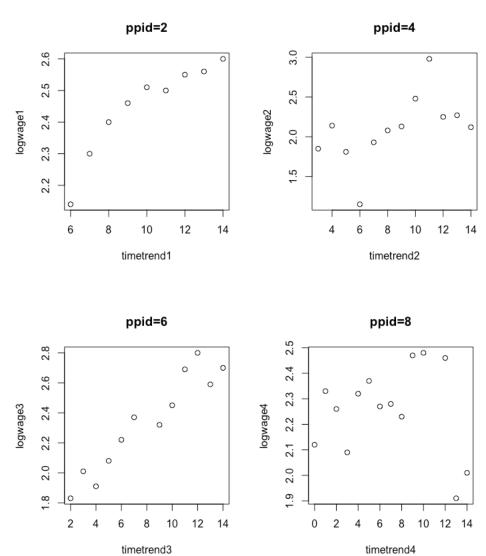
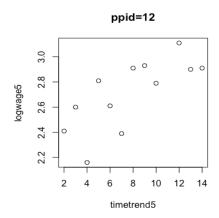
HW4 output

Exercise1 Data Represent the panel dimension of wages





Exercise2 random effects

```
> educ<-as.numeric(kt$EDUC)</pre>
> logwage<-as.numeric(kt$LOGWAGE)</pre>
> potexper<-as.numeric(kt$POTEXPER)</pre>
> re<-as.data.frame(cbind(logwage,educ,potexper))</pre>
> library(nlme)
> gls(logwage~educ+potexper,data = re)
Generalized least squares fit by REML
  Model: logwage ~ educ + potexper
  Data: re
  Log-restricted-likelihood: -12459.95
Coefficients:
(Intercept)
                    educ
                            potexper
0.79419112 0.09386374 0.03740530
Degrees of freedom: 17919 total; 17916 residual
Residual standard error: 0.4846115
```

Exercise3 fixed effects

Between estimators

```
> lm(logwage_avg~educ_avg+potexper_avg,febtw_full)
 Call:
 lm(formula = logwage_avg ~ educ_avg + potexper_avg, data = febtw_full)
 Coefficients:
 (Intercept)
                   educ_avg potexper_avg
      0.8456
                     0.0931
                                   0.0260
within estimators
 > lm(logwage_wtin~educ_wtin+potexper_wtin-1,fewtn)
 Call:
 lm(formula = logwage_wtin ~ educ_wtin + potexper_wtin - 1, data = fewtn)
 Coefficients:
     educ_wtin potexper_wtin
       0.12366
                      0.03856
First time difference estimator
> lm(logwage_3~educ_3+potexper_3,fe_3)
Call:
lm(formula = logwage_3 \sim educ_3 + potexper_3, data = fe_3)
Coefficients:
(Intercept)
                           potexper_3
                  educ_3
   0.049464
                0.038352
                             0.003989
Exercise4 understanding fixed effects
Likelihood function
beta_func<-function(beta){</pre>
   return(-sum(y*log(pnorm(X%*%beta)))+sum((1-y)*log(1-pnorm(X%*%beta))))
}# Generate the likelihood function
Optimize Likelihood function
> beta=optim(par = start,beta_func)$par
> beta
 [1] 0.02500401 0.00253573
Individual fixed effect parameters
```

```
y_ppid<-as.matrix(kt_select_avr$logwage_avg)</pre>
x_ppid<-as.matrix(kt_select_avr[,3:4])</pre>
alpha<-y_ppid-x_ppid%*%beta
Run a regression of estimated individual effects
> lm(y_inv~inv1+inv2+inv3+inv4+inv5,in_ktfull)
Call:
lm(formula = y_inv \sim inv1 + inv2 + inv3 + inv4 + inv5, data = in_ktfull)
Coefficients:
(Intercept)
                     inv1
                                  inv2
                                                inv3
                                                             inv4
                                                                           inv5
                                          -0.0009575
  1.6969783
               0.0453670
                             0.0251907
                                                       -0.0262378
                                                                     -0.0059747
Explain and alternative method to compute standard errors
#The errors are potentially serially correlated like over t
# and heteroskedastic
Use bootstrap
> sd_boot
                                                MOTHERED
                                                            FATHERED
                                                                        BRKNHOME
                        Intercept
                                      ABILITY
corrected_sd_bootstrap 0.2404064 0.07203128 0.02101495 0.06326918 0.01999077
                          SIBLINGS
corrected_sd_bootstrap 0.01564511
```