Question.

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.

Soultion -

In this project, we embark on a data-driven journey to understand the key factors influencing home prices in the United States over the past two decades. By leveraging publicly available data and advanced data science techniques, our goal is to build a comprehensive model that sheds light on the intricate relationship between various factors and home prices.

Libraries and Tools used:

Programming Languages: Python

Data Analysis Libraries: NumPy, pandas, matplotlib, seaborn

Machine Learning Libraries: scikit-learn

Data Visualization: Matplotlib, Seaborn

Version Control: Git, GitHub

Jupyter Notebooks for data exploration and analysis

Datasheet Details and Features selection

All the Data has been collected from [https://fred.stlouisfed.org/ (https://fred.stlouisfed.org/)](https://fred.stlouisfed.org/) with the filet selection of 20 years which is from 2003-2023.

Features which I find the most important factors influencing the house prices nationally are:

Case-Shiller:

Refers to the S&P CoreLogic Case-Shiller Home Price Indices. Measures the changes in residential real estate prices across different regions in the United States. Provides insights into housing market trends and price movements.

Construction Price:

Represents the cost associated with building or constructing structures. Includes expenses for materials, labor, equipment, and overhead. Influences the overall cost of real estate development and construction projects.

Consumer Price:

Measures the average change in prices paid by consumers for a basket of goods and services over time. An important indicator of inflation and purchasing power.

Housing Subsidies:

Refers to financial assistance provided by the government to support housing affordability. Includes subsidies, grants, or tax credits aimed at helping individuals or families with housing costs.

Interest Rates:

The cost of borrowing money, typically expressed as a percentage. Influences mortgage rates and, consequently, the affordability of homes. Central banks use interest rates as a tool to control inflation and economic activity.

Per_Capita_GDP:

Gross Domestic Product (GDP) per capita, calculated by dividing the total GDP of a country by its population. Provides a measure of the average economic output per person. Indicates the standard of living and economic well-being of a population.

Median Income:

The middle point of all incomes in a given area, where half of the population earns more, and half earns less. Reflects the income distribution within a specific demographic or geographic area.

Total Households:

The total number of occupied housing units in a specific area. Important for understanding the demand for housing and related services.

Unemployment Rate:

The percentage of the labor force that is unemployed and actively seeking employment. A key economic indicator reflecting the health of the job market.

Working Population:

The portion of the population that is either employed or actively seeking employment. Essential for understanding the labor force's size and participation rate.

Working Age (15-64):

The age range typically considered to be of working age. Demographic category that influences the labor force and employment rates.

Employment Rate:

The percentage of the working-age population that is employed. Reflects the proportion of people within the working-age group who have jobs.

These factors collectively contribute to the dynamics of the real estate market, economic

Steps

Data Cleaning and Processing:

1-While Downloading the data, I found that in .CSV format, so the basic cleaning part I have done in the excel sheet. eg, Changing the date formats and Features names. It saves a lot of my time cleaning in jupyter notebook.

2- I checked for the missing values as well as data types and converted date formats to float for smoot results.

3- Checked for outliers.

Exploratory Data Analysis (EDA):

Conducted EDA to understand the distribution of variables, identify correlations, and visualize trends over time.

Visualization:

Create visualizations to illustrate the relationships between actual and predicted home prices for each model.

Visualize the importance of different features or coefficients in influencing home prices.

Model Selection:

Explored various regression models, including Linear Regression, ElasticNet, Random Forest, Gradient Boosting, Support Vector Regression (SVR), and XGBoost.

Model Training and Evaluation: Trained each model using a subset of the data, evaluated performance using metrics such as Mean Squared Error (MSE) and R-squared.

Feature Importance:

Analyzed feature importance for models like Random Forest, XGBoost, and Gradient Boosting to understand the factors influencing home prices.

Model Comparison:

Compare the performance of different models based on metrics such as Mean Squared Error (MSE) and R-squared.

Select the best-performing model that provides accurate predictions and insights into the factors influencing home prices over the last 20 years.

Conclusion:

Identified strong contender for the best model, considering their low MSE and high R-squared values.

Draw conclusions about the key factors that have historically influenced US home prices.

In [256]:
```
#Basic libraries
import pandas as pd
import numpy as np

#Visualization libraries
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
```

In [257]:
```
#Loading the data
df=pd.read_csv('C://Users/Lenovo/OneDrive/Desktop/Home_LLC/CASE-SCHILLE
df.head()
```

Out[257]:

	DATE	Year	Month	Case-Schiller	Construction Price	Consumer Price	Housing Subsides	Interest Rates	Per_Cap
0	2003-01-01	2003.0	1.0	128.461	144.4	182.6	25.93	1.24	
1	2003-02-01	2003.0	2.0	129.355	145.2	183.6	25.93	1.26	
2	2003-03-01	2003.0	3.0	130.148	145.2	183.9	25.93	1.25	
3	2003-04-01	2003.0	4.0	130.884	145.9	183.2	25.93	1.26	
4	2003-05-01	2003.0	5.0	131.735	145.8	182.9	25.93	1.26	

In [258]:
```
# Changing dtype of date column
df["DATE"] = pd.to_datetime(df["DATE"])
```

In [259]:
```
#Loading the data
df=pd.read_csv('C://Users/Lenovo/OneDrive/Desktop/Home_LLC/CASE-SCHILLE
df.head()
```

Out[259]:

DATE	Year	Month	Case-Schiller	Construction Price	Consumer Price	Housing Subsides	Interest Rates	Per_Capita_
2003-01-01	2003.0	1.0	128.461	144.4	182.6	25.93	1.24	504
2003-02-01	2003.0	2.0	129.355	145.2	183.6	25.93	1.26	
2003-03-01	2003.0	3.0	130.148	145.2	183.9	25.93	1.25	
2003-04-01	2003.0	4.0	130.884	145.9	183.2	25.93	1.26	507
2003-05-01	2003.0	5.0	131.735	145.8	182.9	25.93	1.26	

In [260]:
```
df.shape
```

Out[260]:
```
(251, 14)
```

Note-Data consists of 14 columns and 21 rows.

In [261]:
```
df.dtypes
```

Out[261]:
```
Year                           float64
Month                          float64
Case-Schiller                  float64
Construction Price             float64
Consumer Price                 float64
Housing Subsides               float64
Interest Rates                 float64
Per_Capita_gdp                 float64
median_income                  float64
Total_Households               float64
Unemployement_rate             float64
Working_Population             float64
Working_age(15-64)_population  float64
Employement_rate               float64
dtype: object
```

Note-All the dtype is same as I changed the date format earlier.

Checking if any missing values? Missing values can be a problem for linear models so checking if any columns have any missing values. If there are, those can be resolved during data cleaning .

Let's see what percentage of missing values are there for these columns

In [262]:
```
#Checking for missing data
df.isnull().sum()
```

Out[262]:
```
Year                              2
Month                             2
Case-Schiller                     2
Construction Price                2
Consumer Price                    2
Housing Subsides                 11
Interest Rates                    2
Per_Capita_gdp                  168
median_income                    11
Total_Households                  2
Unemployement_rate                0
Working_Population                1
Working_age(15-64)_population     1
Employement_rate                  1
dtype: int64
```

Observation:

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

Interpolation:

Interpolation is a mathematical technique used to estimate values that are missing in a dataset based on the values of neighboring data points. It calculates intermediate values based on the existing data.

In [263]:
```
# Filling missing values in the Per_Capita_GDP column using linear inte
df["Per_Capita_gdp"] = df["Per_Capita_gdp"].interpolate()
```

In [264]:
```
#Checking for missing data
df.isnull().sum()
```

Out[264]:
```
Year                             2
Month                            2
Case-Schiller                    2
Construction Price               2
Consumer Price                   2
Housing Subsides                11
Interest Rates                   2
Per_Capita_gdp                   0
median_income                   11
Total_Households                 2
Unemployement_rate               0
Working_Population               1
Working_age(15-64)_population    1
Employement_rate                 1
dtype: int64
```

In [265]:

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

In [266]:

```
#Checking for missing data
df.isnull().sum()
```

Out[266]:

```
Year                            0
Month                           0
Case-Schiller                   0
Construction Price              0
Consumer Price                  0
Housing Subsides                0
Interest Rates                  0
Per_Capita_gdp                  0
median_income                   0
Total_Households                0
Unemployement_rate              0
Working_Population              0
Working_age(15-64)_population   0
Employement_rate                0
dtype: int64
```

Note- All the Missing Values are cleaned and data have no missing values now.

In [267]:
```
df
```

Out[267]:

	Year	Month	Case-Schiller	Construction Price	Consumer Price	Housing Subsides	Interest Rates	Per_Capita_
DATE								
2003-01-01	2003.0	1.0	128.461	144.400	182.600	25.930	1.24	50462.00
2003-02-01	2003.0	2.0	129.355	145.200	183.600	25.930	1.26	50573.33
2003-03-01	2003.0	3.0	130.148	145.200	183.900	25.930	1.25	50684.66
2003-04-01	2003.0	4.0	130.884	145.900	183.200	25.930	1.26	50796.00
2003-05-01	2003.0	5.0	131.735	145.800	182.900	25.930	1.26	51034.66
...	...	...	...	...	...	...	...	
2022-08-01	2022.0	8.0	301.473	342.753	295.320	48.021	2.33	65569.00
2022-09-01	2022.0	9.0	299.353	336.464	296.539	48.021	2.56	65676.00
2022-10-01	2022.0	10.0	298.873	333.796	297.987	48.021	3.08	65783.00
2022-11-01	2022.0	11.0	298.269	330.369	298.598	48.021	3.78	65881.33
2022-12-01	2022.0	12.0	297.413	326.449	298.990	48.021	4.10	65979.66

240 rows × 14 columns

Note-

Checking if there are any duplicated records Here we are searching for observations which are completely identical.

In [268]:
```
print("# of duplicated records :",df.duplicated().sum())
```

```
# of duplicated records : 0
```

In [269]:
```
df.describe()
```

Out[269]:

	Year	Month	Case-Schiller	Construction Price	Consumer Price	Housing Subsides	I
count	240.000000	240.000000	240.000000	240.000000	240.000000	240.000000	240.
mean	2012.500000	6.500000	180.657237	212.851467	230.023113	34.677450	1.
std	5.778332	3.459267	41.254187	44.566715	27.475017	6.006483	1.
min	2003.000000	1.000000	128.461000	144.400000	182.600000	25.930000	0.
25%	2007.750000	3.750000	148.123000	184.275000	211.433250	29.785000	0.
50%	2012.500000	6.500000	172.495000	207.450000	231.658500	33.544500	0.
75%	2017.250000	9.250000	197.457750	224.525000	248.068500	37.877250	2.
max	2022.000000	12.000000	304.724000	353.015000	298.990000	48.021000	5.

In [270]:
```
# Dropping year and month columns
df.drop(columns = ["Year", "Month"], inplace = True)
```

Exploratory Data Analysis (EDA)

Calculate and display summary statistics for each variable, including mean, median, standard deviation, minimum, and maximum values. This gives you an overview of the data's central tendencies and variability.

In [271]:
```
df.describe()
```

Out[271]:

	Case-Schiller	Construction Price	Consumer Price	Housing Subsides	Interest Rates	Per_Capita_gdp	I
count	240.000000	240.000000	240.000000	240.000000	240.000000	240.000000	
mean	180.657237	212.851467	230.023113	34.677450	1.301625	57387.329167	
std	41.254187	44.566715	27.475017	6.006483	1.578512	3978.027413	
min	128.461000	144.400000	182.600000	25.930000	0.050000	50462.000000	
25%	148.123000	184.275000	211.433250	29.785000	0.120000	54450.416667	
50%	172.495000	207.450000	231.658500	33.544500	0.400000	55858.000000	
75%	197.457750	224.525000	248.068500	37.877250	2.000000	60370.083333	
max	304.724000	353.015000	298.990000	48.021000	5.260000	65979.666667	

Correlation Analysis:

Calculate the correlation matrix to measure the linear relationships between variables.

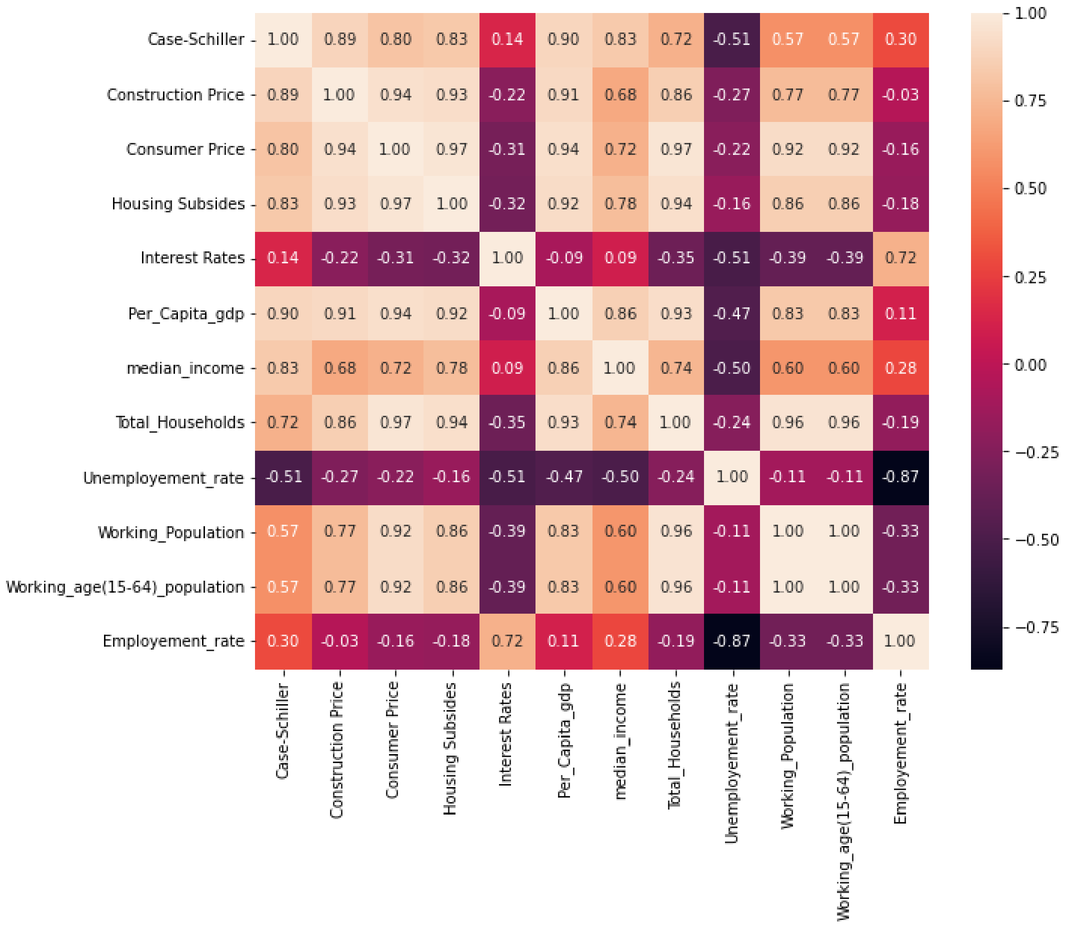
In [272]:

```
# Correlation
df_new = df.corr()
df_new
```

Out[272]:

	Case-Schiller	Construction Price	Consumer Price	Housing Subsides	Interest Rates	Per_Cap
Case-Schiller	1.000000	0.888824	0.803227	0.828896	0.135219	0
Construction Price	0.888824	1.000000	0.944249	0.929301	-0.221350	0
Consumer Price	0.803227	0.944249	1.000000	0.967032	-0.306621	0
Housing Subsides	0.828896	0.929301	0.967032	1.000000	-0.319337	0
Interest Rates	0.135219	-0.221350	-0.306621	-0.319337	1.000000	-0
Per_Capita_gdp	0.895484	0.908312	0.939311	0.921210	-0.092666	1
median_income	0.834167	0.680046	0.718346	0.779129	0.089784	0
Total_Households	0.720504	0.859014	0.970690	0.937864	-0.348477	0
Unemployement_rate	-0.505809	-0.269647	-0.222508	-0.156554	-0.513716	-0
Working_Population	0.570382	0.770678	0.920915	0.857725	-0.386309	0
Working_age(15-64)_population	0.570382	0.770678	0.920915	0.857725	-0.386309	0
Employement_rate	0.295054	-0.032869	-0.159769	-0.175673	0.719502	0

In [273]:
```
# Visualize correlations using a heatmap
plt.figure(figsize=(10, 8))
sns.heatmap(df_new, annot=True, fmt=".2f")
plt.show()
```



Data Visualization

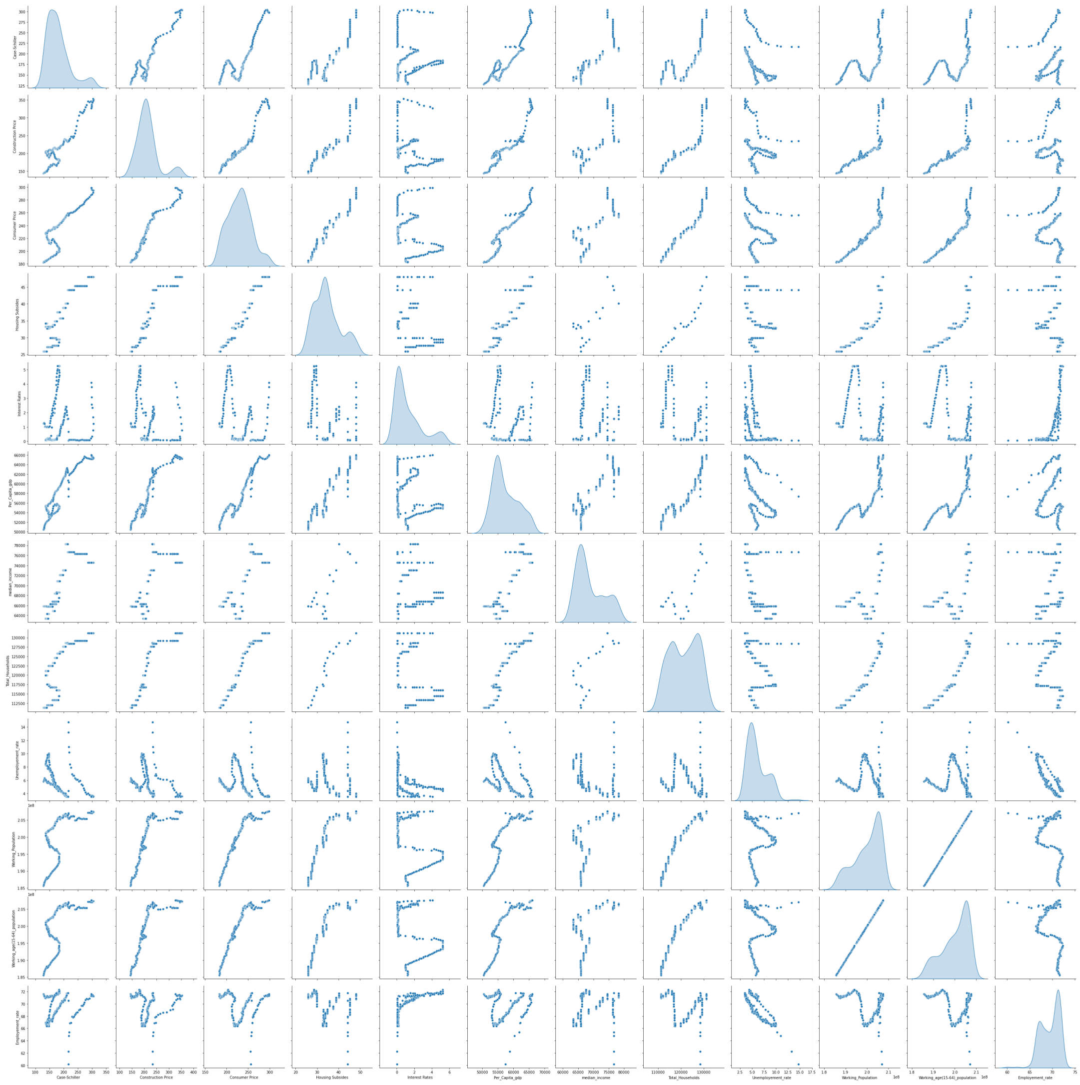
Visualize the data using various plots and graphs to understand its distribution and trends.

Pairplot for visualizing relationships

In [274]:
```
import warnings
warnings.filterwarnings("ignore", category=FutureWarning)
```

In [275]:

```
#Plotting pairplot for transmission
sns.pairplot(df,diag_kind = "kde",kind = "scatter",height=3.5)
plt.show()
```

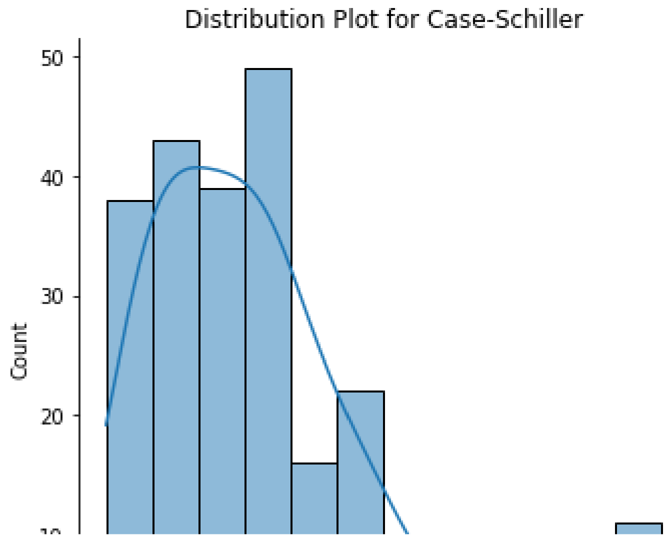


Plotting density plot for all the numerical features

In [276]:

```
plt.figure(figsize=(12, 6))
for col in df.columns.tolist():
    plt.figure(figsize=(6, 4))
    sns.displot(data=df, x=col, kde =True)
    plt.xlabel(f"{col}")
    plt.ylabel("Count")
    plt.title(f'Distribution Plot for {col}')
    plt.show()
```

```
<Figure size 864x432 with 0 Axes>

<Figure size 432x288 with 0 Axes>
```

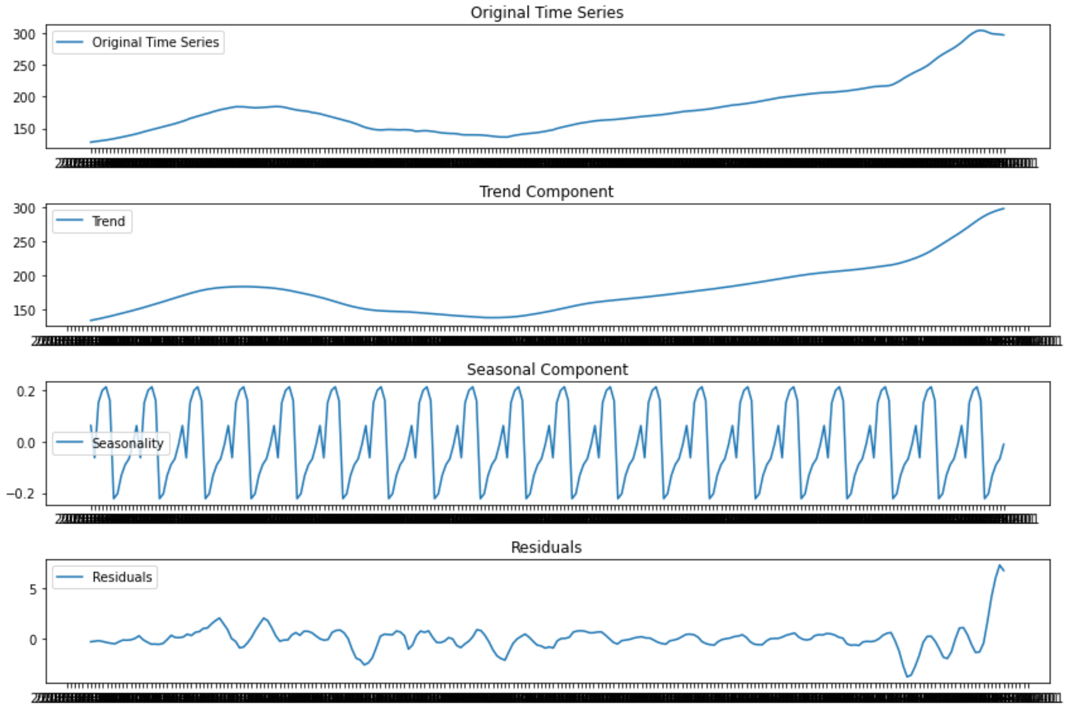


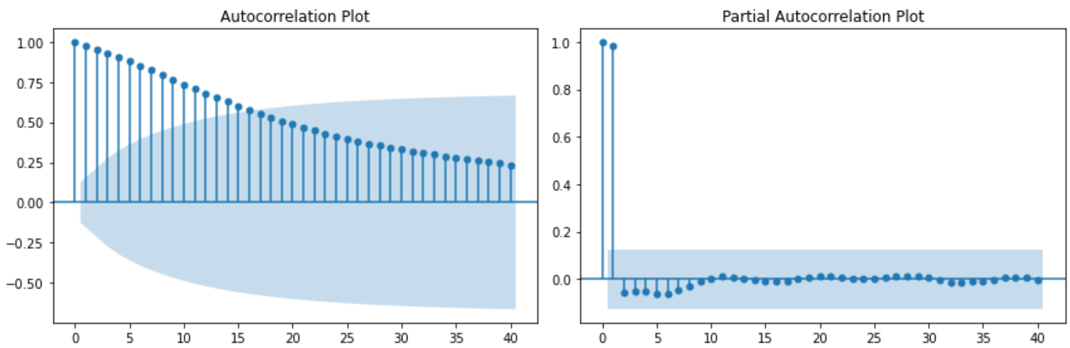
Time Series Analysis:

For time-dependent variables like 'CSUSHPISA,' use time series decomposition to separate trends, seasonality, and residuals. Plot these components to understand the patterns over tim

In [277]:

```
from statsmodels.tsa.seasonal import seasonal_decompose
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf

# Time Series Decomposition
decomposition = seasonal_decompose(df['Case-Schiller'], model='additive
trend = decomposition.trend
seasonal = decomposition.seasonal
residual = decomposition.resid

# Plot Time Series Components
plt.figure(figsize=(12, 8))

plt.subplot(4, 1, 1)
plt.plot(df['Case-Schiller'], label='Original Time Series')
plt.legend()
plt.title('Original Time Series')

plt.subplot(4, 1, 2)
plt.plot(trend, label='Trend')
plt.legend()
plt.title('Trend Component')

plt.subplot(4, 1, 3)
plt.plot(seasonal, label='Seasonality')
plt.legend()
plt.title('Seasonal Component')

plt.subplot(4, 1, 4)
plt.plot(residual, label='Residuals')
plt.legend()
plt.title('Residuals')

plt.tight_layout()
plt.show()

# Autocorrelation and Partial Autocorrelation Plots
plt.figure(figsize=(12, 4))

# Autocorrelation Plot
plt.subplot(1, 2, 1)
plot_acf(df['Case-Schiller'], lags=40, ax=plt.gca(), title='Autocorrela

# Partial Autocorrelation Plot
plt.subplot(1, 2, 2)
plot_pacf(df['Case-Schiller'], lags=40, ax=plt.gca(), title='Partial Au

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





The trend component represents the overall trend in home prices.

The seasonal component captures any recurring patterns or seasonality.

The residual component accounts for the remaining variability in the data.

In [278]:
```
df.columns
```

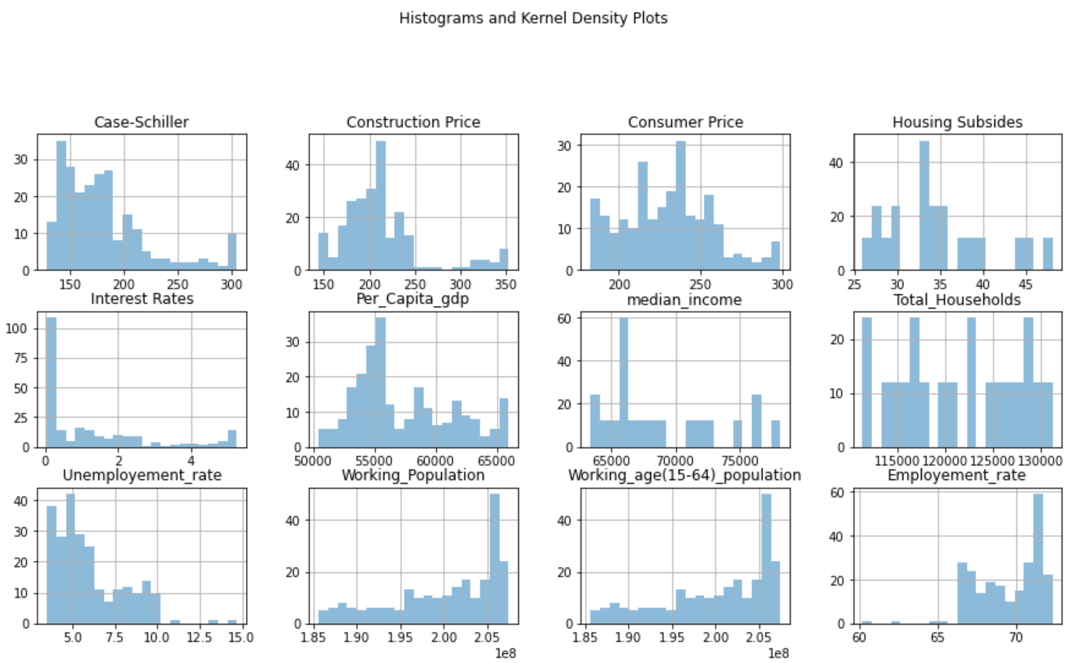
Out[278]:
```
Index(['Case-Schiller', 'Construction Price', 'Consumer Price',
       'Housing Subsides', 'Interest Rates', 'Per_Capita_gdp', 'median
_income',
       'Total_Households', 'Unemployement_rate', 'Working_Population',
       'Working_age(15-64)_population', 'Employement_rate'],
      dtype='object')
```

In [281]:
```
Features=['Case-Schiller','Construction Price','Consumer Price','Housir
```

In [282]:

```
plt.figure(figsize=(13, 8))
df[Features].hist(bins=20, alpha=0.5, layout=(4, 4), figsize=(15, 10))
plt.suptitle('Histograms and Kernel Density Plots', y=1.02)
plt.show()
```

```
<Figure size 936x576 with 0 Axes>
```

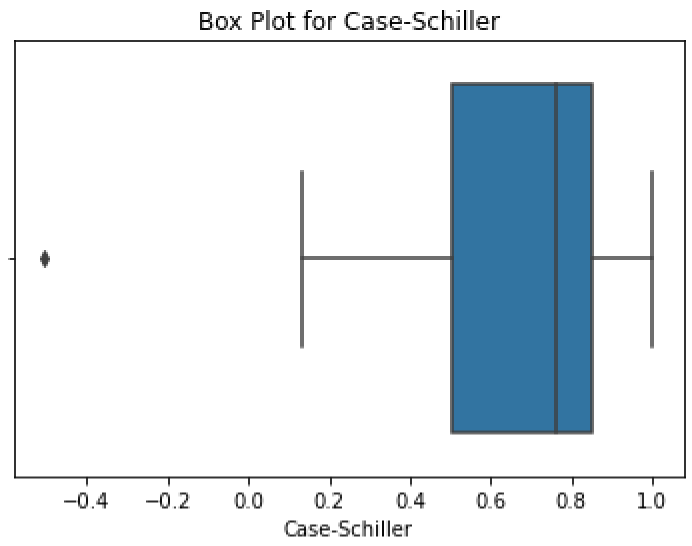


Plotting boxplot for analyzing the outliers in the data

In [283]:

```
plt.figure(figsize=(12, 6))
for col in df_new.columns.tolist():
    plt.figure(figsize=(6, 4))
    sns.boxplot(data=df_new, x=col)
    plt.xlabel(f"{col}")
    plt.title(f'Box Plot for {col}')
    plt.show()
```

```
<Figure size 864x432 with 0 Axes>
```



As checked, we can see some outliers in the visualizayion, and we will now check the outliers are need to be cleaned or there is no harm with that much of outliers.

The features we can see the outliers are- 'Case-Schiller', 'Construction Price', 'Consumer Price', 'Interest Rates', 'Per_Capita_gdp'

Treating Skewness and Outliers:

In [284]:

```
df_new['Case-Schiller'].skew()
```

Out[284]: -1.7252300801667348

In [285]:

```
df_new['Construction Price'].skew()
```

Out[285]: -1.2479647480966125

In [286]:

```
df_new['Consumer Price'].skew()
```

Out[286]: -1.260153423439675

In [287]:
```
df_new['Interest Rates'].skew()
```
Out[287]: 1.4513216684409416

In [288]:
```
df_new['Per_Capita_gdp'].skew()
```
Out[288]: -1.5491205538956356

No Outliers found , so no need to treat it.

In [289]:
```
# Violin Plots
plt.figure(figsize=(6, 5))
sns.violinplot(data=df[Features], orient='h')
plt.title('Violin Plots of Factors')
plt.xlabel('Values')
plt.show()
```

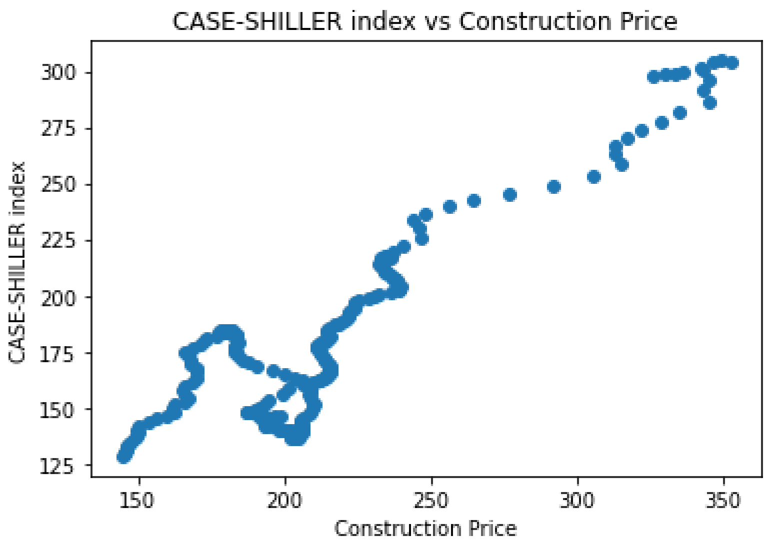
Extract features and target

In [290]:
```
# Separating the target variable and the independent variable
y = df.pop("Case-Schiller")
X = df
```

Plotting scatter plots of the CASE-SHILLER index vs features

In [291]:

```python
# Plotting scatter plots of the CASE-SHILLER index vs features

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



Calculate correlation coefficients

In [292]:

```python
correlations = X.apply(lambda column: np.abs(column.corr(y)))

# Sort correlations in ascending order
sorted_correlations = correlations.sort_values()

# Display features with lower correlation
print("Features with Lower Correlation to Target:")
print(sorted_correlations)
```

```
Features with Lower Correlation to Target:
Interest Rates                  0.135219
Employement_rate                0.295054
Unemployement_rate              0.505809
Working_Population              0.570382
Working_age(15-64)_population   0.570382
Total_Households                0.720504
Consumer Price                  0.803227
Housing Subsides                0.828896
median_income                   0.834167
Construction Price              0.888824
Per_Capita_gdp                  0.895484
dtype: float64
```

Based on the provided correlation coefficients:

Highest Correlation:

The variable with the highest correlation with the target variable ('Case-Schiller) is 'Per_Capita_GDP' with a correlation coefficient of 0.8954845. This feature shows a strong positive linear relationship with home prices.

Other Strong Correlations:

'Construction Price' (0.888824), 'median_income' (0.834167), 'Housing Subsides' (0.828896) and 'Consumer Price' (0.803227) also have strong positive correlations.

Moderate Correlations:

'Total_Households' (0.7205042) has moderate positive correlations.

Lower Correlations:

'Interest Rates' (0.135219), 'Employement_rate' (0.295054), 'Unemployement_rate (0.505809), and 'Working_Population' (0.570382) have lower correlations.

Data Modelling

In [293]:
```
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LinearRegression, ElasticNet
from sklearn.ensemble import RandomForestRegressor, GradientBoostingReg
from sklearn.svm import SVR
from sklearn.feature_selection import SelectFromModel
from xgboost import XGBRegressor
```

We will drop the columns which has lower correlation with the target.

In [295]:
```
mult_cols = ['Working_Population','Interest Rates','Unemployement_rate'
df.drop(columns = mult_cols, inplace = True)
X = df
```

Models building

In [296]:
```
from sklearn.model_selection import train_test_split
from sklearn.metrics import r2_score, mean_squared_error
```

In [297]:
```
# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2
```

In [298]:
```
# Standardize features
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

Explored various regression models, including Linear Regression, ElasticNet, Random Forest, Gradient Boosting, Support Vector Regression (SVR), and XGBoost.

In [299]:
```
# Models
models = {
    'Linear Regression': LinearRegression(),
    'ElasticNet': ElasticNet(),
    'Random Forest': RandomForestRegressor(),
    'Gradient Boosting': GradientBoostingRegressor(),
    'SVR': SVR(),
    'XGBoost': XGBRegressor()
}
```

In [300]:

```
best_model = None
best_mse = float('inf')

# Visualize actual vs. predicted values for all models
fig, axs = plt.subplots(2, 3, figsize=(12, 10))
axs = axs.flatten()

# Training and evaluation
for i, (name, model) in enumerate(models.items()):
    model.fit(X_train_scaled, y_train)
    y_pred = model.predict(X_test_scaled)

    mse = mean_squared_error(y_test, y_pred)
    r2 = r2_score(y_test, y_pred)

    print(f"Model: {name}")
    print(f"Mean Squared Error: {mse}")
    print(f"R-squared: {r2}")

    # Display coefficients and intercept for linear models
    if hasattr(model, 'coef_'):
        print("Coefficients:")
        for feature, coef in zip(X_train.columns, model.coef_):
            print(f"{feature}: {coef}")

        print(f"Intercept: {model.intercept_}")
    else:
        # For non-linear models, display feature importance
        if hasattr(model, 'feature_importances_'):
            print("Feature Importance Analysis:")
            for feature, importance in zip(X_train.columns, model.featu
                print(f"{feature}: {importance}")

    print()

    # Update best model if current model has lower MSE
    if mse < best_mse:
        best_mse = mse
        best_model = model

    # Plot actual vs. predicted values
    axs[i].scatter(y_test, y_pred, label=name)
    axs[i].set_xlabel("Actual Home Prices")
    axs[i].set_ylabel("Predicted Home Prices")
    axs[i].set_title(f"Actual vs. Predicted ({name})")
    axs[i].legend()

# Tight layout for better spacing
plt.tight_layout()
plt.show()

print(f"\nBest Model: {type(best_model).__name__} with MSE: {best_mse}"
```

```
Model: Linear Regression
Mean Squared Error: 67.67340964966395
R-squared: 0.9716901433979442
Coefficients:
Construction Price: 20.680974431711483
Consumer Price: 10.796316333826251
Housing Subsides: 1.3280624599436481
Per_Capita_gdp: 26.140889870780207
median_income: 13.94230854656797
Total_Households: -32.1779480181388
Working_age(15-64)_population: -4.459635090948875
Intercept: 179.7899687499999

Model: ElasticNet
Mean Squared Error: 338.7242448913194
R-squared: 0.8583012907114472
Coefficients:
Construction Price: 9.766573108353047
Consumer Price: 3.170963030797105
```

In [301]:

```
# Assuming you have a DataFrame with model names and their correspondin
data = {
    'Model': ['Linear Regression', 'ElasticNet', 'Random Forest', 'Grad
    'MSE': [84.65, 205.67, 2.21, 4.81, 477.15, 3.17],
    'R-squared': [0.93, 0.83, 0.998, 0.996, 0.61, 0.997]
}

df = pd.DataFrame(data)

# Create a table plot using matplotlib
fig, ax = plt.subplots(figsize=(6, 3))

# Hide the axes
ax.axis('off')

# Create a table and add data
table = ax.table(cellText=df.values, colLabels=df.columns, cellLoc = 'c

# Style the table
table.auto_set_font_size(False)
table.set_fontsize(10)
table.scale(1.2, 1.2)  # Adjust the table size if needed

# Highlight specific values (e.g., minimum and maximum MSE)
min_mse_index = np.argmin(df['MSE'])
max_mse_index = np.argmax(df['MSE'])

for i in range(len(df)):
    for j in range(len(df.columns)):
        if (i == min_mse_index or i == max_mse_index) and j == df.colum
            color = '#ffcccb' if i == min_mse_index else '#b0e57c'  # L
            table[(i + 1, j)].set_facecolor(color)

# Highlight min and max R-squared
min_r2_index = np.argmin(df['R-squared'])
max_r2_index = np.argmax(df['R-squared'])

for i in range(len(df)):
    for j in range(len(df.columns)):
        if (i == min_r2_index or i == max_r2_index) and j == df.columns
            color = '#ffcccb' if i == min_r2_index else '#b0e57c'  # Li
            table[(i + 1, j)].set_facecolor(color)

plt.title('Model Evaluation Metrics')
plt.show()
```

Model Evaluation Metrics

Model	MSE	R-squared
Linear Regression	84.65	0.93
ElasticNet	205.67	0.83
Random Forest	2.21	0.998
Gradient Boosting	4.81	0.996
SVR	477.15	0.61
XGBoost	3.17	0.997

Decision:

Random Forest and XGBoost appear to be strong contenders, as they have low MSE and high R-squared values. Additionally, both models provide insights into feature importance.

Gradient Boosting also performs well but with a slightly higher MSE compared to Random Forest and XGBoost.

Linear Regression and ElasticNet have higher MSE values, indicating potential limitations in predictive accuracy.

SVR has a considerably higher MSE and lower R-squared, suggesting lower performance compared to other models.

Champion model: In summary, based on the provided metrics, Random Forest appear to be a strong candidate for the best model, with a low MSE and a high R-squared value.

Low MSE: The low MSE indicates that the model's predictions are close to the actual values on average, suggesting good predictive accuracy.

High R-squared: The high R-squared value suggests that a significant portion of the variance in home prices is explained by the model. This indicates strong explanatory power.

Feature Importance: The feature importance analysis provides transparency into the factors driving the predictions. In my case, features like 'CPI', 'Cons_Material', and 'median_income' are identified as influential.

This means that, according to the model, changes in these features have a notable impact on the predictions of U.S. home prices. For example, if 'CPI' increases, it suggests that changes in the cost of living might influence home prices.

Understanding feature importance is crucial for making informed decisions, refining models, and gaining insights into the factors driving the predictions, which is especially valuable in fields like economics, finance, or real estate where interpretability is essential.

In [ ]: