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Housing Data: King County, WA

Modeling data to House Price

Authors: Svitlana Glibova & Jamie Dowat (mailto:jamie_dowat44@yahoo.com)

Business Understanding

Real Estate and Data Science

As the world becomes more technologically savvy, highly competitive markets (such as real estate) are reaching for more and more rigorous analytics to help them stay ahead. This desire for more accurate predictive and inferential modeling is so great, apparently, that they are offering formal Data Science bootcamps (https://www.propertyquants.com/training/?utm_source=google&utm_medium=cpc&utm_campaign=P-Real%20Estate%20Data&utm_term=%2Breal%20%2Bestate%20%2Bdata&utm_content=&gclid=Cj0KCQiAvbiBBhD-ARIsAGM48bzsFBf1tarC8f6xwnH9T-HkmdpI_qLjozgbvPXSHuCIemsH85A9eSoaAooVEALw_wcB) that specialize in measuring real estate trends!

Companies like Opendoor (https://www.youtube.com/watch?v=dR5N8cMkIGQ) and Zillow are also taking the industry in a different direction, by working to automate the home-buying and selling process, which requires proper analysis of market trends to determine a houses estimated market value.

Defining the Stakeholder: Residential Realtors

Though there are a number of stakeholders in the industry, from investors to house flippers to renters, we decided to gear our analysis towards maximizing profit for **residential realtors**, whose paycheck directly depends on the price of the house they sell.

In other words, this analysis seeks to answer the question:

How can you best assist your client in setting or offering a home price?

(Is a given client undercharging or overpaying for a home?)

Through a more comprehensive knowledge of house price trends, King County realtors can (hopefully) see more success when helping to set house prices for their clients.

A Quick Preview of Our Results:

Overall, we found that the following variables had the strongest positive correlation with house prices:

- House size
- House Grade
- Location
- Size of neighboring houses
- House condition
- Whether or not the house has a waterfront view

"A COVID Caveat"

It is important to note that our data only consists of homes that were sold between 2014-2015. Considering the current economic situation, we cannot say that our resulting models account for these current trends. For a more detailed account of how house prices have been changing in 2020-2021, take a look at our **presentation.pdf** file.

Data Exploration

This data consists of information for **21,597 homes** within King County, WA.

The data was sourced from the King County website (https://info.kingcounty.gov/assessor/DataDownload/default.aspx)

The data was sourced from the King County website (https://info.kingcounty.gov/assessor/DataDownload/default.aspx).

Let's take a look:

In [1]:
```
import pandas as pd
import numpy as np

import warnings
warnings.filterwarnings('ignore')
```

In [2]:
```
data = pd.read_csv('src/kc_house_data.csv')
```

In [3]:
```
data.head()
```

Out[3]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	...	grade	s
0	7129300520	10/13/2014	221900.0	3	1.00	1180	5650	1.0	NaN	0.0	...	7	1
1	6414100192	12/9/2014	538000.0	3	2.25	2570	7242	2.0	0.0	0.0	...	7	2
2	5631500400	2/25/2015	180000.0	2	1.00	770	10000	1.0	0.0	0.0	...	6	7
3	2487200875	12/9/2014	604000.0	4	3.00	1960	5000	1.0	0.0	0.0	...	7	1
4	1954400510	2/18/2015	510000.0	3	2.00	1680	8080	1.0	0.0	0.0	...	8	1

5 rows × 21 columns

In [4]:
```
data.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
```

Let's take care of our NaN values

In [5]:
```
data.isna().sum()
```

Out[5]:
```
id                  0
date                0
price               0
bedrooms            0
bathrooms           0
sqft_living         0
sqft_lot            0
floors              0
waterfront       2376
view               63
condition           0
grade               0
sqft_above          0
sqft_basement       0
yr_built            0
yr_renovated     3842
zipcode             0
lat                 0
long                0
sqft_living15       0
sqft_lot15          0
dtype: int64
```

In [6]:
```
# Sqft basement has some unknown values we need to deal with as well:

data.sqft_basement.value_counts()
```

Out[6]:
```
0.0       12826
?           454
600.0       217
500.0       209
700.0       208
          ...
225.0         1
2250.0        1
1770.0        1
2310.0        1
2180.0        1
Name: sqft_basement, Length: 304, dtype: int64
```

For the sake of analysis, we didn't find any use with the **yr_renovated**, and **view** columns. We'll drop that along with **id**.

In [7]:
```
from src import boring_code as bc
```

In [8]:
```
nan_columns = ['waterfront', 'sqft_basement']
cols_to_drop = ['view', 'yr_renovated', 'id']
```

In [9]:
```
bc.cleaning(df=data,
        column_names=nan_columns,
        drop=cols_to_drop,
        date_col='date',
        date_suffix=['_sold', '_sold'],
        date_split='/')
```

Out[9]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	condition	grade	sqft_above	sqft_basem
0	221900.0	3	1.00	1180	5650	1.0	NaN	3	7	1180	0.0
1	538000.0	3	2.25	2570	7242	2.0	0.0	3	7	2170	400.0
2	180000.0	2	1.00	770	10000	1.0	0.0	3	6	770	0.0
3	604000.0	4	3.00	1960	5000	1.0	0.0	5	7	1050	910.0
4	510000.0	3	2.00	1680	8080	1.0	0.0	3	8	1680	0.0

In [10]:
```
data.bedrooms.value_counts()
```

Out[10]:
```
3     9824
4     6882
2     2760
5     1601
6      272
1      196
7       38
8       13
9        6
10       3
11       1
33       1
Name: bedrooms, dtype: int64
```

33 bedrooms? When we plugged this house's parcel id (2402100895) into the King County House Finder (https://info.kingcounty.gov/assessor/eMap/default.aspx), we concluded it must be an input error. We decided to replace this bedroom value with **np.nan**:

In [11]:
```
data['bedrooms'].iloc[15856] = np.nan
```

Adding New Features

Here's the list of the new features we added to the data frame:

- **price_per_sqft**
- **yard_size** = sqft_lot - sqft_above - sqft_basement
- **in_city** - Y or N, if the house is located in a Seattle zipcode
- **unincorporated** - if the house is located in an incorporated area (for map of unincorporated/inc areas in KC, see Sources at the bottom of this notebook)
- **zip_psqft** - the average price per sqft for the given house's zipcode
- **price_per_lot_sqft**
- **location_cost** - categorical that identifies the zip-per-sqft range the house's zipcode has
- **decade_built**
- **40yr_section** - if the house was built between 1900-1940, 1940-1980, or 1980-2020
- **waterfront** - change 0s and 1s to Y or N

- **season sold**
- **6plusbathrooms** - 'Y' if the house has 6 or more bathrooms.
- **3plusbathrooms** - 'Y' if the house has 3 or more bathrooms.

We wanted to see if our model would be improved by grouping our categorical variables in different ways.

In [12]:
```
bc.new_features(df=data,
                new_column_names=['price_per_sqft', 'yard_size', 'in_city', 'unincorporated',
                                  'zip_psqft', 'price_per_lot_sqft', 'location_cost', 'decade_built',
                                  '40yr_section', 'waterfront', 'season_sold', '6plusbathrooms', '3plus
bathrooms'])
```

Out[12]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	condition	grade	sqft_above	...	in_city	u
0	221900.0	3.0	1.00	1180	5650	1.0	NaN	3	7	1180	...	Y	N
1	538000.0	3.0	2.25	2570	7242	2.0	N	3	7	2170	...	Y	N
2	180000.0	2.0	1.00	770	10000	1.0	N	3	6	770	...	N	N
3	604000.0	4.0	3.00	1960	5000	1.0	N	5	7	1050	...	Y	N
4	510000.0	3.0	2.00	1680	8080	1.0	N	3	8	1680	...	N	N

5 rows × 31 columns

Looking at Correlations

In [13]:
```
# dropping these columns temporarily for our visualizations... don't worry, we'll we using them later
 ;)
cols = data.drop(labels=['zipcode', 'lat', 'long'], axis=1).columns
corr_df = data[cols].corr()
```

In [14]:
```
corr_table = bc.corr_table(corr_df)
corr_table.head()
```

Out[14]:

	cc
pairs	
(yard_size, sqft_lot)	0.999711

(year_sold, month_sold)	0.971193
(sqft_living15, sqft_living)	0.943227
(sqft_lot, sqft_lot15)	0.943193
(yard_size, sqft_lot15)	0.942230

We'll bring back this table again when we start dealing with multicollinearity. For now, let's find the variables that have the highest correlation with **price**:

In [15]:
```
corr_df['price'][corr_df['price'] > .5].sort_values(ascending=False)
```

Out[15]:
```
price              1.000000
sqft_living        0.701917
grade              0.667951
sqft_above         0.605368
sqft_living15      0.585241
price_per_sqft     0.556056
zip_psqft          0.532667
bathrooms          0.525906
Name: price, dtype: float64
```

Let's explore these higher correlated variables (and some others) with some ***visualizations***...

Visualizing the Data

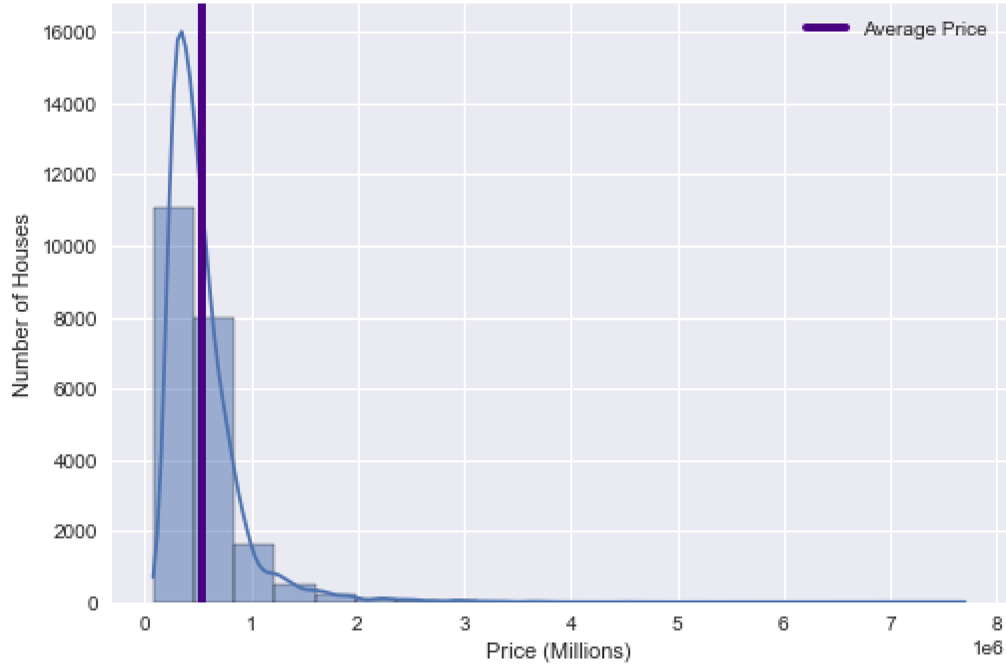
In [16]:
```
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline

plt.style.use('seaborn')
```

First, let's get a sense of how these house prices are distributed:

In [17]:
```
bc.price_distribution(data)
```

Distribution of House Prices, King County



Look's like we have a significant right **(positive) skew**.

In [18]:
```
# Average Price
data.price.mean()
```

Out[18]:
```
540296.5735055795
```

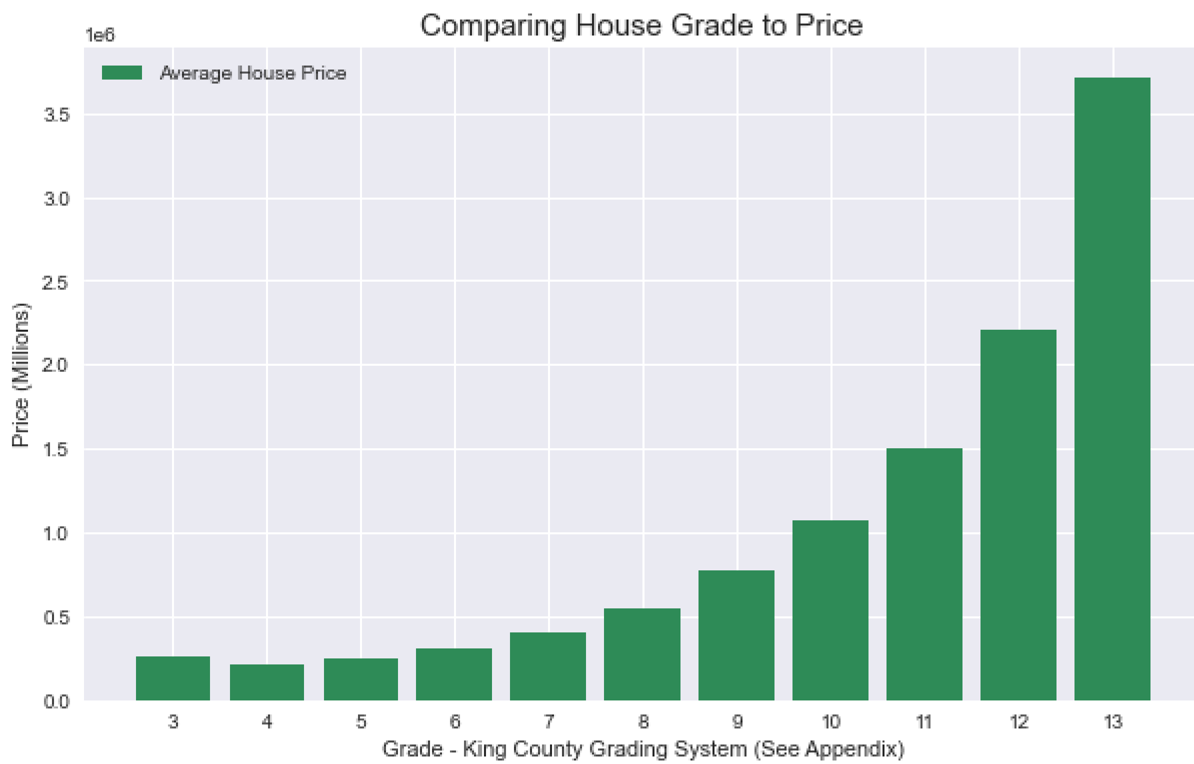
Let's see how price differs by House Grade. Houses in King County are graded by this criteria:

- 1-3: Falls short of minimum building standards. Normally cabin or inferior structure.
- 4: Generally older, low quality construction. Does not meet code.
- 5: Low construction costs and workmanship. Small, simple design.
- 6: Lowest grade currently meeting building code. Low quality materials and simple designs.
- 7: Average grade of construction and design. Commonly seen in plats and older sub-divisions.
- 8: Just above average in construction and design. Usually better materials in both the exterior and interior finish work.
- 9: Better architectural design with extra interior and exterior design and quality.
- 10: Homes of this quality generally have high quality features. Finish work is better and more design quality is seen in the floor plans. Generally have a larger square footage.
- 11: Custom design and higher quality finish work with added amenities of solid woods, bathroom fixtures and more luxurious options.

- 12: Custom design and excellent builders. All materials are of the highest quality and all conveniences are present.
- 13: Generally custom designed and built. Mansion level. Large amount of highest quality cabinet work, wood trim, marble, entry ways etc.

In [19]:
```
bc.price_by_grade(data)
```

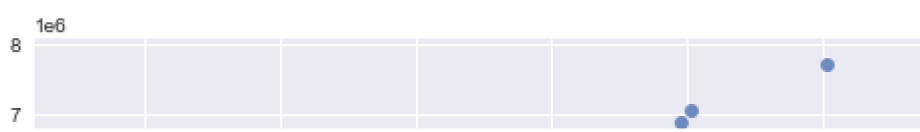
Out[19]:
```
<AxesSubplot:title={'center':'Comparing House Grade to Price'}, xlabel='Grade - King County Grading Sy
stem (See Appendix)', ylabel='Price (Millions)'>
```

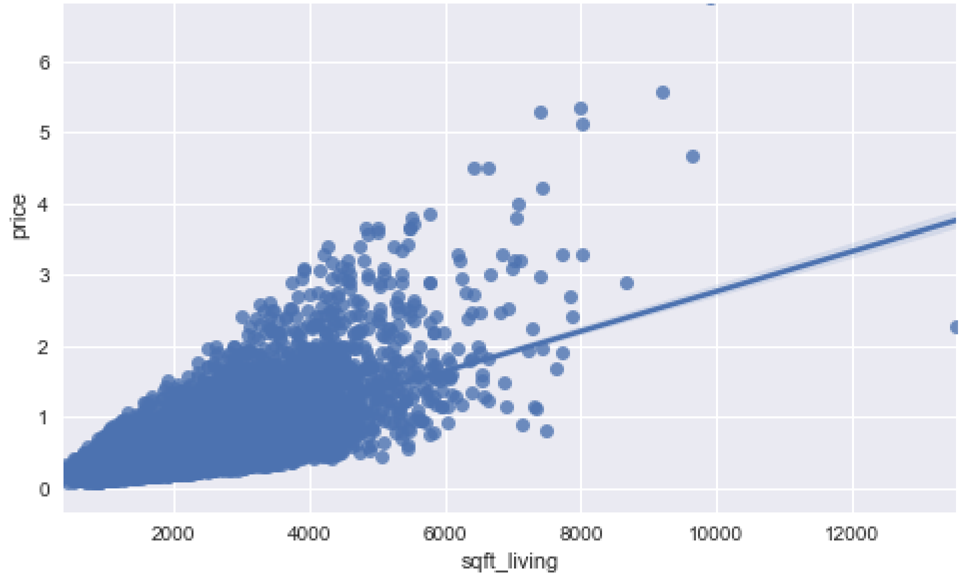


There seems to be a significant positive correlation here, with an **exponential** shape.

Let's see if the size of the house correlates with house price:

In [20]:
```
bc.sqft_living_vs_price(data)
```





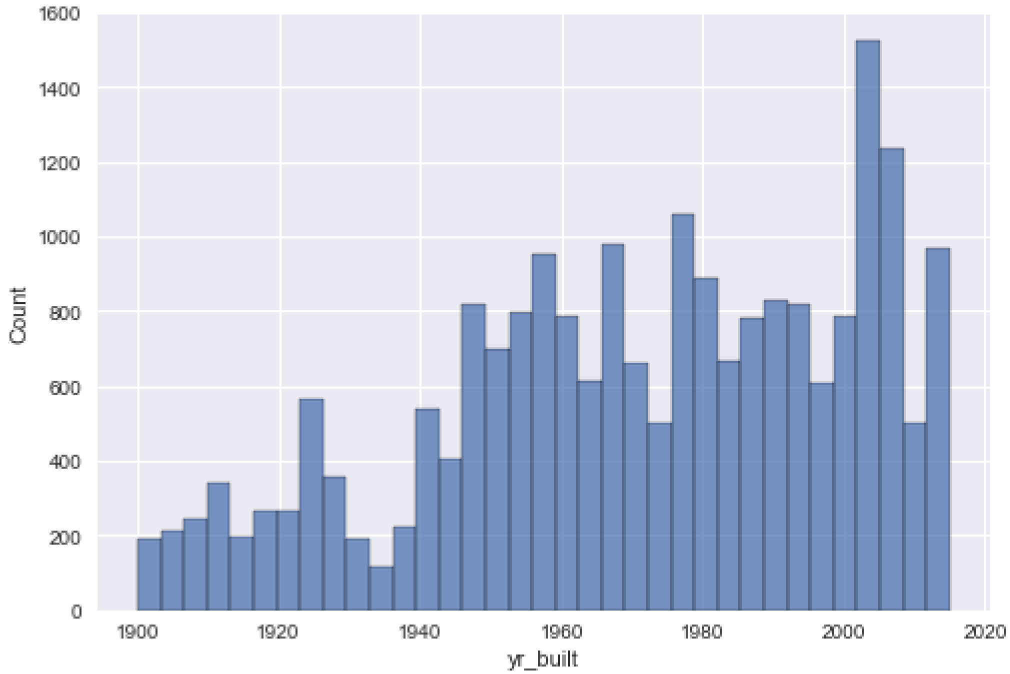
Now, what about waterfront homes? Do they typically price higher?

In [21]:
```
bc.waterfront_price_dist(data)
```

Out[21]:
```
<AxesSubplot:title={'center':'Waterfront or No Waterfront Property? Comparing Price Per Sqft Distribut
ion'}, xlabel='Price per Square Foot', ylabel='Density'>
```

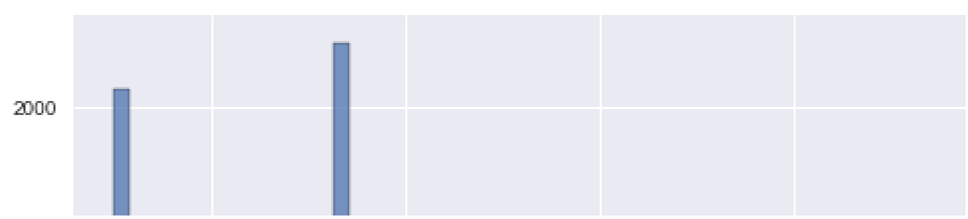
Let's also get a sense of the distribution of YEAR BUILT:

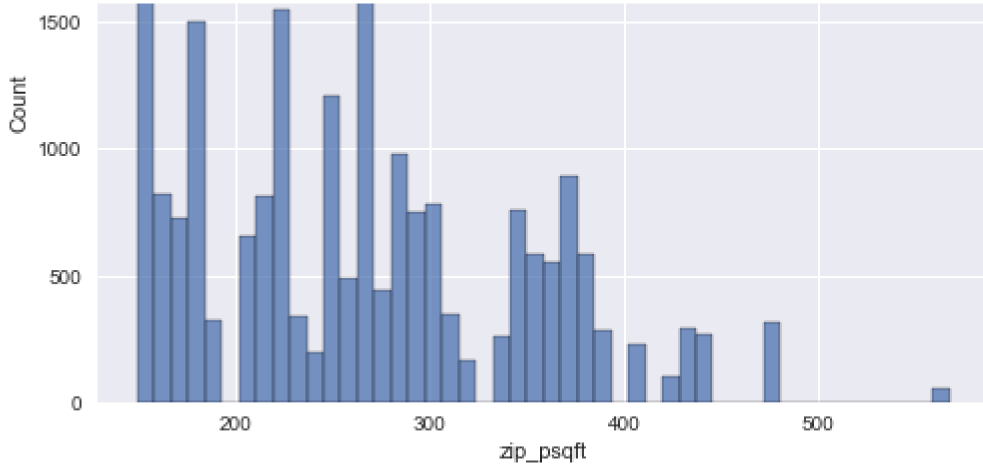
In [22]:
```
bc.yr_built_dist(data)
```



...And Average Price per Sqft per Zipcode

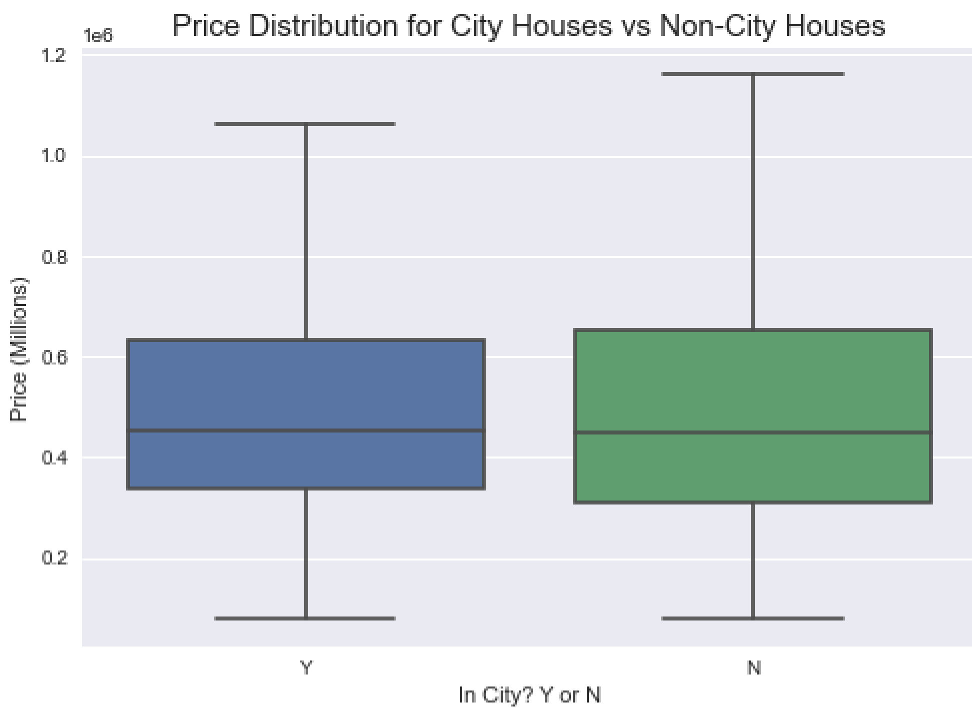
In [23]:
```
bc.zip_price_per_sqft_dist(data)
```





What about LOCATION?

In [24]:
```
# In city vs Out of City Price Distributions
bc.in_city_boxplots(data)
```



These boxplots were surprising-- we were definitely expecting city homes to be priced higher on average.

When we looked at the King County Map (which is located at the bottom of this notebook), we wanted to see if incorporated homes (homes within a municipality) had less "bang for buck" than unincorporated homes.

Click here (https://www.starnewsonline.com/article/NC/20151017/news/605047421/WM) to read an interesting article that expains the pros and cons of incorporated/unincorporated residencies.

In [25]:
```
bc.incorp_vs_unincorp(data)
```

Out[25]:
```
<AxesSubplot:title={'center':'Comparing Average Price per Sqft: Unincorporated vs Incorporated House
s'}, ylabel='Average Price per Sqft'>
```

This bar graph highlights a pretty significance between the two

This bar graph highlights a pretty significance between the two.

To see if the difference between the two was statistically significant, we performed **Welch's t-test**:

Null Hypothesis:

> H_0: The mean difference between incorporated and unincorporated price per sqft is zero. i.e. $\mu_0 = \mu_1$

Alternative Hypothesis

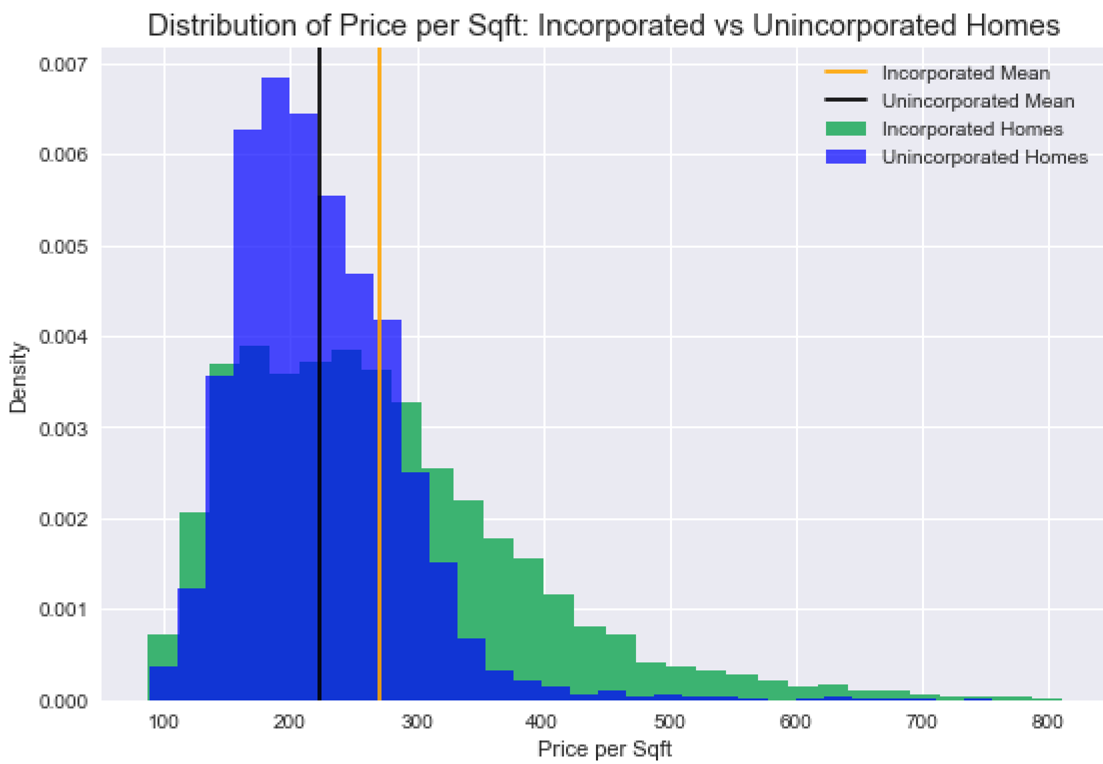
> H_1 (1-tailed): The mean difference between incorporated and unincorporated price per sqft is **greater than** zero.

α = 0.05

First, we verified that the two distributions were relatively normal:

In [26]:
```
bc.ttest_dist_check(data)
```

Out[26]:
```
<AxesSubplot:title={'center':'Distribution of Price per Sqft: Incorporated vs Unincorporated Homes'},
xlabel='Price per Sqft', ylabel='Density'>
```



There is a definite positive skew, but not enough to not be eligible for a t-test.

In [27]:
```
from scipy import stats
```

The variances of the two distributions are relatively similar:

In [28]:
```
data['price_per_sqft'][data['unincorporated']=='N'].describe()
```

Out[28]:
```
count    18714.000000
mean       270.539063
std        114.013676
min         87.588235
25%        183.877554
50%        251.258393
75%        330.243325
max        810.138889
Name: price_per_sqft, dtype: float64
```

In [29]:
```
data['price_per_sqft'][data['unincorporated']=='Y'].describe()
```

Out[29]:
```
count    2883.000000
mean      222.627922
std        65.395154
min        88.000000
25%       176.395939
50%       213.268608
75%       259.870130
max       754.716981
Name: price_per_sqft, dtype: float64
```

Let's get our p_value. Since `scipy.stats.ttest_ind()` only does a two-tailed test, we have to divide this value by 2.

In [30]:
```
alpha = 0.05

p_val = stats.ttest_ind(data['price_per_sqft'][data['unincorporated']=='N'], data['price_per_sqft'][da
ta['unincorporated']=='Y']).pvalue / 2
p_val
```

Out[30]:
```
1.6240521003735314e-106
```

In [31]:
```
p_val < alpha
```

```
In [31]: p_val < alpha
```

```
Out[31]: True
```

Given that the p_value is less than alpha, we can confirm that the mean price per sqft of Incorporated homes is not greater than the mean price per sqft of Unincorporated homes by chance.

Let's do some mappin'!

Click [here (https://www.kingcounty.gov/services/gis/GISData.aspx)](https://www.kingcounty.gov/services/gis/GISData.aspx) to access the King County shapefile website.

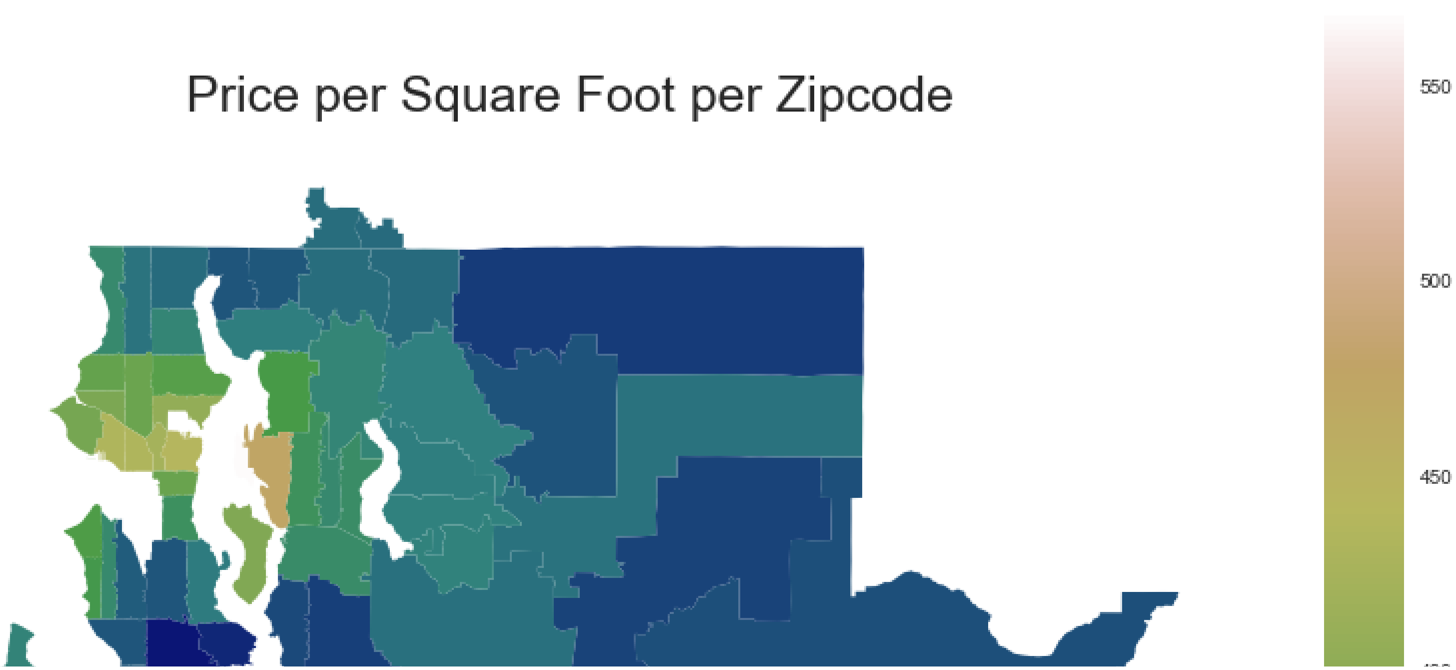
```
In [32]: import geopandas as gpd
```

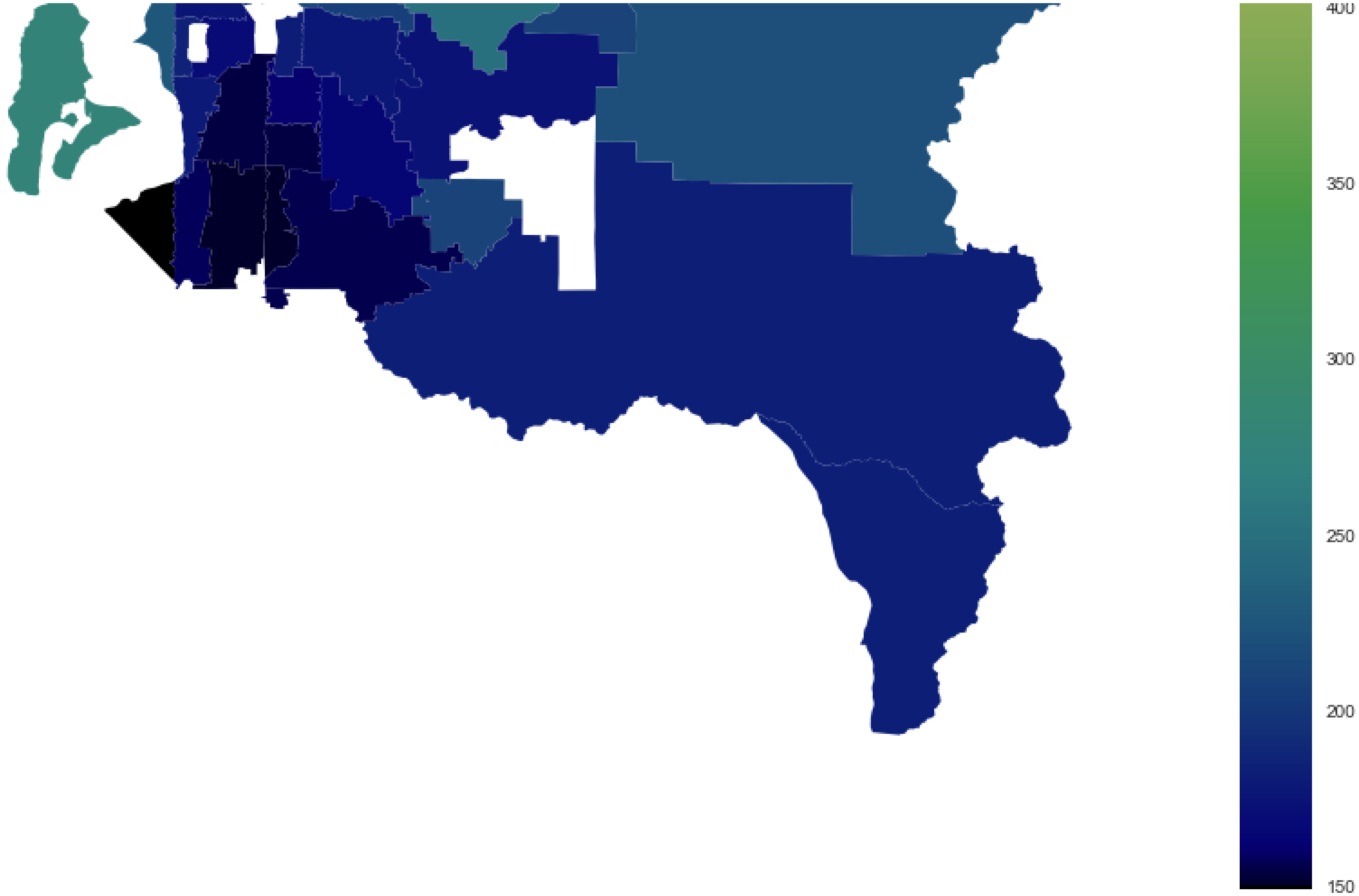
Below is a cloropleth map depicting the Average Price per Square Foot for each zipcode (outlined in the map).

Main takeaway: the zipcodes with the **lowest price per sqft** are concentrated on the **south** half of the map.

```
In [33]: bc.cloropleth(data)
```

```
Out[33]: <AxesSubplot:title={'center':'Price per Square Foot per Zipcode'}>
```



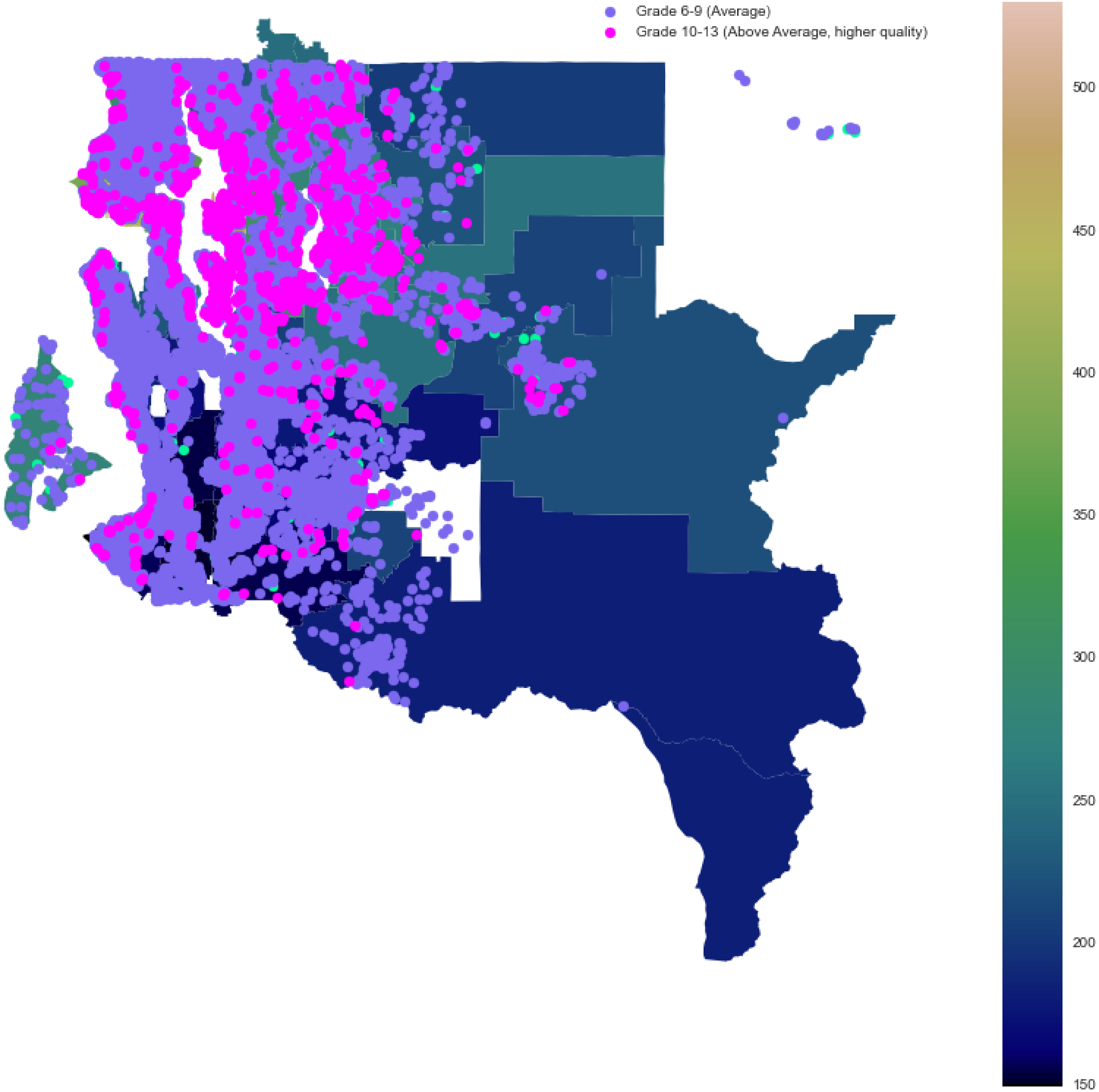


To see the map distribution of different qualities of houses, we layered on **grade** to the cloropleth map:

We found that there was a **higher concentration of higher quality houses on the northern half of the map**.

In [34]:
```
bc.map_grades(data)
```

Out[34]:
```
<AxesSubplot:title={'center':'Distribution of Homes Using the King County Grading System'}>
```

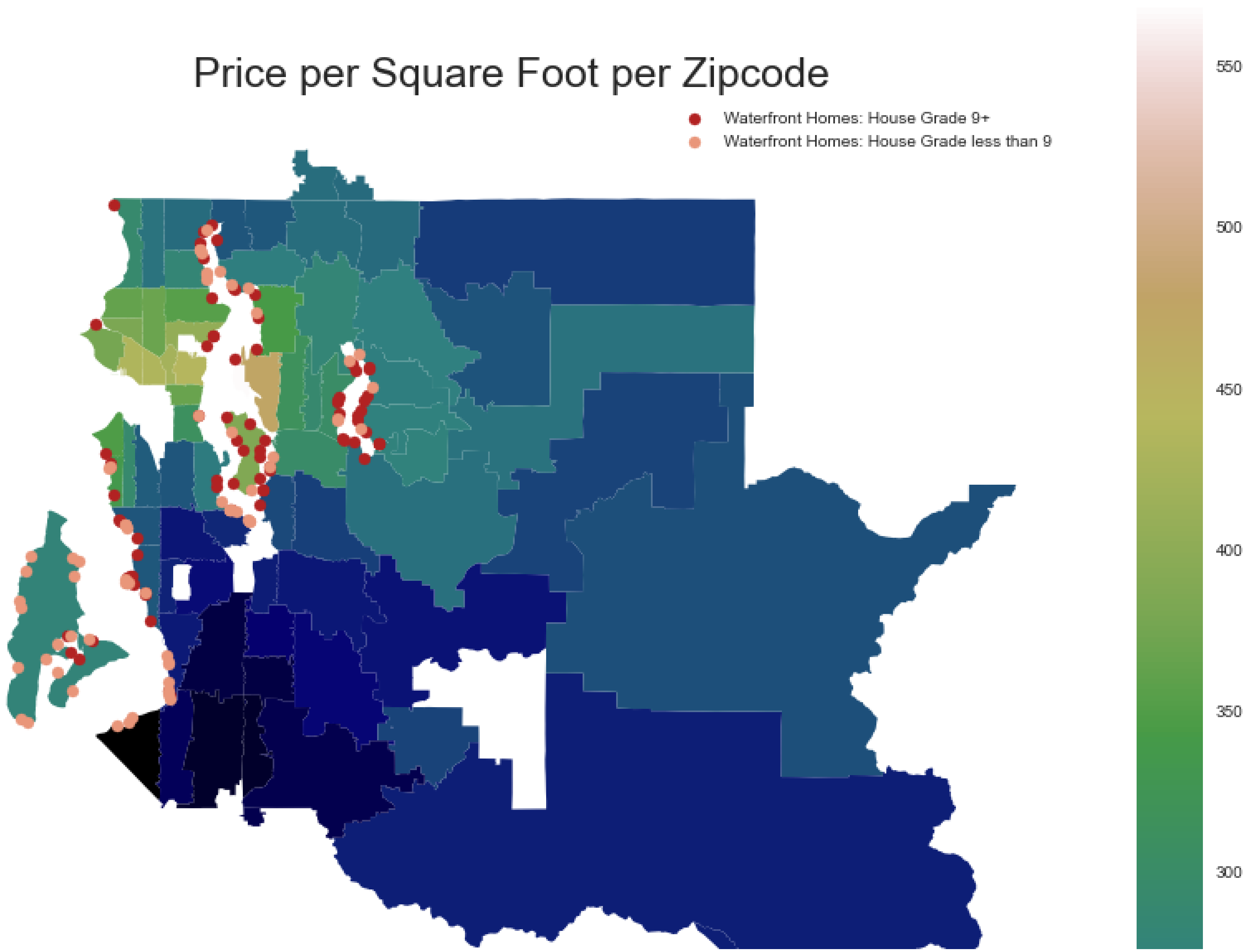

Grade 6-9 (Average)
Grade 10-13 (Above Average, higher quality)
500
450
400
350
300
250
200
150

Wanted to see if there was any notable patterns with **waterfront homes** in terms of house quality.

We found no patterns of note.

In [35]:
```
bc.map_waterfront(data)
```

Out[35]:
```
<AxesSubplot:title={'center':'Price per Square Foot per Zipcode'}>
```



Let's see how the patterns found in our analysis play out in our inferential model development.

Data Prep (for Modeling)

Time to get some some dummies for our categorical variables:

(We did make sure to drop the first column for each variable to avoid that infamous *Dummy Variable Trap*.)

In [36]:
```
from src import modeling_data_prep as mdp
```

In [37]:
```
model_data = mdp.add_dummies(data)
model_data.head() # scroll to the right to see the dummy variables
```

Out[37]:

	price	sqft_living	sqft_lot	sqft_above	sqft_living15	sqft_lot15	price_per_sqft	zip_psqft	price_per_lot_sqft
0	221900.0	1180	5650	1180	1340	5650	188.050847	189.172528	39.274336
1	538000.0	2570	7242	2170	1690	7639	209.338521	282.680191	74.288870
2	180000.0	770	10000	770	2720	8062	233.766234	225.145368	18.000000
3	604000.0	1960	5000	1050	1360	5000	308.163265	337.245108	120.800000
4	510000.0	1680	8080	1680	1800	7503	303.571429	265.686627	63.118812

5 rows × 204 columns

Now that we have our `model_data`, we can start building our **first model**!

Model Iterations

In [38]:
```
from statsmodels.formula.api import ols
import statsmodels.stats.api as sms
from statsmodels.graphics.gofplots import qqplot
```

For our model, we attempted to optimize the following features:

- minimizing p-values for each variable and condition number.
- maximizing F-statistic, Jarque-Bera probability, and R squared.

And, of course, making sure our model doesn't violate these assumptions:

- Normality
- Linearity
- Homoscedasticity

Our *First Simple Model*

Since `sqft_living` has the **highest** correlation with price (0.702), let's build our first model around it!

In [39]:
```
formula = 'price ~ sqft_living'
fsm = ols(formula = formula, data = model_data).fit()
fsm.summary()
```

Out[39]:

Dep. Variable:	price	**R-squared:**	0.493
Model:	OLS	**Adj. R-squared:**	0.493
Method:	Least Squares	**F-statistic:**	2.097e+04
Date:	Fri, 19 Feb 2021	**Prob (F-statistic):**	0.00
Time:	18:23:24	**Log-Likelihood:**	-3.0006e+05
No. Observations:	21597	**AIC:**	6.001e+05
Df Residuals:	21595	**BIC:**	6.001e+05
Df Model:	1		
Covariance Type:	nonrobust		

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

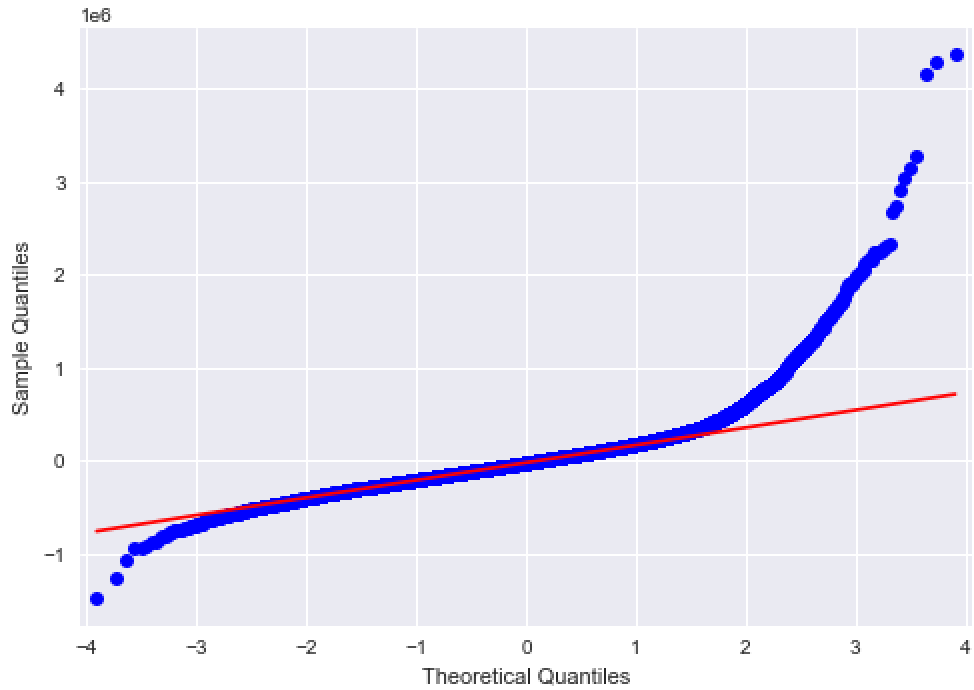
Omnibus:	14801.942	**Durbin-Watson:**	1.982
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	542662.604
Skew:	2.820	**Prob(JB):**	0.00
Kurtosis:	26.901	**Cond. No.**	5.63e+03

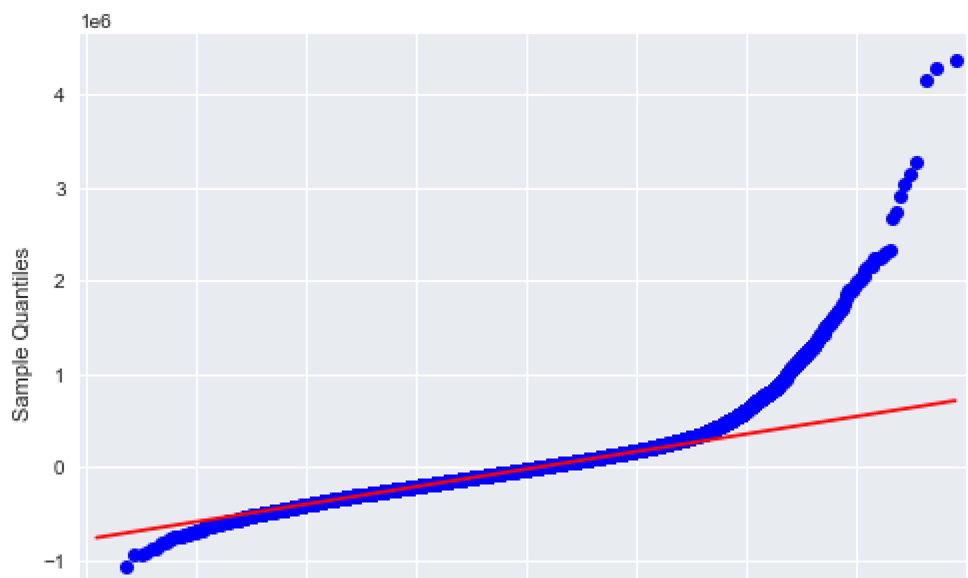
Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 5.63e+03. This might indicate that there are

strong multicollinearity or other numerical problems.

In [40]:
```
qqplot(fsm.resid, line='q')
```

Out[40]:

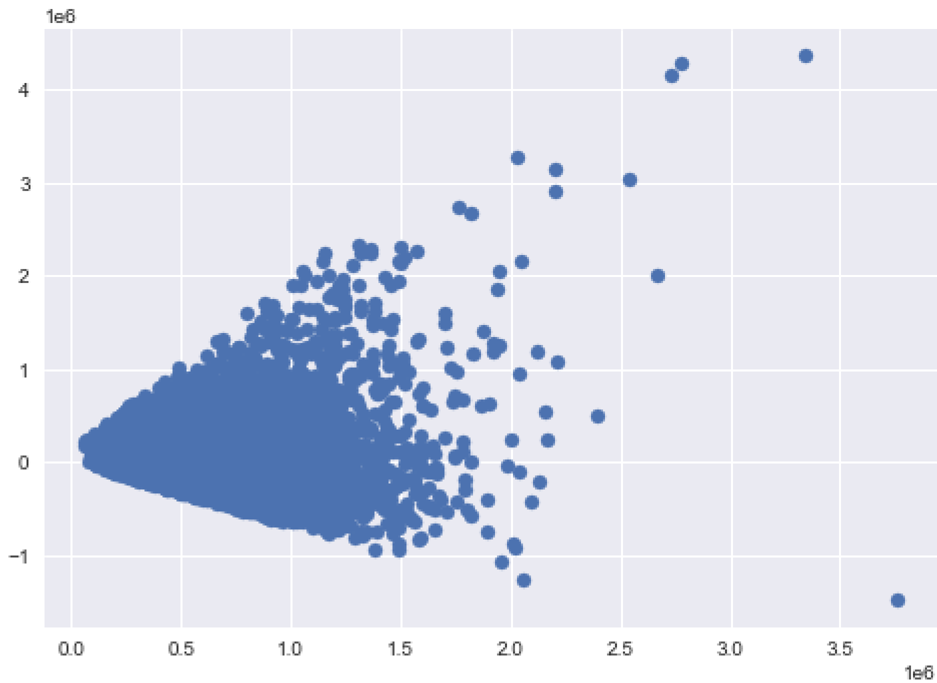




In [41]:

```
# Checking for homoscedasticity
x = fsm.predict(model_data['sqft_living'])
y = fsm.resid
plt.scatter(x, y)
```

Out[41]: <matplotlib.collections.PathCollection at 0x7ffe8a9c2790>



First Simple Model Takeaways:

- low R-squared
- low p-value for `sqft_living`
- **HIGH** condition number (5630)
- QQ-plot - extreme **positive** deviation from the line in the 2nd through 4th quantiles
  - This confirms that our data is not normally distributed, which violates an assumption of linear regression.
  - Our data has a significant **right skew**
- The low Jarque-Bera probability (0.0) is additional confirmation for the lack of normality in error distribution

- The low Jarque-Bera probability (0.0) is additional confirmation for the lack of normality in error distribution.
- Our scatterplot shows **heteroscedasticity** with a right-facing, conical distribution of residuals.

Model 2: Adding in all the variables

We wanted to see how the model will respond if we added all the variables in. We got as high an R-squared as **0.957**! This model below, however, is that model but only with variables with the lowest p-values.

NOTE: This model using all housing data with a condition greater than or equal to a Grade of 6, since we are only looking to see price trends in homes that are up to code.

In [42]:
```
highrsq_model, hrsqdata = mdp.highest_rsquared(model_data)
```

In [43]:
```
highrsq_model.summary()
```

Out[43]:

Dep. Variable:	price	**R-squared:**	0.901
Model:	OLS	**Adj. R-squared:**	0.901
Method:	Least Squares	**F-statistic:**	1.645e+04
Date:	Fri, 19 Feb 2021	**Prob (F-statistic):**	0.00
Time:	18:23:25	**Log-Likelihood:**	-2.8237e+05
No. Observations:	21597	**AIC:**	5.648e+05
Df Residuals:	21584	**BIC:**	5.649e+05
Df Model:	12		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
Intercept	-5.868e+05	3744.870	-156.694	0.000	-5.94e+05	-5.79e+05
sqft_living	288.0371	1.474	195.352	0.000	285.147	290.927
price_per_sqft	1898.9039	12.238	155.163	0.000	1874.916	1922.892
wf_Y	3.546e+05	1.02e+04	34.871	0.000	3.35e+05	3.75e+05
zpsft500plus	3.628e+05	1.72e+04	21.127	0.000	3.29e+05	3.96e+05

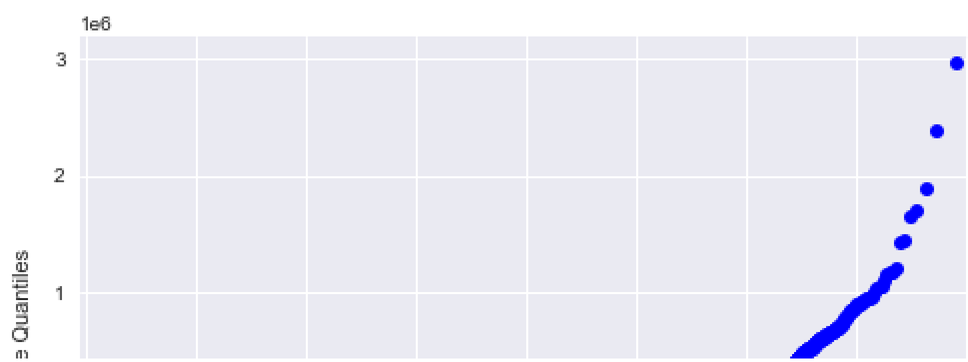
zpsft500plus	3.628e+05	1.72e+04	21.127	0.000	3.29e+05	3.96e+05
price_per_lot_sqft	70.1237	10.429	6.724	0.000	49.683	90.565
grade_13	1.131e+06	3.27e+04	34.573	0.000	1.07e+06	1.19e+06
zpsft200_300	-3.555e+04	1896.243	-18.747	0.000	-3.93e+04	-3.18e+04
zpsft300_400	-5.838e+04	2809.353	-20.779	0.000	-6.39e+04	-5.29e+04
zip_psqft	272.5318	19.033	14.319	0.000	235.226	309.838
sqft_living15	-10.9852	1.926	-5.702	0.000	-14.761	-7.209
incity_Y	-1.457e+04	1998.036	-7.293	0.000	-1.85e+04	-1.07e+04
grade_12	3.719e+05	1.28e+04	29.105	0.000	3.47e+05	3.97e+05

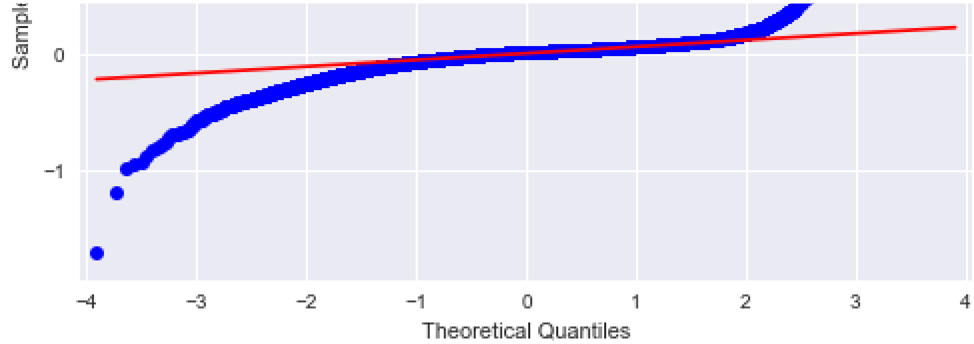
Omnibus:	14169.098	**Durbin-Watson:**	1.974
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	2656150.439
Skew:	2.135	**Prob(JB):**	0.00
Kurtosis:	57.161	**Cond. No.**	1.29e+05

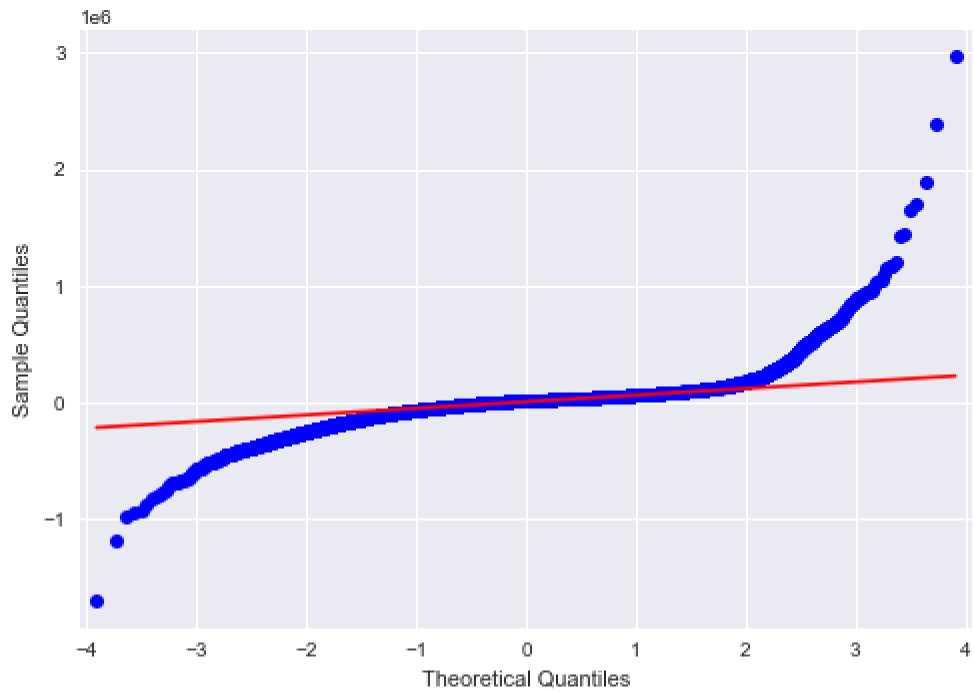
Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 1.29e+05. This might indicate that there are
strong multicollinearity or other numerical problems.

In [44]:
```
qqplot(highrsq_model.resid, line='q')
```

Out[44]:



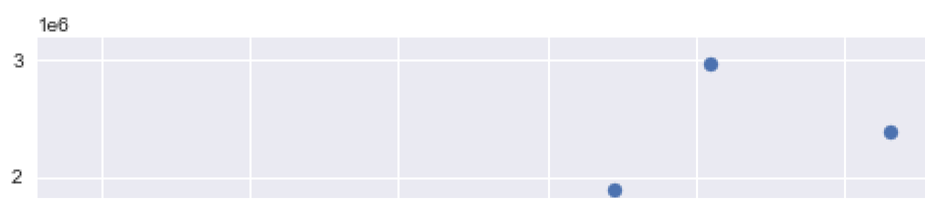


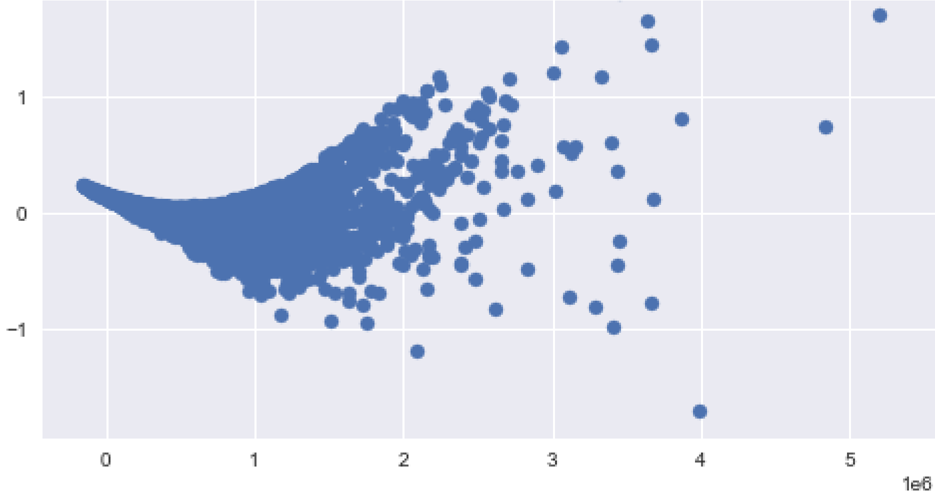


In [45]:

```
x = highrsq_model.predict(hrsqdata)
y = highrsq_model.resid
plt.scatter(x, y)
```

Out[45]: <matplotlib.collections.PathCollection at 0x7ffe8a8abb50>





2nd Model Takeaways:

- HIGH R-squared
- low p-values across the board
- Much **higher** condition number than FSM (129,000)
- QQ-plot - significant deviation from normal line in the 2nd through 4th quantiles AND -4 thru -2 quantiles
  - This confirms that our data is still not normally distributed, which violates an assumption of linear regression.
- The low Jarque-Bera probability (0.0) is additional confirmation for the lack of normality in error distribution.
- Our scatterplot shows **heteroscedasticity** with a right-facing, almost exponential distribution of residuals.

Model 3: Time to normalize

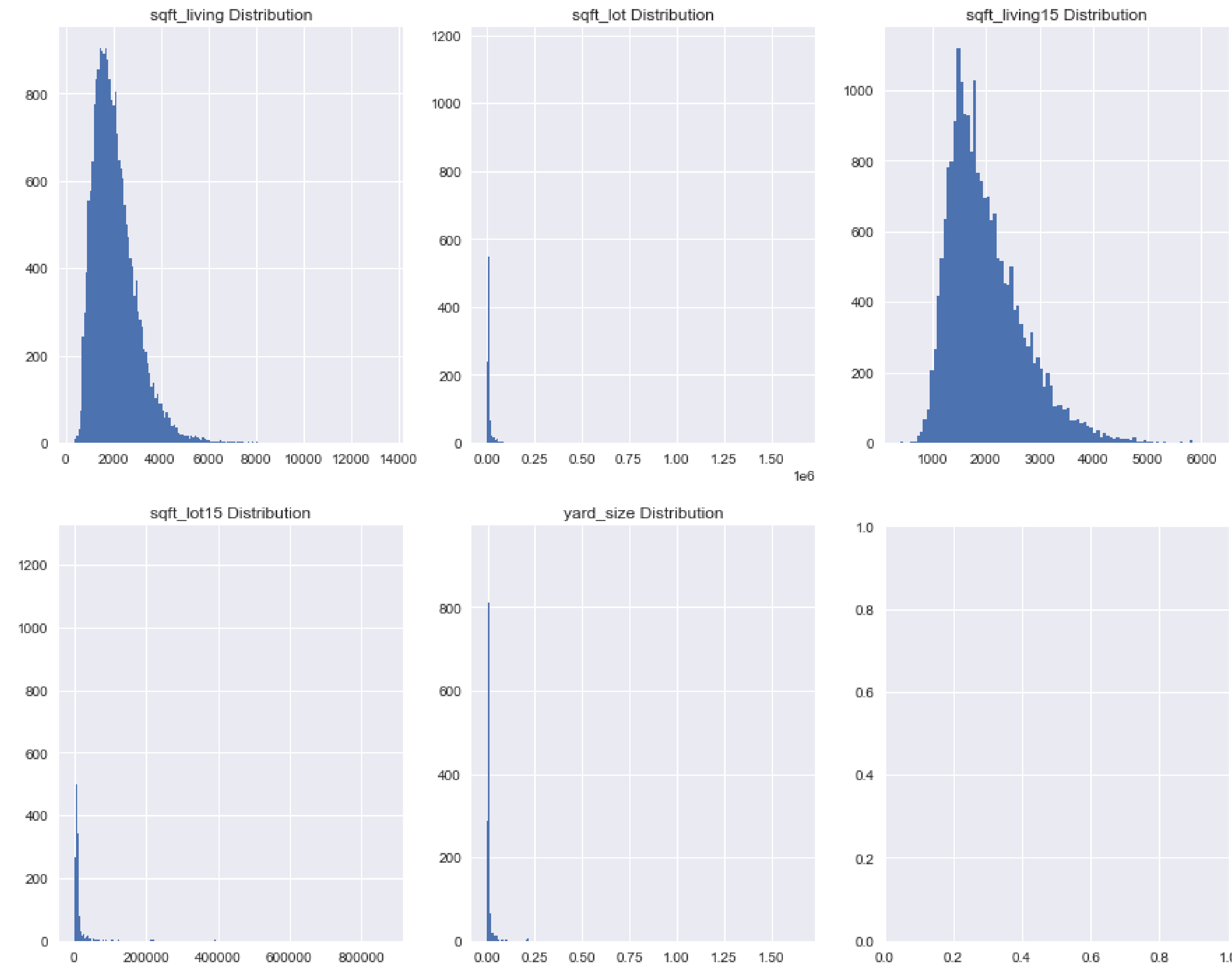
Upon examination of the results of our first two models, let's take a look at our variables and see how we should adjust them for our second model.

Distribution of `sqft_living`

In [46]:
```
continuous_vars = ['sqft_living', 'sqft_lot',
                   'sqft_living15', 'sqft_lot15', 'yard_size']
```

In [47]:
```
mdp.continuous_dists(model_data, continuous_vars)
```

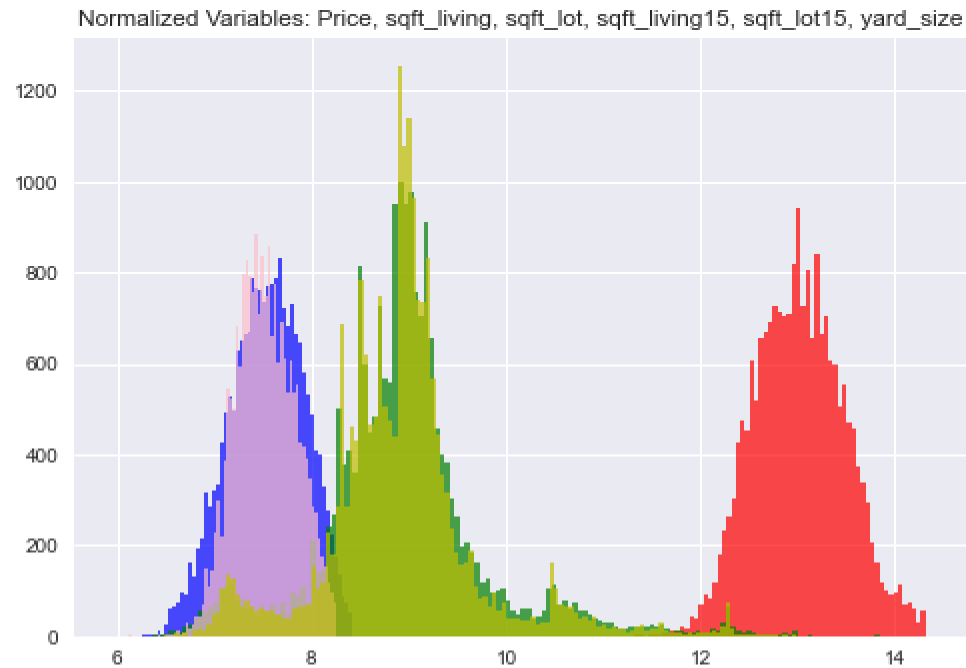
```
Out[47]: array([[<AxesSubplot:title={'center':'sqft_living Distribution'}>,
                 <AxesSubplot:title={'center':'sqft_lot Distribution'}>,
                 <AxesSubplot:title={'center':'sqft_living15 Distribution'}>],
                [<AxesSubplot:title={'center':'sqft_lot15 Distribution'}>,
                 <AxesSubplot:title={'center':'yard_size Distribution'}>,
                 <AxesSubplot:>]], dtype=object)
```



1e6

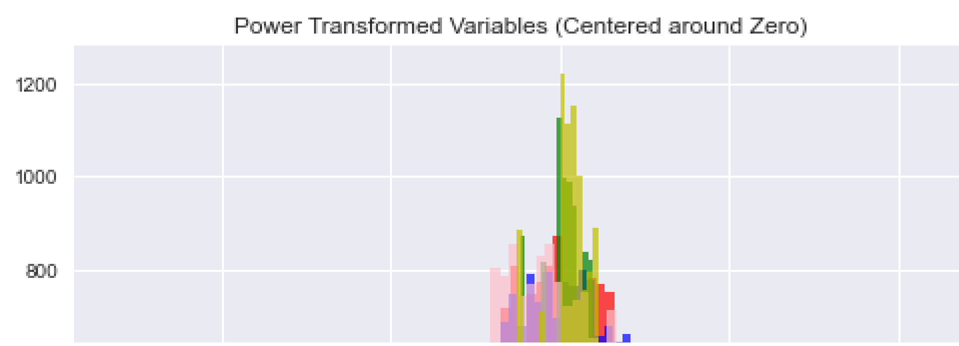
Though it is a bit difficult to see in some of the graphs, each of these variables (including price) have a **positive skew**. Let's normalize all of these variables with a **log transform**:

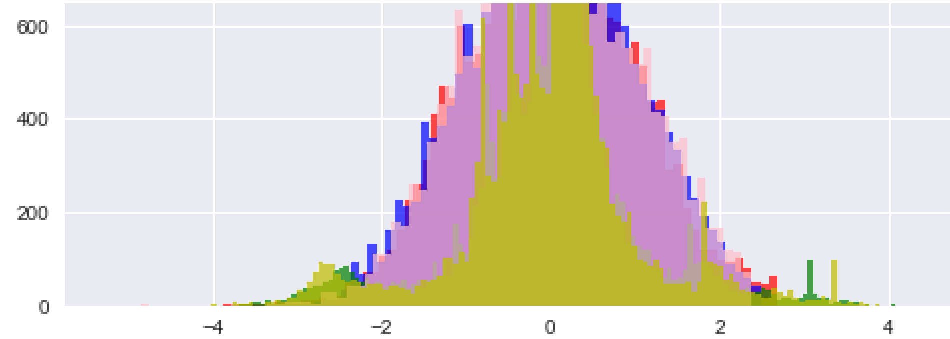
In [48]:
```
log_vars, plot = mdp.normalizing(model_data)
```



While we're at it, let's center the variables around zero using a **power transform**:

In [49]:
```
pwrd_vars, plot = mdp.power_transform(logged=log_vars)
```





Let's see what our model looks like now!

This model is one of the iterations of our **luxury homes model** subset (only using houses with a Grade of 10 or higher).

In [50]:
```
normmodel, norm_data = mdp.most_normal_luxury(data)
```

In [51]:
```
normmodel.summary()
```

Out[51]:

Dep. Variable:	price	**R-squared:**	0.662
Model:	OLS	**Adj. R-squared:**	0.660
Method:	Least Squares	**F-statistic:**	244.2
Date:	Fri, 19 Feb 2021	**Prob (F-statistic):**	0.00
Time:	18:23:55	**Log-Likelihood:**	-1430.9
No. Observations:	1633	**AIC:**	2890.
Df Residuals:	1619	**BIC:**	2965.
Df Model:	13		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	-1.5890	0.060	-26.397	0.000	-1.707	-1.471
sqft_living15	0.1870	0.016	11.608	0.000	0.155	0.219
wf_Y	1.2630	0.081	15.682	0.000	1.105	1.421

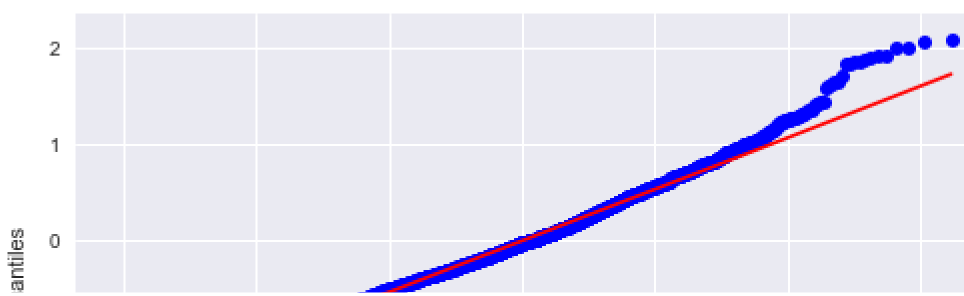
grade_11	0.4872	0.036	13.602	0.000	0.417	0.557
grade_12	1.0009	0.068	14.767	0.000	0.868	1.134
grade_13	1.6594	0.166	10.020	0.000	1.335	1.984
se_spring	0.0789	0.041	1.934	0.053	-0.001	0.159
se_summer	-0.0082	0.040	-0.205	0.837	-0.087	0.070
se_winter	0.0374	0.048	0.784	0.433	-0.056	0.131
zpsft200_300	1.0646	0.056	19.003	0.000	0.955	1.175
zpsft300_400	1.8738	0.062	30.139	0.000	1.752	1.996
zpsft400_500	2.3727	0.067	35.244	0.000	2.241	2.505
zpsft500plus	2.6800	0.135	19.880	0.000	2.416	2.944
inc_Y	-0.0167	0.043	-0.393	0.694	-0.100	0.067

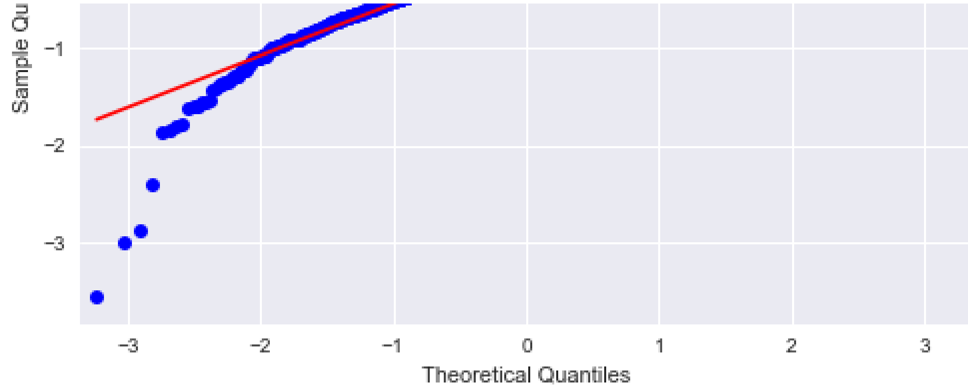
Omnibus:	85.519	**Durbin-Watson:**	1.967
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	314.201
Skew:	-0.016	**Prob(JB):**	5.92e-69
Kurtosis:	5.149	**Cond. No.**	15.5

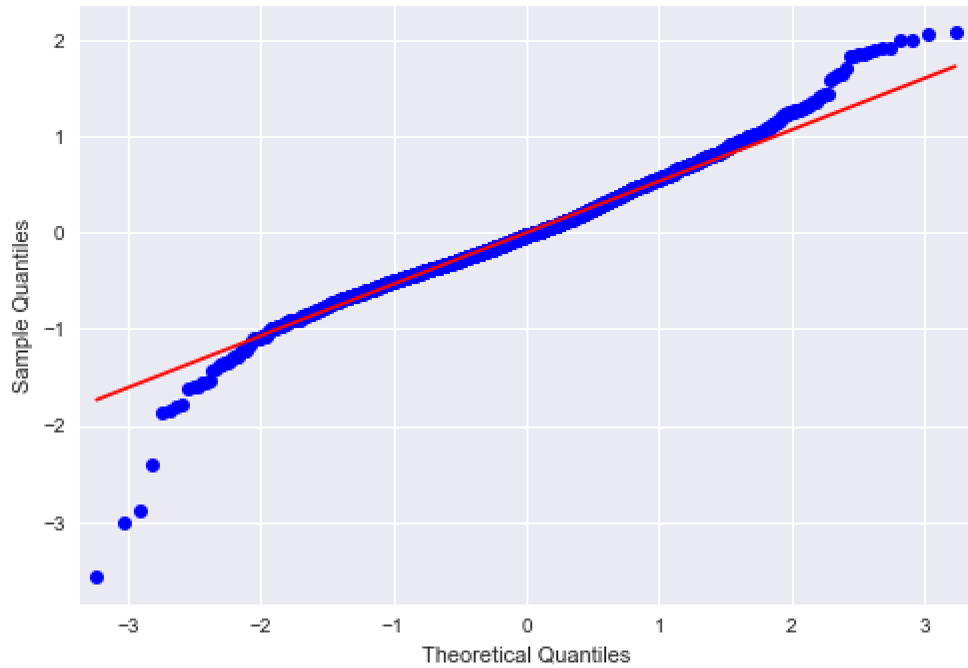
Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

In [52]:
```
qqplot(normmodel.resid, line='q')
```

Out[52]:

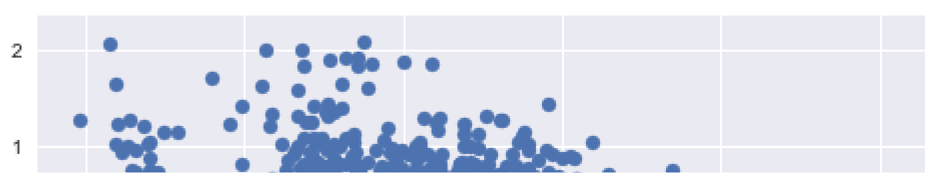


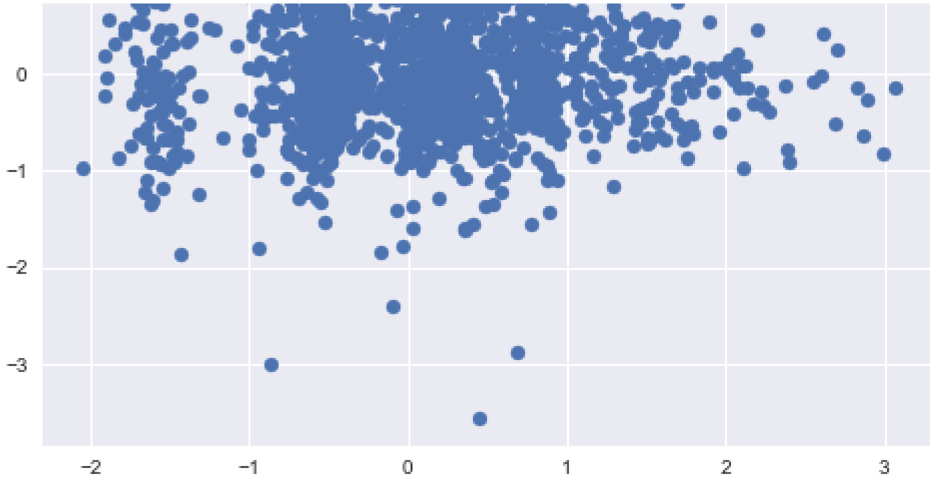




In [53]:
```
x = normmodel.predict(norm_data)
y = normmodel.resid
plt.scatter(x, y)
```

Out[53]: <matplotlib.collections.PathCollection at 0x7ffe78d74be0>





3rd Model Takeaways:

- LOWER R-squared
- Some problematic p-values
- Much **LOWER** condition number than FSM and 2nd Model. (15.5)
- QQ-plot - least amount of deviation from the normal line
- Jarque-Bera probability is higher than the first two models, indicating progress towards normality.
- Our scatterplot is much more **homoscedastic** than the other two, although it does show a slight left-facing, conical shape of the residuals.

FINAL MODELS

Drum roll, please...

Model for *All Homes* (Grades 6+)

In [54]:
```
model, model_data = mdp.final_model_all_homes(data, powered=pwrd_vars)
```

In [55]:
```
model.summary()
```

Out[55]:

Dep. Variable:	price	**R-squared:**	0.805

Model:	OLS	**Adj. R-squared:**	0.805
Method:	Least Squares	**F-statistic:**	7004.
Date:	Fri, 19 Feb 2021	**Prob (F-statistic):**	0.00
Time:	18:23:56	**Log-Likelihood:**	-12275.
No. Observations:	20392	**AIC:**	2.458e+04
Df Residuals:	20379	**BIC:**	2.468e+04
Df Model:	12		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
Intercept	-1.1376	0.012	-91.935	0.000	-1.162	-1.113
sqft_living	0.3514	0.005	70.724	0.000	0.342	0.361
sqft_living15	0.1586	0.005	33.666	0.000	0.149	0.168
grade_7	0.1570	0.012	13.400	0.000	0.134	0.180
grade_8	0.3499	0.014	25.712	0.000	0.323	0.377
grade_9	0.6160	0.017	35.866	0.000	0.582	0.650
grade_10	0.8183	0.022	36.921	0.000	0.775	0.862
grade_11	0.9650	0.042	23.220	0.000	0.884	1.046
grade_12	0.9512	0.256	3.716	0.000	0.450	1.453
zpsft200_300	0.8713	0.008	113.734	0.000	0.856	0.886
zpsft300_400	1.5394	0.009	168.929	0.000	1.522	1.557
zpsft400_500	1.9248	0.015	126.942	0.000	1.895	1.955
zpsft500plus	2.5000	0.104	23.944	0.000	2.295	2.705

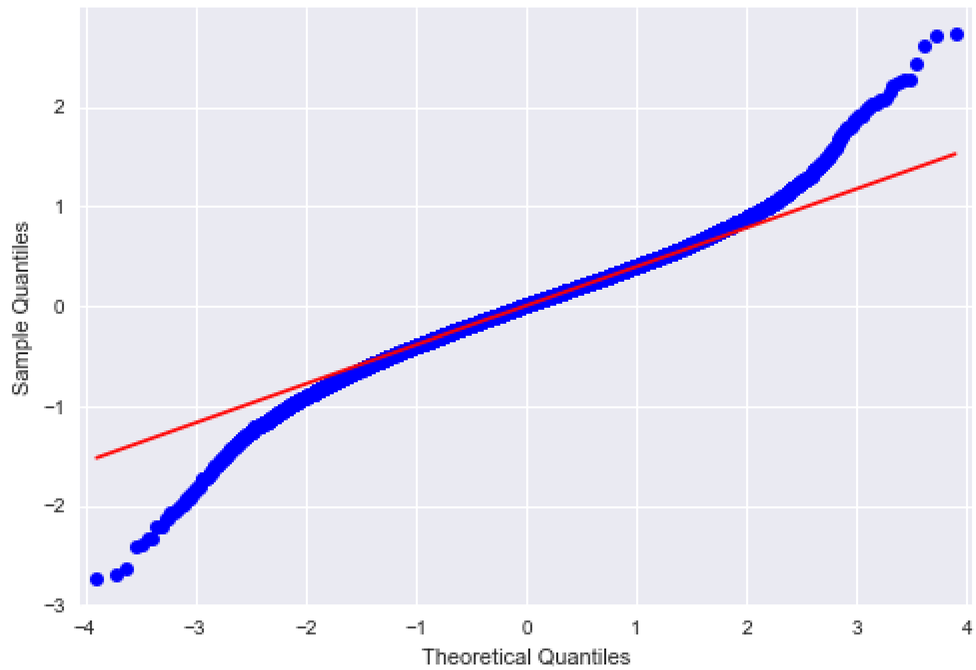
Omnibus:	976.959	**Durbin-Watson:**	1.975
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	3559.417
Skew:	-0.049	**Prob(JB):**	0.00

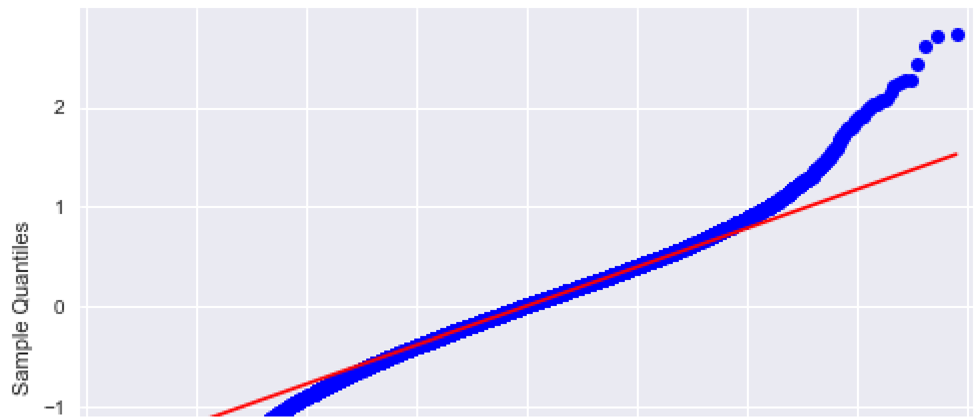
Kurtosis:	5.044	**Cond. No.**	111.

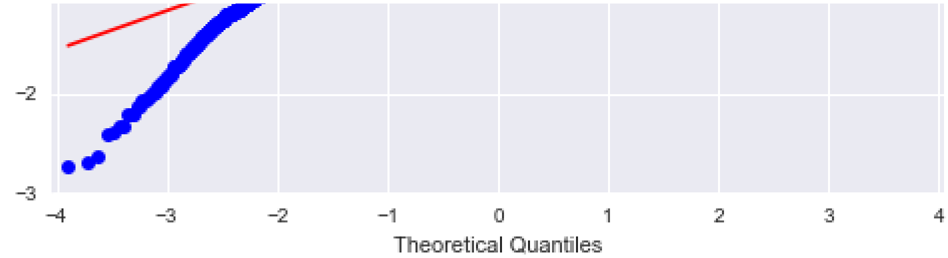
Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

In [56]:
```
qqplot(model.resid, line='q')
```

Out[56]:

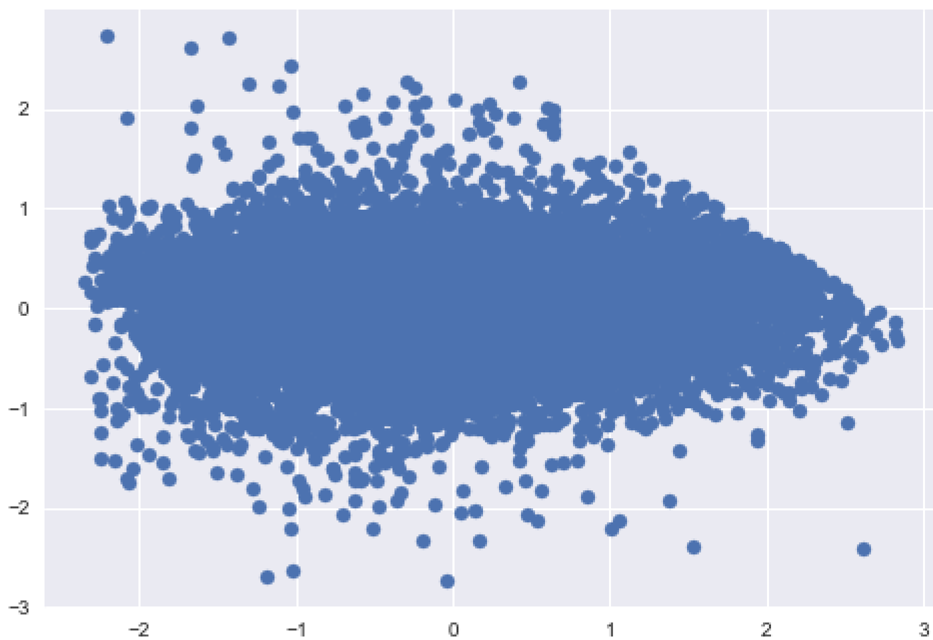






In [57]:
```
x = model.predict(model_data)
y = model.resid
plt.scatter(x, y)
```

Out[57]: <matplotlib.collections.PathCollection at 0x7ffe79288250>



Final Model - All Homes - Takeaways:

- HIGH R-squared
- NO high p-values.
- Much **LOWER** condition number than FSM and 2nd Model. (111)
- QQ-plot - Slight deviation on both ends, but not as much as the FSM or 2nd model.
- Our scatterplot is much more **homoscedastic** than the first three models, although it does show a very slight left-facing, conical

shape of the residuals.

Model for Non-Luxury Homes (Grades 6-9)

In [58]:
```
nonluxmodel, nonlux_data = mdp.final_model_non_lux(data)
```

In [59]:
```
nonluxmodel.summary()
```

Out[59]:

Dep. Variable:	price	**R-squared:**	0.781
Model:	OLS	**Adj. R-squared:**	0.781
Method:	Least Squares	**F-statistic:**	5514.
Date:	Fri, 19 Feb 2021	**Prob (F-statistic):**	0.00
Time:	18:23:57	**Log-Likelihood:**	-11239.
No. Observations:	17032	**AIC:**	2.250e+04
Df Residuals:	17020	**BIC:**	2.260e+04
Df Model:	11		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	-1.1939	0.008	-140.640	0.000	-1.211	-1.177
sqft_living	0.3160	0.005	61.105	0.000	0.306	0.326
sqft_living15	0.1381	0.005	26.525	0.000	0.128	0.148
sqft_lot	0.0958	0.004	21.761	0.000	0.087	0.104
grade_8	0.2746	0.009	30.500	0.000	0.257	0.292
grade_9	0.5853	0.014	42.406	0.000	0.558	0.612
zpsft200_300	1.0052	0.009	113.874	0.000	0.988	1.023
zpsft300_400	1.7990	0.011	162.470	0.000	1.777	1.821
zpsft400_500	2.2486	0.019	121.445	0.000	2.212	2.285

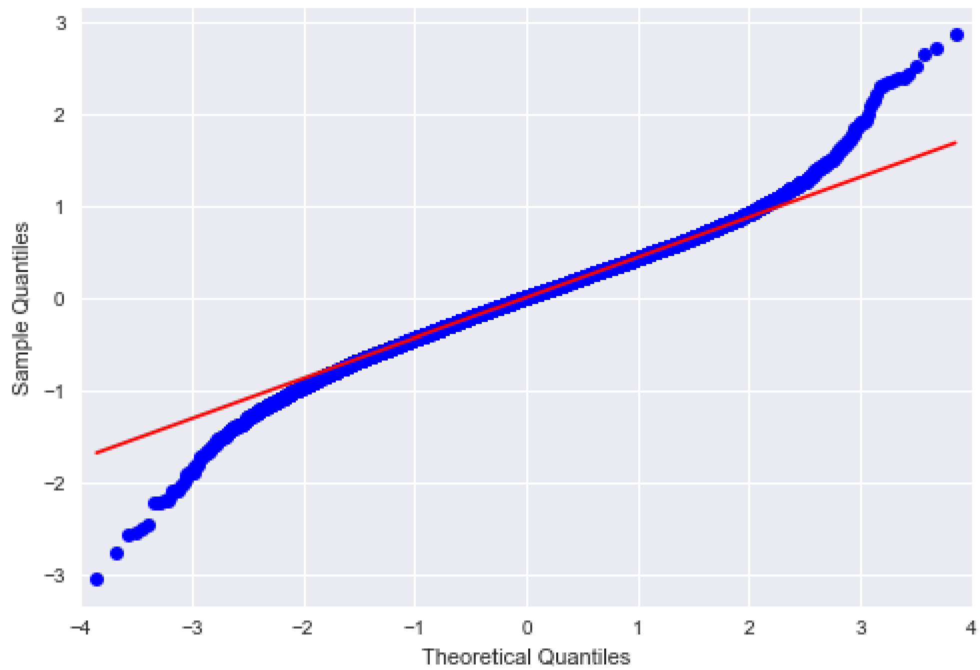
zpsft500plus	2.9085	0.166	17.545	0.000	2.584	3.233
cond_4	0.0864	0.009	10.047	0.000	0.070	0.103
cond_5	0.2591	0.014	18.280	0.000	0.231	0.287

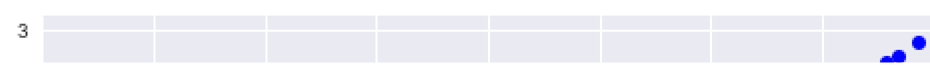
Omnibus:	666.221	**Durbin-Watson:**	2.000
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	2081.021
Skew:	-0.048	**Prob(JB):**	0.00
Kurtosis:	4.710	**Cond. No.**	64.9

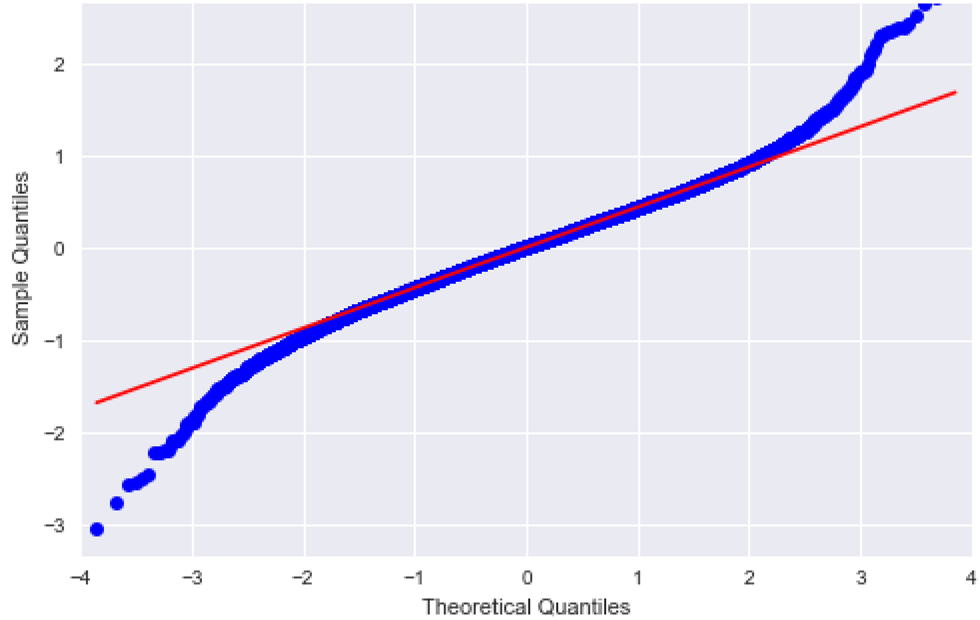
Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

In [60]:
```
qqplot(nonluxmodel.resid, line='q')
```

Out[60]:

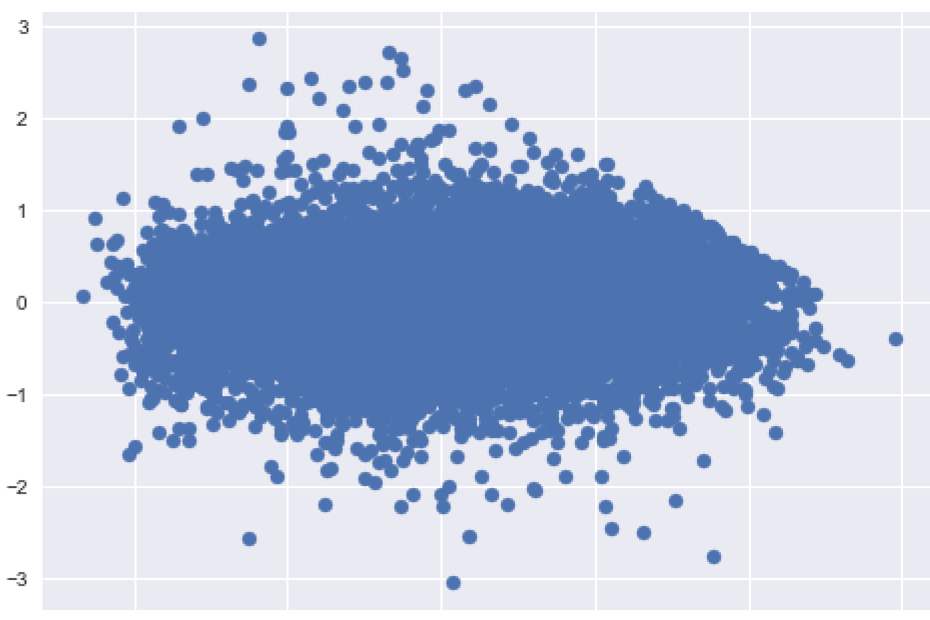






In [61]:
```
x = nonluxmodel.predict(nonlux_data)
y = nonluxmodel.resid
plt.scatter(x, y)
```

Out[61]: <matplotlib.collections.PathCollection at 0x7ffe7895a580>



Final Model - Non Luxury Homes - Takeaways:

- HIGH R-squared
- NO high p-values.
- Much **LOWER** condition number than FSM and 2nd Model. (111)
- QQ-plot - Slight deviation on both ends, but not as much as the FSM or 2nd model.
- Our scatterplot is the same shape as the All Homes final model (not as heteroscadastic).

Model for Luxury Homes (Grades 10+)

In [62]:
```
luxmodel, lux_data = mdp.final_model_luxury(data)
```

In [63]:
```
luxmodel.summary()
```

Out[63]:

Dep. Variable:	price	**R-squared:**	0.757
Model:	OLS	**Adj. R-squared:**	0.755
Method:	Least Squares	**F-statistic:**	388.2
Date:	Fri, 19 Feb 2021	**Prob (F-statistic):**	0.00
Time:	18:23:58	**Log-Likelihood:**	-1161.6
No. Observations:	1633	**AIC:**	2351.
Df Residuals:	1619	**BIC:**	2427.
Df Model:	13		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	-1.5262	0.045	-33.622	0.000	-1.615	-1.437
sqft_living	0.3751	0.016	24.196	0.000	0.345	0.406
sqft_living15	0.0547	0.015	3.737	0.000	0.026	0.083
wf_Y	1.1101	0.069	16.165	0.000	0.975	1.245

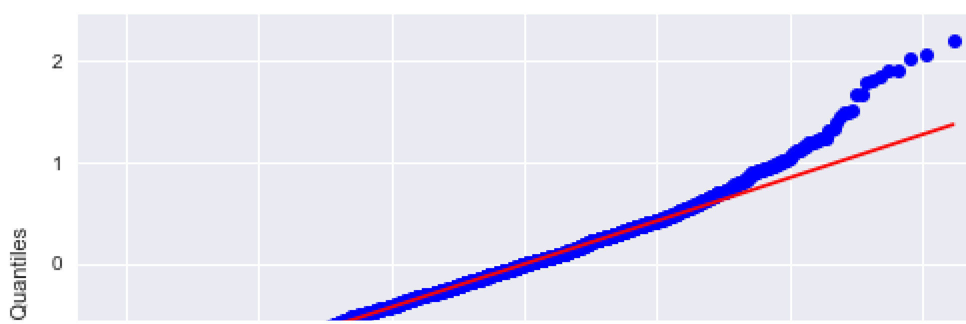
wf_1	1.1101	0.069	16.165	0.000	0.975	1.245
cond_4	0.0855	0.036	2.355	0.019	0.014	0.157
cond_5	0.3987	0.063	6.318	0.000	0.275	0.523
grade_11	0.2690	0.032	8.388	0.000	0.206	0.332
grade_12	0.5619	0.061	9.267	0.000	0.443	0.681
grade_13	0.8330	0.145	5.752	0.000	0.549	1.117
zpsft200_300	1.1576	0.048	24.261	0.000	1.064	1.251
zpsft300_400	1.8402	0.053	34.702	0.000	1.736	1.944
zpsft400_500	2.2912	0.058	39.665	0.000	2.178	2.405
zpsft500plus	2.5381	0.114	22.187	0.000	2.314	2.763
inc_Y	-0.0853	0.036	-2.358	0.019	-0.156	-0.014

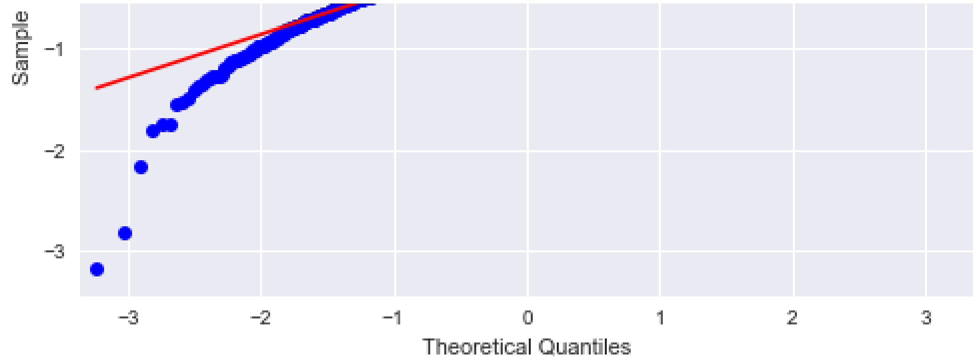
Omnibus:	123.883	**Durbin-Watson:**	1.941
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	652.976
Skew:	0.004	**Prob(JB):**	1.61e-142
Kurtosis:	6.098	**Cond. No.**	15.2

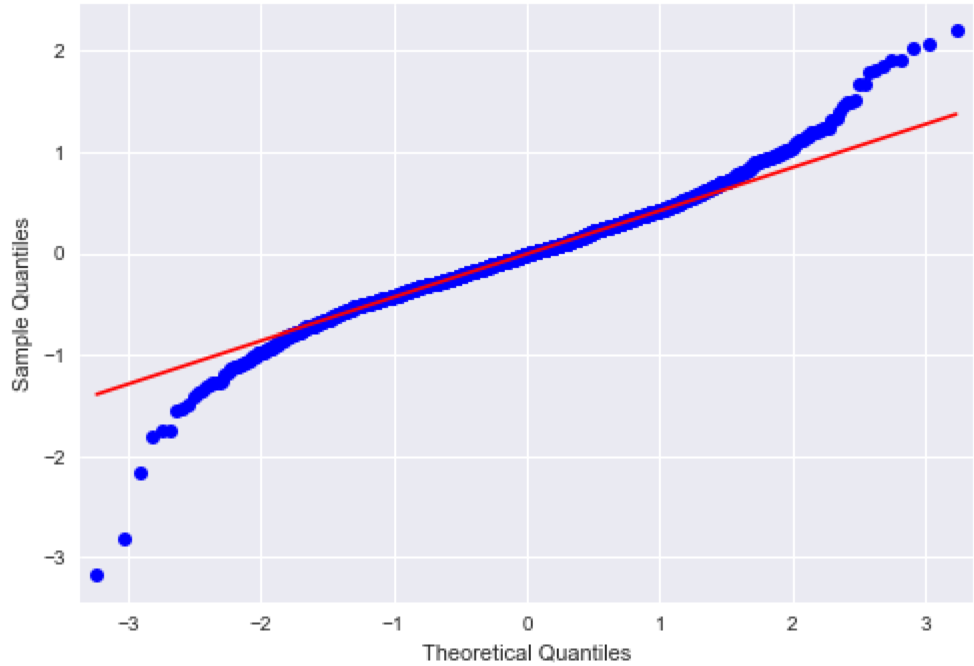
Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

In [64]:
```
qqplot(luxmodel.resid, line='q')
```

Out[64]:

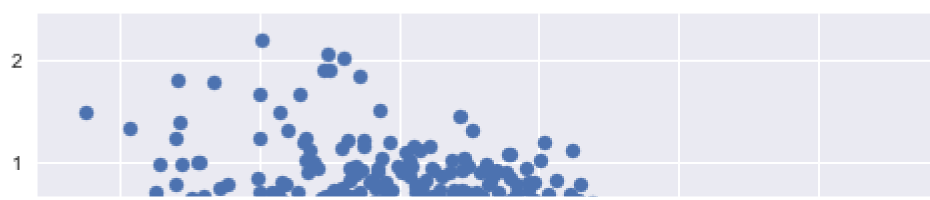


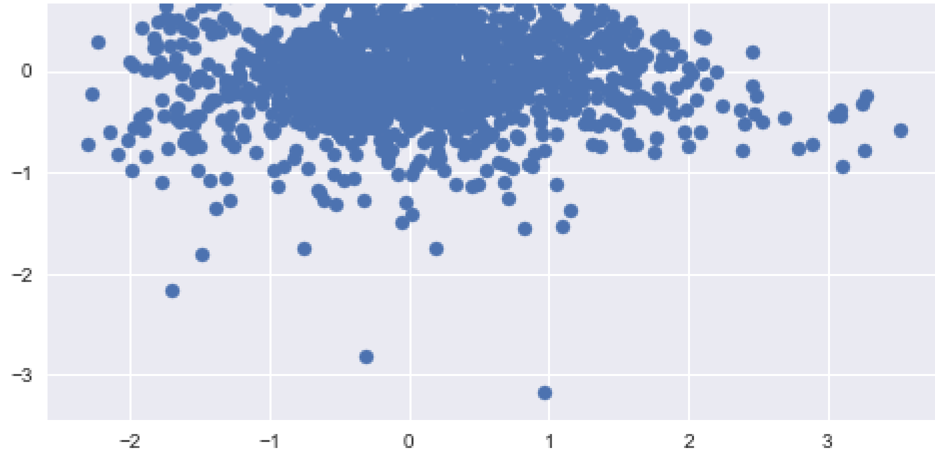




In [65]:
```
x = luxmodel.predict(lux_data)
y = luxmodel.resid
plt.scatter(x, y)
```

Out[65]: <matplotlib.collections.PathCollection at 0x7ffe7a0359a0>





Final Model - LUXURY Homes - Takeaways:

- HIGH R-squared
- NO high p-values.
- Much **LOWER** condition number than FSM and 2nd Model. (15.2)
- QQ-plot - Slight deviation on both ends, but not as much as the FSM or 2nd model.
- Our scatterplot is much more **homoscedastic** than the first three models, although it does show a very slight left-facing, conical shape of the residuals.

Conclusions

So, what can we conclude from these final three models?

1. For all King County homes in general, the **size, grade, location, and size of neighboring houses** have a strong *positive* correlation with house prices.

1. For all **Non-luxury** King County homes (Grades 6-9) have a significant *positive* correlation with **house size, grade, location, size of neighboring houses, and house condition** *(Top 3 in terms of coefficient value: Location, Grade, House Size)*

1. For all **Luxury** King County homes (Grades 10+) have a significant *positive* correlation with **house size, grade, location, size of neighboring houses, house condition,** and whether or not the house has a **waterfront view**. There is also a substantial **negative** correlation with whether or not the house is part of an **incorporated** area. *(Top 3 positive coefficients: Location, Waterfront, Condition)*

Next Steps

- Looking at it's respective graph, **House Grade** seems to have an **exponential** relationship with price. In the future, we could accomodate our model for such non-linear relationships.
- Using more current housing data. (See *Considering COVID* in Appendix of our presentation pdf)
- Develop a function that will automatically take in the dataset and optimize the model to maximize/minimize MULTIPLE specified