Final Project Submission

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- Student pace: self paced
- Scheduled project review date/time: Monday, Aug 1, 1pm
- Instructor name: Abhineet Kulkarni / Claude Fried
- Blog post URL: https://medium.com/@ntdoris/where-to-begin-choosing-a-baseline-linear-regression-model-when-you-have-limited-domain-knowledge-fe589ba10d3b

Introduction

This project uses the King County House Sales dataset help real estate company Royal Homes better understand the housing market in the county. What types of homes should they be looking to sell to make the most profit? What features lend towards higher sale prices?

Data Inspection and Initial Cleaning

Import Data & Necessary Packages

In [1]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
import scipy.stats as stats
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import KFold
from sklearn.metrics import mean_squared_error, r2_score
from sklearn.model_selection import train_test_split
import statsmodels.api as sm
import statsmodels.stats.api as sms
import statsmodels.formula.api as smf
from statsmodels.formula.api import ols
from sklearn.preprocessing import PolynomialFeatures
from sklearn.model_selection import cross_validate, ShuffleSplit
from datetime import datetime
from statsmodels.stats.outliers_influence import variance_inflation_factor
```

```
/Library/Frameworks/Python.framework/Versions/3.10/lib/python3.10/site-package
s/statsmodels/compat/pandas.py:65: FutureWarning: pandas.Int64Index is depreca
ted and will be removed from pandas in a future version. Use pandas.Index with
the appropriate dtype instead.
  from pandas import Int64Index as NumericIndex
```

Loading in data from the King County House Sales dataset:

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

Out[2]:

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

5 rows × 21 columns

The dataset contains 21,596 rows, each representing a house in King County, and 21 distinct columns, including variables describing a house's square footage, number of beds/baths, condition and grade, to name a few.

In [3]:
```
df.info()
```

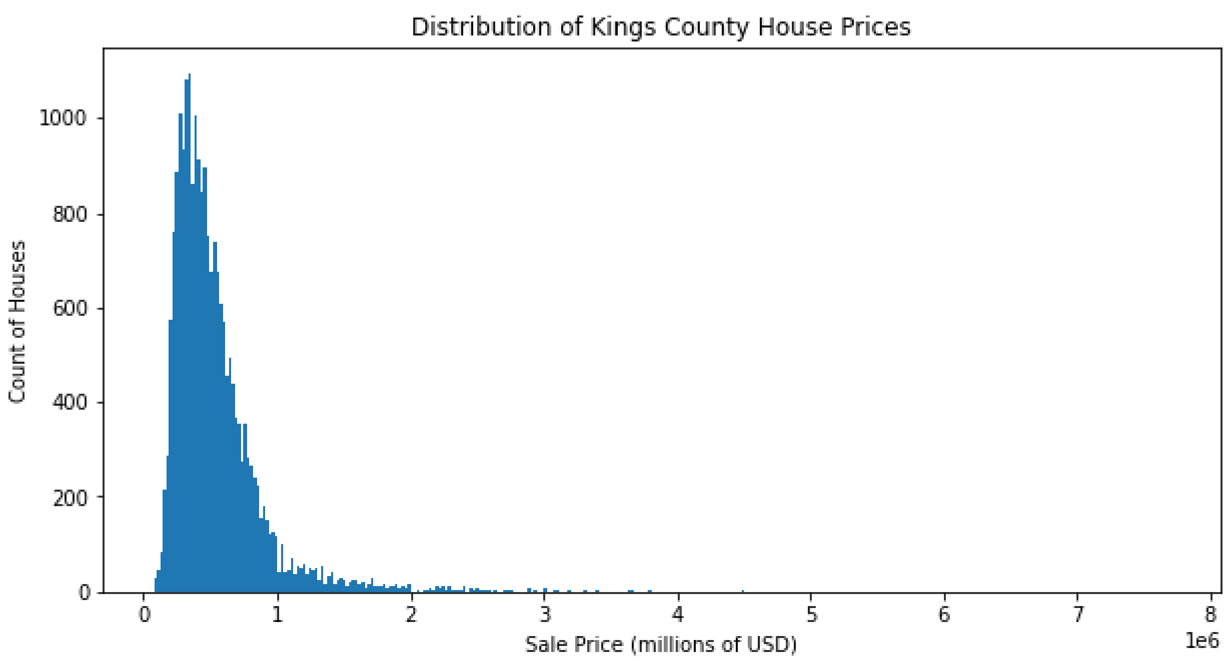
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 21597 entries, 0 to 21596
Data columns (total 21 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   id             21597 non-null  int64
 1   date           21597 non-null  object
 2   price          21597 non-null  float64
 3   bedrooms       21597 non-null  int64
 4   bathrooms      21597 non-null  float64
 5   sqft_living    21597 non-null  int64
 6   sqft_lot       21597 non-null  int64
 7   floors         21597 non-null  float64
 8   waterfront     19221 non-null  object
 9   view           21534 non-null  object
 10  condition      21597 non-null  object
 11  grade          21597 non-null  object
 12  sqft_above     21597 non-null  int64
 13  sqft_basement  21597 non-null  object
 14  yr_built       21597 non-null  int64
 15  yr_renovated   17755 non-null  float64
 16  zipcode        21597 non-null  int64
 17  lat            21597 non-null  float64
 18  long           21597 non-null  float64
 19  sqft_living15  21597 non-null  int64
 20  sqft_lot15     21597 non-null  int64
dtypes: float64(6), int64(9), object(6)
memory usage: 3.5+ MB
```

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

Out[4]:

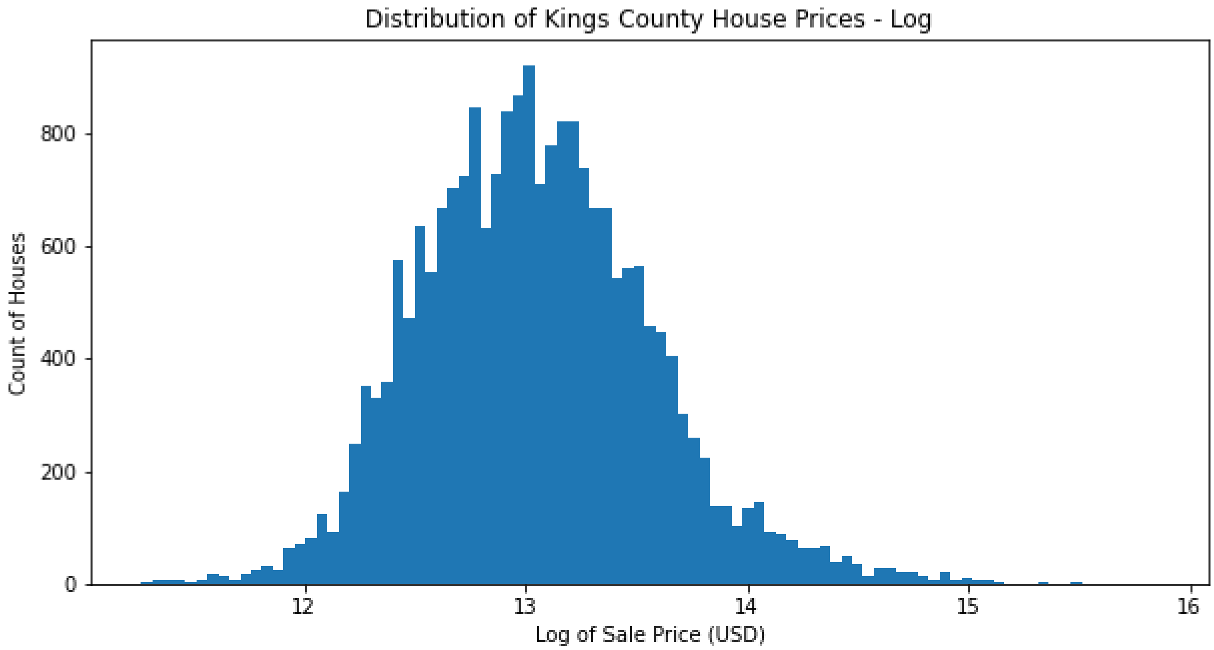
	id	price	bedrooms	bathrooms	sqft_living	sqft_lot
count	2.159700e+04	2.159700e+04	21597.000000	21597.000000	21597.000000	2.159700e+04
mean	4.580474e+09	5.402966e+05	3.373200	2.115826	2080.321850	1.509941e+04
std	2.876736e+09	3.673681e+05	0.926299	0.768984	918.106125	4.141264e+04
min	1.000102e+06	7.800000e+04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

In [3]:
```
fig, ax = plt.subplots(figsize=(10, 5))

ax.hist(df['price'], bins='auto')

ax.set_xlabel("Sale Price (millions of USD)")
ax.set_ylabel("Count of Houses")
ax.set_title("Distribution of Kings County House Prices");
```



Taking the log makes this data much more normal. Will keep that in mind for later.

In [6]:
```
fig, ax = plt.subplots(figsize=(10, 5))

ax.hist(np.log(df['price']), bins='auto')

ax.set_xlabel("Log of Sale Price (USD)")
ax.set_ylabel("Count of Houses")
ax.set_title("Distribution of Kings County House Prices - Log");
```



In [4]:
```
y = df['price']
X = df.drop(['price'], axis=1)
```

Handling Missing Values & Cleaning the Data

In [8]:
```
X.isna().sum()
```

Out[8]:
```
id                  0
date                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 [9]:
```
print(len(df[df["waterfront"].isna()]))
print(len(df[df["view"].isna()]))
print(len(df[df["yr_renovated"].isna()]))
print(" ")
print(len(df[df["yr_renovated"]==0]))
print(len(df[df["view"]=='NONE']))
print(" ")
```

```
print(len(df[df["waterfront"].isna() & (df["view"]=='NONE')])) # houses with wa
print(len(df[df["view"].isna() | (df["view"]=='NONE')]))
```

```
2376
63
3842

17011
19422

2110
19485
```

In [10]:
```
df['waterfront'].value_counts()
```

Out[10]:
```
NO     19075
YES      146
Name: waterfront, dtype: int64
```

In [11]:
```
X['yr_renovated'].value_counts()
```

Out[11]:
```
0.0       17011
2014.0       73
2013.0       31
2003.0       31
2007.0       30
          ...
1951.0        1
1953.0        1
1946.0        1
1976.0        1
1948.0        1
Name: yr_renovated, Length: 70, dtype: int64
```

In [12]:
```
X['sqft_basement'].value_counts()
X['sqft_basement'][X['sqft_basement']=='?'] = 1.0
X['sqft_basement'][X['sqft_basement']==0.0] = 1.0 # setting to 1 so that we car
X['sqft_basement'] = X['sqft_basement'].astype(float)
X['has_basement'] = [0 if basement==1.0 else 1 for basement in X['sqft_basement
X['has_basement'].value_counts()
```

```
/var/folders/wl/4cw_k4nj07d773kdv1fw53tc0000gn/T/ipykernel_28102/3786226204.p
y:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/st
able/user_guide/indexing.html#returning-a-view-versus-a-copy
  X['sqft_basement'][X['sqft_basement']=='?'] = 1.0
/var/folders/wl/4cw_k4nj07d773kdv1fw53tc0000gn/T/ipykernel_28102/3786226204.p
y:3: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/st
able/user_guide/indexing.html#returning-a-view-versus-a-copy
  X['sqft_basement'][X['sqft_basement']==0.0] = 1.0 # setting to 1 so that we
can take the log
```

Out[12]:
```
1    21143
0      454
Name: has_basement, dtype: int64
```

While there aren't many missing values, a significant number of houses have no view, are not waterfront, or have a 0 value for year renovated. I am inclined not to include these variables in the model as very few houses are impacted by these metrics. Nonetheless, I will perform some feature engineering so that I can see how they impact the model.

In [13]:
```
X['yr_renovated'][X['yr_renovated'] == 0] = 'NA'
X['yr_renovated'][X['yr_renovated'].isna()] = 'NA'
X['renovated'] = [0 if house=='NA' else 1 for house in X['yr_renovated']]

sum(X['renovated'])
```

```
/var/folders/wl/4cw_k4nj07d773kdv1fw53tc0000gn/T/ipykernel_28102/1224829936.p
y:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/st
able/user_guide/indexing.html#returning-a-view-versus-a-copy
  X['yr_renovated'][X['yr_renovated'] == 0] = 'NA'
```

Out[13]:
```
744
```

In [14]:
```
X['view'][X['view'].isna()] = 'NA'
set(X['view'])
```

```
/var/folders/wl/4cw_k4nj07d773kdv1fw53tc0000gn/T/ipykernel_28102/670772084.py:
1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/st
able/user_guide/indexing.html#returning-a-view-versus-a-copy
  X['view'][X['view'].isna()] = 'NA'
```

Out[14]:
```
{'AVERAGE', 'EXCELLENT', 'FAIR', 'GOOD', 'NA', 'NONE'}
```

In [15]:
```
X['waterfront'][X['waterfront'].isna()] = 'NA'
X['waterfront'].value_counts()
```

```
/var/folders/wl/4cw_k4nj07d773kdv1fw53tc0000gn/T/ipykernel_28102/808933529.py:
1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/st
able/user_guide/indexing.html#returning-a-view-versus-a-copy
  X['waterfront'][X['waterfront'].isna()] = 'NA'
```

Out[15]:
```
NO     19075
NA      2376
YES      146
Name: waterfront, dtype: int64
```

In [16]:
```
print(X['date'][0])

X['date'] = [datetime.strptime(date, '%m/%d/%Y') for date in X['date']]
X['yr_sold'] = pd.DatetimeIndex(X['date']).year
X['mth_sold'] = pd.DatetimeIndex(X['date']).month

X.head()
```

```
10/13/2014
```

Out[16]:

	id	date	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view
0	7129300520	2014-10-13	3	1.00	1180	5650	1.0	NA	NONE
1	6414100192	2014-12-09	3	2.25	2570	7242	2.0	NO	NONE
2	5631500400	2015-02-25	2	1.00	770	10000	1.0	NO	NONE
3	2487200875	2014-12-09	4	3.00	1960	5000	1.0	NO	NONE
4	1954400510	2015-02-18	3	2.00	1680	8080	1.0	NO	NONE

5 rows × 24 columns

In [17]:

```
X['grade'] = [int(grade.split(" ")[0]) for grade in X['grade']]
set(X['grade'])
```

Out[17]:

```
{3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13}
```

In [18]:

```
set(X['condition']) # need to get rid of space in very good for model purposes
```

Out[18]:

```
{'Average', 'Fair', 'Good', 'Poor', 'Very Good'}
```

In [19]:

```
X['condition'][X['condition']=='Very Good'] = 'VeryGood'
set(X['condition'])
```

```
/var/folders/wl/4cw_k4nj07d773kdv1fw53tc0000gn/T/ipykernel_28102/3950577358.p
y:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/st
able/user_guide/indexing.html#returning-a-view-versus-a-copy
  X['condition'][X['condition']=='Very Good'] = 'VeryGood'
```

Out[19]:

```
{'Average', 'Fair', 'Good', 'Poor', 'VeryGood'}
```

In [20]:

```
X.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 21597 entries, 0 to 21596
Data columns (total 24 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   id             21597 non-null  int64
 1   date           21597 non-null  datetime64[ns]
 2   bedrooms       21597 non-null  int64
 3   bathrooms      21597 non-null  float64
 4   sqft_living    21597 non-null  int64
 5   sqft_lot       21597 non-null  int64
 6   floors         21597 non-null  float64
 7   waterfront     21597 non-null  object
 8   view           21597 non-null  object
 9   condition      21597 non-null  object
 10  grade          21597 non-null  int64
 11  sqft_above     21597 non-null  int64
 12  sqft_basement  21597 non-null  float64
 13  yr_built       21597 non-null  int64
 14  yr_renovated   21597 non-null  object
 15  zipcode        21597 non-null  int64
 16  lat            21597 non-null  float64
 17  long           21597 non-null  float64
 18  sqft_living15  21597 non-null  int64
 19  sqft_lot15     21597 non-null  int64
 20  has_basement   21597 non-null  int64
 21  renovated      21597 non-null  int64
 22  yr_sold        21597 non-null  int64
 23  mth_sold       21597 non-null  int64
dtypes: datetime64[ns](1), float64(5), int64(14), object(4)
memory usage: 4.0+ MB
```

Baseline Model

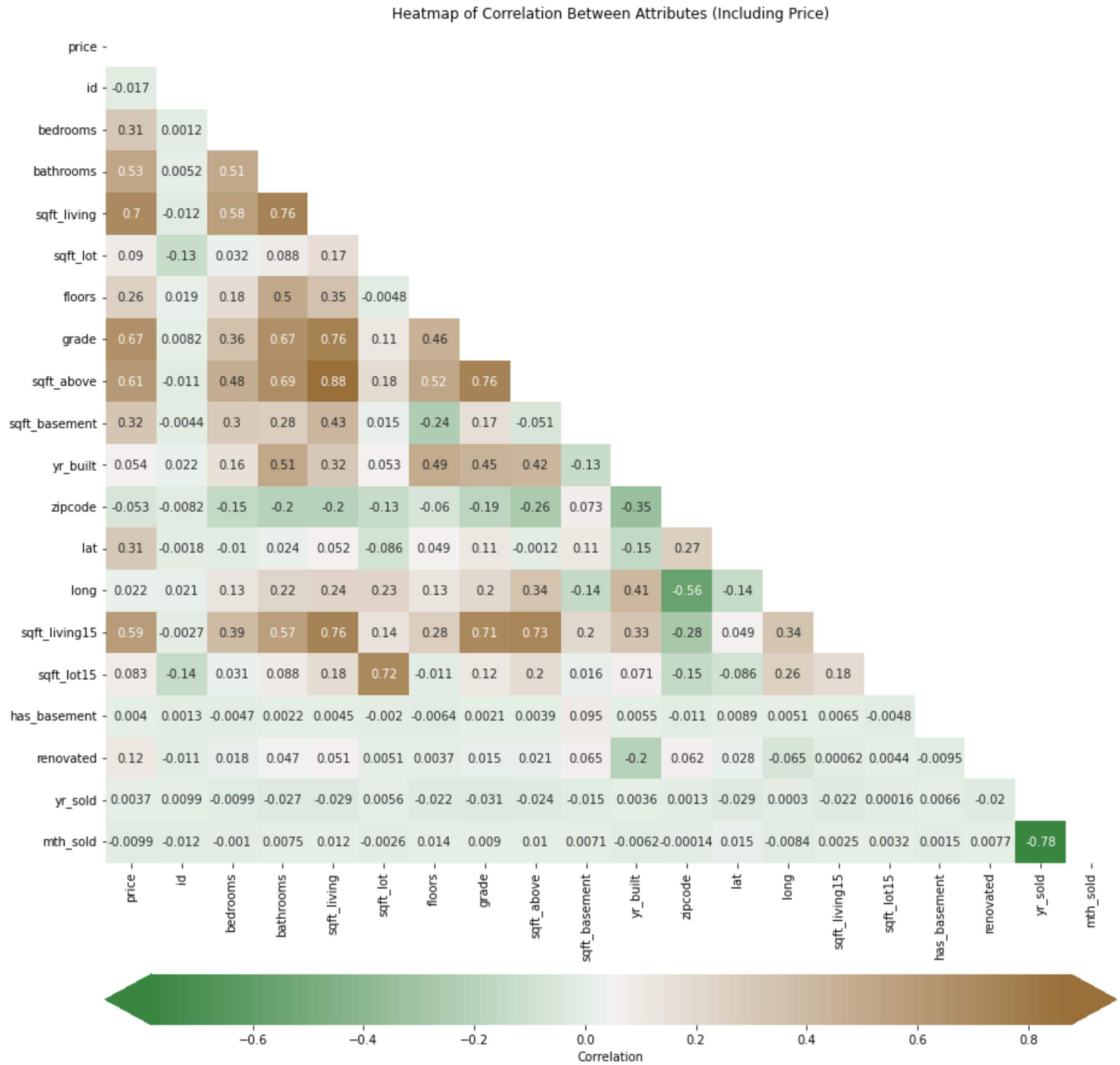
Checking Correlations

In [21]:

```
heatmap_data = pd.concat([y, X], axis=1)
corr = heatmap_data.corr()

fig, ax = plt.subplots(figsize=(15, 17))
mask = np.triu(np.ones_like(corr, dtype=bool))
cmap = sns.diverging_palette(130, 50, as_cmap=True)
cbar_kws = {"label": "Correlation", "orientation": "horizontal", "pad": .1, "ex

sns.heatmap(data=corr, mask=mask, ax=ax, annot=True, cbar_kws=cbar_kws, cmap=cm

ax.set_title("Heatmap of Correlation Between Attributes (Including Price)")
```

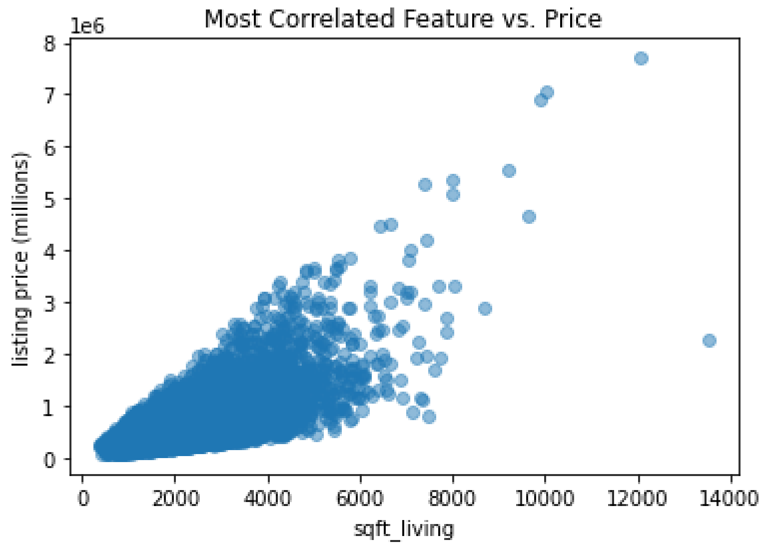
Out[21]:

```
Text(0.5, 1.0, 'Heatmap of Correlation Between Attributes (Including Price)')
```

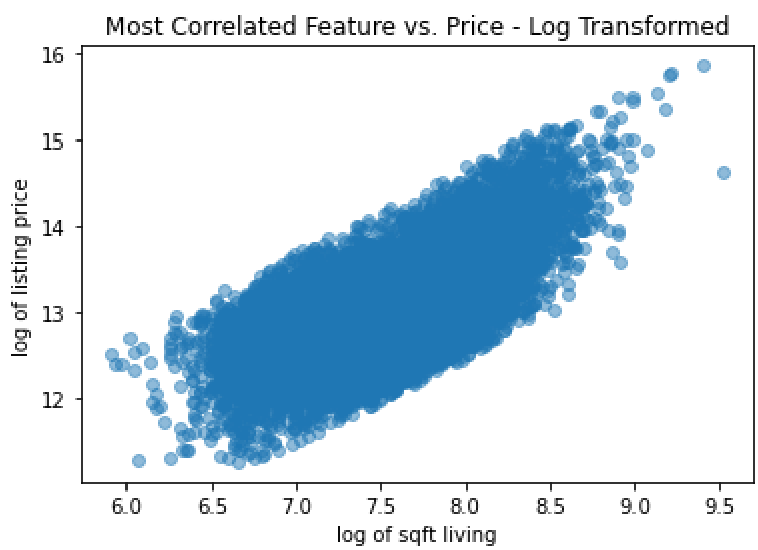


In [6]:

```python
most_correlated_feature = 'sqft_living'

fig, ax = plt.subplots()

ax.scatter(X[most_correlated_feature], y, alpha=0.5)
ax.set_xlabel(most_correlated_feature)
ax.set_ylabel("listing price (millions)")
ax.set_title("Most Correlated Feature vs. Price");
#ax.ticklabel_format(style='plain')

# I suspect a log transformation will improve the linearity
```



In [7]:
```
fig, ax = plt.subplots()

ax.scatter(np.log(X[most_correlated_feature]), np.log(y), alpha=0.5)
ax.set_xlabel("log of sqft living")
ax.set_ylabel("log of listing price")
ax.set_title("Most Correlated Feature vs. Price - Log Transformed");

# very linear after log transformation
```



Build Baseline Model With Most Correlated Feature as Independent Variable

Even if we hadn't used correlation to pick an independent variable for this first model, square footage would have been an obvious choice. It makes sense that a house's square footage has a positive relationship with price.

In [24]:
```
outcome = 'price'
data_ols = pd.concat([X, y], axis=1)
predictors = 'sqft_living'
formula = outcome + '~' + predictors
```

```
base_model = ols(formula=formula, data=data_ols).fit()
base_model.summary()
```

Out[24]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.493
Model:	OLS	**Adj. R-squared:**	0.493
Method:	Least Squares	**F-statistic:**	2.097e+04
Date:	Sun, 31 Jul 2022	**Prob (F-statistic):**	0.00
Time:	22:47:39	**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

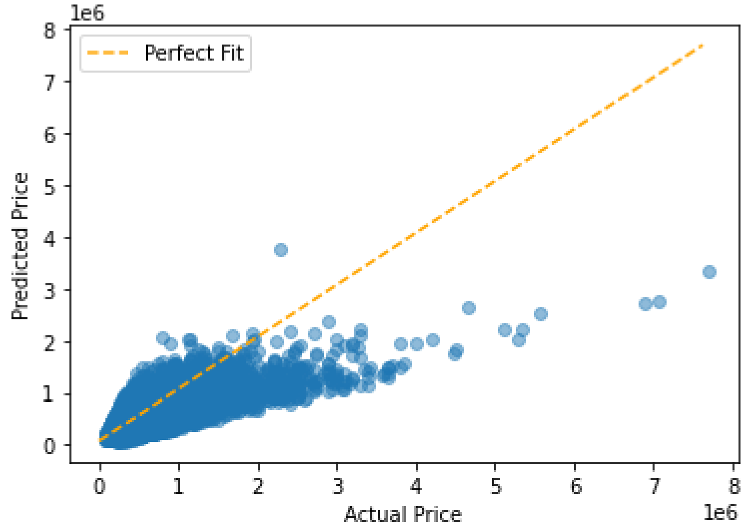
Omnibus:	14801.942	**Durbin-Watson:**	1.982
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	542662.604
Skew:	2.820	**Prob(JB):**	0.00
Kurtosis:	26.901	**Cond. No.**	5.63e+03

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.

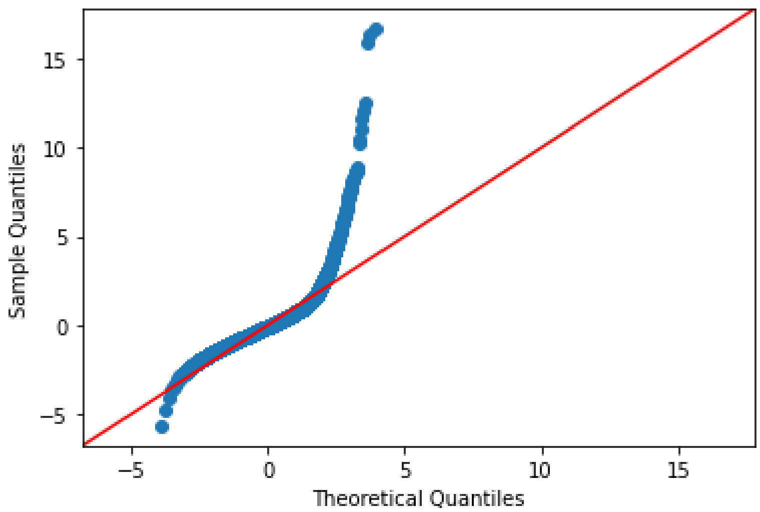
Checking Base Model Assumptions

In [25]:

```
# Linearity check

X_base = X[most_correlated_feature]

preds = base_model.predict(X_base)
fig, ax = plt.subplots()

perfect_line = np.arange(y.min(), y.max())
ax.plot(perfect_line, linestyle="--", color="orange", label="Perfect Fit")
ax.scatter(y, preds, alpha=0.5)
ax.set_xlabel("Actual Price")
ax.set_ylabel("Predicted Price")
ax.legend();
```



In [26]:
```
# Normality check

residuals = (y - preds)
sm.graphics.qqplot(residuals, dist=stats.norm, line='45', fit=True);
```



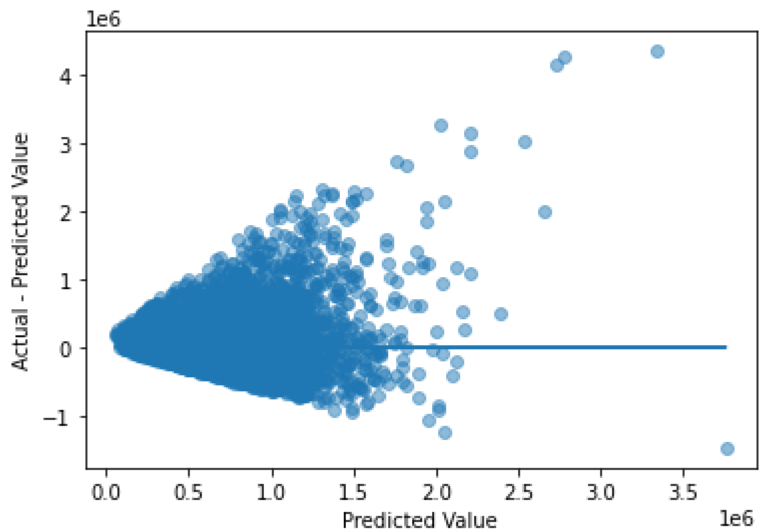
In [27]:
```
# JB test for normality (also shown in model summary)
name = ['Jarque-Bera','Prob','Skew', 'Kurtosis']
test = sms.jarque_bera(base_model.resid)
list(zip(name, test))
```

Out[27]:
```
[('Jarque-Bera', 542662.604395781),
 ('Prob', 0.0),
 ('Skew', 2.8196584324835365),
 ('Kurtosis', 26.90063410219435)]
```

We have a JB value = ~543,000, indicating that errors are not normally distributed. The p-value of 0.0 also favors rejecting the normality null hypothesis at the 5% significance level. Additionally, the kurtosis is above 3, which indicates heavier tails than a normal distribution. The skewness value also shows that underlying data is heavily skewed.

In [28]:
```
# Homoscedasticity check - conelike shape suggests heteroskedasticity of residu

fig, ax = plt.subplots()
```

```
ax.scatter(preds, residuals, alpha=0.5)
ax.plot(preds, [0 for i in range(len(X_base))])
ax.set_xlabel("Predicted Value")
ax.set_ylabel("Actual - Predicted Value");
```



In [29]:

```
# Goldfeld Quandt test for homoscedasticity check

lwr_thresh = data_ols.sqft_living.quantile(q=.45)
upr_thresh = data_ols.sqft_living.quantile(q=.55)
middle_10percent_indices = data_ols[(data_ols.sqft_living >= lwr_thresh)
                                    & (data_ols.sqft_living<=upr_thresh)].index
indices = [x-1 for x in data_ols.index if x not in middle_10percent_indices]

name = ['F statistic', 'p-value']
test = sms.het_goldfeldquandt(base_model.resid.iloc[indices], base_model.model.
list(zip(name, test))
```

Out[29]:

```
[('F statistic', 0.9159859051813802), ('p-value', 0.9999921364751672)]
```

While this relatively large F statistic suggests heteroscedasticity, we cannot confirm this result via the GQ test given the p-value > 0.05. A cone-like shape as seen in the graph above, however, shows obvious heteroscedasticity, in my opinion.

This baseline model fails all of our assumption checks. Let's see if we can improve the next one..

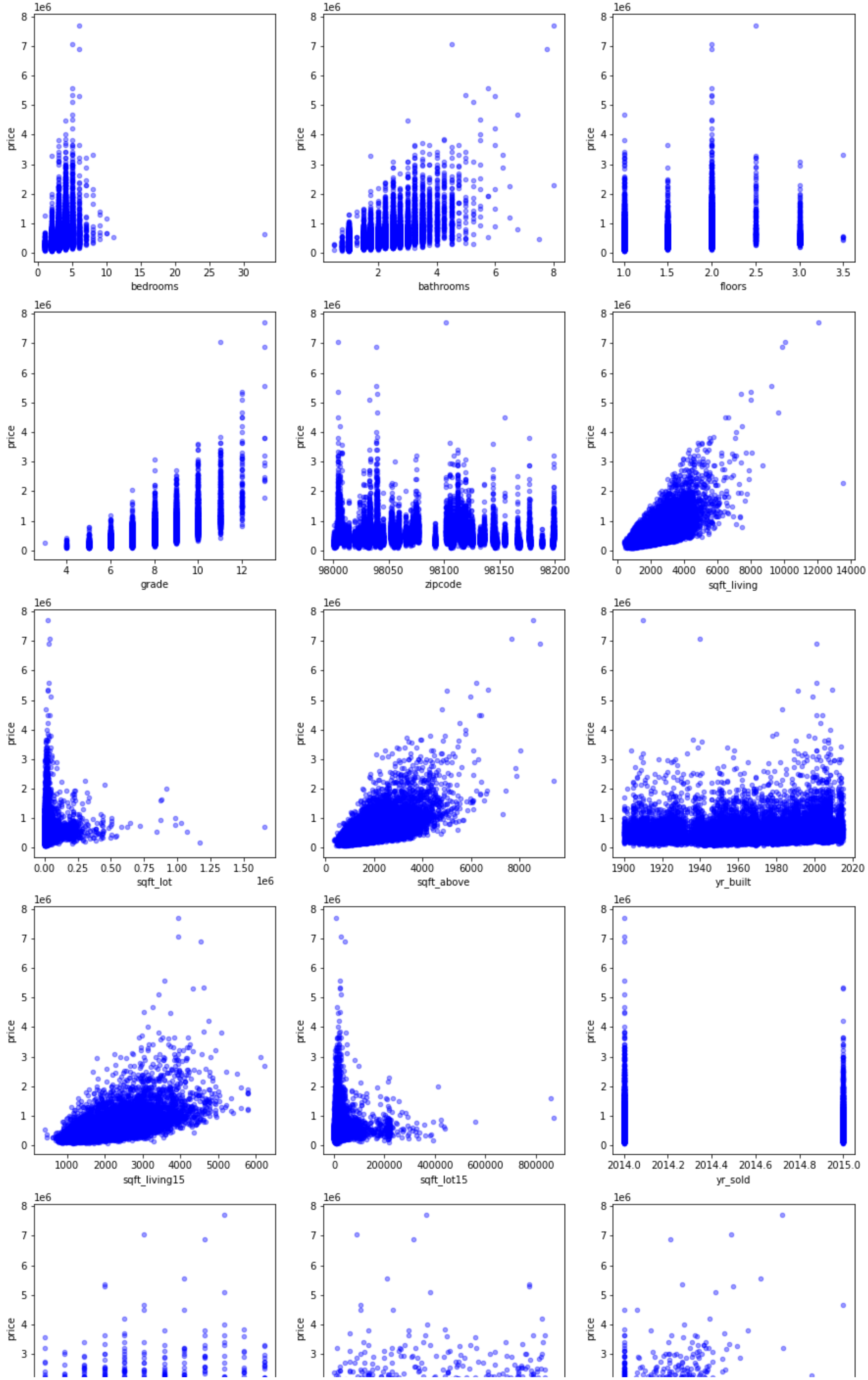
Data Preparation for Second Model

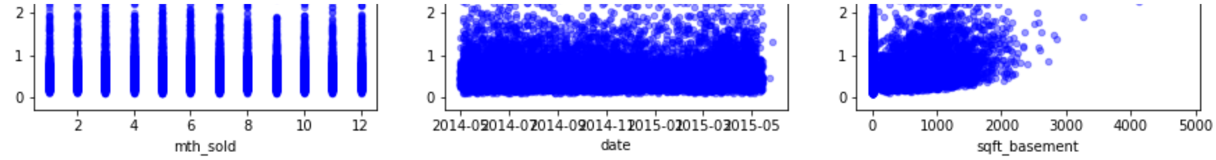
Visually inspecting relationships between numerical variables and price:

In [30]:

```
num_cols = ['bedrooms', # number of bedrooms
            'bathrooms', # number of bathrooms
            'floors', # number of floors (levels) in the house
            'grade', # Overall grade of the house. Related to the construction
            'zipcode', #  zip code
            'sqft_living', # sq. ft. of living space
            'sqft_lot', # Square footage of the lot
            'sqft_above', # Square footage of house apart from basement
```

```
            'yr_built', # year house was built
            'sqft_living15', # sq. ft. of interior housing living space for the
            'sqft_lot15', # sq. ft. of the land lots of the nearest 15 neighbor
            'yr_sold', # year house was sold
            'mth_sold', # month house was sold
            'date',
            'sqft_basement'
           ]

data = pd.concat([X, y], axis=1)
fig, axes = plt.subplots(nrows=5, ncols=3, figsize=(15,27))
axe = axes.ravel()

for xcol, ax in zip(num_cols, axe):
    data.plot(kind='scatter', x=xcol, y='price', ax=ax, alpha=0.4, color='b')
```


price
1e6
bedrooms
bathrooms
floors
grade
zipcode
sqft_living
sqft_lot
sqft_above
yr_built
sqft_living15
sqft_lot15
yr_sold



I am going to exclude latitude and longitude as we can use zip code to represent location/neighborhood. I'd like to treat zip code as a categorical variable since this is not really a linear relationship but it is possible that certain zip codes have a higher average price. I also think keeping zip code categorical makes it easier to interpret.

In [31]:
```
relevant_columns = ['bedrooms', # number of bedrooms
                    'bathrooms', # number of bathrooms
                    'floors', # number of floors (levels) in the house
                    'waterfront', # whether the house is on the waterfront
                    'view', # quality of view from house
                    'condition', # How good the overall condition of the house
                                 # related to maintenance of house.
                    'grade', # Overall grade of the house. Related to the const
                    'zipcode', #  zip code
                    'sqft_living', # sq. ft. of living space
                    'sqft_lot', # Square footage of the lot
                    'sqft_above', # Square footage of house apart from basement
                    'yr_built', # year house was built
                    'sqft_living15', # sq. ft. of interior housing living space
                    'sqft_lot15', # sq. ft. of the land lots of the nearest 15
                    'sqft_basement', # sq. ft. of basement
                    'mth_sold', # month house was sold
                    'yr_sold', # year house was sold
                    'lat', # latitude
                    'renovated', # whether a house had a year populated in the
                    'has_basement' #whether a house has a basement
                   ]

categoricals = ['waterfront', 'view', 'condition', 'zipcode']
continuous = ['bedrooms', 'bathrooms', 'sqft_living', 'sqft_lot', 'sqft_above',
              'sqft_living15', 'sqft_lot15', 'floors', 'lat', 'renovated', 'yr_
              'sqft_basement', 'has_basement'
             ]

X = X[relevant_columns]
X
```

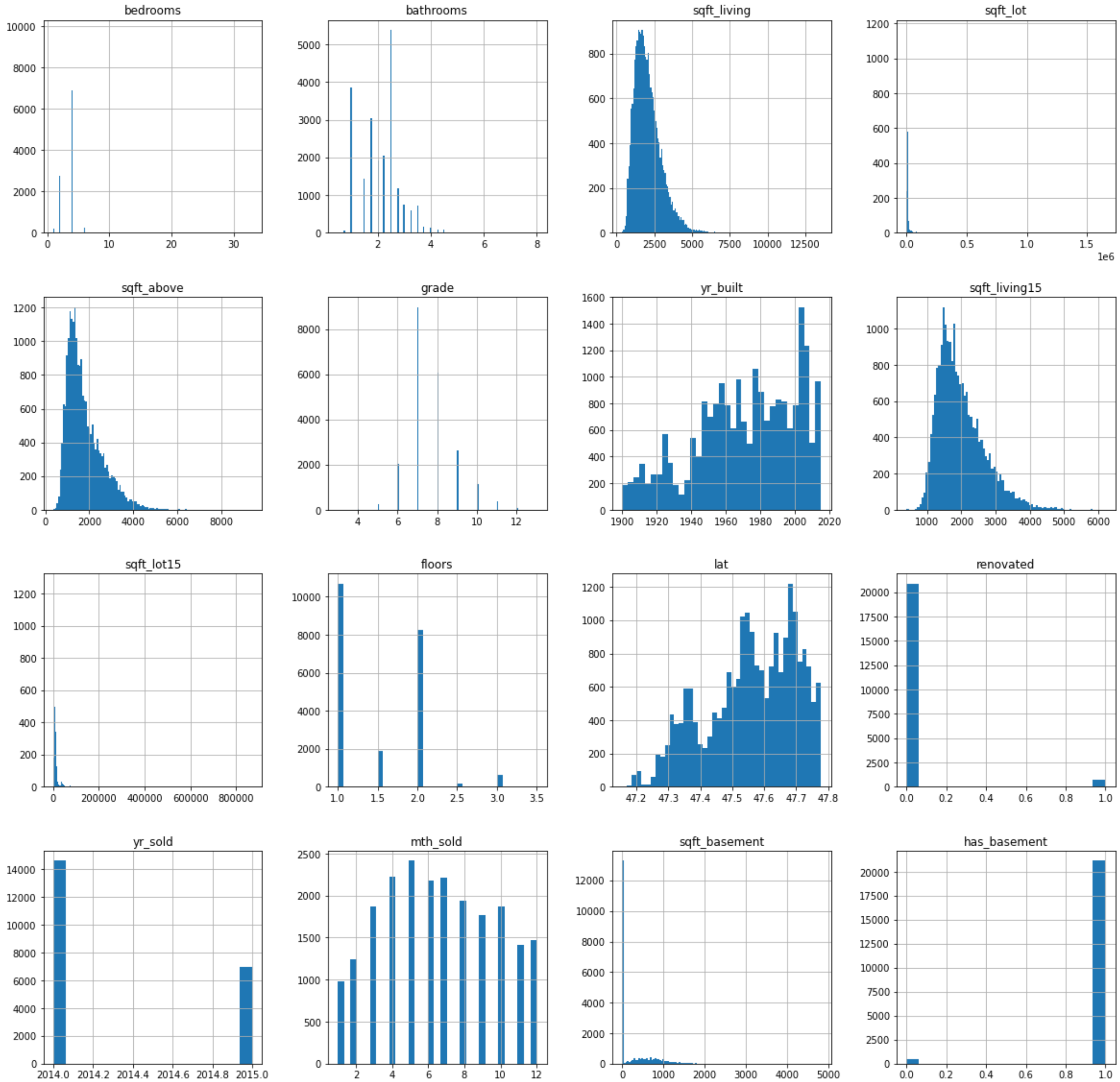
Out[31]:

	bedrooms	bathrooms	floors	waterfront	view	condition	grade	zipcode	sqft_living
0	3	1.00	1.0	NA	NONE	Average	7	98178	1180
1	3	2.25	2.0	NO	NONE	Average	7	98125	2570
2	2	1.00	1.0	NO	NONE	Average	6	98028	770
3	4	3.00	1.0	NO	NONE	VeryGood	7	98136	1960
4	3	2.00	1.0	NO	NONE	Average	8	98074	1680
...	...	...	...	...	...	...	...	...	...
21592	3	2.50	3.0	NO	NONE	Average	8	98103	1530
21593	4	2.50	2.0	NO	NONE	Average	8	98146	2310
21594	2	0.75	2.0	NO	NONE	Average	7	98144	1020
21595	3	2.50	2.0	NA	NONE	Average	8	98027	1600
21596	2	0.75	2.0	NO	NONE	Average	7	98144	1020

21597 rows × 20 columns

In [32]:

```
X[continuous].hist(figsize=[20, 20], bins='auto');
```



Check for Multicollinearity

In [33]:
```
df_corr=X[continuous].corr().abs().stack().reset_index().sort_values(0, ascendi

df_corr['pairs'] = list(zip(df_corr.level_0, df_corr.level_1))
df_corr.set_index(['pairs'], inplace = True)
df_corr.drop(columns=['level_1', 'level_0'], inplace = True)
df_corr.columns = ['cc']
df_corr.drop_duplicates(inplace=True)

df_corr[(df_corr.cc>.70) & (df_corr.cc<0.99)]
```

Out[33]:

pairs	cc
(sqft_above, sqft_living)	0.876448
(mth_sold, yr_sold)	0.782325
(grade, sqft_living)	0.762779
(sqft_living, sqft_living15)	0.756402
(sqft_above, grade)	0.756073
(bathrooms, sqft_living)	0.755758
(sqft_living15, sqft_above)	0.731767
(sqft_lot15, sqft_lot)	0.718204
(sqft_living15, grade)	0.713867

Preprocessing

Taking the kitchen sink approach for this second model - including as many variables as I can without introducing too much multicollinearity.

In [34]:

```
# one hot encode categoricals

dummy_cat = ['condition', 'waterfront', 'view']
df_ohe = pd.get_dummies(X[dummy_cat], prefix=dummy_cat, drop_first=True)
zipcode_dummies = pd.get_dummies(X['zipcode'], prefix='zip', drop_first=True)
```

In [35]:

```
cont = ['sqft_living', 'sqft_lot', 'bedrooms', 'floors', 'mth_sold', 'renovatec
# excluding grade, sqft_above, sqft_living15, bathrooms given high correlation
# excluding yr_sold given high correlation with mth_sold

X_preprocessed = pd.concat([X[cont], df_ohe, zipcode_dummies], axis=1)
X_preprocessed
```

Out[35]:

	sqft_living	sqft_lot	bedrooms	floors	mth_sold	renovated	yr_built	sqft_basement
0	1180	5650	3	1.0	10	0	1955	0.0
1	2570	7242	3	2.0	12	1	1951	400.0
2	770	10000	2	1.0	2	0	1933	0.0
3	1960	5000	4	1.0	12	0	1965	910.0
4	1680	8080	3	1.0	2	0	1987	0.0
...	...	...	...	...	...	...	...	...
21592	1530	1131	3	3.0	5	0	2009	0.0
21593	2310	5813	4	2.0	2	0	2014	0.0
21594	1020	1350	2	2.0	6	0	2009	0.0
21595	1600	2388	3	2.0	1	0	2004	0.0
21596	1020	1076	2	2.0	10	0	2008	0.0

21597 rows × 88 columns

Played around with latitude and zip code a bit to get the following results:

- removing lat, keeping zip yields 0.853 R2 but way lower cond. no (500), similar skew and kurt - best model
- keeping lat, removing zip yields 0.69 R2
- removing both yields very low R2 around 0.523
- keeping both - 0.857 R2, 3544.428 JB, 4.88e+04 cond no, -0.13 skew, 5 kurt

In [36]:

```
X_preprocessed.columns
```

Out[36]:

```
Index(['sqft_living', 'sqft_lot', 'bedrooms', 'floors', 'mth_sold',
       'renovated', 'yr_built', 'sqft_basement', 'condition_Fair',
       'condition_Good', 'condition_Poor', 'condition_VeryGood',
       'waterfront_NO', 'waterfront_YES', 'view_EXCELLENT', 'view_FAIR',
       'view_GOOD', 'view_NA', 'view_NONE', 'zip_98002', 'zip_98003',
       'zip_98004', 'zip_98005', 'zip_98006', 'zip_98007', 'zip_98008',
       'zip_98010', 'zip_98011', 'zip_98014', 'zip_98019', 'zip_98022',
       'zip_98023', 'zip_98024', 'zip_98027', 'zip_98028', 'zip_98029',
       'zip_98030', 'zip_98031', 'zip_98032', 'zip_98033', 'zip_98034',
       'zip_98038', 'zip_98039', 'zip_98040', 'zip_98042', 'zip_98045',
       'zip_98052', 'zip_98053', 'zip_98055', 'zip_98056', 'zip_98058',
       'zip_98059', 'zip_98065', 'zip_98070', 'zip_98072', 'zip_98074',
       'zip_98075', 'zip_98077', 'zip_98092', 'zip_98102', 'zip_98103',
       'zip_98105', 'zip_98106', 'zip_98107', 'zip_98108', 'zip_98109',
       'zip_98112', 'zip_98115', 'zip_98116', 'zip_98117', 'zip_98118',
       'zip_98119', 'zip_98122', 'zip_98125', 'zip_98126', 'zip_98133',
       'zip_98136', 'zip_98144', 'zip_98146', 'zip_98148', 'zip_98155',
       'zip_98166', 'zip_98168', 'zip_98177', 'zip_98178', 'zip_98188',
       'zip_98198', 'zip_98199'],
      dtype='object')
```

Continuous Variables - Transformations

In [37]:
```
# dependent variable - log transformation improves the model
y_log = pd.DataFrame(np.log(y))
```

Second Model - Results and Assumptions Check

In [38]:
```
outcome = 'price'
data_ols = pd.concat([y_log, X_preprocessed], axis=1)
predictors = data_ols.drop('price', axis=1)
pred_sum = '+'.join(predictors.columns)
formula = outcome + '~' + pred_sum

second_model = ols(formula=formula, data=data_ols).fit()
second_model.summary()
```

Out[38]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.857
Model:	OLS	**Adj. R-squared:**	0.856
Method:	Least Squares	**F-statistic:**	1462.
Date:	Sun, 31 Jul 2022	**Prob (F-statistic):**	0.00
Time:	22:48:04	**Log-Likelihood:**	4193.6
No. Observations:	21597	**AIC:**	-8209.
Df Residuals:	21508	**BIC:**	-7499.
Df Model:	88		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	10.4773	0.142	73.933	0.000	10.200	10.755
sqft_living	0.0003	2.55e-06	134.163	0.000	0.000	0.000
sqft_lot	6.631e-07	3.62e-08	18.299	0.000	5.92e-07	7.34e-07
bedrooms	-0.0047	0.002	-2.536	0.011	-0.008	-0.001
floors	-0.0213	0.004	-5.582	0.000	-0.029	-0.014
mth_sold	-0.0050	0.000	-11.512	0.000	-0.006	-0.004
renovated	0.0877	0.008	11.125	0.000	0.072	0.103
yr_built	0.0008	7.23e-05	11.060	0.000	0.001	0.001
sqft_basement	-0.0001	4.3e-06	-28.016	0.000	-0.000	-0.000
condition_Fair	-0.1688	0.016	-10.827	0.000	-0.199	-0.138
condition_Good	0.0413	0.004	11.675	0.000	0.034	0.048
condition_Poor	-0.3377	0.037	-9.046	0.000	-0.411	-0.265
condition_VeryGood	0.1095	0.006	19.625	0.000	0.099	0.120
waterfront_NO	0.0021	0.004	0.487	0.626	-0.006	0.011
waterfront_YES	0.4134	0.021	19.773	0.000	0.372	0.454
view_EXCELLENT	0.2128	0.015	13.969	0.000	0.183	0.243
view_FAIR	0.0071	0.013	0.549	0.583	-0.018	0.032
view_GOOD	0.0869	0.011	7.871	0.000	0.065	0.109
view_NA	-0.0876	0.026	-3.363	0.001	-0.139	-0.037
view_NONE	-0.1528	0.007	-22.241	0.000	-0.166	-0.139
zip_98002	-0.0708	0.018	-4.009	0.000	-0.105	-0.036
zip_98003	0.0391	0.016	2.456	0.014	0.008	0.070
zip_98004	1.1813	0.016	76.126	0.000	1.151	1.212
zip_98005	0.8338	0.019	44.490	0.000	0.797	0.870
zip_98006	0.7182	0.014	51.482	0.000	0.691	0.746

zip_98007	0.7148	0.020	35.973	0.000	0.676	0.754
zip_98008	0.6826	0.016	42.865	0.000	0.651	0.714
zip_98010	0.2263	0.023	9.998	0.000	0.182	0.271
zip_98011	0.4888	0.018	27.511	0.000	0.454	0.524
zip_98014	0.2775	0.021	13.210	0.000	0.236	0.319
zip_98019	0.3207	0.018	17.868	0.000	0.286	0.356
zip_98022	0.0245	0.017	1.440	0.150	-0.009	0.058
zip_98023	-0.0014	0.014	-0.105	0.916	-0.029	0.026
zip_98024	0.4105	0.025	16.494	0.000	0.362	0.459
zip_98027	0.5516	0.014	38.139	0.000	0.523	0.580
zip_98028	0.4435	0.016	27.946	0.000	0.412	0.475
zip_98029	0.6587	0.015	42.792	0.000	0.628	0.689
zip_98030	0.0612	0.016	3.747	0.000	0.029	0.093
zip_98031	0.0861	0.016	5.375	0.000	0.055	0.118
zip_98032	-0.0254	0.021	-1.225	0.220	-0.066	0.015
zip_98033	0.8209	0.014	57.481	0.000	0.793	0.849
zip_98034	0.5624	0.014	41.459	0.000	0.536	0.589
zip_98038	0.1704	0.013	12.722	0.000	0.144	0.197
zip_98039	1.3131	0.030	43.210	0.000	1.254	1.373
zip_98040	0.9561	0.016	59.376	0.000	0.925	0.988
zip_98042	0.0609	0.014	4.489	0.000	0.034	0.087
zip_98045	0.3284	0.017	19.154	0.000	0.295	0.362
zip_98052	0.6979	0.013	51.907	0.000	0.672	0.724
zip_98053	0.5970	0.015	40.819	0.000	0.568	0.626
zip_98055	0.1388	0.016	8.608	0.000	0.107	0.170
zip_98056	0.3061	0.014	21.138	0.000	0.278	0.334
zip_98058	0.1827	0.014	12.972	0.000	0.155	0.210
zip_98059	0.3535	0.014	25.181	0.000	0.326	0.381
zip_98065	0.3861	0.016	24.786	0.000	0.356	0.417
zip_98070	0.3190	0.022	14.677	0.000	0.276	0.362
zip_98072	0.5440	0.016	33.887	0.000	0.513	0.575
zip_98074	0.6331	0.014	44.425	0.000	0.605	0.661
zip_98075	0.6334	0.015	42.129	0.000	0.604	0.663
zip_98077	0.5265	0.018	29.553	0.000	0.492	0.561
zip_98092	0.0480	0.015	3.203	0.001	0.019	0.077
zip_98102	1.0399	0.023	46.096	0.000	0.996	1.084

zip_98103	0.8444	0.014	61.657	0.000	0.818	0.871
zip_98105	1.0122	0.017	58.826	0.000	0.979	1.046
zip_98106	0.3093	0.015	20.287	0.000	0.279	0.339
zip_98107	0.8674	0.016	52.801	0.000	0.835	0.900
zip_98108	0.3581	0.018	19.740	0.000	0.323	0.394
zip_98109	1.0654	0.022	48.127	0.000	1.022	1.109
zip_98112	1.1447	0.017	69.261	0.000	1.112	1.177
zip_98115	0.8422	0.014	61.834	0.000	0.815	0.869
zip_98116	0.7853	0.015	50.776	0.000	0.755	0.816
zip_98117	0.8284	0.014	60.131	0.000	0.801	0.855
zip_98118	0.4506	0.014	32.292	0.000	0.423	0.478
zip_98119	1.0490	0.018	56.847	0.000	1.013	1.085
zip_98122	0.8685	0.016	53.952	0.000	0.837	0.900
zip_98125	0.5680	0.015	39.108	0.000	0.540	0.596
zip_98126	0.5315	0.015	35.141	0.000	0.502	0.561
zip_98133	0.4592	0.014	33.011	0.000	0.432	0.486
zip_98136	0.6915	0.016	42.149	0.000	0.659	0.724
zip_98144	0.6799	0.015	44.383	0.000	0.650	0.710
zip_98146	0.2445	0.016	15.394	0.000	0.213	0.276
zip_98148	0.1560	0.029	5.468	0.000	0.100	0.212
zip_98155	0.4333	0.014	30.528	0.000	0.406	0.461
zip_98166	0.3078	0.016	18.694	0.000	0.276	0.340
zip_98168	0.0370	0.016	2.282	0.022	0.005	0.069
zip_98177	0.6333	0.016	38.437	0.000	0.601	0.666
zip_98178	0.1180	0.016	7.217	0.000	0.086	0.150
zip_98188	0.0772	0.020	3.835	0.000	0.038	0.117
zip_98198	0.0457	0.016	2.859	0.004	0.014	0.077
zip_98199	0.9211	0.016	59.039	0.000	0.891	0.952

Omnibus:	2454.640	**Durbin-Watson:**	2.013
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	12487.516
Skew:	-0.441	**Prob(JB):**	0.00
Kurtosis:	6.619	**Cond. No.**	4.64e+06

Notes:

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

[2] The condition number is large, 4.64e+06. This might indicate that there are strong multicollinearity or other numerical problems.

In [39]:
```
# dropping variables with high p values - improves Cond. No.
X_preprocessed = X_preprocessed.drop(['waterfront_NO', 'view_FAIR', 'zip_98023'
                                      'zip_98032', 'zip_98168'], axis=1)

outcome = 'price'
data_ols = pd.concat([y_log, X_preprocessed], axis=1)
predictors = data_ols.drop('price', axis=1)
pred_sum = '+'.join(predictors.columns)
formula = outcome + '~' + pred_sum

second_model = ols(formula=formula, data=data_ols).fit()
second_model.summary()
```

Out[39]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.857
Model:	OLS	**Adj. R-squared:**	0.856
Method:	Least Squares	**F-statistic:**	1550.
Date:	Sun, 31 Jul 2022	**Prob (F-statistic):**	0.00
Time:	22:48:05	**Log-Likelihood:**	4188.1
No. Observations:	21597	**AIC:**	-8208.
Df Residuals:	21513	**BIC:**	-7538.
Df Model:	83		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	10.5271	0.140	75.178	0.000	10.253	10.802
sqft_living	0.0003	2.55e-06	134.192	0.000	0.000	0.000
sqft_lot	6.628e-07	3.62e-08	18.293	0.000	5.92e-07	7.34e-07
bedrooms	-0.0049	0.002	-2.615	0.009	-0.009	-0.001
floors	-0.0210	0.004	-5.501	0.000	-0.028	-0.013
mth_sold	-0.0050	0.000	-11.516	0.000	-0.006	-0.004
renovated	0.0872	0.008	11.062	0.000	0.072	0.103
yr_built	0.0008	7.18e-05	10.846	0.000	0.001	0.001
sqft_basement	-0.0001	4.3e-06	-27.959	0.000	-0.000	-0.000
condition_Fair	-0.1682	0.016	-10.790	0.000	-0.199	-0.138
condition_Good	0.0405	0.004	11.463	0.000	0.034	0.047
condition_Poor	-0.3366	0.037	-9.016	0.000	-0.410	-0.263
condition_VeryGood	0.1089	0.006	19.527	0.000	0.098	0.120
waterfront_YES	0.4113	0.021	19.989	0.000	0.371	0.452
view_EXCELLENT	0.2110	0.015	14.174	0.000	0.182	0.240
view_GOOD	0.0851	0.011	8.070	0.000	0.064	0.106
view_NA	-0.0897	0.026	-3.475	0.001	-0.140	-0.039
view_NONE	-0.1545	0.006	-25.546	0.000	-0.166	-0.143
zip_98002	-0.0755	0.015	-4.942	0.000	-0.105	-0.046
zip_98003	0.0344	0.013	2.606	0.009	0.009	0.060
zip_98004	1.1769	0.013	92.544	0.000	1.152	1.202
zip_98005	0.8294	0.017	50.261	0.000	0.797	0.862
zip_98006	0.7137	0.011	66.253	0.000	0.693	0.735
zip_98007	0.7101	0.018	39.945	0.000	0.675	0.745
zip_98008	0.6779	0.013	51.337	0.000	0.652	0.704

zip_98010	0.2217	0.021	10.633	0.000	0.181	0.263
zip_98011	0.4841	0.015	31.426	0.000	0.454	0.514
zip_98014	0.2726	0.019	14.293	0.000	0.235	0.310
zip_98019	0.3160	0.016	20.201	0.000	0.285	0.347
zip_98022	0.0196	0.015	1.352	0.176	-0.009	0.048
zip_98024	0.4057	0.023	17.430	0.000	0.360	0.451
zip_98027	0.5471	0.011	47.776	0.000	0.525	0.570
zip_98028	0.4389	0.013	33.350	0.000	0.413	0.465
zip_98029	0.6541	0.013	51.791	0.000	0.629	0.679
zip_98030	0.0566	0.014	4.124	0.000	0.030	0.083
zip_98031	0.0816	0.013	6.105	0.000	0.055	0.108
zip_98033	0.8163	0.011	72.880	0.000	0.794	0.838
zip_98034	0.5577	0.010	54.357	0.000	0.538	0.578
zip_98038	0.1659	0.010	16.419	0.000	0.146	0.186
zip_98039	1.3092	0.029	45.055	0.000	1.252	1.366
zip_98040	0.9518	0.013	70.903	0.000	0.926	0.978
zip_98042	0.0564	0.010	5.474	0.000	0.036	0.077
zip_98045	0.3235	0.015	22.002	0.000	0.295	0.352
zip_98052	0.6933	0.010	68.450	0.000	0.673	0.713
zip_98053	0.5925	0.012	50.661	0.000	0.570	0.615
zip_98055	0.1338	0.013	9.948	0.000	0.107	0.160
zip_98056	0.3015	0.011	26.315	0.000	0.279	0.324
zip_98058	0.1781	0.011	16.251	0.000	0.157	0.200
zip_98059	0.3490	0.011	31.936	0.000	0.328	0.370
zip_98065	0.3814	0.013	29.666	0.000	0.356	0.407
zip_98070	0.3144	0.020	15.842	0.000	0.276	0.353
zip_98072	0.5393	0.013	40.262	0.000	0.513	0.566
zip_98074	0.6285	0.011	56.168	0.000	0.607	0.650
zip_98075	0.6291	0.012	51.585	0.000	0.605	0.653
zip_98077	0.5220	0.015	33.709	0.000	0.492	0.552
zip_98092	0.0435	0.012	3.583	0.000	0.020	0.067
zip_98102	1.0343	0.021	49.958	0.000	0.994	1.075
zip_98103	0.8389	0.010	80.928	0.000	0.819	0.859
zip_98105	1.0070	0.015	68.631	0.000	0.978	1.036
zip_98106	0.3041	0.012	24.593	0.000	0.280	0.328
zip_98107	0.8619	0.014	62.521	0.000	0.835	0.889

zip_98108	0.3529	0.016	22.357	0.000	0.322	0.384
zip_98109	1.0595	0.020	52.376	0.000	1.020	1.099
zip_98112	1.1392	0.014	82.112	0.000	1.112	1.166
zip_98115	0.8368	0.010	81.661	0.000	0.817	0.857
zip_98116	0.7801	0.013	61.876	0.000	0.755	0.805
zip_98117	0.8230	0.010	78.733	0.000	0.802	0.843
zip_98118	0.4453	0.011	41.656	0.000	0.424	0.466
zip_98119	1.0434	0.016	64.710	0.000	1.012	1.075
zip_98122	0.8629	0.013	64.541	0.000	0.837	0.889
zip_98125	0.5629	0.011	49.147	0.000	0.540	0.585
zip_98126	0.5260	0.012	43.162	0.000	0.502	0.550
zip_98133	0.4541	0.011	42.525	0.000	0.433	0.475
zip_98136	0.6866	0.014	49.981	0.000	0.660	0.714
zip_98144	0.6745	0.012	54.247	0.000	0.650	0.699
zip_98146	0.2393	0.013	18.227	0.000	0.214	0.265
zip_98148	0.1507	0.027	5.563	0.000	0.098	0.204
zip_98155	0.4283	0.011	38.787	0.000	0.407	0.450
zip_98166	0.3029	0.014	21.893	0.000	0.276	0.330
zip_98177	0.6283	0.014	45.358	0.000	0.601	0.655
zip_98178	0.1126	0.014	8.231	0.000	0.086	0.139
zip_98188	0.0721	0.018	3.992	0.000	0.037	0.107
zip_98198	0.0409	0.013	3.087	0.002	0.015	0.067
zip_98199	0.9159	0.013	71.693	0.000	0.891	0.941

Omnibus:	2448.320	**Durbin-Watson:**	2.012
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	12440.829
Skew:	-0.440	**Prob(JB):**	0.00
Kurtosis:	6.613	**Cond. No.**	4.56e+06

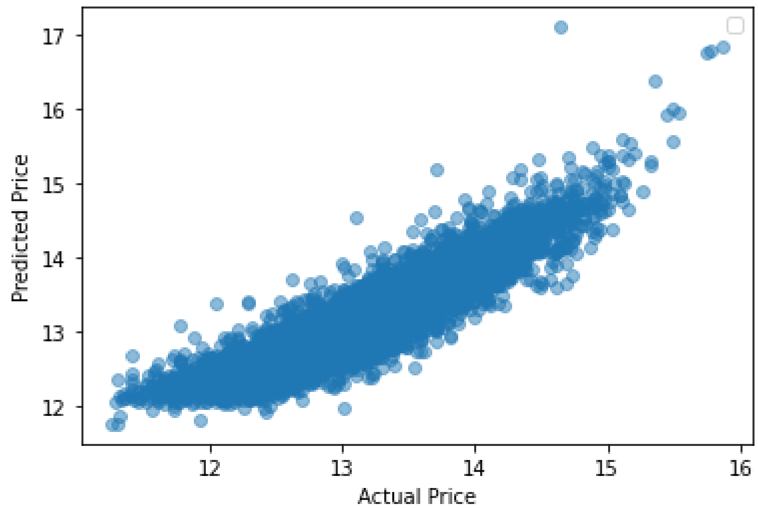
Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 4.56e+06. This might indicate that there are
strong multicollinearity or other numerical problems.

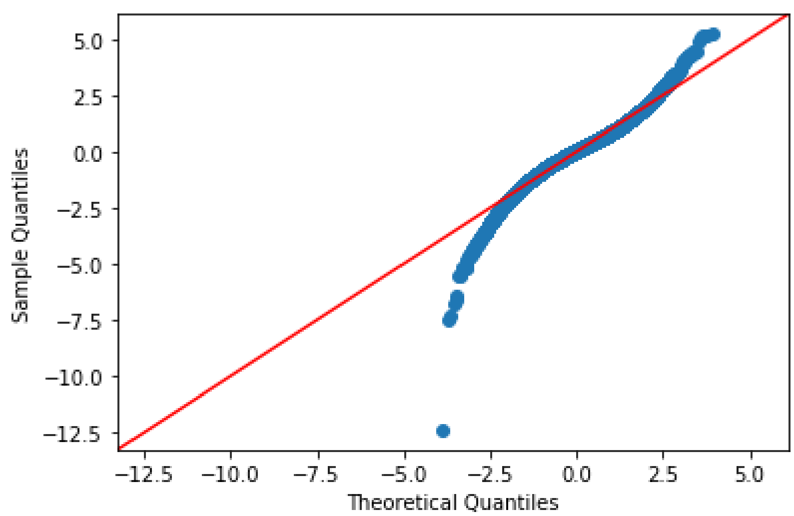
There is certainly improvement in this model compared to the baseline, both in terms of R^2 and the various model assumptions. The JB value is still quite large, indicating that errors are not normally distributed, and kurtosis is above 3, indicating the data has heavier tails than a normal distribution. No VIF is above 5, but a few are in the 2-3 range, which could likely be improved. We can probably get rid of a few independent variables in our next model to reduce multicollinearity even further and even transform some to reduce skew / kurtosis, hopefully without sacrificing R^2 greatly.

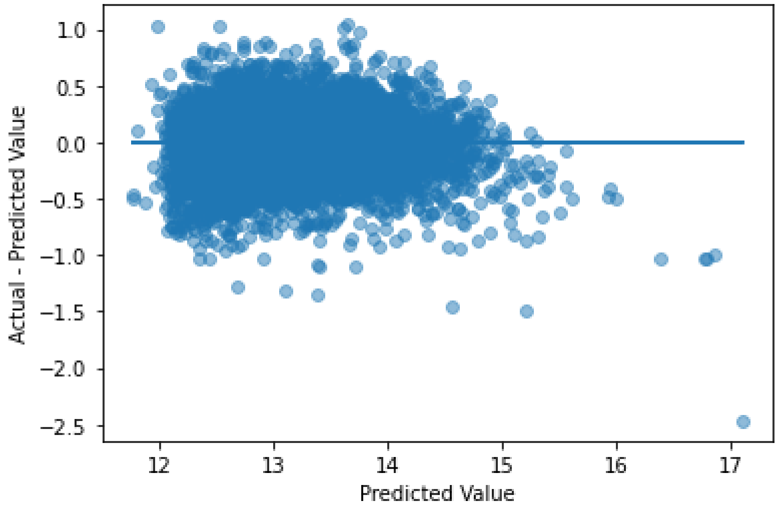
In [40]:
```
# Linearity check

model = second_model
X_model = X_preprocessed
y_model = y_log['price']

preds = model.predict(X_model)
fig, ax = plt.subplots()
ax.scatter(y_model, preds, alpha=0.5)
ax.set_xlabel("Actual Price")
ax.set_ylabel("Predicted Price")
ax.legend();

# Normality of residuals check

residuals = (y_model - preds)
sm.graphics.qqplot(residuals, dist=stats.norm, line='45', fit=True);

# JB test
name = ['Jarque-Bera','Prob','Skew', 'Kurtosis']
test = sms.jarque_bera(model.resid)
print("JB Results", list(zip(name, test)))

# Homoscedasticity check

fig, ax = plt.subplots()

ax.scatter(preds, residuals, alpha=0.5)
ax.plot(preds, [0 for i in range(len(X_model))])
ax.set_xlabel("Predicted Value")
ax.set_ylabel("Actual - Predicted Value");

# multicollinearity

df_corr=X_preprocessed.corr().abs().stack().reset_index().sort_values(0, ascenc
df_corr['pairs'] = list(zip(df_corr.level_0, df_corr.level_1))
df_corr.set_index(['pairs'], inplace = True)
df_corr.drop(columns=['level_1', 'level_0'], inplace = True)
df_corr.columns = ['cc']
df_corr.drop_duplicates(inplace=True)
print(df_corr[(df_corr.cc>.75) & (df_corr.cc<0.99)])

predictors_int = sm.add_constant(predictors)
model = sm.OLS(y_log['price'],predictors_int).fit()
vif = [variance_inflation_factor(predictors_int.values, i) for i in range(predi
vif_ser = pd.Series(vif, index=predictors_int.columns, name="Variance Inflatior
print(vif_ser.sort_values())
```

```
No artists with labels found to put in legend.  Note that artists whose label
start with an underscore are ignored when legend() is called with no argument.
```

```
JB Results [('Jarque-Bera', 12440.829118754615), ('Prob', 0.0), ('Skew', -0.43
96203133317141), ('Kurtosis', 6.6127551167262135)]
Empty DataFrame
Columns: [cc]
Index: []
mth_sold                1.006074
condition_Poor          1.012263
condition_Fair          1.027782
zip_98148               1.046476
view_NA                 1.050705
                          ...
sqft_basement           1.937326
floors                  2.291060
yr_built                2.409667
sqft_living             2.969580
const               10618.345439
Name: Variance Inflation Factor, Length: 84, dtype: float64
```







Final Model

Going to take log of sq footage to see if that improves residuals, also going to get rid of Waterfront_NO, view_FAIR, and zip codes with high p values.

In [41]:
```
X_preprocessed.columns
```

Out[41]:
```
Index(['sqft_living', 'sqft_lot', 'bedrooms', 'floors', 'mth_sold',
       'renovated', 'yr_built', 'sqft_basement', 'condition_Fair',
       'condition_Good', 'condition_Poor', 'condition_VeryGood',
       'waterfront_YES', 'view_EXCELLENT', 'view_GOOD', 'view_NA', 'view_NON
E',
       'zip_98002', 'zip_98003', 'zip_98004', 'zip_98005', 'zip_98006',
       'zip_98007', 'zip_98008', 'zip_98010', 'zip_98011', 'zip_98014',
       'zip_98019', 'zip_98022', 'zip_98024', 'zip_98027', 'zip_98028',
       'zip_98029', 'zip_98030', 'zip_98031', 'zip_98033', 'zip_98034',
       'zip_98038', 'zip_98039', 'zip_98040', 'zip_98042', 'zip_98045',
       'zip_98052', 'zip_98053', 'zip_98055', 'zip_98056', 'zip_98058',
       'zip_98059', 'zip_98065', 'zip_98070', 'zip_98072', 'zip_98074',
       'zip_98075', 'zip_98077', 'zip_98092', 'zip_98102', 'zip_98103',
       'zip_98105', 'zip_98106', 'zip_98107', 'zip_98108', 'zip_98109',
       'zip_98112', 'zip_98115', 'zip_98116', 'zip_98117', 'zip_98118',
       'zip_98119', 'zip_98122', 'zip_98125', 'zip_98126', 'zip_98133',
       'zip_98136', 'zip_98144', 'zip_98146', 'zip_98148', 'zip_98155',
       'zip_98166', 'zip_98177', 'zip_98178', 'zip_98188', 'zip_98198',
       'zip_98199'],
      dtype='object')
```

In [42]:
```
# Log transformation of continuous variables

cont_cols = ['sqft_living', 'sqft_lot', 'sqft_basement']
df_cont = X[cont_cols]

log_names = [f'{column}_log' for column in df_cont.columns]

df_log = np.log(df_cont)
df_log.columns = log_names
```

```
/Library/Frameworks/Python.framework/Versions/3.10/lib/python3.10/site-package
s/pandas/core/internals/blocks.py:402: RuntimeWarning: divide by zero encounte
red in log
  result = func(self.values, **kwargs)
```

In [43]:
```
# Categorical one hot encoding
dummy_cat = ['waterfront', 'condition', 'view']
df_ohe = pd.get_dummies(X[dummy_cat], prefix=dummy_cat, drop_first=True)
```

I went through several iterations of including/exclding different variables. The below model maintains the highest R^2 while significantly reducing skew, kurtosis, condition no. and improves normality of residuals. I also tried including the non log transformed independent variables and concluded that the log transformation improved the model.

- removing renovated doesnt seem to hurt the model at all, so no need to include
- dropping log of sqft_basement reduces R^2 by 0.005 but reduces Kurtosis, JB and condition more
- including has_basement increases kurtosis and doesn't strongly impact R^2

In [44]:
```
X_preprocessed_2 = pd.concat([df_log,  df_ohe, zipcode_dummies], axis=1) #X['re
X_preprocessed_2 = X_preprocessed_2.drop(['waterfront_NO', 'sqft_lot_log', 'sqf
                                          'zip_98032', 'view_FAIR','zip_98023',
                                         axis=1)


X_preprocessed_2
```

Out[44]:

	sqft_living_log	waterfront_YES	condition_Fair	condition_Good	condition_Poor	condit
0	7.073270	0	0	0	0	
1	7.851661	0	0	0	0	
2	6.646391	0	0	0	0	
3	7.580700	0	0	0	0	
4	7.426549	0	0	0	0	
...	...	...	...	...	...	
21592	7.333023	0	0	0	0	
21593	7.745003	0	0	0	0	
21594	6.927558	0	0	0	0	
21595	7.377759	0	0	0	0	
21596	6.927558	0	0	0	0	

21597 rows × 76 columns

Results & Model Assumption Check

In [45]:
```
outcome = 'price'
data_ols = pd.concat([y_log, X_preprocessed_2], axis=1)
predictors = data_ols.drop('price', axis=1)
pred_sum = '+'.join(predictors.columns)
```

```
formula = outcome + '~' + pred_sum

final_model = ols(formula=formula, data=data_ols).fit()
final_model.summary()
```

Out[45]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.845
Model:	OLS	**Adj. R-squared:**	0.845
Method:	Least Squares	**F-statistic:**	1547.
Date:	Sun, 31 Jul 2022	**Prob (F-statistic):**	0.00
Time:	22:48:28	**Log-Likelihood:**	3357.1
No. Observations:	21597	**AIC:**	-6560.
Df Residuals:	21520	**BIC:**	-5946.
Df Model:	76		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	7.5260	0.031	239.220	0.000	7.464	7.588
sqft_living_log	0.6799	0.004	175.090	0.000	0.672	0.687
waterfront_YES	0.4487	0.021	21.034	0.000	0.407	0.491
condition_Fair	-0.1267	0.016	-7.858	0.000	-0.158	-0.095
condition_Good	0.0078	0.003	2.315	0.021	0.001	0.014
condition_Poor	-0.2708	0.039	-6.992	0.000	-0.347	-0.195
condition_VeryGood	0.0564	0.005	10.367	0.000	0.046	0.067
view_EXCELLENT	0.2570	0.015	16.660	0.000	0.227	0.287
view_GOOD	0.1044	0.011	9.547	0.000	0.083	0.126
view_NA	-0.0944	0.027	-3.519	0.000	-0.147	-0.042
view_NONE	-0.1555	0.006	-24.952	0.000	-0.168	-0.143
zip_98003	0.0460	0.014	3.337	0.001	0.019	0.073
zip_98004	1.2450	0.013	94.203	0.000	1.219	1.271
zip_98005	0.8490	0.017	49.425	0.000	0.815	0.883
zip_98006	0.7570	0.011	67.425	0.000	0.735	0.779
zip_98007	0.7167	0.019	38.725	0.000	0.680	0.753
zip_98008	0.6735	0.014	48.914	0.000	0.646	0.700
zip_98010	0.3206	0.022	14.833	0.000	0.278	0.363
zip_98011	0.4811	0.016	29.935	0.000	0.450	0.513
zip_98014	0.3938	0.020	20.087	0.000	0.355	0.432
zip_98019	0.3605	0.016	22.163	0.000	0.329	0.392
zip_98022	0.1071	0.015	7.163	0.000	0.078	0.136
zip_98024	0.5471	0.024	22.809	0.000	0.500	0.594
zip_98027	0.5915	0.012	49.636	0.000	0.568	0.615
zip_98028	0.4366	0.014	31.756	0.000	0.410	0.464

zip_98029	0.6790	0.013	51.782	0.000	0.653	0.705
zip_98030	0.0680	0.014	4.753	0.000	0.040	0.096
zip_98031	0.0927	0.014	6.652	0.000	0.065	0.120
zip_98033	0.8532	0.012	72.914	0.000	0.830	0.876
zip_98034	0.5618	0.011	52.244	0.000	0.541	0.583
zip_98038	0.2032	0.011	19.331	0.000	0.183	0.224
zip_98039	1.5028	0.030	49.980	0.000	1.444	1.562
zip_98040	1.0100	0.014	72.419	0.000	0.983	1.037
zip_98042	0.1034	0.011	9.634	0.000	0.082	0.124
zip_98045	0.3914	0.015	25.643	0.000	0.362	0.421
zip_98052	0.7081	0.011	66.792	0.000	0.687	0.729
zip_98053	0.6888	0.012	57.044	0.000	0.665	0.712
zip_98055	0.1517	0.014	10.801	0.000	0.124	0.179
zip_98056	0.3380	0.012	28.249	0.000	0.315	0.361
zip_98058	0.2040	0.011	17.806	0.000	0.182	0.226
zip_98059	0.3991	0.011	35.083	0.000	0.377	0.421
zip_98065	0.4366	0.013	32.653	0.000	0.410	0.463
zip_98070	0.3950	0.020	19.351	0.000	0.355	0.435
zip_98072	0.5750	0.014	41.175	0.000	0.548	0.602
zip_98074	0.6689	0.012	57.263	0.000	0.646	0.692
zip_98075	0.7034	0.013	55.586	0.000	0.679	0.728
zip_98077	0.6298	0.016	39.319	0.000	0.598	0.661
zip_98092	0.0870	0.013	6.889	0.000	0.062	0.112
zip_98102	1.0448	0.021	49.205	0.000	1.003	1.086
zip_98103	0.8385	0.010	80.408	0.000	0.818	0.859
zip_98105	0.9876	0.015	65.804	0.000	0.958	1.017
zip_98106	0.3350	0.013	25.961	0.000	0.310	0.360
zip_98107	0.8672	0.014	61.434	0.000	0.840	0.895
zip_98108	0.3391	0.016	20.694	0.000	0.307	0.371
zip_98109	1.0381	0.021	49.892	0.000	0.997	1.079
zip_98112	1.1340	0.014	80.631	0.000	1.106	1.162
zip_98115	0.8209	0.011	78.011	0.000	0.800	0.842
zip_98116	0.7679	0.013	59.062	0.000	0.742	0.793
zip_98117	0.8220	0.011	76.733	0.000	0.801	0.843
zip_98118	0.4536	0.011	41.012	0.000	0.432	0.475
zip_98119	1.0158	0.016	61.589	0.000	0.983	1.048

zip_98122	0.8509	0.014	62.432	0.000	0.824	0.878
zip_98125	0.5629	0.012	47.168	0.000	0.540	0.586
zip_98126	0.5550	0.013	43.866	0.000	0.530	0.580
zip_98133	0.4706	0.011	42.223	0.000	0.449	0.492
zip_98136	0.6945	0.014	48.779	0.000	0.667	0.722
zip_98144	0.6733	0.013	52.752	0.000	0.648	0.698
zip_98146	0.2687	0.014	19.627	0.000	0.242	0.296
zip_98148	0.1759	0.028	6.240	0.000	0.121	0.231
zip_98155	0.4443	0.012	38.475	0.000	0.422	0.467
zip_98166	0.3222	0.014	22.347	0.000	0.294	0.350
zip_98168	0.0646	0.014	4.590	0.000	0.037	0.092
zip_98177	0.6342	0.014	43.959	0.000	0.606	0.662
zip_98178	0.1076	0.014	7.557	0.000	0.080	0.136
zip_98188	0.0876	0.019	4.657	0.000	0.051	0.124
zip_98198	0.0601	0.014	4.343	0.000	0.033	0.087
zip_98199	0.8986	0.013	68.120	0.000	0.873	0.924

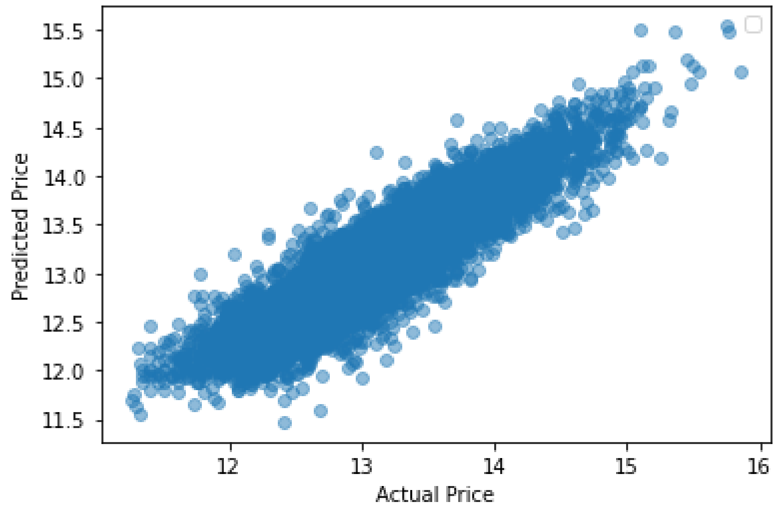
Omnibus:	935.360	**Durbin-Watson:**	2.000
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	3142.856
Skew:	0.053	**Prob(JB):**	0.00
Kurtosis:	4.866	**Cond. No.**	281.

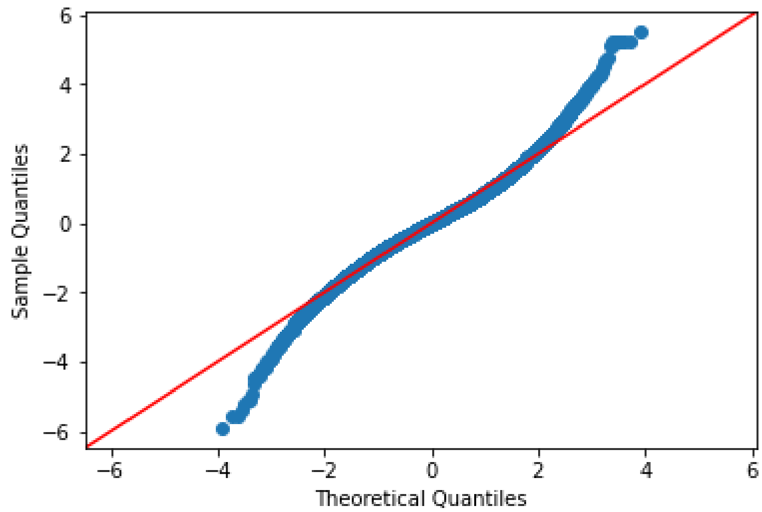
Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

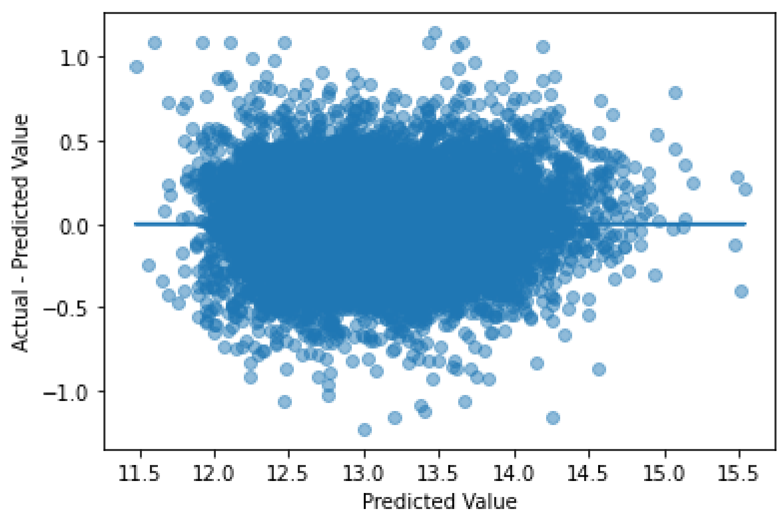
In [46]:
```
# Linearity check

model = final_model
X_model = X_preprocessed_2
y_model = y_log['price']

preds = model.predict(X_model)
fig, ax = plt.subplots()

ax.scatter(y_model, preds, alpha=0.5)
ax.set_xlabel("Actual Price")
ax.set_ylabel("Predicted Price")
ax.legend();

# Normality of residuals check

residuals = (y_model - preds)
sm.graphics.qqplot(residuals, dist=stats.norm, line='45', fit=True);
```

```
# JB test
name = ['Jarque-Bera','Prob','Skew', 'Kurtosis']
test = sms.jarque_bera(model.resid)
print("JB Results", list(zip(name, test)))

# Homoscedasticity check

fig, ax = plt.subplots()

ax.scatter(preds, residuals, alpha=0.5)
ax.plot(preds, [0 for i in range(len(X_model))])
ax.set_xlabel("Predicted Value")
ax.set_ylabel("Actual - Predicted Value");

# Multicollinearity

df_corr=X_model.corr().abs().stack().reset_index().sort_values(0, ascending=Fal
df_corr['pairs'] = list(zip(df_corr.level_0, df_corr.level_1))
df_corr.set_index(['pairs'], inplace = True)
df_corr.drop(columns=['level_1', 'level_0'], inplace = True)
df_corr.columns = ['cc']
df_corr.drop_duplicates(inplace=True)
df_corr[(df_corr.cc>.75) & (df_corr.cc<0.99)]

predictors_int = sm.add_constant(predictors)
model = sm.OLS(y_model,predictors_int).fit()

vif = [variance_inflation_factor(predictors_int.values, i) for i in range(predi
vif_ser = pd.Series(vif, index=predictors_int.columns, name="Variance Inflation
print(vif_ser.sort_values()) # nothing above 5 other than constant which implie
```

```
No artists with labels found to put in legend.  Note that artists whose label
start with an underscore are ignored when legend() is called with no argument.
JB Results [('Jarque-Bera', 3142.856011952616), ('Prob', 0.0), ('Skew', 0.0532
6750222460519), ('Kurtosis', 4.865796774663683)]
condition_Poor      1.008972
condition_Fair      1.018912
zip_98039           1.047384
zip_98148           1.049364
view_NA             1.050290
                      ...
zip_98103           1.477904
waterfront_YES      1.532475
view_EXCELLENT      1.726623
view_NONE           1.764647
const             496.442801
Name: Variance Inflation Factor, Length: 77, dtype: float64
```







This is by far the best model. It is not perfect but shows remarkable improvement in terms of normality of residuals, homoscedasticity and linearity while maintaining a similar R^2 as the second model. Around 85% of the variation in price is explained by the model. Skew of 0.053 is the closest we have seen to 0 thus far, and the kurtosis value of 4.86 is the lowest we've seen thus far.

Conclusion

In [47]:
```
final_model.params.sort_values().tail(50) #top 50 coefficients in terms of magr
```

Out[47]:
```
zip_98108          0.339072
zip_98019          0.360462
zip_98045          0.391448
zip_98014          0.393821
zip_98070          0.394969
zip_98059          0.399139
zip_98065          0.436561
zip_98028          0.436647
zip_98155          0.444322
waterfront_YES     0.448698
zip_98118          0.453604
zip_98133          0.470559
zip_98011          0.481119
zip_98024          0.547078
zip_98126          0.554961
zip_98034          0.561801
zip_98125          0.562930
zip_98072          0.575042
zip_98027          0.591515
zip_98077          0.629763
zip_98177          0.634197
zip_98074          0.668852
zip_98144          0.673332
zip_98008          0.673478
zip_98029          0.678963
sqft_living_log    0.679855
zip_98053          0.688810
zip_98136          0.694462
zip_98075          0.703410
zip_98052          0.708085
zip_98007          0.716704
zip_98006          0.756972
zip_98116          0.767911
zip_98115          0.820940
zip_98117          0.821996
zip_98103          0.838482
zip_98005          0.849017
zip_98122          0.850881
zip_98033          0.853162
zip_98107          0.867193
zip_98199          0.898597
zip_98105          0.987559
zip_98040          1.009959
zip_98119          1.015815
zip_98109          1.038090
zip_98102          1.044787
zip_98112          1.134013
zip_98004          1.244965
zip_98039          1.502781
Intercept          7.526014
dtype: float64
```

In [48]:
```
final_model.params.sort_values().head(30) # bottom 30 coefficients in terms of
```

Out[48]:
```
condition_Poor       -0.270790
view_NONE            -0.155519
condition_Fair       -0.126731
view_NA              -0.094408
condition_Good        0.007843
zip_98003             0.046045
condition_VeryGood    0.056405
zip_98198             0.060128
zip_98168             0.064580
zip_98030             0.068030
zip_98092             0.087010
zip_98188             0.087590
zip_98031             0.092711
zip_98042             0.103425
view_GOOD             0.104433
zip_98022             0.107089
zip_98178             0.107598
zip_98055             0.151720
zip_98148             0.175912
zip_98038             0.203183
zip_98058             0.203987
view_EXCELLENT        0.257027
zip_98146             0.268748
zip_98010             0.320623
zip_98166             0.322191
zip_98106             0.335011
zip_98056             0.337996
zip_98108             0.339072
zip_98019             0.360462
zip_98045             0.391448
dtype: float64
```

In the final model we can see that a house's zip code is highly influential on its sale price given the magnitude of the coefficients of several zip codes, all of which are statistically significant. For example, a house in zip code 98039 is associated with a natural log of sale price that is 1.50 higher, or a price that is about ~4.48 dollars higher.

Square footage of a house's living space also positively impacts sale price. Given a 0.68 coefficient, a 1% increase in sqft_living increases price by 0.68%.

Whether a house is on the waterfront, the quality of view, and how good the condition of the house is also impact sale price. A waterfront property is associated with a log of sale price that is 0.45 higher, or a sale price that is 1.57 dollars higher.

Given the above results, I would recommend the following:

- focus on finding properties in advantageous zip codes
- focus on larger houses, particularity with a larger living space
- waterfront properties and properties with good views tend to yield higher prices
- condition matters. Selecting a house in poor condition can detract from sale price