

stat431 assignment02

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Question 1

(a)

```
y <- rep(c(0,1,0,1,0,1,0,1), c(78,22,46,54,71,40,20,60))
x1 <- rep(c(0,0,1,1,0,0,1,1), c(78,22,46,54,71,40,20,60))
x2 <- rep(c(0,0,0,0,1,1,1,1), c(78,22,46,54,71,40,20,60))
model <- glm(y ~ x1 + x2 + x1*x2, family = binomial(link = logit))
summary(model)

##
## Call:
## glm(formula = y ~ x1 + x2 + x1 * x2, family = binomial(link = logit))
##
## Deviance Residuals:
##      Min       1Q   Median       3Q      Max
## -1.6651  -0.9454  -0.7049   1.1101   1.7402
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)  -1.2657     0.2414  -5.243 1.58e-07 ***
## x1             1.4260     0.3139   4.543 5.55e-06 ***
## x2             0.6919     0.3120   2.217  0.0266 *
## x1:x2         0.2464     0.4520   0.545  0.5856
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##      Null deviance: 538.14  on 390  degrees of freedom
## Residual deviance: 478.45  on 387  degrees of freedom
## AIC: 486.45
##
## Number of Fisher Scoring iterations: 4

c <- 1.96
# beta0 95%
beta0_L <- -1.2657 - c*(0.2414)
beta0_U <- -1.2657 + c*(0.2414)
beta0_L

## [1] -1.738844
```

```

beta0_U

## [1] -0.792556

# beta1 95%
beta1_L <- 1.4260 - c*(0.3139)
beta1_U <- 1.4260 + c*(0.3139)
beta1_L

## [1] 0.810756
beta1_U

## [1] 2.041244

# beta2 95%
beta2_L <- 0.6919 - c*(0.3120)
beta2_U <- 0.6919 + c*(0.3120)
beta2_L

## [1] 0.08038
beta2_U

## [1] 1.30342

# beta3 95%
beta3_L <- 0.2464 - c*(0.4520)
beta3_U <- 0.2464 + c*(0.4520)
beta3_L

## [1] -0.63952
beta3_U

## [1] 1.13232

# Fitted Values Estimated and Confidence Interval
beta_est <- c(-1.2657,1.4260,0.6919,0.2464)

## when X1=1 & X2=1 ##
x_vector11 <- c(1,1,1,1)
beta_fun <- t(x_vector11)%*%beta_est
pie11 <- exp(beta_fun) / (1 + exp(beta_fun))
pie11

##           [,1]
## [1,] 0.7499977

# 95% CI for beta_function
beta_fun_L <- beta_fun - c * sqrt(t(x_vector11) %*% summary(model)$cov.unscaled %*% x_vector11)
beta_fun_U <- beta_fun + c * sqrt(t(x_vector11) %*% summary(model)$cov.unscaled %*% x_vector11)
# 95% CI for fitted value
pie11_L <- exp(beta_fun_L) / (1 + exp(beta_fun_L))
pie11_U <- exp(beta_fun_U) / (1 + exp(beta_fun_U))
pie11_L

##           [,1]
## [1,] 0.6439456

```

```

pie11_U

##           [,1]
## [1,] 0.83267

## when X1=1 & X2=0 ##
x_vector10 <- c(1,1,0,0)
beta_fun <- t(x_vector10)%*%beta_est
pie10 <- exp(beta_fun) / (1 + exp(beta_fun))
pie10

##           [,1]
## [1,] 0.5399894

# 95% CI for beta_function
beta_fun_L <- beta_fun - c * sqrt(t(x_vector10) %*% summary(model)$cov.unscaled %*% x_vector10)
beta_fun_U <- beta_fun + c * sqrt(t(x_vector10) %*% summary(model)$cov.unscaled %*% x_vector10)
# 95% CI for fitted value
pie10_L <- exp(beta_fun_L) / (1 + exp(beta_fun_L))
pie10_U <- exp(beta_fun_U) / (1 + exp(beta_fun_U))
pie10_L

##           [,1]
## [1,] 0.4420219

pie10_U

##           [,1]
## [1,] 0.6349612

## when X1=0 & X2=1 ##
x_vector01 <- c(1,0,1,0)
beta_fun <- t(x_vector01)%*%beta_est
pie01 <- exp(beta_fun) / (1 + exp(beta_fun))
pie01

##           [,1]
## [1,] 0.3603605

# 95% CI for beta_function
beta_fun_L <- beta_fun - c * sqrt(t(x_vector01) %*% summary(model)$cov.unscaled %*% x_vector01)
beta_fun_U <- beta_fun + c * sqrt(t(x_vector01) %*% summary(model)$cov.unscaled %*% x_vector01)
# 95% CI for fitted value
pie01_L <- exp(beta_fun_L) / (1 + exp(beta_fun_L))
pie01_U <- exp(beta_fun_U) / (1 + exp(beta_fun_U))
pie01_L

##           [,1]
## [1,] 0.2766204

pie01_U

##           [,1]
## [1,] 0.4535563

## when X1=0 & X2=0 ##
x_vector00 <- c(1,0,0,0)
beta_fun <- t(x_vector00)%*%beta_est
pie00 <- exp(beta_fun) / (1 + exp(beta_fun))

```

```

pie00

##           [,1]
## [1,] 0.2199942

# 95% CI for beta_function
beta_fun_L <- beta_fun - c * sqrt(t(x_vector00) %*% summary(model)$cov.unscaled %*% x_vector00)
beta_fun_U <- beta_fun + c * sqrt(t(x_vector00) %*% summary(model)$cov.unscaled %*% x_vector00)
# 95% CI for fitted value
pie00_L <- exp(beta_fun_L) / (1 + exp(beta_fun_L))
pie00_U <- exp(beta_fun_U) / (1 + exp(beta_fun_U))
pie00_L

##           [,1]
## [1,] 0.1494593

pie00_U

##           [,1]
## [1,] 0.311621

estimate of beta0 = -1.2657: estimated log odds of response Y when X1=X2=0 ; 95%C.I.: [-1.738844,-0.792556]
estimate of beta1 = 1.4260: estimated log odds ratio of response Y when X1=1 vs X1=0 while keeping X2=0
; 95%C.I.: [0.810756,2.041244]
estimate of beta2 = 0.6919: estimated log odds ratio of response Y when X2=1 vs X2=0 while keeping X1=0
; 95%C.I.: [0.08038,1.30342]
estimate of beta3 = 0.2464: estimated difference between log odds ratio of response Y when X1=1 vs X1=0
while keeping X2=1 and log odds ratio of response Y when X1=1 vs X1=0 while keeping X2=0 ; 95%C.I.: [-0.63952,1.13232]
estimate of fitted value (when X1=1 X2=1) = 0.7499977 ; 95%C.I.: [0.6439456,0.83267]
estimate of fitted value (when X1=1 X2=0) = 0.5399894 ; 95%C.I.: [0.4420219,0.6349612]
estimate of fitted value (when X1=0 X2=1) = 0.3603605 ; 95%C.I.: [0.2766204,0.4535563]
estimate of fitted value (when X1=0 X2=0) = 0.2199942 ; 95%C.I.: [0.1494593,0.311621]

```

(b)

```
model <- lm(y ~ x1*x2)
summary(model)

##
## Call:
## lm(formula = y ~ x1 * x2)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.7500 -0.3604 -0.2200  0.4600  0.7800
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)  0.22000    0.04620   4.762 2.71e-06 ***
## x1           0.32000    0.06533   4.898 1.42e-06 ***
## x2           0.14036    0.06369   2.204  0.0281 *
## x1:x2        0.06964    0.09412   0.740  0.4598
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.462 on 387 degrees of freedom
## Multiple R-squared:  0.1466, Adjusted R-squared:  0.14
## F-statistic: 22.17 on 3 and 387 DF,  p-value: 2.882e-13

c <- qt(0.975, 400-5)

# beta0 95%
beta0_L <- 0.22000 - c*(0.04620)
beta0_U <- 0.22000 + c*(0.04620)
beta0_L

## [1] 0.1291714
beta0_U

## [1] 0.3108286

# beta1 95%
beta1_L <- 0.32000 - c*(0.06533)
beta1_U <- 0.32000 + c*(0.06533)
beta1_L

## [1] 0.191562
beta1_U

## [1] 0.448438

# beta2 95%
beta2_L <- 0.14036 - c*(0.06369)
beta2_U <- 0.14036 + c*(0.06369)
beta2_L

## [1] 0.01514623
beta2_U
```

```
## [1] 0.2655738
# beta3 95%
beta3_L <- 0.06964 - c*(0.09412)
beta3_U <- 0.06964 + c*(0.09412)
beta3_L

## [1] -0.1153988
beta3_U

## [1] 0.2546788
# fitted values and confidence intervals
# when X1=1 X2=1
predict(model, interval = "confidence")[312,]

##          fit          lwr          upr
## 0.7500000 0.6484546 0.8515454
# when X1=1 X2=0
predict(model, interval = "confidence")[101,]

##          fit          lwr          upr
## 0.5400000 0.4491751 0.6308249
# when X1=0 X2=1
predict(model, interval = "confidence")[201,]

##          fit          lwr          upr
## 0.3603604 0.2741532 0.4465676
# when X1=0 X2=0
predict(model, interval = "confidence")[1,]

##          fit          lwr          upr
## 0.2200000 0.1291751 0.3108249

estimate of beta0 = 0.22 : estimated mean of response Y when X1=X2=0 ; 95%C.I.: [0.1291714,0.3108286]
estimate of beta1 = 0.32 : estimated mean of response Y when X1=1 vs X1=0 while keeping X2=0 ;
95%C.I.: [0.191562,0.448438]
estimate of beta2 = 0.14036: estimated mean of response Y when X2=1 vs X2=0 while keeping X1=0 ;
95%C.I.: [0.01514623,0.2655738]
estimate of beta3 = 0.06964: estimated difference between mean of response Y when X1=1 vs X1=0 while keep-
ing X2=1 and mean of response Y when X1=1 vs X1=0 while keeping X2=0 ; 95%C.I.: [-0.1153988,0.2546788]
estimate of fitted value (when X1=1 X2=1) = 0.75 ; 95%C.I.: [0.6484546,0.8515454]
estimate of fitted value (when X1=1 X2=0) = 0.54; 95%C.I.: [0.4491751,0.6308249]
estimate of fitted value (when X1=0 X2=1) = 0.3603604; 95%C.I.: [0.2741532,0.4465676]
estimate of fitted value (when X1=0 X2=0) = 0.22; 95%C.I.: [0.1291751,0.3108249]
```

(d)

For analysis in (a):

pros: Since all assumption of logistic regression model are satisfied, so those maximum likelihood estimators in analysis (a) are valid.

For analysis in (b):

pros: Compared with analysis (a), those coefficients have easier interpretation. (mean difference vs. odds ratio difference)

cons: The assumption of normality and constant variance are violated, so those estimators might be not valid.

Propose a change: weighted least square regression

For analysis in (c):

pros: Compared with analysis (a), those coefficients have easier interpretation. (mean difference vs. odds ratio difference). Besides, all assumptionn of model are satisfied, so those estimators in analysis (c) are valid.

Question (2)

```
### (b)
midpoint <-c(1.34, 1.60, 1.75, 1.85, 1.95, 2.00, 2.14, 2.25, 2.34)
survived <- c(13,19,67,45,71,50,35,7,1)
died <- c(0,0,2,5,8,20,31,49,12)
resp <- cbind(survived, died)
# fit logit link
logit_model <- glm(resp ~ midpoint, family = binomial(link = "logit"))
summary(logit_model)

##
## Call:
## glm(formula = resp ~ midpoint, family = binomial(link = "logit"))
##
## Deviance Residuals:
##      Min       1Q   Median       3Q      Max
## -1.4339  -1.0324  -0.1424   0.4234   1.5489
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)    21.989      2.113   10.41  <2e-16 ***
## midpoint      -10.397      1.021  -10.19  <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##    Null deviance: 198.7115  on 8  degrees of freedom
## Residual deviance:   8.8634  on 7  degrees of freedom
## AIC: 37.402
##
## Number of Fisher Scoring iterations: 5
# fit probit link
probit_model <- glm(resp ~ midpoint, family = binomial(link = "probit"))
summary(probit_model)

##
## Call:
## glm(formula = resp ~ midpoint, family = binomial(link = "probit"))
##
## Deviance Residuals:
##      Min       1Q   Median       3Q      Max
## -1.6284  -0.8056  -0.1565   0.2099   1.6548
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)    12.5444      1.1127   11.27  <2e-16 ***
## midpoint      -5.9364      0.5408  -10.98  <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
```



```
## Null deviance: 198.712 on 8 degrees of freedom
## Residual deviance: 10.133 on 7 degrees of freedom
## AIC: 38.672
##
## Number of Fisher Scoring iterations: 5
```

```
# fit log-log link
cloglog_model <- glm(resp ~ midpoint, family = binomial(link = "cloglog"))
```

```
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
```

```
summary(cloglog_model)
```

```
##
## Call:
## glm(formula = resp ~ midpoint, family = binomial(link = "cloglog"))
##
## Deviance Residuals:
##      Min       1Q   Median       3Q      Max
## -2.69253  -1.05163   0.00000   0.08249   2.32167
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)  11.0497      1.1005  10.041  <2e-16 ***
## midpoint      -5.4184      0.5508  -9.838  <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
## Null deviance: 198.712 on 8 degrees of freedom
## Residual deviance: 19.207 on 7 degrees of freedom
## AIC: 47.746
##
## Number of Fisher Scoring iterations: 7
```

Interpretation:

For logit_model:

beta0_hat=21.989: the estimated log odds when the midpoints is zero (actually third-degree burn area is zero)

beta1_hat=-10.397: the estimated log odds ratio when the midpoint increases one unit

For probit_model:

beta0_hat=12.5444: the inverse CDF of N(0,1) for the probability of surviving when the midpoint is zero (burn area = 0)

beta1_hat=-5.9364: the estimated change of inverse CDF of N(0,1) for the probability of surviving when the midpoint increases one unit

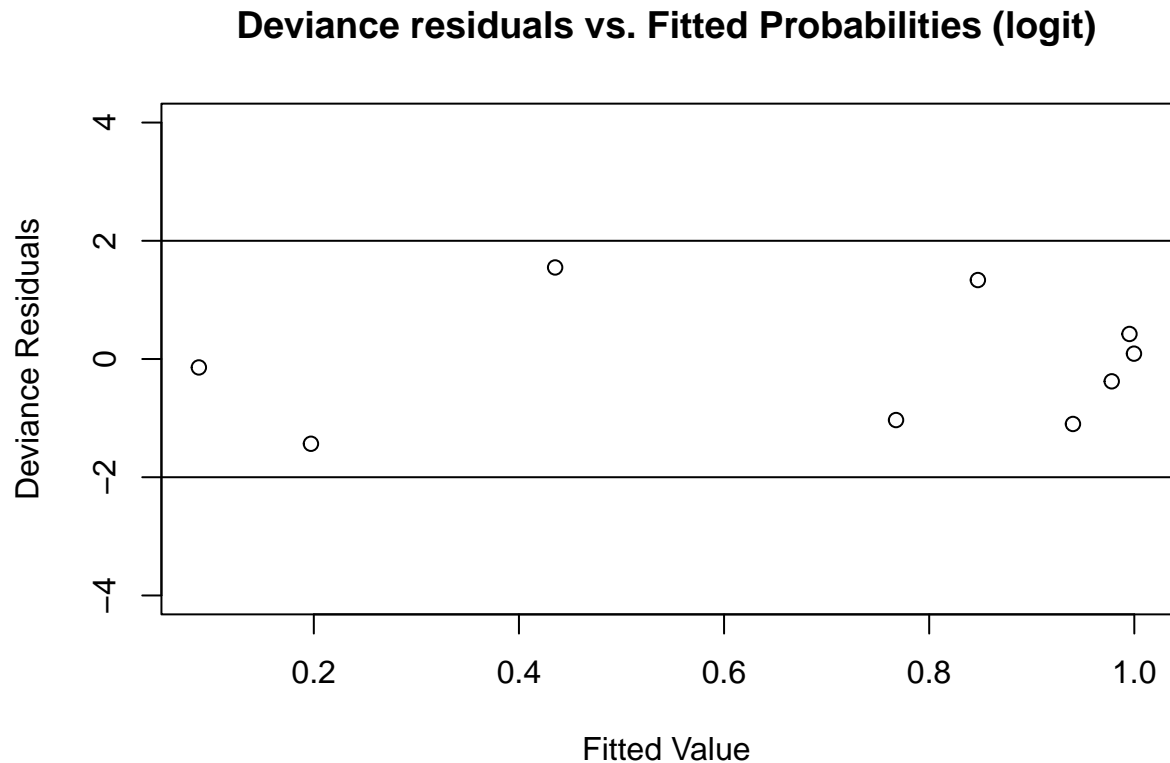
For cloglog_model:

beta0_hat=11.0497: the estimated complimentary log log of the probability of surviving when the midpoint is zero (burn area = 0)

beta1_hat=-5.4184: the estimated change of complimentary log log of the probability of surviving when the midpoint is zero (burn area = 0)

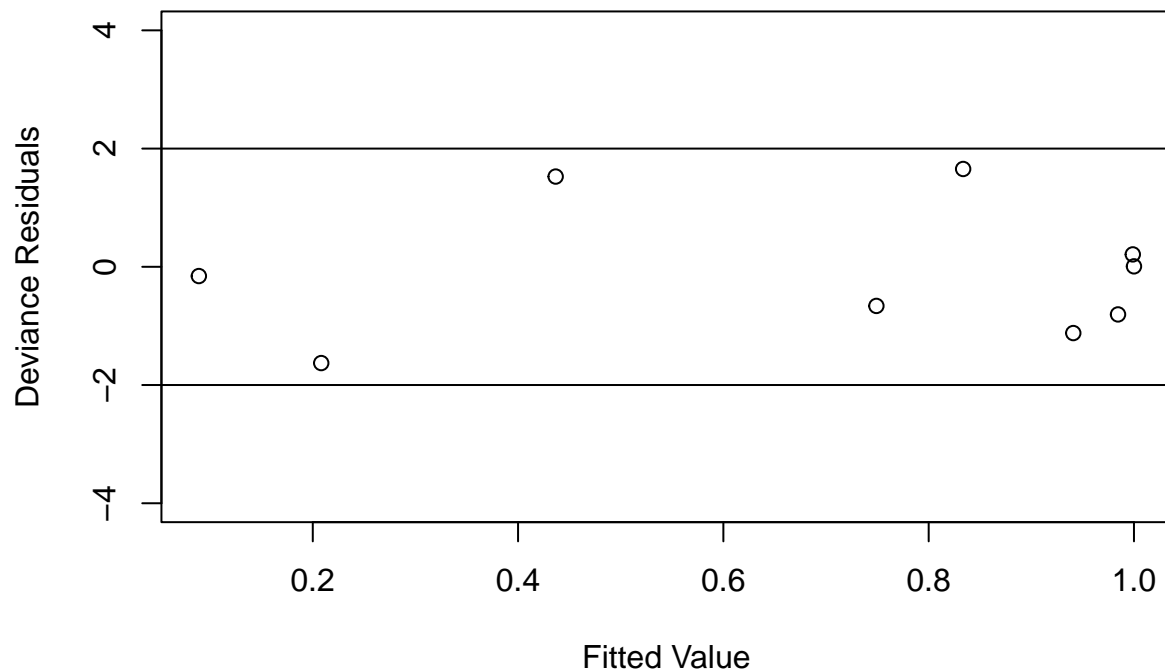
(c)

```
# logit model
rd1 <- residuals.glm(logit_model,"deviance")
fv1 <- logit_model$fitted.values
plot(fv1,rd1,xlab="Fitted Value", ylim=c(-4,4),
     ylab="Deviance Residuals",main="Deviance residuals vs. Fitted Probabilities (logit)")
abline(h=-2) ; abline(h=2) ;
```



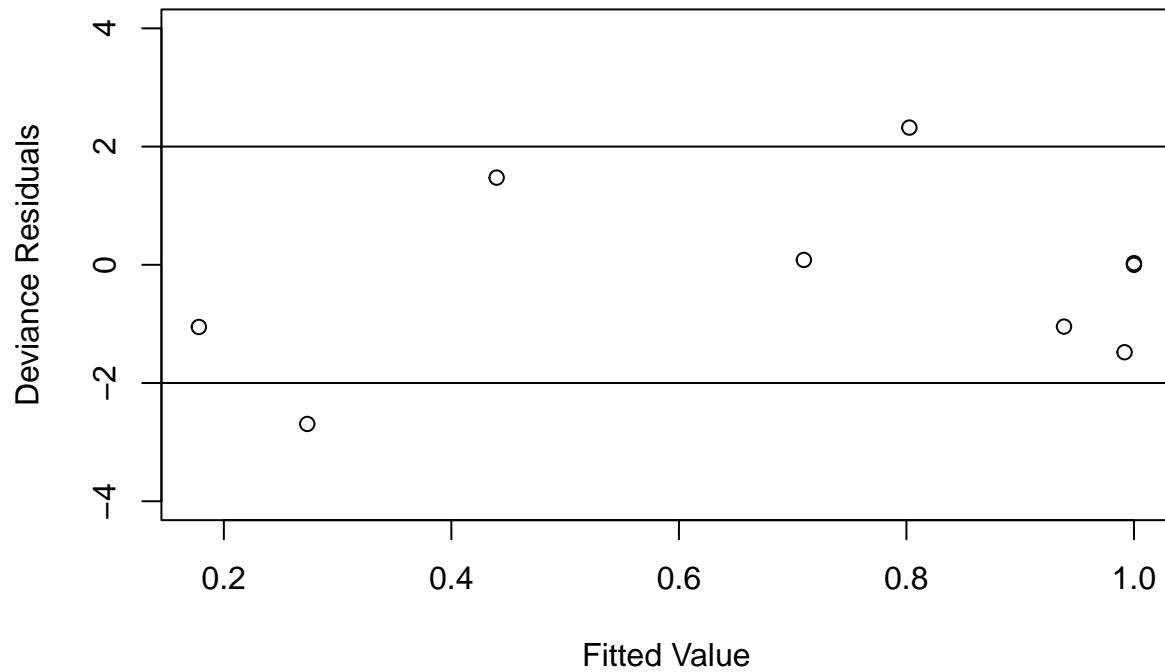
```
# probit model
rd2 <- residuals.glm(probit_model,"deviance")
fv2 <- probit_model$fitted.values
plot(fv2,rd2,xlab="Fitted Value", ylim=c(-4,4),
     ylab="Deviance Residuals",main="Deviance residuals vs. Fitted Probabilities (probit)")
abline(h=-2) ; abline(h=2)
```

Deviance residuals vs. Fitted Probabilities (probit)



```
# c log-log model
rd3 <- residuals.glm(cloglog_model,"deviance")
fv3 <- cloglog_model$fitted.values
plot(fv3,rd3,xlab="Fitted Value", ylim=c(-4,4),
     ylab="Deviance Residuals",main="Deviance residuals vs. Fitted Probabilities (c log-log)")
abline(h=-2) ; abline(h=2)
```

Deviance residuals vs. Fitted Probabilities (c log-log)



Conclusion: Based on 3 plots, we find that logit model is the best. Since for c log-log model, there are 2 points outside $[-1.96, 1.96]$ range. Besides, all plots in logit model are closer to line 0 compared to probit model.

(d)

```
# we select logit model
pie <- 0.8
beta0_hat <- 21.989
beta1_hat <- -10.397

x <- (log(pie/(1-pie))-beta0_hat) / beta1_hat
x
```

```
## [1] 1.981601
```

```
area <- exp(2) - 1
area
```

```
## [1] 6.389056
```

Therefore, the area is estimated to be 6.389056

Question 3

```
# Save the original .csv file in your R Working Directory
# and then run this code block to input the data and
# prepare it for our analysis.
COVIDdata = read.csv("journal.pone.0245327.s010.csv")
# Limit the data to students from NCSU and a restricted set
# of explanatory variables
COVIDdata_NCSU = COVIDdata[(!is.na(COVIDdata$Source) & (COVIDdata$Source ==
  "NCState")), names(COVIDdata) %in% c("Health_General", "Hrs_Screen",
  "Hrs_Outdoor", "Hrs_Exercise", "Class_Self", "Infected_Any",
  "BMI", "Educ_College_Grad", "Age", "Classification_High",
  "Ethnoracial_Group_White1_Asian2", "Age_18to25")]

# Remove observations with missing Ethnoracial data (all
# other variable are complete)
COVIDdata_NCSU = COVIDdata_NCSU[!is.na(COVIDdata_NCSU$Ethnoracial_Group_White1_Asian2),]

# clean up non-integer class values
COVIDdata_NCSU$Class_Self <- round(COVIDdata_NCSU$Class_Self)
# Create factor variables where necessary
COVIDdata_NCSU$Infected_Any = factor(COVIDdata_NCSU$Infected_Any)
COVIDdata_NCSU$Educ_College_Grad = factor(COVIDdata_NCSU$Educ_College_Grad)
COVIDdata_NCSU$Ethnoracial_Group_White1_Asian2 = factor(COVIDdata_NCSU$Ethnoracial_Group_White1_Asian2)
COVIDdata_NCSU$Age_18to25 = factor(COVIDdata_NCSU$Age_18to25)

# str(COVIDdata_NCSU) # Display data set structure,
# commented out to save space
```

(a)

```
# Fit a main effects logistic regression model
modelA = glm(Classification_High ~ +Age + Ethnoracial_Group_White1_Asian2 +
  Class_Self + Health_General + BMI + Hrs_Screen + Hrs_Outdoor +
  Hrs_Exercise + Educ_College_Grad + Infected_Any, family = binomial(link = "logit"),
  data = COVIDdata_NCSU)

summary(modelA)

##
## Call:
## glm(formula = Classification_High ~ +Age + Ethnoracial_Group_White1_Asian2 +
##   Class_Self + Health_General + BMI + Hrs_Screen + Hrs_Outdoor +
##   Hrs_Exercise + Educ_College_Grad + Infected_Any, family = binomial(link = "logit"),
##   data = COVIDdata_NCSU)
##
## Deviance Residuals:
##      Min       1Q   Median       3Q      Max
## -1.6842  -1.0830  -0.8592   1.1886   1.7050
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)    0.592785   0.508024   1.167  0.24327
```

```

## Age25 to 32          0.226878    0.161655    1.403    0.16048
## Age33 to 44          0.605891    0.332882    1.820    0.06874 .
## Age45 to 54          0.657726    0.556496    1.182    0.23724
## Age55 to 64        -12.687259  324.743737   -0.039    0.96884
## Ethnoracial_Group_White1_Asian21  0.287848    0.198502    1.450    0.14703
## Ethnoracial_Group_White1_Asian22  0.439006    0.233072    1.884    0.05962 .
## Class_Self          -0.163984    0.061946   -2.647    0.00812 **
## Health_General      -0.239811    0.058939   -4.069  4.73e-05 ***
## BMI                 -0.004303    0.013186   -0.326    0.74419
## Hrs_Screen           0.027334    0.021813    1.253    0.21018
## Hrs_Outdoor          -0.054803    0.048116   -1.139    0.25471
## Hrs_Exercise          0.017909    0.072284    0.248    0.80432
## Educ_College_Grad1   0.036405    0.145139    0.251    0.80195
## Infected_Any1        0.444331    0.138834    3.200    0.00137 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##    Null deviance: 1809.2  on 1311  degrees of freedom
## Residual deviance: 1753.7  on 1297  degrees of freedom
## AIC: 1783.7
##
## Number of Fisher Scoring iterations: 11
c <- 1.96
# estimated class_self = -0.163984
exp_class_self <- exp(-0.163984)
exp_class_self_L <- exp(-0.163984 - c*0.061946)
exp_class_self_U <- exp(-0.163984 + c*0.061946)
exp_class_self

## [1] 0.8487556
exp_class_self_L

## [1] 0.7517149
exp_class_self_U

## [1] 0.9583235
# estimated infected_any = 0.444331
exp_infected_any <- exp(0.444331)
exp_infected_any_L <- exp(0.444331 - c*0.138834)
exp_infected_any_U <- exp(0.444331 + c*0.138834)
exp_infected_any

## [1] 1.559447
exp_infected_any_L

## [1] 1.187935
exp_infected_any_U

## [1] 2.047144

```

```
# estimated Ethnoracial_Group_White1_Asian21 = 0.287848
exp_asian21 <- exp(0.287848)
exp_asian21_L <- exp(0.287848 - c*0.198502)
exp_asian21_U <- exp(0.287848 + c*0.198502)
exp_asian21
```

```
## [1] 1.333555
```

```
exp_asian21_L
```

```
## [1] 0.9037379
```

```
exp_asian21_U
```

```
## [1] 1.967792
```

```
# estimated Ethnoracial_Group_White1_Asian22 = 0.439006
exp_asian22 <- exp(0.439006)
exp_asian22_L <- exp(0.439006 - c*0.233072)
exp_asian22_U <- exp(0.439006 + c*0.233072)
exp_asian22
```

```
## [1] 1.551165
```

```
exp_asian22_L
```

```
## [1] 0.9823426
```

```
exp_asian22_U
```

```
## [1] 2.449361
```

Interpretation:

estimated exp class self=0.8487556: when remaining other factors unchanged, as the self-reported class increases one level, the odds of high psychological impact is expected to be 0.8487556 times as original odds. The 95% C.I is [0.7517149,0.9583235]

estimated exp infected any=1.559447: when remaining other factors unchanged, the odds of high psychological impact if knowing some infected is 1.559447 times as the odds of high psychological impact without knowing some infected. The 95% C.I is [1.187935,2.047144]

estimated exp asian21=1.333555: when remaining other factors unchanged, the odds of high psychological impact on while people is 1.333555 times as the odds of high psychological impact on black or hispanic. The 95% C.I is [0.9037379,1.967792]

estimated exp asian22=1.551165: when remaining other factors unchanged, the odds of high psychological impact on asian is 1.551165 times of the odds as high psychological impact on black or hispanic. The 95% C.I is [0.9823426,2.449361]

(c)

```
# WE found that beta1 - beta2 means the 22-32 vs. 33-44
estimated_diff <- 0.226878 - 0.605891
# find variance for 22-32, 33-44 and their covariance
summary(modelA)$cov.unscaled
```

```
##              (Intercept)  Age25 to 32  Age33 to 44
## (Intercept)      0.2580885311  0.0005859404  0.0078417931
## Age25 to 32      0.0005859404  0.0261324461  0.0054664518
## Age33 to 44      0.0078417931  0.0054664518  0.1108105523
## Age45 to 54      0.0038094470  0.0061630844  0.0066144150
## Age55 to 64      -0.0038369375  0.0060650203  0.0060329528
## Ethnoracial_Group_White1_Asian21 -0.0337678178  0.0008455126  0.0019015027
## Ethnoracial_Group_White1_Asian22 -0.0381689196 -0.0018917480  0.0010647506
## Class_Self       -0.0088620953  0.0010673847  0.0004085332
## Health_General   -0.0129402437 -0.0007111176 -0.0014935468
## BMI              -0.0048115239 -0.0001968862 -0.0004482746
## Hrs_Screen       -0.0045231060 -0.0001355533  0.0000320836
## Hrs_Outdoor      -0.0018452208 -0.0001581507 -0.0007170866
## Hrs_Exercise     -0.0014946800  0.0006374048  0.0011495826
## Educ_College_Grad1 -0.0004388881 -0.0045136715 -0.0005570443
## Infected_Any1    -0.0036637502  0.0013445121  0.0028733662
##              Age45 to 54  Age55 to 64
## (Intercept)      0.0038094470 -3.836938e-03
## Age25 to 32      0.0061630844  6.065020e-03
## Age33 to 44      0.0066144150  6.032953e-03
## Age45 to 54      0.3096881979  6.059934e-03
## Age55 to 64      0.0060599342  1.054585e+05
## Ethnoracial_Group_White1_Asian21 0.0039257898 -1.066692e-02
## Ethnoracial_Group_White1_Asian22 0.0055338625 -3.286452e-03
## Class_Self       0.0004282546  7.415884e-03
## Health_General   -0.0007625476 -1.326620e-03
## BMI              -0.0006030043 -4.792722e-04
## Hrs_Screen       0.0004913689 -3.425009e-04
## Hrs_Outdoor      0.0006407953  1.936567e-03
## Hrs_Exercise     -0.0011100033  7.592434e-04
## Educ_College_Grad1 -0.0051785339  3.055961e-03
## Infected_Any1    0.0037996132  4.381107e-03
## Ethnoracial_Group_White1_Asian21
## (Intercept)      -0.0337678178
## Age25 to 32      0.0008455126
## Age33 to 44      0.0019015027
## Age45 to 54      0.0039257898
## Age55 to 64      -0.0106669231
## Ethnoracial_Group_White1_Asian21 0.0394028735
## Ethnoracial_Group_White1_Asian22 0.0334410465
## Class_Self       -0.0023710155
## Health_General   -0.0001028943
## BMI              0.0001782523
## Hrs_Screen       0.0003349741
## Hrs_Outdoor      -0.0008681931
## Hrs_Exercise     0.0002241730
## Educ_College_Grad1 0.0005815714
```

```

## Infected_Any1                                0.0009374802
## Ethnoracial_Group_White1_Asian22      Class_Self
## (Intercept)                             -3.816892e-02 -8.862095e-03
## Age25 to 32                             -1.891748e-03  1.067385e-03
## Age33 to 44                             1.064751e-03  4.085332e-04
## Age45 to 54                             5.533863e-03  4.282546e-04
## Age55 to 64                             -3.286452e-03  7.415884e-03
## Ethnoracial_Group_White1_Asian21        3.344105e-02 -2.371015e-03
## Ethnoracial_Group_White1_Asian22        5.432245e-02 -1.605764e-03
## Class_Self                             -1.605764e-03  3.837340e-03
## Health_General                         -7.392678e-05 -5.394259e-04
## BMI                                    3.052118e-04  6.823006e-05
## Hrs_Screen                             1.554307e-04 -2.761036e-05
## Hrs_Outdoor                             7.795445e-04  9.968718e-05
## Hrs_Exercise                           -2.671169e-04 -7.946834e-05
## Educ_College_Grad1                     -1.980868e-03 -4.307830e-05
## Infected_Any1                           2.983463e-03 -3.178784e-04
## Health_General      BMI      Hrs_Screen
## (Intercept)         -1.294024e-02 -4.811524e-03 -4.523106e-03
## Age25 to 32          -7.111176e-04 -1.968862e-04 -1.355533e-04
## Age33 to 44          -1.493547e-03 -4.482746e-04  3.208360e-05
## Age45 to 54          -7.625476e-04 -6.030043e-04  4.913689e-04
## Age55 to 64          -1.326620e-03 -4.792722e-04 -3.425009e-04
## Ethnoracial_Group_White1_Asian21 -1.028943e-04  1.782523e-04  3.349741e-04
## Ethnoracial_Group_White1_Asian22 -7.392678e-05  3.052118e-04  1.554307e-04
## Class_Self           -5.394259e-04  6.823006e-05 -2.761036e-05
## Health_General       3.473838e-03  1.417538e-04  9.284716e-05
## BMI                  1.417538e-04  1.738821e-04 -7.656849e-06
## Hrs_Screen           9.284716e-05 -7.656849e-06  4.758188e-04
## Hrs_Outdoor          -1.954902e-04 -3.763373e-05  2.241826e-04
## Hrs_Exercise          -4.777996e-04 -1.326362e-05  1.402887e-04
## Educ_College_Grad1   -3.878136e-04 -7.754580e-05  1.798010e-05
## Infected_Any1       -1.437905e-04 -6.506259e-05  9.005371e-05
## Hrs_Outdoor  Hrs_Exercise  Educ_College_Grad1
## (Intercept)    -1.845221e-03 -1.494680e-03    -4.388881e-04
## Age25 to 32    -1.581507e-04  6.374048e-04    -4.513672e-03
## Age33 to 44    -7.170866e-04  1.149583e-03    -5.570443e-04
## Age45 to 54     6.407953e-04 -1.110003e-03    -5.178534e-03
## Age55 to 64     1.936567e-03  7.592434e-04     3.055961e-03
## Ethnoracial_Group_White1_Asian21 -8.681931e-04  2.241730e-04     5.815714e-04
## Ethnoracial_Group_White1_Asian22  7.795445e-04 -2.671169e-04    -1.980868e-03
## Class_Self      9.968718e-05 -7.946834e-05    -4.307830e-05
## Health_General  -1.954902e-04 -4.777996e-04    -3.878136e-04
## BMI             -3.763373e-05 -1.326362e-05    -7.754580e-05
## Hrs_Screen      2.241826e-04  1.402887e-04     1.798010e-05
## Hrs_Outdoor     2.315143e-03 -1.583764e-03    -1.997339e-04
## Hrs_Exercise    -1.583764e-03  5.224935e-03     1.837769e-06
## Educ_College_Grad1 -1.997339e-04  1.837769e-06     2.106546e-02
## Infected_Any1   -2.844259e-04  3.721965e-04     1.000053e-03
## Infected_Any1
## (Intercept)    -3.663750e-03
## Age25 to 32     1.344512e-03
## Age33 to 44     2.873366e-03
## Age45 to 54     3.799613e-03

```

```
## Age55 to 64 4.381107e-03
## Ethnoracial_Group_White1_Asian21 9.374802e-04
## Ethnoracial_Group_White1_Asian22 2.983463e-03
## Class_Self -3.178784e-04
## Health_General -1.437905e-04
## BMI -6.506259e-05
## Hrs_Screen 9.005371e-05
## Hrs_Outdoor -2.844259e-04
## Hrs_Exercise 3.721965e-04
## Educ_College_Grad1 1.000053e-03
## Infected_Any1 1.927479e-02
```

```
var_diff <- 0.0261324461 + 0.1108105523 - 2*0.0054664518
# 95% C.I for difference
L <- estimated_diff - 1.96*sqrt(var_diff)
U <- estimated_diff + 1.96*sqrt(var_diff)
# 95% C.I for exp(difference)
exp_L <-exp(L)
exp_U <-exp(U)
exp_L
```

```
## [1] 0.3413756
```

```
exp_U
```

```
## [1] 1.372654
```

Therefore, the 95% C.I is [0.3413756,1.372654]

(d)

```
modelD <- glm(Classification_High ~ +Age + Ethnoracial_Group_White1_Asian2 +
  factor(Class_Self) + Health_General + BMI + Hrs_Screen + Hrs_Outdoor +
  Hrs_Exercise + Educ_College_Grad + Infected_Any, family = binomial(link = "logit"),
  data = COVIDdata_NCSU)
summary(modelD)
```

```
##
## Call:
## glm(formula = Classification_High ~ +Age + Ethnoracial_Group_White1_Asian2 +
##     factor(Class_Self) + Health_General + BMI + Hrs_Screen +
##     Hrs_Outdoor + Hrs_Exercise + Educ_College_Grad + Infected_Any,
##     family = binomial(link = "logit"), data = COVIDdata_NCSU)
##
## Deviance Residuals:
##      Min       1Q   Median       3Q      Max
## -1.7402  -1.0808  -0.8551   1.1883   1.7142
##
## Coefficients:
##                                Estimate Std. Error z value Pr(>|z|)
## (Intercept)                   0.317136    0.510183   0.622  0.53420
## Age25 to 32                   0.216686    0.161996   1.338  0.18103
## Age33 to 44                   0.605888    0.332536   1.822  0.06845 .
## Age45 to 54                   0.685885    0.555882   1.234  0.21725
## Age55 to 64                  -12.608327   324.743754  -0.039  0.96903
## Ethnoracial_Group_White1_Asian21  0.295319    0.198855   1.485  0.13752
## Ethnoracial_Group_White1_Asian22  0.448961    0.233757   1.921  0.05478 .
## factor(Class_Self)2            0.056837    0.215463   0.264  0.79194
## factor(Class_Self)3           -0.277177    0.190497  -1.455  0.14567
## factor(Class_Self)4           -0.429777    0.207625  -2.070  0.03846 *
## factor(Class_Self)5           -0.169289    0.554759  -0.305  0.76025
## Health_General                 -0.236694    0.058990  -4.012 6.01e-05 ***
## BMI                           -0.004032    0.013199  -0.305  0.76001
## Hrs_Screen                     0.028191    0.021858   1.290  0.19715
## Hrs_Outdoor                   -0.056294    0.048141  -1.169  0.24226
## Hrs_Exercise                   0.021721    0.072318   0.300  0.76391
## Educ_College_Grad1            0.032739    0.145383   0.225  0.82183
## Infected_Any1                 0.441932    0.138956   3.180  0.00147 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##      Null deviance: 1809.2  on 1311  degrees of freedom
## Residual deviance: 1751.6  on 1294  degrees of freedom
## AIC: 1787.6
##
## Number of Fisher Scoring iterations: 11
```

(e)

```
beta <- modelA$coefficients
x_vector <- c(1,0,1,0,0,1,0,1,5,28,
              median(COVIDdata_NCSU$Hrs_Screen),
              median(COVIDdata_NCSU$Hrs_Outdoor),
              median(COVIDdata_NCSU$Hrs_Exercise),1,0)
beta_fun <- t(x_vector)%*%beta
pie_est <- exp(beta_fun) / (exp(beta_fun)+1)
pie_est
```

```
##           [,1]
## [1,] 0.5537449
```

Therefore, the estimated probability is 0.5537449

Question 4

```
N <- 10000
x <- rbinom(N,1,0.25)
z <- rnorm(N)
beta0 <- -2
beta1 <- 1
beta2 <- 0.5
n <- 1000
num_iterations <- 2000

# Create a list to store results
beta0_vector <- c(rep(NULL,num_iterations))
beta1_vector <- c(rep(NULL,num_iterations))
beta2_vector <- c(rep(NULL,num_iterations))

# Run the loop
for (i in 1:num_iterations) {

  y <- rbinom(N, 1, exp(beta0 + beta1*x + beta2*z) / (1 + exp(beta0 + beta1*x + beta2*z)))
  data <- data.frame(x=x, z=z, y=y)

  sample <- data[sample(N, n),]

  model <- glm(y ~ x + z, family = binomial(link = "logit"), data = sample)

  beta0_vector[i] <- summary(model)$coefficients[1,1]
  beta1_vector[i] <- summary(model)$coefficients[2,1]
  beta2_vector[i] <- summary(model)$coefficients[3,1]
}

# investigate bias and uncertainty
beta0_hat <- mean(beta0_vector)
beta0_hat

## [1] -2.00844

beta1_hat <- mean(beta1_vector)
beta1_hat

## [1] 1.003283

beta2_hat <- mean(beta2_vector)
beta2_hat

## [1] 0.5032083

beta0_sd <- sd(beta0_vector)
beta0_sd

## [1] 0.1194726

beta1_sd <- sd(beta1_vector)
beta1_sd

## [1] 0.1847332
```

```
beta2_sd <- sd(beta2_vector)
beta2_sd
```

```
## [1] 0.09125081
```

(a)

```
# let beta0_1 = -1
beta0_1 <- -1
beta0_vector <- c(rep(NULL,num_iterations))
beta1_vector <- c(rep(NULL,num_iterations))
beta2_vector <- c(rep(NULL,num_iterations))

# Run the loop
for (i in 1:num_iterations) {

  y <- rbinom(N, 1, exp(beta0_1 + beta1*x + beta2*z) / (1 + exp(beta0_1 + beta1*x + beta2*z)))
  data <- data.frame(x=x, z=z, y=y)

  sample <- data[sample(N, n),]

  model <- glm(y ~ x + z, family = binomial(link = "logit"), data = sample)

  beta0_vector[i] <- summary(model)$coefficients[1,1]
  beta1_vector[i] <- summary(model)$coefficients[2,1]
  beta2_vector[i] <- summary(model)$coefficients[3,1]
}

# investigate bias and uncertainty
beta0_hat_1 <- mean(beta0_vector)
beta0_hat_1
```

```
## [1] -1.002082
```

```
beta1_hat_1 <- mean(beta1_vector)
beta1_hat_1
```

```
## [1] 0.9987938
```

```
beta2_hat_1 <- mean(beta2_vector)
beta2_hat_1
```

```
## [1] 0.5032699
```

```
beta0_sd_1 <- sd(beta0_vector)
beta0_sd_1
```

```
## [1] 0.08387976
```

```
beta1_sd_1 <- sd(beta1_vector)
beta1_sd_1
```

```
## [1] 0.1549929
```

```
beta2_sd_1 <- sd(beta2_vector)
beta2_sd_1
```

```
## [1] 0.07398962
```

```

# let beta0_2 = 0
beta0_2 <- 0
beta0_vector <- c(rep(NULL,num_iterations))
beta1_vector <- c(rep(NULL,num_iterations))
beta2_vector <- c(rep(NULL,num_iterations))

# Run the loop
for (i in 1:num_iterations) {

  y <- rbinom(N, 1, exp(beta0_2 + beta1*x + beta2*z) / (1 + exp(beta0_2 + beta1*x + beta2*z)))
  data <- data.frame(x=x, z=z, y=y)

  sample <- data[sample(N, n),]

  model <- glm(y ~ x + z, family = binomial(link = "logit"), data = sample)

  beta0_vector[i] <- summary(model)$coefficients[1,1]
  beta1_vector[i] <- summary(model)$coefficients[2,1]
  beta2_vector[i] <- summary(model)$coefficients[3,1]
}

# investigate bias and uncertainty
beta0_hat_2 <- mean(beta0_vector)
beta0_hat_2

## [1] -0.001999287

beta1_hat_2 <- mean(beta1_vector)
beta1_hat_2

## [1] 1.00897

beta2_hat_2 <- mean(beta2_vector)
beta2_hat_2

## [1] 0.5028059

beta0_sd_2 <- sd(beta0_vector)
beta0_sd_2

## [1] 0.07527366

beta1_sd_2 <- sd(beta1_vector)
beta1_sd_2

## [1] 0.1619011

beta2_sd_2 <- sd(beta2_vector)
beta2_sd_2

## [1] 0.07172014

# let beta0_3 = -3
beta0_3 <- -3
beta0_vector <- c(rep(NULL,num_iterations))
beta1_vector <- c(rep(NULL,num_iterations))
beta2_vector <- c(rep(NULL,num_iterations))

```



```

# Run the loop
for (i in 1:num_iterations) {

  y <- rbinom(N, 1, exp(beta0_3 + beta1*x + beta2*z) / (1 + exp(beta0_3 + beta1*x + beta2*z)))
  data <- data.frame(x=x, z=z, y=y)

  sample <- data[sample(N, n),]

  model <- glm(y ~ x + z, family = binomial(link = "logit"), data = sample)

  beta0_vector[i] <- summary(model)$coefficients[1,1]
  beta1_vector[i] <- summary(model)$coefficients[2,1]
  beta2_vector[i] <- summary(model)$coefficients[3,1]
}

# investigate bias and uncertainty
beta0_hat_3 <- mean(beta0_vector)
beta0_hat_3

## [1] -3.023142

beta1_hat_3 <- mean(beta1_vector)
beta1_hat_3

## [1] 1.013354

beta2_hat_3 <- mean(beta2_vector)
beta2_hat_3

## [1] 0.5067475

beta0_sd_3 <- sd(beta0_vector)
beta0_sd_3

## [1] 0.1822404

beta1_sd_3 <- sd(beta1_vector)
beta1_sd_3

## [1] 0.2610926

beta2_sd_3 <- sd(beta2_vector)
beta2_sd_3

## [1] 0.1271901

```

Conclusion: After repeat simulation with different beta0, I find that the estimates of beta1 and beta2 are almost unchanged and pretty close to real values no matter the value of beta0, which shows that they are unbiased. Meanwhile, as the beta0 gets smaller, the standard deviation of estimates of beta1 and beta2 will increase, which are unbiased and the uncertainty is affected by values of beta0.

(c)

```
# when beta0 = -1
beta0_1cc <- -1
beta0_vector <- c(rep(NULL,num_iterations))
beta1_vector <- c(rep(NULL,num_iterations))
beta2_vector <- c(rep(NULL,num_iterations))

# Run the loop
for (i in 1:num_iterations) {

  y <- rbinom(N, 1, exp(beta0_1cc + beta1*x + beta2*z) / (1 + exp(beta0_1cc + beta1*x + beta2*z)))
  data <- data.frame(x=x, z=z, y=y)
  data1 <- data[data$y==1,]
  data0 <- data[data$y==0,]

  sample1 <- data1[sample(N, 500),]
  sample0 <- data0[sample(N, 500),]
  sample <- rbind(sample1,sample0)

  model <- glm(y ~ x + z, family = binomial(link = "logit"), data = sample)

  beta0_vector[i] <- summary(model)$coefficients[1,1]
  beta1_vector[i] <- summary(model)$coefficients[2,1]
  beta2_vector[i] <- summary(model)$coefficients[3,1]
}

# investigate bias and uncertainty
beta0_hat_1cc <- mean(beta0_vector)
beta0_hat_1cc

## [1] -1.00338

beta1_hat_1cc <- mean(beta1_vector)
beta1_hat_1cc

## [1] 1.001733

beta2_hat_1cc <- mean(beta2_vector)
beta2_hat_1cc

## [1] 0.5103914

beta0_sd_1cc <- sd(beta0_vector)
beta0_sd_1cc

## [1] 0.1029451

beta1_sd_1cc <- sd(beta1_vector)
beta1_sd_1cc

## [1] 0.2269133

beta2_sd_1cc <- sd(beta2_vector)
beta2_sd_1cc

## [1] 0.109139
```

```

# when beta0 = 0
beta0_2cc <- 0
beta0_vector <- c(rep(NULL,num_iterations))
beta1_vector <- c(rep(NULL,num_iterations))
beta2_vector <- c(rep(NULL,num_iterations))

# Run the loop
for (i in 1:num_iterations) {

  y <- rbinom(N, 1, exp(beta0_2cc + beta1*x + beta2*z) / (1 + exp(beta0_2cc + beta1*x + beta2*z)))
  data <- data.frame(x=x, z=z, y=y)
  data1 <- data[data$y==1,]
  data0 <- data[data$y==0,]

  sample1 <- data1[sample(N, 500),]
  sample0 <- data0[sample(N, 500),]
  sample <- rbind(sample1,sample0)

  model <- glm(y ~ x + z, family = binomial(link = "logit"), data = sample)

  beta0_vector[i] <- summary(model)$coefficients[1,1]
  beta1_vector[i] <- summary(model)$coefficients[2,1]
  beta2_vector[i] <- summary(model)$coefficients[3,1]
}

# investigate bias and uncertainty
beta0_hat_2cc <- mean(beta0_vector)
beta0_hat_2cc

## [1] -0.001832343

beta1_hat_2cc <- mean(beta1_vector)
beta1_hat_2cc

## [1] 1.009092

beta2_hat_2cc <- mean(beta2_vector)
beta2_hat_2cc

## [1] 0.5025666

beta0_sd_2cc <- sd(beta0_vector)
beta0_sd_2cc

## [1] 0.08580688

beta1_sd_2cc <- sd(beta1_vector)
beta1_sd_2cc

## [1] 0.236969

beta2_sd_2cc <- sd(beta2_vector)
beta2_sd_2cc

## [1] 0.100667

# when beta0 = -3
beta0_3cc <- -3

```

```

beta0_vector <- c(rep(NULL,num_iterations))
beta1_vector <- c(rep(NULL,num_iterations))
beta2_vector <- c(rep(NULL,num_iterations))

# Run the loop
for (i in 1:num_iterations) {

  y <- rbinom(N, 1, exp(beta0_3cc + beta1*x + beta2*z) / (1 + exp(beta0_3cc + beta1*x + beta2*z)))
  data <- data.frame(x=x, z=z, y=y)
  data1 <- data[data$y==1,]
  data0 <- data[data$y==0,]

  sample1 <- data1[sample(N, 500),]
  sample0 <- data0[sample(N, 500),]
  sample <- rbind(sample1,sample0)

  model <- glm(y ~ x + z, family = binomial(link = "logit"), data = sample)

  beta0_vector[i] <- summary(model)$coefficients[1,1]
  beta1_vector[i] <- summary(model)$coefficients[2,1]
  beta2_vector[i] <- summary(model)$coefficients[3,1]
}

# investigate bias and uncertainty
beta0_hat_3cc <- mean(beta0_vector)
beta0_hat_3cc

## [1] -3.047579

beta1_hat_3cc <- mean(beta1_vector)
beta1_hat_3cc

## [1] 1.019752

beta2_hat_3cc <- mean(beta2_vector)
beta2_hat_3cc

## [1] 0.511233

beta0_sd_3cc <- sd(beta0_vector)
beta0_sd_3cc

## [1] 0.2575465

beta1_sd_3cc <- sd(beta1_vector)
beta1_sd_3cc

## [1] 0.3726368

beta2_sd_3cc <- sd(beta2_vector)
beta2_sd_3cc

## [1] 0.1870315

```

Conclusion, based on different beta0 values, we find that the estimates of beta1 and beta2 are relatively fixed and close to the real value no matter the values of beta0, which means that they are unbiased. Meanwhile, the estimate of beta0 will be changed with the change of beta0 value, which is biased. The standard deviation of estimates are relatively fixed no matter the values of beta0, which is unbiased.

(d)

In the situation that number of values generated by random sampling simulation study is not balanced. For example, sometimes we have a lot of results with $Y=1$ but only a few results with $Y=0$. In such cases, we can use case control simulation study to reduce the uncertainty.

```

#### (e)
N <- 10000
num_iterations <- 2000
beta1 <- 1
beta2 <- 0.5
x <- rbinom(N,1,0.25)
z <- rnorm(N)

# use probit link
# when beta0 = -1
beta0_1pl <- -1
beta0_vector <- c(rep(NULL,num_iterations))
beta1_vector <- c(rep(NULL,num_iterations))
beta2_vector <- c(rep(NULL,num_iterations))

# Run the loop
for (i in 1:num_iterations) {

  y <- rbinom(N, 1, pnorm(beta0_1pl + beta1*x + beta2*z))
  data <- data.frame(x=x, z=z, y=y)
  data1 <- data[data$y==1,]
  data0 <- data[data$y==0,]

  sample1 <- data1[sample(N, 500),]
  sample0 <- data0[sample(N, 500),]
  sample <- rbind(sample1,sample0)

  model <- glm(y ~ x + z, family = binomial(link = "probit"), data = sample)

  beta0_vector[i] <- summary(model)$coefficients[1,1]
  beta1_vector[i] <- summary(model)$coefficients[2,1]
  beta2_vector[i] <- summary(model)$coefficients[3,1]
}

# investigate bias and uncertainty
beta0_hat_1pl <- mean(beta0_vector)
beta0_hat_1pl

## [1] -1.004929

beta1_hat_1pl <- mean(beta1_vector)
beta1_hat_1pl

## [1] 1.005478

beta2_hat_1pl <- mean(beta2_vector)
beta2_hat_1pl

## [1] 0.5046245

beta0_sd_1pl <- sd(beta0_vector)
beta0_sd_1pl

## [1] 0.07522873

```

```

beta1_sd_1pl <- sd(beta1_vector)
beta1_sd_1pl

## [1] 0.1464388

beta2_sd_1pl <- sd(beta2_vector)
beta2_sd_1pl

## [1] 0.07431727

# when beta0 = 0
beta0_2pl <- 0
beta0_vector <- c(rep(NULL,num_iterations))
beta1_vector <- c(rep(NULL,num_iterations))
beta2_vector <- c(rep(NULL,num_iterations))

# Run the loop
for (i in 1:num_iterations) {

  y <- rbinom(N, 1, pnorm(beta0_2pl + beta1*x + beta2*z))
  data <- data.frame(x=x, z=z, y=y)
  data1 <- data[data$y==1,]
  data0 <- data[data$y==0,]

  sample1 <- data1[sample(N, 500),]
  sample0 <- data0[sample(N, 500),]
  sample <- rbind(sample1,sample0)

  model <- glm(y ~ x + z, family = binomial(link = "probit"), data = sample)

  beta0_vector[i] <- summary(model)$coefficients[1,1]
  beta1_vector[i] <- summary(model)$coefficients[2,1]
  beta2_vector[i] <- summary(model)$coefficients[3,1]
}

# investigate bias and uncertainty
beta0_hat_2pl <- mean(beta0_vector)
beta0_hat_2pl

## [1] 0.001275068

beta1_hat_2pl <- mean(beta1_vector)
beta1_hat_2pl

## [1] 1.008934

beta2_hat_2pl <- mean(beta2_vector)
beta2_hat_2pl

## [1] 0.5044835

beta0_sd_2pl <- sd(beta0_vector)
beta0_sd_2pl

## [1] 0.05376338

beta1_sd_2pl <- sd(beta1_vector)
beta1_sd_2pl

```

```
## [1] 0.1557974
beta2_sd_2pl <- sd(beta2_vector)
beta2_sd_2pl

## [1] 0.06601984
# when beta0 = -3
beta0_3pl <- -3
beta0_vector <- c(rep(NULL,num_iterations))
beta1_vector <- c(rep(NULL,num_iterations))
beta2_vector <- c(rep(NULL,num_iterations))

# Run the loop
for (i in 1:num_iterations) {

  y <- rbinom(N, 1, pnorm(beta0_3pl + beta1*x + beta2*z))
  data <- data.frame(x=x, z=z, y=y)
  data1 <- data[data$y==1,]
  data0 <- data[data$y==0,]

  sample1 <- data1[sample(N, 500),]
  sample0 <- data0[sample(N, 500),]
  sample <- rbind(sample1,sample0)

  model <- glm(y ~ x + z, family = binomial(link = "probit"), data = sample)

  beta0_vector[i] <- summary(model)$coefficients[1,1]
  beta1_vector[i] <- summary(model)$coefficients[2,1]
  beta2_vector[i] <- summary(model)$coefficients[3,1]
}

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
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```


[illegible]

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```
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
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## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
```

```
# investigate bias and uncertainty
beta0_hat_3pl <- mean(beta0_vector)
beta0_hat_3pl
```

```
## [1] -4.247273
```

```
beta1_hat_3pl <- mean(beta1_vector)
beta1_hat_3pl
```

```
## [1] 2.001583
```

```
beta2_hat_3pl <- mean(beta2_vector)
beta2_hat_3pl
```

```
## [1] 0.5876529
```

```
beta0_sd_3pl <- sd(beta0_vector)
beta0_sd_3pl
```

```
## [1] 3.927422
```

```
beta1_sd_3pl <- sd(beta1_vector)
beta1_sd_3pl
```

```
## [1] 2.301005
```

```
beta2_sd_3pl <- sd(beta2_vector)
beta2_sd_3pl
```

```
## [1] 1.163747
```

Conclusion: The relationship we found by probit link is different with by logit link. As the value of beta0 decreases, the bias of beta1 and beta2's estimates get larger, which are unbiased. And the standard deviation get smaller actually, which are unbiased as well.