xtdpdml for Estimating Dynamic Panel Models

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Motivation

Table 3: Articles in the top 1% for $T = 1991 - 2015$

Rank	WoS	Title	Authors	Journal	JEL	Type	USA
1	4285	Some Tests of Specification for Panel Data	Arellano ; Bond	restud-91	C2-J2	D	0
2	3362	Law and Finance	La Porta et al.	jpe-98	K2	D	1
3	2349	Economic Growth in a Cross Section of Countries	Barro	qje-91	O4-O5	D	1
4	2274	A Theory of Fairness, Competition, and Cooperation	Fehr ; Schmidt	qje-99	D6-C7	T	1
5	2252	Estimation and Hypothesis Testing of Cointegration	Johansen	ecma-91	C3	D	0
6	2176	Increasing Returns and Economic Geography	Krugman	jpe-91	R1-R3	T	1
7	2075	A Contribution to the Empirics of Economic Growth	Mankiw et al.	qje-92	O4	D	1
8	1940	The Colonial Origins of Comparative Development	Acemoglu et al.	aer-01	O1-I1	D	1
9	1926	Conditional Heteroskedasticity in Asset Returns	Nelson	ecma-91	C5-G1	D	1
10	1917	Geographic Localization of Knowledge Spillovers as	Jaffe et al.	qje-93	O3	D	0.67
11	1850	Instrumental Variables Regression with Weak Instru	Staiger ; Stock	ecma-97	C3	D	1
12	1774	The Impact of Trade on Intra-industry Reallocation	Melitz	ecma-03	F1-F2	T	1
13	1617	Why Do Some Countries Produce So Much More Output	Hall ; Jones	qje-99	O4-E2	D	1
14	1534	A Sensitivity Analysis of Cross-Country Growth Reg	Levine ; Renelt	aer-92	O4	D	1
15	1516	Corruption and Growth	Mauro	qje-95	D7	D	1
16	1512	A Model of Growth through Creative Destruction	Aghion ; Howitt	ecma-92	O4-O3	T	0
17	1489	How Much Should We Trust Differences-in-Difference	Bertrand et al.	qje-04	C2-J3	D	1
18	1430	Efficient Tests for an Autoregressive Unit Root	Elliott et al.	ecma-96	C2-C5	D	1
19	1406	Loss Aversion in Riskless Choice	Tversky ; Kahneman	qje-91	D1	E	1
20	1374	A Theory of Fads, Fashion, Custom, and Cultural Ch	Bikhchandani et al.	jpe-92	D7-D8	T	1
21	1361	Incorporating Fairness into Game Theory and Econom	Rabin	aer-93	C7-D6	T	1
22	1340	The Penn World Table (Mark 5)	Summers ; Heston	qje-91	O5-E1	D	1
23	1333	Convergence	Barro ; Sala-i-Martin	jpe-92	O4-N1	D	1
24	1328	Does Social Capital Have an Economic Payoff	Knack ; Keefer	qje-97	O4-P1	D	1
25	1326	ERC	Bolton ; Ockenfels	aer-00	D6-C7	T	0.50
26	1310	R&D spillovers and the geography of innovation an	Audretsch ; Feldman	aer(s)-96	O3-R1	D	0.50
27	1263	Heteroskedasticity and Autocorrelation Consistent	Andrews	ecma-91	C2	D	1
28	1221	Growth in Cities	Glaeser et al.	jpe-92	R1-O4	D	0.25

Source: Linnemer and Visser (2016) The Most Cited Articles from the Top-5 Journals (1991-2015).

A gentle reminder

The model

$$y_{it} = \lambda y_{it-1} + \beta x_{it} + \alpha_i + v_{it} \tag{1}$$

$$E\left(v_{it} \mid y_i^{t-1}, x_i^t, \alpha_i\right) = 0 \tag{2}$$

The Arellano-Bond approach $(T = 3)$

$$
\begin{array}{rcll}
E(y_{i0}\Delta v_{i2}) &=& 0 & \text{(3a)} \\
E(x_{i1}\Delta v_{i2}) &=& 0 & \text{(3b)} \\
E(y_{i0}\Delta v_{i3}) &=& 0 & \text{(3c)} \\
E(y_{i1}\Delta v_{i3}) &=& 0 & \text{(3d)} \\
E(x_{i1}\Delta v_{i3}) &=& 0 & \text{(3e)} \\
E(x_{i2}\Delta v_{i3}) &=& 0 & \text{(3f)}
\end{array}
$$

In a nutshell

- Arellano-Bond may be biased in **finite samples** (moderate N, small T) when instruments are weak (Alonso-Borrego and Arellano 1999).

- Several GMM alternatives have been proposed to address this concern (see Hansen et al. 1996; Alonso-Borrego and Arellano 1999).

- A practical limitation of these alternatives is that their implementation requires certain programming capabilities.

- The most popular alternative is thus the so-called system-GMM estimator by Arellano and Bover (1995) that can be easily implemented in Stata:
  - System-GMM requires the **mean stationarity assumption** for consistency.

In a nutshell

- Arellano-Bond may be biased in **finite samples** (moderate N, small T) when instruments are weak (Alonso-Borrego and Arellano 1999).
- Several GMM alternatives have been proposed to address this concern (see Hansen et al. 1996; Alonso-Borrego and Arellano 1999).
- A practical limitation of these alternatives is that their implementation requires certain programming capabilities.
- The most popular alternative is thus the so-called system-GMM estimator by Arellano and Bover (1995) that can be easily implemented in Stata:
    - System-GMM requires the **mean stationarity assumption** for consistency.
- We consider a likelihood-based estimator that alleviates these biases based on the same identifying assumptions as Arellano-Bond.
- We introduce the Stata command `xtdpdml` that implements this estimator.
- It is already available from the Boston College Statistical Software Components (SSC) archive: `ssc install xtdpdml`
- See Williams, Allison and Moral-Benito (2016) available at http://www3.nd.edu/$\sim$rwilliam/dynamic/.

Roadmap

- **The likelihood function**.

- Monte Carlo evidence.

- Empirical illustration.

- The `xtdpdml` command.

The model in matrix form

- In addition to the T equations given by (1), we complete the model with an equation for y_{i0} as well as T additional reduced-form equations for x:

$$
\begin{aligned}
y_{i0} &= v_{i0} & (4) \\
x_{i1} &= \xi_{i1} & (5) \\
&\vdots \\
x_{iT} &= \xi_{iT} & (6)
\end{aligned}
$$

- In order to rewrite the system of equations given by (1) and (4)-(6) in matrix form, we define the following vectors of observed data (R_i) and disturbances (U_i):

$$
\begin{aligned}
R_i &= (y_{i1}, ..., y_{iT}, y_{i0}, x_{i1}, ...x_{iT})' & (7) \\
U_i &= (\alpha_i, v_{i1}, ..., v_{iT}, v_{i0}, \xi_{i1}, ...\xi_{iT})' & (8)
\end{aligned}
$$

- So that:

$$
BR_i = DU_i \qquad (9)
$$

The likelihood function

- Under normality, the joint distribution of R_i is:

$$R_i \sim N\left(0, B^{-1}D\Sigma D'B'^{-1}\right) \tag{10}$$

- with resulting log-likelihood:

$$L \propto -\frac{N}{2}\log\det\left(B^{-1}D\Sigma D'B'^{-1}\right) - \frac{1}{2}\sum_{i=1}^{N} R_i'\left(B^{-1}D\Sigma D'B'^{-1}\right)^{-1} R_i \tag{11}$$

- The maximizer of L is asymptotically equivalent to the Arellano and Bond (1991) GMM estimator regardless of non-normality.
- The parameters to be estimated are place in the matrices B, D, and Σ.

Roadmap

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Simulation experiment

- We explore the finite sample behavior of our ML estimator compared to Arellano-Bond.
- We consider the simulation setting in Bun and Kiviet (2006).
- The data for the dependent variable y and the explanatory variable x are generated according to:

$$
\begin{align}
y_{it} &= \lambda y_{it-1} + \beta x_{it} + \alpha_i + v_{it} \tag{12}\\
x_{it} &= \rho x_{it-1} + \phi y_{it-1} + \pi \alpha_i + \xi_{it} \tag{13}
\end{align}
$$

- where v_{it}, ξ_{it}, and α_i are generated as $v_{it} \sim i.i.d.(0,1)$, $\xi_{it} \sim i.i.d.(0, 6.58)$, and $\alpha_i \sim i.i.d.(0, 2.96)$.
- The parameter ϕ in (13) captures the feedback from the lagged dependent variable to the regressor.
- With respect to the parameter values, we fix $\lambda = 0.75$, $\beta = 0.25$, $\rho = 0.5$, $\phi = -0.17$, and $\pi = 0.67$. This configuration allows for fixed effects correlated with the regressor as well as feedback from y to x.

Simulation results (I)

Table: Simulation results.

Sample size	Bias λ		Bias β		iqr λ		iqr β	
	AB (1)	ML (2)	AB (3)	ML (4)	AB (5)	ML (6)	AB (7)	ML (8)
$N = 100$, $T = 4$	-0.207	-0.007	-0.079	-0.005	0.359	0.238	0.158	0.120
$N = 200$, $T = 4$	-0.150	-0.009	-0.061	-0.003	0.307	0.187	0.141	0.092
$N = 500$, $T = 4$	-0.074	0.005	-0.030	-0.002	0.230	0.153	0.100	0.079
$N = 1000$, $T = 4$	-0.041	0.012	-0.018	0.005	0.178	0.147	0.075	0.063
$N = 5000$, $T = 4$	-0.006	0.001	-0.002	0.001	0.078	0.062	0.033	0.028
$N = 100$, $T = 8$	-0.068	0.011	-0.012	0.005	0.078	0.089	0.034	0.042
$N = 100$, $T = 12$	-0.040	-0.001	-0.004	0.000	0.046	0.046	0.019	0.023
$N = 5000$, $T = 12$	-0.001	0.000	0.000	0.000	0.008	0.006	0.003	0.003

Notes. AB refers to the Arellano and Bond (1991) GMM estimator; Bias refer to the median estimation errors $\hat{\lambda} - \lambda$ and $\hat{\beta} - \beta$; iqr is the $75th$-$25th$ interquartile range; results are based on 1,000 replications. We use the `xtdpdml` Stata command for ML and the `xtdpd` Stata command for AB.

Simulation results (II)

Table: Simulation results under unbalanced panels.

	Bias λ		Bias β		iqr λ		iqr β	
Unbalacedness	AB (1)	ML (2)	AB (3)	ML (4)	AB (5)	ML (6)	AB (7)	ML (8)
				PANEL A: $N = 200$, $T = 4$				
1%	-0.171	-0.005	-0.063	0.006	0.336	0.212	0.134	0.099
5%	-0.218	-0.004	-0.082	0.000	0.381	0.212	0.153	0.091
10%	-0.268	0.005	-0.111	0.003	0.381	0.222	0.154	0.100
				PANEL B: $N = 500$, $T = 4$				
1%	-0.090	-0.003	-0.035	-0.003	0.235	0.160	0.100	0.071
5%	-0.122	0.009	-0.051	0.005	0.282	0.155	0.114	0.070
10%	-0.163	0.016	-0.065	0.005	0.307	0.175	0.125	0.074
				PANEL C: $N = 200$, $T = 8$				
1%	-0.049	0.004	-0.009	0.004	0.067	0.067	0.027	0.029
5%	-0.072	0.015	-0.015	0.010	0.081	0.083	0.032	0.034
10%	-0.104	0.020	-0.027	0.014	0.099	0.087	0.042	0.036
				PANEL D: $N = 500$, $T = 8$				
1%	-0.021	0.006	-0.004	0.003	0.043	0.037	0.018	0.017
5%	-0.035	0.014	-0.008	0.007	0.053	0.043	0.021	0.018
10%	-0.054	0.022	-0.015	0.011	0.063	0.048	0.026	0.019

Notes. AB refers to the Arellano and Bond (1991) GMM estimator; Bias refer to the median estimation errors $\hat{\lambda} - \lambda$ and $\hat{\beta} - \beta$; iqr is the $75th$-$25th$ interquartile range; results are based on 1,000 replications. We use the `xtdpdml` Stata command for ML and the `xtdpd` Stata command for AB.

Roadmap

- The likelihood function.

- Monte Carlo evidence.

- **Empirical illustration**.

- The xtdpdml command.

Empirical illustration (I)

- The growth regressions literature is based on panel data methods accounting for country-specific effects and reverse causality between economic growth and potential growth determinants.

- The influential paper by Levine et al. (2000) found a positive effect of financial development on economic growth using the Arellano-Bond estimator.

- They estimate the following model:

$$y_{it} = \lambda y_{it-1} + \beta FD_{it} + \gamma w_{it} + \alpha_i + v_{it} \qquad (14)$$

where y_{it} refers to the $\log$ of real per capita GDP in country i and lustrum t, FD_{it} refers to financial development, and w_{it} refers to a set of control variables. [Details].

- Following Levine et al. (2000) we assume that both FD_{it} and the control variables w_{it} are predetermined so that feedback from GDP to financial development and other macroeconomic conditions is allowed:

$$E\left(v_{it} \mid y_i^{t-1}, w_i^t, FD_i^t, \alpha_i\right) = 0 \qquad (t=1,...,T)(i=1,...,N) \quad (15)$$

Empirical illustration (II)

Table: Financial development and economic growth.

PANEL A: First-differenced GMM estimator (AB)						
Lagged dep. variable	0.704***	0.617***	0.731***	0.629***	0.638***	0.579***
	(0.066)	(0.049)	(0.056)	(0.048)	(0.057)	(0.049)
Liquid Liabilities	0.040**	0.066***				
	(0.019)	(0.017)				
Commercial-central bank			0.039***	0.039***		
			(0.011)	(0.010)		
Private Credit					0.050***	0.054***
					(0.013)	(0.015)
Control variables	Simple	Policy	Simple	Policy	Simple	Policy
Observations	417	397	429	398	417	396

PANEL B: Maximum likelihood estimator (ML)						
Lagged dep. variable	1.019***	1.004***	0.980***	0.960***	0.955***	0.945***
	(0.043)	(0.050)	(0.044)	(0.048)	(0.040)	(0.042)
Liquid liabilities	0.029**	0.028**				
	(0.012)	(0.014)				
Commercial-central bank			0.044***	0.041***		
			(0.008)	(0.008)		
Private credit					0.053***	0.048***
					(0.010)	(0.009)
Control variables	Simple	Policy	Simple	Policy	Simple	Policy
Observations	417	397	429	398	417	396

Notes. Dependent variable is the $\log$ of real per capita GDP in all cases. Simple set of control variables includes only average years of secondary schooling. The policy conditioning information set includes average years of secondary schooling, government size, openness to trade, inflation, and black market premium as in Levine et al. (2000). All regressors are normalized to have zero mean and unit standard deviation in order to ease the interpretation of the coefficients. We denote significance at 10%, 5% and 1% with *, ** and ***, respectively. Standard errors are denoted in parentheses.

Roadmap

- The likelihood function.

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- **The** `xtdpdml` **command**.

The xtdpdml command

- Allison (in progress) shows that the dynamic panel model is a special case of the general linear structural equation model (SEM) and that our ML estimator can be implemented with Stata's `sem`.

- However, coding the `sem` method is both tedious and error prone.

- Hence we introduce a command named `xtdpdml` with syntax similar to other Stata commands for linear dynamic panel-data estimation.

- `xtdpdml` greatly simplifies the SEM model specification process.

The xtdpdml command

Illustration - [sem problems]

- Allison (in progress) reanalyzes data described by Cornwell and Rupert (1988):
    - wks = number of weeks employed in each year
    - union = 1 if wage set by union contract, else 0, in each year
    - lwage = ln(wage) in each year.
    - ed = years of education in 1976
- using sem:

```
use http://statisticalhorizons.com/wp-content/uploads/wages.dta, clear
keep wks lwage union ed id t
reshape wide wks lwage union, i(id) j(t)
sem    (wks2 <- wks1@b1 lwage1@b2 union1@b3 ed@b4 Alpha@1 E2@1 ) ///
       (wks3 <- wks2@b1 lwage2@b2 union2@b3 ed@b4 Alpha@1 E3@1) ///
       (wks4 <- wks3@b1 lwage3@b2 union3@b3 ed@b4 Alpha@1 E4@1) ///
       (wks5 <- wks4@b1 lwage4@b2 union4@b3 ed@b4 Alpha@1 E5@1) ///
       (wks6 <- wks5@b1 lwage5@b2 union5@b3 ed@b4 Alpha@1 E6@1) ///
       (wks7 <- wks6@b1 lwage6@b2 union6@b3 ed@b4 Alpha@1), ///
       var(e.wks2@0 e.wks3@0 e.wks4@0 e.wks5@0 e.wks6@0) var(Alpha) ///
       cov(Alpha*(ed)@0) cov(Alpha*(E2 E3 E4 E5 E6)@0) ///
       cov(_OEx*(E2 E3 E4 E5 E6)@0) cov(E2*(E3 E4 E5 E6)@0) ///
       cov(E3*(E4 E5 E6)@0) cov(E4*(E5 E6)@0) cov(E5*(E6)@0) ///
       cov(union3*(E2)) cov(union4*(E2 E3)) cov(union5*(E2 E3 E4)) ///
       cov(union6*(E2 E3 E4 E5)) ///
       iterate(250) technique(nr 25 bhhh 25) noxconditional
```

- using xtdpdml:

```
xtdpdml wks L.lwage, inv(ed) pre(L.union)
```

The xtdpdml command
Types of regressors

- The **lagged dependent variable** (e.g. L1.wks) is included by default.
  - This can be changed with the ylag option, e.g. ylag(1 2), ylag(2 4), ylag(0).

- **Strictly exogenous variables** are assumed to be uncorrelated with the error term at all points in time.
  - Specified before the comma: xtdpdml wks L.lwage, inv(ed) pre(L.union).

- **Predetermined variables**, aka sequentially or weakly exogenous, can be affected by prior values of the dependent variables.
  - Specified with the pre option: xtdpdml wks L.lwage, inv(ed) pre(L.union).

- **Time-invariant variables** can also be included under the assumption that they are uncorrelated with the fixed effects.
  - Specified with the inv option: xtdpdml wks L.lwage, inv(ed) pre(L.union).

The `xtdpdml` command
Options

- Some available options are:
  - details shows the complete sem output.
  - showcmd shows the sem command that was generated.
  - fiml causes Full Information Maximum Likelihood to be used for missing data; default is listwise deletion.
  - re Random Effects Model (effects uncorrelated with regressors)
  - errorinv constrains error variances to be equal across waves.
  - tfix recode time variable to equal 1, 2,..., T (number of waves). Set delta = 1.
  - semopts(options) lets additional sem options be included in the generated sem command.

- Time series notation can be used, e.g. xtdpdml y L1.lwage L2.lwage.

- The help menu is very comprehensive: `help xtdpdml`.

- For more information see http://www3.nd.edu/$\sim$ rwilliam/dynamic/

Final remarks

- The Arellano and Bond (1991) estimator is widely-used among applied researchers when estimating dynamic panels with fixed effects and predetermined regressors.

- This estimator might behave poorly in finite samples when the cross-section dimension of the data is small (i.e. small N), especially if the variables under analysis are persistent over time.

- We propose a maximum likelihood estimator that is asymptotically equivalent to Arellano and Bond (1991) but presents better finite sample behavior.

- Moreover, the estimator is easy to implement in Stata using the xtdpdml command as described in Williams, Allison and Moral-Benito (2016) "xtdpdml: Linear Dynamic Panel-Data Estimation using Maximum Likelihood and SEM"

- For more info visit: **http://www3.nd.edu/~ rwilliam/dynamic/**

Endeogeneity in Panel Data

- Three possible situations:
  1. Strict exogeneity
  2. Strict endogeneity
  3. Partial endogeneity (or predetermined)

$$
\begin{array}{cc}
& v_{i1} \\
& \vdots \\
x_{it} & v_{it} \\
& \vdots \\
& v_{iT}
\end{array}
$$

Matrices (I)

- The covariance matrix of the disturbances captures the restrictions imposed by (2) and it is given by:

$$Var\left(U_i\right) = \Sigma = \left(\begin{array}{cccc|cccc}
\sigma_\alpha^2 & & & & & & & \\
0 & \sigma_{v1}^2 & & & & & & \\
\vdots & \vdots & \ddots & & & & & \\
0 & 0 & \cdots & \sigma_{vT}^2 & & & & \\
\hline
\phi_0 & 0 & \cdots & 0 & \sigma_{v0}^2 & & & \\
\phi_1 & 0 & \cdots & 0 & \omega_{01} & \sigma_{\xi_1}^2 & & \\
\phi_2 & \psi_{21} & \cdots & 0 & \omega_{02} & \omega_{12} & \sigma_{\xi_2}^2 & \\
\vdots & \vdots & & \vdots & \vdots & \vdots & \ddots & \\
\phi_T & \psi_{T1} & \psi_{T2} & \cdots & \omega_{0T} & \omega_{1T} & \cdots & \sigma_{\xi_T}^2
\end{array}\right)$$

Matrices (II)

$$
B = \begin{pmatrix}
1 & 0 & 0 & \cdots & 0 & -\lambda & -\beta & 0 & \cdots & 0 \\
-\lambda & 1 & 0 & \cdots & 0 & 0 & 0 & -\beta & \cdots & 0 \\
0 & -\lambda & 1 & \cdots & 0 & 0 & \vdots & & & \ddots \\
\vdots & & & \ddots & & \vdots & & & & \\
0 & \cdots & & -\lambda & 1 & 0 & 0 & \cdots & 0 & -\beta \\
0 & & \cdots & & 0 & & & & & \\
\vdots & & \ddots & & \vdots & & & I_{T+1} & & \\
0 & & \cdots & & 0 & & & & &
\end{pmatrix}
$$

$$
D = \begin{pmatrix} d & I_{2T+1} \end{pmatrix}
$$

where $d = (1, ..., 1, 0, ..., 0)'$ is a column vector with T ones and $T+1$ zeros.

Data details

- We use a panel dataset of 78 countries ($N = 78$) over the period 1960-1995.
- We consider 5-year periods to avoid business cycle fluctuations so that we exploit a maximum of 7 observations per country ($T = 7$).
- The dependent variable is the $\log$ of real per capita GDP (from WDI).
- The main regressors of interest are taken from the International Financial Statistics (IFS) database:
  - **Liquid liabilities** of the financial system (currency plus demand and interest-bearing liabilities of banks and non-bank financial intermediaries) divided by GDP.
  - **Commercial-central bank** defined as the assets of deposit money banks divided by assets of deposit money banks plus central bank assets.
  - **Private credit** refers to the credit by deposit money banks and other financial institutions to the private sector divided by GDP.
- The following **control variables** are also considered: openness to trade (from WDI), government size (from WDI), average years of secondary schooling (from the Barro and Lee dataset), inflation (IFS), and the black market premium (from World Currency Yearbook). For more details on the variables considered see Table 12 in Levine et al. (2000).

Problems with `sem`

- Data need to be in wide format; most dynamic panel data sets will be in long format.
- Coding is lengthy and error prone; getting the covariance structure right is especially difficult.
- Output is voluminous and highly repetitive because of all the equality constraints.
- Limitations of Stata make the coding less straightforward than we might like:
  - Stata won't allow covariances between predetermined Xs and the Y residuals.
  - `xtdpdml` therefore zeroes out most of the Y residuals and replaces them with latent exogenous variables (E2, E3, etc.).
  - Some alternative and/or equivalent codings result in convergence problems or even fatal errors.

help xtdpdml

```
help for xtdpdml
```

Dynamic Panel Data Models using Maximum Likelihood

Syntax

    xtdpdml y [time-varying strictly exogenous vars] [, inv(time-invariant exogenous vars) pre(predetermined vars) other_options]

options	Description
Independent variables (other than strictly exogenous)	
inv(varlist)	Time-invariant exogenous variables, e.g. year of birth
predet(varlist)	Time varying predetermined (sequentially exogenous) variables
ylags(numlist)	Specifies lagged values of y to be included in the model. Default is lag 1.
Dataset options	
wide	Data are already in wide format (default is long format with xtset preceding the command)
staywide	Keep data in wide format after execution. May help with some sem post-estimation commands, e.g. predict.
tfix	Recode time variable to equal 1, 2,..., T (number of waves). Set delta = 1.
std	Standardize all variables in the model to have mean 0 and variance 1
std(varlist)	Standardize specified variables to have mean 0 and variance 1
Model Specification and Constraints Options	
evars	When there are no predetermined variables in the model this sometimes helps with convergence
alphafree	Allow Alpha (fixed) effects to vary across time
xfree	All x effects free to vary across time
xfree(varlist)	x effects of specified variables free to vary across time
yfree	All lagged y effects free to vary across time
yfree(numlist)	effects of specified lagged ys free to vary across time
constinv	constrains constants to be equal across waves. Alias for nocsd