# King County Housing Data Project

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## Business Problem

The ability to accurately appraise a house is of critical importance for a variety of stakeholders. In addition to buyers and sellers, which each have their own interests in finding the fair market price of a house, other entities such as municipalities benefit from such insight as well. Given that property taxes provide the vast majority of tax revenue for municipalities, having an accurate prediction model for house prices can play a key role in efficient financial planning and budgeting. The goal of this project is to provide such a prediction model for the benefit of municipalities in King County, Washington.

## Imports & Settings

In [1]:
```python
# Core tools
import numpy as np
import pandas as pd

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

# Modeling tools
import scipy.stats as stats
import statsmodels.api as sm
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error
from sklearn.preprocessing import RobustScaler
```

Setting the default styling theme for seaborn:

In [2]:
```python
sns.set_theme()
```

The following code forces tables written in Markdown to be aligned to the left of the cell instead of the center which is the default:

In [3]:
```
%%html
<style>
    table {
        display: inline-block
    }
</style>
```

Pulling in the data to a DataFrame:

In [4]:
```python
df = pd.read_csv('data/kc_house_data.csv')
```

## Exploratory Data Analysis

### Summary Statistics and Information

To start, I'll print the first five rows of the dataframe to get a quick feel for the information available.

In [5]:
```python
df.head()
```

Out[5]:

| | id | date | price | bedrooms | bathrooms | sqft_living | sqft_lot | floors | waterfront | view | ... | grade | sqft_above | sqft_basement | yr_built | yr_renovated |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 7129300520 | 10/13/2014 | 221900.0 | 3 | 1.00 | 1180 | 5650 | 1.0 | NaN | 0.0 | ... | 7 | 1180 | 0.0 | 1955 | 0.0 |
| **1** | 6414100192 | 12/9/2014 | 538000.0 | 3 | 2.25 | 2570 | 7242 | 2.0 | 0.0 | 0.0 | ... | 7 | 2170 | 400.0 | 1951 | 1991.0 |
| **2** | 5631500400 | 2/25/2015 | 180000.0 | 2 | 1.00 | 770 | 10000 | 1.0 | 0.0 | 0.0 | ... | 6 | 770 | 0.0 | 1933 | NaN |
| **3** | 2487200875 | 12/9/2014 | 604000.0 | 4 | 3.00 | 1960 | 5000 | 1.0 | 0.0 | 0.0 | ... | 7 | 1050 | 910.0 | 1965 | 0.0 |
| **4** | 1954400510 | 2/18/2015 | 510000.0 | 3 | 2.00 | 1680 | 8080 | 1.0 | 0.0 | 0.0 | ... | 8 | 1680 | 0.0 | 1987 | 0.0 |

5 rows × 21 columns

While most of the 21 columns of data available are fairly self-explanatory, some require a bit more explanation. Along with the original dataset, some metadata on the column names was also provided. Brief descriptions of each column are as follows:

| Column | Description |
|---|---|
| `id` | unique identified for a house |
| `date` | house was sold |
| `price` | is prediction target |
| `bedrooms` | of Bedrooms/House |
| `bathrooms` | of bathrooms/bedrooms |
| `sqft_living` | footage of the home |
| `sqft_lot` | footage of the lot |
| `floors` | floors (levels) in house |
| `waterfront` | House which has a view to a waterfront |
| `view` | Has been viewed |
| `condition` | How good the condition is (Overall) |
| `grade` | overall grade given to the housing unit, based on King County grading system |
| `sqft_above` | square footage of house apart from basement |
| `sqft_basement` | square footage of the basement |
| `yr_built` | Built Year |
| `yr_renovated` | Year when house was renovated |
| `zipcode` | zip |
| `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 |

Expanded definitions for certain columns, such as `condition` and `grade`, can be found within King County's Residential Glossary of Terms.

While most of the provided descriptions seem logical, I do have a concern regarding the `view` column. It seems more logical for this column to be referring to some sort of grading scale for the view available from the house rather than if it has been "viewed" (by whom? for what purpose?). This idea is further supported by "Views" being defined in King County's Condo Glossary of Terms as follows:

> For each classification will display blank for no view or "Fair", "Average", "Good" or "Excellent" to reflect the quality of view for that unit

Next, I'll take a look at the datatypes for each column by calling the `.info()` method.

In [6]:
```
df.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  float64
 9   view           21534 non-null  float64
 10  condition      21597 non-null  int64  
 11  grade          21597 non-null  int64  
 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(8), int64(11), object(2)
memory usage: 3.5+ MB
```

**Observations:**

- The `date` column is stored as a string instead of a datetime object. The date down to the specific day is likely too granular to be useful. Using just the month and year may provide better results. This needs to be explored further.
- The `sqft_basement` column is stored as a string instead of an integer like all other columns regarding square footage.
- The `yr_renovated` column is stored as a float and should be converted to an integer since it is referring to a year.

- The `view`, `condition`, `grade`, and `zipcode` columns represent categorical data. These will need to be dealt with accordingly.

In addition to the above observations, it appears that some columns were missing data. Viewing this in an easier to digest manner yields the following:

In [7]:
```
df.isna().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]:
```
print('Total rows:', df.shape[0])
```

```
Total rows: 21597
```

It appears that the `waterfront` and `yr_renovated` columns have a decent amount of values missing with the `view` column missing a negligible amount.

In [9]:
```
df.describe()
```

Out[9]:

| | id | price | bedrooms | bathrooms | sqft_living | sqft_lot | floors | waterfront | view | condition | grade | sc |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **count** | 2.159700e+04 | 2.159700e+04 | 21597.000000 | 21597.000000 | 21597.000000 | 2.159700e+04 | 21597.000000 | 19221.000000 | 21534.000000 | 21597.000000 | 21597.000000 | 215 |
| **mean** | 4.580474e+09 | 5.402966e+05 | 3.373200 | 2.115826 | 2080.321850 | 1.509941e+04 | 1.494096 | 0.007596 | 0.233863 | 3.409825 | 7.657915 | 17 |
| **std** | 2.876736e+09 | 3.673681e+05 | 0.926299 | 0.768984 | 918.106125 | 4.141264e+04 | 0.539683 | 0.086825 | 0.765686 | 0.650546 | 1.173200 | 8 |
| **min** | 1.000102e+06 | 7.800000e+04 | 1.000000 | 0.500000 | 370.000000 | 5.200000e+02 | 1.000000 | 0.000000 | 0.000000 | 1.000000 | 3.000000 | 3 |
| **25%** | 2.123049e+09 | 3.220000e+05 | 3.000000 | 1.750000 | 1430.000000 | 5.040000e+03 | 1.000000 | 0.000000 | 0.000000 | 3.000000 | 7.000000 | 11 |
| **50%** | 3.904930e+09 | 4.500000e+05 | 3.000000 | 2.250000 | 1910.000000 | 7.618000e+03 | 1.500000 | 0.000000 | 0.000000 | 3.000000 | 7.000000 | 15 |
| **75%** | 7.308900e+09 | 6.450000e+05 | 4.000000 | 2.500000 | 2550.000000 | 1.068500e+04 | 2.000000 | 0.000000 | 0.000000 | 4.000000 | 8.000000 | 22 |
| **max** | 9.900000e+09 | 7.700000e+06 | 33.000000 | 8.000000 | 13540.000000 | 1.651359e+06 | 3.500000 | 1.000000 | 4.000000 | 5.000000 | 13.000000 | 94 |

**Observations:**

- There appears to be an outlier with regard to `bedrooms` - the 75th percentile value is 4 bedrooms while the max is 33. This row may possibly need removed.
- The `yr_renovated` column appears to have a large number of `0` values which doesn't make sense given the context. This will be further explored with the `.value_counts()` method.

## Value Counts

While I already checked the number of missing values in each column, that does not always paint the full picture. As noted above, the `0` values in the `yr_renovated` column are one such instance where the values may not be missing but are nonetheless innaccurate and simply placeholders. Below, I'll loop over the top five values by frequency for each column as a way to check for any additional placeholder values that may not be readily apparent through summary statistics.

In [10]:
```
for col in df.columns:
    print('--- ', col.upper(), ' ---')
    print(df[col].value_counts(normalize=True).head(), '\n\n')
```

```
---  ID  ---
795000620     0.000139
1825069031    0.000093
2019200220    0.000093
7129304540    0.000093
1781500435    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
Name: date, dtype: float64
```

```
---  PRICE  ---
350000.0    0.007964
450000.0    0.007964
550000.0    0.007362
500000.0    0.007038
425000.0    0.006945
Name: price, dtype: float64


---  BEDROOMS  ---
3    0.454878
4    0.318655
2    0.127796
5    0.074131
6    0.012594
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
Name: bathrooms, dtype: float64


---  SQFT_LIVING  ---
1300    0.006390
1400    0.006251
1440    0.006158
1660    0.005973
1010    0.005973
Name: sqft_living, dtype: float64


---  SQFT_LOT  ---
5000    0.016576
6000    0.013428
4000    0.011622
7200    0.010187
7500    0.005510
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
Name: floors, dtype: float64


---  WATERFRONT  ---
0.0    0.992404
1.0    0.007596
Name: waterfront, dtype: float64


---  VIEW  ---
0.0    0.901923
2.0    0.044441
3.0    0.023591
1.0    0.015325
4.0    0.014721
Name: view, dtype: float64


---  CONDITION  ---
3    0.649164
4    0.262861
5    0.078761
2    0.007871
1    0.001343
Name: condition, dtype: float64


---  GRADE  ---
7     0.415521
8     0.280826
9     0.121082
6     0.094365
10    0.052507
Name: grade, dtype: float64


---  SQFT_ABOVE  ---
1300    0.009816
1010    0.009724
1200    0.009538
1220    0.008890
1140    0.008520
```

```
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
Name: sqft_basement, dtype: float64


---  YR_BUILT  ---
2014    0.025883
2006    0.020975
2005    0.020836
2004    0.020049
2003    0.019447
Name: yr_built, dtype: float64


---  YR_RENOVATED  ---
0.0       0.958096
2014.0    0.004112
2003.0    0.001746
2013.0    0.001746
2007.0    0.001690
Name: yr_renovated, dtype: float64


---  ZIPCODE  ---
98103    0.027874
98038    0.027272
98115    0.026994
98052    0.026578
98117    0.025605
Name: zipcode, dtype: float64


---  LAT  ---
47.6624    0.000787
47.5491    0.000787
47.5322    0.000787
47.6846    0.000787
47.6711    0.000741
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
Name: long, dtype: float64


---  SQFT_LIVING15  ---
1540    0.009122
1440    0.009029
1560    0.008890
1500    0.008334
1460    0.007825
Name: sqft_living15, dtype: float64


---  SQFT_LOT15  ---
5000    0.019771
4000    0.016484
6000    0.013335
7200    0.009724
4800    0.006714
Name: sqft_lot15, dtype: float64
```

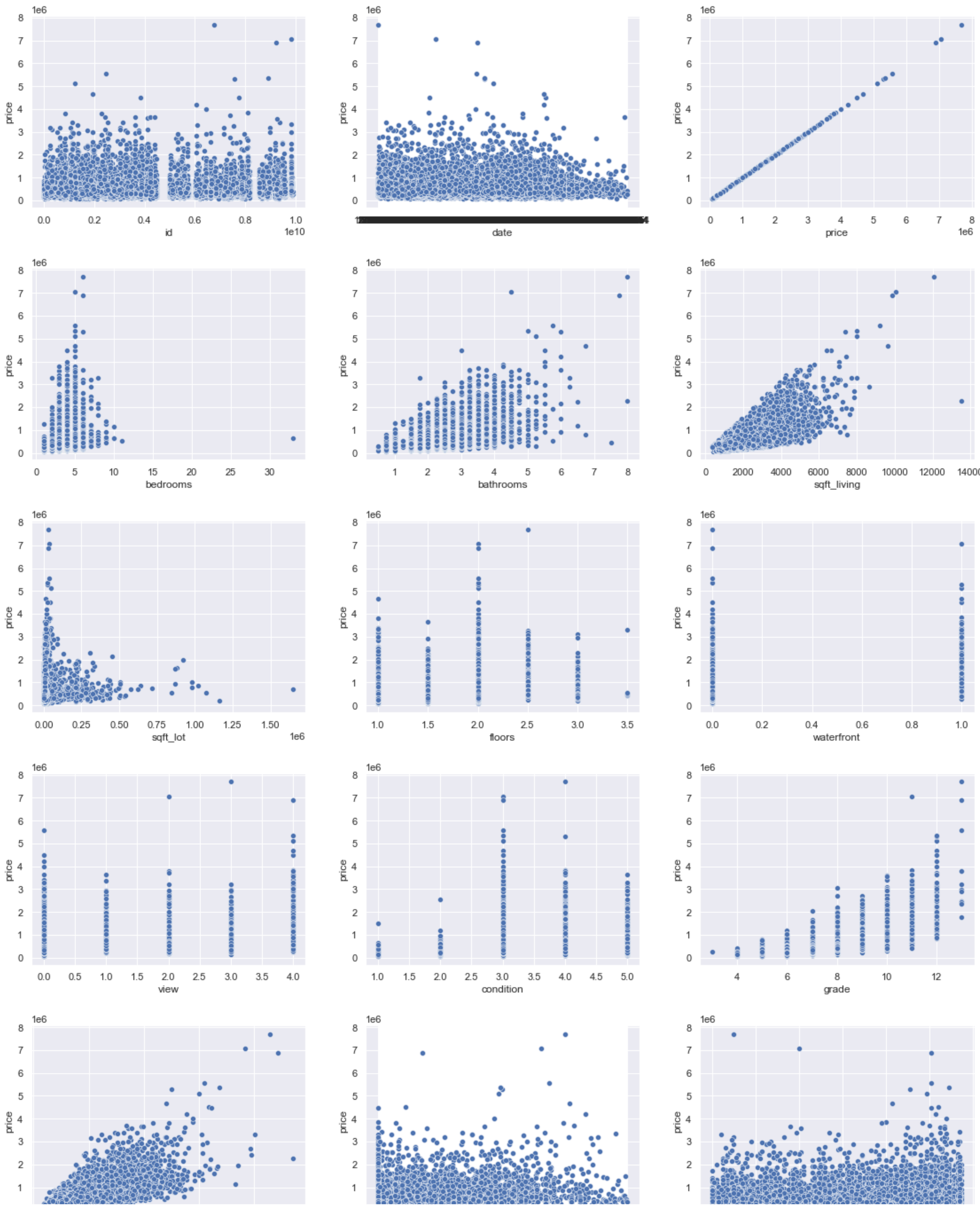
**Observations:**

- The `id` column has values that have higher frequencies than 1, indicating that there may either be duplicate rows or the dataset contains entries for each time a house is sold. Regardless, this column does not provide much information and can be dropped.
- Over 99% of houses are not specified as a waterfront property.
- Over 90% of houses do not have a view that warrants a grade.
- Around 2% of houses have `?` as a value for `sqft_basement` which appears to be a placeholder value. These will need to be dealt with but the existence of such a placeholder value bolsters confidence in the nearly 60% of homes with a value of `0.0` for `sqft_basement` meaning that they truly have no basement (versus `0.0` also potentially being a placeholder value).
- Over 95% of houses have a `yr_renovated` value of `0.0`. As mentioned previously, the context indicates that this is meant as a placeholder value. Combined with the fact that this column has the largest amount of missing data, I will likely be dropping it.

## Basic Visualizations

Plotting each of the columns against `price` will allow me to quickly see which features are most correlated with the value of a house.

In [11]:
```python
fig, axes = plt.subplots(nrows=7, ncols=3, figsize=(16, 28))
# Reshaping axes to a 1-D object for easier iteration
axes = axes.reshape(-1)

for i, col in enumerate(df.columns):
    sns.scatterplot(x=col, y='price', data=df, ax=axes[i])

# Increasing the padding around each subplot for enhanced clarity
fig.tight_layout(pad=2.0);
```

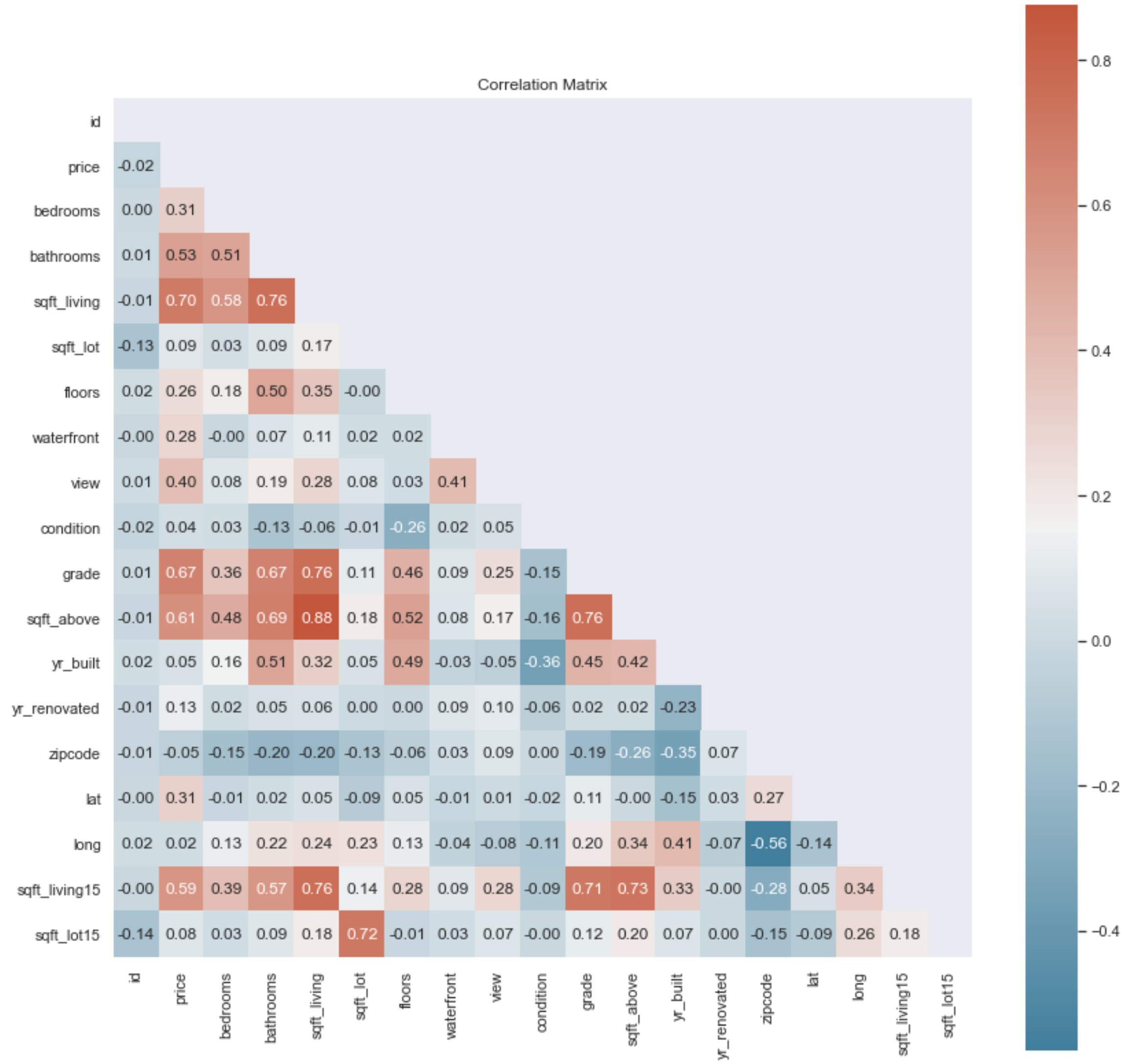



**Observations:**

- Unsurprisingly, the size of the home appears to be strongly correlated with `price`.
- Interestingly, houses with the highest `condition` do not seem to fetch higher average prices than those closer to the middle of the scale.
- Both `waterfront` and `view` appear to have no correlation with `price`.

Next, I'll visualize the actual correlation values via a heatmap:

In [12]:
```
plt.figure(figsize=(14, 14))
plt.title('Correlation Matrix')

# Creating a mask to block the top right half of the heatmap (redundant information)
mask = np.triu(np.ones_like(df.corr()))

# Custom color map
cmap = sns.diverging_palette(230, 20, as_cmap=True)

sns.heatmap(df.corr(), mask=mask, annot=True, fmt='.2f', square=True, cmap=cmap);
```




**Observations:**

- Several columns are highly correlated with one another which will lead to multicollinearity issues in the regression models. This will need to be addressed.

Finally, I'll create a rough map using the latitude and longitude data.

In [13]:
```
plt.figure(figsize=(10, 8))
plt.title('Houses by Location')
sns.scatterplot(data=df, x='long', y='lat', hue='price', alpha=0.7, palette='icefire')
plt.legend(title='Price ($ MM)', loc='lower right')
plt.savefig('images/map.png', dpi=150, facecolor='white');
```


**Observations:**

- Certain areas have a higher density of highly priced homes than others
- This indicates that `lat` and `long` will likely be useful predictors

# Data Preprocessing

---

Based on the observations made in the EDA section, the following list represents the goals for preprocessing the data before moving on to creating the baseline and subsequent prediction models:

1. Drop the `id` column
2. Investigate splitting the `date` column into two columns containing the month and year
3. Convert the `sqft_basement` column to an integer and handle placeholder values
4. Drop the `yr_renovated` column
5. Handle missing values in `waterfront` and `view`
6. Handle multicollinearity between highly correlated columns

## 1. Drop the `id` column

In [14]:
```
df.drop(columns=['id'], inplace=True)
df.columns
```

Out[14]:
```
Index(['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')
```

## 2. Investigate splitting the `date` column into two columns containing the month and year

The idea behind this step is to determine whether decreasing the granularity of the `date` column by extracting just the month and year provides better insight for predicting price versus using the full date. To start, I'll convert the `date` column to datetime objects instead of strings.

In [15]:
```
df.date = pd.to_datetime(df.date)
df.head(2)
```

Out[15]:

| | date | price | bedrooms | bathrooms | sqft_living | sqft_lot | floors | waterfront | view | condition | grade | sqft_above | sqft_basement | yr_built | yr_renovated | zipcode |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 2014-10-13 | 221900.0 | 3 | 1.00 | 1180 | 5650 | 1.0 | NaN | 0.0 | 3 | 7 | 1180 | 0.0 | 1955 | 0.0 | 98178 |
| **1** | 2014-12-09 | 538000.0 | 3 | 2.25 | 2570 | 7242 | 2.0 | 0.0 | 0.0 | 3 | 7 | 2170 | 400.0 | 1951 | 1991.0 | 98125 |

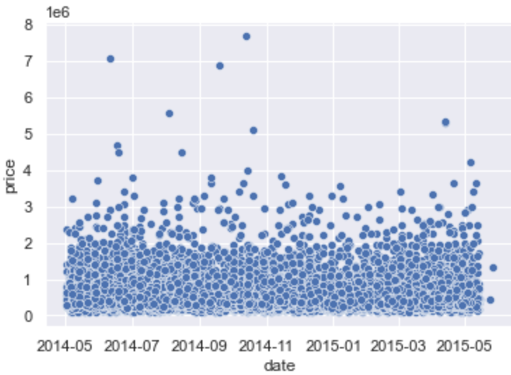
Now that the datatype has been corrected, I want to view the range of dates within the dataset.

In [16]:
```
df.date.describe(datetime_is_numeric=True)
```

```
Out[16]: count                            21597
mean      2014-10-29 04:20:38.171968512
min                 2014-05-02 00:00:00
25%                 2014-07-22 00:00:00
50%                 2014-10-16 00:00:00
75%                 2015-02-17 00:00:00
max                 2015-05-27 00:00:00
Name: date, dtype: object
```

The dataset only covers about a year, from May 2014 to May 2015. There likely won't be much of a difference between the years but I'll check it anyways. I'll start with plotting all of the dates versus price to see if there's any trend.

```
In [17]: sns.scatterplot(x='date', y='price', data=df);
```



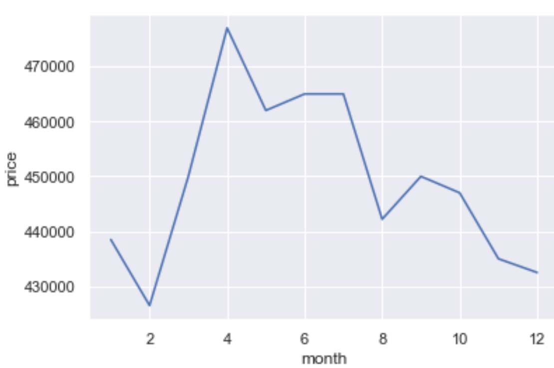

Next, I'll create a column for the month and another for the year. Each of these will be grouped by their respective distinct values and plotted.

```
In [18]: df['month'] = df.date.dt.month
df_month = df.groupby('month').median()
df_month
```

Out[18]:

| month | price | bedrooms | bathrooms | sqft_living | sqft_lot | floors | waterfront | view | condition | grade | sqft_above | yr_built | yr_renovated | zipcode | lat | lo |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 438500.0 | 3.0 | 2.25 | 1890.0 | 7800.0 | 1.0 | 0.0 | 0.0 | 3.0 | 7.0 | 1570.0 | 1974.0 | 0.0 | 98065.0 | 47.55950 | -122.23 |
| 2 | 426500.0 | 3.0 | 2.00 | 1830.0 | 7667.0 | 1.0 | 0.0 | 0.0 | 3.0 | 7.0 | 1489.0 | 1974.0 | 0.0 | 98059.0 | 47.56120 | -122.22 |
| 3 | 450000.0 | 3.0 | 2.25 | 1870.0 | 7560.0 | 1.0 | 0.0 | 0.0 | 3.0 | 7.0 | 1540.0 | 1973.0 | 0.0 | 98065.0 | 47.56480 | -122.22 |
| 4 | 477000.0 | 3.0 | 2.25 | 1900.0 | 7500.0 | 1.5 | 0.0 | 0.0 | 3.0 | 7.0 | 1540.0 | 1976.0 | 0.0 | 98072.0 | 47.56860 | -122.22 |
| 5 | 462000.0 | 3.0 | 2.25 | 1930.0 | 7498.0 | 1.0 | 0.0 | 0.0 | 3.0 | 7.0 | 1540.0 | 1974.0 | 0.0 | 98072.0 | 47.57870 | -122.23 |
| 6 | 465000.0 | 3.0 | 2.25 | 1980.0 | 7700.0 | 1.5 | 0.0 | 0.0 | 3.0 | 8.0 | 1600.0 | 1975.0 | 0.0 | 98072.0 | 47.57605 | -122.22 |
| 7 | 465000.0 | 3.0 | 2.25 | 1950.0 | 7695.0 | 1.5 | 0.0 | 0.0 | 3.0 | 8.0 | 1610.0 | 1977.0 | 0.0 | 98059.0 | 47.57400 | -122.21 |
| 8 | 442200.0 | 3.0 | 2.25 | 1940.0 | 7810.0 | 1.0 | 0.0 | 0.0 | 3.0 | 7.0 | 1590.0 | 1976.0 | 0.0 | 98059.0 | 47.57720 | -122.22 |
| 9 | 450000.0 | 3.0 | 2.25 | 1920.0 | 7620.0 | 1.5 | 0.0 | 0.0 | 3.0 | 7.0 | 1580.0 | 1974.0 | 0.0 | 98065.0 | 47.57400 | -122.23 |
| 10 | 447000.0 | 3.0 | 2.25 | 1905.0 | 7413.0 | 1.5 | 0.0 | 0.0 | 3.0 | 7.0 | 1560.0 | 1974.0 | 0.0 | 98065.0 | 47.57525 | -122.24 |
| 11 | 435000.0 | 3.0 | 2.00 | 1870.0 | 7500.0 | 1.5 | 0.0 | 0.0 | 3.0 | 7.0 | 1560.0 | 1973.0 | 0.0 | 98072.0 | 47.57380 | -122.23 |
| 12 | 432500.0 | 3.0 | 2.25 | 1900.0 | 7725.0 | 1.0 | 0.0 | 0.0 | 3.0 | 7.0 | 1545.0 | 1974.0 | 0.0 | 98070.0 | 47.57865 | -122.24 |

```
In [19]: sns.lineplot(x='month', y='price', data=df_month);
```

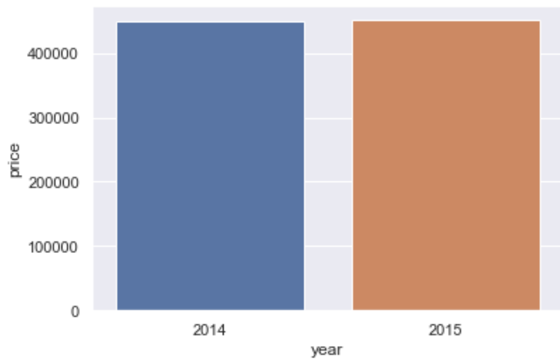



```
In [20]: df['year'] = df.date.dt.year
df_year = df.groupby('year').median()
df_year
```

Out[20]:

| year | price | bedrooms | bathrooms | sqft_living | sqft_lot | floors | waterfront | view | condition | grade | sqft_above | yr_built | yr_renovated | zipcode | lat | long |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 2014 | 450000.0 | 3.0 | 2.25 | 1930.0 | 7633.5 | 1.5 | 0.0 | 0.0 | 3.0 | 7.0 | 1580.0 | 1975.0 | 0.0 | 98065.0 | 47.57645 | -122.231 |
| 2015 | 451000.0 | 3.0 | 2.25 | 1880.0 | 7576.0 | 1.0 | 0.0 | 0.0 | 3.0 | 7.0 | 1540.0 | 1974.0 | 0.0 | 98065.0 | 47.56370 | -122.229 |

In [21]:
```
sns.barplot(x='year', y='price', data=df_year.reset_index());
```




As expected, there isn't much of a trend for the individual dates given the relatively short time horizon. Likewise, there's not much of a different between the values in 2014 and those in 2015. However, there is a clear trend when grouping the data by month with late spring to mid summer seeing the highest median prices. As a result of these findings, the `month` column will be kept in place of the `date` column going forward.

In [22]:
```
df.drop(columns=['date', 'year'], inplace=True)
df.columns
```

Out[22]:
```
Index(['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', 'month'],
      dtype='object')
```

### 3. Convert the `sqft_basement` column to an integer and handle placeholder values

First, I need to handle the placeholder value of `?` discovered while analyzing the value counts. These placeholder values represent about 2% of the data in the column. Since the majority of houses in this dataset do not have a basement at all and I want to keep the contiuous nature of the data in this column, I will simply replace each of the placeholder values with `0`.

In [23]:
```
df.sqft_basement = df.sqft_basement.replace('?', 0)
df.sqft_basement.value_counts(normalize=True).head()
```

Out[23]:
```
0.0      0.593879
0        0.021021
600.0    0.010048
500.0    0.009677
700.0    0.009631
Name: sqft_basement, dtype: float64
```

With the placeholders values out of the way, I can now convert the rest of the values to integers to align with the other columns that deal with square footage information. Due to the presence of `0.0`, which cannot be directly converted to an `int`, I must first convert the values to a `float` and then an `int`.

In [24]:
```
df.sqft_basement = df.sqft_basement.apply(lambda x: int(float(x)))
df.sqft_basement.dtype
```

Out[24]:
```
dtype('int64')
```

### 4. Drop the `yr_renovated` column

This column has the most amount of data missing. Of the data that isn't missing, approximately 95% has a placeholder value of `0.0` which likely indicates the house either hasn't been renovated or the renovation year is unknown. An argument could be made for converting the column to indicate whether a renovation has been made at all regardless of the year. However, given the subjective and arbitrary nature of renovations that cannot be captured quantitatively, the usefulness of that information is debateable at best. Factoring in all of this information, I will simply drop the column from the dataframe.

In [25]:
```
df.drop(columns=['yr_renovated'], inplace=True)
df.columns
```

Out[25]:
```
Index(['price', 'bedrooms', 'bathrooms', 'sqft_living', 'sqft_lot', 'floors',
       'waterfront', 'view', 'condition', 'grade', 'sqft_above',
       'sqft_basement', 'yr_built', 'zipcode', 'lat', 'long', 'sqft_living15',
       'sqft_lot15', 'month'],
      dtype='object')
```

### 5. Handle missing values in `waterfront` and `view`

Starting with `waterfront`, I'll take a look at if the median price for houses with a waterfront is materially different than those without.

In [26]:
```
df.waterfront.value_counts(normalize=True)
```

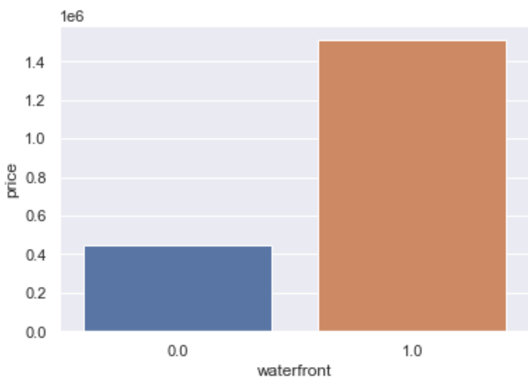
Out[26]:
```
0.0    0.992404
1.0    0.007596
Name: waterfront, dtype: float64
```

In [27]:
```
df_waterfront = df.groupby('waterfront').median().reset_index()
df_waterfront
```

Out[27]:

| | waterfront | price | bedrooms | bathrooms | sqft_living | sqft_lot | floors | view | condition | grade | sqft_above | sqft_basement | yr_built | zipcode | lat | long |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 0.0 | 450000.0 | 3.0 | 2.25 | 1910.0 | 7589.0 | 1.5 | 0.0 | 3.0 | 7.0 | 1560.0 | 0.0 | 1975.0 | 98065.0 | 47.57220 | -122.2300 |
| **1** | 1.0 | 1510000.0 | 3.0 | 2.50 | 2900.0 | 17730.5 | 2.0 | 4.0 | 3.0 | 9.0 | 2200.0 | 535.0 | 1959.5 | 98075.0 | 47.54815 | -122.2735 |

In [28]:
```
sns.barplot(x='waterfront', y='price', data=df_waterfront);
```




Houses with a waterfront have a much higher median value than those without. There are a few different ways to approach handling the missing values in this instance:

- Drop the rows entirely
- Impute the missing values based on the distribution of available values
- Set all missing values equal to the same value

With more than 99% of houses in the dataset not being a waterfront property, I will be setting all of the missing values to `0.0`. Dropping the rows entirely would throw away too much useful information and imputing the values would be better suited for a non-binary variable.

In [29]:
```
df.waterfront.isna().sum()
```

Out[29]: 2376

In [30]:
```
df.waterfront.replace(np.nan, 0.0, inplace=True)
df.waterfront.isna().sum()
```

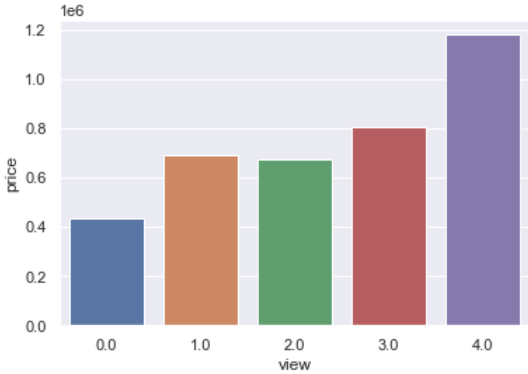
Out[30]: 0

I'll take a similar approach with handling the missing values in the `view` column.

In [31]:
```
df.view.value_counts(normalize=True)
```

Out[31]:
```
0.0    0.901923
2.0    0.044441
3.0    0.023591
1.0    0.015325
4.0    0.014721
Name: view, dtype: float64
```

In [32]:
```
df_view = df.groupby('view').median().reset_index()
sns.barplot(x='view', y='price', data=df_view);
```




There's a clear trend where higher view grades are associated with higher median prices. The same options for dealing with the missing values in the `waterfront` column exist for the `view` column as well. In this instance, however, I *will* impute the values since the variable is non-binary and somewhat subjective. Whereas setting a non-waterfront property to a value of having a waterfront is definitively incorrect, there is more leeway with the view categories.

In [33]:
```
df.view.isna().sum()
```

Out[33]: 63

In [34]:
```
values = df.view.value_counts().reset_index()['index'].values
probs = df.view.value_counts(normalize=True).values
df.view.replace(np.nan, np.random.choice(a=values, p=probs), inplace=True)
df.view.isna().sum()
```

Out[34]: 0

Taking a look at all columns for any remaining missing values:

In [35]:
```
df.isna().sum()
```

Out[35]:
```
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
zipcode          0
lat              0
long             0
sqft_living15    0
sqft_lot15       0
month            0
dtype: int64
```

## 6. Handle multicollinearity between highly correlated columns

The first step in handling multicollinearity is determing which columns have the highest absolute correlation with one another.

In [36]:
```
df_corr = df.corr().abs().stack().reset_index()
df_corr.head()
```

Out[36]:

| | level_0 | level_1 | 0 |
|---|---|---|---|
| **0** | price | price | 1.000000 |
| **1** | price | bedrooms | 0.308787 |
| **2** | price | bathrooms | 0.525906 |
| **3** | price | sqft_living | 0.701917 |
| **4** | price | sqft_lot | 0.089876 |

In [37]:
```
df_corr['pairs'] = list(zip(df_corr.level_0, df_corr.level_1))
df_corr.set_index('pairs', inplace=True)
df_corr.head()
```

Out[37]:

| | level_0 | level_1 | 0 |
|---|---|---|---|
| **pairs** | | | |
| **(price, price)** | price | price | 1.000000 |
| **(price, bedrooms)** | price | bedrooms | 0.308787 |
| **(price, bathrooms)** | price | bathrooms | 0.525906 |
| **(price, sqft_living)** | price | sqft_living | 0.701917 |
| **(price, sqft_lot)** | price | sqft_lot | 0.089876 |

In [38]:
```
df_corr.drop(columns=['level_0', 'level_1'], inplace=True)
df_corr.columns = ['cc']
df_corr.sort_values('cc', ascending=False, inplace=True)
df_corr.drop_duplicates(inplace=True)
df_corr.head()
```

Out[38]:

| | cc |
|---|---|
| **pairs** | |
| **(price, price)** | 1.000000 |
| **(sqft_living, sqft_above)** | 0.876448 |
| **(grade, sqft_living)** | 0.762779 |
| **(sqft_living15, sqft_living)** | 0.756402 |
| **(sqft_above, grade)** | 0.756073 |

In [39]:
```
df_corr[(df_corr.cc > 0.75) & (df_corr.cc < 1.00)]
```

Out[39]:

| | cc |
|---|---|
| **pairs** | |
| **(sqft_living, sqft_above)** | 0.876448 |
| **(grade, sqft_living)** | 0.762779 |
| **(sqft_living15, sqft_living)** | 0.756402 |
| **(sqft_above, grade)** | 0.756073 |
| **(sqft_living, bathrooms)** | 0.755758 |

The `sqft_living` column appears in four of the top five pairs of columns with the highest absolute correlations. As a result, this column will be dropped to help reduce multicollinearity.

In [40]:
```
df.drop(columns=['sqft_living'], inplace=True)
df.columns
```

Out[40]:
```
Index(['price', 'bedrooms', 'bathrooms', 'sqft_lot', 'floors', 'waterfront',
       'view', 'condition', 'grade', 'sqft_above', 'sqft_basement', 'yr_built',
       'zipcode', 'lat', 'long', 'sqft_living15', 'sqft_lot15', 'month'],
      dtype='object')
```

# Modeling

## Baseline Model

In [41]:
```
def fit_model(df, target='price'):
    '''
    Description:
    ------------
    Takes a dataframe and returns a fitted OLS model with price as the dependent variable.

    Parameters:
    ------------
    df : pandas.DataFrame
        This dataframe should include all of the predictors and the target column.

    target: str
        The name of the column being predicted (dependent variable). The default is
        'price'. Useful for transformations where the name is changed for clarity
        (e.g. 'price' --> 'price_log' for a log transformation).

    Example:
    ------------
    >>> fit_model(df)
```

```
    <statsmodels.regression.linear_model.RegressionResultsWrapper>
    '''

    predictors = df.drop(columns=[target])
    predictors = sm.add_constant(predictors)
    model = sm.OLS(df[target], predictors).fit()
    return model

model = fit_model(df)
model.summary()
```

Out[41]:

OLS Regression Results

| | | | |
|---|---|---|---|
| **Dep. Variable:** | price | **R-squared:** | 0.700 |
| **Model:** | OLS | **Adj. R-squared:** | 0.700 |
| **Method:** | Least Squares | **F-statistic:** | 2959. |
| **Date:** | Sun, 06 Jun 2021 | **Prob (F-statistic):** | 0.00 |
| **Time:** | 23:43:45 | **Log-Likelihood:** | -2.9440e+05 |
| **No. Observations:** | 21597 | **AIC:** | 5.888e+05 |
| **Df Residuals:** | 21579 | **BIC:** | 5.890e+05 |
| **Df Model:** | 17 | | |
| **Covariance Type:** | nonrobust | | |

| | **coef** | **std err** | **t** | **P>\|t\|** | **[0.025** | **0.975]** |
|---|---|---|---|---|---|---|
| **const** | 7.343e+06 | 2.93e+06 | 2.510 | 0.012 | 1.61e+06 | 1.31e+07 |
| **bedrooms** | -3.561e+04 | 1896.107 | -18.781 | 0.000 | -3.93e+04 | -3.19e+04 |
| **bathrooms** | 4.593e+04 | 3220.796 | 14.262 | 0.000 | 3.96e+04 | 5.22e+04 |
| **sqft_lot** | 0.1219 | 0.048 | 2.542 | 0.011 | 0.028 | 0.216 |
| **floors** | 6790.4318 | 3589.068 | 1.892 | 0.059 | -244.407 | 1.38e+04 |
| **waterfront** | 6.234e+05 | 1.81e+04 | 34.387 | 0.000 | 5.88e+05 | 6.59e+05 |
| **view** | 5.383e+04 | 2121.194 | 25.379 | 0.000 | 4.97e+04 | 5.8e+04 |
| **condition** | 2.545e+04 | 2318.920 | 10.974 | 0.000 | 2.09e+04 | 3e+04 |
| **grade** | 9.801e+04 | 2157.106 | 45.437 | 0.000 | 9.38e+04 | 1.02e+05 |
| **sqft_above** | 178.8924 | 3.659 | 48.886 | 0.000 | 171.720 | 186.065 |
| **sqft_basement** | 146.9815 | 4.356 | 33.741 | 0.000 | 138.443 | 155.520 |
| **yr_built** | -2776.1082 | 68.907 | -40.288 | 0.000 | -2911.170 | -2641.046 |
| **zipcode** | -587.2023 | 32.996 | -17.796 | 0.000 | -651.877 | -522.527 |
| **lat** | 5.996e+05 | 1.07e+04 | 55.852 | 0.000 | 5.79e+05 | 6.21e+05 |
| **long** | -2.17e+05 | 1.32e+04 | -16.498 | 0.000 | -2.43e+05 | -1.91e+05 |
| **sqft_living15** | 21.1073 | 3.447 | 6.123 | 0.000 | 14.350 | 27.864 |
| **sqft_lot15** | -0.3712 | 0.073 | -5.060 | 0.000 | -0.515 | -0.227 |
| **month** | -3075.1729 | 440.253 | -6.985 | 0.000 | -3938.101 | -2212.245 |

| | | | |
|---|---|---|---|
| **Omnibus:** | 18407.855 | **Durbin-Watson:** | 1.989 |
| **Prob(Omnibus):** | 0.000 | **Jarque-Bera (JB):** | 1866250.699 |
| **Skew:** | 3.579 | **Prob(JB):** | 0.00 |
| **Kurtosis:** | 47.974 | **Cond. No.** | 2.15e+08 |

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 2.15e+08. This might indicate that there are
strong multicollinearity or other numerical problems.

**Observations:**

- `bedrooms` has a negativate coefficient (surprisingly)
- `floors` is not significant at the alpha = 0.05 level
- `yr_built` has a negative coefficient (suprisingly)
- R-squared value for baseline model is 0.700 - pretty good

I also want to keep track of the RMSE for each model, so I'll create a reusable function to do just that:

In [42]:
```
def print_rmse(df, target='price', decimals=2):
    '''
    Description:
    ------------
    Takes a dataframe, splits it into train/test data, fits it to a linear regression model,
    then calculates and prints the RMSE for both the train and test portions rounded to two
    decimal places.

    Parameters:
    ------------
    df : pandas.DataFrame
        This dataframe should include all of the predictors and the target column.

    target: str
        The name of the column being predicted (dependent variable). The default is
        'price'. Useful for transformations where the name is changed for clarity
        (e.g. 'price' --> 'price_log' for a log transformation).
```

```
    decimals: int
        The number of decimals to round the output to.

    Example:
    ------------
    >>> print_rmse(df)

        Train RMSE: 100,000.00
        Test RMSE:  101,250.00
    '''

    x = df.drop(columns=[target])
    y = df[target]

    x_train, x_test, y_train, y_test = train_test_split(x, y, train_size=0.75, random_state=85)
    linreg = LinearRegression()
    linreg.fit(x_train, y_train)

    y_pred_train = linreg.predict(x_train)
    y_pred_test = linreg.predict(x_test)

    rmse_train = mean_squared_error(y_train, y_pred_train, squared=False)
    rmse_test = mean_squared_error(y_test, y_pred_test, squared=False)

    print('Train RMSE:', round(rmse_train, decimals))
    print('Test  RMSE:', round(rmse_test, decimals))
```

In [43]:
```
print_rmse(df)
```

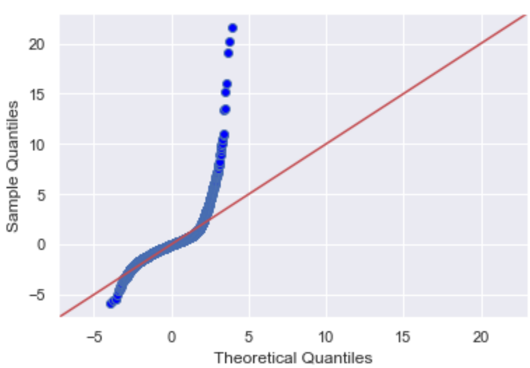
```
Train RMSE: 201973.07
Test  RMSE: 199329.26
```

These are fairly large values for the RMSE but both the train and test splits are relatively in line with one another which indicates an appropriately fitted model.

Finally, I'll plot the residuals in a Q-Q plot to check for normality.

In [44]:
```
def get_qqplot(model):
    '''
    Description:
    ------------
    Takes an OLS model and returns a Q-Q plot of the model residuals.

    Parameters:
    ------------
    model : a fitted statsmodels.api.OLS() model

    Example:
    ------------
    >>> get_qqplot(model)

    <matplotlib.figure.Figure>
    '''

    return sm.graphics.qqplot(model.resid, dist=stats.norm, line='45', fit=True)
```

In [45]:
```
get_qqplot(model);
```




The residuals of the baseline model are not normally distributed which violates a core assumption of linear regression. I will attempt to correct this in subsequent models.

## Removing Outliers

In [46]:
```
df.describe()
```

Out[46]:

| | price | bedrooms | bathrooms | sqft_lot | floors | waterfront | view | condition | grade | sqft_above | sqft_basement | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **count** | 2.159700e+04 | 21597.000000 | 21597.000000 | 2.159700e+04 | 21597.000000 | 21597.000000 | 21597.000000 | 21597.000000 | 21597.000000 | 21597.000000 | 21597.000000 | 21 |
| **mean** | 5.402966e+05 | 3.373200 | 2.115826 | 1.509941e+04 | 1.494096 | 0.006760 | 0.233181 | 3.409825 | 7.657915 | 1788.596842 | 285.716581 | 1 |
| **std** | 3.673681e+05 | 0.926299 | 0.768984 | 4.141264e+04 | 0.539683 | 0.081944 | 0.764673 | 0.650546 | 1.173200 | 827.759761 | 439.819830 | |
| **min** | 7.800000e+04 | 1.000000 | 0.500000 | 5.200000e+02 | 1.000000 | 0.000000 | 0.000000 | 1.000000 | 3.000000 | 370.000000 | 0.000000 | 1 |
| **25%** | 3.220000e+05 | 3.000000 | 1.750000 | 5.040000e+03 | 1.000000 | 0.000000 | 0.000000 | 3.000000 | 7.000000 | 1190.000000 | 0.000000 | 1 |
| **50%** | 4.500000e+05 | 3.000000 | 2.250000 | 7.618000e+03 | 1.500000 | 0.000000 | 0.000000 | 3.000000 | 7.000000 | 1560.000000 | 0.000000 | 1 |
| **75%** | 6.450000e+05 | 4.000000 | 2.500000 | 1.068500e+04 | 2.000000 | 0.000000 | 0.000000 | 4.000000 | 8.000000 | 2210.000000 | 550.000000 | 1 |
| **max** | 7.700000e+06 | 33.000000 | 8.000000 | 1.651359e+06 | 3.500000 | 1.000000 | 4.000000 | 5.000000 | 13.000000 | 9410.000000 | 4820.000000 | 2 |

The maximum amount of bedrooms being 33 immediately jumps out to me as warranting further investigation.

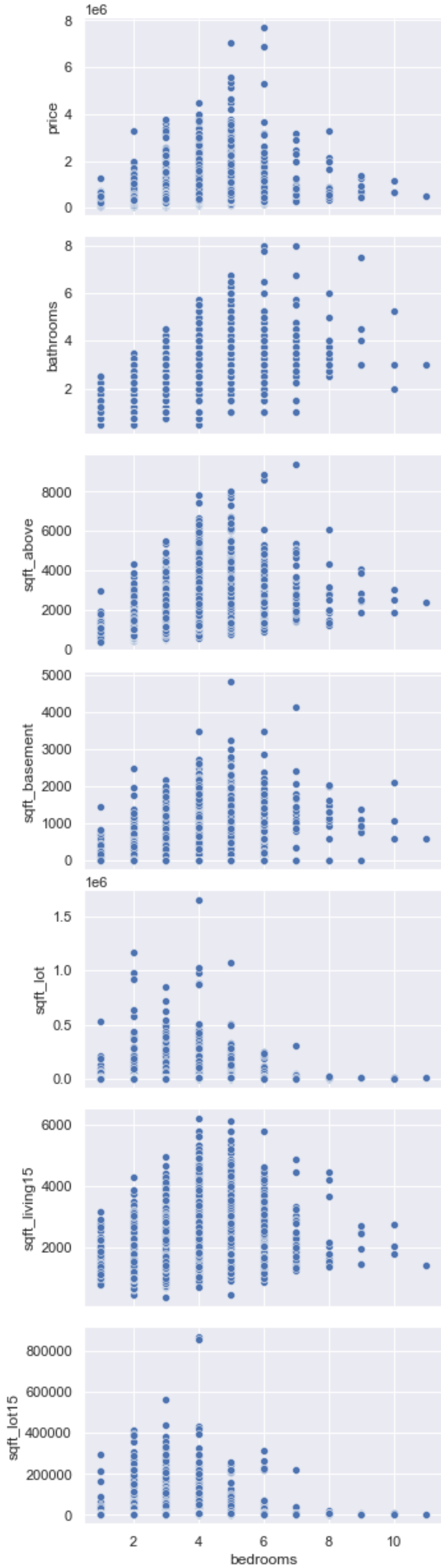
In [47]:
```
df[df.bedrooms == 33]
```

Out[47]:

| | price | bedrooms | bathrooms | sqft_lot | floors | waterfront | view | condition | grade | sqft_above | sqft_basement | yr_built | zipcode | lat | long | sqft_livin |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **15856** | 640000.0 | 33 | 1.75 | 6000 | 1.0 | 0.0 | 0.0 | 5 | 7 | 1040 | 580 | 1947 | 98103 | 47.6878 | -122.331 | 1 |

The price, bathrooms, and square footage of this property do not meet the expectations of a 33 bedroom house. This entry was likely a typo that should have shown only 3 bedrooms. I'll plot bedrooms against some of the other columns as a quick check for anything else that looks off.

In [48]:
```
sns.pairplot(df[df.bedrooms < 33],
             x_vars=['bedrooms'],
             y_vars=['price', 'bathrooms', 'sqft_above', 'sqft_basement', 'sqft_lot',
                     'sqft_living15', 'sqft_lot15'],
             diag_kind=None,
             aspect=2
            );
```




It appears that houses with more than 8 bedrooms have counterintuitive characteristics such as less bathrooms, less square footage, and a lower price. There could be a number of reasons for these discrepencies including:

- Incorrect data entry
- Nontraditional housing such as dorms / communal living
- Older housing

In [49]:
```
print(f'Number of houses with more than 8 bedrooms: {len(df[df.bedrooms > 8])}')
```

```
Number of houses with more than 8 bedrooms: 11
```

With only 11 houses having more than 8 bedrooms, I'm comfortable with simply dropping those rows.

In [50]:
```
df_no_outliers = df[df.bedrooms <= 8]
df_no_outliers.bedrooms.describe()
```

Out[50]:
```
count    21586.000000
mean         3.368989
std          0.894531
min          1.000000
25%          3.000000
50%          3.000000
75%          4.000000
max          8.000000
Name: bedrooms, dtype: float64
```

Next, I also want to investigate the minimum number of bathrooms being only 0.5.

In [51]:
```
df_no_outliers[df_no_outliers.bathrooms == 0.5]
```

Out[51]:

| | price | bedrooms | bathrooms | sqft_lot | floors | waterfront | view | condition | grade | sqft_above | sqft_basement | yr_built | zipcode | lat | long | sqft_livin |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **2259** | 273000.0 | 2 | 0.5 | 7750 | 1.0 | 0.0 | 0.0 | 4 | 6 | 590 | 590 | 1945 | 98155 | 47.7690 | -122.316 | 1 |
| **10413** | 109000.0 | 2 | 0.5 | 6900 | 1.0 | 0.0 | 0.0 | 3 | 5 | 580 | 0 | 1941 | 98118 | 47.5135 | -122.262 | 1 |
| **11662** | 255000.0 | 1 | 0.5 | 1642 | 1.0 | 0.0 | 0.0 | 3 | 6 | 500 | 380 | 1910 | 98126 | 47.5732 | -122.372 | 1 |
| **12029** | 312500.0 | 4 | 0.5 | 5570 | 2.0 | 0.0 | 0.0 | 3 | 8 | 2300 | 0 | 1996 | 98092 | 47.3285 | -122.168 | 1 |

Of the four results, the first three look like they could possibly be a dorm / communal living type of property gvien their `sqft_above` values. The fourth result of a property with 4 bedrooms and 2,300 sqft is definitely an outlier and should have at least one full bath. This will be dropped but I'll keep the first three.

In [52]:
```
df_no_outliers.drop(index=12029, inplace=True)

# Checking to make sure it was correctly dropped
df_no_outliers[df_no_outliers.bathrooms == 0.5]
```

```
E:\Programs\anaconda3\envs\learn-env\lib\site-packages\pandas\core\frame.py:4163: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  return super().drop(
```

Out[52]:

| | price | bedrooms | bathrooms | sqft_lot | floors | waterfront | view | condition | grade | sqft_above | sqft_basement | yr_built | zipcode | lat | long | sqft_livin |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **2259** | 273000.0 | 2 | 0.5 | 7750 | 1.0 | 0.0 | 0.0 | 4 | 6 | 590 | 590 | 1945 | 98155 | 47.7690 | -122.316 | 1 |
| **10413** | 109000.0 | 2 | 0.5 | 6900 | 1.0 | 0.0 | 0.0 | 3 | 5 | 580 | 0 | 1941 | 98118 | 47.5135 | -122.262 | 1 |
| **11662** | 255000.0 | 1 | 0.5 | 1642 | 1.0 | 0.0 | 0.0 | 3 | 6 | 500 | 380 | 1910 | 98126 | 47.5732 | -122.372 | 1 |

The final adjustment for this second model is to remove the `floors` column which is not significant.

In [53]:
```
pd.set_option('mode.chained_assignment', None)  # Supressing the 'SettingWithCopyWarning'
df_no_outliers.drop(columns=['floors'], inplace=True)
df_no_outliers.columns
```

Out[53]:
```
Index(['price', 'bedrooms', 'bathrooms', 'sqft_lot', 'waterfront', 'view',
       'condition', 'grade', 'sqft_above', 'sqft_basement', 'yr_built',
       'zipcode', 'lat', 'long', 'sqft_living15', 'sqft_lot15', 'month'],
      dtype='object')
```

In [54]:
```
model_2 = fit_model(df_no_outliers)
model_2.summary()
```

Out[54]:

| | coef | std err | t | P>\|t\| | [0.025 | 0.975] |
|---|---|---|---|---|---|---|
| const | 6.7e+06 | 2.88e+06 | 2.325 | 0.020 | 1.05e+06 | 1.23e+07 |
| bedrooms | -3.931e+04 | 1993.709 | -19.717 | 0.000 | -4.32e+04 | -3.54e+04 |
| bathrooms | 4.887e+04 | 3115.790 | 15.684 | 0.000 | 4.28e+04 | 5.5e+04 |
| sqft_lot | 0.1174 | 0.048 | 2.451 | 0.014 | 0.024 | 0.211 |
| waterfront | 6.22e+05 | 1.81e+04 | 34.334 | 0.000 | 5.87e+05 | 6.58e+05 |
| view | 5.367e+04 | 2119.850 | 25.316 | 0.000 | 4.95e+04 | 5.78e+04 |
| condition | 2.516e+04 | 2312.953 | 10.880 | 0.000 | 2.06e+04 | 2.97e+04 |
| grade | 9.776e+04 | 2150.289 | 45.464 | 0.000 | 9.35e+04 | 1.02e+05 |
| sqft_above | 182.1754 | 3.623 | 50.288 | 0.000 | 175.075 | 189.276 |
| sqft_basement | 146.4884 | 4.169 | 35.141 | 0.000 | 138.318 | 154.659 |
| yr_built | -2756.7850 | 67.368 | -40.921 | 0.000 | -2888.831 | -2624.739 |
| zipcode | -583.8860 | 32.840 | -17.780 | 0.000 | -648.255 | -519.517 |
| lat | 6.001e+05 | 1.07e+04 | 56.103 | 0.000 | 5.79e+05 | 6.21e+05 |
| long | -2.192e+05 | 1.31e+04 | -16.737 | 0.000 | -2.45e+05 | -1.94e+05 |
| sqft_living15 | 20.2822 | 3.423 | 5.926 | 0.000 | 13.574 | 26.991 |
| sqft_lot15 | -0.3816 | 0.073 | -5.208 | 0.000 | -0.525 | -0.238 |
| month | -3072.4854 | 440.011 | -6.983 | 0.000 | -3934.940 | -2210.031 |

OLS Regression Results

| | | | |
|---|---|---|---|
| **Dep. Variable:** | price | **R-squared:** | 0.700 |
| **Model:** | OLS | **Adj. R-squared:** | 0.700 |
| **Method:** | Least Squares | **F-statistic:** | 3149. |
| **Date:** | Sun, 06 Jun 2021 | **Prob (F-statistic):** | 0.00 |
| **Time:** | 23:43:47 | **Log-Likelihood:** | -2.9422e+05 |
| **No. Observations:** | 21585 | **AIC:** | 5.885e+05 |
| **Df Residuals:** | 21568 | **BIC:** | 5.886e+05 |
| **Df Model:** | 16 | | |
| **Covariance Type:** | nonrobust | | |

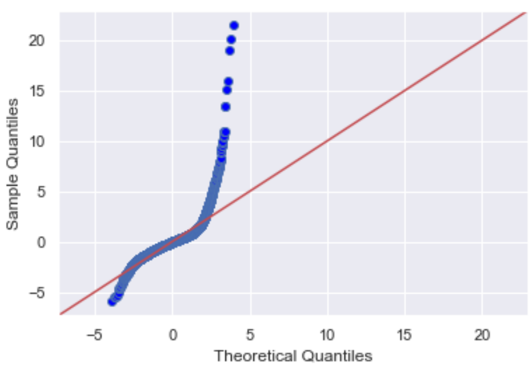
| | | | |
|---|---|---|---|
| **Omnibus:** | 18271.635 | **Durbin-Watson:** | 1.988 |
| **Prob(Omnibus):** | 0.000 | **Jarque-Bera (JB):** | 1821637.635 |
| **Skew:** | 3.544 | **Prob(JB):** | 0.00 |
| **Kurtosis:** | 47.443 | **Cond. No.** | 2.12e+08 |

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 2.12e+08. This might indicate that there are
strong multicollinearity or other numerical problems.

In [55]:
```
print_rmse(df_no_outliers)
```

```
Train RMSE: 206118.02
Test  RMSE: 185727.5
```

In [56]:
```
get_qqplot(model_2);
```




**Observations:**

- No change in the R-squared value - still at 0.700
- Slight decrease in the test RMSE but slight *increase* in the train RMSE
- The Q-Q plot still shows non-normality in the residuals

## Categorical Variables

The first two versions of the model were completing neglecting the fact that certain columns were being treated as continuous data when they are in fact categorical. To adjust for this going forward, I'll convert the categorical columns into multiple columns filled with dummy variables.

In [57]:
```
df_categoricals = df_no_outliers.copy()
df_categoricals.info()
```

```
<class 'pandas.core.frame.DataFrame'>
```

```
Int64Index: 21585 entries, 0 to 21596
Data columns (total 17 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   price          21585 non-null  float64
 1   bedrooms       21585 non-null  int64  
 2   bathrooms      21585 non-null  float64
 3   sqft_lot       21585 non-null  int64  
 4   waterfront     21585 non-null  float64
 5   view           21585 non-null  float64
 6   condition      21585 non-null  int64  
 7   grade          21585 non-null  int64  
 8   sqft_above     21585 non-null  int64  
 9   sqft_basement  21585 non-null  int64  
 10  yr_built       21585 non-null  int64  
 11  zipcode        21585 non-null  int64  
 12  lat            21585 non-null  float64
 13  long           21585 non-null  float64
 14  sqft_living15  21585 non-null  int64  
 15  sqft_lot15     21585 non-null  int64  
 16  month          21585 non-null  int64  
dtypes: float64(6), int64(11)
memory usage: 3.0 MB
```

In [58]:

```python
categoricals = ['waterfront', 'view', 'condition', 'grade', 'zipcode', 'month']

# Generating a temporary dataframe for each of the categorical columns
temp_dfs = [df_categoricals]
for cat in categoricals:
    dummy = pd.get_dummies(df_categoricals[cat], prefix=cat, drop_first=True)
    temp_dfs.append(dummy)

# Combining them all together
df_categoricals = pd.concat(temp_dfs, axis=1)

# Dropping the original columns now that the dummies exist
df_categoricals.drop(columns=categoricals, inplace=True)
```

In [59]:

```python
df_categoricals.info(verbose=True)
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 21585 entries, 0 to 21596
Data columns (total 110 columns):
 #   Column          Dtype  
---  ------          -----  
 0   price           float64
 1   bedrooms        int64  
 2   bathrooms       float64
 3   sqft_lot        int64  
 4   sqft_above      int64  
 5   sqft_basement   int64  
 6   yr_built        int64  
 7   lat             float64
 8   long            float64
 9   sqft_living15   int64  
 10  sqft_lot15      int64  
 11  waterfront_1.0  uint8  
 12  view_1.0        uint8  
 13  view_2.0        uint8  
 14  view_3.0        uint8  
 15  view_4.0        uint8  
 16  condition_2     uint8  
 17  condition_3     uint8  
 18  condition_4     uint8  
 19  condition_5     uint8  
 20  grade_4         uint8  
 21  grade_5         uint8  
 22  grade_6         uint8  
 23  grade_7         uint8  
 24  grade_8         uint8  
 25  grade_9         uint8  
 26  grade_10        uint8  
 27  grade_11        uint8  
 28  grade_12        uint8  
 29  grade_13        uint8  
 30  zipcode_98002   uint8  
 31  zipcode_98003   uint8  
 32  zipcode_98004   uint8  
 33  zipcode_98005   uint8  
 34  zipcode_98006   uint8  
 35  zipcode_98007   uint8  
 36  zipcode_98008   uint8  
 37  zipcode_98010   uint8  
 38  zipcode_98011   uint8  
 39  zipcode_98014   uint8  
 40  zipcode_98019   uint8  
 41  zipcode_98022   uint8  
 42  zipcode_98023   uint8  
 43  zipcode_98024   uint8  
 44  zipcode_98027   uint8  
 45  zipcode_98028   uint8  
 46  zipcode_98029   uint8  
 47  zipcode_98030   uint8  
 48  zipcode_98031   uint8  
```

```
 49  zipcode_98032   uint8
 50  zipcode_98033   uint8
 51  zipcode_98034   uint8
 52  zipcode_98038   uint8
 53  zipcode_98039   uint8
 54  zipcode_98040   uint8
 55  zipcode_98042   uint8
 56  zipcode_98045   uint8
 57  zipcode_98052   uint8
 58  zipcode_98053   uint8
 59  zipcode_98055   uint8
 60  zipcode_98056   uint8
 61  zipcode_98058   uint8
 62  zipcode_98059   uint8
 63  zipcode_98065   uint8
 64  zipcode_98070   uint8
 65  zipcode_98072   uint8
 66  zipcode_98074   uint8
 67  zipcode_98075   uint8
 68  zipcode_98077   uint8
 69  zipcode_98092   uint8
 70  zipcode_98102   uint8
 71  zipcode_98103   uint8
 72  zipcode_98105   uint8
 73  zipcode_98106   uint8
 74  zipcode_98107   uint8
 75  zipcode_98108   uint8
 76  zipcode_98109   uint8
 77  zipcode_98112   uint8
 78  zipcode_98115   uint8
 79  zipcode_98116   uint8
 80  zipcode_98117   uint8
 81  zipcode_98118   uint8
 82  zipcode_98119   uint8
 83  zipcode_98122   uint8
 84  zipcode_98125   uint8
 85  zipcode_98126   uint8
 86  zipcode_98133   uint8
 87  zipcode_98136   uint8
 88  zipcode_98144   uint8
 89  zipcode_98146   uint8
 90  zipcode_98148   uint8
 91  zipcode_98155   uint8
 92  zipcode_98166   uint8
 93  zipcode_98168   uint8
 94  zipcode_98177   uint8
 95  zipcode_98178   uint8
 96  zipcode_98188   uint8
 97  zipcode_98198   uint8
 98  zipcode_98199   uint8
 99  month_2         uint8
 100 month_3         uint8
 101 month_4         uint8
 102 month_5         uint8
 103 month_6         uint8
 104 month_7         uint8
 105 month_8         uint8
 106 month_9         uint8
 107 month_10        uint8
 108 month_11        uint8
 109 month_12        uint8
dtypes: float64(4), int64(7), uint8(99)
memory usage: 4.0 MB
```

With the dummy variables now in place, it's time to check the impact it had on model performance.

In [60]:
```
model_3 = fit_model(df_categoricals)
model_3.summary()
```

Out[60]:

| | coef | std err | t | P>\|t\| | [0.025 | 0.975] |
|---|---|---|---|---|---|---|
| **const** | -3.287e+07 | 5.73e+06 | -5.734 | 0.000 | -4.41e+07 | -2.16e+07 |
| **bedrooms** | -1.334e+04 | 1540.987 | -8.658 | 0.000 | -1.64e+04 | -1.03e+04 |
| **bathrooms** | 2.625e+04 | 2395.777 | 10.957 | 0.000 | 2.16e+04 | 3.09e+04 |
| **sqft_lot** | 0.2442 | 0.036 | 6.817 | 0.000 | 0.174 | 0.314 |
| **sqft_above** | 158.4193 | 2.848 | 55.616 | 0.000 | 152.836 | 164.002 |
| **sqft_basement** | 120.4862 | 3.165 | 38.072 | 0.000 | 114.283 | 126.689 |
| **yr_built** | -682.3172 | 55.697 | -12.251 | 0.000 | -791.487 | -573.147 |
| **lat** | 2.265e+05 | 5.91e+04 | 3.834 | 0.000 | 1.11e+05 | 3.42e+05 |
| **long** | -1.917e+05 | 4.25e+04 | -4.512 | 0.000 | -2.75e+05 | -1.08e+05 |
| **sqft_living15** | 16.9243 | 2.705 | 6.258 | 0.000 | 11.623 | 22.225 |
| **sqft_lot15** | -0.1083 | 0.056 | -1.921 | 0.055 | -0.219 | 0.002 |
| **waterfront_1.0** | 5.973e+05 | 1.54e+04 | 38.696 | 0.000 | 5.67e+05 | 6.28e+05 |
| **view_1.0** | 8.669e+04 | 8523.735 | 10.171 | 0.000 | 7e+04 | 1.03e+05 |
| **view_2.0** | 6.936e+04 | 5208.499 | 13.316 | 0.000 | 5.91e+04 | 7.96e+04 |

| | | | | | | |
|---|---|---|---|---|---|---|
| view_2.0 | 6.936e+04 | 5208.499 | 13.316 | 0.000 | 5.91e+04 | 7.96e+04 |
| view_3.0 | 1.536e+05 | 7113.850 | 21.594 | 0.000 | 1.4e+05 | 1.68e+05 |
| view_4.0 | 2.974e+05 | 1.07e+04 | 27.711 | 0.000 | 2.76e+05 | 3.18e+05 |
| condition_2 | 9.127e+04 | 3.02e+04 | 3.018 | 0.003 | 3.2e+04 | 1.51e+05 |
| condition_3 | 1.035e+05 | 2.81e+04 | 3.678 | 0.000 | 4.83e+04 | 1.59e+05 |
| condition_4 | 1.274e+05 | 2.82e+04 | 4.523 | 0.000 | 7.22e+04 | 1.83e+05 |
| condition_5 | 1.707e+05 | 2.83e+04 | 6.026 | 0.000 | 1.15e+05 | 2.26e+05 |
| grade_4 | -1.029e+05 | 1.53e+05 | -0.674 | 0.501 | -4.02e+05 | 1.97e+05 |
| grade_5 | -1.371e+05 | 1.5e+05 | -0.912 | 0.362 | -4.32e+05 | 1.58e+05 |
| grade_6 | -1.354e+05 | 1.5e+05 | -0.902 | 0.367 | -4.3e+05 | 1.59e+05 |
| grade_7 | -1.291e+05 | 1.5e+05 | -0.860 | 0.390 | -4.23e+05 | 1.65e+05 |
| grade_8 | -1.083e+05 | 1.5e+05 | -0.721 | 0.471 | -4.02e+05 | 1.86e+05 |
| grade_9 | -3.377e+04 | 1.5e+05 | -0.225 | 0.822 | -3.28e+05 | 2.61e+05 |
| grade_10 | 8.805e+04 | 1.5e+05 | 0.586 | 0.558 | -2.07e+05 | 3.83e+05 |
| grade_11 | 2.857e+05 | 1.5e+05 | 1.898 | 0.058 | -9318.928 | 5.81e+05 |
| grade_12 | 6.956e+05 | 1.51e+05 | 4.598 | 0.000 | 3.99e+05 | 9.92e+05 |
| grade_13 | 1.809e+06 | 1.56e+05 | 11.567 | 0.000 | 1.5e+06 | 2.12e+06 |
| zipcode_98002 | 1.534e+04 | 1.35e+04 | 1.137 | 0.255 | -1.11e+04 | 4.18e+04 |
| zipcode_98003 | -1.246e+04 | 1.21e+04 | -1.033 | 0.301 | -3.61e+04 | 1.12e+04 |
| zipcode_98004 | 7.102e+05 | 2.19e+04 | 32.403 | 0.000 | 6.67e+05 | 7.53e+05 |
| zipcode_98005 | 2.605e+05 | 2.34e+04 | 11.123 | 0.000 | 2.15e+05 | 3.06e+05 |
| zipcode_98006 | 2.159e+05 | 1.91e+04 | 11.276 | 0.000 | 1.78e+05 | 2.53e+05 |
| zipcode_98007 | 2.079e+05 | 2.42e+04 | 8.606 | 0.000 | 1.61e+05 | 2.55e+05 |
| zipcode_98008 | 2.239e+05 | 2.3e+04 | 9.751 | 0.000 | 1.79e+05 | 2.69e+05 |
| zipcode_98010 | 1.091e+05 | 2.06e+04 | 5.309 | 0.000 | 6.88e+04 | 1.49e+05 |
| zipcode_98011 | 4.86e+04 | 2.98e+04 | 1.628 | 0.103 | -9898.806 | 1.07e+05 |
| zipcode_98014 | 9.299e+04 | 3.28e+04 | 2.836 | 0.005 | 2.87e+04 | 1.57e+05 |
| zipcode_98019 | 5.743e+04 | 3.23e+04 | 1.776 | 0.076 | -5938.673 | 1.21e+05 |
| zipcode_98022 | 6.849e+04 | 1.79e+04 | 3.828 | 0.000 | 3.34e+04 | 1.04e+05 |
| zipcode_98023 | -4.276e+04 | 1.11e+04 | -3.856 | 0.000 | -6.45e+04 | -2.1e+04 |
| zipcode_98024 | 1.675e+05 | 2.89e+04 | 5.804 | 0.000 | 1.11e+05 | 2.24e+05 |
| zipcode_98027 | 1.6e+05 | 1.96e+04 | 8.149 | 0.000 | 1.21e+05 | 1.98e+05 |
| zipcode_98028 | 3.48e+04 | 2.9e+04 | 1.201 | 0.230 | -2.2e+04 | 9.16e+04 |
| zipcode_98029 | 2.117e+05 | 2.24e+04 | 9.441 | 0.000 | 1.68e+05 | 2.56e+05 |
| zipcode_98030 | 7346.7850 | 1.32e+04 | 0.554 | 0.579 | -1.86e+04 | 3.33e+04 |
| zipcode_98031 | 1.18e+04 | 1.38e+04 | 0.855 | 0.393 | -1.53e+04 | 3.89e+04 |
| zipcode_98032 | -1.11e+04 | 1.6e+04 | -0.693 | 0.489 | -4.25e+04 | 2.03e+04 |
| zipcode_98033 | 2.937e+05 | 2.49e+04 | 11.810 | 0.000 | 2.45e+05 | 3.42e+05 |
| zipcode_98034 | 1.217e+05 | 2.67e+04 | 4.562 | 0.000 | 6.94e+04 | 1.74e+05 |
| zipcode_98038 | 6.713e+04 | 1.49e+04 | 4.508 | 0.000 | 3.79e+04 | 9.63e+04 |
| zipcode_98039 | 1.166e+06 | 2.97e+04 | 39.307 | 0.000 | 1.11e+06 | 1.22e+06 |
| zipcode_98040 | 4.605e+05 | 1.94e+04 | 23.756 | 0.000 | 4.22e+05 | 4.98e+05 |
| zipcode_98042 | 2.3e+04 | 1.27e+04 | 1.812 | 0.070 | -1879.077 | 4.79e+04 |
| zipcode_98045 | 1.602e+05 | 2.75e+04 | 5.822 | 0.000 | 1.06e+05 | 2.14e+05 |
| zipcode_98052 | 1.862e+05 | 2.54e+04 | 7.336 | 0.000 | 1.36e+05 | 2.36e+05 |
| zipcode_98053 | 1.742e+05 | 2.72e+04 | 6.402 | 0.000 | 1.21e+05 | 2.28e+05 |
| zipcode_98055 | 1.823e+04 | 1.54e+04 | 1.187 | 0.235 | -1.19e+04 | 4.83e+04 |
| zipcode_98056 | 6.056e+04 | 1.67e+04 | 3.628 | 0.000 | 2.78e+04 | 9.33e+04 |
| zipcode_98058 | 2.789e+04 | 1.45e+04 | 1.920 | 0.055 | -584.052 | 5.64e+04 |
| zipcode_98059 | 6.541e+04 | 1.64e+04 | 3.991 | 0.000 | 3.33e+04 | 9.75e+04 |
| zipcode_98065 | 1.166e+05 | 2.53e+04 | 4.601 | 0.000 | 6.69e+04 | 1.66e+05 |
| zipcode_98070 | -5.333e+04 | 1.94e+04 | -2.755 | 0.006 | -9.13e+04 | -1.54e+04 |

| | | | | | | |
|---|---|---|---|---|---|---|
| **zipcode_98072** | 8.849e+04 | 2.97e+04 | 2.980 | 0.003 | 3.03e+04 | 1.47e+05 |
| **zipcode_98074** | 1.486e+05 | 2.4e+04 | 6.183 | 0.000 | 1.02e+05 | 1.96e+05 |
| **zipcode_98075** | 1.524e+05 | 2.31e+04 | 6.589 | 0.000 | 1.07e+05 | 1.98e+05 |
| **zipcode_98077** | 5.565e+04 | 3.09e+04 | 1.802 | 0.072 | -4895.790 | 1.16e+05 |
| **zipcode_98092** | -4096.9965 | 1.21e+04 | -0.339 | 0.734 | -2.78e+04 | 1.96e+04 |
| **zipcode_98102** | 3.894e+05 | 2.56e+04 | 15.231 | 0.000 | 3.39e+05 | 4.39e+05 |
| **zipcode_98103** | 2.291e+05 | 2.39e+04 | 9.578 | 0.000 | 1.82e+05 | 2.76e+05 |
| **zipcode_98105** | 3.798e+05 | 2.46e+04 | 15.414 | 0.000 | 3.31e+05 | 4.28e+05 |
| **zipcode_98106** | 5.353e+04 | 1.78e+04 | 3.005 | 0.003 | 1.86e+04 | 8.84e+04 |
| **zipcode_98107** | 2.305e+05 | 2.47e+04 | 9.339 | 0.000 | 1.82e+05 | 2.79e+05 |
| **zipcode_98108** | 5.025e+04 | 1.96e+04 | 2.560 | 0.010 | 1.18e+04 | 8.87e+04 |
| **zipcode_98109** | 4.074e+05 | 2.54e+04 | 16.016 | 0.000 | 3.58e+05 | 4.57e+05 |
| **zipcode_98112** | 5.395e+05 | 2.25e+04 | 23.928 | 0.000 | 4.95e+05 | 5.84e+05 |
| **zipcode_98115** | 2.375e+05 | 2.44e+04 | 9.740 | 0.000 | 1.9e+05 | 2.85e+05 |
| **zipcode_98116** | 2.003e+05 | 1.98e+04 | 10.098 | 0.000 | 1.61e+05 | 2.39e+05 |
| **zipcode_98117** | 2.036e+05 | 2.47e+04 | 8.248 | 0.000 | 1.55e+05 | 2.52e+05 |
| **zipcode_98118** | 9.974e+04 | 1.73e+04 | 5.753 | 0.000 | 6.58e+04 | 1.34e+05 |
| **zipcode_98119** | 3.854e+05 | 2.4e+04 | 16.050 | 0.000 | 3.38e+05 | 4.32e+05 |
| **zipcode_98122** | 2.621e+05 | 2.14e+04 | 12.245 | 0.000 | 2.2e+05 | 3.04e+05 |
| **zipcode_98125** | 1.017e+05 | 2.64e+04 | 3.858 | 0.000 | 5e+04 | 1.53e+05 |
| **zipcode_98126** | 1.134e+05 | 1.82e+04 | 6.217 | 0.000 | 7.77e+04 | 1.49e+05 |
| **zipcode_98133** | 4.866e+04 | 2.72e+04 | 1.787 | 0.074 | -4723.274 | 1.02e+05 |
| **zipcode_98136** | 1.679e+05 | 1.87e+04 | 8.984 | 0.000 | 1.31e+05 | 2.05e+05 |
| **zipcode_98144** | 2.004e+05 | 1.99e+04 | 10.062 | 0.000 | 1.61e+05 | 2.39e+05 |
| **zipcode_98146** | 3.575e+04 | 1.67e+04 | 2.137 | 0.033 | 2966.666 | 6.85e+04 |
| **zipcode_98148** | 2.813e+04 | 2.28e+04 | 1.236 | 0.216 | -1.65e+04 | 7.27e+04 |
| **zipcode_98155** | 3.945e+04 | 2.83e+04 | 1.392 | 0.164 | -1.61e+04 | 9.5e+04 |
| **zipcode_98166** | 1.185e+04 | 1.53e+04 | 0.774 | 0.439 | -1.82e+04 | 4.19e+04 |
| **zipcode_98168** | 3017.1101 | 1.62e+04 | 0.186 | 0.852 | -2.87e+04 | 3.47e+04 |
| **zipcode_98177** | 1.001e+05 | 2.85e+04 | 3.519 | 0.000 | 4.44e+04 | 1.56e+05 |
| **zipcode_98178** | -1.026e+04 | 1.67e+04 | -0.614 | 0.539 | -4.3e+04 | 2.25e+04 |
| **zipcode_98188** | -2469.5797 | 1.71e+04 | -0.144 | 0.885 | -3.61e+04 | 3.11e+04 |
| **zipcode_98198** | -2.703e+04 | 1.3e+04 | -2.080 | 0.038 | -5.25e+04 | -1554.524 |
| **zipcode_98199** | 2.825e+05 | 2.35e+04 | 12.039 | 0.000 | 2.37e+05 | 3.29e+05 |
| **month_2** | 6313.9061 | 6408.665 | 0.985 | 0.325 | -6247.554 | 1.89e+04 |
| **month_3** | 2.914e+04 | 5917.497 | 4.924 | 0.000 | 1.75e+04 | 4.07e+04 |
| **month_4** | 3.587e+04 | 5756.997 | 6.230 | 0.000 | 2.46e+04 | 4.72e+04 |
| **month_5** | 5923.1655 | 5689.028 | 1.041 | 0.298 | -5227.753 | 1.71e+04 |
| **month_6** | 1044.5211 | 5782.228 | 0.181 | 0.857 | -1.03e+04 | 1.24e+04 |
| **month_7** | -2259.1458 | 5767.182 | -0.392 | 0.695 | -1.36e+04 | 9044.961 |
| **month_8** | -2242.4609 | 5891.615 | -0.381 | 0.703 | -1.38e+04 | 9305.544 |
| **month_9** | -7516.5582 | 5975.791 | -1.258 | 0.208 | -1.92e+04 | 4196.438 |
| **month_10** | -6731.4020 | 5918.711 | -1.137 | 0.255 | -1.83e+04 | 4869.712 |
| **month_11** | -4705.9468 | 6245.818 | -0.753 | 0.451 | -1.69e+04 | 7536.322 |
| **month_12** | -2239.0102 | 6191.409 | -0.362 | 0.718 | -1.44e+04 | 9896.612 |

OLS Regression Results

| | | | |
|---|---|---|---|
| **Dep. Variable:** | price | **R-squared:** | 0.835 |
| **Model:** | OLS | **Adj. R-squared:** | 0.834 |
| **Method:** | Least Squares | **F-statistic:** | 997.0 |
| **Date:** | Sun, 06 Jun 2021 | **Prob (F-statistic):** | 0.00 |
| **Time:** | 23:43:48 | **Log-Likelihood:** | -2.8777e+05 |
| **No. Observations:** | 21585 | **AIC:** | 5.758e+05 |
| **Df Residuals:** | 21475 | **BIC:** | 5.766e+05 |
| **Df Model:** | 109 | | |
| **Covariance Type:** | nonrobust | | |

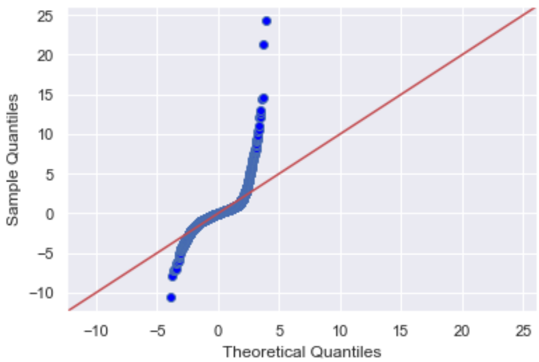
| | | | |
|---|---|---|---|
| **Omnibus:** | 16982.193 | **Durbin-Watson:** | 1.995 |
| **Prob(Omnibus):** | 0.000 | **Jarque-Bera (JB):** | 2206573.086 |
| **Skew:** | 3.044 | **Prob(JB):** | 0.00 |
| **Kurtosis:** | 52.157 | **Cond. No.** | 2.85e+08 |

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 2.85e+08. This might indicate that there are
strong multicollinearity or other numerical problems.

In [61]:
```
print_rmse(df_categoricals)
```

```
Train RMSE: 150761.63
Test  RMSE: 147644.2
```

In [62]:
```
get_qqplot(model_3);
```




**Observations:**

- Large improvement in the R-squared value
- Many of the dummy variable columns are showing non-significant p-values
- Also good improvement in the RMSE values, model remains decently fit
- The Q-Q plot is still showing non-normality in the residuals

## Transformations

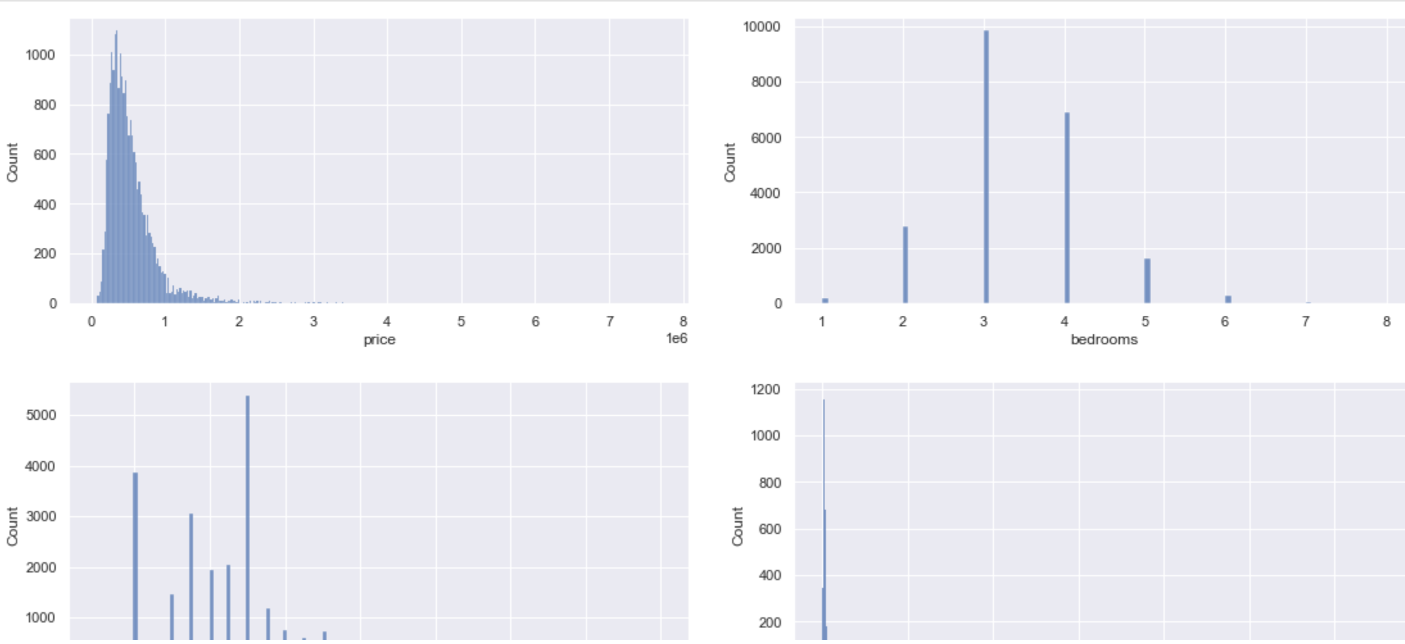
### Log Transformation

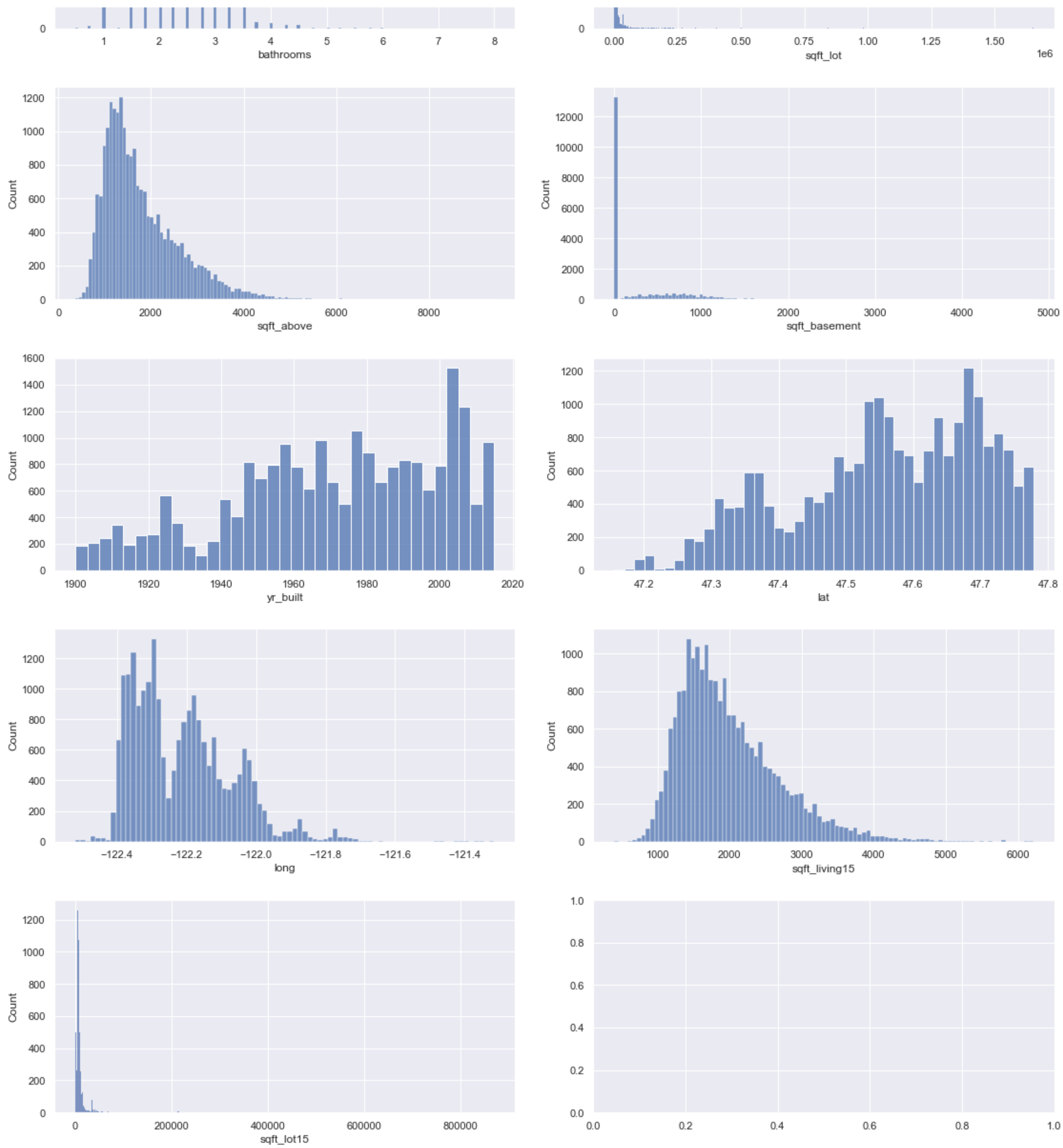
In [63]:
```
df_log = df_categoricals.copy()
continuous = df_log.columns[:11]
continuous
```

Out[63]:
```
Index(['price', 'bedrooms', 'bathrooms', 'sqft_lot', 'sqft_above',
       'sqft_basement', 'yr_built', 'lat', 'long', 'sqft_living15',
       'sqft_lot15'],
      dtype='object')
```

Checking the distributions of each of the continuous variables:

In [64]:
```
fig, axes = plt.subplots(nrows=6, ncols=2, figsize=(16, 24))
axes = axes.reshape(-1)

for i, col in enumerate(continuous):
    sns.histplot(data=df_log[col], ax=axes[i])

fig.tight_layout(pad=2.0)
```






All of the continous variables exhibit skewness to some degree. Applying a log transformation to each of those columns may help and increase the model's R-squared value. However, `sqft_basement` contains many zero values and `long` contains all negative values which are invalid for log transformations. These will remain as they currently are.

In [65]:
```
continuous = continuous.drop(['sqft_basement', 'long'])

for col in continuous:
    df_log[col] = df_log[col].map(lambda x: np.log(x))
    df_log.rename(columns={col: col+'_log'}, inplace=True)
```

In [66]:
```
df_log.head()
```

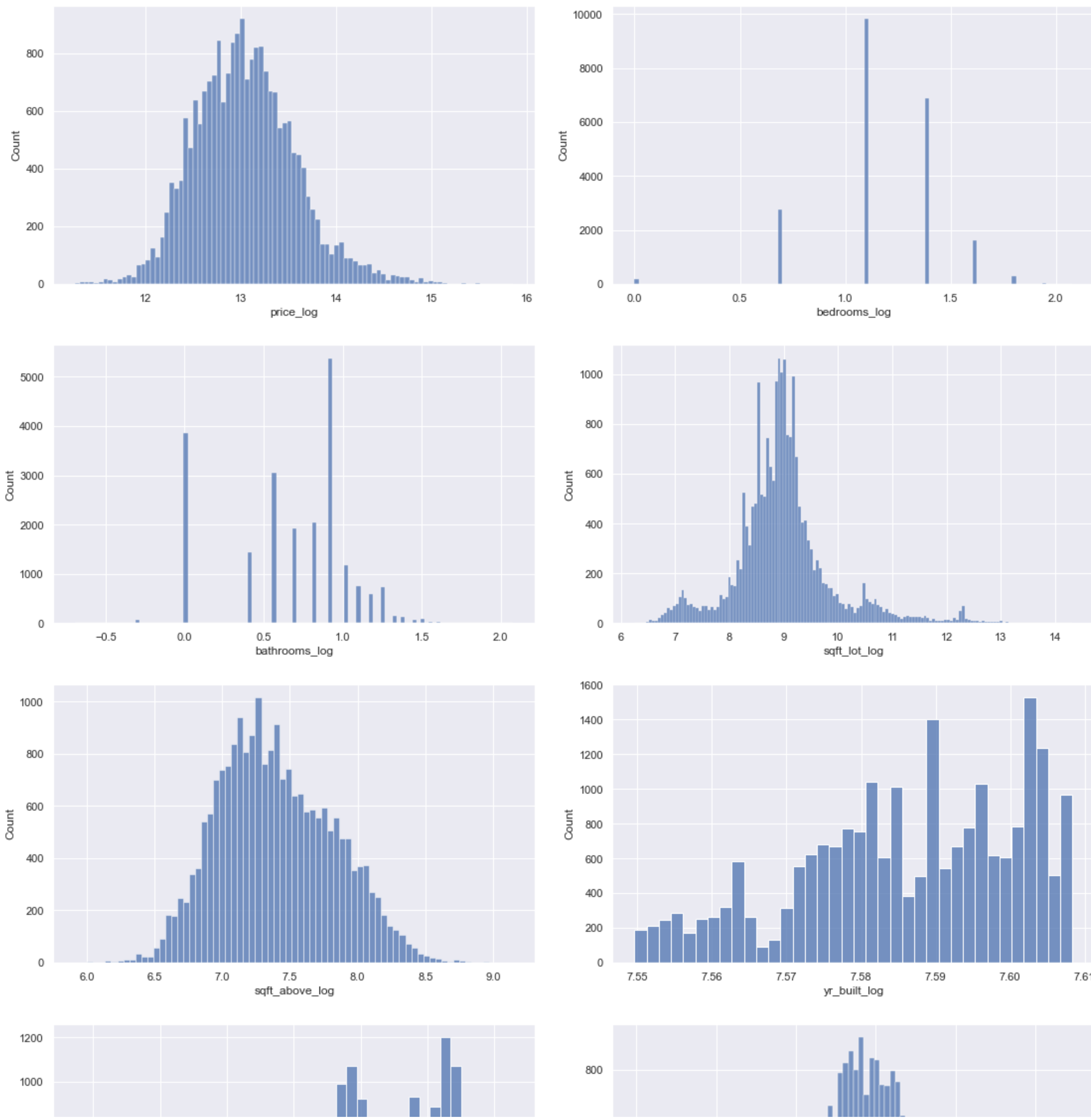
Out[66]:

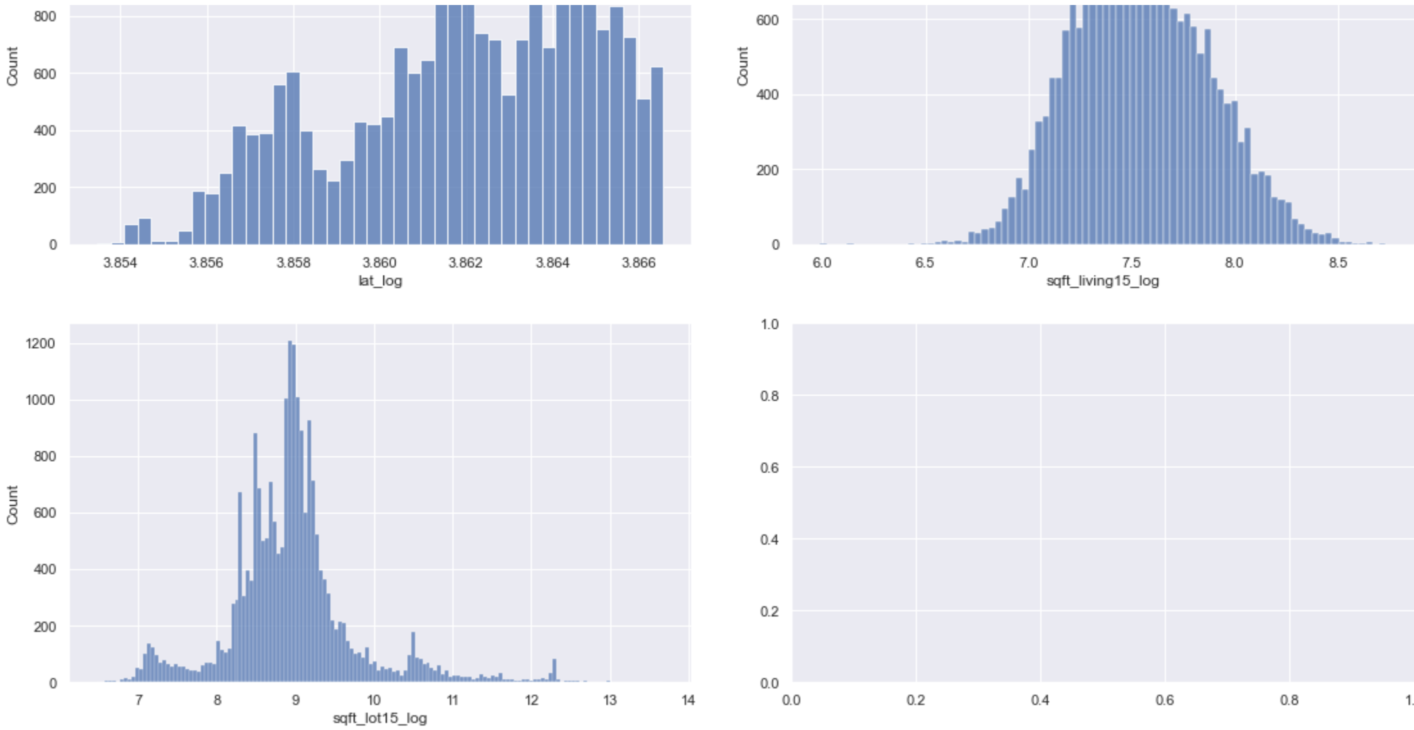
| | price_log | bedrooms_log | bathrooms_log | sqft_lot_log | sqft_above_log | sqft_basement | yr_built_log | lat_log | long | sqft_living15_log | ... | month_3 | month_4 | mo |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 12.309982 | 1.098612 | 0.000000 | 8.639411 | 7.073270 | 0 | 7.578145 | 3.860965 | -122.257 | 7.200425 | ... | 0 | 0 | |
| **1** | 13.195614 | 1.098612 | 0.810930 | 8.887653 | 7.682482 | 400 | 7.576097 | 3.865372 | -122.319 | 7.432484 | ... | 0 | 0 | |
| **2** | 12.100712 | 0.693147 | 0.000000 | 9.210340 | 6.646391 | 0 | 7.566828 | 3.865726 | -122.233 | 7.908387 | ... | 0 | 0 | |
| **3** | 13.311329 | 1.386294 | 1.098612 | 8.517193 | 6.956545 | 910 | 7.583248 | 3.861168 | -122.393 | 7.215240 | ... | 0 | 0 | |
| **4** | 13.142166 | 1.098612 | 0.693147 | 8.997147 | 7.426549 | 0 | 7.594381 | 3.863186 | -122.045 | 7.495542 | ... | 0 | 0 | |

5 rows × 110 columns

Checking the distributions again:

In [67]:
```
fig, axes = plt.subplots(nrows=5, ncols=2, figsize=(16, 24))
axes = axes.reshape(-1)

for i, col in enumerate(continuous):
    sns.histplot(data=df_log[col+'_log'], ax=axes[i])

fig.tight_layout(pad=2.0)
```






It's not perfect, but it's definitely better than before. Time to see how it impacted the model.

In [68]:
```
model_4 = fit_model(df_log, target='price_log')
model_4.summary()
```

Out[68]:

| | coef | std err | t | P>\|t\| | [0.025 | 0.975] |
|---|---|---|---|---|---|---|
| **const** | -132.7702 | 14.085 | -9.426 | 0.000 | -160.378 | -105.162 |
| **bedrooms_log** | -0.0266 | 0.006 | -4.441 | 0.000 | -0.038 | -0.015 |
| **bathrooms_log** | 0.0870 | 0.006 | 15.626 | 0.000 | 0.076 | 0.098 |
| **sqft_lot_log** | 0.0760 | 0.004 | 21.206 | 0.000 | 0.069 | 0.083 |
| **sqft_above_log** | 0.3683 | 0.006 | 57.268 | 0.000 | 0.356 | 0.381 |
| **sqft_basement** | 0.0001 | 3.76e-06 | 32.718 | 0.000 | 0.000 | 0.000 |
| **yr_built_log** | -0.9818 | 0.137 | -7.155 | 0.000 | -1.251 | -0.713 |
| **lat_log** | 25.1273 | 3.359 | 7.480 | 0.000 | 18.543 | 31.711 |
| **long** | -0.4195 | 0.051 | -8.193 | 0.000 | -0.520 | -0.319 |
| **sqft_living15_log** | 0.1636 | 0.007 | 24.858 | 0.000 | 0.151 | 0.176 |
| **sqft_lot15_log** | -0.0179 | 0.004 | -4.501 | 0.000 | -0.026 | -0.010 |
| **waterfront_1.0** | 0.4473 | 0.018 | 24.230 | 0.000 | 0.411 | 0.483 |
| **view_1.0** | 0.1078 | 0.010 | 10.566 | 0.000 | 0.088 | 0.128 |
| **view_2.0** | 0.0979 | 0.006 | 15.713 | 0.000 | 0.086 | 0.110 |
| **view_3.0** | 0.1658 | 0.008 | 19.526 | 0.000 | 0.149 | 0.182 |
| **view_4.0** | 0.2715 | 0.013 | 21.153 | 0.000 | 0.246 | 0.297 |
| **condition_2** | 0.1565 | 0.036 | 4.324 | 0.000 | 0.086 | 0.227 |
| **condition_3** | 0.2988 | 0.034 | 8.865 | 0.000 | 0.233 | 0.365 |
| **condition_4** | 0.3369 | 0.034 | 9.990 | 0.000 | 0.271 | 0.403 |
| **condition_5** | 0.4045 | 0.034 | 11.922 | 0.000 | 0.338 | 0.471 |
| **grade_4** | -0.5180 | 0.183 | -2.833 | 0.005 | -0.876 | -0.160 |
| **grade_5** | -0.5270 | 0.180 | -2.929 | 0.003 | -0.880 | -0.174 |
| **grade_6** | -0.4466 | 0.180 | -2.487 | 0.013 | -0.799 | -0.095 |
| **grade_7** | -0.3674 | 0.180 | -2.046 | 0.041 | -0.720 | -0.015 |
| **grade_8** | -0.2878 | 0.180 | -1.602 | 0.109 | -0.640 | 0.064 |
| **grade_9** | -0.1670 | 0.180 | -0.929 | 0.353 | -0.519 | 0.185 |
| **grade_10** | -0.0758 | 0.180 | -0.421 | 0.674 | -0.428 | 0.277 |
| **grade_11** | 0.0347 | 0.180 | 0.192 | 0.847 | -0.318 | 0.388 |
| **grade_12** | 0.1590 | 0.181 | 0.879 | 0.380 | -0.196 | 0.514 |

| | | | | | | |
|---|---|---|---|---|---|---|
| **grade_12** | 0.1590 | 0.181 | 0.879 | 0.380 | -0.196 | 0.514 |
| **grade_13** | 0.3917 | 0.187 | 2.095 | 0.036 | 0.025 | 0.758 |
| **zipcode_98002** | 0.0212 | 0.016 | 1.312 | 0.190 | -0.010 | 0.053 |
| **zipcode_98003** | 0.0004 | 0.014 | 0.031 | 0.975 | -0.028 | 0.029 |
| **zipcode_98004** | 0.9891 | 0.026 | 37.670 | 0.000 | 0.938 | 1.041 |
| **zipcode_98005** | 0.6080 | 0.028 | 21.681 | 0.000 | 0.553 | 0.663 |
| **zipcode_98006** | 0.5602 | 0.023 | 24.407 | 0.000 | 0.515 | 0.605 |
| **zipcode_98007** | 0.5459 | 0.029 | 18.855 | 0.000 | 0.489 | 0.603 |
| **zipcode_98008** | 0.5623 | 0.028 | 20.427 | 0.000 | 0.508 | 0.616 |
| **zipcode_98010** | 0.3354 | 0.025 | 13.641 | 0.000 | 0.287 | 0.384 |
| **zipcode_98011** | 0.2426 | 0.036 | 6.796 | 0.000 | 0.173 | 0.313 |
| **zipcode_98014** | 0.2789 | 0.039 | 7.114 | 0.000 | 0.202 | 0.356 |
| **zipcode_98019** | 0.2187 | 0.039 | 5.653 | 0.000 | 0.143 | 0.295 |
| **zipcode_98022** | 0.2081 | 0.021 | 9.716 | 0.000 | 0.166 | 0.250 |
| **zipcode_98023** | -0.0549 | 0.013 | -4.138 | 0.000 | -0.081 | -0.029 |
| **zipcode_98024** | 0.4378 | 0.034 | 12.693 | 0.000 | 0.370 | 0.505 |
| **zipcode_98027** | 0.4921 | 0.024 | 20.889 | 0.000 | 0.446 | 0.538 |
| **zipcode_98028** | 0.1901 | 0.035 | 5.483 | 0.000 | 0.122 | 0.258 |
| **zipcode_98029** | 0.5865 | 0.027 | 21.724 | 0.000 | 0.534 | 0.639 |
| **zipcode_98030** | 0.0495 | 0.016 | 3.119 | 0.002 | 0.018 | 0.081 |
| **zipcode_98031** | 0.0595 | 0.017 | 3.597 | 0.000 | 0.027 | 0.092 |
| **zipcode_98032** | -0.0475 | 0.019 | -2.474 | 0.013 | -0.085 | -0.010 |
| **zipcode_98033** | 0.6303 | 0.030 | 21.167 | 0.000 | 0.572 | 0.689 |
| **zipcode_98034** | 0.3596 | 0.032 | 11.267 | 0.000 | 0.297 | 0.422 |
| **zipcode_98038** | 0.2343 | 0.018 | 13.088 | 0.000 | 0.199 | 0.269 |
| **zipcode_98039** | 1.1455 | 0.035 | 32.282 | 0.000 | 1.076 | 1.215 |
| **zipcode_98040** | 0.7558 | 0.023 | 32.551 | 0.000 | 0.710 | 0.801 |
| **zipcode_98042** | 0.0963 | 0.015 | 6.329 | 0.000 | 0.067 | 0.126 |
| **zipcode_98045** | 0.4473 | 0.033 | 13.560 | 0.000 | 0.383 | 0.512 |
| **zipcode_98052** | 0.5088 | 0.030 | 16.732 | 0.000 | 0.449 | 0.568 |
| **zipcode_98053** | 0.4932 | 0.033 | 15.138 | 0.000 | 0.429 | 0.557 |
| **zipcode_98055** | 0.1021 | 0.018 | 5.539 | 0.000 | 0.066 | 0.138 |
| **zipcode_98056** | 0.2591 | 0.020 | 12.937 | 0.000 | 0.220 | 0.298 |
| **zipcode_98058** | 0.1466 | 0.017 | 8.414 | 0.000 | 0.112 | 0.181 |
| **zipcode_98059** | 0.3013 | 0.020 | 15.333 | 0.000 | 0.263 | 0.340 |
| **zipcode_98065** | 0.4630 | 0.031 | 15.176 | 0.000 | 0.403 | 0.523 |
| **zipcode_98070** | 0.1654 | 0.023 | 7.113 | 0.000 | 0.120 | 0.211 |
| **zipcode_98072** | 0.2947 | 0.036 | 8.298 | 0.000 | 0.225 | 0.364 |
| **zipcode_98074** | 0.4807 | 0.029 | 16.684 | 0.000 | 0.424 | 0.537 |
| **zipcode_98075** | 0.5166 | 0.028 | 18.628 | 0.000 | 0.462 | 0.571 |
| **zipcode_98077** | 0.2783 | 0.037 | 7.532 | 0.000 | 0.206 | 0.351 |
| **zipcode_98092** | 0.0619 | 0.014 | 4.284 | 0.000 | 0.034 | 0.090 |
| **zipcode_98102** | 0.8072 | 0.031 | 26.265 | 0.000 | 0.747 | 0.867 |
| **zipcode_98103** | 0.6430 | 0.029 | 22.404 | 0.000 | 0.587 | 0.699 |
| **zipcode_98105** | 0.7778 | 0.030 | 26.294 | 0.000 | 0.720 | 0.836 |
| **zipcode_98106** | 0.2373 | 0.021 | 11.101 | 0.000 | 0.195 | 0.279 |
| **zipcode_98107** | 0.6615 | 0.030 | 22.351 | 0.000 | 0.603 | 0.720 |
| **zipcode_98108** | 0.2610 | 0.024 | 11.081 | 0.000 | 0.215 | 0.307 |
| **zipcode_98109** | 0.8307 | 0.031 | 27.195 | 0.000 | 0.771 | 0.891 |
| **zipcode_98112** | 0.8974 | 0.027 | 33.097 | 0.000 | 0.844 | 0.951 |
| **zipcode_98115** | 0.6442 | 0.029 | 22.039 | 0.000 | 0.587 | 0.702 |
| **zipcode_98116** | 0.6121 | 0.024 | 25.723 | 0.000 | 0.565 | 0.659 |

| | | | | | | |
|---|---|---|---|---|---|---|
| **zipcode_98117** | 0.6151 | 0.030 | 20.791 | 0.000 | 0.557 | 0.673 |
| **zipcode_98118** | 0.3749 | 0.021 | 17.992 | 0.000 | 0.334 | 0.416 |
| **zipcode_98119** | 0.8070 | 0.029 | 27.990 | 0.000 | 0.751 | 0.864 |
| **zipcode_98122** | 0.6846 | 0.026 | 26.569 | 0.000 | 0.634 | 0.735 |
| **zipcode_98125** | 0.3645 | 0.032 | 11.547 | 0.000 | 0.303 | 0.426 |
| **zipcode_98126** | 0.4364 | 0.022 | 19.930 | 0.000 | 0.393 | 0.479 |
| **zipcode_98133** | 0.2294 | 0.033 | 7.039 | 0.000 | 0.165 | 0.293 |
| **zipcode_98136** | 0.5520 | 0.022 | 24.621 | 0.000 | 0.508 | 0.596 |
| **zipcode_98144** | 0.5631 | 0.024 | 23.484 | 0.000 | 0.516 | 0.610 |
| **zipcode_98146** | 0.1642 | 0.020 | 8.190 | 0.000 | 0.125 | 0.203 |
| **zipcode_98148** | 0.0770 | 0.027 | 2.826 | 0.005 | 0.024 | 0.130 |
| **zipcode_98155** | 0.1949 | 0.034 | 5.748 | 0.000 | 0.128 | 0.261 |
| **zipcode_98166** | 0.2116 | 0.018 | 11.533 | 0.000 | 0.176 | 0.248 |
| **zipcode_98168** | -0.0156 | 0.019 | -0.807 | 0.420 | -0.054 | 0.022 |
| **zipcode_98177** | 0.3333 | 0.034 | 9.790 | 0.000 | 0.267 | 0.400 |
| **zipcode_98178** | 0.0864 | 0.020 | 4.315 | 0.000 | 0.047 | 0.126 |
| **zipcode_98188** | 0.0295 | 0.021 | 1.438 | 0.151 | -0.011 | 0.070 |
| **zipcode_98198** | 0.0120 | 0.016 | 0.769 | 0.442 | -0.019 | 0.042 |
| **zipcode_98199** | 0.6620 | 0.028 | 23.544 | 0.000 | 0.607 | 0.717 |
| **month_2** | 0.0212 | 0.008 | 2.772 | 0.006 | 0.006 | 0.036 |
| **month_3** | 0.0484 | 0.007 | 6.833 | 0.000 | 0.034 | 0.062 |
| **month_4** | 0.0690 | 0.007 | 10.015 | 0.000 | 0.055 | 0.082 |
| **month_5** | 0.0116 | 0.007 | 1.708 | 0.088 | -0.002 | 0.025 |
| **month_6** | 0.0015 | 0.007 | 0.222 | 0.825 | -0.012 | 0.015 |
| **month_7** | -0.0045 | 0.007 | -0.659 | 0.510 | -0.018 | 0.009 |
| **month_8** | -0.0037 | 0.007 | -0.518 | 0.604 | -0.017 | 0.010 |
| **month_9** | -0.0096 | 0.007 | -1.339 | 0.181 | -0.024 | 0.004 |
| **month_10** | -0.0102 | 0.007 | -1.446 | 0.148 | -0.024 | 0.004 |
| **month_11** | -0.0100 | 0.007 | -1.332 | 0.183 | -0.025 | 0.005 |
| **month_12** | -0.0007 | 0.007 | -0.098 | 0.922 | -0.015 | 0.014 |

OLS Regression Results

| | | | |
|---|---|---|---|
| **Dep. Variable:** | price_log | **R-squared:** | 0.885 |
| **Model:** | OLS | **Adj. R-squared:** | 0.884 |
| **Method:** | Least Squares | **F-statistic:** | 1517. |
| **Date:** | Sun, 06 Jun 2021 | **Prob (F-statistic):** | 0.00 |
| **Time:** | 23:44:07 | **Log-Likelihood:** | 6565.0 |
| **No. Observations:** | 21585 | **AIC:** | -1.291e+04 |
| **Df Residuals:** | 21475 | **BIC:** | -1.203e+04 |
| **Df Model:** | 109 | | |
| **Covariance Type:** | nonrobust | | |

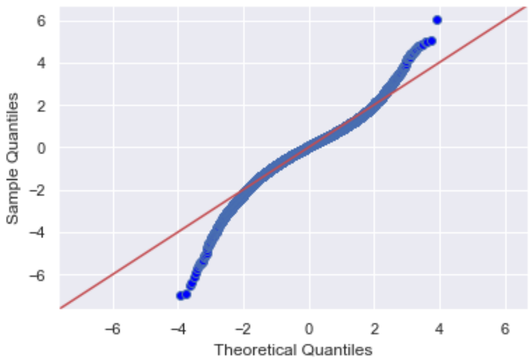
| | | | |
|---|---|---|---|
| **Omnibus:** | 1611.990 | **Durbin-Watson:** | 2.002 |
| **Prob(Omnibus):** | 0.000 | **Jarque-Bera (JB):** | 6753.338 |
| **Skew:** | -0.264 | **Prob(JB):** | 0.00 |
| **Kurtosis:** | 5.689 | **Cond. No.** | 6.25e+06 |

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 6.25e+06. This might indicate that there are
strong multicollinearity or other numerical problems.

In [69]:
```
print_rmse(df_log, target='price_log', decimals=4)
```

```
Train RMSE: 0.178
Test  RMSE: 0.1809
```

In [70]:
```
get_qqplot(model_4);
```




**Observations:**

- Highest R-squared value yet!
- The RMSE is now in log units but is still well fit
- Large improvement in the normality of the residuals but still some issues at the tails
- There's a mismatch in the scale between different coefficients since only some variables have been log transformed while others haven't

### Scaling

In an attempt to deal with the mismatch of scale between certain variables as noted above, I'll apply the `RobustScaler` from `sklearn.preprocessing`. This scaler removes the median and scales the data according to the IQR. Furthermore, this scaler in particular is less sensitive to outliers than other popular scalers such as the `MinMaxScaler` which is ideal for this particular dataset.

In [71]:
```
df_scaled = df_log.copy()
columns = [col+'_scaled' for col in df_scaled.columns]

# Apply the scaler
scaler = RobustScaler()
df_scaled = scaler.fit_transform(df_scaled)

# Converting back to a dataframe and previewing
df_scaled = pd.DataFrame(df_scaled, columns=columns)
df_scaled.head()
```

Out[71]:

| | price_log_scaled | bedrooms_log_scaled | bathrooms_log_scaled | sqft_lot_log_scaled | sqft_above_log_scaled | sqft_basement_scaled | yr_built_log_scaled | lat_log_scaled | long_ |
|---|---|---|---|---|---|---|---|---|---|
| **0** | -1.017737 | 0.000000 | -2.273583 | -0.397967 | -0.450975 | 0.000000 | -0.436758 | -0.292956 | -0. |
| **1** | 0.257106 | 0.000000 | 0.000000 | -0.067692 | 0.533151 | 0.727273 | -0.524646 | 0.719685 | -0.4 |
| **2** | -1.318976 | -1.409421 | -2.273583 | 0.361630 | -1.140559 | 0.000000 | -0.922383 | 0.801062 | -0.0 |
| **3** | 0.423675 | 1.000000 | 0.806567 | -0.560572 | -0.639532 | 1.654545 | -0.217823 | -0.246523 | -0.8 |
| **4** | 0.180169 | 0.000000 | -0.330225 | 0.077985 | 0.119715 | 0.000000 | 0.259937 | 0.217301 | 0.9 |

5 rows × 110 columns

In [72]:
```
model_5 = fit_model(df_scaled, target='price_log_scaled')
model_5.summary()
```

Out[72]:

| | coef | std err | t | P>\|t\| | [0.025 | 0.975] |
|---|---|---|---|---|---|---|
| **const** | -0.1748 | 0.261 | -0.671 | 0.502 | -0.685 | 0.336 |
| **bedrooms_log_scaled** | -0.0110 | 0.002 | -4.441 | 0.000 | -0.016 | -0.006 |
| **bathrooms_log_scaled** | 0.0447 | 0.003 | 15.626 | 0.000 | 0.039 | 0.050 |
| **sqft_lot_log_scaled** | 0.0823 | 0.004 | 21.206 | 0.000 | 0.075 | 0.090 |
| **sqft_above_log_scaled** | 0.3282 | 0.006 | 57.268 | 0.000 | 0.317 | 0.339 |
| **sqft_basement_scaled** | 0.0974 | 0.003 | 32.718 | 0.000 | 0.092 | 0.103 |
| **yr_built_log_scaled** | -0.0329 | 0.005 | -7.155 | 0.000 | -0.042 | -0.024 |
| **lat_log_scaled** | 0.1574 | 0.021 | 7.480 | 0.000 | 0.116 | 0.199 |
| **long_scaled** | -0.1226 | 0.015 | -8.193 | 0.000 | -0.152 | -0.093 |
| **sqft_living15_log_scaled** | 0.1083 | 0.004 | 24.858 | 0.000 | 0.100 | 0.117 |
| **sqft_lot15_log_scaled** | -0.0176 | 0.004 | -4.501 | 0.000 | -0.025 | -0.010 |
| **waterfront_1.0_scaled** | 0.6439 | 0.027 | 24.230 | 0.000 | 0.592 | 0.696 |
| **view_1.0_scaled** | 0.1551 | 0.015 | 10.566 | 0.000 | 0.126 | 0.184 |
| **view_2.0_scaled** | 0.1409 | 0.009 | 15.713 | 0.000 | 0.123 | 0.158 |
| **view_3.0_scaled** | 0.2386 | 0.012 | 19.526 | 0.000 | 0.215 | 0.263 |

| | | | | | | |
|---|---|---|---|---|---|---|
| **view_4.0_scaled** | 0.3909 | 0.018 | 21.153 | 0.000 | 0.355 | 0.427 |
| **condition_2_scaled** | 0.2253 | 0.052 | 4.324 | 0.000 | 0.123 | 0.327 |
| **condition_3_scaled** | 0.4301 | 0.049 | 8.865 | 0.000 | 0.335 | 0.525 |
| **condition_4_scaled** | 0.4849 | 0.049 | 9.990 | 0.000 | 0.390 | 0.580 |
| **condition_5_scaled** | 0.5823 | 0.049 | 11.922 | 0.000 | 0.487 | 0.678 |
| **grade_4_scaled** | -0.7456 | 0.263 | -2.833 | 0.005 | -1.261 | -0.230 |
| **grade_5_scaled** | -0.7586 | 0.259 | -2.929 | 0.003 | -1.266 | -0.251 |
| **grade_6_scaled** | -0.6429 | 0.259 | -2.487 | 0.013 | -1.150 | -0.136 |
| **grade_7_scaled** | -0.5289 | 0.259 | -2.046 | 0.041 | -1.036 | -0.022 |
| **grade_8_scaled** | -0.4143 | 0.259 | -1.602 | 0.109 | -0.921 | 0.093 |
| **grade_9_scaled** | -0.2404 | 0.259 | -0.929 | 0.353 | -0.748 | 0.267 |
| **grade_10_scaled** | -0.1091 | 0.259 | -0.421 | 0.674 | -0.617 | 0.398 |
| **grade_11_scaled** | 0.0499 | 0.259 | 0.192 | 0.847 | -0.458 | 0.558 |
| **grade_12_scaled** | 0.2289 | 0.261 | 0.879 | 0.380 | -0.282 | 0.740 |
| **grade_13_scaled** | 0.5638 | 0.269 | 2.095 | 0.036 | 0.036 | 1.091 |
| **zipcode_98002_scaled** | 0.0306 | 0.023 | 1.312 | 0.190 | -0.015 | 0.076 |
| **zipcode_98003_scaled** | 0.0006 | 0.021 | 0.031 | 0.975 | -0.040 | 0.041 |
| **zipcode_98004_scaled** | 1.4238 | 0.038 | 37.670 | 0.000 | 1.350 | 1.498 |
| **zipcode_98005_scaled** | 0.8752 | 0.040 | 21.681 | 0.000 | 0.796 | 0.954 |
| **zipcode_98006_scaled** | 0.8064 | 0.033 | 24.407 | 0.000 | 0.742 | 0.871 |
| **zipcode_98007_scaled** | 0.7858 | 0.042 | 18.855 | 0.000 | 0.704 | 0.867 |
| **zipcode_98008_scaled** | 0.8094 | 0.040 | 20.427 | 0.000 | 0.732 | 0.887 |
| **zipcode_98010_scaled** | 0.4828 | 0.035 | 13.641 | 0.000 | 0.413 | 0.552 |
| **zipcode_98011_scaled** | 0.3492 | 0.051 | 6.796 | 0.000 | 0.249 | 0.450 |
| **zipcode_98014_scaled** | 0.4015 | 0.056 | 7.114 | 0.000 | 0.291 | 0.512 |
| **zipcode_98019_scaled** | 0.3149 | 0.056 | 5.653 | 0.000 | 0.206 | 0.424 |
| **zipcode_98022_scaled** | 0.2995 | 0.031 | 9.716 | 0.000 | 0.239 | 0.360 |
| **zipcode_98023_scaled** | -0.0791 | 0.019 | -4.138 | 0.000 | -0.117 | -0.042 |
| **zipcode_98024_scaled** | 0.6303 | 0.050 | 12.693 | 0.000 | 0.533 | 0.728 |
| **zipcode_98027_scaled** | 0.7083 | 0.034 | 20.889 | 0.000 | 0.642 | 0.775 |
| **zipcode_98028_scaled** | 0.2736 | 0.050 | 5.483 | 0.000 | 0.176 | 0.371 |
| **zipcode_98029_scaled** | 0.8442 | 0.039 | 21.724 | 0.000 | 0.768 | 0.920 |
| **zipcode_98030_scaled** | 0.0713 | 0.023 | 3.119 | 0.002 | 0.026 | 0.116 |
| **zipcode_98031_scaled** | 0.0857 | 0.024 | 3.597 | 0.000 | 0.039 | 0.132 |
| **zipcode_98032_scaled** | -0.0683 | 0.028 | -2.474 | 0.013 | -0.122 | -0.014 |
| **zipcode_98033_scaled** | 0.9074 | 0.043 | 21.167 | 0.000 | 0.823 | 0.991 |
| **zipcode_98034_scaled** | 0.5176 | 0.046 | 11.267 | 0.000 | 0.428 | 0.608 |
| **zipcode_98038_scaled** | 0.3373 | 0.026 | 13.088 | 0.000 | 0.287 | 0.388 |
| **zipcode_98039_scaled** | 1.6489 | 0.051 | 32.282 | 0.000 | 1.549 | 1.749 |
| **zipcode_98040_scaled** | 1.0880 | 0.033 | 32.551 | 0.000 | 1.023 | 1.154 |
| **zipcode_98042_scaled** | 0.1387 | 0.022 | 6.329 | 0.000 | 0.096 | 0.182 |
| **zipcode_98045_scaled** | 0.6438 | 0.047 | 13.560 | 0.000 | 0.551 | 0.737 |
| **zipcode_98052_scaled** | 0.7324 | 0.044 | 16.732 | 0.000 | 0.647 | 0.818 |
| **zipcode_98053_scaled** | 0.7100 | 0.047 | 15.138 | 0.000 | 0.618 | 0.802 |
| **zipcode_98055_scaled** | 0.1470 | 0.027 | 5.539 | 0.000 | 0.095 | 0.199 |
| **zipcode_98056_scaled** | 0.3729 | 0.029 | 12.937 | 0.000 | 0.316 | 0.429 |
| **zipcode_98058_scaled** | 0.2110 | 0.025 | 8.414 | 0.000 | 0.162 | 0.260 |
| **zipcode_98059_scaled** | 0.4337 | 0.028 | 15.333 | 0.000 | 0.378 | 0.489 |
| **zipcode_98065_scaled** | 0.6665 | 0.044 | 15.176 | 0.000 | 0.580 | 0.753 |
| **zipcode_98070_scaled** | 0.2380 | 0.033 | 7.113 | 0.000 | 0.172 | 0.304 |
| **zipcode_98072_scaled** | 0.4242 | 0.051 | 8.298 | 0.000 | 0.324 | 0.524 |

| | | | | | | |
|---|---|---|---|---|---|---|
| **zipcode_98074_scaled** | 0.6920 | 0.041 | 16.684 | 0.000 | 0.611 | 0.773 |
| **zipcode_98075_scaled** | 0.7437 | 0.040 | 18.628 | 0.000 | 0.665 | 0.822 |
| **zipcode_98077_scaled** | 0.4007 | 0.053 | 7.532 | 0.000 | 0.296 | 0.505 |
| **zipcode_98092_scaled** | 0.0890 | 0.021 | 4.284 | 0.000 | 0.048 | 0.130 |
| **zipcode_98102_scaled** | 1.1620 | 0.044 | 26.265 | 0.000 | 1.075 | 1.249 |
| **zipcode_98103_scaled** | 0.9256 | 0.041 | 22.404 | 0.000 | 0.845 | 1.007 |
| **zipcode_98105_scaled** | 1.1196 | 0.043 | 26.294 | 0.000 | 1.036 | 1.203 |
| **zipcode_98106_scaled** | 0.3416 | 0.031 | 11.101 | 0.000 | 0.281 | 0.402 |
| **zipcode_98107_scaled** | 0.9522 | 0.043 | 22.351 | 0.000 | 0.869 | 1.036 |
| **zipcode_98108_scaled** | 0.3757 | 0.034 | 11.081 | 0.000 | 0.309 | 0.442 |
| **zipcode_98109_scaled** | 1.1958 | 0.044 | 27.195 | 0.000 | 1.110 | 1.282 |
| **zipcode_98112_scaled** | 1.2918 | 0.039 | 33.097 | 0.000 | 1.215 | 1.368 |
| **zipcode_98115_scaled** | 0.9273 | 0.042 | 22.039 | 0.000 | 0.845 | 1.010 |
| **zipcode_98116_scaled** | 0.8811 | 0.034 | 25.723 | 0.000 | 0.814 | 0.948 |
| **zipcode_98117_scaled** | 0.8854 | 0.043 | 20.791 | 0.000 | 0.802 | 0.969 |
| **zipcode_98118_scaled** | 0.5396 | 0.030 | 17.992 | 0.000 | 0.481 | 0.598 |
| **zipcode_98119_scaled** | 1.1617 | 0.042 | 27.990 | 0.000 | 1.080 | 1.243 |
| **zipcode_98122_scaled** | 0.9855 | 0.037 | 26.569 | 0.000 | 0.913 | 1.058 |
| **zipcode_98125_scaled** | 0.5246 | 0.045 | 11.547 | 0.000 | 0.436 | 0.614 |
| **zipcode_98126_scaled** | 0.6281 | 0.032 | 19.930 | 0.000 | 0.566 | 0.690 |
| **zipcode_98133_scaled** | 0.3302 | 0.047 | 7.039 | 0.000 | 0.238 | 0.422 |
| **zipcode_98136_scaled** | 0.7945 | 0.032 | 24.621 | 0.000 | 0.731 | 0.858 |
| **zipcode_98144_scaled** | 0.8106 | 0.035 | 23.484 | 0.000 | 0.743 | 0.878 |
| **zipcode_98146_scaled** | 0.2363 | 0.029 | 8.190 | 0.000 | 0.180 | 0.293 |
| **zipcode_98148_scaled** | 0.1108 | 0.039 | 2.826 | 0.005 | 0.034 | 0.188 |
| **zipcode_98155_scaled** | 0.2805 | 0.049 | 5.748 | 0.000 | 0.185 | 0.376 |
| **zipcode_98166_scaled** | 0.3046 | 0.026 | 11.533 | 0.000 | 0.253 | 0.356 |
| **zipcode_98168_scaled** | -0.0225 | 0.028 | -0.807 | 0.420 | -0.077 | 0.032 |
| **zipcode_98177_scaled** | 0.4798 | 0.049 | 9.790 | 0.000 | 0.384 | 0.576 |
| **zipcode_98178_scaled** | 0.1244 | 0.029 | 4.315 | 0.000 | 0.068 | 0.181 |
| **zipcode_98188_scaled** | 0.0425 | 0.030 | 1.438 | 0.151 | -0.015 | 0.100 |
| **zipcode_98198_scaled** | 0.0172 | 0.022 | 0.769 | 0.442 | -0.027 | 0.061 |
| **zipcode_98199_scaled** | 0.9529 | 0.040 | 23.544 | 0.000 | 0.874 | 1.032 |
| **month_2_scaled** | 0.0306 | 0.011 | 2.772 | 0.006 | 0.009 | 0.052 |
| **month_3_scaled** | 0.0696 | 0.010 | 6.833 | 0.000 | 0.050 | 0.090 |
| **month_4_scaled** | 0.0993 | 0.010 | 10.015 | 0.000 | 0.080 | 0.119 |
| **month_5_scaled** | 0.0167 | 0.010 | 1.708 | 0.088 | -0.002 | 0.036 |
| **month_6_scaled** | 0.0022 | 0.010 | 0.222 | 0.825 | -0.017 | 0.022 |
| **month_7_scaled** | -0.0065 | 0.010 | -0.659 | 0.510 | -0.026 | 0.013 |
| **month_8_scaled** | -0.0053 | 0.010 | -0.518 | 0.604 | -0.025 | 0.015 |
| **month_9_scaled** | -0.0138 | 0.010 | -1.339 | 0.181 | -0.034 | 0.006 |
| **month_10_scaled** | -0.0147 | 0.010 | -1.446 | 0.148 | -0.035 | 0.005 |
| **month_11_scaled** | -0.0143 | 0.011 | -1.332 | 0.183 | -0.035 | 0.007 |
| **month_12_scaled** | -0.0010 | 0.011 | -0.098 | 0.922 | -0.022 | 0.020 |

OLS Regression Results

| | | | |
|---|---|---|---|
| **Dep. Variable:** | price_log_scaled | **R-squared:** | 0.885 |
| **Model:** | OLS | **Adj. R-squared:** | 0.884 |
| **Method:** | Least Squares | **F-statistic:** | 1517. |
| **Date:** | Sun, 06 Jun 2021 | **Prob (F-statistic):** | 0.00 |
| **Time:** | 23:44:08 | **Log-Likelihood:** | -1297.9 |
| **No. Observations:** | 21585 | **AIC:** | 2816. |
| **Df Residuals:** | 21475 | **BIC:** | 3694. |
| **Df Model:** | 109 | | |
| **Covariance Type:** | nonrobust | | |

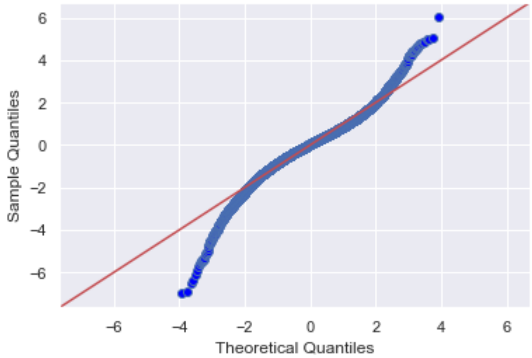
| | | | |
|---|---|---|---|
| **Omnibus:** | 1611.990 | **Durbin-Watson:** | 2.002 |
| **Prob(Omnibus):** | 0.000 | **Jarque-Bera (JB):** | 6753.338 |
| **Skew:** | -0.264 | **Prob(JB):** | 0.00 |
| **Kurtosis:** | 5.689 | **Cond. No.** | 895. |

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

In [73]:
```
print_rmse(df_scaled, target='price_log_scaled', decimals=4)
```

```
Train RMSE: 0.2563
Test  RMSE: 0.2604
```

In [74]:
```
get_qqplot(model_5);
```




**Observations:**

- No change in the R-squared value from just the log transformed model
- Interpretability is much more challenging for this model
- While worth exploring, this model doesn't provide any additional benefit and will not be used as the final version

## Dropping Non-Significant Variables

In [75]:
```
nonsig = model_4.pvalues.where(model_4.pvalues > 0.05)
nonsig.dropna(inplace=True)
nonsig.index
```

Out[75]:
```
Index(['grade_8', 'grade_9', 'grade_10', 'grade_11', 'grade_12',
       'zipcode_98002', 'zipcode_98003', 'zipcode_98168', 'zipcode_98188',
       'zipcode_98198', 'month_5', 'month_6', 'month_7', 'month_8', 'month_9',
       'month_10', 'month_11', 'month_12'],
      dtype='object')
```

In [76]:
```
df_drop_nonsig = df_log.copy()
df_drop_nonsig.drop(columns=nonsig.index, inplace=True)
df_drop_nonsig.columns
```

Out[76]:
```
Index(['price_log', 'bedrooms_log', 'bathrooms_log', 'sqft_lot_log',
       'sqft_above_log', 'sqft_basement', 'yr_built_log', 'lat_log', 'long',
       'sqft_living15_log', 'sqft_lot15_log', 'waterfront_1.0', 'view_1.0',
       'view_2.0', 'view_3.0', 'view_4.0', 'condition_2', 'condition_3',
       'condition_4', 'condition_5', 'grade_4', 'grade_5', 'grade_6',
       'grade_7', 'grade_13', 'zipcode_98004', 'zipcode_98005',
       'zipcode_98006', 'zipcode_98007', 'zipcode_98008', 'zipcode_98010',
       'zipcode_98011', 'zipcode_98014', 'zipcode_98019', 'zipcode_98022',
       'zipcode_98023', 'zipcode_98024', 'zipcode_98027', 'zipcode_98028',
       'zipcode_98029', 'zipcode_98030', 'zipcode_98031', 'zipcode_98032',
       'zipcode_98033', 'zipcode_98034', 'zipcode_98038', 'zipcode_98039',
       'zipcode_98040', 'zipcode_98042', 'zipcode_98045', 'zipcode_98052',
       'zipcode_98053', 'zipcode_98055', 'zipcode_98056', 'zipcode_98058',
       'zipcode_98059', 'zipcode_98065', 'zipcode_98070', 'zipcode_98072',
       'zipcode_98074', 'zipcode_98075', 'zipcode_98077', 'zipcode_98092',
       'zipcode_98102', 'zipcode_98103', 'zipcode_98105', 'zipcode_98106',
       'zipcode_98107', 'zipcode_98108', 'zipcode_98109', 'zipcode_98112',
       'zipcode_98115', 'zipcode_98116', 'zipcode_98117', 'zipcode_98118',
       'zipcode_98119', 'zipcode_98122', 'zipcode_98125', 'zipcode_98126',
       'zipcode_98133', 'zipcode_98136', 'zipcode_98144', 'zipcode_98146',
       'zipcode_98148', 'zipcode_98155', 'zipcode_98166', 'zipcode_98177',
       'zipcode_98178', 'zipcode_98199', 'month_2', 'month_3', 'month_4'],
      dtype='object')
```

In [77]:
```
model_6 = fit_model(df_drop_nonsig, target='price_log')
model_6.summary()
```

Out[77]:

| | coef | std err | t | P>\|t\| | [0.025 | 0.975] |
|---|---|---|---|---|---|---|
| **const** | -143.1816 | 10.431 | -13.727 | 0.000 | -163.626 | -122.737 |
| **bedrooms_log** | -0.0612 | 0.006 | -9.908 | 0.000 | -0.073 | -0.049 |
| **bathrooms_log** | 0.0809 | 0.006 | 13.947 | 0.000 | 0.070 | 0.092 |
| **sqft_lot_log** | 0.0803 | 0.004 | 21.511 | 0.000 | 0.073 | 0.088 |
| **sqft_above_log** | 0.4668 | 0.006 | 74.708 | 0.000 | 0.455 | 0.479 |
| **sqft_basement** | 0.0001 | 3.88e-06 | 37.158 | 0.000 | 0.000 | 0.000 |
| **yr_built_log** | -0.0835 | 0.141 | -0.592 | 0.554 | -0.360 | 0.193 |

| | | | | | | |
|---|---|---|---|---|---|---|
| **lat_log** | 26.7525 | 2.405 | 11.125 | 0.000 | 22.039 | 31.466 |
| **long** | -0.3863 | 0.051 | -7.623 | 0.000 | -0.486 | -0.287 |
| **sqft_living15_log** | 0.2022 | 0.007 | 29.850 | 0.000 | 0.189 | 0.216 |
| **sqft_lot15_log** | -0.0108 | 0.004 | -2.616 | 0.009 | -0.019 | -0.003 |
| **waterfront_1.0** | 0.4552 | 0.019 | 23.677 | 0.000 | 0.418 | 0.493 |
| **view_1.0** | 0.1088 | 0.011 | 10.254 | 0.000 | 0.088 | 0.130 |
| **view_2.0** | 0.1106 | 0.006 | 17.071 | 0.000 | 0.098 | 0.123 |
| **view_3.0** | 0.1910 | 0.009 | 21.656 | 0.000 | 0.174 | 0.208 |
| **view_4.0** | 0.3147 | 0.013 | 23.624 | 0.000 | 0.289 | 0.341 |
| **condition_2** | 0.1795 | 0.038 | 4.760 | 0.000 | 0.106 | 0.253 |
| **condition_3** | 0.3243 | 0.035 | 9.236 | 0.000 | 0.255 | 0.393 |
| **condition_4** | 0.3570 | 0.035 | 10.162 | 0.000 | 0.288 | 0.426 |
| **condition_5** | 0.4273 | 0.035 | 12.087 | 0.000 | 0.358 | 0.497 |
| **grade_4** | -0.1564 | 0.037 | -4.254 | 0.000 | -0.228 | -0.084 |
| **grade_5** | -0.1821 | 0.013 | -13.571 | 0.000 | -0.208 | -0.156 |
| **grade_6** | -0.1207 | 0.006 | -19.147 | 0.000 | -0.133 | -0.108 |
| **grade_7** | -0.0781 | 0.004 | -21.199 | 0.000 | -0.085 | -0.071 |
| **grade_13** | 0.4336 | 0.052 | 8.261 | 0.000 | 0.331 | 0.536 |
| **zipcode_98004** | 1.0178 | 0.018 | 55.892 | 0.000 | 0.982 | 1.054 |
| **zipcode_98005** | 0.6159 | 0.021 | 29.008 | 0.000 | 0.574 | 0.657 |
| **zipcode_98006** | 0.5843 | 0.016 | 35.767 | 0.000 | 0.552 | 0.616 |
| **zipcode_98007** | 0.5496 | 0.023 | 24.362 | 0.000 | 0.505 | 0.594 |
| **zipcode_98008** | 0.5483 | 0.020 | 26.922 | 0.000 | 0.508 | 0.588 |
| **zipcode_98010** | 0.3114 | 0.024 | 13.007 | 0.000 | 0.264 | 0.358 |
| **zipcode_98011** | 0.2125 | 0.025 | 8.445 | 0.000 | 0.163 | 0.262 |
| **zipcode_98014** | 0.2312 | 0.034 | 6.879 | 0.000 | 0.165 | 0.297 |
| **zipcode_98019** | 0.1573 | 0.031 | 5.144 | 0.000 | 0.097 | 0.217 |
| **zipcode_98022** | 0.1770 | 0.020 | 8.714 | 0.000 | 0.137 | 0.217 |
| **zipcode_98023** | -0.0544 | 0.011 | -4.921 | 0.000 | -0.076 | -0.033 |
| **zipcode_98024** | 0.4018 | 0.031 | 12.858 | 0.000 | 0.341 | 0.463 |
| **zipcode_98027** | 0.4800 | 0.019 | 25.486 | 0.000 | 0.443 | 0.517 |
| **zipcode_98028** | 0.1619 | 0.023 | 6.923 | 0.000 | 0.116 | 0.208 |
| **zipcode_98029** | 0.5769 | 0.022 | 26.196 | 0.000 | 0.534 | 0.620 |
| **zipcode_98030** | 0.0305 | 0.014 | 2.247 | 0.025 | 0.004 | 0.057 |
| **zipcode_98031** | 0.0444 | 0.014 | 3.281 | 0.001 | 0.018 | 0.071 |
| **zipcode_98032** | -0.0478 | 0.017 | -2.746 | 0.006 | -0.082 | -0.014 |
| **zipcode_98033** | 0.6329 | 0.020 | 31.384 | 0.000 | 0.593 | 0.672 |
| **zipcode_98034** | 0.3488 | 0.021 | 16.524 | 0.000 | 0.307 | 0.390 |
| **zipcode_98038** | 0.1982 | 0.016 | 12.517 | 0.000 | 0.167 | 0.229 |
| **zipcode_98039** | 1.2044 | 0.030 | 39.602 | 0.000 | 1.145 | 1.264 |
| **zipcode_98040** | 0.7914 | 0.016 | 48.041 | 0.000 | 0.759 | 0.824 |
| **zipcode_98042** | 0.0739 | 0.013 | 5.805 | 0.000 | 0.049 | 0.099 |
| **zipcode_98045** | 0.4097 | 0.031 | 13.226 | 0.000 | 0.349 | 0.470 |
| **zipcode_98052** | 0.4958 | 0.021 | 23.247 | 0.000 | 0.454 | 0.538 |
| **zipcode_98053** | 0.4583 | 0.025 | 18.571 | 0.000 | 0.410 | 0.507 |
| **zipcode_98055** | 0.0891 | 0.014 | 6.320 | 0.000 | 0.061 | 0.117 |
| **zipcode_98056** | 0.2471 | 0.014 | 17.387 | 0.000 | 0.219 | 0.275 |
| **zipcode_98058** | 0.1301 | 0.013 | 9.814 | 0.000 | 0.104 | 0.156 |
| **zipcode_98059** | 0.2809 | 0.015 | 19.269 | 0.000 | 0.252 | 0.310 |
| **zipcode_98065** | 0.4141 | 0.027 | 15.296 | 0.000 | 0.361 | 0.467 |
| **zipcode_98070** | 0.1313 | 0.021 | 6.326 | 0.000 | 0.091 | 0.172 |

| | | | | | | |
|---|---|---|---|---|---|---|
| **zipcode_98072** | 0.2725 | 0.025 | 10.785 | 0.000 | 0.223 | 0.322 |
| **zipcode_98074** | 0.4881 | 0.022 | 22.330 | 0.000 | 0.445 | 0.531 |
| **zipcode_98075** | 0.5287 | 0.022 | 24.100 | 0.000 | 0.486 | 0.572 |
| **zipcode_98077** | 0.2788 | 0.028 | 10.034 | 0.000 | 0.224 | 0.333 |
| **zipcode_98092** | 0.0418 | 0.013 | 3.254 | 0.001 | 0.017 | 0.067 |
| **zipcode_98102** | 0.8612 | 0.024 | 36.645 | 0.000 | 0.815 | 0.907 |
| **zipcode_98103** | 0.6623 | 0.018 | 36.864 | 0.000 | 0.627 | 0.697 |
| **zipcode_98105** | 0.8055 | 0.020 | 39.718 | 0.000 | 0.766 | 0.845 |
| **zipcode_98106** | 0.2589 | 0.014 | 18.199 | 0.000 | 0.231 | 0.287 |
| **zipcode_98107** | 0.6821 | 0.020 | 34.586 | 0.000 | 0.643 | 0.721 |
| **zipcode_98108** | 0.2720 | 0.017 | 15.875 | 0.000 | 0.238 | 0.306 |
| **zipcode_98109** | 0.8713 | 0.023 | 37.749 | 0.000 | 0.826 | 0.917 |
| **zipcode_98112** | 0.9465 | 0.018 | 51.395 | 0.000 | 0.910 | 0.983 |
| **zipcode_98115** | 0.6582 | 0.018 | 35.741 | 0.000 | 0.622 | 0.694 |
| **zipcode_98116** | 0.6376 | 0.016 | 40.283 | 0.000 | 0.607 | 0.669 |
| **zipcode_98117** | 0.6381 | 0.019 | 34.432 | 0.000 | 0.602 | 0.674 |
| **zipcode_98118** | 0.3877 | 0.013 | 29.385 | 0.000 | 0.362 | 0.414 |
| **zipcode_98119** | 0.8453 | 0.020 | 41.792 | 0.000 | 0.806 | 0.885 |
| **zipcode_98122** | 0.7153 | 0.017 | 41.204 | 0.000 | 0.681 | 0.749 |
| **zipcode_98125** | 0.3582 | 0.020 | 17.631 | 0.000 | 0.318 | 0.398 |
| **zipcode_98126** | 0.4590 | 0.014 | 31.756 | 0.000 | 0.431 | 0.487 |
| **zipcode_98133** | 0.2296 | 0.021 | 11.098 | 0.000 | 0.189 | 0.270 |
| **zipcode_98136** | 0.5723 | 0.016 | 36.662 | 0.000 | 0.542 | 0.603 |
| **zipcode_98144** | 0.5829 | 0.016 | 36.768 | 0.000 | 0.552 | 0.614 |
| **zipcode_98146** | 0.1644 | 0.014 | 11.804 | 0.000 | 0.137 | 0.192 |
| **zipcode_98148** | 0.0744 | 0.025 | 2.916 | 0.004 | 0.024 | 0.124 |
| **zipcode_98155** | 0.1847 | 0.022 | 8.474 | 0.000 | 0.142 | 0.227 |
| **zipcode_98166** | 0.2088 | 0.014 | 15.292 | 0.000 | 0.182 | 0.236 |
| **zipcode_98177** | 0.3261 | 0.023 | 14.425 | 0.000 | 0.282 | 0.370 |
| **zipcode_98178** | 0.0803 | 0.014 | 5.562 | 0.000 | 0.052 | 0.109 |
| **zipcode_98199** | 0.6964 | 0.018 | 37.673 | 0.000 | 0.660 | 0.733 |
| **month_2** | 0.0243 | 0.005 | 4.415 | 0.000 | 0.013 | 0.035 |
| **month_3** | 0.0513 | 0.005 | 11.247 | 0.000 | 0.042 | 0.060 |
| **month_4** | 0.0698 | 0.004 | 16.524 | 0.000 | 0.062 | 0.078 |

OLS Regression Results

| | | | |
|---|---|---|---|
| **Dep. Variable:** | price_log | **R-squared:** | 0.875 |
| **Model:** | OLS | **Adj. R-squared:** | 0.874 |
| **Method:** | Least Squares | **F-statistic:** | 1653. |
| **Date:** | Sun, 06 Jun 2021 | **Prob (F-statistic):** | 0.00 |
| **Time:** | 23:44:08 | **Log-Likelihood:** | 5659.9 |
| **No. Observations:** | 21585 | **AIC:** | -1.114e+04 |
| **Df Residuals:** | 21493 | **BIC:** | -1.040e+04 |
| **Df Model:** | 91 | | |
| **Covariance Type:** | nonrobust | | |

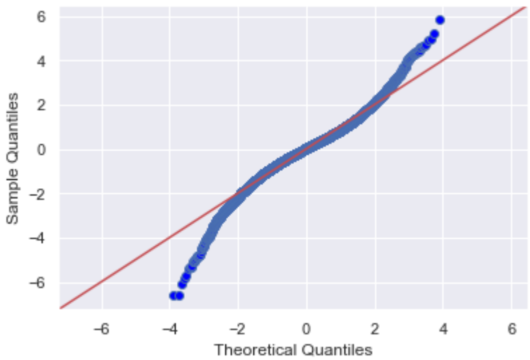
| | | | |
|---|---|---|---|
| **Omnibus:** | 1275.331 | **Durbin-Watson:** | 2.002 |
| **Prob(Omnibus):** | 0.000 | **Jarque-Bera (JB):** | 5006.575 |
| **Skew:** | -0.159 | **Prob(JB):** | 0.00 |
| **Kurtosis:** | 5.338 | **Cond. No.** | 4.42e+06 |

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 4.42e+06. This might indicate that there are
strong multicollinearity or other numerical problems.

In [78]:
```
print_rmse(df_drop_nonsig, target='price_log', decimals=4)
```

```
Train RMSE: 0.1859
Test  RMSE: 0.1878
```

In [79]:
```
get_qqplot(model_6);
```




**Observations:**

- Small decrease in R-squared
- All but one variable ( `yr_built` ) are now significant at the alpha = 0.05 level
- RMSE increased slightly

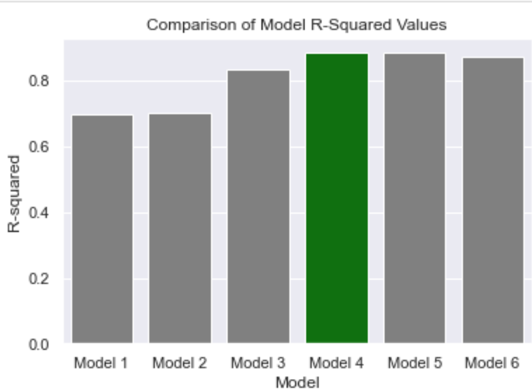
## Model Comparisons

In [80]:
```
rsquareds = [model.rsquared, model_2.rsquared, model_3.rsquared,
             model_4.rsquared, model_5.rsquared, model_6.rsquared]

df_comparison = pd.DataFrame({'Model': [f'Model {i}' for i in range(1, 7)],
                              'R-squared': rsquareds})
df_comparison
```

Out[80]:

| | Model | R-squared |
|---|---|---|
| **0** | Model 1 | 0.699828 |
| **1** | Model 2 | 0.700233 |
| **2** | Model 3 | 0.835001 |
| **3** | Model 4 | 0.885039 |
| **4** | Model 5 | 0.885039 |
| **5** | Model 6 | 0.874982 |

In [81]:
```
sns.barplot(data=df_comparison,
            x='Model',
            y='R-squared',
            palette=['green' if m == 'Model 4' else 'gray' for m in df_comparison.Model]
           )
plt.title('Comparison of Model R-Squared Values')
plt.savefig('images/r2_comp.png', dpi=150, facecolor='white');
```




# Conclusion

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## Results

The fourth model, which removes outliers, includes dummy variables for categorical data, and log transforms continuous data, was the best performing model. This model explains approximately 88.5% of the variations in price for houses in the dataset. Some of the most impactful variables include:

- Being located in zip code 98039 (Medina, WA)
- Having a waterfront property
- Having higher rated `condition` and `grade`

- Being further north (higher latitude)

While not perfect, this model has the potential to be a useful tool for municipalities seeking a better estimate of future tax revenues. Instead of relying on the results of infrequent and costly appraisals for an estimate of taxable value, this model can provide a decently accurate estimate in a short amount of time.

## Next Steps

There are many additional ways in which this model can be improved upon over time.

- Further iteration on the model to test for non-additive interactions and various other transformations
- A direct incorporation of an adjustment to the predicted house values to derive the estimated taxable value
- Enhanced location data that includes items such as proximity to amenities and walkability
- Inclusion of macroeconomic variables such as mortgage rates, new constructions, bank lending conditions, etc.