Introduction

Analyzing the effects of various features on 2015 Kings County housing prices using Linear Regression Modeling. Specifically looking at effects on Price Per Square Foot (PSF). PSF is another measure of value in addition to just overall price.

Imports and Functions

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns

import warnings
warnings.filterwarnings("ignore")

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

from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error
from sklearn.linear_model import LinearRegression
```

In [2]:
```
#Importing model function from class
def model(X_train, X_test, y_train, y_test):

    # statsmodels
    features = X_train.copy()
    features['psf'] = y_train

    formula = 'psf~' + '+'.join(X_train.columns)
    model = ols(formula=formula, data=features).fit()

    # sklearn
    linreg = LinearRegression()
    linreg.fit(X_train, y_train)

    y_hat_train = linreg.predict(X_train)
    y_hat_test = linreg.predict(X_test)

    train_mse = mean_squared_error(y_train, y_hat_train)
    test_mse = mean_squared_error(y_test, y_hat_test)

    print("Train R2: ", linreg.score(X_train, y_train))
    print("Test R2: ", linreg.score(X_test, y_test))

    print("Train RMSE: ", train_mse**0.5)
    print("Test RMSE: ", test_mse**0.5)

    # modified to display summary and return the model
    display(model.summary())
    return model
```

In [3]:
```
# Data Import
df = pd.read_csv('data/kc_house_data.csv')
```

Data Exploration

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

Out[4]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	vi
0	7129300520	10/13/2014	221900.0	3	1.00	1180	5650	1.0	NaN	
1	6414100192	12/9/2014	538000.0	3	2.25	2570	7242	2.0	0.0	
2	5631500400	2/25/2015	180000.0	2	1.00	770	10000	1.0	0.0	
3	2487200875	12/9/2014	604000.0	4	3.00	1960	5000	1.0	0.0	
4	1954400510	2/18/2015	510000.0	3	2.00	1680	8080	1.0	0.0	

5 rows × 21 columns

In [5]:
```
df.columns
```

Out[5]:
```
Index(['id', 'date', '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'],
      dtype='object')
```

In [6]:
```
df.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
```

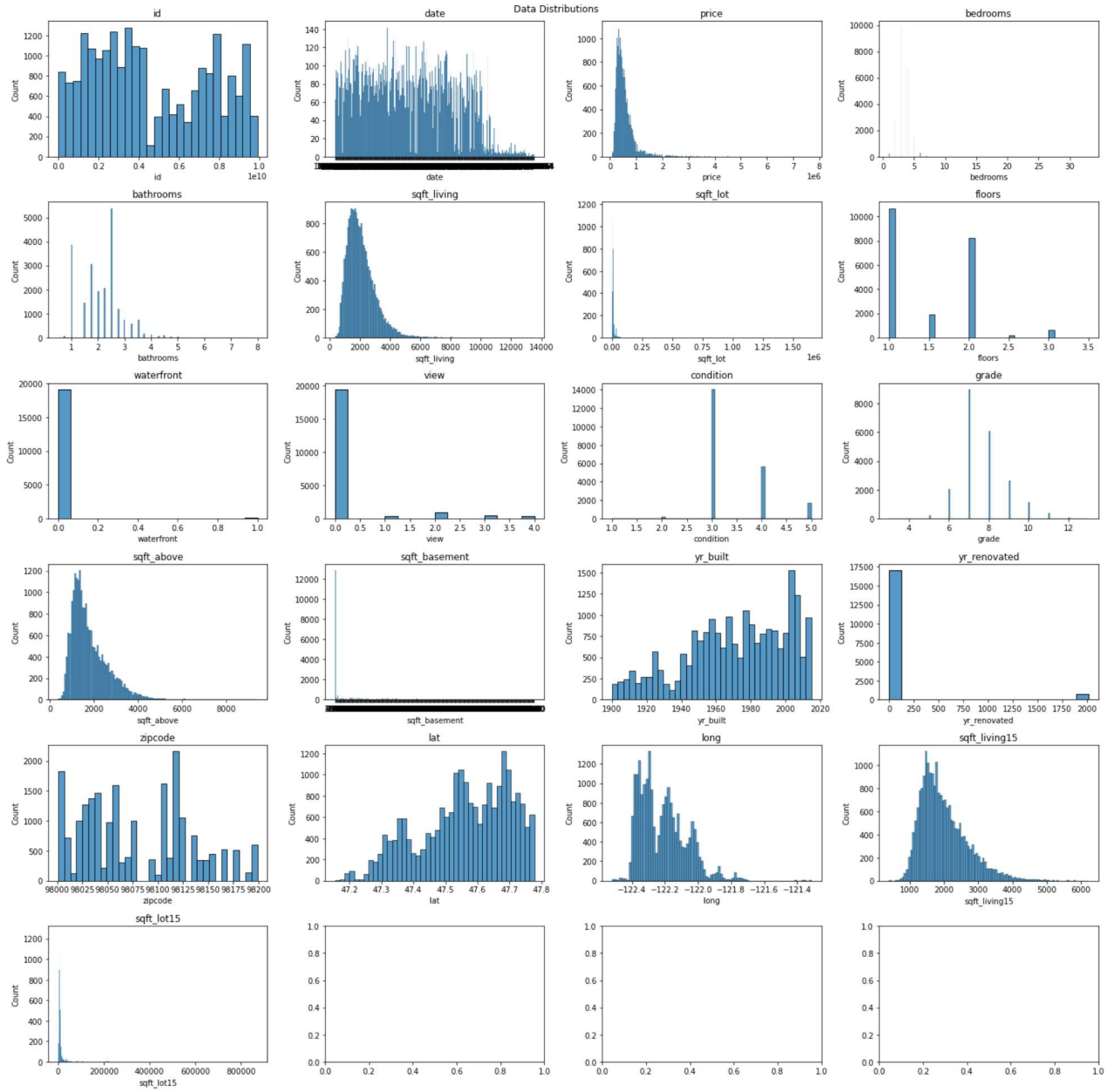
In [7]:
```
df.describe()
```

Out[7]:

	id	price	bedrooms	bathrooms	sqft_living	sqft_lot	floc
count	2.159700e+04	2.159700e+04	21597.000000	21597.000000	21597.000000	2.159700e+04	21597.0000
mean	4.580474e+09	5.402966e+05	3.373200	2.115826	2080.321850	1.509941e+04	1.4940
std	2.876736e+09	3.673681e+05	0.926299	0.768984	918.106125	4.141264e+04	0.5396
min	1.000102e+06	7.800000e+04	1.000000	0.500000	370.000000	5.200000e+02	1.0000
25%	2.123049e+09	3.220000e+05	3.000000	1.750000	1430.000000	5.040000e+03	1.0000
50%	3.904930e+09	4.500000e+05	3.000000	2.250000	1910.000000	7.618000e+03	1.5000
75%	7.308900e+09	6.450000e+05	4.000000	2.500000	2550.000000	1.068500e+04	2.0000
max	9.900000e+09	7.700000e+06	33.000000	8.000000	13540.000000	1.651359e+06	3.5000

Visualizations

In [8]:
```
# Looking at the distributions of each feature
fig, axes = plt.subplots(figsize=(20,20),ncols=4,nrows=6)
for i in range(len(df.columns)):
    col = df.columns[i]
    y = i%4
    x = i//4
    ax = axes[x,y]

    sns.histplot(df[col],ax=ax, bins = 'auto')
    ax.set_title(col)
    fig.suptitle('Data Distributions')
    fig.tight_layout()
```



Findings

- Many of the distributions are skewed to the right with strong outliers
- Other features do not make sense to analyze numerically such as: id, date, zipcodes
- A few others need additional exploration such as: basement sqft, year renovated that also have large 0 value counts

In [9]:
```
continuous_columns = ['price','sqft_living','sq_lot','condition','grade','sqft_above','
categorical_columns = ['bedrooms','bathrooms','floors','waterfront','sqft_basement','yr

#columns to be dropped
dropped_columns = ['id','date','view','sqft_living15','sqft_lot15','zipcode', 'lat','lo
```

Data Cleaning

Dropping Unwanted Columns

In [10]:
```
cleaned_df = df.drop(dropped_columns,axis=1)
```

In [11]:
```
cleaned_df.columns
```

Out[11]:
```
Index(['price', 'bedrooms', 'bathrooms', 'sqft_living', 'sqft_lot', 'floors',
       'waterfront', 'condition', 'grade', 'sqft_above', 'sqft_basement',
       'yr_built', 'yr_renovated'],
      dtype='object')
```

Filling NA values with 0

In [12]:
```
for col in cleaned_df.columns:
    print(col,": ",cleaned_df[col].isna().sum())
```

```
price :  0
bedrooms :  0
bathrooms :  0
sqft_living :  0
sqft_lot :  0
floors :  0
waterfront :  2376
condition :  0
grade :  0
sqft_above :  0
sqft_basement :  0
yr_built :  0
yr_renovated :  3842
```

In [13]:
```
cleaned_df = cleaned_df.fillna(0)
```

In [14]:
```
for col in cleaned_df.columns:
    print(col,": ",cleaned_df[col].isna().sum())
```

```
price :  0
bedrooms :  0
bathrooms :  0
sqft_living :  0
sqft_lot :  0
floors :  0
waterfront :  0
condition :  0
grade :  0
sqft_above :  0
sqft_basement :  0
yr_built :  0
yr_renovated :  0
```

Converting Basement SqFt to Float

In [15]:
```
cleaned_df = cleaned_df.replace(to_replace='?',value=0)
```

In [16]:
```
cleaned_df['sqft_basement'] = cleaned_df.sqft_basement.astype(float)
```

In [17]:
```
cleaned_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 21597 entries, 0 to 21596
```

```
Data columns (total 13 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   sqft_above     21597 non-null  int64
 10  sqft_basement  21597 non-null  float64
 11  yr_built       21597 non-null  int64
 12  yr_renovated   21597 non-null  float64
dtypes: float64(6), int64(7)
memory usage: 2.1 MB
```

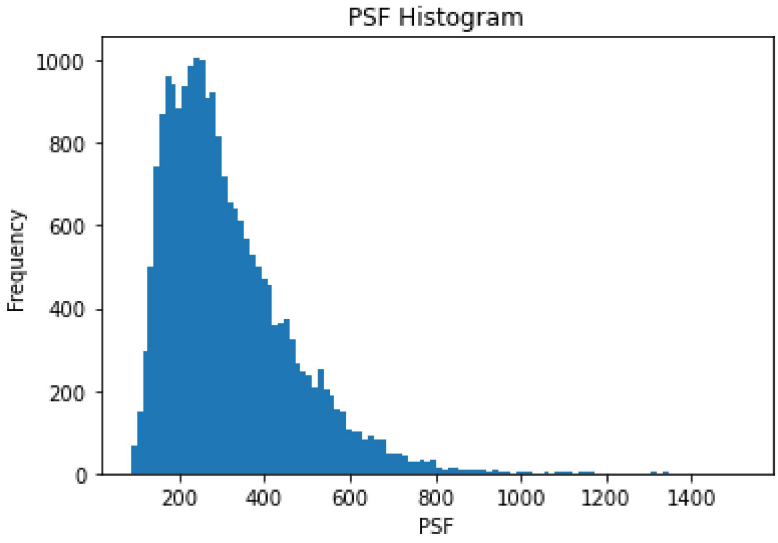
Generating and Modifying Features

In [18]:
```
mod_df = cleaned_df
```

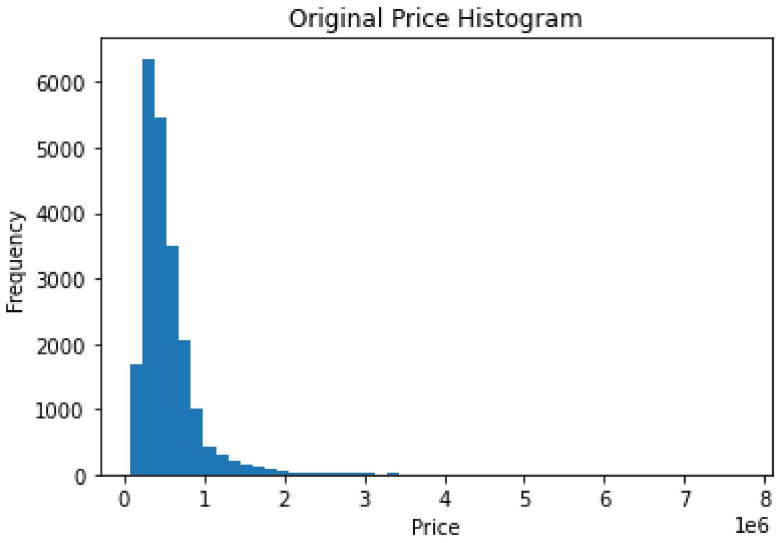
Price Per Square Foot (PSF) Using Sqft_Above

In [19]:
```
mod_df['psf'] = mod_df['price'] / mod_df['sqft_above']
```

In [20]:
```
plt.hist(mod_df['psf'], bins='auto');
plt.title('PSF Histogram')
plt.xlabel('PSF')
plt.ylabel('Frequency');
```



In [21]:
```
plt.hist(mod_df['price'], bins=50);
plt.title('Original Price Histogram')
plt.xlabel('Price')
plt.ylabel('Frequency');
```

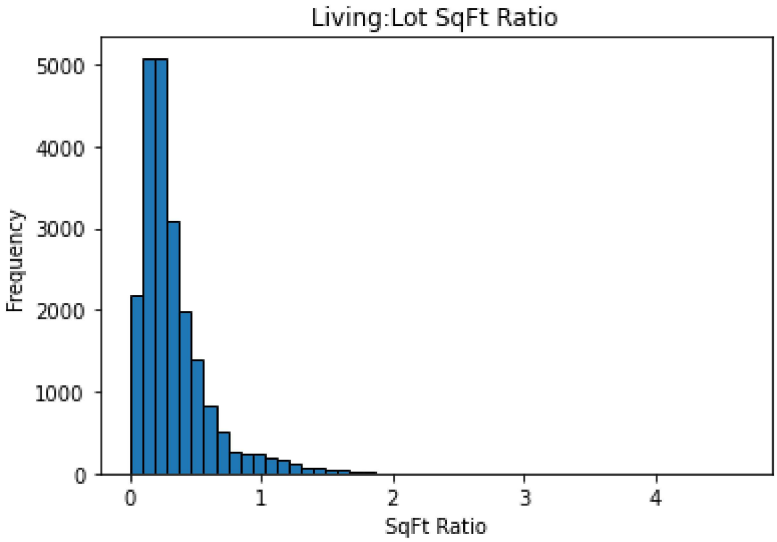


- PSF appears more normally distributed than original price, but distribution remains skewed towards higher PSF

Living to Lot Sqft Ratio

In [22]:
```
mod_df['livtolot'] = mod_df['sqft_living']/mod_df['sqft_lot']
```

In [23]:
```
plt.hist(mod_df['livtolot'], bins=50, ec = 'black');
plt.title('Living:Lot SqFt Ratio')
plt.xlabel('SqFt Ratio')
plt.ylabel('Frequency');
```



Categorical Changes

Basement Sqft to Categorical (Yes or No)

In [24]:
```
mod_df['has_basement'] = mod_df['sqft_basement'] > 0
mod_df['has_basement'] = mod_df['has_basement'].astype(int)
```

In [25]:
```
mod_df['has_basement'].value_counts()
```

Out[25]:
```
0    13280
1     8317
Name: has_basement, dtype: int64
```

Renovation Year to Categorical (Recent Reno or None)

In [26]:
```
# Using 27 years as a cutoff between recent renovations
mod_df['rec_reno'] = (mod_df['yr_renovated'] > 1988).astype(int)
```

In [27]:
```
mod_df['rec_reno'].value_counts()
```

Out[27]:
```
0    21055
1      542
Name: rec_reno, dtype: int64
```

Modified Features Exploration

Dropping Unused Columns

In [28]:
```
processed = mod_df
```

In [29]:
```
processed.columns
```

Out[29]:
```
Index(['price', 'bedrooms', 'bathrooms', 'sqft_living', 'sqft_lot', 'floors',
       'waterfront', 'condition', 'grade', 'sqft_above', 'sqft_basement',
       'yr_built', 'yr_renovated', 'psf', 'livtolot', 'has_basement',
       'rec_reno'],
      dtype='object')
```

In [30]:
```
modded_cols = ['price','sqft_living','sqft_lot','sqft_above','sqft_basement','yr_renova
```

In [31]:
```
processed = processed.drop(modded_cols, axis =1)
```

In [32]:
```
processed.columns
```

Out[32]:
```
Index(['bedrooms', 'bathrooms', 'floors', 'waterfront', 'condition', 'grade',
       'yr_built', 'psf', 'livtolot', 'has_basement', 'rec_reno'],
      dtype='object')
```

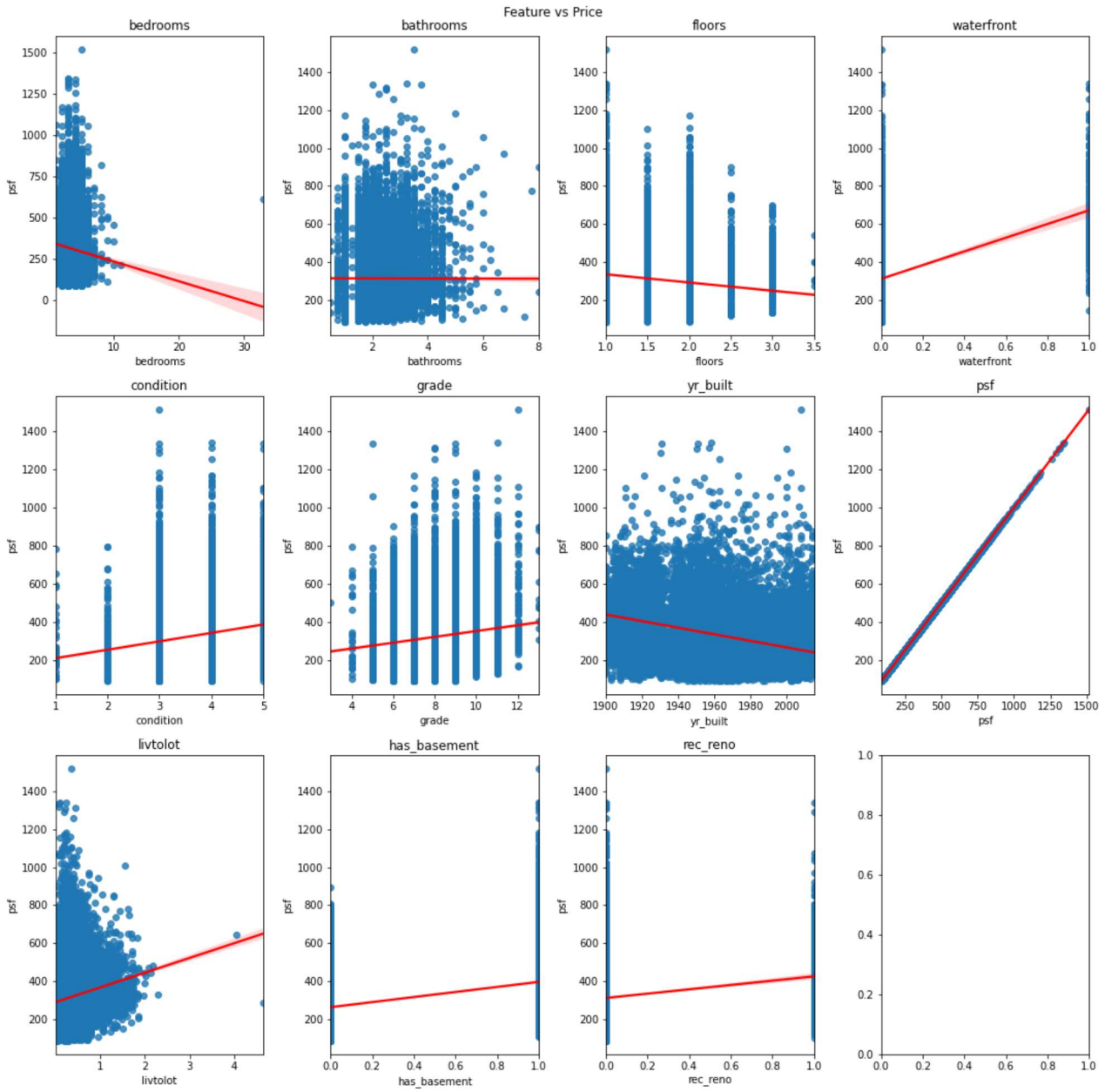
Linearity Checks

In [33]:
```
len(processed.columns)
```

Out[33]:
```
11
```

In [34]:
```
fig, axes = plt.subplots(figsize=(15,15),ncols=4,nrows=3)
for i in range(len(processed.columns)):
    col = processed.columns[i]
    y = i%4
    x = i//4
    ax = axes[x,y]

    sns.regplot(x=col, y='psf', data=processed, ax=ax, line_kws={'color':"red"})
```

```
    ax.set_title(col)
    fig.suptitle('Feature vs Price')
    fig.tight_layout()
```



Removing Erroneous Looking Bedroom Value

In [35]:
```
processed = processed.drop(processed.loc[processed.bedrooms > 30].index)
```

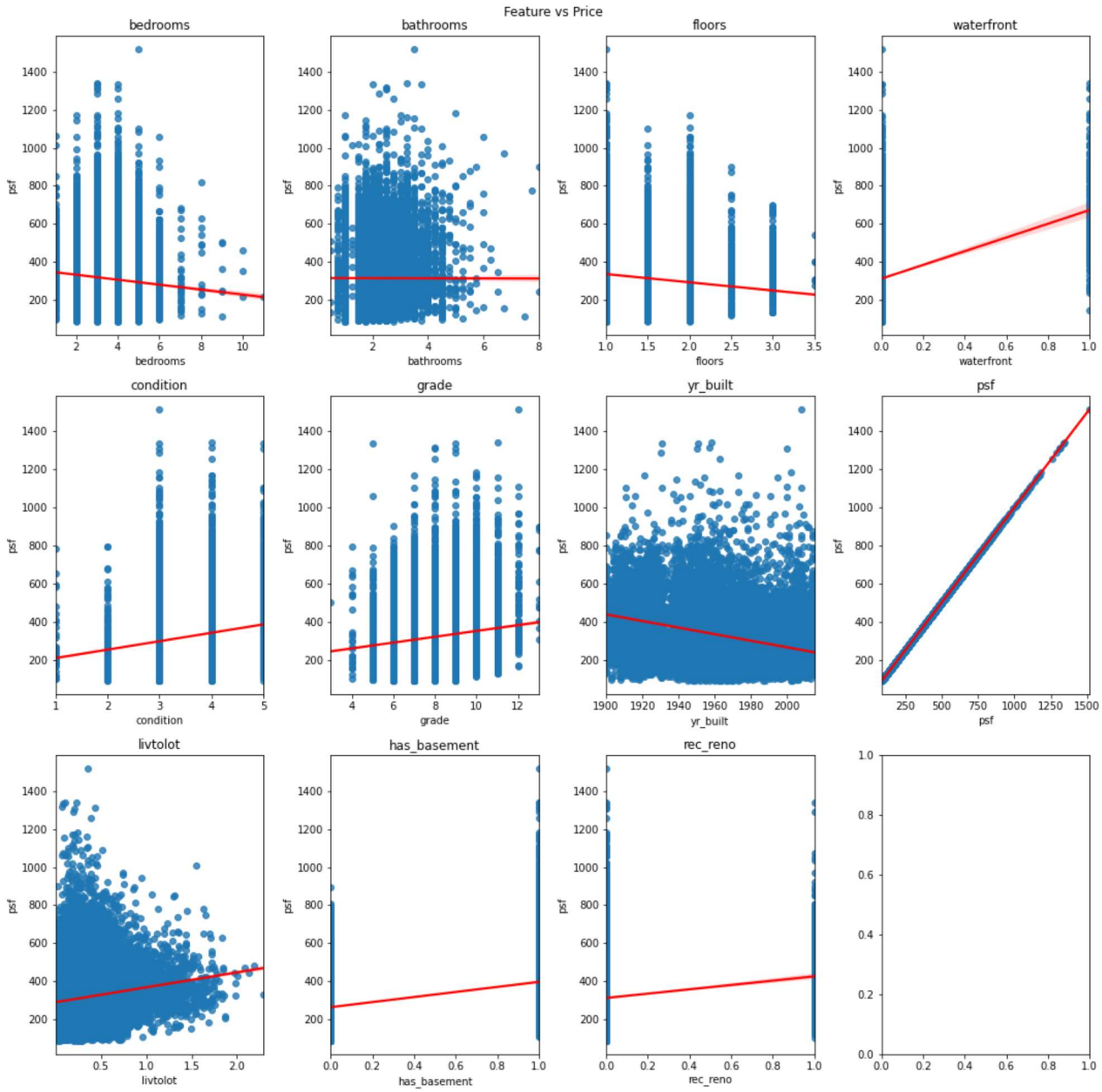
Removing Large Liv to Lot Values

In [36]:
```
processed = processed.drop(processed.loc[processed.livtolot > 4].index)
```

Second Linearity Checks

In [37]:
```
fig, axes = plt.subplots(figsize=(15,15),ncols=4,nrows=3)
for i in range(len(processed.columns)):
    col = processed.columns[i]
    y = i%4
    x = i//4
```

```
    ax = axes[x,y]

    #ax.hist(df[col], bins=50)
    #sns.scatterplot(df[col], df['price'],ax=ax)
    sns.regplot(x=col, y='psf', data=processed, ax=ax, line_kws={'color':"red"})
    ax.set_title(col)
    fig.suptitle('Feature vs Price')
    fig.tight_layout()
```



Findings

- Many of the features do not appear strongly lineary related to PSF
- Considering transformations to improve R Squared after initial analysis

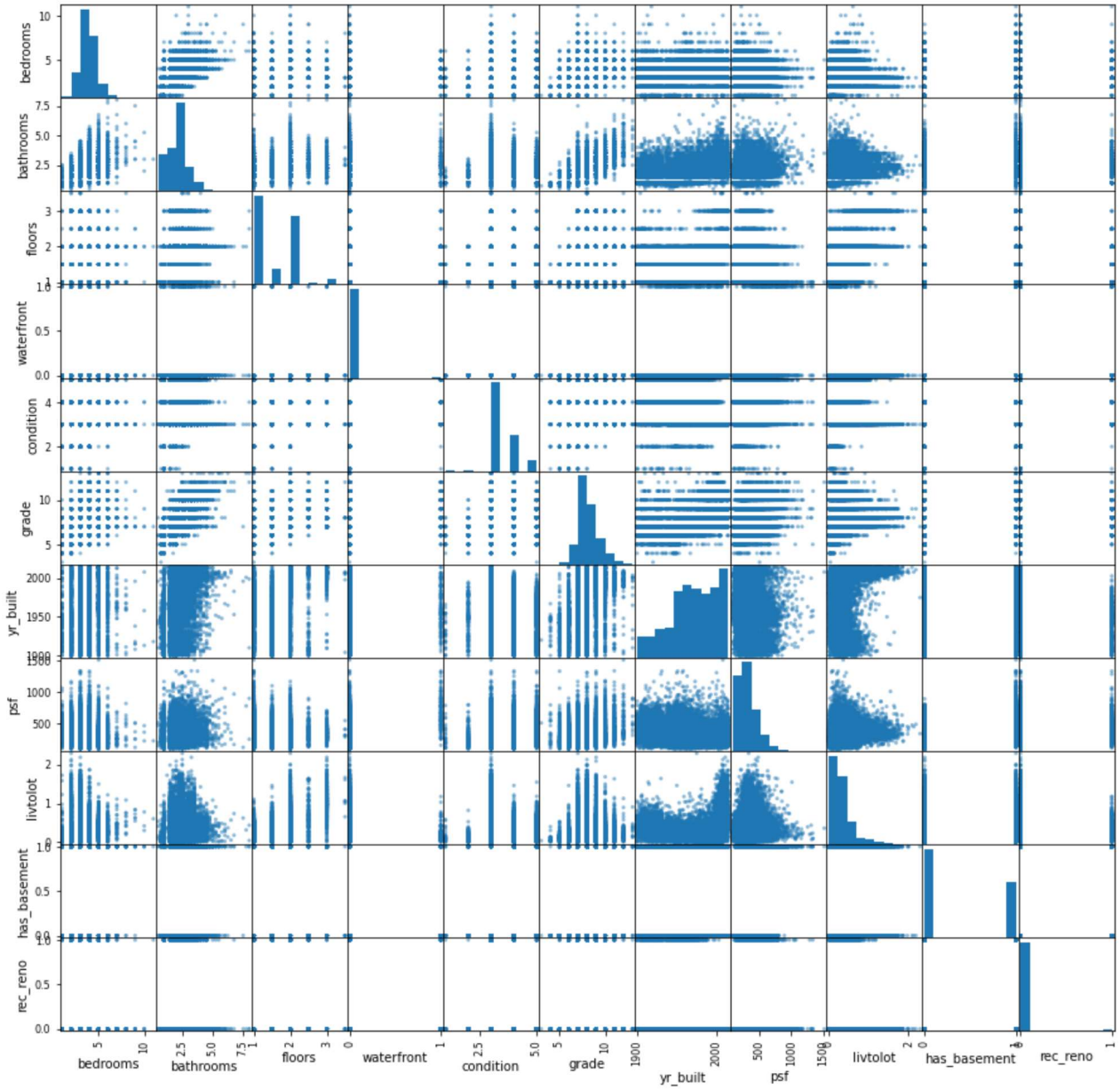
MultiCollinearity

In [38]:
```
processed.corr()
```

Out[38]:

	bedrooms	bathrooms	floors	waterfront	condition	grade	yr_built	psf
bedrooms	1.000000	0.527960	0.183948	-0.002058	0.023418	0.366487	0.160948	-0.079863
bathrooms	0.527960	1.000000	0.502606	0.063629	-0.126446	0.665893	0.507177	-0.001636
floors	0.183948	0.502606	1.000000	0.020808	-0.263984	0.458587	0.489176	-0.157900
waterfront	-0.002058	0.063629	0.020808	1.000000	0.016655	0.082842	-0.024499	0.200305
condition	0.023418	-0.126446	-0.263984	0.016655	1.000000	-0.146818	-0.361657	0.195487
grade	0.366487	0.665893	0.458587	0.082842	-0.146818	1.000000	0.447779	0.121800
yr_built	0.160948	0.507177	0.489176	-0.024499	-0.361657	0.447779	1.000000	-0.344073
psf	-0.079863	-0.001636	-0.157900	0.200305	0.195487	0.121800	-0.344073	1.000000
livtolot	0.028521	0.290111	0.560918	-0.030009	-0.157287	0.192043	0.283016	0.141329
has_basement	0.160524	0.159860	-0.252647	0.039230	0.130444	0.050561	-0.164159	0.438232
rec_reno	0.031583	0.068414	0.007530	0.048175	-0.072412	0.037720	-0.155568	0.120538

In [39]:
```
pd.plotting.scatter_matrix(processed, figsize = [15,15]);
```



Findings

- There aren't any strong multicollinear features present
- Need to keep an eye on the relationship between bathrooms, floors, grade, and year built

Initial Regression Modeling

In [40]:
```
processed.columns
```

Out[40]:
```
Index(['bedrooms', 'bathrooms', 'floors', 'waterfront', 'condition', 'grade',
       'yr_built', 'psf', 'livtolot', 'has_basement', 'rec_reno'],
      dtype='object')
```

In [41]:
```
x = processed[['bedrooms', 'bathrooms', 'floors', 'waterfront', 'condition', 'grade',
       'yr_built','livtolot', 'has_basement','rec_reno']]
y = processed[['psf']].to_numpy().flatten()
x_train, x_test, y_train, y_test = train_test_split(x,y,test_size=0.2)
```

Model Summary

In [42]:
```
initial_model = model(x_train,x_test,y_train,y_test);
```

```
Train R2:  0.43377432194621235
Test R2:  0.40822081321214365
Train RMSE:  110.71677232083508
Test RMSE:  114.30944573409586
```

OLS Regression Results

Dep. Variable:	psf	**R-squared:**	0.434
Model:	OLS	**Adj. R-squared:**	0.433
Method:	Least Squares	**F-statistic:**	1323.
Date:	Tue, 27 Jul 2021	**Prob (F-statistic):**	0.00
Time:	20:40:39	**Log-Likelihood:**	-1.0583e+05
No. Observations:	17275	**AIC:**	2.117e+05
Df Residuals:	17264	**BIC:**	2.118e+05
Df Model:	10		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	3924.9503	77.284	50.786	0.000	3773.465	4076.435
bedrooms	-29.9995	1.122	-26.731	0.000	-32.199	-27.800
bathrooms	0.5633	1.846	0.305	0.760	-3.055	4.182
floors	-38.6460	2.539	-15.221	0.000	-43.623	-33.669
waterfront	274.8170	10.251	26.810	0.000	254.725	294.909
condition	16.5457	1.423	11.625	0.000	13.756	19.336
grade	45.7833	1.007	45.487	0.000	43.810	47.756
yr_built	-1.9987	0.039	-50.795	0.000	-2.076	-1.922
livtolot	132.1307	4.243	31.143	0.000	123.815	140.447
has_basement	89.4726	2.131	41.987	0.000	85.296	93.649
rec_reno	35.1105	5.640	6.225	0.000	24.055	46.166

Omnibus:	3452.405	**Durbin-Watson:**	2.014
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	10834.579
Skew:	1.024	**Prob(JB):**	0.00
Kurtosis:	6.295	**Cond. No.**	1.81e+05

Notes:

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

[2] The condition number is large, 1.81e+05. This might indicate that there are strong multicollinearity or other numerical problems.

Dropping High P Values

In [43]:
```
x_bath = x.drop('bathrooms', axis = 1)
```

Model Summary Update

In [44]:
```
x_train, x_test, y_train, y_test = train_test_split(x_bath,y,test_size=0.2)
initial_model2 = model(x_train,x_test,y_train,y_test);
```

```
Train R2:  0.4242140546352119
Test R2:  0.44561229900341603
Train RMSE:  111.58161271753842
Test RMSE:  110.89446540988133
```

OLS Regression Results

Dep. Variable:	psf	**R-squared:**	0.424
Model:	OLS	**Adj. R-squared:**	0.424
Method:	Least Squares	**F-statistic:**	1413.
Date:	Tue, 27 Jul 2021	**Prob (F-statistic):**	0.00
Time:	20:40:39	**Log-Likelihood:**	-1.0596e+05
No. Observations:	17275	**AIC:**	2.119e+05
Df Residuals:	17265	**BIC:**	2.120e+05
Df Model:	9		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	3859.0573	72.470	53.250	0.000	3717.008	4001.106
bedrooms	-28.8308	1.037	-27.804	0.000	-30.863	-26.798
floors	-39.2296	2.467	-15.902	0.000	-44.065	-34.394
waterfront	278.1893	10.722	25.945	0.000	257.173	299.206
condition	15.8488	1.430	11.083	0.000	13.046	18.652
grade	44.9799	0.925	48.627	0.000	43.167	46.793
yr_built	-1.9617	0.037	-52.583	0.000	-2.035	-1.889
livtolot	132.0443	4.306	30.666	0.000	123.604	140.484
has_basement	89.9748	2.071	43.436	0.000	85.915	94.035
rec_reno	29.5171	5.670	5.206	0.000	18.403	40.631

Omnibus:	3908.105	**Durbin-Watson:**	2.008
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	14175.305
Skew:	1.107	**Prob(JB):**	0.00

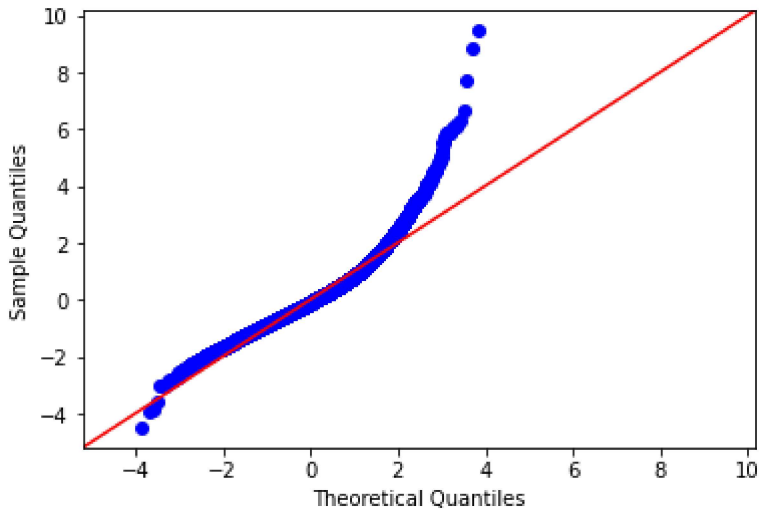
Kurtosis:	6.846	**Cond. No.**	1.68e+05

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 1.68e+05. This might indicate that there are
strong multicollinearity or other numerical problems.

Assumptions Check

Normalization

In [45]:
```
initial_residuals = initial_model2.resid
fig = sm.graphics.qqplot(initial_residuals,dist=stats.norm,line='45',fit=True)
```



Homoscedasticity

In [46]:
```
sns.scatterplot(y_train,initial_residuals)
plt.title('Scatter of Errors')
plt.xlabel('PSF')
plt.ylabel('Error');
```

Findings

- Benchmark R-Squared is .433
- RMSE difference between Train and Test is low at ~4 PSF
- Distribution of Residuals are skewed to the right
- Fails homoscedasticity check, higher PSF are largely underpredicted and lower PSF overpredicted

Iteration 2: Log Transforms

Log Transformation

In [47]:
```
log_df = processed.drop('bathrooms',axis=1)
```

In [48]:
```
log_cont = ['bedrooms','floors','condition','grade','yr_built','psf','livtolot']
```

In [49]:
```
for cat in log_cont:
    log_df[cat] = np.log(log_df[cat])
```

In [50]:
```
log_df.head()
```

Out[50]:

	bedrooms	floors	waterfront	condition	grade	yr_built	psf	livtolot	has_basement	r
0	1.098612	0.000000	0.0	1.098612	1.945910	7.578145	5.236712	-1.566141	0	
1	1.098612	0.693147	0.0	1.098612	1.945910	7.576097	5.513131	-1.035992	1	
2	0.693147	0.000000	0.0	1.098612	1.791759	7.566828	5.454322	-2.563950	0	
3	1.386294	0.000000	0.0	1.609438	1.945910	7.583248	6.354784	-0.936493	1	
4	1.098612	0.000000	0.0	1.098612	2.079442	7.594381	5.715617	-1.570598	0	

Model Summary

In [51]:
```
x_log = log_df[['bedrooms', 'floors', 'waterfront', 'condition', 'grade',
       'yr_built','livtolot', 'has_basement','rec_reno']]
y_log = log_df[['psf']].to_numpy().flatten()
x_train, x_test, y_train, y_test = train_test_split(x_log,y_log,test_size=0.2)
log_model = model(x_train,x_test,y_train,y_test);
```

```
Train R2:  0.41893298397229817
Test R2:  0.40543209595255114
Train RMSE:  0.3374762326415983
Test RMSE:  0.3416505680227557
```

OLS Regression Results

Dep. Variable:	psf	**R-squared:**	0.419
Model:	OLS	**Adj. R-squared:**	0.419
Method:	Least Squares	**F-statistic:**	1383.
Date:	Tue, 27 Jul 2021	**Prob (F-statistic):**	0.00
Time:	20:40:40	**Log-Likelihood:**	-5747.0
No. Observations:	17275	**AIC:**	1.151e+04
Df Residuals:	17265	**BIC:**	1.159e+04
Df Model:	9		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	85.0225	1.658	51.295	0.000	81.774	88.271
bedrooms	-0.3954	0.010	-39.376	0.000	-0.415	-0.376
floors	-0.0788	0.010	-7.687	0.000	-0.099	-0.059
waterfront	0.5595	0.032	17.642	0.000	0.497	0.622
condition	0.1691	0.015	10.981	0.000	0.139	0.199
grade	1.0884	0.022	48.872	0.000	1.045	1.132
yr_built	-10.7189	0.220	-48.786	0.000	-11.150	-10.288
livtolot	0.0704	0.003	20.334	0.000	0.064	0.077
has_basement	0.3269	0.006	54.239	0.000	0.315	0.339
rec_reno	0.0683	0.017	4.077	0.000	0.035	0.101

Omnibus:	39.793	**Durbin-Watson:**	2.023
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	49.334
Skew:	-0.027	**Prob(JB):**	1.94e-11
Kurtosis:	3.256	**Cond. No.**	5.36e+03

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 5.36e+03. This might indicate that there are
strong multicollinearity or other numerical problems.

Model Summary Update - Only Log Transform Features

In [52]:
```
x_log = log_df[['bedrooms', 'floors', 'waterfront', 'condition', 'grade',
       'yr_built','livtolot', 'has_basement','rec_reno']]
y_log = processed[['psf']].to_numpy().flatten()
x_train, x_test, y_train, y_test = train_test_split(x_log,y_log,test_size=0.2)
log_model = model(x_train,x_test,y_train,y_test);
```

```
Train R2:  0.42057306148389706
Test R2:  0.40835279017010895
Train RMSE:  111.94256448586863
Test RMSE:  114.52499877644922
```

OLS Regression Results

Dep. Variable:	psf	**R-squared:**	0.421
Model:	OLS	**Adj. R-squared:**	0.420
Method:	Least Squares	**F-statistic:**	1392.
Date:	Tue, 27 Jul 2021	**Prob (F-statistic):**	0.00
Time:	20:40:40	**Log-Likelihood:**	-1.0602e+05
No. Observations:	17275	**AIC:**	2.121e+05
Df Residuals:	17265	**BIC:**	2.121e+05
Df Model:	9		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	2.684e+04	551.832	48.642	0.000	2.58e+04	2.79e+04
bedrooms	-121.8798	3.338	-36.508	0.000	-128.424	-115.336
floors	-32.9184	3.397	-9.689	0.000	-39.578	-26.259
waterfront	276.1353	10.711	25.780	0.000	255.140	297.130
condition	60.4936	5.152	11.743	0.000	50.396	70.591
grade	349.1528	7.383	47.290	0.000	334.681	363.625
yr_built	-3579.7456	73.148	-48.938	0.000	-3723.123	-3436.368
livtolot	26.1392	1.147	22.790	0.000	23.891	28.387
has_basement	99.9772	2.002	49.933	0.000	96.053	103.902
rec_reno	38.1745	5.598	6.820	0.000	27.203	49.146

Omnibus:	3657.877	**Durbin-Watson:**	1.997
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	12788.998
Skew:	1.048	**Prob(JB):**	0.00

Kurtosis:	6.657	**Cond. No.**	5.38e+03

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 5.38e+03. This might indicate that there are
strong multicollinearity or other numerical problems.

Model Summary Update - Only Log Transform PSF

In [53]:
```
x_log2 = processed[['bedrooms', 'floors', 'waterfront', 'condition', 'grade',
       'yr_built','livtolot', 'has_basement','rec_reno']]
y_log2 = log_df[['psf']].to_numpy().flatten()
x_train2, x_test2, y_train2, y_test2 = train_test_split(x_log2,y_log2,test_size=0.2)
log_model2 = model(x_train2,x_test2,y_train2,y_test2);
```

```
Train R2:  0.430779410910351
Test R2:  0.4225647527332306
Train RMSE:  0.33272575296465207
Test RMSE:  0.3418443082819723
```

OLS Regression Results

Dep. Variable:	psf	**R-squared:**	0.431
Model:	OLS	**Adj. R-squared:**	0.430
Method:	Least Squares	**F-statistic:**	1452.
Date:	Tue, 27 Jul 2021	**Prob (F-statistic):**	0.00
Time:	20:40:40	**Log-Likelihood:**	-5502.1
No. Observations:	17275	**AIC:**	1.102e+04
Df Residuals:	17265	**BIC:**	1.110e+04
Df Model:	9		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	16.3548	0.217	75.358	0.000	15.929	16.780
bedrooms	-0.0996	0.003	-31.953	0.000	-0.106	-0.093
floors	-0.1097	0.007	-14.849	0.000	-0.124	-0.095
waterfront	0.5736	0.031	18.259	0.000	0.512	0.635
condition	0.0469	0.004	11.007	0.000	0.039	0.055
grade	0.1387	0.003	50.103	0.000	0.133	0.144
yr_built	-0.0059	0.000	-52.992	0.000	-0.006	-0.006
livtolot	0.3991	0.013	31.165	0.000	0.374	0.424
has_basement	0.2891	0.006	46.819	0.000	0.277	0.301
rec_reno	0.0493	0.017	2.929	0.003	0.016	0.082

Omnibus:	40.576	**Durbin-Watson:**	1.979
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	48.921
Skew:	-0.045	**Prob(JB):**	2.38e-11
Kurtosis:	3.244	**Cond. No.**	1.69e+05

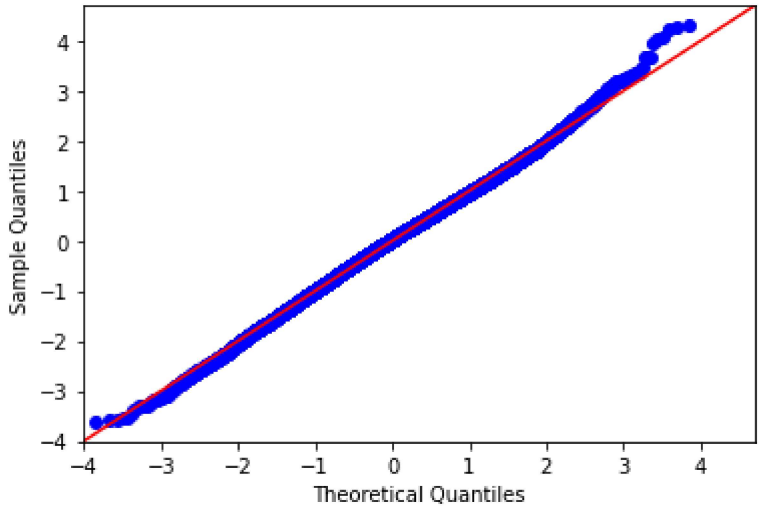
Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 1.69e+05. This might indicate that there are strong multicollinearity or other numerical problems.

In [54]:
```
# Log transforming PSF yielded best results along with no high p values
```

Assumptions Check

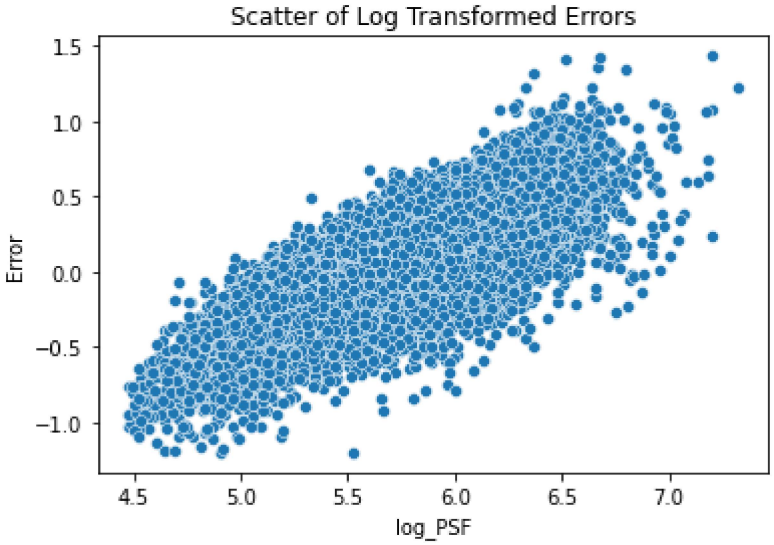
Normalization

In [55]:
```
log_residuals2 = log_model2.resid
fig = sm.graphics.qqplot(log_residuals2,dist=stats.norm,line='45',fit=True)
```



Homoscedasticity

In [56]:
```
sns.scatterplot(y_train2,log_residuals2)
plt.title('Scatter of Log Transformed Errors')
plt.xlabel('log_PSF')
plt.ylabel('Error');
```



Findings

- R Squared is worse at .426 after log transforming just PSF
- Difference in RMSE is low at .001 log(PSF), equates to ~ 1 PSF
- Distribution of residuals is close to normal
- Still fails homoscedasticity. However, appears more randomly distributed

Iteration 3: Adding Back ZipCodes

- Considered adding back some location features to see the effects on the model

Re-updating DataFrame and Cleaning

In [57]:
```
dropped_columns2 = ['id','date','view','sqft_living15','sqft_lot15','bathrooms', 'lat',
```

In [58]:
```
df_zip = df.drop(dropped_columns2,axis=1)
```

In [59]:
```
df_zip.columns
```

Out[59]:
```
Index(['price', 'bedrooms', 'sqft_living', 'sqft_lot', 'floors', 'waterfront',
       'condition', 'grade', 'sqft_above', 'sqft_basement', 'yr_built',
       'yr_renovated', 'zipcode'],
      dtype='object')
```

In [60]:
```
# Handling NA Values
df_zip = df_zip.fillna(0)
df_zip = df_zip.replace(to_replace='?',value=0)

# Feature Generation and Modifications
df_zip['sqft_basement'] = df_zip.sqft_basement.astype(float)
df_zip['psf'] = df_zip['price'] / df_zip['sqft_above']
df_zip['livtolot'] = df_zip['sqft_living']/df_zip['sqft_lot']
df_zip['has_basement'] = df_zip['sqft_basement'] > 0
df_zip['has_basement'] = df_zip['has_basement'].astype(int)
df_zip['rec_reno'] = (df_zip['yr_renovated'] > 1988).astype(int)
```

```
modded_cols = ['price','sqft_living','sqft_lot','sqft_above','sqft_basement','yr_renova
df_zip = df_zip.drop(modded_cols, axis =1)

# Removing Extreme Values
df_zip = df_zip.drop(df_zip.loc[df_zip.bedrooms > 30].index)
df_zip = df_zip.drop(df_zip.loc[df_zip.livtolot > 4].index)
```

In [61]:
```
df_zip.head()
```

Out[61]:

	bedrooms	floors	waterfront	condition	grade	yr_built	zipcode	psf	livtolot	has_baseme
0	3	1.0	0.0	3	7	1955	98178	188.050847	0.208850	
1	3	2.0	0.0	3	7	1951	98125	247.926267	0.354874	
2	2	1.0	0.0	3	6	1933	98028	233.766234	0.077000	
3	4	1.0	0.0	5	7	1965	98136	575.238095	0.392000	
4	3	1.0	0.0	3	8	1987	98074	303.571429	0.207921	

Creating Dummy Variables for Zipcodes

In [62]:
```
dummy_zips = pd.get_dummies(df_zip['zipcode'], prefix='zip', drop_first=True)
df_zip = pd.concat([df_zip, dummy_zips], axis=1)
```

In [63]:
```
df_zip = df_zip.drop('zipcode', axis=1)
```

Model Summary

In [64]:
```
x_zip = df_zip.drop('psf',axis=1)
y_zip = df_zip[['psf']].to_numpy().flatten()
x_train, x_test, y_train, y_test = train_test_split(x_zip,y_zip,test_size=0.2)
zip_model = model(x_train,x_test,y_train,y_test);
```

```
Train R2:  0.7204509150178939
Test R2:  0.7005919511975671
Train RMSE:  77.727043151373
Test RMSE:  81.58722742408328
```

OLS Regression Results

Dep. Variable:	psf	**R-squared:**	0.720
Model:	OLS	**Adj. R-squared:**	0.719
Method:	Least Squares	**F-statistic:**	568.2
Date:	Tue, 27 Jul 2021	**Prob (F-statistic):**	0.00
Time:	20:40:41	**Log-Likelihood:**	-99714.
No. Observations:	17275	**AIC:**	1.996e+05
Df Residuals:	17196	**BIC:**	2.002e+05
Df Model:	78		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	144.4244	68.102	2.121	0.034	10.938	277.911
bedrooms	-20.5132	0.751	-27.300	0.000	-21.986	-19.040
floors	-42.7397	1.771	-24.132	0.000	-46.211	-39.268
waterfront	328.4401	7.525	43.644	0.000	313.689	343.191
condition	19.2524	1.034	18.619	0.000	17.226	21.279
grade	13.4300	0.723	18.571	0.000	12.013	14.847
yr_built	-0.0083	0.035	-0.238	0.812	-0.076	0.060
livtolot	-35.8236	3.663	-9.781	0.000	-43.003	-28.645
has_basement	74.3013	1.485	50.046	0.000	71.391	77.211
rec_reno	37.4289	3.964	9.441	0.000	29.658	45.199
zip_98002	-5.6068	7.695	-0.729	0.466	-20.690	9.476
zip_98003	-3.0284	6.946	-0.436	0.663	-16.642	10.586
zip_98004	384.4756	6.876	55.916	0.000	370.998	397.953
zip_98005	179.7199	8.283	21.698	0.000	163.485	195.955
zip_98006	174.9147	6.105	28.650	0.000	162.948	186.881
zip_98007	156.9835	8.659	18.129	0.000	140.011	173.956
zip_98008	172.1601	6.994	24.616	0.000	158.451	185.869
zip_98010	66.5868	10.169	6.548	0.000	46.655	86.518
zip_98011	90.0815	7.857	11.465	0.000	74.680	105.483
zip_98014	66.1733	9.104	7.269	0.000	48.328	84.018
zip_98019	64.1506	7.797	8.228	0.000	48.868	79.433
zip_98022	14.4117	7.436	1.938	0.053	-0.164	28.988
zip_98023	-14.7937	6.018	-2.458	0.014	-26.589	-2.999
zip_98024	91.3939	10.520	8.687	0.000	70.773	112.015
zip_98027	114.2134	6.392	17.869	0.000	101.685	126.741
zip_98028	90.2415	6.848	13.178	0.000	76.819	103.664
zip_98029	144.1839	6.772	21.293	0.000	130.911	157.457
zip_98030	8.9491	7.188	1.245	0.213	-5.141	23.039
zip_98031	11.5224	6.958	1.656	0.098	-2.116	25.160
zip_98032	-15.2703	9.275	-1.646	0.100	-33.449	2.909
zip_98033	219.4658	6.297	34.851	0.000	207.123	231.809
zip_98034	125.5375	5.974	21.014	0.000	113.828	137.247
zip_98038	40.0817	5.834	6.871	0.000	28.647	51.516
zip_98039	458.2905	13.537	33.855	0.000	431.757	484.824

zip_98040	275.3796	7.102	38.773	0.000	261.458	289.301
zip_98042	9.1712	5.993	1.530	0.126	-2.575	20.918
zip_98045	66.6718	7.395	9.016	0.000	52.178	81.166
zip_98052	150.6054	5.818	25.885	0.000	139.201	162.010
zip_98053	118.4941	6.408	18.493	0.000	105.934	131.054
zip_98055	33.9239	7.001	4.846	0.000	20.202	47.646
zip_98056	69.4059	6.388	10.865	0.000	56.885	81.927
zip_98058	25.1112	6.160	4.076	0.000	13.036	37.186
zip_98059	68.5056	6.128	11.180	0.000	56.495	80.517
zip_98065	85.2505	6.775	12.583	0.000	71.971	98.530
zip_98070	62.9318	9.425	6.677	0.000	44.457	81.406
zip_98072	101.4707	7.003	14.489	0.000	87.743	115.198
zip_98074	128.2952	6.259	20.499	0.000	116.028	140.563
zip_98075	128.3089	6.612	19.407	0.000	115.350	141.268
zip_98077	83.1960	7.795	10.673	0.000	67.916	98.476
zip_98092	3.7925	6.525	0.581	0.561	-8.997	16.582
zip_98102	330.6029	10.093	32.757	0.000	310.820	350.385
zip_98103	270.1824	6.170	43.793	0.000	258.089	282.275
zip_98105	313.1846	7.761	40.355	0.000	297.973	328.396
zip_98106	100.9933	6.676	15.127	0.000	87.907	114.080
zip_98107	289.4424	7.426	38.977	0.000	274.887	303.998
zip_98108	100.5614	7.767	12.947	0.000	85.337	115.786
zip_98109	356.4111	9.755	36.536	0.000	337.290	375.532
zip_98112	357.9295	7.390	48.431	0.000	343.443	372.415
zip_98115	253.5721	6.026	42.079	0.000	241.760	265.384
zip_98116	257.1543	6.892	37.312	0.000	243.645	270.663
zip_98117	259.8362	6.145	42.284	0.000	247.791	271.881
zip_98118	130.8653	6.185	21.160	0.000	118.743	142.988
zip_98119	362.3988	8.077	44.866	0.000	346.566	378.231
zip_98122	265.5572	7.254	36.608	0.000	251.338	279.776
zip_98125	154.4344	6.381	24.201	0.000	141.927	166.942
zip_98126	155.9000	6.728	23.171	0.000	142.712	169.088
zip_98133	111.1280	6.082	18.271	0.000	99.206	123.050
zip_98136	211.9238	7.236	29.288	0.000	197.741	226.107
zip_98144	209.0536	6.834	30.591	0.000	195.659	222.448

zip_98146	71.9472	6.855	10.495	0.000	58.510	85.384
zip_98148	20.3424	12.393	1.641	0.101	-3.950	44.635
zip_98155	92.6447	6.218	14.899	0.000	80.457	104.833
zip_98166	53.9804	7.129	7.572	0.000	40.008	67.953
zip_98168	15.7313	7.139	2.203	0.028	1.737	29.725
zip_98177	157.0242	7.173	21.891	0.000	142.965	171.084
zip_98178	36.9532	7.047	5.244	0.000	23.140	50.766
zip_98188	16.4214	8.583	1.913	0.056	-0.403	33.246
zip_98198	6.1447	7.074	0.869	0.385	-7.720	20.010
zip_98199	290.9293	6.899	42.170	0.000	277.407	304.452

Omnibus:	5447.096	**Durbin-Watson:**	1.996
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	43184.160
Skew:	1.295	**Prob(JB):**	0.00
Kurtosis:	10.300	**Cond. No.**	2.29e+05

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 2.29e+05. This might indicate that there are strong multicollinearity or other numerical problems.

Dropping High P

In [65]:
```
(zip_model.pvalues > .05).sort_values()
```

Out[65]:
```
Intercept    False
zip_98108    False
zip_98107    False
zip_98106    False
zip_98105    False
             ...
zip_98003     True
zip_98030     True
zip_98092     True
zip_98148     True
zip_98042     True
Length: 79, dtype: bool
```

In [66]:
```
high_p = zip_model.pvalues.loc[zip_model.pvalues > .05].index
high_p
```

Out[66]:
```
Index(['yr_built', 'zip_98002', 'zip_98003', 'zip_98022', 'zip_98030',
       'zip_98031', 'zip_98032', 'zip_98042', 'zip_98092', 'zip_98148',
       'zip_98188', 'zip_98198'],
      dtype='object')
```

In [67]:
```
#Intercept excluded for dropping columns
```

```
high_p_indexes = ['yr_built', 'zip_98002', 'zip_98003', 'zip_98022',
       'zip_98030', 'zip_98031', 'zip_98032', 'zip_98042', 'zip_98092',
       'zip_98198']
```

In [68]:
```
zip_df_update = df_zip.drop(high_p_indexes,axis=1)
```

Model Summary Update

In [69]:
```
x_zip2 = zip_df_update.drop('psf',axis=1)
y_zip2= zip_df_update[['psf']].to_numpy().flatten()
x_train2, x_test2, y_train2, y_test2 = train_test_split(x_zip2,y_zip2,test_size=0.2)
zip_model2 = model(x_train2,x_test2,y_train2,y_test2);
```

```
Train R2:  0.7189197728749639
Test R2:  0.7055430384818876
Train RMSE:  77.9891549599039
Test RMSE:  80.7079262098691
```

OLS Regression Results

Dep. Variable:	psf	**R-squared:**	0.719
Model:	OLS	**Adj. R-squared:**	0.718
Method:	Least Squares	**F-statistic:**	647.2
Date:	Tue, 27 Jul 2021	**Prob (F-statistic):**	0.00
Time:	20:40:41	**Log-Likelihood:**	-99772.
No. Observations:	17275	**AIC:**	1.997e+05
Df Residuals:	17206	**BIC:**	2.002e+05
Df Model:	68		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	127.5034	6.183	20.622	0.000	115.384	139.623
bedrooms	-20.0663	0.751	-26.719	0.000	-21.538	-18.594
floors	-43.2345	1.748	-24.732	0.000	-46.661	-39.808
waterfront	325.7472	7.491	43.488	0.000	311.065	340.430
condition	19.3575	0.991	19.539	0.000	17.416	21.299
grade	14.0415	0.686	20.462	0.000	12.696	15.387
livtolot	-36.0096	3.342	-10.775	0.000	-42.560	-29.459
has_basement	73.7640	1.486	49.642	0.000	70.851	76.677
rec_reno	41.4510	3.867	10.718	0.000	33.871	49.031
zip_98004	368.5759	5.254	70.147	0.000	358.277	378.875
zip_98005	178.0890	6.905	25.792	0.000	164.555	191.623
zip_98006	174.2632	4.357	39.993	0.000	165.722	182.804
zip_98007	154.5685	7.333	21.079	0.000	140.195	168.942

zip_98008	161.4693	5.534	29.176	0.000	150.622	172.317
zip_98010	45.1566	9.302	4.855	0.000	26.924	63.389
zip_98011	81.1790	6.474	12.540	0.000	68.490	93.868
zip_98014	59.8702	8.472	7.067	0.000	43.265	76.475
zip_98019	62.1500	6.738	9.224	0.000	48.943	75.357
zip_98023	-21.1232	4.254	-4.965	0.000	-29.462	-12.784
zip_98024	91.1023	9.919	9.185	0.000	71.660	110.544
zip_98027	112.9712	4.657	24.257	0.000	103.842	122.100
zip_98028	86.0577	5.367	16.034	0.000	75.537	96.578
zip_98029	139.0470	5.236	26.556	0.000	128.784	149.310
zip_98033	213.7217	4.515	47.341	0.000	204.873	222.571
zip_98034	121.4577	4.090	29.698	0.000	113.441	129.474
zip_98038	36.1981	3.962	9.137	0.000	28.433	43.963
zip_98039	452.0421	12.545	36.032	0.000	427.452	476.633
zip_98040	265.3038	5.533	47.946	0.000	254.458	276.150
zip_98045	62.4240	6.097	10.238	0.000	50.472	74.376
zip_98052	142.4027	4.019	35.433	0.000	134.525	150.280
zip_98053	114.6077	4.713	24.317	0.000	105.370	123.846
zip_98055	26.4850	5.498	4.817	0.000	15.707	37.263
zip_98056	64.7824	4.715	13.739	0.000	55.540	74.025
zip_98058	20.2324	4.384	4.615	0.000	11.639	28.826
zip_98059	62.0831	4.337	14.315	0.000	53.582	70.584
zip_98065	80.4373	5.168	15.564	0.000	70.308	90.567
zip_98070	49.6897	8.368	5.938	0.000	33.288	66.092
zip_98072	94.2768	5.539	17.022	0.000	83.421	105.133
zip_98074	120.7020	4.525	26.677	0.000	111.834	129.571
zip_98075	126.9434	4.923	25.784	0.000	117.293	136.594
zip_98077	82.1806	6.425	12.790	0.000	69.586	94.775
zip_98102	340.0473	8.835	38.489	0.000	322.730	357.364
zip_98103	262.1197	4.131	63.447	0.000	254.022	270.217
zip_98105	309.7213	6.107	50.714	0.000	297.751	321.692
zip_98106	95.9477	5.159	18.599	0.000	85.836	106.059
zip_98107	282.4634	5.655	49.947	0.000	271.378	293.548
zip_98108	95.9569	6.621	14.492	0.000	82.978	108.935
zip_98109	354.3316	8.676	40.840	0.000	337.326	371.338

zip_98112	357.3529	5.626	63.523	0.000	346.326	368.380
zip_98115	249.4877	4.082	61.116	0.000	241.486	257.489
zip_98116	244.5596	5.114	47.819	0.000	234.535	254.584
zip_98117	257.4704	4.135	62.268	0.000	249.366	265.575
zip_98118	127.9003	4.191	30.518	0.000	119.685	136.115
zip_98119	364.9848	6.675	54.682	0.000	351.902	378.068
zip_98122	262.1657	5.360	48.910	0.000	251.659	272.672
zip_98125	147.6479	4.635	31.858	0.000	138.564	156.732
zip_98126	154.1778	5.020	30.716	0.000	144.339	164.017
zip_98133	108.4525	4.286	25.304	0.000	100.052	116.853
zip_98136	212.3522	5.745	36.966	0.000	201.092	223.612
zip_98144	206.7367	5.152	40.130	0.000	196.639	216.835
zip_98146	68.0793	5.361	12.700	0.000	57.572	78.586
zip_98148	22.6446	12.040	1.881	0.060	-0.954	46.244
zip_98155	90.6221	4.530	20.003	0.000	81.742	99.502
zip_98166	49.7594	5.722	8.696	0.000	38.543	60.976
zip_98168	12.5293	5.678	2.207	0.027	1.400	23.658
zip_98177	150.6983	5.744	26.235	0.000	139.439	161.957
zip_98178	33.1939	5.779	5.744	0.000	21.866	44.522
zip_98188	13.2324	7.840	1.688	0.091	-2.135	28.600
zip_98199	284.5835	5.314	53.554	0.000	274.168	294.999

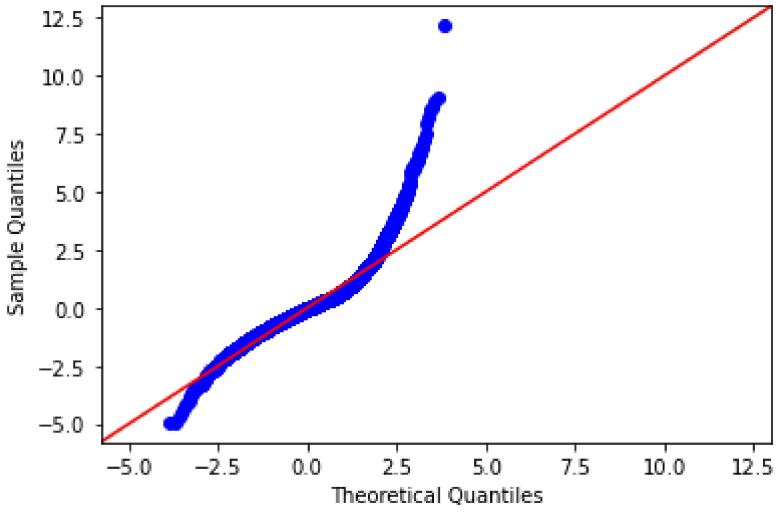
Omnibus:	5880.825	**Durbin-Watson:**	2.021
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	52168.476
Skew:	1.383	**Prob(JB):**	0.00
Kurtosis:	11.052	**Cond. No.**	228.

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

Assumptions Check

Normalization

In [70]:
```
zip_residuals2 = zip_model2.resid
fig = sm.graphics.qqplot(zip_residuals2,dist=stats.norm,line='45',fit=True)
```



Homoscedasticity

In [71]:
```
sns.scatterplot(y_train2,zip_residuals2)
plt.title('Scatter of Errors Including Zipcodes')
plt.xlabel('PSF')
plt.ylabel('Error');
```

Log Transforming PSF for Zip Codes

In [72]:
```
zip_df_update2 = zip_df_update
```

In [73]:
```
zip_df_update2['psf'] = np.log(zip_df_update['psf'])
```

In [74]:
```
x_zip3 = zip_df_update2.drop('psf',axis=1)
y_zip3= zip_df_update2['psf']#.to_numpy().flatten()
x_train3, x_test3, y_train3, y_test3 = train_test_split(x_zip3,y_zip3,test_size=0.2)
zip_model3 = model(x_train3,x_test3,y_train3,y_test3);
```

```
Train R2:  0.7643700571039842
Test R2:  0.7614212261533656
Train RMSE:  0.21530119391305436
Test RMSE:  0.21481536385196573
```

OLS Regression Results

Dep. Variable:	psf	**R-squared:**	0.764
Model:	OLS	**Adj. R-squared:**	0.763
Method:	Least Squares	**F-statistic:**	820.8
Date:	Tue, 27 Jul 2021	**Prob (F-statistic):**	0.00
Time:	20:40:42	**Log-Likelihood:**	2017.4
No. Observations:	17275	**AIC:**	-3897.
Df Residuals:	17206	**BIC:**	-3361.
Df Model:	68		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	5.0397	0.017	295.197	0.000	5.006	5.073
bedrooms	-0.0678	0.002	-32.998	0.000	-0.072	-0.064
floors	-0.1203	0.005	-25.018	0.000	-0.130	-0.111
waterfront	0.6903	0.020	33.822	0.000	0.650	0.730
condition	0.0572	0.003	20.892	0.000	0.052	0.063
grade	0.0381	0.002	20.110	0.000	0.034	0.042
livtolot	-0.1138	0.009	-12.271	0.000	-0.132	-0.096
has_basement	0.2433	0.004	59.573	0.000	0.235	0.251
rec_reno	0.1058	0.011	9.995	0.000	0.085	0.127
zip_98004	1.0875	0.015	74.722	0.000	1.059	1.116
zip_98005	0.6894	0.019	36.401	0.000	0.652	0.727
zip_98006	0.6640	0.012	54.889	0.000	0.640	0.688
zip_98007	0.6488	0.021	30.485	0.000	0.607	0.690
zip_98008	0.6452	0.015	42.494	0.000	0.615	0.675
zip_98010	0.2102	0.024	8.657	0.000	0.163	0.258
zip_98011	0.3943	0.018	21.595	0.000	0.359	0.430
zip_98014	0.2962	0.022	13.583	0.000	0.253	0.339
zip_98019	0.2753	0.018	15.512	0.000	0.241	0.310
zip_98023	-0.0590	0.012	-4.966	0.000	-0.082	-0.036
zip_98024	0.4166	0.027	15.330	0.000	0.363	0.470
zip_98027	0.5005	0.013	39.393	0.000	0.476	0.525
zip_98028	0.3880	0.015	25.565	0.000	0.358	0.418
zip_98029	0.5974	0.014	41.899	0.000	0.569	0.625
zip_98033	0.7669	0.012	61.554	0.000	0.742	0.791

zip_98034	0.5154	0.011	45.666	0.000	0.493	0.538
zip_98038	0.1283	0.011	11.743	0.000	0.107	0.150
zip_98039	1.2458	0.032	38.497	0.000	1.182	1.309
zip_98040	0.8788	0.016	56.487	0.000	0.848	0.909
zip_98045	0.2843	0.017	16.392	0.000	0.250	0.318
zip_98052	0.5975	0.011	53.841	0.000	0.576	0.619
zip_98053	0.5023	0.013	38.077	0.000	0.476	0.528
zip_98055	0.1217	0.015	8.164	0.000	0.092	0.151
zip_98056	0.2799	0.013	22.038	0.000	0.255	0.305
zip_98058	0.1226	0.012	9.889	0.000	0.098	0.147
zip_98059	0.2827	0.012	23.424	0.000	0.259	0.306
zip_98065	0.3390	0.015	23.015	0.000	0.310	0.368
zip_98070	0.3360	0.023	14.477	0.000	0.290	0.381
zip_98072	0.4412	0.016	28.330	0.000	0.411	0.472
zip_98074	0.5240	0.013	41.685	0.000	0.499	0.549
zip_98075	0.5321	0.014	38.573	0.000	0.505	0.559
zip_98077	0.3904	0.018	22.121	0.000	0.356	0.425
zip_98102	1.0671	0.024	43.632	0.000	1.019	1.115
zip_98103	0.9008	0.011	79.871	0.000	0.879	0.923
zip_98105	0.9830	0.016	59.783	0.000	0.951	1.015
zip_98106	0.4103	0.014	28.953	0.000	0.383	0.438
zip_98107	0.9622	0.016	60.493	0.000	0.931	0.993
zip_98108	0.4034	0.018	21.927	0.000	0.367	0.439
zip_98109	1.0587	0.024	43.605	0.000	1.011	1.106
zip_98112	1.0701	0.016	68.180	0.000	1.039	1.101
zip_98115	0.8469	0.011	76.165	0.000	0.825	0.869
zip_98116	0.8285	0.014	58.022	0.000	0.801	0.856
zip_98117	0.8543	0.011	74.620	0.000	0.832	0.877
zip_98118	0.5076	0.012	43.394	0.000	0.485	0.530
zip_98119	1.0709	0.019	57.506	0.000	1.034	1.107
zip_98122	0.8866	0.015	57.508	0.000	0.856	0.917
zip_98125	0.5840	0.013	45.264	0.000	0.559	0.609
zip_98126	0.6052	0.014	44.363	0.000	0.578	0.632
zip_98133	0.4747	0.012	40.461	0.000	0.452	0.498
zip_98136	0.7529	0.015	48.885	0.000	0.723	0.783

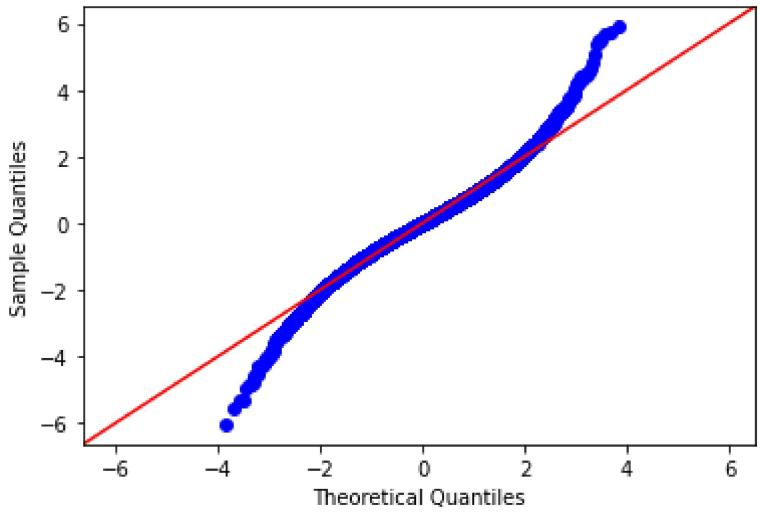
zip_98144	0.7454	0.015	51.382	0.000	0.717	0.774
zip_98146	0.2933	0.015	19.638	0.000	0.264	0.323
zip_98148	0.1251	0.032	3.848	0.000	0.061	0.189
zip_98155	0.4259	0.012	34.846	0.000	0.402	0.450
zip_98166	0.2811	0.016	17.836	0.000	0.250	0.312
zip_98168	0.0750	0.016	4.793	0.000	0.044	0.106
zip_98177	0.5788	0.016	36.762	0.000	0.548	0.610
zip_98178	0.1807	0.015	11.921	0.000	0.151	0.210
zip_98188	0.1001	0.021	4.851	0.000	0.060	0.141
zip_98199	0.9056	0.015	62.126	0.000	0.877	0.934

Omnibus:	755.513	**Durbin-Watson:**	2.008
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	2591.605
Skew:	0.013	**Prob(JB):**	0.00
Kurtosis:	4.897	**Cond. No.**	226.

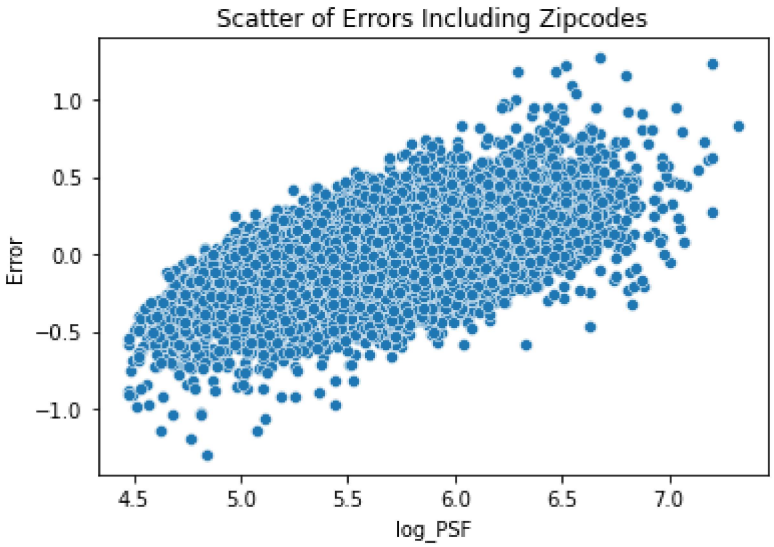
Notes:

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

In [75]:
```
zip_residuals2 = zip_model3.resid
fig = sm.graphics.qqplot(zip_residuals2,dist=stats.norm,line='45',fit=True)
```



In [76]:
```
sns.scatterplot(y_train3,zip_residuals2)
plt.title('Scatter of Errors Including Zipcodes')
plt.xlabel('log_PSF')
plt.ylabel('Error');
```



Findings

- R Squared improved greatly to .76 after adding back zipcodes and log transforming PSF
- Difference in RMSE remains at ~ 1 PSF (.001 log of PSF)
- Residual normality distribution improved, but heavier tails
- Homoscedasticity improved as well, but still does not appear random for larger/smaller PSF

Iteration 4: Dropping Outliers

- Continuing to improve on the log transformed model with zipcodes

Modifying Modeling for Outliers

In [77]:
```
def remove_outliers(df):
    q1 = np.quantile(df,.25)
    q3 = np.quantile(df,.75)
    IQR = q3 - q1
    outliers = df.loc[((q1-1.5*IQR)>df) | (df>(q3+1.5*IQR))].index
    return outliers
```

In [78]:
```
def model_outlier(X_train, X_test, y_train, y_test):
    # remove outliers first to avoid data leakage
    train_outliers = remove_outliers(y_train)
    X_train = X_train.drop(train_outliers)
    y_train = y_train.drop(train_outliers)

    test_outliers = remove_outliers(y_test)
    X_test = X_test.drop(test_outliers)
    y_test = y_test.drop(test_outliers)

    # statsmodels
    features = X_train.copy()
    features['psf'] = y_train

    formula = 'psf~' + '+'.join(X_train.columns)
    model = ols(formula=formula, data=features).fit()
```

```
    #sklearn
    linreg = LinearRegression()
    linreg.fit(X_train, y_train)

    y_hat_train = linreg.predict(X_train)
    y_hat_test = linreg.predict(X_test)

    train_mse = mean_squared_error(y_train, y_hat_train)
    test_mse = mean_squared_error(y_test, y_hat_test)

    print("Train R2: ", linreg.score(X_train, y_train))
    print("Test R2: ", linreg.score(X_test, y_test))

    print("Train RMSE: ", train_mse**0.5)
    print("Test RMSE: ", test_mse**0.5)

    display(model.summary())

    return model
```

Model Summary

In [79]:
```
x_zip4 = zip_df_update2.drop('psf',axis=1)
y_zip4= zip_df_update2['psf']
x_train4, x_test4, y_train4, y_test4 = train_test_split(x_zip4,y_zip4,test_size=0.2)
```

In [80]:
```
zip_model4 = model_outlier(x_train4,x_test4,y_train4,y_test4);
```

```
Train R2:  0.7640677162795037
Test R2:  0.7555272855745525
Train RMSE:  0.21313106763991582
Test RMSE:  0.2185528672217972
```

OLS Regression Results

Dep. Variable:	psf	**R-squared:**	0.764
Model:	OLS	**Adj. R-squared:**	0.763
Method:	Least Squares	**F-statistic:**	818.1
Date:	Tue, 27 Jul 2021	**Prob (F-statistic):**	0.00
Time:	20:40:43	**Log-Likelihood:**	2188.8
No. Observations:	17247	**AIC:**	-4240.
Df Residuals:	17178	**BIC:**	-3704.
Df Model:	68		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	5.0431	0.017	297.626	0.000	5.010	5.076
bedrooms	-0.0686	0.002	-33.656	0.000	-0.073	-0.065
floors	-0.1233	0.005	-25.851	0.000	-0.133	-0.114
waterfront	0.6757	0.021	32.245	0.000	0.635	0.717

condition	0.0581	0.003	21.478	0.000	0.053	0.063
grade	0.0384	0.002	20.474	0.000	0.035	0.042
livtolot	-0.1089	0.009	-11.889	0.000	-0.127	-0.091
has_basement	0.2390	0.004	58.956	0.000	0.231	0.247
rec_reno	0.0931	0.011	8.741	0.000	0.072	0.114
zip_98004	1.0781	0.015	72.810	0.000	1.049	1.107
zip_98005	0.6925	0.019	35.954	0.000	0.655	0.730
zip_98006	0.6569	0.012	56.205	0.000	0.634	0.680
zip_98007	0.6200	0.022	28.516	0.000	0.577	0.663
zip_98008	0.6278	0.015	41.890	0.000	0.598	0.657
zip_98010	0.1825	0.025	7.369	0.000	0.134	0.231
zip_98011	0.4064	0.018	22.705	0.000	0.371	0.441
zip_98014	0.2878	0.022	12.896	0.000	0.244	0.332
zip_98019	0.2736	0.018	15.201	0.000	0.238	0.309
zip_98023	-0.0671	0.012	-5.755	0.000	-0.090	-0.044
zip_98024	0.4198	0.029	14.384	0.000	0.363	0.477
zip_98027	0.4889	0.013	38.407	0.000	0.464	0.514
zip_98028	0.3888	0.015	26.100	0.000	0.360	0.418
zip_98029	0.5938	0.014	42.353	0.000	0.566	0.621
zip_98033	0.7469	0.013	58.899	0.000	0.722	0.772
zip_98034	0.5208	0.011	46.558	0.000	0.499	0.543
zip_98038	0.1237	0.011	11.393	0.000	0.102	0.145
zip_98039	1.2166	0.035	34.602	0.000	1.148	1.286
zip_98040	0.8533	0.015	56.456	0.000	0.824	0.883
zip_98045	0.2914	0.017	17.309	0.000	0.258	0.324
zip_98052	0.5946	0.011	54.221	0.000	0.573	0.616
zip_98053	0.4922	0.013	38.205	0.000	0.467	0.517
zip_98055	0.1256	0.015	8.281	0.000	0.096	0.155
zip_98056	0.2876	0.012	23.041	0.000	0.263	0.312
zip_98058	0.1196	0.012	9.914	0.000	0.096	0.143
zip_98059	0.2776	0.012	23.198	0.000	0.254	0.301
zip_98065	0.3345	0.014	23.563	0.000	0.307	0.362
zip_98070	0.3327	0.022	14.870	0.000	0.289	0.377
zip_98072	0.4308	0.015	28.195	0.000	0.401	0.461
zip_98074	0.5160	0.012	41.644	0.000	0.492	0.540

zip_98075	0.5216	0.013	38.847	0.000	0.495	0.548
zip_98077	0.3982	0.018	22.016	0.000	0.363	0.434
zip_98102	1.0581	0.025	43.107	0.000	1.010	1.106
zip_98103	0.8998	0.011	79.365	0.000	0.878	0.922
zip_98105	0.9655	0.016	59.770	0.000	0.934	0.997
zip_98106	0.4094	0.014	29.382	0.000	0.382	0.437
zip_98107	0.9508	0.016	60.934	0.000	0.920	0.981
zip_98108	0.3894	0.018	21.788	0.000	0.354	0.424
zip_98109	1.0514	0.023	44.751	0.000	1.005	1.097
zip_98112	1.0619	0.015	68.766	0.000	1.032	1.092
zip_98115	0.8504	0.011	76.592	0.000	0.829	0.872
zip_98116	0.8346	0.014	60.025	0.000	0.807	0.862
zip_98117	0.8538	0.011	76.304	0.000	0.832	0.876
zip_98118	0.5101	0.012	43.818	0.000	0.487	0.533
zip_98119	1.0758	0.019	56.090	0.000	1.038	1.113
zip_98122	0.8718	0.015	57.625	0.000	0.842	0.901
zip_98125	0.5840	0.013	46.296	0.000	0.559	0.609
zip_98126	0.6058	0.014	44.727	0.000	0.579	0.632
zip_98133	0.4795	0.012	41.125	0.000	0.457	0.502
zip_98136	0.7580	0.015	49.430	0.000	0.728	0.788
zip_98144	0.7497	0.014	52.261	0.000	0.722	0.778
zip_98146	0.2758	0.014	19.047	0.000	0.247	0.304
zip_98148	0.1218	0.031	3.947	0.000	0.061	0.182
zip_98155	0.4236	0.012	34.419	0.000	0.399	0.448
zip_98166	0.2847	0.016	17.933	0.000	0.254	0.316
zip_98168	0.0814	0.015	5.329	0.000	0.051	0.111
zip_98177	0.5733	0.016	35.799	0.000	0.542	0.605
zip_98178	0.1877	0.016	12.006	0.000	0.157	0.218
zip_98188	0.0972	0.021	4.620	0.000	0.056	0.138
zip_98199	0.8930	0.014	62.108	0.000	0.865	0.921

Omnibus:	737.084	**Durbin-Watson:**	2.005
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	2476.974
Skew:	-0.027	**Prob(JB):**	0.00
Kurtosis:	4.856	**Cond. No.**	227.

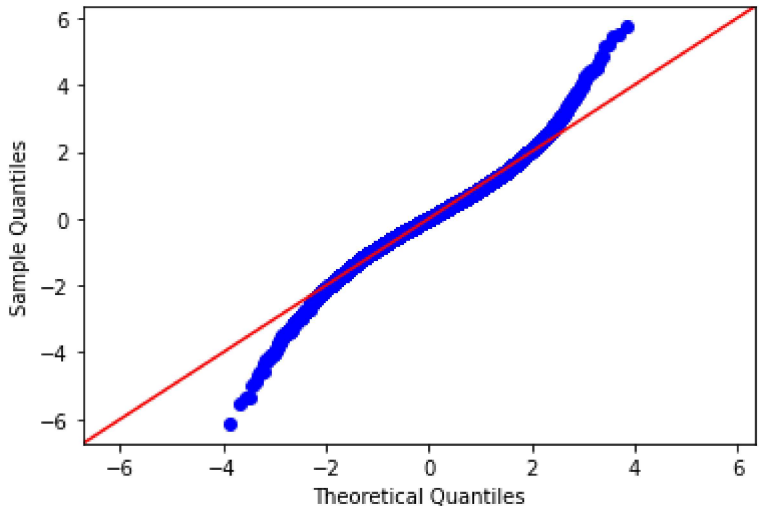
Notes:

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

Assumptions Check

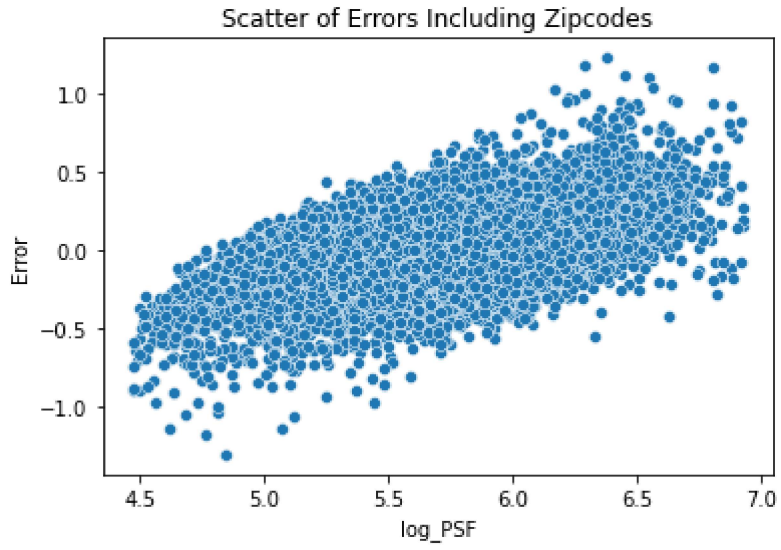
Normalization

In [81]:
```
zip_residuals4 = zip_model4.resid
fig = sm.graphics.qqplot(zip_residuals4,dist=stats.norm,line='45',fit=True)
```



Homoscedasticity

In [82]:
```
sns.scatterplot(y_train4,zip_residuals4)
plt.title('Scatter of Errors Including Zipcodes')
plt.xlabel('log_PSF')
plt.ylabel('Error');
```



Findings

- Model removing outliers after log transformation did not improve overall

Iteration 5: Dropping Outliers before Log Transform

Updating Model Function

In [83]:
```
def model_outlier_log(X_train, X_test, y_train, y_test):
    # remove outliers first to avoid data leakage
    train_outliers = remove_outliers(y_train)
    X_train = X_train.drop(train_outliers)
    y_train = y_train.drop(train_outliers)

    test_outliers = remove_outliers(y_test)
    X_test = X_test.drop(test_outliers)
    y_test = y_test.drop(test_outliers)

    # log transform PSF
    y_train = np.log(y_train)
    y_test = np.log(y_test)

    # statsmodels
    features = X_train.copy()
    features['psf'] = y_train

    formula = 'psf~' + '+'.join(X_train.columns)
    model = ols(formula=formula, data=features).fit()

    #sklearn
    linreg = LinearRegression()
    linreg.fit(X_train, y_train)

    y_hat_train = linreg.predict(X_train)
    y_hat_test = linreg.predict(X_test)

    train_mse = mean_squared_error(y_train, y_hat_train)
    test_mse = mean_squared_error(y_test, y_hat_test)

    print("Train R2: ", linreg.score(X_train, y_train))
    print("Test R2: ", linreg.score(X_test, y_test))

    print("Train RMSE: ", train_mse**0.5)
    print("Test RMSE: ", test_mse**0.5)

    display(model.summary())

    return model
```

In [84]:
```
zip_out_log = zip_df_update
```

Model Summary

In [85]:
```
x_zol = zip_out_log.drop('psf',axis=1)
y_zol= zip_out_log['psf']
```

```
x_train_zol, x_test_zol, y_train_zol, y_test_zol = train_test_split(x_zol,y_zol,test_si
zip_model_out_log = model_outlier_log(x_train_zol,x_test_zol,y_train_zol,y_test_zol);
```

```
Train R2:  0.7615356100253631
Test R2:  0.7558349567329401
Train RMSE:  0.03795745733174601
Test RMSE:  0.038882618189668906
```

OLS Regression Results

Dep. Variable:	psf	**R-squared:**	0.762
Model:	OLS	**Adj. R-squared:**	0.761
Method:	Least Squares	**F-statistic:**	806.6
Date:	Tue, 27 Jul 2021	**Prob (F-statistic):**	0.00
Time:	20:40:43	**Log-Likelihood:**	31944.
No. Observations:	17245	**AIC:**	-6.375e+04
Df Residuals:	17176	**BIC:**	-6.321e+04
Df Model:	68		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	1.6180	0.003	538.881	0.000	1.612	1.624
bedrooms	-0.0122	0.000	-33.491	0.000	-0.013	-0.011
floors	-0.0223	0.001	-26.160	0.000	-0.024	-0.021
waterfront	0.1071	0.004	29.077	0.000	0.100	0.114
condition	0.0102	0.000	21.140	0.000	0.009	0.011
grade	0.0072	0.000	21.532	0.000	0.007	0.008
livtolot	-0.0187	0.002	-11.342	0.000	-0.022	-0.015
has_basement	0.0417	0.001	57.723	0.000	0.040	0.043
rec_reno	0.0152	0.002	8.023	0.000	0.011	0.019
zip_98004	0.1887	0.003	73.488	0.000	0.184	0.194
zip_98005	0.1233	0.003	36.449	0.000	0.117	0.130
zip_98006	0.1178	0.002	55.593	0.000	0.114	0.122
zip_98007	0.1147	0.004	31.109	0.000	0.107	0.122
zip_98008	0.1165	0.003	42.049	0.000	0.111	0.122
zip_98010	0.0424	0.004	9.716	0.000	0.034	0.051
zip_98011	0.0721	0.003	22.810	0.000	0.066	0.078
zip_98014	0.0515	0.004	13.814	0.000	0.044	0.059
zip_98019	0.0467	0.003	14.886	0.000	0.041	0.053
zip_98023	-0.0126	0.002	-6.007	0.000	-0.017	-0.008
zip_98024	0.0741	0.005	15.574	0.000	0.065	0.083

zip_98027	0.0902	0.002	40.113	0.000	0.086	0.095
zip_98028	0.0717	0.003	26.677	0.000	0.066	0.077
zip_98029	0.1089	0.003	43.024	0.000	0.104	0.114
zip_98033	0.1357	0.002	61.937	0.000	0.131	0.140
zip_98034	0.0961	0.002	48.358	0.000	0.092	0.100
zip_98038	0.0204	0.002	10.495	0.000	0.017	0.024
zip_98039	0.2142	0.006	33.273	0.000	0.202	0.227
zip_98040	0.1530	0.003	56.502	0.000	0.148	0.158
zip_98045	0.0549	0.003	18.551	0.000	0.049	0.061
zip_98052	0.1083	0.002	55.070	0.000	0.104	0.112
zip_98053	0.0911	0.002	39.881	0.000	0.087	0.096
zip_98055	0.0206	0.003	7.523	0.000	0.015	0.026
zip_98056	0.0513	0.002	22.880	0.000	0.047	0.056
zip_98058	0.0222	0.002	10.543	0.000	0.018	0.026
zip_98059	0.0527	0.002	24.990	0.000	0.049	0.057
zip_98065	0.0616	0.003	23.634	0.000	0.056	0.067
zip_98070	0.0578	0.004	14.513	0.000	0.050	0.066
zip_98072	0.0828	0.003	31.042	0.000	0.078	0.088
zip_98074	0.0943	0.002	42.616	0.000	0.090	0.099
zip_98075	0.0963	0.002	38.619	0.000	0.091	0.101
zip_98077	0.0745	0.003	24.118	0.000	0.068	0.081
zip_98102	0.1866	0.004	42.731	0.000	0.178	0.195
zip_98103	0.1604	0.002	80.485	0.000	0.156	0.164
zip_98105	0.1726	0.003	58.267	0.000	0.167	0.178
zip_98106	0.0760	0.002	31.224	0.000	0.071	0.081
zip_98107	0.1708	0.003	61.396	0.000	0.165	0.176
zip_98108	0.0756	0.003	22.626	0.000	0.069	0.082
zip_98109	0.1833	0.004	42.921	0.000	0.175	0.192
zip_98112	0.1834	0.003	66.196	0.000	0.178	0.189
zip_98115	0.1523	0.002	78.495	0.000	0.148	0.156
zip_98116	0.1483	0.003	57.101	0.000	0.143	0.153
zip_98117	0.1542	0.002	76.280	0.000	0.150	0.158
zip_98118	0.0925	0.002	44.398	0.000	0.088	0.097
zip_98119	0.1859	0.003	57.342	0.000	0.180	0.192
zip_98122	0.1572	0.003	57.209	0.000	0.152	0.163

zip_98125	0.1063	0.002	46.698	0.000	0.102	0.111
zip_98126	0.1120	0.002	45.544	0.000	0.107	0.117
zip_98133	0.0877	0.002	42.125	0.000	0.084	0.092
zip_98136	0.1368	0.003	49.535	0.000	0.131	0.142
zip_98144	0.1349	0.002	55.324	0.000	0.130	0.140
zip_98146	0.0520	0.003	19.488	0.000	0.047	0.057
zip_98148	0.0267	0.006	4.717	0.000	0.016	0.038
zip_98155	0.0791	0.002	36.598	0.000	0.075	0.083
zip_98166	0.0530	0.003	18.867	0.000	0.048	0.059
zip_98168	0.0143	0.003	5.315	0.000	0.009	0.020
zip_98177	0.1057	0.003	37.449	0.000	0.100	0.111
zip_98178	0.0392	0.003	14.395	0.000	0.034	0.045
zip_98188	0.0170	0.004	4.382	0.000	0.009	0.025
zip_98199	0.1578	0.003	61.586	0.000	0.153	0.163

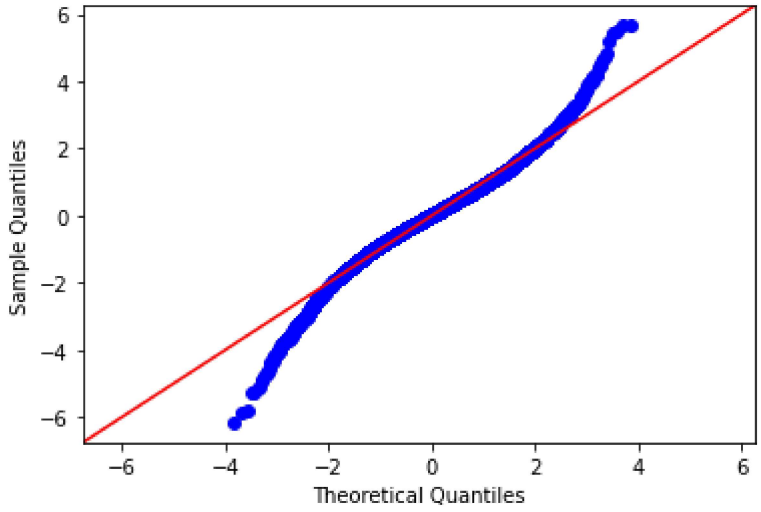
Omnibus:	854.505	**Durbin-Watson:**	2.014
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	2767.065
Skew:	-0.174	**Prob(JB):**	0.00
Kurtosis:	4.931	**Cond. No.**	229.

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

Assumptions Check

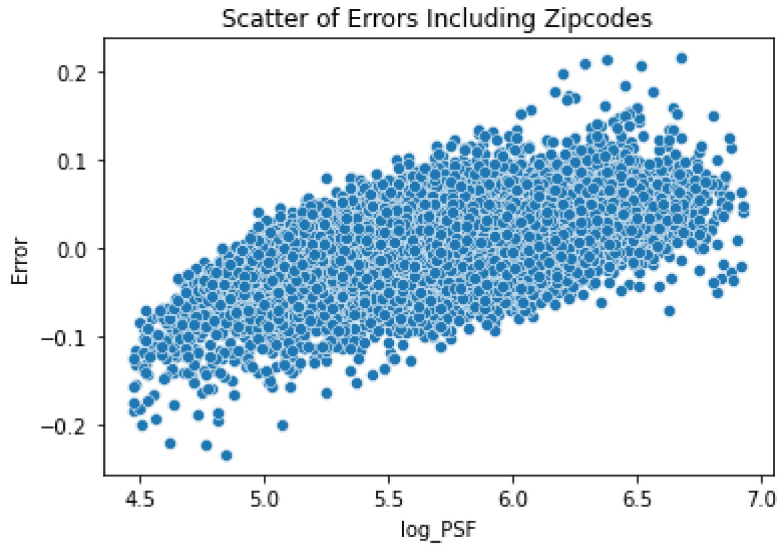
Normality

In [86]:
```
zip_residuals_out_log = zip_model_out_log.resid
fig = sm.graphics.qqplot(zip_residuals_out_log,dist=stats.norm,line='45',fit=True)
```



Homoscedasticity

In [87]:
```
sns.scatterplot(y_train_zol,zip_residuals_out_log)
plt.title('Scatter of Errors Including Zipcodes')
plt.xlabel('log_PSF')
plt.ylabel('Error');
```



Findings

- No meaningful improvement over R Squared, RMSE, or Residuals Assumptions

Iteration 6: Cubed Root Transformation of PSF

Modifying Model Function

In [88]:
```
def model_recip(X_train, X_test, y_train, y_test):


    # Cubed Root Transform to PSF
    y_train = y_train ** (1/3)
```

```
    y_test = y_test ** (1/3)


    # statsmodels
    features = X_train.copy()
    features['psf'] = y_train

    formula = 'psf~' + '+'.join(X_train.columns)
    model = ols(formula=formula, data=features).fit()

    #sklearn
    linreg = LinearRegression()
    linreg.fit(X_train, y_train)

    y_hat_train = linreg.predict(X_train)
    y_hat_test = linreg.predict(X_test)

    train_mse = mean_squared_error(y_train, y_hat_train)
    test_mse = mean_squared_error(y_test, y_hat_test)

    print("Train R2: ", linreg.score(X_train, y_train))
    print("Test R2: ", linreg.score(X_test, y_test))

    print("Train RMSE: ", train_mse**0.5)
    print("Test RMSE: ", test_mse**0.5)

    display(model.summary())

    return model
```

Model Summary

In [89]:
```
zip_recip = zip_df_update
```

In [90]:
```
x_rec = zip_recip.drop('psf',axis=1)
y_rec= zip_recip['psf']
x_train_rec, x_test_rec, y_train_rec, y_test_rec = train_test_split(x_rec,y_rec,test_si
zip_model_rec = model_recip(x_train_rec,x_test_rec,y_train_rec,y_test_rec);
```

```
Train R2:  0.7610377097680574
Test R2:  0.7707773149900959
Train RMSE:  0.022716896641213385
Test RMSE:  0.022333669104030642
```

OLS Regression Results

Dep. Variable:	psf	**R-squared:**	0.761
Model:	OLS	**Adj. R-squared:**	0.760
Method:	Least Squares	**F-statistic:**	805.8
Date:	Tue, 27 Jul 2021	**Prob (F-statistic):**	0.00
Time:	20:40:44	**Log-Likelihood:**	40868.
No. Observations:	17275	**AIC:**	-8.160e+04
Df Residuals:	17206	**BIC:**	-8.106e+04
Df Model:	68		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	1.7153	0.002	953.451	0.000	1.712	1.719
bedrooms	-0.0072	0.000	-32.990	0.000	-0.008	-0.007
floors	-0.0133	0.001	-26.132	0.000	-0.014	-0.012
waterfront	0.0669	0.002	30.775	0.000	0.063	0.071
condition	0.0061	0.000	21.116	0.000	0.006	0.007
grade	0.0041	0.000	20.442	0.000	0.004	0.004
livtolot	-0.0108	0.001	-10.997	0.000	-0.013	-0.009
has_basement	0.0248	0.000	57.487	0.000	0.024	0.026
rec_reno	0.0095	0.001	8.471	0.000	0.007	0.012
zip_98004	0.1142	0.002	74.589	0.000	0.111	0.117
zip_98005	0.0728	0.002	36.298	0.000	0.069	0.077
zip_98006	0.0709	0.001	56.034	0.000	0.068	0.073
zip_98007	0.0682	0.002	30.756	0.000	0.064	0.073
zip_98008	0.0684	0.002	43.311	0.000	0.065	0.071
zip_98010	0.0205	0.003	7.647	0.000	0.015	0.026
zip_98011	0.0434	0.002	23.136	0.000	0.040	0.047
zip_98014	0.0314	0.002	13.451	0.000	0.027	0.036
zip_98019	0.0298	0.002	15.720	0.000	0.026	0.034
zip_98023	-0.0072	0.001	-5.714	0.000	-0.010	-0.005
zip_98024	0.0463	0.003	16.153	0.000	0.041	0.052
zip_98027	0.0538	0.001	39.848	0.000	0.051	0.056
zip_98028	0.0430	0.002	26.829	0.000	0.040	0.046
zip_98029	0.0636	0.002	42.217	0.000	0.061	0.067
zip_98033	0.0805	0.001	61.550	0.000	0.078	0.083
zip_98034	0.0559	0.001	46.874	0.000	0.054	0.058
zip_98038	0.0130	0.001	11.234	0.000	0.011	0.015
zip_98039	0.1285	0.004	34.312	0.000	0.121	0.136
zip_98040	0.0912	0.002	55.966	0.000	0.088	0.094
zip_98045	0.0311	0.002	17.307	0.000	0.028	0.035
zip_98052	0.0643	0.001	55.833	0.000	0.062	0.067
zip_98053	0.0541	0.001	39.792	0.000	0.051	0.057
zip_98055	0.0133	0.002	8.231	0.000	0.010	0.016
zip_98056	0.0303	0.001	22.179	0.000	0.028	0.033
zip_98058	0.0139	0.001	10.797	0.000	0.011	0.016

zip_98059	0.0296	0.001	23.545	0.000	0.027	0.032
zip_98065	0.0364	0.002	23.479	0.000	0.033	0.039
zip_98070	0.0379	0.002	15.724	0.000	0.033	0.043
zip_98072	0.0479	0.002	29.672	0.000	0.045	0.051
zip_98074	0.0562	0.001	42.334	0.000	0.054	0.059
zip_98075	0.0566	0.001	39.131	0.000	0.054	0.059
zip_98077	0.0439	0.002	22.810	0.000	0.040	0.048
zip_98102	0.1085	0.003	42.213	0.000	0.103	0.114
zip_98103	0.0952	0.001	79.226	0.000	0.093	0.098
zip_98105	0.1020	0.002	58.329	0.000	0.099	0.105
zip_98106	0.0445	0.001	30.065	0.000	0.042	0.047
zip_98107	0.1006	0.002	61.468	0.000	0.097	0.104
zip_98108	0.0429	0.002	22.159	0.000	0.039	0.047
zip_98109	0.1103	0.003	41.840	0.000	0.105	0.115
zip_98112	0.1118	0.002	66.051	0.000	0.108	0.115
zip_98115	0.0902	0.001	75.897	0.000	0.088	0.093
zip_98116	0.0886	0.002	57.974	0.000	0.086	0.092
zip_98117	0.0905	0.001	75.425	0.000	0.088	0.093
zip_98118	0.0545	0.001	44.189	0.000	0.052	0.057
zip_98119	0.1123	0.002	57.165	0.000	0.108	0.116
zip_98122	0.0922	0.002	56.488	0.000	0.089	0.095
zip_98125	0.0625	0.001	45.853	0.000	0.060	0.065
zip_98126	0.0644	0.001	44.425	0.000	0.062	0.067
zip_98133	0.0516	0.001	41.900	0.000	0.049	0.054
zip_98136	0.0806	0.002	48.508	0.000	0.077	0.084
zip_98144	0.0797	0.001	53.631	0.000	0.077	0.083
zip_98146	0.0316	0.002	19.550	0.000	0.028	0.035
zip_98148	0.0124	0.003	3.804	0.000	0.006	0.019
zip_98155	0.0467	0.001	36.137	0.000	0.044	0.049
zip_98166	0.0317	0.002	18.966	0.000	0.028	0.035
zip_98168	0.0090	0.002	5.455	0.000	0.006	0.012
zip_98177	0.0634	0.002	38.358	0.000	0.060	0.067
zip_98178	0.0204	0.002	12.178	0.000	0.017	0.024
zip_98188	0.0117	0.002	5.290	0.000	0.007	0.016
zip_98199	0.0950	0.002	62.412	0.000	0.092	0.098

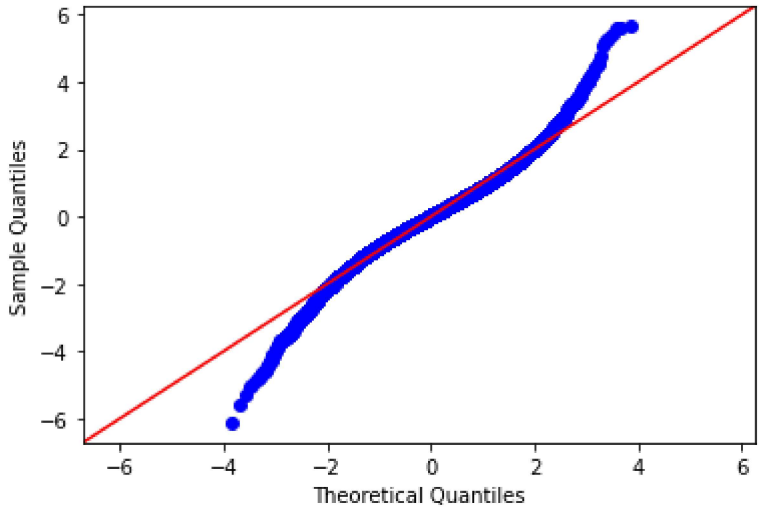
Omnibus:	821.935	**Durbin-Watson:**	2.004
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	2866.061
Skew:	-0.097	**Prob(JB):**	0.00
Kurtosis:	4.986	**Cond. No.**	228.

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

Assumptions

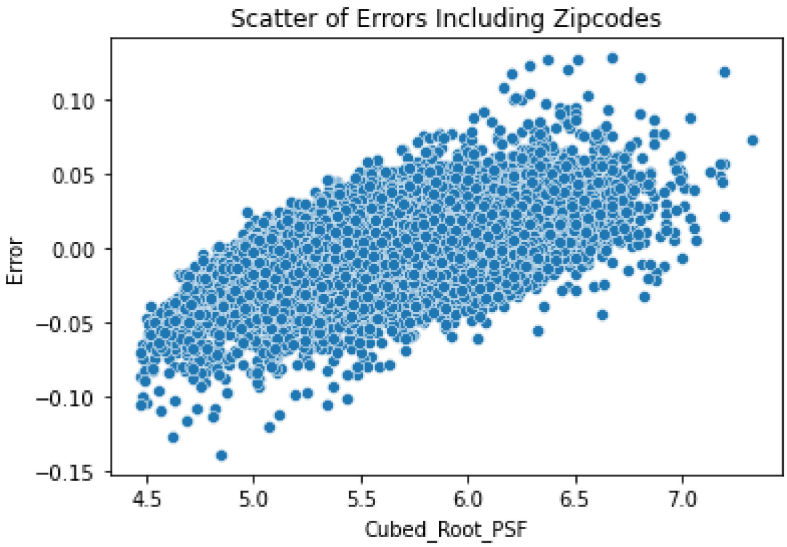
Normalization

In [91]:
```
zip_residuals_rec = zip_model_rec.resid
fig = sm.graphics.qqplot(zip_residuals_rec,dist=stats.norm,line='45',fit=True)
```



Homoscedasticity

In [92]:
```
sns.scatterplot(y_train_rec,zip_residuals_rec)
plt.title('Scatter of Errors Including Zipcodes')
plt.xlabel('Cubed_Root_PSF')
plt.ylabel('Error');
```



Findings

- No improvement overall in correcting the assumptions nor statistical values
- Log transform is a stronger transformation, expected weaker results from the cubed root

Conclusion

Model Summary of Log Transformed PSF including Zipcodes

- Best performing model from the iterations performed above

In [93]:
```
zip_df_update2 = zip_df_update
# Log Transform First
zip_df_update2['psf'] = np.log(zip_df_update['psf'])
```

In [94]:
```
x_zip3 = zip_df_update2.drop('psf',axis=1)
y_zip3= zip_df_update2[['psf']].to_numpy().flatten()
x_train2, x_test2, y_train2, y_test2 = train_test_split(x_zip3,y_zip3,test_size=0.2)
zip_model3 = model(x_train2,x_test2,y_train2,y_test2);
```

```
Train R2:  0.7617206126201899
Test R2:  0.7633558405619651
Train RMSE:  0.03829725932064806
Test RMSE:  0.03806240074357365
```

OLS Regression Results

Dep. Variable:	psf	**R-squared:**	0.762
Model:	OLS	**Adj. R-squared:**	0.761
Method:	Least Squares	**F-statistic:**	808.9
Date:	Tue, 27 Jul 2021	**Prob (F-statistic):**	0.00
Time:	20:40:44	**Log-Likelihood:**	31845.
No. Observations:	17275	**AIC:**	-6.355e+04

Df Residuals:	17206	**BIC:**	-6.302e+04
Df Model:	68		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	1.6166	0.003	533.847	0.000	1.611	1.623
bedrooms	-0.0125	0.000	-34.214	0.000	-0.013	-0.012
floors	-0.0220	0.001	-25.702	0.000	-0.024	-0.020
waterfront	0.1119	0.004	31.852	0.000	0.105	0.119
condition	0.0105	0.000	21.554	0.000	0.010	0.011
grade	0.0072	0.000	21.604	0.000	0.007	0.008
livtolot	-0.0192	0.002	-11.657	0.000	-0.022	-0.016
has_basement	0.0421	0.001	58.077	0.000	0.041	0.044
rec_reno	0.0178	0.002	9.415	0.000	0.014	0.022
zip_98004	0.1896	0.003	74.992	0.000	0.185	0.195
zip_98005	0.1238	0.003	35.382	0.000	0.117	0.131
zip_98006	0.1196	0.002	55.511	0.000	0.115	0.124
zip_98007	0.1166	0.004	31.732	0.000	0.109	0.124
zip_98008	0.1149	0.003	42.552	0.000	0.110	0.120
zip_98010	0.0362	0.004	8.081	0.000	0.027	0.045
zip_98011	0.0742	0.003	23.679	0.000	0.068	0.080
zip_98014	0.0573	0.004	14.552	0.000	0.050	0.065
zip_98019	0.0495	0.003	15.215	0.000	0.043	0.056
zip_98023	-0.0112	0.002	-5.318	0.000	-0.015	-0.007
zip_98024	0.0780	0.005	16.126	0.000	0.068	0.087
zip_98027	0.0905	0.002	38.935	0.000	0.086	0.095
zip_98028	0.0717	0.003	26.815	0.000	0.066	0.077
zip_98029	0.1087	0.003	42.400	0.000	0.104	0.114
zip_98033	0.1364	0.002	61.184	0.000	0.132	0.141
zip_98034	0.0959	0.002	47.453	0.000	0.092	0.100
zip_98038	0.0211	0.002	10.769	0.000	0.017	0.025
zip_98039	0.2146	0.006	33.976	0.000	0.202	0.227
zip_98040	0.1550	0.003	56.316	0.000	0.150	0.160
zip_98045	0.0575	0.003	19.233	0.000	0.052	0.063
zip_98052	0.1093	0.002	55.795	0.000	0.105	0.113

zip_98053	0.0924	0.002	39.841	0.000	0.088	0.097
zip_98055	0.0214	0.003	7.750	0.000	0.016	0.027
zip_98056	0.0549	0.002	23.901	0.000	0.050	0.059
zip_98058	0.0233	0.002	10.700	0.000	0.019	0.028
zip_98059	0.0526	0.002	24.437	0.000	0.048	0.057
zip_98065	0.0631	0.003	24.302	0.000	0.058	0.068
zip_98070	0.0606	0.004	14.623	0.000	0.052	0.069
zip_98072	0.0802	0.003	29.589	0.000	0.075	0.086
zip_98074	0.0956	0.002	42.302	0.000	0.091	0.100
zip_98075	0.0961	0.002	39.565	0.000	0.091	0.101
zip_98077	0.0728	0.003	23.374	0.000	0.067	0.079
zip_98102	0.1842	0.004	41.325	0.000	0.175	0.193
zip_98103	0.1605	0.002	79.722	0.000	0.157	0.164
zip_98105	0.1727	0.003	58.903	0.000	0.167	0.178
zip_98106	0.0765	0.002	30.709	0.000	0.072	0.081
zip_98107	0.1708	0.003	61.223	0.000	0.165	0.176
zip_98108	0.0743	0.003	22.980	0.000	0.068	0.081
zip_98109	0.1851	0.004	44.406	0.000	0.177	0.193
zip_98112	0.1851	0.003	66.236	0.000	0.180	0.191
zip_98115	0.1508	0.002	75.618	0.000	0.147	0.155
zip_98116	0.1490	0.002	59.994	0.000	0.144	0.154
zip_98117	0.1531	0.002	75.651	0.000	0.149	0.157
zip_98118	0.0945	0.002	45.215	0.000	0.090	0.099
zip_98119	0.1881	0.003	56.436	0.000	0.182	0.195
zip_98122	0.1549	0.003	58.376	0.000	0.150	0.160
zip_98125	0.1068	0.002	46.658	0.000	0.102	0.111
zip_98126	0.1107	0.002	45.849	0.000	0.106	0.115
zip_98133	0.0887	0.002	42.368	0.000	0.085	0.093
zip_98136	0.1388	0.003	50.333	0.000	0.133	0.144
zip_98144	0.1359	0.002	54.482	0.000	0.131	0.141
zip_98146	0.0519	0.003	19.529	0.000	0.047	0.057
zip_98148	0.0204	0.006	3.647	0.000	0.009	0.031
zip_98155	0.0786	0.002	35.981	0.000	0.074	0.083
zip_98166	0.0531	0.003	19.460	0.000	0.048	0.058
zip_98168	0.0171	0.003	6.237	0.000	0.012	0.022

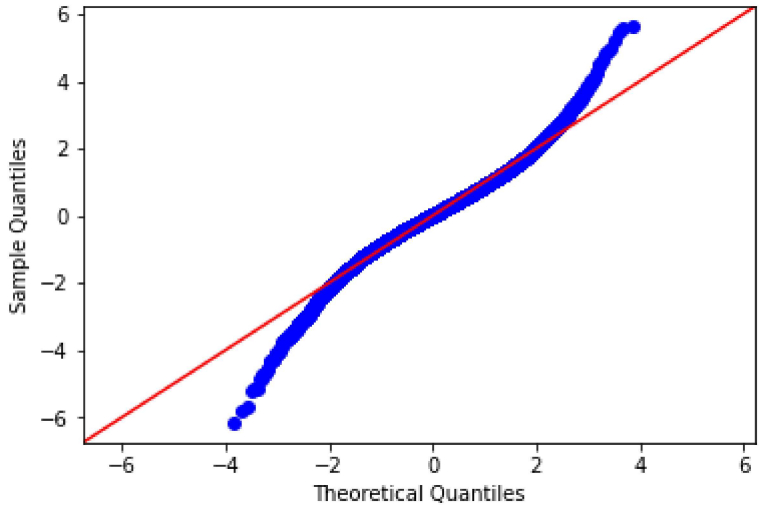
zip_98177	0.1086	0.003	37.868	0.000	0.103	0.114
zip_98178	0.0365	0.003	12.914	0.000	0.031	0.042
zip_98188	0.0204	0.004	5.360	0.000	0.013	0.028
zip_98199	0.1601	0.003	61.848	0.000	0.155	0.165

Omnibus:	864.105	**Durbin-Watson:**	1.986
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	2881.376
Skew:	-0.162	**Prob(JB):**	0.00
Kurtosis:	4.975	**Cond. No.**	228.

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

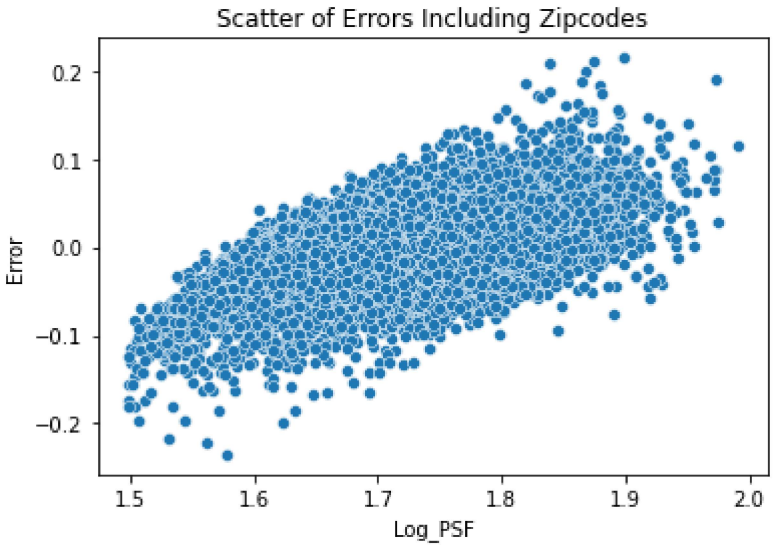
Normalization

In [95]:
```
zip_residuals3 = zip_model3.resid
fig = sm.graphics.qqplot(zip_residuals3,dist=stats.norm,line='45',fit=True)
```

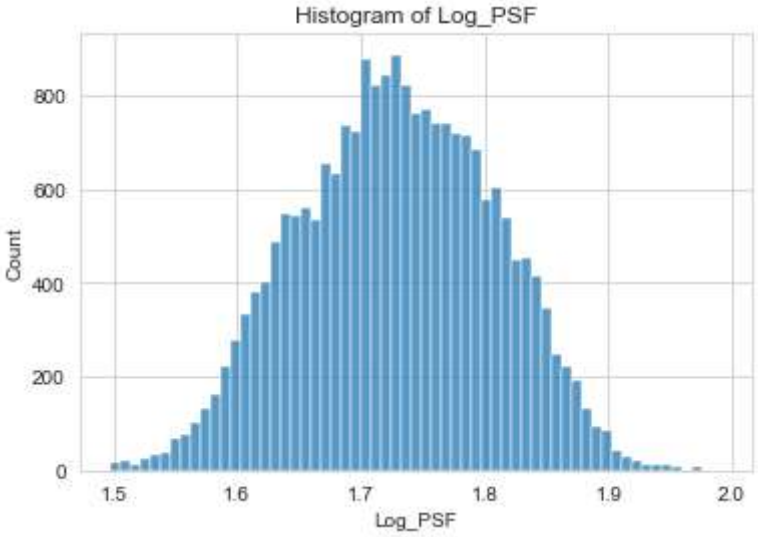


Homoscedasticity

In [96]:
```
sns.scatterplot(y_train2,zip_residuals3)
plt.title('Scatter of Errors Including Zipcodes')
plt.xlabel('Log_PSF')
plt.ylabel('Error');
```



In [131…
```
sns.histplot(y_zip3);
plt.title("Histogram of Log_PSF")
plt.xlabel("Log_PSF");
```



In [97]:
```
print("Train RMSE Exp:",np.e**0.038022)
print("Test RMSE Exp:",np.e**0.039147)
```

```
Train RMSE Exp: 1.0387540852169959
Test RMSE Exp: 1.0399233411460052
```

High Effects on log PSF

In [123…
```
((np.e**(zip_model3.params.sort_values(ascending=False))-1)*100).head(10)
```

Out[123…
```
Intercept    403.595257
zip_98039     23.936597
zip_98004     20.882574
zip_98119     20.691204
zip_98112     20.334079
zip_98109     20.332821
zip_98102     20.224774
zip_98105     18.854082
zip_98107     18.625571
zip_98103     17.407096
dtype: float64
```

Lowest and Negative Effects on log PSF

In [124…
```
((np.e**(zip_model3.params.sort_values(ascending=False))-1)*100).tail(10)
```

Out[124…
```
zip_98148    2.064174
zip_98188    2.056964
rec_reno     1.797206
zip_98168    1.719765
condition    1.051671
grade        0.727114
zip_98023   -1.112282
bedrooms    -1.244346
livtolot    -1.898404
floors      -2.172668
dtype: float64
```

In [122…
```
# Waterfront Coefficient
(np.e**.1119-1)*100
```

Out[122…
```
11.840101495135858
```

In [125…
```
# Basement COefficient
(np.e**.0421-1)*100
```

Out[125…
```
4.299877341328462
```

Visualizing Zipcode Locations

In [109…
```
def high_test(zipcode):
    high_zips = [98039,98004,98109,98119,98112,98102,98105]
    low_zips = [98148,98188,98168,98023]
    if zipcode in high_zips:
        return 2
    if zipcode in low_zips:
        return 0
    else:
        return 1
```

In [110…
```
geo_zips = df
```

In [111…
```
geo_zips['high_zip'] = geo_zips['zipcode'].apply(high_test)
```

In [112…
```
geo_zips.head()
```

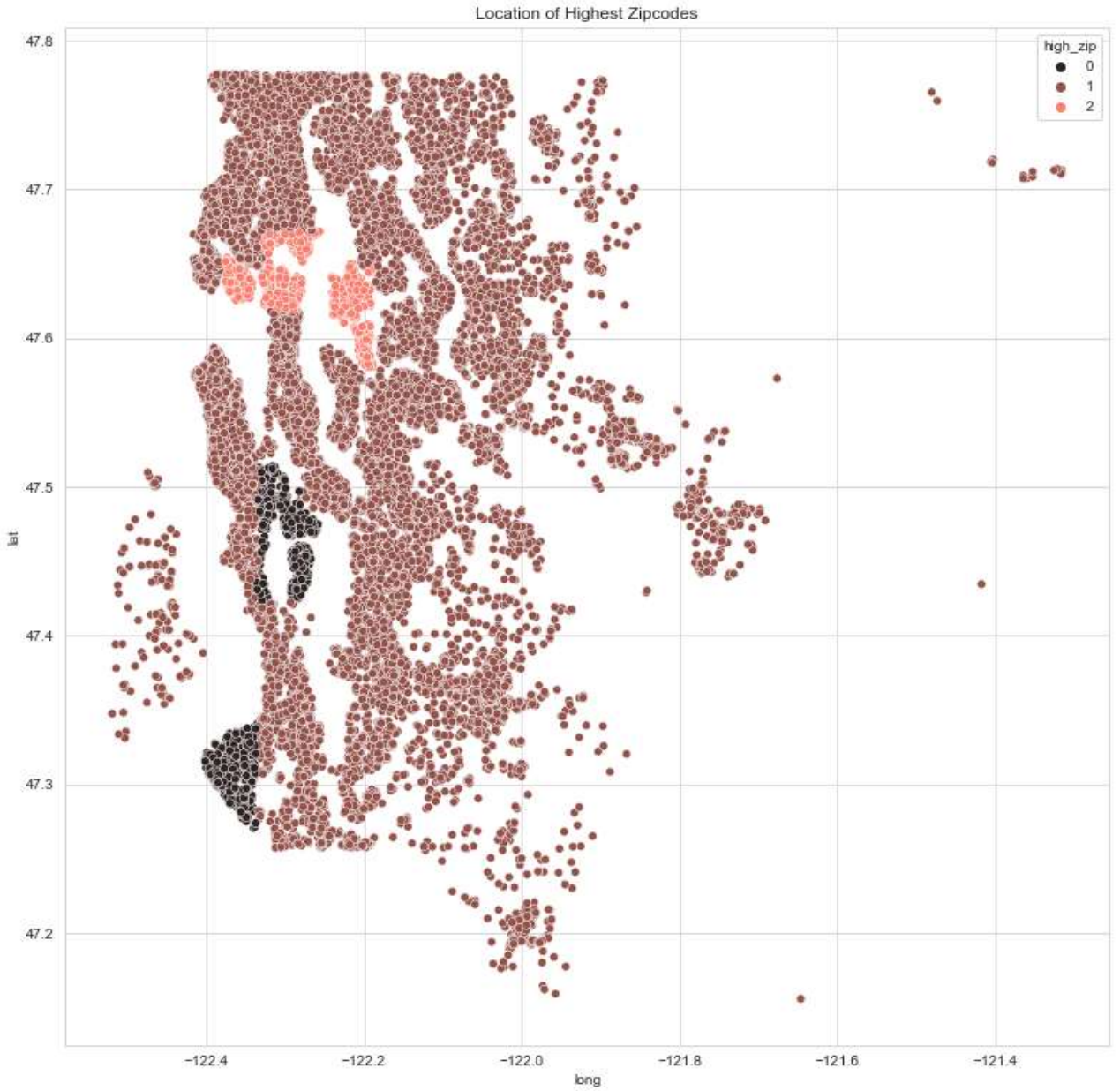
Out[112…

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	vi
0	7129300520	10/13/2014	221900.0	3	1.00	1180	5650	1.0	NaN	
1	6414100192	12/9/2014	538000.0	3	2.25	2570	7242	2.0	0.0	
2	5631500400	2/25/2015	180000.0	2	1.00	770	10000	1.0	0.0	
3	2487200875	12/9/2014	604000.0	4	3.00	1960	5000	1.0	0.0	
4	1954400510	2/18/2015	510000.0	3	2.00	1680	8080	1.0	0.0	

5 rows × 23 columns

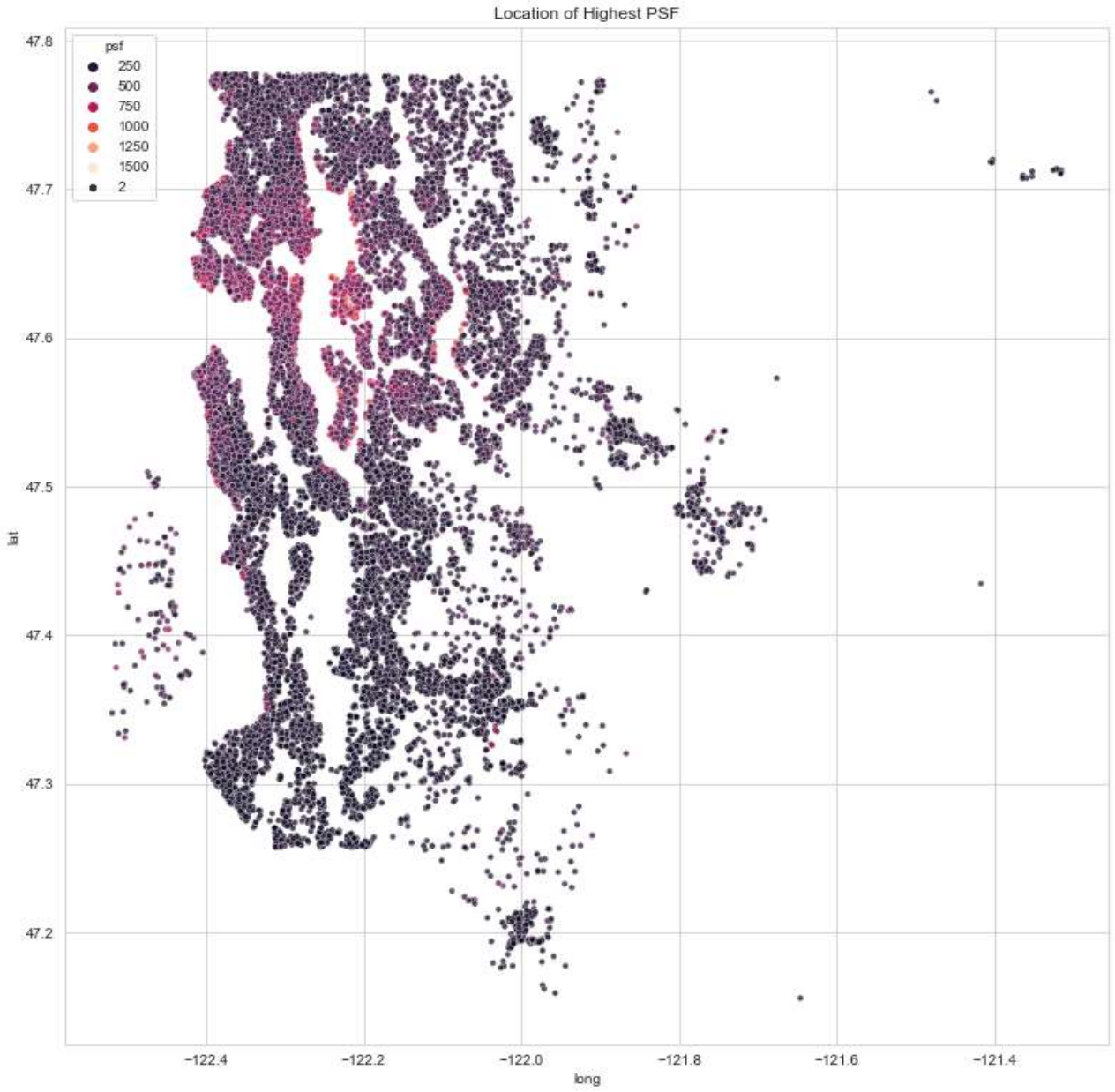
In [121…

```
sns.set_style('whitegrid')
fig, ax = plt.subplots(figsize=(13,13))

sns.scatterplot(y = geo_zips.lat, x = geo_zips.long, hue=geo_zips['high_zip'], ax=ax, p
ax.set_title('Location of Highest Zipcodes');
```



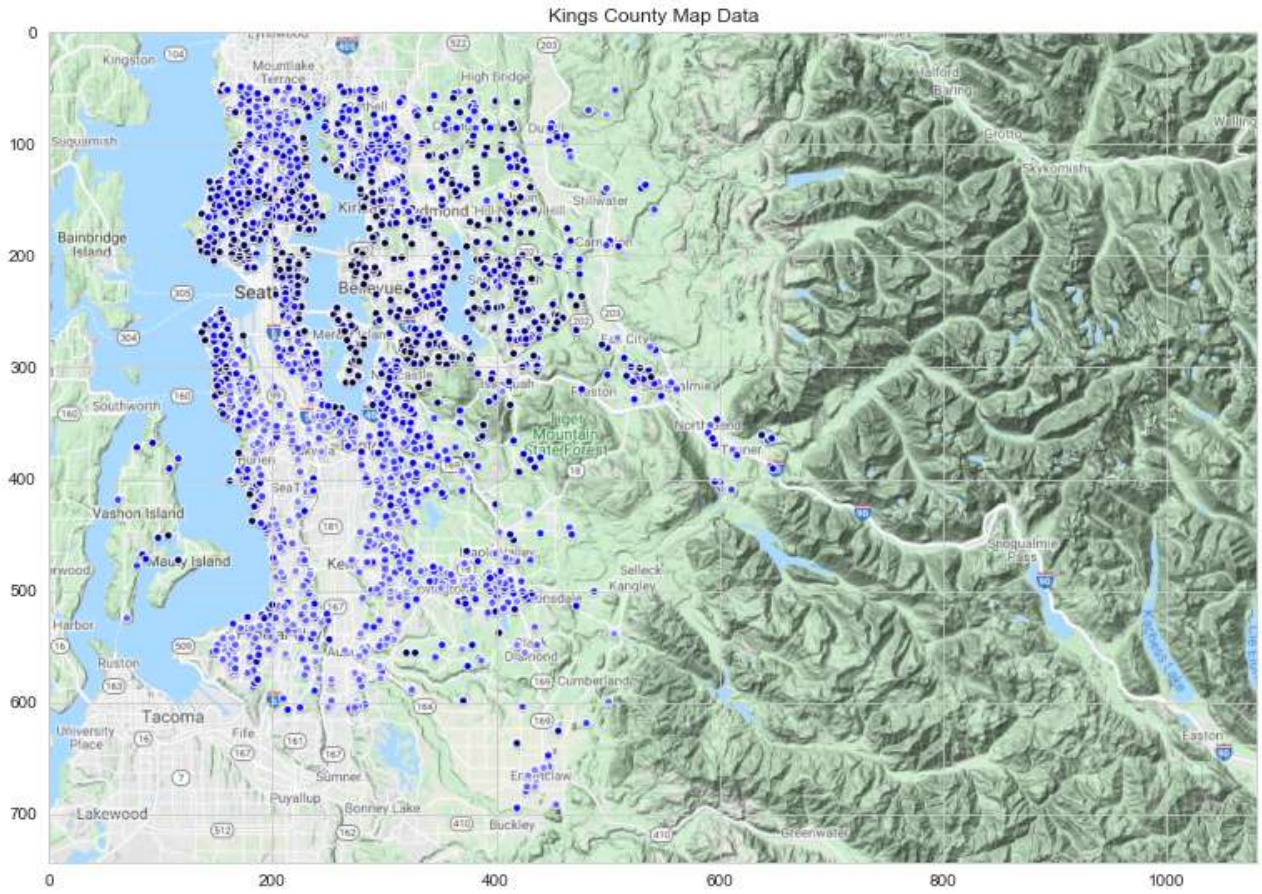
In [107…

```
geo_zips['psf'] = geo_zips['price'] / geo_zips['sqft_above']

fig, ax = plt.subplots(figsize=(13,13))
sns.scatterplot(x=geo_zips.long,y=geo_zips.lat, hue=geo_zips.psf, palette='rocket', alp
ax.set_title('Location of Highest PSF');
```



In [108…

```
import matplotlib.image as mpimg
fig, ax = plt.subplots(figsize=(13,13))
img = mpimg.imread('data/zoomed_map.png')
imgplot = plt.imshow(img)
plt.title('Kings County Map Data');
```



Final Results and Findings:

- R Squared: 0.76, Features explain 76% of the variation in the log of PSF
- Difference between Train and Test Log RSME: ~.001
- Residuals are almost normally distributed, but they have heavy tails indicating that large errors are more likely for extreme values
- Model is heteroscedastic, smaller PSF are overpredicted while larger PSF are underpredicted. Likely due to the inclusion of luxury homes in the data

---

- Highest effect on PSF is location:
    1. PSF for similar homes are 20% higher in areas closer to the mid-northern area of the city compared to our base line zipcode 98001 located in the southern area
    2. PSF for similar homes are 1-2% higher in areas near our base line zipcode of 98001 and around the airports a. Likely due to the effects of noise, or traffic
    3. PSF for similar homes with a waterfront are 12% higher than homes without a waterfront

---

- Home features do not have as high impact on PSF
    1. PSF for homes with basements are 4.3% higher than homes without
    2. Homes with renovations within the last 27 years have 1.8% higher PSF than homes without
    3. A 1 unit increase in the condition or grade of the home leads to ~ 1% increase in PSF
    4. A 1 bedroom increase in similar homes leads to a 1.2% decrease in PSF a. Likely due to a preference for open concepts or larger bedrooms

5. A 1 unit increase to the ratio of living square feet to lot size square feet leads to a 1.9% decrease in PSF a. A larger lot for similar sized homes is preferable
6. The existence of 1 additional floor leads to a 2.2% decrease in PSF a. Climbing more stairs around your home is less desirable