Relationship Between Home Attributes and Price in the Greater Boston Area

Sarah Katz '24, Data Science Major Capstone

Background

- The housing market in the greater Boston area has become highly competitive.
- It is economically and informationally beneficial for brokers, appraisers, lenders, buyers and/or sellers to understand specifically which characteristics of homes are the most valuable.

Question: What home characteristics are most important for explaining the variation in home prices in the greater Boston area?

Data

- A newly developed web scraping program was used to create a dataset from Zillow with recent housing transactions.
- Time: November 2020 to November 2023.
- Location: four counties in Massachusetts (Norfolk, Essex, Suffolk, Middlesex) with 192 total zip codes.
- Cleaning:
  - Data from four counties were merged.
  - Limited to residential home sales, so home type = Townhouse, Condo or Single Family.
  - Removing missingness, unusual and/or impossible values resulted in eliminating 1368 houses (1.5% of rows).
  - Created 3 new variables:
    - distance in miles from Boston city hall
    - urban level categorical variable: 1-5, with 5 indicating the most urban area:
      - 5: 0-3 mi; 4: 3-6 mi; 3: 6-12 mi; 2: 12-20 mi; 1: 20+ mi from Boston city hall
    - renovation binary variable, inferred by tracking renovation indicator words in the home descriptions
- Size: **88,412 houses**

Data Exploration

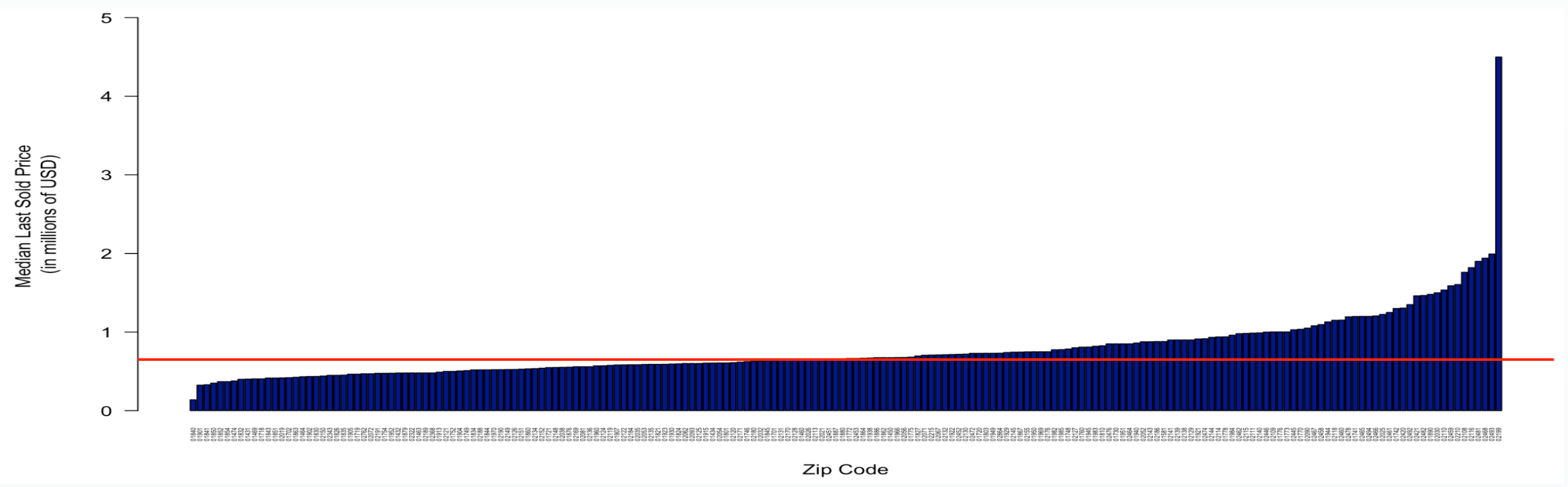


Figure 1: Median last sold prices for Boston area zip codes. Overall median sold price is $660,000. The zip code with the highest median sold price is 02199 (Back Bay) at $4.5 million.

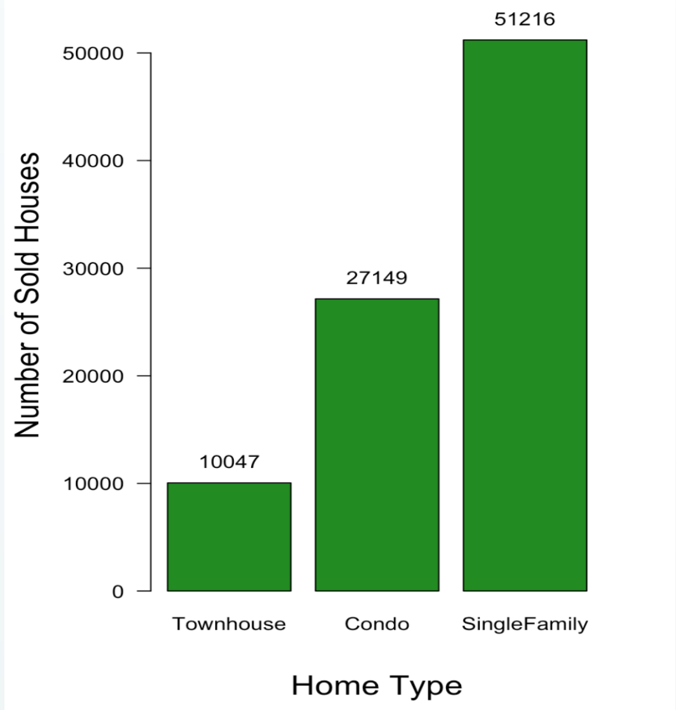


Figure 2: Distribution of home types.

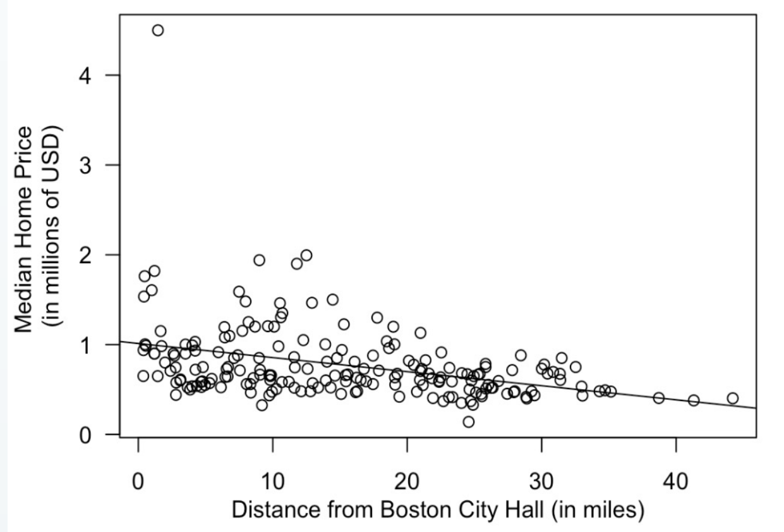


Figure 3: Zip codes by median home price and distance from city center. As expected, home prices decrease as distance from city center increases. Outlier: Back Bay.

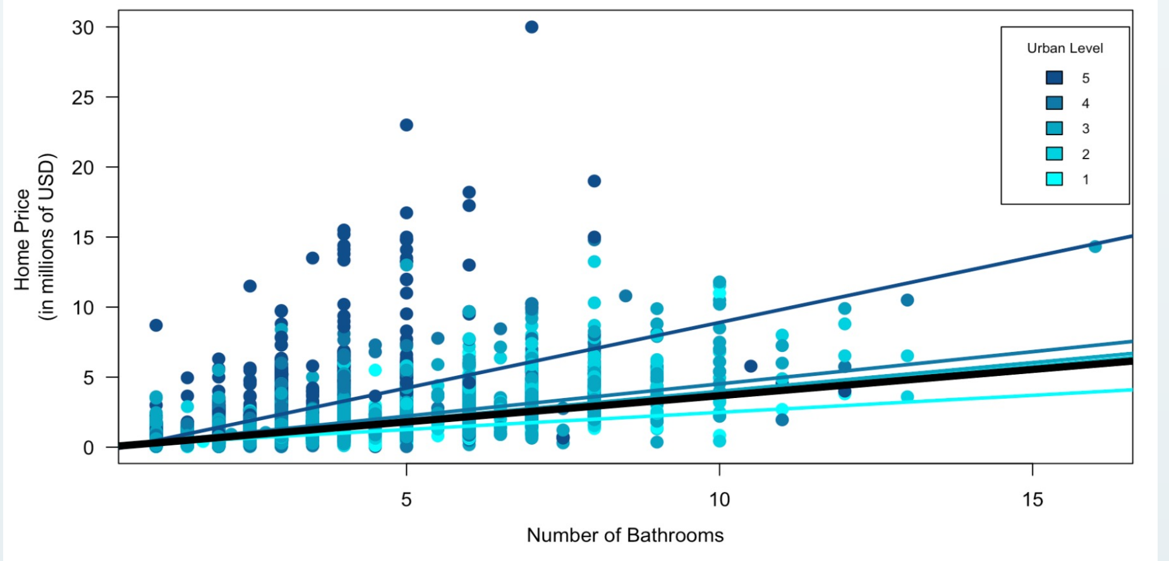


Figure 4: Home price by number of bathrooms, color coded by urban level. The most expensive homes have fewer bathrooms but are closer to the city.

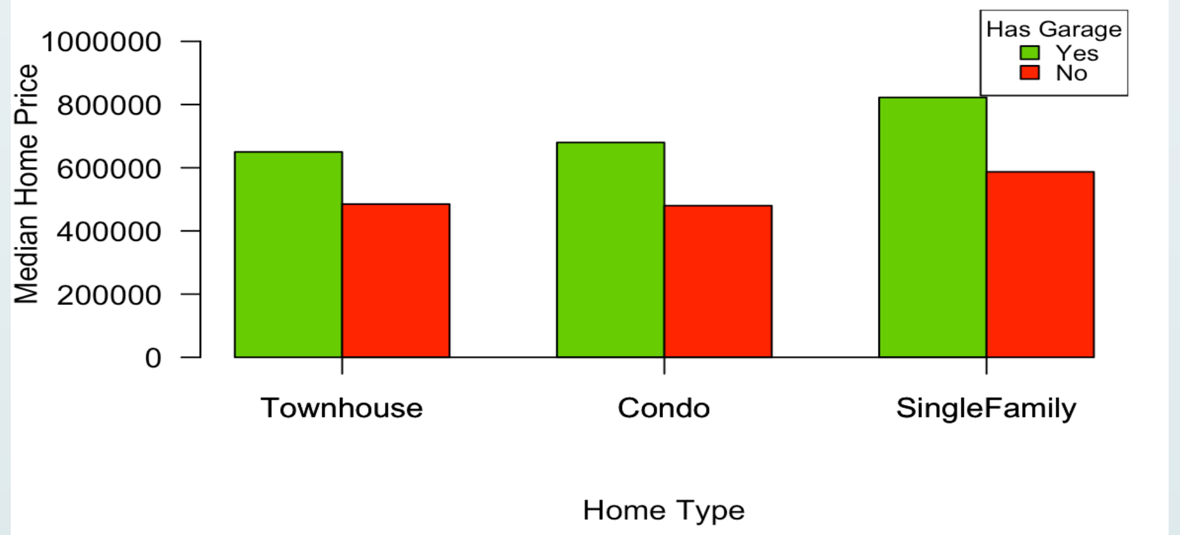


Figure 5: Median home price for different home types, based on whether the house has a garage. For all home types, having a garage increases the median home price.

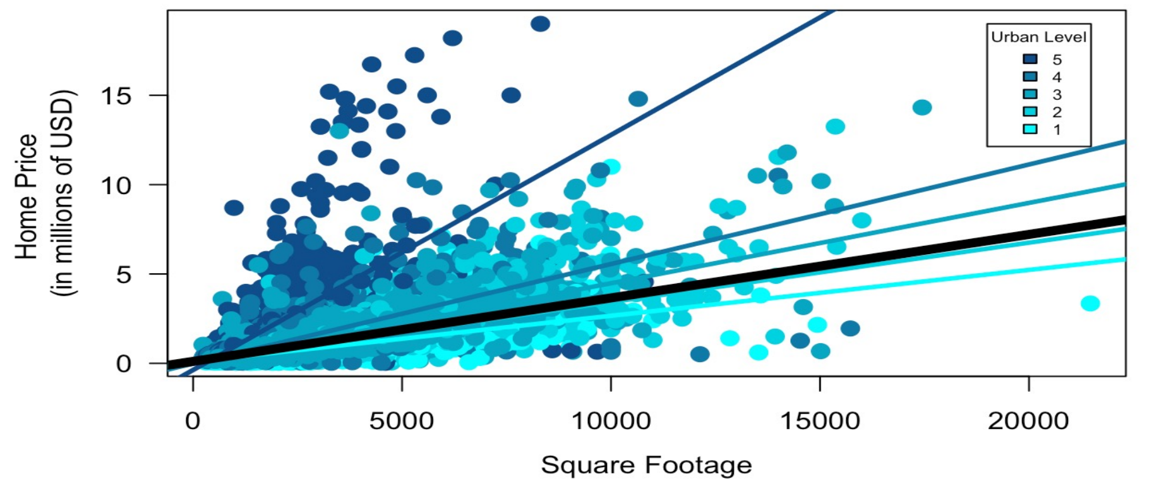


Figure 6: Home price by square footage, color coded by urban level. There is a general tradeoff between the size of a house and its proximity to city center.

Methods

- The home price variable on the original scale is severely right-skewed *(see Figure 7)*.
- A Box-Cox transformation showed optimal lambda = 0, therefore a log transformation on home price was performed *(see Figure 8)*.
- VIF analysis confirmed that there were no multicollinearity issues in the predictors.
- Using Cook's Distance, 2 influential observations were removed.

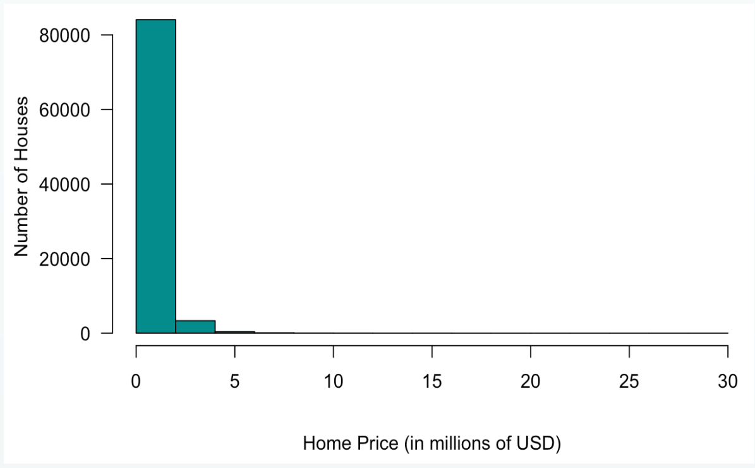


Figure 7: Histogram of home prices before log transformation.

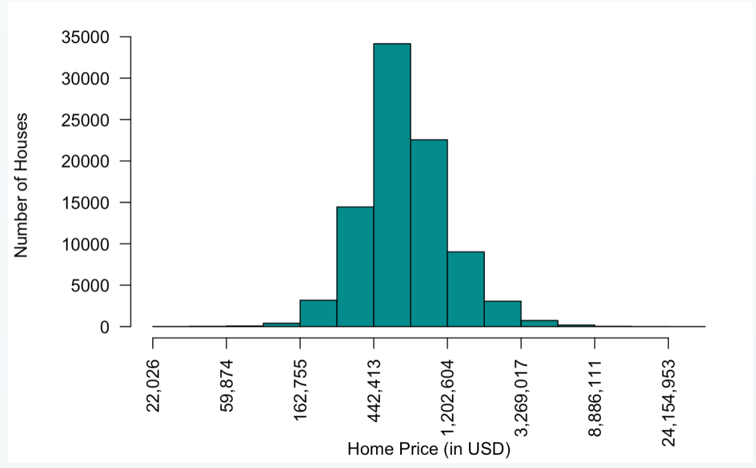
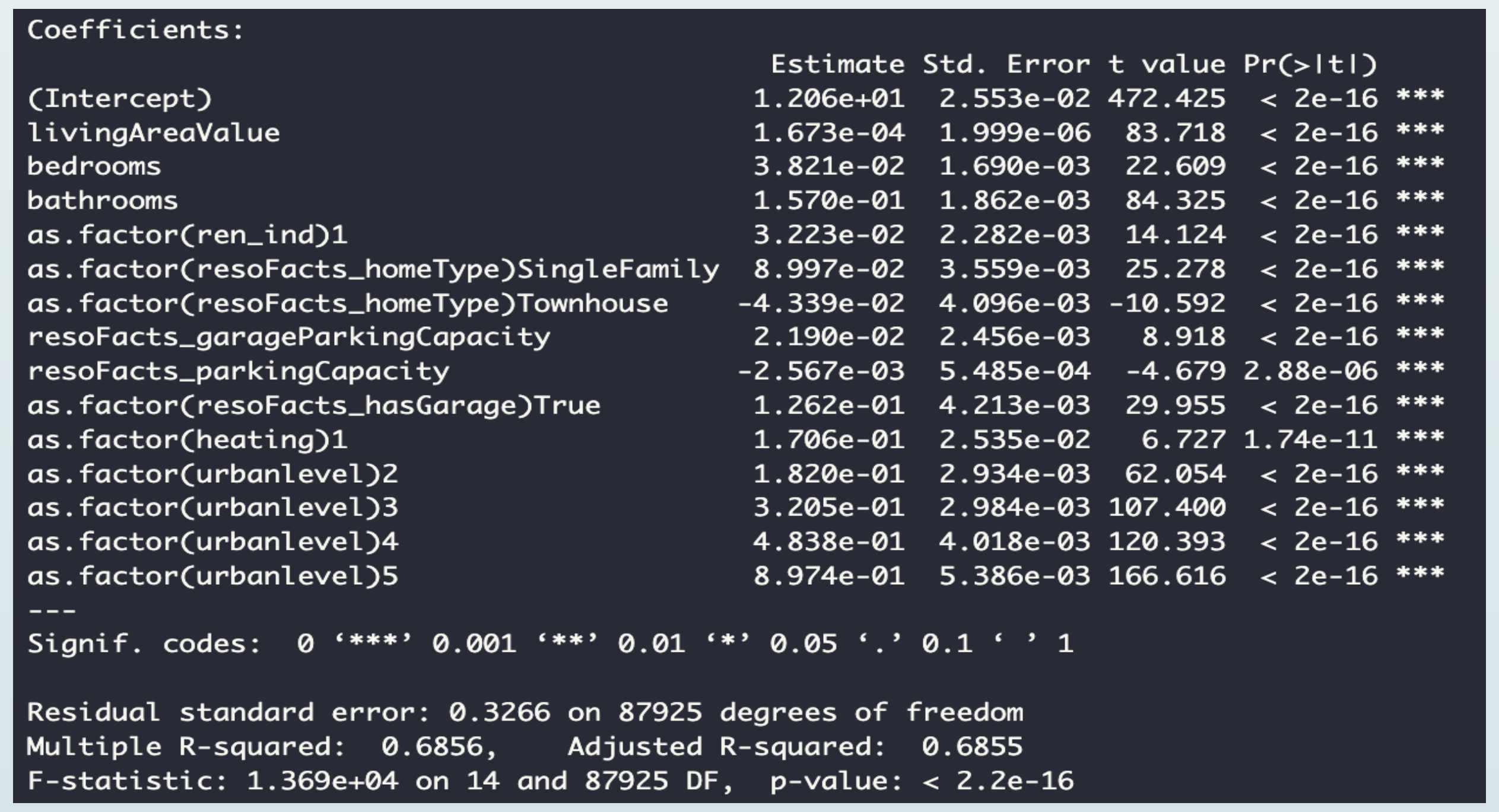


Figure 8: Histogram of home prices after log transformation. Skewness has been reduced.

Model

Predicted Log Sold Price = 12.06 + 0.0002 (Square Footage) + 0.0382 (Bedrooms) + 0.1570 (Bathrooms) + 0.0322 (Is Renovated) + 0.0900 (Is Single Family Home) - 0.0434 (Is Townhouse) + 0.0219 (Garage Parking Capacity) - 0.0026 (General Parking Capacity) + 0.1262 (Has Garage) + 0.1706 (Has Heating) + 0.1820 (Urban Level = 2) + 0.3205 (Urban Level = 3) + 0.4838 (Urban Level = 4) + 0.8974 (Urban Level = 5)

Adjusted R Squared: 68.55%



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Coefficients:
                                          Estimate Std. Error t value Pr(>|t|)    
(Intercept)                              1.206e+01  2.553e-02 472.425  < 2e-16 ***
livingAreaValue                          1.673e-04  1.999e-06  83.718  < 2e-16 ***
bedrooms                                 3.821e-02  1.690e-03  22.609  < 2e-16 ***
bathrooms                                1.570e-01  1.862e-03  84.325  < 2e-16 ***
as.factor(ren_ind)1                      3.223e-02  2.282e-03  14.124  < 2e-16 ***
as.factor(resoFacts_homeType)SingleFamily 8.997e-02  3.559e-03  25.278  < 2e-16 ***
as.factor(resoFacts_homeType)Townhouse  -4.339e-02  4.096e-03 -10.592  < 2e-16 ***
resoFacts_garageParkingCapacity          2.190e-02  2.456e-03   8.918  < 2e-16 ***
resoFacts_parkingCapacity               -2.567e-03  5.485e-04  -4.679 2.88e-06 ***
as.factor(resoFacts_hasGarage)True       1.262e-01  4.213e-03  29.955  < 2e-16 ***
as.factor(heating)1                      1.706e-01  2.535e-02   6.727 1.74e-11 ***
as.factor(urbanlevel)2                   1.820e-01  2.934e-03  62.054  < 2e-16 ***
as.factor(urbanlevel)3                   3.205e-01  2.984e-03 107.400  < 2e-16 ***
as.factor(urbanlevel)4                   4.838e-01  4.018e-03 120.393  < 2e-16 ***
as.factor(urbanlevel)5                   8.974e-01  5.386e-03 166.616  < 2e-16 ***
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Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.3266 on 87925 degrees of freedom
Multiple R-squared:  0.6856,    Adjusted R-squared:  0.6855 
F-statistic: 1.369e+04 on 14 and 87925 DF,  p-value: < 2.2e-16
```

Model Diagnostics

- The residual plot *(see Figure 9)* shows linearity and constant variance only for homes between about $270,000 and $5 million (~12.5 to ~15.5 on the log scale).
- The Q-Q plot shows deviation from normality *(see Figure 10)*.

Figure 9: Residual Plot

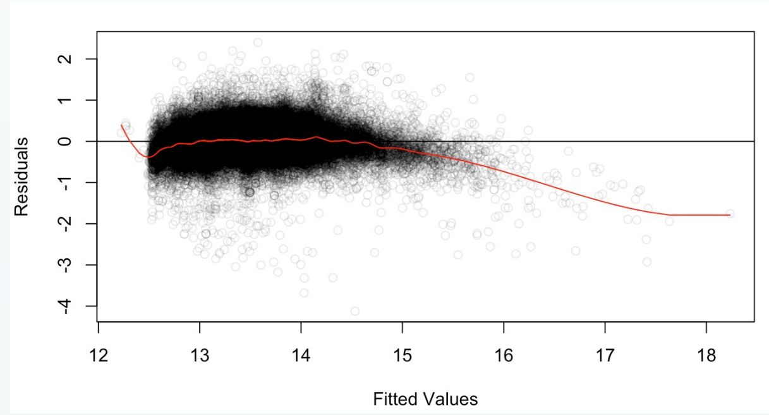
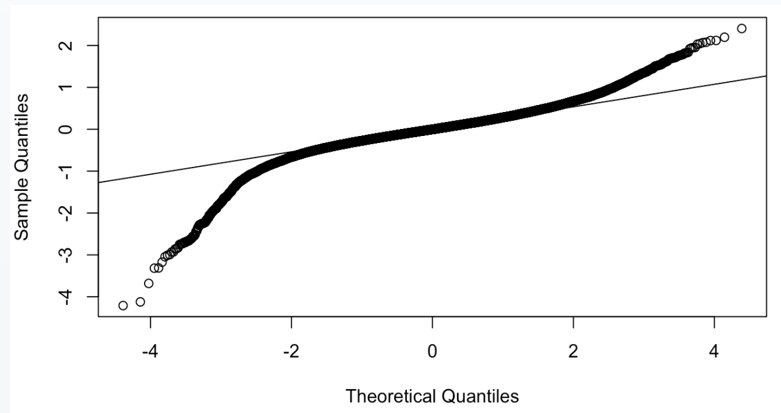


Figure 10: Q-Q Plot



Discussion

Results

- This multiple linear regression model with 14 predictors explains 68.55% of the variation in home prices in the greater Boston area.
- Square footage, bedrooms, bathrooms, home type, renovation status, parking capacity and type, heating and proximity to city center are the most significant home attributes for explaining home price variation.

Considerations

- This model performs best when predicting home prices within the range of $270,000 to $5 million. The model underestimates homes that are priced higher than $5 million.
- The web scraping program can only retrieve a certain number of recently sold homes per zip code, so there may be some zip codes with high turnover rates that do not have transactions going back to 2020.

Acknowledgements

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