> # Exercise 1

> # Set a seed

> set.seed(008)

> # create X1 which is a vector of 10,000 draws from a uniform distribution with range 1:3.

> X1 <- as.vector(runif(10000, min = 1, max = 3))

> # create X2 which is a vector of 10,000 draws from a gamma distribution with shape 3 and scale 2

> X2 <- as.vector(rgamma(10000, shape = 3, scale = 2))

> # create X3 which is a vector of 10,000 draws from a binomial distribution with probability 0.3

> X3 <- as.vector(rbinom(10000, size = 1, prob = 0.3))

> # create eps which is a vector of 10,000 draws from a normal distribution with mean 2 and sd 1

> eps <- as.vector(rnorm(10000, mean = 2, sd = 1))

> # create Y and ydum

> Y <- as.vector(0.5 + 1.2\*X1 + -0.9\*X2 + 0.1\*X3 + eps)

> ydum <- as.matrix(as.numeric(Y>mean(Y)))

>

>

> # Exercise 2

> cor(Y, X1)

[1] 0.2021716

> # The output is 0.1452196, which is quite different from 1.2.

> # create a 10000\*1 vector of number 0.5

> X0 <- data.frame(num=1)

> X0 <- as.vector(X0[rep(1:nrow(X0), each=10000),])

> # combine the four vectors

> X <- cbind(X0, X1, X2, X3)

> # calculate the coefficient

> beta1 <- solve(t(X)%\*%X)%\*%t(X)%\*%Y

>

> # Calculate the estimator

> # s2 = (e'e)/n-k(the residual matrix/the degree of freedom), the data can be taken from the output above

> s2 <- as.numeric((t(eps)%\*%eps)/9996)

> # calculate covariance matrix and standard error

> X\_X <- t(X)%\*%X

> X\_X\_2 <- solve(X\_X)

> se\_b <- s2\*X\_X\_2

> se\_b <- sqrt(se\_b)

> # We only need the data on the diagonal

> se\_\_b <- rbind(se\_b[1,1], se\_b[2,2], se\_b[3,3], se\_b[4,4])

>

> # Bootstrap rep = 49

> # combine Y and X

> XY <- cbind(Y,1,X1,X2,X3)

> # create a 49\*4 matrix

> X\_boot <- matrix(c(0,0,0,0),nrow = 49,ncol = 4)

> # use for loop to resample 49 times, put the data into x\_boot

> for(y in 1:49){

+ i <- sample(1:10000, size = 10000, replace = TRUE)

+ Y <- as.matrix(XY[i,1])

+ X1 <- as.vector(XY[i,3])

+ X2 <- as.vector(XY[i,4])

+ X3 <- as.vector(XY[i,5])

+ X4 <- as.matrix(X1,X2,X3)

+ X\_boot[y,] <- solve(t(X4)%\*%X4)%\*%t(X4)%\*%Y

+ }

> sd\_boot <- as.vector(sd(X\_boot))

>

>

> # Bootstrap rep = 499

> # repeat the process above

> X\_boot2 <- matrix(c(0,0,0,0),nrow = 499,ncol = 4)

> for(y in 1:499){

+ i <- sample(1:10000, size = 10000, replace = TRUE)

+ Y <- as.vector(XY[i,1])

+ X1 <- as.vector(XY[i,3])

+ X2 <- as.vector(XY[i,4])

+ X3 <- as.vector(XY[i,5])

+ X4 <- as.matrix(X1,X2,X3)

+ X\_boot2[y,] <- solve(t(X4)%\*%X4)%\*%t(X4)%\*%Y

+ }

> sd\_boot2 <- as.vector(sd(X\_boot2))

>

>

> # exercise 3

> # get the log likelihood function

> est\_4 <- function(beta,x,y){

+ y <- sum(ydum\*log(pnorm(X%\*%beta))) + sum((1-ydum)\*log(1-pnorm(X%\*%beta)))

+ return(-y)

+ }

>

>

> # set an eps

> d <- 0.00000001

> # set an initial b

> b <- c(3, 1, -1, 0.05)

> # generate the matrix of b+eps

> bn <- as.matrix(cbind(b,b,b,b))

> bn2 <- diag(d, 4)

> bn3 <- bn + bn2

> # calculate the derivative of log likelihood function and determine the direction

> p1 <- (est\_4(bn3[,1])-est\_4(bn[,1]))/d

> p2 <- (est\_4(bn3[,2])-est\_4(bn[,2]))/d

> p3 <- (est\_4(bn3[,3])-est\_4(bn[,3]))/d

> p4 <- (est\_4(bn3[,4])-est\_4(bn[,4]))/d

> p <- as.vector(c(p1,p2,p3,p4))

> # give an initial change rate

> diff <- 1

> while(diff > 0.0001){

+ # generate a new b based on ak and dk, set initial ak = 0.000001

+ b0 <- matrix(b, ncol = 1)

+ b <- matrix(b + 0.000001\*p, ncol = 1)

+ # calculate the change rate of b

+ diff <- est\_4(b)-est\_4(b0)

+ }

>

> # print b

> b

[,1]

[1,] 2.93733490

[2,] 0.86951812

[3,] -1.35844067

[4,] 0.03191312

> # [,1]

> # [1,] 2.93733490

> # [2,] 0.86951812

> # [3,] -1.35844067

> # [4,] 0.03191312

> # The estimated coefficient of X2 is more different from that in true parameters, compared with the others.

>

>

>

> # exercise 4

> # write the log likelihood function of logit model

> logit\_log <- function(beta, x, y){

+ y <- sum(ydum\*log(exp(X%\*%beta)/(1+exp(X%\*%beta)))) + sum((1-ydum)\*log(1-exp(X%\*%beta)/(1+exp(X%\*%beta))))

+ return(-y)

+ }

> # use optimize function to get the MLE

> xmin\_log <- optim(c(0,0,0,0), logit\_log, x = X, y = ydum)$par

> # use glm function to check the result, the two results are same

> ydumX <- as.data.frame(cbind(ydum, X))

> logit <- glm(ydum ~ 0 + X, family=binomial(link="logit"), data=ydumX)

> summary(logit)

Call:

glm(formula = ydum ~ 0 + X, family = binomial(link = "logit"),

data = ydumX)

Deviance Residuals:

Min 1Q Median 3Q Max

-3.4351 -0.1430 0.0394 0.2609 3.2958

Coefficients:

Estimate Std. Error z value Pr(>|z|)

XX0 5.30949 0.18634 28.494 <2e-16 \*\*\*

XX1 2.22403 0.08216 27.071 <2e-16 \*\*\*

XX2 -1.61703 0.03672 -44.040 <2e-16 \*\*\*

XX3 0.05262 0.08566 0.614 0.539

---

Signif. codes: 0 ‘\*\*\*’ 0.001 ‘\*\*’ 0.01 ‘\*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 13862.9 on 10000 degrees of freedom

Residual deviance: 4315.5 on 9996 degrees of freedom

AIC: 4323.5

Number of Fisher Scoring iterations: 7

> # glm(formula = ydum ~ 0 + X, family = binomial(link = "logit"),

> # data = ydumX)

> #

> # Deviance Residuals:

> # Min 1Q Median 3Q Max

> # -3.4351 -0.1430 0.0394 0.2609 3.2958

> #

> # Coefficients:

> # Estimate Std. Error z value Pr(>|z|)

> # XX0 5.30949 0.18634 28.494 <2e-16 \*\*\*

> # XX1 2.22403 0.08216 27.071 <2e-16 \*\*\*

> # XX2 -1.61703 0.03672 -44.040 <2e-16 \*\*\*

> # XX3 0.05262 0.08566 0.614 0.539

> # ---

> # Signif. codes: 0 ‘\*\*\*’ 0.001 ‘\*\*’ 0.01 ‘\*’ 0.05 ‘.’ 0.1 ‘ ’ 1

> #

> # (Dispersion parameter for binomial family taken to be 1)

> #

> # Null deviance: 13862.9 on 10000 degrees of freedom

> # Residual deviance: 4315.5 on 9996 degrees of freedom

> # AIC: 4323.5

> #

> # Number of Fisher Scoring iterations: 7

>

> # interpretation

> # 2.22403 is positive, which means that the probability of success will increase when x1 = 1

> # -1.61703 is negative, which means that the probability of success will decrease when x2 = 1

> # 0.05262 is positive, which means that the probability of success will increase when x3 = 1

> # "\*\*\*" in the summarty means that the estimation of X1 and X2 are signigicant, while that of X3 is not quite significant.

>

> # repeat the process above

> xmin\_pro <- optim(c(0,0,0,0), est\_4, x = X, y = ydum)$par

> probit <- glm(ydum ~ 0 + X, family=binomial(link="probit"), data=ydumX)

> summary(probit)

Call:

glm(formula = ydum ~ 0 + X, family = binomial(link = "probit"),

data = ydumX)

Deviance Residuals:

Min 1Q Median 3Q Max

-3.8746 -0.1081 0.0087 0.2525 3.6264

Coefficients:

Estimate Std. Error z value Pr(>|z|)

XX0 2.92587 0.09857 29.683 <2e-16 \*\*\*

XX1 1.23282 0.04383 28.129 <2e-16 \*\*\*

XX2 -0.89277 0.01818 -49.118 <2e-16 \*\*\*

XX3 0.02977 0.04750 0.627 0.531

---

Signif. codes: 0 ‘\*\*\*’ 0.001 ‘\*\*’ 0.01 ‘\*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 13862.9 on 10000 degrees of freedom

Residual deviance: 4314.1 on 9996 degrees of freedom

AIC: 4322.1

Number of Fisher Scoring iterations: 7

> # glm(formula = ydum ~ 0 + X, family = binomial(link = "probit"),

> # data = ydumX)

> #

> # Deviance Residuals:

> # Min 1Q Median 3Q Max

> # -3.8746 -0.1081 0.0087 0.2525 3.6264

> #

> # Coefficients:

> # Estimate Std. Error z value Pr(>|z|)

> # XX0 2.92587 0.09857 29.683 <2e-16 \*\*\*

> # XX1 1.23282 0.04383 28.129 <2e-16 \*\*\*

> # XX2 -0.89277 0.01818 -49.118 <2e-16 \*\*\*

> # XX3 0.02977 0.04750 0.627 0.531

> # ---

> # Signif. codes: 0 ‘\*\*\*’ 0.001 ‘\*\*’ 0.01 ‘\*’ 0.05 ‘.’ 0.1 ‘ ’ 1

> #

> # (Dispersion parameter for binomial family taken to be 1)

> #

> # Null deviance: 13862.9 on 10000 degrees of freedom

> # Residual deviance: 4314.1 on 9996 degrees of freedom

> # AIC: 4322.1

> #

> # Number of Fisher Scoring iterations: 7

>

> # interpretation

> # 1.23282 is positive, which means that the probability of success will increase when x1 = 1

> # -0.89277 is negative, which means that the probability of success will decrease when x2 = 1

> # 0.02977 is positive, which means that the probability of success will increase when x3 = 1

> # "\*\*\*" in the summarty means that the estimation of X1 and X2 are signigicant, while that of X3 is not quite significant.

> # Logit and probit models yield almost the same result.

>

>

> linear\_probability <- lm(ydum~0 + X, data=ydumX)

> summary(linear\_probability)

Call:

lm(formula = ydum ~ 0 + X, data = ydumX)

Residuals:

Min 1Q Median 3Q Max

-0.94585 -0.26742 0.05788 0.24721 2.02094

Coefficients:

Estimate Std. Error t value Pr(>|t|)

XX0 0.8868259 0.0133142 66.608 <2e-16 \*\*\*

XX1 0.1501367 0.0056936 26.370 <2e-16 \*\*\*

XX2 -0.1038651 0.0009539 -108.879 <2e-16 \*\*\*

XX3 0.0059472 0.0072690 0.818 0.413

---

Signif. codes: 0 ‘\*\*\*’ 0.001 ‘\*\*’ 0.01 ‘\*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.3306 on 9996 degrees of freedom

Multiple R-squared: 0.8064, Adjusted R-squared: 0.8063

F-statistic: 1.041e+04 on 4 and 9996 DF, p-value: < 2.2e-16

> # lm(formula = ydum ~ 0 + X, data = ydumX)

> #

> # Residuals:

> # Min 1Q Median 3Q Max

> # -0.94585 -0.26742 0.05788 0.24721 2.02094

> #

> # Coefficients:

> # Estimate Std. Error t value Pr(>|t|)

> # XX0 0.8868259 0.0133142 66.608 <2e-16 \*\*\*

> # XX1 0.1501367 0.0056936 26.370 <2e-16 \*\*\*

> # XX2 -0.1038651 0.0009539 -108.879 <2e-16 \*\*\*

> # XX3 0.0059472 0.0072690 0.818 0.413

> # ---

> # Signif. codes: 0 ‘\*\*\*’ 0.001 ‘\*\*’ 0.01 ‘\*’ 0.05 ‘.’ 0.1 ‘ ’ 1

> #

> # Residual standard error: 0.3306 on 9996 degrees of freedom

> # Multiple R-squared: 0.8064, Adjusted R-squared: 0.8063

> # F-statistic: 1.041e+04 on 4 and 9996 DF, p-value: < 2.2e-16

>

> # interpretation

> # Since X1 is continuous, 0.1501 is the change in the probability of success given one unit increase in x1.

> # Since X2 is continuous, 0.1501 is the change in the probability of success given one unit increase in x2.

> # Since X3 is discrete, 0.0059 is the difference in the probability of success when x3 = 1 and x3 = 0, holding other xj fixed. It seems that X3 almost doesn't impact the probability.

> # "\*\*\*" in the summarty means that the estimation of X1 and X2 are signigicant, while that of X3 is not quite significant.

>

> # exercise 5

>

> # write the derivative of function of logit

> est\_5 <- function(x){

+ y <- exp(x)/(1+exp(x))^2

+ return(y)

+ }

>

>

> est\_6 <- function(beta){

+ # calculate the mean of the X\*beta and f'(mean(XB))

+ y1 <- X%\*%beta

+ y2 <- mean(y1)

+ # calculate the marginal effect

+ y3 <- est\_5(y2)\*beta

+ y <- as.matrix(y3)

+ return(y)

+ }

>

> # run the result of Q4

> beta3 <- matrix(c(5.30949, 2.22403, -1.61703, 0.05262), ncol = 1)

> me1 <- est\_6(beta3)

>

>

> # repeat the process above, but in this case, we calculate the detivative theoretically

> est\_7 <- function(beta){

+ y1 <- X%\*%beta

+ y2 <- mean(y1)

+ p1 <- dnorm(y2)

+ y <- p1\*beta

+ y <- as.matrix(y)

+ return(y)

+ }

>

> beta4 <- matrix(c(2.86589, 1.22988, -0.88943, 0.09990), ncol = 1)

> me2 <- est\_7(beta4)

>

> # calculate the standard deviations using the delta method

> # generate the Jacobian matrix, calculate each partial derivative

> est\_8 <- function(beta){

+ # calculate the mean of the X\*beta and f'(mean(XB))

+ y1 <- X%\*%beta

+ y2 <- mean(y1)

+ # calculate the marginal effect

+ y3 <- est\_5(y2)\*beta[1,]

+ return(y3)

+ }

>

> # write the similar functions to calculate the marginal effects respective to beta1, 2, 3 and 4

> # Let's call them ME1\_l, ME2\_l, ME3\_l, ME4\_l

> est\_9 <- function(beta){

+ y1 <- X%\*%beta

+ y2 <- mean(y1)

+ y3 <- est\_5(y2)\*beta[2,]

+ return(y3)

+ }

>

> est\_10 <- function(beta){

+ y1 <- X%\*%beta

+ y2 <- mean(y1)

+ y3 <- est\_5(y2)\*beta[3,]

+ return(y3)

+ }

>

> est\_11 <- function(beta){

+ y1 <- X%\*%beta

+ y2 <- mean(y1)

+ y3 <- est\_5(y2)\*beta[4,]

+ return(y3)

+ }

>

> # calculate the partial derivative of ME1\_l repective to beta1

> beta5 <- matrix(c(5.30950, 2.22403, -1.61703, 0.05262), ncol = 1)

> logit\_11 <- (est\_8(beta3)-est\_8(beta5))/0.00001

> # calculate the partial derivative of ME1\_l repective to beta2

> beta6 <- matrix(c(5.30949, 2.22404, -1.61703, 0.05262), ncol = 1)

> logit\_12 <- (est\_8(beta3)-est\_8(beta6))/0.00001

> # calculate the partial derivative of ME1\_l repective to beta3

> beta7 <- matrix(c(5.30949, 2.22403, -1.61702, 0.05262), ncol = 1)

> logit\_13 <- (est\_8(beta3)-est\_8(beta7))/0.00001

> # calculate the partial derivative of ME1\_l repective to beta4

> beta8 <- matrix(c(5.30949, 2.22403, -1.61703, 0.05263), ncol = 1)

> logit\_14 <- (est\_8(beta3)-est\_8(beta8))/0.00001

> # generate the first row of the Jacobian matrix of logit model

> logit\_1 <- t(as.matrix(c(logit\_11, logit\_12, logit\_13, logit\_14)))

>

> # repeat the process above to generate the second line of this matrix

> logit\_21 <- (est\_9(beta3)-est\_9(beta5))/0.00001

> logit\_22 <- (est\_9(beta3)-est\_9(beta6))/0.00001

> logit\_23 <- (est\_9(beta3)-est\_9(beta7))/0.00001

> logit\_24 <- (est\_9(beta3)-est\_9(beta8))/0.00001

> logit\_2 <- t(as.matrix(c(logit\_21, logit\_22, logit\_23, logit\_24)))

>

> # repeat the process above to generate the third line of this matrix

> logit\_31 <- (est\_10(beta3)-est\_10(beta5))/0.00001

> logit\_32 <- (est\_10(beta3)-est\_10(beta6))/0.00001

> logit\_33 <- (est\_10(beta3)-est\_10(beta7))/0.00001

> logit\_34 <- (est\_10(beta3)-est\_10(beta8))/0.00001

> logit\_3 <- t(as.matrix(c(logit\_31, logit\_32, logit\_33, logit\_34)))

>

> # repeat the process above to generate the fourth line of this matrix

> logit\_41 <- (est\_11(beta3)-est\_11(beta5))/0.00001

> logit\_42 <- (est\_11(beta3)-est\_11(beta6))/0.00001

> logit\_43 <- (est\_11(beta3)-est\_11(beta7))/0.00001

> logit\_44 <- (est\_11(beta3)-est\_11(beta8))/0.00001

> logit\_4 <- t(as.matrix(c(logit\_41, logit\_42, logit\_43, logit\_44)))

>

> # generate the whole Jacobian matrix

> logit\_j <- as.matrix(rbind(logit\_1, logit\_2, logit\_3, logit\_4))

>

> # calculate the sd of logit model: the sd of the diagonal of J(T)\*vcovmatrix\*J

> sd\_delta\_logit <- solve(logit\_j)%\*%vcov(logit)%\*%logit\_j

> sd\_delta\_logit <- sd(rbind(sd\_delta\_logit[1,1], sd\_delta\_logit[2,2], sd\_delta\_logit[3,3], sd\_delta\_logit[4,4]))

>

>

> # write the similar functions to calculate the marginal effects respective to beta1, 2, 3 and 4

> # Let's call them ME1\_p, ME2\_p, ME3\_p, ME4\_p

> est\_12 <- function(beta){

+ y1 <- X%\*%beta

+ y2 <- mean(y1)

+ p1 <- dnorm(y2)

+ y <- p1\*beta[1,]

+ return(y)

+ }

>

> est\_13 <- function(beta){

+ y1 <- X%\*%beta

+ y2 <- mean(y1)

+ p1 <- dnorm(y2)

+ y <- p1\*beta[2,]

+ return(y)

+ }

>

> est\_14 <- function(beta){

+ y1 <- X%\*%beta

+ y2 <- mean(y1)

+ p1 <- dnorm(y2)

+ y <- p1\*beta[3,]

+ return(y)

+ }

>

> est\_15 <- function(beta){

+ y1 <- X%\*%beta

+ y2 <- mean(y1)

+ p1 <- dnorm(y2)

+ y <- p1\*beta[4,]

+ return(y)

+ }

>

> # calculate the partial derivative of ME1\_p repective to beta1

> beta9 <- matrix(c(2.86590, 1.22988, -0.88943, 0.09990), ncol = 1)

> probit\_11 <- (est\_12(beta4)-est\_12(beta9))/0.00001

> # calculate the partial derivative of ME1\_p repective to beta2

> beta10 <- matrix(c(2.86589, 1.22989, -0.88943, 0.09990), ncol = 1)

> probit\_12 <- (est\_12(beta4)-est\_12(beta10))/0.00001

> # calculate the partial derivative of ME1\_p repective to beta3

> beta11 <- matrix(c(2.86589, 1.22988, -0.88942, 0.09990), ncol = 1)

> probit\_13 <- (est\_12(beta4)-est\_12(beta11))/0.00001

> # calculate the partial derivative of ME1\_p repective to beta4

> beta12 <- matrix(c(2.86589, 1.22988, -0.88943, 0.09991), ncol = 1)

> probit\_14 <- (est\_12(beta4)-est\_12(beta12))/0.00001

> # generate the first row of the Jacobian matrix of probit model

> probit\_1 <- t(as.matrix(c(probit\_11, probit\_12, probit\_13, probit\_14)))

>

> # repeat the process above to generate the second line of this matrix

> probit\_21 <- (est\_13(beta4)-est\_13(beta9))/0.00001

> probit\_22 <- (est\_13(beta4)-est\_13(beta10))/0.00001

> probit\_23 <- (est\_13(beta4)-est\_13(beta11))/0.00001

> probit\_24 <- (est\_13(beta4)-est\_13(beta12))/0.00001

> probit\_2 <- t(as.matrix(c(probit\_21, probit\_22, probit\_23, probit\_24)))

>

> # repeat the process above to generate the third line of this matrix

> probit\_31 <- (est\_14(beta4)-est\_14(beta9))/0.00001

> probit\_32 <- (est\_14(beta4)-est\_14(beta10))/0.00001

> probit\_33 <- (est\_14(beta4)-est\_14(beta11))/0.00001

> probit\_34 <- (est\_14(beta4)-est\_14(beta12))/0.00001

> probit\_3 <- t(as.matrix(c(probit\_31, probit\_32, probit\_33, probit\_34)))

>

> # repeat the process above to generate the fourth line of this matrix

> probit\_41 <- (est\_15(beta4)-est\_15(beta9))/0.00001

> probit\_42 <- (est\_15(beta4)-est\_15(beta10))/0.00001

> probit\_43 <- (est\_15(beta4)-est\_15(beta11))/0.00001

> probit\_44 <- (est\_15(beta4)-est\_15(beta12))/0.00001

> probit\_4 <- t(as.matrix(c(probit\_41, probit\_42, probit\_43, probit\_44)))

>

> # generate the whole Jacobian matrix

> probit\_j <- as.matrix(rbind(probit\_1, probit\_2, probit\_3, probit\_4))

>

> # calculate the sd of probit model: the sd of the diagonal of J(T)\*vcovmatrix\*J

> sd\_delta\_probit <- solve(probit\_j)%\*%vcov(probit)%\*%probit\_j

> sd\_delta\_probit <- sd(rbind(sd\_delta\_probit[1,1], sd\_delta\_probit[2,2], sd\_delta\_probit[3,3], sd\_delta\_probit[4,4]))

>

>

> # calculate the standard deviations using bootstrap

> # set an empty matrix to turn in data

> me\_bootlogit <- matrix(c(0,0,0,0),nrow = 450, ncol = 4)

> for(r in 1:450){

+ # use bootstrap to generate data for 10000 times

+ i <- sample(1:10000, size = 10000, replace = TRUE)

+ Y <- as.matrix(ydum[i,])

+ X0 <- as.vector(XY[i,2])

+ X1 <- as.vector(XY[i,3])

+ X2 <- as.vector(XY[i,4])

+ X3 <- as.vector(XY[i,5])

+ X4 <- as.data.frame(cbind(Y,X0,X1,X2,X3))

+ # calculate the coefficient of logit model, then calculate the marginal effect

+ betaend <- as.matrix(c(glm(V1 ~ 0 + X, family=binomial(link="logit"), data=X4)$coef))

+ me\_bootstraplogit <- est\_6(betaend)

+ me\_bootstraplogit <- t(me\_bootstraplogit)

+ # put the data into the empty matrix

+ me\_bootlogit[r,] <- me\_bootstraplogit

+ }

> # calculate sd

> sd\_boot\_logit <- as.vector(sd(me\_bootlogit))

>

>

> # repeat the process above for probit model

> me\_bootprobit <- matrix(c(0,0,0,0),nrow = 450, ncol = 4)

> for(r in 1:450){

+ i <- sample(1:10000, size = 10000, replace = TRUE)

+ Y <- as.matrix(ydum[i,])

+ X0 <- as.vector(XY[i,2])

+ X1 <- as.vector(XY[i,3])

+ X2 <- as.vector(XY[i,4])

+ X3 <- as.vector(XY[i,5])

+ X4 <- as.data.frame(cbind(Y,X0,X1,X2,X3))

+ betaend2 <- as.matrix(c(glm(V1 ~ 0 + X, family=binomial(link="probit"), data=X4)$coef))

+ me\_bootstrapprobit <- est\_7(betaend2)

+ me\_bootstrapprobit <- t(me\_bootstrapprobit)

+ me\_bootprobit[r,] <- me\_bootstrapprobit

+ }

> sd\_boot\_probit <- as.vector(sd(me\_bootprobit))