Collaborators

- Student names:

> - Tony Kithinji
> - Janet Khainza
> - Leah George
> - Rael Ndonye
> - Tony Munene
> - Isaac Munyaka

- Student pace: part time : **PT03**

SIXTH SENSE AGENCY HOUSE PREDICTION MODEL

1.0 Business Understanding

1.1 Background

The housing market in King County, Washington experienced a shift in March, 2023, with home prices declining by approximately 10% compared to the previous year. The decrease in prices was attributed to factors such as interest rate increases and economic uncertainty. However, despite the price drop, housing affordability remained a challenge for many potential buyers. Inventory shortages and a lack of new listings were significant concerns, leading to increased competition among buyers. The number of available homes was considerably lower than the previous year, which impacted the overall sales activity in the market.

Overall, the declining home prices, the challenges of affordability, the scarcity of inventory, and the impact of economic factors on the market are very important factors to consider before conducting any analysis on the king county market.

Reference : https://www.seattletimes.com/business/real-estate/king-country-home-prices-plunge-10-as-northwest-housing-market-shifts/

1.2 Problem Statement

The 6th Sense Agency is a premier real estate agency in King County, Washington DC, dedicated to providing exceptional client support in buying, selling, and renting houses. To maintain a competitive edge, deliver superior services and provide affordable housing, the agency has contracted us to provide them with trusted insights and factors that influence the price of a house in order for them to have a deep understanding of the current real estate market as well as make informed decisions to meet the changing needs of buyers and sellers while improving sales.

1.3 Objectives

The main goal of this research project is to identify and analyze the key factors that have a significant influence on house prices in King County. By doing so, the 6th Sense Agency aims to enhance its ability to adapt quickly to market dynamics and offer exceptional service to its clients while improving their sales.

To achieve this objective, the research will address the following questions:

> Q1: What is the correlation between house price and other predictor variables?

> **Q2: Which combinations of features provide the most accurate predictions for housing prices?**
>
> **Q3: Do renovations of a house contribute to a higher house pricing?**

> - **Null Hypopthesis: House price is not affected by features of the house presented**
> - **Alternative hypothesis: House price is greatly affected by presented features**

By analyzing these questions, the research aims to gain valuable insights into the factors that play a crucial role in determining house prices. The findings will empower the 6th Sense Agency to make informed decisions and effectively meet the needs of its clients.

In [1]:

```
from google.colab import drive
drive.mount('/content/drive/')
```

```
Mounted at /content/drive/
```

First, we import all libraries to be used in this project.

In [2]:

```
# Import Libraries
import pandas as pd
import warnings
import statsmodels.api as sm
import numpy as np
import seaborn as sns
import plotly.graph_objects as go
import statsmodels.api as sm
import scipy.stats as stats
import matplotlib.pyplot as plt
%matplotlib inline
from sklearn.metrics import mean_absolute_error, mean_squared_error
from pandas.core.internals.blocks import is_string_dtype
from pandas.core.dtypes.api import is_numeric_dtype


warnings.filterwarnings('ignore')
```

In [3]:

```
# loading the dataset
# data = pd.read_csv('/content/drive/MyDrive/project_02/kc_house_data.csv')
data = pd.read_csv('kc_house_data.csv')
data.sample(10)
```

Out[3]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	...	grade	s
14468	6909700205	4/6/2015	425000.0	2	1.00	1090	6000	1.0	NO	NONE	...	7 Average	
13325	2970800145	4/7/2015	350500.0	3	1.75	2080	5200	1.0	NO	NONE	...	7 Average	
17571	5315101728	3/19/2015	770000.0	4	3.00	2320	7200	1.0	NO	NONE	...	7 Average	
13765	427000065	1/26/2015	537500.0	5	2.50	4340	9108	1.0	NO	NONE	...	8 Good	
6464	723099028	6/26/2014	320000.0	3	2.00	1550	34175	1.5	NO	NONE	...	7 Average	
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	7	

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	...	grade	sq
18148	2517010120	4/13/2015	340000.0	4	2.50	2450	6941	2.0	NO	NONE	...	Average	
14120	4074300150	4/17/2015	460000.0	4	1.75	1560	7200	1.0	NO	NONE	...	6 Low Average	
8646	326069118	6/30/2014	760000.0	4	2.50	3300	165528	2.0	NO	NONE	...	8 Good	
14315	8085400410	3/31/2015	920000.0	3	1.00	1410	9656	1.0	NaN	NONE	...	7 Average	
11662	7987400316	8/14/2014	255000.0	1	0.50	880	1642	1.0	NO	NONE	...	6 Low Average	

10 rows × 21 columns

2.0 Data Understanding

The data is a collection of single family homes in the King County, WA area sold between May 2014 and May 2015. The data contains 21 variables and 21,597 records. This data will be suitable to create a model to predict sale price for homes within the paramaters of this dataset.

Table 1 Variable Names and Descriptions for King County Data Set

- id - Unique identifier for a house
- date - Date house was sold
- price - Sale price (prediction target)
- bedrooms - Number of bedrooms
- bathrooms - Number of bathrooms
- sqft_living - Square footage of living space in the home
- sqft_lot - Square footage of the lot
- floors - Number of floors (levels) in house
- waterfront - Whether the house is on a waterfront
- view - Quality of view from house
- condition - How good the overall condition of the house is. Related to maintenance of house
- grade - Overall grade of the house. Related to the construction and design of the house
- sqft_above - Square footage of house apart from basement
- sqft_basement - Square footage of the basement
- yr_built - Year when house was built
- yr_renovated - Year when house was renovated
- zipcode - ZIP Code used by the United States Postal Service
- lat - Latitude coordinate
- long - Longitude coordinate
- sqft_living15 - The square footage of interior housing living space for the nearest 15 neighbors
- sqft_lot15 - The square footage of the land lots of the nearest 15 neighbors

In [4]:

```
# Total number of rows and columns.

print("The number of rows is", data.shape[0])
print('The number of columns is', data.shape[1])
```

```
The number of rows is 21597
The number of columns is 21
```

In [5]:

```
# Viewing the columns of the dataset, the data type and if there are any null values.

data.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  float64
 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(6), int64(9), object(6)
memory usage: 3.5+ MB
```

In [6]:

```
# Viewing the statistical summary of the dataset.

data.describe()
```

Out[6]:

	id	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	sqft_above	
count	2.159700e+04	2.159700e+04	21597.000000	21597.000000	21597.000000	2.159700e+04	21597.000000	21597.000000	21
mean	4.580474e+09	5.402966e+05	3.373200	2.115826	2080.321850	1.509941e+04	1.494096	1788.596842	1
std	2.876736e+09	3.673681e+05	0.926299	0.768984	918.106125	4.141264e+04	0.539683	827.759761	
min	1.000102e+06	7.800000e+04	1.000000	0.500000	370.000000	5.200000e+02	1.000000	370.000000	1
25%	2.123049e+09	3.220000e+05	3.000000	1.750000	1430.000000	5.040000e+03	1.000000	1190.000000	1
50%	3.904930e+09	4.500000e+05	3.000000	2.250000	1910.000000	7.618000e+03	1.500000	1560.000000	1
75%	7.308900e+09	6.450000e+05	4.000000	2.500000	2550.000000	1.068500e+04	2.000000	2210.000000	1
max	9.900000e+09	7.700000e+06	33.000000	8.000000	13540.000000	1.651359e+06	3.500000	9410.000000	2

Observations

>

- Our data consists of 21597 rows and 21 columns
- The dataset contain a mix of numerical and categorical data types.
- Waterfront, view and year_renovate have missing values
- We can also see the statistical summary of the numerical records based on their count, mean, median, standard deviation,percentiles, minimum and maximum values.
- We can notice that there is 33 bedrooms which might be an outlier

Below are the statistics of price as our target variable:

- mean of approximately $540k
- median of $450k
- standard deviation of approximately $367k
- min and max values of $78k and \$7.7M respectively
- 25th and 75th percentile values of $322k and \$645k respectively

- 25th and 75th percentile values of $322k and \$645k respectively

Firstly let's visualize the distribution of houses and their prices on a map, to understand the locality distribution

In [7]:

```
latitudes = data['lat']
longitudes = data['long']
prices = data['price']

fig = go.Figure(data=go.Scattermapbox(
    lat=latitudes,
    lon=longitudes,
    mode='markers',
    marker=dict(
        size=10,
        color=prices,
        colorscale='Viridis',
        opacity=0.7,
        colorbar=dict(
            title='Price'   # Add a title to the colorbar
        )
    ),
))

fig.update_layout(
    mapbox=dict(
        accesstoken='pk.eyJ1IjoiY2luamkiLCJhIjoiY2xpNzNsZGRtMXdoeTNpbHBvaHpvYjVkNiJ9.DaQ9b5_qWWelaTEzyqJt9w',
        center=dict(
            lat=data['lat'].mean(),
            lon=data['long'].mean()
        ),
        zoom=10
    ),
    title='Distribution of Houses by Coordinates',
    width=1500,  # Adjust the width of the map
    height=1000  # Adjust the height of the map
)

fig.show()
```

The data was collected from states of Seattle, Mearcer Island Most houses are below 2 million in price and the most expensive houses are clustered in the same area.

3.0 Data Preparation

3.1 Data Cleaning

Identify and remove duplicated records

In [8]:

```
# Any dulplicated homes?
duplicates_len = len(data[data.duplicated(subset=['id'],
                                          keep=False)].sort_values(by='id'))

print(f"Results:\nThere are {duplicates_len} duplicated records.")
data[data.duplicated(subset=['id'], keep=False)].sort_values(by='id').head(4)
```

```
Results:
There are 353 duplicated records.
```

Out[8]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	...	grade	sqft
2495	1000102	4/22/2015	300000.0	6	3.0	2400	9373	2.0	NO	NONE	...	7 Average	
2494	1000102	9/16/2014	280000.0	6	3.0	2400	9373	2.0	NaN	NONE	...	7 Average	
16800	7200179	10/16/2014	150000.0	2	1.0	840	12750	1.0	NO	NONE	...	6 Low Average	

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	...	grade	sqft
16801	7200179	4/24/2015	175000.0	2	1.0	840	12750	1.0	NO	NONE	...	6 Low Average	

4 rows × 21 columns

**The duplicated records based on ID are from the same homes that sold within the same year.
These homes have the same attributes except for sale date.
These may be homes that were flipped or sold quickly after an initial sale.
We will keep these records because we are interested in predicting a home's sale price and these give more data for the true value of a house.**

Identifying Missing values

In [9]:

```
# How many columns have NaN?
print(data.isna().sum())
```

```
id                  0
date                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 [10]:

```
# check for placeholders
# Look for top occuring values
print('King County, WA \n Home Sales Dataframe\n')
for col in data.columns:
    print(col, '\n', data[col].value_counts(normalize = True).head(10), '\n')
```

```
King County, WA
 Home Sales Dataframe

id
 795000620     0.000139
8910500150    0.000093
7409700215    0.000093
1995200200    0.000093
9211500620    0.000093
1524079093    0.000093
4305200070    0.000093
1450100390    0.000093
7893805650    0.000093
109200390     0.000093
Name: id, dtype: float64

date
 6/23/2014    0.006575
6/25/2014    0.006066
```

```
6/26/2014    0.006066
7/8/2014     0.005880
4/27/2015    0.005834
3/25/2015    0.005695
7/9/2014     0.005603
4/14/2015    0.005603
4/28/2015    0.005603
4/22/2015    0.005603
Name: date, dtype: float64

price
 450000.0    0.007964
350000.0    0.007964
550000.0    0.007362
500000.0    0.007038
425000.0    0.006945
325000.0    0.006853
400000.0    0.006714
375000.0    0.006390
300000.0    0.006158
525000.0    0.006066
Name: price, dtype: float64

bedrooms
 3     0.454878
4     0.318655
2     0.127796
5     0.074131
6     0.012594
1     0.009075
7     0.001760
8     0.000602
9     0.000278
10    0.000139
Name: bedrooms, dtype: float64

bathrooms
 2.50    0.248970
1.00    0.178312
1.75    0.141131
2.25    0.094782
2.00    0.089364
1.50    0.066907
2.75    0.054869
3.00    0.034866
3.50    0.033847
3.25    0.027272
Name: bathrooms, dtype: float64

sqft_living
 1300    0.006390
1400    0.006251
1440    0.006158
1800    0.005973
1660    0.005973
1010    0.005973
1820    0.005927
1480    0.005788
1720    0.005788
1540    0.005742
Name: sqft_living, dtype: float64

sqft_lot
 5000    0.016576
6000    0.013428
4000    0.011622
7200    0.010187
4800    0.005510
7500    0.005510
4500    0.005279
8400    0.005140
9600    0.005047
```

```
3600    0.004769
Name: sqft_lot, dtype: float64

floors
 1.0    0.494189
2.0    0.381303
1.5    0.088438
3.0    0.028291
2.5    0.007455
3.5    0.000324
Name: floors, dtype: float64

waterfront
 NO     0.992404
YES    0.007596
Name: waterfront, dtype: float64

view
 NONE         0.901923
AVERAGE      0.044441
GOOD         0.023591
FAIR         0.015325
EXCELLENT    0.014721
Name: view, dtype: float64

condition
 Average      0.649164
Good         0.262861
Very Good    0.078761
Fair         0.007871
Poor         0.001343
Name: condition, dtype: float64

grade
 7 Average        0.415521
8 Good           0.280826
9 Better         0.121082
6 Low Average    0.094365
10 Very Good     0.052507
11 Excellent     0.018475
5 Fair           0.011205
12 Luxury        0.004121
4 Low            0.001250
13 Mansion       0.000602
Name: grade, dtype: float64

sqft_above
 1300    0.009816
1010    0.009724
1200    0.009538
1220    0.008890
1140    0.008520
1400    0.008334
1060    0.008242
1180    0.008196
1340    0.008149
1250    0.008057
Name: sqft_above, dtype: float64

sqft_basement
 0.0       0.593879
?         0.021021
600.0     0.010048
500.0     0.009677
700.0     0.009631
800.0     0.009307
400.0     0.008520
1000.0    0.006853
900.0     0.006575
300.0     0.006575
Name: sqft_basement, dtype: float64
```

```
yr_built
 2014    0.025883
2006    0.020975
2005    0.020836
2004    0.020049
2003    0.019447
2007    0.019308
1977    0.019308
1978    0.017919
1968    0.017641
2008    0.016993
Name: yr_built, dtype: float64

yr_renovated
 0.0       0.958096
2014.0    0.004112
2013.0    0.001746
2003.0    0.001746
2007.0    0.001690
2000.0    0.001633
2005.0    0.001633
2004.0    0.001239
1990.0    0.001239
2009.0    0.001183
Name: yr_renovated, dtype: float64

zipcode
 98103    0.027874
98038    0.027272
98115    0.026994
98052    0.026578
98117    0.025605
98042    0.025328
98034    0.025235
98118    0.023475
98023    0.023105
98006    0.023059
Name: zipcode, dtype: float64

lat
 47.5491    0.000787
47.6846    0.000787
47.5322    0.000787
47.6624    0.000787
47.6711    0.000741
47.6955    0.000741
47.6886    0.000741
47.6647    0.000695
47.6904    0.000695
47.6860    0.000695
Name: lat, dtype: float64

long
 -122.290    0.005325
-122.300    0.005140
-122.362    0.004815
-122.291    0.004630
-122.372    0.004584
-122.363    0.004584
-122.288    0.004538
-122.357    0.004445
-122.284    0.004399
-122.365    0.004352
Name: long, dtype: float64

sqft_living15
 1540    0.009122
1440    0.009029
1560    0.008890
1500    0.008334
1460    0.007825
1580    0.007733
```

```
1610    0.007686
1720    0.007686
1800    0.007686
1620    0.007594
Name: sqft_living15, dtype: float64

sqft_lot15
 5000    0.019771
4000    0.016484
6000    0.013335
7200    0.009724
4800    0.006714
7500    0.006575
8400    0.005371
3600    0.005140
4500    0.005140
5100    0.005047
Name: sqft_lot15, dtype: float64
```

Observations

Missing values results

1. **NaN *waterfront***

- **Binary categorical variable (YES or NO)**
- **replace NaN with mode of NO as most likely these properties are not waterfront**

view

- **Ordinal categorical variable**
- **replace NaN with NONE**

yr_renovated

- **Will rename yr_renovated to renovated and changed to countable numerical variable**
- **0 is the most common value with over 95% of values.**
- **Replace NaN with 0 value**

1. **Placeholder**

- **yr_renovated has 0 for missing or unknown values.**
- **sqft_basement has ? for missing or unknown values.**

In [11]:

```
# Was a house renovated or not?

data.yr_renovated.fillna('NO',inplace=True) # replace null with 0 the most common value

data['yr_renovated'] = data['yr_renovated'].replace(0.0, 'NO') # Replace zero with NO

data.loc[data['yr_renovated'] != 'NO', 'yr_renovated'] = 'YES' # Replace the years with Y
ES, as these were renovated

data.rename(columns={'yr_renovated': 'renovated'}, inplace=True)

data.head(7)
```

Out[11]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	...	grade	sqf
0	7129300520	10/13/2014	221900.0	3	1.00	1180	5650	1.0	NaN	NONE	...	7 Average	
1	6414100192	12/9/2014	538000.0	3	2.25	2570	7242	2.0	NO	NONE	...	7 Average	

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	...	grade	sqf
2	5631500400	2/25/2015	180000.0	2	1.00	770	10000	1.0	NO	NONE	...	6 Low Average	
3	2487200875	12/9/2014	604000.0	4	3.00	1960	5000	1.0	NO	NONE	...	7 Average	
4	1954400510	2/18/2015	510000.0	3	2.00	1680	8080	1.0	NO	NONE	...	8 Good	
5	7237550310	5/12/2014	1230000.0	4	4.50	5420	101930	1.0	NO	NONE	...	11 Excellent	
6	1321400060	6/27/2014	257500.0	3	2.25	1715	6819	2.0	NO	NONE	...	7 Average	

7 rows × 21 columns

In [12]:

```
# data cleaning

def process_data(data):
    # Dropping unwanted columns
    data.drop(['date', 'id', 'zipcode', 'sqft_living15', 'sqft_lot15'], axis=1, inplace=
True)

    data['sqft_basement'] = data['sqft_basement'].str.replace(r'\W', '').replace('', np.
nan).astype(float)  # replacing special characters and converting dtype
    data['sqft_basement'].fillna(data['sqft_basement'].median(), inplace=True)   # replac
ed null in sqft_basement with median
    data['waterfront'].fillna('NO', inplace=True)   # replaced null in waterfront with NO
    data['view'].fillna('NONE', inplace=True)   # replace nulls in view with None
    data['bedrooms'] = data['bedrooms'].replace(33, 3)   # replaces 33 with 3 because cle
arly that's an outlier

    return data

data = process_data(data)
```

Assumptions

> - **Without additional information Zipcode is not reliable as a location factor as latitude and longitude. e.g**
>   **Based on our code latitude and longitude are more precise markers.**
> - **Dropped 'sqft_living15', 'sqft_lot15' to focus on the particular house with its sqft_living and sqft_lot**
> - **Null values in waterfront replaced with NO as the mode.**
> - **Replaced 33 bedroomed house with 3 rooms as it made no sense judging from its price and its a 1-floor house. This is clearly an input error**

In [13]:

```
# to confirm that we do not have any more null values
data.isna().sum()
```

Out[13]:

```
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
renovated        0
lat              0
long             0
dtype: int64
```

In [14]:

```
#check the unique values of the categorical attributes
print("waterfront:", data['waterfront'].unique())
print()
print("views:", data['view'].unique())
print()
print("grade:", data['grade'].unique())
print()
print("conditions:", data['condition'].unique())
```

```
waterfront: ['NO' 'YES']

views: ['NONE' 'GOOD' 'EXCELLENT' 'AVERAGE' 'FAIR']

grade: ['7 Average' '6 Low Average' '8 Good' '11 Excellent' '9 Better' '5 Fair'
 '10 Very Good' '12 Luxury' '4 Low' '3 Poor' '13 Mansion']

conditions: ['Average' 'Very Good' 'Good' 'Poor' 'Fair']
```

3.2 Exploratory Data Analysis

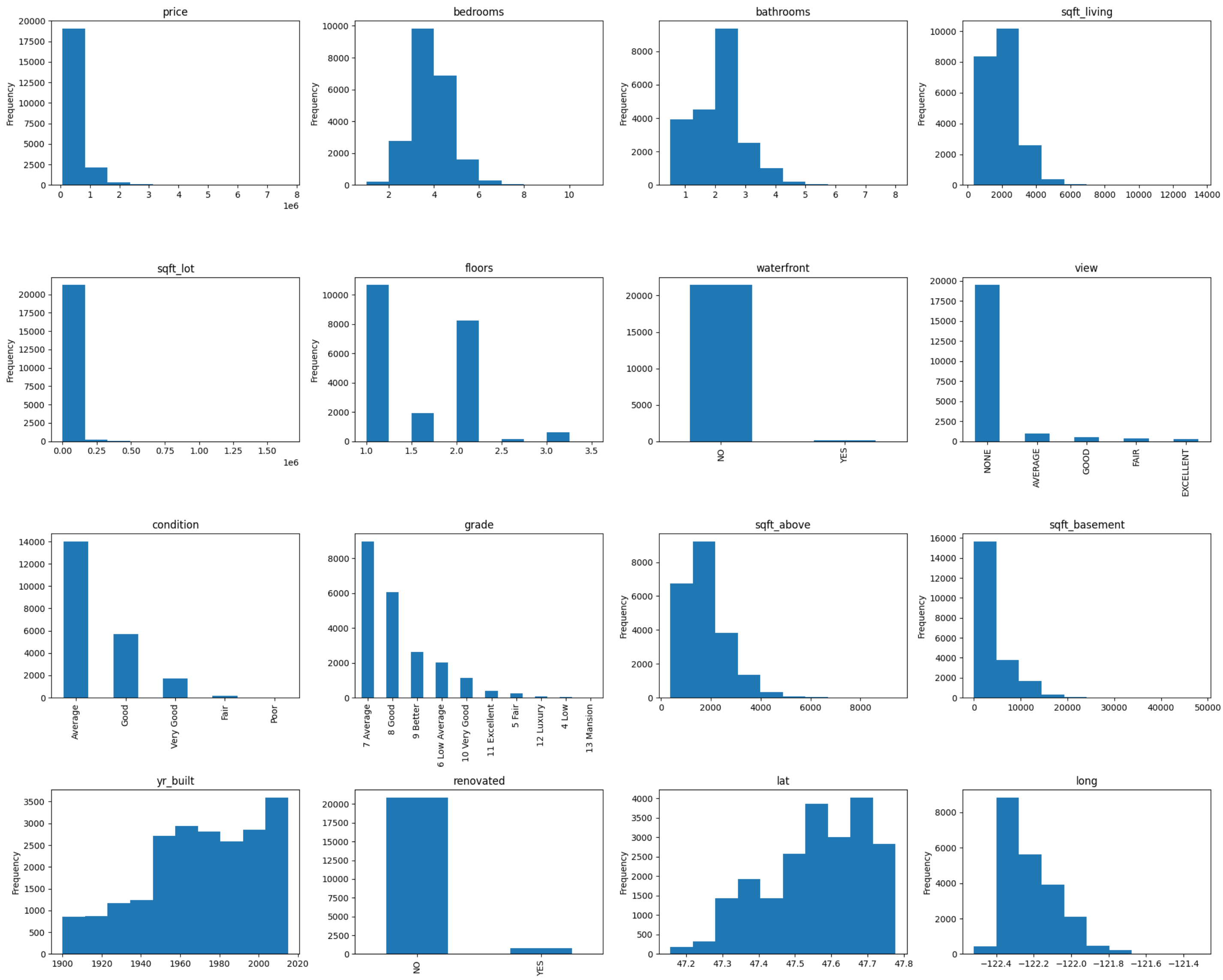
1. Univariate analysis

We will visualise the summary statistics of each individual predictor variable in the dataset.

In [15]:

```
# Create a list of columns to plot
columns_to_plot = data.columns

# Calculate the number of rows and columns for the subplots
num_rows = len(columns_to_plot) // 4 + (len(columns_to_plot) % 4 > 0)
num_cols = min(len(columns_to_plot), 4)

# Create the figure and axes objects
fig, axes = plt.subplots(num_rows, num_cols, figsize=(20, num_rows * 4))

# Flatten the axes array if it's a single row or column
if num_rows == 1:
    axes = axes.reshape(1, -1)
elif num_cols == 1:
    axes = axes.reshape(-1, 1)

# Iterate over the columns and plot on each subplot
for i, column in enumerate(columns_to_plot):
    row_idx = i // num_cols
    col_idx = i % num_cols
    ax = axes[row_idx, col_idx]

    ax.set_title(column)

    if is_numeric_dtype(data[column]):
        data[column].plot(kind='hist', ax=ax)
    elif is_string_dtype(data[column]):
        data[column].value_counts()[:10].plot(kind='bar', ax=ax)

# Adjust the spacing between subplots
plt.tight_layout()

# Show the plot
```

```
plt.show()

# Save the plot as a PDF with reduced DPI
plt.savefig('histogram.pdf', format='pdf', dpi=80)
```




```
<Figure size 640x480 with 0 Axes>
```

Represented continous data with histogram and categorical data with bargraphs
Observations from the above histograms and bargraphs:

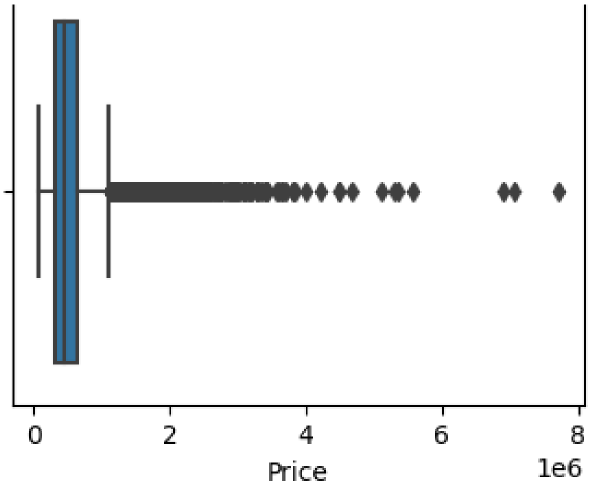
1. **'price' is right skewed. Meaning it is not symmetrical.**
2. **'bedrooms' and 'bathrooms' look to be discrete counts of those home features, as does 'floors'.**
3. **'sqft_above', 'sqft_living', 'sqft_basement' and 'sqft_lot' all look to be continuous, so is 'price'.**

In conlusion, we can note both the presence of some extreme outliers and data skewness in most of the distributions.

- **A box plot to visualize the 'price' distribution.**

In [16]:

```
plt.figure(figsize=(4, 3))
sns.boxplot(x=data['price'])
plt.xlabel('Price')
plt.title('Box Plot of Price')
plt.show()
plt.subplots_adjust(left=0.1, right=0.9, top=0.9, bottom=0.1, wspace=0.4, hspace=0.4)
plt.savefig('boxplot.pdf', format='pdf')
```




```
<Figure size 640x480 with 0 Axes>
```

The box represents the interquartile range (IQR), with the horizontal line inside indicating the median. The whiskers extend to the minimum and maximum non-outlier values, while any data points outside the whiskers are considered outliers.

The observation made is that there are a lot of outliers in the 'price' variable, as indicated by the data points outside the whiskers of the box plot. We will maintain the outliers because it could be a true indication of houes prices in King County.

2. Bivariate Analysis

Converting categorical to Numerical

In [17]:

```
def convert_categorical_to_numerical(data):
    # Mapping for 'renovated'
    renovated_mapping = {'NO': 0, 'YES': 1}
    data['renovated'] = data['renovated'].replace(renovated_mapping).astype(float)

    # Mapping for 'view'
    view_mapping = {'NONE': 0, 'FAIR': 1, 'AVERAGE': 2, 'GOOD': 3, 'EXCELLENT': 4}
    data['view'] = data['view'].replace(view_mapping).astype(float)

    # Mapping for 'condition'
    condition_mapping = {'Poor': 1, 'Fair': 2, 'Average': 3, 'Good': 4, 'Very Good': 5}
    data['condition'] = data['condition'].replace(condition_mapping).astype(float)

    # Mapping for 'waterfront'
    waterfront_mapping = {'NO': 0, 'YES': 1}
    data['waterfront'] = data['waterfront'].replace(waterfront_mapping).astype(float)

    # Mapping for 'grade'
    data['grade'] = data['grade'].map(lambda x: int(x[0:2]))

    return data

data = convert_categorical_to_numerical(data)
```

Converting categorical to numerical values allows for mathematical operations to be performed on those variables e.g logarithm transformation, improve model performance etc.

Correlation between the target variable (Price) and the predictors.

In [18]:

```
# setting the target variable as price; check how the predictor variables correlate with
price and identify the highest correlated
```

```
data.corr()['price'].sort_values(ascending=False)
```

Out[18]:

```
price            1.000000
sqft_living      0.701917
grade            0.667951
sqft_above       0.605368
bathrooms        0.525906
view             0.393497
sqft_basement    0.321108
bedrooms         0.315954
lat              0.306692
waterfront       0.264306
floors           0.256804
renovated        0.117543
sqft_lot         0.089876
yr_built         0.053953
condition        0.036056
long             0.022036
Name: price, dtype: float64
```

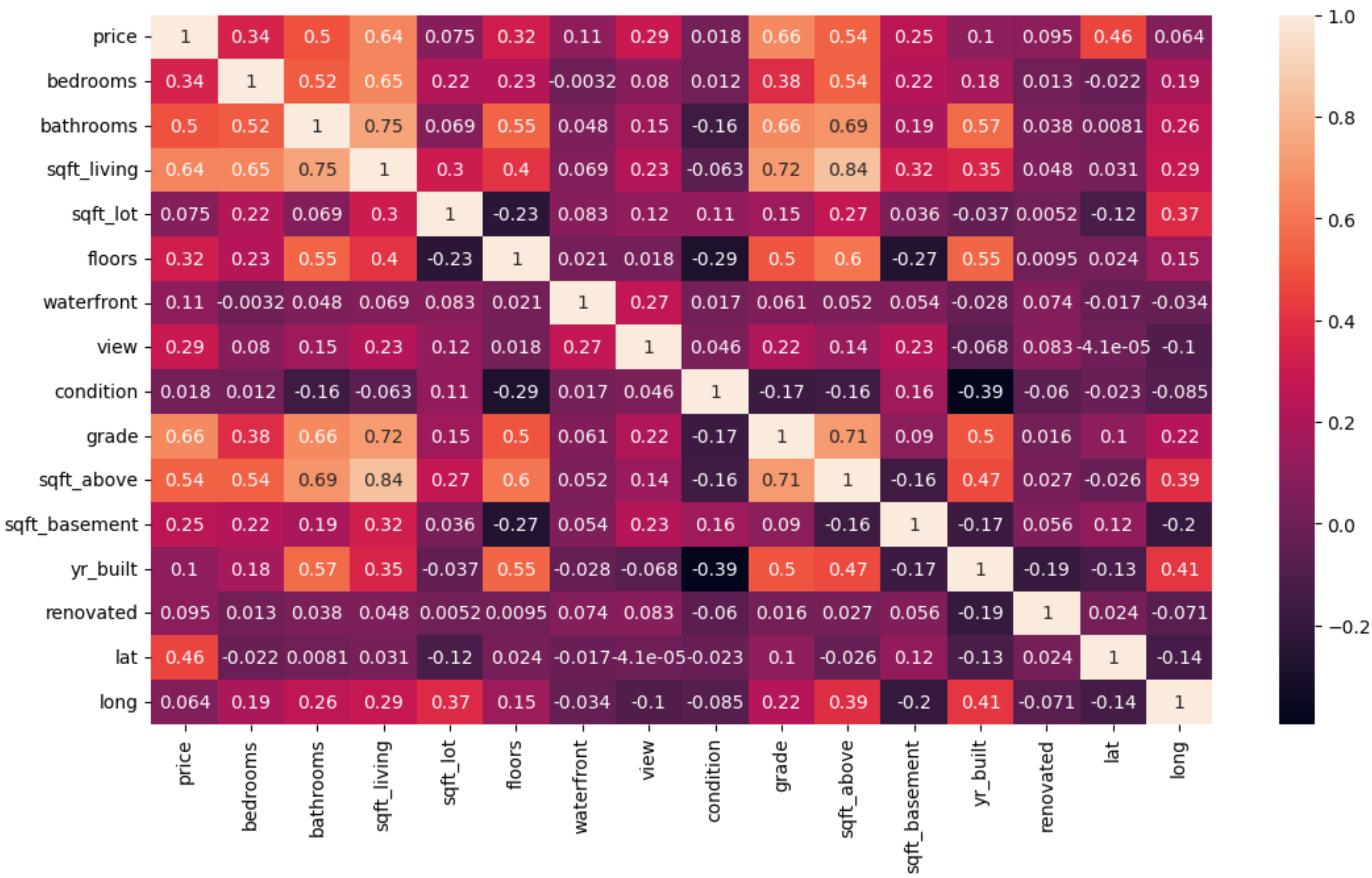
From the results, sqft_living has the highest correlation with price.

grade, sqft_above and bathrooms have a considerably higher correlation with price. This knowledge will guide us in the predictor variables we choose for the model. long, yr_built and sft_lot have a lower correlation wit price.

Visualization of the correlation between all the variables using a heat map

In [19]:

```
# Visualizing the correlation between all the variables

plt.figure(figsize=(13,7))
sns.heatmap(data.corr(method='spearman', numeric_only=True), annot=True);
```



The above correlation heatmap provides a clear and concise way to understand the correlation structure of the dataset. We can be able to see the relationship between different variables

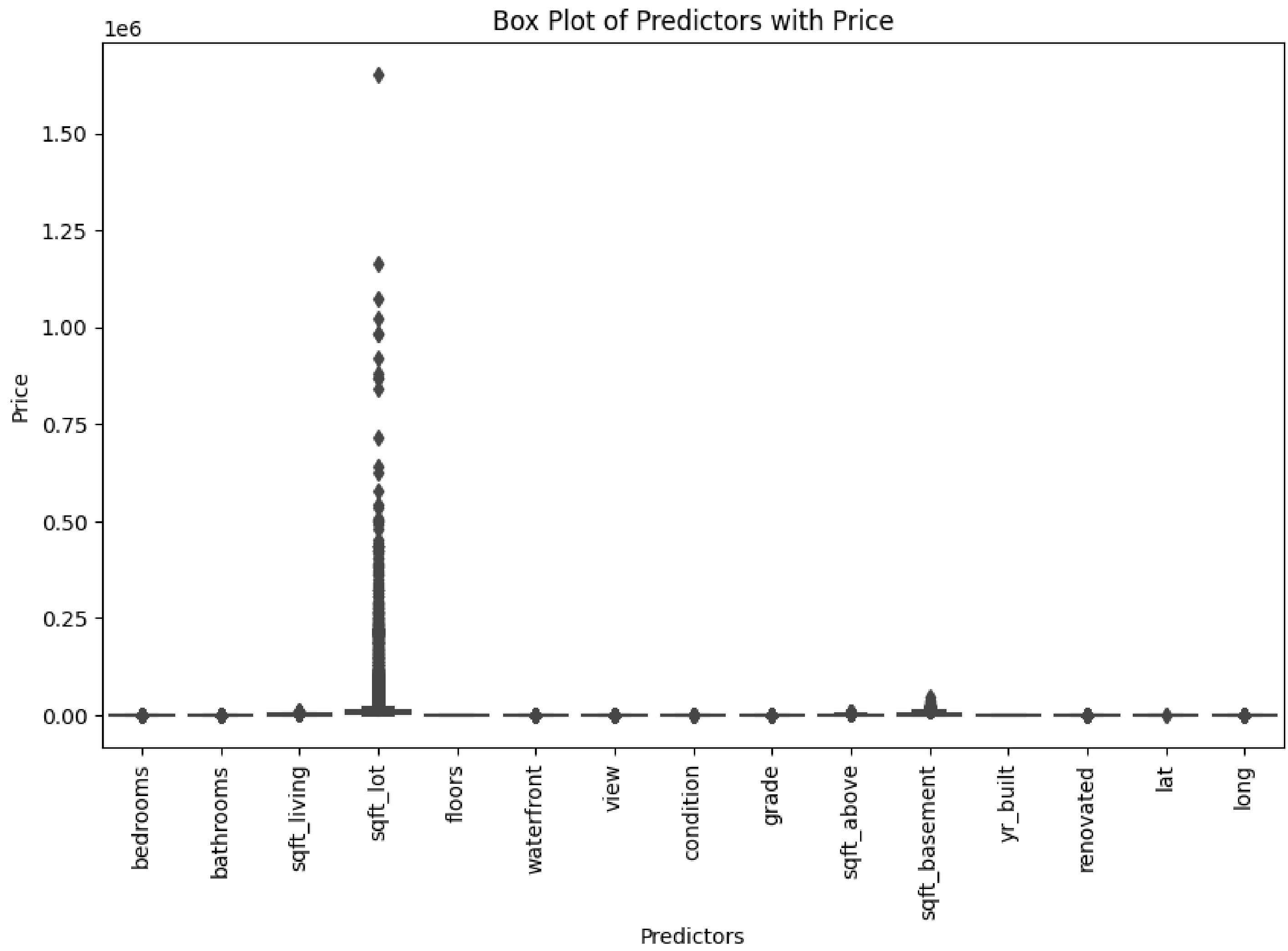
dataset. We can be able to see the relationship between different variables.

sqft_living, bathrooms, grade and sqft_above have 0.7 and above multicollinearity. Based on this information we have to make a decision on the predictors that will satisfy our objectives. This strategy will help avoid using predictors that are highly correlated making our model inaccurate.

- **Next, we will visualize the distribution and variation of the 'price' variable across different predictor variables.**

In [20]:

```
# Selecting the features to plot (excluding 'price')
X = data.drop('price', axis=1)

# Creating a new DataFrame by concatenating the selected features with 'price'
#data_concat = pd.concat([X, data['price']], axis=1)

# Set up the figure and axis
plt.figure(figsize=(10, 6))
ax = sns.boxplot(X)

# Rotate x-axis labels if needed
plt.xticks(rotation=90)

# Set labels and title
plt.xlabel('Predictors')
plt.ylabel('Price')
plt.title('Box Plot of Predictors with Price')

# Show the plot
plt.show()
```



From the above box plot:

1. **we are able to see the spread and variability of the predictor variables in relation to the target variable**

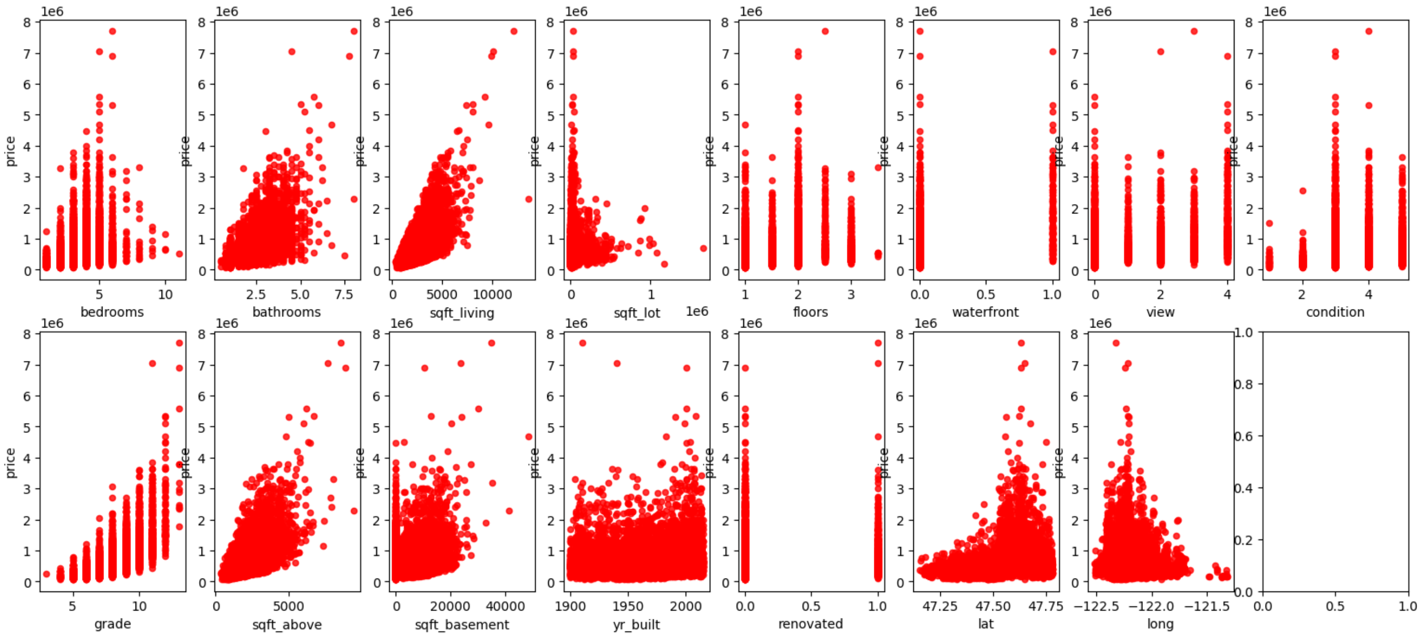
1. We are able to see the spread and variability of the predictor variables in relation to the target variable ('price')
2. From the distributions we can see some outliers especially in 'sqft_lot'.

Dropping the sqft_lot seems like a good idea because it presents some significant outliers and in addition its correlation with our target variable is significantly low.

- **Plotting the Predictors vs. Price**

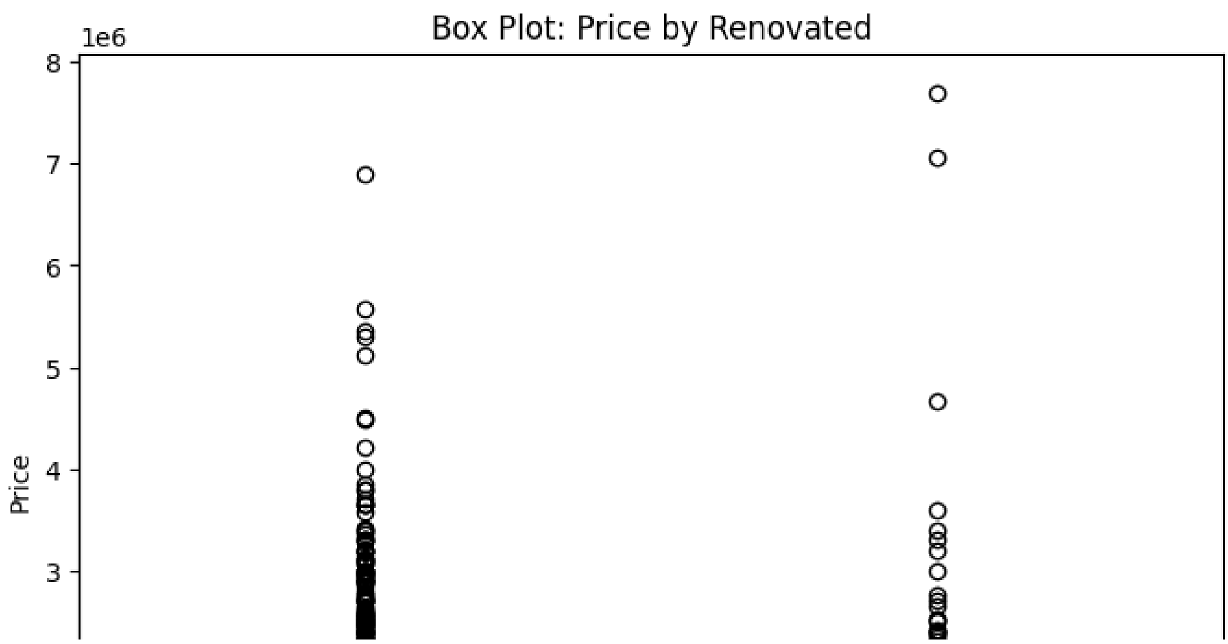
In [21]:

```
# setup figure
fig, axes = plt.subplots(2,8, figsize=(19, 8))

# iterate and plot subplots
for xcol, ax in zip(data.columns[1:], [x for v in axes for x in v]):
    data.plot.scatter(x=xcol, y='price', ax=ax, alpha=0.8, color='r')
```



In [22]:

```
plt.figure(figsize=(8, 6))
plt.boxplot([data[data['renovated'] == 0]['price'], data[data['renovated'] == 1]['price'
]], labels=['Not Renovated', 'Renovated'])
plt.xlabel('Renovated')
plt.ylabel('Price')
plt.title('Box Plot: Price by Renovated')
plt.show()
```



Observations

- There is a strong positive linear relationship between price, our target variable and our predictors, bathrooms, sqft_living and sqft_above. We can conclude that the forementioned predictors shhould be considered when buying or reenovating a house to sell.
- It is quite interesting from our visualization of the dataset that most expensive house are 2-floors. This is different from our general knowledge that houses with more floors are way more expensive.
- A house being at a waterfront is not as significant when it comes to pricing. We have an almost equal relationship between the two categories.
- We can also see that the houses with a higher grade are more expensive.
- Renovations increase the price of a house based on the final boxplot above. infact the outliers identified in the target variables have renovations improvement on them.

Check for Multicollinearity

- Variance Inflation Factor (VIF)

In [23]:

```
from statsmodels.stats.outliers_influence import variance_inflation_factor
from statsmodels.tools.tools import add_constant
X_data=data.drop(['price'], axis=1)
X_data = add_constant(X_data)
vif = pd.DataFrame([variance_inflation_factor(X_data.values, i) for i in range(X_data.sh
ape[1])], index=X_data.columns, columns=['VIF'])
vif = vif.sort_values(by='VIF', ascending=False)

vif
```

Out[23]:

	VIF
const	1.280824e+06
sqft_living	1.466746e+02
sqft_above	1.189174e+02
sqft_basement	3.305468e+01
bathrooms	3.359396e+00
grade	3.134467e+00
yr_built	2.343030e+00
floors	1.962947e+00
bedrooms	1.700850e+00
long	1.419987e+00
view	1.360629e+00
condition	1.225566e+00
waterfront	1.176214e+00
lat	1.121681e+00

	VIF
renovated	1.115316e+00
sqft_lot	1.104349e+00

Interpreting VIF values:

VIF = 1: No multicollinearity. The predictor variable is not correlated with any other predictors in the model.

VIF > 1 and < 5: Moderate multicollinearity. The predictor variable is correlated with other predictors, but it is not highly problematic.

VIF ≥ 5: High multicollinearity. The predictor variable is strongly correlated with other predictors, and it may be necessary to address the multicollinearity issue in the model.

4.0 Model Development

4.1 Build a baseline simple linear regression model

Preparing data for modelling

In [24]:

```
#make a copy of tha data to be used
house = data.copy(deep=True)
```

In [25]:

```
# Regression variables to be used
y = house['price']   #target
X_baseline = house[['sqft_living']] #predictor
```

- **Simple Linear Regression**

We use sqft_living to build the baseline model because it is highly correlated with price.

In [26]:

```
baseline_model = sm.OLS(y, sm.add_constant(X_baseline)).fit()

print(baseline_model.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                  price   R-squared:                       0.493
Model:                            OLS   Adj. R-squared:                  0.493
Method:                 Least Squares   F-statistic:                 2.097e+04
Date:                Fri, 02 Jun 2023   Prob (F-statistic):               0.00
Time:                        21:17:37   Log-Likelihood:            -3.0006e+05
No. Observations:               21597   AIC:                         6.001e+05
Df Residuals:                   21595   BIC:                         6.001e+05
Df Model:                           1
Covariance Type:            nonrobust
===============================================================================
                  coef    std err          t      P>|t|      [0.025      0.975]
-------------------------------------------------------------------------------
const       -4.399e+04   4410.023     -9.975      0.000   -5.26e+04   -3.53e+04
sqft_living   280.8630      1.939    144.819      0.000     277.062     284.664
==============================================================================
Omnibus:                    14801.942   Durbin-Watson:                   1.982
Prob(Omnibus):                  0.000   Jarque-Bera (JB):           542662.604
Skew:                           2.820   Prob(JB):                         0.00
Kurtosis:                      26.901   Cond. No.                     5.63e+03
==============================================================================

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

```
[1] Standard Errors assume that the covariance matrix of the errors is correctly specifie
d.
[2] The condition number is large, 5.63e+03. This might indicate that there are
strong multicollinearity or other numerical problems.
```

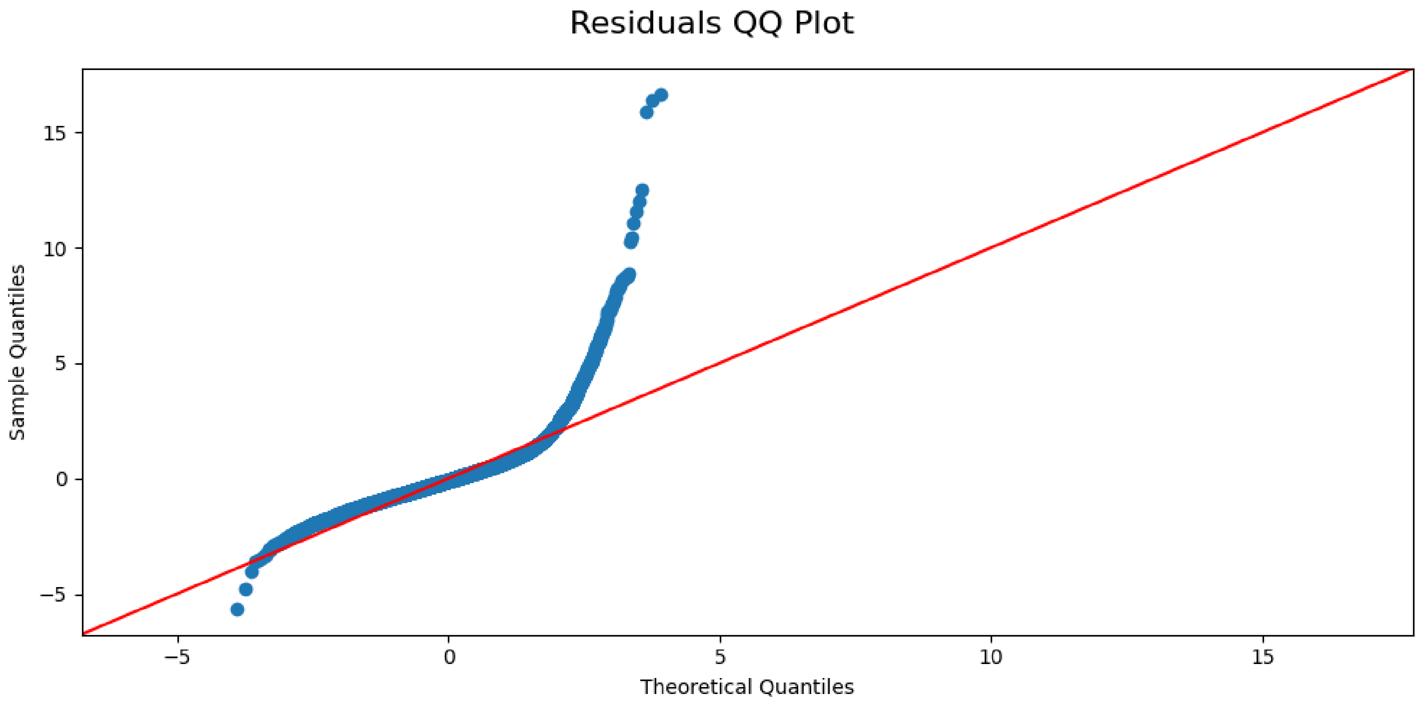
Model observations

Our baseline model is statistically significant shown by the sqft_living coefficient and intercept pvalues of zero,less that our alpha of 0.05.

- **The model explains about 49% of variance in price.**
- **zero 'sqft_living' has a reduction in price of about $44k. This knowledge is not necessary important but it helps us analysis our model.**
- **For a unit increase in square foot of living, there is $280k increase in price.**
- **We shall work to reduce our condition number which is considerably large and increase our r-squared.**

In [27]:

```
# Residual plot
residuals = baseline_model.resid
fig = sm.graphics.qqplot(residuals, line='45', fit=True)
fig.suptitle('Residuals QQ Plot', fontsize=16)
fig.set_size_inches(10, 5)
fig.show()
plt.tight_layout()
```



From the above, the residuals defy the assumption of normalcy.

Clearly, our model does not pass the goodness of fit requirement.

4.2 Multiple Linear Regression

In [28]:

```
X = house[['bedrooms', 'bathrooms', 'sqft_living', 'sqft_lot', 'floors', 'yr_built', 're
novated', 'lat', 'view', 'condition', 'grade']]
# X = house[['sqft_living', 'bedrooms', 'grade']]
y = house['price']

X_pred = sm.add_constant(X)

#building the model
model =  sm.OLS(y, X_pred) .fit()
```

```
#getting the model summary
print(model.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                  price   R-squared:                       0.677
Model:                            OLS   Adj. R-squared:                  0.677
Method:                 Least Squares   F-statistic:                     4108.
Date:                Fri, 02 Jun 2023   Prob (F-statistic):               0.00
Time:                        21:17:37   Log-Likelihood:            -2.9520e+05
No. Observations:               21597   AIC:                         5.904e+05
Df Residuals:                   21585   BIC:                         5.905e+05
Df Model:                          11
Covariance Type:            nonrobust
===============================================================================
                  coef    std err          t      P>|t|      [0.025      0.975]
-------------------------------------------------------------------------------
const       -2.158e+07   5.61e+05    -38.490      0.000   -2.27e+07   -2.05e+07
bedrooms    -4.039e+04   2048.616    -19.716      0.000   -4.44e+04   -3.64e+04
bathrooms    3.957e+04   3336.764     11.858      0.000     3.3e+04    4.61e+04
sqft_living   179.8991      3.193     56.338      0.000     173.640     186.158
sqft_lot       -0.1173      0.035     -3.324      0.001      -0.186      -0.048
floors       1.538e+04   3317.183      4.637      0.000    8880.209    2.19e+04
yr_built    -2664.7334     69.641    -38.264      0.000   -2801.234   -2528.232
renovated    5.443e+04   8218.605      6.622      0.000    3.83e+04    7.05e+04
lat          5.488e+05   1.08e+04     50.954      0.000    5.28e+05     5.7e+05
view         7.598e+04   1995.766     38.072      0.000    7.21e+04    7.99e+04
condition    2.897e+04   2409.224     12.026      0.000    2.43e+04    3.37e+04
grade        1.055e+05   2100.059     50.259      0.000    1.01e+05     1.1e+05
==============================================================================
Omnibus:                    19280.410   Durbin-Watson:                   1.993
Prob(Omnibus):                  0.000   Jarque-Bera (JB):          2006779.548
Skew:                           3.866   Prob(JB):                         0.00
Kurtosis:                      49.586   Cond. No.                     1.74e+07
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specifie
d.
[2] The condition number is large, 1.74e+07. This might indicate that there are
strong multicollinearity or other numerical problems.
```

Model Observations

The model is statistically significant, the p-values of the predictor coefficients are less that our alpha.

- **The model now explains about 68% variance in our price. an improvement from our simple model. Introducing more variables has improved our model performance.**
- **The model condition number has reduced but still significantly high.**
- **The 'yr-built' variable shows that older houses sell for less price. An additional age reduces the house price by about $3k**
- **Any change in 'renovation' variable increases the price by about $54k**
- **It is also interesting that an additional bedroom and sqft_lot reduces the price of the house. that is quite strange based on our background knowledge.**

We will standardize the variables and assess whether there is an improvement in our model

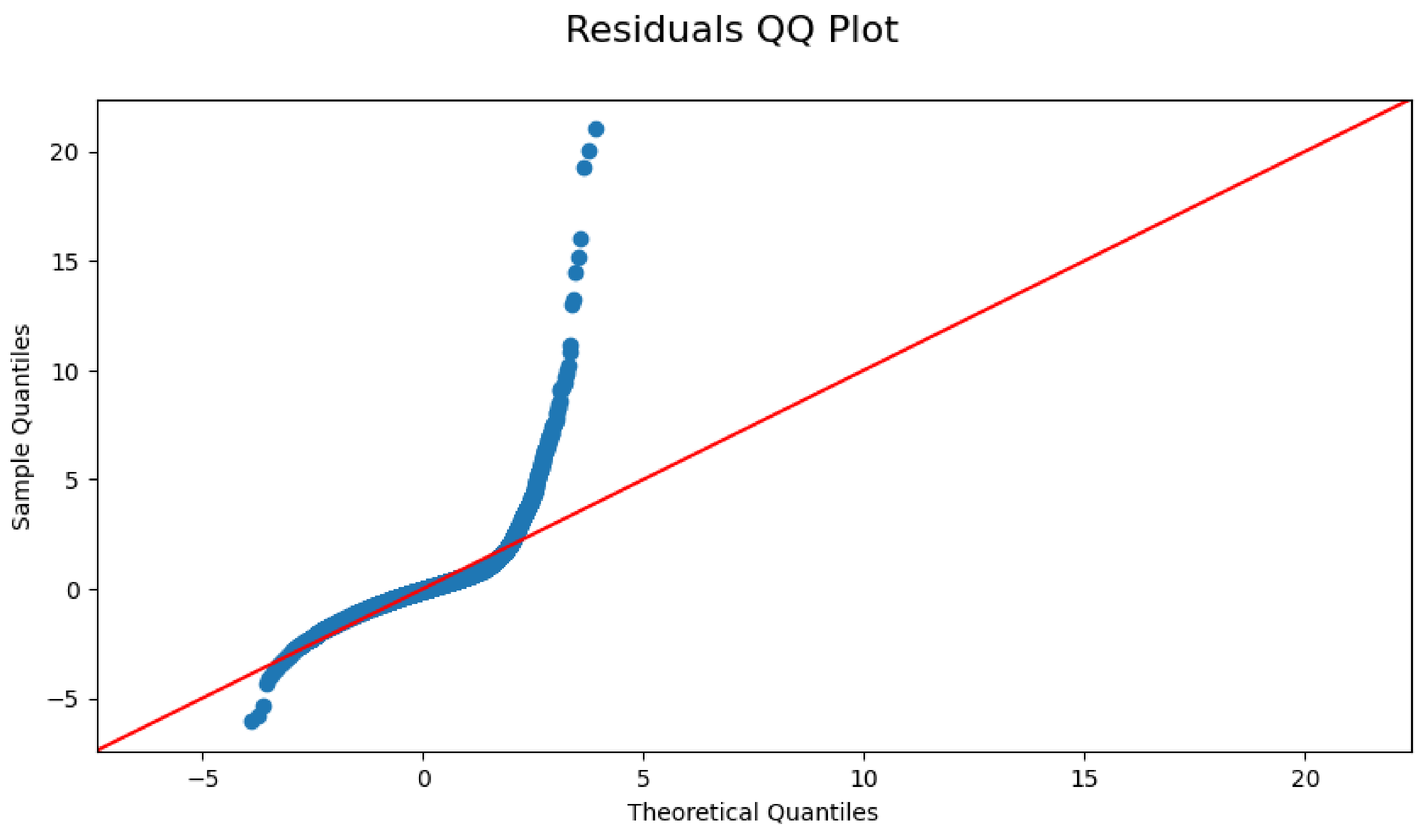
- **Normality**

  A Q-Q plot that compares the distribution of the residuals to a theoretical Gaussian (normal) distribution.

In [29]:

```
# Residual plot
residuals = model.resid
fig = sm.graphics.qqplot(residuals, line='45', fit=True)
fig.suptitle('Residuals QQ Plot', fontsize=16)
```

```
fig.set_size_inches(10, 5)
fig.show()
```

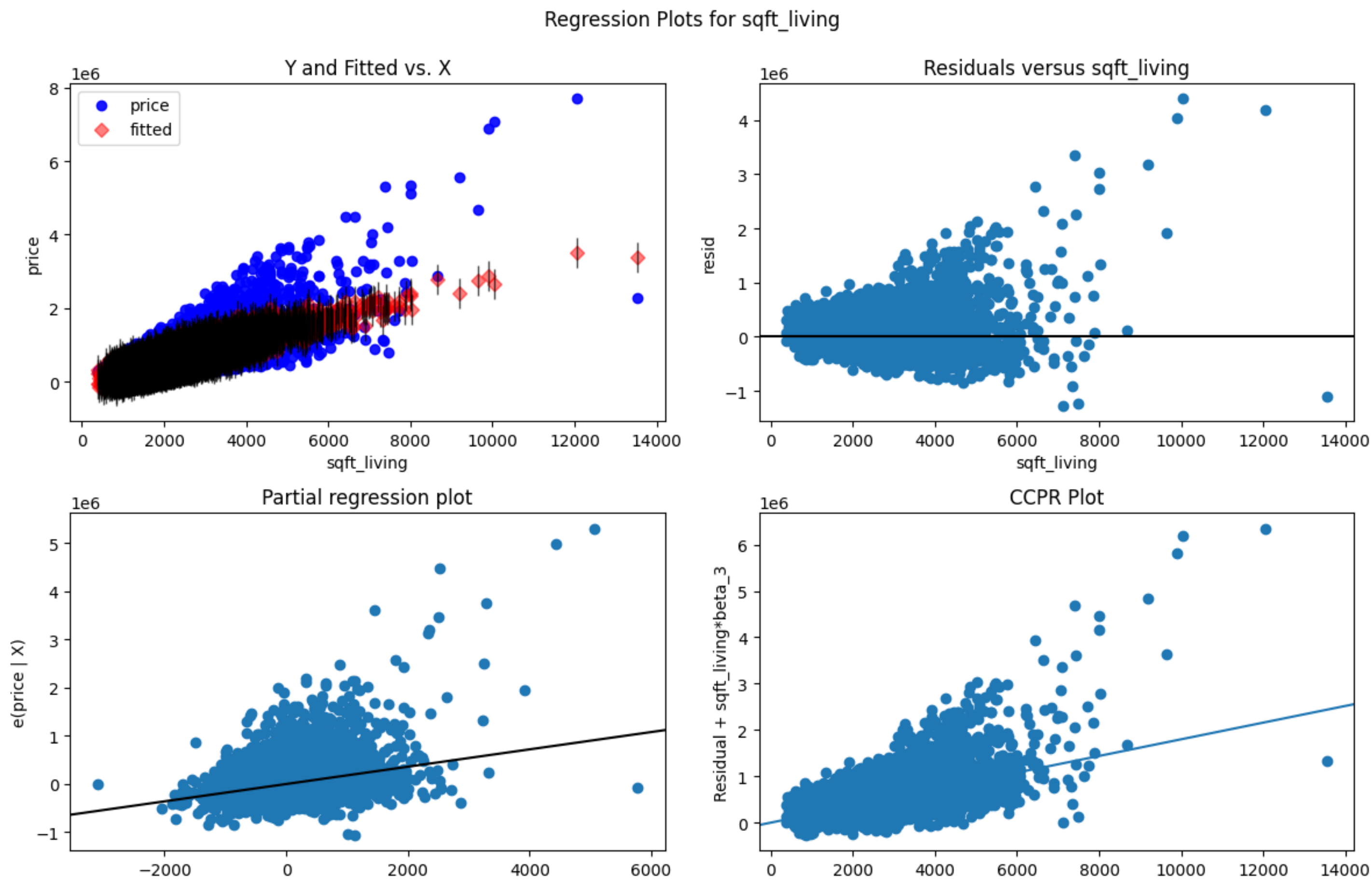


- **We can see from the residual qq-plot above that the residuals do not follow a normal distribution.**
- **Deviations from this pattern may indicate nonlinearity or heteroscedasticity (unequal variance), which can affect the model's accuracy.**

In [30]:

```
sm.graphics.plot_regress_exog(model, "sqft_living", fig=plt.figure(figsize=(12,8)));
```

```
eval_env: 1
```



e(sqft_living | X) sqft_living

1. The **Y and Fitted vs X** plot shows the observed values of the dependent variable against the predicted values. This plot helps assess the linearity assumption by examining the distribution of points around the diagonal line. The deviations indicate non-linearity.
2. The **Residuals versus sft_living** plot displays the residuals against the predicted values. This plot helps assess the assumption of constant variance (homoscedasticity). The increasing spread may indicate heteroscedasticity.
3. The **Partial regression** plot shows the standardized residuals (residuals divided by their standard deviation) against the predicted values. We can identify outliers from the plot.
4. The **CCPR** plot helps assess the normality assumption of the residuals.

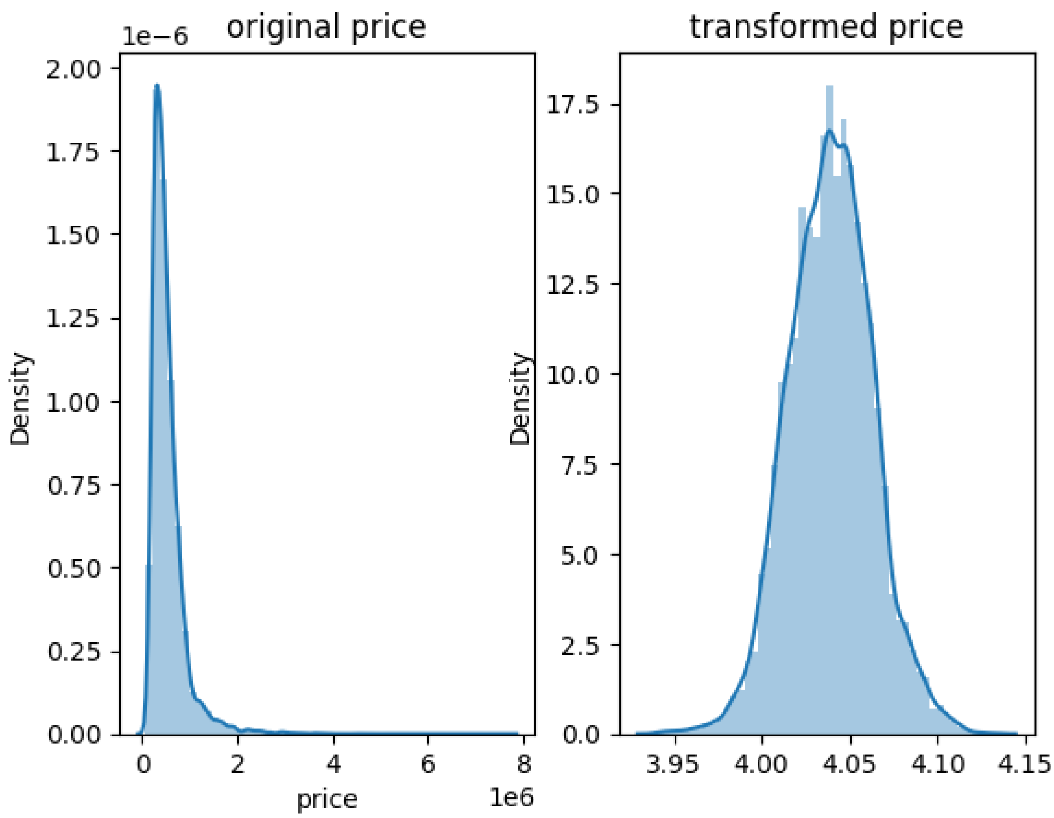
Visualization of the target variable.

In [31]:

```
# Normalizing price
scaled_price=data['price']
norm_price=stats.boxcox(scaled_price)

fig, ax=plt.subplots(1,2)
sns.distplot(scaled_price, ax=ax[0])
ax[0].set_title('original price')
sns.distplot(norm_price[0], ax=ax[1])
ax[1].set_title('transformed price')
```

Out[31]:

```
Text(0.5, 1.0, 'transformed price')
```



- We will apply log transformation to the target variable because of the following reasons:

1. In the regression analysis above the relationship between the predictors and the target variable appears to be multiplicative
2. The target variable exhibits skewness (see the graph above).

By applying a log transformation to the target variable, we can potentially linearize the relationship and improve the model's performance.

In [32]:

```
#log transformation
y1 = np.log(house['price'])
```

- **We will run the model again to check if there's any improvement.**

In [33]:

```
model2 = sm.OLS(y1, sm.add_constant(X)).fit()
print(model2.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                  price   R-squared:                       0.759
Model:                            OLS   Adj. R-squared:                  0.759
Method:                 Least Squares   F-statistic:                     6168.
Date:                Fri, 02 Jun 2023   Prob (F-statistic):               0.00
Time:                        21:17:40   Log-Likelihood:                -1442.1
No. Observations:               21597   AIC:                             2908.
Df Residuals:                   21585   BIC:                             3004.
Df Model:                          11
Covariance Type:            nonrobust
===============================================================================
                  coef    std err          t      P>|t|      [0.025      0.975]
-------------------------------------------------------------------------------
const         -47.1663      0.694    -67.940      0.000     -48.527     -45.806
bedrooms       -0.0141      0.003     -5.559      0.000      -0.019      -0.009
bathrooms       0.0672      0.004     16.270      0.000       0.059       0.075
sqft_living     0.0002   3.95e-06     45.498      0.000       0.000       0.000
sqft_lot     3.034e-07   4.37e-08      6.941      0.000    2.18e-07    3.89e-07
floors          0.0587      0.004     14.289      0.000       0.051       0.067
yr_built       -0.0032   8.62e-05    -37.546      0.000      -0.003      -0.003
renovated       0.0785      0.010      7.712      0.000       0.059       0.098
lat             1.3544      0.013    101.545      0.000       1.328       1.381
view            0.0816      0.002     33.027      0.000       0.077       0.086
condition       0.0660      0.003     22.128      0.000       0.060       0.072
grade           0.1795      0.003     69.033      0.000       0.174       0.185
==============================================================================
Omnibus:                      540.698   Durbin-Watson:                   1.983
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             1307.098
Skew:                           0.023   Prob(JB):                    1.47e-284
Kurtosis:                       4.204   Cond. No.                     1.74e+07
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specifie
d.
[2] The condition number is large, 1.74e+07. This might indicate that there are
strong multicollinearity or other numerical problems.
```

Final Model Observations

We can conclusively say that our model is statistically significant based on our p-values equal to zero.

Our r-squared has improved, the model now explains about 76% of the variance in price.

Coefficients: The coefficients represent the estimated effects of each predictor variable on the house prices. Here are some key coefficients and their interpretations:

1. **An additonal bedroom is associated with reduction of $0.0141 in house price.**
2. **An additional bathroom is associated with an increase of $0.0672 in house price.**
3. **An additional unit in square footage of living space is associated with an increase of** $0.0002 in house price$ **2 in the price of the house** $.10000 units in square foot of living space adds$
4. **The older the house the lower the price (yr_built). An additional**

age to the house reduces the house price by $0.0032

5. An improvement in renovation of the house is associated with $0.0785 in the house price.
6. A step higher in the **view** scale is associated with an increase of $0. 0816 in house price.
7. A step higher in the **grade** scale is associated with an increase of $0. 1795 in house price.
8. Just like grade, a step higher in the **condition** scale is associated with an increase of $0.1795 in house price.

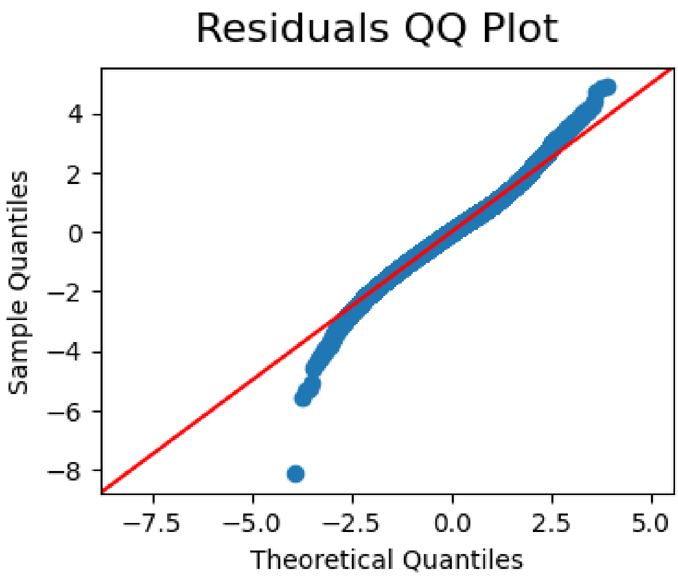
Overall, the model suggests that the number of bedrooms, bathrooms, yr_built,renovation, sqft-living, view, grade, condition are important predictors of house prices.

5.0 Model Evaluation

- Checking the distribution of the residuals using a qq plot.

In [34]:

```
#@title
# Residual plot
residuals = model2.resid
fig = sm.graphics.qqplot(residuals, line='45', fit=True)
fig.suptitle('Residuals QQ Plot', fontsize=16)
fig.set_size_inches(4, 3)
fig.show()
```



From the plot we can now say that it follows the normality assumption.

- We have a close to perfect goodness of fit.

In [35]:

```
# Adding a column of ones to account for the y-intercept
X_with_intercept = np.c_[np.ones(X.shape[0]), X]

# Predict using the modified feature array with the y-intercept
y_pred = model2.predict(X_with_intercept)
```

In [36]:

```
# Assuming y_true contains the actual values and y_pred contains the predicted values
mae = mean_absolute_error(y1, y_pred)
mse = mean_squared_error(y1, y_pred)
rmse = np.sqrt(mse)


print('Model Mean Absolute Error:', mae)
print('Model Mean Standard Error:', mse)
print('Model Root Mean Standard Error:', rmse)
```

```
Model Mean Absolute Error: 0.19889299309258446
Model Mean Standard Error: 0.06691540133661557
Model Root Mean Standard Error: 0.25868011391797313
```

Model Evaluation Observation

- The MAE value of 0.1988 suggests that on average, the model's predictions deviate from the true values by approximately 0.1988 units. The low MAE shows that our model performance is good.
- The MSE value of 0.0669 indicates that on average, the squared difference between the predicted values and the true values is approximately 0.0669. Similar to MAE, the low MSE value shows that our model performance is good.
- The RMSE value of 0.2587 suggests that on average, the model's predictions deviate from the true values by approximately 0.2587 units. Similar to MAE and MSE, the low RMSE shows that our model performance is good.

Data Limitation

- Data is only from 2014 to 2015. Models to predict future sales price would need to be updated with newer data.
- Models to predict future sales price would need to be updated with newer data.
- Some data was missing requiring us to make assumptions that might have affected our model performance

6.0 Conclusions and Recommendations

Conclusions:

1. Square foot of living, grade, square foot above, number of bathrooms and bedrooms, condition, square foot above, square foot of basement, waterfront, view, year the house was built, square foot lot, floors, whether renovated or not, latitiude and longitude significantly influence the price of a house. specifically, Square foot of living, grade, square foot above, bathrooms and view are the top 5 factors showing very high influence in the prices of a house.
2. The house grade and condition are very key factors in price of a house. The higher the house grade, the more price it fetches. The Houses with average condition and above tend to fetch high prices. This could be because several factors e.g a house with average conditon and above could have been renovated, recently build or have a higher square foor of living. The features are highly dependent on each other.
3. From our analysis we can almost conclusively say that renovations have increased the quality of the house thereby increasing in price.

Recommendations:

1. Focus on Property Condition and Grade: Emphasize the significance of property condition and grade in determining house prices. Encourage renovations to improve the overall condition and raise the property's grade as this has a great impact on the value of a house.
2. Highlight the significant impact of square footage of living space on house prices and use this information to justify higher listing prices for properties with more extensive square footage.
3. The number of bathrooms and bedrooms also have a positive correlation with the value of a house. Therefore, during renovation adding may be a bedroom would increase the value of the house.
4. Based on the model, Sixth Sense agency should consider significant features such as grade, square footage of living etc to better advice home buyers on what they can afford based on their budget.

Next Steps:

1. While the model provides insights into specific variables, remember to consider broader market trends and factors influencing real estate prices. Keep track of market conditions, economic indicators, and buyer

factors influencing real estate prices. Keep track of market conditions, economic indicators, and buyer preferences to provide clients with up-to-date and accurate advice.

2. **Continuously Refine and Validate the Model: Understand the limitations and assumptions of the model and its applicability to specific markets. Continuously update and refine the model based on new data and incorporate local market knowledge to improve its accuracy and relevance.**