

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

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What is pdynmc?

pdynmc → panel data

pdynmc → (linear) dynamic models \Rightarrow GMM

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

pdynmc is intended to efficiently estimate models like

$$y_{i,t} = \alpha_1 y_{i,t-1} + \dots + \alpha_p y_{i,t-p} + \beta_1 x_{i,t^*,1}^* + \dots + \beta_q x_{i,t^*,q}^* + \underbrace{\eta_i + \varepsilon_{i,t}}_{u_{i,t}}$$

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

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

where

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

\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):

The data are independently distributed across i ,

$$E(\eta_i) = 0, \quad i = 1, \dots, n,$$

$$E(\varepsilon_{i,t}) = 0, \quad i = 1, \dots, n, \quad t = 2, \dots, T,$$

$$E(\varepsilon_{i,t} \cdot \eta_i) = 0, \quad i = 1, \dots, n, \quad t = 2, \dots, T,$$

$$E(\varepsilon_{i,t} \cdot \varepsilon_{i,s}) = 0, \quad i = 1, \dots, n, \quad t \neq s,$$

$$E(y_{i,1} \cdot \varepsilon_{i,t}) = 0, \quad i = 1, \dots, n, \quad t = 2, \dots, T,$$

$$n \rightarrow \infty, \text{ while } T \text{ is fixed, such that } \frac{T}{n} \rightarrow 0.$$

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

$$y_{i,t} = \alpha_1 y_{i,t-1} + \dots + \alpha_p y_{i,t-p} \\ + \beta_1 x_{i,t^*,1}^* + \dots + \beta_q x_{i,t^*,q}^* + \underbrace{\eta_i + \varepsilon_{i,t}}_{u_{i,t}}$$

Equation in (first) differences

$$\Delta y_{i,t} = \alpha_1 \Delta y_{i,t-1} + \dots + \alpha_p \Delta y_{i,t-p} \\ + \beta_1 \Delta x_{i,t^*,1}^* + \dots + \beta_q \Delta x_{i,t^*,q}^* + \Delta \varepsilon_{i,t}$$

Standard moment conditions

under A1

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

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

Nonlinear moment conditions

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

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

under A1 & A2

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

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

Moment conditions from covariates

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

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

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

where $s = 1, \dots, t - 2$, for endogenous x ,

$s = 1, \dots, t - 1$, for predetermined x ,

$s = 1, \dots, T$, for strictly exogenous x .

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

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

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

where $v = t - 1$; $t = 3, \dots, T$, for endogenous x ,

$v = t$; $t = 2, \dots, T$, 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"  
)
```

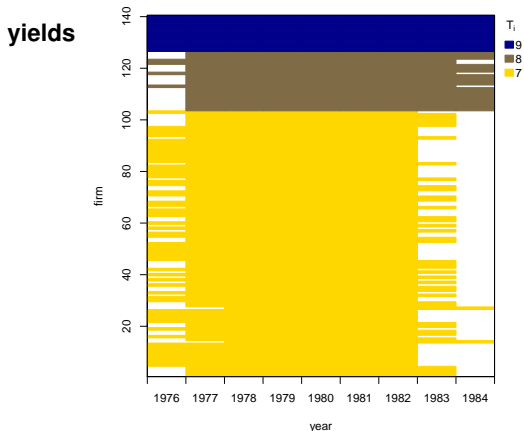
yields

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"  
)
```



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

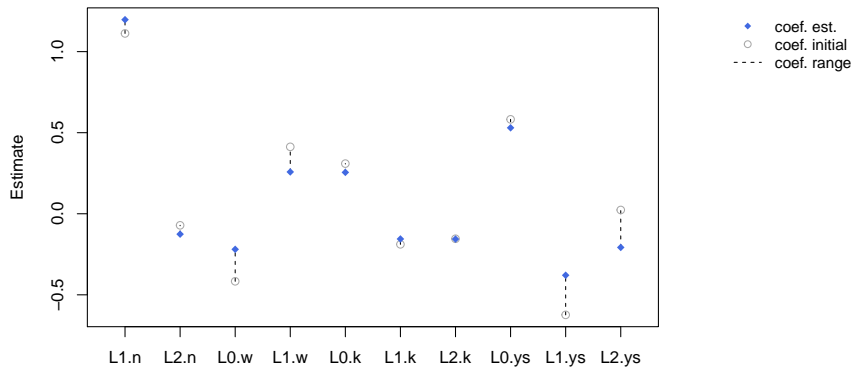
F-Statistic (slope coeff): 92232.95 with 10 DF, pvalue: <0.001

F-Statistic (time dummies): 20.63 with 6 DF, pvalue: 0.0021

Coefficient range plot

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

yields

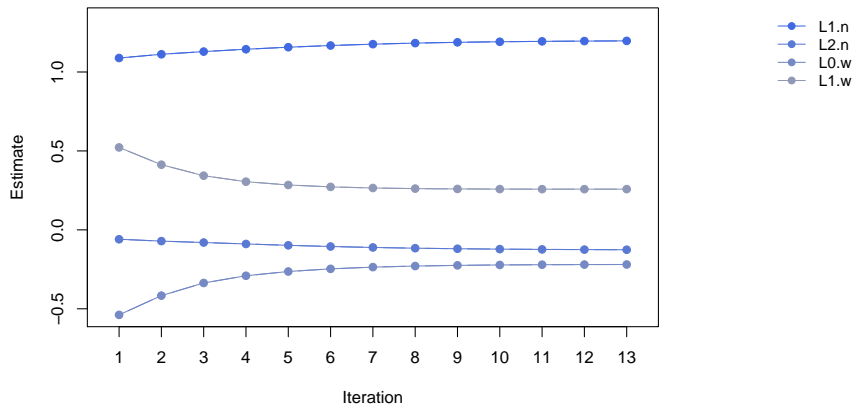


Coefficient path plot (Hansen & Lee, 2020)

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

yields

Coefficient estimates over 13 iterations



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`

	<code>varname.</code>	<code>lagTerms.</code>	<code>maxLags.</code>
<code>.i</code>	+	-	-
<code>.t</code>	+	-	-
<code>.y</code>	+	+	+
<code>.reg.end</code>	+	+	+
<code>.reg.pre</code>	+	+	+
<code>.reg.ex</code>	+	+	+
<code>.reg.instr</code>	+	-	-
<code>.reg.toInstr</code>	+	-	-
<code>.reg.fur</code>	+	+	-
<code>.dum</code>	+	-	-

Arguments of function `pdynmc` (3)

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

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