Final Project Submission

Please fill out:

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- Student pace: self paced
- Scheduled project review date/time:
- Instructor name: Morgan Jones
- Blog post URL: [https://medium.com/@kadoche.k/linear-regression-step-by-step-guide-8970af0a830b (https://medium.com/@kadoche.k/linear-regression-step-by-step-guide-8970af0a830b)](https://medium.com/@kadoche.k/linear-regression-step-by-step-guide-8970af0a830b)

Overview

This following analysis relates to the relationship between property prices and factors that can influence those prices. We are using the King County dataset. The goal of the analysis is to help stakeholders increase the value of their properties.

Business chalenge

A real estate firm want to helps its customers (property owners) increase the sale value. The following analysis was created in orderto help the real estate firms make viable recommendations to their stakeholders to increase the price of their properties.

In [1]:
```
#importing libraries

#raw data handling
import pandas as pd
import numpy as np
import datetime as dt

# data visualiztion
import matplotlib.pyplot as plt
from matplotlib import ticker
import matplotlib.ticker as mtick
import seaborn as sns
from scipy import stats
%matplotlib inline

# model validation
from sklearn.preprocessing import OrdinalEncoder, StandardScaler, OneHotEncoder
from sklearn.datasets import make_regression
from sklearn.linear_model import LinearRegression

# regression modeling
from statsmodels.formula.api import ols
import statsmodels.api as sm

#multicolinearity modeling
from patsy import dmatrices
from statsmodels.stats.outliers_influence import variance_inflation_factor

import warnings
warnings.filterwarnings("ignore")

df = pd.read_csv('data/kc_house_data.csv')
df.head()
```

Out[1]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	...	grade	sqft_above	sqft_basement	yr_built	yr_
0	7129300520	10/13/2014	221900.0	3	1.00	1180	5650	1.0	NaN	NONE	...	7 Average	1180	0.0	1955	
1	6414100192	12/9/2014	538000.0	3	2.25	2570	7242	2.0	NO	NONE	...	7 Average	2170	400.0	1951	
2	5631500400	2/25/2015	180000.0	2	1.00	770	10000	1.0	NO	NONE	...	6 Low Average	770	0.0	1933	
3	2487200875	12/9/2014	604000.0	4	3.00	1960	5000	1.0	NO	NONE	...	7 Average	1050	910.0	1965	
4	1954400510	2/18/2015	510000.0	3	2.00	1680	8080	1.0	NO	NONE	...	8 Good	1680	0.0	1987	

5 rows × 21 columns

In [2]:
```
#checking the data format
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
```

Here we can see that we have different categories: 6 float64, 9 int64 and 6 objects. Before manipulating the data, let's make a copy of the dataset.

In [3]:
```
#creating a copy for backup
df_new = df.copy()
```

In [4]:
```
df_new.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
```

Data cleaning

As seen above, we can identify 2 issues with the data:

1) Columns coded in data type object

2) Columns that contain null values: waterfront, view and yr_renovated.

In [5]:
```
#checking statistics
df_new.describe()
```

Out[5]:

	id	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	sqft_above	yr_built	yr_renovated	zip
count	2.159700e+04	2.159700e+04	21597.000000	21597.000000	21597.000000	2.159700e+04	21597.000000	21597.000000	21597.000000	17755.000000	21597.0C
mean	4.580474e+09	5.402966e+05	3.373200	2.115826	2080.321850	1.509941e+04	1.494096	1788.596842	1970.999676	83.636778	98077.9$
std	2.876736e+09	3.673681e+05	0.926299	0.768984	918.106125	4.141264e+04	0.539683	827.759761	29.375234	399.946414	53.51
min	1.000102e+06	7.800000e+04	1.000000	0.500000	370.000000	5.200000e+02	1.000000	370.000000	1900.000000	0.000000	98001.0C
25%	2.123049e+09	3.220000e+05	3.000000	1.750000	1430.000000	5.040000e+03	1.000000	1190.000000	1951.000000	0.000000	98033.0C
50%	3.904930e+09	4.500000e+05	3.000000	2.250000	1910.000000	7.618000e+03	1.500000	1560.000000	1975.000000	0.000000	98065.0C
75%	7.308900e+09	6.450000e+05	4.000000	2.500000	2550.000000	1.068500e+04	2.000000	2210.000000	1997.000000	0.000000	98118.0C
max	9.900000e+09	7.700000e+06	33.000000	8.000000	13540.000000	1.651359e+06	3.500000	9410.000000	2015.000000	2015.000000	98199.0C

Looking at the data set, we can notice some outliers, such as the property listing with the 33 bedrooms! There is a lot of preprocessing that needs to take place before we can start building a Prediciton model.

- Deleting the useless columns
- fill up the empty rows
- Changing the categories (object -> categories, 'waterfront' -> binary)
- Remove the '?' + '0.0' from sqft_basement

ADD MORE

In [6]:
```
#Deleting useless columns
df_new = df.drop(['id', 'date', 'zipcode', 'lat', 'long'], axis=1)
df_new.head()
```

Out[6]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition	grade	sqft_above	sqft_basement	yr_built	yr_renovated	sqft_li
0	221900.0	3	1.00	1180	5650	1.0	NaN	NONE	Average	7 Average	1180	0.0	1955	0.0	
1	538000.0	3	2.25	2570	7242	2.0	NO	NONE	Average	7 Average	2170	400.0	1951	1991.0	
2	180000.0	2	1.00	770	10000	1.0	NO	NONE	Average	6 Low Average	770	0.0	1933	NaN	
3	604000.0	4	3.00	1960	5000	1.0	NO	NONE	Very Good	7 Average	1050	910.0	1965	0.0	
4	510000.0	3	2.00	1680	8080	1.0	NO	NONE	Average	8 Good	1680	0.0	1987	0.0	

In [7]:
```
#checking for empty rows
df_new.isna().sum()
```

Out[7]:
```
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
sqft_living15       0
sqft_lot15          0
dtype: int64
```

Although it is tempting to just delete the rows with missing data, let's have a conservative approach and fill up the empty rows for now.

In [8]:
```python
df_new.fillna({'waterfront':'NO', 'view': 'NONE', 'yr_renovated': '0'}, inplace=True)
df_new.head()
```

Out[8]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition	grade	sqft_above	sqft_basement	yr_built	yr_renovated	sqft_liv
0	221900.0	3	1.00	1180	5650	1.0	NO	NONE	Average	7 Average	1180	0.0	1955	0	
1	538000.0	3	2.25	2570	7242	2.0	NO	NONE	Average	7 Average	2170	400.0	1951	1991	
2	180000.0	2	1.00	770	10000	1.0	NO	NONE	Average	6 Low Average	770	0.0	1933	0	
3	604000.0	4	3.00	1960	5000	1.0	NO	NONE	Very Good	7 Average	1050	910.0	1965	0	
4	510000.0	3	2.00	1680	8080	1.0	NO	NONE	Average	8 Good	1680	0.0	1987	0	

In [9]:
```python
#checking results
df_new.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 21597 entries, 0 to 21596
Data columns (total 16 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   sqft_lot       21597 non-null  int64
 5   floors         21597 non-null  float64
 6   waterfront     21597 non-null  object
 7   view           21597 non-null  object
 8   condition      21597 non-null  object
 9   grade          21597 non-null  object
 10  sqft_above     21597 non-null  int64
 11  sqft_basement  21597 non-null  object
 12  yr_built       21597 non-null  int64
 13  yr_renovated   21597 non-null  object
```

In [10]:
```python
df_new['view'].isna().sum() == 0
```

Out[10]:
```
True
```

It worked, no more empty rows. Now let's dive deeper into the data preprocessing.

In [11]:
```python
#Writing a for loop in order to get the value count per column for the objects

df_object = df_new[['waterfront', 'view', 'condition', 'grade', 'sqft_basement']]
for col in (df_object):
    print(df_object[col].value_counts(), ':')
    #printing value counts for each 'object'
```

```
NO     21451
YES      146
Name: waterfront, dtype: int64 :
NONE         19485
AVERAGE        957
GOOD           508
FAIR           330
EXCELLENT      317
Name: view, dtype: int64 :
Average      14020
Good          5677
Very Good     1701
Fair           170
Poor            29
Name: condition, dtype: int64 :
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 :
0.0       12826
?           454
600.0       217
500.0       209
700.0       208
          ...
861.0         1
1275.0        1
652.0         1
2240.0        1
506.0         1
Name: sqft_basement, Length: 304, dtype: int64 :
```

In [12]:
```python
#Changing categories using the astype() function
df_new['grade'] = df_new['grade'].astype('category').cat.reorder_categories(['3 Poor', '4 Low', '5 Fair', '6 Low Avera
                                                                              '10 Very Good', '11 Excellent', '12 Luxury
df_new['view'] = df_new['view'].astype('category').cat.reorder_categories(['NONE', 'FAIR', 'AVERAGE', 'GOOD', 'EXCELLE
df_new['condition'] = df_new['condition'].astype('category').cat.reorder_categories(['Poor', 'Average', 'Fair', 'Good'

print(df_new['grade'])
print(df_new['view'])
print(df_new['condition'])
```

```
0            7 Average
1            7 Average
2        6 Low Average
3            7 Average
4               8 Good
             ...
21592           8 Good
21593           8 Good
21594        7 Average
21595           8 Good
21596        7 Average
Name: grade, Length: 21597, dtype: category
Categories (11, object): ['3 Poor', '4 Low', '5 Fair', '6 Low Average', ..., '10 Very Good', '11 Excellent', '12 Lux
ury', '13 Mansion']
0        NONE
1        NONE
2        NONE
3        NONE
4        NONE
```

In [13]:
```
# Assigning numbers to the categories
df_new['view'] = df_new['view'].cat.codes
df_new['condition'] = df_new['condition'].cat.codes
df_new['grade'] = df_new['grade'].cat.codes
df_new.head()
```

Out[13]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition	grade	sqft_above	sqft_basement	yr_built	yr_renovated	sqft_living
0	221900.0	3	1.00	1180	5650	1.0	NO	0	1	4	1180	0.0	1955	0	13
1	538000.0	3	2.25	2570	7242	2.0	NO	0	1	4	2170	400.0	1951	1991	16
2	180000.0	2	1.00	770	10000	1.0	NO	0	1	3	770	0.0	1933	0	27
3	604000.0	4	3.00	1960	5000	1.0	NO	0	4	4	1050	910.0	1965	0	13
4	510000.0	3	2.00	1680	8080	1.0	NO	0	1	5	1680	0.0	1987	0	18

Although the 'waterfront' column contains only 'Yes' or 'No' data, it makes more sense to have a uniform dataset and change it to 0 and 1 (binary).

In [14]:
```
#changing 'waterfront' to a binary colummn
#we already imported sklearn.preprocessing - OrdinalEncoder

#OrdinalEncoding
waterfront_b = df_new[['waterfront']]
enc_waterfront = OrdinalEncoder()
enc_waterfront.fit(waterfront_b)
enc_waterfront.categories_[0]

#counting the values
waterfront_b.value_counts()

#from a non-binary column to an array
waterfront_enc = enc_waterfront.transform(waterfront_b)
waterfront_enc
```

Out[14]:
```
array([[0.],
       [0.],
       [0.],
       ...,
       [0.],
       [0.],
       [0.]])
```

In [15]:
```
#replacing the 'waterfront' colum by the new binary 'waterfront_enc' hotencoded data.

df_new['waterfront'] = waterfront_enc
df_new['waterfront'].value_counts()
#we should have the values 0 and 1
```

Out[15]:
```
0.0    21451
1.0      146
Name: waterfront, dtype: int64
```

In [16]:
```
#checking the values for 'yr_renovated'
df_new['yr_renovated'].value_counts()
```

Out[16]:
```
0.0       17011
0          3842
2014.0       73
2003.0       31
2013.0       31
          ...
1971.0        1
1944.0        1
1934.0        1
1976.0        1
1959.0        1
Name: yr_renovated, Length: 71, dtype: int64
```

Considering that (20853/21597) = 96.56% of the data in the column 'yr_renovated' is equal to 0, we can drop the column.

In [17]:
```
df_new.drop(['yr_renovated'], axis=1)
df_new

#!!!
```

Out[17]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition	grade	sqft_above	sqft_basement	yr_built	yr_renovated	sqft_li
0	221900.0	3	1.00	1180	5650	1.0	0.0	0	1	4	1180	0.0	1955	0	
1	538000.0	3	2.25	2570	7242	2.0	0.0	0	1	4	2170	400.0	1951	1991	
2	180000.0	2	1.00	770	10000	1.0	0.0	0	1	3	770	0.0	1933	0	
3	604000.0	4	3.00	1960	5000	1.0	0.0	0	4	4	1050	910.0	1965	0	
4	510000.0	3	2.00	1680	8080	1.0	0.0	0	1	5	1680	0.0	1987	0	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
21592	360000.0	3	2.50	1530	1131	3.0	0.0	0	1	5	1530	0.0	2009	0	
21593	400000.0	4	2.50	2310	5813	2.0	0.0	0	1	5	2310	0.0	2014	0	
21594	402101.0	2	0.75	1020	1350	2.0	0.0	0	1	4	1020	0.0	2009	0	
21595	400000.0	3	2.50	1600	2388	2.0	0.0	0	1	5	1600	0.0	2004	0	
21596	325000.0	2	0.75	1020	1076	2.0	0.0	0	1	4	1020	0.0	2008	0	

In [18]:
```
df_new.head()
```

Out[18]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition	grade	sqft_above	sqft_basement	yr_built	yr_renovated	sqft_living
0	221900.0	3	1.00	1180	5650	1.0	0.0	0	1	4	1180	0.0	1955	0	13
1	538000.0	3	2.25	2570	7242	2.0	0.0	0	1	4	2170	400.0	1951	1991	16
2	180000.0	2	1.00	770	10000	1.0	0.0	0	1	3	770	0.0	1933	0	27
3	604000.0	4	3.00	1960	5000	1.0	0.0	0	4	4	1050	910.0	1965	0	13
4	510000.0	3	2.00	1680	8080	1.0	0.0	0	1	5	1680	0.0	1987	0	18

In [19]:
```
#removing outliers for 'bedrooms' and 'sqft_living'

df_new = df_new[df_new['bedrooms'] < 10]
df_new = df_new[df_new['sqft_living'] <= 10000]
df_new.describe()
```

Out[19]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition	grade	sqft_a
count	2.158900e+04	21589.000000	21589.000000	21589.000000	2.158900e+04	21589.000000	21589.000000	21589.000000	21589.000000	21589.000000	21589.00
mean	5.395398e+05	3.370189	2.114966	2078.713280	1.508600e+04	1.493932	0.006716	0.232757	1.768401	4.657372	1787.57
std	3.612564e+05	0.898794	0.766518	910.562833	4.137183e+04	0.539577	0.081680	0.763956	1.085727	1.172191	823.93
min	7.800000e+04	1.000000	0.500000	370.000000	5.200000e+02	1.000000	0.000000	0.000000	0.000000	0.000000	370.00
25%	3.220000e+05	3.000000	1.750000	1430.000000	5.040000e+03	1.000000	0.000000	0.000000	1.000000	4.000000	1190.00
50%	4.500000e+05	3.000000	2.250000	1910.000000	7.617000e+03	1.500000	0.000000	0.000000	1.000000	4.000000	1560.00
75%	6.450000e+05	4.000000	2.500000	2550.000000	1.067900e+04	2.000000	0.000000	0.000000	3.000000	5.000000	2210.00
max	6.890000e+06	9.000000	7.750000	9890.000000	1.651359e+06	3.500000	1.000000	4.000000	4.000000	10.000000	8860.00

In [20]:
```
df_new.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 21589 entries, 0 to 21596
Data columns (total 16 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   price          21589 non-null  float64
 1   bedrooms       21589 non-null  int64  
 2   bathrooms      21589 non-null  float64
 3   sqft_living    21589 non-null  int64  
 4   sqft_lot       21589 non-null  int64  
 5   floors         21589 non-null  float64
 6   waterfront     21589 non-null  float64
 7   view           21589 non-null  int8   
 8   condition      21589 non-null  int8   
 9   grade          21589 non-null  int8   
 10  sqft_above     21589 non-null  int64  
 11  sqft_basement  21589 non-null  object 
 12  yr_built       21589 non-null  int64  
 13  yr_renovated   21589 non-null  object 
 14  sqft_living15  21589 non-null  int64  
 15  sqft_lot15     21589 non-null  int64  
dtypes: float64(4), int64(7), int8(3), object(2)
memory usage: 2.4+ MB
```

The column 'sqft_basement' is stored as strings, let's take a look at what the column contains:

In [21]:
```
#value counting the 'sqft_column'
df_new['sqft_basement'].value_counts()
#it contains integers
```

Out[21]:
```
0.0       12826
?           454
600.0       215
500.0       209
700.0       208
          ...  
861.0         1
652.0         1
2240.0        1
1525.0        1
506.0         1
Name: sqft_basement, Length: 301, dtype: int64
```

In order to use the columns with empty rows or unusable data, we need to impute the median:

In [22]:
```
#writing a function to impute the median
def impute_median(df_new, col):
    df_1_col = df_new[[col]]
    df_1_col.fillna(df_1_col.median(), inplace=True)
    df_new[col] = df_1_col[col]
```

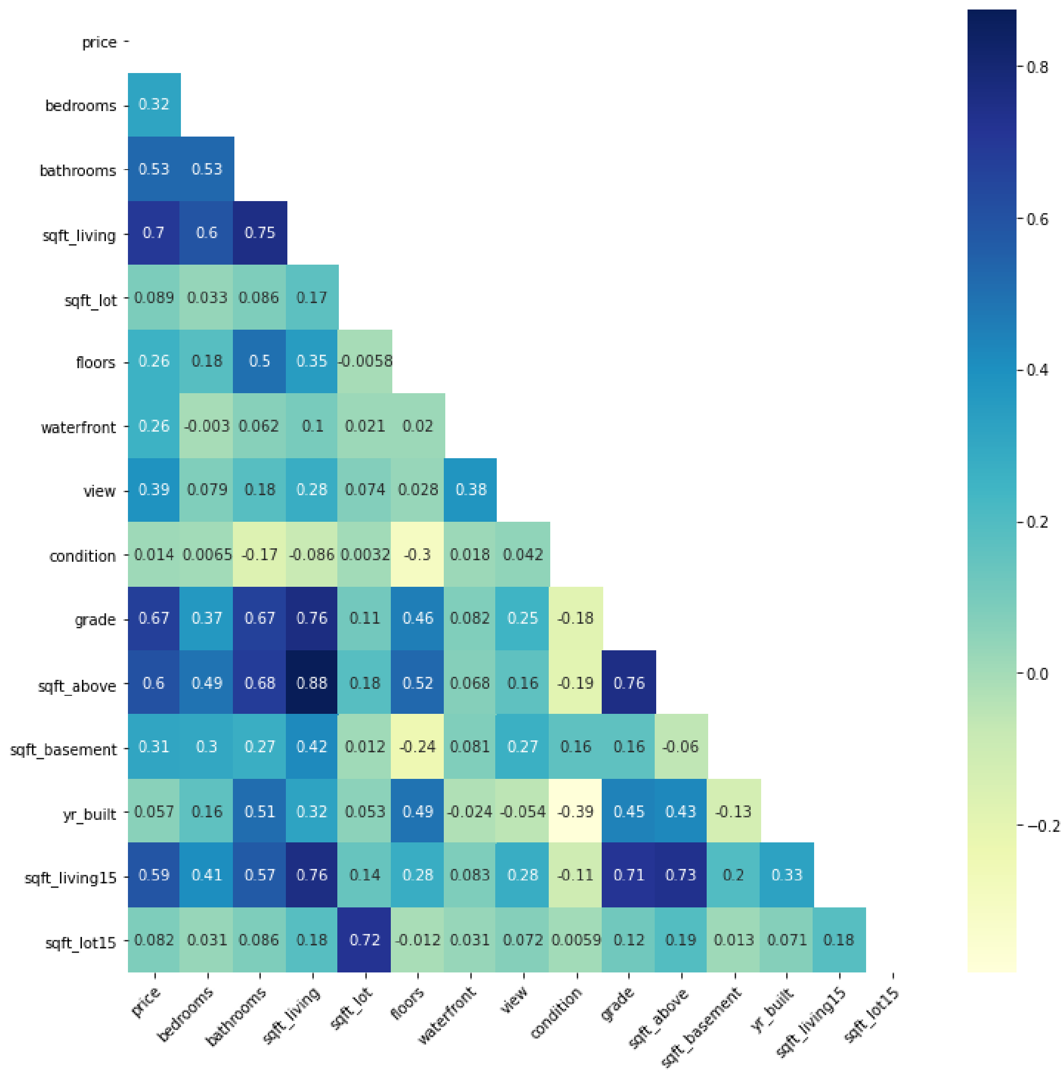
In [23]:
```
#imputing the median for '0.0' and '?' values in 'sqft_basement' and 'yr_renovated'

df_new['sqft_basement'] = df_new.apply(
     lambda row: np.nan if row['sqft_basement'] == '?' else float(row['sqft_basement']),
     axis=1)

impute_median(df_new, 'sqft_basement')
```

In [24]:
```
#or replace 0s in 'sqft_basement'
def replace_0(df_new, col):
    no_zeros = df_new.loc[df_new[col] > 0]
    col_min = no_zeros[col].min()
    offset = col_min/2
    df_new[col] = df_new.apply(lambda row: row[col] + offset, axis=1)

replace_0(df_new, 'sqft_basement')
```

Building the Prediction Model

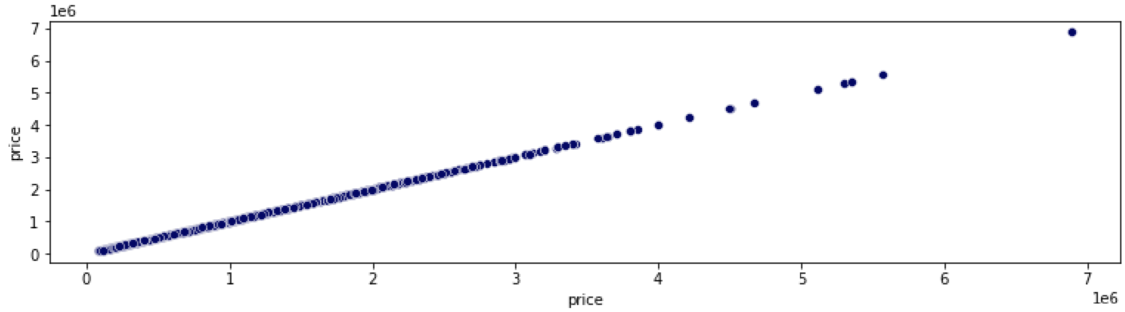
Checking correlations

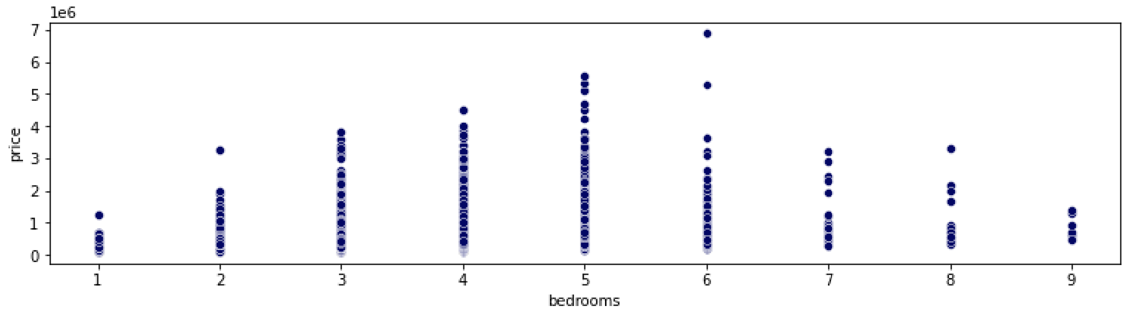
In [25]:
```python
# Visualizing correlations between numerical columns with a seaborn heatmap to show the correlations
fig, ax = plt.subplots(figsize=(12, 12))

corr = df_new.corr()

# Instantiate numpy array of zeroes and assign to `mask`
mask = np.zeros_like(corr,
                     dtype=bool)

# Returns indices from upper triangle of array
mask[np.triu_indices_from(mask)] = True

#plotting the heatmap
sns.heatmap(corr, cmap="YlGnBu", annot=True, mask=mask),
plt.setp(ax.get_xticklabels(),
         rotation=45,
         ha="right",
         rotation_mode="anchor");
```

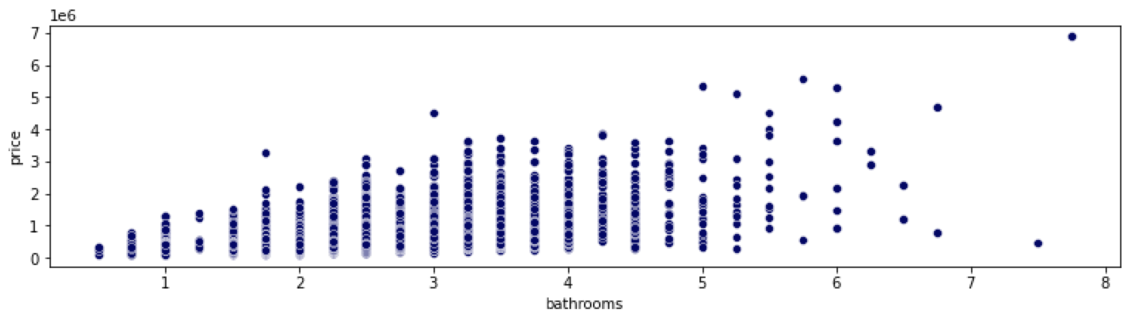


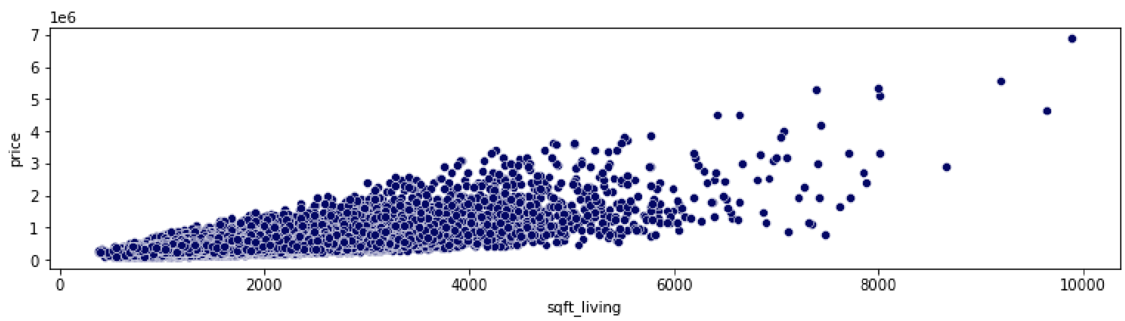
We observe that the variable 'sqft_living' is the variable with the highest correlation (0.7) with the target variable 'price'. From there, we can start a regression model using statsmodel. We also notice the high multicolinearity between sqft_above' and 'sqft_living'.

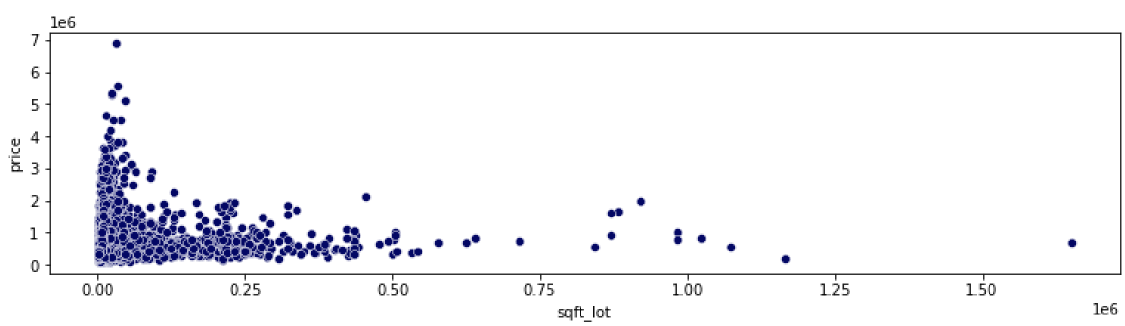
In [26]:
```python
# Using scatter plots to check correlations
for i, col in enumerate(df_new.columns):
    plt.figure(i, figsize=(13,3))
    sns.scatterplot(x=col, y=df_new['price'], data=df_new, color='#030764')

#formatting
import matplotlib.ticker as mtick
fmt = '${x:,.0f}'
tick = mtick.StrMethodFormatter(fmt)
plt.gca().yaxis.set_major_formatter(tick)
```

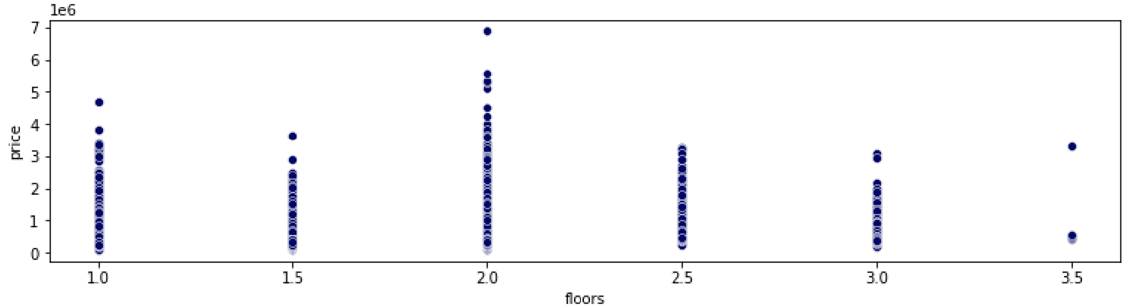


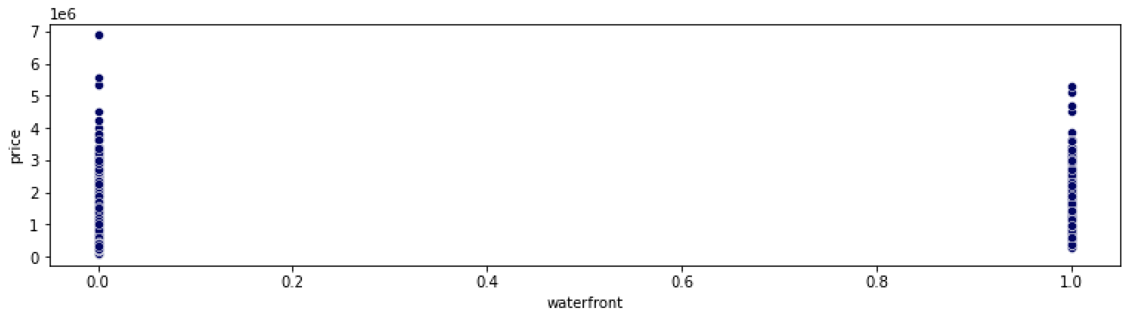


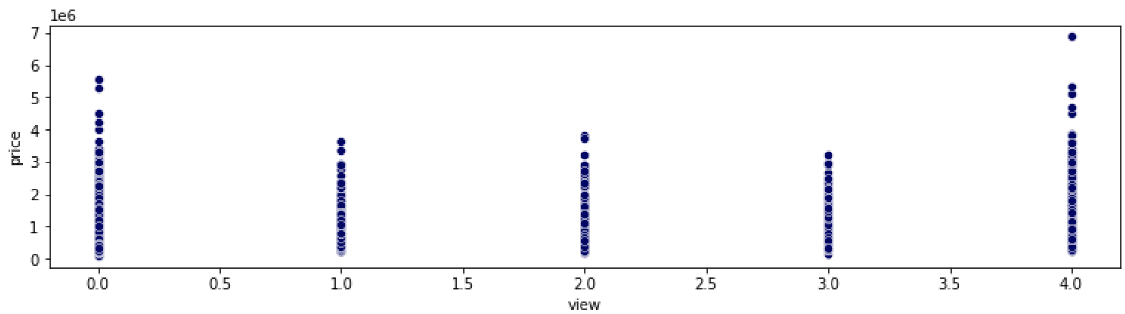


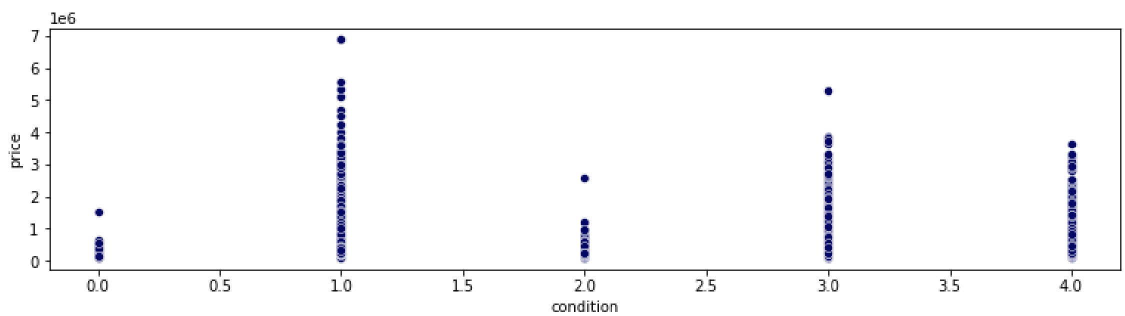


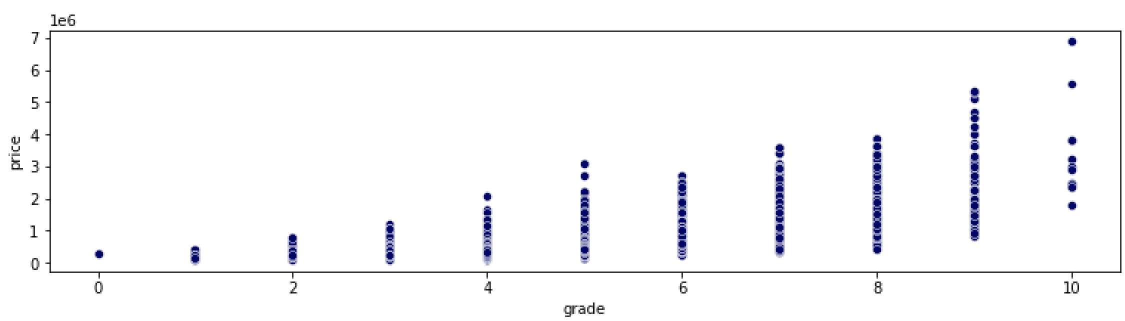


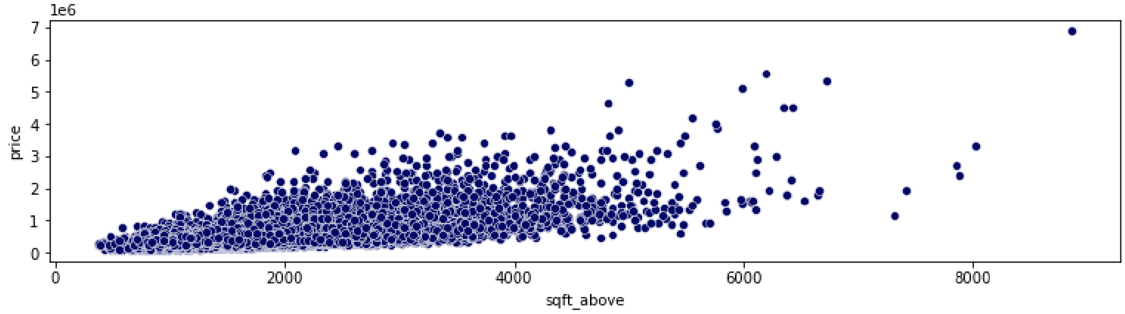

1e6
price
floors

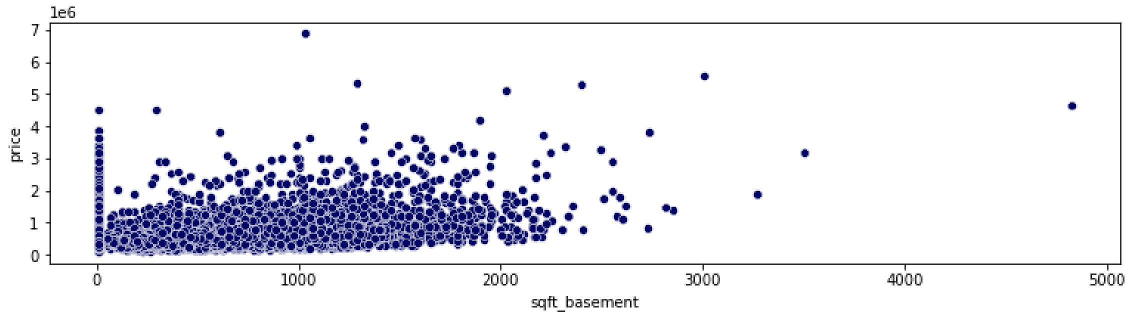

1e6
price
waterfront

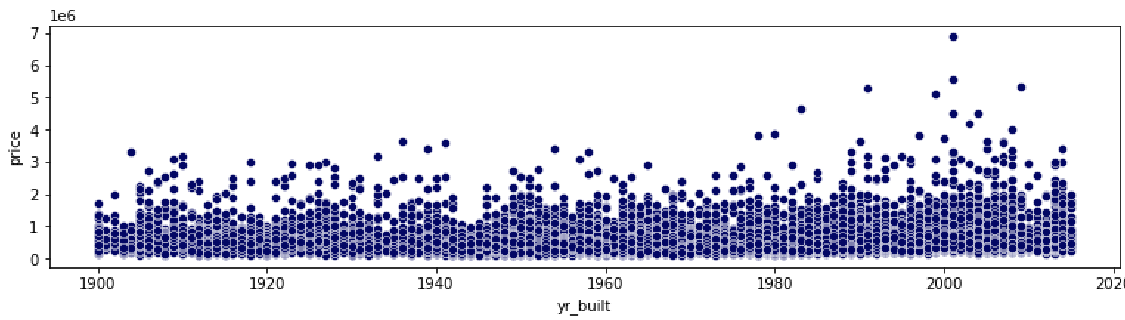

1e6
price
view

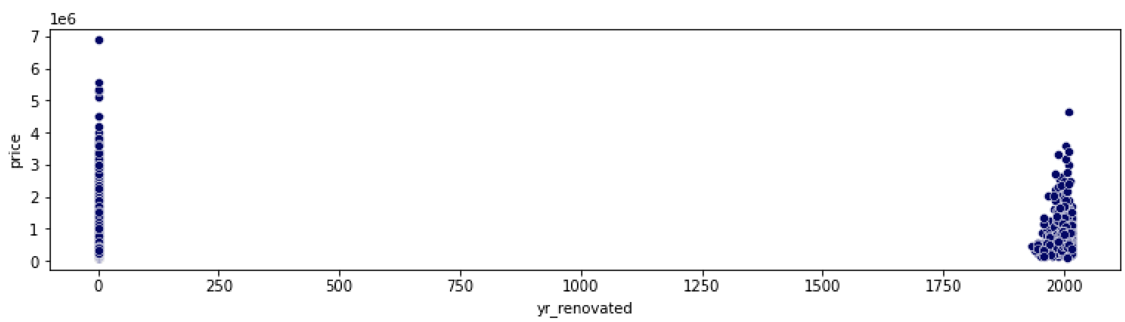

1e6
price
condition

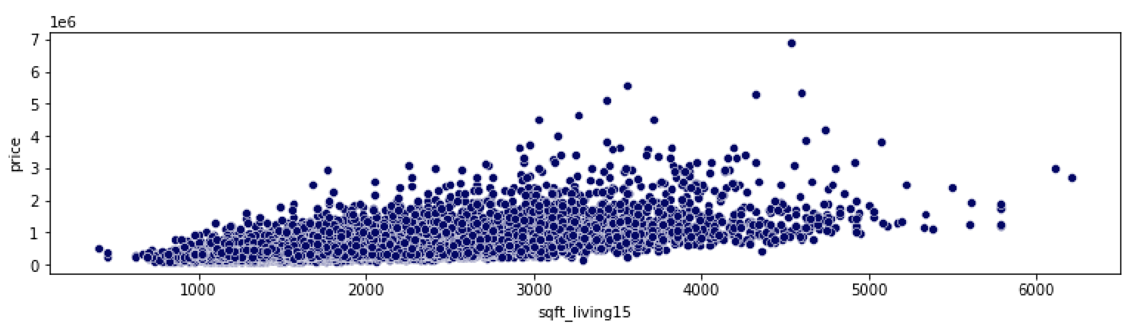

1e6
price
grade

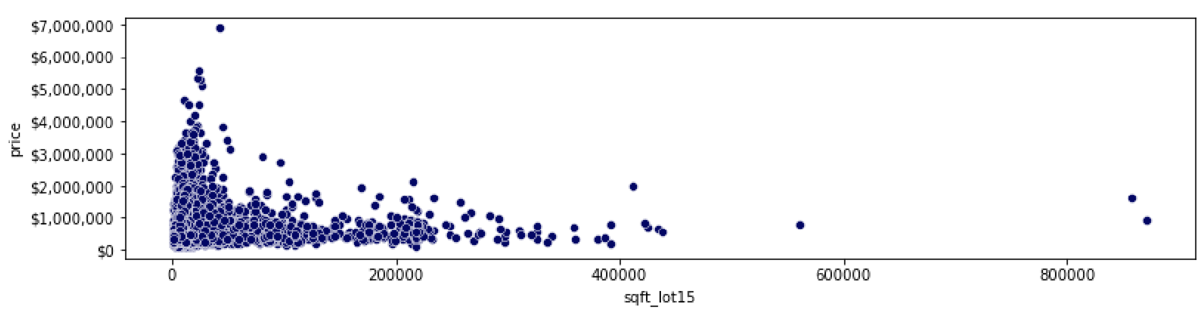

1e6
7
6
5
4
3
2
1
0
price
0
2000
4000
6000
8000
sqft_above


1e6
7
6
5
4
3
2
1
0
price
0
1000
2000
3000
4000
5000
sqft_basement


1e6
7
6
5
4
3
2
1
0
price
1900
1920
1940
1960
1980
2000
2020
yr_built


1e6
7
6
5
4
3
2
1
0
price
0
250
500
750
1000
1250
1500
1750
2000
yr_renovated


1e6
7
6
5
4
3
2
1
0
price
1000
2000
3000
4000
5000
6000
sqft_living15


$7,000,000
$6,000,000
$5,000,000
$4,000,000
$3,000,000
$2,000,000
$1,000,000
$0
price
0
200000
400000
600000
800000
sqft_lot15

REGRESSION MODEL

Checking for linearity

- Our target value is the price. Hence, y = price.

In [27]:
```
#Setting up our base model based on the heatmap correlations (y = target variable
#and X = highest correlated variable) using statsmodel.

y_samp = df_new['price']
X_samp = df_new['sqft_living']

#Now let's calculate the slope of the fit line (beta1) and the
beta1 = np.cov(X_samp, y_samp)[0][1]/X_samp.var()
#indexing by 0 and 1 as we want to get the only 2 relevant value of the covariance matrix
beta2 = y_samp.mean() - beta1*X_samp.mean()
```

In [28]:
```
#Covariance matrix
np.cov(X_samp, y_samp)
```

Out[28]:
```
array([[8.29124672e+05, 2.30117097e+08],
       [2.30117097e+08, 1.30506154e+11]])
```

In [29]:
```
#the slope
beta1
```

Out[29]:
```
277.54221363577267
```

In [30]:
```
#the constant
beta2
```

Out[30]:
```
-37390.868739979574
```

Checking the best fit line

Adding a constant to x in order for it to fit the model

In [31]:
```
#designing the X independant variable for the linear regression
X = df_new['sqft_living']
```

In [32]:
```
#showing the matrix of features
X
```

Out[32]:
```
0        1180
1        2570
2         770
3        1960
4        1680
         ...
21592    1530
21593    2310
21594    1020
21595    1600
21596    1020
Name: sqft_living, Length: 21589, dtype: int64
```

In [33]:
```
#Let's fit the data
results = sm.OLS(y_samp, sm.add_constant(X)).fit()
```

In [34]:
```
#Now let's look at the overall report of our fitted data
results.params
```

Out[34]:
```
const          -37390.868740
sqft_living       277.542214
dtype: float64
```

In [35]:
```
#OLS regression results
results.summary()
#R2 = 0.489
```

Out[35]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.489
Model:	OLS	**Adj. R-squared:**	0.489
Method:	Least Squares	**F-statistic:**	2.069e+04
Date:	Mon, 19 Dec 2022	**Prob (F-statistic):**	0.00
Time:	13:27:27	**Log-Likelihood:**	-2.9966e+05
No. Observations:	21589	**AIC:**	5.993e+05
Df Residuals:	21587	**BIC:**	5.993e+05
Df Model:	1		
Covariance Type:	nonrobust		

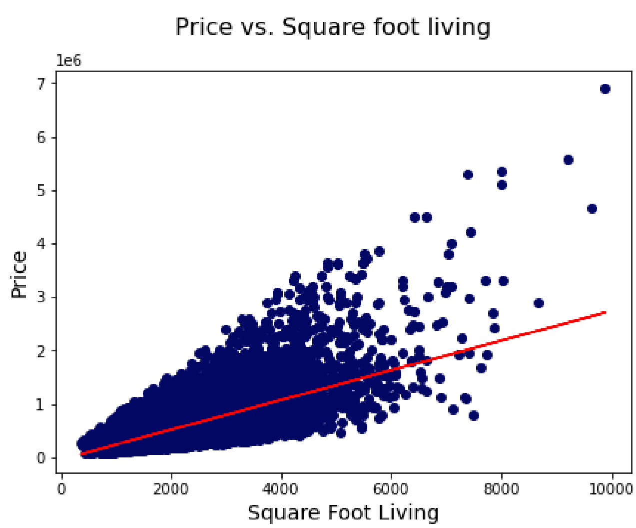
	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
const	-3.739e+04	4378.923	-8.539	0.000	-4.6e+04	-2.88e+04
sqft_living	277.5422	1.930	143.837	0.000	273.760	281.324

Omnibus:	13425.398	**Durbin-Watson:**	1.980
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	331839.191
Skew:	2.568	**Prob(JB):**	0.00
Kurtosis:	21.507	**Cond. No.**	5.66e+03

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 5.66e+03. This might indicate that there are
strong multicollinearity or other numerical problems.

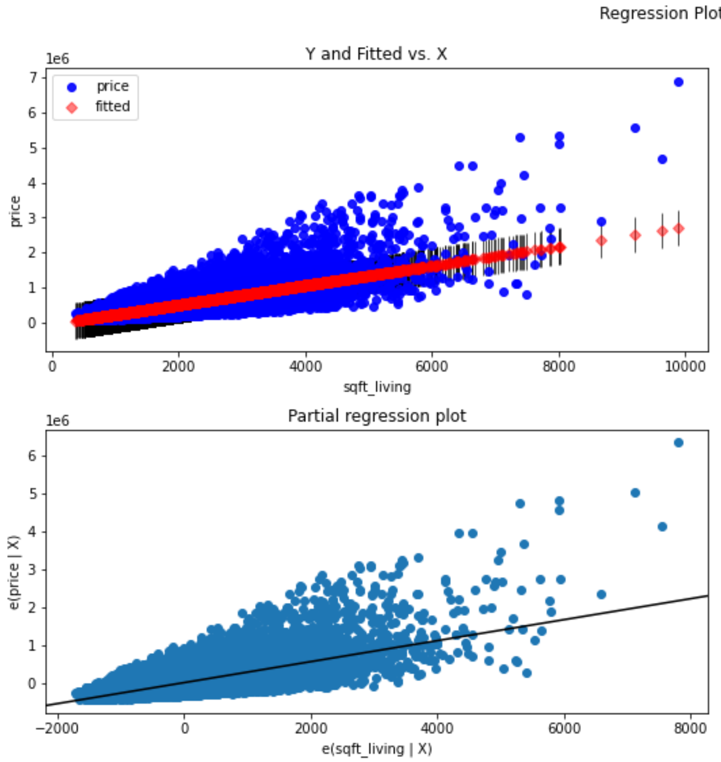
The R2 value here is 0.489, which is the measure of a goodness of fit, which in other word explains the variance between our target variable 'price' and independant variable 'sqft_living'.

In [36]:
```
m, c = np.polyfit(X, y_samp, 1) #setting variables for line
fig = plt.figure(figsize=(7, 5)) #Plotting figure
fig.suptitle('Price vs. Square foot living', fontsize=16) #Setting title
plt.scatter(X, y_samp, color='#030764') #Plotting scatterpoints for X and Y
plt.plot(X, m*X+c, c='red') #Plotting line
plt.xlabel('Square Foot Living', fontsize=14) #Setting label for X
plt.ylabel('Price', fontsize=14) #Setting label for Y
plt.show()
```

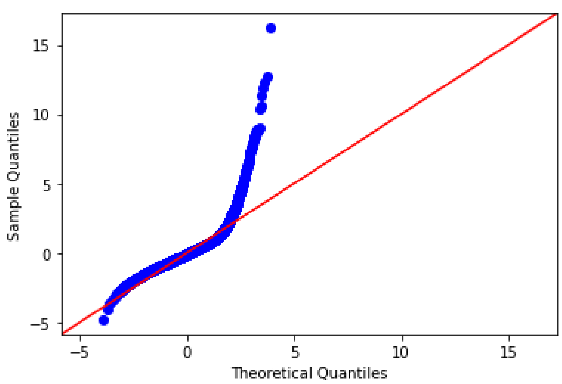


Checking for Normality + Homoscedasticity for the Linear Regression model

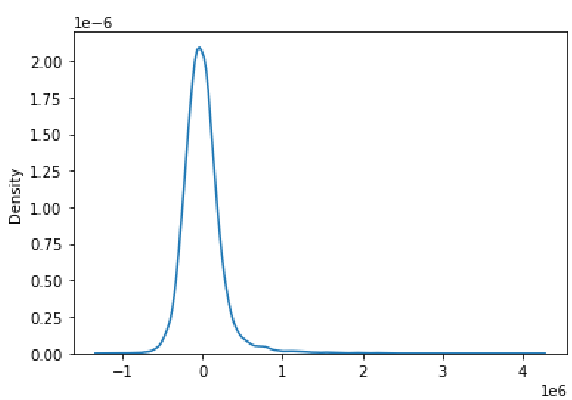
In [37]:
```
fig = plt.figure(figsize=(15,8))
fig = sm.graphics.plot_regress_exog(results, "sqft_living", fig=fig)
plt.show()
```



In [38]:
```
#qqplot of the residuals
import scipy.stats as stats
resids = results.resid
sm.graphics.qqplot(resids, dist=stats.norm, line='45', fit=True)
plt.show()
```



In [39]:
```
#Normality check
sns.kdeplot(x=results.resid);
```



Conclusion is that the normality assumption criteria is not met, because the blue line is not following the red line in the qq plot. Therefore, we need to add more variables.

Modeling with multiple features: Multicolinearity Model 1

In [40]:
```
#Find design matrix for linear regression model using all the variables with 'price' as target variable
y, X = dmatrices('price ~ bedrooms+bathrooms+sqft_living+sqft_lot+floors+waterfront+view+condition+grade+sqft_above+sq

#calculate VIF for each explanatory variable
vif = pd.DataFrame()
vif['VIF'] = [variance_inflation_factor(X.values, i) for i in range(len(X.columns))]
vif['variable'] = X.columns

#view VIF for each explanatory variable
vif.sort_values('VIF', ascending=False)
```

Out[40]:

	VIF	variable
0	7865.615191	Intercept
3	144.334968	sqft_living
10	117.788693	sqft_above
11	32.802228	sqft_basement
2	3.292806	bathrooms
9	3.248202	grade
13	2.810946	sqft_living15
5	1.935039	floors
12	1.821348	yr_built
1	1.701750	bedrooms
7	1.371898	view
8	1.226496	condition
6	1.175133	waterfront
4	1.061324	sqft_lot

As expected, the 3 variables 'sqft_above', 'sqft_living' and 'sqft_basement' have a very high variance inflation factor.

Include interpretation of the values

In [41]:
```
#Adding variables that have a correlation > 0.5 on the heatmap
X_m1 = pd.DataFrame(data=df_new, columns=['sqft_living15', 'sqft_above', 'grade', 'sqft_living', 'bathrooms'])
#setting target variable
y = df_new['price']
X_m1.head()
```

Out[41]:

	sqft_living15	sqft_above	grade	sqft_living	bathrooms
0	1340	1180	4	1180	1.00
1	1690	2170	4	2570	2.25
2	2720	770	3	770	1.00
3	1360	1050	4	1960	3.00
4	1800	1680	5	1680	2.00

In [42]:
```
#Mutilcolinearity check for the 5 variables that have correlation > 0.5 on the heatmap
Multi1 = sm.OLS(y, sm.add_constant(X_m1)).fit()
Multi1.summary()
#R2 = 0.545
```

Out[42]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.545
Model:	OLS	**Adj. R-squared:**	0.545
Method:	Least Squares	**F-statistic:**	5177.
Date:	Mon, 19 Dec 2022	**Prob (F-statistic):**	0.00
Time:	13:27:29	**Log-Likelihood:**	-2.9841e+05
No. Observations:	21589	**AIC:**	5.968e+05
Df Residuals:	21583	**BIC:**	5.969e+05
Df Model:	5		
Covariance Type:	nonrobust		

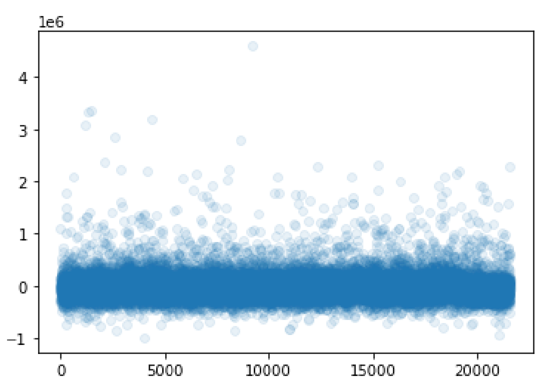
	coef	std err	t	P>|t|	[0.025	0.975]
const	-3.183e+05	7446.950	-42.748	0.000	-3.33e+05	-3.04e+05
sqft_living15	27.7774	3.971	6.995	0.000	19.994	35.560
sqft_above	-81.3410	4.381	-18.567	0.000	-89.928	-72.754
grade	1.137e+05	2431.264	46.759	0.000	1.09e+05	1.18e+05
sqft_living	235.6605	4.482	52.576	0.000	226.875	244.446
bathrooms	-3.368e+04	3382.944	-9.955	0.000	-4.03e+04	-2.7e+04

Omnibus:	15258.361	**Durbin-Watson:**	1.975
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	586320.205
Skew:	2.939	**Prob(JB):**	0.00
Kurtosis:	27.844	**Cond. No.**	1.67e+04

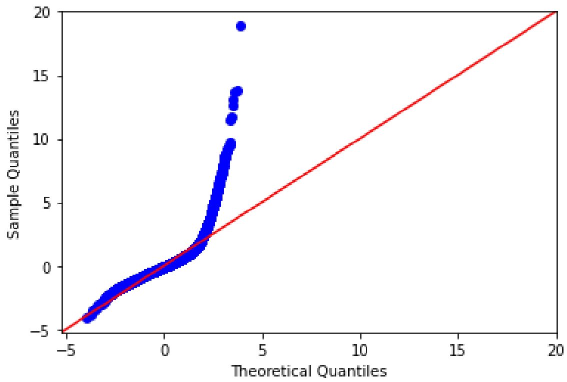
Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 1.67e+04. This might indicate that there are
strong multicollinearity or other numerical problems.

The P-values are much lower than our alpha (0.05) so there seems to be a statistical relationship between our variables and the price.

In [43]:
```
#Plotting scatterplot for check of multicolinearity before log transform
resid0 = Multi1.resid #Setting residuals

plt.scatter(x=range(resid0.shape[0]), y=resid0, alpha=0.1); #Plotting scatterplot for check
```



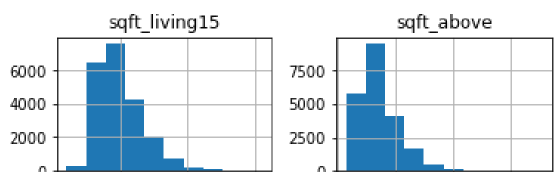
In [44]:
```
#Plotting the residuals for resids1
fig = sm.graphics.qqplot(resid0, dist=stats.norm, line='45', fit=True)
fig.show()
```



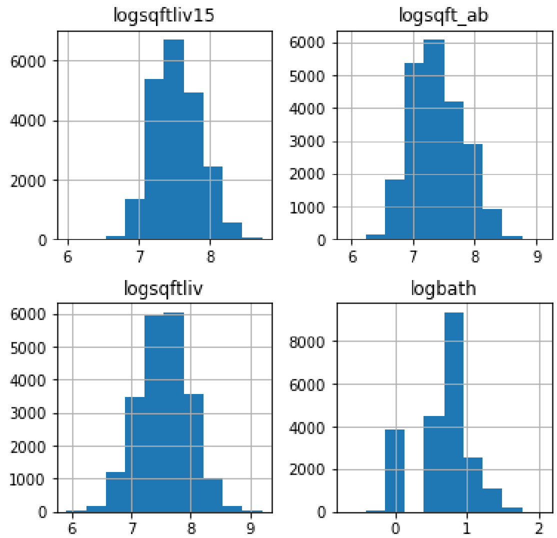
Homoskedasticity + normality check: Log transformation

In [45]:
```
#looking at the normality of the raw features
X_m1.hist(figsize  = [6, 6]);
print("Skewness:", X_m1.skew())
print("Kurtosis:", X_m1.kurtosis())
```

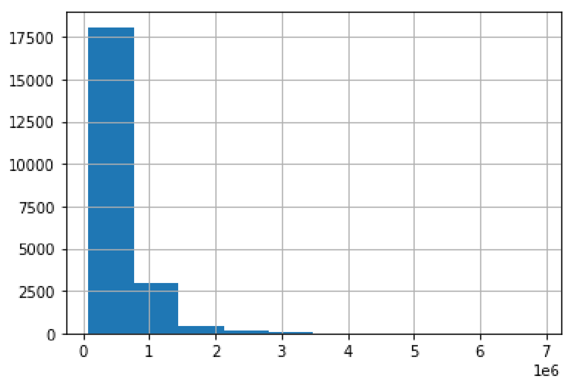
```
Skewness: sqft_living15    1.105218
sqft_above        1.392355
grade             0.784108
sqft_living       1.330630
bathrooms         0.481693
dtype: float64
Kurtosis: sqft_living15    1.587059
sqft_above        2.861298
grade             1.120526
sqft_living       3.439566
bathrooms         0.999164
dtype: float64
```



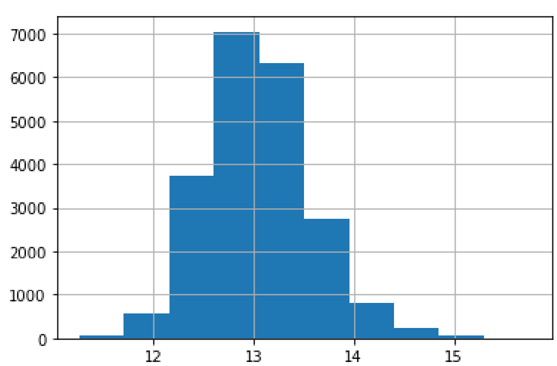
In [46]:
```
#log transforming in order to normalize data (except for 'grade' that already has a normal distribution)
X_m1_log = pd.DataFrame([])
X_m1_log['logsqftliv15'] = np.log(X_m1['sqft_living15'])
X_m1_log['logsqft_ab'] = np.log(X_m1['sqft_above'])
X_m1_log['logsqftliv'] = np.log(X_m1['sqft_living'])
X_m1_log['logbath'] = np.log(X_m1['bathrooms'])

X_m1_log.hist(figsize  = [6, 6]);
```



In [47]:
```
y.hist();
```



In [48]:
```
# Log transforming y (=price)
ylog = np.log(y)
ylog.hist(); #Checking log transformation
```



In [49]:
```
#Mutilcolinearity check for the 5 variables that have correlation > 0.5 on heatmap (X_m1)
Multi1 = sm.OLS(ylog, sm.add_constant(X_m1)).fit()
Multi1.summary()
#R2 = 0.569
#P-values < alpha level of 0.05.
```

Out[49]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.569
Model:	OLS	**Adj. R-squared:**	0.569
Method:	Least Squares	**F-statistic:**	5698.
Date:	Mon, 19 Dec 2022	**Prob (F-statistic):**	0.00
Time:	13:27:30	**Log-Likelihood:**	-7671.6
No. Observations:	21589	**AIC:**	1.536e+04
Df Residuals:	21583	**BIC:**	1.540e+04
Df Model:	5		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	11.6703	0.011	1105.800	0.000	11.650	11.691
sqft_living15	9.037e-05	5.63e-06	16.059	0.000	7.93e-05	0.000
sqft_above	-0.0001	6.21e-06	-23.384	0.000	-0.000	-0.000
grade	0.1911	0.003	55.474	0.000	0.184	0.198
sqft_living	0.0003	6.35e-06	44.636	0.000	0.000	0.000
bathrooms	-0.0104	0.005	-2.175	0.030	-0.020	-0.001

Omnibus:	27.986	**Durbin-Watson:**	1.973
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	27.704
Skew:	0.079	**Prob(JB):**	9.64e-07
Kurtosis:	2.922	**Cond. No.**	1.67e+04

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 1.67e+04. This might indicate that there are
strong multicollinearity or other numerical problems.

In [50]:
```
#Save absolute value of correlation matrix as a data frame
#Converts all values to absolute value
#Stacks the row:column pairs into a multindex
#Reset the index to set the multindex to seperate columns
#Sort values. 0 is the column automatically generated by the stacking

df_multi=X_m1.corr().abs().stack().reset_index().sort_values(0, ascending=False)

#Zip the variable name columns (named level_0 and level_1 by default) in a new column named "pairs"
df_multi['pairs'] = list(zip(df_multi.level_0, df_multi.level_1))

#Set index to pairs
df_multi.set_index(['pairs'], inplace = True)

#Drop level columns
df_multi.drop(columns=['level_1', 'level_0'], inplace = True)

#Rename correlation column as cor rather than 0
df_multi.columns = ['cor']

#Drop duplicates. This is dangerous if there are variables perfectly correlated with variables other than themselves.
df_multi.drop_duplicates(inplace=True)

df_multi[(df_multi.cor > .75) & (df_multi.cor <1)]
```

Out[50]:

pairs	cor
(sqft_above, sqft_living)	0.875386
(sqft_living, grade)	0.764354
(sqft_living, sqft_living15)	0.758302
(grade, sqft_above)	0.756236
(sqft_living, bathrooms)	0.754499

Let's concatenate the 'grade' column with the X_m1_log data

In [51]:
```
#df_new_log contains all the X_m1 variables except 'grade' that didn't need to be logged transformed
#concatenate logged transformed data with unlogged data 'grade'

df_new_log = pd.concat([X_m1_log, X_m1['grade']], axis=1)
df_new_log.head()
```

Out[51]:

	logsqftliv15	logsqft_ab	logsqftliv	logbath	grade
0	7.200425	7.073270	7.073270	0.000000	4
1	7.432484	7.682482	7.851661	0.810930	4
2	7.908387	6.646391	6.646391	0.000000	3
3	7.215240	6.956545	7.580700	1.098612	4
4	7.495542	7.426549	7.426549	0.693147	5

In [52]:
```
#Now let's look at the new model
Multi1 = sm.OLS(ylog, sm.add_constant(df_new_log)).fit()
Multi1.summary()
#R2 = 0.562
#P-values < alpha level 0.05
```

Out[52]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.562
Model:	OLS	**Adj. R-squared:**	0.562
Method:	Least Squares	**F-statistic:**	5530.
Date:	Mon, 19 Dec 2022	**Prob (F-statistic):**	0.00
Time:	13:27:30	**Log-Likelihood:**	-7853.4
No. Observations:	21589	**AIC:**	1.572e+04
Df Residuals:	21583	**BIC:**	1.577e+04
Df Model:	5		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	8.2369	0.081	101.919	0.000	8.078	8.395
logsqftliv15	0.1968	0.012	17.082	0.000	0.174	0.219
logsqft_ab	-0.2523	0.012	-21.605	0.000	-0.275	-0.229
logsqftliv	0.5645	0.013	42.081	0.000	0.538	0.591
logbath	-0.0803	0.009	-8.470	0.000	-0.099	-0.062
grade	0.2116	0.003	63.632	0.000	0.205	0.218

Omnibus:	51.714	**Durbin-Watson:**	1.976
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	51.966
Skew:	0.117	**Prob(JB):**	5.20e-12
Kurtosis:	2.949	**Cond. No.**	476.

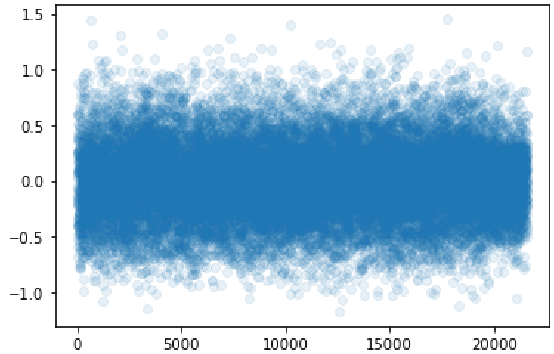
Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Checking for Normality + Homoscedasticity

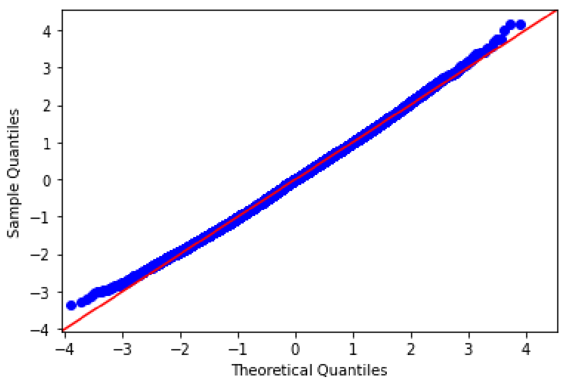
In [53]:
```
#Let's fit the data for homoscedasticity and normality checks
resids1 = Multi1.resid
resids1
```

Out[53]:
```
0       -0.398234
1        0.221146
2       -0.401962
3        0.372517
4        0.109667
           ...
21592   -0.159548
21593   -0.218039
21594    0.272328
21595   -0.052083
21596    0.059450
Length: 21589, dtype: float64
```

In [54]:
```
#Plotting scatterplot for check
plt.scatter(x=range(resids1.shape[0]), y=resids1, alpha=0.1);
```



In [55]:
```
#Plotting the residuals for resids1
fig = sm.graphics.qqplot(resids1, dist=stats.norm, line='45', fit=True)
fig.show()
```



Multicolinearity check Model 2

In [56]:
```
#removing 'sqft_above' from dataset to remove multicolinearty
X_m2 = X_m1.drop(columns = 'sqft_living')
y = df_new['price'] #setting target variable
X_m2.head()
```

Out[56]:

	sqft_living15	sqft_above	grade	bathrooms
0	1340	1180	4	1.00
1	1690	2170	4	2.25
2	2720	770	3	1.00
3	1360	1050	4	3.00
4	1800	1680	5	2.00

In [57]:
```
#Mutilcolinearity check
Multi2 = sm.OLS(ylog, sm.add_constant(X_m2)).fit()
Multi2.summary()
#R2 = 0.529
```

Out[57]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.529
Model:	OLS	**Adj. R-squared:**	0.529
Method:	Least Squares	**F-statistic:**	6064.
Date:	Mon, 19 Dec 2022	**Prob (F-statistic):**	0.00
Time:	13:27:30	**Log-Likelihood:**	-8624.7
No. Observations:	21589	**AIC:**	1.726e+04
Df Residuals:	21584	**BIC:**	1.730e+04
Df Model:	4		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
const	11.5742	0.011	1071.879	0.000	11.553	11.595
sqft_living15	0.0002	5.64e-06	28.598	0.000	0.000	0.000
sqft_above	1.343e-05	5.32e-06	2.525	0.012	3e-06	2.39e-05
grade	0.2098	0.004	58.696	0.000	0.203	0.217
bathrooms	0.0719	0.005	15.536	0.000	0.063	0.081

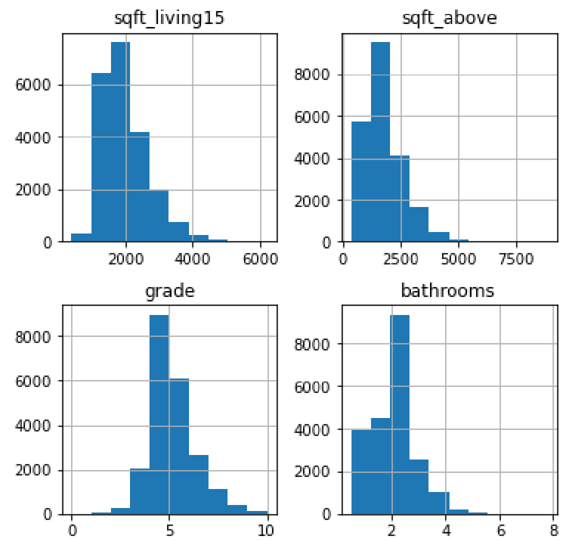
Omnibus:	99.622	**Durbin-Watson:**	1.965
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	96.758
Skew:	0.145	**Prob(JB):**	9.75e-22
Kurtosis:	2.845	**Cond. No.**	1.28e+04

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 1.28e+04. This might indicate that there are
strong multicollinearity or other numerical problems.

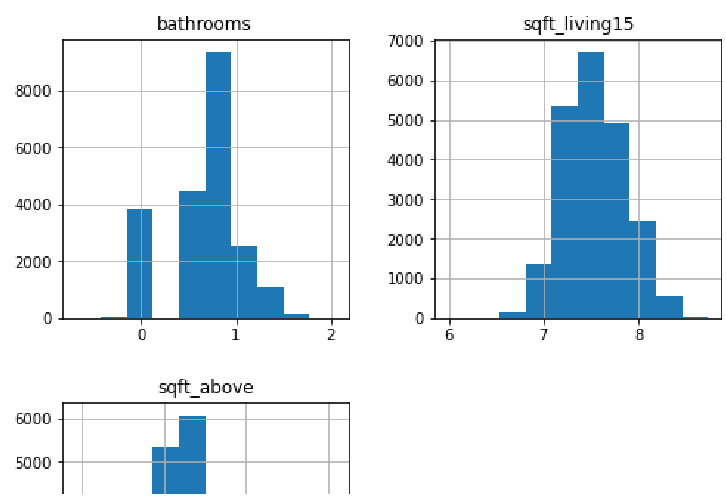
Checking for Normality + Homoscedasticity

In [58]:
```python
#looking at the normality of the raw features
X_m2.hist(figsize = [6, 6]);
print("Skewness:", X_m2.skew())
print("Kurtosis:", X_m2.kurtosis())
```

```
Skewness: sqft_living15    1.105218
sqft_above       1.392355
grade            0.784108
bathrooms        0.481693
dtype: float64
Kurtosis: sqft_living15    1.587059
sqft_above       2.861298
grade            1.120526
bathrooms        0.999164
dtype: float64
```



In [59]:
```python
#log transforming in order to normalize data (except for grade that already has a normal distribution)
X_m2_log = pd.DataFrame([])
X_m2_log['bathrooms'] = np.log(X_m2['bathrooms'])
X_m2_log['sqft_living15'] = np.log(X_m2['sqft_living15'])
X_m2_log['sqft_above'] = np.log(X_m2['sqft_above'])
X_m2_log.hist(figsize = [8, 8]);
```



Repeating the same process of concatenatingf or 'grade' that doesn't need to be log transformed:

In [60]:
```python
#df_new_log2 contains all the X_m2 variables except 'grade' that didn't need to be logged transformed
df_new_log2 = pd.concat([X_m2_log, X_m2['grade']], axis=1)
df_new_log2.head()
```

Out[60]:

	bathrooms	sqft_living15	sqft_above	grade
0	0.000000	7.200425	7.073270	4
1	0.810930	7.432484	7.682482	4
2	0.000000	7.908387	6.646391	3
3	1.098612	7.215240	6.956545	4
4	0.693147	7.495542	7.426549	5

In [61]:
```python
#checking multicolinearity for df_new_log2 and ylog
Multi2 = sm.OLS(ylog, sm.add_constant(df_new_log2)).fit()
Multi2.summary()
#R2 = 0.526
#P-values < 0.05 except for 'sqft_above'
```

Out[61]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.526
Model:	OLS	**Adj. R-squared:**	0.526
Method:	Least Squares	**F-statistic:**	5980.
Date:	Mon, 19 Dec 2022	**Prob (F-statistic):**	0.00
Time:	13:27:30	**Log-Likelihood:**	-8704.6
No. Observations:	21589	**AIC:**	1.742e+04
Df Residuals:	21584	**BIC:**	1.746e+04
Df Model:	4		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	9.2205	0.080	114.578	0.000	9.063	9.378
bathrooms	0.0836	0.009	9.296	0.000	0.066	0.101
sqft_living15	0.3400	0.011	29.701	0.000	0.318	0.362
sqft_above	0.0207	0.010	2.046	0.041	0.001	0.040
grade	0.2265	0.003	65.856	0.000	0.220	0.233

Omnibus:	89.164	**Durbin-Watson:**	1.966
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	89.137
Skew:	0.149	**Prob(JB):**	4.41e-20
Kurtosis:	2.900	**Cond. No.**	383.

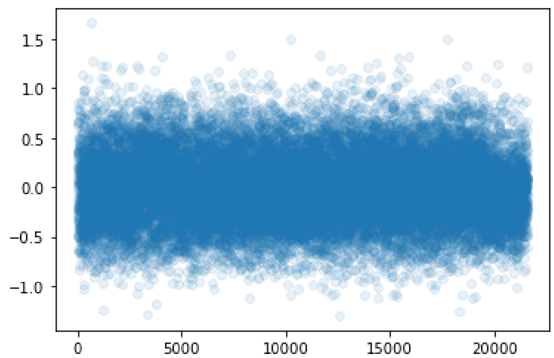
Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Checking for Homoscedasticity

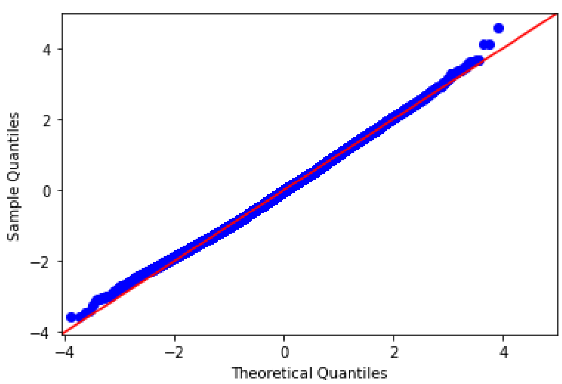
In [62]:
```
#Let's fit the data
resids2 = Multi2.resid
resids2
```

Out[62]:
```
0       -0.410445
1        0.315943
2       -0.625117
3        0.496474
4        0.029720
           ...
21592   -0.280049
21593   -0.244071
21594    0.303849
21595   -0.147844
21596    0.090971
Length: 21589, dtype: float64
```

In [63]:
```
#Plotting scatterplot for check
plt.scatter(x=range(resids2.shape[0]), y=resids2, alpha=0.1);
```



In [64]:
```
#Plotting the residuals for resids1
fig = sm.graphics.qqplot(resids2, dist=stats.norm, line='45', fit=True)
fig.show()
```



Stakeholder : home owners

Interpretation

Multicolinearity Model 3

In [65]:
```
#Creating another variable with correlation below 0.2 from heatmap -- correct: looking at 'condition'
X_m3 = df_new.drop(columns = ['price','sqft_living', 'sqft_lot', 'condition', 'yr_built', 'yr_renovated', 'sqft_lot15'
                              'floors', 'waterfront'])
y = df_new['price']
X_m3.head()
```

Out[65]:

	bedrooms	bathrooms	view	grade	sqft_above	sqft_basement	sqft_living15
0	3	1.00	0	4	1180	5.0	1340
1	3	2.25	0	4	2170	405.0	1690
2	2	1.00	0	3	770	5.0	2720
3	4	3.00	0	4	1050	915.0	1360
4	3	2.00	0	5	1680	5.0	1800

In [66]:
```
#checking model with low correlation data
Multi3 = sm.OLS(ylog, sm.add_constant(X_m3)).fit()
Multi3.summary()
#R2 = 0.582
```

Out[66]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.582
Model:	OLS	**Adj. R-squared:**	0.582
Method:	Least Squares	**F-statistic:**	4288.
Date:	Mon, 19 Dec 2022	**Prob (F-statistic):**	0.00
Time:	13:27:31	**Log-Likelihood:**	-7347.1
No. Observations:	21589	**AIC:**	1.471e+04
Df Residuals:	21581	**BIC:**	1.477e+04
Df Model:	7		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	11.7451	0.013	891.829	0.000	11.719	11.771
bedrooms	-0.0138	0.003	-4.168	0.000	-0.020	-0.007
bathrooms	0.0019	0.005	0.400	0.689	-0.007	0.011
view	0.0854	0.003	26.147	0.000	0.079	0.092
grade	0.1820	0.003	52.694	0.000	0.175	0.189
sqft_above	0.0001	6.02e-06	23.857	0.000	0.000	0.000
sqft_basement	0.0003	6.77e-06	37.558	0.000	0.000	0.000
sqft_living15	7.4e-05	5.58e-06	13.258	0.000	6.31e-05	8.49e-05

Omnibus:	15.346	**Durbin-Watson:**	1.970
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	14.295
Skew:	0.033	**Prob(JB):**	0.000787
Kurtosis:	2.893	**Cond. No.**	1.67e+04

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 1.67e+04. This might indicate that there are
strong multicollinearity or other numerical problems.

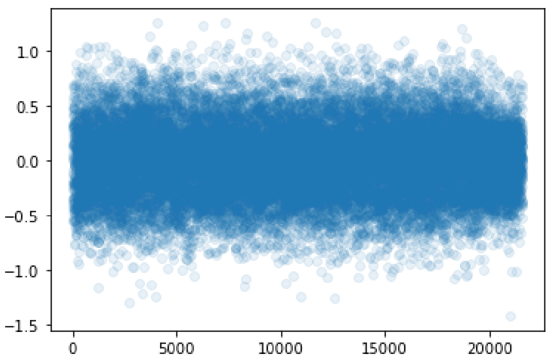
The R2 has gone up to 0.582 which shows that we are moving towards the right direction in removing colinearity.

Checking for Homoscedasticity + normality

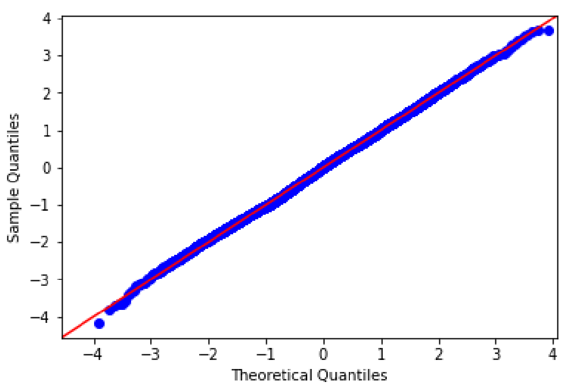
In [67]:
```
#Let's fit the data
resids3 = Multi3.resid
resids3
```

Out[67]:
```
0       -0.393643
1        0.219779
2       -0.477930
3        0.403577
4        0.148704
           ...
21592   -0.159033
21593   -0.174091
21594    0.234140
21595   -0.054849
21596    0.021262
Length: 21589, dtype: float64
```

In [68]:
```
#Plotting scatterplot for check
plt.scatter(x=range(resids3.shape[0]), y=resids3, alpha=0.1);
```



In [69]:
```
#Plotting the residuals for resids3
fig = sm.graphics.qqplot(resids3, dist=stats.norm, line='45', fit=True)
fig.show()
```



In [70]:
```
#multicolinearity check for X_m3
X_m3.corr()
```

Out[70]:

	bedrooms	bathrooms	view	grade	sqft_above	sqft_basement	sqft_living15
bedrooms	1.000000	0.527954	0.079254	0.367447	0.493350	0.301024	0.405936
bathrooms	0.527954	1.000000	0.183069	0.665281	0.684864	0.273268	0.569228
view	0.079254	0.183069	1.000000	0.247552	0.162672	0.267902	0.277595
grade	0.367447	0.665281	0.247552	1.000000	0.756236	0.162896	0.713415
sqft_above	0.493350	0.684864	0.162672	0.756236	1.000000	-0.059955	0.732040
sqft_basement	0.301024	0.273268	0.267902	0.162896	-0.059955	1.000000	0.196842
sqft_living15	0.405936	0.569228	0.277595	0.713415	0.732040	0.196842	1.000000

On the model above we can see that 'sqft_above' and 'grade" have a correlaiton of 75.6%.

In [71]:
```
# save absolute value of correlation matrix as a data frame
# converts all values to absolute value
# stacks the row:column pairs into a multindex
# reset the index to set the multindex to seperate columns
# sort values. 0 is the column automatically generated by the stacking

df_multi=X_m3.corr().abs().stack().reset_index().sort_values(0, ascending=False)

# zip the variable name columns (Which were only named level_0 and level_1 by default) in a new column named "pairs"
df_multi['pairs'] = list(zip(df_multi.level_0, df_multi.level_1))

# set index to pairs
df_multi.set_index(['pairs'], inplace = True)

#drop level columns
df_multi.drop(columns=['level_1', 'level_0'], inplace = True)

# rename correlation column as cor rather than 0
df_multi.columns = ['cor']

# drop duplicates. This could be dangerous if you have variables perfectly correlated with variables other than themse
# for the sake of exercise, kept it in.
df_multi.drop_duplicates(inplace=True)

df_multi[(df_multi.cor > .75) & (df_multi.cor <1)]
```

Out[71]:

	cor
pairs	
(grade, sqft_above)	0.756236

Conclusion

The purpose of the above analysis was to make a viable recommendation for real estate companies in order to help their homeowners clients sell their properties at best value.

The grade of a property is the highest factor that needs to be adressed: in order to increase the sale value: if we look at the grade coefficient, 0.1820, we can in fact read that for every 1 notch increase in the grade, the value of the property increases dy 18.2%.

There are several ways in which a property can be improved, depending on what would need to be done on the interior and/or exterior. For example, the homeowner can improve the quality of the AC/heating units, the plumbing pipes, the kitchen appliances, the flooring, the bathroom appliances, the alarm system, etc. Another detail that tends to increase the value of a home is to have it re-arranged by an interior designer.

For the exterior of the house, the outisde appearance of the property plays a very important role in the price component. Repainting the walls and re-cementing the front driveway for example can be considered as factors, such as re-doingthe roof or planting bushes.

When looking at the other coefficients, we can see that bedrooms and bathrooms are negative, which translates into the fact that it can negatively impact the price by 1.1% to 1.6% respectively of a home if only working on having nice bedrooms and bathrooms as opposed to the property. Some properties might be bigger but old, hence won't have a better grade than a smaller property that has a high grade.

The r-squared value, 0.582, indicates that the model can account for about 58% of the variability of price around its mean. The null hypothesis for multiple regression is that there is no relationship between the chosen explanatory variables and the response variable. Also, all of the p-values round to 0, which means we can reject the null hypothesis. Now we can confirm that the model satisfies the assumptions of normality and homoscedasticity.

What could be the next steps?

1. Have a better understanding of what is taken into account when assessing the grade of a property. For example, does the property have a driveway, is it easy access for strollers/wheelchairs, or simply understand what components of the house matter the most to home buyers: new bathroom/kitchen appliances over fresh paint on the walls for example. Another factor that could help increase the sale of the property could be the choice of windows, whether they are double glazed or not.
2. Other factors that could help increase the value of a property that are harder to quantify such as the choices of plants/flowers/trees in the backyard, heated pool, outdoor shower...etc. All of these are factors that the property owner can improve.