Assignment 1

David Gyaraki, Thao Le

Contents

```r
# load packages
if(!require(pacman)){install.packages("pacman")}

p_load(devtools,tidyverse,dplyr,ggplot2,latex2exp,cowplot,tseries,sampleSelection)

#load data
dfData = read.csv("assignment1_2023.csv")
attach(dfData)
```

1 Question 1

1.1 (i)

```r
lm_model = lm(logwage ~ age + agesq + schooling, data = dfData)
summary(lm_model)
```

```
Call:
lm(formula = logwage ~ age + agesq + schooling, data = dfData)

Residuals:
    Min      1Q  Median      3Q     Max 
-3.3224 -1.1782  0.0024  1.2208  3.1957 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)    
(Intercept) 26.409280   8.057036   3.278  0.00113 ** 
age         -0.341890   0.521078  -0.656  0.51211    
agesq       -0.011142   0.008374  -1.331  0.18408    
schooling    0.215996   0.031534   6.850 2.71e-11 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.499 on 412 degrees of freedom
  (250 observations deleted due to missingness)
Multiple R-squared:  0.8148,	Adjusted R-squared:  0.8135 
F-statistic: 604.3 on 3 and 412 DF,  p-value: < 2.2e-16
```

1.2 (ii)

The sample selection problem here is to choose observations of the non-employed, which are those who have no income. The selection equation is then:

$$I_i = \begin{cases} 1 \text{ if logwage} > 0 \\ 0 \text{ otherwise,} \end{cases}$$

and the second regression equation is:

$$Y_i^* = \mathbf{X_i}'\beta + U_i.$$

We select a sample consisting of:

$$Y_i = \begin{cases} Y_i^* \text{ if } I_i = 1 \\ \text{missing if } I_i = 0, \end{cases}$$

An OLS may fail in this context because the dependent variable (logwage) is missing for the non-employed sample, thus, it is not possible to derive an estimate of this variable for the non-employed

1.3 (iii)

The exclusion restriction variable is one that is included in $\mathbf{Z_i}$ but excluded from $\mathbf{X_i}$, I would choose 'married' as a suitable candidate for the sample selection model. My motivation is that married people tends to have stable income, and thus, employed.

```
# Create I variable:
dfData = mutate(dfData, vI = if_else(logwage > 0, TRUE, FALSE))
dfData["vI"][is.na(dfData["vI"])] <- FALSE

# Heckman model with restriction
heckman_rest = heckit( vI ~ married+age + agesq + schooling, logwage ~ age + agesq + schoo
summary(heckman_rest)
```

```
--------------------------------------------
Tobit 2 model (sample selection model)
2-step Heckman / heckit estimation
666 observations (250 censored and 416 observed)
12 free parameters (df = 655)
Probit selection equation:
```

```
             Estimate Std. Error t value Pr(>|t|)
(Intercept) -5.315285   5.293574  -1.004    0.316
married      0.432572   0.100338   4.311 1.87e-05 ***
age          0.332077   0.342618   0.969    0.333
agesq       -0.005141   0.005512  -0.933    0.351
schooling    0.018246   0.022309   0.818    0.414
Outcome equation:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) 27.209400   8.517748   3.194  0.00147 **
age         -0.385453   0.541932  -0.711  0.47718
agesq       -0.010459   0.008692  -1.203  0.22932
schooling    0.214536   0.031874   6.731 3.69e-11 ***
Multiple R-Squared:0.8148,  Adjusted R-Squared:0.813
   Error terms:
              Estimate Std. Error t value Pr(>|t|)
invMillsRatio  -0.1737     0.6148  -0.283    0.778
sigma           1.4971         NA      NA       NA
rho            -0.1160         NA      NA       NA
--------------------------------------------
```

```r
# Heckman model without restriction
heckman_unrest = heckit( vI ~ married+age + agesq + schooling, logwage ~ age + agesq + sch
summary(heckman_unrest)
```

```
--------------------------------------------
Tobit 2 model (sample selection model)
2-step Heckman / heckit estimation
666 observations (250 censored and 416 observed)
13 free parameters (df = 654)
Probit selection equation:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) -5.315285   5.293574  -1.004    0.316
married      0.432572   0.100338   4.311 1.87e-05 ***
age          0.332077   0.342618   0.969    0.333
agesq       -0.005141   0.005512  -0.933    0.351
schooling    0.018246   0.022309   0.818    0.414
Outcome equation:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) 94.14571   30.04111   3.134   0.0018 **
age         -3.68541    2.91861  -1.263   0.2071
agesq        0.04058    0.04759   0.853   0.3941
schooling    0.03527    0.19887   0.177   0.8593
```

```
married      -4.30249        NaN     NaN      NaN
Multiple R-Squared:0.8153,   Adjusted R-Squared:0.8131
   Error terms:
              Estimate Std. Error t value Pr(>|t|)
invMillsRatio  -17.976        NaN     NaN      NaN
sigma           13.399         NA      NA       NA
rho             -1.342         NA      NA       NA
--------------------------------------------
```

- STILL NEED TO COMPARE OUTCOMES

1.4 (iv)

```r
# Maximum likelihood estimator, restricted
ML_rest = selection(vI ~ married+age + agesq + schooling, logwage ~ age + agesq + schoolin
summary(ML_rest)
```

```
--------------------------------------------
Tobit 2 model (sample selection model)
Maximum Likelihood estimation
Newton-Raphson maximisation, 2 iterations
Return code 8: successive function values within relative tolerance limit (reltol)
Log-Likelihood: -1186.617
666 observations (250 censored and 416 observed)
11 free parameters (df = 655)
Probit selection equation:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) -5.347695   5.290476  -1.011    0.312
married      0.432671   0.100314   4.313 1.86e-05 ***
age          0.334151   0.342394   0.976    0.329
agesq       -0.005174   0.005508  -0.939    0.348
schooling    0.018294   0.022308   0.820    0.412
Outcome equation:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) 27.091220   8.430218   3.214  0.00138 **
age         -0.378997   0.537729  -0.705  0.48118
agesq       -0.010560   0.008627  -1.224  0.22139
schooling    0.214749   0.031784   6.757 3.13e-11 ***
   Error terms:
      Estimate Std. Error t value Pr(>|t|)
sigma  1.49568    0.06006  24.902   <2e-16 ***
```

```
rho   -0.09931    0.37382  -0.266    0.791
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
--------------------------------------------
```

```
# Maximum likelihood estimator, unrestricted
ML_unrest = selection(vI ~ married + age + agesq + schooling, logwage ~ age + agesq + scho
summary(ML_unrest)
```

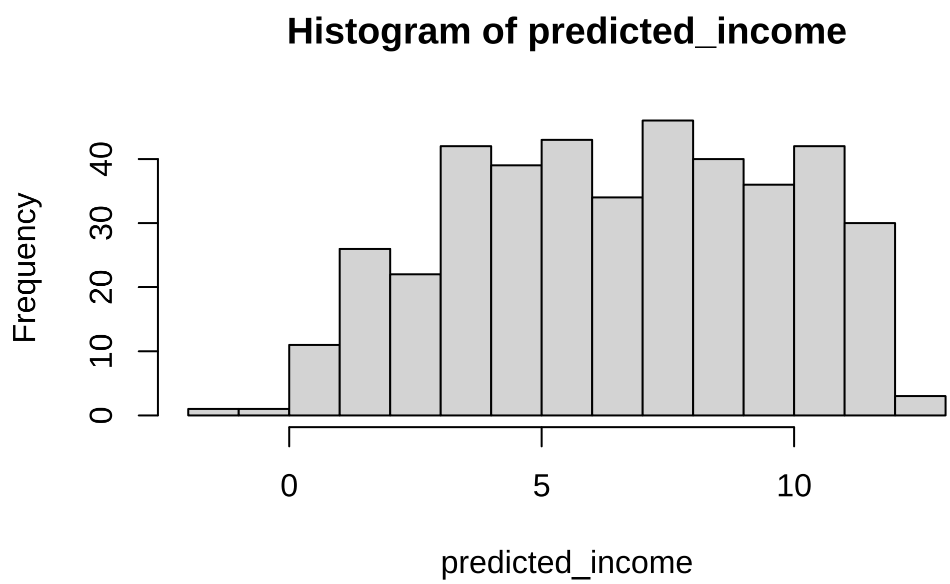
```
--------------------------------------------
Tobit 2 model (sample selection model)
Maximum Likelihood estimation
Newton-Raphson maximisation, 2 iterations
Return code 3: Last step could not find a value above the current.
Boundary of parameter space?
Consider switching to a more robust optimisation method temporarily.
Log-Likelihood: -1501.802
666 observations (250 censored and 416 observed)
12 free parameters (df = 654)
Probit selection equation:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) -5.315285   5.597136  -0.950    0.343
married      0.432572   0.099200   4.361 1.51e-05 ***
age          0.332077   0.362958   0.915    0.361
agesq       -0.005141   0.005849  -0.879    0.380
schooling    0.018246   0.021917   0.833    0.405
Outcome equation:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) 94.10255   35.31853   2.664   0.0079 **
age         -4.29420    2.29499  -1.871   0.0618 .
agesq        0.05014    0.03695   1.357   0.1752
schooling    0.08000    0.14232   0.562   0.5742
married     -3.79447    0.54690  -6.938 9.57e-12 ***
   Error terms:
      Estimate Std. Error t value Pr(>|t|)
sigma    7.648        NaN     NaN      NaN
rho     -0.990        NaN     NaN      NaN
--------------------------------------------
```

- STILL NEED TO COMPARE OUTCOMES

1.5 (v)

`get fitted values =\> plot histogram`

```r
predicted_income <- fitted(ML_rest)
hist(predicted_income)
```



The distribution is relatively normal, but a bit left-skewed

2 Question 2

2.1 (i)

```r
# Get subsample of employed individuals
dfEmployed = dfData[dfData$vI == TRUE, ]

model0 = lm(logwage ~ schooling + age + agesq, data = dfEmployed)
summary(model0)
```

```
Call:
lm(formula = logwage ~ schooling + age + agesq, data = dfEmployed)

Residuals:
    Min      1Q  Median      3Q     Max 
-3.3224 -1.1782  0.0024  1.2208  3.1957 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)    
(Intercept) 26.409280   8.057036   3.278  0.00113 ** 
schooling    0.215996   0.031534   6.850 2.71e-11 ***
age         -0.341890   0.521078  -0.656  0.51211    
agesq       -0.011142   0.008374  -1.331  0.18408    
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.499 on 412 degrees of freedom
Multiple R-squared:  0.8148,	Adjusted R-squared:  0.8135 
F-statistic: 604.3 on 3 and 412 DF,  p-value: < 2.2e-16
```

Here we can talk about causation, but not association. The effect of schooling is statistically significant meaning … is associated with …

NEED TO: address whether or not it is plausible that regularity conditions for applying OLS are satisfied.

2.2 (ii)

```r
# Using distance as instrument variable
model1 = lm(schooling ~ distance)
X.hat.1 = fitted.values(model1)

# Fit Linear regression model again using the fitted values of first step
model2 =lm(logwage ~ X.hat.1 + age + agesq)
summary(model2)
```

```
Call:
lm(formula = logwage ~ X.hat.1 + age + agesq)

Residuals:
```

```
    Min      1Q  Median      3Q     Max 
-3.4199 -1.2578 -0.0541  1.2115  3.5095 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)   
(Intercept) 26.129437   8.731501   2.993  0.00293 **
X.hat.1      0.507475   0.315840   1.607  0.10888   
age         -0.460586   0.547910  -0.841  0.40105   
agesq       -0.009026   0.008804  -1.025  0.30585   
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.577 on 412 degrees of freedom
  (250 observations deleted due to missingness)
Multiple R-squared:  0.795, Adjusted R-squared:  0.7935 
F-statistic: 532.6 on 3 and 412 DF,  p-value: < 2.2e-16
```

```r
# Using subsidy as instrument variable
model3 = lm(schooling ~ subsidy)
X.hat.3 = fitted.values(model3)

# Fit Linear regression model again using the fitted values of first step

model4 =lm(logwage ~ X.hat.3 + age + agesq)
summary(model4)
```

```
Call:
lm(formula = logwage ~ X.hat.3 + age + agesq)

Residuals:
    Min      1Q  Median      3Q     Max 
-3.4083 -1.2306 -0.0321  1.3012  3.6294 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)    
(Intercept) 25.716242   8.408480   3.058 0.002371 ** 
X.hat.3      0.441019   0.116721   3.778 0.000181 ***
age         -0.413512   0.540517  -0.765 0.444691    
agesq       -0.009649   0.008684  -1.111 0.267186    
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
Residual standard error: 1.555 on 412 degrees of freedom
  (250 observations deleted due to missingness)
Multiple R-squared:  0.8006,    Adjusted R-squared:  0.7992
F-statistic: 551.5 on 3 and 412 DF,  p-value: < 2.2e-16
```

```r
# Using subsidy and distance as instrument variable
model5 = lm(schooling ~ subsidy+distance)
X.hat.5 = fitted.values(model3)

model6 =lm(logwage ~ X.hat.5 + age + agesq)
summary(model6)
```

```
Call:
lm(formula = logwage ~ X.hat.5 + age + agesq)

Residuals:
    Min      1Q  Median      3Q     Max
-3.4083 -1.2306 -0.0321  1.3012  3.6294

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) 25.716242   8.408480   3.058 0.002371 **
X.hat.5      0.441019   0.116721   3.778 0.000181 ***
age         -0.413512   0.540517  -0.765 0.444691
agesq       -0.009649   0.008684  -1.111 0.267186
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.555 on 412 degrees of freedom
  (250 observations deleted due to missingness)
Multiple R-squared:  0.8006,    Adjusted R-squared:  0.7992
F-statistic: 551.5 on 3 and 412 DF,  p-value: < 2.2e-16
```

2.3 (iii)

I would use only subsidy as the instrument variable to avoid overidentification.