Time Series Project - monthly housing sales by zip code

For this analysis I will be working as a Data Scientist for a financial investment firm that is looking for short-term real estate investment opportunities for it's smaller investors to diversify their investment profiles. I will be analyzing median monthly housing sales prices for over 14,000 United States zip codes and choosing the best areas to further analyze for potential investment. I will then forecast future real estate prices in those zip codes.

Contents

Dataset information

This data represents median monthly housing sales prices for 265 zip codes over the period of April 1996 through April 2018 as reported by Zillow.

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

There are 14,723 rows and 272 variables:

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

Some ideas for exploration:

1. Look at ROI for each zip code, over the whole dataset, avg for each year, 3 year avg, 5 year avg, 10 year avg
2. Plot median sales price against ROI to get quadrants for comparison
3. Which zips have highest and lowest ROI?
4. Business case - choose highest ROI for small investors

Data Preprocessing

Import and basic info

Output - zillow

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import itertools
import time
from user_functions import *
from datetime import datetime
import warnings
warnings.filterwarnings('ignore')
```

Contents

In [2]:

```
# Set default visualization parameters

CB91_Blue = '#2CBDFE'
CB91_Green = '#47DBCD'
CB91_Pink = '#F3A0F2'
CB91_Purple = '#9D2EC5'
CB91_Violet = '#661D98'
CB91_Amber = '#F5B14C'
color_list = [CB91_Blue, CB91_Pink, CB91_Green, CB91_Amber, CB91_Purple, CB91_Violet]
plt.rcParams['axes.prop_cycle'] = plt.cycler(color=color_list)
sns.set_context("notebook", rc={"font.size":16, "axes.titlesize":20, "axes.labelsize":18})
sns.set(font='Franklin Gothic Book',
rc={'axes.axisbelow': False,
'axes.edgecolor': 'lightgrey',
# 'axes.edgecolor': 'white',
'axes.facecolor': 'None',
'axes.grid': False,
'axes.labelcolor': 'dimgrey',
# 'axes.labelcolor': 'white',
'axes.spines.right': False,
'axes.spines.top': False,
'axes.prop_cycle': plt.cycler(color=color_list),
'figure.facecolor': 'white',
'lines.solid_capstyle': 'round',
'patch.edgecolor': 'w',
'patch.force_edgecolor': True,
'text.color': 'dimgrey',
# 'text.color': 'white',
'xtick.bottom': False,
'xtick.color': 'dimgrey',
# 'xtick.color': 'white',
'xtick.direction': 'out',
'xtick.top': False,
'ytick.color': 'dimgrey',
# 'ytick.color': 'white',
'ytick.direction': 'out',
'ytick.left': False,
'ytick.right': False})
%matplotlib inline

'''font = {'family' : 'normal',
        'weight' : 'bold',
        'size'   : 22}

matplotlib.rc('font', **font)

# NOTE: if you visualizations are too cluttered to read, try calling 'plt.gcf().autofmt_xdate()'!'''
```

Out[2]:

```
"font = {'family' : 'normal',\n        'weight' : 'bold',\n        'size'   : 22}\n\nmatplotlib.rc('font', **font)\n\n# NOTE:
if you visualizations are too cluttered to read, try calling 'plt.gcf().autofmt_xdate()'!"
```

Contents

In [3]:
```
zillow = pd.read_csv('zillow_data.csv')
zillow.info()
# I see 4 string object columns, not sure why 49 are int and others float.
# Most column names will be changed to datetime
# Zip codes are actually not continuous so maybe they should be strings
# Don't know if RegionID has any meaning, seems unneeded if zip codes are unique.
```

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

In [4]:
```
zillow.head()
```

Out[4]:

	RegionID	RegionName	City	State	Metro	CountyName	SizeRank	1996-04	1996-05	1996-06	...	2017-07	2017-08	2017-09	2017-10	2017
0	84654	60657	Chicago	IL	Chicago	Cook	1	334200.0	335400.0	336500.0	...	1005500	1007500	1007800	1009600	1013
1	90668	75070	McKinney	TX	Dallas-Fort Worth	Collin	2	235700.0	236900.0	236700.0	...	308000	310000	312500	314100	315
2	91982	77494	Katy	TX	Houston	Harris	3	210400.0	212200.0	212200.0	...	321000	320600	320200	320400	320
3	84616	60614	Chicago	IL	Chicago	Cook	4	498100.0	500900.0	503100.0	...	1289800	1287700	1287400	1291500	1296
4	93144	79936	El Paso	TX	El Paso	El Paso	5	77300.0	77300.0	77300.0	...	119100	119400	120000	120300	120

5 rows × 272 columns

Contents

In [5]:
```
# Data appears to be sorted by SizeRank, largest to smallest
# I see some Nan values in Metro
# And some 4 digit zip codes which I assume should start with a zero
zillow.tail(10)
```

Out[5]:

	RegionID	RegionName	City	State	Metro	CountyName	SizeRank	1996-04	1996-05	1996-06	...	2017-07	2017-08	2017-09	2017-10
14713	59187	3765	Haverhill	NH	Claremont	Grafton	14714	80800.0	80100.0	79400.0	...	119800	120000	120800	121600
14714	94711	84781	Pine Valley	UT	St. George	Washington	14715	135900.0	136300.0	136600.0	...	241100	243200	244300	248900
14715	62556	12429	Esopus	NY	Kingston	Ulster	14716	78300.0	78300.0	78200.0	...	164200	166600	170000	171000
14716	99032	97028	Rhododendron	OR	Portland	Clackamas	14717	136200.0	136600.0	136800.0	...	332600	332900	335600	338900
14717	62697	12720	Bethel	NY	NaN	Sullivan	14718	62500.0	62600.0	62700.0	...	122200	122700	122300	122000
14718	58333	1338	Ashfield	MA	Greenfield Town	Franklin	14719	94600.0	94300.0	94000.0	...	216800	217700	218600	218500
14719	59107	3293	Woodstock	NH	Claremont	Grafton	14720	92700.0	92500.0	92400.0	...	202100	208400	212200	215200
14720	75672	40404	Berea	KY	Richmond	Madison	14721	57100.0	57300.0	57500.0	...	121800	122800	124600	126700
14721	93733	81225	Mount Crested Butte	CO	NaN	Gunnison	14722	191100.0	192400.0	193700.0	...	662800	671200	682400	695600
14722	95851	89155	Mesquite	NV	Las Vegas	Clark	14723	176400.0	176300.0	176100.0	...	333800	336400	339700	343800

10 rows × 272 columns

In [6]:
```
# Can see missing values in Metro
zillow.isna().sum()
```

Out[6]:
```
RegionID         0
RegionName       0
City             0
State            0
Metro         1043
              ...
2017-12          0
2018-01          0
2018-02          0
2018-03          0
2018-04          0
Length: 272, dtype: int64
```

In [7]:
```
# There will be lots of other missing values in the time series data
zillow.isna().sum().sum()
```

Out[7]:
```
157934
```

Analyze 'RegionID'

All unique, cast to string

Contents

In [8]:
```
# Starting analysis of first variable, RegionID
# 14723 unique values
print(zillow.RegionID.value_counts())
print(zillow.RegionID.nunique())
print(zillow.RegionID.min())
print(zillow.RegionID.max())
```

```
73724     1
70551     1
99221     1
76688     1
82829     1
         ..
71176     1
91654     1
65029     1
100380    1
98304     1
Name: RegionID, Length: 14723, dtype: int64
14723
58196
753844
```

In [9]:
```
zillow[zillow.RegionID >= 200000]
```

Out[9]:

	RegionID	RegionName	City	State	Metro	CountyName	SizeRank	1996-04	1996-05	1996-06	...	2017-07	2017-08	2017-09	2017-10
444	417444	85142	Queen Creek	AZ	Phoenix	Pinal	445	117400.0	115500.0	113800.0	...	281200	283700	286200	288200
750	399576	33578	Riverview	FL	Tampa	Hillsborough	751	74700.0	74200.0	73800.0	...	189600	190100	190400	191400
863	417437	85122	Casa Grande	AZ	Phoenix	Pinal	864	82700.0	83500.0	84300.0	...	152600	155000	157200	158400
926	399724	77407	Richmond	TX	Houston	Fort Bend	927	119800.0	119600.0	119700.0	...	247100	247200	247100	247000
1101	399638	78665	Round Rock	TX	Austin	Williamson	1102	160700.0	160300.0	160100.0	...	258000	257400	257700	258400
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
12263	399644	80927	Colorado Springs	CO	Colorado Springs	El Paso	12264	147800.0	148500.0	149100.0	...	335900	335700	335200	334700
12407	399666	89034	Mesquite	NV	Las Vegas	Clark	12408	196000.0	196000.0	195900.0	...	289400	294500	299800	304700
13498	417445	85145	Marana	AZ	Tucson	Pima	13499	NaN	NaN	NaN	...	141000	143800	145900	146600
14181	399514	3285	Thornton	NH	Claremont	Grafton	14182	92000.0	91800.0	91500.0	...	200500	204900	208600	211600
14672	399675	91008	Bradbury	CA	Los Angeles-Long Beach-Anaheim	Los Angeles	14673	351200.0	351200.0	351300.0	...	1231800	1248800	1269200	1273600

106 rows × 272 columns

Contents

In [10]:
```
# It doesn't seem to mean anything and all are unique.  Lets make them strings.
zillow.RegionID = zillow.RegionID.astype('string')
```

In [11]:
```
zillow.RegionID.unique()
```

Out[11]:
```
<StringArray>
['84654', '90668', '91982', '84616', '93144', '91733', '61807', '84640',
 '91940', '97564',
 ...
 '59187', '94711', '62556', '99032', '62697', '58333', '59107', '75672',
 '93733', '95851']
Length: 14723, dtype: string
```

Analyze 'Region Name'

Output -

Cast to string, add 0 to 4 digit zip codes

In [12]:
```
# Now look at RegionName, this is the zip code
zillow.RegionName.value_counts() # 14723 unique values
```

Out[12]:
```
55324    1
74561    1
73538    1
31546    1
82070    1
        ..
75182    1
55343    1
1450     1
73129    1
65536    1
Name: RegionName, Length: 14723, dtype: int64
```

In [13]:
```
# All zip codes are unique.  I will cast to string and add 0 to the four digit one.
zillow.RegionName = zillow.RegionName.astype('string')
```

In [14]:
```
for i in range(len(zillow)):
    zillow.RegionName[i] = zillow.RegionName[i].rjust(5, '0')
```

In [15]:
```
zillow.RegionName.min()
```

Out[15]:
```
'01001'
```

In [16]:
```
zillow.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 14723 entries, 0 to 14722
Columns: 272 entries, RegionID to 2018-04
dtypes: float64(219), int64(47), object(4), string(2)
memory usage: 30.6+ MB
```

In [17]:
```
zillow[['RegionName', 'State']].sort_values(by=['RegionName'])
```

Out[17]:

	RegionName	State
5850	01001	MA
4199	01002	MA
11213	01005	MA
6850	01007	MA
14547	01008	MA
...	...	...
4526	99709	AK
8438	99712	AK
4106	99801	AK
8658	99835	AK
7293	99901	AK

14723 rows × 2 columns

Analyze 'City'

In [18]:
```
# There are 7554 unique values.
zillow.City.nunique()
```

Out[18]: 7554

Analyze 'State'

In [19]:
```
zillow.State.nunique()
```

Out[19]: 51

In [20]:
```
# Includes DC
zillow.State.unique()
```

Out[20]:
```
array(['IL', 'TX', 'NY', 'CA', 'FL', 'TN', 'NC', 'GA', 'DC', 'MO', 'OK',
       'AZ', 'NJ', 'MD', 'VA', 'WA', 'OH', 'MI', 'MA', 'KS', 'NM', 'CT',
       'NV', 'PA', 'CO', 'OR', 'IN', 'SC', 'KY', 'AR', 'ND', 'MN', 'AL',
       'DE', 'LA', 'MS', 'ID', 'MT', 'HI', 'WI', 'UT', 'ME', 'SD', 'WV',
       'IA', 'RI', 'NE', 'WY', 'AK', 'NH', 'VT'], dtype=object)
```

Analyze 'Metro'

Fillna with None

In [21]:
```
print(zillow.Metro.value_counts())
print(zillow.Metro.nunique())
```

```
New York                        779
Los Angeles-Long Beach-Anaheim  347
Chicago                         325
Philadelphia                    281
Washington                      249
                               ...
Gallup                            1
Alamogordo                        1
Salina                            1
Stephenville                      1
Cullman                           1
Name: Metro, Length: 701, dtype: int64
701
```

In [22]:
```
zillow.Metro[151]
```

Out[22]:
```
nan
```

In [23]:
```
zillow.Metro.fillna('None', inplace=True)
```

In [24]:
```
zillow.Metro.value_counts()
```

Out[24]:
```
None                            1043
New York                         779
Los Angeles-Long Beach-Anaheim   347
Chicago                          325
Philadelphia                     281
                                ...
Gallup                             1
Alamogordo                         1
Salina                             1
Stephenville                       1
Cullman                            1
Name: Metro, Length: 702, dtype: int64
```

Analyze 'CountyName'

In [25]:
```
zillow.CountyName.value_counts()
```

Out[25]:
```
Los Angeles    264
Jefferson      175
Orange         166
Washington     164
Montgomery     159
               ...
Wilbarger        1
Summers          1
Seward           1
Licking          1
Wilcox           1
Name: CountyName, Length: 1212, dtype: int64
```

In [26]:
```
zillow.CountyName.isna().sum()
```

Out[26]:
```
0
```

Analyze 'SizeRank'

In [27]:
```
zillow.SizeRank.unique()
```

Out[27]:
```
array([    1,     2,     3, ..., 14721, 14722, 14723], dtype=int64)
```

Analyze missing sales values

Contents

In [28]:
```
# 1039 zip codes don't have full data
zillow[zillow['1996-04'].isna()]
```

Out[28]:

	RegionID	RegionName	City	State	Metro	CountyName	SizeRank	1996-04	1996-05	1996-06	...	2017-07	2017-08	2017-09	2017-10	20
20	61625	10011	New York	NY	New York	New York	21	NaN	NaN	NaN	...	12137600	12112600	12036600	12050100	120
36	61796	10456	New York	NY	New York	Bronx	37	NaN	NaN	NaN	...	357900	357100	356500	357200	3(
105	84613	60611	Chicago	IL	Chicago	Cook	106	NaN	NaN	NaN	...	1475200	1473900	1469500	1472100	14
156	62048	11238	New York	NY	New York	Kings	157	NaN	NaN	NaN	...	2673300	2696700	2716500	2724000	27
232	69533	27834	Greenville	NC	Greenville	Pitt	233	NaN	NaN	NaN	...	100100	98700	97400	96100	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
14703	94323	83821	Coolin	ID	Sandpoint	Bonner	14704	NaN	NaN	NaN	...	550500	550700	542900	539100	5
14705	79929	49768	Paradise	MI	Sault Ste. Marie	Chippewa	14706	NaN	NaN	NaN	...	86700	86900	87000	87200	
14706	59046	03215	Waterville Valley	NH	Claremont	Grafton	14707	NaN	NaN	NaN	...	786000	780900	774100	767800	7
14707	69681	28039	East Spencer	NC	Charlotte	Rowan	14708	NaN	NaN	NaN	...	27300	26400	25500	25100	
14708	99401	97733	Crescent	OR	Klamath Falls	Klamath	14709	NaN	NaN	NaN	...	197700	203700	207900	208100	2(

1039 rows × 272 columns

In [29]:
```
# But all zip codes have some data
zillow[zillow['2018-04'].isna()]
```

Out[29]:

RegionID	RegionName	City	State	Metro	CountyName	SizeRank	1996-04	1996-05	1996-06	...	2017-07	2017-08	2017-09	2017-10	2017-11	2017-12	2018-01	2018-02	2018-03

0 rows × 272 columns

In [30]:
```
# I need to find an ROI that I can compare them all on
# Find the zips with the least data
for col in reversed(zillow.columns):
    if zillow[col].isna().sum() >0:
        print(col)
        break
```

```
2014-06
```

In [31]:
```
# 56 zip codes only go back to 07-2014
zillow[zillow['2014-06'].isna()]
```

Out[31]:

	RegionID	RegionName	City	State	Metro	CountyName	SizeRank	1996-04	1996-05	1996-06	...	2017-07	2017-08	2017-09	2017-10	2017
2946	73623	35810	Huntsville	AL	Huntsville	Madison	2947	NaN	NaN	NaN	...	61000	61000	61100	61900	628
3330	58630	02116	Boston	MA	Boston	Suffolk	3331	NaN	NaN	NaN	...	1931100	1995600	2031100	2049600	20578
6153	73629	35816	Huntsville	AL	Huntsville	Madison	6154	NaN	NaN	NaN	...	61500	62500	62800	63300	641
7587	78091	46320	Hammond	IN	Chicago	Lake	7588	NaN	NaN	NaN	...	66000	67900	68200	68700	696
7635	78566	47371	Portland	IN	None	Jay	7636	NaN	NaN	NaN	...	86300	86600	87400	88200	891
8263	88723	70647	Iowa	LA	Lake Charles	Calcasieu	8264	NaN	NaN	NaN	...	111600	117900	125300	128900	129
8338	73630	35824	Huntsville	AL	Huntsville	Madison	8339	NaN	NaN	NaN	...	217200	216800	216300	215100	2157
8668	75206	39202	Jackson	MS	Jackson	Hinds	8669	NaN	NaN	NaN	...	152700	154300	155800	157500	1581
8746	90561	74857	Norman	OK	Oklahoma City	Cleveland	8747	NaN	NaN	NaN	...	141800	141800	141700	141700	142
8780	78097	46327	Hammond	IN	Chicago	Lake	8781	NaN	NaN	NaN	...	75200	74600	73200	72500	728
9054	73597	35759	Meridianville	AL	Huntsville	Madison	9055	NaN	NaN	NaN	...	164000	161800	159600	159300	1607
9218	71997	32435	Defuniak Springs	FL	Crestview-Fort Walton Beach-Destin	Walton	9219	NaN	NaN	NaN	...	102100	102600	103600	103800	1027
9594	76778	43619	Northwood	OH	Toledo	Wood	9595	NaN	NaN	NaN	...	98800	100200	101100	101800	1021
9684	99311	97467	Reedsport	OR	Roseburg	Douglas	9685	NaN	NaN	NaN	...	156200	156200	156100	157400	1581
9739	59298	04009	Bridgton	ME	Portland	Cumberland	9740	NaN	NaN	NaN	...	175600	177300	179000	179800	1819
10373	87291	66739	Galena	KS	None	Cherokee	10374	NaN	NaN	NaN	...	46900	47000	46500	45800	450
10453	88587	70431	Bush	LA	New Orleans	Saint Tammany	10454	NaN	NaN	NaN	...	168000	171100	176300	180200	1816
10599	73598	35760	New Hope	AL	Huntsville	Madison	10600	NaN	NaN	NaN	...	104900	105500	105100	102300	995
10781	75219	39216	Jackson	MS	Jackson	Hinds	10782	NaN	NaN	NaN	...	161200	163600	166700	169600	1720
11073	79629	49245	Homer	MI	Battle Creek	Calhoun	11074	NaN	NaN	NaN	...	72900	73000	73200	74300	768
11391	81629	54230	Reedsville	WI	Manitowoc	Manitowoc	11392	NaN	NaN	NaN	...	138100	139600	142300	143400	1390
11521	77878	45872	North Baltimore	OH	Toledo	Wood	11522	NaN	NaN	NaN	...	79800	78500	78300	78300	772
11523	82857	56441	Crosby	MN	Brainerd	Crow Wing	11524	NaN	NaN	NaN	...	100100	101800	103800	105200	1051
11767	78635	47512	Bicknell	IN	Vincennes	Knox	11768	NaN	NaN	NaN	...	53300	54000	54400	54600	549
11772	67332	22625	Cross Junction	VA	Winchester	Frederick	11773	NaN	NaN	NaN	...	225800	229100	232000	234200	2356
11888	64657	16625	Greenfield	PA	Altoona	Blair	11889	NaN	NaN	NaN	...	100400	100300	99200	98800	968
11905	69706	28088	Landis	NC	Charlotte	Rowan	11906	NaN	NaN	NaN	...	119400	120800	122200	123000	1232
11922	79637	49253	Manitou Beach	MI	Adrian	Lenawee	11923	NaN	NaN	NaN	...	153500	154100	155100	156800	1613
11969	89717	72718	Cave Springs	AR	Fayetteville	Benton	11970	NaN	NaN	NaN	...	251700	251300	250200	249200	2485
11988	78538	47336	Dunkirk	IN	None	Jay	11989	NaN	NaN	NaN	...	80800	81200	81700	82900	843
12049	88638	70515	Basile	LA	None	Evangeline	12050	NaN	NaN	NaN	...	75000	75700	76000	75600	724

Contents

Contents

	RegionID	RegionName	City	State	Metro	CountyName	SizeRank	1996-04	1996-05	1996-06	...	2017-07	2017-08	2017-09	2017-10	2017
12187	76690	43450	Pemberville	OH	Toledo	Wood	12188	NaN	NaN	NaN	...	132400	132500	134300	135500	1356
12193	87644	67544	Hoisington	KS	Great Bend	Barton	12194	NaN	NaN	NaN	...	57700	55600	54800	55700	559
12408	85788	62922	Creal Springs	IL	Carbondale	Williamson	12409	NaN	NaN	NaN	...	138100	141300	144600	146200	1477
12673	77203	44491	West Farmington	OH	Youngstown	Trumbull	12674	NaN	NaN	NaN	...	122400	123600	124900	125900	1265
12684	89991	73173	Oklahoma City	OK	Oklahoma City	Oklahoma	12685	NaN	NaN	NaN	...	286000	282000	280600	279700	2785
12887	86745	65259	Huntsville	MO	Moberly	Randolph	12888	NaN	NaN	NaN	...	110600	112500	113200	111000	1069
13078	81145	53015	Cleveland	WI	Manitowoc	Manitowoc	13079	NaN	NaN	NaN	...	159400	161800	166100	168100	1630
13185	85340	62216	Aviston	IL	St. Louis	Clinton	13186	NaN	NaN	NaN	...	163300	162900	162500	162600	1622
13348	85752	62882	Sandoval	IL	Centralia	Marion	13349	NaN	NaN	NaN	...	27900	27500	27300	27300	277
13368	99281	97435	Drain	OR	Roseburg	Douglas	13369	NaN	NaN	NaN	...	142200	145900	150000	153100	1544
13573	80051	49950	Mohawk	MI	Houghton	Keweenaw	13574	NaN	NaN	NaN	...	114100	116500	117500	121500	1278
13584	71553	31527	Brunswick	GA	Brunswick	Glynn	13585	NaN	NaN	NaN	...	394700	399200	400100	398800	4009
13603	78567	47373	Redkey	IN	None	Jay	13604	NaN	NaN	NaN	...	81500	82600	83900	85100	860
13604	85741	62870	Odin	IL	Centralia	Marion	13605	NaN	NaN	NaN	...	33200	33100	33100	33100	334
13615	99337	97499	Yoncalla	OR	Roseburg	Douglas	13616	NaN	NaN	NaN	...	125900	127900	129200	131400	1339
13811	88122	68730	Crofton	NE	None	Knox	13812	NaN	NaN	NaN	...	126400	129200	131000	132600	1350
13820	76701	43466	Wayne	OH	Toledo	Wood	13821	NaN	NaN	NaN	...	79400	79200	79000	79300	798
14063	76685	43443	Luckey	OH	Toledo	Wood	14064	NaN	NaN	NaN	...	118700	119400	120600	121200	1211
14157	76663	43406	Bradner	OH	Toledo	Wood	14158	NaN	NaN	NaN	...	72700	72100	71700	71400	707
14206	66105	19954	Houston	DE	Dover	Kent	14207	NaN	NaN	NaN	...	157000	156400	155700	154900	1532
14207	85339	62215	Albers	IL	St. Louis	Clinton	14208	NaN	NaN	NaN	...	151300	147900	144500	143300	1429
14267	79020	48157	Luna Pier	MI	Monroe	Monroe	14268	NaN	NaN	NaN	...	95700	96500	97000	95900	934
14341	79832	49636	Glen Arbor	MI	Traverse City	Leelanau	14342	NaN	NaN	NaN	...	580500	594300	610000	636300	6779
14577	85489	62440	Lerna	IL	Charleston	Coles	14578	NaN	NaN	NaN	...	81500	83500	85200	86400	880
14707	69681	28039	East Spencer	NC	Charlotte	Rowan	14708	NaN	NaN	NaN	...	27300	26400	25500	25100	251

56 rows × 272 columns

EDA on zip codes

In [32]:
```
# Create a 4 year ROI since that is the most data we have for some zips
zillow['4_yr_ROI'] = (zillow['2018-04'] - zillow['2014-07'])/(zillow['2014-07'])
zillow['4_yr_ROI']
```

Out[32]:
```
0        0.154346
1        0.338046
2        0.134847
3        0.119294
4        0.066725
           ...
14718    0.103903
14719    0.239297
14720    0.280230
14721    0.234256
14722    0.293266
Name: 4_yr_ROI, Length: 14723, dtype: float64
```

In [33]:
```
# Lowest values
zillow.sort_values('4_yr_ROI').head()[['RegionName','City','State','4_yr_ROI']]
```

Out[33]:

	RegionName	City	State	4_yr_ROI
11391	54230	Reedsville	WI	-0.388060
12436	45390	Union City	OH	-0.335992
13485	45346	New Madison	OH	-0.282334
13078	53015	Cleveland	WI	-0.265185
4294	45331	Greenville	OH	-0.249827

In [34]:
```
# Highest values
zillow.sort_values('4_yr_ROI',ascending=False).head()[['RegionName','City','State','4_yr_ROI']]
```

Out[34]:

	RegionName	City	State	4_yr_ROI
13409	27980	Hertford	NC	1.948770
842	30032	Candler-Mcafee	GA	1.489011
6563	15201	Pittsburgh	PA	1.261294
4554	33805	Lakeland	FL	1.233115
6105	37210	Nashville	TN	1.142857

In [35]:
```
# Check most recent one year ROI
zillow['recent_1_yr_ROI'] = (zillow['2018-04'] - zillow['2017-04'])/(zillow['2017-04'])
zillow['recent_1_yr_ROI']
```

Out[35]:
```
0        0.041852
1        0.057162
2        0.030937
3        0.019103
4        0.029661
           ...
14718   -0.010402
14719    0.162120
14720    0.104305
14721    0.121350
14722    0.100092
Name: recent_1_yr_ROI, Length: 14723, dtype: float64
```

In [36]:
```
# Lowest values
zillow.sort_values('recent_1_yr_ROI').head()[['RegionName','City','State','recent_1_yr_ROI']]
```

Out[36]:

	RegionName	City	State	recent_1_yr_ROI
14618	66023	Effingham	KS	-0.218135
7286	70583	Scott	LA	-0.197955
11914	71023	Doyline	LA	-0.186260
6445	30642	Greensboro	GA	-0.170560
9457	70090	Vacherie	LA	-0.167689

In [37]:
```
# Highest values
zillow.sort_values('recent_1_yr_ROI',ascending=False).head()[['RegionName','City','State','recent_1_yr_ROI']]
```

Out[37]:

	RegionName	City	State	recent_1_yr_ROI
4211	07106	Newark	NJ	0.508078
13409	27980	Hertford	NC	0.474385
3285	19601	Reading	PA	0.437500
3540	07103	Newark	NJ	0.435213
4309	29405	North Charleston	SC	0.431034

In [38]:
```
# Find avg one year ROI over past 3 years
def average_one_year_ROI(df):
    average_one_year_ROI = []
    for i in range(len(df)):
        year_1_ROI = df['recent_1_yr_ROI'][i]
        year_2_ROI = (df.iloc[i,-15] - df.iloc[i,-27])/df.iloc[i,-27]
        year_3_ROI = (df.iloc[i,-27] - df.iloc[i,-39])/df.iloc[i,-39]
        avg_ROI = (year_1_ROI + year_2_ROI + year_3_ROI)/3
        average_one_year_ROI.append(avg_ROI)
    return average_one_year_ROI
```

Contents

In [39]:
```
zillow['avg_one_yr_ROI'] = average_one_year_ROI(zillow)
```

In [40]:
```
# Lowest values
zillow.sort_values('avg_one_yr_ROI').head()[['RegionName','City','State','avg_one_yr_ROI']]
```

Out[40]:

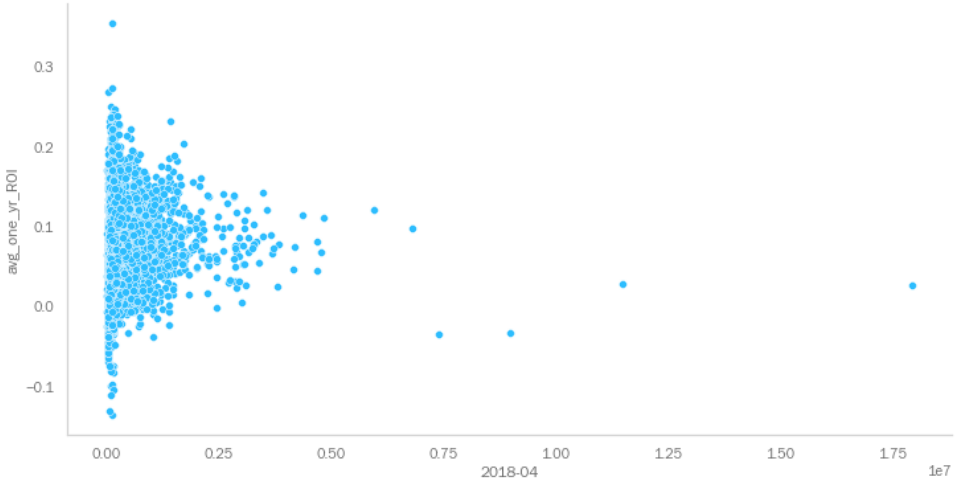
	RegionName	City	State	avg_one_yr_ROI
11391	54230	Reedsville	WI	-0.135889
12436	45390	Union City	OH	-0.129479
13485	45346	New Madison	OH	-0.109924
13078	53015	Cleveland	WI	-0.103355
4294	45331	Greenville	OH	-0.098901

In [41]:
```
# Highest values
zillow.sort_values('avg_one_yr_ROI', ascending=False).head()[['RegionName','City','State','avg_one_yr_ROI','2018-04']]
```

Out[41]:

	RegionName	City	State	avg_one_yr_ROI	2018-04
13409	27980	Hertford	NC	0.355009	143900
842	30032	Candler-Mcafee	GA	0.273701	135900
466	19134	Philadelphia	PA	0.268561	46600
1821	28208	Charlotte	NC	0.250809	113400
2661	33705	Saint Petersburg	FL	0.247735	177300

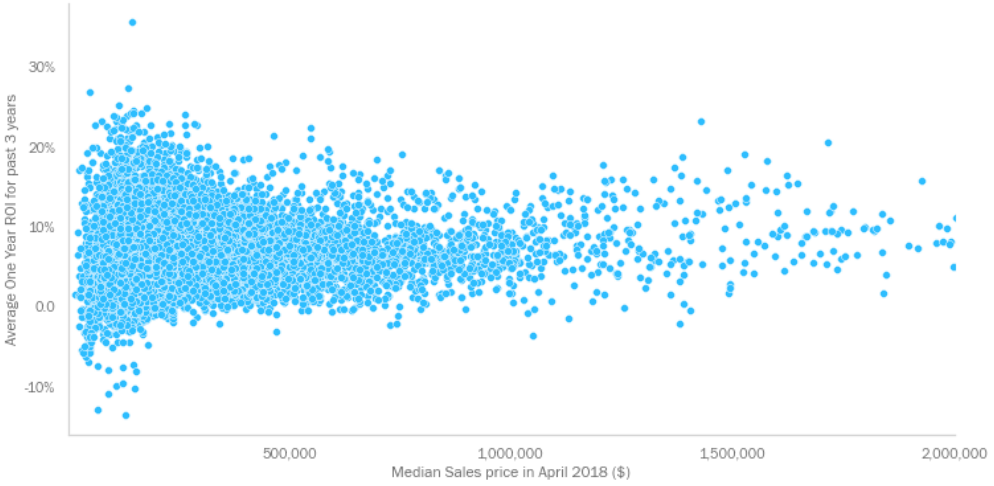
In [42]:
```
# Plotting median home price versus avg ROI. Some crazy 20 million dollar home values in New York.
plt.figure(figsize = (12,6))
sns.scatterplot(data=zillow, x='2018-04', y='avg_one_yr_ROI')
plt.savefig('Images/scatterplot1.png');
```



Contents

In [43]:

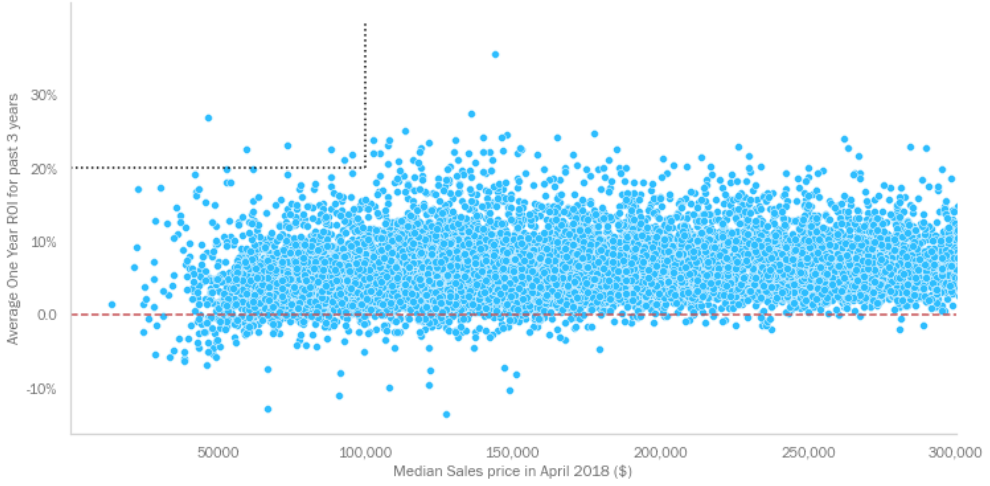
```
# Eliminate the high outliers
plt.figure(figsize = (12,6))
sns.scatterplot(data=zillow, x='2018-04', y='avg_one_yr_ROI')
plt.xlim(0,2000000)
plt.xticks([500000,1000000,1500000,2000000],['500,000','1,000,000','1,500,000','2,000,000'])
plt.xlabel('Median Sales price in April 2018 ($)')
plt.ylabel('Average One Year ROI for past 3 years')
plt.yticks([-0.10, 0, 0.10, 0.20, 0.30], ['-10%', '0.0', '10%', '20%', '30%'])
plt.savefig('Images/scatterplot2.png');
```



Contents

In [44]:

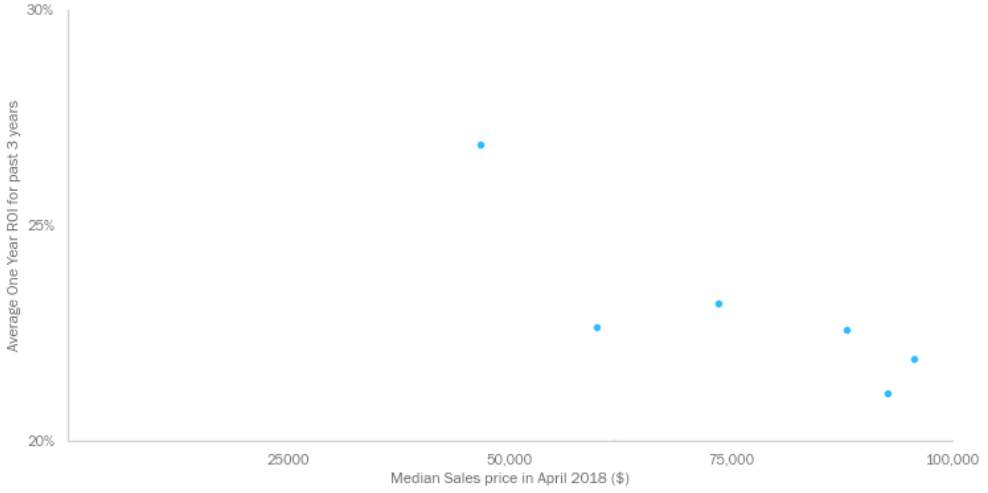
```
# Further reduce price
# Per my business case, I am looking for highest ROI for small investors
plt.figure(figsize = (12,6))
sns.scatterplot(data=zillow, x='2018-04', y='avg_one_yr_ROI')
plt.xlim(0,300000)
plt.xticks([50000,100000,150000,200000,250000,300000],['50000','100,000','150,000','200,000','250,000','300,000'])
plt.xlabel('Median Sales price in April 2018 ($)')
plt.ylabel('Average One Year ROI for past 3 years')
plt.hlines(0, 0, 300000, color='r', linestyles='dashed')
plt.hlines(.20, 0, 100000, color = 'black', linestyles='dotted')
plt.vlines(100000,.2,.4,color='black', linestyles='dotted')
plt.yticks([-0.10, 0, 0.10, 0.20, 0.30], ['-10%', '0.0', '10%', '20%', '30%'])
plt.savefig('Images/scatterplot3.png');
```



Contents

In [45]:

```
# Zoom in
plt.figure(figsize = (12,6))
sns.scatterplot(data=zillow, x='2018-04', y='avg_one_yr_ROI')
plt.xlim(0,100000)
plt.ylim(.20,.30)
plt.xticks([25000, 50000,75000,100000],['25000','50,000','75,000','100,000'])
plt.xlabel('Median Sales price in April 2018 ($)')
plt.ylabel('Average One Year ROI for past 3 years')
# plt.hlines(0, 0, 300000, color='r', linestyles='dashed')
# plt.hlines(.20, 0, 100000, color = 'black', linestyles='dotted')
# plt.vlines(100000,.2,.4,color='black', linestyles='dotted')
plt.yticks([0.20, 0.25, 0.30], ['20%', '25%', '30%'])
plt.savefig('Images/scatterplot4.png');
```



Subset data on top zip codes

In [46]:
```
# Choose zips with 'current' price under $100,000 and avg ROI greater than 20%
zillow_top = zillow[(zillow['2018-04'] < 100000) & (zillow['avg_one_yr_ROI'] > 0.20)]
zillow_top
```

Out[46]:

	RegionID	RegionName	City	State	Metro	CountyName	SizeRank	1996-04	1996-05	1996-06	...	2017-10	2017-11	2017-12	2018-01	2018-02
466	65801	19134	Philadelphia	PA	Philadelphia	Philadelphia	467	27600.0	27500.0	27500.0	...	39600	40600	41600	42600	44000
1754	78022	46203	Indianapolis	IN	Indianapolis	Marion	1755	NaN	NaN	NaN	...	67000	66600	67400	69200	70600
2199	71793	32114	Daytona Beach	FL	Daytona Beach	Volusia	2200	47700.0	48000.0	48300.0	...	85500	86700	87900	89000	90400
3853	76575	43206	Columbus	OH	Columbus	Franklin	3854	NaN	NaN	NaN	...	69400	71800	75700	78800	81300
4293	87104	66104	Kansas City	KS	Kansas City	Wyandotte	4294	41300.0	41200.0	41200.0	...	51600	54200	55700	55700	55900
5682	74373	37411	Chattanooga	TN	Chattanooga	Hamilton	5683	54800.0	55000.0	55200.0	...	87400	89200	90500	91700	93500

6 rows × 275 columns

In [47]:
```
zillow_top[['RegionName', 'City','State','Metro', 'SizeRank','2018-04','avg_one_yr_ROI']]
```

Out[47]:

	RegionName	City	State	Metro	SizeRank	2018-04	avg_one_yr_ROI
466	19134	Philadelphia	PA	Philadelphia	467	46600	0.268561
1754	46203	Indianapolis	IN	Indianapolis	1755	73500	0.231818
2199	32114	Daytona Beach	FL	Daytona Beach	2200	92600	0.210909
3853	43206	Columbus	OH	Columbus	3854	88100	0.225806
4293	66104	Kansas City	KS	Kansas City	4294	59800	0.226380
5682	37411	Chattanooga	TN	Chattanooga	5683	95600	0.219015

Clustering?

What info does this really give me?

Convert to date types

In [48]:
```
# Function provided in starter notebook
def get_datetimes(df):
    return pd.to_datetime(df.columns.values[:], format='%Y-%m')
```

Contents

In [49]:
```
# These are my date columns only.  Running them through the function.
zillow_top_date_df = zillow_top.iloc[:,7:-3]
zillow_top_date_df.columns = list(get_datetimes(zillow_top_date_df))
zillow_top_date_df
```

Out[49]:

	1996-04-01	1996-05-01	1996-06-01	1996-07-01	1996-08-01	1996-09-01	1996-10-01	1996-11-01	1996-12-01	1997-01-01	...	2017-07-01	2017-08-01	2017-09-01	2017-10-01	2017-11-01	2017-12-01	2018-01-01	201 02-
466	27600.0	27500.0	27500.0	27400.0	27400.0	27300.0	27300.0	27200.0	27200.0	27300.0	...	39000	39100	39100	39600	40600	41600	42600	440
1754	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	66700	66700	66900	67000	66600	67400	69200	706
2199	47700.0	48000.0	48300.0	48400.0	48500.0	48500.0	48500.0	48400.0	48400.0	48400.0	...	82300	83300	84300	85500	86700	87900	89000	904
3853	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	67600	68600	68800	69400	71800	75700	78800	813
4293	41300.0	41200.0	41200.0	41100.0	41000.0	40800.0	40700.0	40500.0	40500.0	40500.0	...	47300	47900	49700	51600	54200	55700	55700	559
5682	54800.0	55000.0	55200.0	55400.0	55700.0	55900.0	56200.0	56400.0	56700.0	57000.0	...	82300	84500	85800	87400	89200	90500	91700	935

6 rows × 265 columns

In [50]:
```
# Now put the df back together, 7 info columns, 3 feature columns of ROI calculation, then date columns.
zillow_top_date = pd.concat([zillow_top.iloc[:, :7], zillow_top.iloc[:, -3:], zillow_top_date_df], axis=1)
zillow_top_date
```

Out[50]:

	RegionID	RegionName	City	State	Metro	CountyName	SizeRank	4_yr_ROI	recent_1_yr_ROI	avg_one_yr_ROI	...	2017-07-01 00:00:00	2017-08-01 00:00:00
466	65801	19134	Philadelphia	PA	Philadelphia	Philadelphia	467	0.834646	0.259459	0.268561	...	39000	39100
1754	78022	46203	Indianapolis	IN	Indianapolis	Marion	1755	1.047354	0.137771	0.231818	...	66700	66700
2199	71793	32114	Daytona Beach	FL	Daytona Beach	Volusia	2200	0.909278	0.169192	0.210909	...	82300	83300
3853	76575	43206	Columbus	OH	Columbus	Franklin	3854	0.984234	0.409600	0.225806	...	67600	68600
4293	87104	66104	Kansas City	KS	Kansas City	Wyandotte	4294	0.986711	0.300000	0.226380	...	47300	47900
5682	74373	37411	Chattanooga	TN	Chattanooga	Hamilton	5683	0.623090	0.283221	0.219015	...	82300	84500

6 rows × 275 columns

In [51]:
```
zillow_top_date.isna().sum().sum()
```

Out[51]: 324

Reshape from wide to long format

Contents

In [52]:
```
# Create a separate data frame for each of the 6 top zip codes.
Philly = zillow_top_date[zillow_top_date['RegionName']=='19134']
Indy = zillow_top_date[zillow_top_date['RegionName']=='46203']
Daytona = zillow_top_date[zillow_top_date['RegionName']=='32114']
Columbus = zillow_top_date[zillow_top_date['RegionName']=='43206']
KC = zillow_top_date[zillow_top_date['RegionName']=='66104']
Chattanooga = zillow_top_date[zillow_top_date['RegionName']=='37411']
```

In [53]:
```
# Columbus and Indy have missing data.  I don't want to back fill multiple years worth of data.
# I'd rather slice off what I have and backfill only occasional missing data
Indy.isna().sum().sum()
```

Out[53]:
```
111
```

In [54]:
```
Indy.columns[Indy.isnull().any()] # Indy begins recording data at 2005-07-01
```

Out[54]:
```
Index([1996-04-01 00:00:00, 1996-05-01 00:00:00, 1996-06-01 00:00:00,
       1996-07-01 00:00:00, 1996-08-01 00:00:00, 1996-09-01 00:00:00,
       1996-10-01 00:00:00, 1996-11-01 00:00:00, 1996-12-01 00:00:00,
       1997-01-01 00:00:00,
       ...
       2004-09-01 00:00:00, 2004-10-01 00:00:00, 2004-11-01 00:00:00,
       2004-12-01 00:00:00, 2005-01-01 00:00:00, 2005-02-01 00:00:00,
       2005-03-01 00:00:00, 2005-04-01 00:00:00, 2005-05-01 00:00:00,
       2005-06-01 00:00:00],
      dtype='object', length=111)
```

In [55]:
```
Columbus.columns[Columbus.isnull().any()] # Columbus begins recording data at 2014-01-01
```

Out[55]:
```
Index([1996-04-01 00:00:00, 1996-05-01 00:00:00, 1996-06-01 00:00:00,
       1996-07-01 00:00:00, 1996-08-01 00:00:00, 1996-09-01 00:00:00,
       1996-10-01 00:00:00, 1996-11-01 00:00:00, 1996-12-01 00:00:00,
       1997-01-01 00:00:00,
       ...
       2013-03-01 00:00:00, 2013-04-01 00:00:00, 2013-05-01 00:00:00,
       2013-06-01 00:00:00, 2013-07-01 00:00:00, 2013-08-01 00:00:00,
       2013-09-01 00:00:00, 2013-10-01 00:00:00, 2013-11-01 00:00:00,
       2013-12-01 00:00:00],
      dtype='object', length=213)
```

In [56]:
```
Indy_notnull = Indy[Indy.columns.drop(Indy.columns[Indy.isnull().any()])]
Columbus_notnull = Columbus[Columbus.columns.drop(Columbus.columns[Columbus.isnull().any()])]
```

In [57]:
```
Indy_notnull
```

Out[57]:

	RegionID	RegionName	City	State	Metro	CountyName	SizeRank	4_yr_ROI	recent_1_yr_ROI	avg_one_yr_ROI	...	2017-07-01 00:00:00	2017-08-01 00:00:00
1754	78022	46203	Indianapolis	IN	Indianapolis	Marion	1755	1.047354	0.137771	0.231818	...	66700	66700

1 rows × 164 columns

In [58]:
```
def melt_data(list_of_dfs): # changed to take in a list of dataframes for scalability
    """Convert list of time series dataframes into melted format"""
    return_list = []
    for df in list_of_dfs:
        melted = pd.melt(df, id_vars=['RegionID','RegionName', 'City', 'State', 'Metro', 'CountyName',
                                      'SizeRank', '4_yr_ROI', 'recent_1_yr_ROI','avg_one_yr_ROI'], var_name='time')
        melted['time'] = pd.to_datetime(melted['time'], infer_datetime_format=True)
#         melted = melted.dropna(subset=['value'])
        melted = melted.bfill() # I'm adding this to try backfill instead of dropna
        return_list.append(melted.groupby('time').aggregate({'value':'mean'}))
    return return_list
```

In [59]:
```
zips_to_melt = [Philly, Indy_notnull, Daytona, Columbus_notnull, KC, Chattanooga]
Philly_melted, Indy_melted, Daytona_melted, Columbus_melted, KC_melted, Chattanooga_melted = melt_data(zips_to_melt)

Indy_melted
```

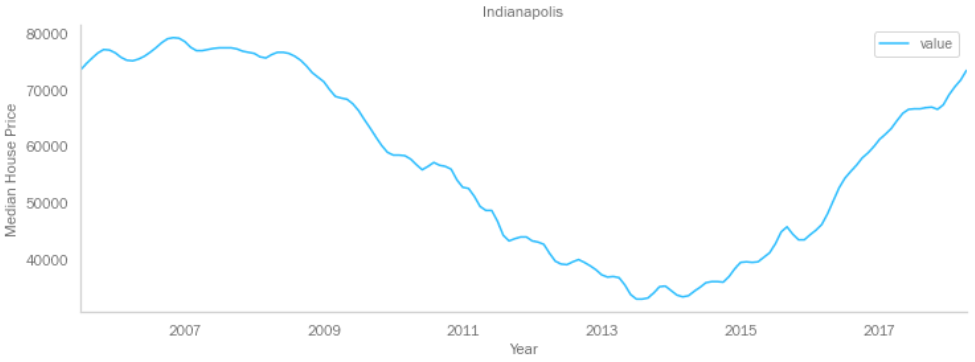
Out[59]:

time	value
2005-07-01	73600.0
2005-08-01	74700.0
2005-09-01	75700.0
2005-10-01	76600.0
2005-11-01	77200.0
...	...
2017-12-01	67400.0
2018-01-01	69200.0
2018-02-01	70600.0
2018-03-01	71800.0
2018-04-01	73500.0

154 rows × 1 columns

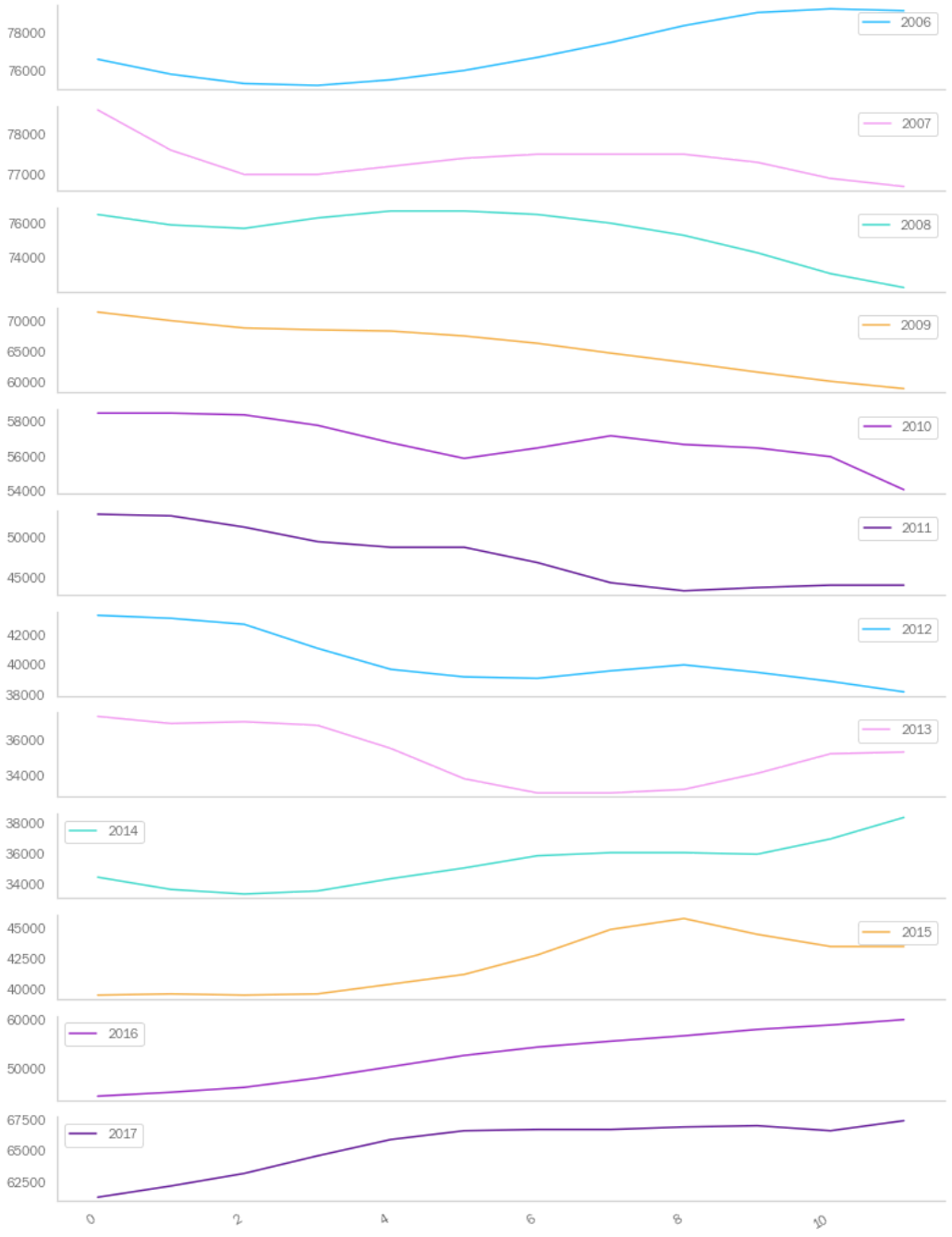
Visualize time series plots

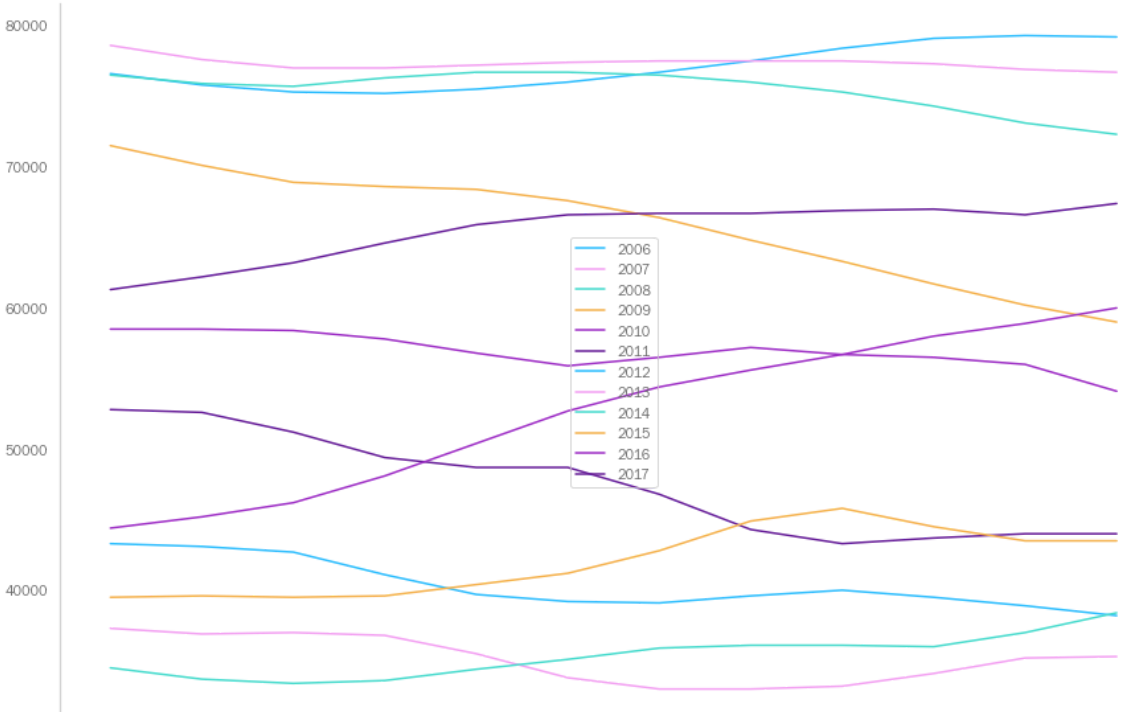
In [60]:
```
visualize_time_series(Indy_melted, 'Indianapolis') # functioned defined in user_functions.py

# I don't really find the annual breakout graphs to be that helpful for visualization
```



Contents

Contents

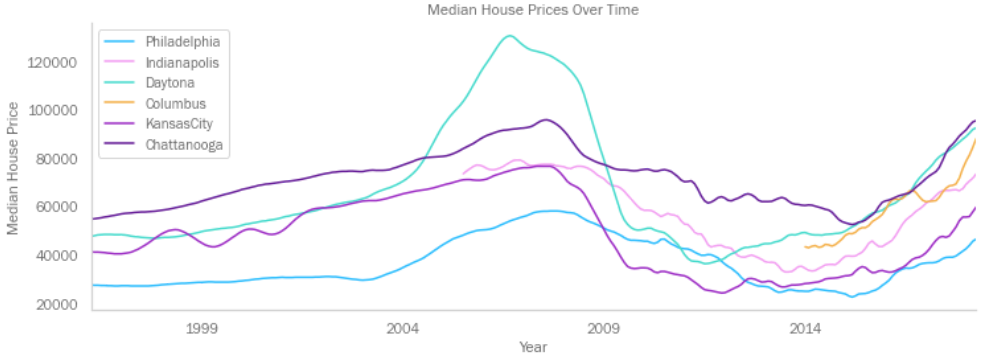




Contents

In [61]:

```
# Plot all 6 chosen zip codes together
all_dfs = [Philly_melted, Indy_melted, Daytona_melted, Columbus_melted, KC_melted, Chattanooga_melted]
names = ['Philadelphia','Indianapolis','Daytona','Columbus','KansasCity','Chattanooga']
visualize_all_series(all_dfs, names) # Function defined in user_functions.py
```



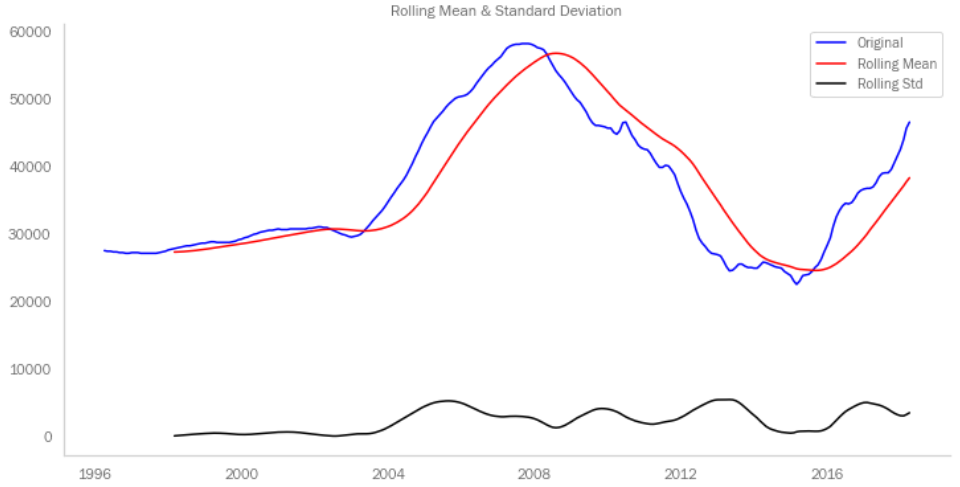
Checking for trends, stationarity, seasonality

```
Best Log Transformed Differences (0-5) with p-values

{'Philadelphia': (1, 0.03194585744150177),
 'Indianapolis': (2, 0.7150685269034184),
 'Daytona': (5, 0.15351111071221946),
 'Columbus': (4, 0.018148301922587158),
 'Kansas City': (1, 0.14000751949106677),
 'Chattanooga': (1, 0.14039677392972233)}
```

Contents

In [62]:

```
stationarity_check(Philly_melted) # Function defined in user_functions.py
# p-value is greater than .05 (it is .927!) so the series is not stationary
```




```
Results of Dickey-Fuller Test:

Test Statistic                  -0.288166
p-value                          0.927164
#Lags Used                       0.000000
Number of Observations Used    264.000000
Critical Value (1%)             -3.455365
Critical Value (5%)             -2.872551
Critical Value (10%)            -2.572638
dtype: float64
```

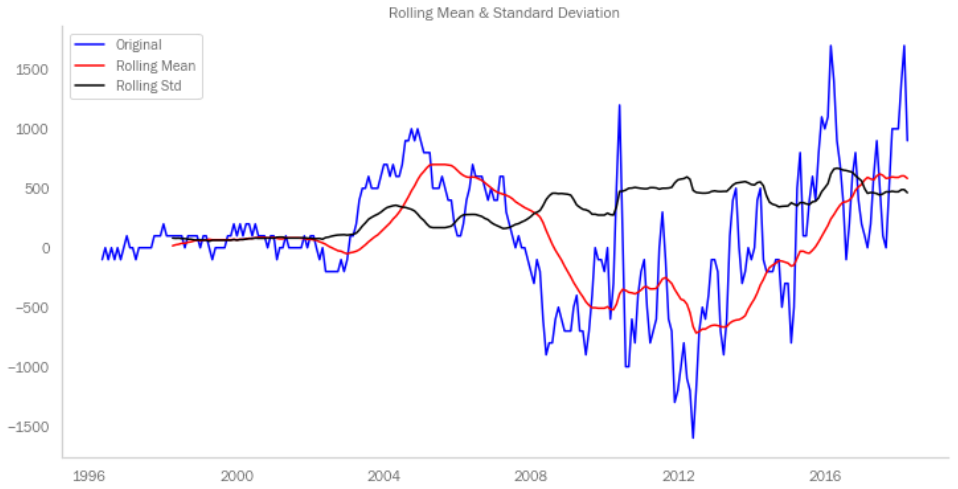
In [63]:
```
#See what differencing does
data_diff = Philly_melted.diff(periods=1)
data_diff.head(10)
```

Out[63]:

time	value
1996-04-01	NaN
1996-05-01	-100.0
1996-06-01	0.0
1996-07-01	-100.0
1996-08-01	0.0
1996-09-01	-100.0
1996-10-01	0.0
1996-11-01	-100.0
1996-12-01	0.0
1997-01-01	100.0

Contents

In [64]:
```
stationarity_check(data_diff[1:])
# p-value is down to .13 but still not stationary
```




```
Results of Dickey-Fuller Test:

Test Statistic                  -2.422182
p-value                          0.135573
#Lags Used                       8.000000
Number of Observations Used    255.000000
Critical Value (1%)             -3.456257
Critical Value (5%)             -2.872942
Critical Value (10%)            -2.572846
dtype: float64
```

Contents

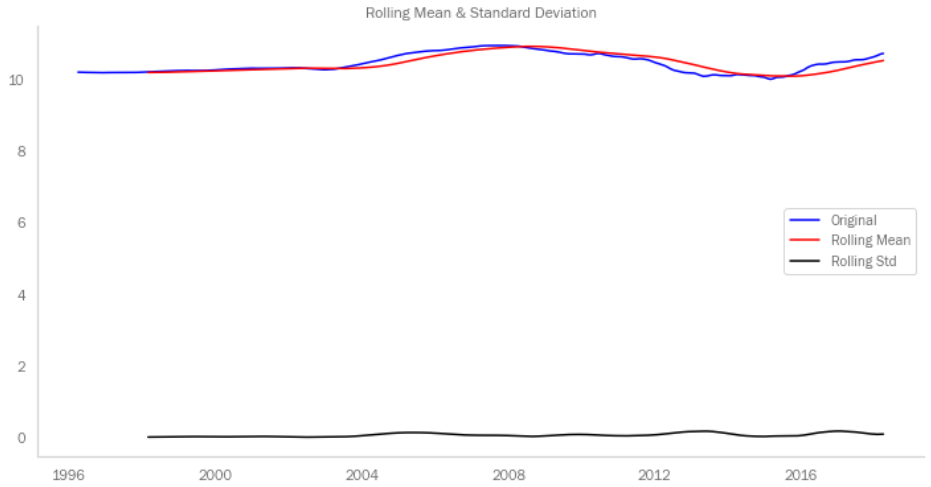
Contents

In [65]:

```
from statsmodels.tsa.stattools import adfuller

def find_best_difference(data):
    for i in range(0,25):
        difference = data.diff(periods=i)
        dftest = adfuller(difference[i:])
        print(i,dftest[1])

find_best_difference(Philly_melted)
```

```
0 nan
1 0.1355732285119607
2 0.11919275051848399
3 0.46881217920610363
4 0.06815812325627901
5 0.5883509233410241
6 0.6625687149487411
7 0.6594311981817602
8 0.6800038226664793
9 0.6534124137040307
10 0.4258803417746362
11 0.37733392014565237
12 0.35832937865646863
13 0.5086076402133188
14 0.7541136387628624
15 0.774362568776317
16 0.9158068216563182
17 0.6293119733269782
18 0.7908159564611525
19 0.7702364848871605
20 0.6899295894240023
21 0.5526525850677468
22 0.3944823143309037
23 0.15231458968681078
24 0.25381820081799567
```

In [66]:
```
# Well it doesn't appear that differencing is enough to make this data stationary.  I will try a log transform.

stationarity_check(np.log(Philly_melted))
```




```
Results of Dickey-Fuller Test:

Test Statistic                  -2.205328
p-value                          0.204317
#Lags Used                      15.000000
Number of Observations Used    249.000000
Critical Value (1%)             -3.456888
Critical Value (5%)             -2.873219
Critical Value (10%)            -2.572994
dtype: float64
```

Contents

In [67]:
```
find_best_difference(np.log(Philly_melted)) # Looks like 1 period difference on the log is enough!
```

```
0 nan
1 0.03194585744150177
2 0.05755421697421712
3 0.41215000402719315
4 0.3328238500504311
5 0.5219180086033582
6 0.6242970016812888
7 0.5848581976590658
8 0.6510232059347572
9 0.5855397938521867
10 0.2152804651715723
11 0.31644676563329477
12 0.3180101413235155
13 0.5066454466043491
14 0.7145389957289219
15 0.7496413895092593
16 0.9257344998971225
17 0.5027490612893842
18 0.785076746341453
19 0.4866291610367524
20 0.5239041024548403
21 0.6558632056717053
22 0.3828486937258605
23 0.15615792830432296
24 0.10144107169157374
```

In [68]:
```
find_best_difference(Indy_melted) # Similarly, Indy will also not be stationary just with differencing

# I will log transform all data from this point for consistency
```

```
0 nan
1 0.6607367844729298
2 0.6710288605269173
3 0.6538440854875729
4 0.8180384416636614
5 0.9168834702182442
6 0.7272629085524935
7 0.972985914001579
8 0.9077547267914667
9 0.9250468892100571
10 0.9475248432116631
11 0.9567961891949055
12 0.8959853887922271
13 0.8727363146890167
14 0.9364298296713139
15 0.9631269272782114
16 0.8440507229682248
17 0.7932262718023664
18 0.6247702692033436
19 0.8627990295543804
20 0.4749649338554318
21 0.4731927953954632
22 0.2701763743725465
23 0.4080676060217747
24 0.4125021871455804
```

In [69]:
```
find_best_difference(np.log(Indy_melted))
```

```
0 nan
1 0.7169611824126959
2 0.7150685269034184
3 0.7706040494740733
4 0.7316064027092836
5 0.8342752473849291
6 0.7934513927344009
7 0.9239429975367102
8 0.8022629832205488
9 0.8736470080397349
10 0.8879831714495896
11 0.9083559498230531
12 0.8595828254320502
13 0.7216980892314375
14 0.736487471121519
15 0.8862216762430716
16 0.6717269713827985
17 0.26786907914893804
18 0.28044792795807144
19 0.22406085021268823
20 0.1610621757219327
21 0.14248605509675633
22 0.05064913563009264
23 0.09326162148773787
24 0.10517892475263818
```

In [70]:
```
# I'm going to get my best difference parameter within 0-5
def find_all_best_log_differences(dfs, names):
    best_scores={}
    for idx, df in enumerate(dfs):
        lowest_score=1 # These are p-values so 1 is the highest
        for i in range(0,6):
            difference = (np.log(df)).diff(periods=i)
            dftest = adfuller(difference[i:])
            if dftest[1] < lowest_score:
                lowest_score = dftest[1]
                best_combo=(i,lowest_score)
        best_scores[names[idx]] = best_combo
    return best_scores

best_diff = find_all_best_log_differences(all_dfs,names)
best_diff
```

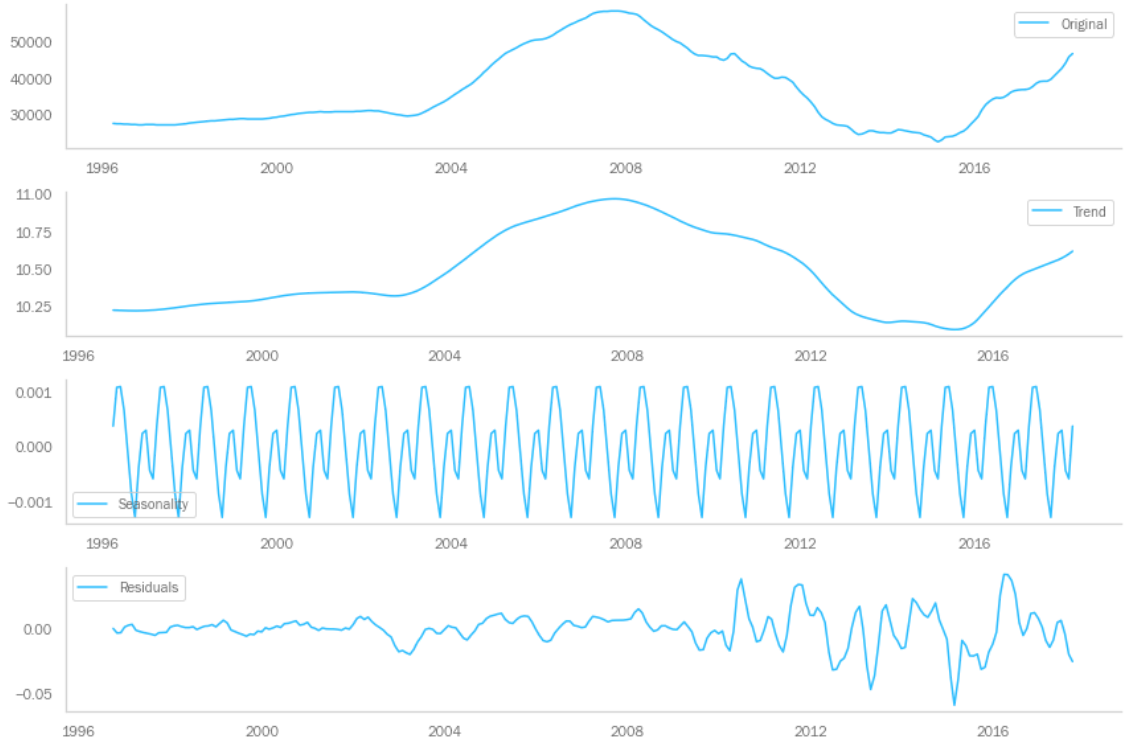
Out[70]:
```
{'Philadelphia': (1, 0.03194585744150177),
 'Indianapolis': (2, 0.7150685269034184),
 'Daytona': (5, 0.15351111071221946),
 'Columbus': (4, 0.018148301922587158),
 'KansasCity': (1, 0.14000751949106677),
 'Chattanooga': (1, 0.14039677392972233)}
```

Seasonal decomposition

Contents

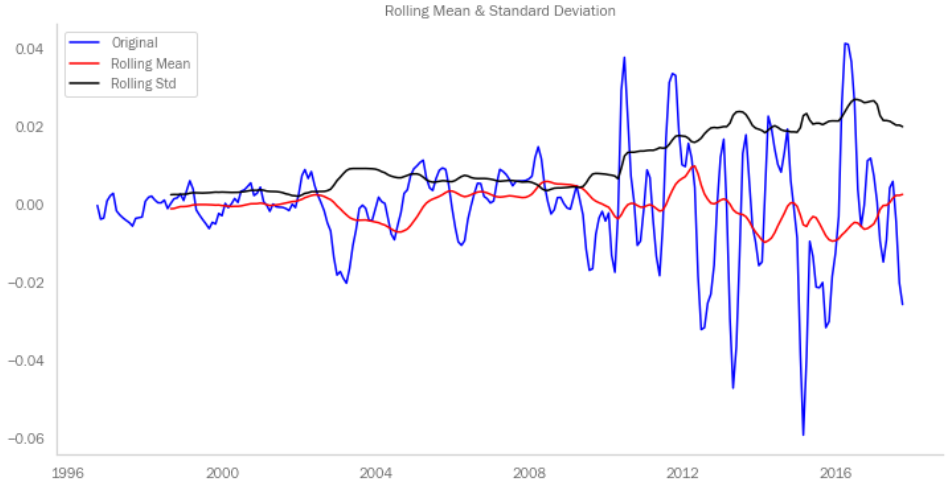
In [71]:

```
# I will be using logged and difference data in the models but would like to look at how decomposition works for EDA

# Import and apply seasonal_decompose()
from statsmodels.tsa.seasonal import seasonal_decompose
decomposition = seasonal_decompose(np.log(Philly_melted))

# 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(Philly_melted, label='Original')#np.log(ts)
plt.legend(loc='best')
plt.subplot(412)
plt.plot(trend, label='Trend')
plt.legend(loc='best')
plt.subplot(413)
plt.plot(seasonal,label='Seasonality')
plt.legend(loc='best')
plt.subplot(414)
plt.plot(residual, label='Residuals')
plt.legend(loc='best')
plt.savefig('Images/decomposition.png')
plt.tight_layout()
```



Contents

In [72]:
```
# Drop missing values from residuals
Philly_residuals = residual
Philly_residuals.dropna(inplace=True)

# Check stationarity
stationarity_check(Philly_residuals)

# Although the std dev still appears to be trending upward, the p-value indicates stationarity
```




```
Results of Dickey-Fuller Test:

Test Statistic                -6.009296e+00
p-value                        1.587583e-07
#Lags Used                     8.000000e+00
Number of Observations Used    2.440000e+02
Critical Value (1%)           -3.457438e+00
Critical Value (5%)           -2.873459e+00
Critical Value (10%)          -2.573122e+00
dtype: float64
```

Correlation

Contents

In [73]:
```
# To check correlation lets concat all series together
df_group = pd.concat(all_dfs, axis=1)
df_group.columns = names
df_group.corr()

# Highly correlated but they are not stationary at this point
```

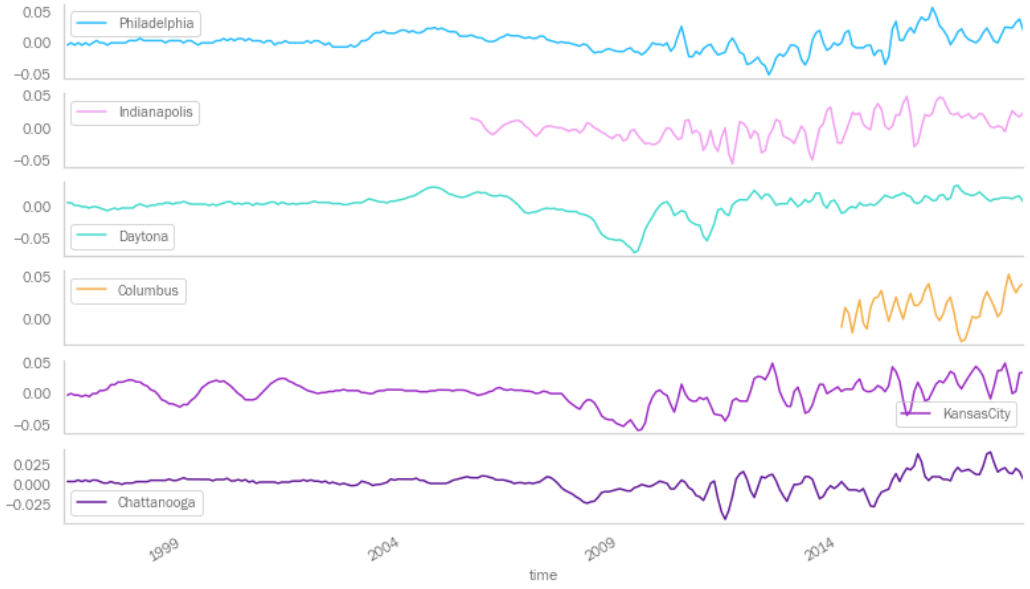
Out[73]:

	Philadelphia	Indianapolis	Daytona	Columbus	KansasCity	Chattanooga
Philadelphia	1.000000	0.928714	0.788810	0.937542	0.568138	0.856833
Indianapolis	0.928714	1.000000	0.869279	0.933518	0.898426	0.928332
Daytona	0.788810	0.869279	1.000000	0.936875	0.829742	0.864986
Columbus	0.937542	0.933518	0.936875	1.000000	0.901098	0.882271
KansasCity	0.568138	0.898426	0.829742	0.901098	1.000000	0.777869
Chattanooga	0.856833	0.928332	0.864986	0.882271	0.777869	1.000000

In [74]:
```
# Let's difference them all then check correlation again
df_group_diff = np.log(df_group).diff(periods=1)
df_group_diff.plot(figsize=(15,6))
plt.xlabel('Year', fontsize=14)
plt.savefig('Images/zips_differenced.png');
```

Contents

In [75]:
```
df_group_diff.plot(figsize=(13,8), subplots=True, legend=True)
plt.savefig('Images/differenced_subplots.png');
```



In [76]:
```
df_group_diff.corr() # Less correlated when they are differenced 1 period, nothing over .639
```

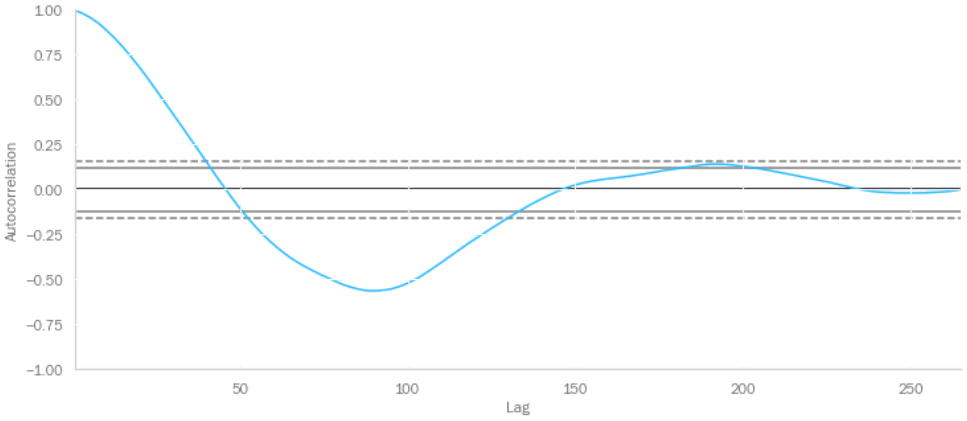
Out[76]:

	Philadelphia	Indianapolis	Daytona	Columbus	KansasCity	Chattanooga
Philadelphia	1.000000	0.368891	0.378077	0.319255	0.267676	0.443239
Indianapolis	0.368891	1.000000	0.388933	0.055788	0.372529	0.250858
Daytona	0.378077	0.388933	1.000000	-0.080285	0.639956	0.431938
Columbus	0.319255	0.055788	-0.080285	1.000000	-0.048437	0.103480
KansasCity	0.267676	0.372529	0.639956	-0.048437	1.000000	0.393031
Chattanooga	0.443239	0.250858	0.431938	0.103480	0.393031	1.000000

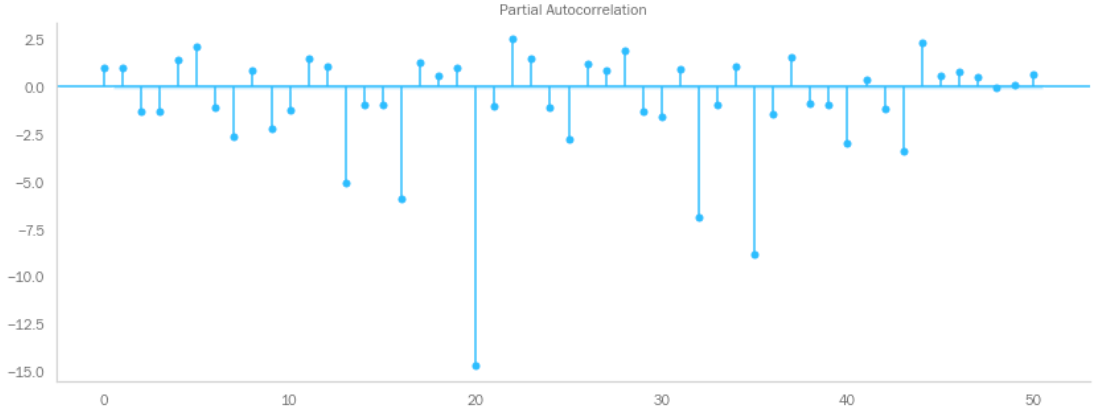
ACF and PACF

Contents

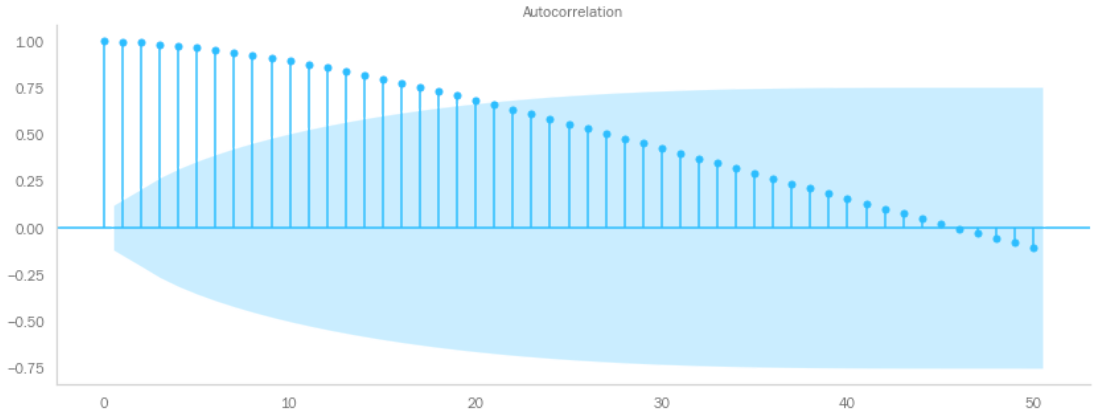
In [77]:
```
plt.figure(figsize=(12,5))
pd.plotting.autocorrelation_plot(Philly_melted);
# Don't see spikes for yearly correlations
```



In [78]:
```
from statsmodels.graphics.tsaplots import plot_pacf
from matplotlib.pylab import rcParams

rcParams['figure.figsize'] = 14, 5

plot_pacf(Philly_melted, lags=50);
```



In [79]:
```
from statsmodels.graphics.tsaplots import plot_acf

rcParams['figure.figsize'] = 14, 5

plot_acf(Philly_melted, lags=50);
```



Contents

Train Test Split

Contents

In [80]:
```
# My times series have different lengths, some are very short
# I originally split the testing data to be 20% of the data, rather than a particular time period
# However, my training data failed to capture the recent upward trends
# So now I will segment the test/forecasting data to only the most recent year
# Function takes in a list for scalability
# We already created the list and names for a previous function

def test_split(list_of_df, names):
    return_list=[]
    for i, df in enumerate(list_of_df):
#         test_nobs=int((len(df))*.20)
#         training_data = df[:-(test_nobs)]
#         test_data = df[-(test_nobs):]
        training_data = df[:-12]
        test_data = df[-12:]
        return_list.extend([training_data, test_data])
        print(names[i], ': ', df.shape, 'Train: ', training_data.shape, 'Test: ', test_data.shape)
    return return_list

Philly_train, Philly_test, Indy_train, Indy_test, Daytona_train, Daytona_test, \
    Columbus_train, Columbus_test, KC_train, KC_test, Chattanooga_train, Chattanooga_test = test_split(all_dfs, names)
```

```
Philadelphia :  (265, 1) Train:  (253, 1) Test:  (12, 1)
Indianapolis :  (154, 1) Train:  (142, 1) Test:  (12, 1)
Daytona :  (265, 1) Train:  (253, 1) Test:  (12, 1)
Columbus :  (52, 1) Train:  (40, 1) Test:  (12, 1)
KansasCity :  (265, 1) Train:  (253, 1) Test:  (12, 1)
Chattanooga :  (265, 1) Train:  (253, 1) Test:  (12, 1)
```

In [81]:
```
Columbus_test
```

Out[81]:

time	value
2017-05-01	63900.0
2017-06-01	66000.0
2017-07-01	67600.0
2017-08-01	68600.0
2017-09-01	68800.0
2017-10-01	69400.0
2017-11-01	71800.0
2017-12-01	75700.0
2018-01-01	78800.0
2018-02-01	81300.0
2018-03-01	84500.0
2018-04-01	88100.0

In [82]:
```
# Making lists to run through models together
all_train_df = [Philly_train, Indy_train, Daytona_train, Columbus_train, KC_train, Chattanooga_train]
all_test_df = [Philly_test, Indy_test, Daytona_test, Columbus_test, KC_test, Chattanooga_test]
```

Baseline ARIMA modeling

	Name	Order	Seasonal_Order	Fit_Time	Const	ar.L1	ma.L1	sigma2	AIC Score
0	Philadelphia	(1, 0, 1)	(0, 0, 0, 0)	0.1751	36279.03	0.9975	0.7643	105736.54	3660.12
1	Indianapolis	(1, 0, 1)	(0, 0, 0, 0)	0.1616	56143.06	0.9971	0.8044	365498.65	2237.24
2	Daytona	(1, 0, 1)	(0, 0, 0, 0)	0.1536	65794.06	0.9976	0.9413	541074.22	4074.94
3	Columbus	(1, 0, 1)	(0, 0, 0, 0)	0.0608	54074.93	0.9913	0.9994	362743.00	642.68
4	Kansas City	(1, 0, 1)	(0, 0, 0, 0)	0.1556	48263.62	0.9970	0.8875	209724.01	3834.07
5	Chattanooga	(1, 0, 1)	(0, 0, 0, 0)	0.2144	70698.40	0.9979	0.8266	167378.79	3776.88

In [84]:

```
from statsmodels.tsa.arima.model import ARIMA
import statsmodels.api as sm

# Establish a metrics dataframe to store models
column_metrics = ['Name', 'Order', 'Seasonal_Order', 'Fit_Time',
                  'Const', 'ar.L1', 'ma.L1', 'sigma2', 'AIC Score']
metrics_df = pd.DataFrame(columns = column_metrics)

# Start with a baseline model of AR(1) and MA(1)
order=(1,0,1)

for i, train_df in enumerate(all_train_df):
    metrics_df = run_arima_models(names[i], train_df, all_test_df[i], order, metrics_df) # Function in user_functions.py

metrics_df
```

Out[84]:

	Name	Order	Seasonal_Order	Fit_Time	Const	ar.L1	ma.L1	sigma2	AIC Score
0	Philadelphia	(1, 0, 1)	(0, 0, 0, 0)	0.1396	36279.03	0.9975	0.7643	105736.54	3660.12
1	Indianapolis	(1, 0, 1)	(0, 0, 0, 0)	0.1297	56143.06	0.9971	0.8044	365498.65	2237.24
2	Daytona	(1, 0, 1)	(0, 0, 0, 0)	0.1366	65794.06	0.9976	0.9413	541074.22	4074.94
3	Columbus	(1, 0, 1)	(0, 0, 0, 0)	0.0648	54074.93	0.9913	0.9994	362743.00	642.68
4	KansasCity	(1, 0, 1)	(0, 0, 0, 0)	0.1297	48263.62	0.9970	0.8875	209724.01	3834.07
5	Chattanooga	(1, 0, 1)	(0, 0, 0, 0)	0.1875	70698.40	0.9979	0.8266	167378.79	3776.88

Find Optimal p,d,q

Philly

```
pdq         (2, 1, 2)
pdqs    (1, 0, 1, 12)
aic          -1818.25
Name: 226, dtype: object
```

Contents

In [85]:
```
# Putting in the best d value calculated earlier saves a lot of time in the grid search, though potentially gives
# different values

tic = time.time()
Philly_grid_search = grid_search_arima(np.log(Philly_train),
                                       d = best_diff['Philadelphia'][0]) # Function in user_functions.py
print(time.time()-tic)
```

```
pdq         (2, 1, 2)
pdqs    (1, 0, 1, 12)
aic          -1818.25
Name: 226, dtype: object
366.6337876319885
```

In [86]:
```
'''There is no problem with a positive log-likelihood. It is a common misconception that the log-likelihood must be
negative.  If the likelihood is derived from a probability density it can quite reasonably exceed 1 which means that
log-likelihood is positive, hence the deviance and the AIC are negative. This is what occurred in your model.

If you believe that comparing AICs is a good way to choose a model then it would still be the case that the (algebraically)
lower AIC is preferred not the one with the lowest absolute AIC value. To reiterate you want the most negative number in
your example.'''
```

Out[86]:
```
'There is no problem with a positive log-likelihood. It is a common misconception that the log-likelihood must be \nnegative.
If the likelihood is derived from a probability density it can quite reasonably exceed 1 which means that\nlog-likelihood is
positive, hence the deviance and the AIC are negative. This is what occurred in your model.\n\nIf you believe that comparing
AICs is a good way to choose a model then it would still be the case that the (algebraically)\nlower AIC is preferred not the
one with the lowest absolute AIC value. To reiterate you want the most negative number in\nyour example.'
```

In [87]:
```
Philly_model = ARIMA(np.log(Philly_train), order=(2,1,2), seasonal_order=(1,0,1,12), freq='MS')
Philly_results = Philly_model.fit()
print(Philly_results.aic)
```

```
-1818.2534500111883
```

Contents

In [88]:
```
# Because so many values came up as '2' in my grid search, I would like to expand my grid to higher values.
tic = time.time()
p = d = q = range(2, 5)
pdq = list(itertools.product(p, d, q))
pdqs = [(1,0,1,12)]
ans = []
for comb in pdq:
    for combs in pdqs:
        try:
            grid_model = ARIMA(np.log(Philly_train), order=comb, seasonal_order=combs, freq='MS')
            grid_results = grid_model.fit()
            ans.append([comb, combs, grid_results.aic])
            print('ARIMA {} x {}12 : AIC Calculated ={}'.format(comb, combs, results.aic))
        except:
            continue
ans_df = pd.DataFrame(ans, columns=['pdq', 'pdqs', 'aic'])
print(ans_df.loc[ans_df['aic'].idxmin()])
print(time.time()-tic)
```

```
pdq         (2, 2, 3)
pdqs    (1, 0, 1, 12)
aic          -1822.04
Name: 1, dtype: object
21.523201942443848
```

In [89]:
```
# So with (2,1,2) aic was -1818. With (2,2,3) aic is -1822. I'm not sure that is enough difference to justify the
# addition of the extra parameters
```

In [90]:
```
Philly_metrics = track_final_metrics(Philly_grid_search, Philly_results, names[0]) # function in user_functions.py
```

Indy

```
pdq         (1, 2, 2)
pdqs    (2, 0, 2, 12)
aic          -867.448
Name: 155, dtype: object
```

In [91]:
```
tic = time.time()
Indy_grid_search = grid_search_arima(np.log(Indy_train), d = best_diff['Indianapolis'][0])
print(time.time()-tic)
```

```
pdq         (1, 2, 2)
pdqs    (2, 0, 2, 12)
aic          -867.448
Name: 155, dtype: object
309.1987555027008
```

In [92]:
```
Indy_model = ARIMA(np.log(Indy_train), order=(1,2,2), seasonal_order=(2,0,2,12), freq='MS')
Indy_results = Indy_model.fit()
print(Indy_results.aic)
```

```
-867.4478406929932
```

In [93]:
```
Indy_metrics = track_final_metrics(Indy_grid_search, Indy_results, names[1]) # function in user_functions.py
```


Daytona

```
pdq         (0, 5, 2)
pdqs    (0, 0, 0, 12)
aic          -1824.65
Name: 54, dtype: object
```

In [94]:
```
tic = time.time()
Daytona_grid_search = grid_search_arima(np.log(Daytona_train), d = best_diff['Daytona'][0])
print(time.time()-tic)
```

```
pdq         (0, 5, 2)
pdqs    (0, 0, 0, 12)
aic          -1824.65
Name: 54, dtype: object
596.0486102104187
```

In [95]:
```
Daytona_grid_search
```

Out[95]:

	pdq	pdqs	aic
0	(0, 5, 0)	(0, 0, 0, 12)	-1414.539641
1	(0, 5, 0)	(0, 0, 1, 12)	-1417.087372
2	(0, 5, 0)	(0, 0, 2, 12)	-1413.983055
3	(0, 5, 0)	(0, 1, 0, 12)	-1151.848313
4	(0, 5, 0)	(0, 1, 1, 12)	-1288.018780
...	...	...	...
238	(2, 5, 2)	(2, 1, 1, 12)	-1459.375987
239	(2, 5, 2)	(2, 1, 2, 12)	-1504.250667
240	(2, 5, 2)	(2, 2, 0, 12)	-1249.043222
241	(2, 5, 2)	(2, 2, 1, 12)	-1243.620754
242	(2, 5, 2)	(2, 2, 2, 12)	-1288.388315

243 rows × 3 columns

In [96]:
```
Daytona_model = ARIMA(np.log(Daytona_train), order=(0,5,2), seasonal_order=(0,0,0,12), freq='MS')
Daytona_results = Daytona_model.fit()
print(Daytona_results.aic)
```

```
-1824.6532776198896
```

In [97]:
```
Daytona_metrics = track_final_metrics(Daytona_grid_search, Daytona_results, names[2]) # function in user_functions.py
```

Columbus

```
pdq         (2, 4, 1)
pdqs    (1, 0, 0, 12)
aic          -194.596
Name: 198, dtype: object
```

Contents

In [98]:
```
tic = time.time()
Columbus_grid_search = grid_search_arima(np.log(Columbus_train), d = best_diff['Columbus'][0])
print(time.time()-tic)
```

```
pdq         (2, 4, 1)
pdqs    (1, 0, 0, 12)
aic          -194.596
Name: 198, dtype: object
170.1638731956482
```

In [99]:
```
Columbus_model = ARIMA(np.log(Columbus_train), order=(2,4,1), seasonal_order=(1,0,0,12), freq='MS')
Columbus_results = Columbus_model.fit()
print(Columbus_results.aic)
```

```
-194.5958648817607
```

In [100]:
```
Columbus_metrics = track_final_metrics(Columbus_grid_search, Columbus_results, names[3]) # function in user_functions.py
```

Kansas City

```
pdq         (1, 1, 2)
pdqs    (0, 0, 2, 12)
aic          -1801.54
Name: 137, dtype: object
```

In [101]:
```
tic = time.time()
KC_grid_search = grid_search_arima(np.log(KC_train), d = best_diff['KansasCity'][0])
print(time.time()-tic)
```

```
pdq         (1, 1, 2)
pdqs    (0, 0, 2, 12)
aic          -1801.54
Name: 137, dtype: object
382.5188422203064
```

In [102]:
```
KC_model = ARIMA(np.log(KC_train), order=(1,1,2), seasonal_order=(0,0,2,12), freq='MS')
KC_results = KC_model.fit()
print(KC_results.aic)
```

```
-1801.535745337077
```

In [103]:
```
KC_metrics = track_final_metrics(KC_grid_search, KC_results, names[4]) # function in user_functions.py
```

Chattanooga

```
pdq         (1, 1, 2)
pdqs    (0, 0, 2, 12)
aic          -2068.06
Name: 137, dtype: object
```

Contents

In [104]:

```
tic = time.time()
Chattanooga_grid_search = grid_search_arima(np.log(Chattanooga_train), d = best_diff['Chattanooga'][0])
print(time.time()-tic)
```

```
pdq         (1, 1, 2)
pdqs    (0, 0, 2, 12)
aic          -2068.06
Name: 137, dtype: object
373.5620331764221
```

In [105]:

```
Chattanooga_model = ARIMA(np.log(Chattanooga_train), order=(1,1,2), seasonal_order=(0,0,2,12), freq='MS')
Chattanooga_results = Chattanooga_model.fit()
print(Chattanooga_results.aic)
```

```
-2068.064330716703
```

In [106]:
```
Chattanooga_results.summary()
```

Out[106]:

SARIMAX Results

Dep. Variable:	value	**No. Observations:**	253
Model:	ARIMA(1, 1, 2)x(0, 0, 2, 12)	**Log Likelihood**	1040.032
Date:	Sun, 31 Jan 2021	**AIC**	-2068.064
Time:	18:18:17	**BIC**	-2046.888
Sample:	04-01-1996	**HQIC**	-2059.543
	- 04-01-2017		
Covariance Type:	opg		

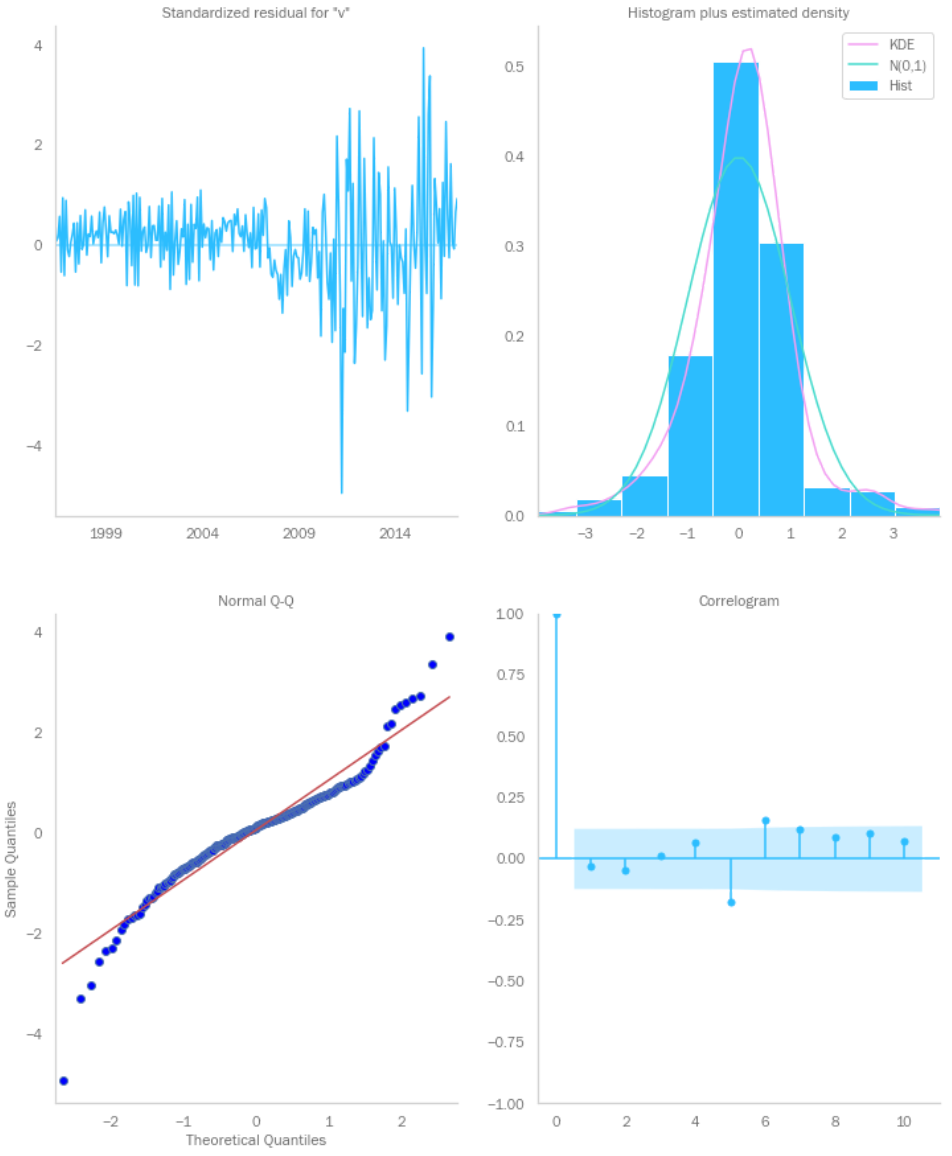
	coef	std err	z	P>|z|	[0.025	0.975]
ar.L1	0.7161	0.039	18.303	0.000	0.639	0.793
ma.L1	0.7526	0.049	15.384	0.000	0.657	0.848
ma.L2	0.2969	0.044	6.726	0.000	0.210	0.383
ma.S.L12	-0.1871	0.064	-2.938	0.003	-0.312	-0.062
ma.S.L24	-0.1307	0.057	-2.282	0.022	-0.243	-0.018
sigma2	1.501e-05	9.31e-07	16.111	0.000	1.32e-05	1.68e-05

Ljung-Box (L1) (Q):	0.31	**Jarque-Bera (JB):**	172.83
Prob(Q):	0.58	**Prob(JB):**	0.00
Heteroskedasticity (H):	8.97	**Skew:**	-0.34
Prob(H) (two-sided):	0.00	**Kurtosis:**	7.00

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

In [107]:
```
Chattanooga_metrics = track_final_metrics(Chattanooga_grid_search, Chattanooga_results, names[5])
```

In [108]:
```
Chattanooga_results.plot_diagnostics(figsize=(12, 15))
plt.savefig('Images/Chat_diagnostics.png')
```



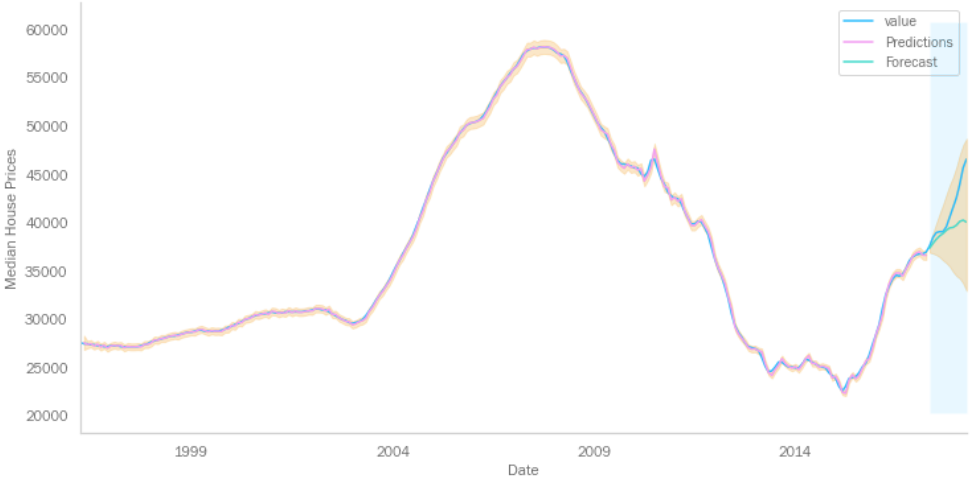
Contents

Contents

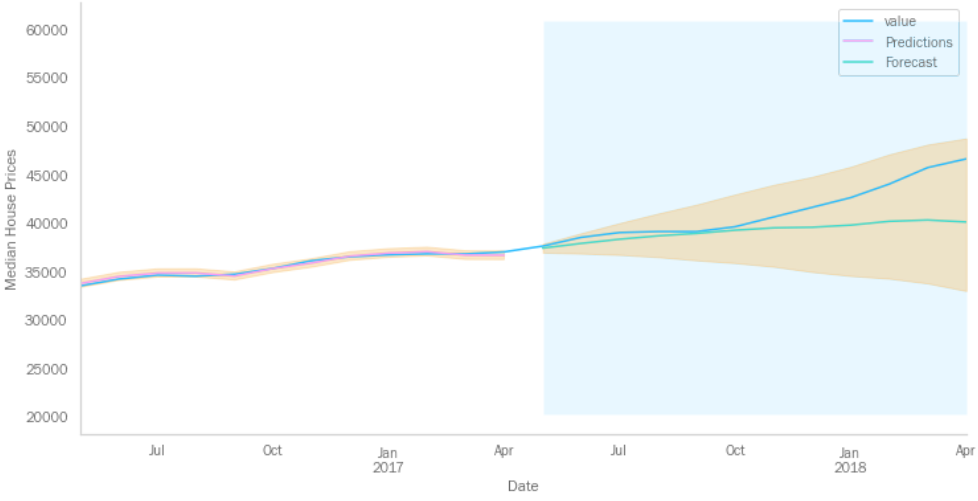
Visualize predictions and Calculate RMSE for top models

In [109]:
```
Philly_pred, Philly_forecast, Philly_train_rmse, Philly_test_rmse = \
    run_preds_and_plot(Philly_results, Philly_train, Philly_test, 'Philadelphia', best_diff)
Philly_metrics.update({'train rmse': Philly_train_rmse, 'test rmse': Philly_test_rmse})
```

Contents

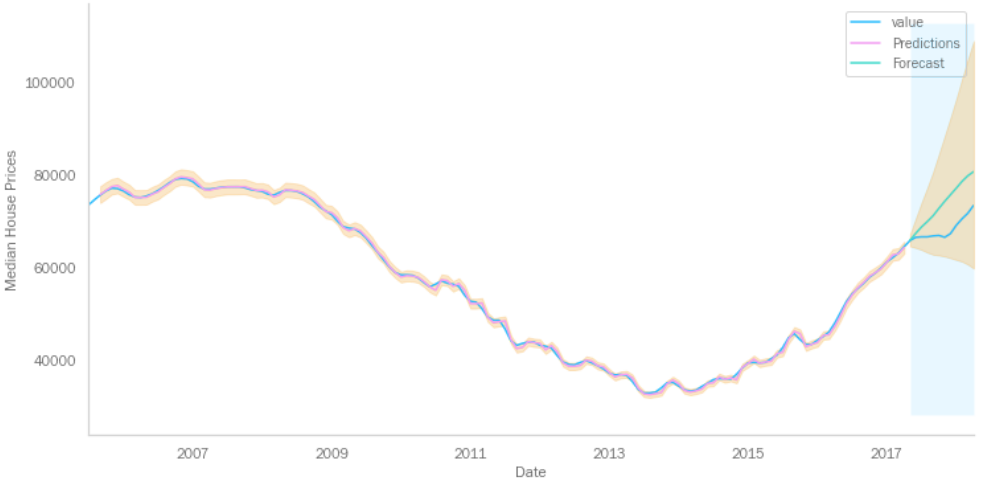



```
The Root Mean Squared Error of Philadelphia predictions is 210.12
The Root Mean Squared Error of Philadelphia forecasts is 2904.6
```

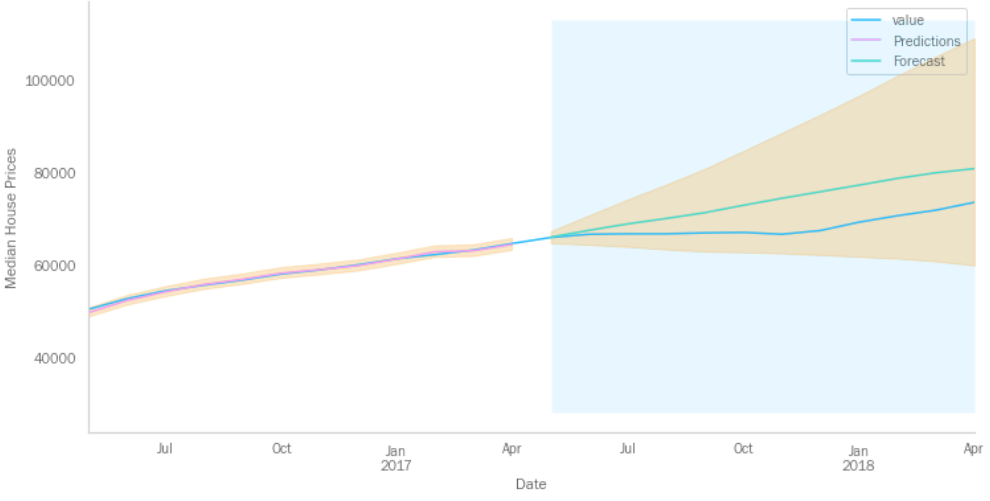


In [110]:
```
Indy_pred, Indy_forecast, Indy_train_rmse, Indy_test_rmse = run_preds_and_plot(Indy_results,
                                                                               Indy_train, Indy_test, 'Indianapolis',
                                                                              best_diff)
Indy_metrics.update({'train rmse': Indy_train_rmse, 'test rmse': Indy_test_rmse})
```

Contents



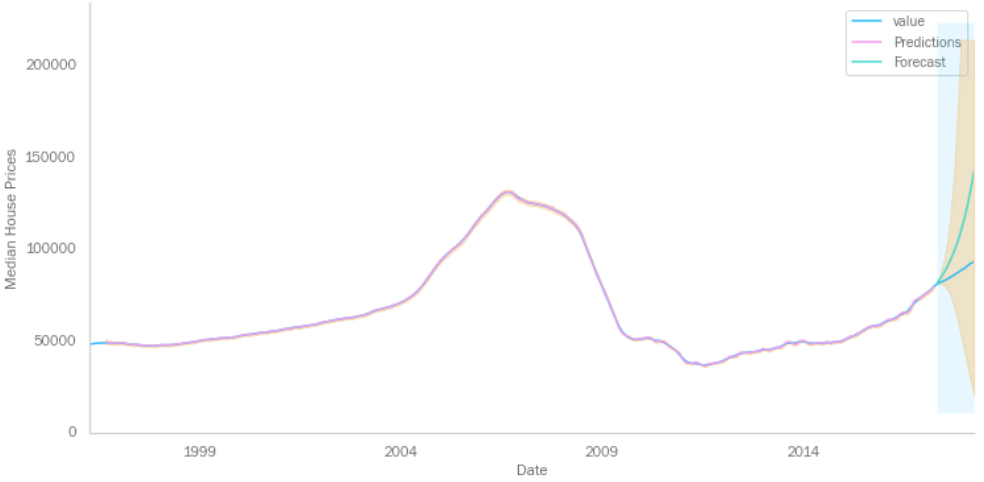

```
The Root Mean Squared Error of Indianapolis predictions is 473.98
The Root Mean Squared Error of Indianapolis forecasts is 6108.44
```



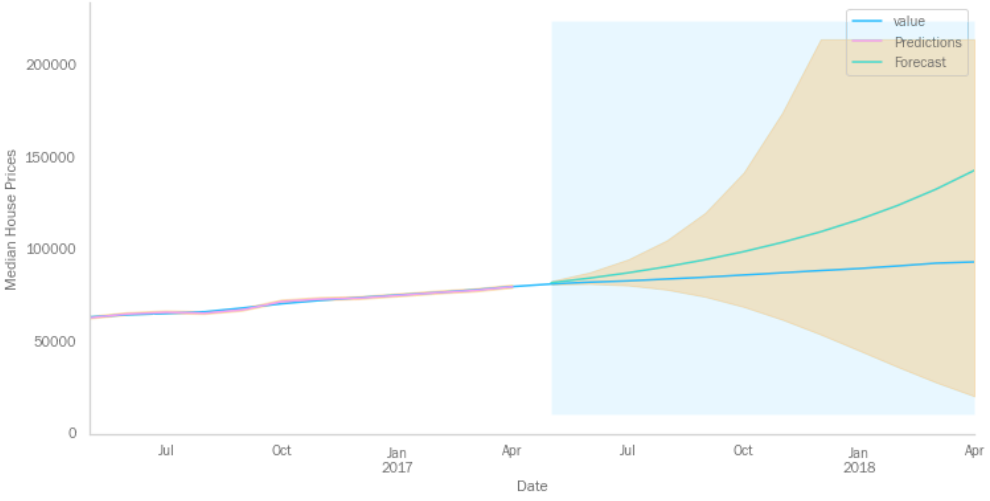
Contents

In [111]:
```
Daytona_pred, Daytona_forecast, Daytona_train_rmse, Daytona_test_rmse = \
    run_preds_and_plot(Daytona_results, Daytona_train, Daytona_test, 'Daytona', best_diff)
Daytona_metrics.update({'train rmse': Daytona_train_rmse, 'test rmse': Daytona_test_rmse})
```

Contents

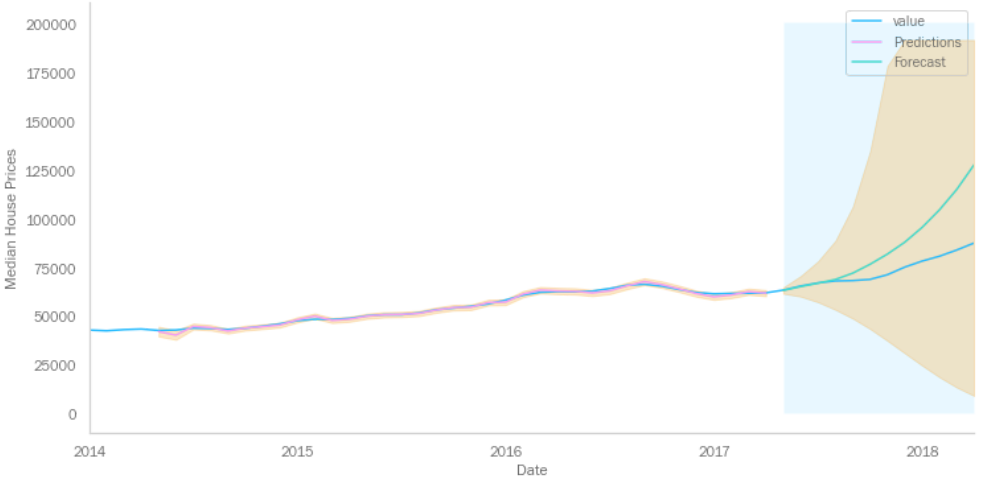



```
The Root Mean Squared Error of Daytona predictions is 318.07
The Root Mean Squared Error of Daytona forecasts is 23990.07
```

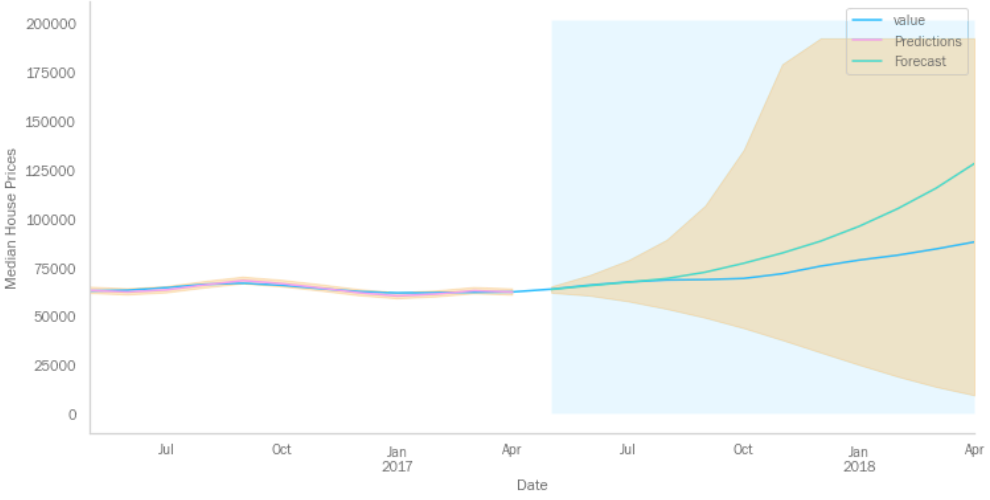


In [112]:
```
Columbus_pred, Columbus_forecast, Columbus_train_rmse, Columbus_test_rmse = \
    run_preds_and_plot(Columbus_results, Columbus_train, Columbus_test, 'Columbus', best_diff)
Columbus_metrics.update({'train rmse': Columbus_train_rmse, 'test rmse': Columbus_test_rmse})
```

Contents

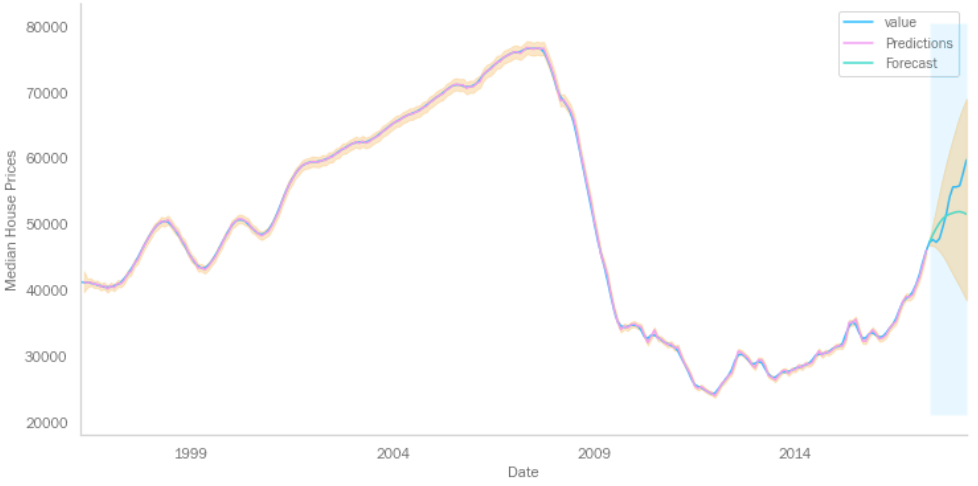



```
The Root Mean Squared Error of Columbus predictions is 844.18
The Root Mean Squared Error of Columbus forecasts is 17797.27
```

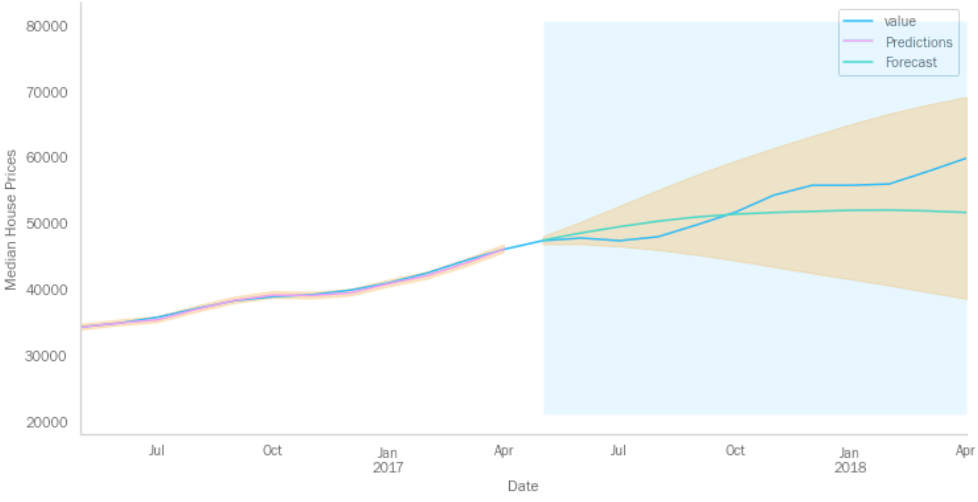


Contents

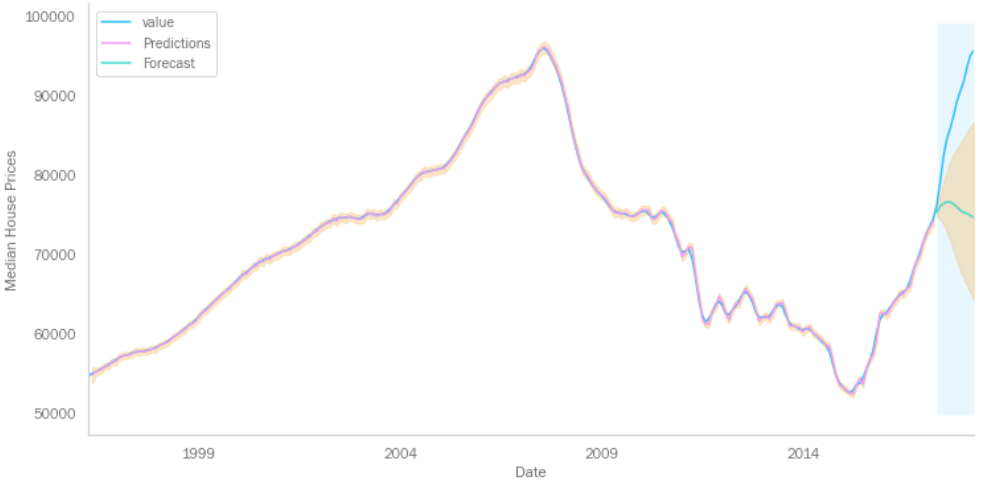
In [113]:
```
KC_pred, KC_forecast, KC_train_rmse, KC_test_rmse = run_preds_and_plot(KC_results, KC_train, KC_test, 'KansasCity',
                                                                       best_diff)
KC_metrics.update({'train rmse': KC_train_rmse, 'test rmse': KC_test_rmse})
```



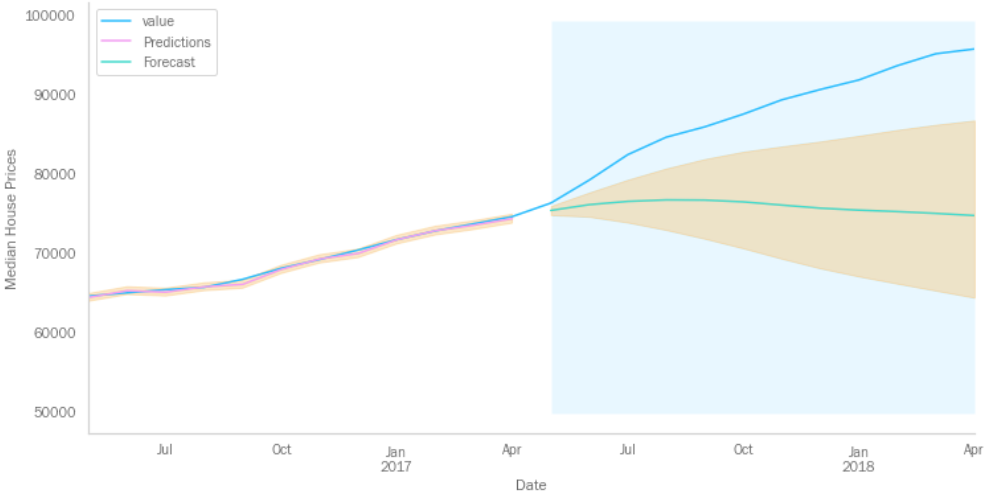

```
The Root Mean Squared Error of KansasCity predictions is 243.3
The Root Mean Squared Error of KansasCity forecasts is 3745.08
```



In [114]:
```
Chattanooga_pred, Chattanooga_forecast, Chattanooga_train_rmse, Chattanooga_test_rmse = \
    run_preds_and_plot(Chattanooga_results, Chattanooga_train, Chattanooga_test, 'Chattanooga', best_diff)
Chattanooga_metrics.update({'train rmse': Chattanooga_train_rmse, 'test rmse': Chattanooga_test_rmse})
```




```
The Root Mean Squared Error of Chattanooga predictions is 254.97
The Root Mean Squared Error of Chattanooga forecasts is 13426.12
```



Facebook Prophet

In [115]:
```
from fbprophet import Prophet
```

In [116]:
```
Philly_proph = Philly_train.reset_index()
Philly_proph.columns = ['ds', 'y']
Philly_proph
```

Out[116]:

	ds	y
0	1996-04-01	27600.0
1	1996-05-01	27500.0
2	1996-06-01	27500.0
3	1996-07-01	27400.0
4	1996-08-01	27400.0
...	...	...
248	2016-12-01	36500.0
249	2017-01-01	36700.0
250	2017-02-01	36800.0
251	2017-03-01	36800.0
252	2017-04-01	37000.0

253 rows × 2 columns

In [117]:
```
prophet_model = Prophet()
prophet_model.fit(Philly_proph)
```

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

Out[117]:
```
<fbprophet.forecaster.Prophet at 0x238b49b6430>
```

In [118]:
```
future = prophet_model.make_future_dataframe(freq ='MS', periods=12)
future.tail()
```

Out[118]:

	ds
260	2017-12-01
261	2018-01-01
262	2018-02-01
263	2018-03-01
264	2018-04-01

In [119]:
```
forecast = prophet_model.predict(future)
forecast[['ds','yhat','yhat_lower','yhat_upper']].tail()
```

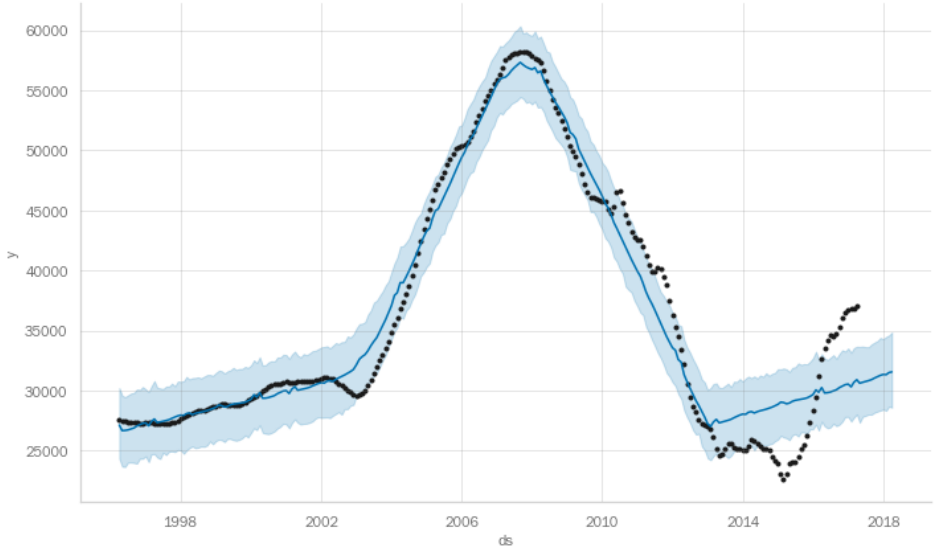
Out[119]:

	ds	yhat	yhat_lower	yhat_upper
260	2017-12-01	31263.594936	28343.943331	34389.437167
261	2018-01-01	31343.365536	28419.795132	34293.161551
262	2018-02-01	31325.741272	28325.238875	34484.651475
263	2018-03-01	31495.508175	28673.347796	34593.682411
264	2018-04-01	31553.705527	28587.227066	34844.157742

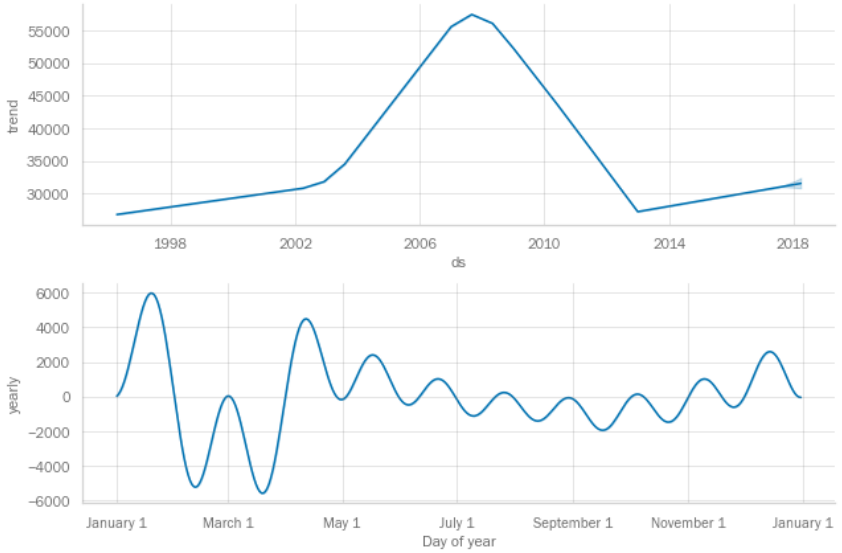
In [143]:
```
prophet_ROI = ((forecast.yhat.iloc[-1]) - (forecast.yhat.iloc[-12]))/(forecast.yhat.iloc[-12])
prophet_ROI # ARIMA model forecast 7%, actual value was 25%
```

Out[143]: 0.030605143650945077

In [120]:
```
fig1 = prophet_model.plot(forecast)
```



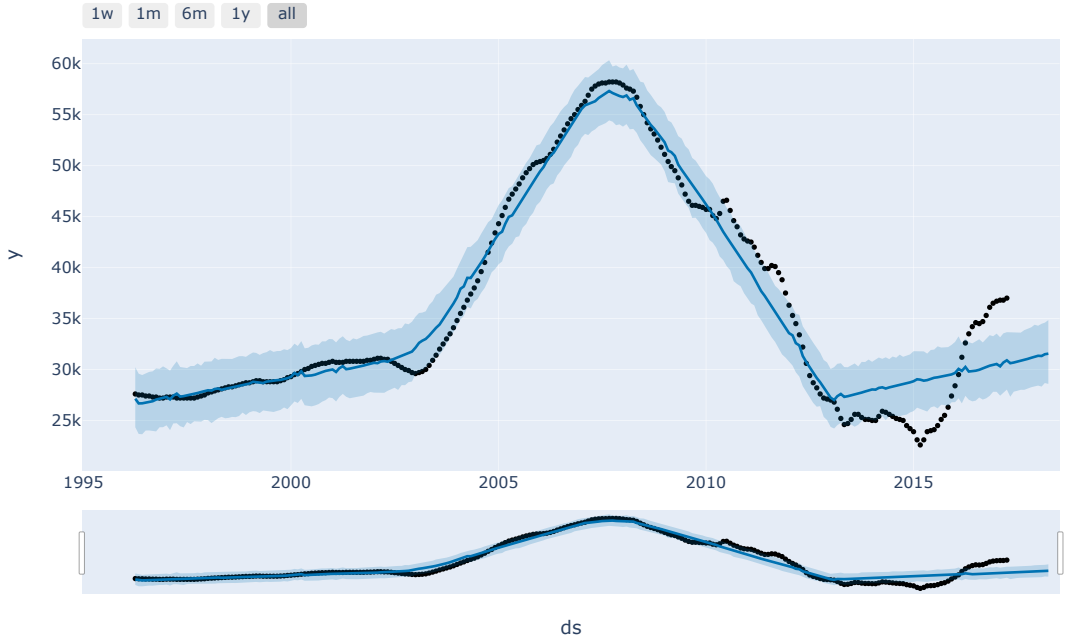
In [121]:
```
fig2 = prophet_model.plot_components(forecast)
```



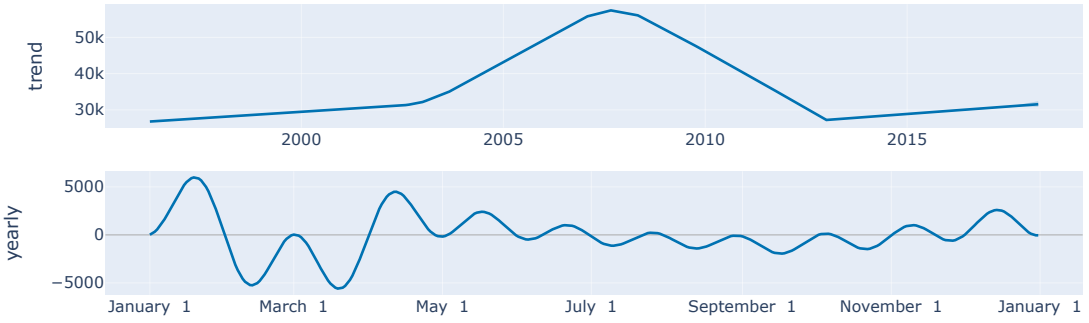
Contents

In [122]:
```
from fbprophet.plot import plot_plotly, plot_components_plotly

plot_plotly(prophet_model, forecast)
```

Contents



In [123]:
```
plot_components_plotly(prophet_model, forecast)
```

Interpret Results / Conclusions

In [124]:
```
pd.DataFrame([Philly_metrics, Indy_metrics, Daytona_metrics, Columbus_metrics, KC_metrics, Chattanooga_metrics])
```

Out[124]:

	name	order	seasonal order	ar.L1	ar.L2	ma.L1	ma.L2	ar.S.L12	ma.S.L12	sigma2	aic	train rmse	test rmse	ar.S.L24	ma.S.L24
0	Philadelphia	(2, 1, 2)	(1, 0, 1, 12)	1.1489	-0.1829	-0.1092	-0.3715	0.5673	-0.9261	0.0000	-1818.25	210.120410	2904.602710	NaN	NaN
1	Indianapolis	(1, 2, 2)	(2, 0, 2, 12)	0.4495	NaN	-0.2736	-0.5485	-0.2887	0.2439	0.0001	-867.45	473.983586	6108.436530	0.367	-0.6304
2	Daytona	(0, 5, 2)	(0, 0, 0, 12)	NaN	NaN	-1.9436	0.9541	NaN	NaN	0.0000	-1824.65	318.066481	23990.065072	NaN	NaN
3	Columbus	(2, 4, 1)	(1, 0, 0, 12)	-0.0722	-0.8108	-0.9405	NaN	-0.2056	NaN	0.0002	-194.60	844.184953	17797.268489	NaN	NaN
4	KansasCity	(1, 1, 2)	(0, 0, 2, 12)	0.7820	NaN	0.7766	0.2137	NaN	-0.1090	0.0000	-1801.54	243.298505	3745.083869	NaN	-0.1074
5	Chattanooga	(1, 1, 2)	(0, 0, 2, 12)	0.7161	NaN	0.7526	0.2969	NaN	-0.1871	0.0000	-2068.06	254.974561	13426.120075	NaN	-0.1307

In [125]:
```
original_dfs = [Philly, Indy, Daytona, Columbus, KC, Chattanooga]
forecast_dfs = [Philly_forecast, Indy_forecast, Daytona_forecast, Columbus_forecast, KC_forecast, Chattanooga_forecast]
for df in original_dfs:
    df.reset_index(drop=True, inplace=True)
```

In [126]:
```
def calc_forecast_ROI(forecast):
    return ((np.exp(forecast.predicted_mean)[-1] - np.exp(forecast.predicted_mean)[-12])/
            np.exp(forecast.predicted_mean)[-12])
```

In [127]:
```
def final_ROI(dfs, forecasts):
    comparison = pd.DataFrame(index=['Zip Code','median housing price','actual 2018 ROI', 'forecast 2018 ROI'])
    for i, df in enumerate(dfs):
        metrics = [df['RegionName'][0], df.iloc[0,-1], round(100*df['recent_1_yr_ROI'][0],2),
                   round(100*calc_forecast_ROI(forecasts[i]),2)]
        comparison[df['City'][0]] = metrics
    return comparison

ROI_comparison = final_ROI(original_dfs, forecast_dfs)
ROI_comparison
```

Out[127]:

	Philadelphia	Indianapolis	Daytona Beach	Columbus	Kansas City	Chattanooga
Zip Code	19134	46203	32114	43206	66104	37411
median housing price	46600	73500	92600	88100	59800	95600
actual 2018 ROI	25.95	13.78	16.92	40.96	30	28.32
forecast 2018 ROI	7.21	22.42	75.04	101.29	8.87	-0.85

Results:

- All training data outperformed the test data.
- The models are all very skewed because of the market crash in 2009.
- Columbus and Daytona had very large confidence intervals and overly high forecasts.
- Chattanooga has outperformed even the confidence intervals of the model.
- Philadelphia is potentially a good 50K investment , Indianapolis at 75K and Chattanooga at 100K investment

Caveats:

- Logged and differenced the data but some still did not test as stationary according to the Dickey Fuller test.
- Real estate predictions can vary due to unseen fluctuations in the market

Next Steps/Future Work:

- Obtain current data after 2018 for current predictions. Found zip data on Redfin but it is rolling avg by zip code.
- Investigate why some of the models seem so far off in their forecasts.

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