Panel Data

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Overview

Required R Packages

- plm
- lmtest

Documentation

- Panel data econometrics in R

Note regarding Notation

- Use of the package stargazer due to the large number of variables.

Introduction I

Pooled data: Combination of multiple cross-sectional data over time

- Two or more different observational units over time
- Grades in an economics class based on students' concentration combined from multiple semesters
- American Community Survey (ACS)

Panel data: Repeated measurement on the same individuals i over time t.

- Individual units can be people, states, firms, counties, countries, etc.
- National Longitudinal Survey (NLSY79)
- Necessary adjustments of standard error due to correlation across time.

For NLSY79: Accessing data $\Rightarrow$ investigator $\Rightarrow$ Begin searching as guest $\Rightarrow$ Pick income as an example

Introduction II

Some assumptions about linear panel models:

- Regular time intervals
- Errors are correlated
- Parameters may vary across individuals or time
- Intercept: Individual specific effects model (fixed or random)

Note that the General Social Survey (GSS) is not a panel data set because different respondents are questioned every year.

Examples and Advantages

Panel Study of Income Dynamics (PSID)

- Data on approximately 5,000 families on various socioeconomic and demographic variables

Survey of Income and Program Participation (SIPP)

- Interviews about economic condition of respondents

Advantages

- Takes into account heterogeneity among observational units, e.g., firms, states, counties, etc.
- Better understanding on the dynamics of change for observational units over time.
- Combines cross-sectional data with time series data leading to more complete behavioral models

Terminology and Types

Balanced versus unbalance panel:

- A balanced panel has the same number of time-series observations for each subject or observational unit, whereas an unbalanced panel does not.

Short versus long panel:

- A short panel has a larger number of subjects or observational units than there are time periods. A long panel has a greater number of time periods than observational units.

Types of regression models:

- Pooled Ordinary Least Square model
- Fixed effects model
- Random effects model

Simple Panel Data Methods

`fertil1`: Variables

Data from the General Social Survey for the years 1974 to 1984

- *year*: 72 to 84, even
- *educ*: years of schooling
- *meduc* and *feduc*: mother's and father's education
- *kids*: number children ever born
- *east*, *northcentral*, and *west*: 1 if lived in at 16
- *farm*: 1 if on farm at 16
- *otherrural*: 1 if other rural at 16
- *town*: 1 if lived in town at 16
- *smallcity*: 1 if in small city at 16

Source: Jeffrey Wooldridge, Introductory Econometrics: A Modern Approach

fertil1: Estimation

```
##
## ===============================================
##                         Dependent variable:
##                     ---------------------------
##                                kids
## -----------------------------------------------
## educ                     -0.130*** (0.019)
## age                      0.499*** (0.141)
## I(age2)                  -0.005*** (0.002)
## east                       0.061 (0.133)
## northcentral              0.220* (0.121)
## west                       0.051 (0.168)
## y82                      -0.414** (0.174)
## y84                      -0.565*** (0.177)
## Constant                 -6.785** (3.099)
## -----------------------------------------------
## Observations                   1,129
## R2                             0.099
## Adjusted R2                    0.086
## Residual Std. Error      1.581 (df = 1112)
## F Statistic          7.671*** (df = 16; 1112)
## ===============================================
## Note:               *p<0.1; **p<0.05; ***p<0.01
```

`fertil1`: Interpretation

Evolution of fertility rates over time after controlling of other observable factors:

- Base year: 1972
- Negative coefficients indicate a drop in fertility in the early 1980's
- Coefficient of $y82$ (-0.41) indicates that women had on average 0.41 less children, i.e., 100 women had 41 kids less than 1972
- This drop is independent from education since we are controlling for education.
- More educated women have fewer children
- Assumes that the effect of each explanatory variable remains constant.

cps7885: Setup

Interact year dummy with key explanatory variables to see if the effect of that variable has changed over time:

$$\begin{aligned}\ln(wage) =& \beta_0 + \gamma_0 \cdot y85 + \beta_1 \cdot educ + \gamma_1 \cdot y85 \cdot educ + \beta_2 \cdot exper + \beta_3 \cdot exper^2 \\ & + \beta_4 \cdot union + \beta_5 \cdot female + \gamma_5 \cdot y85 \cdot female\end{aligned}$$

Interpretation:

- β_0 is the 1978 intercept
- $\beta_0 + \gamma_0$ is the 1985 intercept
- β_1 is the return to education in 1978
- $\beta_1 + \gamma_1$ is the return to education in 1985
- γ_1 measures how the return to education has changed over the seven year period

cps7885: Estimation

```
cps7885$y85     = ifelse(cps7885$year==85,1,0)
bhat            = lm(log(wage)~y85+educ+y85:educ+exper+
                    I(exper^2)+union+female+y85:female,
                    data=cps7885)
```

cps7885: Results

```
stargazer(bhat,type="text",no.space=TRUE,single.row=TRUE)
```

```
##
## ===============================================
##                        Dependent variable:
##                    ----------------------------
##                             log(wage)
## -----------------------------------------------
## y85                        0.118 (0.124)
## educ                     0.075*** (0.007)
## exper                    0.030*** (0.004)
## I(exper2)               -0.0004*** (0.0001)
## union                    0.202*** (0.030)
## female                   -0.317*** (0.037)
## y85:educ                  0.018** (0.009)
## y85:female                0.085* (0.051)
## Constant                 0.459*** (0.093)
## -----------------------------------------------
## Observations                   1,084
## R2                             0.426
## Adjusted R2                    0.422
## Residual Std. Error      0.413 (df = 1075)
## F Statistic          99.804*** (df = 8; 1075)
## ===============================================
## Note:               *p<0.1; **p<0.05; ***p<0.01
```

cps7885: Interpretation

Interpretation

- 1978 return to education: 7.47%
- 1985 return to education: 7.47%+1.85% = 9.32%
- 1978 gender gap: 31.67%
- 1985 gender gap: 31.67% - 8.51% = 23.16%

Data `kiel`: Setup I

Data set about home values near the location of an garbage incinerator

- Run 1981 data
- Run 1978 data

Difference-in-difference estimator: -\$30,688-(-\$18,824)=-\$11,864

$$\hat{\delta}_1 = (price_{81,near} - price_{81,far}) - (price_{78,near} - price_{78,far})$$

where $\hat{\delta}_1$ represents the difference over time in average differences in housing prices in the two locations.

Data `kiel`: Setup II

To determine statistical significance:

$$price = \beta_0 + \gamma_0 \cdot y81 + \beta_1 \cdot nearinc + \gamma_1 \cdot y81 \cdot nearinc$$

Interpretation

- β_0: Average home value which is not near the garbage incinerator
- $\gamma_0 \cdot y81$: Average change in housing values for all homes
- $\beta_1 \cdot nearinc$: Location effect that is not due to the incinerator
- γ_1: Decline in housing values due to incinerator

Homes have lost 9.3% in values when including additional independent variables and using the natural logarithm of price.

Data kiel: Naive Implementation in R

```
kiel81          = subset(kiel,year==1981)
bhat81          = lm(rprice~nearinc,data=kiel81)
kiel78          = subset(kiel,year==1978)
bhat78          = lm(rprice~nearinc,data=kiel78)
```

Data kiel: Naive Results

```
##
## =====================================================================
##                                 Dependent variable:
##                     -------------------------------------------------
##                                       rprice
##                              (1)                        (2)
## ---------------------------------------------------------------------
## nearinc             -30,688.270*** (5,827.709) -18,824.370*** (4,744.594)
## Constant            101,307.500*** (3,093.027) 82,517.230*** (2,653.790)
## ---------------------------------------------------------------------
## Observations                 142                        179
## R2                          0.165                      0.082
## Adjusted R2                 0.159                      0.076
## Residual Std. Error   31,238.040 (df = 140)      29,431.960 (df = 177)
## F Statistic          27.730*** (df = 1; 140)    15.741*** (df = 1; 177)
## =====================================================================
## Note:                                  *p<0.1; **p<0.05; ***p<0.01
```

Data kiel: Implementation in R

```
bhat1      = lm(rprice~y81+nearinc+y81nrinc,data=kiel)
bhat2      = lm(rprice~y81+nearinc+y81nrinc+age+agesq,data=kiel)
bhat3      = lm(rprice~y81+nearinc+y81nrinc+age+agesq+cbd+rooms+
                 area+land+baths,data=kiel)
```

Data kiel: Results

```
##
## ===========================================================================================
##                                              Dependent variable:
##                     -----------------------------------------------------------------------
##                                                     rprice
##                               (1)                     (2)                     (3)
## -------------------------------------------------------------------------------------------
## y81                      18,790.290***          21,321.040***           14,115.710***
##                           (4,050.065)            (3,443.631)             (2,802.303)
## nearinc                 -18,824.370***           9,397.936*              3,618.020
##                           (4,875.322)            (4,812.222)             (4,644.530)
## y81nrinc                 -11,863.900           -21,920.270***          -14,269.820***
##                           (7,456.646)            (6,359.745)             (4,999.499)
## rooms                                                                    3,310.163**
##                                                                          (1,665.357)
## area                                                                      17.920***
##                                                                            (2.310)
## land                                                                       0.136***
##                                                                            (0.031)
## Constant                 82,517.230***          89,116.540***           13,055.760
##                           (2,726.910)            (2,406.051)             (11,272.270)
## -------------------------------------------------------------------------------------------
## Observations                  321                     321                     321
## R2                           0.174                   0.414                   0.658
## Adjusted R2                  0.166                   0.405                   0.647
## Residual Std. Error  30,242.900 (df = 317)   25,543.290 (df = 315)   19,667.290 (df = 310)
## F Statistic         22.251*** (df = 3; 317) 44.591*** (df = 5; 315) 59.742*** (df = 10; 310)
## ===========================================================================================
## Note:                                                     *p<0.1; **p<0.05; ***p<0.01
```

Grunfeld Data

The data set is used in many textbooks and comes also with the package plm. Data on 10 companies over the period 1935 to 1954:

- *inv*: Investment
- *value*: Value of the firm
- *capital*: Capital stock

Companies of interest for this class: GM (firm 1), U.S. Steel (firm 2), GE (firm 3), Westinghouse (firm 8)

Pooled OLS Model

Pooling all cross-sectional and time series observations into a single data set and running an OLS regression.

$$inv_i = \beta_0 + \beta_1 \cdot value_i + \beta_2 \cdot capital_i$$

General formulation of the pooled model

$$y_{it} = \beta_0 + \beta_1 \cdot x_i + \epsilon_i$$

Issues with pooled OLS model:

- Ignores heterogeneity among the observations and time.

With heterogeneity: Biased and inconsistent estimates due to correlation between independent variables and error term.

Data Preparation and Pooled OLS Model

Use of firms 1, 2, 3, and 8:

```
grunfeld = subset(grunfeld,grunfeld$firm %in% c(1,2,3,8))
```

To use the functions from plm, define data as a panel data set:

```
grunfeld = pdata.frame(grunfeld,index=c("firm","year"))
```

Running a simple OLS model on the data:

- Using the regular `lm()` function
- Using the `plm()` function and specifying the model as **pooling**
- Name the outputs `grunfeld.ols` and `grunfeld.pooling`

Pooled OLS Model

```
grunfeld.ols        = lm(inv~value+capital,data=grunfeld)
grunfeld.pooling    = plm(inv~value+capital,data=grunfeld,
                          model="pooling")
```

Pooled OLS Model

```
stargazer(grunfeld.ols,grunfeld.pooling,no.space=TRUE,
          single.row=TRUE,type="text")
```

```
##
## ==============================================================
##                                    Dependent variable:
##                          -------------------------------------
##                                           inv
##                                  OLS                panel
##                                                     linear
##                                  (1)                 (2)
## --------------------------------------------------------------
## value                     0.111*** (0.014)   0.111*** (0.014)
## capital                   0.300*** (0.049)   0.300*** (0.049)
## Constant                 -62.832** (29.725) -62.832** (29.725)
## --------------------------------------------------------------
## Observations                     80                  80
## R2                              0.755               0.755
## Adjusted R2                     0.748               0.748
## Residual Std. Error      142.916 (df = 77)
## F Statistic (df = 2; 77)     118.424***          118.424***
## ==============================================================
## Note:                              *p<0.1; **p<0.05; ***p<0.01
```

Fixed Effects Model

Theoretical Concepts I

Fixed effects model or Least-Squares Dummy Variable (LSDV) regression

- Constant slope coefficients but varying intercept over i

Regression equation:

$$inv_{it} = \beta_{0i} + \beta_1 \cdot value_{it} + \beta_2 \cdot capital_{it}$$

with $i = 1, 2, 3, 4$ and $t = 1, 2, \ldots, 20$. This model can also be written as

$$inv_{it} = \alpha_0 + \alpha_1 \cdot D_{1i} + \alpha_2 \cdot D_{2i} + \alpha_3 \cdot D_{3i} + \beta_1 \cdot value_{it} + \beta_2 \cdot capital_{it}$$

Individual specific effects:

$$y_{it} = \alpha_i + \beta_i \cdot x_{it} + \epsilon_{it}$$

α_i can be fixed or random

Theoretical Concepts II

Fixed effects model

- Intercept β_{0i} is firm specific.
- For an individual, this could be education and/or ability, possibly correlated with independent variables
- Intercept is time-invariant.
- Slope coefficients do not vary across individuals (firms) or time

Implementation in R

```
grunfeld.fixed = plm(inv~value+capital,data=grunfeld,
                     model="within")
```

Results

```
stargazer(grunfeld.fixed,no.space=TRUE,
          single.row=TRUE,type="text")
```

```
##
## ========================================
##                   Dependent variable:
##               ---------------------------
##                          inv
## ----------------------------------------
## value             0.108*** (0.018)
## capital           0.345*** (0.027)
## ----------------------------------------
## Observations             80
## R2                      0.806
## Adjusted R2             0.792
## F Statistic    153.291*** (df = 2; 74)
## ========================================
## Note:         *p<0.1; **p<0.05; ***p<0.01
```

Firm-Specific Intercepts and Hypothesis Test

In order to get the firm specific intercepts:

```
fixef(grunfeld.fixed)
```

```
##        1        2        3        8
##  -85.515   94.988 -246.228  -59.386
```

Testing whether a fixed effects or OLS is appropriate (H_0: OLS better):

```
pFtest(grunfeld.fixed,grunfeld.ols)
```

```
##
##  F test for individual effects
##
## data:  inv ~ value + capital
## F = 67.215, df1 = 3, df2 = 74, p-value < 2.2e-16
## alternative hypothesis: significant effects
```

If the p-value is below 0.05 then the fixed effects model is a better choice.

Implementation in R using `lm()`

Implementation of a fixed effects model with the command `lm()`

```
bhat = lm(inv~value+capital+factor(firm),data=grunfeld)
```

Random Effects Model

Theoretical Concepts

The general fixed effects model can be expressed as

$$y_{it} = \beta_{0i} + \beta_1 \cdot x_{1,it} + \beta_2 \cdot x_{2,it} + \epsilon_{it}$$

Instead of treating β_{0i} as fixed, the random model assumes

$$\beta_{0i} = \beta_0 + \upsilon_i$$

where υ_i is random error term with a mean of zero and variance σ_υ^2. According to Gujarati: *What we are essentially saying is that the four firms included in our sample are a drawing from a much larger universe of such companies and that they have a common mean value for the intercept* β_0 *and the individual differences in the intercept values of each company are reflected in the error term* υ_i*.*

Implementation in R

```
grunfeld.random = plm(inv~value+capital,data=grunfeld,model="random")
stargazer(grunfeld.random,no.space=TRUE,single.row=TRUE,type="text")
```

```
##
## ========================================
##                   Dependent variable:
##               ---------------------------
##                          inv
## ----------------------------------------
## value             0.108*** (0.017)
## capital           0.345*** (0.027)
## Constant          -73.085 (81.172)
## ----------------------------------------
## Observations              80
## R2                       0.803
## Adjusted R2              0.798
## F Statistic           314.851***
## ========================================
## Note:        *p<0.1; **p<0.05; ***p<0.01
```

Breusch-Pagan Lagrange Multiplier (LM) Test

For random effects models: Null hypothesis of no panel effect, i.e., OLS is better. If p-value is below 0.05, we reject the null hypothesis and thus, a random effects model is more appropriate than the OLS.

```
plmtest(grunfeld.pooling,type=c("bp"))
```

```
##
##  Lagrange Multiplier Test - (Breusch-Pagan)
##
## data:  inv ~ value + capital
## chisq = 378.44, df = 1, p-value < 2.2e-16
## alternative hypothesis: significant effects
```

Hausman Test: Fixed or Random Model

The Hausman Test tests the null hypothesis that the preferred model is a random effects model. It basically tests whether the unique errors are correlated with the regressors.

```
phtest(grunfeld.random,grunfeld.fixed)
```

```
##
##  Hausman Test
##
## data:  inv ~ value + capital
## chisq = 0.14882, df = 2, p-value = 0.9283
## alternative hypothesis: one model is inconsistent
```

Testing for Heteroscedasticity

```
bptest(inv~value+capital+factor(firm),data=grunfeld)
```

```
##
##  studentized Breusch-Pagan test
##
## data:  inv ~ value + capital + factor(firm)
## BP = 25.375, df = 5, p-value = 0.0001179
```

If the p-value is below 0.05, then we face heteroscedasticity.

Heteroscedasticity Consistent Coefficients and Standard Errors

```
coeftest(grunfeld.fixed,vcovHC)
```

```
##
## t test of coefficients:
##
##         Estimate Std. Error t value  Pr(>|t|)
## value   0.108400   0.014293  7.5839 7.902e-11 ***
## capital 0.345058   0.031152 11.0765 < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```