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Assignment #9

PANEL DATA

Question 15.6 (p.573). No need for part 3(d) of this question

(part a)

```
Balanced Panel: n = 754, T = 4, N = 3016
          Estimate Std. Error t-value  Pr(>|t|)    
bar       0.298455   0.134450  2.2198 0.0265299 *  
street    0.455159   0.130465  3.4887 0.0004946 ***
nocondom  0.170282   0.025817  6.5957 5.256e-11 ***
rich      0.082636   0.020528  4.0254 5.875e-05 ***
regular   0.037219   0.016849  2.2090 0.0272770 *  
alcohol  -0.056856   0.026139 -2.1751 0.0297261 *  
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares:    111.72
Residual Sum of Squares: 107.6
R-Squared:      0.03688
Adj. R-Squared: -0.28715
F-statistic: 14.3978 on 6 and 2256 DF, p-value: 3.5477e-16
```

(i)
we omitted the sex worker characteristic because during the years those characteristics will remai n constant and variation will be negligible. No change is expected in categories like school & attr active.

part (ii)

all estimates are significantly more than 0 at 5% level

part (iii)

If transaction originated in bar then it is estimated to be 29.8% higher
If transaction originated in Street then it is estimated to be 29.8% higher
Risk premium for No condom is 17% extra.
If client is rich than price is 8.2% more
If Client is regular than price is 3..7% more.
If client had alcohol then price is 5.6% lower

(part b)

```
Balanced Panel: n = 754, T = 4, N = 3016

Coefficients:
              Estimate Std. Error t-value  Pr(>|t|)
(Intercept)  5.9103651  0.1303194 45.3529 < 2.2e-16 ***
age         -0.0257651  0.0027534 -9.3574 < 2.2e-16 ***
school       0.2161494  0.0453396  4.7673 1.955e-06 ***
attractive   0.2768274  0.0602379  4.5956 4.494e-06 ***
bar          0.4642454  0.0998912  4.6475 3.504e-06 ***
street       0.1032864  0.1010769  1.0219    0.3069
nocondom     0.1389842  0.0250266  5.5535 3.045e-08 ***
rich         0.1160067  0.0200346  5.7903 7.751e-09 ***
regular      0.0236290  0.0161849  1.4599    0.1444
alcohol      0.0148896  0.0249556  0.5966    0.5508
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares:    167.65
Residual Sum of Squares: 149.03
R-Squared:      0.11104
Adj. R-Squared: 0.10838
F-statistic: 41.7209 on 9 and 3006 DF, p-value: < 2.22e-16
```

Now age, school & Attractive are added and their variation is compared within the individual data set and with others. RE is giving us a better picture of how these characteristics influence the price.

Bar was significantly higher than FE
Street , no condom and regular all dropped compared to FE
Rich was increased from 8.2% to 11.6%
Alcohol is 1.4% higher compared to negative 5.6%
Age decreased the price per year by 2.5% as expected
Having secondary school added 21.6% to the price
Being attractive added 27.6% to the price
A client will have to pay approximately 61% extra to have unprotected sex with an attractive and secondary school passed worker

(Part c)

	Beta FE	STD ERROR FE	VAR FE	Beta RE	STD ERROR RE	VAR RE	T val
bar	0.298455	0.13445	0.018076803	0.464245	0.0998912	0.009978	-1.842280383
street	0.455159	0.130465	0.017021116	0.103286	0.1010769	0.010217	4.265646865
nocondom	0.170282	0.025817	0.000666517	0.138984	0.0250266	0.000626	4.937103122
rich	0.082636	0.020528	0.000421399	0.116007	0.0200346	0.000401	-7.45938206
regular	0.037219	0.016849	0.000283889	0.023629	0.0161849	0.000262	2.901501449
alcohol	-0.056856	0.026139	0.000683247	0.01489	0.0249556	0.000623	-9.226606258

All T values with the exception of bar are significant at 5%. Critical t is at +/- 1.96 Meaning that HO can be rejected.

In this case HO is that estimates from FE and estimates from RE are similar. But with high t values we can reject the Null and accept that they are not similar and we will go with Fixed effects.

Question 15.10 (p.576-577)

(part a)

(i) deterrence increases, will decrease crime rate
(ii) wage increase in the private sector will decrease the crime rate
(iii) population density increase, will increase the crime rate
(iv) percentage of young males may increase the crime rate

(part b)

OLS model summary

```
             Estimate Std. Error t value Pr(>|t|)    
(Intercept)  -6.08610    0.36536 -16.658  < 2e-16 ***
log(prbarr)  -0.65658    0.04035 -16.274  < 2e-16 ***
log(prbconv) -0.44658    0.02774 -16.098  < 2e-16 ***
log(prbpris)  0.20823    0.07267   2.865   0.0043 ** 
log(avgsen)  -0.05863    0.06060  -0.967   0.3337    
log(wmfg)     0.29206    0.06190   4.718 2.94e-06 ***
---
```

(i)

Increase in Probability of arrests is estimated to decrease the crime rate. This is as expected

Increase in Probability of conviction is estimated to decrease the crime rate. This is as expected

Increase in Probability of Prison is estimated to increase the crime rate. This is not as expected

Increase in Average sentence is estimated to decrease the crime rate. This is as expected

Increase in WFMG is estimated to increase the crime rate. This is not as expected

(ii)

Increase in Probability of arrests is estimated to decrease the crime rate. This is as expected because fear of getting arrest should discourage criminals from committing crimes.

(part C)

Summary of Fixed effects model

Balanced Panel: n = 90, T = 7, N = 630

```
log(prbarr)  -0.231271   0.037648 -6.1429 1.582e-09 ***
log(prbconv) -0.137803   0.022187 -6.2110 1.059e-09 ***
log(prbpris) -0.143137   0.039303 -3.6418  0.000297 ***
log(avgsen)   0.018281   0.030950  0.5907  0.554994
log(wmfg)    -0.166641   0.055267 -3.0152  0.002690 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    17.991
Residual Sum of Squares: 16.149
R-Squared:      0.10238
Adj. R-Squared: -0.05533
F-statistic: 12.2044 on 5 and 535 DF, p-value: 3.2268e-11
```

Increase in Probability of arrests is estimated to decrease the crime rate. This is as expected
Increase in Probability of conviction is estimated to decrease the crime rate. This is as expected
Increase in Probability of Prison is estimated to decrease the crime rate. This is as expected

Increase in Average sentence is estimated to increase the crime rate. This is not as expected but estimate is clos
P val is high so we it is not significant at 5%. This is telling us that severity of deterrence has low impact or no i
Crime rate.

Increase in WFMG is estimated to decrease the crime rate. This is as expected

PrbArr was decreasing crime rate by 65% in OLS but is only decreasing crime rate by 23% in FE.

(part d)

We will calculate the effects of county thru F test

SSE.U =   16.149 This is the FE model that has intercepts of 90 counties

SSE.R =   106.81 This is the pooled model that only has 6 DF

n = 630   is the total observations

k = 95   89 counties + 6 DF from Restricted models

J = 89 because there are 50 more variables in FE the Unrestricted model

fVAL = ((SSE.R - SSE.U)/89)/ (SSE.U/(n-k)) = 33.74

fc <- qf(0.95,89,535) = 1.28

Ho can be rejected meaning that counties should have their own intercept and FE model is preferred

(Part e)

	estimates OLS	**STD ERR OLS**	**estimate FE**	**std err FE**
(Intercept)	-3.67693	0.46621	n/a	n/a
log(prbarr)	-0.42453	0.04191	-0.195152	0.036704
log(prbconv)	-0.2827	0.02879	-0.111339	0.02173
log(prbpris)	0.08771	0.06935	-0.097664	0.038424
log(avgsen)	-0.10834	0.05774	-0.023963	0.03146
log(wmfg)	0.01598	0.07049	-0.576231	0.13295
ldensity	0.30521	0.02737	0.769421	0.33774
lpctymle	0.15907	0.08405	1.246044	0.434637
d82	-0.01757	0.05737	0.02528	0.027297
d83	-0.06686	0.05786	0.021608	0.03517
d84	-0.11935	0.05855	0.01207	0.042636
d85	-0.10563	0.05998	0.058874	0.052797
d86	-0.06574	0.06117	0.158618	0.065225
d87	-0.01011	0.06166	0.278223	0.077213

Results are different compared to OLS . FE results are significantly different compared to OLS.

(ii)

We will compare two OLS equations one with dummy variables and one with no dummy variables

Equation in R studio are as follows:

```
U.OLS.model <- lm( Lcrmrte ~ log(prbarr) + log(prbconv)+ log(prbpris) + log(avgsen)+ log(wmfg)
        + ldensity + lpctymle+ d82 +d83 + d84 + d85+ d86 + d87, data=context)
```

```
SSE.U = sum( (U.OLS.model$residuals)^2)
```

```
R.OLS.model <- lm( Lcrmrte ~ log(prbarr) + log(prbconv)+ log(prbpris) + log(avgsen)+ log(wmfg)
             + ldensity + lpctymle, data=context)

SSE.R = sum( (R.OLS.model$residuals)^2)

# restricted model is OLS with dummy variables

n = 630
k = 14
## J = 89 because there are 50 more variables in FE the Unrestricted model
fVAL = ((SSE.R - SSE.U)/6)/ (SSE.U/(n-k))  = 1.323
fc <-  qf(0.95,6,616) = 2.11
```

This shows that HO cannot be rejected and dummy variables are not needed

In this part we will compare two FE equations with each other

compare FE models with and without dummy variables

```
U.FE.model <- plm( Lcrmrte ~ log(prbarr) + log(prbconv)+ log(prbpris) + log(avgsen)+ log(wmfg)
              + ldensity + lpctymle+ d82 +d83 + d84 + d85+ d86 + d87,
              data=context, index=c("county","year"), model = "within")
summary(U.FE.model)

SSE.U = 14.383

R.FE.model <- plm( Lcrmrte ~ log(prbarr) + log(prbconv)+ log(prbpris) + log(avgsen)+ log(wmfg)
              + ldensity + lpctymle,
              data=context, index=c("county","year"), model = "within")
summary(R.FE.model)
```

SSE.R = 15.876

n = 630

k = 14

J = 6

fVAL = ((SSE.R - SSE.U)/6)/ (SSE.U/(n-k)) = 10.65

fc <- qf(0.95,6,616)= 2.11

We can reject HO that estimates of dummy variables are o. And we accept H1 that they are not 0.

(iii)

With OLS model, the crime rate increase by 0.015% with an increase in 1% in wage.

With fixed effects model, the crime rate decreases by 0.57% with 1% increase in wage, which sounds reasonable as better salaries lead to less crime.

(f) Public policies that will have the highest impact to control crime are increase in arrests, convictions and prison sentences, which indicate a strong legal system. Less population density will also lead to less crime.

```
########################################### Code for assignment #9
## QUESTION 15.6
rm(list=ls(all=TRUE))


#library(multcomp)
library(data.table)
library(dplyr)
library(plotly)
#library(lmtest)
#library(sandwich)
#library(car)
library(AER)
library(plm)

context <- fread("mexican.csv")

## Part a
fixed.model <- plm(lnprice ~bar +street + nocondom +rich +regular +alcohol,
                 data = context,index =c("id", "trans") , model = "within")
# within means that varuation within one individual or entity
summary(fixed.model)
## part(i)

## part b

random.model <- plm(lnprice ~age+school+attractive+bar +street + nocondom +rich +regular +alcohol,
                 data = context,index =c("id", "trans"), model = "random")
```

```
summary(random.model)


#########################

rm(list=ls(all=TRUE))

#library(multcomp)

library(data.table)

library(dplyr)

library(plotly)

#library(lmtest)

#library(sandwich)

#library(car)

library(AER)

library(plm)


context <- fread("crime.csv")

context <- mutate(context,Lcrmrte = log(crmrte))


#(i) deterrence increases, will decrease crime rate

#(ii) wage increase in the private sector will decrease the crime rate

#(iii) population density increase, will increase the crime rate

#(iv) percentage of young males may increase the crime rate



## part b


OLS.model <- lm( Lcrmrte ~ log(prbarr) + log(prbconv)+ log(prbpris) + log(avgsen)+ log(wmfg),
data=context)

summary(OLS.model)
```

```
## part c

FE.model <- plm( Lcrmrte ~ log(prbarr) + log(prbconv)+ log(prbpris) + log(avgsen)+ log(wmfg),
data=context,

             index=c("county","year"), model="within")

summary(FE.model)



## part d

# Unrestricted model will be FE model

# restricted model will be Pooled model

SSE.U =   16.149


pooled.model <- plm( Lcrmrte ~ log(prbarr) + log(prbconv)+ log(prbpris) + log(avgsen)+ log(wmfg),
data=context,

              model="pooling")

summary(pooled.model)


SSE.R =   106.81




 n = 630

 k = 95

## J = 89 because there are 50 more variables in FE the Unrestricted model

fVAL = ((SSE.R - SSE.U)/89)/ (SSE.U/(n-k))

fc <-  qf(0.95,89,535)



## part e
```

```
## lets compare OLS model with FE model with dummy variables

OLS.model <- lm( Lcrmrte ~ log(prbarr) + log(prbconv)+ log(prbpris) + log(avgsen)+ log(wmfg)
            + ldensity + lpctymle+ d82 +d83 + d84 + d85+ d86 + d87, data=context)
summary(OLS.model)

FE.model <- plm( Lcrmrte ~ log(prbarr) + log(prbconv)+ log(prbpris) + log(avgsen)+ log(wmfg)
            + ldensity + lpctymle+ d82 +d83 + d84 + d85+ d86 + d87, data=context,
index=c("county","year"),
           model="within" )
summary(FE.model)

#(ii)
## compare OLS models with and without dummy variables

U.OLS.model <- lm( Lcrmrte ~ log(prbarr) + log(prbconv)+ log(prbpris) + log(avgsen)+ log(wmfg)
            + ldensity + lpctymle+ d82 +d83 + d84 + d85+ d86 + d87, data=context)

SSE.U = sum( (U.OLS.model$residuals)^2)



R.OLS.model <- lm( Lcrmrte ~ log(prbarr) + log(prbconv)+ log(prbpris) + log(avgsen)+ log(wmfg)
            + ldensity + lpctymle, data=context)

SSE.R = sum( (R.OLS.model$residuals)^2)

# restricted model is OLS with dummy variables

n = 630
```

```
k = 14

## J = 6

fVAL = ((SSE.R - SSE.U)/6)/ (SSE.U/(n-k))

fc <-  qf(0.95,6,616)


## compare FE models with and without dummy variables


U.FE.model <- plm( Lcrmrte ~ log(prbarr) + log(prbconv)+ log(prbpris) + log(avgsen)+ log(wmfg)

          + ldensity + lpctymle+ d82 +d83 + d84 + d85+ d86 + d87,

          data=context, index=c("county","year"), model = "within")

summary(U.FE.model)


SSE.U = 14.383


R.FE.model <- plm( Lcrmrte ~ log(prbarr) + log(prbconv)+ log(prbpris) + log(avgsen)+ log(wmfg)

          + ldensity + lpctymle,

          data=context, index=c("county","year"), model = "within")

summary(R.FE.model)


SSE.R = 15.876



n = 630

k = 14

## J = 6

fVAL = ((SSE.R - SSE.U)/6)/ (SSE.U/(n-k))

fc <-  qf(0.95,6,616)
```