Project 2 Final Notebook

Stakeholder and Business Problem
Howard S Wright Construction Company

Howard S Wright is a well-known construction company that is prevalent within the King County area. Howard S Wright wants to know what ***features*** should they focus on in order to maximize their profit when building a new home in King County.
Some factors that we intitially thought that Howard S Wright could focus on were:

- Square Footage (specifically the building footprint and the total living space)
- Location
- Numbers of beds and bathrooms
- Quality of the home

In this notebook, we will explore and analyze the data in order to provide the best recommendations to focus on for Howard S Wright to maximize their profit when building a home. (this might be a little redundant, please change if necessary -- I'll go over the notebook one more time before we submit)

Exploratory Data Analysis

In [1]:
```
# Imported appropriate libraries for use in this notebook and our multilinear regressio
import pandas as pd
import numpy as np
import seaborn as sns
from matplotlib import pyplot as plt
from sklearn.linear_model import LinearRegression
from sklearn.feature_selection import RFE
from sklearn.preprocessing import PolynomialFeatures, StandardScaler
import statsmodels
from statsmodels.formula.api import ols
from sklearn.model_selection import train_test_split
from sklearn.dummy import DummyRegressor
from statsmodels.tools.eval_measures import rmse
from statsmodels.api import qqplot
from scipy import stats
from sklearn.preprocessing import OneHotEncoder
from folium.plugins import FastMarkerCluster
import folium
from sklearn.metrics import r2_score
import matplotlib.ticker as ticker
```

Created functions to help with ease of access in our linear regression analysis

In [2]:
```
def sm_metrics(model, y, X):
    # import associated tools
```

```python
    from statsmodels.tools.eval_measures import rmse, mse, meanabs

    # now generate predictions
    ypred = model.predict(X)

    # Print values
    print('Metrics:')
    # MAE
    print(f"Mean Absolute Error: {meanabs(y, ypred):.3f}")
    # MSE
    print(f"Mean Squared Error: {mse(y, ypred):.3f}")
    # RMSE
    print(f"Root Mean Squared Error: {rmse(y, ypred):.3f}")
    return
```

In [3]:

```python
def sk_metrics(y, model):
    from sklearn.metrics import mean_squared_error, mean_absolute_error

    print("Metrics:")
    # R2
    print(f"R2: {r2_score(y, model):.3f}")
    # MAE
    print(f"Mean Absolute Error: {mean_absolute_error(y, model):.3f}")
    # MSE
    print(f"Mean Squared Error: {mean_squared_error(y, model):.3f}")
    # RMSE - just MSE but set squared=False
    print(f"Root Mean Squared Error: {mean_squared_error(y, model, squared=False):.3f}"
    return
```

In [4]:

```python
def qq(x_test, x_train, y_test, y_train):
    # QQ plots are generally great tools for checking for normality.
    import statsmodels.api as sm
    from sklearn.linear_model import LinearRegression

    # Calculating residuals
    lr = LinearRegression()
    lr.fit(x_train, y_train)
    y_hat = lr.predict(x_test)

    residuals = y_test - y_hat


    sm.qqplot(residuals, line = 'r');
    return
```

In [5]:

```python
# evaluates the Variance Inflation Factor of X_train variables

def vif(X_train):
    from statsmodels.stats.outliers_influence import variance_inflation_factor
    # defining an empty dataframe to capture the VIF scores
    vif = pd.DataFrame()

    # For each column,run a variance_inflaction_factor against all other columns to get
    vif["VIF"] = [variance_inflation_factor(X_train.values, i) for i in range(len(X_tra

    # label the scores with their related columns
```

```
    vif["features"] = X_train.columns

    # print out the vif table and return
    print(vif)
    return
```

In [6]:

```
def lr_model_metrics(x_test, x_train, y_test, y_train, cat_vars):
    # One hot encoding cat vars
    onehot = OneHotEncoder(sparse=False, handle_unknown = 'ignore')
    x_train_cat = pd.DataFrame(onehot.fit_transform(x_train[cat_vars]))
    x_train_cat.columns = onehot.get_feature_names(cat_vars)
    x_test_cat = pd.DataFrame(onehot.transform(x_test[cat_vars]))
    x_test_cat.columns = onehot.get_feature_names(cat_vars)

    # Resetting indices to avoid joining conflicts and creation of NaN entries
    x_train_cat.reset_index(drop=True, inplace=True)
    x_test_cat.reset_index(drop=True, inplace=True)
    x_train.reset_index(drop=True, inplace=True)
    x_test.reset_index(drop=True, inplace=True)

    # Combine dummied cat vars with non-cat
    x_train_df = x_train_cat.join(x_train.drop(cat_vars, axis = 1))
    x_test_df = x_test_cat.join(x_test.drop(cat_vars, axis = 1))

    # Run linear regression model for data
    lr = LinearRegression()
    model = lr.fit(x_train_df, y_train)

    print('Train Data')
    sk_metrics(y_train, model.predict(x_train_df.values))

    print('Test Data')
    sk_metrics(y_test, model.predict(x_test_df.values))
    return x_train_df, x_test_df, model
```

We utilized the `kc_house_data` as well as demographics data `demographic_spatial_join.xls` that we acquired online from King County's census data. We utilized a GIS software in order to retrieve the specific data that we needed.

Performing some basic initial exploratory data analysis to see what data we're working with and if there are any missing data values that we need to take into consideration.

In [7]:

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

In [8]:

```
housedf.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 [9]:

```
housedf.head()
```

Out[9]:

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

5 rows × 21 columns

In [10]:

```
housedf.columns
```

Out[10]:

```
Index(['id', 'date', 'price', 'bedrooms', 'bathrooms', 'sqft_living',
       'sqft_lot', 'floors', 'waterfront', 'view', 'condition', 'grade',
       'sqft_above', 'sqft_basement', 'yr_built', 'yr_renovated', 'zipcode',
       'lat', 'long', 'sqft_living15', 'sqft_lot15'],
      dtype='object')
```

Created a few dataframes for different use cases:

- **dfinit**: used to drop columns that we were not utilizing in our model/data analysis (mostly categorical columns)
- **dfrev1**: used to drop numerical columns
- **dfrevcopy**: used for testing some modeling so that I didn't have to re-run everything when I made a mistake

Also engineered some features and added them to the original housedf:

- **sqft_per_bedroom**: the sqft_living divided by bedrooms value for avg sqft per bedroom
- **footprint**: the sqft_living divided by sqft_lot for relative sqft of usage
- **bedbathratio**: the number of bedrooms divided by bathrooms since these values have high multicollinearity

In [11]:

```
housedf.drop_duplicates(keep= 'first', inplace = True)
dfinit = housedf.drop(['id', 'date', 'yr_renovated', 'condition', 'waterfront', 'lat',
                  'sqft_above', 'sqft_basement', 'view'], axis=1).copy()
# Created duplicate dataframes so that we could work on data without accidentally affec
dfrev1 = dfinit.drop(['sqft_living15', 'sqft_lot15'], axis=1).copy()
dfrevcopy = dfinit.drop(['sqft_living15', 'sqft_lot15'], axis=1).copy()

# Feature engineered sqft_per_bedroom as a data column since for our stakeholder, knowi
# would be useful in deciding which direction to go for homebuilding.
housedf['sqft_per_bedroom'] = housedf['sqft_living'] / housedf['bedrooms']

# Feature engineered the footprint column to visualized the relationship between sqft o
# stakeholder would know on avg what home sizes they would be working with.
housedf['footprint'] = housedf['sqft_living'] / housedf['sqft_lot']

# Feature engineered the bedbathratio since they have decently high multicollinearity -
# ratio might give us a better R^2 value
housedf['bedbathratio'] = housedf['bedrooms'] / housedf['bathrooms']

# Printed out housedf just to check that columns were added correctly
housedf
```

Out[11]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfron
0	7129300520	10/13/2014	221900.0	3	1.00	1180	5650	1.0	NaN
1	6414100192	12/9/2014	538000.0	3	2.25	2570	7242	2.0	NO
2	5631500400	2/25/2015	180000.0	2	1.00	770	10000	1.0	NO
3	2487200875	12/9/2014	604000.0	4	3.00	1960	5000	1.0	NO
4	1954400510	2/18/2015	510000.0	3	2.00	1680	8080	1.0	NO
...	...	...	...	...	...	...	...	...	.
21592	263000018	5/21/2014	360000.0	3	2.50	1530	1131	3.0	NO
21593	6600060120	2/23/2015	400000.0	4	2.50	2310	5813	2.0	NO
21594	1523300141	6/23/2014	402101.0	2	0.75	1020	1350	2.0	NO
21595	291310100	1/16/2015	400000.0	3	2.50	1600	2388	2.0	NaN
21596	1523300157	10/15/2014	325000.0	2	0.75	1020	1076	2.0	NO

21597 rows × 24 columns

Pulled kc_zips information from the King County Website. We identified the unique zipcode values and created a list with those values to use in our modeling. After creating this new dataframe, we did intiial exploratory data analysis in a similar fashion for this dataset as we did for the `kc_house_data.csv`

In [12]:
```
kc_zips = [98178, 98125, 98028, 98136, 98074, 98053, 98003, 98198,
           98146, 98038, 98007, 98115, 98107, 98126, 98019, 98103,
           98002, 98133, 98040, 98092, 98030, 98119, 98112, 98052,
           98027, 98117, 98058, 98001, 98056, 98166, 98023, 98070,
           98148, 98105, 98042, 98008, 98059, 98122, 98144, 98004,
           98005, 98034, 98075, 98116, 98010, 98118, 98199, 98032,
           98045, 98102, 98077, 98108, 98168, 98177, 98065, 98029,
           98006, 98109, 98022, 98033, 98155, 98024, 98011, 98031,
           98106, 98072, 98188, 98014, 98055, 98039]
```

In [13]:
```
df2 = pd.read_excel('data/demographic_spatial_join.xls')

b_series = df2.ZCTA5CE10.isin(kc_zips)
df_zips = df2[b_series]

df_names = df_zips[['ZCTA5CE10', 'NAME']]
df_names.head()
```

Out[13]:

	ZCTA5CE10	NAME
0	98001	Southeast
1	98001	Southwest
2	98002	Southeast
3	98003	Southeast
4	98003	Southwest

In [14]:
```
df_names.NAME.value_counts()
```

Out[14]:
```
Northeast    33
West         29
Southeast    26
Southwest    17
Shoreline    12
Name: NAME, dtype: int64
```

In [15]:
```
df_names
```

Out[15]:

	ZCTA5CE10	NAME
0	98001	Southeast
1	98001	Southwest
2	98002	Southeast
3	98003	Southeast
4	98003	Southwest

	ZCTA5CE10	NAME
...	...	...
138	98188	Southeast
139	98188	Southwest
141	98198	Southeast
142	98198	Southwest
143	98199	West

117 rows × 2 columns

In [16]:

```
# Dropping duplicates randomly, for the moment
df_names.drop_duplicates(subset=['ZCTA5CE10'], inplace=True)
df_names.ZCTA5CE10
```

```
<ipython-input-16-af7d0a158eea>: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/stable/user_
guide/indexing.html#returning-a-view-versus-a-copy
  df_names.drop_duplicates(subset=['ZCTA5CE10'], inplace=True)
```

Out[16]:

```
0      98001
2      98002
3      98003
5      98004
6      98005
       ...
131    98177
135    98178
138    98188
141    98198
143    98199
Name: ZCTA5CE10, Length: 70, dtype: int64
```

In [17]:

```
# lists of zipcodes
northeast = df_names.query('NAME=="Northeast"')['ZCTA5CE10'].to_list()
west = df_names.query('NAME=="West"')['ZCTA5CE10'].to_list()
shoreline = df_names.query('NAME=="Shoreline"')['ZCTA5CE10'].to_list()
southwest = df_names.query('NAME=="Southwest"')['ZCTA5CE10'].to_list()
southeast = df_names.query('NAME=="Southeast"')['ZCTA5CE10'].to_list()
print("Northeast: ", northeast)
print("Shoreline: ", shoreline)
```

```
Northeast:  [98004, 98005, 98006, 98007, 98008, 98011, 98014, 98019, 98024, 98027, 9802
8, 98029, 98033, 98034, 98038, 98039, 98040, 98045, 98052, 98053, 98056, 98059, 98065, 9
8072, 98074, 98075, 98077]
Shoreline:  [98125, 98133, 98155, 98177]
```

In [18]:

```
# Create new  DF for revisions, change type
dfrev2 = dfrev1.copy()
#dfrev2 = dfrev2.astype({"zipcode": str})
# use lists to make categorical bins
dfrev2['zipcode'] = dfrev2.zipcode.replace(to_replace=northeast, value = "Northeast")
```

```
dfrev2['zipcode'] = dfrev2.zipcode.replace(to_replace=west, value = "West")
dfrev2['zipcode'] = dfrev2.zipcode.replace(to_replace=shoreline, value = "Shoreline")
dfrev2['zipcode'] = dfrev2.zipcode.replace(to_replace=southwest, value = "Southwest")
dfrev2['zipcode'] = dfrev2.zipcode.replace(to_replace=southeast, value = "Southeast")

dfrev2.zipcode.value_counts()
```

Out[18]:

```
Northeast    8560
West         4442
Southeast    4126
Southwest    2866
Shoreline    1603
Name: zipcode, dtype: int64
```

Correlation and Heatmap Visualization

Prior to running the model on our datasets, we had to check the data for any correlation or multicollinearity so that we could accomodate for that in our model.

In [19]:

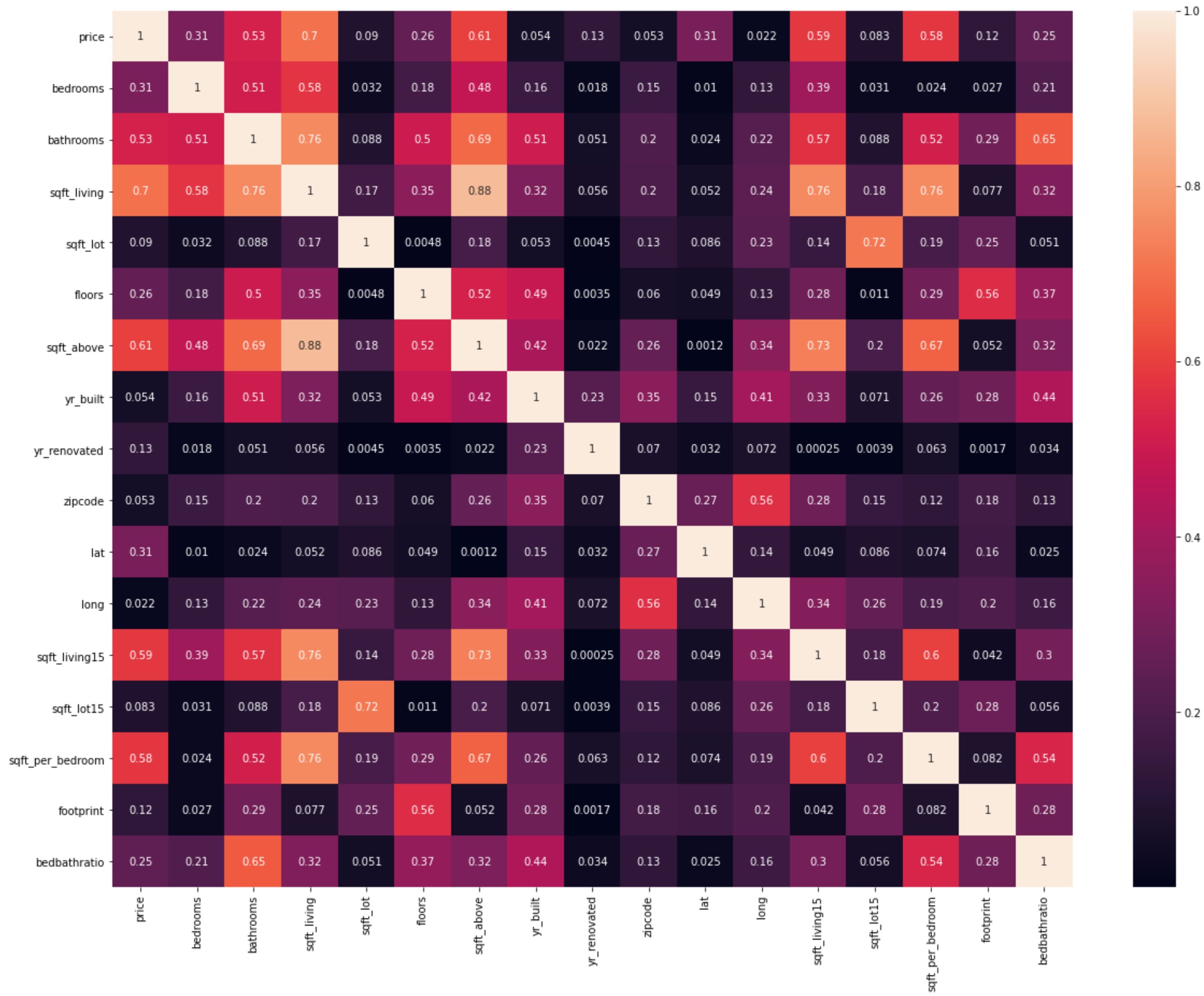
```
housedf.corr()
```

Out[19]:

	id	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	sqft_ab
id	1.000000	-0.016772	0.001150	0.005162	-0.012241	-0.131911	0.018608	-0.01
price	-0.016772	1.000000	0.308787	0.525906	0.701917	0.089876	0.256804	0.60
bedrooms	0.001150	0.308787	1.000000	0.514508	0.578212	0.032471	0.177944	0.47
bathrooms	0.005162	0.525906	0.514508	1.000000	0.755758	0.088373	0.502582	0.68
sqft_living	-0.012241	0.701917	0.578212	0.755758	1.000000	0.173453	0.353953	0.87
sqft_lot	-0.131911	0.089876	0.032471	0.088373	0.173453	1.000000	-0.004814	0.18
floors	0.018608	0.256804	0.177944	0.502582	0.353953	-0.004814	1.000000	0.52
sqft_above	-0.010799	0.605368	0.479386	0.686668	0.876448	0.184139	0.523989	1.00
yr_built	0.021617	0.053953	0.155670	0.507173	0.318152	0.052946	0.489193	0.42
yr_renovated	-0.012010	0.129599	0.018495	0.051050	0.055660	0.004513	0.003535	0.02
zipcode	-0.008211	-0.053402	-0.154092	-0.204786	-0.199802	-0.129586	-0.059541	-0.26
lat	-0.001798	0.306692	-0.009951	0.024280	0.052155	-0.085514	0.049239	-0.00
long	0.020672	0.022036	0.132054	0.224903	0.241214	0.230227	0.125943	0.34
sqft_living15	-0.002701	0.585241	0.393406	0.569884	0.756402	0.144763	0.280102	0.73
sqft_lot15	-0.138557	0.082845	0.030690	0.088303	0.184342	0.718204	-0.010722	0.19
sqft_per_bedroom	-0.011922	0.580109	-0.024076	0.517415	0.755398	0.190583	0.290654	0.67
footprint	0.088238	0.123063	0.026798	0.287015	0.076988	-0.252601	0.556700	0.05
bedbathratio	-0.014457	-0.249948	0.209444	-0.653476	-0.324152	-0.050648	-0.374139	-0.31

In [20]:

```
plt.figure(figsize = (20,15))
sns.heatmap(housedf.drop(['id'], axis = 1).corr().abs(), annot=True);
```



Model Creation and Application

Created training and test datasets for the housedf dataframe. Utilized a 80 / 20 split.

In [21]:
```
y = housedf['price']
X = housedf[['bedrooms','bathrooms','sqft_living','sqft_lot','floors', 'yr_built', 'zip
             'sqft_per_bedroom', 'footprint', 'bedbathratio']]
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=5
```

Dummy Regressor

Created a Dummy Regressor on the mean for use as our baseline model.

- We used the predict function on our baseline model to check if the printed out array was filled with the same values or not.
- We then checked the score of the baseline model. We know that the score should give us a 0 since it is only accounting for the intercepts. Since this is our baseline model, we will be comparing all of our other models to this as a measurement of success.

In [22]:

```
#Dummy Regressor

basemodel = DummyRegressor(strategy = 'mean')
basemodel.fit(X_train, y_train)
basemodel.predict(X_train)
```

Out[22]:

```
array([540946.37500724, 540946.37500724, 540946.37500724, ...,
       540946.37500724, 540946.37500724, 540946.37500724])
```

In [23]:

```
basemodel.score(X_train, y_train)
```

Out[23]:

```
0.0
```

We defined the `sk_metrics` function at the beginning of our notebook, and by calling it on our `y_train` and basemodel we can evaluate the initial R^2 and RMSE value of our basemodel. These are the baseline scores that we are going to be comparing our future models to in order to gauge success.

In [24]:

```
sk_metrics(y_train, basemodel.predict(X_train))
```

```
Metrics:
R2: 0.000
Mean Absolute Error: 233710.087
Mean Squared Error: 135491967490.227
Root Mean Squared Error: 368092.336
```

In [25]:

```
sk_metrics(y_test, basemodel.predict(X_test))
```

```
Metrics:
R2: -0.000
Mean Absolute Error: 236167.828
Mean Squared Error: 132800122046.262
Root Mean Squared Error: 364417.511
```

StandardScalar and OneHotEncoder

Created a StandardScalar for our dataset because we had data values such as 1 bedroom vs. thousands of sqft. We wanted to see a more accurate representation of our dataset as a whole.

In [26]:

```
X_train_plus_y = pd.concat((X_train, y_train), axis=1)
X_test_plus_y = pd.concat((X_test, y_test), axis=1)
ss = StandardScaler()
ss.fit(X_train)
```

Out[26]:

```
StandardScaler()
```

Created a OneHotEncoder for our initial model

In [27]:

```
ohe = OneHotEncoder()
ohe.fit_transform(X_train)
```

```
<17277x26611 sparse matrix of type '<class 'numpy.float64'>'
```

Out[27]: with 172770 stored elements in Compressed Sparse Row format>

Created a training data sat based on the StandardScalar values and our training/test split. We reset the index at the end of each training/test split to avoid any join conflicts/creation of NaNs that would increase number of entries in our dataset.

In [28]:

```
# Training dataset
X_train_scaled = pd.DataFrame(ss.transform(X_train))
X_train_scaled.columns = X.columns
y_train.reset_index(drop=True,inplace=True)
X_train_scaled_plus_y = pd.concat((X_train_scaled, y_train), axis=1)
X_train.reset_index(drop=True, inplace=True)
```

Created the test dataset based on our StandardScalar values and our training/test split

In [29]:

```
# Testing dataset
X_test_scaled = pd.DataFrame(ss.transform(X_test))
X_test_scaled.columns = X.columns
y_test.reset_index(drop=True,inplace=True)
X_test_scaled_plus_y = pd.concat((X_test_scaled,y_test),axis=1)
X_test.reset_index(drop=True, inplace=True)
```

First Model - our initial multilinear regression model

Created our first model based on the values in our heatmap that had the highest correlation with price, in this case that was the sqft_living + bedrooms + floors columns. We will then use this first model to check and see if the predictors have any significant impact on the price of the homes.

In [30]:

```
# Keep first model as sqft_living + bedrooms + floors to show that was our first model
# 2nd model should be 'price ~ sqft_living + bedrooms + sqft_per_bedroom + footprint' t
formula = 'price ~  sqft_living + bedrooms + floors'
model = ols(formula, X_train_scaled_plus_y).fit()
model.summary()
```

Out[30]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.505
Model:	OLS	**Adj. R-squared:**	0.505
Method:	Least Squares	**F-statistic:**	5874.
Date:	Fri, 18 Feb 2022	**Prob (F-statistic):**	0.00
Time:	15:26:56	**Log-Likelihood:**	-2.3986e+05
No. Observations:	17277	**AIC:**	4.797e+05
Df Residuals:	17273	**BIC:**	4.798e+05
Df Model:	3		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
Intercept	5.409e+05	1970.511	274.521	0.000	5.37e+05	5.45e+05

sqft_living	2.882e+05	2530.414	113.894	0.000	2.83e+05	2.93e+05
bedrooms	-5.411e+04	2402.875	-22.520	0.000	-5.88e+04	-4.94e+04
floors	1412.8026	2110.123	0.670	0.503	-2723.252	5548.857

Omnibus:	11809.269	**Durbin-Watson:**	1.991
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	435749.399
Skew:	2.803	**Prob(JB):**	0.00
Kurtosis:	26.956	**Cond. No.**	2.11

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

After running the model, we see that sqft_living and bedrooms are a significant factor in determining the price of a home. Since the p-value of floors > 0.05, we can say that floors are not a significant factor in determining the price of a home. This pertains to our business question since the lots of land themselves are expensive, but homes are cheaper to build vertically.

Once again calling the function `sm_metrics` that we defined earlier to find the metrics of our model. We prioritize/focus on RMSE because it provides us with more accuracy. The values in this case make sense since we are dealing with homes that are in the hundreds of thousands range.

In [31]:
```
sm_metrics(model, y_test, X_test_scaled)
```

```
Metrics:
Mean Absolute Error: 169584.127
Mean Squared Error: 64475389966.508
Root Mean Squared Error: 253920.046
```

We then calculate the predicted values of our models to calculate the residuals and see if our models were implemented correctly.

In [32]:
```
y_hat = model.predict(X_train_scaled)
y_pred = model.predict(X_test_scaled)
```

We calculate the residuals

In [33]:
```
residuals = (y_train - y_hat)
print(residuals)
```

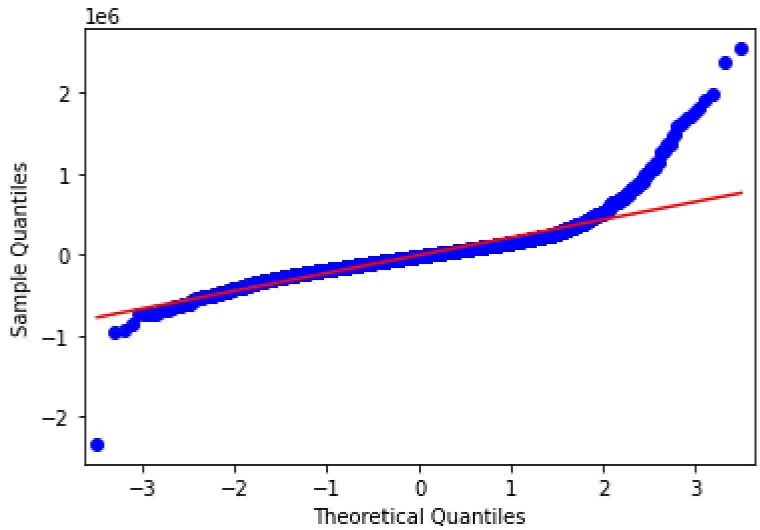
```
0         134054.190256
1        -177151.427931
2         -39418.666228
3         211972.734232
4        -284322.633742
              ...
17272    -108179.962734
17273     -18228.613749
```

```
17274   -141713.668295
17275    -61076.700318
17276     34848.286680
Length: 17277, dtype: float64
```

Then we plot on a qqplot to visualize the residuals and see where our error lies. We see that some of our residuals break off towaards the left and right side of the plot; however, for the most part, most of our residuals lie along the line.

In [34]:

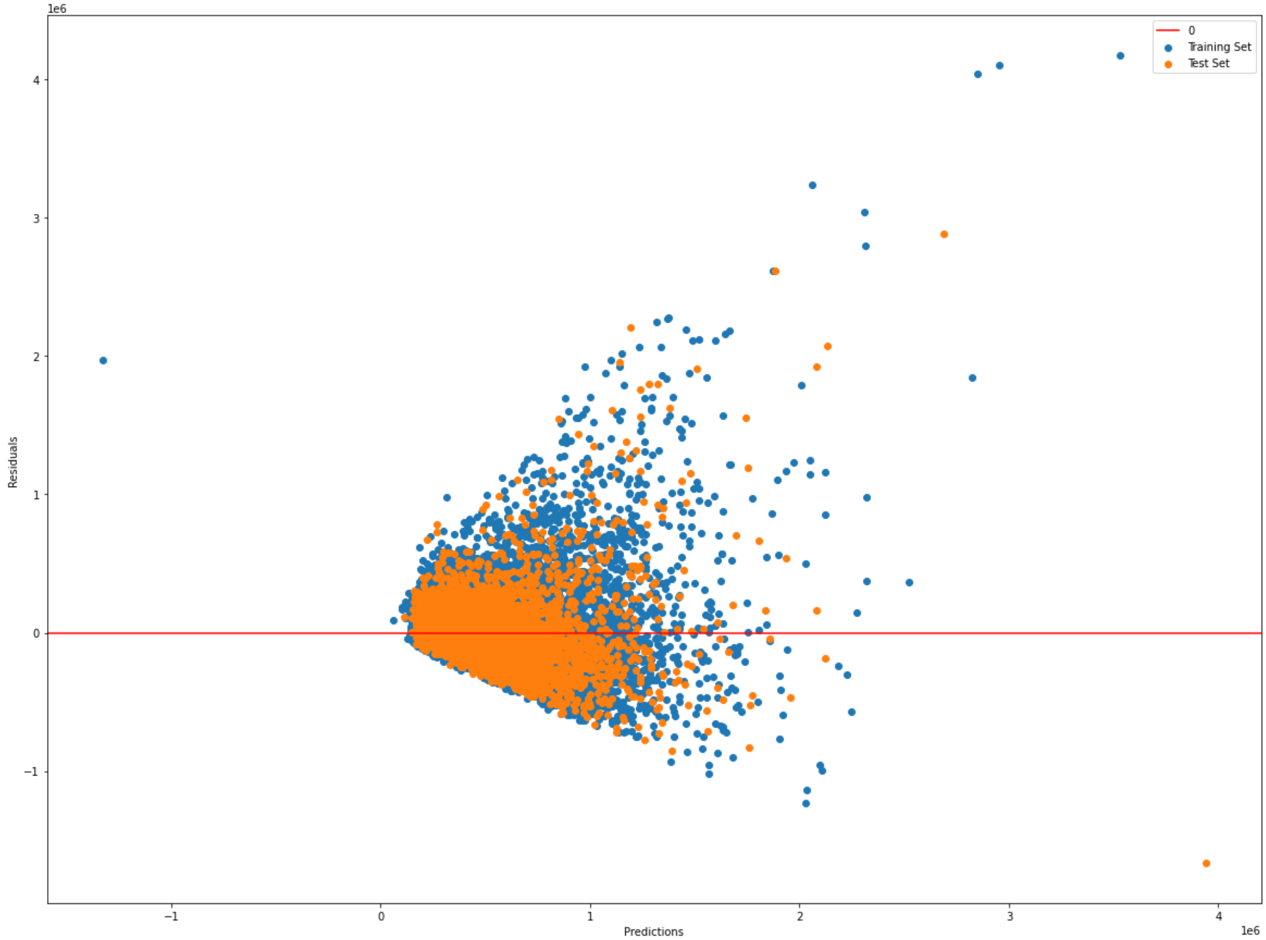
```
qq(X_test_scaled, X_train_scaled, y_test, y_train)
```



Plotted a heteroskedasticity plot for visualization of any recognizable patterns to check if our model was ran correctly.

In [35]:

```
plt.figure(figsize = (20,15))
plt.scatter(y_hat, y_train - y_hat, label = 'Training Set')
plt.scatter(y_pred, y_test - y_pred, label = 'Test Set')

plt.axhline(y = 0, color = 'red', label = '0')
plt.xlabel('Predictions')
plt.ylabel('Residuals')
plt.legend()
plt.show()
```



We see after plotting the heterskedasticity of our plots that a funnel pattern is a semi-recognizable. This means that our data is (i don't remember what to say here), so we have to log our data in order to get a normalized plot, and so we will apply that to our second model.

In [36]:

```
X_train_scaled.corr()
```

Out[36]:

	bedrooms	bathrooms	sqft_living	sqft_lot	floors	yr_built	zipcode	sqft_pe
bedrooms	1.000000	0.509423	0.571636	0.026344	0.178529	0.154396	-0.152053	
bathrooms	0.509423	1.000000	0.752564	0.085556	0.503355	0.511066	-0.205060	
sqft_living	0.571636	0.752564	1.000000	0.170260	0.356378	0.320881	-0.201041	
sqft_lot	0.026344	0.085556	0.170260	1.000000	-0.001869	0.053034	-0.128976	
floors	0.178529	0.503355	0.356378	-0.001869	1.000000	0.488497	-0.058795	
yr_built	0.154396	0.511066	0.320881	0.053034	0.488497	1.000000	-0.347291	
zipcode	-0.152053	-0.205060	-0.201041	-0.128976	-0.058795	-0.347291	1.000000	
sqft_per_bedroom	-0.024644	0.517643	0.759121	0.194870	0.293768	0.261316	-0.124074	
footprint	0.030371	0.289180	0.077961	-0.250546	0.553484	0.279235	0.177918	
bedbathratio	0.217513	-0.653090	-0.324053	-0.049564	-0.373462	-0.440836	0.126029	

We then check the VIF to see if we missed anything about multicollinearity between the variables.

In [37]:

```
# Check the VIFs after running the model to see if any values are > 10
vif(X_train_scaled)
```

```
         VIF         features
0   8.133196         bedrooms
1  10.414278        bathrooms
2  15.034290      sqft_living
3   1.142210         sqft_lot
4   1.955622           floors
5   1.739823         yr_built
6   1.276777          zipcode
7   9.195762  sqft_per_bedroom
8   1.764403        footprint
9   6.343995      bedbathratio
```

Our initial model produced an R^2 value of 0.505. Of our intiial predictors, we identified that sqft_living and bedrooms were significant in accounting for the variation in price while floors was **NOT** significant in the variation of price (due to its extremely high P value). In our next model, we are going to identify the predictors that we engineered.

Second Model - reducing complexity

We engineered this feature so as to reduce the complexity of this model and get rid of discrete categorical variables. We wanted to see if removing these variables and reducing the complexity would increase the efficiency of our model.

- Some of the initial predictors that we had in our intial dataset had multicollinearity with each other so we decided to remove them from our 2nd model.

In [38]:

```
formula2 = 'price ~  sqft_living + sqft_per_bedroom + footprint + bedbathratio'
model2 = ols(formula2, X_train_plus_y).fit()
model2.summary()
```

Out[38]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.502
Model:	OLS	**Adj. R-squared:**	0.502
Method:	Least Squares	**F-statistic:**	4354.
Date:	Fri, 18 Feb 2022	**Prob (F-statistic):**	0.00
Time:	15:26:57	**Log-Likelihood:**	-2.3992e+05
No. Observations:	17277	**AIC:**	4.798e+05
Df Residuals:	17272	**BIC:**	4.799e+05
Df Model:	4		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	-1.93e+05	1.26e+04	-15.347	0.000	-2.18e+05	-1.68e+05

sqft_living	240.5972	3.365	71.492	0.000	234.001	247.194
sqft_per_bedroom	248.7397	16.059	15.489	0.000	217.263	280.217
footprint	1.062e+05	7706.949	13.781	0.000	9.11e+04	1.21e+05
bedbathratio	2.561e+04	3731.289	6.865	0.000	1.83e+04	3.29e+04

Omnibus:	12444.927	**Durbin-Watson:**	1.989
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	551350.015
Skew:	2.973	**Prob(JB):**	0.00
Kurtosis:	30.029	**Cond. No.**	1.61e+04

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 1.61e+04. This might indicate that there are
strong multicollinearity or other numerical problems.

In [39]:

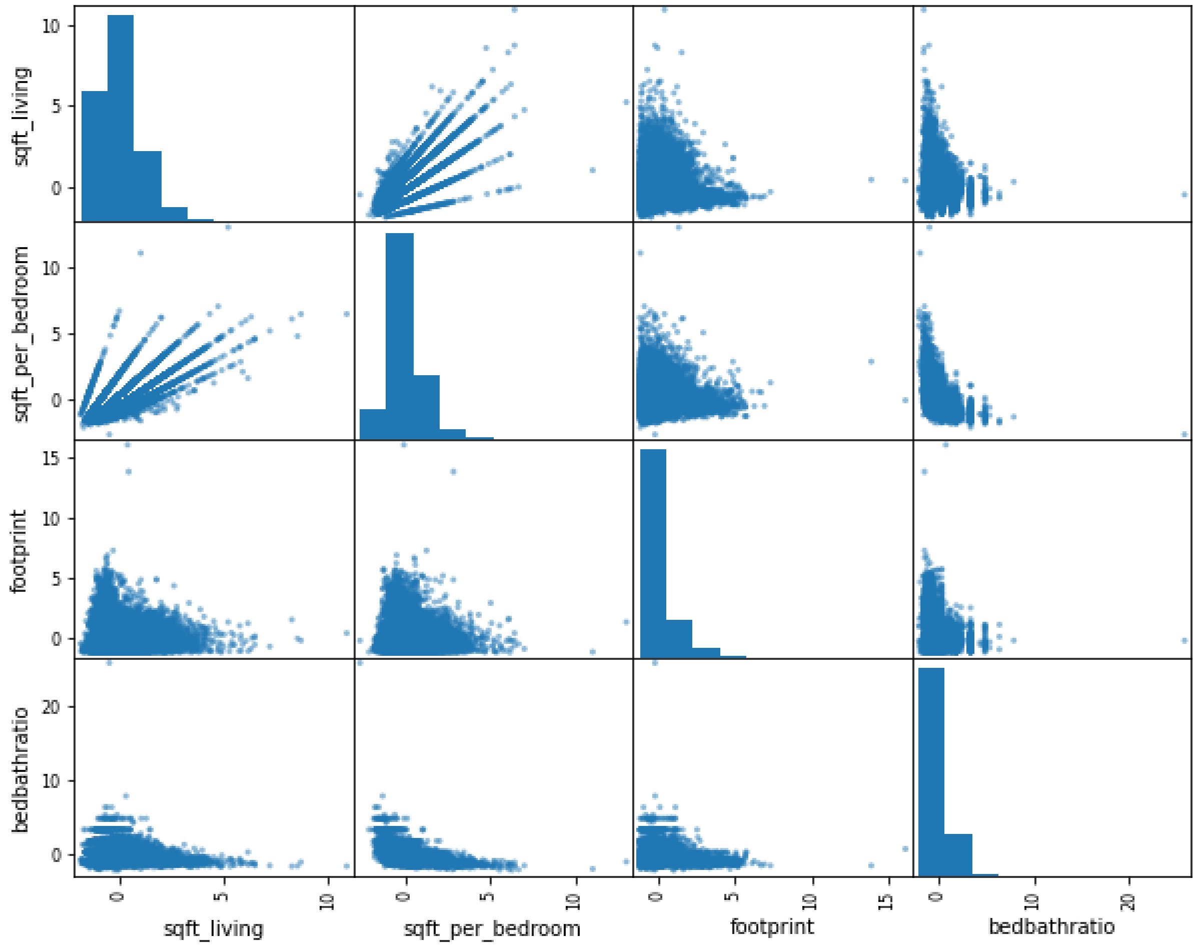
```
# Check the VIFs after running the model to see if any values are > 10
vif(X_train_scaled[['sqft_living', 'sqft_per_bedroom', 'footprint', 'bedbathratio']])
```

```
        VIF          features
0  2.429858       sqft_living
1  3.082085  sqft_per_bedroom
2  1.097728         footprint
3  1.570652      bedbathratio
```

Created a scatter matrix to check for distribution and heteroskedasticity.

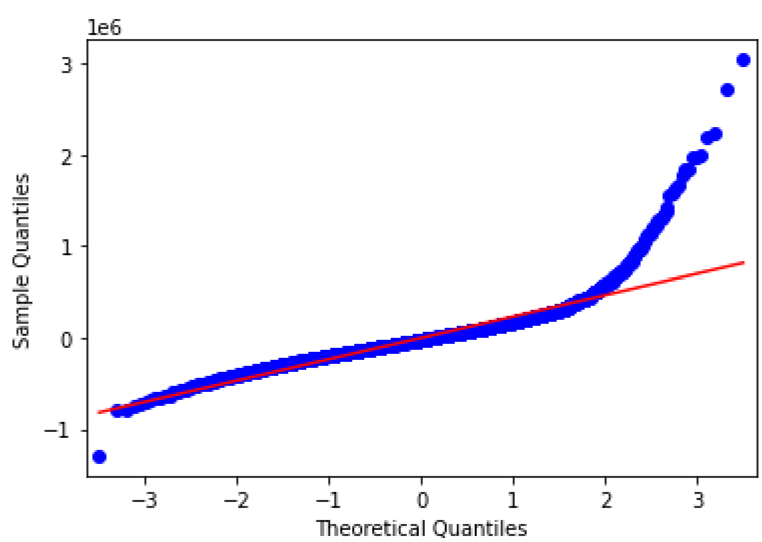
In [40]:

```
pd.plotting.scatter_matrix(X_train_scaled[['sqft_living', 'sqft_per_bedroom', 'footprin
```



We now run the second model to see if there were any changes to the R^2 value. We also wanted to test and see if keeping the bedrooms/bathrooms variables would reduce the complexity of our models. Removing the bedrooms variable in our model reduces our R^2 value by 0.015.

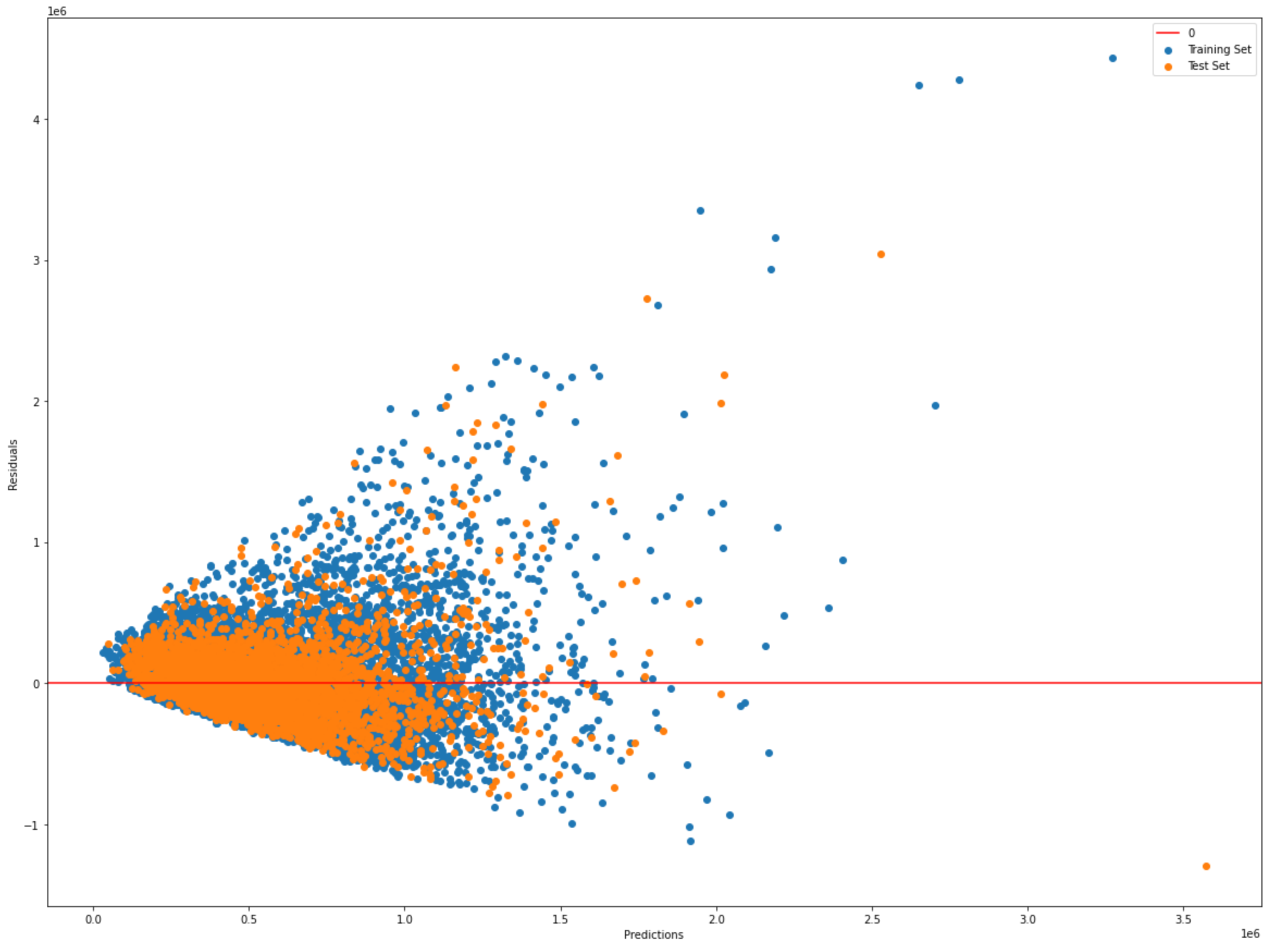
In [41]:
```
qq(X_test_scaled[['sqft_living', 'sqft_per_bedroom', 'footprint', 'bedbathratio']],
   X_train_scaled[['sqft_living', 'sqft_per_bedroom', 'footprint', 'bedbathratio']], y_
```



In [42]:
```
y_hat2 = model2.predict(X_train[['sqft_living', 'sqft_per_bedroom', 'footprint', 'bedba
y_pred2 = model2.predict(X_test[['sqft_living', 'sqft_per_bedroom', 'footprint', 'bedba
```

In [43]:

```
plt.figure(figsize = (20,15))
plt.scatter(y_hat2, y_train - y_hat2, label = 'Training Set')
plt.scatter(y_pred2, y_test - y_pred2, label = 'Test Set')

plt.axhline(y = 0, color = 'red', label = '0')
plt.xlabel('Predictions')
plt.ylabel('Residuals')
plt.legend()
plt.show()
```



After we check for heteroskedasticity, we identified a similar "funnel" pattern in our dataset. This led us to believe that the data is not being scaled correctly, so we took the log of the data and plotted the data below to visualize a more normal distribution of our findings.

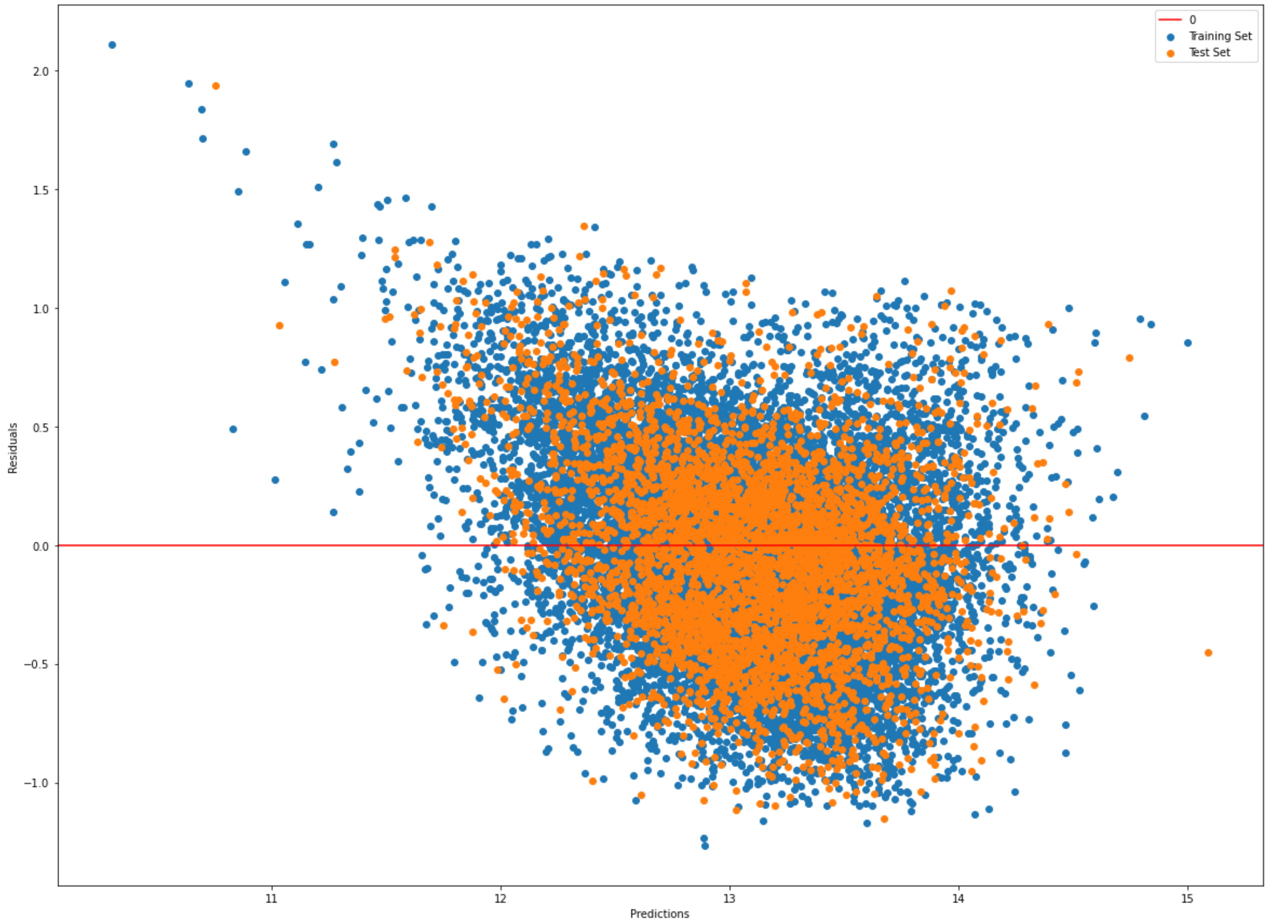
In [44]:

```
ylog_test2 = np.log(abs(y_pred2))
ylog_train2 = np.log(abs(y_hat2))
```

In [45]:

```
plt.figure(figsize = (20,15))
plt.scatter(ylog_train2, np.log(abs(y_train)) - ylog_train2, label = 'Training Set')
plt.scatter(ylog_test2, np.log(abs(y_test)) - ylog_test2, label = 'Test Set')

plt.axhline(y = 0, color = 'red', label = '0')
plt.xlabel('Predictions')
plt.ylabel('Residuals')
```

```
plt.legend()
plt.show()
```



In [46]:

```
model2.params
```

Out[46]:

```
Intercept           -193006.506017
sqft_living             240.597198
sqft_per_bedroom        248.739665
footprint            106212.265597
bedbathratio          25613.591120
dtype: float64
```

We run the defined function `sm_metrics` to compare the RMSE values of our training and test dataset, and we identified that the RMSE values are relatively close between the training dataset and the test dataset. The margin of error is still decently high; however, compared to our base model, our new model is more efficient.

In [47]:

```
sm_metrics(model2, y_train, X_train)
```

```
Metrics:
Mean Absolute Error: 170311.199
Mean Squared Error: 67468439768.192
Root Mean Squared Error: 259746.876
```

In [48]:

```
sm_metrics(model2, y_test, X_test)
```

```
Metrics:
```

```
Mean Absolute Error: 168308.110
Mean Squared Error: 64746046225.220
Root Mean Squared Error: 254452.444
```

In conclusion, this 3rd model produced an R^2 value of 0.502 and an RMSE of about 260,000. Compared to our second model, this model is more efficient since we utilize less variables and still get about the same R^2 value.

Third Model - focusing on sqft_living and sqft_per_bedroom

We recognize that sqft_living is one of the most important factors that we extrapolated from this model and our dataset. We decided to run a new model that focused primarily on the sqft_living predictors and the sqft_per_bedroom predictor that we engineered.

In [49]:

```
formula3 = 'price ~  sqft_living + sqft_per_bedroom'
model3 = ols(formula3, X_train_plus_y).fit()
model3.summary()
```

Out[49]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.496
Model:	OLS	**Adj. R-squared:**	0.496
Method:	Least Squares	**F-statistic:**	8510.
Date:	Fri, 18 Feb 2022	**Prob (F-statistic):**	0.00
Time:	15:27:01	**Log-Likelihood:**	-2.4001e+05
No. Observations:	17277	**AIC:**	4.800e+05
Df Residuals:	17274	**BIC:**	4.801e+05
Df Model:	2		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
Intercept	-9.454e+04	6031.466	-15.674	0.000	-1.06e+05	-8.27e+04
sqft_living	245.5396	3.335	73.615	0.000	239.002	252.077
sqft_per_bedroom	201.1258	14.132	14.232	0.000	173.425	228.826

Omnibus:	12274.680	**Durbin-Watson:**	1.990
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	520725.641
Skew:	2.925	**Prob(JB):**	0.00
Kurtosis:	29.251	**Cond. No.**	7.16e+03

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 7.16e+03. This might indicate that there are
strong multicollinearity or other numerical problems.

After running our model, we get a R^2 value of 0.496. The fact that model produces an R^2 value of 0.496 with only two predictors signifies that sqft has a significant impact on the variation of the price of a home. The coefficients of our predictors in this model are reasonable numbers.

In [50]:

```
sm_metrics(model3, y_train, X_train)
```

```
Metrics:
Mean Absolute Error: 172693.467
Mean Squared Error: 68246302116.105
Root Mean Squared Error: 261239.932
```

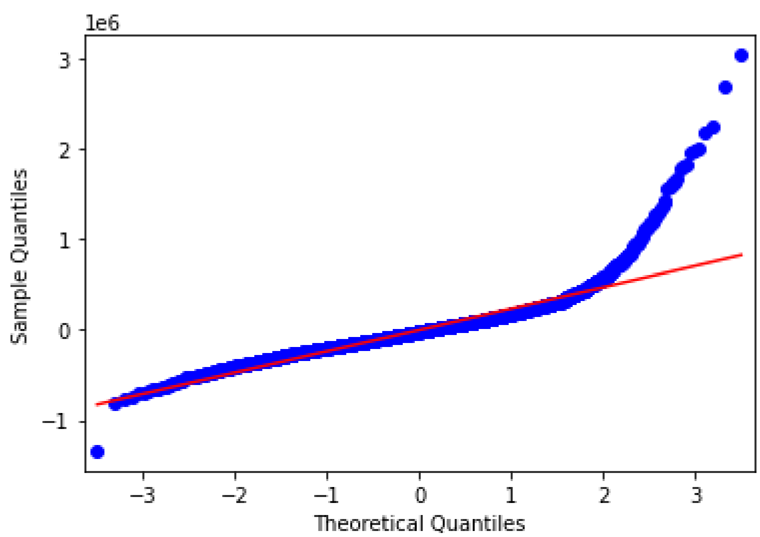
In [51]:

```
sm_metrics(model3, y_test, X_test)
```

```
Metrics:
Mean Absolute Error: 170805.475
Mean Squared Error: 65423939839.562
Root Mean Squared Error: 255781.039
```

In [52]:

```
qq(X_test_scaled[['sqft_living', 'sqft_per_bedroom']],
   X_train_scaled[['sqft_living', 'sqft_per_bedroom']], y_test, y_train)
```



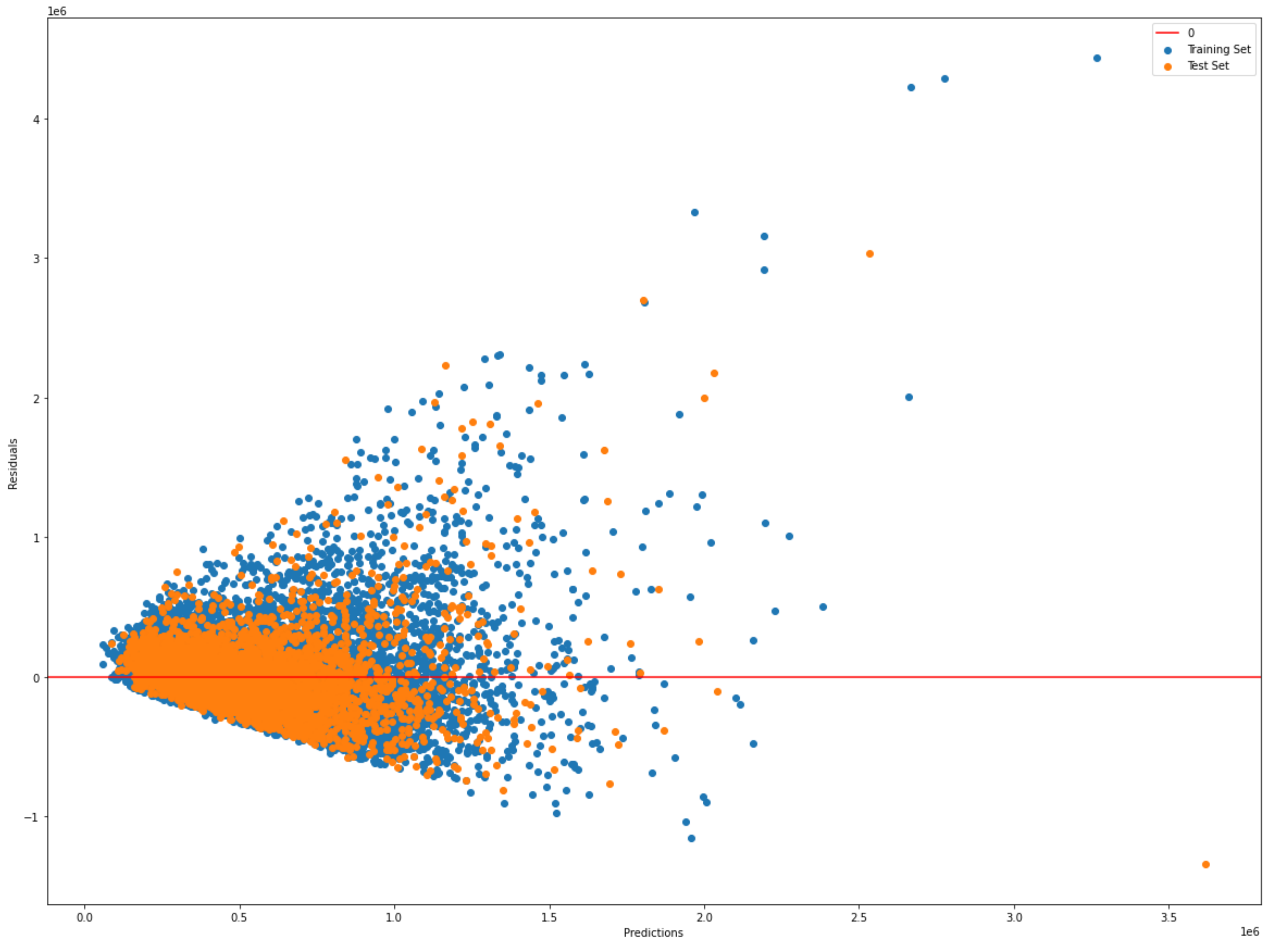
In [53]:

```
y_hat3 = model3.predict(X_train[['sqft_living', 'sqft_per_bedroom', 'footprint', 'bedba
y_pred3 = model3.predict(X_test[['sqft_living', 'sqft_per_bedroom', 'footprint', 'bedba
```

In [54]:

```
plt.figure(figsize = (20,15))
plt.scatter(y_hat3, y_train - y_hat3, label = 'Training Set')
plt.scatter(y_pred3, y_test - y_pred3, label = 'Test Set')

plt.axhline(y = 0, color = 'red', label = '0')
plt.xlabel('Predictions')
plt.ylabel('Residuals')
```

```
plt.legend()
plt.show()
```

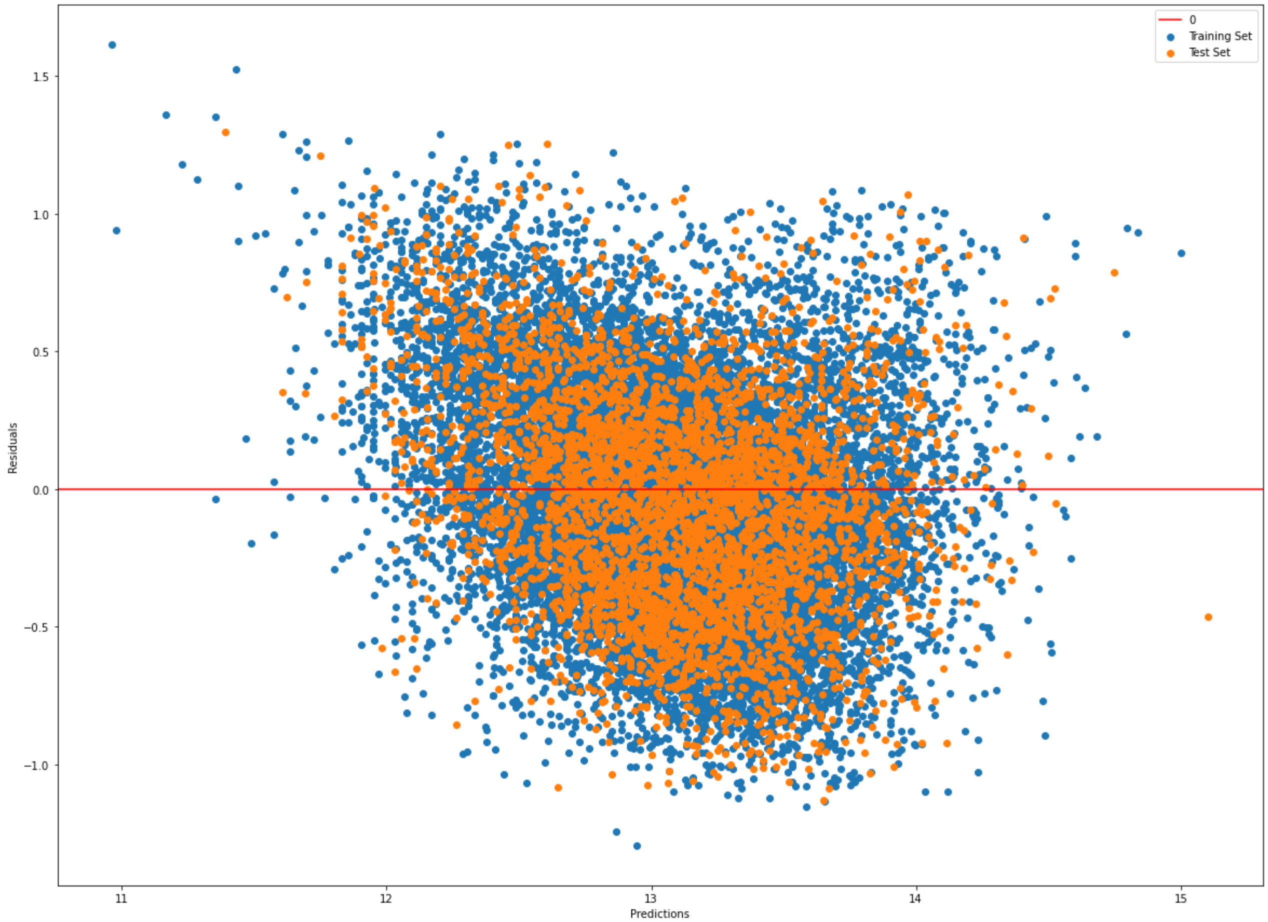


In [55]:

```
ylog_test3 = np.log(abs(y_pred3))
ylog_train3 = np.log(abs(y_hat3))
```

In [56]:

```
plt.figure(figsize = (20,15))
plt.scatter(ylog_train3, np.log(abs(y_train)) - ylog_train3, label = 'Training Set')
plt.scatter(ylog_test3, np.log(abs(y_test)) - ylog_test3, label = 'Test Set')

plt.axhline(y = 0, color = 'red', label = '0')
plt.xlabel('Predictions')
plt.ylabel('Residuals')
plt.legend()
plt.show()
```



Fourth Model - implementing categorical variables

This model implements the categorical variables 'grade' and 'zipcode' that we identified in our datasets. We want to run this model to see if the categorical predictors that we identified from our dataset have a significant influence on the price of a home or not.

In [57]:
```
y1 = dfrev2['price']
X1 = dfrev2[['bedrooms','bathrooms','sqft_living','sqft_lot','floors', 'yr_built', 'zip
X1_train, X1_test, y1_train, y1_test = train_test_split(X1, y1, test_size=0.2, random_s
```

Created a DummyRegressor in similar fashion to the one made for the three models above.

In [58]:
```
X1_train_cont = X1_train.drop(['zipcode', 'grade'], axis = 1).copy()
X1_test_cont = X1_test.drop(['zipcode', 'grade'], axis = 1).copy()
ss1 = StandardScaler()
ss1.fit(X1_train_cont)

X1_train_scaled = ss1.transform(X1_train_cont)
X1_test_scaled = ss1.transform(X1_test_cont)

#Dummy Regressor

basemodel1 = DummyRegressor(strategy = 'mean')
basemodel1.fit(X1_train, y1_train)
basemodel1.predict(X1_train)
```

```
array([540946.37500724, 540946.37500724, 540946.37500724, ...,
```

Out[58]:
```
540946.37500724, 540946.37500724, 540946.37500724])
```

Dropped the numerical columns from our dataframe so that we could only focus on and OneHotEncode the categorical values we pulled from our demographics XLS

In [59]:
```
X1_cat = X1_train[['zipcode', 'grade']]
ohe1 = OneHotEncoder(sparse = False)
ohe_df = pd.DataFrame(ohe1.fit_transform(X1_cat))
```

In [60]:
```
ohe_df.columns = ohe1.get_feature_names(['zipcode', 'grade'])
```

In [61]:
```
X1_train_df = pd.DataFrame(X1_train_scaled)
X1_train_df.columns = X1_train_cont.columns.tolist()
```

In [62]:
```
X1_train_df
```

Out[62]:

	bedrooms	bathrooms	sqft_living	sqft_lot	floors	yr_built
0	-0.404166	-0.148210	-0.591864	-0.174771	-0.917505	1.123192
1	0.670108	0.832246	0.489562	-0.020598	0.937801	0.884897
2	-0.404166	0.178609	-0.307853	-0.201845	0.937801	0.408307
3	0.670108	0.505427	0.631567	-0.274556	0.937801	-2.076770
4	0.670108	0.832246	2.128085	-0.115790	0.937801	-0.953379
...	...	...	...	...	...	...
17272	-1.478441	0.178609	-0.482629	-0.309172	0.937801	0.306180
17273	1.744382	1.485883	1.319747	-0.208081	0.937801	1.395529
17274	-0.404166	1.485883	1.778533	0.567548	0.937801	0.918939
17275	0.670108	-0.475029	-0.602787	-0.151807	0.010148	-0.102325
17276	-1.478441	-1.455485	-1.028803	-0.161718	-0.917505	-0.783169

17277 rows × 6 columns

In [63]:
```
ohe_df.head()
```

Out[63]:

	zipcode_Northeast	zipcode_Shoreline	zipcode_Southeast	zipcode_Southwest	zipcode_West	grade_10 Very Good
0	0.0	1.0	0.0	0.0	0.0	0.0
1	1.0	0.0	0.0	0.0	0.0	0.0
2	1.0	0.0	0.0	0.0	0.0	0.0
3	0.0	0.0	0.0	0.0	1.0	0.0

	zipcode_Northeast	zipcode_Shoreline	zipcode_Southeast	zipcode_Southwest	zipcode_West	grade_10 Very Good
4	0.0	1.0	0.0	0.0	0.0	0.0

Created a dataframe with the new OHE values for our categorical columns from housedf, ad we added the price column from our original dataframe to the OHE dataframe to check for correlation between these variables and if they had an effect on home pricing.

In [64]:

```
combined_df = ohe_df.join(X1_train_df)
X_train_predictors = combined_df.copy()
combined_df['price'] = y_train
combined_df
```

Out[64]:

	zipcode_Northeast	zipcode_Shoreline	zipcode_Southeast	zipcode_Southwest	zipcode_West	grac
0	0.0	1.0	0.0	0.0	0.0	
1	1.0	0.0	0.0	0.0	0.0	
2	1.0	0.0	0.0	0.0	0.0	
3	0.0	0.0	0.0	0.0	1.0	
4	0.0	1.0	0.0	0.0	0.0	
...	...	...	...	...	...	
17272	0.0	1.0	0.0	0.0	0.0	
17273	1.0	0.0	0.0	0.0	0.0	
17274	1.0	0.0	0.0	0.0	0.0	
17275	0.0	0.0	1.0	0.0	0.0	
17276	0.0	1.0	0.0	0.0	0.0	

17277 rows × 22 columns

In [65]:

```
# Before running our model, run correlation to check for multicollinearity.
combined_df.corr()
```

Out[65]:

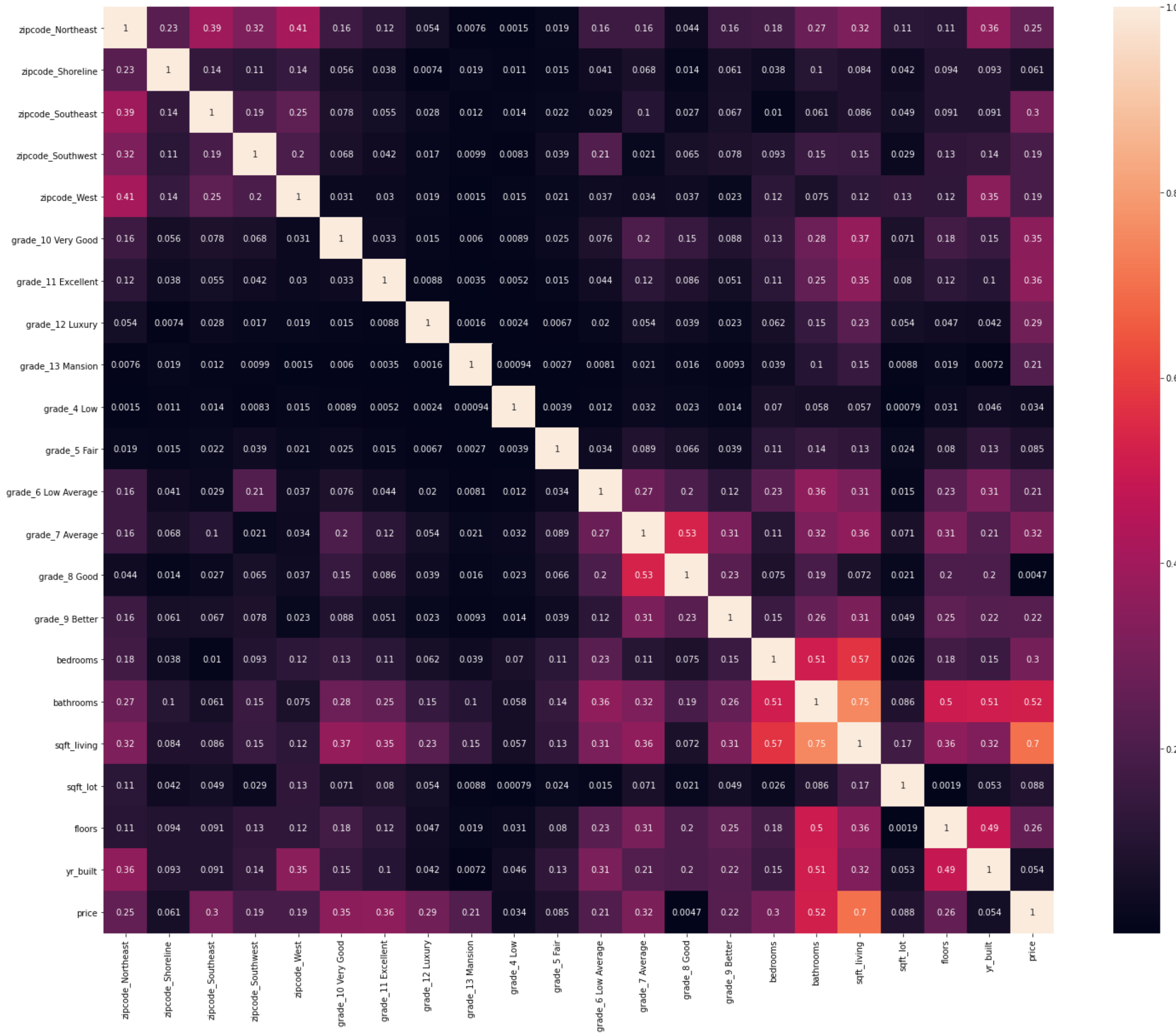
	zipcode_Northeast	zipcode_Shoreline	zipcode_Southeast	zipcode_Southwest	zipcod
zipcode_Northeast	1.000000	-0.229578	-0.392327	-0.317999	-0.
zipcode_Shoreline	-0.229578	1.000000	-0.136507	-0.110646	-0.
zipcode_Southeast	-0.392327	-0.136507	1.000000	-0.189083	-0.

	zipcode_Northeast	zipcode_Shoreline	zipcode_Southeast	zipcode_Southwest	zipcod
zipcode_Southwest	-0.317999	-0.110646	-0.189083	1.000000	-0.
zipcode_West	-0.414327	-0.144162	-0.246360	-0.199686	1.
grade_10 Very Good	0.164717	-0.055653	-0.077874	-0.067689	-0.
grade_11 Excellent	0.117355	-0.037506	-0.054909	-0.041655	-0.
grade_12 Luxury	0.053578	-0.007378	-0.028241	-0.016679	-0.
grade_13 Mansion	0.007630	0.019168	-0.012191	-0.009881	-0.
grade_4 Low	0.001459	-0.010541	0.013731	0.008289	-0.
grade_5 Fair	-0.019479	-0.014841	0.021668	0.039150	-0.
grade_6 Low Average	-0.162514	0.040858	0.028627	0.214182	-0.
grade_7 Average	-0.159235	0.067950	0.100784	0.020687	0.
grade_8 Good	0.043572	-0.013586	-0.026789	-0.065107	0.
grade_9 Better	0.158288	-0.060654	-0.066623	-0.077702	-0.
bedrooms	0.175478	-0.038443	0.010241	-0.093382	-0.
bathrooms	0.273140	-0.103396	-0.060813	-0.154872	-0.
sqft_living	0.317908	-0.083594	-0.085776	-0.152231	-0.
sqft_lot	0.110997	-0.042083	0.048762	-0.029336	-0.
floors	0.108523	-0.094373	-0.090932	-0.127626	0.
yr_built	0.360141	-0.092777	0.090581	-0.137272	-0.
price	0.250924	-0.061293	-0.304331	-0.188512	0.

22 rows × 22 columns

In [66]:

```
# Run a heatmap to better visualize the correlation between the variables that we ident
plt.figure(figsize = (25, 20))
sns.heatmap(combined_df.corr().abs(), annot=True);
```



As we can see from the `df_corrs` and the heatmap generated above, there is some correlation between the categorical variables we identified (grade/zipcode/floors) and their effect on price.

After we check the correlation and lack of multicollinearity, we can now run a model on the variables on these variables.

In [67]:
```
lr = LinearRegression()
model4 = lr.fit(X_train_predictors, y_train)
model4.score(X_train_predictors, y_train)
```
Out[67]:
```
0.7016031747477318
```

In [68]:
```
y_pred_model = lr.predict(X_train_predictors.values)
```

In [69]:
```
sk_metrics(y_train, y_pred_model)
```
```
Metrics:
R2: 0.702
Mean Absolute Error: 118807.607
Mean Squared Error: 40430372946.267
Root Mean Squared Error: 201073.054
```

In [70]:

```
lr_model_metrics(X1_test, X1_train, y1_test, y1_train, ['grade','zipcode']);
```

```
Train Data
Metrics:
R2: 0.702
Mean Absolute Error: 118783.298
Mean Squared Error: 40429737661.469
Root Mean Squared Error: 201071.474
Test Data
Metrics:
R2: 0.702
Mean Absolute Error: 118921.240
Mean Squared Error: 39508992531.045
Root Mean Squared Error: 198768.691
```

Fifth Model - incorporating features from previous model and just the discrete 'grade' feature

In [71]:

```
y5 = dfrev2['price']
X5 = dfrev2[['bedrooms','bathrooms','sqft_living','sqft_lot','floors', 'yr_built', 'gra
X5_train, X5_test, y5_train, y5_test = train_test_split(X5, y5, test_size=0.2, random_s
```

In [72]:

```
# Define cat_vars
cat_vars = ['grade']

x5_train = pd.DataFrame()
x5_test = pd.DataFrame()
x5_train = X5_train[cat_vars]
x5_train['ID'] = 1
x5_test = X5_test[cat_vars]
x5_test['ID'] = 1

# One hot encoding cat vars
onehot = OneHotEncoder(sparse=False, handle_unknown = 'ignore')
x_train_cat = pd.DataFrame(onehot.fit_transform(x5_train))
x_train_cat.columns = onehot.get_feature_names(x5_train.columns.tolist())
x_test_cat = pd.DataFrame(onehot.transform(x5_test))
x_test_cat.columns = onehot.get_feature_names(x5_train.columns.tolist())

# Drop ID column
x_train_cat.drop(['ID_1'], axis=1, inplace=True)
x_test_cat.drop(['ID_1'], axis=1, inplace=True)

# Resetting indices
x_train_cat.reset_index(drop=True, inplace=True)
x_test_cat.reset_index(drop=True, inplace=True)
X5_train.reset_index(drop=True, inplace=True)
X5_test.reset_index(drop=True, inplace=True)

# Combine dummied cat vars with non-cat
x_train_df = x_train_cat.join(X5_train.drop(cat_vars, axis = 1))
x_test_df = x_test_cat.join(X5_test.drop(cat_vars, axis = 1))
```

```
<ipython-input-72-0da3b2a3dac0>:7: SettingWithCopyWarning:
```

```
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_
guide/indexing.html#returning-a-view-versus-a-copy
  x5_train['ID'] = 1
<ipython-input-72-0da3b2a3dac0>:9: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_
guide/indexing.html#returning-a-view-versus-a-copy
  x5_test['ID'] = 1
```

In [73]:

```
x_train_df
```

Out[73]:

	grade_10 Very Good	grade_11 Excellent	grade_12 Luxury	grade_13 Mansion	grade_4 Low	grade_5 Fair	grade_6 Low Average	grade_7 Average	grade_8 Good	grade_ Bett
0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0
1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0
2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0
3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0
4	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0
...	...	...	...	...	...	...	...	...	...	
17272	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0
17273	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1
17274	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0
17275	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0
17276	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0

17277 rows × 16 columns

After we ran the model, we checked the score value of the training set vs the test set. We also doublecheck the metrics to see if there are any differences we failed to identify.

In [74]:

```
lr = LinearRegression()
model5 = lr.fit(x_train_df, y5_train)
model5.score(x_train_df, y5_train)
```

Out[74]:

```
0.644614517676586
```

In [75]:

```
model5.score(x_test_df, y5_test)
```

Out[75]:

```
0.6448091772630099
```

In [76]:
```
sk_metrics(y5_train, model5.predict(x_train_df))
```

```
Metrics:
R2: 0.645
Mean Absolute Error: 140500.728
Mean Squared Error: 48151878217.462
Root Mean Squared Error: 219435.362
```

In [77]:
```
sk_metrics(y5_test, model5.predict(x_test_df))
```

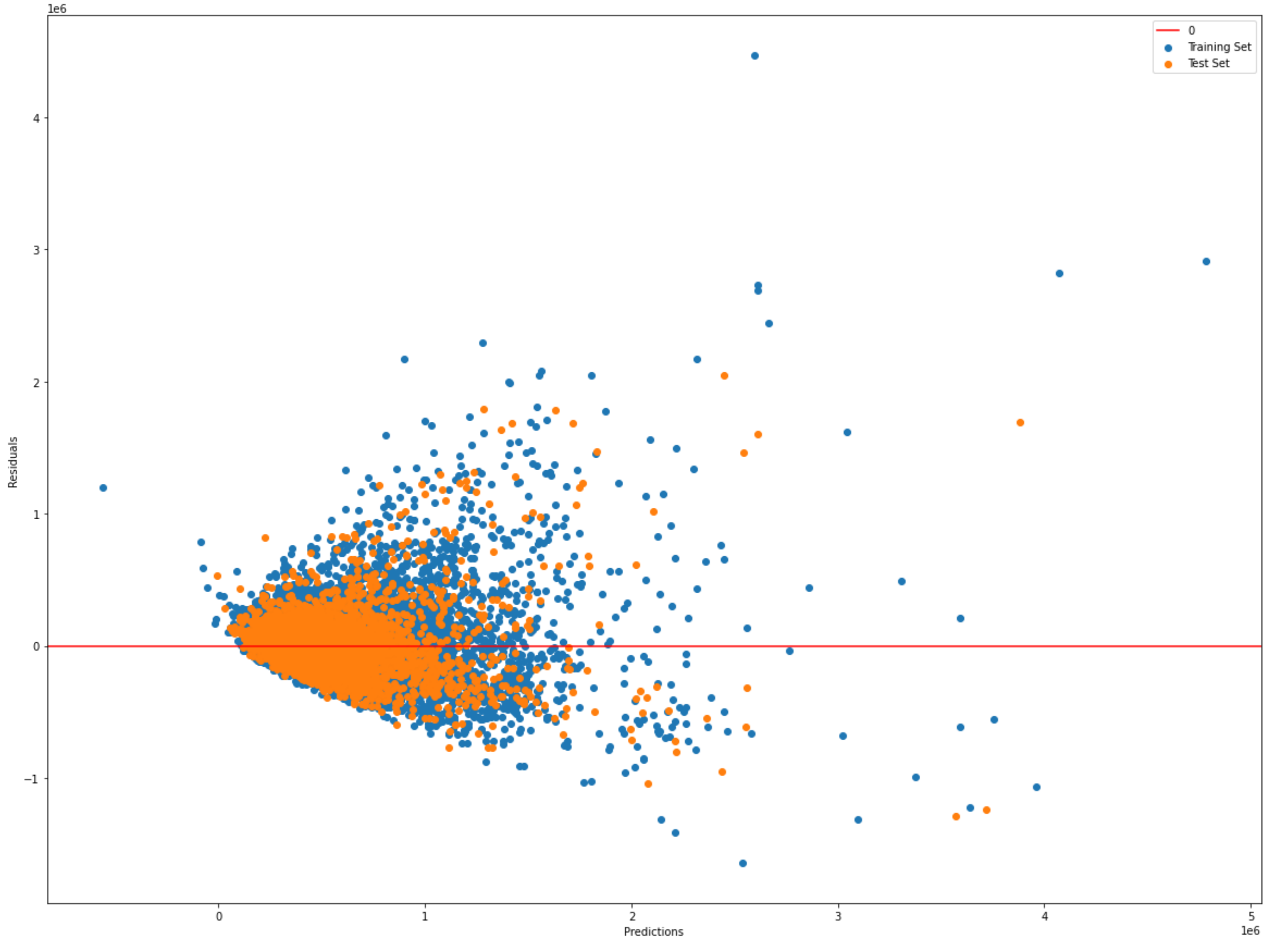
```
Metrics:
R2: 0.645
Mean Absolute Error: 140062.150
Mean Squared Error: 47165636238.606
Root Mean Squared Error: 217176.509
```

After running this model, we see that the R^2 value is 0.645. This is roughly a 15% increase from the model that we ran without the categorical variables. We recognize that the model is a good model since the RMSE values are not extranously high. Thus we can conclude that this model is more efficient than

In [78]:
```
print(x_test_df.columns)
print(model5.coef_)
```

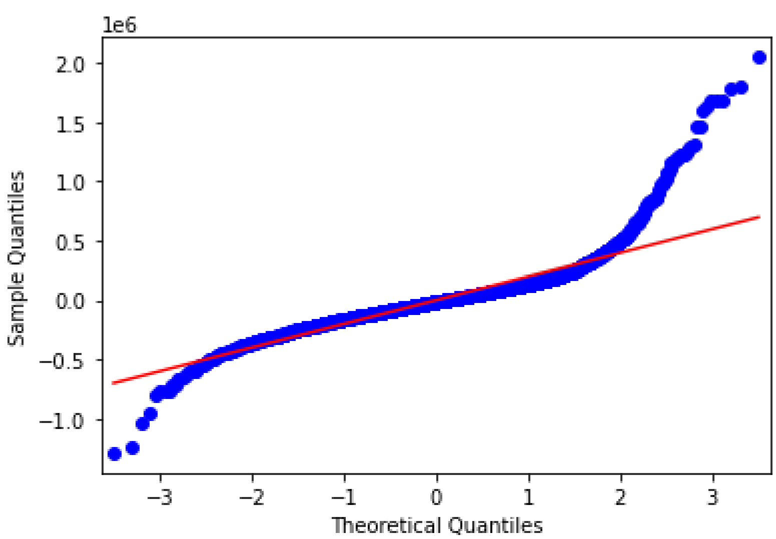
```
Index(['grade_10 Very Good', 'grade_11 Excellent', 'grade_12 Luxury',
       'grade_13 Mansion', 'grade_4 Low', 'grade_5 Fair',
       'grade_6 Low Average', 'grade_7 Average', 'grade_8 Good',
       'grade_9 Better', 'bedrooms', 'bathrooms', 'sqft_living', 'sqft_lot',
       'floors', 'yr_built'],
      dtype='object')
[-2.69101389e+04  2.34921054e+05  8.03776296e+05  1.81228481e+06
 -6.13175604e+05 -5.98404401e+05 -5.50234177e+05 -4.63710683e+05
 -3.68105276e+05 -2.30441881e+05 -3.39039328e+04  5.81524173e+04
  1.54814698e+02 -2.61255318e-01  2.67150446e+04 -3.85123851e+03]
```

In [79]:
```
plt.figure(figsize = (20,15))
plt.scatter(model5.predict(x_train_df), y5_train - model5.predict(x_train_df), label =
plt.scatter(model5.predict(x_test_df), y5_test - model5.predict(x_test_df), label = 'Te

plt.axhline(y = 0, color = 'red', label = '0')
plt.xlabel('Predictions')
plt.ylabel('Residuals')
plt.legend()
plt.show()
```



In [80]:

```
qq(x_test_df, x_train_df, y5_test, y5_train)
```



After we ran our model, we ran a qqplot and heteroskedasticity check to see if there were any huge errors in our modeling. We recognize that there is a pattern in most of our data that is likely attributed to the lack of normal distribution between of our data(it is data from only one year after all.)

Sixth Model - Modeling with just sqft_living, zipcode, and grade of homes

After we ran the previous model, we wanted to create our last and final model to see the significance of just the three most important predictors that we identified over the course of our analysis and modeling: 'sqft_living', 'zipcode', and 'grade'.

In [82]:
```
y6 = dfrev2['price']
X6 = dfrev2[['sqft_living', 'zipcode', 'grade']]
x6_train, x6_test, y6_train, y6_test = train_test_split(X6, y6, test_size=0.2, random_s
```

In [83]:
```
# Onehot encode

# Define cat_vars
cat_vars = ['grade', 'zipcode']


# One hot encoding cat vars
onehot = OneHotEncoder(sparse=False, handle_unknown = 'ignore')
x6_train_cat = pd.DataFrame(onehot.fit_transform(x6_train[cat_vars]))
x6_train_cat.columns = onehot.get_feature_names(cat_vars)
x6_test_cat = pd.DataFrame(onehot.transform(x6_test[cat_vars]))
x6_test_cat.columns = onehot.get_feature_names(cat_vars)

# Resetting indices
x6_train_cat.reset_index(drop=True, inplace=True)
x6_test_cat.reset_index(drop=True, inplace=True)
x6_train.reset_index(drop=True, inplace=True)
x6_test.reset_index(drop=True, inplace=True)

# Combine dummied cat vars with non-cat
x6_train_df = x6_train_cat.join(x6_train.drop(cat_vars, axis = 1))
x6_test_df = x6_test_cat.join(x6_test.drop(cat_vars, axis = 1))
```

In [84]:
```
# Run regression

lr = LinearRegression()
model6 = lr.fit(x6_train_df, y6_train)
model6.score(x6_train_df, y6_train)
```

Out[84]:
```
0.6792846894781521
```

In [85]:
```
model6.score(x6_test_df, y6_test)
```

Out[85]:
```
0.6803566979982765
```

As you can see, this final model provided us with an R^2 value of 0.680, which is significantly better than our initial model that we produced with just the continuous data. After checking the R^2 value, we need perform a qqplot and heteroskedasticity check to identify normal distribution within our modeling.

In [86]:
```
vif(x6_train_df)
```

```
C:\Users\Beter\anaconda3\envs\learn-env\lib\site-packages\statsmodels\stats\outliers_inf
```

```
luence.py:193: RuntimeWarning: divide by zero encountered in double_scalars
  vif = 1. / (1. - r_squared_i)
         VIF            features
0        inf   grade_10 Very Good
1        inf   grade_11 Excellent
2        inf      grade_12 Luxury
3        inf     grade_13 Mansion
4        inf          grade_4 Low
5        inf         grade_5 Fair
6        inf  grade_6 Low Average
7        inf      grade_7 Average
8        inf         grade_8 Good
9        inf       grade_9 Better
10       inf    zipcode_Northeast
11       inf    zipcode_Shoreline
12       inf    zipcode_Southeast
13       inf    zipcode_Southwest
14       inf         zipcode_West
15  2.583583          sqft_living
```

In [87]:

```
sk_metrics(y6_train, model6.predict(x6_train_df))
```

```
Metrics:
R2: 0.679
Mean Absolute Error: 123400.864
Mean Squared Error: 43454348426.844
Root Mean Squared Error: 208457.066
```

In [88]:

```
sk_metrics(y6_test, model6.predict(x6_test_df))
```

```
Metrics:
R2: 0.680
Mean Absolute Error: 122776.053
Mean Squared Error: 42445296283.693
Root Mean Squared Error: 206022.563
```

Once again we checked the metrics and we can see that the RMSE of this last model is signficantly lower than the RMSE of our baseline model. Since these values are relatively low, we can conclude that our models are not overfit on the dataset and that the **predictors 'sqft_living', 'zipcode', and 'grade' account for ~68% of the variation in the price of a home.**

In [89]:

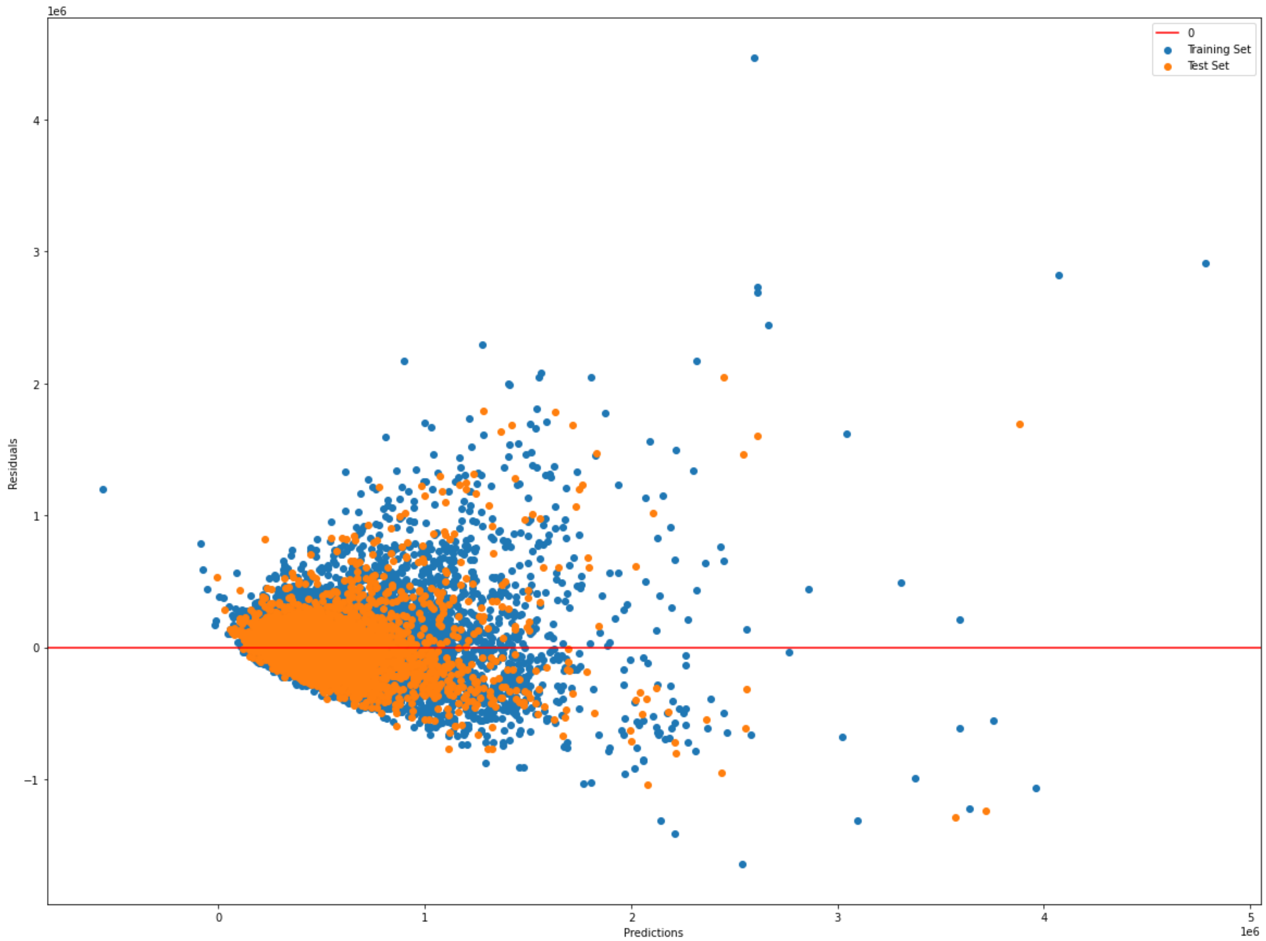
```
print(x6_test_df.columns)
print(model6.coef_)
```

```
Index(['grade_10 Very Good', 'grade_11 Excellent', 'grade_12 Luxury',
       'grade_13 Mansion', 'grade_4 Low', 'grade_5 Fair',
       'grade_6 Low Average', 'grade_7 Average', 'grade_8 Good',
       'grade_9 Better', 'zipcode_Northeast', 'zipcode_Shoreline',
       'zipcode_Southeast', 'zipcode_Southwest', 'zipcode_West',
       'sqft_living'],
      dtype='object')
[-1.21259720e+05  1.27964757e+05  6.96803430e+05  1.74215418e+06
 -4.08425392e+05 -4.41443189e+05 -4.28565748e+05 -4.44161409e+05
 -4.10033064e+05 -3.13033841e+05  2.06300341e+04  1.09723229e+04
 -1.59947475e+05 -6.95254609e+04  1.97870579e+05  1.78539231e+02]
```

We once again plot the heteroskedasticity and qqplot to check for normal distribution within our predictors and dataframe.

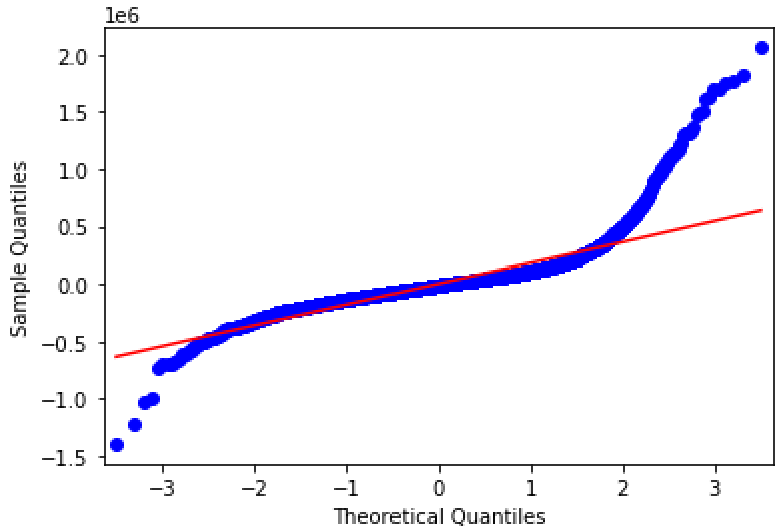
In [90]:

```
plt.figure(figsize = (20,15))
plt.scatter(model5.predict(x_train_df), y5_train - model5.predict(x_train_df), label =
plt.scatter(model5.predict(x_test_df), y5_test - model5.predict(x_test_df), label = 'Te

plt.axhline(y = 0, color = 'red', label = '0')
plt.xlabel('Predictions')
plt.ylabel('Residuals')
plt.legend()
plt.show()
```



In [91]:

```
qq(x6_test_df, x6_train_df, y6_test, y6_train)
```



Visualizations

We decided to extrapolate the data that we produced from our modeling and created bargraphs for easier visualization of our main points about the sqft_living, zipcode(region), grade(condition) and their significance in home pricing.

In [92]:

```
# Binning living space by house size as per National Association of Home Builder (NAHB)

living_price = housedf[['sqft_living', 'price']]

bins = [1., 2000., 3000., 4000., 14000]
bin_labels = ['Small House', 'Medium House', 'Large House', 'Bigger Houses']

living_price['bins'] = pd.cut(x=living_price['sqft_living'], bins=bins, labels=bin_labe
```

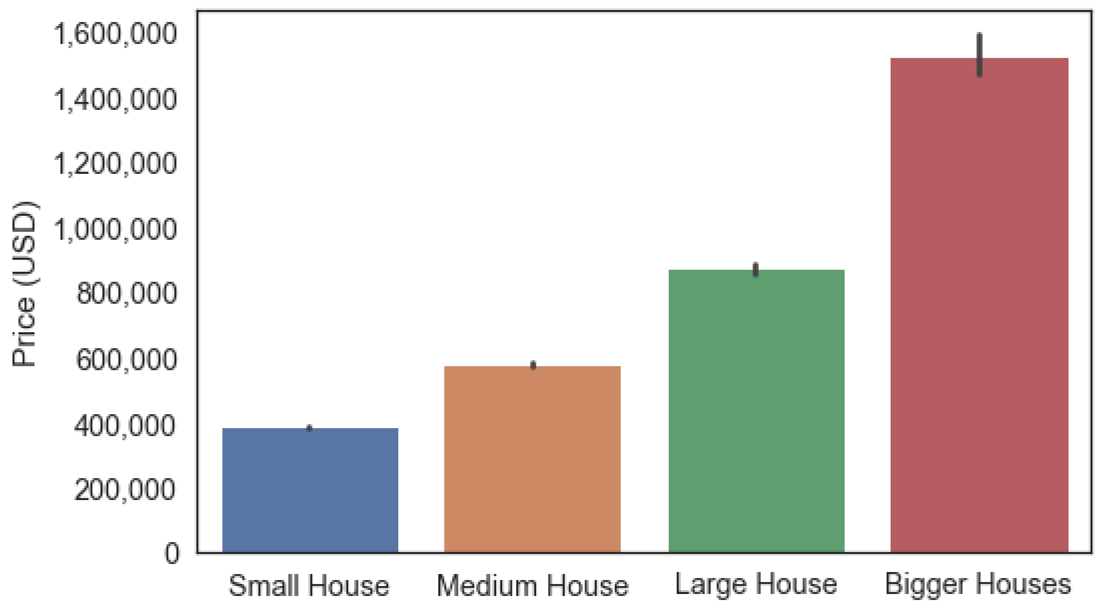
```
<ipython-input-92-44b9be3c1b63>:8: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_
guide/indexing.html#returning-a-view-versus-a-copy
  living_price['bins'] = pd.cut(x=living_price['sqft_living'], bins=bins, labels=bin_lab
els)
```

In [93]:

```
# Plot living area bins versus price
plt.figure(figsize=(8, 5))
sns.set(font_scale=1.3, style="white")
v = sns.barplot(x='bins', y='price', data=living_price)
v.yaxis.set_major_formatter(ticker.StrMethodFormatter('{x:,.0f}'))
v.set_xlabel(" ")
v.set_ylabel("Price (USD)")
```

Out[93]:

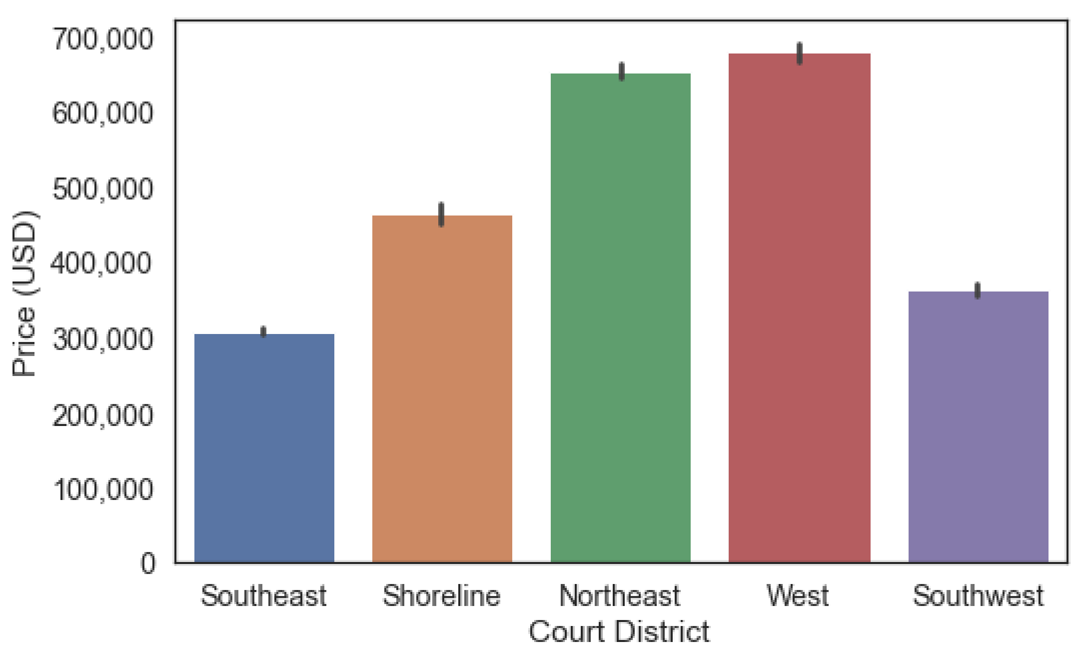
```
Text(0, 0.5, 'Price (USD)')
```



In [94]:

```
# Plot price by region
region_price = dfrev2[['zipcode', 'price']]

plt.figure(figsize=(8, 5))
sns.set(font_scale=1.3, style="white")
v = sns.barplot(x='zipcode', y='price', data=region_price)
v.yaxis.set_major_formatter(ticker.StrMethodFormatter('{x:,.0f}'))
v.set_xlabel("Court District")
v.set_ylabel("Price (USD)")
```

Out[94]: Text(0, 0.5, 'Price (USD)')



In [95]:

```
# Plot price by grade

# Bin grades
grade_price = housedf[['price','grade']]
```

```
grade_def = {'4 Low': 'Low', '3 Poor': 'Low', '6 Low Average': 'Low', '5 Fair' : 'Low'



grade_price['grade'] = grade_price['grade'].map(grade_def)

grade_price['grade'].value_counts().sum()
```

```
<ipython-input-95-8c42c9c7613c>:10: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_
guide/indexing.html#returning-a-view-versus-a-copy
  grade_price['grade'] = grade_price['grade'].map(grade_def)
```

Out[95]:

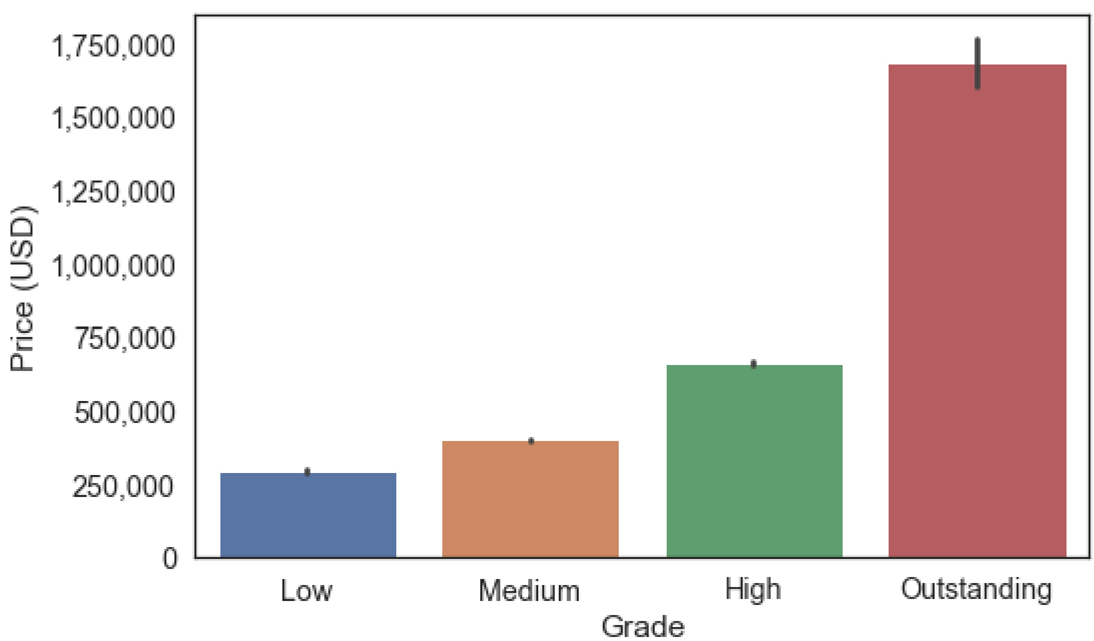
```
21597
```

In [96]:

```
# Plot price by grade

grade_order= ['Low', 'Medium', 'High', 'Outstanding']

plt.figure(figsize=(8, 5))
sns.set(font_scale=1.3, style="white")
v = sns.barplot(x='grade', y='price', data=grade_price, order=grade_order)
v.yaxis.set_major_formatter(ticker.StrMethodFormatter('{x:,.0f}'))
v.set_xlabel("Grade")
v.set_ylabel("Price (USD)")
```

Out[96]:

```
Text(0, 0.5, 'Price (USD)')
```



Conclusion

Our business stakeholder is Howard S Wright construction company, and we identified **three important factors** that they should while building a home:

- **Square Footage**
- **Region to build in(zipcode)**
- **Quality of the home**

These factors are the most signficant predictors in maximizing their profit on building a home.
We ran a multilinear regression models to identify that these predictors/factor account for **68% of the variation in the price of home** in King County.