# House Price Analysis

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## Overview

Jim's Real Estate wants to help homeowners make the most of their property and would like to know how renovations affect house prices. Using linear regression we found two variables that affected house prices the most. Using that information, real estate agents can provide meaningful advice for homeowners.

### Business Understanding

There are a variety of variables when determining the value of a property. Creating a model for real estate agents will help them advise homewoeners about how renovating affects the value of their property. To do this we will explore house data from King County to build a basic model then reiterate the process to improve on the model.

In [1]:
```
#import packages
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import statsmodels.api as sm
from sklearn import preprocessing
import scipy.stats as stats
import seaborn as sns
from sklearn.metrics import mean_squared_error
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression

pd.options.mode.chained_assignment = None

%matplotlib inline
```

In [2]:
```
#read data from file
kc_house_data_df = pd.read_csv('data/kc_house_data.csv')
```

### Data Understanding

We have obtained house data from King County to help us build the model. This includes useful information like the price of the property, the living area in square feet and the year the poroprty was renovated to name a few.
After getting an idea of the data we are dealing with we can see most of our data are numerical with some columns missing data like 'waterfront' and 'yr_renovated'. We will need to clean those up later
There are some data which is not really relevant to our model which we can remove.

In [3]:
```
kc_house_data_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
```

In [4]:
```
drop = ['date','view','zipcode','lat','long','sqft_living15','sqft_lot15',
kc_house_data_df.drop(drop, axis=1, inplace=True)
```

Taking a closer look we can observe a few points

- A possible outlier with 33 bedrooms when the mean is only 3.
- Condition of the house is form 1-5
- There is a grading system from 3 - 13
- And house data from 1900 - 2015
- sqft_basement has '?' which could explain why it is an object instead of being numeric

In [5]:
```
kc_house_data_df.describe()
```

Out[5]:

| | id | price | bedrooms | bathrooms | sqft_living | sqft_lot |
|---|---|---|---|---|---|---|
| **count** | 2.159700e+04 | 2.159700e+04 | 21597.000000 | 21597.000000 | 21597.000000 | 2.159700e+04 |
| **mean** | 4.580474e+09 | 5.402966e+05 | 3.373200 | 2.115826 | 2080.321850 | 1.509941e+04 |
| **std** | 2.876736e+09 | 3.673681e+05 | 0.926299 | 0.768984 | 918.106125 | 4.141264e+04 |
| **min** | 1.000102e+06 | 7.800000e+04 | 1.000000 | 0.500000 | 370.000000 | 5.200000e+02 |
| **25%** | 2.123049e+09 | 3.220000e+05 | 3.000000 | 1.750000 | 1430.000000 | 5.040000e+03 |
| **50%** | 3.904930e+09 | 4.500000e+05 | 3.000000 | 2.250000 | 1910.000000 | 7.618000e+03 |
| **75%** | 7.308900e+09 | 6.450000e+05 | 4.000000 | 2.500000 | 2550.000000 | 1.068500e+04 |

In [6]:
```
kc_house_data_df.head(10)
```

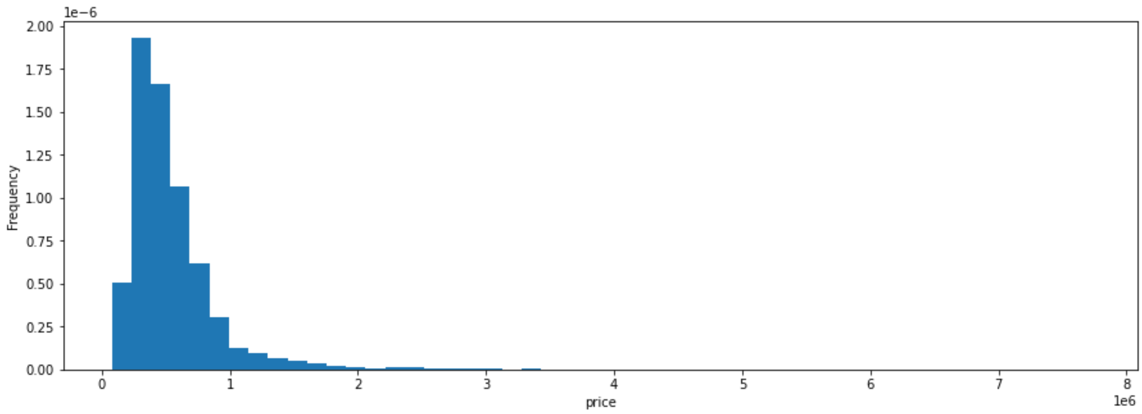
Out[6]:

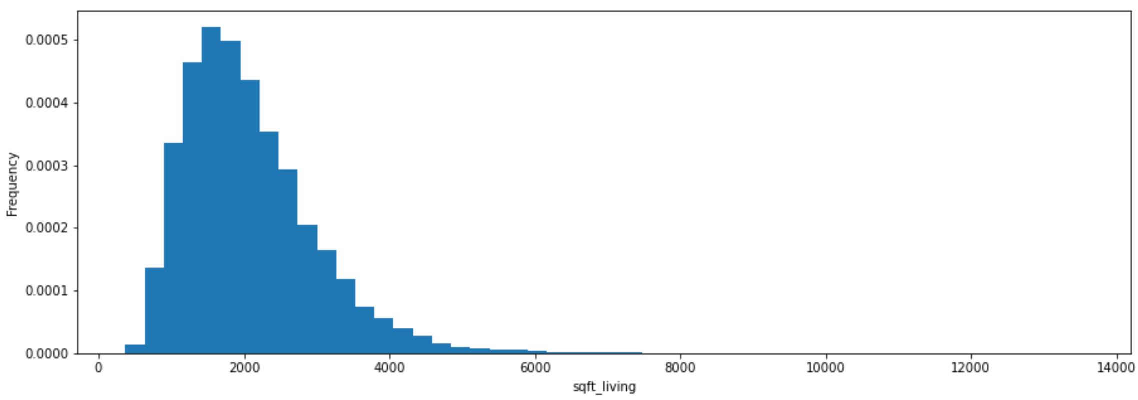
| | id | price | bedrooms | bathrooms | sqft_living | sqft_lot | floors | condition | grad |
|---|---|---|---|---|---|---|---|---|---|
| **0** | 7129300520 | 221900.0 | 3 | 1.00 | 1180 | 5650 | 1.0 | 3 | |
| **1** | 6414100192 | 538000.0 | 3 | 2.25 | 2570 | 7242 | 2.0 | 3 | |
| **2** | 5631500400 | 180000.0 | 2 | 1.00 | 770 | 10000 | 1.0 | 3 | |
| **3** | 2487200875 | 604000.0 | 4 | 3.00 | 1960 | 5000 | 1.0 | 5 | |
| **4** | 1954400510 | 510000.0 | 3 | 2.00 | 1680 | 8080 | 1.0 | 3 | |
| **5** | 7237550310 | 1230000.0 | 4 | 4.50 | 5420 | 101930 | 1.0 | 3 | 1 |
| **6** | 1321400060 | 257500.0 | 3 | 2.25 | 1715 | 6819 | 2.0 | 3 | |
| **7** | 2008000270 | 291850.0 | 3 | 1.50 | 1060 | 9711 | 1.0 | 3 | |
| **8** | 2414600126 | 229500.0 | 3 | 1.00 | 1780 | 7470 | 1.0 | 3 | |
| **9** | 3793500160 | 323000.0 | 3 | 2.50 | 1890 | 6560 | 2.0 | 3 | |

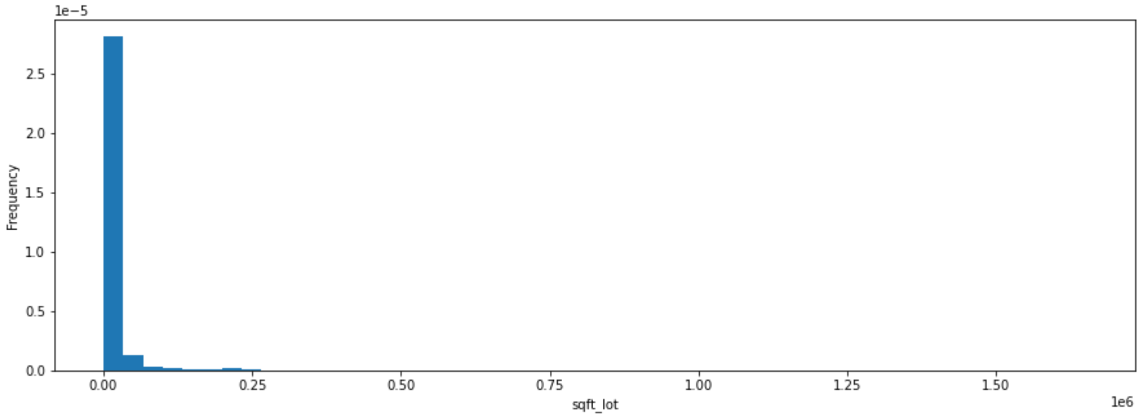
### Continuous data

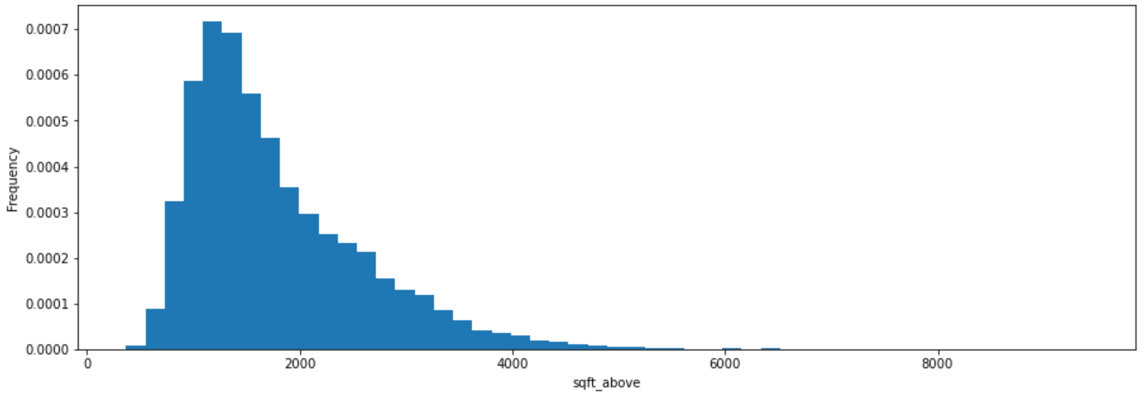
The histograms show the data being positively skewed. We will need to run log transformations to make them more normal.

In [7]:
```
continuous = ['price', 'sqft_living', 'sqft_lot', 'sqft_above']

for cont in continuous:
    plt.figure(figsize=(15,5))
    kc_house_data_df[cont].plot.hist(bins=50, density=True)
    plt.xlabel(cont)
    plt.show()
```



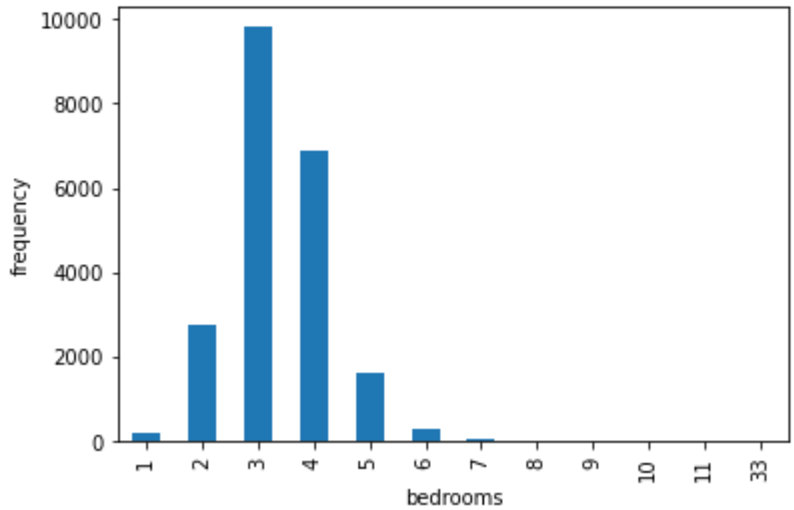


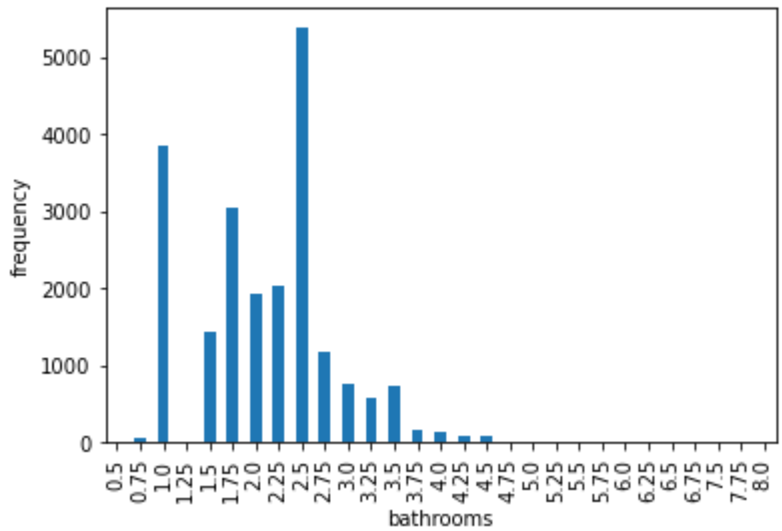



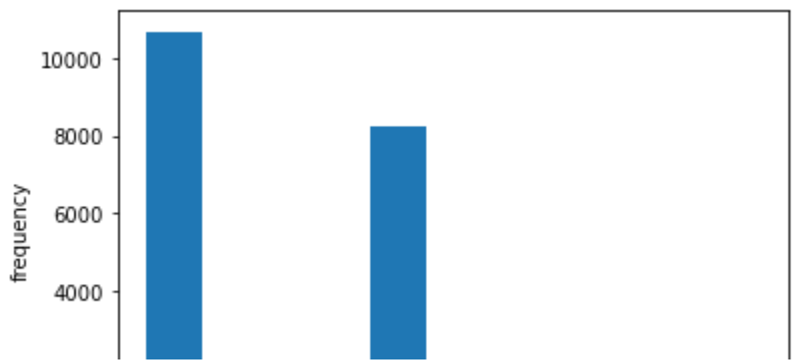

#### Categorical Data

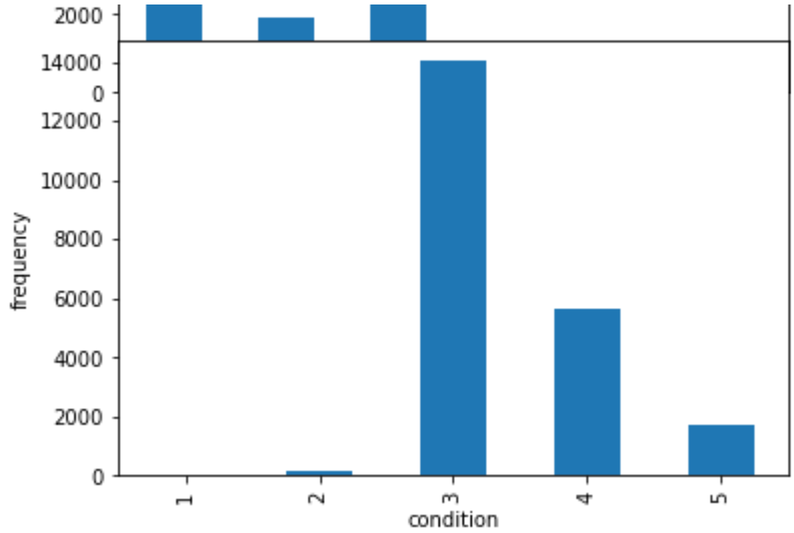
The house with 33 bedrooms is an outlier which we can drop when cleaning
We can see there wasn't many renovations happening (less than 10) until after 1982
Knowing if the property has been renovated or not would be more useful than the year the property was renovated

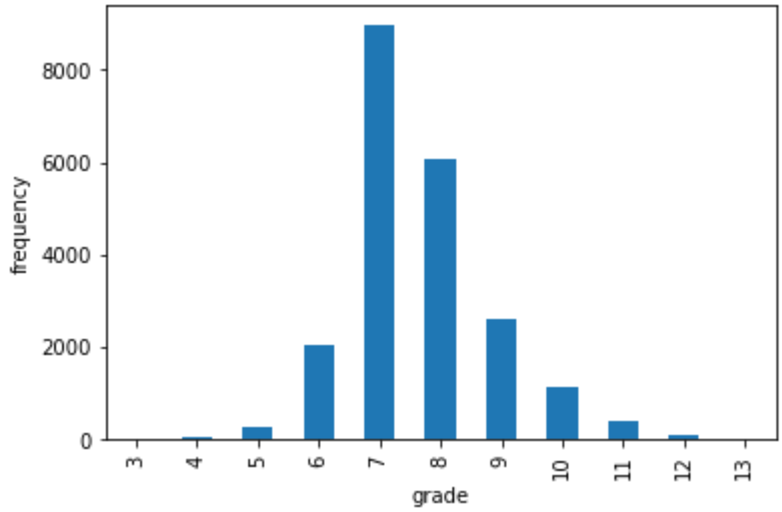
In [8]:
```
categorical = ['bedrooms', 'bathrooms', 'floors','condition', 'grade','yr_bu


for cat in categorical:
    if cat == 'yr_built':
        plt.figure(figsize=(20,10))
    kc_house_data_df.groupby([cat])[cat].count().plot.bar()
    plt.ylabel('frequency')
    plt.show()

#better view of when properties were renovated
plt.figure(figsize=(20,10))
yr_reno = kc_house_data_df.loc[kc_house_data_df['yr_renovated'] > 0]
yr_reno.groupby(yr_reno['yr_renovated'])['yr_renovated'].count().plot.bar()
plt.ylabel('frequency')
plt.show()
```

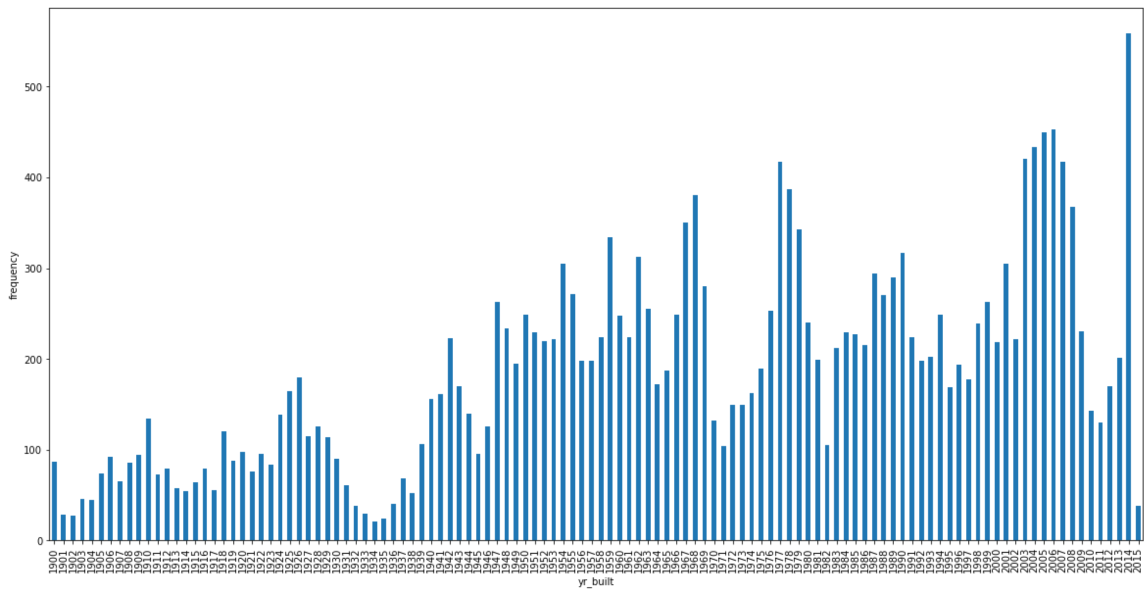


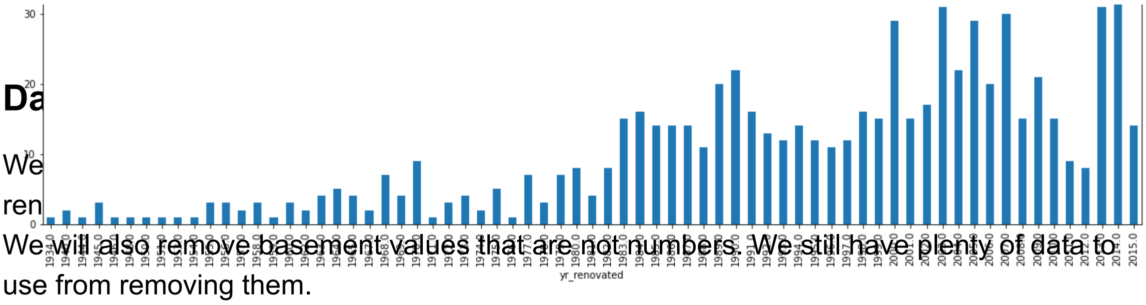




frequency
condition


frequency
grade


frequency
yr_built


frequency




## Da

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We will also remove basement values that are not numbers. We still have plenty of data to use from removing them.

Remove the outlier in bedrooms

In [9]:
```python
clean_house_data_df = kc_house_data_df.dropna(subset=['yr_renovated'])
clean_house_data_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 17755 entries, 0 to 21596
Data columns (total 13 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   id             17755 non-null  int64  
 1   price          17755 non-null  float64
 2   bedrooms       17755 non-null  int64  
 3   bathrooms      17755 non-null  float64
 4   sqft_living    17755 non-null  int64  
 5   sqft_lot       17755 non-null  int64  
 6   floors         17755 non-null  float64
 7   condition      17755 non-null  int64  
 8   grade          17755 non-null  int64  
 9   sqft_above     17755 non-null  int64  
 10  sqft_basement  17755 non-null  object 
 11  yr_built       17755 non-null  int64  
 12  yr_renovated   17755 non-null  float64
dtypes: float64(4), int64(8), object(1)
memory usage: 1.9+ MB
```

In [10]:
```
# Convert basement to numeric and remove the ones that are unknown
clean_house_data_df['sqft_basement'] = pd.to_numeric(clean_house_data_df['s
clean_house_data_df.dropna(subset=['sqft_basement'], inplace=True)
clean_house_data_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 17389 entries, 0 to 21596
Data columns (total 13 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   id             17389 non-null  int64
 1   price          17389 non-null  float64
 2   bedrooms       17389 non-null  int64
 3   bathrooms      17389 non-null  float64
 4   sqft_living    17389 non-null  int64
 5   sqft_lot       17389 non-null  int64
 6   floors         17389 non-null  float64
 7   condition      17389 non-null  int64
 8   grade          17389 non-null  int64
 9   sqft_above     17389 non-null  int64
 10  sqft_basement  17389 non-null  float64
 11  yr_built       17389 non-null  int64
 12  yr_renovated   17389 non-null  float64
dtypes: float64(5), int64(8)
memory usage: 1.9 MB
```

In [11]:
```
# remove outlier in bedrooms
clean_house_data_df.loc[(clean_house_data_df['bedrooms'] >= 10)].sort_value
clean_house_data_df.drop(labels=15856, axis=0, inplace=True)
```

In [12]:
```
#change year to property been renovated or not
clean_house_data_df.loc[(clean_house_data_df['yr_renovated'] > 0), 'yr_reno
clean_house_data_df.rename(columns={'yr_renovated':'renovated'}, inplace=Tr
```

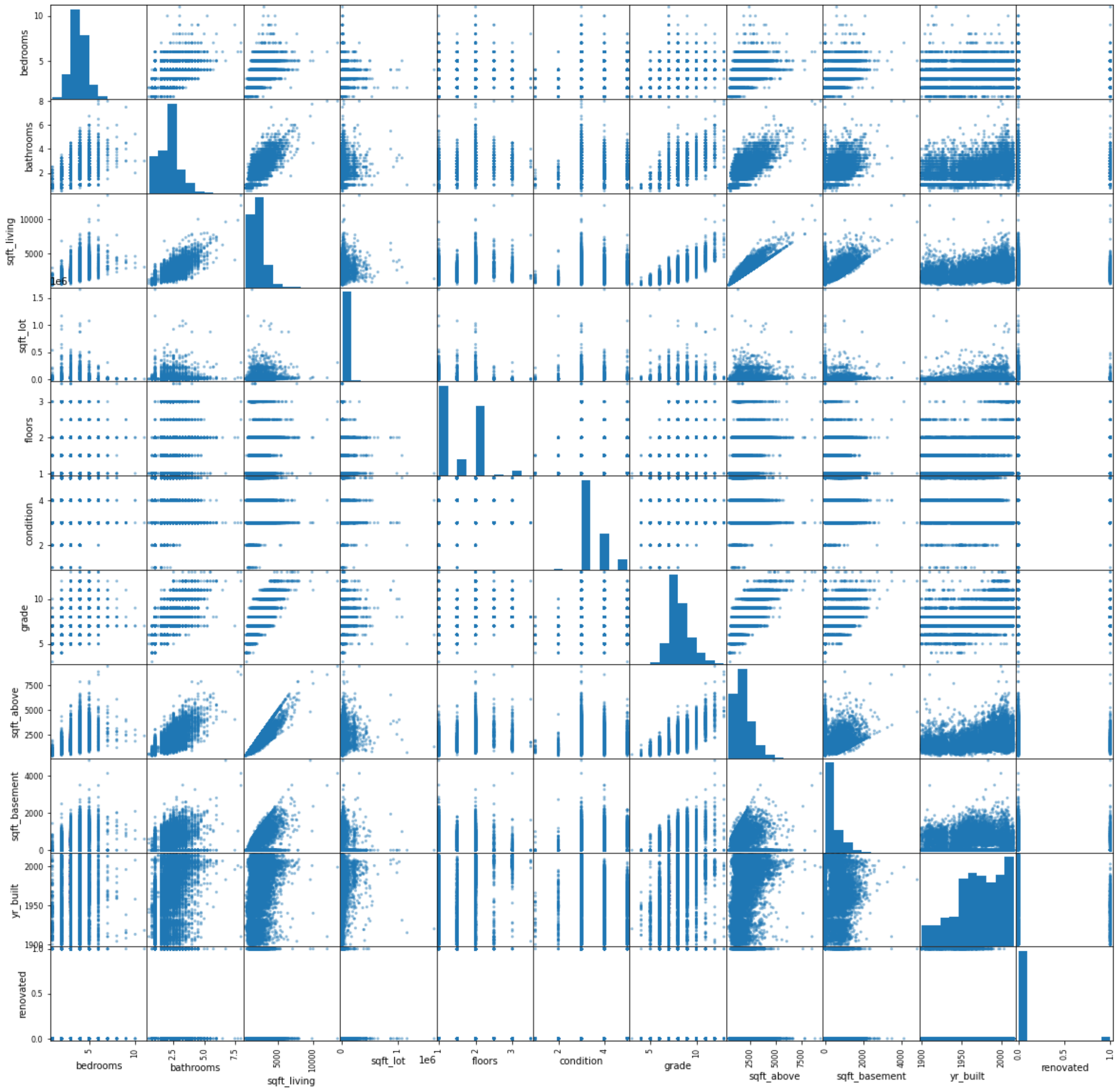
In [13]:
```
#percentage of houses renovated
no_reno, yes_reno = (clean_house_data_df[['renovated']] > 0).value_counts()
(yes_reno/(yes_reno + no_reno))*100
```

Out[13]: 4.158040027605245

### Check for Multicollinearity

Variables that are highly correlated to another variable will cause problems for our regression analysis. Making the results unreliable. To fix that we look for highly correlated variables and remove some.
We removed 'sqft_basement' and 'bathrooms'

In [14]:
```
house_pred = clean_house_data_df.iloc[:,2:14]
pd.plotting.scatter_matrix(house_pred, figsize  = [20, 20]);
plt.show()
```




In [15]:
```
house_pred.corr()
```

Out[15]:

| | bedrooms | bathrooms | sqft_living | sqft_lot | floors | condition | grade |
|---|---|---|---|---|---|---|---|
| **bedrooms** | 1.000000 | 0.527457 | 0.592664 | 0.031053 | 0.185320 | 0.017068 | 0.366044 |
| **bathrooms** | 0.527457 | 1.000000 | 0.753504 | 0.085354 | 0.503906 | -0.131313 | 0.665489 |
| **sqft_living** | 0.592664 | 0.753504 | 1.000000 | 0.167745 | 0.356532 | -0.066163 | 0.764592 |
| **sqft_lot** | 0.031053 | 0.085354 | 0.167745 | 1.000000 | -0.008833 | -0.011021 | 0.108905 |
| **floors** | 0.185320 | 0.503906 | 0.356532 | -0.008833 | 1.000000 | -0.263477 | 0.460728 |
| **condition** | 0.017068 | -0.131313 | -0.066163 | -0.011021 | -0.263477 | 1.000000 | -0.151378 |
| **grade** | 0.366044 | 0.665489 | 0.764592 | 0.108905 | 0.460728 | -0.151378 | 1.000000 |
| **sqft_above** | 0.491095 | 0.685983 | 0.875885 | 0.175682 | 0.527141 | -0.161946 | 0.758232 |
| **sqft_basement** | 0.310868 | 0.280347 | 0.436399 | 0.019582 | -0.245058 | 0.165047 | 0.168573 |
| **yr_built** | 0.160033 | 0.506510 | 0.317275 | 0.048982 | 0.487741 | -0.366227 | 0.445345 |
| **renovated** | 0.019734 | 0.051249 | 0.054029 | 0.003594 | 0.003153 | -0.061755 | 0.016509 |

In [16]:
```
df=house_pred.corr().abs().stack().reset_index().sort_values(0, ascending=F

# zip the variable name columns (Which were only named level_0 and level_1 l
df['pairs'] = list(zip(df.level_0, df.level_1))

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

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

# rename correlation column as cc rather than 0
df.columns = ['cc']

# drop duplicates. This could be dangerous if you have variables perfectly c
# for the sake of exercise, kept it in.
df.drop_duplicates(inplace=True)

df[(df.cc>0.75) & (df.cc <1)]
```

Out[16]:

| pairs | cc |
|---|---|
| **(sqft_above, sqft_living)** | 0.875885 |
| **(sqft_living, grade)** | 0.764592 |
| **(sqft_above, grade)** | 0.758232 |
| **(bathrooms, sqft_living)** | 0.753504 |

In [17]:
```
clean_house_data_df.drop(['sqft_basement', 'bathrooms'], axis=1, inplace=Tru
clean_house_data_df.reset_index(drop=True, inplace=True)
clean_house_data_df.head()
```

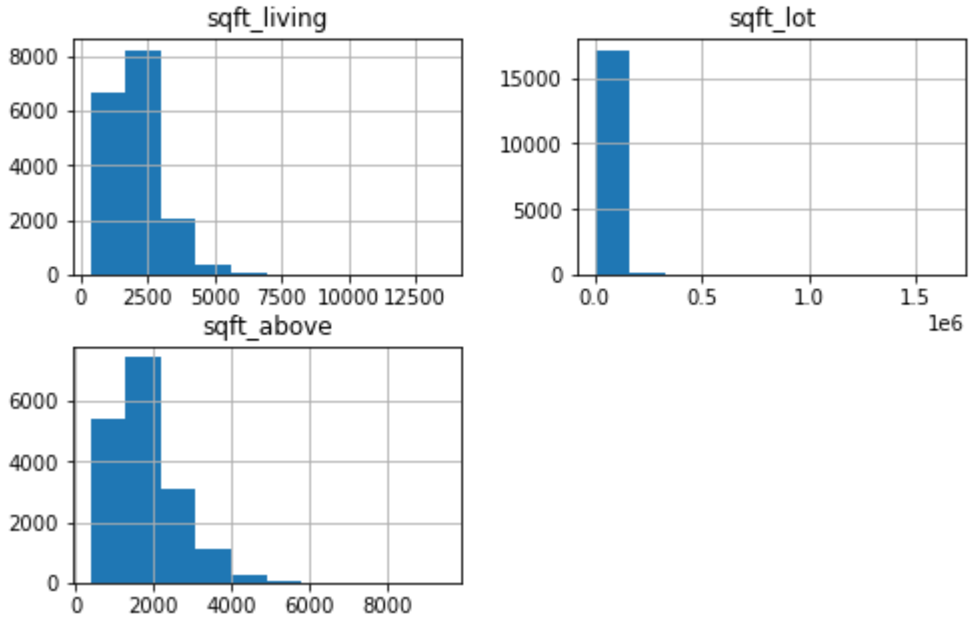
Out[17]:

| | id | price | bedrooms | sqft_living | sqft_lot | floors | condition | grade | sqft_abov |
|---|---|---|---|---|---|---|---|---|---|
| **0** | 7129300520 | 221900.0 | 3 | 1180 | 5650 | 1.0 | 3 | 7 | 118 |
| **1** | 6414100192 | 538000.0 | 3 | 2570 | 7242 | 2.0 | 3 | 7 | 217 |
| **2** | 2487200875 | 604000.0 | 4 | 1960 | 5000 | 1.0 | 5 | 7 | 105 |
| **3** | 1954400510 | 510000.0 | 3 | 1680 | 8080 | 1.0 | 3 | 8 | 168 |
| **4** | 7237550310 | 1230000.0 | 4 | 5420 | 101930 | 1.0 | 3 | 11 | 389 |

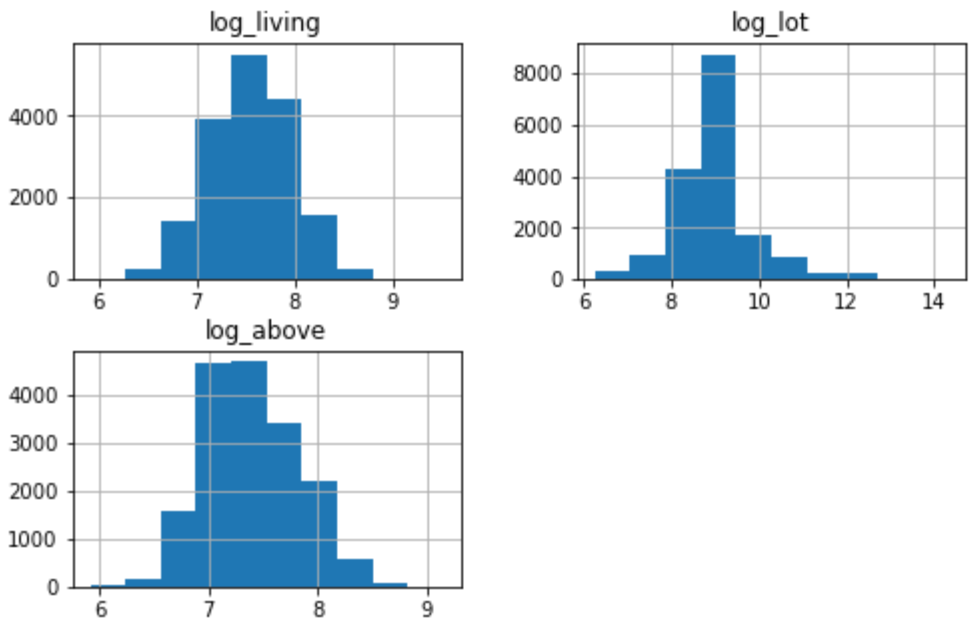
### Normalise

Our data is positively skewed so we need to do log transformation to make it have a more normal distribution. After that we need to standardise our data making the mean 0

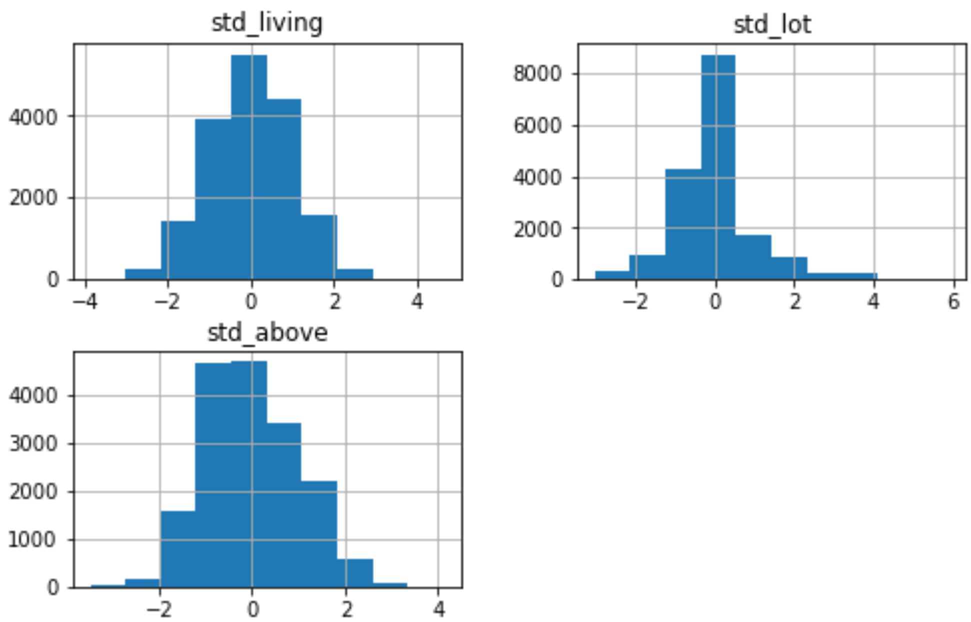
In [18]:
```
# original predictors
data_pred = clean_house_data_df.iloc[:,2:10]
data_pred[['sqft_living', 'sqft_lot', 'sqft_above']].hist(figsize =[8,5]);
```




In [19]:
```
# predictors after log transform
data_log = pd.DataFrame([])
data_log['log_living'] = np.log(data_pred['sqft_living'])
data_log['log_lot'] = np.log(data_pred['sqft_lot'])
data_log['log_above'] = np.log(data_pred['sqft_above'])
data_log.hist(figsize =[8,5]);
```



In [20]:
```
# standard
std_scale = preprocessing.StandardScaler().fit(data_log[['log_living', 'log_
df_std = std_scale.transform(data_log[['log_living', 'log_lot', 'log_above'
standard_df = pd.DataFrame(df_std, columns=['std_living', 'std_lot', 'std_al
standard_df.hist(figsize=[8,5]);
```




In [21]:
```
clean_house_data_df2 = pd.concat([clean_house_data_df['price'], standard_df
```

### One Hot Encode

For linear regression, categorical data should be transformed using one-hot encoding. In order to not have so many predictors for the year built we categorised them into 5 year increments.

In [22]:
```
# categorise yr_built in 5 year increments
def categorise_yr(yr):
    yr_mod = yr % 10
    if yr_mod > 0 and yr_mod < 5:
        yr -= yr_mod
    elif yr_mod > 5 and yr_mod < 10:
        yr -= yr_mod - 5
    return yr

clean_house_data_df['yr_cat'] = clean_house_data_df['yr_built'].map(categor
```

In [23]:
```
# dummy variable
br_dum = pd.get_dummies(clean_house_data_df['bedrooms'], prefix='br', drop_
fl_dum = pd.get_dummies(clean_house_data_df['floors'], prefix='fl', drop_fi
cond_dum = pd.get_dummies(clean_house_data_df['condition'], prefix='cond', 
gr_dum = pd.get_dummies(clean_house_data_df['grade'], prefix='grade', drop_
yb_dum = pd.get_dummies(clean_house_data_df['yr_cat'], prefix='yr_built', d

# add dummy variables
clean_house_data_df3 = pd.concat([clean_house_data_df2, br_dum, fl_dum, con
clean_house_data_df3.head()
```

Out[23]:

| | price | std_living | std_lot | std_above | renovated | br_2 | br_3 | br_4 | br_5 | br_6 | ... |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 221900.0 | -1.134041 | -0.391525 | -0.760796 | 0.0 | 0 | 1 | 0 | 0 | 0 | ... |

| | price | std_living | std_lot | std_above | renovated | br_2 | br_3 | br_4 | br_5 | br_6 | ... | y |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **1** | 538000.0 | 0.704189 | -0.117255 | 0.667971 | 1.0 | 0 | 1 | 0 | 0 | 0 | ... | |
| **2** | 604000.0 | 0.064293 | -0.526558 | -1.034546 | 0.0 | 0 | 0 | 1 | 0 | 0 | ... | |
| **3** | 510000.0 | -0.299745 | 0.003721 | 0.067739 | 0.0 | 0 | 1 | 0 | 0 | 0 | ... | |
| **4** | 1230000.0 | 2.466373 | 2.804408 | 2.036862 | 0.0 | 0 | 0 | 1 | 0 | 0 | ... | |

## Modeling

In [24]:

```
house_df = clean_house_data_df3
#variables for categorical predictors
price = house_df[['price']]
bedrooms = house_df.iloc[:,5:15]
floors = house_df.iloc[:,15:20]
condition = house_df.iloc[:,20:24]
grade = house_df.iloc[:,24:34]
yr_built = house_df.iloc[:,34:57]

house_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 17388 entries, 0 to 17387
Data columns (total 57 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   price          17388 non-null  float64
 1   std_living     17388 non-null  float64
 2   std_lot        17388 non-null  float64
 3   std_above      17388 non-null  float64
 4   renovated      17388 non-null  float64
 5   br_2           17388 non-null  uint8
 6   br_3           17388 non-null  uint8
 7   br_4           17388 non-null  uint8
 8   br_5           17388 non-null  uint8
 9   br_6           17388 non-null  uint8
 10  br_7           17388 non-null  uint8
 11  br_8           17388 non-null  uint8
 12  br_9           17388 non-null  uint8
 13  br_10          17388 non-null  uint8
 14  br_11          17388 non-null  uint8
 15  fl_1.5         17388 non-null  uint8
 16  fl_2.0         17388 non-null  uint8
 17  fl_2.5         17388 non-null  uint8
 18  fl_3.0         17388 non-null  uint8
 19  fl_3.5         17388 non-null  uint8
 20  cond_2         17388 non-null  uint8
 21  cond_3         17388 non-null  uint8
```

### Model 1

Our first model used all the available predictors and got an R-Squared value of 0.633 which is reasonable, being able to explain 63% of variations of our model.
std_above and conditions had p-values greater than 0.05 so we will remove those for the next model.

In [25]:
```
# all predictors
price = house_df['price']
predictors = house_df.iloc[:,1:57]
predictors_int = sm.add_constant(predictors)
model = sm.OLS(price, predictors_int).fit()
model.summary()
```

Out[25]:

OLS Regression Results

| | | | |
|---|---|---|---|
| **Dep. Variable:** | price | **R-squared:** | 0.633 |
| **Model:** | OLS | **Adj. R-squared:** | 0.632 |
| **Method:** | Least Squares | **F-statistic:** | 533.9 |
| **Date:** | Sat, 11 Jun 2022 | **Prob (F-statistic):** | 0.00 |
| **Time:** | 21:56:41 | **Log-Likelihood:** | -2.3890e+05 |
| **No. Observations:** | 17388 | **AIC:** | 4.779e+05 |
| **Df Residuals:** | 17331 | **BIC:** | 4.784e+05 |
| **Df Model:** | 56 | | |
| **Covariance Type:** | nonrobust | | |

| | coef | std err | t | P>\|t\| | [0.025 | 0.975] |
|---|---|---|---|---|---|---|
| **const** | 6.503e+05 | 2.31e+05 | 2.815 | 0.005 | 1.98e+05 | 1.1e+06 |
| **std_living** | 1.379e+05 | 4276.659 | 32.233 | 0.000 | 1.29e+05 | 1.46e+05 |
| **std_lot** | -1.62e+04 | 2316.634 | -6.994 | 0.000 | -2.07e+04 | -1.17e+04 |
| **std_above** | -932.2023 | 4489.225 | -0.208 | 0.836 | -9731.536 | 7867.132 |
| **renovated** | 8.674e+04 | 9159.535 | 9.469 | 0.000 | 6.88e+04 | 1.05e+05 |
| **br_2** | -4.594e+04 | 1.93e+04 | -2.375 | 0.018 | -8.39e+04 | -8032.671 |
| **br_3** | -9.772e+04 | 1.95e+04 | -5.017 | 0.000 | -1.36e+05 | -5.95e+04 |
| **br_4** | -1.324e+05 | 2e+04 | -6.617 | 0.000 | -1.72e+05 | -9.32e+04 |
| **br_5** | -9.4e+04 | 2.11e+04 | -4.458 | 0.000 | -1.35e+05 | -5.27e+04 |
| **br_6** | -7.267e+04 | 2.53e+04 | -2.871 | 0.004 | -1.22e+05 | -2.31e+04 |
| **br_7** | 5526.2010 | 4.96e+04 | 0.111 | 0.911 | -9.17e+04 | 1.03e+05 |
| **br_8** | 1.745e+05 | 7.15e+04 | 2.440 | 0.015 | 3.43e+04 | 3.15e+05 |
| **br_9** | -1.785e+05 | 9.46e+04 | -1.887 | 0.059 | -3.64e+05 | 6923.749 |
| **br_10** | -6.378e+04 | 1.31e+05 | -0.485 | 0.628 | -3.22e+05 | 1.94e+05 |
| **br_11** | -3.947e+05 | 2.26e+05 | -1.746 | 0.081 | -8.38e+05 | 4.84e+04 |
| **fl_1.5** | -1.217e+04 | 7435.389 | -1.636 | 0.102 | -2.67e+04 | 2408.040 |
| **fl_2.0** | 7148.2418 | 6289.004 | 1.137 | 0.256 | -5178.840 | 1.95e+04 |
| **fl_2.5** | 1.036e+05 | 2.11e+04 | 4.909 | 0.000 | 6.22e+04 | 1.45e+05 |
| **fl_3.0** | 8.658e+04 | 1.27e+04 | 6.817 | 0.000 | 6.17e+04 | 1.11e+05 |
| **fl_3.5** | 1.178e+05 | 9.29e+04 | 1.269 | 0.205 | -6.42e+04 | 3e+05 |
| **cond_2** | -5.008e+04 | 5.17e+04 | -0.969 | 0.333 | -1.51e+05 | 5.13e+04 |
| **cond_3** | -3.032e+04 | 4.84e+04 | -0.627 | 0.531 | -1.25e+05 | 6.45e+04 |
| **cond_4** | 1384.9881 | 4.84e+04 | 0.029 | 0.977 | -9.35e+04 | 9.63e+04 |
| **cond_5** | 4.229e+04 | 4.87e+04 | 0.869 | 0.385 | -5.31e+04 | 1.38e+05 |
| **grade_4** | -3335.2368 | 2.31e+05 | -0.014 | 0.988 | -4.57e+05 | 4.5e+05 |
| **grade_5** | -5.714e+04 | 2.26e+05 | -0.253 | 0.800 | -5e+05 | 3.86e+05 |
| **grade_6** | -3.668e+04 | 2.26e+05 | -0.162 | 0.871 | -4.79e+05 | 4.06e+05 |
| **grade_7** | 4.634e+04 | 2.26e+05 | 0.205 | 0.837 | -3.96e+05 | 4.89e+05 |
| **grade_8** | 1.545e+05 | 2.26e+05 | 0.684 | 0.494 | -2.88e+05 | 5.97e+05 |
| **grade_9** | 3.306e+05 | 2.26e+05 | 1.463 | 0.144 | -1.12e+05 | 7.74e+05 |
| **grade_10** | 5.889e+05 | 2.26e+05 | 2.604 | 0.009 | 1.46e+05 | 1.03e+06 |
| **grade_11** | 9.444e+05 | 2.26e+05 | 4.171 | 0.000 | 5.01e+05 | 1.39e+06 |
| **grade_12** | 1.632e+06 | 2.28e+05 | 7.165 | 0.000 | 1.19e+06 | 2.08e+06 |
| **grade_13** | 2.823e+06 | 2.36e+05 | 11.949 | 0.000 | 2.36e+06 | 3.29e+06 |
| **yr_built_1905** | 2.457e+04 | 2.07e+04 | 1.188 | 0.235 | -1.6e+04 | 6.51e+04 |
| **yr_built_1910** | 7147.3649 | 2.08e+04 | 0.344 | 0.731 | -3.36e+04 | 4.79e+04 |
| **yr_built_1915** | -799.0763 | 2.08e+04 | -0.038 | 0.969 | -4.16e+04 | 4e+04 |
| **yr_built_1920** | -1441.6611 | 2.02e+04 | -0.071 | 0.943 | -4.1e+04 | 3.81e+04 |

| | | | | | | |
|---|---|---|---|---|---|---|
| **yr_built_1925** | 8021.9628 | 1.92e+04 | 0.418 | 0.676 | -2.96e+04 | 4.56e+04 |
| **yr_built_1930** | -3.122e+04 | 2.34e+04 | -1.334 | 0.182 | -7.71e+04 | 1.46e+04 |
| **yr_built_1935** | 6773.2950 | 2.24e+04 | 0.302 | 0.763 | -3.72e+04 | 5.07e+04 |
| **yr_built_1940** | -4.195e+04 | 1.9e+04 | -2.206 | 0.027 | -7.92e+04 | -4675.008 |
| **yr_built_1945** | -4.731e+04 | 1.88e+04 | -2.515 | 0.012 | -8.42e+04 | -1.04e+04 |
| **yr_built_1950** | -5.598e+04 | 1.84e+04 | -3.041 | 0.002 | -9.21e+04 | -1.99e+04 |
| **yr_built_1955** | -1.168e+05 | 1.85e+04 | -6.296 | 0.000 | -1.53e+05 | -8.04e+04 |
| **yr_built_1960** | -1.443e+05 | 1.86e+04 | -7.740 | 0.000 | -1.81e+05 | -1.08e+05 |
| **yr_built_1965** | -1.639e+05 | 1.84e+04 | -8.892 | 0.000 | -2e+05 | -1.28e+05 |
| **yr_built_1970** | -1.5e+05 | 1.96e+04 | -7.636 | 0.000 | -1.88e+05 | -1.11e+05 |
| **yr_built_1975** | -2.1e+05 | 1.84e+04 | -11.437 | 0.000 | -2.46e+05 | -1.74e+05 |
| **yr_built_1980** | -1.811e+05 | 1.9e+04 | -9.513 | 0.000 | -2.18e+05 | -1.44e+05 |
| **yr_built_1985** | -2.512e+05 | 1.87e+04 | -13.431 | 0.000 | -2.88e+05 | -2.15e+05 |
| **yr_built_1990** | -2.949e+05 | 1.89e+04 | -15.567 | 0.000 | -3.32e+05 | -2.58e+05 |
| **yr_built_1995** | -2.69e+05 | 1.92e+04 | -14.040 | 0.000 | -3.07e+05 | -2.31e+05 |
| **yr_built_2000** | -2.437e+05 | 1.87e+04 | -13.058 | 0.000 | -2.8e+05 | -2.07e+05 |
| **yr_built_2005** | -2.308e+05 | 1.85e+04 | -12.482 | 0.000 | -2.67e+05 | -1.95e+05 |
| **yr_built_2010** | -2.254e+05 | 1.91e+04 | -11.810 | 0.000 | -2.63e+05 | -1.88e+05 |
| **yr_built_2015** | -1.922e+05 | 4.61e+04 | -4.167 | 0.000 | -2.83e+05 | -1.02e+05 |

| | | | |
|---|---|---|---|
| **Omnibus:** | 13866.889 | **Durbin-Watson:** | 1.976 |
| **Prob(Omnibus):** | 0.000 | **Jarque-Bera (JB):** | 1113381.178 |
| **Skew:** | 3.275 | **Prob(JB):** | 0.00 |
| **Kurtosis:** | 41.650 | **Cond. No.** | 685. |

Notes:

### Model 2

Removing the two predictors have lowered our R-Squared score slightly
Skew and Kurtosis is still quite high
Doing a QQ-plot shows it is not normal so we run log transformation on price as well.

In [26]:
```
data1 = house_df[['std_living', 'renovated']]
data2 = pd.concat([bedrooms, floors, grade, yr_built], axis=1)
predictors = pd.concat([data1, data2], axis=1)

predictors_int = sm.add_constant(predictors)
model = sm.OLS(price, predictors_int).fit()
model.summary()
```

Out[26]:

OLS Regression Results

| | | | |
|---|---|---|---|
| **Dep. Variable:** | price | **R-squared:** | 0.629 |

| | | | |
|---|---|---|---|
| **Model:** | OLS | **Adj. R-squared:** | 0.628 |
| **Method:** | Least Squares | **F-statistic:** | 587.8 |
| **Date:** | Sat, 11 Jun 2022 | **Prob (F-statistic):** | 0.00 |
| **Time:** | 21:56:42 | **Log-Likelihood:** | -2.3900e+05 |
| **No. Observations:** | 17388 | **AIC:** | 4.781e+05 |
| **Df Residuals:** | 17337 | **BIC:** | 4.785e+05 |
| **Df Model:** | 50 | | |
| **Covariance Type:** | nonrobust | | |

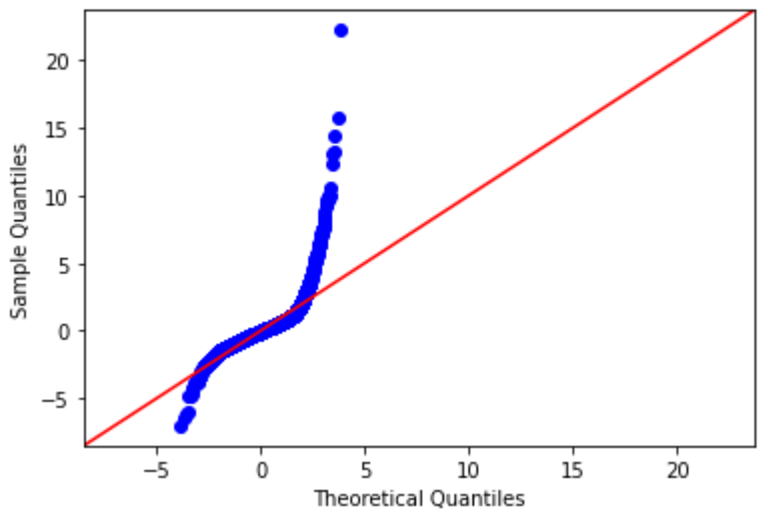
| | coef | std err | t | P>\|t\| | [0.025 | 0.975] |
|---|---|---|---|---|---|---|
| **const** | 6.745e+05 | 2.27e+05 | 2.972 | 0.003 | 2.3e+05 | 1.12e+06 |
| **std_living** | 1.328e+05 | 3277.778 | 40.514 | 0.000 | 1.26e+05 | 1.39e+05 |
| **renovated** | 6.815e+04 | 9054.610 | 7.527 | 0.000 | 5.04e+04 | 8.59e+04 |
| **br_2** | -3.806e+04 | 1.94e+04 | -1.960 | 0.050 | -7.61e+04 | 0.450 |
| **br_3** | -8.783e+04 | 1.95e+04 | -4.497 | 0.000 | -1.26e+05 | -4.95e+04 |
| **br_4** | -1.212e+05 | 2.01e+04 | -6.041 | 0.000 | -1.61e+05 | -8.19e+04 |
| **br_5** | -8.199e+04 | 2.11e+04 | -3.877 | 0.000 | -1.23e+05 | -4.05e+04 |
| **br_6** | -6.271e+04 | 2.54e+04 | -2.470 | 0.014 | -1.12e+05 | -1.29e+04 |
| **br_7** | 1.683e+04 | 4.98e+04 | 0.338 | 0.735 | -8.08e+04 | 1.14e+05 |
| **br_8** | 1.908e+05 | 7.19e+04 | 2.655 | 0.008 | 4.99e+04 | 3.32e+05 |
| **br_9** | -1.843e+05 | 9.5e+04 | -1.939 | 0.052 | -3.71e+05 | 1971.127 |
| **br_10** | -4.838e+04 | 1.32e+05 | -0.366 | 0.714 | -3.07e+05 | 2.11e+05 |
| **br_11** | -3.934e+05 | 2.27e+05 | -1.731 | 0.083 | -8.39e+05 | 5.2e+04 |
| **fl_1.5** | -1.181e+04 | 7199.974 | -1.641 | 0.101 | -2.59e+04 | 2300.042 |
| **fl_2.0** | 1.233e+04 | 5608.036 | 2.198 | 0.028 | 1335.255 | 2.33e+04 |
| **fl_2.5** | 1.146e+05 | 2.09e+04 | 5.480 | 0.000 | 7.36e+04 | 1.56e+05 |
| **fl_3.0** | 1.09e+05 | 1.21e+04 | 8.980 | 0.000 | 8.52e+04 | 1.33e+05 |
| **fl_3.5** | 1.475e+05 | 9.33e+04 | 1.581 | 0.114 | -3.53e+04 | 3.3e+05 |
| **grade_4** | -5.935e+04 | 2.32e+05 | -0.255 | 0.798 | -5.15e+05 | 3.96e+05 |
| **grade_5** | -9.82e+04 | 2.27e+05 | -0.432 | 0.666 | -5.44e+05 | 3.47e+05 |
| **grade_6** | -7.345e+04 | 2.27e+05 | -0.324 | 0.746 | -5.18e+05 | 3.71e+05 |
| **grade_7** | 1.701e+04 | 2.27e+05 | 0.075 | 0.940 | -4.28e+05 | 4.62e+05 |
| **grade_8** | 1.262e+05 | 2.27e+05 | 0.556 | 0.578 | -3.19e+05 | 5.71e+05 |
| **grade_9** | 2.978e+05 | 2.27e+05 | 1.311 | 0.190 | -1.47e+05 | 7.43e+05 |
| **grade_10** | 5.519e+05 | 2.27e+05 | 2.429 | 0.015 | 1.07e+05 | 9.97e+05 |
| **grade_11** | 9.04e+05 | 2.28e+05 | 3.973 | 0.000 | 4.58e+05 | 1.35e+06 |
| **grade_12** | 1.587e+06 | 2.29e+05 | 6.935 | 0.000 | 1.14e+06 | 2.04e+06 |
| **grade_13** | 2.781e+06 | 2.37e+05 | 11.717 | 0.000 | 2.32e+06 | 3.25e+06 |
| **yr_built_1905** | 2.773e+04 | 2.08e+04 | 1.334 | 0.182 | -1.3e+04 | 6.85e+04 |
| **yr_built_1910** | 8816.9599 | 2.09e+04 | 0.422 | 0.673 | -3.22e+04 | 4.98e+04 |

| | | | | | | |
|---|---|---|---|---|---|---|
| **yr_built_1915** | -626.7098 | 2.09e+04 | -0.030 | 0.976 | -4.16e+04 | 4.03e+04 |
| **yr_built_1920** | -4932.6092 | 2.03e+04 | -0.243 | 0.808 | -4.47e+04 | 3.48e+04 |
| **yr_built_1925** | 7723.2561 | 1.93e+04 | 0.401 | 0.689 | -3e+04 | 4.55e+04 |
| **yr_built_1930** | -3.892e+04 | 2.35e+04 | -1.657 | 0.098 | -8.5e+04 | 7122.242 |
| **yr_built_1935** | -5119.2584 | 2.25e+04 | -0.227 | 0.820 | -4.92e+04 | 3.9e+04 |
| **yr_built_1940** | -5.215e+04 | 1.91e+04 | -2.734 | 0.006 | -8.95e+04 | -1.48e+04 |
| **yr_built_1945** | -6.156e+04 | 1.89e+04 | -3.265 | 0.001 | -9.85e+04 | -2.46e+04 |
| **yr_built_1950** | -7.276e+04 | 1.84e+04 | -3.947 | 0.000 | -1.09e+05 | -3.66e+04 |
| **yr_built_1955** | -1.348e+05 | 1.86e+04 | -7.269 | 0.000 | -1.71e+05 | -9.85e+04 |
| **yr_built_1960** | -1.622e+05 | 1.86e+04 | -8.705 | 0.000 | -1.99e+05 | -1.26e+05 |
| **yr_built_1965** | -1.808e+05 | 1.84e+04 | -9.818 | 0.000 | -2.17e+05 | -1.45e+05 |
| **yr_built_1970** | -1.699e+05 | 1.96e+04 | -8.660 | 0.000 | -2.08e+05 | -1.31e+05 |
| **yr_built_1975** | -2.334e+05 | 1.83e+04 | -12.741 | 0.000 | -2.69e+05 | -1.97e+05 |
| **yr_built_1980** | -2.125e+05 | 1.89e+04 | -11.218 | 0.000 | -2.5e+05 | -1.75e+05 |
| **yr_built_1985** | -2.85e+05 | 1.86e+04 | -15.322 | 0.000 | -3.21e+05 | -2.49e+05 |
| **yr_built_1990** | -3.329e+05 | 1.88e+04 | -17.694 | 0.000 | -3.7e+05 | -2.96e+05 |
| **yr_built_1995** | -3.075e+05 | 1.9e+04 | -16.151 | 0.000 | -3.45e+05 | -2.7e+05 |
| **yr_built_2000** | -2.769e+05 | 1.86e+04 | -14.925 | 0.000 | -3.13e+05 | -2.41e+05 |
| **yr_built_2005** | -2.579e+05 | 1.84e+04 | -14.006 | 0.000 | -2.94e+05 | -2.22e+05 |
| **yr_built_2010** | -2.537e+05 | 1.9e+04 | -13.361 | 0.000 | -2.91e+05 | -2.16e+05 |
| **yr_built_2015** | -2.171e+05 | 4.63e+04 | -4.688 | 0.000 | -3.08e+05 | -1.26e+05 |

| | | | |
|---|---|---|---|
| **Omnibus:** | 13776.736 | **Durbin-Watson:** | 1.976 |
| **Prob(Omnibus):** | 0.000 | **Jarque-Bera (JB):** | 1075858.613 |
| **Skew:** | 3.250 | **Prob(JB):** | 0.00 |
| **Kurtosis:** | 40.983 | **Cond. No.** | 600. |

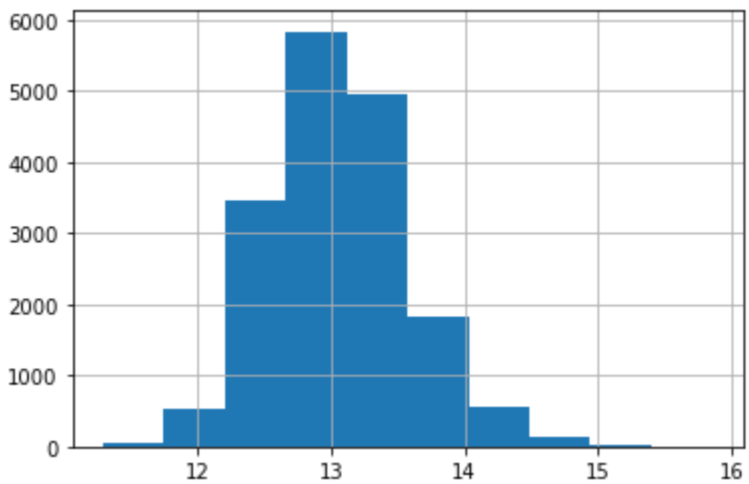
Notes:

In [27]:
```
resid1 = model.resid
fig = sm.graphics.qqplot(resid1, dist=stats.norm, line='45', fit=True)
```




In [28]:
```
price = np.log(house_df['price'])
price.hist()
```

Out[28]: <AxesSubplot:>




**Model 3**

After log transformation on price we can see if has improved the distribution to be more normal
Improved Skewness from highly positive skew to slightly negative skew. Improved skew which is now between -0.5 and 0.5 meaning the data is pretty symmetrical as shown in the QQ-plot below
R-Squared value has also increased to 0.646 meaning 64.6% of the variance is explained by the model.

In [29]:
```
data1 = house_df[['std_living', 'renovated']]
data2 = pd.concat([bedrooms, floors, grade, yr_built], axis=1)
predictors = pd.concat([data1, data2], axis=1)

predictors_int = sm.add_constant(predictors)
model = sm.OLS(price, predictors_int).fit()
model.summary()
```

Out[29]:

OLS Regression Results

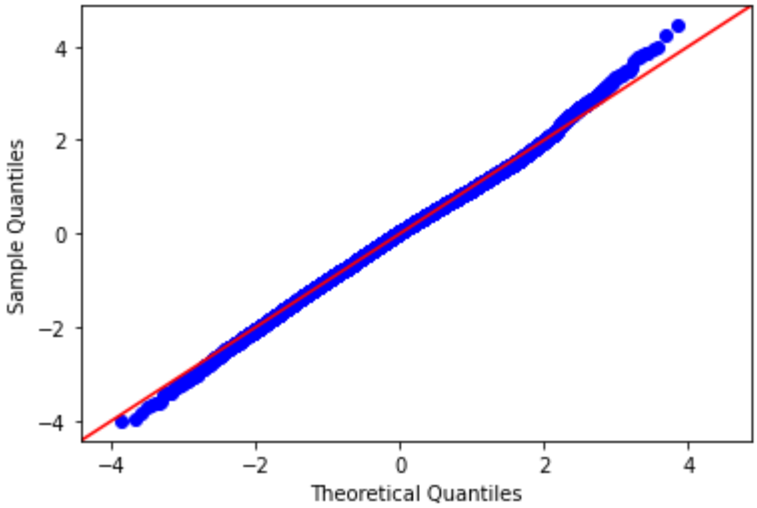
| | | | |
|---|---|---|---|
| **Dep. Variable:** | price | **R-squared:** | 0.646 |
| **Model:** | OLS | **Adj. R-squared:** | 0.645 |
| **Method:** | Least Squares | **F-statistic:** | 633.8 |
| **Date:** | Sat, 11 Jun 2022 | **Prob (F-statistic):** | 0.00 |
| **Time:** | 21:56:42 | **Log-Likelihood:** | -4467.5 |
| **No. Observations:** | 17388 | **AIC:** | 9037. |
| **Df Residuals:** | 17337 | **BIC:** | 9433. |
| **Df Model:** | 50 | | |
| **Covariance Type:** | nonrobust | | |

| | coef | std err | t | P>\|t\| | [0.025 | 0.975] |
|---|---|---|---|---|---|---|
| **const** | 13.2076 | 0.315 | 41.941 | 0.000 | 12.590 | 13.825 |
| **std_living** | 0.2268 | 0.005 | 49.874 | 0.000 | 0.218 | 0.236 |
| **renovated** | 0.0344 | 0.013 | 2.735 | 0.006 | 0.010 | 0.059 |
| **br_2** | -0.0489 | 0.027 | -1.817 | 0.069 | -0.102 | 0.004 |
| **br_3** | -0.1369 | 0.027 | -5.050 | 0.000 | -0.190 | -0.084 |
| **br_4** | -0.1696 | 0.028 | -6.094 | 0.000 | -0.224 | -0.115 |
| **br_5** | -0.1508 | 0.029 | -5.139 | 0.000 | -0.208 | -0.093 |
| **br_6** | -0.1633 | 0.035 | -4.636 | 0.000 | -0.232 | -0.094 |
| **br_7** | -0.1575 | 0.069 | -2.279 | 0.023 | -0.293 | -0.022 |
| **br_8** | 0.0288 | 0.100 | 0.289 | 0.773 | -0.167 | 0.224 |
| **br_9** | -0.2198 | 0.132 | -1.667 | 0.096 | -0.478 | 0.039 |
| **br_10** | -0.0326 | 0.183 | -0.178 | 0.859 | -0.392 | 0.327 |
| **br_11** | -0.4777 | 0.315 | -1.515 | 0.130 | -1.096 | 0.140 |
| **fl_1.5** | 0.0006 | 0.010 | 0.056 | 0.955 | -0.019 | 0.020 |
| **fl_2.0** | 0.0139 | 0.008 | 1.788 | 0.074 | -0.001 | 0.029 |
| **fl_2.5** | 0.0303 | 0.029 | 1.043 | 0.297 | -0.027 | 0.087 |
| **fl_3.0** | 0.1887 | 0.017 | 11.199 | 0.000 | 0.156 | 0.222 |
| **fl_3.5** | 0.1056 | 0.129 | 0.816 | 0.415 | -0.148 | 0.359 |
| **grade_4** | -0.3337 | 0.322 | -1.035 | 0.301 | -0.966 | 0.298 |
| **grade_5** | -0.2638 | 0.315 | -0.837 | 0.403 | -0.882 | 0.354 |
| **grade_6** | -0.0925 | 0.315 | -0.294 | 0.769 | -0.710 | 0.525 |
| **grade_7** | 0.1851 | 0.315 | 0.588 | 0.557 | -0.432 | 0.802 |
| **grade_8** | 0.4256 | 0.315 | 1.351 | 0.177 | -0.192 | 1.043 |
| **grade_9** | 0.6683 | 0.315 | 2.121 | 0.034 | 0.051 | 1.286 |
| **grade_10** | 0.9005 | 0.315 | 2.856 | 0.004 | 0.283 | 1.519 |
| **grade_11** | 1.1192 | 0.316 | 3.545 | 0.000 | 0.500 | 1.738 |
| **grade_12** | 1.3894 | 0.318 | 4.376 | 0.000 | 0.767 | 2.012 |

| | | | | | | |
|---|---|---|---|---|---|---|
| **grade_13** | 1.6329 | 0.329 | 4.958 | 0.000 | 0.987 | 2.278 |
| **yr_built_1905** | 0.0069 | 0.029 | 0.239 | 0.811 | -0.050 | 0.063 |
| **yr_built_1910** | -0.0545 | 0.029 | -1.879 | 0.060 | -0.111 | 0.002 |
| **yr_built_1915** | -0.0442 | 0.029 | -1.526 | 0.127 | -0.101 | 0.013 |
| **yr_built_1920** | -0.0353 | 0.028 | -1.253 | 0.210 | -0.090 | 0.020 |
| **yr_built_1925** | -0.0489 | 0.027 | -1.831 | 0.067 | -0.101 | 0.003 |
| **yr_built_1930** | -0.1559 | 0.033 | -4.781 | 0.000 | -0.220 | -0.092 |
| **yr_built_1935** | -0.1078 | 0.031 | -3.451 | 0.001 | -0.169 | -0.047 |
| **yr_built_1940** | -0.1731 | 0.026 | -6.542 | 0.000 | -0.225 | -0.121 |
| **yr_built_1945** | -0.1642 | 0.026 | -6.277 | 0.000 | -0.215 | -0.113 |
| **yr_built_1950** | -0.2182 | 0.026 | -8.529 | 0.000 | -0.268 | -0.168 |
| **yr_built_1955** | -0.3376 | 0.026 | -13.114 | 0.000 | -0.388 | -0.287 |
| **yr_built_1960** | -0.3906 | 0.026 | -15.107 | 0.000 | -0.441 | -0.340 |
| **yr_built_1965** | -0.4303 | 0.026 | -16.840 | 0.000 | -0.480 | -0.380 |
| **yr_built_1970** | -0.3855 | 0.027 | -14.160 | 0.000 | -0.439 | -0.332 |
| **yr_built_1975** | -0.4821 | 0.025 | -18.968 | 0.000 | -0.532 | -0.432 |
| **yr_built_1980** | -0.4429 | 0.026 | -16.848 | 0.000 | -0.494 | -0.391 |
| **yr_built_1985** | -0.5286 | 0.026 | -20.481 | 0.000 | -0.579 | -0.478 |
| **yr_built_1990** | -0.6020 | 0.026 | -23.060 | 0.000 | -0.653 | -0.551 |
| **yr_built_1995** | -0.5464 | 0.026 | -20.687 | 0.000 | -0.598 | -0.495 |
| **yr_built_2000** | -0.5149 | 0.026 | -20.004 | 0.000 | -0.565 | -0.464 |
| **yr_built_2005** | -0.4995 | 0.026 | -19.551 | 0.000 | -0.550 | -0.449 |
| **yr_built_2010** | -0.5064 | 0.026 | -19.218 | 0.000 | -0.558 | -0.455 |
| **yr_built_2015** | -0.4373 | 0.064 | -6.806 | 0.000 | -0.563 | -0.311 |

| | | | |
|---|---|---|---|
| **Omnibus:** | 62.741 | **Durbin-Watson:** | 1.968 |
| **Prob(Omnibus):** | 0.000 | **Jarque-Bera (JB):** | 82.237 |
| **Skew:** | -0.039 | **Prob(JB):** | 1.39e-18 |
| **Kurtosis:** | 3.328 | **Cond. No.** | 600. |

In [30]:
```
resid1 = model.resid
fig = sm.graphics.qqplot(resid1, dist=stats.norm, line='45', fit=True)
```

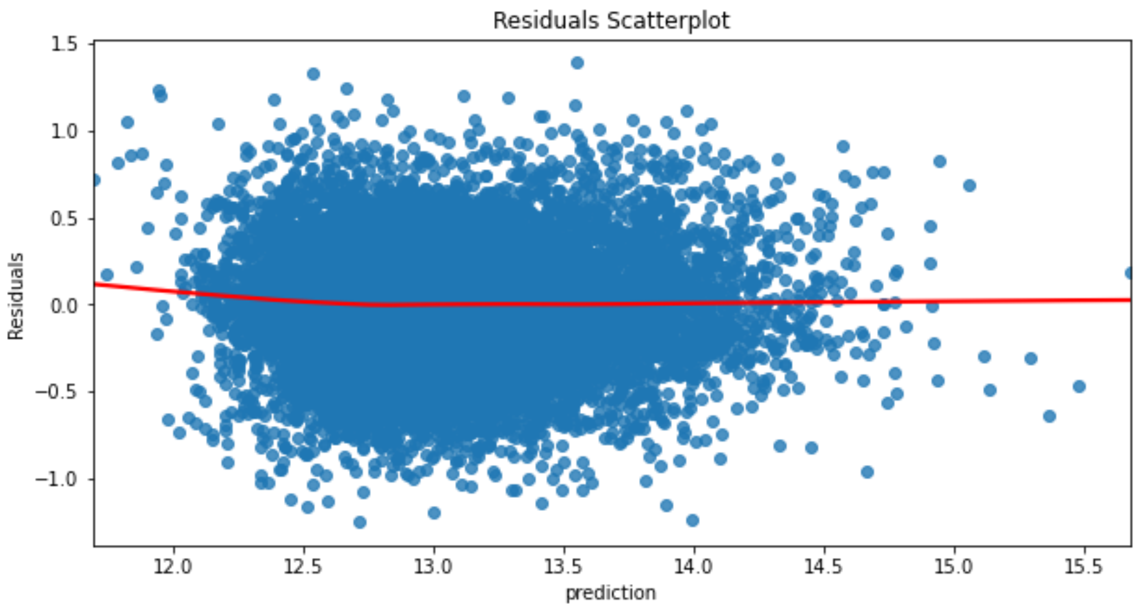



### Homoscedasticity

Scatterplot to show homoscedasticity. No cone like pattern

In [31]:
```
plt.figure(figsize=(10,5))
sns.regplot(x=model.predict(), y=model.resid, lowess=True, line_kws={'color
plt.title('Residuals Scatterplot')
plt.xlabel('prediction')
plt.ylabel('Residuals')
```

Out[31]: Text(0, 0.5, 'Residuals')




### Training

With training and test MSE being similar, we can expect the model to perform similarly on different data.
Accuracy of the model is 63.42

In [32]:
```
y = price
```

```
X = predictors
X_train, X_test, y_train, y_test = train_test_split(X, y)

linreg = LinearRegression()
linreg.fit(X_train, y_train)

y_hat_train = linreg.predict(X_train)
y_hat_test = linreg.predict(X_test)

train_mse = mean_squared_error(y_train, y_hat_train)
test_mse = mean_squared_error(y_test, y_hat_test)
print('Train Mean Squared Error:', train_mse)
print('Test Mean Squared Error:', test_mse)
```

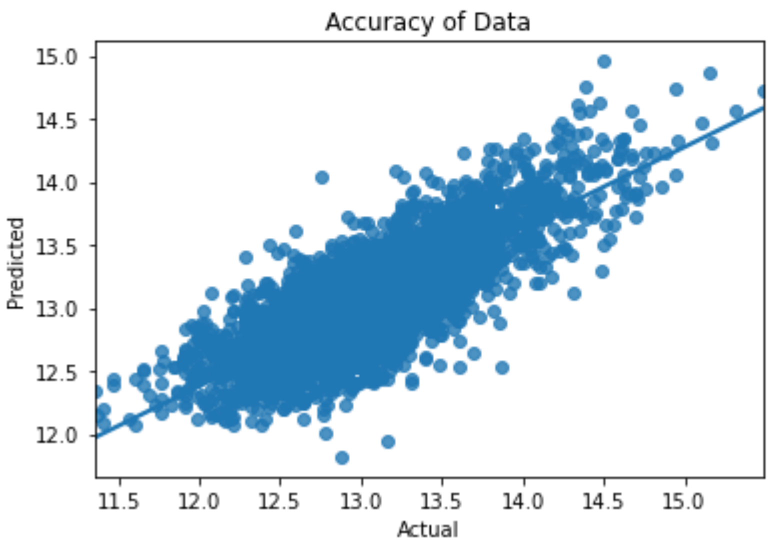
```
Train Mean Squared Error: 0.09779224976352793
Test Mean Squared Error: 0.09848355578437429
```

In [33]:
```
from sklearn.metrics import r2_score

Accuracy=r2_score(y_test,y_hat_test)*100
print(" Accuracy of the model is %.2f" %Accuracy)
```

```
 Accuracy of the model is 63.10
```

In [34]:
```
plot = sns.regplot(x=y_test,y=y_hat_test,ci=None).set(title='Accuracy of Da
```




## Conclusion

With our final model the OLS regression results tell us that the R-Squared value is 0.646 meaning 64.6% of the variance can be explained by the model. The results also tells us the skewness is -0.039 which is between -0.5 to 0.5 meaning the data is symmetrical, satisfying the normality assumption. This can also be seen from the QQ-plot with points mostly following the line. If we observed a QQ-plot like in model 2 then the distribution would be non-normal. Another assumption for linear regression is that data must be homoscedastic. To check this we created a scatterplot and did not observe any cone like shapes which would indicated the data is heteroscedastic.
The living space of a property has the strongest relationship with house prices. This is determined by the t value of 49.874 which tells us how statistically significant the coefficient is. This makes sense as we spend most of the time inside the house and having a larger living area generally means more rooms or floors making it appealing to buyers. Floor had

the next highest t value of 11.1 but only for 3 floors. Having more floors generally means more living area which can increase the value. Grades are also significant as it represents the quality of the home. Renovated has a t value of 2.7 which is not as high. This might be because the data for unrenovated homes heavily outweighed that of renovated homes.