London Housing Data Analysis Report

Introduction

This report presents an Exploratory Data Analysis (EDA) of the London housing dataset. The analysis aims to uncover insights into housing prices, the impact of various features, and highlight key trends across different time periods and property types. Each step includes visualizations, explanations, and insights.

Data Source: London Datastore – Greater London Authority

Step 1: Data Loading and Overview

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

In [2]:
```
# Load the dataset
df = pd.read_csv("City_of_London_link_26122024.csv")
```

In [3]:
```
# Overview of the dataset
df.info()
df.head()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5836 entries, 0 to 5835
Data columns (total 16 columns):
 #   Column                         Non-Null Count  Dtype  
---  ------                         --------------  -----  
 0   priceper                       5836 non-null   float64
 1   year                           5836 non-null   int64  
 2   dateoftransfer                 5836 non-null   object 
 3   propertytype                   5836 non-null   object 
 4   duration                       5836 non-null   object 
 5   price                          5836 non-null   int64  
 6   postcode                       5836 non-null   object 
 7   lad23cd                        5836 non-null   object 
 8   transactionid                  5836 non-null   object 
 9   lmk_key                        5836 non-null   object 
 10  tfarea                         5836 non-null   float64
 11  numberrooms                    5039 non-null   float64
 12  classt                         5836 non-null   int64  
 13  CURRENT_ENERGY_EFFICIENCY      5836 non-null   int64  
 14  POTENTIAL_ENERGY_EFFICIENCY    5836 non-null   int64  
 15  CONSTRUCTION_AGE_BAND          5686 non-null   object 
dtypes: float64(3), int64(5), object(8)
memory usage: 729.6+ KB
```

Out[3]:

	priceper	year	dateoftransfer	propertytype	duration	price	postcode	lad23cd	transactionid
0	4351.648352	2002	2002-12-06	F	L	198000	E1 8RB	E09000001	{6C4E5F5C-3C58-446D-8676-C3CDD961CAB8}
1	3619.588361	2000	2000-03-08	F	L	153000	EC4V 3PL	E09000001	{D4886E7B-0F98-4255-93F5-42946A43D503}
2	5441.211261	2002	2002-09-26	F	L	230000	EC4V 3PL	E09000001	{25475B09-53BE-4738-AD78-22315C76E705}
3	11462.765957	2014	2014-05-27	F	L	1077500	EC1A 7HN	E09000001	{5F107CC0-E753-41BE-8747-41680C2642C9}
4	3170.212766	1999	1999-04-23	F	L	298000	EC1A 7HN	E09000001	{527813A5-9E07-406A-9F17-7F5A9C83B9A4}

Conclusion:

- 5836 rows and 16 columns
- Key features: price, propertytype, duration, postcode, construction_age_band, dateoftransfer, and more.
- Missing values were identified in the numberrooms and CONSTRUCTION_AGE_BAND columns.

Step 2: Handling Missing Values

In [4]:

```
# Filling missing values
df['numberrooms'].fillna(df['numberrooms'].mean(), inplace=True)
df['CONSTRUCTION_AGE_BAND'].fillna(df['CONSTRUCTION_AGE_BAND'].mode()[0], inplace=True)
```

Conclusion:

Both columns were successfully filled using appropriate methods:

- numberrooms was filled using the mean value to maintain balance in continuous numerical data. Since the distribution of this column was not heavily skewed, using the mean ensures minimal impact on data integrity.

- CONSTRUCTION_AGE_BAND was filled with the mode (most frequent value), which is appropriate for categorical data and helps retain the most common construction period in the dataset.

These approaches ensured that no missing data remained in the dataset, improving data completeness for subsequent analyses.

Step 3: Date Conversion and Feature Extraction

In [5]:

```
df['dateoftransfer'] = pd.to_datetime(df['dateoftransfer'])
df['transfer_year'] = df['dateoftransfer'].dt.year
```

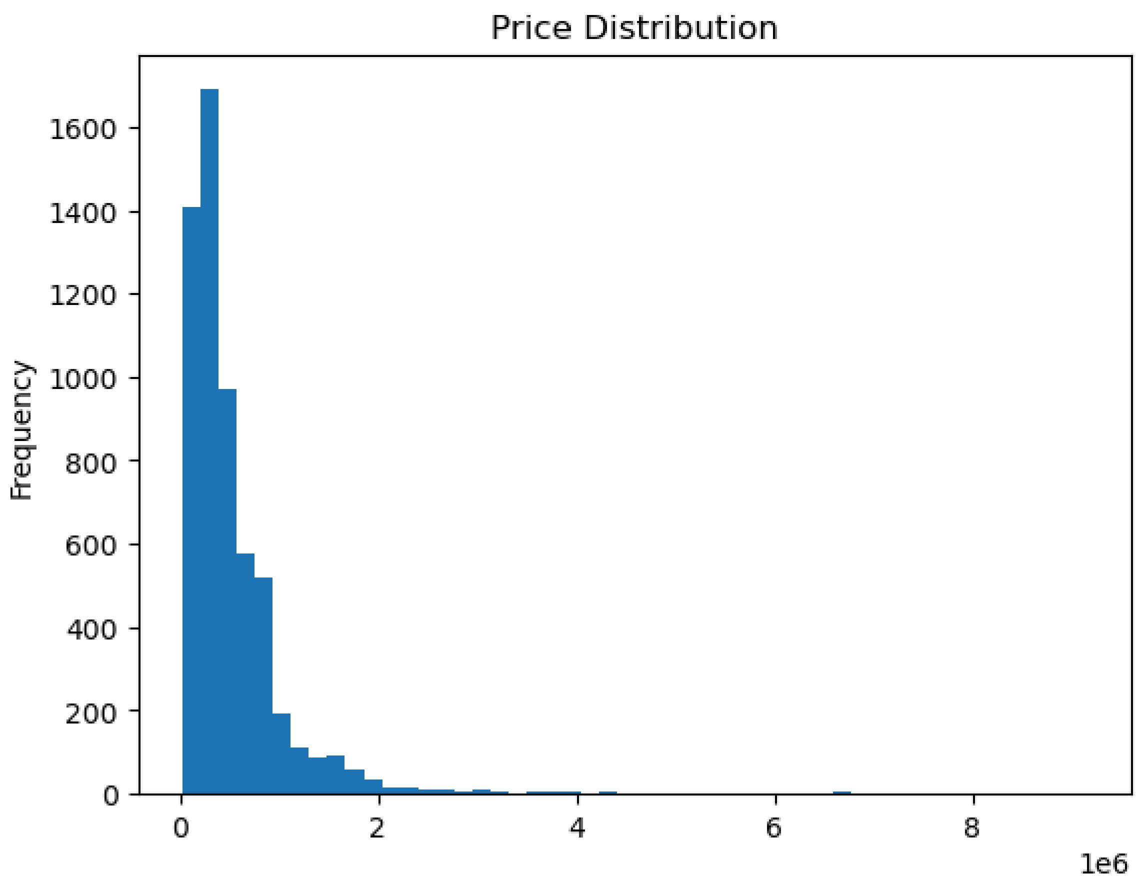
```python
df['transfer_month'] = df['dateoftransfer'].dt.month
df['transfer_day'] = df['dateoftransfer'].dt.day
```

Conclusion:

The date conversion enables better time-based analysis, while the new features allow for more flexible trend identification.

Step 4: Price Distribution Analysis

In [6]:
```python
# Price distribution
df["price"].plot(kind = "hist", bins = 50, title = "Price Distribution")
plt.show()
```



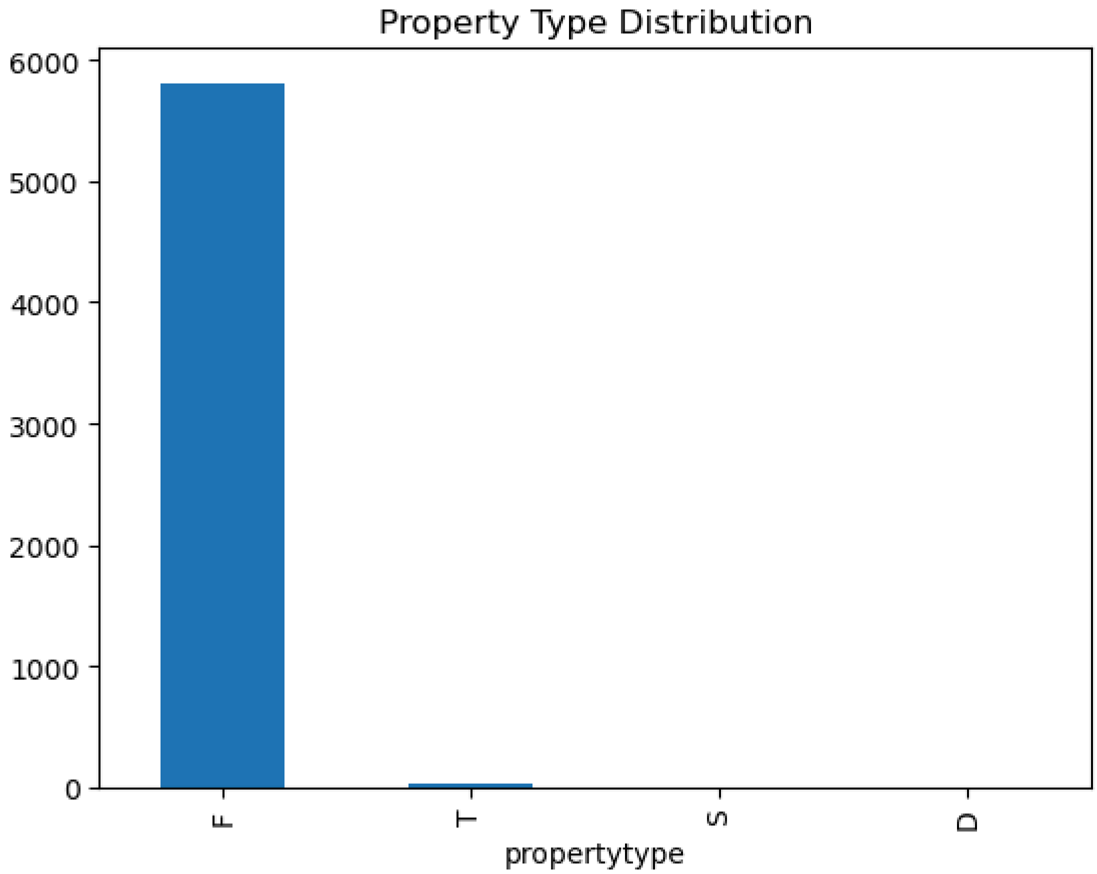
In [7]:
```python
# Capping extreme values
upper_limit = 1357500
df['price'] = df['price'].clip(upper=upper_limit)
```

Conclusion:

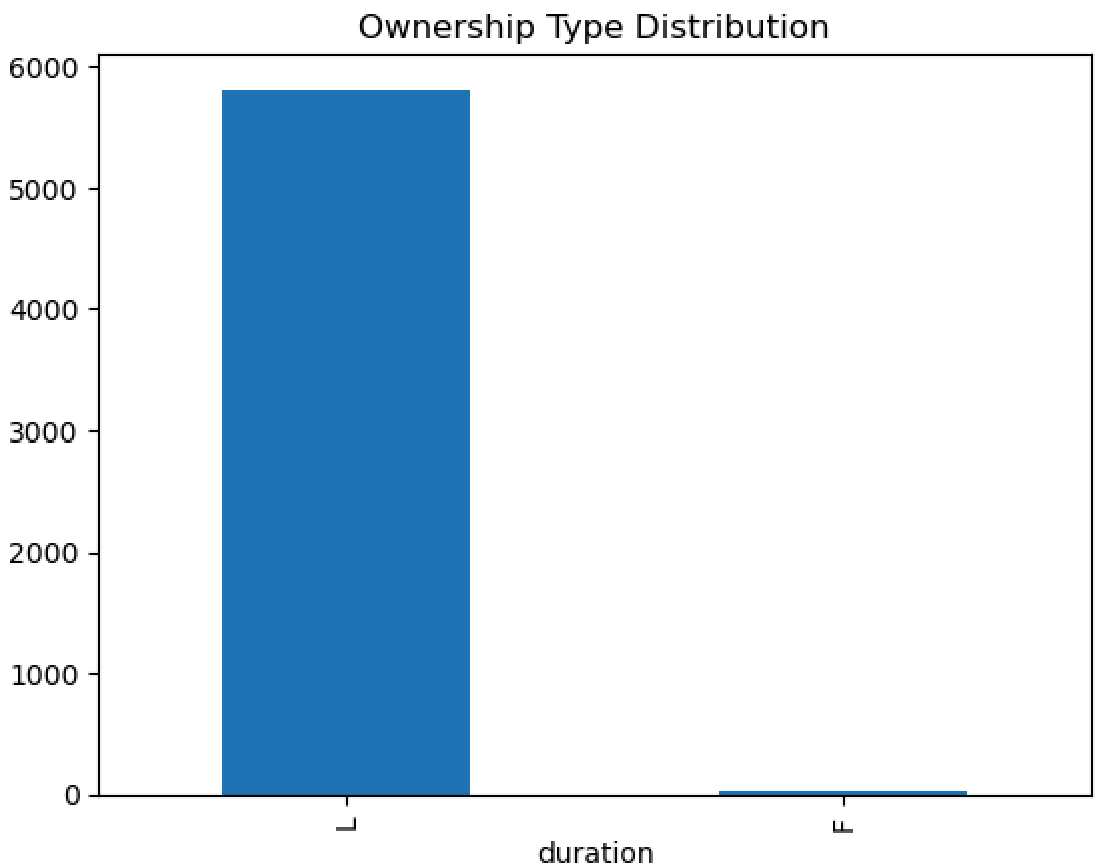
- Housing prices showed a right-skewed distribution.
- After capping, the dataset retained its core distribution while reducing the influence of extreme values.

Step 5: Categorical Feature Analysis

In [8]:
```python
# Property Type Distribution
df['propertytype'].value_counts().plot(kind='bar', title='Property Type Distribution')
plt.show()
```



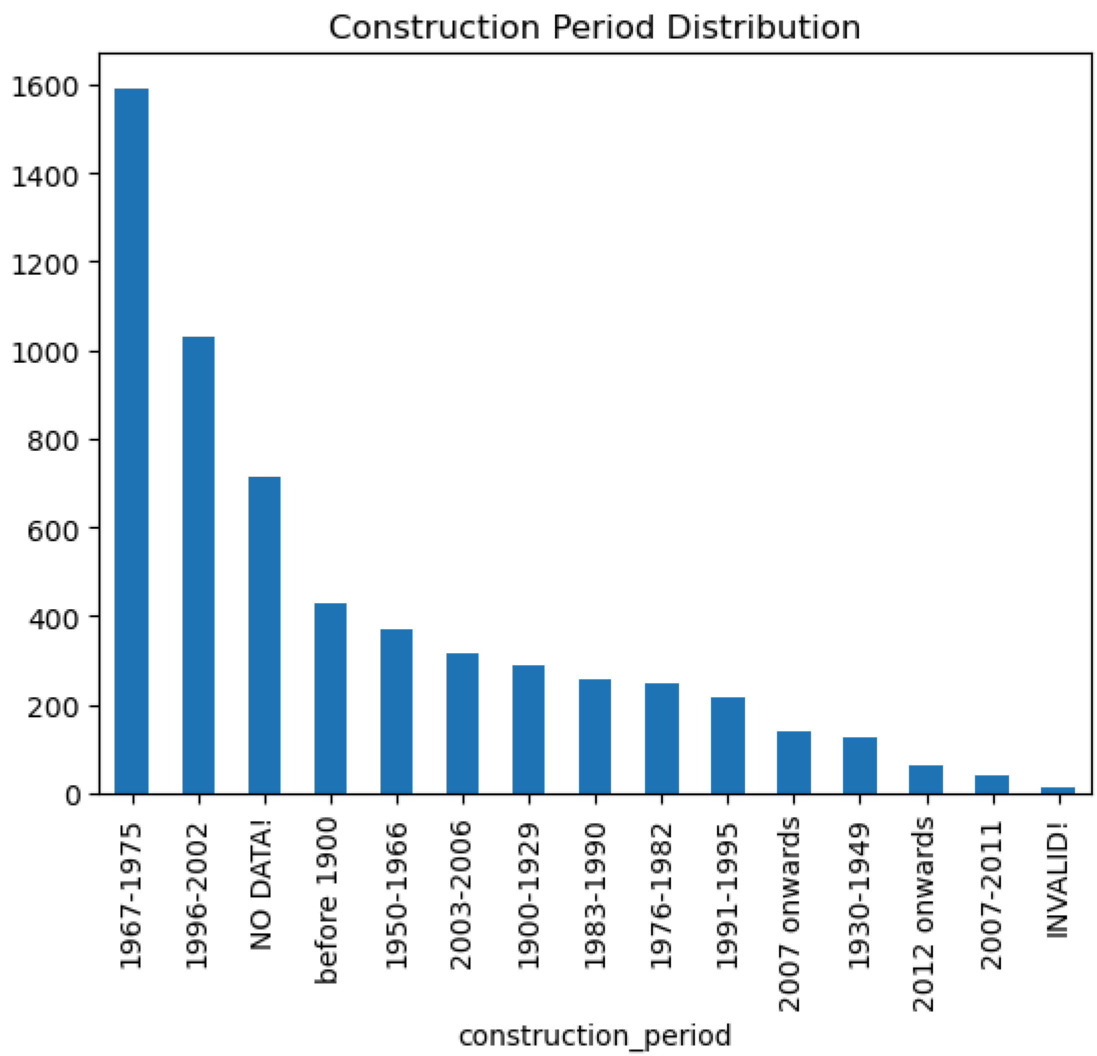
In [9]:
```
# Ownership Type Distribution
df['duration'].value_counts().plot(kind='bar', title='Ownership Type Distribution')
plt.show()
```



In [10]:
```
# Extracting construction period
df['construction_period'] = df['CONSTRUCTION_AGE_BAND'].str.replace('England and Wales: ', ''
```

In [11]:
```
# Visualizing construction periods
df['construction_period'].value_counts().plot(kind='bar', title='Construction Period Distribu
```

```
plt.show()
```

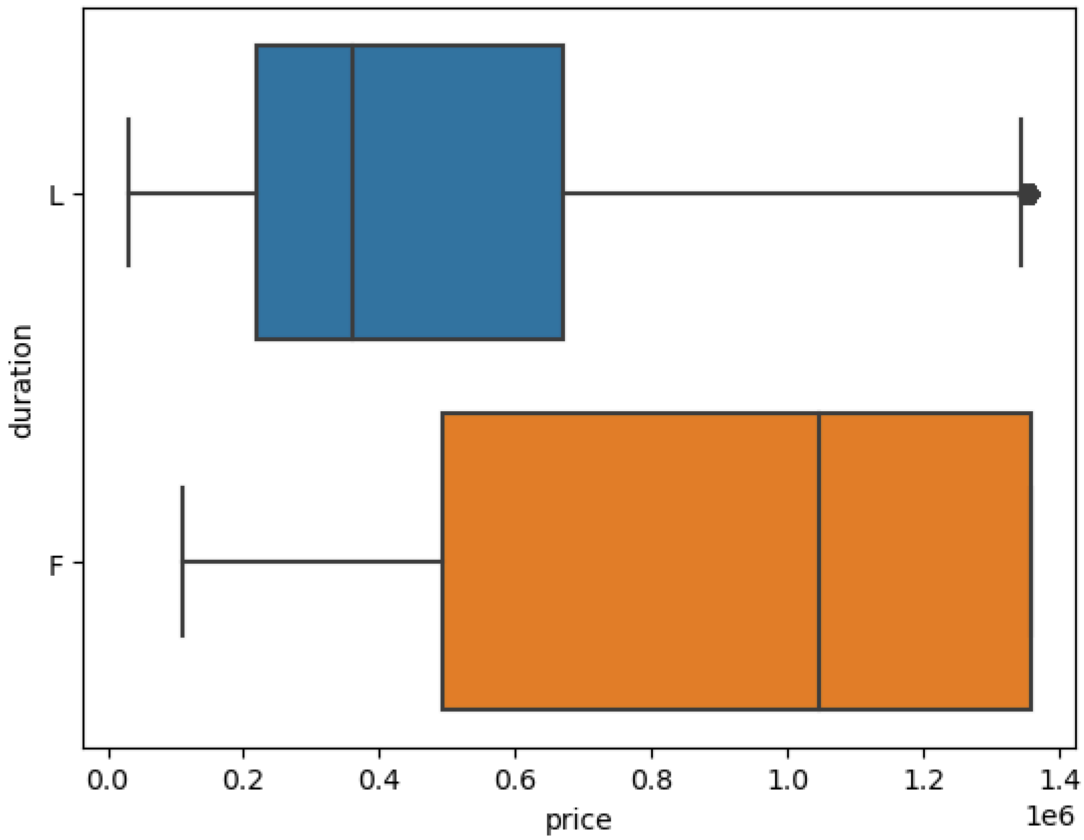


Conclusion:

- Flats were confirmed as the most common property type based on the frequency analysis.
- Leasehold ownership was confirmed to be significantly more common than Freehold.
- The most common construction periods were 1950-1966 and 1996-2002.

Step 7: Impact of Ownership Type (duration) on Price

In [12]:
```
# Ownership type price analysis
sns.boxplot(data=df, x='price', y='duration')
plt.show()
```

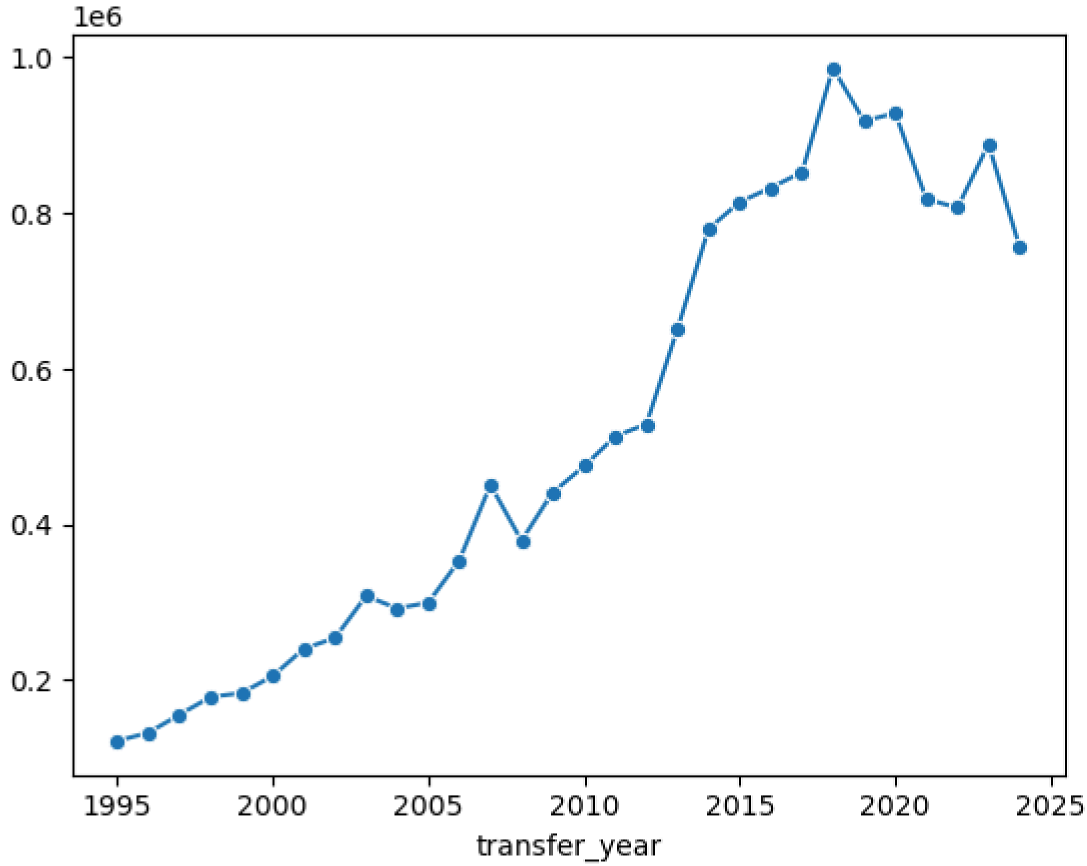


Conclusion:

Freehold properties were significantly more expensive than Leasehold properties.

Step 8: Time-Series Analysis

In [13]:
```
# Time-series price trend analysis
price_trend = df.groupby('transfer_year')['price'].mean()
sns.lineplot(x=price_trend.index, y=price_trend.values, marker='o')
plt.show()
```



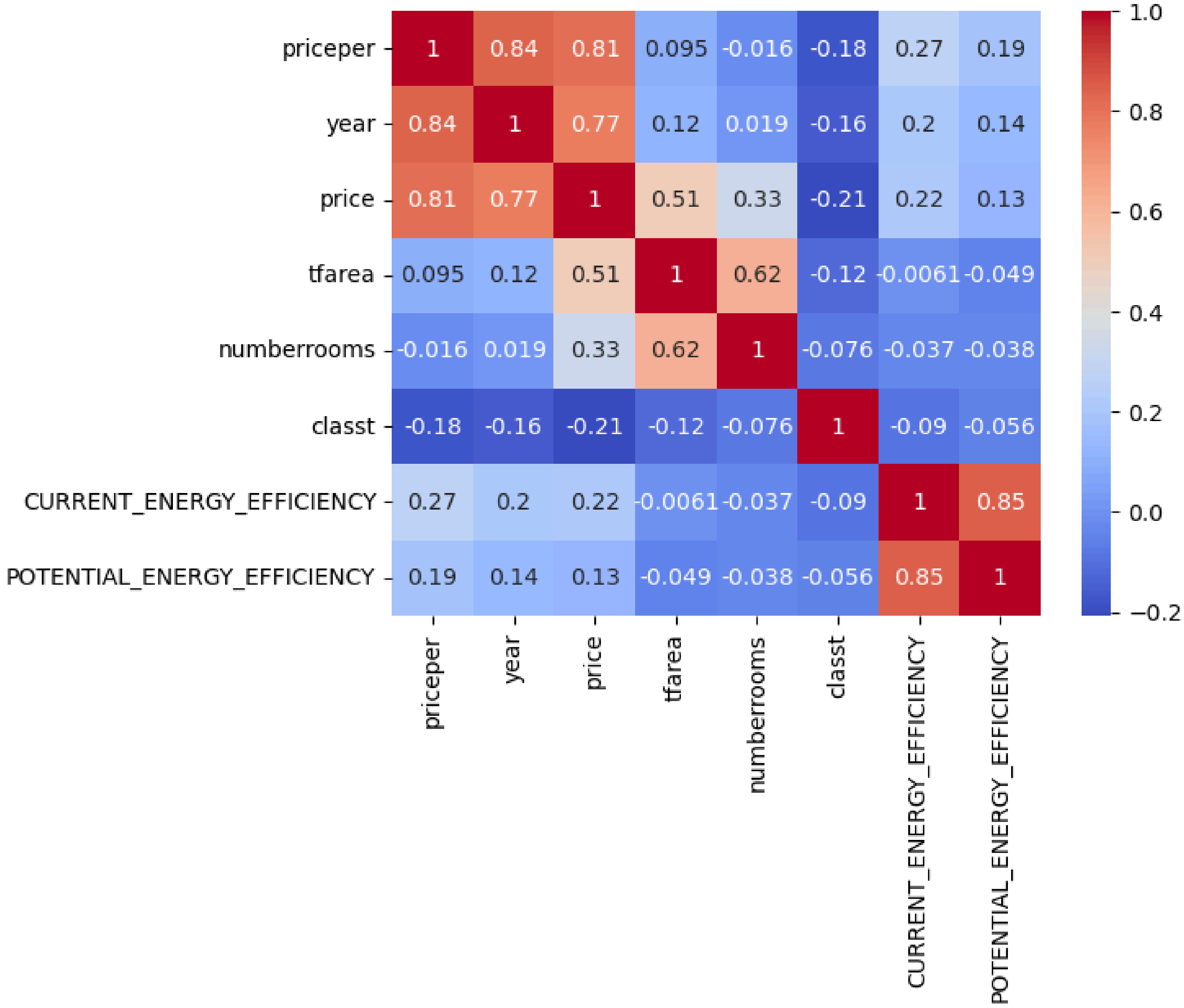
Conclusion:

- Prices rose significantly from 2000 to 2008, followed by a sharp drop during the 2008 financial crisis.
- Prices peaked around 2016, likely influenced by Brexit and economic uncertainties.
- The post-2016 period showed volatility, with mixed price trends.

Step 9: Correlation Analysis

In [14]:
```
# Select only numerical columns
numeric_data = df.select_dtypes(include=['float64', 'int64'])

# Correlation matrix
correlation_matrix = numeric_data.corr()
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm')
plt.show()
```



Conclusion:

- Strongest correlations with price were seen in:
    - priceper (+0.88)
    - tfarea (+0.57)
- numberrooms (+0.49)

Energy efficiency ratings showed minimal correlation with property prices.

```
In [ ]:
```