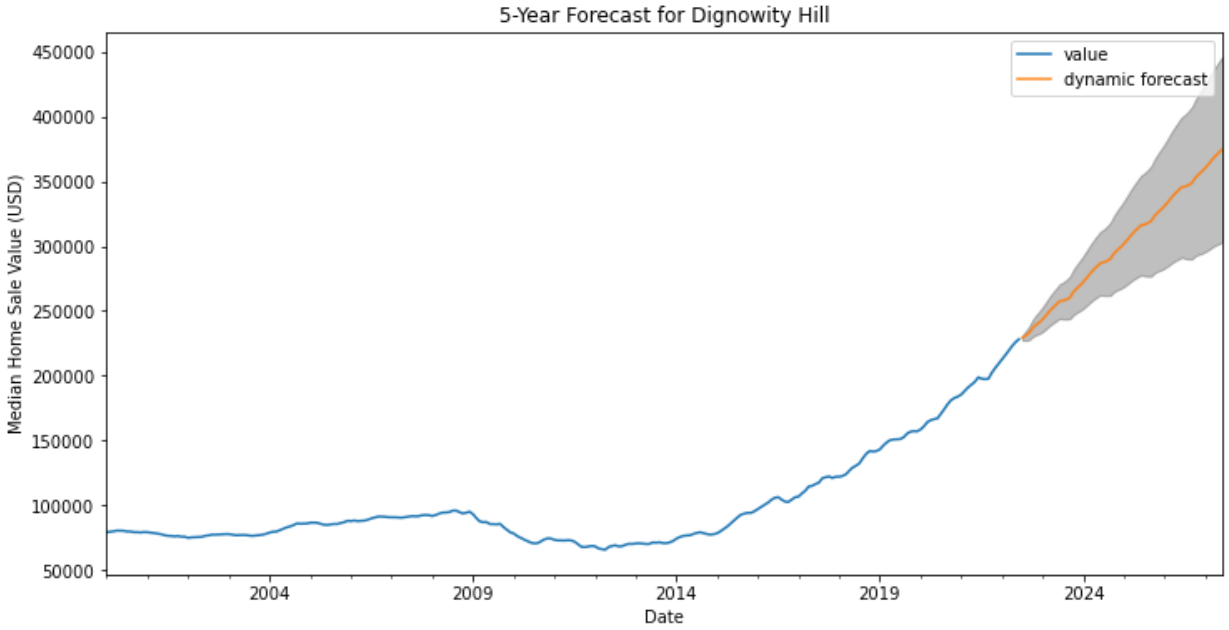

Correlogram
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00
0
2
4
6
8
10

In [47]:
```
1 ose_forecast(dig_hill, output_dig_hill, neighborhood='Dignowity Hill'
```

```
The RMSE of our forecasts is 1446.54
```



In [48]:
```
1 dynamic_forecast(dig_hill, output_dig_hill, neighborhood='Dignowity Hi
```



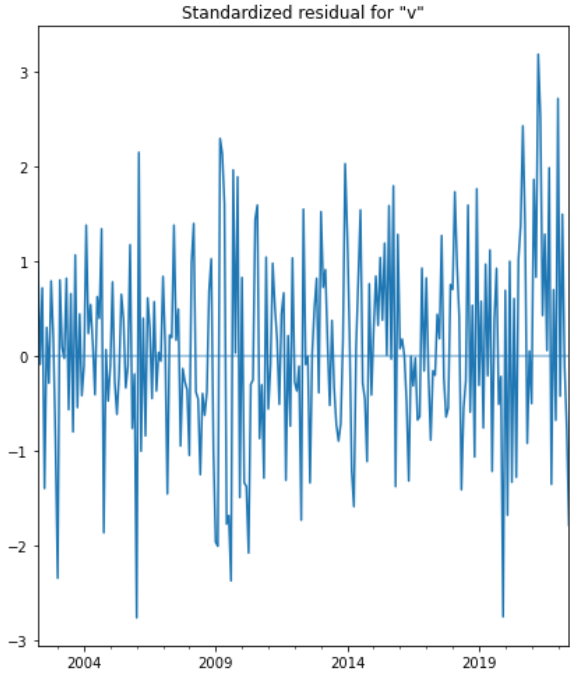
Out[48]:
```
{'forecast': 374878.0, 'minimum': 303162.0, 'maximum': 446593.0}
```

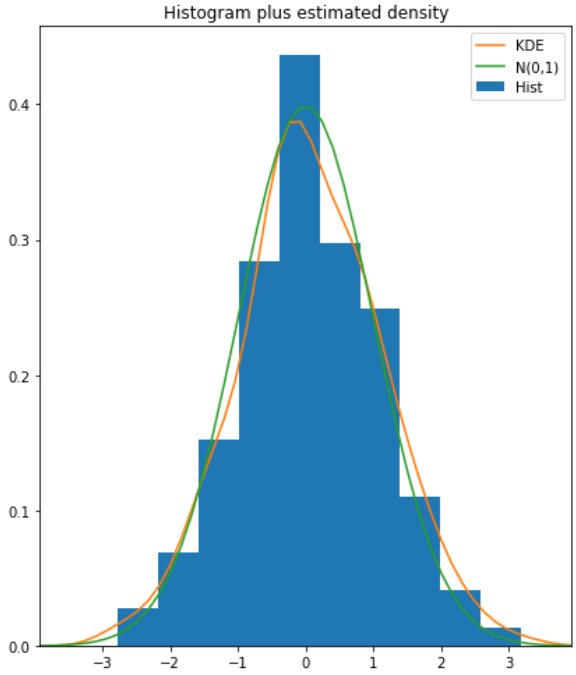
Once again, we see negative correlation at month 3, this should be expected with all of the rest of our zipcode plots. The residuals do have a few tail outliers, but are distributed normally. The confidence interval of our forecasts is smaller than what we saw in the Arena District, and the RMSE is lower at $1446.

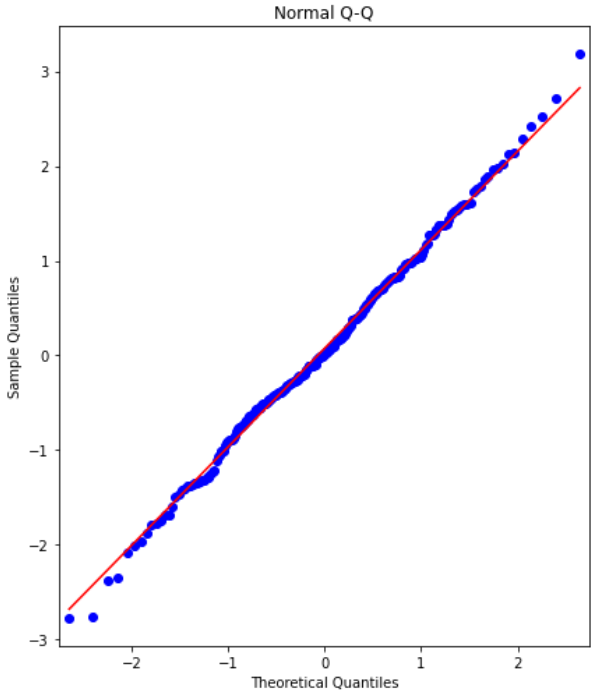
5.6.3 Gardendale / Brady Gardens

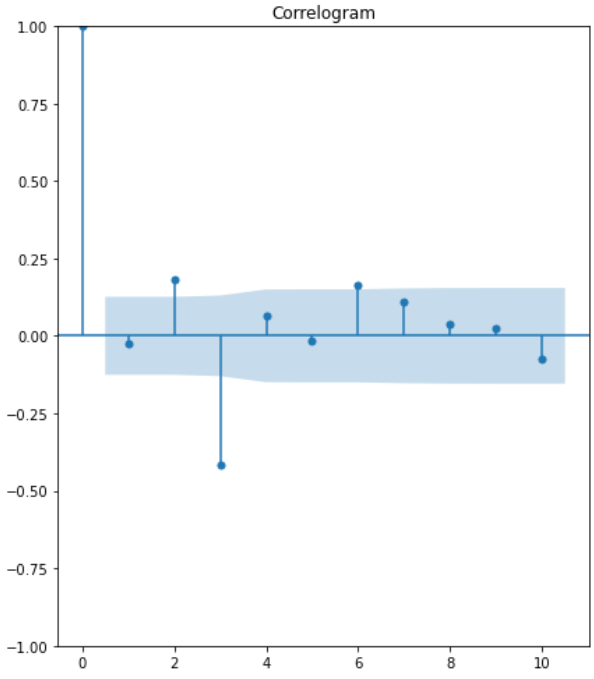
In [49]:
```
b_gardens = zip_df[2]
output_b_gardens = sarimax(b_gardens, order=(1, 1, 1), seasonal_order=
```

```
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.L1          0.7256      0.049     14.850      0.000       0.630      0.821
ma.L1          0.0109      0.070      0.156      0.876      -0.126      0.147
ma.S.L12      -0.6518      0.043    -15.195      0.000      -0.736     -0.568
sigma2      3.649e+05    3.2e+04     11.394      0.000    3.02e+05    4.28e+05
==============================================================================
```


Standardized residual for "v"
3
2
1
0
−1
−2
−3
2004
2009
2014
2019

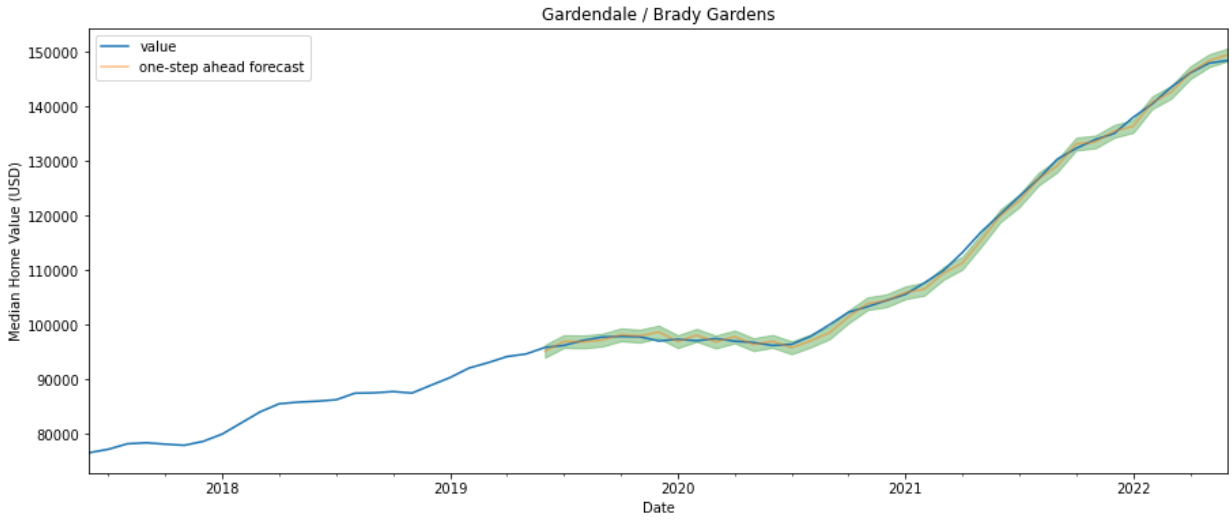

Histogram plus estimated density
KDE
N(0,1)
Hist
0.4
0.3
0.2
0.1
0.0
−3
−2
−1
0
1
2
3


Normal Q-Q
Sample Quantiles
Theoretical Quantiles
3
2
1
0
−1
−2
−3
−2
−1
0
1
2

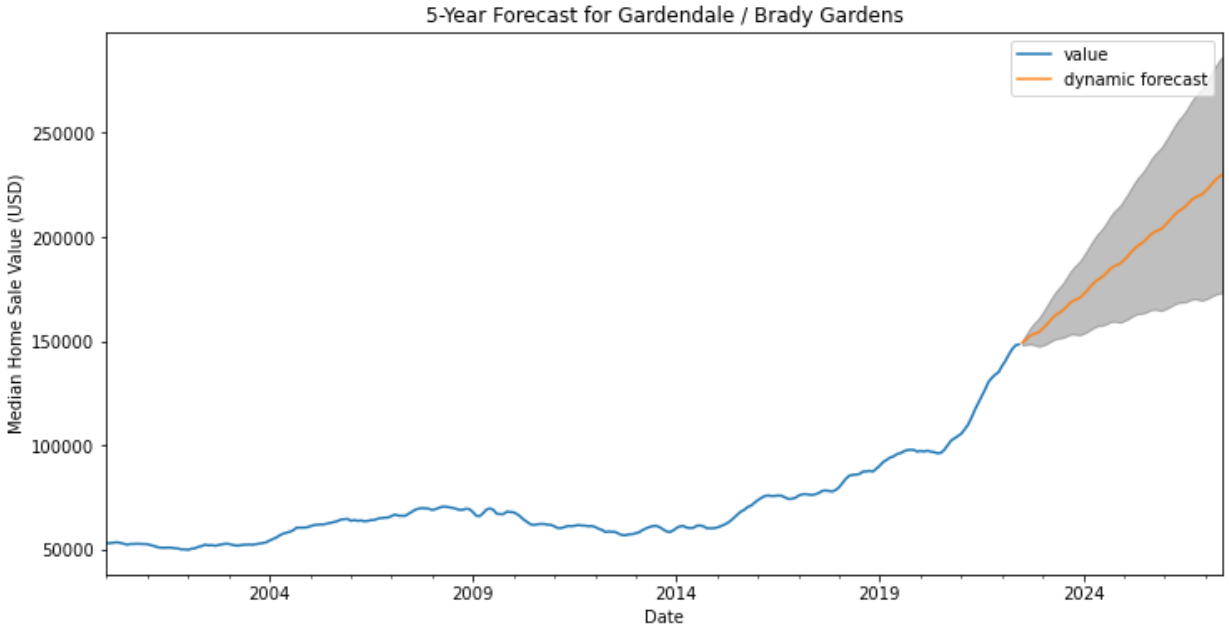

Correlogram
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00
0
2
4
6
8
10

In [50]:
```
1 ose_forecast(b_gardens, output_b_gardens, neighborhood='Gardendale / I
```

```
The RMSE of our forecasts is 856.1
```



In [51]:
```
1 dynamic_forecast(b_gardens, output_b_gardens, neighborhood='Gardendale
```



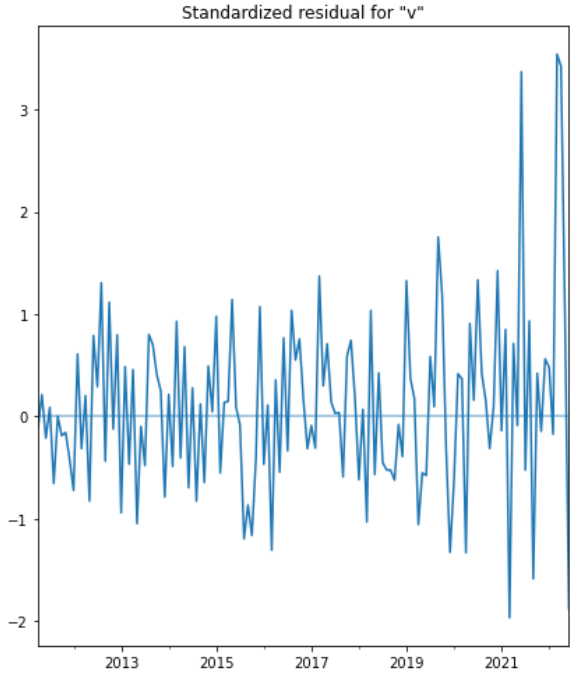
Out[51]:
```
{'forecast': 229884.0, 'minimum': 173058.0, 'maximum': 286710.0}
```

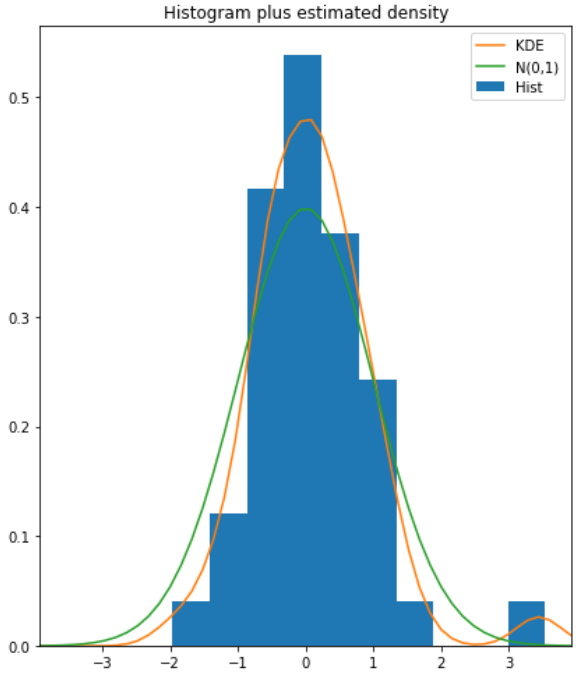
Once again, we achieved a lower RMSE for Gardendale area at $856. The residuals are normally distributed without any significant outliers.

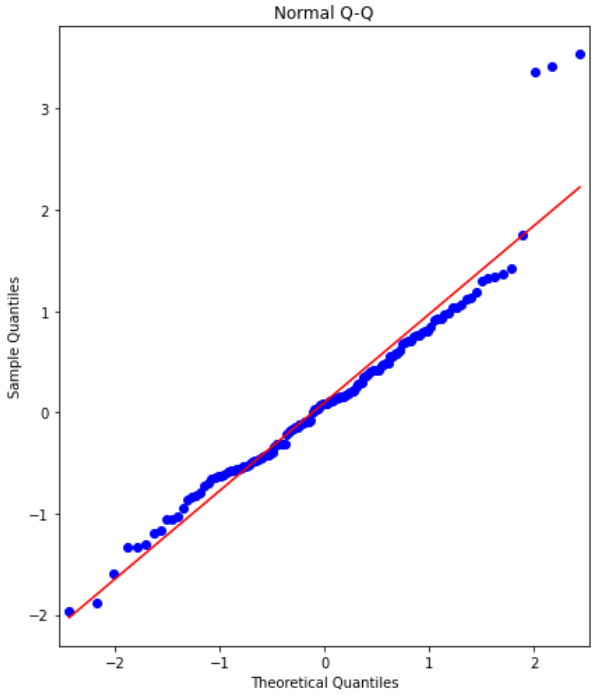
5.6.4 Kingsbury

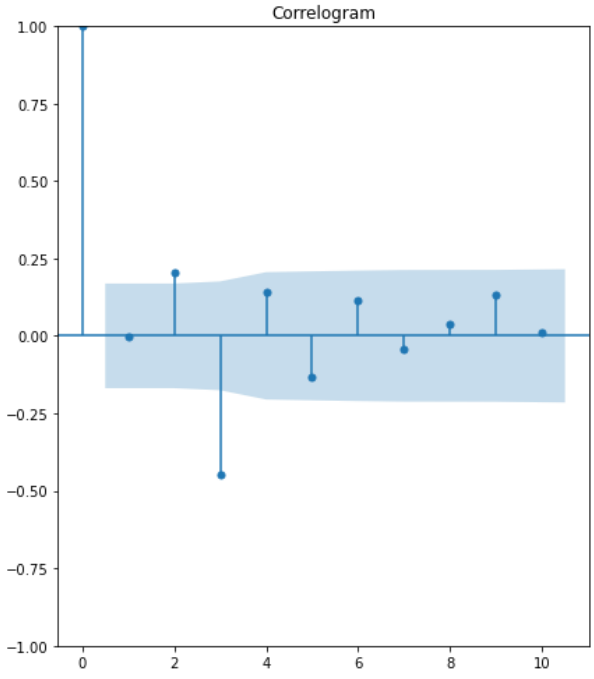
In [52]:
```
kingsbury = zip_df[3]
output_kingsbury = sarimax(kingsbury, order=(1, 1, 1), seasonal_order=
```

```
==============================================================================
=====
                 coef    std err          z      P>|z|      [0.025
0.975]
------------------------------------------------------------------------------
-----
ar.L1          0.6708      0.102      6.553      0.000       0.470
0.871
ma.L1          0.0476      0.137      0.348      0.728      -0.221
0.316
ar.S.L12      -0.5986      0.112     -5.325      0.000      -0.819      -
0.378
ma.S.L12      -0.0105      0.061     -0.171      0.864      -0.131
0.110
sigma2      2.151e+07   2.25e-09   9.56e+15      0.000    2.15e+07    2.1
5e+07
==============================================================================
=====
```


Standardized residual for "v"
3
2
1
0
−1
−2
2013
2015
2017
2019
2021

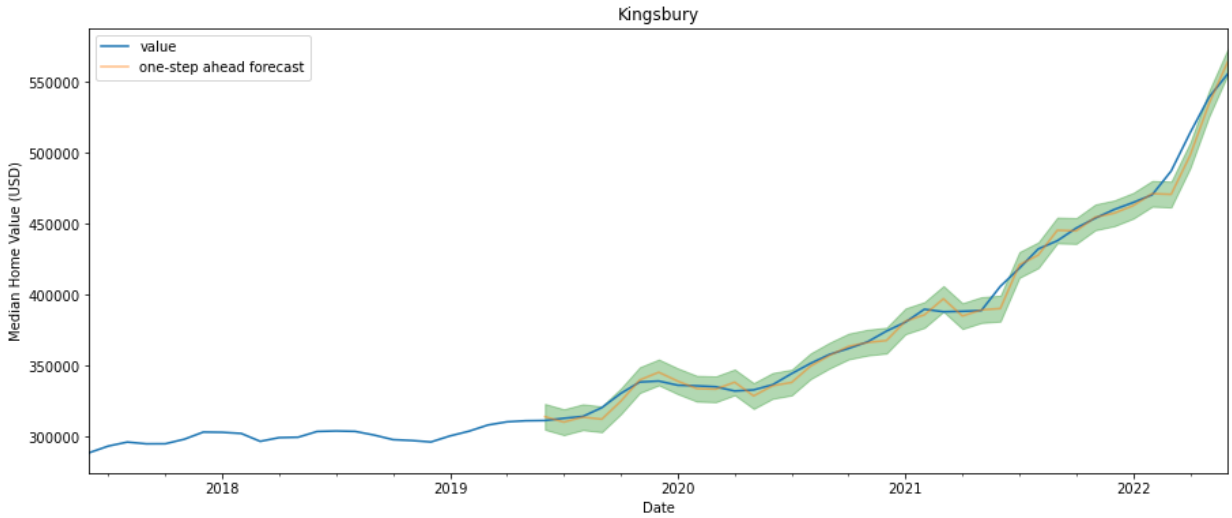

Histogram plus estimated density
KDE
N(0,1)
Hist
0.5
0.4
0.3
0.2
0.1
0.0
−3
−2
−1
0
1
2
3


Normal Q-Q
Sample Quantiles
Theoretical Quantiles
3
2
1
0
−1
−2
−2
−1
0
1
2

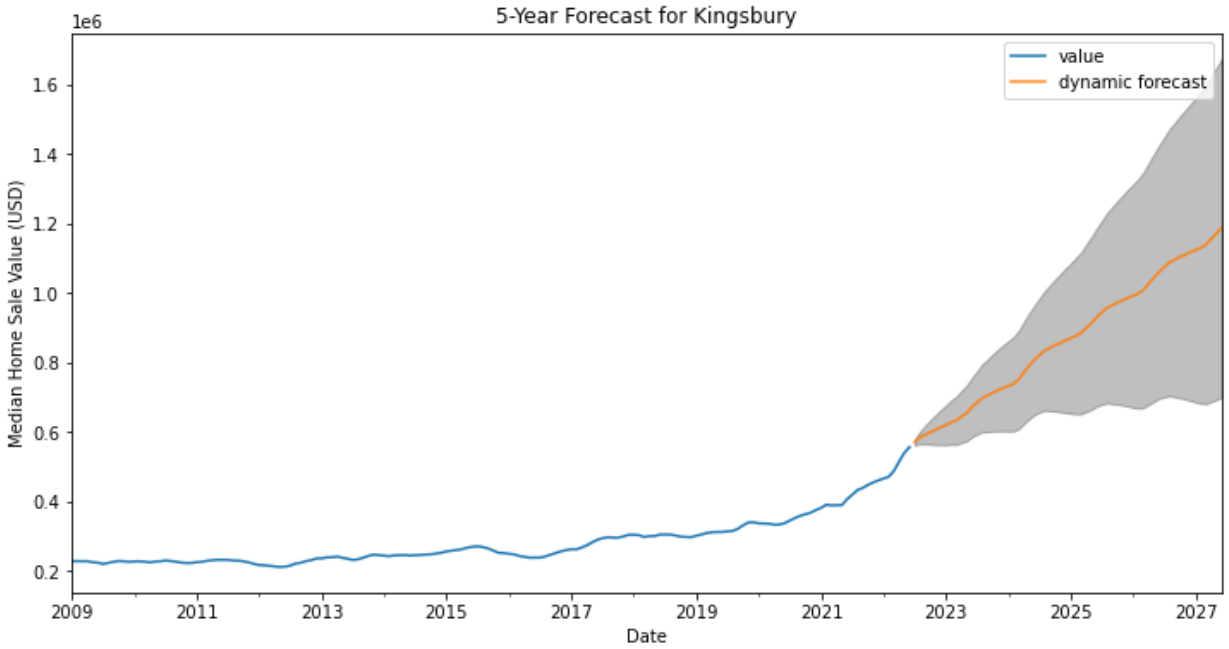

Correlogram
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00
0
2
4
6
8
10

In [53]:
```
ose_forecast(kingsbury, output_kingsbury, neighborhood='Kingsbury')
```

```
The RMSE of our forecasts is 6104.66
```



In [54]:
```
1 dynamic_forecast(kingsbury, output_kingsbury, neighborhood='Kingsbury
```



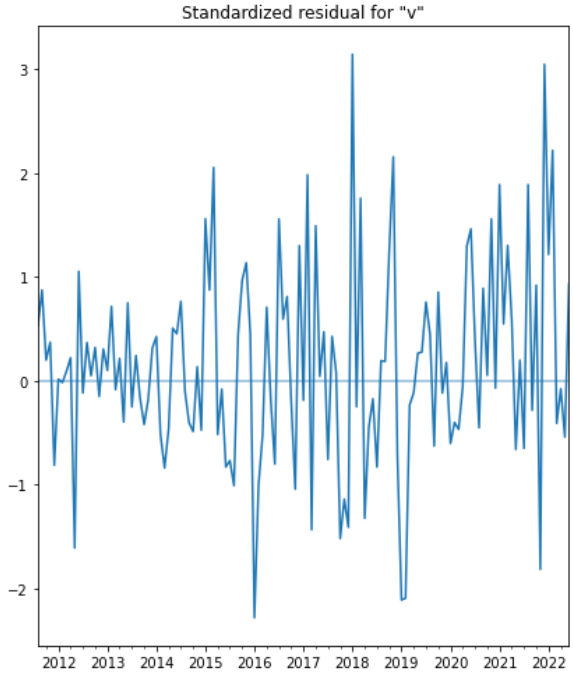
Out[54]:
```
{'forecast': 1187524.0, 'minimum': 698989.0, 'maximum': 1676059.0}
```

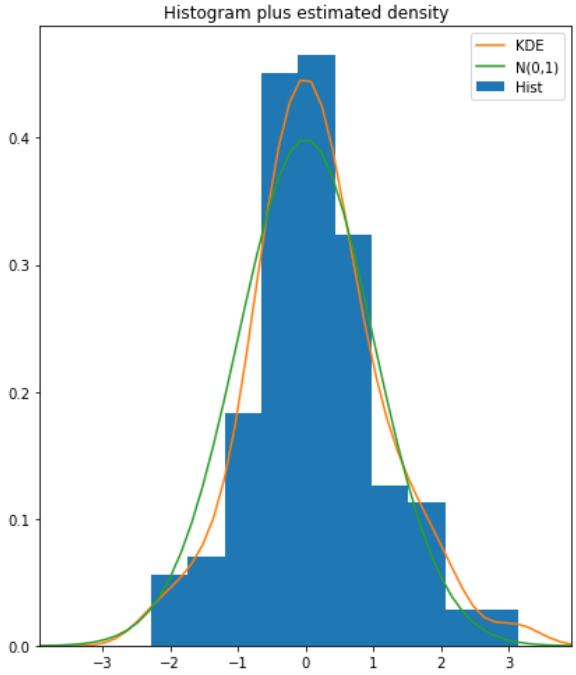
The RMSE of our predictions is $6,104 which is higher than our other zipcodes but the price of the homes are much higher in Kingsbury than the other areas. However, Kingsbury has some pretty significant outliers on the high end which is skewing the distribution of the residuals.

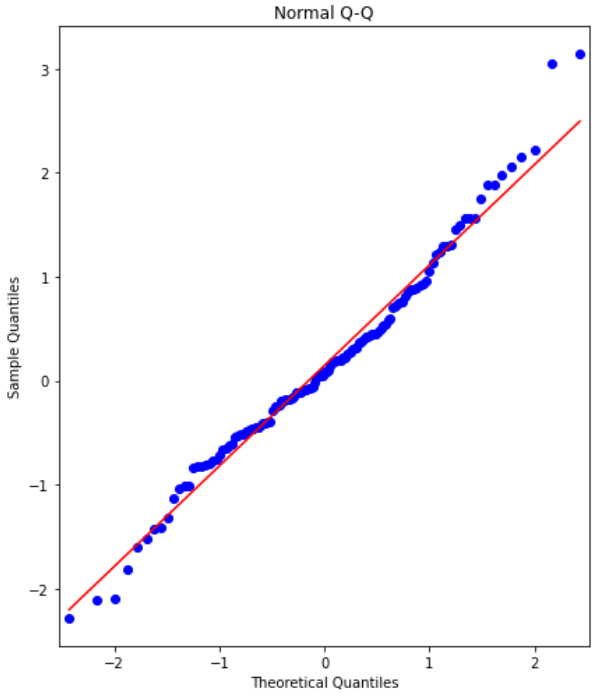
5.6.5 Medina

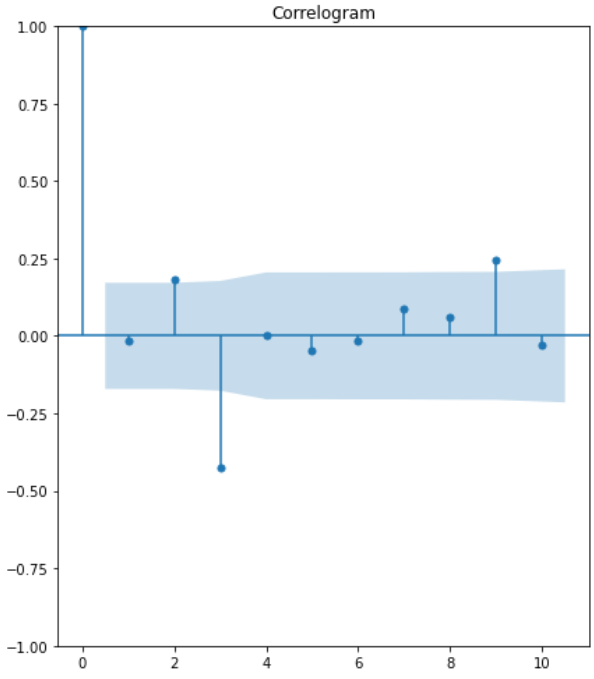
In [55]:
```
1 medina = zip_df[4]
2 output_medina = sarimax(medina, order=(1, 1, 1), seasonal_order=(0, 1,
```

```
==========================================================================
=====
                 coef    std err          z      P>|z|      [0.025
0.975]
--------------------------------------------------------------------------
-----
ar.L1          0.6341      0.093      6.837      0.000       0.452
0.816
ma.L1          0.0627      0.119      0.527      0.599      -0.171
0.296
ma.S.L12      -0.2064      0.039     -5.249      0.000      -0.284      -
0.129
sigma2      2.866e+06   3.32e+05      8.626      0.000    2.21e+06    3.5
2e+06
==========================================================================
=====
```


Standardized residual for "v"
3
2
1
0
−1
−2
2012
2013
2014
2015
2016
2017
2018
2019
2020
2021
2022

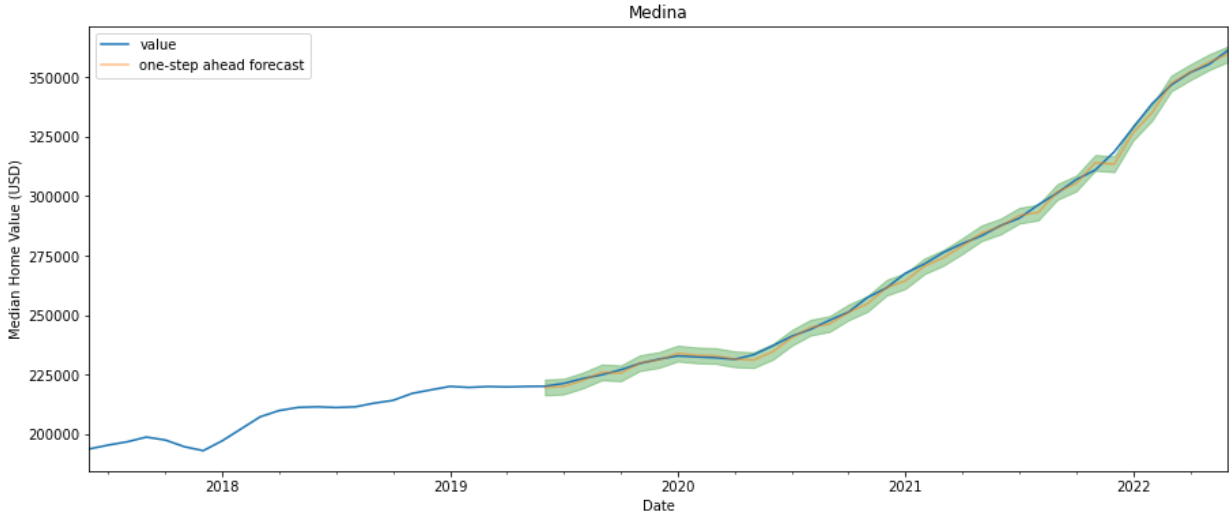

Histogram plus estimated density
KDE
N(0,1)
Hist
0.4
0.3
0.2
0.1
0.0
−3
−2
−1
0
1
2
3


Normal Q-Q
Sample Quantiles
Theoretical Quantiles
3
2
1
0
−1
−2
−2
−1
0
1
2

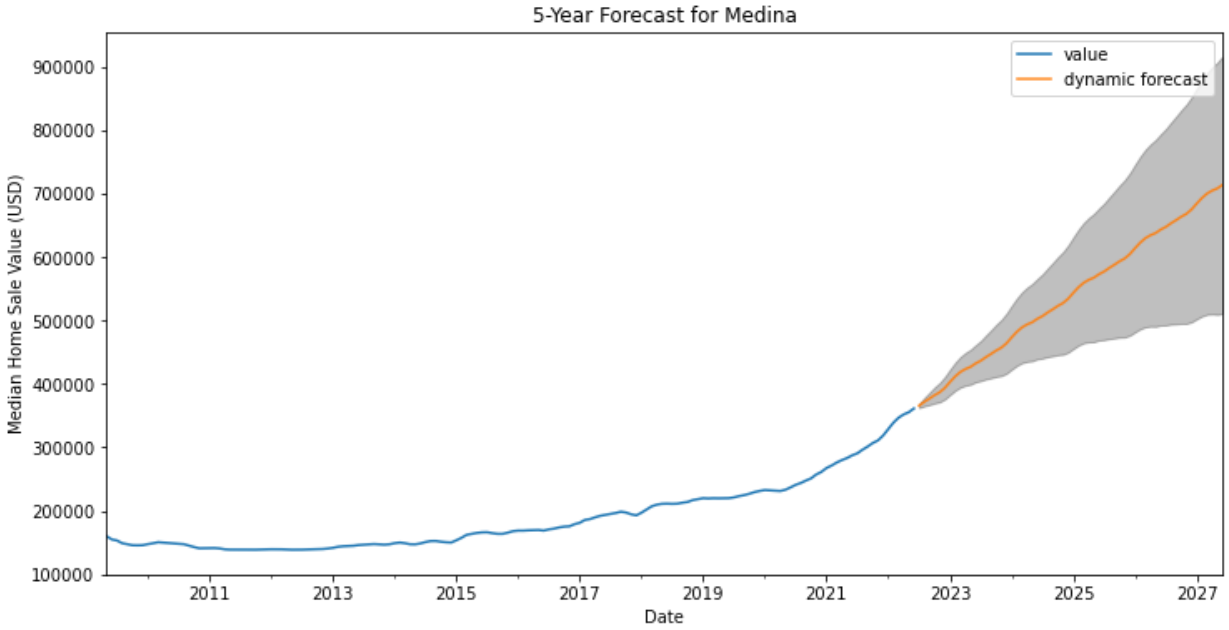

Correlogram
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00
0
2
4
6
8
10

In [56]:
```
1 ose_forecast(medina, output_medina, neighborhood='Medina')
```

```
The RMSE of our forecasts is 1798.26
```



In [57]:
```
1 dynamic_forecast(medina, output_medina, neighborhood='Medina', years=
```



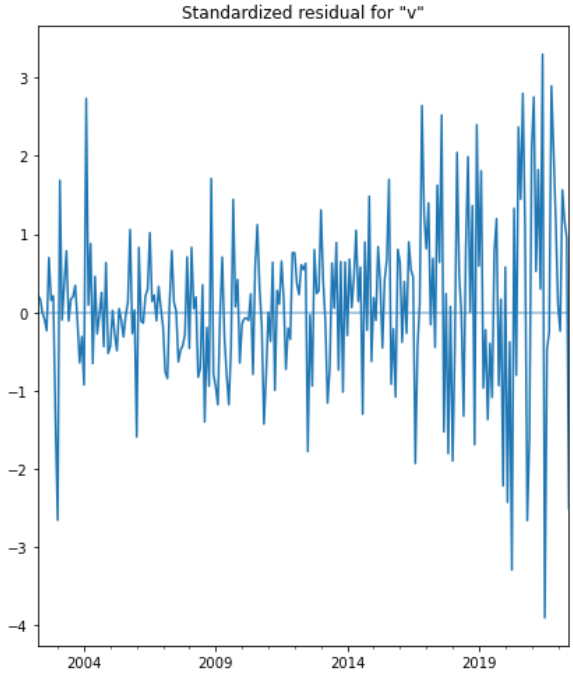
Out[57]:
```
{'forecast': 713491.0, 'minimum': 510850.0, 'maximum': 916132.0}
```

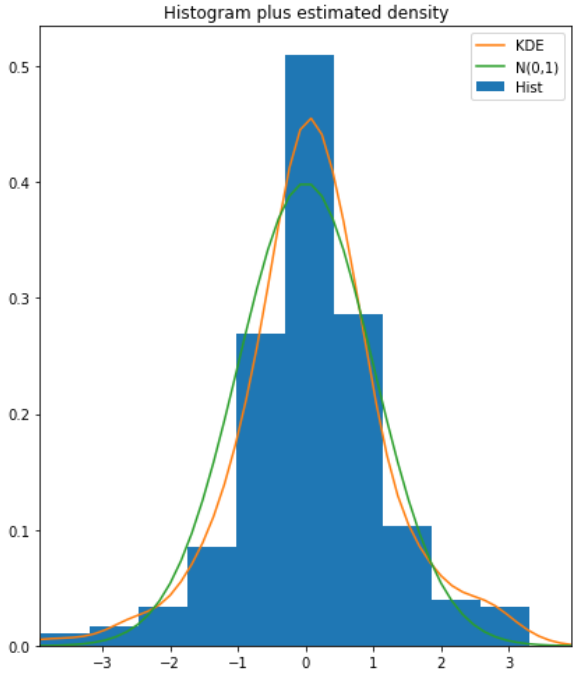
The RMSE of our predictions for Medina is $1,798, which is similar to some of our other zipcodes we have already seen, and we can see the presence of a few outliers in the Q-Q plot.

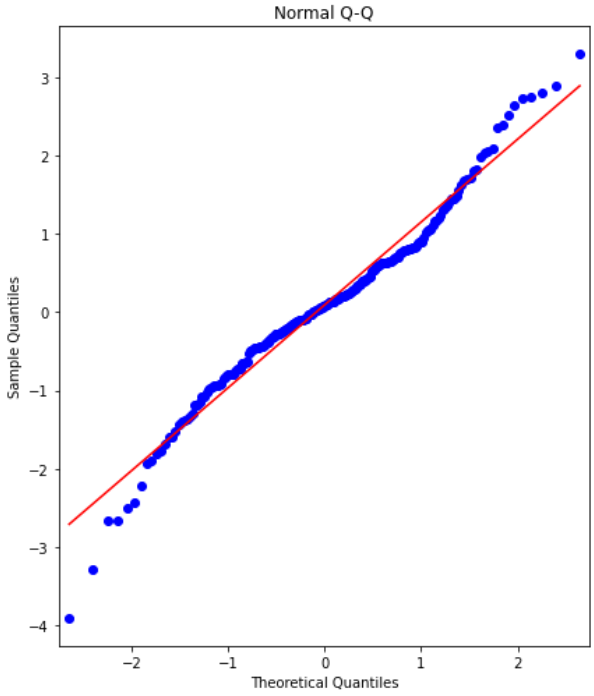
5.6.6 Denver Heights / Highland Park

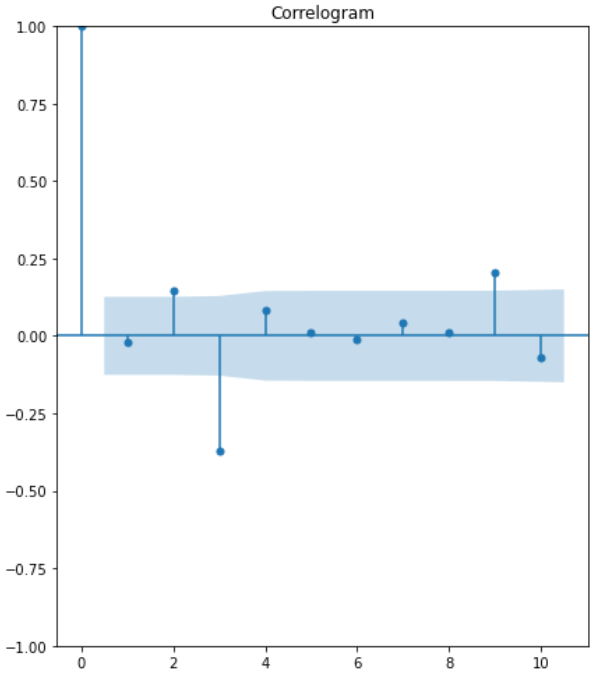
In [58]:
```
highland_park = zip_df[5]
output_highland_park = sarimax(highland_park, order=(1, 1, 1), seasona
```

```
==============================================================================
=====
                 coef    std err          z      P>|z|      [0.025
0.975]
------------------------------------------------------------------------------
-----
ar.L1          0.6916      0.040     17.311      0.000       0.613
0.770
ma.L1          0.1066      0.067      1.597      0.110      -0.024
0.237
ma.S.L12      -0.5716      0.034    -16.696      0.000      -0.639      -
0.504
sigma2       4.35e+05   3.03e+04     14.333      0.000    3.76e+05    4.9
4e+05
==============================================================================
=====
```


Standardized residual for "v"
3
2
1
0
−1
−2
−3
−4
2004
2009
2014
2019

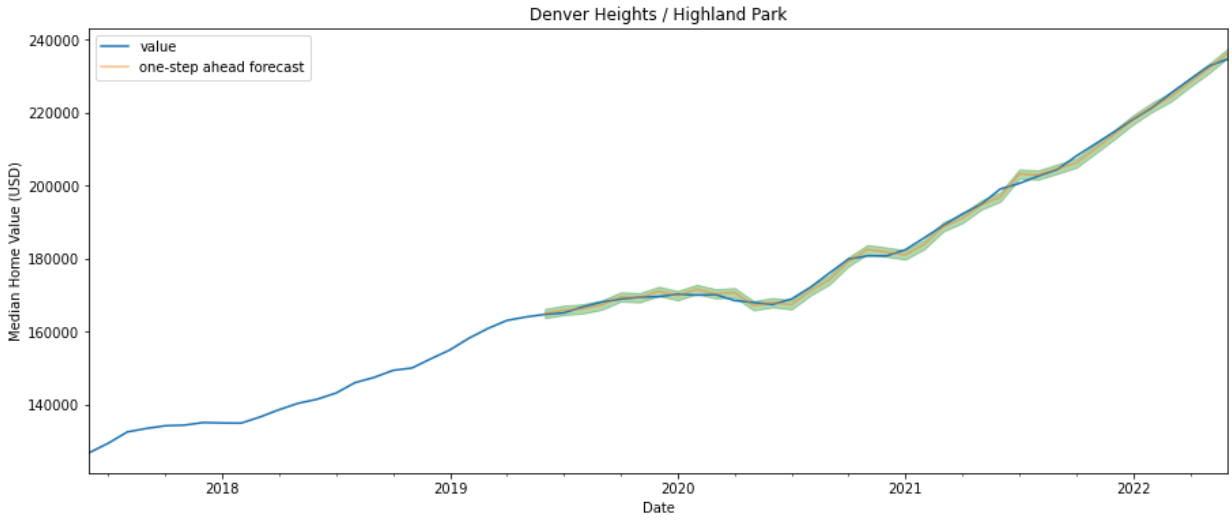

Histogram plus estimated density
KDE
N(0,1)
Hist
0.5
0.4
0.3
0.2
0.1
0.0
−3
−2
−1
0
1
2
3


Normal Q-Q
Sample Quantiles
Theoretical Quantiles
3
2
1
0
−1
−2
−3
−4
−2
−1
0
1
2

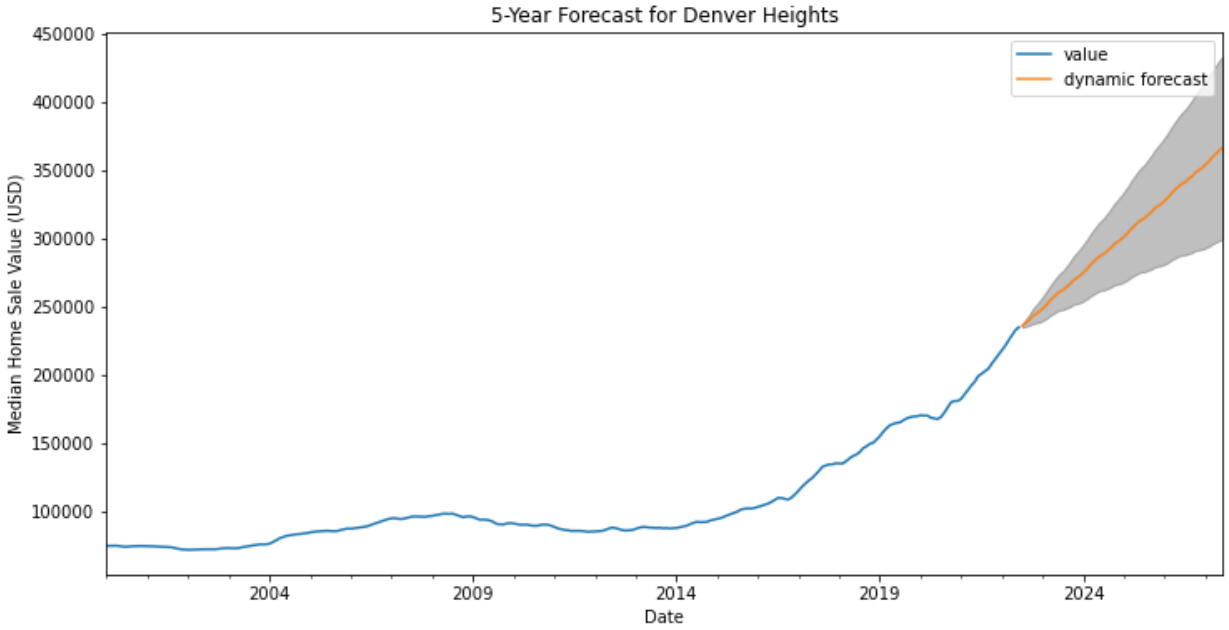

Correlogram
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00
0
2
4
6
8
10

In [59]:
```
1 ose_forecast(highland_park, output_highland_park, neighborhood='Denve
```

```
The RMSE of our forecasts is 1198.29
```



In [60]:
```
1 dynamic_forecast(highland_park, output_highland_park, neighborhood='De
```



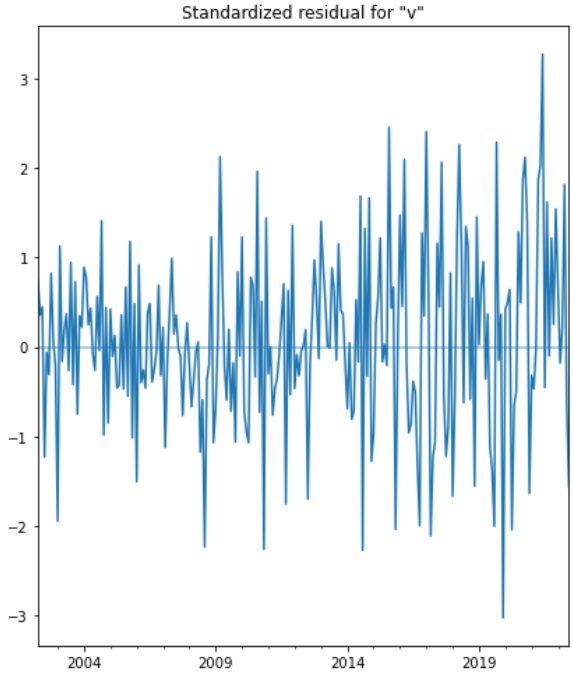
Out[60]:
```
{'forecast': 366017.0, 'minimum': 298896.0, 'maximum': 433138.0}
```

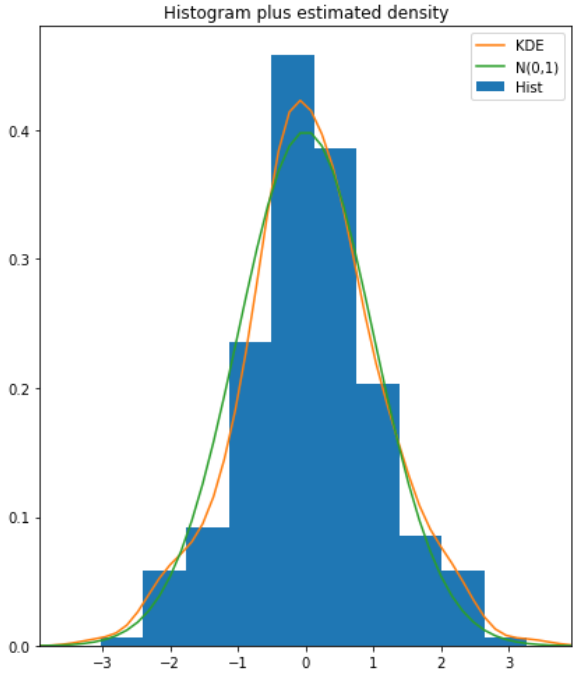
Once again, residuals are mostly normal with outliers on the tails. The RMSE of our predictions is $1198. The confidence interval appears to be smaller than several others we have seen.

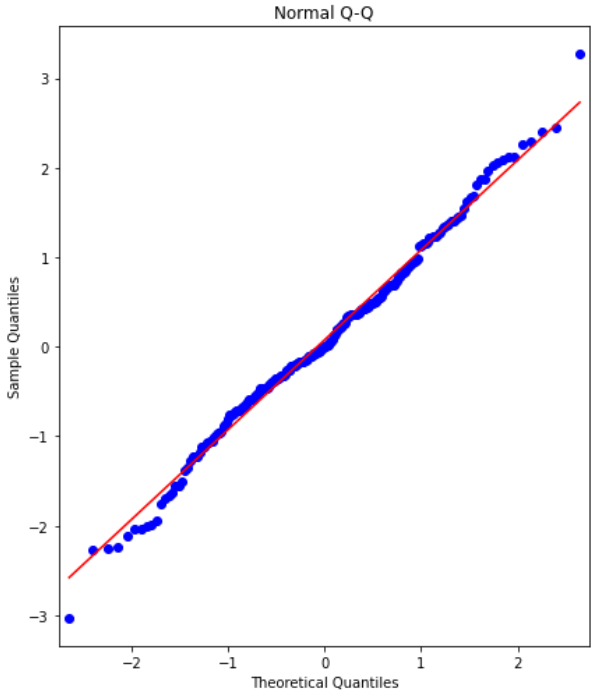
5.6.7 Inner Westside

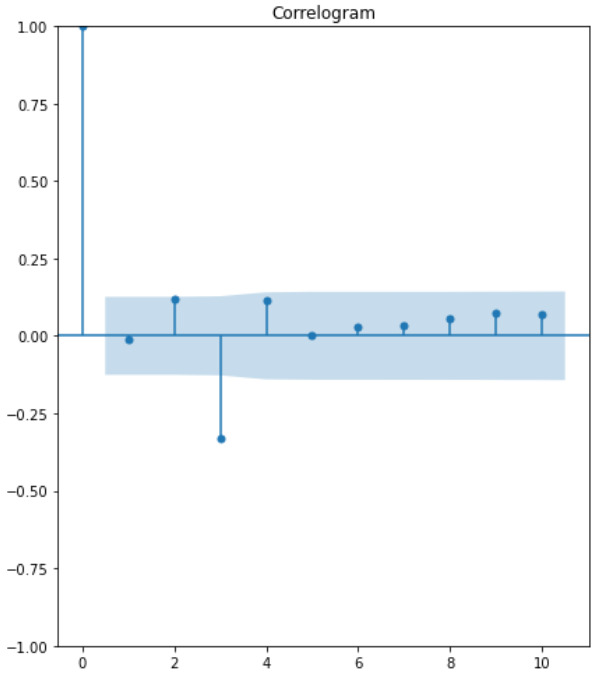
In [61]:
```
inner_westside = zip_df[6]
output_inner_westside = sarimax(inner_westside, order=(1, 1, 1), seas
```

```
==============================================================================
=====
                 coef    std err          z      P>|z|      [0.025
0.975]
------------------------------------------------------------------------------
-----
ar.L1          0.6936      0.065     10.635      0.000       0.566
0.821
ma.L1          0.0103      0.096      0.108      0.914      -0.177
0.198
ar.S.L12      -0.4601      0.063     -7.347      0.000      -0.583      -
0.337
ma.S.L12      -0.1084      0.034     -3.156      0.002      -0.176      -
0.041
sigma2      4.368e+05   3.72e+04     11.730      0.000    3.64e+05     5.
1e+05
==============================================================================
=====
```


Standardized residual for "v"
3
2
1
0
−1
−2
−3
2004
2009
2014
2019

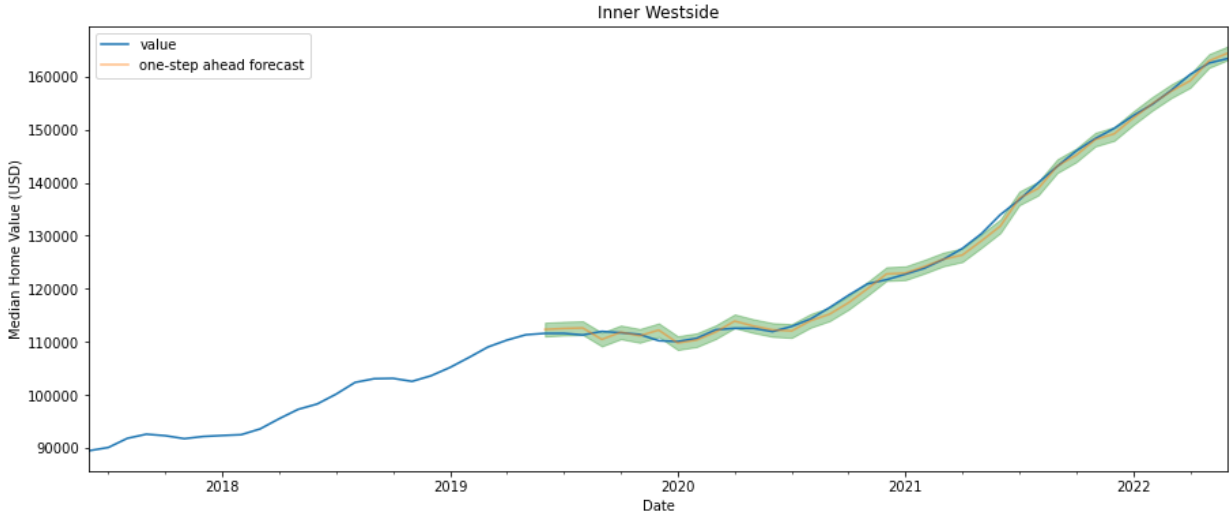

Histogram plus estimated density
KDE
N(0,1)
Hist
0.4
0.3
0.2
0.1
0.0
−3
−2
−1
0
1
2
3


Normal Q-Q
Sample Quantiles
Theoretical Quantiles
3
2
1
0
−1
−2
−3
−2
−1
0
1
2

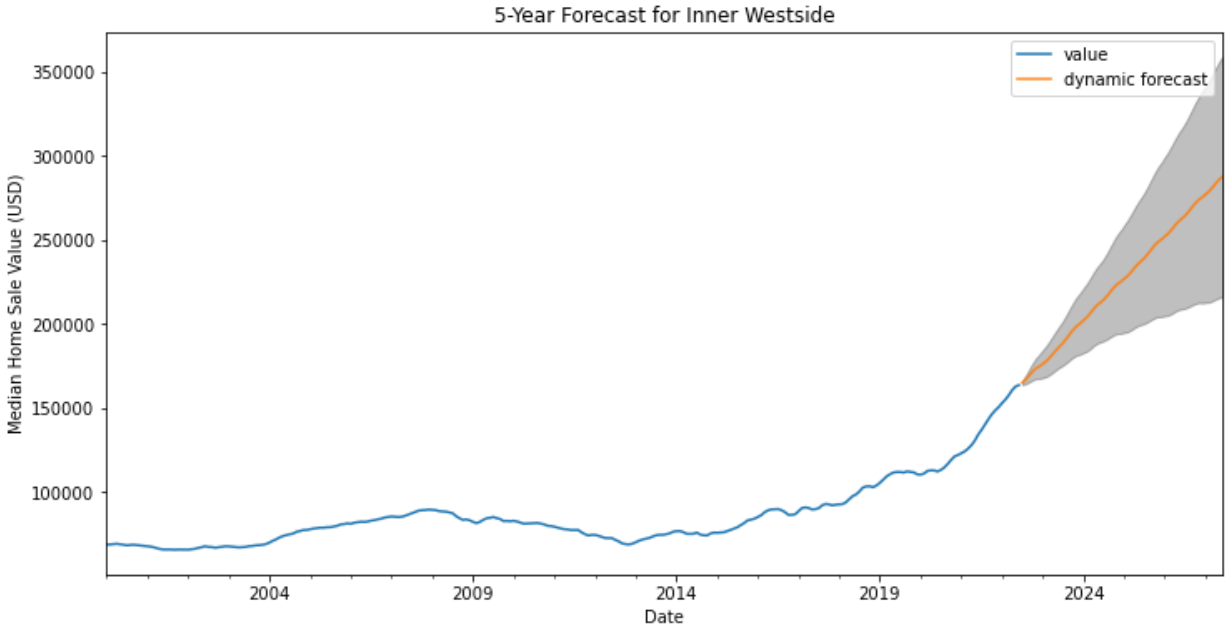

Correlogram
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00
0
2
4
6
8
10

In [62]:
```
1 ose_forecast(inner_westside, output_inner_westside, neighborhood='Inne
```

```
The RMSE of our forecasts is 933.67
```



In [63]:
```
1 dynamic_forecast(inner_westside, output_inner_westside, neighborhood=
```



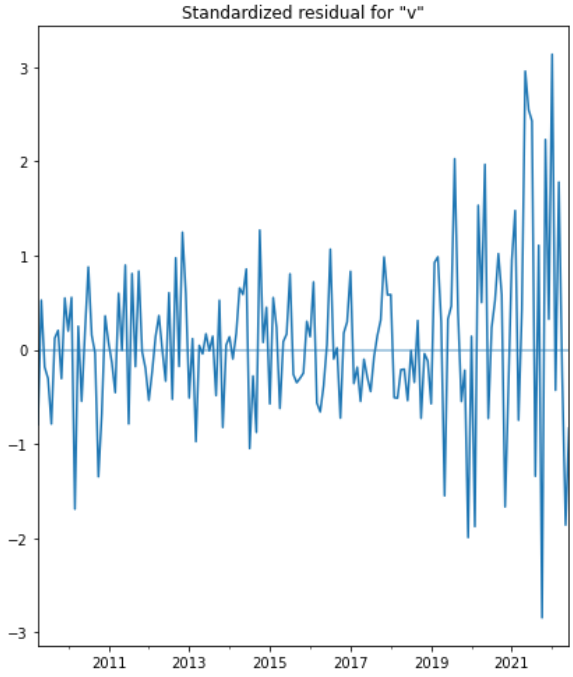
Out[63]:
```
{'forecast': 287589.0, 'minimum': 215798.0, 'maximum': 359380.0}
```

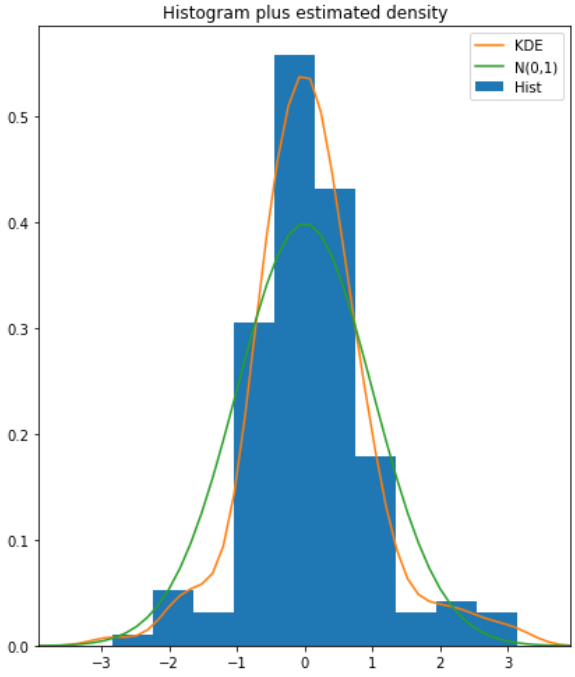
The residuals are normal for the inner westside zipcode, and we have an RMSE of $933. The price point for this neighborhood is is around 150k right now, with the forecast expected to increase to 287k in 5 years.

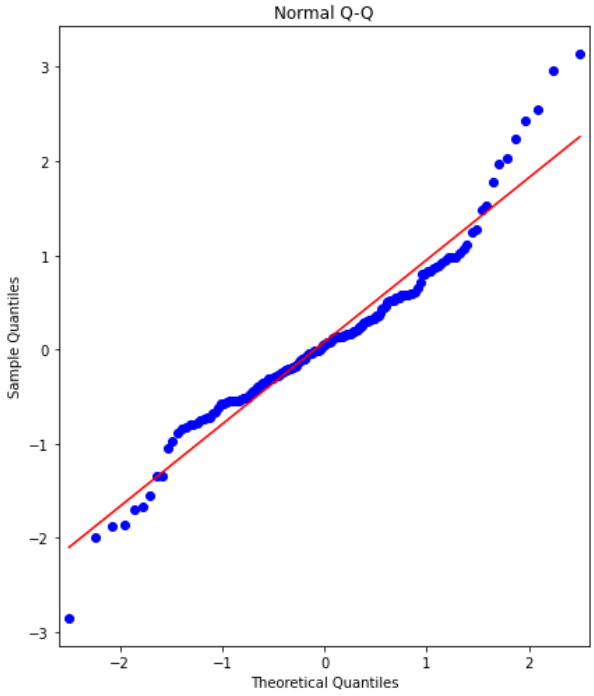
5.6.8 Fisher

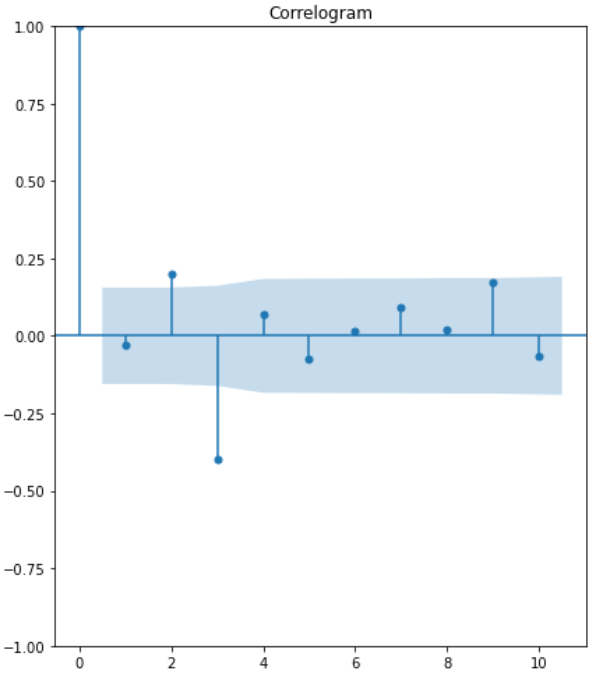
In [64]:
```
fisher = zip_df[7]
output_fisher = sarimax(fisher, order=(1, 1, 1), seasonal_order=(1, 1
```

```
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.L1          0.8604      0.033     25.747      0.000       0.795      0.926
ma.L1          0.1090      0.075      1.456      0.145      -0.038      0.256
ar.S.L12      -0.6351      0.085     -7.473      0.000      -0.802     -0.469
ma.S.L12       0.0176      0.046      0.385      0.700      -0.072      0.108
sigma2      2.488e+06   2.55e+05      9.751      0.000    1.99e+06    2.99e+06
==============================================================================
```


Standardized residual for "v"
3
2
1
0
−1
−2
−3
2011
2013
2015
2017
2019
2021

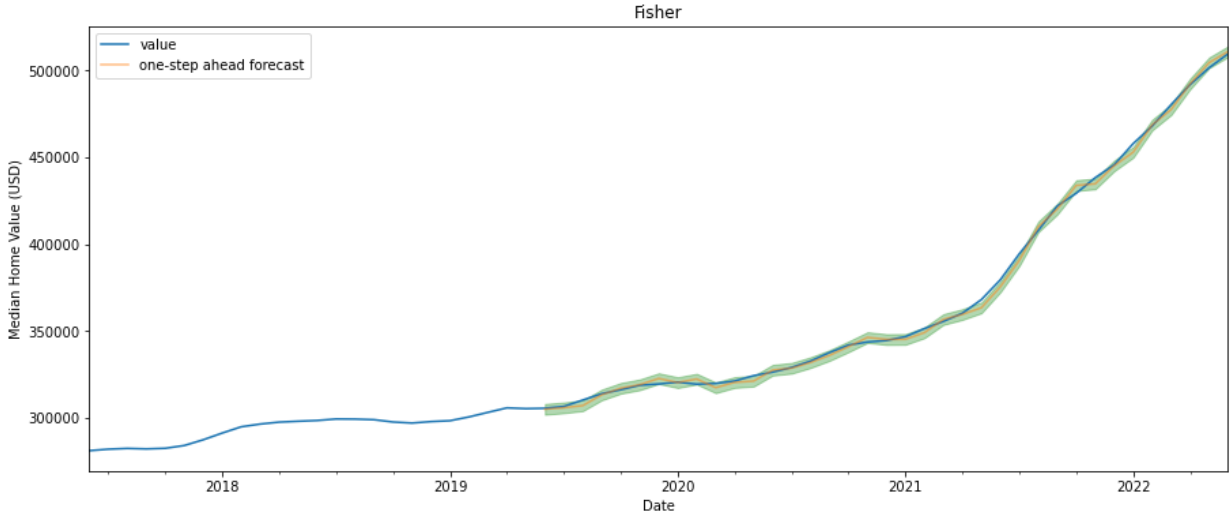

Histogram plus estimated density
KDE
N(0,1)
Hist
0.5
0.4
0.3
0.2
0.1
0.0
−3
−2
−1
0
1
2
3


Normal Q-Q
Sample Quantiles
Theoretical Quantiles
3
2
1
0
−1
−2
−3
−2
−1
0
1
2

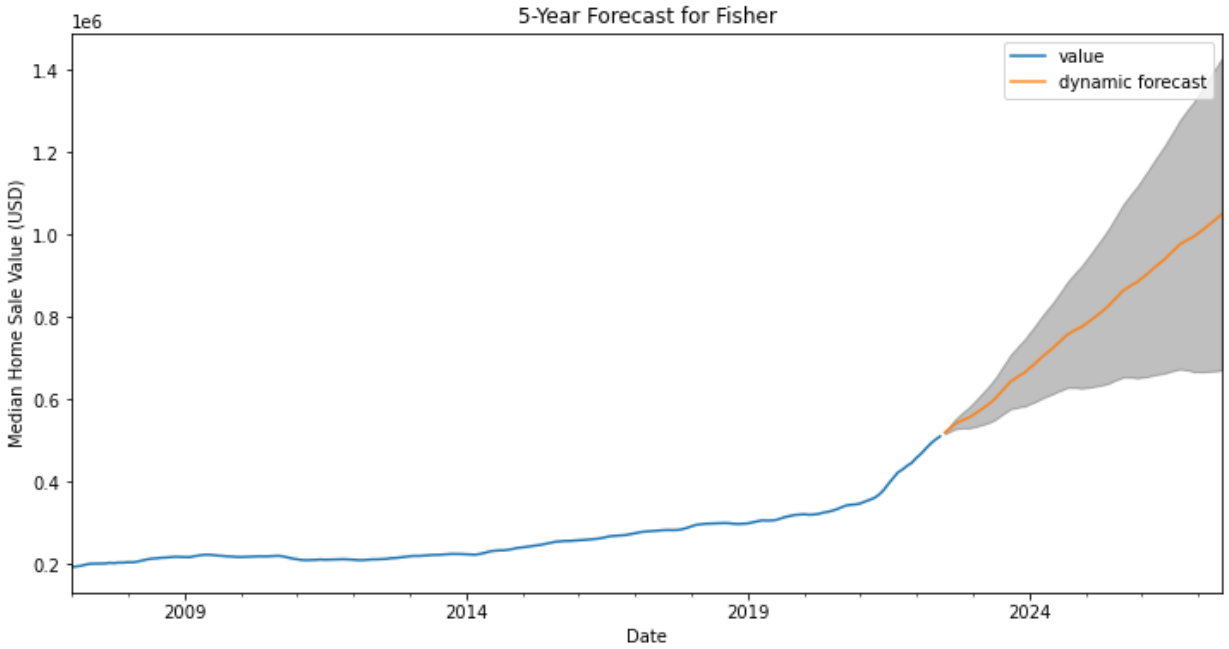

Correlogram
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00
0
2
4
6
8
10

In [65]:
```
1 ose_forecast(fisher, output_fisher, neighborhood='Fisher')
```

```
The RMSE of our forecasts is 2358.43
```



In [66]:
```
1 dynamic_forecast(fisher, output_fisher, neighborhood='Fisher', years=
```



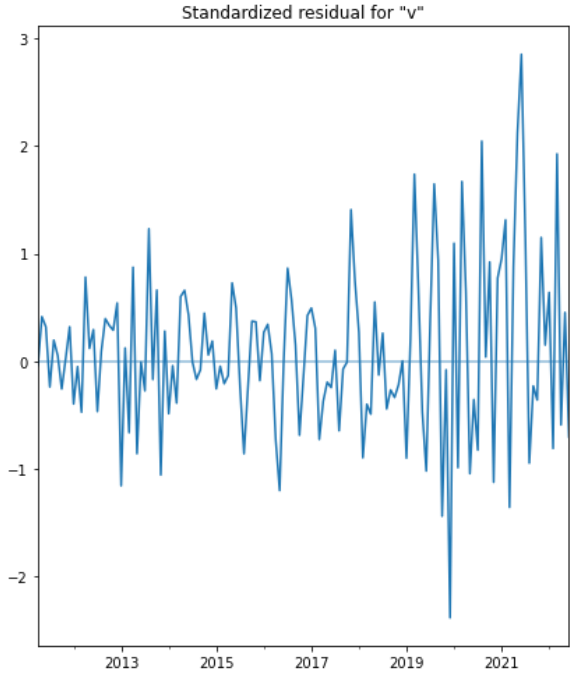
Out[66]:
```
{'forecast': 1048416.0, 'minimum': 669827.0, 'maximum': 1427004.0}
```

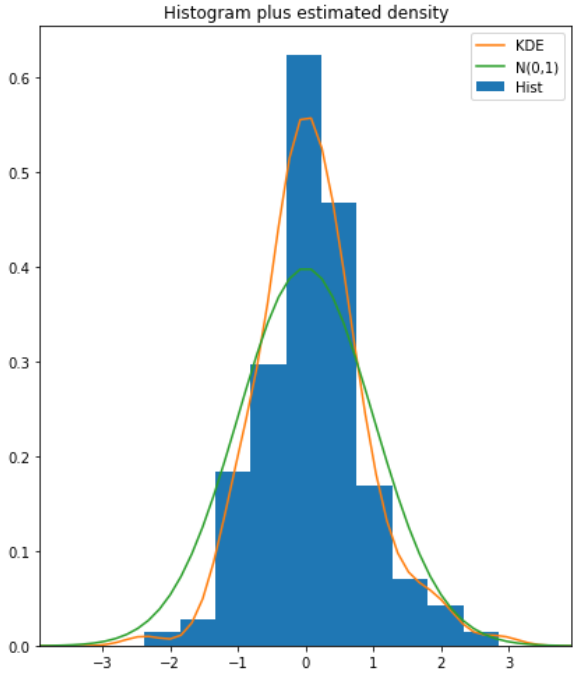
We can see the presence of heavy outliers. This is an area that is relatively new near Canyon Lake. There are many custom luxury homes in the area due to its location near the lake. The RMSE of our predictions is $2358. The confidence interval for our forecasts is very large, which means there is a large amount of uncertainty. The median home value has shot up 150k in the past 2 years due to it becoming a highly desirable area for retirees. While the gains could be huge in this area, it is not likely to be the safest investment based on the very steep increase over the past 2 years which could taper off.

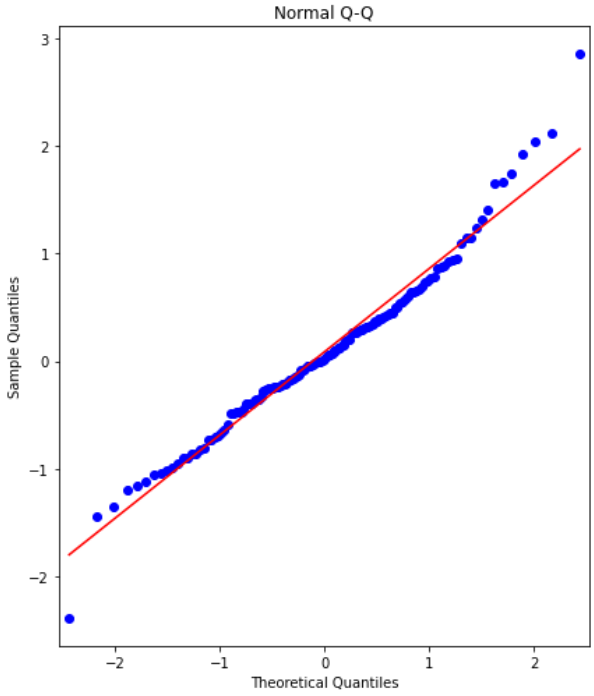
5.6.9 Canyon Lake

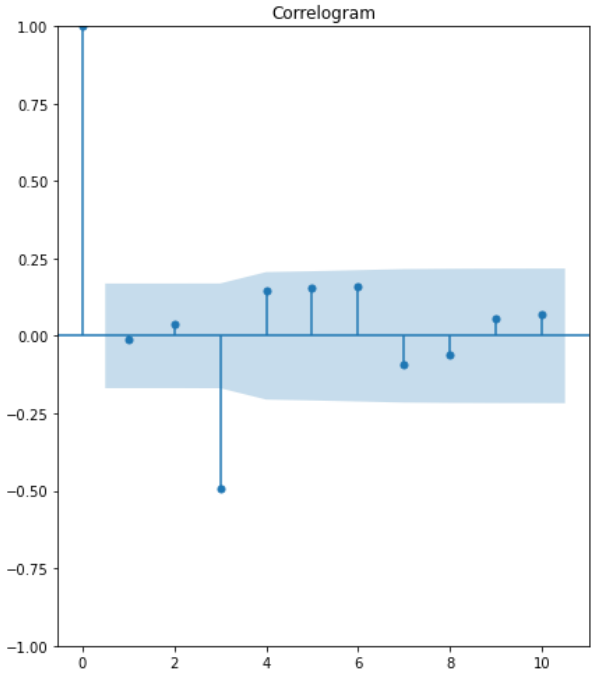
In [67]:
```
canyon_lake = zip_df[8]
output_canyon_lake = sarimax(canyon_lake, order=(1, 1, 1), seasonal_o
```

```
==========================================================================
=====
                 coef    std err          z      P>|z|      [0.025
0.975]
--------------------------------------------------------------------------
-----
ar.L1          0.9157      0.061     14.986      0.000       0.796
1.035
ma.L1          0.1537      0.137      1.121      0.262      -0.115
0.422
ar.S.L12      -0.7337      0.125     -5.855      0.000      -0.979      -
0.488
ma.S.L12      -0.0034      0.067     -0.052      0.959      -0.134
0.127
sigma2      2.152e+06   3.35e+05      6.429      0.000     1.5e+06    2.8
1e+06
==========================================================================
=====
```


Standardized residual for "v"
3
2
1
0
−1
−2
2013
2015
2017
2019
2021

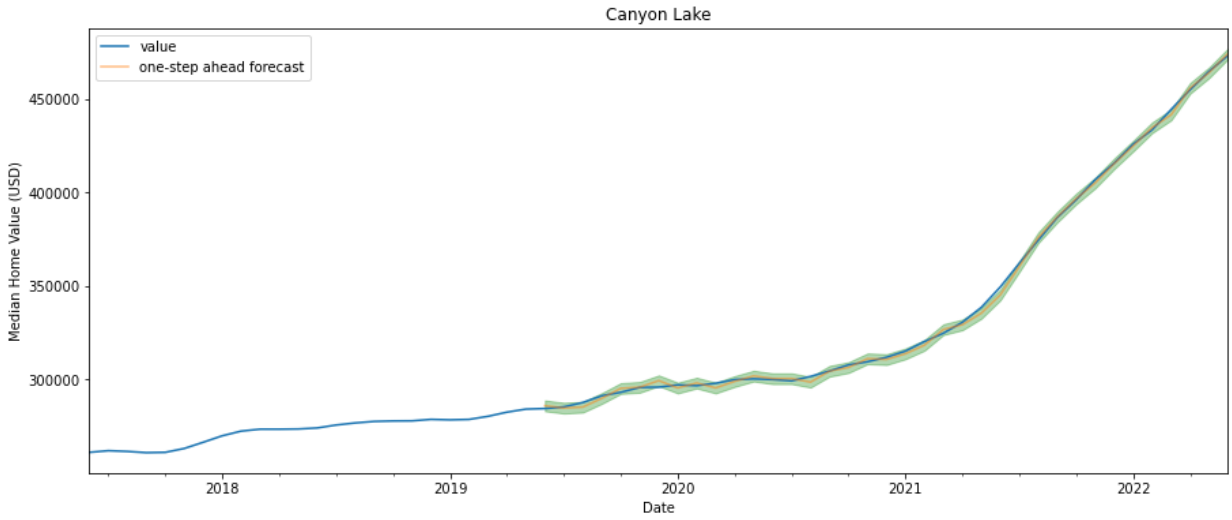

Histogram plus estimated density
KDE
N(0,1)
Hist
0.6
0.5
0.4
0.3
0.2
0.1
0.0
−3
−2
−1
0
1
2
3


Normal Q-Q
Sample Quantiles
Theoretical Quantiles
3
2
1
0
−1
−2
−2
−1
0
1
2

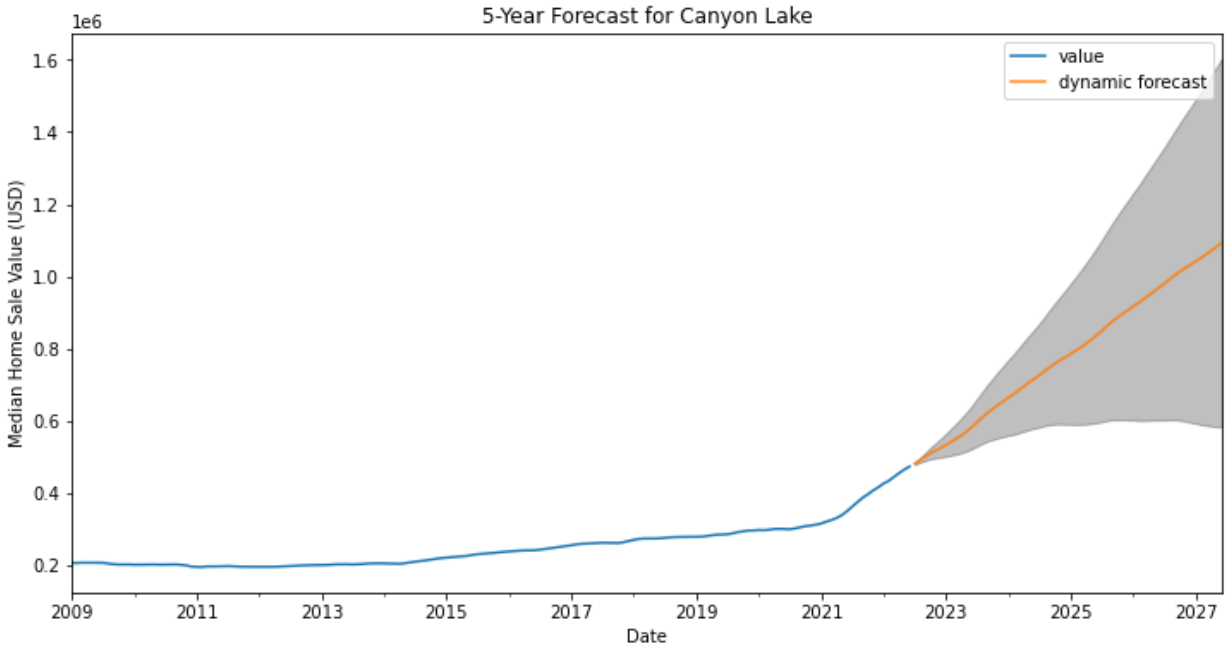

Correlogram
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00
0
2
4
6
8
10

In [68]:
```
1 ose_forecast(canyon_lake, output_canyon_lake, neighborhood='Canyon Lal
```

```
The RMSE of our forecasts is 1773.47
```



In [69]:
```
1 dynamic_forecast(canyon_lake, output_canyon_lake, neighborhood='Canyo
```



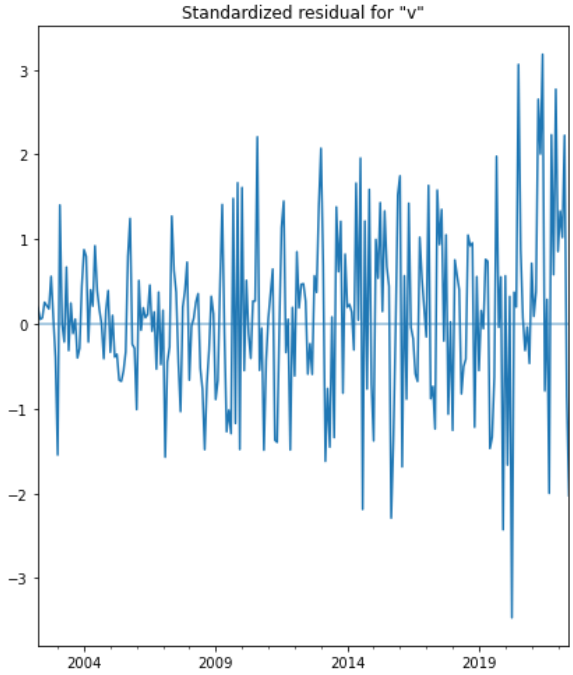
Out[69]:
```
{'forecast': 1093740.0, 'minimum': 582966.0, 'maximum': 1604515.0}
```

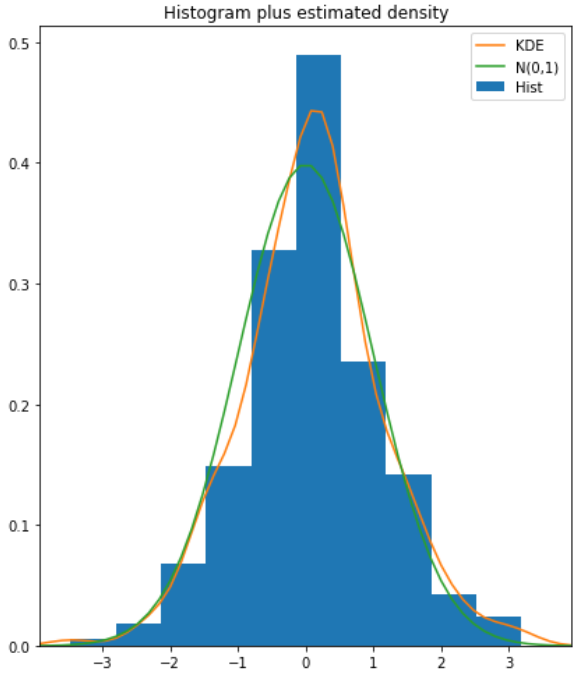
We can see the same thing happening in Canyon Lake, the median value of homes has shot up 150k in the past year, and Canyon Lake also has a high entry point into the market right now. Due to the high increases in the past year, the confidence interval is very large for Canyon Lake and this would be a riskier investment. There is a spread of 1 million dollars in our confidence interval!

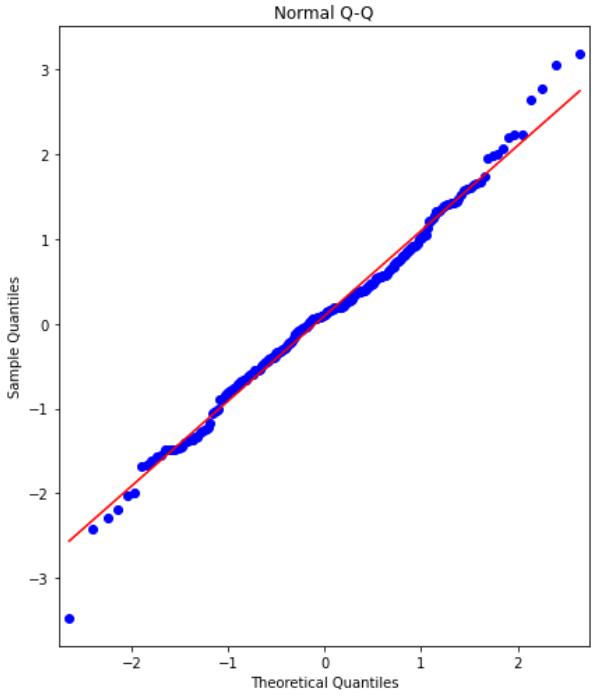
5.6.10 Eastside

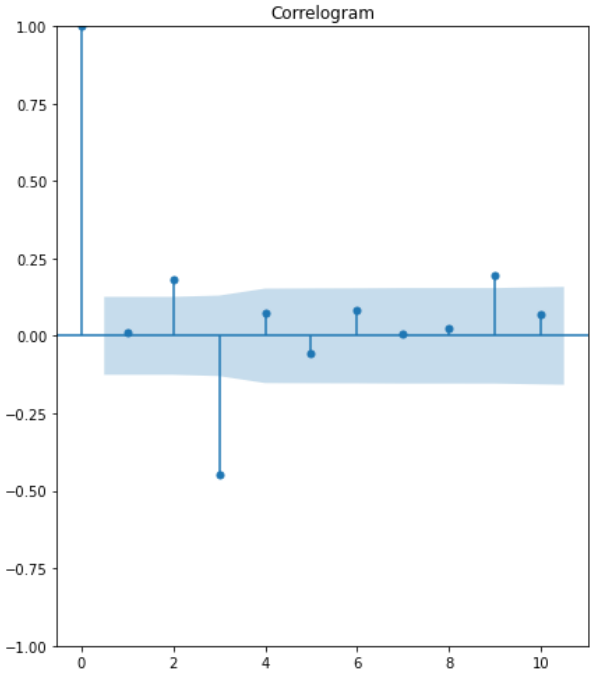
In [70]:
```
eastside = zip_df[9]
output_eastside = sarimax(eastside, order=(1, 1, 1), seasonal_order=(
```

```
==============================================================================
=====
                 coef    std err          z      P>|z|      [0.025
0.975]
------------------------------------------------------------------------------
-----
ar.L1          0.6822      0.051     13.399      0.000       0.582
0.782
ma.L1          0.0998      0.078      1.284      0.199      -0.053
0.252
ar.S.L12      -0.5868      0.054    -10.903      0.000      -0.692      -
0.481
ma.S.L12      -0.1070      0.034     -3.151      0.002      -0.174      -
0.040
sigma2      3.593e+05   2.94e+04     12.241      0.000    3.02e+05    4.1
7e+05
==============================================================================
=====
```


Standardized residual for "v"
3
2
1
0
−1
−2
−3
2004
2009
2014
2019

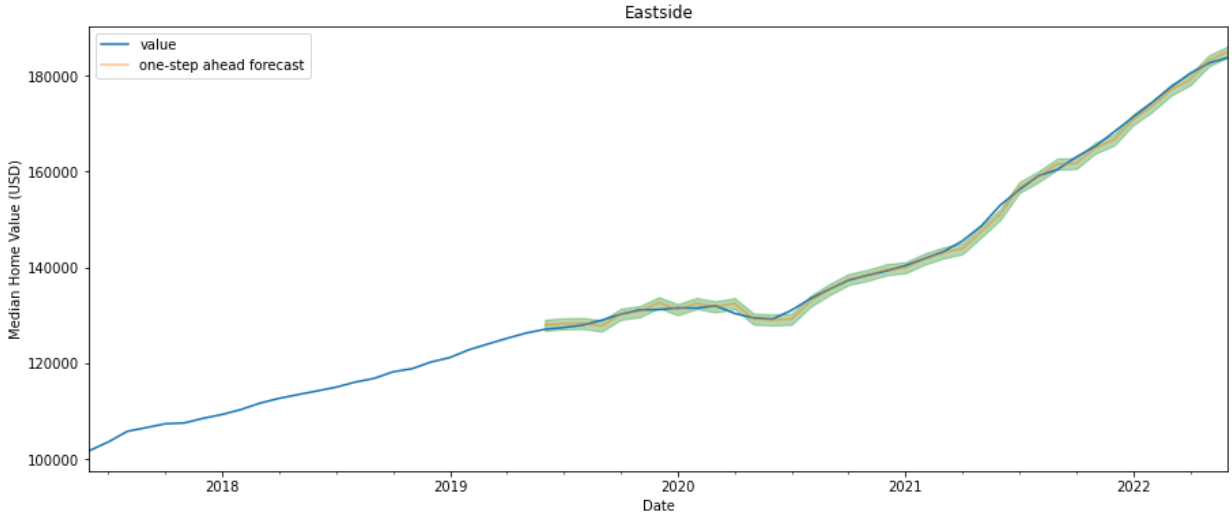

Histogram plus estimated density
KDE
N(0,1)
Hist
0.5
0.4
0.3
0.2
0.1
0.0
−3
−2
−1
0
1
2
3


Normal Q-Q
Sample Quantiles
Theoretical Quantiles
3
2
1
0
−1
−2
−3
−2
−1
0
1
2

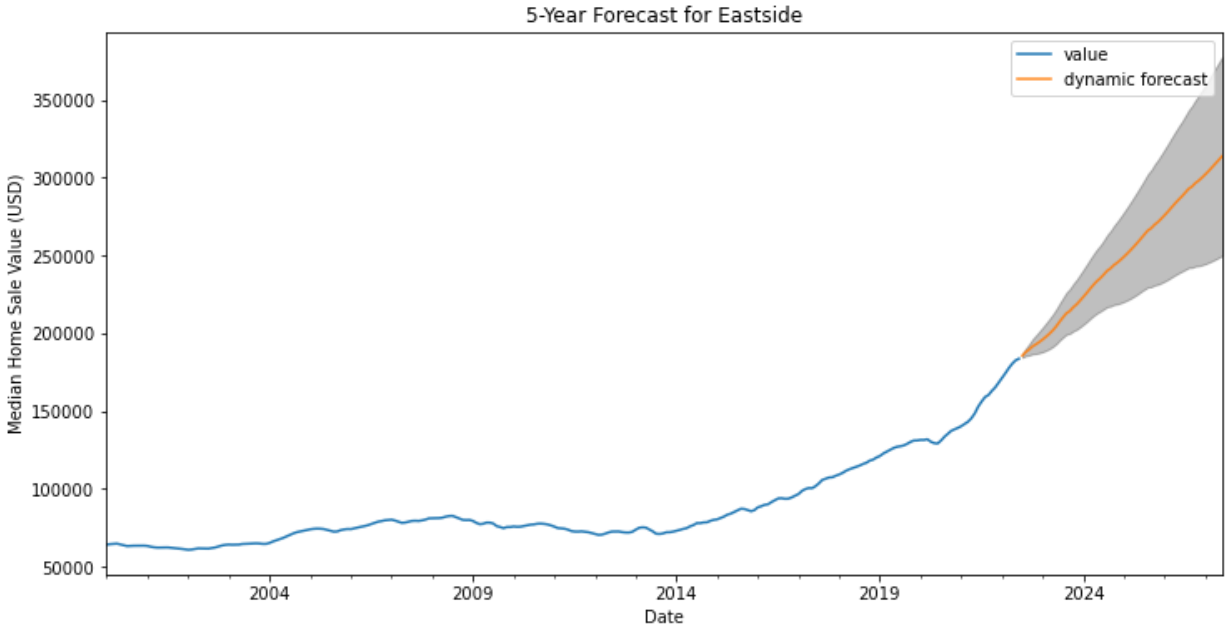

Correlogram
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00
0
2
4
6
8
10

In [71]:
```
1 ose_forecast(eastside, output_eastside, neighborhood='Eastside')
```

```
The RMSE of our forecasts is 951.41
```



In [72]:
```
1 dynamic_forecast(eastside, output_eastside, neighborhood='Eastside', 
```



Out[72]:
```
{'forecast': 313952.0, 'minimum': 249978.0, 'maximum': 377926.0}
```

The RMSE of our predictions for the Eastside is $951, with a relatively small confidence interval for our forecasts. The entry point into the neighborhood is low at around 180k, with our 5 year forecast predicting to increase to 313k. The residuals are normal with some outliers on the tails.

6 Interpret Results

6.1 Projections for 3 and 5 year ROI

I am now going to make a dataframe that will contain our projected metrics based upon our sarimax model forecasting.

In [73]:

```
def projections(ts, zipcodes, years):
    '''
    Calculate projections for each zip code.
        - Current Value
        - ROI (return on investment)

    Input:
        ts : time series data.
        zipcodes : list of zip codes to iterate through.
        years : n-number of years to forecast.

    Output:
        Returns dataframe with:
        - zip code
        - current value
        - predicted value
        - predicted ROI

    '''

    # Define steps for forecasting
    steps = years*12

    # Create list to append projection metrics
    projections = []

    # Iterate through time series of each zip code
    for zipcode in zipcodes:

        # Time series of zip code
        zip_ts = ts[ts['RegionName'] == zipcode]
        to_drop = ['RegionName']
        zip_ts = zip_ts.drop(to_drop, axis=1)

        # Plug the optimal parameter values into a new SARIMAX model
        # I used the values that were the most frequent for out top 1
        SARIMAX = sm.tsa.statespace.SARIMAX(zip_ts,
                                            order=(1, 1, 1),
                                            seasonal_order=(1, 1, 1,
                                            enforce_stationarity=Fals
                                            enforce_invertibility=Fal

        # Fit the model and print results
        output = SARIMAX.fit()

        # Get forecast and confidence interval for steps ahead in futu
        forecast = output.get_forecast(steps=steps, dynamic=True)
        conf_int = forecast.conf_int()

        # Show prediction for end of step-period
        pred_mean = forecast.predicted_mean[-1]
        pred_mean_min = conf_int.iloc[-1,0]
        pred_mean_max = conf_int.iloc[-1,1]

        # Last value of the time series - this will be used to calcul
        current_value = zip_ts['value'][-1]
```

```
57
58          # ROI (Return on Investment) as Percentage
59          ROI = ((pred_mean-current_value)/current_value *100)
60          ROI_min = ((pred_mean_min-current_value)/current_value *100)
61          ROI_max = ((pred_mean_max-current_value)/current_value *100)
62
63          # Create DataFrame
64
65          # Initiate empty dictionary
66          predicted = {}
67
68          # Columns for df
69          predicted['zipcode'] = zipcode
70          predicted['predicted_mean'] = pred_mean
71          predicted['predicted_mean_min'] = pred_mean_min
72          predicted['predicted_mean_max'] = pred_mean_max
73          predicted['current_value'] = current_value
74          predicted['ROI'] = ROI
75          predicted['ROI_min'] = ROI_min
76          predicted['ROI_max'] = ROI_max
77
78          # Append to list
79          projections.append(predicted)
80
81          # Return in DataFrame format
82      return pd.DataFrame.from_dict(projections)
```

In [74]:

```
1 # Get 3 year projections for top 10 zip codes
2 three_year_projections = projections(model_df, zip_list, years=3)
3 three_year_projections
```

Out[74]:

	zipcode	predicted_mean	predicted_mean_min	predicted_mean_max	current_value	ROI	
0	78203	339839.659781	283808.209827	3.958711e+05	241568.0	40.680744	1
1	78202	316210.201653	277737.856239	3.546825e+05	228219.0	38.555599	2
2	78207	217501.235532	180366.222136	2.546362e+05	148461.0	46.503954	2
3	78638	930184.768415	673410.443085	1.186959e+06	555727.0	67.381604	2
4	78055	569344.073180	465645.706910	6.730424e+05	361314.0	57.575979	2
5	78210	337287.142431	295798.772725	3.787755e+05	234712.0	43.702556	2
6	78237	237227.359318	199425.668841	2.750290e+05	163415.0	45.168656	2
7	78623	827218.413706	638932.679286	1.015504e+06	509544.0	62.344844	2
8	78133	837285.818728	594395.248170	1.080176e+06	473175.0	76.950561	2
9	78220	260936.102386	226854.292676	2.950179e+05	183720.0	42.029231	2

In [75]:
```
# Get 5 year projections for top 10 zip codes
five_year_projections = projections(model_df, zip_list, years=5)
five_year_projections
```

Out[75]:

	zipcode	predicted_mean	predicted_mean_min	predicted_mean_max	current_value	ROI	
0	78203	4.056760e+05	301026.597381	5.103253e+05	241568.0	67.934482	2
1	78202	3.748779e+05	303162.465320	4.465933e+05	228219.0	64.262353	3
2	78207	2.647553e+05	195127.425476	3.343833e+05	148461.0	78.333262	3
3	78638	1.187524e+06	698988.571529	1.676059e+06	555727.0	113.688333	2
4	78055	7.087825e+05	507903.173453	9.096617e+05	361314.0	96.168003	4
5	78210	4.061204e+05	327701.408459	4.845394e+05	234712.0	73.029237	3
6	78237	2.875893e+05	215798.425616	3.593803e+05	163415.0	75.987118	3
7	78623	1.048416e+06	669826.723065	1.427004e+06	509544.0	105.755657	3
8	78133	1.093740e+06	582965.843622	1.604515e+06	473175.0	131.149225	2
9	78220	3.139520e+05	249978.261510	3.779257e+05	183720.0	70.886124	3

In [76]:
```
# Sort values based on ROI for 3 year projections
three_year_projections.sort_values('ROI')
```

Out[76]:

	zipcode	predicted_mean	predicted_mean_min	predicted_mean_max	current_value	ROI	
1	78202	316210.201653	277737.856239	3.546825e+05	228219.0	38.555599	2
0	78203	339839.659781	283808.209827	3.958711e+05	241568.0	40.680744	1
9	78220	260936.102386	226854.292676	2.950179e+05	183720.0	42.029231	2
5	78210	337287.142431	295798.772725	3.787755e+05	234712.0	43.702556	2
6	78237	237227.359318	199425.668841	2.750290e+05	163415.0	45.168656	2
2	78207	217501.235532	180366.222136	2.546362e+05	148461.0	46.503954	2
4	78055	569344.073180	465645.706910	6.730424e+05	361314.0	57.575979	2
7	78623	827218.413706	638932.679286	1.015504e+06	509544.0	62.344844	2
3	78638	930184.768415	673410.443085	1.186959e+06	555727.0	67.381604	2
8	78133	837285.818728	594395.248170	1.080176e+06	473175.0	76.950561	2

In [77]:
```
# Sort values based on ROI for 5 year projections
five_year_projections.sort_values('ROI')
```

Out[77]:

	zipcode	predicted_mean	predicted_mean_min	predicted_mean_max	current_value	ROI
1	78202	3.748779e+05	303162.465320	4.465933e+05	228219.0	64.262353
0	78203	4.056760e+05	301026.597381	5.103253e+05	241568.0	67.934482
9	78220	3.139520e+05	249978.261510	3.779257e+05	183720.0	70.886124
5	78210	4.061204e+05	327701.408459	4.845394e+05	234712.0	73.029237
6	78237	2.875893e+05	215798.425616	3.593803e+05	163415.0	75.987118
2	78207	2.647553e+05	195127.425476	3.343833e+05	148461.0	78.333262
4	78055	7.087825e+05	507903.173453	9.096617e+05	361314.0	96.168003
7	78623	1.048416e+06	669826.723065	1.427004e+06	509544.0	105.755657
3	78638	1.187524e+06	698988.571529	1.676059e+06	555727.0	113.688333
8	78133	1.093740e+06	582965.843622	1.604515e+06	473175.0	131.149225

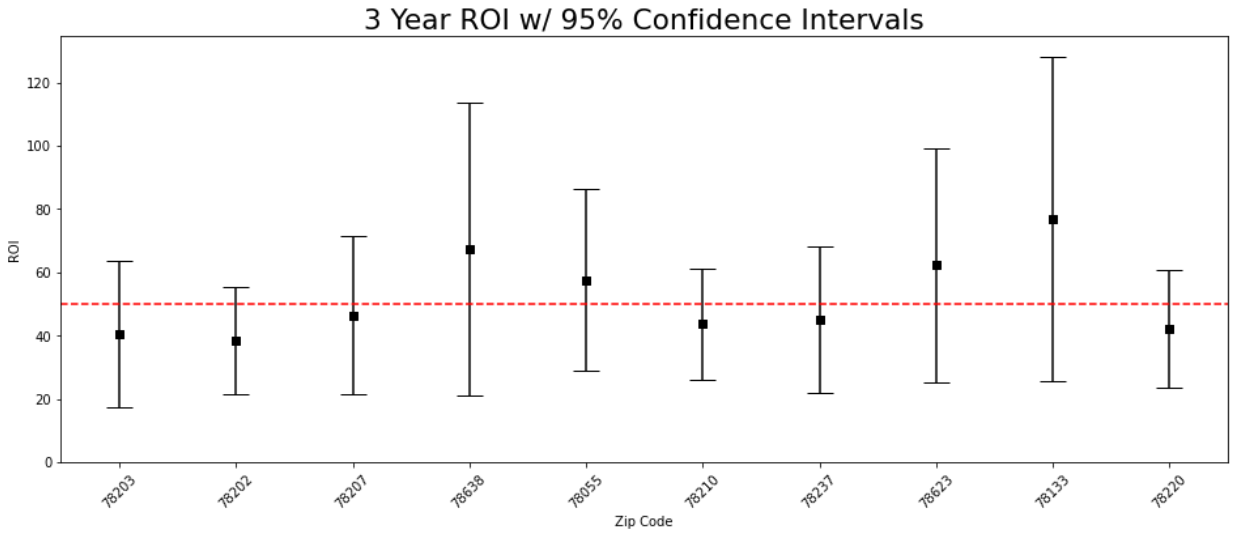
Our projections for 3 years and 5 years have the same ranking order of each zip code which is great. In order to aid visualization, I am going to write a function to produce a bar plot with predicted ROI and errors associated with each zip code.

6.2 Barplots of ROI Projections and Errors

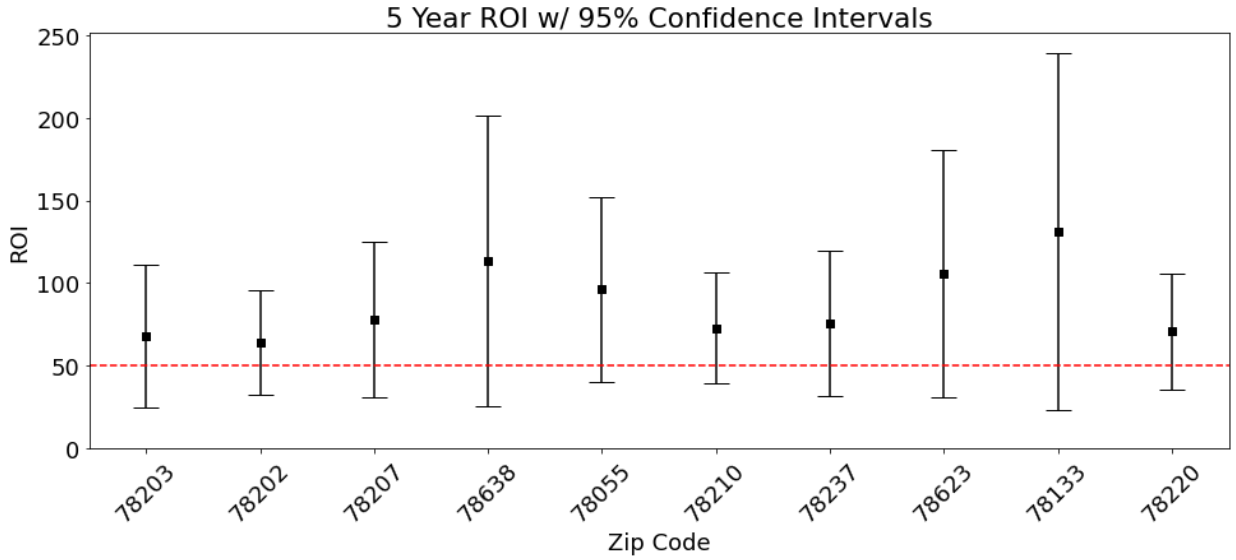
In [78]:

```
# Barplot for x years projection with 95% confidence intervals
def projection_barplot(df, years=3, save_fig=False):
    # Plot Predicted Mean Home Sale Values #

    # Get errors; (pred mean - lower bound of conf interval)
    errors = df['ROI'] - df['ROI_min']
    df['errors'] = errors

    # Zipcode x-labels
    variables = list(df.zipcode.values)
    df['variables'] = variables

    # Define figure, axes, and plot
    fig, ax = plt.subplots(figsize=(16, 6))

    # Plot barplot of ROI with errors
    plt.rcParams.update({'font.size': 18})
    df.plot(x='variables',
            y='ROI',
            kind='bar',
            ax=ax,
            color='none',
            ecolor='black',
            capsize=10,
            yerr='errors',
            legend=False)
    #Labels
    ax.set_xlabel('Zip Code')
    ax.set_ylabel('ROI')
    plt.title(f'{years} Year ROI w/ 95% Confidence Intervals')

    # Predicted ROI
    ax.scatter(x=pd.np.arange(df.shape[0]),
               marker='s',
               s=40,
               y=df['ROI'],
               color='black')

    # Line to help visualize on the y-axis
    ax.axhline(y=50, linestyle='--', color='red', linewidth=1.5)

    if save_fig:
        fig.savefig(f'./images/barplot_{years}.jpeg')

    # Rotate zip code labels 45 degrees
    plt.xticks(rotation=45)
    plt.show();
```

In [79]:
```
# 3 year ROI projections
projection_barplot(three_year_projections, years=3)
```



In [80]:
```
# 5 year ROI projections
projection_barplot(five_year_projections, years=5)
```



Since my client very concerned with low risk investments, I am going to select the top 5 zip codes from this list with the smallest confidence intervals. This will remove those zip codes that have large variability and more fluctuation in the market vales. These zip codes also happen to be the ones with the lowest ROI, but it appears it is hard to go wrong with any zip code in this metro area right now with it's massive growth with no end in sight.

6.3 Top 5 Zip Codes

In [81]:
```
# Top 5 zip codes
top_zip_projections = three_year_projections.sort_values('ROI')[0:5].s
top_zip_projections
```

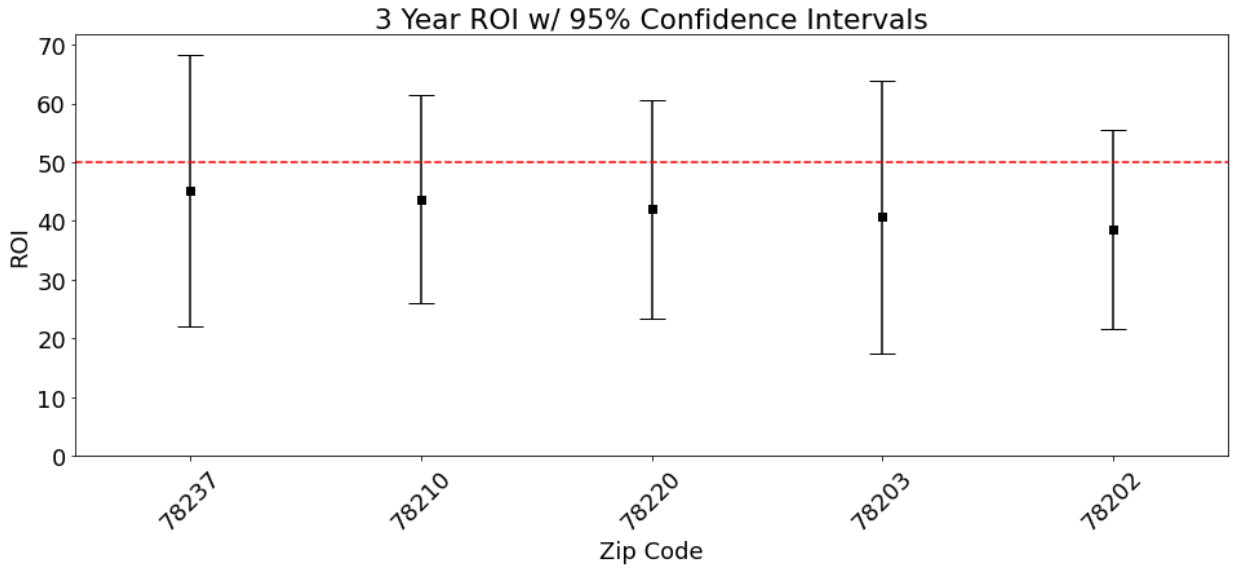
Out[81]:

	zipcode	predicted_mean	predicted_mean_min	predicted_mean_max	current_value	ROI	
6	78237	237227.359318	199425.668841	275029.049795	163415.0	45.168656	2
5	78210	337287.142431	295798.772725	378775.512136	234712.0	43.702556	2
9	78220	260936.102386	226854.292676	295017.912095	183720.0	42.029231	2
0	78203	339839.659781	283808.209827	395871.109736	241568.0	40.680744	1
1	78202	316210.201653	277737.856239	354682.547066	228219.0	38.555599	2

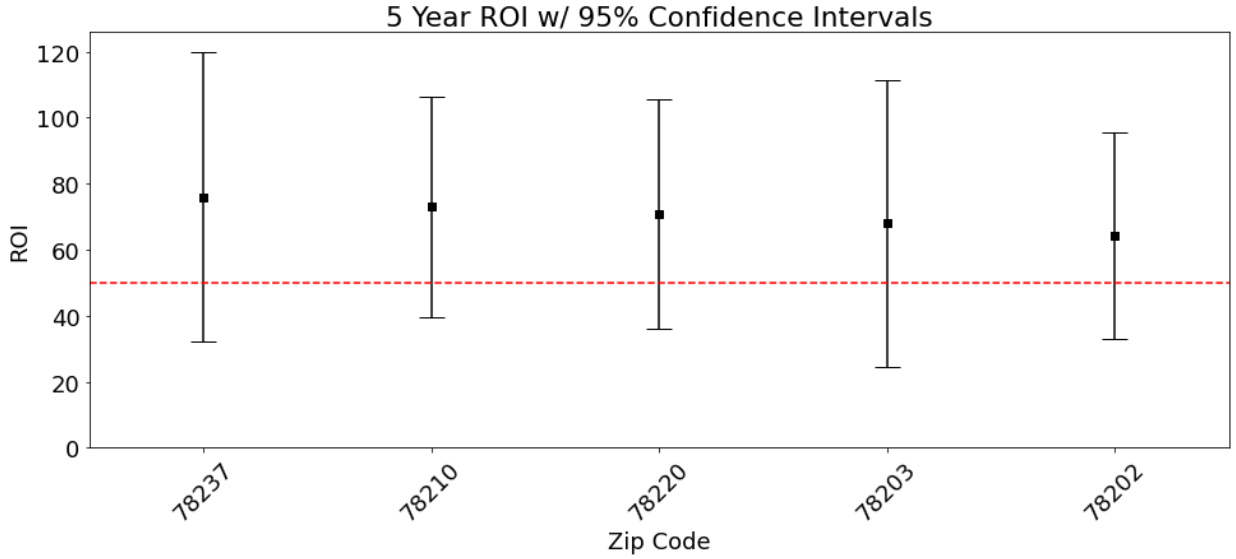
Our top 5 zip codes are 78237 - Inner Westside, 78210 - Denver Heights, 78220 - Eastside, 78203 - Arena District, and 78202 - Dignowity Hill. All 5 of these zip codes boast projected returns of 38% to 45%, and have great entry point prices ranging form 163k to 241k, far lower than the median value of the city.

78237 - Inner Westside, has the highest projected 3 year ROI and the lowest entry point at 163k, while 78202 - Dignowity Hill has the smallest variation and is therefore the safest investment.

In [82]:
```
# Barplot of our 3 year projected ROI for top zip codes
projection_barplot(top_zip_projections, years=3, save_fig=True)
```



In [83]:
```
# Barplot of our 5 year projected ROI for our top zip codes
top_5year_projections = five_year_projections.sort_values('ROI')[0:5]
top_5year_projections
projection_barplot(top_5year_projections, years=5, save_fig=True)
```

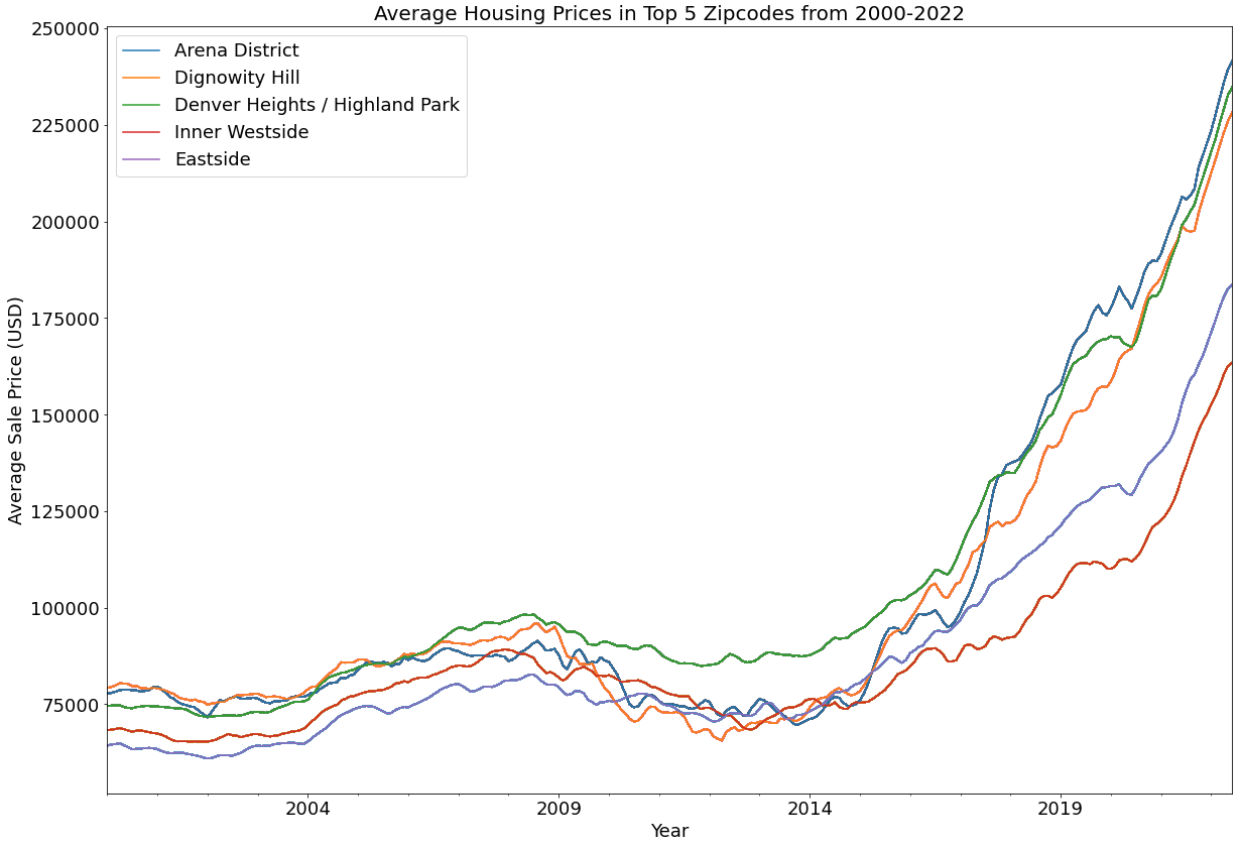


Our top zip codes have projected 5 year ROI of 64% to 76%! Now lets visualize the average sale prices or our top 5 zip codes over 22 years.

6.4 Average Housing Prices of our Top 5 Zip Codes from 2000 - 2022

In [84]:

```
# Top 5 zip codes
top_5_zipcodes = [78203,78202,78210,78237,78220]

#plot the values grouped by zip code
plt.figure(figsize=(20,14))
for zipcode in model_df.RegionName.unique():
    for zipcode in top_5_zipcodes:
        model_df.loc[model_df['RegionName'] == zipcode].value.plot(lab

plt.legend(labels=('Arena District','Dignowity Hill','Denver Heights /
                   'Inner Westside','Eastside'), loc='upper left')

plt.xlabel("Year", fontsize = 18)
plt.ylabel("Average Sale Price (USD)", fontsize=18)
plt.title('Average Housing Prices in Top 5 Zipcodes from 2000-2022', f
# Save fig
plt.savefig('./images/top_5_over_time.jpeg')
plt.show();
```



We can see a similiar trend among all of our top 5 zip codes, although a bit more pronounced in the Arena District, Dignowity Hill, and Denver Heights. This is likely due to the gentrification that has been taking place in these neighborhoods over the past several years and becoming desirable hotspots. Unfortunately, the crime rate is high in all of these neighborhoods and the schools all have below average ratings. It will likely take the schools several years to improve with the transition.

7 Conclusions

The top 5 zip codes ranked by highest return on investment (ROI) with the least amount of unpredictability and variation are:

- 78237: Inner Westside (lowest entry point)
- 78210: Denver Heights / Highland Park
- 78220: Eastside
- 78203: Arena District
- 78202: Dignowity Hill (safest investment - smallest variation)

These 5 zip codes boast projected returns on a 3 year investment ranging from 38% to 45%, and 5 year returns from 64% to 75%! The entry price into these neighborhoods range from 163k to 241k, much lower than the average median price of the whole SA metro area at 348k.

It should be noted that there is a caveat to these low prices, the schools are below average in every one of these zip codes and the rate of crime is high. This is typical in big cities, and the schools typically improve as time goes on in neighborhoods with increasing home value. If any of these factors are a concern, I recommend taking a look at the other zip codes that were in our top 10 ROI. These other zip codes are in more desirable suburban areas that have good schools, but also come at a much higher entry point and more risk associated with the purchase.

Some next steps in this project include added exogenous factors to our model, such as the median income of each zip code over time. We could also do a facebook prophet model to compare the results of the sarimax model to.