Analyses of Supply-Demand Factors Impacting U.S. Home Prices

Two datasets are collected for this assignment :-

1. Supply Data

2. Demand Data

These datasets contain quarterly data on key supply-demand factors that influence US home prices nationally in the last 20 years and are collected from Kaggle.

In [1]:

```
import numpy as np
import pandas as pd
from matplotlib import pyplot as plt
import seaborn as sns
import numpy as np
import pandas as pd
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import MinMaxScaler
from sklearn.model_selection import train_test_split, cross_val_score,KFold

from sklearn.linear_model import LinearRegression
from sklearn.ensemble import RandomForestRegressor
from sklearn.svm import SVR
from sklearn.tree import DecisionTreeRegressor
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import mean_squared_error
from xgboost import XGBRegressor
from sklearn.metrics import classification_report, confusion_matrix
from sklearn import metrics
from sklearn.metrics import r2_score
from sklearn.pipeline import Pipeline
from sklearn.linear_model import Ridge
```

Reading the Data

Supply

In [2]:

```
df_supply = pd.read_csv("data/supply.csv")
df_supply.head()
```

Out[2]:

	DATE	CSUSHPISA	MSACSR	PERMIT	TLRESCONS	EVACANTUSQ176N
0	01-01-2003	129.321	4.2	1806.333333	421328.6667	14908
1	01-04-2003	131.756	3.833333333	1837.666667	429308.6667	15244

	DATE	CSUSHPISA	MSACSR	PERMIT	TLRESCONS	EVACANTUSQ176N
2	01-07-2003	135.013	3.633333333	1937.333333	458890	15614
3	01-10-2003	138.8356667	3.966666667	1972.333333	491437.3333	15654
4	01-01-2004	143.2986667	3.7	1994.666667	506856.3333	15895

1. CSUSHPISA :- S&P/Case-Shiller U.S. National Home Price Index (Index Jan 2000=100, Seasonally Adjusted)
2. MSACSR :- Monthly Supply of New Houses in the United States (Seasonally Adjusted)
3. PERMIT :- New Privately-Owned Housing Units Authorized in Permit-Issuing Places: Total Units (Thousands of Units, Seasonally Adjusted Annual Rate)
4. TLRESCONS :- Total Construction Spending: Residential in the United States (Millions of Dollars, Seasonally Adjusted Annual Rate)
5. EVACANTUSQ176N :- Housing Inventory Estimate: Vacant Housing Units in the United States (Thousands of Units, Not Seasonally Adjusted)

In [3]:

```
df_supply.shape
```

Out[3]:

```
(82, 6)
```

In [4]:

```
df_supply.dtypes
```

Out[4]:

```
DATE              object
CSUSHPISA         object
MSACSR            object
PERMIT            object
TLRESCONS         object
EVACANTUSQ176N    object
dtype: object
```

In [5]:

```
df_supply['DATE'] = pd.to_datetime(df_supply['DATE'])
df_supply['CSUSHPISA'] = pd.to_numeric(df_supply['CSUSHPISA'], errors='coerce')
df_supply['MSACSR'] = pd.to_numeric(df_supply['MSACSR'], errors='coerce')
df_supply['PERMIT'] = pd.to_numeric(df_supply['PERMIT'], errors='coerce')
df_supply['TLRESCONS'] = pd.to_numeric(df_supply['TLRESCONS'], errors='coerce')
df_supply['EVACANTUSQ176N'] = pd.to_numeric(df_supply['EVACANTUSQ176N'], errors='coerce
```

In [6]:

```
df_supply.isna().sum()
```

Out[6]:

```
DATE              0
CSUSHPISA         2
MSACSR            1
PERMIT            1
TLRESCONS         1
EVACANTUSQ176N    1
dtype: int64
```

Handling the missing value in supply

In [7]:
```
df_supply['CSUSHPISA'] = df_supply['CSUSHPISA'].fillna(df_supply['CSUSHPISA'].mean())
df_supply['MSACSR'] = df_supply['MSACSR'].fillna(df_supply['MSACSR'].mean())
df_supply['PERMIT'] = df_supply['PERMIT'].fillna(df_supply['PERMIT'].mean())
df_supply['TLRESCONS'] = df_supply['TLRESCONS'].fillna(df_supply['TLRESCONS'].mean())
df_supply['EVACANTUSQ176N'] = df_supply['EVACANTUSQ176N'].fillna(df_supply['EVACANTUSQ1
```

In [8]:
```
df_supply.isna().sum()
```

Out[8]:
```
DATE              0
CSUSHPISA         0
MSACSR            0
PERMIT            0
TLRESCONS         0
EVACANTUSQ176N    0
dtype: int64
```

In [9]:
```
df_supply.head()
```

Out[9]:

	DATE	CSUSHPISA	MSACSR	PERMIT	TLRESCONS	EVACANTUSQ176N
0	2003-01-01	129.321000	4.200000	1806.333333	421328.6667	14908.0
1	2003-01-04	131.756000	3.833333	1837.666667	429308.6667	15244.0
2	2003-01-07	135.013000	3.633333	1937.333333	458890.0000	15614.0
3	2003-01-10	138.835667	3.966667	1972.333333	491437.3333	15654.0
4	2004-01-01	143.298667	3.700000	1994.666667	506856.3333	15895.0

Demand

In [10]:
```
df_demand = pd.read_csv("data/demand.csv")
df_demand.head()
```

Out[10]:

	DATE	CSUSHPISA	MORTGAGE30US	UMCSENT	INTDSRUSM193N	MSPUS	GDP
0	01-01-2003	129.321000	5.840769	79.966667	2.250000	186000	11174.129
1	01-04-2003	131.756000	5.506923	89.266667	2.166667	191800	11312.766
2	01-07-2003	135.013000	6.033846	89.300000	2.000000	191900	11566.669
3	01-10-2003	138.835667	5.919286	91.966667	2.000000	198800	11772.234
4	01-01-2004	143.298667	5.597500	98.000000	2.000000	212700	11923.447

1. CSUSHPISA :- S&P/Case-Shiller U.S. National Home Price Index (Index Jan 2000=100, Seasonally Adjusted)
2. MORTGAGE15US :- 30-Year Fixed Rate Mortgage Average in the United States (Percent, Not Seasonally Adjusted)
3. UMCSENT :- University of Michigan: Consumer Sentiment

4. INTDSRUSM193N :- Interest Rates, Discount Rate for United States (Billions of Dollars, Seasonally Adjusted Annual Rate)
5. MSPUS :- Median Sales Price of Houses Sold for the United States (Not Seasonally Adjusted)
6. GDP :- Gross Domestic Product (Billions of Dollars, Seasonally Adjusted Annual Rate)

In [11]:
```
df_demand.shape
```

Out[11]:
```
(81, 7)
```

In [12]:
```
df_demand.dtypes
```

Out[12]:
```
DATE              object
CSUSHPISA        float64
MORTGAGE30US     float64
UMCSENT          float64
INTDSRUSM193N    float64
MSPUS              int64
GDP              float64
dtype: object
```

In [13]:
```
df_demand['DATE'] = pd.to_datetime(df_demand['DATE'])
df_demand.dtypes
```

Out[13]:
```
DATE             datetime64[ns]
CSUSHPISA               float64
MORTGAGE30US            float64
UMCSENT                 float64
INTDSRUSM193N           float64
MSPUS                     int64
GDP                     float64
dtype: object
```

In [14]:
```
df_demand.isna().sum()
```

Out[14]:
```
DATE             0
CSUSHPISA        1
MORTGAGE30US     0
UMCSENT          0
INTDSRUSM193N    7
MSPUS            0
GDP              0
dtype: int64
```

Handling the missing value in demand

In [15]:
```
imputer = SimpleImputer(strategy='mean')
df_demand['INTDSRUSM193N'] = imputer.fit_transform(df_demand[['INTDSRUSM193N']])

df_demand['CSUSHPISA'] = df_demand['CSUSHPISA'].fillna(df_demand['CSUSHPISA'].mean())
```

In [16]:
```
df_demand.isna().sum()
```

Out[16]:
```
DATE            0
CSUSHPISA       0
MORTGAGE30US    0
UMCSENT         0
INTDSRUSM193N   0
MSPUS           0
GDP             0
dtype: int64
```

In [17]:
```
df_demand.tail()
```

Out[17]:

	DATE	CSUSHPISA	MORTGAGE30US	UMCSENT	INTDSRUSM193N	MSPUS	GDP
76	2022-01-01	290.868000	3.822308	63.133333	1.961712	433100	24740.480
77	2022-01-04	303.422667	5.266154	57.866667	1.961712	449300	25248.476
78	2022-01-07	301.726333	5.623077	56.100000	1.961712	468000	25723.941
79	2022-01-10	297.896667	6.664615	58.800000	1.961712	479500	26137.992
80	2023-01-01	180.658712	6.372308	64.633333	1.961712	436800	26465.865

Merging the demand and supply data

In [18]:
```
df_supply = df_supply.sort_values('DATE')
df_demand = df_demand.sort_values('DATE')
```

In [19]:
```
df_merged = pd.merge(df_supply, df_demand, on='DATE')
```

In [20]:
```
df_merged.head()
```

Out[20]:

	DATE	CSUSHPISA_x	MSACSR	PERMIT	TLRESCONS	EVACANTUSQ176N	CSUSHPISA_y	MORTGA
0	2003-01-01	129.321000	4.200000	1806.333333	421328.6667	14908.0	129.321000	
1	2003-01-04	131.756000	3.833333	1837.666667	429308.6667	15244.0	131.756000	
2	2003-01-07	135.013000	3.633333	1937.333333	458890.0000	15614.0	135.013000	
3	2003-01-10	138.835667	3.966667	1972.333333	491437.3333	15654.0	138.835667	
4	2004-01-01	143.298667	3.700000	1994.666667	506856.3333	15895.0	143.298667	

In [21]:
```
df_merged.drop('CSUSHPISA_y', axis=1, inplace=True)
```

In [22]:
```
df_merged.rename(columns={'CSUSHPISA_x': 'CSUSHPISA'}, inplace=True)
```

In [23]:
```
df_merged.head()
```

Out[23]:

	DATE	CSUSHPISA	MSACSR	PERMIT	TLRESCONS	EVACANTUSQ176N	MORTGAGE30US	UMCSE
0	2003-01-01	129.321000	4.200000	1806.333333	421328.6667	14908.0	5.840769	79.966
1	2003-01-04	131.756000	3.833333	1837.666667	429308.6667	15244.0	5.506923	89.266
2	2003-01-07	135.013000	3.633333	1937.333333	458890.0000	15614.0	6.033846	89.300
3	2003-01-10	138.835667	3.966667	1972.333333	491437.3333	15654.0	5.919286	91.966
4	2004-01-01	143.298667	3.700000	1994.666667	506856.3333	15895.0	5.597500	98.000

In [24]:
```
df_merged.dtypes
```

Out[24]:
```
DATE               datetime64[ns]
CSUSHPISA                 float64
MSACSR                    float64
PERMIT                    float64
TLRESCONS                 float64
EVACANTUSQ176N            float64
MORTGAGE30US              float64
UMCSENT                   float64
INTDSRUSM193N             float64
MSPUS                       int64
GDP                       float64
dtype: object
```

Changing the name of colums for better understanding

In [25]:
```
df_merged.rename(columns={'CSUSHPISA':'National_home_price_index','MSACSR':'Monthly_sup
                  ,'EVACANTUSQ176N':'Housing_inventory_estimate','MORTGAGE30US':'30y_fi
                  ,'MSPUS':'Median_sales_price','DATE':'Date'},inplace = True)
```

In [26]:
```
df_merged.head()
```

Out[26]:

	Date	National_home_price_index	Monthly_supply	Permit_issued	Total_construction_spending	Housi
0	2003-01-01	129.321000	4.200000	1806.333333	421328.6667	
1	2003-01-04	131.756000	3.833333	1837.666667	429308.6667	
2	2003-01-07	135.013000	3.633333	1937.333333	458890.0000	

	Date	National_home_price_index	Monthly_supply	Permit_issued	Total_construction_spending	Housi
3	2003-01-10	138.835667	3.966667	1972.333333	491437.3333	
4	2004-01-01	143.298667	3.700000	1994.666667	506856.3333	

Exploratory Data Analysis

Plotting the data

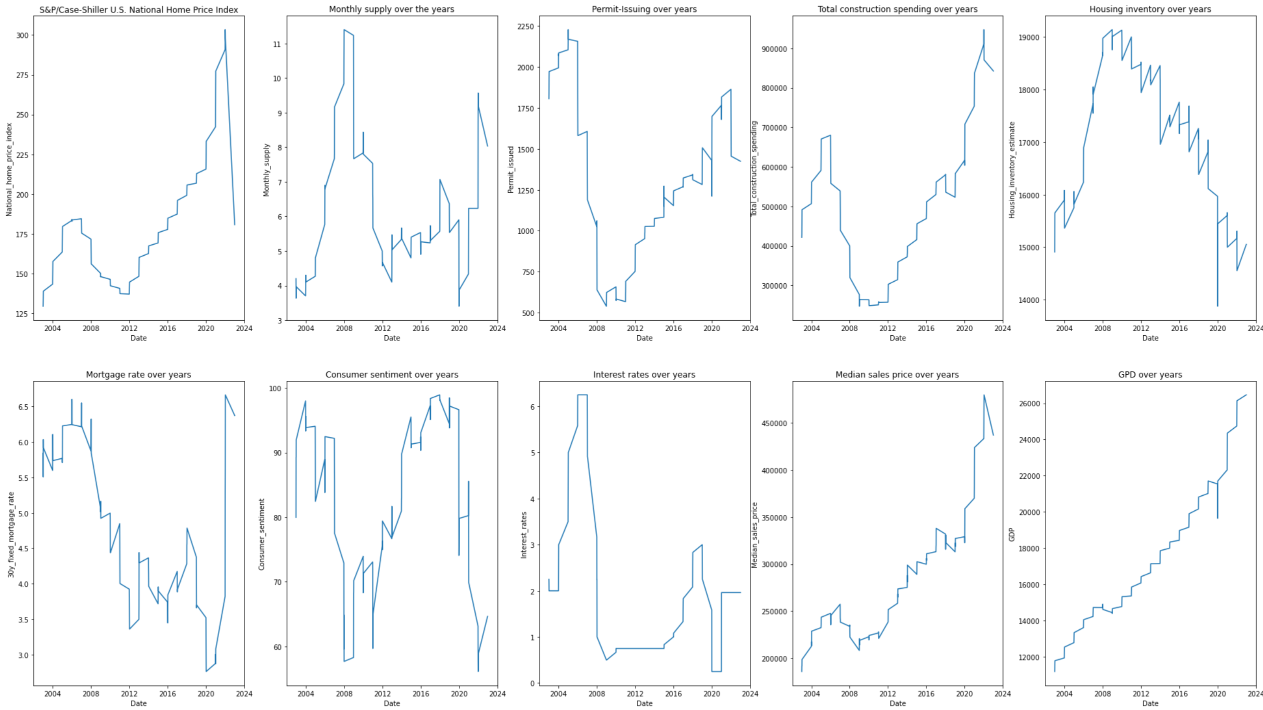
In [27]:

```
figure,ax = plt.subplots(nrows = 2,ncols = 5,figsize=(32,18))

sns.lineplot(ax = ax[0,0],x='Date',y='National_home_price_index',data = df_merged);
sns.lineplot(ax = ax[0,1],x='Date',y='Monthly_supply',data = df_merged);
sns.lineplot(ax = ax[0,2],x='Date',y='Permit_issued',data = df_merged);
sns.lineplot(ax = ax[0,3],x='Date',y='Total_construction_spending',data = df_merged);
sns.lineplot(ax = ax[0,4],x='Date',y='Housing_inventory_estimate',data = df_merged);
sns.lineplot(ax = ax[1,0],x='Date',y='30y_fixed_mortgage_rate',data = df_merged);

sns.lineplot(ax = ax[1,1],x='Date',y='Consumer_sentiment',data = df_merged);
sns.lineplot(ax = ax[1,2],x='Date',y='Interest_rates',data =df_merged);
sns.lineplot(ax = ax[1,3],x='Date',y='Median_sales_price',data =df_merged);
sns.lineplot(ax = ax[1,4],x='Date',y='GDP',data = df_merged);

ax[0,0].title.set_text('S&P/Case-Shiller U.S. National Home Price Index')
ax[0,1].title.set_text('Monthly supply over the years')
ax[0,2].title.set_text('Permit-Issuing over years')
ax[0,3].title.set_text('Total construction spending over years')
ax[0,4].title.set_text('Housing inventory over years')
ax[1,0].title.set_text('Mortgage rate over years')
ax[1,1].title.set_text('Consumer sentiment over years')
ax[1,2].title.set_text('Interest rates over years')
ax[1,3].title.set_text('Median sales price over years')
ax[1,4].title.set_text('GPD over years')
```



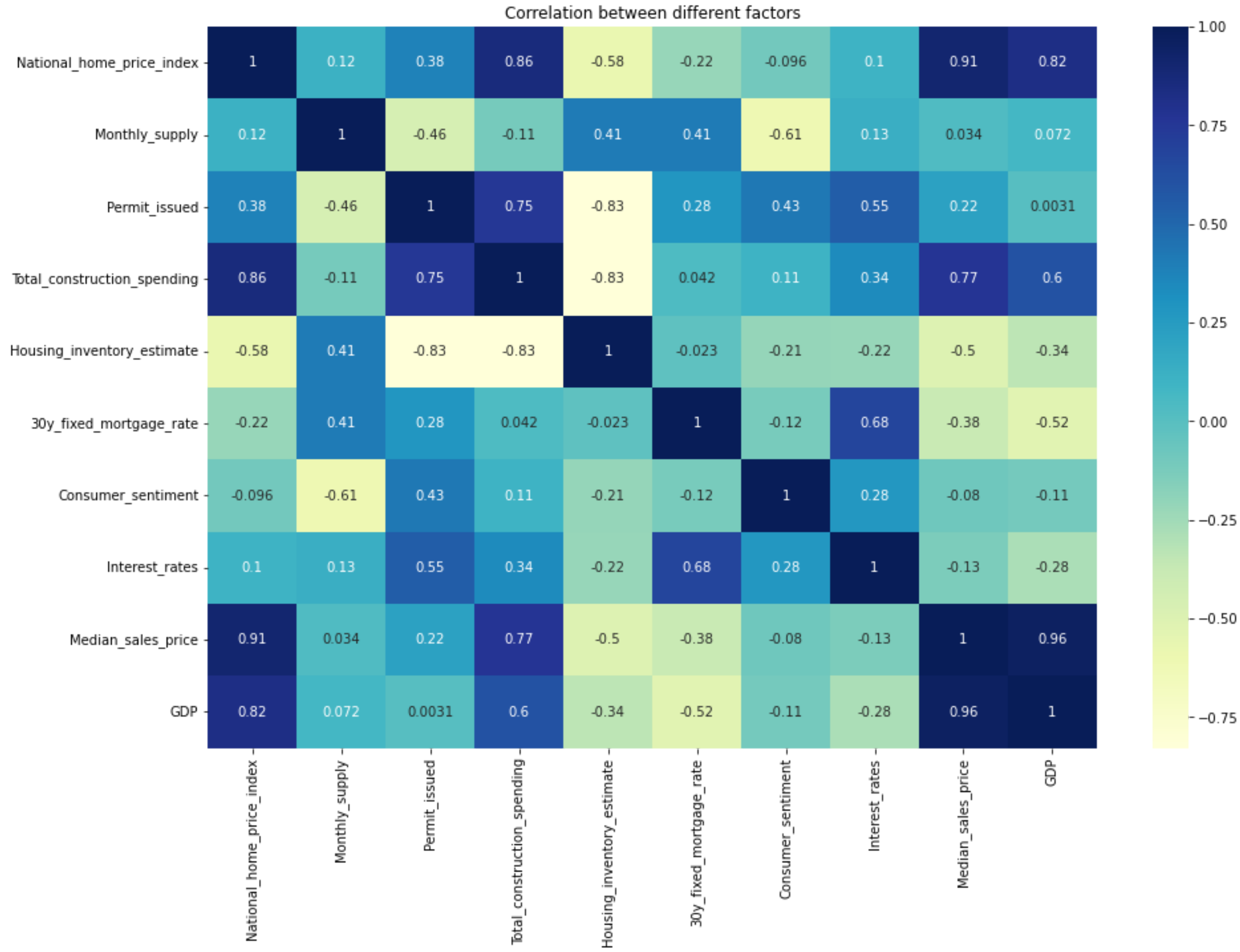
Correlation Heatmap

In [28]:

```
corr = df_merged.corr()
plt.figure(figsize=(15,10))
sns.heatmap(data = corr,cmap="YlGnBu", annot=True)
plt.title('Correlation between different factors')
```

Out[28]:

```
Text(0.5, 1.0, 'Correlation between different factors')
```



Monthly supply of new homes and authorized housing units have positive but varying impacts on home prices, while increased construction spending strongly raises prices. Conversely, a higher number of vacant housing units, mortgage rates, and lower consumer sentiment can modestly reduce home prices. Strong correlations exist between median sales prices, GDP, and higher home prices.

Key factors influencing home prices include supply and demand dynamics, construction spending, vacant housing units, mortgage rates, consumer sentiment, interest rates, median sales prices, and GDP, with varying degrees of impact.

Correlation Analysis of important factors on National Home price Index

To understand how the House Price Index is changing in the last 20 years, we have plotted a quarterly line plot of highly correlated factors with the National House Price Index.

In [29]:
```
df = df_merged.copy()
```

In [30]:
```
df.head()
```

Out[30]:

	Date	National_home_price_index	Monthly_supply	Permit_issued	Total_construction_spending	Housi
0	2003-01-01	129.321000	4.200000	1806.333333	421328.6667	
1	2003-01-04	131.756000	3.833333	1837.666667	429308.6667	
2	2003-01-07	135.013000	3.633333	1937.333333	458890.0000	
3	2003-01-10	138.835667	3.966667	1972.333333	491437.3333	
4	2004-01-01	143.298667	3.700000	1994.666667	506856.3333	

In [31]:

```
df.Date
```

Out[31]:

```
0     2003-01-01
1     2003-01-04
2     2003-01-07
3     2003-01-10
4     2004-01-01
         ...
76    2022-01-01
77    2022-01-04
78    2022-01-07
79    2022-01-10
80    2023-01-01
Name: Date, Length: 81, dtype: datetime64[ns]
```

In [32]:

```
df = df.set_index('Date')
```

In [33]:

```
df['QUARTER'] = df.index.to_period('Q')
df['QUARTER'] = df['QUARTER'].astype(str)

def plot_highly_corr(factor,col):
    grouped_data = df.groupby('QUARTER').agg({factor: 'sum', 'National_home_price_index


    scaler = MinMaxScaler()
    grouped_data[[factor, 'National_home_price_index']] = scaler.fit_transform(grouped_


    grouped_data = grouped_data.sort_values('QUARTER')


    plt.figure(figsize=(16, 6))  # Adjust the figure size as per your preference

    bar_width = 0.4
    opacity = 0.8


    #plt.bar(grouped_data['QUARTER'], grouped_data[factor], width=bar_width, alpha=opac
    plt.plot(grouped_data['QUARTER'], grouped_data[factor], marker='o', linestyle='-',
```

```
    plt.plot(grouped_data['QUARTER'], grouped_data['National_home_price_index'], marker

    plt.title(factor + ' vs National Home Price Index (Normalized)')
    plt.xlabel('Quarter')
    plt.ylabel('Normalized Values')
    plt.legend()

    plt.grid(True)
    plt.xticks(rotation=45, ha='right', fontsize=8)  # Rotate and align x-axis tick lab

    plt.tight_layout()
    return plt.show()
```

In [34]:

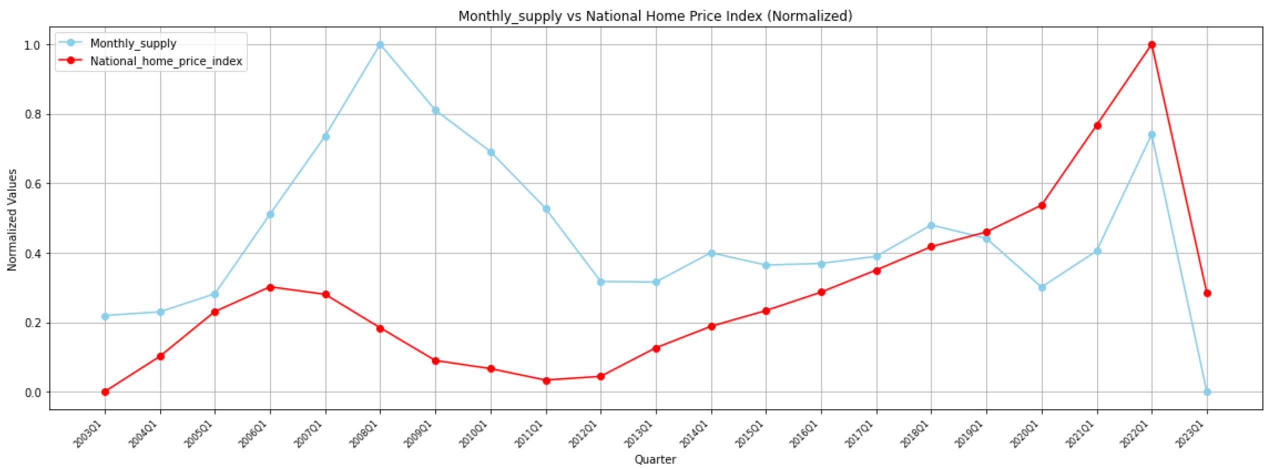
```
columns = df.columns[1:-1]
columns
```

Out[34]:

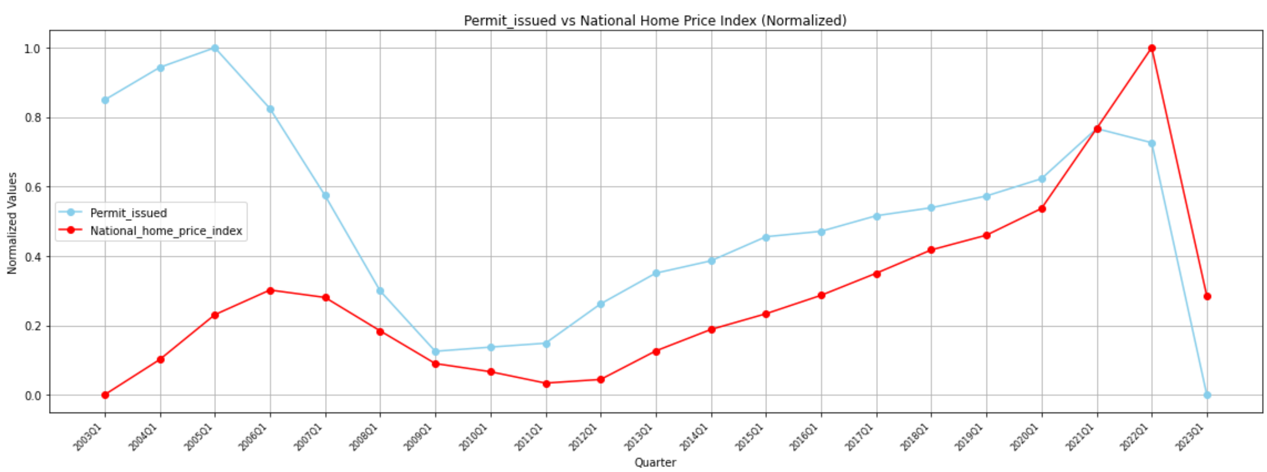
```
Index(['Monthly_supply', 'Permit_issued', 'Total_construction_spending',
       'Housing_inventory_estimate', '30y_fixed_mortgage_rate',
       'Consumer_sentiment', 'Interest_rates', 'Median_sales_price', 'GDP'],
      dtype='object')
```

In [35]:

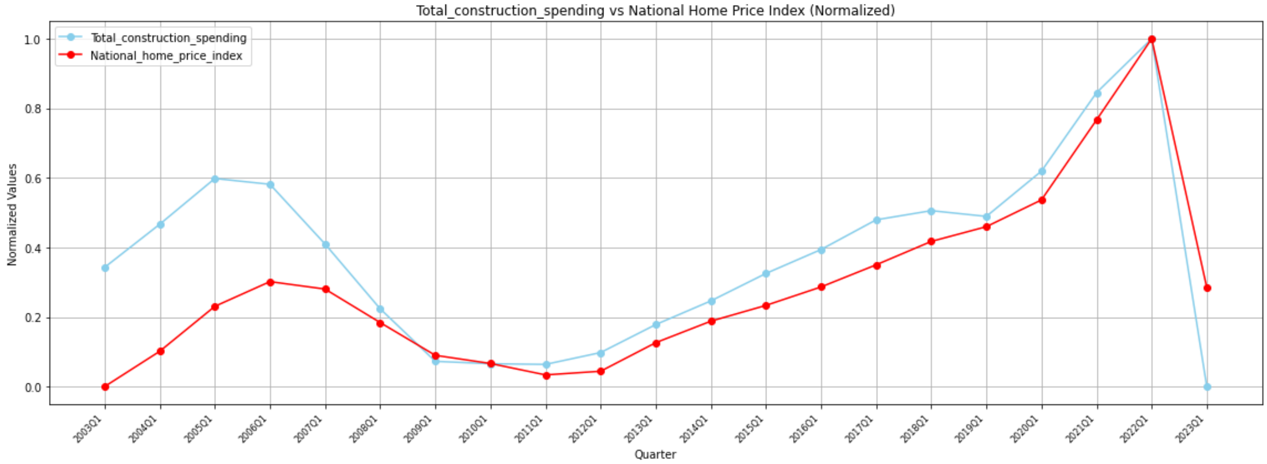
```
for i in columns:
    print(plot_highly_corr(i,'skyblue'))
```



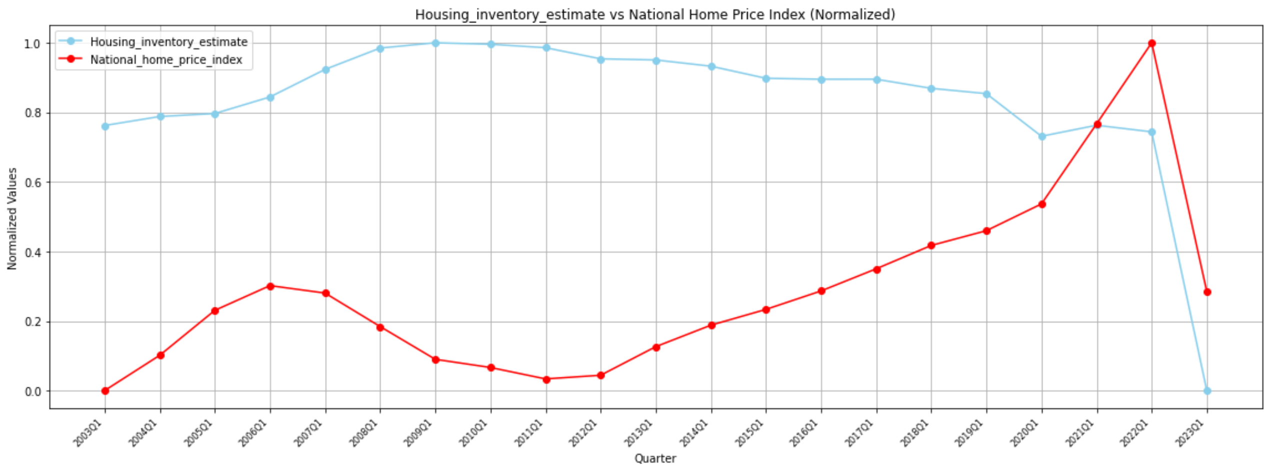
None



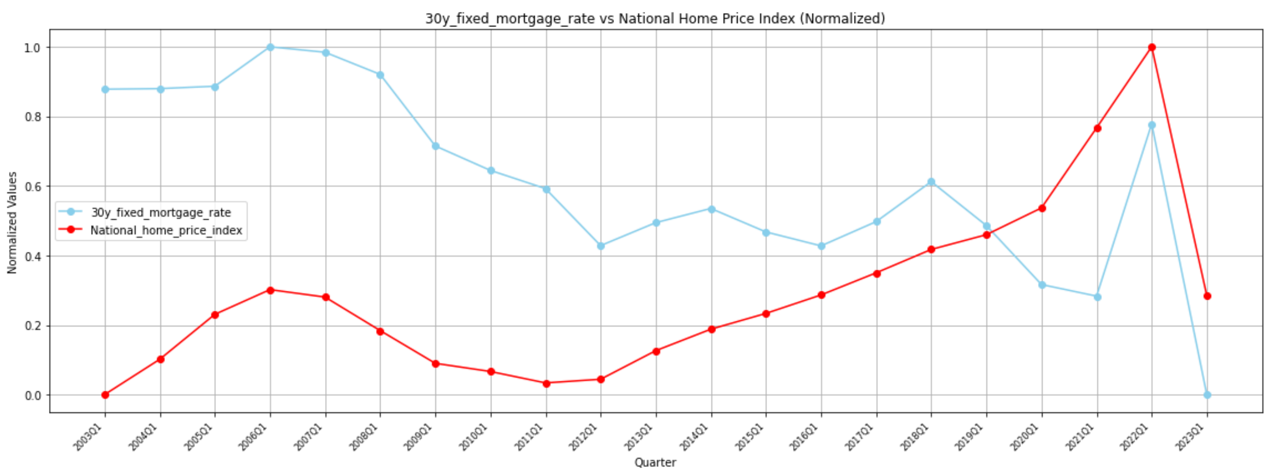
None



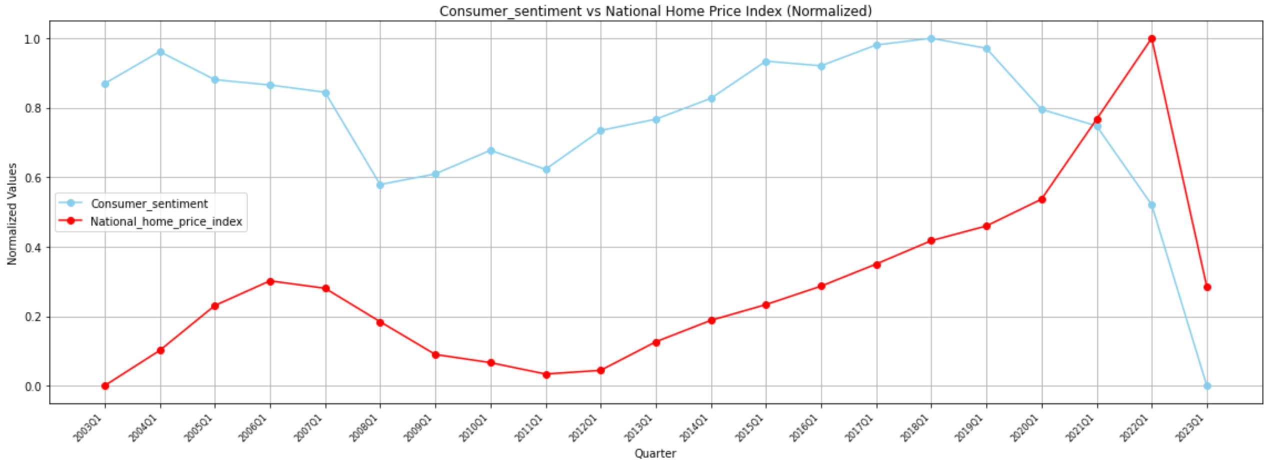
None



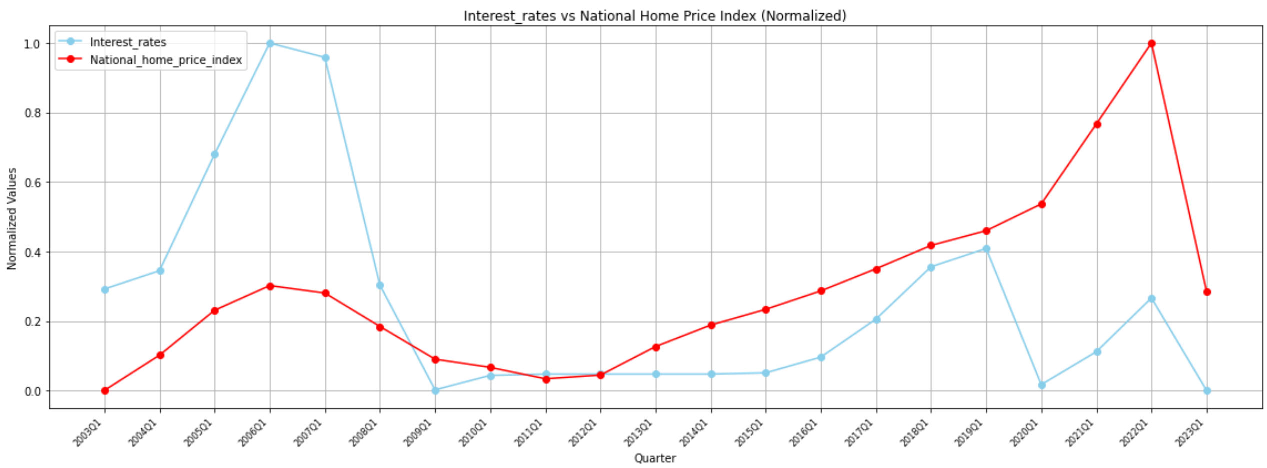
None



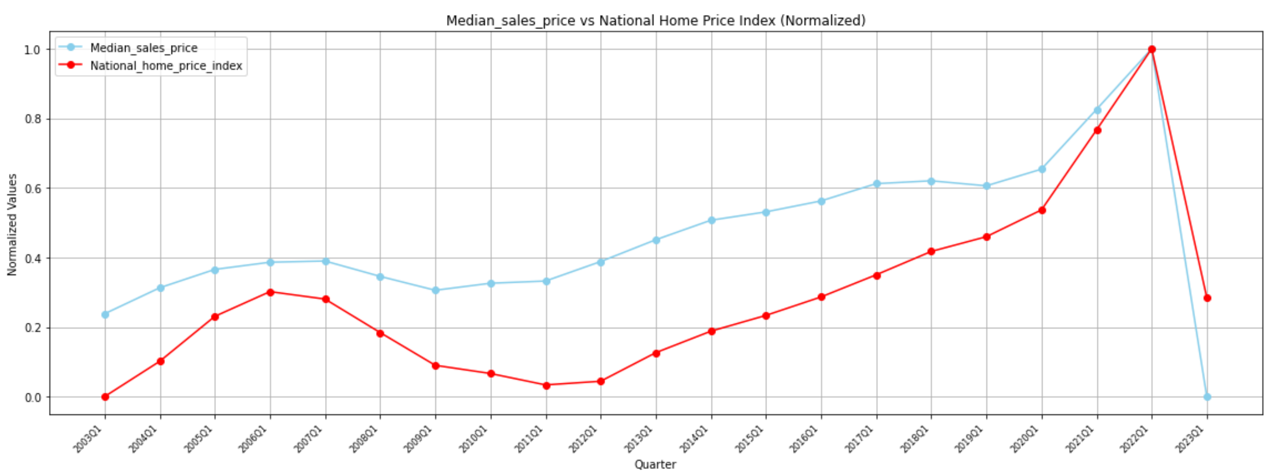
None



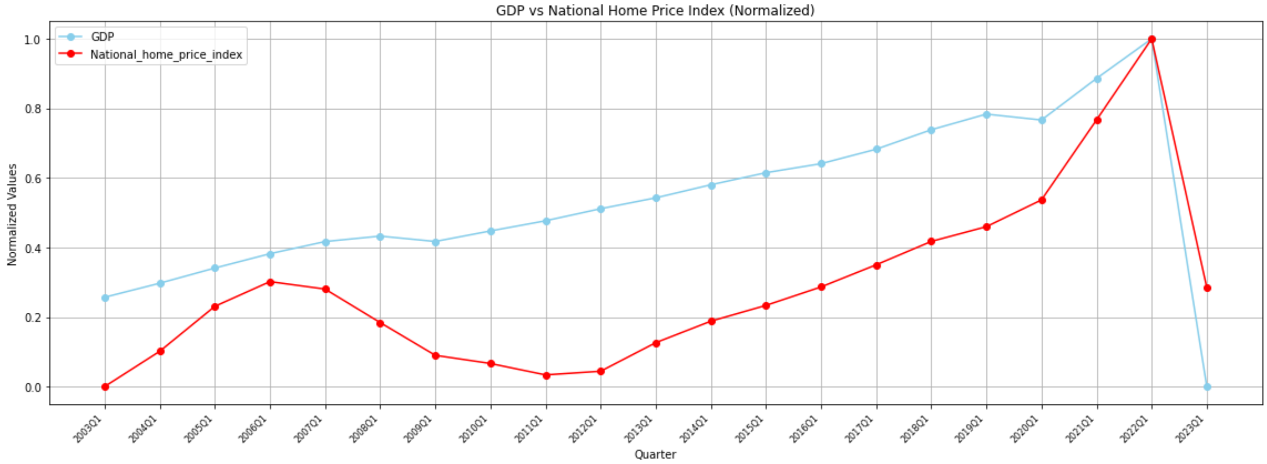
None



None



None



None

ML Model

In [36]:
```
df_merged= df_merged.drop('Date',axis=1)
X= df_merged.drop('National_home_price_index',axis=1)
y= df_merged['National_home_price_index']
```

In [37]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3,random_state=42

scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

In [38]:
```
model_lr = LinearRegression()
model_xgb = XGBRegressor()
model_rf = RandomForestRegressor(n_estimators=100, max_depth=5)
model_dt = DecisionTreeRegressor()
model_ridge = Ridge(alpha=10)
```

In [39]:
```
model_lr.fit(X_train_scaled,y_train)
model_xgb.fit(X_train_scaled,y_train)
model_rf.fit(X_train_scaled,y_train)
model_dt.fit(X_train_scaled,y_train)
model_ridge.fit(X_train_scaled,y_train)
```

Out[39]:
```
▾    Ridge
Ridge(alpha=10)
```

In [40]:
```
models = ['LinearRegression','XGBRegressor','RandomForestRegressor','DescisionTreeRegre
model_r2score = []
model_mse = []

model_r2score.append(r2_score(y_test, model_lr.predict(X_test_scaled)))
model_r2score.append(r2_score(y_test, model_xgb.predict(X_test_scaled)))
model_r2score.append(r2_score(y_test, model_rf.predict(X_test_scaled)))
model_r2score.append(r2_score(y_test, model_dt.predict(X_test_scaled)))
```

```
model_r2score.append(r2_score(y_test, model_ridge.predict(X_test_scaled)))

model_mse.append(mean_squared_error(y_test, model_lr.predict(X_test_scaled)))
model_mse.append(mean_squared_error(y_test, model_xgb.predict(X_test_scaled)))
model_mse.append(mean_squared_error(y_test, model_rf.predict(X_test_scaled)))
model_mse.append(mean_squared_error(y_test, model_dt.predict(X_test_scaled)))
model_mse.append(mean_squared_error(y_test, model_ridge.predict(X_test_scaled)))


model_r2score = list(map(lambda x: round(x, ndigits=4), model_r2score))
model_mse = list(map(lambda x: round(x, ndigits=4), model_mse))
```

In [49]:

```
model_r2score_df = pd.DataFrame({'Models': models, 'R2 Score': model_r2score})
model_r2score_df
```

Out[49]:

	Models	R2 Score
0	LinearRegression	0.9307
1	XGBRegressor	0.9341
2	RandomForestRegressor	0.9675
3	DescisionTreeRegressor	0.9012
4	Ridge	0.9626

In [50]:

```
model_mse_df = pd.DataFrame({'Models': models, 'MSE': model_mse})
model_mse_df
```

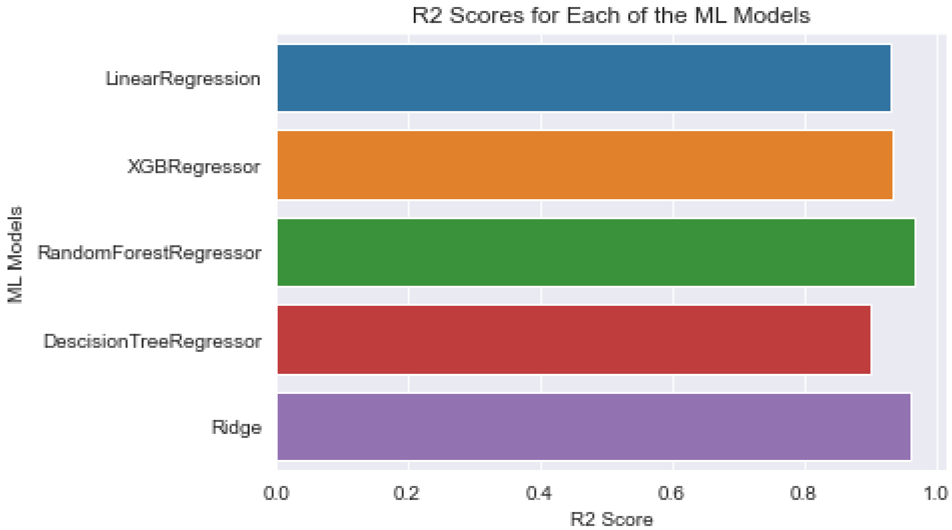
Out[50]:

	Models	MSE
0	LinearRegression	68.8879
1	XGBRegressor	65.4954
2	RandomForestRegressor	32.3335
3	DescisionTreeRegressor	98.2115
4	Ridge	37.2031

In [42]:

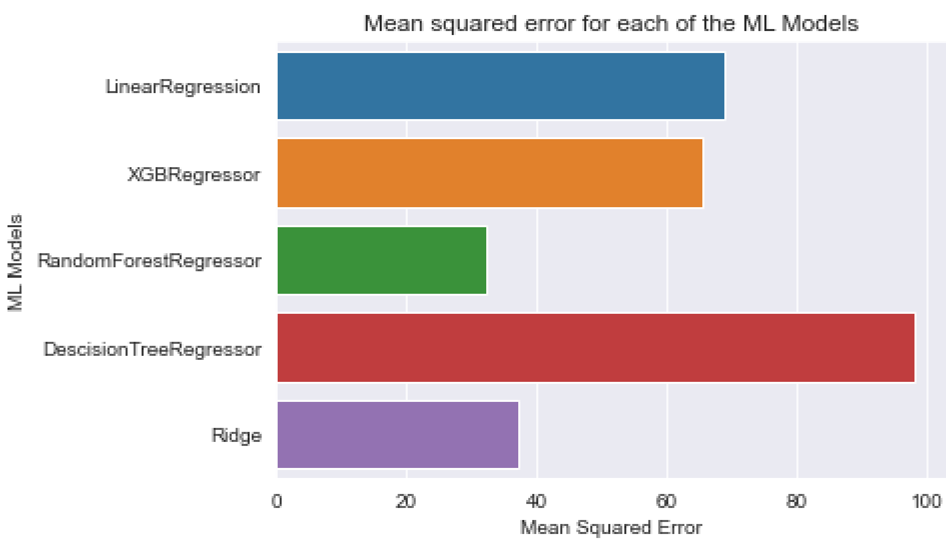
```
sns.set_style('darkgrid')
sns.barplot(model_r2score, models)
plt.title('R2 Scores for Each of the ML Models')
plt.xlabel('R2 Score')
plt.ylabel('ML Models')
plt.show()
```

```
C:\Users\acer\anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass
the following variables as keyword args: x, y. From version 0.12, the only valid positio
nal argument will be `data`, and passing other arguments without an explicit keyword wil
l result in an error or misinterpretation.
  warnings.warn(
```



In [43]:
```
sns.set_style('darkgrid')
sns.barplot(model_mse, models)
plt.title('Mean squared error for each of the ML Models')
plt.xlabel('Mean Squared Error')
plt.ylabel('ML Models')
plt.show()
```

```
C:\Users\acer\anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass
the following variables as keyword args: x, y. From version 0.12, the only valid positio
nal argument will be `data`, and passing other arguments without an explicit keyword wil
l result in an error or misinterpretation.
  warnings.warn(
```



In this evaluation, the Random Forest Regressor model demonstrated strong performance. The Mean Squared Error (MSE) for the testing dataset was 32.33, indicating that prediction errors were relatively low. Additionally, the R-squared score stood at 0.9675, signifying that the model can account for approximately 96.75% of the variability observed in the target variable.

Calculate permutation feature importances

In [44]:
```
# Calculate permutation feature importances
feature_importances = model_rf.feature_importances_
```

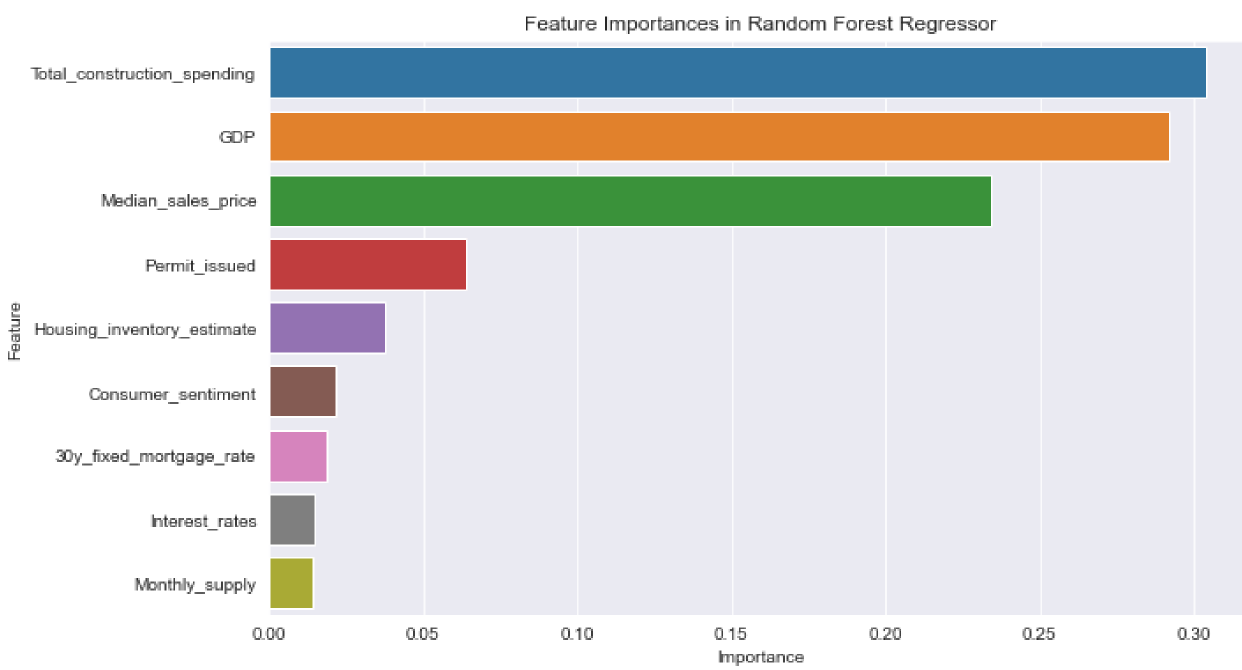
```
feature_importance_df = pd.DataFrame({'Feature': X.columns, 'Importance': feature_impor
sorted_feature_importance = feature_importance_df.sort_values(by='Importance', ascendin
sorted_feature_importance
```

Out[44]:

	Feature	Importance
2	Total_construction_spending	0.303657
8	GDP	0.292082
7	Median_sales_price	0.233893
1	Permit_issued	0.064084
3	Housing_inventory_estimate	0.037668
5	Consumer_sentiment	0.021352
4	30y_fixed_mortgage_rate	0.018615
6	Interest_rates	0.014440
0	Monthly_supply	0.014208

In [45]:

```
plt.figure(figsize=(10, 6))
sns.barplot(x='Importance', y='Feature', data=sorted_feature_importance)
plt.title('Feature Importances in Random Forest Regressor')
plt.show()
```



All the features are significantly impacting the predicted home price index but the features like Total construction spending, GDP, Median Sales Price and Permit issued which also had the highest correlation with national home price index have more impact than rest of the factors.

Conclusion

After analyzing the correlation, different ML Models and Random forest Regressor coefficients , we conclude that :-

1. Supply-related factors, such as housing inventory and the authorization of housing units, positively impact home prices. Increased spending on residential construction projects also significantly contributes to higher home prices.
2. On the other hand, demand-related factors like mortgage interest rates have a negative effect on home prices. Elevated mortgage rates and reduced consumer sentiment are associated with slightly lower home prices.
3. Economic factors, including GDP, Total Construction Spending, interest rates, play a pivotal role in determining home prices. A robust economy characterized by higher GDP and somewhat lower interest rates tends to bolster higher home prices.
4. The median sales price of houses sold strongly correlates with home prices, illustrating the significance of market dynamics and buyer behavior in shaping home price trends.
5. These insights hold value for various stakeholders in the real estate sector, such as homebuyers, sellers, developers, and policymakers. Understanding the factors that influence home prices can facilitate well-informed decisions regarding investments, financing, and economic strategies.

In [ ]: