Group 7 Project Submission

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In [1]:
```
# import standard packages

import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
import numpy as np
import warnings
warnings.filterwarnings ('ignore')
import matplotlib.pyplot as plt
plt.style.use('ggplot')
from scipy import stats
import statsmodels.api as sm
import statsmodels.graphics as smg
import statsmodels.stats.api as sms
from statsmodels.stats.outliers_influence import variance_inflation_factor
import datetime as dt
```

In [2]:
```
#Loading data set for Analysis
kc = pd.read_csv(r"C:\Users\HP\Documents\Flatiron\Assignments\Phase 2 Project\kc_house_data.csv")

kc.head(5)
```

Out[2]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	...	grade	sqft_above	sqft
0	7129300520	10/13/2014	221900	3	1.00	1180	5650	1.0	NaN	NONE	...	7 Average	1180	
1	6414100192	12/9/2014	538000	3	2.25	2570	7242	2.0	NO	NONE	...	7 Average	2170	
2	5631500400	2/25/2015	180000	2	1.00	770	10000	1.0	NO	NONE	...	6 Low Average	770	
3	2487200875	12/9/2014	604000	4	3.00	1960	5000	1.0	NO	NONE	...	7 Average	1050	
4	1954400510	2/18/2015	510000	3	2.00	1680	8080	1.0	NO	NONE	...	8 Good	1680	

5 rows × 21 columns

In [3]:
```
#Data understanding and exploration
kc.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 21597 entries, 0 to 21596
Data columns (total 21 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   id             21597 non-null  int64  
 1   date           21597 non-null  object 
 2   price          21597 non-null  int64  
 3   bedrooms       21597 non-null  int64  
 4   bathrooms      21597 non-null  float64
 5   sqft_living    21597 non-null  int64  
 6   sqft_lot       21597 non-null  int64  
 7   floors         21597 non-null  float64
 8   waterfront     19221 non-null  object 
 9   view           21534 non-null  object 
 10  condition      21597 non-null  object 
 11  grade          21597 non-null  object 
 12  sqft_above     21597 non-null  int64  
 13  sqft_basement  21597 non-null  object 
 14  yr_built       21597 non-null  int64  
 15  yr_renovated   17755 non-null  float64
 16  zipcode        21597 non-null  int64  
 17  lat            21597 non-null  float64
 18  long           21597 non-null  float64
 19  sqft_living15  21597 non-null  int64  
 20  sqft_lot15     21597 non-null  int64  
dtypes: float64(5), int64(10), object(6)
memory usage: 3.5+ MB
```

In [4]:
```
kc.describe()
```

Out[4]:

	id	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	sqft_above	yr_built
count	2.159700e+04	2.159700e+04	21597.000000	21597.000000	21597.000000	2.159700e+04	21597.000000	21597.000000	21597.000000
mean	4.580474e+09	5.402966e+05	3.373200	2.115826	2080.321850	1.509941e+04	1.494096	1788.596842	1970.999676
std	2.876736e+09	3.673681e+05	0.926299	0.768984	918.106125	4.141264e+04	0.539683	827.759761	29.375234
min	1.000102e+06	7.800000e+04	1.000000	0.500000	370.000000	5.200000e+02	1.000000	370.000000	1900.000000
25%	2.123049e+09	3.220000e+05	3.000000	1.750000	1430.000000	5.040000e+03	1.000000	1190.000000	1951.000000
50%	3.904930e+09	4.500000e+05	3.000000	2.250000	1910.000000	7.618000e+03	1.500000	1560.000000	1975.000000
75%	7.308900e+09	6.450000e+05	4.000000	2.500000	2550.000000	1.068500e+04	2.000000	2210.000000	1997.000000
max	9.900000e+09	7.700000e+06	33.000000	8.000000	13540.000000	1.651359e+06	3.500000	9410.000000	2015.000000

In [5]:
```
#changing the selling date to  and updating the column name to yr_sold
kc['date']=pd.to_datetime(kc['date'])
kc['date'] = kc['date'].dt.year
```

In [6]:
```
kc.rename (columns={'date': 'yr_sold'}, inplace=True)
```

In [8]:
```
kc['yr_sold']= kc['yr_sold'].astype(int)
```

In [9]:
```
kc.head(5)
```

Out[9]:

	id	yr_sold	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	...	grade	sqft_above	sqft_ba
0	7129300520	2014	221900	3	1.00	1180	5650	1.0	NaN	NONE	...	7 Average	1180	
1	6414100192	2014	538000	3	2.25	2570	7242	2.0	NO	NONE	...	7 Average	2170	
2	5631500400	2015	180000	2	1.00	770	10000	1.0	NO	NONE	...	6 Low Average	770	
3	2487200875	2014	604000	4	3.00	1960	5000	1.0	NO	NONE	...	7 Average	1050	
4	1954400510	2015	510000	3	2.00	1680	8080	1.0	NO	NONE	...	8 Good	1680	

5 rows × 21 columns

In [10]:
```
kc.isna().sum()
```

Out[10]:
```
id                0
yr_sold           0
price             0
bedrooms          0
bathrooms         0
sqft_living       0
sqft_lot          0
floors            0
waterfront     2376
view             63
condition         0
grade             0
sqft_above        0
sqft_basement     0
yr_built          0
yr_renovated   3842
zipcode           0
lat               0
long              0
sqft_living15     0
sqft_lot15        0
dtype: int64
```

In [11]:
```
#Filling missing values in the 'view' and 'waterfront' columns
kc['waterfront'].fillna('NO', inplace=True)
kc['view'].fillna('NONE', inplace=True)
kc.isna().sum()
```

Out[11]:
```
id                0
yr_sold           0
price             0
bedrooms          0
bathrooms         0
sqft_living       0
sqft_lot          0
floors            0
waterfront        0
view              0
condition         0
grade             0
sqft_above        0
sqft_basement     0
yr_built          0
yr_renovated     3842
zipcode           0
lat               0
long              0
sqft_living15     0
sqft_lot15        0
dtype: int64
```

In [12]:
```
#Counting the occurences of unique values in 'yr_revovated'
kc['yr_renovated'].value_counts()
```

Out[12]:
```
0.0       17011
2014.0       73
2003.0       31
2013.0       31
2007.0       30
            ...
1946.0        1
1959.0        1
1971.0        1
1951.0        1
1954.0        1
Name: yr_renovated, Length: 70, dtype: int64
```

In [13]:
```
kc['yr_renovated'].fillna(0.0, inplace=True)
```

In [14]:
```
kc['yr_renovated'].astype(int)
```

Out[14]:
```
0           0
1        1991
2           0
3           0
4           0
          ...
21592       0
21593       0
21594       0
21595       0
21596       0
Name: yr_renovated, Length: 21597, dtype: int32
```

In [15]:
```
kc.isna().sum()
```

Out[15]:
```
id               0
yr_sold          0
price            0
bedrooms         0
bathrooms        0
sqft_living      0
sqft_lot         0
floors           0
waterfront       0
view             0
condition        0
grade            0
sqft_above       0
sqft_basement    0
yr_built         0
yr_renovated     0
zipcode          0
lat              0
long             0
sqft_living15    0
sqft_lot15       0
dtype: int64
```

In [17]:
```
yr_renovated = kc['yr_renovated']
kc['renovated_last_10'] = (yr_renovated >= (kc['yr_sold'] - 10))
kc['renovated_last_10'] = kc['renovated_last_10'].map({True: 'Yes', False: 'No'})
```

In [18]:
```
kc.head(5)
```

Out[18]:

	id	yr_sold	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	...	sqft_above	sqft_basement
0	7129300520	2014	221900	3	1.00	1180	5650	1.0	NO	NONE	...	1180	0
1	6414100192	2014	538000	3	2.25	2570	7242	2.0	NO	NONE	...	2170	400
2	5631500400	2015	180000	2	1.00	770	10000	1.0	NO	NONE	...	770	0
3	2487200875	2014	604000	4	3.00	1960	5000	1.0	NO	NONE	...	1050	910
4	1954400510	2015	510000	3	2.00	1680	8080	1.0	NO	NONE	...	1680	0

5 rows × 22 columns

In [19]:
```
kc['Age'] = kc['yr_sold']-kc['yr_built']
```

In [20]:
```
kc.head(5)
```

Out[20]:

	id	yr_sold	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	...	sqft_basement	yr_built	yr_
0	7129300520	2014	221900	3	1.00	1180	5650	1.0	NO	NONE	...	0	1955	
1	6414100192	2014	538000	3	2.25	2570	7242	2.0	NO	NONE	...	400	1951	
2	5631500400	2015	180000	2	1.00	770	10000	1.0	NO	NONE	...	0	1933	
3	2487200875	2014	604000	4	3.00	1960	5000	1.0	NO	NONE	...	910	1965	
4	1954400510	2015	510000	3	2.00	1680	8080	1.0	NO	NONE	...	0	1987	

5 rows × 23 columns

In [21]:
```
#Dropping columns that are not needed
columns_to_drop = ['id','zipcode','lat','long','sqft_living15','sqft_lot15','sqft_basement','yr_sold','yr_ren
kc.drop(columns_to_drop, axis = 1, inplace = True)
```

In [22]:
```
#Confirming the new dataframe
kc.head(5)
```

Out[22]:

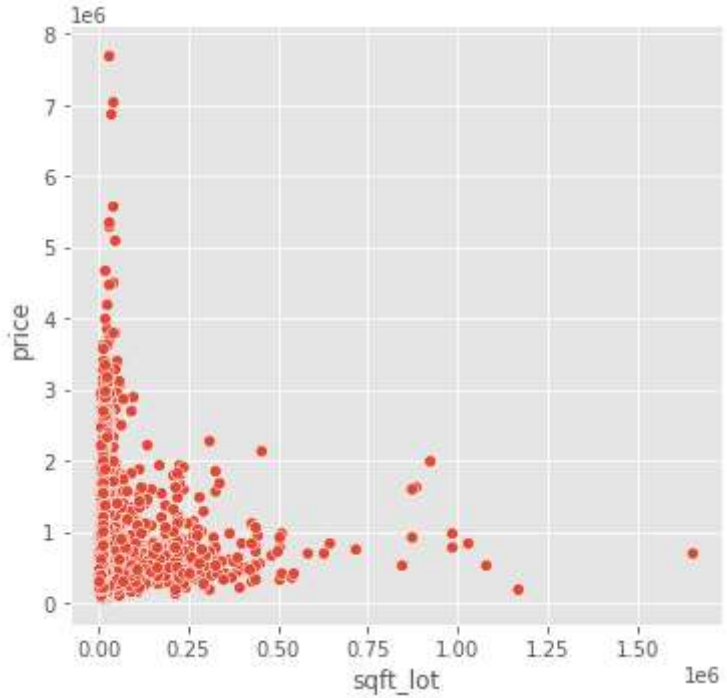
	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition	grade	sqft_above	yr_built	renovated_la
0	221900	3	1.00	1180	5650	1.0	NO	NONE	Average	7 Average	1180	1955	
1	538000	3	2.25	2570	7242	2.0	NO	NONE	Average	7 Average	2170	1951	
2	180000	2	1.00	770	10000	1.0	NO	NONE	Average	6 Low Average	770	1933	
3	604000	4	3.00	1960	5000	1.0	NO	NONE	Very Good	7 Average	1050	1965	
4	510000	3	2.00	1680	8080	1.0	NO	NONE	Average	8 Good	1680	1987	

Visualizing

In [24]:
```
#Creating a plotting function for ease or resizing in different plots
def resizeplot(l,a):
    plt.figure(figsize=(l,a));
```

In [25]:
```
#Creating a plot that will visualize the relationship between price and sqft_lot
resizeplot(6,4)
sns.relplot(x='sqft_lot',y='price',data=kc,palette='terrain');
plt.show()
```

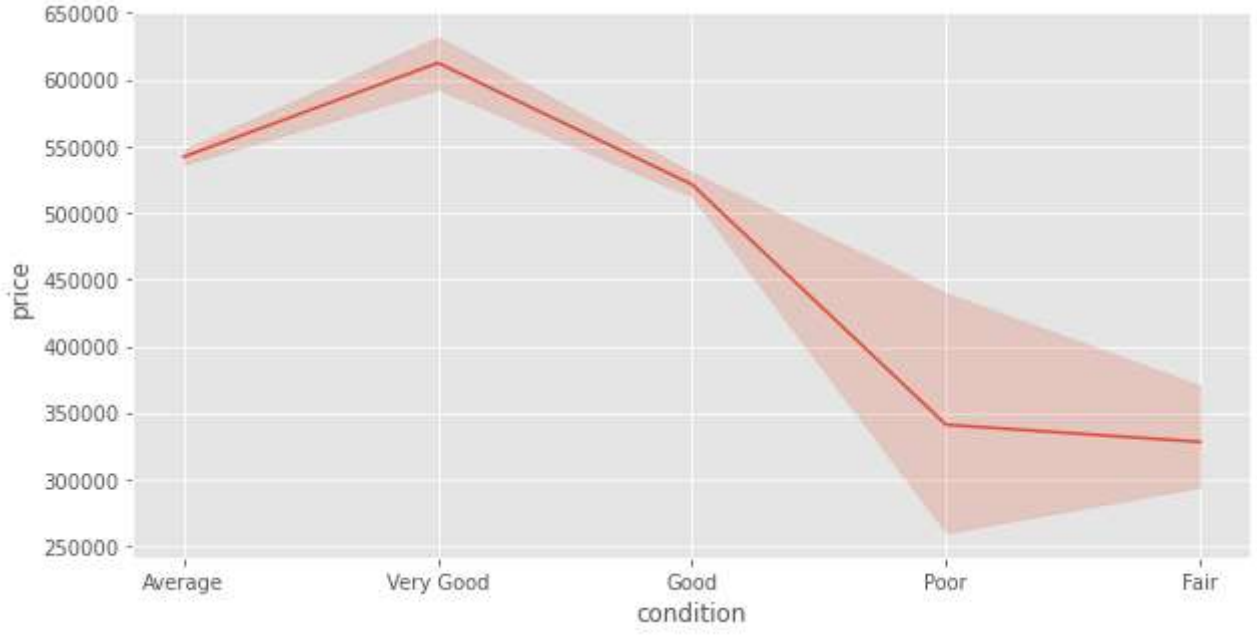
```
<Figure size 432x288 with 0 Axes>
```



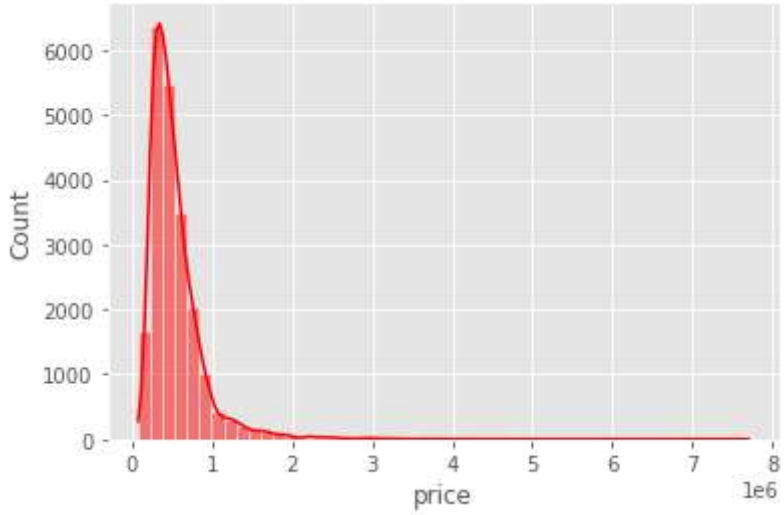
In [26]:
```
#Finding out the occurences of bedroom values
bedrooms_counts = kc['bedrooms'].value_counts()
bedrooms_counts
```

Out[26]:
```
3     9824
4     6882
2     2760
5     1601
6      272
1      196
7       38
8       13
9        6
10       3
11       1
33       1
Name: bedrooms, dtype: int64
```

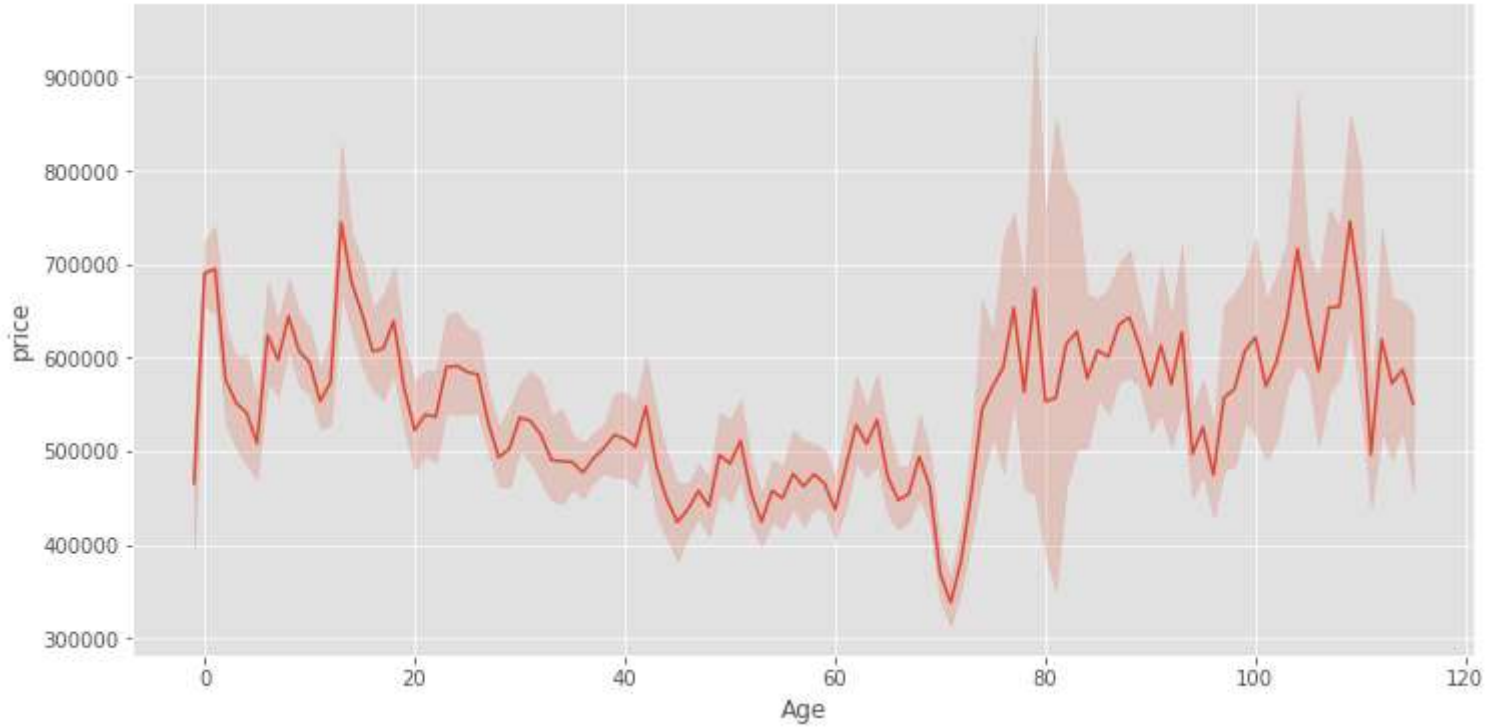
In [27]:
```
#Confirming how the conditon of the house over the year affects the price
#We can see that if the conditon of the house- is improved then the price of the house is higher
#Poor conditons leads to lower price
resizeplot(10,5)
sns.lineplot(x='condition',y='price',data=kc,palette='terrain')
plt.show()
```



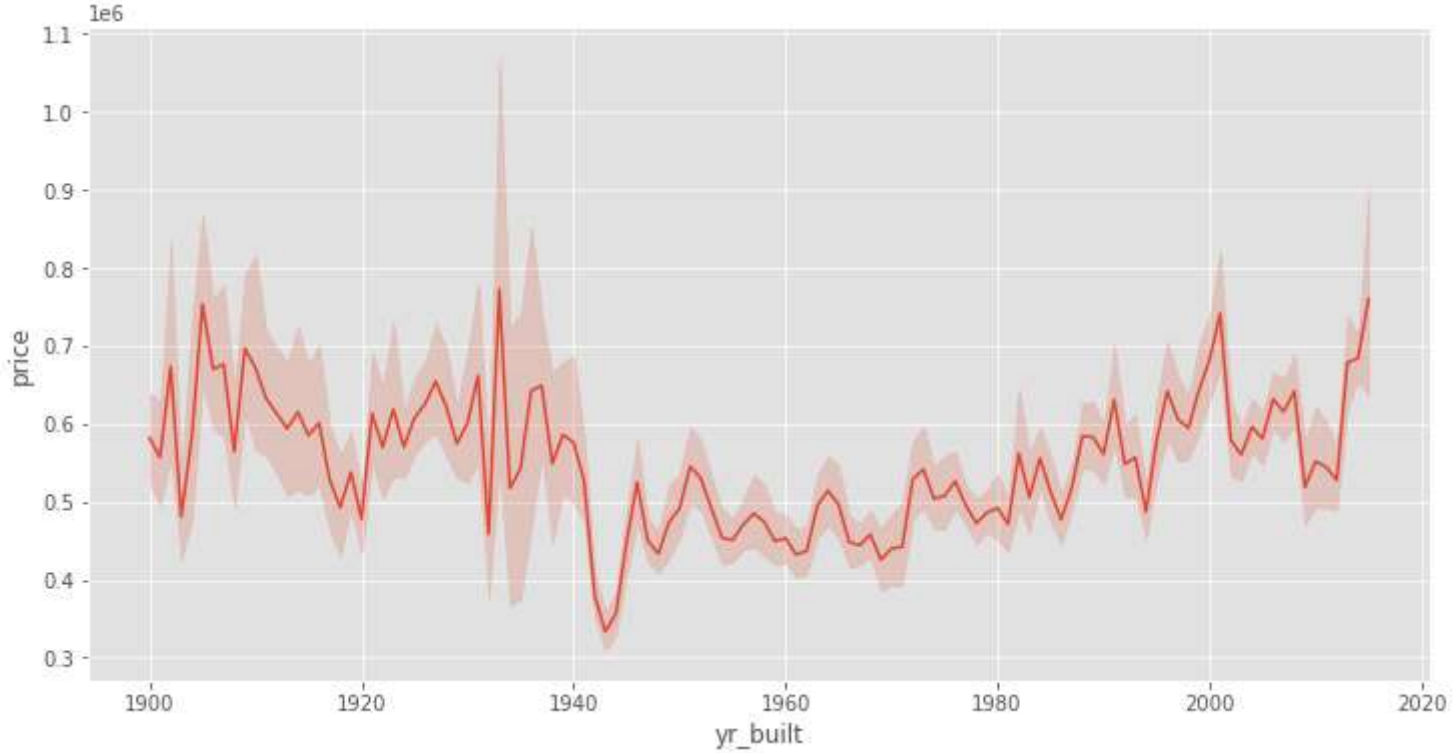
In [28]:
```
#Using histogram to visualize the distribution of the price
#As the count is high then the price increases
resizeplot(6,4)
sns.histplot(kc['price'],kde=True,bins=50, color = 'red');
```



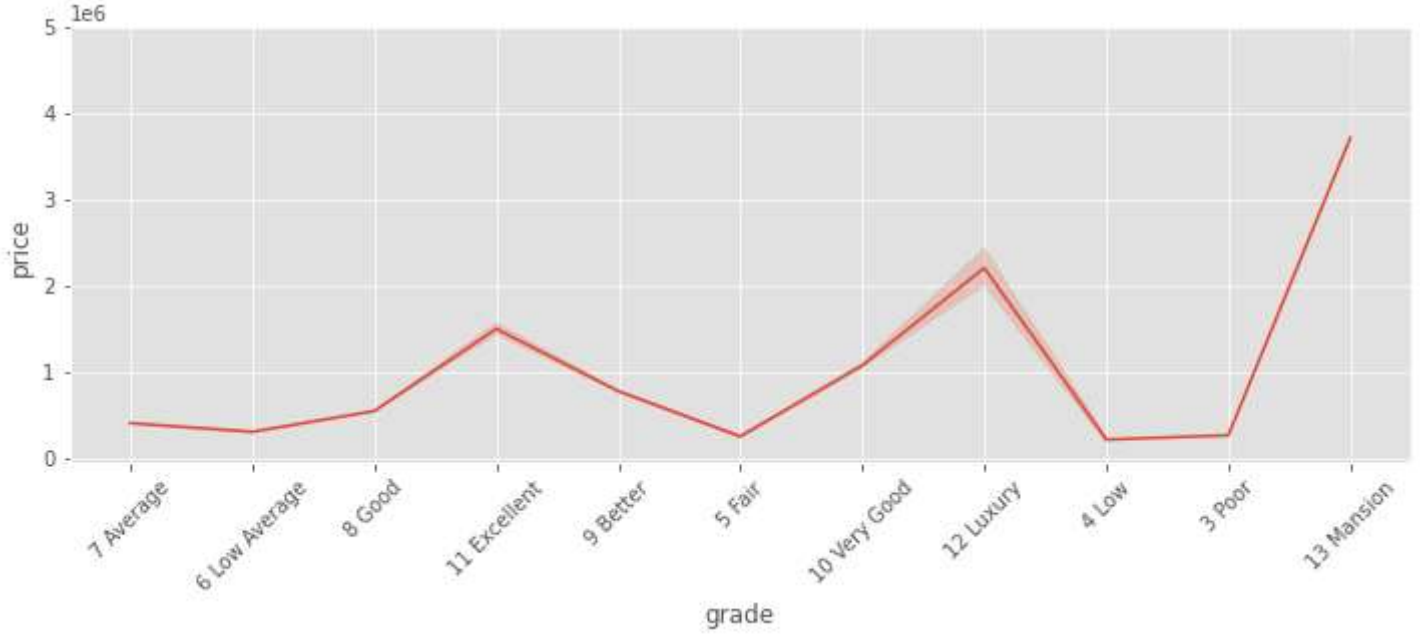
In [29]:
```
#Using linear to analyse price increament over the year
#At the begginging of the yrs the price is low as the yrs increases then the price has a higher peak

resizeplot(12,6)
sns.lineplot(x='Age',y='price',data=kc);
```



In [30]:
```
#Price trend over the years
#The price from 2000 to 2015 was good meaning the owners of real estaste were getting good profit
#It seems that the houses had been reinovated

resizeplot(12,6)
sns.lineplot(x='yr_built',y='price',data=kc,palette = 'deep');
```

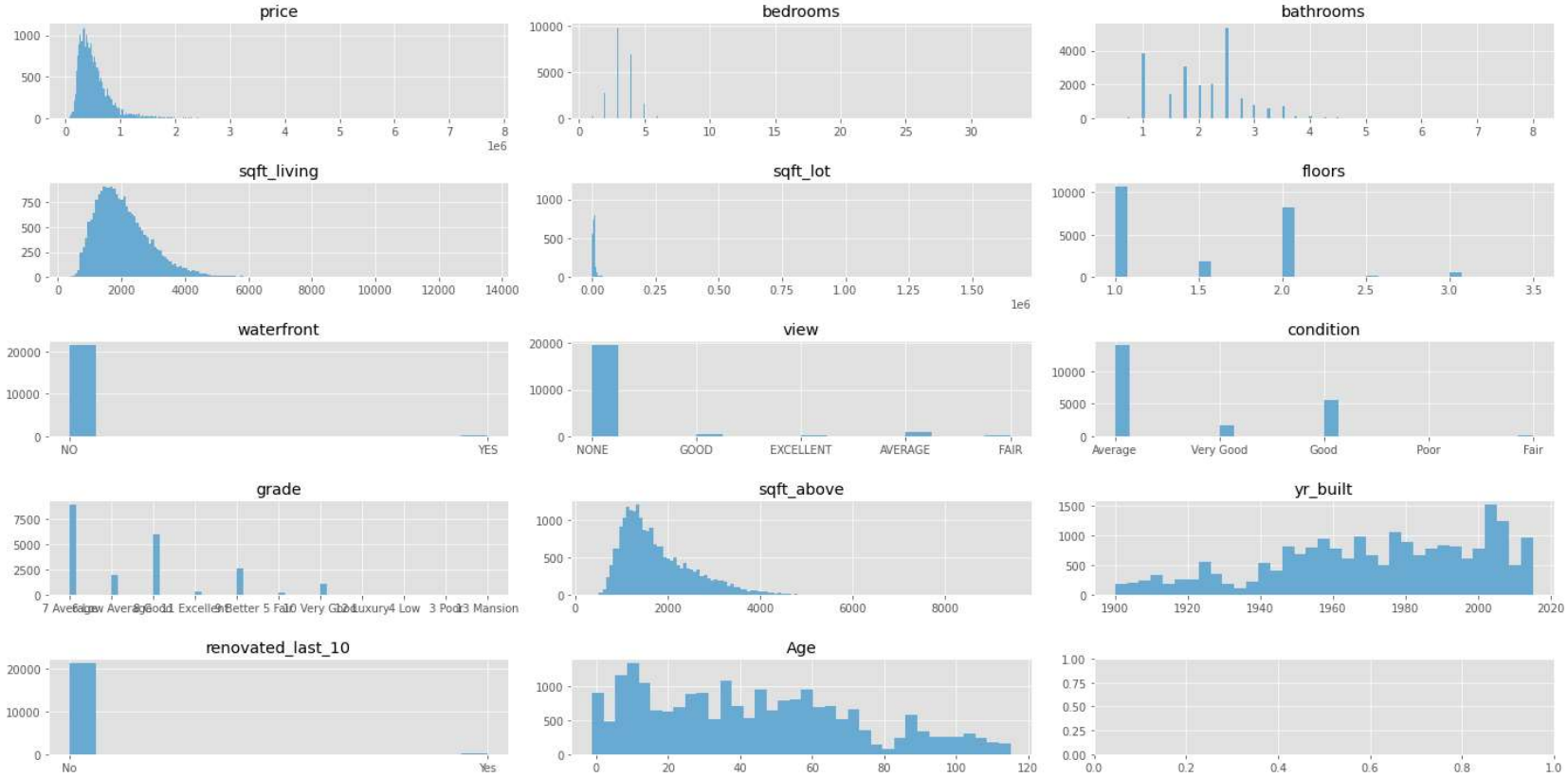


In [31]:
```
#Showing the price changes in relation to unit grade
# poor grade causes the price to decrease and vice versa
resizeplot(12,4)# changed the size to give a better view of the grade.
sns.lineplot(x='grade',y='price',data=kc,palette='terrain');
plt.xticks(rotation=45)
plt.show()
```



Categorical Variables

In [32]:
```
# Plotting histogram for columns within the dataset
#The histogram shows us how different features in each column affect each other

fig, axes = plt.subplots(nrows=(5), ncols=3, figsize=(20,10))
df_cols = kc.columns

# Using sns color pallets for each plot

color = sns.color_palette("Blues", n_colors=1)[0]

# creation of a function for plotting the hustogram for the given columns

for col, ax in zip(df_cols, axes.flatten()):
    ax.hist(kc[col].dropna(), bins='auto', color=color )
    ax.set_title(col)


# automatically adjusting subplot params so that the subplot(s) fits in to the figure area

fig.tight_layout()
```


price
bedrooms
bathrooms
sqft_living
sqft_lot
floors
waterfront
NO
YES
view
NONE
GOOD
EXCELLENT
AVERAGE
FAIR
condition
Average
Very Good
Good
Poor
Fair
grade
sqft_above
yr_built
renovated_last_10
No
Yes
Age

In [33]:
```
#From the above plots we can see that floors,waterfront,condition,grade,renovated_last_10,bedrooms,bathrooms

#Creating a category of values to work with
categories = ['bedrooms', 'bathrooms', 'floors', 'waterfront', 'view', 'condition', 'grade', 'renovated_last_

for cate in categories:

    # getting the  value counts

    counts = kc[cate].value_counts()

    # Isolate offending categories for each variable

    bad_cate = counts[counts < 50].index

    # Isolate indices in the dataset where offending categories are found

    to_drop = kc[kc[cate].isin(bad_cate)].index
    # Dropping unnecessary data within the category in dataset
    kc.drop(to_drop, inplace=True)
```

In [34]:
```
# converting view into binary (binarzing)
#for consistent and easier to compare in the view.
view_dict = {
    'FAIR': 1,
    'AVERAGE': 1,
    'GOOD': 1,
    'EXCELLENT': 1,
    'NONE': 0
}

kc['view'] = kc['view'].map(view_dict)

# Binarizing waterfront
waterfront_dict = {
    'YES': 1,
    'NO': 0
}

kc['waterfront'] = kc['waterfront'].map(waterfront_dict)

# Binarizing renovated_last_10
renovated_dict = {
    'Yes': 1,
    'No': 0
}

kc['renovated_last_10'] = kc['renovated_last_10'].map(renovated_dict)
```

OneHotEncoding

In [35]:
```
#Creating a copy of the dataset so as not to alter the original copy incase
kc2= kc.copy()
```

Generating dummies

In [36]:
```
#Converting the 3columns: bedrooms,bathrooms,floors to string for pandas to be able to dumify them
col = ['bedrooms', 'bathrooms', 'floors']
kc[col] =  kc[col].astype(str)
```

In [37]:
```
#Checking if the conversion was successful
kc.dtypes
```

Out[37]:
```
price                 int64
bedrooms             object
bathrooms            object
sqft_living           int64
sqft_lot              int64
floors               object
waterfront            int64
view                  int64
condition            object
grade                object
sqft_above            int64
yr_built              int64
renovated_last_10     int64
Age                   int64
dtype: object
```

In [38]:
```
# Creating variable from the already cleaned original dataset
kc_binary = kc[['waterfront', 'view', 'renovated_last_10']]
kc_num = kc[['price', 'sqft_living', 'sqft_lot', 'Age']]
kc_cate = kc[['floors', 'bedrooms', 'bathrooms', 'condition', 'grade']]
```

In [39]:
```
# Applying one-hot encoding to the categorical features
kc_cate_dummies = pd.get_dummies(kc_cate, dtype=int)
```

In [40]:
```
#Creating a list of dummies to be dropped

dummies_to_drop = [
    'floors_1.0',
    'bedrooms_1',
    'bathrooms_0.75',
    'condition_Fair',
    'grade_5 Fair'
    ]
#Dropping the specified dummies

kc_cate_dummies.drop(
    dummies_to_drop,
     axis = 1,
     inplace=True)
```

In [41]:
```
#Combining the variable into a single variable
kc = pd.concat([kc_num, kc_binary, kc_cate_dummies], axis=1)
```

In [42]:
```
#Confirming if the event was successful
kc.head()
```

Out[42]:

	price	sqft_living	sqft_lot	Age	waterfront	view	renovated_last_10	floors_1.5	floors_2.0	floors_2.5	...	condition_Average	cond
0	221900	1180	5650	59	0	0	0	0	0	0	...	1	
1	538000	2570	7242	63	0	0	0	0	1	0	...	1	
2	180000	770	10000	82	0	0	0	0	0	0	...	1	
3	604000	1960	5000	49	0	0	0	0	0	0	...	0	
4	510000	1680	8080	28	0	0	0	0	0	0	...	1	

5 rows × 40 columns

In [43]:
```
#Confirming the columns
kc.columns
```

Out[43]:
```
Index(['price', 'sqft_living', 'sqft_lot', 'Age', 'waterfront', 'view',
       'renovated_last_10', 'floors_1.5', 'floors_2.0', 'floors_2.5',
       'floors_3.0', 'bedrooms_2', 'bedrooms_3', 'bedrooms_4', 'bedrooms_5',
       'bedrooms_6', 'bathrooms_1.0', 'bathrooms_1.5', 'bathrooms_1.75',
       'bathrooms_2.0', 'bathrooms_2.25', 'bathrooms_2.5', 'bathrooms_2.75',
       'bathrooms_3.0', 'bathrooms_3.25', 'bathrooms_3.5', 'bathrooms_3.75',
       'bathrooms_4.0', 'bathrooms_4.25', 'bathrooms_4.5', 'condition_Average',
       'condition_Good', 'condition_Very Good', 'grade_10 Very Good',
       'grade_11 Excellent', 'grade_12 Luxury', 'grade_6 Low Average',
       'grade_7 Average', 'grade_8 Good', 'grade_9 Better'],
      dtype='object')
```

In [44]:
```
#Setting the columns in an asceding order for easy analysis
grade_columns = [
    'grade_6 Low Average',
    'grade_7 Average',
    'grade_8 Good',
    'grade_9 Better',
    'grade_10 Very Good',
    'grade_11 Excellent',
    'grade_12 Luxury'
]

# Extracting other columns not related to 'grade'

other_columns = [col for col in kc.columns if col not in grade_columns]

# Reordering columns

reordered_columns = other_columns + grade_columns
kc = kc[reordered_columns]
```

In [45]:
```
#Accessing the columns
kc.columns
```

Out[45]:
```
Index(['price', 'sqft_living', 'sqft_lot', 'Age', 'waterfront', 'view',
       'renovated_last_10', 'floors_1.5', 'floors_2.0', 'floors_2.5',
       'floors_3.0', 'bedrooms_2', 'bedrooms_3', 'bedrooms_4', 'bedrooms_5',
       'bedrooms_6', 'bathrooms_1.0', 'bathrooms_1.5', 'bathrooms_1.75',
       'bathrooms_2.0', 'bathrooms_2.25', 'bathrooms_2.5', 'bathrooms_2.75',
       'bathrooms_3.0', 'bathrooms_3.25', 'bathrooms_3.5', 'bathrooms_3.75',
       'bathrooms_4.0', 'bathrooms_4.25', 'bathrooms_4.5', 'condition_Average',
       'condition_Good', 'condition_Very Good', 'grade_6 Low Average',
       'grade_7 Average', 'grade_8 Good', 'grade_9 Better',
       'grade_10 Very Good', 'grade_11 Excellent', 'grade_12 Luxury'],
      dtype='object')
```

In [46]:
```
#Accessing the columns and rows
kc.head()
```

Out[46]:

	price	sqft_living	sqft_lot	Age	waterfront	view	renovated_last_10	floors_1.5	floors_2.0	floors_2.5	...	condition_Average	cond
0	221900	1180	5650	59	0	0	0	0	0	0	...	1	
1	538000	2570	7242	63	0	0	0	0	1	0	...	1	
2	180000	770	10000	82	0	0	0	0	0	0	...	1	
3	604000	1960	5000	49	0	0	0	0	0	0	...	0	
4	510000	1680	8080	28	0	0	0	0	0	0	...	1	

5 rows × 40 columns

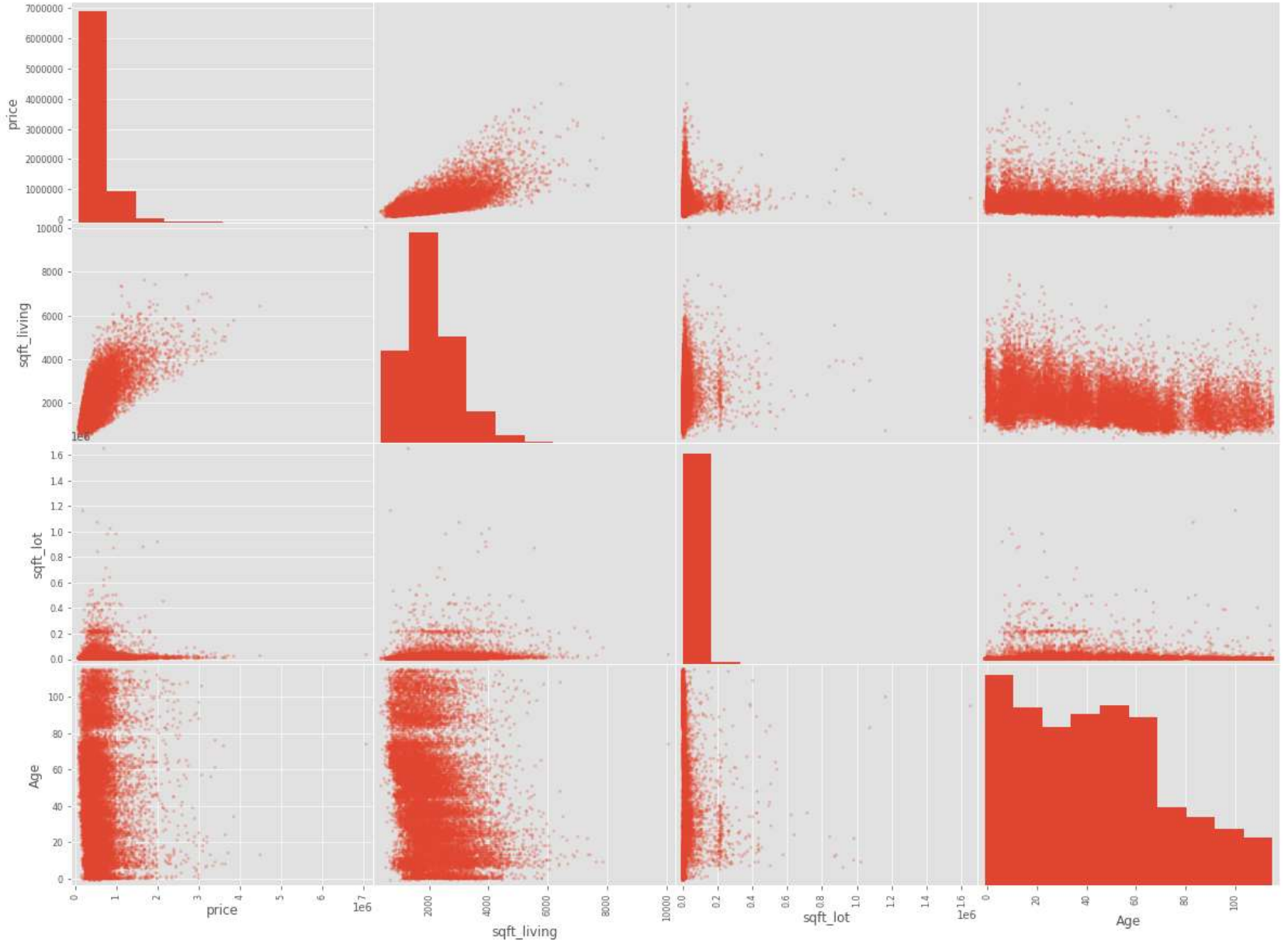
Modeling

In [47]:
```
#Confirming the linear relationship between variable and price
kc_num.head()
```

Out[47]:

	price	sqft_living	sqft_lot	Age
0	221900	1180	5650	59
1	538000	2570	7242	63
2	180000	770	10000	82
3	604000	1960	5000	49
4	510000	1680	8080	28

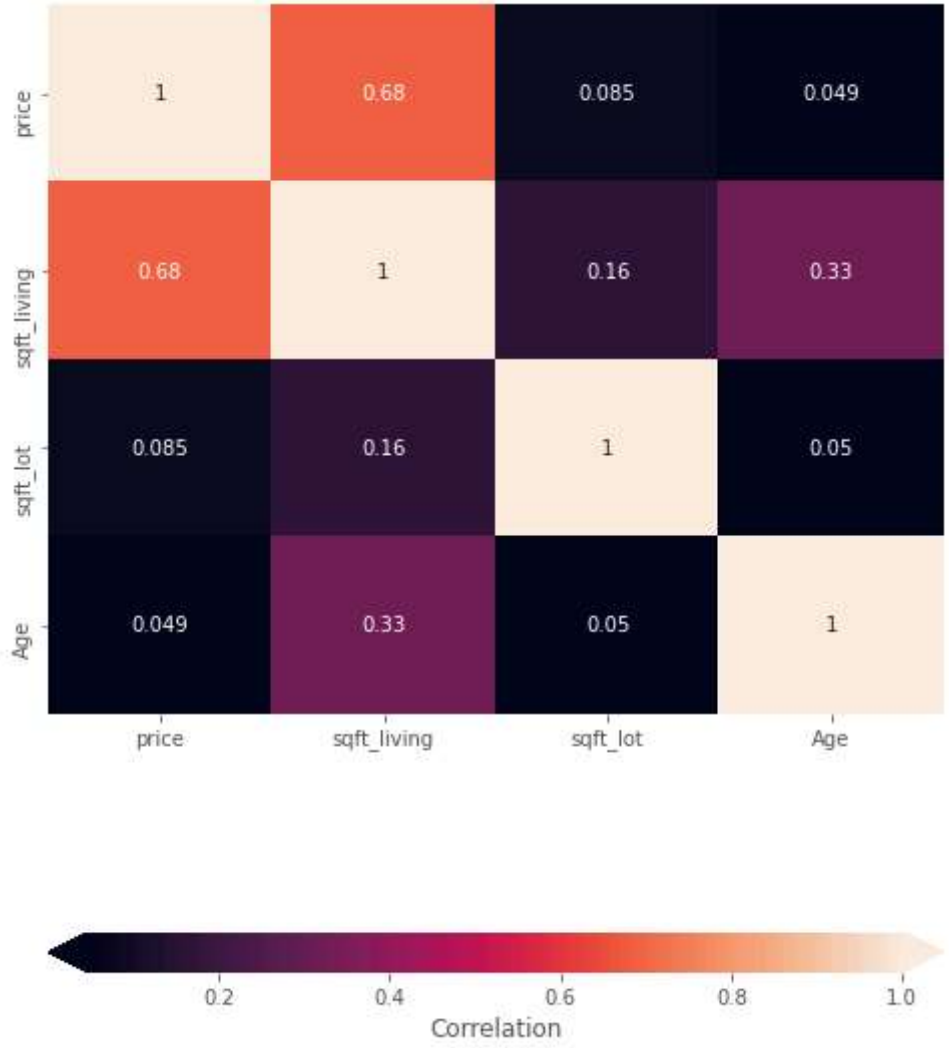
In [48]:
```
#Plotting scatter plot for clear visulaization of different features
pd.plotting.scatter_matrix(kc_num, figsize=(20,15), alpha=.3);
```



In [49]:
```
#Displaying the correlation matrix in responce to  price in descending order
kc_num.corr()['price'].sort_values(ascending=False)
```

Out[49]:
```
price          1.000000
sqft_living    0.682342
sqft_lot       0.084739
Age           -0.048693
Name: price, dtype: float64
```

In [50]:
```
#Ensuring proper visualization using heatmap
#the lighter the color the stronger the correlation

fig, ax = plt.subplots(figsize = (8,10))

sns.heatmap(
    kc_num.corr().abs(),
#     mask=np.triu(np.ones_like(data.corr(), dtype=bool)),
    ax=ax,
    annot=True,
    cbar_kws={"label": "Correlation", "orientation": "horizontal", "pad": .2, "extend": "both"}
);
```



**sqft_living: 0.682342 (Strong positive correlation) sqft_lot: 0.084739 (Weak positive correlation) Age: -0.048722 (Weak negative correlation)

Assessing Multicollinearity Across Predictor Combinations

In [51]:
```
# Create the correlation matrix directly and then reshape it for visualizatio
# Dropping the 'price' column
df = kc_num.drop('price', axis=1)

# Creating a correlation matrix
corr_matrix = df.corr().abs()

# Reshaping the correlation matrix for visualization
df_predictor = corr_matrix.stack().reset_index()
df_predictor.columns = ['Variable 1', 'Variable 2', 'Coefficient']

# Dropping duplicate rows where variables are the same
df_predictor = df_predictor[df_predictor['Variable 1'] != df_predictor['Variable 2']]

# Sorting by coefficient in descending order
df_predictor.sort_values(by='Coefficient', ascending=False, inplace=True)

df_predictor.head()
```

Out[51]:

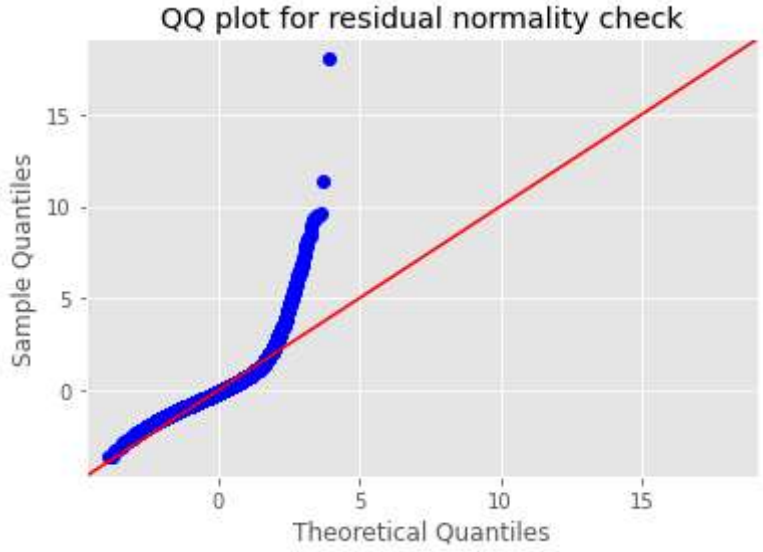
	Variable 1	Variable 2	Coefficient
2	sqft_living	Age	0.326558
6	Age	sqft_living	0.326558
1	sqft_living	sqft_lot	0.164552
3	sqft_lot	sqft_living	0.164552
5	sqft_lot	Age	0.049919

In [52]:
```
#sqft_lot and Age lack linear relationship
kc_num.drop(['sqft_lot', 'Age'], axis=1, inplace=True)
```

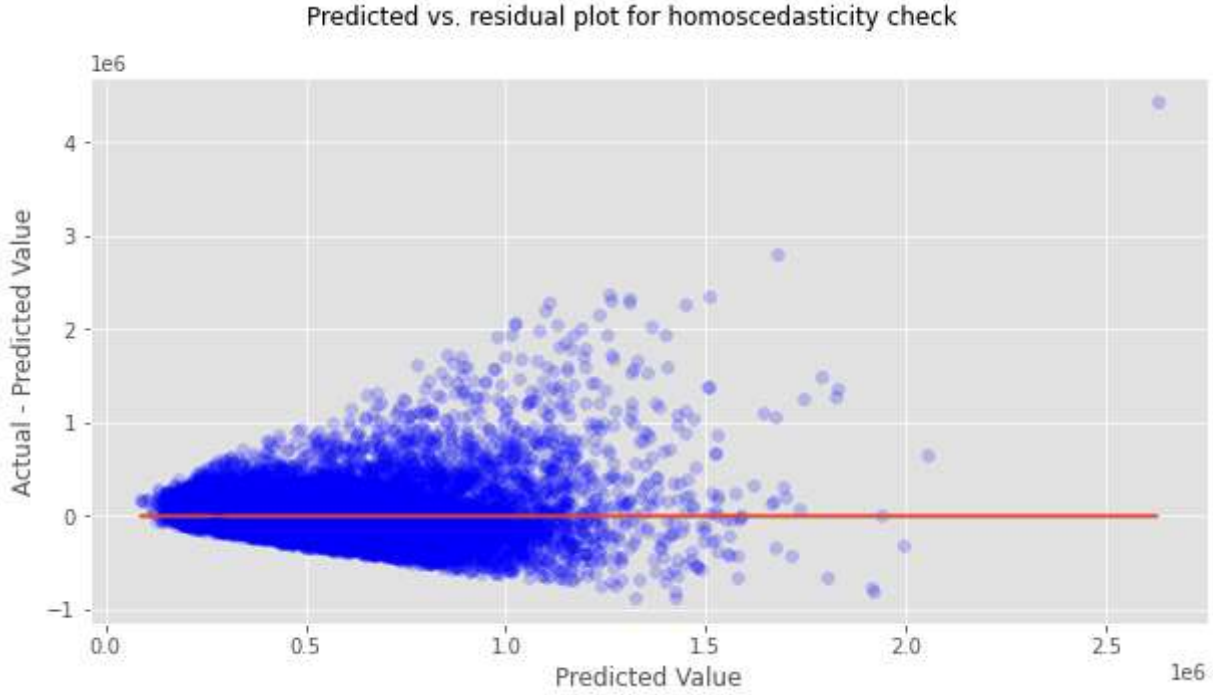
In [53]:
```
def reg_qq_sced(y, X, add_constant=True, qq=True, sced=True):
    """
    Fits a linear regression model, display its summary, and output plots to check linear regression assumpti

    Parameters:
    - y: Target variable.
    - X: Predictor variables.
    - add_constant: Whether to add a constant term to the predictors (default: True).
    - qq: Whether to display a QQ plot for residual normality check (default: True).
    - sced: Whether to display a plot of predicted values vs. residuals for homoscedasticity check (default:
    """
    # Add a constant to the predictors if required
    X_sm = sm.add_constant(X, has_constant='add') if add_constant else X

    # Run a linear regression and display the summary
    model = sm.OLS(y, X_sm).fit()
    display(print(model.summary()))

    # Display a QQ plot for residual normality check
    if qq:
        sm.qqplot(model.resid, line='45', fit=True)
        plt.title('QQ plot for residual normality check')
        plt.show()
    else:
        pass

    # Display a plot of predicted values vs. residuals for homoscedasticity check
    if sced:
        preds = model.predict(X_sm)
        residuals = model.resid
        fig_resid, ax = plt.subplots(figsize=(10, 5))
        fig_resid.suptitle('Predicted vs. residual plot for homoscedasticity check')
        ax.scatter(preds, residuals, alpha=0.2, color= "blue")
        ax.plot(preds, [0 for _ in range(len(X_sm))])
        ax.set_xlabel("Predicted Value")
        ax.set_ylabel("Actual - Predicted Value")
    else:
        pass

    # Output additional model performance metrics
    print(f'Model adjusted R-squared: {model.rsquared_adj}')
    print(f'Model RMSE: {np.sqrt(model.mse_resid)}')
```

In [54]:
```
# Set baseline predictor as 'sqft_living'

baseline = 'sqft_living'

# Define target variable and predictor

y = kc.price
X = kc[baseline]

# Feed these inputs into our function

reg_qq_sced(y, X)
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                  price   R-squared:                       0.466
Model:                            OLS   Adj. R-squared:                  0.466
Method:                 Least Squares   F-statistic:                 1.862e+04
Date:                Sat, 06 Apr 2024   Prob (F-statistic):               0.00
Time:                        11:34:37   Log-Likelihood:            -2.9572e+05
No. Observations:               21378   AIC:                         5.914e+05
Df Residuals:                   21376   BIC:                         5.915e+05
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const      -9704.3054   4318.156     -2.247      0.025   -1.82e+04   -1240.397
sqft_living   262.8635      1.926    136.467      0.000     259.088     266.639
==============================================================================
Omnibus:                    12569.130   Durbin-Watson:                   1.978
Prob(Omnibus):                  0.000   Jarque-Bera (JB):           271238.797
Skew:                           2.414   Prob(JB):                         0.00
Kurtosis:                      19.769   Cond. No.                     5.75e+03
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 5.75e+03. This might indicate that there are
strong multicollinearity or other numerical problems.

None
```




```
Model adjusted R-squared: 0.4655655910250339
Model RMSE: 246222.6375951674
```



The linear regression results indicate that the model's R-squared value is 0.466, suggesting that approximately 46.6% of the variance in the target variable (price) is explained by the predictor variable (sqft_living).

The coefficient for the constant term (intercept) is -9704.3054, indicating the predicted price when sqft_living is zero. The coefficient for sqft_living is 262.8635, indicating that for every unit increase in sqft_living, the price is expected to increase by approximately $262.86. The p-value for sqft_living is less than 0.05, indicating that the predictor variable is statistically significant. The confidence interval for the coefficient of sqft_living ranges from 259.088 to 266.639. The residual plots indicate that there might be some heteroscedasticity present, as the spread of residuals increases with predicted values. The QQ plot suggests that the residuals are approximately normally distributed, but there might be some deviations, especially in the tails.

Overall, the model performs reasonably well, but there might be room for improvement, especially in addressing heteroscedasticity.

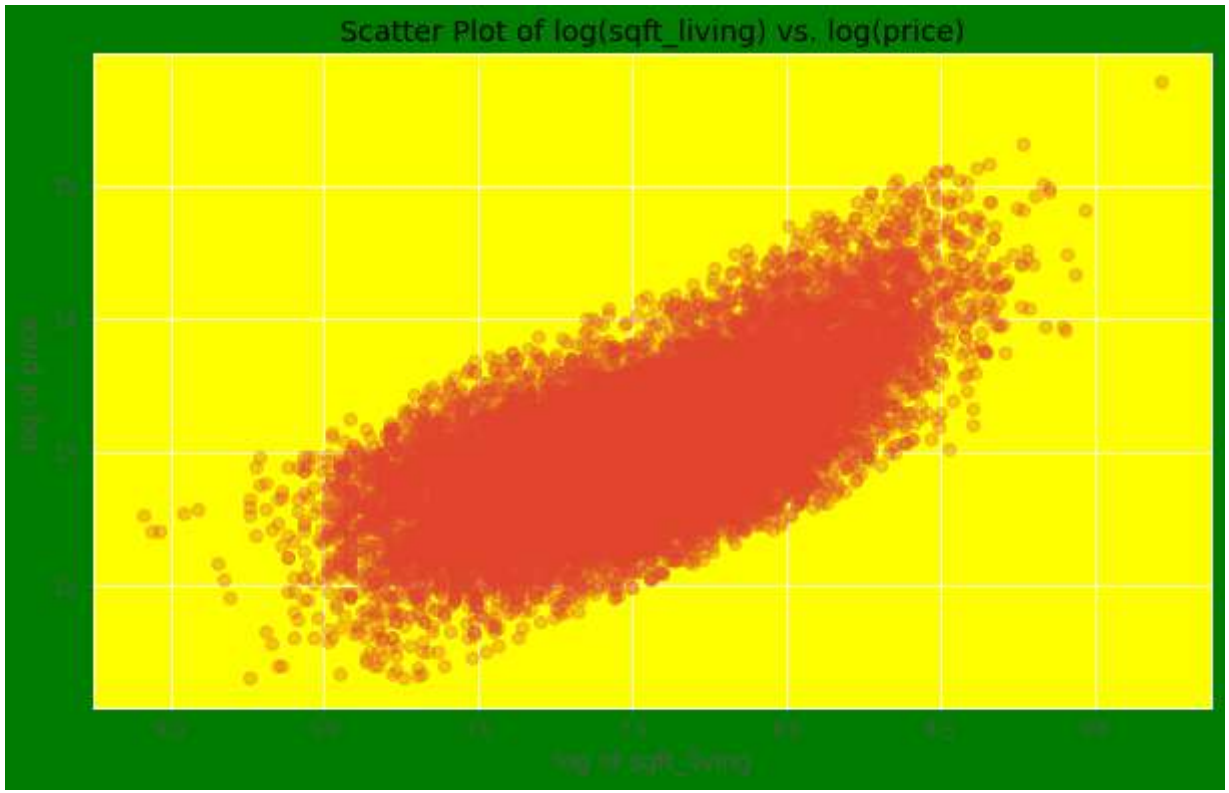
In [55]:
```
# Isolating columns to be transformed

log_trans_cols = ['price', 'sqft_living']
kc_logged = kc.copy()[log_trans_cols]

# Log transforming and renaming columns

kc_logged = np.log(kc_logged)
kc_logged.columns = kc_logged.columns.map(lambda x: 'log_' + x)

# Merge it with the rest of the dataset

kc_transformed = kc_logged.join(kc.drop(log_trans_cols, axis=1))


kc_transformed.head()
```

Out[55]:

	log_price	log_sqft_living	sqft_lot	Age	waterfront	view	renovated_last_10	floors_1.5	floors_2.0	floors_2.5	...	condition_Averag
0	12.309982	7.073270	5650	59	0	0	0	0	0	0	...	
1	13.195614	7.851661	7242	63	0	0	0	0	1	0	...	
2	12.100712	6.646391	10000	82	0	0	0	0	0	0	...	
3	13.311329	7.580700	5000	49	0	0	0	0	0	0	...	
4	13.142166	7.426549	8080	28	0	0	0	0	0	0	...	

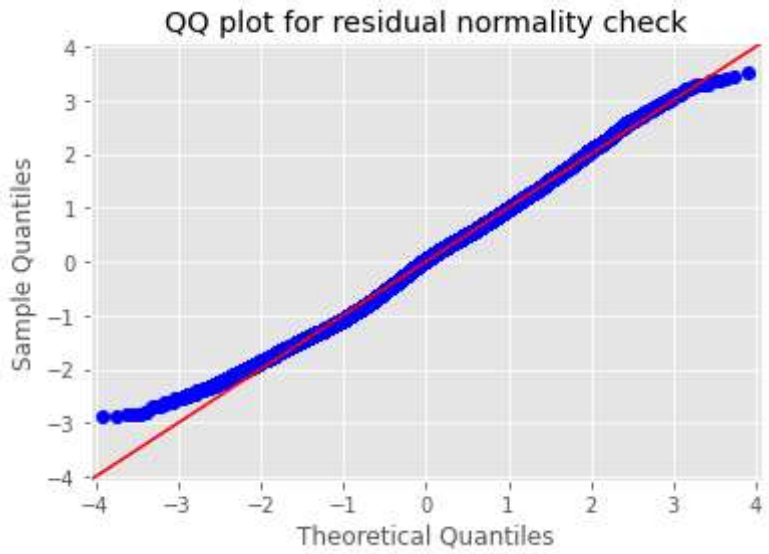
5 rows × 40 columns

In [56]:
```
# visualizing linearity between the transformed predictor and target variable
# The plot helps visualize the linearity between these two variables, which is essential for linear regressio

fig, ax = plt.subplots(figsize= (10,6))
ax = plt.gca()
plt.plot(kc_transformed['log_sqft_living'], kc_transformed['log_price'], 'o', alpha=0.3)

# Set the background color of the axis

ax.set_facecolor('yellow')
plt.gcf().set_facecolor('green')
plt.xlabel('log of sqft_living')
plt.ylabel('log of price')
plt.title('Scatter Plot of log(sqft_living) vs. log(price)')
plt.show()
```

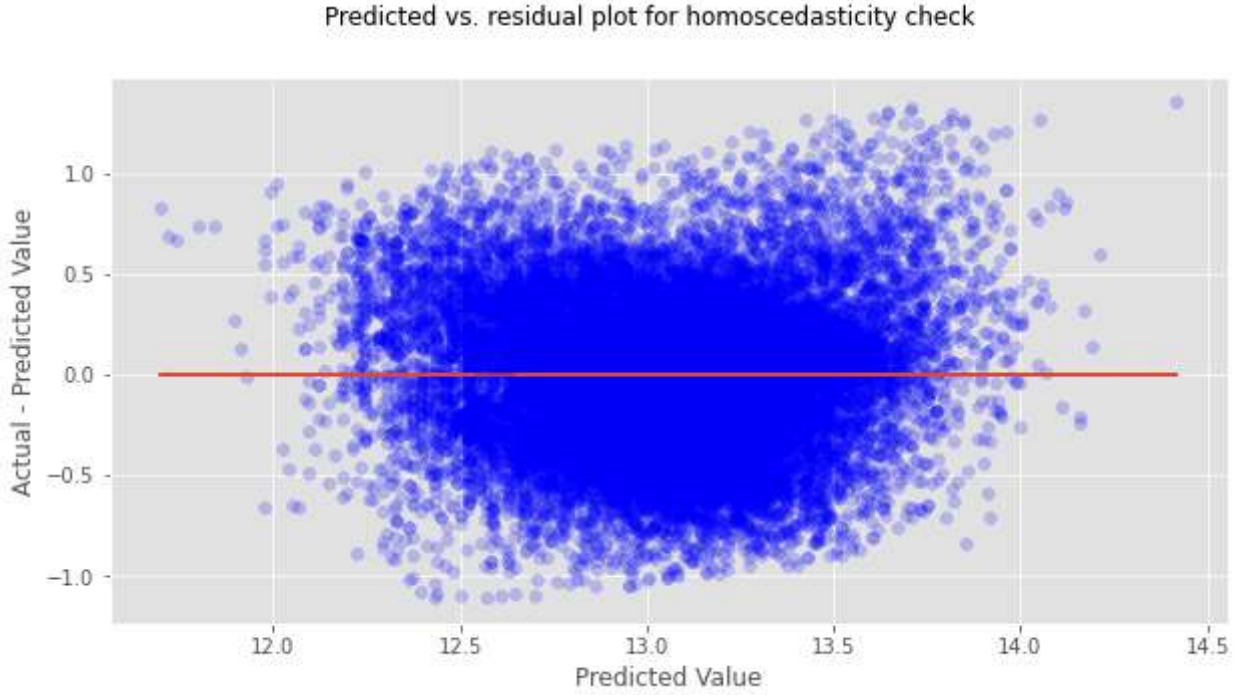


In [57]:
```
baseline = 'log_sqft_living'

y = kc_transformed.log_price
X = kc_transformed.log_sqft_living

# Feeding these inputs into our function

model = reg_qq_sced(y, X)
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:              log_price   R-squared:                       0.441
Model:                            OLS   Adj. R-squared:                  0.441
Method:                 Least Squares   F-statistic:                 1.688e+04
Date:                Sat, 06 Apr 2024   Prob (F-statistic):               0.00
Time:                        11:35:49   Log-Likelihood:                -9972.4
No. Observations:               21378   AIC:                         1.995e+04
Df Residuals:                   21376   BIC:                         1.996e+04
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          6.8236      0.048    142.328      0.000       6.730       6.918
log_sqft_living     0.8241      0.006    129.925      0.000       0.812       0.837
==============================================================================
Omnibus:                      118.666   Durbin-Watson:                   1.974
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              106.556
Skew:                           0.130   Prob(JB):                     7.27e-24
Kurtosis:                       2.772   Cond. No.                         140.
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

None
```




```
Model adjusted R-squared: 0.44121910929171504
Model RMSE: 0.38580857869279717
```



The regression results indicate that the logarithm of square footage of living space (log_sqft_living) is a significant predictor of the logarithm of price (log_price). Here's a summary of the regression results:

R-squared: The coefficient of determination indicates that approximately 44.1% of the variance in the logarithm of price can be explained by the logarithm of square footage of living space.

Coefficient Estimates:

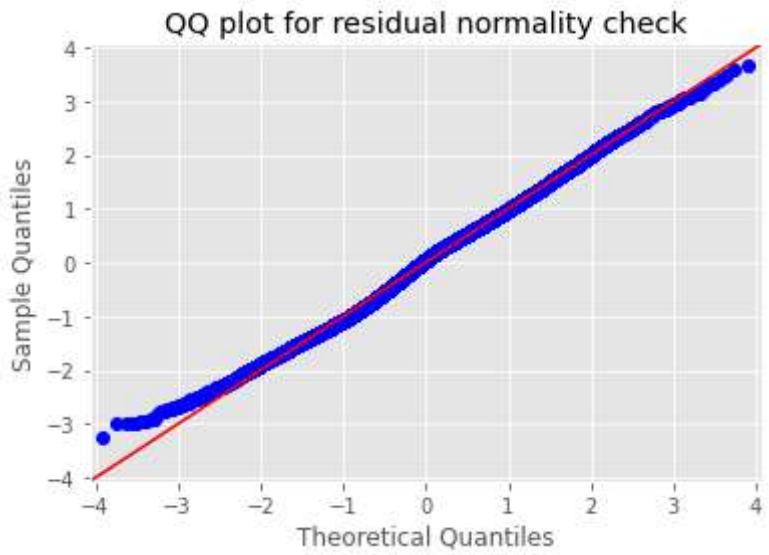
The coefficient for log_sqft_living is approximately 0.8241, indicating that for every one-unit increase in the logarithm of square footage of living space, the logarithm of price is expected to increase by approximately 0.8241 units. The intercept (constant) term is approximately 6.8236, which represents the estimated logarithm of price when the logarithm of square footage of living space is zero. Statistical Significance: Both coefficients are statistically significant with p-values < 0.05, suggesting that they are unlikely to be zero.

Model Fit: The model's goodness of fit is indicated by the adjusted R-squared value of approximately 0.441, which is a measure of how well the independent variable explains the variation in the dependent variable.

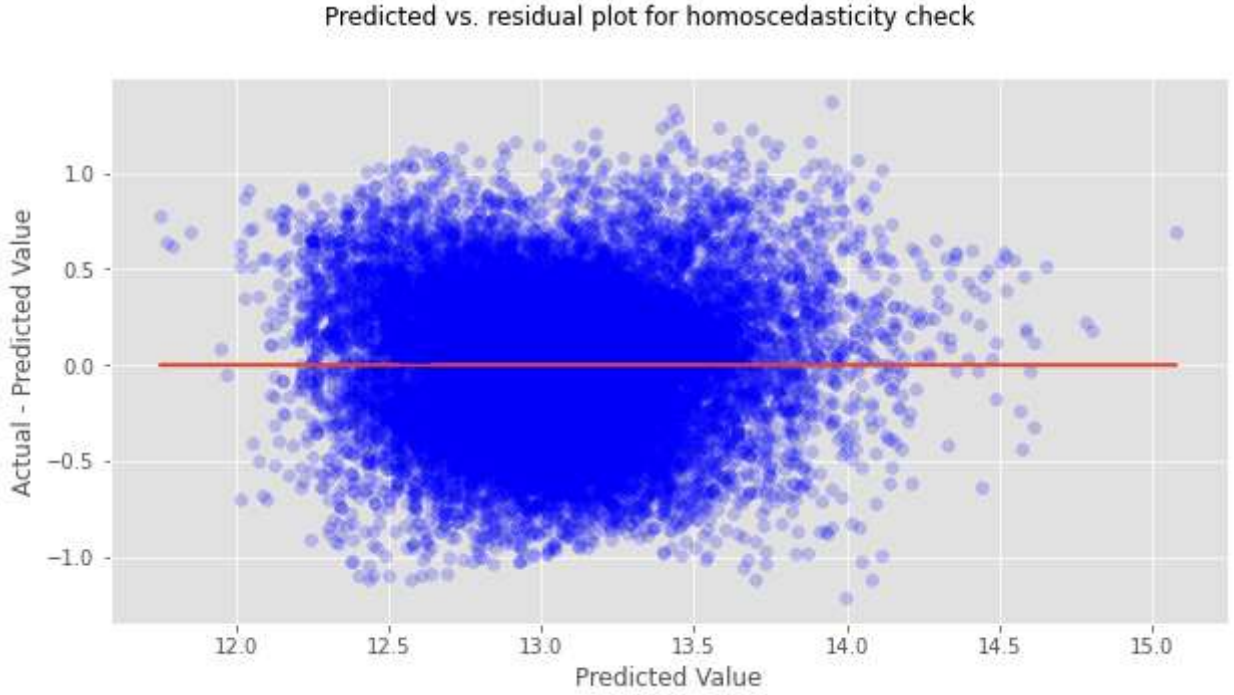
Overall, based on these results, we can conclude that there is a strong linear relationship between the logarithm of square footage of living space and the logarithm of price.

In [58]:
```
baseline = 'log_sqft_living'


# Define target variable and predictors

y = kc_transformed.log_price
X = kc_transformed[[baseline, 'waterfront', 'view', 'renovated_last_10']]

model = reg_qq_sced(y, X)
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:              log_price   R-squared:                       0.480
Model:                            OLS   Adj. R-squared:                  0.480
Method:                 Least Squares   F-statistic:                     4933.
Date:                Sat, 06 Apr 2024   Prob (F-statistic):               0.00
Time:                        11:39:45   Log-Likelihood:                -9203.6
No. Observations:               21378   AIC:                         1.842e+04
Df Residuals:                   21373   BIC:                         1.846e+04
Df Model:                           4
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          7.2015      0.047    152.047      0.000       7.109       7.294
log_sqft_living    0.7696      0.006    122.307      0.000       0.757       0.782
waterfront     0.5078      0.033     15.372      0.000       0.443       0.573
view           0.2787      0.009     30.498      0.000       0.261       0.297
renovated_last_10     0.2415      0.022     10.759      0.000       0.197       0.285
==============================================================================
Omnibus:                      111.385   Durbin-Watson:                   1.966
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               82.736
Skew:                           0.044   Prob(JB):                     1.08e-18
Kurtosis:                       2.708   Cond. No.                         143.
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

None
```




```
Model adjusted R-squared: 0.47992149934586015
Model RMSE: 0.3722078753617302
```



The updated regression results indicate that the model now includes additional predictors: waterfront, view, and renovated_last_10, in addition to log_sqft_living. Here's a summary of the updated regression results:

R-squared: The coefficient of determination has increased to approximately 0.480, suggesting that the additional predictors have improved the model's ability to explain the variance in the logarithm of price.

Coefficient Estimates:

The coefficient for log_sqft_living remains significant and has a value of approximately 0.7696. The coefficients for the additional predictors (waterfront, view, and renovated_last_10) are also significant: waterfront: Coefficient is approximately 0.5078, indicating that waterfront properties tend to have higher prices. view: Coefficient is approximately 0.2787, suggesting that properties with better views tend to have higher prices. renovated_last_10: Coefficient is approximately 0.2415, indicating that recently renovated properties tend to have higher prices. Statistical Significance: All coefficients are statistically significant with p-values < 0.05.

Model Fit: The adjusted R-squared value of approximately 0.480 indicates that the model with the additional predictors provides a better fit to the data compared to the previous model.

Overall, based on these results, we can conclude that the model including log_sqft_living, waterfront, view, and renovated_last_10 as predictors explains a significant portion of the variance in the logarithm of price and provides valuable insights into the factors influencing house prices.

In [59]:
```
# Grouping the dummies together into lists form

dummies = ['floors', 'bedrooms', 'bathrooms', 'condition', 'grade']
floors_dummies = []
bedrooms_dummies = []
bathrooms_dummies = []
condition_dummies = []
grade_dummies = []

for col in list(kc.columns):
    for cate in dummies:
        if col.startswith(cate):
            eval(cate + '_dummies').append(col)
```

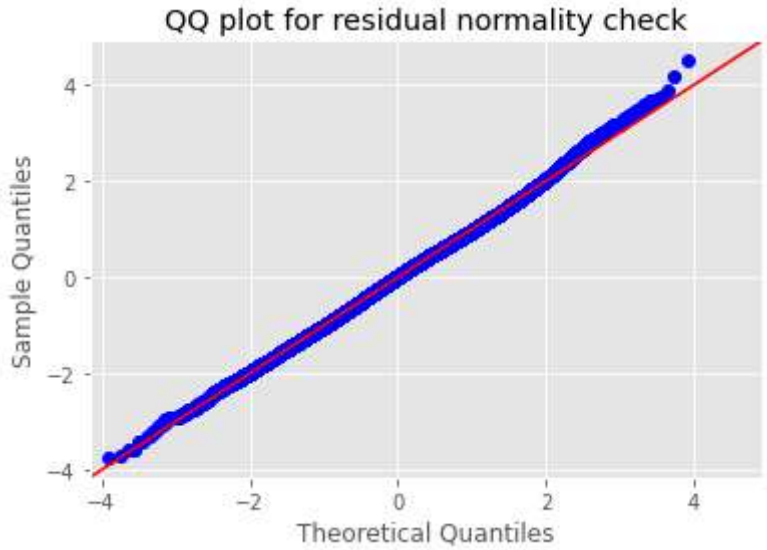
In [60]:
```
# Defining the target variable and predictors

y = kc_transformed.log_price
X = kc_transformed[floors_dummies +
                   bedrooms_dummies +
                   bathrooms_dummies +
                   condition_dummies +
                   grade_dummies +
                   ['log_sqft_living']]

model = reg_qq_sced(y, X)
```

OLS Regression Results

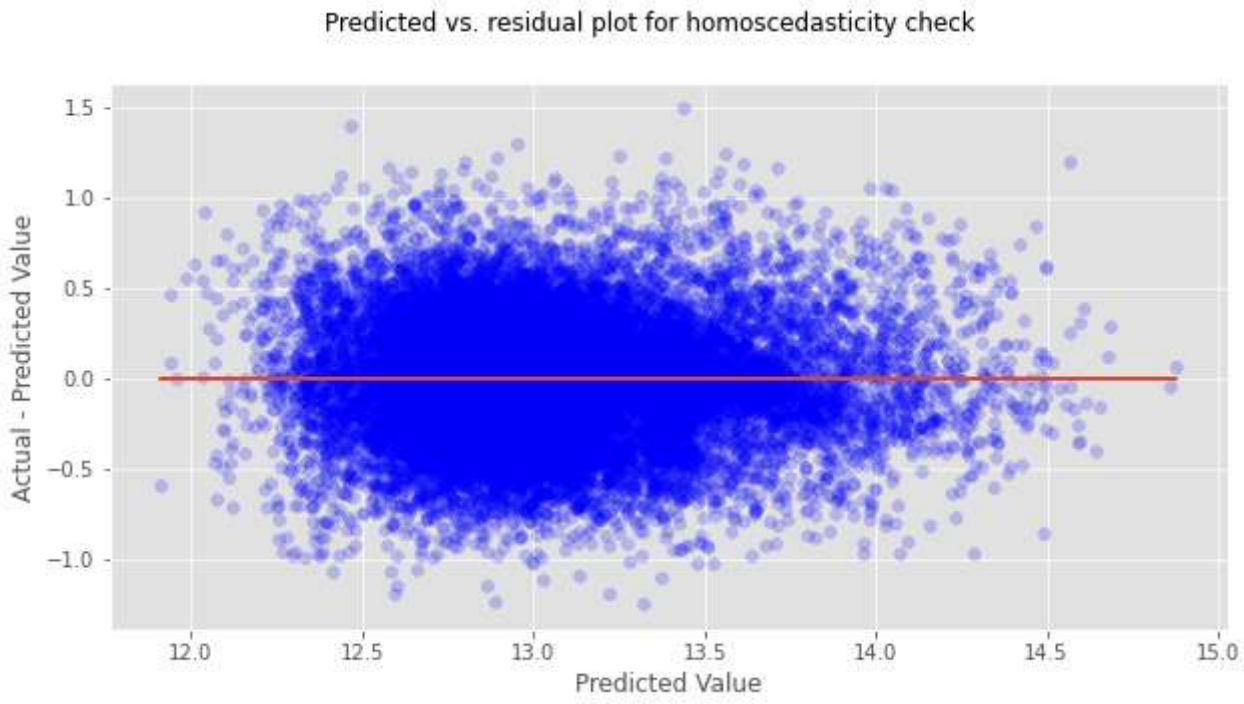
Dep. Variable:	log_price	R-squared:	0.583
Model:	OLS	Adj. R-squared:	0.583
Method:	Least Squares	F-statistic:	878.4
Date:	Sat, 06 Apr 2024	Prob (F-statistic):	0.00
Time:	11:40:18	Log-Likelihood:	-6839.2
No. Observations:	21378	AIC:	1.375e+04
Df Residuals:	21343	BIC:	1.403e+04
Df Model:	34		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	8.8143	0.093	95.087	0.000	8.633	8.996
floors_1.5	0.1731	0.008	20.419	0.000	0.157	0.190
floors_2.0	-0.0271	0.007	-4.061	0.000	-0.040	-0.014
floors_2.5	0.1376	0.028	4.955	0.000	0.083	0.192
floors_3.0	0.1154	0.015	7.663	0.000	0.086	0.145
bedrooms_2	-0.0525	0.027	-1.971	0.049	-0.105	-0.000
bedrooms_3	-0.2178	0.027	-8.145	0.000	-0.270	-0.165
bedrooms_4	-0.2409	0.027	-8.798	0.000	-0.295	-0.187
bedrooms_5	-0.2386	0.029	-8.295	0.000	-0.295	-0.182
bedrooms_6	-0.2437	0.035	-6.981	0.000	-0.312	-0.175
bathrooms_1.0	-0.0238	0.046	-0.521	0.602	-0.113	0.066
bathrooms_1.5	-0.0738	0.047	-1.584	0.113	-0.165	0.018
bathrooms_1.75	-0.0394	0.046	-0.850	0.395	-0.130	0.051
bathrooms_2.0	-0.0467	0.047	-1.004	0.315	-0.138	0.044
bathrooms_2.25	-0.0610	0.047	-1.302	0.193	-0.153	0.031
bathrooms_2.5	-0.1134	0.047	-2.427	0.015	-0.205	-0.022
bathrooms_2.75	-0.0405	0.047	-0.853	0.394	-0.134	0.053
bathrooms_3.0	-0.0168	0.048	-0.350	0.727	-0.111	0.078
bathrooms_3.25	0.0535	0.049	1.095	0.273	-0.042	0.149
bathrooms_3.5	0.0151	0.049	0.311	0.756	-0.080	0.111
bathrooms_3.75	0.1316	0.055	2.415	0.016	0.025	0.238
bathrooms_4.0	0.0916	0.056	1.635	0.102	-0.018	0.201
bathrooms_4.25	0.1385	0.061	2.256	0.024	0.018	0.259
bathrooms_4.5	0.0741	0.059	1.256	0.209	-0.042	0.190
condition_Average	0.1112	0.026	4.233	0.000	0.060	0.163
condition_Good	0.1838	0.026	6.957	0.000	0.132	0.236
condition_Very Good	0.3102	0.027	11.368	0.000	0.257	0.364
grade_6 Low Average	0.1578	0.023	6.737	0.000	0.112	0.204
grade_7 Average	0.3625	0.023	15.617	0.000	0.317	0.408

```
grade_8 Good            0.5742      0.024     23.873      0.000       0.527       0.621
grade_9 Better          0.8102      0.025     32.025      0.000       0.761       0.860
grade_10 Very Good      0.9899      0.027     36.520      0.000       0.937       1.043
grade_11 Excellent      1.1615      0.032     36.636      0.000       1.099       1.224
grade_12 Luxury         1.3819      0.049     28.251      0.000       1.286       1.478
log_sqft_living         0.5071      0.011     44.533      0.000       0.485       0.529
==============================================================================
Omnibus:                       23.248   Durbin-Watson:                   1.976
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               24.161
Skew:                           0.062   Prob(JB):                     5.67e-06
Kurtosis:                       3.109   Cond. No.                         604.
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

None
```




```
Model adjusted R-squared: 0.5825424094184519
Model RMSE: 0.3334703984977778
```



The regression results show the coefficients, standard errors, t-values, and p-values for each predictor in the model. Here's a summary of the results:

R-squared: The coefficient of determination, indicating the proportion of the variance in the dependent variable that is predictable from the independent variables. In this case, the R-squared value is 0.583, which means that approximately 58.3% of the variance in the logarithm of price can be explained by the predictors in the model.

Adjusted R-squared: A version of R-squared that adjusts for the number of predictors in the model. It penalizes excessive complexity. The adjusted R-squared value is also 0.583.

F-statistic: A measure of the overall significance of the regression model. It tests whether at least one of the predictors has a non-zero coefficient. Here, the F-statistic is 878.4, with a very low p-value, indicating that the overall model is statistically significant.

Coefficients: The estimated coefficients for each predictor variable. These represent the expected change in the dependent variable for a one-unit change in the predictor, holding all other predictors constant.

P-values: The p-values associated with each coefficient estimate. They indicate the statistical significance of each predictor. In this context, a p-value less than 0.05 suggests that the predictor is statistically significant.

Overall, the regression model appears to be statistically significant, with several predictors showing significant associations with the logarithm of price.

In [61]:
```
# Defining target variable and predictors

y = kc_transformed.log_price
X = kc_transformed[floors_dummies +
                   condition_dummies +
                   grade_dummies +
                   ['view']+
                   ['waterfront']+
                   ['renovated_last_10']+
                   ['log_sqft_living']]

model = reg_qq_sced(y, X)
```

OLS Regression Results

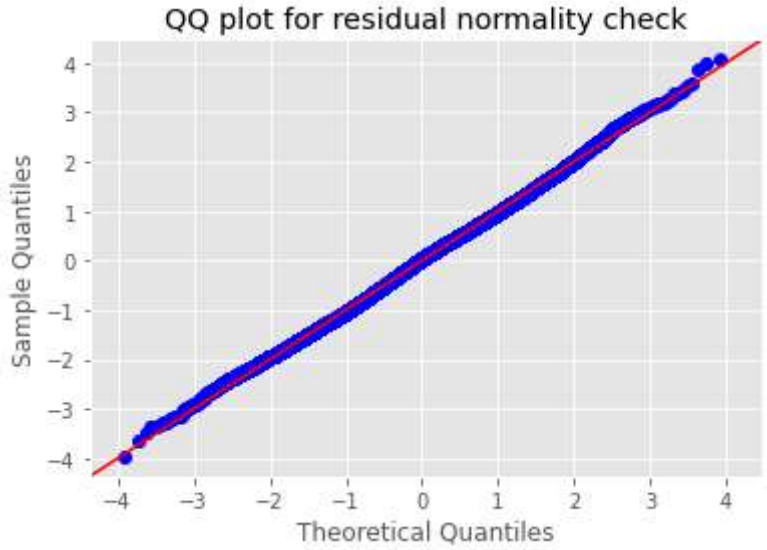
Dep. Variable:	log_price	R-squared:	0.590
Model:	OLS	Adj. R-squared:	0.590
Method:	Least Squares	F-statistic:	1709.
Date:	Sat, 06 Apr 2024	Prob (F-statistic):	0.00
Time:	11:40:47	Log-Likelihood:	-6659.6
No. Observations:	21378	AIC:	1.336e+04
Df Residuals:	21359	BIC:	1.351e+04
Df Model:	18		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	9.5268	0.065	145.617	0.000	9.399	9.655
floors_1.5	0.1646	0.008	19.801	0.000	0.148	0.181
floors_2.0	-0.0263	0.006	-4.392	0.000	-0.038	-0.015
floors_2.5	0.1541	0.027	5.625	0.000	0.100	0.208
floors_3.0	0.1166	0.014	8.083	0.000	0.088	0.145
condition_Average	0.1003	0.026	3.855	0.000	0.049	0.151
condition_Good	0.1696	0.026	6.481	0.000	0.118	0.221
condition_Very Good	0.2948	0.027	10.908	0.000	0.242	0.348
grade_6 Low Average	0.1458	0.023	6.342	0.000	0.101	0.191
grade_7 Average	0.3187	0.023	14.145	0.000	0.275	0.363
grade_8 Good	0.5209	0.023	22.306	0.000	0.475	0.567
grade_9 Better	0.7676	0.025	31.053	0.000	0.719	0.816
grade_10 Very Good	0.9833	0.026	37.124	0.000	0.931	1.035
grade_11 Excellent	1.1868	0.031	38.524	0.000	1.126	1.247
grade_12 Luxury	1.4009	0.048	29.249	0.000	1.307	1.495
view	0.2068	0.008	25.051	0.000	0.191	0.223
waterfront	0.4650	0.029	15.815	0.000	0.407	0.523
renovated_last_10	0.2649	0.020	13.224	0.000	0.226	0.304
log_sqft_living	0.3822	0.008	45.510	0.000	0.366	0.399

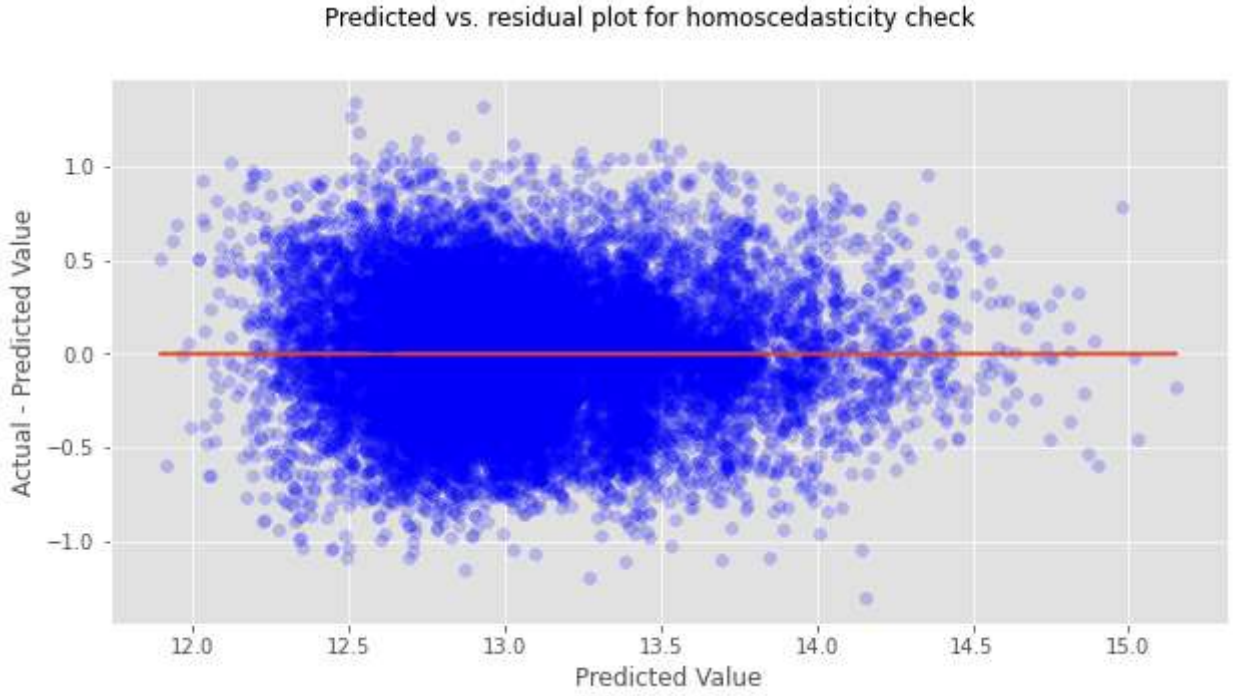
Omnibus:	4.847	Durbin-Watson:	1.967
Prob(Omnibus):	0.089	Jarque-Bera (JB):	4.859
Skew:	0.032	Prob(JB):	0.0881
Kurtosis:	2.965	Cond. No.	238.

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

None




```
Model adjusted R-squared: 0.5898050113220741
Model RMSE: 0.3305569423039113
```



The regression results indicate the following:

R-squared: The coefficient of determination is 0.590, suggesting that approximately 59.0% of the variance in the logarithm of price can be explained by the predictors in the model.

Adjusted R-squared: The adjusted R-squared value is also 0.590, indicating that the model's explanatory power is not compromised by the inclusion of additional predictors.

F-statistic: The F-statistic is 1709.0 with a very low p-value, indicating that the overall model is statistically significant.

Coefficients: The coefficients represent the estimated change in the logarithm of price for a one-unit change in the corresponding predictor variable, holding all other predictors constant. For example, a one-unit increase in log_sqft_living is associated with an increase of approximately 0.3822 in the logarithm of price.

P-values: The p-values associated with each coefficient estimate indicate the statistical significance of the predictors. All predictors have p-values less than 0.05, suggesting that they are statistically significant in predicting the logarithm of price.

Overall, the model appears to be statistically significant, with several predictors showing significant associations with the logarithm of price.

Justification Of Linear Regression:

regression models is best fit due to its simplicity, interpretability and because the relationship between the independent and dependent variables seem linear, if it were non-linear a different technique would be employed

linearity in the sense that the data columns exhibit a relationship with each other therefore affecting each other

this relationship is best explained using a model performance metric like the R-Squared and coefficients which represent the strength and relationship between feature and target variables which is done via modelling

by examining the coefficients we were able to identify which features have the most impact on our outcome variable. this helped us understand the driving forces behind the observed trends....essentially how a house's attributes affect its price

Linear regression is also a computationally efficient allowing quick exploratory analysis and as it can serve as a baseline model, more models can be compared to the baseline allowing for a clearer understanding of our data

In [ ]: