Overview

```
This project analyses the housing in Kings County to identify what features have a strong relationship with price.
```

Data Understanding and Preparation

In [1]:
```
# Import Standard Packages
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
import statsmodels.api as sm
from statsmodels.formula.api import ols


sales = pd.read_csv('data/kc_house_data.csv')
pd.options.display.float_format = '{:,.0f}'.format
sales.head()
```

Out[1]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	...	grade	sqft_above	sqft_basement	yr_built	yr_renovated	zipco
0	7129300520	10/13/2014	221,900	3	1	1180	5650	1	nan	0	...	7	1180	0.0	1955	0	981
1	6414100192	12/9/2014	538,000	3	2	2570	7242	2	0	0	...	7	2170	400.0	1951	1,991	981
2	5631500400	2/25/2015	180,000	2	1	770	10000	1	0	0	...	6	770	0.0	1933	nan	980
3	2487200875	12/9/2014	604,000	4	3	1960	5000	1	0	0	...	7	1050	910.0	1965	0	981
4	1954400510	2/18/2015	510,000	3	2	1680	8080	1	0	0	...	8	1680	0.0	1987	0	980

5 rows × 21 columns

In [2]:
```
sales.info()
```

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

In [3]:
```
#check for any NAN value
sales.isna().sum()
```

Out[3]:
```
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
```

Based on the above, Waterfront and Yr Renovated require data cleasning

In [4]:
```
#drop columns that are not useful to the purpose of this data analysis
sales.drop(sales.iloc[:, 16:21], inplace=True, axis=1)
sales.drop(sales.iloc[:, 12:14], inplace=True, axis=1)
sales.drop(sales.iloc[:, 9:10], inplace=True, axis=1)
sales.drop(sales.iloc[:, 0:2], inplace=True, axis=1)

#replace NAN value
sales["waterfront"] = sales["waterfront"].fillna(0)
sales["yr_renovated"] = sales["yr_renovated"].fillna(0)
#add "age" column
sales['age']=[2023] - sales.loc[:,"yr_built"]
```

In [5]:
```
sales.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 21597 entries, 0 to 21596
Data columns (total 12 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   price         21597 non-null  float64
 1   bedrooms      21597 non-null  int64
 2   bathrooms     21597 non-null  float64
 3   sqft_living   21597 non-null  int64
 4   sqft_lot      21597 non-null  int64
 5   floors        21597 non-null  float64
 6   waterfront    21597 non-null  float64
 7   condition     21597 non-null  int64
 8   grade         21597 non-null  int64
 9   yr_built      21597 non-null  int64
 10  yr_renovated  21597 non-null  float64
 11  age           21597 non-null  int64
dtypes: float64(5), int64(7)
memory usage: 2.0 MB
```

Base Model

In [6]:
```
X = sales.drop('price', axis=1)
y=sales['price']
import statsmodels.api as sm
X_int = sm.add_constant(X)
model = sm.OLS(y,X_int).fit()
model.summary()
```

Out[6]:

OLS Regression Results

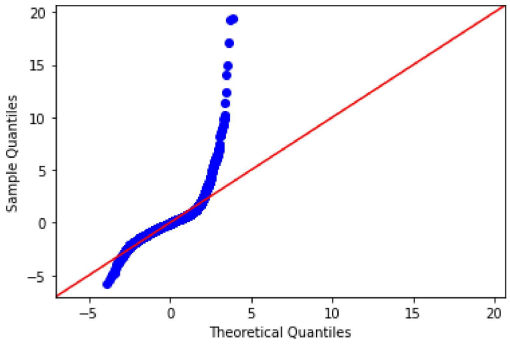
Dep. Variable:	price	**R-squared:**	0.646
Model:	OLS	**Adj. R-squared:**	0.646
Method:	Least Squares	**F-statistic:**	3936.
Date:	Sun, 12 Feb 2023	**Prob (F-statistic):**	0.00
Time:	17:49:56	**Log-Likelihood:**	-2.9618e+05
No. Observations:	21597	**AIC:**	5.924e+05
Df Residuals:	21586	**BIC:**	5.925e+05
Df Model:	10		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
const	1.3376	0.033	41.137	0.000	1.274	1.401
bedrooms	-4.238e+04	2051.101	-20.661	0.000	-4.64e+04	-3.84e+04
bathrooms	4.935e+04	3480.907	14.178	0.000	4.25e+04	5.62e+04
sqft_living	177.3030	3.303	53.682	0.000	170.829	183.777
sqft_lot	-0.2437	0.037	-6.626	0.000	-0.316	-0.172
floors	2.055e+04	3461.733	5.936	0.000	1.38e+04	2.73e+04
waterfront	7.518e+05	1.84e+04	40.893	0.000	7.16e+05	7.88e+05
condition	2.02e+04	2515.446	8.031	0.000	1.53e+04	2.51e+04
grade	1.299e+05	2155.845	60.276	0.000	1.26e+05	1.34e+05
yr_built	-535.6120	8.685	-61.669	0.000	-552.636	-518.588
yr_renovated	14.3579	4.309	3.332	0.001	5.913	22.803
age	3241.6102	67.284	48.178	0.000	3109.728	3373.493

Omnibus:	15847.393	**Durbin-Watson:**	1.976
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	1006948.729
Skew:	2.936	**Prob(JB):**	0.00
Kurtosis:	35.932	**Cond. No.**	2.06e+18

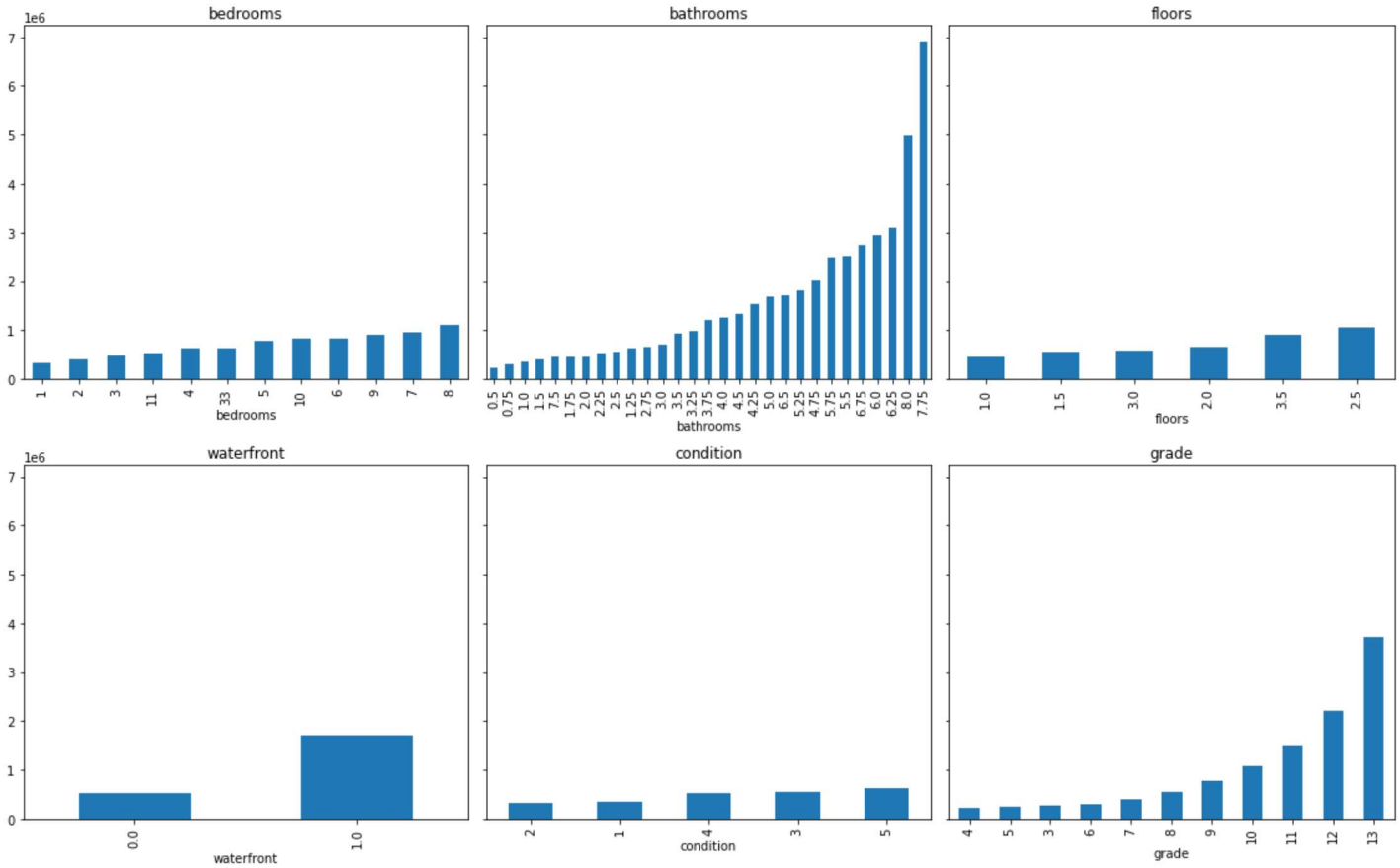
Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The smallest eigenvalue is 9.92e-24. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.

In [7]:
```
import scipy.stats as stats
residuals = model.resid
sm.graphics.qqplot(residuals, dist=stats.norm, line='45', fit=True)
plt.show()
```



Transformation and validation

In [8]:
```
#Check categorical variables

fig, axes = plt.subplots(nrows=2, ncols=3, figsize=(16,10), sharey=True)

categoricals = ['bedrooms', 'bathrooms', 'floors', 'waterfront', 'condition', 'grade']

for col, ax in zip(categoricals, axes.flatten()):
    (sales.groupby(col)                 # group values together by column of interest
         .mean()['price']         # take the mean of the saleprice for each group
         .sort_values()               # sort the groups in ascending order
         .plot
         .bar(ax=ax))                 # create a bar graph on the ax

    ax.set_title(col)                 # Make the title the name of the column

fig.tight_layout()
```



In [9]:
```
#drop 'waterfront' "Floors" and "conditions" as they do not show a significant relationship to price
sales.drop(sales.iloc[:, 9:11], inplace=True, axis=1)
sales.drop(sales.iloc[:, 7:8], inplace=True, axis=1)
sales.drop(sales.iloc[:, 6:7], inplace=True, axis=1)

sales.head()
```

Out[9]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	grade	age
0	221,900	3	1	1180	5650	1	7	68
1	538,000	3	2	2570	7242	2	7	72
2	180,000	2	1	770	10000	1	6	90
3	604,000	4	3	1960	5000	1	7	58
4	510,000	3	2	1680	8080	1	8	36

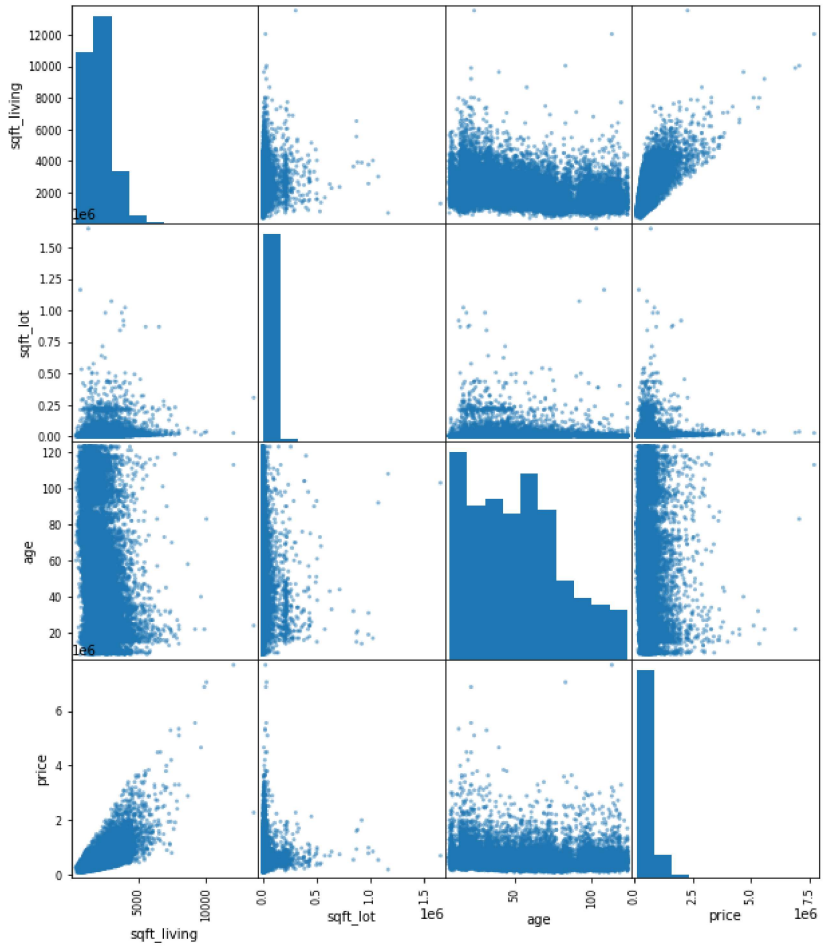
In [10]:
```
#split bedrooms, bathrooms and grade into 2 groups to create dummies and drop the original columns

sales['beds'] = ['1-4beds' if x <=4 else '4+beds' for x in sales['bedrooms']]
sales['baths']=['1-5baths' if x <=5 else '5+baths' for x in sales['bathrooms']]
sales['quality']=['low' if x <=8 else 'high' for x in sales['grade']]
sales= sales.drop(['bedrooms','bathrooms','floors','grade'], axis=1)

sales.head()
```

Out[10]:

	price	sqft_living	sqft_lot	age	beds	baths	quality
0	221,900	1180	5650	68	1-4beds	1-5baths	low
1	538,000	2570	7242	72	1-4beds	1-5baths	low
2	180,000	770	10000	90	1-4beds	1-5baths	low
3	604,000	1960	5000	58	1-4beds	1-5baths	low
4	510,000	1680	8080	36	1-4beds	1-5baths	low

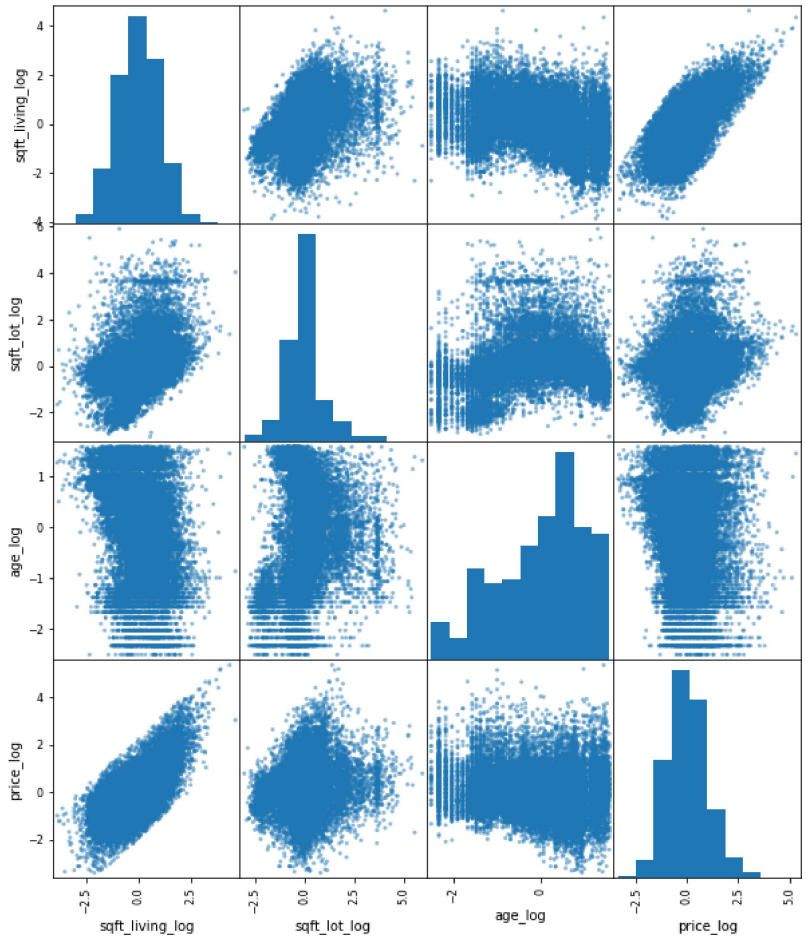
In [11]:
```
#create dummies:

categoricals = ['beds', 'baths', 'quality']
sales_ohe=pd.get_dummies(sales[categoricals], prefix=categoricals, drop_first=True)
```

In [12]:
```
# check distribution of the continuous variables

continuous = ['sqft_living','sqft_lot','age','price']
sales_cont = sales[continuous]
pd.plotting.scatter_matrix(sales_cont, figsize=(10,12));
```



In [13]:
```
# log features
log_names = [f'{column}_log' for column in sales_cont.columns]

sales_log = np.log(sales_cont)
sales_log.columns = log_names

# normalize (subract mean and divide by std)

def normalize(feature):
    return (feature - feature.mean()) / feature.std()

sales_log_norm = sales_log.apply(normalize)
```

In [14]:
```
pd.plotting.scatter_matrix(sales_log_norm, figsize=(10,12));
```



In [15]:
```
preprocessed = pd.concat([sales_log_norm, sales_ohe], axis=1)
preprocessed.head()
```

Out[15]:

	sqft_living_log	sqft_lot_log	age_log	price_log	beds_4+beds	baths_5+baths	quality_low
0	-1	-0	1	-1	0	0	1
1	1	-0	1	0	0	0	1
2	-2	0	1	-2	0	0	1
3	0	-1	0	0	0	0	1
4	-0	0	-0	0	0	0	1

In [16]:
```
#rerun the model
X = preprocessed.drop('price_log', axis=1)
y = preprocessed['price_log']
```

In [17]:
```
import statsmodels.api as sm
X_int = sm.add_constant(X)
model = sm.OLS(y,X_int).fit()
model.summary()
```

Out[17]:

OLS Regression Results

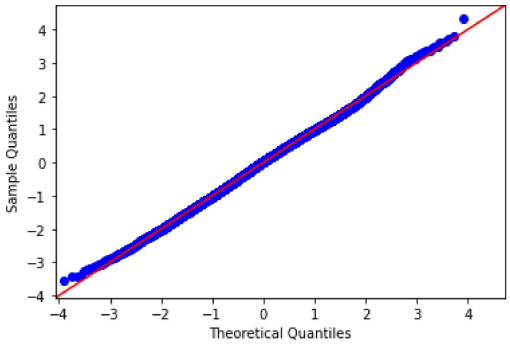
Dep. Variable:	price_log	**R-squared:**	0.549
Model:	OLS	**Adj. R-squared:**	0.549
Method:	Least Squares	**F-statistic:**	4379.
Date:	Sun, 12 Feb 2023	**Prob (F-statistic):**	0.00
Time:	17:50:02	**Log-Likelihood:**	-22047.
No. Observations:	21597	**AIC:**	4.411e+04
Df Residuals:	21590	**BIC:**	4.416e+04
Df Model:	6		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	0.6483	0.012	52.155	0.000	0.624	0.673
sqft_living_log	0.6116	0.006	96.263	0.000	0.599	0.624
sqft_lot_log	-0.1587	0.005	-31.369	0.000	-0.169	-0.149
age_log	0.2048	0.005	39.568	0.000	0.195	0.215
beds_4+beds	-0.0541	0.017	-3.167	0.002	-0.088	-0.021
baths_5+baths	0.9173	0.104	8.852	0.000	0.714	1.120
quality_low	-0.8034	0.014	-55.903	0.000	-0.832	-0.775

Omnibus:	0.610	**Durbin-Watson:**	1.968
Prob(Omnibus):	0.737	**Jarque-Bera (JB):**	0.586
Skew:	-0.005	**Prob(JB):**	0.746
Kurtosis:	3.024	**Cond. No.**	30.5

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

In [18]:
```
import scipy.stats as stats
residuals = model.resid
sm.graphics.qqplot(residuals, dist=stats.norm, line='45', fit=True)
plt.show()
```



In [19]:
```
#drop ages and check if it has improved the model R square
preprocessed= preprocessed.drop(['age_log'], axis=1)
```

In [20]:
```
X = preprocessed.drop('price_log', axis=1)
y = preprocessed['price_log']
import statsmodels.api as sm
X_int = sm.add_constant(X)
model = sm.OLS(y,X_int).fit()
model.summary()
```

Out[20]:

OLS Regression Results

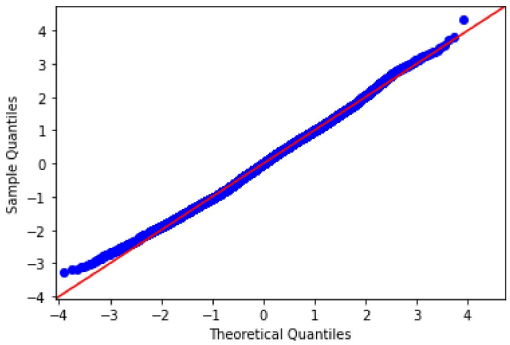
Dep. Variable:	price_log	**R-squared:**	0.516
Model:	OLS	**Adj. R-squared:**	0.516
Method:	Least Squares	**F-statistic:**	4608.
Date:	Sun, 12 Feb 2023	**Prob (F-statistic):**	0.00
Time:	17:50:02	**Log-Likelihood:**	-22803.
No. Observations:	21597	**AIC:**	4.562e+04
Df Residuals:	21591	**BIC:**	4.567e+04
Df Model:	5		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	0.5613	0.013	44.298	0.000	0.536	0.586
sqft_living_log	0.5399	0.006	85.608	0.000	0.527	0.552
sqft_lot_log	-0.1005	0.005	-20.049	0.000	-0.110	-0.091
beds_4+beds	0.0122	0.018	0.691	0.489	-0.022	0.047
baths_5+baths	0.9037	0.107	8.421	0.000	0.693	1.114
quality_low	-0.7024	0.015	-47.955	0.000	-0.731	-0.674

Omnibus:	67.267	**Durbin-Watson:**	1.975
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	65.111
Skew:	0.116	**Prob(JB):**	7.27e-15
Kurtosis:	2.862	**Cond. No.**	30.2

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

In [21]:
```
import scipy.stats as stats
residuals = model.resid
sm.graphics.qqplot(residuals, dist=stats.norm, line='45', fit=True)
plt.show()
```



In [22]:
```
preprocessed= preprocessed.drop(['beds_4+beds'], axis=1)
X = preprocessed.drop('price_log', axis=1)
y = preprocessed['price_log']
```

In [23]:
```
import statsmodels.api as sm
X_int = sm.add_constant(X)
model = sm.OLS(y,X_int).fit()
model.summary()
```

Out[23]:

OLS Regression Results

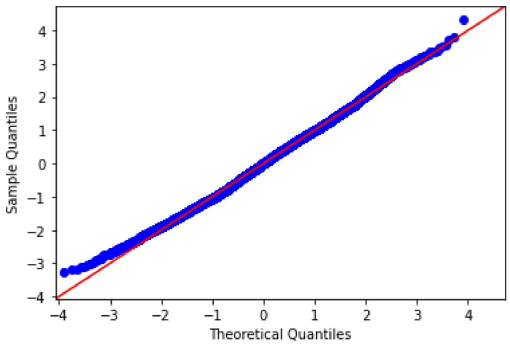
Dep. Variable:	price_log	**R-squared:**	0.516
Model:	OLS	**Adj. R-squared:**	0.516
Method:	Least Squares	**F-statistic:**	5760.
Date:	Sun, 12 Feb 2023	**Prob (F-statistic):**	0.00
Time:	17:50:02	**Log-Likelihood:**	-22803.
No. Observations:	21597	**AIC:**	4.562e+04
Df Residuals:	21592	**BIC:**	4.566e+04
Df Model:	4		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	0.5617	0.013	44.398	0.000	0.537	0.587
sqft_living_log	0.5411	0.006	89.843	0.000	0.529	0.553
sqft_lot_log	-0.1006	0.005	-20.074	0.000	-0.110	-0.091
baths_5+baths	0.9087	0.107	8.487	0.000	0.699	1.119
quality_low	-0.7016	0.015	-48.041	0.000	-0.730	-0.673

Omnibus:	67.763	**Durbin-Watson:**	1.975
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	65.605
Skew:	0.116	**Prob(JB):**	5.68e-15
Kurtosis:	2.862	**Cond. No.**	30.1

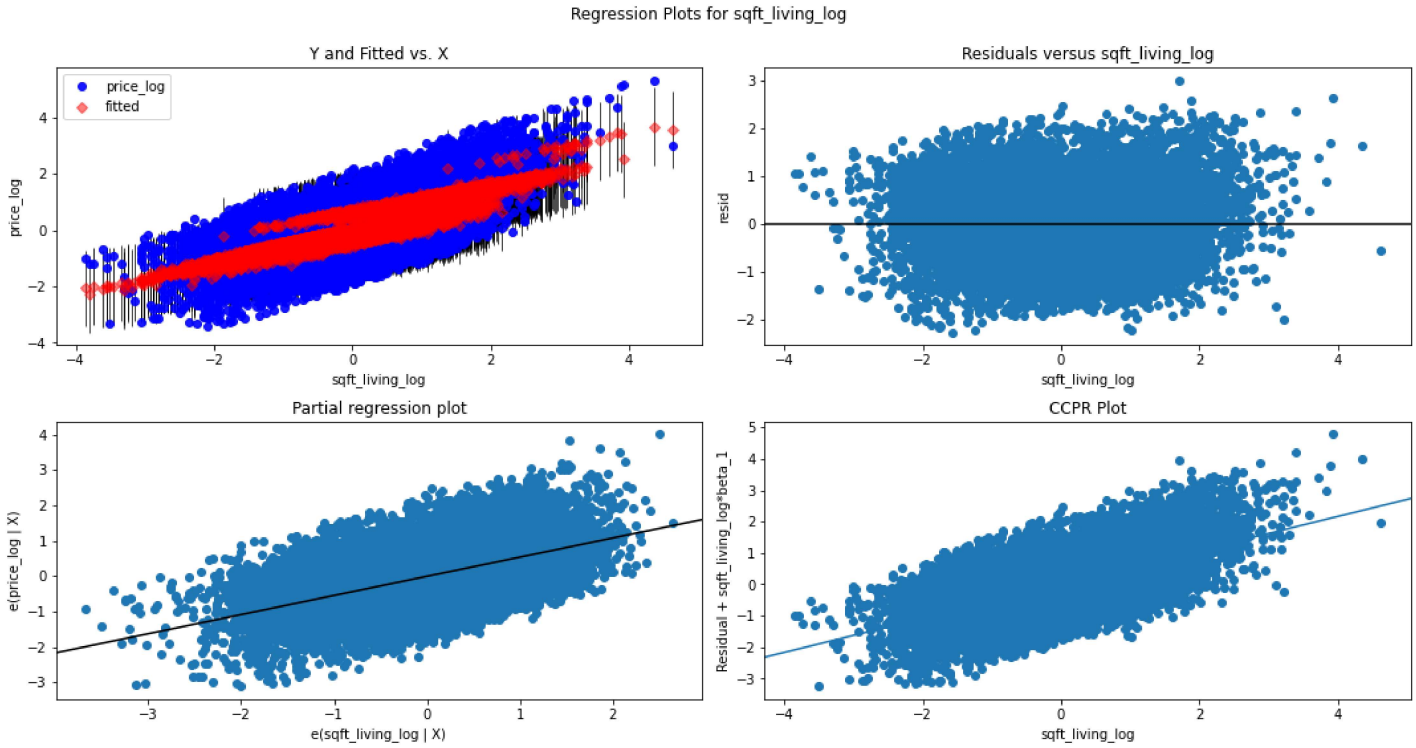
Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

In [24]:
```
import scipy.stats as stats
residuals = model.resid
sm.graphics.qqplot(residuals, dist=stats.norm, line='45', fit=True)
plt.show()
```



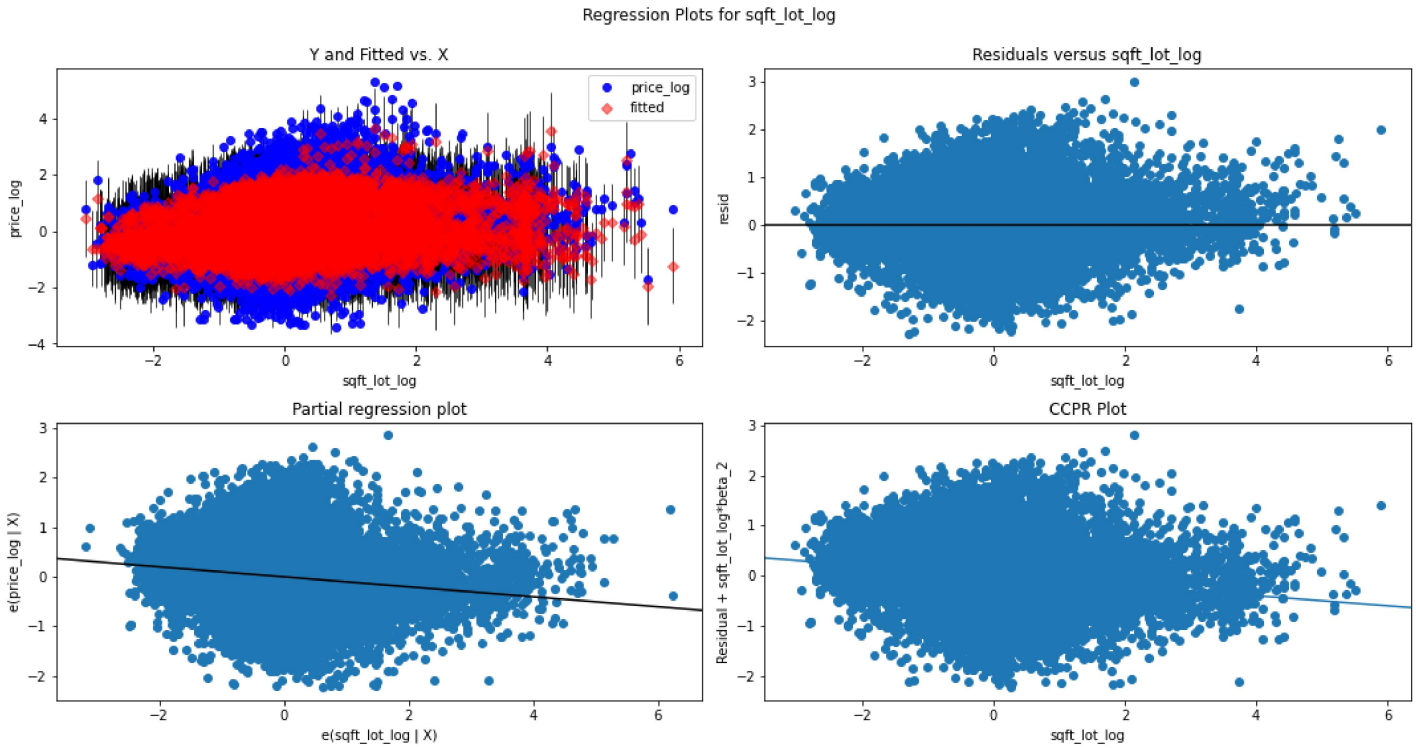
QQ plot shows that the normality assumption of the residuals seems fulfilled.

In [25]:
```
fig = plt.figure(figsize=(15,8))
fig = sm.graphics.plot_regress_exog(model, "sqft_living_log", fig=fig)
plt.show()
```



From the first and second plot in the first row, we see the residuals appear to be equal across the regression line which is a sign of Homoscedasticity.

In [26]:
```
fig = plt.figure(figsize=(15,8))
fig = sm.graphics.plot_regress_exog(model, "sqft_lot_log", fig=fig)
plt.show()
```



However, for the Lot area, the residuals do not appear to be equal across the regression line which is a sign of heteroscedasticity i.e. the residuals are heteroscedastic. This violates an assumption.

Train-Test Split: Perform a train-test split with a test set of 20% and a random state of 4.

In [27]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=4)
```

In [28]:
```
#Fit a linear regression model on the training set

from sklearn.linear_model import LinearRegression
linreg = LinearRegression()
linreg.fit(X_train, y_train)
```

Out[28]:
```
LinearRegression()
```

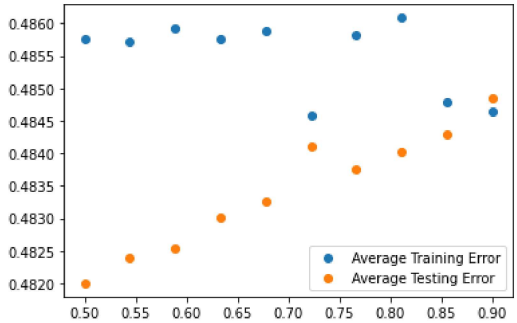
In [29]:
```
#Generate Predictions on Training and Test Sets
y_hat_train = linreg.predict(X_train)
y_hat_test = linreg.predict(X_test)
```

In [30]:
```
#Calculate the Mean Squared Error (MSE)
from sklearn.metrics import mean_squared_error
train_mse = mean_squared_error(y_train, y_hat_train)
test_mse = mean_squared_error(y_test, y_hat_test)
print('Train Mean Squared Error:', train_mse)
print('Test Mean Squared Error: ', test_mse)
```

```
Train Mean Squared Error: 0.48344525331522825
Test Mean Squared Error:  0.48512251743393336
```

The difference between Test MSE and Train MSE is quite small (appx 0.35%)

In [31]:
```
##Evaluate the effect of train tesst split size:
#Iterate over a range of train-test split sizes from .5 to .9
#For each train-test split size, generate 10 iterations of models/errors and save the average train/test error.
from sklearn.preprocessing import FunctionTransformer, OneHotEncoder

categoricals = ['baths_5+baths', 'quality_low']
continuous = ['sqft_living_log','sqft_lot_log']

log_transformer = FunctionTransformer(np.log, validate=True)
ohe = OneHotEncoder(drop='first', sparse=False)

train_mses = []
test_mses = []

t_sizes = np.linspace(0.5, 0.9, 10)
for t_size in t_sizes:

    inner_train_mses = []
    inner_test_mses = []
    for i in range(10):
        # Create new split
        X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=t_size, random_state=i)

        # Fit model
        linreg.fit(X_train, y_train)

        # Append metrics to their respective lists
        y_hat_train = linreg.predict(X_train)
        y_hat_test = linreg.predict(X_test)
        inner_train_mses.append(mean_squared_error(y_train, y_hat_train))
        inner_test_mses.append(mean_squared_error(y_test, y_hat_test))

    train_mses.append(np.mean(inner_train_mses))
    test_mses.append(np.mean(inner_test_mses))

fig, ax = plt.subplots()
ax.scatter(t_sizes, train_mses, label='Average Training Error')
ax.scatter(t_sizes, test_mses, label='Average Testing Error')
ax.legend();
```



As above, the average testing error is generally lower than the training error. This suggests that the model may generalize well to future cases.

Interpretation

The model summary shows that the R-squared value is 0.516 i.e. 51.6% of the house price can be explained by the dependent variables.

sqft_living_log - footage of the home; ; sqft_lot_log - footage of the lot; number of bathrooms and grade are found to tatistically significant to the pricing of a property in King County.

Footage of the home and the number of bathrooms have a positive relationship with the house price i.e. # increase in home footage or a home with more than 5 bathroom results in an increase in the house price. Similarly, quality_low - grade - a lower grade of a property is associated with a lower value in house price.

Wheras, sqft_lot_log - footage of the lot has an inversed relationship with the house price. Increase in footage of the lot is associated with a decrease in price of the house.

Model validation: QQ plot shows that the normality assumption of the residuals seems fulfilled.

In further analysis, for living footage, we can see the residuals appear to be equal across the regression line which is a sign of Homoscedasticity. However, for the Lot area, the residuals do not appear to be equal across the regression line which is a sign of heteroscedasticity i.e. the residuals are heteroscedastic. Therefore, living footage may be a better indicator/feature to be used.

The first train test shows that the difference between Test MSE and Train MSE is quite small (appx 0.35%). Similarly when run the train over 10 iterations over a range of train-test split sizes from .5 to .9, the Testing Error are better than the training error and the difference is also quite small. This suggests that the model is fitting well.