Real Estate Property Investments

Invest with sound, objective data driven recommendations

Syracuse Applied Data Science, IST-707 Data Analytics

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DATE: 9/8/2019 ASSIGNMENT: Final Project

1. Introduction

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A real estate transaction can be an emotional time for everyone. The complexities between buyers and sellers are the result of different experiences and expectations. Success in today's market is guided by knowledge, communication, and partnership.

Buyers are waiting later in life to purchase their first home. They have very specific expecations on what they are looking for, and willing to take the time to get exactly what they want. To be successful, buyers will turn to experienced professionals to guide them through the buying process and to sift through the voluminous of data.

Sellers past experiences have been rooted in market conditions significantly different than we aree seeing today. Many are resisting the realities of the market and are slow to react to the valuable feedback the data provides. To be successful, sellers will need to utilize skilled professionals to interpret the specifics of today's market and take swift action to adjust for changing trends.

1.1 Problem Statement:

- How to predict a low risk / high yield return on property investment in a volatile market.
- Where and when to buy and sell that maximizes investment profits.
- Forecast future growth and decline of a region in order to guide investors with optimized, data driven, recommendations.

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1.2 About the Data

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Base Real Estate data provided by: Zillow (files.zillowstatic.com/research/public/Zip/Zip_Zhvi_SingleFamilyResidence.csv)
Base Federal Reserve data provided by: [kaggle] (https://www.kaggle.com/federalreserve/interest-rates (https://www.kaggle.com/federalreserve/interest-rates)

Base Economic data sets provided by: `[datahub.io](https://datahub.io/core/cpi-us![image.png](attachment:image.png) (https://datahub.io/core/cpi-us!%5Bimage.png%5D(attachment:image.png))`

Zillow Data: Timeseries Real Estate data by ZipCode U.S.
Zillow Home Value Index (ZHVI): A smoothed, seassonally adjusted measure of the median estimated home value across a given region and housing type. It is a dollar-denominated alternative to repeat-sales indices.

- Zip_Zhvi_SingleFamilyResidence.csv
- Zip_Zhvi_AllHomes.csv
- Zip_MedianRentalPricePerSqft_Sfr.csv
- Zip_MedianRentalPrice_AllHomes.csv
- Zip_MedianListingPrice_AllHomes.csv

Datahub.io: U.S., National Yearly Economic Reports

- interest_rates.csv
  - Inflation, GDP deflator (annual %) and Inflation, consumer prices (annual %) for most countries in the world when it has been measured. Data The data comes from The World Bank (CPI), The World Bank (GDP) and is collected from 1973 to 2014. There are some values missing from data
- inflation-consumer.csv
- inflation-gdp.csv
- education_budget_data.csv
  - United States of America Education budget to GDP analysis Data Data comes from Office of Management and Budget, President's Budget from white house official
- population.csv
  - Population figures for countries, regions (e.g. Asia) and the world. Data comes originally from World Bank and has been converted into standard CSV
- investor_flow_funds_monthly.csv
  - Monthly net new cash flow by US investors into various mutual fund investment classes (equities, bonds etc). Statistics come from the Investment Company Institute (ICI)
- housing_price_cities.csv
  - Case-Shiller Index of US residential house prices. Data comes from S&P Case-Shiller data and includes both the national index and the indices for 20 metropolitan regions. The indices are created using a repeat-sales methodology.
- household-income.csv
  - Upper limits of annual incomes for each fifth and lower limit of income for top 5 percent of all housholds from 1967 to last year Data This dataset is acquired from U.S. Census Bureau, Current Population Survey, Annual Social and Economic Supplements.
- employment.csv
  - US Employment and Unemployment rates since 1940. Official title: *Employment status of the civilian noninstitutional population, 1940 to date* from USA Bureau of Labor Statistics. Data Numbers are in thousands. US Employment and Unemployment rates since 1940 From the USA Bureau of Labor
- cpi.csv
  - Consumer Price Index for All Urban Consumers (CPI-U) from U.S. Department Of Labor Bureau of Labor Statistics. This is a monthly time series from January 1913. Values are U.S. city averages for all items and 1982-84=100.

- cash-surp-def_csv.csv
  - Repository of the data package of the Cash Surplus or Deficit, in percentage of GDP, from 1990 to 2013. Data Data comes originally from World Bank!
- bonds_yields_10y.csv
  - 10 year nominal yields on US government bonds from the Federal Reserve. The 10 year government bond yield is considered a standard indicator of long-term interest rates.
- gdp_quarter.csv
- gdp_year.csv
  - Gross Domestic Product (GDP) of the United States (US) both nominal and real on an annual and quarterly basis. Annual data is provided since 1930 and quarterly data since 1947. Both total GDP (levels) and annualized percentage change in GDP are provided.

Dataset Info: Economic

- The Time series data range our modeling and analysis was centered on was from **1997 through 2018**. All of the Realestate datasets achieved this desired range, however some of the Economic datasets did not. To achieve paraty and have a fuller dataset for baseline testing, time series future forecast methods were applied. More will be described in section 2 on Time Series forecasting.
- GDP Yearly: Forecasted for 2016, 2017, 2018 values
- Inflation: Forecasted for 2017, 2018 values
- Interest Rates: Forecasted for 2016, 2017, 2018
- Note: Kaggel Federal Reserve datasets proved to be useless, full of gaps and limited time series data to provide value. Economic data was pulled from the above mentioned sources and munged together to form a more useable data set.

Dataset Info: Real Estate

- This data is our base datasets and provides the core insights into preditable housing market trends given prior knowledge of price performance coupled with economic fluctuations. Timeseries prediction models are created for each type of housing dataset mentioned above by ZipCode and it's monthly price value from 1997 to 2018. For this initial analysis, ZipCode's were focused to the U.S. State of Washington. This represents 351 unique zipcodes that were modeled with a five year future price prediction. These zipcodes then were combined with the economic features above, in order to create a dataset that could be used in identifing and or predicting events that could have a positive or negative impact on housing prices given a unique zipcode.

In [1]:

```
# toggle for working with colab
isColab = False
```

In [256]:

```
#*ONLY RUN WHEN WORKING ON COLAB*
#====================================================
# mount google drive for working in colab

#from google.colab import drive
#drive.mount('/content/gdrive', force_remount=True)

# working within colab, set base working directory
#base_dir = "./gdrive/My Drive/IST707_PRJ_Realestate/buy_rent_sell/"

# validate directory mapping
#ls f'{base_dir}'

# upload custome python files
#from google.colab import files
#uploaded_files = files.upload()

# print files uploaded
#for f in uploaded_files.keys():
#  print(f'file name: {f}')

#isColab = True
```

In [74]:

```
# import packages
import pandas as pd                                # data frame operations
import numpy as np                              # arrays and match functions
import random
import time
import gc
import os
import pickle
from pathlib import Path

import seaborn as sns                              # uses for visualizations
import matplotlib.pyplot as plt                    # used for 2D plotting
%matplotlib inline
plt.style.use('fivethirtyeight')

import warnings
warnings.filterwarnings('ignore')
from timeit import default_timer                   # performance processing time
import logging                                     # logging framework
```

In [3]:

```
# custome python packages
import rtimbroo_ist_utils as rt                    # custome python helper functi
import brs_utils as brs # custome functions specific to buy_sell_rent project
```

```
All the files are downloaded
```

In [4]:

```
#from sklearn.preprocessing import LabelEncoder
from sklearn.metrics import confusion_matrix, precision_score, accuracy_score
from sklearn.model_selection import train_test_split, cross_val_score
from sklearn.preprocessing import LabelEncoder
from sklearn.tree import DecisionTreeClassifier
from sklearn import tree
from sklearn.ensemble import RandomForestClassifier

from sklearn.naive_bayes import GaussianNB
from scipy.cluster.hierarchy import linkage, dendrogram
from sklearn.svm import SVC
from sklearn.cluster import KMeans, SpectralClustering
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import silhouette_samples, silhouette_score
```

In [75]:

```
# timeseries packages
'''Time series models at scale.  Based on the research from facebook - [Proph
Initial code modeled after Digital Ocean's [tutorial](https://www.digitalocea
**Data Tranansformations:**
Prophet requires columns to be in certain formats
Use python transpose

*[Prophet Quick Start Guide:](https://facebook.github.io/prophet/docs/quick_s

from fbprophet import Prophet
```

In [6]:

```
# set global properties
if not isColab:
    dataDir = './data'
    outputDir = './output'
    configDir = './config'
    logOutDir = './logs/'
    imageDir = './images'
    modelDir = './models'
else:
    # working within colab
    dataDir = f'{base_dir}data'
    outputDir = f'{base_dir}output'
    configDir = f'{base_dir}config'
    logOutDir = f'{base_dir}logs'
    imageDir = f'{base_dir}images'
    modelDir = f'{base_dir}models'

# perform scrubbing and cleaning techniques
modelsPerformance = {'ModelName':[], 'TestAccuracyScore':[],'PredictAccuracyS
# plots
report_plots = {}

modelNames = 'zip_time_series'
appName = 'rt_brs_time_series'
loglevel = 10 # 10-DEBUG, 20-INFO, 30-WARNING, 40-ERROR, 50-CRITICAL

# focus in on a single state and selected set of regions for this initial pro
focus_state = 'WA'
regions = []

# time series training set years
ts_col_years = [str(y) for y in range(2000,2019)]
ts_train_years = [str(y) for y in range(2000,2018)]
ts_validate_year = '2018'

# sub directory for storing models
trainDir = 'train'
future5Dir = 'future_5'
# time series model projection time
ts_pred_periods = 12*5
```

In [7]:

```
# get a logger for troubleshooting / data exploration
logger = rt.getFileLogger(logOutDir,appName,level=loglevel)
np.random.seed(42) # NumPy
```

In [8]:

```
# create base output directories if they don't exist
if not os.path.exists(outputDir): os.mkdir(outputDir)
#if not os.path.exists(logOutDir): os.mkdir(logOutDir)
if not os.path.exists(imageDir): os.mkdir(imageDir)
if not os.path.exists(modelDir): os.mkdir(modelDir)
```

1.3 Obtain the data

- Using the base data available from [Zillow (files.zillowstatic.com/research/public/Zip/Zip_Zhvi_SingleFamilyResidence.csv)]

Zillow Home Value Index (ZHVI): A smoothed, seassonally adjusted measure of the median estimated home value across a given region and housing type. It is a dollar-denominated alternative to repeat-sales indices (https://wp.zillowstatic.com/3/ZHVI-InfoSheet-04ed2b.pdf).

- OBTAIN Interest Rates data from Kaggel
  - Using the dataset provided by the kaggel Federal Reserve Interest Rates (https://www.kaggle.com/federalreserve/interest-rates/downloads/interest-rates.zip/1)
- Obtain Economic Data from datahub.io (https://datahub.io/core/cpi-us!%5Bimage.png%5D(attachment:image.png))

In [9]:

```
# data files to load
zip_zillow_sfr_file = 'Zip_Zhvi_SingleFamilyResidence.csv'
zip_zillow_all_homes_file = 'Zip_Zhvi_AllHomes.csv'
zip_zillow_rpsf_sfr_file = 'Zip_MedianRentalPricePerSqft_Sfr.csv'
zip_zillow_rp_all_homes_file = 'Zip_MedianRentalPrice_AllHomes.csv'
zip_zillow_lp_all_homes_file = 'Zip_MedianListingPrice_AllHomes.csv'

# interest rate data set - kaggel
interest_rates_file = 'interest_rates_kaggel.csv'

# economic datasets - https://datahub.io/core
interest_rates_dh = 'interest_rates.csv'
inflation_consumer = 'inflation-consumer.csv'
inflation_gdp = 'inflation-gdp.csv'
education_budget = 'education_budget_data.csv'
population = 'population.csv'
investor_flow_monthly = 'investor_flow_funds_monthly.csv'
housing_price_cities = 'housing_price_cities.csv'
household_income = 'household-income.csv'
employment = 'employment.csv'
cpi = 'cpi.csv'
cash_surp_def = 'cash-surp-def_csv.csv'
bonds_yeilds_10y = 'bonds_yields_10y.csv'
gdp_quarter = 'gdp_quarter.csv'
gdp_year = 'gdp_year.csv'
```

In [10]:

```
zip_zillow_sfr = pd.read_csv(dataDir+'/'+zip_zillow_sfr_file, error_bad_lines
zip_zillow_all = pd.read_csv(dataDir+'/'+zip_zillow_all_homes_file, error_bad
zip_zillow_rpsf_sfr = pd.read_csv(dataDir+'/'+zip_zillow_rpsf_sfr_file, error
zip_zillow_rp_all = pd.read_csv(dataDir+'/'+zip_zillow_rp_all_homes_file, err
zip_zillow_lp_all = pd.read_csv(dataDir+'/'+zip_zillow_lp_all_homes_file, err

re_datasets = {'Single_Family_Residence':zip_zillow_sfr,'All_Homes':zip_zillo
             'RentalPrice_PSF':zip_zillow_rpsf_sfr,'RentalPrice_All_Homes':zip
            'ListingPrice_All_Homes':zip_zillow_lp_all}

# dataset from kaggle
interest_rates = pd.read_csv(f'{dataDir}/{interest_rates_file}',error_bad_lin

# economic data from datahub.io/core
interest_rates_dh = pd.read_csv(f'{dataDir}/{interest_rates_dh}',error_bad_li
inflation_consumer = pd.read_csv(f'{dataDir}/{inflation_consumer}',error_bad_
inflation_gdp = pd.read_csv(f'{dataDir}/{inflation_gdp}',error_bad_lines=Fals
education_budget = pd.read_csv(f'{dataDir}/{education_budget}',error_bad_line
population = pd.read_csv(f'{dataDir}/{population}',error_bad_lines=False, enc
investor_flow_monthly = pd.read_csv(f'{dataDir}/{investor_flow_monthly}',erro
housing_price_cities = pd.read_csv(f'{dataDir}/{housing_price_cities}',error_
household_income = pd.read_csv(f'{dataDir}/{household_income}',error_bad_line
employment = pd.read_csv(f'{dataDir}/{employment}',error_bad_lines=False, enc
cpi = pd.read_csv(f'{dataDir}/{cpi}',error_bad_lines=False, encoding = "ISO-8
cash_surp_def = pd.read_csv(f'{dataDir}/{cash_surp_def}',error_bad_lines=Fals
bonds_yeilds_10y = pd.read_csv(f'{dataDir}/{bonds_yeilds_10y}',error_bad_line
gdp_quarter = pd.read_csv(f'{dataDir}/{gdp_quarter}',error_bad_lines=False, e
gdp_year = pd.read_csv(f'{dataDir}/{gdp_year}',error_bad_lines=False, encodin

ec_datasets = {} # used to hold the economic datasets after they are transfor
```

In [12]:

```
# REAL ESTATE DATASET
# look over the datasets
for k,v in re_datasets.items():
    logger.debug(f'{k} shape: {v.shape}')
    logger.debug(f'{k} memory usage: {rt.mem_usage(v)}')
    #logger.debug(f'{k} info: {v.info()}')
    logger.debug(f'{k} NaN Count: {rt.getNaNCount(v)}')
    rt.findColumnsNaN(v,logger,rowIndex=False)
    #print('')
```

In [14]:

```
# quick look at interest rates
logger.debug(f'interest_rates shape: {interest_rates.shape}')
logger.debug(f'interest_rates memory usage: {rt.mem_usage(interest_rates)}')
#logger.debug(f'interest_rates info: {interest_rates.info()}')
logger.debug(f'interest_rates NaN Count: {rt.getNaNCount(interest_rates)}')
rt.findColumnsNaN(interest_rates,logger,rowIndex=False)
logger.debug(f'interest_rates head: {interest_rates.head()}')
```

In [46]:
```
gdp_year.head()
```

Out[46]:

	date	level-current	level-chained	change-current	change-chained
0	1930	92.2	966.7	-16.0	-6.4
1	1931	77.4	904.8	-23.1	-12.9
2	1932	59.5	788.2	-4.0	-1.3
3	1933	57.2	778.3	16.9	10.8
4	1934	66.8	862.2	11.1	8.9

In [45]:
```
gdp_quarter.head()
```

Out[45]:

	date	level-current	level-chained	change-current	change-chained
0	1947-04-01	246.3	1932.3	6.4	-0.4
1	1947-07-01	250.1	1930.3	17.3	6.4
2	1947-10-01	260.3	1960.7	9.3	6.0
3	1948-01-01	266.2	1989.5	10.5	6.7
4	1948-04-01	272.9	2021.9	10.0	2.3

In [76]:
```
# interest rate -  keep Year, Month, Federal Funds Target Rate - get rid of t
ir = interest_rates_dh[~interest_rates_dh['Federal Funds Target Rate'].isna()
#logger.info(ir.Year.unique())
ir.head()
```

Out[76]:

	Year	Month	Day	Federal Funds Target Rate	Federal Funds Upper Target	Federal Funds Lower Target	Effective Federal Funds Rate	Real GDP (Percent Change)	Unemployment Rate	Inflatio Rat
339	1982	9	27	10.25	NaN	NaN	NaN	NaN	NaN	Nal
340	1982	10	1	10.00	NaN	NaN	9.71	0.4	10.4	5.!
341	1982	10	7	9.50	NaN	NaN	NaN	NaN	NaN	Nal
342	1982	11	1	9.50	NaN	NaN	9.20	NaN	10.8	5.:
343	1982	11	19	9.00	NaN	NaN	NaN	NaN	NaN	Nal

In [43]:

```
# inflation_consumer - filter on Country = 'United States', keep Year, Inflat
ic = inflation_consumer[inflation_consumer.Country.str.contains('United State
ic.head()
```

Out[43]:

	Country	Country Code	Year	Inflation
10559	United States	USA	1961	1.350154
10560	United States	USA	1962	1.244635
10561	United States	USA	1963	1.088386
10562	United States	USA	1964	1.503940
10563	United States	USA	1965	1.919826

In [42]:

```
# education_budget - keep Year, Value
education_budget.head()
```

Out[42]:

	YEAR	BUDGET_ON_EDUCATION	GDP	RATIO
0	1976	9314.0	1877587.0	0.496
1	1977	10568.0	2085951.0	0.507
2	1978	11625.0	2356571.0	0.493
3	1979	13996.0	2632143.0	0.532
4	1980	15209.0	2862505.0	0.531

In [41]:

```
# population - keep Year, Value - drop the rest
pop = population[population['Country Name'].str.contains('United States')]
pop.head()
```

Out[41]:

	Country Name	Country Code	Year	Value
14288	United States	USA	1960	180671000.0
14289	United States	USA	1961	183691000.0
14290	United States	USA	1962	186538000.0
14291	United States	USA	1963	189242000.0
14292	United States	USA	1964	191889000.0

In [37]:
```
investor_flow_monthly.head()
```

Out[37]:

	Date	Total Equity	Domestic Equity	World Equity	Hybrid	Total Bond	Taxable Bond	Municipal Bond	Total
0	2007-01-31	27364	5723	21641	5321	15287	12453	2834	47972
1	2007-02-28	25306	8411	16895	5164	15064	11926	3137	45533
2	2007-03-31	6551	-486	7037	3764	15782	12925	2857	26097
3	2007-04-30	16063	-163	16225	4384	13701	12346	1355	34148
4	2007-05-31	-2876	-14176	11300	4318	20813	17215	3598	22256

In [39]:
```
housing_price_cities.head()
```

Out[39]:

	Date	AZ-Phoenix	CA-Los Angeles	CA-San Diego	CA-San Francisco	CO-Denver	DC-Washington	FL-Miami	FL-Tampa	GA-Atlanta	...
0	1987-01-01	NaN	59.33	54.67	46.61	50.20	64.11	68.50	77.33	NaN	...
1	1987-02-01	NaN	59.65	54.89	46.87	49.96	64.77	68.76	77.93	NaN	...
2	1987-03-01	NaN	59.99	55.16	47.32	50.15	65.71	69.23	77.76	NaN	...
3	1987-04-01	NaN	60.81	55.85	47.69	50.55	66.40	69.20	77.56	NaN	...
4	1987-05-01	NaN	61.67	56.35	48.31	50.63	67.27	69.46	77.85	NaN	...

5 rows × 24 columns

In [35]:
```
# household_income - keep Year, Number(thousands), Top 5 percent
household_income.head()
```

Out[35]:

	Year	Number (thousands)	Lowest	Second	Third	Fourth	Top 5 percent
0	2016	126224	24518	46581	76479	123621.0	230095
1	2015	125819	23591	45020	74498	121060.0	221900
2	2014	124587	22213	42688	70699	116355.0	214100
3	2013	123931	22134	43251	70830	116186.0	216208
4	2013	122952	22029	42358	69039	111631.0	206587

In [34]:
```
# employment - interesting attributes year, population, labor_force, employed
employment.head()
```

Out[34]:

	year	population	labor_force	population_percent	employed_total	employed_percent	agricu
0	1941	99900	55910	56.0	50350	50.4	
1	1942	98640	56410	57.2	53750	54.5	
2	1943	94640	55540	58.7	54470	57.6	
3	1944	93220	54630	58.6	53960	57.9	
4	1945	94090	53860	57.2	52820	56.1	

In [31]:
```
cpi.head()
```

Out[31]:

	Date	Index	Inflation
0	1913-01-01	9.8	NaN
1	1913-02-01	9.8	0.00
2	1913-03-01	9.8	0.00
3	1913-04-01	9.8	0.00
4	1913-05-01	9.7	-1.02

In [32]:
```
cash_surp_def.head()
```

Out[32]:

	Country Name	Country Code	Year	Value
0	Afghanistan	AFG	2006	-2.027860
1	Afghanistan	AFG	2007	-1.731230
2	Afghanistan	AFG	2008	-2.314250
3	Afghanistan	AFG	2009	0.281700
4	Afghanistan	AFG	2010	1.495567

In [33]:
```
bonds_yeilds_10y.head()
```

Out[33]:

	Date	Rate
0	1953-04-02	2.83
1	1953-05-02	3.05
2	1953-06-02	3.11
3	1953-07-02	2.93
4	1953-08-02	2.95

1.4 Data Exploration - SCRUB - CLEAN - Transform

Clean and perform initial transformations steps of the data

REAL ESTATE DATATSETS - ZILLOW

- Rename 'Region Name' Column to ZipCode
- Convert ZipCode field to string
- Remove columns of non-interest:
  - 'RegionID','SizeRank','City','Metro','CountyName'
  - '1996-04','1996-05','1996-06','1996-07','1996-08','1996-09','1996-10','1996-11','1996-12'
  - '2019-01','2019-02', '2019-03', '2019-04', '2019-05', '2019-06', '2019-07','2019-08','2019-09'
- Fill NaN with median value

In [15]:

```
# REAL ESTATE DATA
# Region Name is the zip code - rename for clarity
for k,v in re_datasets.items():
    v = v.rename(index=str, columns={'RegionName':'ZipCode'})
    v.ZipCode = v.ZipCode.astype(str)
    re_datasets[k] = v
```

In [16]:

```
# REAL ESTATE DATA
# convert ZipCode field to strings
keep_year_month_cols = []
month = 1
for y in ts_col_years:
    m = ''
    for i in range(1,13):
        if i < 10:
            m = '0'+str(month)
        else:
            m = str(month)
        month = month+1

        keep_year_month_cols.append(f'{y}-{m}')

    month = 1
#keep_year_month_cols
```

In [17]:

```
# REAL ESTATE DATA
# remove certain columns
# keep years
#ts_col_years
# un needed columns
dropCols = ['RegionID','SizeRank','City','Metro','CountyName']
# remove columns dates prior to 1997
pre1997Cols = ['1996-04','1996-05','1996-06','1996-07','1996-08','1996-09','1
post2018Cols = ['2019-01','2019-02', '2019-03', '2019-04', '2019-05', '2019-0

for k,v in re_datasets.items():
    # drop category columns that aren't useful
    for c in dropCols:
        if c in v.columns:
            v = v.drop(columns=c)
    # drop columns pre 1997
    for c in pre1997Cols:
        if c in v.columns:
            v = v.drop(columns=c)
    # drop columns post 2018
    for c in post2018Cols:
        if c in v.columns:
            v = v.drop(columns=c)

    # filter out by selected focus state ('WA')
    v = v[v.State==focus_state]

    re_datasets[k] = v
```

In [18]:

```
# fill NaN with median value
for k,v in re_datasets.items():
    a = v[['ZipCode','State']]
    b = v.drop(columns=['ZipCode','State'])
    b = b.T
    for c in b:
        median = np.median(b[c].sort_values().dropna())
        b[c].fillna(median,inplace=True)
    b = b.T
    re_datasets[k] = pd.concat([a,b],axis=1)
```

In [19]:
```
# REAL ESTATE DATA
# create a set of training datasets
re_datasets_train = {}
re_datasets_validate = {}

for k,v in re_datasets.items():
    # drop 2018
    i = 0
    df = pd.DataFrame(v[['ZipCode','State']])
    for c in v.columns:
        if ts_validate_year in c:

            if i == 0:
                df = v[c]
            else:
                df2 = v[c]
                df = pd.concat([df,df2], axis=1)

            v = v.drop(columns=c)

        i=i+1

    re_datasets_validate[k] = df
    re_datasets_train[k] = v
```

Zillow Single Family Residence DataFrame Head:

In [20]:
```
sfr = re_datasets_validate['Single_Family_Residence']
sfr.head()
```

Out[20]:

	ZipCode	State	2018-01	2018-02	2018-03	2018-04	2018-05	2018-06	2018-07	:
68	98052	WA	899700.0	909000.0	909900.0	908600.0	913100.0	916700.0	913900.0	9
137	98012	WA	575800.0	585100.0	594200.0	602400.0	608500.0	612100.0	614100.0	6
159	99301	WA	219800.0	220300.0	219600.0	219500.0	220900.0	223200.0	225600.0	2:
171	98103	WA	854600.0	861300.0	862800.0	862200.0	862800.0	860400.0	853800.0	8.
301	98682	WA	298900.0	300600.0	302000.0	303100.0	305600.0	308200.0	309700.0	3

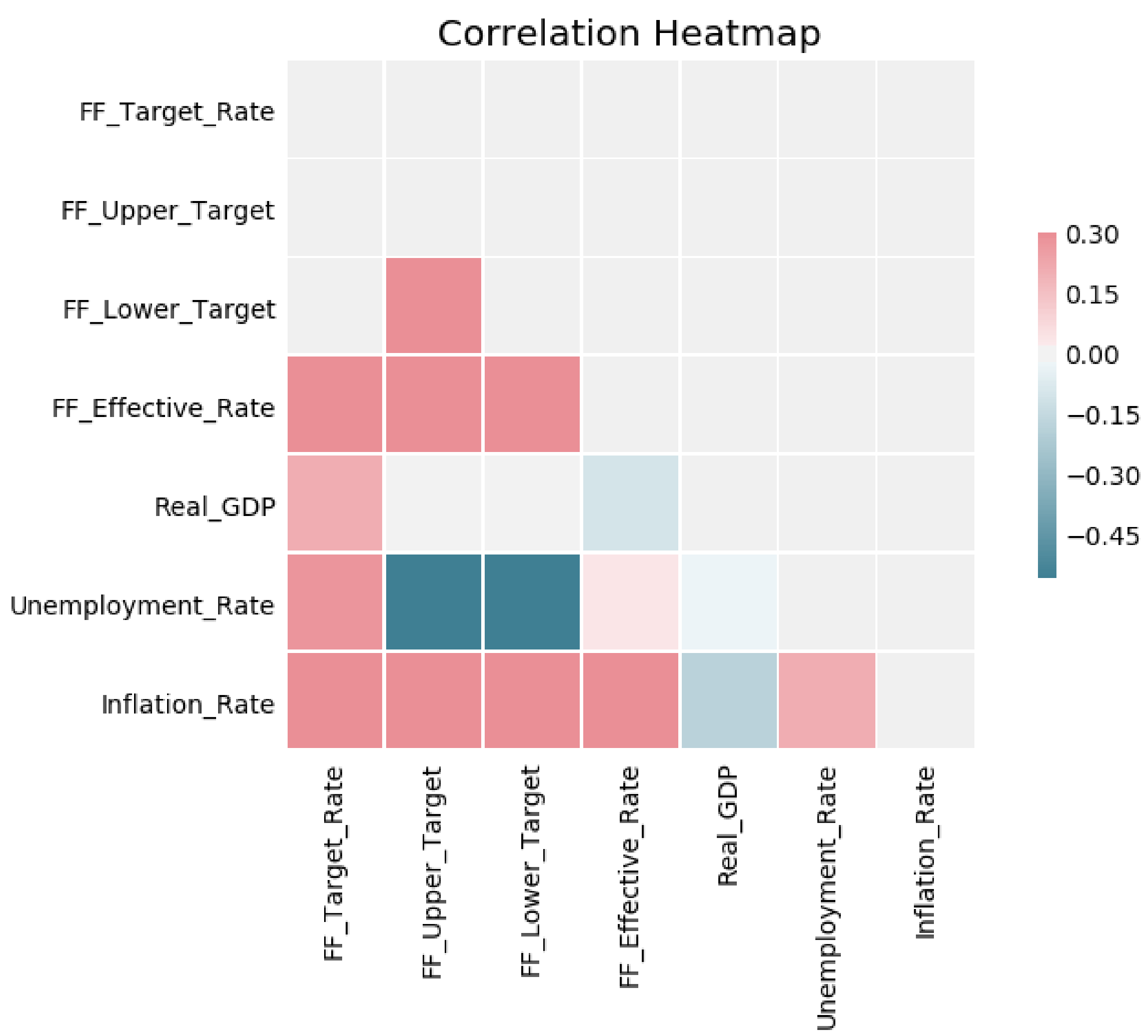
INTEREST RATE DATASET - KAGGEL

- Datasets:
  - Interest Rate:
    - Rename column names to make it easier to work with
    - View the new column names in a correlation heatmap

In [22]:
```
# INTEREST RATE DATASET
# Rename column names - easier to work with...
logger.debug(f'interest_rates.columns before renaming... \n{list(interest_rat
interest_rates = interest_rates.rename(index=str, columns={'Federal Funds Tar
                                                           'Federal Funds Uppe
                                                           'Federal Funds Lowe
                                                           'Effective Federal
                                                           'Real GDP (Percent
                                                           'Unemployment Rate'
                                                           'Inflation Rate':'I
logger.debug(f'interest_rates.columns after renaming... \n{list(interest_rate
```

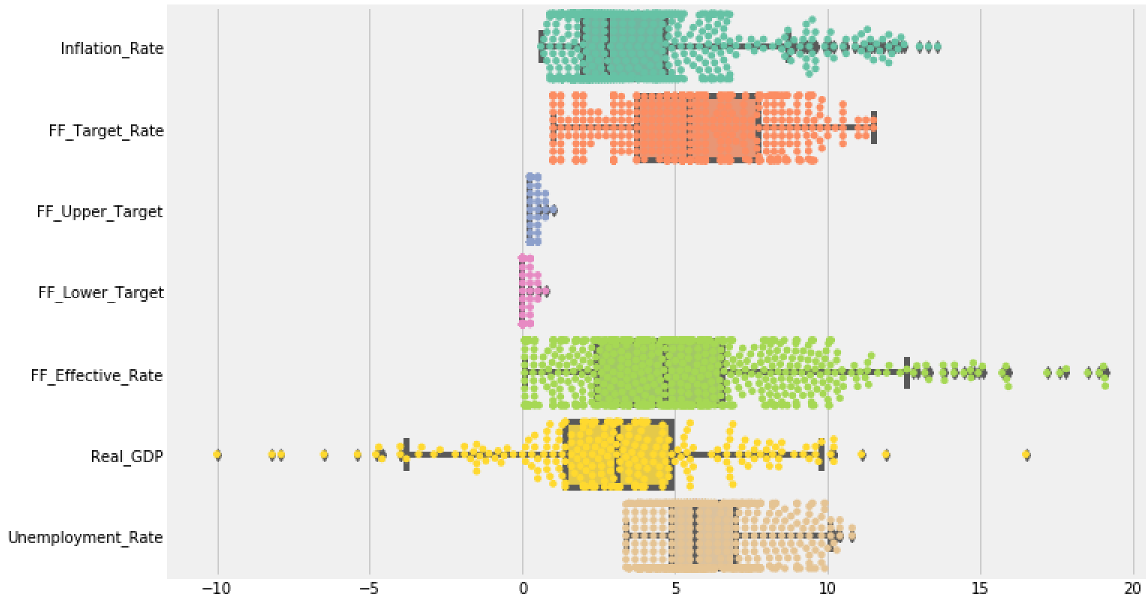
In [26]:
```
# INTEREST RATE DATASET
plt.figure(figsize=(8,5))
rt.plot_corr_heatmap(interest_rates,interest_rates.drop(columns=['Year', 'Mor
```

```
<Figure size 576x360 with 0 Axes>
```



A look at the datasets distributions of elements to determin best methods for cleaning the data

In [28]:
```
# look at distributions of dataset elements, determin best methods for cleani
cols =['Inflation_Rate','FF_Target_Rate', 'FF_Upper_Target', 'FF_Lower_Target
plt.figure(figsize=(10.5,7))
sns.boxplot(data=interest_rates[cols], orient='h',palette='Set2');
sns.swarmplot(data=interest_rates[cols], orient='h',palette='Set2');
plt.show()
```



ECONOMIC DATASETS - DATAHUB.IO

- Datasets:
  - Interest Rate:
    - keep Year, Month, Federal Funds Target Rate
  - Inflation Consumer:
    - filter on Country = 'United States', keep Year, Inflation - drop the rest
  - GDP Year:
    - Change column names

This process continuous for the remainder of the datasets. See accompaning notebook for details.

In [58]:
```
# interest_rates
# interest rate -  keep Year, Month, Federal Funds Target Rate - get rid of t
ir = interest_rates_dh[~interest_rates_dh['Federal Funds Target Rate'].isna()
ir = ir[['Year','Month','Federal Funds Target Rate']]
ir = ir.rename(index=str, columns={'Federal Funds Target Rate':'FF_Target_Rat
logger.debug(ir.Year.unique())
ec_datasets['Interest_Rate_Month'] = ir
#ir.head()
```

In [53]:
```
# interest_rates - average by year
ir_y = pd.DataFrame(ir.groupby('Year').mean()['FF_Target_Rate'])
ir_y = ir_y.rename(index=str, columns={'FF_Target_Rate':'FF_Target_Rate_Avg'}
ir_y = ir_y.reset_index()
ec_datasets['Interest_Rate_Year'] = ir_y
#ir_y.head()
```

In [59]:
```
# inflation_consumer - filter on Country = 'United States', keep Year, Inflat
ic = inflation_consumer[inflation_consumer.Country.str.contains('United State
ic = ic[['Year','Inflation']]
ec_datasets['Inflation_Year'] = ic
#ic.head()
```

In [60]:
```
# gdp_year
'''
level-current -> GDP in billions of current dollars
change-current -> GDP percent change based on current dollars
'''
gdp_y = gdp_year[['date','level-current','change-current']]
gdp_y = gdp_y.rename(index=str, columns={'date':'Year', 'level-current':'GDP'
ec_datasets['GDP_Year'] = gdp_y
#gdp_y.head()
```

In [62]:
```
# gdp_quarter
gdp_q = gdp_quarter[['date','level-current','change-current']]
gdp_q = gdp_q.rename(index=str, columns={'date':'Date', 'level-current':'GDP'
gdp_q['Date'] = pd.to_datetime(gdp_q['Date'])
gdp_q['Year'], gdp_q['Month'] = gdp_q['Date'].dt.year, gdp_q['Date'].dt.month
gdp_q = gdp_q.drop(columns=['Date'])
gdp_q = gdp_q[['Year','Month','GDP','GDP_Percent_Change']]

ec_datasets['GDP_Quarter'] = gdp_q
#gdp_q.head()
```

In [63]:
```
# create a gdp_monthly by averaging the quarterly for the year

# TODO - need to group by year, then quarter, take average and span that over

gdp_m = pd.DataFrame(gdp_q.groupby('Year', as_index=False)['GDP','GDP_Percent
gdp_m = gdp_m.rename(index=str, columns={'GDP':'GDP_Avg', 'GDP_Percent_Change

ec_datasets['GDP_Month'] = gdp_m
#gdp_m.head()
```

In [64]:

```
# education_budget
'''
United States of America education budget analysis
United States of America Education budget to GDP analysis Data Data comes fro
BUDGET_ON_EDUCATION -> budget in millions of dollars
GDP -> GDP in millions of dollars
RATIO -> education expendature / GDP in percentage
'''
logger.debug(f'education budget, before... \n{education_budget.head()}')
eb = education_budget[['YEAR','BUDGET_ON_EDUCATION']]
eb = eb.rename(index=str, columns={'YEAR':'Year', 'BUDGET_ON_EDUCATION':'Educ
logger.debug(f'education budget, after... \n{eb.head()}')

ec_datasets['Eduction_Budget'] = eb
#eb.head()
```

In [65]:

```
# population
'''
Population figures for countries, regions (e.g. Asia) and the world.
'''
# population - keep Year, Value - drop the rest
pop = population[population['Country Name'].str.contains('United States')]
pop = pop[['Year','Value']]
pop = pop.rename(index=str, columns={'Value':'Population'})
ec_datasets['Population'] = pop
#pop.head()
```

In [66]:

```
# investor_flow_monthly
'''
Monthly net new cash flow by US investors into various mutual fund investment
'''
logger.debug(f'us investor flow monthly ... {investor_flow_monthly.head()}')

ifm_t = investor_flow_monthly[['Date','Total']]
ifm_t = ifm_t.rename(index=str, columns={'Total':'Investor_Flow'})
ifm_t['Date'] = pd.to_datetime(ifm_t['Date'])
ifm_t['Year'], ifm_t['Month'] = ifm_t['Date'].dt.year, ifm_t['Date'].dt.month

ifm_t = ifm_t[['Year','Month','Investor_Flow']]
logger.debug(f'us investor flow monthly total ... {investor_flow_monthly.head

ec_datasets['Investor_Flow_Month'] = ifm_t
#ifm_t.head()
```

In [67]:

```
# investor_flow_monthly - average out to yea
ifm_t_y = pd.DataFrame(ifm_t.groupby('Year').mean()['Investor_Flow'])
ifm_t_y = ifm_t_y.rename(index=str, columns={'Investor_Flow':'Investor_Flow_A
ifm_t_y = ifm_t_y.reset_index()

ec_datasets['Investor_Flow_Year'] = ifm_t_y
#ifm_t_y.head()
```

In [68]:

```
# housing_price_city
'''
US House Price Index (Case-Shiller) - narrow down to national index
'''
logger.debug(f'US House Price Index ... {housing_price_cities.head()}')

hp_index_m = housing_price_cities[['Date','National-US']]
hp_index_m = hp_index_m.rename(index=str, columns={'National-US':'National_Ho
hp_index_m['Date'] = pd.to_datetime(hp_index_m['Date'])
hp_index_m['Year'], hp_index_m['Month'] = hp_index_m['Date'].dt.year, hp_inde
hp_index_m = hp_index_m[['Year','Month','National_House_Price_Index']]

ec_datasets['Houseing_Price_Index_Month'] = hp_index_m
#hp_index_m.head()
```

In [69]:

```
# housing_price_city - aggregate to yearly average price index
hp_idex_y = pd.DataFrame(hp_index_m.groupby('Year').mean()['National_House_Pr
hp_idex_y = hp_idex_y.rename(index=str, columns={'National_House_Price_Index'
hp_idex_y = hp_idex_y.reset_index()

ec_datasets['Houseing_Price_City_Year'] = hp_idex_y
#hp_idex_y.head()
```

In [70]:

```
# household_income - keep Year, Number(thousands), Top 5 percent
'''

'''
logger.debug(f'{household_income.head()}')
hh_i = household_income[['Year','Number (thousands)']]
hh_i = hh_i.rename(index=str, columns={'Number (thousands)':'House_Hold_Incom
hh_i = hh_i.sort_values('Year')

ec_datasets['House_Hold_Income_Year'] = hh_i
#hh_i.head()
```

In [71]:

```
# employment
'''
US Employment and Unemployment rates since 1940. Official title:
*Employment status of the civilian noninstitutional population, 1940 to date*
'''
logger.debug(f'employment ... {employment.head()}')
emp = employment[['year','employed_total','employed_percent','unemployed','ur
emp = emp.rename(index=str, columns={'year':'Year','employed_total':'Employed

ec_datasets['Employment_Year'] = emp
#emp.head()
```

In [77]:

```
# cpi
'''
Consumer Price Index for All Urban Consumers (CPI-U) from U.S. Department Of
This is a monthly time series from January 1913. Values are U.S. city average
'''
#logger.debug(f'cpi ... {cpi.head()}')
cpi_m = cpi[['Date','Index']]
cpi_m['Date'] = pd.to_datetime(cpi_m['Date'])
cpi_m['Year'], cpi_m['Month'] = cpi_m['Date'].dt.year, cpi_m['Date'].dt.month
cpi_m = cpi_m.rename(index=str, columns={'Index':'CPI_Index'})
cpi_m = cpi_m[['Year','Month','CPI_Index']]

ec_datasets['Consumer_Price_Index_Month'] = cpi_m
#cpi_m.head()
```

In [78]:

```
# cpi - yearly average
cpi_y = pd.DataFrame(cpi_m.groupby('Year').mean()['CPI_Index'])
cpi_y = cpi_y.rename(index=str, columns={'CPI_Index':'CPI_Index_Avg'})
cpi_y = cpi_y.reset_index()

ec_datasets['Consumer_Price_Index_Year'] = cpi_y
#cpi_y.head()
```

In [79]:

```
# cash_surp_def
'''

'''
csd = cash_surp_def[cash_surp_def['Country Name'].str.contains('United States
csd = csd[['Year','Value']]
csd = csd.rename(index=str, columns={'Value':'Cash_Surp_Def'})

ec_datasets['Cash_Surpluse_Defesit_Year'] = csd
#csd.head()
```

In [80]:

```
# bonds_yeilds_10y
'''
10 year US Government Bond Yields (long-term interest rate)
10 year nominal yields on US government bonds from the Federal Reserve.
The 10 year government bond yield is considered a standard indicator of long-
'''
logger.debug(f'bonds yeilds 10y:\n{bonds_yeilds_10y.head()}')

by_10y_m = bonds_yeilds_10y[['Date','Rate']]
by_10y_m['Date'] = pd.to_datetime(by_10y_m['Date'])
by_10y_m['Year'], by_10y_m['Month'] = by_10y_m['Date'].dt.year, by_10y_m['Dat
by_10y_m = by_10y_m[['Year','Month','Rate']]
by_10y_m = by_10y_m.rename(index=str, columns={'Rate':'Bond_Yield_10y'})

ec_datasets['Bonds_Yeilds_10y_Month'] = by_10y_m
#by_10y_m.head()
```

In [81]:
```
# bonds_yeilds_10y - averaged over the year
by_10y_y = pd.DataFrame(by_10y_m.groupby('Year').mean()['Bond_Yield_10y'])
by_10y_y = by_10y_y.rename(index=str, columns={'Bond_Yield_10y':'Bond_Yield_1
by_10y_y = by_10y_y.reset_index()

ec_datasets['Bonds_Yeilds_10y_Year'] = by_10y_y
#by_10y_y.head()
```

In [82]:
```
# merge tables by year - basd on the smallest range in the dataset, this is l
ir_y['Year'] = ir_y['Year'].astype(str)
ic['Year'] = ic['Year'].astype(str)
gdp_y['Year'] = gdp_y['Year'].astype(str)
eb['Year'] = eb['Year'].astype(str)
pop['Year'] = pop['Year'].astype(str)
ifm_t_y['Year'] = ifm_t_y['Year'].astype(str)
hp_idex_y['Year'] = hp_idex_y['Year'].astype(str)
hh_i['Year'] = hh_i['Year'].astype(str)
emp['Year'] = emp['Year'].astype(str)
cpi_y['Year'] = cpi_y['Year'].astype(str)
csd['Year'] = csd['Year'].astype(str)
by_10y_y['Year'] = by_10y_y['Year'].astype(str)


ir['Year'] = ir['Year'].astype(str)
gdp_m['Year'] = gdp_m['Year'].astype(str)
ifm_t['Year'] = ifm_t['Year'].astype(str)
hp_index_m['Year'] = hp_index_m['Year'].astype(str)
cpi_m['Year'] = cpi_m['Year'].astype(str)
by_10y_m['Year'] = by_10y_m['Year'].astype(str)

#ir_y.head()
```

In [84]:
```
# merge tables by year - basd on the smallest range in the dataset, this is l
d = pd.merge(ir_y, ic, on='Year', how='left')
d = pd.merge(d, gdp_y, on='Year', how='left')
d = pd.merge(d, eb, on='Year', how='left')
d = pd.merge(d, pop, on='Year', how='left')
d = pd.merge(d, ifm_t_y, on='Year', how='left')
d = pd.merge(d, hp_idex_y, on='Year', how='left')
d = pd.merge(d, hh_i, on='Year', how='left')
d = pd.merge(d, emp, on='Year', how='left')
d = pd.merge(d, cpi_y, on='Year', how='left')
d = pd.merge(d, csd, on='Year', how='left')
d = pd.merge(d, by_10y_y, on='Year', how='left')

economicDf_year = d

del d

# save df as new data source
save_as = f'{dataDir}/economic_yearly_data.csv'
economicDf_year.to_csv(save_as,index=False)
```

Merged Dataframe of Economic features aggregated from their individual source files

In [85]:
```
economicDf_year.head()
```

Out[85]:

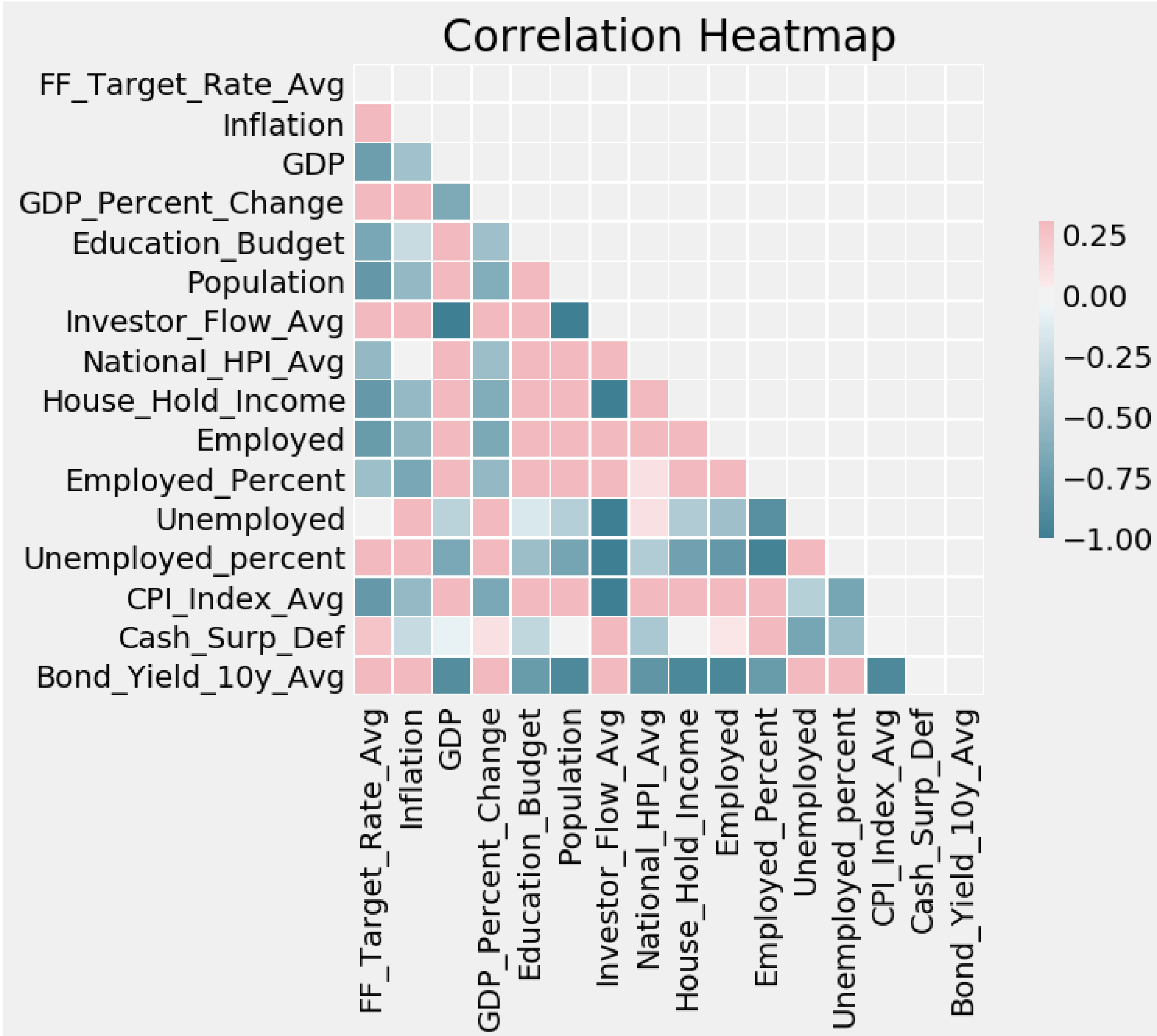
	Year	FF_Target_Rate_Avg	Inflation	GDP	GDP_Percent_Change	Education_Budget	Po
0	1982	9.392857	6.203740	3345.0	8.8	15374.0	2316
1	1983	9.053125	3.948367	3638.1	11.1	15267.0	2337
2	1984	10.150000	3.548237	4040.7	7.6	15336.0	2358
3	1985	8.044643	3.199612	4346.7	5.6	18952.0	2379
4	1986	6.740132	2.017624	4590.2	6.1	17750.0	2401

In [86]:
```
try:
    del gdp_year,gdp_y,gdp_quarter,gdp_q,gdp_m,eb,ir,ir_y,ic,education_budget
    investor_flow_monthly,
    housing_price_cities,
    household_income,
    employment,
    cpi,
    cash_surp_def,
    bonds_yeilds_10y,
    ifm_t,
    ifm_t_y,
    hp_index_m,
    hp_idex_y,
    hh_i,
    emp,
    cpi_m,
    cpi_y,
    csd,
    by_10y_m,
    by_10y_y,
    datasets_to_merge_year,
    datasets_to_merge_month
except:
    pass
```

Correlation Heatmap of the new Economic Dataset's features

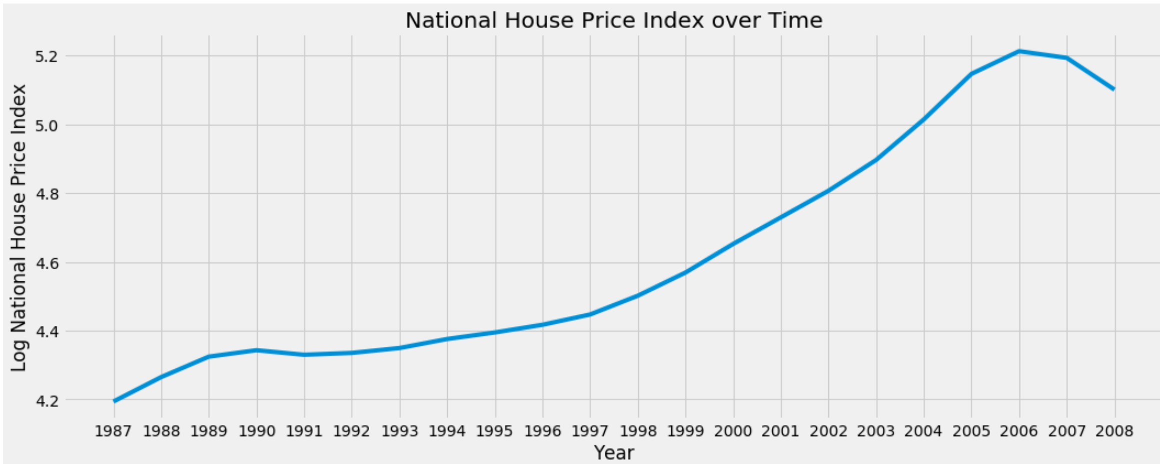
In [90]:

```
#plt.figure(figsize=(12,8))
rt.plot_corr_heatmap(economicDf_year,economicDf_year.drop(columns=['Year']).c
#plt.show()
```



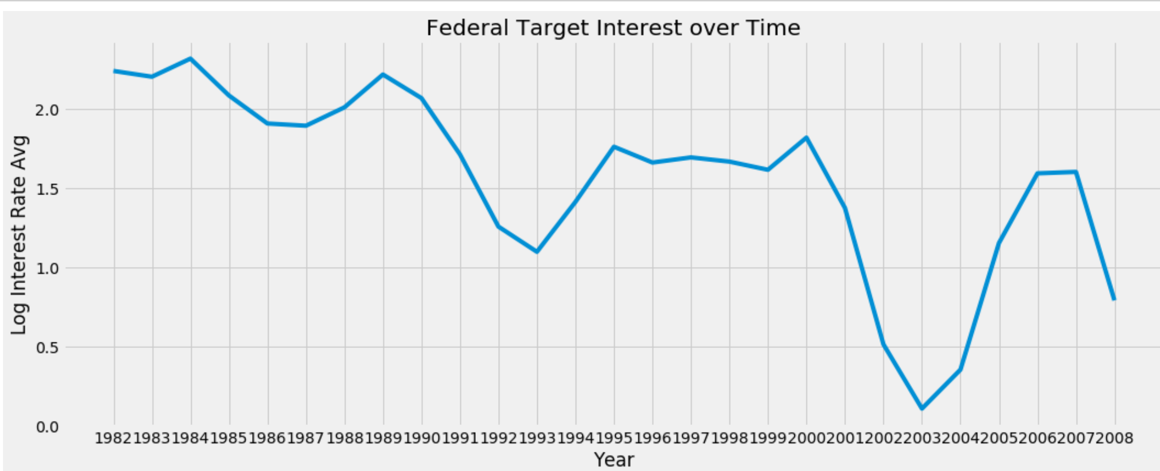
In [91]:

```
p = economicDf_year
p['National_HPI_Avg'] = np.log(p['National_HPI_Avg'])
plt.figure(figsize=(16,6))
ax = sns.lineplot(x='Year',y='National_HPI_Avg',data=p)
plt.title('National House Price Index over Time')
plt.ylabel('Log National House Price Index')

plt.show()
del p
```

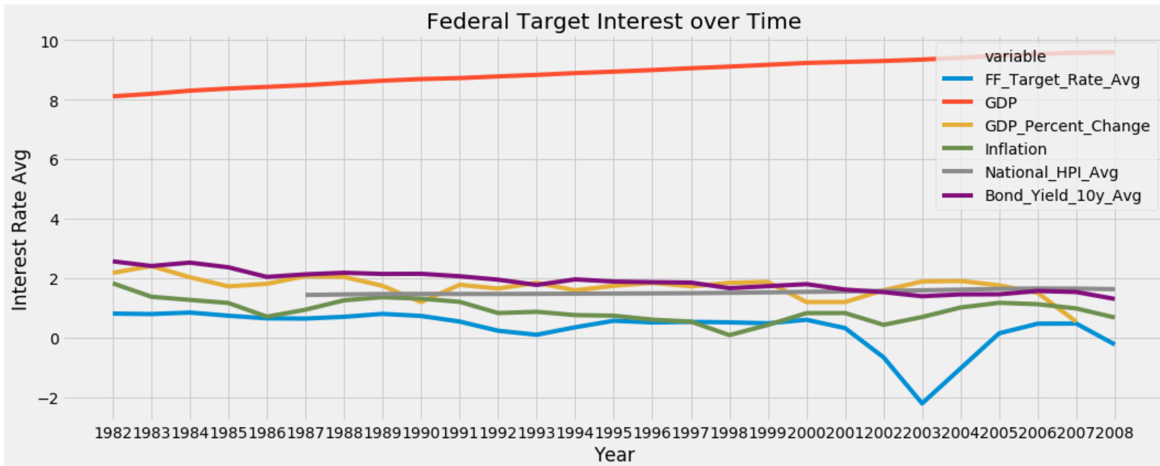


In [92]:

```
p = economicDf_year
p['FF_Target_Rate_Avg'] = np.log(p['FF_Target_Rate_Avg'])
plt.figure(figsize=(16,6))
ax = sns.lineplot(x='Year',y='FF_Target_Rate_Avg',data=p)
plt.title('Federal Target Interest over Time')
plt.ylabel('Log Interest Rate Avg')

plt.show()
del p
```



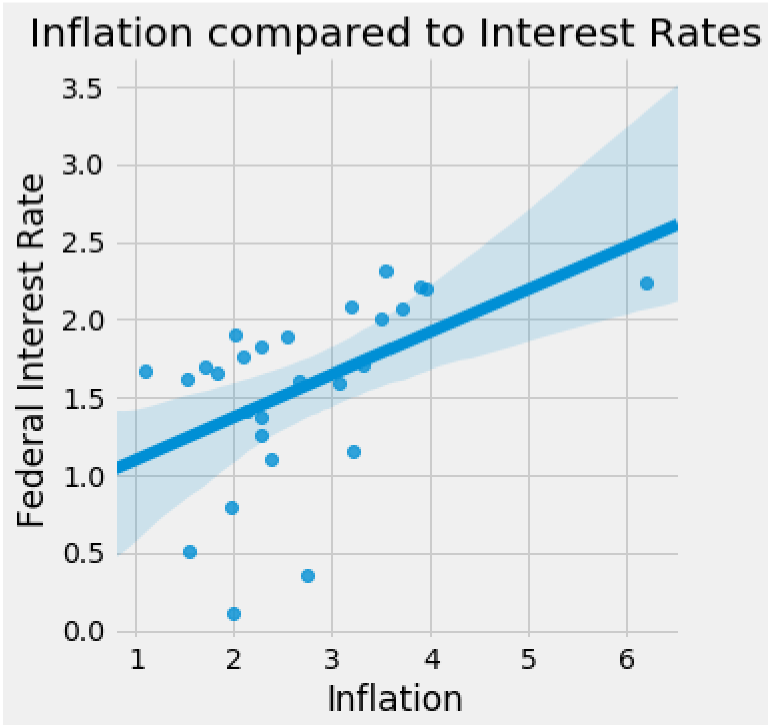
In [93]:
```
factors = ['Year','FF_Target_Rate_Avg','GDP','GDP_Percent_Change','Inflation'
melt = pd.melt(economicDf_year[factors], ['Year'])
melt['value'] = np.log(melt['value'])
plt.figure(figsize=(16,6))
sns.lineplot(x='Year',y='value',hue='variable',
             data=melt)


plt.title('Federal Target Interest over Time')
plt.ylabel('Interest Rate Avg')
plt.show()
del melt
```



In [94]:

```
plt.figure(figsize=(16,6))
sns.lmplot(x='Inflation',y='FF_Target_Rate_Avg',data=economicDf_year)
plt.title('Inflation compared to Interest Rates')
plt.xlabel('Inflation')
plt.ylabel('Federal Interest Rate')
plt.show();
```

```
<Figure size 1152x432 with 0 Axes>
```

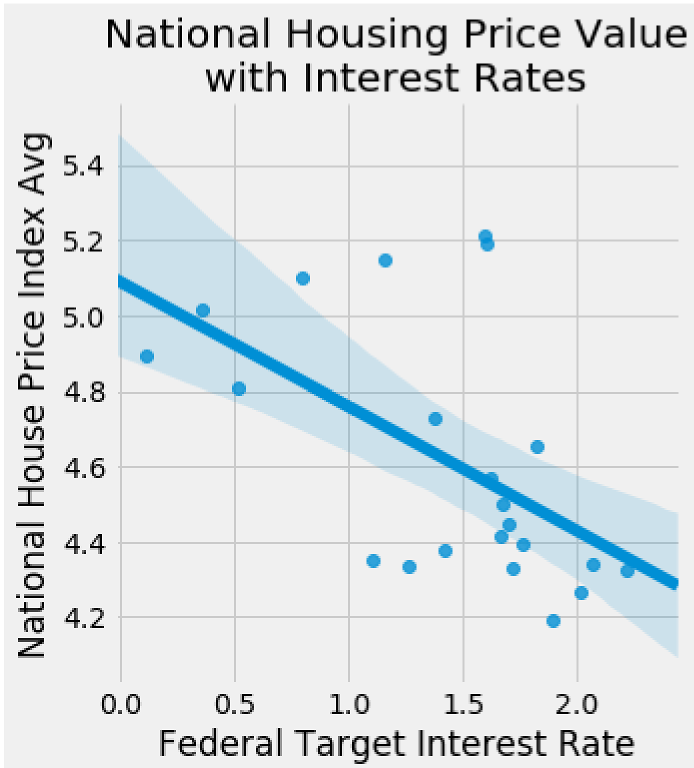


Impacts of Economic Factors on National Housing Price Index Avg

In [95]:

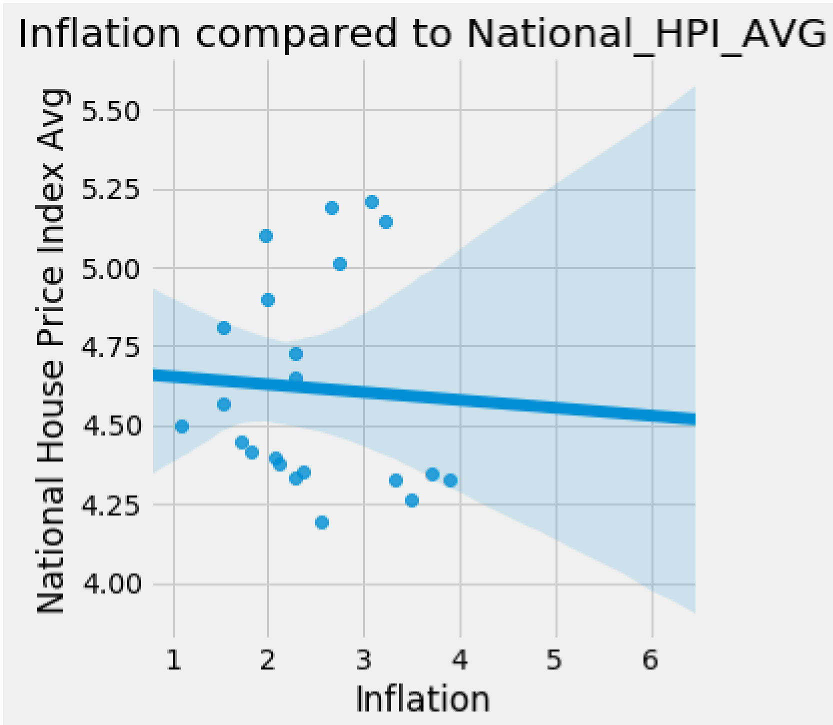
```
plt.figure(figsize=(16,6))
sns.lmplot(x='FF_Target_Rate_Avg',y='National_HPI_Avg',data=economicDf_year)
plt.title('National Housing Price Value\nwith Interest Rates')
plt.xlabel('Federal Target Interest Rate')
plt.ylabel('National House Price Index Avg')
plt.show();
```

```
<Figure size 1152x432 with 0 Axes>
```



In [96]:
```
plt.figure(figsize=(16,6))
sns.lmplot(x='Inflation',y='National_HPI_Avg',data=economicDf_year)
plt.title('Inflation compared to National_HPI_AVG')
plt.xlabel('Inflation')
plt.ylabel('National House Price Index Avg')
plt.show();
```

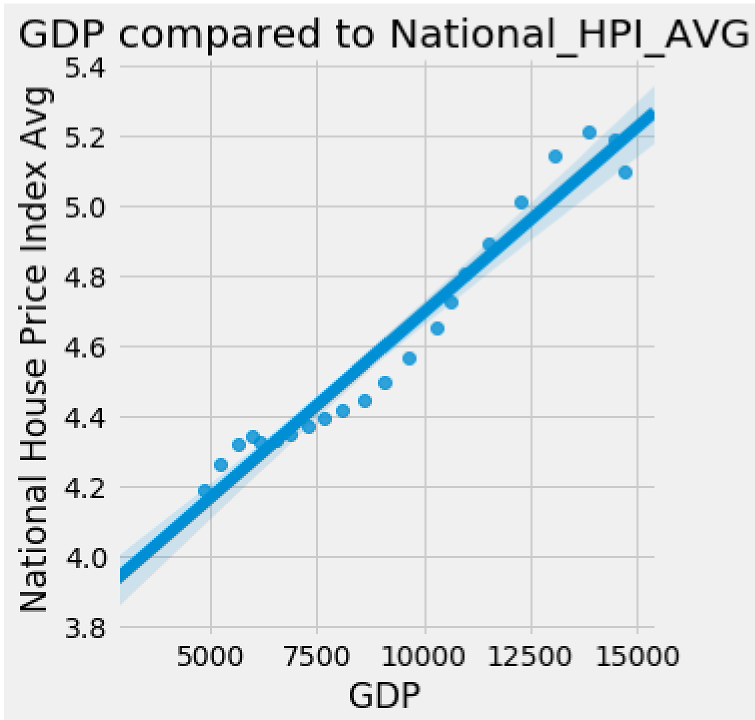
```
<Figure size 1152x432 with 0 Axes>
```



In [97]:

```
plt.figure(figsize=(16,6))
sns.lmplot(x='GDP',y='National_HPI_Avg',data=economicDf_year)
plt.title('GDP compared to National_HPI_AVG')
plt.xlabel('GDP')
plt.ylabel('National House Price Index Avg')
plt.show();
```

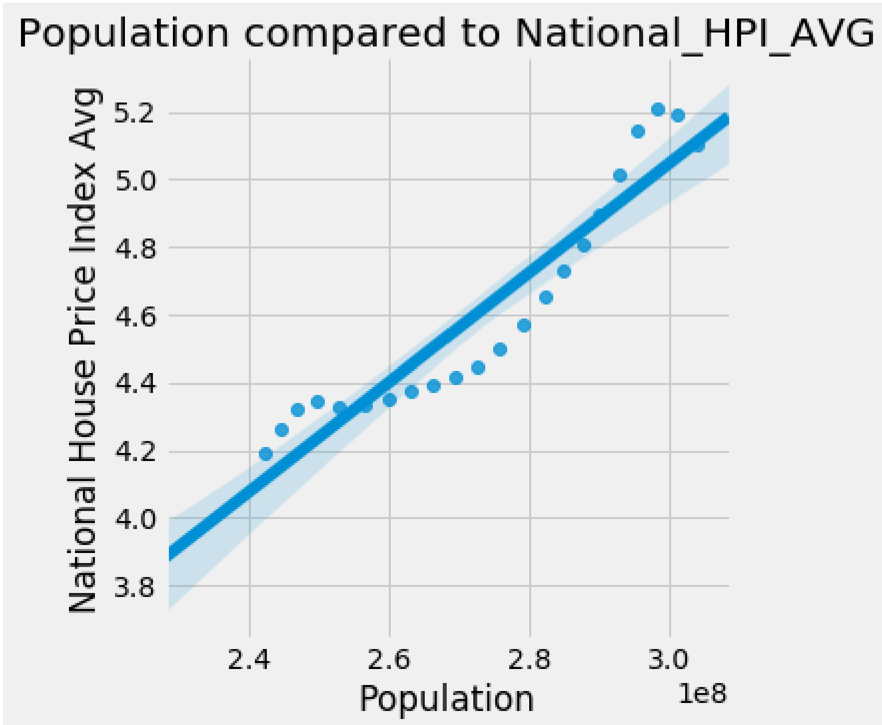
```
<Figure size 1152x432 with 0 Axes>
```



In [102]:

```
plt.figure(figsize=(12,6));
sns.lmplot(x='Population',y='National_HPI_Avg',data=economicDf_year);
plt.title('Population compared to National_HPI_AVG')
plt.xlabel('Population')
plt.ylabel('National House Price Index Avg')
plt.show();
```

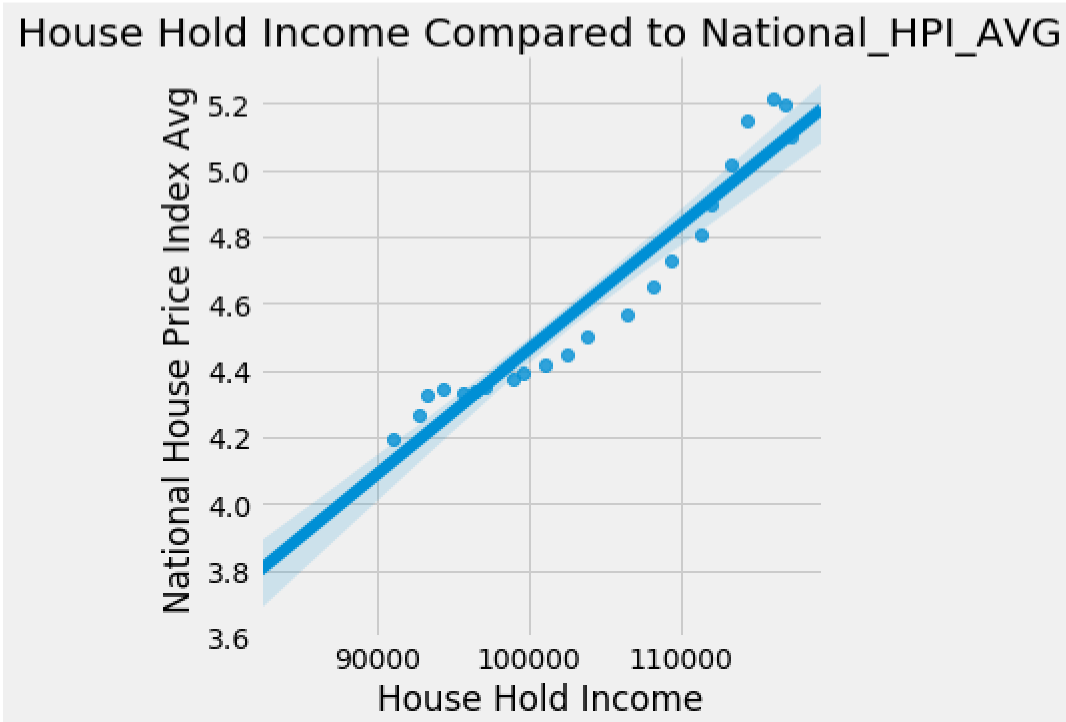
```
<Figure size 864x432 with 0 Axes>
```



In [103]:

```
plt.figure(figsize=(12,6))
sns.lmplot(x='House_Hold_Income',y='National_HPI_Avg',data=economicDf_year)
plt.title('House Hold Income Compared to National_HPI_AVG')
plt.xlabel('House Hold Income')
plt.ylabel('National House Price Index Avg')
plt.show();
```

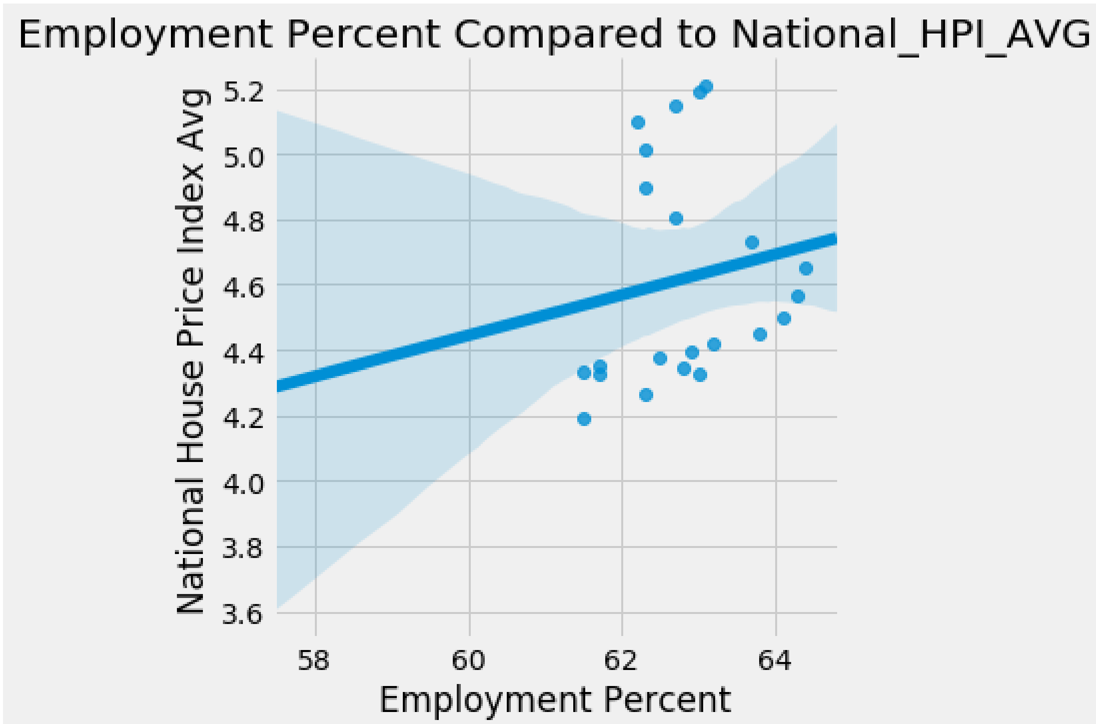
```
<Figure size 864x432 with 0 Axes>
```



In [104]:

```
plt.figure(figsize=(16,6))
sns.lmplot(x='Employed_Percent',y='National_HPI_Avg',data=economicDf_year)
plt.title('Employment Percent Compared to National_HPI_AVG')
plt.xlabel('Employment Percent')
plt.ylabel('National House Price Index Avg')
plt.show();
```

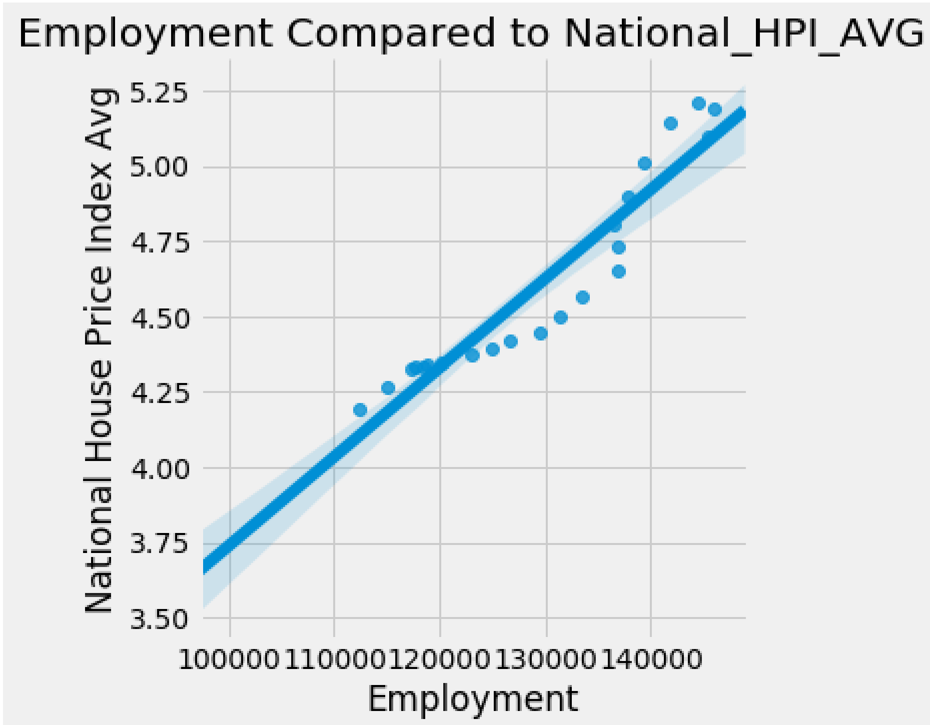
```
<Figure size 1152x432 with 0 Axes>
```



In [105]:

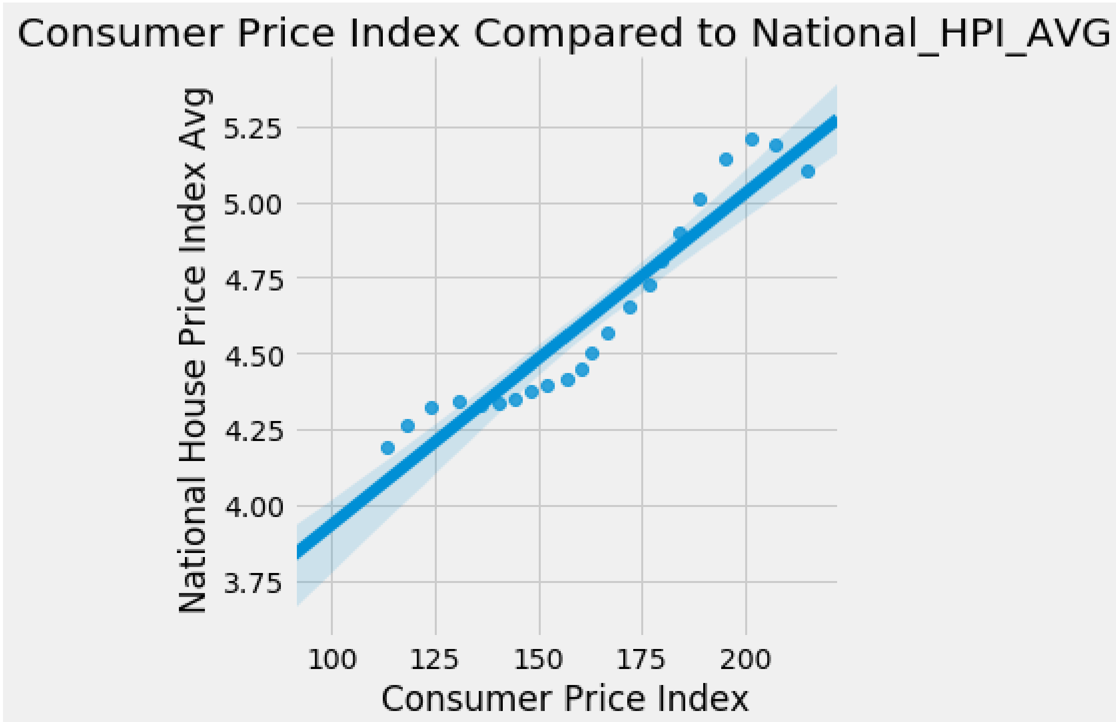
```
plt.figure(figsize=(16,6))
sns.lmplot(x='Employed',y='National_HPI_Avg',data=economicDf_year)
plt.title('Employment Compared to National_HPI_AVG')
plt.xlabel('Employment')
plt.ylabel('National House Price Index Avg')
plt.show();
```

```
<Figure size 1152x432 with 0 Axes>
```



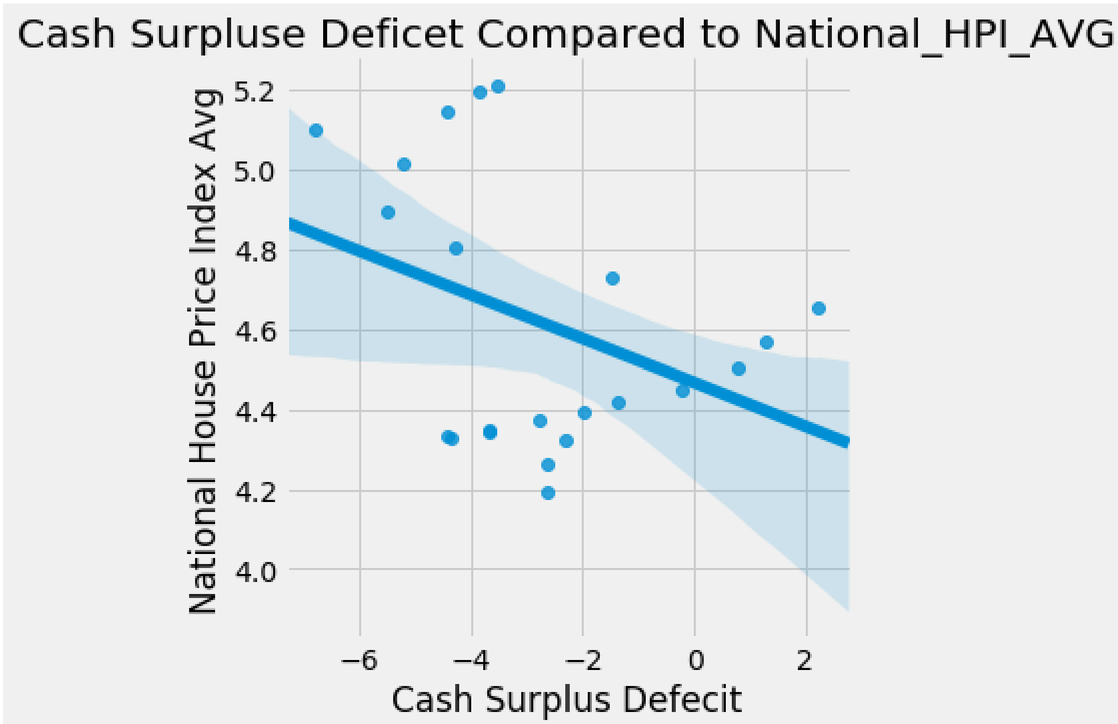
In [106]:
```
plt.figure(figsize=(16,6))
sns.lmplot(x='CPI_Index_Avg',y='National_HPI_Avg',data=economicDf_year)
plt.title('Consumer Price Index Compared to National_HPI_AVG')
plt.xlabel('Consumer Price Index')
plt.ylabel('National House Price Index Avg')
plt.show();
```

```
<Figure size 1152x432 with 0 Axes>
```



In [107]:
```
plt.figure(figsize=(16,6))
sns.lmplot(x='Cash_Surp_Def',y='National_HPI_Avg',data=economicDf_year)
plt.title('Cash Surpluse Deficet Compared to National_HPI_AVG')
plt.xlabel('Cash Surplus Defecit')
plt.ylabel('National House Price Index Avg')
plt.show();
```

```
<Figure size 1152x432 with 0 Axes>
```



2. Time Series Analysis

Time series analysis on real estate median average price by zipcode

- Single Family Home Value
- Rental Price psf
- Listing Price Create future prediction models for all WA State zipcodes historical monthly housing price values.

2.1 Analysis

Transform Data

Transform Real Estate data for time series analysis

In [109]:
```
# Transform Datasets for Prophet Timeseries Analysis
# training datasets
re_datasets_train_prophet = {}
for k,v in re_datasets_train.items():
    re_datasets_train_prophet[k] = brs.dfTransformForProphet(v,['State'],'Zip

# validation datasets
re_datasets_validate_prophet = {}
for k,v in re_datasets_validate.items():
    re_datasets_validate_prophet[k] = brs.dfTransformForProphet(v,['State'],'

# full datasets
re_datasets_full_prophet = {}
for k,v in re_datasets.items():
    re_datasets_full_prophet[k] = brs.dfTransformForProphet(v,['State'],'ZipC
```

In [110]:
```
sfr_price_zipcode_date = re_datasets['Single_Family_Residence'].drop(columns=
sfr_price_zipcode_date_t = sfr_price_zipcode_date.set_index('ZipCode')
sfr_price_zipcode_date_t = sfr_price_zipcode_date_t.T
```

In [111]:
```
#sfr_price_zipcode_date_t.head()

# reset index - bring date up as feature
sfr_price_zip = sfr_price_zipcode_date_t.reset_index()
sfr_price_zip = sfr_price_zip.rename(columns={'index':'Date'})
sfr_price_zip['Date'] = pd.to_datetime(sfr_price_zip['Date'])
sfr_price_zip.head()

# save to file
# save df as new data source
save_as = f'{dataDir}/sfr_price_zip.csv'
sfr_price_zip.to_csv(save_as,index=False)
```

2.2 Exploration

In [112]:
```
# have a look over the datasets shape after transformation
for k,v in re_datasets_train_prophet.items():
    logger.info(f'{k} shape: {v.shape}')

for k,v in re_datasets_validate_prophet.items():
    logger.info(f'{k} shape: {v.shape}')

for k,v in re_datasets_full_prophet.items():
    logger.info(f'{k} shape: {v.shape}')
```

```
INFO:file_logger:Single_Family_Residence shape: (252, 351)
INFO:file_logger:All_Homes shape: (252, 353)
INFO:file_logger:RentalPrice_PSF shape: (95, 66)
INFO:file_logger:RentalPrice_All_Homes shape: (95, 82)
INFO:file_logger:ListingPrice_All_Homes shape: (96, 261)
INFO:file_logger:Single_Family_Residence shape: (12, 351)
INFO:file_logger:All_Homes shape: (12, 353)
INFO:file_logger:RentalPrice_PSF shape: (12, 66)
INFO:file_logger:RentalPrice_All_Homes shape: (12, 82)
INFO:file_logger:ListingPrice_All_Homes shape: (12, 261)
INFO:file_logger:Single_Family_Residence shape: (264, 351)
INFO:file_logger:All_Homes shape: (264, 353)
INFO:file_logger:RentalPrice_PSF shape: (107, 66)
INFO:file_logger:RentalPrice_All_Homes shape: (107, 82)
INFO:file_logger:ListingPrice_All_Homes shape: (108, 261)
```

2.3 Model

Note: All timeseries models were ran prior on google colab and saved as pickle files for continued downstream application

In [114]:

```
# perform ZipCod model creation and validation techniques
# build time series models
# perform exploratory data analysis techiques
# Build prophet timeseries models for the metro area, save to dictionary obje
#


#zipCodeModels = {}
#t = 0.0
#trainDir = 'train'

#make directories
#for k in datasets.keys():
#    if not os.path.exists(f'{modelDir}/{trainDir}/{k}'):
#        os.makedirs(f'{modelDir}/{trainDir}/{k}')


#with rt.elapsed_timer() as elapsed:

#    for k,v in datasets_train_prophet.items():
#        logger.info(f'Starting... {k} prophet modeling... elapsed time: {ela

#        for zipcode, price in tqdm(v.items()):
#            logger.info(f'Starting... {zipcode} prophet modeling... elapsed 
#            model = brs.beProphet(zipcode,price,f'{modelDir}/{trainDir}/{k}/

#    logger.info(f'total elapsed time: {elapsed()}')
```

In [115]:

```
#make directories
#for k in datasets.keys():
    #if not os.path.exists(f'{imageDir}/{trainDir}/{k}'):
      # os.makedirs(f'{imageDir}/{trainDir}/{k}')
```

In [116]:

```
# train and predict future zipcode performance

#zipCodeModels = {}
#t = 0.0
#future5Dir = 'future_5'
# time series model projection time
#ts_pred_periods = 12*5

#make directories
#for k in datasets.keys():
#    if not os.path.exists(f'{modelDir}/{future5Dir}/{k}'):
#        os.makedirs(f'{modelDir}/{future5Dir}/{k}')

#
#with rt.elapsed_timer() as elapsed:

#    for k,v in datasets_full_prophet.items():
#        logger.info(f'Starting... {k} prophet modeling... elapsed time: {ela

#        for zipcode, price in v.items():
#            logger.info(f'Starting... {zipcode} prophet modeling... elapsed
#            model = brs.beProphet(zipcode,price,f'{modelDir}/{future5Dir}/{k

#    logger.info(f'total elapsed time: {elapsed()}')
```

In [117]:

```
#ec_datasets.keys()
```

In [119]:

```
# store economic prediction models
#ec_prophet_models = {}
```

In [118]:

```
#c = ec_datasets['Cash_Surpluse_Defesit_Year']
#c['Date'] = pd.to_datetime(c.Year.astype(str)+'-'+c.Month.astype(str))
#c['Date'] = pd.to_datetime(c.Year)
#c = c.drop(columns=['Year','Month'])
#c = c.drop(columns=['Year'])
#c['Cash_Surp_Def'] = np.log(c['Cash_Surp_Def'])
#c.tail()
```

In [120]:
```
#model_ds = 'Cash_Surp_Def'
#end_date = '2023-11-30'
#inf = c
#inf = inf.rename(index=str, columns={'Date':'ds', 'Cash_Surp_Def':'y'})
#predPeriods = (12*5) # monthly
#predPeriods = 10   # yearly

# setting uncertainty interval to 95%
#model = Prophet(interval_width=0.95)
#model_fit = model.fit(inf)
#ec_prophet_models[f'{model_ds}_model_fit'] = model_fit

# make future dates dataframe
#future_dates = model.make_future_dataframe(periods=predPeriods, freq='Y', ir

# model forecast
#forecast = model.predict(future_dates)
#ec_prophet_models[f'{model_ds}_model_forecast'] = forecast


#save model to file
#with open(f'{modelDir}/{model_ds}_fit','wb') as f:
#    pickle.dump(model,f)

#with open(f'{modelDir}/{model_ds}_forecast','wb') as f:
#    pickle.dump(forecast,f)
```

In [121]:
```
#forecast[['ds', 'yhat', 'yhat_lower', 'yhat_upper']].tail(10)
#forecast.shape
```

In [123]:
```
#title = 'Cash_Surp_Def'
#plt.figure(figsize=(20,15))
#p_fit = model_fit.plot(forecast,uncertainty=True)
#ax = p_fit.get_axes()
#ax[0].set_title('Prophet Forcast', fontsize="15", color="black", horizontala
#ax[0].set_xlabel('ZipCode: '+zipcode+' | '+'Date')
#ax[0].set_ylabel('')

#plt.savefig(imageDir+'/'+title+'_fit_plot.png')
#plt.show()


#pc_fit = model_fit.plot_components(forecast)
#ax = pc_fit.get_axes()
#ax[0].set_title(title)
#ax[0].set_xlabel('ZipCode: '+zipcode+' | '+'Date')
#ax[0].set_ylabel('Log Mean Home Prices')
#plt.figure(figsize=(16,6))
#plt.savefig(imageDir+'/'+title+'_fit_component_plot.png')
#plt.show()
```

In [124]:

```
#ec_prophet_models
# build data frame from forecasted economic factors
#ec_forecast_df = {}
#for k,v in ec_prophet_models.items():
    #print(k)
#    if 'forecast' in k:
#        ec_forecast_df[k] = v[['ds','yhat']]
        #print(v.head())
```

In [128]:

```
#*Read Models From File System*
#ec_forecast_df.keys()
```

In [127]:

```
# FEATURE ENGINEERING OF MISSING ECONOMIC TIME SERIES DATA - FORECAST PRODUCE
#
# rename the yhat attributes to feature names
#start_date = pd.to_datetime('1997-01-01')

#cpi = ec_forecast_df['cpi_model_forecast']
#cpi = cpi.rename(columns={'yhat':'CPI_Index_Avg_f', 'ds':'Date'})
#mask = (cpi.Date >= start_date)
#cpi = cpi[mask]
#ec_forecast_df['cpi_model_forecast'] = cpi

#ir = ec_forecast_df['interest_rate_model_forecast']
#ir = ir.rename(columns={'yhat':'Interest_Rate_f', 'ds':'Date'})
#mask = (ir.Date >= start_date)
#ir = ir[mask]
#ec_forecast_df['interest_rate_model_forecast'] = ir

#ifm = ec_forecast_df['investor_flow_model_forecast']
#ifm = ifm.rename(columns={'yhat':'Investor_Flow_f', 'ds':'Date'})
#mask = (ifm.Date >= start_date)
#ifm = ifm[mask]
#ec_forecast_df['investor_flow_model_forecast'] = ifm

#hpi = ec_forecast_df['housing_price_index_model_forecast']
#hpi = hpi.rename(columns={'yhat':'Housing_Price_Index_f', 'ds':'Date'})
#mask = (hpi.Date >= start_date)
#hpi = hpi[mask]
#ec_forecast_df['housing_price_index_model_forecast'] = hpi

#by10 = ec_forecast_df['Bonds_Yeilds_10y_model_forecast']
#by10 = by10.rename(columns={'yhat':'Bond_Yeild_10y_f', 'ds':'Date'})
#mask = (by10.Date >= start_date)
#by10 = by10[mask]
#ec_forecast_df['Bonds_Yeilds_10y_model_forecast'] = by10

#inf = ec_forecast_df['Inflation_model_forecast']
#inf = inf.rename(columns={'yhat':'Inflation_f', 'ds':'Date'})
#mask = (inf.Date >= start_date)
#inf = inf[mask]
#ec_forecast_df['Inflation_model_forecast'] = inf

#gdp = ec_forecast_df['GDP_model_forecast']
#gdp = gdp.rename(columns={'yhat':'GDP_f', 'ds':'Date'})
#mask = (gdp.Date >= start_date)
#gdp = gdp[mask]
#ec_forecast_df['GDP_model_forecast'] = gdp

#pop = ec_forecast_df['Population_model_forecast']
#pop = pop.rename(columns={'yhat':'Population_f', 'ds':'Date'})
#mask = (pop.Date >= start_date)
#pop = pop[mask]
#ec_forecast_df['Population_model_forecast'] = pop

#hhi = ec_forecast_df['House_Hold_Income_Year_model_forecast']
#hhi = hhi.rename(columns={'yhat':'House_Hold_Income_f', 'ds':'Date'})
#mask = (hhi.Date >= start_date)
```

```
#hhi = hhi[mask]
#ec_forecast_df['House_Hold_Income_Year_model_forecast'] = hhi

#emp = ec_forecast_df['Employment_model_forecast']
#emp = emp.rename(columns={'yhat':'Employment_f', 'ds':'Date'})
#mask = (emp.Date >= start_date)
#emp = emp[mask]
#ec_forecast_df['Employment_model_forecast'] = emp

#csd = ec_forecast_df['Cash_Surp_Def_model_forecast']
#csd = csd.rename(columns={'yhat':'Cash_Surp_Def_f', 'ds':'Date'})
#mask = (csd.Date >= start_date)
#csd = csd[mask]
#ec_forecast_df['Cash_Surp_Def_model_forecast'] = csd
```

In [129]:

```
#ec_forecast_df['cpi_model_forecast'].head()

#df = None
#df_hold_first = None
#i = 0
#for k,v in ec_forecast_df.items():
#    print(k)
#    if i == 0:
#        df_hold_first = v
#    elif i == 1:
#        df = pd.merge(df_hold_first, v, on='Date', how='left')
#    else:
#        df = pd.merge(df, v, on='Date', how='left')
#    i = i+1

#economicDf_forecast = df


# save df as new data source
#save_as = f'{dataDir}/economic_forecast_data.csv'
#economicDf_forecast.to_csv(save_as,index=False)
```

In [130]:

```
#economicDf_forecast.tail(
```

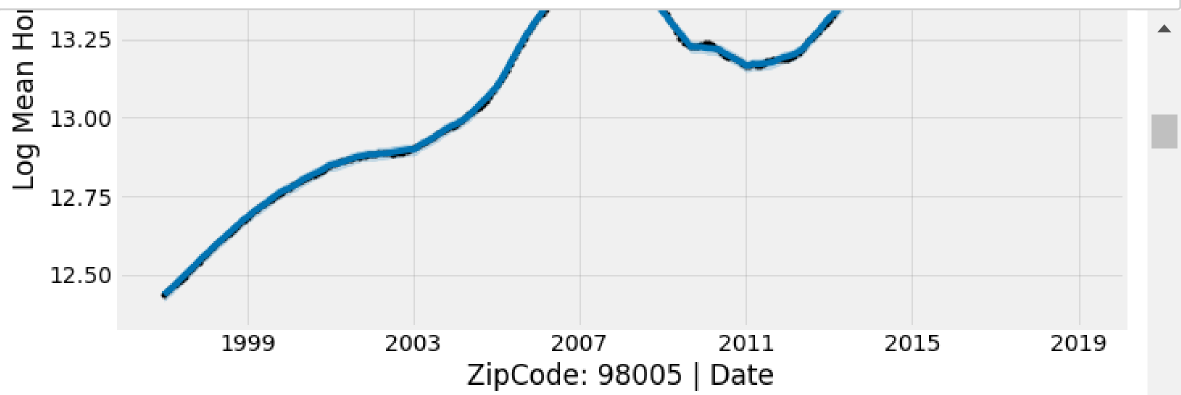
2.4 Results

Training Data Sets

Price Trend from 1997 through 2017 - With a 12 month future prediction...

In [132]:

```
# pull in forecast samples
ran_zips = np.random.choice(re_datasets['Single_Family_Residence'].ZipCode,10
zipcode_eval = [] #
i = 0
m_fit = None
m_forecast = None

for data_key in re_datasets.keys():

    for z in ran_zips:
        try:
            fitFile = f'{modelDir}/{trainDir}/{data_key}/{z}_fit'
            forecastFile = f'{modelDir}/{trainDir}/{data_key}/{z}_forecast'

            with open(fitFile,'rb') as f:
                m_fit = pickle.load(f)
                logger.debug(f'saved pickled timeseries model [{fitFile}] dat

            with open(forecastFile,'rb') as f:
                m_forecast = pickle.load(f)
                logger.debug(f'saved pickled timeseries model [{forecastFile}


            brs.plotFit(z,m_fit,m_forecast,f'{z} Random {str(i+1)} Subset Sam
            i = i+1
            if i >= 5: break

        except FileNotFoundError:
            logger.debug('file not found...')
```

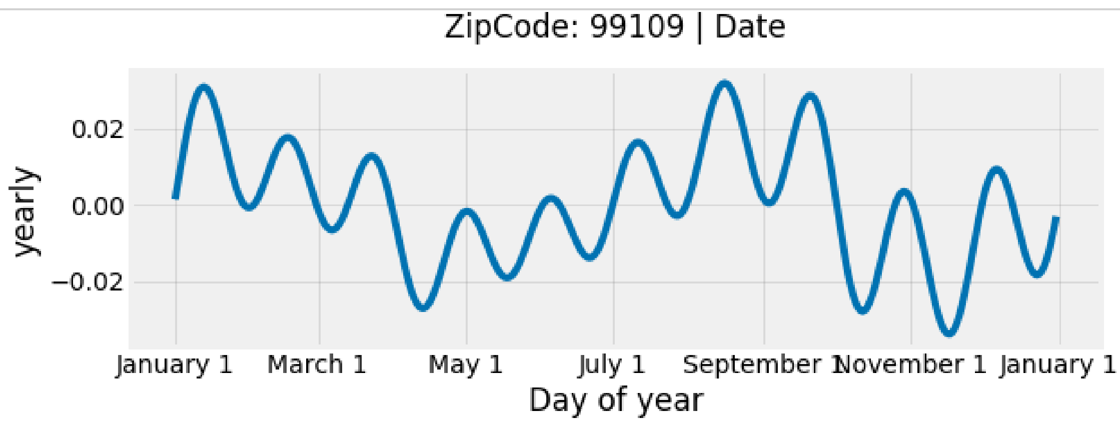


Future Prediction Trends

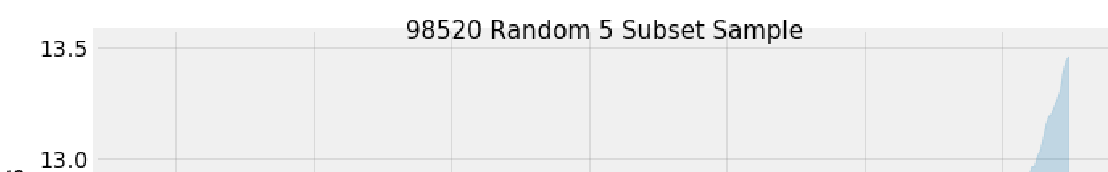
Price Trend from 1997 through 2018 - With a 5 year future prediction...

In [133]:

```
# pull in forecast samples
ran_zips = np.random.choice(re_datasets['Single_Family_Residence'].ZipCode,1(
zipcode_eval = [] #
i = 0
m_fit = None
m_forecast = None

for data_key in re_datasets.keys():

    for z in ran_zips:
        try:
            fitFile = f'{modelDir}/{future5Dir}/{data_key}/{z}_fit'
            forecastFile = f'{modelDir}/{future5Dir}/{data_key}/{z}_forecast'

            with open(fitFile,'rb') as f:
                m_fit = pickle.load(f)
                logger.debug(f'saved pickled timeseries model [{fitFile}] dat

            with open(forecastFile,'rb') as f:
                m_forecast = pickle.load(f)
                logger.debug(f'saved pickled timeseries model [{forecastFile}


            brs.plotFit(z,m_fit,m_forecast,f'{z} Random {str(i+1)} Subset Sam
            i = i+1
            if i >= 5: break

        except FileNotFoundError:
            logger.debug('file not found...')
```




```
<Figure size 1440x1080 with 0 Axes>
```



In [134]:

```
from fbprophet.diagnostics import cross_validation, performance_metrics
df_cv = cross_validation(m_fit, horizon='90 days')

df_p = performance_metrics(df_cv)
```

```
INFO:fbprophet:Making 63 forecasts with cutoffs between 2011-01-12 00:00:00
and 2018-09-02 00:00:00
INFO:fbprophet:n_changepoints greater than number of observations.Using 9.
INFO:fbprophet:n_changepoints greater than number of observations.Using 10.
INFO:fbprophet:n_changepoints greater than number of observations.Using 11.
INFO:fbprophet:n_changepoints greater than number of observations.Using 12.
INFO:fbprophet:n_changepoints greater than number of observations.Using 14.
INFO:fbprophet:n_changepoints greater than number of observations.Using 15.
INFO:fbprophet:n_changepoints greater than number of observations.Using 16.
INFO:fbprophet:n_changepoints greater than number of observations.Using 17.
INFO:fbprophet:n_changepoints greater than number of observations.Using 19.
INFO:fbprophet:n_changepoints greater than number of observations.Using 19.
INFO:fbprophet:n_changepoints greater than number of observations.Using 21.
INFO:fbprophet:n_changepoints greater than number of observations.Using 22.
INFO:fbprophet:n_changepoints greater than number of observations.Using 23.
INFO:fbprophet:n_changepoints greater than number of observations.Using 24.
```

Timeseries Models Performance Metrics - 90 days Horizon

In [136]:

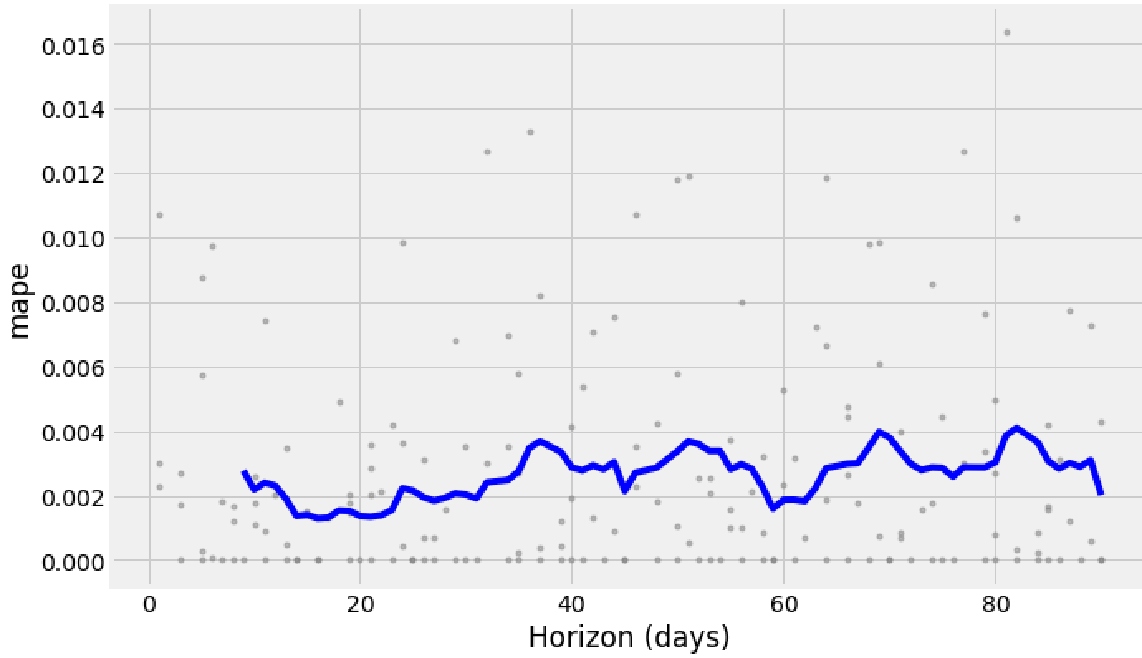
```
# save df as new data source
save_as = f'{dataDir}/prophet_cross_fold_diagnostics.csv'
df_p.to_csv(save_as,index=False)
df_p.head(5)
```

Out[136]:

	horizon	mse	rmse	mae	mape	coverage
0	9 days	0.003058	0.055295	0.034677	0.002765	0.722222
1	10 days	0.002039	0.045157	0.027378	0.002181	0.777778
2	11 days	0.002459	0.049593	0.030191	0.002397	0.777778
3	12 days	0.002257	0.047510	0.029036	0.002303	0.805556
4	13 days	0.001648	0.040594	0.024076	0.001906	0.888889

*Timeseries Models Cross Validation Metric Mape - 90 day Horizon***

In [138]:
```
from fbprophet.plot import plot_cross_validation_metric
fig = plot_cross_validation_metric(df_cv, metric='mape')
```



3. Clustering

- K-means - unsupervised
- Mean-Shift - unsupervised

Description: Run k-means for three choices for k and choose the best.
A loop of 10 iterations were ran of the zipecode models generated from the Timeseries process ran above. Based on the output of the Elbow technique K=4 was the best chosen choose.

Intent: Try and use unsupervised learing techniques to classify Timeseries models produced by prophet.
Which are the best forecasters?

- Try and group into 3 classes using unsupervised learning
- Focus on single familey homes

3.1 K-means Clustering

Python package: scikit-learn v0.21.3 [sklearn.cluster.KMeans (https://scikit-learn.org/stable/modules/generated/sklearn.cluster.KMeans.html#sklearn.cluster.KMeans)](https://scikit-learn.org/stable/modules/generated/sklearn.cluster.KMeans.html#sklearn.cluster.KMeans)

Description: ...

3.1.1 Analysis

In [139]:

```
modelsPerformance = {'ModelName':[], 'TestAccuracyScore':[],'PredictAccuracyS
```

In [142]:

```
# which are the best forecasters - try and group into 3 classes using unsuper
# focus on single familey homes
zipcodes = re_datasets['Single_Family_Residence'].ZipCode
data_key = 'Single_Family_Residence'
zip_ts_forcasts = {}

# get zip forcasts
for z in zipcodes:
    forecastFile = f'{modelDir}/{future5Dir}/{data_key}/{z}_forecast'

    with open(forecastFile,'rb') as f:
            m_forcast = pickle.load(f)
            zip_ts_forcasts[z] = m_forcast
            logger.debug(f'saved pickled timeseries model [{forecastFile}] da
```

3.1.2 Exploration

Get all of the zip code forecast prediction models that generated in section 2 from disc, and prep for kmeans

In [143]:

```
# get all of the zip code forecast predictions and prep for kmea

zip_forecasts = None
i = 0
for k,v in zip_ts_forcasts.items(): #351
    p = zip_ts_forcasts[k]
    #p = p.drop(columns=['ds']) #drop the date field, adds no value for clust
    p['ZipCode'] = k
    if i == 0:
        zip_forecasts = p
    else:
        zip_forecasts = pd.concat([zip_forecasts,p])
    i=i+1

#save data off as new data object file
rt.save_df(zip_forecasts, f'{dataDir}/wa_sfh_zip_forecasts.pkl',logger)
```

In [144]:

```
logger.debug(f'unique zipcodes {zip_forecasts.ZipCode.unique()}\n')
logger.debug(f'wa single family home, zipcode predicted forecast dataset:\n{z
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 113724 entries, 0 to 323
Data columns (total 17 columns):
ds                            113724 non-null datetime64[ns]
trend                         113724 non-null float64
yhat_lower                    113724 non-null float64
yhat_upper                    113724 non-null float64
trend_lower                   113724 non-null float64
trend_upper                   113724 non-null float64
additive_terms                113724 non-null float64
additive_terms_lower          113724 non-null float64
additive_terms_upper          113724 non-null float64
yearly                        113724 non-null float64
yearly_lower                  113724 non-null float64
yearly_upper                  113724 non-null float64
multiplicative_terms          113724 non-null float64
multiplicative_terms_lower    113724 non-null float64
multiplicative_terms_upper    113724 non-null float64
yhat                          113724 non-null float64
ZipCode                       113724 non-null object
dtypes: datetime64[ns](1), float64(15), object(1)
memory usage: 15.6+ MB
```

In [145]:

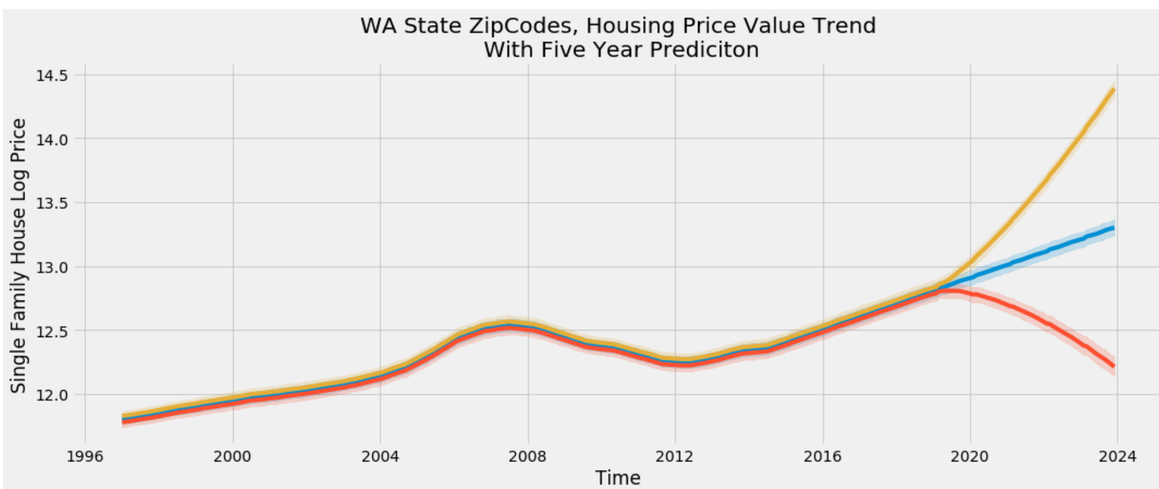
```
zip_forecasts.tail()
```

Out[145]:

	ds	trend	yhat_lower	yhat_upper	trend_lower	trend_upper	additive_terms	addi
319	2023-07-31	13.155514	11.837246	14.674990	11.853864	14.682746	-0.007654	
320	2023-08-31	13.161885	11.835639	14.753381	11.823744	14.737809	-0.003536	
321	2023-09-30	13.168051	11.815777	14.783577	11.801436	14.793408	0.007843	
322	2023-10-31	13.174423	11.787066	14.854134	11.784665	14.850861	0.012167	
323	2023-11-30	13.180589	11.754081	14.922188	11.741391	14.906460	0.006648	

In [146]:

```
plt.figure(figsize=(16,6))
sns.lineplot(x='ds', y='yhat', data=zip_forecasts)
sns.lineplot(x='ds', y='yhat_lower', data=zip_forecasts)
sns.lineplot(x='ds', y='yhat_upper', data=zip_forecasts)
plt.title('WA State ZipCodes, Housing Price Value Trend\n With Five Year Pred
plt.xlabel('Time')
plt.ylabel('Single Family House Log Price')
plt.show()
```



In [147]:

```
# limite the features for clustering - and the observations to just the predi
trend_cols = ['trend','trend_lower','trend_upper']
future_price_yhat_cols = ['yhat','yhat_lower','yhat_upper']
X_zip_forecast = zip_forecasts[['ds','ZipCode','yhat','yhat_lower','yhat_uppe
X_zip_forecast.tail()
#  - keep all the data this round
end_date = X_zip_forecast.iloc[-1].ds
start_date = pd.to_datetime('2018-01-01')
mask = (X_zip_forecast.ds >= start_date) & (X_zip_forecast.ds <= end_date)
X_zip = X_zip_forecast[mask]
X_zip.head()
X_zip_forecast.head()

# save this formate
# save df as new data source
save_as = f'{dataDir}/sfr_yhat_forecast.csv'
X_zip_forecast.to_csv(save_as,index=False)
```

Clean the forecast dataset for clustering

- limite the features for clustering - and the observations to just the predition time (5 years) + one year observed
- remove additive terms and multiplicative terms as well as the datetimestamp
- save series objects for later re joining

In [149]:

```
# clean the forecast dataset for clustering
# remove additive terms and multiplicative terms as well as the datetimestamp
# save series objects for later re joining
X_zip_zipcodes = X_zip['ZipCode']
X_zip_ds = X_zip['ds']
X_zip_clust = X_zip.drop(columns=['ds','ZipCode'])
X_zip_forecast_t = X_zip_forecast.drop(columns=['ds','ZipCode'])
#logger.info(f'wa single family home, modified zipcode predicted forecast dat

X_zip_clust_features = X_zip_clust.columns
```

In [150]:

```
X_zip.head()
```

Out[150]:

	ds	ZipCode	yhat	yhat_lower	yhat_upper	trend	trend_lower	trend_upper
252	2018-01-01	98052	13.675667	13.655640	13.696859	13.673974	13.673974	13.673974
253	2018-02-01	98052	13.685759	13.666272	13.705942	13.683988	13.683988	13.683988
254	2018-03-01	98052	13.695788	13.676042	13.716392	13.693034	13.693034	13.693034
255	2018-04-01	98052	13.705396	13.683485	13.724888	13.703048	13.703048	13.703048
256	2018-05-01	98052	13.715385	13.695982	13.736280	13.712740	13.712740	13.712740

Pull in generated datasets for modeling...

- Economic Date - economic_forecast_date_norm.csv --- economic factors per date
- Real Esate Date - sfr_price_zip.csv --- single family homes price value per zipcode and date

In [151]:

```
# pull in generated datasets for modeling...
# Economic Date - economic_forecast_date_norm.csv  --- economic factors per d
# Real Esate Date - sfr_price_zip.csv --- single family homes price value per
economic_norm_data = 'economic_forecast_data_norm.csv'
realestate_sfr_prices = 'sfr_price_zip.csv'

economic_norm_data = pd.read_csv(f'{dataDir}/{economic_norm_data}', error_bad
realestate_sfr_prices = pd.read_csv(f'{dataDir}/{realestate_sfr_prices}', err

logger.info(f'economic_norm_date shape: {economic_norm_data.shape}')
logger.info(f'realestate_sfr_prices shape: {realestate_sfr_prices.shape}')
```

```
INFO:file_logger:economic_norm_date shape: (261, 11)
INFO:file_logger:realestate_sfr_prices shape: (264, 352)
```

In [152]:

```
realestate_sfr_prices.head()
```

Out[152]:

	Date	98052	98012	99301	98103	98682	98115	98122	98133	9
0	1997-01-01	229300.0	199500.0	88700.0	183800.0	131100.0	191700.0	175800.0	155400.0	1170
1	1997-02-01	231400.0	200700.0	88600.0	185500.0	131400.0	193500.0	177300.0	156300.0	1173
2	1997-03-01	233500.0	202000.0	88400.0	187200.0	131500.0	195200.0	178700.0	157100.0	1177
3	1997-04-01	235600.0	203300.0	88000.0	189100.0	131400.0	197000.0	180500.0	158100.0	1181
4	1997-05-01	237800.0	204600.0	87500.0	191200.0	131100.0	198800.0	182400.0	159100.0	1184

5 rows × 352 columns

In [153]:
```
economic_norm_data['Date'] = pd.to_datetime(economic_norm_data['Date'])
economic_norm_data['Date'] = pd.to_datetime(economic_norm_data['Date'].dt.str
economic_norm_data.head()
```

Out[153]:

	Date	CPI_Index_Avg_f	Interest_Rate_f	Housing_Price_Index_f	Bond_Yeild_10y_f	Inflation_
0	1997-01-01	157.959370	4.814434	83.076214	6.055381	2.81244:
1	1997-02-01	158.404761	4.731693	83.392929	6.015761	2.81244:
2	1997-03-01	158.947674	4.633084	82.836534	6.073349	2.81244:
3	1997-04-01	159.387626	4.378458	83.893792	6.079290	2.81244:
4	1997-05-01	159.765440	4.652420	85.006970	6.126489	2.81244:

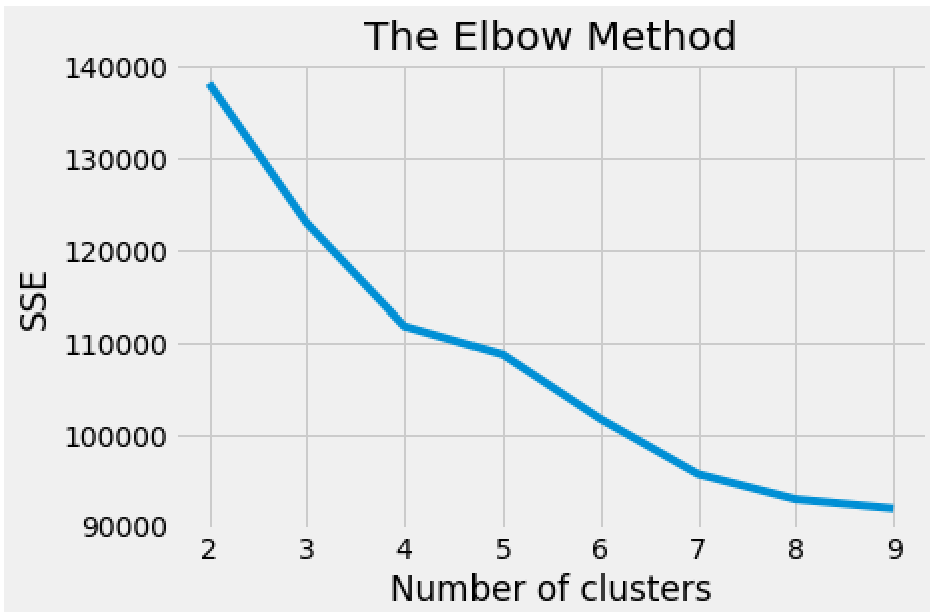
3.1.3 Model - KMeans

- Run multiple k means to determin optimal k size for final model creation
  - 8 iterations were ran, where k 4 was the most optimal

In [154]:
```
#from sklearn.cluster import KMeans, SpectralClustering
#from sklearn.preprocessing import StandardScaler
#from sklearn.metrics import silhouette_samples, silhouette_score

def build_kmeans(n_clusters,random_state,n_jobs,verbose=0):
    km = KMeans(
        n_clusters=n_clusters,
        init="k-means++", # using elbow to figure out k for kmeans
        n_init=10,
        max_iter=300,
        tol=0.0001,
        precompute_distances="auto",
        verbose=verbose,
        random_state=random_state, # determines random number generation for
        copy_x=True,
        n_jobs=n_jobs,
        algorithm="auto")

    return km
```

In [155]:

```
#%%time
# Run multiple k means to determin optimal k size for final model creation

sse = {} # store output for analysis
# set range from 2 - 10, assum max number of clusters to be 10
for k in range(2,10):
    km = build_kmeans(n_clusters=k,random_state=0,n_jobs=None)
    X_std = km.fit_transform(X_zip_forecast_t) #X_zip_forecast_t X_zip_clust
    kmeans = km.fit(X_std)
    sse[k] = kmeans.inertia_ # Inertia: sum of distances of samples to their

# plot elbow
plt.figure()
plt.plot(list(sse.keys()), list(sse.values()))
plt.title('The Elbow Method')
plt.xlabel('Number of clusters')
plt.ylabel('SSE')
plt.show()
```



In [156]:

```
logger.debug(f'kmeans class labels... {kmeans.labels_}')
logger.debug(f'kmeans parameters... {kmeans.get_params()}')
logger.debug(f'sse out analysis, multiple k-means trials\n: {list(sse.keys()}
```

Build KMeans based on ideal cluster state found by Elbow method - 4

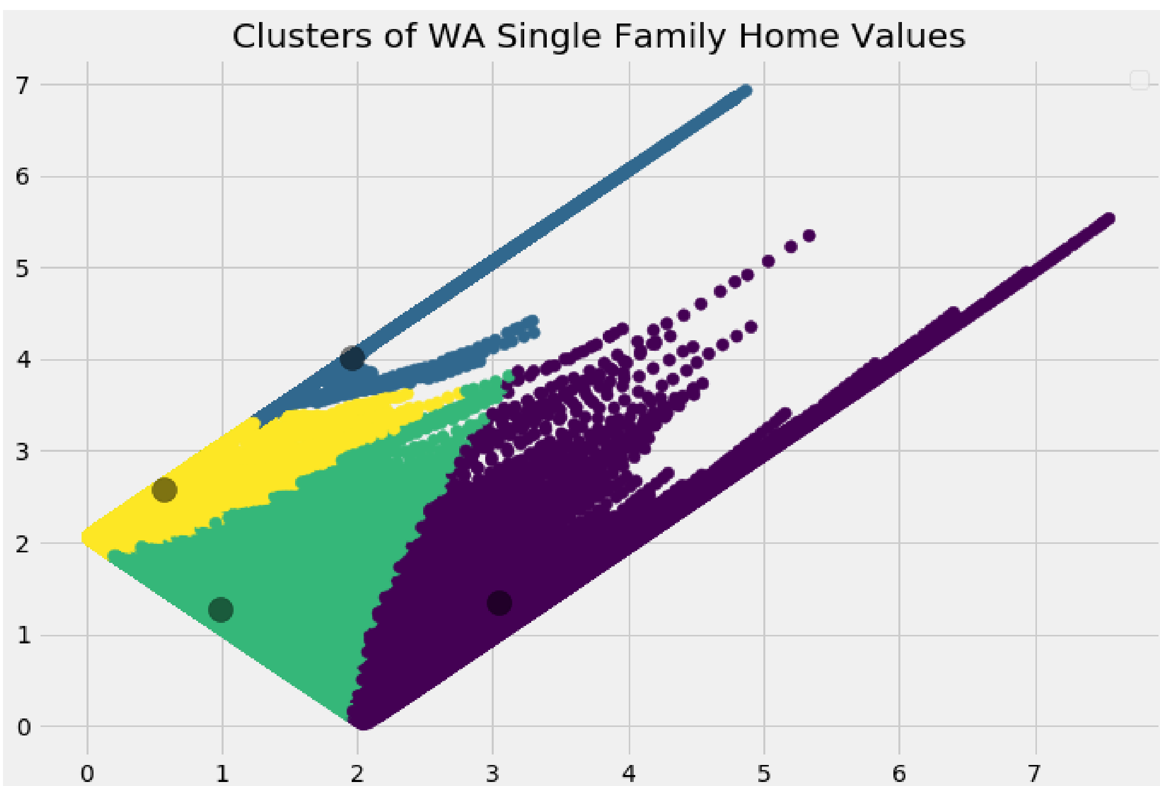
In [157]:
```
# build KMeans based on ideal cluster state found above - 4

# build with k=4 clusters
km_model = build_kmeans(n_clusters=4,random_state=0,n_jobs=None)
y_kmeans = km_model.fit_predict(X_std) # for unsupervised learning - use fit_
# add clusters to the data
#X_zip['label'] = y_kmeans
X_zip_forecast['label'] = y_kmeans
#save off labeled dataframe
rt.save_df(X_zip_forecast,f'{dataDir}/labeled_wa_sfa_predicted_future_home_pr

logger.debug(f'km_model.labels_ ... {km_model.labels_}')
logger.debug(f'km_model.cluster_centers_ ... {km_model.cluster_centers_}')
```

3.1.4 Results

Rusulting Cluster Classification at K equal 4

In [158]:
```
plt.figure(figsize=(10.5,7))
plt.scatter(X_std[:,0], X_std[:,1], c=y_kmeans, s=50, cmap='viridis')
centers = km_model.cluster_centers_
plt.scatter(centers[:,0], centers[:,1], c='black', s=200, alpha=0.5)
plt.title('Clusters of WA Single Family Home Values')
plt.xlabel('')
plt.ylabel('')
plt.legend()
plt.show()
```

```
WARNING:matplotlib.legend:No handles with labels found to put in legend.
```



4. Decision Tree

- Decision Tree - supervised
  - Include three different trees and their visualizations

Python package: [scikit-learn sklearn.tree.DecisionTreeClassifier (https://scikit-learn.org/stable/modules/generated/sklearn.tree.DecisionTreeClassifier.html)](https://scikit-learn.org/stable/modules/generated/sklearn.tree.DecisionTreeClassifier.html)

*Build a decision tree model.

4.1 Analysis

- Transformation of the data's necessary to merge the datasets together after processed through prophet.
- Look over the distribution of key features
- Set price thresholds for supervised learning classification
- Price_Point_Class is a generated feature for supervised classification. Details are shown below

In [170]:

```
#X_zip_forecast.tail()
```

transform this data set to be in the shape: columns are zip codes, yhat is the value as prices, date

In [160]:

```
sfr_forecast = X_zip_forecast[['ds','ZipCode','yhat']]
sfr_forecast = sfr_forecast.rename(columns={'ds':'Date'})
sfr_forecast['Date'] = pd.to_datetime(sfr_forecast['Date'])
sfr_forecast = sfr_forecast.set_index('Date')
#sfr_forecast = sfr_forecast.rename(columns={'yhat':''})
# pivot dataframe, spread rows into columns
sfr_forecast = sfr_forecast.pivot(columns='ZipCode', values='yhat')
sfr_forecast = sfr_forecast.reset_index()
sfr_forecast['Date'] = pd.to_datetime(sfr_forecast['Date'])
# save as csv
# save df as new data source
save_as = f'{dataDir}/sfr_forecast.csv'
sfr_forecast.to_csv(save_as,index=False)
sfr_forecast.head(5)
```

Out[160]:

ZipCode	Date	98001	98002	98003	98004	98005	98006	98007
0	1997-01-01	11.873703	11.731146	11.854656	12.930965	12.434717	12.474191	12.147111
1	1997-02-01	11.880200	11.735203	11.860957	12.941784	12.446799	12.486282	12.159336
2	1997-03-01	11.884774	11.735696	11.865059	12.947822	12.452669	12.491204	12.164220
3	1997-04-01	11.891682	11.740681	11.871427	12.957818	12.464837	12.503393	12.176328
4	1997-05-01	11.898385	11.745872	11.877825	12.967831	12.476572	12.515002	12.187934

5 rows × 352 columns

In [161]:

```
# read file backin
sfr_forecast = 'sfr_forecast.csv'
sfr_forecast = pd.read_csv(f'{dataDir}/sfr_forecast.csv')
sfr_forecast['Date'] = pd.to_datetime(sfr_forecast['Date'])
#sfr_forecast.head()
```

In [162]:

```
wa_sfr_forecast_long = 'wa_sfr_forecast_long_log.csv'
wa_sfr_forecast_long = pd.read_csv(f'{dataDir}/wa_sfr_forecast_long.csv')
wa_sfr_forecast_long['Date'] = pd.to_datetime(wa_sfr_forecast_long['Date'])
#wa_sfr_forecast_long.shape
```

In [163]:

```
#wa_sfr_forecast_long.head()
```

In [164]:

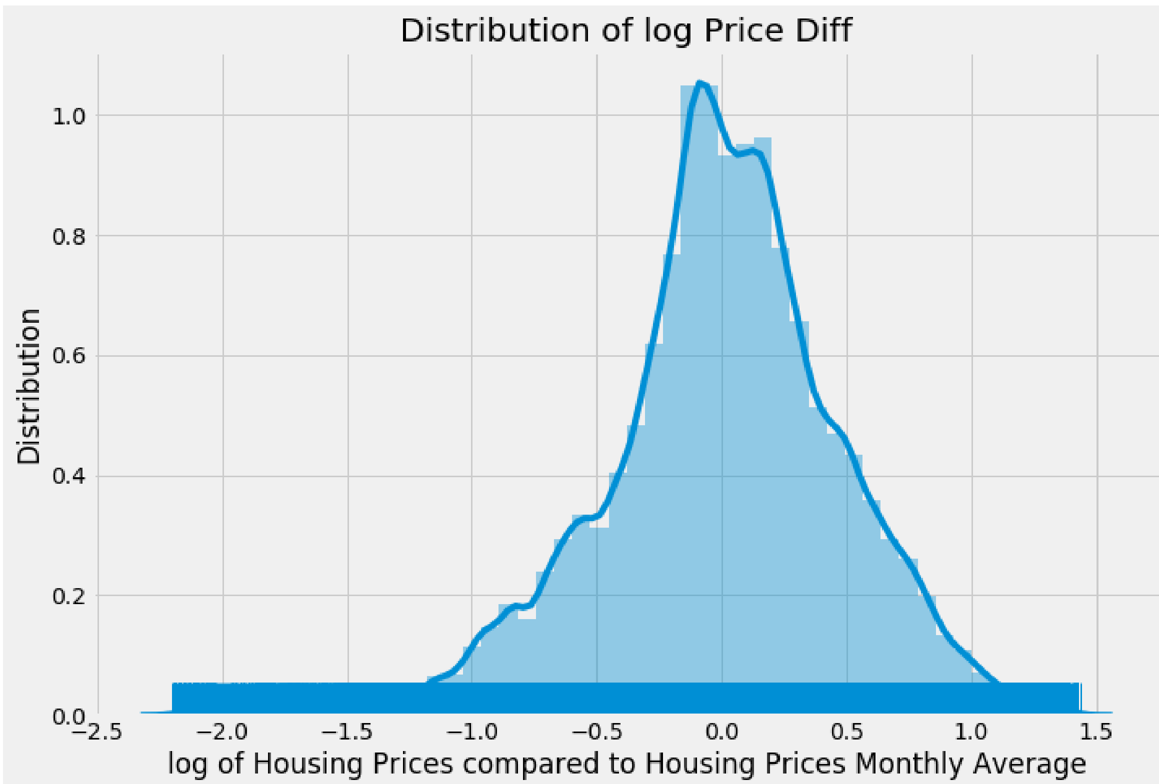
```
wa_sfr_forecast_long['log_Price_Monthly_Avg'] = wa_sfr_forecast_long.log_Pric
## save df as new data source
#save_as = f'{dataDir}/wa_sfr_forecast_long_log.csv'
#wa_sfr_forecast_long.to_csv(save_as,index=False)
```

In [165]:
```
wa_sfr_forecast_long['log_Price_diff'] = wa_sfr_forecast_long.log_Price_Montl
```

In [166]:
```
#wa_sfr_forecast_long.head()
```

In [167]:
```
#wa_sfr_forecast_long.log_Price_diff.describe()
```

In [168]:
```
plt.figure(figsize=(10.5,7))
sns.distplot(wa_sfr_forecast_long.log_Price_diff, hist=True, rug=True)
plt.title('Distribution of log Price Diff')
plt.ylabel('Distribution')
plt.xlabel('log of Housing Prices compared to Housing Prices Monthly Average'
plt.show()
```



In [169]:
```
threshold_low = wa_sfr_forecast_long.log_Price_diff.describe()[4] #25%
threshold_neutral = wa_sfr_forecast_long.log_Price_diff.describe()[5] #50#
threshold_high = wa_sfr_forecast_long.log_Price_diff.describe()[6]
threshold_high_x = threshold_high + (threshold_high/4)
threshold_high_mid = threshold_high - (threshold_high/2)
logger.info(f'threshold_low [{threshold_low}] | threshold_neutral [{threshol
            threshold_high_mid [{threshold_high_mid}]')
```

```
INFO:file_logger:threshold_low [-0.25401387500000006] | threshold_neutral
[0.010042959999999823] | threshold_high [0.29538362500000037] | threshold_h
igh_x [0.36922953125000046] |             threshold_high_mid [0.14769181250
000019]
```

In [171]:

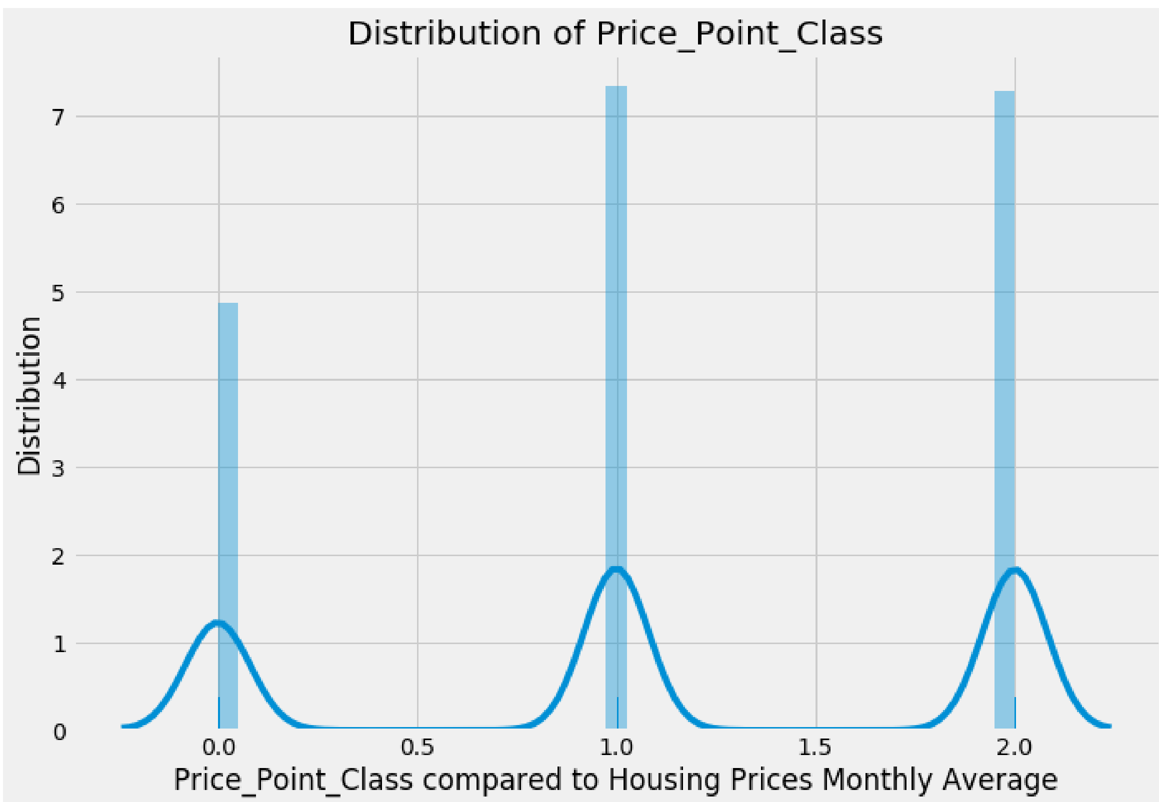
```
wa_sfr_forecast_long['Price_Point_Class'] = wa_sfr_forecast_long.log_Price_di
    lambda x: 0 if x <= threshold_low else (1 if x <= threshold_high_mid else

# save df as new data source
save_as = f'{dataDir}/wa_sfr_forecast_long_log_final.csv'
wa_sfr_forecast_long.to_csv(save_as,index=False)

wa_sfr_forecast_long.head()
```

Out[171]:

	Date	ZipCode	log_Price	log_Price_Monthly_Avg	log_Price_diff	Price_Point_Class
0	1997-01-01	98052	12.342486	11.804569	-0.537917	0
1	1997-02-01	98052	12.352806	11.808970	-0.543837	0
2	1997-03-01	98052	12.357526	11.811044	-0.546482	0
3	1997-04-01	98052	12.367903	11.815443	-0.552460	0
4	1997-05-01	98052	12.378131	11.819842	-0.558289	0

In [172]:

```
plt.figure(figsize=(10.5,7))
sns.distplot(wa_sfr_forecast_long.Price_Point_Class, hist=True, rug=True)
plt.title('Distribution of Price_Point_Class')
plt.ylabel('Distribution')
plt.xlabel('Price_Point_Class compared to Housing Prices Monthly Average')
plt.show()
```



In [173]:
```
# read zip data back in after transformation completed above
wa_sfr_forecast_long = 'wa_sfr_forecast_long_log_final.csv'
wa_sfr_forecast_long = pd.read_csv(f'{dataDir}/{wa_sfr_forecast_long}')
wa_sfr_forecast_long['Date'] = pd.to_datetime(wa_sfr_forecast_long['Date'])
#wa_sfr_forecast_long.shape
#wa_sfr_forecast_long.duplicated().sum()
```

In [174]:
```
#wa_sfr_forecast_long.tail()
```

In [175]:
```
# merge economic data set / features with zipcode to create final dataset to
# read zip data back in after transformation completed above
economic_forecast_ = 'economic_forecast_data_clean.csv'
economic_forecast_ = pd.read_csv(f'{dataDir}/{economic_forecast_}')
economic_forecast_['Date'] = pd.to_datetime(economic_forecast_['Date'])
#economic_forecast_.shape
```

In [177]:
```
#economic_forecast_.Date[economic_forecast_.Date.duplicated()]
```

In [176]:
```
#economic_forecast_.tail()
```

In [179]:
```
zips = list(wa_sfr_forecast_long.ZipCode.unique())
economic_df_chunks = {}
#chunk_cnt = wa_sfr_forecast_long.shape[0]
for z in zips:
    economic_df_chunks[z] = economic_forecast_.copy()
    #print(z)

#len(economic_df_chunks)
```

Out[179]: 351

In [180]:
```
econ = None
for k,v in economic_df_chunks.items():
    #print(k)
    #print(v.shape)

    p = economic_df_chunks[k]
    if i == 0:
        econ = p
    else:
        econ = pd.concat([econ,p])

    i=i+1

econ = econ.reset_index()
econ = econ.drop(columns=['index'])
#econ.shape
```

In [182]:
```
end_date = pd.to_datetime('2017-12-31')
mask = (wa_sfr_forecast_long.Date <= end_date) # & (wa_sfr_forecast_long.ds <
wa_sfr_forecast_long_filt = wa_sfr_forecast_long[mask]

mask = (econ.Date <= end_date) # & (wa_sfr_forecast_long.ds <= end_date)
econ_filt = econ[mask]

#wa_sfr_forecast_long_filt.shape # (105651, 6)
#econ_filt.shape
```

In [183]:
```
save_as = f'{dataDir}/econ_filt.csv'
econ_filt.to_csv(save_as,index=False)

save_as = f'{dataDir}/wa_sfr_forecast_long_filt.csv'
wa_sfr_forecast_long_filt.to_csv(save_as,index=False)
```

Final Merged Dataset - Real Estate Combined with Economic Data Features

Time range - 1997 - 2017 (that was the cleanest that could be achieved at this time...
*Train classifiers on Feature 'Price_Point_Class'

- 0: means observation's price value is < 25% of the State Price Average
- 1: means observations fall within the normal (average) range of the State Price Average
- 2: means observations falls above the 75% range of the State Price Average

--Determin if classifiers can identify future home value classes based on prior date, location and economic features that have the most impact on both postive and negative price value swings...

- Dataset Shape: (88452, 16)

In [184]:
```
modelsPerformance = {'ModelName':[], 'TestAccuracyScore':[],'PredictAccuracyS
```

In [185]:
```
# get final dataset for modeling
zip_eco_combo_final = 'zip_eco_combo_final.csv'
zip_eco_combo_final = pd.read_csv(f'{dataDir}/{zip_eco_combo_final}')
zip_eco_combo_final['Date'] = pd.to_datetime(zip_eco_combo_final['Date'])
#logger.info(f'zip_eco_combo_final shape: {zip_eco_combo_final.shape}')
```

In [186]:
```
zip_eco_combo_final.head()
```

Out[186]:

	Date	ZipCode	log_Price	log_Price_Monthly_Avg	log_Price_diff	Price_Point_Class	CPI_In
0	1997-01-01	98052	12.342486	11.804569	-0.537918	0	
1	1997-02-01	98052	12.352806	11.808970	-0.543837	0	
2	1997-03-01	98052	12.357526	11.811044	-0.546482	0	
3	1997-04-01	98052	12.367903	11.815443	-0.552460	0	
4	1997-05-01	98052	12.378131	11.819842	-0.558289	0	

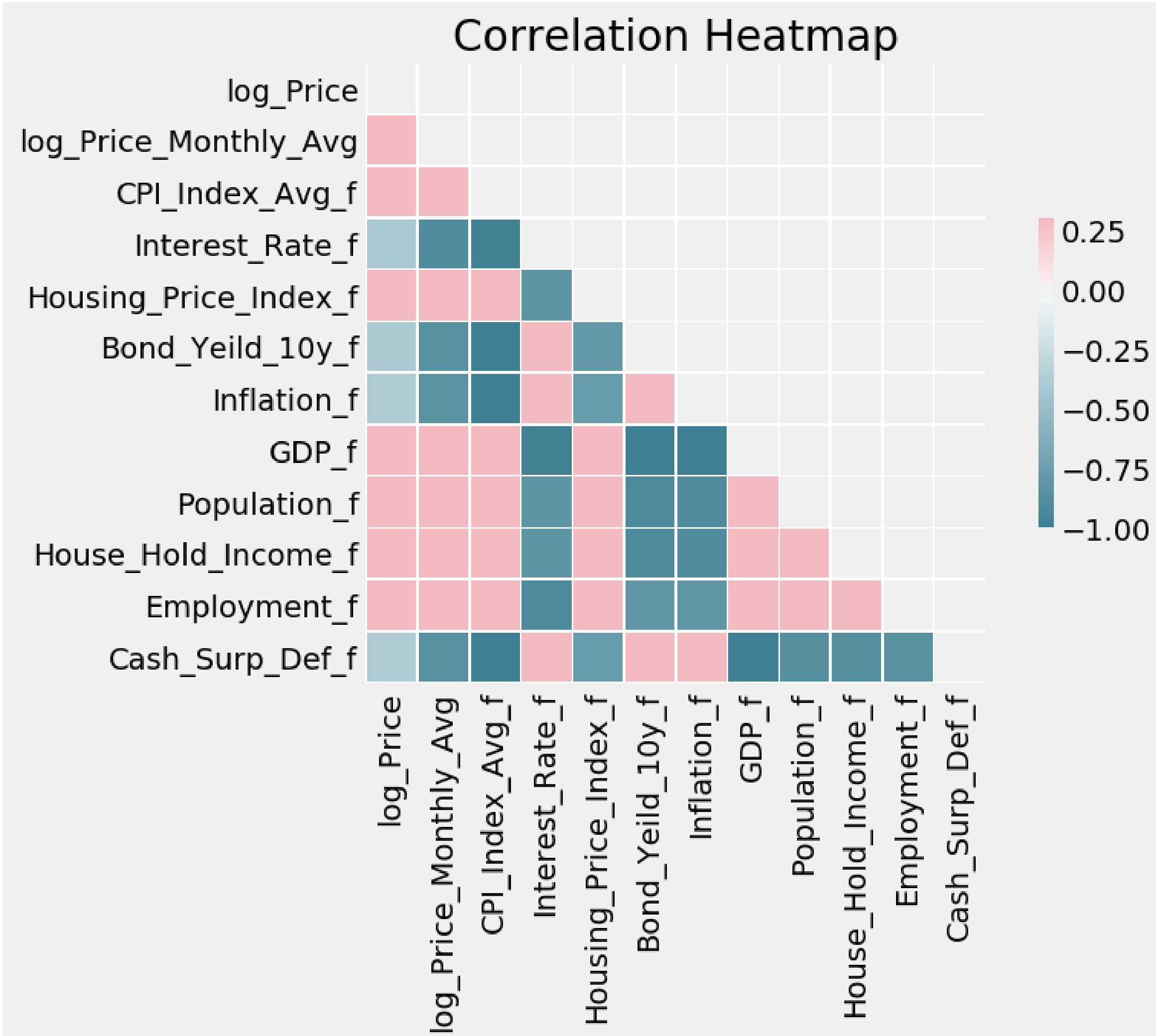
4.2 Exploration

In [187]:
```
#plt.figure(figsize=(10.5,7))
#vis = sns.distplot(zip_eco_combo_final.Price_Point_Class, hist=True, rug=Tru
#plt.title('Distribution of Price_Point_Class')
#plt.ylabel('Distribution')
#plt.xlabel('Price_Point_Class compared to Housing Prices Monthly Average')
#plt.savefig(f'{imageDir}/dist_of_price_point_class.png', dpi=300)
#plt.show()

# save visual
#report_plots['Dist_Price_Points'] = vis
```

In [188]:

```
plt.figure(figsize=(8,6))
rt.plot_corr_heatmap(zip_eco_combo_final,zip_eco_combo_final.drop(columns=['D
plt.savefig(f'{imageDir}/zip_eco_combo_corr.png', dpi=300)
```

```
<Figure size 576x432 with 0 Axes>
```



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

In [191]:

```
logger.debug(f'zip_eco_combo_final columns:\n{zip_eco_combo_final.columns}')
ze = zip_eco_combo_final[['Date','Price_Point_Class','ZipCode','log_Price','I
       'Interest_Rate_f', 'Housing_Price_Index_f', 'Bond_Yeild_10y_f',
       'Inflation_f', 'GDP_f', 'Population_f', 'House_Hold_Income_f',
       'Employment_f', 'Cash_Surp_Def_f']]
```

In [192]:

```
modelsPerformance = {'ModelName':[], 'TestAccuracyScore':[],'PredictAccuracyS
```

In [193]:

```
# dataset normalization & transformation
features = ['Date','ZipCode','log_CPI_Index_Avg_f', 'log_Interest_Rate_f',
            'log_Bond_Yeild_10y_f','log_Inflation_f', 'log_GDP_f', 'log_Popul
            'Cash_Surp_Def_f']

drop_cols_modeling = ['Price_Point_Class','log_Price_diff','log_Price','log_P
                      'Population_f','GDP_f','CPI_Index_Avg_f','Interest_Rate
                     'Bond_Yeild_10y_f','Inflation_f']

# do a little zscore normalization
ze.Price_Point_Class = ze.Price_Point_Class.astype('category')
#ze['Date'] = ze.Date.astype('category')
ze['ZipCode'] = ze.ZipCode.astype('category')
ze['log_Population_f'] = np.log(ze.Population_f)
ze['log_GDP_f'] = np.log(ze.GDP_f)
#ze['log_House_Hold_Income_f'] = np.log(ze.House_Hold_Income_f)
#ze['log_Employment_f'] = np.log(ze.Employment_f)
ze['log_CPI_Index_Avg_f'] = np.log(ze.CPI_Index_Avg_f)
ze['log_Interest_Rate_f'] = np.log(ze.Interest_Rate_f)
ze['log_Bond_Yeild_10y_f'] = np.log(ze.Bond_Yeild_10y_f)
ze['log_Inflation_f'] = np.log(ze.Inflation_f)
#ze['log_Cash_Surp_Def_f'] = np.log(ze.Cash_Surp_Def_f)
```

In [194]:

```
# hold out 2016 - 2017 for final test eval
start_date = pd.to_datetime('2016-01-01')
end_date = pd.to_datetime('2017-12-31')

# test set - future unseen
mask = (ze.Date >= start_date)  & (ze.Date <= end_date)
ze_2016_2017_test = ze[mask]

# train set
mask = (ze.Date <= start_date)#  & (ze.Date <= end_date)
ze_train = ze[mask]

logger.debug(f'ze_2016_2017_test shape: {ze_2016_2017_test.shape} | ze_train
```

In [195]:
```
# set dates to be used as categories
ze_2016_2017_test['Date'] = ze_2016_2017_test.Date.astype('category')
ze_train['Date'] = ze_train.Date.astype('category')
```

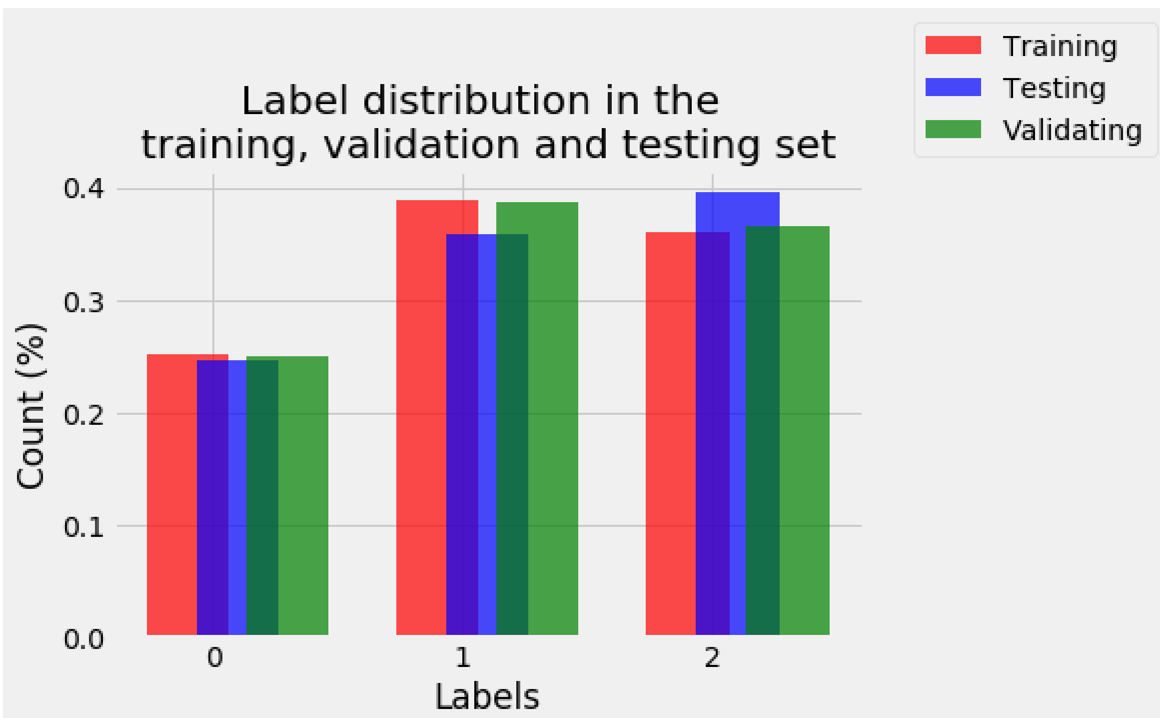
In [196]:
```
#from sklearn.model_selection import train_test_split, cross_val_score
# create training test splicts


y = ze_train[['Price_Point_Class']]
X = ze_train.drop(columns=drop_cols_modeling)

y_test = ze_2016_2017_test[['Price_Point_Class']]
X_test = ze_2016_2017_test.drop(columns=drop_cols_modeling)

# cast as np arrays
X = np.asarray(X)
y = np.asarray(y)
X_test = np.asarray(X_test)
y_test = np.asarray(y_test)

# reduce memory
#X = X.astype(np.int32) #
#y = y.astype(np.int32) #
#y_test = y_test.astype(np.int32)


# validation splits
X_train, X_val, y_train, y_val = train_test_split(X,y,test_size=0.33,random_s

# test splits
#X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.33,rando
```

In [197]:
```
logger.debug(f'X_train shape: {X_train.shape} |  X_val shape: {X_val.shape} |
logger.debug(f'y_train shape: {y_train.shape} |  y_val shape: {y_val.shape} |
```

Look for imbalance in the sample observations for the target class

In [198]:

```
# number of label classes
n_classes = 3

# look for imbalance in the sample observations for the class
training_counts = [None] * n_classes
testing_counts = [None] * n_classes
validation_counts = [None] * n_classes

for i in range(n_classes):
    training_counts[i] = len(y_train[y_train == i])/len(y_train)
    testing_counts[i] = len(y_test[y_test == i])/len(y_test)
    validation_counts[i] = len(y_val[y_val == i])/len(y_val)

# plot histogram of the data
train_bar = plt.bar(np.arange(n_classes)-0.1, training_counts, align='center'
test_bar = plt.bar(np.arange(n_classes)+0.1, testing_counts, align='center',
val_bar = plt.bar(np.arange(n_classes)+0.3, validation_counts, align='center'


plt.xlabel('Labels')
plt.xticks((0,1,2))
plt.ylabel('Count (%)')
plt.title('Label distribution in the \ntraining, validation and testing set')
plt.legend(bbox_to_anchor=(1.05, 1), handles=[train_bar, test_bar, val_bar],
plt.grid(True)
plt.savefig(f'{imageDir}/dt_explore_label_distribution.png', dpi=300)
plt.show()
```



In [199]:

```
# function used for clocking processing time to build/run models
from contextlib import contextmanager
from timeit import default_timer

@contextmanager
def elapsed_timer():
    start = default_timer()
    elapser = lambda: default_timer() - start
    yield lambda: elapser()
    end = default_timer()
    elapser = lambda: end-start
```

In [200]:

```
# Confusion matrix
import itertools
def plot_confusion_matrix(cm, classes,
                          normalize = False,
                          title = 'Confusion matrix',
                          cmap = plt.cm.Blues) :
    plt.imshow(cm, interpolation = 'nearest', cmap = cmap)
    plt.title(title)
    plt.colorbar()
    tick_marks = np.arange(len(classes))
    plt.xticks(tick_marks, classes, rotation = 0)
    plt.yticks(tick_marks, classes)

    thresh = cm.max() / 2.
    for i, j in itertools.product(range(cm.shape[0]), range(cm.shape[1])) :
        plt.text(j, i, cm[i, j],
                 horizontalalignment = 'center',
                 color = 'white' if cm[i, j] > thresh else 'black')

    #plt.tight_layout()
    plt.ylabel('True label')
    plt.xlabel('Predicted label')
    plt.savefig(f'{imageDir}/{model_name}_cm.png', dpi=150)
    plt.show()
```

4.3 Model - DecisionTree Classifier

```
* max_depth: None (default)
* min_samples_split: 2
* randome_state: 42
```

In [201]:

```
def build_tree(random_state,max_depth,min_samples_split):
    t = tree.DecisionTreeClassifier(
        criterion="gini",
        splitter="best",
        max_depth=max_depth,
        min_samples_split=min_samples_split,
        min_samples_leaf=1,
        min_weight_fraction_leaf=0.0,
        max_features=None,
        random_state=None,
        max_leaf_nodes=None,
        min_impurity_decrease=0.0,
        min_impurity_split=None,
        class_weight=None,
        presort=False)

    return t
```

In [202]:

```
max_depth = None
min_samples_split = 2
with_zip = 'zip_true'
model_name = f'DecisionTree_{max_depth}_{min_samples_split}_{with_zip}'


dtc = build_tree(random_state=42,max_depth=max_depth,min_samples_split=min_sa
t = 0.0
with elapsed_timer() as elapsed:
    # fit the forest to the training data
    dtc_fit = dtc.fit(X_train, y_train)
    t = elapsed()
    logger.info(f'DecisionTreeClassifier Model Build Time: [{t}]')

modelsPerformance['ModelName'].append(model_name)
modelsPerformance['FitTime'].append(t)
```

```
INFO:file_logger:DecisionTreeClassifier Model Build Time: [0.35558430000128
28]
```

In [203]:

```
t = 0.0
with elapsed_timer() as elapsed:
    dtc_score =  dtc.score(X_val, y_val)
    t = elapsed()
    logger.info(f'DecisionTreeClassifier Model Fit Score: {[dtc_score]}')
    logger.info(f'DecisionTreeClassifier Model Fit Score Time: [{t}]')

modelsPerformance['TestAccuracyScore'].append(dtc_score)
modelsPerformance['ScoreTime'].append(elapsed())
```

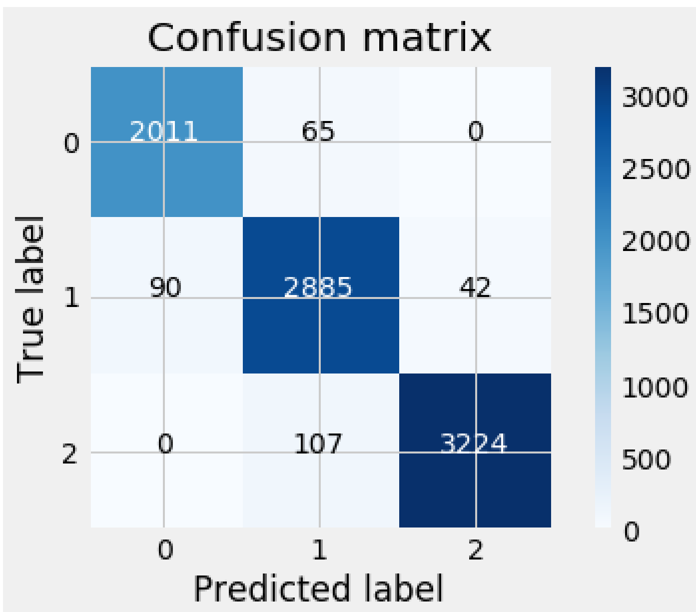
```
INFO:file_logger:DecisionTreeClassifier Model Fit Score: [0.991442358440775
1]
INFO:file_logger:DecisionTreeClassifier Model Fit Score Time: [0.0391119999
98567626]
```

In [204]:
```
#%%time
# predictions of test set split from training set
t = 0.0
with elapsed_timer() as elapsed:
    dtc_pred = dtc.predict(X_test)
    t = elapsed()
    logger.info(f'DecisionTreeClassifier Predict Time: [{t}]')

modelsPerformance['PredictTime'].append(t)
```

```
INFO:file_logger:DecisionTreeClassifier Predict Time: [0.00388510000084352
2]
```

4.4 Results

In [205]:
```
cm = confusion_matrix(y_test,dtc_pred, labels=[0,1,2])
plot_confusion_matrix(cm,classes=[0,1,2])
```

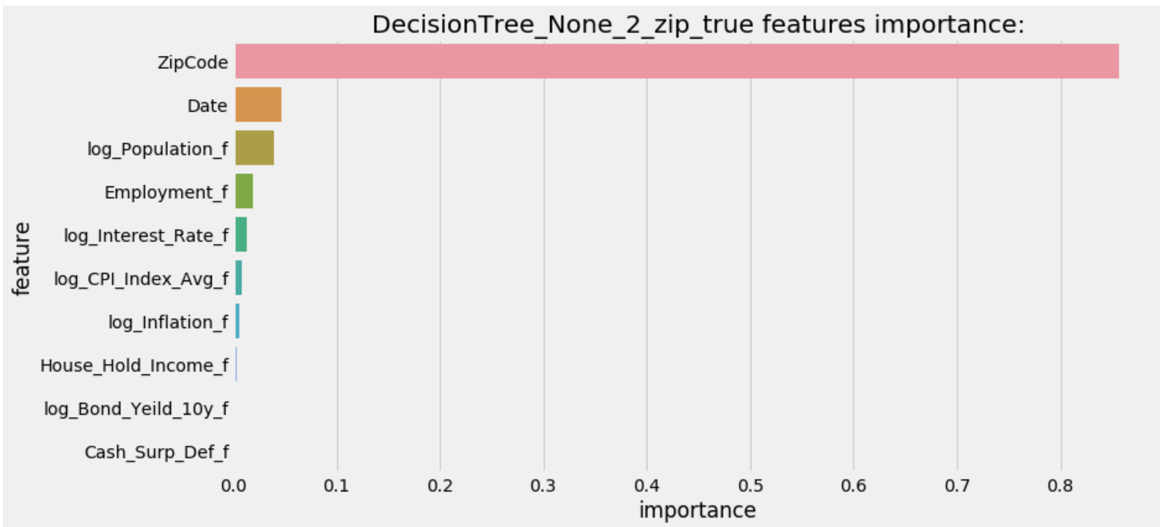


In [206]:
```
#print classification report table
n_classes=3
targetNames = ["Class{}".format(i) for i in range(n_classes)]
print(f'\n{classification_report(y_test, dtc_pred, target_names=targetNames)}
```

```
              precision    recall  f1-score   support

      Class0       0.96      0.97      0.96      2076
      Class1       0.94      0.96      0.95      3017
      Class2       0.99      0.97      0.98      3331

   micro avg       0.96      0.96      0.96      8424
   macro avg       0.96      0.96      0.96      8424
weighted avg       0.96      0.96      0.96      8424
```

In [207]:
```
# Decision Tree - Feature importance
plt.savefig(f'{imageDir}/{model_name}_fimp.png', dpi=300)
rt.plot_feature_importances(features, dtc, model_name, logger)
#dtc.feature_importances_
```

```
INFO:file_logger:                  feature  importance
1                ZipCode    0.856557
0                   Date    0.046343
7         log_Population_f    0.040113
9             Employment_f    0.019456
3      log_Interest_Rate_f    0.012984
2      log_CPI_Index_Avg_f    0.008199
5          log_Inflation_f    0.006408
8      House_Hold_Income_f    0.003751
4     log_Bond_Yeild_10y_f    0.002397
10          Cash_Surp_Def_f    0.001922

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



4.5 Random Forest Classifier

Python Package: scikit-learn v0.21.3 [sklearn.ensemble.RandomForestClassifier (https://scikit-learn.org/stable/modules/generated/sklearn.ensemble.RandomForestClassifier.html)](https://scikit-learn.org/stable/modules/generated/sklearn.ensemble.RandomForestClassifier.html)

A random forest is a meta estimator that fits a number of decision tree classifiers on various sub-samples of the dataset and uses averaging to improve the predictive accuracy and control over-fitting. The sub-sample size is always the same as the original input sample size but the samples are drawn with replacement if bootstrap=True (default).

- n_estimators: 100
- max_depth: None (default)
- min_samples_plit=2

In [208]:
```
rf_base = RandomForestClassifier(n_estimators=100,          # The number c
                                 criterion="gini",          # The function
                                 max_depth=None,            # The maximum
                                 min_samples_split=2,       # The minimum
                                 min_samples_leaf=1,        # The minimum
                                 min_weight_fraction_leaf=0.0, # The minimum
                                 max_features="auto",       # The number c
                                 max_leaf_nodes=None,       # Grow trees w
                                 min_impurity_decrease=0.0,   # A node will
                                 min_impurity_split=None,     # Threshold fo
                                 bootstrap=True,            # Whether boot
                                 oob_score=False,           # Whether to u
                                 n_jobs=None,               # The number c
                                 random_state=None,         # if int, rand
                                 verbose=1,                 # Controls the
                                 warm_start=False,          # When set to
                                 class_weight=None          # Weights asso
                                )
```

In [209]:
```
# fit the Random Forest model
with_zip = 'zip_true'
model_name = f'RandomForest_{with_zip}'

t = 0.0
with rt.elapsed_timer() as elapsed:
    #
    rf_base_fit = rf_base.fit(X_train, y_train)
    t = elapsed()
    logger.info(f'Random Forest Classification Model Build Time: [{t}]')

modelsPerformance['ModelName'].append(model_name)
modelsPerformance['FitTime'].append(t)

#save model to file
with open(modelDir+'/'+'rf_base','wb') as f:
    pickle.dump(rf_base,f)

with open(modelDir+'/'+'rf_base_fit','wb') as f:
    pickle.dump(rf_base_fit,f)
```

```
[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent wor
kers.
[Parallel(n_jobs=1)]: Done 100 out of 100 | elapsed:    6.8s finished
INFO:file_logger:Random Forest Classification Model Build Time: [7.04667369
9998792]
```

In [210]:
```
rf_base.get_params(deep=True)
```

Out[210]:
```
{'bootstrap': True,
 'class_weight': None,
 'criterion': 'gini',
 'max_depth': None,
 'max_features': 'auto',
 'max_leaf_nodes': None,
 'min_impurity_decrease': 0.0,
 'min_impurity_split': None,
 'min_samples_leaf': 1,
 'min_samples_split': 2,
 'min_weight_fraction_leaf': 0.0,
 'n_estimators': 100,
 'n_jobs': None,
 'oob_score': False,
 'random_state': None,
 'verbose': 1,
 'warm_start': False}
```

In [211]:
```
# Score the Random Forest model
t = 0.0
with rt.elapsed_timer() as elapsed:
    rf_base_score =  rf_base.score(X_val, y_val)
    t = elapsed()
    logger.info(f'Random Forest Base Classification Model Fit Score: {[rf_bas
    logger.info(f'Random Forest Base Classification Model Fit Score Time: [{t

modelsPerformance['TestAccuracyScore'].append(rf_base_score)
modelsPerformance['ScoreTime'].append(t)
```

```
[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent wor
kers.
[Parallel(n_jobs=1)]: Done 100 out of 100 | elapsed:    0.8s finished
INFO:file_logger:Random Forest Base Classification Model Fit Score: [0.6437
080600165875]
INFO:file_logger:Random Forest Base Classification Model Fit Score Time:
[0.9830512999997154]
```

In [212]:
```
#%%time
# predictions of test set split from training set
t = 0.0
with rt.elapsed_timer() as elapsed:
    rf_base_pred = rf_base.predict(X_test)
    t = elapsed()
    logger.info(f'Random Forest Base Classification Predict Time: [{t}]')

modelsPerformance['PredictTime'].append(t)
```

```
[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent wor
kers.
[Parallel(n_jobs=1)]: Done 100 out of 100 | elapsed:    0.0s finished
INFO:file_logger:Random Forest Base Classification Predict Time: [0.1275378
999998793]
```

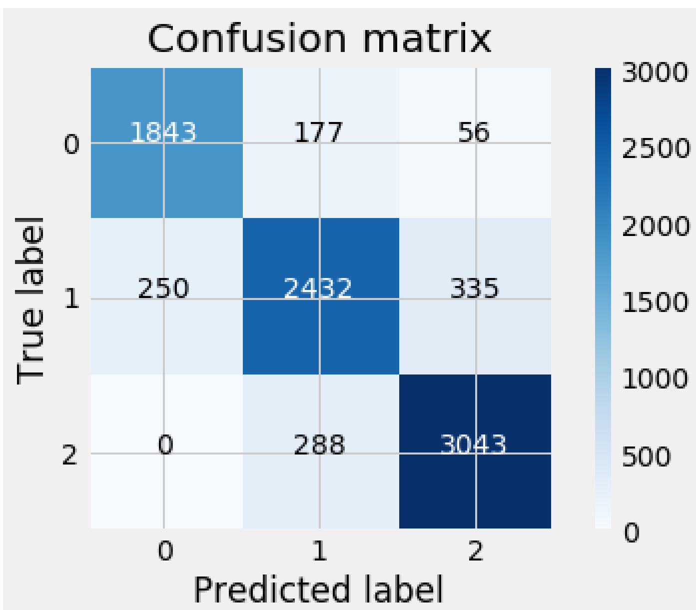
In [214]:

```
#%%time
#logger.info(f'y_test size: {y_test.size} rf_base_pred size: {rf_base_pred.si

#correct and inccorrect
correct = np.nonzero(rf_base_pred==y_test)[0]
incorrect = np.nonzero(rf_base_pred!=y_test)[0]

d = {'Label':y_test, 'Prediction':rf_base_pred}
#rf_base_PredictionsDf = pd.DataFrame(d)
#logger.info(f'Random Forest Base Classification DF Shape: {rf_base_Predictio

# which test observations were miss classified
#rf_base_missClassified_DT = rf_base_PredictionsDf[(rf_base_PredictionsDf['La

#logger.info(f'Miss Classified DF Shape: {rf_base_missClassified_DT.shape}')
#logger.info(f'Miss Classified Percent: {rf_base_missClassified_DT.shape[0]/y
#logger.info(f'Total Number of points: [{X_test.shape[0]}]  Mislabeled Points
```

4.5.2 Randome Forest Results

In [215]:

```
cm = confusion_matrix(y_test,rf_base_pred, labels=[0,1,2])
plt.savefig(f'{imageDir}/{model_name}_cm.png', dpi=300)
plot_confusion_matrix(cm,classes=[0,1,2])
```

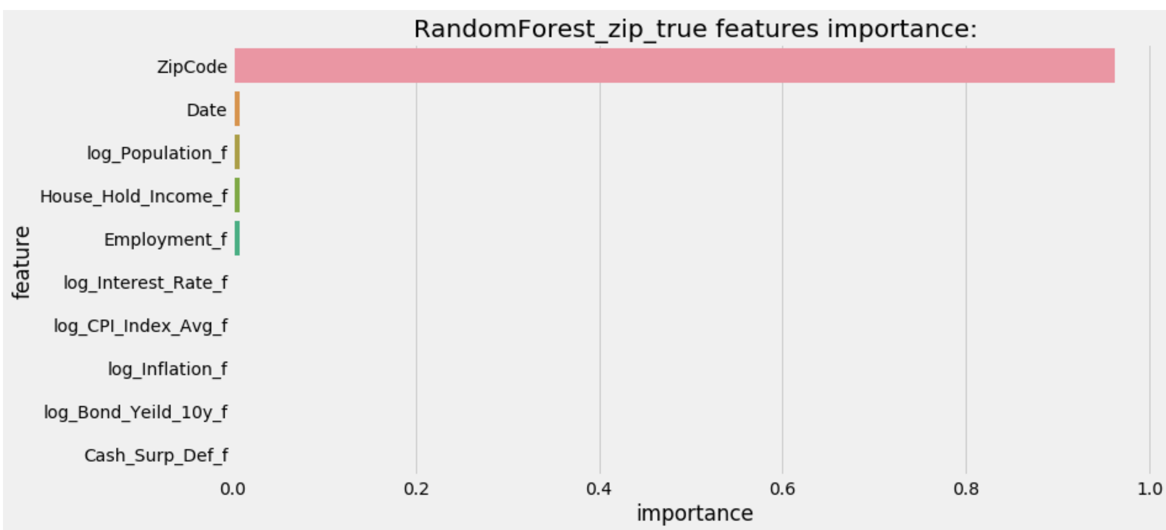


In [216]:
```
#print classification report table
n_classes=3
targetNames = ["Class{}".format(i) for i in range(n_classes)]
print(f'\n{classification_report(y_test, rf_base_pred, target_names=targetNar
```

```
              precision    recall  f1-score   support

      Class0       0.88      0.89      0.88      2076
      Class1       0.84      0.81      0.82      3017
      Class2       0.89      0.91      0.90      3331

   micro avg       0.87      0.87      0.87      8424
   macro avg       0.87      0.87      0.87      8424
weighted avg       0.87      0.87      0.87      8424
```

In [217]:
```
# Decision Tree - Feature importance
plt.savefig(f'{imageDir}/{model_name}_fimp.png', dpi=300)
rt.plot_feature_importances(features, rf_base, model_name, logger)
```

```
INFO:file_logger:                 feature  importance
1                ZipCode    0.961918
0                   Date    0.008418
7       log_Population_f    0.008186
8     House_Hold_Income_f    0.007558
9           Employment_f    0.007557
3     log_Interest_Rate_f    0.002031
2      log_CPI_Index_Avg_f    0.001115
5         log_Inflation_f    0.001005
4     log_Bond_Yeild_10y_f    0.000770
10         Cash_Surp_Def_f    0.000725

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



5. Naive Bayes

Python Package: SciKit-Learn [Gaussian Naive Bayes (https://scikit-learn.org/stable/modules/naive_bayes.html#gaussian-naive-bayes)](https://scikit-learn.org/stable/modules/naive_bayes.html#gaussian-naive-bayes)
Build a naïve Bayes model. Tune the parameters, such as the discretization options, to compare results.

5.1 Analysis - Naive Bayes

In [218]:
```
logger.debug(f'X_train shape: {X_train.shape} |  X_val shape: {X_val.shape} |
logger.debug(f'y_train shape: {y_train.shape} |  y_val shape: {y_val.shape} |
```

5.2 Exploration - Naive Bayes

In [ ]:

5.3 Model - Naive Bayes

* priors: None (default)

In [219]:
```
def build_nb(priors):
    nb = GaussianNB(priors=None, var_smoothing=1e-09)

    return nb
```

In [222]:
```
# MODEL BUILD - Naive Bayes

with_zip = 'zip_true'
model_name = f'NaiveBayes_{with_zip}'

gnb = build_nb(None)
t = 0.0
with elapsed_timer() as elapsed:
    # fit the GNB to the training data
    gnb.fit(X_train, y_train)
    t = elapsed()
    logger.info(f'GNB Model Build Time: [{t}]')

modelsPerformance['ModelName'].append(model_name)
modelsPerformance['FitTime'].append(t)
```

```
INFO:file_logger:GNB Model Build Time: [0.08762639999986277]
```

In [223]:
```
# Model Output to kaggel training dataset split into training/testing
t = 0.0
gnb_score = 0.0
with elapsed_timer() as elapsed:
    gnb_score = gnb.score(X_val, y_val)
    t = elapsed()
    logger.info(f'GNB Fit Score: [{gnb_score}]')
    logger.info(f'GNB Score Time: [{t}]')

modelsPerformance['TestAccuracyScore'].append(gnb_score)
modelsPerformance['ScoreTime'].append(t)
```

```
INFO:file_logger:GNB Fit Score: [0.38724270527030086]
INFO:file_logger:GNB Score Time: [0.049470199999632314]
```

In [224]:
```
%%time
# predictions of test set split from training set
t = 0.0
with elapsed_timer() as elapsed:
    gnb_pred = gnb.predict(X_test)
    t = elapsed()
    logger.info(f'GNB Model Predict Time: [{t}]')

modelsPerformance['PredictTime'].append(t)
```

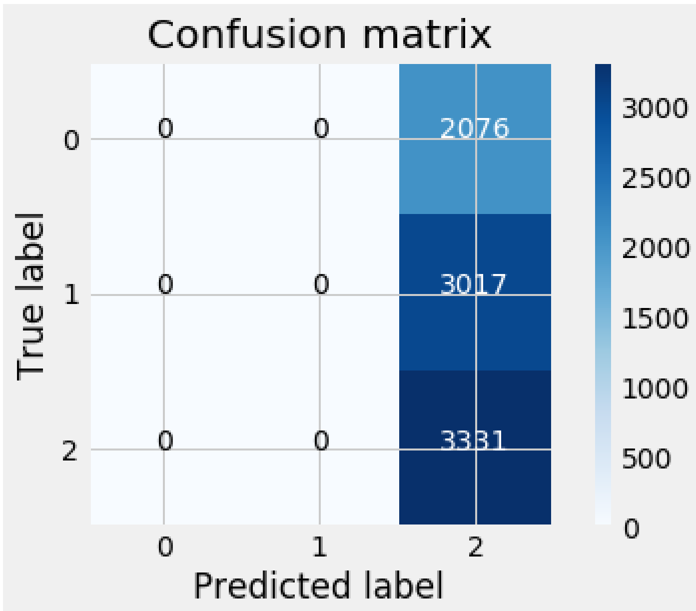
```
INFO:file_logger:GNB Model Predict Time: [0.007201399999757996]

Wall time: 8.98 ms
```

5.4 Results

In [225]:

```
misLabeled = (y_test != gnb_pred).sum()/X_test.shape[0]
nbAccuractelyLabeled = 1-misLabeled

#logger.info(f'Total Number of points: [{X_test.shape[0]}]  Mislabeled Points
#logger.info(f'Percent Mislabeled: [{((X_val != gnb_pred).sum()/X_test.shape[
logger.info(f'Percent Accurately Labeled: [{nbAccuractelyLabeled}]')
modelsPerformance['PredictAccuracyScore'].append(nbAccuractelyLabeled)

# confusion matrix evaluation
cm = confusion_matrix(y_test,gnb_pred, labels=[0,1,2])
plot_confusion_matrix(cm,classes=[0,1,2])
```

```
INFO:file_logger:Percent Accurately Labeled: [-5092.0]
```



In [226]:

```
#print classification report table
n_classes=3
targetNames = ["Class{}".format(i) for i in range(n_classes)]
print(f'\n{classification_report(y_test, gnb_pred, target_names=targetNames)}
```

```
              precision    recall  f1-score   support

      Class0       0.00      0.00      0.00      2076
      Class1       0.00      0.00      0.00      3017
      Class2       0.40      1.00      0.57      3331

   micro avg       0.40      0.40      0.40      8424
   macro avg       0.13      0.33      0.19      8424
weighted avg       0.16      0.40      0.22      8424
```

6. Support Vector Classification - SVMs

Python Package: scikit-learn v0.21.3 [sklearn.svm.SVC (https://scikit-learn.org/stable/modules/generated/sklearn.svm.SVC.html#sklearn.svm.SVC)](https://scikit-learn.org/stable/modules/generated/sklearn.svm.SVC.html#sklearn.svm.SVC)

6.1 Analysis

In [227]:
```
logger.debug(f'X_train shape: {X_train.shape} |  X_val shape: {X_val.shape} |
logger.debug(f'y_train shape: {y_train.shape} |  y_val shape: {y_val.shape} |
```

In [228]:
```
y_train = np.ravel(y_train)
y_val = np.ravel(y_val)
y_test = np.ravel(y_test)
```

In [229]:
```
logger.debug(f'X_train shape: {X_train.shape} |  X_val shape: {X_val.shape} |
logger.debug(f'y_train shape: {y_train.shape} |  y_val shape: {y_val.shape} |
```

6.2 Exploration

In [251]:
```
# one hot encoding
#lbe = LabelEncoder()
#y_train = lbe.fit_transform(y_train).astype('int32')
#y_val = lbe.fit_transform(y_val).astype('int32')
#y_test = lbe.fit_transform(y_val).astype('int32')
```

6.3 Model - SVM

- Three rounds with different kernel's being evaluated
  - 1st: rbf
    - Results:
      - Class1 - Best f1-score of .53 `![image.png](attachment:image.png)`
  - 2nd: poly
    - Results:
      - Class2 - Best f1-score of .57 `![image.png](attachment:image.png)`
  - 3rd: sigmoid
    - Results:
      - Class1 - Best f1-score of .53 `![image.png](attachment:image.png)`

In [230]:

```
def build_svc(kernel,verbose=True):
    # base SVC model
    svc_base = SVC(C=1.0,                          # Penalty parameter C of th
                   cache_size=200,                 # Specify the size of the k
                   class_weight=None,              # Set the parameter C of cl
                   coef0=0.0,                      # Independent term in kerne
                   decision_function_shape='ovr', # Whether to return a one-v
                   degree=3,                       # Degree of the polynomial
                   gamma='auto',                   # Kernel coefficient for 'r
                   kernel=kernel,                  # Specifies the kernel type
                   max_iter=-1,                    # Hard limit on iterations
                   probability=False,              # Whether to enable probabi
                   random_state=None,              # The seed of the pseudo ra
                   shrinking=True,                 # Whether to use the shrink
                   tol=0.001,                      # Tolerance for stopping cr
                   verbose=verbose                 # Enable verbose output. No
                  )
    return svc_base
```

In [245]:

```
kernel = 'sigmoid' # must be one of 'linear', 'poly', 'rbf', 'sigmoid', 'prec
with_zip = 'zip_false'
model_name = f'SupportVector_{kernel}_{with_zip}'

svc = build_svc(kernel,verbose=True)
t = 0.0
with elapsed_timer() as elapsed:
    # fit the svc to the training data
    svc_fit = svc.fit(X_train, y_train)
    t = elapsed()
    logger.info(f'SupportVectorClassifier Model {model_name} Build Time: [{t}

modelsPerformance['ModelName'].append(model_name)
modelsPerformance['FitTime'].append(t)
```

```
[LibSVM]

INFO:file_logger:SupportVectorClassifier Model SupportVector_sigmoid_zip_fa
lse Build Time: [89.3771115999989]
```

In [246]:

```
# Score the svc model
t = 0.0
with rt.elapsed_timer() as elapsed:
    svc_score =  svc.score(X_val, y_val)
    t = elapsed()
    logger.info(f'Support Vector Classification Model {model_name} Fit Score:
    logger.info(f'Support Vector Classification Model {model_name} Fit Score

modelsPerformance['TestAccuracyScore'].append(svc_score)
modelsPerformance['ScoreTime'].append(t)
```

```
INFO:file_logger:Support Vector Classification Model SupportVector_sigmoid_
zip_false Fit Score: [0.3864133303174244]
INFO:file_logger:Support Vector Classification Model SupportVector_sigmoid_
zip_false Fit Score Time: [25.591142700001]
```

In [247]:

```
#%%time
# predictions of test set split from training set
t = 0.0
with rt.elapsed_timer() as elapsed:
    svc_pred = svc.predict(X_test)
    t = elapsed()
    logger.info(f'Support Vector Classification {model_name} Predict Time: [{

modelsPerformance['PredictTime'].append(t)
```

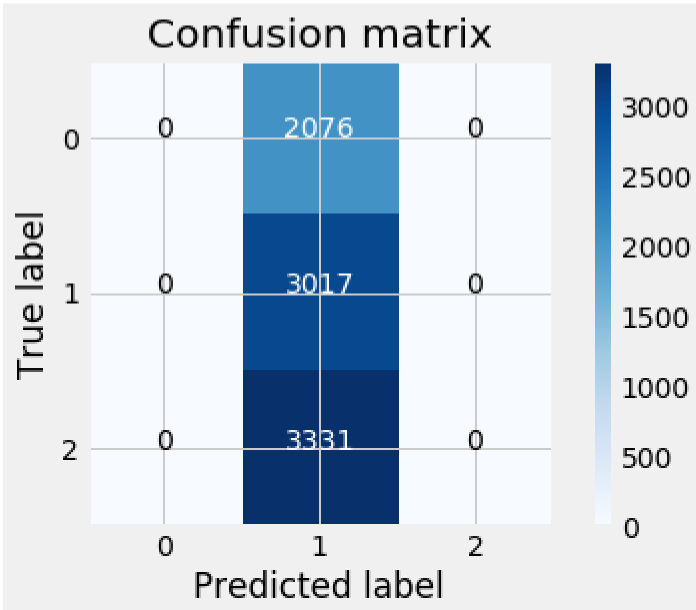
```
INFO:file_logger:Support Vector Classification SupportVector_sigmoid_zip_fa
lse Predict Time: [7.811279999999897]
```

In [248]:

```
logger.debug(f'X_train shape: {X_train.shape} |  X_val shape: {X_val.shape} |
logger.debug(f'y_train shape: {y_train.shape} |  y_val shape: {y_val.shape} |
```

In [249]:

```
#misLabeled = (y_test != svc_pred).sum()/X_test.shape[0]
#nbAccuractelyLabeled = 1-misLabeled

#logger.info(f'Total Number of points: [{X_test.shape[0]}]  Mislabeled Points
#logger.info(f'Percent Mislabeled: [{((X_val != gnb_pred).sum()/X_test.shape[
#logger.info(f'Percent Accurately Labeled: [{nbAccuractelyLabeled}]')
#modelsPerformance['PredictAccuracyScore'].append(nbAccuractelyLabeled)

# confusion matrix evaluation
cm = confusion_matrix(y_test,svc_pred, labels=[0,1,2])
plot_confusion_matrix(cm,classes=[0,1,2])
```



In [250]:

```
#print classification report table
n_classes=3
targetNames = ["Class{}".format(i) for i in range(n_classes)]
print(f'\n{classification_report(y_test, svc_pred, target_names=targetNames)}
```

```
              precision    recall  f1-score   support

      Class0       0.00      0.00      0.00      2076
      Class1       0.36      1.00      0.53      3017
      Class2       0.00      0.00      0.00      3331

   micro avg       0.36      0.36      0.36      8424
   macro avg       0.12      0.33      0.18      8424
weighted avg       0.13      0.36      0.19      8424
```

6.4 Results

In [252]:
```
#pd.DataFrame(modelsPerformance)
modelsPerformance
```

Out[252]:
```
{'ModelName': ['DecisionTree_None_2_zip_true',
  'RandomForest_zip_true',
  'NaiveBayes_zip_false',
  'NaiveBayes_zip_true',
  'SupportVector_rbf_zip_false',
  'SupportVector_poly_zip_false',
  'SupportVector_sigmoid_zip_false'],
 'TestAccuracyScore': [0.9914423584407751,
  0.6437080600165875,
  0.38724270527030086,
  0.38724270527030086,
  0.5570383774410013,
  0.36454799065068233,
  0.36454799065068233,
  0.3864133303174244],
 'PredictAccuracyScore': [-5092.0],
 'FitTime': [0.3555843000012828,
  7.046673699998792,
  0.08719380000002275,
  0.08762639999986277,
  284.62899259999904,
  0.10550850000072387,
  89.3771115999989],
 'ScoreTime': [0.04137609999997949,
  0.9830512999997154,
  0.0912466999998287,
  0.049470199999632314,
  95.96742810000069,
  0.045794699999532895,
  0.04900169999928039,
  25.591142700001],
 'PredictTime': [0.003885100000843522,
  0.1275378999998793,
  0.007201399999757996,
  29.593625200001043,
  0.009665300000051502,
  7.811279999999897]}
```

8. Final Results & Conclusion

Real estate housing market trends are impacted by many factors that require deep data mining techniques and domain experts to pull the right data together and engineer it in meaningful ways to gain insights into this industry. Data proved to be the most challenging component of this research. There is a lack of quality datasets that are easily found which inhibits possible discoveries.

Certainly economic indicators are present that signal swings in price trends... Further research on comprehensive, state level economics is needed to expand on the datasets used in this study, which were at the national level. Most likely it's this that caused the inconsistencies with the models performance. The Real estate data being focused on was at the state level, whereas the economic data was at the national yearly average. This abstraction could have been a leading cause.

In [257]:

```
# for report auto generation
# testing markup report generation
from nbconvert import HTMLExporter
import codecs
import os
import datetime

stamp = datetime.date.today().strftime("%m-%d-%Y")
exporter = HTMLExporter(template_file='report.tpl')
output, resources = exporter.from_filename('ist707_prj.ipynb')
new_fnw = 'Ryan_Timbrook_Project_Report_.html'
codecs.open(new_fnw, 'w',encoding='utf-8').write(output)
```