613_hw4

Q1

```
library(Matrix)
DATA<-read.csv("~/Desktop/613/hw4/Koop-Tobias.csv")
set.seed(100)
#Randomly select 5 individuals
vect<-as.vector(sample(1:2178, size=5))
#Set a vector to store the panel dimension of these 5 individuals
freque<-c()
w<-table(DATA$PERSONID)
w<-as.data.frame(w)
w<-as.matrix(w)
for (i in 1:5){
  ans<-w[vect[i],2]
  freque<-c(freque,ans)
}
#Print the outcome
print(vect)
```

```
## [1]  671  561 1202  123 1019
```

```
print(freque)
```

```
## Freq Freq Freq Freq Freq
## "14" " 5" " 8" " 9" " 3"
```

Q2

```
library(nlme)
model_q2<-gls(LOGWAGE~EDUC+POTEXPER, data=DATA)
summary(model_q2)
```

```
## Generalized least squares fit by REML
##   Model: LOGWAGE ~ EDUC + POTEXPER
##   Data: DATA
##        AIC      BIC    logLik
##   24927.91 24959.08 -12459.95
##
## Coefficients:
##                Value   Std.Error  t-value p-value
## (Intercept) 0.7941911 0.027359284 29.02821       0
## EDUC        0.0938637 0.001929927 48.63590       0
## POTEXPER    0.0374053 0.000898886 41.61293       0
##
##  Correlation:
##          (Intr) EDUC
## EDUC     -0.954
## POTEXPER -0.470  0.219
##
## Standardized residuals:
##         Min          Q1         Med          Q3         Max
## -5.16347553 -0.57658469  0.04692351  0.65688942  4.38118968
##
## Residual standard error: 0.4846115
## Degrees of freedom: 17919 total; 17916 residual
```

Q3

Between Estimator

```
fact<-as.factor(DATA$PERSONID)
#Calculate average logwage_i overtime
groupDATAwage<-as.matrix(tapply(DATA$LOGWAGE,fact,FUN=mean))
freque<-as.data.frame(table(DATA$PERSONID))
Freque<-as.matrix(freque$Freq)
DATAlogwagenew<-c()
for (i in 1:nrow(Freque)){
  DATAlogwagenew<-c(DATAlogwagenew,as.vector(rep(groupDATAwage[i,1],Freque[i,1])))
}
#Calculate average educ_i overtime
groupDATAeduc<-as.matrix(tapply(DATA$EDUC,fact,FUN=mean))
DATAeducnew<-c()
for (i in 1:nrow(Freque)){
  DATAeducnew<-c(DATAeducnew,as.vector(rep(groupDATAeduc[i,1],Freque[i,1])))
}
#Calculate average potexper_i overtime
groupDATApote<-as.matrix(tapply(DATA$POTEXPER,fact,FUN=mean))
DATApotenew<-c()
for (i in 1:nrow(Freque)){
  DATApotenew<-c(DATApotenew,as.vector(rep(groupDATApote[i,1],Freque[i,1])))
}
DATApersonidnew<-as.matrix(DATA$PERSONID)
constant<-matrix(1,nrow=17919,ncol=1)
#Do Estimation (Between model)
DATA_q3between<-data.frame(DATApersonidnew,DATAlogwagenew,DATAeducnew,DATApotenew)
DATA_q3between<- DATA_q3between[!duplicated(DATA_q3between$DATApersonidnew),]
model_between<-lm(DATAlogwagenew~DATAeducnew+DATApotenew,data=DATA_q3between)
summary(model_between)$coefficients
```

```
##               Estimate  Std. Error   t value     Pr(>|t|)
## (Intercept) 0.84556883 0.077017914 10.978859 2.483879e-27
## DATAeducnew 0.09309987 0.004668494 19.942162 2.128692e-81
## DATApotenew 0.02599874 0.003604887  7.212084 7.571723e-13
```

Within Estimator

```
#Modify the data
DATAlogwagenew_deta<-as.matrix(DATA$LOGWAGE)-DATAlogwagenew
DATAeducnew_deta<-as.matrix(DATA$EDUC)-DATAeducnew
DATApotenew_deta<-as.matrix(DATA$POTEXPER)-DATApotenew
DATApersonidnew<-as.matrix(DATA$PERSONID)
DATA_q3within<-as.matrix(data.frame(DATApersonidnew,DATAlogwagenew_deta,DATAeducnew_d
eta,DATApotenew_deta))
#Use ols method to calculate within model estimators
X_q3within<-DATA_q3within[,3:4]
Y_q3within<-as.matrix(DATAlogwagenew_deta)
beta_q3within<-solve((t(X_q3within)%*%X_q3within))%*%(t(X_q3within)%*%Y_q3within)
print(beta_q3within)
```

```
##                          [,1]
## DATAeducnew_deta 0.12366202
## DATApotenew_deta 0.03856107
```

```
#Use lm package to check the answer
DATA_q3within<-data.frame(DATApersonidnew,DATAlogwagenew_deta,DATAeducnew_deta,DATApo
tenew_deta)
model_within<-lm(DATAlogwagenew_deta~DATAeducnew_deta+DATApotenew_deta,data=DATA_q3wi
thin)
summary(model_within)$coefficients
```

```
##                       Estimate  Std. Error      t value      Pr(>|t|)
## (Intercept)      9.231826e-17 0.002348813 3.930422e-14  1.000000e+00
## DATAeducnew_deta 1.236620e-01 0.005400471 2.289837e+01 2.107861e-114
## DATApotenew_deta 3.856107e-02 0.000710902 5.424245e+01  0.000000e+00
```

First time difference Estimator

```r
diff_wage<-c()
diff_educ<-c()
diff_potex<-c()
logwage<-as.matrix(DATA$LOGWAGE)
educ<-as.matrix(DATA$EDUC)
potex<-as.matrix(DATA$POTEXPER)
index<-1
#Take the difference of the data
for (i in 1:2178){
  if(Freque[i]>=2){
    #Take variables at time t-1: logwage_t-1, educ_t-1, potexper_t-1
    i_lag_wage<-logwage[index:(index-1+Freque[i]-1),1]
    i_lag_educ<-educ[index:(index-1+Freque[i]-1),1]
    i_lag_potex<-potex[index:(index-1+Freque[i]-1),1]
    #Take variables at time t: logwage_t, educ_t, potexper_t
    #print(index+1)
    #print(freque[i,1])
    i_t_wage<-logwage[(index+1):(index-1+Freque[i]),1]
    i_t_educ<-educ[(index+1):(index-1+Freque[i]),1]
    i_t_potex<-potex[(index+1):(index-1+Freque[i]),1]
    i_diff_wage<-i_t_wage-i_lag_wage
    i_diff_educ<-i_t_educ-i_lag_educ
    i_diff_potex<-i_t_potex-i_lag_potex
    diff_wage<-c(diff_wage,i_diff_wage)
    diff_educ<-c(diff_educ,i_diff_educ)
    diff_potex<-c(diff_potex,i_diff_potex)
    index<-index+Freque[i,1]
  }
}
#Do estimation (First Difference Model)
DATA_q3diff<-as.matrix(data.frame(diff_wage,diff_educ,diff_potex))
X_q3diff<-DATA_q3diff[,2:3]
Y_q3diff<-DATA_q3diff[,1]
beta_q3diff<-solve((t(X_q3diff)%*%X_q3diff))%*%(t(X_q3diff)%*%Y_q3diff)
#Print out the outcome
print(beta_q3diff)
```

```
##                  [,1]
## diff_educ  0.08558180
## diff_potex 0.03796838
```

```r
#Use lm package to check the answer
DATA_q3diff<-data.frame(diff_wage,diff_educ,diff_potex)
model_diff<-lm(diff_wage~diff_educ+diff_potex,data=DATA_q3diff)
summary(model_diff)$coefficients
```

```
##                  Estimate  Std. Error    t value      Pr(>|t|)
## (Intercept) -0.0008820122 0.003423167 -0.2576597  7.966729e-01
## diff_educ    0.0855828031 0.003472454 24.6462057 1.249147e-131
## diff_potex   0.0379680401 0.000945046 40.1758632  0.000000e+00
```

Q3.4 Compare beta_1 and beta_2 under different models.

The beta calculated by using between model and using first difference model are very close.

The coefficient of potexper calculated by using all three types of fixed effect model and that by using the random effect model are very similar as well.

However, the coefficient of education of the random effect model is a little bit different from that calculated by using fixed effect models.

This implies that the individual effect might be somekind correlated with the explaining variables

Q4

Q4.1

```
###Select 100 samples
set.seed(613)
Sample_q4<-sample(1:2178, 100)
DATA_q4<-matrix(0,nrow=1,ncol=9)
for (i in 1:100){
  WAGE_i<-as.matrix(DATA$LOGWAGE[DATA$PERSONID==Sample_q4[i]])
  EDUC_i<-as.matrix(DATA$EDUC[DATA$PERSONID==Sample_q4[i]])
  POTEXPER_i<-as.matrix(DATA$POTEXPER[DATA$PERSONID==Sample_q4[i]])
  PERSONID_i<-as.matrix(DATA$PERSONID[DATA$PERSONID==Sample_q4[i]])
  ABILITY_i<-as.matrix(DATA$ABILITY[DATA$PERSONID==Sample_q4[i]])
  MOTHERED_i<-as.matrix(DATA$MOTHERED[DATA$PERSONID==Sample_q4[i]])
  FATHERED_i<-as.matrix(DATA$FATHERED[DATA$PERSONID==Sample_q4[i]])
  BRKNHOME_i<-as.matrix(DATA$BRKNHOME[DATA$PERSONID==Sample_q4[i]])
  SIBLINGS_i<-as.matrix(DATA$SIBLINGS[DATA$PERSONID==Sample_q4[i]])
  PERSONID_i<-as.matrix(DATA$PERSONID[DATA$PERSONID==Sample_q4[i]])
  individual<-as.matrix(data.frame(PERSONID_i,WAGE_i,EDUC_i,POTEXPER_i,ABILITY_i,MOTH
ERED_i,FATHERED_i,BRKNHOME_i,SIBLINGS_i))
  DATA_q4<-rbind(DATA_q4,individual)
}

M<-nrow(DATA_q4)
DATA_q4<-DATA_q4[2:M,]
DATA_q4df<-as.data.frame(DATA_q4)
#Get frequency matrix which stores the frequency of each individual's observations
W_q4<-as.data.frame(table(DATA_q4df$PERSONID_i))
Freque_q4<-as.matrix(W_q4$Freq)
#Construct a likelihood function
likelihood<-function(par,DATA.=DATA_q4){
  likewage<-DATA.[,2]
  likeeduc<-DATA.[,3]
  likepotexper<-DATA.[,4]
  alfa<-par[2:101]
  beta1<-par[102]
  beta2<-par[103]
  alfanew<-rep(alfa,Freque_q4)
  alfanew<-as.matrix(alfanew)
  Estimation<-alfanew+likeeduc*beta1+likepotexper*beta2
  proEstimation<-dnorm((likewage- Estimation)/par[1])
  proEstimation[proEstimation<0.00001]<-0.00001
  proEstimation[proEstimation>0.99999]<-0.99999
  loglikelihood<--sum(log(proEstimation))
  return(loglikelihood)
}
#Set initial value for the parameter
parameter<-rnorm(102)
parameter<-c(1,parameter)
#Optimize the likelihood function
result_q4.1<-optim(par = parameter,likelihood)
print(result_q4.1)
```

```
## $par
##   [1]  1.00000000 -1.25077351 -1.23742224  0.69523430 -1.17679012
##   [6] -0.08068324  0.46081104  0.91278708  1.59763959 -1.98707776
##  [11]  0.08445674  1.29185357  1.53491371 -0.55306496  0.54951946
##  [16]  0.58542189  1.20576095 -1.73014998 -0.25530253 -1.82794356
##  [21]  0.56809363  0.10682645  0.48153848 -1.22774092 -1.52015605
##  [26] -0.12177822  0.66043497  0.43014612  0.23186502  0.14623862
##  [31] -2.55806843 -0.46124848  0.46038107 -0.73495133 -1.10109127
##  [36]  0.15664930 -0.83188237 -1.24190168  1.50975916 -0.02710235
##  [41]  0.44862196 -1.84793619 -3.97142785  0.28449669 -0.32978955
##  [46] -0.15063015  0.31059439  0.29797915 -0.90850221  0.84660544
##  [51] -0.08764736 -0.65966377 -1.59920585  0.07589521 -1.89898829
##  [56] -1.06989123 -0.55748048 -0.85508621 -0.74909498  1.03530167
##  [61] -0.63154088  0.39075821 -0.12786100  1.25552988  0.25942019
##  [66] -1.51348038  0.46534419 -1.05643416  0.28022557  0.81562739
##  [71] -0.18974537  0.87958593  0.23597572 -1.07435090  2.13786887
##  [76]  0.15546938  0.95314884 -0.45760452  2.19346820 -0.07392728
##  [81] -1.32512697  1.67854378 -1.91708432  0.43020511 -1.11165067
##  [86]  0.73019837  0.45803767  1.14799478 -2.05271300 -1.07523924
##  [91]  1.10489036 -0.25848502  1.55271742 -0.67354231 -0.48442545
##  [96] -0.59664023  2.17925548  0.23984158 -0.98578039 -1.59232450
## [101]  0.58990485 -1.10913704 -0.10000147
##
## $value
## [1] 9947.168
##
## $counts
## function gradient
##      104       NA
##
## $convergence
## [1] 0
##
## $message
## NULL
```

Q4.2

```
#Get alfa by using ols method (Sample: 100 individuals)
result_q4.2<-lm(WAGE_i~EDUC_i+POTEXPER_i+factor(PERSONID_i),data=DATA_q4df)
alfa_q4.2<-as.matrix(coef(result_q4.2))
alfa_q4.2<-alfa_q4.2[3:102]
DATA_q4dfNEW<- DATA_q4df[!duplicated(DATA_q4df$PERSONID_i),]
DATA_4.2dfnew<-data.frame(alfa_q4.2,DATA_q4dfNEW)
#Run a regression of estimated individual fixed effets on the invariant variables.
result_q4.2new<-lm(alfa_q4.2~ABILITY_i+MOTHERED_i+FATHERED_i+BRKNHOME_i+SIBLINGS_i,da
ta=DATA_4.2dfnew)
#Print the outcome
summary(result_q4.2new)
```

```
##
## Call:
## lm(formula = alfa_q4.2 ~ ABILITY_i + MOTHERED_i + FATHERED_i +
##     BRKNHOME_i + SIBLINGS_i, data = DATA_4.2dfnew)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -1.16532 -0.30995  0.02221  0.23708  1.05565
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) -1.101043   0.215052  -5.120 1.62e-06 ***
## ABILITY_i   -0.061407   0.053026  -1.158    0.250
## MOTHERED_i   0.011262   0.019115   0.589    0.557
## FATHERED_i  -0.001082   0.016940  -0.064    0.949
## BRKNHOME_i  -0.153286   0.129872  -1.180    0.241
## SIBLINGS_i   0.028928   0.018830   1.536    0.128
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.4222 on 94 degrees of freedom
## Multiple R-squared:  0.04843,    Adjusted R-squared:  -0.002185
## F-statistic: 0.9568 on 5 and 94 DF,  p-value: 0.4484
```

Q4.3

The standard errors in the previous model are wrong because of some auto-correlation issues in the model.

In this case, the standard errors we calculated in the previous model by using ols method can hardly get the robust standard error of coefficients

Alternative approach: We can use robust ols method to get the adjusted standard errors of coefficients.We can also use gls to get robust standard errors of coefficients.