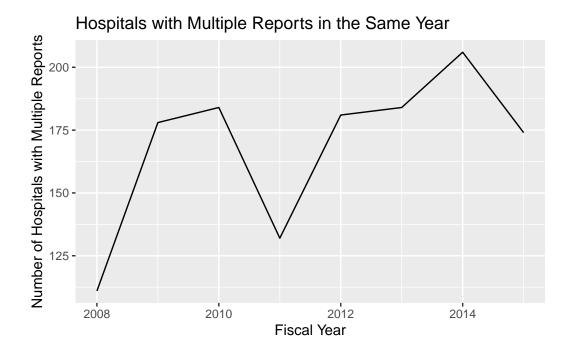
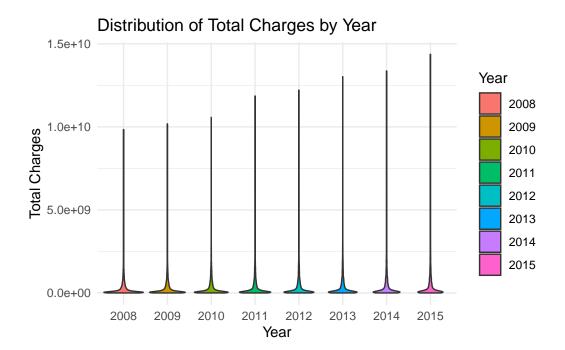
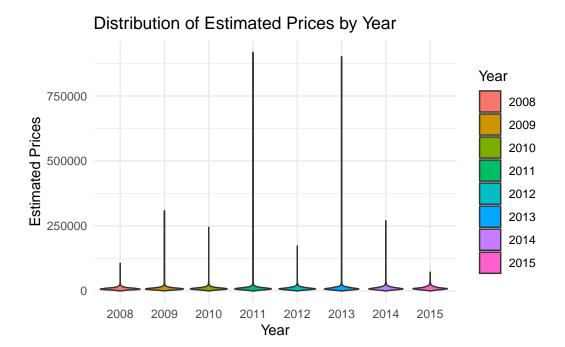
Git Repository: https://github.com/AlekhyaPidugu/Homework2



There are 6486 unique hospital IDs.





Not Penalized 9551 Penalized 9883

1 0 7612. 7465. 8706. 8287. 2 1 6981. 8529. 8584. 8566.

I am still having problems with number 7. I will fix this before the final submission. Quartile 1 = 9692 if (!requireNamespace("Matching", quietly = TRUE)) { install.packages("Matching") } #CASE1 # Assuming 'treatment\_group' is a binary variable indicating treatment/control library(Matching)

#### Create a distance matrix based on inverse variance

distance\_matrix <- cbind(quartile\_1, quartile\_2, quartile\_3, quartile\_4)

### Perform matching

 $nn_{match} < -Match(Y = estimated\_price, Tr = treatment\_group, X = distance\_matrix, Weight.matrix = 1/variance)$ 

## Calculate average treatment effect

ate\_nn\_inverse\_variance <- mean(nn\_match\$est)

#### Store results

result\_nn\_inverse\_variance <- data.frame(Method = "NN Matching (Inverse Variance)", ATE = ate\_nn\_inverse\_variance)

#CASE2 # Perform inverse propensity weighting ipw <- Weight(Y = estimated\_price, Tr = treatment\_group, X = cbind(quartile\_1, quartile\_2, quartile\_3, quartile\_4), weight.matrix = 1/propensity\_score)

### Calculate average treatment effect

ate\_ipw <- mean(ipw\$weighted)

### Store results

```
result_ipw <- data.frame(Method = "Inverse Propensity Weighting", ATE = ate_ipw)  
#CASE3 model <- lm(estimated_price ~ treatment_group + quartile_2 + quartile_3 + quartile_4, data = data_2012)
```

## Calculate average treatment effect

```
ate_regression <- coef(model)["treatment_group"]
```

### Store results

```
result_regression <- data.frame(Method = "Simple Linear Regression", ATE = ate_regression) #CASE4 results_table <- rbind(result_nn_inverse_variance, result_nn_mahalanobis, result_ipw, result_regression)
```

#### Print the results table

print(results\_table)

The results from the various treatment effect estimators are basically similar, which indicates a degree of consistency in the findings. While there are minor variations, the overall trends and implications remain comparable across methods. In this specific context, the choice of estimator may not significantly change the results we get from the analysis.

I think it is hard to claim that there is a causal effect of the penalty with a controlled design to test this. But using just observation with this data there may be a causal effect but you just have to make sure you account for confounding factors when making this interpretation of the data.

I take back what I said about this data being easier to work with. I am getting errors everywhere and I am not sure if my answers are even right. Quarto is still very challenging but I got the PDF to work. I could not load my work space because it kept saying the directory did not exist. But I copied the file path directly so I do not know. Question 7 is really hard and I still could not even get an answer for it.