# Phase2Pro - Iteration

BUSINESS PROBLEM: King County Realty is a newly established local business in Northwestern America. They are seeking some information regarding what attracts local buyers in this area to purchase new homes. We will inspect the data set to determine what relationships and connections buyers have to purchasing a home and help King County Realty market their new business to suit.

What makes buyers in this area buy particular homes?

A linear regression model will be used to understand the connections to the business problem usingthe OSMIN Model a our Data Science Process.

In [30]:
```
#Import packages
import numpy as np
import pandas as pd
import statsmodels.api as sm
import scipy.stats as stats
from scipy import stats
from statsmodels.formula.api import ols
import matplotlib.pyplot as plt
from matplotlib.lines import Line2D
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error
from sklearn.preprocessing import OneHotEncoder
from sklearn.model_selection import train_test_split
import random
from math import sqrt
import seaborn as sns
plt.style.use('seaborn')
```

**OBTAIN** - Data has been sourced from kc_house_data.csv.

In [31]:
```
#Import data set
data = pd.read_csv('data\\kc_house_data.csv')
data.isnull().sum()
```

Out[31]:
```
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
dtype: int64
```

**SCRUB**: During this stage, we'll focus on cleaning the data.

#Note that although technically, categorical data should be one-hot encoded during this step, in practice, it's usually done after data exploration. This is because it is much less time-consuming to visualize and explore a few columns containing categorical data than it is to explore many different dummy columns that have been one-hot encoded.

In [32]:
```
#refined dataset and drop unnecessary column data
data.drop(['id', 'date', 'waterfront', 'sqft_above', 'sqft_basement', 'lat', 'lor
```

In [33]:
```
#Removed duplicates, show completed - Scrub
data.drop_duplicates(inplace=True)
#Show unique values for column data
data.nunique()
```

Out[33]:
```
price          3622
bedrooms         12
bathrooms        29
sqft_living    1034
sqft_lot       9776
floors            6
condition         5
grade            11
yr_built        116
zipcode          70
dtype: int64
```

In [34]:
```
#Look at correlations between variables to identify best predictor for response (
data.corr()
#Can see the strongest predictor of price is sqft_lot at 89% and sqft_living with
#with grade in close second at 67%
```

Out[34]:

| | price | bedrooms | bathrooms | sqft_living | sqft_lot | floors | condition | grade | yr_built | zi |
|---|---|---|---|---|---|---|---|---|---|---|
| **price** | 1 | 0.31 | 0.53 | 0.70 | 0.09 | 0.26 | 0.04 | 0.67 | 0.05 | |
| **bedrooms** | 0.31 | 1 | 0.51 | 0.58 | 0.03 | 0.18 | 0.03 | 0.36 | 0.16 | |
| **bathrooms** | 0.53 | 0.51 | 1 | 0.76 | 0.09 | 0.50 | -0.13 | 0.67 | 0.51 | |
| **sqft_living** | 0.70 | 0.58 | 0.76 | 1 | 0.17 | 0.35 | -0.06 | 0.76 | 0.32 | |
| **sqft_lot** | 0.09 | 0.03 | 0.09 | 0.17 | 1 | -0.00 | -0.01 | 0.11 | 0.05 | |
| **floors** | 0.26 | 0.18 | 0.50 | 0.35 | -0.00 | 1 | -0.26 | 0.46 | 0.49 | |
| **condition** | 0.04 | 0.03 | -0.13 | -0.06 | -0.01 | -0.26 | 1 | -0.15 | -0.36 | |
| **grade** | 0.67 | 0.36 | 0.67 | 0.76 | 0.11 | 0.46 | -0.15 | 1 | 0.45 | |
| **yr_built** | 0.05 | 0.16 | 0.51 | 0.32 | 0.05 | 0.49 | -0.36 | 0.45 | 1 | |
| **zipcode** | -0.05 | -0.15 | -0.20 | -0.20 | -0.13 | -0.06 | 0.00 | -0.19 | -0.35 | |

In [35]:
```
#Show current types - Scrub
print(data.dtypes)
data = data.astype("int64", errors='ignore')
data.info()
```

```
price          float64
bedrooms         int64
bathrooms      float64
sqft_living      int64
sqft_lot         int64
floors         float64
condition        int64
grade            int64
yr_built         int64
zipcode          int64
dtype: object
<class 'pandas.core.frame.DataFrame'>
Int64Index: 21589 entries, 0 to 21596
Data columns (total 10 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   price        21589 non-null  int64
 1   bedrooms     21589 non-null  int64
 2   bathrooms    21589 non-null  int64
 3   sqft_living  21589 non-null  int64
 4   sqft_lot     21589 non-null  int64
 5   floors       21589 non-null  int64
 6   condition    21589 non-null  int64
 7   grade        21589 non-null  int64
 8   yr_built     21589 non-null  int64
 9   zipcode      21589 non-null  int64
dtypes: int64(10)
memory usage: 1.8 MB
```

In [36]:
```
#discover pop mean (sqft_lot)
population_mean = data.sqft_lot.mean()
population_mean
```

Out[36]:
```
15103.896197137432
```

In [37]:
```
#discover pop mean
population_mean = data.sqft_living.mean()
population_mean
```

Out[37]:
```
2080.4155356894717
```

In [38]:
```
# Take a sample of 50 records
sample = data.sample(n=50, random_state=22)
# Calculate the sample mean
sample_mean = sample.sqft_lot.mean()
sample_mean
```

Out[38]:
```
9925.96
```

In [39]:
```
# Find the difference between the sample and population means
err = np.abs(sample_mean - population_mean)
# Divide by the population mean to find a percent error
per_err = err / population_mean
per_err
```

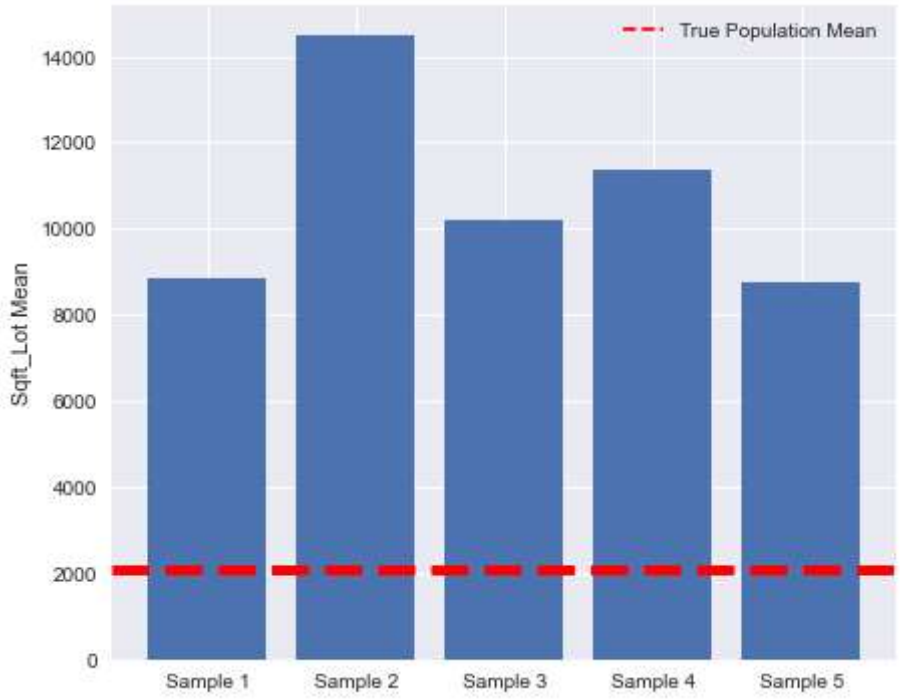
Out[39]:
```
3.7711429902922884
```

In [ ]:
```
#Create sample test
five_sample_means = []
for i in range(5):
    sample = data.sample(n=50, random_state=i+100)
    five_sample_means.append(sample.sqft_lot.mean())

five_sample_means
```

In [41]:
```
#Ctreate sample mean
five_sample_errors = [np.abs(sample_mean-population_mean)/population_mean for sam
five_sample_errors
```

Out[41]:
```
[3.2560631989635493,
 5.961013197394999,
 3.892609108798394,
 4.456159985960753,
 3.2045158046279947]
```

In [42]:
```
#Visual
x_labels = [f"Sample {x}" for x in range(1, 6)]

fig, ax = plt.subplots(figsize=(7,6))

ax.bar(x_labels, five_sample_means)
ax.set_ylabel("Sqft_Lot Mean")
ax.axhline(y=population_mean, color="red", linewidth=5, linestyle="--")
ax.legend(
    handles=[Line2D([0],[0], color="red", linestyle="--")],
    labels=["True Population Mean"],
    fontsize="medium"
);
#Roughly displays the mean at 2000 across all samples for Sqft_lot
```



In [43]:
```
#to view statistics - Scrub
#lamba function to remove exponential values - Scrub
pd.options.display.float_format = lambda x : '{:.0f}'.format(x) if int(x) == x el
data.describe()
```

Out[43]:

| | price | bedrooms | bathrooms | sqft_living | sqft_lot | floors | condition | grade | yr_built |
|---|---|---|---|---|---|---|---|---|---|
| **count** | 21589 | 21589 | 21589 | 21589 | 21589 | 21589 | 21589 | 21589 | 21589 |
| **mean** | 540,308.35 | 3.37 | 1.75 | 2,080.42 | 15,103.90 | 1.45 | 3.41 | 7.66 | 1,970.99 |
| **std** | 367,428.32 | 0.93 | 0.73 | 918.23 | 41,419.63 | 0.55 | 0.65 | 1.17 | 29.37 |
| **min** | 78000 | 1 | 0 | 370 | 520 | 1 | 1 | 3 | 1900 |
| **25%** | 322000 | 3 | 1 | 1430 | 5042 | 1 | 3 | 7 | 1951 |
| **50%** | 450000 | 3 | 2 | 1910 | 7620 | 1 | 3 | 7 | 1975 |
| **75%** | 645000 | 4 | 2 | 2550 | 10688 | 2 | 4 | 8 | 1997 |
| **max** | 7700000 | 33 | 8 | 13540 | 1651359 | 3 | 5 | 13 | 2015 |

In [44]:
```
# Your solution here
import math
import scipy.stats as stats
mu = 150
sigma = 100
n=21
x_bar = 151
z = (x_bar - mu)/(sigma/math.sqrt(n))
p = 1 - stats.norm.cdf(z)

p,z

# (p = 0.48, z = 0.45)
```

Out[44]: (0.48172456464754565, 0.04582575694955839)

** HYPOTHESIS **

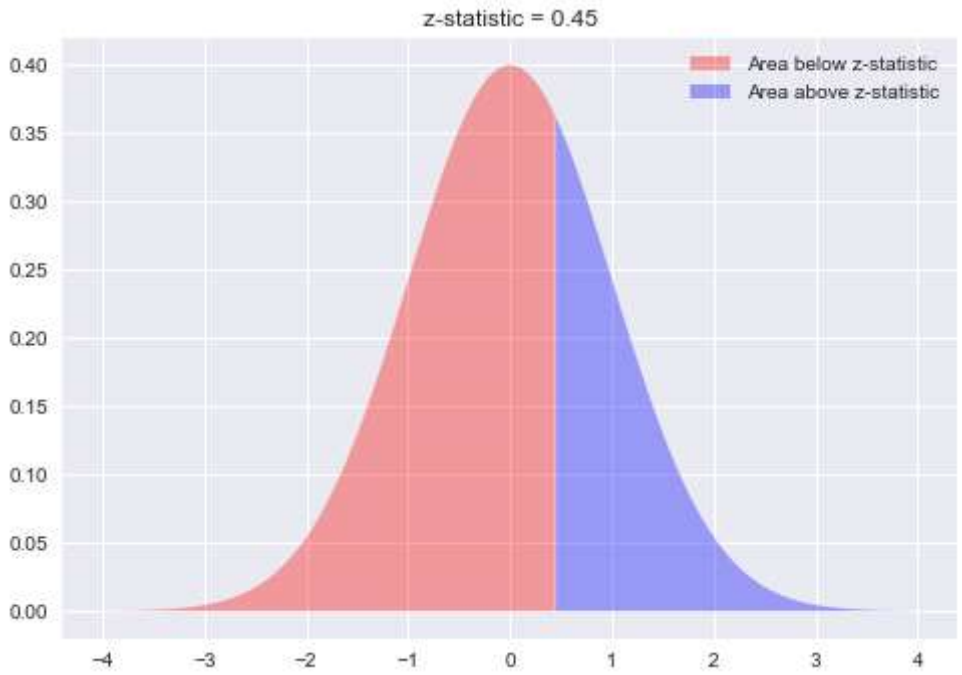
Below we set to explore the data set by deriving statistics and creating visualisation with dummy test data.

Null hypothesis: There is no difference between experimental and control group - when comparing sqft_lot against sqft_living does NOT affect a buyers decision to purchase a home. $\mu$1=$\mu$2μ1=μ2

Alternative Hypothesis: There is a difference between experimental and control group - the sqft_living DOES affect a buyers decision when purchasing a home. $\mu$1≠$\mu$2μ1≠μ2

#alpha value is 0.35

In [45]:
```
#running z test
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline

plt.style.use('seaborn')
plt.fill_between(x=np.arange(-4,0.45,0.01),
                 y1= stats.norm.pdf(np.arange(-4,0.45,0.01)) ,
                 facecolor='red',
                 alpha=0.35,
                 label= 'Area below z-statistic'
                 )

plt.fill_between(x=np.arange(0.45,4,0.01),
                 y1= stats.norm.pdf(np.arange(0.45,4,0.01)) ,
                 facecolor='blue',
                 alpha=0.35,
                 label= 'Area above z-statistic')
plt.legend()
plt.title ('z-statistic = 0.45');
```



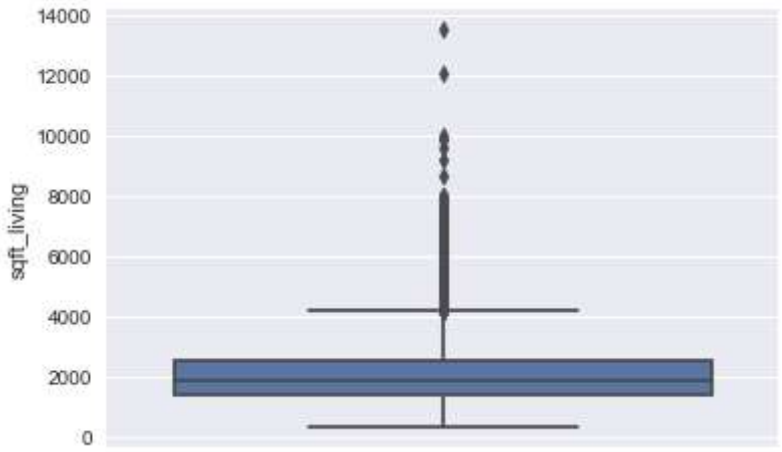

In [46]:
```
#show norm with degree of freedom
stats.norm.cdf(z)
```

Out[46]:
```
0.5182754353524544
```

In [47]:
```
#Pvalue minus degree of freedom
pval = 1 - stats.norm.cdf(z)
pval
```

Out[47]:
```
0.48172456464754565
```

In [48]:
```
# creating boxplots to see the outliers in the price variable

plt.figure(figsize=(6,4))
sns.boxplot(y=data['sqft_living']).set_title
plt.show()
```




In [49]:
```
#let us numerically draw conclusions
#creating function that can calculate interquartile range of the data
def calc_interquartile(data, column):
    global lower, upper
    #calculating the first and third quartile
    first_quartile, third_quartile = np.percentile(data[column], 25), np.percenti
    #calculate the interquartilerange
    iqr = third_quartile - first_quartile
    # outlier cutoff (1.5 is a generally taken as a threshold thats why i am alsc
    cutoff = iqr*1.5
    #calculate the lower and upper limits
    lower, upper = first_quartile - cutoff , third_quartile + cutoff
    #remove the outliers from the columns
    upper_outliers = data[data[column] > upper]
    lower_outliers = data[data[column] < lower]
    print('Lower outliers', lower_outliers.shape[0])
    print('Upper outliers', upper_outliers.shape[0])
    return print('total outliers', upper_outliers.shape[0] + lower_outliers.shape
```

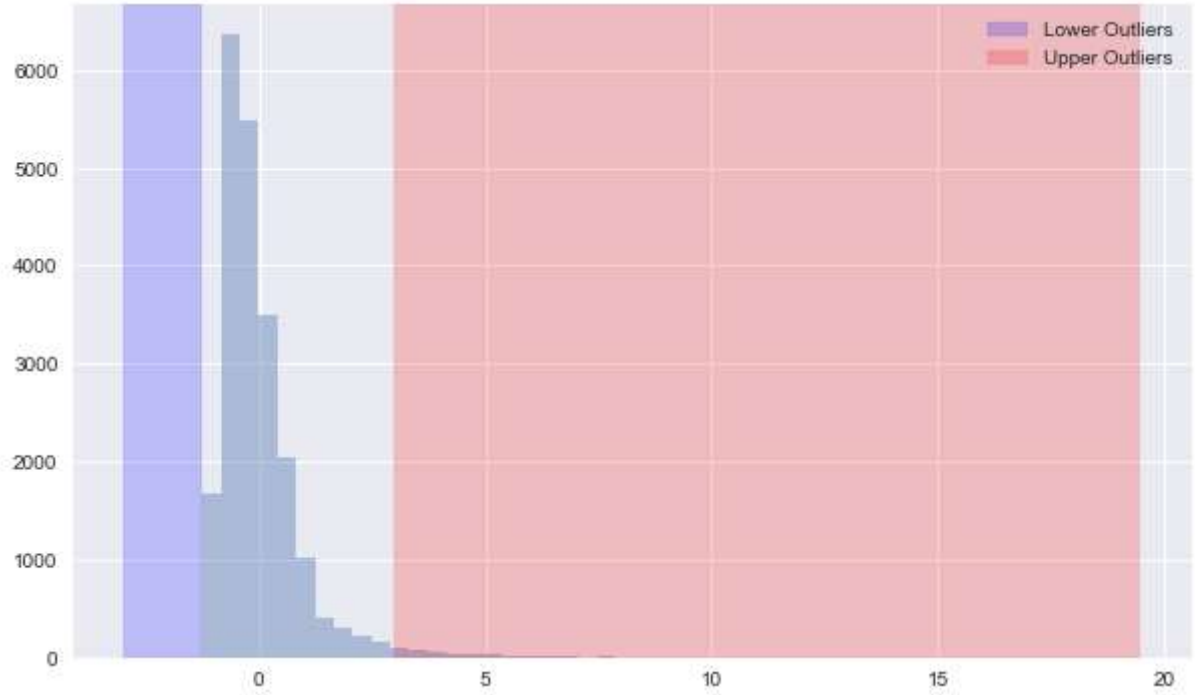
In [50]:
```
#applying the above function on columns to find the total outliers in every featu
for i in data.columns:
    print('Total outliers in ', i)
    calc_interquartile(data, i)
    print()
```

```
Total outliers in  price
Lower outliers 0
Upper outliers 1158
total outliers 1158

Total outliers in  bedrooms
Lower outliers 196
Upper outliers 334
total outliers 530

Total outliers in  bathrooms
Lower outliers 0
Upper outliers 402
total outliers 402

Total outliers in  sqft_living
Lower outliers 0
Upper outliers 571
total outliers 571

Total outliers in  sqft_lot
Lower outliers 0
Upper outliers 2419
total outliers 2419

Total outliers in  floors
Lower outliers 0
Upper outliers 0
total outliers 0

Total outliers in  condition
Lower outliers 29
Upper outliers 0
total outliers 29

Total outliers in  grade
Lower outliers 270
Upper outliers 1635
total outliers 1905

Total outliers in  yr_built
Lower outliers 0
Upper outliers 0
total outliers 0

Total outliers in  zipcode
Lower outliers 0
Upper outliers 0
total outliers 0
```

In [51]:
```
""" creating function for calculating zscore which is subtracting the mean from e
is less than -3 or greater than 3, then that data point is an outlier"""

def z_score(data, column):
    #creating global variables for plotting the graph for better demonstration
    global zscore, outlier
    #creating lists to store zscore and outliers
    zscore = []
    outlier =[]
    # for zscore generally taken thresholds are 2.5, 3 or 3.5 - used 3 here
    threshold = 3
    # calculating the mean of the passed column
    mean = np.mean(data[column])
    # calculating the standard deviation of the passed column
    std = np.std(data[column])
    for i in data[column]:
        z = (i-mean)/std
        zscore.append(z)
        #if the zscore is greater than threshold = 3 that means it is an outlier
        if np.abs(z) > threshold:
            outlier.append(i)
    return print('total outliers', len(outlier))
```

In [52]:
```
#plotting outliers graph for 'price' feature
z_score(data, 'price')
plt.figure(figsize = (10,6))
sns.distplot(zscore, kde=False)
print(upper, lower)
plt.axvspan(xmin = -3 ,xmax= min(zscore),alpha=0.2, color='blue', label='Lower Ou
plt.axvspan(xmin = 3 ,xmax= max(zscore),alpha=0.2, color='red', label='Upper Outl
plt.legend()
plt.show()
```

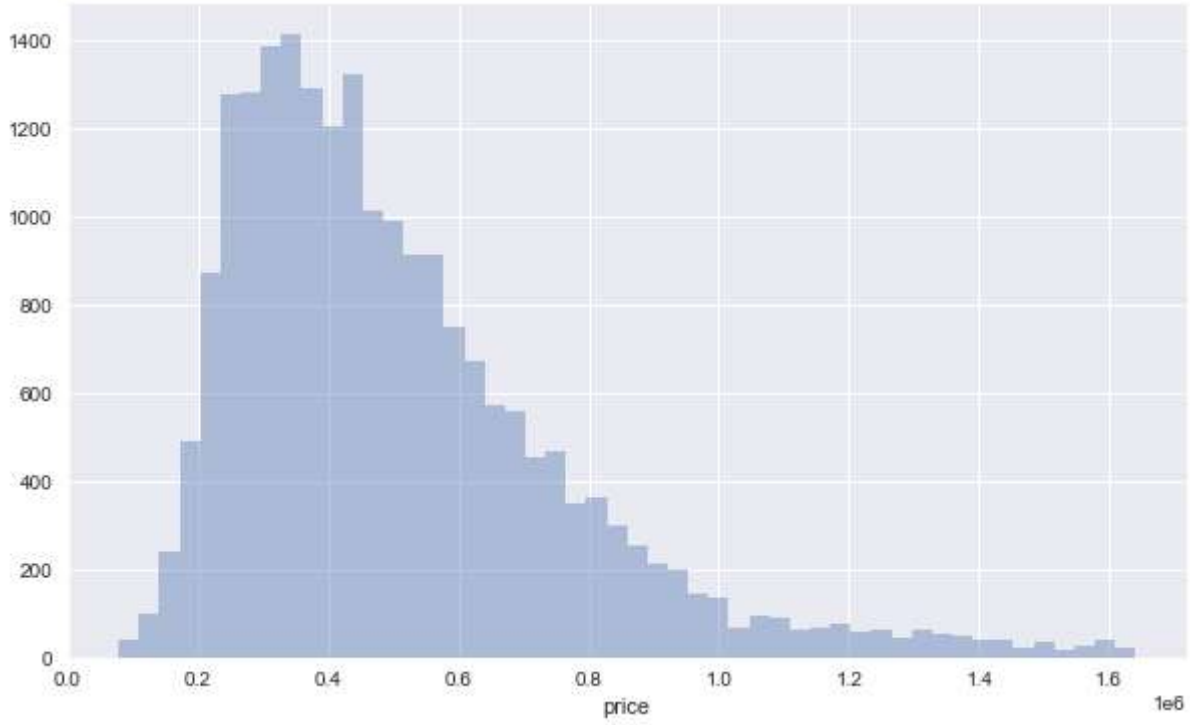
```
total outliers 406
98245.5 97905.5

C:\Users\racar\anaconda3\lib\site-packages\seaborn\distributions.py:2619: Futur
eWarning: `distplot` is a deprecated function and will be removed in a future v
ersion. Please adapt your code to use either `displot` (a figure-level function
with similar flexibility) or `histplot` (an axes-level function for histogram
s).
  warnings.warn(msg, FutureWarning)
```



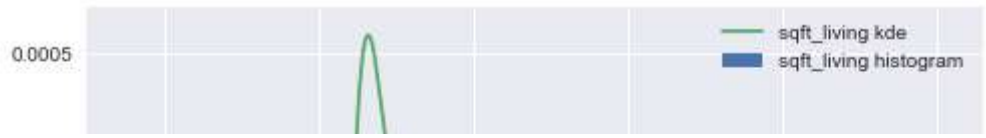

In [53]:
```
#remove the outliers from price using zscore
dj=[]
for i in data.price:
    if i in set(outlier):
        dj.append(0.0)
    else:
        dj.append(i)

data['P'] = dj

x = data.drop(data[data['P'] == 0.0].index)
x.shape
```

Out[53]: (21183, 11)

In [54]:
```
plt.figure(figsize = (10,6))
sns.distplot(x['price'], kde=False)
plt.show()
```




In [55]:
```
#Plotted KDE - Explore
for column in data:
    data[column].plot.hist(density=True, label = column+' histogram')
    data[column].plot.kde(label =column+' kde')
    plt.legend()
    plt.show()
```



In [56]:
```
# import libraries for OLS - Obtain
import statsmodels.api as sm
import statsmodels.formula.api as smf

# build the formula - Explore
f = 'price~sqft_lot'
# create a fitted model in one line
model = smf.ols(formula=f, data=data).fit()
#Display OLS Summary - Explore
model.summary()
```

Out[56]:

OLS Regression Results

| | | | |
|---|---|---|---|
| **Dep. Variable:** | price | **R-squared:** | 0.008 |
| **Model:** | OLS | **Adj. R-squared:** | 0.008 |
| **Method:** | Least Squares | **F-statistic:** | 175.8 |
| **Date:** | Sun, 29 May 2022 | **Prob (F-statistic):** | 5.85e-40 |
| **Time:** | 17:51:48 | **Log-Likelihood:** | -3.0719e+05 |
| **No. Observations:** | 21589 | **AIC:** | 6.144e+05 |
| **Df Residuals:** | 21587 | **BIC:** | 6.144e+05 |
| **Df Model:** | 1 | | |
| **Covariance Type:** | nonrobust | | |

| | coef | std err | t | P>\|t\| | [0.025 | 0.975] |
|---|---|---|---|---|---|---|
| **Intercept** | 5.283e+05 | 2651.042 | 199.268 | 0.000 | 5.23e+05 | 5.33e+05 |
| **sqft_lot** | 0.7972 | 0.060 | 13.258 | 0.000 | 0.679 | 0.915 |

| | | | |
|---|---|---|---|
| **Omnibus:** | 19126.972 | **Durbin-Watson:** | 1.968 |
| **Prob(Omnibus):** | 0.000 | **Jarque-Bera (JB):** | 1146565.357 |
| **Skew:** | 4.029 | **Prob(JB):** | 0.00 |
| **Kurtosis:** | 37.780 | **Cond. No.** | 4.69e+04 |

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 4.69e+04. This might indicate that there are strong multicollinearity or other numerical problems.

In [57]:
```
# import libraries for OLS - Obtain
import statsmodels.api as sm
import statsmodels.formula.api as smf

# build the formula - Explore
f = 'price~sqft_living'
# create a fitted model in one line
model = smf.ols(formula=f, data=data).fit()
#Display OLS Summary - Explore
model.summary()
```

Out[57]:

OLS Regression Results

| | | | |
|---|---|---|---|
| **Dep. Variable:** | price | **R-squared:** | 0.493 |
| **Model:** | OLS | **Adj. R-squared:** | 0.493 |
| **Method:** | Least Squares | **F-statistic:** | 2.097e+04 |
| **Date:** | Sun, 29 May 2022 | **Prob (F-statistic):** | 0.00 |
| **Time:** | 17:51:48 | **Log-Likelihood:** | -2.9995e+05 |
| **No. Observations:** | 21589 | **AIC:** | 5.999e+05 |
| **Df Residuals:** | 21587 | **BIC:** | 5.999e+05 |
| **Df Model:** | 1 | | |
| **Covariance Type:** | nonrobust | | |

| | coef | std err | t | P>\|t\| | [0.025 | 0.975] |
|---|---|---|---|---|---|---|
| **Intercept** | -4.404e+04 | 4411.108 | -9.984 | 0.000 | -5.27e+04 | -3.54e+04 |
| **sqft_living** | 280.8815 | 1.940 | 144.801 | 0.000 | 277.079 | 284.684 |

| | | | |
|---|---|---|---|
| **Omnibus:** | 14794.997 | **Durbin-Watson:** | 1.982 |
| **Prob(Omnibus):** | 0.000 | **Jarque-Bera (JB):** | 542159.026 |
| **Skew:** | 2.819 | **Prob(JB):** | 0.00 |
| **Kurtosis:** | 26.894 | **Cond. No.** | 5.63e+03 |

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 5.63e+03. This might indicate that there are strong multicollinearity or other numerical problems.

Note that the R squared value is between 0 and 1 with a value of 0.493. This is a great sign that the "sqft_lot" coefficient has a strong relationship to sale price aswell as the sqft_lot R squared testing above. This info will add value to further research regarding understanding the relationships connecting Kings County homebuyers' requirements of buying a property.

In [58]:
```
#create the column data
data = pd.read_csv('data\\kc_house_data.csv')
continuous = ['price', 'bedrooms', 'bathrooms', 'yr_built']
categoricals = ['sqft_living', 'sqft_lot', 'grade', 'zipcode', 'floors', 'conditi
data_cont = data[continuous]
```

In [59]:
```
# Log features
log_names = [f'{column}_log' for column in data_cont.columns]
data_log = np.log(data_cont)
data_log.columns = log_names
```

In [60]:
```
# normalize
def normalize(feature):
    return (feature - feature.mean()) / feature.std()
data_log_norm = data_log.apply(normalize)
```

In [61]:
```
# one hot encode categoricals
data_ohe = pd.get_dummies(data[categoricals], prefix=categoricals[0], drop_first=
preprocessed = pd.concat([data_log_norm, data_ohe], axis=1)
X = preprocessed.drop('sqft_living', axis=1)
y = preprocessed['sqft_living']
```

In [62]:
```
# Split the data into training and test sets (assign 20% to test set)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.20)
```

In [63]:
```
# A train-test split
print(len(X_train), len(X_test), len(y_train), len(y_test))
```

```
17277 4320 17277 4320
```

In [64]:
```
from sklearn.linear_model import LinearRegression
linreg = LinearRegression()

linreg.fit(X_train, y_train)
y_hat_test = linreg.predict(X_test)
data.fillna(999, inplace=True)
```

In [65]:
```
# Your code here
from sklearn.metrics import mean_squared_error
test_residuals = y_hat_test - y_test

test_mse = mean_squared_error(y_test, y_hat_test)
test_mse
```

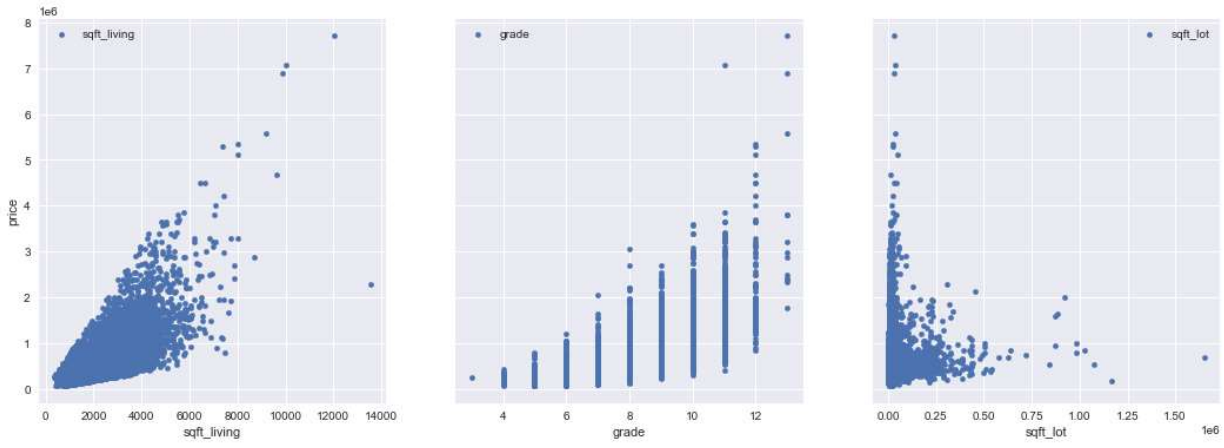
Out[65]:
```
212925.57492737804
```

In [66]:
```
def kfolds(data, k):
    # push data as pandas DataFrame
    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 Size will be 1 larger to account for 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
```

In [67]:
```
data_data = pd.concat([X.reset_index(drop=True), y], axis=1)
```

In [68]:
```
data_folds = kfolds(data_data, 5)
```

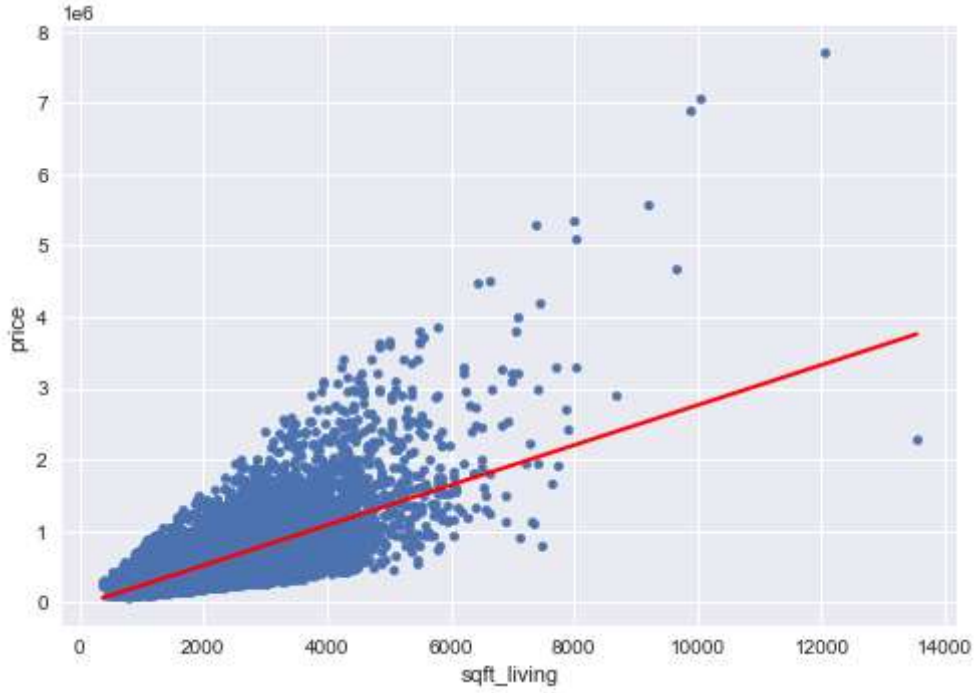
In [69]:
```
#Created a scatter plot for linearity - Explore
fig, axs = plt.subplots(1, 3, sharey=True, figsize=(18, 6))
for idx, channel in enumerate(['sqft_living', 'grade', 'sqft_lot']):
    data.plot(kind='scatter', x=channel, y='price', ax=axs[idx], label=channel)
plt.legend()
plt.show()
```




As we can see, compared amongst the three variables that the sqft_living relationship is linear in some way across the data. There are some outliers here, however if outliers are removed, you can discern that the size of sqft_lot does have a relationship with price as well as grade and sqft_living.

In [70]:
```
# create a DataFrame with the minimum and maximum values of Sqft_Living - Model
X_new = pd.DataFrame({'sqft_living': [data.sqft_living.min(), data.sqft_living.ma
print(X_new.head())

# make predictions for those x values and store them - Model
preds = model.predict(X_new)
print (preds)

# first, plot the observed data and the least squares line - Model
data.plot(kind='scatter', x='sqft_living', y='price')
plt.plot(X_new, preds, c='red', linewidth=2)
plt.show()
```

```
   sqft_living
0          370
1        13540
0      59,884.22
1   3,759,093.93
dtype: float64
```




In [71]:
```
# Split the data into training and test sets (assign 20% to test set)
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.20)
```

In [72]:
```
# A brief preview of train-test split to create test training data and dummy data
print(len(X_train), len(X_test), len(y_train), len(y_test))
```

```
17277 4320 17277 4320
```

In [73]:
```
#apply model to the train set created
from sklearn.linear_model import LinearRegression
linreg = LinearRegression()

linreg.fit(X_train, y_train)
y_hat_test = linreg.predict(X_test)
```

In [74]:
```
#calculate training and test MSE
from sklearn.metrics import mean_squared_error
test_residuals = y_hat_test - y_test

test_mse = mean_squared_error(y_test, y_hat_test)
test_mse
```

Out[74]:
```
204138.90402299163
```

MSE is calculated by taking the average of the square of the difference between the original and predicted values of the data. The mean squared error is used to determine the model's performance.

##Explore: the data set by deriving statistics and creating visualisation with dummy test data

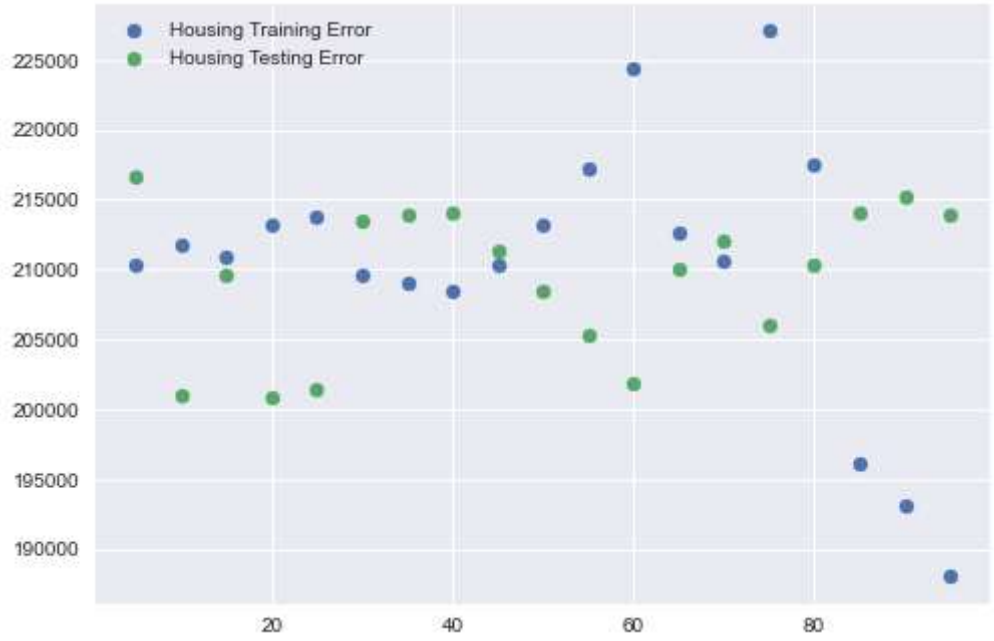
In [75]:
```
from sklearn.metrics import mean_squared_error, make_scorer
from sklearn.model_selection import cross_val_score
mse = make_scorer(mean_squared_error)
cv_5_results = cross_val_score(linreg, X, y, cv=5, scoring=mse)
```

In [76]:
```
cv_5_results.mean()
```

Out[76]:
```
213811.30898585747
```

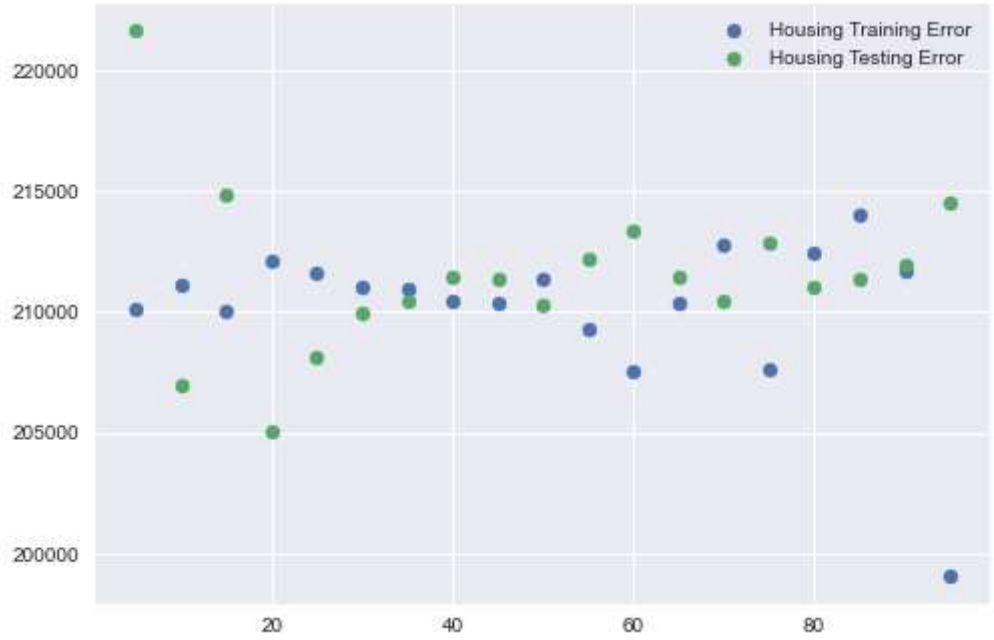
In [77]:
```
import random
random.seed(110)

train_err = []
test_err = []
t_sizes = list(range(5,100,5))
for t_size in t_sizes:
    X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=t_size/10
    linreg.fit(X_train, y_train)
    y_hat_train = linreg.predict(X_train)
    y_hat_test = linreg.predict(X_test)
    train_err.append(mean_squared_error(y_train, y_hat_train))
    test_err.append(mean_squared_error(y_test, y_hat_test))
plt.scatter(t_sizes, train_err, label='Housing Training Error')
plt.scatter(t_sizes, test_err, label='Housing Testing Error')
plt.legend()
```

Out[77]: <matplotlib.legend.Legend at 0x19a7194a850>



In [78]:
```
#train set 2
random.seed(900)

train_err = []
test_err = []
t_sizes = range(5,100,5)
for t_size in t_sizes:
    temp_train_err = []
    temp_test_err = []
    for i in range(10):
        X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=t_siz
        linreg.fit(X_train, y_train)
        y_hat_train = linreg.predict(X_train)
        y_hat_test = linreg.predict(X_test)
        temp_train_err.append(mean_squared_error(y_train, y_hat_train))
        temp_test_err.append(mean_squared_error(y_test, y_hat_test))
    train_err.append(np.mean(temp_train_err))
    test_err.append(np.mean(temp_test_err))
plt.scatter(t_sizes, train_err, label='Housing Training Error')
plt.scatter(t_sizes, test_err, label='Housing Testing Error')
plt.legend()
```

Out[78]:
```
<matplotlib.legend.Legend at 0x19a718f09a0>
```



In [79]:
```
#Paired sample t-test

data = pd.read_csv('data\\kc_house_data.csv')
data[['price','sqft_living', 'sqft_lot']].describe()
ttest,pval = stats.ttest_rel(data['price'], data['sqft_living'])
print(pval)
if pval<0.05:
    print("reject null hypothesis")
else:
    print("accept null hypothesis")
```

```
0.0
reject null hypothesis
```

```
                                        **  ALTERNATIVE HYPOTHESIS CONFIRMED  **
```

Below we set to explore the data set by deriving statistics and creating visualisation with dummy test data.

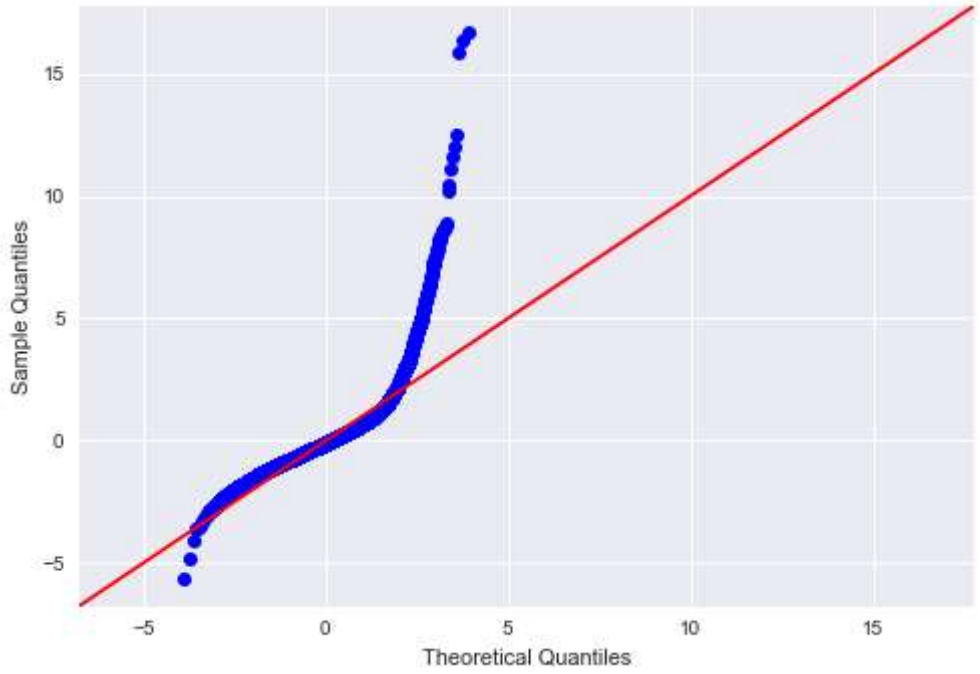
Null hypothesis: There is no difference between experimental and control group - when comparing sqft_lot against sqft_living does NOT affect a buyers decision to purchase a home. $\mu$1=$\mu$2μ1=μ2

Alternative Hypothesis: There is a difference between experimental and control group - the sqft_living and sqft_Lot DOES affect a buyers decision when purchasing a home by

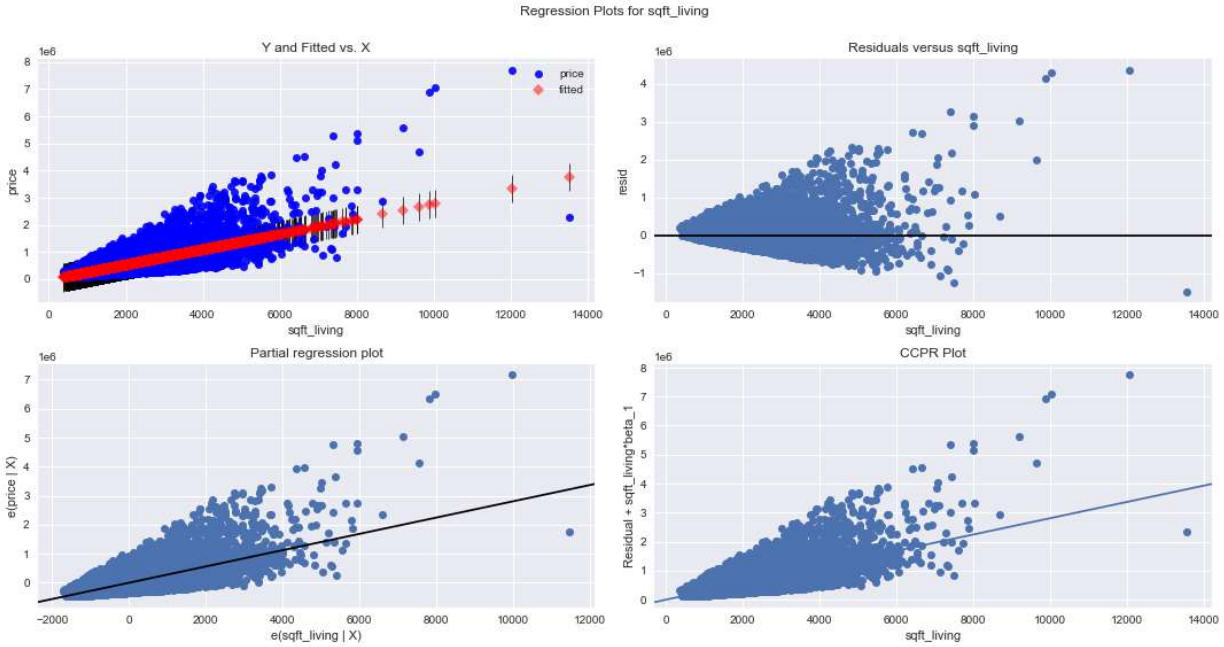
$\mu$1≠$\mu$2μ1≠μ2 #alpha value is 0.35

In [80]:
```
#import scipy.stats as stats
residuals = model.resid
fig = sm.graphics.qqplot(residuals, dist=stats.norm, line='45', fit=True)
fig.show()
```

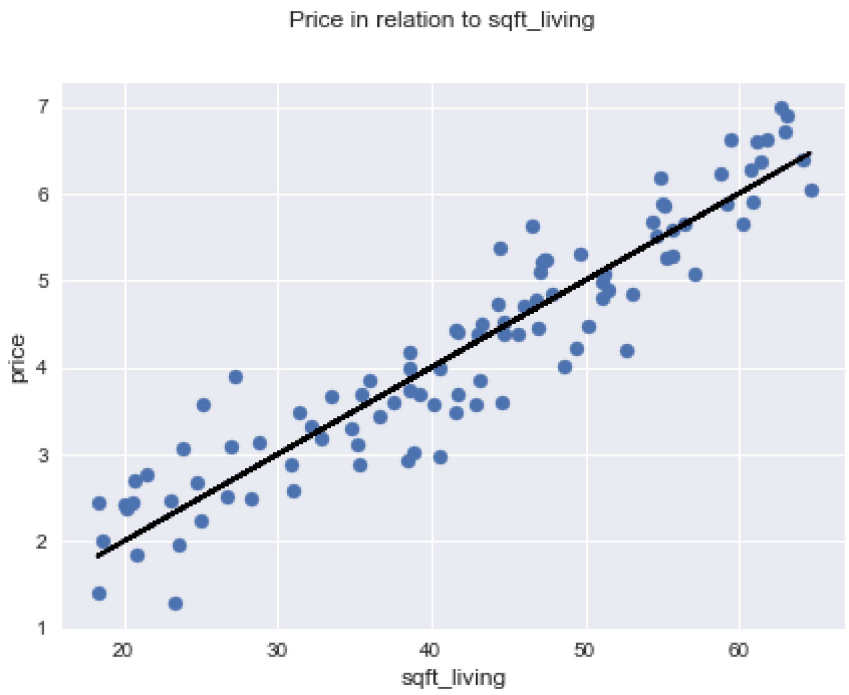
```
C:\Users\racar\anaconda3\lib\site-packages\statsmodels\graphics\gofplots.py:993: UserWarning: marker is redundantly defined by the 'marker' keyword argument and the fmt string "bo" (-> marker='o'). The keyword argument will take precedence.
  ax.plot(x, y, fmt, **plot_style)
C:\Users\racar\AppData\Local\Temp/ipykernel_5712/1081638490.py:4: UserWarning: Matplotlib is currently using module://matplotlib_inline.backend_inline, which is a non-GUI backend, so cannot show the figure.
  fig.show()
```



In [81]:
```
#visualisation used to model and interpret the data
fig = plt.figure(figsize=(15,8))
fig = sm.graphics.plot_regress_exog(model, "sqft_living", fig=fig)
plt.show()
```



In [82]:
```
#Visualize price of houses in relation to sqft_living
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline

np.random.seed(1234)
sen = np.random.uniform(18, 65, 100)
income = np.random.normal((sen/10), 0.5)
sen = sen.reshape(-1, 1)

fig = plt.figure(figsize=(7, 5))
fig.suptitle('Price in relation to sqft_living', fontsize=12)
plt.scatter(sen, income)
plt.plot(sen, sen/10, c='black')
plt.xlabel('sqft_living', fontsize=12)
plt.ylabel('price', fontsize=12)
plt.show()
```




In [83]:
```
#setting predictors location
data_pred = data.iloc[:,0:12]
data_pred.head()
```

Out[83]:

| | id | date | price | bedrooms | bathrooms | sqft_living | sqft_lot | floors | waterfront |
|---|---|---|---|---|---|---|---|---|---|
| **0** | 7129300520 | 10/13/2014 | 221900 | 3 | 1 | 1180 | 5650 | 1 | NaN |
| **1** | 6414100192 | 12/9/2014 | 538000 | 3 | 2.25 | 2570 | 7242 | 2 | 0 |
| **2** | 5631500400 | 2/25/2015 | 180000 | 2 | 1 | 770 | 10000 | 1 | 0 |
| **3** | 2487200875 | 12/9/2014 | 604000 | 4 | 3 | 1960 | 5000 | 1 | 0 |
| **4** | 1954400510 | 2/18/2015 | 510000 | 3 | 2 | 1680 | 8080 | 1 | 0 |

In [84]:
```
#visualse value of correlation percentage
data_pred.corr()
```

Out[84]:

| | id | price | bedrooms | bathrooms | sqft_living | sqft_lot | floors | waterfront | view | cond |
|---|---|---|---|---|---|---|---|---|---|---|
| **id** | 1 | -0.02 | 0.00 | 0.01 | -0.01 | -0.13 | 0.02 | -0.00 | 0.01 | |
| **price** | -0.02 | 1 | 0.31 | 0.53 | 0.70 | 0.09 | 0.26 | 0.28 | 0.40 | |
| **bedrooms** | 0.00 | 0.31 | 1 | 0.51 | 0.58 | 0.03 | 0.18 | -0.00 | 0.08 | |
| **bathrooms** | 0.01 | 0.53 | 0.51 | 1 | 0.76 | 0.09 | 0.50 | 0.07 | 0.19 | |
| **sqft_living** | -0.01 | 0.70 | 0.58 | 0.76 | 1 | 0.17 | 0.35 | 0.11 | 0.28 | |
| **sqft_lot** | -0.13 | 0.09 | 0.03 | 0.09 | 0.17 | 1 | -0.00 | 0.02 | 0.08 | |
| **floors** | 0.02 | 0.26 | 0.18 | 0.50 | 0.35 | -0.00 | 1 | 0.02 | 0.03 | |
| **waterfront** | -0.00 | 0.28 | -0.00 | 0.07 | 0.11 | 0.02 | 0.02 | 1 | 0.41 | |
| **view** | 0.01 | 0.40 | 0.08 | 0.19 | 0.28 | 0.08 | 0.03 | 0.41 | 1 | |
| **condition** | -0.02 | 0.04 | 0.03 | -0.13 | -0.06 | -0.01 | -0.26 | 0.02 | 0.05 | |
| **grade** | 0.01 | 0.67 | 0.36 | 0.67 | 0.76 | 0.11 | 0.46 | 0.09 | 0.25 | |

In [85]:
```
#check for connections
abs(data_pred.corr()) >= 0.70
```

Out[85]:

| | id | price | bedrooms | bathrooms | sqft_living | sqft_lot | floors | waterfront | view | con |
|---|---|---|---|---|---|---|---|---|---|---|
| **id** | True | False | False | False | False | False | False | False | False | |
| **price** | False | True | False | False | True | False | False | False | False | |
| **bedrooms** | False | False | True | False | False | False | False | False | False | |
| **bathrooms** | False | False | False | True | True | False | False | False | False | |
| **sqft_living** | False | True | False | True | True | False | False | False | False | |
| **sqft_lot** | False | False | False | False | False | True | False | False | False | |
| **floors** | False | False | False | False | False | False | True | False | False | |
| **waterfront** | False | False | False | False | False | False | False | True | False | |
| **view** | False | False | False | False | False | False | False | False | True | |
| **condition** | False | False | False | False | False | False | False | False | False | |
| **grade** | False | False | False | False | True | False | False | False | False | |

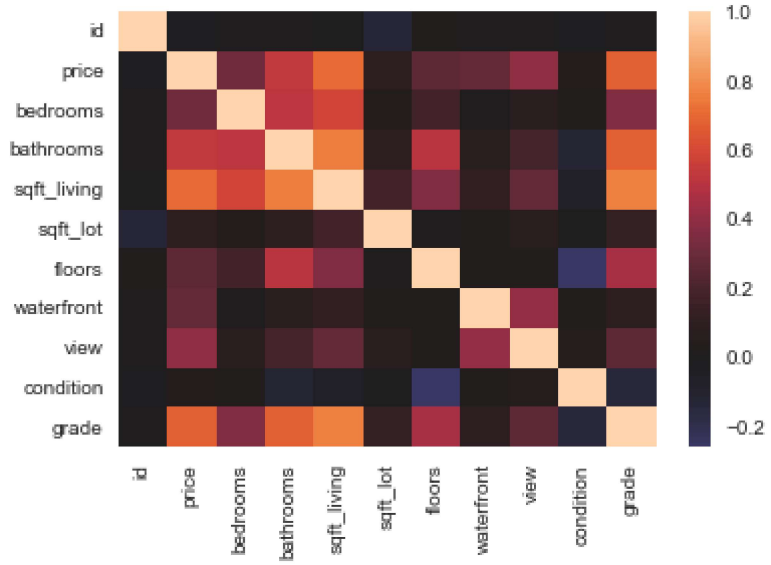
In [86]:
```
#Cleaning data
data=data_pred.corr().abs().stack().reset_index().sort_values(0, ascending=False)
# combine the variable name columns (Which were only named level_0 and level_1 by
data['pairs'] = list(zip(data.level_0, data.level_1))
# set index to pairs
data.set_index(['pairs'], inplace = True)
#drop level columns
data.drop(columns=['level_1', 'level_0'], inplace = True)
# rename correlation column to cc
data.columns = ['cc']
# drop duplicates.
data.drop_duplicates(inplace=True)
```

In [87]:
```
#quick preview to confirm
data[(data.cc>=.70) & (data.cc <1)]
```

Out[87]:

| | cc |
|---|---|
| **pairs** | |
| **(grade, sqft_living)** | 0.76 |
| **(sqft_living, bathrooms)** | 0.76 |
| **(price, sqft_living)** | 0.70 |

In [88]:
```
#creating a heatmap to learn even more
import seaborn as sns
sns.heatmap(data_pred.corr(), center=0);
```




Each square shows the correlation between the variables on each axis. Correlation ranges from -2 to +1. Data closer to zero means there is no linear relationship between the two variables. We add further complexity when connecti.

In [89]:
```
#3 important parameter estimates or statistics.
```

In [90]:
```
#after you finish refining your models, you should provide 1-3 paragraphs discuss
```

In [91]:
```
 #your notebook and presentation should discuss at least two features that have s
```