R-Package “pdynmc”: GMM Estimation of Dynamic Panel Data Models Based on Nonlinear Moment Conditions

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Outline

1. Introduction
2. GMM estimation
3. A short note on nonlinear moment conditions
4. Package `pdynmc` — a first tour
5. Conclusion

What is pdynmc?

pdynmc $\longrightarrow$ panel data

pdynmc $\longrightarrow$ (linear) dynamic models $\Longrightarrow$ GMM

pdynmc $\longrightarrow$ (linear and/or) nonlinear moment conditions (w.r.t. α_j, β_k)

pdynmc is intended to efficiently estimate models like

$$\begin{aligned} y_{i,t} &= \alpha_1 y_{i,t-1} + \ldots + \alpha_p y_{i,t-p} \\ &+ \beta_1 x^*_{i,t^*,1} + \ldots + \beta_q x^*_{i,t^*,q} + \underbrace{\eta_i + \varepsilon_{i,t}}_{u_{i,t}} \end{aligned}$$

where

x^* means that we allow for endogenous, predetermined, and/or exogenous covariates (could also be time/etc. dummies), and

t^* means that arbitrary lags of the covariates can be included.

Key features of pdynmc (and conclusion)

pdynmc allows for GMM estimation of linear dynamic panel data models based on linear and/or nonlinear moment conditions and provides the following features:

- R-package $\Rightarrow$ open source.
- Comprehensive control over all configuration/specification decisions.
- Can handle arbitrary unbalancedness (given moment conditions can be derived).
- State-of-the-art estimation (iterated GMM, Hansen & Lee, 2020) of linear dynamic panel data models.
- Specification tests and analysis of stability of coefficient estimates.
- Panel structure analysis (visualizations and figures).

GMM estimation, moment conditions, assumptions

GMM estimation is performed by minimizing the objective function

$$L = \overline{\mathbf{m}}' \cdot \mathbf{W} \cdot \overline{\mathbf{m}}$$

where

$\overline{\mathbf{m}}$ is the sample analogon to the population moment conditions $E\left(\cdot\right)$,

$\mathbf{W}$ is the (moment condition) weighting matrix.

The moment conditions are derived from different (sets of) assumptions.

Sets of assumptions

A1 (Ahn & Schmidt, 1995):

$$\begin{aligned}
&\text{The data are independently distributed across } i,\\
&E(\eta_i) = 0, \quad i = 1, \dots, n,\\
&E(\varepsilon_{i,t}) = 0, \quad i = 1, \dots, n,\ t = 2, \dots, T,\\
&E(\varepsilon_{i,t} \cdot \eta_i) = 0, \quad i = 1, \dots, n,\ t = 2, \dots, T,\\
&E(\varepsilon_{i,t} \cdot \varepsilon_{i,s}) = 0, \quad i = 1, \dots, n,\ t \neq s,\\
&E(y_{i,1} \cdot \varepsilon_{i,t}) = 0, \quad i = 1, \dots, n,\ t = 2, \dots, T,\\
&n \to \infty, \text{ while } T \text{ is fixed, such that } \frac{T}{n} \to 0.
\end{aligned}$$

A2 (Arellano, 2003; Kiviet, 2007; Bun & Sarafidis, 2015):

$$E(\Delta y_{i,t} \cdot \eta_i) = 0, \quad i = 1, \dots, n.$$

Moment conditions are derived w.r.t.

Equation in levels

$$\begin{aligned} y_{i,t} &= \alpha_1 y_{i,t-1} + \ldots + \alpha_p y_{i,t-p} \\ &+ \beta_1 x^*_{i,t^*,1} + \ldots + \beta_q x^*_{i,t^*,q} + \underbrace{\eta_i + \varepsilon_{i,t}}_{u_{i,t}} \end{aligned}$$

Equation in (first) differences

$$\begin{aligned} \Delta y_{i,t} &= \alpha_1 \Delta y_{i,t-1} + \ldots + \alpha_p \Delta y_{i,t-p} \\ &+ \beta_1 \Delta x^*_{i,t^*,1} + \ldots + \beta_q \Delta x^*_{i,t^*,q} + \Delta \varepsilon_{i,t} \end{aligned}$$

Standard moment conditions

under A1

Linear moment conditions w.r.t. **equation in differences**

$$E\big(y_{i,s} \cdot \Delta u_{i,t}\big) = 0, \qquad t = 3, \ldots, T; \qquad s = 1, \ldots, t-2. \quad \text{(MYD)}$$

Nonlinear moment conditions

$$E\big(u_{i,t} \cdot \Delta u_{i,t-1}\big) = 0, \qquad t = 4, \ldots, T. \quad \text{(MN)}$$

$$E\big(u_{i,T} \cdot \Delta u_{i,t-1}\big) = 0, \qquad t = 4, \ldots, T. \quad \text{(MNAS)}$$

under A1 & A2

Linear moment conditions w.r.t. **equation in levels**

$$E\big(\Delta y_{i,t-1} \cdot u_{i,t}\big) = 0, \quad t = 3, \ldots, T. \quad \text{(MYL)}$$

Moment conditions from covariates

Linear moment conditions w.r.t. **equation in differences**

$$E\left(\sum_{t=2}^{T} \Delta x_{it} \Delta u_{it}\right) = 0 \qquad \text{for exogenous } x. \qquad \text{(MFCD)}$$

$$\text{Alternatively} \quad E\left(x_{i,s} \cdot \Delta u_{i,t}\right) = 0, \qquad t = 3, \ldots, T, \qquad \text{(MXD)}$$

$$\text{where} \quad s = 1, \ldots, t-2, \qquad \text{for endogenous } x,$$

$$s = 1, \ldots, t-1, \qquad \text{for predetermined } x,$$

$$s = 1, \ldots, T, \qquad \text{for strictly exogenous } x.$$

Linear moment conditions w.r.t. **equation in levels**

$$E\left(\sum_{t=1}^{T} x_{it} u_{it}\right) = 0 \qquad \text{for exogenous } x. \qquad \text{(MFCL)}$$

$$\text{Alternatively} \quad E\left(\Delta x_{i,v} \cdot u_{i,t}\right) = 0, \qquad \text{(MXL)}$$

$$\text{where} \quad v = t-1;\ t = 3, \ldots, T, \quad \text{for endogenous } x,$$

$$v = t;\ t = 2, \ldots, T, \quad \text{otherwise.}$$

Note: MXD/MXL require analogous assumptions to A1 and/or A2 w.r.t. x.

Why we should care about nonlinear moment conditions

When the lag parameter is close to one, ...

...linear moment conditions derived from A1 fail to identify the lag parameter.

...additional linear moment conditions derived from A2

- provide a remedy, but:
- A2 may be suspect in many contexts (e.g., Arellano's worker example).

...nonlinear moment conditions from A1 can

- identify the lag parameter $\Rightarrow$ estimate consistently.
- serve as robustness check $\Rightarrow$ A2 valid?

Installing and loading package

```
### Install CRAN-Version

install.packages("pdynmc")
```

```
### Install most recent version from Github

install.packages("devtools")
library(devtools)
install_github("markusfritsch/pdynmc")
```

```
### Load installed package

library(pdynmc)
```

Note: Copy & paste the code to R should work.

Load and adjust example data set

Employment and Wages in the United Kingdom

(Arellano & Bond, 1991)

```
data(EmplUK, package = "plm")
dat <- EmplUK
dat[,c(4:7)] <- log(dat[,c(4:7)])
names(dat)[4:7] <- c("n", "w", "k", "ys")
```

Function `data.info`

```
data.info(
  dat,
  i.name = "firm",
  t.name = "year"
)
```

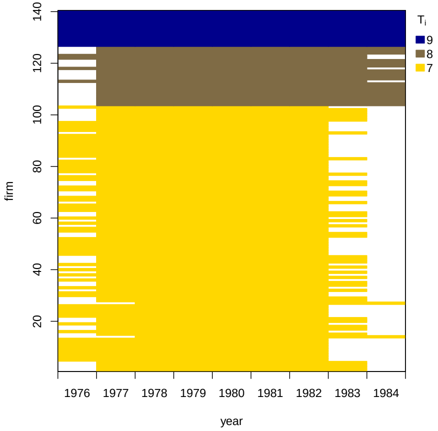
yields

```
Unbalanced panel data set with 1031 rows and
the following time period frequencies:
1976 1977 1978 1979 1980 1981 1982 1983 1984
  80  138  140  140  140  140  140   78   35
```

Function strucUPD.plot

```
strucUPD.plot(
  dat,
  i.name = "firm",
  t.name = "year"
)
```

yields



Function pdynmc

```
reg <- pdynmc(
  dat = dat, varname.i = "firm", varname.t = "year",

  use.mc.diff = TRUE, use.mc.lev = FALSE, use.mc.nonlin = TRUE,

  include.y = TRUE,
  varname.y = "n", lagTerms.y = 2,

  fur.con = TRUE,
  fur.con.diff = TRUE, fur.con.lev = TRUE,
  varname.reg.fur = c("w", "k", "ys"),
  lagTerms.reg.fur = c(1,2,2),

  include.dum = TRUE,
  dum.diff = TRUE, dum.lev = FALSE,
  varname.dum = "year",

  w.mat = "iid.err", std.err = "corrected",
  estimation = "iterative",
#  max.iter = 4,
  opt.meth = "BFGS"
)

summary(reg)
```

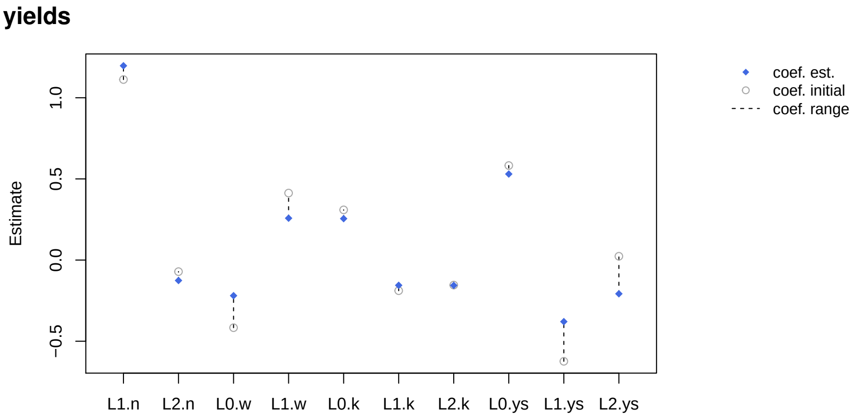
yields . . .

Model output for object `reg` (excerpt)

```
Dynamic linear panel estimation (iterative)
Estimation steps: 13

Coefficients:
      Estimate Std.Err.rob z-value.rob Pr(>|z.rob|)
L1.n   1.19704     0.06855      17.463      < 2e-16 ***
L2.n  -0.12589     0.06799      -1.852      0.06403 .
L0.w  -0.21935     0.12697      -1.728      0.08399 .
L1.w   0.25791     0.13753       1.875      0.06079 .
L0.k   0.25521     0.05568       4.583      < 2e-16 ***
L1.k  -0.15546     0.07673      -2.026      0.04276 *
L2.k  -0.15599     0.05498      -2.837      0.00455 **
L0.ys  0.53006     0.18336       2.891      0.00384 **
L1.ys -0.37925     0.22256      -1.704      0.08838 .
L2.ys -0.20770     0.15186      -1.368      0.17131
1979   0.03124     0.01015       3.077      0.00209 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

 53 total instruments are employed to estimate 16 parameters
 27 linear (DIF) 4 nonlinear
 8 further controls (DIF) 8 further controls (LEV)
 6 time dummies (DIF)

J-Test (overid restrictions):  48.1 with 37 DF, pvalue: 0.1046
F-Statistic (slope coeff):  92232.95 with 10 DF, pvalue: <0.001
F-Statistic (time dummies):  20.63 with 6 DF, pvalue: 0.0021
```

Coefficient range plot

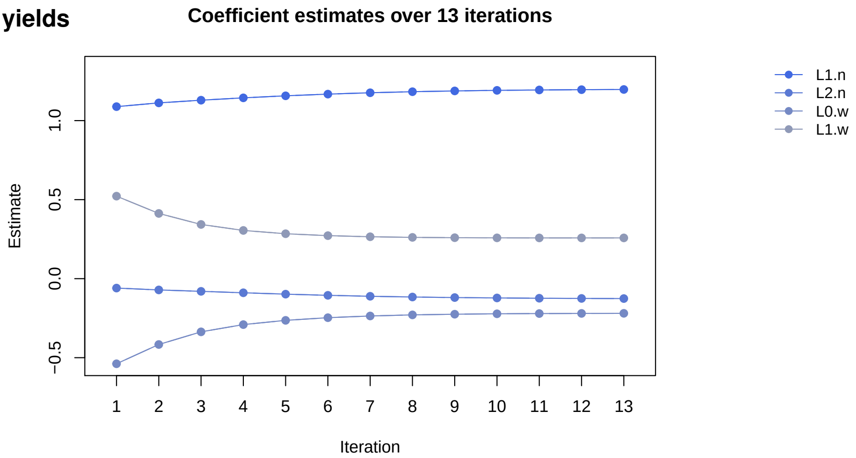
```
plot(reg, type = "coef.range", omit1step = TRUE)
```



Coefficient path plot (Hansen & Lee, 2020)

```
plot(reg, type = "coef.path", omit1step = TRUE,
  co = c("L1.n", "L2.n", "L0.w", "L1.w")
)
```

yields



Arguments of function `pdynmc` (1)

R-command	Type of moment conditions
`use.mc.diff`	MYD/MFCD/MXD
`use.mc.lev`	MYL/MFCL/MXL
`use.mc.nonlin`	MN
`use.mc.nonlinAS`	MNAS

R-command	Estimate parameter(s)	Derive moment condition(s)
`include.y`	+	MYD/MYL
`fur.con/include.dum`	+	MFCD/MFCL
`include.x`	+	MXD/MXL
`include.x.instr`	-	MXD/MXL
`include.x.toInstr`	+	-

Note: Essential arguments are indicated in bold (**`dat`**, **`varname.i`**, **`varname.t`**).

Arguments of function `pdynmc` (2)

- Relate to data set columns: `varname.reg.end`
- Restrict number of parameters: `lagTerms.reg.end`
- Restrict number of moment conditions: `maxLags.reg.end`

	`varname.`	`lagTerms.`	`maxLags.`
`.i`	+	-	-
`.t`	+	-	-
`.y`	+	+	+
`.reg.end`	+	+	+
`.reg.pre`	+	+	+
`.reg.ex`	+	+	+
`.reg.instr`	+	-	-
`.reg.toInstr`	+	-	-
`.reg.fur`	+	+	-
`.dum`	+	-	-

Arguments of function pdynmc (3)

Context	R-command
Basic configuration	w.mat std.err estimation
Handle multicollinearity	col_tol inst.thresh
Stata-conformity	inst.stata w.mat.stata
Iterated estimation	max.iter iter.tol
Nonlinear optimization	opt.method hessian optCtrl
Starting values	custom.start.val start.val start.val.lo start.val.hi seed.input

References

- Ahn, S. C. & P. Schmidt (1995), Efficient estimation of models for dynamic panel data. *Journal of Econometrics*, **68(1)**, 5–27.
- M. Arellano (2003), *Panel Data Econometrics*, Oxford University Press.
- Arellano, M. & S. Bond (1991), Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations. *Review of Economic Studies* **58**, 277–297.
- Bun, M. J. G. & V. Sarafidis (2015), Chapter 3 – Dynamic panel data models. In B. H. Baltagi, Editor, *The Oxford Handbook of Panel Data*, 76–110, Oxford University Press.
- Fritsch, M., Pua, A. & J. Schnurbus (2020), pdynmc - An package for estimating linear dynamic panel data models based on nonlinear moment conditions, *Working Paper*.
- Hansen, B. E. & S. Lee (2020), Inference for Iterated GMM Under Misspecification, *Econometrica, forthcoming*.
- J. F. Kiviet (2007), Chapter 11 – Judging contending estimators by simulation: Tournaments in dynamic panel data models. In Phillips, G. D. A. & E. Tzavalis, Editors, *The Refinement of Econometric Estimation and Test Procedures: Finite Sample and Asymptotic Analysis*, 282–318. Cambridge University Press.
- R Core Team (2020) R: A language and environment for statistical computing. *R Foundation for Statistical Computing*. Vienna, Austria.