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**_Pontificia Universidad Católica Argentina_**
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# *Dynamic Panel Data*

# *A Brief Survey of Estimation Methods*

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# Dynamic Panel Data:

# A Brief Survey of Estimation Methods

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**Abstract**

The most common estimators for linear dynamic panel data models are described. Special attention is paid to small-sample and endogeneity issues, which are important for the kind of datasets typically used in macroeconomic studies.

**Resumen**

En este artículo se describen los estimadores más comunes para modelos lineales dinámicos con estructura de panel. Se presta especial atención a las propiedades de los estimadores cuando el tamaño de la muestra es pequeño y las variables explicativas son potencialmente endógenas. Estos problemas son particularmente importantes para los estudios empíricos que utilizan variables macroeconómicas.

**Estimators for Linear Dynamic Panel Data Models**

Consider a dynamic panel data (DPD) model of the form

$$y_{it} = \alpha y_{it-1} + \boldsymbol{\beta}'\mathbf{x}_{it} + \eta_i + \varepsilon_{it}, \quad i \in \{1,...,N\}, \quad t \in \{1,...,T\}, \tag{1}$$

where $y_{it}$ is the dependent variable for individual *i* in period *t*, $\mathbf{x}_{it}$ is a vector of explanatory variables other than $y_{it-1}$ (observed heterogeneity),[1] $\eta_i$ represents unobserved individual-specific factors (unobserved heterogeneity), $\varepsilon_{it}$ is the observation-specific disturbance, and $(\alpha, \boldsymbol{\beta}')$ is the vector of parameters to be estimated. It is assumed that $y_{i0}$ is observed.

The individual-specific effects are assumed to be uncorrelated across individuals ($E\eta_i\eta_j = 0, \forall i \neq j$) and with the disturbance of any individual at all leads and lags ($E\eta_i\varepsilon_{jt} = 0, \forall i,j,t$), but may be correlated with the explanatory variables ($E\mathbf{x}_{it}\eta_j = unknown, \forall i,j,t$). The mean of $\eta_i$ is zero ($E\eta_i = 0, \forall i$) and its variance ($\sigma^2_{\eta i}$) may differ across individuals.[2] The observation-specific disturbance has mean zero ($E\varepsilon_{it} = 0, \forall i,t$) and is uncorrelated across individuals and periods ($E\varepsilon_{it}\varepsilon_{js} = 0 \ \forall i \neq j, t \neq s$). In general, its variance ($\sigma^2_{\varepsilon it}$) may differ across both individuals and periods. The initial observation $y_{i0}$ is uncorrelated with the disturbance of any individual for all periods ($Ey_{i0}\varepsilon_{jt} = 0 \ \forall i,j,t$), but may be correlated with the individual effects ($Ey_{i0}\eta_j = unknown, \forall i,j$). The autoregressive parameter satisfies $|\alpha| < 1$ (dynamic stability). The vector $\mathbf{x}_{it}$ may include lags of explanatory variables. It may also include

[1] Explanatory variables (including $y_{it-1}$) are also called covariates, or regressors. The vector $\mathbf{x}_{it}$ may include a constant.

[2] The zero-mean assumption is without loss of generality as long as the model contains a constant term.

covariates that are fixed over time for a given individual, and/or covariates that vary over time but are shared by all individuals. A generic element of $\mathbf{x}_{it}$ is denoted by $x_{it}$.

There are two important issues to deal with when estimating a model like (1) using macroeconomic data: the presence of endogenous and/or predetermined covariates, and the small time-series and cross-sectional dimensions of the typical data set. In what follows, we briefly discuss the way in which these two problems have been treated in the literature. For future reference, an explanatory variable is called (strictly) exogenous if it is uncorrelated with the observation-specific disturbance at all leads and lags, is called predetermined if it is correlated only with past observation-specific disturbances, and is called endogenous if it is correlated only with past and current observation-specific disturbances. Notice that, with these definitions, our assumptions imply that the lagged dependent variable in (1) is predetermined.

Suppose all covariates in $\mathbf{x}_{it}$ are strictly exogenous. The *ordinary least squares* (OLS) estimator of $(\alpha, \boldsymbol{\beta}')$ is inconsistent (asymptotically biased), even in the absence of correlation between $\mathbf{x}_{it}$ and the unobserved individual effect $\eta_i$. The reason is that $\eta_i$ will certainly be correlated with $y_{it-1}$, since $y_{it-1} = \alpha y_{it-2} + \boldsymbol{\beta}'\mathbf{x}_{it-1} + \eta_i + \varepsilon_{it-1}$.

Consider now the *least squares dummy variable* (LSDV) estimator, also known as the *fixed-effects* or *within-group* estimator (see, for example, Greene (1997)). We still assume that the explanatory variables in $\mathbf{x}_{it}$ are strictly exogenous. Estimates of $(\alpha, \boldsymbol{\beta}')$ are obtained by applying OLS to the model expressed in deviations from time means:

$$y_{it} - \bar{y}_i = \alpha(y_{it-1} - \bar{y}_{i.-1}) + \boldsymbol{\beta}'(\mathbf{x}_{it} - \bar{\mathbf{x}}_i) + (\varepsilon_{it} - \bar{\varepsilon}_i), \quad t \in \{1,...,T\} \qquad (2)$$

where $\bar{z}_i \equiv \frac{1}{T}\sum_{t=1}^{T} z_{it}$ and $\bar{z}_{i,-1} \equiv \frac{1}{T}\sum_{t=1}^{T} z_{it-1}$, for any variable *z*. This transformation wipes out the unobserved individual effects, eliminating one possible source of inconsistency: the correlation between $\mathbf{x}_{it}$ and $\eta_i$.[3] In a truly dynamic panel ($\alpha \neq 0$), however, there will still be correlation between $y_{it-1} - \bar{y}_{i,-1}$ and $\varepsilon_{it} - \bar{\varepsilon}_i$. The reason is that $\bar{\varepsilon}_i$ contains $\varepsilon_{i1},...,\varepsilon_{it-1}$, which are correlated with $y_{it-1}$. As a consequence, the LSDV estimator will be inconsistent for finite $T$ and $N \to \infty$.[4] The asymptotic bias disappears as $T \to \infty$, however, because $\text{plim}_{T\to\infty} \bar{\varepsilon}_i = 0$. We conclude that, for panels with a relatively short time dimension, the use of the LSDV estimator may produce poor results.

Anderson and Hsiao (1981) proposed an instrumental-variable (IV) estimator that is consistent for fixed $T$ and $N \to \infty$. The AH estimator eliminates the unobserved heterogeneity by first-differencing the model:[5]

$$y_{it} - y_{it-1} = \alpha(y_{it-1} - y_{it-2}) + \boldsymbol{\beta}'(\mathbf{x}_{it} - \mathbf{x}_{it-1}) + (\varepsilon_{it} - \varepsilon_{it-1}), \quad t \in \{2,...,T\}. \qquad (3)$$

It is clear from (3) that $y_{it-1} - y_{it-2}$ will be correlated with $\varepsilon_{it} - \varepsilon_{it-1}$, because $y_{it-1}$ is correlated with $\varepsilon_{it-1}$. Therefore, it is necessary to use instrumental variables. Anderson and Hsiao (1981) propose using either $y_{it-2}$ or $y_{it-2} - y_{it-3}$ as instruments. Both are valid

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[3] Notice that any time-independent covariate will also be eliminated by the deviation-from-time-mean transformation. Therefore, the coefficients on this kind of variables cannot be identified with this procedure.

[4] Various estimates of the asymptotic bias are available in the literature (see Nickell (1981) and the references provided in Kiviet (1995))

[5] Notice that first differencing also eliminates any time-independent covariate. Therefore, the coefficients on this kind of variables are not identified by the AH estimator.

instruments, since they are correlated with $y_{it-1} - y_{it-2}$ and uncorrelated with $\varepsilon_{it} - \varepsilon_{it-1}$.[6] The use of $y_{it-2}$ is usually recommended (see Arellano (1989) and Arellano and Bond (1991)). Since we are assuming that the covariates in $\mathbf{x}_{it}$ are strictly exogenous, $\mathbf{x}_{it} - \mathbf{x}_{it-1}$ serves as its own instrument.

The AH estimator is consistent but not efficient because it does not use all the available moment conditions. Arellano and Bond (1991) propose a generalized method of moments (GMM) estimator - henceforth, the AB estimator - that also relies on first-differencing the model.[7] They obtain additional instruments from the orthogonality conditions between the lagged values of $y_{it}$ and the disturbances $\varepsilon_{it} - \varepsilon_{it-1}$.[8] To understand their idea, consider the first-differenced model for period $t = 2$: $y_{i2} - y_{i1} = \alpha(y_{i1} - y_{i0}) + \boldsymbol{\beta}'(\mathbf{x}_{i2} - \mathbf{x}_{i1}) + (\varepsilon_{i2} - \varepsilon_{i1})$. Clearly, $y_{i0}$ is a valid instrument, since it is correlated with $y_{i1} - y_{i0}$, and uncorrelated with $\varepsilon_{i2} - \varepsilon_{i1}$. For $t = 3$ we get: $y_{i3} - y_{i2} = \alpha(y_{i2} - y_{i1}) + \boldsymbol{\beta}'(\mathbf{x}_{i3} - \mathbf{x}_{i2}) + (\varepsilon_{i3} - \varepsilon_{i2})$. Now $y_{i0}$ *and* $y_{i1}$ are valid instruments, since both are correlated with $y_{i2} - y_{i1}$, and uncorrelated with $\varepsilon_{i3} - \varepsilon_{i2}$. In general, for any given $t \geq 2$, the lagged levels of the dependent variable $y_{i0}$, …, $y_{it-2}$ will be valid instruments for $y_{it-1} - y_{it-2}$.[9] The relevant

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[6] One additional observation is lost when $y_{it-2} - y_{it-3}$ is used as instrument.

[7] For GMM estimation methods see Hayashi (2000).

[8] These are not the only orthogonality conditions available (see Arellano and Bond (1991)).

[9] Instead of using $y_{i0}, \dots, y_{it-2}$ as instruments for $y_{it-1} - y_{it-2}$, we could use $y_{i1} - y_{i0}, \dots, y_{it-2} - y_{it-3}$. As with the AH estimator, using levels is generally preferred.

orthogonality conditions can be written in compact notation as follows: $E\{y_{it-1-s}(\varepsilon_{it}-\varepsilon_{it-1})\}=0$, for $t\geq 2$ and $1\leq s<t$.[10]

A very useful feature of the AB estimator is that the explanatory variables in $\mathbf{x}_{it}$ need not be strictly exogenous; predetermined and endogenous covariates can be easily accommodated. When $x_{it}$ is strictly exogenous, the following orthogonality conditions are valid: $E\{x_{is}(\varepsilon_{it}-\varepsilon_{it-1})\}=0$ for all $t\geq 2$, $s\geq 1$. That is, the complete time series $x_{i1},...,x_{iT}$ can be used to instrument for $x_{it}-x_{it-1}$.[11] If an explanatory variable is predetermined, $x_{it}-x_{it-1}$ will be correlated with $\varepsilon_{it}-\varepsilon_{it-1}$, because $x_{it}$ is correlated with $\varepsilon_{it-1}$. In this case, $x_{i1},\ldots,x_{it-1}$ are valid instruments, since they are all uncorrelated with $\varepsilon_{it}-\varepsilon_{it-1}$ and correlated with $x_{it}-x_{it-1}$. Therefore, the moment conditions for predetermined variables are: $E\{x_{it-s}(\varepsilon_{it}-\varepsilon_{it-1})\}=0$ for $t\geq 2$ and $1\leq s<t$. If an explanatory variable is endogenous, $x_{it}-x_{it-1}$ will be correlated with $\varepsilon_{it}-\varepsilon_{it-1}$, because $x_{it-1}$ is correlated with $\varepsilon_{it-1}$ and $x_{it}$ is correlated with both $\varepsilon_{it}$ and $\varepsilon_{it-1}$. In this case, $x_{i1}$, …, $x_{it-2}$ are valid instruments, since they are all uncorrelated with $\varepsilon_{it}-\varepsilon_{it-1}$ and correlated with $x_{it}-x_{it-1}$. Therefore, the moment conditions for endogenous covariates are: $E\{x_{it-s}(\varepsilon_{it}-\varepsilon_{it-1})\}=0$ for $t\geq 3$ and $2\leq s<t$.[12]

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[10] Notice that the AH estimator can be seen as a particular case of the AB estimator in which the only moment condition used is $E\{y_{it-2}(\varepsilon_{it}-\varepsilon_{it-1})\}=0$.

[11] In this case, it would also be possible to apply standard IV methods, and use differences in the exogenous explanatory variables as their own instruments. This would be valid because, if $x_{it}$ is strictly exogenous, $x_{it}-x_{it-1}$ is uncorrelated with $\varepsilon_{it}-\varepsilon_{it-1}$.

[12] Additional moment conditions can be obtained if $\varepsilon_{it}$ is homoskedastic through time: $\sigma^2_{\varepsilon it}=\sigma^2_{\varepsilon i}\ \forall t$ (see Ahn and Schmidt (1995) and Blundell and Bond (1998)).

The AB estimator, usually called *difference* GMM, is not free of problems. "In dynamic data models where the autoregressive parameter is moderately large and the number of time series observations moderately small, the widely used linear generalized method of moments (GMM) estimator obtained after first differencing has been found to have large finite sample bias and poor precision in simulation studies…. Lagged levels of the series provide weak instruments for first differences in this case" (Blundell and Bond (1998)).[13] To ameliorate these problems, Arellano and Bover (1995) and Blundell and Bond (1998) develop the so-called *system* GMM estimator (or BB estimator). The idea consists in using lagged *differences* of explanatory variables as instruments for equations in *levels*, in addition to using - as in AB - lagged levels of explanatory variables as instruments for equations in first differences. Suppose we keep our assumption that the explanatory variables are possibly correlated with the individual effects but we are willing to assume that the first *differences* of this variables are uncorrelated with $\eta_i$: $E\{(y_{it-1} - y_{it-2})\eta_i\} = 0$ and $E\{(\mathbf{x}_{it} - \mathbf{x}_{it-1})\eta_i\} = 0$ for all $t \geq 2$.[14] Now we can use $y_{i1} - y_{i0}, \ldots, y_{it-1} - y_{it-2}$ as instruments in the levels equation (1), since they are all correlated with $y_{it-1}$ but uncorrelated with $\eta_i + \varepsilon_{it}$. The appropriate moment conditions are: $E\{(y_{it-1-s} - y_{it-2-s})(\eta_i + \varepsilon_{it})\} = 0$ for $t \geq 2$ and $0 \leq s < t-1$. If an explanatory variable $x_{it}$ is strictly exogenous, $x_{i2} - x_{i1}, ..., x_{iT} - x_{iT-1}$ are valid instruments, since they are all uncorrelated with $\eta_i + \varepsilon_{it}$ and correlated with $x_{it}$. The moment conditions are: $E\{(x_{is} - x_{is-1})(\eta_i + \varepsilon_{it})\} = 0$ $t \geq 2$ and $s \geq 2$. For predetermined covariates, the available

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[13] An instrument is said to be weak if its correlation with the included non-exogenous variables is small. For a survey of this issue see Stock, Wright and Yogo (2002).

[14] Blundell and Bond (1998) provide conditions under which this assumption is satisfied.

instruments are: $x_{i2} - x_{i1}, ..., x_{it} - x_{it-1}$. The relevant moment conditions are then: $E\{(x_{it-s} - x_{it-1-s})(\eta_i + \varepsilon_{it})\} = 0$ for $t \geq 2$ and $0 \leq s < t-1$. For endogenous covariates, the instruments are $x_{i2} - x_{i1}, ..., x_{it-1} - x_{it-2}$, with moment conditions: $E\{(x_{it-s} - x_{it-1-s})(\eta_i + \varepsilon_{it})\} = 0$ for $t \geq 3$ and $1 \leq s < t-1$. When we combine the equations in levels with the equations in differences, many of these moment conditions become redundant.[15, 16]

In particular circumstances, some of the covariates in $\mathbf{x}_{it}$ may be not only exogenous (with respect to $\varepsilon_{it}$) but uncorrelated with $\eta_i$ as well. When using either AB or BB, these covariates can be treated in standard IV form, using $x_{it} - x_{it-1}$ as its own instrument in the equations in differences and $x_{it}$ as its own instrument in the equations in levels.

Simulations carried out using Monte Carlo methods show that the BB estimator does much better than the AB estimator in terms of precision and small sample bias, especially when the autoregressive coefficient is relatively high and the number of periods is small (see Blundell and Bond (1998) and Bond (2002)). An additional advantage of BB over AB is the possibility of including time-invariant covariates that are uncorrelated with $\eta_i + \varepsilon_{it}$.[17] In actual applications, these advantages have to be weighted against the possibility that the

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[15] For example, if $x_{it}$ is predetermined, BB adds only the following moment conditions to the ones used by AB: $E\{(x_{it} - x_{it-1})(\eta_i + \varepsilon_{it})\} = 0$ for $t \geq 2$ (see Arellano and Bover (1995)).

[16] Additional moment conditions can be obtained if $\varepsilon_{it}$ is homoskedastic through time: $\sigma^2_{\varepsilon it} = \sigma^2_{\varepsilon i}\ \forall t$ (see Ahn and Schmidt (1995) and Blundell and Bond (1998)).

[17] If the time-invariant explanatory variables are correlated with $\eta_i + \varepsilon_{it}$, the parameters corresponding to the former cannot be identified because the time-invariant covariates are absorbed into the individual effect (Arellano (2003), p. 164).

additional assumptions needed to make BB work are not satisfied. If these restrictions are violated, the BB estimates can be seriously biased.

Like all linear GMM estimators, both AB and BB can be obtained using one- or two-step procedures. The two-step estimator is asymptotically more efficient, but Monte Carlo studies have shown that its asymptotic standard errors tend to be severely downward biased in small samples, especially when the disturbances are nonnormal or heteroskedastic. The one-step estimator does not have this problem (see Arellano and Bond (1991) and Blundell and Bond (1998)). As is well known, the one-step estimator weights the moment conditions by a matrix that is independent of the parameters of the model, while the matrix used by the two-step estimator does depend on model parameters. To obtain the two-step estimates, the true parameters are substituted with a consistent estimate coming from the first step. Windmeijer (2005) shows that "the extra variation due to the presence of these estimated parameters in the weight matrix accounts for much of the difference between the finite sample and the asymptotic variance of the two-step GMM estimator that utilizes moment conditions that are linear in the parameters. This difference can be estimated, resulting in finite sample bias corrected estimates of the variance. In a Monte Carlo study of a panel data model, it is shown that this corrected variance approximates the finite sample variance of the two-step GMM estimator well, leading to more accurate inference."

From the descriptions given above, it is not difficult to see that the number of instruments used by the AB and BB estimators may become very large. "Where the number of columns in $\mathbf{Z}_i$ [the matrix of instruments] is very large, computational considerations may require those columns containing the least informative instruments to be deleted. Even when computer speed is not an issue, it may be advisable not to use the whole history of the series as instruments in the later cross-sections. For a given cross-sectional sample size (*N*), the use of too many instruments may result in (small sample) overfitting biases. When overfitting results from the number of time periods (*T*) becoming large relative to the number of individuals (*N*), and there are no endogenous regressors present, these GMM estimators are biased towards within groups, which is not a serious concern since the within groups estimator is itself consistent for models with predetermined variables as *T* becomes large (see Alvarez and Arellano (1998)). However, in models with endogenous regressors, using too many instruments in the later cross-sections could result in seriously biased estimates. This possibility can be investigated in practice by comparing the GMM and within groups estimates." (Doornik, Bond and Arellano (2002)).

Not all the DPD estimators proposed in the literature are of the GMM type. Kiviet (1995) derives an approximation of the small sample bias (finite *T and* finite *N*) for the LSDV estimator of a dynamic *balanced* panel data model like (1), with strictly exogenous vector $\mathbf{x}_{it}$ and homoskedastic disturbance. This is then used to construct a (*bias*) *corrected least squares dummy variable* (LSDVC) estimator by subtracting the bias approximation from the original LSDV estimator. The variance-covariance matrix is calculated using Monte Carlo simulations. Bun and Kiviet (2003) derive a more accurate approximation of the small sample bias, and Bruno (2005a) extends it to *unbalanced* panels. Since the bias approximation depends on the value of the true parameters of the model, obtaining consistent bias-corrected estimates requires a two-step procedure. In the first step, consistent estimates of $(\alpha, \boldsymbol{\beta}')$ and $\sigma_{\varepsilon}^2$ are obtained using a consistent estimator, like AH, AB or BB. In the second step, the estimate of the bias correction calculated using the first-step results is subtracted from the original LSDV estimates.

Bruno (2005b) performs a Monte Carlo study "to evaluate the finite-sample performance of the bias corrected LSDV estimator in comparison to the original LSDV estimator and the three popular *N*-consistent estimators: Arellano-Bond, Anderson-Hsiao and Blundell-Bond. Results strongly support the bias-corrected LSDV estimator according to bias and root mean squared error criteria when the number of individuals is small." Similar results are found in Judson and Owen (1999), Galiani and González-Rozada (2002), and Bun and Kiviet (2003). Unfortunately, extensions of the LSDVC estimator to the case of non-exogenous explanatory variables are yet to be derived.

**Software**

All estimators described in this survey are available in Stata 9. OLS, LSDV, AH and AB are built-in options. BB can be obtained using the module `xtabond2`, written by Roodman (2005).[18] LSDVC can be obtained using the module `xtlsdvc`, presented in Bruno (2005b).

[18] This module also provides the AH and AB estimators. For the two-step versions of the GMM estimators it incorporates the finite-sample variance correction developed in Windmeijer (2005).

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