Project Overview

This repository contains data analysis and visualization using Jupiter Notebook And Tableau to explore the relationship between housing market indicators and key factors that influence home prices nationally.

Data Collection

The dataset utilized for this analysis comprises the following housing market indicators

Indicator : Source

Label (HPI) : https://fred.stlouisfed.org/series/CSUSHPISA

GDP : https://fred.stlouisfed.org/graph/?g=znfe

UNEMPLOYMENT RATE : https://fred.stlouisfed.org/series/UNRATE

MORTGAGE RATE : https://fred.stlouisfed.org/graph/?g=zneW

Inflation : https://www.usinflationcalculator.com/inflation/current-inflation-rates/

Population growth rate : https://fred.stlouisfed.org/series/POPTHM

Monthly supply rate : https://fred.stlouisfed.org/series/MSACSR

Median Sales Price : https://fred.stlouisfed.org/series/MSPNHSUS

Housing Units Started: https://fred.stlouisfed.org/series/HOUST1F

Disposable Personal Income : https://fred.stlouisfed.org/series/DSPI

Personal Saving Rate : https://fred.stlouisfed.org/series/PSAVERT

Personal Consumption Expenditures : https://fred.stlouisfed.org/series/PCE

Total Construction Spending : https://fred.stlouisfed.org/series/TTLCONS

Data Analysis and Visualization

Problem Statement

Q. Find publicly available data for key factors that influence US home prices nationally. Then, build a data science model that explains how these factors impacted home prices over the last 20 years. Use the S&P Case-Schiller Home Price Index as a proxy for home prices: fred.stlouisfed.org/series/CSUSHPISA.

Importing libraries

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns

from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error, r2_score
from sklearn.ensemble import RandomForestRegressor

import warnings
warnings.filterwarnings('ignore')

pd.options.display.max_columns = None
```

In [2]:
```
df = pd.read_excel(r"C:\Users\kiran\Desktop\datatrained\Home LLC Interview\dat
df
```

Out[2]:

	Date	HPI	UNEMP_RATE	DSPI	GDP	HOUST1F	Inflation	M_SP	Supply_Ra
0	2003-01-01	128.461	5.8	8268.0	98.336393	1537	2.6	181700	[illegible]
1	2003-02-01	129.355	5.9	8274.7	98.329348	1301	3.0	187000	[illegible]
2	2003-03-01	130.148	5.9	8313.4	98.368090	1399	3.0	185100	[illegible]
3	2003-04-01	130.884	6.0	8342.9	98.453754	1374	2.2	189500	[illegible]
4	2003-05-01	131.735	6.1	8394.8	98.584413	1391	2.1	195500	[illegible]
...	...	...	...	...	...	...	...	...	
244	2023-05-01	302.566	3.7	20185.4	99.943470	1012	4.0	421200	[illegible]
245	2023-06-01	304.593	3.6	20208.4	100.045476	930	3.0	417600	[illegible]
246	2023-07-01	306.767	3.5	20229.6	100.164368	988	3.2	435800	[illegible]
247	2023-08-01	309.155	3.8	20306.7	100.289174	948	3.7	439900	[illegible]
248	2023-09-01	311.175	3.8	20388.3	100.410037	968	3.7	422300	[illegible]

249 rows × 15 columns

In [3]:
```
df.columns
```

Out[3]:
```
Index(['Date', 'HPI', 'UNEMP_RATE', 'DSPI', 'GDP', 'HOUST1F', 'Inflation',
       'M_SP', 'Supply_Rate', 'MORTGAGE', 'PCE', 'PSAVERT', 'POPTHM',
       'Growth Rate', 'TTLCONS '],
      dtype='object')
```

Columns

- Date - The date of observation
- UNEMP_RATE - Unemployment Rate (in %)
- DSPI -Disposable Personal Income (in Billions)
- GDP -Gross Domestic Product (GDP): Normalised for United States
- HOUST1F - New Privately-Owned Housing Units Started (in Thousands)
- Inflation - U.S Annual Inflation Rates.
- M_SP - Median Sales Price for New Houses Sold in the United States
- Supply_Rate - Monthly Supply of New Houses in the United States
- MORTGAGE - Mortgage Intrest Rate (in %)

- PCE - Personal Consumption Expenditures (in Billions)
- PSAVERT - Personal Saving Rate (in %)
- POPTHM - Population (in Thousands)
- Growth Rate - Population Growth Rate
- TTLCONS - Total Construction Spending (in Millions)

Target

1. HPI - S&P/Case-Shiller U.S. National Home Price Index

Analising basic metrics

In [4]:
```
df.shape
```

Out[4]:
```
(249, 15)
```

In [5]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 249 entries, 0 to 248
Data columns (total 15 columns):
 #   Column       Non-Null Count  Dtype         
---  ------       --------------  -----         
 0   Date         249 non-null    datetime64[ns]
 1   HPI          249 non-null    float64       
 2   UNEMP_RATE   249 non-null    float64       
 3   DSPI         249 non-null    float64       
 4   GDP          249 non-null    float64       
 5   HOUST1F      249 non-null    int64         
 6   Inflation    249 non-null    float64       
 7   M_SP         249 non-null    int64         
 8   Supply_Rate  249 non-null    float64       
 9   MORTGAGE     249 non-null    float64       
 10  PCE          249 non-null    float64       
 11  PSAVERT      249 non-null    float64       
 12  POPTHM       249 non-null    int64         
 13  Growth Rate  249 non-null    float64       
 14  TTLCONS      249 non-null    int64         
dtypes: datetime64[ns](1), float64(10), int64(4)
memory usage: 29.3 KB
```

Findings

- There are 13 Numerical columns and 1 Date columns
- Date column must be converted into datetime data type

In [6]:
```
# Convert the 'date_column' to datetime data type
df['Date'] = pd.to_datetime(df['Date'])

# Extract Month and Year
df['month'] = df['Date'].dt.month
df['year'] = df['Date'].dt.year
```

In [7]:
```
df.isnull().sum()
```

Out[7]:
```
Date           0
HPI            0
UNEMP_RATE     0
DSPI           0
GDP            0
HOUST1F        0
Inflation      0
M_SP           0
Supply_Rate    0
MORTGAGE       0
PCE            0
PSAVERT        0
POPTHM         0
Growth Rate    0
TTLCONS        0
month          0
year           0
dtype: int64
```

- No Null Values can be observed

In [8]:
```
df.nunique()
```

Out[8]:
```
Date           249
HPI            249
UNEMP_RATE      64
DSPI           248
GDP            249
HOUST1F        220
Inflation       72
M_SP           227
Supply_Rate     72
MORTGAGE       238
PCE            249
PSAVERT         78
POPTHM         249
Growth Rate    249
TTLCONS        249
month           12
year            21
dtype: int64
```

- All columns are continous

In [9]:
```
df.describe()
```

Out[9]:

	HPI	UNEMP_RATE	DSPI	GDP	HOUST1F	Inflation	M
count	249.000000	249.000000	249.000000	249.000000	249.000000	249.000000	249.00
mean	185.081968	5.924498	13179.864659	99.870250	917.212851	2.553414	283452.61
std	46.531700	2.047836	3280.418809	1.215264	389.720928	1.910771	70742.59
min	128.461000	3.400000	8268.000000	92.031035	353.000000	-2.100000	181700.00
25%	148.278000	4.400000	10745.400000	99.622947	614.000000	1.500000	228300.00
50%	174.342000	5.400000	12441.900000	99.943470	843.000000	2.200000	262200.00
75%	202.913000	7.200000	15508.800000	100.421834	1136.000000	3.400000	321400.00
max	311.175000	14.700000	21858.100000	101.871442	1823.000000	9.100000	496800.00

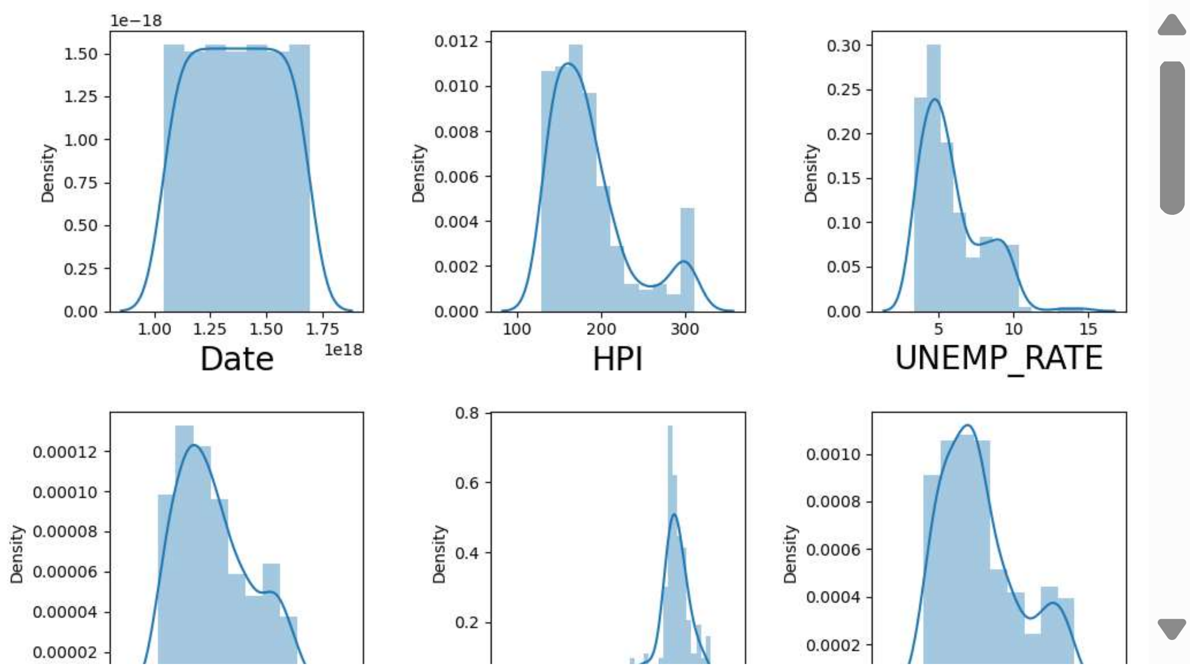
Observations

- Distribution
  - Majority of the data seems Normally Distributed (Since Mean ~= Median), But a hint of skewness can be observed in few columns.
  - Normally distributed (Since Mean ~= Median)
    - HPI
    - UNEMP_RATE
    - DSPI
    - GDP
    - HOUST1F
    - Inflation
    - M_SP
    - Supply_Rate
    - MORTGAGE
    - PCE
    - PSAVERT
    - POPTHM
    - Growth Rate
    - TTLCONS
  - Right skewed (mean > median)
    - UNEMP_RATE
    - PSAVERT
  - LEFT skewed (mean < median)
    - GDP
    - Growth Rate
- From Above obervation we cannot find the presence of outliers(i.e. No Differences Between Max & 75%,Min & 25%) can be observed

Data Visualization

Distribution Plot

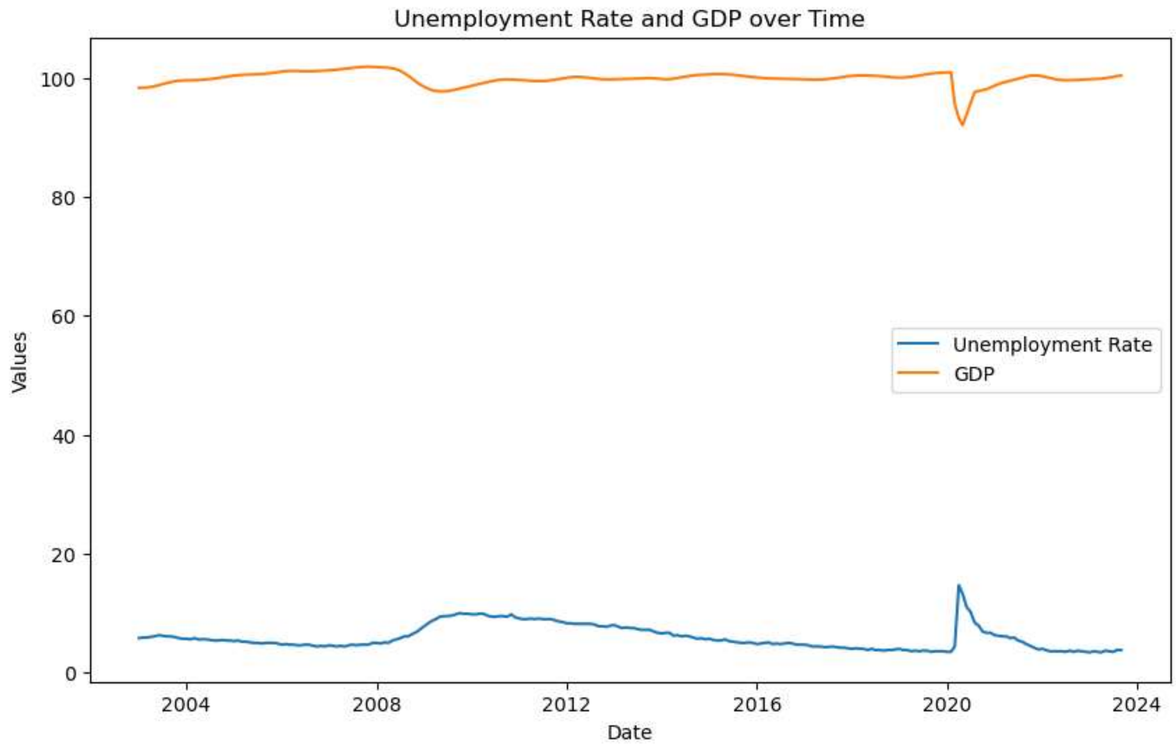
In [10]:
```
plt.figure(figsize=(10,20))
pn = 1
for column in df.columns:

    sns.distplot(df[column],ax=plt.subplot(6,3,pn))
    plt.xlabel(column,fontsize = 20)
    pn +=1

plt.tight_layout()
```



- We can observe that Most of the columns are Not skewed (Normally Distrubuted)
- Skeweness is as discussed earlier

Line Plot

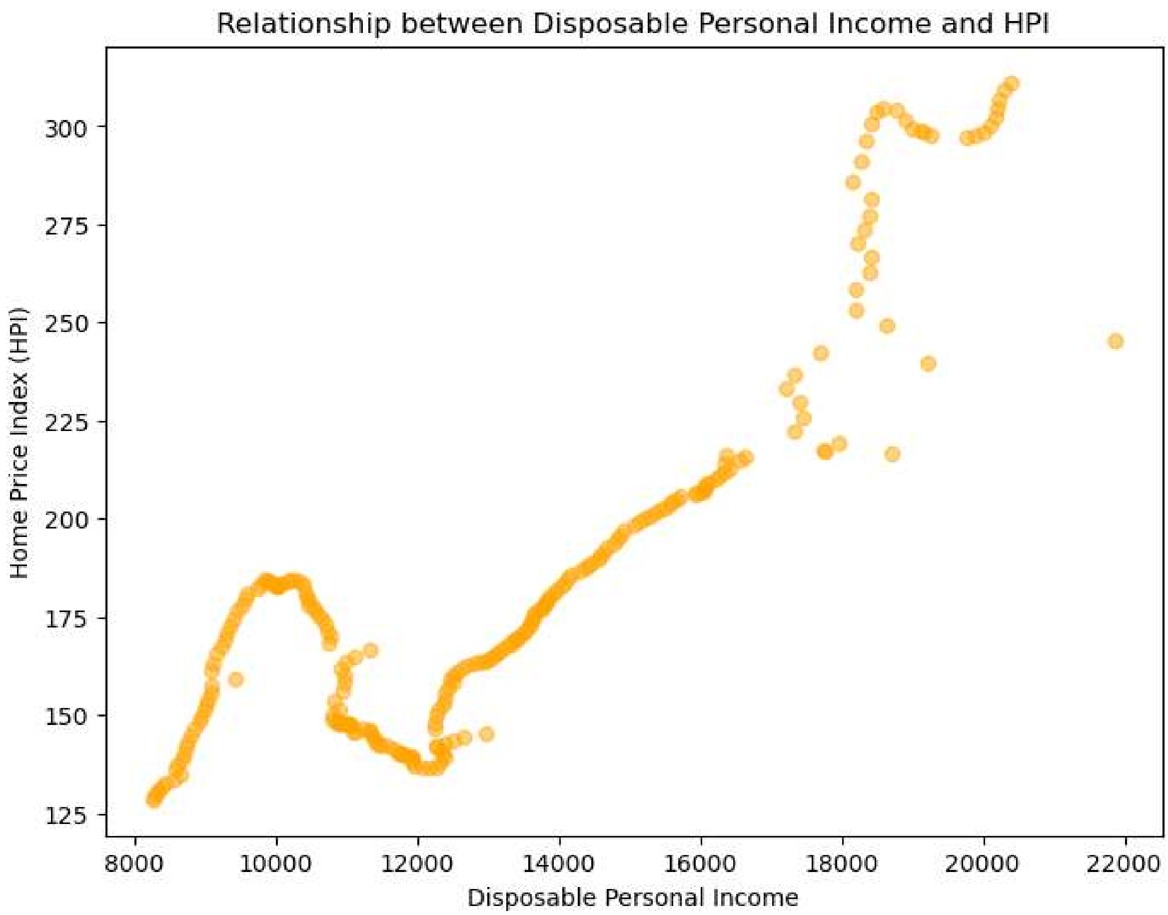
In [11]:
```
plt.figure(figsize=(10, 6))
plt.plot(df['Date'], df['UNEMP_RATE'], label='Unemployment Rate')
plt.plot(df['Date'], df['GDP'], label='GDP')
plt.xlabel('Date')
plt.ylabel('Values')
plt.title('Unemployment Rate and GDP over Time')
plt.legend()
plt.show()
```



- we can observe that GDP and Unemployment rate are inversly related i.e. increase in unemploymnt rate dicreases GDP

Scatter Plot

In [12]:
```
plt.figure(figsize=(8, 6))
plt.scatter(df['DSPI'], df['HPI'], alpha=0.5, color='orange')
plt.xlabel('Disposable Personal Income')
plt.ylabel('Home Price Index (HPI)')
plt.title('Relationship between Disposable Personal Income and HPI')
plt.show()
```



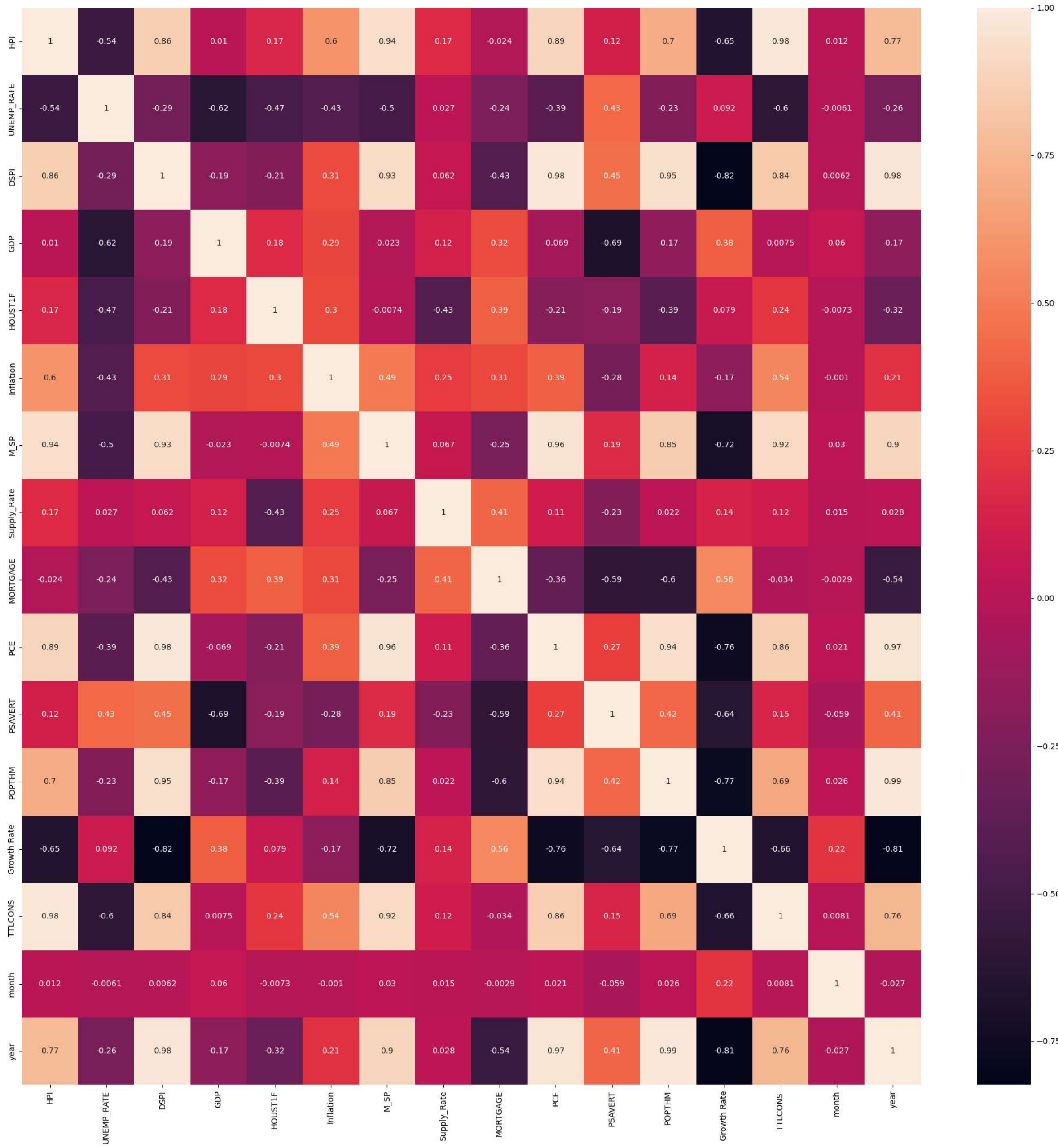
- we can observe that HPI AND Disposable Personal Income are **positively** corelated

Year wise Median sale price

In [13]:
```
median_price_by_year = df.groupby('year')['M_SP'].median()
plt.figure(figsize=(10, 6))
bar_plot = median_price_by_year.plot(kind='bar', color='skyblue')

for idx, value in enumerate(median_price_by_year):
    plt.text(idx, value + 1000, f'{value:.0f}', ha='center', va='bottom', font

plt.xlabel('Year')
plt.ylabel('Median Sales Price')
plt.title('Median Sales Price by Year')
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```

Corelation Analysis

```
In [14]: plt.figure(figsize=(20,20))
         sns.heatmap(df.corr(),annot=True,annot_kws={'size':10})
         plt.tight_layout()
```



Important Observations

- HPI:
  - Strong positive correlations with: DSPI (0.858), M_SP (0.941), PCE (0.886), TTLCONS (0.983)
- UNEMP_RATE:
  - negative correlations with: GDP (-0.617), HOUST1F (-0.471), PSAVERT (-0.429)
- DSPI:
  - Strong positive correlations with: HPI (0.858), M_SP (0.930), PCE (0.982), TTLCONS (0.843)
- GDP:

    - Strong negative correlation with: UNEMP_RATE (-0.617)
- Inflation:
    - Moderate positive correlations with: HPI (0.597), M_SP (0.494), PCE (0.388), TTLCONS (0.538)
- M_SP:
    - Strong positive correlations with: HPI (0.941), DSPI (0.930), PCE (0.958), TTLCONS (0.921)
- Growth Rate:
    - Strong negative correlations with: DSPI (-0.824), TTLCONS (-0.656), year (-0.806)
- POPTHM:
    - Strong positive correlations with: DSPI (0.948), HPI (0.701), year (0.992)

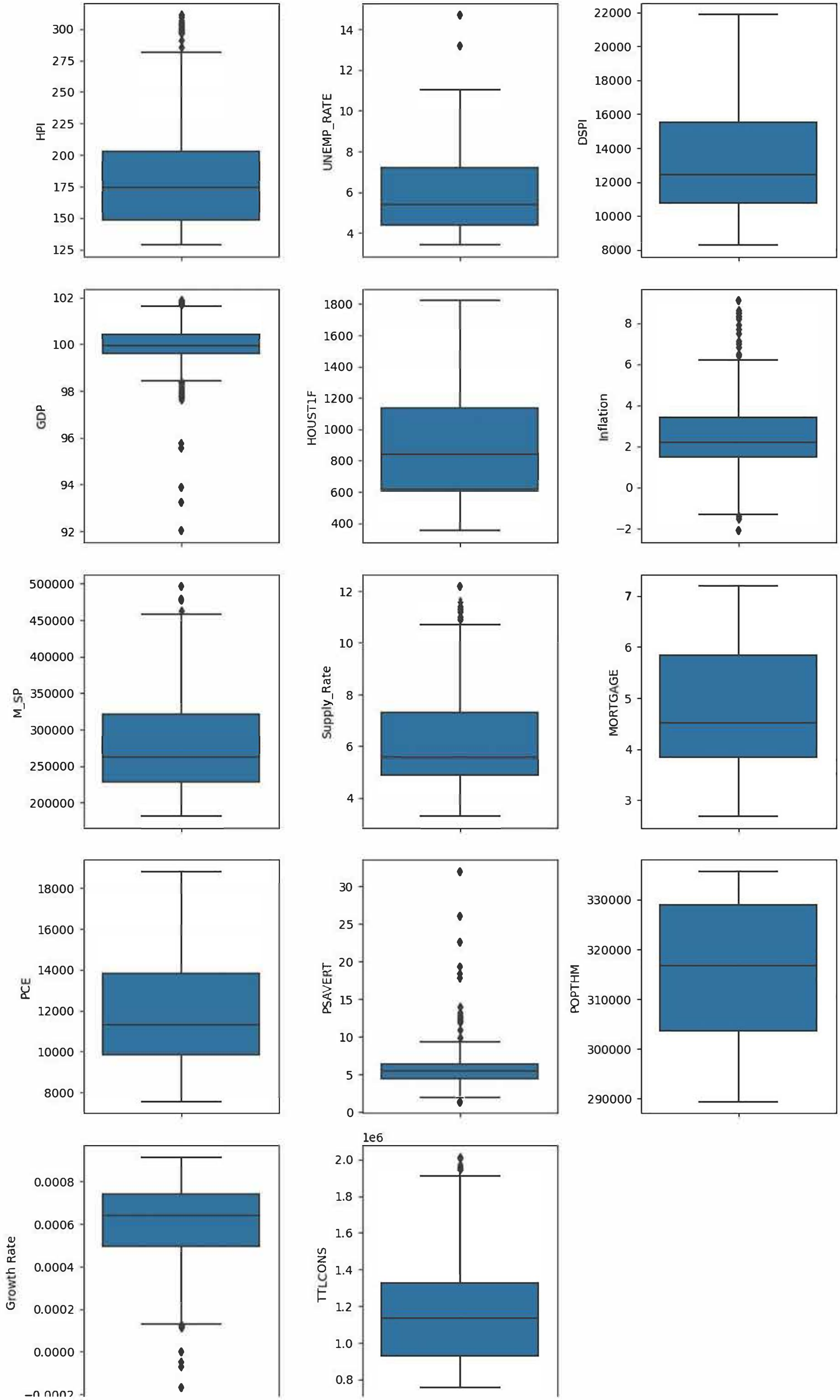
Outliers

In [15]:

```
df1 = df.drop(columns=['month','year','Date']).copy()
```

In [16]:

```
plt.figure(figsize=(10,20))
pn=1
for i in df1.columns:
    sns.boxplot(data=df1,y=i,ax=plt.subplot(6,3,pn))
    pn+=1
plt.tight_layout()
```



HPI
300
275
250
225
200
175
150
125
UNEMP_RATE
14
12
10
8
6
4
DSPI
22000
20000
18000
16000
14000
12000
10000
8000
GDP
102
100
98
96
94
92
HOUST1F
1800
1600
1400
1200
1000
800
600
400
Inflation
8
6
4
2
0
−2
M_SP
500000
450000
400000
350000
300000
250000
200000
Supply_Rate
12
10
8
6
4
MORTGAGE
7
6
5
4
3
PCE
18000
16000
14000
12000
10000
8000
PSAVERT
30
25
20
15
10
5
0
POPTHM
330000
320000
310000
300000
290000
Growth Rate
0.0008
0.0006
0.0004
0.0002
0.0000
−0.0002
TTLCONS
1e6
2.0
1.8
1.6
1.4
1.2
1.0
0.8

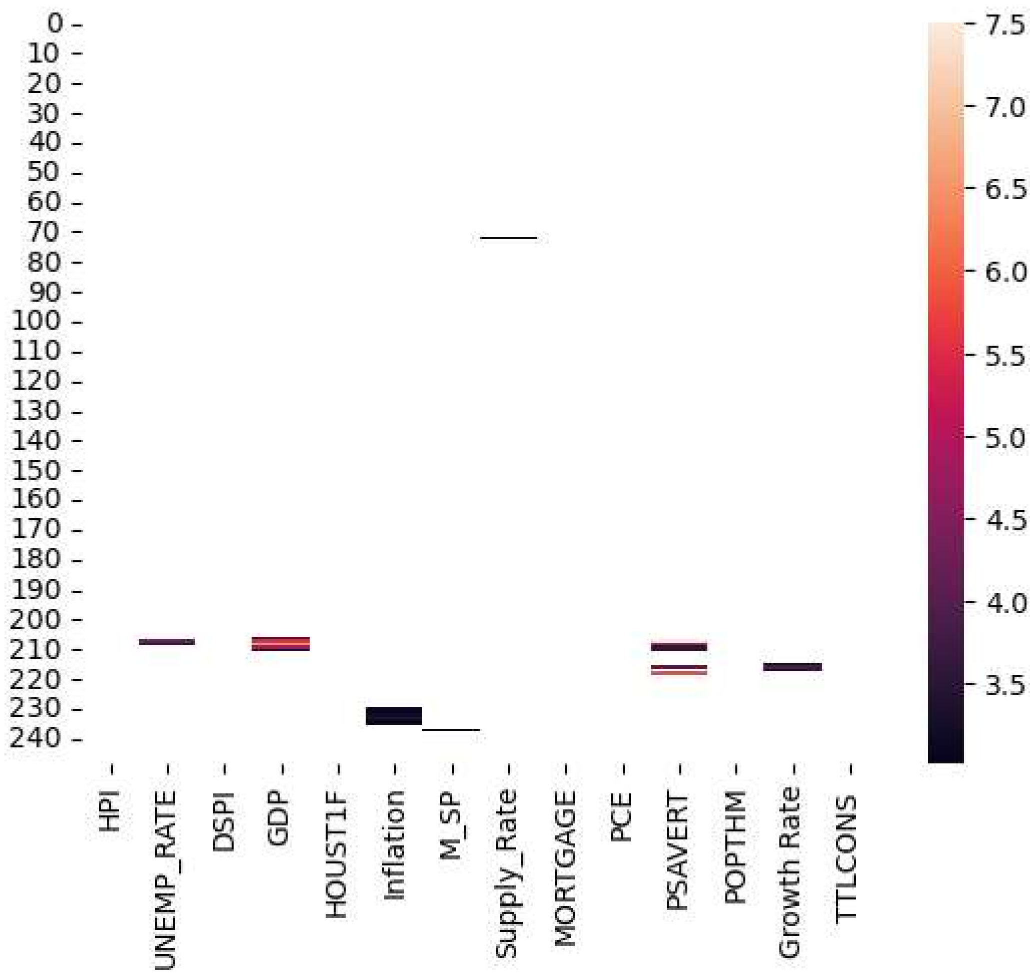
- There are Many outliers which are needed to be Checked

In [17]:
```python
# finding outliers using z score
from scipy.stats import zscore
z = np.abs(zscore(df1))
z[z>3].count()
```

Out[17]:
```
HPI             0
UNEMP_RATE      2
DSPI            0
GDP             5
HOUST1F         0
Inflation       6
M_SP            1
Supply_Rate     1
MORTGAGE        0
PCE             0
PSAVERT         6
POPTHM          0
Growth Rate     3
TTLCONS         0
dtype: int64
```

In [18]:
```
sns.heatmap(z[z>3])
```

Out[18]: <AxesSubplot: >



- We can observe that Majority of the outliers are aound years 2021,2022.
- This can be due to **Covid 19 Pandamic**
- so i,Feel It is wise to keep these outliers for gaining valuable insights.

Treating Skewness

In [19]:
```
df1.skew().abs()
```

Out[19]:
```
HPI            1.311186
UNEMP_RATE     1.051399
DSPI           0.556285
GDP            2.543659
HOUST1F        0.726292
Inflation      1.082925
M_SP           0.993782
Supply_Rate    0.932554
MORTGAGE       0.197052
PCE            0.645530
PSAVERT        3.648431
POPTHM         0.266724
Growth Rate    1.047579
TTLCONS        0.912868
dtype: float64
```

In [20]:
```
skewed_columns = [x for x in df1.columns if df1[x].skew() > 1 or df1[x].skew()
skewed_columns
```

Out[20]:
```
['HPI', 'UNEMP_RATE', 'GDP', 'Inflation', 'PSAVERT', 'Growth Rate']
```

skeweness of 'HPI', 'UNEMP_RATE', 'GDP', 'Inflation', 'PSAVERT' & 'Growth Rate' Needs to be Treated

In [21]:
```
from sklearn.preprocessing import PowerTransformer
pt = PowerTransformer(method='yeo-johnson',standardize=False)
df1[skewed_columns] = pt.fit_transform(df1[skewed_columns])
df1
```

Out[21]:

	HPI	UNEMP_RATE	DSPI	GDP	HOUST1F	Inflation	M_SP	Supply_Rate
0	0.539097	0.875639	8268.0	3.787013e+61	1537	2.016832	181700	4.0
1	0.539098	0.877936	8274.7	3.778539e+61	1301	2.271700	187000	4.5
2	0.539099	0.877936	8313.4	3.825366e+61	1399	2.271700	185100	4.1
3	0.539099	0.880169	8342.9	3.930911e+61	1374	1.752193	189500	4.1
4	0.539100	0.882340	8394.8	4.097343e+61	1391	1.684320	195500	3.9
...	...	...	...	...	...	...	...	...
244	0.539149	0.805378	20185.4	6.286895e+61	1012	2.873938	421200	7.2
245	0.539149	0.800467	20208.4	6.490686e+61	930	2.271700	417600	7.5
246	0.539149	0.795343	20229.6	6.736289e+61	988	2.395884	435800	7.1
247	0.539149	0.810088	20306.7	7.003786e+61	948	2.697932	439900	7.8
248	0.539150	0.810088	20388.3	7.272619e+61	968	2.697932	422300	7.2

249 rows × 14 columns

Removing Unwanted Columns

- The Following columns have High Multicolinearity and Presence of direct High corelation with HPI
  - M_SP
  - TTLCONS
- For Better Model Training And to understand Feature Importance Better, We can remove these columns

In [22]:
```
x = df1.drop(columns=['HPI',"M_SP","PCE","TTLCONS "])
y=df1['HPI']
```

Standerd Scaling

In [23]:
```
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()
x_sc = scaler.fit_transform(x)
```

Model Building

Linar Regression

In [24]:
```
# Train Test Split
X_train, X_test, y_train, y_test = train_test_split(x_sc, y, test_size=0.2, ra

# Initializing and fitting the linear regression model
linear_reg = LinearRegression()
linear_reg.fit(X_train, y_train)

# Predicting on the test set
y_pred = linear_reg.predict(X_test)

# Evaluating the model
mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)

print(f"Linear Regression Mean Squared Error: {mse}")
print(f"Linear Regression R-squared: {r2}")
```

```
Linear Regression Mean Squared Error: 7.421402640693978e-12
Linear Regression R-squared: 0.9529587278313972
```

Random Forest Regression

In [25]:
```
# Initializing and fitting the random forest regression model
rf_reg = RandomForestRegressor(random_state=42)
rf_reg.fit(X_train, y_train)

# Predicting on the test set
y_pred_rf = rf_reg.predict(X_test)

# Evaluating the model
mse_rf = mean_squared_error(y_test, y_pred_rf)
r2_rf = r2_score(y_test, y_pred_rf)

print(f"Random Forest Regression Mean Squared Error: {mse_rf}")
print(f"Random Forest Regression R-squared: {r2_rf}")
```

```
Random Forest Regression Mean Squared Error: 6.872577556948824e-13
Random Forest Regression R-squared: 0.9956437508243586
```

- We can observe that our Models Linear regression and Random Forest classifier Have Given Good R2 Scores i.e. 95% and 99% respectively

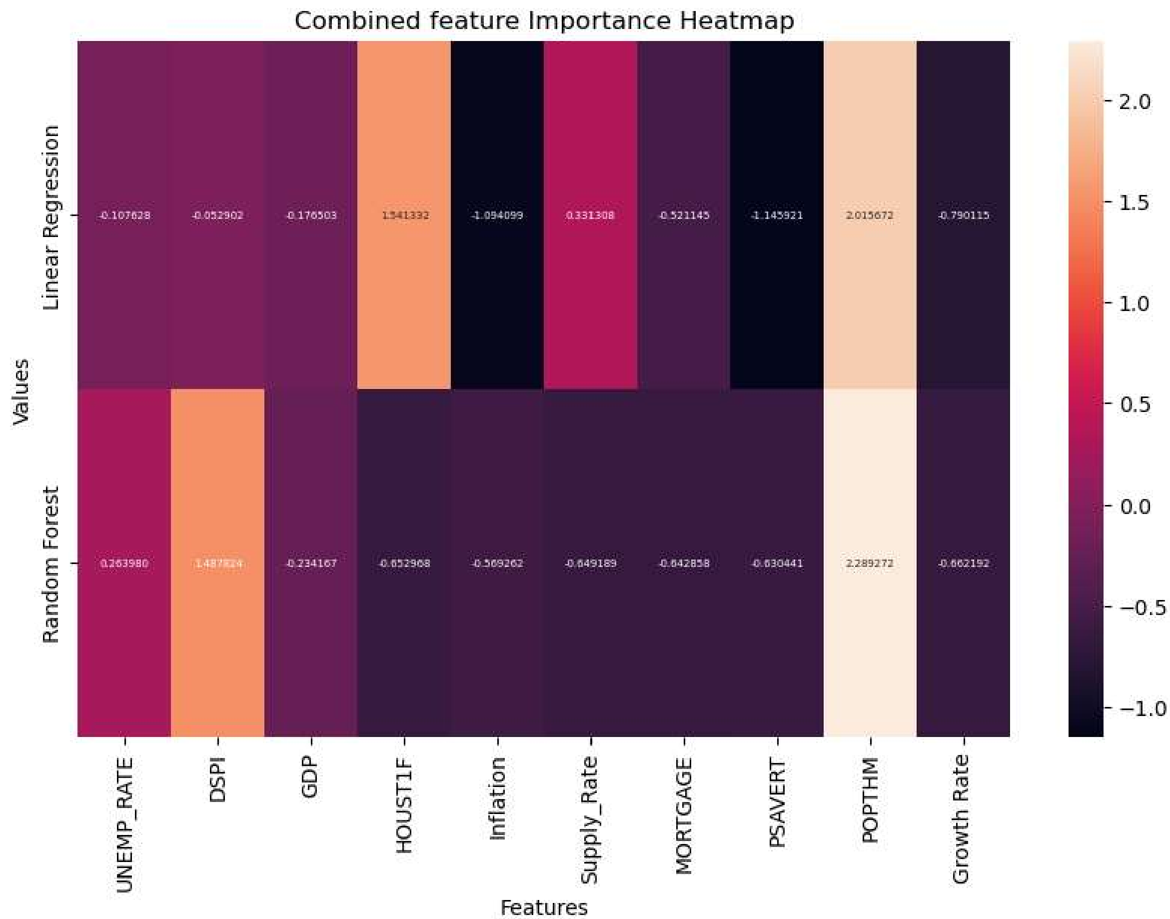
Getting Features or coefficient deatils from models

In [26]:
```
# Coefficients for Linear Regression
linear_coefficients = linear_reg.coef_
sc_l_coef = scaler.fit_transform(linear_coefficients.reshape(10,1))

# Feature importance for Random Forest
rf_feature_importances = rf_reg.feature_importances_
sc_rf_coef = scaler.fit_transform(rf_feature_importances.reshape(10,1))
```

Plotting Heatmaps of feature Importance

In [27]:

```
plt.figure(figsize=(10, 6))
sns.heatmap(np.reshape(list(sc_l_coef) + list(sc_rf_coef),(2,10)), annot=True,
plt.title('Combined feature Importance Heatmap')
plt.xlabel('Features')
plt.ylabel('Values')
plt.show()
```



observations

- FROM both Models we can observe that the important factors affecting Housing price index are
  - Population
  - Disposable Personal Income
  - inflation
  - Personal Saving Rate
  - Housing Units Started

Test Prediction

lets predict each model on trail data by changing 1 varible by 1 unit in each step

In [28]:
```
z = np.array([[0,0,0,0,0,0,0,0,0,0],
             [1,0,0,0,0,0,0,0,0,0],
             [0,1,0,0,0,0,0,0,0,0],
             [0,0,1,0,0,0,0,0,0,0],
             [0,0,0,1,0,0,0,0,0,0],
             [0,0,0,0,1,0,0,0,0,0],
             [0,0,0,0,0,1,0,0,0,0],
             [0,0,0,0,0,0,1,0,0,0],
             [0,0,0,0,0,0,0,1,0,0],
             [0,0,0,0,0,0,0,0,1,0],
             [0,0,0,0,0,0,0,0,0,1]])
z.shape
```

Out[28]:
```
(11, 10)
```

In [29]:
```
z_pred_rf = rf_reg.predict(z)
z_pred_rf
```

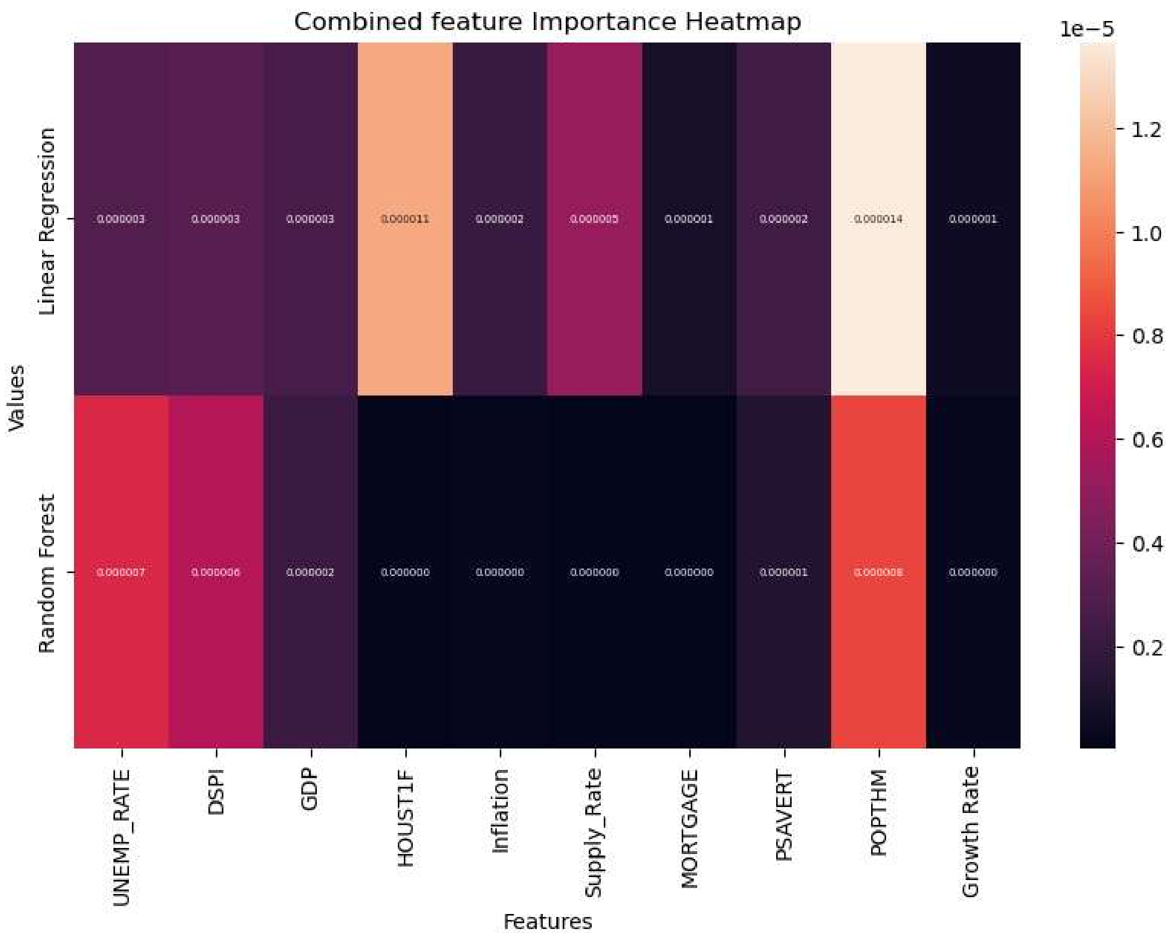
Out[29]:
```
array([0.53911969, 0.53911224, 0.53912575, 0.53912182, 0.53911958,
       0.53911949, 0.53911968, 0.53911964, 0.53911843, 0.53912804,
       0.53911943])
```

In [30]:
```
z_pred_lr = linear_reg.predict(z)
z_pred_lr
```

Out[30]:
```
array([0.53912467, 0.53912759, 0.53912787, 0.53912725, 0.53913593,
       0.53912261, 0.53912981, 0.5391255 , 0.53912235, 0.53913833,
       0.53912414])
```

In [31]:
```
Feature_Importance =np.reshape(list(np.abs(z_pred_lr[1:] - z_pred_lr[0])) + li
```

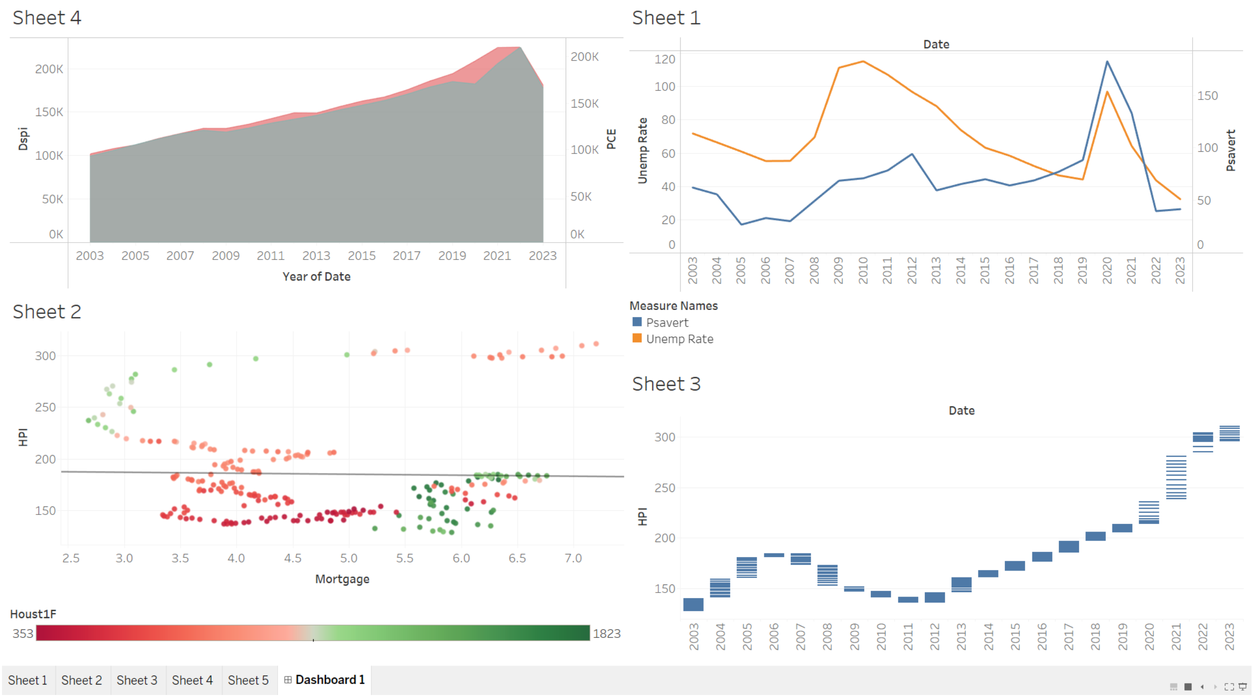
In [32]:
```
plt.figure(figsize=(10, 6))
sns.heatmap(Feature_Importance, annot=True,fmt='.6f',annot_kws={'size':5},  yt
plt.title('Combined feature Importance Heatmap')
plt.xlabel('Features')
plt.ylabel('Values')
plt.show()
```



Conclusion

- Primary Factor affecting Housing Price index is **Population**
- Other Factors that impact HPI are *Unemployment Rate and Housing Units Started*

Power BI DashBoard



1. Sheet 1
    a. We can observe that unemployment Rate and Public saving rate are positively co related
    b. Effect of Covid 19 can be clearly Observed in years of 2019,2020,2021,2022
2. Sheet 2
    a. New House start Rate is High when mortgage rates are High and HPI is low
    b. New House start Rate is low when mortgage rates are Low and HPI is low
3. Sheet 3
    a. Due to Covid19 Pandamic we can see variation in inflation over years of 2021 and 2022
4. Sheet 4
    a. High Positive corelation can be observed between Disposable Personal Income and Personal Consumption Expenditures