



# HOME PRICING STATISTICAL ANALYSIS

IN KANSAS CITY, MO

for KC Residential Investment Group

by Zack Strathe  
STAT 705 Final Project

# INTRODUCTION

- The home pricing market is notoriously difficult to predict
- Real estate investment companies utilizing large and complex price prediction models have incurred huge losses when those models failed
- For KC Residential Investment Group, I propose instead utilizing a simple linear model to decide where to focus their efforts on purchasing, improving, and re-selling residential homes in Kansas City, MO
  - Utilize linear model to identify best postal code by growth in home sales price, identified by the LM slope parameter
  - Evaluate the linear model predictive performance versus a more-complex model

# DATA SET

- Data from Realtor.com's Real Estate Data Library
- Contains home pricing data aggregated by postal code, every month from July 2016 through February 2022
- Data is often incomplete (i.e., many postal codes are missing entries for some months)
- Response variable: "median\_listing\_price\_per\_square\_foot"
- Predictor variables: "postal\_code", "month\_date\_yyyymm"
- Transformed "month\_date\_yyyymm" data from "yyymm" format into an integer representation for the linear model to correctly utilize it

# LINEAR MODEL DEFINITION

- Linear model equation:

$$y = \beta_{0,i} \text{'postal code'}_i + \beta_1 \text{month} + \beta_{2,i} \text{month. 'postal code'}_i + \epsilon_{\text{month.postal code}_i}$$

- $\beta_{0,i}$  represents the model intercept, where for each postal code:

$$\beta_{0,i} \text{'postal code'}_i = \begin{cases} 1 & \text{if } i = \text{'postal\_code'} \\ \text{else } 0 \end{cases}$$

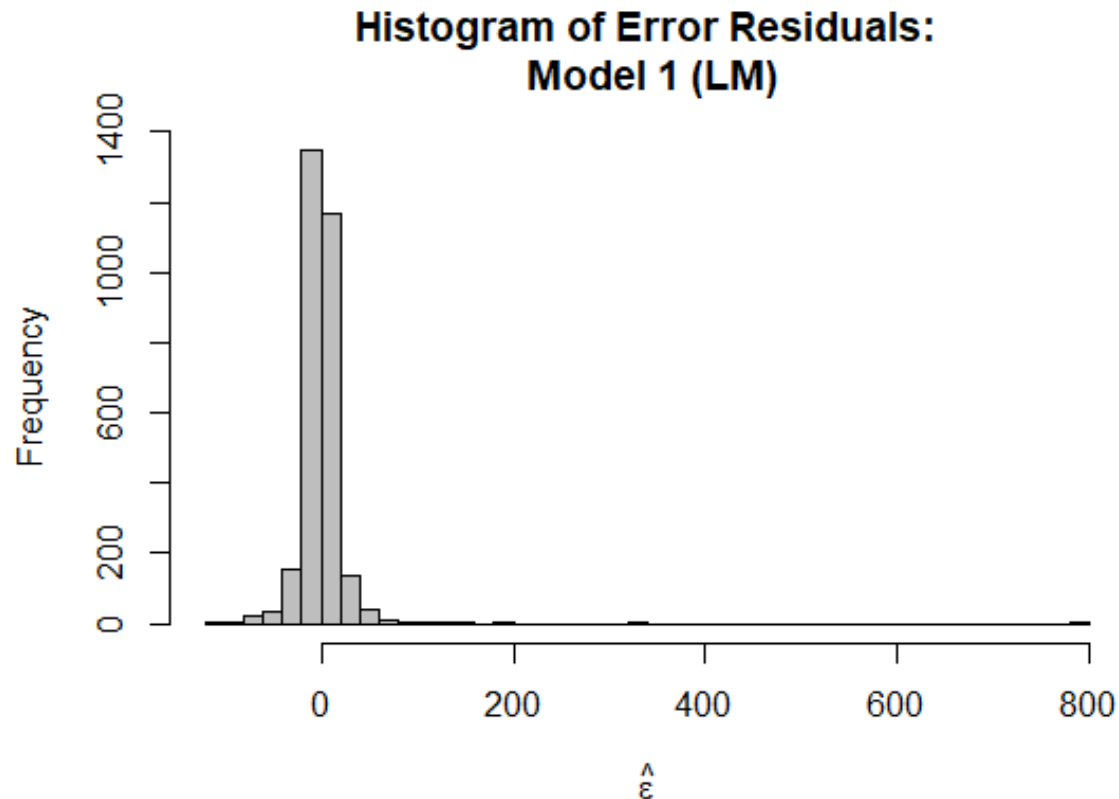
- $\beta_1 \text{month}$  represents the model's “base slope” (for the first postal code in the data set)

- $\beta_{2,i}$  represents the slope added onto the base slope, where for each postal code:

$$\beta_{2,i} \text{month. 'postal code'}_i = \begin{cases} 1 & \text{if } i = \text{'postal\_code'} \\ \text{else } 0 \end{cases}$$

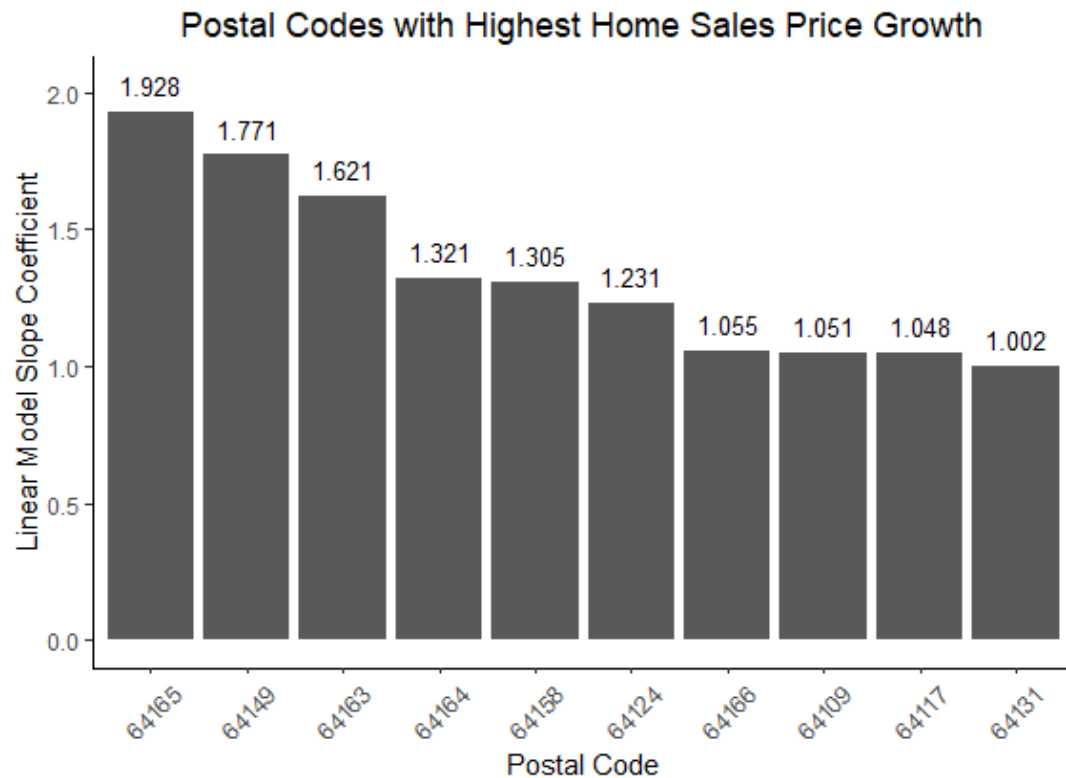
- $\epsilon_{\text{month. 'postal code'}_i}$  represents the error term, the discrepancy between model prediction and actual value for each combination of month and postal code

# LINEAR MODEL EVALUATION – RESIDUALS ANALYSIS



- Histogram plot of linear model error residuals
- Appears to be approximately normally distributed (except for some outliers in the right-tail)
  - Indicates that model is a good fit to the data

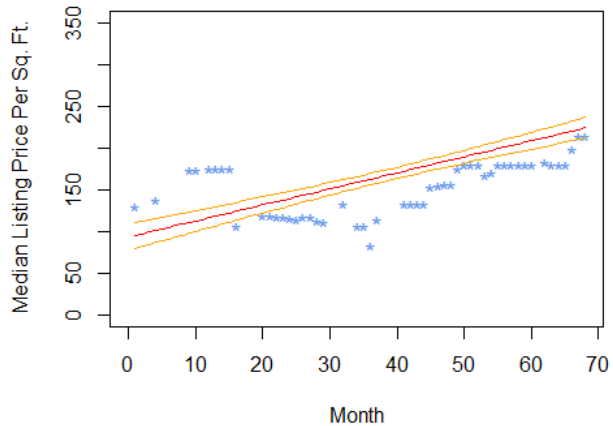
# LINEAR MODEL EVALUATION – IDENTIFICATION OF BEST POSTAL CODE BY PRICE GROWTH (1/2)



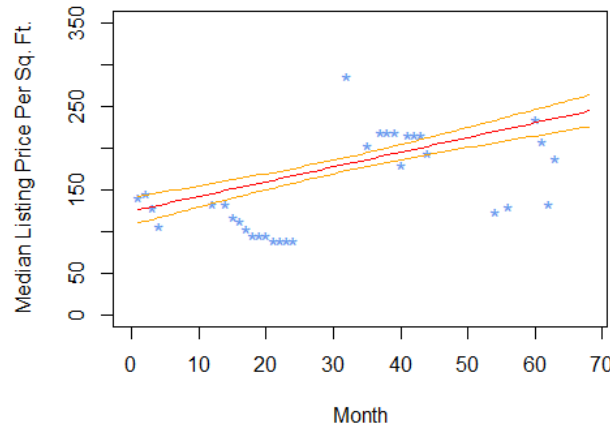
- Slope coefficients extracted from linear model and processed to combine base slope coefficient ( $\beta_1$ ) with the individual slope ( $\beta_{2,i}month.'postal\ code'_i$ ) for each postal code
- Extracted coefficients sorted in descending order to identify those with highest growth in home sales listing prices

# LINEAR MODEL EVALUATION – IDENTIFICATION OF BEST POSTAL CODE BY PRICE GROWTH (2/2)

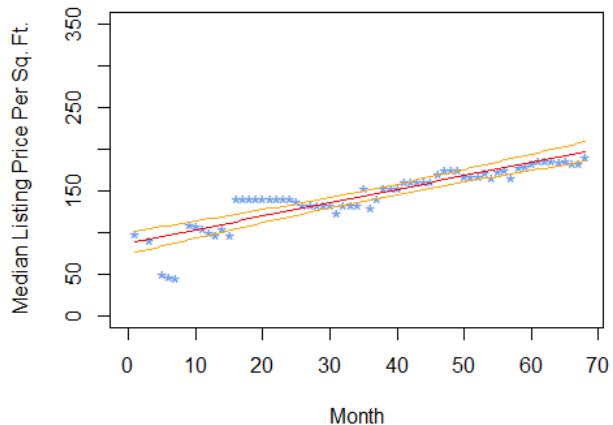
Linear model fitted line and confidence interval for postal code: 64165



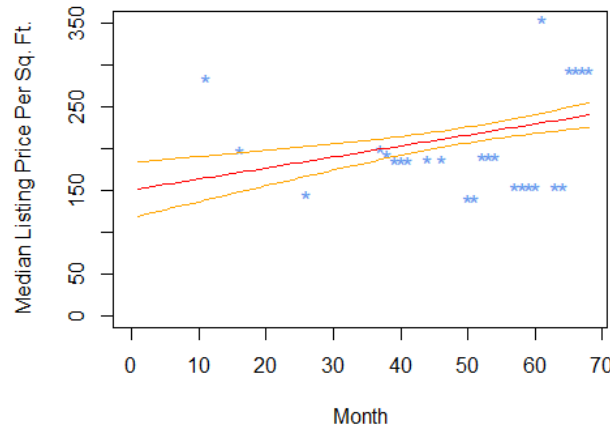
Linear model fitted line and confidence interval for postal code: 64149



Linear model fitted line and confidence interval for postal code: 64163



Linear model fitted line and confidence interval for postal code: 64164



- Plots of data, fitted line, and slope coefficient confidence interval for each postal code
- Some non-linear patterns in the data are visible

# LINEAR MODEL EVALUATION – IDENTIFICATION OF BEST POSTAL CODE BY PRICE GROWTH (3/3)

Postal Code	$\beta > 0$ at 95% Confidence	$\beta > 0$ at 99% Confidence
64165	✓ Yes	✗ No
64149	✓ Yes	✗ No
64163	✓ Yes	✓ Yes
64164	✗ No	✗ No

- Table of hypothesis testing results for each postal code, testing the null and alternative hypothesis:

$$H_0: \beta_2 = 0$$

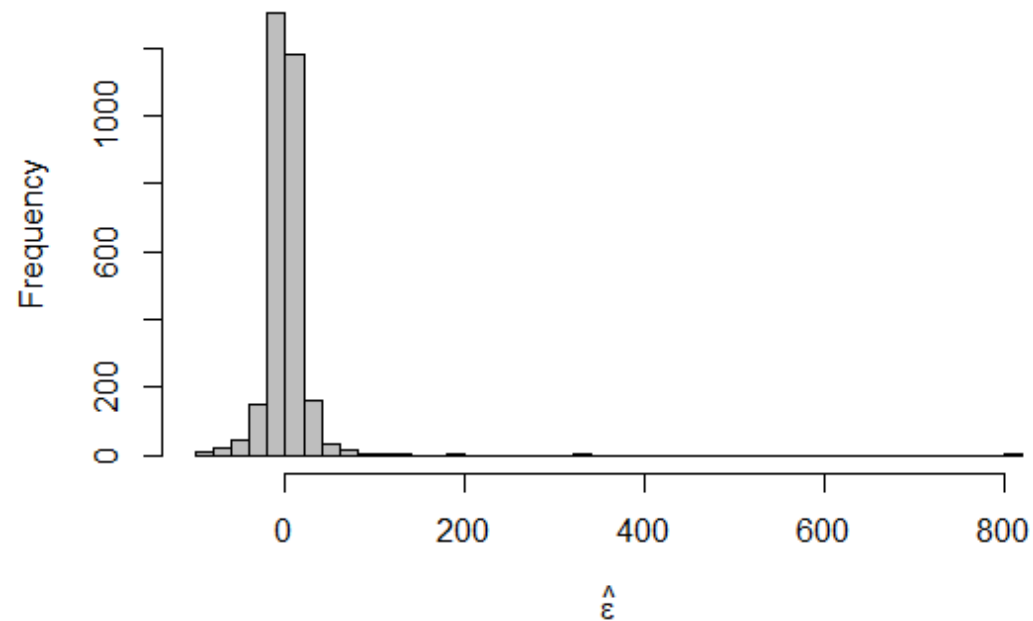
$$H_a: \beta_2 > 0$$

- Postal code 64163 is statistically the best, with the test statistic indicating that the slope in the linear model for this postal code is greater than zero at 99% confidence.



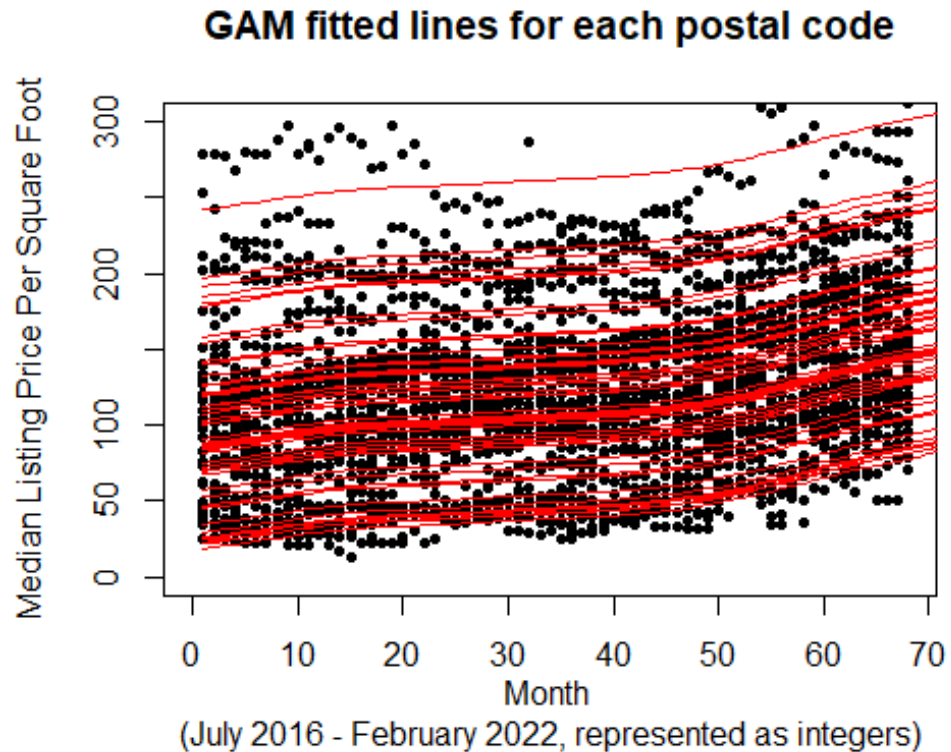
# GENERALIZED ADDITIVE MODEL EVALUATION – RESIDUAL ANALYSIS

Histogram of Error Residuals:  
Model 2 (GAM)



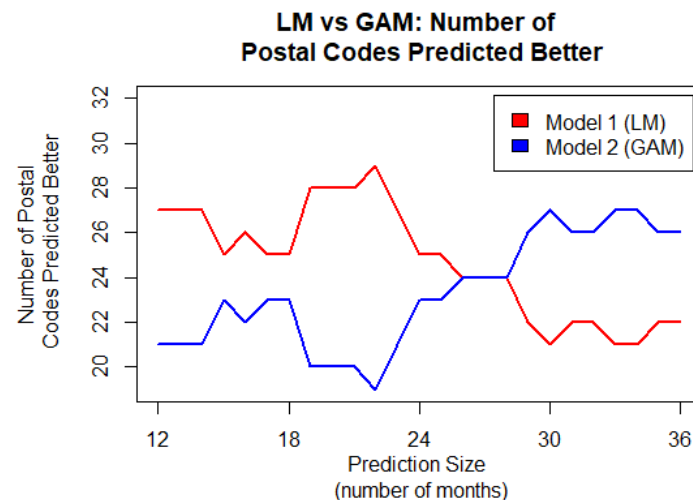
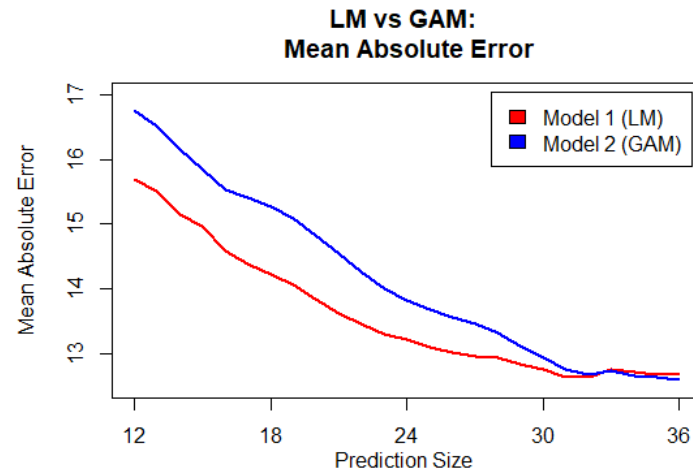
- Histogram plot of GAM model error residuals
- Appears to be approximately normally distributed (except for some outliers in the right-tail)
  - Indicates that model is a good fit to the data

# GENERALIZED ADDITIVE MODEL EVALUATION – ANALYSIS



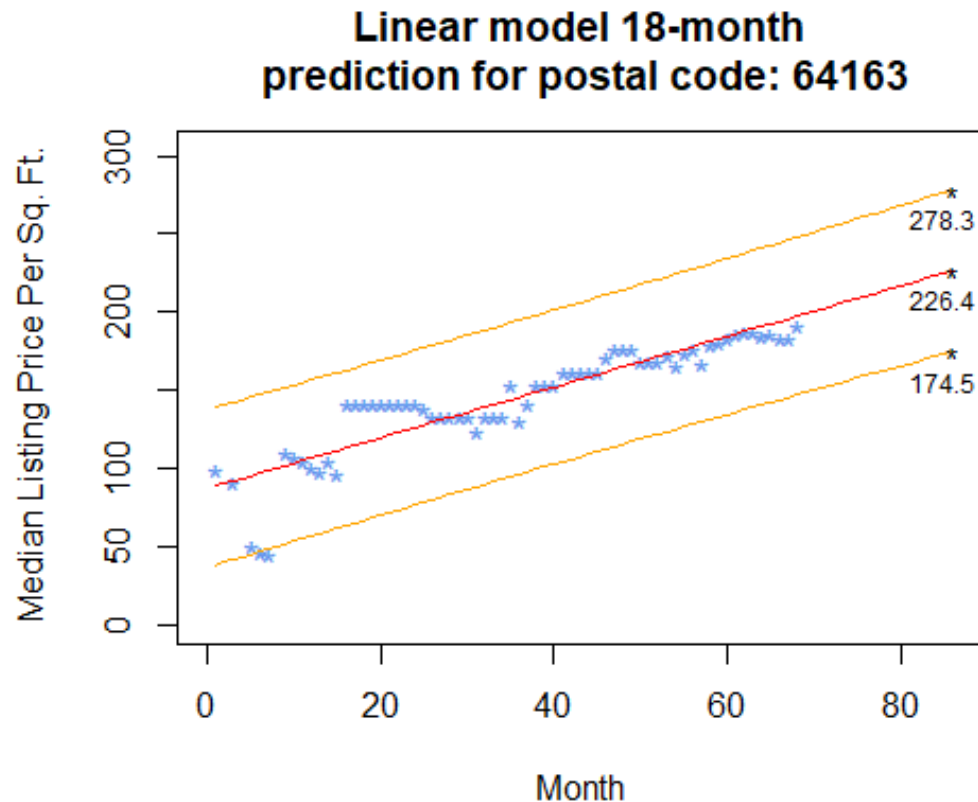
- GAM is able to use spline curves to model non-linear relationships in the data
- Cannot differentiate slope between postal codes
  - Only the intercepts vary in this model

# COMPARISON OF LINEAR MODEL VS. GENERALIZED ADDITIVE MODEL IN PREDICTIVE PERFORMANCE



- Comparison of LM versus GAM for prediction ranges between 12 and 36 months (by varying split between training and evaluation data sets)
  - At each prediction range, calculated absolute error and how many postal codes were better predicted by each model
- Linear model appears to have lower absolute error in general
- Around 28 months and longer prediction ranges, GAM appears to perform better (based on count of individual postal code performance)

# RECOMMENDATIONS



- For KC Residential Investment Group 18-months at maximum seems like a reasonable estimate for the time to purchase, make improvements to, and sell a home
  - Utilizing linear model for predictions since it performed better at this prediction range
- With the best postal code identified (64163), the price predictions from the linear model are plotted
  - Showing predicted median price per square foot at +18 months (August 2023), with 95% prediction interval