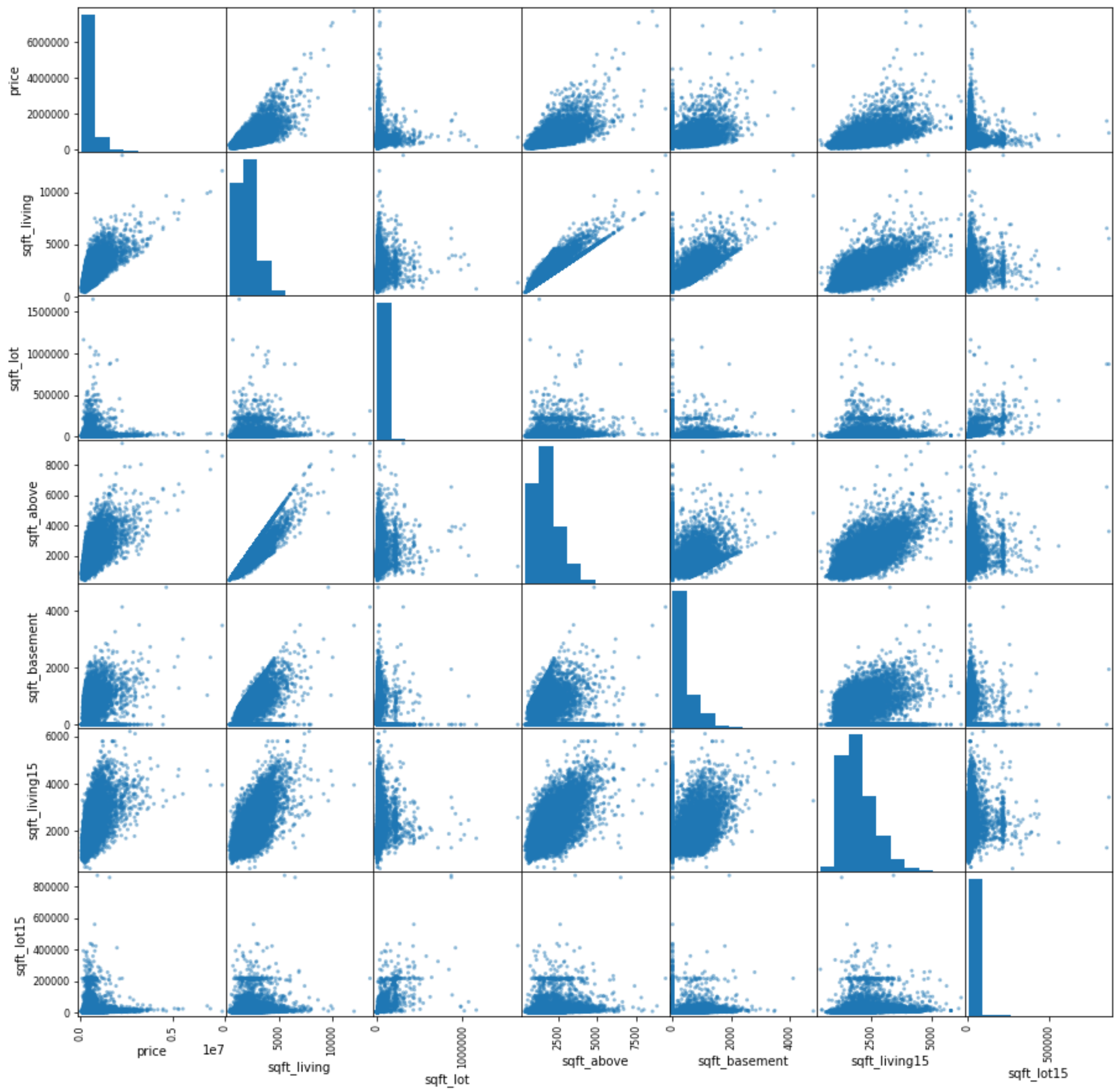
Creating the model

In [70]:
```
import pandas as pd
import numpy as np
from statsmodels.formula.api import ols
import statsmodels.api as sm
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error
from sklearn.metrics import mean_absolute_error
from sklearn.model_selection import cross_val_score

cleandata = pd.read_csv('cleaned_kc_house_data.csv')

data = pd.read_csv('kc_house_data.csv')
```

In [137]:
```
data_pred = (cleandata[['price', 'sqft_living', 'sqft_lot', 'sqft_above'
,'sqft_basement',
                        'sqft_living15', 'sqft_lot15']]).astype(int)
target = ['price']
```

Variable Distribution

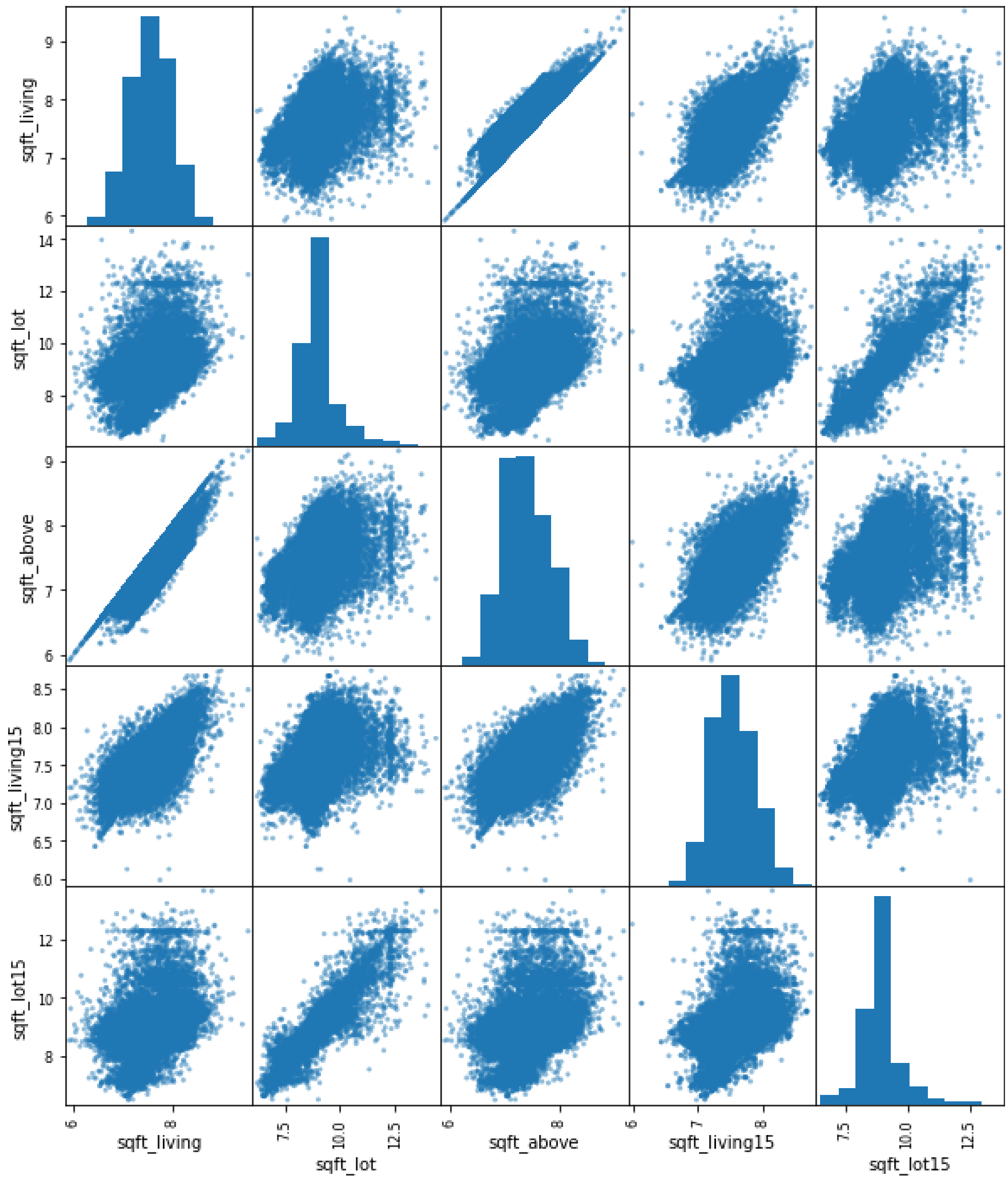
In [141]:
```
predictors = '+'.join(data_pred)
formula = target[0] + "~" + predictors
model = ols(formula=formula, data=data_pred).fit()
model.summary()

#predictors
#target
pd.plotting.scatter_matrix(data_pred,figsize = [15, 15]);
#data_pred
```



Log Normalization

In [5]:
```
# Min-Max Scaling, Standardization, Mean Normalization, Unit/Vector Tran
sformation
# can be explored as possibilities in the future
```

In [151]:
```
#Using log normalization to closer resemble a normal distribution.
normalize = ['sqft_living', 'sqft_lot', 'sqft_above',
             'sqft_living15', 'sqft_lot15']
#I left out basement because the majority of the value_counts was 0
for feat in normalize:
    df[feat] = cleandata[feat].map(lambda x: np.log(x))
pd.plotting.scatter_matrix(df[normalize], figsize=(10,12));
```



Heatmap

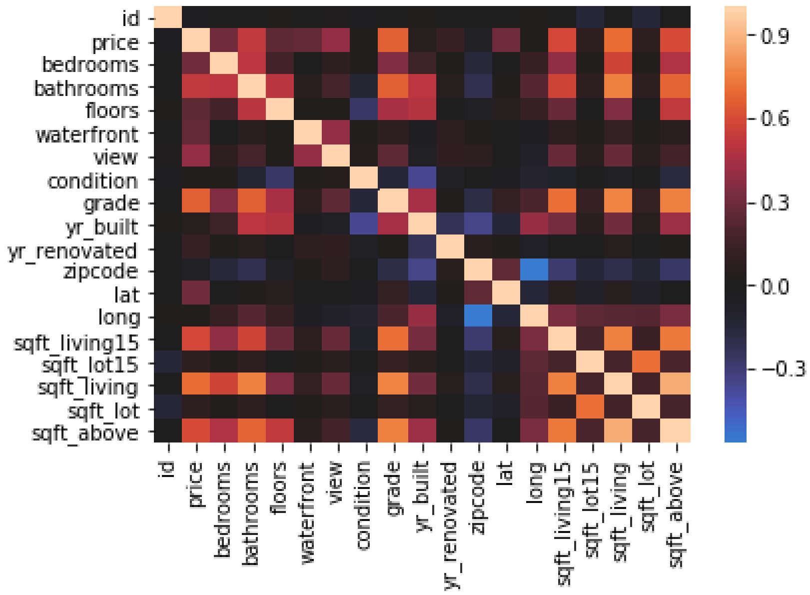
In [33]:
```
#grouped heatmap to have all sqft metrics next to each other for easier
 comparison
#I also look at variables outside the scope of the square footage model
 to gain insight into our location models
data_heatmap = data[['id', 'date', 'price', 'bedrooms', 'bathrooms', 'fl
oors',
                     'waterfront', 'view', 'condition', 'grade','yr_buil
t',
                     'yr_renovated', 'zipcode', 'lat', 'long', 'sqft_liv
ing15',
                     'sqft_lot15', 'sqft_living','sqft_lot', 'sqft_abov
e', 'sqft_basement',]]
```

In [34]:
```
data_heatmap.corr()
```

Out[34]:

	id	price	bedrooms	bathrooms	floors	waterfront	view	cond
id	1.000000	-0.016772	0.001150	0.005162	0.018608	-0.004176	0.011592	-0.02
price	-0.016772	1.000000	0.308787	0.525906	0.256804	0.276295	0.395734	0.03
bedrooms	0.001150	0.308787	1.000000	0.514508	0.177944	-0.002386	0.078523	0.02
bathrooms	0.005162	0.525906	0.514508	1.000000	0.502582	0.067282	0.186451	-0.12
floors	0.018608	0.256804	0.177944	0.502582	1.000000	0.021883	0.028436	-0.26
waterfront	-0.004176	0.276295	-0.002386	0.067282	0.021883	1.000000	0.406654	0.01
view	0.011592	0.395734	0.078523	0.186451	0.028436	0.406654	1.000000	0.04
condition	-0.023803	0.036056	0.026496	-0.126479	-0.264075	0.017642	0.045735	1.00
grade	0.008188	0.667951	0.356563	0.665838	0.458794	0.087383	0.249727	-0.14
yr_built	0.021617	0.053953	0.155670	0.507173	0.489193	-0.026079	-0.054564	-0.36
yr_renovated	-0.012010	0.129599	0.018495	0.051050	0.003535	0.087244	0.100964	-0.06
zipcode	-0.008211	-0.053402	-0.154092	-0.204786	-0.059541	0.031057	0.085277	0.00
lat	-0.001798	0.306692	-0.009951	0.024280	0.049239	-0.012772	0.006141	-0.01
long	0.020672	0.022036	0.132054	0.224903	0.125943	-0.039864	-0.077894	-0.10
sqft_living15	-0.002701	0.585241	0.393406	0.569884	0.280102	0.088860	0.279561	-0.09
sqft_lot15	-0.138557	0.082845	0.030690	0.088303	-0.010722	0.032002	0.073332	-0.00
sqft_living	-0.012241	0.701917	0.578212	0.755758	0.353953	0.110230	0.282532	-0.05
sqft_lot	-0.131911	0.089876	0.032471	0.088373	-0.004814	0.023143	0.075298	-0.00
sqft_above	-0.010799	0.605368	0.479386	0.686668	0.523989	0.075463	0.166299	-0.15

In [35]:
```
sns.heatmap(data_heatmap.corr(), center=0);
```



In [ ]:
```
#latitude isn't a strong correlation with zipcode, and longitude is inve
rsely correlated,
#perhaps because the shape of King County is tall but narrow
```

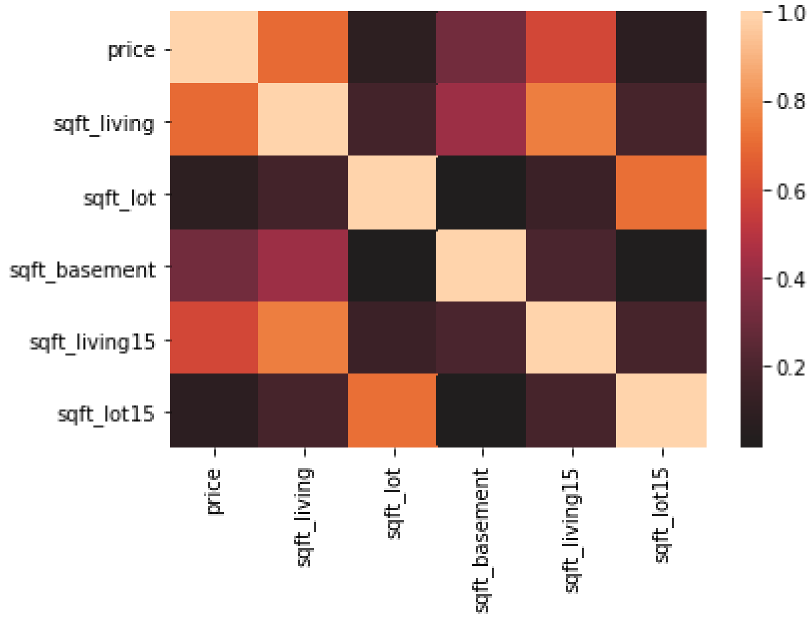
In [186]:
```
#correlations of our dataset once it has been cleaned and categorical va
riables dropped
cleandata_heatmap = cleandata[['price', 'sqft_living', 'sqft_lot', 'sqft
_basement',
                                'sqft_living15', 'sqft_lot15']]
```

In [187]:
```
cleandata_heatmap.corr()
```

Out[187]:

	price	sqft_living	sqft_lot	sqft_basement	sqft_living15	sqft_lot15
price	1.000000	0.701917	0.089876	0.321108	0.585241	0.082845
sqft_living	0.701917	1.000000	0.173453	0.428660	0.756402	0.184342
sqft_lot	0.089876	0.173453	1.000000	0.015031	0.144763	0.718204
sqft_basement	0.321108	0.428660	0.015031	1.000000	0.199288	0.015885
sqft_living15	0.585241	0.756402	0.144763	0.199288	1.000000	0.183515
sqft_lot15	0.082845	0.184342	0.718204	0.015885	0.183515	1.000000

In [188]:
```
sns.heatmap(cleandata_heatmap.corr(), center=0);
```



OLS

In [157]:
```
#The essence of my model will be attempting to answer the question of
#if measures of a house's own square footage are more important
#than measures of the neighbor's square footage
sqft_metrics_within = cleandata[['sqft_living', 'sqft_lot', 'sqft_baseme
nt']]
sqft_metrics_without = cleandata[['sqft_living15', 'sqft_lot15']]
y = cleandata['price']
y1 = cleandata['price']
sqft_metrics_within.shape
sqft_metrics_without.shape
```

Out[157]:
```
(21597, 2)
```

In [158]:
```
cleandata.describe()
```

Out[158]:

	id	price	sqft_living	sqft_lot	sqft_above	sqft_basement	
count	2.159700e+04	2.159700e+04	21597.000000	2.159700e+04	21597.000000	21597.000000	21
mean	4.580474e+09	5.402966e+05	2080.321850	1.509941e+04	1788.596842	285.716581	
std	2.876736e+09	3.673681e+05	918.106125	4.141264e+04	827.759761	439.819830	
min	1.000102e+06	7.800000e+04	370.000000	5.200000e+02	370.000000	0.000000	
25%	2.123049e+09	3.220000e+05	1430.000000	5.040000e+03	1190.000000	0.000000	
50%	3.904930e+09	4.500000e+05	1910.000000	7.618000e+03	1560.000000	0.000000	
75%	7.308900e+09	6.450000e+05	2550.000000	1.068500e+04	2210.000000	550.000000	
max	9.900000e+09	7.700000e+06	13540.000000	1.651359e+06	9410.000000	4820.000000	

8 rows × 150 columns

In [159]:
```
sqft_metrics_without.shape
```

Out[159]: (21597, 2)

In [160]:
```
#R squared is higher for sqft_within, although Fstat is lower (than sqft
_without ...see below for comparison)
#Refined model by removing sqft_above as a metric because its P-value wa
s greater than .05 (it was .142)
model = sm.OLS(y, sqft_metrics_within).fit()
model.summary()
```

Out[160]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.839
Model:	OLS	**Adj. R-squared:**	0.839
Method:	Least Squares	**F-statistic:**	3.763e+04
Date:	Wed, 08 May 2019	**Prob (F-statistic):**	0.00
Time:	13:43:47	**Log-Likelihood:**	-3.0008e+05
No. Observations:	21597	**AIC:**	6.002e+05
Df Residuals:	21594	**BIC:**	6.002e+05
Df Model:	3		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
sqft_living	261.4732	1.087	240.656	0.000	259.344	263.603
sqft_lot	-0.2707	0.044	-6.184	0.000	-0.356	-0.185
sqft_basement	24.8016	4.447	5.577	0.000	16.085	33.519

Omnibus:	15815.760	**Durbin-Watson:**	1.980
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	662156.048
Skew:	3.075	**Prob(JB):**	0.00
Kurtosis:	29.420	**Cond. No.**	111.

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

In [161]:
```
model = sm.OLS(y, sqft_metrics_without).fit()
model.summary()
```

Out[161]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.791
Model:	OLS	**Adj. R-squared:**	0.791
Method:	Least Squares	**F-statistic:**	4.077e+04
Date:	Wed, 08 May 2019	**Prob (F-statistic):**	0.00
Time:	13:43:47	**Log-Likelihood:**	-3.0294e+05
No. Observations:	21597	**AIC:**	6.059e+05
Df Residuals:	21595	**BIC:**	6.059e+05
Df Model:	2		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
sqft_living15	278.5002	1.087	256.195	0.000	276.369	280.631
sqft_lot15	-0.3206	0.076	-4.226	0.000	-0.469	-0.172

Omnibus:	20919.274	**Durbin-Watson:**	1.980
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	2133317.049
Skew:	4.466	**Prob(JB):**	0.00
Kurtosis:	50.863	**Cond. No.**	16.1

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

Training and Testing

In [162]:
```
# Setting up two parallel sets of test and training data, one for each w
ithin/without metric
```

In [163]:
```
x_train, x_test, y_train, y_test = train_test_split(sqft_metrics_within,
y, test_size = 0.2)
```

In [164]:
```
print(len(x_train), len(x_test), len(y_train), len(y_test))
```

```
17277 4320 17277 4320
```

In [165]:
```
x1_train, x1_test, y1_train, y1_test = train_test_split(sqft_metrics_wit
hout, y1, test_size = 0.2)
```

In [166]:
```
print(len(x1_train), len(x1_test), len(y1_train), len(y1_test))
```

```
17277 4320 17277 4320
```

In [167]:
```
linreg1 = LinearRegression()
linreg1.fit(x_train, y_train)

y_hat_train = linreg1.predict(x_train)
y_hat_test = linreg1.predict(x_test)
```

In [168]:
```
linreg2 = LinearRegression()
linreg2.fit(x1_train, y1_train)

y1_hat_train = linreg2.predict(x1_train)
y1_hat_test = linreg2.predict(x1_test)
```

In [169]:
```
# the four measures of square footage within a single property appear to
have a
# significantly higher score
model = LinearRegression().fit(sqft_metrics_within, y)
print(model.score(sqft_metrics_within, y))
model1 = LinearRegression().fit(sqft_metrics_without, y1)
print(model1.score(sqft_metrics_without, y1))
```

```
0.49414625841304816
0.34313126558269624
```

In [189]:
```
#log-normalized variables include columns from within and without,
#and so the score is in the middle of the models above
x_train, x_test, y_train, y_test = train_test_split(df[normalize], y, te
st_size = 0.2)
model = LinearRegression().fit(df[normalize], y)
print(model.score(df[normalize], y))
```

```
0.3965735492331866
```

In [170]:
```
train_residuals = y_hat_train - y_train
test_residuals = y_hat_test - y_test
```

MSE

In [171]:
```
#Mean Squared Error is extremely high due to the high standard deviation
of price in the dataset
```

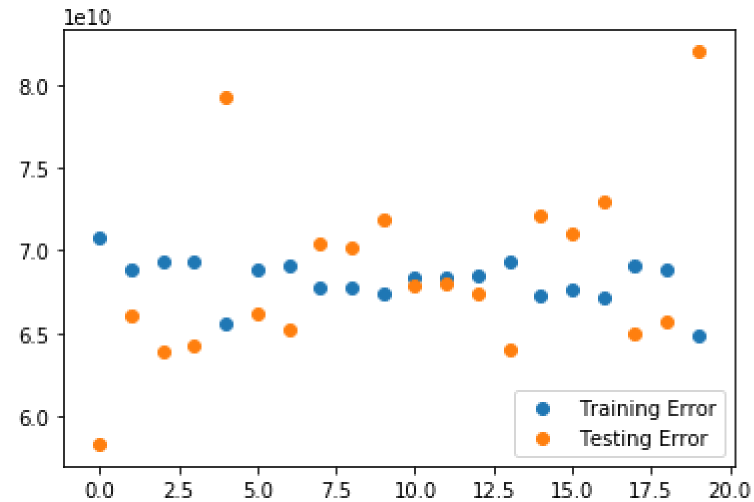
In [172]:
```
train_mse = mean_squared_error(y_train, y_hat_train)
test_mse = mean_squared_error(y_test, y_hat_test)
print('Train Mean Squared Error:', train_mse)
print('Test Mean Squared Error:', test_mse)
```

```
Train Mean Squared Error: 66624475575.98741
Test Mean Squared Error: 74912563012.68956
```

In [173]:
```
train_mse = mean_squared_error(y1_train, y1_hat_train)
test_mse = mean_squared_error(y1_test, y1_hat_test)
print('Train Mean Squared Error:', train_mse)
print('Test Mean Squared Error:', test_mse)
```

```
Train Mean Squared Error: 86899215674.53073
Test Mean Squared Error: 95640619513.20694
```

In [174]:
```
#Plotting the training and testing errors for the "within" metrics using a for loop
num = 20
train_err = []
test_err = []
for i in range(num):
    x_train, x_test, y_train, y_test = train_test_split(sqft_metrics_within, y, test_size=0.2)
    linreg1.fit(x_train, y_train)
    y_hat_train = linreg1.predict(x_train)
    y_hat_test = linreg1.predict(x_test)
    train_err.append(mean_squared_error(y_train, y_hat_train))
    test_err.append(mean_squared_error(y_test, y_hat_test))
plt.scatter(list(range(num)), train_err, label='Training Error')
plt.scatter(list(range(num)), test_err, label='Testing Error')
plt.legend();
```



In [175]:
```
#Plotting the training and testing errors for the "without" metrics usin
g a for loop
num = 20
train_err = []
test_err = []
for i in range(num):
    x1_train, x1_test, y1_train, y1_test = train_test_split(sqft_metrics
_without, y1, test_size=0.2)
    linreg2.fit(x1_train, y1_train)
    y1_hat_train = linreg2.predict(x1_train)
    y1_hat_test = linreg2.predict(x1_test)
    train_err.append(mean_squared_error(y1_train, y1_hat_train))
    test_err.append(mean_squared_error(y1_test, y1_hat_test))
plt.scatter(list(range(num)), train_err, label='Training Error')
plt.scatter(list(range(num)), test_err, label='Testing Error')
plt.legend();
```

MAE

In [176]:
```
#MAE - Mean Absolute Error -  Seems to be more valuable because of the p
rice metric's high standard deviation
mean_absolute_error(y_test, y_hat_test)
mean_absolute_error(y_train, y_hat_train)
```

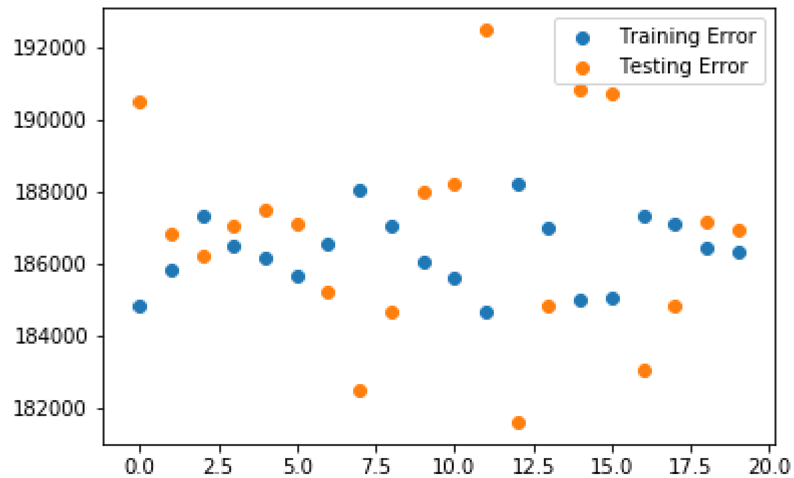
Out[176]: 170158.88038258936

In [177]:
```
mean_absolute_error(y1_test, y1_hat_test)
mean_absolute_error(y1_train, y1_hat_train)
```

Out[177]: 188781.54274154778

In [178]:
```
#Repeating the process for the MAE for both within and without square fo
otage variables
num = 20
train_err = []
test_err = []
for i in range(num):
    x_train, x_test, y_train, y_test = train_test_split(sqft_metrics_wit
hin, y, test_size=0.2)
    linreg1.fit(x_train, y_train)
    y_hat_train = linreg1.predict(x_train)
    y_hat_test = linreg1.predict(x_test)
    train_err.append(mean_absolute_error(y_train, y_hat_train))
    test_err.append(mean_absolute_error(y_test, y_hat_test))
plt.scatter(list(range(num)), train_err, label='Training Error')
plt.scatter(list(range(num)), test_err, label='Testing Error')
plt.legend();
```

In [179]:
```
num = 20
train_err = []
test_err = []
for i in range(num):
    x1_train, x1_test, y1_train, y1_test = train_test_split(sqft_metrics
_without, y1, test_size=0.2)
    linreg2.fit(x1_train, y1_train)
    y1_hat_train = linreg2.predict(x1_train)
    y1_hat_test = linreg2.predict(x1_test)
    train_err.append(mean_absolute_error(y1_train, y1_hat_train))
    test_err.append(mean_absolute_error(y1_test, y1_hat_test))
plt.scatter(list(range(num)), train_err, label='Training Error')
plt.scatter(list(range(num)), test_err, label='Testing Error')
plt.legend();
```



Cross-Validation

In [180]:
```
#Again, going by MAE is better than MSE
```

In [181]:
```
# cv_5_results = np.mean(cross_val_score(linreg1, sqft_metrics_within,
 y, cv=5, scoring="neg_mean_squared_error"))
# cv_10_results = np.mean(cross_val_score(linreg1, sqft_metrics_within,
 y, cv=10, scoring="neg_mean_squared_error"))
# cv_20_results = np.mean(cross_val_score(linreg1, sqft_metrics_within,
 y, cv=20, scoring="neg_mean_squared_error"))
# print(cv_5_results)
# print(cv_10_results)
# print(cv_20_results)
```

In [182]:
```
# cv1_5_results = np.mean(cross_val_score(linreg2, sqft_metrics_without, y1, cv=5, scoring="neg_mean_squared_error"))
# cv1_10_results = np.mean(cross_val_score(linreg2, sqft_metrics_without, y1, cv=10, scoring="neg_mean_squared_error"))
# cv1_20_results = np.mean(cross_val_score(linreg2, sqft_metrics_without, y1, cv=20, scoring="neg_mean_squared_error"))
# print(cv1_5_results)
# print(cv1_10_results)
# print(cv1_20_results)
```

In [183]:
```
cv_5_results = np.mean(cross_val_score(linreg1, sqft_metrics_within, y, cv=5, scoring="neg_mean_absolute_error"))
cv_10_results = np.mean(cross_val_score(linreg1, sqft_metrics_within, y, cv=10, scoring="neg_mean_absolute_error"))
cv_20_results = np.mean(cross_val_score(linreg1, sqft_metrics_within, y, cv=20, scoring="neg_mean_absolute_error"))
print(cv_5_results)
print(cv_10_results)
print(cv_20_results)
```

```
-173777.17827228116
-173747.7992601606
-173644.71320845376
```

In [184]:
```
cv1_5_results = np.mean(cross_val_score(linreg2, sqft_metrics_without, y1, cv=5, scoring="neg_mean_absolute_error"))
cv1_10_results = np.mean(cross_val_score(linreg2, sqft_metrics_without, y1, cv=10, scoring="neg_mean_absolute_error"))
cv1_20_results = np.mean(cross_val_score(linreg2, sqft_metrics_without, y1, cv=20, scoring="neg_mean_absolute_error"))
print(cv1_5_results)
print(cv1_10_results)
print(cv1_20_results)
```

```
-186977.23882091732
-186970.75027538088
-186724.40741423814
```

In [185]:
```
#Level-Up: split the dataset on median price and run each group through the MAE model again
```