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# Summary


In this task, I successfully collected and utilized publicly available datasets to address the impact of key supply-demand factors on US home prices over the last 20 years. To ensure a comprehensive analysis, I gathered historical data from 1987 onward, allowing for a robust examination of long-term trends. I used the S&P Case-Schiller Home Price Index as a reliable proxy for home prices. Through data science modeling techniques, I explored the relationships between this index and various supply-demand factors, such as mortgage rates, unemployment rates, building permits, population growth, and relevant economic indicators. My analysis aimed to uncover the driving forces behind home price fluctuations, contributing valuable insights for understanding the dynamics of the US housing market over the past two decades


# About Datasets

I've downloaded a total of 17 CSV files from FRED (Federal Reserve Economic Data). These files fall into four different categories. The first set contains data collected on a monthly basis, the second set on a quarterly basis, and the third set on an annual basis. All of this data has been collected since 1987. The fourth category consists of quarterly data, which has been collected since the year 2000.

### 1. Monthly Basis collected datasets

- Population
- Consumer Price Index
- Customer Sentiment Index
- Mortgage Rate
- M3
- Unemployment Rate
- Employment Rate
- New House Permit
- Single House Permit

- More Than 5 Unit House Prmit
- Mortgage Orgnization fees & discount
- Home Price Index

### 2. Quarterly Basis Collected Datasets

- Gross Domestic Product
- Gross Domestic Income

### 3. Yearly Basis Collected Datasets

- Human Capital Index
- Inflation Data

### 4. Quaterly Basis Collected data since 2000

- Number of House

# Data Processing

### Mounting Google drive on colab

```
# Import the 'drive' module from the 'google.colab' library
from google.colab import drive

# Mount (connect) your Google Drive to this Colab notebook
drive.mount('/content/drive')

Drive already mounted at /content/drive; to attempt to forcibly
remount, call drive.mount("/content/drive", force_remount=True).
```

### Importing libraries

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import MinMaxScaler
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error
from sklearn.ensemble import GradientBoostingRegressor
from sklearn.model_selection import GridSearchCV
```

### Loading All Data

```
# Load the 'Population.csv' file from Google Drive into a DataFrame
population_df = pd.read_csv('/content/drive/MyDrive/Population.csv')

# Load the 'Consumer Price index.csv' file from Google Drive into a
DataFrame
```

```
Consumer_price_index_df = pd.read_csv('/content/drive/MyDrive/Cunsumer
Price index.csv')

# Load the 'Total New house permit.csv' file from Google Drive into a
DataFrame
new_house_permit_df = pd.read_csv("/content/drive/MyDrive/Total New
house permit.csv")

# Load the 'single family house permit.csv' file from Google Drive
into a DataFrame
single_house_permit = pd.read_csv("/content/drive/MyDrive/single
family house permit.csv")

# Load the '5 units house permit.csv' file from Google Drive into a
DataFrame
more_than_5_unit_house_permit = pd.read_csv("/content/drive/MyDrive/5
units house permit.csv")

# Load the 'Employment_rate.csv' file from Google Drive into a
DataFrame
employment_rate =
pd.read_csv("/content/drive/MyDrive/Employment_rate.csv")

# Load the 'unemployment rate.csv' file from Google Drive into a
DataFrame
unemployment_rate = pd.read_csv("/content/drive/MyDrive/unemployment
rate.csv")

# Load the 'm3.csv' file from Google Drive into a DataFrame
m3_df = pd.read_csv("/content/drive/MyDrive/m3.csv")

# Load the 'consumer sentiment index.csv' file from Google Drive into
a DataFrame
customer_sentiment_df = pd.read_csv("/content/drive/MyDrive/consumer
sentiment index.csv")

# Load the 'Home price index.csv' file from Google Drive into a
DataFrame
home_price_index = pd.read_csv("/content/drive/MyDrive/Home price
index.csv")

# Load the 'Mortgage orgnition fee and dicounts.csv' file from Google
Drive into a DataFrame
Mortgage_org_fees_discount_df =
pd.read_csv("/content/drive/MyDrive/Mortgage orgnition fee and
dicounts.csv")

# Load the 'Human capital index.csv' file from Google Drive into a
DataFrame
human_capital_index_df = pd.read_csv("/content/drive/MyDrive/Human
```

```
capital index.csv")

# Load the 'Housing Inventory Estimate Total Housing Units in the
United States.csv' file from Google Drive into a DataFrame
number_of_house_df = pd.read_csv("/content/drive/MyDrive/Housing
Inventory Estimate Total Housing Units in the United States.csv")

# Load the 'Mortgage_rate.csv' file from Google Drive into a DataFrame
mortgage_rate =
pd.read_csv("/content/drive/MyDrive/Mortgage_rate.csv")

# Load the 'Gross domestic income.csv' file from Google Drive into a
DataFrame
GDI_df = pd.read_csv("/content/drive/MyDrive/Gross domestic
income.csv")

# Load the 'GDP.csv' file from Google Drive into a DataFrame
GDP_df = pd.read_csv("/content/drive/MyDrive/GDP.csv")

# Load the 'inflation_data.csv' file from Google Drive into a
DataFrame
inflation_df =
pd.read_csv('/content/drive/MyDrive/inflation_data.csv')
```

**Overview of Population dataset**

```
# Print top 5 row
population_df.head()
```

```
         DATE    POPTHM
0  1987-01-01  241857.0
1  1987-02-01  242005.0
2  1987-03-01  242166.0
3  1987-04-01  242338.0
4  1987-05-01  242516.0
```

```
# print size of dataset
population_df.shape
```

```
(439, 2)
```

```
#check data types
population_df.dtypes
```

```
DATE       object
POPTHM    float64
dtype: object
```

```
# Checking Null values
population_df.isnull().sum()
```

```
DATE      0
POPTHM    0
dtype: int64
```

```
#checking duplicates
population_df.duplicated().sum()
```

```
0
```

**Overview of Cunsumer Price index dataset**

```
# print top 5 row
Consumer_price_index_df.head()
```

```
         DATE  CPALTT01USM657N
0  1987-01-01         0.633484
1  1987-02-01         0.359712
2  1987-03-01         0.448029
3  1987-04-01         0.535236
4  1987-05-01         0.354925
```

```
# print size of dataset
Consumer_price_index_df.shape
```

```
(438, 2)
```

```
# check data types
Consumer_price_index_df.dtypes
```

```
DATE                object
CPALTT01USM657N    float64
dtype: object
```

```
# check null values
Consumer_price_index_df.isnull().sum()
```

```
DATE               0
CPALTT01USM657N    0
dtype: int64
```

```
# check duplicate
Consumer_price_index_df.duplicated().sum()
```

```
0
```

**Overview of New house permit dataset**

```
# print top 5 row
new_house_permit_df.head()
```

```
         DATE  PERMIT
0  1987-01-01  1690.0
```

```
1  1987-02-01  1689.0
2  1987-03-01  1704.0
3  1987-04-01  1601.0
4  1987-05-01  1500.0
```

```
# print size of dataset
new_house_permit_df.shape
```

```
(439, 2)
```

```
# check data types
new_house_permit_df.dtypes
```

```
DATE       object
PERMIT    float64
dtype: object
```

```
# check null values
new_house_permit_df.isnull().sum()
```

```
DATE      0
PERMIT    0
dtype: int64
```

```
# check duplicates
new_house_permit_df.duplicated().sum()
```

```
0
```

**Overview of single house permit dataset**

```
# print top 5 row
single_house_permit.head()
```

```
         DATE  PERMIT1
0  1987-01-01   1088.0
1  1987-02-01   1195.0
2  1987-03-01   1132.0
3  1987-04-01   1057.0
4  1987-05-01   1006.0
```

```
# print shape of dataset
print(single_house_permit.shape)

# print data types of dataset
print(single_house_permit.dtypes)
```

```
(439, 2)
DATE        object
PERMIT1    float64
dtype: object
```

```python
# check null values
print(single_house_permit.isnull().sum())

# check duplicates
print(single_house_permit.duplicated().sum())
```

```
DATE       0
PERMIT1    0
dtype: int64
0
```

**Overview of more than 5 unit house permit dataset**

```python
# print top 5 row
more_than_5_unit_house_permit.head()
```

```
         DATE  PERMIT5
0  1987-01-01    502.0
1  1987-02-01    391.0
2  1987-03-01    475.0
3  1987-04-01    447.0
4  1987-05-01    403.0
```

```python
# print shape of dataset
print(more_than_5_unit_house_permit.shape)

# print data types of dataset
print(more_than_5_unit_house_permit.dtypes)
```

```
(439, 2)
DATE        object
PERMIT5    float64
dtype: object
```

```python
# check null values
print(more_than_5_unit_house_permit.isnull().sum())
# check duplicates
print(more_than_5_unit_house_permit.duplicated().sum())
```

```
DATE       0
PERMIT5    0
dtype: int64
0
```

**Overview of employment rate dataset**

```python
# print top 5 row
employment_rate.head()
```

```
         DATE  LREM64TTUSM156S
0  1987-01-01        70.164507
```

```
1  1987-02-01        70.290528
2  1987-03-01        70.323792
3  1987-04-01        70.500492
4  1987-05-01        70.811981
```

```python
# print shape of dataset
employment_rate.shape
```

```
(438, 2)
```

```python
# print data types of dataset
employment_rate.dtypes
```

```
DATE                 object
LREM64TTUSM156S    float64
dtype: object
```

```python
# check null values
employment_rate.isnull().sum()
```

```
DATE               0
LREM64TTUSM156S    0
dtype: int64
```

**Overview of unemployment rate dataset**

```python
# print top 5 row
unemployment_rate.head()
```

```
         DATE  UNRATE
0  1987-01-01     6.6
1  1987-02-01     6.6
2  1987-03-01     6.6
3  1987-04-01     6.3
4  1987-05-01     6.3
```

```python
# print shape of dataset
unemployment_rate.shape
```

```
(440, 2)
```

```python
# print data types of dataset
unemployment_rate.dtypes
```

```
DATE       object
UNRATE    float64
dtype: object
```

```python
# check null values
unemployment_rate.isnull().sum()
```

```
DATE      0
UNRATE    0
dtype: int64
```

```
# check duplicates
unemployment_rate.duplicated().sum()
```

```
0
```

#### Overview of m3 dataset

```
# print top 5 row
m3_df.head()
```

```
      DATE            m3
0  1987-01  2.743900e+12
1  1987-02  2.747500e+12
2  1987-03  2.753700e+12
3  1987-04  2.767700e+12
4  1987-05  2.772900e+12
```

```
# print shape of dataset
m3_df.shape
```

```
(438, 2)
```

```
# print data types of dataset
m3_df.dtypes
```

```
DATE                 object
MABMM301USM189S     float64
dtype: object
```

```
# check null values
m3_df.isnull().sum()
```

```
DATE               0
MABMM301USM189S    0
dtype: int64
```

## Over view of Customer Sentiment data

```
# print top 5 row
customer_sentiment_df.head()
```

```
         DATE  UMCSENT
0  1987-01-01     90.4
1  1987-02-01     90.2
2  1987-03-01     90.8
3  1987-04-01     92.8
4  1987-05-01     91.1
```

```
# print shape of dataset
customer_sentiment_df.shape
```

```
(439, 2)
```

```
# print data types of dataset
customer_sentiment_df.dtypes
```

```
DATE          object
UMCSENT      float64
dtype: object
```

```
# check null values
customer_sentiment_df.isnull().sum()
```

```
DATE       0
UMCSENT    0
dtype: int64
```

```
# check duplicates
customer_sentiment_df.duplicated().sum()
```

```
0
```

**Overview of home price index dataset**

```
# print top 5 row
home_price_index.head()
```

```
        DATE     hpi
0 1987-01-01  63.965
1 1987-02-01  64.424
2 1987-03-01  64.735
3 1987-04-01  65.131
4 1987-05-01  65.563
```

```
# print shape of dataset
home_price_index.shape
```

```
(438, 2)
```

```
# print data types of dataset
home_price_index.dtypes
```

```
DATE           object
CSUSHPISA     float64
dtype: object
```

```
# check null values
home_price_index.isnull().sum()
```

```
DATE         0
CSUSHPISA    0
dtype: int64
```

```
# check duplicates
home_price_index.duplicated().sum()
```

```
0
```

**Over view of Mortgage Organizational fees & discount dataset**

```
# print top 5 row
Mortgage_org_fees_discount_df.head()
```

```
         DATE MORTPTS30US
0  1987-01-02        2.20
1  1987-01-09        2.20
2  1987-01-16        2.10
3  1987-01-23        2.20
4  1987-01-30        2.20
```

```
# print shape of dataset
Mortgage_org_fees_discount_df.shape
```

```
(1900, 2)
```

```
# print data types of dataset
Mortgage_org_fees_discount_df.dtypes
```

```
DATE           object
MORTPTS30US    object
dtype: object
```

```
# check null values
Mortgage_org_fees_discount_df.isnull().sum()
```

```
DATE           0
MORTPTS30US    0
dtype: int64
```

```
# check duplicates
Mortgage_org_fees_discount_df.duplicated().sum()
```

```
0
```

**Overview of Human capital index dataset**

```
# print top 5 row
human_capital_index_df.head()
```

```
         DATE  HCIYISUSA066NRUG
0  1987-01-01          3.408786
```

```
1  1988-01-01          3.417534
2  1989-01-01          3.426304
3  1990-01-01          3.435097
4  1991-01-01          3.452302
```

```python
# print shape of dataset
human_capital_index_df.shape
```

```
(33, 2)
```

```python
# print data types of dataset
human_capital_index_df.dtypes
```

```
DATE                  object
HCIYISUSA066NRUG    float64
dtype: object
```

```python
# check null values
human_capital_index_df.isnull().sum()
```

```
DATE                0
HCIYISUSA066NRUG    0
dtype: int64
```

```python
# check duplicates
human_capital_index_df.duplicated().sum()
```

```
0
```

**Over view of Number of house in USA dataset**

```python
# print top 5 row
number_of_house_df.head()
```

```
        DATE  ETOTALUSQ176N
0 2000-04-01       116047.0
1 2000-07-01       116482.0
2 2000-10-01       116914.0
3 2001-01-01       117347.0
4 2001-04-01       117786.0
```

```python
# print shape of dataset
number_of_house_df.shape
```

```
(93, 2)
```

```python
# print data types of dataset
number_of_house_df.dtypes
```

```
DATE               object
ETOTALUSQ176N    float64
dtype: object
```

```python
# check null values
number_of_house_df.isnull().sum()
```

```
DATE             0
ETOTALUSQ176N    0
dtype: int64
```

```python
# check duplicates
number_of_house_df.duplicated().sum()
```

```
0
```

**Overview of Mortgage Rate dataset**

```python
# print top 5 row
mortgage_rate.head()
```

```
         DATE  MORTGAGE30US
0  1987-01-02          9.37
1  1987-01-09          9.32
2  1987-01-16          9.21
3  1987-01-23          9.04
4  1987-01-30          9.08
```

```python
# print shape of dataset
mortgage_rate.shape
```

```
(1914, 2)
```

```python
# print data types of dataset
mortgage_rate.dtypes
```

```
DATE             object
MORTGAGE30US    float64
dtype: object
```

```python
# check null values
mortgage_rate.isnull().sum()
```

```
DATE            0
MORTGAGE30US    0
dtype: int64
```

```python
# check duplicates
mortgage_rate.duplicated().sum()
```

```
0
```

**Overview of Gross Domestic Income dataset**

```python
# print top 5 row
GDI_df.head()
```

```
         DATE       GDI
0  1987-01-01  4652.187
1  1987-04-01  4759.142
2  1987-07-01  4864.953
3  1987-10-01  4969.278
4  1988-01-01  5068.055
```

```python
# print shape of dataset
GDI_df.shape
```

```
(146, 2)
```

```python
# print data types of dataset
GDI_df.dtypes
```

```
DATE     object
GDI     float64
dtype: object
```

```python
# check null values
GDI_df.isnull().sum()
```

```
DATE    0
GDI     0
dtype: int64
```

```python
# check duplicates
GDI_df.duplicated().sum()
```

```
0
```

### Overview of Gross Domestice Product Dataset

```python
# print top 5 row
GDP_df.head()
```

```
        DATE       GDP
0 1987-01-01  4722.156
1 1987-04-01  4806.160
2 1987-07-01  4884.555
3 1987-10-01  5007.994
4 1988-01-01  5073.372
```

```python
# print shape of dataset
GDP_df.tail()
```

```
           DATE        GDP
141  2022-04-01  25248.476
142  2022-07-01  25723.941
143  2022-10-01  26137.992
144  2023-01-01  26529.774
145  2023-04-01  26798.605
```

```
# print shape of dataset
GDP_df.shape
```

```
(144, 2)
```

```
# check data types
GDP_df.dtypes
```

```
DATE     object
GDP     float64
dtype: object
```

```
# check null values
GDP_df.isnull().sum()
```

```
DATE    0
GDP     0
dtype: int64
```

```
# check duplicates values
GDP_df.duplicated().sum()
```

```
0
```

**Overview of inflation data**

```
# print top 5 row
inflation_df.head()
```

```
                           year  amount  inflation rate
0 1970-01-01 00:00:00.000001987    1.00            0.04
1 1970-01-01 00:00:00.000001988    1.04            0.04
2 1970-01-01 00:00:00.000001989    1.09            0.05
3 1970-01-01 00:00:00.000001990    1.15            0.05
4 1970-01-01 00:00:00.000001991    1.20            0.04
```

```
# print shape of dateset
inflation_df.shape
```

```
(37, 3)
```

```
# check null values
inflation_df.isnull().sum()
```

```
year              0
amount            0
inflation rate    0
dtype: int64
```

```
# check duplicates
inflation_df.duplicated().sum()
```

```
0
```

## Change the data type of date in every data set

```
# Convert the 'DATE' column in the 'GDP_df' DataFrame to datetime
format
GDP_df['DATE'] = pd.to_datetime(GDP_df['DATE'])

# Convert the 'DATE' column in the 'GDI_df' DataFrame to datetime
format
GDI_df['DATE'] = pd.to_datetime(GDI_df['DATE'])

# Convert the 'DATE' column in the 'mortgage_rate' DataFrame to
datetime format
mortgage_rate['DATE'] = pd.to_datetime(mortgage_rate['DATE'])

# Convert the 'DATE' column in the 'number_of_house_df' DataFrame to
datetime format
number_of_house_df['DATE'] =
pd.to_datetime(number_of_house_df['DATE'])

# Convert the 'DATE' column in the 'human_capital_index_df' DataFrame
to datetime format
human_capital_index_df['DATE'] =
pd.to_datetime(human_capital_index_df['DATE'])

# Convert the 'DATE' column in the 'Mortgage_org_fees_discount_df'
DataFrame to datetime format
Mortgage_org_fees_discount_df['DATE'] =
pd.to_datetime(Mortgage_org_fees_discount_df['DATE'])

# Convert the 'DATE' column in the 'home_price_index' DataFrame to
datetime format
home_price_index['DATE'] = pd.to_datetime(home_price_index['DATE'])

# Convert the 'DATE' column in the 'customer_sentiment_df' DataFrame
to datetime format
customer_sentiment_df['DATE'] =
pd.to_datetime(customer_sentiment_df['DATE'])

# Convert the 'DATE' column in the 'm3_df' DataFrame to datetime
format
m3_df['DATE'] = pd.to_datetime(m3_df['DATE'])

# Convert the 'DATE' column in the 'unemployment_rate' DataFrame to
datetime format
unemployment_rate['DATE'] = pd.to_datetime(unemployment_rate['DATE'])

# Convert the 'DATE' column in the 'employment_rate' DataFrame to
datetime format
employment_rate['DATE'] = pd.to_datetime(employment_rate['DATE'])

# Convert the 'DATE' column in the 'more_than_5_unit_house_permit'
```

```
DataFrame to datetime format
more_than_5_unit_house_permit['DATE'] =
pd.to_datetime(more_than_5_unit_house_permit['DATE'])

# Convert the 'DATE' column in the 'single_house_permit' DataFrame to
datetime format
single_house_permit['DATE'] =
pd.to_datetime(single_house_permit['DATE'])

# Convert the 'DATE' column in the 'new_house_permit_df' DataFrame to
datetime format
new_house_permit_df['DATE'] =
pd.to_datetime(new_house_permit_df['DATE'])

# Convert the 'DATE' column in the 'population_df' DataFrame to
datetime format
population_df['DATE'] = pd.to_datetime(population_df['DATE'])

# Convert the 'DATE' column in the 'Consumer_price_index_df' DataFrame
to datetime format
Consumer_price_index_df['DATE'] =
pd.to_datetime(Consumer_price_index_df['DATE'])

# Convert the 'year' column in the 'inflation_df' DataFrame to
datetime format with a specified format ('%Y')
inflation_df['year'] = pd.to_datetime(inflation_df['year'],
format='%Y')

# Convert the 'MORTPTS30US' column to numeric values in the
'Mortgage_org_fees_discount_df' DataFrame
# If any value cannot be converted to a numeric type, set it to NaN
(Not a Number)
Mortgage_org_fees_discount_df['MORTPTS30US'] =
pd.to_numeric(Mortgage_org_fees_discount_df['MORTPTS30US'],
errors='coerce')
```

## Change the column name

```
# Rename the 'POPTHM' column to 'population' in the 'population_df'
DataFrame
population_df.rename(columns={'POPTHM': 'population'}, inplace=True)

# Rename the 'CPALTT01USM657N' column to 'Consumer_price_index' in the
'Consumer_price_index_df' DataFrame
Consumer_price_index_df.rename(columns={'CPALTT01USM657N':
'Consumer_price_index'}, inplace=True)

# Rename the 'LREM64TTUSM156S' column to 'employment_rate' in the
'employment_rate' DataFrame
employment_rate.rename(columns={'LREM64TTUSM156S': 'employment_rate'},
```

```
inplace=True)

# Rename the 'UNRATE' column to 'unemployment_rate' in the
'unemployment_rate' DataFrame
unemployment_rate.rename(columns={'UNRATE': 'unemployment_rate'},
inplace=True)

# Rename the 'MABMM301USM189S' column to 'm3' in the 'm3_df' DataFrame
m3_df.rename(columns={'MABMM301USM189S': 'm3'}, inplace=True)

# Rename the 'UMCSENT' column to 'Customer_sentiment_index' in the
'customer_sentiment_df' DataFrame
customer_sentiment_df.rename(columns={'UMCSENT':
'Customer_sentiment_index'}, inplace=True)

# Rename the 'CSUSHPISA' column to 'Home_price_index' in the
'home_price_index' DataFrame
home_price_index.rename(columns={'CSUSHPISA': 'Home_price_index'},
inplace=True)

# Rename the 'MORTPTS30US' column to 'Mort_org_fee&discount' in the
'Mortgage_org_fees_discount_df' DataFrame
Mortgage_org_fees_discount_df.rename(columns={'MORTPTS30US':
'Mort_org_fee&discount'}, inplace=True)

# Rename the 'HCIYISUSA066NRUG' column to 'Human_capital_index' in the
'human_capital_index_df' DataFrame
human_capital_index_df.rename(columns={'HCIYISUSA066NRUG':
'Human_capital_index'}, inplace=True)

# Rename the 'MORTGAGE30US' column to 'mortgage_rate' in the
'mortgage_rate' DataFrame
mortgage_rate.rename(columns={'MORTGAGE30US': 'mortgage_rate'},
inplace=True)

# Rename the 'ETOTALUSQ176N' column to 'Total_house' in the
'number_of_house_df' DataFrame
number_of_house_df.rename(columns={'ETOTALUSQ176N': 'Total_house'},
inplace=True)

# Rename the 'amount' column to '$1 adjusted for inflation' in the
'inflation_df' DataFrame
inflation_df.rename(columns={'amount': '$1 adjusted for inflation'},
inplace=True)

# Rename the 'year' column to 'DATE' in the 'inflation_df' DataFrame
inflation_df.rename(columns={'year': 'DATE'}, inplace=True)
```

## Grouping data from day to monthly basis

Here we are going to group by month using the DATE colum

```
# Group the 'mortgage_rate' DataFrame by month using the 'DATE' column
# Calculate the mean mortgage rate for each month
# Reset the index to make the result a DataFrame
mortgage_rate =
mortgage_rate.groupby(mortgage_rate['DATE'].dt.to_period('M'))
['mortgage_rate'].mean().reset_index()

# Convert the 'DATE' column to a timestamp format (removing the day
information)
mortgage_rate['DATE'] = mortgage_rate['DATE'].dt.to_timestamp()

# Display the first few rows of the modified 'mortgage_rate' DataFrame
mortgage_rate.head()
```

|   | DATE | mortgage_rate |
|---|---|---|
| 0 | 1987-01-01 | 9.2040 |
| 1 | 1987-02-01 | 9.0825 |
| 2 | 1987-03-01 | 9.0350 |
| 3 | 1987-04-01 | 9.8325 |
| 4 | 1987-05-01 | 10.5960 |

```
# print size
mortgage_rate.shape
```

```
(440, 2)
```

```
# Group the 'Mortgage_org_fees_discount_df' DataFrame by month using
the 'DATE' column
# Calculate the mean of the 'Mort_org_fee&discount' column for each
month
# Reset the index to make the result a DataFrame
Mortgage_org_fees_discount_df =
Mortgage_org_fees_discount_df.groupby(Mortgage_org_fees_discount_df['D
ATE'].dt.to_period('M'))['Mort_org_fee&discount'].mean().reset_index()

# Convert the 'DATE' column to a timestamp format (removing the day
information)
Mortgage_org_fees_discount_df['DATE'] =
Mortgage_org_fees_discount_df['DATE'].dt.to_timestamp()

# Display the first few rows of the modified
'Mortgage_org_fees_discount_df' DataFrame
Mortgage_org_fees_discount_df.head()
```

|   | DATE | Mort_org_fee&discount |
|---|---|---|
| 0 | 1987-01-01 | 2.18 |
| 1 | 1987-02-01 | 2.10 |

```
2 1987-03-01                     2.05
3 1987-04-01                     2.25
4 1987-05-01                     2.26

# Apply a lambda function to format the values in the 'm3' column
m3_df['m3'] = m3_df['m3'].apply(lambda x: '{:.2f}'.format(x / 1e12))

# Display the first few rows of the modified 'm3_df' DataFrame
m3_df.head()

        DATE    m3
0 1987-01-01  2.74
1 1987-02-01  2.75
2 1987-03-01  2.75
3 1987-04-01  2.77
4 1987-05-01  2.77
```

**Here we will merge all monthly data and create a dataset merged_df1**

```
# List of DataFrames to be merged
dataframes_to_merge = [
    population_df,
    Consumer_price_index_df,
    customer_sentiment_df,
    mortgage_rate,
    m3_df,
    unemployment_rate,
    employment_rate,
    new_house_permit_df,
    single_house_permit,
    more_than_5_unit_house_permit,
    Mortgage_org_fees_discount_df,
    home_price_index
]

# Initialize the merged DataFrame with the first DataFrame in the list
merged_df1 = dataframes_to_merge[0]

# Loop through the remaining DataFrames in the list and merge them
with the initialized DataFrame
for df in dataframes_to_merge[1:]:
    # pd.merge combines DataFrames using an outer join on the 'DATE'
column
    # 'how='outer'' means that all rows with matching 'DATE' values
are included, and missing values are filled with NaN
    merged_df1 = pd.merge(merged_df1, df, on='DATE', how='outer')

# print top 5 row
merged_df1.head()
```

```
        DATE  population  Consumer_price_index
Customer_sentiment_index  \
0 1987-01-01    241857.0              0.633484
90.4
1 1987-02-01    242005.0              0.359712
90.2
2 1987-03-01    242166.0              0.448029
90.8
3 1987-04-01    242338.0              0.535236
92.8
4 1987-05-01    242516.0              0.354925
91.1

   mortgage_rate    m3  unemployment_rate  employment_rate  PERMIT
PERMIT1  \
0         9.2040  2.74                6.6        70.164507  1690.0
1088.0
1         9.0825  2.75                6.6        70.290528  1689.0
1195.0
2         9.0350  2.75                6.6        70.323792  1704.0
1132.0
3         9.8325  2.77                6.3        70.500492  1601.0
1057.0
4        10.5960  2.77                6.3        70.811981  1500.0
1006.0

   PERMIT5  Mort_org_fee&discount  Home_price_index
0    502.0                   2.18            63.965
1    391.0                   2.10            64.424
2    475.0                   2.05            64.735
3    447.0                   2.25            65.131
4    403.0                   2.26            65.563
```

```
# print the size of dataset
merged_df1.shape
```

```
(440, 13)
```

### Here we merge all quaterly data and create merged_df2 dataset

we convert the home price index data from monthly to quaterly

```
# Group the 'home_price_index' DataFrame by quarter using the 'DATE'
column
# Calculate the mean of the 'Home_price_index' column for each quarter
# Reset the index to make the result a DataFrame
home_price_index_1 =
home_price_index.groupby(home_price_index['DATE'].dt.to_period('Q'))
['Home_price_index'].mean().reset_index()
```

```
# Convert the 'DATE' column to a timestamp format (removing the day
and month information)
home_price_index_1['DATE'] =
home_price_index_1['DATE'].dt.to_timestamp()

# Display the first few rows of the modified 'home_price_index_1'
DataFrame
home_price_index_1.head()
```

```
        DATE  Home_price_index
0 1987-01-01         64.374667
1 1987-04-01         65.588333
2 1987-07-01         66.924667
3 1987-10-01         68.116333
4 1988-01-01         69.252667
```

```
# List of DataFrames to be merged
dataframes_to_merge = [
    GDP_df,
    GDI_df,
    home_price_index_1
]

# Initialize the merged DataFrame with the first DataFrame in the list
merged_df2 = dataframes_to_merge[0]

# Loop through the remaining DataFrames in the list and merge them
with the initialized DataFrame
for df in dataframes_to_merge[1:]:
    # pd.merge combines DataFrames using an outer join on the 'DATE'
column
    # 'how='outer'' means that all rows with matching 'DATE' values
are included, and missing values are filled with NaN
    merged_df2 = pd.merge(merged_df2, df, on='DATE', how='outer')

merged_df2.head()
```

```
        DATE       GDP       GDI  Home_price_index
0 1987-01-01  4722.156  4652.187         64.374667
1 1987-04-01  4806.160  4759.142         65.588333
2 1987-07-01  4884.555  4864.953         66.924667
3 1987-10-01  5007.994  4969.278         68.116333
4 1988-01-01  5073.372  5068.055         69.252667
```

```
merged_df2.shape
```

```
(146, 4)
```

**Here we merge all yearly basis data and create merged_df3 dataset**

```python
# Group the 'home_price_index' DataFrame by year using the 'DATE'
column
# Calculate the mean of the 'Home_price_index' column for each year
# Reset the index to make the result a DataFrame
home_price_index_2 =
home_price_index.groupby(home_price_index['DATE'].dt.to_period('Y'))
['Home_price_index'].mean().reset_index()

# Convert the 'DATE' column to a timestamp format (setting it to the
first day of each year)
home_price_index_2['DATE'] =
home_price_index_2['DATE'].dt.to_timestamp()

# Display the first few rows of the modified 'home_price_index_2'
DataFrame
home_price_index_2.head()
```

```
        DATE  Home_price_index
0 1987-01-01         66.251000
1 1988-01-01         71.134167
2 1989-01-01         75.502000
3 1990-01-01         76.936167
4 1991-01-01         75.921667
```

```python
# Merge the 'human_capital_index_df' and 'home_price_index_2'
DataFrames using an inner join on the 'DATE' column
merged_df3_1 = pd.merge(human_capital_index_df, home_price_index_2,
on='DATE', how='inner')

# Print the shape (number of rows and columns) of the merged DataFrame
print(merged_df3_1.shape)

# Display the first few rows of the merged DataFrame
merged_df3_1.head()
```

```
(33, 3)
```

```
        DATE  Human_capital_index  Home_price_index
0 1987-01-01             3.408786         66.251000
1 1988-01-01             3.417534         71.134167
2 1989-01-01             3.426304         75.502000
3 1990-01-01             3.435097         76.936167
4 1991-01-01             3.452302         75.921667
```

```python
# Merge the 'merged_df3_1', 'inflation_df', and 'DATE' DataFrames
using an inner join on the 'DATE' column
merged_df3 = pd.merge(merged_df3_1, inflation_df, on='DATE',
how='inner')
```

```
print(merged_df3.shape)
merged_df3.head()
```

```
(33, 5)
```

```
         DATE  Human_capital_index  Home_price_index  \
0 1987-01-01             3.408786         66.251000
1 1988-01-01             3.417534         71.134167
2 1989-01-01             3.426304         75.502000
3 1990-01-01             3.435097         76.936167
4 1991-01-01             3.452302         75.921667

   $1 adjusted for inflation  inflation rate
0                       1.00            0.04
1                       1.04            0.04
2                       1.09            0.05
3                       1.15            0.05
4                       1.20            0.04
```

**Here we take home price index data since 2000 and merge it with Number of house and create merged_df4 dataset**

```
# Define the start and end dates as datetime objects
start_date = pd.to_datetime('2000-04-01')
end_date = pd.to_datetime('2023-12-31')

# Filter the 'home_price_index_1' DataFrame to include rows with dates between the start and end dates
home_price_index_4 = home_price_index_1[(home_price_index_1['DATE'] >= start_date) & (home_price_index_1['DATE'] <= end_date)]

# Display the first few rows of the filtered DataFrame
home_price_index_4.head()
```

```
          DATE  Home_price_index
53 2000-04-01        103.674333
54 2000-07-01        105.786333
55 2000-10-01        108.274333
56 2001-01-01        110.484333
57 2001-04-01        112.203333
```

```
# Merge the 'number_of_house_df' and 'home_price_index_4' DataFrames using an inner join on the 'DATE' column
merged_df4 = pd.merge(number_of_house_df, home_price_index_4, on='DATE', how='inner')

# Print the shape (number of rows and columns) of the merged DataFrame
print(merged_df4.shape)

# Display the first few rows of the merged DataFrame
merged_df4.head()
```

```
(93, 3)

        DATE  Total_house  Home_price_index
0 2000-04-01     116047.0        103.674333
1 2000-07-01     116482.0        105.786333
2 2000-10-01     116914.0        108.274333
3 2001-01-01     117347.0        110.484333
4 2001-04-01     117786.0        112.203333
```

# Data Analysis

## Merged_df1 Data Analysis

```
# print top 5 row
merged_df1.head()

        DATE  population  Consumer_price_index
Customer_sentiment_index  \
0 1987-01-01    241857.0              0.633484
90.4
1 1987-02-01    242005.0              0.359712
90.2
2 1987-03-01    242166.0              0.448029
90.8
3 1987-04-01    242338.0              0.535236
92.8
4 1987-05-01    242516.0              0.354925
91.1

   mortgage_rate    m3  unemployment_rate  employment_rate  PERMIT
PERMIT1  \
0         9.2040  2.74                6.6        70.164507  1690.0
1088.0
1         9.0825  2.75                6.6        70.290528  1689.0
1195.0
2         9.0350  2.75                6.6        70.323792  1704.0
1132.0
3         9.8325  2.77                6.3        70.500492  1601.0
1057.0
4        10.5960  2.77                6.3        70.811981  1500.0
1006.0

   PERMIT5  Mort_org_fee&discount  Home_price_index
0    502.0                   2.18            63.965
1    391.0                   2.10            64.424
2    475.0                   2.05            64.735
3    447.0                   2.25            65.131
4    403.0                   2.26            65.563
```

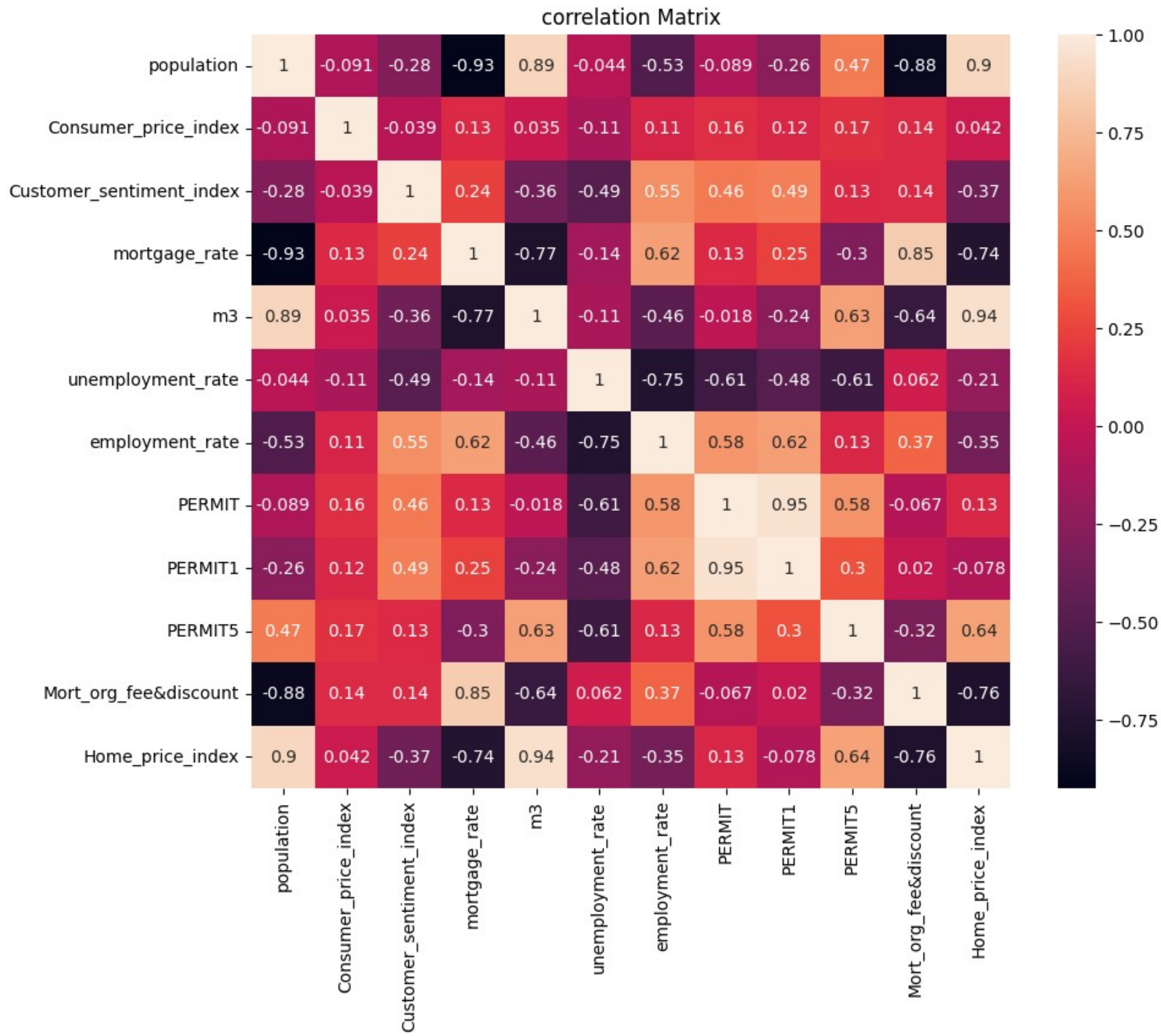
```python
# Remove 'T' and convert 'm3' column to float
merged_df1['m3'] = merged_df1['m3'].str.replace('T', '').astype(float)

# List of columns to be scaled
columns_to_scaler = [
    'population',
    'Consumer_price_index',
    'Customer_sentiment_index',
    'mortgage_rate',
    'm3',
    'unemployment_rate',
    'employment_rate',
    'PERMIT',
    'PERMIT1',
    'PERMIT5',
    'Mort_org_fee&discount',
    'Home_price_index'
]

# Extract the data to be scaled from the 'merged_df1' DataFrame
data_to_scaler = merged_df1[columns_to_scaler]

# Initialize the MinMaxScaler
scaler = MinMaxScaler()

# Fit and transform the data using the scaler
scaler_data = scaler.fit_transform(data_to_scaler)

# Create a new DataFrame with the scaled data, maintaining column
names
merged_scaler_df1 = pd.DataFrame(scaler_data,
columns=columns_to_scaler)

# Add the 'DATE' column back to the DataFrame
merged_scaler_df1['DATE'] = merged_df1['DATE']

# Display the first few rows of the scaled DataFrame
merged_scaler_df1.head()
```

```
   population  Consumer_price_index  Customer_sentiment_index
mortgage_rate  \
0    0.000000              0.774963                  0.651613
0.760261
1    0.001583              0.691722                  0.648387
0.746094
2    0.003306              0.718575                  0.658065
0.740555
3    0.005146              0.745090                  0.690323
0.833547
```

```
4    0.007050              0.690266                  0.662903
0.922575

         m3  unemployment_rate  employment_rate    PERMIT   PERMIT1
PERMIT5  \
0  0.000000           0.283186         0.696303  0.672571  0.514031
0.643411
1  0.000527           0.283186         0.705113  0.672000  0.587269
0.471318
2  0.000527           0.283186         0.707438  0.680571  0.544148
0.601550
3  0.001582           0.256637         0.719790  0.621714  0.492813
0.558140
4  0.001582           0.256637         0.741564  0.564000  0.457906
0.489922

   Mort_org_fee&discount  Home_price_index       DATE
0               0.957895          0.000000 1987-01-01
1               0.915789          0.001906 1987-02-01
2               0.889474          0.003197 1987-03-01
3               0.994737          0.004841 1987-04-01
4               1.000000          0.006635 1987-05-01
```

```python
# Save the 'merged_scaler_df1' DataFrame as a pickle file
merged_scaler_df1.to_pickle('/content/drive/MyDrive/USA_House_price_an
alysis/merged_scaler_df1')

import seaborn as sns
import matplotlib.pyplot as plt

# Set the figure size for the plot
plt.figure(figsize=(10, 8))

# Calculate the correlation matrix for the DataFrame
cor = merged_scaler_df1.corr()

# Create a heatmap of the correlation matrix with annotations
sns.heatmap(cor, annot=True)

# Set the title for the plot
plt.title('Correlation Matrix')

# Show the plot
plt.show()
```

```
<ipython-input-26-2f806da1f10d>:3: 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.
  cor = merged_scaler_df1.corr()
```

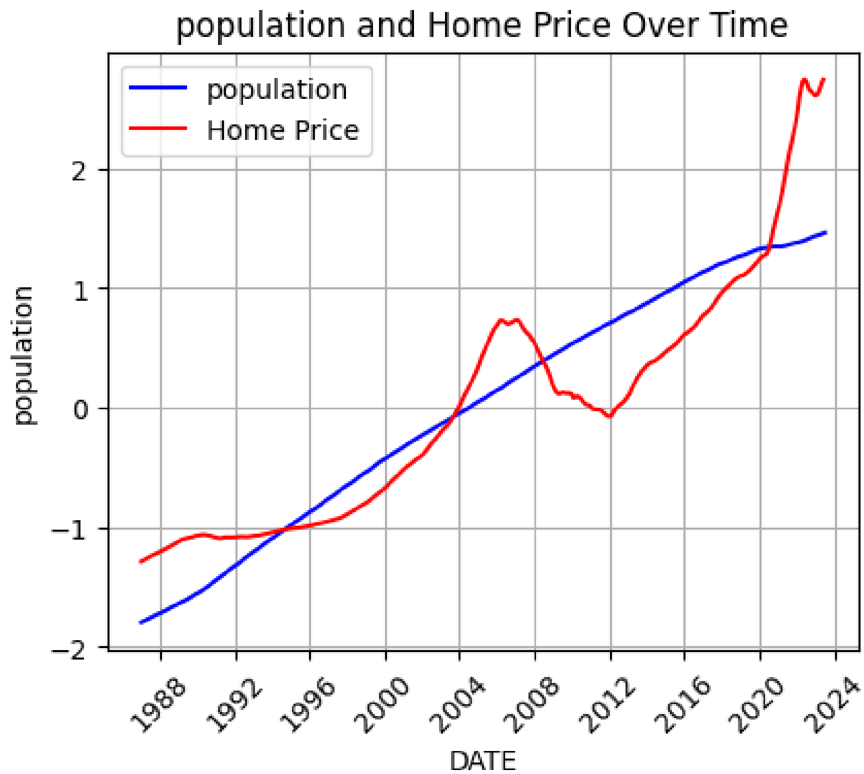



## Observation

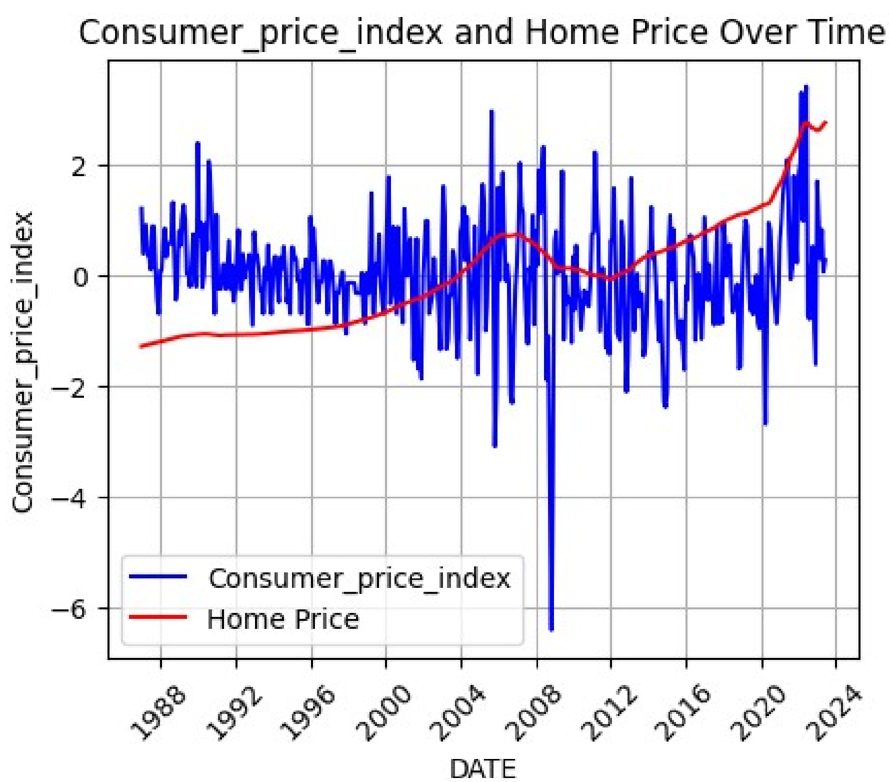
Upon examining the correlation heatmap, we observe that there is a strong positive linear relationship between '**m3**' and the **Home Price Index**. Additionally, variables such as **Population**, **More than 5 units building permits**, and **the Consumer Price Index** exhibit positive correlations with the Home Price Index. This suggests that when these factors increase, the home prices also tend to increase. On the contrary, variables like **Mortgage Organizational fees & discount**, **Mortgage Rate**, **Consumer Sentiment Index**, **employment**, and **unemployment** display negative relationships with the Home Price Index. In other words, as these factors rise, home prices generally decrease.

```
# Iterate over columns and create line graphs against 'DATE' with
'Home_price_index'
for column_name in merged_scaler_df1.columns:
    if column_name != 'DATE' and column_name != 'Home_price_index':
        # Create a new figure for each plot (adjust the figure size if
```

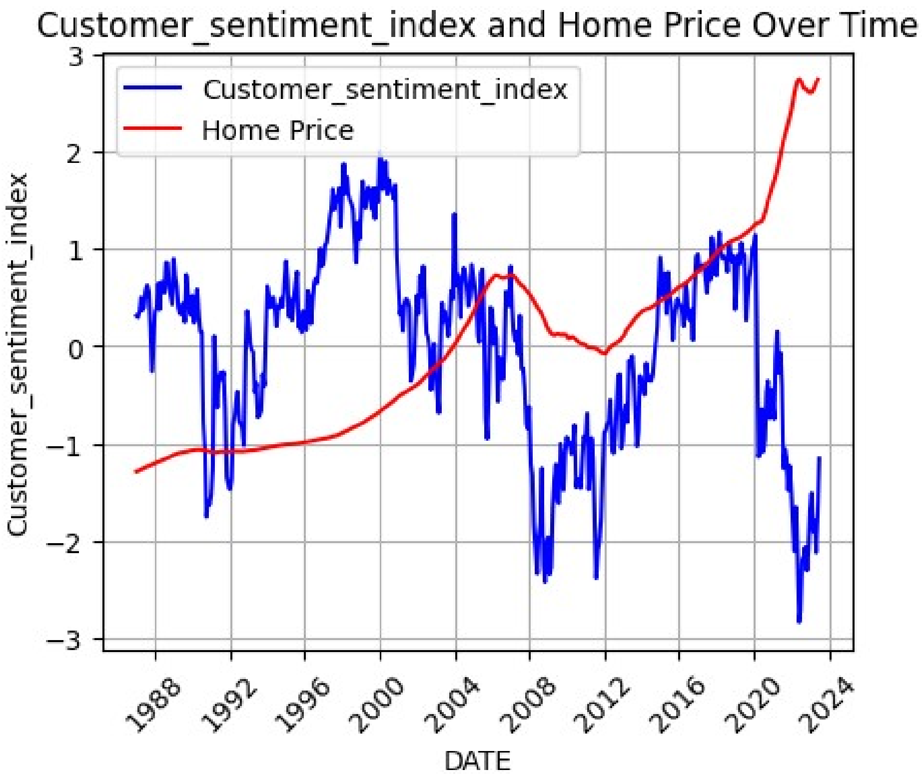
```
needed)
        plt.figure(figsize=(5, 4))

        # Plot the column against 'DATE'
        plt.plot(merged_scaler_df1['DATE'],
merged_scaler_df1[column_name], label=column_name, linestyle='-',
color='blue')

        # Plot 'Home_price_index' against 'DATE'
        plt.plot(merged_scaler_df1['DATE'],
merged_scaler_df1['Home_price_index'], label='Home Price',
linestyle='-', color='red')

        # Set labels, title, and legend
        plt.xlabel('DATE')
        plt.ylabel(column_name)
        plt.title(f'{column_name} and Home Price Over Time')
        plt.legend()

        # Rotate x-axis labels for better readability
        plt.xticks(rotation=45)

        # Enable gridlines
        plt.grid(True)

        # Show the plot
        plt.show()
```



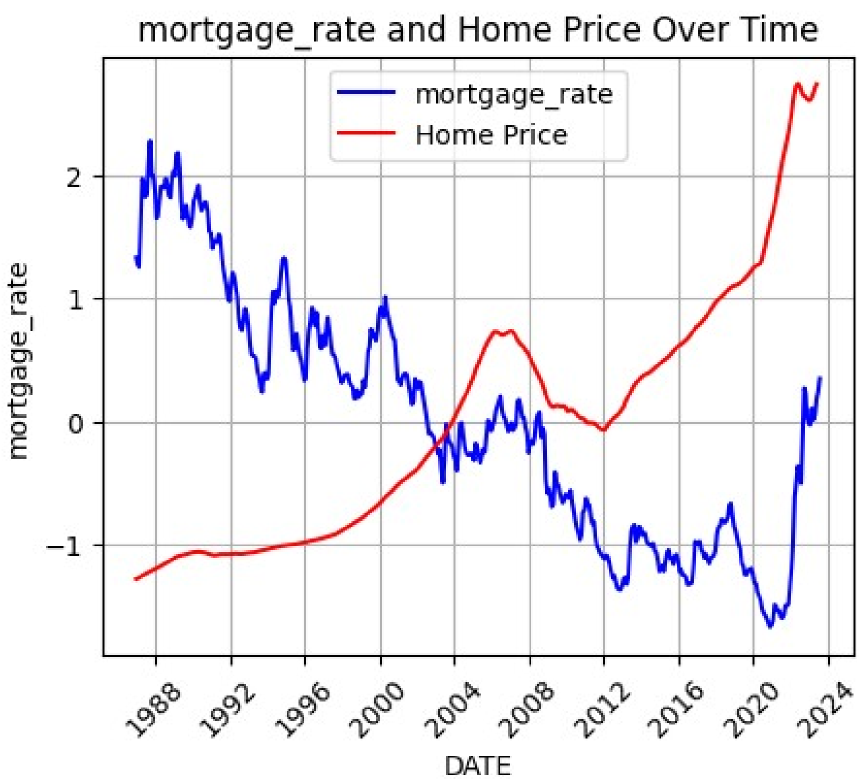
population and Home Price Over Time
population
Home Price
population
DATE

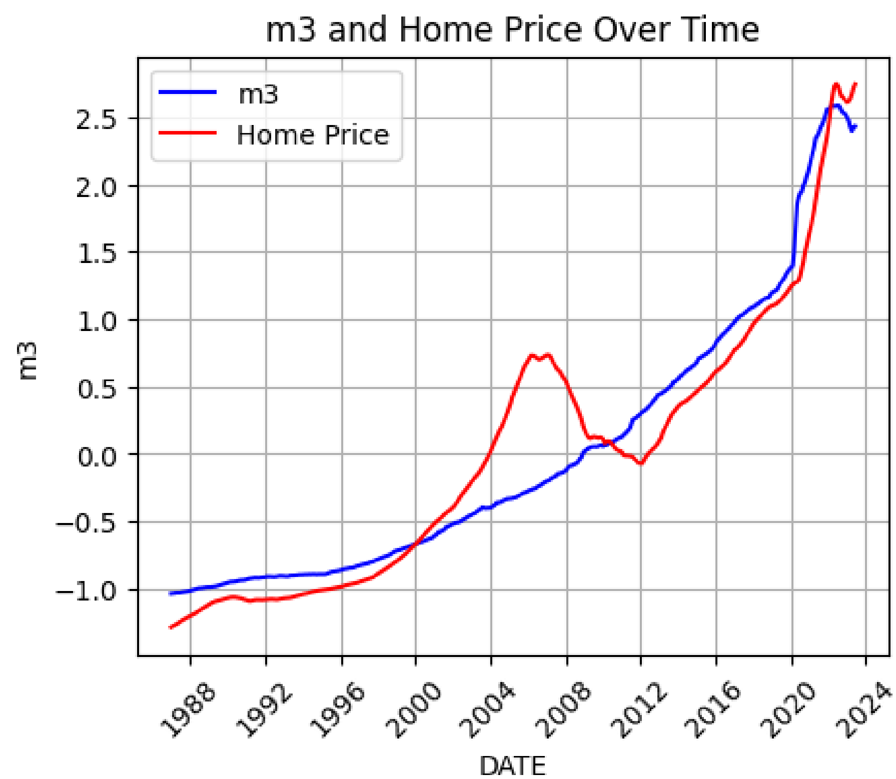
Consumer_price_index and Home Price Over Time
Consumer_price_index
Home Price
Consumer_price_index
DATE

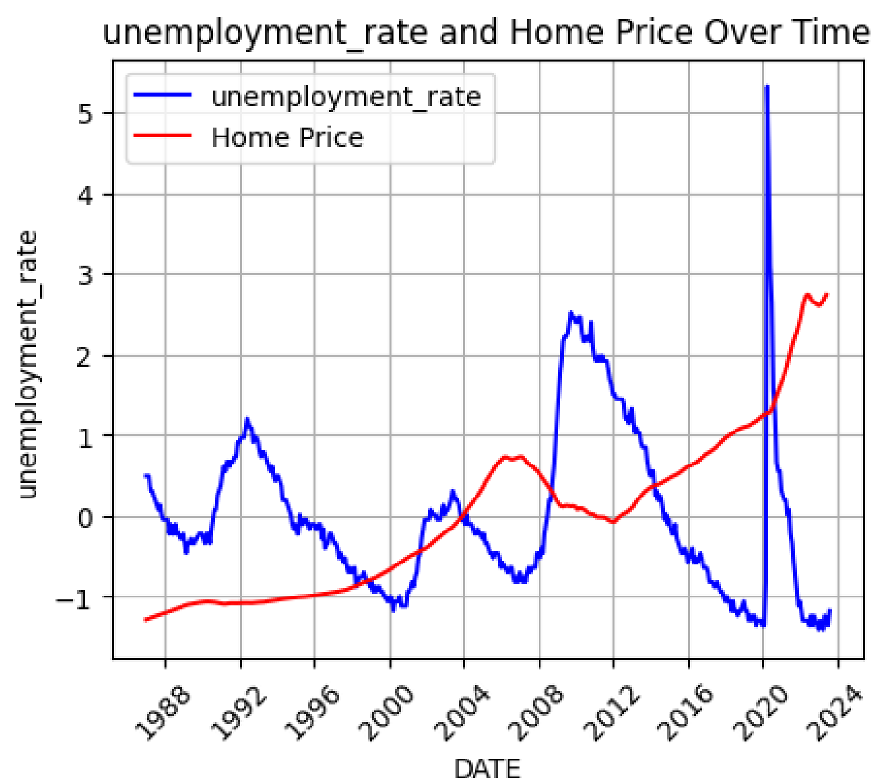


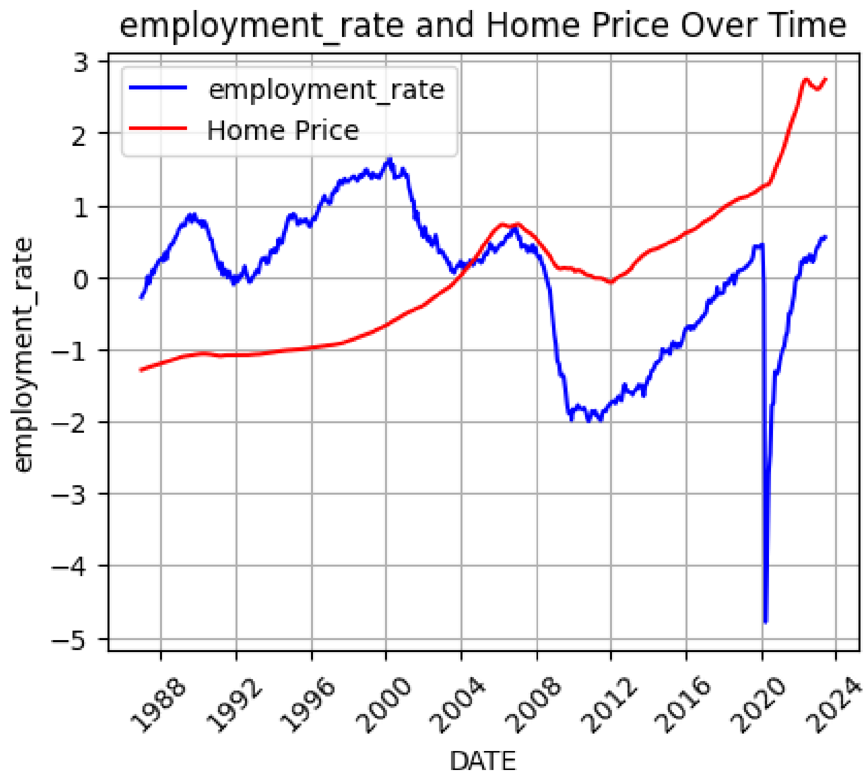
Customer_sentiment_index and Home Price Over Time
Customer_sentiment_index
Home Price
Customer_sentiment_index
DATE

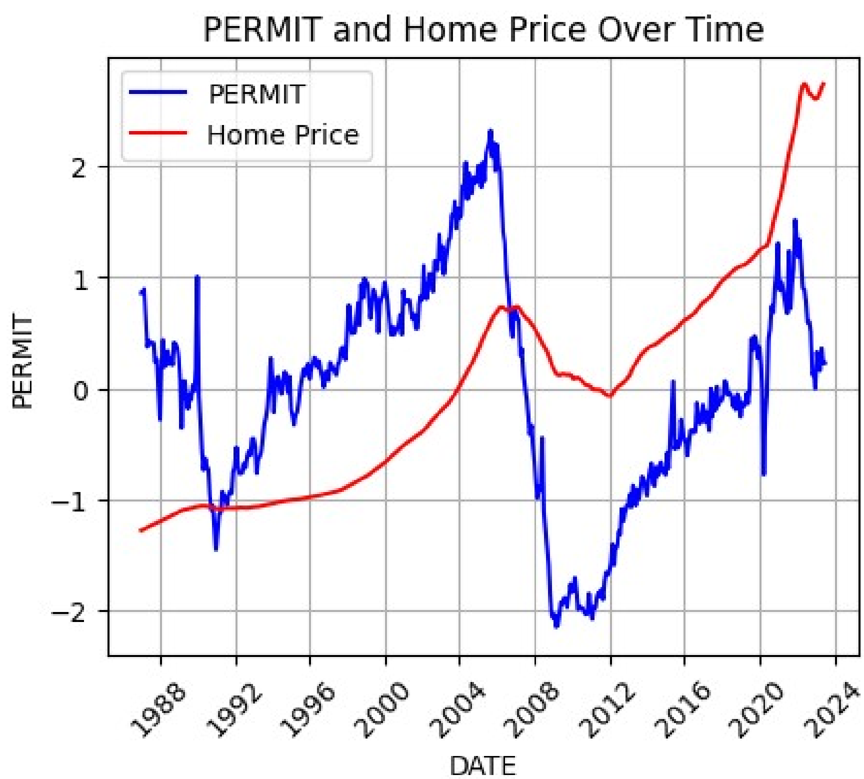



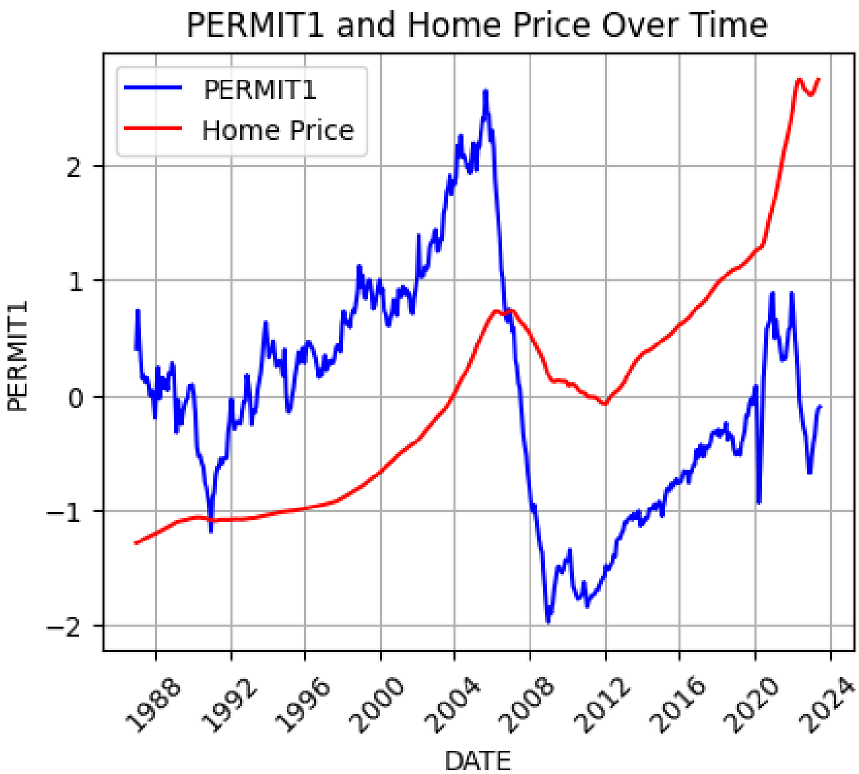
mortgage_rate and Home Price Over Time
mortgage_rate
Home Price
mortgage_rate
DATE

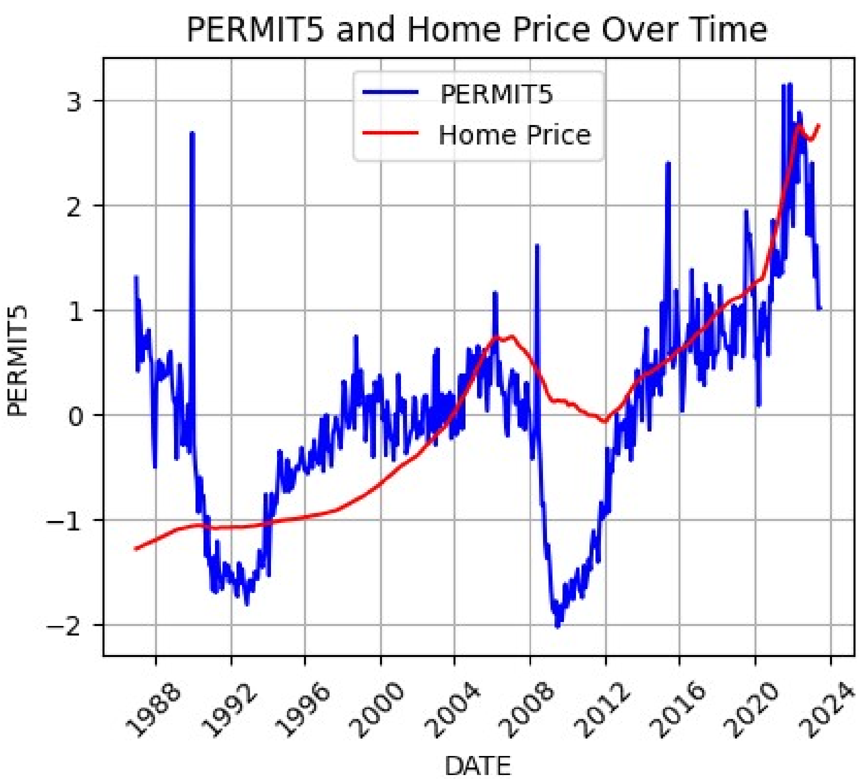

m3 and Home Price Over Time
m3
Home Price
m3
DATE
2.5
2.0
1.5
1.0
0.5
0.0
−0.5
−1.0
1988
1992
1996
2000
2004
2008
2012
2016
2020
2024

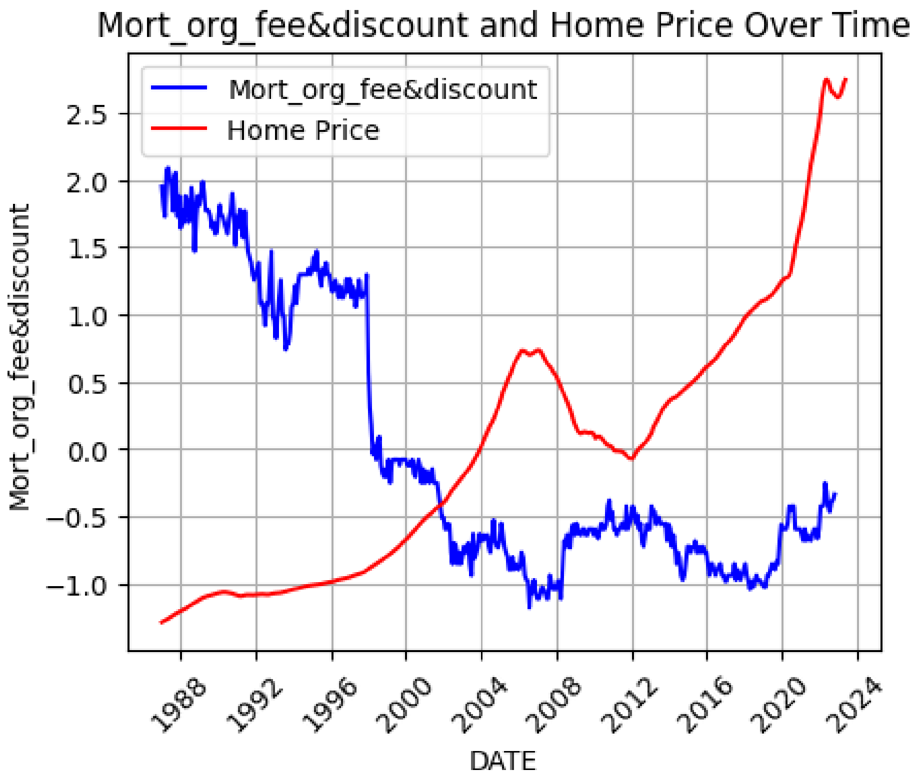

unemployment_rate and Home Price Over Time
unemployment_rate
Home Price
unemployment_rate
DATE
5
4
3
2
1
0
−1
1988
1992
1996
2000
2004
2008
2012
2016
2020
2024


employment_rate and Home Price Over Time
employment_rate
Home Price
employment_rate
DATE
3
2
1
0
−1
−2
−3
−4
−5
1988
1992
1996
2000
2004
2008
2012
2016
2020
2024


PERMIT and Home Price Over Time
PERMIT
Home Price
PERMIT
DATE
2
1
0
−1
−2
1988
1992
1996
2000
2004
2008
2012
2016
2020
2024


PERMIT1 and Home Price Over Time
PERMIT1
Home Price
2
1
0
−1
−2
1988
1992
1996
2000
2004
2008
2012
2016
2020
2024
DATE


PERMIT5 and Home Price Over Time
PERMIT5
Home Price
3
2
1
0
−1
−2
1988
1992
1996
2000
2004
2008
2012
2016
2020
2024
DATE




**Observation**

1. **Population**: Population and Home Price Index line graph is very similar, but after 2020 Home price increased explonentialy and population slightly decreased.

2. **Consumer Price Index**: Consumer Price Index and Home Price Index have positive relation.

3. **Customer Index**: Customer Sentiment Index and Home Price Index have very similar positive trend till 2020. after that have very negetive relation.

4. **Mortgage Rate Index**: Mortgage Rate Index and Home Price Index have Negetive Relation till 2020. After 2020 both are increasing explonentialy.

5. **M3**: M3 index and Home Price Index have linearly positive relation.

6. **Emplોment Rate**: Employment rate and Home Price Index have very postive relation. when employment rate increased home price also increased.

7. **Unemployment Rate** : Unemployment rate and Home Price Index have negetive relationship. When unemployment rate increased then home price decreased.

8. **New House Permit(PERMIT)** : It have very positive relation with Home Price Index till 2020. after that Home price increase explonentialy and new house permit start decreasing.

9. **More Than 1, 2 Unit House Permit(PERMIT1):** It have very same relation with Home Price Index like PERMIT.

10. **More than 5 units Building Permit(PERMIT5):** PERMIT 5 have very positive relation with Home Price Index even after 2020.

11. **Mortgage Org Fees & Discount:** It have very negetive relation with Home Price Index.

### Merged_df2 data analysis

```
#merged_df2 =
pd.read_pickle('/content/drive/MyDrive/USA_House_price_analysis/merged
_df2.pkl')
merged_df2.head()
```

| | DATE | GDP | GDI | Home_price_index |
|---|---|---|---|---|
| 0 | 1987-01-01 | 4722.156 | 4652.187 | 64.374667 |
| 1 | 1987-04-01 | 4806.160 | 4759.142 | 65.588333 |
| 2 | 1987-07-01 | 4884.555 | 4864.953 | 66.924667 |
| 3 | 1987-10-01 | 5007.994 | 4969.278 | 68.116333 |
| 4 | 1988-01-01 | 5073.372 | 5068.055 | 69.252667 |

```
# List of columns to be scaled
columns_to_scaler = ['GDP', 'GDI', 'Home_price_index']

# Extract the data to be scaled from the 'merged_df2' DataFrame
data_to_scaler = merged_df2[columns_to_scaler]

# Initialize the MinMaxScaler
scaler = MinMaxScaler()

# Fit and transform the data using the scaler
scaler_data = scaler.fit_transform(data_to_scaler)

# Create a new DataFrame with the scaled data, maintaining column
names
merged_scl_df2 = pd.DataFrame(scaler_data, columns=columns_to_scaler)

# Add the 'DATE' column back to the DataFrame
merged_scl_df2['DATE'] = merged_df2['DATE']

# Display the first few rows of the scaled DataFrame
merged_scl_df2.head()
```

| | GDP | GDI | Home_price_index | DATE |
|---|---|---|---|---|
| 0 | 0.000000 | 0.000000 | 0.000000 | 1987-01-01 |
| 1 | 0.003805 | 0.004941 | 0.005084 | 1987-04-01 |
| 2 | 0.007356 | 0.009828 | 0.010681 | 1987-07-01 |
| 3 | 0.012948 | 0.014648 | 0.015673 | 1987-10-01 |
| 4 | 0.015909 | 0.019210 | 0.020432 | 1988-01-01 |

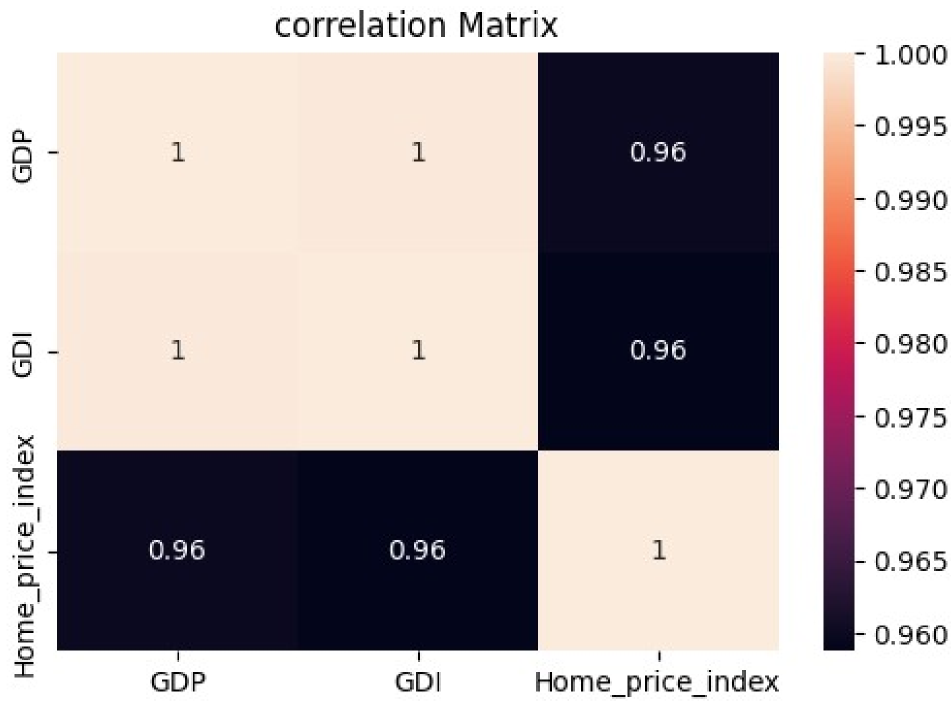
```python
# Save the 'merged_scl_df2' DataFrame as a pickle file
merged_scl_df2.to_pickle('/content/drive/MyDrive/USA_House_price_analy
sis/merged_scl_df2.pkl')
```

```python
merged_scl_df2.shape
```

```
(146, 4)
```

```python
import seaborn as sns
import matplotlib.pyplot as plt

# Set the figure size for the plot
plt.figure(figsize=(6, 4))

# Calculate the correlation matrix for the DataFrame
cor = merged_scl_df2.corr()

# Create a heatmap of the correlation matrix with annotations
sns.heatmap(cor, annot=True)

# Set the title for the plot
plt.title('Correlation Matrix')

# Show the plot
plt.show()
```

```
<ipython-input-27-efe3d00921b9>:3: 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.
  cor = merged_scl_df2.corr()
```

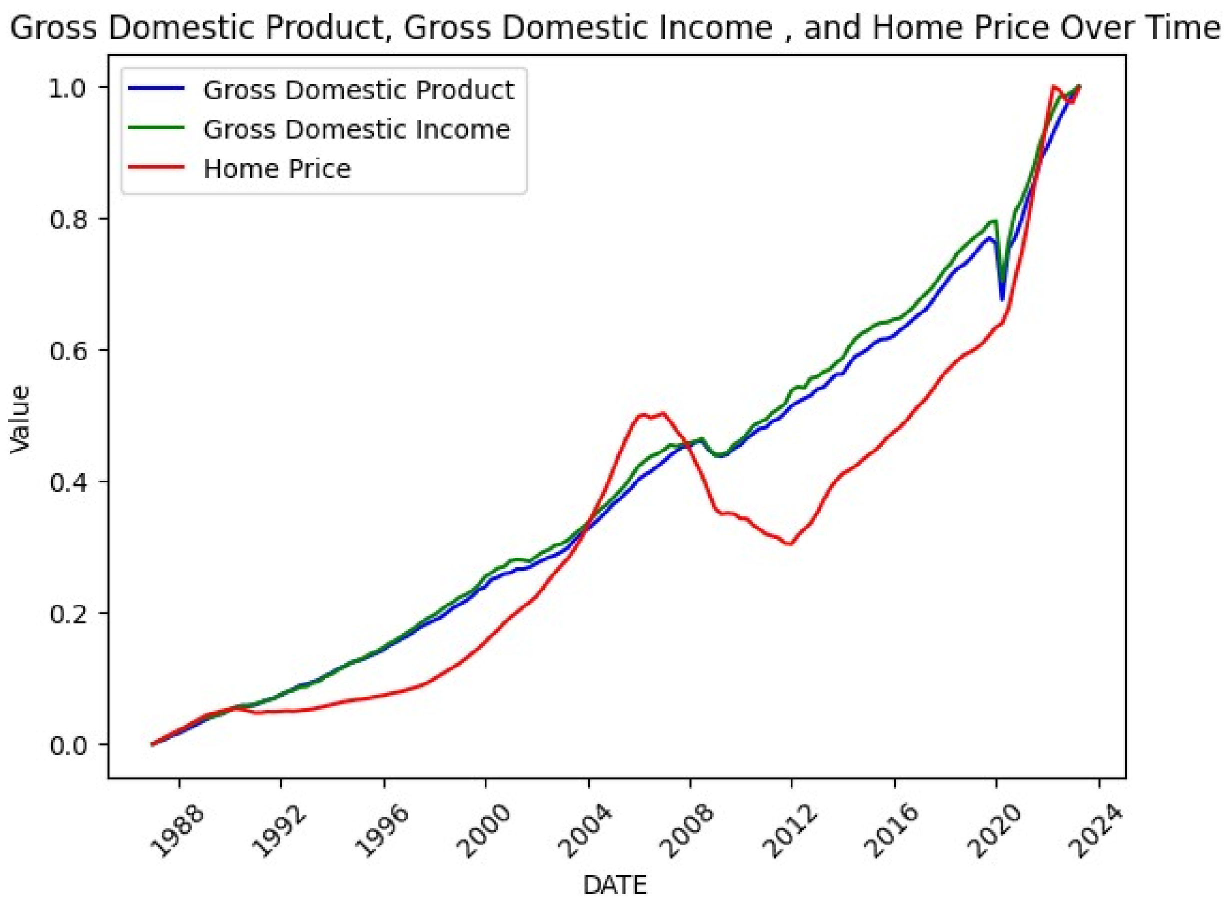



### Observation

Gross Domestic Income (GDI) and Gross Domestic Product (GDP) exhibit a highly positive correlation with the Home Price Index, with a remarkable similarity of 96%. This substantial similarity between GDI, GDP, and the Home Price Index stands out as the highest among all the indicators examined.

```
# Create the line graph
plt.figure(figsize=(7, 5))  # Adjust the figure size if needed

# Plot 'DATE' vs. 'GDP'
plt.plot(merged_scl_df2['DATE'], merged_scl_df2['GDP'], label='Gross Domestic Product', linestyle='-', color='blue')

# Plot 'DATE' vs. 'GDI'
plt.plot(merged_scl_df2['DATE'], merged_scl_df2['GDI'], label='Gross Domestic Income', linestyle='-', color='green')

# Plot 'DATE' vs. 'hpi'
plt.plot(merged_scl_df2['DATE'], merged_scl_df2['Home_price_index'], label='Home Price', linestyle='-', color='red')

# Set labels and title
plt.xlabel('DATE')
plt.ylabel('Value')
plt.title('Gross Domestic Product, Gross Domestic Income , and Home Price Over Time')
```

```
# Add a legend
plt.legend()

# Rotate the x-axis labels for better readability (optional)
plt.xticks(rotation=45)

# Show the plot
#plt.grid(True)
plt.show()
```




### Observation

In this analysis, we observe a positive relationship between GDP, GDI, and the Home Price Index. This suggests that when people's income increases, there is a corresponding increase in house prices.

### Merged_df3 Data Analysis

```
#merged_df3 =
pd.read_pickle('/content/drive/MyDrive/USA_House_price_analysis/merged
```

```
_df3.pkl')
merged_df3.head()
```

```
        DATE  Human_capital_index  Home_price_index  \
0 1987-01-01             3.408786         66.251000
1 1988-01-01             3.417534         71.134167
2 1989-01-01             3.426304         75.502000
3 1990-01-01             3.435097         76.936167
4 1991-01-01             3.452302         75.921667

   $1 adjusted for inflation  inflation rate
0                       1.00            0.04
1                       1.04            0.04
2                       1.09            0.05
3                       1.15            0.05
4                       1.20            0.04
```

```
# List of columns to be scaled
columns_to_scaler = ['Human_capital_index', 'Home_price_index', '$1
adjusted for inflation', 'inflation rate']

# Extract the data to be scaled from the 'merged_df3' DataFrame
data_to_scaler = merged_df3[columns_to_scaler]

# Initialize the MinMaxScaler
scaler = MinMaxScaler()

# Fit and transform the data using the scaler
scaler_data = scaler.fit_transform(data_to_scaler)

# Create a new DataFrame with the scaled data, maintaining column
names
merged_scl_df3 = pd.DataFrame(scaler_data, columns=columns_to_scaler)

# Add the 'DATE' column back to the DataFrame
merged_scl_df3['DATE'] = merged_df3['DATE']

# Display the first few rows of the scaled DataFrame
merged_scl_df3.head()
```

```
   Human_capital_index  Home_price_index  $1 adjusted for inflation  \
0             0.000000          0.000000                      0.000
1             0.025686          0.034095                      0.032
2             0.051439          0.064592                      0.072
3             0.077257          0.074605                      0.120
4             0.127781          0.067522                      0.160

   inflation rate       DATE
0             0.8 1987-01-01
1             0.8 1988-01-01
2             1.0 1989-01-01
```

```
3               1.0 1990-01-01
4               0.8 1991-01-01
```

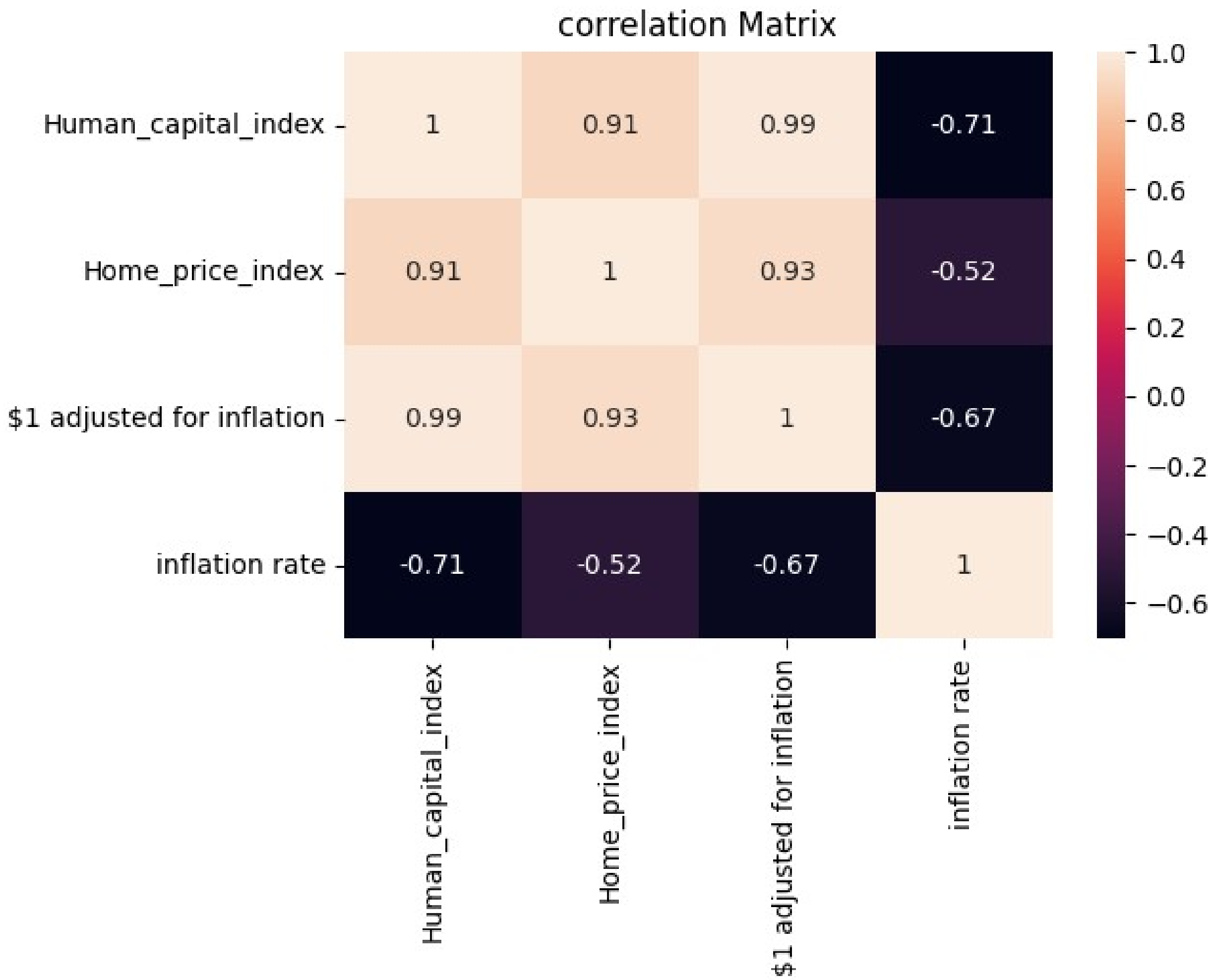
```
# Save the 'merged_scl_df3' DataFrame as a pickle file
merged_scl_df3.to_pickle('/content/drive/MyDrive/USA_House_price_analy
sis/merged_scl_df3.pkl')
```

```
merged_scl_df3.shape
```

```
(33, 5)
```

```
import seaborn as sns
import matplotlib.pyplot as plt

# Set the figure size for the plot
plt.figure(figsize=(6, 4))

# Calculate the correlation matrix for the DataFrame
cor = merged_scl_df3.corr()

# Create a heatmap of the correlation matrix with annotations
sns.heatmap(cor, annot=True)

# Set the title for the plot
plt.title('Correlation Matrix')

# Show the plot
plt.show()
```

```
<ipython-input-38-b29d0490fb76>:3: 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.
  cor = merged_scl_df3.corr()
```

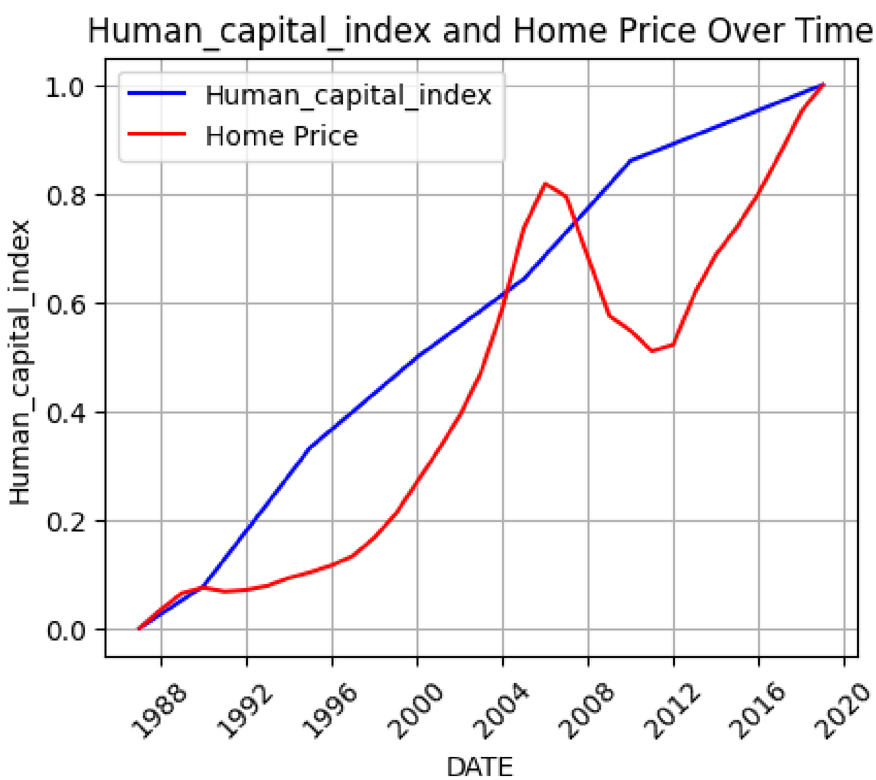


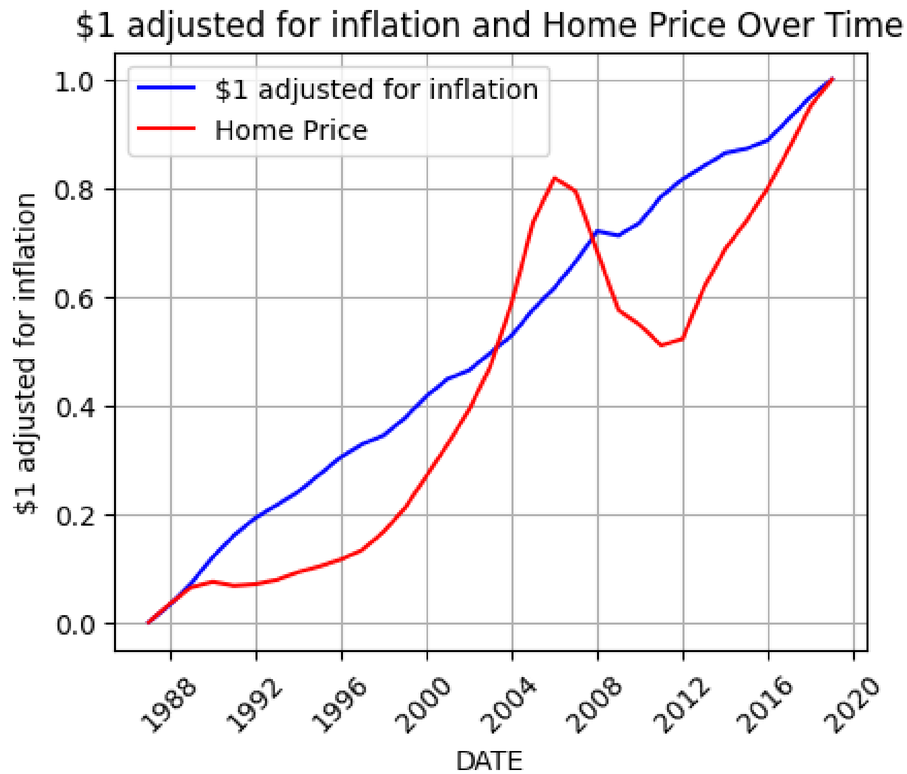

### Observation

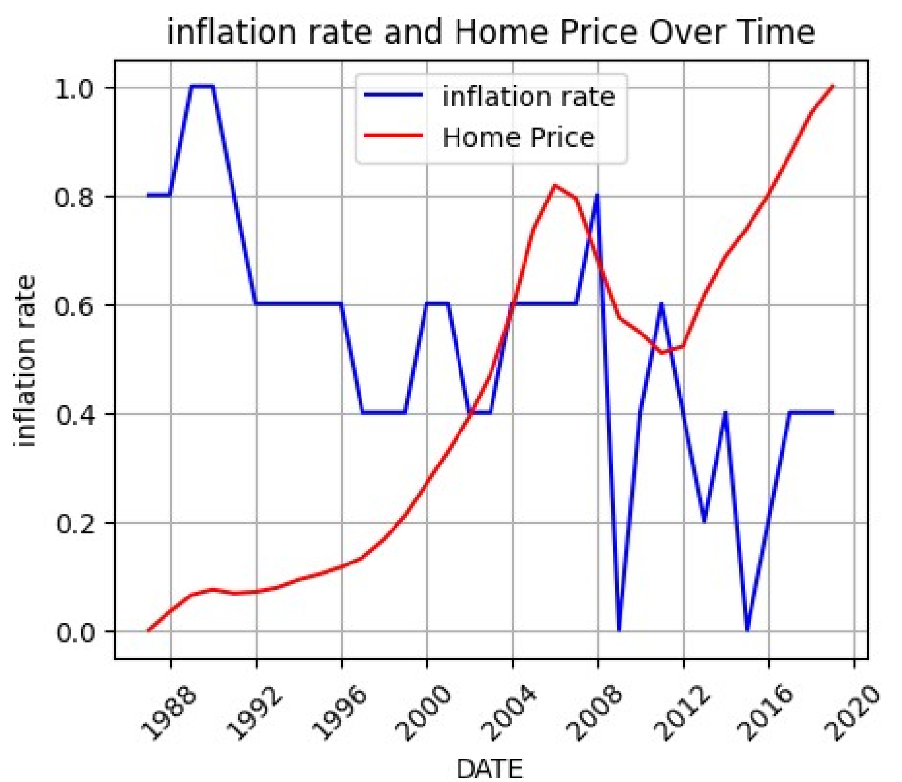
In the heatmap of the correlation matrix, a notably strong positive relationship is evident between the variables: "$ 1 in 1987, adjusted inflation" and the Home Price Index. Additionally, the "Human Capital Index" also exhibits a notably strong positive correlation with the Home Price Index.

```
# Iterate over columns and create line graphs against 'DATE' with
'Home_price_index'
for column_name in merged_scl_df3.columns:
    if column_name != 'DATE' and column_name != 'Home_price_index':
        # Create a new figure for each plot (adjust the figure size if
needed)
        plt.figure(figsize=(5, 4))

        # Plot the column against 'DATE'
        plt.plot(merged_scl_df3['DATE'], merged_scl_df3[column_name],
label=column_name, linestyle='-', color='blue')
```

```
        # Plot 'Home_price_index' against 'DATE'
        plt.plot(merged_scl_df3['DATE'],
merged_scl_df3['Home_price_index'], label='Home Price', linestyle='-',
color='red')

        # Set labels, title, and legend
        plt.xlabel('DATE')
        plt.ylabel(column_name)
        plt.title(f'{column_name} and Home Price Over Time')
        plt.legend()

        # Rotate x-axis labels for better readability
        plt.xticks(rotation=45)

        # Enable gridlines
        plt.grid(True)

        # Show the plot
        plt.show()
```




$1 adjusted for inflation and Home Price Over Time
$1 adjusted for inflation
Home Price
$1 adjusted for inflation
1.0
0.8
0.6
0.4
0.2
0.0
1988
1992
1996
2000
2004
2008
2012
2016
2020
DATE


inflation rate and Home Price Over Time
inflation rate
Home Price
inflation rate
1.0
0.8
0.6
0.4
0.2
0.0
1988
1992
1996
2000
2004
2008
2012
2016
2020
DATE

### Observation

In the line plot, it's apparent that $ 1 in 1987, adjusted inflation and the Human Capital Index have a positive relationship with the House Price Index. This suggests that as 1 dollar in 1987, adjusted inflation and the Human Capital Index increase, the House Price Index tends to rise as well. Conversely, inflation shows a negative relationship with the House Price Index, indicating that as inflation increases, house prices tend to decrease.

### Merged_df4 Data Analysis

```
#merged_df4 =
pd.read_pickle('/content/drive/MyDrive/USA_House_price_analysis/merged
_df4.pkl')
merged_df4.head()
```

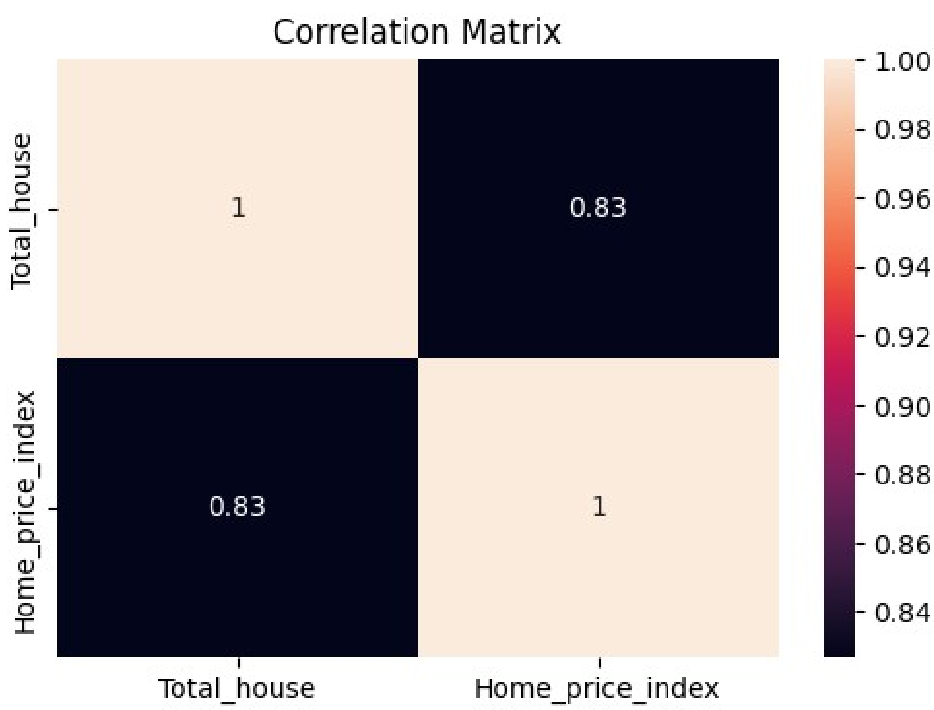
|  | DATE | Total_house | Home_price_index |
|---|---|---|---|
| 0 | 2000-04-01 | 116047.0 | 103.674333 |
| 1 | 2000-07-01 | 116482.0 | 105.786333 |
| 2 | 2000-10-01 | 116914.0 | 108.274333 |
| 3 | 2001-01-01 | 117347.0 | 110.484333 |
| 4 | 2001-04-01 | 117786.0 | 112.203333 |

```
# List of columns to be standardized
columns_to_standardize = ['Total_house', 'Home_price_index']

# Extract the data to be standardized from the 'merged_df4' DataFrame
data_to_standardize = merged_df4[columns_to_standardize]

# Initialize the StandardScaler
scaler = StandardScaler()

# Fit and transform the data using the scaler
standardized_data = scaler.fit_transform(data_to_standardize)

# Create a new DataFrame with the standardized data, maintaining
column names
merged_std_df4 = pd.DataFrame(standardized_data,
columns=columns_to_standardize)

# Add the 'DATE' column back to the DataFrame
merged_std_df4['DATE'] = merged_df4['DATE']

# Display the first few rows of the standardized DataFrame
merged_std_df4.head()
```

|  | Total_house | Home_price_index | DATE |
|---|---|---|---|
| 0 | -2.060047 | -1.509267 | 2000-04-01 |
| 1 | -2.003042 | -1.464826 | 2000-07-01 |
| 2 | -1.946430 | -1.412472 | 2000-10-01 |
| 3 | -1.889687 | -1.365968 | 2001-01-01 |
| 4 | -1.832158 | -1.329796 | 2001-04-01 |

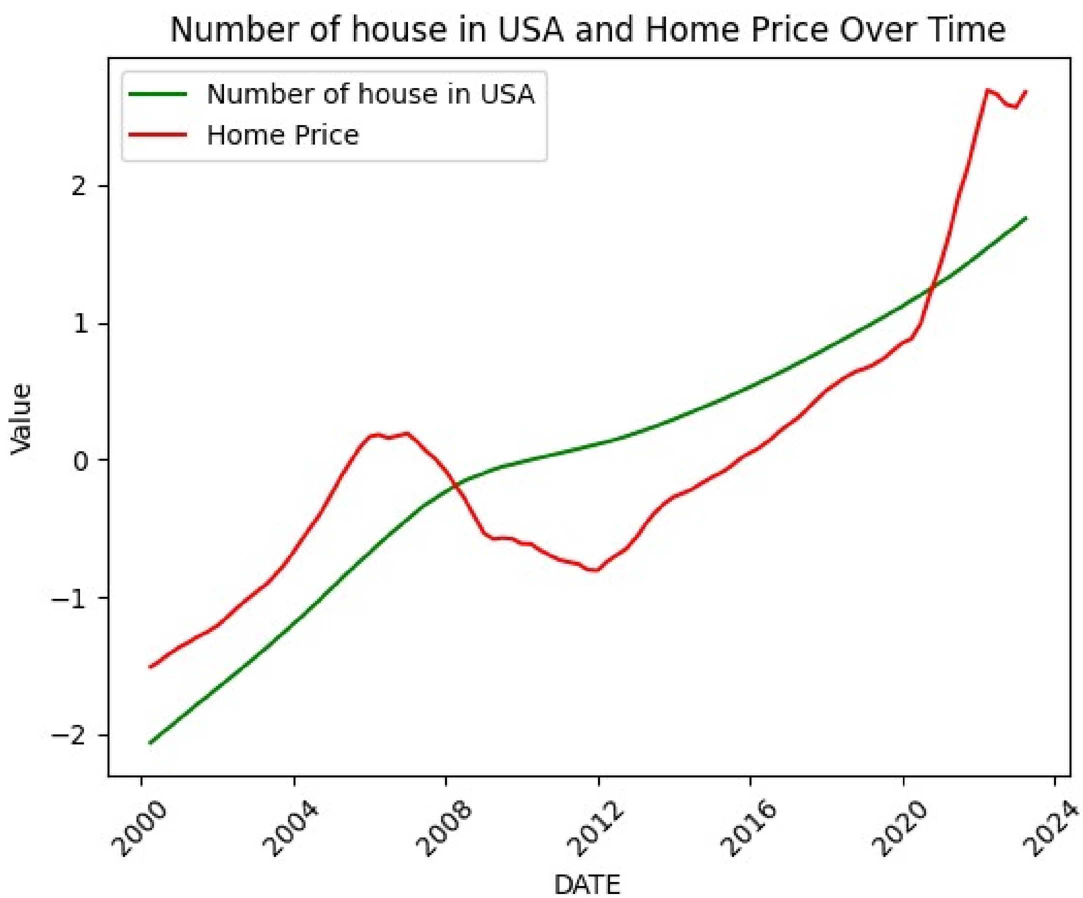
```
import seaborn as sns
import matplotlib.pyplot as plt

# Set the figure size for the plot
plt.figure(figsize=(6, 4))

# Calculate the correlation matrix for the DataFrame
cor = merged_std_df4.corr()

# Create a heatmap of the correlation matrix with annotations
sns.heatmap(cor, annot=True)

# Set the title for the plot
plt.title('Correlation Matrix')

# Show the plot
plt.show()
```

```
<ipython-input-52-5fda4f1bedbb>:8: 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.
  cor = merged_std_df4.corr()
```




```
# Save the 'merged_df4' DataFrame as a pickle file
merged_df4.to_pickle('/content/drive/MyDrive/USA_House_price_analysis/
merged_df4.pkl')
```

```
# Plot 'DATE' vs. 'GDI'
plt.plot(merged_std_df4['DATE'], merged_std_df4['Total_house'],
label='Number of house in USA', linestyle='-', color='green')

# Plot 'DATE' vs. 'hpi'
plt.plot(merged_std_df4['DATE'], merged_std_df4['Home_price_index'],
label='Home Price', linestyle='-', color='red')

# Set labels and title
plt.xlabel('DATE')
plt.ylabel('Value')
plt.title('Number of house in USA and Home Price Over Time')

# Add a legend
plt.legend()

# Rotate the x-axis labels for better readability (optional)
plt.xticks(rotation=45)

# Show the plot
#plt.grid(True)
plt.show()
```



### Observation

In this graph, a clear and linear positive relationship is evident between the Number of House Index and the House Price Index. Notably, there is an exponential decrease in the House Price Index around the year 2008, likely indicating the impact of a housing market downturn. Conversely, after 2020, there is a notable exponential increase in house prices, suggesting a period of significant growth in the housing market.

# Experimenting with Machine Learning

We now have a total of four datasets. The first dataset, named "merged_scaler_df1," comprises 13 columns and contains 440 rows of data. The second dataset, "merged_scl_df2," is composed of 4 columns and 146 rows. Moving on to the third dataset, "merged_scl_df3," it consists of 5 columns and 33 rows. Lastly, the fourth dataset, "merged_df4," encompasses 3 columns and 93 rows.

It's worth noting that the first dataset, "merged_scaler_df1," is the most substantial, with a shape of (440, 13). Consequently, this dataset will be used for our data modeling endeavors. As for the other datasets, they contain insufficient data points to adequately train a machine learning model.

### Goals

Determine which variables are most important for **USA Home Price**

**"We are dealing with a regression problem, which means our objective is to predict numerical values. Consequently, we are exclusively utilizing regression models to identify the most relevant features for our task."**

```
# Read the pickle file into a Pandas DataFrame
merged_scaler_df1 =
pd.read_pickle("/content/drive/MyDrive/USA_House_price_analysis/merged
_scaler_df1")

# printing top 5 row
merged_scaler_df1.head()
```

```
   population  Consumer_price_index  Customer_sentiment_index
mortgage_rate  \
0    0.000000              0.774963                  0.651613
0.760261
1    0.001583              0.691722                  0.648387
0.746094
2    0.003306              0.718575                  0.658065
0.740555
3    0.005146              0.745090                  0.690323
0.833547
4    0.007050              0.690266                  0.662903
0.922575
```

```
          m3  unemployment_rate  employment_rate    PERMIT   PERMIT1
PERMIT5  \
0  0.000000           0.283186         0.696303  0.672571  0.514031
0.643411
1  0.000527           0.283186         0.705113  0.672000  0.587269
0.471318
2  0.000527           0.283186         0.707438  0.680571  0.544148
0.601550
3  0.001582           0.256637         0.719790  0.621714  0.492813
0.558140
4  0.001582           0.256637         0.741564  0.564000  0.457906
0.489922

   Mort_org_fee&discount  Home_price_index       DATE
0               0.957895          0.000000 1987-01-01
1               0.915789          0.001906 1987-02-01
2               0.889474          0.003197 1987-03-01
3               0.994737          0.004841 1987-04-01
4               1.000000          0.006635 1987-05-01
```

```
merged_scaler_df1.shape
```

```
(440, 13)
```

```
# checking null values
merged_scaler_df1.isnull().sum()
```

```
population                   1
Consumer_price_index         2
Customer_sentiment_index     1
mortgage_rate                0
m3                           2
unemployment_rate            0
employment_rate              2
PERMIT                       1
PERMIT1                      1
PERMIT5                      1
Mort_org_fee&discount        9
Home_price_index             2
DATE                         0
dtype: int64
```

```
# Removing rows with missing (NaN) values from the DataFrame
'merged_scaler_df1'
merged_scaler_df1 = merged_scaler_df1.dropna()

# Checking and print the number of missing values (NaN) in each column
of the DataFrame
missing_values = merged_scaler_df1.isnull().sum()
```

```
# Removing the 'DATE' column from 'merged_scaler_df1' DataFrame
merged_std_df1 = merged_scaler_df1.drop(['DATE'], axis=1)
merged_scaler_df1.head()

   population  Consumer_price_index  Customer_sentiment_index
mortgage_rate  \
0    0.000000              0.774963                  0.651613
0.760261
1    0.001583              0.691722                  0.648387
0.746094
2    0.003306              0.718575                  0.658065
0.740555
3    0.005146              0.745090                  0.690323
0.833547
4    0.007050              0.690266                  0.662903
0.922575

         m3  unemployment_rate  employment_rate    PERMIT   PERMIT1
PERMIT5  \
0  0.000000           0.283186         0.696303  0.672571  0.514031
0.643411
1  0.000527           0.283186         0.705113  0.672000  0.587269
0.471318
2  0.000527           0.283186         0.707438  0.680571  0.544148
0.601550
3  0.001582           0.256637         0.719790  0.621714  0.492813
0.558140
4  0.001582           0.256637         0.741564  0.564000  0.457906
0.489922

   Mort_org_fee&discount  Home_price_index       DATE
0               0.957895          0.000000 1987-01-01
1               0.915789          0.001906 1987-02-01
2               0.889474          0.003197 1987-03-01
3               0.994737          0.004841 1987-04-01
4               1.000000          0.006635 1987-05-01

# Splitting the dataset into features (X) and target variable (y) for
machine learning.
# Then, splitting the data into training and testing sets.

# 'y' contains the 'Home_price_index' column, which is the target
variable.
y = merged_std_df1['Home_price_index']

# 'X' contains all the features except 'Home_price_index' (the
predictors).
X = merged_std_df1.drop(['Home_price_index'], axis=1)

# Using train_test_split to create training and testing sets.
```

```
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=30)

print(X_train.shape)
print(y_train.shape)
print(X_test.shape)
print(y_test.shape)
```

```
(344, 11)
(344,)
(87, 11)
(87,)
```

```
y_train.head()
```

```
368    0.538958
403    0.658159
78     0.055902
141    0.115220
385    0.593007
Name: Home_price_index, dtype: float64
```

```
X_train.head()
```

```
     population  Consumer_price_index  Customer_sentiment_index  \
368    0.914552              0.743343                  0.727419
403    0.962994              0.678224                  0.388710
78     0.198498              0.582350                  0.435484
141    0.377471              0.656691                  0.764516
385    0.941512              0.710875                  0.706452

     mortgage_rate        m3  unemployment_rate  employment_rate
PERMIT  \
368       0.130714  0.579114           0.079646         0.718185
0.436571
403       0.029268  0.823312           0.442478         0.464901
0.600571
78        0.527285  0.036920           0.309735         0.779072
0.377714
141       0.469450  0.082806           0.097345         0.954848
0.689143
385       0.196595  0.618671           0.035398         0.757798
0.450857

      PERMIT1   PERMIT5  Mort_org_fee&discount
368  0.337440  0.502326               0.086842
403  0.498973  0.551938               0.231579
78   0.438056  0.088372               0.663158
141  0.602327  0.534884               0.305263
385  0.316222  0.586047               0.047368
```

**DecisionTreeRegressor Model**

```
from sklearn.tree import DecisionTreeRegressor

# Create a decision tree regression model
tree_model = DecisionTreeRegressor()  # You can adjust the max_depth
hyperparameter

# Define a grid of hyperparameters to search
param_grid = {
    'max_depth': [None, 5, 10, 15],  # Maximum depth of the tree
    'min_samples_split': [2, 5, 10],  # Minimum samples required to
split an internal node
    'min_samples_leaf': [1, 2, 4]  # Minimum samples required at a
leaf node
}

# Create a grid search cross-validation object
grid_search = GridSearchCV(estimator=tree_model,
param_grid=param_grid, scoring='neg_mean_squared_error', cv=5)

# Fit the grid search to the training data
grid_search.fit(X_train, y_train)

# Get the best hyperparameters
best_params = grid_search.best_params_

# Create a DecisionTreeRegressor model with the best hyperparameters
best_tree_model =
DecisionTreeRegressor(max_depth=best_params['max_depth'],

min_samples_split=best_params['min_samples_split'],

min_samples_leaf=best_params['min_samples_leaf'])


# Fit the model to the training data
best_tree_model.fit(X_train, y_train)

# Make predictions on the test data
y_pred = best_tree_model.predict(X_test)

# Evaluate the model
mse = mean_squared_error(y_test, y_pred)
print(f"Mean Squared Error: {mse}")
```

```
Mean Squared Error: 0.00016648108435715636
```

```
feature_importances = best_tree_model.feature_importances_

# Assuming you have already calculated the feature importances
importance_features = list(zip(X.columns, feature_importances))
```

```
# Sort the list in descending order of feature importances
importance_features_sorted = sorted(importance_features, key=lambda x:
x[1], reverse=True)

# Print the sorted feature importances
for feature, importance in importance_features_sorted:
    print(f"{feature}: {importance}")
```

```
m3: 0.7334955337816257
population: 0.22818435252150418
unemployment_rate: 0.031904292246392595
Mort_org_fee&discount: 0.002726632902913623
employment_rate: 0.0017705037108679772
mortgage_rate: 0.001040581245042088
PERMIT1: 0.000603324007296465
PERMIT: 0.00016132441054107606
PERMIT5: 5.244497205718609e-05
Consumer_price_index: 4.658858643530405e-05
Customer_sentiment_index: 1.4421615323781477e-05
```

### Observation

**Based on the analysis conducted with this model, it has been identified that the most influential factors affecting the USA Home Price are, in descending order of importance, M3, Population, Unemployment Rate, and Mortgage Organization Fees & Discounts.**

### Lasso Model

```
from sklearn.linear_model import Lasso

# Create a lasso regression model
lasso_model = Lasso() # You can adjust the alpha hyperparameter

param_grid = {
    'alpha': [0.01, 0.1, 1, 10]
}

grid_search = GridSearchCV(estimator=lasso_model,
param_grid=param_grid, scoring='neg_mean_squared_error', cv=5)
grid_search.fit(X_train, y_train)

best_params = grid_search.best_params_
best_lasso = Lasso(alpha=best_params['alpha'])

# Fit the model to the training data
best_lasso.fit(X_train, y_train)

y_pred = best_lasso.predict(X_test)

# Evaluate the model
```

```
mse = mean_squared_error(y_test, y_pred)
print(f"Mean Squared Error: {mse}")

Mean Squared Error: 0.006385623218152029

coefficients = best_lasso.coef_

# Combine feature names and coefficients using zip
importance_feature = list(zip(X.columns, coefficients))

# Sort the list in descending order of coefficients
importance_feature_sorted = sorted(importance_feature, key=lambda x:
abs(x[1]), reverse=True)

# Print the sorted feature coefficients
for feature, coefficient in importance_feature_sorted:
    print(f"{feature}: {coefficient}")

m3: 0.5606837599480693
Mort_org_fee&discount: -0.13199589243822946
population: 0.040085853582720925
Consumer_price_index: 0.0
Customer_sentiment_index: -0.0
mortgage_rate: -0.0
unemployment_rate: -0.0
employment_rate: 0.0
PERMIT: 0.0
PERMIT1: 0.0
PERMIT5: 0.0
```

### Observation

**Based on the analysis conducted with this model, it has been identified that the most influential factors affecting the USA Home Price are, in descending order of importance, M3, Mortgage Organization Fees & Discounts and Population.**

### Gradient Boosting Regressor

```
# Create a Gradient Boosting Regressor model
gb_regressor = GradientBoostingRegressor()

# Define a grid of hyperparameters to search
param_grid = {
    'n_estimators': [100, 200, 300],
    'learning_rate': [0.01, 0.1, 0.2],
    'max_depth': [3, 4, 5],
    'min_samples_split': [2, 3, 4]
}

# Create a grid search cross-validation object
grid_search = GridSearchCV(estimator=gb_regressor,
```

```python
param_grid=param_grid, scoring='neg_mean_squared_error', cv=5)

# Fit the grid search to the training data
grid_search.fit(X_train, y_train)

# Get the best hyperparameters
best_params = grid_search.best_params_

# Create a Gradient Boosting Regressor model with the best
hyperparameters
best_gb_regressor = GradientBoostingRegressor(
    n_estimators=best_params['n_estimators'],
    learning_rate=best_params['learning_rate'],
    max_depth=best_params['max_depth'],
    min_samples_split=best_params['min_samples_split']
)

# Fit the best model to the training data
best_gb_regressor.fit(X_train, y_train)

# Make predictions on the test data using the best model
y_pred_best = best_gb_regressor.predict(X_test)

# Evaluate the best model
mse_best = mean_squared_error(y_test, y_pred_best)
print(f"Best Model Mean Squared Error: {mse_best}")
```

```
Best Model Mean Squared Error: 4.0710307720907446e-05
```

```python
feature_importances = best_gb_regressor.feature_importances_

# Assuming you have already calculated the feature importances
importance_features = list(zip(X.columns, feature_importances))

# Sort the list in descending order of feature importances
importance_features_sorted = sorted(importance_features, key=lambda x:
x[1], reverse=True)

# Print the sorted feature importances
for feature, importance in importance_features_sorted:
    print(f"{feature}: {importance}")
```

```
population: 0.5475156665711257
m3: 0.4079142466598929
unemployment_rate: 0.03573076601831929
Mort_org_fee&discount: 0.003924185415146351
mortgage_rate: 0.0016529668560125704
PERMIT1: 0.0010053913201857087
employment_rate: 0.0007519083241097052
PERMIT: 0.0007341191856928611
Customer_sentiment_index: 0.0004388693215979569
```

```
PERMIT5: 0.0002610969883395385
Consumer_price_index: 7.078333957724e-05
```

### Observation

**Based on the analysis conducted with this model, it has been identified that the most influential factors affecting the USA Home Price are, in descending order of importance, Population, m3, Unemployment Rate, and Mortgage Organization Fees & Discounts.**

# Finding

**Following an extensive data analysis and modeling process, it has become evident that there are nine factors displaying significant positive and negative correlations with the USA Home Price. These factors exert their influence on the national landscape of the USA Home Price.**

1. **Gross Domestic Income**
2. **Gross Domestic Product**
3. **M3**
4. **Inflation**
5. **Human Capital Index**
6. **Population**
7. **Number of house**
8. **Mortgage Rate**
9. **Mortgage Organizational Fees & Discount**