In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline

sns.set_style('darkgrid')

import warnings
warnings.filterwarnings('ignore')

import statsmodels.api as sm
from statsmodels.formula.api import ols
import statsmodels.api as sm
import scipy.stats as stats
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
import sklearn.metrics as metrics
from sklearn.preprocessing import OneHotEncoder, StandardScaler
import statsmodels.formula.api as smf
```

In [2]:
```
df = pd.read_csv('data/data_cleaned.csv')
df.head()
```

Out[2]:

	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	co
0	10/13/2014	221900.0	3	1.00	1180	5650	1.0	0.0	0.0	
1	12/9/2014	538000.0	3	2.25	2570	7242	2.0	0.0	0.0	
2	2/25/2015	180000.0	2	1.00	770	10000	1.0	0.0	0.0	
3	12/9/2014	604000.0	4	3.00	1960	5000	1.0	0.0	0.0	
4	2/18/2015	510000.0	3	2.00	1680	8080	1.0	0.0	0.0	

5 rows × 22 columns

In [3]:
```
df.drop(['date'], axis=1, inplace=True)
```

In [4]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 21420 entries, 0 to 21419
Data columns (total 21 columns):
 #   Column          Non-Null Count  Dtype  
---  ------          --------------  -----  
 0   price           21420 non-null  float64
 1   bedrooms        21420 non-null  int64  
 2   bathrooms       21420 non-null  float64
 3   sqft_living     21420 non-null  int64  
 4   sqft_lot        21420 non-null  int64  
 5   floors          21420 non-null  float64
 6   waterfront      21420 non-null  float64
 7   view            21420 non-null  float64
 8   condition       21420 non-null  int64  
 9   grade           21420 non-null  int64  
 10  sqft_basement   21420 non-null  float64
 11  yr_built        21420 non-null  int64  
 12  yr_renovated    21420 non-null  int64  
```

```
 13  zipcode          21420 non-null  int64
 14  lat              21420 non-null  float64
 15  long             21420 non-null  float64
 16  sqft_living15    21420 non-null  int64
 17  sqft_lot15       21420 non-null  int64
 18  month            21420 non-null  int64
 19  yrs_since_reno   21420 non-null  int64
 20  bed_bath_ratio   21420 non-null  float64
dtypes: float64(9), int64(12)
memory usage: 3.4 MB
```

Baseline Model

In [5]:
```
outcome = 'price'
predictors = df.drop('price', axis = 1)
pred_sum = "+".join(predictors.columns)
formula = outcome + '~' + pred_sum
```

In [6]:
```
baseline_model = ols(formula=formula, data=df).fit()
```

In [7]:
```
type(baseline_model)
```

Out[7]:
```
statsmodels.regression.linear_model.RegressionResultsWrapper
```

In [8]:
```
baseline_model.summary()
```

Out[8]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.706
Model:	OLS	**Adj. R-squared:**	0.706
Method:	Least Squares	**F-statistic:**	2567.
Date:	Thu, 10 Jun 2021	**Prob (F-statistic):**	0.00
Time:	12:12:59	**Log-Likelihood:**	-2.9178e+05
No. Observations:	21420	**AIC:**	5.836e+05
Df Residuals:	21399	**BIC:**	5.838e+05
Df Model:	20		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	-6.477e+07	9.91e+06	-6.537	0.000	-8.42e+07	-4.53e+07
bedrooms	-9.655e+04	3277.786	-29.455	0.000	-1.03e+05	-9.01e+04
bathrooms	1.476e+05	5719.983	25.801	0.000	1.36e+05	1.59e+05
sqft_living	169.9092	3.666	46.350	0.000	162.724	177.094
sqft_lot	0.1070	0.048	2.251	0.024	0.014	0.200
floors	8795.4473	3556.855	2.473	0.013	1823.745	1.58e+04
waterfront	5.231e+05	1.66e+04	31.568	0.000	4.91e+05	5.56e+05
view	5.449e+04	2088.540	26.091	0.000	5.04e+04	5.86e+04
condition	3.145e+04	2348.638	13.392	0.000	2.68e+04	3.61e+04

grade	9.593e+04	2150.447	44.608	0.000	9.17e+04	1e+05
sqft_basement	-19.3381	4.312	-4.485	0.000	-27.789	-10.887
yr_built	-2508.3562	71.819	-34.926	0.000	-2649.126	-2367.586
yr_renovated	3.655e+04	4692.400	7.789	0.000	2.74e+04	4.57e+04
zipcode	-607.1898	32.863	-18.476	0.000	-671.604	-542.775
lat	6.06e+05	1.07e+04	56.739	0.000	5.85e+05	6.27e+05
long	-2.123e+05	1.31e+04	-16.226	0.000	-2.38e+05	-1.87e+05
sqft_living15	28.7309	3.442	8.348	0.000	21.985	35.477
sqft_lot15	-0.3955	0.073	-5.436	0.000	-0.538	-0.253
month	1361.0379	703.639	1.934	0.053	-18.147	2740.223
yrs_since_reno	3.652e+04	4692.297	7.784	0.000	2.73e+04	4.57e+04
bed_bath_ratio	1.158e+05	5143.535	22.509	0.000	1.06e+05	1.26e+05

Omnibus:	17324.207	**Durbin-Watson:**	1.999
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	1506830.177
Skew:	3.327	**Prob(JB):**	0.00
Kurtosis:	43.547	**Cond. No.**	7.32e+08

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 7.32e+08. This might indicate that there are
strong multicollinearity or other numerical problems.

Observations:

- Confidence interval for month includes 0. Chance of no relationship with target
- Bedrooms has a negative coefficient (need to examine)
- According to sqft_living coeff, price per sqft is about $170
- sqft_basement has negative coeff
- sqft_lot15 has negative coeff
- sqft_lot has very small coeff
- yr_built has negative coeff, while yr_renovated is positive
- month has p-value slightly over 0.05 (0.053), making it the least relevant feature currently

JB value of 6 or higher indicates that errors are not normally distributed

- JB = 1506830.177

In [9]:
```
X = df.drop("price", axis = 1)
Y = df['price']
```

In [10]:
```
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size = 0.25, rand
```

```
baseline_linreg = LinearRegression()
baseline_linreg.fit(X_train, Y_train)
Y_pred = baseline_linreg.predict(X_test)
```

In [11]:
```
from sklearn.metrics import mean_squared_error
```

In [12]:
```
mse_train = mean_squared_error(Y_train, baseline_linreg.predict(X_train))
mse_test = mean_squared_error(Y_test, Y_pred)

print("Train RMSE:", np.sqrt(mse_train))
print("Test RMSE:", np.sqrt(mse_test))
```

```
Train RMSE: 204049.23830834476
Test RMSE: 185223.8167396286
```

In [13]:
```
X.columns
```

Out[13]:
```
Index(['bedrooms', 'bathrooms', 'sqft_living', 'sqft_lot', 'floors',
       'waterfront', 'view', 'condition', 'grade', 'sqft_basement', 'yr_built',
       'yr_renovated', 'zipcode', 'lat', 'long', 'sqft_living15', 'sqft_lot15',
       'month', 'yrs_since_reno', 'bed_bath_ratio'],
      dtype='object')
```

Another multicolinearity check

In [14]:
```
from statsmodels.stats.outliers_influence import variance_inflation_factor
```

In [15]:
```
X = predictors
vif = [variance_inflation_factor(X.values, i) for i in range(X.shape[1])]
list(zip(predictors, vif))
```

Out[15]:
```
[('bedrooms', 70.78386833025283),
 ('bathrooms', 89.46528453170541),
 ('sqft_living', 37.50211921849836),
 ('sqft_lot', 2.375589147278171),
 ('floors', 17.19979550455687),
 ('waterfront', 1.1596190900935792),
 ('view', 1.5022566615906274),
 ('condition', 35.47877427156492),
 ('grade', 149.6151425103302),
 ('sqft_basement', 2.752195121453835),
 ('yr_built', 10676.587579403915),
 ('yr_renovated', 141361.62048229066),
 ('zipcode', 5232304.820490609),
 ('lat', 138906.45723803443),
 ('long', 1375973.3662308326),
 ('sqft_living15', 28.11223408766165),
 ('sqft_lot15', 2.5962005270497666),
 ('month', 6.1845506248446345),
 ('yrs_since_reno', 4024134.8385890764),
 ('bed_bath_ratio', 49.83760638553746)]
```

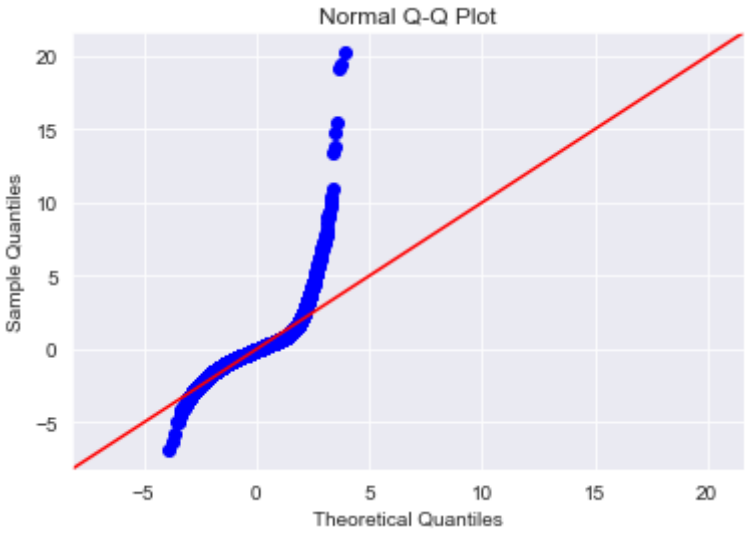
Suggests there is moderate multicolinearity in some of the variables. Variables that exhibit the least multicolinearity are sqft_lot, waterfront, view, sqft_basement, month

Normality Check

Already have seen pretty high JB value

In [16]:
```
resid1 = baseline_model.resid
```

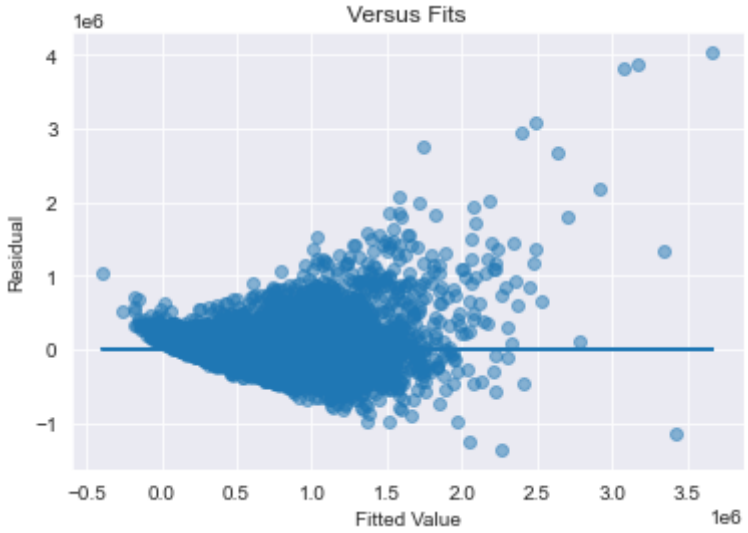
```
fig = sm.graphics.qqplot(resid1, dist=stats.norm, line='45', fit=True)
plt.title('Normal Q-Q Plot')
plt.savefig('images/baseline-qq.png')
```



We've got quite a few outliers still in the dataframe, which could be contributing to this awful plot. The non-normally distributed errors also suggest that the data could benefit from a log transform

Homoscedasticity check

In [17]:
```
plt.scatter(baseline_model.predict(predictors), baseline_model.resid, alpha=0.5)
plt.plot(baseline_model.predict(predictors), [0 for i in range(len(df))])
plt.title('Versus Fits')
plt.xlabel('Fitted Value')
plt.ylabel('Residual')
plt.savefig('images/baseline-homosc.png')
```



Errors seem to increase based on target variable/ cone-shaped. Model is heteroscedastic. Errors start getting quite high above ~2.25.

Treat outliers

In [18]:
```
def diagnostic_plots(df, variable):
```

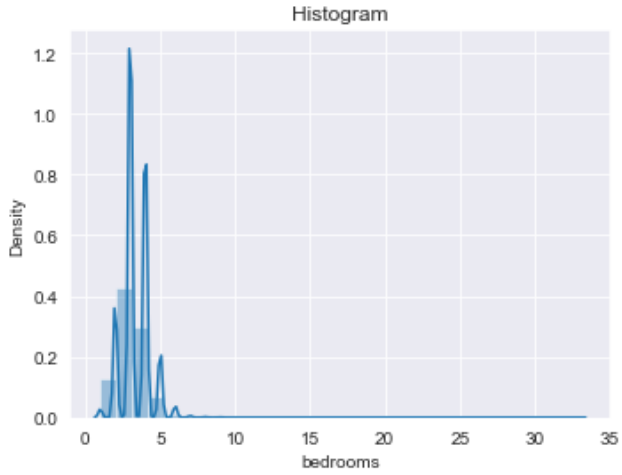
```
    # function takes a dataframe (df) and
    # the variable of interest as arguments

    plt.figure(figsize=(12, 4))

    # histogram
    plt.subplot(1, 2, 1)
    sns.distplot(df[variable], bins=30)
    plt.title('Histogram')

    # boxplot
    plt.subplot(1, 2, 2)
    sns.boxplot(y=df[variable])
    plt.title('Boxplot')

    plt.show()
```

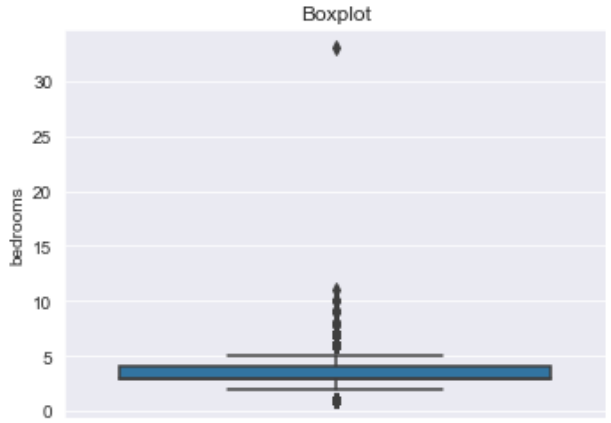
In [19]:
```
def qqplot_feat(df, variable):
    f = 'price~' + variable
    model = ols(formula=f, data=df).fit()
    resid = model.resid
    sm.graphics.qqplot(resid, dist=stats.norm, line='45', fit=True);
```

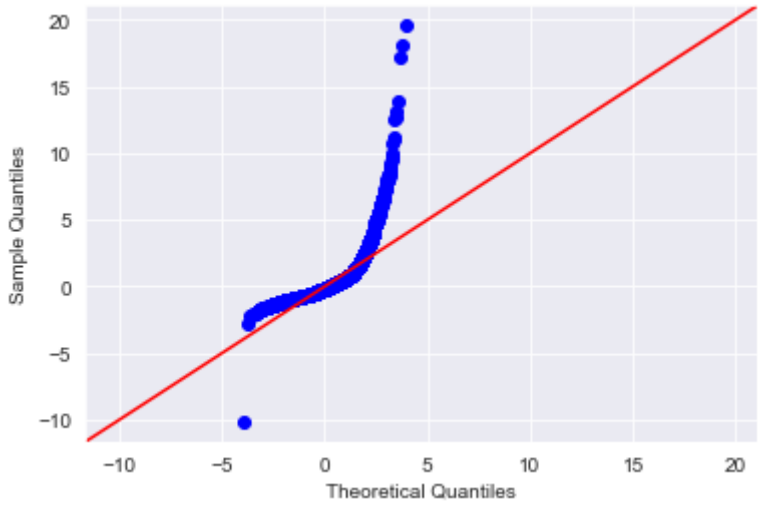
In [20]:
```
def log_diagnostic_plots(df, variable):
    # function takes a dataframe (df) and
    # the variable of interest as arguments

    plt.figure(figsize=(12, 4))

    # histogram
    plt.subplot(1, 2, 1)
    sns.distplot(np.log(df[variable]), bins=30)
    plt.title('Histogram')

    # boxplot
    plt.subplot(1, 2, 2)
    sns.boxplot(y=np.log(df[variable]))
    plt.title('Boxplot')

    plt.show()
```

Bedrooms

In [21]:
```
diagnostic_plots(df, 'bedrooms')
qqplot_feat(df, 'bedrooms')
```







In [22]:
```
df[df['bedrooms'] > 7]
```

Out[22]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	conditio
1643	490000.0	8	5.00	2800	2580	2.0	0.0	0.0	
3997	2150000.0	8	6.00	4340	9415	2.0	0.0	0.0	
4029	373000.0	8	3.00	2850	12714	1.0	0.0	0.0	
4057	599999.0	9	4.50	3830	6988	2.5	0.0	0.0	
4196	700000.0	9	3.00	3680	4400	2.0	0.0	0.0	
6025	1280000.0	9	4.50	3650	5000	2.0	0.0	0.0	
6120	340000.0	8	2.75	2790	6695	1.0	0.0	0.0	
8469	450000.0	9	7.50	4050	6504	2.0	0.0	0.0	
8679	520000.0	11	3.00	3000	4960	2.0	0.0	0.0	
8996	700000.0	8	2.50	2280	3000	1.5	0.0	0.0	
9363	900000.0	8	4.00	4020	7500	1.0	0.0	0.0	
10853	1650000.0	8	2.75	4040	20666	1.0	0.0	0.0	
12758	808000.0	8	3.75	3460	4600	2.0	0.0	0.0	
13182	1150000.0	10	5.25	4590	10920	1.0	0.0	2.0	

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	conditio
14922	430000.0	8	3.25	4300	10441	2.0	0.0	0.0	
15011	650000.0	10	2.00	3610	11914	2.0	0.0	0.0	
15512	680000.0	8	2.75	2530	4800	2.0	0.0	0.0	
15710	640000.0	33	1.75	1620	6000	1.0	0.0	0.0	
16680	1400000.0	9	4.00	4620	5508	2.5	0.0	0.0	
17068	1970000.0	8	3.50	4440	6480	2.0	0.0	3.0	
18265	934000.0	9	3.00	2820	4480	2.0	0.0	0.0	
18299	3300000.0	8	4.00	7710	11750	3.5	0.0	0.0	
19070	660000.0	10	3.00	2920	3745	2.0	0.0	0.0	
19118	575000.0	8	3.00	3840	15990	1.0	0.0	0.0	

24 rows × 21 columns

In [23]:
```
from matplotlib import ticker
```

In [24]:
```
sns.set_context('paper', font_scale = 1.3)

ax = sns.scatterplot('bedrooms', 'price', data=df[df['bedrooms'] < 33], color='#
ax.set_title('Price by Number of Bedrooms')
ax.yaxis.get_major_formatter().set_scientific(False)
ax.yaxis.set_major_formatter(ticker.FuncFormatter(lambda x, pos: '{:,.1f}'.forma
```

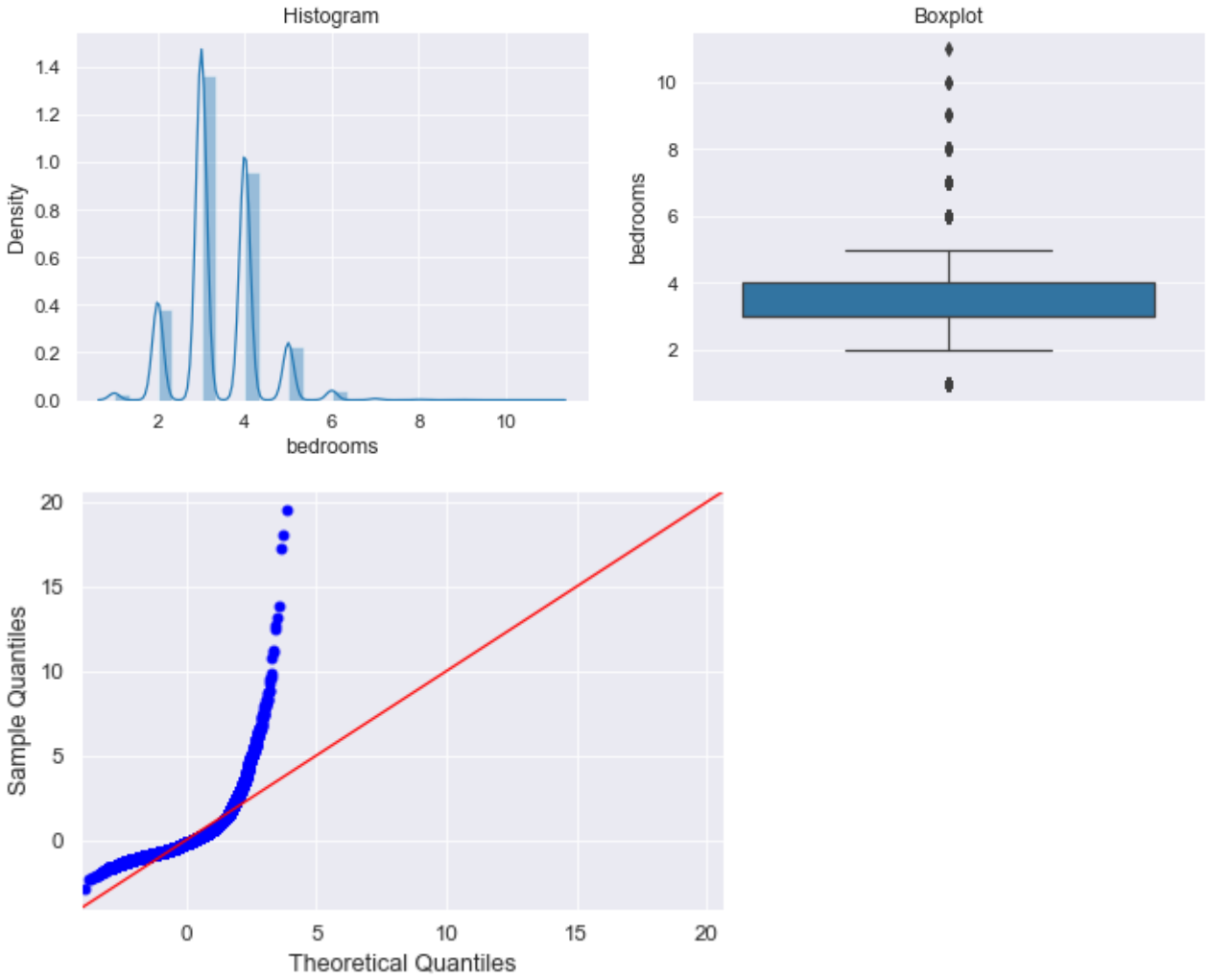
In [25]:
```
#Finding a cutoff point
for i in range(90, 101):
    q = i / 100
    print('{} percentile: {}'.format(q, df['bedrooms'].quantile(q=q)))
```

```
0.9 percentile: 4.0
0.91 percentile: 4.0
0.92 percentile: 5.0
0.93 percentile: 5.0
0.94 percentile: 5.0
0.95 percentile: 5.0
```

```
0.96 percentile: 5.0
0.97 percentile: 5.0
0.98 percentile: 5.0
0.99 percentile: 6.0
1.0 percentile: 33.0
```

In [26]:
```
df_no_fliers = df[df['bedrooms'] <= 12]
```

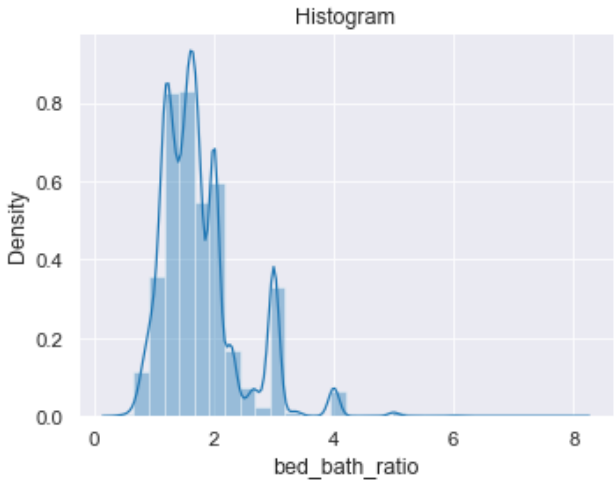
In [27]:
```
diagnostic_plots(df_no_fliers, 'bedrooms')
qqplot_feat(df_no_fliers, 'bedrooms')
```

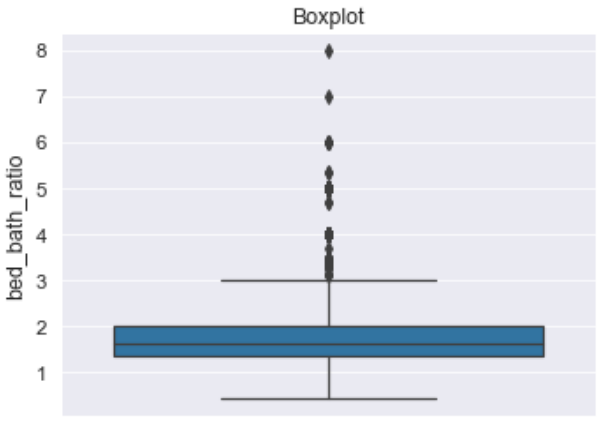


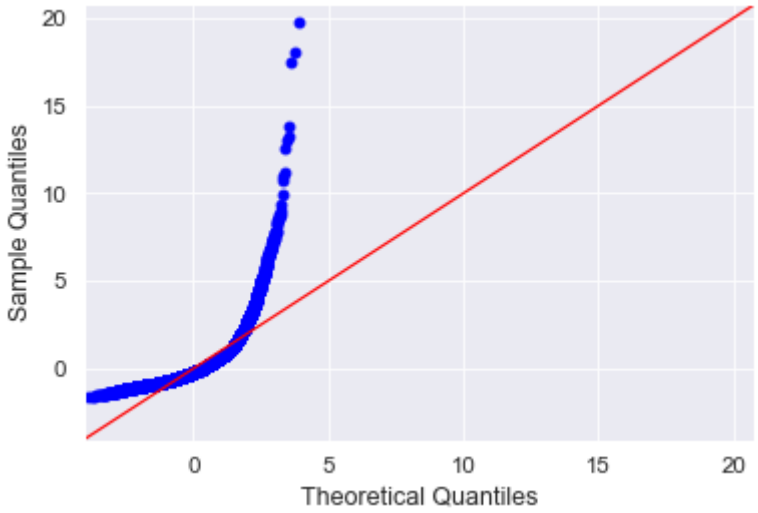
Some improvements but doesn't totally take care of the problem. Should examine this data for more than one slope.

Bed-bath ratio

In [28]:
```
diagnostic_plots(df_no_fliers, 'bed_bath_ratio')
qqplot_feat(df_no_fliers, 'bed_bath_ratio')
```







In [29]:
```
#Finding a cutoff point
for i in range(90, 101):
    q = i / 100
    print('{} percentile: {}'.format(q, df_no_fliers['bed_bath_ratio'].quantile(
```

```
0.9 percentile: 3.0
0.91 percentile: 3.0
0.92 percentile: 3.0
0.93 percentile: 3.0
0.94 percentile: 3.0
0.95 percentile: 3.0
0.96 percentile: 3.0
0.97 percentile: 3.0
0.98 percentile: 3.333333333333333
0.99 percentile: 4.0
1.0 percentile: 8.0
```

Bed_bath_ratio of 8.0 is a clear outlier. 8 bedrooms to one bathroom seems to be a mistake or possibly a communal bathroom situation. A person or family pricing their home is not likely to have this situation.

In [30]:
```
df_no_fliers[df_no_fliers['bed_bath_ratio'] > 4]
```

Out[30]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	conditio
941	435000.0	5	1.00	1410	6750	1.5	0.0	0.0	
1794	300000.0	5	1.00	1940	8875	1.0	0.0	0.0	

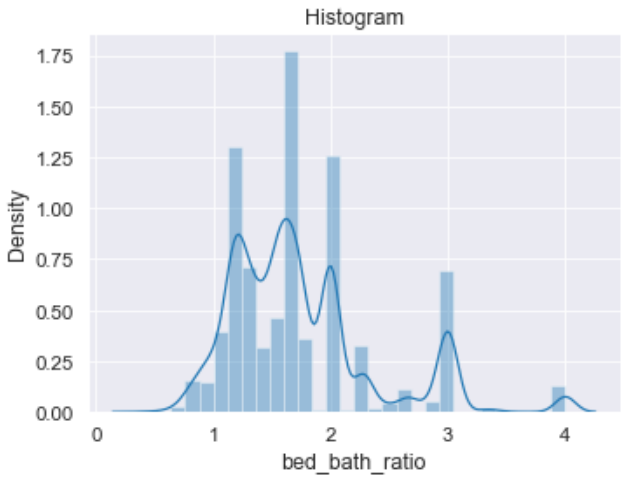
	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition
1985	560000.0	5	1.00	1710	9100	1.5	0.0	0.0	
2221	1000000.0	5	1.00	2010	5210	1.5	0.0	0.0	
2343	230000.0	5	1.00	1920	19040	1.0	0.0	0.0	
2679	239950.0	5	1.00	1460	6032	2.0	0.0	0.0	
3427	345950.0	5	1.00	1340	11198	1.5	0.0	0.0	
3581	563000.0	6	1.00	1730	2760	1.5	0.0	0.0	
4135	438000.0	5	1.00	1950	6250	1.5	0.0	0.0	
4231	544500.0	5	1.00	1690	3240	1.5	0.0	0.0	
4665	775000.0	5	1.00	1860	3040	1.5	0.0	0.0	
5388	540000.0	5	1.00	2480	4400	1.5	0.0	0.0	
5700	525000.0	5	1.00	1280	3876	1.5	0.0	0.0	
6321	800000.0	6	1.00	1430	20620	2.0	0.0	0.0	
7438	549000.0	5	1.00	1500	3978	2.0	0.0	0.0	
8112	495000.0	5	1.00	1810	11205	1.5	0.0	2.0	
8266	1300000.0	5	1.00	1670	6400	1.5	0.0	0.0	
8380	340000.0	5	1.00	1880	3774	1.5	0.0	0.0	
8552	575000.0	7	1.50	2670	11250	1.5	0.0	0.0	
9049	310000.0	7	1.50	2660	15111	1.5	0.0	0.0	
9058	320000.0	5	1.00	1740	27350	1.0	0.0	0.0	
9119	625000.0	5	1.00	3240	5324	2.0	0.0	0.0	
9481	274000.0	5	1.00	1680	9383	1.0	0.0	0.0	
9646	518000.0	5	1.00	1590	5000	1.5	0.0	0.0	
10306	185000.0	5	1.00	1590	6700	1.5	0.0	0.0	
10319	630000.0	5	1.00	3020	4800	2.0	0.0	0.0	
10548	295832.0	5	1.00	1410	6400	1.0	0.0	0.0	
11332	340000.0	5	1.00	1120	9022	1.5	0.0	0.0	
11925	312500.0	4	0.50	2300	5570	2.0	0.0	0.0	
12218	415000.0	6	1.00	1370	5080	1.5	0.0	0.0	
12483	291000.0	7	1.00	2350	8636	1.0	0.0	0.0	
12867	260000.0	5	1.00	1600	7350	1.0	0.0	0.0	
12953	677500.0	5	1.00	2340	4730	2.0	0.0	0.0	
12996	346000.0	5	1.00	1790	30456	1.0	0.0	0.0	
13018	950000.0	6	1.00	2330	5000	1.5	0.0	0.0	
13390	620000.0	5	1.00	2230	16800	1.5	0.0	3.0	
13548	550000.0	5	1.00	2150	262231	1.5	0.0	0.0	

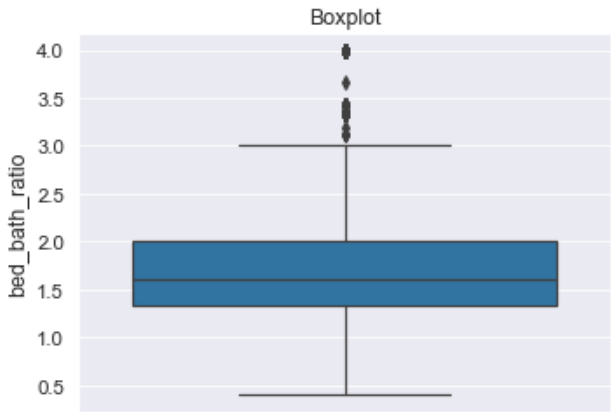
	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	conditio
14085	142500.0	4	0.75	1440	13300	1.0	0.0	0.0	
14363	435000.0	5	1.00	2170	65340	1.5	0.0	0.0	
14571	590000.0	5	1.00	1840	6710	1.5	0.0	0.0	
15011	650000.0	10	2.00	3610	11914	2.0	0.0	0.0	
15177	520000.0	4	0.75	1960	8277	1.0	1.0	4.0	
15479	235000.0	5	1.00	1500	9282	1.5	0.0	0.0	
15803	180000.0	5	1.00	1460	11726	1.5	0.0	0.0	
15967	780500.0	5	1.00	1760	4264	2.0	0.0	0.0	
16103	847000.0	5	1.00	2550	4623	2.5	0.0	0.0	
16179	890000.0	5	1.00	2590	4652	2.0	0.0	0.0	
16845	230000.0	5	1.00	1410	9000	1.0	0.0	0.0	
17070	569950.0	5	1.00	1420	6250	1.5	0.0	0.0	
17594	539000.0	5	1.00	1700	11727	1.5	0.0	0.0	
17699	642000.0	6	1.00	1530	4305	1.5	0.0	0.0	
18113	397000.0	5	1.00	1170	6757	1.0	0.0	0.0	
18349	220000.0	5	1.00	1260	8382	1.5	0.0	0.0	
18498	262000.0	5	1.00	1870	7800	1.0	0.0	0.0	
18903	774900.0	5	1.00	1750	3861	1.5	0.0	0.0	

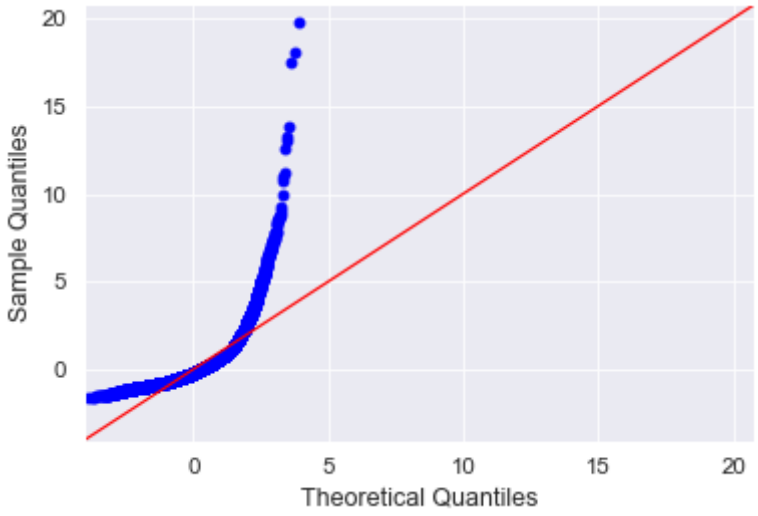
55 rows × 21 columns

In [31]:
```
df_no_fliers = df_no_fliers[df_no_fliers['bed_bath_ratio'] <= 4]
```

In [32]:
```
diagnostic_plots(df_no_fliers, 'bed_bath_ratio')
qqplot_feat(df_no_fliers, 'bed_bath_ratio')
```

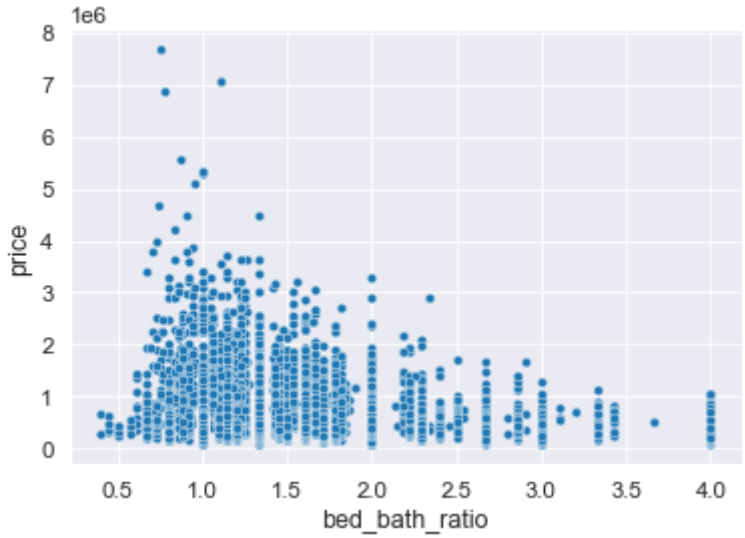






In [33]:
```
sns.scatterplot('bed_bath_ratio', 'price', data=df_no_fliers)
```

Out[33]:
```
<AxesSubplot:xlabel='bed_bath_ratio', ylabel='price'>
```



Minor improvement with removal of outlier. Dropped bed_bath_ratio over 4 to reduce noise. Also, more than 4 bedrooms to 1 bathroom isn't very representative of most living situations.

Bathrooms

In [34]:
```
#Finding a cutoff point
for i in range(0, 10):
    q = i / 100
    print('{} percentile: {}'.format(q, df_no_fliers['bathrooms'].quantile(q=q)))
```

```
0.0 percentile: 0.5
0.01 percentile: 1.0
0.02 percentile: 1.0
0.03 percentile: 1.0
0.04 percentile: 1.0
0.05 percentile: 1.0
0.06 percentile: 1.0
0.07 percentile: 1.0
0.08 percentile: 1.0
0.09 percentile: 1.0
```

In [35]:
```
df_no_fliers = df_no_fliers[df_no_fliers['bathrooms'] >= 1]
```

Under one bathroom means a property has no bathrooms or only a powder room/ no shower or bath.

In [36]:
```
df_no_fliers.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 21293 entries, 0 to 21418
Data columns (total 21 columns):
 #   Column          Non-Null Count  Dtype  
---  ------          --------------  -----  
 0   price           21293 non-null  float64
 1   bedrooms        21293 non-null  int64  
 2   bathrooms       21293 non-null  float64
 3   sqft_living     21293 non-null  int64  
 4   sqft_lot        21293 non-null  int64  
 5   floors          21293 non-null  float64
 6   waterfront      21293 non-null  float64
 7   view            21293 non-null  float64
 8   condition       21293 non-null  int64  
 9   grade           21293 non-null  int64  
 10  sqft_basement   21293 non-null  float64
 11  yr_built        21293 non-null  int64  
 12  yr_renovated    21293 non-null  int64  
 13  zipcode         21293 non-null  int64  
 14  lat             21293 non-null  float64
 15  long            21293 non-null  float64
 16  sqft_living15   21293 non-null  int64  
 17  sqft_lot15      21293 non-null  int64  
 18  month           21293 non-null  int64  
 19  yrs_since_reno  21293 non-null  int64  
 20  bed_bath_ratio  21293 non-null  float64
dtypes: float64(9), int64(12)
memory usage: 3.6 MB
```

Price

There are some obvious price outliers across most predictors, looking at the scatterplots in my previous notebook. This could improve the relationships between price and X across multiple dimensions

In [37]:
```
#Finding a cutoff point
for i in range(90, 101):
    q = i / 100
    print('{} percentile: {}'.format(q, df_no_fliers['price'].quantile(q=q)))
```

```
0.9 percentile: 890000.0
0.91 percentile: 920000.0
0.92 percentile: 953962.5199999991
0.93 percentile: 998912.0000000002
0.94 percentile: 1070000.0
0.95 percentile: 1160000.0
0.96 percentile: 1260000.0
0.97 percentile: 1400000.0
0.98 percentile: 1600000.0
0.99 percentile: 1980000.0
1.0 percentile: 7700000.0
```

In [38]:
```
df_no_fliers[df_no_fliers['price'] > 5000000].count()
```

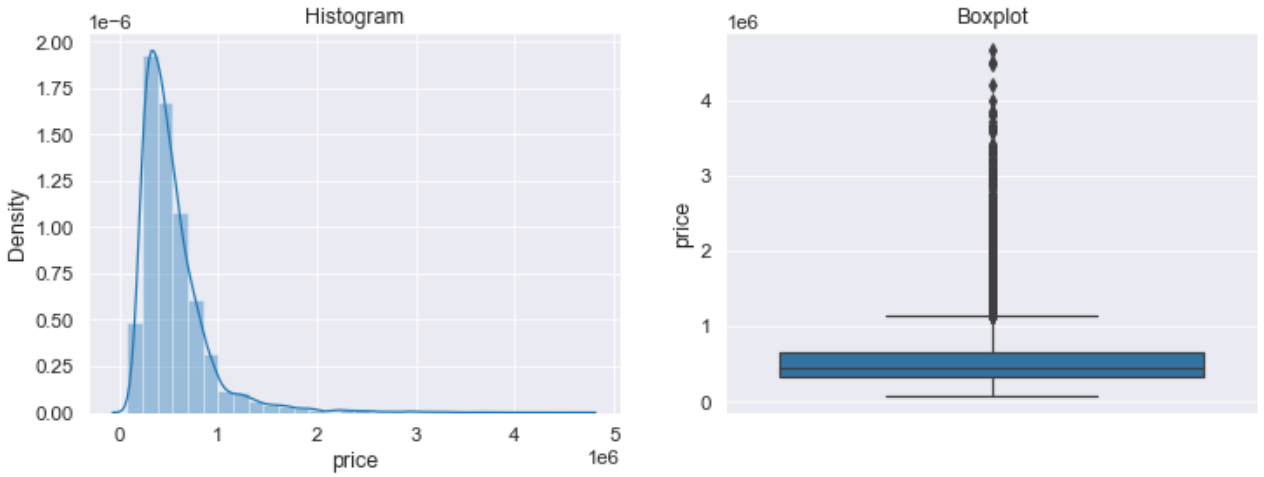
Out[38]:
```
price             7
```

```
bedrooms          7
bathrooms         7
sqft_living       7
sqft_lot          7
floors            7
waterfront        7
view              7
condition         7
grade             7
sqft_basement     7
yr_built          7
yr_renovated      7
zipcode           7
lat               7
long              7
sqft_living15     7
sqft_lot15        7
month             7
yrs_since_reno    7
bed_bath_ratio    7
dtype: int64
```

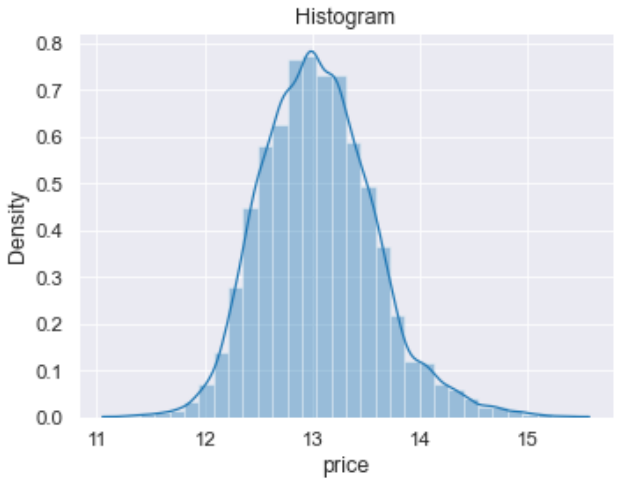
In [39]:
```
df_no_fliers = df_no_fliers[df_no_fliers['price'] <= 5000000]
```

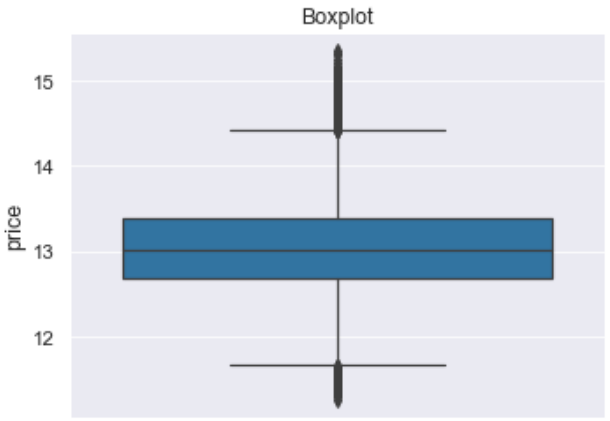
Chose 5000000 as a cutoff value for price based on scatterplots of all variables and the potential cut-off values shown when inspecting quantiles.

In [40]:
```
diagnostic_plots(df_no_fliers, 'price')
```



In [41]:
```
log_diagnostic_plots(df_no_fliers, 'price')
```

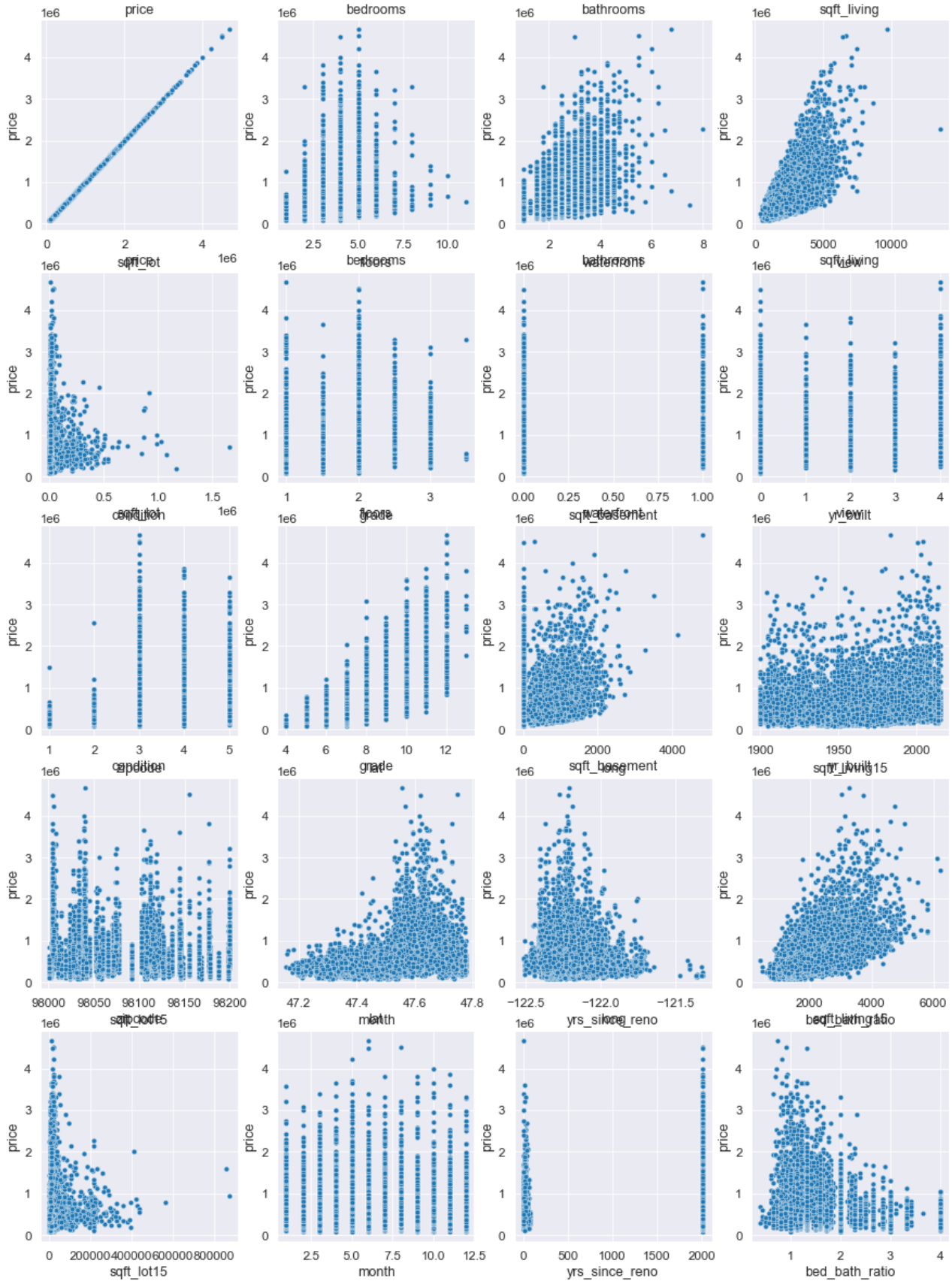




Price data will greatly benefit from a log transformation

In [42]:
```
df_no_fliers.drop(['yr_renovated'], axis=1, inplace=True)
```

In [43]:
```
plt.figure(figsize=(15,25))

for index, col in enumerate(df_no_fliers.columns):
    ax = plt.subplot(6, 4, index+1)
    sns.scatterplot(x=col, y='price', data=df_no_fliers, ax=ax)
    ax.set_title('{}'.format(col))
```



In [44]:
```
df_no_fliers.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 21286 entries, 0 to 21418
Data columns (total 20 columns):
 #   Column          Non-Null Count  Dtype
```

```
 ---  ------           --------------  -----
  0   price            21286 non-null  float64
  1   bedrooms         21286 non-null  int64
  2   bathrooms        21286 non-null  float64
  3   sqft_living      21286 non-null  int64
  4   sqft_lot         21286 non-null  int64
  5   floors           21286 non-null  float64
  6   waterfront       21286 non-null  float64
  7   view             21286 non-null  float64
  8   condition        21286 non-null  int64
  9   grade            21286 non-null  int64
  10  sqft_basement    21286 non-null  float64
  11  yr_built         21286 non-null  int64
  12  zipcode          21286 non-null  int64
  13  lat              21286 non-null  float64
  14  long             21286 non-null  float64
  15  sqft_living15    21286 non-null  int64
  16  sqft_lot15       21286 non-null  int64
  17  month            21286 non-null  int64
  18  yrs_since_reno   21286 non-null  int64
  19  bed_bath_ratio   21286 non-null  float64
dtypes: float64(9), int64(11)
memory usage: 3.4 MB
```

Decisions

Dropping more multicolinear features:

- drop yr_renovated, keep yrs_since_reno as yrs_since_reno is independent of the exact year renovated. We don't necessarily need to know exact year, but the time between a home's last reno and last sale is informative. Also these variables are perfectly multicolinear
- Will consider dropping yr_built in the next model

Outlier removal:

- drop bed_bath_ratio over 4
- drop bedrooms over 12
- drop bathrooms under 1
- drop price over 5000000

Model 2

In [45]:
```
outcome = 'price'
predictors = df_no_fliers.drop('price', axis = 1)
pred_sum = "+".join(predictors.columns)
formula = outcome + '~' + pred_sum
```

In [46]:
```
model2 = ols(formula=formula, data=df_no_fliers).fit()
```

In [47]:
```
model2.summary()
```

Out[47]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.711
Model:	OLS	**Adj. R-squared:**	0.711
Method:	Least Squares	**F-statistic:**	2759.

Date:	Thu, 10 Jun 2021	**Prob (F-statistic):**	0.00
Time:	12:13:14	**Log-Likelihood:**	-2.8892e+05
No. Observations:	21286	**AIC:**	5.779e+05
Df Residuals:	21266	**BIC:**	5.780e+05
Df Model:	19		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	7.07e+06	2.79e+06	2.535	0.011	1.6e+06	1.25e+07
bedrooms	-8.472e+04	3247.324	-26.089	0.000	-9.11e+04	-7.84e+04
bathrooms	1.319e+05	5612.550	23.504	0.000	1.21e+05	1.43e+05
sqft_living	149.2797	3.551	42.041	0.000	142.320	156.240
sqft_lot	0.1311	0.045	2.890	0.004	0.042	0.220
floors	1.265e+04	3400.510	3.721	0.000	5989.166	1.93e+04
waterfront	4.968e+05	1.61e+04	30.792	0.000	4.65e+05	5.28e+05
view	5.516e+04	1998.161	27.606	0.000	5.12e+04	5.91e+04
condition	3.172e+04	2245.696	14.127	0.000	2.73e+04	3.61e+04
grade	1e+05	2067.792	48.372	0.000	9.6e+04	1.04e+05
sqft_basement	-16.1362	4.119	-3.918	0.000	-24.210	-8.063
yr_built	-2477.3664	68.800	-36.008	0.000	-2612.219	-2342.513
zipcode	-578.7664	31.415	-18.423	0.000	-640.343	-517.190
lat	6.004e+05	1.02e+04	58.878	0.000	5.8e+05	6.2e+05
long	-2.06e+05	1.25e+04	-16.418	0.000	-2.31e+05	-1.81e+05
sqft_living15	37.1266	3.302	11.243	0.000	30.654	43.599
sqft_lot15	-0.3643	0.069	-5.243	0.000	-0.500	-0.228
month	-2881.4596	418.108	-6.892	0.000	-3700.984	-2061.936
yrs_since_reno	-25.7291	3.780	-6.806	0.000	-33.139	-18.319
bed_bath_ratio	1.014e+05	5235.618	19.360	0.000	9.11e+04	1.12e+05

Omnibus:	12456.139	**Durbin-Watson:**	1.989
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	302278.875
Skew:	2.357	**Prob(JB):**	0.00
Kurtosis:	20.850	**Cond. No.**	2.16e+08

Notes:

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

[2] The condition number is large, 2.16e+08. This might indicate that there are strong multicollinearity or other numerical problems.

Observations

- Previously had JB value 1506830.177. New JB of 302278.875 is much lower
- Confidence interval for month no longer crosses 0
- bedrooms coefficient still negative
- sqft_basement coeff still negative
- sqft_lot15 coeff still negative
- yrs_since_reno now negative (makes more sense than a positive coefficient, as more years since reno means less "new")
- some improved p-values

In [48]:
```
X = df_no_fliers.drop("price", axis = 1)
Y = df_no_fliers['price']
```

In [49]:
```
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size = 0.25, rand
linreg2 = LinearRegression()
linreg2.fit(X_train, Y_train)
Y_pred = linreg2.predict(X_test)
```

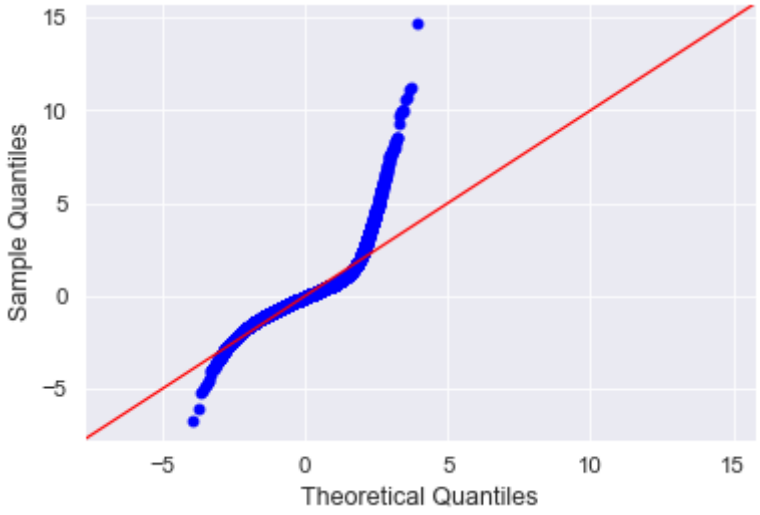
In [50]:
```
mse_train = mean_squared_error(Y_train, linreg2.predict(X_train))
mse_test = mean_squared_error(Y_test, Y_pred)

print("Train RMSE:", np.sqrt(mse_train))
print("Test RMSE:", np.sqrt(mse_test))
```

```
Train RMSE: 190805.6573800126
Test RMSE: 187310.7175347925
```

RMSE values of test & train data are closer together

Normality Check

In [51]:
```
resid2 = model2.resid
fig = sm.graphics.qqplot(resid2, dist=stats.norm, line='45', fit=True)
```

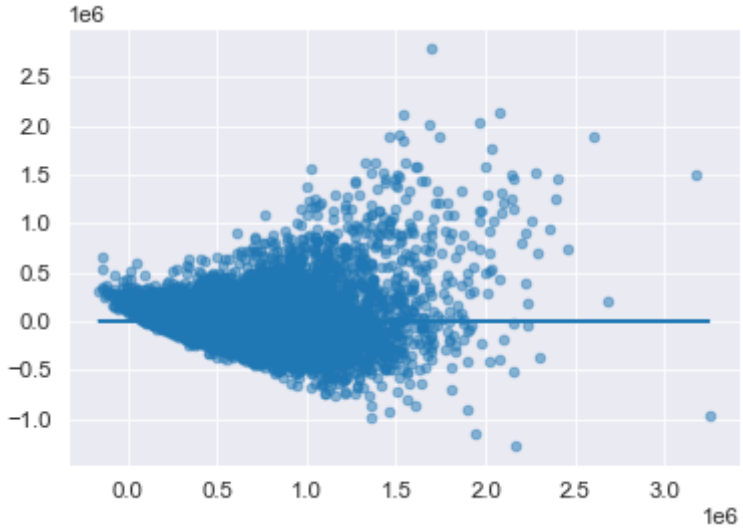


Much better than first iteration. Improved normality of residuals

Homoscedasticity Check

In [52]:
```
plt.scatter(model2.predict(predictors), model2.resid, alpha=0.5)
plt.plot(model2.predict(predictors), [0 for i in range(len(df_no_fliers))])
```

Out[52]:
```
[<matplotlib.lines.Line2D at 0x7f87028ddeb0>]
```

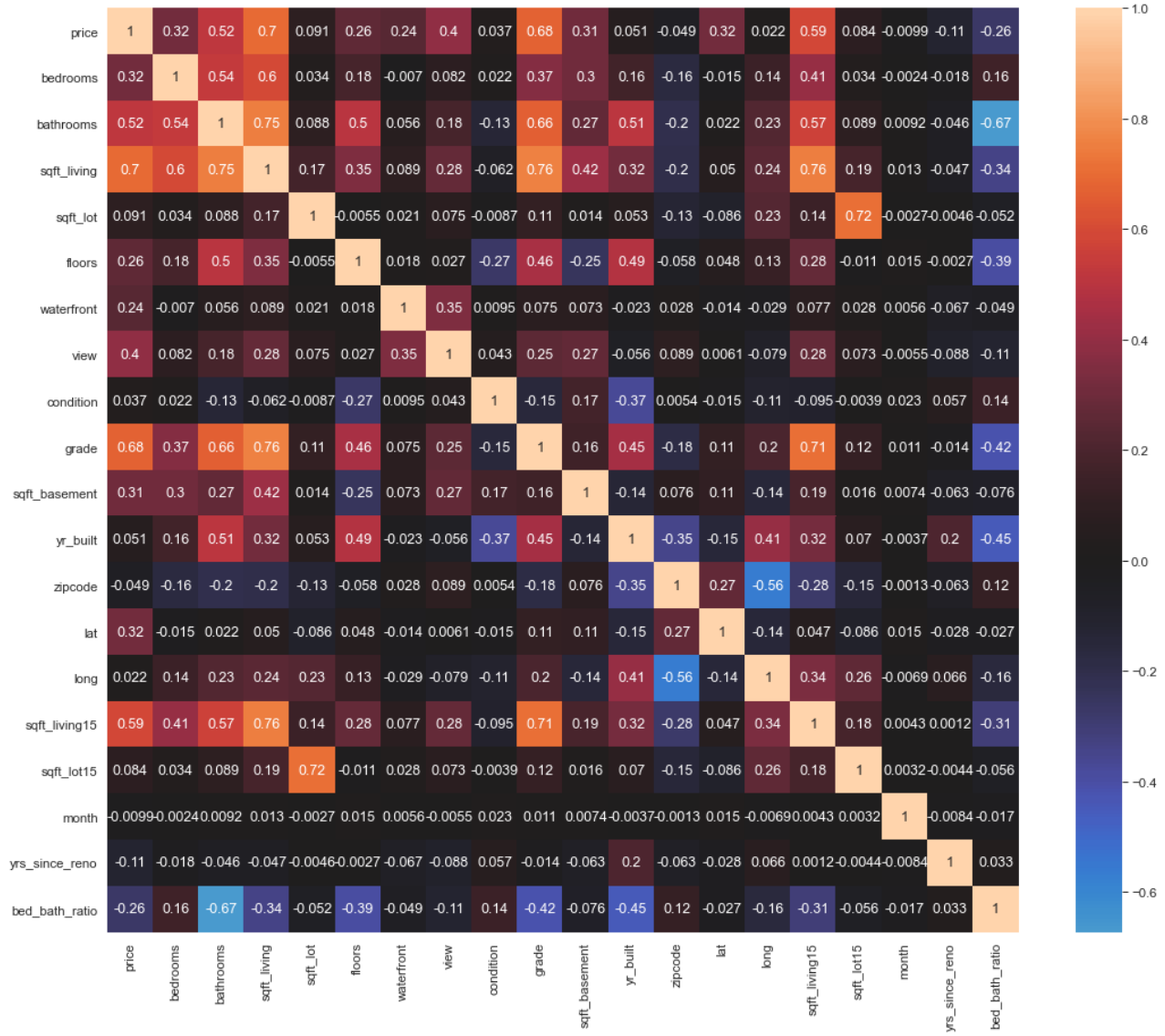


Less heteroscedastic than baseline model

Multicolinearity Check

In [53]:
```
corr = df_no_fliers.corr()

plt.figure(figsize=(18,15))
sns.heatmap(data = corr, center= 0, annot= True)
```

Out[53]:
```
<AxesSubplot:>
```



Observations

Correlation with absolute value of 0.7-0.8 is considered high.

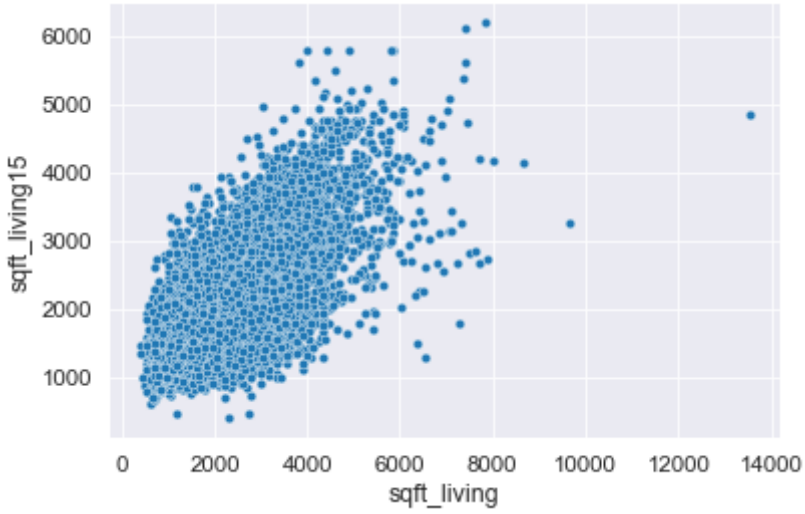
Sqft_living has the highest correlation with price (0.7), followed by grade (0.67)

Correlations among features (0.75 cutoff value):

- sqft_living and grade (0.76) --> is sqft_living factor into the grade of a home?
- sqft_living and sqft_living15 (0.76)
- sqft_living and bathrooms (0.75)

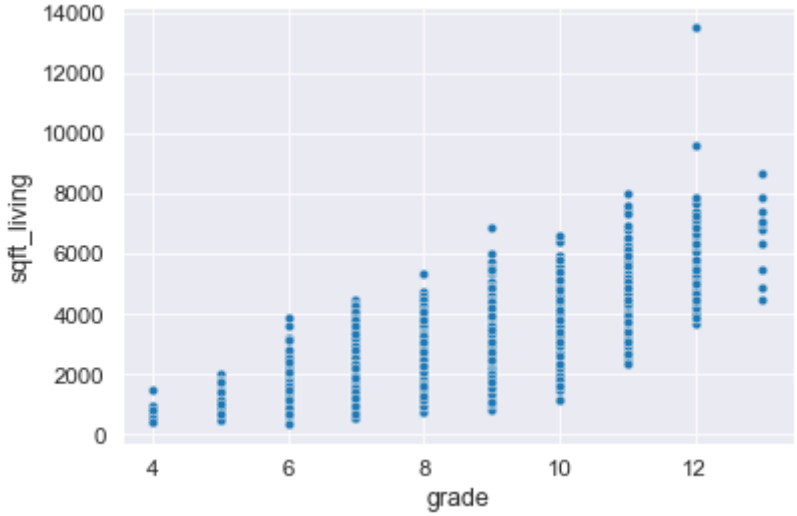
In [54]:
```
sns.scatterplot('sqft_living', 'sqft_living15', data=df_no_fliers)
```

Out[54]:
```
<AxesSubplot:xlabel='sqft_living', ylabel='sqft_living15'>
```



In [55]:
```
sns.scatterplot('grade', 'sqft_living', data=df_no_fliers)
```

Out[55]:
```
<AxesSubplot:xlabel='grade', ylabel='sqft_living'>
```



grade seems to be a function of square_ft_living. This may not be an issue when we get dummy variables for grade.

In [56]:
```
df_no_fliers.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 21286 entries, 0 to 21418
Data columns (total 20 columns):
 #   Column          Non-Null Count  Dtype  
---  ------          --------------  -----  
 0   price           21286 non-null  float64
 1   bedrooms        21286 non-null  int64  
 2   bathrooms       21286 non-null  float64
 3   sqft_living     21286 non-null  int64  
 4   sqft_lot        21286 non-null  int64  
 5   floors          21286 non-null  float64
 6   waterfront      21286 non-null  float64
 7   view            21286 non-null  float64
 8   condition       21286 non-null  int64  
 9   grade           21286 non-null  int64  
 10  sqft_basement   21286 non-null  float64
 11  yr_built        21286 non-null  int64  
 12  zipcode         21286 non-null  int64  
```

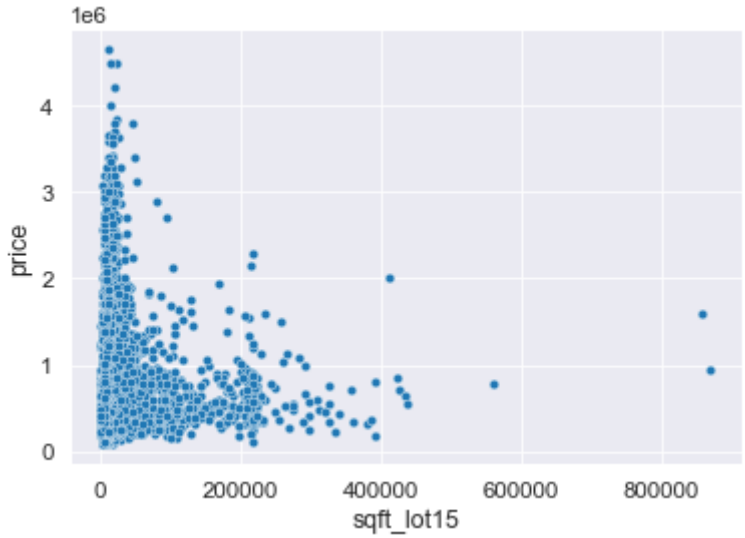
```
 13  lat              21286 non-null  float64
 14  long             21286 non-null  float64
 15  sqft_living15    21286 non-null  int64
 16  sqft_lot15       21286 non-null  int64
 17  month            21286 non-null  int64
 18  yrs_since_reno   21286 non-null  int64
 19  bed_bath_ratio   21286 non-null  float64
dtypes: float64(9), int64(11)
memory usage: 3.4 MB
```

More outliers

sqft_lot15

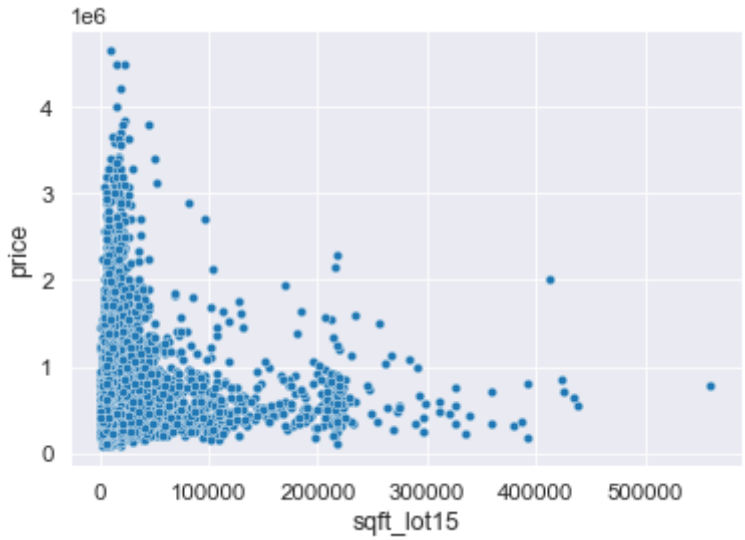
In [57]:
```
sns.scatterplot('sqft_lot15', 'price', data=df_no_fliers)
```

Out[57]:
```
<AxesSubplot:xlabel='sqft_lot15', ylabel='price'>
```



In [58]:
```
sns.scatterplot('sqft_lot15', 'price', data=df_no_fliers[df_no_fliers['sqft_lot1
```

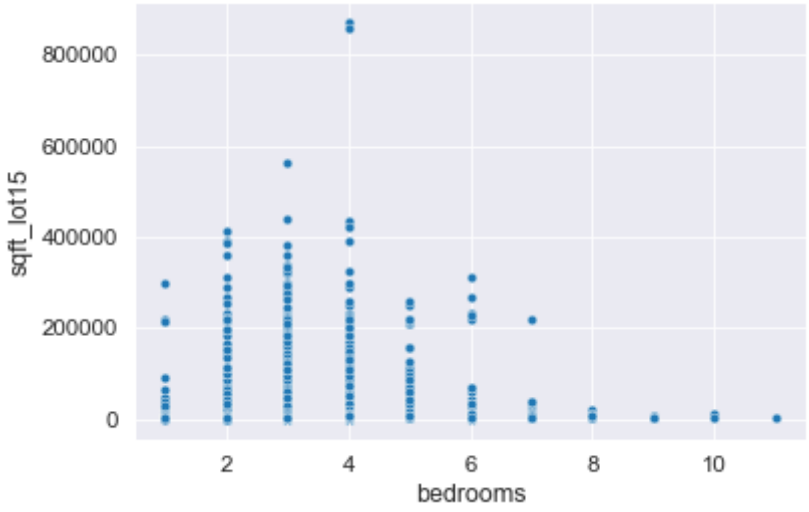
Out[58]:
```
<AxesSubplot:xlabel='sqft_lot15', ylabel='price'>
```



The influence of sqft_lot15 peaks around 10000, then there seems to be a more negative relationship. May need to address this later.

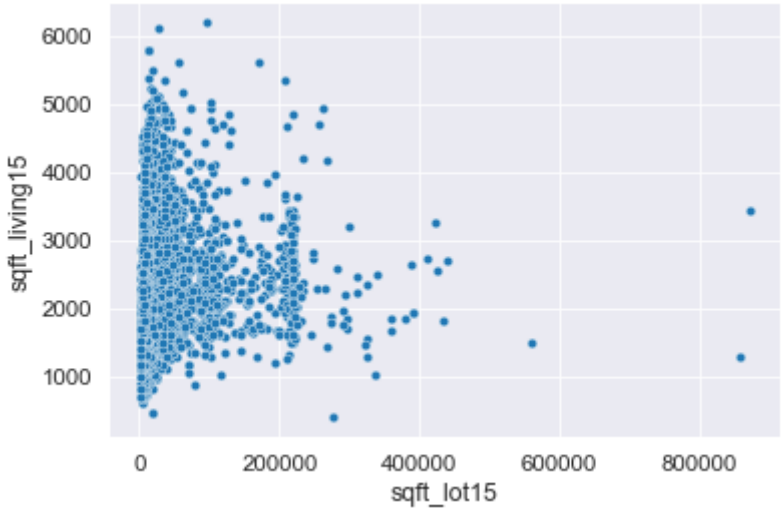
In [59]:
```
sns.scatterplot('bedrooms', 'sqft_lot15', data=df_no_fliers)
```

Out[59]:
```
<AxesSubplot:xlabel='bedrooms', ylabel='sqft_lot15'>
```



In [60]:
```
sns.scatterplot('sqft_lot15', 'sqft_living15', data=df_no_fliers)
```

Out[60]:
```
<AxesSubplot:xlabel='sqft_lot15', ylabel='sqft_living15'>
```



The variability in sqft_living15 decreases with sqft_lot15. Possibly, sqft_living15 decreases with increasing sqft_lot15. In any case, lot size does not increase with living space size for the nearest 15 neighbors. Meanwhile, sqft_living15 is positively correlated with price. sqft_lot15 increases with bedrooms up to 3 bedrooms, then decreases beyond 3 bedrooms

In [61]:
```
#Finding a cutoff point
for i in range(90, 101):
    q = i / 100
    print('{} percentile: {}'.format(q, df_no_fliers['sqft_lot15'].quantile(q=q)
```

```
0.9 percentile: 17701.0
0.91 percentile: 19858.100000000013
0.92 percentile: 22321.000000000004
0.93 percentile: 27824.14999999994
0.94 percentile: 35039.7
0.95 percentile: 37067.0
0.96 percentile: 42656.19999999997
0.97 percentile: 51422.50000000004
```

```
0.98 percentile: 80366.09999999947
0.99 percentile: 157883.0500000019
1.0 percentile: 871200.0
```

In [62]:
```
df_no_fliers[df_no_fliers['sqft_lot15'] > 500000].count()
```

Out[62]:
```
price             3
bedrooms          3
bathrooms         3
sqft_living       3
sqft_lot          3
floors            3
waterfront        3
view              3
condition         3
grade             3
sqft_basement     3
yr_built          3
zipcode           3
lat               3
long              3
sqft_living15     3
sqft_lot15        3
month             3
yrs_since_reno    3
bed_bath_ratio    3
dtype: int64
```

In [63]:
```
# drop sqft_lot15 outlier
df_no_fliers = df_no_fliers[df_no_fliers['sqft_lot15'] <= 500000]
```

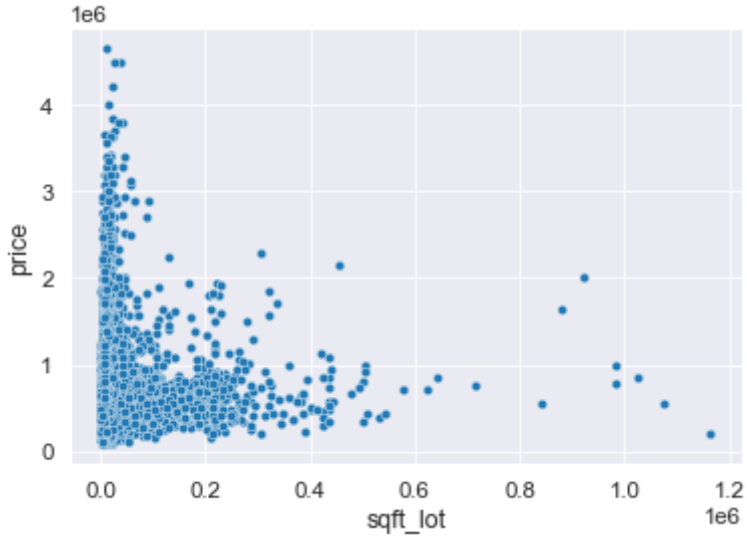
sqft_lot

In [64]:
```
#Finding a cutoff point
for i in range(90, 101):
    q = i / 100
    print('{} percentile: {}'.format(q, df_no_fliers['sqft_lot'].quantile(q=q)))
```

```
0.9 percentile: 21339.199999999997
0.91 percentile: 24063.299999999985
0.92 percentile: 28359.64000000019
0.93 percentile: 34834.68000000004
0.94 percentile: 37568.35999999992
0.95 percentile: 43176.29999999999
0.96 percentile: 50613.719999999936
0.97 percentile: 67426.24000000009
0.98 percentile: 107157.0
0.99 percentile: 212227.36000000016
1.0 percentile: 1651359.0
```

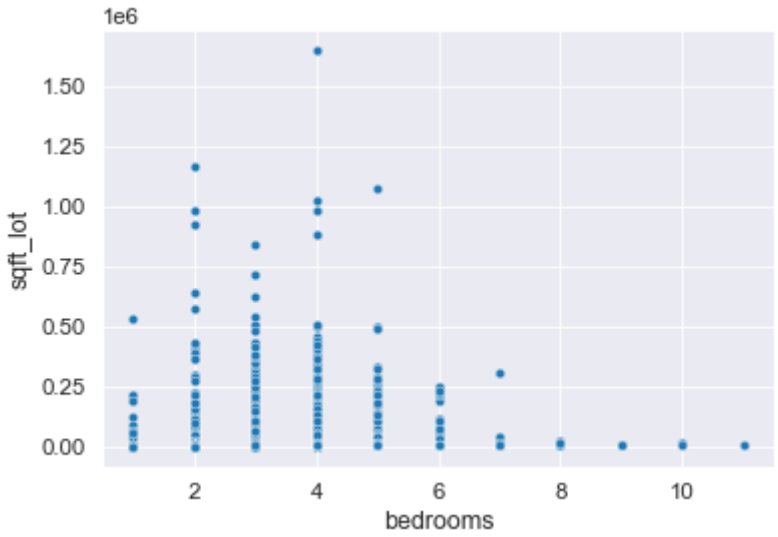
In [65]:
```
sns.scatterplot('sqft_lot', 'price', data=df_no_fliers[df_no_fliers['sqft_lot']
```

Out[65]:
```
<AxesSubplot:xlabel='sqft_lot', ylabel='price'>
```



In [66]:
```
sns.scatterplot('bedrooms', 'sqft_lot', data=df_no_fliers)
```

Out[66]:
```
<AxesSubplot:xlabel='bedrooms', ylabel='sqft_lot'>
```



Remove sqft_lot outliers

In [67]:
```
df_no_fliers = df_no_fliers[df_no_fliers['sqft_lot'] <= 800000]
```

In [68]:
```
df_no_fliers.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 21274 entries, 0 to 21418
Data columns (total 20 columns):
 #   Column          Non-Null Count  Dtype  
---  ------          --------------  -----  
 0   price           21274 non-null  float64
 1   bedrooms        21274 non-null  int64  
 2   bathrooms       21274 non-null  float64
 3   sqft_living     21274 non-null  int64  
 4   sqft_lot        21274 non-null  int64  
 5   floors          21274 non-null  float64
 6   waterfront      21274 non-null  float64
 7   view            21274 non-null  float64
 8   condition       21274 non-null  int64  
 9   grade           21274 non-null  int64  
```

```
 10  sqft_basement   21274 non-null  float64
 11  yr_built        21274 non-null  int64
 12  zipcode         21274 non-null  int64
 13  lat             21274 non-null  float64
 14  long            21274 non-null  float64
 15  sqft_living15   21274 non-null  int64
 16  sqft_lot15      21274 non-null  int64
 17  month           21274 non-null  int64
 18  yrs_since_reno  21274 non-null  int64
 19  bed_bath_ratio  21274 non-null  float64
dtypes: float64(9), int64(11)
memory usage: 3.4 MB
```

Binning and dummies

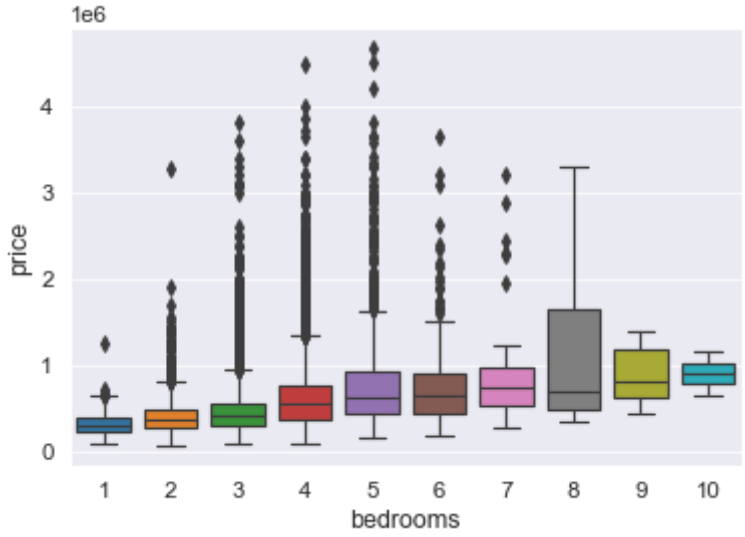
bedroom

In [69]:
```
df_no_fliers = df_no_fliers[df_no_fliers['bedrooms'] <= 10]
```

In [70]:
```
ax = sns.scatterplot('bedrooms', 'price', data=df_no_fliers, color='#18637b')
ax.set_title('Price by Number of Bedrooms')
ax.yaxis.get_major_formatter().set_scientific(False)
ax.yaxis.set_major_formatter(ticker.FuncFormatter(lambda x, pos: '{:,.1f}'.forma
plt.savefig('images/bedrooms.png')
plt.savefig('images/hr-bedrooms.png', dpi=200)
```

In [71]:
```
sns.boxplot('bedrooms', 'price', data=df_no_fliers)
```

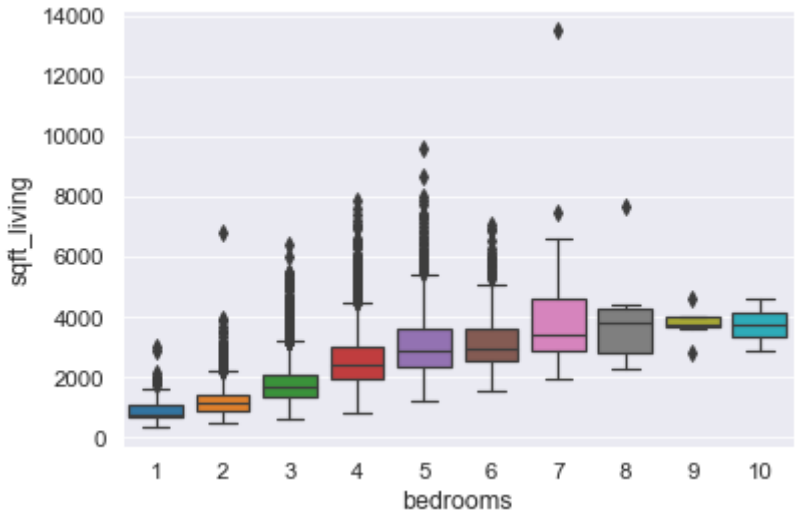
Out[71]:
```
<AxesSubplot:xlabel='bedrooms', ylabel='price'>
```



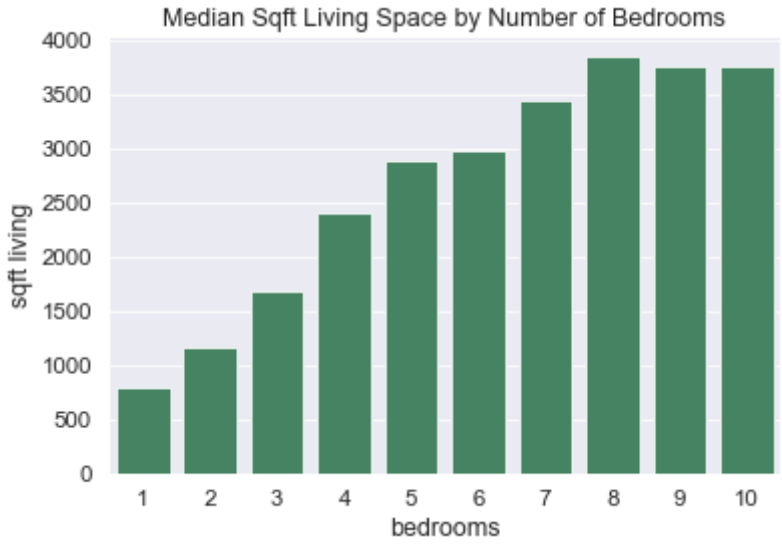
There is a positive relationship between bedrooms and price up to 5 bedrooms, then there is a slight negative relationship with price (or at the very least, the relationship changes). It's possible that beyond 6 bedrooms the houses are more cramped. I.e. smaller ratio of bedrooms per unit sqft_living

In [72]:
```
sns.boxplot('bedrooms', 'sqft_living', data=df_no_fliers)
```

Out[72]: <AxesSubplot:xlabel='bedrooms', ylabel='sqft_living'>

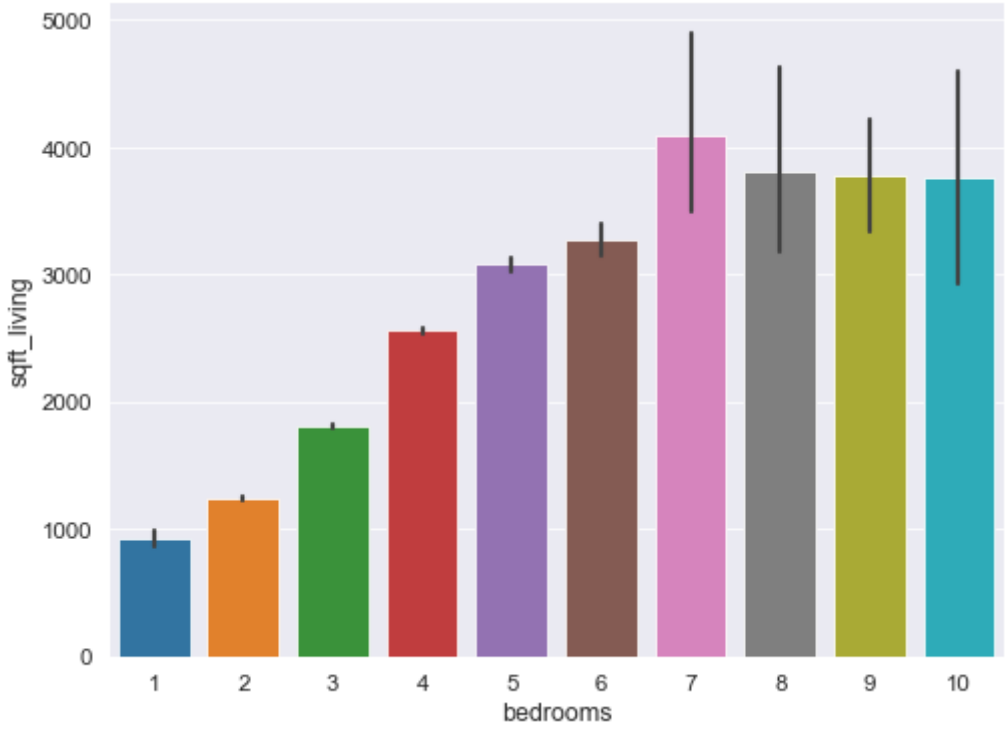


In [73]:
```
ax = sns.barplot('bedrooms', 'sqft_living', data=df_no_fliers.groupby(['bedrooms
ax.set_title('Median Sqft Living Space by Number of Bedrooms')
ax.set_ylabel('sqft living')
plt.savefig('images/sqftliving-bedrooms.png')
plt.savefig('images/hr-sqftliving-bedrooms.png', dpi=200);
```



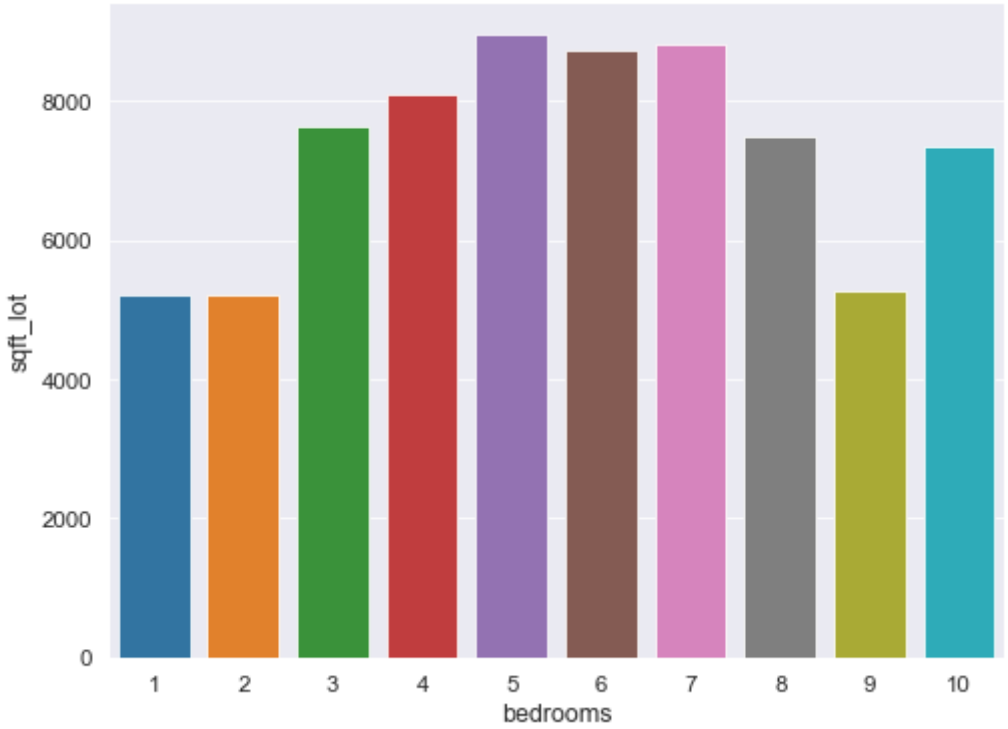
In [74]:
```
plt.figure(figsize=(8,6))
sns.barplot('bedrooms', 'sqft_living', data=df_no_fliers)
```

Out[74]:
```
<AxesSubplot:xlabel='bedrooms', ylabel='sqft_living'>
```



In [75]:
```
plt.figure(figsize=(8,6))
sns.barplot('bedrooms', 'sqft_lot', data=df_no_fliers.groupby(['bedrooms']).medi
```

Out[75]:
```
<AxesSubplot:xlabel='bedrooms', ylabel='sqft_lot'>
```



After 5 bedrooms, the living space begins tapering off (does not increase as quickly) while sqft_lot begins decreasing. Less square footage of living space per bedroom/ more cramped housing or decreasing lot size can have something to do with the decreasing price beyond 5 bedrooms

In [76]:
```
df_no_fliers['bedrooms'].value_counts(normalize=True)
```

Out[76]:
```
3     0.456588
4     0.321534
2     0.127156
5     0.072298
6     0.012081
1     0.007709
7     0.001645
8     0.000611
9     0.000282
10    0.000094
Name: bedrooms, dtype: float64
```

In [77]:
```
df_no_fliers.to_csv('data/data_no_fliers')
```

In [78]:
```
bins = [0, 4, 10]
labels = ['under5', '5plus']
df_no_fliers['binned_bedrooms'] = pd.cut(df_no_fliers['bedrooms'], bins, labels=
```

In [79]:
```
cat = ['binned_bedrooms']
bedroom_dummies = pd.get_dummies(df_no_fliers[cat], prefix='bedrooms', drop_firs
```

view dummies

In [80]:
```
ax = sns.barplot('view', 'price', data=df_no_fliers.groupby('view').median().res
ax.set_title('Median Price by View Quality')
ax.yaxis.get_major_formatter().set_scientific(False)
ax.yaxis.set_major_formatter(ticker.FuncFormatter(lambda x, pos: '{:,.1f}'.forma
```

```
plt.savefig('images/pirce-view.png')
plt.savefig('images/hr-price-view.png', dpi=200)
```

In [81]:
```
bins = [-1, 0, 2, 3, 4]
labels = ['0', '1_2', '3', '4']
df_no_fliers['binned_view'] = pd.cut(df_no_fliers['view'], bins, labels=labels)
view_dummies = pd.get_dummies(df_no_fliers['binned_view'], prefix='view', drop_f
```

In [82]:
```
df_no_fliers[['view', 'binned_view']][df_no_fliers['view']==2]
```

Out[82]:

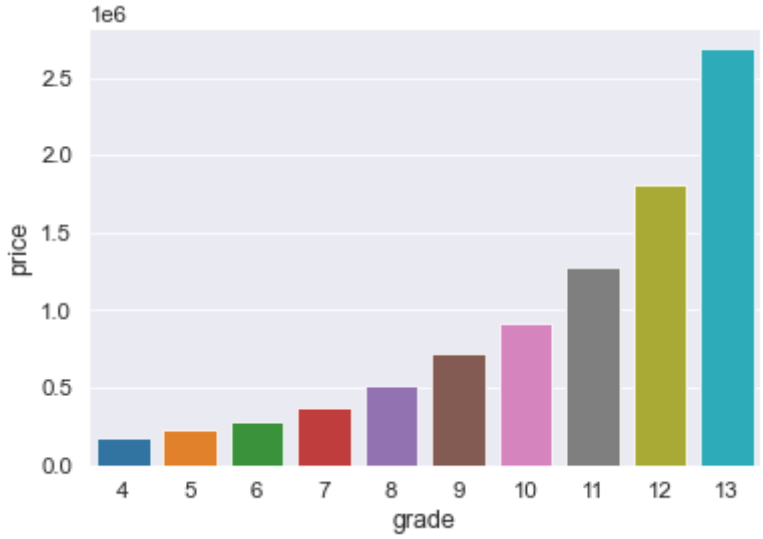
	view	binned_view
49	2.0	1_2
98	2.0	1_2
112	2.0	1_2
119	2.0	1_2
125	2.0	1_2
...	...	...
21337	2.0	1_2
21362	2.0	1_2
21387	2.0	1_2
21400	2.0	1_2
21405	2.0	1_2

947 rows × 2 columns

grade dummies

In [83]:
```
sns.barplot('grade', 'price', data=df_no_fliers.groupby('grade').median().reset_
```

Out[83]:
```
<AxesSubplot:xlabel='grade', ylabel='price'>
```



In [84]:
```
df_no_fliers.grade.value_counts()
```

Out[84]:
```
7     8836
8     6031
9     2603
6     1959
10    1127
11     392
5      217
12      84
4       14
13      10
Name: grade, dtype: int64
```

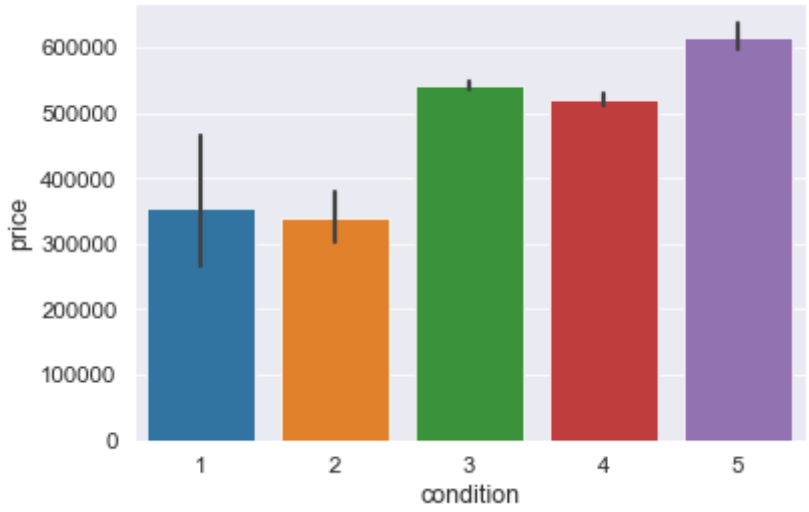
In [85]:
```
grade_dummies = pd.get_dummies(df_no_fliers['grade'], prefix='grade', drop_first
```

condition dummies

In [86]:
```
ax = sns.barplot('condition', 'price', data=df_no_fliers.groupby('condition').me
ax.set_title('Median Price by Condition')
ax.yaxis.get_major_formatter().set_scientific(False)
ax.yaxis.set_major_formatter(ticker.FuncFormatter(lambda x, pos: '{:,.1f}'.forma
plt.savefig('images/price-condition.png')
plt.savefig('images/hr-price-condition.png', dpi=200)
```

In [87]:
```
sns.barplot('condition', 'price', data=df_no_fliers)
```

Out[87]:
```
<AxesSubplot:xlabel='condition', ylabel='price'>
```



Will bin condition by values with similar mean and median prices

In [88]:
```
bins = [0, 2, 4, 6]
labels = ['1_2', '3_4', '5']
df_no_fliers['binned_condition'] = pd.cut(df_no_fliers['condition'], bins, label
condition_dummies = pd.get_dummies(df_no_fliers['binned_condition'], prefix='con
```

In [89]:
```
df_no_fliers[df_no_fliers['condition'] == 2.0].head()
```

Out[89]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition	g
38	240000.0	4	1.0	1220	8075	1.0	0.0	0.0	2	
241	455000.0	2	1.0	1430	5000	1.5	0.0	0.0	2	
325	186375.0	3	1.0	1000	7636	1.0	0.0	0.0	2	
697	480000.0	4	2.0	2180	10575	1.0	0.0	0.0	2	
872	200000.0	4	2.0	1920	4822	1.0	0.0	0.0	2	

5 rows × 23 columns

In [90]:
```
df_binned_dummies = pd.concat([df_no_fliers, bedroom_dummies, grade_dummies, vie
```

In [91]:
```
df_binned_dummies.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 21273 entries, 0 to 21418
Data columns (total 38 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   price             21273 non-null  float64
 1   bedrooms          21273 non-null  int64
 2   bathrooms         21273 non-null  float64
 3   sqft_living       21273 non-null  int64
 4   sqft_lot          21273 non-null  int64
 5   floors            21273 non-null  float64
 6   waterfront        21273 non-null  float64
```

```
 7   view              21273 non-null  float64
 8   condition         21273 non-null  int64
 9   grade             21273 non-null  int64
 10  sqft_basement     21273 non-null  float64
 11  yr_built          21273 non-null  int64
 12  zipcode           21273 non-null  int64
 13  lat               21273 non-null  float64
 14  long              21273 non-null  float64
 15  sqft_living15     21273 non-null  int64
 16  sqft_lot15        21273 non-null  int64
 17  month             21273 non-null  int64
 18  yrs_since_reno    21273 non-null  int64
 19  bed_bath_ratio    21273 non-null  float64
 20  binned_bedrooms   21273 non-null  category
 21  binned_view       21273 non-null  category
 22  binned_condition  21273 non-null  category
 23  bedrooms_5plus    21273 non-null  uint8
 24  grade_5           21273 non-null  uint8
 25  grade_6           21273 non-null  uint8
 26  grade_7           21273 non-null  uint8
 27  grade_8           21273 non-null  uint8
 28  grade_9           21273 non-null  uint8
 29  grade_10          21273 non-null  uint8
 30  grade_11          21273 non-null  uint8
 31  grade_12          21273 non-null  uint8
 32  grade_13          21273 non-null  uint8
 33  view_1_2          21273 non-null  uint8
 34  view_3            21273 non-null  uint8
 35  view_4            21273 non-null  uint8
 36  condition_3_4     21273 non-null  uint8
 37  condition_5       21273 non-null  uint8
dtypes: category(3), float64(9), int64(11), uint8(15)
memory usage: 4.4 MB
```

In [92]:
```
df_dummies = df_binned_dummies.drop(['bedrooms', 'binned_bedrooms', 'condition',
                                     'view', 'binned_view'], axis=1)
```

In [93]:
```
df_dummies.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 21273 entries, 0 to 21418
Data columns (total 31 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   price            21273 non-null  float64
 1   bathrooms        21273 non-null  float64
 2   sqft_living      21273 non-null  int64
 3   sqft_lot         21273 non-null  int64
 4   floors           21273 non-null  float64
 5   waterfront       21273 non-null  float64
 6   sqft_basement    21273 non-null  float64
 7   yr_built         21273 non-null  int64
 8   zipcode          21273 non-null  int64
 9   lat              21273 non-null  float64
 10  long             21273 non-null  float64
 11  sqft_living15    21273 non-null  int64
 12  sqft_lot15       21273 non-null  int64
 13  month            21273 non-null  int64
 14  yrs_since_reno   21273 non-null  int64
 15  bed_bath_ratio   21273 non-null  float64
 16  bedrooms_5plus   21273 non-null  uint8
 17  grade_5          21273 non-null  uint8
 18  grade_6          21273 non-null  uint8
 19  grade_7          21273 non-null  uint8
```

```
 20  grade_8          21273 non-null  uint8
 21  grade_9          21273 non-null  uint8
 22  grade_10         21273 non-null  uint8
 23  grade_11         21273 non-null  uint8
 24  grade_12         21273 non-null  uint8
 25  grade_13         21273 non-null  uint8
 26  view_1_2         21273 non-null  uint8
 27  view_3           21273 non-null  uint8
 28  view_4           21273 non-null  uint8
 29  condition_3_4    21273 non-null  uint8
 30  condition_5      21273 non-null  uint8
dtypes: float64(8), int64(8), uint8(15)
memory usage: 3.7 MB
```

Decisions

Outlier removal:

- drop sqft_lot over 800000
- drop sqft_lot15 over 500000
- drop bedrooms over 10

Dummies:

- bedrooms (under5, 5plus)
- view (0, 1_2, 3, 4)
- grade (all)
- condition (1_2, 3_4, 5)

Model 3

In [94]:
```
df_dummies.columns
```

Out[94]:
```
Index(['price', 'bathrooms', 'sqft_living', 'sqft_lot', 'floors', 'waterfront',
       'sqft_basement', 'yr_built', 'zipcode', 'lat', 'long', 'sqft_living15',
       'sqft_lot15', 'month', 'yrs_since_reno', 'bed_bath_ratio',
       'bedrooms_5plus', 'grade_5', 'grade_6', 'grade_7', 'grade_8', 'grade_9',
       'grade_10', 'grade_11', 'grade_12', 'grade_13', 'view_1_2', 'view_3',
       'view_4', 'condition_3_4', 'condition_5'],
      dtype='object')
```

In [95]:
```
outcome = 'price'
predictors = df_dummies.drop('price', axis = 1)
pred_sum = "+".join(predictors.columns)
formula = outcome + '~' + pred_sum
```

In [96]:
```
model3 = ols(formula=formula, data=df_dummies).fit()
```

In [97]:
```
model3.summary()
```

Out[97]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.727
Model:	OLS	**Adj. R-squared:**	0.727
Method:	Least Squares	**F-statistic:**	1889.

Date:	Thu, 10 Jun 2021	**Prob (F-statistic):**	0.00
Time:	12:13:32	**Log-Likelihood:**	-2.8812e+05
No. Observations:	21273	**AIC:**	5.763e+05
Df Residuals:	21242	**BIC:**	5.765e+05
Df Model:	30		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	1.043e+07	2.69e+06	3.880	0.000	5.16e+06	1.57e+07
bathrooms	3.402e+04	3938.235	8.638	0.000	2.63e+04	4.17e+04
sqft_living	110.4890	3.534	31.267	0.000	103.563	117.415
sqft_lot	0.1540	0.059	2.629	0.009	0.039	0.269
floors	2.544e+04	3344.892	7.606	0.000	1.89e+04	3.2e+04
waterfront	4.266e+05	1.74e+04	24.583	0.000	3.93e+05	4.61e+05
sqft_basement	3.7376	4.064	0.920	0.358	-4.228	11.703
yr_built	-2287.6871	65.914	-34.707	0.000	-2416.884	-2158.490
zipcode	-615.2930	30.396	-20.243	0.000	-674.872	-555.715
lat	6.126e+05	9925.606	61.719	0.000	5.93e+05	6.32e+05
long	-2.072e+05	1.22e+04	-16.919	0.000	-2.31e+05	-1.83e+05
sqft_living15	31.7703	3.235	9.822	0.000	25.430	38.111
sqft_lot15	-0.3257	0.079	-4.135	0.000	-0.480	-0.171
month	-2754.3303	406.426	-6.777	0.000	-3550.957	-1957.704
yrs_since_reno	-29.4888	3.655	-8.068	0.000	-36.653	-22.324
bed_bath_ratio	-6613.3520	3277.909	-2.018	0.044	-1.3e+04	-188.402
bedrooms_5plus	-6336.4110	5382.325	-1.177	0.239	-1.69e+04	4213.354
grade_5	8010.9930	5.09e+04	0.157	0.875	-9.18e+04	1.08e+05
grade_6	3.277e+04	4.96e+04	0.660	0.509	-6.45e+04	1.3e+05
grade_7	7.315e+04	4.96e+04	1.476	0.140	-2.4e+04	1.7e+05
grade_8	1.386e+05	4.97e+04	2.791	0.005	4.13e+04	2.36e+05
grade_9	2.657e+05	4.99e+04	5.320	0.000	1.68e+05	3.64e+05
grade_10	4.391e+05	5.03e+04	8.727	0.000	3.4e+05	5.38e+05
grade_11	6.92e+05	5.12e+04	13.509	0.000	5.92e+05	7.92e+05
grade_12	1.099e+06	5.47e+04	20.076	0.000	9.91e+05	1.21e+06
grade_13	1.643e+06	7.78e+04	21.105	0.000	1.49e+06	1.8e+06
view_1_2	8.779e+04	5587.584	15.712	0.000	7.68e+04	9.87e+04
view_3	1.46e+05	8721.514	16.743	0.000	1.29e+05	1.63e+05
view_4	3.108e+05	1.29e+04	24.106	0.000	2.85e+05	3.36e+05

condition_3_4	2.974e+04	1.39e+04	2.146	0.032	2570.763	5.69e+04
condition_5	9.068e+04	1.45e+04	6.248	0.000	6.22e+04	1.19e+05

Omnibus:	11156.152	**Durbin-Watson:**	1.984
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	225917.525
Skew:	2.073	**Prob(JB):**	0.00
Kurtosis:	18.417	**Cond. No.**	2.13e+08

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 2.13e+08. This might indicate that there are strong multicollinearity or other numerical problems.

Observations

- JB came down a bit more
- high p-values: sqft_basement, bedrooms_5plus, grade_5, grade_6, grade_7
- high p-value predictors also have confidence intervals that cross zero

In [98]:
```
X = df_dummies.drop("price", axis = 1)
Y = df_dummies['price']
```

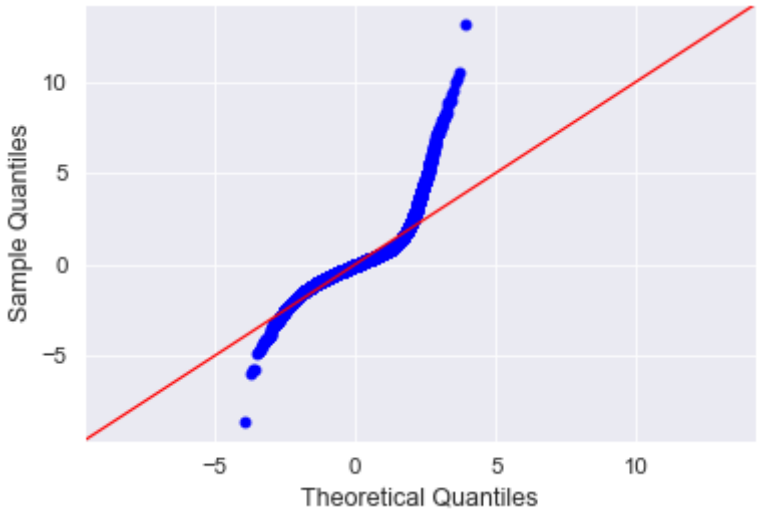
In [99]:
```
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size = 0.25, rand
linreg3 = LinearRegression()
linreg3.fit(X_train, Y_train)
Y_pred = linreg3.predict(X_test)
```

In [100…
```
mse_train = mean_squared_error(Y_train, linreg3.predict(X_train))
mse_test = mean_squared_error(Y_test, Y_pred)

print("Train RMSE:", np.sqrt(mse_train))
print("Test RMSE:", np.sqrt(mse_test))
```

```
Train RMSE: 182629.68619495793
Test RMSE: 190847.14810530355
```

Normality check

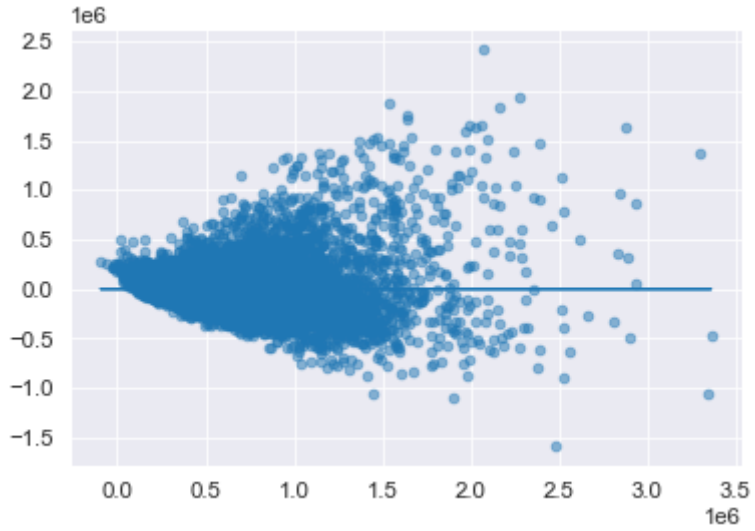
In [101…
```
resid3 = model3.resid
fig = sm.graphics.qqplot(resid3, dist=stats.norm, line='45', fit=True)
```



Homoscedasticity check

In [102…
```
plt.scatter(model3.predict(predictors), model3.resid, alpha=0.5)
plt.plot(model3.predict(predictors), [0 for i in range(len(df_dummies))])
```

Out[102…
```
[<matplotlib.lines.Line2D at 0x7f870365b550>]
```



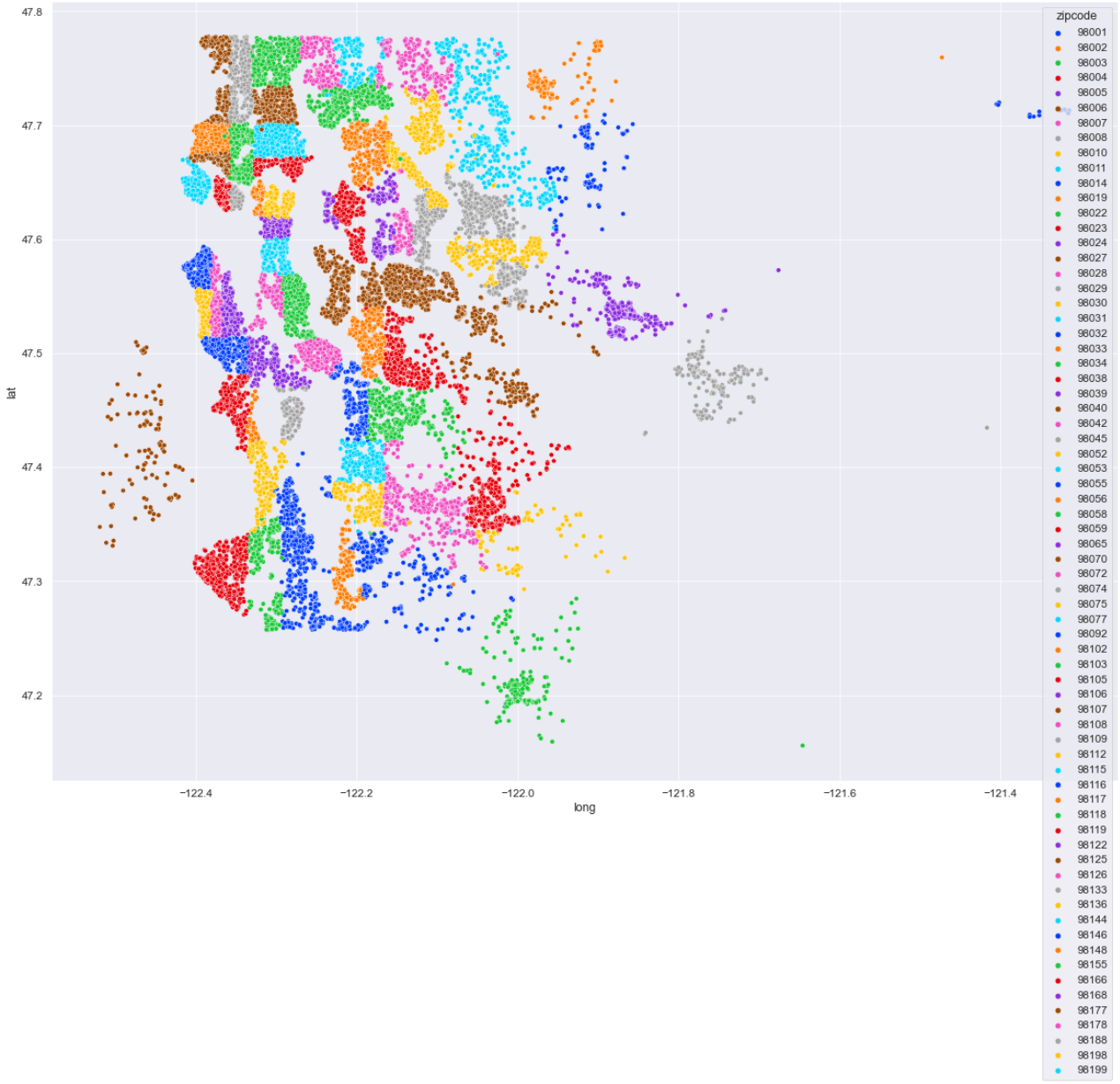
Drop sqft_basement

In [103…
```
df4 = df_dummies.drop(['sqft_basement'], axis=1)
```

Location data

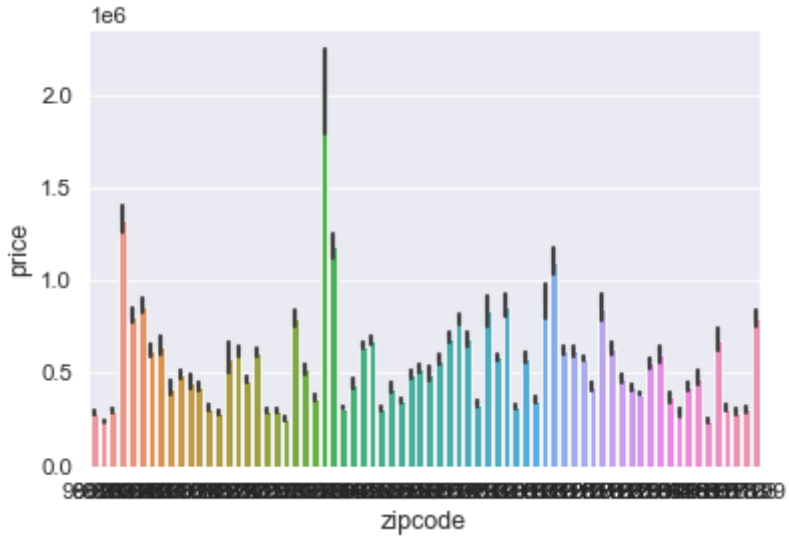
In [104…
```
plt.figure(figsize=(20, 15))
sns.scatterplot(x = "long", y = "lat", hue = "zipcode",  data = df4, palette='br
```

Out[104…
```
<AxesSubplot:xlabel='long', ylabel='lat'>
```



In [105…
```
sns.barplot('zipcode', 'price', data=df4)
```

Out[105… <AxesSubplot:xlabel='zipcode', ylabel='price'>



using zipcode results in a lot of categories, and will translate to many dummies/new columns. Let's try to find some other means to group locations.

In [106…
```
location_df = pd.read_csv('data/All_Zipcodes_and_PO_Box_as_Centroids_for_King_Co
location_df.head(20)
```

Out[106…

	X	Y	OBJECTID	ZIP	ZIPCODE	COUNTY	ZIP_TYPE	PREFERRED_CITY
0	-122.584242	47.855762	1	98364	98364	35.0	PO Box	PORT GAMBLE
1	-122.202454	47.620601	2	98009	98009	33.0	PO Box	BELLEVUE
2	-122.186795	47.611861	3	98015	98015	33.0	PO Box	BELLEVUE
3	-121.972726	47.419935	4	98025	98025	33.0	PO Box	HOBART
4	-122.234416	47.380592	5	98035	98035	33.0	PO Box	KENT
5	-122.199724	47.761150	6	98041	98041	33.0	PO Box	BOTHELL
6	-121.935435	47.525299	7	98050	98050	33.0	PO Box	PRESTON
7	-122.361610	47.466937	8	98062	98062	33.0	PO Box	SEAHURST
8	-122.314202	47.307128	9	98063	98063	33.0	PO Box	FEDERAL WAY
9	-122.199165	47.387373	10	98064	98064	33.0	PO Box	KENT
10	-122.230054	47.310482	11	98071	98071	33.0	PO Box	AUBURN
11	-122.194421	47.678519	12	98083	98083	33.0	PO Box	KIRKLAND
12	-122.357513	47.300153	13	98093	98093	33.0	PO Box	FEDERAL WAY
13	-122.328387	47.581518	14	98124	98124	33.0	PO Box	SEATTLE
14	-122.254990	47.456756	15	98138	98138	33.0	PO Box	SEATTLE
15	-122.312845	47.659517	16	98145	98145	33.0	PO Box	SEATTLE
16	-122.346375	47.733683	17	98160	98160	33.0	PO Box	SEATTLE
17	-122.338619	47.611384	18	98181	98181	33.0	Unique	SEATTLE
18	-122.333625	47.606268	19	98185	98185	33.0	Unique	SEATTLE
19	-122.334454	47.613208	20	98191	98191	33.0	Unique	SEATTLE

In [107…
```
location_df = location_df.drop(['X', 'Y', 'OBJECTID', 'ZIP', 'ZIP_TYPE', 'FEATUR
```

In [108…
```
location_df.head()
```

Out[108…

	ZIPCODE	COUNTY	PREFERRED_CITY
0	98364	35.0	PORT GAMBLE
1	98009	33.0	BELLEVUE
2	98015	33.0	BELLEVUE
3	98025	33.0	HOBART
4	98035	33.0	KENT

In [109…
```
df4.columns
```

Out[109…
```
Index(['price', 'bathrooms', 'sqft_living', 'sqft_lot', 'floors', 'waterfront',
       'yr_built', 'zipcode', 'lat', 'long', 'sqft_living15', 'sqft_lot15',
       'month', 'yrs_since_reno', 'bed_bath_ratio', 'bedrooms_5plus',
       'grade_5', 'grade_6', 'grade_7', 'grade_8', 'grade_9', 'grade_10',
       'grade_11', 'grade_12', 'grade_13', 'view_1_2', 'view_3', 'view_4',
       'condition_3_4', 'condition_5'],
      dtype='object')
```

In [110…
```
location_df = location_df.rename(columns={'ZIPCODE': 'zipcode', 'COUNTY': 'count
location_df.columns
```

Out[110…
```
Index(['zipcode', 'county', 'city'], dtype='object')
```

In [111…
```
location_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 261 entries, 0 to 260
Data columns (total 3 columns):
 #   Column   Non-Null Count  Dtype  
---  ------   --------------  -----  
 0   zipcode  261 non-null    int64  
 1   county   260 non-null    float64
 2   city     261 non-null    object 
dtypes: float64(1), int64(1), object(1)
memory usage: 6.2+ KB
```

In [112…
```
location = location_df.drop(['county'], axis=1)
```

In [113…
```
location.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 261 entries, 0 to 260
Data columns (total 2 columns):
 #   Column   Non-Null Count  Dtype 
---  ------   --------------  ----- 
 0   zipcode  261 non-null    int64 
 1   city     261 non-null    object
dtypes: int64(1), object(1)
memory usage: 4.2+ KB
```

In [114…
```
df4.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 21273 entries, 0 to 21418
Data columns (total 30 columns):
 #   Column          Non-Null Count  Dtype  
---  ------          --------------  -----  
 0   price           21273 non-null  float64
 1   bathrooms       21273 non-null  float64
 2   sqft_living     21273 non-null  int64  
 3   sqft_lot        21273 non-null  int64  
 4   floors          21273 non-null  float64
 5   waterfront      21273 non-null  float64
 6   yr_built        21273 non-null  int64  
 7   zipcode         21273 non-null  int64  
 8   lat             21273 non-null  float64
 9   long            21273 non-null  float64
 10  sqft_living15   21273 non-null  int64  
 11  sqft_lot15      21273 non-null  int64  
 12  month           21273 non-null  int64  
 13  yrs_since_reno  21273 non-null  int64  
 14  bed_bath_ratio  21273 non-null  float64
 15  bedrooms_5plus  21273 non-null  uint8  
```

```
 16  grade_5          21273 non-null  uint8
 17  grade_6          21273 non-null  uint8
 18  grade_7          21273 non-null  uint8
 19  grade_8          21273 non-null  uint8
 20  grade_9          21273 non-null  uint8
 21  grade_10         21273 non-null  uint8
 22  grade_11         21273 non-null  uint8
 23  grade_12         21273 non-null  uint8
 24  grade_13         21273 non-null  uint8
 25  view_1_2         21273 non-null  uint8
 26  view_3           21273 non-null  uint8
 27  view_4           21273 non-null  uint8
 28  condition_3_4    21273 non-null  uint8
 29  condition_5      21273 non-null  uint8
dtypes: float64(7), int64(8), uint8(15)
memory usage: 3.5 MB
```

In [115…
```
location[location.duplicated(subset='zipcode', keep=False)]
```

Out[115…

	zipcode	city
21	98447	TACOMA
72	98022	ENUMCLAW
73	98022	ENUMCLAW
93	98047	PACIFIC
94	98047	PACIFIC
106	98072	WOODINVILLE
107	98072	WOODINVILLE
110	98077	WOODINVILLE
111	98077	WOODINVILLE
113	98092	AUBURN
114	98092	AUBURN
199	98354	MILTON
200	98354	MILTON
233	98422	TACOMA
234	98422	TACOMA
244	98447	TACOMA

In [116…
```
location = location.drop_duplicates(subset='zipcode', keep='first')
```

In [117…
```
location.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 253 entries, 0 to 260
Data columns (total 2 columns):
 #   Column   Non-Null Count  Dtype
---  ------   --------------  -----
 0   zipcode  253 non-null    int64
 1   city     253 non-null    object
dtypes: int64(1), object(1)
memory usage: 5.9+ KB
```

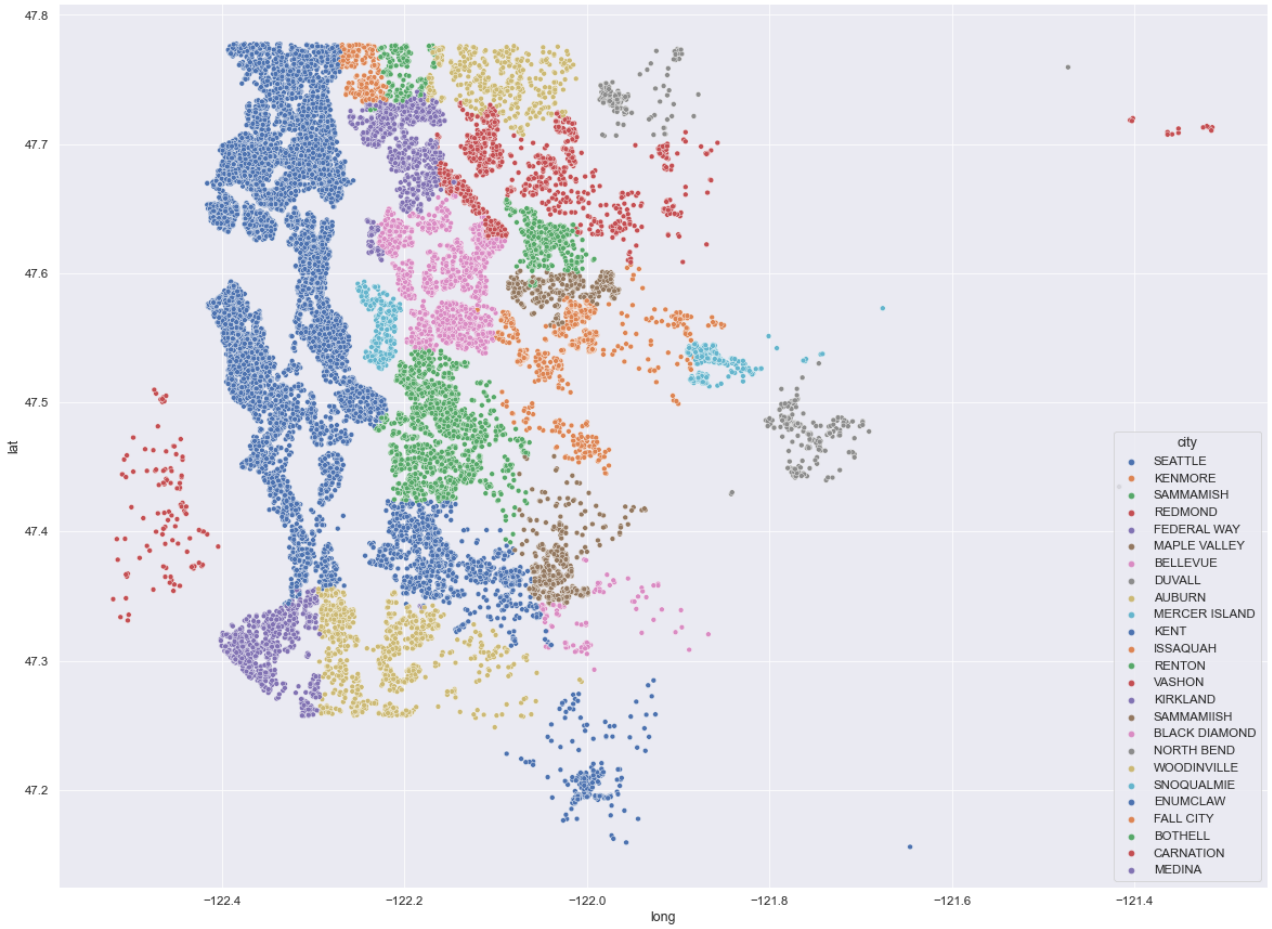
In [118…
```
df5 = pd.merge(df4, location, how='left', on='zipcode')
```

In [119…
```
df5.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 21273 entries, 0 to 21272
Data columns (total 31 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   price            21273 non-null  float64
 1   bathrooms        21273 non-null  float64
 2   sqft_living      21273 non-null  int64  
 3   sqft_lot         21273 non-null  int64  
 4   floors           21273 non-null  float64
 5   waterfront       21273 non-null  float64
 6   yr_built         21273 non-null  int64  
 7   zipcode          21273 non-null  int64  
 8   lat              21273 non-null  float64
 9   long             21273 non-null  float64
 10  sqft_living15    21273 non-null  int64  
 11  sqft_lot15       21273 non-null  int64  
 12  month            21273 non-null  int64  
 13  yrs_since_reno   21273 non-null  int64  
 14  bed_bath_ratio   21273 non-null  float64
 15  bedrooms_5plus   21273 non-null  uint8  
 16  grade_5          21273 non-null  uint8  
 17  grade_6          21273 non-null  uint8  
 18  grade_7          21273 non-null  uint8  
 19  grade_8          21273 non-null  uint8  
 20  grade_9          21273 non-null  uint8  
 21  grade_10         21273 non-null  uint8  
 22  grade_11         21273 non-null  uint8  
 23  grade_12         21273 non-null  uint8  
 24  grade_13         21273 non-null  uint8  
 25  view_1_2         21273 non-null  uint8  
 26  view_3           21273 non-null  uint8  
 27  view_4           21273 non-null  uint8  
 28  condition_3_4    21273 non-null  uint8  
 29  condition_5      21273 non-null  uint8  
 30  city             21273 non-null  object 
dtypes: float64(7), int64(8), object(1), uint8(15)
memory usage: 3.1+ MB
```

In [120…
```
plt.figure(figsize=(20, 15))
sns.scatterplot(x = "long", y = "lat", hue = "city",  data = df5, palette='deep'
```

Out[120…
```
<AxesSubplot:xlabel='long', ylabel='lat'>
```



In [121…
```
df5['city'].value_counts(normalize=True)
```

Out[121…
```
SEATTLE          0.413811
RENTON           0.073943
BELLEVUE         0.065341
KENT             0.055892
REDMOND          0.045645
KIRKLAND         0.045551
AUBURN           0.042401
FEDERAL WAY      0.036055
ISSAQUAH         0.034316
MAPLE VALLEY     0.027547
WOODINVILLE      0.021953
SAMMAMISH        0.020401
SAMMAMIISH       0.016829
SNOQUALMIE       0.014149
KENMORE          0.013209
MERCER ISLAND    0.013209
ENUMCLAW         0.010765
NORTH BEND       0.010154
BOTHELL          0.009073
DUVALL           0.008837
CARNATION        0.005359
VASHON           0.005124
BLACK DIAMOND    0.004607
FALL CITY        0.003620
MEDINA           0.002209
Name: city, dtype: float64
```

In [122…
```
import folium
```

In [123…
```
df5.lat.min()
```

Out[123…
```
47.1559
```

In [124…
```
df5.lat.mean()
```

Out[124…
```
47.56023275043482
```

In [125…
```
df5.long.mean()
```

Out[125…
```
-122.21371085413433
```

In [126…
```
kc_coordinates = (47.55, -122.21)
```

In [127…
```
kc_map = folium.Map(location=kc_coordinates)
kc_map
```

Out[127… Make this Notebook Trusted to load map: File -> Trust Notebook

from folium.plugins import HeatMap HeatMap(data=data).add_to(kc_map) display(kc_map)

In [128…
```
df5['city'] = df5['city'].str.title()
```

In [129…
```
df5['city'].value_counts()
```

Out[129…
```
Seattle          8803
Renton           1573
Bellevue         1390
Kent             1189
Redmond           971
Kirkland          969
Auburn            902
Federal Way       767
Issaquah          730
Maple Valley      586
Woodinville       467
Sammamish         434
```

```
Sammamiish         358
Snoqualmie         301
Kenmore            281
Mercer Island      281
Enumclaw           229
North Bend         216
Bothell            193
Duvall             188
Carnation          114
Vashon             109
Black Diamond       98
Fall City           77
Medina              47
Name: city, dtype: int64
```

In [130…
```
df5 = df5.replace(['Sammamiish'],'Sammamish')
```

In [131…
```
df5['city'].value_counts()
```

Out[131…
```
Seattle           8803
Renton            1573
Bellevue          1390
Kent              1189
Redmond            971
Kirkland           969
Auburn             902
Sammamish          792
Federal Way        767
Issaquah           730
Maple Valley       586
Woodinville        467
Snoqualmie         301
Mercer Island      281
Kenmore            281
Enumclaw           229
North Bend         216
Bothell            193
Duvall             188
Carnation          114
Vashon             109
Black Diamond       98
Fall City           77
Medina              47
Name: city, dtype: int64
```

In [132…
```
city_dummies = pd.get_dummies(df5['city'], prefix='city', drop_first=True)
df6 = pd.concat([df5, city_dummies], axis=1)
df6.columns
```

Out[132…
```
Index(['price', 'bathrooms', 'sqft_living', 'sqft_lot', 'floors', 'waterfront',
       'yr_built', 'zipcode', 'lat', 'long', 'sqft_living15', 'sqft_lot15',
       'month', 'yrs_since_reno', 'bed_bath_ratio', 'bedrooms_5plus',
       'grade_5', 'grade_6', 'grade_7', 'grade_8', 'grade_9', 'grade_10',
       'grade_11', 'grade_12', 'grade_13', 'view_1_2', 'view_3', 'view_4',
       'condition_3_4', 'condition_5', 'city', 'city_Bellevue',
       'city_Black Diamond', 'city_Bothell', 'city_Carnation', 'city_Duvall',
       'city_Enumclaw', 'city_Fall City', 'city_Federal Way', 'city_Issaquah',
       'city_Kenmore', 'city_Kent', 'city_Kirkland', 'city_Maple Valley',
       'city_Medina', 'city_Mercer Island', 'city_North Bend', 'city_Redmond',
       'city_Renton', 'city_Sammamish', 'city_Seattle', 'city_Snoqualmie',
       'city_Vashon', 'city_Woodinville'],
      dtype='object')
```

```
df6.columns = ['price', 'bathrooms', 'sqft_living', 'sqft_lot', 'floors', 'water
```

In [133…
```
        'yr_built', 'zipcode', 'lat', 'long', 'sqft_living15', 'sqft_lot15',
        'month', 'yrs_since_reno', 'bed_bath_ratio', 'bedrooms_5plus',
        'grade_5', 'grade_6', 'grade_7', 'grade_8', 'grade_9', 'grade_10',
        'grade_11', 'grade_12', 'grade_13', 'view_1_2', 'view_3', 'view_4',
        'condition_3_4', 'condition_5', 'city', 'city_Bellevue',
        'city_Black_Diamond', 'city_Bothell', 'city_Carnation', 'city_Duvall',
        'city_Enumclaw', 'city_Fall_City', 'city_Federal_Way', 'city_Issaquah',
        'city_Kenmore', 'city_Kent', 'city_Kirkland', 'city_Maple_Valley',
        'city_Medina', 'city_Mercer_Island', 'city_North_Bend', 'city_Redmond',
        'city_Renton', 'city_Sammamish', 'city_Seattle', 'city_Snoqualmie',
        'city_Vashon', 'city_Woodinville']
```

In [134…
```
import json
```

In [144…
```
import os
geo_data_file = os.path.join('data', 'Cities_and_Unincorporated_King_County___ci
```

In [ ]:
```
with open(geo_data_file) as f:
    geo_data = json.load(f)
print(type(data))
```

Remove unwanted cities from geodata

In [ ]:
```
tmp = geo_data

# remove cities not in data
geocities = []
for i in range(len(tmp['features'])):
    if tmp['features'][i]['properties']['CITYNAME'] in list(df6['city'].unique()
        geocities.append(tmp['features'][i])

# creating new JSON object
new_json = dict.fromkeys(['type','features'])
new_json['type'] = 'FeatureCollection'
new_json['features'] = geocities

# save uodated JSON object
open("data/cleaned_city_geodata.json", "w").write(json.dumps(new_json, sort_keys
```

In [158…
```
geo_data_cleaned = "data/cleaned_city_geodata.json"
```

In [159…
```
kc_map = folium.Map(location=kc_coordinates, tiles="cartodbpositron", zoom_start
```

In [160…
```
kc_map.choropleth(geo_data=geo_data_cleaned,
             data=df6, # my dataset
             name='choropleth',
             columns=['city', 'price'], # city is here for matching the geojson
             key_on='feature.properties.CITYNAME', # this path contains zipcodes
             fill_color='GnBu', fill_opacity=0.7, line_opacity=0.2,
             legend_name='Price Scale')
kc_map
```

Out[160… Make this Notebook Trusted to load map: File -> Trust Notebook

Decisions

Removed feature:

- dropped 'sqft_basement' due to high p-value. Also, scatterplot shows that there are plenty of high priced homes with no basements.

Dummies:

- cities

Model 4

In [149…
```
df6.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 21273 entries, 0 to 21272
Data columns (total 54 columns):
 #   Column              Non-Null Count  Dtype  
---  ------              --------------  -----  
 0   price               21273 non-null  float64
 1   bathrooms           21273 non-null  float64
 2   sqft_living         21273 non-null  int64  
 3   sqft_lot            21273 non-null  int64  
 4   floors              21273 non-null  float64
 5   waterfront          21273 non-null  float64
 6   yr_built            21273 non-null  int64  
 7   zipcode             21273 non-null  int64  
 8   lat                 21273 non-null  float64
 9   long                21273 non-null  float64
 10  sqft_living15       21273 non-null  int64  
 11  sqft_lot15          21273 non-null  int64  
 12  month               21273 non-null  int64  
 13  yrs_since_reno      21273 non-null  int64  
 14  bed_bath_ratio      21273 non-null  float64
 15  bedrooms_5plus      21273 non-null  uint8  
 16  grade_5             21273 non-null  uint8  
 17  grade_6             21273 non-null  uint8  
 18  grade_7             21273 non-null  uint8  
 19  grade_8             21273 non-null  uint8  
 20  grade_9             21273 non-null  uint8  
 21  grade_10            21273 non-null  uint8  
```

```
 22  grade_11             21273 non-null  uint8
 23  grade_12             21273 non-null  uint8
 24  grade_13             21273 non-null  uint8
 25  view_1_2             21273 non-null  uint8
 26  view_3               21273 non-null  uint8
 27  view_4               21273 non-null  uint8
 28  condition_3_4        21273 non-null  uint8
 29  condition_5          21273 non-null  uint8
 30  city                 21273 non-null  object
 31  city_Bellevue        21273 non-null  uint8
 32  city_Black_Diamond   21273 non-null  uint8
 33  city_Bothell         21273 non-null  uint8
 34  city_Carnation       21273 non-null  uint8
 35  city_Duvall          21273 non-null  uint8
 36  city_Enumclaw        21273 non-null  uint8
 37  city_Fall_City       21273 non-null  uint8
 38  city_Federal_Way     21273 non-null  uint8
 39  city_Issaquah        21273 non-null  uint8
 40  city_Kenmore         21273 non-null  uint8
 41  city_Kent            21273 non-null  uint8
 42  city_Kirkland        21273 non-null  uint8
 43  city_Maple_Valley    21273 non-null  uint8
 44  city_Medina          21273 non-null  uint8
 45  city_Mercer_Island   21273 non-null  uint8
 46  city_North_Bend      21273 non-null  uint8
 47  city_Redmond         21273 non-null  uint8
 48  city_Renton          21273 non-null  uint8
 49  city_Sammamish       21273 non-null  uint8
 50  city_Seattle         21273 non-null  uint8
 51  city_Snoqualmie      21273 non-null  uint8
 52  city_Vashon          21273 non-null  uint8
 53  city_Woodinville     21273 non-null  uint8
dtypes: float64(7), int64(8), object(1), uint8(38)
memory usage: 3.5+ MB
```

In [150…

```
outcome = 'price'
cols = list(df6.columns)
unwanted = ['price', 'zipcode', 'city']
x_cols = [e for e in cols if e not in unwanted]
```

In [151…

```
pred_sum = '+'.join(x_cols)
formula = outcome + '~' + pred_sum
model4 = ols(formula=formula, data=df6).fit()
model4.summary()
```

Out[151…

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.773
Model:	OLS	**Adj. R-squared:**	0.773
Method:	Least Squares	**F-statistic:**	1421.
Date:	Thu, 10 Jun 2021	**Prob (F-statistic):**	0.00
Time:	12:33:00	**Log-Likelihood:**	-2.8615e+05
No. Observations:	21273	**AIC:**	5.724e+05
Df Residuals:	21221	**BIC:**	5.728e+05
Df Model:	51		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	-7.379e+07	3.51e+06	-21.048	0.000	-8.07e+07	-6.69e+07
bathrooms	3.033e+04	3592.753	8.441	0.000	2.33e+04	3.74e+04
sqft_living	116.6287	2.915	40.016	0.000	110.916	122.342
sqft_lot	0.2710	0.054	5.048	0.000	0.166	0.376
floors	3.079e+04	2825.053	10.899	0.000	2.53e+04	3.63e+04
waterfront	4.286e+05	1.59e+04	26.884	0.000	3.97e+05	4.6e+05
yr_built	-1811.9726	62.273	-29.097	0.000	-1934.032	-1689.913
lat	6.14e+05	1.83e+04	33.547	0.000	5.78e+05	6.5e+05
long	-3.943e+05	2.83e+04	-13.939	0.000	-4.5e+05	-3.39e+05
sqft_living15	29.4016	3.013	9.757	0.000	23.495	35.308
sqft_lot15	-0.2326	0.074	-3.164	0.002	-0.377	-0.089
month	-2842.5568	371.007	-7.662	0.000	-3569.759	-2115.354
yrs_since_reno	-21.0860	3.342	-6.310	0.000	-27.636	-14.536
bed_bath_ratio	-6581.6718	2994.075	-2.198	0.028	-1.25e+04	-713.057
bedrooms_5plus	-2.066e+04	4916.225	-4.203	0.000	-3.03e+04	-1.1e+04
grade_5	1805.8696	4.65e+04	0.039	0.969	-8.93e+04	9.29e+04
grade_6	9341.8402	4.53e+04	0.206	0.837	-7.94e+04	9.81e+04
grade_7	4.746e+04	4.52e+04	1.049	0.294	-4.12e+04	1.36e+05
grade_8	9.872e+04	4.54e+04	2.177	0.030	9824.049	1.88e+05
grade_9	2.094e+05	4.56e+04	4.593	0.000	1.2e+05	2.99e+05
grade_10	3.648e+05	4.59e+04	7.943	0.000	2.75e+05	4.55e+05
grade_11	5.863e+05	4.68e+04	12.542	0.000	4.95e+05	6.78e+05
grade_12	9.429e+05	5e+04	18.870	0.000	8.45e+05	1.04e+06
grade_13	1.551e+06	7.1e+04	21.846	0.000	1.41e+06	1.69e+06
view_1_2	6.478e+04	5122.029	12.648	0.000	5.47e+04	7.48e+04
view_3	1.261e+05	7962.544	15.831	0.000	1.1e+05	1.42e+05
view_4	2.968e+05	1.17e+04	25.278	0.000	2.74e+05	3.2e+05
condition_3_4	3.104e+04	1.27e+04	2.453	0.014	6236.957	5.58e+04
condition_5	8.682e+04	1.33e+04	6.551	0.000	6.08e+04	1.13e+05
city_Bellevue	1.995e+05	9308.213	21.436	0.000	1.81e+05	2.18e+05
city_Black_Diamond	1.434e+05	1.9e+04	7.557	0.000	1.06e+05	1.81e+05
city_Bothell	-1.404e+05	1.57e+04	-8.944	0.000	-1.71e+05	-1.1e+05
city_Carnation	3.502e+04	2.11e+04	1.656	0.098	-6428.232	7.65e+04
city_Duvall	-5.854e+04	1.75e+04	-3.336	0.001	-9.29e+04	-2.41e+04
city_Enumclaw	1.562e+05	1.41e+04	11.073	0.000	1.29e+05	1.84e+05

city_Fall_City	1.336e+05	2.26e+04	5.911	0.000	8.93e+04	1.78e+05
city_Federal_Way	-7.03e+04	9013.777	-7.800	0.000	-8.8e+04	-5.26e+04
city_Issaquah	1.045e+05	1.1e+04	9.460	0.000	8.29e+04	1.26e+05
city_Kenmore	-1.645e+05	1.41e+04	-11.667	0.000	-1.92e+05	-1.37e+05
city_Kent	-4645.2926	7727.160	-0.601	0.548	-1.98e+04	1.05e+04
city_Kirkland	2.979e+04	1.07e+04	2.784	0.005	8814.815	5.08e+04
city_Maple_Valley	7.758e+04	1.05e+04	7.390	0.000	5.7e+04	9.82e+04
city_Medina	9.491e+05	2.61e+04	36.398	0.000	8.98e+05	1e+06
city_Mercer_Island	3.109e+05	1.27e+04	24.569	0.000	2.86e+05	3.36e+05
city_North_Bend	1.851e+05	1.86e+04	9.941	0.000	1.49e+05	2.22e+05
city_Redmond	4.91e+04	1.13e+04	4.349	0.000	2.7e+04	7.12e+04
city_Renton	-1.729e+04	7934.290	-2.179	0.029	-3.28e+04	-1737.914
city_Sammamish	3.905e+04	1.15e+04	3.394	0.001	1.65e+04	6.16e+04
city_Seattle	-2.237e+04	8604.905	-2.599	0.009	-3.92e+04	-5498.839
city_Snoqualmie	9.33e+04	1.59e+04	5.870	0.000	6.21e+04	1.24e+05
city_Vashon	-1.021e+05	1.9e+04	-5.367	0.000	-1.39e+05	-6.48e+04
city_Woodinville	-9.489e+04	1.32e+04	-7.212	0.000	-1.21e+05	-6.91e+04

Omnibus:	11711.388	**Durbin-Watson:**	1.988
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	287417.147
Skew:	2.155	**Prob(JB):**	0.00
Kurtosis:	20.484	**Cond. No.**	1.36e+08

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 1.36e+08. This might indicate that there are strong multicollinearity or other numerical problems.

Observations

High p-values:

- Grade 5, 6, 7
- city_Carnation (not too bad), city_Kent

In [152…
```
X = df6[x_cols]
Y = df6['price']
```

In [153…
```
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size = 0.25, rand
linreg4 = LinearRegression()
```

```
linreg4.fit(X_train, Y_train)
Y_pred = linreg4.predict(X_test)
```

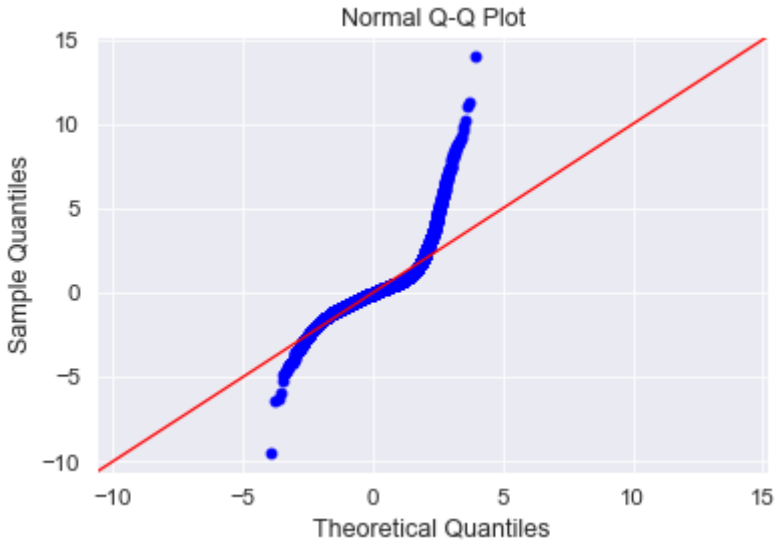
In [154…
```
mse_train = mean_squared_error(Y_train, linreg4.predict(X_train))
mse_test = mean_squared_error(Y_test, Y_pred)

print("Train RMSE:", np.sqrt(mse_train))
print("Test RMSE:", np.sqrt(mse_test))
```

```
Train RMSE: 166369.9225799707
Test RMSE: 174414.09314273568
```

Lowest MSE so far

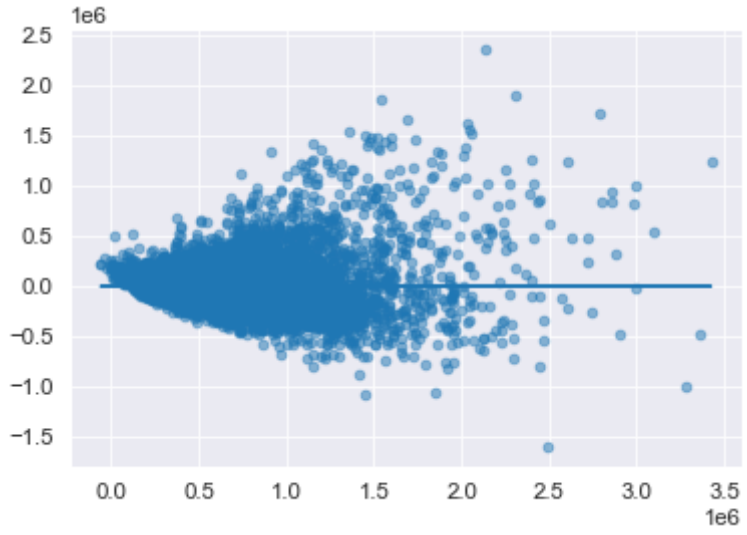
In [155…
```
resid4 = model4.resid
fig = sm.graphics.qqplot(resid4, dist=stats.norm, line='45', fit=True)
plt.title('Normal Q-Q Plot')
```

Out[155… `Text(0.5, 1.0, 'Normal Q-Q Plot')`



In [156…
```
plt.scatter(model4.predict(df6[x_cols]), model4.resid, alpha=0.5)
plt.plot(model4.predict(df6[x_cols]), [0 for i in range(len(df6))])
```

Out[156… `[<matplotlib.lines.Line2D at 0x7f86e8353e20>]`



In [157…
```
df6.to_csv('data/data_fin.csv')
```

In [ ]:

In [ ]: