

```

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> ##Date: 02/03/2022
> ##Purpose: Econ 613 Assignment 2
>
> #####
> ##    Question 1    ##
> #####
> require(tidyverse)
> #X: the age of individuals plus intercept
> #Y: Wage
> #Import data
> datind2009 <- read.csv("~/Desktop/Duke study/Econ613/A2/datind2009.csv")
>
> ##1. Calculate the correlation between Y and X
> cor(datind2009$age, datind2009$wage, use = "complete.obs")
[1] -0.1788512
>
>
> ##2. Calculate the coefficients on this regression. remember
> #Beta =  $(X'X)^{-1}X'Y$ 
> datind2009_nona <- datind2009 %>% select(age, wage) %>% drop_na()
> age <- as.matrix(datind2009_nona$age)
> one <- rep(1, length(datind2009_nona$age))
> dim(one) <- c(length(datind2009_nona$age), 1)
> X <- cbind(one, age)
> Y <- as.matrix(datind2009_nona$wage)
> beta <- solve(t(X)%*%X)%*%t(X)%*%Y
> beta
      [,1]
[1,] 22075.1066
[2,] -180.1765
>
>
> ##3.1 Calculate the standard errors of beta
> Y_hat <- X%*%beta
> residual <- Y - Y_hat
> sigma_square <- (t(residual)%*%residual)/length(residual)-2
> SE_beta <- sigma_square[1,1]*solve(t(X)%*%X)
> SE_constant <- sqrt(SE_beta[1,1])
> SE_beta <- sqrt(SE_beta[2,2])
> SE_constant

```

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[1] 357.8098
> SE_beta
[1] 6.968308
>
> ##3.2 Using bootstrap with 49 and 499 replications respectively. Comment on the difference between
> #the two strategies.
>
> #49 replications
> num <- 1:49
> data <- cbind(Y, X)
> colnames(data) <- c("wage", "one", "age")
> result <- matrix(1, nrow = 49, ncol = 2)
> for (i in num) {
+   sample <- data[sample(nrow(data), 10000), ]
+   beta <- solve(t(sample[,2:3]))%*%sample[,2:3])%*%t(sample[,2:3])%*%sample[,1]
+   result[i,1] <- beta[1,1]
+   result[i,2] <- beta[2,1]
+ }
> #bootstrap constant: 49 replication
> mean(result[,1])
[1] 22085.7
> #bootstrap beta
> mean(result[,2])
[1] -180.6486
>
> #499 replications
> num <- 1:499
> result <- matrix(1, nrow = 499, ncol = 2)
> for (i in num) {
+   sample <- data[sample(nrow(data), 10000), ]
+   beta <- solve(t(sample[,2:3]))%*%sample[,2:3])%*%t(sample[,2:3])%*%sample[,1]
+   result[i,1] <- beta[1,1]
+   result[i,2] <- beta[2,1]
+ }
> #bootstrap constant: 499 replication
> mean(result[,1])
[1] 22097.94
> #bootstrap beta: 499 replication
> mean(result[,2])
[1] -180.499
>

```

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> #####
> ##      Question 2      ##
> #####
> #Import data
> rm(list = ls())
> datind_file <- list.files(pattern = "^datind")
> datind_combined <- read.csv(datind_file[1])
> datind_file <- datind_file[-1]
> for(file in datind_file){
+   csv <- read.csv(file)
+   datind_combined <- rbind(datind_combined, csv)
+ }
> datind_combined_2005_2018 <- datind_combined %>% as_tibble() %>% filter(year>2004&year<2019)
>
> ##1.Create a categorical variable ag, which bins the age variables into the following groups: "18-25", "26-
> #30", "31-35", "36-40","41-45", "46-50","51-55", "56-60", and "60+".
> datind_combined_2005_2018 <- datind_combined_2005_2018 %>% mutate(ag = as.factor(ifelse(18 <=
datind_combined_2005_2018$age & datind_combined_2005_2018$age<= 25 , '18-25',
+
ifelse(26 <= datind_combined_2005_2018$age & datind_combined_2005_2018$age<= 30, '26-30',
+
ifelse(31 <= datind_combined_2005_2018$age & datind_combined_2005_2018$age<= 35, '31-35',
+
ifelse(36 <= datind_combined_2005_2018$age & datind_combined_2005_2018$age<= 40, '36-40',
+
ifelse(41 <= datind_combined_2005_2018$age & datind_combined_2005_2018$age<= 45, "41-45",
+
ifelse(46 <= datind_combined_2005_2018$age & datind_combined_2005_2018$age<= 50, "46-50",
+
ifelse(51 <= datind_combined_2005_2018$age & datind_combined_2005_2018$age<= 55, "51-55",
+
ifelse(56 <= datind_combined_2005_2018$age & datind_combined_2005_2018$age<= 60, "56-60",
"60+")))))))))))
>
>
> ##2.Plot the wage of each age group across years. Is there a trend?
> plot(datind_combined_2005_2018$ag, datind_combined_2005_2018$wage)
> #trend: with age increasing, wage concentrates on higher income
>
> ##3.Fixed effect model
> #we use fast dummy package to create time fixed effect dummy

```

```

> #install.packages("fastDummies")
> require(fastDummies)
> datind_combined_2005_2018 <- dummy_cols(datind_combined_2005_2018,select_columns = "year")
> data <- datind_combined_2005_2018 %>% select(wage, age, year_2005:year_2018) %>% drop_na()
> X <- as.matrix(select(data, age, year_2005:year_2018))
> Y <- as.matrix(select(data, wage))
> results <- solve(t(X)%*%X)%*%t(X)%*%Y
> results

```

```

          wage
age      -186.8793
year_2005 20675.0583
year_2006 20696.9955
year_2007 20969.8609
year_2008 22100.2489
year_2009 22395.4188
year_2010 22544.5834
year_2011 22791.0759
year_2012 23276.2858
year_2013 23153.9017
year_2014 23424.7333
year_2015 23796.0275
year_2016 24085.1717
year_2017 24154.0902
year_2018 24311.2098

```

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> #the OLS results underestimate the coefficient of age

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> #####

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> ##      Question3      ##

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> #####

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> datind_2007 <- read.csv("~/Desktop/Duke study/Econ613/A2/datind2007.csv")

```

```

> datind_2007_tbl <- datind_2007 %>% as_tibble()

```

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>

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```

> ##1. exclude inactive respondents

```

```

> datind_2007_wage_age <- datind_2007_tbl %>% select(wage, age, empstat) %>% drop_na()

```

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> ##2.

```

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> # Decide feature and label

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```

> df_tbl <- datind_2007_wage_age %>% select(empstat, age, wage) %>% drop_na()

```

```

> df_tbl <- df_tbl %>% mutate(employ_dummy = ifelse(df_tbl$empstat == "employed", 1,0))

```

```

> X <- as.matrix(df_tbl$age)
> Y <- as.matrix(df_tbl$employ_dummy)
>
> # Likelihood Function
> Likelihood <- function(X = X, y = Y, beta){
+   num <- 1:length(X)
+   L = 0
+   for (i in num) {
+     x_i = X[i,]
+     y_i = y[i]
+     L = L * ((pnorm(x_i%%beta,0,1))^y_i) * ((1- pnorm(x_i%%beta,0,1))^(1-y_i))
+   }
+   return(L)
+ }
>
>
>
>
> #####
> ## Question4 ``##
> #####
> ##Exclude all individuals who are inactive.
> datind_2005_2015 <- datind_combined %>% filter(year >= 2005 & year <= 2015)
> datind_2005_2015 <- dummy_cols(datind_2005_2015,select_columns = "year") %>% select(age, empstat,
year) %>% drop_na()
> #empstat: individual's participation in the labor market
> df <- datind_2005_2015 %>%mutate(employ_dummy = ifelse(datind_2005_2015$empstat == "Employed",
1,0), year_factor = as.factor(year))
>
> ##Write and optimize the probit, logit, and the linear probability models.
> ##OLS, probit, logit
> require(glm2)
>
> #LPM
> LPM <- lm(employ_dummy~age + year_factor, data = df)
> summary(LPM)

```

Call:

```
lm(formula = employ_dummy ~ age + year_factor, data = df)
```

Residuals:

	Min	1Q	Median	3Q	Max
	-0.4929	-0.4173	-0.3563	0.5907	0.6461

Coefficients:

	Estimate	Std. Error	t value	Pr(> t )
(Intercept)	3.489e-01	3.471e-03	100.506	< 2e-16 ***
age	1.373e-03	3.894e-05	35.261	< 2e-16 ***
year_factor2006	-1.701e-03	4.410e-03	-0.386	0.699620
year_factor2007	2.001e-03	4.369e-03	0.458	0.646869
year_factor2008	6.683e-03	4.385e-03	1.524	0.127553
year_factor2009	-2.250e-03	4.381e-03	-0.514	0.607552
year_factor2010	-3.187e-03	4.344e-03	-0.734	0.463139
year_factor2011	1.164e-03	4.324e-03	0.269	0.787694
year_factor2012	-1.080e-03	4.272e-03	-0.253	0.800431
year_factor2013	-1.043e-02	4.352e-03	-2.396	0.016584 *
year_factor2014	-1.070e-02	4.336e-03	-2.468	0.013594 *
year_factor2015	-1.558e-02	4.342e-03	-3.589	0.000331 ***

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

Residual standard error: 0.4889 on 288115 degrees of freedom

Multiple R-squared: 0.004407, Adjusted R-squared: 0.004369

F-statistic: 115.9 on 11 and 288115 DF, p-value: < 2.2e-16

> #probit

> Probit <- glm(employ\_dummy~age + year\_factor, data = df, family = binomial(link = "probit"))

> summary(Probit)

Call:

glm(formula = employ\_dummy ~ age + year\_factor, family = binomial(link = "probit"),  
data = df)

Deviance Residuals:

	Min	1Q	Median	3Q	Max
	-1.1759	-1.0405	-0.9348	1.3368	1.4451

Coefficients:

	Estimate	Std. Error	z value	Pr(> z )
(Intercept)	-0.3953542	0.0090318	-43.774	< 2e-16 ***
age	0.0037591	0.0001012	37.133	< 2e-16 ***
year_factor2006	-0.0044737	0.0114527	-0.391	0.696075

year_factor2007	0.0051530	0.0113415	0.454	0.649574
year_factor2008	0.0172643	0.0113781	1.517	0.129182
year_factor2009	-0.0059321	0.0113782	-0.521	0.602115
year_factor2010	-0.0084036	0.0112829	-0.745	0.456387
year_factor2011	0.0028293	0.0112239	0.252	0.800982
year_factor2012	-0.0030504	0.0110900	-0.275	0.783274
year_factor2013	-0.0273775	0.0113113	-2.420	0.015505 *
year_factor2014	-0.0281670	0.0112681	-2.500	0.012429 *
year_factor2015	-0.0409693	0.0112899	-3.629	0.000285 ***

---

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

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 387903 on 288126 degrees of freedom  
 Residual deviance: 386562 on 288115 degrees of freedom  
 AIC: 386586

Number of Fisher Scoring iterations: 4

```
> #logit
> Logit <- glm(employ_dummy~age + year_factor, data = df, family = binomial(link = "logit"))
> summary(Logit)
```

Call:

```
glm(formula = employ_dummy ~ age + year_factor, family = binomial(link = "logit"),
     data = df)
```

Deviance Residuals:

Min	1Q	Median	3Q	Max
-1.1691	-1.0389	-0.9393	1.3373	1.4405

Coefficients:

	Estimate	Std. Error	z value	Pr(> z )
(Intercept)	-0.6204247	0.0145623	-42.605	< 2e-16 ***
age	0.0057317	0.0001631	35.135	< 2e-16 ***
year_factor2006	-0.0071359	0.0184455	-0.387	0.698856
year_factor2007	0.0083168	0.0182600	0.455	0.648776
year_factor2008	0.0277757	0.0183116	1.517	0.129308
year_factor2009	-0.0094823	0.0183242	-0.517	0.604827
year_factor2010	-0.0134115	0.0181714	-0.738	0.460481

```

year_factor2011 0.0047471 0.0180693 0.263 0.792771
year_factor2012 -0.0046276 0.0178567 -0.259 0.795517
year_factor2013 -0.0437949 0.0182267 -2.403 0.016271 *
year_factor2014 -0.0449385 0.0181566 -2.475 0.013322 *
year_factor2015 -0.0655199 0.0181991 -3.600 0.000318 ***

```

---

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

(Dispersion parameter for binomial family taken to be 1)

```

Null deviance: 387903 on 288126 degrees of freedom
Residual deviance: 386632 on 288115 degrees of freedom
AIC: 386656

```

Number of Fisher Scoring iterations: 4

```

>
> ## Interpret and compare the estimated coefficients. How significant are they?
> # All model's coefficient are statistically significant at 5 % level, but the linear probability model
> # returns the extremely small coefficient. In conclusion, age is positively correlated with employment
> # Older people are more likely to get a job.
>
>
> #####
> ##      Question 5      ##
> #####
> #install.packages("ggeffects")
> #install.packages("prediction")
> require(ggeffects, prediction)
>
>
> ## Marginal effects
> #LPM
> LPM_effects <- ggpredict(LPM, "age")
> LPM_effects
# Predicted values of employ_dummy

```

age   Predicted	95% CI
-5	0.34   [0.34, 0.35]
10	0.36   [0.36, 0.37]

-----



20	0.38   [0.37, 0.38]
35	0.40   [0.39, 0.40]
50	0.42   [0.41, 0.42]
65	0.44   [0.43, 0.44]
80	0.46   [0.45, 0.47]
105	0.49   [0.49, 0.50]

Adjusted for:

\* year\_factor = 2005

> #Probit

> Probit\_effects <- ggpredict(Probit, "age")

Data were 'prettified'. Consider using `terms="age [all]"` to get smooth plots.

> Probit\_effects

# Predicted probabilities of employ\_dummy

age   Predicted	95% CI
-----	
-5	0.34   [0.33, 0.35]
10	0.36   [0.35, 0.37]
20	0.37   [0.37, 0.38]
35	0.40   [0.39, 0.40]
50	0.42   [0.41, 0.42]
65	0.44   [0.43, 0.45]
80	0.46   [0.46, 0.47]
105	0.50   [0.49, 0.51]

Adjusted for:

\* year\_factor = 2005

> #Logit

> Logit\_effects <- ggpredict(Logit, "age")

Data were 'prettified'. Consider using `terms="age [all]"` to get smooth plots.

> Logit\_effects

# Predicted probabilities of employ\_dummy

age   Predicted	95% CI
-----	
-5	0.34   [0.34, 0.35]
10	0.36   [0.36, 0.37]
20	0.38   [0.37, 0.38]
35	0.40   [0.39, 0.40]
50	0.42   [0.41, 0.42]

65	0.44   [0.43, 0.45]
80	0.46   [0.45, 0.47]
105	0.50   [0.49, 0.50]

Adjusted for:

\* year\_factor = 2005

>

> ##Standard error of marginal effects

> #LPM

> SD\_LPM\_effects <- cbind(as.matrix(LPM\_effects)[,1], as.matrix(LPM\_effects)[,3])

> SD\_LPM\_effects

      [,1]  [,2]

[1,] " -5" "0.003558843"

[2,] "  0" "0.003471461"

[3,] "  5" "0.003393014"

[4,] " 10" "0.003324135"

[5,] " 15" "0.003265428"

[6,] " 20" "0.003217450"

[7,] " 25" "0.003180688"

[8,] " 30" "0.003155532"

[9,] " 35" "0.003142263"

[10,] " 40" "0.003141030"

[11,] " 45" "0.003151848"

[12,] " 50" "0.003174593"

[13,] " 55" "0.003209012"

[14,] " 60" "0.003254735"

[15,] " 65" "0.003311292"

[16,] " 70" "0.003378141"

[17,] " 75" "0.003454684"

[18,] " 80" "0.003540292"

[19,] " 85" "0.003634324"

[20,] " 90" "0.003736145"

[21,] " 95" "0.003845136"

[22,] "100" "0.003960705"

[23,] "105" "0.004082293"

> #Probit

> SD\_Probit\_effects <- cbind(as.matrix(Probit\_effects)[,1], as.matrix(Probit\_effects)[,3])

> SD\_Probit\_effects

      [,1]  [,2]

[1,] " -5" "0.009260736"

[2,] "  0" "0.009031807"

```

[3,] " 5" "0.008826000"
[4,] " 10" "0.008644967"
[5,] " 15" "0.008490291"
[6,] " 20" "0.008363436"
[7,] " 25" "0.008265683"
[8,] " 30" "0.008198072"
[9,] " 35" "0.008161353"
[10,] " 40" "0.008155944"
[11,] " 45" "0.008181905"
[12,] " 50" "0.008238942"
[13,] " 55" "0.008326414"
[14,] " 60" "0.008443377"
[15,] " 65" "0.008588625"
[16,] " 70" "0.008760751"
[17,] " 75" "0.008958208"
[18,] " 80" "0.009179359"
[19,] " 85" "0.009422537"
[20,] " 90" "0.009686083"
[21,] " 95" "0.009968382"
[22,] "100" "0.010267886"
[23,] "105" "0.010583136"
> #Logit
> SD_Logit_effects <- cbind(as.matrix(Logit_effects)[,1], as.matrix(Logit_effects)[,3])
> SD_Logit_effects
      [,1] [,2]
[1,] "-5" "0.01493298"
[2,] " 0" "0.01456228"
[3,] " 5" "0.01422872"
[4,] "10" "0.01393498"
[5,] "15" "0.01368362"
[6,] "20" "0.01347702"
[7,] "25" "0.01331725"
[8,] "30" "0.01320602"
[9,] "35" "0.01314455"
[10,] "40" "0.01313356"
[11,] "45" "0.01317315"
[12,] "50" "0.01326289"
[13,] "55" "0.01340176"
[14,] "60" "0.01358826"
[15,] "65" "0.01382046"
[16,] "70" "0.01409610"

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[17,] " 75" "0.01441268"  
[18,] " 80" "0.01476758"  
[19,] " 85" "0.01515811"  
[20,] " 90" "0.01558158"  
[21,] " 95" "0.01603539"  
[22,] "100" "0.01651704"  
[23,] "105" "0.01702415"  
>
```