King County Housing Data Project

Overview

A company that buys houses to flip and resell is interested in finding out what pre-existine features of houses are likely to lead to a higher sale price. Since they plan on "flipping" the house, or adding their own renovations, they aren't as interested in details such as the overall condition of the house and are more interested in things such as location, how big of a lot the house is built on, etc.

Business Understanding

The features of the data from a housing dataset that I will be looking at, and comparing to the sale price of the houses, include number of bedrooms, number of bathrooms, square footage of the living area, square footage of the lot, number of floors, whether the house is on a waterfront, whether the house is adjacent to a green belt, whether the house has traffic noise or other nuisances, and the quality of the view of the house. After performing exploratory data analysis and determining which of these factors seem to relate to sale price, I will narrow down my efforts to determine which of those factors are the best predictors of sale price.

Data Understanding

I begin by importing the necessary modules and the dataset I will be using, which includes housing data for King County.

In [1]:
```
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
import statsmodels.api as sm
import numpy as np
import math
import matplotlib.cm as cm
%matplotlib nbagg
import seaborn as sns
from sklearn.linear_model import LinearRegression
```

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

Out[2]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	greenbelt	...	sewer_system
0	7399300360	5/24/2022	675000.0	4	1.0	1180	7140	1.0	NO	NO	...	PUBLIC
1	8910500230	12/13/2021	920000.0	5	2.5	2770	6703	1.0	NO	NO	...	PUBLIC
2	1180000275	9/29/2021	311000.0	6	2.0	2880	6156	1.0	NO	NO	...	PUBLIC
3	1604601802	12/14/2021	775000.0	3	3.0	2160	1400	2.0	NO	NO	...	PUBLIC
4	8562780790	8/24/2021	592500.0	2	2.0	1120	758	2.0	NO	NO	...	PUBLIC

5 rows × 25 columns

Next, I try to find out more about the data and narrow down the dataframe I will be using to only include the necessary columns.

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

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 30155 entries, 0 to 30154
Data columns (total 25 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   id             30155 non-null  int64  
 1   date           30155 non-null  object 
 2   price          30155 non-null  float64
 3   bedrooms       30155 non-null  int64  
 4   bathrooms      30155 non-null  float64
 5   sqft_living    30155 non-null  int64  
 6   sqft_lot       30155 non-null  int64  
 7   floors         30155 non-null  float64
 8   waterfront     30155 non-null  object 
 9   greenbelt      30155 non-null  object 
 10  nuisance       30155 non-null  object 
 11  view           30155 non-null  object 
 12  condition      30155 non-null  object 
 13  grade          30155 non-null  object 
 14  heat_source    30123 non-null  object 
 15  sewer_system   30141 non-null  object 
 16  sqft_above     30155 non-null  int64  
 17  sqft_basement  30155 non-null  int64  
 18  sqft_garage    30155 non-null  int64  
 19  sqft_patio     30155 non-null  int64  
 20  yr_built       30155 non-null  int64  
 21  yr_renovated   30155 non-null  int64  
 22  address        30155 non-null  object 
 23  lat            30155 non-null  float64
 24  long           30155 non-null  float64
dtypes: float64(5), int64(10), object(10)
memory usage: 5.8+ MB
```

In [4]:
```
data_ = pd.to_datetime(data['date'])
```

In [5]:
```
data_.describe(datetime_is_numeric=True)
```

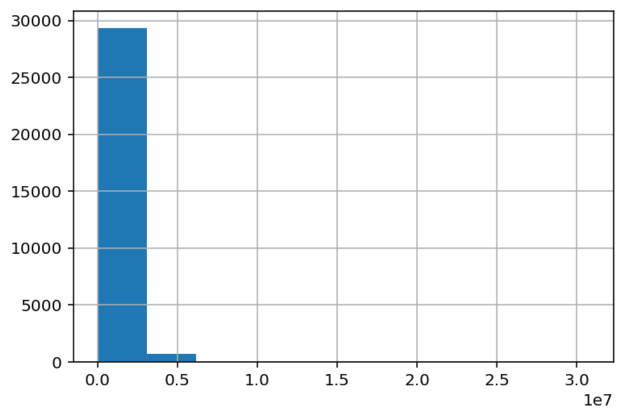
Out[5]:
```
count                              30155
mean     2021-11-21 01:02:13.351019776
min                2021-06-10 00:00:00
25%                2021-08-18 00:00:00
50%                2021-11-03 00:00:00
75%                2022-03-07 00:00:00
max                2022-06-09 00:00:00
Name: date, dtype: object
```

Data Preparation

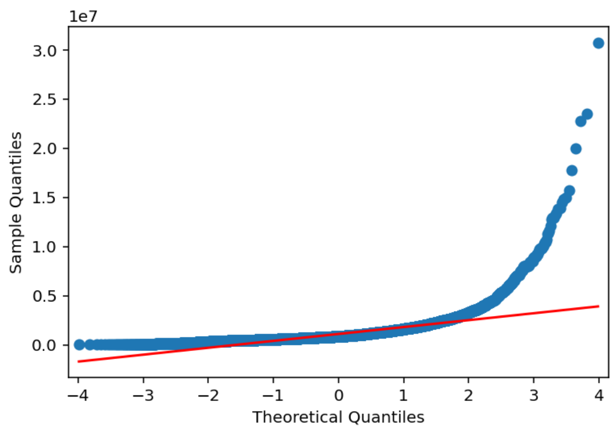
Before I look at the predictors, I want to investigate the target variable ('price'):

I start by plotting the target variable's distribution with a histogram and its residuals with a QQ plot.

In [6]:
```
data['price'].hist();
```



In [7]:
```
price_qq = sm.qqplot(data['price'], line='r');
```



The histogram does not seem to show a perfectly normal looking distribution, and the QQ plot shows the residuals getting further and further away from the theoretical fit line.

In [8]:
```
lower_lim = np.mean(data['price']) - (2*np.std(data['price']))
upper_lim = np.mean(data['price']) + (2*np.std(data['price']))
```

In [9]:
```
lower_lim
```

Out[9]:
```
-684205.7543299033
```

In [10]:
```
upper_lim
```

Out[10]:
```
2901277.4300719034
```

This indicates that the data becomes unreliable outside of plus or minus 2 standard deviations from the mean, or outside of the range where price equals between 684,205.75 and 2,901,227.43 dollars.

Choosing a baseline model feature:

Next, I want to know which variables are most correlated with price, so that I can choose a feature for the baseline model. However, first I want to make sure that if any features are causing multicollinearity, that they are removed so that they will not later affect my results.

In [11]:
```
data_all = data.copy()
```

In [12]:
```
data_pred = data_all.iloc[:,2:21]
data_pred.head()
```

Out[12]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	greenbelt	nuisance	view	condition	grade	he
0	675000.0	4	1.0	1180	7140	1.0	NO	NO	NO	NONE	Good	7 Average	
1	920000.0	5	2.5	2770	6703	1.0	NO	NO	YES	AVERAGE	Average	7 Average	
2	311000.0	6	2.0	2880	6156	1.0	NO	NO	NO	AVERAGE	Average	7 Average	
3	775000.0	3	3.0	2160	1400	2.0	NO	NO	NO	AVERAGE	Average	9 Better	
4	592500.0	2	2.0	1120	758	2.0	NO	NO	YES	NONE	Average	7 Average	

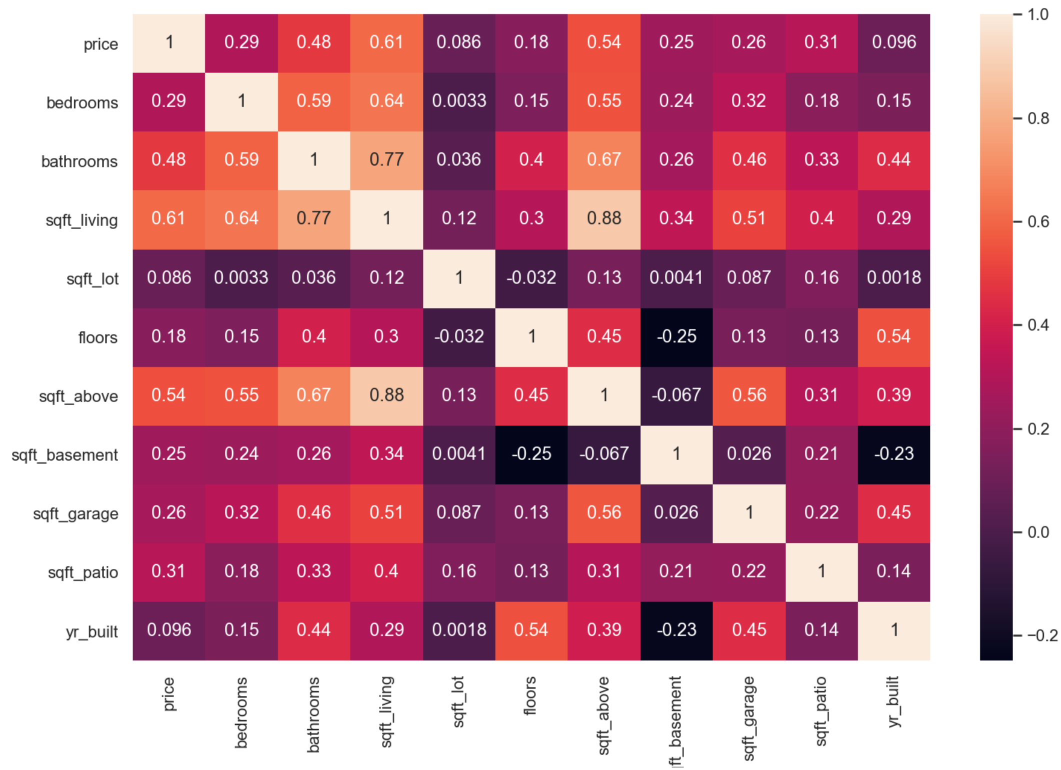
In [13]:
```
data_pred.corr()
```

Out[13]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	sqft_above	sqft_basement	sqft_garage	sqft_pa
price	1.000000	0.289204	0.480401	0.608521	0.085730	0.180576	0.538651	0.245058	0.264169	0.3134
bedrooms	0.289204	1.000000	0.589273	0.637874	0.003306	0.147592	0.547164	0.238502	0.319441	0.1834
bathrooms	0.480401	0.589273	1.000000	0.772677	0.035886	0.404412	0.674924	0.260902	0.457022	0.3275
sqft_living	0.608521	0.637874	0.772677	1.000000	0.119563	0.304240	0.883984	0.338460	0.511740	0.3960
sqft_lot	0.085730	0.003306	0.035886	0.119563	1.000000	-0.032097	0.129231	0.004111	0.087169	0.1552
floors	0.180576	0.147592	0.404412	0.304240	-0.032097	1.000000	0.448281	-0.248093	0.132656	0.1251
sqft_above	0.538651	0.547164	0.674924	0.883984	0.129231	0.448281	1.000000	-0.066801	0.560551	0.3121
sqft_basement	0.245058	0.238502	0.260902	0.338460	0.004111	-0.248093	-0.066801	1.000000	0.026361	0.2105
sqft_garage	0.264169	0.319441	0.457022	0.511740	0.087169	0.132656	0.560551	0.026361	1.000000	0.2163
sqft_patio	0.313409	0.183439	0.327551	0.396030	0.155250	0.125183	0.312117	0.210500	0.216354	1.0000
yr_built	0.096013	0.146191	0.443648	0.291694	0.001750	0.544646	0.387448	-0.230226	0.447560	0.1384

In [14]:

```

sns.set(rc={'figure.figsize':(12,8)})
sns.heatmap(data_pred.corr(), annot=True);
```



In [15]:

```
df=data_pred.corr().abs().stack().reset_index().sort_values(0, ascending=False)

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

df.set_index(['pairs'], inplace = True)

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

df.columns = ['cc']

df.drop_duplicates(inplace=True)

```

In [16]:
```
abs(df) > 0.75
```

Out[16]:

	cc
pairs	
(price, price)	True
(sqft_living, sqft_above)	True
(sqft_living, bathrooms)	True
(bathrooms, sqft_above)	False
(bedrooms, sqft_living)	False
(price, sqft_living)	False
(bedrooms, bathrooms)	False
(sqft_garage, sqft_above)	False
(bedrooms, sqft_above)	False
(yr_built, floors)	False
(price, sqft_above)	False
(sqft_garage, sqft_living)	False
(bathrooms, price)	False
(bathrooms, sqft_garage)	False
(floors, sqft_above)	False
(yr_built, sqft_garage)	False
(yr_built, bathrooms)	False
(bathrooms, floors)	False
(sqft_patio, sqft_living)	False
(yr_built, sqft_above)	False
(sqft_basement, sqft_living)	False
(sqft_patio, bathrooms)	False
(bedrooms, sqft_garage)	False
(sqft_patio, price)	False
(sqft_patio, sqft_above)	False
(sqft_living, floors)	False
(yr_built, sqft_living)	False
(price, bedrooms)	False
(sqft_garage, price)	False
(sqft_basement, bathrooms)	False
(sqft_basement, floors)	False
(price, sqft_basement)	False
(bedrooms, sqft_basement)	False
(sqft_basement, yr_built)	False
(sqft_patio, sqft_garage)	False
(sqft_basement, sqft_patio)	False
(bedrooms, sqft_patio)	False
(price, floors)	False
(sqft_patio, sqft_lot)	False
(floors, bedrooms)	False
(yr_built, bedrooms)	False
(yr_built, sqft_patio)	False

pairs	cc
(floors, sqft_garage)	False
(sqft_lot, sqft_above)	False
(sqft_patio, floors)	False
(sqft_living, sqft_lot)	False
(yr_built, price)	False
(sqft_lot, sqft_garage)	False
(sqft_lot, price)	False
(sqft_above, sqft_basement)	False
(sqft_lot, bathrooms)	False
(sqft_lot, floors)	False
(sqft_garage, sqft_basement)	False
(sqft_lot, sqft_basement)	False
(bedrooms, sqft_lot)	False
(yr_built, sqft_lot)	False

In [17]:

```
df[(df.cc>.75) & (df.cc <1)]
```

Out[17]:

pairs	cc
(sqft_living, sqft_above)	0.883984
(sqft_living, bathrooms)	0.772677

The only pairs of features that have correlations higher than 0.75 are sqft_living and sqft_above, and sqft_living and bathrooms. This makes sense, because the square feet of the living area is likely a large portion of the square feet above ground for a house.

Also, it would make sense that the larger amount of square footage of living space, the higher number of bathrooms a house would have. Following this same logic, the 'bedrooms' feature would also likely cause multicollinearity.

Looking at the correlations, I see that the bedrooms and bathrooms features are more correlated with the feature 'sqft_living' than they are with price, so this indicates multicollinearity. Because sqft_living is the most correlated with the target variable out of these, I am going to exclude the variables sqft_above, bedrooms, and bathrooms moving forward.

Now, to look at the rest of the features:

I start by creating a new dataframe with only the features that I will be using:

In [18]:

```
data1 = data_all.copy()
data1 = data1[['price', 'sqft_living', 'sqft_lot', 'floors', 'waterfront', 'greenbelt', 'nuis
data1.head()
```

Out[18]:

	price	sqft_living	sqft_lot	floors	waterfront	greenbelt	nuisance	view	heat_source	sewer_system
0	675000.0	1180	7140	1.0	NO	NO	NO	NONE	Gas	PUBLIC
1	920000.0	2770	6703	1.0	NO	NO	YES	AVERAGE	Oil	PUBLIC
2	311000.0	2880	6156	1.0	NO	NO	NO	AVERAGE	Gas	PUBLIC
3	775000.0	2160	1400	2.0	NO	NO	NO	AVERAGE	Gas	PUBLIC
4	592500.0	1120	758	2.0	NO	NO	YES	NONE	Electricity	PUBLIC

In [19]:
```
data1.corr()["price"]
```

Out[19]:
```
price          1.000000
sqft_living    0.608521
sqft_lot       0.085730
floors         0.180576
Name: price, dtype: float64
```

Then, I create a dataframe of only the relevant *numeric* variables, to further investigate them:

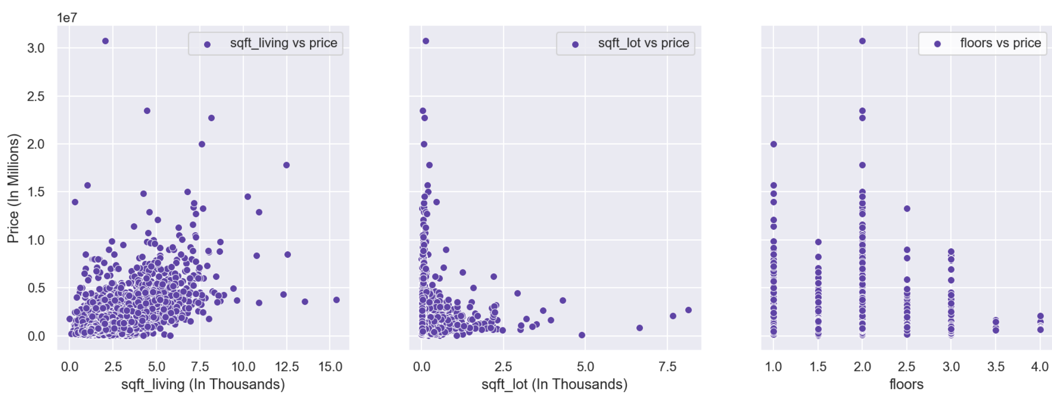
In [20]:
```
data_num = data1.copy().select_dtypes("number")
data_num.dropna(inplace=True)
data_num
```

Out[20]:

	price	sqft_living	sqft_lot	floors
0	675000.0	1180	7140	1.0
1	920000.0	2770	6703	1.0
2	311000.0	2880	6156	1.0
3	775000.0	2160	1400	2.0
4	592500.0	1120	758	2.0
...	...	...	...	...
30150	1555000.0	1910	4000	1.5
30151	1313000.0	2020	5800	2.0
30152	800000.0	1620	3600	1.0
30153	775000.0	2570	2889	2.0
30154	500000.0	1200	11058	1.0

In [21]:

```
import matplotlib.pyplot as plt
from matplotlib import ticker

sns.set_palette("twilight", 2)
# Plot scatterplots for multiple columns
fig, (ax1, ax2, ax3) = plt.subplots(figsize=(15,5), sharey=True, nrows=1, ncols=3)
ax1 = sns.scatterplot(data = data_pred, x='sqft_living', y='price', label='sqft_living vs pr
ax2 = sns.scatterplot(data = data_pred, x='sqft_lot', y='price', label='sqft_lot vs price', a
ax3 = sns.scatterplot(data = data_pred, x='floors', y='price', label='floors vs price', ax=a

# A function can also be used directly as a formatter. The function must take
# two arguments: ``x`` for the tick value and ``pos`` for the tick position,
# and must return a ``str``. This creates a FuncFormatter automatically.
#setup(ax1, title="lambda x, pos: str(x-5)")
#ax1.yaxis.set_major_formatter(ticker.FormatStrFormatter("$%.2d")*1e-8)
#ylabels = ['${:,f}'.format(x) for x in ax1.get_xticks()]
#ax1.set_yticklabels(ylabels)
ax1.set_ylabel("Price (In Millions)")

xlabels = ['{:,.1f}'.format(x) for x in ax1.get_xticks()/1000]
ax1.set_xticklabels(xlabels)
ax2.set_xticklabels(xlabels)
ax1.set_xlabel("sqft_living (In Thousands)")
ax2.set_xlabel("sqft_lot (In Thousands)")

sns.set_style("whitegrid")
sns.despine()
plt.legend()
plt.show();
```

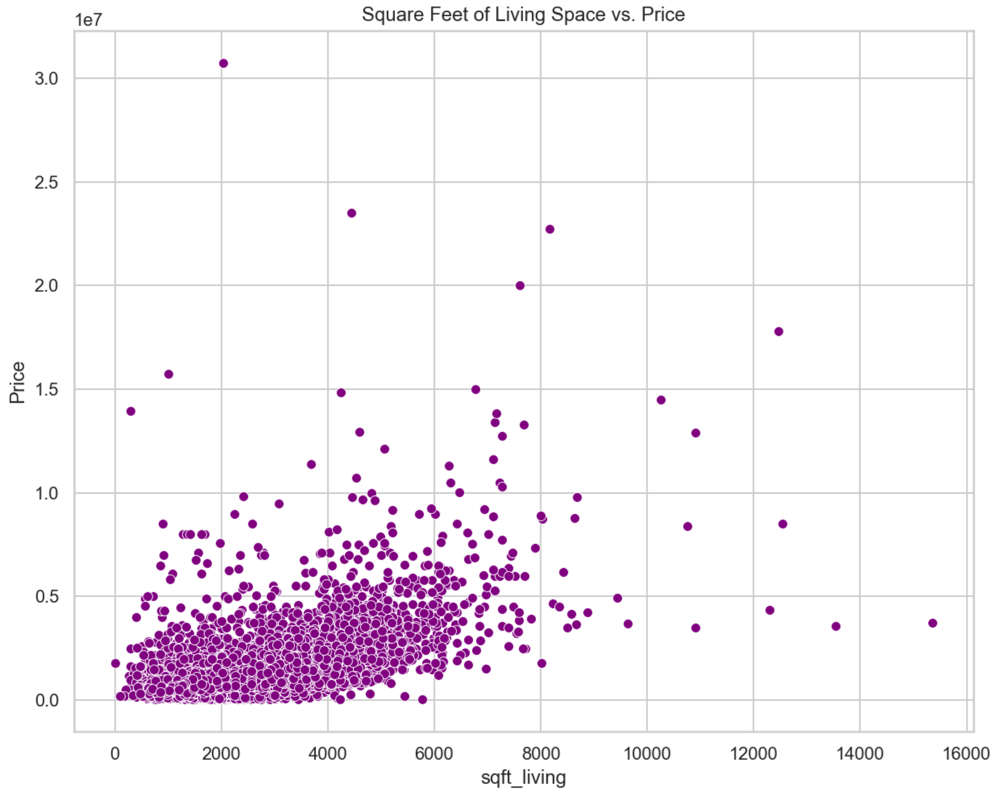



```
<ipython-input-21-9150ee68638b>:21: UserWarning: FixedFormatter should only be used together w
ith FixedLocator
  ax1.set_xticklabels(xlabels)
<ipython-input-21-9150ee68638b>:22: UserWarning: FixedFormatter should only be used together w
ith FixedLocator
  ax2.set_xticklabels(xlabels)
```

Of the numeric variables in the data, aside from those already removed, it looks like the feature most correlated with price and having the strongest linear relationship with price is sqft_living. Therefore, this seems like a good feature to use for the baseline model.

Scatterplot of just sqft_living vs. price:

In [22]:
```
sns.set_style()
fig, ax = plt.subplots(figsize=(10,8))
g = sns.scatterplot(data=data_num, x='sqft_living', y='price', color="purple", ax=ax)
g.set_title("Square Feet of Living Space vs. Price")
g.set_ylabel("Price")
g.set_xlabel("sqft_living");
```



Modeling

First, a baseline model is created using the variable sqft_living, as it is the most correlated with sale price, to compare all other models to.

In [23]:
```
y = data1[['price']]
X_baseline = data1[['sqft_living']]
```

Baseline results:

In [24]:
```
baseline_model = sm.OLS(y, sm.add_constant(X_baseline))
baseline_results = baseline_model.fit()

print(baseline_results.summary())
```

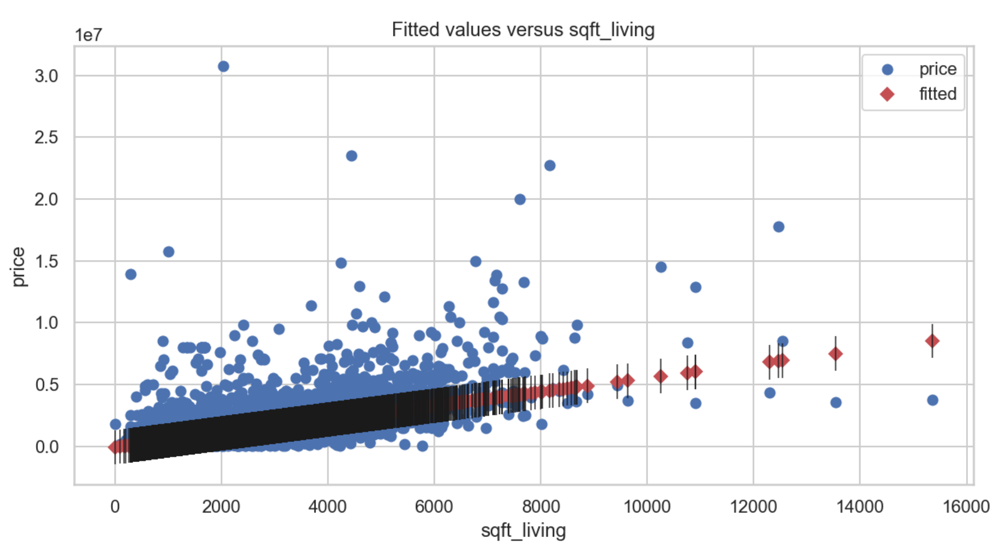
```
                            OLS Regression Results
==============================================================================
Dep. Variable:                  price   R-squared:                       0.370
Model:                            OLS   Adj. R-squared:                  0.370
Method:                 Least Squares   F-statistic:                 1.773e+04
Date:                Mon, 12 Jun 2023   Prob (F-statistic):               0.00
Time:                        13:05:20   Log-Likelihood:            -4.4912e+05
No. Observations:               30155   AIC:                         8.982e+05
Df Residuals:                   30153   BIC:                         8.983e+05
Df Model:                           1
Covariance Type:            nonrobust
===============================================================================
                  coef    std err          t      P>|t|      [0.025      0.975]
-------------------------------------------------------------------------------
const       -7.443e+04   9782.728     -7.609      0.000   -9.36e+04   -5.53e+04
sqft_living   560.0050      4.206    133.160      0.000     551.762     568.248
==============================================================================
Omnibus:                    43429.367   Durbin-Watson:                   1.862
Prob(Omnibus):                  0.000   Jarque-Bera (JB):         47159181.471
Skew:                           8.188   Prob(JB):                         0.00
Kurtosis:                     196.042   Cond. No.                     5.56e+03
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 5.56e+03. This might indicate that there are
strong multicollinearity or other numerical problems.
```

In [25]:
```
baseline_results.pvalues
```

Out[25]:
```
const          2.852024e-14
sqft_living    0.000000e+00
dtype: float64
```

Plotting the actual vs. predicted values of this model:

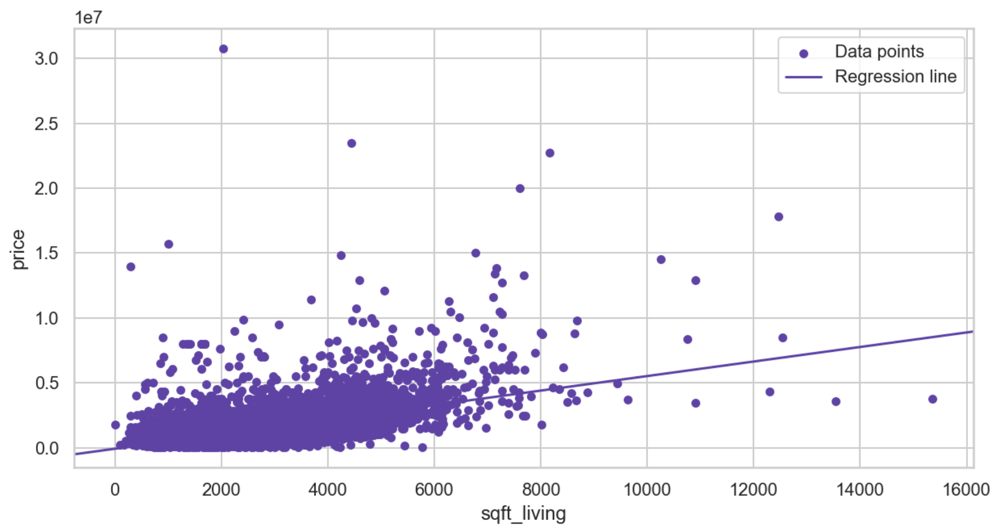
In [26]:
```
fig, ax = plt.subplots(figsize=(10,5))
sm.graphics.plot_fit(baseline_results, "sqft_living", ax=ax)
plt.show()
```



This shows the true (blue) vs. predicted (red) values, with the particular predictor (in this case, `sqft_living`) along the x-axis.

Plotting the regression line:

In [27]:
```
fig, ax = plt.subplots(figsize=(10,5))
data1.plot.scatter(x="sqft_living", y="price", label="Data points", ax=ax)
sm.graphics.abline_plot(model_results=baseline_results, label="Regression line", ax=ax)
ax.legend();
```

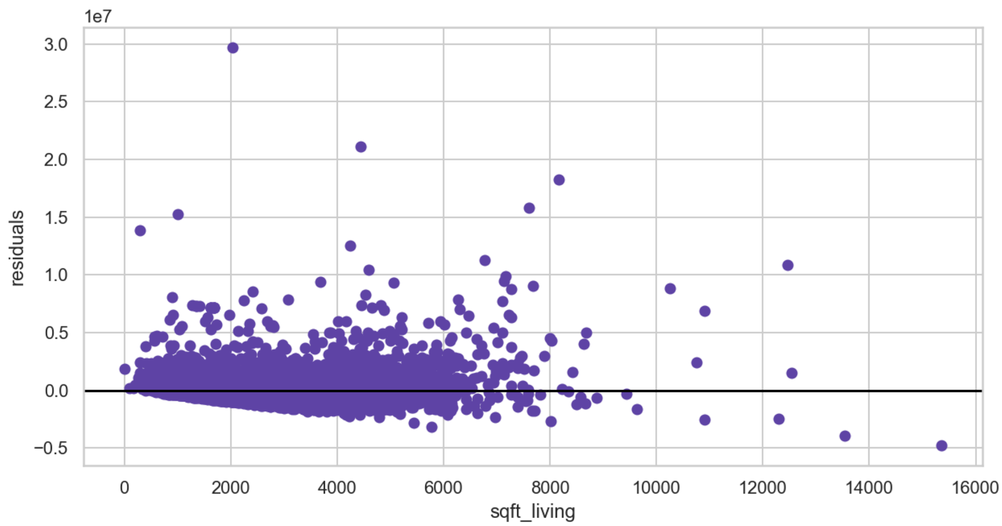



```
/Users/nicolemichaud/opt/anaconda3/envs/learn-env/lib/python3.8/site-packages/pandas/plotting/
_matplotlib/core.py:1010: UserWarning: *c* argument looks like a single numeric RGB or RGBA se
quence, which should be avoided as value-mapping will have precedence in case its length match
es with *x* & *y*.  Please use the *color* keyword-argument or provide a 2D array with a singl
e row if you intend to specify the same RGB or RGBA value for all points.
  scatter = ax.scatter(
/Users/nicolemichaud/opt/anaconda3/envs/learn-env/lib/python3.8/site-packages/pandas/plotting/
_matplotlib/core.py:1010: UserWarning: No data for colormapping provided via 'c'. Parameters
'cmap' will be ignored
  scatter = ax.scatter(
```

This linear regression plot shows the the data points for the predictor, sqft_living, against price.

Plotting the residuals:

In [28]:
```
fig, ax = plt.subplots(figsize=(10,5))

ax.scatter(data1["sqft_living"], baseline_results.resid)
ax.axhline(y=0, color="black")
ax.set_xlabel("sqft_living")
ax.set_ylabel("residuals");
```



The model residuals are the *differences* between the actual and predicted values. From this plot, it looks like this model guessed values too high more often than it guessed them too low.

Numeric data:

Now, to add all of the numeric features to a multiple linear regression to see if it improves our model:

In [29]:
```
X_all = data1.drop(['price'], axis=1).select_dtypes("number")
X_all
```

Out[29]:

	sqft_living	sqft_lot	floors
0	1180	7140	1.0
1	2770	6703	1.0
2	2880	6156	1.0
3	2160	1400	2.0
4	1120	758	2.0
...	...	...	...
30150	1910	4000	1.5
30151	2020	5800	2.0
30152	1620	3600	1.0
30153	2570	2889	2.0
30154	1200	11058	1.0

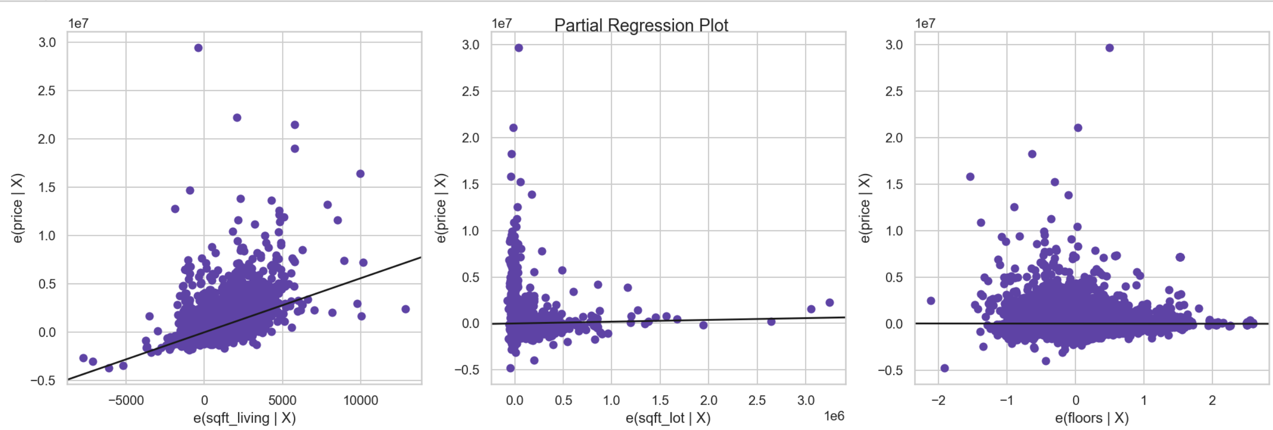
30155 rows × 3 columns

Results for all numeric variables:

In [30]:
```python
model = sm.OLS(y, sm.add_constant(X_all))
results_allnum = model.fit()

print(results_allnum.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                  price   R-squared:                       0.370
Model:                            OLS   Adj. R-squared:                  0.370
Method:                 Least Squares   F-statistic:                     5915.
Date:                Mon, 12 Jun 2023   Prob (F-statistic):               0.00
Time:                        13:05:42   Log-Likelihood:            -4.4912e+05
No. Observations:               30155   AIC:                         8.982e+05
Df Residuals:                   30151   BIC:                         8.983e+05
Df Model:                           3
Covariance Type:            nonrobust
===============================================================================
                  coef    std err          t      P>|t|      [0.025      0.975]
-------------------------------------------------------------------------------
const       -6.716e+04   1.32e+04     -5.083      0.000   -9.31e+04   -4.13e+04
sqft_living   559.7226      4.456    125.623      0.000     550.989     568.456
sqft_lot        0.1912      0.069      2.791      0.005       0.057       0.325
floors      -6399.5386   7593.611     -0.843      0.399   -2.13e+04    8484.263
==============================================================================
Omnibus:                    43413.876   Durbin-Watson:                   1.862
Prob(Omnibus):                  0.000   Jarque-Bera (JB):         47138661.786
Skew:                           8.182   Prob(JB):                         0.00
Kurtosis:                     196.001   Cond. No.                     2.19e+05
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 2.19e+05. This might indicate that there are
strong multicollinearity or other numerical problems.
```

In [31]:
```python
fig = plt.figure(figsize=(15,5))
sm.graphics.plot_partregress_grid(
    results_allnum,
    exog_idx=list(X_all.columns.values),
    grid=(1,3),
    fig=fig)

plt.show();
```



These models look worse than the initial scatterplots, so likely we included too many features. Since the numeric features of sqft_lot, and floors do not appear to have a positive linear relationship with price, we will remove those features.

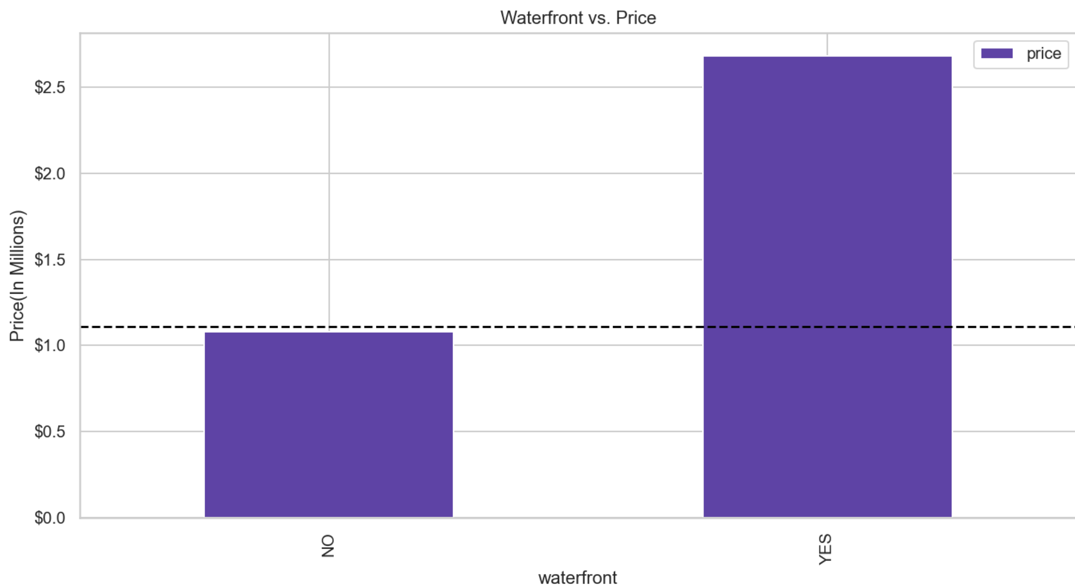
Categorical data:

Now, before the categorical variables can be modeled, they will need to be transformed using one-hot encoding.

In [32]:
```
X_wf = data1[["waterfront"]]
X_gb = data1[["greenbelt"]]
X_nu = data1[["nuisance"]]
X_vw = data1[["view"]]
```

'waterfront' feature:

In [33]:
```
fig, ax = plt.subplots(figsize=(12,6))
data1.groupby("waterfront").mean().plot.bar(y="price", ax=ax).set(ylabel="Price(In Millions)
ax.axhline(y=data1["price"].mean(), label="mean", color="black", linestyle="--")
ylabels = ['${:,.1f}'.format(x) for x in ax.get_yticks()/1000000]
ax.set_yticklabels(ylabels);
```




```
<ipython-input-33-052e0b7bcb93>:5: UserWarning: FixedFormatter should only be used together wi
th FixedLocator
  ax.set_yticklabels(ylabels);
```

In [34]:
```
waterfront_X = pd.get_dummies(X_wf, columns=["waterfront"], drop_first=True)
waterfront_X
```

Out[34]:

	waterfront_YES
0	0
1	0
2	0
3	0
4	0
...	...
30150	0
30151	0
30152	0
30153	0
30154	0

30155 rows × 1 columns

In [35]:
```
waterfront_model = sm.OLS(y, sm.add_constant(waterfront_X))
wf_results = waterfront_model.fit()

print(wf_results.summary())
```

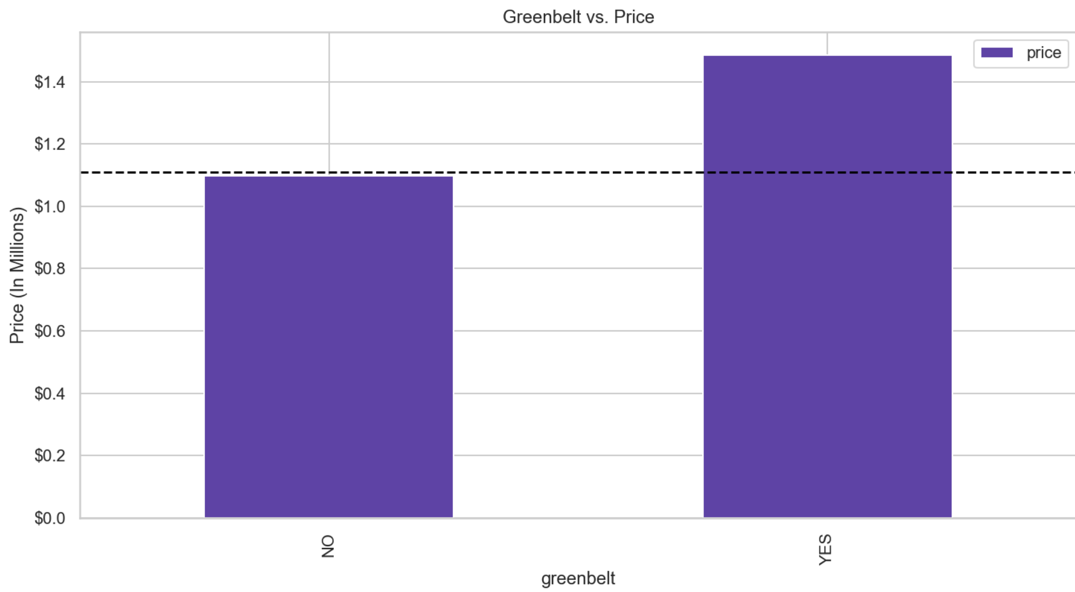
```
                            OLS Regression Results
==============================================================================
Dep. Variable:                  price   R-squared:                       0.054
Model:                            OLS   Adj. R-squared:                  0.054
Method:                 Least Squares   F-statistic:                     1719.
Date:                Mon, 12 Jun 2023   Prob (F-statistic):               0.00
Time:                        13:06:21   Log-Likelihood:            -4.5526e+05
No. Observations:               30155   AIC:                         9.105e+05
Df Residuals:                   30153   BIC:                         9.105e+05
Df Model:                           1
Covariance Type:            nonrobust
==================================================================================
                     coef    std err          t      P>|t|      [0.025      0.975]
----------------------------------------------------------------------------------
const           1.081e+06   5064.675    213.436      0.000    1.07e+06    1.09e+06
waterfront_YES  1.601e+06   3.86e+04     41.463      0.000    1.53e+06    1.68e+06
==============================================================================
Omnibus:                    35538.027   Durbin-Watson:                   1.907
Prob(Omnibus):                  0.000   Jarque-Bera (JB):         10944460.954
Skew:                           5.884   Prob(JB):                         0.00
Kurtosis:                      95.585   Cond. No.                         7.69
==============================================================================

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

Interpretation:

This model is statistically significant and explains about 5.4% of the variance in price. Compared to a house that is not on a waterfront, for a house with a waterfront we see an associated increase of about $1,601,000 in price.

'greenbelt' feature:

In [36]:
```
fig, ax = plt.subplots(figsize=(12,6))
data1.groupby("greenbelt").mean().plot.bar(y="price", ax=ax).set(ylabel="Price (In Millions)
ax.axhline(y=data1["price"].mean(), label="mean", color="black", linestyle="--")
ylabels = ['${:,.1f}'.format(x) for x in ax.get_yticks()/1000000]
ax.set_yticklabels(ylabels);
```




```
<ipython-input-36-5d4b2b7c76a6>:5: UserWarning: FixedFormatter should only be used together wi
th FixedLocator
  ax.set_yticklabels(ylabels);
```

In [37]:
```
greenbelt_X = pd.get_dummies(X_gb, columns=["greenbelt"], drop_first=True)
greenbelt_X
```

Out[37]:

	greenbelt_YES
0	0
1	0
2	0
3	0
4	0
...	...
30150	0
30151	0
30152	0
30153	0
30154	0

30155 rows × 1 columns

In [38]:
```
greenbelt_model = sm.OLS(y, sm.add_constant(greenbelt_X))
gb_results = greenbelt_model.fit()

print(gb_results.summary())
```

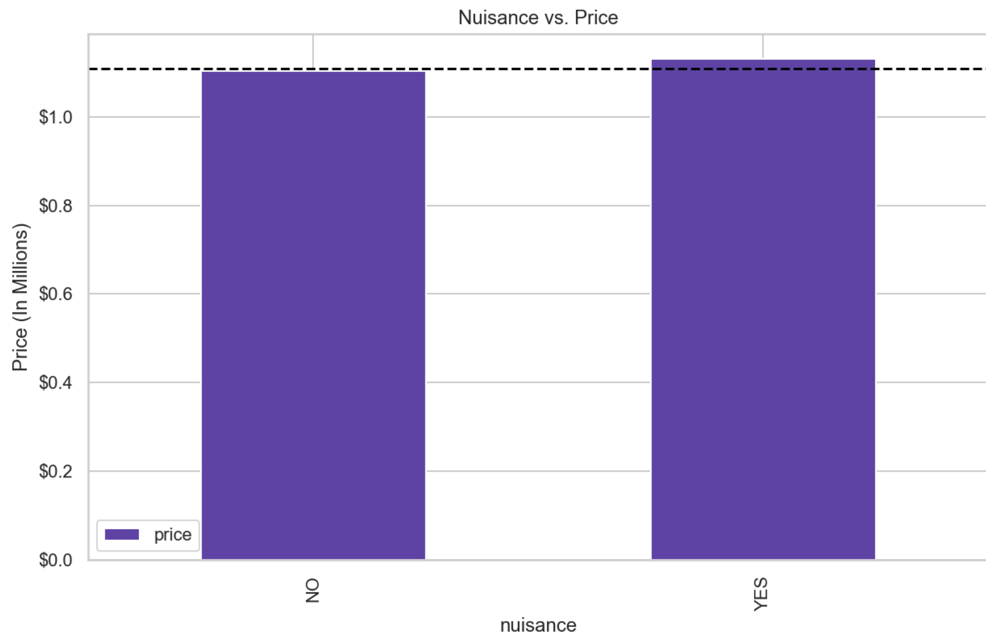
```
                            OLS Regression Results
==============================================================================
Dep. Variable:                  price   R-squared:                       0.005
Model:                            OLS   Adj. R-squared:                  0.005
Method:                 Least Squares   F-statistic:                     141.1
Date:                Mon, 12 Jun 2023   Prob (F-statistic):           1.77e-32
Time:                        13:06:26   Log-Likelihood:            -4.5603e+05
No. Observations:               30155   AIC:                         9.121e+05
Df Residuals:                   30153   BIC:                         9.121e+05
Df Model:                           1
Covariance Type:            nonrobust
=================================================================================
                    coef    std err          t      P>|t|      [0.025      0.975]
---------------------------------------------------------------------------------
const          1.099e+06   5217.319    210.570      0.000    1.09e+06    1.11e+06
greenbelt_YES  3.871e+05   3.26e+04     11.880      0.000    3.23e+05    4.51e+05
==============================================================================
Omnibus:                    38131.263   Durbin-Watson:                   1.913
Prob(Omnibus):                  0.000   Jarque-Bera (JB):         14716007.254
Skew:                           6.655   Prob(JB):                         0.00
Kurtosis:                     110.402   Cond. No.                         6.33
==============================================================================

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

Interpretation:

This model is statistically significant and explains about 0.5% of the variance in price Compared to a house that is not near a greenbelt, for a house that is near a greenbelt we see an associated increase of about $387,100 in price.

'nuisance' feature:

In [39]:
```
fig, ax = plt.subplots(figsize=(10,6))
data1.groupby("nuisance").mean().plot.bar(y="price", ax=ax).set(ylabel="Price (In Millions)"
ax.axhline(y=data1["price"].mean(), label="mean", color="black", linestyle="--")
ylabels = ['${:,.1f}'.format(x) for x in ax.get_yticks()/1000000]
ax.set_yticklabels(ylabels);
```




```
<ipython-input-39-d7fc6cb13915>:5: UserWarning: FixedFormatter should only be used together wi
th FixedLocator
  ax.set_yticklabels(ylabels);
```

In [40]:
```
nuisance_X = pd.get_dummies(X_nu, columns=["nuisance"], drop_first=True)
nuisance_X
```

Out[40]:

	nuisance_YES
0	0
1	1
2	0
3	0
4	1
...	...
30150	0
30151	0
30152	1
30153	0
30154	0

30155 rows × 1 columns

In [41]:
```
nuisance_model = sm.OLS(y, sm.add_constant(nuisance_X))
nu_results = nuisance_model.fit()

print(nu_results.summary())
```

```
                            OLS Regression Results                            
==============================================================================
Dep. Variable:                  price   R-squared:                       0.000
Model:                            OLS   Adj. R-squared:                  0.000
Method:                 Least Squares   F-statistic:                     4.021
Date:                Mon, 12 Jun 2023   Prob (F-statistic):             0.0449
Time:                        13:06:31   Log-Likelihood:            -4.5609e+05
No. Observations:               30155   AIC:                         9.122e+05
Df Residuals:                   30153   BIC:                         9.122e+05
Df Model:                           1                                         
Covariance Type:            nonrobust                                         
================================================================================
                   coef    std err          t      P>|t|      [0.025      0.975]
--------------------------------------------------------------------------------
const         1.104e+06   5681.127    194.288      0.000    1.09e+06    1.11e+06
nuisance_YES  2.727e+04   1.36e+04      2.005      0.045     614.521    5.39e+04
==============================================================================
Omnibus:                    37941.688   Durbin-Watson:                   1.914
Prob(Omnibus):                  0.000   Jarque-Bera (JB):         14348330.387
Skew:                           6.598   Prob(JB):                         0.00
Kurtosis:                     109.045   Cond. No.                         2.73
==============================================================================

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

Interpretation:

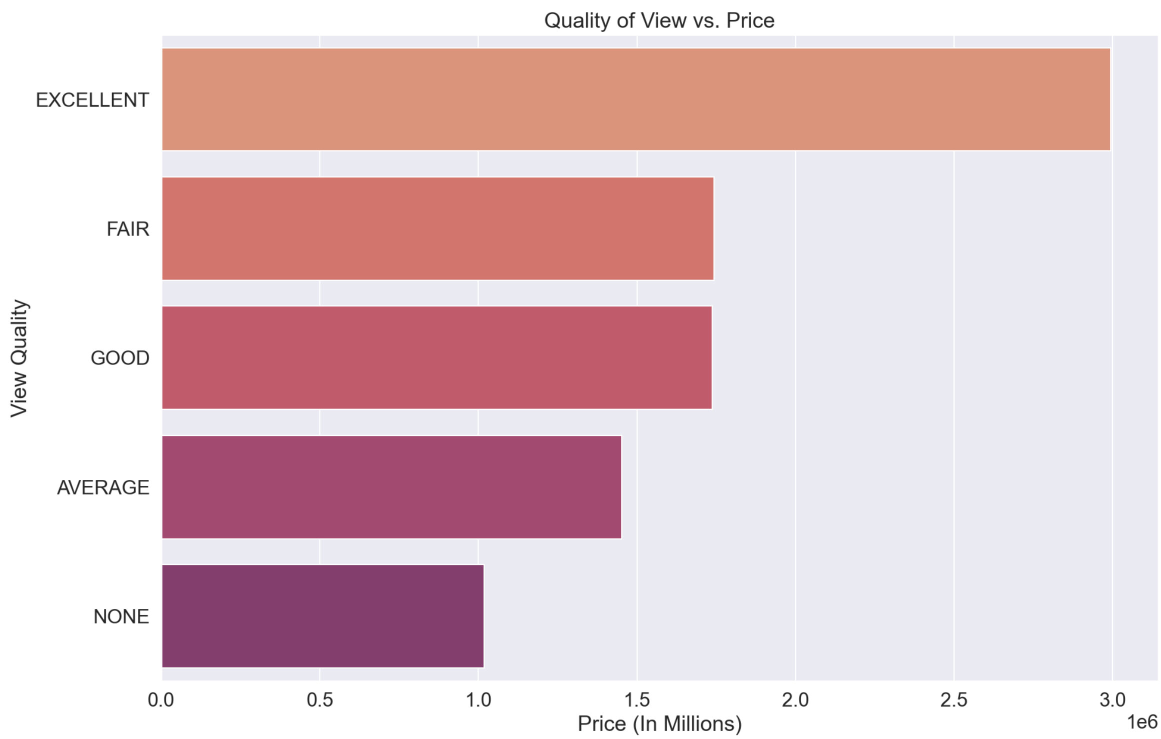
This model is not statistically significant and it explains 0% of the variance in price. This indicates that this model is not a good model to use to predict price and it may not be suited for linear regression.

'view' feature:

In [42]:
```
fig, ax = plt.subplots(figsize=(12,8))

sns.set(font_scale=1.5)
#sns.barplot(data=data1, x='view', y='price')
data1.groupby("view").mean().sort_values("price",ascending=False).plot.bar(y="price", ax=ax)
ax.axhline(y=data1["price"].mean(), label="mean", color="black", linestyle="--")
ylabels = ['${:,.1f}'.format(x) for x in ax.get_yticks()/1000000]
ax.set_yticklabels(ylabels);
```


```
<ipython-input-42-27b42950445d>:8: UserWarning: FixedFormatter should only be used together wi
th FixedLocator
  ax.set_yticklabels(ylabels);
```

In [43]:
```
view_sorted = data1.groupby("view").mean().sort_values("price",ascending=False).reset_index(
sns.set_palette('flare')
fig, ax = plt.subplots(figsize=(15,10))
sns.barplot(data=view_sorted, x="price", y="view", orient='h').set(xlabel="Price (In Million
```



In [44]:
```
view_X = pd.get_dummies(X_vw, columns=["view"], drop_first=True)
view_X
```

Out[44]:

	view_EXCELLENT	view_FAIR	view_GOOD	view_NONE
0	0	0	0	1
1	0	0	0	0
2	0	0	0	0
3	0	0	0	0
4	0	0	0	1
...	...	...	...	...
30150	0	0	0	1
30151	0	1	0	0
30152	0	0	0	1
30153	0	0	0	1
30154	0	0	0	1

30155 rows × 4 columns

In [45]:
```
view_model = sm.OLS(y, sm.add_constant(view_X))
vw_results = view_model.fit()

print(vw_results.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                  price   R-squared:                       0.117
Model:                            OLS   Adj. R-squared:                  0.117
Method:                 Least Squares   F-statistic:                     1001.
Date:                Mon, 12 Jun 2023   Prob (F-statistic):               0.00
Time:                        13:07:45   Log-Likelihood:            -4.5421e+05
No. Observations:               30155   AIC:                         9.084e+05
Df Residuals:                   30150   BIC:                         9.085e+05
Df Model:                           4
Covariance Type:            nonrobust
==================================================================================
                     coef    std err          t      P>|t|      [0.025      0.975]
----------------------------------------------------------------------------------
const           1.452e+06   1.92e+04     75.442      0.000    1.41e+06    1.49e+06
view_EXCELLENT  1.542e+06   4.07e+04     37.929      0.000    1.46e+06    1.62e+06
view_FAIR       2.901e+05      6e+04      4.838      0.000    1.73e+05    4.08e+05
view_GOOD       2.844e+05   3.43e+04      8.286      0.000    2.17e+05    3.52e+05
view_NONE      -4.334e+05   1.99e+04    -21.748      0.000   -4.72e+05   -3.94e+05
==============================================================================
Omnibus:                    35987.016   Durbin-Watson:                   1.899
Prob(Omnibus):                  0.000   Jarque-Bera (JB):         12283194.866
Skew:                           5.987   Prob(JB):                         0.00
Kurtosis:                     101.146   Cond. No.                         17.4
==============================================================================

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

Interpretation:

This model is statistically signficant and it explains about 11.7% of the variance in price. Compared to a house with an average view, we see an associated increase of about 1,542,000 dollars in price for a house with an excellent view, an increase of about 284,400 dollars in price for a house with a good view, an increase of about 290,100 dollars for a house with a fair view, and a **decrease** of about 433,400 dollars for a house with no view.

Of the categorical variables, the one that appears to be the best predictors of price is **view**.

Regression Results

Creating a multiple regression model with sqft_living and view:

Since 'view' is the categorical variable that seems to be the best predictor of price, I am going to add it to a model with sqft_living to see if it is an improvement to the baseline.

In [46]:
```
multi_x = data1[['sqft_living', 'view']]
```

In [47]:
```
multi_x_forvis = pd.get_dummies(multi_x, columns=["view"]).drop('sqft_living', axis=1)
multi_x_forvis
```

Out[47]:

	view_AVERAGE	view_EXCELLENT	view_FAIR	view_GOOD	view_NONE
0	0	0	0	0	1
1	1	0	0	0	0
2	1	0	0	0	0
3	1	0	0	0	0
4	0	0	0	0	1
...	...	...	...	...	...
30150	0	0	0	0	1
30151	0	0	1	0	0
30152	0	0	0	0	1
30153	0	0	0	0	1
30154	0	0	0	0	1

30155 rows × 5 columns

In [48]:
```
multi_x = pd.get_dummies(multi_x, columns=["view"], drop_first=True)
multi_x
```

Out[48]:

	sqft_living	view_EXCELLENT	view_FAIR	view_GOOD	view_NONE
0	1180	0	0	0	1
1	2770	0	0	0	0
2	2880	0	0	0	0
3	2160	0	0	0	0
4	1120	0	0	0	1
...	...	...	...	...	...
30150	1910	0	0	0	1
30151	2020	0	1	0	0
30152	1620	0	0	0	1
30153	2570	0	0	0	1
30154	1200	0	0	0	1

30155 rows × 5 columns

Multiple linear regression results:

In [49]:
```
multi_model = sm.OLS(y, sm.add_constant(multi_x))
multi_results = multi_model.fit()

print(multi_results.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                  price   R-squared:                       0.416
Model:                            OLS   Adj. R-squared:                  0.416
Method:                 Least Squares   F-statistic:                     4289.
Date:                Mon, 12 Jun 2023   Prob (F-statistic):               0.00
Time:                        13:08:10   Log-Likelihood:            -4.4800e+05
No. Observations:               30155   AIC:                         8.960e+05
Df Residuals:                   30149   BIC:                         8.961e+05
Df Model:                           5
Covariance Type:            nonrobust
==================================================================================
                     coef    std err          t      P>|t|      [0.025      0.975]
----------------------------------------------------------------------------------
const            1.48e+05   1.89e+04      7.850      0.000    1.11e+05    1.85e+05
sqft_living      518.4362      4.179    124.065      0.000     510.246     526.627
view_EXCELLENT  1.196e+06   3.32e+04     36.039      0.000    1.13e+06    1.26e+06
view_FAIR       2.259e+05   4.88e+04      4.631      0.000     1.3e+05    3.22e+05
view_GOOD       8.875e+04    2.8e+04      3.173      0.002    3.39e+04    1.44e+05
view_NONE      -1.824e+05   1.63e+04    -11.163      0.000   -2.14e+05    -1.5e+05
==============================================================================
Omnibus:                    41848.759   Durbin-Watson:                   1.850
Prob(Omnibus):                  0.000   Jarque-Bera (JB):         41845060.297
Skew:                           7.606   Prob(JB):                         0.00
Kurtosis:                     184.859   Cond. No.                     3.00e+04
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large,  3e+04. This might indicate that there are
strong multicollinearity or other numerical problems.
```

In [50]:
```
multi_results.pvalues
```

Out[50]:
```
const             4.313516e-15
sqft_living       0.000000e+00
view_EXCELLENT   1.714013e-278
view_FAIR         3.662044e-06
view_GOOD         1.512205e-03
view_NONE         7.013998e-29
dtype: float64
```

Interpretation:

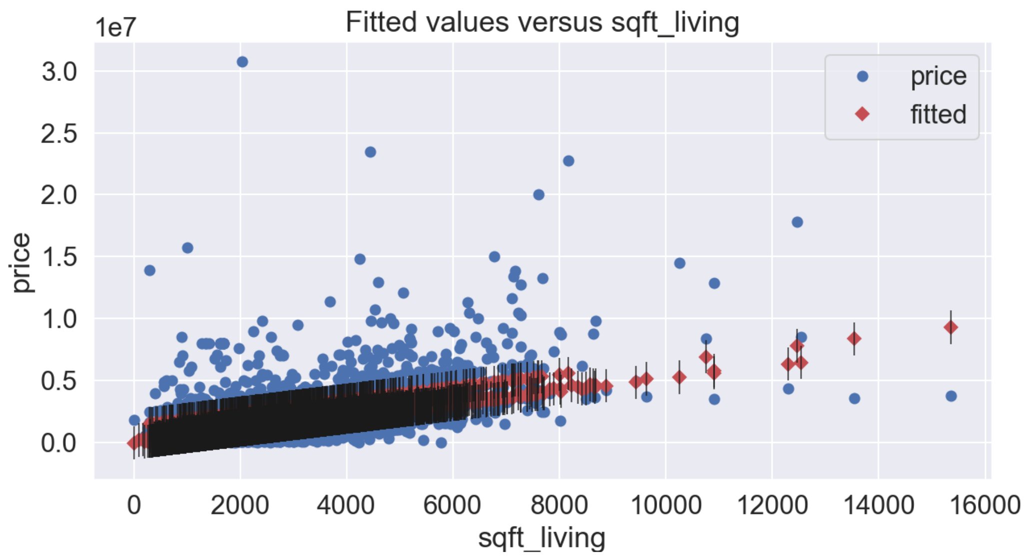
This model is statistically significant and explains about 41.6% of the variance in price, which is an improvement from the baseline model that only explained about 37%.

For each increase by 1 square foot of living space, we expect to see an increase in price of about 521 dollars. Compared to a house with an average view, for a house with an excellent view we see an associated increase in price of about of about 1,196,00 dollars. For a house with a good view, we see an associated increase in price of aboutof about 88,750 dollars. For a house with a fair view, we see an associated increase in price of about 225,900 dollars. For a house with no view, we see an associated decrease in price of about 182,400 dollars.

Multiple Linear Regression Visualization:

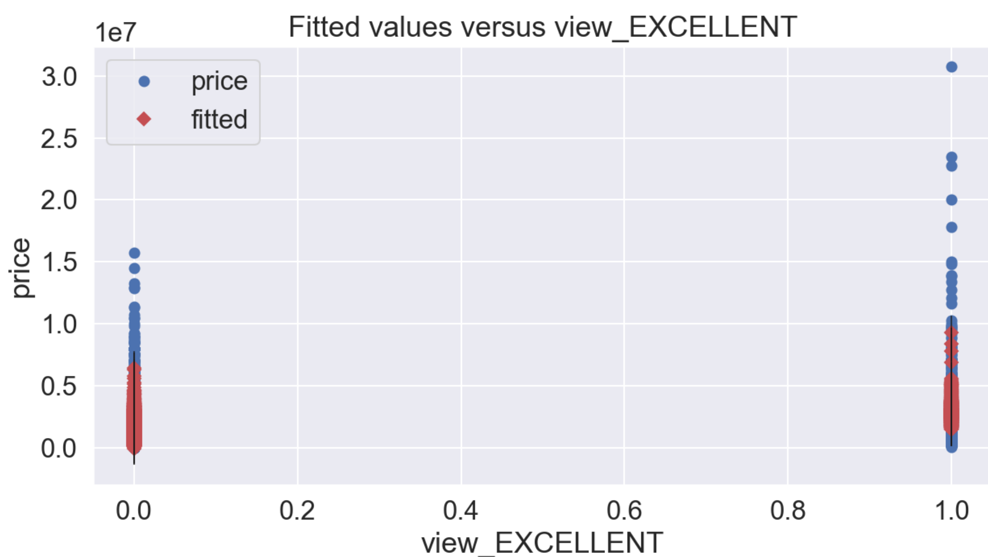
Plotting the actual vs. predicted values of this model:

In [51]:
```
fig, ax = plt.subplots(figsize=(10,5))
sm.graphics.plot_fit(multi_results, "sqft_living", ax=ax)
plt.show()
```



This shows the true (blue) vs. predicted (red) values, with the particular predictor (in this case, `sqft_living`) along the x-axis.

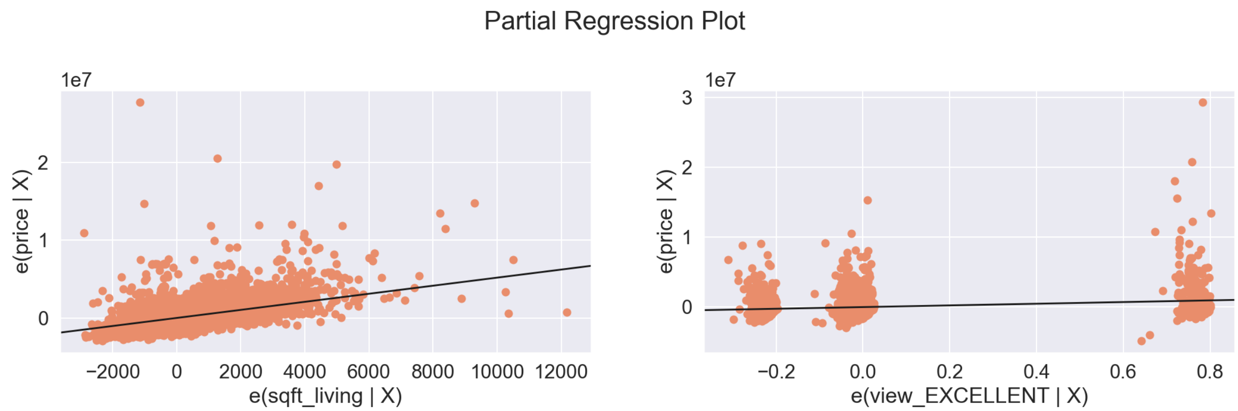
In [52]:
```
fig, ax = plt.subplots(figsize=(10,5))
sm.graphics.plot_fit(multi_results, "view_EXCELLENT", ax=ax)
plt.show()
```



This shows the true (blue) vs. predicted (red) values, with the particular predictor (in this case, `view_EXCELLENT`) along the x-axis.

Plotting the regression line:

In [53]:
```
fig = plt.figure(figsize=(15,5))
sm.graphics.plot_partregress_grid(multi_results, exog_idx=["sqft_living", "view_EXCELLENT"],
plt.tight_layout()
plt.show()
```

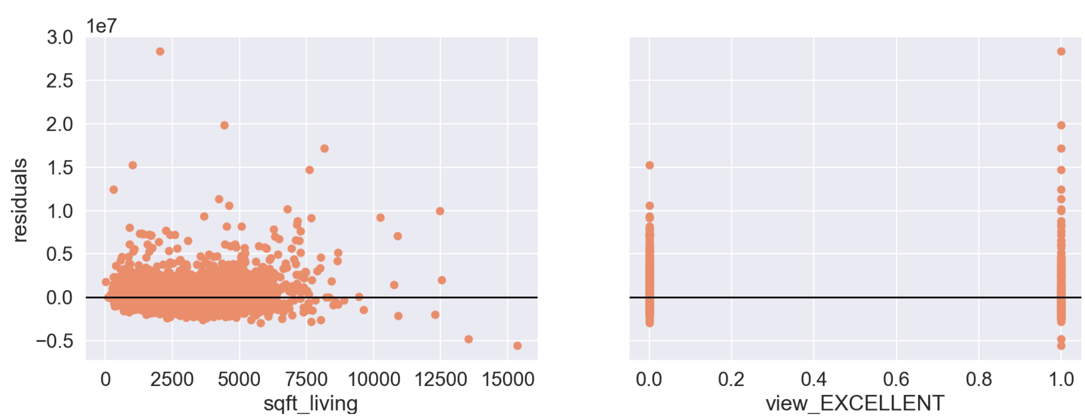


This partial regression plot on the left shows the *marginal contribution* of the predictor, sqft_living. On the x-axis, it is showing the part of "sqft_living" that is not explained by the rest of the model, and on the y-axis, the part of 'price' that is not explained by the rest of the model.

This partial regression plot on the right shows the *marginal contribution* of the predictor, view_EXCELLENT. On the x-axis, it is showing the part of "view_EXCELLENT" that is not explained by the rest of the model, and on the y-axis, the part of 'price' that is not explained by the rest of the model.

Plotting the residuals:

In [54]:
```
fig, axes = plt.subplots(ncols=2, figsize=(15,5), sharey=True)

sqftliving_ax = axes[0]
sqftliving_ax.scatter(multi_x["sqft_living"], multi_results.resid)
sqftliving_ax.axhline(y=0, color="black")
sqftliving_ax.set_xlabel("sqft_living")
sqftliving_ax.set_ylabel("residuals")

view_ax = axes[1]
view_ax.scatter(multi_x["view_EXCELLENT"], multi_results.resid)
view_ax.axhline(y=0, color="black")
view_ax.set_xlabel("view_EXCELLENT");
```



The model residuals are the *differences* between the actual and predicted values. From this plot, it looks like this model guessed values too high more often than it guessed them too low (similarly to the baseline model).

MAE for interpretability of models:

MAE for baseline:

In [55]:
```
mae = baseline_results.resid.abs().sum() / len(y)
mae
```

Out[55]: 396335.99168420106

Our baseline model is off by about $396,336 in a given prediction. This is pretty high for housing prices.

MAE for multiple linear regression model:

In [56]:
```
mae = multi_results.resid.abs().sum() / len(y)
mae
```

Out[56]: 388646.59853549825

The first multiple linear regression model is off by about $388,646.60 in a given prediction.

The model with the most improvement overall to the baseline model is the multiple linear regression model that included both sqft_living and view. This model had a higher R-squared (adjusted) value than the baseline and it had a lower MAE (mean absolute error) value.

Conclusion

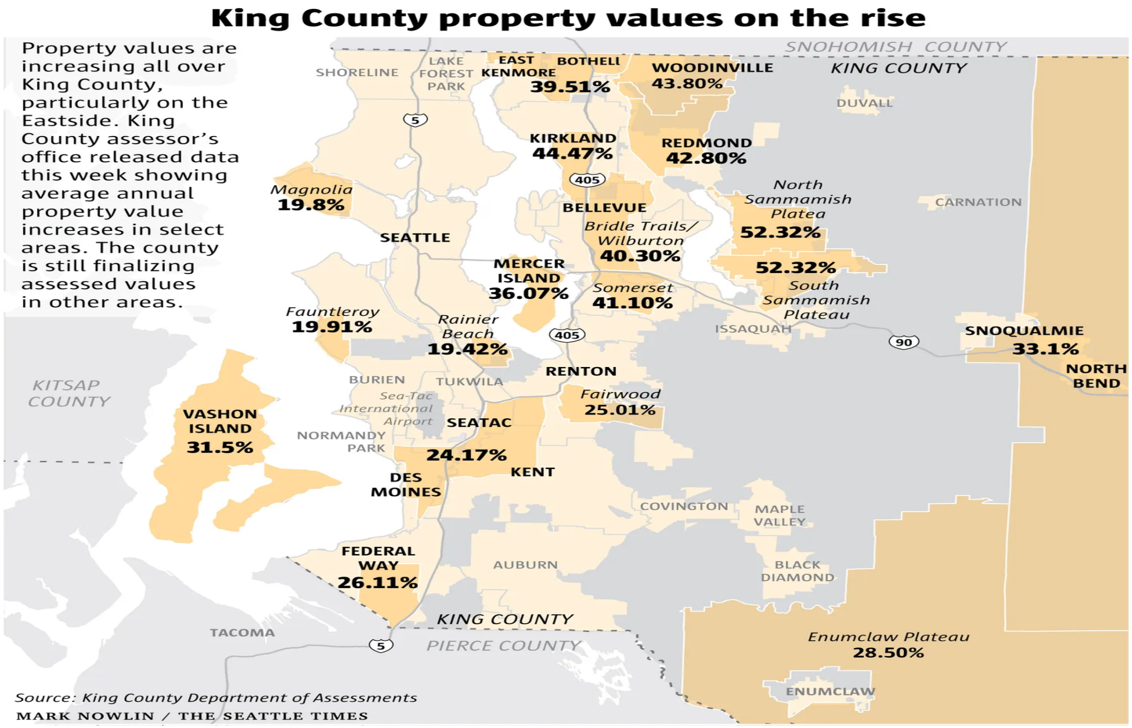
The models created show that the features that are most predictive of house sale price are the square feet of living space and the quality of the view. If the stakeholder is to only go off of this information, those are the two factors that they should look for when deciding which houses to buy in order to flip and make the highest possible profits.

Limitations:

As can be seen in the QQ plot of the target variable 'price', the model becomes unreliable more than plus or minus 2 standard deviations away from the mean, or outside of the price range of 684,205.75 and 2,901,227.43 dollars. The best model that was found still only explained 41.6% of the variance in price and was still estimated to be off by about 388,646.60 dollars on a given predicition, which is a pretty high number. Additionally, this dataset does not include information on certain housing features that would likely be even more related to sale price, such as the subdivision that the house is in.

Next Steps:

In order to get a better idea of the true best predictors of housing sale prices, further analysis should be conducted on more datasets that include more features, such as housing subdivision.



This image shows how even within a county, housing prices can vary based on subdivision.