housingmarket_linearregression

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1 MATH 6266 Linear Statistical Models: Housing Market Data Analysis

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[26]:
```
# Imports
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import statsmodels.api as sm
import statsmodels.formula.api as smf
```

1.1 Load the data

[2]:
```
## Load the data
df = pd.read_csv('data\zillowcleanedup.csv')
```

[4]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 60 entries, 0 to 59
Data columns (total 12 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   House #           60 non-null     int64
 1   Selling price     60 non-null     int64
 2   Zip code          60 non-null     int64
 3   Formal Date       60 non-null     float64
 4   beds              60 non-null     int64
 5   bath              60 non-null     float64
 6   House type        60 non-null     object
 7   sqft              60 non-null     int64
 8   year built        60 non-null     object
 9   last sold price   60 non-null     int64
 10  last sold date    60 non-null     float64
 11  Zestimate         60 non-null     int64
```

```
dtypes: float64(3), int64(7), object(2)
memory usage: 5.8+ KB
```

[3]:
```
df.head()
```

[3]:
```
   House #  Selling price  Zip code  Formal Date  beds  bath     House type  \
0        1          48800     30310    2012.0531     2   2.0     Ranch home
1        2          42000     30310    2014.0805     3   3.0     Ranch home
2        3          60000     30310    2013.1113     3   1.0  single family
3        4          36000     30310    2014.1118     3   1.5  single family
4        5          25000     30310    2014.1016     3   2.0  single family

   sqft year built  last sold price  last sold date  Zestimate
0  1188      @1950             7400       2011.0719      32412
1  1352      @1956             7000       2011.1227      54362
2  1050      @1950           108000       2007.0613      53873
3  1131      @1962            36000       2008.1210      52829
4  1110      @1920            25000       2008.0611      64275
```

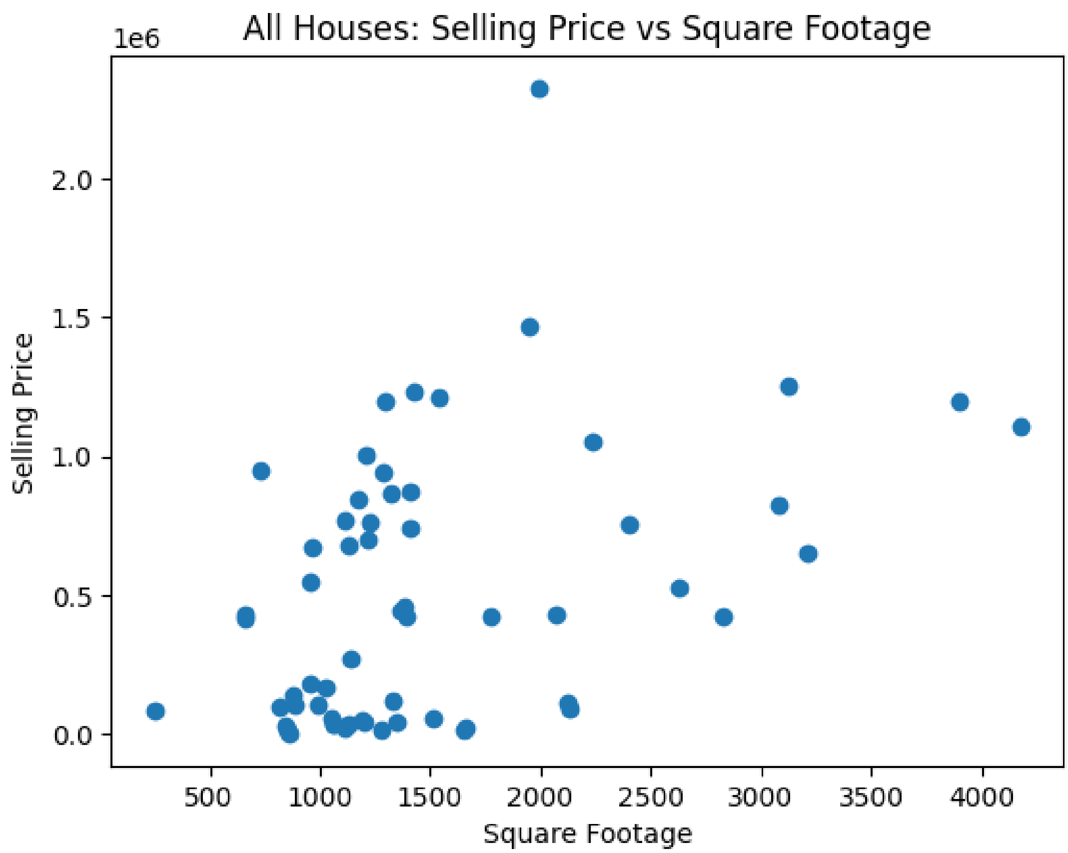
2 Exploratory Data Analysis (EDA)

[10]:
```
# Get stats on df
df.describe()
```

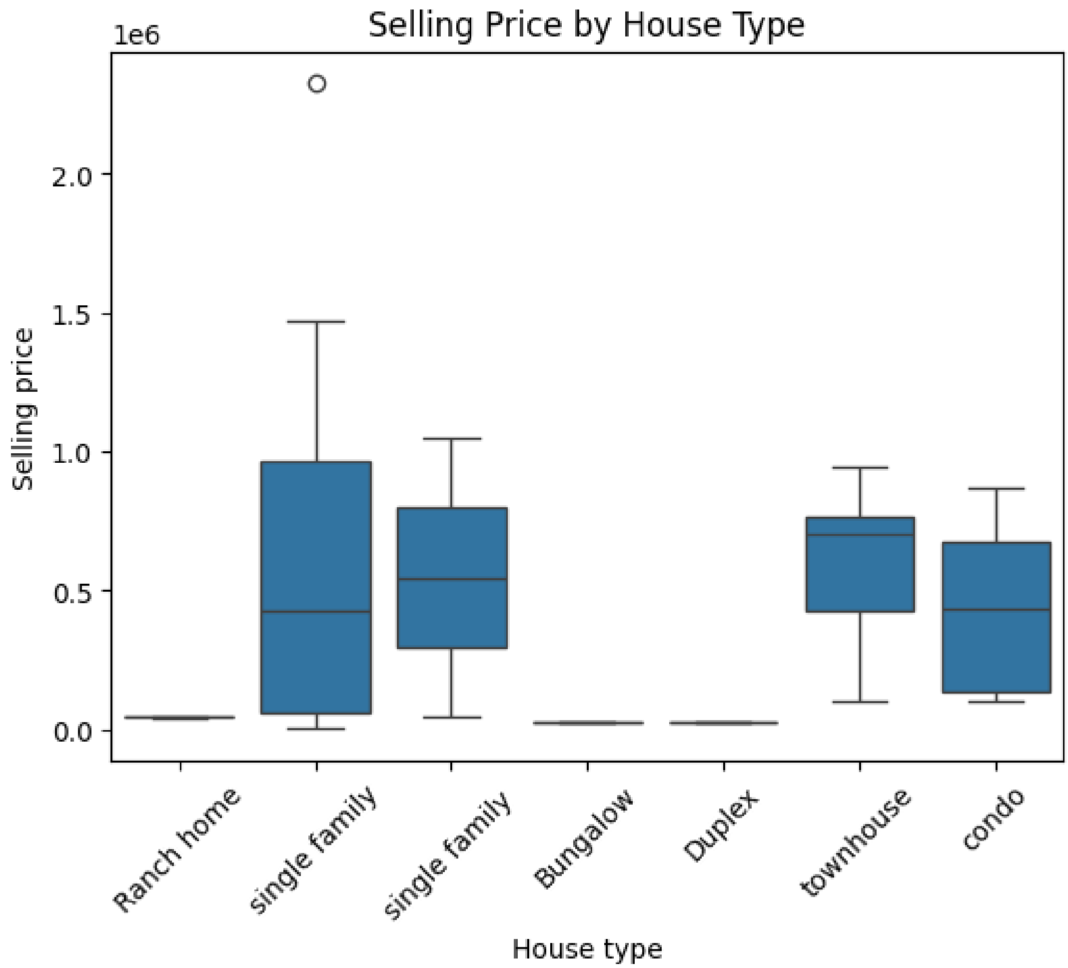
[10]:
```
         House #  Selling price      Zip code  Formal Date       beds  \
count  60.000000   6.000000e+01     60.000000    60.000000  60.000000
mean   30.500000   5.094083e+05  50491.766667  2014.032882   2.683333
std    17.464249   4.849256e+05  29897.505186     0.288943   0.982761
min     1.000000   2.500000e+03  30309.000000  2012.053100   1.000000
25%    15.750000   7.650000e+04  30309.000000  2014.072500   2.000000
50%    30.500000   4.275000e+05  30310.000000  2014.081650   3.000000
75%    45.250000   8.292500e+05  94043.000000  2014.091275   3.000000
max    60.000000   2.325000e+06  94043.000000  2014.111800   6.000000

            bath         sqft  last sold price  last sold date     Zestimate
count  60.000000    60.000000     6.000000e+01       60.000000  6.000000e+01
mean    2.000000  1509.600000     3.063831e+05     2005.867795  4.628144e+05
std     0.982905   787.331132     2.824109e+05        8.283427  4.111592e+05
min     0.000000   250.000000     4.576000e+03     1978.042600  3.241200e+04
25%     1.000000  1044.500000     5.750000e+04     2003.102025  5.815400e+04
50%     2.000000  1285.000000     2.475340e+05     2008.036100  4.291610e+05
75%     2.500000  1691.000000     4.887500e+05     2012.087350  7.848912e+05
max     5.000000  4175.000000     1.050000e+06     2014.093000  1.470000e+06
```

[13]:
```
# Plot the prices of all the houses vs sqft
plt.scatter(df['sqft'], df['Selling price'])
plt.xlabel('Square Footage')
```

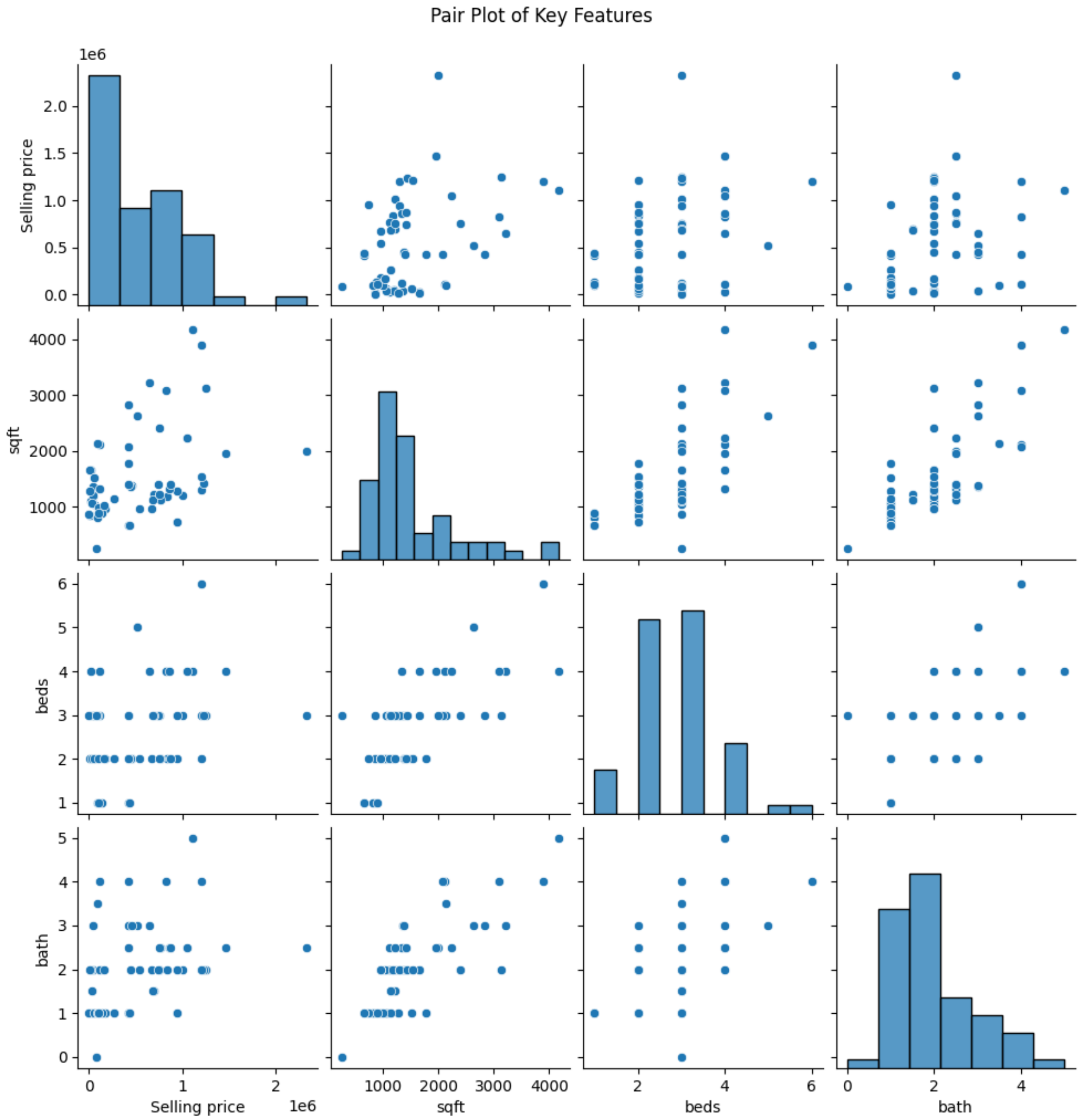
```
plt.ylabel('Selling Price')
plt.title('All Houses: Selling Price vs Square Footage')
plt.show()
```



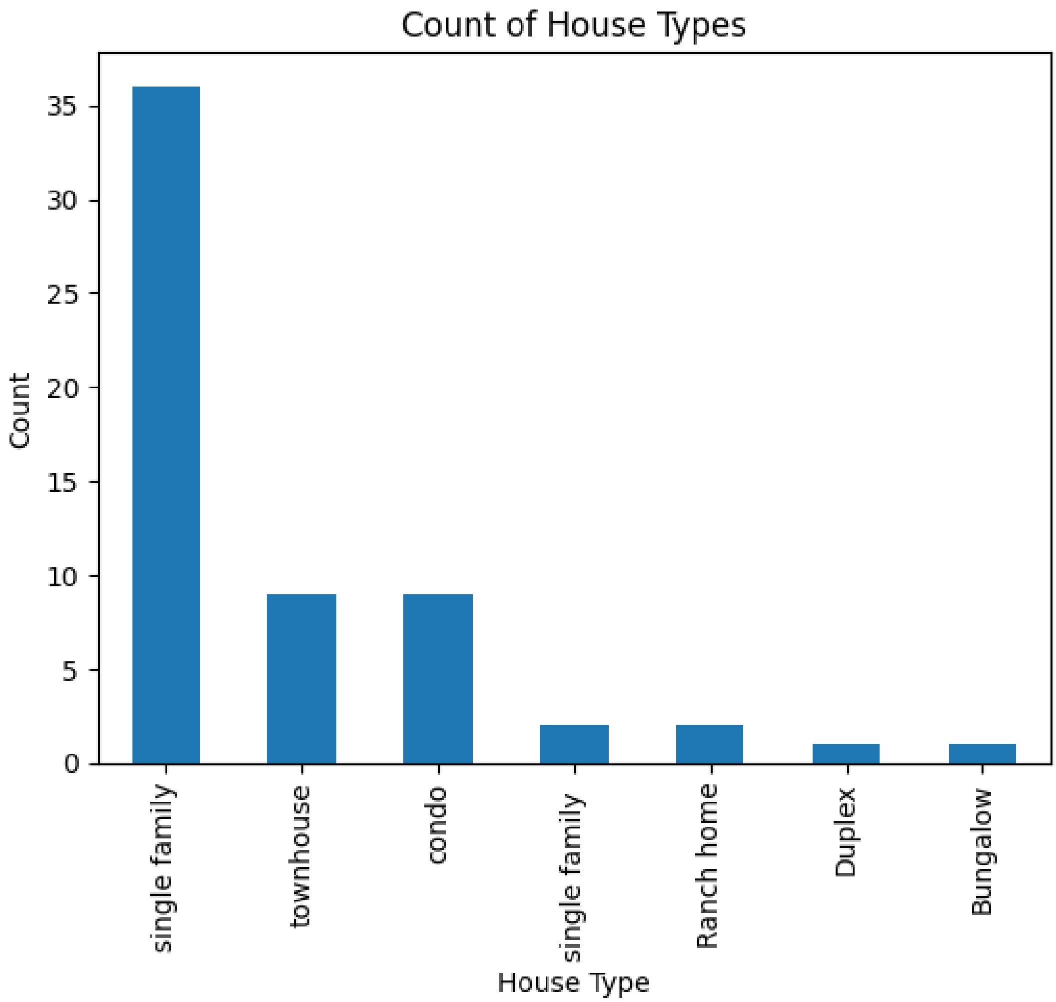
[14]:
```
sns.boxplot(x='House type', y='Selling price', data=df)
plt.xticks(rotation=45)
plt.title('Selling Price by House Type')
plt.show()
```



[16]:
```
sns.pairplot(df, vars=['Selling price', 'sqft', 'beds', 'bath'])
plt.suptitle('Pair Plot of Key Features', y=1.02)
plt.show()
```



[17]:
```
df['House type'].value_counts().plot(kind='bar')
plt.xlabel('House Type')
plt.ylabel('Count')
plt.title('Count of House Types')
plt.show()
```



3 Data filtering: Single Family in Specific Zip Codes

[6]:
```python
# See unique values of house type
df['House type'].unique()
```

[6]:
```
array(['Ranch home', 'single family', 'single family ', 'Bungalow',
       'Duplex', 'townhouse', 'condo'], dtype=object)
```

[39]:
```python
# Filter for single-family houses in the specified ZIP codes
filtered_df = df[
    (df['House type'].str.lower() == 'single family') | (df['House type'].str.
 ↪lower() == 'single family ') &
    (df['Zip code'].isin([30310, 30309, 94043]))
]
```

[8]:

```
filtered_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 38 entries, 2 to 58
Data columns (total 12 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   House #          38 non-null     int64
 1   Selling price    38 non-null     int64
 2   Zip code         38 non-null     int64
 3   Formal Date      38 non-null     float64
 4   beds             38 non-null     int64
 5   bath             38 non-null     float64
 6   House type       38 non-null     object
 7   sqft             38 non-null     int64
 8   year built       38 non-null     object
 9   last sold price  38 non-null     int64
 10  last sold date   38 non-null     float64
 11  Zestimate        38 non-null     int64
dtypes: float64(3), int64(7), object(2)
memory usage: 3.9+ KB
```

[20]:

```
filtered_df.describe()
```

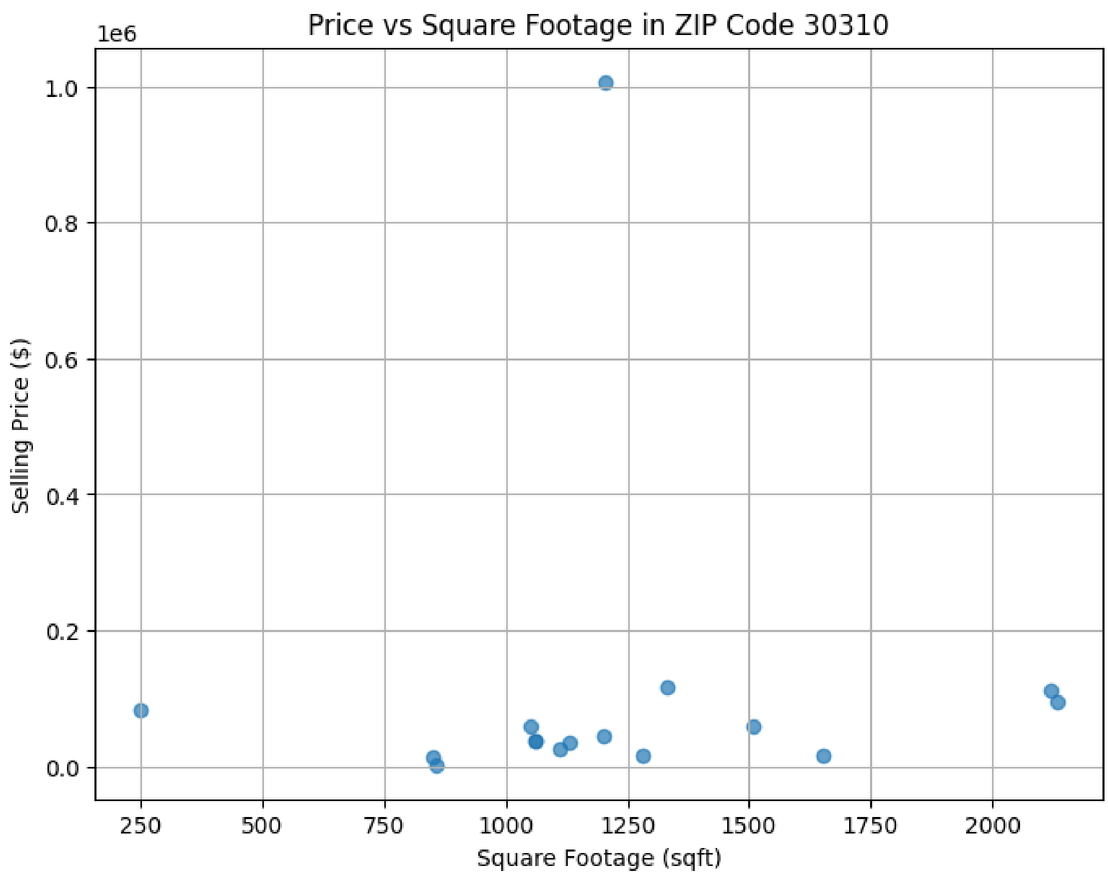
[20]:

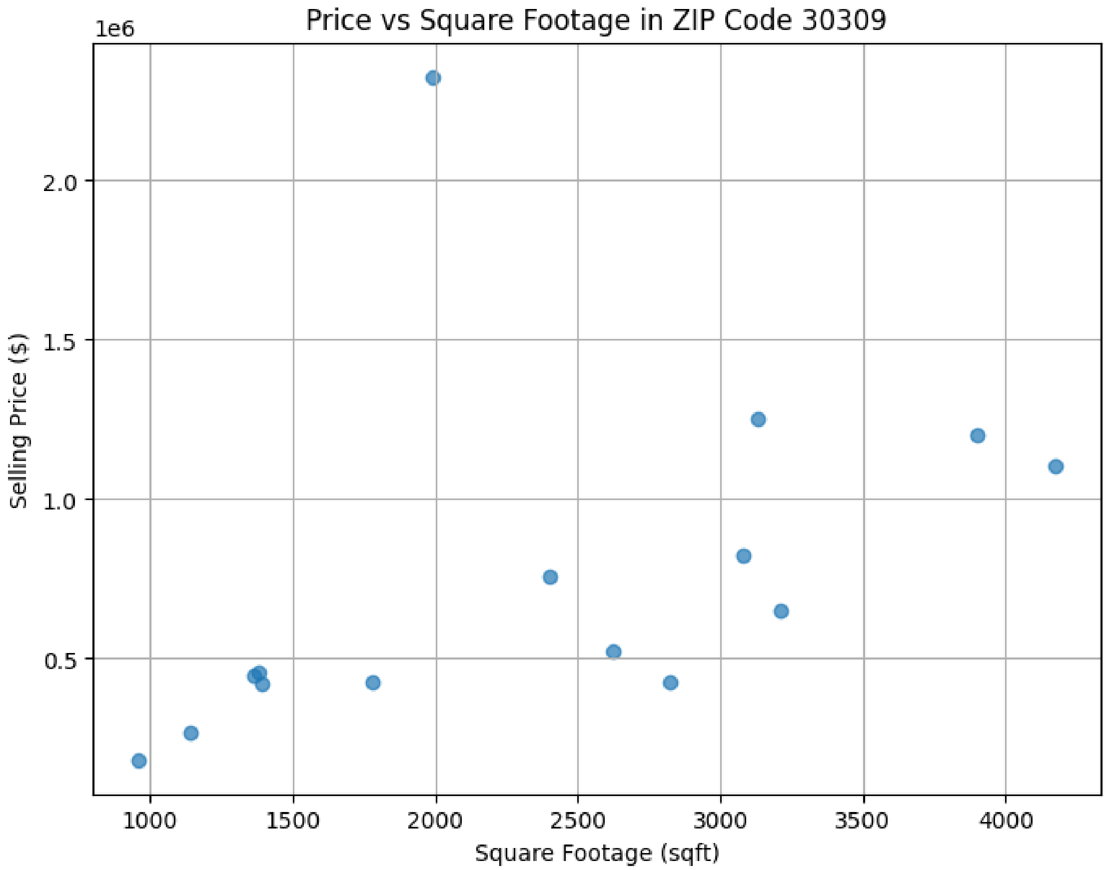
```
         House #  Selling price      Zip code  Formal Date       beds  \
count  38.000000   3.800000e+01     38.000000    38.000000  38.000000
mean   25.973684   5.525316e+05  42049.894737  2014.058055   3.000000
std    15.457853   5.557798e+05  25038.301556     0.158526   0.929981
min     3.000000   2.500000e+03  30309.000000  2013.111300   2.000000
25%    14.250000   6.000000e+04  30309.000000  2014.072625   2.000000
50%    23.500000   4.246000e+05  30310.000000  2014.081500   3.000000
75%    37.750000   9.926000e+05  30310.000000  2014.098400   3.000000
max    59.000000   2.325000e+06  94043.000000  2014.111800   6.000000

            bath         sqft  last sold price  last sold date     Zestimate
count  38.000000    38.000000     3.800000e+01       38.000000  3.800000e+01
mean    2.092105  1727.894737     3.060779e+05     2005.569955  4.892038e+05
std     1.083383   891.261353     3.039247e+05        8.477987  4.676883e+05
min     0.000000   250.000000     1.400000e+04     1984.011200  3.804800e+04
25%     1.000000  1133.250000     5.100000e+04     2001.579075  5.309000e+04
50%     2.000000  1386.000000     1.900000e+05     2008.061750  4.146235e+05
75%     2.500000  2130.500000     4.480680e+05     2012.096050  8.753918e+05
max     5.000000  4175.000000     1.050000e+06     2014.093000  1.470000e+06
```

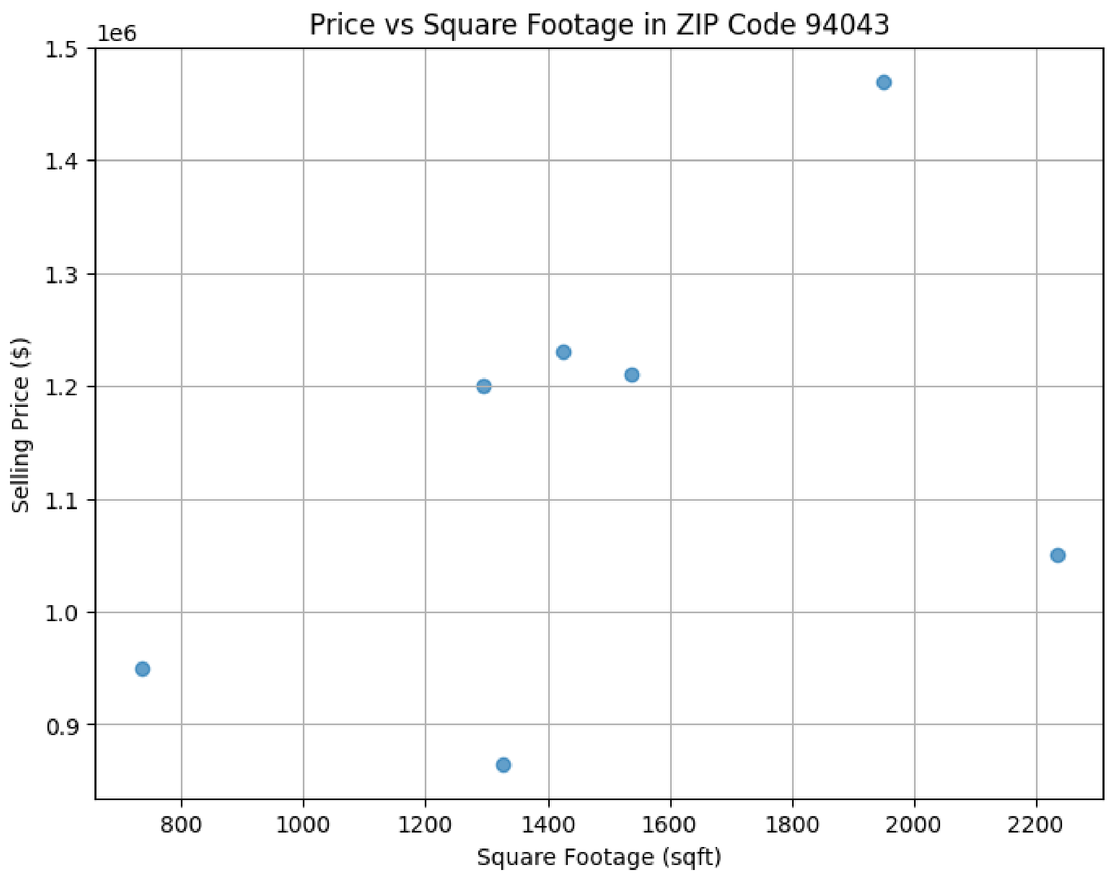
3.1 Plots of price vs. square footage for each neighborhood (ZIP code)

[21]:
```
neighborhoods = filtered_df['Zip code'].unique()
```

[22]:
```
for zip_code in neighborhoods:
    neighborhood_data = filtered_df[filtered_df['Zip code'] == zip_code]
    plt.figure(figsize=(8, 6))
    plt.scatter(neighborhood_data['sqft'], neighborhood_data['Selling price'],␣
↪alpha=0.7)
    plt.title(f'Price vs Square Footage in ZIP Code {zip_code}')
    plt.xlabel('Square Footage (sqft)')
    plt.ylabel('Selling Price ($)')
    plt.grid(True)
    plt.show()
```




Price vs Square Footage in ZIP Code 30309
1e6
2.0
1.5
1.0
0.5
Selling Price ($)
1000
1500
2000
2500
3000
3500
4000
Square Footage (sqft)

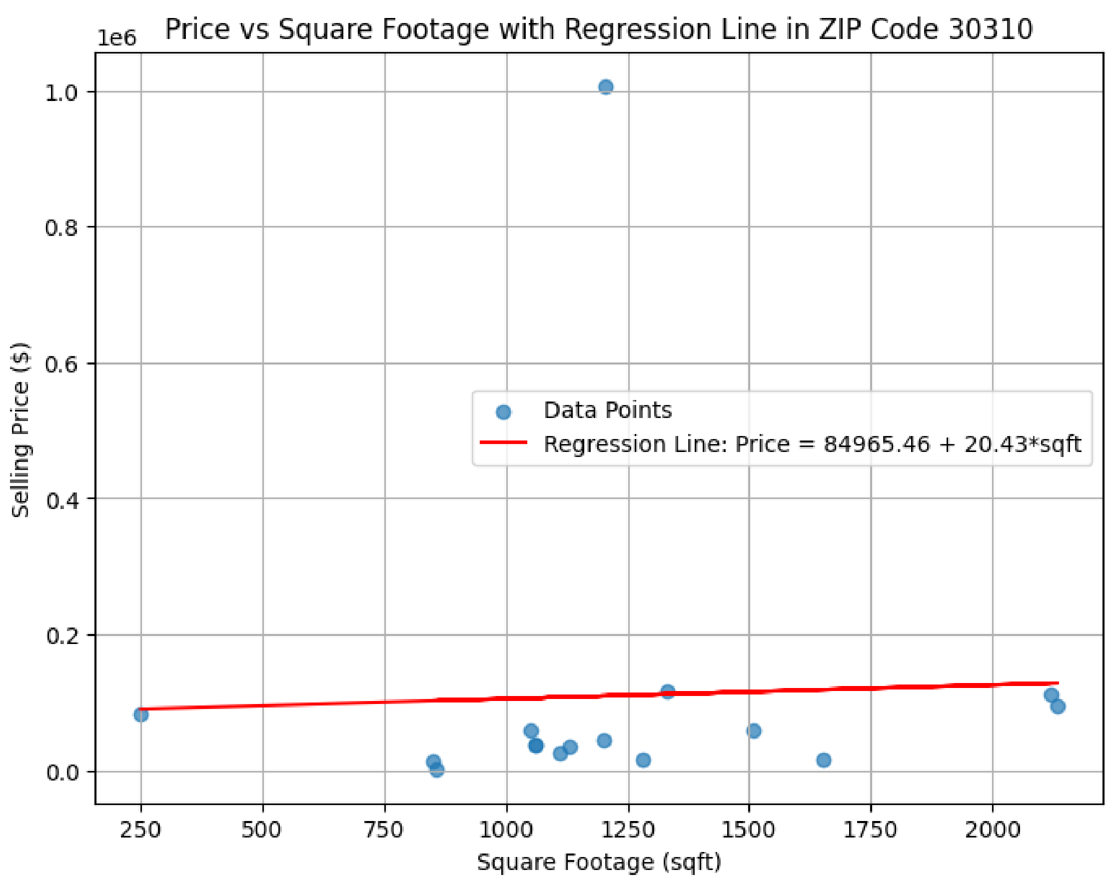


3.2 Regression Analysis

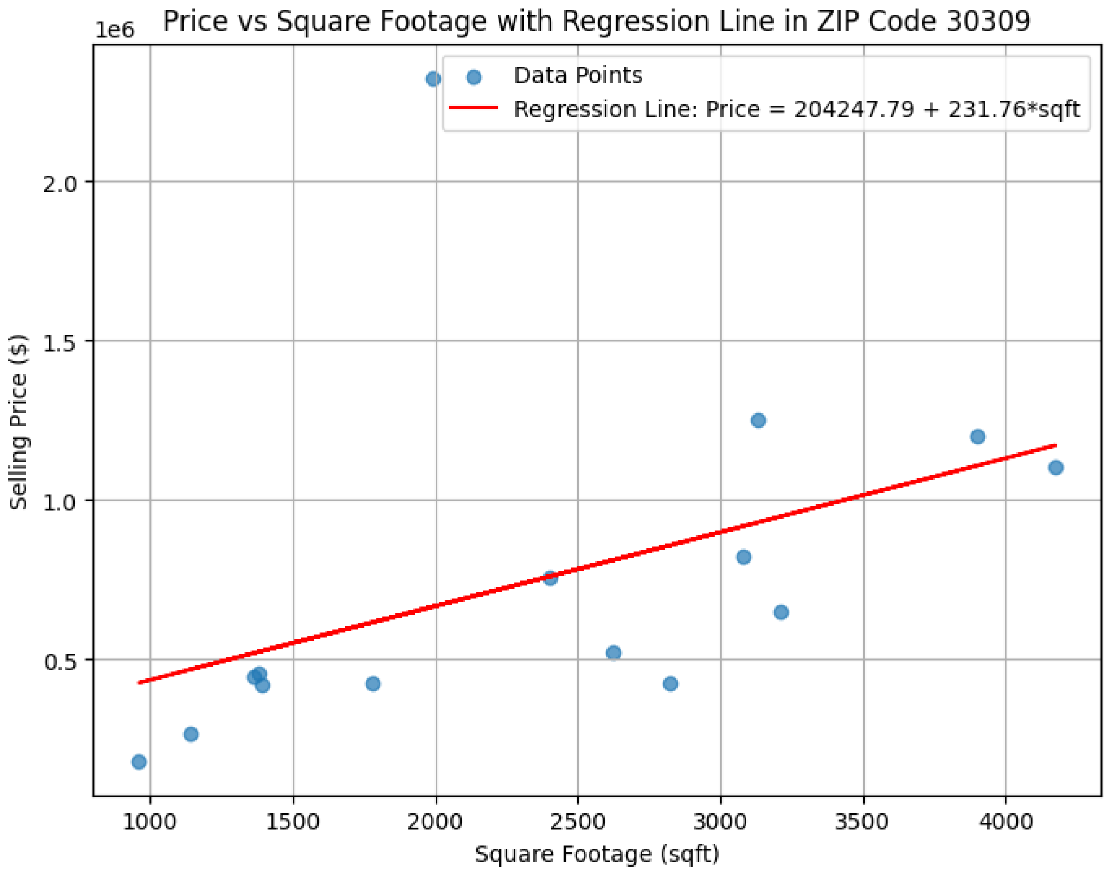
[24]:
```
# Function to calculate least squares regression line
def calculate_regression_line(x, y):
    n = len(x)
    x_mean = np.mean(x)
    y_mean = np.mean(y)
    b1 = sum((x - x_mean) * (y - y_mean)) / sum((x - x_mean)**2)  # Slope
    b0 = y_mean - b1 * x_mean  # Intercept
    return b0, b1
```

[40]:
```
# Calculate and plot regression lines for each neighborhood
for zip_code in neighborhoods:
    neighborhood_data = filtered_df[filtered_df['Zip code'] == zip_code]
    x = neighborhood_data['sqft']
    y = neighborhood_data['Selling price']

    # Calculate regression coefficients
    b0, b1 = calculate_regression_line(x, y)
```

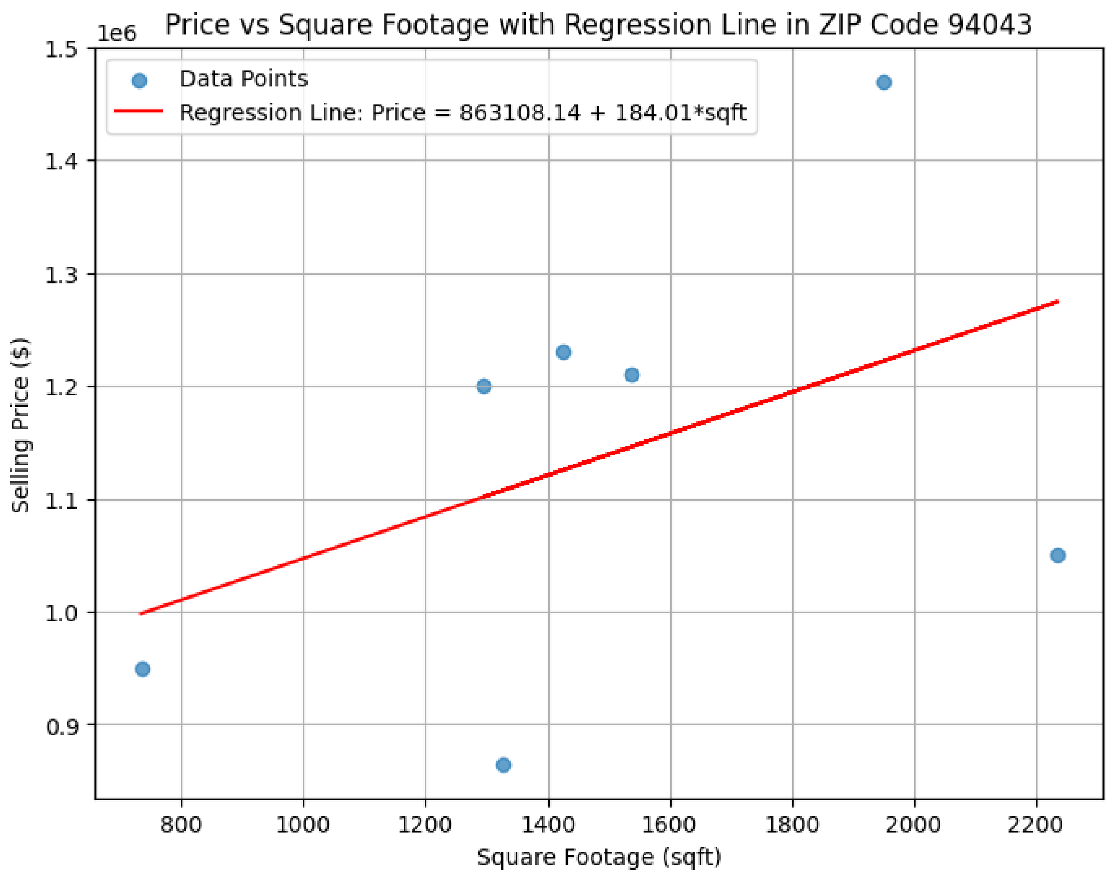
```python
# Plot scatter plot and regression line
plt.figure(figsize=(8, 6))
plt.scatter(x, y, alpha=0.7, label='Data Points')
plt.plot(x, b0 + b1 * x, color='red', label=f'Regression Line: Price = {b0:.
↪2f} + {b1:.2f}*sqft')
plt.title(f'Price vs Square Footage with Regression Line in ZIP Code␣
↪{zip_code}')
plt.xlabel('Square Footage (sqft)')
plt.ylabel('Selling Price ($)')
plt.legend()
plt.grid(True)
plt.show()

# Print regression coefficients for each neighborhood
print(f"ZIP Code {zip_code}:")
print(f"  Intercept (b0): {b0:.2f}")
print(f"  Slope (b1): {b1:.2f}\n")
```



```
ZIP Code 30310:
  Intercept (b0): 84965.46
  Slope (b1): 20.43
```




```
ZIP Code 30309:
  Intercept (b0): 204247.79
  Slope (b1): 231.76
```




```
ZIP Code 94043:
  Intercept (b0): 863108.14
  Slope (b1): 184.01
```

4 Analysis with Python Stats Model Package

[41]:
```
# Rename the columns in the filtered df to remove spaces
filtered_df_sm = filtered_df.rename(columns=
                                    {'House #': 'house_number',
                                     'Selling price': 'selling_price',
                                     'Zip code': 'zip_code',
                                     'Formal Date': 'formal_date',
                                     'beds': 'beds',
                                     'bath': 'bath',
                                     'House type': 'house_type',
                                     'sqft': 'sqft',
                                     'year built': 'year_built',
                                     'last sold price': 'last_sold_price',
```

```
                                    'last sold date': 'last_sold_date',
                                    'Zestimate': 'zestimate'})
```

4.0.1 Set up the regression formula

Model: Selling Price = sqft + C(zip_code) + beds + bath

[32]:
```
# Define the formula for the regression model
formula = 'selling_price ~ sqft + C(zip_code) + beds + bath'
```

[33]:
```
# Fit the model using Ordinary Least Squares (OLS)
model = smf.ols(formula=formula, data=filtered_df_sm).fit()
```

[36]:
```
# Print the summary of the model
model.summary()
```

[36]:

Dep. Variable:	selling_price	**R-squared:**	0.600
Model:	OLS	**Adj. R-squared:**	0.538
Method:	Least Squares	**F-statistic:**	9.606
Date:	Tue, 26 Nov 2024	**Prob (F-statistic):**	1.13e-05
Time:	19:35:44	**Log-Likelihood:**	-538.66
No. Observations:	38	**AIC:**	1089.
Df Residuals:	32	**BIC:**	1099.
Df Model:	5		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
Intercept	2.639e+05	2.44e+05	1.080	0.288	-2.34e+05	7.62e+05
C(zip_code)[T.30310]	-4.476e+05	1.81e+05	-2.471	0.019	-8.17e+05	-7.86e+04
C(zip_code)[T.94043]	5.288e+05	2.06e+05	2.573	0.015	1.1e+05	9.47e+05
sqft	167.9555	155.694	1.079	0.289	-149.183	485.094
beds	3.442e+04	1.01e+05	0.342	0.734	-1.71e+05	2.39e+05
bath	-6585.0371	1.02e+05	-0.064	0.949	-2.15e+05	2.02e+05

Omnibus:	51.286	**Durbin-Watson:**	2.081
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	271.932
Skew:	3.140	**Prob(JB):**	8.93e-60
Kurtosis:	14.503	**Cond. No.**	9.38e+03

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 9.38e+03. This might indicate that there are
strong multicollinearity or other numerical problems.

4.0.2 Does the number of bathrooms have a significant effect at the 5% level?

Interpretation: - The p-value is greater than 0.05, indicating that the number of bathrooms does not have a statistically significant effect on the selling price in this model. - Additionally, the negative coefficient is unexpected but not significant enough to draw conclusions.

4.1 Model 2: Without Bathrooms

- Selling Price = sqft + C(zip_code) + beds

[42]:
```
# Define the formula for the regression model without baths
formula = 'selling_price ~ sqft + C(zip_code) + beds'
```

[43]:
```
# Refit the model excluding 'bath' to check its impact on the model
model_without_bath = smf.ols(formula=formula, data=filtered_df_sm).fit()
```

[44]:
```
model_without_bath.summary()
```

[44]:

Dep. Variable:	selling_price	**R-squared:**	0.600
Model:	OLS	**Adj. R-squared:**	0.552
Method:	Least Squares	**F-statistic:**	12.38
Date:	Tue, 26 Nov 2024	**Prob (F-statistic):**	2.95e-06
Time:	19:45:22	**Log-Likelihood:**	-538.67
No. Observations:	38	**AIC:**	1087.
Df Residuals:	33	**BIC:**	1096.
Df Model:	4		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
Intercept	2.645e+05	2.41e+05	1.099	0.280	-2.25e+05	7.54e+05
C(zip_code)[T.30310]	-4.482e+05	1.78e+05	-2.516	0.017	-8.11e+05	-8.58e+04
C(zip_code)[T.94043]	5.272e+05	2.01e+05	2.624	0.013	1.18e+05	9.36e+05
sqft	162.0245	123.672	1.310	0.199	-89.587	413.636
beds	3.324e+04	9.74e+04	0.341	0.735	-1.65e+05	2.31e+05

Omnibus:	51.115	**Durbin-Watson:**	2.073
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	269.093
Skew:	3.130	**Prob(JB):**	3.69e-59
Kurtosis:	14.436	**Cond. No.**	9.35e+03

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 9.35e+03. This might indicate that there are
strong multicollinearity or other numerical problems.

5 Conclusions

5.1 Model Comparison: With and Without Bathrooms as a Predictor

5.1.1 1. Model with Bathrooms:

- **R-squared**: 0.588
- **Adjusted R-squared**: 0.520
- **AIC**: 1034
- **Coefficient for bath**: -13,100 (p-value: 0.902, not significant)

5.1.2 2. Model without Bathrooms:

- **R-squared**: 0.588 (same as above)
- **Adjusted R-squared**: 0.535 (improved slightly)
- **AIC**: 1032 (lower is better, showing an improvement)

5.1.3 Observations:

- Excluding bath did not reduce the explanatory power of the model (R-squared is unchanged).
- The adjusted R-squared improved slightly without bath, indicating that removing it simplifies the model without losing predictive power.
- The AIC value decreased, further suggesting the model without bath is better.

5.1.4 Conclusion:

- The number of bathrooms does not significantly contribute to explaining the selling price in this dataset.
- It is safe to exclude this variable from the model.