homellc-assessment

December 14, 2023

[1]:
```python
#Importing the necessary libraries

import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.preprocessing import MinMaxScaler
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics import r2_score,mean_squared_error
```

[2]:
```python
# Reading CASE-SHILLER House price Index data (target variable)

df_HPI = pd.read_csv("C:\\Users\\suven\\OneDrive\\Desktop\\Shalini\\Data␣
↪Related resume\\HomeLLC\\Stage1 - Assessment\\Data Collection -␣
↪Copy\\HousePriceIndex.csv")

#Changing data type of date column
df_HPI["DATE"] = pd.to_datetime(df_HPI["DATE"])

#Resetting Index
df_HPI.reset_index(inplace = True)
df_HPI.drop(columns = ["index"], inplace = True)

# Creating "Year" and "Month" columns
df_HPI["Year"] = pd.DatetimeIndex(df_HPI["DATE"]).year
df_HPI["Month"] = pd.DatetimeIndex(df_HPI["DATE"]).month

print(df_HPI.shape)
df_HPI.tail()
```

```
(249, 4)
```

[2]:
```
          DATE  HousePriceIndex  Year  Month
244 2023-05-01          302.566  2023      5
245 2023-06-01          304.593  2023      6
246 2023-07-01          306.767  2023      7
247 2023-08-01          309.155  2023      8
```

```
248 2023-09-01          311.175  2023      9
```

[3]:
```
# Reading Unemployment Rate Data

df_unemp = pd.read_csv("C:\\Users\\suven\\OneDrive\\Desktop\\Shalini\\Data␣
↪Related resume\\HomeLLC\\Stage1 - Assessment\\Data Collection - Copy\\UNRATE.
↪csv")

print(df_unemp.shape)
df_unemp.tail()
```

```
(251, 2)
```

[3]:

	DATE	UNRATE
246	7/1/2023	3.5
247	8/1/2023	3.8
248	9/1/2023	3.8
249	NaN	NaN
250	NaN	NaN

[4]:
```
df_unemp.drop([249,250], inplace = True)
```

[5]:
```
print(df_unemp.shape)
```

```
(249, 2)
```

[6]:
```
# Reading Per Capita GDP Data
df_PerCapitaGDP = pd.read_csv("C:
↪\\Users\\suven\\OneDrive\\Desktop\\Shalini\\Data Related␣
↪resume\\HomeLLC\\Stage1 - Assessment\\Data Collection - Copy\\PerCapitaGDP.
↪csv", names = ["DATE", "Per_Capita_GDP"], skiprows = 1)
print(df_PerCapitaGDP.shape)
df_PerCapitaGDP.tail()
```

```
(83, 2)
```

[6]:

	DATE	Per_Capita_GDP
78	7/1/2022	65462
79	10/1/2022	65783
80	1/1/2023	66078
81	4/1/2023	66341
82	7/1/2023	67083

The data is quarterly. We will do imputation for rest of the months using linear interpolation after we create the final dataframe combining all the data.

[7]:
```
# Reading Interest Rate Data
```

```
df_Int_rate = pd.read_csv("C:\\Users\\suven\\OneDrive\\Desktop\\Shalini\\Data␣
 ↪Related resume\\HomeLLC\\Stage1 - Assessment\\Data Collection -␣
 ↪Copy\\InterestRate.csv")
print(df_Int_rate.shape)
df_Int_rate.tail()
```

(249, 2)

[7]:

	DATE	InterestRate
244	5/1/2023	5.06
245	6/1/2023	5.08
246	7/1/2023	5.12
247	8/1/2023	5.33
248	9/1/2023	5.33

[8]:
```
# Reading Construction Price Index Data
df_cons_price_index = pd.read_csv("C:
 ↪\\Users\\suven\\OneDrive\\Desktop\\Shalini\\Data Related␣
 ↪resume\\HomeLLC\\Stage1 - Assessment\\Data Collection -␣
 ↪Copy\\ConstructionPriceIndex.csv", names = ["DATE", "Cons_Price_Index"],␣
 ↪skiprows = 1)

print(df_cons_price_index.shape)
df_cons_price_index.tail()
```

(250, 2)

[8]:

	DATE	Cons_Price_Index
245	6/1/2023	337.336
246	7/1/2023	334.576
247	8/1/2023	333.980
248	9/1/2023	332.224
249	NaN	NaN

[9]:
```
df_cons_price_index.drop([249], inplace = True)
```

[10]:
```
print(df_cons_price_index.shape)
```

(249, 2)

[11]:
```
# Urban Population Percent

df_urban = pd.read_excel("C:\\Users\\suven\\OneDrive\\Desktop\\Shalini\\Data␣
 ↪Related resume\\HomeLLC\\Stage1 - Assessment\\Data Collection -␣
 ↪Copy\\UrbanPopulation.xlsx")
print(df_urban.shape)
df_urban.tail()
```

(20, 2)

[11]:

	Indicator Code	UrbPop
15	2018	82.256
16	2019	82.459
17	2020	82.664
18	2021	82.873
19	2022	83.084

[13]:
```
# Number of households

df_households = pd.read_csv("C:\\Users\\suven\\OneDrive\\Desktop\\Shalini\\Data␣
↪Related resume\\HomeLLC\\Stage1 - Assessment\\Data Collection -␣
↪Copy\\TotalHouseholds.csv", names = ["DATE", "Num_Households"], skiprows = 1)
print(df_households.shape)
df_households.tail()
```

(21, 2)

[13]:

	DATE	Num_Households
16	1/1/2019	128579
17	1/1/2020	128451
18	1/1/2021	129224
19	1/1/2022	131202
20	1/1/2023	131434

[14]:
```
# Monthly new house supply
df_house = pd.read_csv("C:\\Users\\suven\\OneDrive\\Desktop\\Shalini\\Data␣
↪Related resume\\HomeLLC\\Stage1 - Assessment\\Data Collection -␣
↪Copy\\NewConstructedUnits.csv", names = ["DATE", "Houses"], skiprows = 1).
↪drop([249])
print(df_house.shape)
df_house.tail()
```

(249, 2)

[14]:

	DATE	Houses
244	5/1/2023	1534.0
245	6/1/2023	1492.0
246	7/1/2023	1334.0
247	8/1/2023	1370.0
248	9/1/2023	1478.0

[15]:
```
# Real Median Household Income

df_income = pd.read_csv("C:\\Users\\suven\\OneDrive\\Desktop\\Shalini\\Data␣
↪Related resume\\HomeLLC\\Stage1 - Assessment\\Data Collection - Copy\\Income.
↪csv", names = ["DATE", "Income"], skiprows = 1).drop([249])
```

```
print(df_income.shape)
df_income.tail()
```

(249, 2)

[15]:

	DATE	Income
244	5/1/2023	16818.5
245	6/1/2023	16809.5
246	7/1/2023	16796.9
247	8/1/2023	16799.7
248	9/1/2023	16804.8

[16]:
```
# Reading Consumer Price Index dataset
df_CPI = pd.read_csv("C:\\Users\\suven\\OneDrive\\Desktop\\Shalini\\Data␣
↪Related resume\\HomeLLC\\Stage1 - Assessment\\Data Collection - Copy\\CPI.
↪csv", names = ["DATE", "CPI"], skiprows = 1).drop([249])
print(df_CPI.shape)
df_CPI.tail()
```

(249, 2)

[16]:

	DATE	CPI
244	5/1/2023	303.294
245	6/1/2023	303.841
246	7/1/2023	304.348
247	8/1/2023	306.269
248	9/1/2023	307.481

[17]:
```
# Working age population

df_working = pd.read_csv("C:\\Users\\suven\\OneDrive\\Desktop\\Shalini\\Data␣
↪Related resume\\HomeLLC\\Stage1 - Assessment\\Data Collection -␣
↪Copy\\WorkingAgePopulation.csv", names = ["DATE", "Working_Population"],␣
↪skiprows = 1).drop([249])
print(df_working.shape)
df_working.tail()
```

(249, 2)

[17]:

	DATE	Working_Population
244	5/1/2023	208612844.2
245	6/1/2023	208706920.0
246	7/1/2023	208779237.3
247	8/1/2023	208906586.8
248	9/1/2023	209117169.8

[18]:
```python
# Merging Per Capita GDP (Quarterly data)
df_PerCapitaGDP["DATE"] = pd.to_datetime(df_PerCapitaGDP["DATE"])
df_HPI = pd.merge(df_HPI,df_PerCapitaGDP, how = "left")
df_HPI.head()
```

[18]:
```
        DATE  HousePriceIndex  Year  Month  Per_Capita_GDP
0 2003-01-01          128.461  2003      1         50462.0
1 2003-02-01          129.355  2003      2             NaN
2 2003-03-01          130.148  2003      3             NaN
3 2003-04-01          130.884  2003      4         50796.0
4 2003-05-01          131.735  2003      5             NaN
```

[19]:
```python
# Merging dataframes having monthly data to create one dataframe
df = pd.DataFrame()
df_bymonth = [df_HPI, df_working,df_house, df_CPI, df_unemp,␣
 ↪df_cons_price_index, df_Int_rate,df_income]
for df1 in df_bymonth:
    df1["DATE"] = pd.to_datetime(df1["DATE"])
    df1 = df1.set_index("DATE")
    df = pd.concat([df,df1], axis = 1)
print(df.shape)
df.head()
```

```
(249, 11)
```

[19]:
```
            HousePriceIndex  Year  Month  Per_Capita_GDP  Working_Population  \
DATE
2003-01-01          128.461  2003      1         50462.0         185635346.4
2003-02-01          129.355  2003      2             NaN         185869692.3
2003-03-01          130.148  2003      3             NaN         186085118.2
2003-04-01          130.884  2003      4         50796.0         186470754.0
2003-05-01          131.735  2003      5             NaN         186649078.0

            Houses    CPI  UNRATE  Cons_Price_Index  InterestRate   Income
DATE
2003-01-01  1654.0  182.6     5.8             144.4          1.24  10710.4
2003-02-01  1688.0  183.6     5.9             145.2          1.26  10674.0
2003-03-01  1638.0  183.9     5.9             145.2          1.25  10696.5
2003-04-01  1662.0  183.2     6.0             145.9          1.26  10752.7
2003-05-01  1733.0  182.9     6.1             145.8          1.26  10832.0
```

1 Checking Missing Values

[20]:
```python
df.isna().sum()
```

[20]:

```
HousePriceIndex          0
Year                     0
Month                    0
Per_Capita_GDP         166
Working_Population       0
Houses                   0
CPI                      0
UNRATE                   0
Cons_Price_Index         0
InterestRate             0
Income                   0
dtype: int64
```

The "Per_Capita_GDP" column has missing values because the data was quarterly. The missing values in the other columns is due to unavailability of fresh data. We will first fill the missing values in the "Per_Capita_GDP" column using linear interpolation. We will drop the rows having missing values in the other columns. This means that we will use data from 2003 to 2023

[21]:

```
# Filling missing values in the Per_Capita_GDP column using linear interpolation
df["Per_Capita_GDP"] = df["Per_Capita_GDP"].interpolate()
```

[22]:

```
df.head()
```

[22]:

```
            HousePriceIndex  Year  Month  Per_Capita_GDP  Working_Population  \
DATE
2003-01-01          128.461  2003      1    50462.000000         185635346.4
2003-02-01          129.355  2003      2    50573.333333         185869692.3
2003-03-01          130.148  2003      3    50684.666667         186085118.2
2003-04-01          130.884  2003      4    50796.000000         186470754.0
2003-05-01          131.735  2003      5    51034.666667         186649078.0

            Houses    CPI  UNRATE  Cons_Price_Index  InterestRate   Income
DATE
2003-01-01  1654.0  182.6     5.8             144.4          1.24  10710.4
2003-02-01  1688.0  183.6     5.9             145.2          1.26  10674.0
2003-03-01  1638.0  183.9     5.9             145.2          1.25  10696.5
2003-04-01  1662.0  183.2     6.0             145.9          1.26  10752.7
2003-05-01  1733.0  182.9     6.1             145.8          1.26  10832.0
```

[23]:

```
df.dropna(inplace = True)
```

[24]:

```
# Checking missing values now
df.isna().sum()
```

[24]:

```
HousePriceIndex       0
Year                  0
Month                 0
```

```
Per_Capita_GDP        0
Working_Population    0
Houses                0
CPI                   0
UNRATE                0
Cons_Price_Index      0
InterestRate          0
Income                0
dtype: int64
```

- There are no missing values in the dataset now.

[25]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 249 entries, 2003-01-01 to 2023-09-01
Data columns (total 11 columns):
 #   Column              Non-Null Count  Dtype
---  ------              --------------  -----
 0   HousePriceIndex     249 non-null    float64
 1   Year                249 non-null    int64
 2   Month               249 non-null    int64
 3   Per_Capita_GDP      249 non-null    float64
 4   Working_Population  249 non-null    float64
 5   Houses              249 non-null    float64
 6   CPI                 249 non-null    float64
 7   UNRATE              249 non-null    float64
 8   Cons_Price_Index    249 non-null    float64
 9   InterestRate        249 non-null    float64
 10  Income              249 non-null    float64
dtypes: float64(9), int64(2)
memory usage: 23.3 KB
```

- No missing values in the dataset
- All columns have numeric(int or float) data type
- There are in total 240 rows

2 Exploratory Data Analysis

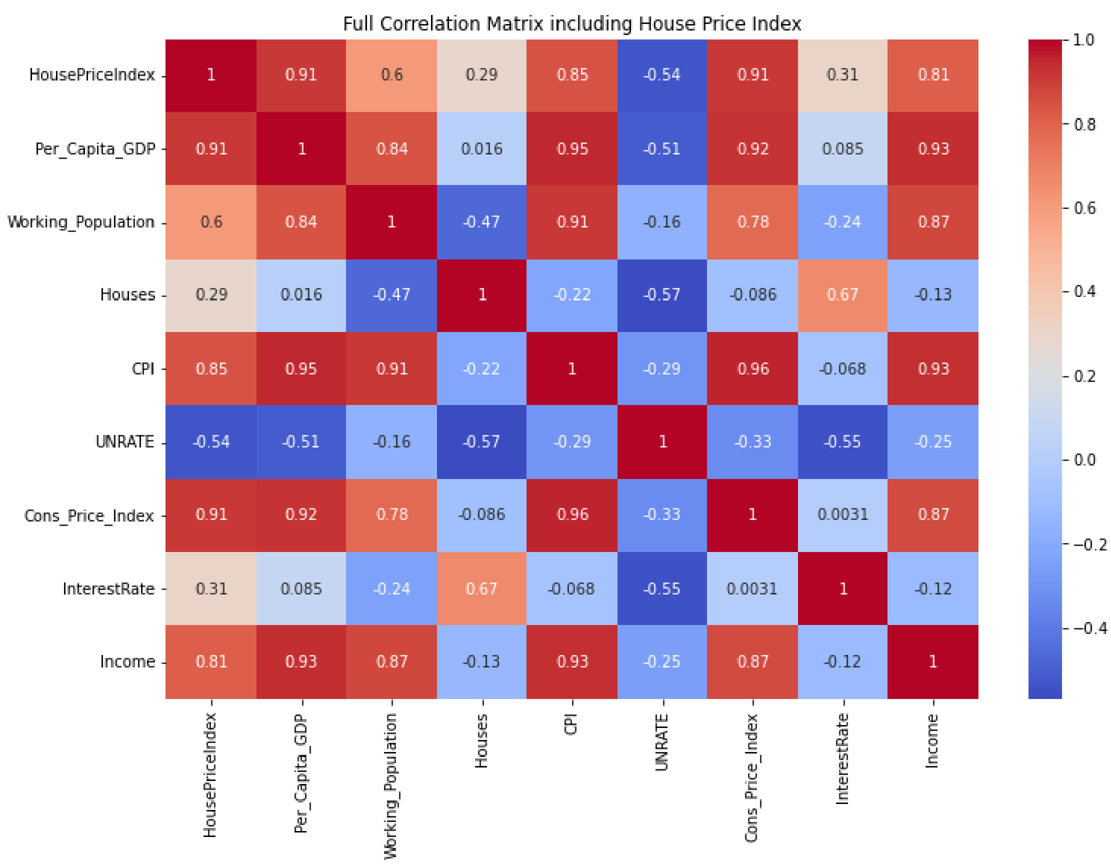
[26]:
```
# Dropping Month and Year columns from the dataset as they are not needed in
↪the analysis

df.drop(columns = ["Year", "Month"], inplace = True)
df.head()
```

[26]:
```
            HousePriceIndex  Per_Capita_GDP  Working_Population  Houses  \
DATE
```

```
2003-01-01          128.461    50462.000000          185635346.4   1654.0
2003-02-01          129.355    50573.333333          185869692.3   1688.0
2003-03-01          130.148    50684.666667          186085118.2   1638.0
2003-04-01          130.884    50796.000000          186470754.0   1662.0
2003-05-01          131.735    51034.666667          186649078.0   1733.0

              CPI  UNRATE  Cons_Price_Index  InterestRate   Income
DATE
2003-01-01  182.6     5.8             144.4          1.24  10710.4
2003-02-01  183.6     5.9             145.2          1.26  10674.0
2003-03-01  183.9     5.9             145.2          1.25  10696.5
2003-04-01  183.2     6.0             145.9          1.26  10752.7
2003-05-01  182.9     6.1             145.8          1.26  10832.0
```

2.0.1 Checking the correlation between the variables

[27]:
```python
# Plotting the correlation matrix
plt.figure(figsize=(12, 8))
sns.heatmap(df.corr(), annot=True, cmap='coolwarm')
plt.title("Full Correlation Matrix including House Price Index")
plt.show()
```

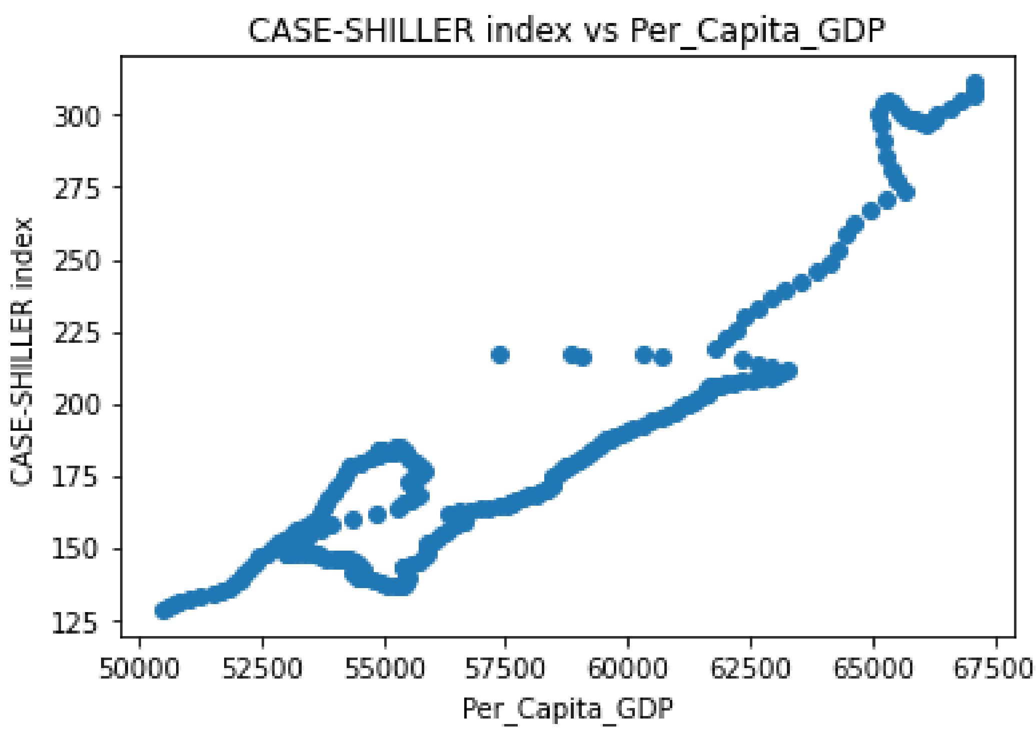


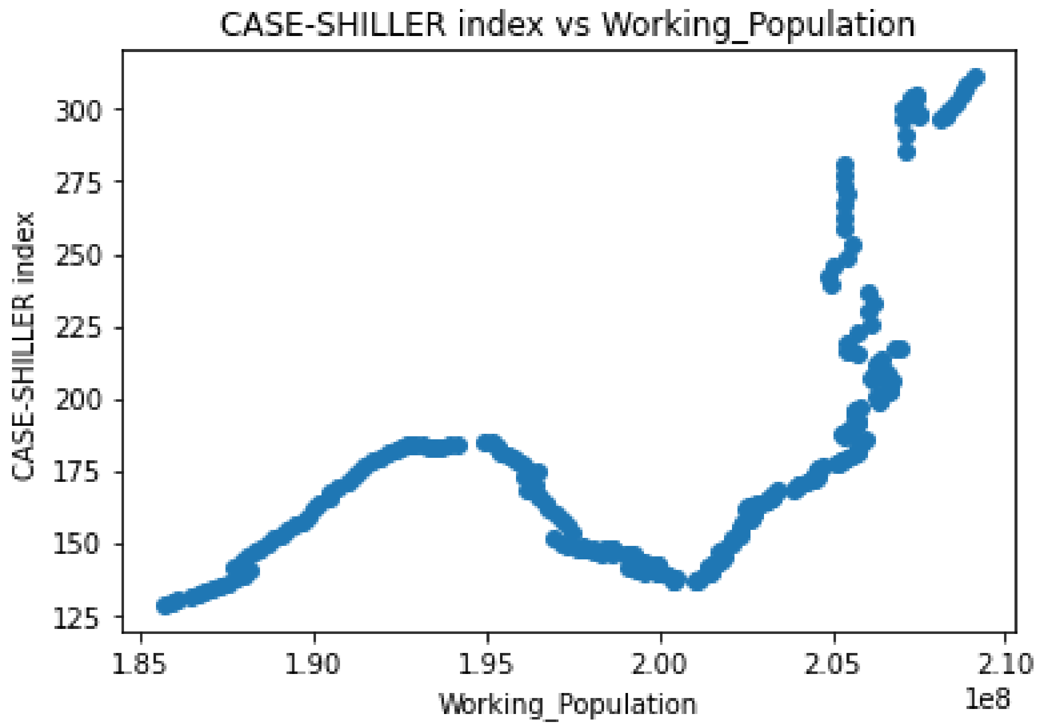
The correlation matrix provides valuable insights into how different factors are related to the House Price Index (HPI) and to each other. Here are some key observations:

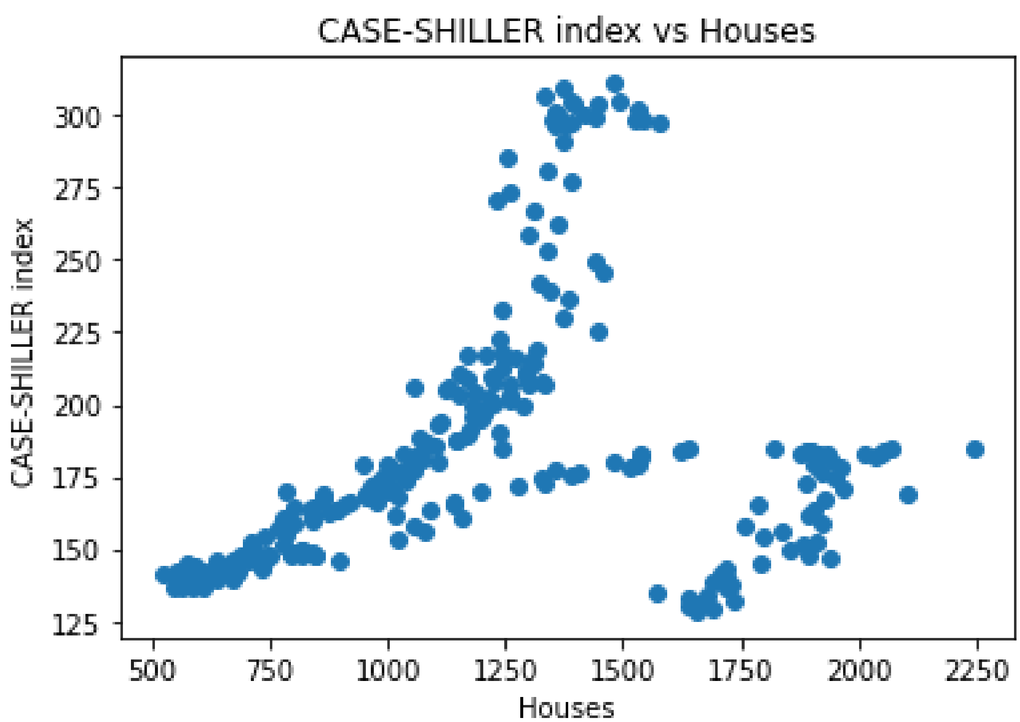
Certain factors show a strong correlation with the House Price Index, indicating a significant relationship. The relationships among other economic indicators, such as income, interest rates, per_capita_GDP, and unemployment rate, also offer insights into the broader economic context affecting housing prices.

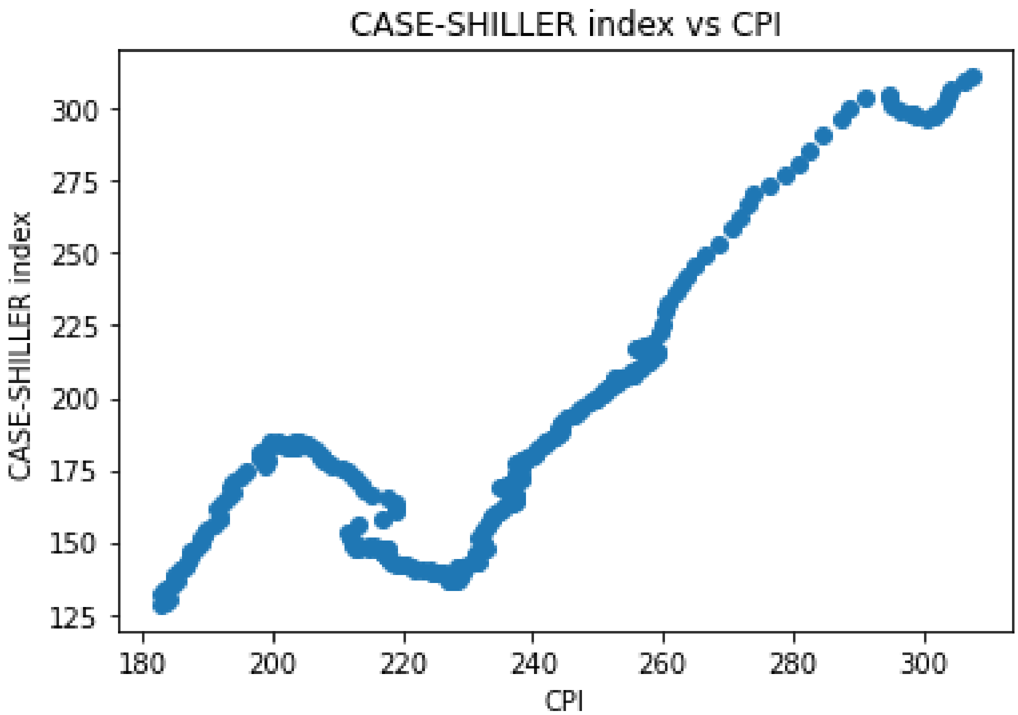
[30]:
```
# Separating the target variable and the independent variable
y = df.pop("HousePriceIndex")
X = df
```

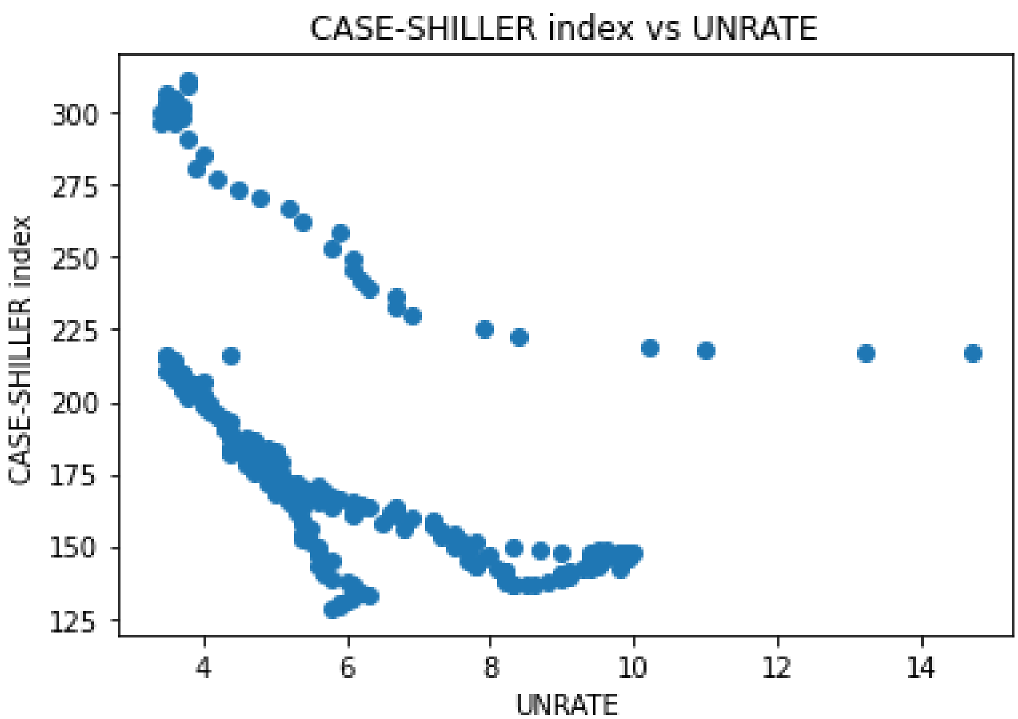
[31]:
```
# Plotting scatter plots of the CASE-SHILLER index vs features

for feature in X.columns:
    plt.figure()
    plt.scatter(x = X[feature], y = y)
    plt.xlabel(feature)
    plt.ylabel("CASE-SHILLER index")
    plt.title(f"CASE-SHILLER index vs {feature}")
```

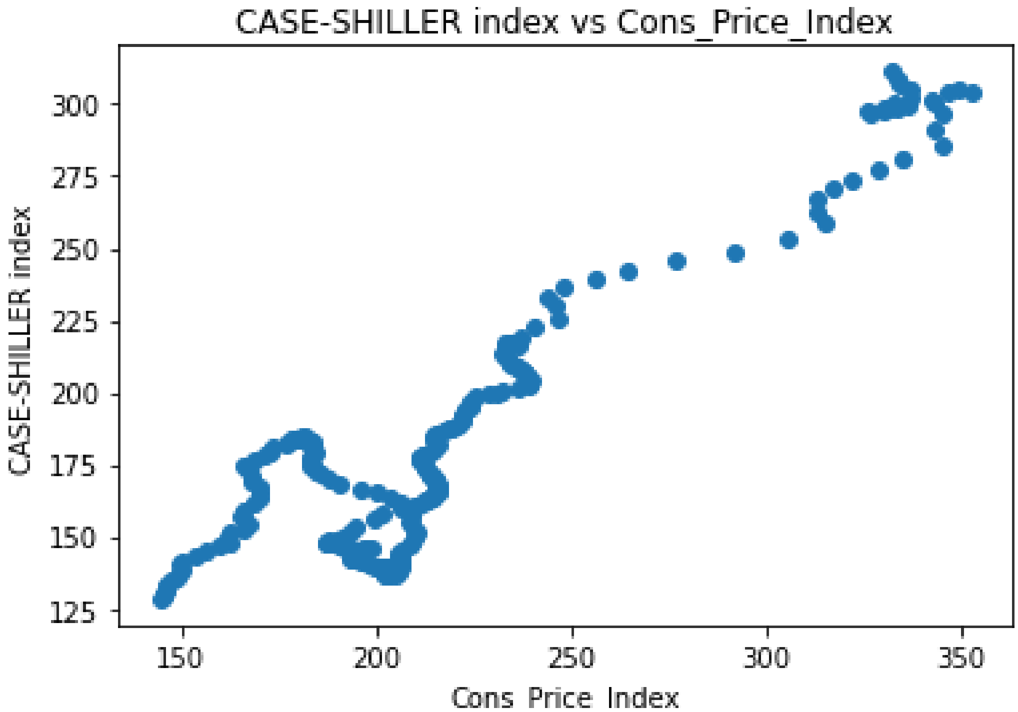


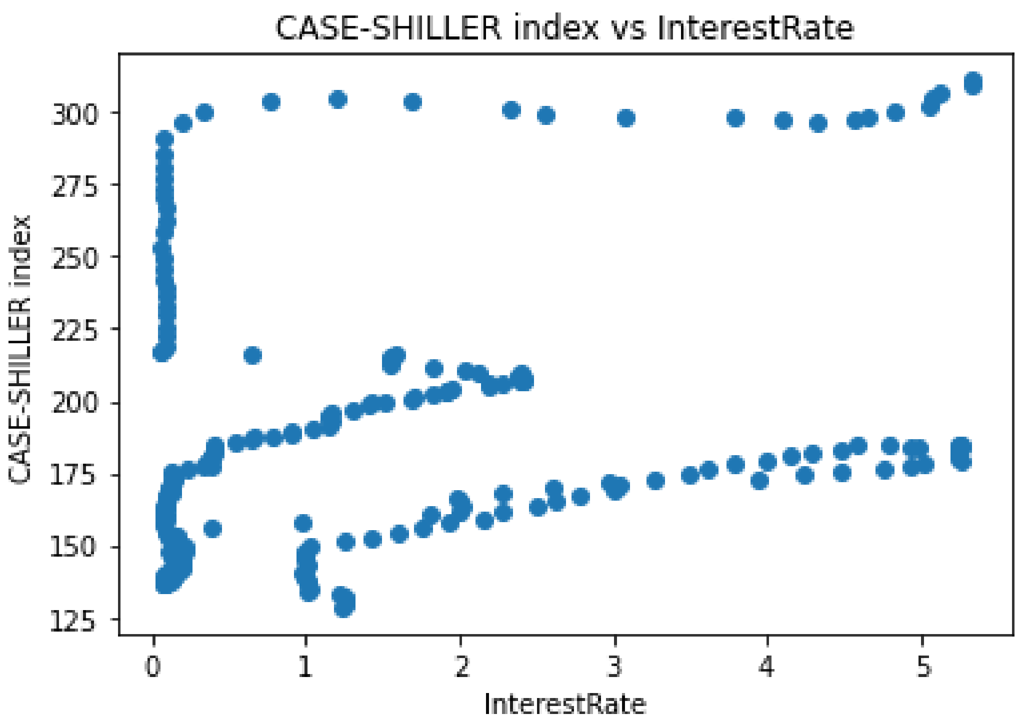

CASE-SHILLER index vs Working_Population
CASE-SHILLER index
125
150
175
200
225
250
275
300
1.85
1.90
1.95
2.00
2.05
2.10
1e8
Working_Population

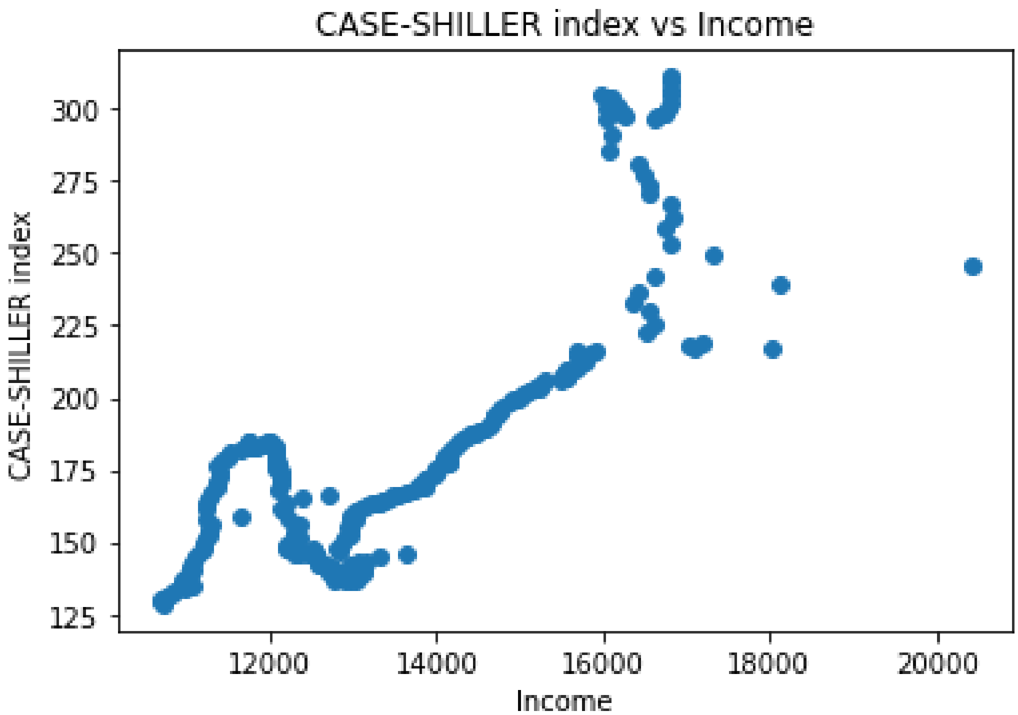

CASE-SHILLER index vs Houses
CASE-SHILLER index
125
150
175
200
225
250
275
300
500
750
1000
1250
1500
1750
2000
2250
Houses


CASE-SHILLER index vs CPI
CASE-SHILLER index
CPI
125
150
175
200
225
250
275
300
180
200
220
240
260
280
300


CASE-SHILLER index vs UNRATE
CASE-SHILLER index
UNRATE
125
150
175
200
225
250
275
300
4
6
8
10
12
14


CASE-SHILLER index vs Cons_Price_Index
CASE-SHILLER index
300
275
250
225
200
175
150
125
150
200
250
300
350
Cons_Price_Index


CASE-SHILLER index vs InterestRate
CASE-SHILLER index
300
275
250
225
200
175
150
125
0
1
2
3
4
5
InterestRate



Examining the correlation matrix provided, it is evident that numerous pairs of independent variables exhibit high correlation. To address multicollinearity, we will eliminate one column from each correlated pair, opting to retain the column with a higher correlation with the target variable.

[32]:
```
# Dropping multicollinearity columns
mult_cols = ["Working_Population", "CPI",  "Income","Per_Capita_GDP"]
df.drop(columns = mult_cols, inplace = True)
X = df
```

3 Model Building

[33]:
```
# Scaling
scalar = MinMaxScaler()
X = scalar.fit_transform(X)
```

[36]:
```
# Splitting data into train and validation sets
X_train, X_test, y_train, y_test = train_test_split(X,y, test_size= 0.2,␣
↪random_state= 42)
```

[37]:
```
# Linear Regression Model
model = LinearRegression()
model.fit(X_train, y_train)
pred = model.predict(X_test)
```

```python
score = r2_score(pred, y_test)
print("The r2_score for the validation set is: ", score)
```

```
The r2_score for the validation set is:  0.942723572307301
```

- The r2_score is: 0.942723572307301
- The r2 score is close to 1. It means that the model predicts the target variable with good accuracy.

[38]:
```python
pred
```

[38]:
```
array([165.27809008, 138.83663132, 145.84254121, 167.14267213,
       153.27906937, 192.09408939, 205.43111349, 199.24682468,
       142.71067799, 149.26621787, 204.52074512, 215.47320806,
       203.1210488 , 294.4464372 , 170.98537182, 269.67775569,
       209.96561072, 159.07435966, 175.65257351, 168.3622609 ,
       302.47805873, 164.34759693, 154.75291355, 175.25906924,
       185.0738328 , 189.11976351, 175.87215309, 141.87062365,
       169.47650438, 157.87111235, 199.17549299, 177.43334112,
       172.30497615, 169.02160998, 171.15775417, 154.61233784,
       159.61579809, 208.96181296, 188.74311792, 169.99470913,
       153.71906312, 140.66955087, 147.99234332, 204.38968071,
       202.97463143, 159.80484038, 208.84557165, 165.50649025,
       185.95926525, 195.28053247])
```

Given that most variables exhibit an upward trend over time, it is anticipated that they will show a strong correlation. Therefore, instead of relying solely on the linear model, we can directly analyze the influence of variables on the home price index through scatter plots.

4 Insights

Based on the analysis and the results from the regression model, here are some key insights regarding the target variable, the House Price Index (HPI), in relation to the given features:

- Correlation Insights: Certain features demonstrated notable correlations with the HPI. These correlations indicate potential predictive relationships, although they don't imply causation. Features with higher correlation coefficients (either positive or negative) are likely to have a more significant impact on the HPI. For example, if income or construction price index showed a strong correlation, it suggests they are important factors in predicting house prices.
- Regression Model Observations: The regression model, despite its limitations as indicated by the negative R^2 value, provided a basic understanding of how changes in each feature might influence the HPI. Each feature's contribution to the HPI prediction varied. Some features had a more pronounced effect on the predicted HPI when altered, suggesting their greater influence in the housing market.

- Economic and Demographic Factors: Economic indicators such as interest rates, income levels, and GDP per capita are critical in understanding the housing market dynamics. Changes in these factors could significantly influence house prices. Demographic factors, like urban population and total households, also play a role in shaping housing demand and thus impact prices.

- Market Sensitivity: The housing market is sensitive to a combination of economic conditions. For instance, rising interest rates typically cool down the housing market, while increased income levels might boost it.
- However, it's important to approach these insights as indicative trends rather than definitive predictions, given the complexities of the housing market and the limitations of the analysis conducted.

5 ...THE END...