# Problem Set 3

### Applied Stats/Quant Methods 1

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#### Instructions

- Please show your work! You may lose points by simply writing in the answer. If the problem requires you to execute commands in R, please include the code you used to get your answers. Please also include the .R file that contains your code. If you are not sure if work needs to be shown for a particular problem, please ask.
- Your homework should be submitted electronically on GitHub.
- This problem set is due before 23:59 on Sunday November 11, 2024. No late assignments will be accepted.

In this problem set, you will run several regressions and create an add variable plot (see the lecture slides) in R using the incumbents\_subset.csv dataset. Include all of your code.

# Question 1

We are interested in knowing how the difference in campaign spending between incumbent and challenger affects the incumbent's vote share.

1. Run a regression where the outcome variable is **voteshare** and the explanatory variable is **difflog**.

```
# Run a linear regression model
model <- lm(voteshare ~ difflog, data = inc.sub)
summary(model)

Call:
lm(formula = voteshare ~ difflog, data = inc.sub)

Residuals:
Min 1Q Median 3Q Max
```

```
-0.26832 -0.05345 -0.00377 0.04780 0.32749

Coefficients:
Estimate Std. Error t value Pr(>|t|)
(Intercept) 0.579031 0.002251 257.19 <2e-16 ***
difflog 0.041666 0.000968 43.04 <2e-16 ***
---
Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.07867 on 3191 degrees of freedom
Multiple R-squared: 0.3673, Adjusted R-squared: 0.3671
```

F-statistic: 1853 on 1 and 3191 DF, p-value: < 2.2e-16

```
summary(model)
#vote share=0.579+0.0417*difflog
```

The model equation is voteshare =  $0.579 + 0.0417 \times \text{difflog}$ . The intercept is 0.579, indicating that when difflog is 0, the predicted voteshare is 0.579. The coefficient for difflog is 0.0417, meaning that for every 1-unit increase in difflog, voteshare increases by 0.0417 on average, and this effect is highly significant (p-value; 0.001).

The t-value for difflog is 43.04, and the p-value is much smaller than 0.001, indicating a significant positive impact of difflog on voteshare. The F-statistic is 1853, showing the overall significance of the model.

The model's goodness of fit, represented by the R-squared  $R^2$ , is 0.3673, suggesting that difflog explains about 36.73

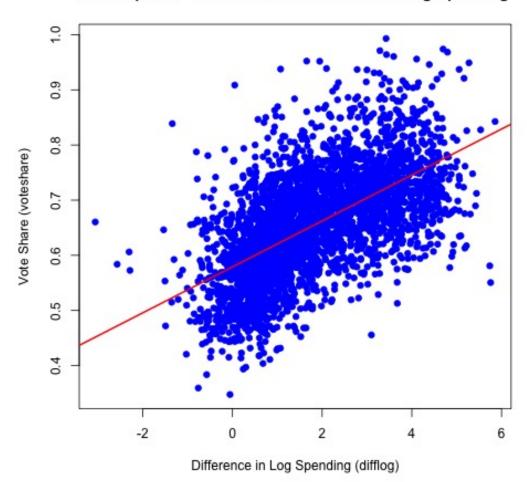
In conclusion, the difference in logs (difflog) has a significant positive effect on the incumbent's vote share (voteshare). Each unit increase in difflog results in a 0.0417-unit increase in voteshare, with this result being statistically highly significant.

2. Make a scatterplot of the two variables and add the regression line.

```
jpeg("scatterplot_voteshare_difflog.jpg")
# Plotting scatterplots
plot(inc.sub$difflog, inc.sub$voteshare,
main = "Scatterplot of Vote Share vs. Difference in Log Spending",
xlab = "Difference in Log Spending (difflog)",
ylab = "Vote Share (voteshare)",
pch = 19, col = "blue")
```

```
8
9 # Adding a regression line
10 abline(model, col = "red", lwd = 2)
11 dev.off()
```

### Scatterplot of Vote Share vs. Difference in Log Spending



3. Save the residuals of the model in a separate object.

```
# Run the regression model
model <- lm(voteshare ~ difflog, data = inc.sub)

# Save residuals to a separate object
residuals_model <- residuals(model)

# View the first few residual values
head(residuals_model)
```

```
1 2 3 4 5 6
-0.0004227622 -0.0316840149 -0.0045514943 0.0386688767 0.0355287965 0.03228325
```

4. Write the prediction equation.

 $voteshare = 0.579 + 0.0417 \times difflog$ 

Intercept: 0.579, represents the predicted voteshare when difflog is 0. difflog coefficient: 0.0417, means that for every unit of difflog, voteshare increases by 0.0417 units.

We are interested in knowing how the difference between incumbent and challenger's spending and the vote share of the presidential candidate of the incumbent's party are related.

1. Run a regression where the outcome variable is presvote and the explanatory variable is difflog.

```
1 # Run a linear regression model
presvote_model <- lm(presvote ~ difflog, data = inc.sub)</pre>
3 summary (presvote_model)
     Call:
     lm(formula = presvote ~ difflog, data = inc.sub)
     Residuals:
     Min
               1Q
                    Median
                                  3Q
                                          Max
     -0.32196 -0.07407 -0.00102 0.07151 0.42743
     Coefficients:
     Estimate Std. Error t value Pr(>|t|)
     (Intercept) 0.507583
                             0.003161
                                       160.60
                                                <2e-16 ***
     difflog
                 0.023837
                             0.001359
                                        17.54
                                                <2e-16 ***
     Signif. codes:
                     0 '*** 0.001 '** 0.01 '* 0.05 '. '0.1 ' '1
     Residual standard error: 0.1104 on 3191 degrees of freedom
     Multiple R-squared: 0.08795, Adjusted R-squared: 0.08767
     F-statistic: 307.7 on 1 and 3191 DF, p-value: < 2.2e-16
```

```
1 #presvote=0.5076+0.0238*difflog
```

The model equation is:

presvote = 
$$0.5076 + 0.0238 \times \text{difflog}$$

The intercept is 0.5076, indicating that when difflog is 0, the predicted presvote is 0.5076. The coefficient for difflog is 0.0238, meaning that for every 1-unit increase in difflog, presvote increases by 0.0238 on average, with this result being statistically highly significant (p-value; 0.001).

The t-value for difflog is 17.54, and the p-value is much smaller than 0.001, indicating a significant positive impact of difflog on presvote. However, the model's goodness of fit

is relatively low, with an R-squared  $\mathbb{R}^2$  of 0.08795, suggesting that difflog only explains about 8.8

In conclusion, the difference in logs (difflog) has a significant positive effect on the incumbent party's presidential vote share (presvote). Each unit increase in difflog results in a 0.0238-unit increase in presvote, but the model has limited explanatory power for the variability in presvote.

2. Make a scatterplot of the two variables and add the regression line.

```
jpeg("scatterplot_presvote_difflog2.jpg")

# Plotting scatterplots

plot(inc.sub$difflog, inc.sub$presvote,

main = "Scatterplot of Presidential Vote Share vs. Difference in Log Spending",

xlab = "Difference in Log Spending (difflog)",

ylab = "Presidential Vote Share (presvote)",

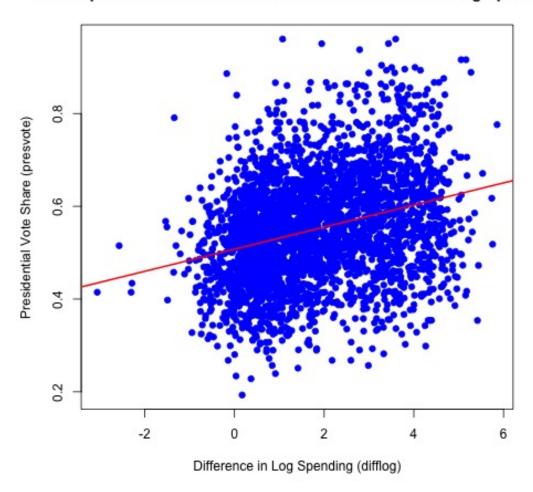
pch = 19, col = "blue")

# Adding regression lines

abline(presvote_model, col = "red", lwd = 2)

dev.off()
```

### Scatterplot of Presidential Vote Share vs. Difference in Log Spendin



3. Save the residuals of the model in a separate object.

```
# Save the residuals of the model into a new object

presvote_residuals <- residuals (presvote_model)

Wiew the first few values of the residual object

head (presvote_residuals)
```

1 2 3 4 5 6 0.005605594 0.037578519 -0.053134788 -0.052993694 -0.045842994 0.074339701

4. Write the prediction equation. presvote= $0.5076+0.0238 \times \text{difflog}$ 

Intercept: 0.5076, representing the predicted presvote when difflog is 0. difflog coefficient: 0.0238, indicating that presvote increases by an average of 0.0238 per unit of difflog.

We are interested in knowing how the vote share of the presidential candidate of the incumbent's party is associated with the incumbent's electoral success.

1. Run a regression where the outcome variable is **voteshare** and the explanatory variable is **presvote**.

```
model_presvote <- lm(voteshare ~ presvote, data = inc.sub)
2 summary ( model _ presvote )
    Call:
    lm(formula = voteshare ~ presvote, data = inc.sub)
    Residuals:
    Min
              1Q
                                 ЗQ
                   Median
                                         Max
    -0.27330 -0.05888 0.00394 0.06148 0.41365
    Coefficients:
    Estimate Std. Error t value Pr(>|t|)
    (Intercept) 0.441330
                            0.007599
                                       58.08
                                               <2e-16 ***
    presvote
                0.388018
                            0.013493
                                       28.76
                                               <2e-16 ***
                    0 '***, 0.001 '**, 0.01 '*, 0.05 '., 0.1 ', 1
    Signif. codes:
    Residual standard error: 0.08815 on 3191 degrees of freedom
    Multiple R-squared: 0.2058, Adjusted R-squared:
    F-statistic:
                   827 on 1 and 3191 DF, p-value: < 2.2e-16
```

```
#regression equation
#Vote Share= 0.4413+0.3880*Presvote
```

The model equation is:

voteshare = 
$$0.4413 + 0.3880 \times \text{presvote}$$

The intercept is 0.4413, indicating that when presvote is 0, the predicted voteshare is 0.4413. The coefficient for presvote is 0.3880, meaning that for every 1-unit increase in presvote, voteshare increases by 0.3880 on average, with this result being highly significant (p-value less than 0.001).

The t-value for presvote is 28.76, and the p-value is much smaller than 0.001, showing a significant positive impact of presvote on voteshare. The model's goodness of fit,

represented by the R-squared  $\mathbb{R}^2$ , is 0.2058, suggesting that presvote explains about 20.58

In conclusion, the presidential candidate's vote share (presvote) has a significant positive effect on the incumbent's electoral success (voteshare). Each unit increase in presvote results in a 0.3880-unit increase in voteshare. Although the effect is significant, the explanatory power of the variable for the total variation is only 20.58

2. Make a scatterplot of the two variables and add the regression line.

```
jpeg("scatterplot_voteshare_presvote3.jpg")

# Plotting scatterplots

plot(inc.sub$presvote, inc.sub$voteshare,

main = "Scatterplot of Vote Share vs. Presidential Vote Share",

xlab = "Presidential Vote Share (presvote)",

ylab = "Vote Share (voteshare)",

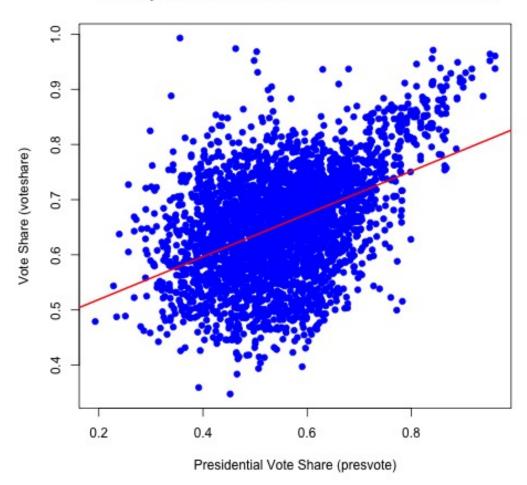
pch = 19, col = "blue")

# Adding a regression line

abline(model_presvote, col = "red", lwd = 2)

dev.off()
```

### Scatterplot of Vote Share vs. Presidential Vote Share



#### 3. Write the prediction equation.

Vote Share= $0.4413+0.3880\times Presvote$ 

Intercept: 0.4413, which represents the predicted voteshare when presvote is zero. presvote coefficient: 0.3880, means that for every unit of presvote, voteshare increases by 0.3880 on average.

The residuals from part (a) tell us how much of the variation in **voteshare** is *not* explained by the difference in spending between incumbent and challenger. The residuals in part (b) tell us how much of the variation in **presvote** is *not* explained by the difference in spending between incumbent and challenger in the district.

1. Run a regression where the outcome variable is the residuals from Question 1 and the explanatory variable is the residuals from Question 2.

```
1 # Getting the residuals
2 residuals_question1 <- residuals(model)</pre>
3 residuals_question2 <- residuals(model_presvote)</pre>
5 # Setting the dependent and independent variables
6 model_residuals <- lm(residuals_question1 ~ residuals_question2)
8 summary(model_residuals)
    Call:
    lm(formula = residuals_question1 ~ residuals_question2)
    Residuals:
                     Median
               10
    Min
                                    3Q
                                             Max
    -0.209551 -0.033091 0.001036 0.033227 0.257696
    Coefficients:
    Estimate Std. Error t value Pr(>|t|)
    (Intercept)
                         -3.353e-18 9.702e-04
                                                   0.00
    residuals_question2 6.401e-01 1.101e-02
                                                 58.14
                                                          <2e-16 ***
    Signif. codes: 0 '*** 0.001 '** 0.01 '* 0.05 '.' 0.1 ' ' 1
    Residual standard error: 0.05482 on 3191 degrees of freedom
    Multiple R-squared: 0.5144, Adjusted R-squared:
    F-statistic: 3380 on 1 and 3191 DF, p-value: < 2.2e-16
```

```
_{1} #Residuals from Question _{1}=-3.353e-18+0.6401*Residuals from Question 2
```

The model equation is:

```
residuals_question1 = -3.353 \times 10^{-18} + 0.6401 \times \text{residuals\_question2}
```

The intercept is -3.353e-18, which is close to 0 and has no statistical significance. The coefficient for esiduals question 2 is 0.6401, indicating that for every 1-unit increase in

residuals question2, residuals question1 increases by 0.6401 on average, with this result being highly significant (p-value less than 0.001).

The t-value for residuals question 2 is 58.14, and the p-value is much smaller than 0.001, showing a significant impact of residuals question 2 on residuals question 1. The model's goodness of fit, represented by the R-squared  $R^2$ , is 0.5144, suggesting that residuals question 2 explains about 51.44

In conclusion, residuals question has a significant impact on residuals question, with the model's explanatory power being 51.44

2. Make a scatterplot of the two residuals and add the regression line.

```
jpeg("scatterplot_residuals_question1_vs_question2.jpg")

# Scatterplotting

plot(residuals_question2, residuals_question1,

main = "Scatterplot of Residuals from Question 1 vs. Question 2",

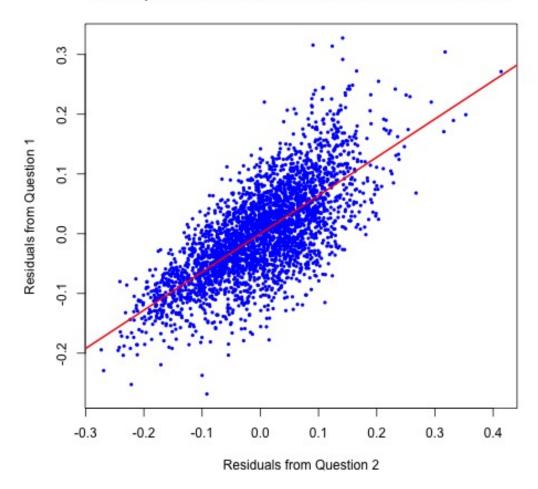
xlab = "Residuals from Question 2", ylab = "Residuals from Question 1",

pch = 16, col = "blue", cex = 0.6)

# Adding a regression line
abline(lm(residuals_question1 ~ residuals_question2), col = "red", lwd = 2)

dev.off()
```

### Scatterplot of Residuals from Question 1 vs. Question 2



3. Write the prediction equation.  ${\it residuals~question 1=-3.353e-18+0.6401\times residuals~question 2}$ 

Intercept: -3.353e-18, close to 0 and therefore negligible. Coefficient of residuals question2: 0.6401, indicating that residuals question1 increases by 0.6401 for every 1 unit increase in residuals question2.

What if the incumbent's vote share is affected by both the president's popularity and the difference in spending between incumbent and challenger?

1. Run a regression where the outcome variable is the incumbent's voteshare and the explanatory variables are difflog and presvote.

```
1 # Running a multiple regression model
2 model_voteshare_multiple <- lm(voteshare ~ difflog + presvote, data = inc
4 # View regression results
summary(model_voteshare_multiple)
    Call:
    lm(formula = voteshare ~ difflog + presvote, data = inc.sub)
    Residuals:
    Min
              1Q
                   Median
                                 3Q
                                         Max
    -0.25928 -0.04737 -0.00121
                                0.04618 0.33126
    Coefficients:
    Estimate Std. Error t value Pr(>|t|)
    (Intercept) 0.4486442
                           0.0063297
                                        70.88
                                                <2e-16 ***
                                        37.59
                           0.0009455
                                                <2e-16 ***
    difflog
                0.0355431
    presvote
                0.2568770
                           0.0117637
                                        21.84
                                                <2e-16 ***
                    0 '***, 0.001 '**, 0.01 '*, 0.05 '., 0.1 ', 1
    Signif. codes:
    Residual standard error: 0.07339 on 3190 degrees of freedom
    Multiple R-squared: 0.4496, Adjusted R-squared:
    F-statistic: 1303 on 2 and 3190 DF, p-value: < 2.2e-16
```

```
_{1} #voteshare=0.4486+0.0355*difflog+0.2569*presvote
```

The model equation is:

```
voteshare = 0.4486 + 0.0355 \times \text{difflog} + 0.2569 \times \text{presvote}
```

The intercept is 0.4486, indicating that when both difflog and presvote are 0, the predicted voteshare is 0.4486. The coefficient for difflog is 0.0355, meaning that for every 1-unit increase in difflog, voteshare increases by 0.0355 on average, with this result being highly significant (p-value less than 0.001). The coefficient for presvote

is 0.2569, suggesting that voteshare increases by 0.2569 for every 1-unit increase in presvote, also highly significant (p-value less than 0.001).

The p-values for all variables (difflog and presvote) are much smaller than 0.001, indicating significant effects on voteshare. The model's goodness of fit, represented by the R-squared  $R^2$ , is 0.4496, suggesting that difflog and presvote together explain about 44.96

In conclusion, the incumbent's vote share (voteshare) is significantly influenced by presidential popularity (presvote) and the spending difference compared to the challenger (difflog). The model indicates that these two factors explain 44.96

2. Write the prediction equation.

 $voteshare = 0.4486 + 0.0355 \times difflog + 0.2569 \times presvote$ 

Intercept: 0.4486, representing the predicted voteshare when both difflog and presvote are 0.

difflog coefficient: 0.0355, indicating that for every unit of difflog, voteshare increases by 0.0355 on average.

presvote coefficient: 0.2569, means that for every unit of presvote, voteshare increases by 0.2569.

3. What is it in this output that is identical to the output in Question 4? Why do you think this is the case?

I noticed that some parts were actually pretty similar to what I saw in Question 4. Specifically, the relationship between difflog and voteshare stayed significant, just like before. Also, the p-values for the variables are still showing high significance.

So, why is this happening? Well, I think it's because Question 5's regression model uses both difflog and presvote together, which gives a more complete explanation of the variation in voteshare. In Question 4, I was looking at how the residuals from voteshare and presvote were related, and here in Question 5, I'm seeing a similar trend. It seems like both factors (difflog and presvote) are strongly connected and influence the incumbent's vote share together.