Edinburgh School of Economics

Discussion Paper Series

Number 154

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Date
January 2007

Published by
School of Economics
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Edinburgh EH8 9JT
+44 (0)131 650 8361
http://www.ed.ac.uk/schools-departments/economics

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Empirical Likelihood: Improved Inference within Dynamic Panel Data Models

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January 18, 2007

Abstract

This paper proposes and analyses an hybrid of Owen's (1988, 1990, 1991) Empirical Likelihood (EL) and bootstrap, EL-bootstrap, as an alternative to the General Method of Moments (GMM) within dynamic panel data models. We concentrate on the finite-sample size properties of their overidentification tests. Our results show that EL-bootstrap may be a good alternative to GMM estimation within this setting. The practical usefulness of our findings is illustrated *via* application on an AR(1) univariate panel data model with individual effects using the cash-flow series of 174 firms in the United States.

1 Introduction

Dynamic panel econometric models are of interest in a wide range of economic and financial applications. Through these models the dynamic relationships from cross section units and heterogeneity in adjustment dynamics between different types of individuals, households or firms can be analysed.

In this paper we focus on autoregressive panel data models with individual effects. These models are intuitive because they introduce a generic individual effect in the random term, that is typically related to a large number of non-observable random causes. Moreover, since the coefficients of the slope parameters are typically the object of interest in applied work rather than the individual differences, estimation can be carried out though appropriate techniques.

It is fairly well known that OLS estimates for the parameters within autoregressive panel data models with individual effects are not consistent. We can use GMM to obtain asymptotically efficient estimators in dynamic panel data settings. First-differenced GMM estimators for the AR(1) panel data model

*Thanks are due to Manuel Arellano, Francesco Bravo and Patrick Marsh.

were developed by Arellano and Bond (1991), Holtz-Eakin *et al* (1988), Anderson and Hsiao (1981). We mainly concentrate on Arellano and Bond's (1991) work. Under relatively weak assumptions about the heterogeneity and error term processes, they differentiate the AR(1) specification and use all the orthogonality conditions that exist between lagged values of the endogenous variables and the disturbances, the so-called DIF conditions.[1] This procedure leads to optimal linear GMM estimators that are the most efficient in the class of instrumental variables' estimators (Arellano and Bond, 1991). However, it has been extensively documented that if the series are highly autoregressive, the GMM estimators based on DIF conditions have large finite-sample bias and poor precision in simulation studies (see Alonso-Borrego and Arellano, 1999; Blundell and Bond, 1998). One response to these limitations has been to consider further moment restrictions. Ahn and Schmidt (1995) consider non-linear moment conditions implied by the standard error components formulation. Blundell and Bond (1998) propose further restrictions on the initial conditions process, the so-called LEV conditions[2].

In this paper we propose an hybrid of Owen's (1988, 1990, 1991) Empirical Likelihood (EL) and bootstrap as an alternative to the GMM approach in dynamic panel data models and investigate whether the limitations encountered within GMM estimation are extended to EL. We mainly compare the finite-sample size properties[3] of their overidentifying restrictions tests[4].

The finite-sample behaviour of the Sargan test in an AR(1) dynamic panel data setting has been the subject of prior study. Among others, the work of Brown and Newey (2001) and Bowsher (2000, 2000a) have contributed to this literature. Brown and Newey (2001) also examine an hybrid of GMM and bootstrap, *i.e.* GMM-bootstrap. GMM-bootstrap resamples from the EL distribution, that incorporates the moment restrictions, rather than the empirical distribution. They do not find a significant improvement in accuracy for the Sargan test when using efficient-bootstrap critical values as an alter-

[1] We will define DIF moment conditions in Section 3.

[2] We will define LEV moment conditions in Section 4. The system formed by both DIF and LEV conditions is known as SYS moment conditions.

[3] We define size (level) as estimates of Type I error probabilities. We will refer to Monte Carlo sizes and rejection frequencies, interchangeably.

[4] We will refer to overidentifying restrictions tests, moment restrictions tests, overidentification tests and J-tests interchangeably. The test based on the GMM is also known as the Sargan test.

native to asymptotic critical values[5]. Bowsher (2000a) examines tilting parameter alternatives to the Sargan statistic.[6] His findings show that tilting parameter tests of overidentifying restrictions have worse finite-sample properties than the Sargan test in the context of the AR(1) dynamic panel data model. Although both tests are sensitive to the number of T −the time periods− becoming large, tilting parameter tests can be very oversized in panels where the Sargan test is well behaved.

We define EL-bootstrap analogously to Brown and Newey's (2001) GMM-bootstrap technique. For both methods we use non-uniform weights to resample. These weights, obtained using the EL distribution, are more "efficient" than those given by the empirical distribution because they incorporate the information given by the moment equations. The main difference with Brown and Newey's GMM-bootstrap procedure is that for EL-boostrap we estimate the coefficients through standard EL, rather than GMM. We are not aware of any other study which has assesses the size properties of the EL-bootstrap overidentification test within dynamic panel data models. Hence, we concentrate on analyzing in depth this statistic and compare it to the conventional two-step GMM overidentification test. The relevance of extending EL to this setting is evident because empirical applications which deal with dynamic panel data models are numerous. Moreover, given the already defined limitations of GMM estimators (large sample biases if series are highly autoregressive and worse size properties of its Sargan test as T increases) it is worthwhile to look for estimation alternatives to GMM.

The plan for the rest of the paper is as follows. Section 2 reviews autoregressive models with individual effects and lays out the underlying assumptions. We concentrate on an AR(1) process since the main insights generalize in a straightforward way to higher order multivariate cases. Section 3 and Section 4 present the moment equations, the so-called DIF and LEV conditions, implied by the model's assumptions. Section 5 details the GMM overidentification test and that based on EL-bootstrap within the context of panel data models and analyses their finite-sample size properties through Monte Carlo experiments. An empirical application on an AR(1) univariate panel data model with individual effects

[5] Although the improvement is substantial for the coverage probability of the confidence interval.
[6] Tilting parameter tests were introduced by Imbens *et al* (1998).

using the cash-flow series of 174 firms in the United States from 1981 to 1985 is carried out in Section 6. Section 7 concludes. Appendices contain all of the results derived from our simulations.

2 The Model

We consider a first-order univariate autoregressive panel data model of the form

$$y_{it} = \rho y_{i,t-1} + u_{it}, \tag{1}$$

$$u_{it} = \eta_i + \upsilon_{it}; \tag{2}$$

$$for \quad i = 1, 2, ..., n \quad and \quad t = 2, , ..., T,$$

where y_{it} is an observation on some series for individual i in period t, η_i is an unobserved individual-specific time-invariant effect which allows for heterogeneity and υ_{it} is a disturbance term.

We assume that n is large, T is fixed, $|\rho| < 1$, and η_i and υ_{it} are independently distributed across i.

We make the following standard assumptions (Ahn and Schmidt, 1995):

(A1) $E(\eta_i) = 0$, $E(\upsilon_{it}) = 0$, $for\ t = 2, ..., T$ and $\forall\ i$.

(A2) $E(\upsilon_{it}\upsilon_{is}) = 0$, $\forall\ t \neq s$ and $\forall\ i$.

(A3) $E(\upsilon_{it}\eta_i) = 0$, $for\ t = 2, ..., T$ and $\forall\ i$.

(A4) $E(y_{i1}\upsilon_{it}) = 0$, $for\ t = 2, ..., T$ and $\forall\ i$.

$(A2)$ implies that the υ_{it} $'s$ are not serially correlated and $(A4)$ specifies that the initial conditions y_{i1} are predetermined. We will also assume $(A5)$, which is discussed in Section 4.

Given these assumptions, the OLS estimator of ρ in the level equation (1) is inconsistent because $y_{i,t-1}$ is positively correlated with the error term, u_{it}, due to the presence of the individual effects. Matyás and Sevestre (1996) show that this correlation does not disappear as the number of individuals in the sample gets larger. Standard results for omitted variables biases indicate that the OLS levels estimator is biased upwards.

The so-called Within Groups estimator eliminates this source of inconsistency by transforming the equation to eliminate η_i. Specifically, the original observations are expressed as deviations from the mean values of y_{it}, $y_{i,t-1}$, η_i and υ_{it} across the $T-1$ observations for each individual i. OLS is then used to estimate ρ from

$$y_{it} - \overline{y}_i = \rho \left(y_{i,t-1} - \overline{y}_{i\_1} \right) + \upsilon_{it} - \overline{\upsilon}_i,$$

where $\overline{y}_i$, $\overline{y}_{i\_1}, \overline{\eta}_i$ and $\overline{\upsilon}_i$ are the mean values.

In panels where the number of time periods available is small, this transformation induces a correlation between the transformed lagged dependent variable and the transformed error term. Nickell (1981) shows that this correlation is negative. Standard results for omitted variables biases indicate that the Within Groups estimator is biased downwards.[7]

There are two approaches discussed in literature in which one can proceed to tackle the inconsistency of OLS and Within Groups estimators. The first uses a kind of Two-Stage Least Squares estimator as proposed by Balestra and Nerlove (1966). The second uses instrumental variables as proposed by Arellano and Bond (1991) and Anderson and Hsiao (1982, 1981). In what follows we focus on Arellano and Bond's (1991) work and on extensions provided by Blundell and Bond (1998).

3 DIF Moment Conditions

Assumptions $(A1) - (A4)$ imply moment conditions that are sufficient to identify and estimate ρ for $T \geq 3$.

Applying first differences to (1) yields

$$\Delta y_{it} = \rho \Delta y_{i,t-1} + \Delta \upsilon_{it}, \tag{3}$$

where $\Delta y_{it} = y_{it} - y_{i,t-1}$ and $\Delta \upsilon_{it} = \upsilon_{it} - \upsilon_{i,t-1}$,

for $i = 1, ..., n$ and $t = 3, ..., T$.

[7] Note that the OLS and Within Groups estimators are biased in opposite directions.

Equation (1) together with assumptions $(A1)-(A4)$ imply the following $m_d = .5\,(T-1)\,(T-2)$ linear moment restrictions

$$E\left(y_{i,t-s}\Delta v_{it}\right) = 0 \quad for \quad t = 3, ..., T \quad \text{and} \quad s \geq 2. \tag{4}$$

These equations are known as DIF moment conditions because they involve the use of lagged levels of y_{it} as instruments for the first differenced equations. They can be expressed as

$$E\left(Z_{di}^{\tau}\Delta v_i\right) = 0, \tag{5}$$

where Z_{di} is the $(T-2) \times m_d$ matrix of instruments given by

$$Z_{di} = \begin{bmatrix} y_{i1} & 0 & 0 & ... & 0 & ... & 0 \\ 0 & y_{i1} & y_{i2} & ... & 0 & ... & 0 \\ \vdots & \vdots & \vdots & ... & \vdots & ... & \vdots \\ 0 & 0 & 0 & ... & y_{i1} & ... & y_{iT-2} \end{bmatrix}, \tag{6}$$

and Δv_i is the $(T-2)$ vector

$$\Delta v_i = \left(\Delta v_{i3}, \Delta v_{i4}, ..., \Delta v_{iT}\right)^{\tau}. \tag{7}$$

The subindex d emphasizes the fact that these are instruments for the differenced equations.

4 SYS Moment Conditions

By $(A1)-(A4)$ and

(A5) $E\left(\eta_i \Delta y_{i2}\right) = 0 \; \forall \; i,$

which is an additional assumption on initial conditions, lagged differences are valid instruments for equations in levels (Blundell and Bond, 1998). Thus, the further $m_l = (T-2)$ moment conditions

$$E\left[u_{it}\Delta y_{i,t-1}\right] = 0 \text{ for } t = 3, ..., T \text{ and } \forall \; i, \tag{8}$$

are available. These can be expressed as

$$E\left(Z_{li}^{\tau}\, u_i\right) = 0, \tag{9}$$

where Z_{li} is the $(T-2) \times m_l$ matrix of instruments given by

$$Z_{li} = \begin{bmatrix} \Delta y_{i2} & 0 & ... & ... & 0 \\ 0 & \Delta y_{i3} & ... & ... & 0 \\ 0 & 0 & ... & ... & \\ \vdots & \vdots & ... & ... & 0 \\ 0 & 0 & ... & ... & \Delta y_{iT-1} \end{bmatrix}, \tag{10}$$

and u_i is the $(T-2)$ vector $(u_{i3},\ u_{i4},\ ...,u_{it})^{\tau}$.

We refer to (9) as the LEV moment conditions since they use lagged differences as instruments for equations in levels. Note that the subindex l is used to emphasize the fact that these instruments are valid for equations in levels.

$(A5)$ is a restriction on the initial conditions process that generates y_{i1}. Let $y_{i1} = \dfrac{\eta_i}{1-\rho} + \varepsilon_{i1}$, where initial deviations from the long run mean of the y_{it} process are represented by ε_{i1}. Then

$$E\left(\varepsilon_{i1}\eta_i\right) = 0 \tag{11}$$

are necessary and sufficient conditions for $(A5)$ to hold.It must be the case that the initial deviation from the long run mean is uncorrelated across individuals with the level of that long run mean. Two cases in which (11) holds is (i) if an infinite past is assumed for the dynamic process in (1) or (ii) if there is any initial deviation from $\dfrac{\eta_i}{1-\rho}$ which is randomly distributed across individuals.

The system of moment equations formed by the DIF moment conditions, (5), and the LEV moment conditions, (9), are the so-called SYS conditions. These are the $.5\,(T+1)\,(T-2) + (T-2)$ equations

$$E\left(Z_i^{*\tau}\ \Delta v_i^*\right) = 0, \tag{12}$$

where Z_i^* is the instrument matrix given by

$$Z_i^* = \begin{pmatrix} Z_{di} & 0 & 0 & ... & 0 \\ 0 & \Delta y_{i2} & 0 & ... & 0 \\ 0 & 0 & \Delta y_{i3} & ... & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & ... & \Delta y_{i,T-1} \end{pmatrix} = \begin{pmatrix} Z_{di} & 0 \\ 0 & Z_{li} \end{pmatrix}, \tag{13}$$

and

$$\Delta v_i^* = \left(\Delta v_i^{\tau},\ u_{i3},\ u_{i4}, ...u_{iT}\right)^{\tau}. \tag{14}$$

5 Finite-Sample Size Properties of Overidentification Tests

In what follows we employ Monte Carlo experiments to study the finite-sample size properties of two overidentification tests within a dynamic panel data framework. We analyse the EL-bootstrap overidentification test, W_j^b, and two-step GMM test, J_{2GMM}, based on DIF and SYS moment conditions. These tests are used to evaluate the null hypothesis that there is a value of ρ consistent with $E\left(Z_{di}^{\tau}\ \Delta v_i\right) = 0$ for DIF estimation and $E\left(Z_i^{*\tau}\ \Delta v_i^*\right) = 0$ for SYS estimation. Under the null hypothesis the two statistics are asymptotically distributed as $\chi^2_{(m-1)}$. Where $m = .5\left(T+1\right)\left(T-2\right)$ for DIF estimation and $m = .5\left(T+1\right)\left(T-2\right) + \left(T-2\right)$ for SYS estimation.

To revise how the tests are calculated, we introduce some notation. Let $\Delta v = \left(\Delta v_1^{\tau} ..., \ \Delta v_N^{\tau}\right)^{\tau}$ be formed by vertically stacking Δv_i for $i = 1, ...N$ (the dimension of Δv is $N\left(T-2\right) \times\ 1$). Let $\Delta y_i = \left(\Delta y_{i3}, ..., \Delta y_{iT}\right)^{\tau}$, $\Delta y = \left(\Delta y_i^{\tau}, ..., \Delta y_N^{\tau}\right)^{\tau}$ and define $\Delta y_{i,-1} = \left(\Delta y_{i2}, ..., \Delta y_{i,T-1}\right)^{\tau}$ −its stacked version is Δy_{-1}. The $N\left(T-2\right) \times m_d$ matrix $Z_d = \left(Z_{d1}^{\tau} .....Z_{dN}^{\tau}\right)^{\tau}$ is formed by vertically stacking the instrument matrices Z_{di} used for GMM-DIF estimation.

The one-step GMM-DIF estimator, $\overline{\rho}$, is obtained from

$$\overline{\rho} = \min_{\rho}\left(\Delta v^{\tau} Z_d W Z_d^{\tau} \Delta v\right) = \left(\Delta y_{-1}^{\tau} Z_d W Z_d^{\tau} \Delta y_{-1}\right)^{-1} \left(\Delta y_{-1}^{\tau} Z_d W Z_d^{\tau} \Delta y\right)$$

where W is the identity matrix. The two-step GMM-DIF estimator, $\widehat{\rho}_{2GMM}$, may be calculated by setting

$$\widehat{W} = \left(n^{-1} \sum Z_{di}^{\tau} \Delta \widehat{v}_i^{*} \Delta \widehat{v}_i^{*\tau} Z_{di}\right), \tag{15}$$

where $\Delta \widehat{v}_i^{*} = \Delta y_i - \overline{\rho}\ \Delta y_{i,-1}$.

The GMM overidentifying statistic based on the DIF moment conditions is denoted by

$$J_{2GMM} = \Delta \widehat{v}^{\tau} Z_{di} \left(\sum Z_{di}^{\tau} \Delta \widehat{v}_i \Delta \widehat{v}_i^{\tau} Z_{di}\right)^{-1} Z_{di} \Delta \widehat{v},$$

where $\Delta \widehat{v} = \Delta y -\ \widehat{\rho}_{2GMM} \Delta y_{-1}$.

The procedure for obtaining the Sargan statistic based on SYS conditions is very similar to that corresponding to DIF conditions. We proceed in an analogous way to GMM-DIF estimation but using Z_i^* in (13) and Δv_i^* in (14) instead of Z_{di} in (6) and Δv_i in (7).

To obtain the EL-bootstrap overidentification statistic we follow the main theory for EL given in Qin and Lawless (1994). Let

$y_i = (y_{i1}, y_{i2}, ...y_{iT})^\tau$. The moment equations that are used as constraints on the non-parametric likelihood problem are

$$g(y_i, \rho) = Z_{di}^\tau \Delta v_i,$$

for DIF estimation and

$$g(y_i, \rho) = Z_i^{\tau *} \Delta v_i^*$$

for SYS estimation. The maximum empirical likelihood estimates of the probabilities (see Theorem 1 in Qin and Lawless, 1994) are imposed on the bootstrap distribution, rather than 1/n as for the probability of the *ith* observation. To compute bootstrap critical values for the overidentification statistic we calculate 1000 statistics -see Corollary 4 in Qin and Lawless (1994)- from the simulated data, where each sample consists of 100 observations[8].

5.1 The Data Generating Process

We generate y_{it} as

$$y_{it} = \rho\, y_{i,t-1} + \eta_i + v_{it},$$

$$y_{i0} = \frac{\eta_i}{1-\rho} + e_i,$$

where $0 \leq \rho < 1$, $t = 1, 2, ..., T$ and $i = 1, ...n$.

η_i and v_{it} are $N(0,1)$ random variables, $e_i \sim N\left(0, 1/1-\rho^2\right)$ and the $\nu_{it}\ ' s$, $\eta_i's$ and e_i are mutually independent. Note that y_{it} is stationary over time because of the specification of the equation describing y_{i0}.

[8] For further details of how bootstrap critical values are obtained refer to Gonzalez, A. (2005)

For this DGP, Equations $(A1) - (A5)$ are satisfied. Thus, the DIF moment conditions, (5), and the SYS moment conditions, (12), are both valid. In other words, the null hypothesis that the true DGP is nested in the model given in equation (1) and assumptions $(A_1) - (A_5)$ is true.

Our aim is to examine the effects of varying the sample size and the dimensions of the panels within our estimations. We are also interested in assessing the implications of using weak and strong instruments[9] and the benefits, if any, of exploiting additional moment conditions in our calculations. The importance of each one is discussed below.

(i) Sample Size

Within dynamic panel data models, asymptotic theory is based on $n \to \infty$ (rather than on T). Given this, it is interesting to assess if the asymptotic approximation of the overidentifying restrictions tests improves as n increases.

(ii) Dimensionality

The number of available moment conditions increases rapidly as T increases (keeping n fixed) due to the dependence on T^2 (see Table 1). Bowsher (2000a) examines the implications of dimensionality on the performance of Sargan tests and a tilting parameter overidentification statistic. His findings show that when the number of moment conditions increases, the size properties of both tests deteriorate and that the tilting parameter test of overidentifying restrictions has worse size properties than the Sargan test in the context of the AR(1) dynamic panel data model. We analyse whether this dimensionality problem is also found for the EL-bootstrap overidentifying statistic.

(iii) Strong and weak instruments

As we have previously discussed, Blundell and Bond (1998) illustrate that GMM-DIF estimators have pronounced bias in the presence of weak instruments. We are interested in examining if the

[9] When the lagged levels of the series are only weakly correlated with subsequent first differences, then the instruments available for the differenced equations are weak. This may arise when marginal processes for y_{it} are highly persisent or close to random walk processes.

GMM overidentifying statistic is also sensitive to high values of the autoregressive coefficient. In addition, we want to see if the size properties of the EL-bootstrap overidentification test are worse for weak instruments than for strong instruments.

(iv) SYS *versus* DIF conditions

Blundell and Bond (1998) find evidence of large benefits from introducing additional restrictions on the initial conditions of the AR(1) process (in terms of bias and/or precision) in GMM estimators, in the presence of highly persistent series. In light of these results we examine whether these gains are extended to its overidentification test. In other words, we assess if the finite-sample size properties of overidentification tests based on SYS moment conditions are better than those based on DIF equations. We distinguish two opposite effects: a positive effect of incorporating correct moment equations into our calculations and a negative dimensionality effect. Here, we are interested in the overall effect of exploiting extra moment equations.

Number of estimating equations
Dynamic Panel Data

	DIF	SYS
	$\frac{1}{2}(T-1)(T-2)$	$\frac{1}{2}(T-1)(T-2)+(T-2)$
T=3	1	2
T=4	3	5
T=5	6	9
T=6	10	14
T=10	36	44

T is the time periods.

Table 1: Dynamic Panel Data - Number of Estimating Equations

All of our results are based on 5000 Monte Carlo replications with 1000 bootstrap trials in each experiment. We consider two sample sizes: $n = 100$ and $n = 175$;[10] four different values for the autoregressive component: $\rho = \{.2, .5, .7, .9\}$; and three time periods: $T = \{4, 5, 6\}$. By considering these values of ρ we intend to cover representative stationary cases. It would have been more illustrative

[10] n=175 was chosen to match the sample size of our empirical example, given in Section 6.

to have considered longer time periods to study the dimensionality effect. However, computational restrictions played a decisive part in this respect.

First, we investigate the implications of varying the sample size within our estimations using both DIF and SYS moment conditions. We concentrate on T=6.[11]

Empirical Levels of J-tests
Dynamic Panel Data
Sample Size effects

$T = 6$
DIF Moment Conditions

		W_j^b		J_{2GMM}	
Levels	ρ	$n = 100$	$n = 175$	$n = 100$	$n = 175$
.10		.0772	.0948	.0984	.1098
.05	.2	.0394	.0482	.0448	.0528
.01		.0080	.0094	.0086	.0100
.10		.1160	.0948	.1066	.1126
.05	.5	.0524	.0474	.0472	.0552
.01		.0062	.0074	.0076	.0088
.10		.1158	.0972	.1186	.1166
.05	.7	.0532	.0398	.0594	.0610
.01		.0050	.0226	.0084	.0136
.10		.1282	.1162	.1092	.1188
.05	.9	.0598	.0668	.0512	.0604
.01		.0108	.0134	.0070	.0128

W_j^b and J_{2GMM} are overidentification tests based on EL-bootstrap and two-step GMM; respectively. T is the time periods, ρ the autoregressive coefficient and n is the sample size.

Table 2: Finite-Sample Size Properties - Dynamic Panel Data (Sample Size Effects: DIF)

Table 2 summarizes the rejection frequencies[12] of W_j^b and J_{2GMM} based on DIF moment conditions. Those corresponding to SYS estimation are reported in Table 3. Note that there is a single parameter to be estimated, ρ. The reference distributions for this specification are $\chi^2_{(9)}$ and $\chi^2_{(13)}$ for the DIF and SYS context; respectively (refer to Table 1).

[11] Alternative time periods lead to similar conclusions to those corresponding to T=6. The results for the complete set of time periods are provided in the Appendices of this Chapter.

[12] Note that for W_j^b the rejection frequencies are the proportion of the simulated data test statistics that exceeds the bootstrap critical values.

Empirical Levels of J-tests
Dynamic Panel Data
Sample Size effects

$T = 6$
SYS Moment Conditions

		W_j^b		J_{2GMM}	
Levels	ρ	$n = 100$	$n = 175$	$n = 100$	$n = 175$
.10		.1047	.1235	.1028	.1058
.05	.2	.0541	.0704	.0490	.0564
.01		.0095	.0190	.0090	.0112
.10		.1148	.1159	.1144	.1118
.05	.5	.0534	.0569	.0522	.0552
.01		.0104	.0100	.0086	.0120
.10		.0926	.0728	.1218	.1312
.05	.7	.0362	.0334	.0612	.0694
.01		.0062	.0034	.0134	.0166
.10		.1042	.1002	.1256	.1434
.05	.9	.0452	.0478	.0684	.0746
.01		.0062	.0078	.0100	.0176

W_j^b and J_{2GMM} are overidentification tests based on EL-bootstrap and two-step GMM; respectively. T is the time periods, ρ the autoregressive coefficient and n is the sample size.

Table 3: Finite-Sample Size Properties - Dynamic Panel Data (Sample Size Effects: SYS)

The Tables show that increasing n does not necessarily lead to better size properties of both tests. Moreover, there are several cases in which the size distortions of both statistics increase as n increases.

Now, we examine the effect of increasing the number of time periods, the so-called dimensionality effect, on the finite-sample size properties of both overidentifying statistics. We consider the weak instrument case, $\rho = \{.7, .9\}$.[13] Results based on DIF moment conditions are summarized in Table 4. The reference distributions for these tests are respectively $\chi^2_{(2)}$, $\chi^2_{(5)}$, $\chi^2_{(9)}$ for T=$\{4, 5, 6\}$. Results corresponding to SYS conditions are given in Table 5. Here, the reference distributions are respectively $\chi^2_{(4)}$, $\chi^2_{(8)}$, $\chi^2_{(13)}$ for T=$\{4, 5, 6\}$.[14]

[13] There is no evidence of a dimensionality effect for $\rho = \{.2, .5\}$. Refer to the Appendices of this Chapter.
[14] To calculate the degrees of freedom refer to Table 1.

Empirical Levels of J-tests Dynamic Panel Data Dimensionality Effect DIF Moment Conditions							
		n=100					
		T=4		T=5		T=6	
Levels	ρ	W_j^b	J_{2GMM}	W_j^b	J_{2GMM}	W_j^b	J_{2GMM}
.10		.1006	.1270	.0884	.1292	.1158	.1186
.05	.7	.0492	.0710	.0392	.0656	.0532	.0594
.01		.0110	.0204	.0048	.0136	.0050	.0084
.10		.1282	.1018	.1142	.1056	.1282	.1092
.05	.9	.0682	.0492	.0615	.0464	.0598	.0512
.01		.0154	.0068	.0071	.0072	.0108	.0070
		n=175					
.10		.0946	.1080	.1143	.1326	.0972	.1166
.05	.7	.0506	.0588	.0603	.0688	.0398	.0610
.01		.0084	.0152	.0126	.0128	.0226	.0136
.10		.1010	.0990	.1006	.1148	.1162	.1188
.05	.9	.0544	.0524	.0520	.0604	.0668	.0604
.01		.0118	.0096	.0110	.0114	.0134	.0128

W_j^b and J_{2GMM} are overidentification tests based on EL-bootstrap and two-step GMM. T is the time periods, n is the sample size and ρ is the autoregressive coefficient.

Table 4: Finite-Sample Size Properties - Dynamic Panel Data (DIF: Dimensionality Effect)

For the experiments based on DIF moment conditions there is no evidence of a worsening in the size properties of both overidentification tests as T increases. However, when SYS conditions are used (see Table 5) there are several cases in which the asymptotic χ^2 approximation of the finite-sample distribution deteriorates for J_{2GMM} as T increases. These results are consistent with prior simulation evidence (see Table 3.2 of Bowsher, 2000a). The results for W_j^b show that there are some specifications for which this test becomes undersized as T increases. We observe that W_j^b is not particularly sensitive to variations in T.

Empirical Levels of J-tests
Dynamic Panel Data
Dimensionality Effect
SYS Conditions

		T=4		T=5		T=6	
		W_j^b	J_{2GMM}	W_j^b	J_{2GMM}	W_j^b	J_{2GMM}
Levels	ρ						
				$n=100$			
.10		.0992	.1164	.1024	.1196	.0926	.1218
.05	.7	.0480	.0578	.0500	.0592	.0362	.0612
.01		.0074	.0102	.0094	.0106	.0062	.0134
.10		.0994	.1060	.0954	.1208	.1042	.1256
.05	.9	.0474	.0540	.0410	.0578	.0452	.0684
.01		.0086	.0096	.0036	.0100	.0062	.0100
				$n=175$			
.10		.1106	.1094	.0910	.1072	.0728	.1312
.05	.7	.0608	.0614	.0396	.0556	.0334	.0694
.01		.0114	.0146	.0038	.0114	.0034	.0166
.10		.1050	.1220	.0924	.1198	.1002	.1434
.05	.9	.0636	.0636	.0420	.0638	.0478	.0746
.01		.0136	.0136	.0064	.0146	.0078	.0176

W_j^b and J_{2GMM} are overidentification tests based on EL-bootstrap and two-step GMM; respectively. T is the time periods, ρ is the autoregressive coefficient and n is the sample size.

Table 5: Finite-Sample Size Properties - Dynamic Panel Data (SYS: Dimensionality Effect)

The effects of weak and strong instruments are analysed in Table 6. Consider the DIF moment conditions, n=100 and T=$\{4,5,6\}$ [15]. The reference distributions are $\chi^2_{(2)}$, $\chi^2_{(5)}$ and $\chi^2_{(9)}$.[16]

[15] Our main interest is to assess the effects of weak instruments using DIF moment conditions. Refer to the Appendices of this Chapter for the results corresponding to SYS estimation.

[16] To calculate the degrees of freedom refer to Table 1.

		Empirical Levels of J-tests Dynamic Panel Data Weak and Strong Instruments					
				n=100			
		T=4		T=5		T=6	
Levels	ρ	W_j^b	J_{2GMM}	W_j^b	J_{2GMM}	W_j^b	J_{2GMM}
.10		.1006	.1084	.1044	.1042	.0772	.0984
.05	.2	.0526	.0532	.0576	.0526	.0394	.0448
.01		.0124	.0086	.0108	.0084	.0080	.0086
.10		.1196	.1074	.1040	.1114	.1160	.1066
.05	.5	.0604	.0564	.0530	.0564	.0524	.0472
.01		.0134	.0148	.0124	.0126	.0062	.0076
.10		.1006	.1270	.0884	.1292	.1158	.1186
.05	.7	.0492	.0710	.0392	.0656	.0532	.0594
.01		.0110	.0204	.0048	.0136	.0050	.0084
.10		.1282	.1018	.1142	.1056	.1282	.1092
.05	.9	.0682	.0492	.0615	.0464	.0598	.0512
.01		.0154	.0068	.0071	.0072	.0108	.0070

W_j^b and J_{2GMM} are overidentification tests based on EL-bootstrap and two-step GMM. T is the time periods, n is the sample size and ρ is the autoregressive coefficient.

Table 6: Finite-Sample Size Properties - Dynamic Panel Data (Weak and Strong Instruments: DIF n=100)

The main result is that for $n = 100$ and $\rho = .7$ the asymptotic approximation for J_{2GMM} is the worst. In Monte Carlo results reported by Blundell and Bond (1998) GMM estimators are biased for highly autoregressive series and these biases are dramatic for $\rho = .9$. However, note that J_{2GMM} has better sizes for $\rho = .9$ than for $\rho = .7$. Moreover, the results for $\rho = .2$ do not differ to those corresponding to $\rho = .9$ in a large extent. We find that W_j^b is not very sensitive to the problem of weak instruments (although we observe that W_j^b is more oversized for T=4 and $\rho = .9$).

The objective of the next set of simulations is to test whether there is an improvement in accuracy for the overidentification tests from using additional moment conditions. We are particularly interested on assessing whether this is the case for a weak instruments specification: $\rho = .9$. For DIF estimation and T=$\{4, 5, 6\}$; the reference distributions are $\chi^2_{(2)}$, $\chi^2_{(5)}$, $\chi^2_{(9)}$. For the analysis based on SYS moment equations and T=$\{4,5,6\}$; these are $\chi^2_{(4)}$, $\chi^2_{(8)}$, $\chi^2_{(13)}$.[17] Results for W^b_j are provided in Table 7 and those for J_{2GMM} are reported in Table 8.

Empirical Levels of W^b_j
Dynamic Panel Data
DIF versus SYS

	T=4		T=5		T=6	
Levels	DIF	SYS	DIF	SYS	DIF	SYS
			$n = 100$ and $\rho = .9$			
.10	.1282	.0994	.1142	.0954	.1282	.1042
.05	.0582	.0474	.0615	.0410	.0598	.0452
.01	.0154	.0086	.0071	.0036	.0108	.0062
			$n = 175$ and $\rho = .9$			
.10	.1010	.1050	.1006	.0924	.1162	.1002
.05	.0544	.0470	.0520	.0420	.0668	.0478
.01	.0118	.0108	.0110	.0064	.0134	.0078

W^b_j is an overidentification tests based on EL-bootstrap. T is the time periods, n is the sample size and ρ is the autoregressive coefficient

Table 7: Finite-Sample Size Properties - EL-bootstrap: Dynamic Panel Data (DIF versus SYS)

Although the size properties of W^b_j at the .10 and .05 levels are better for SYS than for DIF moment conditions for n=100, this is not the case for n=175.

Our results for J_{2GMM} in Table 8 are unexpected. The finite-sample size properties of the Sargan tests based on SYS moment conditions are worse than those based on DIF conditions. These findings have the implication that as we add moment conditions to reduce the sample bias of GMM estimators due to weak instrumentation, as recommended by Blundell and Bond (1998), we could negatively be affecting the finite-size properties of its Sargan test.

[17] To calculate the degrees of freedom refer to Table 1.

Empirical Levels of J_{2GMM} Dynamic Panel Data DIF versus SYS						
	T=4		T=5		T=6	
Levels	DIF	SYS	DIF	SYS	DIF	SYS
			$n = 100$ and $\rho = .9$			
.10	.1018	.1060	.1056	.1208	.1092	.1256
.05	.0492	.0540	.0464	.0578	.0512	.0684
.01	.0068	.0096	.0072	.0100	.0070	.0100
			$n = 175$ and $\rho = .9$			
.10	.0990	.1220	.1148	.1198	.1188	.1434
.05	.0524	.0636	.0604	.0638	.0604	.0746
.01	.0096	.0136	.0114	.0146	.0128	.0176

J_{2GMM} is an overidentification tests based on the two-step GMM estimator.
T is the time periods, n is the sample size and ρ is the autoregressive coefficient

Table 8: Finite-Sample Size Properties - Two-step GMM: Dynamic Panel Data (DIF versus SYS)

6 Empirical Application

6.1 Data

The data set we use was kindly provided by Bronwyn Hall. It is a balanced panel of 174 firms for the United States for 1978-1989. Hall *et al* (1998) use this data set to test for causal relationship among sales and cash-flow, and research and development and investment. These 174 firms belong to the science-based industries and include Chemicals, Pharmaceuticals, Electrical Machinery, Computing Equipment, Electronics, and Scientific Instruments. The original data set consists of 863 firms and the variables analysed are sales, research and development, investment, cash-flow and employment. Hall *et al* (1998) apply the following "cleaning" rules:

(i) Only firms with growth rates between -90% and 900% were considered.

(ii) In order to remove erroneous data values, firms with at least one of the following characteristics were eliminated:

- Sequential employment and/or sales growth rates that were large, *e.g.* below -50% or above 100%, and alternate in sign.

- Sequential investment and/or cash-flow growth rates that were large, *e.g.* below -80% or above 400%, and alternate in sign.
- Sequential research and development growth rates that were large, *e.g.* between -67% and 200%, and alternate in sign.

(iii) Firms with negative cash-flows and with jumps in observations were removed from the data set.

We choose the years 1981-1985. This reflects the desire to have a short panel, *e.g.* $T = 5$. This leaves us with a total of 870 observations for each series. The series were deflated as in Hall *et al* (1998). Among the 5 different variables we looked for those compatible with models where heterogeneity across firms is summarized by an individual effect. Another important feature that we explored was the stationarity of the process and the order of the autoregressive component. We now present the analysis for the series corresponding to cash-flow.

6.2 Cash-flow: Descriptive Statistics

Table 9 shows the means, standard deviations, and autocorrelations for the cash-flow series. In general, the means and standard deviations of cash-flow do not change much over time. Note that the correlation matrix illustrates the fact that cash-flow is highly autocorrelated.

Empirical First and Second Moments real log (cash-flow)							
	Mean	St Dev	Correlation Matrix				
Year			**1981**	**1982**	**1983**	**1984**	**1985**
1981	4.2033	1.9862	1	.9818	.9745	.9645	.9598
1982	4.1548	1.9806	.9818	1	.9835	.9754	.9671
1983	4.3062	1.9158	.9745	.9835	1	.9877	.9750
1984	4.4531	1.8744	.9645	.9754	.9877	1	.9829
1985	4.3888	1.8588	.9598	.9671	.9750	.9829	1

Table 9: Cash-flow Descriptive Statistics

6.3 Cash-flow: The Model

The model is

$$cf_{it} = \sum_{k=1}^{K} \rho_k cf_{it-k} + u_{it}, \tag{16}$$

$$u_{it} = \eta_i + \upsilon_{it} \quad \text{for} \quad i = 1, ...174 \quad \text{and } t = 1, ...5;$$

where cf_{it} is the logarithm of real cash-flow of the i^{th} individual at time t.

Before analyzing the results it is important to review some key points.

1. First, identification requires to assess properties such as orders of integration and cointegration. Where differencing transformations are employed to eliminate unobserved individual effects, identification requires the existence of instrumental variables. These instruments must be correlated with first-differences of the data. Because in a pure random walk the lagged values of the series are not correlated with first-differences, the first-differenced instrumental variables estimators are uninformative on the parameter of interest. Thus, the presence of a unit root will invalidate the commonly used GMM specification.[18]

   It is therefore important to assess the time series properties of the series under consideration. In this regard, our analysis is greatly influenced by the studies of Bond *et al* (2002) and Hall and Mairesse (2002). They investigate the properties of several unit roots tests in short panel data. Their findings illustrate that a test based on the model estimated under the null of a unit root (that is, where the OLS can be used because there are no "individual effects") provides a simple robust test with high power. We rely on this test, denoted by BNW, and allow for heteroscedasticity by using a Seemingly Unrelated Regression (SUR) framework with each year being an equation (as in Hall and Mairesse, 2002).

[18] In the presence of a unit root, the identifiability of GMM is preserved if this method is based on quadratic moments (see Alvarez and Arellano (2004)).

2. Second, assumption ($A2$) states that there is no serial correlation in the $v_{it}'s$. This assumption allows the identification of ρ in our model. If the assumption of no serial correlation is not valid then the moment equations would not hold. Thus, it is important to report tests of serial correlation in the first differenced residuals. If the errors in levels are serially independent, those in first-differences will exhibit first-order −but not second-order− serial correlation. Moreover, the first-order serial correlation coefficient must be equal to -0.5. An informal diagnostic test is provided by inspecting the autocorrelation matrix of the errors in first differences (see Chapter 6 of Arellano, 2003). Arellano and Bond (1991) propose formal tests of serial correlation: m_2 and m_1. These statistics test respectively for lack of second-order serial correlation and first-order serial correlation in the differenced residuals. There is no second-order correlation if the errors in the model in levels are not serially correlated, but also if the errors in levels follow a random walk process. To discriminate between the two situations we calculate an m_1 statistic. (see Arellano and Bond, 1991).

   Summing up, if the disturbances v_{it} are not serially correlated there should be evidence of significant negative first order serial correlation in differenced residuals and no evidence of second order serial correlation in the differenced residuals. The statistics m_1 and m_2 are based on the standardized average residual autocovariance. These tests are asymptotically distributed as $N(0,1)$ under the null of no autocorrelation.

3. Finally, the fact that the OLS and Within Groups estimators are likely to be biased in opposite directions is very useful (recall that OLS is biased upwards and Within Groups is biased downwards). Thus if the cash-flow series is well represented by an autoregressive model with individual effects, the GMM estimator will lie between the OLS and Within Groups estimator (or at least not be significantly higher than the former or significantly lower than the latter (Bond, 2002)).

We now analyse in depth an AR(1) model.[19] A constant term and time dummies are included. Our

[19] We first examined and AR(2) model (a higher order was not studied since we have a short series: $T = 5$, and three

estimations are solely based on DIF conditions. Most of our calculations are performed using DPD98 for GAUSS and our own GAUSS programs.

For an AR(1) model the DIF moment equations are $E\left(Z_{di}^{\tau}\Delta v_i\right) = 0$. Here Z_{di} is the matrix of instruments given by

$$Z_{di} = \begin{bmatrix} cf_{i1} & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & cf_{i1} & cf_{i2} & 0 & 0 & 0 & 1 & 1 & 0 \\ 0 & 0 & 0 & cf_{i1} & cf_{i2} & cf_{i3} & 1 & 0 & 1 \end{bmatrix}; \tag{17}$$

and Δv_i is denoted by $\left(\Delta v_{i3}, \Delta v_{i4}, \Delta v_{i5}\right)^{\tau}$,

where

$$\begin{array}{l} \Delta v_{i3} = cf_{i3} - cf_{i2} - \zeta_1 1 - \rho_1 \left(cf_{i2} - cf_{i1}\right), \\ \Delta v_{i4} = cf_{i4} - cf_{i3} - \zeta_1 1 - \rho_1 \left(cf_{i3} - cf_{i2}\right) - \zeta_2 1, \\ \Delta v_{i5} = cf_{i5} - cf_{i4} - \zeta_1 1 - \rho_1 \left(cf_{i4} - cf_{i3}\right) - \zeta_3 1. \end{array} \tag{18}$$

ζ_1 is the constant term and ζ_2 and ζ_2 are the coefficients of the time dummies for 1984 or $T = 4$ and 1985 or $T = 5$; respectively. Note that these coefficients are multiplied by a $(n \times 1)$ row vector of ones. Therefore, we have 9 moment equations and 4 parameters: ζ_1, ζ_2, ζ_3 and ρ_1; to be estimated. Results for the levels of the OLS, Within Groups and GMM estimators are reported in Table 10.

6.4 Cash-flow: Results

Since the GMM estimate lies between the OLS estimate and the Within Groups estimate, we have some evidence that the logarithm of cash-flow is well represented by a dynamic AR(1) model with individual effects. For example, the OLS is considerably higher than the Within Groups estimate and the GMM lies between both.

To test for serial correlation we examine informal and formal tests. A serial matrix for cash-flow based on GMM residuals is

cross sections are already lost in constructing lags and taking first differences for this specification). We discriminated between an AR(1) model and an AR(2) model using conventional procedures. Main results for an AR(2) model are given in the Appendix: Table 15.

Dynamic Panel Data AR(1) Cash-flow			
	OLS LEVELS	WITHIN GROUPS	GMM DIF
cf_{t-1}	.9677 (.000)	.1888 (.006)	.6729 (.000)
m_1	-2.299 (.021)	-3.090 (.002)	-3.263 (.001)
m_2	$-.4859$ (.627)	$-.6345$ (.526)	.2628 (.793)
BNW	-5.22 [$std.error$ .00532]		
J_{2GMM} [5 df]			10.01 (.075)

p-values are reported inside parenthesis. df refers to the degrees of freedom. m_1 and m_2 test for serial correlation. J_{2GMM} is the Sargan test. BNW is a unit root test suggested by Bond et al (2002).

Table 10: AR(1) Cash-flow

$$\begin{pmatrix} 1 & -.5501 & .0296 \\ -.5501 & 1 & -.4122 \\ .0296 & -.4122 & 1 \end{pmatrix},$$

which broadly conforms to the expected pattern.

Formal tests of serial correlation are provided by the m_1 and m_2 statistics in Table 10. m_1 and m_2 are not reliable for the OLS and the Within Groups methods because the estimators of ρ and hence the estimates of the first-differenced residuals are likely to be biased. The serial correlation tests based on GMM are consistent with our assumptions: m_1 is negative and significant whilst m_2 is insignificant.

To test for unit roots, $H_0 : \rho = 1$, we follow Bond *et al* (2002). Our OLS test is based on the following model

$$y_{it} = \rho_k y_{it-1} + \upsilon_{it} \quad \text{for} \quad i = 1, ..., 174 \quad \text{and} \quad t = 1, ..., 5,$$

$$E\left[\upsilon_i \upsilon_i'\right] = \Omega,$$

where $\upsilon_i = (\upsilon_{i1}, \upsilon_{i2}, ...\upsilon_{i5})$.

Under the null BNW has an asymptotic standard normal distribution. The method of estimation is SUR with a weighting matrix based on the first stage estimate of Ω. According to BNW, in Table 10, there is no evidence of unit roots.

The Sargan statistic, J_{2GMM}, is 10.01 with a p-value equal to .075. It would certainly be appealing to have a stronger result (a higher p-value) to assess whether the AR(1) model is well specified for cash-flow. Because our simulations showed that the GMM statistic rejects too frequently for this particular specification, *e.g.* $n = 175$ and $\rho = .7$ (refer to Table 4), we now consider the EL-bootstrap overidentification test. Although W_j^b is also oversized, this is to a lower extent. Hence, if the validity of the moment equations is not rejected by W_j^b at any conventional significance level we would have stronger evidence to support the hypothesis that the AR(1) model is well defined for the cash-flow series.

We also note that it is likely that $\widehat{\rho}_{2GMM} = .6729$ is biased downwards (see the simulation evidence given by Blundell and Bond, 1998). Blundell and Bond (1998) show that for persistent series GMM-SYS estimators were better than those obtained through DIF conditions. Using GMM-SYS estimation for our cash-flow series yields a ρ estimate close to .90. From Table 4 it is the case that although J_{2GMM} and W_j^b are both oversized for $n = 175$ and $\rho = .9$, the latter statistic over-rejects to a lesser extent. Hence, it is still worthwhile to report the EL-bootstrap overidentification statistic in this case.

To calculate the EL-bootstrap overidentification test we use the same set of estimating equations that were used for the GMM estimations.

1000 bootstrap trials are considered and the coefficients given in Table 10 are taken as the initial values in our algorithms. From our experiments we obtain the following efficient-bootstrap critical values for 10%, 5% and 1%: $\{11.12, 12.23, 16.59\}$. These values are larger than the asymptotic $\chi^2_{(5)}$ values: $\{9.24, 11.07, 15.09\}$.

The EL-bootstrap overidentification test yields a statistic

$$W_j^b = 10.90,$$

which is smaller than the efficient-bootstrap critical values. Therefore, the validity of the moment equations is not rejected at any conventional significance level.

We can now can conclude that there is evidence that the logarithm of cash-flow is well represented by an AR(1) model with individual effects.

7 Conclusions

The objectives of this paper were twofold:

- To extend EL estimation to a widely used framework: dynamic panel data models.
- To examine EL as an alternative to GMM estimation in the context of autoregressive models with individual effects.

We studied the finite-sample size properties of the overidentification test based on EL and bootstrap, which we referred to as EL-bootstrap, and compared them to those of the Sargan statistic.

Asymptotic theory, in the context that we examine, is based on the sample size rather than on the number of time periods. We analysed the effect of increasing the sample size within the finite-sample size properties of both overidentification tests. We found no indication of better size properties for both tests based on DIF and SYS conditions as n increases.

According to Bowsher (2000a), tilting parameter tests of overidentifying restrictions have worse size properties than the conventional Sargan test in the context of the AR(1) dynamic panel data model. The former tests appear to be more sensitive to the problem of T becoming large and can be very oversized in panels where the Sargan test is well behaved. Therefore, we analysed the extent to which the dimensionality effect was also a problem for the EL-bootstrap statistic. For the three periods that we analysed and for the specifications of our experiments, there was no evidence of a size distortion effect in the size properties of this statistic.

Several simulation studies have found that for high values of the autoregressive coefficient, GMM estimators based on DIF conditions have large finite-sample bias and poor precision. It turned out that this might also be true for its Sargan test, for $\rho = .7$, as we found evidence of its finite-sample size properties being worse for this specification. However, the Sargan statistic has better sizes for $\rho = .9$ than for $\rho = .7$. Moreover, the results corresponding to $\rho = .2$ do not differ to those corresponding to $\rho = .9$ in a large extent. Our findings suggest that the finite-sample size properties of the EL-bootstrap statistic based on DIF conditions are not sensitive to weak instruments (except for T=4 and $\rho = .9$)

It has been widely documented that incorporating information relating to initial conditions is an effective way of reducing the sample bias and imprecision of GMM estimators in the weak instruments case. However, contrary to our initial expectations, our experiments show that the size-properties of the Sargan statistic can be worse for estimations based on SYS conditions than for those based on DIF conditions. This means that while trying to reduce some of the bias in GMM estimators −due to the presence of persistent series− by incorporating additional conditions we could be negatively affecting the size properties of its overidentification test (this conclusions holds for $\rho = .9$). Thus, it was interesting to examine the extent to which this behaviour was also applicable to the EL-bootstrap statistic. We found some evidence of better size properties derived from exploiting additional moment conditions for n=100 and $\rho = .9$ (not for n=175).

Finally, we carried out an empirical application. We considered the cash-flow series of 174 firms from the United States from 1981-1985. Except for the Sargan statistic, the different tests that we studied −both formal and informal− provided strong evidence that pointed to cash-flow being well-represented as an AR(1) model with individual effects. The p-value of the Sargan statistic was only 7.5%. Our simulations showed that the Sargan test over-rejected the null hypothesis for the same sample size and the same number of time periods for our empirical example. Whereas even if the EL-bootstrap over-rejected for this specification, this was to a lesser extent. Hence, we calculated the EL-bootstrap statistic for the cash-flow series. The null hypothesis was not rejected at any conventional statistical level. Given these results, we have stronger evidence that supports cash-flow as being well represented by an AR(1) panel data model with individual effects.

8 Appendix

Empirical Levels of J-tests
Dynamic Panel Data
DIF Moment Conditions

		n=100					
		T=4		T=5		T=6	
Levels	ρ	W_j^b	J_{2GMM}	W_j^b	J_{2GMM}	W_j^b	J_{2GMM}
.10		.1006	.1084	.1044	.1042	.0772	.0984
.05	.2	.0526	.0532	.0576	.0526	.0394	.0448
.01		.0124	.0086	.0108	.0084	.0080	.0086
.10		.1196	.1074	.1040	.1114	.1160	.1066
.05	.5	.0604	.0564	.0530	.0564	.0524	.0472
.01		.0134	.0148	.0124	.0126	.0062	.0076
.10		.1006	.1270	.0884	.1292	.1158	.1186
.05	.7	.0492	.0710	.0392	.0656	.0532	.0594
.01		.0110	.0204	.0048	.0136	.0050	.0084
.10		.1282	.1018	.1142	.1056	.1282	.1092
.05	.9	.0682	.0492	.0615	.0464	.0598	.0512
.01		.0154	.0068	.0071	.0072	.0108	.0070

W_j^b and J_{2GMM} are overidentification tests based on EL-bootstrap and two-step GMM. T is the time periods, n is the sample size and ρ is the autoregressive coefficient.

Table 11: Finite-Sample Size Properties - Dynamic Panel Data (DIF conditions n=100)

Empirical Levels of J-tests
Dynamic Panel Data
DIF Moment Conditions

n=175

Levels	ρ	T=4 W_j^b	T=4 J_{2GMM}	T=5 W_j^b	T=5 J_{2GMM}	T=6 W_j^b	T=6 J_{2GMM}
.10		.1162	.0968	.1214	.0936	.0948	.1098
.05	.2	.0596	.0466	.0632	.0506	.0482	.0528
.01		.0148	.0078	.0118	.0094	.0094	.0100
.10		.0978	.1004	.1004	.1140	.0948	.1126
.05	.5	.0450	.0518	.0462	.0562	.0474	.0552
.01		.0068	.0166	.0100	.0130	.0074	.0088
.10		.0946	.1080	.1143	.1326	.0972	.1166
.05	.7	.0506	.0588	.0603	.0688	.0398	.061
.01		.0084	.0152	.0126	.0128	.0226	.0136
.10		.1010	.0990	.1006	.1148	.1162	.1188
.05	.9	.0544	.0524	.0520	.0604	.0668	.0604
.01		.0118	.0096	.0110	.0114	.0134	.0128

W_j^b and J_{2GMM} are overidentification tests based on EL-bootstrap and two-step GMM estimators. T is the time periods, n is the sample size and ρ is the autoregressive coefficient

Table 12: Finite-Sample Size Properties - Dynamic Panel Data (DIF conditions n=175)

Empirical Levels of J-tests
Dynamic Panel Data
SYS Moment Conditions

n=100

Levels	ρ	T=4 W_j^b	T=4 J_{2GMM}	T=5 W_j^b	T=5 J_{2GMM}	T=6 W_j^b	T=6 J_{2GMM}
.10		.0894	.1094	.1035	.1118	.1047	.1028
.05	.2	.0552	.0538	.0544	.0590	.0541	.0490
.01		.0188	.0096	.0123	.0092	.0095	.0090
.10		.0994	.1036	.1164	.1148	.1148	.1144
.05	.5	.0450	.0496	.0558	.0572	.0534	.0522
.01		.0052	.0098	.0108	.0106	.0104	.0086
.10		.0992	.1164	.1024	.1196	.0926	.1218
.05	.7	.0480	.0578	.0500	.0592	.0362	.0612
.01		.0074	.0102	.0094	.0106	.0062	.0134
.10		.0994	.1060	.0954	.1208	.1042	.1256
.05	.9	.0474	.0540	.0410	.0578	.0452	.0684
.01		.0086	.0096	.0036	.0100	.0062	.0100

W_j^b and J_{2GMM} are overidentification tests based on EL-bootstrap and two-step GMM estimators. T is the time periods and ρ is the autoregressive coefficient.

Table 13: Finite-Sample Size Properties - Dynamic Panel Data (SYS conditions n=100)

Empirical Levels of J-Tests Dynamic Panel Data SYS Moment Conditions							
				n=175			
		T=4		T=5		T=6	
Level	ρ	W_j^b	J_{2GMM}	W_j^b	J_{2GMM}	W_j^b	J_{2GMM}
.10		.1031	.0938	.1250	.1076	.1235	.1058
.05	.2	.0510	.0458	.0658	.0500	.0704	.0564
.01		.0119	.0100	.0138	.0088	.0190	.0112
.10		.1204	.1034	.0993	.1044	.1159	.1118
.05	.5	.0652	.0540	.0487	.0548	.0569	.0552
.01		.0124	.0092	.0096	.0120	.0100	.012
.10		.1106	.1094	.0910	.1072	.0728	.1312
.05	.7	.0608	.0614	.0396	.0556	.0334	.0694
.01		.0114	.0146	.0038	.0114	.0034	.0166
.10		.1050	.1220	.0924	.1198	.1002	.1434
.05	.9	.0470	.0636	.0420	.0638	.0478	.0746
.01		.0108	.0136	.0064	.0146	.0078	.0176

W_j^b and J_{2GMM} are overidentification tests based on EL-bootstrap and two-step GMM estimators. T is the time periods, n is the sample size and ρ is the autoregressive coefficient.

Table 14: Finite-Sample Size Properties - Dynamic Panel Data (SYS conditions n=175)

Dynamic Panel Data AR(2) Cash-flow GMM estimation (DIF conditions)				
	Coeff.	s.e.	t-value	p-value
cf_{t-1}	.4892	.1798	2.72	.007
cf_{t-2}	.0426	.0806	.529	.597
Constant	.0749	.0306	2.44	.015
T1985	-.2176	.0454	-4.78	.000
Wald (joint) (2 df)	7.910			.019
Wald (dummy) (2df)	23.18			.000
Wald (time) (2 df)	23.18			.000
J_{2GMM} (3 df)	6.473			.091
m_1	-2.075			.038

p-values are reported inside parenthesis. df refers to the degrees of freedom. m_1 is a test for serial correlation. J_{2GMM} is the Sargan test. Note: m_2 could not be calculated because there are not enough observations (for an AR(2) process we need T$\geq$6).

Table 15: AR(2) Cash-flow

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