Final Project Submission

Please fill out:

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- Student pace: Self paced
- Scheduled project review date/time: April 29th, 2022, 9AM
- Instructor name: Claude Fried
- Blog post URL:

Overview

This project analyzes the relationship between home ownership prices and factors that can influence those prices. Information from the data comes from King County data. Predictive analysis is done to help with possible upgrades to benefit homeowners.

Business Problem

A real estate firm wants to help their clients (Homeowners) sell their homes at a great price. The analysis can help show correlations between what drives the value of a home and may advise the homeowner to make the necessary upgrades to get better value for their homes.

Data Understanding

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

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

Out[1]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront
0	7129300520	10/13/2014	221900.0	3	1.00	1180	5650	1.0	NaN
1	6414100192	12/9/2014	538000.0	3	2.25	2570	7242	2.0	NO
2	5631500400	2/25/2015	180000.0	2	1.00	770	10000	1.0	NO
3	2487200875	12/9/2014	604000.0	4	3.00	1960	5000	1.0	NO
4	1954400510	2/18/2015	510000.0	3	2.00	1680	8080	1.0	NO

5 rows × 21 columns

In [2]:
```
#Checking the information, there is a notice of object types in the information w
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
```

In [3]:
```
#checking stats
df.describe()
```

Out[3]:

	id	price	bedrooms	bathrooms	sqft_living	sqft_lot	
count	2.159700e+04	2.159700e+04	21597.000000	21597.000000	21597.000000	2.159700e+04	21597
mean	4.580474e+09	5.402966e+05	3.373200	2.115826	2080.321850	1.509941e+04	1
std	2.876736e+09	3.673681e+05	0.926299	0.768984	918.106125	4.141264e+04	C
min	1.000102e+06	7.800000e+04	1.000000	0.500000	370.000000	5.200000e+02	1
25%	2.123049e+09	3.220000e+05	3.000000	1.750000	1430.000000	5.040000e+03	1
50%	3.904930e+09	4.500000e+05	3.000000	2.250000	1910.000000	7.618000e+03	1
75%	7.308900e+09	6.450000e+05	4.000000	2.500000	2550.000000	1.068500e+04	2
max	9.900000e+09	7.700000e+06	33.000000	8.000000	13540.000000	1.651359e+06	3

Data Preprocessing

In [4]:
```
#choosing relevant columns
df_new = df.drop(['id', 'date', 'lat', 'long', 'zipcode'], axis=1)
df_new.head()
```

Out[4]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition	gra
0	221900.0	3	1.00	1180	5650	1.0	NaN	NONE	Average	Aver
1	538000.0	3	2.25	2570	7242	2.0	NO	NONE	Average	Aver
2	180000.0	2	1.00	770	10000	1.0	NO	NONE	Average	6 L Aver
3	604000.0	4	3.00	1960	5000	1.0	NO	NONE	Very Good	Aver
4	510000.0	3	2.00	1680	8080	1.0	NO	NONE	Average	8 G

In [5]:
```
#checking columns after dropping
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     19221 non-null  object 
 7   view           21534 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   17755 non-null  float64
 14  sqft_living15  21597 non-null  int64  
 15  sqft_lot15     21597 non-null  int64  
dtypes: float64(4), int64(7), object(5)
memory usage: 2.6+ MB
```

In [6]:
```
#Checking for missing values

df_new.isna().sum()
```

Out[6]:
```
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
```

In [7]:
```
#filling missing values for waterfront, view, yr_renovated with no type replaceme
df_new.fillna({'waterfront':'NO', 'view':'NONE', 'yr_renovated': 0.0}, inplace=Tr
```

In [8]:
```
df_new['yr_renovated'].value_counts()
```

Out[8]:
```
0.0       20853
2014.0       73
2003.0       31
2013.0       31
2007.0       30
          ...
1946.0        1
1959.0        1
1971.0        1
1951.0        1
1954.0        1
Name: yr_renovated, Length: 70, dtype: int64
```

In [9]:
```
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  float64
 14  sqft_living15  21597 non-null  int64  
 15  sqft_lot15     21597 non-null  int64  
dtypes: float64(4), int64(7), object(5)
memory usage: 2.6+ MB
```

In [10]:
```
#checking objects
df_objects = df_new[['waterfront', 'view', 'condition', 'grade', 'sqft_basement']
for col in (df_objects):
    print(df_objects[col].value_counts(),
          "---------------")
```

```
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
          ...
2310.0        1
2490.0        1
2196.0        1
792.0         1
1816.0        1
Name: sqft_basement, Length: 304, dtype: int64 ---------------
```

In [11]:
```
# converting sqft_basement to float and converting "?" to nan value
df_new['sqft_basement'].replace('?', np.nan, inplace=True)
df_new['sqft_basement'].astype('float64')
```

Out[11]:
```
0          0.0
1        400.0
2          0.0
3        910.0
4          0.0
         ...  
21592      0.0
21593      0.0
21594      0.0
21595      0.0
21596      0.0
Name: sqft_basement, Length: 21597, dtype: float64
```

In [12]:
```
#Converting sqft_basement "?" to column for imputing
from sklearn.impute import MissingIndicator

basement = df_new[['sqft_basement']]
missing_indicator = MissingIndicator()
missing_indicator.fit(basement)
basement_result = missing_indicator.transform(basement)

basement_result
```

Out[12]:
```
array([[False],
       [False],
       [False],
       ...,
       [False],
       [False],
       [False]])
```

In [13]:
```
df_new['sqft_basement_missing'] = basement_result
df_new
```

Out[13]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition
0	221900.0	3	1.00	1180	5650	1.0	NO	NONE	Average
1	538000.0	3	2.25	2570	7242	2.0	NO	NONE	Average
2	180000.0	2	1.00	770	10000	1.0	NO	NONE	Average
3	604000.0	4	3.00	1960	5000	1.0	NO	NONE	Very Good
4	510000.0	3	2.00	1680	8080	1.0	NO	NONE	Average
...	...	...	...	...	...	...	...	...	...
21592	360000.0	3	2.50	1530	1131	3.0	NO	NONE	Average
21593	400000.0	4	2.50	2310	5813	2.0	NO	NONE	Average
21594	402101.0	2	0.75	1020	1350	2.0	NO	NONE	Average
21595	400000.0	3	2.50	1600	2388	2.0	NO	NONE	Average
21596	325000.0	2	0.75	1020	1076	2.0	NO	NONE	Average

21597 rows × 17 columns

In [14]:
```
#imputing missing values for sqft_basement

from sklearn.impute import SimpleImputer

imputer = SimpleImputer(strategy='mean')

imputer.fit(basement)
basement_imputed = imputer.transform(basement)

basement_imputed
```

Out[14]:
```
array([[  0.],
       [400.],
       [  0.],
       ...,
       [  0.],
       [  0.],
       [  0.]])
```

In [15]:
```
df_new['sqft_basement'] = basement_imputed
df_new
```

Out[15]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition
0	221900.0	3	1.00	1180	5650	1.0	NO	NONE	Average
1	538000.0	3	2.25	2570	7242	2.0	NO	NONE	Average
2	180000.0	2	1.00	770	10000	1.0	NO	NONE	Average
3	604000.0	4	3.00	1960	5000	1.0	NO	NONE	Very Good
4	510000.0	3	2.00	1680	8080	1.0	NO	NONE	Average
...	...	...	...	...	...	...	...	...	...
21592	360000.0	3	2.50	1530	1131	3.0	NO	NONE	Average
21593	400000.0	4	2.50	2310	5813	2.0	NO	NONE	Average
21594	402101.0	2	0.75	1020	1350	2.0	NO	NONE	Average
21595	400000.0	3	2.50	1600	2388	2.0	NO	NONE	Average
21596	325000.0	2	0.75	1020	1076	2.0	NO	NONE	Average

21597 rows × 17 columns

In [16]:
```
df_new.isna().sum()
```

Out[16]:
```
price                    0
bedrooms                 0
bathrooms                0
sqft_living              0
sqft_lot                 0
floors                   0
waterfront               0
view                     0
condition                0
grade                    0
sqft_above               0
sqft_basement            0
yr_built                 0
yr_renovated             0
sqft_living15            0
sqft_lot15               0
sqft_basement_missing    0
dtype: int64
```

In [17]:
```
#converting boolean column sqft_basement_missing to binary values
df_new['sqft_basement_missing'] = df_new['sqft_basement_missing'].astype(int)
df_new
```

Out[17]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition
0	221900.0	3	1.00	1180	5650	1.0	NO	NONE	Average
1	538000.0	3	2.25	2570	7242	2.0	NO	NONE	Average
2	180000.0	2	1.00	770	10000	1.0	NO	NONE	Average
3	604000.0	4	3.00	1960	5000	1.0	NO	NONE	Very Good
4	510000.0	3	2.00	1680	8080	1.0	NO	NONE	Average
...	...	...	...	...	...	...	...	...	...
21592	360000.0	3	2.50	1530	1131	3.0	NO	NONE	Average
21593	400000.0	4	2.50	2310	5813	2.0	NO	NONE	Average
21594	402101.0	2	0.75	1020	1350	2.0	NO	NONE	Average
21595	400000.0	3	2.50	1600	2388	2.0	NO	NONE	Average
21596	325000.0	2	0.75	1020	1076	2.0	NO	NONE	Average

21597 rows × 17 columns

In [18]:
```
#Dealing with ordinal categories using pandas

df_new['view'] = df_new['view'].astype('category')
df_new['condition'] = df_new['condition'].astype('category')
df_new['grade'] = df_new['grade'].astype('category')

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

```
0        NONE
1        NONE
2        NONE
3        NONE
4        NONE
         ...
21592    NONE
21593    NONE
21594    NONE
21595    NONE
21596    NONE
Name: view, Length: 21597, dtype: category
Categories (5, object): ['AVERAGE', 'EXCELLENT', 'FAIR', 'GOOD', 'NONE']
0          Average
1          Average
2          Average
3        Very Good
4          Average
           ...
21592      Average
21593      Average
21594      Average
21595      Average
21596      Average
Name: condition, Length: 21597, dtype: category
Categories (5, object): ['Average', 'Fair', 'Good', 'Poor', 'Very Good']
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): ['10 Very Good', '11 Excellent', '12 Luxury', '13 Mans
ion', ..., '6 Low Average', '7 Average', '8 Good', '9 Better']
```

In [19]:

```
#reordering categories

df_new['view'] = df_new['view'].cat.reorder_categories(['NONE', 'FAIR', 'AVERAGE'
df_new['condition'] = df_new['condition'].cat.reorder_categories(['Poor', 'Fair',
df_new['grade'] = df_new['grade'].cat.reorder_categories(['3 Poor', '4 Low', '5 F
                                                          '9 Better', '10 Very Go
```

In [20]:

```
# 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
```

Out[20]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition	g
0	221900.0	3	1.00	1180	5650	1.0	NO	0	2	
1	538000.0	3	2.25	2570	7242	2.0	NO	0	2	
2	180000.0	2	1.00	770	10000	1.0	NO	0	2	
3	604000.0	4	3.00	1960	5000	1.0	NO	0	4	
4	510000.0	3	2.00	1680	8080	1.0	NO	0	2	
...	...	...	...	...	...	...	...	...	...	
21592	360000.0	3	2.50	1530	1131	3.0	NO	0	2	
21593	400000.0	4	2.50	2310	5813	2.0	NO	0	2	
21594	402101.0	2	0.75	1020	1350	2.0	NO	0	2	
21595	400000.0	3	2.50	1600	2388	2.0	NO	0	2	
21596	325000.0	2	0.75	1020	1076	2.0	NO	0	2	

21597 rows × 17 columns

In [21]:

```
#Dealing with binary category

from sklearn.preprocessing import OrdinalEncoder

waterfront_binary = df_new[['waterfront']]

encoder_waterfront = OrdinalEncoder()

encoder_waterfront.fit(waterfront_binary)

encoder_waterfront.categories_[0]
```

Out[21]:

```
array(['NO', 'YES'], dtype=object)
```

In [22]:
```
waterfront_encoded = encoder_waterfront.transform(waterfront_binary)
waterfront_encoded = waterfront_encoded.flatten()
waterfront_encoded
```

Out[22]:
```
array([0., 0., 0., ..., 0., 0., 0.])
```

In [23]:
```
#replacing column

df_new['waterfront'] = waterfront_encoded
df_new
```

Out[23]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition	g
0	221900.0	3	1.00	1180	5650	1.0	0.0	0	2	
1	538000.0	3	2.25	2570	7242	2.0	0.0	0	2	
2	180000.0	2	1.00	770	10000	1.0	0.0	0	2	
3	604000.0	4	3.00	1960	5000	1.0	0.0	0	4	
4	510000.0	3	2.00	1680	8080	1.0	0.0	0	2	
...	...	...	...	...	...	...	...	...	...	
21592	360000.0	3	2.50	1530	1131	3.0	0.0	0	2	
21593	400000.0	4	2.50	2310	5813	2.0	0.0	0	2	
21594	402101.0	2	0.75	1020	1350	2.0	0.0	0	2	
21595	400000.0	3	2.50	1600	2388	2.0	0.0	0	2	
21596	325000.0	2	0.75	1020	1076	2.0	0.0	0	2	

21597 rows × 17 columns

In [24]:
```
df_new['waterfront'].value_counts()
```

Out[24]:
```
0.0    21451
1.0      146
Name: waterfront, dtype: int64
```

In [25]:
```
df_new.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 21597 entries, 0 to 21596
Data columns (total 17 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  float64
 7   view                  21597 non-null  int8   
 8   condition             21597 non-null  int8   
 9   grade                 21597 non-null  int8   
 10  sqft_above            21597 non-null  int64  
 11  sqft_basement         21597 non-null  float64
 12  yr_built              21597 non-null  int64  
 13  yr_renovated          21597 non-null  float64
 14  sqft_living15         21597 non-null  int64  
 15  sqft_lot15            21597 non-null  int64  
 16  sqft_basement_missing 21597 non-null  int32  
dtypes: float64(6), int32(1), int64(7), int8(3)
memory usage: 2.3 MB
```

In [26]:
```
df_new.describe()
```

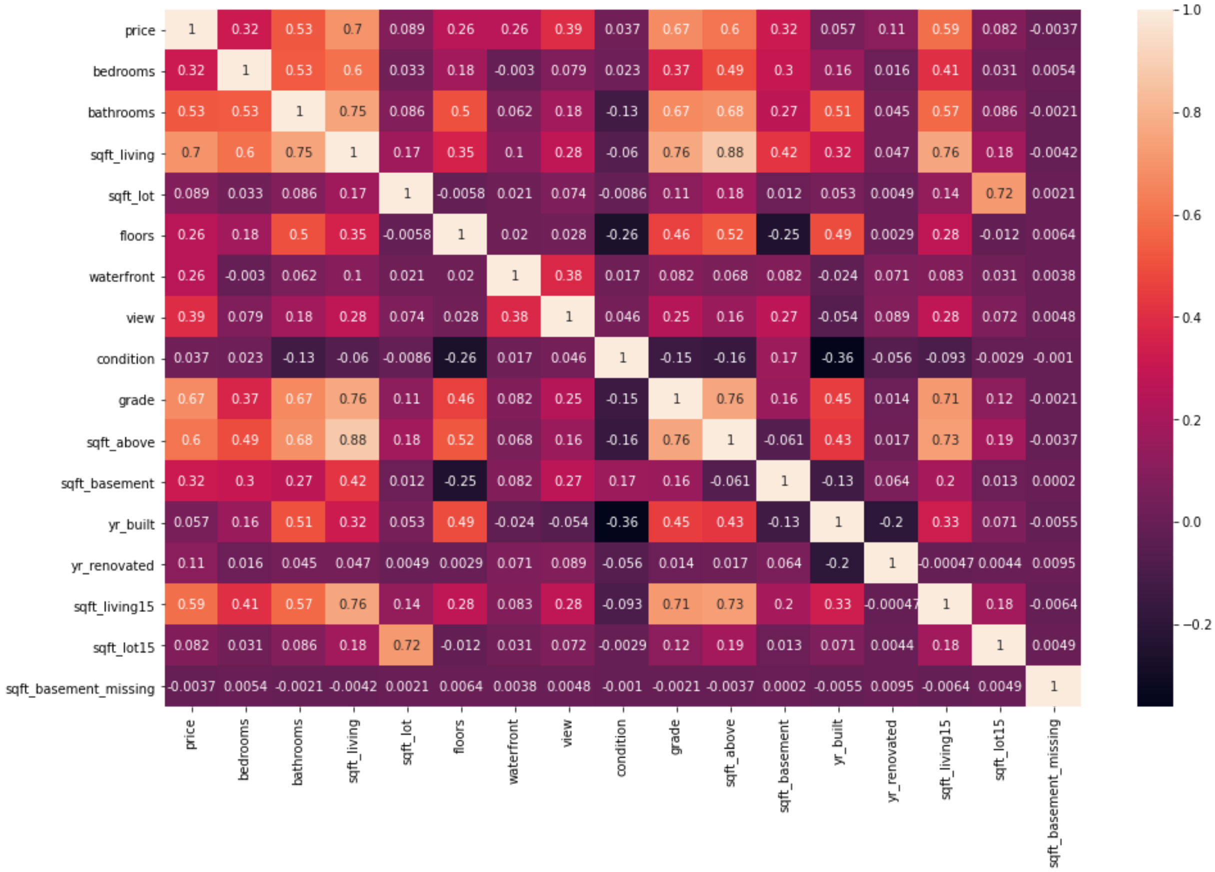
Out[26]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	wa
count	2.159700e+04	21597.000000	21597.000000	21597.000000	2.159700e+04	21597.000000	21597
mean	5.402966e+05	3.373200	2.115826	2080.321850	1.509941e+04	1.494096	0
std	3.673681e+05	0.926299	0.768984	918.106125	4.141264e+04	0.539683	0
min	7.800000e+04	1.000000	0.500000	370.000000	5.200000e+02	1.000000	0
25%	3.220000e+05	3.000000	1.750000	1430.000000	5.040000e+03	1.000000	0
50%	4.500000e+05	3.000000	2.250000	1910.000000	7.618000e+03	1.500000	0
75%	6.450000e+05	4.000000	2.500000	2550.000000	1.068500e+04	2.000000	0
max	7.700000e+06	33.000000	8.000000	13540.000000	1.651359e+06	3.500000	1

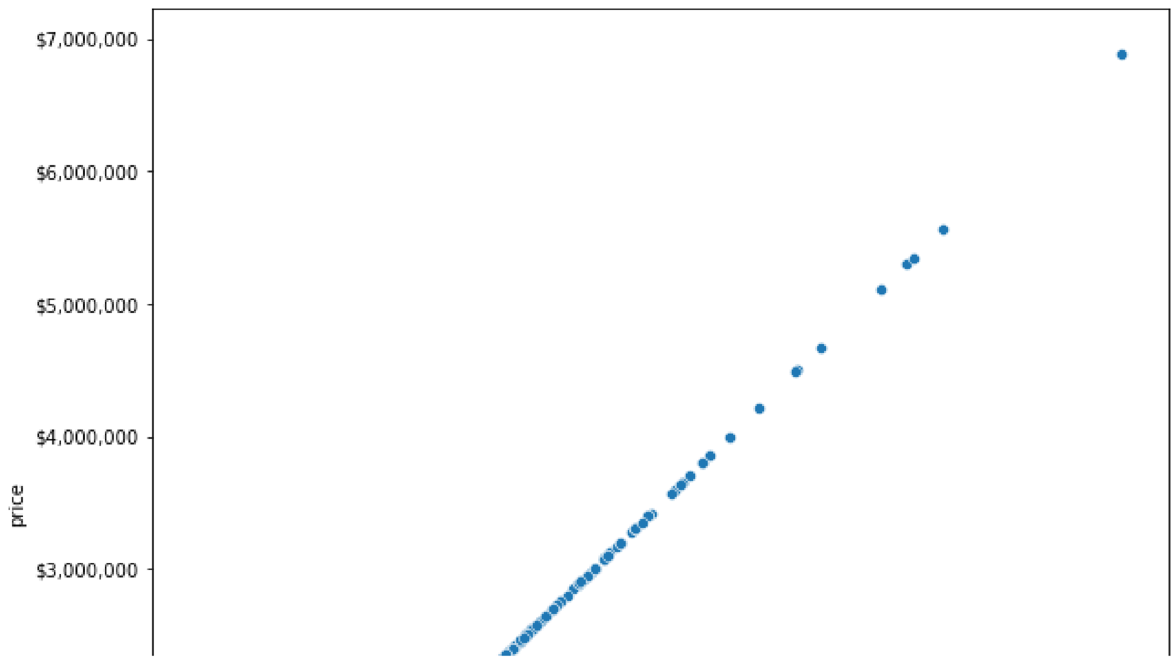
In [27]:
```
#dealing with extreme outlier in bedrooms and sqft_living
df_new = df_new[df_new['bedrooms'] < 10]
df_new = df_new[df_new['sqft_living'] <= 10000]
df_new.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 21589 entries, 0 to 21596
Data columns (total 17 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  float64
 12  yr_built             21589 non-null  int64  
 13  yr_renovated         21589 non-null  float64
 14  sqft_living15        21589 non-null  int64  
 15  sqft_lot15           21589 non-null  int64  
 16  sqft_basement_missing  21589 non-null  int32  
dtypes: float64(6), int32(1), int64(7), int8(3)
memory usage: 2.5 MB
```

In [28]:
```
#Checking heatmap for possible correlations to price
fig, ax = plt.subplots(figsize=(16,10))
sns.heatmap(df_new.corr(), annot=True);
```



In [29]:
```
# Using scatter plots to check correlations
for i, col in enumerate(df_new.columns):
    plt.figure(i, figsize=(10,10))
    sns.scatterplot(x=col, y=df_new['price'], data=df_new)
    import matplotlib.ticker as mtick #importing ticker to customize tickers
    fmt = '${x:,.0f}' #setting the format to $
    tick = mtick.StrMethodFormatter(fmt) #appending it to a formatter
    plt.gca().yaxis.set_major_formatter(tick) #applying the format
```



Modeling

Baseline Model

In [30]:
```
#setting up base model with highest correlated column to price from heatmap
import statsmodels.api as sm
import statsmodels.formula.api as smf

x_basic = df_new['sqft_living']
y_basic = df_new['price']

model = sm.OLS(y_basic, sm.add_constant(x_basic)).fit()
model.summary()
```

Out[30]:

OLS Regression Results

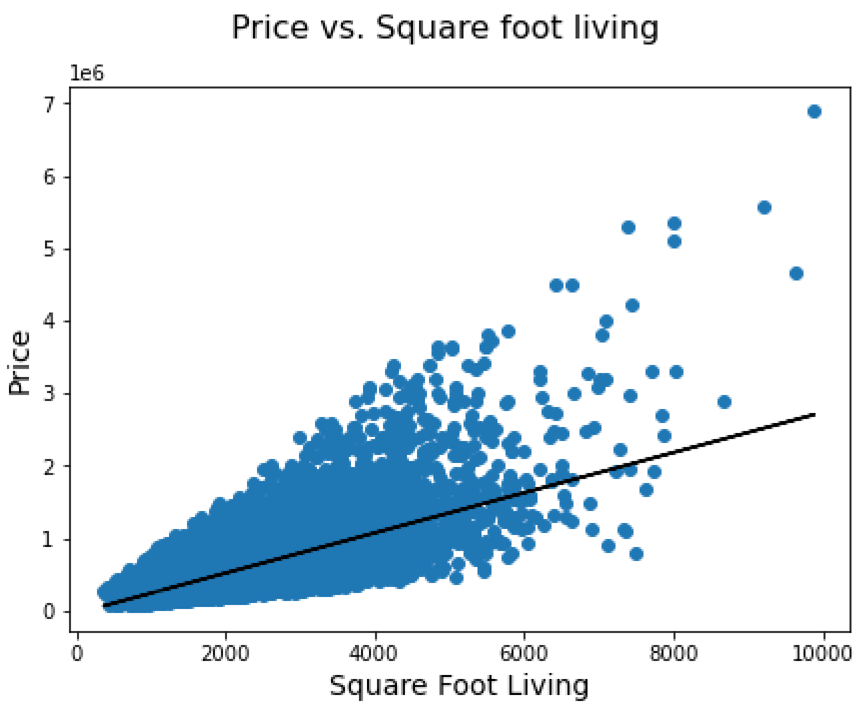
Dep. Variable:	price	**R-squared:**	0.489
Model:	OLS	**Adj. R-squared:**	0.489
Method:	Least Squares	**F-statistic:**	2.069e+04
Date:	Thu, 28 Apr 2022	**Prob (F-statistic):**	0.00
Time:	11:50:55	**Log-Likelihood:**	-2.9966e+05
No. Observations:	21589	**AIC:**	5.993e+05
Df Residuals:	21587	**BIC:**	5.993e+05
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.

In [57]:
```
m, c = np.polyfit(x_basic, y_basic, 1)

fig = plt.figure(figsize=(7, 5))
fig.suptitle('Price vs. Square foot living', fontsize=16)
plt.scatter(x_basic, y_basic)
plt.plot(x_basic, m*x_basic+c, c='black')
plt.xlabel('Square Foot Living', fontsize=14)
plt.ylabel('Price', fontsize=14)
plt.show()
```

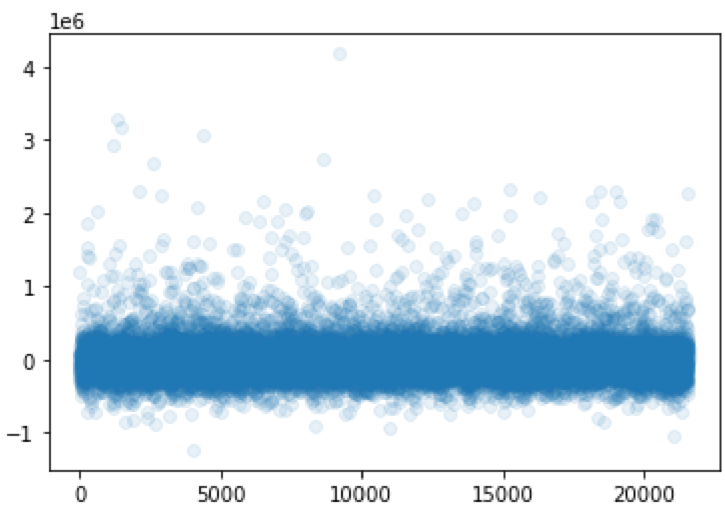


Homoscedasticity Check for Baseline Model

In [32]:
```
model.predict(sm.add_constant(x_basic))
```

Out[32]:
```
0        290108.943350
1        675892.620304
2        176316.635760
3        506591.869986
4        428880.050168
             ...
21592    387248.718123
21593    603731.644759
21594    245702.189169
21595    406676.673077
21596    245702.189169
Length: 21589, dtype: float64
```

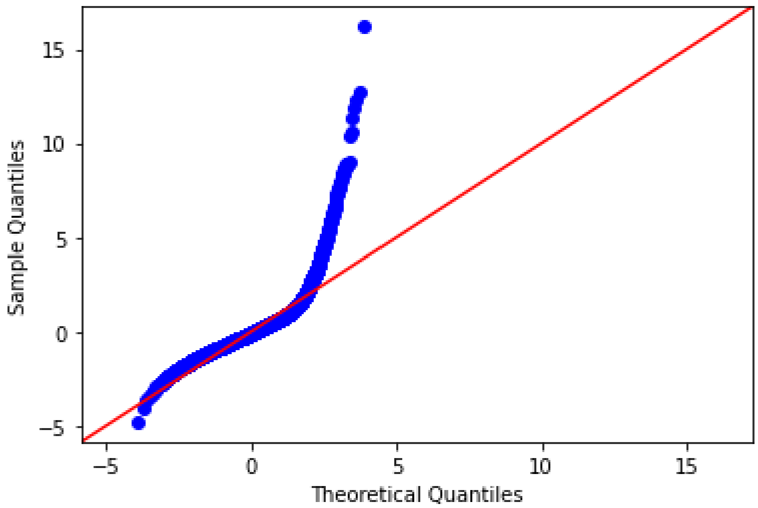
In [33]:
```
#Checking for homoscedasticity
residuals = model.resid

plt.scatter(x=range(residuals.shape[0]), y=residuals, alpha=0.1);
```



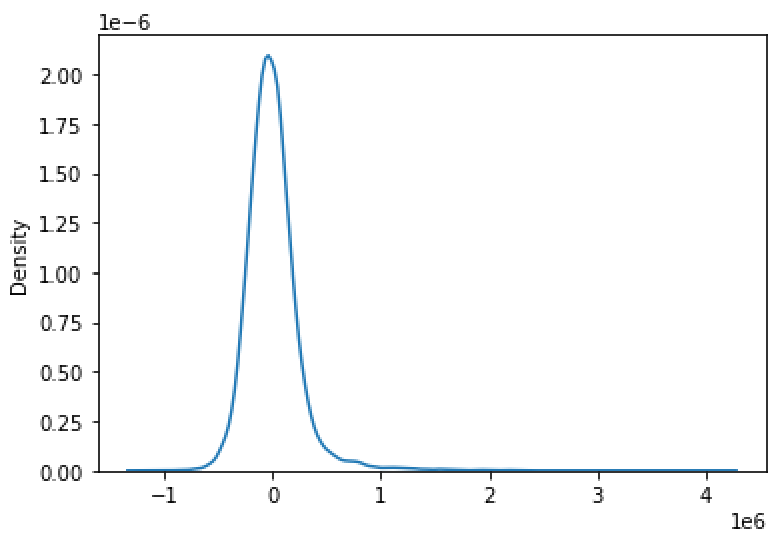
Normality Check for Baseline Model

In [34]:
```
import scipy.stats as stats
fig = sm.graphics.qqplot(residuals, dist=stats.norm, line='45', fit=True)
fig.show()
```

```
<ipython-input-34-d7327fda397e>:3: UserWarning: Matplotlib is currently using m
odule://ipykernel.pylab.backend_inline, which is a non-GUI backend, so cannot s
how the figure.
  fig.show()
```



In [35]:
```
#Checking for linear regression assumptions for the baseline. Checking for normal
sns.kdeplot(x=model.resid);
```



Model 2

In [36]:
```
## Adding features to the model to see if it will improve scores. Adding features
#heatmap

X = pd.DataFrame(data=df_new, columns=['sqft_living', 'grade', 'sqft_above', 'sq
y = df_new['price']
X.head()
```

Out[36]:

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

In [37]:
```python
model2 = sm.OLS(y, sm.add_constant(X)).fit()
model2.summary()
```

Out[37]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.543
Model:	OLS	**Adj. R-squared:**	0.543
Method:	Least Squares	**F-statistic:**	6417.
Date:	Thu, 28 Apr 2022	**Prob (F-statistic):**	0.00
Time:	11:50:56	**Log-Likelihood:**	-2.9846e+05
No. Observations:	21589	**AIC:**	5.969e+05
Df Residuals:	21584	**BIC:**	5.970e+05
Df Model:	4		
Covariance Type:	nonrobust		

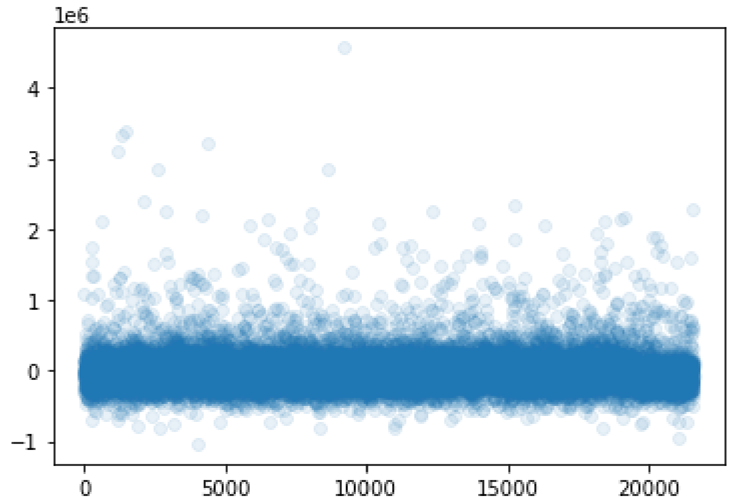
	coef	std err	t	P>|t|	[0.025	0.975]
const	-3.342e+05	7291.222	-45.835	0.000	-3.48e+05	-3.2e+05
sqft_living	218.5031	4.147	52.689	0.000	210.375	226.632
grade	1.086e+05	2381.907	45.584	0.000	1.04e+05	1.13e+05
sqft_above	-82.6951	4.389	-18.842	0.000	-91.298	-74.093
sqft_living15	31.0497	3.966	7.829	0.000	23.276	38.824

Omnibus:	15263.820	**Durbin-Watson:**	1.972
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	578114.258
Skew:	2.946	**Prob(JB):**	0.00
Kurtosis:	27.657	**Cond. No.**	1.64e+04

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 1.64e+04. This might indicate that there are
strong multicollinearity or other numerical problems.

Homoscedasticity Check for Model 2

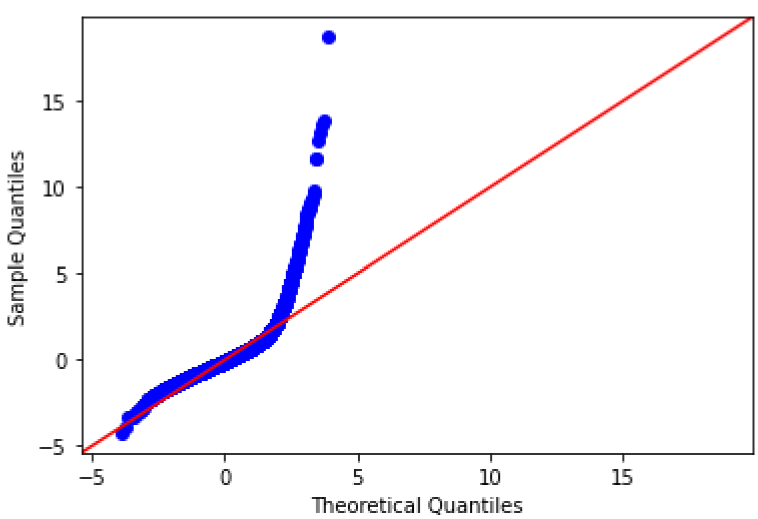
In [38]:
```
residuals_m2 = model2.resid

plt.scatter(x=range(residuals_m2.shape[0]), y=residuals_m2, alpha=0.1);
```



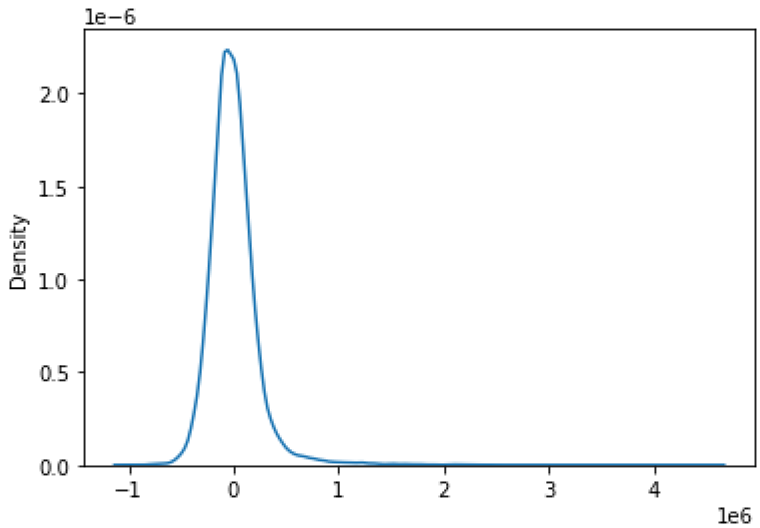
Normality Check for Model 2

In [39]:
```
fig = sm.graphics.qqplot(residuals_m2, dist=stats.norm, line='45', fit=True)
fig.show()
```

```
<ipython-input-39-6105dfd15eb7>:2: UserWarning: Matplotlib is currently using m
odule://ipykernel.pylab.backend_inline, which is a non-GUI backend, so cannot s
how the figure.
  fig.show()
```



In [40]:
```
#Checking for linear regression assumptions for the baseline. Checking for normal
sns.kdeplot(x=model2.resid);
```



Multicollinearity Check for Model 2

In [41]:
```
#Checking for values that have strong multicollnearity
df = X.corr().abs().stack().reset_index().sort_values(0, ascending=False)

df['pairs'] = list(zip(df.level_0, df.level_1))
df.set_index(['pairs'], inplace=True)

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

df.columns = ['cc']

df.drop_duplicates(inplace=True)

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

Out[41]:

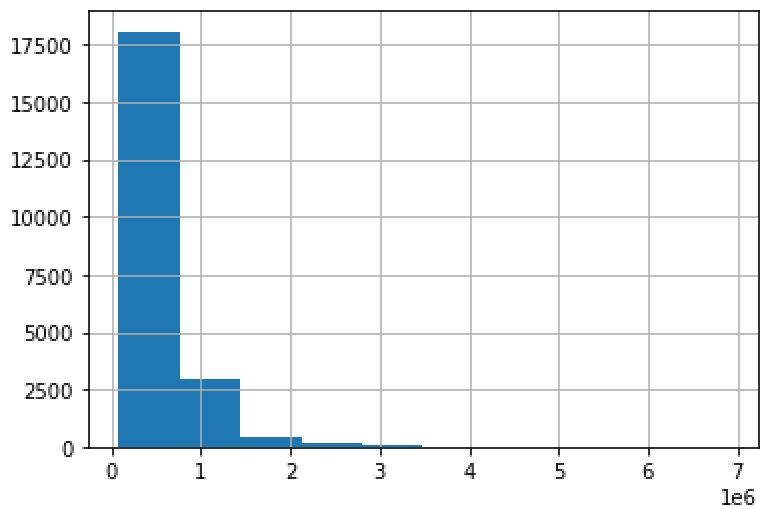
pairs	cc
(sqft_living, sqft_above)	0.875386
(sqft_living, grade)	0.764354
(sqft_living, sqft_living15)	0.758302
(grade, sqft_above)	0.756236

In [42]:
```
#Checking VIF scores to remove highly correlated variables.
from statsmodels.stats.outliers_influence import variance_inflation_factor
from statsmodels.tools.tools import add_constant
X_vif1 = add_constant(X)
pd.Series([variance_inflation_factor(X_vif1.values, i)
               for i in range(X_vif1.shape[1])], index=X_vif1.columns)
```

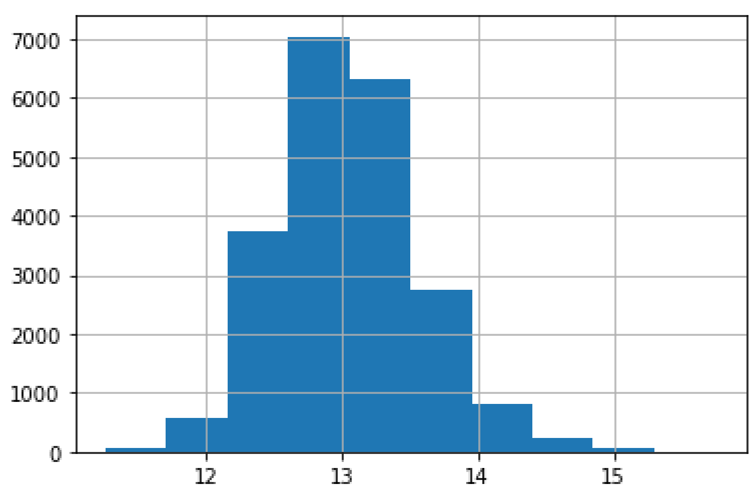
Out[42]:
```
const            19.249482
sqft_living       5.162920
grade             2.822569
sqft_above        4.734643
sqft_living15     2.670811
dtype: float64
```

Checking target for transformation

In [43]:
```
#Checking y hist to see if it needs transforming
y.hist();
```



In [44]:
```
# Transforming y using log
y_log = np.log(y)
y_log.hist();
```



Model 3

In [45]:
```
# Creating new model using new logged target and dropping highest multicollinear
X_3 = X.drop(columns = 'sqft_living')
model3 = sm.OLS(y_log, sm.add_constant(X_3)).fit()
model3.summary()
```

Out[45]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.524
Model:	OLS	**Adj. R-squared:**	0.524
Method:	Least Squares	**F-statistic:**	7917.
Date:	Thu, 28 Apr 2022	**Prob (F-statistic):**	0.00
Time:	11:50:57	**Log-Likelihood:**	-8744.7
No. Observations:	21589	**AIC:**	1.750e+04
Df Residuals:	21585	**BIC:**	1.753e+04
Df Model:	3		
Covariance Type:	nonrobust		

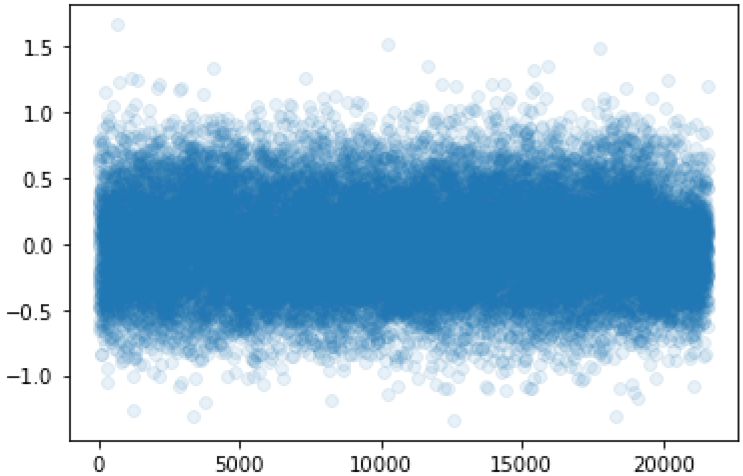
	coef	std err	t	P>|t|	[0.025	0.975]
const	11.5993	0.011	1080.475	0.000	11.578	11.620
grade	0.2254	0.003	65.354	0.000	0.219	0.232
sqft_above	4.086e-05	5.05e-06	8.095	0.000	3.1e-05	5.08e-05
sqft_living15	0.0002	5.67e-06	28.903	0.000	0.000	0.000

Omnibus:	78.737	**Durbin-Watson:**	1.970
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	77.659
Skew:	0.134	**Prob(JB):**	1.37e-17
Kurtosis:	2.879	**Cond. No.**	1.27e+04

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 1.27e+04. This might indicate that there are
strong multicollinearity or other numerical problems.

Homoscedasticity Check for Model 3

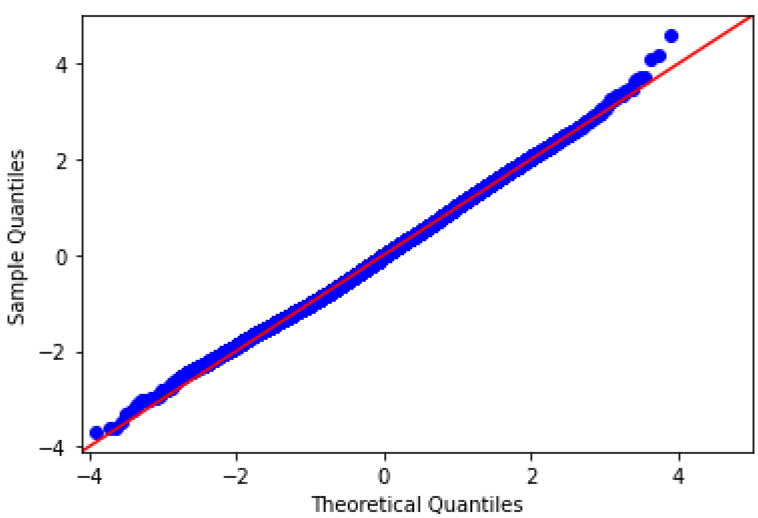
In [46]:
```
#Checking for homoscedasticity
residuals_m3 = model3.resid

plt.scatter(x=range(residuals_m3.shape[0]), y=residuals_m3, alpha=0.1);
```



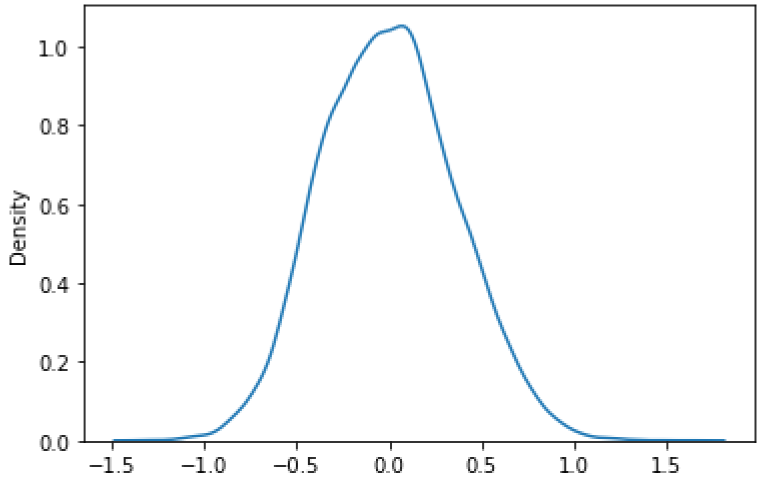
Normality Check for Model 3

In [47]:
```
fig = sm.graphics.qqplot(residuals_m3, dist=stats.norm, line='45', fit=True)
fig.show()
```

```
<ipython-input-47-80110c023be7>:2: UserWarning: Matplotlib is currently using m
odule://ipykernel.pylab.backend_inline, which is a non-GUI backend, so cannot s
how the figure.
  fig.show()
```



In [48]:
```
#Checking for linear regression assumptions for the baseline. Checking for normal
sns.kdeplot(x=model3.resid);
```



Multicollinearity Check for Model 3

In [49]:
```
#Checking for values that have strong multicollnearity
df = X_3.corr().abs().stack().reset_index().sort_values(0, ascending=False)

df['pairs'] = list(zip(df.level_0, df.level_1))
df.set_index(['pairs'], inplace=True)

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

df.columns = ['cc']

df.drop_duplicates(inplace=True)

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

Out[49]:

pairs	cc
(grade, sqft_above)	0.756236

Model 4

In [50]:
```
# Adding features from correlation map above .2

X_m4 = df_new.drop(columns = ['price','sqft_living', 'sqft_lot','condition', 'yr_
                              'sqft_basement_missing'])

X_m4.head()
```

Out[50]:

	bedrooms	bathrooms	floors	waterfront	view	grade	sqft_above	sqft_basement	sqft_living15
0	3	1.00	1.0	0.0	0	4	1180	0.0	1340
1	3	2.25	2.0	0.0	0	4	2170	400.0	1690
2	2	1.00	1.0	0.0	0	3	770	0.0	2720
3	4	3.00	1.0	0.0	0	4	1050	910.0	1360
4	3	2.00	1.0	0.0	0	5	1680	0.0	1800

In [51]:
```
model4 = sm.OLS(y_log, sm.add_constant(X_m4)).fit()
model4.summary()
```

Out[51]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.586
Model:	OLS	**Adj. R-squared:**	0.586
Method:	Least Squares	**F-statistic:**	3400.
Date:	Thu, 28 Apr 2022	**Prob (F-statistic):**	0.00
Time:	11:50:57	**Log-Likelihood:**	-7223.5
No. Observations:	21589	**AIC:**	1.447e+04
Df Residuals:	21579	**BIC:**	1.455e+04
Df Model:	9		
Covariance Type:	nonrobust		

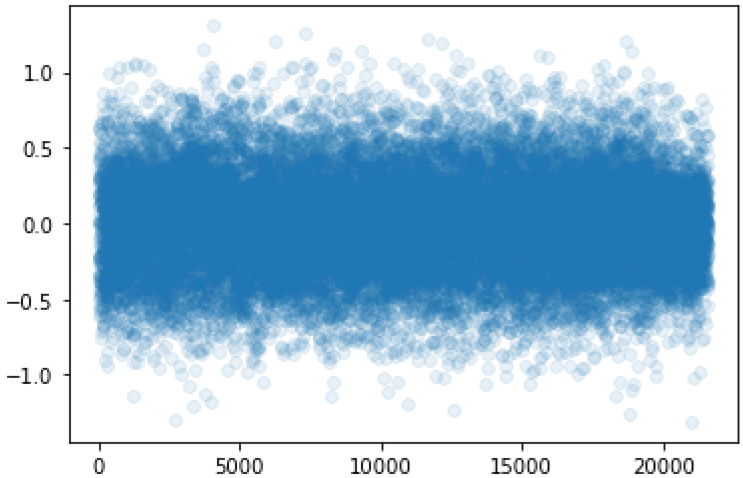
	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
const	11.7059	0.014	859.499	0.000	11.679	11.733
bedrooms	-0.0113	0.003	-3.414	0.001	-0.018	-0.005
bathrooms	-0.0164	0.005	-3.209	0.001	-0.026	-0.006
floors	0.0548	0.006	9.517	0.000	0.044	0.066
waterfront	0.3582	0.031	11.728	0.000	0.298	0.418
view	0.0697	0.003	19.975	0.000	0.063	0.077
grade	0.1768	0.003	50.700	0.000	0.170	0.184
sqft_above	0.0001	6.05e-06	22.433	0.000	0.000	0.000
sqft_basement	0.0003	7.22e-06	38.870	0.000	0.000	0.000
sqft_living15	8.383e-05	5.62e-06	14.921	0.000	7.28e-05	9.48e-05

Omnibus:	14.443	**Durbin-Watson:**	1.970
Prob(Omnibus):	0.001	**Jarque-Bera (JB):**	13.826
Skew:	0.042	**Prob(JB):**	0.000995
Kurtosis:	2.908	**Cond. No.**	3.80e+04

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 3.8e+04. This might indicate that there are
strong multicollinearity or other numerical problems.

Homoscedasticity Check for Model 4

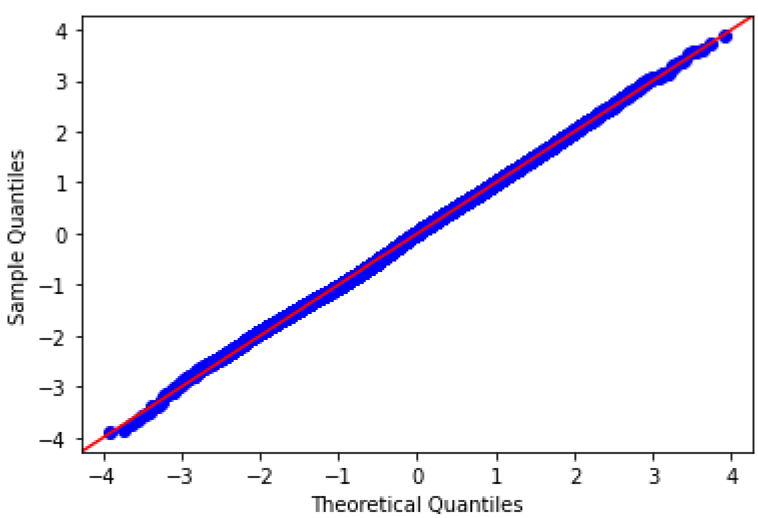
In [52]:
```
#Checking homoscedasticity
residuals_m4 = model4.resid

plt.scatter(x=range(residuals_m4.shape[0]), y=residuals_m4, alpha=0.1, );
```



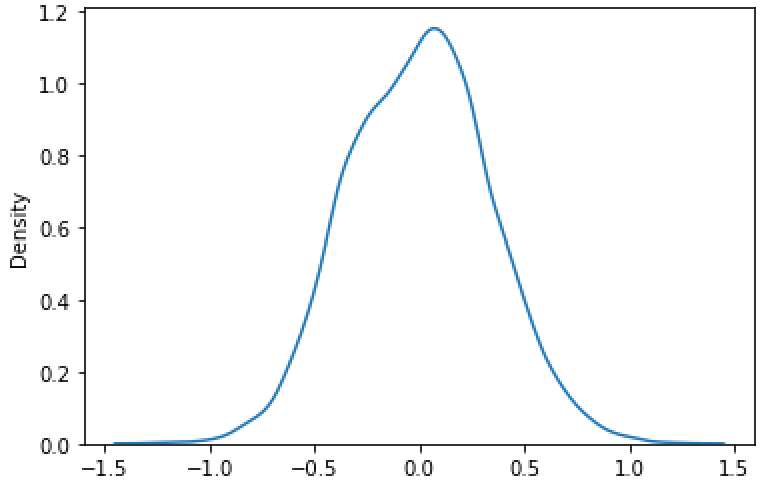
Normality Check for Model 4

In [53]:
```
fig = sm.graphics.qqplot(residuals_m4, dist=stats.norm, line='45', fit=True)
fig.show()
```

```
<ipython-input-53-04e01d904544>:2: UserWarning: Matplotlib is currently using m
odule://ipykernel.pylab.backend_inline, which is a non-GUI backend, so cannot s
how the figure.
  fig.show()
```



In [54]:
```
sns.kdeplot(x=model4.resid);
```



Multicollinearity Check for Model 4

In [55]:
```
#Checking for values that have strong multicollnearity
df = X_m4.corr().abs().stack().reset_index().sort_values(0, ascending=False)

df['pairs'] = list(zip(df.level_0, df.level_1))
df.set_index(['pairs'], inplace=True)

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

df.columns = ['cc']

df.drop_duplicates(inplace=True)

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

Out[55]:

	cc
pairs	
(sqft_above, grade)	0.756236

In [56]:
```
X_vif2 = add_constant(X_m4)
pd.Series([variance_inflation_factor(X_vif2.values, i)
               for i in range(X_vif2.shape[1])], index=X_vif2.columns)
```

Out[56]:
```
const            35.010929
bedrooms          1.674202
bathrooms         2.905953
floors            1.820664
waterfront        1.174861
view              1.340636
grade             3.154466
sqft_above        4.684944
sqft_basement     1.870827
sqft_living15     2.793846
dtype: float64
```

Conclusion

This analysis leads to this recommendation on what the real estate company should advise homeowners on when it comes to increasing the value of their home for sale.

- **Grade is one of the most important factors that can be controlled by the homeowner for price.**

A per grade increase of a home (housing construction including quality materials for exterior and interior) can increase the value of a home by 17.7%. Homeowners should modify their homes with higher quality materials for interiors and exteriors structures.

For the interior of homes:

Plumbing, Flooring, Climate control, Electrical are components of a home that can improve grade.

For the exterior of homes:

Exterior walls and Roofing are components of a home that can improve grade.

While quality materials are desirable for a home upgrade, craftsmanship plays an important role in grading. If a home has the highest quality materials but poorly constructed, grade could be negatively affected.

To highlight this, if we were to focus on adding bedrooms and bathrooms instead of upgrades that focus on grade, it could possibly have a negative effect on pricing with a roughly 0.1% and % 0.2% per bed or bath decrease in the value of the home.

Homes could have less bedrooms and bathrooms but yet still hold the same value as a home with more bedrooms or bathrooms.

Next Steps

Further analyses could yield additional insights to growth:

- **Better grade evaluation.** This model could include whether exterior or interior builds have more of an impact on home value.
- **Renovation allocations vs Expected value.** Information on renovation costs vs value increase for those did renovations or kitchen upgrades could provide further insights.
- **Landscaping impact.** Homes are not only the house itself but the surround of the entire property. It adds to the exterior presence which could possibly influence demand and therefore could lead to an adjustment in price.