EXCERSISES IN APPLIED PANEL DATA ANALYSIS #4

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1. Introduction

This R example will introduce you to estimation of the unobserved effects model under the random effects framework. Recall that the random effects framework assumes that the covariates in the model are uncorrelated with the unobserved effects. We will be using the `plm` library exclusively to discuss a prominent applied example. Given that we also learned that the random effects GLS estimator is a weighted combination of the within estimator and the between estimator, we will also use the `between` option in the `plm` framework.

2. Estimating the Unoberved Effects Model Under the Random Effects Framework

2.1. **Estimating the Demand for Gasoline.** In a classic study Baltagi & Griffin (1983) estimated a demand equation for gasoline at the country level. Their balanced panel constituted 18 OECD countries over the period 1960-1978. Their baseline econometric model is

$$\ln(Gas/Car)_{it} = \beta_0 + \beta_1 \ln(GDP/Pop)_{it} + \beta_2 \ln(P_{Gas}/P_{GDP})_{it} + \beta_3 \ln(Car/Pop)_{it} + c_i + \varepsilon_{it}, \tag{1}$$

where Gas/Car is gasoline consumption per car, GDP/Pop is per capita income, P_{Gas}/P_{GDP} is the price of gasoline and Car/Pop is the stock of cars per capita. The key coefficient of interest in β_2, which identifies the price elasticity of gasoline.

```
> library(plm)
> ## Load in dataset of Baltagi and Griffin (1983)
> data("Gasoline")
> ## Look at first 6 rows to see the data
> head(Gasoline)
```

We can get an initial sense for what the data looks like across time and country using the `coplot` function. This is a great way to investigate data in a panel setting. The coplot appears in Figure 1.

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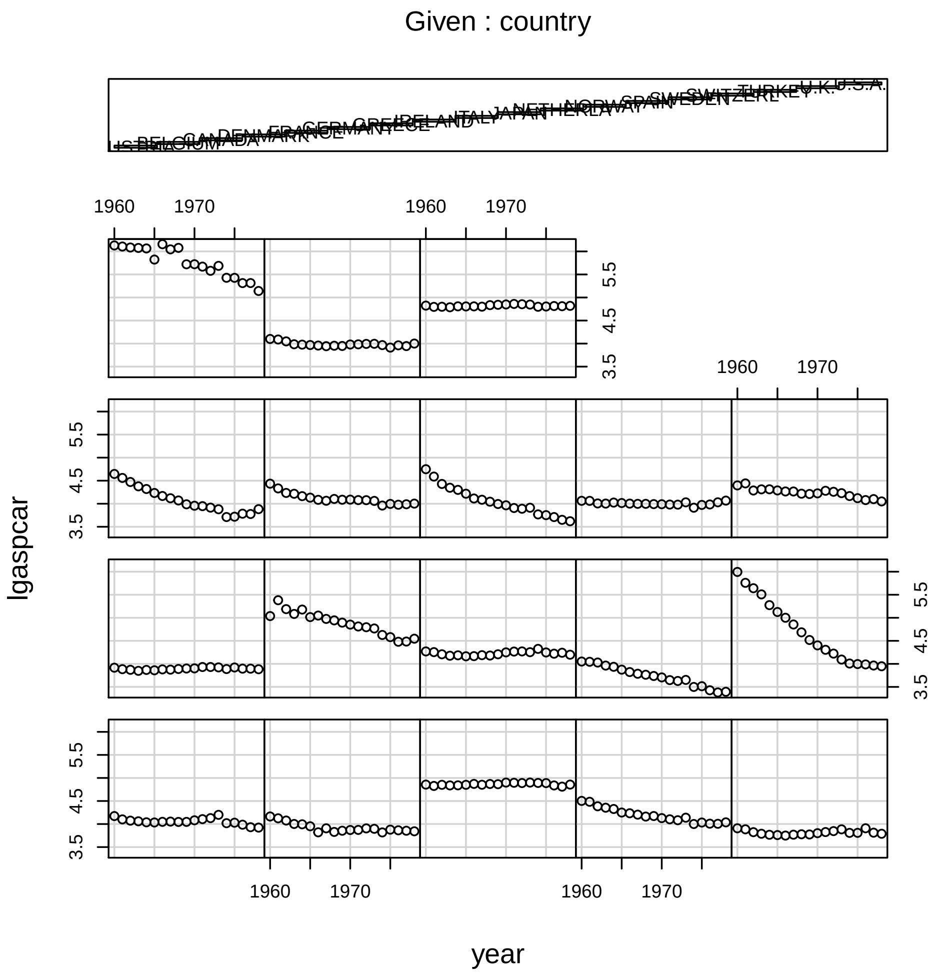
```
> ## Now lets plot out gasoline demand over time, conditioning on country
> coplot(lgaspcar~year|country,type="b", data=Gasoline)
```

Figure 1. Coplots of Gasoline Demand.



Next we can estimate the pooled linear panel data model as well as the within transformation of the fixed effects framework for the unobserved effects model.

```
> gas.pooled <- plm(lgaspcar~lincomep+lrpmg+
+                       lcarpcap,
+                     model="pooling",data=Gasoline)
> gas.wn    <- plm(lgaspcar~lincomep+lrpmg+
+                      lcarpcap,
+                    model="within",effect="individual",
+                    data=Gasoline)
```

Next, to estimate the between model we change `model="within"` to `model="between"`. Under the random effects setting we would change the optin to `random` and then we would need to invoke one of the four different methods to construct the unknown variances for feasible GLS.

```
> gas.bw <- plm(lgaspcar~lincomep+lrpmg+
+                    lcarpcap,
+                  model="between",effect="individual",
+               data=Gasoline)
> gas.rd.nerl <- plm(lgaspcar~lincomep+lrpmg+
+                         lcarpcap,
+                       model="random",
+                       effect="individual",
+                       random.method="nerl",
+                       data=Gasoline)
```

```
[1] 342  18
```

```
> gas.rd.swar <- plm(lgaspcar~lincomep+lrpmg+
+                         lcarpcap,
+                       model="random",
+                       effect="individual",
+                       random.method="swar",
+                       data=Gasoline)
> gas.rd.wh <- plm(lgaspcar~lincomep+lrpmg+
+                         lcarpcap,
+                       model="random",
+                       effect="individual",
+                       random.method="walhus",
+                       data=Gasoline)
> gas.rd.amem <- plm(lgaspcar~lincomep+lrpmg+
+                         lcarpcap,
+                       model="random",
+                       effect="individual",
+                       random.method="amemiya",
+                       data=Gasoline)
```

Comparing our results to those in Baltagi & Griffin (1983, Table 2) we see that indeed we have replicated their findings. To extract the estimates of the variance components from the random effects models extract `ercomp` from the model summary.

```
> sum.pool <- summary(gas.pooled)
> sum.wn   <- summary(gas.wn)
> sum.bw   <- summary(gas.bw)
```

```
> sum.rdsa <- summary(gas.rd.swar)
> sum.rdnl <- summary(gas.rd.nerl)
> sum.rdam <- summary(gas.rd.amem)
> sum.rdwh <- summary(gas.rd.wh)
> rbind(sum.pool$coefficients[,1],sum.pool$coefficients[,3])
     (Intercept)   lincomep       lrpmg    lcarpcap
[1,]    2.391326  0.8899617  -0.8917979  -0.7633727
[2,]   20.450166 24.8552290 -29.4179589 -41.0232487
> rbind(sum.wn$coefficients[,1],sum.wn$coefficients[,3])
      lincomep      lrpmg    lcarpcap
[1,] 0.6622497 -0.3217025  -0.6404829
[2,] 9.0241906 -7.2949638 -21.5804473
> rbind(sum.bw$coefficients[,1],sum.bw$coefficients[,3])
     (Intercept)  lincomep      lrpmg   lcarpcap
[1,]     2.54163 0.9675764 -0.9635504 -0.7952991
[2,]     4.82480 6.2157123 -7.2490219 -9.6430025
> rbind(sum.rdam$coefficients[,1],sum.rdam$coefficients[,3])
     (Intercept)  lincomep      lrpmg  lcarpcap
[1,]    2.183014 0.6005398 -0.3667288  -0.62027
[2,]   10.160503 9.1607454 -8.8411904 -22.76615
> rbind(sum.rdwh$coefficients[,1],sum.rdwh$coefficients[,3])
     (Intercept)  lincomep       lrpmg    lcarpcap
[1,]    1.905802 0.5434565  -0.4711081  -0.6061304
[2,]   11.475654 9.9939524 -12.0979619 -24.9358820
> rbind(sum.rdsa$coefficients[,1],sum.rdsa$coefficients[,3])
     (Intercept)  lincomep       lrpmg    lcarpcap
[1,]    1.996698 0.5549857  -0.4203892  -0.6068401
[2,]   10.832430 9.3861449 -10.5154788 -23.7836200
> rbind(sum.rdnl$coefficients[,1],sum.rdnl$coefficients[,3])
     (Intercept)  lincomep      lrpmg    lcarpcap
[1,]     2.20177 0.6056099 -0.3624312  -0.6218869
[2,]    10.07977 9.1602292 -8.7090528 -22.6970324
> ## Error Components
> sum.rdam$ercomp
                   var  std.dev share
idiosyncratic 0.008525 0.092330 0.069
```

```
individual    0.114199 0.337933 0.931
theta:  0.9374
> sum.rdwh$ercomp
                  var std.dev share
idiosyncratic 0.01351 0.11623  0.31
individual    0.03007 0.17341  0.69
theta:  0.848
> sum.rdsa$ercomp
                   var  std.dev share
idiosyncratic 0.008525 0.092330 0.182
individual    0.038238 0.195545 0.818
theta:  0.8923
> sum.rdnl$ercomp
                   var  std.dev share
idiosyncratic 0.008001 0.089451 0.062
individual    0.121392 0.348413 0.938
theta:  0.9412
```

Notice the wide difference in the estimates of θ across the four different random effects specifications for the feasible GLS estimator. While all of the methods suggesta θ near 1, the approach of Wallace & Hussain (1969) yields by far the smallest θ, of 0.85. Both the approaches of Amemiya (1971) and Nerlove (1971) suggest that the random effects transformation is 'close' to the within transformation.

Some interesting insights emerge from this simple example. First, the choice of estimator has a large impact on the perceived elasticity of gasoline demand. The between estimator produces an estimated elasticity that is almost three times as large as the estimated elasticity from the within estimator (-0.96 vs. -0.32). Second, there is not much variation across the estimated elasticities of the four random effect specifications. However, a 95% confidence interval suggests that the individual elasticity estimates are statistically different. Thus, even if we think the estimates are economically close, statistically they are not the same and so the choice of estimator is important.

Another interesting aspect of the Baltagi & Griffin (1983) modeling setup is that even if the debate between the fixed or random effects framework suggest small differences in the estimated elasticities, it is not clear that the model is correctly capturing dynamics. To account for latent dynamics, Baltagi & Griffin (1983, Table 3) append lagged gasoline consumption per car into the model in (1). Doing so results in lower (in magnitude) estimates for the short run elasticity on the real price of gasoline. The long run elasticity is found by dividing the short run elasticity by $1-\beta_4$, where β_4 is the coefficient on lagged gasoline per auto consumption.

```
> gas.pooled.lag <- plm(lgaspcar~lincomep+lrpmg+
+                      lcarpcap+lag(lgaspcar,1),
```

```
+                    model="pooling",data=Gasoline)
> gas.wn.lag    <- plm(lgaspcar~lincomep+lrpmg+
+                     lcarpcap+lag(lgaspcar,1),
+                   model="within",effect="individual",
+                   data=Gasoline)
> gas.bw.lag <- plm(lgaspcar~lincomep+lrpmg+
+                      lcarpcap+lag(lgaspcar,1),
+                    model="between",effect="individual",
+                data=Gasoline)
> gas.rd.nerl.lag <- plm(lgaspcar~lincomep+lrpmg+
+                          lcarpcap+lag(lgaspcar,1),
+                       model="random",
+                       effect="individual",
+                       random.method="nerl",
+                       data=Gasoline)
```

```
[1] 324  18
```

```
> gas.rd.swar.lag <- plm(lgaspcar~lincomep+lrpmg+
+                          lcarpcap+lag(lgaspcar,1),
+                       model="random",
+                       effect="individual",
+                       random.method="swar",
+                       data=Gasoline)
> gas.rd.wh.lag <- plm(lgaspcar~lincomep+lrpmg+
+                          lcarpcap+lag(lgaspcar,1),
+                       model="random",
+                       effect="individual",
+                       random.method="walhus",
+                       data=Gasoline)
> gas.rd.amem.lag <- plm(lgaspcar~lincomep+lrpmg+
+                          lcarpcap+lag(lgaspcar,1),
+                       model="random",
+                       effect="individual",
+                       random.method="amemiya",
+                       data=Gasoline)
```

Comparing our results to those in Baltagi & Griffin (1983, Table 3) we see that indeed we have replicated their findings. To extract the estimates of the variance components from the random effects models extract `ercomp` from the model summary.

```
> sum.pool.lag <- summary(gas.pooled.lag)
> sum.wn.lag   <- summary(gas.wn.lag)
> sum.bw.lag   <- summary(gas.bw.lag)
> sum.rdsa.lag <- summary(gas.rd.swar.lag)
> sum.rdnl.lag <- summary(gas.rd.nerl.lag)
> sum.rdam.lag <- summary(gas.rd.amem.lag)
> sum.rdwh.lag <- summary(gas.rd.wh.lag)
> rbind(sum.pool.lag$coefficients[,1],sum.pool.lag$coefficients[,3])
     (Intercept)   lincomep       lrpmg    lcarpcap lag(lgaspcar, 1)
[1,]    0.254099 0.06647615 -0.07827209 -0.04363944        0.9287855
[2,]    4.929009 3.70898607 -4.65279097 -3.18181199       57.4828602
> rbind(sum.wn.lag$coefficients[,1],sum.wn.lag$coefficients[,3])
      lincomep      lrpmg   lcarpcap lag(lgaspcar, 1)
[1,] 0.1932957 -0.1591322 -0.1860584        0.6920107
[2,] 3.9866519 -5.9304772 -6.9621077       22.9165009
> rbind(sum.bw.lag$coefficients[,1],sum.bw.lag$coefficients[,3])
     (Intercept)    lincomep       lrpmg   lcarpcap lag(lgaspcar, 1)
[1,]  0.04417504 -0.01574678 0.002784614 0.02404827         1.012026
[2,]  0.39919295 -0.39540163 0.073467642 0.78498703        28.556239
> rbind(sum.rdam.lag$coefficients[,1],sum.rdam.lag$coefficients[,3])
     (Intercept)  lincomep      lrpmg   lcarpcap lag(lgaspcar, 1)
[1,]   0.5962061 0.1631956 -0.1709261 -0.1593927        0.7336758
[2,]   5.8317837 5.0135605 -7.2174323 -7.5844360       27.0860179
> rbind(sum.rdwh.lag$coefficients[,1],sum.rdwh.lag$coefficients[,3])
     (Intercept)  lincomep      lrpmg   lcarpcap lag(lgaspcar, 1)
[1,]    0.423747 0.1270039 -0.1391658 -0.0998361        0.8505524
[2,]    6.173796 5.5409484 -6.6941215 -5.8045572       40.4568932
> rbind(sum.rdsa.lag$coefficients[,1],sum.rdsa.lag$coefficients[,3])
     (Intercept)  lincomep      lrpmg   lcarpcap lag(lgaspcar, 1)
[1,]   0.4399933 0.1320564 -0.1443785 -0.1054016        0.8416961
[2,]   6.2478283 5.6402295 -6.8444582 -6.0253865       39.1326940
> rbind(sum.rdnl.lag$coefficients[,1],sum.rdnl.lag$coefficients[,3])
     (Intercept)  lincomep     lrpmg   lcarpcap lag(lgaspcar, 1)
[1,]   0.6033972 0.1642836 -0.170568 -0.1613786        0.7294506
[2,]   5.7477427 4.9267134 -7.164336 -7.5873937       26.7195095
> ## Error Components
> sum.rdam.lag$ercomp
```

```
                   var  std.dev share
idiosyncratic 0.002734 0.052288 0.301
individual    0.006347 0.079665 0.699
theta:  0.8471
> sum.rdwh.lag$ercomp
                   var  std.dev share
idiosyncratic 0.003262 0.057116 0.868
individual    0.000497 0.022293 0.132
theta:  0.4831
> sum.rdsa.lag$ercomp
                    var   std.dev share
idiosyncratic 0.0027341 0.0522885 0.844
individual    0.0005066 0.0225088 0.156
theta:  0.5197
> sum.rdnl.lag$ercomp
                   var  std.dev share
idiosyncratic 0.002548 0.050482  0.27
individual    0.006881 0.082950  0.73
theta:  0.858
```

References

Amemiya, T. (1971), 'The estimation of variances in a variance components model', *International Economic Review* **12**, 1–13.

Baltagi, B. H. & Griffin, J. M. (1983), 'Gasoline demand in the OECD: An application of pooling and testing procedures', *European Economic Review* **22**, 117–137.

Nerlove, M. (1971), 'Further evidence on the estimation of dynamic economic relations from a time-series of cross-sections', *Econometrica* **39**, 359–382.

Wallace, T. D. & Hussain, A. (1969), 'The use of error components models in combining cross-section with time-series data', *Econometrica* **37**, 55–72.