King County House Sales Data Analysis Project

For this preoject, regression modeling will be used on the King County House sales dataset in order to analyze house sales in a Northwestern county of Washington. The file kc_house_data.csv contained the data utilized in this project. The data will help inform the models and features highlighted to address the stakeholder's needs.

Business Understanding

Stakeholders

- The stakeholders in this project is Ramtuck Realty Group

Consumer Use

- Ramtuck Realty group will use the results obtained from this project to help their clients who have made specific requests about the home they are looking for within King County.

Data Understanding

We will be focusing on price as our target variable since it is dependent on various features present on our dataset. Presented below is the outline and description of the columns present in our dataset.

Column Names and descriptions for Kings County Data Set

- **id** - unique identified for a house
- **date** - house was sold
- **price** - is prediction target
- **bedroomsNumber** - of Bedrooms/House
- **bathroomsNumber** - of bathrooms/bedrooms
- **sqft_livingsquare** - footage of the home
- **sqft_lotsquare** - footage of the lot
- **floorsTotal** - floors (levels) in house
- **waterfront** - House which has a view to a waterfront
- **view** - Has been viewed
- **condition** - How good the condition is (Overall)
- **grade** - overall grade given to the housing unit, based on King County grading system
- **sqft_above** - square footage of house apart from basement
- **sqft_basement** - square footage of the basement
- **yr_built** - Built Year
- **yr_renovated** - Year when house was renovated
- **zipcode** - zip
- **lat** - Latitude coordinate
- **long** - Longitude coordinate
- **sqft_living15** - The square footage of interior housing living space for the nearest 15 neighbors
- **sqft_lot15** - The square footage of the land lots of the nearest 15 neighbors

For our purposes we will be disregarging the following columns in the data

- **date**
- **id**

First, we will import the libraries that we will require in order to analyze our data. We will also import our dataset as 'data'

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import scipy.stats as stats
import seaborn as sns
%matplotlib inline
import warnings
warnings.filterwarnings('ignore')

import statsmodels.api as sm
from statsmodels.formula.api import ols

from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LinearRegression
linreg = LinearRegression()
from sklearn.model_selection import train_test_split
from sklearn.model_selection import KFold
from sklearn.model_selection import cross_val_score
from sklearn.svm import SVR
```

```
import sklearn.metrics as metrics
from sklearn.metrics import mean_squared_error
```

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

We look at the descriptive information of our dataset

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

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

In [4]:
```
data.head()
```

Out[4]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	...	grade	sqft_above	sqft_basement	yr_built
0	7129300520	10/13/2014	221900.0	3	1.00	1180	5650	1.0	NaN	0.0	...	7	1180	0.0	1955
1	6414100192	12/9/2014	538000.0	3	2.25	2570	7242	2.0	0.0	0.0	...	7	2170	400.0	1951
2	5631500400	2/25/2015	180000.0	2	1.00	770	10000	1.0	0.0	0.0	...	6	770	0.0	1933
3	2487200875	12/9/2014	604000.0	4	3.00	1960	5000	1.0	0.0	0.0	...	7	1050	910.0	1965
4	1954400510	2/18/2015	510000.0	3	2.00	1680	8080	1.0	0.0	0.0	...	8	1680	0.0	1987

5 rows × 21 columns

Determine the number of rows and columns in the dataset.

In [5]:
```
data.shape
```

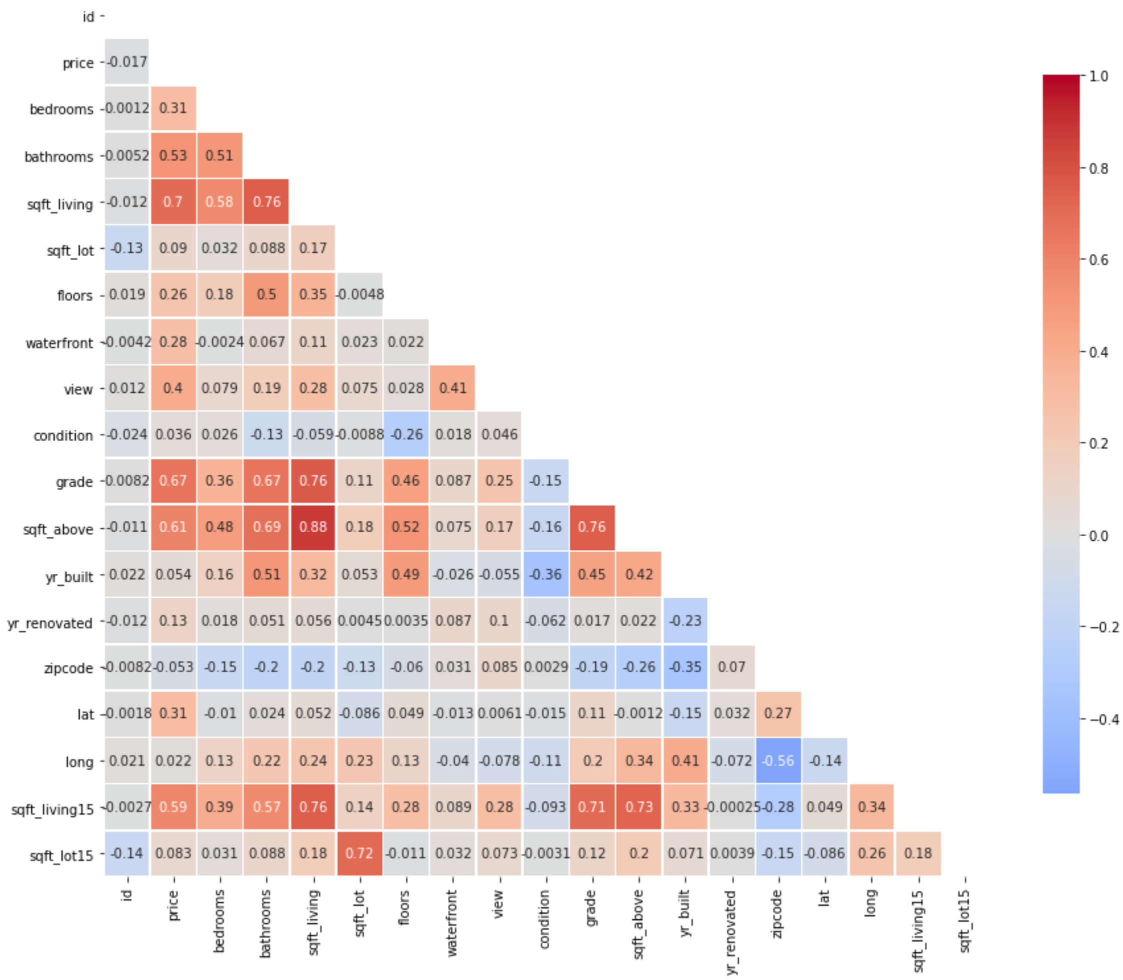
Out[5]: (21597, 21)

Initial analysis of the correlation between variables in the dataset

In [6]:
```
corr = data.corr()
mask = np.zeros_like(corr)
mask[np.triu_indices_from(mask)] = True

f, ax = plt.subplots(figsize=(15, 20))

sns.heatmap(corr, mask=mask, cmap='coolwarm', vmax=1, center=0,
            square=True, linewidths=.5,annot=True, cbar_kws={"shrink": .5});
```



From the inital correlation analysis we can interpret:

- Darker red boxes outline our variables that have strong positive linear relationships
- Darker blue boxes outline our variables that have strong negative linear relationships

We will focus on the variables that focus on condition and size since they share some positive relationships with price. We will also work on creating observations regarding square footage

Data Preparation

Drop the columns that are not required from the dataset

In [7]:
```
data = data.drop(columns= ['id','date'])
```

In [8]:
```
data.head()
```

Out[8]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition	grade	sqft_above	sqft_basement	yr_built	yr_renovated	zip
0	221900.0	3	1.00	1180	5650	1.0	NaN	0.0	3	7	1180	0.0	1955	0.0	9
1	538000.0	3	2.25	2570	7242	2.0	0.0	0.0	3	7	2170	400.0	1951	1991.0	9
2	180000.0	2	1.00	770	10000	1.0	0.0	0.0	3	6	770	0.0	1933	NaN	9
3	604000.0	4	3.00	1960	5000	1.0	0.0	0.0	5	7	1050	910.0	1965	0.0	9
4	510000.0	3	2.00	1680	8080	1.0	0.0	0.0	3	8	1680	0.0	1987	0.0	9

There are a couple of NaN and 0 values that I will work on cleaning up

In [9]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 21597 entries, 0 to 21596
Data columns (total 19 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   price          21597 non-null  float64
 1   bedrooms       21597 non-null  int64
 2   bathrooms      21597 non-null  float64
 3   sqft_living    21597 non-null  int64
 4   sqft_lot       21597 non-null  int64
```

```
 5   floors         21597 non-null  float64
 6   waterfront     19221 non-null  float64
 7   view           21534 non-null  float64
 8   condition      21597 non-null  int64
 9   grade          21597 non-null  int64
 10  sqft_above     21597 non-null  int64
 11  sqft_basement  21597 non-null  object
 12  yr_built       21597 non-null  int64
 13  yr_renovated   17755 non-null  float64
 14  zipcode        21597 non-null  int64
 15  lat            21597 non-null  float64
 16  long           21597 non-null  float64
 17  sqft_living15  21597 non-null  int64
 18  sqft_lot15     21597 non-null  int64
dtypes: float64(8), int64(10), object(1)
memory usage: 3.1+ MB
```

In [10]:
```
data.isna().sum()
```

Out[10]:
```
price               0
bedrooms            0
bathrooms           0
sqft_living         0
sqft_lot            0
floors              0
waterfront       2376
view               63
condition           0
grade               0
sqft_above          0
sqft_basement       0
yr_built            0
yr_renovated     3842
zipcode             0
lat                 0
long                0
sqft_living15       0
sqft_lot15          0
dtype: int64
```

In order to clean up some of the NaN that are present the following will be completed:

- Set NaNs in 'waterfront' to 0, meaning there is no waterfront present
- Set NaNs in 'views' to 0, meaning that the property has not been viewed
- Set 0.0 in 'yr_renovated' to null, meaning that the property has not been renovated
- Set 0.0 and ? in 'sqft_basement' to null, meaning that the property does not have a basement

In [11]:
```
data['waterfront'] = data['waterfront'].fillna(0)
data['view'] = data['view'].fillna(0)
data['yr_renovated'] = data['yr_renovated'].replace(0,np.nan)
data['sqft_basement'] = data['sqft_basement'].replace('0.0',np.nan)
data['sqft_basement'] = data['sqft_basement'].replace('?',np.nan)
```

There are two additional items that need to be done with the data:

- Set the 'zipcode' column to a string for ease of use
- Set the 'sqft_basement' data type to float

In [12]:
```
data.zipcode = data.zipcode.astype(str)
data['sqft_basement'] = data['sqft_basement'].astype(float)
```

At this point, we can review the dataset to see the changes that have been made.

In [13]:
```
data.head()
```

Out[13]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition	grade	sqft_above	sqft_basement	yr_built	yr_renovated	zip
0	221900.0	3	1.00	1180	5650	1.0	0.0	0.0	3	7	1180	NaN	1955	NaN	9
1	538000.0	3	2.25	2570	7242	2.0	0.0	0.0	3	7	2170	400.0	1951	1991.0	9
2	180000.0	2	1.00	770	10000	1.0	0.0	0.0	3	6	770	NaN	1933	NaN	9
3	604000.0	4	3.00	1960	5000	1.0	0.0	0.0	5	7	1050	910.0	1965	NaN	9
4	510000.0	3	2.00	1680	8080	1.0	0.0	0.0	3	8	1680	NaN	1987	NaN	9

In [14]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 21597 entries, 0 to 21596
Data columns (total 19 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   price          21597 non-null  float64
 1   bedrooms       21597 non-null  int64
 2   bathrooms      21597 non-null  float64
 3   sqft_living    21597 non-null  int64
 4   sqft_lot       21597 non-null  int64
 5   floors         21597 non-null  float64
 6   waterfront     21597 non-null  float64
 7   view           21597 non-null  float64
 8   condition      21597 non-null  int64
 9   grade          21597 non-null  int64
```

```
 10  sqft_above     21597 non-null  int64
 11  sqft_basement  8317 non-null   float64
 12  yr_built       21597 non-null  int64
 13  yr_renovated   744 non-null    float64
 14  zipcode        21597 non-null  object
 15  lat            21597 non-null  float64
 16  long           21597 non-null  float64
 17  sqft_living15  21597 non-null  int64
 18  sqft_lot15     21597 non-null  int64
dtypes: float64(9), int64(9), object(1)
memory usage: 3.1+ MB
```

Get some descriptive statistics for each of the column.

In [15]:
```
data.describe()
```

Out[15]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition	grade	
count	2.159700e+04	21597.000000	21597.000000	21597.000000	2.159700e+04	21597.000000	21597.000000	21597.000000	21597.000000	21597.000000	21
mean	5.402966e+05	3.373200	2.115826	2080.321850	1.509941e+04	1.494096	0.006760	0.233181	3.409825	7.657915	17
std	3.673681e+05	0.926299	0.768984	918.106125	4.141264e+04	0.539683	0.081944	0.764673	0.650546	1.173200	
min	7.800000e+04	1.000000	0.500000	370.000000	5.200000e+02	1.000000	0.000000	0.000000	1.000000	3.000000	
25%	3.220000e+05	3.000000	1.750000	1430.000000	5.040000e+03	1.000000	0.000000	0.000000	3.000000	7.000000	1
50%	4.500000e+05	3.000000	2.250000	1910.000000	7.618000e+03	1.500000	0.000000	0.000000	3.000000	7.000000	15
75%	6.450000e+05	4.000000	2.500000	2550.000000	1.068500e+04	2.000000	0.000000	0.000000	4.000000	8.000000	2
max	7.700000e+06	33.000000	8.000000	13540.000000	1.651359e+06	3.500000	1.000000	4.000000	5.000000	13.000000	9

Modeling

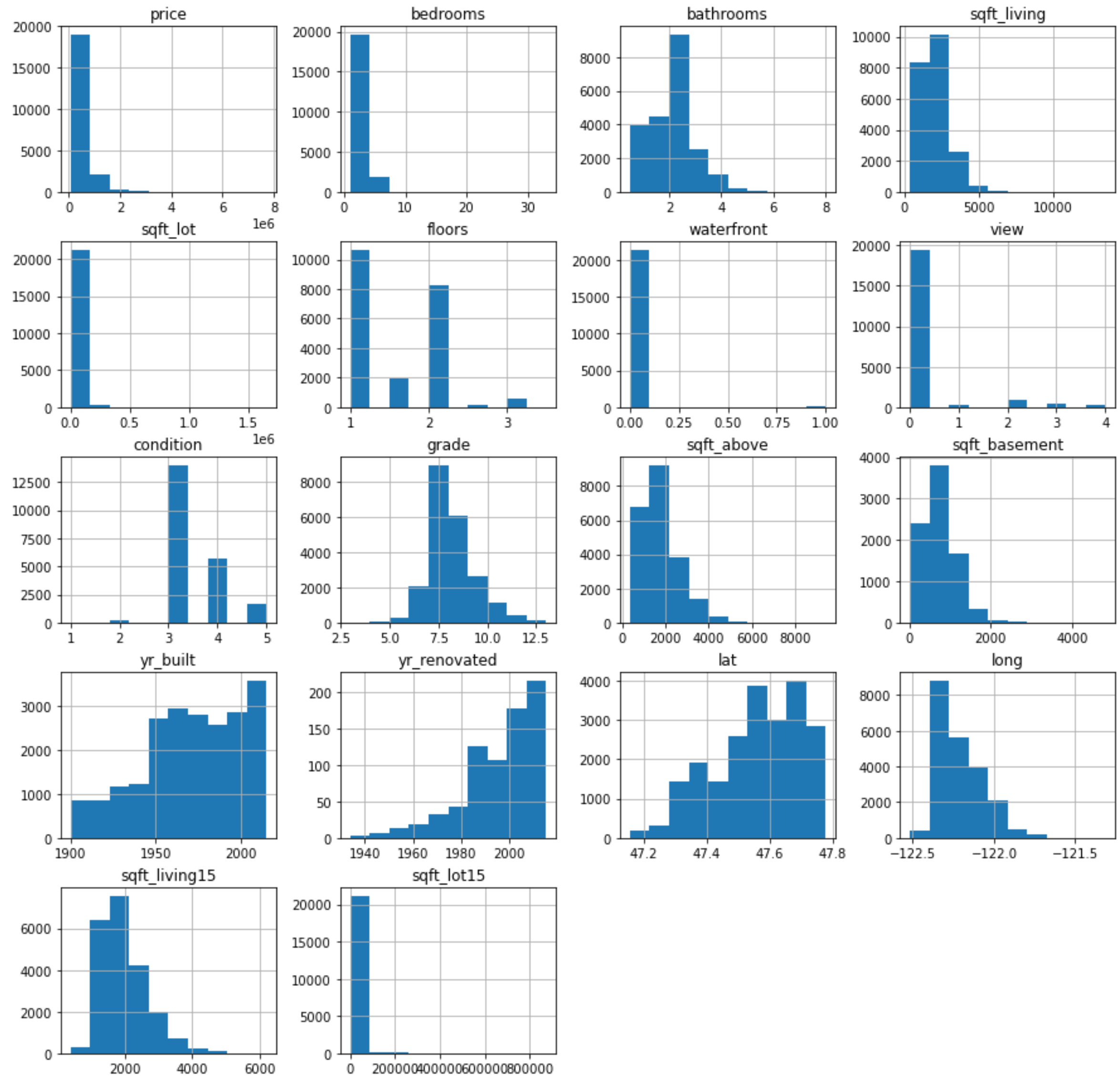
Initial Visualizations for Modeling

We will evaluate our dataset in order to inform our feature engineering. In order to complete this task we will use the following methods:

- Histogram of our x variables
- Simple Linear Regression graphs of the most promising x variables vs 'Price', our target variable.
- R squared values in order to test how close the data is to the fitted regression line

Histogram

In [16]:
```
data.hist(figsize=([15,15]));
```



Linear Regression with Promising X variables

We will be creating visualizations for the following x variables:

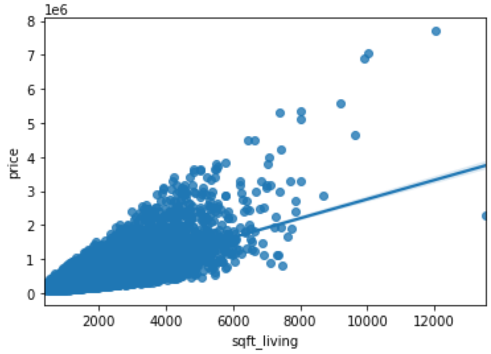
- **sqft_living**
- **grade**
- **sqft_above**
- **sqft_living15**
- **bathrooms**
- **bedrooms**
- **view**
- **lat**

Sqft_Living vs Price

In [17]:
```
y = data['price']
sqft_living_x = data['sqft_living']
model = ols(formula = 'y~sqft_living_x', data=data).fit()
print('R squared:', model.rsquared)

sns.regplot(x='sqft_living', y='price', data=data);
```

```
R squared: 0.49268789904035093
```



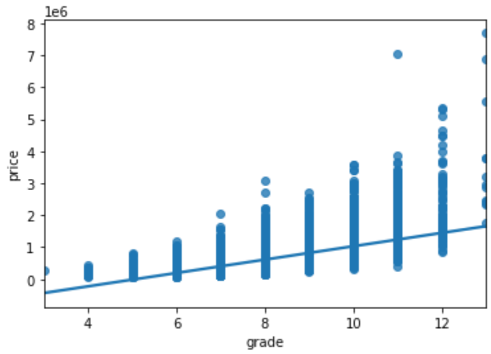
Grade vs Price

In [18]:

```
grade_x = data['grade']
model = ols(formula = 'y~grade_x', data=data).fit()
print('R squared:', model.rsquared)

sns.regplot(x='grade', y='price', data=data);
```

```
R squared: 0.44615823299735025
```

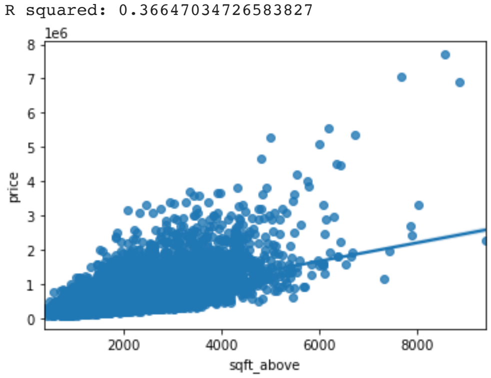


Sqft_above vs Price

In [19]:

```
sqft_above_x = data['sqft_above']
model = ols(formula = 'y~sqft_above_x', data=data).fit()
print('R squared:', model.rsquared)
sns.regplot(x='sqft_above', y='price', data=data);
```

```
R squared: 0.36647034726583827
```



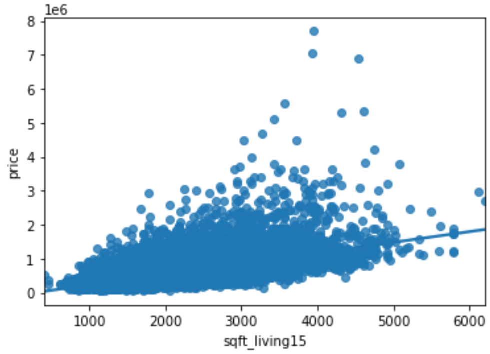
Sqft_living15 vs Price

In [20]:

```
sqft_living15_x = data['sqft_living15']
model = ols(formula = 'y~sqft_living15_x', data=data).fit()
print('R squared:', model.rsquared)

sns.regplot(x='sqft_living15', y='price', data=data);
```

```
R squared: 0.34250726417201915
```

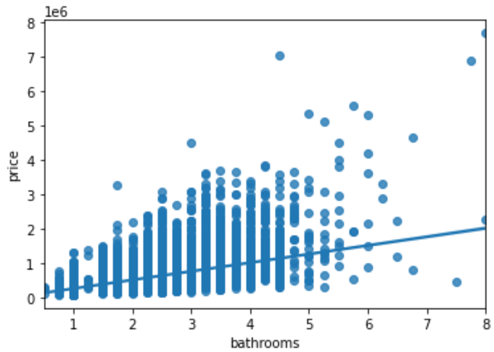


Bathrooms vs Price

In [21]:
```
bathrooms_x = data['bathrooms']
model = ols(formula = 'y~bathrooms_x', data=data).fit()
print('R squared:', model.rsquared)

sns.regplot(x='bathrooms', y='price', data=data);
```

```
R squared: 0.27657672267607736
```

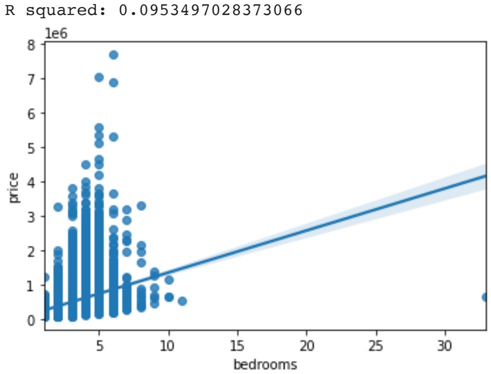


Bedrooms vs Price

In [22]:
```
bedrooms_x = data['bedrooms']
model = ols(formula = 'y~bedrooms_x', data=data).fit()
print('R squared:', model.rsquared)

sns.regplot(x='bedrooms', y='price', data=data);
```

```
R squared: 0.0953497028373066
```

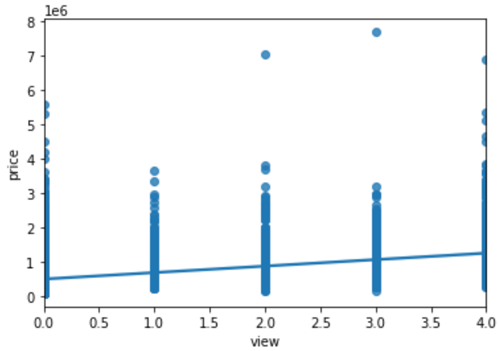


View vs Price

In [23]:
```
view_x = data['view']
model = ols(formula = 'y~view_x', data=data).fit()
print('R squared:', model.rsquared)

sns.regplot(x='view', y='price', data=data);
```

```
R squared: 0.15483962881266589
```

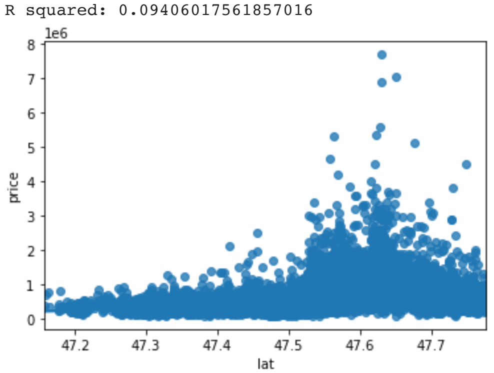


Lat vs Price

In [24]:
```
lat_x = data['lat']
model = ols(formula = 'y~lat_x', data=data).fit()
print('R squared:', model.rsquared)

sns.regplot(x='lat', y='price', data=data);
```

```
R squared: 0.09406017561857016
```



Functions for Multiple Linear Regressions and Error

Stats_reg summary does the following:

- outputs regression summary through statsmodels for a DataFrame
- sets predictors as a numpy array of X
- adds a constant to predictors
- passes DV and predictors through OLS
- provides OLS summary

In [25]:
```
def stats_linreg_summary(df):
    X = df.drop(['log_price', 'price'], axis=1)
    y = df.log_price
    predictors = np.asarray(X)
    predictors_int = sm.add_constant(predictors)
    model = sm.OLS(y, predictors_int).fit()
    print('List of Predictors:', X.columns)
    print(model.summary())
```

Sk_linreg_summary does the following:

- outputs R squared and error metrics through sklearn for a DataFrame
- creates test-train-split
- provides the list of predictors
- Calculates our R squared value
- Provides necessary Mean Absolute Error and Mean Squared Error Value
- Calculates the RMSE from the obtained MSE

In [26]:
```
def sk_linreg_summary(df):
    X = df.drop(['log_price', 'price'], axis=1)
    y = df.log_price
    ss = StandardScaler()
    X_scaled = ss.fit_transform(X)
    np.random.seed(33)
    X_train, X_test, y_train, y_test = train_test_split(X_scaled, y)
    linreg = LinearRegression()
    linreg.fit(X_train, y_train)
    coeff_array = linreg.coef_
    r_2 = metrics.r2_score(y_test, linreg.predict(X_test))
    mae = metrics.mean_absolute_error(np.exp(y_test), np.exp(linreg.predict(X_test)))
    mse = metrics.mean_squared_error(np.exp(y_test), np.exp(linreg.predict(X_test)))
```

```
    print('Results of Sklearn Train Test Split:')
    print('Array of coefficients:', [coeff_array])
    print('List of Predictors:', X.columns)
    print('R squared:', r_2)
    print('Mean Absolute Error:', mae)
    print('Mean Squared Error:', mse)
    print('Root Mean Squared Error:', np.sqrt(mse))
```

kfolds does the following:

- Forces the data as a pandas dataframes
- Creates a list for our folds
- Makes fold size 1 unit larger to account for leftovers

In [27]:

```
def kfolds(data, k):
    data = pd.DataFrame(data)
    num_observations = len(data)
    fold_size = num_observations//k
    leftovers = num_observations%k
    folds = []
    start_obs = 0
    for fold_n in range(1,k+1):
        if fold_n <= leftovers:
            fold = data.iloc[start_obs: start_obs + fold_size + 1]
            folds.append(fold)
            start_obs += fold_size + 1
        else:
            fold = data.iloc[start_obs: start_obs + fold_size]
            folds.append(fold)
            start_obs += fold_size
    return folds
```

kfolds_error_summary does the following:

- Applies kfolds function to a given dataframe
- Outputs R squares and error metrics
- Splits train and test values for folds
- Fits our linear regression model
- Evaluates our train and test errors
- Provides our MSE, MAE and RMSE values

In [28]:

```
def kfolds_error_summary(df,k):
    X = df.drop(['log_price', 'price'], axis=1)
    y = df[['log_price']]
    k_folds_df = kfolds(df, k)
    MSE_test_err = []
    MSE_train_err = []
    MAE_test_err = []
    MAE_train_err = []
    k=k
    linreg = LinearRegression()
    cv_kresults = cross_val_score(linreg, X, y, cv=k, scoring='r2')
    for n in range(k):
        train = pd.concat([fold for i, fold in enumerate(k_folds_df) if i !=n])
        test = k_folds_df[n]
        linreg.fit(train[X.columns], train[y.columns])
        y_hat_train = linreg.predict(train[X.columns])
        y_hat_test = linreg.predict(test[X.columns])
        test_residuals = np.exp(y_hat_test) - np.exp(test[y.columns])
        train_residuals = np.exp(y_hat_train) - np.exp(train[y.columns])
        MSE_test_err.append(np.mean(test_residuals.astype(float)**2))
        MSE_train_err.append(np.mean(train_residuals.astype(float)**2))
        MAE_test_err.append(np.mean(abs(test_residuals.astype(float))))
        MAE_train_err.append(np.mean(abs(train_residuals.astype(float))))

    print('List of Predictors:', X.columns)
    print('R squared when k={k}:', np.mean(cv_kresults))
    print('Average training Mean Absolute Error when k={k}:', np.mean(MAE_train_err))
    print('Average training Mean Square Error when k={k}:', np.mean(MSE_train_err))
    print('Average Root Mean Square Error when k={k}:', np.sqrt(np.mean(MSE_train_err)))
```

Initial Model: Multiple Linear Regression with 6 Features

From the initial evaluation we did with 8 features above, we have limited the features that we will be using for our model to 6. This is so that we can highlihght those features that appear to have the strongest relationship with our target variable 'price'.

The features that we will be including in 'data_t6' which represents our top 6 features are:

- bathrooms
- sqft_living
- grade
- sqft_above
- view

- sqft_living15

We will then be using our functions in order to determine model efficacy through its metrics.

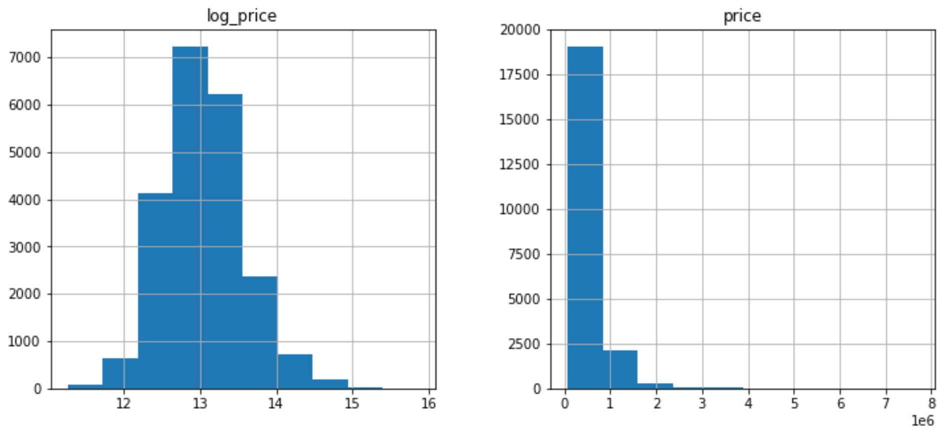
Additionally we will be log transforming our target variable as well, since it is not normally distributed. This also helps us stay within the linear regression assumptions of normality. A visualization of the difference will be presented.

In [29]:
```
data_t6 = data[['price', 'sqft_living', 'grade', 'sqft_above', 'sqft_living15', 'bathrooms', 'view']]
```

In [30]:
```
data_t6['log_price'] = np.log(data_t6['price'])
```

Histogram for comparison of original price vs log_price

In [31]:
```
data_t6[['log_price', 'price']].hist(figsize=(12,5));
```



Statsmodel Results

In [32]:
```
stats_linreg_summary(data_t6)
```

```
List of Predictors: Index(['sqft_living', 'grade', 'sqft_above', 'sqft_living15', 'bathrooms',
       'view'],
      dtype='object')
                            OLS Regression Results
==============================================================================
Dep. Variable:              log_price   R-squared:                       0.583
Model:                            OLS   Adj. R-squared:                  0.583
Method:                 Least Squares   F-statistic:                     5034.
Date:                Thu, 25 Mar 2021   Prob (F-statistic):               0.00
Time:                        19:09:28   Log-Likelihood:                -7343.4
No. Observations:               21597   AIC:                         1.470e+04
Df Residuals:                   21590   BIC:                         1.476e+04
Df Model:                           6
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const         11.1621      0.019    594.801      0.000      11.125      11.199
x1             0.0002   6.34e-06     38.996      0.000       0.000       0.000
x2             0.1845      0.003     54.286      0.000       0.178       0.191
x3            -0.0001   6.26e-06    -17.566      0.000      -0.000   -9.76e-05
x4          7.349e-05   5.57e-06     13.195      0.000    6.26e-05    8.44e-05
x5            -0.0051      0.005     -1.073      0.283      -0.014       0.004
x6             0.0855      0.003     26.295      0.000       0.079       0.092
==============================================================================
Omnibus:                        9.927   Durbin-Watson:                   1.970
Prob(Omnibus):                  0.007   Jarque-Bera (JB):                9.351
Skew:                           0.024   Prob(JB):                      0.00932
Kurtosis:                       2.910   Cond. No.                     2.98e+04
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 2.98e+04. This might indicate that there are
strong multicollinearity or other numerical problems.
```

Sklearn Results

In [33]:
```
sk_linreg_summary(data_t6)
```

```
Results of Sklearn Train Test Split:
Array of coefficients: [array([ 0.22286925,  0.21561096, -0.08675588,  0.05233619, -0.00474355,
        0.06411343])]
List of Predictors: Index(['sqft_living', 'grade', 'sqft_above', 'sqft_living15', 'bathrooms',
       'view'],
      dtype='object')
R squared: 0.5941566537740015
Mean Absolute Error: 145721.69281836363
Mean Squared Error: 49489790470.363
Root Mean Squared Error: 222463.00921807878
```

Kfolds Results

In [34]:
```
kfolds_error_summary(data_t6,5)
```

```
List of Predictors: Index(['sqft_living', 'grade', 'sqft_above', 'sqft_living15', 'bathrooms',
       'view'],
      dtype='object')
R squared when k={k}: 0.5807327492042109
Average training Mean Absolute Error when k={k}: 146071.1318599914
Average training Mean Square Error when k={k}: 56550273327.68461
Average Root Mean Square Error when k={k}: 237803.0137060601
```

First Multiple Linear Regression Results Analysis

R squared

- Statsmodels: 0.58
- Sklearn: 0.59
- Kfold: 0.57

Mean Absolute Error

- Sklearn: 145,721
- Kfolds: 145,885

Root Square Means Error

- Sklearn: 222,463
- Kfolds: 243,433

Observations

- Compared to the R squared values we have seen such as 0.49 for sqft_living variable, we have been able to obtain a small but at the same time relatively significant increase to 0.58. It appears that including the 6 top variables in a MLR that we were able to improve on our metrics, although our MSE and MAE still need work. These values will give us a baseline to work of off as we continue to improve the model and take into account factors such as multicollinearity which can affect our results. We will work to improve the results of our current MLR model.

Multiple Regression Model Tests for Improvement

Since we have been able to deduce that sqft_living is our highest predictor from previous analysis, we will work on manipulating 'data_t6' variables in order to see if this results in improvement in our model. We will take into consideration variables that are highly correlated with sqft_living within 'data_t6. We will also consider, if necessary, adding variables from our original dataset 'data' in order to see if there are additional improvements that can be made beyond the variables in 'data_t6'.

First Test: Removing 'sqft_above'

- Since 'sqft_above' and 'sqft_living' are highly correlated (0.88), it is important to see if this relationship may be a source of collinearity leading to obfuscation of our model.

In [35]:
```
data2 = data_t6.drop(['sqft_above'], axis=1)
data2.head()
```

Out[35]:

	price	sqft_living	grade	sqft_living15	bathrooms	view	log_price
0	221900.0	1180	7	1340	1.00	0.0	12.309982
1	538000.0	2570	7	1690	2.25	0.0	13.195614
2	180000.0	770	6	2720	1.00	0.0	12.100712
3	604000.0	1960	7	1360	3.00	0.0	13.311329
4	510000.0	1680	8	1800	2.00	0.0	13.142166

We will rerun the functions we previously used for 'data_t6'

In [36]:
```
stats_linreg_summary(data2)
```

```
List of Predictors: Index(['sqft_living', 'grade', 'sqft_living15', 'bathrooms', 'view'], dtype='object')
                            OLS Regression Results
==============================================================================
Dep. Variable:              log_price   R-squared:                       0.577
Model:                            OLS   Adj. R-squared:                  0.577
Method:                 Least Squares   F-statistic:                     5895.
Date:                Thu, 25 Mar 2021   Prob (F-statistic):               0.00
Time:                        19:09:28   Log-Likelihood:                -7496.6
No. Observations:               21597   AIC:                         1.501e+04
Df Residuals:                   21591   BIC:                         1.505e+04
Df Model:                           5
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const         11.2401      0.018    612.145      0.000      11.204      11.276
x1             0.0002   5.13e-06     35.271      0.000       0.000       0.000
x2             0.1709      0.003     51.279      0.000       0.164       0.177
x3          5.747e-05   5.53e-06     10.387      0.000    4.66e-05    6.83e-05
x4            -0.0067      0.005     -1.419      0.156      -0.016       0.003
```

```
x5             0.0977      0.003     30.543      0.000       0.091       0.104
==============================================================================
Omnibus:                       33.484   Durbin-Watson:                   1.971
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               28.774
Skew:                           0.031   Prob(JB):                     5.65e-07
Kurtosis:                       2.832   Cond. No.                     2.45e+04
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 2.45e+04. This might indicate that there are
strong multicollinearity or other numerical problems.
```

In [37]:
```
sk_linreg_summary(data2)
```

```
Results of Sklearn Train Test Split:
Array of coefficients: [array([ 0.16479521,  0.20013731,  0.04226941, -0.0061546 ,  0.07299624])]
List of Predictors: Index(['sqft_living', 'grade', 'sqft_living15', 'bathrooms', 'view'], dtype='object')
R squared: 0.5868925696731291
Mean Absolute Error: 147108.20373288167
Mean Squared Error: 49398906678.23131
Root Mean Squared Error: 222258.6481517228
```

In [38]:
```
kfolds_error_summary(data2,5)
```

```
List of Predictors: Index(['sqft_living', 'grade', 'sqft_living15', 'bathrooms', 'view'], dtype='object')
R squared when k={k}: 0.5747232810060643
Average training Mean Absolute Error when k={k}: 147381.3432385779
Average training Mean Square Error when k={k}: 56366428450.22713
Average Root Mean Square Error when k={k}: 237416.1503567673
```

First Test: Removing 'sqft_above' Analysis

The results from our first test are as follows:

R squared

- Statsmodels: 0.57
- Sklearn: 0.58
- Kfolds: 0.57

Mean Absolute Error

- Sklearn: 147,108
- Kfolds: 147,381

Root Mean Square Error

- Sklearn: 222,258
- Kfolds: 237,416

Observations

From this test we were able to determine that removing 'sqft_above' does not improve our values overall. While there was improvement for our RMSE, R Squared and MAE increased. Therefore, it would be advisable to keep 'sqft_above' in our dataset.

Second Test: Removing 'grade'

- Since 'grade' and 'sqft_living' are highly correlated (0.76), it is important to see if this relationship may be a source of collinearity leading to obfuscation of our model.

In [39]:
```
data3 = data_t6.drop(['grade'], axis=1)
data3.head()
```

Out[39]:

	price	sqft_living	sqft_above	sqft_living15	bathrooms	view	log_price
0	221900.0	1180	1180	1340	1.00	0.0	12.309982
1	538000.0	2570	2170	1690	2.25	0.0	13.195614
2	180000.0	770	770	2720	1.00	0.0	12.100712
3	604000.0	1960	1050	1360	3.00	0.0	13.311329
4	510000.0	1680	1680	1800	2.00	0.0	13.142166

We will rerun the functions we previously used for 'data_t6' and 'data2'

Statsmodels Results

In [40]:
```
stats_linreg_summary(data3)
```

```
List of Predictors: Index(['sqft_living', 'sqft_above', 'sqft_living15', 'bathrooms', 'view'], dtype='object')
                            OLS Regression Results
==============================================================================
Dep. Variable:              log_price   R-squared:                       0.526
Model:                            OLS   Adj. R-squared:                  0.526
Method:                 Least Squares   F-statistic:                     4796.
Date:                Thu, 25 Mar 2021   Prob (F-statistic):               0.00
Time:                        19:09:28   Log-Likelihood:                -8725.1
```

```
No. Observations:               21597   AIC:                         1.746e+04
Df Residuals:                   21591   BIC:                         1.751e+04
Df Model:                           5
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const         12.0811      0.009   1399.337      0.000      12.064      12.098
x1             0.0003   6.73e-06     41.680      0.000       0.000       0.000
x2         -3.261e-05    6.5e-06     -5.021      0.000   -4.53e-05   -1.99e-05
x3             0.0002    5.7e-06     27.590      0.000       0.000       0.000
x4             0.0501      0.005     10.185      0.000       0.040       0.060
x5             0.0996      0.003     28.830      0.000       0.093       0.106
==============================================================================
Omnibus:                       38.455   Durbin-Watson:                   1.971
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               31.718
Skew:                          -0.005   Prob(JB):                     1.30e-07
Kurtosis:                       2.812   Cond. No.                     1.33e+04
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 1.33e+04. This might indicate that there are
strong multicollinearity or other numerical problems.
```

Sklearn Results

In [41]:
```
sk_linreg_summary(data3)
```

```
Results of Sklearn Train Test Split:
Array of coefficients: [array([ 0.2529943 , -0.0228562 ,  0.10897113,  0.03800081,  0.07501292])]
List of Predictors: Index(['sqft_living', 'sqft_above', 'sqft_living15', 'bathrooms', 'view'], dtype='object')
R squared: 0.5360006723292332
Mean Absolute Error: 158673.8370112104
Mean Squared Error: 65446506240.57118
Root Mean Squared Error: 255825.1477876465
```

Kfolds Results

In [42]:
```
kfolds_error_summary(data3,5)
```

```
List of Predictors: Index(['sqft_living', 'sqft_above', 'sqft_living15', 'bathrooms', 'view'], dtype='object')
R squared when k={k}: 0.5215339143442559
Average training Mean Absolute Error when k={k}: 158253.99286723376
Average training Mean Square Error when k={k}: 90103892521.7644
Average Root Mean Square Error when k={k}: 300173.10426113196
```

Second Test: Removing 'grade' Analysis

The results from our first test are as follows:

R squared

- Statsmodels: 0.52
- Sklearn: 0.52
- Kfolds: 0.50

Mean Absolute Error

- Sklearn: 162,973
- Kfolds: 162,371

Root Mean Square Error

- Sklearn: 341,561
- Kfolds: 404,754

Observations

From this test we were able to determine that removing 'grade' does not improve our values overall. There was an increase for RMSE, R Squared decreased and MAE increased. Therefore, it would be advisable to keep 'grade' in our dataset.

Third Test: Adding 'yr_built' and 'yr_renovated' as a new feature

- For this test we will attempt to add a new variable to our dataset by engineering a feature that helps consolidate the data from two sources, 'yr_built' and 'yr_renovated' to get the maximum (read most recent date) of construction/remodeling of a property to see if this improves our values.

In [43]:
```
data['yr_new_construction'] = data[['yr_built', 'yr_renovated']].max(axis=1)
data['log_price'] = np.log(data['price']) #log had to be redone since we are accessing original cleaned data
```

In [44]:
```
data4 = data[['price','log_price','sqft_living', 'grade', 'sqft_above', 'sqft_living15', 'bathrooms',
       'view', 'yr_new_construction']]
```

In [45]:
```
data4.head()
```

Out[45]:

	price	log_price	sqft_living	grade	sqft_above	sqft_living15	bathrooms	view	yr_new_construction
0	221900.0	12.309982	1180	7	1180	1340	1.00	0.0	1955.0

	price	log_price	sqft_living	grade	sqft_above	sqft_living15	bathrooms	view	yr_new_construction
1	538000.0	13.195614	2570	7	2170	1690	2.25	0.0	1991.0
2	180000.0	12.100712	770	6	770	2720	1.00	0.0	1933.0
3	604000.0	13.311329	1960	7	1050	1360	3.00	0.0	1965.0
4	510000.0	13.142166	1680	8	1680	1800	2.00	0.0	1987.0

Statsmodel Results

In [46]:
```
stats_linreg_summary(data4)
```

```
List of Predictors: Index(['sqft_living', 'grade', 'sqft_above', 'sqft_living15', 'bathrooms',
       'view', 'yr_new_construction'],
      dtype='object')
                            OLS Regression Results
==============================================================================
Dep. Variable:              log_price   R-squared:                       0.626
Model:                            OLS   Adj. R-squared:                  0.626
Method:                 Least Squares   F-statistic:                     5168.
Date:                Thu, 25 Mar 2021   Prob (F-statistic):               0.00
Time:                        19:09:28   Log-Likelihood:                -6164.5
No. Observations:               21597   AIC:                         1.234e+04
Df Residuals:                   21589   BIC:                         1.241e+04
Df Model:                           7
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const         20.3144      0.184    110.251      0.000      19.953      20.676
x1             0.0002    6.3e-06     24.131      0.000       0.000       0.000
x2             0.2179      0.003     66.280      0.000       0.211       0.224
x3         -4.524e-05   6.06e-06     -7.460      0.000   -5.71e-05   -3.34e-05
x4          7.908e-05   5.27e-06     14.992      0.000    6.87e-05    8.94e-05
x5             0.0966      0.005     19.659      0.000       0.087       0.106
x6             0.0680      0.003     21.965      0.000       0.062       0.074
x7            -0.0048    9.7e-05    -49.904      0.000      -0.005      -0.005
==============================================================================
Omnibus:                       46.862   Durbin-Watson:                   1.959
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               50.273
Skew:                          -0.084   Prob(JB):                     1.21e-11
Kurtosis:                       3.166   Cond. No.                     3.44e+05
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 3.44e+05. This might indicate that there are
strong multicollinearity or other numerical problems.
```

Sklearn Results

In [47]:
```
sk_linreg_summary(data4)
```

```
Results of Sklearn Train Test Split:
Array of coefficients: [array([ 0.13505761,  0.2542307 , -0.0333684 ,  0.05678141,  0.074552  ,
        0.05084877, -0.14097672])]
List of Predictors: Index(['sqft_living', 'grade', 'sqft_above', 'sqft_living15', 'bathrooms',
       'view', 'yr_new_construction'],
      dtype='object')
R squared: 0.635435847695165
Mean Absolute Error: 137985.7172432393
Mean Squared Error: 48168746677.32594
Root Mean Squared Error: 219473.79496724874
```

Kfolds Results

In [48]:
```
kfolds_error_summary(data4,5)
```

```
List of Predictors: Index(['sqft_living', 'grade', 'sqft_above', 'sqft_living15', 'bathrooms',
       'view', 'yr_new_construction'],
      dtype='object')
R squared when k={k}: 0.620760384975466
Average training Mean Absolute Error when k={k}: 137856.05535186446
Average training Mean Square Error when k={k}: 52896497306.666725
Average Root Mean Square Error when k={k}: 229992.38532322482
```

Third Test: Adding 'yr_built' and 'yr_renovated' as a new feature

The results from our first test are as follows:

R squared

- Statsmodels: 0.62
- Sklearn: 0.63
- Kfolds: 0.62

Mean Absolute Error

- Sklearn: 137,985
- Kfolds: 137,856

Root Mean Square Error

- Sklearn: 219,473
- Kfolds: 229,992

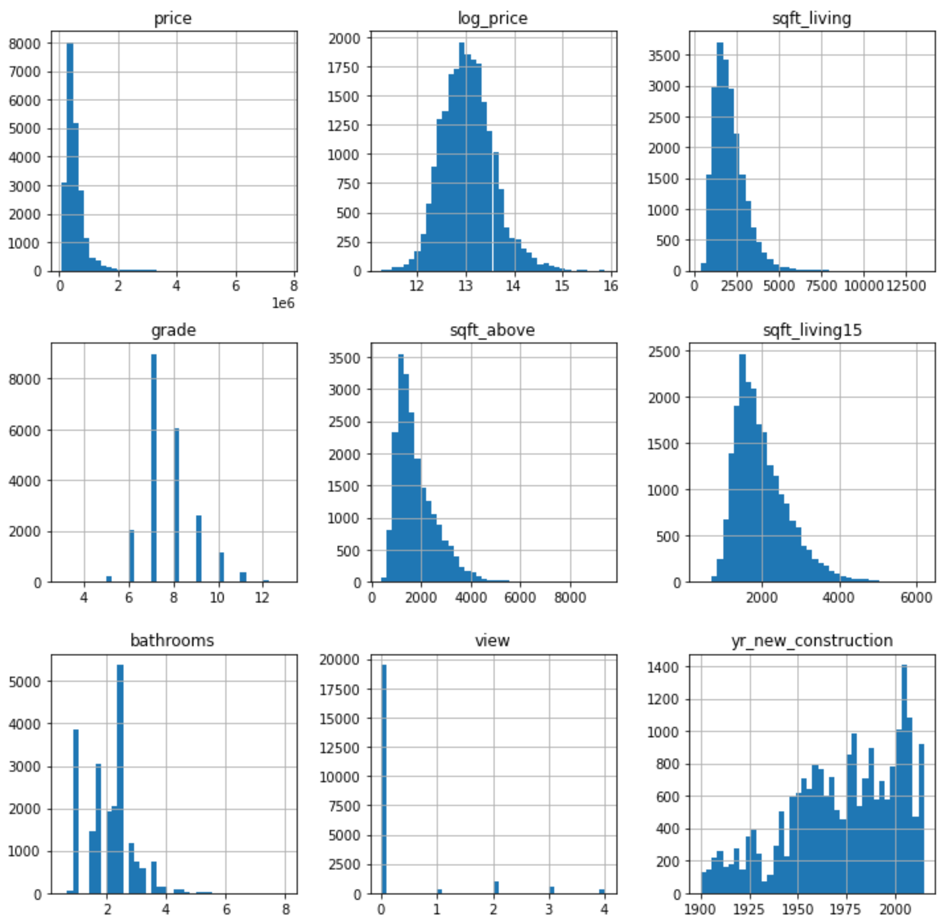
Observations

From this test we were able to determine that adding the new feature 'yr_new_construction improved our values overall. There was an decrease for RMSE, R Squared increased and MAE decreased. Therefore, it would be advisable to keep 'yr_new_construction' in our dataset.

Assessment of 'Data4' for Transformation

- We will look at the current state of our variable distributions to see if we can improve our models and meet the assumptions necessary for linear regression.

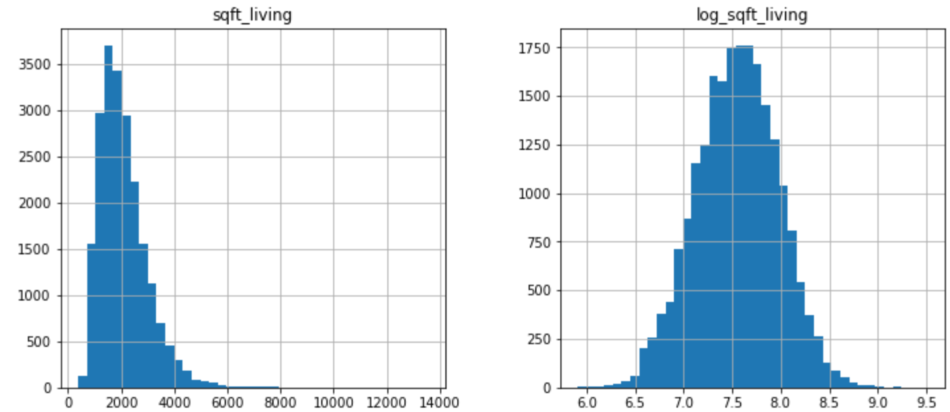
In [49]:
```
data4.hist(figsize=(12,12), bins=40);
```



From the histogram we see that we can transform two variables in hopes of improving normality. Included will also be histograms before and after transformation so we can visualize the change.

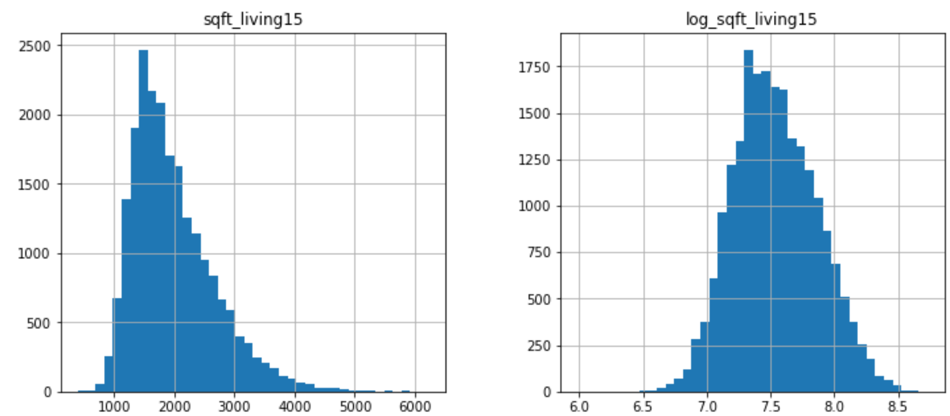
Transformation of 'sqft_living'

In [50]:
```
data4['log_sqft_living'] = np.log(data4['sqft_living'])
data4[['sqft_living', 'log_sqft_living']].hist(figsize=(12,5), bins=40);
```



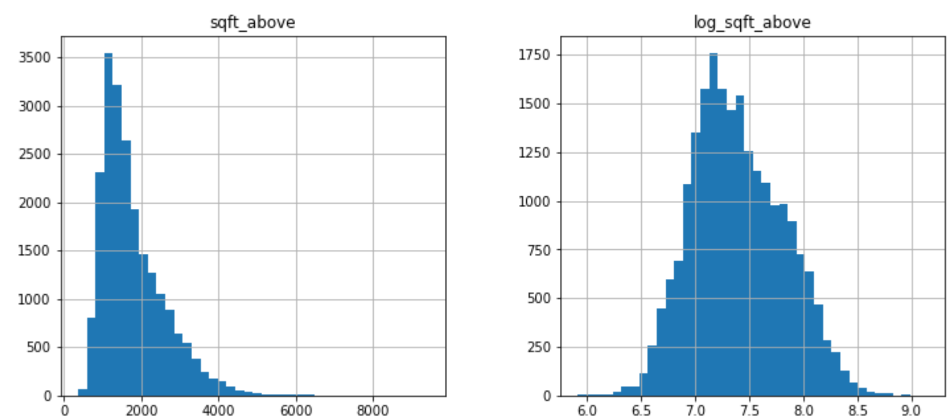
Transformation of 'sqft_living15'

In [51]:
```
data4['log_sqft_living15'] = np.log(data4['sqft_living15'])
data4[['sqft_living15', 'log_sqft_living15']].hist(figsize=(12,5), bins=40);
```



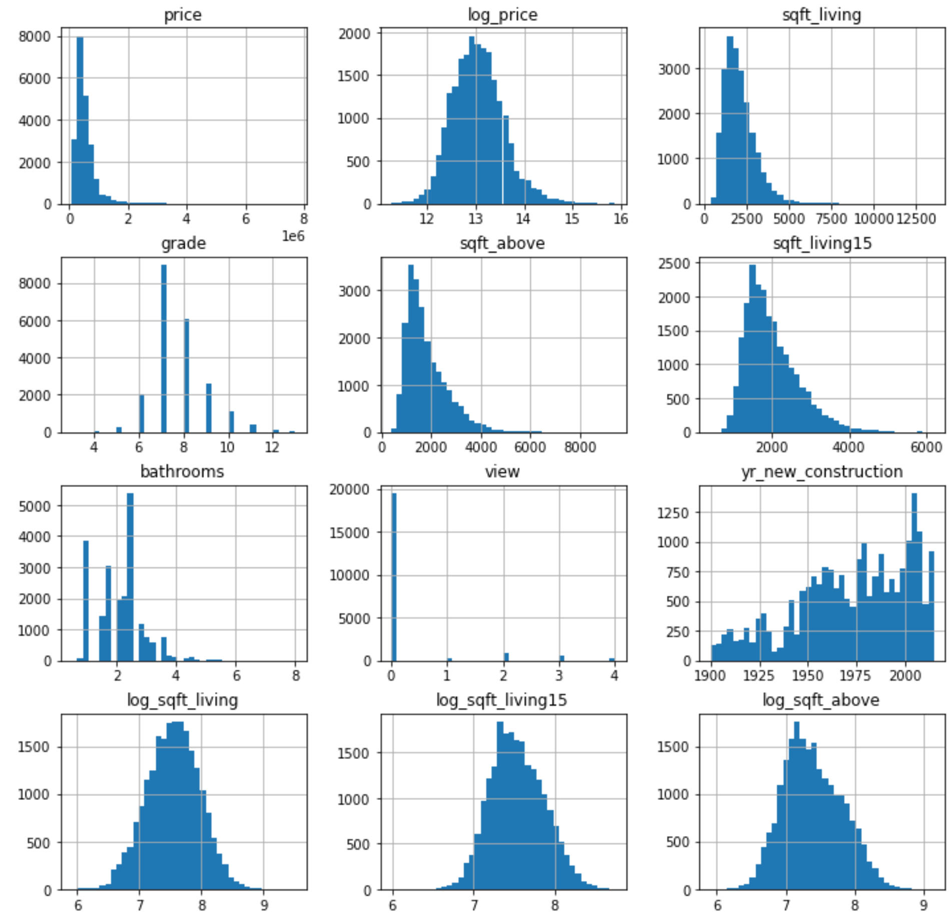
Transformation of 'sqft_above'

In [52]:
```
data4['log_sqft_above'] = np.log(data4['sqft_above'])
data4[['sqft_above', 'log_sqft_above']].hist(figsize=(12,5), bins=40);
```



Re-visualization

In [53]:
```
data4.hist(figsize=(12,12), bins=40);
```



We will need to drop the old columns in the dataset for the variables that we have transformed.

In [54]:
```
data4.head()
```

Out[54]:

	price	log_price	sqft_living	grade	sqft_above	sqft_living15	bathrooms	view	yr_new_construction	log_sqft_living	log_sqft_living15	log_sqft_ab
0	221900.0	12.309982	1180	7	1180	1340	1.00	0.0	1955.0	7.073270	7.200425	7.073
1	538000.0	13.195614	2570	7	2170	1690	2.25	0.0	1991.0	7.851661	7.432484	7.682
2	180000.0	12.100712	770	6	770	2720	1.00	0.0	1933.0	6.646391	7.908387	6.646
3	604000.0	13.311329	1960	7	1050	1360	3.00	0.0	1965.0	7.580700	7.215240	6.956
4	510000.0	13.142166	1680	8	1680	1800	2.00	0.0	1987.0	7.426549	7.495542	7.426

In [55]:
```
data5 = data4.drop(columns=['sqft_living', 'sqft_living15', 'sqft_above'])
```

In [56]:
```
data5.head()
```

Out[56]:

	price	log_price	grade	bathrooms	view	yr_new_construction	log_sqft_living	log_sqft_living15	log_sqft_above
0	221900.0	12.309982	7	1.00	0.0	1955.0	7.073270	7.200425	7.073270
1	538000.0	13.195614	7	2.25	0.0	1991.0	7.851661	7.432484	7.682482
2	180000.0	12.100712	6	1.00	0.0	1933.0	6.646391	7.908387	6.646391
3	604000.0	13.311329	7	3.00	0.0	1965.0	7.580700	7.215240	6.956545
4	510000.0	13.142166	8	2.00	0.0	1987.0	7.426549	7.495542	7.426549

Fourth Test: Implementing our Log Transformations

- Now that our three variables above have been transformed to be closer to nromality we will implement them to see if they improve our metrics

Statsmodel Results

In [57]:
```
stats_linreg_summary(data5)
```

```
List of Predictors: Index(['grade', 'bathrooms', 'view', 'yr_new_construction', 'log_sqft_living',
       'log_sqft_living15', 'log_sqft_above'],
      dtype='object')
                            OLS Regression Results
==============================================================================
Dep. Variable:              log_price   R-squared:                       0.627
Model:                            OLS   Adj. R-squared:                  0.627
```

```
Method:                 Least Squares   F-statistic:                     5194.
Date:                Thu, 25 Mar 2021   Prob (F-statistic):               0.00
Time:                        19:09:31   Log-Likelihood:                -6130.8
No. Observations:               21597   AIC:                         1.228e+04
Df Residuals:                   21589   BIC:                         1.234e+04
Df Model:                           7
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const         18.0498      0.198     91.024      0.000      17.661      18.438
x1             0.2245      0.003     71.016      0.000       0.218       0.231
x2             0.0958      0.005     19.585      0.000       0.086       0.105
x3             0.0746      0.003     24.415      0.000       0.069       0.081
x4            -0.0051   9.55e-05    -52.950      0.000      -0.005      -0.005
x5             0.3036      0.013     23.786      0.000       0.279       0.329
x6             0.1689      0.011     15.754      0.000       0.148       0.190
x7            -0.0712      0.011     -6.363      0.000      -0.093      -0.049
==============================================================================
Omnibus:                       17.790   Durbin-Watson:                   1.957
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               19.157
Skew:                          -0.038   Prob(JB):                     6.92e-05
Kurtosis:                       3.124   Cond. No.                     1.79e+05
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 1.79e+05. This might indicate that there are
strong multicollinearity or other numerical problems.
```

Sklearn Results

In [58]:
```
sk_linreg_summary(data5)
```

```
Results of Sklearn Train Test Split:
Array of coefficients: [array([ 0.26245038,  0.07295565,  0.05559668, -0.14695202,  0.12661806,
        0.05648824, -0.02748581])]
List of Predictors: Index(['grade', 'bathrooms', 'view', 'yr_new_construction', 'log_sqft_living',
       'log_sqft_living15', 'log_sqft_above'],
      dtype='object')
R squared: 0.6362843816027675
Mean Absolute Error: 136207.79071410105
Mean Squared Error: 45283998118.27409
Root Mean Squared Error: 212800.37151817686
```

Kfolds Results

In [59]:
```
kfolds_error_summary(data5,5)
```

```
List of Predictors: Index(['grade', 'bathrooms', 'view', 'yr_new_construction', 'log_sqft_living',
       'log_sqft_living15', 'log_sqft_above'],
      dtype='object')
R squared when k={k}: 0.6215179528939674
Average training Mean Absolute Error when k={k}: 136028.95346884333
Average training Mean Square Error when k={k}: 47074053131.3965
Average Root Mean Square Error when k={k}: 216965.55747720995
```

Fourth Test: Implementing our Log Transformations

The results from our first test are as follows:

R squared

- Statsmodels: 0.62
- Sklearn: 0.63
- Kfolds: 0.62

Mean Absolute Error

- Sklearn: 136,207
- Kfolds: 136,028

Root Mean Square Error

- Sklearn: 212,800
- Kfolds: 216,965

Observations

From this test we were able to determine that adding the new transformed variables slighlty improved some of our values. There was an decrease for RMSE, R Squared stayed the same and MAE decreased. Therefore, it would be advisable to keep the transformed variables in our dataset.

Fifth Test: Adding 'sqft_lot15' and 'waterfront'

- We will be including two new variables 'sqft_lot15' and 'waterfront' to highlight other variables that might present unique relationships given the landscape of King County. These features may lead to a better assessment of the market in this area.

In [60]:
```
data_sw = data.drop(columns=['price', 'bedrooms', 'bathrooms', 'sqft_living', 'sqft_lot', 'floors', 'view',
                            'condition', 'grade', 'sqft_above', 'sqft_basement', 'yr_built', 'yr_renovated',
                            'zipcode', 'lat', 'long', 'sqft_living15', 'yr_new_construction','log_price'])
```

```
data_sw.head()

data6 = pd.concat([data5, data_sw], axis=1)
data6.head()
```

Out[60]:

	price	log_price	grade	bathrooms	view	yr_new_construction	log_sqft_living	log_sqft_living15	log_sqft_above	waterfront	sqft_lot15
0	221900.0	12.309982	7	1.00	0.0	1955.0	7.073270	7.200425	7.073270	0.0	5650
1	538000.0	13.195614	7	2.25	0.0	1991.0	7.851661	7.432484	7.682482	0.0	7639
2	180000.0	12.100712	6	1.00	0.0	1933.0	6.646391	7.908387	6.646391	0.0	8062
3	604000.0	13.311329	7	3.00	0.0	1965.0	7.580700	7.215240	6.956545	0.0	5000
4	510000.0	13.142166	8	2.00	0.0	1987.0	7.426549	7.495542	7.426549	0.0	7503

Statsmodels Results

In [61]:

```
stats_linreg_summary(data6)
```

```
List of Predictors: Index(['grade', 'bathrooms', 'view', 'yr_new_construction', 'log_sqft_living',
       'log_sqft_living15', 'log_sqft_above', 'waterfront', 'sqft_lot15'],
      dtype='object')
                            OLS Regression Results
==============================================================================
Dep. Variable:              log_price   R-squared:                       0.631
Model:                            OLS   Adj. R-squared:                  0.631
Method:                 Least Squares   F-statistic:                     4103.
Date:                Thu, 25 Mar 2021   Prob (F-statistic):               0.00
Time:                        19:09:31   Log-Likelihood:                -6023.9
No. Observations:               21597   AIC:                         1.207e+04
Df Residuals:                   21587   BIC:                         1.215e+04
Df Model:                           9
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const         17.9772      0.198     90.833      0.000      17.589      18.365
x1             0.2242      0.003     71.235      0.000       0.218       0.230
x2             0.0944      0.005     19.356      0.000       0.085       0.104
x3             0.0582      0.003     17.780      0.000       0.052       0.065
x4            -0.0051   9.51e-05    -53.162      0.000      -0.005      -0.005
x5             0.3078      0.013     24.222      0.000       0.283       0.333
x6             0.1761      0.011     16.461      0.000       0.155       0.197
x7            -0.0725      0.011     -6.490      0.000      -0.094      -0.051
x8             0.4024      0.029     13.994      0.000       0.346       0.459
x9         -3.604e-07   8.16e-08     -4.416      0.000    -5.2e-07      -2e-07
==============================================================================
Omnibus:                       23.641   Durbin-Watson:                   1.958
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               25.279
Skew:                          -0.052   Prob(JB):                     3.24e-06
Kurtosis:                       3.131   Cond. No.                     2.74e+06
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 2.74e+06. This might indicate that there are
strong multicollinearity or other numerical problems.
```

Sklearn Results

In [62]:

```
sk_linreg_summary(data6)
```

```
Results of Sklearn Train Test Split:
Array of coefficients: [array([ 0.2619687 ,  0.07210587,  0.0419685 , -0.14695142,  0.12845428,
        0.05898431, -0.02819165,  0.03349745, -0.00871521])]
List of Predictors: Index(['grade', 'bathrooms', 'view', 'yr_new_construction', 'log_sqft_living',
       'log_sqft_living15', 'log_sqft_above', 'waterfront', 'sqft_lot15'],
      dtype='object')
R squared: 0.6393956385241562
Mean Absolute Error: 134632.69162008783
Mean Squared Error: 43707509100.97699
Root Mean Squared Error: 209063.40928287042
```

Kfolds Results

In [63]:

```
kfolds_error_summary(data6,5)
```

```
List of Predictors: Index(['grade', 'bathrooms', 'view', 'yr_new_construction', 'log_sqft_living',
       'log_sqft_living15', 'log_sqft_above', 'waterfront', 'sqft_lot15'],
      dtype='object')
R squared when k={k}: 0.6250499234667881
Average training Mean Absolute Error when k={k}: 134210.3096824595
Average training Mean Square Error when k={k}: 43990832724.541985
Average Root Mean Square Error when k={k}: 209739.9168602438
```

Fifth Test: Adding 'sq_lot15' and 'waterfront'

The results from our first test are as follows:

R squared

- Statsmodels: 0.63
- Sklearn: 0.63

- Kfolds: 0.62

Mean Absolute Error

- Sklearn: 134,632
- Kfolds: 134,210

Root Mean Square Error

- Sklearn: 209,063
- Kfolds: 209,739

Observations

From this test we were able to determine that adding 'sqft_lot15' and 'waterfront' variables slighlty improved some of our values. There was an decrease for RMSE, R Squared stayed the same and MAE decreased. Therefore, it would be advisable to keep 'sqft_lot15' and 'waterfront' variables in our dataset.

Sixth Test: Create Dummies for 'zipcode' and add to dataset

- The goal of this test is to create dummy variables for our 'zipcodes variables' in order to be able to apply the information contained within this categorical variable. This will hopefully highlight some of the locality prediction influence as in the fifth test.

In [64]:
```
df_zip_dums = pd.get_dummies(data['zipcode'])
data7 = pd.concat([data6, df_zip_dums], axis=1)
data7.head().T
```

Out[64]:

	0	1	2	3	4
price	221900.000000	538000.000000	180000.000000	604000.000000	510000.000000
log_price	12.309982	13.195614	12.100712	13.311329	13.142166
grade	7.000000	7.000000	6.000000	7.000000	8.000000
bathrooms	1.000000	2.250000	1.000000	3.000000	2.000000
view	0.000000	0.000000	0.000000	0.000000	0.000000
...	...	...	...	...	...
98177	0.000000	0.000000	0.000000	0.000000	0.000000
98178	1.000000	0.000000	0.000000	0.000000	0.000000
98188	0.000000	0.000000	0.000000	0.000000	0.000000
98198	0.000000	0.000000	0.000000	0.000000	0.000000
98199	0.000000	0.000000	0.000000	0.000000	0.000000

81 rows × 5 columns

Statsmodels Results

In [65]:
```
stats_linreg_summary(data7)
```

```
List of Predictors: Index(['grade', 'bathrooms', 'view', 'yr_new_construction', 'log_sqft_living',
       'log_sqft_living15', 'log_sqft_above', 'waterfront', 'sqft_lot15',
       '98001', '98002', '98003', '98004', '98005', '98006', '98007', '98008',
       '98010', '98011', '98014', '98019', '98022', '98023', '98024', '98027',
       '98028', '98029', '98030', '98031', '98032', '98033', '98034', '98038',
       '98039', '98040', '98042', '98045', '98052', '98053', '98055', '98056',
       '98058', '98059', '98065', '98070', '98072', '98074', '98075', '98077',
       '98092', '98102', '98103', '98105', '98106', '98107', '98108', '98109',
       '98112', '98115', '98116', '98117', '98118', '98119', '98122', '98125',
       '98126', '98133', '98136', '98144', '98146', '98148', '98155', '98166',
       '98168', '98177', '98178', '98188', '98198', '98199'],
      dtype='object')
                            OLS Regression Results
==============================================================================
Dep. Variable:              log_price   R-squared:                       0.874
Model:                            OLS   Adj. R-squared:                  0.874
Method:                 Least Squares   F-statistic:                     1921.
Date:                Thu, 25 Mar 2021   Prob (F-statistic):               0.00
Time:                        19:09:32   Log-Likelihood:                 5614.4
No. Observations:               21597   AIC:                        -1.107e+04
Df Residuals:                   21518   BIC:                        -1.044e+04
Df Model:                          78
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const         10.0077      0.134     74.508      0.000       9.744      10.271
x1             0.0957      0.002     47.489      0.000       0.092       0.100
x2             0.0287      0.003      9.848      0.000       0.023       0.034
x3             0.0670      0.002     33.684      0.000       0.063       0.071
x4            -0.0012   6.28e-05    -19.422      0.000      -0.001      -0.001
x5             0.3268      0.008     43.397      0.000       0.312       0.342
x6             0.1579      0.007     23.272      0.000       0.145       0.171
x7             0.1113      0.007     16.335      0.000       0.098       0.125
x8             0.4931      0.017     28.927      0.000       0.460       0.527
x9          8.471e-07   5.29e-08     16.000      0.000    7.43e-07    9.51e-07
x10           -0.3225      0.010    -31.662      0.000      -0.342      -0.303
```

```
x11           -0.3245      0.013    -24.223      0.000      -0.351      -0.298
x12           -0.3148      0.011    -27.761      0.000      -0.337      -0.293
x13            0.8041      0.011     74.640      0.000       0.783       0.825
x14            0.4123      0.015     28.423      0.000       0.384       0.441
x15            0.3247      0.009     36.635      0.000       0.307       0.342
x16            0.3179      0.016     20.222      0.000       0.287       0.349
x17            0.3206      0.011     28.551      0.000       0.299       0.343
x18           -0.0474      0.019     -2.519      0.012      -0.084      -0.011
x19            0.1064      0.014      7.832      0.000       0.080       0.133
x20           -0.0142      0.017     -0.824      0.410      -0.048       0.020
x21           -0.0152      0.014     -1.094      0.274      -0.043       0.012
x22           -0.2549      0.013    -20.162      0.000      -0.280      -0.230
x23           -0.3553      0.009    -40.708      0.000      -0.372      -0.338
x24            0.1215      0.021      5.766      0.000       0.080       0.163
x25            0.1813      0.010     18.825      0.000       0.162       0.200
x26            0.0784      0.011      6.910      0.000       0.056       0.101
x27            0.2490      0.011     23.021      0.000       0.228       0.270
x28           -0.2813      0.012    -23.524      0.000      -0.305      -0.258
x29           -0.2508      0.012    -21.693      0.000      -0.273      -0.228
x30           -0.3416      0.017    -20.474      0.000      -0.374      -0.309
x31            0.4618      0.009     49.726      0.000       0.444       0.480
x32            0.2103      0.008     25.236      0.000       0.194       0.227
x33           -0.1632      0.008    -19.205      0.000      -0.180      -0.147
x34            1.0019      0.026     38.104      0.000       0.950       1.053
x35            0.5664      0.011     49.560      0.000       0.544       0.589
x36           -0.2480      0.009    -29.002      0.000      -0.265      -0.231
x37            0.0097      0.013      0.753      0.452      -0.016       0.035
x38            0.2987      0.008     35.938      0.000       0.282       0.315
x39            0.2641      0.010     26.442      0.000       0.244       0.284
x40           -0.1905      0.012    -16.483      0.000      -0.213      -0.168
x41            0.0100      0.010      1.040      0.298      -0.009       0.029
x42           -0.1585      0.009    -17.388      0.000      -0.176      -0.141
x43            0.0176      0.009      1.907      0.057      -0.000       0.036
x44            0.0635      0.011      5.628      0.000       0.041       0.086
x45            0.0106      0.018      0.592      0.554      -0.024       0.046
x46            0.1635      0.012     14.090      0.000       0.141       0.186
x47            0.2169      0.009     23.027      0.000       0.198       0.235
x48            0.2323      0.010     22.148      0.000       0.212       0.253
x49            0.1380      0.014     10.109      0.000       0.111       0.165
x50           -0.3097      0.010    -29.676      0.000      -0.330      -0.289
x51            0.5920      0.018     32.560      0.000       0.556       0.628
x52            0.4684      0.008     60.535      0.000       0.453       0.484
x53            0.5891      0.012     47.860      0.000       0.565       0.613
x54            0.0241      0.010      2.317      0.021       0.004       0.045
x55            0.4926      0.011     42.876      0.000       0.470       0.515
x56            0.0203      0.014      1.485      0.138      -0.007       0.047
x57            0.6234      0.018     35.123      0.000       0.589       0.658
x58            0.6877      0.011     60.056      0.000       0.665       0.710
x59            0.4736      0.008     60.118      0.000       0.458       0.489
x60            0.4206      0.010     40.519      0.000       0.400       0.441
x61            0.4725      0.008     58.548      0.000       0.457       0.488
x62            0.1230      0.008     14.553      0.000       0.106       0.140
x63            0.6077      0.014     44.296      0.000       0.581       0.635
x64            0.4464      0.011     40.683      0.000       0.425       0.468
x65            0.2292      0.009     24.395      0.000       0.211       0.248
x66            0.2272      0.010     22.563      0.000       0.208       0.247
x67            0.1350      0.009     15.618      0.000       0.118       0.152
x68            0.3459      0.012     29.834      0.000       0.323       0.369
x69            0.3268      0.010     32.158      0.000       0.307       0.347
x70           -0.0433      0.011     -3.881      0.000      -0.065      -0.021
x71           -0.1833      0.025     -7.471      0.000      -0.231      -0.135
x72            0.1067      0.009     11.816      0.000       0.089       0.124
x73           -0.0125      0.012     -1.053      0.292      -0.036       0.011
x74           -0.2472      0.012    -21.420      0.000      -0.270      -0.225
x75            0.2575      0.012     21.786      0.000       0.234       0.281
x76           -0.1891      0.012    -16.182      0.000      -0.212      -0.166
x77           -0.2295      0.016    -14.341      0.000      -0.261      -0.198
x78           -0.2615      0.011    -23.015      0.000      -0.284      -0.239
x79            0.5153      0.011     48.664      0.000       0.495       0.536
==============================================================================
Omnibus:                     1452.972   Durbin-Watson:                   2.007
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             6583.232
Skew:                          -0.154   Prob(JB):                         0.00
Kurtosis:                       5.687   Cond. No.                     5.44e+19
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The smallest eigenvalue is 6.63e-27. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.
```

Sklearn Results

In [66]:

```python
sk_linreg_summary(data7)
```

```
Results of Sklearn Train Test Split:
Array of coefficients: [array([ 1.12258214e-01,  2.22538976e-02,  5.02571532e-02, -3.59804006e-02,
        1.38161677e-01,  5.15799649e-02,  4.98479386e-02,  4.12675326e-02,
        2.23220905e-02,  3.63870117e+11,  2.71187433e+11,  3.21069084e+11,
        3.41327967e+11,  2.49351522e+11,  4.25992584e+11,  2.28581126e+11,
        3.22761800e+11,  1.92683869e+11,  2.68473186e+11,  2.14443870e+11,
        2.65039825e+11,  2.93207906e+11,  4.26409967e+11,  1.72421843e+11,
        3.88256981e+11,  3.22761800e+11,  3.43442422e+11,  3.07173535e+11,
        3.17082367e+11,  2.15301813e+11,  3.97381313e+11,  4.45144859e+11,
        4.62281413e+11,  1.36406429e+11,  3.22198603e+11,  4.45939707e+11,
        2.84997565e+11,  4.56519909e+11,  3.84074451e+11,  3.14202094e+11,
        3.85474073e+11,  4.07600927e+11,  4.13255677e+11,  3.36518868e+11,
        2.08337045e+11,  3.17082367e+11,  4.01413990e+11,  3.62877853e+11,
        2.70511520e+11,  3.58879439e+11,  1.96481479e+11,  4.67210523e+11,
```

```
        2.90707415e+11,  3.50736441e+11,  3.13042178e+11,  2.62259590e+11,
        2.01125750e+11,  3.14780367e+11,  4.59986485e+11,  3.48150094e+11,
        4.48314869e+11,  4.29732995e+11,  2.60857964e+11,  3.26675514e+11,
        3.86868230e+11,  3.60384402e+11,  4.23898890e+11,  3.11293785e+11,
        3.54832858e+11,  3.25562376e+11,  1.45618552e+11,  4.03635460e+11,
        3.05985623e+11,  3.14780367e+11,  3.06580183e+11,  3.10708690e+11,
        2.24517843e+11,  3.21069084e+11,  3.41327967e+11])]
List of Predictors: Index(['grade', 'bathrooms', 'view', 'yr_new_construction', 'log_sqft_living',
       'log_sqft_living15', 'log_sqft_above', 'waterfront', 'sqft_lot15',
       '98001', '98002', '98003', '98004', '98005', '98006', '98007', '98008',
       '98010', '98011', '98014', '98019', '98022', '98023', '98024', '98027',
       '98028', '98029', '98030', '98031', '98032', '98033', '98034', '98038',
       '98039', '98040', '98042', '98045', '98052', '98053', '98055', '98056',
       '98058', '98059', '98065', '98070', '98072', '98074', '98075', '98077',
       '98092', '98102', '98103', '98105', '98106', '98107', '98108', '98109',
       '98112', '98115', '98116', '98117', '98118', '98119', '98122', '98125',
       '98126', '98133', '98136', '98144', '98146', '98148', '98155', '98166',
       '98168', '98177', '98178', '98188', '98198', '98199'],
      dtype='object')
R squared: 0.8775913748768904
Mean Absolute Error: 75400.89422298747
Mean Squared Error: 19023875960.7312
Root Mean Squared Error: 137927.06754198467
```

Kfold Results

In [67]:

```
kfolds_error_summary(data7,5)
```

```
List of Predictors: Index(['grade', 'bathrooms', 'view', 'yr_new_construction', 'log_sqft_living',
       'log_sqft_living15', 'log_sqft_above', 'waterfront', 'sqft_lot15',
       '98001', '98002', '98003', '98004', '98005', '98006', '98007', '98008',
       '98010', '98011', '98014', '98019', '98022', '98023', '98024', '98027',
       '98028', '98029', '98030', '98031', '98032', '98033', '98034', '98038',
       '98039', '98040', '98042', '98045', '98052', '98053', '98055', '98056',
       '98058', '98059', '98065', '98070', '98072', '98074', '98075', '98077',
       '98092', '98102', '98103', '98105', '98106', '98107', '98108', '98109',
       '98112', '98115', '98116', '98117', '98118', '98119', '98122', '98125',
       '98126', '98133', '98136', '98144', '98146', '98148', '98155', '98166',
       '98168', '98177', '98178', '98188', '98198', '98199'],
      dtype='object')
R squared when k={k}: 0.8724879575294235
Average training Mean Absolute Error when k={k}: 75451.65702625389
Average training Mean Square Error when k={k}: 17913654998.191124
Average Root Mean Square Error when k={k}: 133841.90299824314
```

Sixth Test: Create Dummies for 'zipcode' and add to dataset

The results from our first test are as follows:

R squared

- Statsmodels: 0.87
- Sklearn: 0.87
- Kfolds: 0.87

Mean Absolute Error

- Sklearn: 75,400
- Kfolds: 75,451

Root Mean Square Error

- Sklearn: 137,927
- Kfolds: 133,841

Observations

From this test we were able to determine that adding dummies for 'zipcode' greatly improved our values. There was an decrease for RMSE, R Squared increased greatly and MAE decreased. Therefore, we will keep zipcode as it helps improve our model.

In [68]:

```
data7.describe()
```

Out[68]:

	price	log_price	grade	bathrooms	view	yr_new_construction	log_sqft_living	log_sqft_living15	log_sqft_above	v
count	2.159700e+04	21597.000000	21597.000000	21597.000000	21597.000000	21597.000000	21597.000000	21597.000000	21597.000000	215
mean	5.402966e+05	13.048211	7.657915	2.115826	0.233181	1972.945131	7.550720	7.539494	7.395148	
std	3.673681e+05	0.526555	1.173200	0.768984	0.764673	28.945393	0.424191	0.327467	0.427140	
min	7.800000e+04	11.264464	3.000000	0.500000	0.000000	1900.000000	5.913503	5.988961	5.913503	
25%	3.220000e+05	12.682307	7.000000	1.750000	0.000000	1954.000000	7.265430	7.306531	7.081709	
50%	4.500000e+05	13.017003	7.000000	2.250000	0.000000	1977.000000	7.554859	7.517521	7.352441	
75%	6.450000e+05	13.377006	8.000000	2.500000	0.000000	1999.000000	7.843849	7.766417	7.700748	
max	7.700000e+06	15.856731	13.000000	8.000000	4.000000	2015.000000	9.513404	8.733916	9.149528	

8 rows × 81 columns

Model Discussion and Key Features

In [69]:

```
import folium
from folium.plugins import HeatMap
# creating basemap on which I will create heatmap
def generateBaseMap(default_location=[47.6062,-122.3321], default_zoom_start=10):
    base_map = folium.Map(location=default_location,\
    control_scale=True, zoom_start=default_zoom_start)
    return base_map
base_map = generateBaseMap()

# plotting heatmap using lat/long data
HeatMap(data=data[['lat', 'long', 'price']].groupby(['lat','long'])
        .sum().reset_index().values.tolist(),
        radius=8, max_zoom=13).add_to(base_map)
# adding markers to folium for Amazon and Microsoft
folium.Marker([47.6162208, -122.342192],
              'Amazon Headquarters').add_to(base_map)
folium.Marker([47.6449162,-122.1424701],
              'Microsoft Headquarters').add_to(base_map)
# displaying base map
base_map
```

Out[69]: Make this Notebook Trusted to load map: File -> Trust Notebook

In [70]:

```
# importing library and settings
import bokeh.io
from bokeh.io import output_notebook, show
from bokeh.resources import INLINE
output_notebook()
from bokeh.plotting import gmap
from bokeh.models import (GMapPlot, GMapOptions, ColumnDataSource,
    Circle, LogColorMapper, BasicTicker, ColorBar, Range1d,
    PanTool, WheelZoomTool, BoxSelectTool)
from bokeh.models.mappers import ColorMapper, LinearColorMapper
from bokeh.palettes import Viridis5
```

BokehJS 2.3.0 successfully loaded.

In [71]:

```
%%HTML
<div class='tableauPlaceholder' id='viz1616718597680' style='position: relative'><noscript><a href='#'><img alt='Grade vs. Price
```

In [72]:
```
%%HTML
<div class='tableauPlaceholder' id='viz1616718700422' style='position: relative'><noscript><a href='#'><img alt='Square Feet Abov
```

In [73]:

```
%%HTML
<div class='tableauPlaceholder' id='viz1616718726034' style='position: relative'><noscript><a href='#'><img alt='Grade vs. Price
```

In [74]:

```
%%HTML
<div class='tableauPlaceholder' id='viz1616718761777' style='position: relative'><noscript><a href='#'><img alt='Square Feet Livi
```

With a R-squared of 0.87, an MAE of 75,000 USD, and a RMSE averaging around 136,000 USD, our model seems to have significant predictive power. There is always additional room for model iteration and closer analysis of factors that may be limiting the quality of the model, its current levels promote an acceptable model when compared to our first model's values. The assumptions made in each test proved to be insightful regarding what features would positively or negatively impact the validity of our model. We are able to see with our final model some of the impacts that various features have on our target variable 'y' in order to better inform our stakeholders.

For grade vs. price we were able to determine a coefficient of 0.0957, which leads to a change of 10.04% in price for every increment, while all other variables are held constant. For sqft above vs. price we were able to determine a coefficient of 0.1113, which leads to a change of 11.77% in price for every increment, while all other variables are held constant. For log of sqft_living15 vs. price we were able to determine a coefficient of 0.1579, which leads to a change of 17.10% in price for every increment, while all other variables are held constant. These were calculated by computing e^(coefficient).

From our visualizations we can note that there are also price increases around economic hubs and city centers. As assumed, prices also increase with proximity to waterfront as well. As we move further away from main cities such as Bellevue and Seattle, prices tend to decrease, while it is also important to note that there are outliers in the data regarding this point. High prices outside of the city can be accounted for by grade and lot size as they can be assumed to be large homes (i.e. mansions) which sizable land associated with them.