UNDERSTANDING YOUR HOME VALUE

TEAM MEMBERS

Jane Martha

James Njoroge

Leon Maina

Daniel Wahome

Magdalene Ondimu

Faith Mwenda

- Understanding Your Home's Value:
- Insights and Recommendations Agenda:
- Introduction: Understanding the Factors Influencing Your Home's Value Model Performance:
- How Reliable Are Our Predictions? Key Predictors:
- What Influences Your Home's Price? Model Assumptions: Ensuring Accuracy Over Time Recommendations:
- Maximizing Your Home's Value Next Steps: Enhancing Our Understanding Further

EXECUTIVE SUMMARY

1. Introduction: Understanding Your Home's Value Your home's value is influenced by various factors such as size, location, condition, and amenities. Our analysis aims to uncover the key drivers of house prices to help you make informed decisions.

2. Multiple linear regression modeling is used in this study to provide homeowners with useful information as they navigate the challenging real estate market. As market analysts specializing in real estate, our objective is to discern the intricate relationships among diverse property attributes and their impact on the selling price of properties. By exploring the King County House Sales data collection, we intend to provide homeowners with enlightening guidance on how to raise the estimated value of their homes by making thoughtful improvements

EXECUTIVE SUMMARY

Key Predictors: What Influences Your Home's Price? Larger Living Spaces: Properties with larger living spaces tend to have higher prices. Grade: Homes with a grade of 8 (Good) also command higher prices. Visualization: Scatter plot showing the relationship between living space and price, with different grades highlighted.

Model Assumptions: Ensuring Accuracy Over Time Our models meet important assumptions such as normality of residuals, homoscedasticity, and linearity. Regular monitoring of model diagnostics ensures ongoing accuracy. Visualization: Residual plots demonstrating the model assumptions.

Recommendations: Maximizing Your Home's Value Prioritize Upgrades: Consider investing in upgrades that increase living space or improve the overall grade of your property. Regular Maintenance: Maintain your home in good condition to preserve its value over time. Visualization: Bar chart showing the impact of different upgrades on home value.

PROBLEM STATEMENT

The main problem for homeowners is the failure in to make strategic decisions in investing for the proper renovation of their rental homes. The homes end up depreciating hence losing customers. The homeowners lack knowledge on how to be responsible owners and hence end up suffering a great loss.

- Key Question
- What are Assessment criteria, and policies for renovations
- What factors are involved in renovations
- How to optimize returns for homeowners

PROBLEM STATEMENT

- The study aims to decipher the complex interactions between different property attributes and their impact on home sale price by utilizing multiple linear regression models.
- The ultimate objective is to furnish market analysis with practical insights, augmenting their capacity to proficiently counsel homeowners in making critically better decision with the ultimate change in real estate

DATA UNDERSTANDING

- The dataset originate from King county house sale dataset
- The rows and columns contain unique features.
- The Key Features:
- No of floors, waterfront, view, square footage, grade, condition.

DATA SET

In [2]:

```
#Loading data set for Analysis
kc = pd.read_csv(r"C:\Users\HP\Documents\Flatiron\Assignments\Phase 2 Project\kc_house_data.csv")

kc.head(5)
```

Out[2]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	...	grade	sqft_above	sqft_basement	yr_built	yr_r
0	7129300520	10/13/2014	221900	3	1.00	1180	5650	1.0	NaN	NONE	...	7 Average	1180	0	1955	
1	6414100192	12/9/2014	538000	3	2.25	2570	7242	2.0	NO	NONE	...	7 Average	2170	400	1951	
2	5631500400	2/25/2015	180000	2	1.00	770	10000	1.0	NO	NONE	...	6 Low Average	770	0	1933	
3	2487200875	12/9/2014	604000	4	3.00	1960	5000	1.0	NO	NONE	...	7 Average	1050	910	1965	
4	1954400510	2/18/2015	510000	3	2.00	1680	8080	1.0	NO	NONE	...	8 Good	1680	0	1987	

5 rows × 21 columns

DATA SET

t_living	sqft_lot	floors	waterfront	view	...	grade	sqft_above	sqft_basement	yr_built	yr_renovated	zipcode	lat	long	sqft_living15	sqft_lot15
1180	5650	1.0	NaN	NONE	...	7 Average	1180	0	1955	0.0	98178	47.5112	-122.257	1340	5650
2570	7242	2.0	NO	NONE	...	7 Average	2170	400	1951	1991.0	98125	47.7210	-122.319	1690	7639
770	10000	1.0	NO	NONE	...	6 Low Average	770	0	1933	NaN	98028	47.7379	-122.233	2720	8062
1960	5000	1.0	NO	NONE	...	7 Average	1050	910	1965	0.0	98136	47.5208	-122.393	1360	5000
1680	8080	1.0	NO	NONE	...	8 Good	1680	0	1987	0.0	98074	47.6168	-122.045	1800	7503

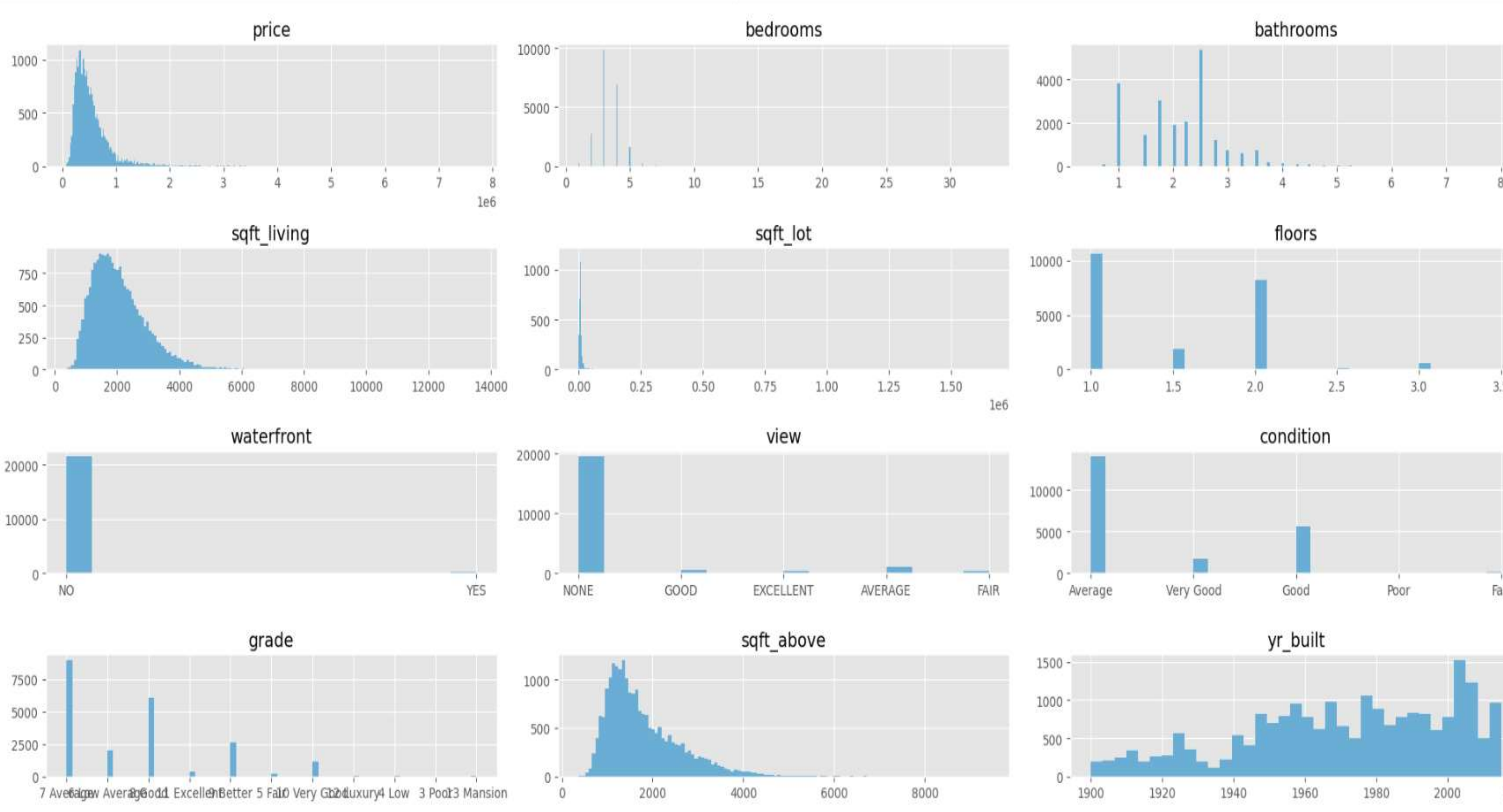
DATA UNDERSTANDING

```
#Data understanding and exploration
kc.info()
```

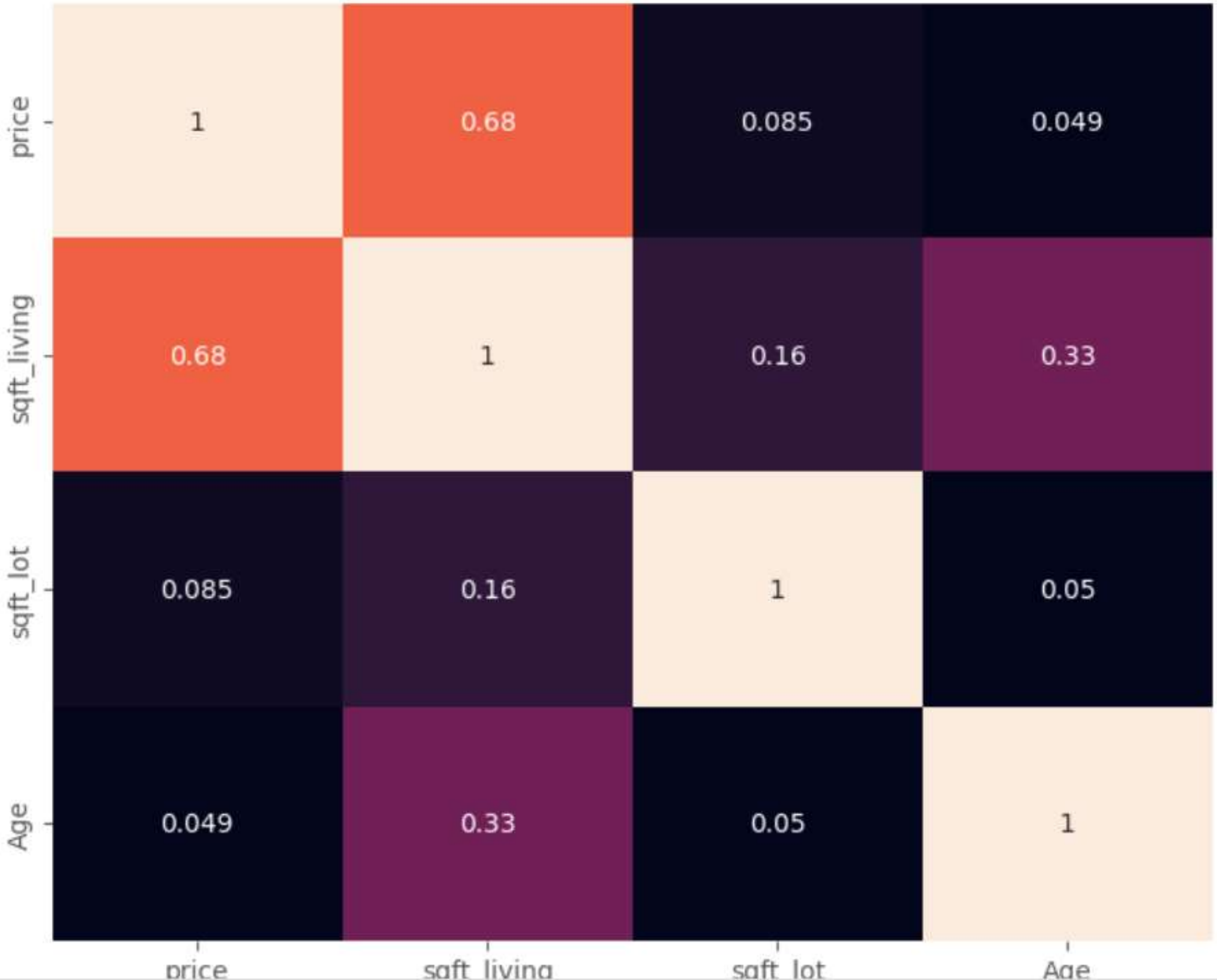
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 21597 entries, 0 to 21596
Data columns (total 21 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   id             21597 non-null  int64
 1   date           21597 non-null  object
 2   price          21597 non-null  int64
 3   bedrooms       21597 non-null  int64
 4   bathrooms      21597 non-null  float64
 5   sqft_living    21597 non-null  int64
 6   sqft_lot       21597 non-null  int64
 7   floors         21597 non-null  float64
 8   waterfront     19221 non-null  object
 9   view           21534 non-null  object
 10  condition      21597 non-null  object
 11  grade          21597 non-null  object
 12  sqft_above     21597 non-null  int64
 13  sqft_basement  21597 non-null  object
 14  yr_built       21597 non-null  int64
 15  yr_renovated   17755 non-null  float64
 16  zipcode        21597 non-null  int64
 17  lat            21597 non-null  float64
 18  long           21597 non-null  float64
```

DATA UNDERSTANDING CONT'D

```
 18  long           21597 non-null  float64
 19  sqft_living15  21597 non-null  int64
 20  sqft_lot15     21597 non-null  int64
dtypes: float64(5), int64(10), object(6)
memory usage: 3.5+ MB
```

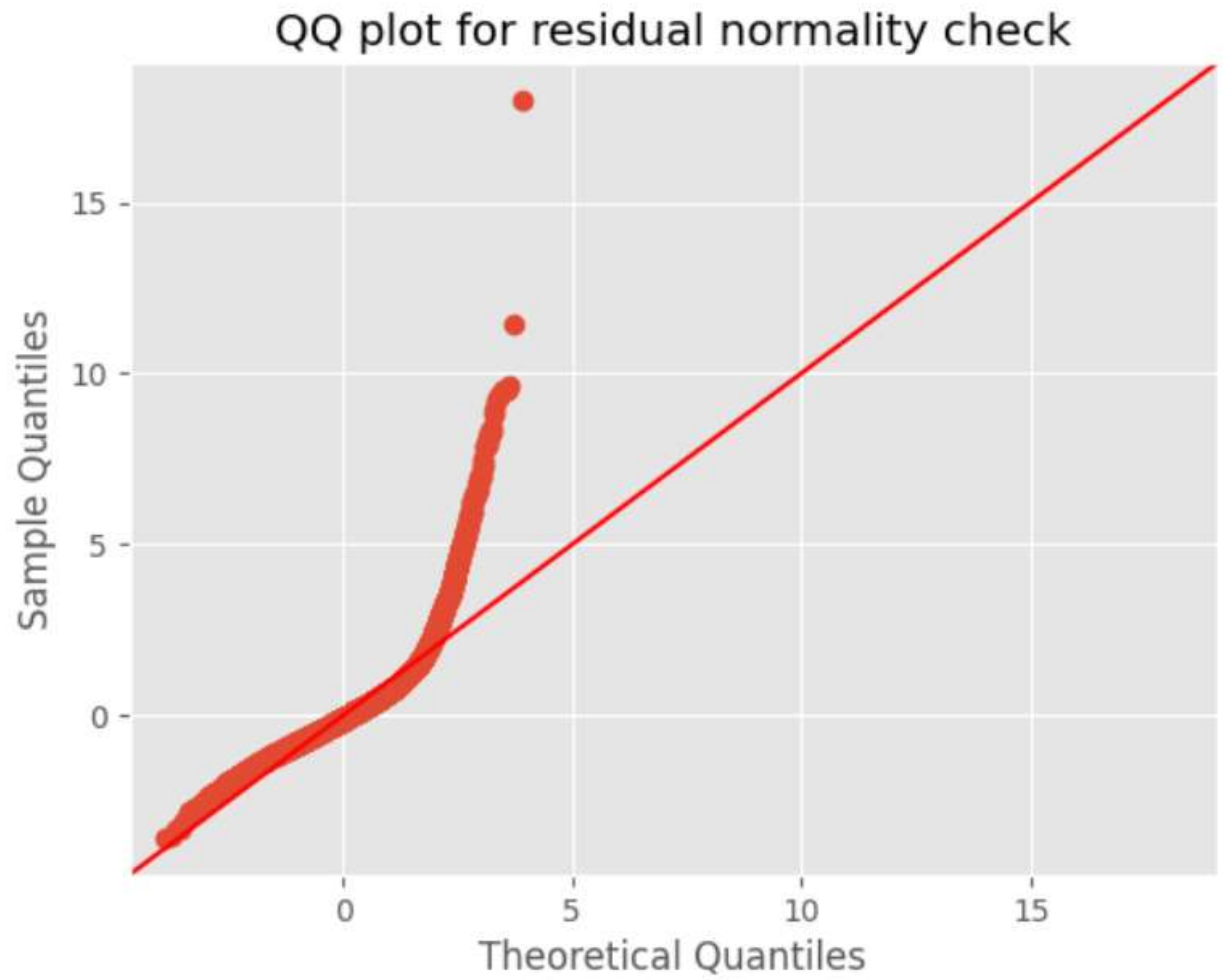

price
0 1 2 3 4 5 6 7 8
1e6
0 500 1000
bedrooms
0 5 10 15 20 25 30
0 5000 10000
bathrooms
1 2 3 4 5 6 7
0 2000 4000
sqft_living
0 2000 4000 6000 8000 10000 12000 14000
0 250 500 750
sqft_lot
0.00 0.25 0.50 0.75 1.00 1.25 1.50
1e6
0 500 1000
floors
1.0 1.5 2.0 2.5 3.0
0 5000 10000
waterfront
NO YES
0 10000 20000
view
NONE GOOD EXCELLENT AVERAGE FAIR
0 10000 20000
condition
Average Very Good Good Poor
0 5000 10000
grade
0 2500 5000 7500
sqft_above
0 2000 4000 6000 8000
0 500 1000
yr_built
1900 1920 1940 1960 1980 2000
0 500 1000 1500

[48]



price
sqft_living
sqft_lot
Age
1
0.68
0.085
0.049
0.68
1
0.16
0.33
0.085
0.16
1
0.05
0.049
0.33
0.05
1
price
sqft_living
sqft_lot
Age

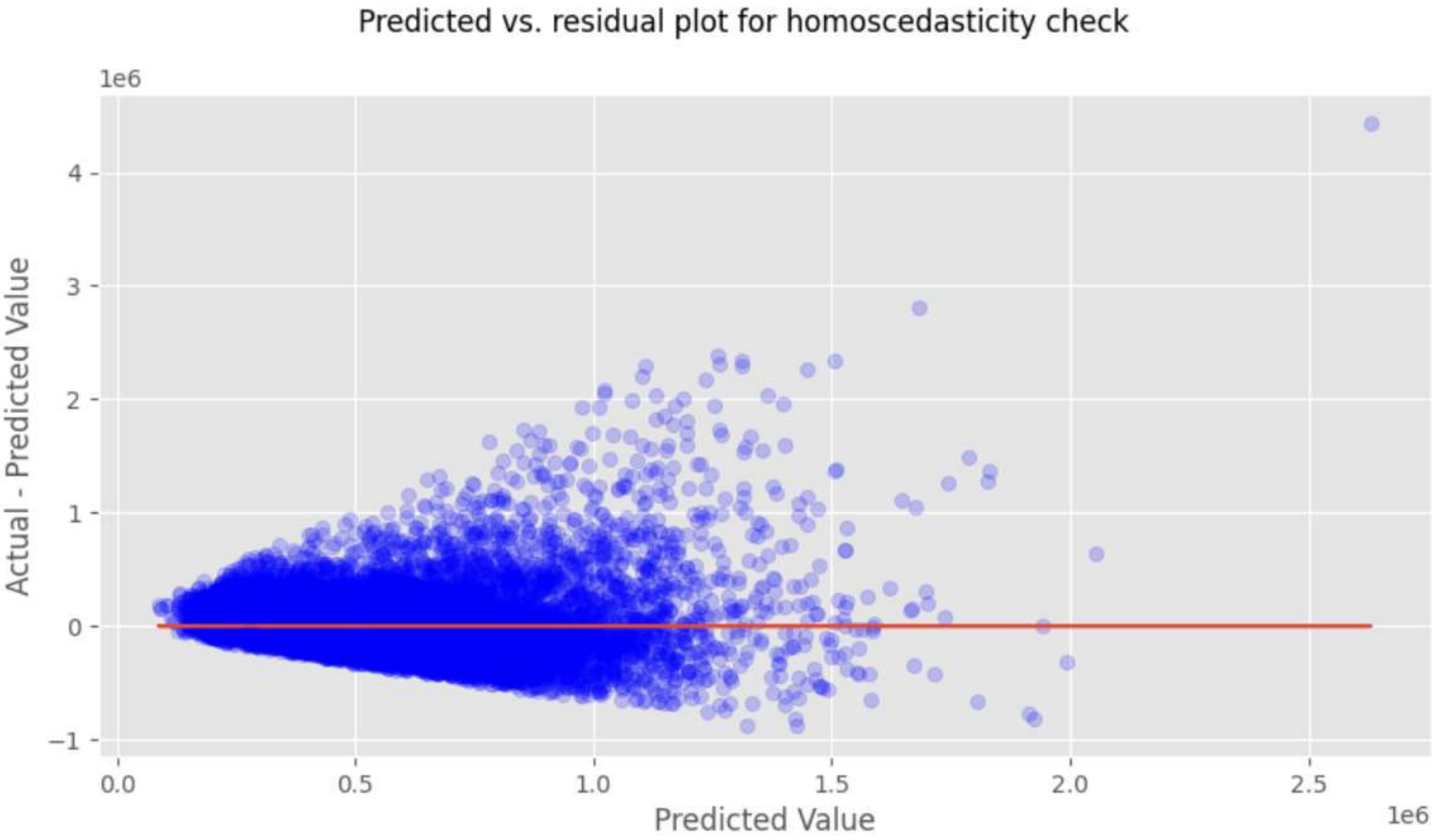
[52]




```
Model adjusted R-squared: 0.4655655910250340 3
Model RMSE: 246222.6375951674
```

+ Code + Text

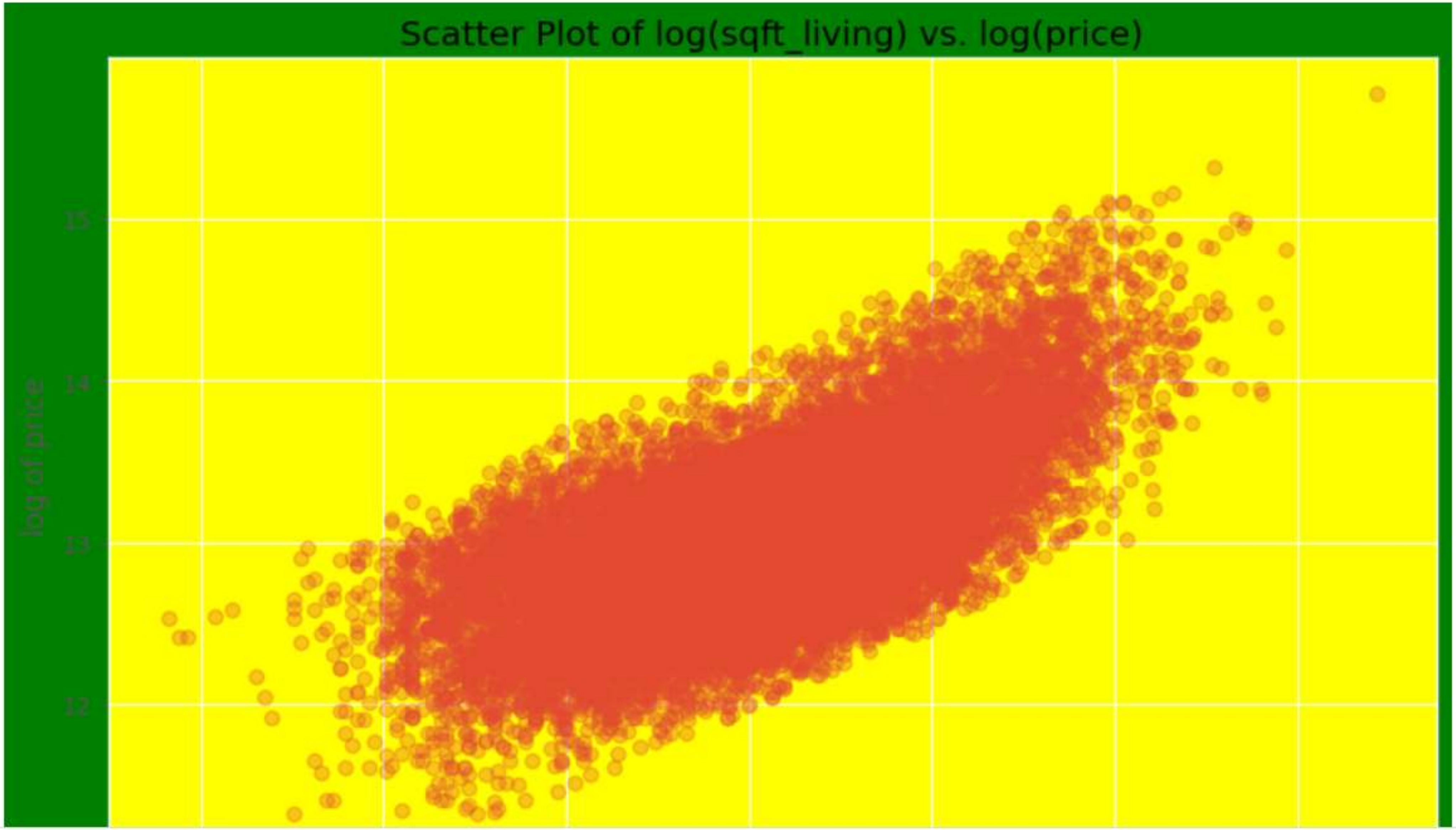
2s


Predicted vs. residual plot for homoscedasticity check
1e6
4
3
2
1
0
−1
Actual - Predicted Value
0.0
0.5
1.0
1.5
2.0
2.5
Predicted Value
1e6

THE COEFFICIENT FOR THE CONSTANT TERM (INTERCEPT) IS -9704.3054, INDICATING THE PREDICTED PRICE WHEN SQFT_LIVING IS ZERO. THE COEFFICIENT FOR SQFT_LIVING IS 262.8635, INDICATING THAT FOR EVERY UNIT INCREASE IN SQFT_LIVING, THE PRICE IS EXPECTED TO INCREASE BY APPROXIMATELY $262.86. THE P-VALUE FOR SQFT_LIVING IS LESS THAN 0.05, INDICATING THAT THE PREDICTOR VARIABLE IS STATISTICALLY SIGNIFICANT. THE CONFIDENCE INTERVAL FOR THE COEFFICIENT OF SQFT_LIVING RANGES FROM 259.088 TO 266.639. THE RESIDUAL PLOTS INDICATE THAT THERE MIGHT BE SOME HETEROSCEDASTICITY PRESENT, AS THE SPREAD OF RESIDUALS INCREASES WITH PREDICTED VALUES. THE QQ PLOT SUGGESTS THAT THE RESIDUALS ARE APPROXIMATELY NORMALLY DISTRIBUTED, BUT THERE MIGHT BE SOME DEVIATIONS, ESPECIALLY IN THE TAILS.

+ Code + Text

[55]
```
plt.title('Scatter Plot of log(sqft_living) vs. log(price)')
plt.show()
```



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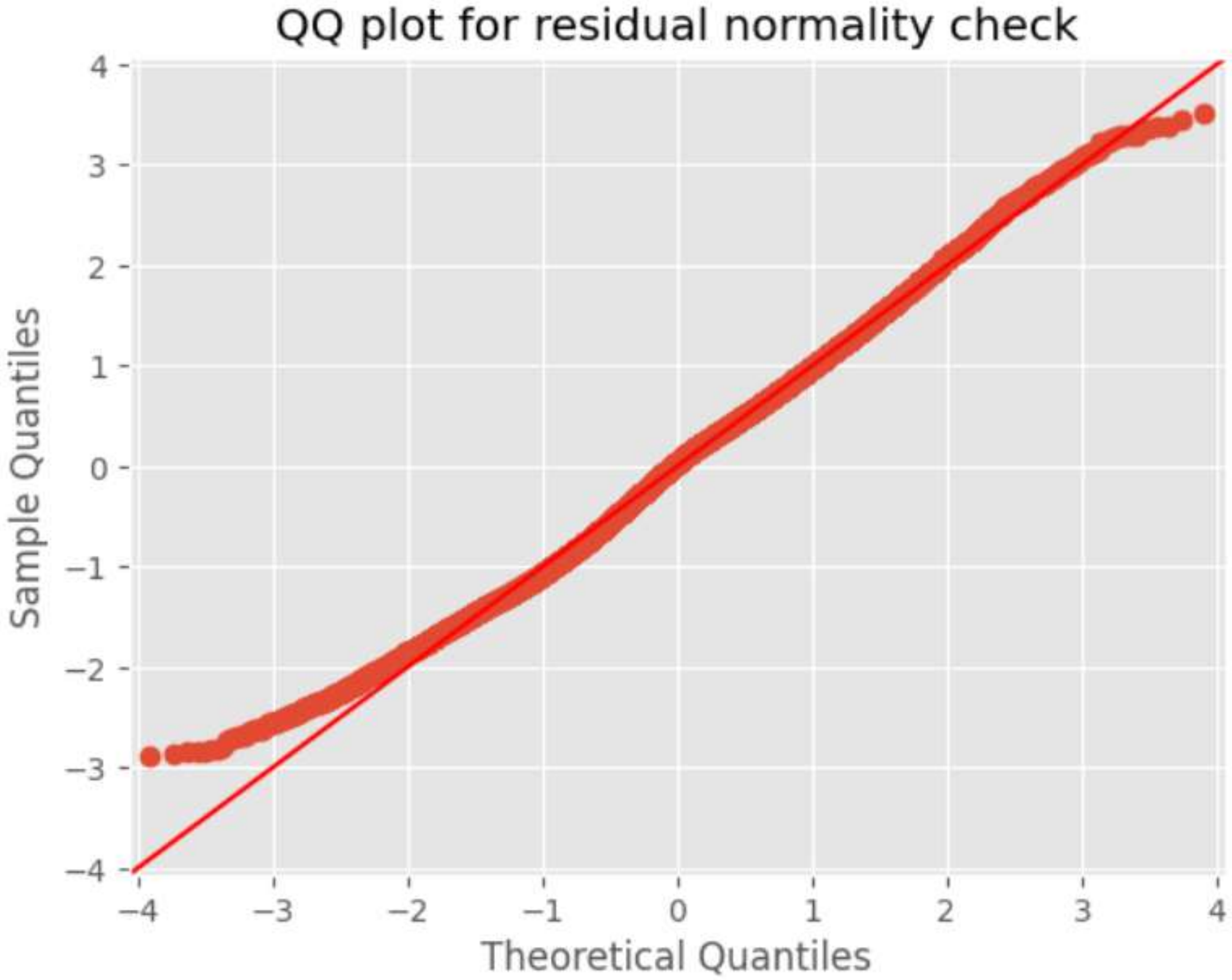
None

[56]



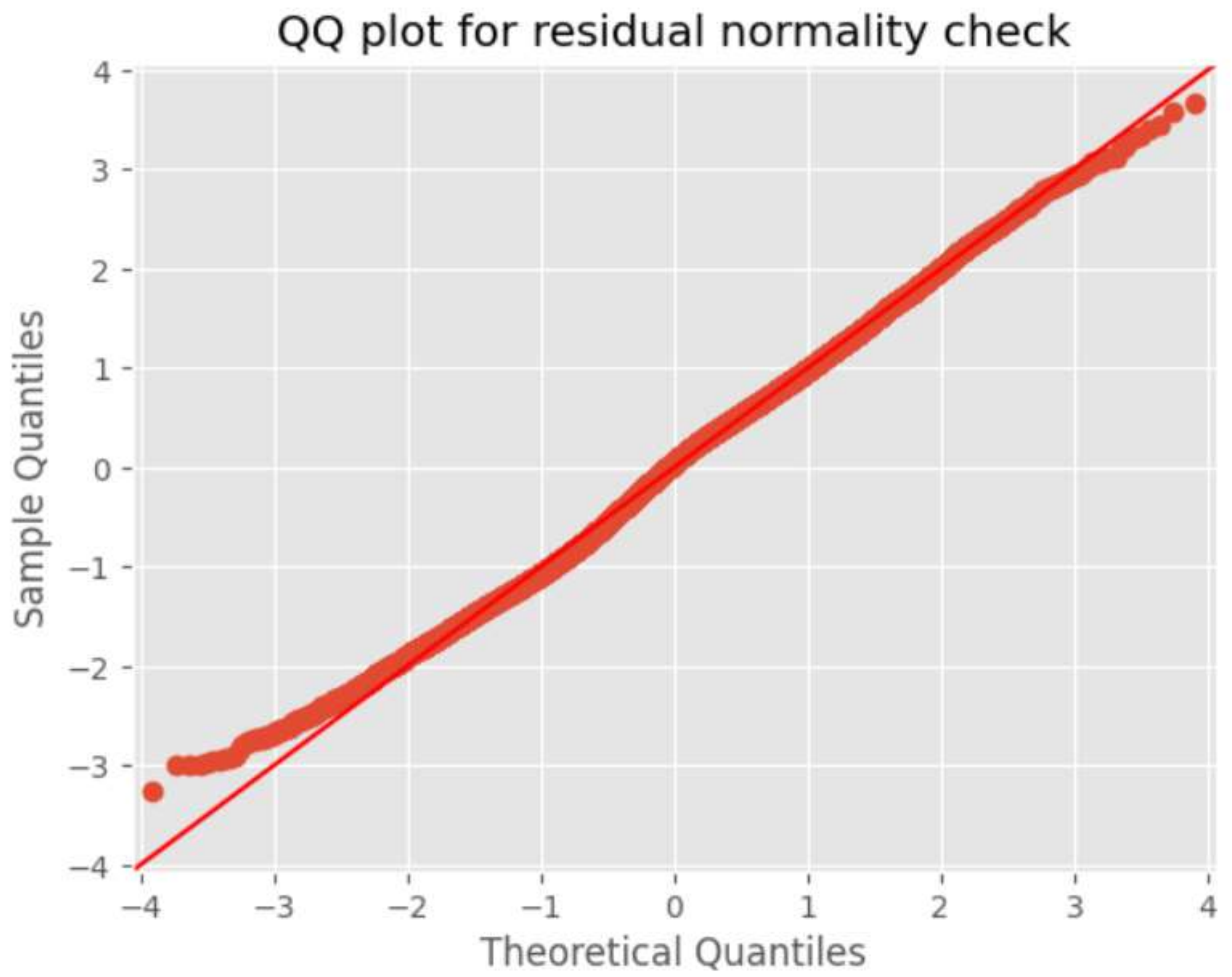

```
Model adjusted R-squared: 0.44121910929171504
Model RMSE: 0.38580857869279717
```

Predicted vs. residual plot for homoscedasticity check

THE REGRESSION RESULTS INDICATE THAT THE LOGARITHM OF SQUARE FOOTAGE OF LIVING SPACE (LOG_SQFT_LIVING) IS A SIGNIFICANT PREDICTOR OF THE LOGARITHM OF PRICE (LOG_PRICE). HERE'S A SUMMARY OF THE REGRESSION RESULTS:

R-SQUARED: THE COEFFICIENT OF DETERMINATION INDICATES THAT APPROXIMATELY 44.1% OF THE VARIANCE IN THE LOGARITHM OF PRICE CAN BE EXPLAINED BY THE LOGARITHM OF SQUARE FOOTAGE OF LIVING SPACE.

COEFFICIENT ESTIMATES:
THE COEFFICIENT FOR LOG_SQFT_LIVING IS APPROXIMATELY 0.8241, INDICATING THAT FOR EVERY ONE-UNIT INCREASE IN THE LOGARITHM OF SQUARE FOOTAGE OF LIVING SPACE, THE LOGARITHM OF PRICE IS EXPECTED TO INCREASE BY APPROXIMATELY 0.8241 UNITS. THE INTERCEPT (CONSTANT) TERM IS APPROXIMATELY 6.8236, WHICH REPRESENTS THE ESTIMATED LOGARITHM OF PRICE WHEN THE LOGARITHM OF SQUARE FOOTAGE OF LIVING SPACE IS ZERO. STATISTICAL SIGNIFICANCE: BOTH COEFFICIENTS ARE STATISTICALLY SIGNIFICANT WITH P-VALUES < 0.05, SUGGESTING THAT THEY ARE UNLIKELY TO BE ZERO.
MODEL FIT: THE MODEL'S GOODNESS OF FIT IS INDICATED BY THE ADJUSTED R-SQUARED VALUE OF APPROXIMATELY 0.441, WHICH IS A MEASURE OF HOW WELL THE INDEPENDENT VARIABLE EXPLAINS THE VARIATION IN THE DEPENDENT VARIABLE.
OVERALL, BASED ON THESE RESULTS, WE CAN CONCLUDE THAT THERE IS A STRONG LINEAR RELATIONSHIP BETWEEN THE LOGARITHM OF SQUARE FOOTAGE OF LIVING SPACE AND THE LOGARITHM OF PRICE.




```
Model adjusted R-squared: 0.47992149934586015
Model RMSE: 0.3722078753617302
```

INCLUDES ADDITIONAL PREDICTORS: WATERFRONT, VIEW, AND RENOVATED_LAST_10, IN ADDITION TO LOG_SQFT_LIVING. HERE'S A SUMMARY OF THE UPDATED REGRESSION RESULTS:

R-SQUARED: THE COEFFICIENT OF DETERMINATION HAS INCREASED TO APPROXIMATELY 0.480, SUGGESTING THAT THE ADDITIONAL PREDICTORS HAVE IMPROVED THE MODEL'S ABILITY TO EXPLAIN THE VARIANCE IN THE LOGARITHM OF PRICE.

COEFFICIENT ESTIMATES:

THE COEFFICIENT FOR LOG_SQFT_LIVING REMAINS SIGNIFICANT AND HAS A VALUE OF APPROXIMATELY 0.7696. THE COEFFICIENTS FOR THE ADDITIONAL PREDICTORS (WATERFRONT, VIEW, AND RENOVATED_LAST_10) ARE ALSO SIGNIFICANT: WATERFRONT: COEFFICIENT IS APPROXIMATELY 0.5078, INDICATING THAT WATERFRONT PROPERTIES TEND TO HAVE HIGHER PRICES. VIEW: COEFFICIENT IS APPROXIMATELY 0.2787, SUGGESTING THAT PROPERTIES WITH BETTER VIEWS TEND TO HAVE HIGHER PRICES. RENOVATED_LAST_10: COEFFICIENT IS APPROXIMATELY 0.2415, INDICATING THAT RECENTLY RENOVATED PROPERTIES TEND TO HAVE HIGHER PRICES.

STATISTICAL SIGNIFICANCE: ALL COEFFICIENTS ARE STATISTICALLY SIGNIFICANT WITH P-VALUES < 0.05.

MODEL FIT: THE ADJUSTED R-SQUARED VALUE OF APPROXIMATELY 0.480 INDICATES THAT THE MODEL WITH THE ADDITIONAL PREDICTORS PROVIDES A BETTER FIT TO THE DATA COMPARED TO THE PREVIOUS MODEL.

OVERALL, BASED ON THESE RESULTS, WE CAN CONCLUDE THAT THE MODEL INCLUDING LOG_SQFT_LIVING, WATERFRONT, VIEW, AND RENOVATED_LAST_10 AS PREDICTORS EXPLAINS A SIGNIFICANT PORTION OF THE VARIANCE IN THE LOGARITHM OF PRICE AND PROVIDES VALUABLE INSIGHTS INTO THE FACTORS INFLUENCING HOUSE PRICES.

```
[62] # Defining target variable and predictors

     y = kc_transformed.log_price
     X = kc_transformed[floors_dummies +
                         condition_dummies +
                         grade_dummies +
                         ['view']+
                         ['waterfront']+
                         ['renovated_last_10']+
                         ['log_sqft_living']]

     model = reg_qq_sced(y, X)
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:              log_price   R-squared:                       0.590
Model:                            OLS   Adj. R-squared:                  0.590
Method:                 Least Squares   F-statistic:                     1709.
Date:                Thu, 28 Mar 2024   Prob (F-statistic):               0.00
Time:                        14:32:48   Log-Likelihood:                -6659.6
No. Observations:               21378   AIC:                         1.336e+04
Df Residuals:                   21359   BIC:                         1.351e+04
Df Model:                          18
Covariance Type:            nonrobust
==================================================================================
                      coef    std err          t      P>|t|      [0.025      0.975]
----------------------------------------------------------------------------------
const               9.5268      0.065    145.617      0.000       9.399       9.655
```

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68°

11:20 PM
3/28/2024

	coef	std err	t	P>|t|	[0.025	0.975]
const	8.8143	0.093	95.087	0.000	8.633	8.996
floors_1.5	0.1731	0.008	20.419	0.000	0.157	0.190
floors_2.0	-0.0271	0.007	-4.061	0.000	-0.040	-0.014
floors_2.5	0.1376	0.028	4.955	0.000	0.083	0.192
floors_3.0	0.1154	0.015	7.663	0.000	0.086	0.145
bedrooms_2	-0.0525	0.027	-1.971	0.049	-0.105	-0.000
bedrooms_3	-0.2178	0.027	-8.145	0.000	-0.270	-0.165
bedrooms_4	-0.2409	0.027	-8.798	0.000	-0.295	-0.187
bedrooms_5	-0.2386	0.029	-8.295	0.000	-0.295	-0.182
bedrooms_6	-0.2437	0.035	-6.981	0.000	-0.312	-0.175
bathrooms_1.0	-0.0238	0.046	-0.521	0.602	-0.113	0.066
bathrooms_1.5	-0.0738	0.047	-1.584	0.113	-0.165	0.018
bathrooms_1.75	-0.0394	0.046	-0.850	0.395	-0.130	0.051
bathrooms_2.0	-0.0467	0.047	-1.004	0.315	-0.138	0.044
bathrooms_2.25	-0.0610	0.047	-1.302	0.193	-0.153	0.031
bathrooms_2.5	-0.1134	0.047	-2.427	0.015	-0.205	-0.022
bathrooms_2.75	-0.0405	0.047	-0.853	0.394	-0.134	0.053
bathrooms_3.0	-0.0168	0.048	-0.350	0.727	-0.111	0.078

	coef	std err	t	P>|t|	[0.025	0.975]
const	8.8143	0.093	95.087	0.000	8.633	8.996
floors_1.5	0.1731	0.008	20.419	0.000	0.157	0.190
floors_2.0	-0.0271	0.007	-4.061	0.000	-0.040	-0.014
floors_2.5	0.1376	0.028	4.955	0.000	0.083	0.192
floors_3.0	0.1154	0.015	7.663	0.000	0.086	0.145
bedrooms_2	-0.0525	0.027	-1.971	0.049	-0.105	-0.000
bedrooms_3	-0.2178	0.027	-8.145	0.000	-0.270	-0.165
bedrooms_4	-0.2409	0.027	-8.798	0.000	-0.295	-0.187
bedrooms_5	-0.2386	0.029	-8.295	0.000	-0.295	-0.182
bedrooms_6	-0.2437	0.035	-6.981	0.000	-0.312	-0.175
bathrooms_1.0	-0.0238	0.046	-0.521	0.602	-0.113	0.066
bathrooms_1.5	-0.0738	0.047	-1.584	0.113	-0.165	0.018
bathrooms_1.75	-0.0394	0.046	-0.850	0.395	-0.130	0.051
bathrooms_2.0	-0.0467	0.047	-1.004	0.315	-0.138	0.044
bathrooms_2.25	-0.0610	0.047	-1.302	0.193	-0.153	0.031
bathrooms_2.5	-0.1134	0.047	-2.427	0.015	-0.205	-0.022
bathrooms_2.75	-0.0405	0.047	-0.853	0.394	-0.134	0.053
bathrooms_3.0	-0.0168	0.048	-0.350	0.727	-0.111	0.078

+ Code + Text

[ ]

```
grade_10 Very Good      0.9899      0.027     36.520      0.000       0.937       1.043
grade_11 Excellent      1.1615      0.032     36.636      0.000       1.099       1.224
grade_12 Luxury         1.3819      0.049     28.251      0.000       1.286       1.478
log_sqft_living         0.5071      0.011     44.533      0.000       0.485       0.529
==============================================================================
Omnibus:                       23.248   Durbin-Watson:                   1.976
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               24.161
Skew:                           0.062   Prob(JB):                     5.67e-06
Kurtosis:                       3.109   Cond. No.                         604.
==============================================================================

Notes:
```

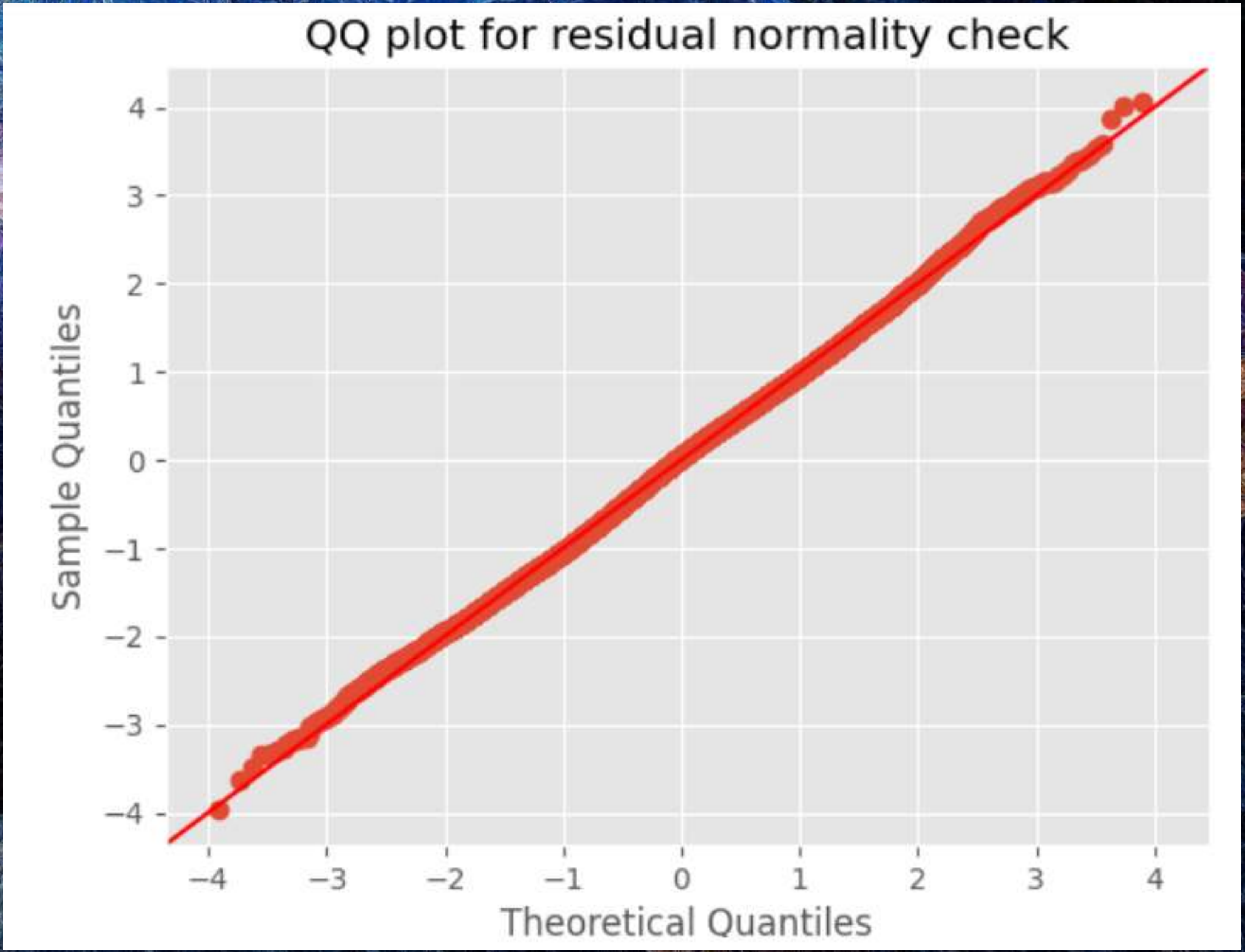
- THE REGRESSION RESULTS SHOW THE COEFFICIENTS, STANDARD ERRORS, T-VALUES, AND P-VALUES FOR EACH PREDICTOR IN THE MODEL. HERE'S A SUMMARY OF THE RESULTS:
  R-SQUARED: THE COEFFICIENT OF DETERMINATION, INDICATING THE PROPORTION OF THE VARIANCE IN THE DEPENDENT VARIABLE THAT IS PREDICTABLE FROM THE INDEPENDENT VARIABLES. IN THIS CASE, THE R-SQUARED VALUE IS 0.583, WHICH MEANS THAT APPROXIMATELY 58.3% OF THE VARIANCE IN THE LOGARITHM OF PRICE CAN BE EXPLAINED BY THE PREDICTORS IN THE MODEL.

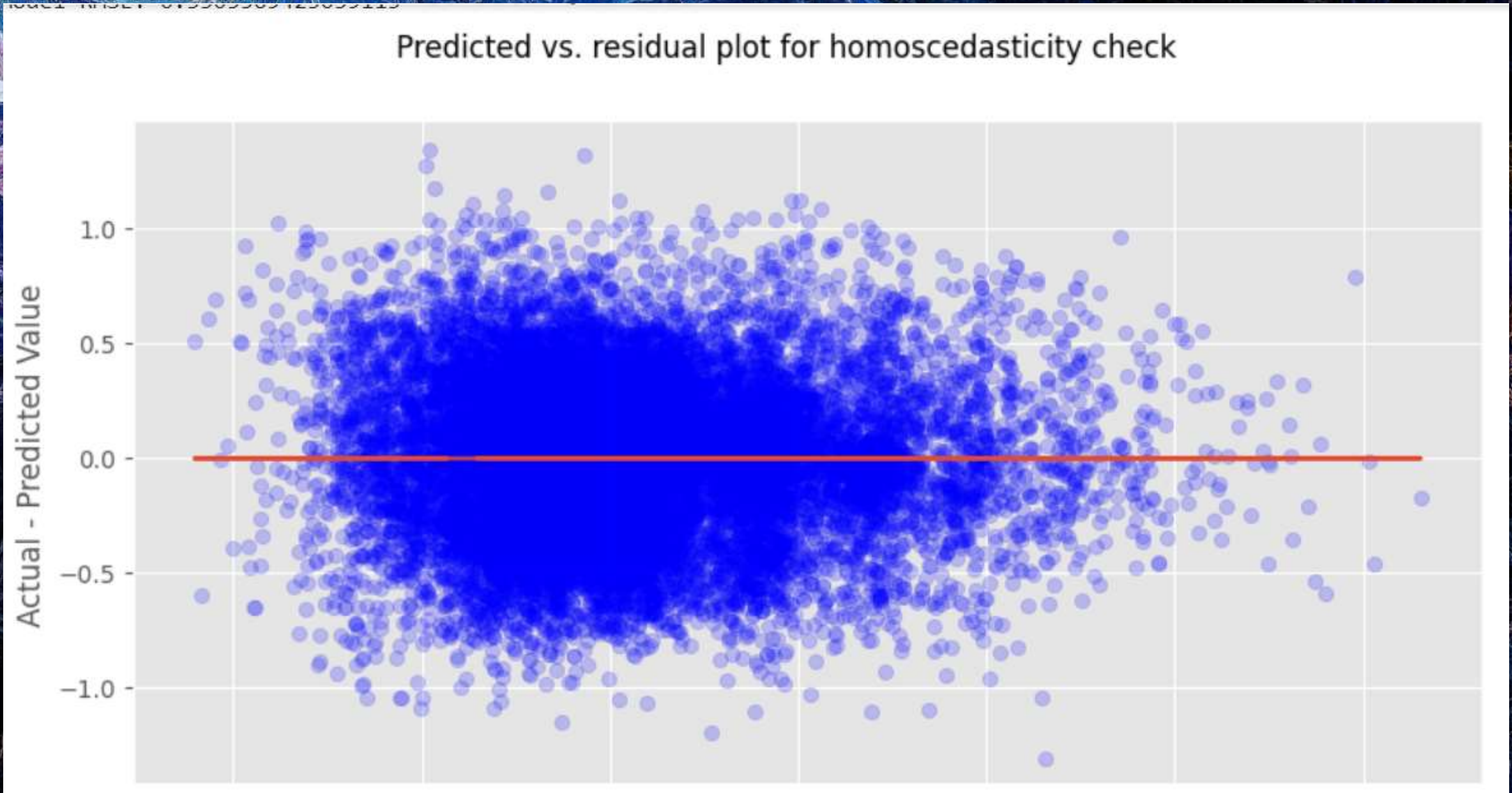
ADJUSTED R-SQUARED: A VERSION OF R-SQUARED THAT ADJUSTS FOR THE NUMBER OF PREDICTORS IN THE MODEL. IT PENALIZES EXCESSIVE COMPLEXITY. THE ADJUSTED R-SQUARED VALUE IS ALSO 0.583.
F-STATISTIC: A MEASURE OF THE OVERALL SIGNIFICANCE OF THE REGRESSION MODEL. IT TESTS WHETHER AT LEAST ONE OF THE PREDICTORS HAS A NON-ZERO COEFFICIENT. HERE, THE F-STATISTIC IS 878.4, WITH A VERY LOW P-VALUE, INDICATING THAT THE OVERALL MODEL IS STATISTICALLY SIGNIFICANT.

COEFFICIENTS: THE ESTIMATED COEFFICIENTS FOR EACH PREDICTOR VARIABLE. THESE REPRESENT THE EXPECTED CHANGE IN THE DEPENDENT VARIABLE FOR A ONE-UNIT CHANGE IN THE PREDICTOR, HOLDING ALL OTHER PREDICTORS CONSTANT.

P-VALUES: THE P-VALUES ASSOCIATED WITH EACH COEFFICIENT ESTIMATE. THEY INDICATE THE STATISTICAL SIGNIFICANCE OF EACH PREDICTOR. IN THIS CONTEXT, A P-VALUE LESS THAN 0.05 SUGGESTS THAT THE PREDICTOR IS STATISTICALLY SIGNIFICANT.

OVERALL, THE REGRESSION MODEL APPEARS TO BE STATISTICALLY SIGNIFICANT, WITH SEVERAL PREDICTORS SHOWING SIGNIFICANT ASSOCIATIONS WITH THE LOGARITHM OF PRICE.


QQ plot for residual normality check
Sample Quantiles
4
3
2
1
0
−1
−2
−3
−4
−4
−3
−2
−1
0
1
2
3
4
Theoretical Quantiles


Predicted vs. residual plot for homoscedasticity check
Actual - Predicted Value
1.0
0.5
0.0
−0.5
−1.0

R-SQUARED: THE COEFFICIENT OF DETERMINATION IS 0.590, SUGGESTING THAT APPROXIMATELY 59.0% OF THE VARIANCE IN THE LOGARITHM OF PRICE CAN BE EXPLAINED BY THE PREDICTORS IN THE MODEL.
ADJUSTED R-SQUARED: THE ADJUSTED R-SQUARED VALUE IS ALSO 0.590, INDICATING THAT THE MODEL'S EXPLANATORY POWER IS NOT COMPROMISED BY THE INCLUSION OF ADDITIONAL PREDICTORS.
F-STATISTIC: THE F-STATISTIC IS 1709.0 WITH A VERY LOW P-VALUE, INDICATING THAT THE OVERALL MODEL IS STATISTICALLY SIGNIFICANT.
COEFFICIENTS: THE COEFFICIENTS REPRESENT THE ESTIMATED CHANGE IN THE LOGARITHM OF PRICE FOR A ONE-UNIT CHANGE IN THE CORRESPONDING PREDICTOR VARIABLE, HOLDING ALL OTHER PREDICTORS CONSTANT. FOR EXAMPLE, A ONE-UNIT INCREASE IN LOG_SQFT_LIVING IS ASSOCIATED WITH AN INCREASE OF APPROXIMATELY 0.3822 IN THE LOGARITHM OF PRICE.

P-VALUES: THE P-VALUES ASSOCIATED WITH EACH COEFFICIENT ESTIMATE INDICATE THE STATISTICAL SIGNIFICANCE OF THE PREDICTORS.
ALL PREDICTORS HAVE P-VALUES LESS THAN 0.05, SUGGESTING THAT THEY ARE STATISTICALLY SIGNIFICANT IN PREDICTING THE LOGARITHM OF PRICE.
OVERALL, THE MODEL APPEARS TO BE STATISTICALLY SIGNIFICANT, WITH SEVERAL PREDICTORS SHOWING SIGNIFICANT ASSOCIATIONS WITH THE LOGARITHM OF PRICE.

OBSERVATIONS

OBSERVATIONS

- An observation is made based on market analysis that the property value type is the one that impact the correlation of renovation method selected.
- There is strong correlation between the price and the grade since the quality of the house determines the price in which the owner will spend on renovating

OBSERVATIONS

- Owners should give priority to the renovations that are more unique in order to be able to increase the property value.

POSITIVE EFFECTS OF RENOVATION

RENOVATION IMPACTS

- Owners estimating the duration in which were constructed and lastly renovated so as to know when to decide on renovation
- Renovating houses after a short duration makes it more attractive since customers will presume it as quality and durable.
- Paying attention to areas such floors, bathrooms, bedrooms, and other crucial areas makes it more

RENOVATIONS IMPACT

- The condition of the house gives it a proper estimate value.

WHAT TO GIVE PRIORTY

CONCLUSIONS

- Providing a large area for living space. This makes a customer feel better since there is adequate space instead of congestion.
- Proper maintenance. Ensuring that everything is in good condition such as no leakage, rotted wood, or rusted metals gives a convincing way for one to want to rent.
- Ensuring that the house structures are quality and in current trend.

RECOMMENDATIONS

- Be keen observation of the current trend
- Invest in proper and quality renovations
- Give priority to areas that will give you more profit
- Ensure frequent maintenance
- To avoid costs caused by customers' damage during their occupation in the houses, set extra charges for every damage by customers during the stay in.

CONCLUSION

- Owners of real estate should be ready to take risks when it comes to the interest of the customers. They should stay ahead and know the current trends in order to boost the quality of houses and meet customers expectations.

THANK YOU!

CONTACT INFORMATION