Problem Set 3

Applied Stats/Quant Methods 1

Due: November 11, 2024

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`.

```r
model <- lm(voteshare ~ difflog, data = df)
summary(model)#Output regression analysis results
```

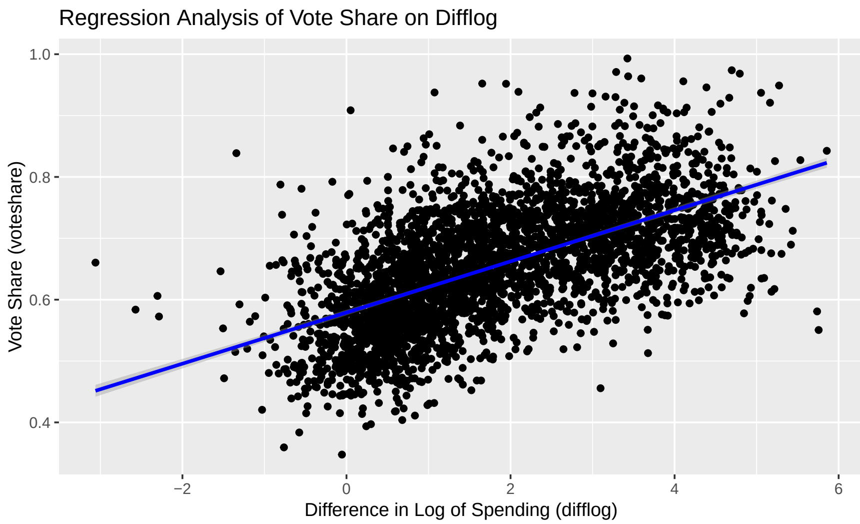
```
Call:
lm(formula = voteshare ~ difflog, data = df)

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 '**' 0.01 '*' 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
```

Data analysis:
The residual standard error is 0.07867, which measures the average difference between observed values and model predictions. The degree of freedom is 3191. The coefficient of determination is 0.3673. This value represents the proportion of variability explained by the model, meaning that the model explained 36.73% of the variability. The adjusted coefficient of determination is 0.3671, and the R-squared value has been adjusted to avoid overfitting due to the addition of irrelevant variables. The F-statistic is 1853, which is used to test whether all coefficients in the model are significantly different from 0. The F-statistic of 1853 is very high, indicating that the model is significant. The degrees of freedom of the F-statistic are 1 and 3191. The p-value of the F-statistic is<2.2e-16, indicating that the F-statistic is significant and the model has at least one coefficient significantly different from 0.

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

```r
ggplot(df, aes(x = difflog, y = voteshare)) +
  geom_point() +
  geom_smooth(method = "lm", color = "blue") +
  labs(title = "Regression Analysis of Vote Share on Difflog",
       x = "Difference in Log of Spending (difflog)",
       y = "Vote Share (voteshare)")#Draw regression lines and scatter plots
```

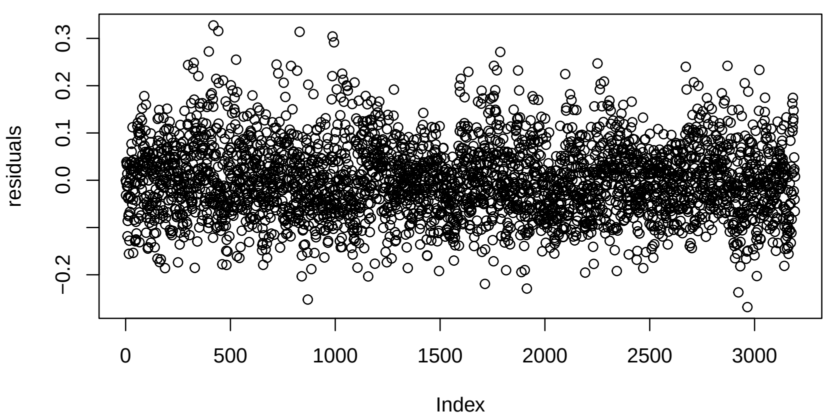


3. Save the residuals of the model in a separate object.

```
residuals <- residuals(model)
head(residuals)
plot(residuals)
```

```
View the first few data items:
            1             2             3
-0.0004227622 -0.0316840149 -0.0045514943
            4             5             6
 0.0386688767  0.0355287965  0.0322832521
```

```
Use a scatter plot to view the distribution of residuals
```



4. Write the prediction equation.

```r
intercept <- coef(model)[1]#Extracted is intercept
slope <- coef(model)[2]#Extracted is slope
prediction_equation <- paste("voteshare =", intercept, " + ", slope, "*
    difflog")
print(prediction_equation)
```

```
the prediction equation:
   voteshare = 0.579030710920674  +  0.0416663238227399 * difflog
```

Question 2

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`.

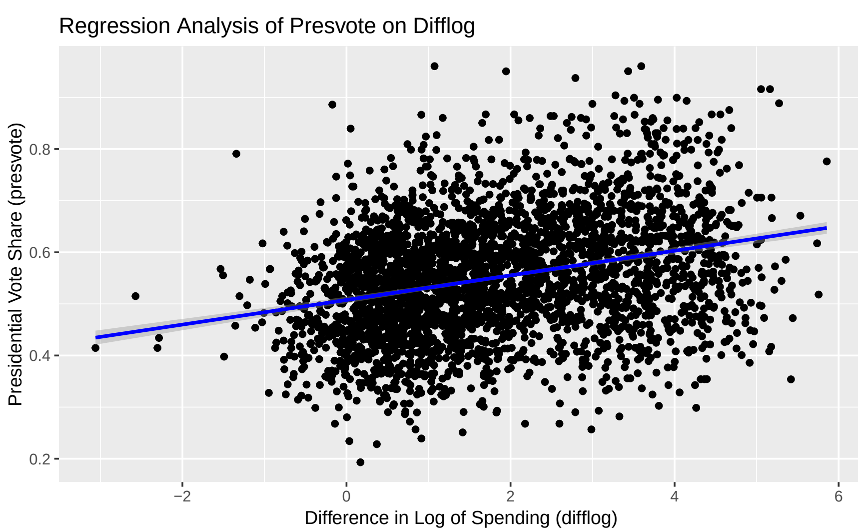
```r
model_presvote <- lm(presvote ~ difflog , data = df)
summary(model_presvote)#Output regression analysis results
```

```
Call:
lm(formula = presvote ~ difflog, data = df)

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


Data analysis:
Residual analysis shows that the minimum residual is -0.32196,
the first quartile is -0.07407, the median is -0.00102,
the third and fourth quartiles are 0.07151, and the maximum residual is 0.42743.
This indicates that the residuals are distributed within a certain range and
there are no obvious outliers. The intercept is 0.507583, the standard error is
0.003161, the t-value is 160.60, and the p-value is less than 2e-16.
This means that the intercept is statistically significant. The slope is 0.02383
the standard error is 0.001359, the t-value is 17.54, and the p-value is less
than 2e-16. This indicates a significant positive correlation between difflog
and presvote.The residual standard error is 0.1104, based on 3191 degrees of
freedom. The coefficient of determination is 0.08795, and the adjusted
```

```
coefficient of determination is 0.08767. This indicates that difflog can explain
approximately 8.795% of the presvote variation. The F-statistic is 307.7,
based on 1 model degree of freedom and 3191 error degrees of freedom,
with a p-value less than 2.2e-16. This indicates that the overall model is
statistically significant.

Conclusion:
For every unit increase in difflog, the average increase in votes is 0.023837
units. The model is statistically significant, but its explanatory power is
limited, only explaining about 8.795% of the presvote variation. These results
indicate that although difflog has a significant impact on pre voting,
there may be other factors that are also affecting pre voting.
Further analysis may require consideration of more explanatory variables.
```

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

```r
ggplot(df, aes(x = difflog, y = presvote)) +
  geom_point() +
  geom_smooth(method = "lm", color = "blue") +
  labs(title = "Regression Analysis of Presvote on Difflog",
       x = "Difference in Log of Spending (difflog)",
       y = "Presidential Vote Share (presvote)")#Draw regression lines and scatter plots
```

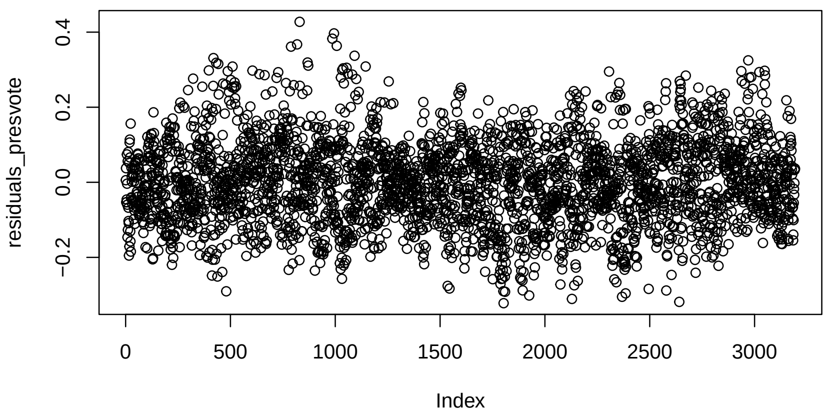


3. Save the residuals of the model in a separate object.

```r
residuals_presvote <- residuals(model_presvote)
head(residuals_presvote)
plot(residuals_presvote)
```

```
View the first few data items:
          1           2           3
0.005605594  0.037578519 -0.053134788
          4           5           6
 -0.052993694 -0.045842994  0.074339701
```

```
Use a scatter plot to view the distribution of residuals
```



4. Write the prediction equation.

```r
intercept_presvote <- coef(model_presvote)[1]#Extracted is intercept
slope_presvote <- coef(model_presvote)[2]#Extracted is slope
prediction_equation_presvote <- paste("presvote =", intercept_presvote, "
    + ", slope_presvote, "* difflog")
print(prediction_equation_presvote)
```

```
the prediction equation:
presvote = 0.507583328405015  +  0.023837233841334 * difflog
```

Question 3

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`.

```r
model_voteshare <- lm(voteshare ~ presvote, data = df)
summary(model_voteshare)#Output regression analysis results
```

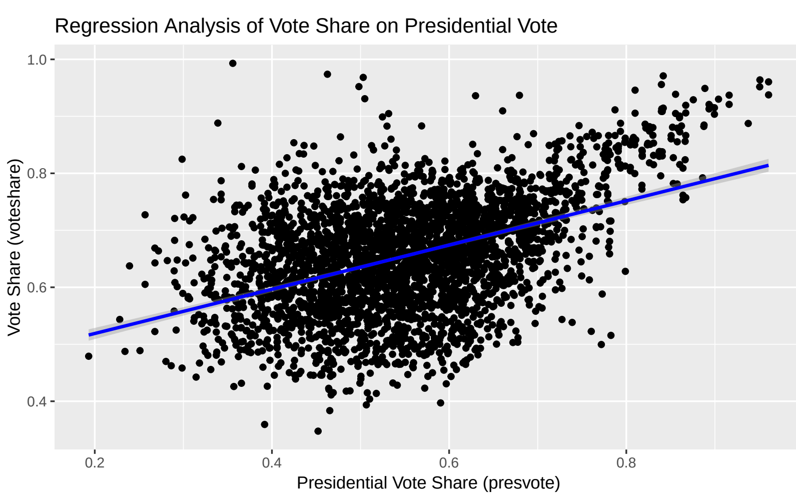
```
Call:
lm(formula = voteshare ~ presvote, data = df)

Residuals:
     Min       1Q   Median       3Q      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 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.08815 on 3191 degrees of freedom
Multiple R-squared:  0.2058, Adjusted R-squared:  0.2056
F-statistic:   827 on 1 and 3191 DF,  p-value: < 2.2e-16
```

```
Data analysis:
Residual analysis shows that the minimum residual is -0.27330, the first quartile
is -0.05888, the median is 0.00394, the third and fourth quartiles
are 0.06148, and the maximum residual is 0.41365. This indicates that
the residuals are distributed within a certain range and there are no
obvious outliers. The intercept is 0.441330, the standard error is
0.007599, the t-value is 58.08, and the p-value is less than 2e-16.
This means that the intercept is statistically significant. Presvote:
0.388018, standard error of 0.013493, t-value of 28.76, p-value less
than 2e-16. This indicates a significant positive correlation between
presvote and vote share.
The residual standard error is 0.08815, based on 3191 degrees of
freedom. The coefficient of determination is 0.2058, and the adjusted
```

```
coefficient of determination is 0.2056. This indicates that presvote
can explain approximately 20.58% of the variability in voteshare. The
F-statistic is 827, based on 1 model degree of freedom and 3191 error
degrees of freedom, with a p-value less than 2.2e-16. This indicates
that the overall model is statistically significant.

Conclusion:
For every additional unit of presvote, the average increase in voters
is 0.388018 units.
The model is statistically significant and explains approximately
20.58% of the variance in vote share, indicating that presvote is a
useful variable for predicting vote share. These results indicate a
significant positive correlation between the voting share in the
presidential election and the voting share in the House of
Representatives election. However, it should be noted that although
the correlation is significant, the explanatory power of the model is
limited and can only explain a portion of the variation in voting
shares. This indicates that there are other factors also affecting
the voting share.
```

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

```r
ggplot(df, aes(x = presvote, y = voteshare)) +
  geom_point() +
  geom_smooth(method = "lm", color = "blue") +
  labs(title = "Regression Analysis of Vote Share on Presidential Vote",
       x = "Presidential Vote Share (presvote)",
       y = "Vote Share (voteshare)")#Draw regression lines and scatter plots
```



3. Write the prediction equation.

```
intercept_voteshare <- coef(model_voteshare)[1]#Extracted is intercept
slope_voteshare <- coef(model_voteshare)[2]#Extracted is slope
prediction_equation_voteshare <- paste("voteshare =", intercept_voteshare, " + ", slope_voteshare, "* presvote")
print(prediction_equation_voteshare)
```

```
the prediction equation:
voteshare = 0.441329881204297  +  0.38801844338744 * presvote
```

Question 4

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.

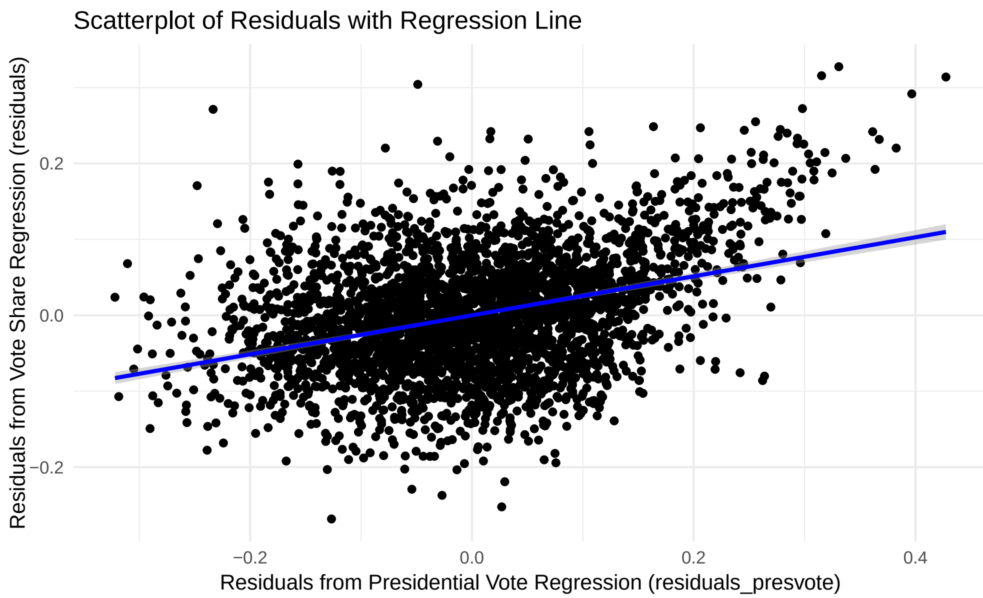
```r
model_residuals <- lm(residuals ~ residuals_presvote, data = df)
summary(model_residuals)#Output regression analysis results
```

```
Call:
lm(formula = residuals ~ residuals_presvote, data = df)

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)        -5.934e-18    1.299e-03    0.00         1
residuals_presvote  2.569e-01    1.176e-02    21.84   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.07338 on 3191 degrees of freedom
Multiple R-squared:   0.13, Adjusted R-squared:  0.1298
F-statistic:   477 on 1 and 3191 DF,  p-value: < 2.2e-16


Data analysis:
Residual analysis shows that the minimum residual is -0.25928,
the first quartile is -0.04737, the median is -0.00121, the third
and fourth quartiles are 0.04618, and the maximum residual is
0.33126. This indicates that the residuals are distributed within
a certain range and there are no obvious outliers. The intercept
is -5.934e-18, the standard error is 1.299e-3, the t-value is
0.00, and the p-value is 1. This means that the intercept is not
statistically significant and can be considered close to 0.
The slope is 0.2569, the standard error is 1.176e-2, the t-value
is 21.84, and the p-value is less than 2.2e-16. This indicates a
significant positive correlation between residuals_redisvote and
```

```
residues.
The residual standard error is 0.07338, based on 3191 degrees of
freedom. The coefficient of determination is 0.13, and the
adjusted coefficient of determination is 0.1298. This indicates
that residuals_redisvote can explain approximately 13% of the
variance in residuals. F-statistic: 477, based on 1 model degree
of freedom and 3191 error degrees of freedom, p-value less than
2.2e-16. This indicates that the overall model is statistically
significant.

Conclusion:
For every unit increase in residuals_redisvote, the average
increase in residuals is 0.2569 units. The model is statistically
significant and explains approximately 13% of the variance in
residuals, indicating that resitus_presvote is a useful variable
for predicting residuals. These results indicate a significant
positive correlation between the residuals of voting shares in
presidential elections and those in House of Representatives
elections. However, it should be noted that although the
correlation is significant, the explanatory power of the model is
limited and can only explain a part of the residual variation.
This indicates that there are other factors also affecting the
residuals.
```

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

```
ggplot(df, aes(x = residuals_presvote, y = residuals)) +
  geom_point() +
  geom_smooth(method = "lm", color = "blue") +
  labs(title = "Scatterplot of Residuals with Regression Line",
       x = "Residuals from Presidential Vote Regression (residuals_presvote)",
       y = "Residuals from Vote Share Regression (residuals)")#Draw regression lines and scatter plots
```



3. Write the prediction equation.

```r
intercept_residuals <- coef(model_residuals)[1]#Extracted is intercept
slope_residuals <- coef(model_residuals)[2]#Extracted is slope
prediction_equation <- paste("residuals =", intercept_residuals, " + ",
    slope_residuals, " * residuals_presvote")
print(prediction_equation)
```

```
the prediction equation:
residuals = -5.93407792400741e-18  +  0.256877012700097  * residuals_presvote
```

Question 5

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`.

```r
model_voteshare <- lm(voteshare ~ difflog + presvote, data = df)
summary(model_voteshare)#Output regression analysis results
```

```
Call:
lm(formula = voteshare ~ difflog + presvote, data = df)

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 ***
difflog     0.0355431   0.0009455   37.59   <2e-16 ***
presvote    0.2568770   0.0117637   21.84   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.07339 on 3190 degrees of freedom
Multiple R-squared:  0.4496, Adjusted R-squared:  0.4493
F-statistic:  1303 on 2 and 3190 DF,  p-value: < 2.2e-16


Data analysis:
The minimum value is -0.25928. The first quartile is -0.04737.
The median is -0.00121. The third and fourth percentiles are
0.04618. The maximum value is 0.33126. According to the residual
distribution, most residual values are close to 0, indicating
that the model fits properly. The distribution range of residuals
is from -0.25928 to 0.33126, which is reasonable.
The intercept is 0.4486442. The coefficient of difflog is
0.0355431. The coefficient of presvote is 0.2568770. There are
standard errors, t-values, and p-values next to the estimated
values of each coefficient. All coefficients have p-values less
than 2e-16, which means they are statistically significant.
The residual standard error is 0.07339. The degree of freedom is
```

```
3190. The coefficient of determination is 0.4496. The adjusted
coefficient of determination is 0.4493. The F-statistic is 1303.
The degrees of freedom of the F-statistic are 2 and 3190. The
p-value of the F-statistic<2.2e-16 indicates that the model
explains 44.96% of the dependent variable variability. The
adjusted coefficient of determination takes into account the
number of independent variables in the model and slightly
decreases to 44.93%. The F-statistic and its p-value indicate
that the model as a whole is significant.

Conclusion:
This linear regression model is statistically significant and explains a signifi
```

2. Write the prediction equation.

```r
intercept <- coef(model_voteshare)[1]
coef_difflog <- coef(model_voteshare)[2]
coef_presvote <- coef(model_voteshare)[3]
prediction_equation <- paste("voteshare =", intercept,
                             " +", coef_difflog, "* difflog",
                             " +", coef_presvote, "* presvote")
print(prediction_equation)
```

```
the prediction equation:
voteshare = 0.448644221823622  + 0.0355430864025444 * difflog
            + 0.256877012700097 * presvote
```

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

```
Similarities
(1) Residual: The residual statistical data of the two outputs
are exactly the same: minimum value: -0.25928, first quartile:
-0.04737, median: -0.00121, third and fourth quartiles: 0.04618,
maximum value: 0.33126.
(2) Residual standard error: The residual standard errors of the
two outputs are very close, with the fifth output being 0.07339
and the fourth output being 0.07338.
(3) F-statistic and its p-value: The F-statistic and its p-value
of both outputs indicate that the model is significant overall,
although the specific F-statistic values are different.
```

Reasons:
(1) Same dataset or subset: using the same dataset and subset of data. This means that they may have similar residual distributions, resulting in identical residual statistical data.
(2) May have similar error structures, with error terms following similar distributions in both models.
(3) Same sample size: If the same number of observations are used, their degrees of freedom will be very close (one is 3190, the other is 3191), resulting in very close residual standard errors
(4) The significance of the models: The F-statistic and p-value of both models indicate that the models are statistically significant, indicating that both models can effectively explain the variability of the dependent variable.
(5) The linear relationship of the model: Although the specific variables of the model are different, both models may capture the linear relationship between the independent and dependent variables, which may lead to similarity in the residual distribution.
(6) The fit of the model: Although the fit of the two models is different, both indicate that the models can explain a certain proportion of data variability.
(7) Random error: In large sample situations, even if the models are different, random error may produce similar residual patterns