King County Housing Regression Project

Table Of Contents

INTRODUCTION

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- Pace: Part time
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In this notebook we're going to be using the OSEMN model to do OLS regression on housing data from King County in 2015. Here we'll be looking to answer questions like:

What factors impact the price of a home?

What factors impact the price of a home for different income levels?

If you're looking to move to king county, where is the best bang for your buck?

Import Tools

In [1]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import mlxtend
```

In [2]:
```
import scipy.stats as stats
import statsmodels.api as sm
import statsmodels.stats.api as sms
import matplotlib.pyplot as plt
import matplotlib.ticker as ticker
```

```
import matplotlib as mpl
import matplotlib.patches as mpatches
```

In [3]:
```
from math import sin, cos, sqrt, atan2, radians
from sklearn import svm
from cycler import cycler
from matplotlib import rcParams
from scipy.stats import zscore
from sklearn import linear_model
from statsmodels.formula.api import ols
from sklearn.pipeline import make_pipeline
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score
from sklearn.neighbors import NearestNeighbors, KNeighborsClassifier,
KNeighborsRegressor
from sklearn.model_selection import cross_val_predict, KFold, train_test_split
from mlxtend.feature_selection import SequentialFeatureSelector as SFS
from statsmodels.stats.outliers_influence import variance_inflation_factor
```

Editing Our Settings

We have too many columns to view normally, and it's difficult to get a good grasp of our data with how much is normally cut off.

In [4]:
```
# for the sake of reading this notebook, we'll be removing these settings before
running through,
# but when you're exploring your own data or checking out our work here,
# we'd reccomend increasing all of your output displays so you can really see all your
data
# pd.set_option('display.max_rows', 50)
# pd.set_option('display.max_columns', 500)
# pd.set_option('display.width', 1000)
```

In [5]:
```
%matplotlib inline
mpl.rcParams['lines.linewidth'] = 2
mpl.rcParams['lines.color'] = '#FBE122'
mpl.rcParams['grid.linewidth'] = 0.5
mpl.rcParams['grid.color'] = '#A2AAAD'
mpl.rcParams['grid.linestyle'] = ':'
mpl.rcParams['axes.labelcolor'] = '#A2AAAD'
mpl.rcParams['axes.facecolor'] = 'black'
mpl.rcParams['axes.prop_cycle'] = mpl.cycler(color=["#2C5234", "#46664d", "#687a6c"])
mpl.rcParams['figure.facecolor'] = 'black'
mpl.rcParams['figure.edgecolor'] = 'black'
```

```
mpl.rcParams['image.cmap'] = 'YlGn'
mpl.rcParams['text.color'] = '#A2AAAD'
mpl.rcParams['xtick.color'] = '#A2AAAD'
mpl.rcParams['ytick.color'] = '#A2AAAD'
```

Define functions

In [6]:

```
def getClosest(home_lat: float, home_lon: float, dest_lat_series: 'series',
dest_lon_series: 'series'):
    """Pass 1 set of coordinates and one latitude or longitude column you would like to
compare it's distance to"""
    #radius of the earth in miles
    r = 3963
    #setting variables to use to iterate through
    closest = 100
    within_mile = 0
    i = 0
    #using a while loop to iterate over our data and calculate the distance between
each datapoint and our homes
    while i < dest_lat_series.size:
        lat_dist = radians(home_lat) - (dest_lat := radians(dest_lat_series.iloc[i]))
        lon_dist = radians(home_lon) - (radians(dest_lon_series.iloc[i]))
        a = sin(lat_dist / 2)**2 + cos(radians(home_lat)) * cos(radians(dest_lat)) *
sin(lon_dist / 2)**2
        c = 2 * atan2(sqrt(a), sqrt(1 - a))
        c = r * c
        #find the closest data to our homes by keeping our smallest (closest) value
        if (c < closest):
            closest = c
        #find all of the points that fall within one mile and count them
        if (c <= 1.0):
            within_mile += 1
        i += 1
    return [closest, within_mile]
```

In [7]:

```
# this function is directly from the matplotlib documentation
# https://matplotlib.org/_modules/matplotlib/figure.html#Figure.set_frameon
def set_frameon(self, b):
        """
        Set the figure's background patch visibility, i.e.
        whether the figure background will be drawn. Equivalent to
        ``Figure.patch.set_visible()``.

        Parameters
        ----------
        b : bool
```

```
        """
        self.patch.set_visible(b)
        self.stale = True
```

In [8]:

```
def plotcoef(model):
    """Takes in OLS results and returns a plot of the coefficients"""
    #make dataframe from summary of results
    coef_df = pd.DataFrame(model.summary().tables[1].data)
    #rename your columns
    coef_df.columns = coef_df.iloc[0]
    #drop header row
    coef_df = coef_df.drop(0)
    #set index to variables
    coef_df = coef_df.set_index(coef_df.columns[0])
    #change dtype from obj to float
    coef_df = coef_df.astype(float)
    #get errors
    err = coef_df['coef'] - coef_df['[0.025']
    #append err to end of dataframe
    coef_df['errors'] = err
    #sort values for plotting
    coef_df = coef_df.sort_values(by=['coef'])
    ## plotting time ##
    var = list(coef_df.index.values)
    #add variables column to dataframe
    coef_df['var'] = var
    # define fig
    fig, ax = plt.subplots(figsize=(8,5))
    #error bars for 95% confidence interval
    coef_df.plot(x='var', y='coef', kind='bar',
                ax=ax, fontsize=15, yerr='errors', color='#FBE122', ecolor = '#FBE122')
    #set title and label
    plt.title('Coefficients of Features in With 95% Confidence Interval', fontsize=20)
    ax.set_ylabel('Coefficients', fontsize=15)
    ax.set_xlabel(' ')
    #coefficients
    ax.scatter(x= np.arange(coef_df.shape[0]),
              marker='+', s=50,
              y=coef_df['coef'], color='#FBE122')
    plt.legend(fontsize= 15,frameon=True, fancybox=True, facecolor='black')
    set_frameon(ax, False)
    set_frameon(fig, False)
    return plt.show()
```

In [9]:

```
def make_ols(df, x_columns,target='price'):
```

```
    """Pass in a DataFrame & your predictive columns to return an OLS regression model
"""
    #set your x and y variables
    X = df[x_columns]
    y = df[target]
    # pass them into stats models OLS package
    ols = sm.OLS(y, X)
    #fit your model
    model = ols.fit()
    #display the model summarry
    display(model.summary())
    #plot the residuals
    fig = sm.graphics.qqplot(model.resid, dist=stats.norm, line='r', color='y',
alpha=.65, fit=True, markerfacecolor="#FBE122")
    plt.xlim(-2, 2)
    plt.ylim(-2, 2)
    fig = set_frameon(fig, False)
    #return model for later use
    return model
```

In [10]:

```
def get_percentile(data_n_col):
    """Print out all of your percentiles for a given column in a dataframe
       Example: data['price'] """
    for i in range(1,100):
        q = i / 100
        print('{} percentile: {}'.format(q, data_n_col.quantile(q=q)))
```

In [11]:

```
def quadregplot(model, column):
    """Pass in model and column to stats model to create 4 regression plots in Seattle
Storm colors"""
    fig = plt.figure(figsize=(15,8))
    fig = sm.graphics.plot_regress_exog(model, column, fig=fig)
    ax1, ax2, ax3, ax4 = fig.get_axes()
    ax1.properties()['children'][0].set_color('#A2AAAD')
    ax1.properties()['children'][1].set_color('#FBE122')
    ax1.properties()['children'][2].set_color('#2C5234')
    ax2.properties()['children'][0].set_color('#2C5234')
    ax2.properties()['children'][1].set_color('#FBE122')
    ax3.properties()['children'][1].set_color('#FBE122')
    ax1.grid(True)
    ax2.grid(True)
    ax3.grid(True)
    ax4.grid(True)
    green_patch = mpatches.Patch(color='#FBE122', label='Price')
```

```
    yellow_patch = mpatches.Patch(color='#2C5234', label='Fitted')
    ax1.legend(handles=[green_patch, yellow_patch])
```

In [12]:

```
def reformat_large_ticker_values(ticker_val, pos):
    """
    Turns large tick values (in the billions, millions and thousands) such as 4500 into
4.5K and also appropriately turns 4000 into 4K (no zero after the decimal).
    Code Sourced from "https://dfrieds.com/data-visualizations/how-format-large-tick-
values.html"
    """
    if ticker_val >= 1000000000:
        val = round(ticker_val/1000000000, 1)
        new_ticker_format = '{:}B'.format(val)
    elif ticker_val >= 1000000:
        val = round(ticker_val/1000000, 1)
        new_ticker_format = '{:}M'.format(val)
    elif ticker_val >= 1000:
        val = round(ticker_val/1000, 1)
        new_ticker_format = '{:}K'.format(val)
    elif ticker_val < 1000:
        new_ticker_format = round(ticker_val, 1)
    else:
        new_ticker_format = ticker_val
    # make new_tick_format into a string value
    new_ticker_format = str(new_ticker_format)
    # code below will keep 4.5M as is but change values such as 4.0M to 4M since that
zero after the decimal isn't needed
    index_of_decimal = new_ticker_format.find(".")
    if index_of_decimal != -1:
        value_after_decimal = new_ticker_format[index_of_decimal+1]
        if value_after_decimal == "0":
            # remove the 0 after the decimal point since it's not needed
            new_ticker_format = new_ticker_format[0:index_of_decimal] +
new_ticker_format[index_of_decimal+2:]
    return new_ticker_format
```

OBTAIN DATA

Here we'll be working with the King County housing data provided to us by FlatIron and data about schools in King County gathered by ArcGis. We'll be importing them via the Pandas library.

In [13]:

```
#wrote up our data types to save on computer space and stop some of them from being
inccorectly read as objs
kc_dtypes = {'id': int, 'date' : str,  'price': float, 'bedrooms' : int, 'bathrooms' :
float, 'sqft_living': int, 'sqft_lot': int,
```

```
            'floors': float, 'waterfront': float, 'view' : float, 'condition': float,
'grade': int, 'sqft_above': int,
            'yr_built': int, 'yr_renovated': float, 'zipcode': float, 'lat': float,
'long': float}
```

In [14]:
```
# Data provided from Flatiron
kc_data = pd.read_csv(r'~\Documents\Flatiron\pro2\data\kc_house_data.csv', parse_dates
= ['date'], dtype=kc_dtypes)
# Data gathered from ArcGis
schools = pd.read_csv(r'~\Documents\Flatiron\pro2\data\Schools.csv')
foods = pd.read_csv(r'~\Documents\Flatiron\pro2\foods.csv')
```

In [15]:
```
# Removing latitudes and longitudes that couldn't be found from adresses in ArcGis data
foods = foods.loc[foods['lat'] != '[0.0]'].copy()
foods = foods.loc[foods['long'] != '[0.0]'].copy()
# Convert latitude and longitude into floats so we can use them to calculate distance
foods['lat'] = foods['lat'].astype(dtype=float)
foods['long'] = foods['long'].astype(dtype=float)
```

In [16]:
```
# Seperate grocery stores from restaurants
rest = foods.loc[foods['SEAT_CAP'] != 'Grocery']
groc = foods.loc[foods['SEAT_CAP'] == 'Grocery']
```

In [17]:
```
# we can't append these directly into a DataFrame very easily, so we're going to start
an empty dictionary
# that's going to store all of our values and be converted into a dataframe later on
kc_dict = {}
```

In [18]:
```
i = 0
# here we're going to iterate over the latitude and longitude of each house, and
calculate the
# distance between our housing and our other dataframes
while i < kc_data['lat'].size:
    school = getClosest(kc_data['lat'].iloc[i], kc_data['long'].iloc[i],
schools['LAT_CEN'], schools['LONG_CEN'])
    restaurant = getClosest(kc_data['lat'].iloc[i], kc_data['long'].iloc[i],
rest['lat'], rest['long'])
    grocery = getClosest(kc_data['lat'].iloc[i], kc_data['long'].iloc[i], groc['lat'],
groc['long'])
    kc_dict[i] = {
        "closest school": school[0],
        "schools within mile": school[1],
        "closest restaurant": restaurant[0],
        "restaurants within mile": restaurant[1],
```

```
        "closest grocery": grocery[0],
        "groceries within mile": grocery[1]}
    i += 1
```

That's all of the data we need to start. Now we'll be adding the last of our data, merging in the distance between the schools and our homes.

In [20]:
```
# let's turn our dictionary into a dataframe we can work with
kc = pd.DataFrame.from_dict(kc_dict, orient='index')
# it will be the same length as our dataframe and in the same order, so we're going to
merge it on index
kc_data = kc_data.merge(kc, left_index=True, right_index=True)
```

In [21]:
```
# though nice in dictionary form, we shouldnt have spaces in our names for our
dataframes so we'll
# be renaming them here, but keeping the dictionary in case anyone needs to reference
what each name means
kc_data = kc_data.rename(columns ={'closest school': 'mi_2_scl', 'schools within mile':
'scls_in_mi', 'closest restaurant':'mi_2_rest',
                          'restaurants within mile':'rest_in_mi','closest grocery':
'mi_2_groc', 'groceries within mile': 'groc_in_mi'})
```

Now let's take a look at our data to see what we are working with and what we might need to fix

In [22]:
```
kc_data.isnull().sum()
```

Out[22]:
```
Unnamed: 0          0
id                  0
date                0
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
mi_2_scl            0
scls_in_mi          0
mi_2_rest           0
rest_in_mi          0
mi_2_groc           0
groc_in_mi          0
dtype: int64
```

SCRUB

Cleaning up our data, filling NaN values, dropping unnecessary columns

In [23]:
```
kc_data = kc_data.drop(['id', 'date'], 1)
```

In [24]:
```
#to use sqft basment later on we need to convert it to a float
kc_data['sqft_basement'] = kc_data['sqft_basement'].replace({'?': 0})
kc_data['sqft_basement'] = kc_data['sqft_basement'].astype(dtype=float)
```

As we can see we have 3 columns with null values, after exploring them, it makes the most sense to fill the null values with zeros, which is what they had been using to indicate a column without anything anyways.

In [25]:
```
kc_data = kc_data.fillna(0)
```

In [26]:
```
#Convert to integer for whole number year, not sure why it'll let us reassign it here
but raise errors in dtypes
kc_data['yr_renovated'] = kc_data['yr_renovated'].astype('int')
```

Add Dummy Variables

Catagorical columns needs to be transformed so we can use them in our model.</p>

thankfully, the Pandas library has got us covered with pd.get_dummies()

In [27]:
```
# fixing condition to be a good or bad, hoping that'll help get rid of the
multicolinearity
kc_data['condition'] = kc_data.condition.replace(to_replace = [1.0, 2.0, 3.0, 4.0,
5.0],  value= ['bad', 'bad', 'good', 'good', 'good'])
```

In [28]:
```
#we have 70 zipcodes and 120 years, it would add too much complexity to our data to
increase it by 190 columns
# so instead, we're going to go through and bin them!
zips = []
years = []


for zipcode in kc_data.zipcode:
    zips.append(zipcode)
for year in kc_data.yr_built:
    years.append(year)

zips = list(set(zips))
```

```
years = list(set(years))

zips.sort()
years.sort()
```

In [29]:

```
#will have to find a way to write this into a loop at some point, but, I can't figure
out how to get .replace()
#to adequatley read lists of lists while also giving them unique names, so for now this
works
kc_data['zipcode'] = kc_data.zipcode.replace(to_replace = zips[0:5],  value=
'zip001t005')
kc_data['zipcode'] = kc_data.zipcode.replace(to_replace = zips[5:10], value=
'zip006t011')
kc_data['zipcode'] = kc_data.zipcode.replace(to_replace = zips[10:15], value=
'zip014t024')
kc_data['zipcode'] = kc_data.zipcode.replace(to_replace = zips[15:20], value=
'zip027t031')
kc_data['zipcode'] = kc_data.zipcode.replace(to_replace = zips[20:25], value=
'zip032t039')
kc_data['zipcode'] = kc_data.zipcode.replace(to_replace = zips[25:30], value=
'zip040t053')
kc_data['zipcode'] = kc_data.zipcode.replace(to_replace = zips[30:35], value=
'zip055t065')
kc_data['zipcode'] = kc_data.zipcode.replace(to_replace = zips[35:40], value=
'zip070t077')
kc_data['zipcode'] = kc_data.zipcode.replace(to_replace = zips[40:45], value=
'zip092t106')
kc_data['zipcode'] = kc_data.zipcode.replace(to_replace = zips[45:50], value=
'zip107t115')
kc_data['zipcode'] = kc_data.zipcode.replace(to_replace = zips[50:55], value=
'zip116t122')
kc_data['zipcode'] = kc_data.zipcode.replace(to_replace = zips[55:60], value=
'zip125t144')
kc_data['zipcode'] = kc_data.zipcode.replace(to_replace = zips[60:65], value=
'zip146t168')
kc_data['zipcode'] = kc_data.zipcode.replace(to_replace = zips[65:70], value=
'zip177t199')
```

In [30]:

```
#gonna do the same for year built by 20 years, will give us 6 new columns, may be
illuminating
kc_data['yr_built'] = kc_data.yr_built.replace(to_replace = years[0:20], value=
'thru20')
kc_data['yr_built'] = kc_data.yr_built.replace(to_replace = years[20:40], value=
'thru40')
kc_data['yr_built'] = kc_data.yr_built.replace(to_replace = years[40:60], value=
```

```
'thru60')
kc_data['yr_built'] = kc_data.yr_built.replace(to_replace = years[60:80], value=
'thru80')
kc_data['yr_built'] = kc_data.yr_built.replace(to_replace = years[80:100], value=
'thru2000')
kc_data['yr_built'] = kc_data.yr_built.replace(to_replace = years[100:120], value=
'thru2020')
```

In [31]:
```
# get dummies of our new variables
dummys = ['zipcode', 'yr_built', 'condition', ]

for dummy in dummys:
    dumm = pd.get_dummies(kc_data[dummy], drop_first=True)
    kc_data = kc_data.merge(dumm, left_index=True, right_index=True)

#we're doing something unique to these variables so it wouldn't save us any time to put
them into a loop
dumm = pd.get_dummies(kc_data['view'], prefix='view', drop_first=True, dtype=int)
kc_data = kc_data.merge(dumm, left_index=True, right_index=True)
dumm = pd.get_dummies(kc_data['grade'], prefix='gra', drop_first=True, dtype=int)
kc_data = kc_data.merge(dumm, left_index=True, right_index=True)
```

In [32]:
```
#break up variables into diverse ranges & renaming our dummies so that they'r easier to
interpret
kc_data = kc_data.rename({'view_1.0': 'view1', 'view_2.0': 'view2', 'view_3.0':
'view3', 'view_4.0':'view4'},axis=1)
kc_data = kc_data.rename({'gra_4': 'D', 'gra_5':'Cmin', 'gra_6':'C','gra_7':'Cpl',
'gra_8':'Bmin', 'gra_9':'B',
                          'gra_10':'Bpl', 'gra_11':'Amin', 'gra_12':'A',
'gra_13':'Apl'},axis=1)
```

EXPLORE

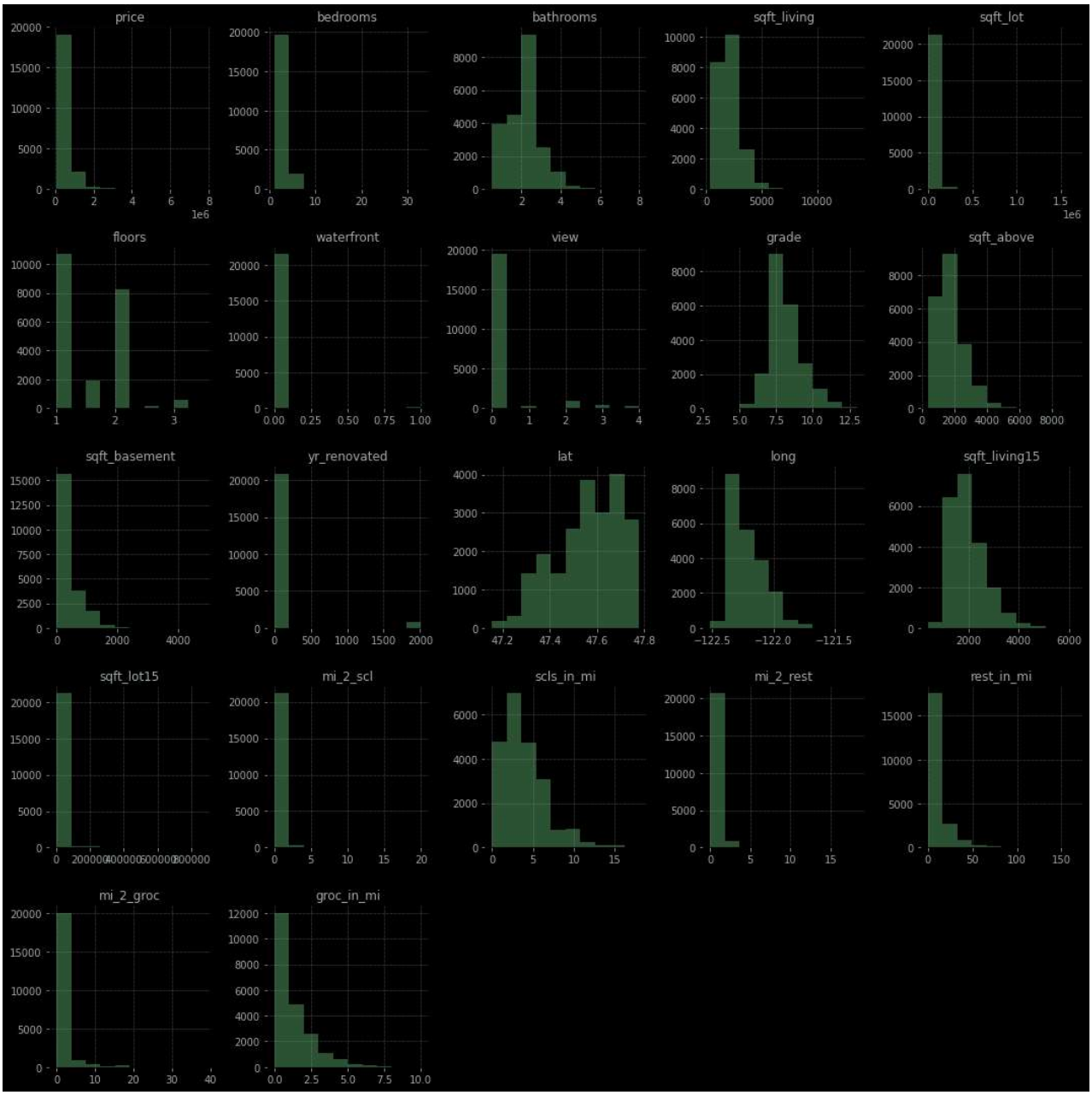
Now that we have all of the data we'll need ready to go we can really start digging in and checking it out!

Histogram

In [33]:
```
# looking at a histogram of value counts for al of our data can give us a sense of how
it's
#distributed and what columns we might have issues with
hist = kc_data[['price', 'bedrooms', 'bathrooms', 'sqft_living', 'sqft_lot', 'floors',
'waterfront', 'view',
                'condition', 'grade', 'sqft_above', 'sqft_basement', 'yr_built',
'yr_renovated', 'zipcode',
```

```
                'lat', 'long', 'sqft_living15', 'sqft_lot15', 'mi_2_scl', 'scls_in_mi',
'mi_2_rest',
                'rest_in_mi', 'mi_2_groc', 'groc_in_mi']]

hist.hist(figsize=(15,15), color='#2C5234')
plt.tight_layout()
```

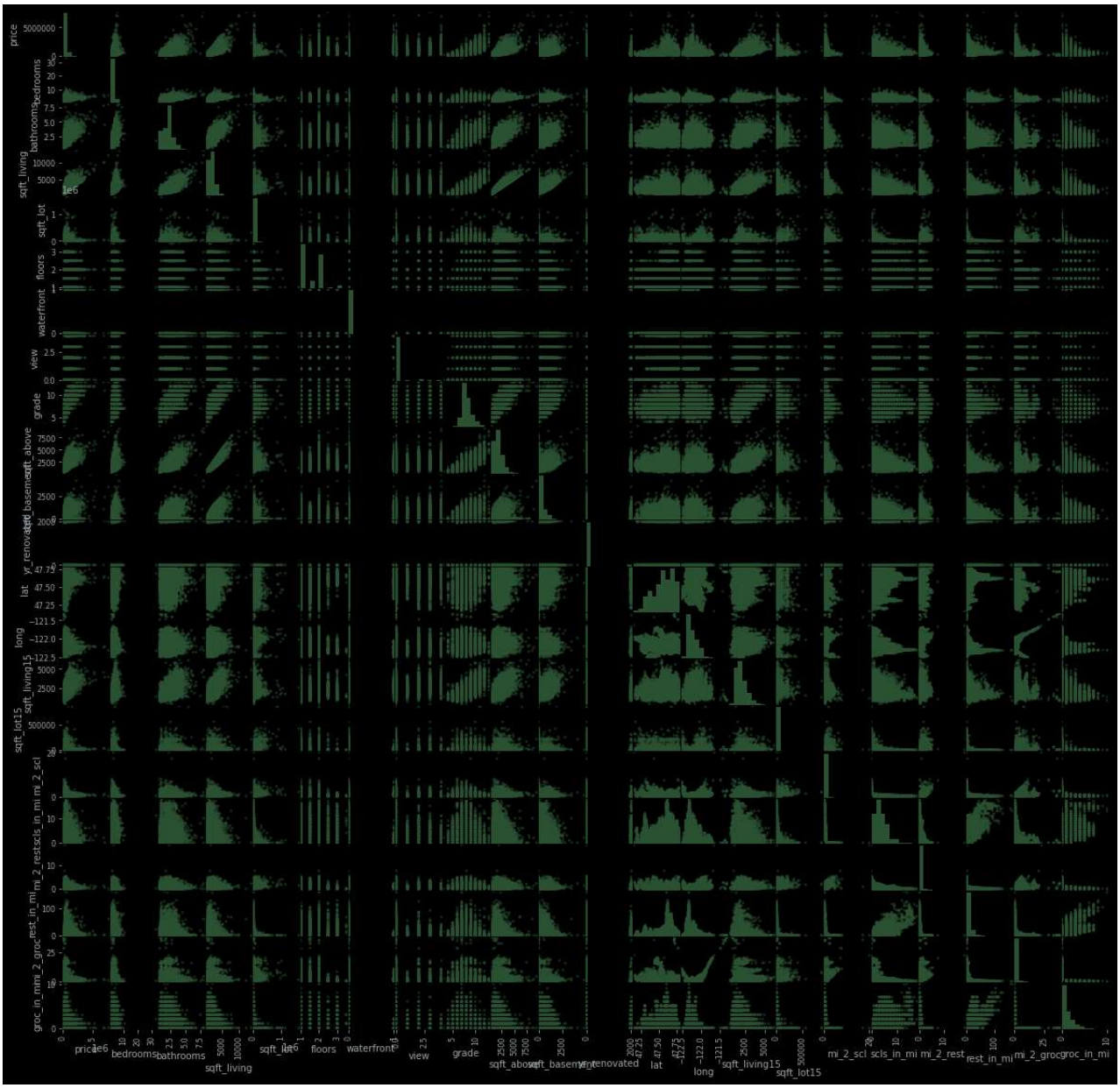


Scatter Matrix

In [34]:

```
# a scatter matrix will compare all of our columns against eachother, it's very large
and takes a while
# with so much data, but can be really informative
scatter = kc_data[['price', 'bedrooms', 'bathrooms', 'sqft_living', 'sqft_lot',
'floors', 'waterfront', 'view',
                'condition', 'grade', 'sqft_above', 'sqft_basement', 'yr_built',
```

```
'yr_renovated', 'zipcode',
                'lat', 'long', 'sqft_living15', 'sqft_lot15', 'mi_2_scl', 'scls_in_mi',
'mi_2_rest',
                'rest_in_mi', 'mi_2_groc', 'groc_in_mi']]
fig = pd.plotting.scatter_matrix(scatter,figsize=(20,20));
```

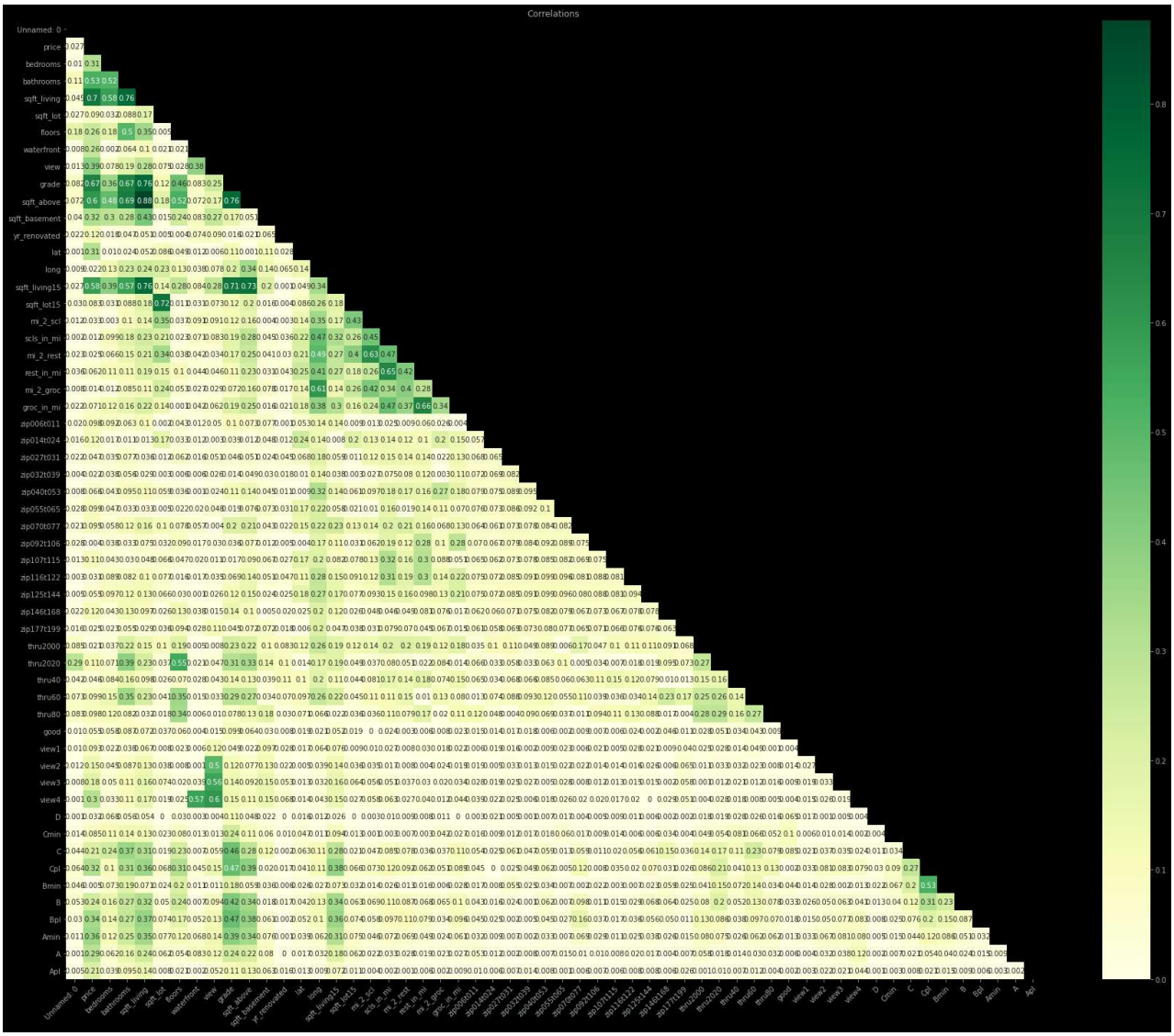


Heatmap

In [35]:

```
#a heatmap will help visualize the multicolinearity in our data and help us to see if
anything stands out l
fig, ax = plt.subplots(figsize=(25,20))
corr = kc_data.corr().abs().round(3)
mask = np.triu(np.ones_like(corr, dtype=np.bool))
sns.heatmap(corr, annot=True, mask=mask, cmap='YlGn', ax=ax)
plt.setp(ax.get_xticklabels(),
         rotation=45,
```

```
        ha="right",
        rotation_mode="anchor")
ax.set_title('Correlations')
set_frameon(ax, True)
fig.tight_layout()
```



We can see some colinearity between our features, it's best to either remove or transform them if we want to use them in our model

If we were to multiply by basement to try and get rid of the correlation, we'd be multiplying by a bunch of zeros and it wouldn't adequetly represent our data. By adding one to every 'sqft_basement' that is equal to zero, when we multiply if there are no basement values we still keep our 'sqft_above' values.

In [36]:
```
kc_data['sqft_basement'] = kc_data['sqft_basement'].map(lambda x :  1 if x == 0 else x
)
```

In [37]:
```
#getting rid of multicolinearity in sqftage
kc_data['sqft_total'] = kc_data['sqft_living']*kc_data['sqft_lot']
```

```
kc_data['sqft_neighb'] = kc_data['sqft_living15']*kc_data['sqft_lot15']
kc_data['sqft_habitable'] = kc_data['sqft_above']*kc_data['sqft_basement']
```

In [38]:
```
#print columns we will be using going forward
kc_data.columns
```

Out[38]:
```
Index(['Unnamed: 0', 'price', 'bedrooms', 'bathrooms', 'sqft_living',
       'sqft_lot', 'floors', 'waterfront', 'view', 'condition', 'grade',
       'sqft_above', 'sqft_basement', 'yr_built', 'yr_renovated', 'zipcode',
       'lat', 'long', 'sqft_living15', 'sqft_lot15', 'mi_2_scl', 'scls_in_mi',
       'mi_2_rest', 'rest_in_mi', 'mi_2_groc', 'groc_in_mi', 'zip006t011',
       'zip014t024', 'zip027t031', 'zip032t039', 'zip040t053', 'zip055t065',
       'zip070t077', 'zip092t106', 'zip107t115', 'zip116t122', 'zip125t144',
       'zip146t168', 'zip177t199', 'thru2000', 'thru2020', 'thru40', 'thru60',
       'thru80', 'good', 'view1', 'view2', 'view3', 'view4', 'D', 'Cmin', 'C',
       'Cpl', 'Bmin', 'B', 'Bpl', 'Amin', 'A', 'Apl', 'sqft_total',
       'sqft_neighb', 'sqft_habitable'],
      dtype='object')
```

In [39]:
```
#make a copy of the dataframe holding only columns we'll be including
kc_data = kc_data[['price', 'bedrooms', 'bathrooms', 'floors','waterfront',
                   'yr_renovated', 'lat', 'long',
                   'sqft_total', 'sqft_neighb', 'sqft_habitable',
                   'good', 'view1', 'view2', 'view3', 'view4',
                   'D', 'Cmin', 'C', 'Cpl', 'Bmin', 'B', 'Bpl', 'Amin',
                   'zip006t011', 'zip014t024', 'zip027t031', 'zip032t039',
                   'zip040t053', 'zip055t065', 'zip070t077', 'zip092t106',
                   'zip107t115', 'zip116t122', 'zip125t144', 'zip146t168',
                   'zip177t199',
                   'thru2000', 'thru2020', 'thru40', 'thru60', 'thru80',
                   'mi_2_scl', 'scls_in_mi', 'mi_2_rest', 'rest_in_mi', 'mi_2_groc',
'groc_in_mi']].copy()
```

MODEL

Initial Models on Price

We're using StatsModel to perform OLS regression, first we'll break up our prices into multiple income brackets and take a look at all of our columns. Then, we'll go back through and refine our model.

In [40]:
```
#seperating our data into different income brackets, as a 100,000 house is unlikely to
be helpful
#in predicting the price of a 1,000,000 house
hightier = kc_data[kc_data.price >800000]
midtier = kc_data[(kc_data.price > 300001) & (kc_data.price<=800000) ]
lowtier = kc_data[kc_data.price <=300000]
```

In [41]:
```
#as we go through we will notice that some features apply to different income brackets,
#so seperating them out helps us choose the features that best apply to each of them

highincome = ['bedrooms', 'bathrooms', 'floors', 'waterfront',
          'yr_renovated', 'lat', 'long',
          'sqft_total', 'sqft_neighb', 'sqft_habitable',
          'good', 'view1', 'view2', 'view3', 'view4',
          'D', 'Cmin', 'C', 'Cpl', 'Bmin', 'B', 'Bpl', 'Amin',
          'zip006t011', 'zip014t024', 'zip027t031', 'zip032t039',
          'zip040t053', 'zip055t065', 'zip070t077', 'zip092t106',
          'zip107t115', 'zip116t122', 'zip125t144', 'zip146t168',
          'zip177t199',
          'thru2000', 'thru2020', 'thru40', 'thru60', 'thru80',
          'mi_2_scl', 'scls_in_mi', 'mi_2_rest', 'rest_in_mi', 'mi_2_groc',
'groc_in_mi']

mediumincome = ['bedrooms', 'bathrooms', 'floors', 'waterfront',
          'yr_renovated', 'lat', 'long',
          'sqft_total', 'sqft_neighb', 'sqft_habitable',
          'good', 'view1', 'view2', 'view3', 'view4',
          'D', 'Cmin', 'C', 'Cpl', 'Bmin', 'B', 'Bpl', 'Amin',
          'zip006t011', 'zip014t024', 'zip027t031', 'zip032t039',
          'zip040t053', 'zip055t065', 'zip070t077', 'zip092t106',
          'zip107t115', 'zip116t122', 'zip125t144', 'zip146t168',
          'zip177t199',
          'thru2000', 'thru2020', 'thru40', 'thru60', 'thru80',
          'mi_2_scl', 'scls_in_mi', 'mi_2_rest', 'rest_in_mi', 'mi_2_groc',
'groc_in_mi']

lowincome = ['bedrooms', 'bathrooms', 'floors', 'waterfront',
          'yr_renovated', 'lat', 'long',
          'sqft_total', 'sqft_neighb', 'sqft_habitable',
          'good', 'view1', 'view2', 'view3', 'view4',
          'D', 'Cmin', 'C', 'Cpl', 'Bmin', 'B', 'Bpl', 'Amin',
          'zip006t011', 'zip014t024', 'zip027t031', 'zip032t039',
          'zip040t053', 'zip055t065', 'zip070t077', 'zip092t106',
          'zip107t115', 'zip116t122', 'zip125t144', 'zip146t168',
          'zip177t199',
          'thru2000', 'thru2020', 'thru40', 'thru60', 'thru80',
          'mi_2_scl', 'scls_in_mi', 'mi_2_rest', 'rest_in_mi', 'mi_2_groc',
'groc_in_mi']
```

In [42]:
```
#putting all of our price brackets together to go into our model
price_tiers = [('high', hightier, highincome),
               ('mid', midtier, mediumincome),
               ('low', lowtier, lowincome)]
```

In [43]:
```
#using the model function we defined earlier to model and plot our qq plots for each
income bracket
for name, tier, income in price_tiers:
    print(name.upper())
    make_ols(tier, income)
```

HIGH

OLS Regression Results

Dep. Variable:	price	**R-squared (uncentered):**	0.930
Model:	OLS	**Adj. R-squared (uncentered):**	0.929
Method:	Least Squares	**F-statistic:**	862.0
Date:	Wed, 16 Dec 2020	**Prob (F-statistic):**	0.00
Time:	21:59:40	**Log-Likelihood:**	-41752.
No. Observations:	2943	**AIC:**	8.359e+04
Df Residuals:	2898	**BIC:**	8.386e+04
Df Model:	45		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
bedrooms	-1707.3755	8627.274	-0.198	0.843	-1.86e+04	1.52e+04
bathrooms	1.119e+05	1.18e+04	9.452	0.000	8.87e+04	1.35e+05
floors	4.862e+04	1.77e+04	2.749	0.006	1.39e+04	8.33e+04
waterfront	6.687e+05	4.38e+04	15.252	0.000	5.83e+05	7.55e+05
yr_renovated	12.1525	12.816	0.948	0.343	-12.976	37.281
lat	-2.198e+05	1.1e+05	-2.001	0.045	-4.35e+05	-4421.496
long	-1.03e+05	4.28e+04	-2.406	0.016	-1.87e+05	-1.9e+04
sqft_total	1.057e-05	3.51e-05	0.301	0.763	-5.82e-05	7.93e-05
sqft_neighb	-0.0001	8.73e-05	-1.523	0.128	-0.000	3.82e-05
sqft_habitable	0.0565	0.004	14.432	0.000	0.049	0.064
good	-2264.8966	1.46e+05	-0.015	0.988	-2.89e+05	2.85e+05
view1	9.187e+04	3.44e+04	2.668	0.008	2.44e+04	1.59e+05
view2	6.542e+04	2.2e+04	2.972	0.003	2.23e+04	1.09e+05
view3	1.29e+05	2.56e+04	5.037	0.000	7.88e+04	1.79e+05
view4	2.395e+05	3.18e+04	7.531	0.000	1.77e+05	3.02e+05
D	2.148e-05	2.08e-06	10.305	0.000	1.74e-05	2.56e-05
Cmin	-2.536e-06	2.46e-07	-10.312	0.000	-3.02e-06	-2.05e-06
C	-1.23e+06	1.18e+05	-10.433	0.000	-1.46e+06	-9.99e+05

Cpl	-1.232e+06	5.34e+04	-23.063	0.000	-1.34e+06	-1.13e+06
Bmin	-1.127e+06	4.48e+04	-25.163	0.000	-1.21e+06	-1.04e+06
B	-9.91e+05	4.16e+04	-23.813	0.000	-1.07e+06	-9.09e+05
Bpl	-7.987e+05	4.03e+04	-19.812	0.000	-8.78e+05	-7.2e+05
Amin	-5.669e+05	4.13e+04	-13.741	0.000	-6.48e+05	-4.86e+05
zip006t011	-3.905e+05	3.16e+04	-12.364	0.000	-4.52e+05	-3.29e+05
zip014t024	-3.417e+05	8.39e+04	-4.070	0.000	-5.06e+05	-1.77e+05
zip027t031	-5.289e+05	4.35e+04	-12.160	0.000	-6.14e+05	-4.44e+05
zip032t039	-8.378e+04	3.14e+04	-2.666	0.008	-1.45e+05	-2.22e+04
zip040t053	-2.615e+05	2.91e+04	-8.979	0.000	-3.19e+05	-2.04e+05
zip055t065	-5.841e+05	5.1e+04	-11.453	0.000	-6.84e+05	-4.84e+05
zip070t077	-4.598e+05	3.27e+04	-14.060	0.000	-5.24e+05	-3.96e+05
zip092t106	-2.359e+05	3.61e+04	-6.531	0.000	-3.07e+05	-1.65e+05
zip107t115	-1.658e+05	3.31e+04	-5.016	0.000	-2.31e+05	-1.01e+05
zip116t122	-3.669e+05	3.42e+04	-10.736	0.000	-4.34e+05	-3e+05
zip125t144	-4.262e+05	4.43e+04	-9.629	0.000	-5.13e+05	-3.39e+05
zip146t168	-6.712e+05	6.35e+04	-10.571	0.000	-7.96e+05	-5.47e+05
zip177t199	-4.128e+05	3.61e+04	-11.440	0.000	-4.84e+05	-3.42e+05
thru2000	-3.301e+05	3.42e+04	-9.645	0.000	-3.97e+05	-2.63e+05
thru2020	-2.362e+05	3.29e+04	-7.183	0.000	-3.01e+05	-1.72e+05
thru40	-6.226e+04	3.17e+04	-1.962	0.050	-1.24e+05	-41.571
thru60	-7.914e+04	3.38e+04	-2.340	0.019	-1.45e+05	-1.28e+04
thru80	-2.293e+05	3.42e+04	-6.697	0.000	-2.96e+05	-1.62e+05
mi_2_scl	-4.26e+04	2.41e+04	-1.764	0.078	-8.99e+04	4741.699
scls_in_mi	-3819.4113	3631.436	-1.052	0.293	-1.09e+04	3301.046
mi_2_rest	3e+04	1.81e+04	1.656	0.098	-5517.130	6.55e+04
rest_in_mi	267.9390	804.468	0.333	0.739	-1309.447	1845.325
mi_2_groc	-2.317e+04	5739.074	-4.037	0.000	-3.44e+04	-1.19e+04
groc_in_mi	-2.719e+04	1.03e+04	-2.638	0.008	-4.74e+04	-6984.540

Omnibus:	1221.494	**Durbin-Watson:**	2.029
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	18551.156
Skew:	1.556	**Prob(JB):**	0.00
Kurtosis:	14.900	**Cond. No.**	1.09e+16

Notes:

[1] R^2 is computed without centering (uncentered) since the model does not contain a constant.

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

[3] The smallest eigenvalue is 2.39e-12. This might indicate that there are strong multicollinearity problems or that the design matrix is singular.

```
MID
```

OLS Regression Results

Dep. Variable:	price	**R-squared (uncentered):**	0.966
Model:	OLS	**Adj. R-squared (uncentered):**	0.966
Method:	Least Squares	**F-statistic:**	8615.
Date:	Wed, 16 Dec 2020	**Prob (F-statistic):**	0.00
Time:	21:59:40	**Log-Likelihood:**	-1.8142e+05
No. Observations:	14093	**AIC:**	3.629e+05
Df Residuals:	14046	**BIC:**	3.633e+05
Df Model:	47		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
bedrooms	1.063e+04	1051.014	10.110	0.000	8565.381	1.27e+04
bathrooms	3.454e+04	1909.079	18.093	0.000	3.08e+04	3.83e+04
floors	3434.5050	2270.008	1.513	0.130	-1015.013	7884.023
waterfront	8.803e+04	1.94e+04	4.528	0.000	4.99e+04	1.26e+05
yr_renovated	1.7188	2.497	0.688	0.491	-3.176	6.614
lat	3.481e+05	7423.274	46.893	0.000	3.34e+05	3.63e+05
long	1.314e+05	1.11e+04	11.788	0.000	1.1e+05	1.53e+05
sqft_total	7.952e-05	1.12e-05	7.090	0.000	5.75e-05	0.000
sqft_neighb	0.0001	1.86e-05	6.131	0.000	7.77e-05	0.000
sqft_habitable	0.0134	0.001	9.421	0.000	0.011	0.016
good	1.894e+04	1.04e+04	1.814	0.070	-1531.305	3.94e+04
view1	7.14e+04	6855.200	10.415	0.000	5.8e+04	8.48e+04
view2	5.256e+04	4158.765	12.639	0.000	4.44e+04	6.07e+04
view3	7.022e+04	6297.972	11.150	0.000	5.79e+04	8.26e+04
view4	9.998e+04	1.28e+04	7.840	0.000	7.5e+04	1.25e+05
D	-1.335e+05	1.43e+06	-0.094	0.925	-2.93e+06	2.66e+06
Cmin	-9.822e+04	1.43e+06	-0.069	0.945	-2.89e+06	2.7e+06
C	-1.204e+05	1.43e+06	-0.084	0.933	-2.92e+06	2.68e+06

Cpl	-6.389e+04	1.43e+06	-0.045	0.964	-2.86e+06	2.73e+06
Bmin	5858.8388	1.43e+06	0.004	0.997	-2.79e+06	2.8e+06
B	9.821e+04	1.43e+06	0.069	0.945	-2.7e+06	2.89e+06
Bpl	1.626e+05	1.43e+06	0.114	0.909	-2.63e+06	2.96e+06
Amin	1.964e+05	1.43e+06	0.138	0.891	-2.6e+06	2.99e+06
zip006t011	-1.272e+04	6084.986	-2.090	0.037	-2.46e+04	-788.422
zip014t024	-1.175e+05	6643.285	-17.682	0.000	-1.3e+05	-1.04e+05
zip027t031	-5.568e+04	5926.821	-9.395	0.000	-6.73e+04	-4.41e+04
zip032t039	-5.289e+04	5853.503	-9.035	0.000	-6.44e+04	-4.14e+04
zip040t053	-1.83e+04	5940.650	-3.080	0.002	-2.99e+04	-6654.617
zip055t065	-6.203e+04	5724.937	-10.835	0.000	-7.33e+04	-5.08e+04
zip070t077	-2.836e+04	6170.831	-4.596	0.000	-4.05e+04	-1.63e+04
zip092t106	-4.506e+04	6061.810	-7.433	0.000	-5.69e+04	-3.32e+04
zip107t115	-2.616e+04	6245.536	-4.188	0.000	-3.84e+04	-1.39e+04
zip116t122	-2.368e+04	5971.544	-3.965	0.000	-3.54e+04	-1.2e+04
zip125t144	-7.3e+04	5866.849	-12.443	0.000	-8.45e+04	-6.15e+04
zip146t168	-9.392e+04	6291.398	-14.929	0.000	-1.06e+05	-8.16e+04
zip177t199	-5.49e+04	6414.874	-8.559	0.000	-6.75e+04	-4.23e+04
thru2000	-1.282e+05	4434.302	-28.910	0.000	-1.37e+05	-1.2e+05
thru2020	-1.251e+05	4490.342	-27.851	0.000	-1.34e+05	-1.16e+05
thru40	-5231.0554	4193.075	-1.248	0.212	-1.35e+04	2987.930
thru60	-4.833e+04	3855.830	-12.535	0.000	-5.59e+04	-4.08e+04
thru80	-1.113e+05	4146.870	-26.851	0.000	-1.19e+05	-1.03e+05
mi_2_scl	1.04e+04	2101.949	4.947	0.000	6279.048	1.45e+04
scls_in_mi	-593.1226	432.378	-1.372	0.170	-1440.640	254.395
mi_2_rest	-8236.1188	2011.954	-4.094	0.000	-1.22e+04	-4292.421
rest_in_mi	1338.3953	101.170	13.229	0.000	1140.088	1536.702
mi_2_groc	-2917.4323	462.136	-6.313	0.000	-3823.281	-2011.584
groc_in_mi	-9349.2857	932.744	-10.023	0.000	-1.12e+04	-7520.983

Omnibus:	343.350	**Durbin-Watson:**	2.015
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	371.575
Skew:	0.378	**Prob(JB):**	2.06e-81
Kurtosis:	3.248	**Cond. No.**	6.30e+11

Notes:

[1] R^2 is computed without centering (uncentered) since the model does not contain a constant.

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

[3] The condition number is large, 6.3e+11. This might indicate that there are strong multicollinearity or other numerical problems.

LOW

OLS Regression Results

Dep. Variable:	price	**R-squared (uncentered):**	0.978
Model:	OLS	**Adj. R-squared (uncentered):**	0.978
Method:	Least Squares	**F-statistic:**	4506.
Date:	Wed, 16 Dec 2020	**Prob (F-statistic):**	0.00
Time:	21:59:40	**Log-Likelihood:**	-54335.
No. Observations:	4561	**AIC:**	1.088e+05
Df Residuals:	4516	**BIC:**	1.091e+05
Df Model:	45		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
bedrooms	5000.6701	850.440	5.880	0.000	3333.391	6667.949
bathrooms	1.901e+04	1456.422	13.050	0.000	1.62e+04	2.19e+04
floors	1950.4887	1881.319	1.037	0.300	-1737.817	5638.794
waterfront	4.215e+04	3.17e+04	1.328	0.184	-2.01e+04	1.04e+05
yr_renovated	1.2960	1.946	0.666	0.506	-2.520	5.112
lat	8.423e+04	6232.485	13.514	0.000	7.2e+04	9.64e+04
long	3.099e+04	2421.649	12.796	0.000	2.62e+04	3.57e+04
sqft_total	8.017e-05	2.26e-05	3.541	0.000	3.58e-05	0.000
sqft_neighb	1.295e-05	2.27e-05	0.571	0.568	-3.15e-05	5.74e-05
sqft_habitable	0.0115	0.002	6.185	0.000	0.008	0.015
good	3.505e+04	3628.665	9.658	0.000	2.79e+04	4.22e+04
view1	3.14e+04	1.02e+04	3.081	0.002	1.14e+04	5.14e+04
view2	2.01e+04	5098.013	3.942	0.000	1.01e+04	3.01e+04
view3	2.249e+04	1.05e+04	2.135	0.033	1836.976	4.31e+04
view4	4.303e+04	3.02e+04	1.426	0.154	-1.61e+04	1.02e+05
D	-1.11e+05	3.73e+04	-2.977	0.003	-1.84e+05	-3.79e+04
Cmin	-9.278e+04	3.66e+04	-2.538	0.011	-1.64e+05	-2.11e+04
C	-6.974e+04	3.65e+04	-1.911	0.056	-1.41e+05	1789.018

Cpl	-5.358e+04	3.65e+04	-1.467	0.142	-1.25e+05	1.8e+04
Bmin	-4.142e+04	3.66e+04	-1.133	0.257	-1.13e+05	3.03e+04
B	-4.631e+04	3.75e+04	-1.236	0.217	-1.2e+05	2.72e+04
Bpl	-2.647e-11	6.99e-11	-0.379	0.705	-1.64e-10	1.11e-10
Amin	-5.322e-10	2.85e-10	-1.866	0.062	-1.09e-09	2.71e-11
zip006t011	7472.1142	5544.517	1.348	0.178	-3397.852	1.83e+04
zip014t024	5290.4672	2295.729	2.304	0.021	789.715	9791.219
zip027t031	5386.5259	2618.441	2.057	0.040	253.101	1.05e+04
zip032t039	2924.2244	2730.256	1.071	0.284	-2428.414	8276.863
zip040t053	2501.3695	2684.268	0.932	0.351	-2761.109	7763.848
zip055t065	1.181e+04	2571.133	4.595	0.000	6772.819	1.69e+04
zip070t077	3.774e+04	7918.899	4.766	0.000	2.22e+04	5.33e+04
zip092t106	9040.6905	2638.404	3.427	0.001	3868.128	1.42e+04
zip107t115	6163.5910	4821.326	1.278	0.201	-3288.567	1.56e+04
zip116t122	1.251e+04	3709.824	3.372	0.001	5237.536	1.98e+04
zip125t144	2.304e+04	3456.018	6.667	0.000	1.63e+04	2.98e+04
zip146t168	2308.3719	2599.637	0.888	0.375	-2788.188	7404.932
zip177t199	-2947.7825	2491.186	-1.183	0.237	-7831.727	1936.162
thru2000	1169.1416	3382.202	0.346	0.730	-5461.630	7799.913
thru2020	3737.0082	3739.202	0.999	0.318	-3593.658	1.11e+04
thru40	6517.9477	3344.701	1.949	0.051	-39.302	1.31e+04
thru60	1219.8587	2915.706	0.418	0.676	-4496.353	6936.070
thru80	-4533.9515	3129.354	-1.449	0.147	-1.07e+04	1601.115
mi_2_scl	-1832.6043	1616.798	-1.133	0.257	-5002.319	1337.110
scls_in_mi	-540.3489	347.136	-1.557	0.120	-1220.906	140.208
mi_2_rest	5506.8663	1494.370	3.685	0.000	2577.170	8436.562
rest_in_mi	201.7996	134.778	1.497	0.134	-62.431	466.031
mi_2_groc	-898.5775	266.435	-3.373	0.001	-1420.920	-376.235
groc_in_mi	-401.1592	682.430	-0.588	0.557	-1739.055	936.737

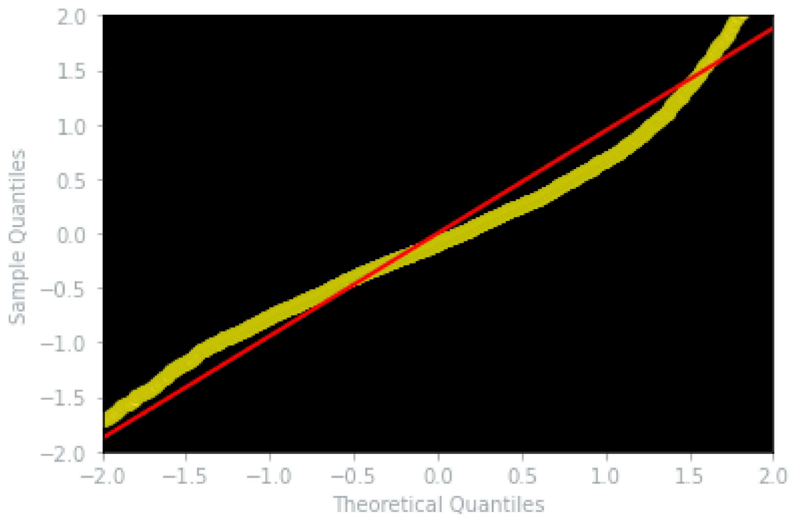
Omnibus:	243.052	**Durbin-Watson:**	1.997
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	285.806
Skew:	-0.573	**Prob(JB):**	8.67e-63
Kurtosis:	3.437	**Cond. No.**	1.18e+16

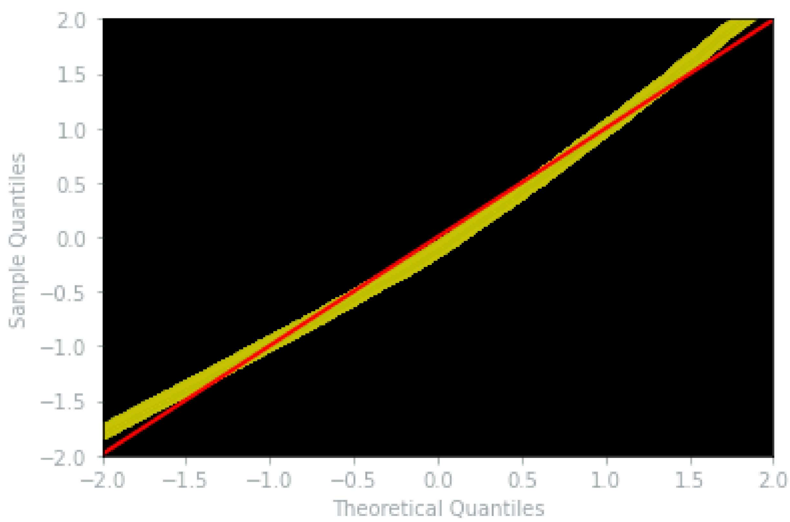
Notes:

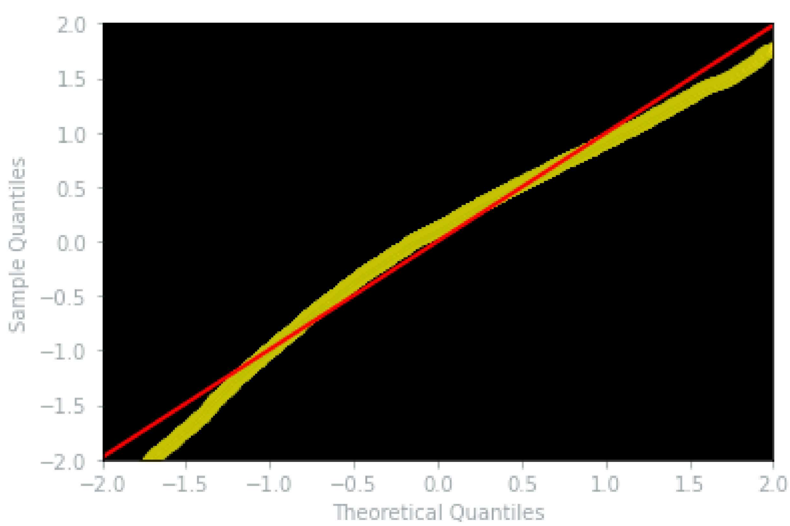
[1] R^2 is computed without centering (uncentered) since the model does not contain a constant.

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

[3] The smallest eigenvalue is 5.36e-14. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.





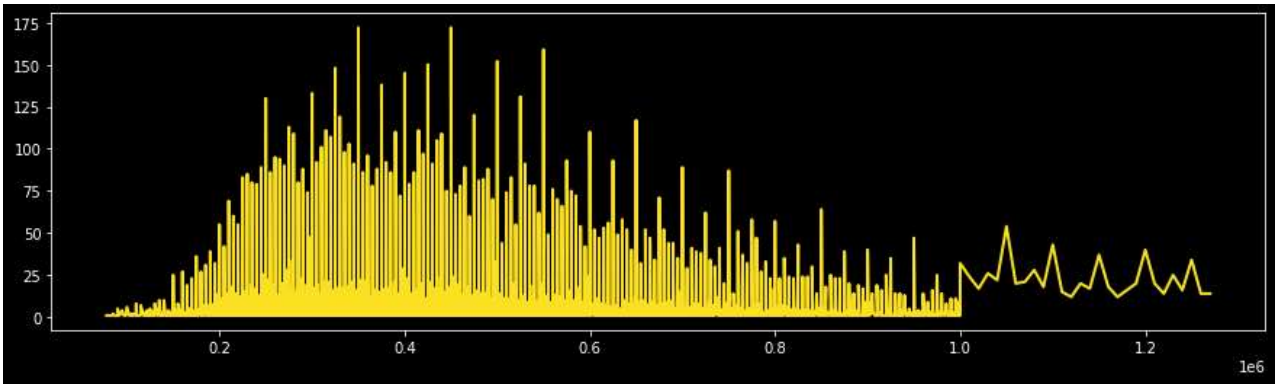


Refinement

First we're going to start filtering out outliers, helping normalize our data should improve our model

In [44]:
```
# we're going to normalize price a bit by filtering out all of our homes more than or
less than 2
# standard deviations from our mean housing price
for col in ['price']:
    col_zscore = str(col + '_zscore')
    kc_data[col_zscore] = (kc_data[col] - kc_data[col].mean())/kc_data[col].std()
    kc_data = kc_data.loc[kc_data[col_zscore] < 2]
    kc_data = kc_data.loc[kc_data[col_zscore] > (-2)]
    #we're also going to drop our z scored price, after exploring with it for a while
    #we found the regular price much more helpful
    kc_data = kc_data.drop(col_zscore, axis = 1)
```

In [45]:
```
# taking a look at our prices to make sure they're normal enough for us to use
with plt.style.context('dark_background'):
    plt.figure(figsize=(15,4))
    plt.plot(kc_data['price'].value_counts().sort_index(), color='#FBE122')
# looks good!
```



Then we can start checking our data for other outliers.

In [46]:
```
# checking out our percentiles to see if there's anything weird we can see
get_percentile(kc_data['price'])
```

```
0.01 percentile: 152720.0
0.02 percentile: 175000.0
0.03 percentile: 190000.0
0.04 percentile: 200000.0
0.05 percentile: 210000.0
0.06 percentile: 218000.0
0.07 percentile: 225000.0
0.08 percentile: 230000.0
0.09 percentile: 238000.0
0.1 percentile: 245000.0
0.11 percentile: 249902.5
0.12 percentile: 253000.0
0.13 percentile: 259000.0
0.14 percentile: 264500.0
```

0.15 percentile: 269000.0
0.16 percentile: 274000.0
0.17 percentile: 278500.0
0.18 percentile: 282000.0
0.19 percentile: 288000.0
0.2 percentile: 293000.0
0.21 percentile: 299000.0
0.22 percentile: 301000.0
0.23 percentile: 307000.0
0.24 percentile: 312000.0
0.25 percentile: 317000.0
0.26 percentile: 322000.0
0.27 percentile: 325000.0
0.28 percentile: 330000.0
0.29 percentile: 335000.0
0.3 percentile: 340000.0
0.31 percentile: 345000.0
0.32 percentile: 350000.0
0.33 percentile: 353000.0
0.34 percentile: 358350.00000000035
0.35 percentile: 363000.0
0.36 percentile: 369950.0
0.37 percentile: 375000.0
0.38 percentile: 379900.0
0.39 percentile: 385000.0
0.4 percentile: 390000.0
0.41 percentile: 395000.0
0.42 percentile: 400000.0
0.43 percentile: 405000.0
0.44 percentile: 410000.0
0.45 percentile: 415000.0
0.46 percentile: 420000.0
0.47 percentile: 425000.0
0.48 percentile: 430000.0
0.49 percentile: 435000.0
0.5 percentile: 440000.0
0.51 percentile: 446452.50000000006
0.52 percentile: 450000.0
0.53 percentile: 455000.0
0.54 percentile: 462000.0
0.55 percentile: 469000.0
0.56 percentile: 475000.0
0.57 percentile: 480000.0
0.58 percentile: 489000.0
0.59 percentile: 495000.0
0.6 percentile: 500000.0
0.61 percentile: 507000.0
0.62 percentile: 515000.0
0.63 percentile: 524347.4999999999
0.64 percentile: 529950.0
0.65 percentile: 535000.0
0.66 percentile: 542000.0
0.67 percentile: 550000.0
0.68 percentile: 554689.4000000001
0.69 percentile: 562000.0
0.7 percentile: 570000.0
0.71 percentile: 578024.9999999995
0.72 percentile: 585000.0
0.73 percentile: 595000.0
0.74 percentile: 602000.0
0.75 percentile: 613275.0
0.76 percentile: 624880.0000000001
0.77 percentile: 632500.0
0.78 percentile: 645000.0
0.79 percentile: 650934.0000000001

```
0.8 percentile: 665000.0
0.81 percentile: 675000.0
0.82 percentile: 689000.0
0.83 percentile: 700000.0
0.84 percentile: 715000.0
0.85 percentile: 725998.75
0.86 percentile: 740000.0
0.87 percentile: 755000.0
0.88 percentile: 772000.0
0.89 percentile: 788595.0000000001
0.9 percentile: 805000.0
0.91 percentile: 825000.0
0.92 percentile: 849000.0
0.93 percentile: 870000.0
0.94 percentile: 898349.9999999986
0.95 percentile: 925000.0
0.96 percentile: 963998.0
0.97 percentile: 1000000.0
0.98 percentile: 1080000.0
0.99 percentile: 1180000.0
```

In [47]:
```
#taking a quick peak at our minumumns, maximums & other data provided by a .describe()
we can easily see some outliers
kc_data.describe()
```

Out[47]:

	price	bedrooms	bathrooms	floors	waterfront	yr_renovated	la
count	2.075600e+04	20756.000000	20756.000000	20756.000000	20756.000000	20756.000000	20756.00000
mean	4.877262e+05	3.341492	2.065451	1.480415	0.002987	62.394777	47.55778
std	2.244543e+05	0.912440	0.718717	0.536986	0.054574	347.315866	0.14038
min	7.800000e+04	1.000000	0.500000	1.000000	0.000000	0.000000	47.15590
25%	3.170000e+05	3.000000	1.500000	1.000000	0.000000	0.000000	47.46290
50%	4.400000e+05	3.000000	2.250000	1.000000	0.000000	0.000000	47.56820
75%	6.132750e+05	4.000000	2.500000	2.000000	0.000000	0.000000	47.67940
max	1.270000e+06	33.000000	7.500000	3.500000	1.000000	2015.000000	47.77760

8 rows × 48 columns

In [48]:
```
#in bedrooms, we can clearly see a single outlier that is likely just a typo
kc_data[kc_data['bedrooms'] == 33]
# wouldn't be realistic for a house with 33 bedrooms to only have a sqft_living of 1620
and only 1 3/4 bathrooms so we will adjust to 3
kc_data[kc_data['bedrooms'] == 33] = kc_data[kc_data['bedrooms'] == 33].replace(33,3)
```

In [49]:
```
# to fix other outliers we will explore our data and find cutoffs that seem reasonable
kc_data = kc_data.loc[kc_data['sqft_total'] <= 1.000000e+09]
kc_data = kc_data.loc[kc_data['sqft_total'] >= 400000]
kc_data = kc_data.loc[kc_data['sqft_neighb'] <= 1.000000e+09]
kc_data = kc_data.loc[kc_data['sqft_habitable'] >= 400000]
```

```
kc_data = kc_data.loc[kc_data['sqft_habitable'] <= 1.000000e+07]
kc_data =  kc_data.loc[kc_data['bathrooms'] >= 1]
kc_data =  kc_data.loc[kc_data['bathrooms'] <= 5]
kc_data =  kc_data.loc[kc_data['bedrooms'] <= 7]
```

The Final Models

These models have been run through dozens of times testing which is model is the most accurate, what features best match each income bracket, and where each income bracket in our model should fall.

In [50]:
```
# after quite a bit of modeling, these came down to our best price ranges per income bracket
hightier = kc_data[(kc_data.price >= 640000) & (kc_data.price <= 900000)]
uppermidtier = kc_data[(kc_data.price >= 480000) & (kc_data.price <= 640000) ]
midtier = kc_data[(kc_data.price >= 348000) & (kc_data.price <= 480000) ]
lowtier = kc_data[(kc_data.price >= 210000) & (kc_data.price <= 348000) ]
```

In [51]:
```
# these are the features for each income bracket that have significant p-values & low correlation scores
# that help us produce the best fit model
highincome = ['bathrooms', 'floors', 'sqft_neighb',
              'sqft_habitable', 'thru2020',
              'zip006t011', 'zip107t115',
              'zip116t122', 'zip177t199',
              'mi_2_scl', 'scls_in_mi', 'mi_2_rest',
              'mi_2_groc', 'groc_in_mi']

uppermedincome = ['bathrooms',  'lat', 'sqft_habitable',
                  'C', 'Bmin', 'B',
                  'zip014t024', 'zip027t031', 'zip032t039',
                  'zip070t077', 'zip125t144', 'zip146t168',
                  'thru2000', 'thru2020', 'thru60', 'thru80']

mediumincome = ['bathrooms',  'lat', 'long',
                'sqft_habitable', 'view2',
                'Cpl', 'Bmin', 'B', 'Bpl',
                'zip006t011', 'zip014t024', 'zip032t039',
                'zip055t065', 'zip070t077', 'zip092t106',
                'zip177t199', 'rest_in_mi', 'groc_in_mi',
                'thru2000', 'thru2020', 'thru60', 'thru80']

lowincome = ['bathrooms', 'waterfront', 'lat', 'long',
             'sqft_total', 'sqft_habitable',
             'view1', 'view2', 'view3',
```

```
            'C', 'Cpl', 'Bmin', 'B',
            'zip040t053', 'zip055t065', 'zip092t106',
            'zip107t115', 'zip146t168',
            'groc_in_mi']
```

In [52]:
```
# since we added another price bracket we need to redefine our price tiers
price_tiers = [('high', hightier, highincome),
               ('upmid', uppermidtier, uppermedincome),
               ('mid', midtier, mediumincome),
               ('low', lowtier, lowincome)]
```

In [53]:
```
# getting our final model, printing them in income order followed by their qq-plots
for name, tier, income in price_tiers:
    print(name.upper())
    make_ols(tier, income)
```

HIGH

OLS Regression Results

Dep. Variable:	price	**R-squared (uncentered):**	0.965
Model:	OLS	**Adj. R-squared (uncentered):**	0.965
Method:	Least Squares	**F-statistic:**	2721.
Date:	Wed, 16 Dec 2020	**Prob (F-statistic):**	0.00
Time:	21:59:41	**Log-Likelihood:**	-18305.
No. Observations:	1379	**AIC:**	3.664e+04
Df Residuals:	1365	**BIC:**	3.671e+04
Df Model:	14		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
bathrooms	1.299e+05	6505.247	19.967	0.000	1.17e+05	1.43e+05
floors	1.156e+05	9680.582	11.937	0.000	9.66e+04	1.35e+05
sqft_neighb	-0.0002	8.71e-05	-2.861	0.004	-0.000	-7.83e-05
sqft_habitable	0.0261	0.005	5.149	0.000	0.016	0.036
thru2020	-1.524e+05	1.24e+04	-12.309	0.000	-1.77e+05	-1.28e+05
zip006t011	5.735e+04	1.4e+04	4.100	0.000	2.99e+04	8.48e+04
zip107t115	3.518e+04	1.31e+04	2.683	0.007	9459.682	6.09e+04
zip116t122	5.478e+04	1.17e+04	4.677	0.000	3.18e+04	7.78e+04
zip177t199	1.303e+05	1.38e+04	9.428	0.000	1.03e+05	1.57e+05
mi_2_scl	1.031e+05	1.39e+04	7.423	0.000	7.58e+04	1.3e+05
scls_in_mi	2.103e+04	1624.014	12.946	0.000	1.78e+04	2.42e+04

mi_2_rest	8.013e+04	1.26e+04	6.381	0.000	5.55e+04	1.05e+05
mi_2_groc	6538.8325	3115.740	2.099	0.036	426.675	1.27e+04
groc_in_mi	9388.9098	3683.686	2.549	0.011	2162.610	1.66e+04

Omnibus:	94.518	**Durbin-Watson:**	1.914
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	146.829
Skew:	-0.535	**Prob(JB):**	1.31e-32
Kurtosis:	4.187	**Cond. No.**	2.56e+08

Notes:
[1] R^2 is computed without centering (uncentered) since the model does not contain a constant.
[2] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[3] The condition number is large, 2.56e+08. This might indicate that there are
strong multicollinearity or other numerical problems.

`UPMID`

OLS Regression Results

Dep. Variable:	price	**R-squared (uncentered):**	0.994
Model:	OLS	**Adj. R-squared (uncentered):**	0.994
Method:	Least Squares	**F-statistic:**	1.719e+04
Date:	Wed, 16 Dec 2020	**Prob (F-statistic):**	0.00
Time:	21:59:41	**Log-Likelihood:**	-20469.
No. Observations:	1692	**AIC:**	4.097e+04
Df Residuals:	1676	**BIC:**	4.106e+04
Df Model:	16		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
bathrooms	8953.9234	2220.935	4.032	0.000	4597.825	1.33e+04
lat	1.136e+04	97.483	116.536	0.000	1.12e+04	1.16e+04
sqft_habitable	0.0078	0.002	4.430	0.000	0.004	0.011
C	-2.515e+04	7950.739	-3.163	0.002	-4.07e+04	-9555.700
Bmin	1.546e+04	2505.203	6.173	0.000	1.06e+04	2.04e+04
B	2.438e+04	4711.434	5.174	0.000	1.51e+04	3.36e+04
zip014t024	-2.17e+04	8201.155	-2.646	0.008	-3.78e+04	-5618.161
zip027t031	-1.279e+04	4456.597	-2.871	0.004	-2.15e+04	-4052.078
zip032t039	-1.038e+04	4467.540	-2.324	0.020	-1.91e+04	-1620.032
zip070t077	-8563.0595	4286.680	-1.998	0.046	-1.7e+04	-155.250

zip125t144	-1.224e+04	3467.766	-3.531	0.000	-1.9e+04	-5442.646
zip146t168	-1.721e+04	5123.460	-3.358	0.001	-2.73e+04	-7156.203
thru2000	-2.787e+04	4386.117	-6.355	0.000	-3.65e+04	-1.93e+04
thru2020	-2.502e+04	5018.121	-4.986	0.000	-3.49e+04	-1.52e+04
thru60	-9157.4647	3416.426	-2.680	0.007	-1.59e+04	-2456.554
thru80	-2.526e+04	3500.447	-7.216	0.000	-3.21e+04	-1.84e+04

Omnibus:	218.189	**Durbin-Watson:**	1.975
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	57.615
Skew:	0.073	**Prob(JB):**	3.08e-13
Kurtosis:	2.108	**Cond. No.**	1.10e+07

Notes:
[1] R^2 is computed without centering (uncentered) since the model does not contain a constant.
[2] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[3] The condition number is large, 1.1e+07. This might indicate that there are
strong multicollinearity or other numerical problems.

```
MID
```

OLS Regression Results

Dep. Variable:	price	**R-squared (uncentered):**	0.993
Model:	OLS	**Adj. R-squared (uncentered):**	0.993
Method:	Least Squares	**F-statistic:**	1.036e+04
Date:	Wed, 16 Dec 2020	**Prob (F-statistic):**	0.00
Time:	21:59:42	**Log-Likelihood:**	-18521.
No. Observations:	1561	**AIC:**	3.709e+04
Df Residuals:	1539	**BIC:**	3.720e+04
Df Model:	22		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
bathrooms	6011.6770	2014.842	2.984	0.003	2059.552	9963.802
lat	7.359e+04	7872.108	9.348	0.000	5.81e+04	8.9e+04
long	2.543e+04	3068.290	8.289	0.000	1.94e+04	3.15e+04
sqft_habitable	0.0078	0.002	4.263	0.000	0.004	0.011
view2	1.377e+04	4375.178	3.147	0.002	5188.000	2.24e+04
Cpl	8660.5119	3823.641	2.265	0.024	1160.414	1.62e+04
Bmin	2.319e+04	4260.868	5.443	0.000	1.48e+04	3.16e+04

B	3.573e+04	6977.245	5.121	0.000	2.2e+04	4.94e+04
Bpl	5.675e+04	1.15e+04	4.948	0.000	3.43e+04	7.92e+04
zip006t011	1.61e+04	4015.373	4.009	0.000	8222.417	2.4e+04
zip014t024	-1.868e+04	5439.259	-3.435	0.001	-2.94e+04	-8015.040
zip032t039	1.453e+04	3243.249	4.479	0.000	8166.447	2.09e+04
zip055t065	-1.605e+04	3452.999	-4.649	0.000	-2.28e+04	-9278.269
zip070t077	1.114e+04	4271.481	2.608	0.009	2761.815	1.95e+04
zip092t106	-1.389e+04	4029.110	-3.447	0.001	-2.18e+04	-5985.807
zip177t199	-1.144e+04	3638.708	-3.143	0.002	-1.86e+04	-4300.106
rest_in_mi	648.2073	132.261	4.901	0.000	388.777	907.637
groc_in_mi	-2286.3251	900.896	-2.538	0.011	-4053.439	-519.211
thru2000	-1.737e+04	4070.207	-4.268	0.000	-2.54e+04	-9388.915
thru2020	-9762.5072	4804.642	-2.032	0.042	-1.92e+04	-338.169
thru60	-9730.4651	3414.660	-2.850	0.004	-1.64e+04	-3032.587
thru80	-1.89e+04	3604.101	-5.244	0.000	-2.6e+04	-1.18e+04

Omnibus:	95.366	**Durbin-Watson:**	2.067
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	36.790
Skew:	-0.087	**Prob(JB):**	1.03e-08
Kurtosis:	2.268	**Cond. No.**	1.68e+07

Notes:
[1] R^2 is computed without centering (uncentered) since the model does not contain a constant.
[2] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[3] The condition number is large, 1.68e+07. This might indicate that there are
strong multicollinearity or other numerical problems.

```
LOW
```

OLS Regression Results

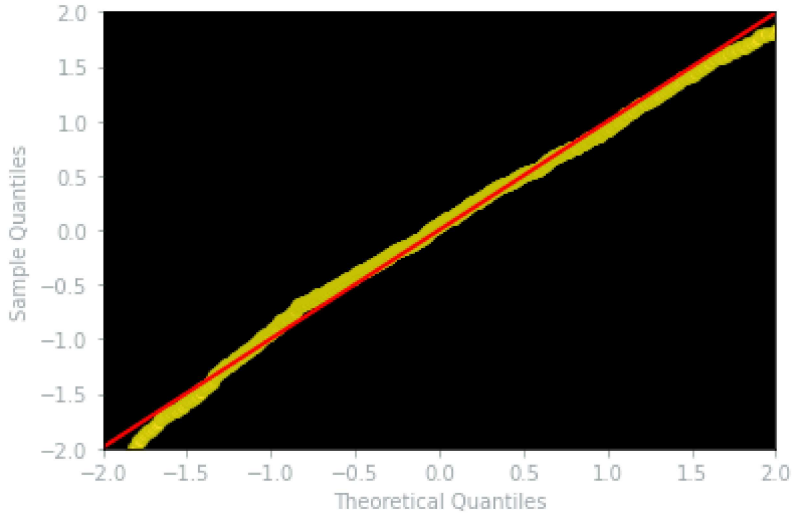
Dep. Variable:	price	**R-squared (uncentered):**	0.989
Model:	OLS	**Adj. R-squared (uncentered):**	0.989
Method:	Least Squares	**F-statistic:**	5956.
Date:	Wed, 16 Dec 2020	**Prob (F-statistic):**	0.00
Time:	21:59:42	**Log-Likelihood:**	-14113.
No. Observations:	1203	**AIC:**	2.826e+04
Df Residuals:	1185	**BIC:**	2.835e+04
Df Model:	18		

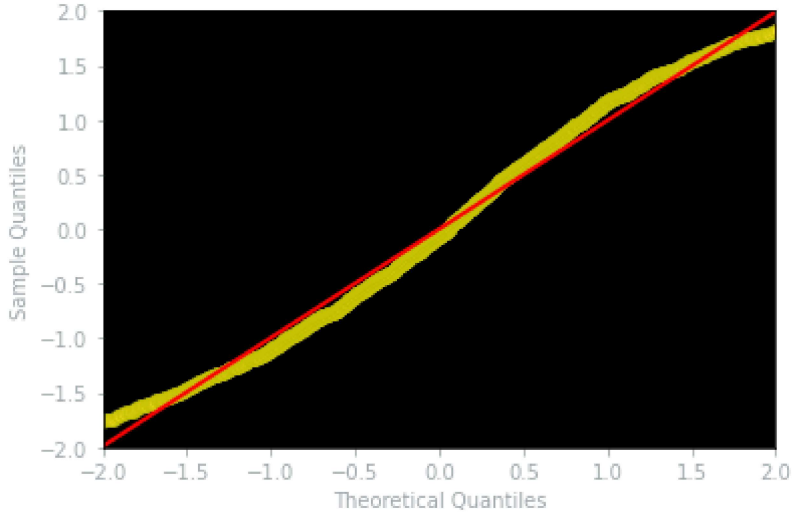
Covariance Type: nonrobust

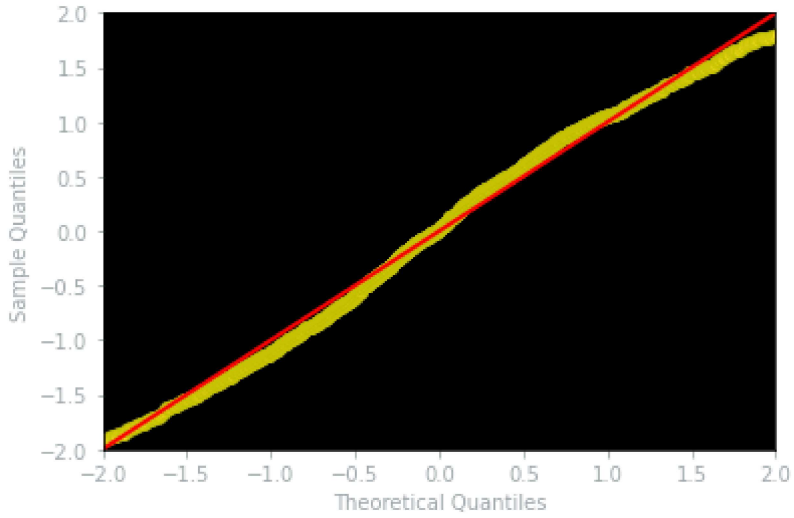
	coef	std err	t	P>|t|	[0.025	0.975]
bathrooms	6685.2849	1789.688	3.735	0.000	3173.975	1.02e+04
waterfront	5.107e-05	7.1e-06	7.192	0.000	3.71e-05	6.5e-05
lat	1.117e+05	8057.908	13.862	0.000	9.59e+04	1.28e+05
long	4.168e+04	3126.918	13.330	0.000	3.55e+04	4.78e+04
sqft_total	0.0002	5.22e-05	4.787	0.000	0.000	0.000
sqft_habitable	0.0148	0.002	5.936	0.000	0.010	0.020
view1	2.894e+04	9241.758	3.132	0.002	1.08e+04	4.71e+04
view2	1.158e+04	5318.252	2.177	0.030	1143.458	2.2e+04
view3	2.573e+04	1.02e+04	2.522	0.012	5712.425	4.57e+04
C	3.192e+04	1.4e+04	2.279	0.023	4435.039	5.94e+04
Cpl	4.32e+04	1.37e+04	3.152	0.002	1.63e+04	7.01e+04
Bmin	5.752e+04	1.39e+04	4.140	0.000	3.03e+04	8.48e+04
B	6.565e+04	1.79e+04	3.661	0.000	3.05e+04	1.01e+05
zip040t053	-1.064e+04	4126.293	-2.578	0.010	-1.87e+04	-2540.778
zip055t065	1.618e+04	2745.268	5.895	0.000	1.08e+04	2.16e+04
zip092t106	9966.5253	3857.924	2.583	0.010	2397.402	1.75e+04
zip107t115	2.381e+04	5711.167	4.169	0.000	1.26e+04	3.5e+04
zip146t168	7588.0355	2974.927	2.551	0.011	1751.323	1.34e+04
groc_in_mi	3099.8130	835.577	3.710	0.000	1460.438	4739.188

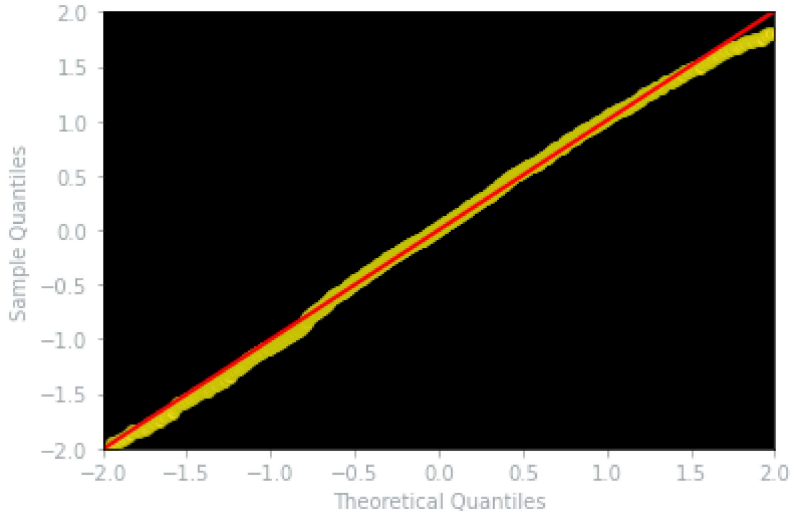
Omnibus:	8.928	**Durbin-Watson:**	1.978
Prob(Omnibus):	0.012	**Jarque-Bera (JB):**	7.871
Skew:	-0.139	**Prob(JB):**	0.0195
Kurtosis:	2.718	**Cond. No.**	1.34e+19

Notes:
[1] R^2 is computed without centering (uncentered) since the model does not contain a constant.
[2] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[3] The smallest eigenvalue is 5.01e-21. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.


Sample Quantiles
Theoretical Quantiles
2.0
1.5
1.0
0.5
0.0
−0.5
−1.0
−1.5
−2.0
−2.0
−1.5
−1.0
−0.5
0.0
0.5
1.0
1.5
2.0


Sample Quantiles
Theoretical Quantiles
2.0
1.5
1.0
0.5
0.0
−0.5
−1.0
−1.5
−2.0
−2.0
−1.5
−1.0
−0.5
0.0
0.5
1.0
1.5
2.0


Sample Quantiles
Theoretical Quantiles
2.0
1.5
1.0
0.5
0.0
−0.5
−1.0
−1.5
−2.0
−2.0
−1.5
−1.0
−0.5
0.0
0.5
1.0
1.5
2.0



Train Split Test - High Income

To prevent yourself from overfitting your model, you'll want to split it into training and testing data. Checking that you get similar results with both datasets will make sure that your model doesn't only work on the data provided.

In [54]:
```
#first step is to seperate out the data we're going to use for this model
high_data = hightier[['price', 'bathrooms', 'floors', 'sqft_neighb',
                      'sqft_habitable', 'thru2020',
                      'zip006t011', 'zip107t115',
                      'zip116t122', 'zip177t199',
                      'mi_2_scl', 'scls_in_mi', 'mi_2_rest',
                      'mi_2_groc', 'groc_in_mi']].copy()
# splitting it into 25/75 training/testing data to make sure our model is consistent
training_data, testing_data = train_test_split(high_data, test_size=0.25,
random_state=44)
```

In [55]:
```
#split columns
target = 'price'
predictive_cols = training_data.drop('price', 1).columns
```

In [56]:
```
#assign model a name so we can call on it to plot later on
high_model = make_ols(hightier, predictive_cols)
```

OLS Regression Results

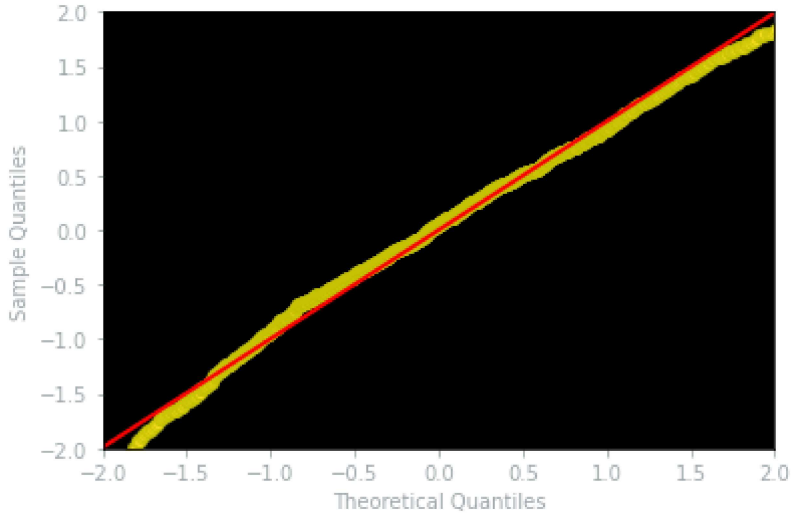
Dep. Variable:	price	**R-squared (uncentered):**	0.965
Model:	OLS	**Adj. R-squared (uncentered):**	0.965
Method:	Least Squares	**F-statistic:**	2721.
Date:	Wed, 16 Dec 2020	**Prob (F-statistic):**	0.00
Time:	21:59:43	**Log-Likelihood:**	-18305.

No. Observations:	1379	**AIC:**	3.664e+04
Df Residuals:	1365	**BIC:**	3.671e+04
Df Model:	14		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
bathrooms	1.299e+05	6505.247	19.967	0.000	1.17e+05	1.43e+05
floors	1.156e+05	9680.582	11.937	0.000	9.66e+04	1.35e+05
sqft_neighb	-0.0002	8.71e-05	-2.861	0.004	-0.000	-7.83e-05
sqft_habitable	0.0261	0.005	5.149	0.000	0.016	0.036
thru2020	-1.524e+05	1.24e+04	-12.309	0.000	-1.77e+05	-1.28e+05
zip006t011	5.735e+04	1.4e+04	4.100	0.000	2.99e+04	8.48e+04
zip107t115	3.518e+04	1.31e+04	2.683	0.007	9459.682	6.09e+04
zip116t122	5.478e+04	1.17e+04	4.677	0.000	3.18e+04	7.78e+04
zip177t199	1.303e+05	1.38e+04	9.428	0.000	1.03e+05	1.57e+05
mi_2_scl	1.031e+05	1.39e+04	7.423	0.000	7.58e+04	1.3e+05
scls_in_mi	2.103e+04	1624.014	12.946	0.000	1.78e+04	2.42e+04
mi_2_rest	8.013e+04	1.26e+04	6.381	0.000	5.55e+04	1.05e+05
mi_2_groc	6538.8325	3115.740	2.099	0.036	426.675	1.27e+04
groc_in_mi	9388.9098	3683.686	2.549	0.011	2162.610	1.66e+04

Omnibus:	94.518	**Durbin-Watson:**	1.914
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	146.829
Skew:	-0.535	**Prob(JB):**	1.31e-32
Kurtosis:	4.187	**Cond. No.**	2.56e+08

Notes:
[1] R^2 is computed without centering (uncentered) since the model does not contain a constant.
[2] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[3] The condition number is large, 2.56e+08. This might indicate that there are
strong multicollinearity or other numerical problems.



Interpreting High Income

In [57]:
```
#print and take a look at our coefficients
high_model.params.sort_values()
```

Out[57]:
```
thru2020         -152439.241198
sqft_neighb           -0.000249
sqft_habitable         0.026095
mi_2_groc           6538.832469
groc_in_mi          9388.909791
scls_in_mi         21025.150029
zip107t115         35179.008971
zip116t122         54783.569269
zip006t011         57346.841388
mi_2_rest          80134.655626
mi_2_scl          103064.882671
floors            115554.792618
bathrooms         129887.385510
zip177t199        130306.445355
dtype: float64
```

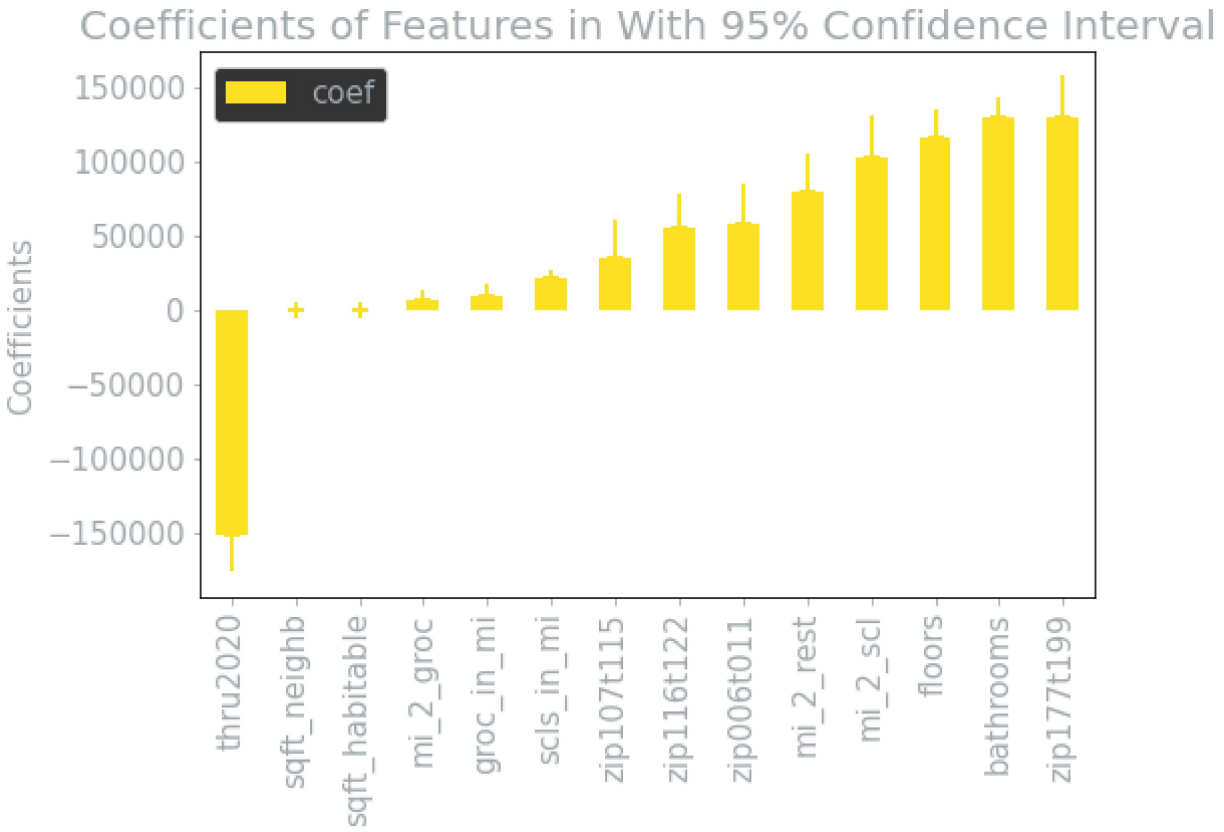
In [58]:
```
# assign your predictions
y_pred_train = high_model.predict(training_data[predictive_cols])
y_pred_test = high_model.predict(testing_data[predictive_cols])
# then get the scores:
train_mse = mean_squared_error(training_data[target], y_pred_train)
test_mse = mean_squared_error(testing_data[target], y_pred_test)
```

In [59]:
```
#calculating MSE and converting it to $
print('Training MSE:', train_mse, '\nTesting MSE:', test_mse)
print('Training Error: $', sqrt(train_mse), '\nTesting Error:', sqrt(test_mse))
```

```
Training MSE: 19786689216.778683
Testing MSE: 19970927110.655766
Training Error: $ 140665.16703426858
Testing Error: 141318.53066974538
```

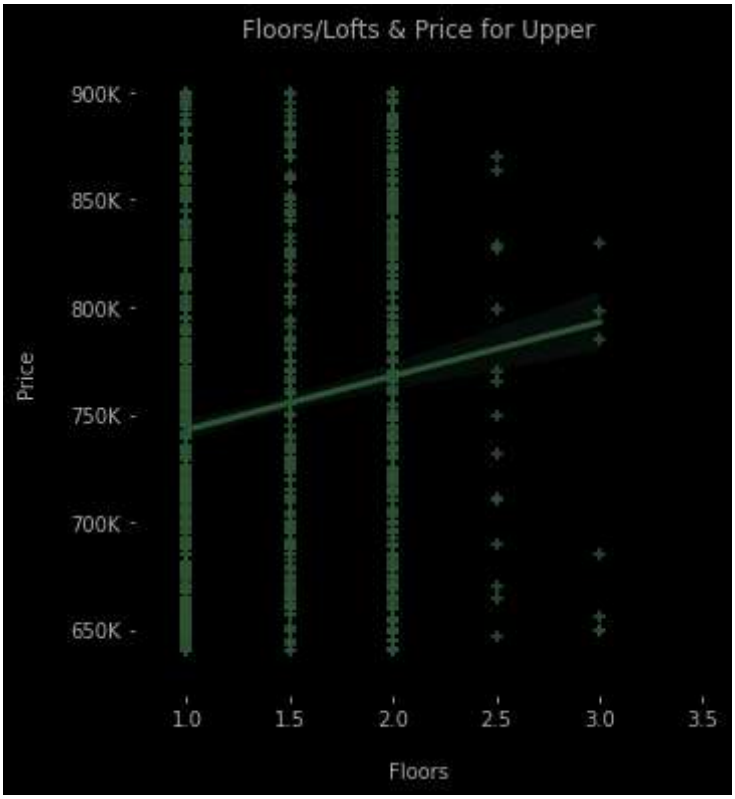
In [60]:
```
#plotting our coefficients
```

```
plotcoef(high_model)
```



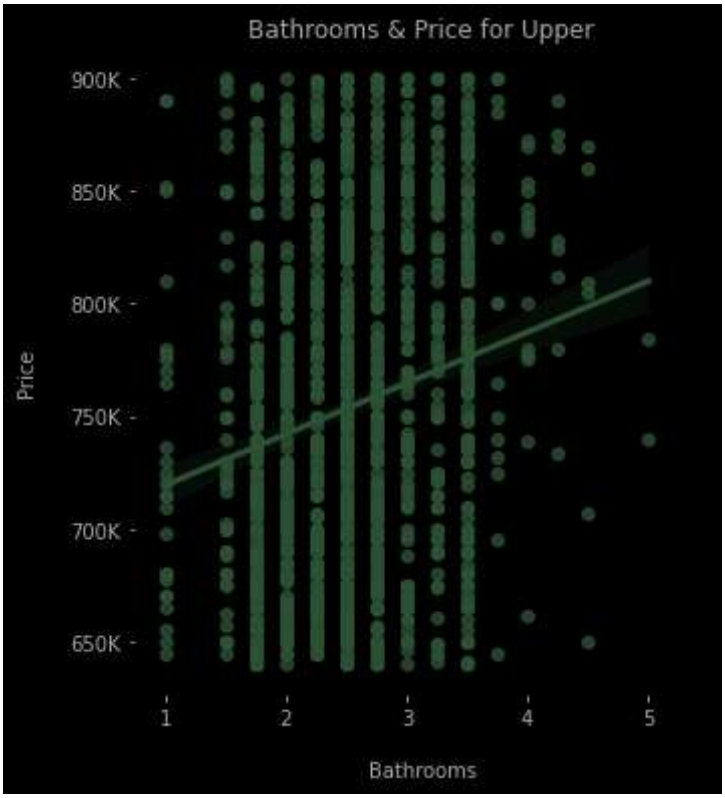
In [61]:

```
sns.lmplot(data=high_data, x='floors',y='price', palette=['#fbe122'], markers='+')
plt.xlabel('Floors',labelpad=16)
plt.ylabel('Price',labelpad=16)
plt.title("Floors/Lofts & Price for Upper")
ax = plt.gca()
ax.yaxis.set_major_formatter(ticker.FuncFormatter(reformat_large_ticker_values));
plt.xlim(.75, 3.5)
plt.ylim(620000, 920000)
plt.show()
```



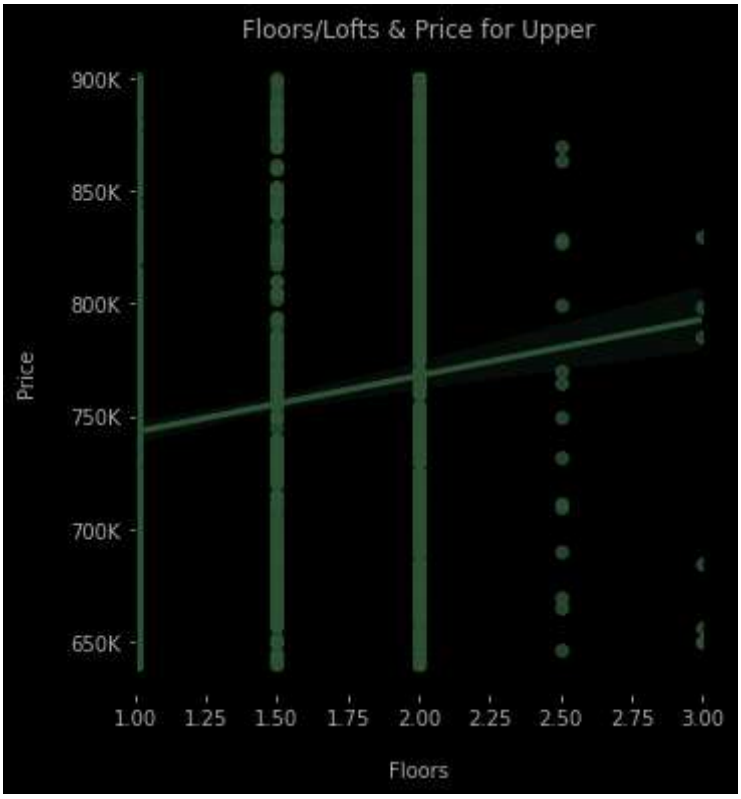
In [62]:

```
sns.lmplot(data=high_data, x='bathrooms',y='price',palette=['#FBE122', '#C9BF26',
'#939A2B', '#62772F', '#44644C', '#657C6E', '#84938E', '#A2AAAD'])
plt.xlabel('Bathrooms',labelpad=16)
plt.ylabel('Price',labelpad=16)
plt.title("Bathrooms & Price for Upper")
ax = plt.gca()
ax.yaxis.set_major_formatter(ticker.FuncFormatter(reformat_large_ticker_values));
plt.xlim(0.75, 5.5)
plt.show()
```

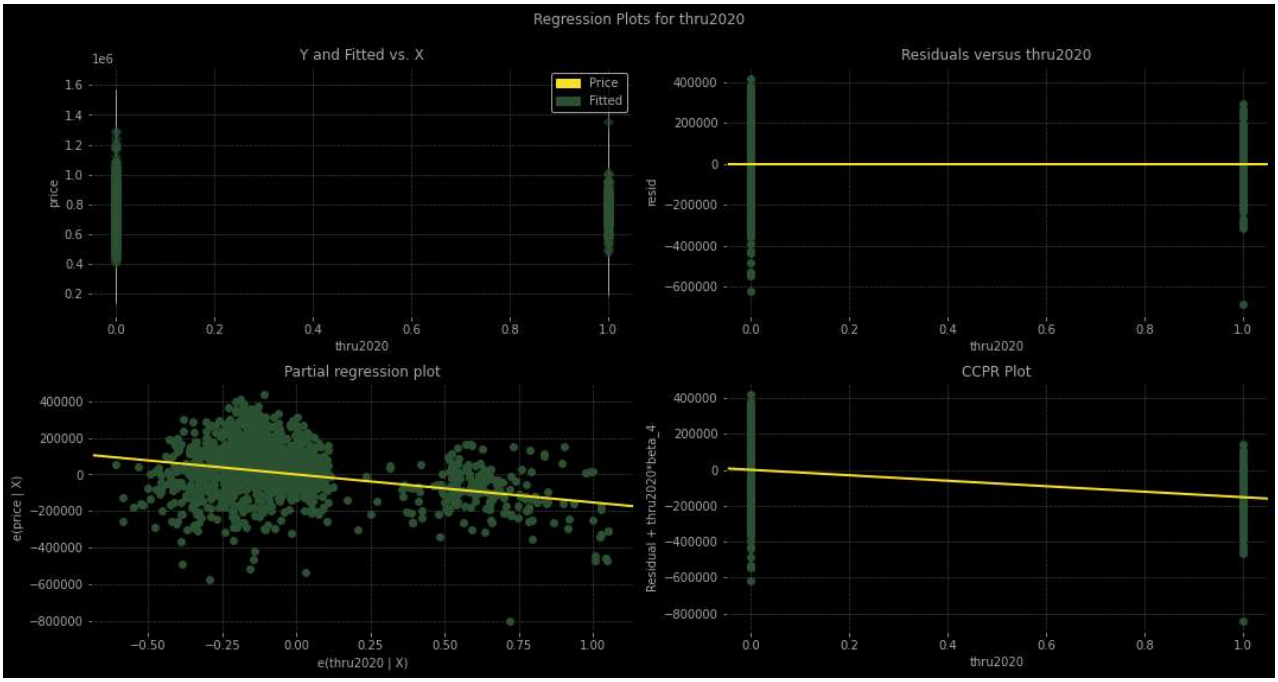


In [63]:

```
sns.lmplot(data=high_data, x='floors',y='price',palette=[])
plt.xlabel('Floors',labelpad=16)
plt.ylabel('Price',labelpad=16)
plt.title("Floors/Lofts & Price for Upper")
ax = plt.gca()
ax.yaxis.set_major_formatter(ticker.FuncFormatter(reformat_large_ticker_values));
plt.show()
```



In [64]:
```
quadregplot(high_model, 'thru2020')
```



Testing - Upper-Medium Income

In [65]:
```
#first step is to seperate out the data we're going to use for this model
upper_med_data = uppermidtier[['bathrooms',  'lat', 'sqft_habitable',
                               'C', 'Bmin', 'B', 'price',
                               'zip014t024', 'zip027t031', 'zip032t039',
                               'zip070t077', 'zip125t144', 'zip146t168',
                               'thru2000', 'thru2020', 'thru60', 'thru80']].copy()
# splitting it into 25/75 training/testing data to make sure our model is consistent
training_data, testing_data = train_test_split(upper_med_data,test_size=0.30,
random_state=55)
```

In [66]:
```
#split columns
target = 'price'
predictive_cols = training_data.drop('price', 1).columns
```

In [67]:
```
#assign model a name so we can call on it to plot later on
uppmid_model = make_ols(training_data, predictive_cols)
```

OLS Regression Results

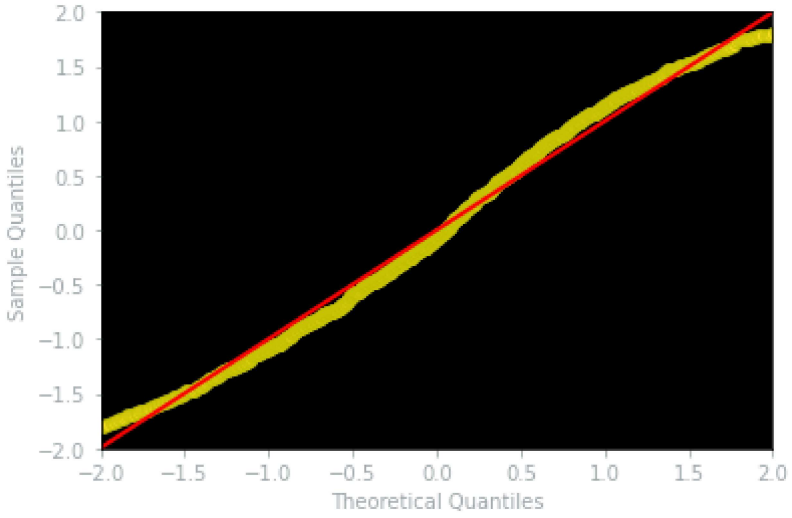
Dep. Variable:	price	**R-squared (uncentered):**	0.994
Model:	OLS	**Adj. R-squared (uncentered):**	0.994
Method:	Least Squares	**F-statistic:**	1.195e+04
Date:	Wed, 16 Dec 2020	**Prob (F-statistic):**	0.00

Time:	21:59:46	**Log-Likelihood:**	-14327.
No. Observations:	1184	**AIC:**	2.869e+04
Df Residuals:	1168	**BIC:**	2.877e+04
Df Model:	16		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
bathrooms	7154.1438	2659.550	2.690	0.007	1936.115	1.24e+04
lat	1.143e+04	116.568	98.081	0.000	1.12e+04	1.17e+04
sqft_habitable	0.0068	0.002	3.281	0.001	0.003	0.011
C	-1.127e+04	1.06e+04	-1.065	0.287	-3.2e+04	9487.835
Bmin	1.729e+04	3037.073	5.692	0.000	1.13e+04	2.32e+04
B	3.08e+04	5592.671	5.507	0.000	1.98e+04	4.18e+04
zip014t024	-2.961e+04	1.02e+04	-2.913	0.004	-4.96e+04	-9664.640
zip027t031	-1.144e+04	5390.363	-2.123	0.034	-2.2e+04	-868.932
zip032t039	-1.261e+04	5291.267	-2.384	0.017	-2.3e+04	-2233.227
zip070t077	-1.12e+04	5402.620	-2.072	0.038	-2.18e+04	-596.024
zip125t144	-1.312e+04	4072.725	-3.221	0.001	-2.11e+04	-5126.175
zip146t168	-1.537e+04	6400.234	-2.401	0.017	-2.79e+04	-2808.884
thru2000	-2.63e+04	5364.627	-4.903	0.000	-3.68e+04	-1.58e+04
thru2020	-2.474e+04	6239.325	-3.965	0.000	-3.7e+04	-1.25e+04
thru60	-6322.2154	4068.149	-1.554	0.120	-1.43e+04	1659.481
thru80	-2.4e+04	4176.344	-5.747	0.000	-3.22e+04	-1.58e+04

Omnibus:	139.685	**Durbin-Watson:**	1.974
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	38.547
Skew:	0.056	**Prob(JB):**	4.26e-09
Kurtosis:	2.123	**Cond. No.**	1.18e+07

Notes:
[1] R^2 is computed without centering (uncentered) since the model does not contain a constant.
[2] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[3] The condition number is large, 1.18e+07. This might indicate that there are
strong multicollinearity or other numerical problems.



Interpreting Upper Medium Income

In [68]:
```
#print and take a look at our coefficients
uppmid_model.params.sort_values()
```

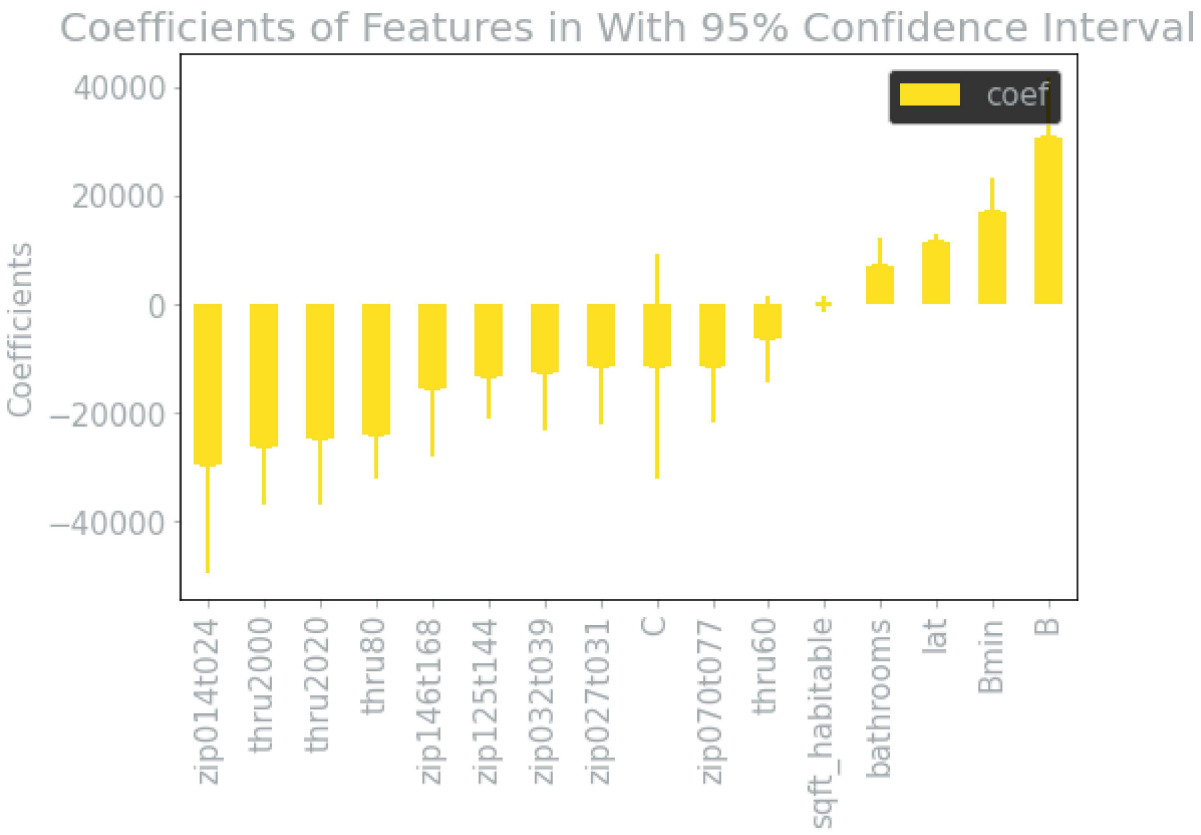
Out[68]:
```
zip014t024       -29608.004350
thru2000         -26304.921995
thru2020         -24739.614665
thru80           -24001.176646
zip146t168       -15366.125102
zip125t144       -13116.848770
zip032t039       -12614.678051
zip027t031       -11444.809354
C                -11274.380188
zip070t077       -11195.948182
thru60            -6322.215394
sqft_habitable        0.006819
bathrooms          7154.143802
lat               11433.153142
Bmin              17285.913155
B                 30798.130657
dtype: float64
```

In [69]:
```
# assign your predictions
y_pred_train = uppmid_model.predict(training_data[predictive_cols])
y_pred_test = uppmid_model.predict(testing_data[predictive_cols])
# then get the scores:
train_mse = mean_squared_error(training_data[target], y_pred_train)
test_mse = mean_squared_error(testing_data[target], y_pred_test)
```

In [70]:
```
#calculating MSE and converting it to $
print('Training MSE:', train_mse, '\nTesting MSE:', test_mse)
print('Training Error: $', sqrt(train_mse), '\nTesting Error:', sqrt(test_mse))
```

```
Training MSE: 1896478217.5414462
Testing MSE: 1896787318.4337904
Training Error: $ 43548.573082725066
Testing Error: 43552.12185914471
```

In [71]:
```
#plotting our coefficients
plotcoef(uppmid_model)
```



In [72]:
```
sns.violinplot(data=upper_med_data, x='B',y='price',palette=['#2C5234', '#FBE122'])
plt.xlabel('B Rating',labelpad=16)
plt.ylabel('Price',labelpad=16)
plt.title("B Rating Price Value Upper Middle")
ax = plt.gca()
ax.yaxis.set_major_formatter(ticker.FuncFormatter(reformat_large_ticker_values));
plt.xticks(ticks=[0,1], labels=['Not B', 'B'])
plt.show()
```

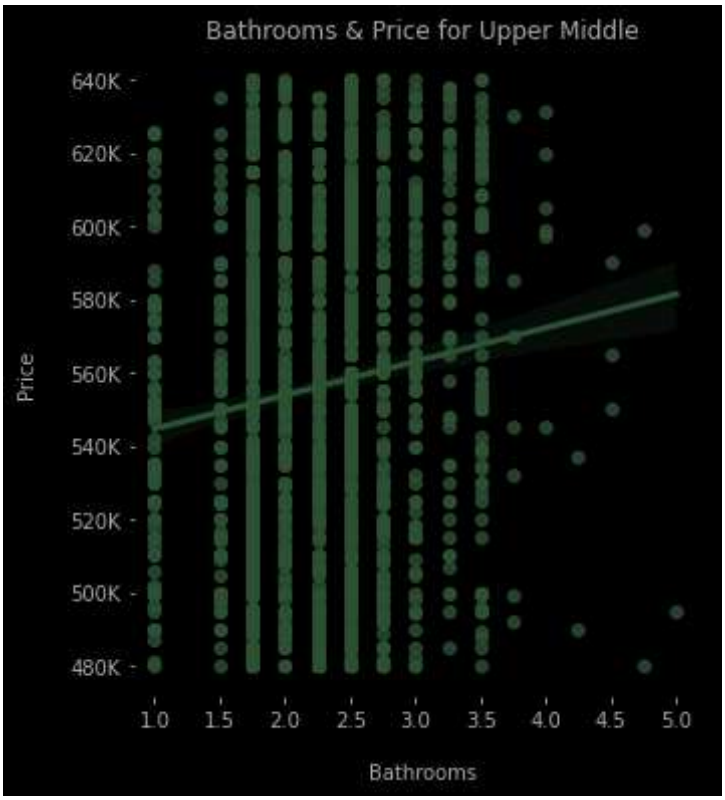
In [73]:

```
sns.violinplot(data=upper_med_data, x='Bmin',y='price',palette=['#2C5234', '#FBE122'])
plt.xlabel('Bmin Rating',labelpad=16)
plt.ylabel('Price',labelpad=16)
plt.title("Bmin Rating Price Value Upper Middle")
ax = plt.gca()
ax.yaxis.set_major_formatter(ticker.FuncFormatter(reformat_large_ticker_values));
plt.xticks(ticks=[0,1], labels=['Not B', 'B'])
plt.show()
```

In [74]:

```
sns.violinplot(data=upper_med_data, x='C',y='price',palette=['#2C5234', '#FBE122'])
plt.xlabel('C Rating',labelpad=16)
plt.ylabel('Price',labelpad=16)
plt.title("C Rating Price Value Upper Midde")
ax = plt.gca()
ax.yaxis.set_major_formatter(ticker.FuncFormatter(reformat_large_ticker_values));
plt.xticks(ticks=[0,1], labels=['Not C', 'C'])
plt.show()
```

In [75]:
```
sns.lmplot(data=upper_med_data, x='bathrooms',y='price',palette=[])
plt.xlabel('Bathrooms',labelpad=16)
plt.ylabel('Price',labelpad=16)
plt.title("Bathrooms & Price for Upper Middle")
ax = plt.gca()
ax.yaxis.set_major_formatter(ticker.FuncFormatter(reformat_large_ticker_values));
plt.xlim(.85, 5.25)
plt.show()
```



Testing - Medium Income

In [76]:
```
#first step is to seperate out the data we're going to use for this model
mid_data = midtier[['bathrooms',  'lat', 'long',
                    'sqft_habitable', 'view2', 'price',
                    'Cpl', 'Bmin', 'B', 'Bpl',
                    'zip006t011', 'zip014t024', 'zip032t039',
                    'zip055t065', 'zip070t077', 'zip092t106',
                    'zip177t199', 'rest_in_mi', 'groc_in_mi',
                    'thru2000', 'thru2020', 'thru60', 'thru80']].copy()
# splitting it into 25/75 training/testing data to make sure our model is consistent
training_data, testing_data = train_test_split(mid_data, test_size=0.30,
random_state=70)
```

In [77]:
```
#split columns
target = 'price'
predictive_cols = training_data.drop('price', 1).columns
```

In [78]:
```
#assign model a name so we can call on it to plot later on
mid_model = make_ols(mid_data, predictive_cols)
```

OLS Regression Results

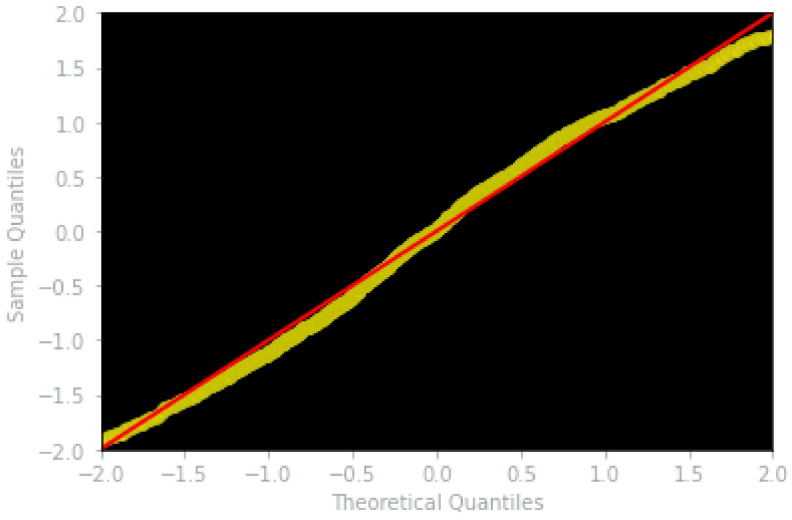
Dep. Variable:	price	**R-squared (uncentered):**	0.993
Model:	OLS	**Adj. R-squared (uncentered):**	0.993
Method:	Least Squares	**F-statistic:**	1.036e+04
Date:	Wed, 16 Dec 2020	**Prob (F-statistic):**	0.00
Time:	21:59:48	**Log-Likelihood:**	-18521.
No. Observations:	1561	**AIC:**	3.709e+04
Df Residuals:	1539	**BIC:**	3.720e+04
Df Model:	22		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
bathrooms	6011.6770	2014.842	2.984	0.003	2059.552	9963.802
lat	7.359e+04	7872.108	9.348	0.000	5.81e+04	8.9e+04
long	2.543e+04	3068.290	8.289	0.000	1.94e+04	3.15e+04
sqft_habitable	0.0078	0.002	4.263	0.000	0.004	0.011
view2	1.377e+04	4375.178	3.147	0.002	5188.000	2.24e+04
Cpl	8660.5119	3823.641	2.265	0.024	1160.414	1.62e+04
Bmin	2.319e+04	4260.868	5.443	0.000	1.48e+04	3.16e+04
B	3.573e+04	6977.245	5.121	0.000	2.2e+04	4.94e+04
Bpl	5.675e+04	1.15e+04	4.948	0.000	3.43e+04	7.92e+04

zip006t011	1.61e+04	4015.373	4.009	0.000	8222.417	2.4e+04
zip014t024	-1.868e+04	5439.259	-3.435	0.001	-2.94e+04	-8015.040
zip032t039	1.453e+04	3243.249	4.479	0.000	8166.447	2.09e+04
zip055t065	-1.605e+04	3452.999	-4.649	0.000	-2.28e+04	-9278.269
zip070t077	1.114e+04	4271.481	2.608	0.009	2761.815	1.95e+04
zip092t106	-1.389e+04	4029.110	-3.447	0.001	-2.18e+04	-5985.807
zip177t199	-1.144e+04	3638.708	-3.143	0.002	-1.86e+04	-4300.106
rest_in_mi	648.2073	132.261	4.901	0.000	388.777	907.637
groc_in_mi	-2286.3251	900.896	-2.538	0.011	-4053.439	-519.211
thru2000	-1.737e+04	4070.207	-4.268	0.000	-2.54e+04	-9388.915
thru2020	-9762.5072	4804.642	-2.032	0.042	-1.92e+04	-338.169
thru60	-9730.4651	3414.660	-2.850	0.004	-1.64e+04	-3032.587
thru80	-1.89e+04	3604.101	-5.244	0.000	-2.6e+04	-1.18e+04

Omnibus:	95.366	**Durbin-Watson:**	2.067
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	36.790
Skew:	-0.087	**Prob(JB):**	1.03e-08
Kurtosis:	2.268	**Cond. No.**	1.68e+07

Notes:
[1] R^2 is computed without centering (uncentered) since the model does not contain a constant.
[2] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[3] The condition number is large, 1.68e+07. This might indicate that there are
strong multicollinearity or other numerical problems.



Interpreting Medium Income

In [79]:
```
#print and take a look at our coefficients
mid_model.params.sort_values()
```

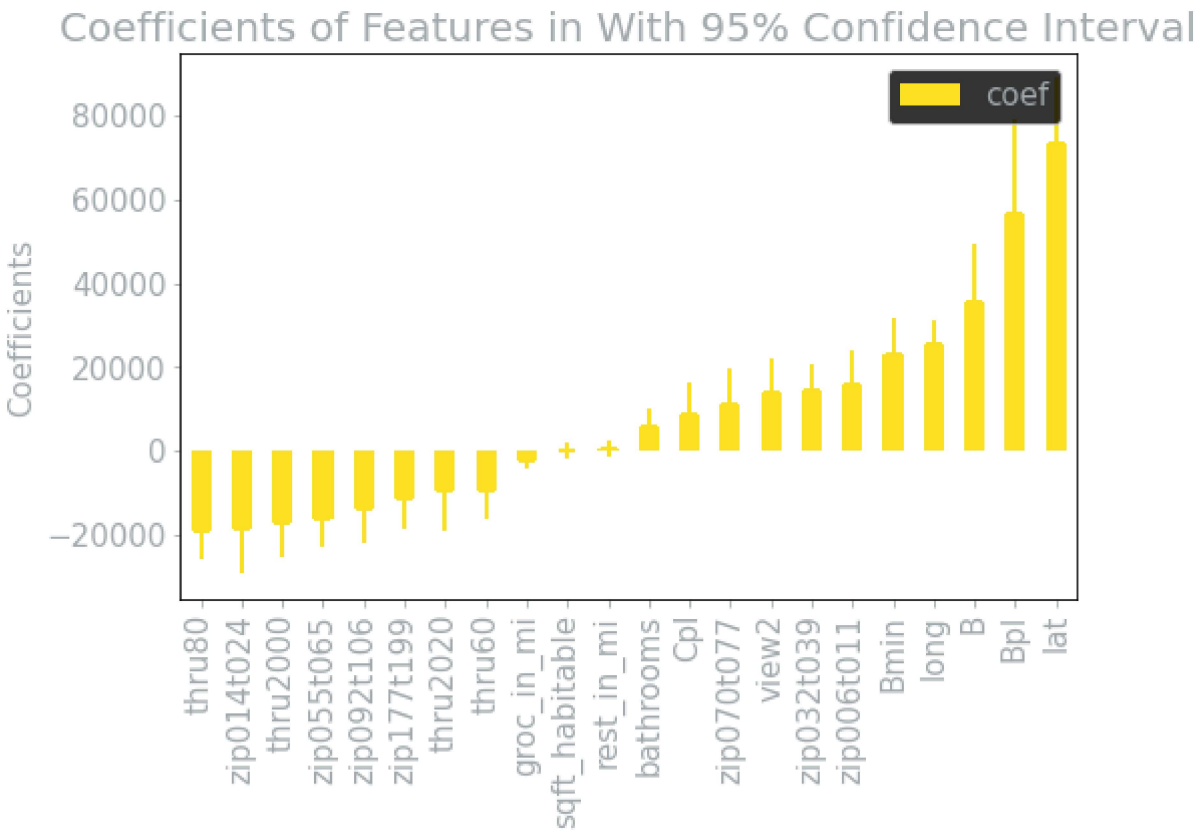
Out[79]:
```
thru80           -18899.174319
zip014t024       -18684.182864
thru2000         -17372.651997
zip055t065       -16051.348733
zip092t106       -13888.933520
zip177t199       -11437.456606
thru2020          -9762.507182
thru60            -9730.465105
groc_in_mi        -2286.325066
sqft_habitable        0.007762
rest_in_mi          648.207308
bathrooms          6011.676982
Cpl                8660.511945
zip070t077        11140.353426
view2             13769.940499
zip032t039        14528.102034
zip006t011        16098.596502
Bmin              23193.661364
long              25432.200978
B                 35731.160303
Bpl               56745.550579
lat               73590.590769
dtype: float64
```

In [80]:
```
# assign your preditions
y_pred_train = mid_model.predict(training_data[predictive_cols])
y_pred_test = mid_model.predict(testing_data[predictive_cols])
# then get the scores:
train_mse = mean_squared_error(training_data[target], y_pred_train)
test_mse = mean_squared_error(testing_data[target], y_pred_test)
```

In [81]:
```
#calculating MSE and converting it to $
print('Training MSE:', train_mse, '\nTesting MSE:', test_mse)
print('Training Error: $', sqrt(train_mse), '\nTesting Error:', sqrt(test_mse))
```

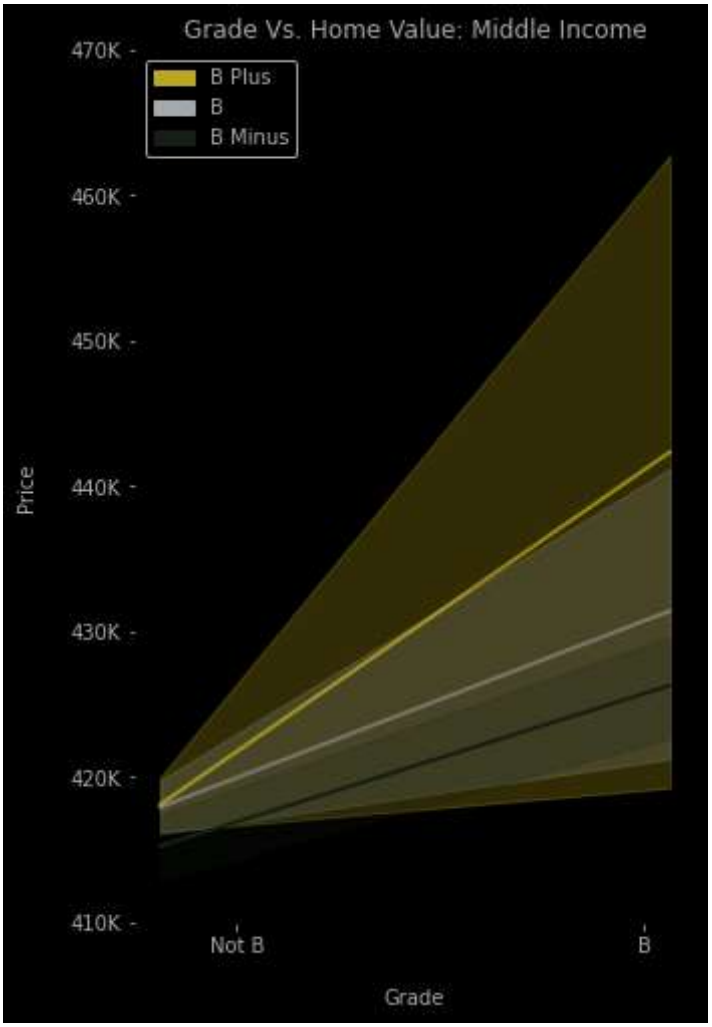
```
Training MSE: 1174108957.3746374
Testing MSE: 1203709924.776451
Training Error: $ 34265.27334451948
Testing Error: 34694.52297952014
```

In [82]:
```
#plotting our coefficients
plotcoef(mid_model)
```



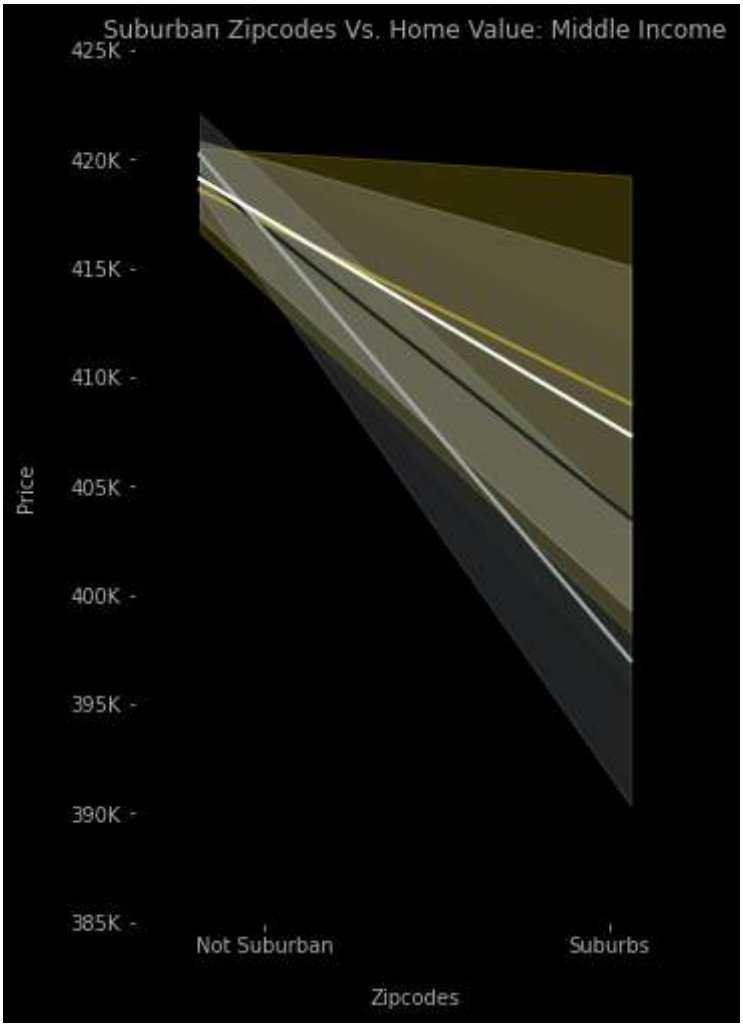
In [83]:

```
plt.figure(figsize=(5,8))
sns.lineplot(data=mid_data, x='Bpl',y='price',color='#FBE122', alpha=.50)
plt.xlabel('Grade',labelpad=16)
plt.ylabel('Price',labelpad=16)
plt.title("Grade Vs. Home Value: Middle Income")
ax = plt.gca()
ax.yaxis.set_major_formatter(ticker.FuncFormatter(reformat_large_ticker_values));
sns.lineplot(data=mid_data, x='B',y='price',color='#A2AAAD', ax=ax, alpha=0.5)
sns.lineplot(data=mid_data, x='Bmin',y='price',color='#151f17', ax=ax)
plt.ylim(410000, 470000)
green_patch = mpatches.Patch(color='#baa823', label='B Plus')
yellow_patch = mpatches.Patch(color='#A2AAAD', label='B')
grey_patch = mpatches.Patch(color='#151f17', label='B Minus')
ax.legend(handles=[green_patch, yellow_patch, grey_patch], labels=['B Plus', 'B', 'B
Minus'], loc='upper left')
plt.xticks(ticks=[0.15,.95], labels=['Not B', 'B'])
plt.show()
```



In [84]:

```
plt.figure(figsize=(5,8))
sns.lineplot(data=mid_data, x='zip014t024',y='price',color='#FBE122', alpha=.50)
plt.xlabel('Zipcodes',labelpad=16)
plt.ylabel('Price',labelpad=16)
plt.title("Suburban Zipcodes Vs. Home Value: Middle Income")
ax = plt.gca()
ax.yaxis.set_major_formatter(ticker.FuncFormatter(reformat_large_ticker_values));
sns.lineplot(data=mid_data, x='zip092t106',y='price',color='#151f17', ax=ax, alpha=1)
sns.lineplot(data=mid_data, x='zip055t065',y='price',color='#A2AAAD', ax=ax)
sns.lineplot(data=mid_data, x='zip177t199',y='price',color='#ffffff', ax=ax, alpha=1)
plt.ylim(385000, 425000)
plt.xlim(-.15, 1.15)
plt.xticks(ticks=[0.15,.95], labels=['Not Suburban', 'Suburbs'])
plt.show()
```



In [85]:

```
sns.violinplot(data=mid_data, x='Bmin',y='price',palette=['#2C5234', '#FBE122'])
plt.xlabel('B Minus Rating',labelpad=16)
plt.ylabel('Price',labelpad=16)
plt.title("B Minus Rating Price Value Middle")
ax = plt.gca()
ax.yaxis.set_major_formatter(ticker.FuncFormatter(reformat_large_ticker_values));
plt.xticks(ticks=[0,1], labels=['Not B', 'B'])
plt.show()
```

Testing - Low Income

In [86]:
```
#first step is to seperate out the data we're going to use for this model
low_data = lowtier[['bathrooms', 'waterfront', 'lat', 'long',
                    'sqft_total', 'sqft_habitable',
                    'view1', 'view2', 'view3',
                    'C', 'Cpl', 'Bmin', 'B', 'price',
                    'zip040t053', 'zip055t065', 'zip092t106',
                    'zip107t115', 'zip146t168',
                    'groc_in_mi']].copy()

training_data, testing_data = train_test_split(low_data, test_size=0.25,
random_state=66)
```

In [87]:
```
#split columns
target = 'price'
predictive_cols = training_data.drop('price', 1).columns
```

In [88]:
```
#assign model a name so we can call on it to plot later on
low_model = make_ols(low_data, predictive_cols)
```

OLS Regression Results

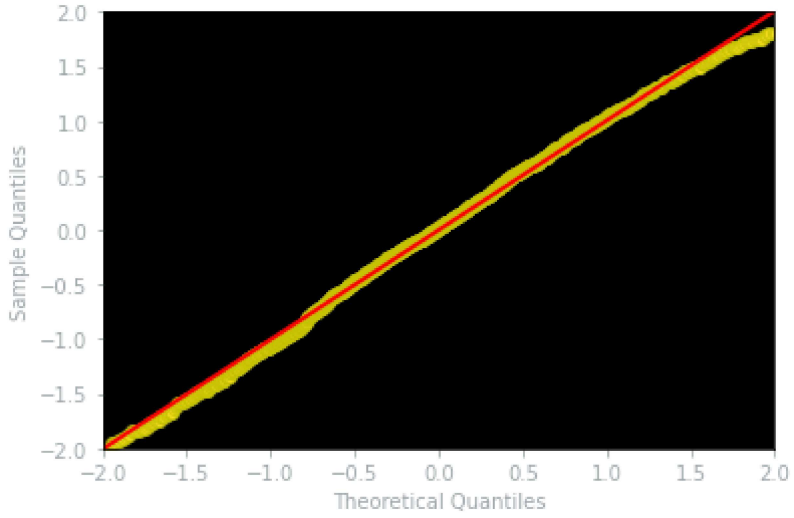
Dep. Variable:	price	**R-squared (uncentered):**	0.989
Model:	OLS	**Adj. R-squared (uncentered):**	0.989
Method:	Least Squares	**F-statistic:**	5956.
Date:	Wed, 16 Dec 2020	**Prob (F-statistic):**	0.00
Time:	21:59:50	**Log-Likelihood:**	-14113.
No. Observations:	1203	**AIC:**	2.826e+04

Df Residuals:	1185	**BIC:**	2.835e+04
Df Model:	18		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
bathrooms	6685.2849	1789.688	3.735	0.000	3173.975	1.02e+04
waterfront	5.107e-05	7.1e-06	7.192	0.000	3.71e-05	6.5e-05
lat	1.117e+05	8057.908	13.862	0.000	9.59e+04	1.28e+05
long	4.168e+04	3126.918	13.330	0.000	3.55e+04	4.78e+04
sqft_total	0.0002	5.22e-05	4.787	0.000	0.000	0.000
sqft_habitable	0.0148	0.002	5.936	0.000	0.010	0.020
view1	2.894e+04	9241.758	3.132	0.002	1.08e+04	4.71e+04
view2	1.158e+04	5318.252	2.177	0.030	1143.458	2.2e+04
view3	2.573e+04	1.02e+04	2.522	0.012	5712.425	4.57e+04
C	3.192e+04	1.4e+04	2.279	0.023	4435.039	5.94e+04
Cpl	4.32e+04	1.37e+04	3.152	0.002	1.63e+04	7.01e+04
Bmin	5.752e+04	1.39e+04	4.140	0.000	3.03e+04	8.48e+04
B	6.565e+04	1.79e+04	3.661	0.000	3.05e+04	1.01e+05
zip040t053	-1.064e+04	4126.293	-2.578	0.010	-1.87e+04	-2540.778
zip055t065	1.618e+04	2745.268	5.895	0.000	1.08e+04	2.16e+04
zip092t106	9966.5253	3857.924	2.583	0.010	2397.402	1.75e+04
zip107t115	2.381e+04	5711.167	4.169	0.000	1.26e+04	3.5e+04
zip146t168	7588.0355	2974.927	2.551	0.011	1751.323	1.34e+04
groc_in_mi	3099.8130	835.577	3.710	0.000	1460.438	4739.188

Omnibus:	8.928	**Durbin-Watson:**	1.978
Prob(Omnibus):	0.012	**Jarque-Bera (JB):**	7.871
Skew:	-0.139	**Prob(JB):**	0.0195
Kurtosis:	2.718	**Cond. No.**	1.34e+19

Notes:
[1] R^2 is computed without centering (uncentered) since the model does not contain a constant.
[2] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[3] The smallest eigenvalue is 5.01e-21. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.



Interpreting Low Income Model

In [89]:
```
#print and take a look at our coefficients
low_model.params.sort_values()
```

Out[89]:
```
zip040t053        -10636.432730
waterfront            0.000051
sqft_total            0.000250
sqft_habitable        0.014809
groc_in_mi         3099.812983
bathrooms          6685.284904
zip146t168         7588.035549
zip092t106         9966.525265
view2             11577.698059
zip055t065        16184.563036
zip107t115        23807.963751
view3             25729.309161
view1             28942.727776
C                 31922.868796
long              41681.468302
Cpl               43201.341729
Bmin              57517.470809
B                 65654.540799
lat              111701.902308
dtype: float64
```

In [90]:
```
# assign your predictions
y_pred_train = low_model.predict(training_data[predictive_cols])
y_pred_test = low_model.predict(testing_data[predictive_cols])
# then get the scores:
train_mse = mean_squared_error(training_data[target], y_pred_train)
test_mse = mean_squared_error(testing_data[target], y_pred_test)
```

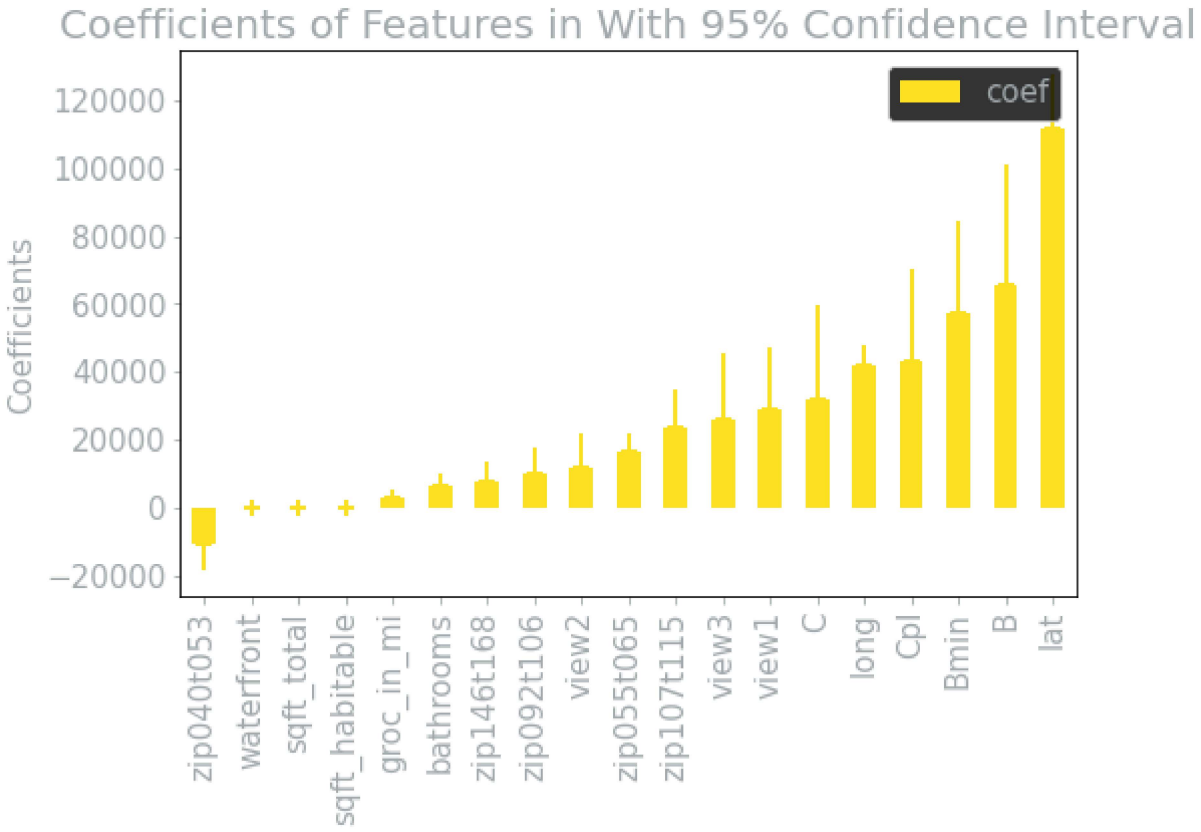
In [91]:
```
#calculating MSE and converting it to $
print('Training MSE:', train_mse, '\nTesting MSE:', test_mse)
print('Training Error: $', round(sqrt(train_mse), 2), '\nTesting Error: $',
round(sqrt(test_mse), 2))
```

```
Training MSE: 912877759.7470982
```

```
Testing MSE: 890508475.1377867
Training Error: $ 30213.87
Testing Error: $ 29841.39
```

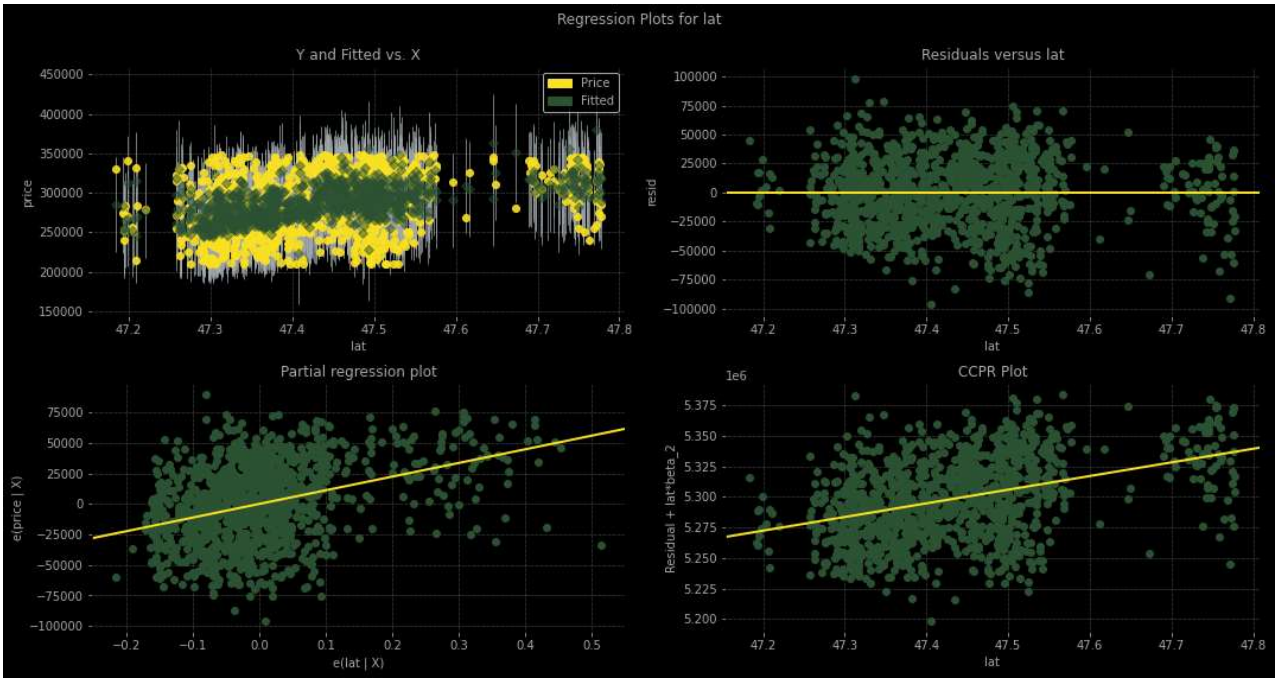
In [92]:

```
#plotting our coefficients
plotcoef(low_model)
```



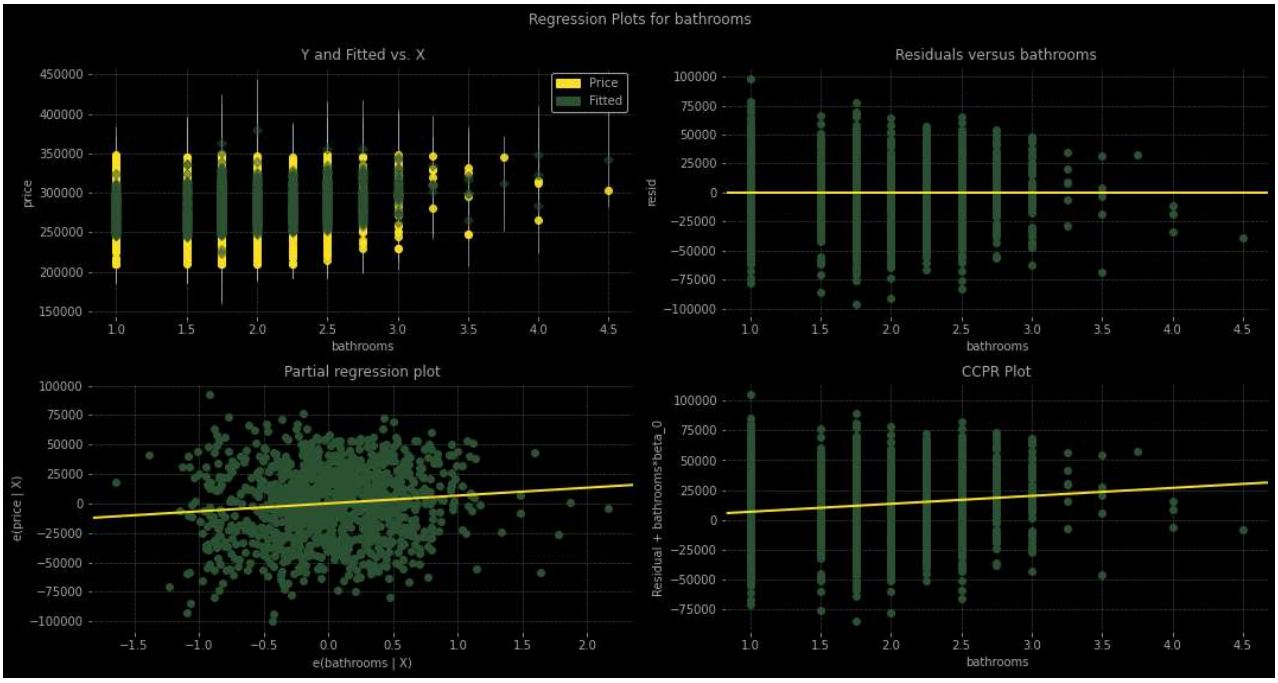
In [93]:

```
quadregplot(low_model, 'lat')
#as you can see here, the farther west, towards the cities, you go, the more expensive
homes become.
#please note we are not missing data in those gaps, those represent bodies of water
where few people live on small islands or in house boats
```



In [94]:

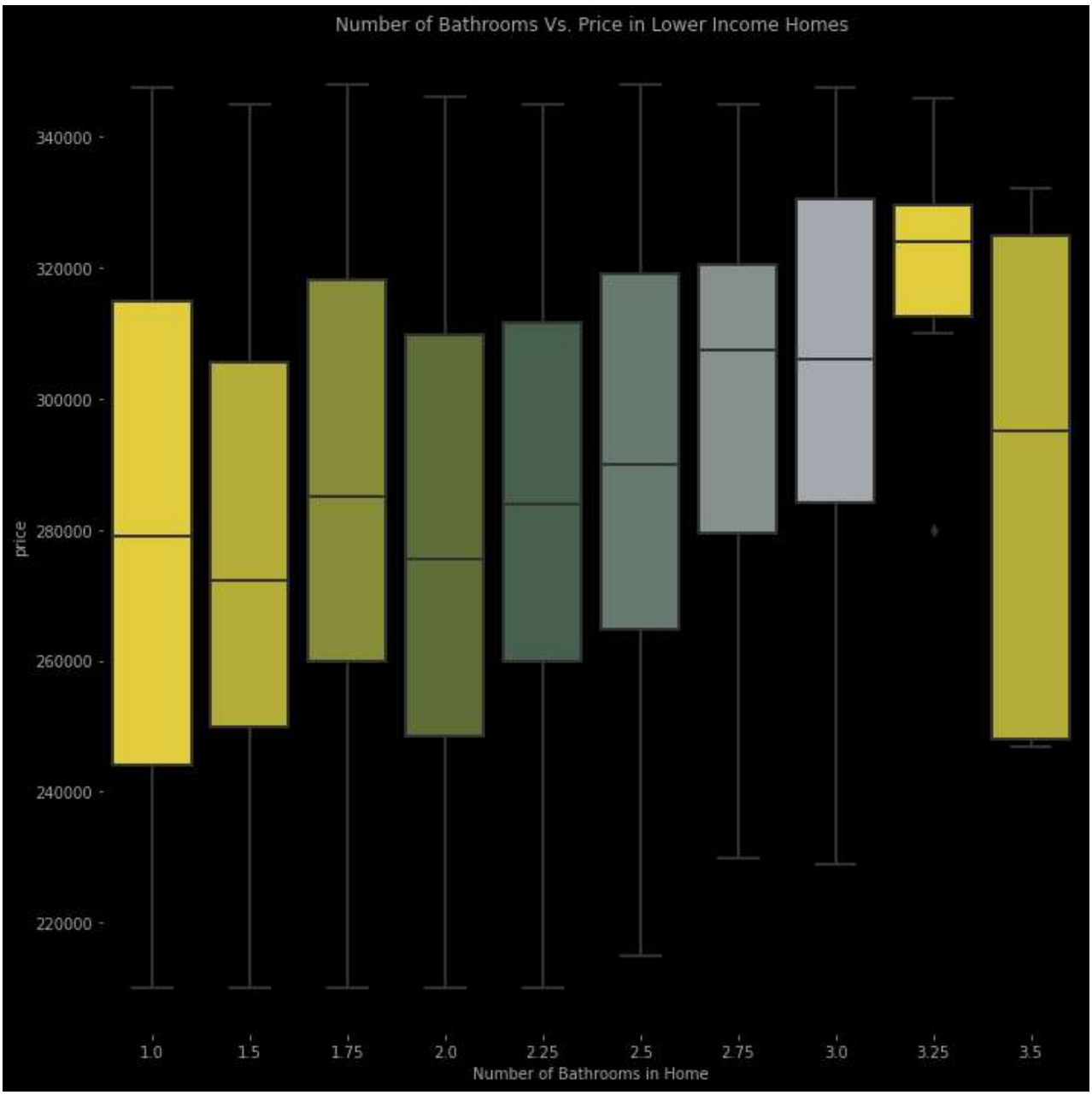
```
quadregplot(low_model,'bathrooms')
# 6,000$ doesn't look like much compared to prices in the 450,000, but, an increase
from 1 to 4 could add over 20k and possibly bump you up to a higher
# grade, making your home worth even more.
```



In [95]:

```
#Bathrooms High
fig = plt.figure(figsize=(10,10))
sns.boxplot(x='bathrooms',y='price',data=low_data,color='#2C5234', palette=['#fbe122',
'#c9bf26', '#939a2b', '#62772f', '#44644c', '#657c6e', '#84938e', '#a2aaad'])
plt.title('Number of Bathrooms Vs. Price in Lower Income Homes')
plt.xlabel('Number of Bathrooms in Home')
```

```
plt.xlim(-.5, 9.5)
plt.tight_layout()
```



Conclusions & Recommendations

Observations

- Different incomes have different priorities when it comes to buying or selling a home. In short, Low income tends to put more priority on pragmatic space, While Middle Income homes tend to put more on location and grade, a trend that will increase with importance as you go up income brackets. Here are our best reccomendations.

Reccomendations

Upper Class

Buyer - If you want to live in Bill Gates neighborhood, near the waterfront, Downtown, or in one of Seattles Art Districts, you'll want to look for home built recently, as homes built after 2000 cost an average of 152,439.24 less. Seller - Add a loft, it's the most affordable and hip way to increase the number of stories you have and add an average of 115,554.79, while you're at it, we'd recommend adding another bathroom as well, so long as you don't pass a 1:1 ratio with bedrooms.

Upper Middle Class

Buyer - Move into a newer, more bland home. Homes built after 1960 cost around 25,000 less than more antique homes, but if they have a slightly above average design, they'll still cost a bit more. However, if you aim for a completely average home without any frills, you're likely to save around an additional 11,274.38, letting you buy an Upper Middle Class home for ~35k less overall. Seller - Make your homes look nicer by doing things like: adding a nice walkway, garden, some trim or fix up your roof; bringing your grade up to at least a B will increase your house worth by 30,798.13.

Middle Class

Buyer - Tech & buisness heavy neighborhoods like Downtown Seattle/Bellevue, and some of the surrounding areas, dont have very many grocery stores despite being very expensive, living just outside of this range will be cheaper by around a minimum of 11,437.45 and give you more access to grocery stores, while keeping you close enough for a short commute and generally being able to walk everywhere. *Seller* - Add a balcony, bathroom, and other finishing touches to your home. Giving your home a view of something, and some extra features to increase your grade to a B+ will increase the value by over 56,745.55

Lower Class

Buyer - To save the most money & have easy access to grocery stores, it's best to live in more rural areas. Moving a few miles farther North or South of downtown Seattle/Bellevue, will save you 10-23k on average, and you can stay away from the city noise/dust while still being in a good distance for adequate public transit or to driving. *Seller* - In real estate many experts believe the best ratio is a minimum of 2 bathrooms for every 3 bedrooms, and that fitting your property to that ratio will likely increase your value significantly. Our numbers agree with this conclusion, so we recommend you add a bathroom or two, so long as you don't exceed a 1:1 ratio for bedrooms and bathrooms, each bathroom will add around 6,685.28.

Thank you for reading!