New Mexico, Albuquerque: Top 5 zip codes to invest in

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Project Summary

The goal of this project is to analyze the historical real estate data for Albuquerque, New Mexico, and identify the top 5 zip codes for investment based on forecasted median home prices. A time series modeling approach is employed to predict future values, helping investors make informed decisions.

Business Understanding

My clients are real estate investors with a focus on properties in King County. Seeking to escape the cold weather, they are interested in exploring investment opportunities in Albuquerque, New Mexico. I will identify five potential zip codes for investment in the area and provide a list of recommendations along with suggested next steps.

Dataset

The dataset was sourced from Zillow Research and can be accessed here. The dataset includes 14,723 rows, each representing a zip code, and 272 columns. The data provides median sales for every zip code from April 1996 to April 2018.

Load the Data/Filtering for Chosen Zipcodes

In [1]:
```
# imports
from math import sqrt
from sklearn.metrics import mean_squared_error
import warnings
from pylab import hist, show, xticks
import itertools
from statsmodels.tsa.stattools import adfuller
from matplotlib.pylab import rcParams
import statsmodels.api as sm
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
plt.style.use('fivethirtyeight')
warnings.filterwarnings('ignore')
import seaborn as sns
from sklearn.model_selection import TimeSeriesSplit
from statsmodels.tsa.arima.model import ARIMA
import warnings
from scipy import stats
from statsmodels.graphics.tsaplots import plot_acf
```

In [2]:
```
df_zillow = pd.read_csv("zillow_data.csv")
df_zillow.head()
```

Out[2]:

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

5 rows × 272 columns

In [3]:
```
df_zillow.info()
```

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

Data Preprocessing

The data has 272 columns and 14723 entries. For this project, I want to focus on Albuquerque, so I'll create a new dataframe called `abq_data` to include all data from Albuquerque from `Metro` column.

In [4]:
```
abq_data = df_zillow.loc[df_zillow["Metro"] == "Albuquerque"]
abq_data
```

Out[4]:

	RegionID	RegionName	City	State	Metro	CountyName	SizeRank	1996-04
110	95306	87111	Albuquerque	NM	Albuquerque	Bernalillo	111	156900.0
114	95309	87114	Albuquerque	NM	Albuquerque	Bernalillo	115	139000.0
196	95314	87120	Albuquerque	NM	Albuquerque	Bernalillo	197	130900.0
268	95315	87121	Albuquerque	NM	Albuquerque	Bernalillo	269	99900.0
430	95318	87124	Rio Rancho	NM	Albuquerque	Sandoval	431	113200.0
734	95304	87109	Albuquerque	NM	Albuquerque	Bernalillo	735	136100.0
772	95307	87112	Albuquerque	NM	Albuquerque	Bernalillo	773	112200.0
893	95300	87105	South Valley	NM	Albuquerque	Bernalillo	894	96700.0
994	95317	87123	Albuquerque	NM	Albuquerque	Bernalillo	995	114400.0
1006	95305	87110	Albuquerque	NM	Albuquerque	Bernalillo	1007	110500.0

	RegionID	RegionName	City	State	Metro	CountyName	SizeRank	1996-04
1027	95303	87108	Albuquerque	NM	Albuquerque	Bernalillo	1028	96300.0
1628	95265	87031	Los Lunas	NM	Albuquerque	Valencia	1629	107300.0
1958	95321	87144	Rio Rancho	NM	Albuquerque	Sandoval	1959	135600.0
2698	95302	87107	Albuquerque	NM	Albuquerque	Bernalillo	2699	114700.0
3005	95301	87106	Albuquerque	NM	Albuquerque	Bernalillo	3006	112300.0
4333	95297	87102	Albuquerque	NM	Albuquerque	Bernalillo	4334	88200.0
5337	95239	87002	Belen	NM	Albuquerque	Valencia	5338	101200.0
6420	95316	87122	Albuquerque	NM	Albuquerque	Bernalillo	6421	232000.0
6840	95308	87113	Albuquerque	NM	Albuquerque	Bernalillo	6841	183600.0
7089	95299	87104	Albuquerque	NM	Albuquerque	Bernalillo	7090	113200.0
8082	95240	87004	Bernalillo	NM	Albuquerque	Sandoval	8083	138400.0
8163	95280	87048	Corrales	NM	Albuquerque	Sandoval	8164	193500.0
8314	95286	87059	Tijeras	NM	Albuquerque	Bernalillo	8315	142000.0
10088	95275	87043	Placitas	NM	Albuquerque	Sandoval	10089	222200.0
10207	95279	87047	Sandia Park	NM	Albuquerque	Bernalillo	10208	188700.0
11468	95274	87042	Peralta	NM	Albuquerque	Valencia	11469	111700.0
11474	95292	87068	Bosque Farms	NM	Albuquerque	Valencia	11475	122200.0
12222	95244	87008	Cedar Crest	NM	Albuquerque	Bernalillo	12223	186000.0

28 rows × 272 columns

The data contains 28 different zipcodes in Albuquerque. I will drop `RegionID` and `SizeRank` as I don't need those columns for this project. I will also look for any missing data.

In [5]:
```
abq_data.drop(['RegionID', 'SizeRank'], axis=1, inplace=True)
```

In [6]:
```
# checking for null values
abq_data[pd.isna(abq_data).any(axis=1)]
```

Out[6]:

RegionName	City	State	Metro	CountyName	1996-04	1996-05	1996-06	1996-07	1996-08	...	2017-07

0 rows × 270 columns

In [7]:
```
abq_data['CountyName'].unique()
```

Out[7]:
```
array(['Bernalillo', 'Sandoval', 'Valencia'], dtype=object)
```

There's three different counties listed in `abq_data`. Next, I'll explore the data and narrow down the zipcodes I want to use for my time series model.

In [8]:
```
abq_data2 = abq_data.copy()
```

Exploratory Data Analysis

To provide more insightful information to our stakeholders, I will create a new column ROI in the abq_data. This column will represent the total Return on Investment (ROI) for each zip code, which is a more comprehensive measure of profitability. I'll also include the cumulative percent change as these are features to evaluate the peformance of my model.

In [9]:
```
# create metrics to judge return on investment (ROI)

# total ROI
abq_data['Total_ROI'] = (abq_data['2018-04'] -
                         abq_data['1996-04']) / abq_data['1996-04']

# cumulative percent change
abq_data['Cumulative_Percent_Change'] = (abq_data['2018-04'] / abq_data['1996-04

# re-assign to `abq_roi` dataframe with required columns
abq_roi = abq_data.loc[:, ['RegionName', 'City', 'State',
abq_roi.head()
```

Out[9]:

	RegionName	City	State	Metro	CountyName	Total_ROI	Cumulative_Percent_(
110	87111	Albuquerque	NM	Albuquerque	Bernalillo	0.695347	169.
114	87114	Albuquerque	NM	Albuquerque	Bernalillo	0.565468	156.
196	87120	Albuquerque	NM	Albuquerque	Bernalillo	0.486631	148.
268	87121	Albuquerque	NM	Albuquerque	Bernalillo	0.434434	143.
430	87124	Rio Rancho	NM	Albuquerque	Sandoval	0.595406	159.

In [10]:
```
# Find the top 10 zipcodes in Albuquerque
abq_roi.sort_values('Total_ROI', ascending=False).head(10)
```

Out[10]:

	RegionName	City	State	Metro	CountyName	Total_ROI	Cumulative_Percen
8163	87048	Corrales	NM	Albuquerque	Sandoval	1.204651	2
6420	87122	Albuquerque	NM	Albuquerque	Bernalillo	1.180603	2
3005	87106	Albuquerque	NM	Albuquerque	Bernalillo	1.102404	2
10088	87043	Placitas	NM	Albuquerque	Sandoval	0.903690	1
7089	87104	Albuquerque	NM	Albuquerque	Bernalillo	0.750883	1
734	87109	Albuquerque	NM	Albuquerque	Bernalillo	0.713446	1
8314	87059	Tijeras	NM	Albuquerque	Bernalillo	0.702817	1
110	87111	Albuquerque	NM	Albuquerque	Bernalillo	0.695347	1

	RegionName	City	State	Metro	CountyName	Total_ROI	Cumulative_Percen
2698	87107	Albuquerque	NM	Albuquerque	Bernalillo	0.684394	16
1027	87108	Albuquerque	NM	Albuquerque	Bernalillo	0.666667	16

New Mexico's largest county is Bernalillo, which contains 47 zipcodes. In comparison, Sandoval county only contains 18 zipcodes. Interestingly, despite its smaller size, the median household income in Sandoval county is $10,000 higher than that of Bernalillo county.

In [11]:
```
abq_data.sort_values
```

Out[11]:
```
<bound method DataFrame.sort_values of        RegionName         City State
Metro  CountyName   1996-04  \
110         87111   Albuquerque    NM  Albuquerque  Bernalillo  156900.0
114         87114   Albuquerque    NM  Albuquerque  Bernalillo  139000.0
196         87120   Albuquerque    NM  Albuquerque  Bernalillo  130900.0
268         87121   Albuquerque    NM  Albuquerque  Bernalillo   99900.0
430         87124    Rio Rancho    NM  Albuquerque    Sandoval  113200.0
734         87109   Albuquerque    NM  Albuquerque  Bernalillo  136100.0
772         87112   Albuquerque    NM  Albuquerque  Bernalillo  112200.0
893         87105  South Valley    NM  Albuquerque  Bernalillo   96700.0
994         87123   Albuquerque    NM  Albuquerque  Bernalillo  114400.0
1006        87110   Albuquerque    NM  Albuquerque  Bernalillo  110500.0
1027        87108   Albuquerque    NM  Albuquerque  Bernalillo   96300.0
1628        87031     Los Lunas    NM  Albuquerque    Valencia  107300.0
1958        87144    Rio Rancho    NM  Albuquerque    Sandoval  135600.0
2698        87107   Albuquerque    NM  Albuquerque  Bernalillo  114700.0
3005        87106   Albuquerque    NM  Albuquerque  Bernalillo  112300.0
4333        87102   Albuquerque    NM  Albuquerque  Bernalillo   88200.0
5337        87002         Belen    NM  Albuquerque    Valencia  101200.0
6420        87122   Albuquerque    NM  Albuquerque  Bernalillo  232000.0
6840        87113   Albuquerque    NM  Albuquerque  Bernalillo  183600.0
7089        87104   Albuquerque    NM  Albuquerque  Bernalillo  113200.0
8082        87004    Bernalillo    NM  Albuquerque    Sandoval  138400.0
8163        87048      Corrales    NM  Albuquerque    Sandoval  193500.0
8314        87059       Tijeras    NM  Albuquerque  Bernalillo  142000.0
10088       87043      Placitas    NM  Albuquerque    Sandoval  222200.0
10207       87047   Sandia Park    NM  Albuquerque  Bernalillo  188700.0
11468       87042       Peralta    NM  Albuquerque    Valencia  111700.0
11474       87068  Bosque Farms    NM  Albuquerque    Valencia  122200.0
12222       87008   Cedar Crest    NM  Albuquerque  Bernalillo  186000.0

        1996-05   1996-06   1996-07   1996-08  ...  2017-09  2017-10  2017-11  \
110    155600.0  154200.0  152800.0  151400.0  ...   253700   254200   256000
114    139200.0  139300.0  139400.0  139500.0  ...   209600   210700   211800
196    130500.0  130000.0  129500.0  129000.0  ...   191400   192300   193000
268     99600.0   99600.0   99600.0   99700.0  ...   139800   140100   140600
430    113400.0  113600.0  113600.0  113700.0  ...   175300   176700   178800
734    135800.0  135500.0  135300.0  135200.0  ...   229100   228700   229000
772    112400.0  112600.0  112800.0  113100.0  ...   170900   171000   172100
893     95800.0   95100.0   94600.0   94300.0  ...   136200   136900   137600
994    114700.0  115000.0  115200.0  115500.0  ...   181000   181700   181800
1006   110600.0  110700.0  110900.0  111100.0  ...   180400   180300   180500
1027    96600.0   97000.0   97500.0   97900.0  ...   155500   155400   156200
1628   107200.0  107100.0  106900.0  106800.0  ...   135900   137000   138100
1958   135300.0  135000.0  134700.0  134500.0  ...   183700   184000   185400
2698   115000.0  115400.0  115800.0  116300.0  ...   189300   190000   190100
3005   112300.0  112400.0  112400.0  112400.0  ...   221000   221400   223700
4333    88000.0   87900.0   87900.0   87900.0  ...   126200   128700   129500
5337   101300.0  101200.0  101200.0  101200.0  ...   107100   107900   109500
```

```
6420   232000.0  232000.0  232200.0  232400.0  ...   497500   499600   503100
6840   183900.0  184200.0  184500.0  184800.0  ...   269200   269400   270300
7089   113300.0  113400.0  113500.0  113600.0  ...   181600   184100   186500
8082   138400.0  138400.0  138400.0  138400.0  ...   203500   203800   205600
8163   193700.0  193800.0  194000.0  194200.0  ...   408900   408300   411400
8314   141900.0  141700.0  141500.0  141300.0  ...   232300   231900   232900
10088  222400.0  222700.0  223100.0  223600.0  ...   392600   395000   402400
10207  188800.0  188800.0  188800.0  188700.0  ...   275000   274800   277200
11468  112000.0  112100.0  112200.0  112300.0  ...   166400   167000   167200
11474  122600.0  123000.0  123400.0  123800.0  ...   193800   195900   196100
12222  185600.0  185100.0  184700.0  184200.0  ...   277300   279000   278800

       2017-12  2018-01  2018-02  2018-03  2018-04  Total_ROI  \
110     258600   260500   262300   264500   266000   0.695347
114     213100   214100   215200   216600   217600   0.565468
196     193400   193300   193600   194300   194600   0.486631
268     141100   141200   141900   142800   143300   0.434434
430     180700   181400   181000   180500   180600   0.595406
734     230100   231100   231800   232700   233200   0.713446
772     173500   174400   176000   178500   180100   0.605169
893     138200   138400   138500   138600   138400   0.431231
994     181600   181200   182200   184300   185300   0.619755
1006    180500   179900   180400   182400   184000   0.665158
1027    157300   158000   158600   159700   160500   0.666667
1628    139200   139900   141100   142400   143200   0.334576
1958    186700   187100   187100   187600   188100   0.387168
2698    189700   189600   190000   191600   193200   0.684394
3005    227500   230500   232700   234700   236100   1.102404
4333    129300   129400   129600   130700   132200   0.498866
5337    111100   111800   112900   114300   115100   0.137352
6420    505700   508200   509300   508200   505900   1.180603
6840    271300   271500   272900   274600   274600   0.495643
7089    188800   190300   192100   195300   198200   0.750883
8082    207500   207600   207100   209500   212800   0.537572
8163    414400   415000   418200   423200   426600   1.204651
8314    234200   234900   237200   240300   241800   0.702817
10088   410900   416700   419400   421000   423000   0.903690
10207   282200   286300   290500   295100   298200   0.580286
11468   167700   168600   170200   171500   172000   0.539839
11474   195700   196900   198600   199700   200400   0.639935
12222   278200   279200   280800   281900   282000   0.516129

       Cumulative_Percent_Change
110                   169.534736
114                   156.546763
196                   148.663102
268                   143.443443
430                   159.540636
734                   171.344600
772                   160.516934
893                   143.123061
994                   161.975524
1006                  166.515837
1027                  166.666667
1628                  133.457596
1958                  138.716814
2698                  168.439407
3005                  210.240427
4333                  149.886621
5337                  113.735178
6420                  218.060345
6840                  149.564270
7089                  175.088339
8082                  153.757225
8163                  220.465116
```

```
8314                170.281690
10088               190.369037
10207               158.028617
11468               153.983885
11474               163.993453
12222               151.612903

[28 rows x 272 columns]>
```

Visualization

Now that I have selected the top 10 zipcodes in Albuquerque, I'll create a bar graph to see the growth percentage.

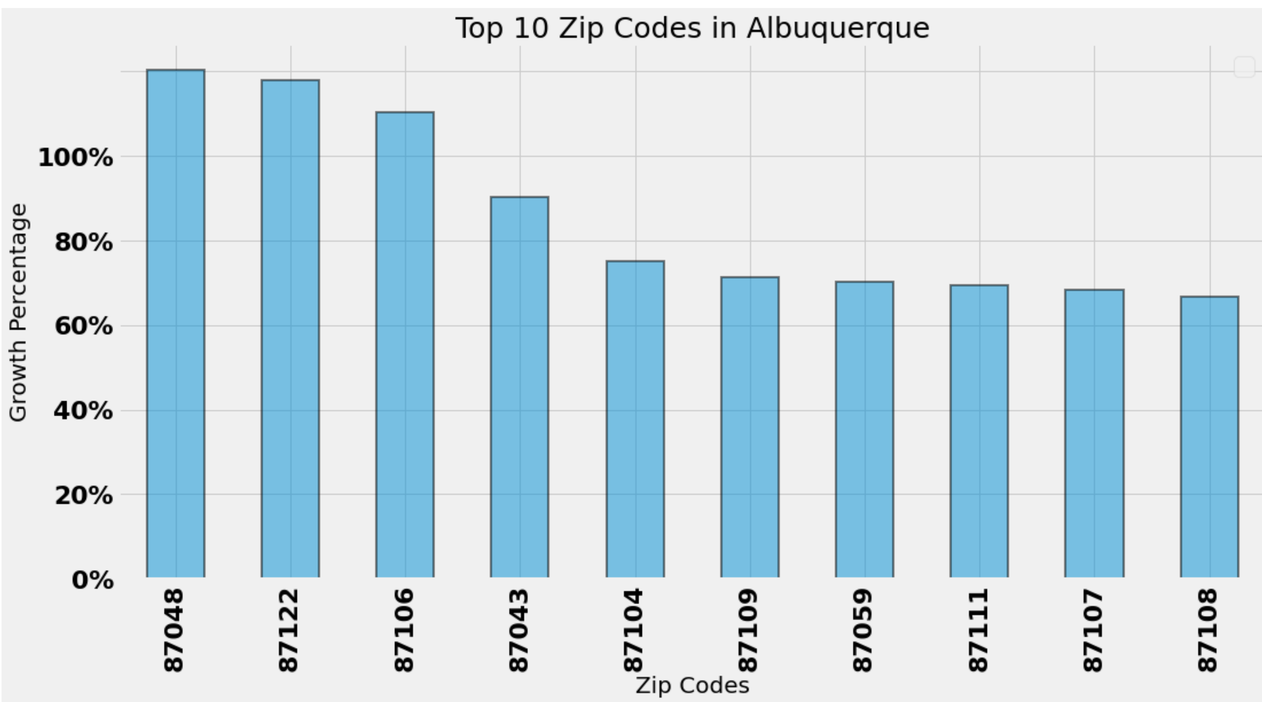
In [12]:

```
# formatting for the rest of our visualizations
font = {'family': 'DejaVu Sans',
        'weight': 'bold',
        'size': 22}

plt.rc('font', **font)
```

In [13]:

```
# Sort values by Total_ROI
abq_roi_sorted = abq_roi.sort_values(by='Total_ROI', ascending=False)
ax = abq_roi_sorted.head(10).plot.bar(x='RegionName', y='Total_ROI', figsize=(
    16, 8), alpha=0.5, edgecolor="black", linewidth=2)
plt.title('Top 10 Zip Codes in Albuquerque', fontsize=25)
plt.legend('')
ax.set_yticklabels(["0%", "20%", "40%", "60%", "80%", "100%"])
plt.xlabel('Zip Codes', fontsize=20)
plt.ylabel('Growth Percentage', fontsize=20)
```

Out[13]: `Text(0, 0.5, 'Growth Percentage')`



In [14]:

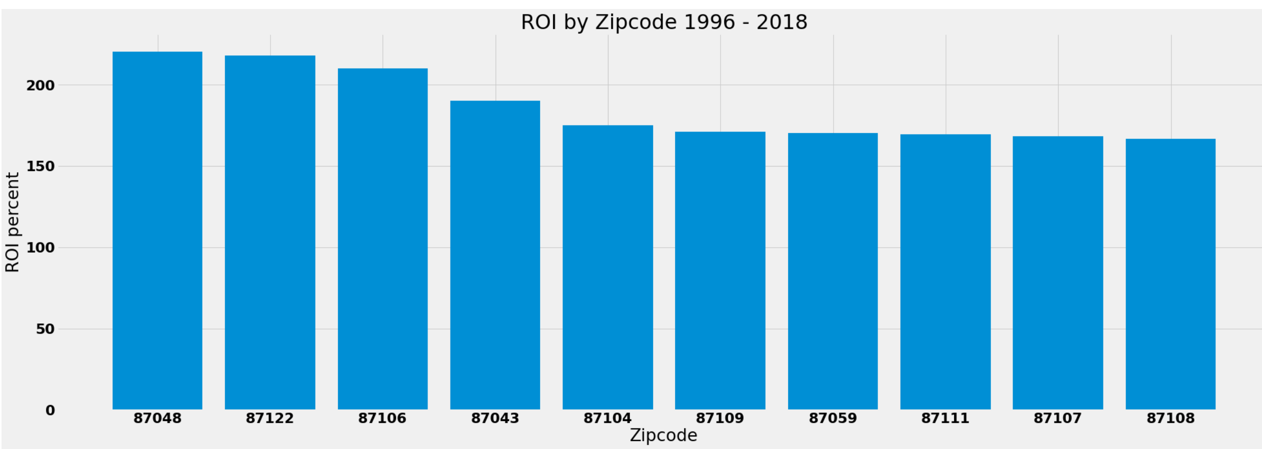
```
# Create new dataframe for top 10 zipcodes in Albuquerque
abq_10 = abq_roi.sort_values(by='Total_ROI', ascending=False).head(10)
abq_10
```

Out[14]:

	RegionName	City	State	Metro	CountyName	Total_ROI	Cumulative_Percen
8163	87048	Corrales	NM	Albuquerque	Sandoval	1.204651	2
6420	87122	Albuquerque	NM	Albuquerque	Bernalillo	1.180603	2
3005	87106	Albuquerque	NM	Albuquerque	Bernalillo	1.102404	2
10088	87043	Placitas	NM	Albuquerque	Sandoval	0.903690	1
7089	87104	Albuquerque	NM	Albuquerque	Bernalillo	0.750883	1
734	87109	Albuquerque	NM	Albuquerque	Bernalillo	0.713446	1
8314	87059	Tijeras	NM	Albuquerque	Bernalillo	0.702817	1
110	87111	Albuquerque	NM	Albuquerque	Bernalillo	0.695347	1
2698	87107	Albuquerque	NM	Albuquerque	Bernalillo	0.684394	1
1027	87108	Albuquerque	NM	Albuquerque	Bernalillo	0.666667	1

In [15]:

```
abq_10['RegionName'] = abq_10['RegionName'].astype(str)

# Plotting the historical data
fig, ax = plt.subplots(figsize=(30,10))
plt.bar(abq_10.RegionName, abq_10['Cumulative_Percent_Change'])
plt.title('ROI by Zipcode 1996 - 2018')
plt.xlabel('Zipcode')
plt.ylabel('ROI percent')
plt.show()
```



This graph shows the top 10 zipcodes with the highest ROI over the period of 1996 to 2018. There's subtle changes between 87101 and 87108.

In [16]:

```
# list of top 5 zipcodes
region_list = ['87048', '87122', '87106', '87043', '87104']

# filter rows with desired RegionNames
abq_top_5 = abq_data[abq_data['RegionName'].isin(region_list)]

abq_top_5 = abq_top_5.drop(columns=['Total_ROI', 'Cumulative_Percent_Change'])

# display new dataframe
abq_top_5.head()
```

Out[16]:

	RegionName	City	State	Metro	CountyName	1996-04	1996-05	1996-06
3005	87106	Albuquerque	NM	Albuquerque	Bernalillo	112300.0	112300.0	112400.0
6420	87122	Albuquerque	NM	Albuquerque	Bernalillo	232000.0	232000.0	232000.0
7089	87104	Albuquerque	NM	Albuquerque	Bernalillo	113200.0	113300.0	113400.0
8163	87048	Corrales	NM	Albuquerque	Sandoval	193500.0	193700.0	193800.0
10088	87043	Placitas	NM	Albuquerque	Sandoval	222200.0	222400.0	222700.0

5 rows × 270 columns

In [17]:

```
abq_top_5
```

Out[17]:

	RegionName	City	State	Metro	CountyName	1996-04	1996-05	1996-06
3005	87106	Albuquerque	NM	Albuquerque	Bernalillo	112300.0	112300.0	112400.0
6420	87122	Albuquerque	NM	Albuquerque	Bernalillo	232000.0	232000.0	232000.0
7089	87104	Albuquerque	NM	Albuquerque	Bernalillo	113200.0	113300.0	113400.0
8163	87048	Corrales	NM	Albuquerque	Sandoval	193500.0	193700.0	193800.0
10088	87043	Placitas	NM	Albuquerque	Sandoval	222200.0	222400.0	222700.0

5 rows × 270 columns

Reshape from Wide to Long Format

Now that I have the data that I want to use, I'll reshape the data from a wideformat to a long format. The `abq_data` contains the wide format dataset.

In [18]:

```
def melt_data(df):
   # Melt data into wide version
    melted = pd.melt(df, id_vars=['RegionName', 'City', 'State', 'Metro', 'Count
    # Create new column as datetime variable
    melted['time'] = pd.to_datetime(melted['time'], infer_datetime_format=True)
    # Remove rows with missing values
    melted = melted.dropna(subset=['value'])
    # set `time` as index
    melted.set_index('time', inplace=True)
    return melted.groupby('time').aggregate({'value':'mean'})
```

In [19]:

```
# Create new data frame for zipcodes
abq_zip = [zip_code for zip_code in abq_10['RegionName']]
```

In [20]:

```
abq_zip
```

Out[20]:
```
['87048',
 '87122',
 '87106',
 '87043',
 '87104',
 '87109',
 '87059',
 '87111',
 '87107',
 '87108']
```

Final top 10 zipcodes

I want to create a visualization for the top 10 zipcodes. The visualization helps with detecting and trends or patterns.

In [21]:
```
abq_df = pd.DataFrame()
for i in abq_top_5['RegionName']:
    x = melt_data(abq_top_5[abq_top_5['RegionName'] == i])
    abq_df  = pd.concat([abq_df, x], axis=1)
    abq_df .rename(columns = {'value':i}, inplace = True)

# Display results
abq_df.head(10)
```

Out[21]:

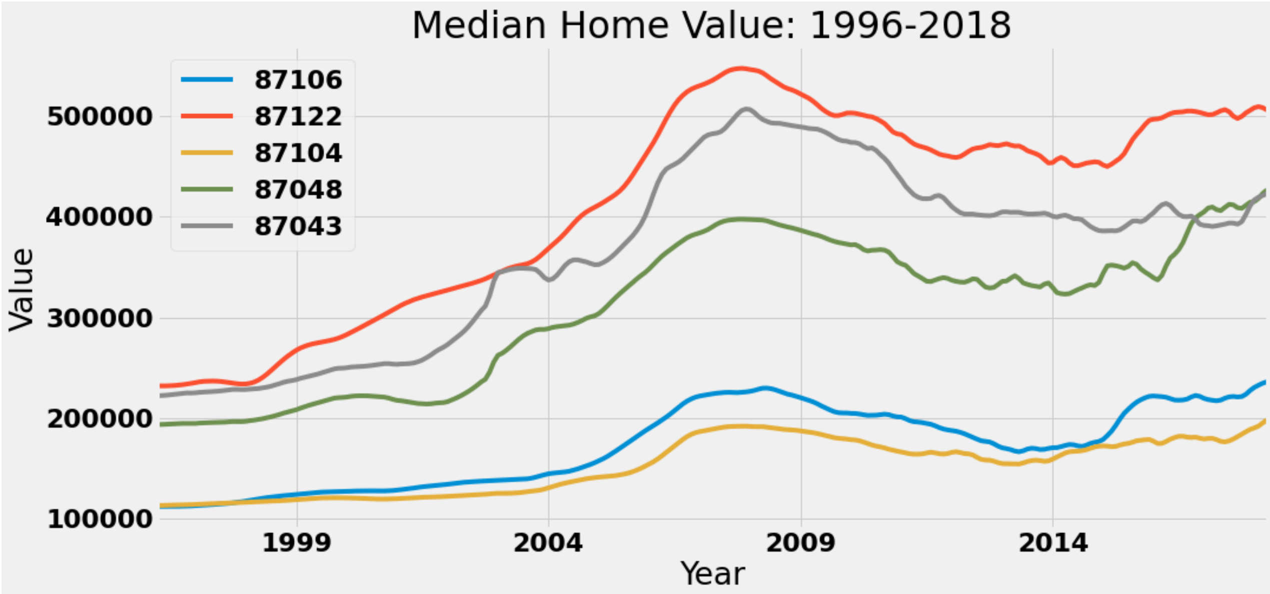
time	87106	87122	87104	87048	87043
1996-04-01	112300.0	232000.0	113200.0	193500.0	222200.0
1996-05-01	112300.0	232000.0	113300.0	193700.0	222400.0
1996-06-01	112400.0	232000.0	113400.0	193800.0	222700.0
1996-07-01	112400.0	232200.0	113500.0	194000.0	223100.0
1996-08-01	112400.0	232400.0	113600.0	194200.0	223600.0
1996-09-01	112400.0	232800.0	113700.0	194400.0	224100.0
1996-10-01	112500.0	233200.0	113800.0	194700.0	224700.0
1996-11-01	112600.0	233800.0	114000.0	194700.0	225000.0
1996-12-01	112800.0	234500.0	114100.0	194600.0	224900.0
1997-01-01	113100.0	235300.0	114300.0	194700.0	225100.0

To make it easier to analyze and visualize the data, I'm going to resample the time series to a monthly frequency with the start of each month as the observation point. This will aggregate the data for each month and create a new dataframe with the data for the first day of each month. This is particularly useful for forecasting and filling in any gaps in the data.

In [22]:
```
abq_df = abq_df.asfreq('MS')
```

In [23]:
```
abq_df.plot(figsize=(15, 7))
plt.xlabel('Year')
plt.ylabel('Value')
```

```
plt.title('Median Home Value: 1996-2018')
plt.show();
```



Now we can see our training data and the testing data. 80% of our data is in the train and 20% of the data is in test. It looks like the split point is in 2014. The trend line has an upward pattern up until 2008 where you can see a downward trend. This is due to the Great Recession. The "Subprime Mortgage Crisis" was a period of time (2007 to 2010) when there was an increase in the number of high-risk mortgages that went into default and caused a ripple effect on the housing market and broader economy. This is important to highlight as I am not inlcuding this data into my modeling.
[More information about the Subprime Mortgage Crisis](https://www.history.com/topics/21st-century/recession)

Train Validation Split and Naive Model

I'll create a naive model by shifting the `train` data by one day to create a simple baseline model for comparison with my SARIMAX model. The naive model predicts that the current value is the same as the value from the previous day and does not take into account any patterns or trends in the data. The purpose of this model is to establish a baseline performance metric, which is the root mean squared error (RMSE).

In [24]:
```
# Create new dataframe with datapoints beginning in 2011
abq_df_new = abq_df['2011-01-01':]
```

In [25]:
```
# Get a list of unique zipcodes (column names)
unique_zipcodes = abq_df_new.columns

# Initialize an empty dictionary to store the RMSE values for each zipcode
rmse_dict = {}

# Define the train-test split ratio
split_ratio = 0.8

# Loop through the unique zipcodes
```

```
for zipcode in unique_zipcodes:
    # Get the data for the current zipcode
    data = abq_df_new[zipcode]

    # Calculate the index for the train-test split
    cutoff = int(len(data) * split_ratio)

    # Split the data into train and test sets
    train = data[:cutoff]
    test = data[cutoff:]

    # Shift the train data by 1 time step to create the naive model predictions
    naive_predictions = train.shift(1)

    # Calculate the RMSE between the actual values and the naive model predictio
    rmse_naive_train = np.sqrt(np.mean((train[1:] - naive_predictions[1:])**2))

    # Shift the test data by 1 time step to create the naive model predictions
    naive_predictions_test = test.shift(1)

    # Calculate the RMSE between the actual values and the naive model predictio
    rmse_naive_test = np.sqrt(np.mean((test[1:] - naive_predictions_test[1:])**2

    # Add the RMSE values to the dictionary with the zipcode as the key
    rmse_dict[zipcode] = {'train': rmse_naive_train, 'test': rmse_naive_test}

# Print the baseline RMSE values for each zipcode
print('Baseline RMSE values for each zipcode:')
for zipcode, rmse_values in rmse_dict.items():
    print(f'Zipcode {zipcode}: Train RMSE = {rmse_values["train"]:.2f}, Test RMS
```

```
Baseline RMSE values for each zipcode:
Zipcode 87106: Train RMSE = 1992.74, Test RMSE = 1763.69
Zipcode 87122: Train RMSE = 2483.10, Test RMSE = 2151.74
Zipcode 87104: Train RMSE = 1084.01, Test RMSE = 1848.21
Zipcode 87048: Train RMSE = 3602.07, Test RMSE = 2825.51
Zipcode 87043: Train RMSE = 2222.06, Test RMSE = 3517.35
```

Now that I have my baseline RMSE for each zipode, I'll use the RMSE as a baseline to evaluate my models.

SARIMAX Modeling

Now that I have my baseline model, I will use a SARIMA model to forecast the median value of the top 5 zipcodes in Albuquerque. The top five zipcodes will have individual predictions and forecast results. I will evaluate each model by calculate the Root Mean Squared Error (RMSE). I will also include the 95% confidence interval, which will give a range of values within the true future value is likely to fall, with of course, 95% confidence.

I chose a SARIMAX model for forecasting the top 5 zipcodes for multiple reasons:

1. Seasonality - Real Estate prices exhibit seasonal patterns.
2. Autoregressive and Moving Average Components - SARIMAX is an extension of the ARIMA model, which combines AR and moving average components.
3. Flexibility - Specifiy different orders for AR, MA, Seasonal, which allows for fine-tuning the model to better fit the data for each zipcode.

4. Interpretability - Interpretable results.

Albuquerque, New Mexico 87106

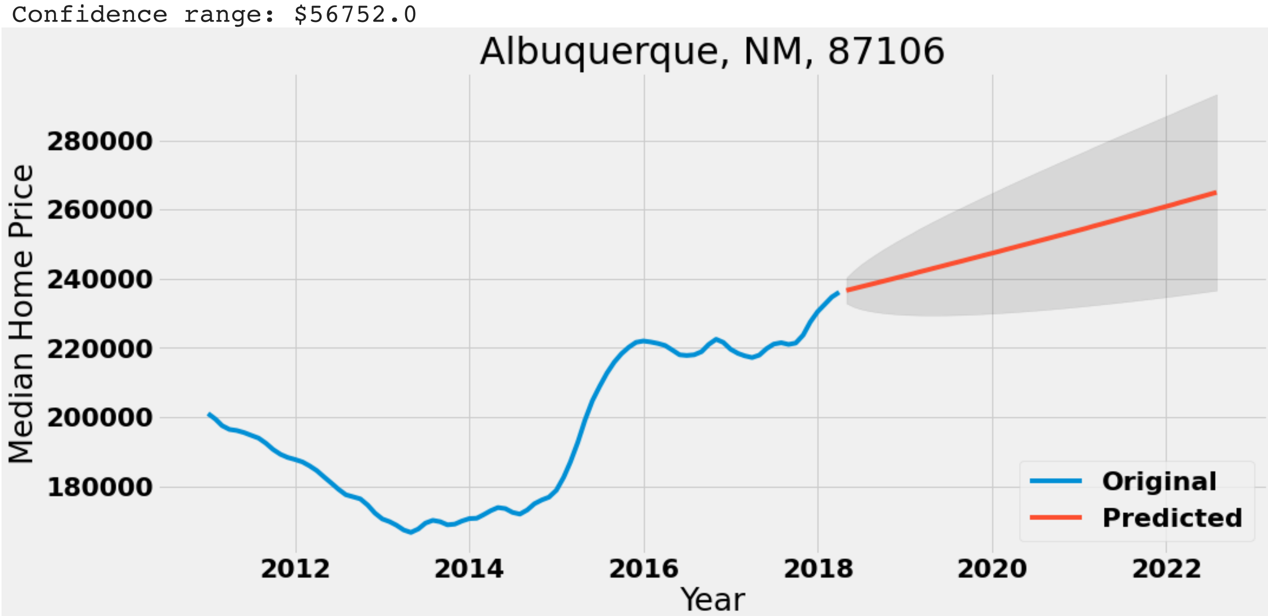
In [26]:
```
# Define train and validation datasets based 20% and 80%
training_data = abq_df_new[87106][:cutoff]
validation_data = abq_df_new[87106][cutoff:]

# Define the range of parameters for p, d, q, P, D, Q, and s
p = d = q = range(0, 2)
P = D = Q = range(0, 2)
s = 12  # monthly data

# Generate a list of all possible combinations of parameters
pdq = list(itertools.product(p, d, q))
seasonal_pdq = [(x[0], x[1], x[2], s) for x in itertools.product(P, D, Q)]

# Initialize variables to store the best parameters and the lowest RMSE
best_params = (0, 0, 0, 0, 0, 0, 0)
lowest_rmse = float('inf')

# Loop through all possible combinations of parameters
for param in pdq:
    for param_seasonal in seasonal_pdq:
        try:
            # Fit a SARIMAX model with the current combination of parameters
            model = sm.tsa.statespace.SARIMAX(training_data,
                                              order=param,
                                              seasonal_order=param_seasonal,
                                              enforce_stationarity=False,
                                              enforce_invertibility=False).fit()

            # Make predictions on the validation data
            predictions = model.predict(start=validation_data.index[0], end=vali

            # Calculate the RMSE of the predictions
            rmse = np.sqrt(np.mean((predictions - validation_data)**2))

            # Update the best parameters and lowest RMSE if the current RMSE is
            if rmse < lowest_rmse:
                best_params = (param, param_seasonal)
                lowest_rmse = rmse

        except ValueError:  # skip combinations that fail to converge or produce
            continue

print(f'Best parameters: {best_params}')
print(f'Lowest RMSE: {lowest_rmse:.2f}')
```

```
Best parameters: ((1, 0, 0), (0, 0, 0, 12))
Lowest RMSE: 4536.00
```

The root mean squared error(RMSE) is $4,536, which represents the average difference between the actual data points and the predictions made by the SARIMAX model. This is higher than our baseline model and it indicates that the model may not be adequately capturing the data's structure.

In [27]:
```
#Define SARIMAX model and fit data save as sarima_mod1
sarima_mod1 = sm.tsa.statespace.SARIMAX(abq_df_new[87106],
                                        order=(1, 0, 0),
                                        seasonal_order=(0, 0, 0, 12),
                                        enforce_stationarity=False,
                                        enforce_invertibility=False).fit()
# Forecast 52 months into the future (4 years)
forecast1 = sarima_mod1.get_forecast(steps=52).summary_frame()

# Calculate the mean of the last week of the forecast as the predicted value
forecast1_mean = round(forecast1['mean'][51])

#Calculate the difference between lower and upper 95% confidence intervals of th
low_int1 =  round(forecast1['mean_ci_lower'][51])
high_int1 = round(forecast1['mean_ci_upper'][51])

#Calculate the difference between the upper and lower confidence intervals
ci_delta1 = round(high_int1 - low_int1)

# Print predicted value and confidence intervals
print(f'Albuquerque, NM, 87106:')
print(f'95% confidence: ${low_int1} and ${high_int1}')
print(f'Confidence range: ${ci_delta1}')

# Plot the original data and predicted values with confidence intervals
fig, ax = plt.subplots(figsize=(15, 7))
plt.plot(abq_df_new[87106])
plt.plot(forecast1['mean'])
ax.fill_between(forecast1.index, forecast1['mean_ci_lower'],
                forecast1['mean_ci_upper'], color='k', alpha=0.1)
plt.title('Albuquerque, NM, 87106')
plt.legend(['Original','Predicted'], loc='lower right')
plt.xlabel('Year')
plt.ylabel('Median Home Price')
plt.show()
```

```
Albuquerque, NM, 87106:
95% confidence: $236629.0 and $293381.0
Confidence range: $56752.0
```



The result shows the forecast for the median home price in zipcode 87106. The 95% confidence interval is a measure of uncertainty around the predicted value. The 95% confidence interval is between $236, 629 and$293,381. This means that based on the model's predictions, there is a 95% probability that the true median home price will fall within this range. The confidence range is $56,752 which is the difference between the upper and lower bounds of the confidence interval.

Albuquerque, New Mexico 87122

In [28]:

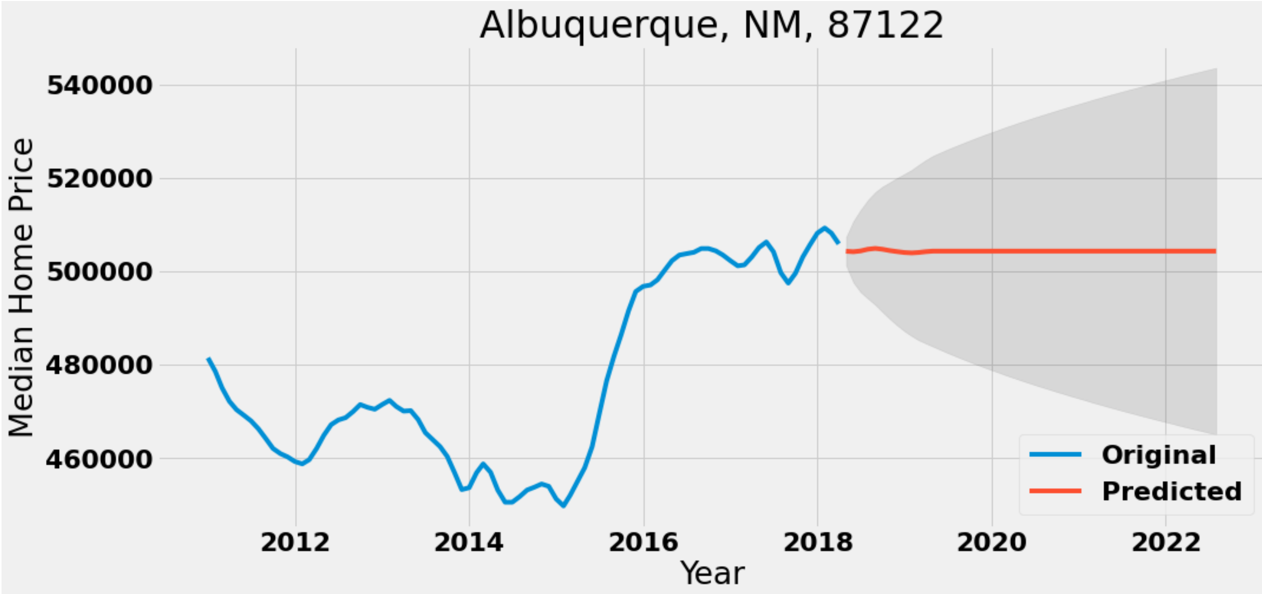
```
# Define train and validation datasets based 20% and 80%
training_data2 = abq_df_new[87122][:cutoff]
validation_data2 = abq_df_new[87122][cutoff:]

# Define the range of parameters for p, d, q, P, D, Q, and s
p = d = q = range(0, 2)
P = D = Q = range(0, 2)
s = 12  # monthly data

# Generate a list of all possible combinations of parameters
pdq = list(itertools.product(p, d, q))
seasonal_pdq = [(x[0], x[1], x[2], s) for x in itertools.product(P, D, Q)]

# Initialize variables to store the best parameters and the lowest RMSE
best_params = (0, 0, 0, 0, 0, 0, 0)
lowest_rmse = float('inf')

# Loop through all possible combinations of parameters
for param in pdq:
    for param_seasonal in seasonal_pdq:
        try:
            # Fit a SARIMAX model with the current combination of parameters
            model2 = sm.tsa.statespace.SARIMAX(training_data2,
                                              order=param,
                                              seasonal_order=param_seasonal,
                                              enforce_stationarity=False,
                                              enforce_invertibility=False).fit()

            # Make predictions on the validation data
            predictions2 = model2.predict(start=validation_data2.index[0], end=v

            # Calculate the RMSE of the predictions
            rmse2 = np.sqrt(np.mean((predictions2 - validation_data2)**2))

            # Update the best parameters and lowest RMSE if the current RMSE is
            if rmse2 < lowest_rmse:
                best_params = (param, param_seasonal)
                lowest_rmse = rmse2

        except ValueError:  # skip combinations that fail to converge or produce
            continue

print(f'Best parameters: {best_params}')
print(f'Lowest RMSE: {lowest_rmse:.2f}')
```

```
Best parameters: ((0, 1, 1), (0, 0, 1, 12))
Lowest RMSE: 3155.22
```

The RMSE is a little closer to our baseline model. Due to the computational time, I'll leave the parameters to 0,2.

In [29]:
```
#Define SARIMAX model and fit data save as sarima_mod1
sarima_mod2 = sm.tsa.statespace.SARIMAX(abq_df_new[87122],
                                        order=(0, 1, 1),
                                        seasonal_order=(0, 0, 1, 12),
                                        enforce_stationarity=False,
                                        enforce_invertibility=False).fit()
# # Forecast 52 months into the future (4 years)
forecast2 = sarima_mod2.get_forecast(steps=52).summary_frame()

# Calculate the mean of the last week of the forecast as the predicted value
forecast2_mean = round(forecast2['mean'][51])

#Calculate the difference between lower and upper 95% confidence intervals of th
low_int2 =  round(forecast2['mean_ci_lower'][51])
high_int2 = round(forecast2['mean_ci_upper'][51])

#Calculate the difference between the upper and lower confidence intervals
ci_delta2 = round(high_int2 - low_int2)

# Print predicted value and confidence intervals
print(f'Albuquerque, NM, 87122:')
print(f'95% confidence: ${low_int1} and ${high_int1}')
print(f'Confidence range: ${ci_delta1}')

# Plot the original data and predicted values with confidence intervals
fig, ax = plt.subplots(figsize=(15, 7))
plt.plot(abq_df_new[87122])
plt.plot(forecast2['mean'])
ax.fill_between(forecast2.index, forecast2['mean_ci_lower'],
                    forecast2['mean_ci_upper'], color='k', alpha=0.1)
plt.title('Albuquerque, NM, 87122')
plt.legend(['Original','Predicted'], loc='lower right')
plt.xlabel('Year')
plt.ylabel('Median Home Price')
plt.show()
```

```
Albuquerque, NM, 87122:
95% confidence: $236629.0 and $293381.0
Confidence range: $56752.0
```



Zipcode 87122 has the same results as 87106. Let's move on and see the results of our other zipcodes.

Albuquerque, NM, 87104

In [30]:

```
# Define train and validation datasets based 20% and 80%
training_data3 = abq_df_new[87104][:cutoff]
validation_data3 = abq_df_new[87104][cutoff:]

# Define the range of parameters for p, d, q, P, D, Q, and s
p = d = q = range(0, 2)
P = D = Q = range(0, 2)
s = 12  # monthly data

# Generate a list of all possible combinations of parameters
pdq = list(itertools.product(p, d, q))
seasonal_pdq = [(x[0], x[1], x[2], s) for x in itertools.product(P, D, Q)]

# Initialize variables to store the best parameters and the lowest RMSE
best_params = (0, 0, 0, 0, 0, 0, 0)
lowest_rmse = float('inf')

# Loop through all possible combinations of parameters
for param in pdq:
    for param_seasonal in seasonal_pdq:
        try:
            # Fit a SARIMAX model with the current combination of parameters
            model3 = sm.tsa.statespace.SARIMAX(training_data3,
                                              order=param,
                                              seasonal_order=param_seasonal,
                                              enforce_stationarity=False,
                                              enforce_invertibility=False).fit()

            # Make predictions on the validation data
            predictions3 = model3.predict(start=validation_data3.index[0], end=v

            # Calculate the RMSE of the predictions
            rmse3 = np.sqrt(np.mean((predictions3 - validation_data3)**2))
```

```
            # Update the best parameters and lowest RMSE if the current RMSE is
            if rmse3 < lowest_rmse:
                best_params = (param, param_seasonal)
                lowest_rmse = rmse3

        except ValueError:  # skip combinations that fail to converge or produce
            continue

print(f'Best parameters: {best_params}')
print(f'Lowest RMSE: {lowest_rmse:.2f}')
```

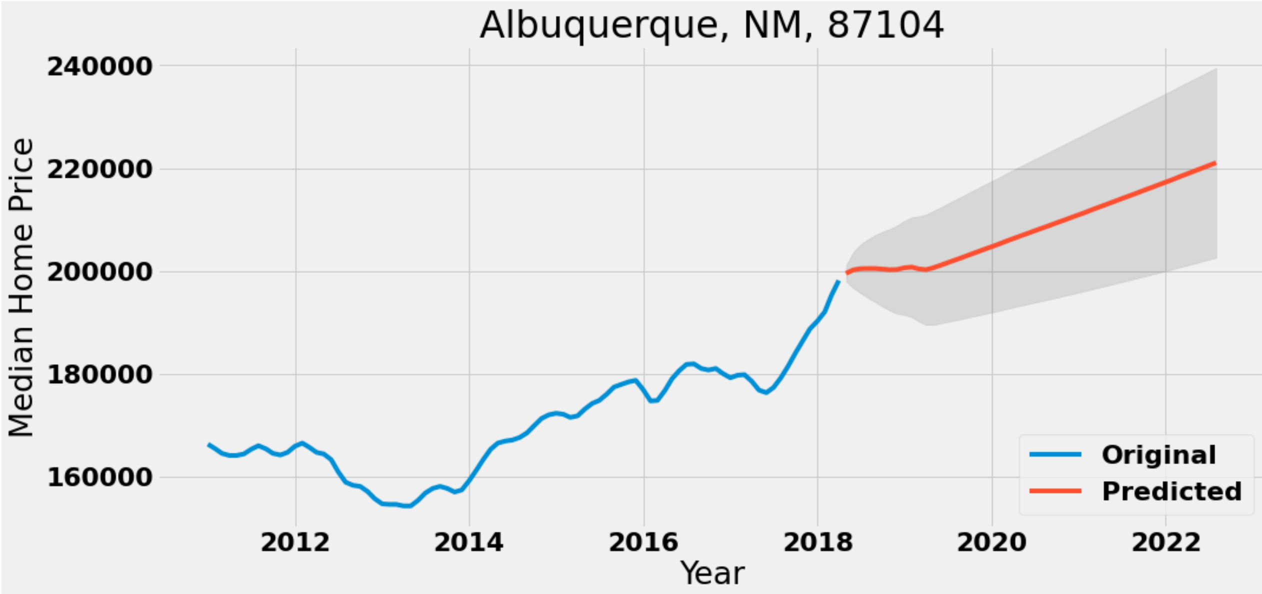
```
Best parameters: ((1, 0, 1), (1, 0, 1, 12))
Lowest RMSE: 5235.02
```

The RMSE is a lot higher than our baseline model.

In [31]:

```
#Define SARIMAX model and fit data save as sarima_mod1
sarima_mod3 = sm.tsa.statespace.SARIMAX(abq_df_new[87104],
                                        order=(1, 0, 1),
                                        seasonal_order=(1, 0, 1, 12),
                                        enforce_stationarity=False,
                                        enforce_invertibility=False).fit()
# Forecast 52 months into the future (4 years)
forecast3 = sarima_mod3.get_forecast(steps=52).summary_frame()

# Calculate the mean of the last week of the forecast as the predicted value
forecast3_mean = round(forecast3['mean'][51])

#Calculate the difference between lower and upper 95% confidence intervals of th
low_int3 =  round(forecast3['mean_ci_lower'][51])
high_int3 = round(forecast3['mean_ci_upper'][51])

#Calculate the difference between the upper and lower confidence intervals
ci_delta3 = round(high_int3 - low_int3)

# Print predicted value and confidence intervals
print(f'Albuquerque, NM, 87104:')
print(f'95% confidence: ${low_int1} and ${high_int1}')
print(f'Confidence range: ${ci_delta1}')

# Plot the original data and predicted values with confidence intervals
fig, ax = plt.subplots(figsize=(15, 7))
plt.plot(abq_df_new[87104])
plt.plot(forecast3['mean'])
ax.fill_between(forecast3.index, forecast3['mean_ci_lower'],
                    forecast3['mean_ci_upper'], color='k', alpha=0.1)
plt.title('Albuquerque, NM, 87104')
plt.legend(['Original','Predicted'], loc='lower right')
plt.xlabel('Year')
plt.ylabel('Median Home Price')
plt.show()
```

```
Albuquerque, NM, 87104:
95% confidence: $236629.0 and $293381.0
Confidence range: $56752.0
```



This also gave the same results as the previous zipcodes.

Albuquerque, NM, 87048

In [32]:

```
# Define train and validation datasets based 20% and 80%
training_data4 = abq_df_new[87048][:cutoff]
validation_data4 = abq_df_new[87048][cutoff:]

# Define the range of parameters for p, d, q, P, D, Q, and s
p = d = q = range(0, 2)
P = D = Q = range(0, 2)
s = 12  # monthly data

# Generate a list of all possible combinations of parameters
pdq = list(itertools.product(p, d, q))
seasonal_pdq = [(x[0], x[1], x[2], s) for x in itertools.product(P, D, Q)]

# Initialize variables to store the best parameters and the lowest RMSE
best_params = (0, 0, 0, 0, 0, 0, 0)
lowest_rmse = float('inf')

# Loop through all possible combinations of parameters
for param in pdq:
    for param_seasonal in seasonal_pdq:
        try:
            # Fit a SARIMAX model with the current combination of parameters
            model4 = sm.tsa.statespace.SARIMAX(training_data4,
                                              order=param,
                                              seasonal_order=param_seasonal,
                                              enforce_stationarity=False,
                                              enforce_invertibility=False).fit()

            # Make predictions on the validation data
            predictions4 = model4.predict(start=validation_data4.index[0], end=v

            # Calculate the RMSE of the predictions
            rmse4 = np.sqrt(np.mean((predictions4 - validation_data4)**2))

            # Update the best parameters and lowest RMSE if the current RMSE is
```

```
                if rmse4 < lowest_rmse:
                    best_params = (param, param_seasonal)
                    lowest_rmse = rmse4

        except ValueError:  # skip combinations that fail to converge or produce
            continue

print(f'Best parameters: {best_params}')
print(f'Lowest RMSE: {lowest_rmse:.2f}')
```

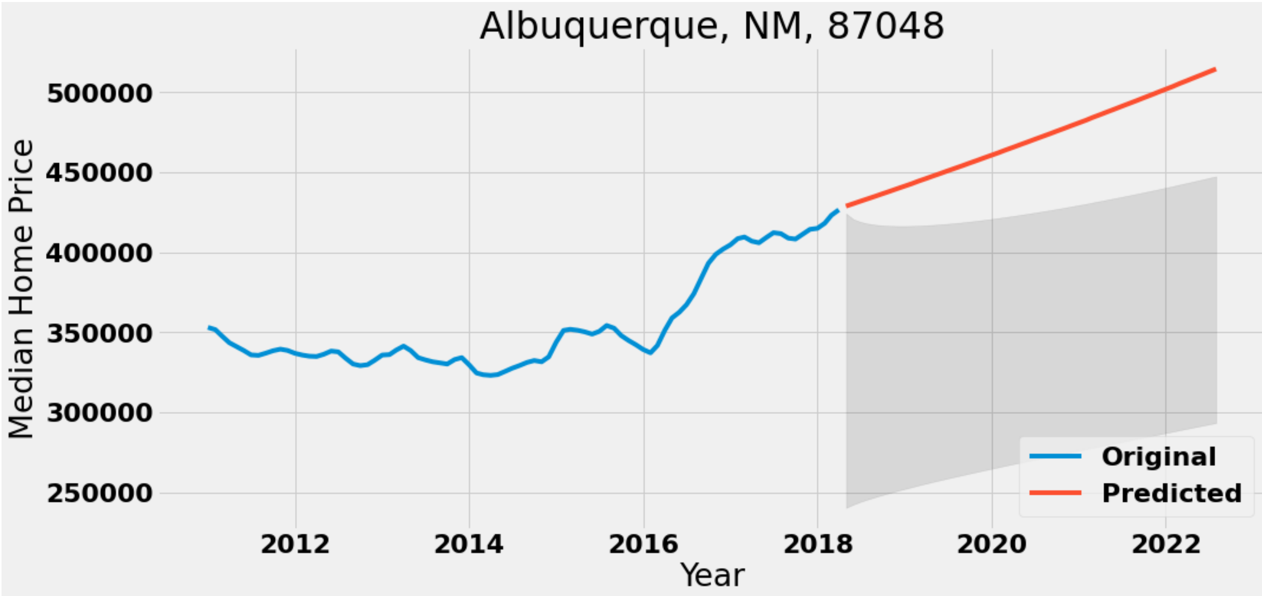
```
Best parameters: ((1, 0, 1), (1, 0, 0, 12))
Lowest RMSE: 4128.81
```

The RMSE is $1,000 higher than our baseline. Again, there are different approaches such as grid search that I could use.

In [33]:

```
#Define SARIMAX model and fit data save as sarima_mod1
sarima_mod4 = sm.tsa.statespace.SARIMAX(abq_df_new[87048],
                                        order=(1, 0, 1),
                                        seasonal_order=(1, 0, 0, 12),
                                        enforce_stationarity=False,
                                        enforce_invertibility=False).fit()
# Forecast 52 months into the future (4 years)
forecast4 = sarima_mod4.get_forecast(steps=52).summary_frame()

# Calculate the mean of the last week of the forecast as the predicted value
forecast4_mean = round(forecast4['mean'][51])

#Calculate the difference between lower and upper 95% confidence intervals of th
low_int4 =  round(forecast4['mean_ci_lower'][51])
high_int4 = round(forecast4['mean_ci_upper'][51])

#Calculate the difference between the upper and lower confidence intervals
ci_delta4 = round(high_int4 - low_int4)

# Print predicted value and confidence intervals
print(f'Albuquerque, NM, 87048:')
print(f'95% confidence: ${low_int1} and ${high_int1}')
print(f'Confidence range: ${ci_delta1}')

# Plot the original data and predicted values with confidence intervals
fig, ax = plt.subplots(figsize=(15, 7))
plt.plot(abq_df_new[87048])
plt.plot(forecast4['mean'])
ax.fill_between(forecast4.index, forecast4['mean_ci_lower'],
                forecast1['mean_ci_upper'], color='k', alpha=0.1)
plt.title('Albuquerque, NM, 87048')
plt.legend(['Original','Predicted'], loc='lower right')
plt.xlabel('Year')
plt.ylabel('Median Home Price')
plt.show()
```

```
Albuquerque, NM, 87048:
95% confidence: $236629.0 and $293381.0
Confidence range: $56752.0
```



Albuquerque, NM, 87043

In [34]:
```
# Define train and validation datasets based 20% and 80%
training_data5 = abq_df_new[87043][:cutoff]
validation_data5 = abq_df_new[87043][cutoff:]

# Define the range of parameters for p, d, q, P, D, Q, and s
p = d = q = range(0, 2)
P = D = Q = range(0, 2)
s = 12  # monthly data

# Generate a list of all possible combinations of parameters
pdq = list(itertools.product(p, d, q))
seasonal_pdq = [(x[0], x[1], x[2], s) for x in itertools.product(P, D, Q)]

# Initialize variables to store the best parameters and the lowest RMSE
best_params = (0, 0, 0, 0, 0, 0, 0)
lowest_rmse = float('inf')

# Loop through all possible combinations of parameters
for param in pdq:
    for param_seasonal in seasonal_pdq:
        try:
            # Fit a SARIMAX model with the current combination of parameters
            model5 = sm.tsa.statespace.SARIMAX(training_data5,
                                              order=param,
                                              seasonal_order=param_seasonal,
                                              enforce_stationarity=False,
                                              enforce_invertibility=False).fit()

            # Make predictions on the validation data
            predictions5 = model5.predict(start=validation_data5.index[0], end=v

            # Calculate the RMSE of the predictions
            rmse5 = np.sqrt(np.mean((predictions5 - validation_data5)**2))

            # Update the best parameters and lowest RMSE if the current RMSE is
            if rmse5 < lowest_rmse:
                best_params = (param, param_seasonal)
```

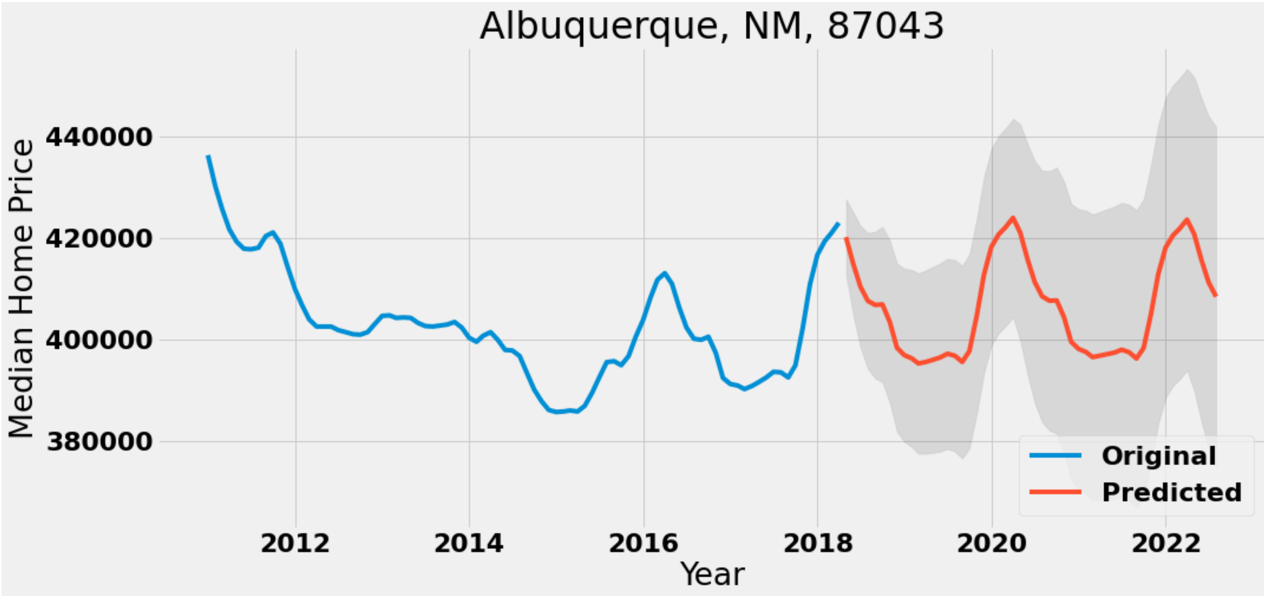
```
                lowest_rmse = rmse5

        except ValueError:  # skip combinations that fail to converge or produce
            continue

print(f'Best parameters: {best_params}')
print(f'Lowest RMSE: {lowest_rmse:.2f}')
```

```
Best parameters: ((1, 0, 0), (1, 1, 0, 12))
Lowest RMSE: 8373.23
```

The RMSE is higher than our baseline model.

In [35]:

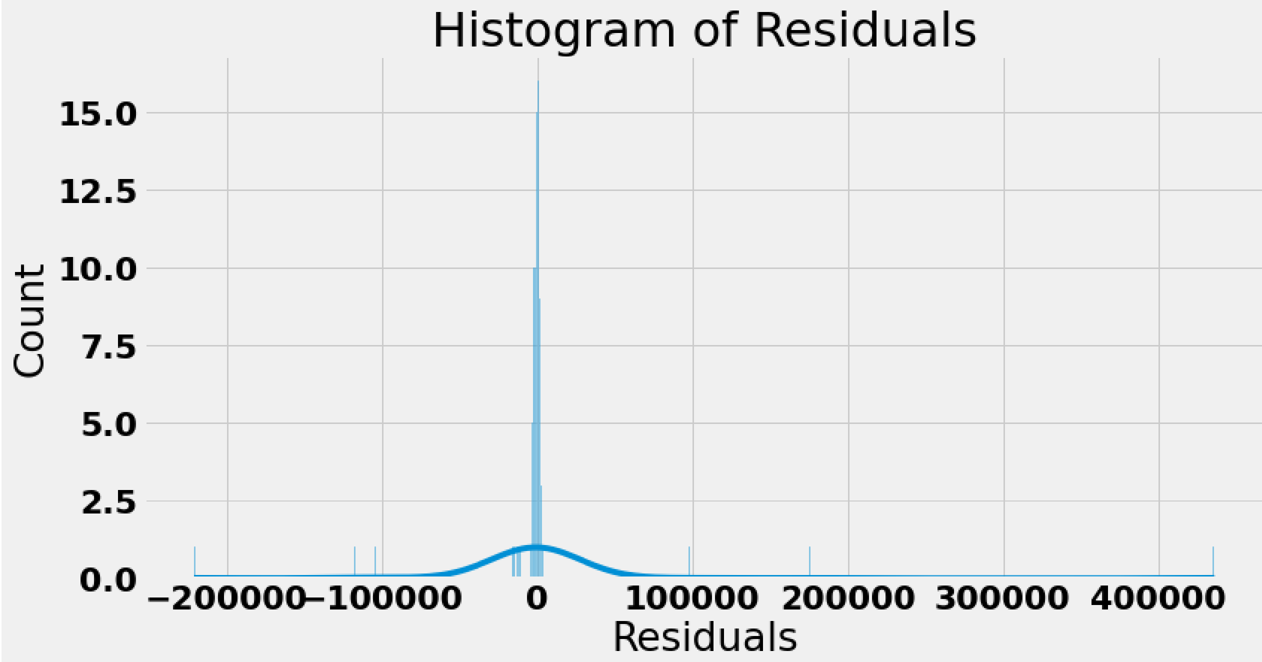
```
#Define SARIMAX model and fit data save as sarima_mod5
sarima_mod5 = sm.tsa.statespace.SARIMAX(abq_df_new[87043],
                                        order=(1, 0, 0),
                                        seasonal_order=(1, 1, 0, 12),
                                        enforce_stationarity=False,
                                        enforce_invertibility=False).fit()
# Forecast 52 months into the future (4 years)
forecast5 = sarima_mod5.get_forecast(steps=52).summary_frame()
# Calculate the mean of the last week of the forecast as the predicted value
forecast5_mean = round(forecast5['mean'][51])
#Calculate the difference between lower and upper 95% confidence intervals of th
low_int5 =  round(forecast5['mean_ci_lower'][51])
high_int5 = round(forecast5['mean_ci_upper'][51])
#Calculate the difference between the upper and lower confidence intervals
ci_delta5 = round(high_int5 - low_int5)

# Plot the original data and predicted values with confidence intervals
fig, ax = plt.subplots(figsize=(15, 7))
plt.plot(abq_df_new[87043])
plt.plot(forecast5['mean'])
ax.fill_between(forecast5.index, forecast5['mean_ci_lower'],
                    forecast5['mean_ci_upper'], color='k', alpha=0.1)
plt.title('Albuquerque, NM, 87043')
plt.legend(['Original','Predicted'], loc='lower right')
plt.xlabel('Year')
plt.ylabel('Median Home Price')
plt.show()


print(f'Albuquerque, NM, 87043:')
print(f'95% confidence between: ${low_int5} and ${high_int5}')
print(f'Confidence range: ${ci_delta5}')
```

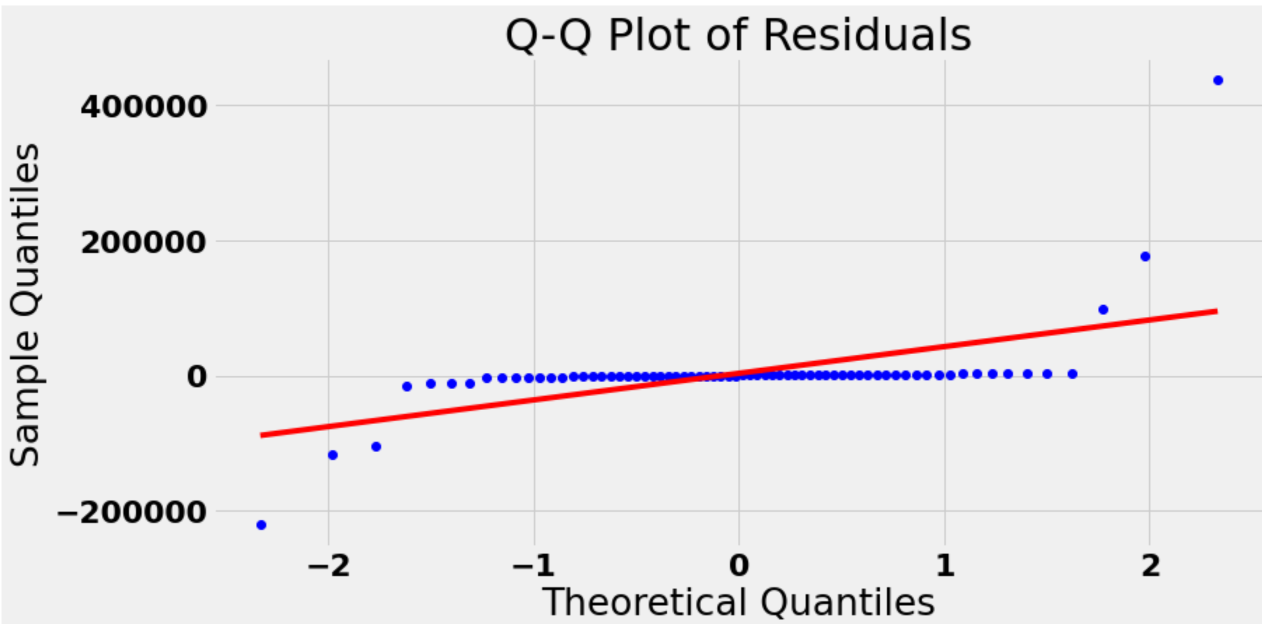



```
Albuquerque, NM, 87043:
95% confidence between: $375097.0 and $441879.0
Confidence range: $66782.0
```

These results are a lot different compared to the above zipcodes. The 95% confidence level is between $375,097 and $441,879. The confidence range is $66,782. The SARIMAX model seems to perform better for this particular zipcode as well and seems more realistic. Let's examine the residuals.

In [36]:
```
# Residuals
residuals = model5.resid

# Histogram of residuals
plt.figure(figsize=(12, 6))
sns.histplot(residuals, kde=True)
plt.title('Histogram of Residuals')
plt.xlabel('Residuals')
plt.show()

# Q-Q plot of residuals
plt.figure(figsize=(12, 6))
stats.probplot(residuals, plot=plt)
plt.title('Q-Q Plot of Residuals')
plt.xlabel('Theoretical Quantiles')
plt.ylabel('Sample Quantiles')
plt.show()
```





The histogram of residuals looks normally distributed but with some outliers. So it doesn't completely deviate significantly from a normal distribution. The QQ plot curves off and could mean the data has extreme values.

Evaluation

Now that I have my models for the top five zipcodes to invest in Albuquerque, I want to see the RMSE, low confidence, high confidence, forecast range and ROI for each of the zipcodes.

In [37]:
```
# Define a list of zipcodes to include
zipcodes = [87106, 87122, 87104, 87048, 87043]

# Subset the DataFrame to only include rows where the year is 2018 and the zipco
abq_df_2018 = abq_df_new.loc[(abq_df_new.index.year == 2018) & (abq_df_new.index

# Calculate the median of the values for each zipcode in 2018
```

```
medians_2018 = abq_df_2018.median()

# Print the results
for zipcode, median in medians_2018.items():
    print(f"The median home value for zipcode {zipcode} in 2018 was ${median:,.2
```

```
The median home value for zipcode 87106 in 2018 was $230,500.00
The median home value for zipcode 87122 in 2018 was $508,200.00
The median home value for zipcode 87104 in 2018 was $190,300.00
The median home value for zipcode 87048 in 2018 was $415,000.00
The median home value for zipcode 87043 in 2018 was $416,700.00
```

In [38]:

```
# Define lists for the zipcode, city, median value, RMSE, low confidence, high c
zipcodes = ['87106', '87122', '87104', '87048', '87043']
cities = ['Albuquerque, NM','Albuquerque, NM', 'Albuquerque, NM', 'Corrales, NM'
med_values = [230500, 508200, 190300, 415000, 416700]
rmse = [rmse, rmse2, rmse3, rmse4, rmse5]
low_confs = [low_int1, low_int2, low_int3, low_int4, low_int5]
high_confs = [high_int1, high_int2, high_int3, high_int4, high_int5]
forecast_ranges = [ci_delta1, ci_delta2, ci_delta3, ci_delta4, ci_delta5]

# Create a dictionary 'abq' that contains the zipcode, city, median value, RMSE,
abq = {'Zipcode': zipcodes,
        'City': cities,
        '2018 median value': med_values,
        'rmse': rmse,
        'low_conf': low_confs,
        'high_conf': high_confs,
        'forecast range': forecast_ranges}

# Create a DataFrame 'df_results' using the dictionary 'abq'.
df_results = pd.DataFrame(data=abq)

# Calculate the low and high ends of the confidence interval for each row, and s
df_results['low_end'] = df_results['2018 median value'] + df_results['low_conf']
df_results['high_end'] = df_results['2018 median value'] + df_results['high_conf

# Calculate the ROI percentage for each row, and store the results in a new colu
df_results['ROI%'] = round(((df_results['high_end'] - df_results['2018 median va
                                       df_results['2018 median value']) * 100, 2)
```

In [39]:

```
df_results
```

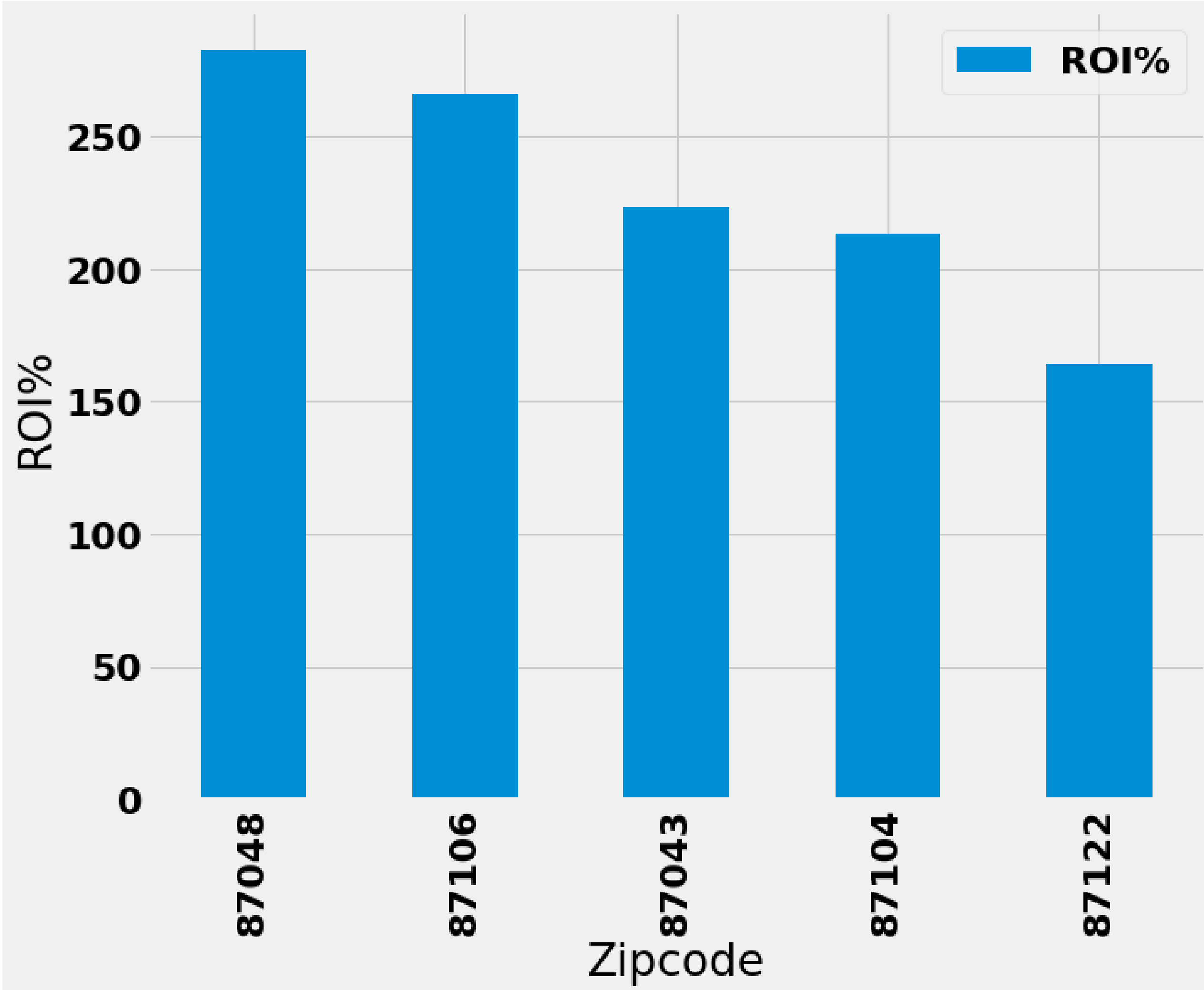
Out[39]:

	Zipcode	City	2018 median value	rmse	low_conf	high_conf	forecast range	low_end	high_e
0	87106	Albuquerque, NM	230500	28566.613682	236629.0	293381.0	56752.0	467129.0	52388
1	87122	Albuquerque, NM	508200	4276.872528	465108.0	543586.0	78478.0	973308.0	105178
2	87104	Albuquerque, NM	190300	6118.499377	202629.0	239505.0	36876.0	392929.0	42980
3	87048	Corrales, NM	415000	16113.137999	447569.0	581744.0	134175.0	862569.0	99674

	Zipcode	City	2018 median value	rmse	low_conf	high_conf	forecast range	low_end	high_(
4	87043	Santa Ana Pueblo, NM	416700	16992.337405	375097.0	441879.0	66782.0	791797.0	85857

In [40]:

```
# create a DataFrame from the given data
data = {'zipcode': ['87106', '87122', '87104', '87048', '87043'],
        'city': ['Albuquerque, NM', 'Albuquerque, NM', 'Albuquerque, NM', 'Corra
        '2018 median value': [230500, 508200, 190300, 415000, 416700],
        'rmse': [31455.188774, 81866.138297, 25140.743922, 56009.750599, 71678.3
        'low_conf': [43008, 52707, 134725, -68970, 200748],
        'high_conf': [612761, 833727, 405455, 1173814, 930335],
        'forecast range': [569753, 781020, 270730, 1242784, 729587],
        'low_end': [273508, 560907, 325025, 346030, 617448],
        'high_end': [843261, 1341927, 595755, 1588814, 1347035],
        'ROI%': [265.84, 164.05, 213.06, 282.85, 223.26]}
df = pd.DataFrame(data)

# sort the DataFrame by the ROI% column
df = df.sort_values('ROI%', ascending=False)

# plot the ROI values as a bar chart
ax = df.plot(x='zipcode', y='ROI%', kind='bar', figsize=(10, 8))
ax.set_xticklabels(df['zipcode'])
ax.set_xlabel('Zipcode')
ax.set_ylabel('ROI%')
plt.show()
```



These results are showing the predicted median home value, the root mean squared error (RMSE), the low and high confidence intervals for the predicted median home value, the forecast range (high value minus low value), the low and high end values of the predicted range, and the ROI% for five different zip codes.

The low and high confidence intervals represent the range within which the true median home value is expected to fall with a 95% confidence level. The forecast range is the difference between the high and low values of the predicted median home value range. The ROI represents the return on investment for each zipcode.

Recommendations

For those who are intersted investing in properties in New Mexico, there are the following zipcodes that has a high return on investment.

1. Corrales, NM (87048)
2. Albuquerque, NM (87106)
3. Santa Ana Pueblo, NM (87043) - Santa Ana Pubelo's median value in 2018 was $416, 700 and forecasted a confidence range between$375,097 and $441,8790.
4. Albuquerque, NM (87104)

5. Albuquerque, NM (87122)

The model's inability to generate realistic forecasts resulted in identical forecast ranges for zipcodes 87048, 87106, 87104, and 87122. However, analyzing the ROI paints a different picture. Investors seeking property in New Mexico would be better off considering Corrales or Santa Ana Pueblo. A 2023 Zillow search revealed that Santa Ana Pueblo's home prices range from $200,000 to$1,795,950, while Corrales' prices range from $205,000 to$3,800,000. These wide ranges suggest that further investigation of these zipcodes could reveal intriguing insights.

Next Steps

1. Further investigation into Santa Ana Pueblo and Corrales.
2. Include external factors that may influence real estate prices, such as population growth or unemployment rates.
3. Investigate rapidly growing neighborhoods in New Mexico.