Final Project Submission

Please fill out:

- Student name: Group 14 (Richard Gachiri, David Githaiga, Linah Ogumbeh, Allan Eshiter and Lemiso Eric)
- Student pace: part time
- Scheduled project review date/time:
- Instructor name:
- Blog post URL:

a) Introduction

This study aims to address the importance of identifying the factors that significantly influence home costs,Because conventional methods rely on anecdotal evidence or limited research, they often yield incorrect findings. This knowledge gap makes it more difficult for stakeholders to predict and assess changes in house prices. To solve this issue, we are using multiple regression modeling techniques to thoroughly analyze home sales data. Multiple regression is a useful tool for analyzing the relationship between different attributes and home sales prices since it takes into consideration the combined impact of several independent variables.

b) Business Problem

Real estate valuation poses significant challenges for Rittenhouse Brothers, particularly when determining property values influenced by unique features and the impact of renovations or upgrades. The subjective nature of valuation, varying interprations among appraisers and professionals, and the absense of a purely objective methodology contribute to vakuation discrepancie

c) Main Objective

This Analysis aims to establish an objective property valuation model, focusing specifically on Property Unique features and the impact of renovations or upgrades. The primary goal is to minimize variations in valution estimates and provide Rittenhouse Brothers with a more standardized and reliable method for assessing property values.

d) Specific Objectives

1. Perform exploratory data analysis to uncover connections between various variables and the target variable. This process aids in identifying pertinent variables for inclusion in a regression model.
2. Create a multiple regression model to forecast house sale prices by taking into account chosen independent variables and examining their influence on the dependent variable. Validate the model assumptions, evaluate its fitness for the data, and refine the model as needed.
3. Analyze the coefficients of the independent variables within the model to discern their individual contributions to house prices. Identify the most impactful factors infl

1. Loading Data

In [1]:
```
# Your code here - remember to use markdown cells for comments as well!
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import scipy.stats as stats
import seaborn as sns

# Load data into pandas and engineer "make" feature
data = pd.read_csv("./data/kc_house_data.csv")
data.tail(50)
```

Out[1]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	...	grade	sqft_above	sq
21547	9406530090	10/20/2014	337000.0	4	2.50	2470	5100	2.0	NO	NONE	...	8 Good	2470	
21548	7168100015	10/9/2014	579950.0	5	2.75	3080	5752	2.0	NO	NONE	...	9 Better	3080	
21549	5007500120	2/26/2015	341780.0	4	2.75	2260	4440	2.0	NO	NONE	...	7 Average	2260	
21550	3528900770	4/23/2015	710200.0	4	3.00	1670	2642	2.0	NaN	NONE	...	8 Good	1350	
21551	9521100031	6/18/2014	690000.0	3	3.25	1540	1428	3.0	NO	NONE	...	9 Better	1540	
21552	524059330	1/30/2015	1700000.0	4	3.50	3830	8963	2.0	NO	NONE	...	10 Very Good	3120	
21553	6021503705	10/15/2014	329000.0	2	2.50	980	1020	3.0	NO	NONE	...	8 Good	980	
21554	3438501862	5/13/2014	330000.0	3	2.50	1450	5008	1.0	NO	NONE	...	7 Average	840	
21555	3345700207	5/2/2015	608500.0	4	3.50	2850	5577	2.0	NO	NONE	...	8 Good	1950	
21556	6056111067	7/7/2014	230000.0	3	1.75	1140	1201	2.0	NO	NONE	...	8 Good	1140	
21557	8562790760	5/20/2014	785000.0	4	3.50	3070	4684	2.0	NO	NONE	...	10 Very Good	2190	
21558	1931300090	5/7/2014	610950.0	3	3.00	1680	1570	3.0	NO	NONE	...	8 Good	1680	
21559	9578500790	11/11/2014	399950.0	3	2.50	3087	5002	2.0	NO	NONE	...	8 Good	3087	
21560	9253900271	1/7/2015	3570000.0	5	4.50	4850	10584	2.0	YES	EXCELLENT	...	10 Very Good	3540	
21561	3881900317	1/23/2015	579000.0	4	3.25	1900	2631	2.0	NO	NONE	...	9 Better	1250	
21562	567000385	6/23/2014	362500.0	2	1.50	940	1768	2.0	NaN	NONE	...	7 Average	940	
21563	7011201004	5/29/2014	645000.0	3	3.25	1730	1229	2.0	NO	AVERAGE	...	9 Better	1320	
21564	7853420110	10/3/2014	594866.0	3	3.00	2780	6000	2.0	NO	NONE	...	9 Better	2780	
21565	7853420110	5/4/2015	625000.0	3	3.00	2780	6000	2.0	NO	NONE	...	9 Better	2780	
21566	3052700432	11/12/2014	490000.0	3	2.25	1500	1290	2.0	NO	NONE	...	8 Good	1220	
21567	2025049203	6/10/2014	399950.0	2	1.00	710	1157	2.0	NaN	NONE	...	7 Average	710	

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	...	grade	sqft_above	sq
21568	952006823	12/2/2014	380000.0	3	2.50	1260	900	2.0	NO	NONE	...	7 Average	940	
21569	3832050760	8/28/2014	270000.0	3	2.50	1870	5000	2.0	NO	NONE	...	7 Average	1870	
21570	2767604724	10/15/2014	505000.0	2	2.50	1430	1201	3.0	NO	NONE	...	8 Good	1430	
21571	6632300207	3/5/2015	385000.0	3	2.50	1520	1488	3.0	NO	NONE	...	8 Good	1520	
21572	2767600688	11/13/2014	414500.0	2	1.50	1210	1278	2.0	NO	NONE	...	8 Good	1020	
21573	7570050450	9/10/2014	347500.0	3	2.50	2540	4760	2.0	NO	NONE	...	8 Good	2540	
21574	7430200100	5/14/2014	1220000.0	4	3.50	4910	9444	1.5	NO	NONE	...	11 Excellent	3110	
21575	4140940150	10/2/2014	572000.0	4	2.75	2770	3852	2.0	NO	NONE	...	8 Good	2770	
21576	1931300412	4/16/2015	475000.0	3	2.25	1190	1200	3.0	NO	NONE	...	8 Good	1190	
21577	8672200110	3/17/2015	1090000.0	5	3.75	4170	8142	2.0	NO	AVERAGE	...	10 Very Good	4170	
21578	5087900040	10/17/2014	350000.0	4	2.75	2500	5995	2.0	NaN	NONE	...	8 Good	2500	
21579	1972201967	10/31/2014	520000.0	2	2.25	1530	981	3.0	NO	NONE	...	8 Good	1480	
21580	7502800100	8/13/2014	679950.0	5	2.75	3600	9437	2.0	NO	NONE	...	9 Better	3600	
21581	191100405	4/21/2015	1580000.0	4	3.25	3410	10125	2.0	NO	NONE	...	10 Very Good	3410	
21582	8956200760	10/13/2014	541800.0	4	2.50	3118	7866	2.0	NaN	AVERAGE	...	9 Better	3118	
21583	7202300110	9/15/2014	810000.0	4	3.00	3990	7838	2.0	NO	NONE	...	9 Better	3990	
21584	249000205	10/15/2014	1540000.0	5	3.75	4470	8088	2.0	NO	NONE	...	11 Excellent	4470	
21585	5100403806	4/7/2015	467000.0	3	2.50	1425	1179	3.0	NO	NONE	...	8 Good	1425	
21586	844000965	6/26/2014	224000.0	3	1.75	1500	11968	1.0	NaN	NONE	...	6 Low Average	1500	
21587	7852140040	8/25/2014	507250.0	3	2.50	2270	5536	2.0	NaN	NONE	...	8 Good	2270	
21588	9834201367	1/26/2015	429000.0	3	2.00	1490	1126	3.0	NO	NONE	...	8 Good	1490	
21589	3448900210	10/14/2014	610685.0	4	2.50	2520	6023	2.0	NO	NaN	...	9 Better	2520	

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	...	grade	sqft_above	sq
21590	7936000429	3/26/2015	1010000.0	4	3.50	3510	7200	2.0	NO	NONE	...	9 Better	2600	
21591	2997800021	2/19/2015	475000.0	3	2.50	1310	1294	2.0	NO	NONE	...	8 Good	1180	
21592	263000018	5/21/2014	360000.0	3	2.50	1530	1131	3.0	NO	NONE	...	8 Good	1530	
21593	6600060120	2/23/2015	400000.0	4	2.50	2310	5813	2.0	NO	NONE	...	8 Good	2310	
21594	1523300141	6/23/2014	402101.0	2	0.75	1020	1350	2.0	NO	NONE	...	7 Average	1020	
21595	291310100	1/16/2015	400000.0	3	2.50	1600	2388	2.0	NaN	NONE	...	8 Good	1600	
21596	1523300157	10/15/2014	325000.0	2	0.75	1020	1076	2.0	NO	NONE	...	7 Average	1020	

50 rows × 21 columns

2. Exploratory Data

In [2]:
```
data.shape
```

Out[2]:
```
(21597, 21)
```

In [3]:
```
data.describe() # Statistical distribution of the dataset
```

Out[3]:

	id	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	sqft_above	yr_built	yr_renovat
count	2.159700e+04	2.159700e+04	21597.000000	21597.000000	21597.000000	2.159700e+04	21597.000000	21597.000000	21597.000000	17755.000(
mean	4.580474e+09	5.402966e+05	3.373200	2.115826	2080.321850	1.509941e+04	1.494096	1788.596842	1970.999676	83.6367
std	2.876736e+09	3.673681e+05	0.926299	0.768984	918.106125	4.141264e+04	0.539683	827.759761	29.375234	399.946
min	1.000102e+06	7.800000e+04	1.000000	0.500000	370.000000	5.200000e+02	1.000000	370.000000	1900.000000	0.000(
25%	2.123049e+09	3.220000e+05	3.000000	1.750000	1430.000000	5.040000e+03	1.000000	1190.000000	1951.000000	0.000(
50%	3.904930e+09	4.500000e+05	3.000000	2.250000	1910.000000	7.618000e+03	1.500000	1560.000000	1975.000000	0.000(
75%	7.308900e+09	6.450000e+05	4.000000	2.500000	2550.000000	1.068500e+04	2.000000	2210.000000	1997.000000	0.000(
max	9.900000e+09	7.700000e+06	33.000000	8.000000	13540.000000	1.651359e+06	3.500000	9410.000000	2015.000000	2015.000(

In [4]:
```
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 [5]:
```
data.columns
```

Out[5]:
```
Index(['id', 'date', 'price', 'bedrooms', 'bathrooms', 'sqft_living',
       'sqft_lot', 'floors', 'waterfront', 'view', 'condition', 'grade',
       'sqft_above', 'sqft_basement', 'yr_built', 'yr_renovated', 'zipcode',
       'lat', 'long', 'sqft_living15', 'sqft_lot15'],
      dtype='object')
```

In [6]:
```
data.dtypes
```

Out[6]:
```
id                 int64
date              object
price            float64
bedrooms           int64
bathrooms        float64
sqft_living        int64
sqft_lot           int64
floors           float64
waterfront        object
view              object
condition         object
grade             object
sqft_above         int64
sqft_basement     object
yr_built           int64
yr_renovated     float64
zipcode            int64
lat              float64
long             float64
sqft_living15      int64
sqft_lot15         int64
dtype: object
```

3. Data Preparation

a) Data Cleaning

In [7]:
```
data.isnull().sum()
```

Out[7]:
```
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 [8]:
```
missing_values = data.isna() # Checks missing values
missing_values.head()
```

Out[8]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	...	grade	sqft_above	sqft_basement	yr_built	yr_ren
0	False	False	False	False	False	False	False	False	True	False	...	False	False	False	False	
1	False	False	False	False	False	False	False	False	False	False	...	False	False	False	False	
2	False	False	False	False	False	False	False	False	False	False	...	False	False	False	False	
3	False	False	False	False	False	False	False	False	False	False	...	False	False	False	False	
4	False	False	False	False	False	False	False	False	False	False	...	False	False	False	False	

5 rows × 21 columns

In [9]:
```
def missing_values(data):
    # identify the total missing values per column
    # sort in order
    miss = data.isnull().sum().sort_values(ascending = False)

    # calculate percentage of the missing values
    percentage_miss = (data.isnull().sum() / len(data)).sort_values(ascending = False)

    # store in a dataframe
    missing = pd.DataFrame({"Missing Values": miss, "Percentage": percentage_miss}).reset_index()

    # remove values that are missing
    missing.drop(missing[missing["Percentage"] == 0].index, inplace = True)

    return missing
```

In [10]:
```
missing_data = missing_values(data)
missing_data
```

Out[10]:

	index	Missing Values	Percentage
0	yr_renovated	3842	0.177895
1	waterfront	2376	0.110015
2	view	63	0.002917

Replace the rows with the missing values for **View** with the mode of view

In [11]:
```
data['view'].value_counts()
```

Out[11]:
```
NONE         19422
AVERAGE        957
GOOD           508
FAIR           330
EXCELLENT      317
Name: view, dtype: int64
```

In [12]:
```
data['view'] = data['view'].fillna(data['view'].mode().iloc[0])
```

In [13]:
```
data.isna().sum()
```

Out[13]:
```
id                  0
date                0
price               0
bedrooms            0
bathrooms           0
sqft_living         0
sqft_lot            0
floors              0
waterfront       2376
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
```

Drop the rows with missing values in **Waterfront**

In [14]:
```
data['waterfront'].value_counts()
```

Out[14]:
```
NO     19075
YES      146
Name: waterfront, dtype: int64
```

In [15]:
```
# Mode imputation for the missing values in waterfront
data['waterfront'] = data['waterfront'].fillna(data['waterfront'].mode().iloc[0])
```

In [16]:
```
# check forthe count unique values in the year renoveted colum
data['yr_renovated'].value_counts()
```

Out[16]:
```
0.0       17011
2014.0       73
2013.0       31
2003.0       31
2007.0       30
          ...
1951.0        1
1953.0        1
1946.0        1
1976.0        1
1948.0        1
Name: yr_renovated, Length: 70, dtype: int64
```

In [17]:
```
# Replace null with the most frequent value
data['yr_renovated'].fillna(0,inplace=True)
```

In [18]:
```
data.isna().sum()
```

Out[18]:
```
id               0
date             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
```

No Missing Values

In [19]:
```
# Drop rows with '?' in 'sqft_basement'
data = data[data['sqft_basement'] != '?']

# Reset the index of the DataFrame
data.reset_index(drop=True, inplace=True)
```

In [20]:
```
# Convert 'sqft_basement' column to float
data['sqft_basement'] = data['sqft_basement'].astype(float)
```

In [21]:
```
## Covert the data type for data
data['date'] = pd.to_datetime(data['date'], format = '%m/%d/%Y' )
```

In [22]:
```
data.shape
```

Out[22]:
```
(21143, 21)
```

b) Encoding Categorical Columns in the Data

In [23]:
```
# Encode the column waterfront
waterfront_category_order = {
    'NO': 0,
    "YES" : 1
}

# Perform ordinal encoding on the "waterfront" column
data["waterfront_encoded"] = data["waterfront"].map(waterfront_category_order)

# Replace the original "waterfront" column with the encoded values
data["waterfront"] = data["waterfront_encoded"]

data['waterfront'].value_counts()
```

Out[23]:
```
0    21001
1      142
Name: waterfront, dtype: int64
```

In [24]:
```
# Let's check the count of the encoded column of waterfront
data['waterfront'].value_counts()
```

Out[24]:
```
0    21001
1      142
Name: waterfront, dtype: int64
```

In [25]:
```
# Encode the column view
# Define the order of the categories
view_category_order = {
    "NONE": 0,
    "AVERAGE": 1,
    "GOOD": 2,
    "FAIR": 3,
    "EXCELLENT": 4
}

# Perform ordinal encoding on the "view" column
data["view_encoded"] = data["view"].map(view_category_order)

# Replace the original "view" column with the encoded values
data["view"] = data["view_encoded"]

data['view'].value_counts()
```

Out[25]:
```
0    19079
1      930
2      496
3      327
4      311
Name: view, dtype: int64
```

In [26]:
```
# Let's encode the condition column
condition_category_order = {
    "Poor": 1,
    "Fair": 2,
    "Average": 3,
    "Good": 4,
    "Very Good": 5
}

# Perform ordinal encoding on the "condition" column
data["condition_encoded"] = data["condition"].map(condition_category_order)

# Replace the original "condition" column with the encoded values
data["condition"] = data["condition_encoded"]

data['condition'].value_counts()
```

Out[26]:
```
3    13726
4     5557
5     1666
2      166
1       28
Name: condition, dtype: int64
```

In [27]:
```
# Encode the grade column
grade_category_order = {
    "3 Poor": 3,
    "5 Fair": 5,
    "4 Low": 4,
    "6 Low Average": 6,
    "7 Average": 7,
    "8 Good": 8,
    "9 Better": 9,
    "10 Very Good": 10,
    "11 Excellent": 11,
    "12 Luxury": 12,
    "13 Mansion": 13
}

# Perform ordinal encoding on the "grade" column
data["grade_encoded"] = data["grade"].replace(grade_category_order)

# Replace the original "grade" column with the encoded values
data["grade"] = data["grade_encoded"]

data['grade'].value_counts()
```

Out[27]:
```
7     8788
8     5933
9     2557
6     1997
10    1112
11     391
5      235
12      89
4       27
13      13
3        1
Name: grade, dtype: int64
```

In [28]:
```
encoded_data = data
encoded_data
```

Out[28]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	...	yr_renovated	zipcode	lat	lo
0	7129300520	2014-10-13	221900.0	3	1.00	1180	5650	1.0	0	0	...	0.0	98178	47.5112	-122.2
1	6414100192	2014-12-09	538000.0	3	2.25	2570	7242	2.0	0	0	...	1991.0	98125	47.7210	-122.3
2	5631500400	2015-02-25	180000.0	2	1.00	770	10000	1.0	0	0	...	0.0	98028	47.7379	-122.2
3	2487200875	2014-12-09	604000.0	4	3.00	1960	5000	1.0	0	0	...	0.0	98136	47.5208	-122.3
4	1954400510	2015-02-18	510000.0	3	2.00	1680	8080	1.0	0	0	...	0.0	98074	47.6168	-122.0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
21138	263000018	2014-05-21	360000.0	3	2.50	1530	1131	3.0	0	0	...	0.0	98103	47.6993	-122.3
21139	6600060120	2015-02-23	400000.0	4	2.50	2310	5813	2.0	0	0	...	0.0	98146	47.5107	-122.3
21140	1523300141	2014-06-23	402101.0	2	0.75	1020	1350	2.0	0	0	...	0.0	98144	47.5944	-122.2
21141	291310100	2015-01-16	400000.0	3	2.50	1600	2388	2.0	0	0	...	0.0	98027	47.5345	-122.0
21142	1523300157	2014-10-15	325000.0	2	0.75	1020	1076	2.0	0	0	...	0.0	98144	47.5941	-122.2

21143 rows × 25 columns

In [29]:
```
data.dtypes
```

Out[29]:
```
id                          int64
date               datetime64[ns]
price                     float64
bedrooms                    int64
bathrooms                 float64
sqft_living                 int64
sqft_lot                    int64
floors                    float64
waterfront                  int64
view                        int64
condition                   int64
grade                       int64
sqft_above                  int64
sqft_basement             float64
yr_built                    int64
yr_renovated              float64
zipcode                     int64
lat                       float64
long                      float64
sqft_living15               int64
sqft_lot15                  int64
waterfront_encoded          int64
view_encoded                int64
condition_encoded           int64
grade_encoded               int64
dtype: object
```

In [30]:
```python
# Drop the encoded columns
data_updated= encoded_data.drop(["waterfront_encoded", "view_encoded", "condition_encoded", "grade_encoded"], axis=1)

# Check the updated dataset
data_updated
```

Out[30]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	...	grade	sqft_above	sqft_basement	yr
0	7129300520	2014-10-13	221900.0	3	1.00	1180	5650	1.0	0	0	...	7	1180	0.0	
1	6414100192	2014-12-09	538000.0	3	2.25	2570	7242	2.0	0	0	...	7	2170	400.0	
2	5631500400	2015-02-25	180000.0	2	1.00	770	10000	1.0	0	0	...	6	770	0.0	
3	2487200875	2014-12-09	604000.0	4	3.00	1960	5000	1.0	0	0	...	7	1050	910.0	
4	1954400510	2015-02-18	510000.0	3	2.00	1680	8080	1.0	0	0	...	8	1680	0.0	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
21138	263000018	2014-05-21	360000.0	3	2.50	1530	1131	3.0	0	0	...	8	1530	0.0	
21139	6600060120	2015-02-23	400000.0	4	2.50	2310	5813	2.0	0	0	...	8	2310	0.0	
21140	1523300141	2014-06-23	402101.0	2	0.75	1020	1350	2.0	0	0	...	7	1020	0.0	
21141	291310100	2015-01-16	400000.0	3	2.50	1600	2388	2.0	0	0	...	8	1600	0.0	
21142	1523300157	2014-10-15	325000.0	2	0.75	1020	1076	2.0	0	0	...	7	1020	0.0	

21143 rows × 21 columns

In [31]:
```
# New feature (number of years from yr_builf to yr_renovated)
data_updated['YrsB4Renovation'] = data_updated['yr_renovated'] - data_updated['yr_built']
```

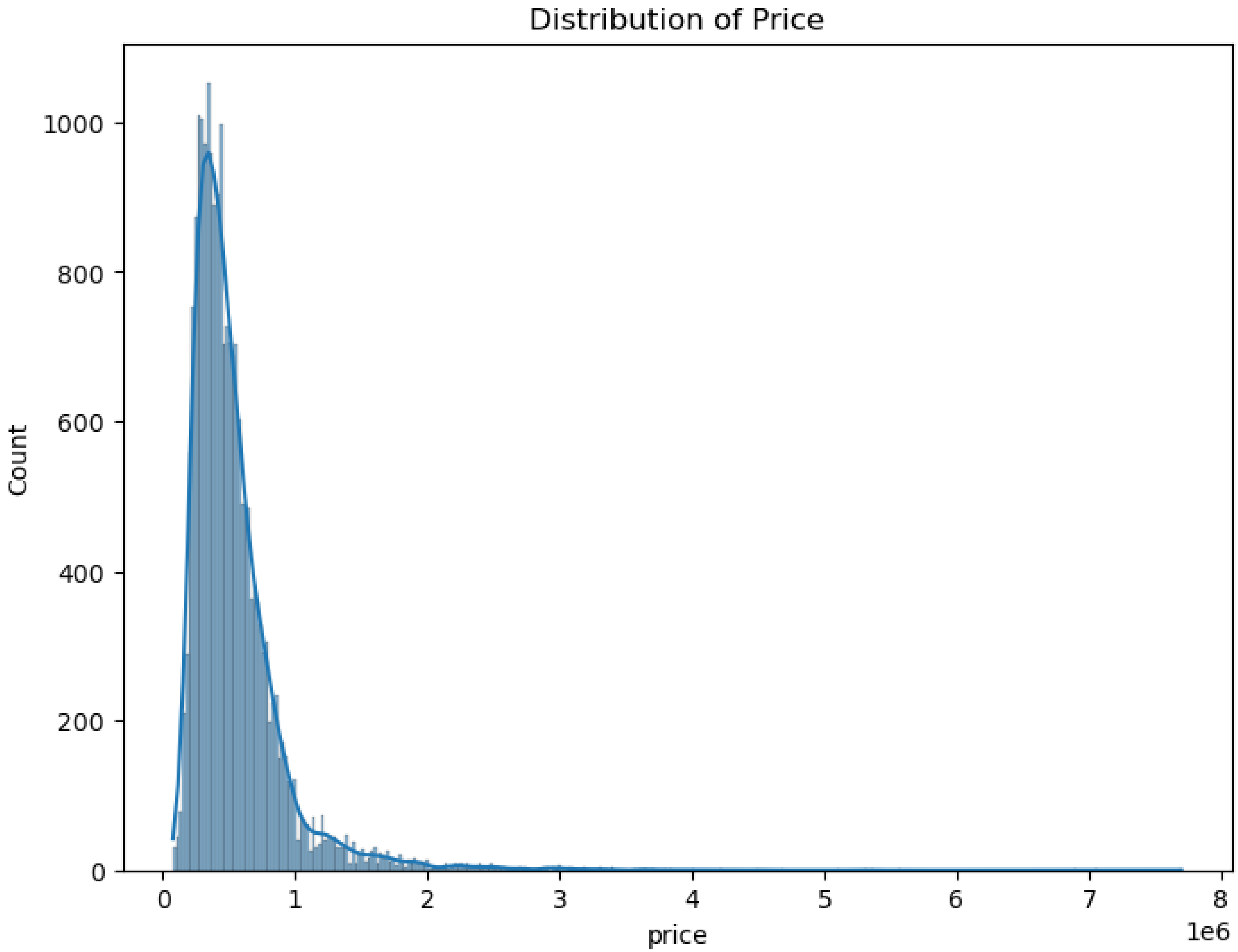
In [32]:
```
### Drop the unnecessary
data_updated.drop(['id','yr_built','yr_renovated'], axis=1,inplace=True)
data_updated.head()
```

Out[32]:

	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition	grade	sqft_above	sqft_basement	zipcode	
0	2014-10-13	221900.0	3	1.00	1180	5650	1.0	0	0	3	7	1180	0.0	98178	47.
1	2014-12-09	538000.0	3	2.25	2570	7242	2.0	0	0	3	7	2170	400.0	98125	47.
2	2015-02-25	180000.0	2	1.00	770	10000	1.0	0	0	3	6	770	0.0	98028	47.
3	2014-12-09	604000.0	4	3.00	1960	5000	1.0	0	0	5	7	1050	910.0	98136	47.
4	2015-02-18	510000.0	3	2.00	1680	8080	1.0	0	0	3	8	1680	0.0	98074	47.

4. Explanatory Data Analysis

In [33]:
```
# Distribution of the target variable
plt.figure(figsize=(8, 6))
sns.histplot(data_updated, x='price', kde=True)
plt.title("Distribution of Price")
plt.show()
```



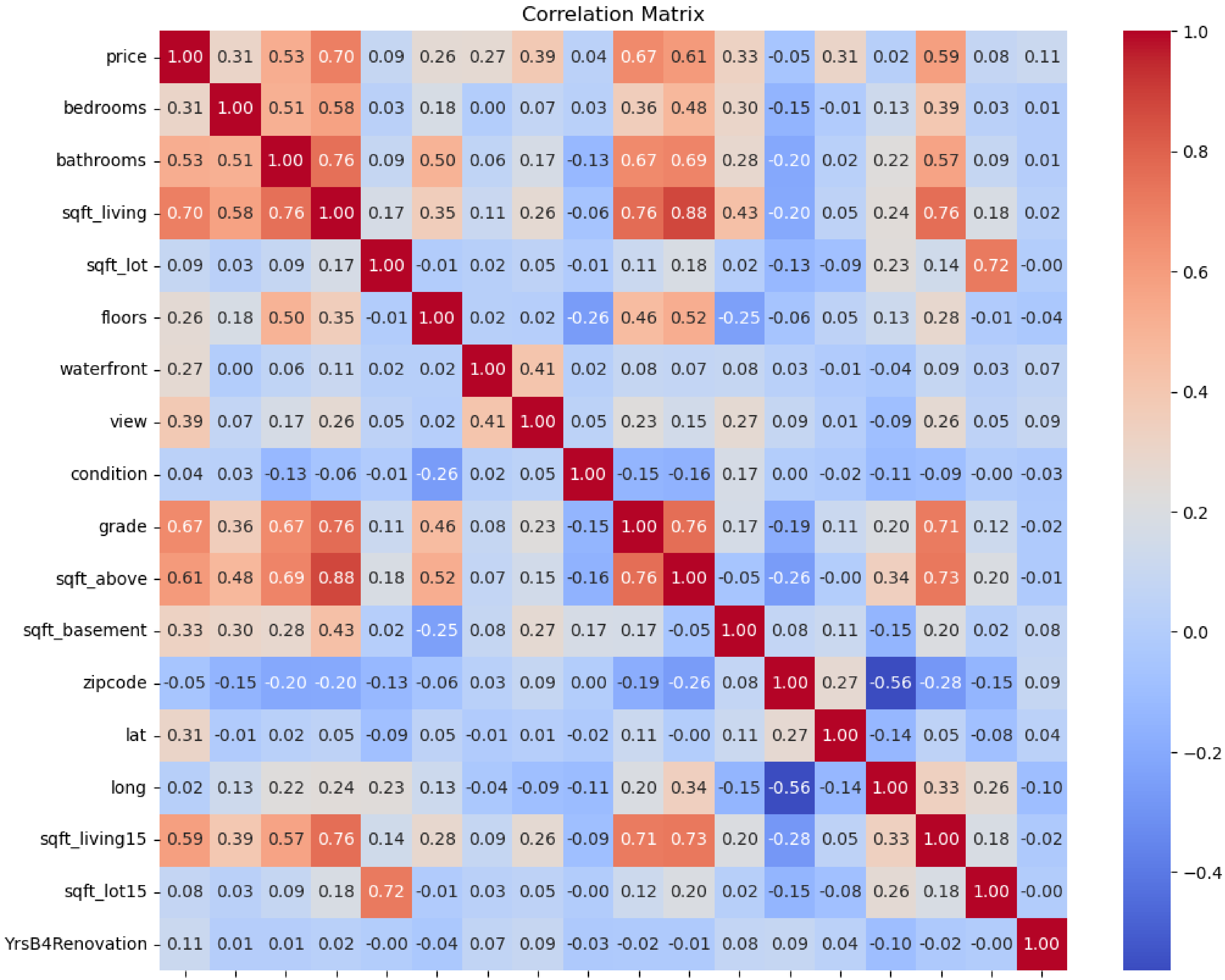
The diagram shows a positively skewed distribution of the price

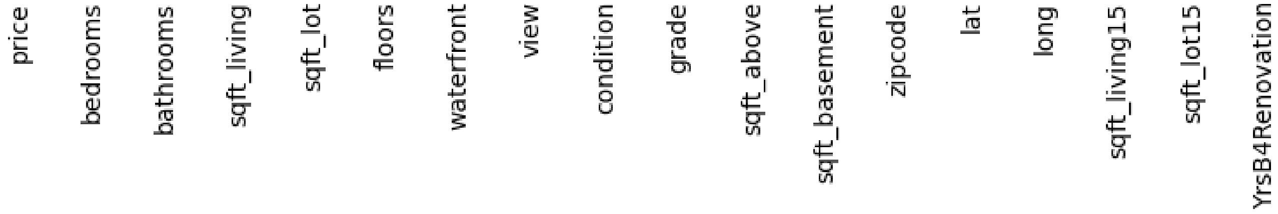
In [34]:
```
### Check Correlation
data_updated.corr(numeric_only=True)
```

Out[34]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition	grade	sqft_above	sqft_b
price	1.000000	0.309204	0.525889	0.702328	0.087937	0.256355	0.265969	0.387878	0.035290	0.667738	0.605143	
bedrooms	0.309204	1.000000	0.513840	0.577998	0.032262	0.179044	0.000061	0.072502	0.025710	0.356882	0.479210	
bathrooms	0.525889	0.513840	1.000000	0.755278	0.087884	0.504071	0.064626	0.171079	-0.128015	0.666493	0.686456	
sqft_living	0.702328	0.577998	0.755278	1.000000	0.172941	0.354688	0.106039	0.263900	-0.061294	0.763101	0.876678	
sqft_lot	0.087937	0.032262	0.087884	0.172941	1.000000	-0.007522	0.021211	0.050720	-0.009671	0.113402	0.183461	
floors	0.256355	0.179044	0.504071	0.354688	-0.007522	1.000000	0.020307	0.016255	-0.264280	0.459214	0.524225	-
waterfront	0.265969	0.000061	0.064626	0.106039	0.021211	0.020307	1.000000	0.408943	0.016728	0.083602	0.072201	
view	0.387878	0.072502	0.171079	0.263900	0.050720	0.016255	0.408943	1.000000	0.046585	0.227733	0.150351	
condition	0.035290	0.025710	-0.128015	-0.061294	-0.009671	-0.264280	0.016728	0.046585	1.000000	-0.148508	-0.159289	
grade	0.667738	0.356882	0.666493	0.763101	0.113402	0.459214	0.083602	0.227733	-0.148508	1.000000	0.756382	
sqft_above	0.605143	0.479210	0.686456	0.876678	0.183461	0.524225	0.072201	0.150351	-0.159289	0.756382	1.000000	-
sqft_basement	0.325008	0.302683	0.282693	0.434576	0.015533	-0.245144	0.084949	0.266334	0.170972	0.168023	-0.052293	
zipcode	-0.053166	-0.152628	-0.204306	-0.198906	-0.129355	-0.058976	0.028152	0.085423	0.003437	-0.185131	-0.260814	
lat	0.306507	-0.009521	0.024994	0.052986	-0.085457	0.048977	-0.011567	0.014825	-0.015592	0.113380	-0.000346	
long	0.022101	0.131093	0.224479	0.240797	0.230583	0.125922	-0.036371	-0.089194	-0.106285	0.199187	0.344543	-
sqft_living15	0.586415	0.392476	0.570129	0.756389	0.143428	0.280294	0.085174	0.261981	-0.093493	0.713574	0.731016	
sqft_lot15	0.083192	0.030479	0.088834	0.184466	0.720649	-0.011545	0.030250	0.052490	-0.004860	0.121921	0.195638	
YrsB4Renovation	0.110193	0.005652	0.006731	0.023686	-0.000082	-0.035371	0.070794	0.093260	-0.026427	-0.019954	-0.014552	

In [35]:
```
# Correlation matrix
plt.figure(figsize=(12, 10))
sns.heatmap(data_updated.corr(numeric_only=True), annot=True, cmap='coolwarm', fmt='.2f')
plt.title("Correlation Matrix")
plt.show()
```

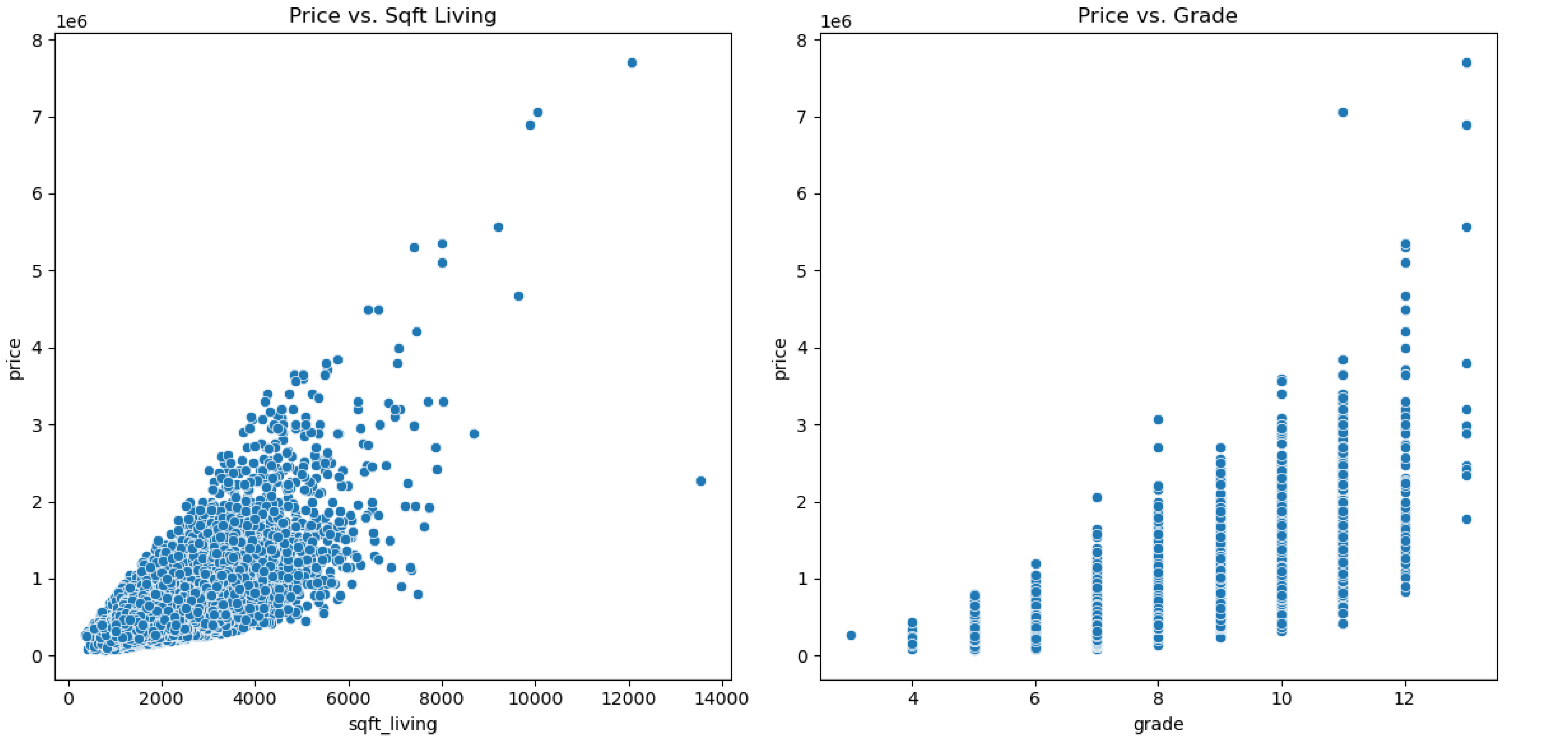

Correlation Matrix
price
bedrooms
bathrooms
sqft_living
sqft_lot
floors
waterfront
view
condition
grade
sqft_above
sqft_basement
zipcode
lat
long
sqft_living15
sqft_lot15
YrsB4Renovation
1.0
0.8
0.6
0.4
0.2
0.0
−0.2
−0.4

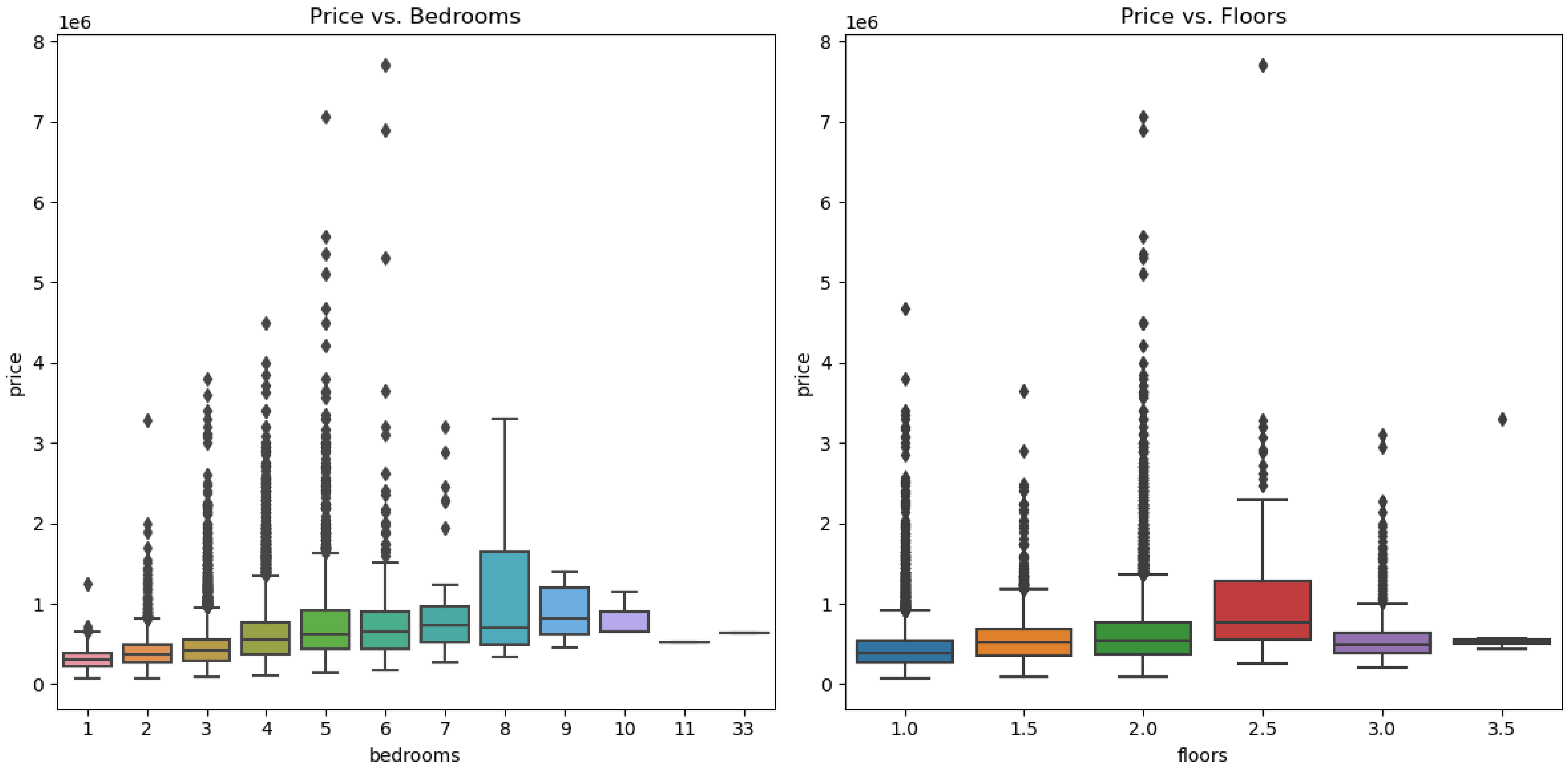


We have so many numbers on the heatmap but we are only interested in the large values that are equal or more than 0.75

This will check for multicollinearity within independent variables. High multicollinearity might lead to poor performance of our model

In [36]:
```
# Scatter plots
plt.figure(figsize=(12, 6))
plt.subplot(1, 2, 1)
sns.scatterplot(data_updated, x='sqft_living', y='price')
plt.title("Price vs. Sqft Living")

plt.subplot(1, 2, 2)
sns.scatterplot(data_updated, x='grade', y='price')
plt.title("Price vs. Grade")

plt.tight_layout()
plt.show()

# Box plots
plt.figure(figsize=(12, 6))
plt.subplot(1, 2, 1)
sns.boxplot(data_updated, x='bedrooms', y='price')
plt.title("Price vs. Bedrooms")

plt.subplot(1, 2, 2)
sns.boxplot(data_updated, x='floors', y='price')
plt.title("Price vs. Floors")

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


Price vs. Sqft Living
1e6
price
sqft_living
0
2000
4000
6000
8000
10000
12000
14000
1
2
3
4
5
6
7
8
Price vs. Grade
1e6
price
grade
4
6
8
10
12


Price vs. Bedrooms
1e6
price
bedrooms
1
2
3
4
5
6
7
8
9
10
11
33
Price vs. Floors
1e6
price
floors
1.0
1.5
2.0
2.5
3.0
3.5

In [37]:
```
data = data_updated
data.head()
```

Out[37]:

	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition	grade	sqft_above	sqft_basement	zipcode	
0	2014-10-13	221900.0	3	1.00	1180	5650	1.0	0	0	3	7	1180	0.0	98178	47.
1	2014-12-09	538000.0	3	2.25	2570	7242	2.0	0	0	3	7	2170	400.0	98125	47.
2	2015-02-25	180000.0	2	1.00	770	10000	1.0	0	0	3	6	770	0.0	98028	47.
3	2014-12-09	604000.0	4	3.00	1960	5000	1.0	0	0	5	7	1050	910.0	98136	47.
4	2015-02-18	510000.0	3	2.00	1680	8080	1.0	0	0	3	8	1680	0.0	98074	47.

In [38]:
```
data.shape
```

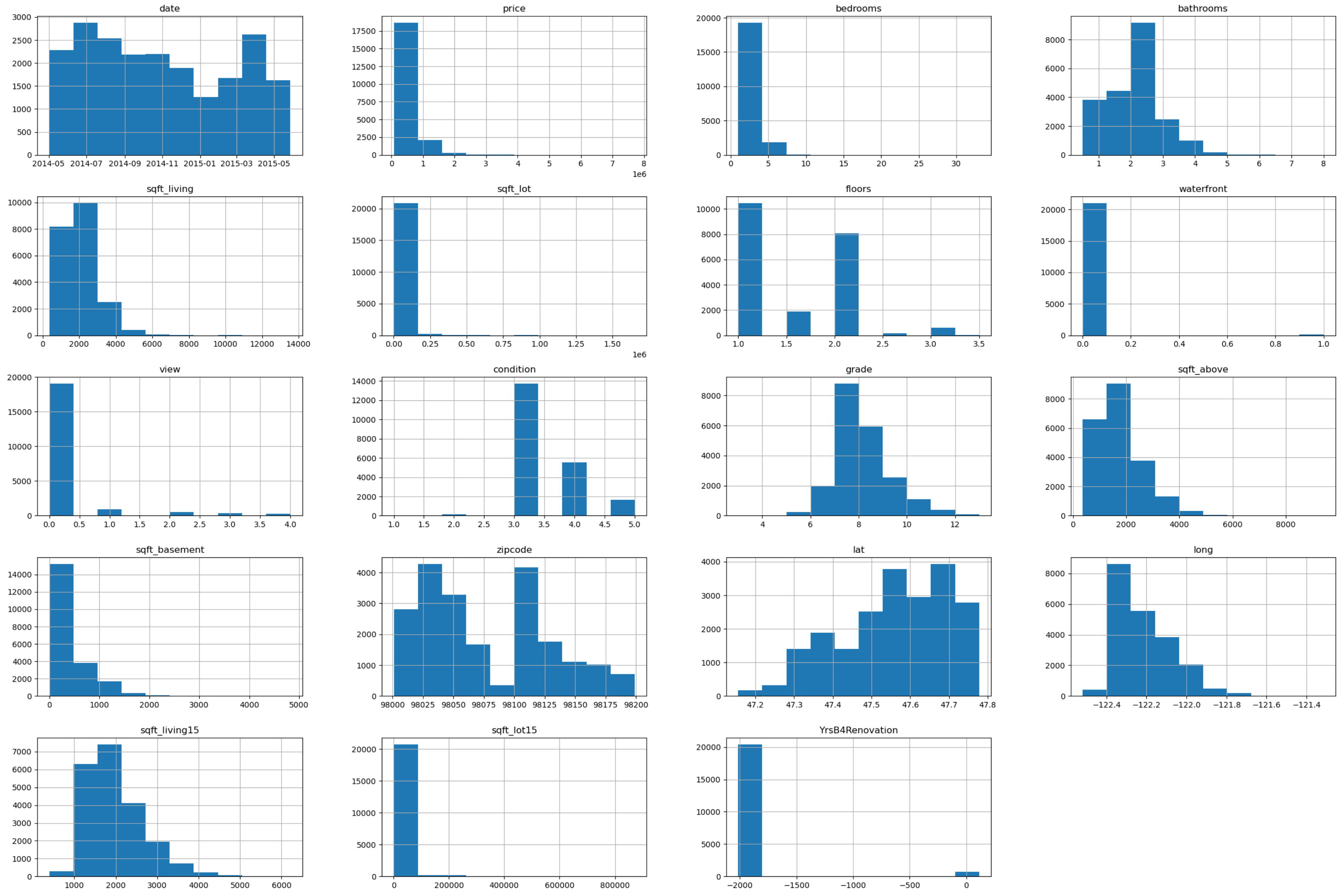
Out[38]: (21143, 19)

5. Model Iterations

In [39]:
```
data.corr(numeric_only=True)['price']
```

Out[39]:
```
price              1.000000
bedrooms           0.309204
bathrooms          0.525889
sqft_living        0.702328
sqft_lot           0.087937
floors             0.256355
waterfront         0.265969
view               0.387878
condition          0.035290
grade              0.667738
sqft_above         0.605143
sqft_basement      0.325008
zipcode           -0.053166
lat                0.306507
long               0.022101
sqft_living15      0.586415
sqft_lot15         0.083192
YrsB4Renovation    0.110193
Name: price, dtype: float64
```

In [40]:
```
data.hist(figsize=(30,20))
plt.show()
```



a) Basic Model: Simple Linear Regression with 'sqft_living': (Baseline Model)

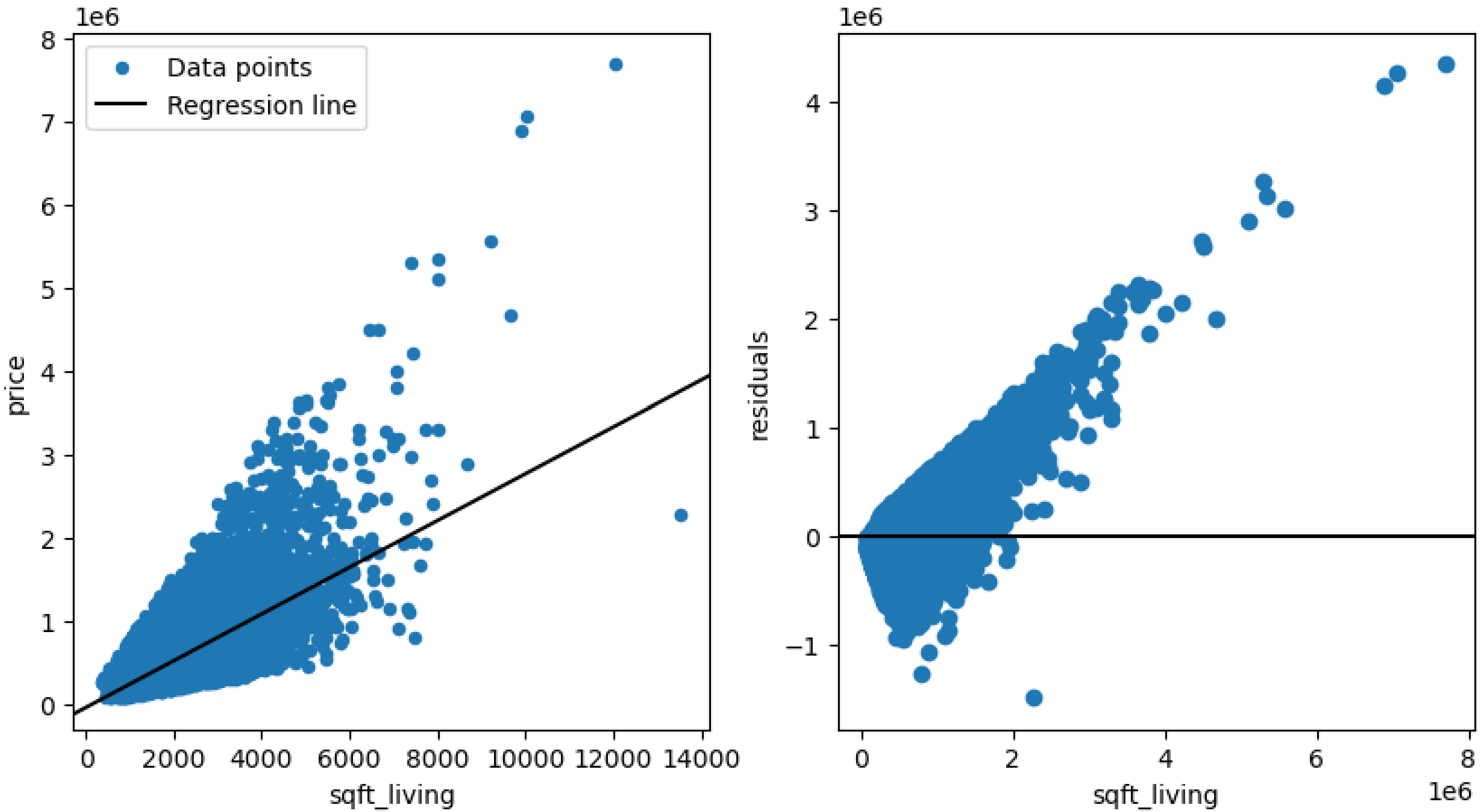
In [41]:
```
import statsmodels.api as sm
```

In [42]:
```
# Selecting the feature and target variable
X_baseline = data[['sqft_living']]  # Feature (independent variable)
y = data['price'] # Target (dependent variable)

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

print(baseline_results.summary())
```

```
                            OLS Regression Results                            
==============================================================================
Dep. Variable:                  price   R-squared:                       0.493
Model:                            OLS   Adj. R-squared:                  0.493
Method:                 Least Squares   F-statistic:                 2.058e+04
Date:                Tue, 02 Jan 2024   Prob (F-statistic):               0.00
Time:                        19:53:21   Log-Likelihood:            -2.9378e+05
No. Observations:               21143   AIC:                         5.876e+05
Df Residuals:                   21141   BIC:                         5.876e+05
Df Model:                           1                                         
Covariance Type:            nonrobust                                         
===============================================================================
                  coef    std err          t      P>|t|      [0.025      0.975]
-------------------------------------------------------------------------------
const       -4.513e+04   4462.443    -10.113      0.000   -5.39e+04   -3.64e+04
sqft_living   281.4327      1.962    143.454      0.000     277.587     285.278
==============================================================================
Omnibus:                    14518.924   Durbin-Watson:                   1.986
Prob(Omnibus):                  0.000   Jarque-Bera (JB):           535834.159
Skew:                           2.825   Prob(JB):                         0.00
Kurtosis:                      27.006   Cond. No.                     5.63e+03
==============================================================================

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

Regression Line:

In [43]:
```
fig, ax = plt.subplots(1,2, figsize= (10,5))
data.plot.scatter(x="sqft_living", y="price", label="Data points", ax=ax[0])
sm.graphics.abline_plot(model_results=baseline_results, label="Regression line", ax=ax[0], color="black")
ax[0].legend();

ax[1].scatter(data["price"], baseline_results.resid)
ax[1].axhline(y=0, color="black")
ax[1].set_xlabel("sqft_living")
ax[1].set_ylabel("residuals");
```



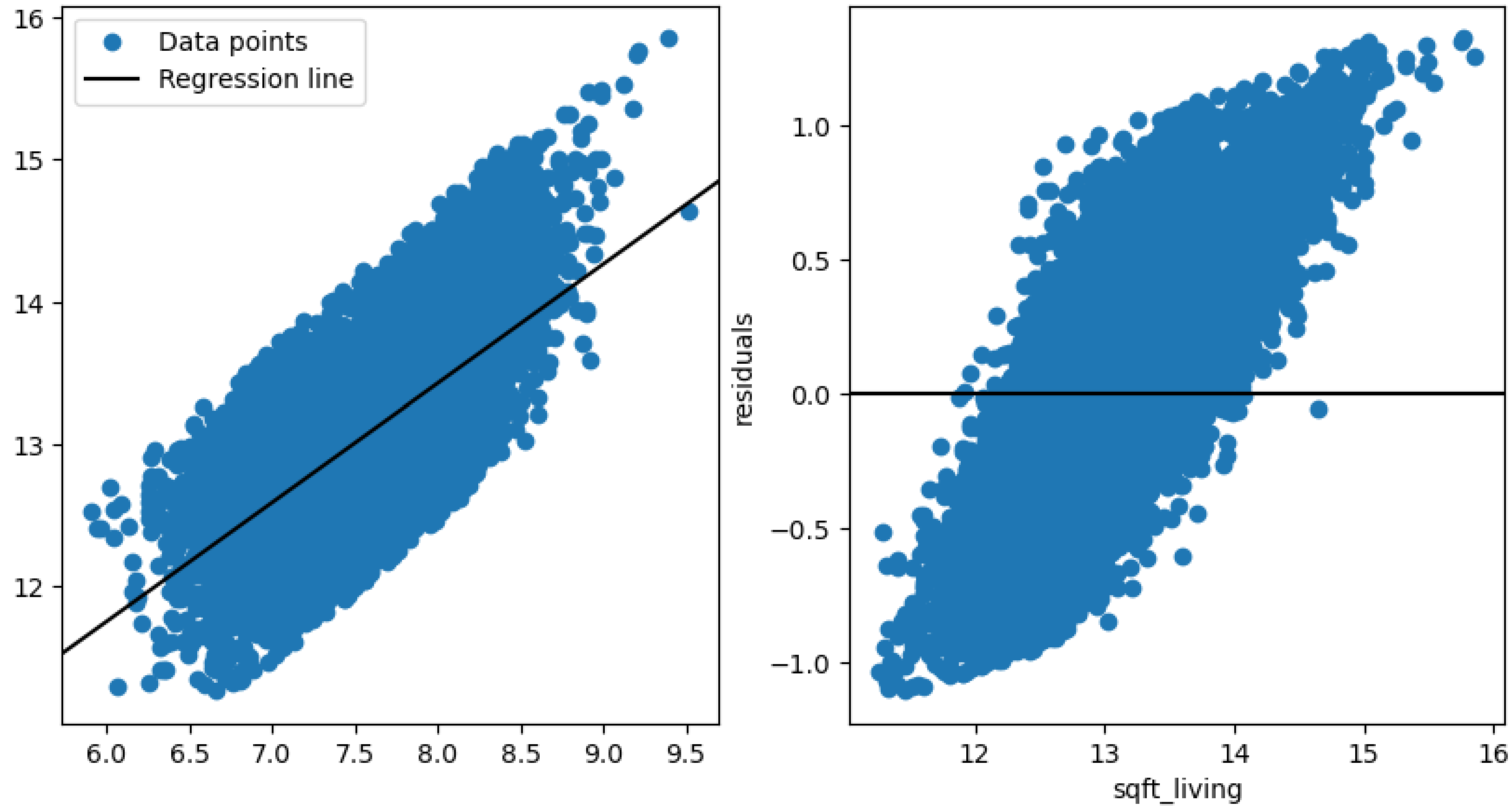
The residuals:

In [44]:
```
# Log-transform target and predictor variables in baseline model
Xlog_baseline = np.log(data[['sqft_living']])  # Feature (independent variable)
ylog = np.log(data['price']) # Target (dependent variable)

log_baseline_model = sm.OLS(ylog, sm.add_constant(Xlog_baseline))
log_baseline_results = log_baseline_model.fit()

print(log_baseline_results.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                  price   R-squared:                       0.455
Model:                            OLS   Adj. R-squared:                  0.455
Method:                 Least Squares   F-statistic:                 1.766e+04
Date:                Tue, 02 Jan 2024   Prob (F-statistic):               0.00
Time:                        19:53:22   Log-Likelihood:                -10023.
No. Observations:               21143   AIC:                         2.005e+04
Df Residuals:                   21141   BIC:                         2.007e+04
Df Model:                           1
Covariance Type:            nonrobust
===============================================================================
                  coef    std err          t      P>|t|      [0.025      0.975]
-------------------------------------------------------------------------------
const           6.7210      0.048    140.939      0.000       6.628       6.814
sqft_living     0.8380      0.006    132.895      0.000       0.826       0.850
==============================================================================
Omnibus:                      120.771   Durbin-Watson:                   1.979
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              111.909
Skew:                           0.144   Prob(JB):                     5.00e-25
Kurtosis:                       2.790   Cond. No.                         137.
==============================================================================

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

A 1% increase in sqft_living leads to a 0.84% increase in house price

In [45]:
```
fig, ax = plt.subplots(1,2, figsize= (10,5))
ax[0].scatter(np.log(data['sqft_living']), np.log(data["price"]), label="Data points")
sm.graphics.abline_plot(model_results=log_baseline_results, label="Regression line", ax=ax[0], color="black")
ax[0].legend();

ax[1].scatter(np.log(data["price"]), log_baseline_results.resid)
ax[1].axhline(y=0, color="black")
ax[1].set_xlabel("sqft_living")
ax[1].set_ylabel("residuals");
```



Despite having a slightly lower R-squared value, the model with log-tranformation baseline model performs better based on the relatively AIC and BIC values

b) Add More Features for Multiple Regression with raw data

In [46]:
```
features = ['sqft_living', 'floors', 'lat','zipcode', 'view']

X_one= data[features].copy()
X_one['sqft_living'] = np.log(X_one['sqft_living'])
y = np.log(data['price'])

subset_model_one = sm.OLS(y, sm.add_constant(X_one))
subset_results_one = subset_model_one.fit()

print(subset_results_one.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                  price   R-squared:                       0.672
Model:                            OLS   Adj. R-squared:                  0.672
Method:                 Least Squares   F-statistic:                     8673.
Date:                Tue, 02 Jan 2024   Prob (F-statistic):               0.00
Time:                        19:53:22   Log-Likelihood:                -4649.1
No. Observations:               21143   AIC:                             9310.
Df Residuals:                   21137   BIC:                             9358.
Df Model:                           5
Covariance Type:            nonrobust
===============================================================================
                  coef    std err          t      P>|t|      [0.025      0.975]
-------------------------------------------------------------------------------
const         -33.6187      3.972     -8.464      0.000     -41.404     -25.834
sqft_living     0.7181      0.006    128.021      0.000       0.707       0.729
floors          0.0692      0.004     16.656      0.000       0.061       0.077
lat             1.6340      0.016    104.540      0.000       1.603       1.665
zipcode        -0.0004   4.19e-05     -8.910      0.000      -0.000      -0.000
view            0.1508      0.003     48.050      0.000       0.145       0.157
==============================================================================
Omnibus:                      387.036   Durbin-Watson:                   1.994
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              504.870
Skew:                           0.246   Prob(JB):                    2.34e-110
Kurtosis:                       3.576   Cond. No.                     1.88e+08
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 1.88e+08. This might indicate that there are
strong multicollinearity or other numerical problems.
```

c) Add More Features for Multiple Regression and using standardised predictor variables

In [47]:
```
X_two = X_one.copy()
for col in X_two.columns:
    X_two[col] = (X_two[col] - X_two[col].mean())/X_two[col].std()

subset_model_two = sm.OLS(y, sm.add_constant(X_two))
subset_results_two = subset_model_two.fit()

print(subset_results_two.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                  price   R-squared:                       0.672
Model:                            OLS   Adj. R-squared:                  0.672
Method:                 Least Squares   F-statistic:                     8673.
Date:                Tue, 02 Jan 2024   Prob (F-statistic):               0.00
Time:                        19:53:22   Log-Likelihood:                -4649.1
No. Observations:               21143   AIC:                             9310.
Df Residuals:                   21137   BIC:                             9358.
Df Model:                           5
Covariance Type:            nonrobust
===============================================================================
                  coef    std err          t      P>|t|      [0.025      0.975]
-------------------------------------------------------------------------------
const          13.0484      0.002   6292.472      0.000      13.044      13.052
sqft_living     0.3045      0.002    128.021      0.000       0.300       0.309
floors          0.0373      0.002     16.656      0.000       0.033       0.042
lat             0.2265      0.002    104.540      0.000       0.222       0.231
zipcode        -0.0200      0.002     -8.910      0.000      -0.024      -0.016
view            0.1038      0.002     48.050      0.000       0.100       0.108
==============================================================================
Omnibus:                      387.036   Durbin-Watson:                   1.994
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              504.870
Skew:                           0.246   Prob(JB):                    2.34e-110
Kurtosis:                       3.576   Cond. No.                         1.73
==============================================================================

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

Based on the standardised model, sqft_living has the largest impact on the house prices since it has the largest co-efficient.

In [48]:
```
#Mean centered predictors
X_centered = X_one.copy()
for col in X_centered.columns:
    X_centered[col] -= X_centered[col].mean()

model = sm.OLS(y, sm.add_constant(X_centered)).fit()
print(model.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                  price   R-squared:                       0.672
Model:                            OLS   Adj. R-squared:                  0.672
Method:                 Least Squares   F-statistic:                     8673.
Date:                Tue, 02 Jan 2024   Prob (F-statistic):               0.00
Time:                        19:53:22   Log-Likelihood:                -4649.1
No. Observations:               21143   AIC:                             9310.
Df Residuals:                   21137   BIC:                             9358.
Df Model:                           5
Covariance Type:            nonrobust
===============================================================================
                  coef    std err          t      P>|t|      [0.025      0.975]
-------------------------------------------------------------------------------
const          13.0484      0.002   6292.472      0.000      13.044      13.052
sqft_living     0.7181      0.006    128.021      0.000       0.707       0.729
floors          0.0692      0.004     16.656      0.000       0.061       0.077
lat             1.6340      0.016    104.540      0.000       1.603       1.665
zipcode        -0.0004   4.19e-05     -8.910      0.000      -0.000      -0.000
view            0.1508      0.003     48.050      0.000       0.145       0.157
==============================================================================
Omnibus:                      387.036   Durbin-Watson:                   1.994
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              504.870
Skew:                           0.246   Prob(JB):                    2.34e-110
Kurtosis:                       3.576   Cond. No.                         404.
==============================================================================

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

Since only price, i.e. the target variable, and sqft_living has been been log-transformed, the model interpretation means that for 1 unit increase in floors leads to a 9.4% increase in house prices. A one level improvement in condition leads to a 7.34% increase in house prices while a one level improvement in view leads to a 14% increase house price

d) Mean Square Errors

In [49]:
```
from sklearn.metrics import mean_squared_error
```

In [50]:
```
# Make predictions using the baseline model
predictions = baseline_results.predict(sm.add_constant(X_baseline))

# Calculate MSE
mse = mean_squared_error(y, predictions)
print(f"Mean Squared Error: {mse}")
```

```
Mean Squared Error: 358961456587.6772
```

In [51]:
```
# Make predictions using the log-transformed baseline model
predictions = log_baseline_results.predict(sm.add_constant(Xlog_baseline))

# Calculate MSE
mse = mean_squared_error(y, predictions)
print(f"Mean Squared Error: {mse}")
```

```
Mean Squared Error: 0.15111301799281243
```

In [52]:
```
# Make predictions using the mean-centered model
predictions = subset_results_one.predict(sm.add_constant(X_one))

# Calculate MSE
mse = mean_squared_error(y, predictions)
print(f"Mean Squared Error: {mse}")
```

```
Mean Squared Error: 0.09089019618976422
```

In [53]:
```
# Make predictions using the standardised model
predictions = subset_results_two.predict(sm.add_constant(X_two))

# Calculate MSE
mse = mean_squared_error(y, predictions)
print(f"Mean Squared Error: {mse}")
```

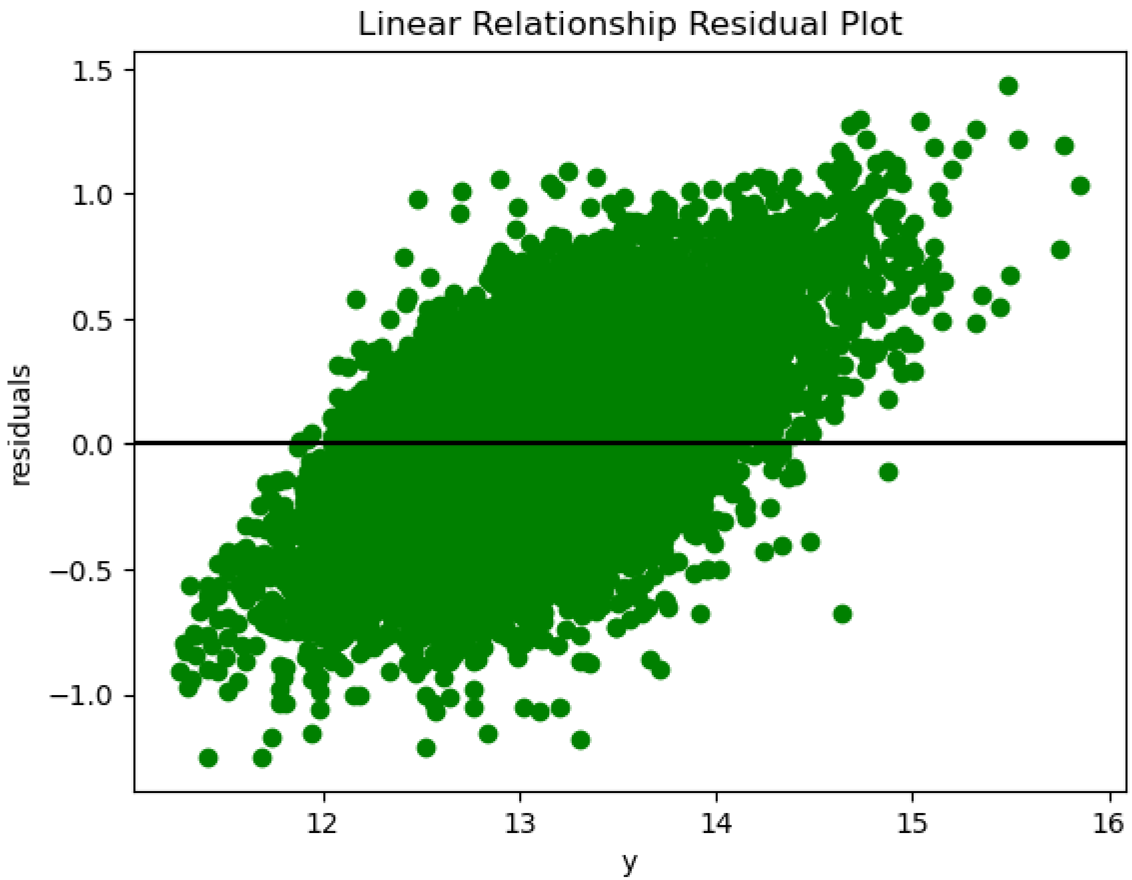
```
Mean Squared Error: 0.09089019618976431
```

6. Asumptions

We will inspect **linearity, independence, nomrality and Equal Variance**

a) The Linearity Assumption

In [54]:
```
fig, ax = plt.subplots()

ax.scatter(y, subset_results_two.resid, color="green")
ax.axhline(y=0, color="black")
ax.set_xlabel("y")
ax.set_ylabel("residuals")
ax.set_title("Linear Relationship Residual Plot");
```



In [55]:
```
# performing a rainbow test to test linearity statistically
from statsmodels.stats.diagnostic import linear_rainbow
linear_rainbow(subset_results_one)
```

Out[55]:
```
(0.9604358952019966, 0.9810006700501094)
```

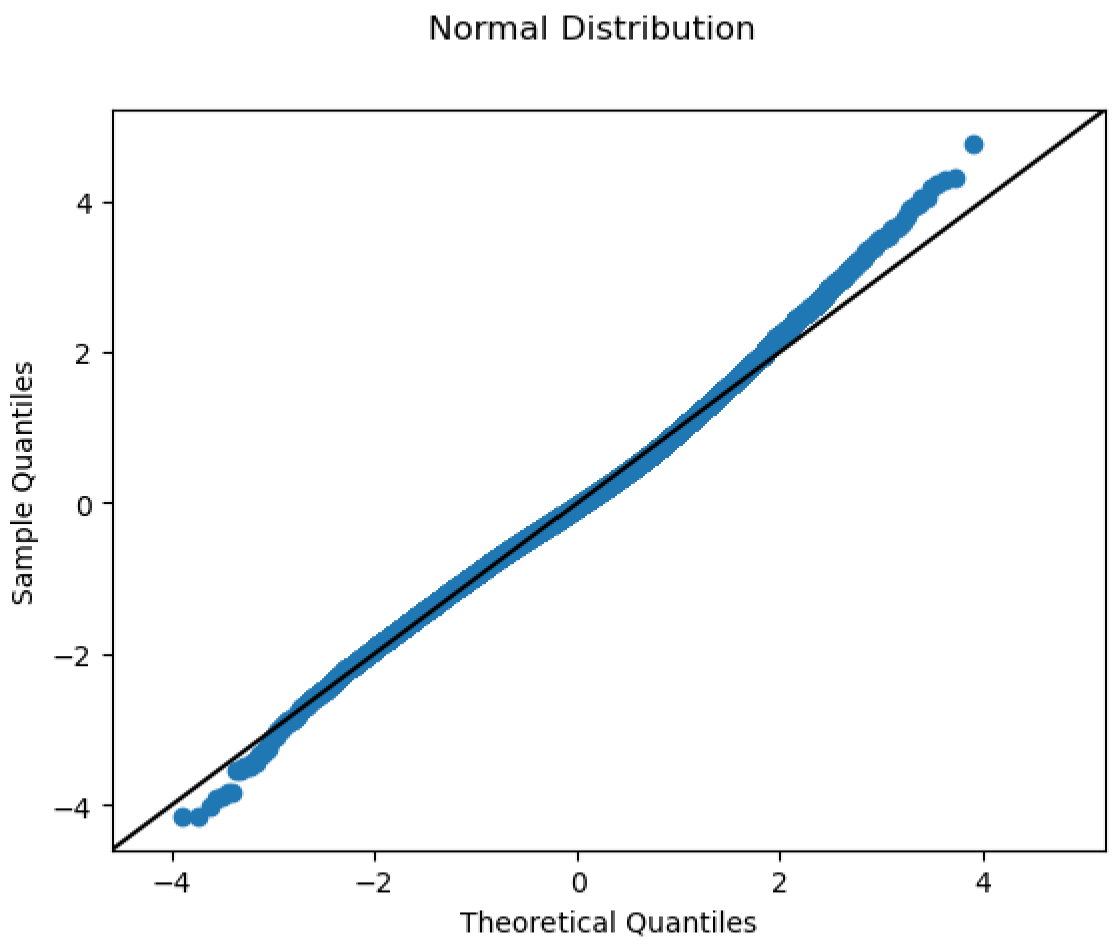
b) Independence Assumption

The Durbin-Watson value in our instance is 1.994, which is quite near to 2, indicating that the residuals show little indication of first-order autocorrelation. This is advantageous since it upholds the regression model's independence assumption. The independence assumption, which presupposes that the residuals are uncorrelated with one another, is essential to the validity of regression analysis.

In conclusion, a Durbin-Watson value of 1.994 indicates that the residuals of the regression model do not substantially display first-order autocorrelation, supporting the independence assumption.

c) Normality Assumption

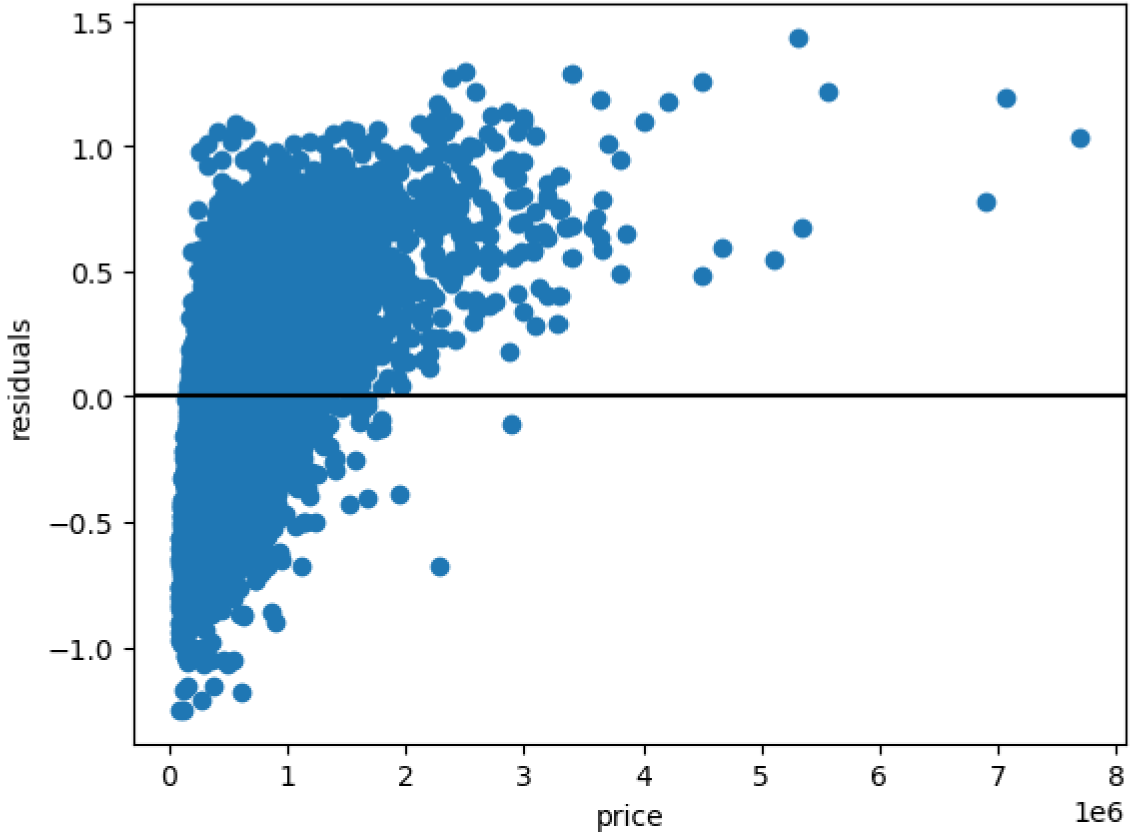
In [56]:
```
# Use qqplot function from StatsModels
fig, ax = plt.subplots()
sm.graphics.qqplot(subset_results_two.resid, dist=stats.norm, line='45', fit=True, ax=ax)

# Customize plot appearance
line = ax.lines[1]
line.set_color("black")
fig.suptitle("Normal Distribution");
```



From the above plot we can see that our model has passed the normality assumption.

d) The Homoscedasticity Assumption

In [57]:
```
fig, ax = plt.subplots()

ax.scatter(x = data["price"], y = subset_results_two.resid)
ax.axhline(y=0, color="black")
ax.set_xlabel("price")
ax.set_ylabel("residuals");
```



Model residual plot shows an increase in error rate with increasing house prices

7. Results Interpretation

Based on the correlation matrix, and correlation heatmap, and the model results for the standardised data, squarefoot living variable is the single most signficant variable in affecting house prices, then followed by view based on our model.

A 1% increase in sqft_living leads to a 0.84% increase in house price

Since only price, i.e. the target variable, and sqft_living has been been log-transformed, the model interpretation means that for 1 unit increase in floors leads to a 9.4% increase in house prices. A one level improvement in condition leads to a 7.34% increase in house prices while a one level improvement in view leads to a 14% increase house price

8. Limitations and Scope

1. The model's error rate seems to increase with increasing house prices hence predicitions for high house prices may not be as accurate as with lower house prices
2. The project's scope is limited to factors directly related to unique property features and the effects of renovations or upgrades. External factors, such as market volatility, regulatory changes, and broader economic shifts, are not included in the model
3. Latitude and Zipcode predictor variables seem to have a significant impact on house prices. However without further context on geography of the regions from which the data emanated it is difficult to interpret this relationship.

9. Recommendations

1. Further to no.3 above, more analysis is required to show how geographical location of a house affect it's price
2. Ways to improve the accuracy, especially for high-value homes, so we can provide even more reliable estimates across the entire range of house prices is needed.
3. Market Segmentation: To determine market segmentation or particular buyer preferences, examine the link between the independent factors and housing prices. For example, a market sector of luxury or high-end homes may be indicated if the prices of houses tend to be higher.