PS02 Claire

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1 Introduction

```
climatesupport ;- read.csv("datasets/climateSupport.RData") install.packages("ggplot2") library("ggplot2") climateSupport ;-load(url("https://github.com/ASDS-TCD/StatsII_spring2022/blob/main/datasets/climaterue"))
```

2 Question 1

```
\label{eq:climateSupport} \begin{split} & \text{summary}(\text{climateSupport}) \\ & \text{climateSupport} choice < -as.numeric(as.factor(climateSupportchoice))-1} \\ & \text{climateSupport} sanctions < -as.numeric(as.factor(climateSupportsanctions))-1} \\ & \text{climateSupport} countries < -as.numeric(as.factor(climateSupportcountries))-1} \\ & \text{climateSupport} choice \\ & \text{sanctions line 2 is 15} \\ & 1 \text{ is 5} \\ & \text{climateSupport} \\ & \text{model}_1 < -glm(choice ., periodfunctions as omnibus selector(kitchens in kadditive model)} \\ & data = climateSupport, family = "binomial"(link = "logit"))) \end{split}
```

```
summary(model_1)
 -0,14458 = intercept
countries = 0.32436
   -0.12353 = sanctions
plot(model_1)
exp(coef(model_1))
exponential coefficients returns\\
intercept = 0.8653845
countries = 1.03831405
sanctions = 0.8837921
countries
0
                                 20
                                  80
1
                                 160
2
sanctions
0
                                5
                                 15
1
2
                                  20
model_null < -glm(as.factor(choice) \ 1, data = climateSupport, family = "binomial")1 = (as.factor(choice) \ 1, data = climateSupport, family = "binomial")1 = (as.factor(choice) \ 1, data = climateSupport, family = "binomial")1 = (as.factor(choice) \ 1, data = climateSupport, family = "binomial")1 = (as.factor(choice) \ 1, data = climateSupport, family = "binomial")1 = (as.factor(choice) \ 1, data = climateSupport, family = "binomial")1 = (as.factor(choice) \ 1, data = climateSupport, family = "binomial")1 = (as.factor(choice) \ 1, data = climateSupport, family = "binomial")1 = (as.factor(choice) \ 1, data = climateSupport, family = "binomial")1 = (as.factor(choice) \ 1, data = climateSupport, family = "binomial")1 = (as.factor(choice) \ 1, data = climateSupport, family = "binomial")1 = (as.factor(choice) \ 1, data = climateSupport, family = (as.factor(choice) \ 1, data = climateSupport, family = (as.factor(choice) \ 1, data = climateSupport, family = (as.factor(choice) \ 1, data = (as.factor(choice) \ 1, 
 fitan intercept only (i.e. sort of a"mean")
anova(model_1, test = "Chisq")
running an an ova of model one \\
anova(model_1)
running an an ovamodel shows that the model returns a small pvalue\\
the null hypothesis is that an individual has an affect on support for policy taking into account the number of counting the property of the
exp(confint(model_1))Transformtooddsratiousingexp()
An option for making a data. frame of confints and coefficients \\
conf_reg < -data.frame(cbind(lower = exp(confint(model_1)[,1]), coefs = exp(coef(model_1)), upper = confine(cbind(lower = exp(confint(model_1)[,1]), coefs = exp(coef(model_1)), upper = confine(cbind(lower = exp(coef(model_1)[,1]), coefs = exp(coef(model_1)), upper = coefs = exp(coefs), upper = coefs = coefs = exp(coefs), upper = coefs = exp(coefs), upper = coefs = coefs = exp(coefs), upper = coefs = exp(coefs), upper = coefs = coefs = exp(coefs), upper = coefs = coefs
exp(confint(model_1)[,2])))
```

this creates a confidence interval of the model

```
Intercept = \\ lower = 0.791 \\ coefs = 0.865 \\ upper = 0.945 \\ confidence interval for countries \\ lower = 1.312 \\ coefs = 1.383 \\ 1.458 \\ sanctions confidence interval \\ lower = 0.850 \\ coefs = 0.884 \\ upper = 0.918 \\ ggplot(data = conf_reg, mapping = aes(x = row.names(conf_reg), y = coefs)) + geom_point() + geom_errorbar(aes(ymin = lower, ymax = upper), colour = "red") + coord_flip()
```

3 Question2

above 160 use number 2

3.1 Part A

```
5 use 1 15 \text{ use } 2 Y = bO + b1x1 + b1X2 + X3 Y = -0.14458 + 0.32436*\text{countries} + -0.12353*\text{sanctions} Y \text{ } \text{;-} \text{ } -0.14458 + 0.032436*2 + -0.12353*1} Y1 \text{ } \text{;-} \text{ } -0.14458 + 0.032436*2 + -0.12353*2} DIFF \text{ } \text{;-} \text{ } Y1 \text{ } \text{Y} DIFF
```

```
0.12353 \text{ Y} - \text{Y1} = 0.12353
-0.12353 \text{ when diff} = \text{Y1} - \text{Y}
\exp(0.12353)
\exp(0.12353) = 1.131484
```

 $\exp(0.12353) = 1.131484$

for the policy for when nearly all countries participate and increasing sanctions from 5 to 15 percent it changes the log odds of support for the policy by 1.131484 from the baseline odds ratio

this suggests that the more countries that participate the more the log odds are affected

3.2 Part B

 $\begin{array}{c} 20 \text{ OF } 192 \\ 5\text{-}15 \text{ use } 1 \end{array}$

```
\begin{array}{l} {\rm Y2=bO+b1x1+b1X2+X3} \\ {\rm -0.14458+0.32436*countries+-0.12353*sanctions} \\ {\rm Y2~j--0.14458+0.032436*0+-0.12353*1} \\ {\rm Y3~j--0.14458+0.032436*0+-0.12353*2} \\ {\rm DIFF2~j-~Y3-Y2} \\ {\rm DIFF2} \end{array}
```

```
DIFF Y3 -Y2 = -0.12353
DIFF2 Y2 - Y3 = 0.012353
exp(-0.12353)
exp(-0.12353) = 0.8837951
```

for the policy for when very few countries participate and there is the same increase in policy from 5 to 15 percent it changes the log odds that they will support the policy to 0.8837951 from the basline odds ratio

This may suggest that sampling fewer countries perhaps if they are all of a certain economic status may have an impact on support

3.3 Part C

```
Y=bO+b1x1+b1X2+X3\\-0.14458+0.32436*countries+-0.12353*sanctions+choice*countries*sanctions Y8 ;--0.14458+0.32436*1+-0.12353*0+1*1 Y8
```

```
Y8 is equal to 1.17978

\exp(1.17978)

\exp(1.17978) = 3.253658
```

the estimated probability that if there is no account taken for sanctions that an individual will support policy has a log odds that is much higher of 3.252658 this suggests that sanctions do play a part in peoples support for policy

3.4 Part D

```
Y = -0.14458 + 0.32436*countries + -0.12353*sanctions + choice*countries*sanctions
Y4 : -0.14458 + 0.032436*2 + -0.12353*1 + 0*2*1
Y5 : -0.14458 + 0.032436*2 + -0.12353*2 + 1*2*1
DIFF3 ;- Y5 - Y4
DIFF3
1.87647
\exp(1.87647)
\exp 1.18647 = 6.530412
\hat{Y} = -0.14458 + 0.32436 * countries + -0.12353 * sanctions + choice * countries * -0.12353 * sanctions + choice * -0.12353 * -0.12353 * -0.12353 * -0.12353 * -0.12353 * -0.12353 * -0.12353 * -0.12353 * -0.12353 * -0.12353 * -0.12353 * -0.12353 * -0.12353 * -0.12353 * -0.12353 * -0.12353 * -0.12353 * -0.12353 * -0.12353 * -0.12353 * -0.12353 * -0.12353 * -0.12353 * -0.12353 * -0.12353 * -0.12353 * -0.12353 * -0.12353 * -0.12353 * -0.12353 * -0.12353 * -0.12353 * -0.12353 * -0.12353 * -0.12353 * -0.12353 * -0.12353 * -0.12353 * -0.12353 * -0.12353 * -0.12353 * -0.12353 * -0.12353 * -0.12353 * -0.12353 * -0.12353 * -0.12353 * -0.12353 * -0.12353 * -0.12353 * -0.12353 * -0.12353 * -0.12353 * -0.12353 * -0.12353 * -0.12353 * -0.12353 * -0.12353 * -0.12353 * -0.12353 * -0.12353 * -0.12353 * -0.12353 * -0.12353 * -0.12353 * -0.12353 * -0.12353 * -0.12353 * -0.12353 * -0.12353 * -0.12353 * -0.12353 * -0.12353 * -0.12353 * -0.12353 * -0.12353 * -0.12353 * -0.12353 * -0.12353 * -0.12353 * -0.12353 * -0.12353 * -0.12353 * -0.12353 * -0.12353 * -0.12353 * -0.12353 * -0.12353 * -0.12353 * -0.12353 * -0.12353 * -0.12353 * -0.12353 * -0.12353 * -0.12353 * -0.12353 * -0.12353 * -0.12353 * -0.123
sanctions
Y6 < -0.14458 + 0.032436 * 0 + -0.12353 * 1 + 0 * 0 * 1
Y7 < -0.14458 + 0.032436 * 0 + -0.12353 * 2 + 1 * 0 * 2
DIFF4 ;- Y7 - Y6
DIFF4
DIFF4 = -0.12353
\exp(-0.12353) = 0.8837951
```

this shows us the adding in the interaction to 2b is not effected as if returns the same expoential log odd however it does affect 2a.

if individual choice was accounted for on a large scale it would suggest there would be greater variation in support for policy and in choice.

```
plot1; interaction.plot(model_1, pred = countries, modx = sanctions)
```

 $predicted_data < -with(climateSupport, expand.grid(choice = unique(choice), countries = unique(countries), sanctions = unique(sanctions)))$

 $predicted_data < -cbind(predicted_data, predict(model_1, newdata = predicted_data, type = "response", se = TRUE))$

 $predicted_data$

 $predicted_{d}ata < -within(predicted_{d}ata, PredictedProb < -plogis(fit)LL < -plogis(fit - (1.96*se.fit)) \\ predicted_{d}ata$