In [1]:

```
# Import packages
import pandas as pd # Reading csv file
from shapely.geometry import Point # Shapely for converting latitude/longtitude to geo
import geopandas as gpd # To create GeodataFrame
import matplotlib.pyplot as plt # for plotting
from pyproj import CRS
```

In [2]:

```
# import housing data
df_all = pd.read_csv('data/kc_house_data.csv')
df_all.head(10)
```

Out[2]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors
0	7129300520	10/13/2014	221900	3	1.00	1180	5650	1.0
1	6414100192	12/9/2014	538000	3	2.25	2570	7242	2.0
2	5631500400	2/25/2015	180000	2	1.00	770	10000	1.0
3	2487200875	12/9/2014	604000	4	3.00	1960	5000	1.0
4	1954400510	2/18/2015	510000	3	2.00	1680	8080	1.0
5	7237550310	5/12/2014	1230000	4	4.50	5420	101930	1.0
6	1321400060	6/27/2014	257500	3	2.25	1715	6819	2.0
7	2008000270	1/15/2015	291850	3	1.50	1060	9711	1.0
8	2414600126	4/15/2015	229500	3	1.00	1780	7470	1.0
9	3793500160	3/12/2015	323000	3	2.50	1890	6560	2.0

10 rows × 21 columns

In [3]:

```
# clean data--convert "NaN" to 0 and replace "?" with 0
df_all = df_all.fillna(0).replace('?',0)
df_all.head(10)
```

Out[3]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors
0	7129300520	10/13/2014	221900	3	1.00	1180	5650	1.0
1	6414100192	12/9/2014	538000	3	2.25	2570	7242	2.0
2	5631500400	2/25/2015	180000	2	1.00	770	10000	1.0
3	2487200875	12/9/2014	604000	4	3.00	1960	5000	1.0
4	1954400510	2/18/2015	510000	3	2.00	1680	8080	1.0
5	7237550310	5/12/2014	1230000	4	4.50	5420	101930	1.0
6	1321400060	6/27/2014	257500	3	2.25	1715	6819	2.0
7	2008000270	1/15/2015	291850	3	1.50	1060	9711	1.0
8	2414600126	4/15/2015	229500	3	1.00	1780	7470	1.0
9	3793500160	3/12/2015	323000	3	2.50	1890	6560	2.0

10 rows × 21 columns

In [4]:

```
# want to look at houses with two bedrooms or less
df = df_all[(df_all['bedrooms'] <= 2)]
df.info
```

Out[4]:

```
<bound method DataFrame.info of                id        date    price
bedrooms  bathrooms  sqft_living  \
2      5631500400   2/25/2015  180000         2       1.00          770
11     9212900260   5/27/2014  468000         2       1.00         1160
18       16000397   12/5/2014  189000         2       1.00         1200
23     8091400200   5/16/2014  252700         2       1.50         1070
31     2426039314   12/1/2014  280000         2       1.50         1190
...           ...         ...      ...       ...        ...          ...
21570  2767604724  10/15/2014  505000         2       2.50         1430
21572  2767600688  11/13/2014  414500         2       1.50         1210
21579  1972201967  10/31/2014  520000         2       2.25         1530
21594  1523300141   6/23/2014  402101         2       0.75         1020
21596  1523300157  10/15/2014  325000         2       0.75         1020

       sqft_lot  floors  waterfront  view  ...  grade  sqft_above  \
2         10000     1.0         0.0   0.0  ...      6         770
11         6000     1.0         0.0   0.0  ...      7         860
18         9850     1.0         0.0   0.0  ...      7        1200
23         9643     1.0         0.0   0.0  ...      7        1070
31         1265     3.0         0.0   0.0  ...      7        1190
...         ...     ...         ...   ...  ...    ...         ...
21570      1201     3.0         0.0   0.0  ...      8        1430
21572      1278     2.0         0.0   0.0  ...      8        1020
21579       981     3.0         0.0   0.0  ...      8        1480
21594      1350     2.0         0.0   0.0  ...      7        1020
21596      1076     2.0         0.0   0.0  ...      7        1020

      sqft_basement yr_built  yr_renovated  zipcode      lat     long
\
2                 0     1933           0.0    98028  47.7379 -122.233
11              300     1942           0.0    98115  47.6900 -122.292
18                0     1921           0.0    98002  47.3089 -122.210
23                0     1985           0.0    98030  47.3533 -122.166
31                0     2005           0.0    98133  47.7274 -122.357
...             ...      ...           ...      ...      ...      ...
21570             0     2009           0.0    98107  47.6707 -122.381
21572           190     2007           0.0    98117  47.6756 -122.375
21579            50     2006           0.0    98103  47.6533 -122.346
21594             0     2009           0.0    98144  47.5944 -122.299
21596             0     2008           0.0    98144  47.5941 -122.299

       sqft_living15  sqft_lot15
2               2720        8062
```

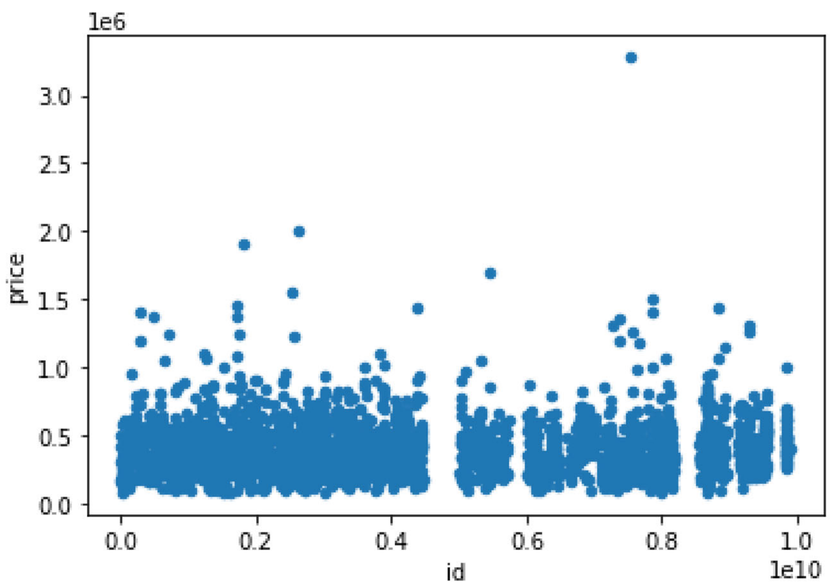
```
11              1330        6000
18              1060        5095
23              1220        8386
31              1390        1756
...              ...         ...
21570           1430        1249
21572           1210        1118
21579           1530        1282
21594           1020        2007
21596           1020        1357

[2956 rows x 21 columns]>
```

In [5]:

```
# want to look at price range
df.plot(kind='scatter', x='id', y='price')
```

Out[5]:

```
<AxesSubplot:xlabel='id', ylabel='price'>
```



In [6]:

```
# limit price range to less than $2 mill to remove obvious outlier
df = df[(df['price'] <= 2000000)]
df.info
```

Out[6]:

```
<bound method DataFrame.info of                  id        date   price
bedrooms  bathrooms  sqft_living  \
2      5631500400   2/25/2015  180000         2       1.00          770
11     9212900260   5/27/2014  468000         2       1.00         1160
18       16000397   12/5/2014  189000         2       1.00         1200
23     8091400200   5/16/2014  252700         2       1.50         1070
31     2426039314   12/1/2014  280000         2       1.50         1190
...           ...         ...     ...       ...        ...          ...
21570  2767604724  10/15/2014  505000         2       2.50         1430
21572  2767600688  11/13/2014  414500         2       1.50         1210
21579  1972201967  10/31/2014  520000         2       2.25         1530
21594  1523300141   6/23/2014  402101         2       0.75         1020
21596  1523300157  10/15/2014  325000         2       0.75         1020

       sqft_lot  floors  waterfront  view  ...  grade  sqft_above  \
2         10000     1.0         0.0   0.0  ...      6         770
11         6000     1.0         0.0   0.0  ...      7         860
18         9850     1.0         0.0   0.0  ...      7        1200
23         9643     1.0         0.0   0.0  ...      7        1070
31         1265     3.0         0.0   0.0  ...      7        1190
...         ...     ...         ...   ...  ...    ...         ...
21570      1201     3.0         0.0   0.0  ...      8        1430
21572      1278     2.0         0.0   0.0  ...      8        1020
21579       981     3.0         0.0   0.0  ...      8        1480
21594      1350     2.0         0.0   0.0  ...      7        1020
21596      1076     2.0         0.0   0.0  ...      7        1020

      sqft_basement yr_built  yr_renovated  zipcode      lat     long
\
2                 0     1933           0.0    98028  47.7379 -122.233
11              300     1942           0.0    98115  47.6900 -122.292
18                0     1921           0.0    98002  47.3089 -122.210
23                0     1985           0.0    98030  47.3533 -122.166
31                0     2005           0.0    98133  47.7274 -122.357
...             ...      ...           ...      ...      ...      ...
21570             0     2009           0.0    98107  47.6707 -122.381
21572           190     2007           0.0    98117  47.6756 -122.375
21579            50     2006           0.0    98103  47.6533 -122.346
21594             0     2009           0.0    98144  47.5944 -122.299
21596             0     2008           0.0    98144  47.5941 -122.299

       sqft_living15  sqft_lot15
2               2720        8062
```

```
11              1330        6000
18              1060        5095
23              1220        8386
31              1390        1756
...              ...         ...
21570           1430        1249
21572           1210        1118
21579           1530        1282
21594           1020        2007
21596           1020        1357

[2955 rows x 21 columns]>
```

In [7]:

```
# function to create GeoDataFrame
def add_geo_col(df):
    # create a geometry column
    geometry = [Point(xy) for xy in zip(df['long'], df['lat'])]

    # Coordinate reference system : WGS84 (the GPS model for conversion)
    crs = CRS('epsg:4326')

    # Creating a Geographic data frame
    gdf = gpd.GeoDataFrame(df, crs=crs, geometry=geometry).reset_index()
    return gdf
```

In [8]:

```
gdf = add_geo_col(df)
gdf.head()
```

Out[8]:

	index	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	flo
0	2	5631500400	2/25/2015	180000	2	1.0	770	10000	
1	11	9212900260	5/27/2014	468000	2	1.0	1160	6000	
2	18	16000397	12/5/2014	189000	2	1.0	1200	9850	
3	23	8091400200	5/16/2014	252700	2	1.5	1070	9643	
4	31	2426039314	12/1/2014	280000	2	1.5	1190	1265	

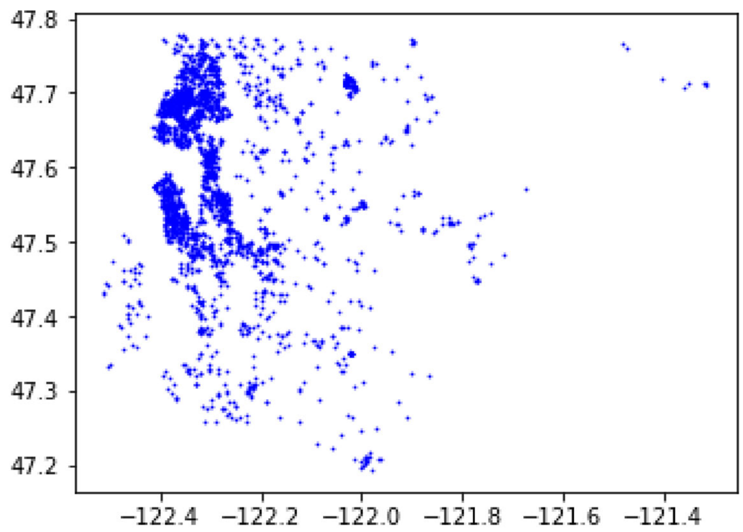
5 rows × 23 columns

In [9]:

```
# Plot all points
gdf.plot(marker='o', color='b', markersize=0.5)
```

Out[9]:

```
<AxesSubplot:>
```



In [10]:

```
# check what projection is used
gdf.crs
```

Out[10]:

```
<Geographic 2D CRS: EPSG:4326>
Name: WGS 84
Axis Info [ellipsoidal]:
- Lat[north]: Geodetic latitude (degree)
- Lon[east]: Geodetic longitude (degree)
Area of Use:
- name: World
- bounds: (-180.0, -90.0, 180.0, 90.0)
Datum: World Geodetic System 1984
- Ellipsoid: WGS 84
- Prime Meridian: Greenwich
```

In [11]:

```
# function to convert meters to miles
def m_2_mi(meters):
    return meters * 0.00062137
```

In [12]:

```
# function to find distance between two Points
def dist_to_point(point1, point2):
    pt1_gdf = gpd.GeoSeries([point1], crs=4326)
    pt2_gdf = gpd.GeoSeries([point2], crs=4326)
    pt1_gdf = pt1_gdf.to_crs(3857)
    pt2_gdf = pt2_gdf.to_crs(3857)
    distance = m_2_mi(pt1_gdf.distance(pt2_gdf))
    return round(distance.at[0], 3)
```

In [13]:

```
# Want to compile list of top 5 employers in Seattle area with a centralized campus
# Source is https://www.huduser.gov/portal/publications/pdf/SeattleWA-CHMA-19.pdf
df_top10_employers = pd.read_csv('data/top_employers.csv')
df_central5 = df_top10_employers[df_top10_employers['centralized_campus']=='y'].reset
df_central5 = add_geo_col(df_central5)
df_central5
```

Out[13]:

	level_0	index	rank	employer	no_employees	long	lat	centralized
0	0	0	1	The Boeing Company	64,300	-122.312023	47.532685	
1	1	1	2	Amazon.com, Inc.	45,000	-122.339688	47.615875	
2	2	2	3	Microsoft Corporation	43,031	-122.339688	47.645744	
3	3	3	4	University of Washington	30,200	-122.303644	47.655544	
4	4	7	8	Starbucks Corporation	11,239	-122.336000	47.580700	

In [14]:

```
# function to find the average distance of a house to the top 5 employers
def avg_dists(point1, gdf):
    dists = [dist_to_point(point1, point2) for point2 in gdf['geometry']]
    avg = sum(dists)/len(dists)
    return avg
```

In [15]:

```
downtown = Point(-122.3344, 47.6050) # coordinates for center of downtown Seattle

# Calculate average distance of each property to central downtown
gdf['dist_2_downtown'] = [dist_to_point(point, downtown) for point in gdf['geometry']]
```

In [16]:

```
# Calculate average distance of each property to the top 5 employers
gdf['avg_dists'] = [avg_dists(point, df_central5) for point in gdf['geometry']]
```

In [17]:

```
gdf.head()
```

Out[17]:

	index	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	flo
0	2	5631500400	2/25/2015	180000	2	1.0	770	10000	
1	11	9212900260	5/27/2014	468000	2	1.0	1160	6000	
2	18	16000397	12/5/2014	189000	2	1.0	1200	9850	
3	23	8091400200	5/16/2014	252700	2	1.5	1070	9643	
4	31	2426039314	12/1/2014	280000	2	1.5	1190	1265	

5 rows × 25 columns

In [18]:

```
gdf.to_pickle('data/geodata.pkl')
```

In [1]:

```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import statsmodels.api as sm
import numpy as np
from statsmodels.stats.outliers_influence import variance_inflation_factor
import scipy.stats as stats
from statsmodels.formula.api import ols
from statsmodels.stats.diagnostic import het_white
```

In [2]:

```
# Load data from other notebook
gdf = pd.read_pickle('data/geodata.pkl')
df = pd.DataFrame(gdf)
```

In [3]:

```
df.columns
```

Out[3]:

```
Index(['index', 'id', 'date', 'price', 'bedrooms', 'bathrooms', 'sqft_l
iving',
       'sqft_lot', 'floors', 'waterfront', 'view', 'condition', 'grad
e',
       'sqft_above', 'sqft_basement', 'yr_built', 'yr_renovated', 'zipc
ode',
       'lat', 'long', 'sqft_living15', 'sqft_lot15', 'geometry',
       'dist_2_downtown', 'avg_dists'],
      dtype='object')
```

In [4]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2955 entries, 0 to 2954
Data columns (total 25 columns):
 #   Column          Non-Null Count  Dtype   
---  ------          --------------  -----   
 0   index           2955 non-null   int64   
 1   id              2955 non-null   int64   
 2   date            2955 non-null   object  
 3   price           2955 non-null   int64   
 4   bedrooms        2955 non-null   int64   
 5   bathrooms       2955 non-null   float64 
 6   sqft_living     2955 non-null   int64   
 7   sqft_lot        2955 non-null   int64   
 8   floors          2955 non-null   float64 
 9   waterfront      2955 non-null   float64 
 10  view            2955 non-null   float64 
 11  condition       2955 non-null   int64   
 12  grade           2955 non-null   int64   
 13  sqft_above      2955 non-null   object  
 14  sqft_basement   2955 non-null   object  
 15  yr_built        2955 non-null   int64   
 16  yr_renovated    2955 non-null   float64 
 17  zipcode         2955 non-null   int64   
 18  lat             2955 non-null   float64 
 19  long            2955 non-null   float64 
 20  sqft_living15   2955 non-null   int64   
 21  sqft_lot15      2955 non-null   int64   
 22  geometry        2955 non-null   geometry
 23  dist_2_downtown 2955 non-null   float64 
 24  avg_dists       2955 non-null   float64 
dtypes: float64(9), geometry(1), int64(12), object(3)
memory usage: 577.3+ KB
```

In [5]:

```
# Clean up the data to change strings to integers and delete unnecessary columns
df['sqft_above'] = df['sqft_above'].astype('int64')
df['sqft_basement'] = df['sqft_basement'].astype('int64')
df['date'] = pd.DatetimeIndex(df['date']).month # get month from date
df = df.drop(columns=['index', 'id', 'geometry'])
df = pd.get_dummies(df)
df.info()
```

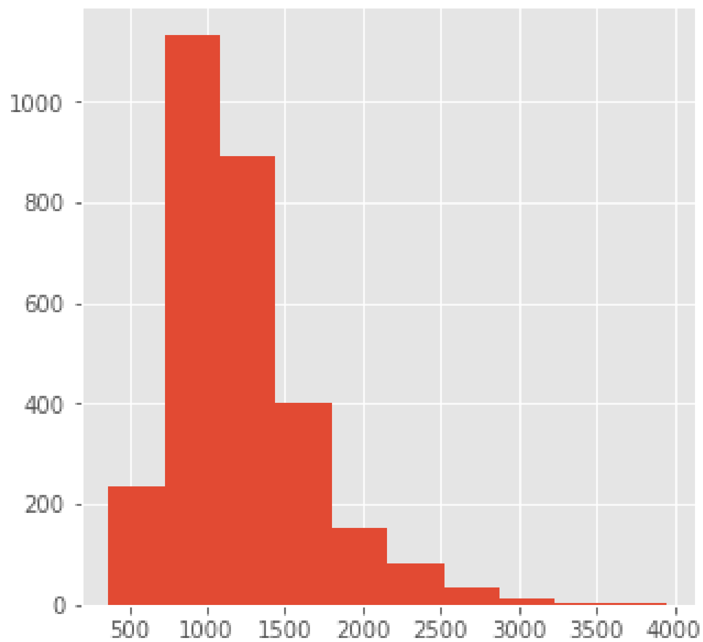
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2955 entries, 0 to 2954
Data columns (total 22 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   date             2955 non-null   int64  
 1   price            2955 non-null   int64  
 2   bedrooms         2955 non-null   int64  
 3   bathrooms        2955 non-null   float64
 4   sqft_living      2955 non-null   int64  
 5   sqft_lot         2955 non-null   int64  
 6   floors           2955 non-null   float64
 7   waterfront       2955 non-null   float64
 8   view             2955 non-null   float64
 9   condition        2955 non-null   int64  
 10  grade            2955 non-null   int64  
 11  sqft_above       2955 non-null   int64  
 12  sqft_basement    2955 non-null   int64  
 13  yr_built         2955 non-null   int64  
 14  yr_renovated     2955 non-null   float64
 15  zipcode          2955 non-null   int64  
 16  lat              2955 non-null   float64
 17  long             2955 non-null   float64
 18  sqft_living15    2955 non-null   int64  
 19  sqft_lot15       2955 non-null   int64  
 20  dist_2_downtown  2955 non-null   float64
 21  avg_dists        2955 non-null   float64
dtypes: float64(9), int64(13)
memory usage: 508.0 KB
```

In [6]:

```
# Create histograms to get a sense of data
plt.style.use('ggplot')
df.hist(figsize = (20,18));
```

In [7]:

```
# Create histograms of sqft_living to get a better look
plt.style.use('ggplot')
df['sqft_living'].hist(figsize = (5,5));
```

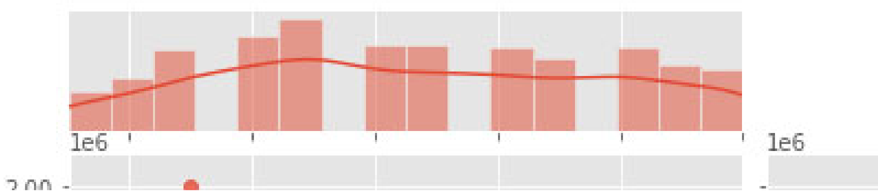


In [8]:

```
# look at features vs. price to get a sense what the influencers are
cols = list(df.columns)
cols.remove('price')
print(cols)
for col in cols:
    sns.jointplot(x=col, y='price', data=df, kind='reg');
```

```
['date', 'bedrooms', 'bathrooms', 'sqft_living', 'sqft_lot', 'floor
s', 'waterfront', 'view', 'condition', 'grade', 'sqft_above', 'sqft_
basement', 'yr_built', 'yr_renovated', 'zipcode', 'lat', 'long', 'sq
ft_living15', 'sqft_lot15', 'dist_2_downtown', 'avg_dists']
```

```
C:\Users\cm_fr\anaconda3\envs\geo\lib\site-packages\seaborn\axisgri
d.py:1559: RuntimeWarning: More than 20 figures have been opened. Fi
gures created through the pyplot interface (`matplotlib.pyplot.figur
e`) are retained until explicitly closed and may consume too much me
mory. (To control this warning, see the rcParam `figure.max_open_war
ning`).
  f = plt.figure(figsize=(height, height))
```

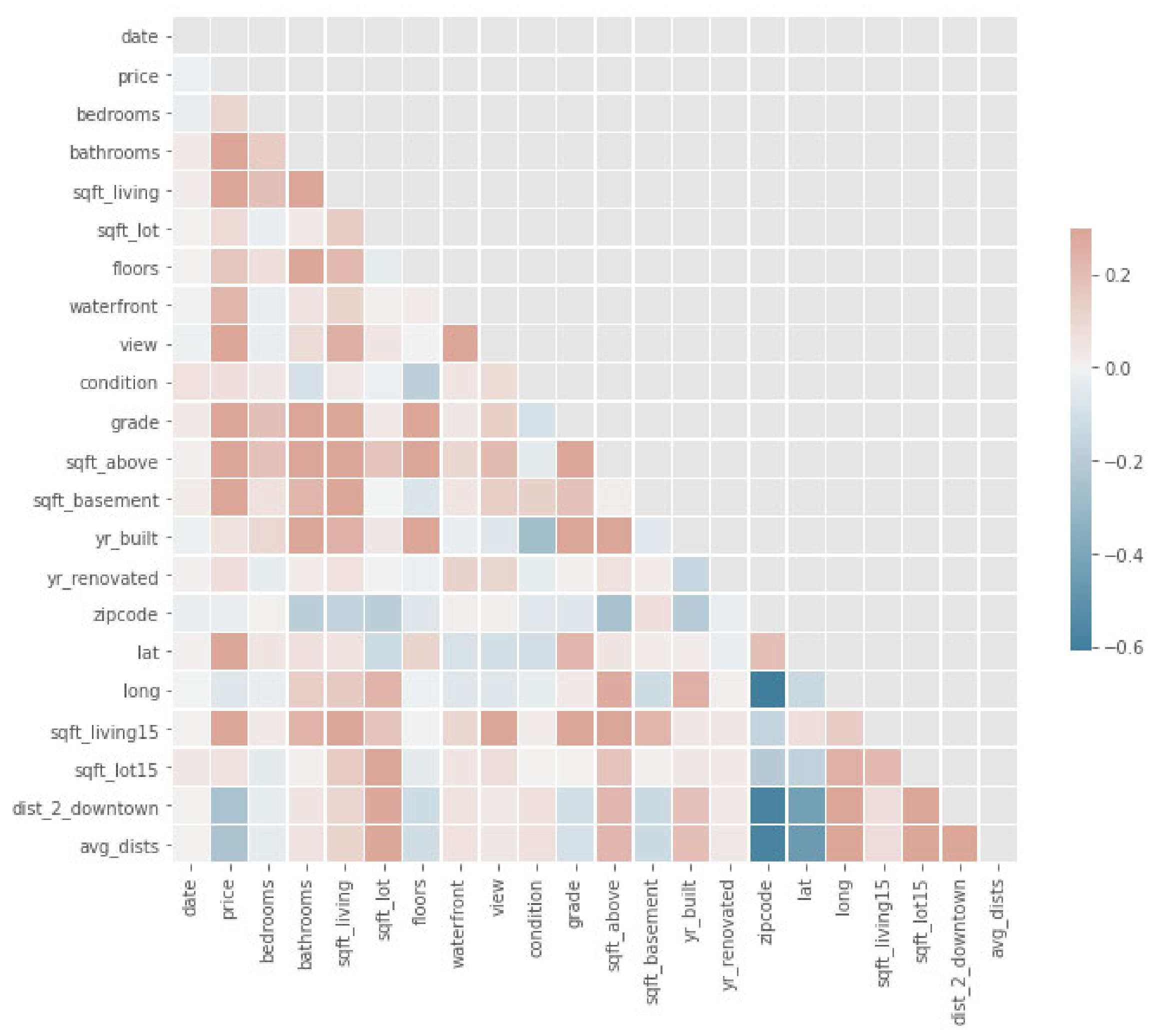


In [9]:

```
# Create a heatmap to identify any features with obvious multicollinearity

corr = df.corr()

# Generate a mask for the upper triangle
mask = np.triu(np.ones_like(corr, dtype=bool))

# Set up the matplotlib figure
f, ax = plt.subplots(figsize=(11, 9))

# Generate a custom diverging colormap
cmap = sns.diverging_palette(230, 20, as_cmap=True)

# Draw the heatmap with the mask and correct aspect ratio
sns.heatmap(corr, mask=mask, cmap=cmap, vmax=.3, center=0,
            square=True, linewidths=.5, cbar_kws={"shrink": .5})
```

Out[9]:

```
<AxesSubplot:>
```



In [10]:

```
# Drop location-related columns, leaving "dist_2_downtown"
df = df.drop(columns=['lat', 'long', 'zipcode', 'avg_dists'])
```

In [11]:

```
# Trim obvious outliers
df[(df['price'] <= 1500000) & (df['dist_2_downtown'] <= 50)].reset_index()
```

Out[11]:

	index	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfron
0	0	2	180000	2	1.00	770	10000	1.0	0.(
1	1	5	468000	2	1.00	1160	6000	1.0	0.(
2	2	12	189000	2	1.00	1200	9850	1.0	0.(
3	3	5	252700	2	1.50	1070	9643	1.0	0.(
4	4	12	280000	2	1.50	1190	1265	3.0	0.(
...	...	...	...	...	...	...	...	...	.
2937	2950	10	505000	2	2.50	1430	1201	3.0	0.(
2938	2951	11	414500	2	1.50	1210	1278	2.0	0.(
2939	2952	10	520000	2	2.25	1530	981	3.0	0.(
2940	2953	6	402101	2	0.75	1020	1350	2.0	0.(
2941	2954	10	325000	2	0.75	1020	1076	2.0	0.(

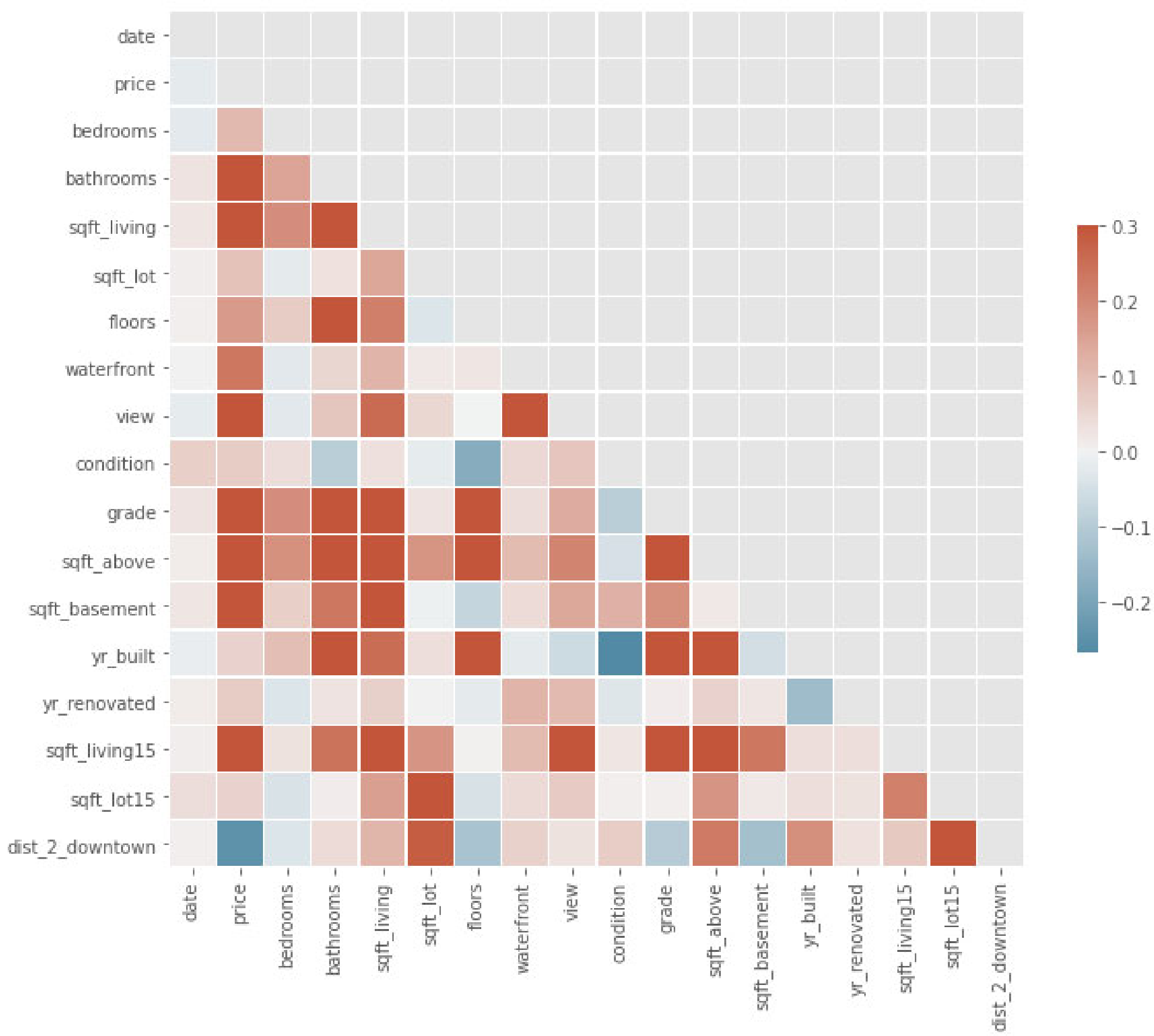
2942 rows × 19 columns

In [12]:

```
# Check heatmap again
corr = df.corr()
mask = np.triu(np.ones_like(corr, dtype=bool))
f, ax = plt.subplots(figsize=(11, 9))
cmap = sns.diverging_palette(230, 20, as_cmap=True)
sns.heatmap(corr, mask=mask, cmap=cmap, vmax=.3, center=0,
            square=True, linewidths=.5, cbar_kws={"shrink": .5})
```

Out[12]:

<AxesSubplot:>



In [13]:

```
# First Model
outcome = 'price' # dependent variable
x_cols = list(df.columns[2:])
x_cols.append('date')# independence variables --> everything except price
print((x_cols))
# Fitting the actual model using OLS
predictors = '+'.join(x_cols)
formula = outcome + '~' + predictors
model = ols(formula=formula, data=df).fit()
model.summary()
```

```
['bedrooms', 'bathrooms', 'sqft_living', 'sqft_lot', 'floors', 'waterfr
ont', 'view', 'condition', 'grade', 'sqft_above', 'sqft_basement', 'yr_
built', 'yr_renovated', 'sqft_living15', 'sqft_lot15', 'dist_2_downtow
n', 'date']
```

Out[13]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.619
Model:	OLS	**Adj. R-squared:**	0.616
Method:	Least Squares	**F-statistic:**	280.2
Date:	Thu, 17 Dec 2020	**Prob (F-statistic):**	0.00
Time:	23:23:40	**Log-Likelihood:**	-38671.
No. Observations:	2955	**AIC:**	7.738e+04
Df Residuals:	2937	**BIC:**	7.749e+04
Df Model:	17		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	1.37e+06	2.06e+05	6.653	0.000	9.66e+05	1.77e+06
bedrooms	-1.419e+04	8971.257	-1.581	0.114	-3.18e+04	3403.123
bathrooms	2.364e+04	6337.707	3.730	0.000	1.12e+04	3.61e+04
sqft_living	99.8358	48.896	2.042	0.041	3.962	195.710
sqft_lot	0.3004	0.058	5.205	0.000	0.187	0.414
floors	-1.299e+04	5824.127	-2.230	0.026	-2.44e+04	-1569.843
waterfront	2.123e+05	2.52e+04	8.420	0.000	1.63e+05	2.62e+05
view	3.056e+04	3983.074	7.672	0.000	2.27e+04	3.84e+04

condition	1.92e+04	3439.793	5.581	0.000	1.25e+04	2.59e+04
grade	6.254e+04	3483.867	17.951	0.000	5.57e+04	6.94e+04
sqft_above	47.1311	49.241	0.957	0.339	-49.419	143.681
sqft_basement	-20.1155	49.155	-0.409	0.682	-116.498	76.267
yr_built	-850.6321	109.839	-7.744	0.000	-1066.001	-635.263
yr_renovated	3.5353	5.918	0.597	0.550	-8.068	15.139
sqft_living15	80.4626	6.521	12.339	0.000	67.676	93.249
sqft_lot15	0.0427	0.106	0.402	0.687	-0.165	0.251
dist_2_downtown	-6100.5962	292.038	-20.890	0.000	-6673.215	-5527.977
date	-2450.4876	690.013	-3.551	0.000	-3803.445	-1097.530

Omnibus:	413.792	**Durbin-Watson:**	1.987
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	1359.832
Skew:	0.701	**Prob(JB):**	5.20e-296
Kurtosis:	6.013	**Cond. No.**	5.08e+06

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 5.08e+06. This might indicate that there are strong multicollinearity or other numerical problems.

In [14]:

```
# Model Refinement I
# Remove unecessary features
```

In [15]:

```
# Keep columns with p-value less than 0.05
outcome = 'price' # dependent variable
x_cols = ['bathrooms', 'floors', 'sqft_living', 'sqft_lot', 'waterfront', 'view', 'co
          'grade',  'yr_built', 'sqft_living15', 'dist_2_downtown', 'date'] # indepen

# Fitting the model again
predictors = '+'.join(x_cols)
formula = outcome + '~' + predictors
model = ols(formula=formula, data=df).fit()
model.summary()
```

Out[15]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.614
Model:	OLS	**Adj. R-squared:**	0.612
Method:	Least Squares	**F-statistic:**	389.9
Date:	Thu, 17 Dec 2020	**Prob (F-statistic):**	0.00
Time:	23:23:40	**Log-Likelihood:**	-38688.
No. Observations:	2955	**AIC:**	7.740e+04
Df Residuals:	2942	**BIC:**	7.748e+04
Df Model:	12		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	1.426e+06	2.01e+05	7.091	0.000	1.03e+06	1.82e+06
bathrooms	2.273e+04	6333.000	3.589	0.000	1.03e+04	3.51e+04
floors	-5281.4152	5703.626	-0.926	0.355	-1.65e+04	5902.088
sqft_living	115.8976	7.448	15.560	0.000	101.293	130.502
sqft_lot	0.3241	0.048	6.731	0.000	0.230	0.419
waterfront	2.161e+05	2.52e+04	8.561	0.000	1.67e+05	2.66e+05
view	3.042e+04	3995.141	7.613	0.000	2.26e+04	3.82e+04
condition	1.674e+04	3415.873	4.901	0.000	1e+04	2.34e+04
grade	6.594e+04	3425.071	19.253	0.000	5.92e+04	7.27e+04
yr_built	-898.1095	107.505	-8.354	0.000	-1108.902	-687.317
sqft_living15	85.7034	6.447	13.293	0.000	73.062	98.345
dist_2_downtown	-5551.4009	274.244	-20.243	0.000	-6089.130	-5013.671

date	-2444.7245	692.283	-3.531	0.000	-3802.132	-1087.317

Omnibus:	439.504	**Durbin-Watson:**	2.001
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	1478.218
Skew:	0.737	**Prob(JB):**	0.00
Kurtosis:	6.136	**Cond. No.**	4.58e+06

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 4.58e+06. This might indicate that there are strong multicollinearity or other numerical problems.

In [16]:

```
# need to drop "floors" this time
outcome = 'price'
x_cols = ['bathrooms', 'sqft_living', 'sqft_lot', 'waterfront', 'view', 'condition',
          'grade',  'yr_built', 'sqft_living15', 'dist_2_downtown', 'date']

# Fitting the model again
predictors = '+'.join(x_cols)
formula = outcome + '~' + predictors
model = ols(formula=formula, data=df).fit()
model.summary()
```

Out[16]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.614
Model:	OLS	**Adj. R-squared:**	0.612
Method:	Least Squares	**F-statistic:**	425.3
Date:	Thu, 17 Dec 2020	**Prob (F-statistic):**	0.00
Time:	23:23:40	**Log-Likelihood:**	-38689.
No. Observations:	2955	**AIC:**	7.740e+04
Df Residuals:	2943	**BIC:**	7.747e+04
Df Model:	11		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
Intercept	1.496e+06	1.86e+05	8.029	0.000	1.13e+06	1.86e+06
bathrooms	2.115e+04	6098.350	3.468	0.001	9191.130	3.31e+04
sqft_living	116.3032	7.435	15.642	0.000	101.724	130.882
sqft_lot	0.3233	0.048	6.715	0.000	0.229	0.418
waterfront	2.153e+05	2.52e+04	8.534	0.000	1.66e+05	2.65e+05
view	3.032e+04	3993.702	7.592	0.000	2.25e+04	3.82e+04
condition	1.678e+04	3415.494	4.914	0.000	1.01e+04	2.35e+04
grade	6.57e+04	3414.887	19.239	0.000	5.9e+04	7.24e+04
yr_built	-936.5623	99.158	-9.445	0.000	-1130.989	-742.136
sqft_living15	86.2147	6.423	13.422	0.000	73.620	98.809
dist_2_downtown	-5490.5062	266.236	-20.623	0.000	-6012.534	-4968.479
date	-2447.5704	692.259	-3.536	0.000	-3804.932	-1090.209

Omnibus:	439.866	**Durbin-Watson:**	2.001
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	1477.938
Skew:	0.738	**Prob(JB):**	0.00
Kurtosis:	6.135	**Cond. No.**	4.24e+06

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 4.24e+06. This might indicate that there are strong multicollinearity or other numerical problems.

In [17]:

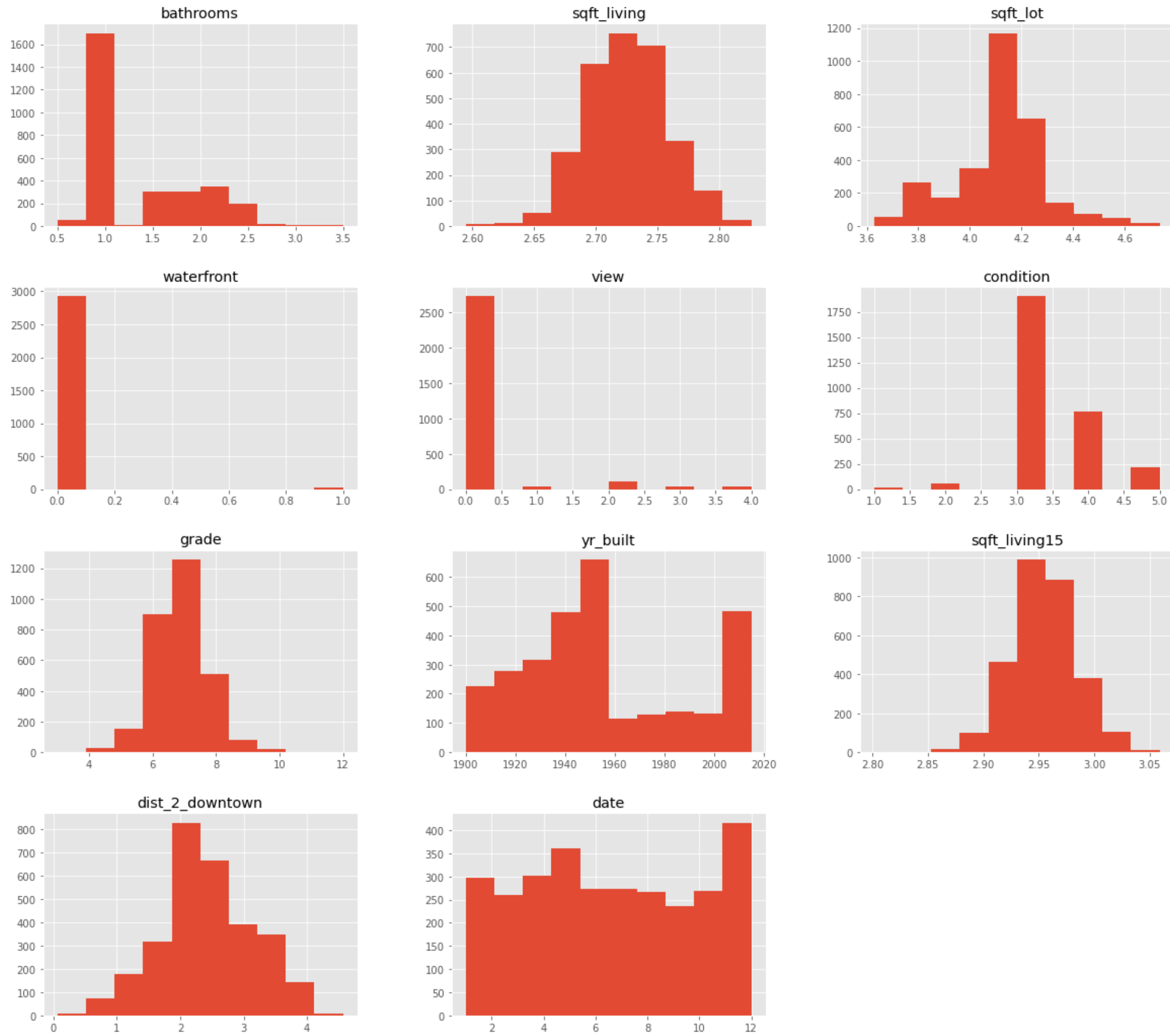
```
# Model Refinement II
# normalize and standardize features
```

In [18]:

```
# try to normalize non-normal features via box-cox transformation
non_normal = ['sqft_living', 'sqft_lot', 'sqft_living15', 'dist_2_downtown']
for feat in non_normal:
    fitted_data, fitted_lambda = stats.boxcox(df[feat])
    df[feat] = fitted_data
```

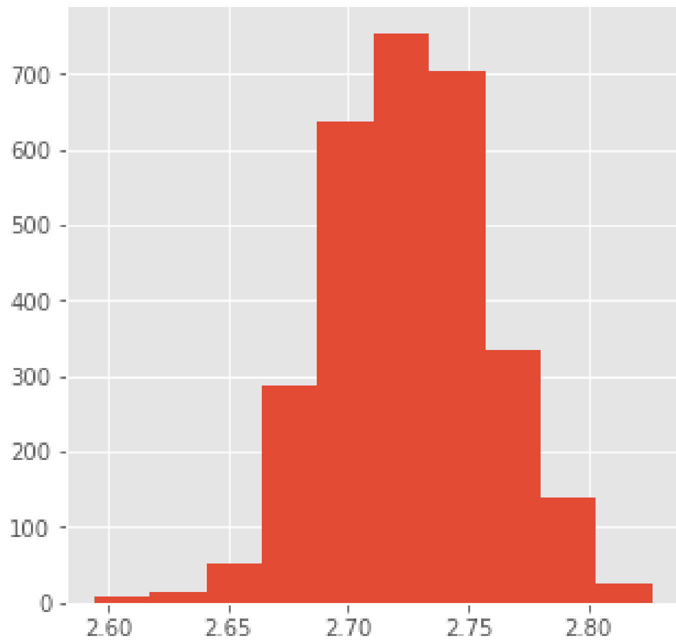
In [19]:

```
df[x_cols].hist(figsize = (20,18));
```



In [20]:

```
# Create histograms of sqft_living to get a better look
plt.style.use('ggplot')
df['sqft_living'].hist(figsize = (5,5));
```



In [21]:

```
# apply the z-score method in Pandas using the .mean() and .std() methods to standard

# copy the dataframe
df_std = df.copy()
# apply the z-score method
for column in x_cols:
    df_std[column] = (df_std[column] - df_std[column].mean()) / df_std[column].std()

# call the z_score function
df = df_std
```

In [22]:

```
predictors = '+'.join(x_cols)
formula = outcome + '~' + predictors
model = ols(formula=formula, data=df).fit()
model.summary()
```

Out[22]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.597
Model:	OLS	**Adj. R-squared:**	0.595
Method:	Least Squares	**F-statistic:**	395.9
Date:	Thu, 17 Dec 2020	**Prob (F-statistic):**	0.00
Time:	23:23:43	**Log-Likelihood:**	-38753.
No. Observations:	2955	**AIC:**	7.753e+04
Df Residuals:	2943	**BIC:**	7.760e+04
Df Model:	11		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	3.949e+05	2212.373	178.495	0.000	3.91e+05	3.99e+05
bathrooms	2.232e+04	3381.513	6.600	0.000	1.57e+04	2.89e+04
sqft_living	3.446e+04	3460.357	9.958	0.000	2.77e+04	4.12e+04
sqft_lot	2.418e+04	3364.899	7.185	0.000	1.76e+04	3.08e+04
waterfront	2.205e+04	2629.772	8.386	0.000	1.69e+04	2.72e+04
view	2.531e+04	2756.396	9.184	0.000	1.99e+04	3.07e+04
condition	1.309e+04	2348.465	5.575	0.000	8488.842	1.77e+04
grade	6.93e+04	3495.800	19.823	0.000	6.24e+04	7.62e+04
yr_built	-2.645e+04	3421.957	-7.730	0.000	-3.32e+04	-1.97e+04
sqft_living15	3.496e+04	2742.348	12.749	0.000	2.96e+04	4.03e+04
dist_2_downtown	-5.971e+04	3018.161	-19.783	0.000	-6.56e+04	-5.38e+04
date	-8514.4862	2221.674	-3.832	0.000	-1.29e+04	-4158.294

Omnibus:	685.455	**Durbin-Watson:**	1.998
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	3596.651
Skew:	1.002	**Prob(JB):**	0.00

Kurtosis:	8.019	**Cond. No.**	3.70

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

In [23]:

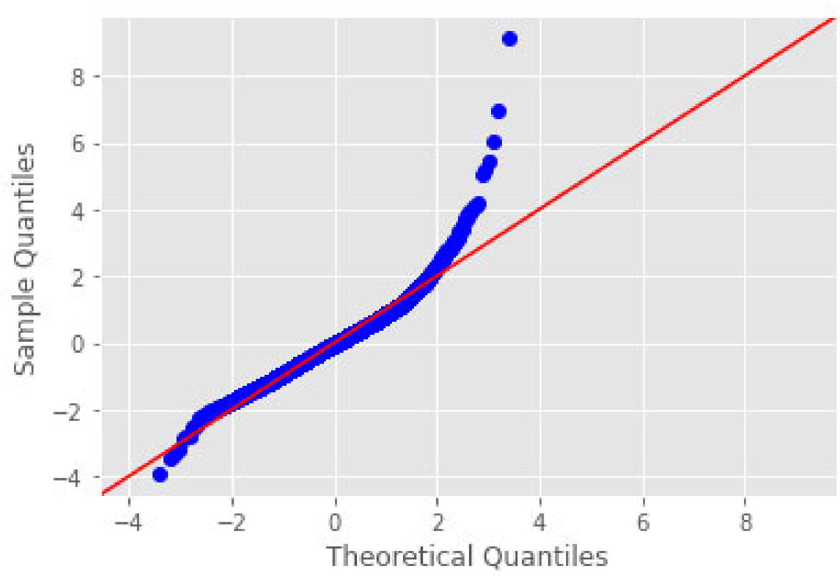
```
# Check for Multicollinearity --> want values < 5
X = df[x_cols]
vif = [variance_inflation_factor(X.values, i) for i in range(X.shape[1])]
list(zip(x_cols, vif))
```

Out[23]:

```
[('bathrooms', 2.3353840550342766),
 ('sqft_living', 2.445559021737623),
 ('sqft_lot', 2.3124919492147544),
 ('waterfront', 1.4124483621605053),
 ('view', 1.5517416117950533),
 ('condition', 1.126430138174815),
 ('grade', 2.4959132009887193),
 ('yr_built', 2.3915818257117696),
 ('sqft_living15', 1.5359655109787187),
 ('dist_2_downtown', 1.8604633795396446),
 ('date', 1.008084245232352)]
```

In [24]:

```
# Q-Q Plot to check normality of residuals
residuals = model.resid
fig = sm.graphics.qqplot(residuals, dist=stats.norm, line='45', fit=True)
```

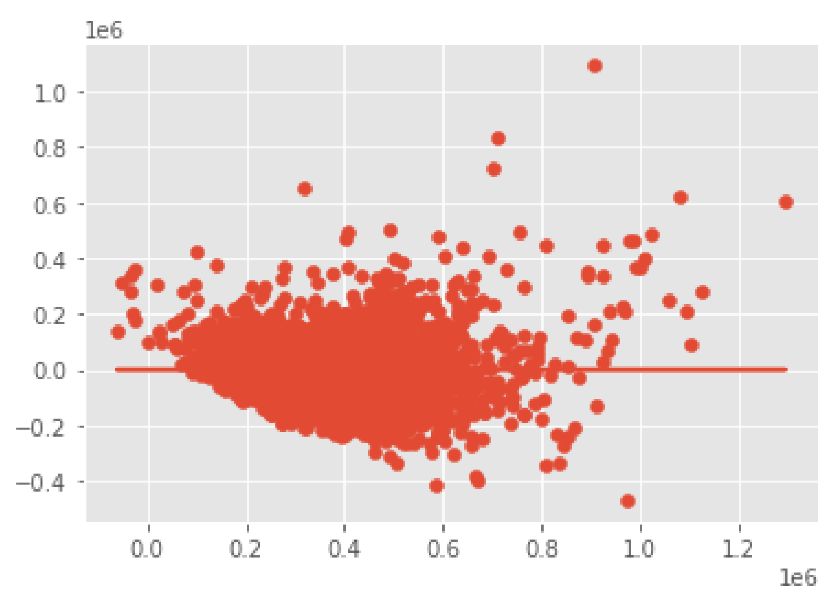


In [25]:

```
# Checking for Homoscedasticity
plt.scatter(model.predict(df[x_cols]), model.resid)
plt.plot(model.predict(df[x_cols]), [0 for i in range(len(df))])
```

Out[25]:

```
[<matplotlib.lines.Line2D at 0x1de1c792bb0>]
```



In [26]:

```
white_test = het_white(model.resid,  model.model.exog)
labels = ['LM Statistic', 'LM-Test p-value', 'F-Statistic', 'F-Test p-value']
print(dict(zip(labels, white_test)))
```

```
{'LM Statistic': 876.2726504950575, 'LM-Test p-value': 2.28473260763542
73e-136, 'F-Statistic': 15.963162121167544, 'F-Test p-value': 3.9135691
99280514e-166}
```

In [27]:

```
# Model Refinement III
# Address residual normality issues and heteroscedasticity
```

In [28]:

```
# Finding a cutoff point to narrow the price range
for i in range(0, 20):
    q = i / 100
    print('{} percentile: {}'.format(q, df['price'].quantile(q=q)))

print('---')

for i in range(80, 100):
    q = i / 100
    print('{} percentile: {}'.format(q, df['price'].quantile(q=q)))
```

```
0.0 percentile: 78000.0
0.01 percentile: 109270.0
0.02 percentile: 124540.0
0.03 percentile: 144990.5
0.04 percentile: 155000.0
0.05 percentile: 163710.0
0.06 percentile: 174120.0
0.07 percentile: 179989.0
0.08 percentile: 187524.0
0.09 percentile: 192500.0
0.1 percentile: 199950.0
0.11 percentile: 202000.0
0.12 percentile: 208408.16
0.13 percentile: 212000.0
0.14 percentile: 216500.0
0.15 percentile: 220754.99999999997
0.16 percentile: 226512.0
0.17 percentile: 230000.0
0.18 percentile: 235000.0
0.19 percentile: 239950.0
---
0.8 percentile: 515000.0
0.81 percentile: 525000.0
0.82 percentile: 530000.0
0.83 percentile: 540000.0
0.84 percentile: 549000.0
0.85 percentile: 553000.0
0.86 percentile: 563160.0000000001
0.87 percentile: 575000.0
0.88 percentile: 582260.0
0.89 percentile: 599057.0
0.9 percentile: 605075.0
0.91 percentile: 626129.9999999994
0.92 percentile: 650000.0
0.93 percentile: 665000.0
0.94 percentile: 695000.0
0.95 percentile: 716499.9999999986
0.96 percentile: 751469.9999999994
```

```
0.97 percentile: 800000.0
0.98 percentile: 850000.0
0.99 percentile: 1054600.0000000005
```

In [29]:

```
# Keep values between 1% and 90%
lower = 109270
upper = 605075

subset = df[(df['price'] >= lower) & (df['price'] <= upper)].reset_index()
print('Percent removed:',(len(df) - len(subset))/len(df))

predictors = '+'.join(x_cols)
formula = outcome + '~' + predictors
model = ols(formula=formula, data=subset).fit()
model.summary()
```

```
Percent removed: 0.11032148900169204
```

Out[29]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.455
Model:	OLS	**Adj. R-squared:**	0.452
Method:	Least Squares	**F-statistic:**	198.4
Date:	Thu, 17 Dec 2020	**Prob (F-statistic):**	0.00
Time:	23:23:44	**Log-Likelihood:**	-33681.
No. Observations:	2629	**AIC:**	6.739e+04
Df Residuals:	2617	**BIC:**	6.746e+04
Df Model:	11		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
Intercept	3.677e+05	1775.217	207.101	0.000	3.64e+05	3.71e+05
bathrooms	1.172e+04	2720.179	4.307	0.000	6381.653	1.7e+04
sqft_living	2.458e+04	2720.795	9.034	0.000	1.92e+04	2.99e+04
sqft_lot	6325.1069	2710.246	2.334	0.020	1010.664	1.16e+04
waterfront	1.208e+04	2939.983	4.111	0.000	6319.982	1.78e+04
view	4451.3717	2834.572	1.570	0.116	-1106.859	1e+04
condition	9573.2081	1859.675	5.148	0.000	5926.626	1.32e+04
grade	4.401e+04	2888.104	15.240	0.000	3.84e+04	4.97e+04
yr_built	-2.13e+04	2709.633	-7.862	0.000	-2.66e+04	-1.6e+04

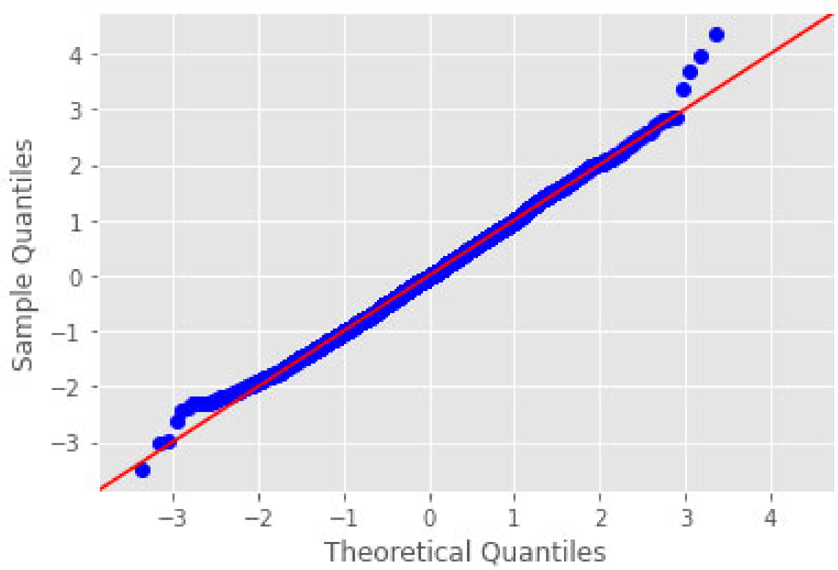
sqft_living15	2.558e+04	2147.554	11.910	0.000	2.14e+04	2.98e+04
dist_2_downtown	-4.623e+04	2365.351	-19.545	0.000	-5.09e+04	-4.16e+04
date	-4564.8015	1728.501	-2.641	0.008	-7954.169	-1175.434

Omnibus:	9.387	**Durbin-Watson:**	1.958
Prob(Omnibus):	0.009	**Jarque-Bera (JB):**	9.477
Skew:	0.146	**Prob(JB):**	0.00875
Kurtosis:	2.962	**Cond. No.**	3.57

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

In [30]:

```
fig = sm.graphics.qqplot(model.resid, dist=stats.norm, line='45', fit=True)
```



In [31]:

```
plt.scatter(model.predict(subset[x_cols]), model.resid)
plt.plot(model.predict(subset[x_cols]), [0 for i in range(len(subset))])
```

Out[31]:

```
[<matplotlib.lines.Line2D at 0x1de1e7b0f10>]
```

In [32]:

```
white_test = het_white(model.resid,  model.model.exog)
labels = ['LM Statistic', 'LM-Test p-value', 'F-Statistic', 'F-Test p-value']
print(dict(zip(labels, white_test)))
```

```
{'LM Statistic': 285.32266762438934, 'LM-Test p-value': 5.5278189791947
92e-26, 'F-Statistic': 4.087949610992519, 'F-Test p-value': 6.075933533
120562e-28}
```

In [33]:

```
# Model Refinement IV
# Residual normality improved but still not homoscedastic
# Try building a model from the ground up
```

In [34]:

```
outcome = 'price'

x_cols = ['grade', 'sqft_living', 'dist_2_downtown', 'waterfront']
subset = df[(df['price'] >= lower) & (df['price'] <= upper)].reset_index()
print('Percent removed:',(len(df) - len(subset))/len(df))
# subset['price'] = subset['price'].map(np.log)
predictors = '+'.join(x_cols)
formula = outcome + '~' + predictors
model = ols(formula=formula, data=subset).fit()
model.summary()
```

```
Percent removed: 0.11032148900169204
```

Out[34]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.378
Model:	OLS	**Adj. R-squared:**	0.377
Method:	Least Squares	**F-statistic:**	399.0
Date:	Thu, 17 Dec 2020	**Prob (F-statistic):**	9.60e-269
Time:	23:23:45	**Log-Likelihood:**	-33854.
No. Observations:	2629	**AIC:**	6.772e+04
Df Residuals:	2624	**BIC:**	6.775e+04
Df Model:	4		
Covariance Type:	nonrobust		

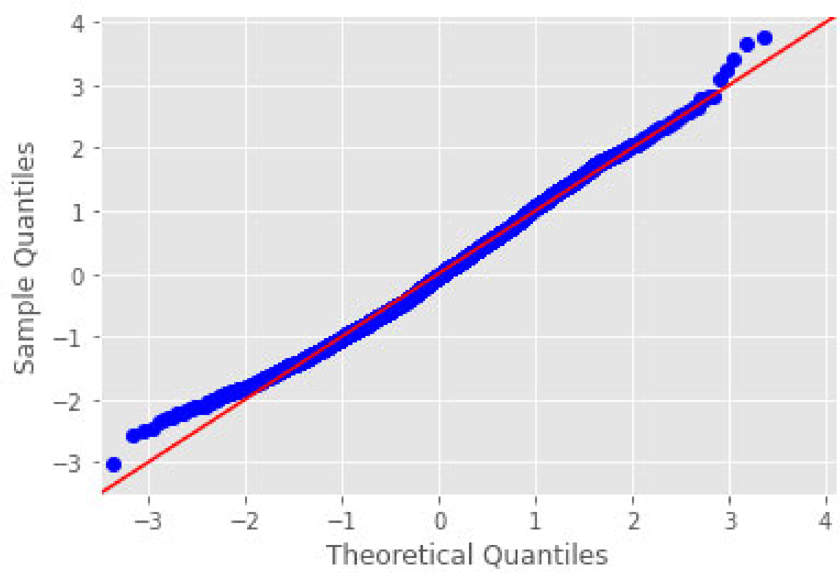
	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
Intercept	3.642e+05	1873.671	194.367	0.000	3.61e+05	3.68e+05
grade	2.84e+04	2533.560	11.210	0.000	2.34e+04	3.34e+04
sqft_living	4.358e+04	2470.423	17.639	0.000	3.87e+04	4.84e+04
dist_2_downtown	-4.678e+04	1946.414	-24.033	0.000	-5.06e+04	-4.3e+04
waterfront	1.651e+04	2694.059	6.128	0.000	1.12e+04	2.18e+04

Omnibus:	36.631	**Durbin-Watson:**	1.930
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	34.449
Skew:	0.242	**Prob(JB):**	3.31e-08
Kurtosis:	2.718	**Cond. No.**	2.04

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

In [35]:

```
fig = sm.graphics.qqplot(model.resid, dist=stats.norm, line='45', fit=True)
```

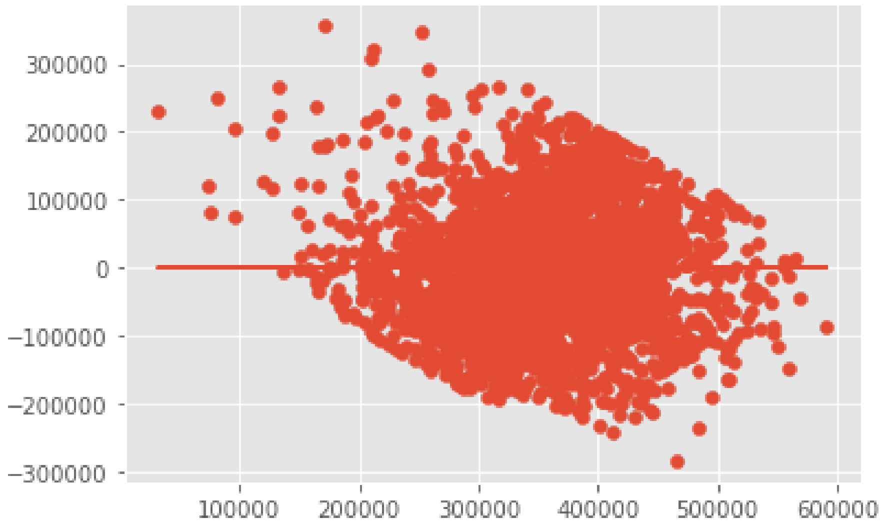


In [36]:

```
plt.scatter(model.predict(subset[x_cols]), model.resid)
plt.plot(model.predict(subset[x_cols]), [0 for i in range(len(subset))])
```

Out[36]:

```
[<matplotlib.lines.Line2D at 0x1de1c7a0c10>]
```



In [37]:

```
white_test = het_white(model.resid,  model.model.exog)
labels = ['LM Statistic', 'LM-Test p-value', 'F-Statistic', 'F-Test p-value']
print(dict(zip(labels, white_test)))
```

```
{'LM Statistic': 18.91835463694957, 'LM-Test p-value': 0.12565691921969
73, 'F-Statistic': 1.4580002908665912, 'F-Test p-value': 0.125437345918
53972}
```

In [38]:

```
# y_pred = model.predict([4, 5, 6])
# >>> print('predicted response:', y_pred, sep='\n')
```

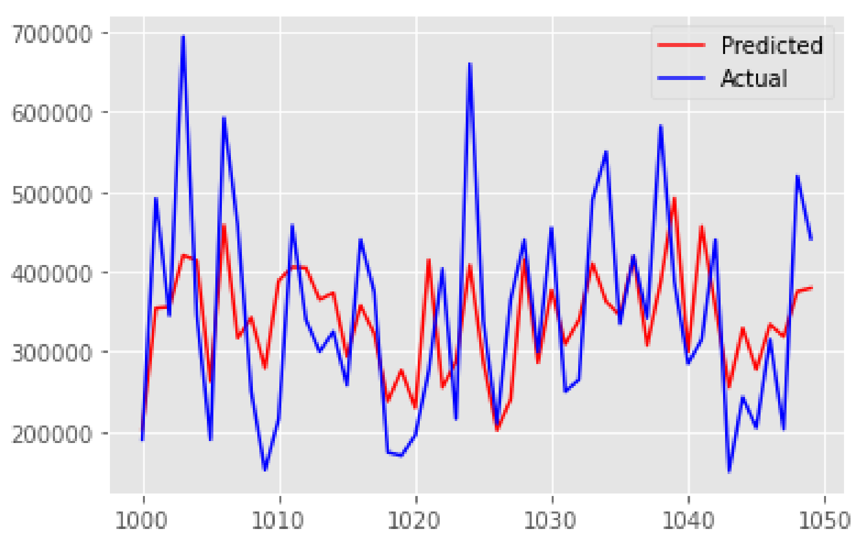
In [39]:

```
ypred = model.predict(X)
print(ypred)
```

```
0       259450.339020
1       380019.283149
2       298321.347142
3       291268.453849
4       361253.661936
            ...
2950    449338.296909
2951    426249.590790
2952    484226.440510
2953    446353.837983
2954    446034.272898
Length: 2955, dtype: float64
```

In [40]:

```
fig, ax = plt.subplots()
bot = 1000
top = 1050
x = ypred.index[bot:top]
y_pred = ypred[bot:top]
y_actual = df['price'][bot:top]
ax.plot(x, y_pred, 'r-', label="Predicted") # predicted values
ax.plot(x, y_actual, 'b-', label="Actual") # actual values
# ax.plot(np.hstack((x, x)), np.hstack((y_pred, y_actual)), 'r')
ax.legend(loc="best");
```



In [41]:

```
# create additional graphics
from shapely.geometry import Point # Shapely for converting latitude/longtitude to ge
import geopandas as gpd # To create GeodataFram
import pandas as pd
from pyproj import CRS
import matplotlib.pyplot as plt
```

In [42]:

```
def add_geo_col(df):
    # create a geometry column
    geometry = [Point(xy) for xy in zip(df['long'], df['lat'])]

    # Coordinate reference system : WGS84 (the GPS model for conversion)
    crs = CRS('epsg:4326')

    # Creating a Geographic data frame
    gdf = gpd.GeoDataFrame(df, crs=crs, geometry=geometry).reset_index()
    return gdf
```

In [43]:

```
gdf2 = pd.read_pickle('data/geodata.pkl')
```

In [44]:

```
df_top10_employers = pd.read_csv('data/top_employers.csv')
df3 = df_top10_employers[df_top10_employers['centralized_campus']=='y'].reset_index()
gdf3 = add_geo_col(df3)
```

In [45]:

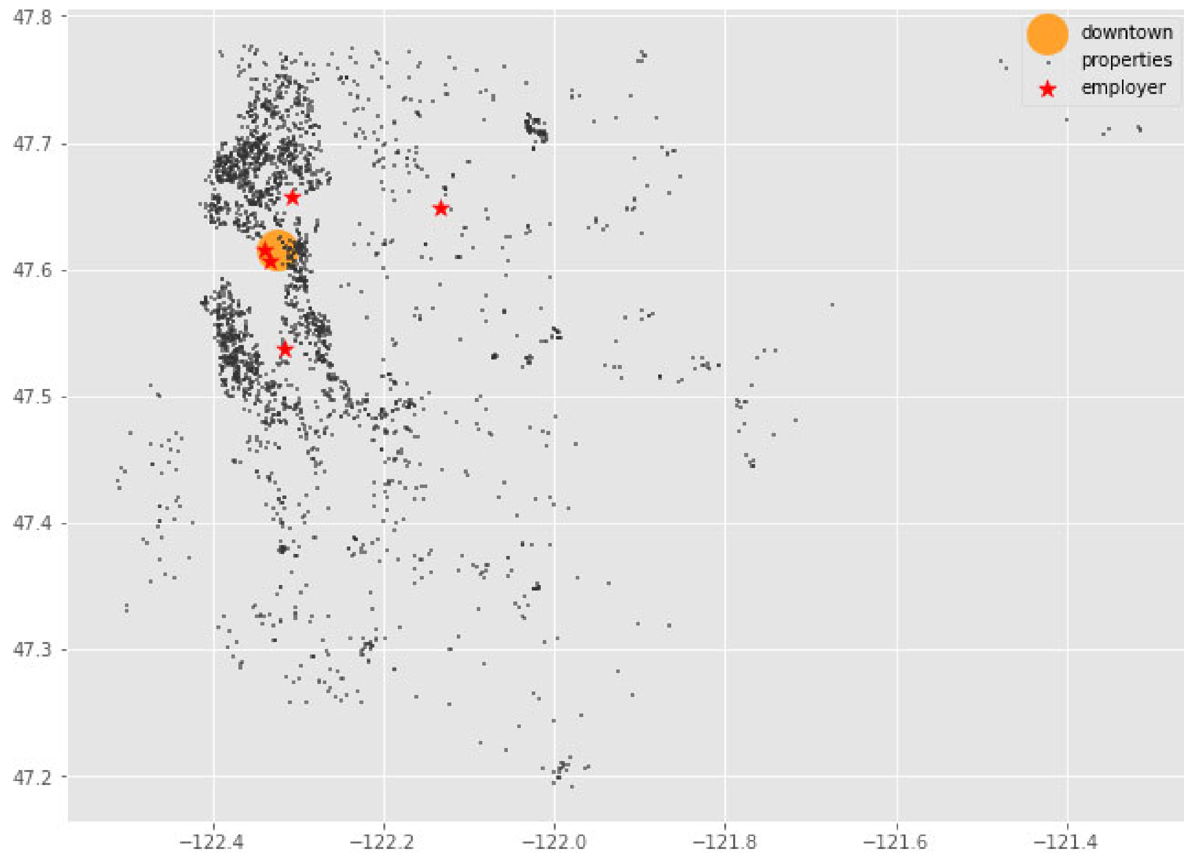
```
downtown = Point(-122.3244, 47.6150)
gdf4 = gpd.GeoSeries(downtown, crs=4326)
```

In [46]:

```
fig, ax = plt.subplots(ncols=1, sharex=True, sharey=True, figsize=(11, 20))
gdf4.plot(ax=ax, marker='o', color='#FFA12A', markersize=500, label='downtown')
gdf2.plot(ax=ax, marker='s', color='#333333', markersize=1, label='properties')
gdf3.plot(ax=ax, marker='*', color='r', markersize=100, label='employer')
ax.legend()
# gdf2.plot(marker='o', color='b', markersize=0.5)
# gdf3.plot(marker='o', color='r', markersize=0.5)
```

Out[46]:

```
<matplotlib.legend.Legend at 0x1de1b77bbb0>
```



In [ ]:

```
```