How can you improve the value of your home?

The goal of this project is to examine how an existing homeowner can improve the value of their home. Using King County, WA sales data from 2014-15, I will determine which features are most valuable.

In [970]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from scipy import stats
import statsmodels.api as sm
from statsmodels.formula.api import ols
from sklearn.model_selection import train_test_split
from sklearn.model_selection import cross_validate, ShuffleSplit
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error
df = pd.read_csv('kc_house_data.csv')
df
```

Out[970]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	wat
0	7129300520	10/13/2014	221900.0	3	1.00	1180	5650	1.0	
1	6414100192	12/9/2014	538000.0	3	2.25	2570	7242	2.0	
2	5631500400	2/25/2015	180000.0	2	1.00	770	10000	1.0	
3	2487200875	12/9/2014	604000.0	4	3.00	1960	5000	1.0	
4	1954400510	2/18/2015	510000.0	3	2.00	1680	8080	1.0	
...	...	...	...	...	...	...	...	...	
21592	263000018	5/21/2014	360000.0	3	2.50	1530	1131	3.0	
21593	6600060120	2/23/2015	400000.0	4	2.50	2310	5813	2.0	
21594	1523300141	6/23/2014	402101.0	2	0.75	1020	1350	2.0	
21595	291310100	1/16/2015	400000.0	3	2.50	1600	2388	2.0	
21596	1523300157	10/15/2014	325000.0	2	0.75	1020	1076	2.0	

21597 rows × 21 columns

Let's examine the columns:

In [971]:
```
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  object 
 9   view           21534 non-null  object 
 10  condition      21597 non-null  object 
 11  grade          21597 non-null  object 
 12  sqft_above     21597 non-null  int64  
 13  sqft_basement  21597 non-null  object 
 14  yr_built       21597 non-null  int64  
 15  yr_renovated   17755 non-null  float64
 16  zipcode        21597 non-null  int64  
 17  lat            21597 non-null  float64
 18  long           21597 non-null  float64
 19  sqft_living15  21597 non-null  int64  
 20  sqft_lot15     21597 non-null  int64  
dtypes: float64(6), int64(9), object(6)
memory usage: 3.5+ MB
```

Let's create a 'Month' columns:

In [972]:
```
df['Month'] = pd.DatetimeIndex(df['date']).month
df['Month']
```

Out[972]:
```
0        10
1        12
2         2
3        12
4         2
         ..
21592     5
21593     2
21594     6
21595     1
21596    10
Name: Month, Length: 21597, dtype: int64
```

In [973]:
```
df['Month'].value_counts()
```

Out[973]:

```
5     2414
4     2229
7     2211
6     2178
8     1939
10    1876
3     1875
9     1771
```

Eliminating irrelevant columns:

In [974]:

```
relevant_columns = ['price', 'bedrooms', 'bathrooms','sqft_living', 'floor

df = df.loc[:, relevant_columns]
df
```

Out[974]:

	price	bedrooms	bathrooms	sqft_living	floors	condition	yr_renovated	Month	gr
0	221900.0	3	1.00	1180	1.0	Average	0.0	10	Aver
1	538000.0	3	2.25	2570	2.0	Average	1991.0	12	Aver
2	180000.0	2	1.00	770	1.0	Average	NaN	2	6 l Aver
3	604000.0	4	3.00	1960	1.0	Very Good	0.0	12	Aver
4	510000.0	3	2.00	1680	1.0	Average	0.0	2	8 G
...	...	...	...	...	...	...	...	...	
21592	360000.0	3	2.50	1530	3.0	Average	0.0	5	8 G
21593	400000.0	4	2.50	2310	2.0	Average	0.0	2	8 G
21594	402101.0	2	0.75	1020	2.0	Average	0.0	6	Aver
21595	400000.0	3	2.50	1600	2.0	Average	0.0	1	8 G
21596	325000.0	2	0.75	1020	2.0	Average	0.0	10	Aver

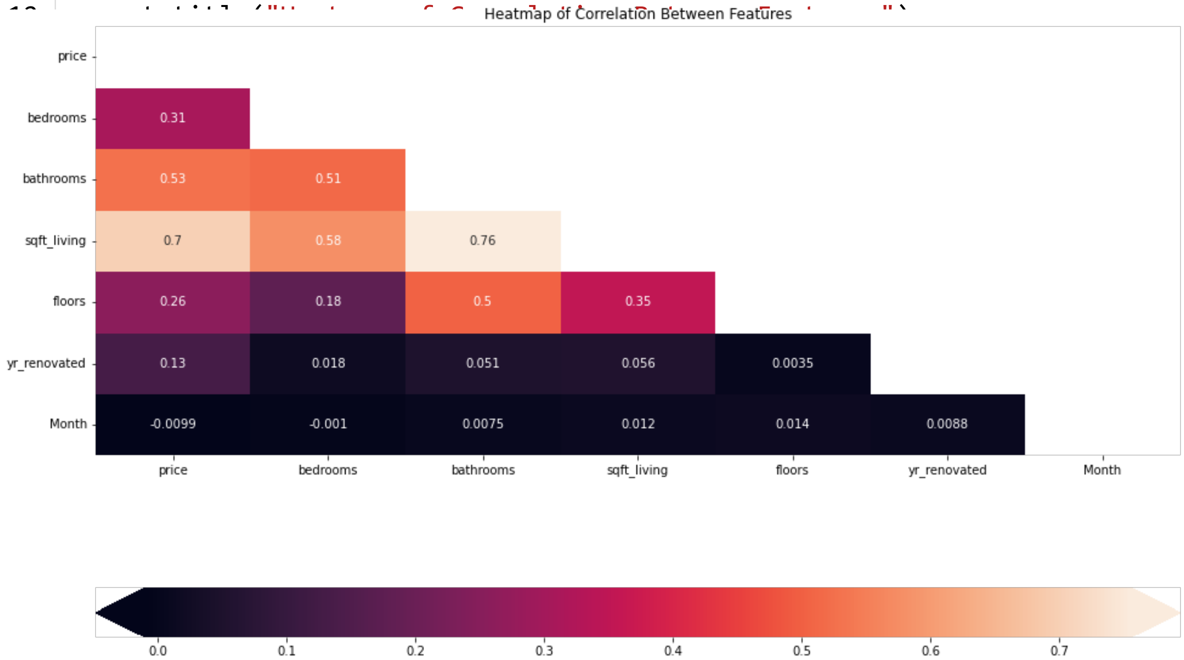
21597 rows × 9 columns

Correlation Heat Map:

In [975]:

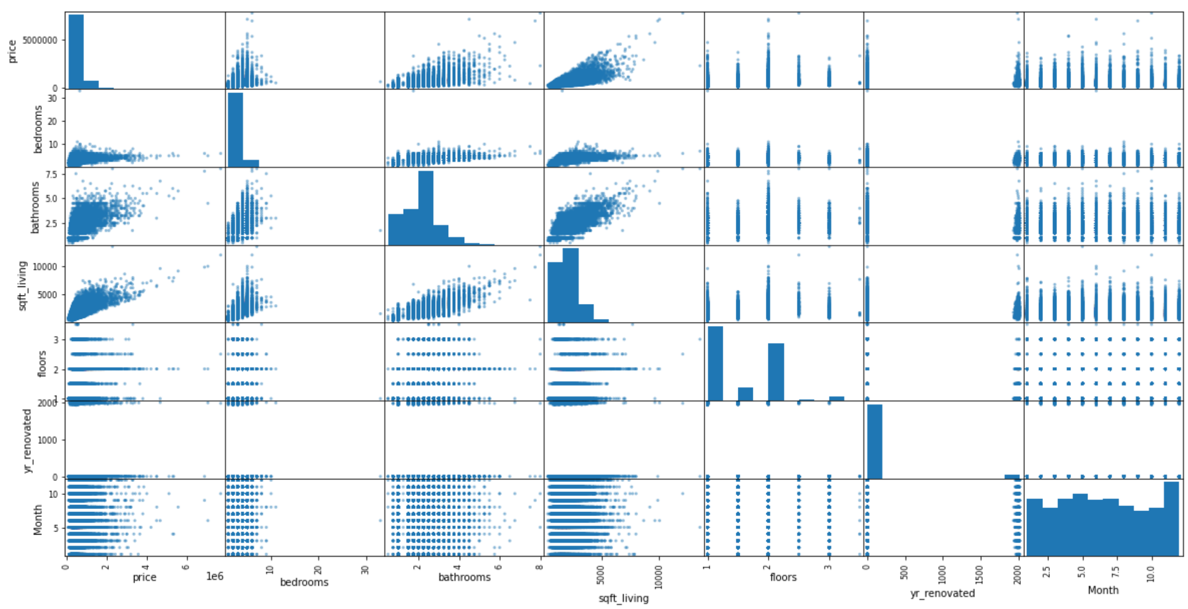
```
df_corr = df.corr()

fig, ax = plt.subplots(figsize=(16, 10))

sns.heatmap(
    data=df_corr,
    mask=np.triu(np.ones_like(df_corr, dtype=bool)),
    ax=ax,
    annot=True,
```

```
    cbar_kws={"label": "Correlation", "orientation": "horizontal", "pad":
)
```



'Sqft_Living' has the highest correlation with 'price'. Let's look at scatter plots and histograms to check the linearity and whether each variable is uniformly distributed.

In [976]:

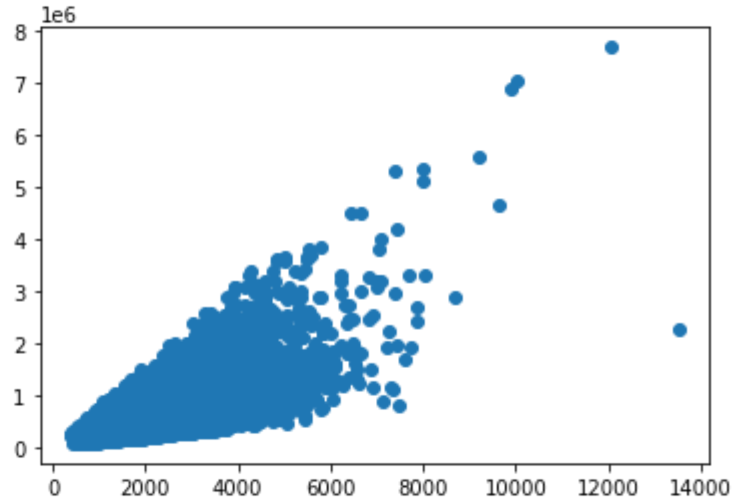


Let's take a closer look at 'sqft_living' and price:

In [977]:

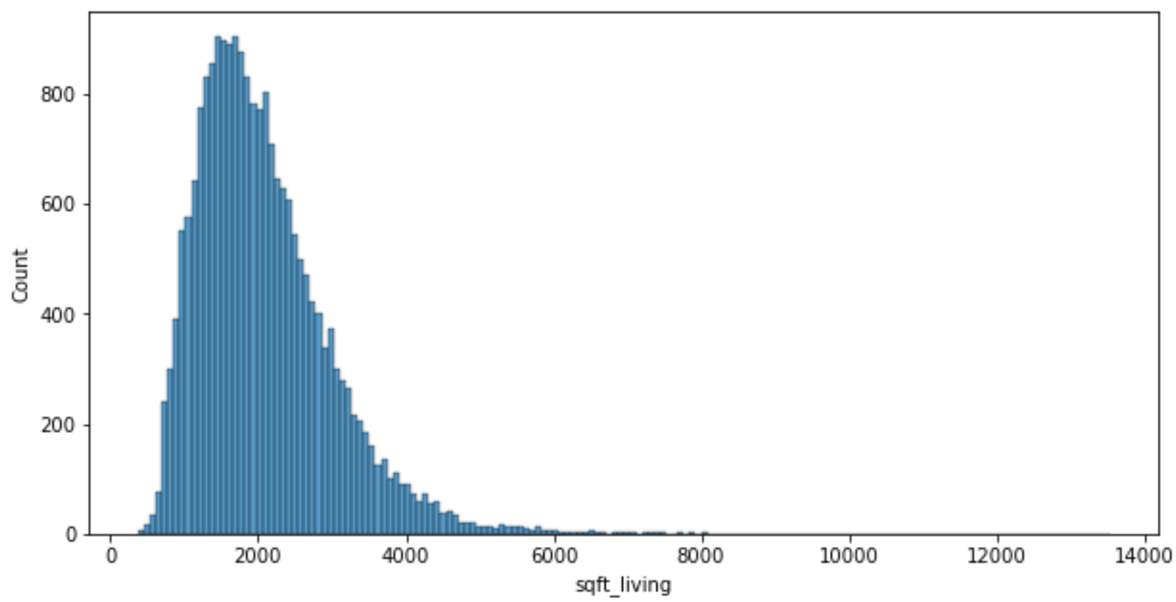
Out[977]:

```
<matplotlib.collections.PathCollection at 0x2873cc999a0>
```



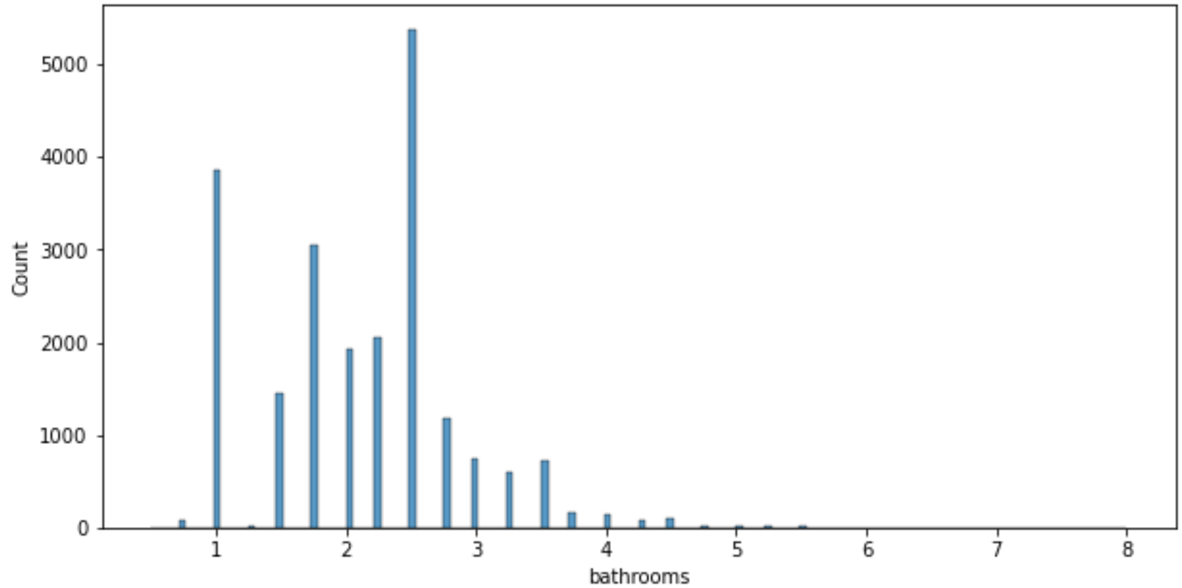
In [978]:

```
1 fig, ax = plt.subplots(figsize=(10, 5))
```

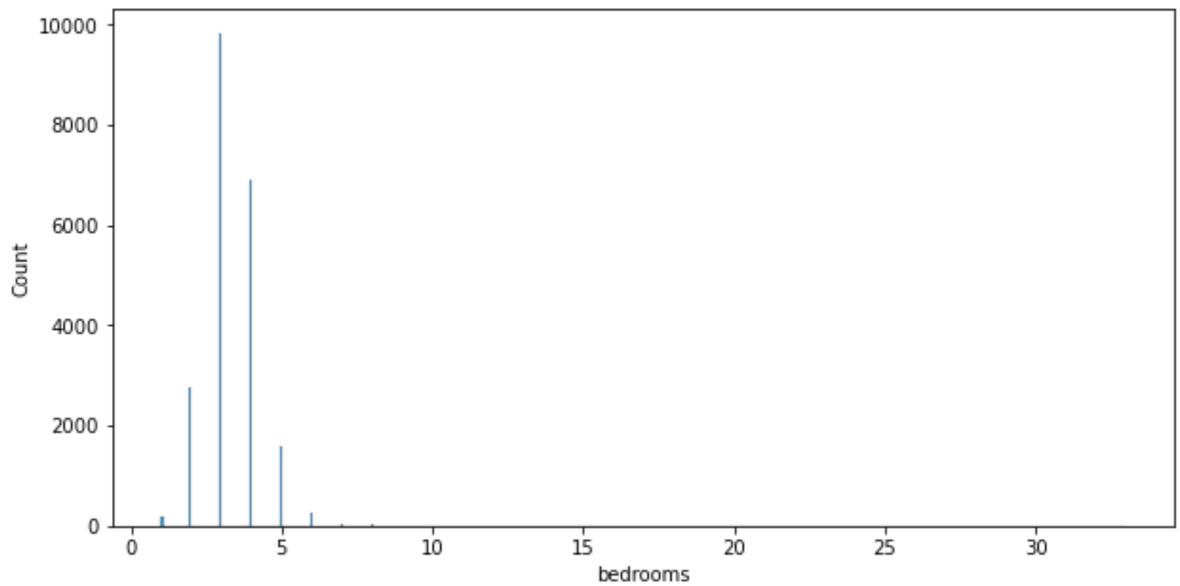


The relationship is certainly linear but it isn't normally distributed. Let's look at the distributions of some of the other variables.

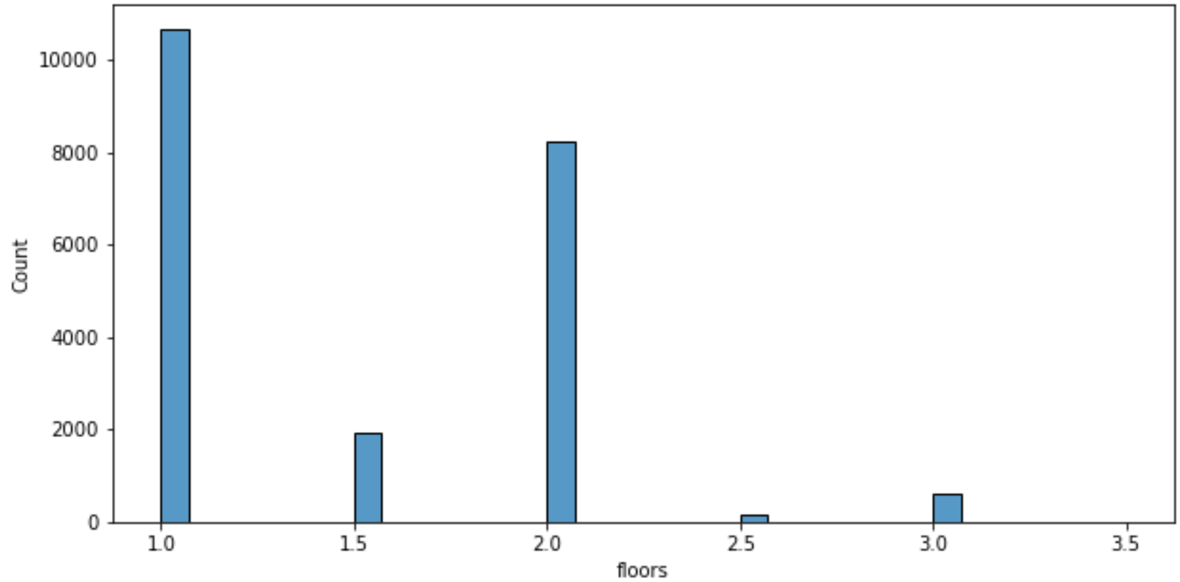
In [979]:
```
fig, ax = plt.subplots(figsize=(10, 5))
```



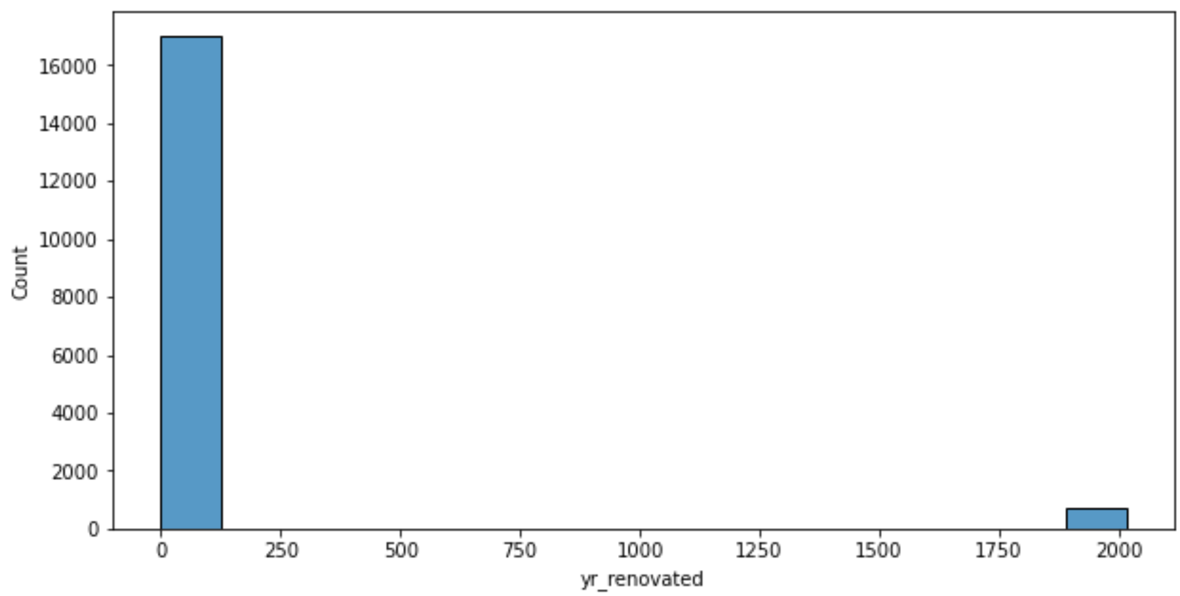
In [980]:
```
fig, ax = plt.subplots(figsize=(10, 5))
```



In [981]:
```
fig, ax = plt.subplots(figsize=(10, 5))
```



In [982]:
```
fig, ax = plt.subplots(figsize=(10, 5))
```



Ok, so it looks like it's best to use 'sqft_living' for our independent variable. So, let's do it:

In [983]:
```
X_baseline= df['sqft_living']
y_baseline= df['price']
```

Out[983]:

```
0        1180
1        2570
2         770
3        1960
```

In [984]:

```
X_baseline= sm.add_constant(X_baseline)

```

```
C:\Users\isaia\anaconda3\lib\site-packages\statsmodels\tsa\tsatools.py:142: F
utureWarning: In a future version of pandas all arguments of concat except fo
r the argument 'objs' will be keyword-only
  x = pd.concat(x[::order], 1)
```

In [985]:

Out[985]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.493
Model:	OLS	**Adj. R-squared:**	0.493
Method:	Least Squares	**F-statistic:**	2.097e+04
Date:	Thu, 19 May 2022	**Prob (F-statistic):**	0.00
Time:	13:02:17	**Log-Likelihood:**	-3.0006e+05
No. Observations:	21597	**AIC:**	6.001e+05
Df Residuals:	21595	**BIC:**	6.001e+05
Df Model:	1		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
const	-4.399e+04	4410.023	-9.975	0.000	-5.26e+04	-3.53e+04
sqft_living	280.8630	1.939	144.819	0.000	277.062	284.664

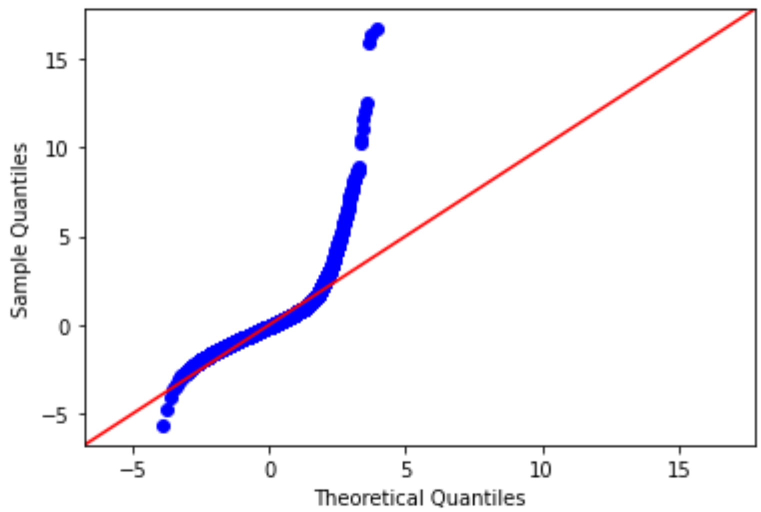
Omnibus:	14801.942	**Durbin-Watson:**	1.982
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	542662.604
Skew:	2.820	**Prob(JB):**	0.00
Kurtosis:	26.901	**Cond. No.**	5.63e+03

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

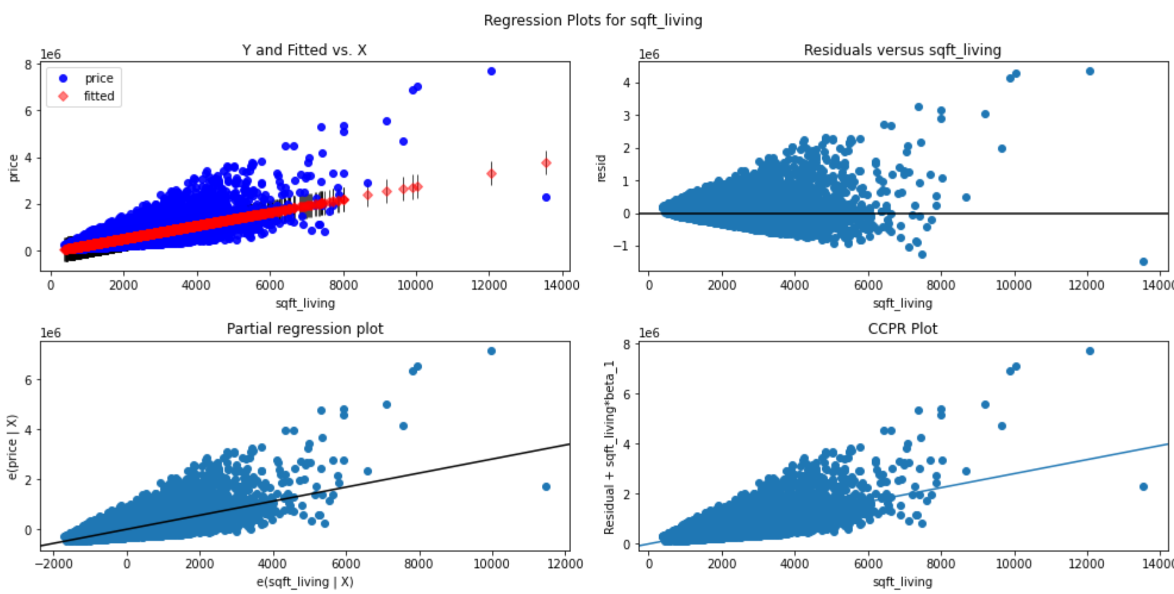
In [986]:

```
residuals = baseline_model.resid
fig = sm.graphics.qqplot(residuals, dist=stats.norm, fit=True, line='45',)
```

```
C:\Users\isaia\anaconda3\lib\site-packages\statsmodels\graphics\gofplots.py:9
93: UserWarning: marker is redundantly defined by the 'marker' keyword argume
```



In [987]:



Ok, it really isn't a great fit at all and the residuals are not homoscedastic. ***Let's improve by adding more features.***

Data Preparation ,Cleaning, and Preprocessing

So, before we add more features, let's get it ready for processing.

In [988]:

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 21597 entries, 0 to 21596
Data columns (total 9 columns):
 #   Column        Non-Null Count  Dtype  
---  ------        --------------  -----  
 0   price         21597 non-null  float64
 1   bedrooms      21597 non-null  int64  
 2   bathrooms     21597 non-null  float64
 3   sqft_living   21597 non-null  int64  
 4   floors        21597 non-null  float64
 5   condition     21597 non-null  object 
 6   yr_renovated  17755 non-null  float64
 7   Month         21597 non-null  int64  
 8   grade         21597 non-null  object 
```

Fill in null values for 'yr_renovated'. 0 is actually the mode of this column so it's a good pick.

In [989]:

```
df['yr_renovated'].fillna(0.0, inplace=True)
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 21597 entries, 0 to 21596
Data columns (total 9 columns):
 #   Column        Non-Null Count  Dtype  
---  ------        --------------  -----  
 0   price         21597 non-null  float64
 1   bedrooms      21597 non-null  int64  
 2   bathrooms     21597 non-null  float64
 3   sqft_living   21597 non-null  int64  
 4   floors        21597 non-null  float64
 5   condition     21597 non-null  object 
 6   yr_renovated  21597 non-null  float64
 7   Month         21597 non-null  int64  
 8   grade         21597 non-null  object 
dtypes: float64(4), int64(3), object(2)
memory usage: 1.5+ MB
```

In [990]:

```
df['yr_renovated'].isna().value_counts()
```

Out[990]:

```
False    21597
Name: yr_renovated, dtype: int64
```

In [991]:

Out[991]:

	price	bedrooms	bathrooms	sqft_living	floors	condition	yr_renovated	Month	gr
0	221900.0	3	1.00	1180	1.0	Average	0.0	10	Aver
1	538000.0	3	2.25	2570	2.0	Average	1991.0	12	Aver
2	180000.0	2	1.00	770	1.0	Average	0.0	2	6 l Aver
3	604000.0	4	3.00	1960	1.0	Very Good	0.0	12	Aver

	price	bedrooms	bathrooms	sqft_living	floors	condition	yr_renovated	Month	gr
4	510000.0	3	2.00	1680	1.0	Average	0.0	2	8 G
...	...	...	...	...	...	...	...	...	
21592	360000.0	3	2.50	1530	3.0	Average	0.0	5	8 G

Let's make a model with only numeric features:

In [992]:

In [993]:

Out[993]:

	price	bedrooms	bathrooms	sqft_living	floors	yr_renovated
0	221900.0	3	1.00	1180	1.0	0.0
1	538000.0	3	2.25	2570	2.0	1991.0
2	180000.0	2	1.00	770	1.0	0.0
3	604000.0	4	3.00	1960	1.0	0.0
4	510000.0	3	2.00	1680	1.0	0.0
...	...	...	...	...	...	...
21592	360000.0	3	2.50	1530	3.0	0.0
21593	400000.0	4	2.50	2310	2.0	0.0
21594	402101.0	2	0.75	1020	2.0	0.0
21595	400000.0	3	2.50	1600	2.0	0.0
21596	325000.0	2	0.75	1020	2.0	0.0

21597 rows × 6 columns

In [994]:

```
1 X_numeric= Numeric.drop('price', axis=1)
```

In [995]:

```
1 X_numeric = sm.add_constant(X_numeric)
```

```
C:\Users\isaia\anaconda3\lib\site-packages\statsmodels\tsa\tsatools.py:142: F
utureWarning: In a future version of pandas all arguments of concat except fo
r the argument 'objs' will be keyword-only
  x = pd.concat(x[::order], 1)
```

In [996]:

Out[996]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.513
Model:	OLS	**Adj. R-squared:**	0.513
Method:	Least Squares	**F-statistic:**	4556.
Date:	Thu, 19 May 2022	**Prob (F-statistic):**	0.00

Time:	13:02:22	**Log-Likelihood:**	-2.9961e+05
No. Observations:	21597	**AIC:**	5.992e+05
Df Residuals:	21591	**BIC:**	5.993e+05
Df Model:	5		
Covariance Type:	nonrobust		

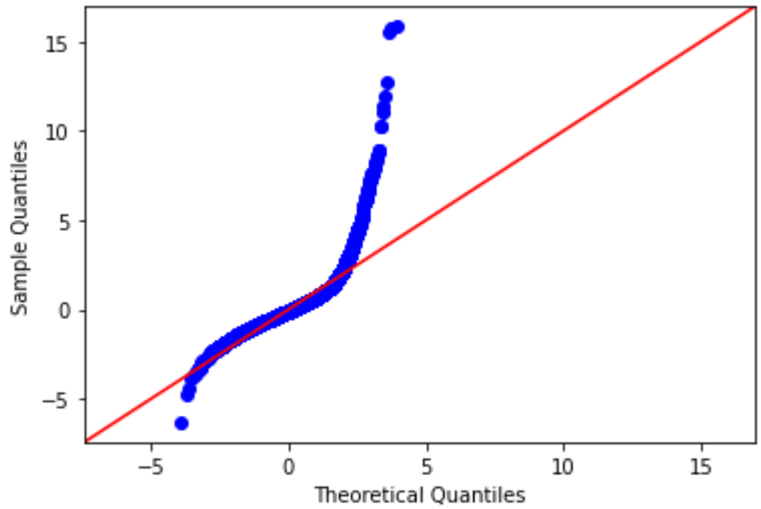
	coef	std err	t	P>|t|	[0.025	0.975]
const	7.171e+04	7661.047	9.361	0.000	5.67e+04	8.67e+04
bedrooms	-5.78e+04	2344.310	-24.654	0.000	-6.24e+04	-5.32e+04
bathrooms	5910.5602	3808.216	1.552	0.121	-1553.825	1.34e+04
sqft_living	308.7572	3.083	100.162	0.000	302.715	314.799
floors	2104.8528	3761.480	0.560	0.576	-5267.927	9477.632
yr_renovated	81.2053	4.799	16.920	0.000	71.798	90.612

Omnibus:	14310.293	**Durbin-Watson:**	1.987
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	479360.010
Skew:	2.709	**Prob(JB):**	0.00
Kurtosis:	25.435	**Cond. No.**	1.04e+04

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 1.04e+04. This might indicate that there are
strong multicollinearity or other numerical problems.

In [997]:

```
C:\Users\isaia\anaconda3\lib\site-packages\statsmodels\graphics\gofplots.py:9
93: UserWarning: marker is redundantly defined by the 'marker' keyword argume
nt and the fmt string "bo" (-> marker='o'). The keyword argument will take pr
ecedence.
  ax.plot(x, y, fmt, **plot_style)
```



So, this looks ok but there are problems as the quantiles increase too dramatically and skew the line. This is sort of similar to the fat tails of the sqft_living histogram from earlier. Log transforming might help it out. But, let's look at the categorical values first.

One Hot Encoding categories

In [998]:

Out[998]:

```
7 Average        8974
8 Good           6065
9 Better         2615
6 Low Average    2038
10 Very Good     1134
11 Excellent      399
5 Fair            242
12 Luxury          89
4 Low              27
13 Mansion         13
3 Poor              1
Name: grade, dtype: int64
```

In [999]:

```
new_grades = {'3 Poor':3, '4 Low':4, '5 Fair':5, '6 Low Average':6, '7 Ave
              '10 Very Good':10, '11 Excellent':11, '12 Luxury':12, '13 Mar
```

In [1000]:

Out[1000]:

	price	bedrooms	bathrooms	sqft_living	floors	condition	yr_renovated	Month	grad

	price	bedrooms	bathrooms	sqft_living	floors	condition	yr_renovated	Month	grad
0	221900.0	3	1.00	1180	1.0	Average	0.0	10	
1	538000.0	3	2.25	2570	2.0	Average	1991.0	12	
2	180000.0	2	1.00	770	1.0	Average	0.0	2	
3	604000.0	4	3.00	1960	1.0	Very Good	0.0	12	
4	510000.0	3	2.00	1680	1.0	Average	0.0	2	
...	...	...	...	...	...	...	...	...	
21592	360000.0	3	2.50	1530	3.0	Average	0.0	5	
21593	400000.0	4	2.50	2310	2.0	Average	0.0	2	
21594	402101.0	2	0.75	1020	2.0	Average	0.0	6	
21595	400000.0	3	2.50	1600	2.0	Average	0.0	1	
21596	325000.0	2	0.75	1020	2.0	Average	0.0	10	

In [1001]:

```python
from sklearn.preprocessing import OneHotEncoder
Conditions = df[['condition']]
ohe = OneHotEncoder(categories="auto", sparse=False, handle_unknown="ignor
ohe.fit(Conditions)
```

Out[1001]: `[array(['Average', 'Fair', 'Good', 'Poor', 'Very Good'], dtype=object)]`

In [1002]:

```python
Conditions_encoded = ohe.transform(Conditions)
```

Out[1002]:

```
array([[1., 0., 0., 0., 0.],
       [1., 0., 0., 0., 0.],
       [1., 0., 0., 0., 0.],
       ...,
       [1., 0., 0., 0., 0.],
       [1., 0., 0., 0., 0.],
       [1., 0., 0., 0., 0.]])
```

In [1003]:

```python
Conditions_encoded = pd.DataFrame(Conditions_encoded, columns=ohe.categori
```

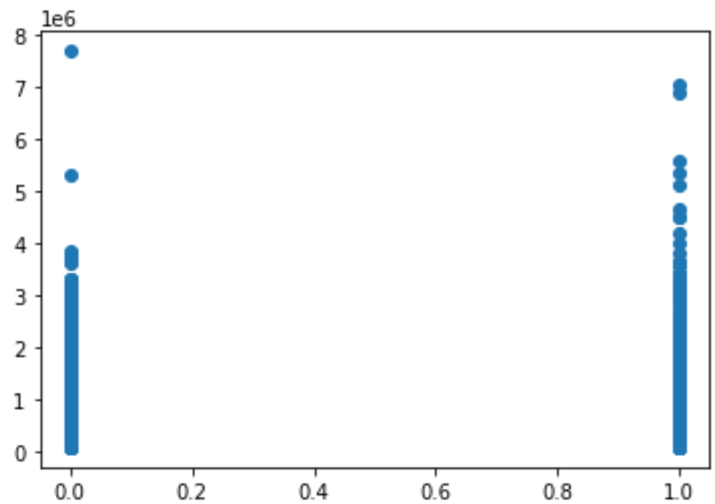
Out[1003]:

	Average	Fair	Good	Poor	Very Good
0	1.0	0.0	0.0	0.0	0.0
1	1.0	0.0	0.0	0.0	0.0
2	1.0	0.0	0.0	0.0	0.0
3	0.0	0.0	0.0	0.0	1.0
4	1.0	0.0	0.0	0.0	0.0
...	...	...	...	...	...
21592	1.0	0.0	0.0	0.0	0.0
21593	1.0	0.0	0.0	0.0	0.0
21594	1.0	0.0	0.0	0.0	0.0

	Average	Fair	Good	Poor	Very Good
21595	1.0	0.0	0.0	0.0	0.0
21596	1.0	0.0	0.0	0.0	0.0

In [1004]:

Out[1004]: `<matplotlib.collections.PathCollection at 0x2873a9c4be0>`



In [1005]:

```
Month = df[['Month']]
ohe = OneHotEncoder(categories="auto", sparse=False, handle_unknown="ignor
ohe.fit(Month)
```

Out[1005]:

```
[array([ 1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12], dtype=int64)]
```

In [1006]:

```
Month_encoded = ohe.transform(Month)
```

Out[1006]:

```
array([[0., 0., 0., ..., 1., 0., 0.],
       [0., 0., 0., ..., 0., 0., 1.],
       [0., 1., 0., ..., 0., 0., 0.],
       ...,
       [0., 0., 0., ..., 0., 0., 0.],
       [1., 0., 0., ..., 0., 0., 0.],
       [0., 0., 0., ..., 1., 0., 0.]])
```

In [1007]:

```
Month_encoded = pd.DataFrame(Month_encoded, columns=ohe.categories_[0], ir
```

Out[1007]:

	1	2	3	4	5	6	7	8	9	10	11	12
0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0
1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0
2	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0
4	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
...	...	...	...	...	...	...	...	...	...	...	...	...

	1	2	3	4	5	6	7	8	9	10	11	12
21592	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
21593	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
21594	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0
21595	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
21596	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0

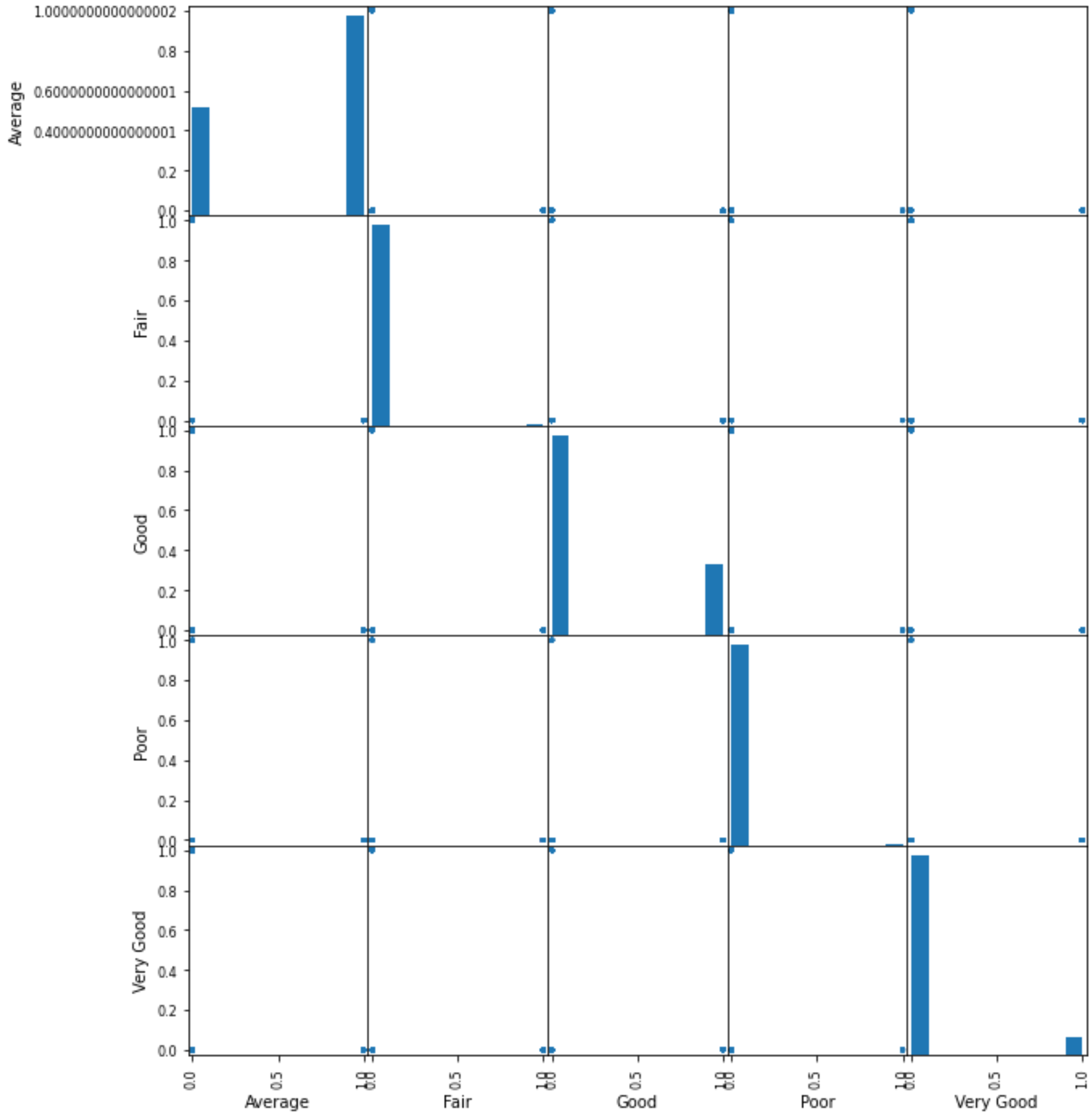
In [1008]:

```
Month_encoded.columns = ['January', 'February', 'March', 'April', 'May', '
                         'September', 'October', 'November','December']
```

Out[1008]:

	January	February	March	April	May	June	July	August	September	October	Novemb
0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	(
1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	(
2	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	(
3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	(
4	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	(
...	...	...	...	...	...	...	...	...	...	...	
21592	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	(
21593	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	(
21594	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	(
21595	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	(
21596	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	(

In [1009]:



Creating a Completed Renovations Column and a Recent renovations Column:

In [1010]:

```
df['Completed_renovation']=df['yr_renovated'] > 1
```

In [1011]:

In [1012]:

Out[1012]:

	price	bedrooms	bathrooms	sqft_living	floors	condition	yr_renovated	Month	grad
0	221900.0	3	1.00	1180	1.0	Average	0.0	10	
1	538000.0	3	2.25	2570	2.0	Average	1991.0	12	
2	180000.0	2	1.00	770	1.0	Average	0.0	2	

	price	bedrooms	bathrooms	sqft_living	floors	condition	yr_renovated	Month	grad
3	604000.0	4	3.00	1960	1.0	Very Good	0.0	12	
4	510000.0	3	2.00	1680	1.0	Average	0.0	2	
...	...	...	...	...	...	...	...	...	
21592	360000.0	3	2.50	1530	3.0	Average	0.0	5	
21593	400000.0	4	2.50	2310	2.0	Average	0.0	2	
21594	402101.0	2	0.75	1020	2.0	Average	0.0	6	

In [1013]:

```
Finished_Reno = df[['Completed_renovation']]
ohe = OneHotEncoder(categories="auto", sparse=False, handle_unknown="ignor
ohe.fit(Finished_Reno)
```

Out[1013]:

```
[array([False,  True])]
```

In [1014]:

```
Finished_Reno_encoded = ohe.transform(Finished_Reno)
```

Out[1014]:

```
array([[1., 0.],
       [0., 1.],
       [1., 0.],
       ...,
       [1., 0.],
       [1., 0.],
       [1., 0.]])
```

In [1015]:

```
Finished_Reno_encoded = pd.DataFrame(Finished_Reno_encoded, columns=ohe.ca
Finished_Reno_encoded.columns=['Not_Renovated', 'Renovated']
```

Out[1015]:

	Not_Renovated	Renovated
0	1.0	0.0
1	0.0	1.0
2	1.0	0.0
3	1.0	0.0
4	1.0	0.0
...	...	...
21592	1.0	0.0
21593	1.0	0.0
21594	1.0	0.0
21595	1.0	0.0
21596	1.0	0.0

In [1016]:
```
Recent_Reno = df[['Recent_Renovation']]
ohe = OneHotEncoder(categories="auto", sparse=False, handle_unknown="ignor
ohe.fit(Recent_Reno)
```

Out[1016]:
```
[array([False,  True])]
```

In [1017]:
```
Recent_Reno_encoded = ohe.transform(Recent_Reno)
```

Out[1017]:
```
array([[1., 0.],
       [1., 0.],
       [1., 0.],
       ...,
       [1., 0.],
       [1., 0.],
       [1., 0.]])
```

In [1018]:
```
Recent_Reno_encoded = pd.DataFrame(Recent_Reno_encoded, columns=ohe.catego
Recent_Reno_encoded.columns=['Not_Renovated Recently', 'Renovated Recently
```

Out[1018]:

	Not_Renovated Recently	Renovated Recently
0	1.0	0.0
1	1.0	0.0
2	1.0	0.0
3	1.0	0.0
4	1.0	0.0
...	...	...
21592	1.0	0.0
21593	1.0	0.0
21594	1.0	0.0
21595	1.0	0.0
21596	1.0	0.0

Combining numerical features:

In [1019]:
```
month_and_cond= pd.concat((Month_encoded, Conditions_encoded, Recent_Reno_
```

Out[1019]:

	January	February	March	April	May	June	July	August	September	October	...	Dec
0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	...	
1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	
2	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	
3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	
4	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	

	January	February	March	April	May	June	July	August	September	October	...	Dec
...	...	...	...	...	...	...	...	...	...	...	...	
21592	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	...	
21593	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	
21594	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	...	
21595	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	

In [1020]:

```
df= pd.concat((df,month_and_cond), axis=1)
df
```

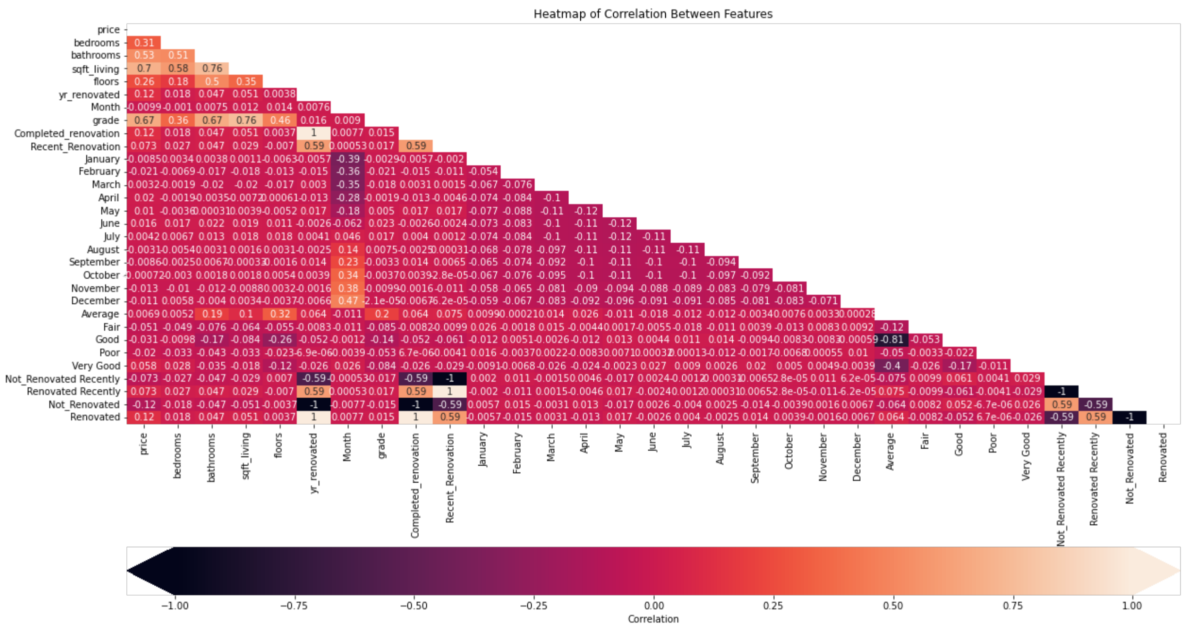
Out[1020]:

	price	bedrooms	bathrooms	sqft_living	floors	condition	yr_renovated	Month	grad
0	221900.0	3	1.00	1180	1.0	Average	0.0	10	
1	538000.0	3	2.25	2570	2.0	Average	1991.0	12	
2	180000.0	2	1.00	770	1.0	Average	0.0	2	
3	604000.0	4	3.00	1960	1.0	Very Good	0.0	12	
4	510000.0	3	2.00	1680	1.0	Average	0.0	2	
...	...	...	...	...	...	...	...	...	
21592	360000.0	3	2.50	1530	3.0	Average	0.0	5	
21593	400000.0	4	2.50	2310	2.0	Average	0.0	2	
21594	402101.0	2	0.75	1020	2.0	Average	0.0	6	
21595	400000.0	3	2.50	1600	2.0	Average	0.0	1	
21596	325000.0	2	0.75	1020	2.0	Average	0.0	10	

21597 rows × 32 columns

In [1021]:

```
df_corr_2 = df.corr()

fig, ax = plt.subplots(figsize=(20, 12))

sns.heatmap(
    data=df_corr_2,
    mask=np.triu(np.ones_like(df_corr_2, dtype=bool)),
    ax=ax,
    annot=True,
    cbar_kws={"label": "Correlation", "orientation": "horizontal", "pad":
)
```



Some of the correlations are on the Boolean columns will probably create noise in any model.

In [1022]:

```
df
```

Out[1022]:

	price	bedrooms	bathrooms	sqft_living	floors	condition	yr_renovated	Month	grad
0	221900.0	3	1.00	1180	1.0	Average	0.0	10	
1	538000.0	3	2.25	2570	2.0	Average	1991.0	12	
2	180000.0	2	1.00	770	1.0	Average	0.0	2	
3	604000.0	4	3.00	1960	1.0	Very Good	0.0	12	
4	510000.0	3	2.00	1680	1.0	Average	0.0	2	
...	...	...	...	...	...	...	...	...	
21592	360000.0	3	2.50	1530	3.0	Average	0.0	5	
21593	400000.0	4	2.50	2310	2.0	Average	0.0	2	
21594	402101.0	2	0.75	1020	2.0	Average	0.0	6	
21595	400000.0	3	2.50	1600	2.0	Average	0.0	1	

On to the model:

In [1023]:

In [1024]:

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 21597 entries, 0 to 21596
Data columns (total 29 columns):
 #   Column                 Non-Null Count  Dtype  
---  ------                 --------------  -----  
 0   price                  21597 non-null  float64
 1   bedrooms               21597 non-null  int64  
 2   bathrooms              21597 non-null  float64
 3   sqft_living            21597 non-null  int64  
 4   floors                 21597 non-null  float64
 5   yr_renovated           21597 non-null  float64
 6   Month                  21597 non-null  int64  
 7   grade                  21597 non-null  int64  
 8   January                21597 non-null  float64
 9   February               21597 non-null  float64
 10  March                  21597 non-null  float64
 11  April                  21597 non-null  float64
 12  May                    21597 non-null  float64
 13  June                   21597 non-null  float64
 14  July                   21597 non-null  float64
 15  August                 21597 non-null  float64
 16  September              21597 non-null  float64
 17  October                21597 non-null  float64
 18  November               21597 non-null  float64
 19  December               21597 non-null  float64
 20  Average                21597 non-null  float64
 21  Fair                   21597 non-null  float64
 22  Good                   21597 non-null  float64
 23  Poor                   21597 non-null  float64
 24  Very Good              21597 non-null  float64
 25  Not_Renovated Recently  21597 non-null  float64
 26  Renovated Recently     21597 non-null  float64
 27  Not_Renovated          21597 non-null  float64
 28  Renovated              21597 non-null  float64
dtypes: float64(25), int64(4)
memory usage: 4.8 MB
```

In [1025]:

```python
X_model_4= df.drop('price', axis=1)
```

In [1026]:

```python
X_model_4= sm.add_constant(X_model_4)
```

```
C:\Users\isaia\anaconda3\lib\site-packages\statsmodels\tsa\tsatools.py:142: F
utureWarning: In a future version of pandas all arguments of concat except fo
r the argument 'objs' will be keyword-only
  x = pd.concat(x[::order], 1)
```

In [1027]:

Out[1027]:

OLS Regression Results

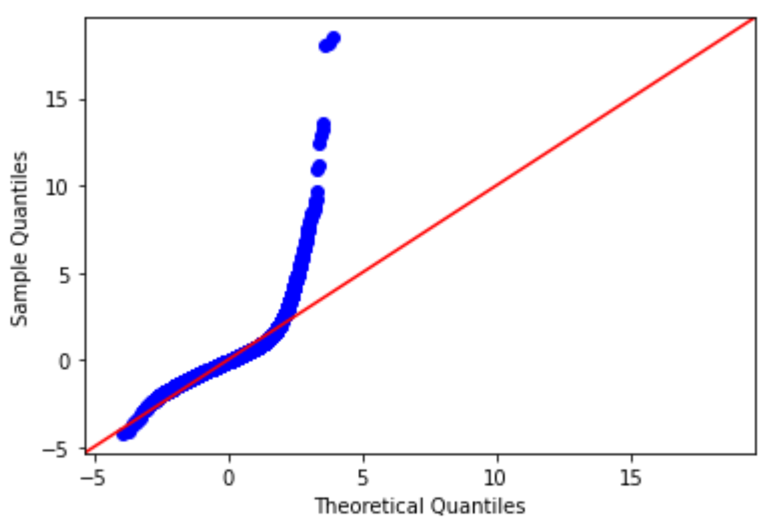
Dep. Variable:	price	**R-squared:**	0.570
Model:	OLS	**Adj. R-squared:**	0.569
Method:	Least Squares	**F-statistic:**	1242.
Date:	Thu, 19 May 2022	**Prob (F-statistic):**	0.00
Time:	13:02:34	**Log-Likelihood:**	-2.9828e+05
No. Observations:	21597	**AIC:**	5.966e+05
Df Residuals:	21573	**BIC:**	5.968e+05
Df Model:	23		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	-1.595e+06	3.07e+05	-5.193	0.000	-2.2e+06	-9.93e+05

In [1028]:

```
residuals = Fourth_model.resid
fig = sm.graphics.qqplot(residuals, dist=stats.norm, fit=True, line='45',)
```

```
C:\Users\isaia\anaconda3\lib\site-packages\statsmodels\graphics\gofplots.py:9
93: UserWarning: marker is redundantly defined by the 'marker' keyword argume
nt and the fmt string "bo" (-> marker='o'). The keyword argument will take pr
ecedence.
  ax.plot(x, y, fmt, **plot_style)
```



Again, this model violates the assumption of normality of errors so we need to do a few things to change the data. First, let's drop some boolean and redundant columns.

In [1029]:

```
#drop not recently renovated, not renovated, Month
```

In [1030]:

Out[1030]:

	price	bedrooms	bathrooms	sqft_living	floors	yr_renovated	grade	January	Februa
0	221900.0	3	1.00	1180	1.0	0.0	7	0.0	
1	538000.0	3	2.25	2570	2.0	1991.0	7	0.0	
2	180000.0	2	1.00	770	1.0	0.0	6	0.0	
3	604000.0	4	3.00	1960	1.0	0.0	7	0.0	
4	510000.0	3	2.00	1680	1.0	0.0	8	0.0	
...	...	...	...	...	...	...	...	...	
21592	360000.0	3	2.50	1530	3.0	0.0	8	0.0	
21593	400000.0	4	2.50	2310	2.0	0.0	8	0.0	
21594	402101.0	2	0.75	1020	2.0	0.0	7	0.0	
21595	400000.0	3	2.50	1600	2.0	0.0	8	1.0	
21596	325000.0	2	0.75	1020	2.0	0.0	7	0.0	

21597 rows × 26 columns

In [1031]:

```
X_model_5= df.drop('price', axis=1)
```

In [1032]:

```
X_model_5= sm.add_constant(X_model_5)
```

```
C:\Users\isaia\anaconda3\lib\site-packages\statsmodels\tsa\tsatools.py:142: F
utureWarning: In a future version of pandas all arguments of concat except fo
r the argument 'objs' will be keyword-only
  x = pd.concat(x[::order], 1)
```

In [1033]:

Out[1033]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.570
Model:	OLS	**Adj. R-squared:**	0.569
Method:	Least Squares	**F-statistic:**	1242.
Date:	Thu, 19 May 2022	**Prob (F-statistic):**	0.00
Time:	13:02:35	**Log-Likelihood:**	-2.9828e+05
No. Observations:	21597	**AIC:**	5.966e+05
Df Residuals:	21573	**BIC:**	5.968e+05
Df Model:	23		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]

const	-3.908e+05	1.32e+04	-29.591	0.000	-4.17e+05	-3.65e+05
bedrooms	-4.305e+04	2247.409	-19.158	0.000	-4.75e+04	-3.86e+04
bathrooms	-1.356e+04	3631.989	-3.733	0.000	-2.07e+04	-6440.477
sqft_living	212.7252	3.544	60.016	0.000	205.778	219.673
floors	-1.663e+04	3752.016	-4.433	0.000	-2.4e+04	-9279.393
yr_renovated	3707.6403	787.462	4.708	0.000	2164.156	5251.124
grade	1.1e+05	2344.069	46.938	0.000	1.05e+05	1.15e+05
January	-4.107e+04	7328.167	-5.604	0.000	-5.54e+04	-2.67e+04
February	-3.701e+04	6556.983	-5.644	0.000	-4.99e+04	-2.42e+04
March	-5258.1896	5466.352	-0.962	0.336	-1.6e+04	5456.264
April	892.5514	5084.056	0.176	0.861	-9072.574	1.09e+04
May	-2.797e+04	4905.965	-5.701	0.000	-3.76e+04	-1.84e+04
June	-3.353e+04	5149.683	-6.511	0.000	-4.36e+04	-2.34e+04
July	-4.41e+04	5106.588	-8.636	0.000	-5.41e+04	-3.41e+04
August	-4.043e+04	5405.426	-7.479	0.000	-5.1e+04	-2.98e+04
September	-4.401e+04	5604.592	-7.853	0.000	-5.5e+04	-3.3e+04
October	-3.156e+04	5466.775	-5.772	0.000	-4.23e+04	-2.08e+04
November	-3.93e+04	6201.602	-6.338	0.000	-5.15e+04	-2.71e+04
December	-4.749e+04	6086.226	-7.802	0.000	-5.94e+04	-3.56e+04
Average	-1.607e+05	9076.636	-17.704	0.000	-1.78e+05	-1.43e+05
Fair	-1.126e+05	1.73e+04	-6.521	0.000	-1.46e+05	-7.87e+04
Good	-9.55e+04	9106.462	-10.487	0.000	-1.13e+05	-7.77e+04
Poor	-1.744e+04	3.74e+04	-0.467	0.641	-9.07e+04	5.58e+04
Very Good	-4600.8581	9903.028	-0.465	0.642	-2.4e+04	1.48e+04
Renovated Recently	-4.954e+04	2.56e+04	-1.936	0.053	-9.97e+04	622.763
Renovated	-7.19e+06	1.57e+06	-4.593	0.000	-1.03e+07	-4.12e+06

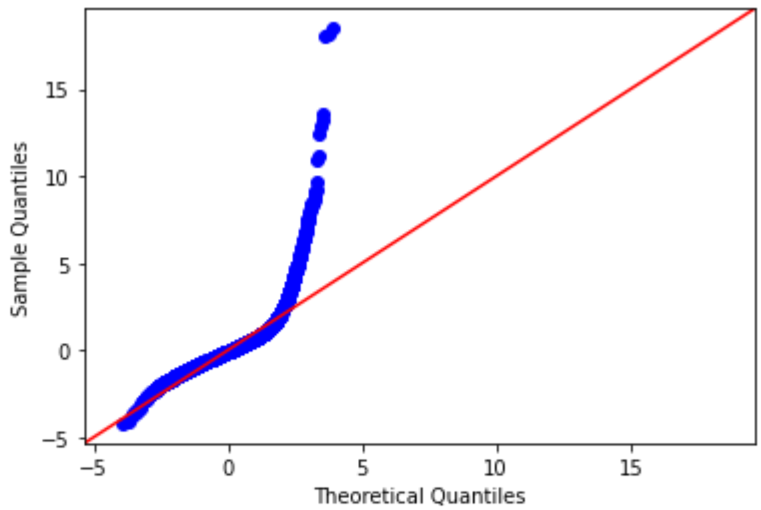
Omnibus:	16634.219	**Durbin-Watson:**	1.990
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	964690.215
Skew:	3.209	**Prob(JB):**	0.00
Kurtosis:	35.107	**Cond. No.**	3.09e+17

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The smallest eigenvalue is 1.17e-24. This might indicate that there are

In [ ]:
```
1
```

In [1034]:
```
residuals = Fifth_model.resid
fig = sm.graphics.qqplot(residuals, dist=stats.norm, fit=True, line='45',)
```

```
C:\Users\isaia\anaconda3\lib\site-packages\statsmodels\graphics\gofplots.py:9
93: UserWarning: marker is redundantly defined by the 'marker' keyword argume
nt and the fmt string "bo" (-> marker='o'). The keyword argument will take pr
ecedence.
  ax.plot(x, y, fmt, **plot_style)
```



Again, the assumption of normality is violated. The solution may lie in log transforming.

Log transforming

In [1035]:
```
continuous = ['sqft_living', 'price']
df_conti= df[continuous]
log_names = [f'{column}_log' for column in df_conti.columns]
df_log = np.log(df_conti)
df_log.columns = log_names
def normalize(feature):
    return (feature - feature.mean()) / feature.std()

```

In [1036]:

In [1037]:
```
X_log= df_log_normal.drop(['price', 'price_log','bathrooms','sqft_living',
                           'Good', 'Very Good'], axis=1)
y_log= df_log_normal['price_log']
```

In [1038]:
```
X_log = sm.add_constant(X_log)
```

```
C:\Users\isaia\anaconda3\lib\site-packages\statsmodels\tsa\tsatools.py:142: F
utureWarning: In a future version of pandas all arguments of concat except fo
r the argument 'objs' will be keyword-only
  x = pd.concat(x[::order], 1)
```

In [1039]:

Out[1039]:

OLS Regression Results

Dep. Variable:	price_log	**R-squared:**	0.558
Model:	OLS	**Adj. R-squared:**	0.557
Method:	Least Squares	**F-statistic:**	1601.
Date:	Thu, 19 May 2022	**Prob (F-statistic):**	0.00
Time:	13:02:36	**Log-Likelihood:**	-21833.
No. Observations:	21597	**AIC:**	4.370e+04
Df Residuals:	21579	**BIC:**	4.385e+04
Df Model:	17		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	-2.5342	0.050	-50.841	0.000	-2.632	-2.436
sqft_living_log	0.3725	0.008	45.081	0.000	0.356	0.389
bedrooms	-0.0510	0.006	-7.998	0.000	-0.063	-0.038
floors	-0.0492	0.009	-5.204	0.000	-0.068	-0.031
yr_renovated	0.0002	1.55e-05	13.887	0.000	0.000	0.000
grade	0.3875	0.006	62.933	0.000	0.375	0.400
January	-0.2673	0.020	-13.059	0.000	-0.307	-0.227
February	-0.2380	0.018	-13.004	0.000	-0.274	-0.202
March	-0.1508	0.015	-9.821	0.000	-0.181	-0.121
April	-0.1006	0.014	-7.039	0.000	-0.129	-0.073
May	-0.1822	0.014	-13.157	0.000	-0.209	-0.155
June	-0.1941	0.014	-13.410	0.000	-0.223	-0.166
July	-0.2239	0.014	-15.616	0.000	-0.252	-0.196
August	-0.2270	0.015	-15.002	0.000	-0.257	-0.197
September	-0.2288	0.016	-14.573	0.000	-0.260	-0.198
October	-0.2163	0.015	-14.119	0.000	-0.246	-0.186
November	-0.2406	0.017	-13.863	0.000	-0.275	-0.207
December	-0.2645	0.017	-15.523	0.000	-0.298	-0.231
Renovated Recently	0.0731	0.051	1.428	0.153	-0.027	0.173

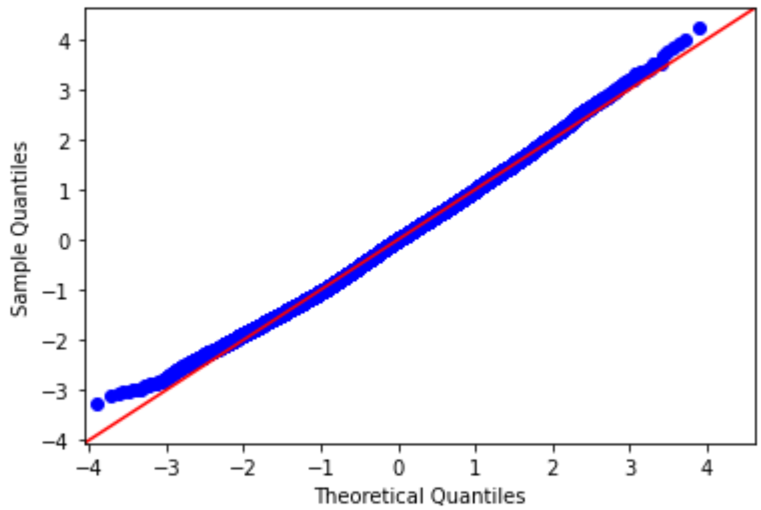
Omnibus:	81.303	**Durbin-Watson:**	1.978
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	81.949
Skew:	0.148	**Prob(JB):**	1.60e-18
Kurtosis:	2.937	**Cond. No.**	2.28e+17

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The smallest eigenvalue is 5.72e-26. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.

In [1040]:

```
resid = log_model.resid

```

```
C:\Users\isaia\anaconda3\lib\site-packages\statsmodels\graphics\gofplots.py:9
93: UserWarning: marker is redundantly defined by the 'marker' keyword argume
nt and the fmt string "bo" (-> marker='o'). The keyword argument will take pr
ecedence.
  ax.plot(x, y, fmt, **plot_style)
```



In [1041]:

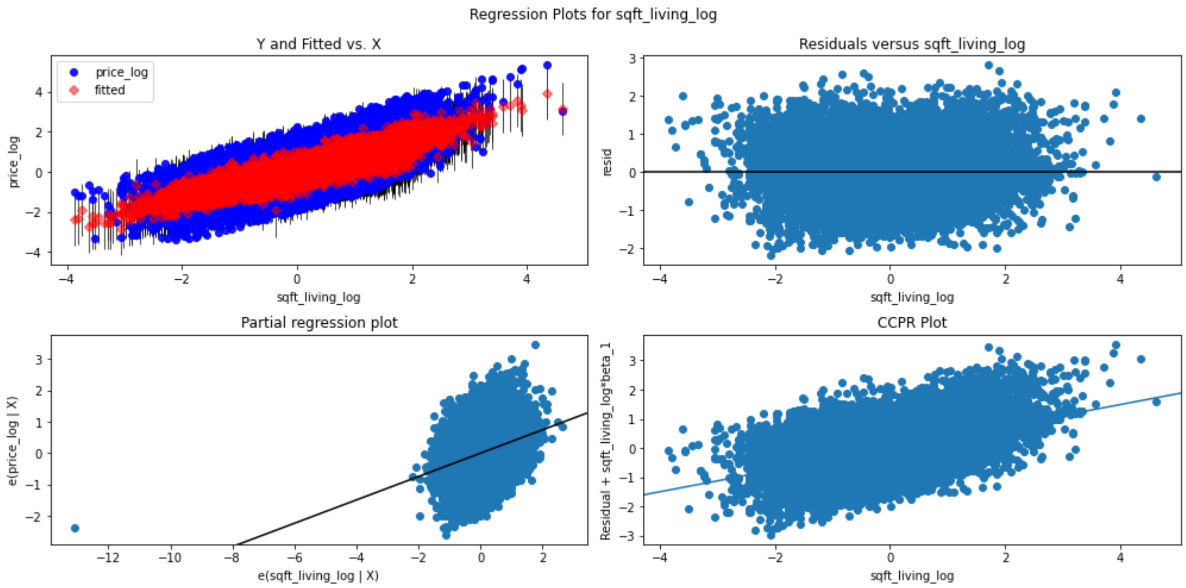
```

import statsmodels.stats.api as sms
name = ['Jarque-Bera','Prob','Skew', 'Kurtosis']
test = sms.jarque_bera(log_model.resid)
```

Out[1041]:

```
[('Jarque-Bera', 81.94898639194479),
 ('Prob', 1.6032590726147647e-18),
 ('Skew', 0.1476112765272201),
 ('Kurtosis', 2.9374642366512265)]
```

So, this looks alot better. Now, we have a much better fit. Also, the skewness and kurtosis have decreased to acceptable numbers. Now let's look at the scedasticity of 'sqft_living_log'.

In [1042]:



Calculations for Square Footage, Grade, and Renovation.

For a 5% increase in square footage:

In [1043]:

Out[1043]: 1.0183901806917963

1 unit change in grade:

In [1044]:

Out[1044]: 38.75

Recently Renovated:

In [1045]:

Out[1045]: 7.31

Recommendations

1. Improving the square footage by 5% leads to an increase in price of 2%.

2. Improving the grade by 1 unit will increase price by 39%.

3. Recently Renovated homes sell for 7% more.

In [1046]:

```
1.05 ** .3735
```

Out[1046]: 1.0183901806917963

Overall, it looks good but there are certainly some concerns. First, the model may be overfitted as it hues very closely to the line for most of its duration. Another concern is the R-squared value although the R-squared value is a reflection is of the fact that the model does not contain many important features like zip code, waterfront, and view. Even so, those factors should be excluded because an existing homeowner cannot change them.

We also should be weary of generalizing too much with this data since it is from a very unique real estate market where prices have continued to rise over the last few decades. Comparing the Seattle area with other areas of comparable size may not work since Seattle is home to so much wealth. However, for homeowners in this area, the results are very valuable and can lead to greater potential profits.