King County Housing Sale Price Predictions

The Business Problem

Phil and Nancy are partners own a house in King County and are looking to renovate their home in order to maximize the value of their home. They have some spare money and have come to the AA Consulting Agency to seek advice on what they should renovate in their house in order to maximize the resale value. They are looking to renovate their house with the intention of flipping it to make a profit and move into a bigger house somewhere else in King County. Our analysis is aimed to help them decide which features to renovate and by how much their home value will increase. Our statistical analysis is aimed to predict home price based on certain renovations. We will test which renovations have the biggest impact on price, and create a predictive model which can help them make an informed data-driven decision.

This data was pulled from the King County government website and outlines home prices along with other features of the home in a csv file. We will be importing the file into two dateframes for use in the analysis. The data is generally clean, but contains zip codes from locations outside of King County, so we will be removing those as they are not relevant to the data. The address, lat, and long fields were gathered using a third party geocoding API, which explains why there was some discrepency.

IMPORTS

In [1]:
```
import pandas as pd
pd.option_context('display.max_rows', None, 'display.max_columns', None)
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from matplotlib import ticker
import scipy.stats as stats
import statsmodels.api as sm
from statsmodels.stats.outliers_influence import variance_inflation_factor as VIF
import sklearn.linear_model as lm
from sklearn import metrics
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler,OneHotEncoder,OrdinalEncoder,PolynomialFeatures
from sklearn.preprocessing import PowerTransformer
from sklearn.preprocessing import OneHotEncoder
from sklearn.preprocessing import LabelEncoder
from sklearn.preprocessing import OrdinalEncoder
from sklearn.preprocessing import PolynomialFeatures
from sklearn.feature_selection import RFE
from sklearn.decomposition import PCA
from itertools import chain, combinations
import warnings
warnings.filterwarnings(action='ignore')
sns.set_style('darkgrid')

%matplotlib inline
```

DATA

```
In [2]: df = pd.read_csv('data/kc_house_data.csv', index_col=0) # (30155,25), 3 duplicated entries
        print(f"Duplicates found and removed: * {df.loc[df.duplicated()].shape[0]} *")
        df.drop_duplicates(inplace=True)

        print("\nHEAD:")
        display(df.head())

        print("\nTAIL:")
        display(df.tail())

        print("\nINFO:")
        df.info()
```

```
Duplicates found and removed: * 3 *

HEAD:
```

id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	greenbelt	nuisance	...	sewer_system	sqft_above	sqft_basen
7399300360	5/24/2022	675000.0	4	1.0	1180	7140	1.0	NO	NO	NO	...	PUBLIC	1180	
8910500230	12/13/2021	920000.0	5	2.5	2770	6703	1.0	NO	NO	YES	...	PUBLIC	1570	1
1180000275	9/29/2021	311000.0	6	2.0	2880	6156	1.0	NO	NO	NO	...	PUBLIC	1580	1
1604601802	12/14/2021	775000.0	3	3.0	2160	1400	2.0	NO	NO	NO	...	PUBLIC	1090	1
8562780790	8/24/2021	592500.0	2	2.0	1120	758	2.0	NO	NO	YES	...	PUBLIC	1120	

5 rows × 24 columns

```
TAIL:
```

id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	greenbelt	nuisance	...	sewer_system	sqft_above	sqft_base
7834800180	11/30/2021	1555000.0	5	2.0	1910	4000	1.5	NO	NO	NO	...	PUBLIC	1600	
194000695	6/16/2021	1313000.0	3	2.0	2020	5800	2.0	NO	NO	NO	...	PUBLIC	2020	
7960100080	5/27/2022	800000.0	3	2.0	1620	3600	1.0	NO	NO	YES	...	PUBLIC	940	
2781280080	2/24/2022	775000.0	3	2.5	2570	2889	2.0	NO	NO	NO	...	PUBLIC	1830	
9557800100	4/29/2022	500000.0	3	1.5	1200	11058	1.0	NO	NO	NO	...	PUBLIC	1200	

5 rows × 24 columns

```
INFO:
<class 'pandas.core.frame.DataFrame'>
Int64Index: 30152 entries, 7399300360 to 9557800100
Data columns (total 24 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   date           30152 non-null  object 
 1   price          30152 non-null  float64
 2   bedrooms       30152 non-null  int64  
 3   bathrooms      30152 non-null  float64
 4   sqft_living    30152 non-null  int64  
 5   sqft_lot       30152 non-null  int64  
 6   floors         30152 non-null  float64
 7   waterfront     30152 non-null  object 
 8   greenbelt      30152 non-null  object 
 9   nuisance       30152 non-null  object 
 10  view           30152 non-null  object 
 11  condition      30152 non-null  object 
 12  grade          30152 non-null  object 
 13  heat_source    30120 non-null  object 
 14  sewer_system   30138 non-null  object 
 15  sqft_above     30152 non-null  int64  
 16  sqft_basement  30152 non-null  int64  
 17  sqft_garage    30152 non-null  int64  
 18  sqft_patio     30152 non-null  int64  
 19  yr_built       30152 non-null  int64  
 20  yr_renovated   30152 non-null  int64  
 21  address        30152 non-null  object 
 22  lat            30152 non-null  float64
 23  long           30152 non-null  float64
dtypes: float64(5), int64(9), object(10)
memory usage: 5.8+ MB
```

EDA

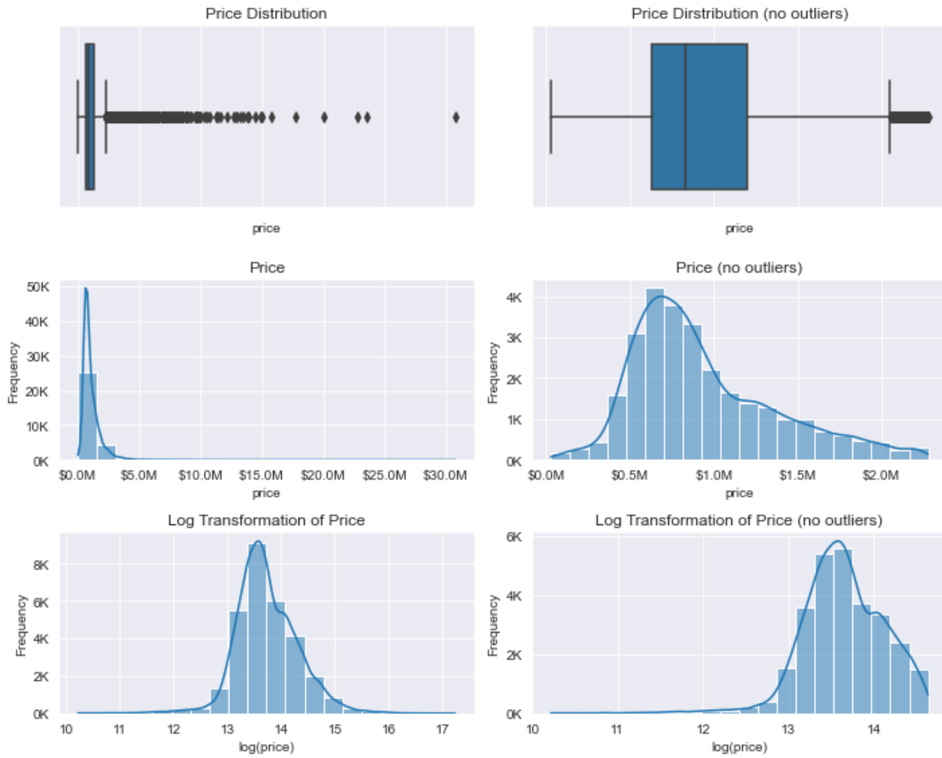
Column Names and Descriptions
for King County Data Set

- `id` - Unique identifier for a house
- `date` - Date house was sold
- `price` - Sale price (prediction target)
- `bedrooms` - Number of bedrooms
- `bathrooms` - Number of bathrooms
- `sqft_living` - Square footage of living space in the home
- `sqft_lot` - Square footage of the lot
- `floors` - Number of floors (levels) in house
- `waterfront` - Whether the house is on a waterfront
  - Includes Duwamish, Elliott Bay, Puget Sound, Lake Union, Ship Canal, Lake Washington, Lake Sammamish, other lake, and river/slough waterfronts
- `greenbelt` - Whether the house is adjacent to a green belt
- `nuisance` - Whether the house has traffic noise or other recorded nuisances
- `view` - Quality of view from house
  - Includes views of Mt. Rainier, Olympics, Cascades, Territorial, Seattle Skyline, Puget Sound, Lake Washington, Lake Sammamish, small lake / river / creek, and other
- `condition` - How good the overall condition of the house is. Related to maintenance of house.
  - See the [King County Assessor Website (https://info.kingcounty.gov/assessor/esales/Glossary.aspx?type=r)](https://info.kingcounty.gov/assessor/esales/Glossary.aspx?type=r) for further explanation of each condition code
- `grade` - Overall grade of the house. Related to the construction and design of the house.
  - See the [King County Assessor Website (https://info.kingcounty.gov/assessor/esales/Glossary.aspx?type=r)](https://info.kingcounty.gov/assessor/esales/Glossary.aspx?type=r) for further explanation of each building grade code
- `heat_source` - Heat source for the house
- `sewer_system` - Sewer system for the house
- `sqft_above` - Square footage of house apart from basement
- `sqft_basement` - Square footage of the basement
- `sqft_garage` - Square footage of garage space
- `sqft_patio` - Square footage of outdoor porch or deck space
- `yr_built` - Year when house was built
- `yr_renovated` - Year when house was renovated
- `address` - The street address
- `lat` - Latitude coordinate
- `long` - Longitude coordinate

Target (Price) Analysis

We want to ensure normality in the target data as part of the assumtions for linear regression, so lets look at the log transformation of Price and Price with outliers removed.

In [3]:
```
# Using Interquartile Range method to determine outliers
IQR = df['price'].quantile(.75) - df['price'].quantile(.25)
IQR_scaler = 1.5
price_outlier_u_bound = df['price'].quantile(.75) + IQR_scaler * IQR
price_outlier_l_bound = df['price'].quantile(.25) - IQR_scaler * IQR

# Series with outliers sliced off
price_no_outliers = df.loc[(df['price'] <= price_outlier_u_bound) & \
                           (df['price'] >= price_outlier_l_bound),'price']


fig, ax = plt.subplots(3,2, figsize = (10,8))
# boxplot of target
sns.boxplot(x=df['price'], ax=ax[0][0])
ax[0][0].set_title('Price Distribution')
ax[0][0].set_xticklabels([])

# boxplot of target - target_outliers
sns.boxplot(x=price_no_outliers, ax=ax[0][1])
ax[0][1].set_title('Price Dirstribution (no outliers)')
ax[0][1].set_xticklabels([])

# histogram of target
sns.histplot(df['price'], bins=20, kde=True, ax=ax[1][0])
ax[1][0].set_title('Price')
ax[1][0].set_ylabel('Frequency')
ax[1][0].set_xlabel('price')
formatter = ticker.FuncFormatter(lambda x, pos: '%1.0fK' % (x * 1e-3))
ax[1][0].yaxis.set_major_formatter(formatter)
formatter = ticker.FuncFormatter(lambda x, pos: '$%1.1fM' % (x * 1e-6))
ax[1][0].xaxis.set_major_formatter(formatter)

# histogram of target - target_outliers
sns.histplot(price_no_outliers, bins=20, kde=True, ax=ax[1][1])
ax[1][1].set_title('Price (no outliers)')
ax[1][1].set_ylabel('Frequency')
ax[1][1].set_xlabel('price')
formatter = ticker.FuncFormatter(lambda x, pos: '%1.0fK' % (x * 1e-3))
ax[1][1].yaxis.set_major_formatter(formatter)
formatter = ticker.FuncFormatter(lambda x, pos: '$%1.1fM' % (x * 1e-6))
ax[1][1].xaxis.set_major_formatter(formatter)

# histograms of log(target)
sns.histplot(np.log(df['price']), bins=20, kde=True, ax=ax[2][0])
ax[2][0].set_title('Log Transformation of Price')
ax[2][0].set_ylabel('Frequency')
ax[2][0].set_xlabel('log(price)')
formatter = ticker.FuncFormatter(lambda x, pos: '%1.0fK' % (x * 1e-3))
ax[2][0].yaxis.set_major_formatter(formatter)

# histograms of log(target - target_outliers)
sns.histplot(np.log(price_no_outliers), bins=20, kde=True, ax=ax[2][1])
ax[2][1].set_title('Log Transformation of Price (no outliers)')
ax[2][1].set_ylabel('Frequency')
ax[2][1].set_xlabel('log(price)')
formatter = ticker.FuncFormatter(lambda x, pos: '%1.0fK' % (x * 1e-3))
ax[2][1].yaxis.set_major_formatter(formatter)

# organize axes
plt.tight_layout()
# save fig to png
plt.savefig('imgs/price_outliers.png')
plt.show()
print('price outliers count: {}'.format(df.shape[0] - price_no_outliers.shape[0]))
```



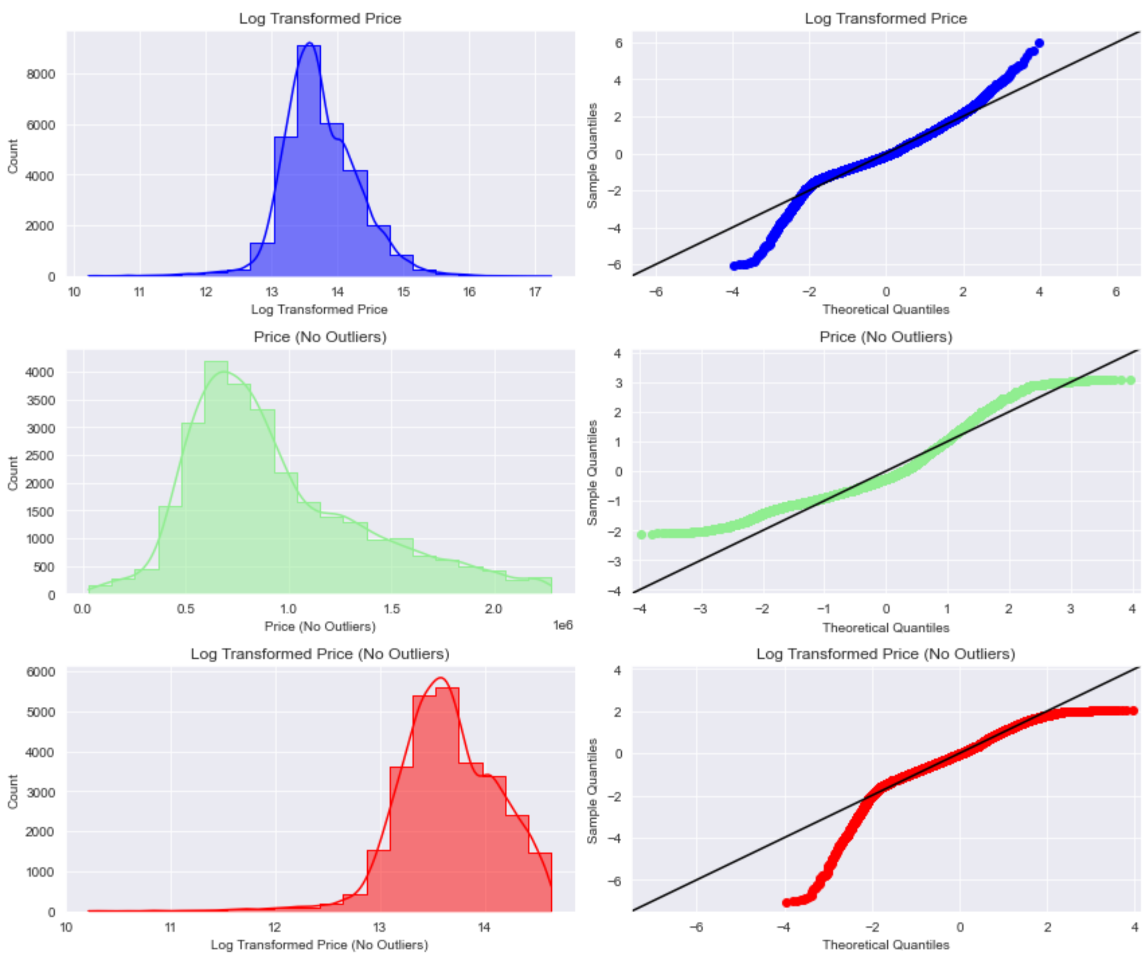

```
price outliers count: 1991
```

Log(Price), Price_no_outliers and log(Price) have the most normal-like distributions.

Price Normality

Lets look deeper on whether we should log transform price for linear regression

In [4]:
```python
# Compare normality of target_no_outliers vs log_target_no_outliers

# Set up plot and properties of two targets
fig, axes = plt.subplots(nrows=3, ncols=2, figsize=(12,10))
targets = [np.log(df['price']), price_no_outliers, np.log(price_no_outliers)]
labels = ['Log Transformed Price', "Price (No Outliers)", "Log Transformed Price (No Outliers)"]
colors = ["blue", "lightgreen", 'red']

# Plot histograms
for index, ax in enumerate([axes[0][0],axes[1][0],axes[2][0]]):
    sns.histplot(targets[index], bins=20, element="step", kde=True, color=colors[index], ax=ax)
    ax.set_xlabel(labels[index])
    ax.set_title(labels[index])

# Plot Q-Q plots
for index, ax in enumerate([axes[0][1],axes[1][1],axes[2][1]]):
    sm.graphics.qqplot(targets[index], dist=stats.norm, line='45', fit=True, ax=ax)
    scatter = ax.lines[0]
    line = ax.lines[1]
    scatter.set_markeredgecolor(colors[index])
    scatter.set_markerfacecolor(colors[index])
    line.set_color("black")
    ax.set_title(labels[index])

fig.tight_layout()
```



From the qq-plots we can rank normality:

1. Log transformed price
2. Price without outliers
3. Log transformed price without outliers

Numeric and Categorical Split

Splitting the dataframe into two for independant EDA

In [5]:
```
numeric_df = df.select_dtypes([int, float]).copy()
cat_df = df.select_dtypes(object)
```

Numeric EDA

In [6]:
```
display(numeric_df.head())
display(numeric_df.describe(percentiles=[.05,.25,.5,.75,.95]))
```

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	sqft_above	sqft_basement	sqft_garage	sqft_patio	yr_built	yr_renovated	lat
id													
7399300360	675000.0	4	1.0	1180	7140	1.0	1180	0	0	40	1969	0	47.461975
8910500230	920000.0	5	2.5	2770	6703	1.0	1570	1570	0	240	1950	0	47.711525
1180000275	311000.0	6	2.0	2880	6156	1.0	1580	1580	0	0	1956	0	47.502045
1604601802	775000.0	3	3.0	2160	1400	2.0	1090	1070	200	270	2010	0	47.566110
8562780790	592500.0	2	2.0	1120	758	2.0	1120	550	550	30	2012	0	47.532470

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	sqft_above	sqft_basement	sqft_garage	sqft_patio	y
count	3.015200e+04	30152.000000	30152.000000	30152.000000	3.015200e+04	30152.000000	30152.000000	30152.000000	30152.000000	30152.000000	30152.(
mean	1.108029e+06	3.413571	2.334671	2112.408729	1.672492e+04	1.543380	1809.839347	476.010812	330.227414	217.396856	1975.1
std	8.946277e+05	0.981653	0.889548	974.052997	6.038545e+04	0.567615	878.325182	579.635101	285.770425	245.309503	32.(
min	2.736000e+04	0.000000	0.000000	3.000000	4.020000e+02	1.000000	2.000000	0.000000	0.000000	0.000000	1900.(
5%	4.250000e+05	2.000000	1.000000	940.000000	1.196000e+03	1.000000	830.000000	0.000000	0.000000	0.000000	1916.(
25%	6.480000e+05	3.000000	2.000000	1420.000000	4.850000e+03	1.000000	1180.000000	0.000000	0.000000	40.000000	1953.(
50%	8.600000e+05	3.000000	2.500000	1920.000000	7.480000e+03	1.500000	1560.000000	0.000000	400.000000	150.000000	1977.(
75%	1.300000e+06	4.000000	3.000000	2619.250000	1.057925e+04	2.000000	2270.000000	940.000000	510.000000	320.000000	2003.(
95%	2.500000e+06	5.000000	4.000000	3890.000000	4.573800e+04	2.000000	3460.000000	1500.000000	780.000000	680.000000	2021.(
max	3.075000e+07	13.000000	10.500000	15360.000000	3.253932e+06	4.000000	12660.000000	8020.000000	3580.000000	4370.000000	2022.(

We can tell immediately that most columns have outliers

Dropping Lat/Long

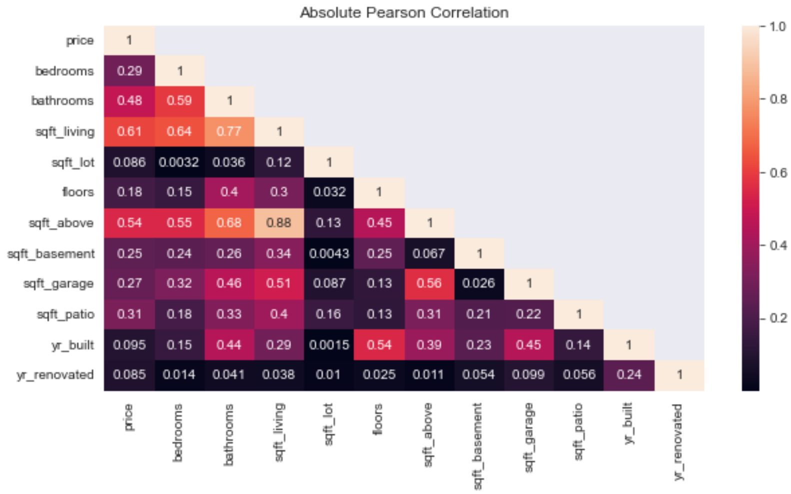
In [7]:
```
# We remove latitude and longitute columns, as they are implicitly determined by the zipcode categorical variable
numeric_df.drop(columns=['lat','long'], inplace=True)

# drop suspicious row with 4 bathrooms and bedrooms but no living space
display(numeric_df.loc[[1549500215], :])
numeric_df.drop(index=1549500215, inplace=True)
```

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	sqft_above	sqft_basement	sqft_garage	sqft_patio	yr_built	yr_renovated
id												
1549500215	1803000.0	4	4.0	3	326701	2.0	2	1	1	0	2021	0

Heatmap

Now we check the pearson correlation between all the continuous numeric columns

In [8]:
```
corr_df = numeric_df.corr().abs()

fig, ax = plt.subplots(figsize=(10,5))
sns.set_style('white')
mask = np.triu(np.ones_like(corr_df), k=1)
sns.heatmap(corr_df, annot=True, mask=mask, ax=ax).set(title='Absolute Pearson Correlation')

plt.show()
print("numeric abs(correlation) order: \n{}".format(corr_df['price'].sort_values(ascending=False)[1:]))
```




```
numeric abs(correlation) order:
sqft_living      0.610040
sqft_above       0.540142
bathrooms        0.481183
sqft_patio       0.313659
bedrooms         0.290017
sqft_garage      0.265311
sqft_basement    0.245532
floors           0.179608
yr_built         0.095408
sqft_lot         0.085952
yr_renovated     0.085088
Name: price, dtype: float64
```

From the heatmap, we can see there is a high correlation between the square footage measurements. Which will most likely violate the assumption of independance between the features for linear regression

Home Square feet

From our understanding of the data, sqft_living encompasses information from sqft_basement, sqft_patio, sqft_above and sqft_garage.
We could keep only sqft_living, but instead we will make a new column: sqft_home, which is a linear combination of these correlated columns, weighted by their correlations with price. This way we can avoid multicolinearity while preserving most of the information between these columns.

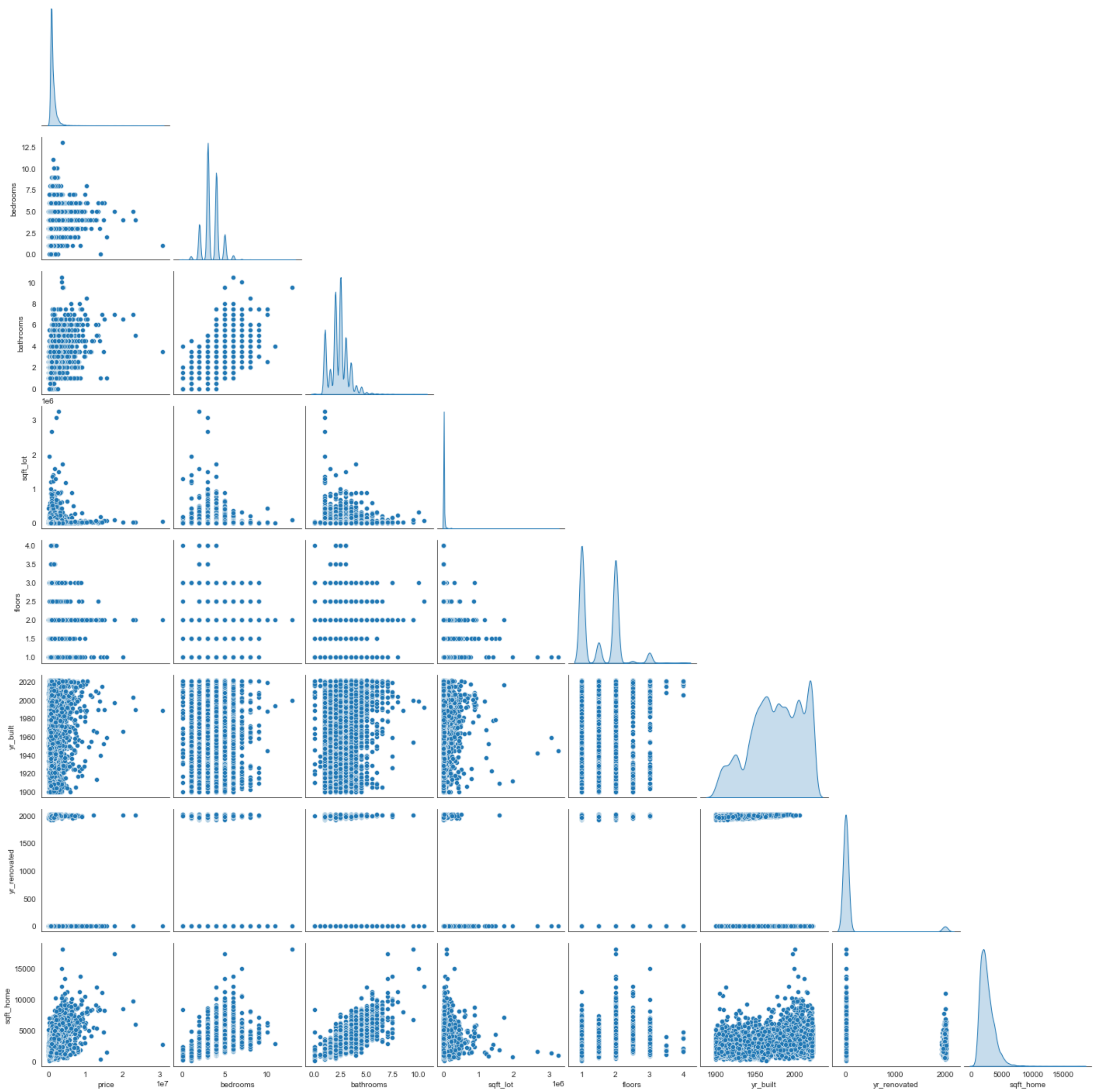
We will recalculate the weights in this process after train-test split to avoid Data Leakage

In [9]:
```
# Create Aggregate feature sqft_home
numeric_df["sqft_home"] = (.61*numeric_df['sqft_living'] + \
                           .54*numeric_df['sqft_above'] + \
                           .25*numeric_df['sqft_basement'] + \
                           .27*numeric_df['sqft_garage'] + \
                           .31*numeric_df['sqft_patio'])
```

PairPlots

Now lets plot all numeric features against each other to vizualize their correlations, paying specific attention to price.
With seaborn's pairplot we can also check normality of the feature distributions and homoscedasticity.

In [10]:
```
# plot only lower triangle due to symmetry
sns.pairplot(numeric_df.drop(columns=['sqft_living','sqft_above','sqft_basement','sqft_garage','sqft_patio']),
             corner=True,
             diag_kind='kde')
plt.show()
```

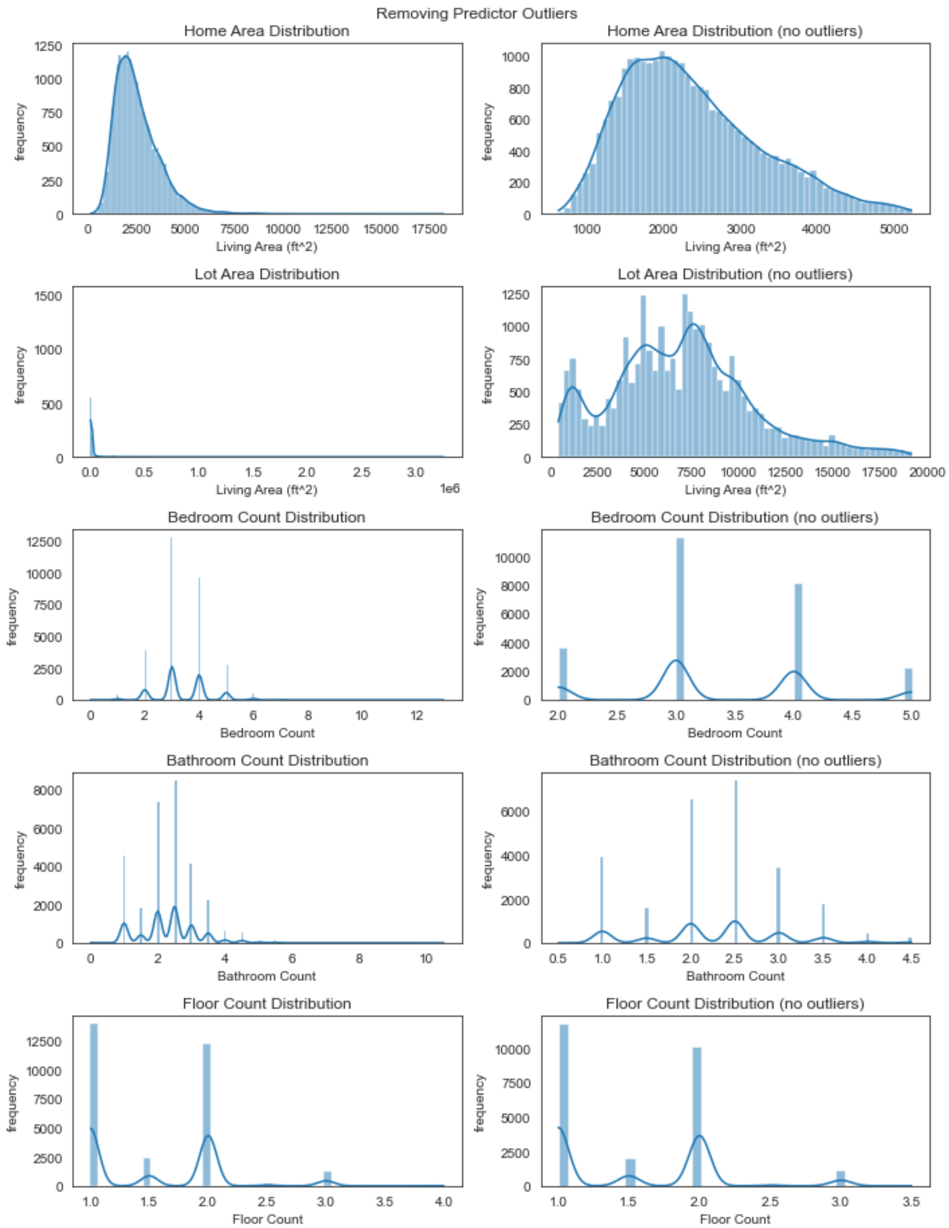


Removing outliers for skewed Numeric features

'sqft_home', 'sqft_lot', 'bedrooms', 'bathrooms' and 'floors' have concerning outliers, and their plots against price seems heteroscedatic, showing variability in the predictive capability of these features at large values.

In [11]:

```
# remove outliers from features
outlier_features = ['sqft_home', 'sqft_lot', 'bedrooms', 'bathrooms', 'floors']
outlier_u_bound = {}
outlier_l_bound = {}
# df to modify and compare with numeric_df
outlier_df = numeric_df.copy()

# calculate outlier bounds with Inter Quartile Range Method on X_train
for col in outlier_features:
    IQR = numeric_df[col].quantile(.75) - numeric_df[col].quantile(.25)
    IQR_scaler = 1.5
    outlier_u_bound[col] = numeric_df[col].quantile(.75) + IQR_scaler * IQR
    outlier_l_bound[col] = numeric_df[col].quantile(.25) - IQR_scaler * IQR

# slice out outliers from data
for col in outlier_features:
    outlier_df = outlier_df.loc[(outlier_df[col] <= outlier_u_bound[col]) &\
                                (outlier_df[col] >= outlier_l_bound[col])]

# setup axes and seaborn plot background
fig, ax = plt.subplots(nrows=len(outlier_features), ncols=2, figsize=(10,13))
sns.set_style('darkgrid')


# title for the entire figure
fig.suptitle('Removing Predictor Outliers')

# data and label iterables for graphing in a loop
data = [numeric_df, outlier_df]
titles = [['Home Area Distribution', 'Home Area Distribution (no outliers)'],
        ['Lot Area Distribution', 'Lot Area Distribution (no outliers)'],
        ['Bedroom Count Distribution', 'Bedroom Count Distribution (no outliers)'],
        ['Bathroom Count Distribution', 'Bathroom Count Distribution (no outliers)'],
        ['Floor Count Distribution','Floor Count Distribution (no outliers)']]
xlabels = ['Living Area (ft^2)','Living Area (ft^2)','Bedroom Count','Bathroom Count','Floor Count']

# Side by side comparisons of the feature distributions before and after removing outliers
for row in range(len(outlier_features)):
    for col in range(2):
        sns.histplot(x=outlier_features[row], data=data[col], kde=True, bins='auto', ax=ax[row][col])
        ax[row][col].set_xlabel(xlabels[row])
        ax[row][col].set_ylabel('frequency')
        ax[row][col].set_title(titles[row][col])


plt.tight_layout()

plt.savefig('imgs/feature_outliers_all.png')
plt.show()
```



In [12]:
```
# check for clean numeric data
numeric_df.isna().sum()
```

Out[12]:
```
price            0
bedrooms         0
bathrooms        0
sqft_living      0
sqft_lot         0
floors           0
sqft_above       0
sqft_basement    0
sqft_garage      0
sqft_patio       0
yr_built         0
yr_renovated     0
sqft_home        0
dtype: int64
```

Categorical EDA

In [13]:
```
cat_df.head()
```

Out[13]:

	date	waterfront	greenbelt	nuisance	view	condition	grade	heat_source	sewer_system	address
id										
7399300360	5/24/2022	NO	NO	NO	NONE	Good	7 Average	Gas	PUBLIC	2102 Southeast 21st Court, Renton, Washington ...
8910500230	12/13/2021	NO	NO	YES	AVERAGE	Average	7 Average	Oil	PUBLIC	11231 Greenwood Avenue North, Seattle, Washing...
1180000275	9/29/2021	NO	NO	NO	AVERAGE	Average	7 Average	Gas	PUBLIC	8504 South 113th Street, Seattle, Washington 9...
1604601802	12/14/2021	NO	NO	NO	AVERAGE	Average	9 Better	Gas	PUBLIC	4079 Letitia Avenue South, Seattle, Washington...
8562780790	8/24/2021	NO	NO	YES	NONE	Average	7 Average	Electricity	PUBLIC	2193 Northwest Talus Drive, Issaquah, Washingt...

Ordinal Encoding

We need the labels to be numbers so we will encode in their proper orders

In [14]:
```
oe_cols = ['view', 'condition', 'grade', 'waterfront','greenbelt', 'nuisance']
oe_orders = [['NONE','FAIR','AVERAGE','GOOD','EXCELLENT'],
            ['Poor','Fair','Average','Good','Very Good'],
            ['1 Cabin',
            '2 Substandard',
            '3 Poor',
            '4 Low',
            '5 Fair',
            '6 Low Average',
            '7 Average',
            '8 Good',
            '9 Better',
            '10 Very Good',
            '11 Excellent',
            '12 Luxury',
            '13 Mansion'],
            ['NO','YES'],
            ['NO','YES'],
            ['NO','YES']]

for col, order in zip(oe_cols,oe_orders):
    cat_df[col] = OrdinalEncoder([order]).fit_transform(cat_df[[col]])
cat_df.head()
```

Out[14]:

	date	waterfront	greenbelt	nuisance	view	condition	grade	heat_source	sewer_system	address
id										
7399300360	5/24/2022	0.0	0.0	0.0	0.0	3.0	6.0	Gas	PUBLIC	2102 Southeast 21st Court, Renton, Washington ...
8910500230	12/13/2021	0.0	0.0	1.0	2.0	2.0	6.0	Oil	PUBLIC	11231 Greenwood Avenue North, Seattle, Washing...
1180000275	9/29/2021	0.0	0.0	0.0	2.0	2.0	6.0	Gas	PUBLIC	8504 South 113th Street, Seattle, Washington 9...
1604601802	12/14/2021	0.0	0.0	0.0	2.0	2.0	8.0	Gas	PUBLIC	4079 Letitia Avenue South, Seattle, Washington...
8562780790	8/24/2021	0.0	0.0	1.0	0.0	2.0	6.0	Electricity	PUBLIC	2193 Northwest Talus Drive, Issaquah, Washingt...

Zipcode Encoding

The zipcode in the address will be a useful feature, so we will one hot encode them
We keep only the data in King County

In [15]:
```
# King County Zipcodes
# https://www.ciclt.net/sn/clt/capitolimpact/gw_ziplist.aspx?FIPS=53033
ci_zips = ['98002 (Auburn)', '98092 (Auburn)', '98224 (Baring)', '98004 (Bellevue)', '98005 (Bellevue)', '98006 (Belle
ci_zips = set([x.split()[0] for x in ci_zips])

# strip zipcode from address and populate new columns 'zipcode', if zipcode not in King county, set to nan
cat_df['zipcode'] = [address.split(',')[-2][-5:] for address in cat_df['address']]
cat_df['zipcode'] = cat_df['zipcode'].apply(lambda x: x if x in ci_zips else np.nan)
cat_df.dropna(inplace=True)

# columns to one-hot encode
ohe_cols_preprocessed = ['heat_source','sewer_system','zipcode']

# Set up encoder, dropping the first column after processing for: Degrees of freedom = 1
ohe = OneHotEncoder(sparse = False, drop='first')
ohe.fit(cat_df[ohe_cols_preprocessed])
ohe_cols = ohe.get_feature_names()

# Excecute transformation
cat_df[ohe_cols] = ohe.transform(cat_df[ohe_cols_preprocessed])

# Drop old columns
cat_df.drop(columns=ohe_cols_preprocessed + ['address', 'date'], inplace=True)

cat_df.head()
```

Out[15]:

	waterfront	greenbelt	nuisance	view	condition	grade	x0_Electricity/Solar	x0_Gas	x0_Gas/Solar	x0_Oil	...	x2_98155	x2_98166	x2_98168	x2_9
id															
7399300360	0.0	0.0	0.0	0.0	3.0	6.0	0.0	1.0	0.0	0.0	...	0.0	0.0	0.0	
8910500230	0.0	0.0	1.0	2.0	2.0	6.0	0.0	0.0	0.0	1.0	...	0.0	0.0	0.0	
1180000275	0.0	0.0	0.0	2.0	2.0	6.0	0.0	1.0	0.0	0.0	...	0.0	0.0	0.0	
1604601802	0.0	0.0	0.0	2.0	2.0	8.0	0.0	1.0	0.0	0.0	...	0.0	0.0	0.0	
8562780790	0.0	0.0	1.0	0.0	2.0	6.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	

5 rows × 90 columns

In [16]:
```
# sanity check for and drop nulls
display(cat_df.isna().sum().sum())
cat_df.dropna(inplace=True)
```

0

Helper Functions

Defining useful scoring and printing functions

In [17]:
```python
def get_train_score(xtrain, ytrain):
    """
    create sklearn linear model and return the R2 score on training data
    params:
        xtrain -> array of shape (sample_size, num_features)
        ytrain -> array of shape (sample_size, num_targets)
    returns:
        float R2 score of training linear regression
    """
    lr = lm.LinearRegression()
    lr.fit(xtrain, ytrain)
    return lr.score(xtrain, ytrain)

def get_adjusted_train_score(xtrain, ytrain):
    """
    create sklearn linear model and return the adjusted R2 score on training data
    params:
        xtrain -> array of shape (sample_size, num_features)
        ytrain -> array of shape (sample_size, num_targets)
    returns:
        float Adjusted R2 score of training linear regression
    """
    R2 = get_train_score(xtrain,ytrain)
    # number of observations in train data
    n = xtrain.shape[0]
    # number of features in train data (including constant)
    k = xtrain.shape[1] + 1
    return 1 - ( (1-R2) * ( (n-1)/(n-k-1 ) ) )

def get_test_score(xtrain, ytrain, xtest, ytest):
    """
    create sklearn linear model and return the R2 score on test data
    params:
        xtrain -> array of shape (sample_size, num_features)
        ytrain -> array of shape (sample_size, num_targets)
        xtest -> array of shape (sample_size, num_features)
        ytest -> array of shape (sample_size, num_targets)
    returns:
        float R2 score of test data from linear regression
    """
    lr = lm.LinearRegression()
    lr.fit(xtrain, ytrain)
    return lr.score(xtest, ytest)

def get_adjusted_test_score(xtrain, ytrain, xtest, ytest):
    """
    create sklearn linear model and return the adjustec R2 score on test data
    params:
        xtrain -> array of shape (sample_size, num_features)
        ytrain -> array of shape (sample_size, num_targets)
        xtest -> array of shape (sample_size, num_features)
        ytest -> array of shape (sample_size, num_targets)
    returns:
        float adjusted R2 score of test data from linear regression
    """
    R2 = get_test_score(xtrain,ytrain,xtest,ytest)
    # number of observations in test data
    n = xtest.shape[0]
    # number of features in test data (including constant)
    k = xtest.shape[1] + 1
    return 1 - ( (1-R2) * ( (n-1)/(n-k-1 ) ) )

def print_train_scores(xtrain, ytrain):
    # Print train data R2 and ajusted R2 in sequence
    print(f"         Train R2: {get_train_score(xtrain, ytrain)}")
    print(f"Train Adjusted R2: {get_train_score(xtrain, ytrain)}")

def print_test_scores(xtrain, ytrain, xtest, ytest):
    # Print test data R2 and ajusted R2 in sequence
    print(f"          Test R2: {get_test_score(xtrain, ytrain, xtest, ytest)}")
    print(f" Test Adjusted R2: {get_test_score(xtrain, ytrain, xtest, ytest)}")

def print_errors(pred, ytest):
    # print Mean Squared, Root Mean Squared and Absolute Error
    print("              MSE:",metrics.mean_squared_error(ytest, pred))
    print("             RMSE:",metrics.mean_squared_error(ytest, pred,squared=False) )
    print("              MAE:",metrics.mean_absolute_error(ytest, pred))

def print_stats(res):
    # print condition number
    print(f"Condition Number: {res.condition_number}")
```

Combine and Train Test Split

In [18]:
```
# joining numeric and categorical features by index
clean_df = numeric_df.join(cat_df, how='inner')
clean_outlier_df = outlier_df.join(cat_df, how='inner')

# numeric Train test split (.75 train, .25 test)
X_train, X_test, y_train, y_test = \
    train_test_split(clean_df.drop(columns='price'),
                     clean_df[['price']],
                     test_size=.25,
                     random_state=42)

print(f"Train/Test X shapes: {X_train.shape}, {X_test.shape}")
print(f"Train/Test y shapes: {y_train.shape}, {y_test.shape}\n\nColumns:")
print(f"clean_df\n{np.array(clean_df.columns.to_list())}")
```

```
Train/Test X shapes: (21860, 102), (7287, 102)
Train/Test y shapes: (21860, 1), (7287, 1)

Columns:
clean_df
['price' 'bedrooms' 'bathrooms' 'sqft_living' 'sqft_lot' 'floors'
 'sqft_above' 'sqft_basement' 'sqft_garage' 'sqft_patio' 'yr_built'
 'yr_renovated' 'sqft_home' 'waterfront' 'greenbelt' 'nuisance' 'view'
 'condition' 'grade' 'x0_Electricity/Solar' 'x0_Gas' 'x0_Gas/Solar'
 'x0_Oil' 'x0_Oil/Solar' 'x0_Other' 'x1_PRIVATE RESTRICTED' 'x1_PUBLIC'
 'x1_PUBLIC RESTRICTED' 'x2_98002' 'x2_98003' 'x2_98004' 'x2_98005'
 'x2_98006' 'x2_98007' 'x2_98008' 'x2_98010' 'x2_98011' 'x2_98014'
 'x2_98019' 'x2_98022' 'x2_98023' 'x2_98024' 'x2_98027' 'x2_98028'
 'x2_98029' 'x2_98030' 'x2_98031' 'x2_98032' 'x2_98033' 'x2_98034'
 'x2_98038' 'x2_98039' 'x2_98040' 'x2_98042' 'x2_98045' 'x2_98047'
 'x2_98050' 'x2_98051' 'x2_98052' 'x2_98053' 'x2_98055' 'x2_98056'
 'x2_98057' 'x2_98058' 'x2_98059' 'x2_98065' 'x2_98070' 'x2_98072'
 'x2_98074' 'x2_98075' 'x2_98077' 'x2_98092' 'x2_98102' 'x2_98103'
 'x2_98105' 'x2_98106' 'x2_98107' 'x2_98108' 'x2_98109' 'x2_98112'
 'x2_98115' 'x2_98116' 'x2_98117' 'x2_98118' 'x2_98119' 'x2_98122'
 'x2_98125' 'x2_98126' 'x2_98133' 'x2_98136' 'x2_98144' 'x2_98146'
 'x2_98148' 'x2_98155' 'x2_98166' 'x2_98168' 'x2_98177' 'x2_98178'
 'x2_98188' 'x2_98198' 'x2_98199' 'x2_98224' 'x2_98288']
```

Intercept only model

For Initial comparison, a model that predicts the average of y_train

In [19]:
```
# set X to mean(y_train)
y = y_train.copy()
X = np.array([y['price'].mean()] * len(y)).reshape(-1,1)
ytest = y_test.copy()
xtest = np.array([y['price'].mean()] * len(y_test)).reshape(-1,1)

# Use sklearn to get R2 results and metrics
lr = lm.LinearRegression()
lr.fit(X,y)
print_train_scores(X,y)
print_errors(lr.predict(xtest),ytest)
```

```
         Train R2: 0.0
Train Adjusted R2: 0.0
              MSE: 746232505051.7286
             RMSE: 863847.5010392335
              MAE: 526591.703061393
```

Regressive Model Iterations

Baseline Model

For a baseline model, we will score the numeric feature with highest correlation with price on unseen data X_test

In [20]:
```
X = X_train[['sqft_home']].copy()
xtest = X_test[['sqft_home']].copy()

y, ytest = y_train.copy(), y_test.copy()

# sklearn
lr = lm.LinearRegression()
lr.fit(X, y_train)
print("Train R2:", get_train_score(X, y))
print("Train Adjusted R2:", get_adjusted_train_score(X, y))
print_test_scores(X, y, xtest[['sqft_home']], ytest)
print_errors(lr.predict(xtest), ytest)

# print model statistics
results = sm.OLS(y_train,sm.add_constant(X)).fit()
print_stats(results)
```

```
Train R2: 0.38912017997934834
Train Adjusted R2: 0.3890642821141317
          Test R2: 0.3518565444743025
 Test Adjusted R2: 0.3518565444743025
              MSE: 483574265611.467
             RMSE: 695395.0428436105
              MAE: 403638.722185664
Condition Number: 6883.092953416579
```

Regression Model 1

Use all the numeric and categorical features

In [21]:
```
X, xtest = X_train.copy(), X_test.copy()
y, ytest = y_train.copy(), y_test.copy()

# sklearn
lr = lm.LinearRegression()
lr.fit(X, y)
print_train_scores(X, y)
print_test_scores(X, y, xtest, ytest)
print_errors(lr.predict(xtest),ytest)

# statstics data
results = sm.OLS(y_train,sm.add_constant(X)).fit()
print_stats(results)
```

```
         Train R2: 0.6603394245872392
Train Adjusted R2: 0.6603394245872392
          Test R2: 0.6473374287937927
 Test Adjusted R2: 0.6473374287937927
              MSE: 263118515547.41473
             RMSE: 512950.79252050555
              MAE: 262639.1301189698
Condition Number: 1.8514570307466122e+17
```

There was an increase in R2 from the basemodel, although the extreme multicolinearity suggests we should scale the features

Regression Model 2

We will use all the numeric and categorical features and Standard Scale them

In [22]:
```python
scale_cols = clean_df.drop(columns='price').columns.to_list()

#print scale_cols
np.array(scale_cols)
```

Out[22]:
```
array(['bedrooms', 'bathrooms', 'sqft_living', 'sqft_lot', 'floors',
       'sqft_above', 'sqft_basement', 'sqft_garage', 'sqft_patio',
       'yr_built', 'yr_renovated', 'sqft_home', 'waterfront', 'greenbelt',
       'nuisance', 'view', 'condition', 'grade', 'x0_Electricity/Solar',
       'x0_Gas', 'x0_Gas/Solar', 'x0_Oil', 'x0_Oil/Solar', 'x0_Other',
       'x1_PRIVATE RESTRICTED', 'x1_PUBLIC', 'x1_PUBLIC RESTRICTED',
       'x2_98002', 'x2_98003', 'x2_98004', 'x2_98005', 'x2_98006',
       'x2_98007', 'x2_98008', 'x2_98010', 'x2_98011', 'x2_98014',
       'x2_98019', 'x2_98022', 'x2_98023', 'x2_98024', 'x2_98027',
       'x2_98028', 'x2_98029', 'x2_98030', 'x2_98031', 'x2_98032',
       'x2_98033', 'x2_98034', 'x2_98038', 'x2_98039', 'x2_98040',
       'x2_98042', 'x2_98045', 'x2_98047', 'x2_98050', 'x2_98051',
       'x2_98052', 'x2_98053', 'x2_98055', 'x2_98056', 'x2_98057',
       'x2_98058', 'x2_98059', 'x2_98065', 'x2_98070', 'x2_98072',
       'x2_98074', 'x2_98075', 'x2_98077', 'x2_98092', 'x2_98102',
       'x2_98103', 'x2_98105', 'x2_98106', 'x2_98107', 'x2_98108',
       'x2_98109', 'x2_98112', 'x2_98115', 'x2_98116', 'x2_98117',
       'x2_98118', 'x2_98119', 'x2_98122', 'x2_98125', 'x2_98126',
       'x2_98133', 'x2_98136', 'x2_98144', 'x2_98146', 'x2_98148',
       'x2_98155', 'x2_98166', 'x2_98168', 'x2_98177', 'x2_98178',
       'x2_98188', 'x2_98198', 'x2_98199', 'x2_98224', 'x2_98288'],
      dtype='<U21')
```

In [23]:
```python
X, xtest = X_train.copy(), X_test.copy()
y, ytest = y_train.copy(), y_test.copy()

# scale the features to have a mean of 0 and standard deviation of 1
scaler = StandardScaler().fit(X)
X[scale_cols], xtest[scale_cols] = scaler.transform(X), scaler.transform(xtest)

# sklearn
lr = lm.LinearRegression()
lr.fit(X, y)
print_train_scores(X, y)
print_test_scores(X, y, xtest, ytest)
print_errors(lr.predict(xtest),ytest)

# statstics data
results = sm.OLS(y_train,sm.add_constant(X)).fit()
print_stats(results)
```

```
         Train R2: 0.6603395424433508
Train Adjusted R2: 0.6603395424433508
          Test R2: 0.6473240905020876
 Test Adjusted R2: 0.6473240905020876
              MSE: 263128467132.30054
             RMSE: 512960.49275972566
              MAE: 262655.7777069954
Condition Number: 2295809634200880.0
```

Scaling the features had no effect on the R2, but reduced some multicolinearity.

Regression Model 3

In our EDA we saw that log('price') had the most normal distribution, so we will implement that

In [24]:
```
X, xtest = X_train.copy(), X_test.copy()
y, ytest = np.log(y_train.copy()), np.log(y_test.copy())

# scale the features to have a mean of 0 and standard deviation of 1
scaler = StandardScaler().fit(X)
X[scale_cols], xtest[scale_cols] = scaler.transform(X), scaler.transform(xtest)

# sklearn
lr = lm.LinearRegression()
lr.fit(X, y)
print_train_scores(X, y)
print_test_scores(X, y, xtest, ytest)
# inverse log transform to see Errors in $ Dollar units
print_errors(np.exp(lr.predict(xtest)),np.exp(ytest))

# statstics data
results = sm.OLS(y_train,sm.add_constant(X)).fit()
print_stats(results)
```

```
         Train R2: 0.7101373438015719
Train Adjusted R2: 0.7101373438015719
          Test R2: 0.6939157650664806
 Test Adjusted R2: 0.6939157650664806
              MSE: 437244083108.2394
             RMSE: 661244.3444810997
              MAE: 220193.2860215568
Condition Number: 2295809634200880.0
```

We can see that following the normality assumptions of linear regression has an effect on its predictive power.
We should take that one step further and apply the outlier removal we observed in EDA.
Now, to deal with the high multicolinearity, we should remove the features whos information is encapsulated by our 'sqft_home' feature.

Regression Model 4

Removing dependant features and feature outliers

In [25]:
```
clean_outlier_df.drop(columns=['sqft_living','sqft_above','sqft_basement','sqft_garage','sqft_patio'], inplace=True)
scale_cols = clean_outlier_df.drop(columns='price').columns.to_list()
```

In [26]:
```
# Train test splitting from dataframe with feature's outliers removed
X_train, X_test, y_train, y_test = train_test_split(clean_outlier_df.drop(columns=['price']),
                                                    clean_outlier_df[['price']],
                                                    test_size=.25,
                                                    random_state=42)

X, xtest = X_train.copy(), X_test.copy()
y, ytest = np.log(y_train.copy()), np.log(y_test.copy())

# scale the features to have a mean of 0 and standard deviation of 1
scaler = StandardScaler().fit(X)
X[scale_cols], xtest[scale_cols] = scaler.transform(X), scaler.transform(xtest)

# sklearn
lr = lm.LinearRegression()
lr.fit(X, y)
print_train_scores(X, y)
print_test_scores(X, y, xtest, ytest)
print_errors(np.exp(lr.predict(xtest)),np.exp(ytest))

# statstics data
results = sm.OLS(y_train,sm.add_constant(X)).fit()
print_stats(results)
```

```
         Train R2: 0.6972597421880891
Train Adjusted R2: 0.6972597421880891
          Test R2: 0.6832713611282084
 Test Adjusted R2: 0.6832713611282084
              MSE: 90784167606.39491
             RMSE: 301304.1114993204
              MAE: 177201.50710497578
Condition Number: 3.7225381428801965e+17
```

Unfortunately, that didn't seem to help our R2

Regression Model 5

Using no outlier price instead of log transformed price

In [27]:
```
# remove target outliers from clean_outlier_df
# Using Interquartile Range method to determine outliers
IQR = df['price'].quantile(.75) - df['price'].quantile(.25)
IQR_scaler = 1.5
price_outlier_u_bound = df['price'].quantile(.75) + IQR_scaler * IQR
price_outlier_l_bound = df['price'].quantile(.25) - IQR_scaler * IQR

# Series with outliers sliced off
clean_outlier_df = clean_outlier_df.loc[(clean_outlier_df['price'] <= price_outlier_u_bound) & \
                                        (clean_outlier_df['price'] >= price_outlier_l_bound)]

# Train test splitting from dataframe with feature's outliers removed
X_train, X_test, y_train, y_test = train_test_split(clean_outlier_df.drop(columns='price'),
                                                    clean_outlier_df[['price']],
                                                    test_size=.25,
                                                    random_state=42)

X, xtest = X_train.copy(), X_test.copy()
y, ytest = y_train.copy(), y_test.copy()

# scale the features to have a mean of 0 and standard deviation of 1
scaler = StandardScaler().fit(X)
X[scale_cols], xtest[scale_cols] = scaler.transform(X), scaler.transform(xtest)

# sklearn
lr = lm.LinearRegression()
lr.fit(X, y)
print_train_scores(X, y)
print_test_scores(X, y, xtest, ytest)
print_errors(lr.predict(xtest),ytest)

# statstics data
results = sm.OLS(y_train,sm.add_constant(X)).fit()
print_stats(results)
```

```
         Train R2: 0.721615832570706
Train Adjusted R2: 0.721615832570706
          Test R2: 0.723048626563473
 Test Adjusted R2: 0.723048626563473
              MSE: 49631570962.6705
             RMSE: 222781.44214155385
              MAE: 159140.2116252196
Condition Number: 4481280365648220.5
```

Checking VIF

Our predictor has improved although the condition number still indicates high multicolinearity,

In [28]:
```
vif_data = pd.DataFrame()
vif_data["feature"] = X.columns.to_list()
# calculating VIF for each feature
vif_data["VIF"] = [VIF(X.values, i) for i in range(X.shape[1])]
# get regression coefficients from linear model
vif_data['coef_'] = pd.Series(lr.coef_.flatten())
# get pvals from statsmodel results, exclude const
vif_data['pval'] = results.pvalues.to_list()[1:]
# sort the dataframe to see the features with highest variance inflation
vif_data.sort_values(by='VIF', ascending=False, inplace=True)

# show all 20 rows
with pd.option_context('display.max_rows', None, 'display.max_columns', None):
    display(vif_data.head(20))
```

	feature	VIF	coef_	pval
6	sqft_home	4.119887	163621.819372	0.000000e+00
4	yr_built	3.457281	-18551.862233	4.720611e-09
12	grade	2.801636	73160.971207	1.139674e-142
1	bathrooms	2.768567	8126.657308	4.122695e-03
67	x2_98103	2.670590	92746.774388	3.637941e-236
76	x2_98117	2.575255	91389.232782	1.023359e-237
74	x2_98115	2.552052	94630.681144	1.811446e-256
47	x2_98042	2.490493	2179.261355	4.212566e-01
44	x2_98038	2.314458	17352.518688	2.144754e-11
2	sqft_lot	2.306730	20597.560222	1.761685e-15
82	x2_98133	2.266018	47944.036739	2.412492e-77
3	floors	2.230678	-6131.580574	1.591266e-02
43	x2_98034	2.198330	85282.125969	1.999227e-242
34	x2_98023	2.183650	-7825.321512	1.882353e-03
77	x2_98118	2.173039	45000.996994	3.289373e-71
69	x2_98106	2.089770	33177.766358	3.462284e-41
57	x2_98058	2.075752	14228.739842	6.674028e-09
79	x2_98122	1.966740	63387.105341	3.059709e-152
70	x2_98107	1.956321	73379.024063	4.332107e-203
80	x2_98125	1.948400	49676.777702	8.295845e-96

The VIF's for all features are good, < 5.

Final Regression Model Showing all steps

Increase Dimentionality by including polynomial features for all columns except one_hot encoded

In [29]:
```
df = pd.read_csv('data/kc_house_data.csv', index_col=0) # (30155,25), 3 duplicated entries
# display(df.loc[df.duplicated(keep=False)])
df.drop_duplicates(inplace=True)

# drop suspicious row with 4 bathrooms and bedrooms but no living space
df.drop(index=1549500215, inplace=True)

# numeric Train test split (.75 train, .25 test)
X_train, X_test, y_train, y_test = train_test_split(df.drop(columns='price'), df[['price']], test_size=.25, random_sta

# Aggregate feature
sql_corr = X_train['sqft_living'].corr(y_train['price'])
sqa_corr = X_train['sqft_above'].corr(y_train['price'])
sqb_corr = X_train['sqft_basement'].corr(y_train['price'])
sqg_corr = X_train['sqft_garage'].corr(y_train['price'])
sqp_corr = X_train['sqft_patio'].corr(y_train['price'])
X_train["sqft_home"] = (sql_corr*X_train['sqft_living'] + \
                        sqa_corr*X_train['sqft_above'] + \
                        sqb_corr*X_train['sqft_basement'] + \
                        sqg_corr*X_train['sqft_garage'] + \
                        sqp_corr*X_train['sqft_patio'])
X_test["sqft_home"] =  (sql_corr*X_test['sqft_living'] + \
                        sqa_corr*X_test['sqft_above'] + \
                        sqb_corr*X_test['sqft_basement'] + \
                        sqg_corr*X_test['sqft_garage'] + \
                        sqp_corr*X_test['sqft_patio'])

# Using Interquartile Range method to calculate and remove price outliers
IQR = y_train['price'].quantile(.75) - y_train['price'].quantile(.25)
IQR_scaler = 6
price_outlier_u_bound = y_train['price'].quantile(.75) + IQR_scaler * IQR
price_outlier_l_bound = y_train['price'].quantile(.25) - IQR_scaler * IQR
print(price_outlier_u_bound)
y_train = y_train.loc[(y_train['price'] > price_outlier_l_bound) & (y_train['price'] < price_outlier_u_bound)]
y_test = y_test.loc[(y_test['price'] > price_outlier_l_bound) & (y_test['price'] < price_outlier_u_bound)]
# y_train = y_train.loc[(y_train['price'] > 78000) & (y_train['price'] < 7000000)]
# y_test = y_test.loc[(y_test['price'] > 78000) & (y_test['price'] < 7000000)]

# slice Feature data to match target data indicies
X_train = X_train.loc[y_train.index]
X_test = X_test.loc[y_test.index]

# remove outliers from features
outlier_features = ['sqft_home', 'bedrooms', 'bathrooms', 'sqft_lot', 'floors']
outlier_u_bound = {}
outlier_l_bound = {}

# calculate outlier bounds with Inter Quartile Range Method on X_train
for col in outlier_features:
    IQR = X_train[col].quantile(.75) - X_train[col].quantile(.25)
    IQR_scaler = 1.5
    outlier_u_bound[col] = X_train[col].quantile(.75) + IQR_scaler * IQR
    outlier_l_bound[col] = X_train[col].quantile(.25) - IQR_scaler * IQR

# slice out outliers from data
for col in outlier_features:
    X_train = X_train.loc[(X_train[col] <= outlier_u_bound[col]) &\
                    (X_train[col] >= outlier_l_bound[col])]
    X_test = X_test.loc[(X_test[col] <= outlier_u_bound[col]) &\
                    (X_test[col] >= outlier_l_bound[col])]


# Ordinal Encoding
oe_cols = ['view', 'condition', 'grade']
oe_orders = [['NONE','FAIR','AVERAGE','GOOD','EXCELLENT'],
            ['Poor','Fair','Average','Good','Very Good'],
            ['1 Cabin',
            '2 Substandard',
            '3 Poor',
            '4 Low',
            '5 Fair',
            '6 Low Average',
            '7 Average',
            '8 Good',
            '9 Better',
            '10 Very Good',
            '11 Excellent',
            '12 Luxury',
            '13 Mansion']]

for col, order in zip(oe_cols,oe_orders):
    oe = OrdinalEncoder([order]).fit(X_train[[col]])
    X_train[col] = oe.transform(X_train[[col]])
    X_test[col] = oe.transform(X_test[[col]])
```

```
# label Encoding
le_cols = ['waterfront','greenbelt', 'nuisance']

for col in le_cols:
    le = LabelEncoder().fit(X_train[[col]])
    X_train[col] = le.transform(X_train[[col]])
    X_test[col] = le.transform(X_test[[col]])



# setting up zipcode column
# King County Zipcodes
# https://www.ciclt.net/sn/clt/capitolimpact/gw_ziplist.aspx?FIPS=53033
ci_zips = ['98002 (Auburn)', '98092 (Auburn)', '98224 (Baring)', '98004 (Bellevue)', '98005 (Bellevue)', '98006 (Belle
ci_zips = set([x.split()[0] for x in ci_zips])

X_train['zipcode'] = [address.split(',')[-2][-5:] for address in X_train['address']]
X_train['zipcode'] = X_train['zipcode'].apply(lambda x: x if x in ci_zips else np.nan)

X_test['zipcode'] = [address.split(',')[-2][-5:] for address in X_test['address']]
X_test['zipcode'] = X_test['zipcode'].apply(lambda x: x if x in ci_zips else np.nan)

# drop rows outside King county
old_idxs = set(X_train.index)
X_train.dropna(inplace=True)

old_idxs = set(X_test.index)
X_test.dropna(inplace=True)


ohe_cols = ['zipcode']

ohe = OneHotEncoder(sparse = False, drop='first')
train_ohe_df = ohe.fit_transform(X_train[ohe_cols])
train_ohe_df = pd.DataFrame(train_ohe_df, columns = ohe.get_feature_names(), index = X_train.index)
train_ohe_df

test_ohe_df = ohe.transform(X_test[ohe_cols])
test_ohe_df = pd.DataFrame(test_ohe_df, columns = ohe.get_feature_names(), index = X_test.index)

# Regular Scaling
numeric_cols = ['bedrooms',
                'bathrooms',
                'sqft_lot',
                'floors',
                'yr_built',
                'sqft_home',
                'yr_renovated'] + oe_cols

# Unstandardized polynomial features **for LATER coeficient analysis**
poly = PolynomialFeatures(2, interaction_only=True, include_bias=False)
poly_ = pd.DataFrame(data=poly.fit_transform(X_train[numeric_cols]),
                    index=X_train.index,
                    columns=poly.get_feature_names(numeric_cols))
p_mean = poly_.mean()
poly_means = {col:p_mean[col] for col in p_mean.index}
p_std = poly_.std()
poly_std = {col:p_std[col] for col in p_std.index}

# standardize continuous features
scaler = StandardScaler()
X_train[numeric_cols] = scaler.fit_transform(X_train[numeric_cols])
X_test[numeric_cols] = scaler.transform(X_test[numeric_cols])

# POLYNOIAL FEATURES
# squared polynomial features
poly = PolynomialFeatures(2, interaction_only=False, include_bias=False)
train_poly = pd.DataFrame(data=poly.fit_transform(X_train[numeric_cols]),
                        index=X_train.index,
                        columns=poly.get_feature_names(numeric_cols))
test_poly = pd.DataFrame(data=poly.transform(X_test[numeric_cols]),
                        index=X_test.index,
                        columns=poly.get_feature_names(numeric_cols))

X_train = X_train[le_cols]
X_train = pd.concat([X_train, train_poly], 1)
X_train = pd.concat([X_train, train_ohe_df], 1)

X_test = X_test[le_cols]
X_test = pd.concat([X_test, test_poly], 1)
X_test = pd.concat([X_test, test_ohe_df], 1)


# slice target data to match feature data indicies
y_train = y_train.loc[X_train.index]
```

```python
y_test = y_test.loc[X_test.index]


# sklearn
lr = lm.LinearRegression()
lr.fit(X_train,y_train)
print("Train R2:", get_train_score(X_train, y_train))
print("Train Adjusted R2:", get_adjusted_train_score(X_train, y_train))
print_test_scores(X_train, y_train, X_test, y_test)

# # statsmodel
model = sm.OLS(y_train,sm.add_constant(X_train))
results = model.fit()

print("MSE:",metrics.mean_squared_error(y_test, lr.predict(X_test)))
print("RMSE:",metrics.mean_squared_error(y_test, lr.predict(X_test),squared=False) )
print("MAE:",metrics.mean_absolute_error(y_test, lr.predict(X_test)))
results.summary()
```

```
5224000.0
Train R2: 0.7605936383412051
Train Adjusted R2: 0.758698426332945
          Test R2: 0.7815262346516275
 Test Adjusted R2: 0.7815262346516275
MSE: 70101052890.4598
RMSE: 264766.0342461997
MAE: 174192.4507748189
```

Out[29]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.761
Model:	OLS	**Adj. R-squared:**	0.759
Method:	Least Squares	**F-statistic:**	404.2
Date:	Sat, 18 Feb 2023	**Prob (F-statistic):**	0.00
Time:	07:55:44	**Log-Likelihood:**	-2.5417e+05

Visualizing the Predicted vs. Actual Prices

In [30]:
```python
y_hat = lr.predict(X_test)

y_df = pd.DataFrame({'hat':y_hat.flatten()}, index=range(y_hat.shape[0]))
y_df['actual'] = y_test['price'].to_list()
y_df['resid'] = y_df['hat'] - y_df['actual']

fig, ax = plt.subplots(figsize=(8,6))
# sns.jointplot(x= 'actual',y= 'resid', data=y_df).set()
sns.scatterplot(x='hat',y='actual', data=y_df, hue=-np.abs(y_df['resid']))
ax.legend([],[], frameon=False)
plt.xlabel('Predicted Price', fontdict={'fontsize':14,
                                        'fontweight':'bold'})
plt.ylabel('Actual Price', fontdict={'fontsize':14,
                                     'fontweight':'bold'})
plt.title('Predicted price vs. Actual Price', fontdict={'fontsize':20,
                                                        'fontweight':'bold'})
formatter = ticker.FuncFormatter(lambda x, pos: '$%1.1fM' % (x * 1e-6))
ax.yaxis.set_major_formatter(formatter)
ax.xaxis.set_major_formatter(formatter)
plt.plot([0, y_df['hat'].max()], [0, y_df['actual'].max()], linewidth=2, color='black', dashes=[2,2])
plt.tight_layout()

# plt.savefig('imgs/final_resid.png')
plt.show()
```

Final Recommendations

With a Decent predictor for price, we can interpret the coeficients of the model to approximate the increase in Housing sale price for each unit increase of a feature
To do so we inverse standard scale transform the coeficients.
We will be disconsidering zipcode coeficients as one cannot renovate a zipcode.

In [31]:
```
# features excluding zipcodes
feat_names = X.columns.to_list()[:68]
with pd.option_context('display.max_rows', None, 'display.max_columns', None):
    coefs = pd.DataFrame(columns=['feature','abs_coef_'])

    # take feature coeficients from linear model
    coefs['coef_'] = lr.coef_.flatten()[:68]
    coefs['feature'] = feat_names

    # inverse Standard SCale the coeficients
    price_increments = []
    for i, (col, coef) in enumerate(zip(feat_names,coefs['coef_'])):
        if col in p_mean.index.to_list():
            price_increments.append((coef - poly_means[col])/poly_std[col])
        else:
            price_increments.append(coef)
    coefs['price_increments'] = price_increments

    # bring in pvalue per coeficient to analyze significance
    coefs['pval'] = results.pvalues.to_list()[1:69]

    # create abs(coeficient) column for sorting dataframe
    coefs['abs_coef_'] = np.abs(coefs['coef_'])
    coefs = coefs.sort_values(by='abs_coef_', ascending=False)

    exclude_zips = ['x2' not in feat for feat in coefs['feature']]
    display(coefs.loc[exclude_zips])
```

	feature	abs_coef_	coef_	price_increments	pval
9	nuisance	1.893438e+06	-1.893438e+06	-1.893438e+06	1.146552e-13
0	bedrooms	4.161658e+05	4.161658e+05	5.043986e+05	3.330104e-44
8	greenbelt	1.588871e+05	1.588871e+05	1.588871e+05	3.628352e-195
12	grade	8.026283e+04	8.026283e+04	8.132733e+04	2.006261e-94
5	yr_renovated	6.819778e+04	6.819778e+04	1.691012e+02	4.818921e-55
2	sqft_lot	5.331506e+04	-5.331506e+04	-1.682950e+01	1.280502e-19
11	condition	5.134239e+04	5.134239e+04	7.296362e+04	2.055618e-45
1	bathrooms	4.999748e+04	4.999748e+04	6.443909e+04	2.903502e-04
7	waterfront	4.889266e+04	4.889266e+04	4.889266e+04	7.704450e-20
4	yr_built	2.436282e+04	2.436282e+04	6.952279e+02	1.623766e-10
10	view	1.498497e+04	-1.498497e+04	-1.967145e+04	2.392390e-02
18	x0_Other	1.125845e+04	-1.125845e+04	-1.125845e+04	7.064906e-02
14	x0_Gas	1.027657e+04	1.027657e+04	1.027657e+04	2.705521e-02
13	x0_Electricity/Solar	6.763253e+03	-6.763253e+03	-6.763253e+03	1.829647e-02
17	x0_Oil/Solar	6.487854e+03	6.487854e+03	6.487854e+03	9.783527e-02
20	x1_PUBLIC	4.445026e+03	4.445026e+03	4.445026e+03	1.193616e-01
15	x0_Gas/Solar	4.249414e+03	4.249414e+03	4.249414e+03	2.270411e-01
3	floors	4.119129e+03	4.119129e+03	7.517482e+03	1.869028e-01
16	x0_Oil	1.931161e+03	1.931161e+03	1.931161e+03	6.347407e-01
21	x1_PUBLIC RESTRICTED	1.472936e+03	-1.472936e+03	-1.472936e+03	6.387155e-01
6	sqft_home	9.859510e+02	-9.859510e+02	-3.756440e+00	7.983247e-01
19	x1_PRIVATE RESTRICTED	3.080863e+02	-3.080863e+02	-3.080863e+02	9.139830e-01

Vizualizing Home Sale Price increment per relevant features

In [32]:

```
# Set the figure size
fig, ax = plt.subplots(figsize=(10, 8))
# bar
data = coefs.loc[(coefs['feature'] == 'waterfront') | \
                 (coefs['feature'] == 'grade') | \
                 (coefs['feature'] == 'condition') | \
                 (coefs['feature'] == 'bathrooms') | \
                 (coefs['feature'] == 'x0_Gas') | \
                 (coefs['feature'] == 'floors') | \
                 (coefs['feature'] == 'yr_built')]
sns.barplot(
    x="price_increments",
    y="feature",
    data=data,
    color='#69b3a2',
    ax = ax
)
formatter = ticker.FuncFormatter(lambda x, pos: '$%1.0f' % (x))
ax.xaxis.set_major_formatter(formatter)
ax.set_xlabel('Price')
ax.set_ylabel('Feature')
ax.set_title("Homesale Price Increment per unit increase in features")

plt.tight_layout()
plt.savefig('imgs/PriceIncrements.png')
plt.show()
```