# u-s-home-assignment-final

December 13, 2023

**Data Science Project: Analyzing Key Factors Influencing US Home Prices**

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***Introduction***

The data for this analysis was collected from various publicly available sources, focusing on key factors believed to influence home prices in the United States. Using techniques such as VLOOKUP and HLOOKUP in Excel, the collected data was merged to create a comprehensive dataset. This dataset is now imported into this Colab notebook for further analysis and exploration.

***Objective***

The primary objective of this data science project is to build a predictive model that explains how different factors have impacted home prices in the United States over the last two decades (20 years). The analysis will revolve around understanding the relationship between various economic, demographic, and housing market indicators and the fluctuations in home prices.

[2]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
from sklearn.metrics import r2_score, mean_squared_error, mean_absolute_error
```

[3]:
```
df = pd.read_csv("/content/Assignment_1.csv")
```

[4]:
```
df.head(1)
```

[4]:
```
         date  new_constructed_units  unemployment_rate  interest_rates  \
0  01-01-1947                    NaN                NaN             NaN

   income  home_price_index  per_capita_gdp  urban_population
0     NaN               NaN           15248               NaN
```

[5]:
```
df.tail(1)
```

```
[5]:            date  new_constructed_units  unemployment_rate  interest_rates  \
     921  01-10-2023                 1410.0                3.9            5.33

           income  home_price_index  per_capita_gdp  urban_population
     921  16848.7           311.175           67083            83.084
```

```
[6]: df.describe().T
```

```
[6]:                        count          mean           std        min  \
     new_constructed_units  670.0   1396.762687    358.271084    520.000
     unemployment_rate      910.0      5.709670      1.708239      2.500
     interest_rates         832.0      4.599916      3.596581      0.050
     income                 778.0   8255.129820   4299.805894   2318.400
     home_price_index       442.0    142.293441     61.649943     63.965
     per_capita_gdp         922.0  37430.843818  15402.352634  15032.000
     urban_population       766.0     76.764057      3.788336     69.996

                                   25%        50%         75%        max
     new_constructed_units  1190.00000   1396.000   1641.7500   2299.000
     unemployment_rate         4.40000      5.500      6.7000     14.700
     interest_rates            1.79000      4.160      6.2425     19.100
     income                 4539.62500   7282.850  12069.1750  20422.600
     home_price_index         82.25075    141.275    179.0250    311.175
     per_capita_gdp        24176.75000  35582.000  52835.0000  67083.000
     urban_population         73.65550     75.701     80.2690     83.084
```

```
[7]: df.nunique()
```

```
[7]: date                     922
     new_constructed_units    536
     unemployment_rate         83
     interest_rates           503
     income                   777
     home_price_index         440
     per_capita_gdp           307
     urban_population          63
     dtype: int64
```

```
[8]: df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 922 entries, 0 to 921
Data columns (total 8 columns):
 #   Column                 Non-Null Count  Dtype
---  ------                 --------------  -----
 0   date                   922 non-null    object
 1   new_constructed_units  670 non-null    float64
 2   unemployment_rate      910 non-null    float64
 3   interest_rates         832 non-null    float64
 4   income                 778 non-null    float64
 5   home_price_index       442 non-null    float64
 6   per_capita_gdp         922 non-null    int64
 7   urban_population       766 non-null    float64
dtypes: float64(6), int64(1), object(1)
memory usage: 57.8+ KB
```

```
[9]: df['date'] = pd.to_datetime(df['date'])
```

```
[10]: df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 922 entries, 0 to 921
Data columns (total 8 columns):
 #   Column                 Non-Null Count  Dtype
---  ------                 --------------  -----
 0   date                   922 non-null    datetime64[ns]
 1   new_constructed_units  670 non-null    float64
 2   unemployment_rate      910 non-null    float64
 3   interest_rates         832 non-null    float64
 4   income                 778 non-null    float64
 5   home_price_index       442 non-null    float64
 6   per_capita_gdp         922 non-null    int64
 7   urban_population       766 non-null    float64
dtypes: datetime64[ns](1), float64(6), int64(1)
memory usage: 57.8 KB
```

```
[11]: df.head(1)
```

```
[11]:         date  new_constructed_units  unemployment_rate  interest_rates  \
      0 1947-01-01                    NaN                NaN             NaN

         income  home_price_index  per_capita_gdp  urban_population
      0     NaN               NaN           15248               NaN
```

```
[12]: df_20 = df[(df["date"] >= '01-01-2003') & (df["date"] <= '01-10-2023')]
```

```
[13]: df_20.head(1)
```

```
[13]:           date  new_constructed_units  unemployment_rate  interest_rates  \
      672 2003-01-01                 1654.0                5.8            1.24

            income  home_price_index  per_capita_gdp  urban_population
      672  10710.4           128.461           50462            79.583
```

```
[14]: df_20.tail(1)
```

```
[14]:           date  new_constructed_units  unemployment_rate  interest_rates  \
     921 2023-01-10                 1410.0                3.9            5.33

          income  home_price_index  per_capita_gdp  urban_population
     921  16848.7           311.175           67083            83.084
```

```
[15]: df_20.isnull().sum()
```

```
[15]: date                     0
      new_constructed_units    0
      unemployment_rate        0
      interest_rates           0
      income                   0
      home_price_index         0
      per_capita_gdp           0
      urban_population         0
      dtype: int64
```

There are no Null Values on our dataset.

```
[16]: df_20.duplicated().sum()
```

```
[16]: 0
```

There are no Duplicate columns present in our dataset.

```
[17]: df_20.nunique()
```

```
[17]: date                     250
      new_constructed_units    228
      unemployment_rate         64
      interest_rates           118
      income                   250
      home_price_index         249
      per_capita_gdp            83
      urban_population          20
      dtype: int64
```

Above info shows that there are no categorical variables present in the dataset.

```
[18]: df_20['year'] = df_20['date'].dt.year
```

```
<ipython-input-18-b94521149b84>:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
```

```
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df_20['year'] = df_20['date'].dt.year
```

Creating a new variable "Year" to make Year wise Analysis for the variables.

[19]:
```
df_20.head()
```

[19]:
```
           date  new_constructed_units  unemployment_rate  interest_rates  \
672  2003-01-01                 1654.0                5.8            1.24
673  2003-01-02                 1688.0                5.9            1.26
674  2003-01-03                 1638.0                5.9            1.25
675  2003-01-04                 1662.0                6.0            1.26
676  2003-01-05                 1733.0                6.1            1.26

      income  home_price_index  per_capita_gdp  urban_population  year
672  10710.4           128.461           50462            79.583  2003
673  10674.0           129.355           50462            79.583  2003
674  10696.5           130.148           50462            79.583  2003
675  10752.7           130.884           50796            79.583  2003
676  10832.0           131.735           50796            79.583  2003
```

[20]:
```
pd.set_option('display.max_columns',None)
df_20.
 ↪groupby('year')['new_constructed_units','unemployment_rate','interest_rates','income','home
 ↪agg(['mean', 'max', 'min']).T
```

```
<ipython-input-20-7ada3471925c>:2: FutureWarning: Indexing with multiple keys
(implicitly converted to a tuple of keys) will be deprecated, use a list
instead.
  df_20.groupby('year')['new_constructed_units','unemployment_rate','interest_ra
tes','income','home_price_index','per_capita_gdp','urban_population'].agg(['mean
', 'max', 'min']).T
```

[20]:
```
year                              2003          2004          2005  \
new_constructed_units mean   1676.750000   1834.583333   1929.333333
                      max    1733.000000   1938.000000   2103.000000
                      min    1570.000000   1709.000000   1787.000000
unemployment_rate     mean      5.991667      5.541667      5.083333
                      max       6.300000      5.800000      5.400000
                      min       5.700000      5.400000      4.900000
interest_rates        mean      1.127500      1.349167      3.213333
                      max       1.260000      2.160000      4.160000
                      min       0.980000      1.000000      2.280000
income                mean  10884.391667  11233.175000  11364.858333
                      max   11066.700000  11659.000000  11535.200000
                      min   10674.000000  11051.200000  11226.500000
home_price_index      mean    133.731333    150.440250    171.737000
                      max     140.179000    159.330000    180.910000
                      min    128.461000   141.646000   161.288000
per_capita_gdp        mean 51189.000000 52681.250000 54014.250000
                      max  51986.000000 53242.000000 54317.000000
                      min  50462.000000 52179.000000 53719.000000
urban_population      mean    79.583000    79.757000    79.928000
                      max     79.583000    79.757000    79.928000
                      min     79.583000    79.757000    79.928000

year                               2006         2007         2008  \
new_constructed_units mean  1989.000000  1513.833333  1126.833333
                      max   2245.000000  1822.000000  1331.000000
                      min   1877.000000  1328.000000  1017.000000
unemployment_rate     mean     4.608333     4.616667     5.800000
                      max      4.800000     5.000000     7.300000
                      min      4.400000     4.400000     4.900000
interest_rates        mean     4.964167     5.019167     1.927500
                      max      5.250000     5.260000     3.940000
                      min      4.290000     4.240000     0.160000
income                mean 11777.783333 12054.300000 12244.325000
                      max  11958.600000 12120.500000 12696.200000
                      min  11651.800000 11956.600000 12100.800000
home_price_index      mean   183.447500   179.918917   164.057417
                      max    184.364000   184.598000   173.132000
                      min    182.321000   174.342000   153.619000
per_capita_gdp        mean 54993.500000 55560.000000 55105.250000
                      max  55216.000000 55857.000000 55705.000000
                      min  54886.000000 55260.000000 53941.000000
urban_population      mean    80.099000    80.269000    80.438000
                      max     80.099000    80.269000    80.438000
                      min     80.099000    80.269000    80.438000

year                               2009         2010         2011  \
new_constructed_units mean   795.500000   653.750000   584.583333
                      max    846.000000   894.000000   634.000000
                      min    721.000000   552.000000   520.000000
unemployment_rate     mean     9.283333     9.608333     8.933333
                      max     10.000000     9.900000     9.100000
                      min      7.800000     9.300000     8.500000
interest_rates        mean     0.160000     0.175000     0.101667
                      max      0.220000     0.200000     0.170000
                      min      0.120000     0.110000     0.070000
income                mean 12273.441667 12505.291667 12775.250000
                      max  12500.100000 12680.600000 12898.500000
                      min  12193.200000 12285.800000 12705.300000
home_price_index      mean   148.545083   144.674500   139.259500
                      max    151.507000   147.396000   141.521000
                      min    147.694000   142.060000   136.674000
```

```
per_capita_gdp        mean  53212.500000  54188.250000  54603.000000
                      max   53531.000000  54569.000000  54979.000000
                      min   53017.000000  53683.000000  54341.000000
urban_population      mean     80.606000     80.772000     80.944000
                      max      80.606000     80.772000     80.944000
                      min      80.606000     80.772000     80.944000

year                                2012          2013          2014  \
new_constructed_units mean    641.416667    763.166667    882.666667
                      max     730.000000    839.000000    975.000000
                      min     545.000000    708.000000    800.000000
unemployment_rate     mean      8.075000      7.358333      6.158333
                      max       8.300000      8.000000      6.700000
                      min       7.700000      6.700000      5.600000
interest_rates        mean      0.140000      0.107500      0.089167
                      max       0.160000      0.150000      0.120000
                      min       0.080000      0.080000      0.070000
income                mean  13125.383333  12937.191667  13383.675000
                      max   13642.700000  13027.500000  13719.100000
                      min   12961.600000  12813.900000  13079.500000
home_price_index      mean    140.993833    154.520750    164.698167
                      max     145.503000    160.994000    168.050000
                      min     136.533000    146.827000    161.927000
per_capita_gdp        mean  55422.250000  56171.750000  57137.750000
                      max   55490.000000  56642.000000  57702.000000
                      min   55342.000000  55859.000000  56345.000000
urban_population      mean     81.119000     81.299000     81.483000
                      max      81.119000     81.299000     81.483000
                      min      81.119000     81.299000     81.483000

year                               2015        2016         2017  \
new_constructed_units mean    965.25000   1060.5000  1151.833333
                      max    1040.00000   1244.0000  1236.000000
                      min     781.00000    945.0000  1069.000000
unemployment_rate     mean      5.27500      4.8750     4.358333
                      max       5.70000      5.1000     4.700000
                      min       5.00000      4.7000     4.100000
interest_rates        mean      0.13250      0.3950     1.001667
                      max       0.24000      0.5400     1.300000
                      min       0.11000      0.3400     0.650000
income                mean  13908.57500  14172.2500 14613.966667
                      max   14060.20000  14313.7000 14797.900000
                      min   13797.70000  14095.5000 14373.700000
home_price_index      mean    172.18175    180.9255   191.397667
                      max     176.54300    185.7220   197.172000
                      min     168.63400    177.2740   186.805000
per_capita_gdp        mean  58363.25000  58967.7500 60000.750000
```

```
                     max   58486.00000  59296.0000  60674.000000
                     min   58121.00000  58704.0000  59494.000000
urban_population     mean     81.67100     81.8620     82.058000
                     max      81.67100     81.8620     82.058000
                     min      81.67100     81.8620     82.058000

year                                2018          2019          2020  \
new_constructed_units mean   1190.000000   1260.666667   1286.333333
                     max    1288.000000   1334.000000   1446.000000
                     min    1053.000000   1150.000000   1171.000000
unemployment_rate    mean      3.891667      3.683333      8.091667
                     max       4.100000      4.000000     14.700000
                     min       3.700000      3.500000      3.500000
interest_rates       mean      1.831667      2.158333      0.375833
                     max       2.270000      2.420000      1.580000
                     min       1.410000      1.550000      0.050000
income               mean  15143.616667  15608.908333  16607.466667
                     max   15506.500000  15778.200000  18020.200000
                     min   14886.600000  15501.700000  15696.300000
home_price_index     mean    202.476417    209.463333    222.143417
                     max     206.156000    213.933000    236.486000
                     min     198.315000    206.539000    214.994000
per_capita_gdp       mean  61417.500000  62605.500000  60984.750000
                     max   61622.000000  63257.000000  62414.000000
                     min   61093.000000  61889.000000  57386.000000
urban_population     mean     82.256000     82.459000     82.664000
                     max      82.256000     82.459000     82.664000
                     min      82.256000     82.459000     82.664000

year                                2021          2022        2023
new_constructed_units mean   1340.666667   1387.666667   1451.6000
                     max    1459.000000   1543.000000   1577.0000
                     min    1232.000000   1256.000000   1334.0000
unemployment_rate    mean      5.366667      3.641667      3.6200
                     max       6.300000      4.000000      3.9000
                     min       3.900000      3.500000      3.4000
interest_rates       mean      0.080000      1.683333      4.9630
                     max       0.100000      4.100000      5.3300
                     min       0.060000      0.080000      4.3300
income               mean  17138.716667  16117.050000  16763.0200
                     max   20422.600000  16265.100000  16848.7000
                     min   16418.500000  15963.400000  16601.9000
home_price_index     mean    260.045667    298.486750    303.8848
                     max     281.342000    304.724000    311.1750
                     min     239.560000    285.924000    297.0300
per_capita_gdp       mean  64412.500000  65414.500000  66558.9000
                     max   65651.000000  65783.000000  67083.0000
```

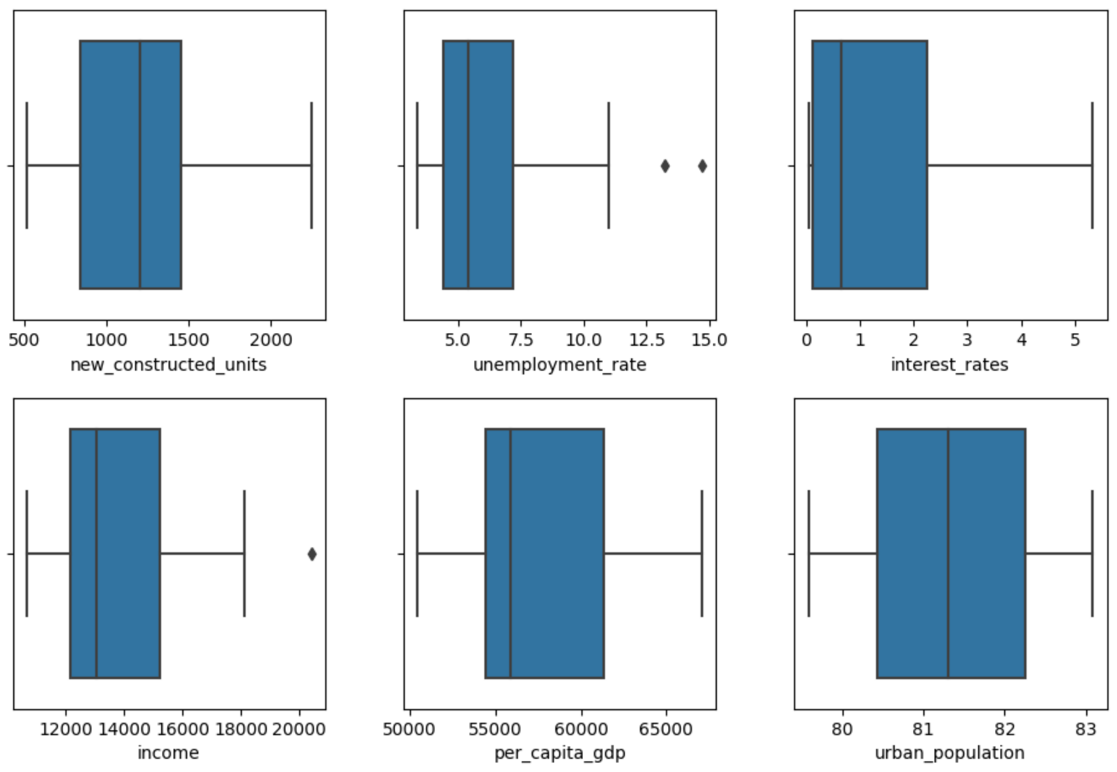
```
                        min    63227.000000  65127.000000  66078.0000
urban_population        mean      82.873000     83.084000     83.0840
                        max       82.873000     83.084000     83.0840
                        min       82.873000     83.084000     83.0840
```

1. The number of new constructed units has generally increased over the years, with a noticeable peak in 2005 and a subsequent decline until around 2009.
2. The unemployment rate shows a pattern of decrease from 2003 to 2007, followed by a significant increase during the 2008 financial crisis.
3. Interest rates have experienced a general decline over the years, reaching a minimum around 2009.
4. The maximum income has consistently increased, reflecting overall economic growth.

## 1 Exploratory data analysis (EDA)

[21]:
```
cols =  ['new_constructed_units','unemployment_rate','interest_rates',
         'income','per_capita_gdp','urban_population']
```

[22]:
```
fig = plt.figure(figsize = (60,60))

gs = fig.add_gridspec(15,15)

gs.update(wspace = 0.25,hspace = 0.25)

ax0 = fig.add_subplot(gs[0,0],)
ax1 = fig.add_subplot(gs[0,1])
ax2 = fig.add_subplot(gs[0,2])
ax3 = fig.add_subplot(gs[1,0])
ax4 = fig.add_subplot(gs[1,1])
ax5 = fig.add_subplot(gs[1,2])

Axis = [ax0,ax1,ax2,ax3,ax4,ax5]

for ax,col in zip(Axis,cols):
    sns.boxplot(ax = ax,data = df_20, x = col)
plt.show()
```

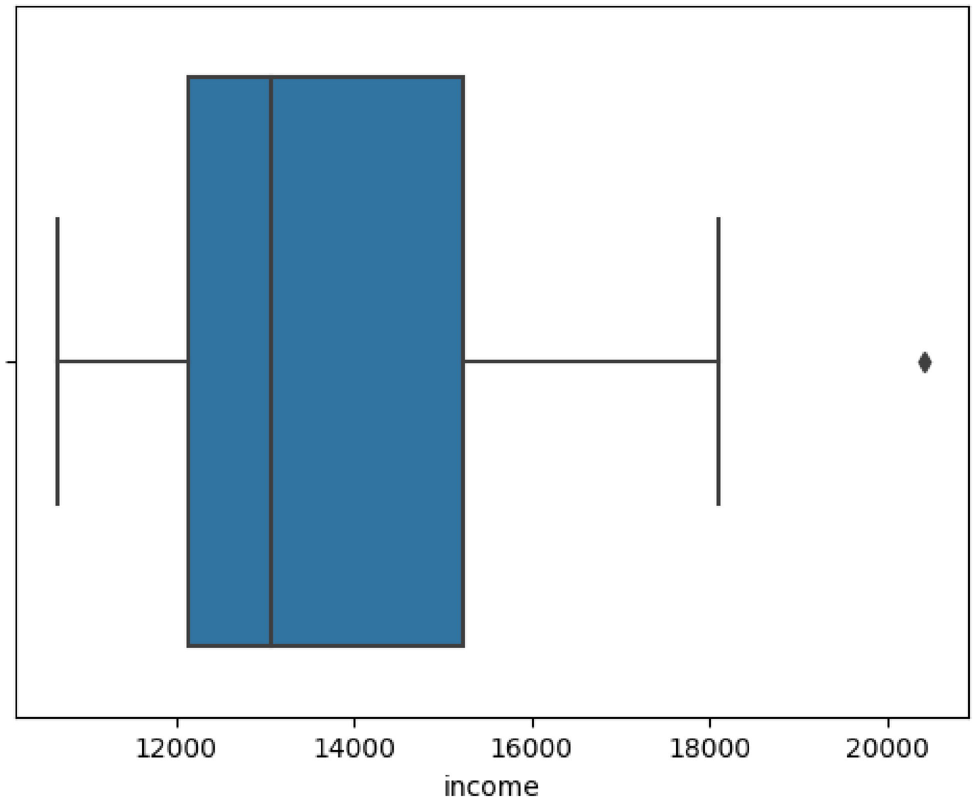


1. Income has 1 outliers greater than upper bound (19853.34) or lower than lower bound(7509.24). Cap them or remove them.
2. Unemployement Rate has 3 outliers greater than upper bound (11.40) or lower than lower bound(0.20). Cap them or remove them.

So below we are calculating the IQR and on the basis of lower and Upper limit we are capping the outliers.

[23]:
```
sns.boxplot(data=df_20, x= 'income')
```

[23]:
```
<Axes: xlabel='income'>
```



[24]:
```
q1_income = df_20['income'].quantile(0.25)
q3_income = df_20['income'].quantile(0.75)
income_IQR = q3_income - q1_income

upper_limit_income = q3_income + 1.5 * income_IQR
lower_limit_income = q1_income - 1.5 * income_IQR

print(upper_limit_income)
print(lower_limit_income)
```

```
19853.337499999998
7509.2375
```

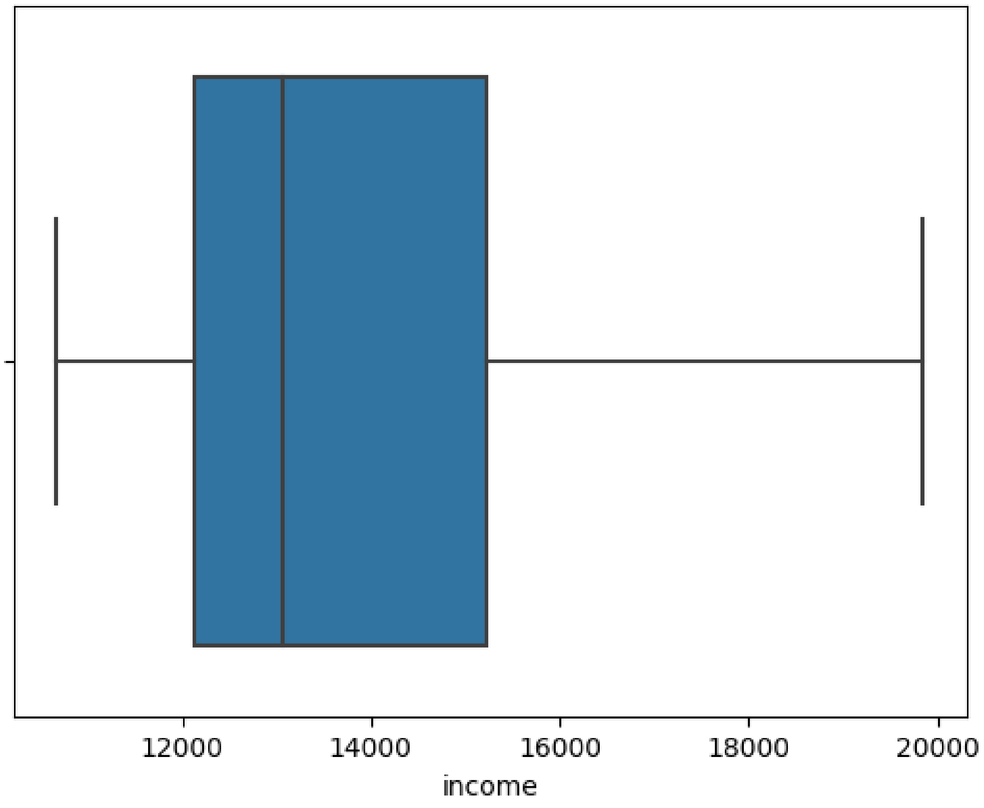
[25]:
```
df_20['income'] = df_20['income'].clip(lower=lower_limit_income,␣
 ↪upper=upper_limit_income)
```

```
<ipython-input-25-2109b2de28d0>:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
```

```
  df_20['income'] = df_20['income'].clip(lower=lower_limit_income,
upper=upper_limit_income)
```

[26]:
```
sns.boxplot(data=df_20, x= 'income')
```

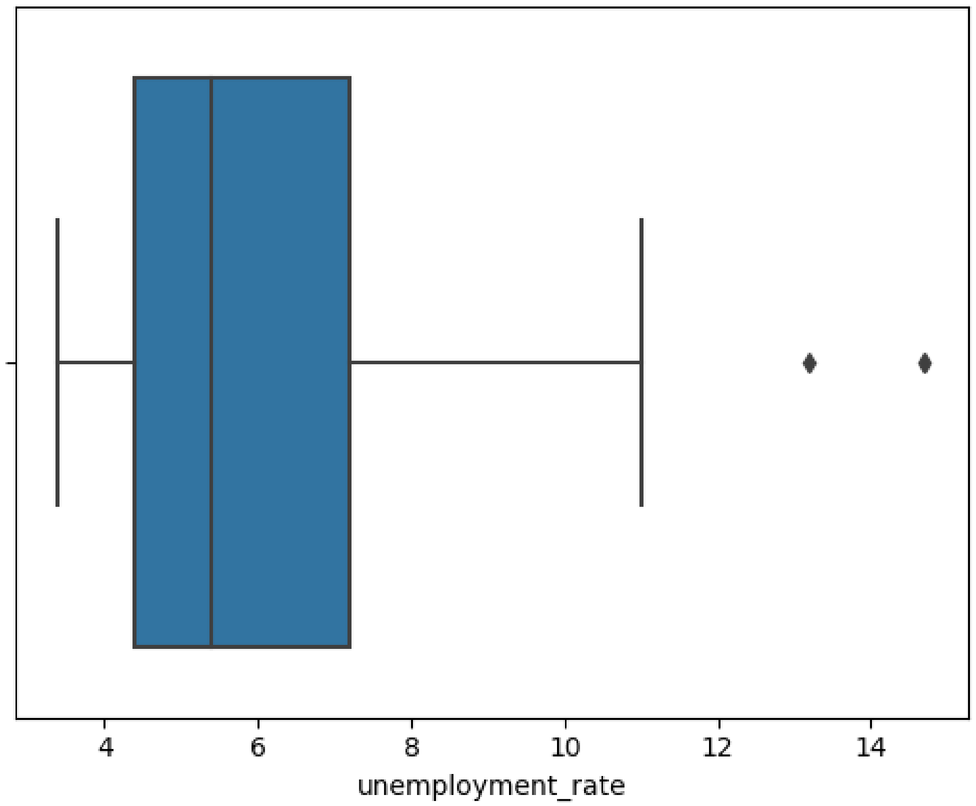
[26]:
```
<Axes: xlabel='income'>
```



We can see now there are no outliers present in the income data.

[27]:
```
sns.boxplot(data=df_20, x= 'unemployment_rate')
```

[27]:
```
<Axes: xlabel='unemployment_rate'>
```



[28]:
```
q1_ur = df_20['unemployment_rate'].quantile(0.25)
q3_ur = df_20['unemployment_rate'].quantile(0.75)
ur_IQR = q3_ur - q1_ur

upper_limit_ur = q3_ur + 1.5 * ur_IQR
lower_limit_ur = q1_ur - 1.5 * ur_IQR

print(upper_limit_ur)
print(lower_limit_ur)
```

```
11.399999999999999
0.20000000000000107
```

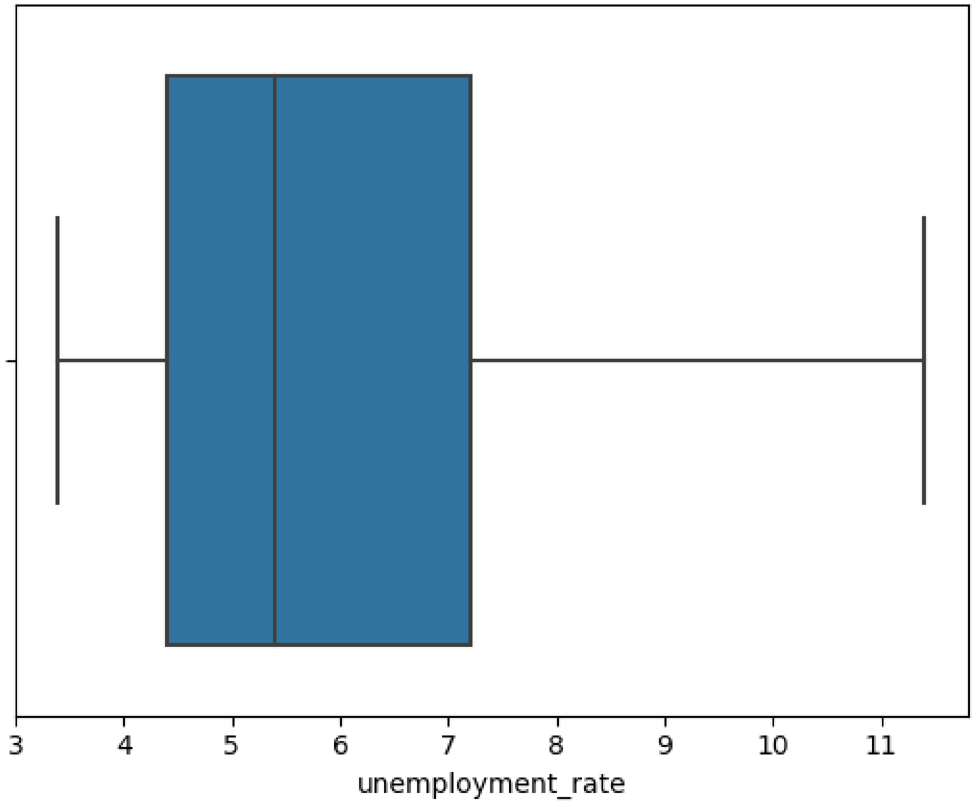
[29]:
```
df_20['unemployment_rate'] = df_20['unemployment_rate'].
  ↪clip(lower=lower_limit_ur, upper=upper_limit_ur)
```

```
<ipython-input-29-d67fd013cfd2>:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
```

```
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df_20['unemployment_rate'] =
df_20['unemployment_rate'].clip(lower=lower_limit_ur, upper=upper_limit_ur)
```

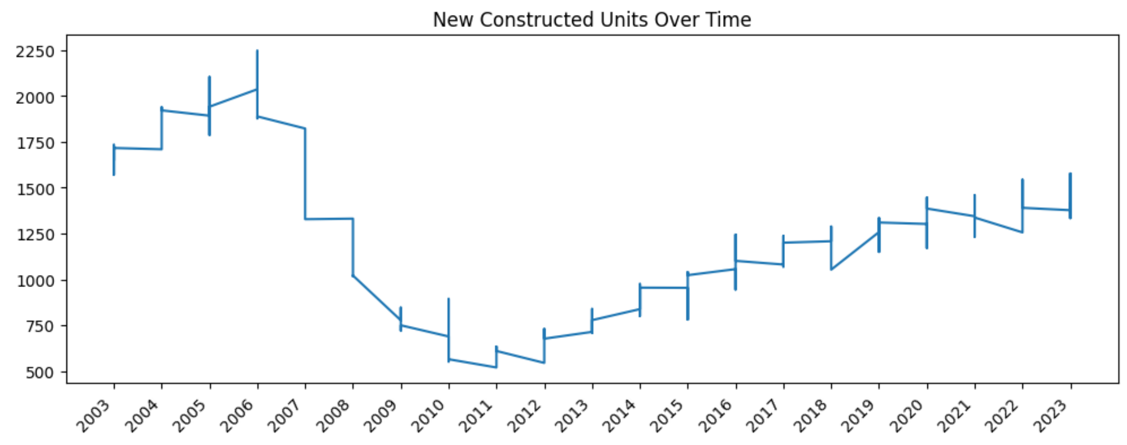
[30]:
```
sns.boxplot(data=df_20, x= 'unemployment_rate')
```

[30]:
```
<Axes: xlabel='unemployment_rate'>
```

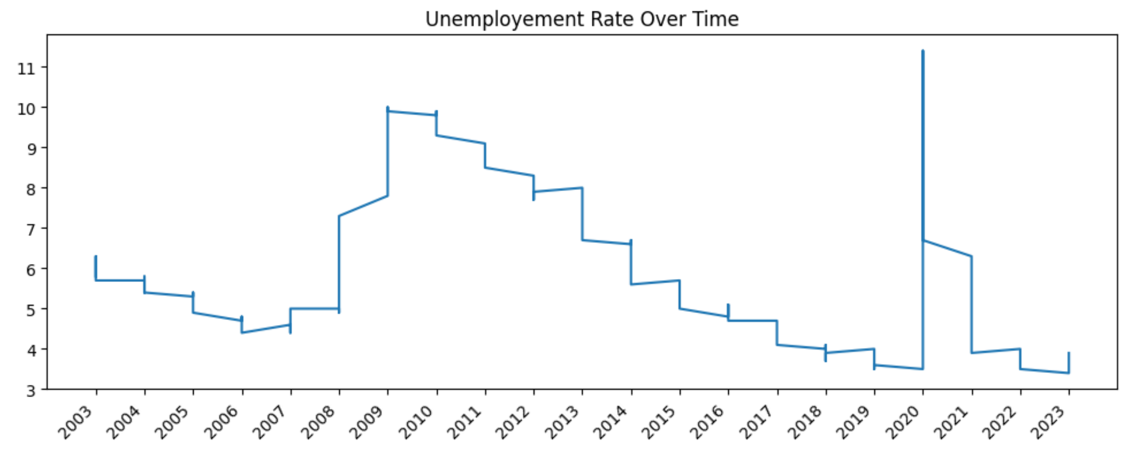


We can see now there are no outliers present in the Unemployemt Rate data.

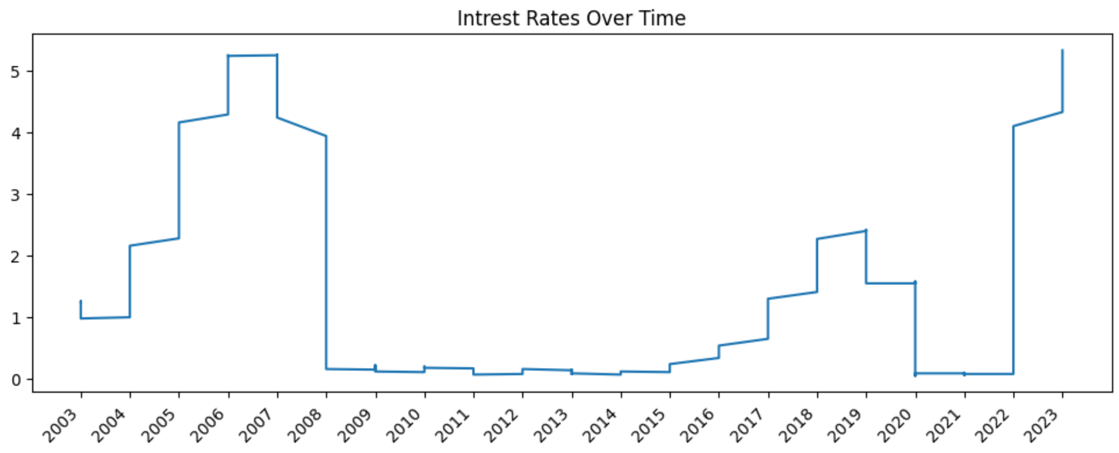
[31]:
```
plt.figure(figsize = (12,4))
plt.plot(df_20['year'], df_20['new_constructed_units'])
plt.title("New Constructed Units Over Time")
plt.xticks(df_20['year'].unique(), rotation=45, ha="right")
plt.show()
```



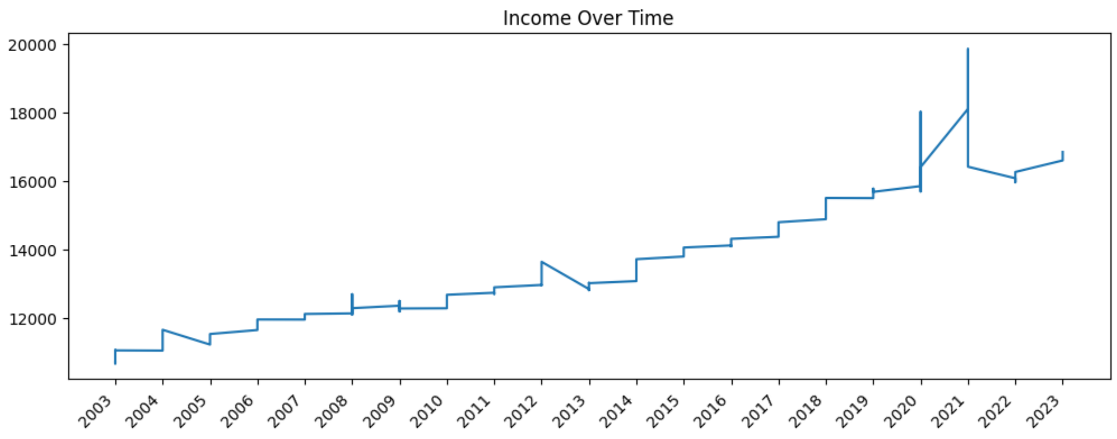
```
[32]: plt.figure(figsize = (12,4))
      plt.plot(df_20['year'], df_20['unemployment_rate'])
      plt.title("Unemployement Rate Over Time")
      plt.xticks(df_20['year'].unique(), rotation=45, ha="right")
      plt.show()
```



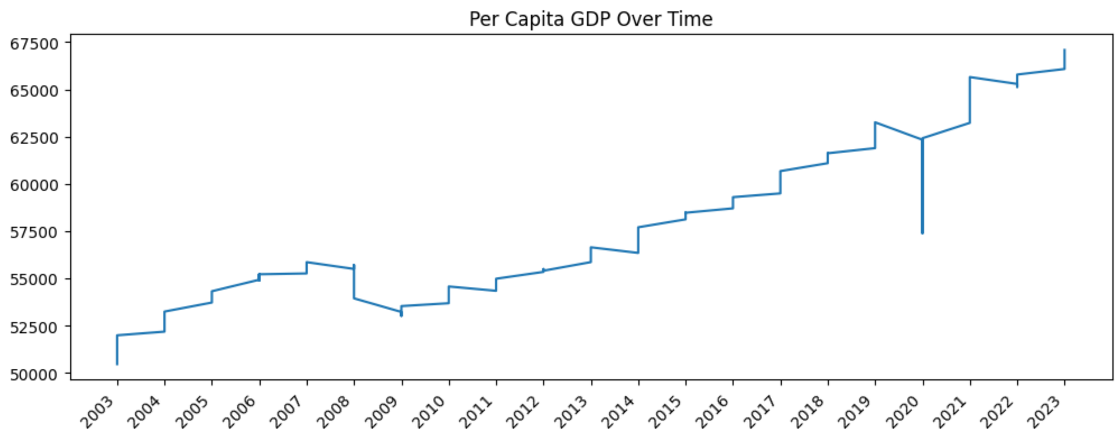
```
[33]: plt.figure(figsize = (12,4))
      plt.plot(df_20['year'], df_20['interest_rates'])
      plt.title("Intrest Rates Over Time")
      plt.xticks(df_20['year'].unique(), rotation=45, ha="right")
      plt.show()
```



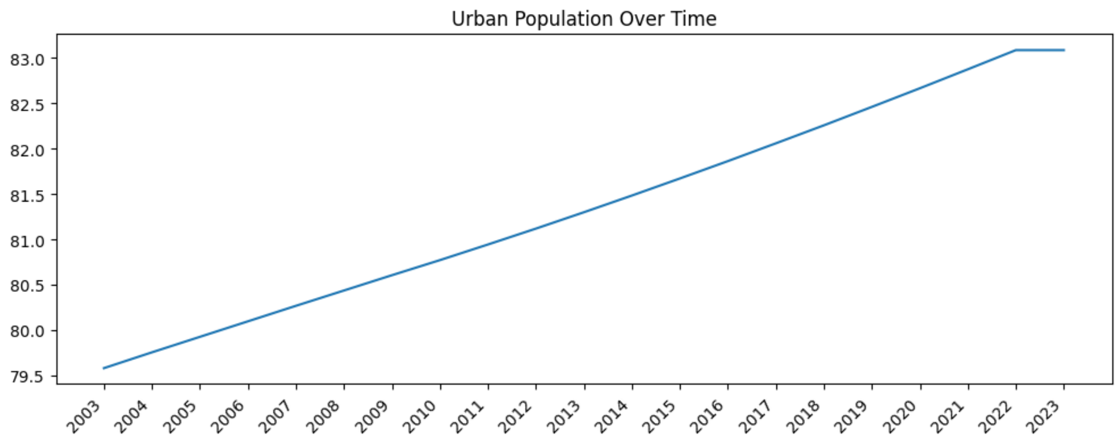
```
[34]: plt.figure(figsize = (12,4))
      plt.plot(df_20['year'], df_20['income'])
      plt.title("Income Over Time")
      plt.xticks(df_20['year'].unique(), rotation=45, ha="right")
      plt.show()
```



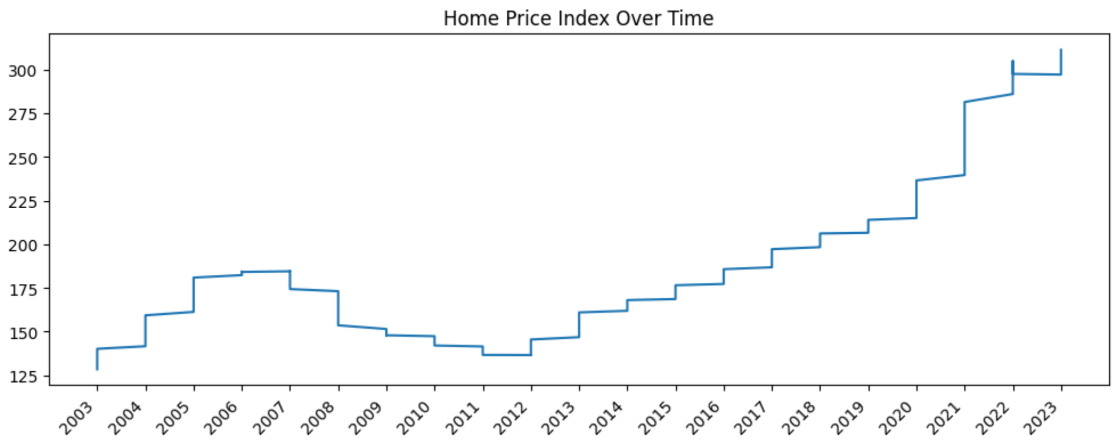
```
[35]: plt.figure(figsize = (12,4))
      plt.plot(df_20['year'], df_20['per_capita_gdp'])
      plt.title("Per Capita GDP Over Time")
      plt.xticks(df_20['year'].unique(), rotation=45, ha="right")
      plt.show()
```



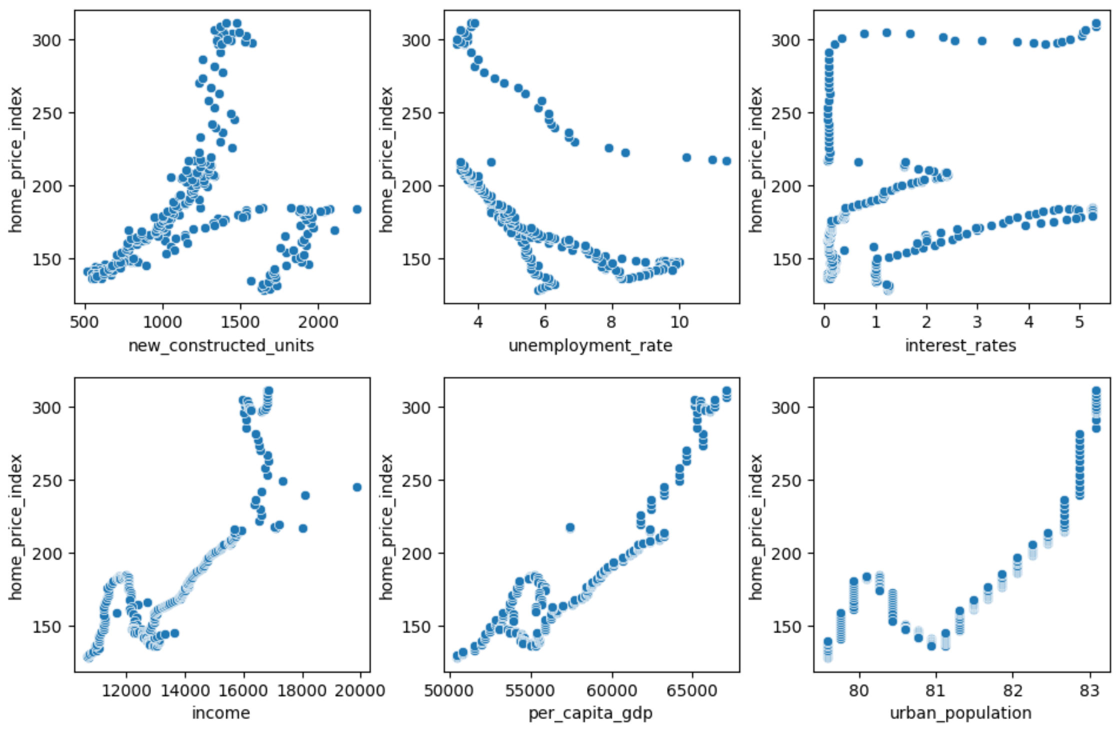
[36]:
```
plt.figure(figsize = (12,4))
plt.plot(df_20['year'], df_20['urban_population'])
plt.title("Urban Population Over Time")
plt.xticks(df_20['year'].unique(), rotation=45, ha="right")
plt.show()
```



[37]:
```
plt.figure(figsize = (12,4))
plt.plot(df_20['year'], df_20['home_price_index'])
plt.title("Home Price Index Over Time")
plt.xticks(df_20['year'].unique(), rotation=45, ha="right")
plt.show()
```

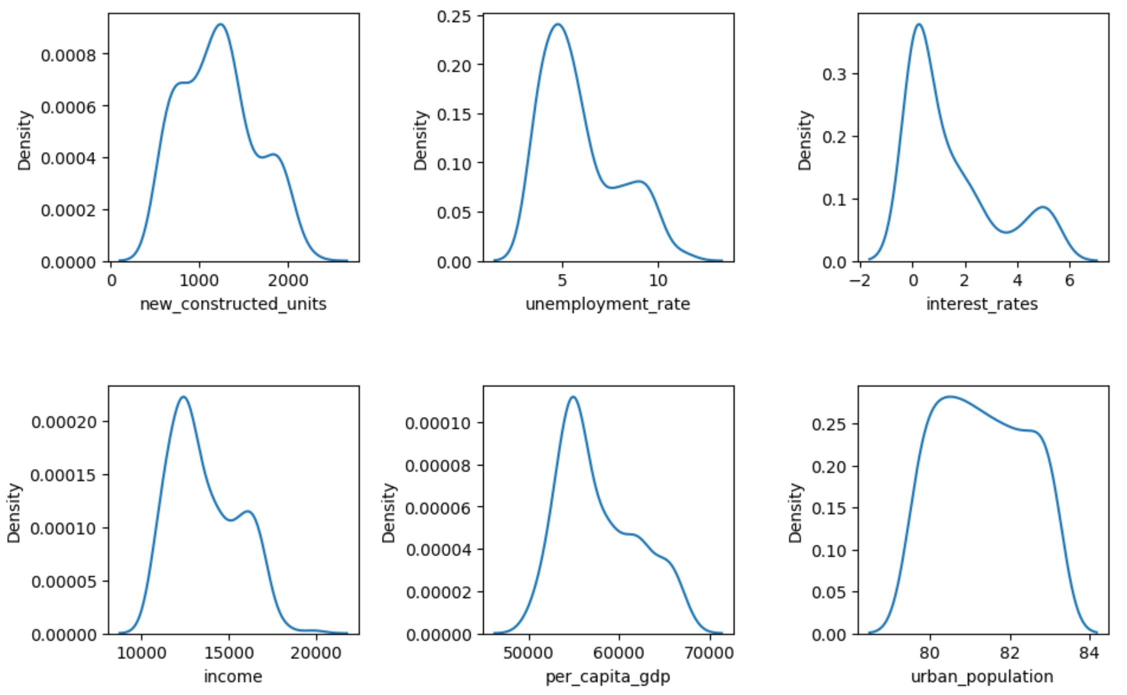


[38]:
```
fig = plt.figure(figsize = (60,60))
gs = fig.add_gridspec(15,15)

gs.update(wspace = 0.25,hspace = 0.25)

ax0 = fig.add_subplot(gs[0,0],)
ax1 = fig.add_subplot(gs[0,1])
ax2 = fig.add_subplot(gs[0,2])
ax3 = fig.add_subplot(gs[1,0])
ax4 = fig.add_subplot(gs[1,1])
ax5 = fig.add_subplot(gs[1,2])

Axis = [ax0,ax1,ax2,ax3,ax4,ax5]

for ax,col in zip(Axis,cols):
    sns.scatterplot(df_20, ax=ax ,x = col, y = 'home_price_index')
plt.show()
```



**"Scatter Plots of Factors vs. Home Price Index"**

[39]:
```
fig = plt.figure(figsize = (60,60))

gs = fig.add_gridspec(15,15)

gs.update(wspace = 0.50,hspace = 0.50)

ax0 = fig.add_subplot(gs[0,0],)
ax1 = fig.add_subplot(gs[0,1])
ax2 = fig.add_subplot(gs[0,2])
ax3 = fig.add_subplot(gs[1,0])
ax4 = fig.add_subplot(gs[1,1])
ax5 = fig.add_subplot(gs[1,2])

Axis = [ax0,ax1,ax2,ax3,ax4,ax5]

for ax,col in zip(Axis,cols):
    sns.kdeplot(df_20, ax=ax ,x = col)
plt.show()
```



The variables new_constructed_units and urban_population exhibit Normal distributions, while the remaining variables show slight right-skewness. This mild skewness, although present, is deemed acceptable for model building, and we will proceed with our analysis considering these distribution characteristics as Normal.

[64]:
```
df.corr()
```

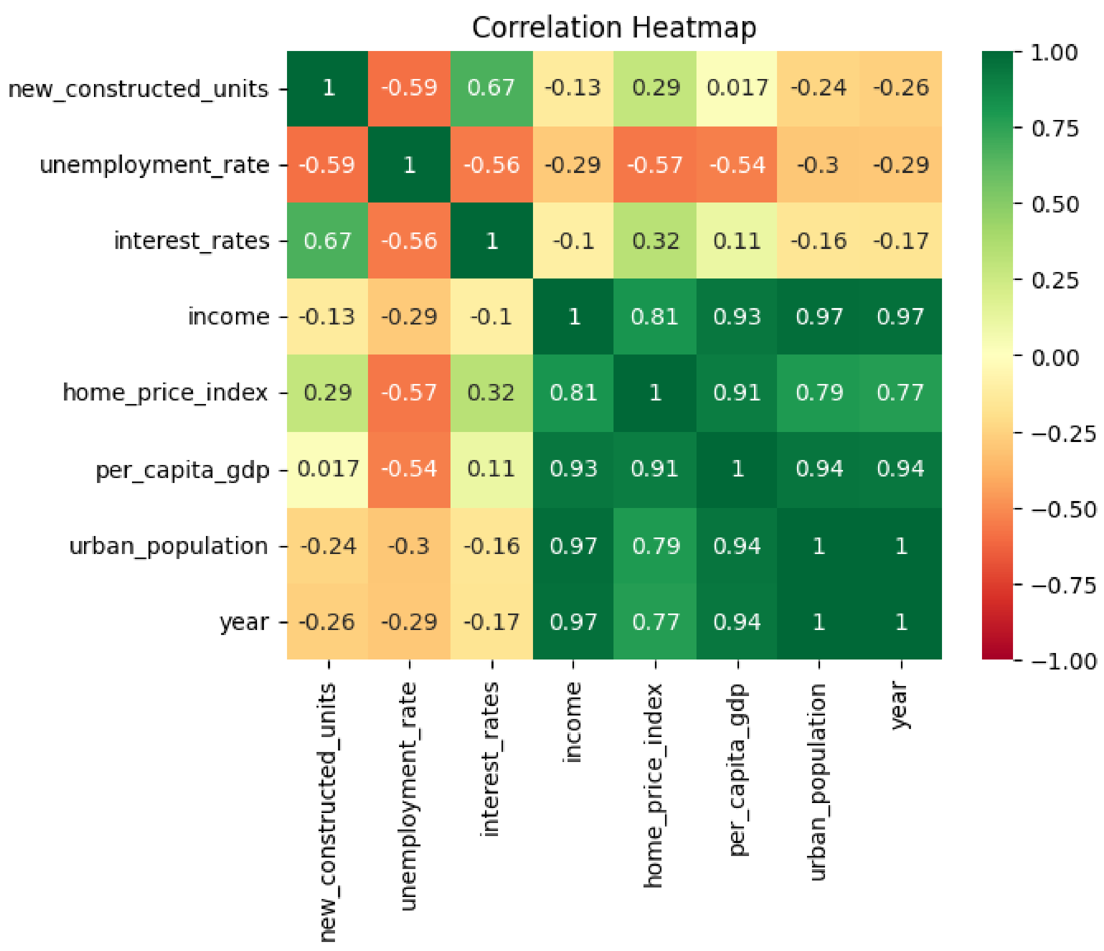
```
<ipython-input-64-2f6f6606aa2c>:1: FutureWarning: The default value of
numeric_only in DataFrame.corr is deprecated. In a future version, it will
default to False. Select only valid columns or specify the value of numeric_only
to silence this warning.
  df.corr()
```

[64]:
```
                       new_constructed_units  unemployment_rate  \
new_constructed_units               1.000000          -0.390979
unemployment_rate                  -0.390979           1.000000
interest_rates                      0.418073           0.066943
income                             -0.411212          -0.046088
home_price_index                   -0.062159          -0.231612
per_capita_gdp                     -0.376994           0.103897
urban_population                   -0.418469          -0.068268

                       interest_rates    income  home_price_index  \
new_constructed_units        0.418073 -0.411212         -0.062159
unemployment_rate            0.066943 -0.046088         -0.231612
```

```
interest_rates               1.000000 -0.541979         -0.542286
income                      -0.541979  1.000000          0.935364
home_price_index            -0.542286  0.935364          1.000000
per_capita_gdp              -0.374240  0.987732          0.943785
urban_population            -0.552013  0.986303          0.889301

                       per_capita_gdp  urban_population
new_constructed_units       -0.376994         -0.418469
unemployment_rate            0.103897         -0.068268
interest_rates              -0.374240         -0.552013
income                       0.987732          0.986303
home_price_index             0.943785          0.889301
per_capita_gdp               1.000000          0.990761
urban_population             0.990761          1.000000
```

[40]:
```
sns.heatmap(df_20.corr(),vmax = 1, vmin = -1 , annot = True , cmap = "RdYlGn")
plt.title("Correlation Heatmap")
plt.show()
```

```
<ipython-input-40-748b961f0c4e>:1: FutureWarning: The default value of
numeric_only in DataFrame.corr is deprecated. In a future version, it will
default to False. Select only valid columns or specify the value of numeric_only
to silence this warning.
  sns.heatmap(df_20.corr(),vmax = 1, vmin = -1 , annot = True , cmap = "RdYlGn")
```



The above Heatmap indicates that few of these variables provide similar information, and their high correlation might lead to multicollinearity issues in regression analysis.

## 2 Standardization

Standardization is performed on the dataset to bring all features to a common scale. This is crucial when working with machine learning models that are sensitive to the magnitude of input variables.

[41]:
```
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
```

[42]:
```
X = df_20.drop(columns = ['home_price_index','date','year'])
y = df_20["home_price_index"]
```

[43]:
```
X_train,X_test,y_train,y_test = train_test_split(X,y,test_size= 0.33,␣
  ↪random_state=2)
```

[44]:
```
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

## 3 MODEL BUILDING

## 4 Linear Regression

[45]:
```
from sklearn.linear_model import LinearRegression
lr = LinearRegression()
```

[46]:
```
lr.fit(X_train_scaled,y_train)
lr_pred = lr.predict(X_test_scaled)
```

[47]:
```
r2_lr = r2_score(y_test,lr_pred)
print("R squared Value")
print(r2_score(y_test,lr_pred))
mse_lr = mean_squared_error(y_test,lr_pred)
print("\nMSE")
print(mean_squared_error(y_test,lr_pred))
mae_lr = mean_absolute_error(y_test,lr_pred)
print("\nMAE")
print(mean_absolute_error(y_test,lr_pred))
```

```
R squared Value
0.9527354255690559

MSE
119.27608462812941

MAE
7.788883975430829
```

**R2 Score for LR model indicates 95.27% of the variability in the dependent variable is explained by the model.**

## 5 Random forest Model

[48]:
```
from sklearn.ensemble import RandomForestRegressor
rr = RandomForestRegressor()
```

[49]:
```
rr.fit(X_train_scaled,y_train)
rr_pred = rr.predict(X_test_scaled)
```

[50]:
```
r2_rr = r2_score(y_test,rr_pred)
print("R squared Value")
print( r2_score(y_test,rr_pred))
```

```
mse_rr = mean_squared_error(y_test,rr_pred)
print("\nMSE")
print( mean_squared_error(y_test,rr_pred))
mae_rr =  mean_absolute_error(y_test,rr_pred)
print("\nMAE")
print( mean_absolute_error(y_test,rr_pred))
```

```
R squared Value
0.9962608494326256

MSE
9.436057446430266

MAE
2.0383102409638623
```

**R2 Score for RR model indicates 99.65% of the variability in the dependent variable is explained by the model.**

## 6 ADA BOOST

[51]:
```
from sklearn.ensemble import AdaBoostRegressor
ada = AdaBoostRegressor()
```

[52]:
```
ada.fit(X_train_scaled,y_train)
ada_pred = ada.predict(X_test_scaled)
```

[53]:
```
r2_ab = r2_score(y_test,ada_pred )
print("R squared Value")
print( r2_score(y_test,ada_pred ))
mse_ab = mean_squared_error(y_test,ada_pred )
print("\nMSE")
print( mean_squared_error(y_test,ada_pred ))
mae_ab =  mean_absolute_error(y_test,ada_pred )
print("\nMAE")
print( mean_absolute_error(y_test,ada_pred ))
```

```
R squared Value
0.9900592689000133

MSE
25.086261713407538

MAE
3.834583774110322
```

**R2 Score for ADA Boosting model indicates 98.84% of the variability in the dependent variable is explained by the model.**

## 7 Gradient Boosting

[54]:
```
from sklearn.ensemble import GradientBoostingRegressor
gb = GradientBoostingRegressor()
```

[55]:
```
gb.fit(X_train_scaled, y_train)
gb_pred = gb.predict(X_test_scaled)
```

[56]:
```
r2_gb = r2_score(y_test,gb_pred )
print("R squared Value")
print( r2_score(y_test,gb_pred ))
mse_gb = mean_squared_error(y_test,gb_pred )
print("\nMSE")
print( mean_squared_error(y_test,gb_pred ))
mae_gb =  mean_absolute_error(y_test,gb_pred )
print("\nMAE")
print( mean_absolute_error(y_test,gb_pred ))
```

```
R squared Value
0.9947513910680241

MSE
13.245301172974209

MAE
2.6471187223910935
```

**R2 Score for Gradient Boosting model indicates 99.48% of the variability in the dependent variable is explained by the model.**

## 8 XG Boosting Model

[57]:
```
from xgboost import XGBRegressor
xg = XGBRegressor()
```

[58]:
```
xg.fit(X_train_scaled, y_train)
xg_pred = xg.predict(X_test_scaled)
```

[59]:
```
r2_xg = r2_score(y_test,xg_pred )
print("R squared Value")
print( r2_score(y_test,xg_pred ))
mse_xg = mean_squared_error(y_test,xg_pred )
print("\nMSE")
print( mean_squared_error(y_test,xg_pred ))
mae_xg =  mean_absolute_error(y_test,xg_pred )
print("\nMAE")
print( mean_absolute_error(y_test,xg_pred ))
```

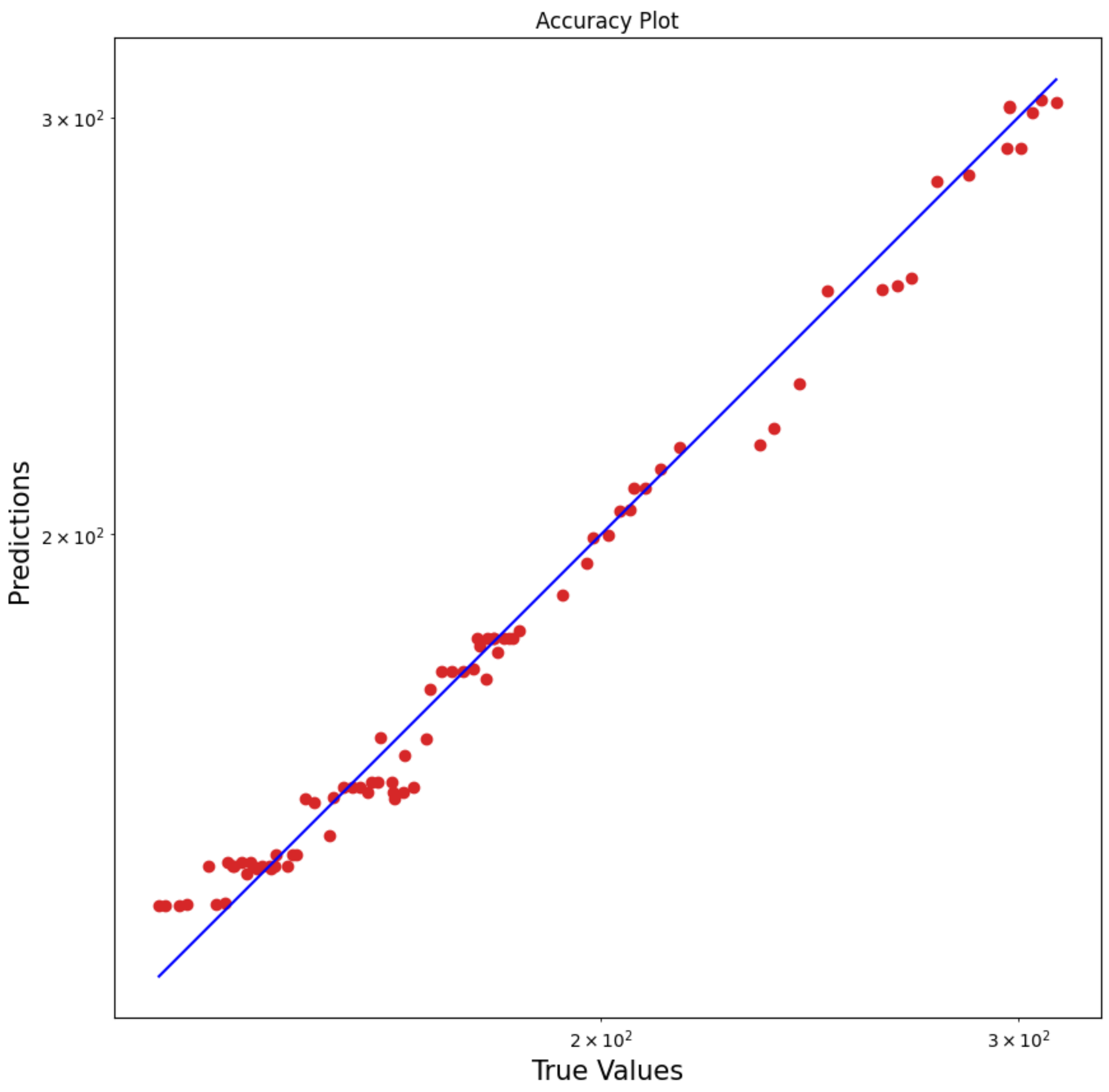
```
R squared Value
0.9953096425659546

MSE
11.836507087496674

MAE
2.3933190462043488
```

**R2 Score for ADA Boosting model indicates 99.53% of the variability in the dependent variable is explained by the model.**

## 9 Observation

Random Forest and XGBoosting consistently outperform other models, demonstrating their effectiveness in capturing the underlying patterns in the data. Below is the graph that shoes the actual and the predicted value for the Ada Boost Algorithmn.

[63]:
```
fit_data = ada.fit(X_train_scaled,y_train)
prediction = fit_data.predict(X_test_scaled)

plt.figure(figsize=(10,10))
plt.scatter(y_test, prediction, c ='#d62728')
plt.yscale('log')
plt.xscale('log')

p1 = max(max(prediction), max(y_test))
p2 = min(min(prediction), min(y_test))
plt.plot([p1, p2], [p1, p2], 'b-')
plt.xlabel('True Values', fontsize=15)
plt.ylabel('Predictions', fontsize=15)
plt.title("Accuracy Plot")
plt.axis('equal')
plt.show()
```


Accuracy Plot
Predictions
True Values
$3 \times 10^2$
$2 \times 10^2$
$2 \times 10^2$
$3 \times 10^2$

```
[ ]:
```