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Persistence, Signal-Noise Pattern and Heterogeneity in Panel Data: With an Application to the Impact of Foreign Direct Investment on GDP

Erik Biørn and Xuehui Han

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P. O.Box 1095 Blindern
N-0317 OSLO Norway
Telephone: + 47 22855127
Fax: + 47 22855035
Internet: http://www.sv.uio.no/econ
e-mail: econdep@econ.uio.no

In co-operation with
The Frisch Centre for Economic Research

Gaustadalleén 21
N-0371 OSLO Norway
Telephone: +47 22 95 88 20
Fax: +47 22 95 88 25
Internet: http://www.frisch.uio.no
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Persistence, Signal-Noise Pattern and Heterogeneity in Panel Data:
With an Application to the Impact of Foreign Direct investment on GDP

Erik Biørn*

Xuehui Han**

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*Department of Economics, University of Oslo,
P.O. Box 1095 Blindern, 0317 Oslo, Norway
E-mail: erik.biorn@econ.uio.no

**Economics and Research Department, Asian Development Bank,
6 ADB Avenue Mandaluyong City 1550, Metro Manila, Philippines
E-mail: xuehuihan@adb.org

Abstract: GMM estimation of autoregressive panel data equations in error-ridden variables when the noise has memory, is considered. The impact of variation in the memory length in signal and noise spread and in the degree of individual heterogeneity are discussed with respect to finite sample bias, using Monte Carlo simulations. Also explored are also the impact of the strength of autocorrelation and the size of the IV set. GMM procedures using IVs in differences on equations in levels, in general perform better in small samples than procedures using IVs in levels on equations in differences. A case-study of the impact of Foreign Direct Investment (FDI) on GDP, *inter alia*, contrasting the manufacturing and the service sector, based on country panel data supplements the simulation results.

Keywords: Panel data, Measurement error, ARMA, GMM, Error memory, Monte Carlo, Foreign Direct Investment, Economic development, Country panel

JEL classification: C21, C23, C31, C33, O11, O14

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1 Introduction

Moment-based estimation of first-order autoregressive, AR(1), models from 'short panels' has seen a growing interest for more than 20 years, and estimator properties have been considered in several contexts. While consistency in well-specified models is easy to ensure, even with short panels, substantial finite sample biases may occur, as demonstrated through Monte Carlo (MC) simulations by, *e.g.*, Kiviet (1995), Ziliak (1997) and Bun and Kiviet (2006). Also for static panel data models with mis-measured regressors, moment-based estimation is useful.[1] On the general level, panel data may help coming to grips with three problems that may occur simultaneously: autoregression, error-ridden regressors, and finite memory of the errors.

In this paper fixed effects AR(1) models with errors in variables (EIV) and finite sample properties of Generalized Method of Moments (GMM) procedures mixing variables in levels and in differences are explored and illustrated. This is done partly by experiments with synthetic data and partly by an application using country panels. A distinctive feature of the approach is that the errors are allowed to have a memory – the 'noise' memory is superimposed on the 'signal' memory. For short panels with N units, a multitude of N-consistent GMM estimators exist. The difficulty in obtaining analytical expressions for their finite sample expectations and small-sample biases calls for MC studies.

Selected issues in GMM panel data estimation of AR(1) models with EIV have been discussed through MC simulations in a related study, Biørn and Han (2013), *inter alia*, the impact on finite sample bias of changes in the noise variances and noise memories, the potential gains obtained by supplementing IV sets based on exogenous variables with IVs based on endogenous variables, and the importance of unit-specific heterogeneity. In this study, we bring other ideas into focus, *inter alia*: (a) The impact on estimated short-run versus long-run responses of changed noise and signal pattern. (b) The impact on estimator bias of increased time-invariant heterogeneity in the equation and in the signal. (c) The impact on performance of changed panel size and time-series length. The empirical illustration is related to the impact of Foreign Direct Investment (FDI) on GDP growth, where studies from the last decade have given the measurement error problem attention. A novelty is that the service FDI is compared with the manufacturing FDI.

2 Model and estimators

We consider an AR(1) model for a balanced design with N individuals, indexed by i, observed in T periods, indexed by t, including K strictly exogenous variables, allowing for fixed, time-invariant heterogeneity, α_i and for measurement errors in all variables:

$$(1)\qquad \begin{aligned} &\mu_{it} = \alpha_i + \boldsymbol{\xi}_{it}\boldsymbol{\beta} + \mu_{i,t-1}\lambda + u_{it}, \qquad |\lambda| < 1,\\ &\boldsymbol{q}_{it} = \boldsymbol{\xi}_{it} + \boldsymbol{\eta}_{it},\\ &y_{it} = \mu_{it} + \nu_{it},\\ &\boldsymbol{\xi}_{it} \perp \boldsymbol{\eta}_{it} \perp u_{it} \perp \nu_{it}. \end{aligned}$$

Here $(\mu_{it}, \boldsymbol{\xi}_{it})$ are latent variables, $\boldsymbol{\xi}_{it}$ with finite memory N_ξ; $(y_{it}, \boldsymbol{q}_{it})$ are their observable counterparts; $(\nu_{it}, \boldsymbol{\eta}_{it})$ are errors with zero means and memories (N_ν, N_η); $(\boldsymbol{\xi}_{it}, \boldsymbol{\eta}_{it})$ are

[1] For the EIV case, see, *inter alia*, Griliches and Hausman (1986), Biørn (2000), Wansbeek and Meijer (2000, section 6.9), Wansbeek (2001), Biørn and Krishnakumar (2008, Section 10.2), and Xiao *et al.* (2007, 2010). For the AR-case, see, *inter alia*, Arellano and Bond (1991), Ahn and Schmidt (1995), Arellano and Bover (1995), and Blundell and Bond (1998).

$(1 \times K)$-vectors; u_{it} is a disturbance with memory N_u; $\boldsymbol{\beta}$ is a $(K \times 1)$ coefficient vector and λ is a scalar constant.[2] Eliminating μ_{it} and $\boldsymbol{\xi}_{it}$, letting $\omega_{it} = u_{it} + \nu_{it} - \nu_{i,t-1}\lambda$ and

$$(2) \qquad w_{it} = \omega_{it} - \boldsymbol{\eta}_{it} = u_{it} + \nu_{it} - \nu_{i,t-1}\lambda - \boldsymbol{\eta}_{it}\boldsymbol{\beta},$$

we obtain the following relationships in observable variables

$$(3) \qquad y_{it} = \alpha_i + \boldsymbol{q}_{it}\boldsymbol{\beta} + y_{i,t-1}\lambda + w_{it},$$
$$(4) \qquad \Delta y_{it} = \Delta\boldsymbol{q}_{it}\boldsymbol{\beta} + \Delta y_{i,t-1}\lambda + \Delta w_{it}.$$

Obviously, $(y_{it}, \boldsymbol{q}_{i,t+\tau})$ and $w_{i,t+\theta}$ will be correlated for some (τ, θ), uncorrelated for others. In Biørn (2015) it is shown that *potential* q-IVs[3] for, respectively, (3) and (4) are:

$$(5) \qquad \Delta\boldsymbol{q}_{i,t+\tau},\ \tau \notin [-N_\eta, N_\eta+1],\ \tau \in [-N_q, N_q+1],$$
$$(6) \qquad \boldsymbol{q}_{i,t+\tau},\ \tau \notin [-(N_\eta+1), N_\eta],\ \tau \in [-(N_q+1), N_q].$$

where $N_q = \max[N_\xi, N_\eta]$ and $N_\omega = \max[N_u, N_\nu+1]$ are the memories of $\boldsymbol{q}_{it}$ and ω_{it}. Letting $\boldsymbol{x}_{it} = (\boldsymbol{q}_{it}, y_{i,t-1}), \boldsymbol{\gamma} = (\boldsymbol{\beta}', \lambda)'$ and denoting levels and differences by L- and D-subscripts, respectively, (3)–(4), after stacking by all relevant periods, read in compact notation

$$(7) \qquad \boldsymbol{y}_{Li} = \boldsymbol{\alpha}_i + \boldsymbol{X}_{Li}\boldsymbol{\gamma} + \boldsymbol{w}_{Li},$$
$$(8) \qquad \boldsymbol{y}_{Di} = \boldsymbol{X}_{Di}\boldsymbol{\gamma} + \boldsymbol{w}_{Di}.$$

Following (5) and (6), we let $\boldsymbol{Z}_{Di}$ be the IV matrix for $\boldsymbol{X}_{Li}$ in (7), constructed by selecting the relevant elements from (the matrix in differences) $\boldsymbol{X}_{Di}$, and let $\boldsymbol{Z}_{Li}$ be the IV matrix for $\boldsymbol{X}_{Di}$ in (8), constructed by selecting the relevant elements from (the matrix in levels) $\boldsymbol{X}_{Li}$. The *'step-two' GMM* estimators, to be considered for $\boldsymbol{\gamma}$ are, respectively,

$$(9) \qquad \widetilde{\boldsymbol{\gamma}}_L = \{[\textstyle\sum_i \boldsymbol{X}'_{Li}\boldsymbol{Z}_{Di}][\sum_i \boldsymbol{Z}'_{Di}\widehat{\boldsymbol{w}}_{Li}\widehat{\boldsymbol{w}}'_{Li}\boldsymbol{Z}_{Di}]^{-1}[\sum_i \boldsymbol{Z}'_{Di}\boldsymbol{X}_{Li}]\}^{-1} \times \{[\sum_i \boldsymbol{X}'_{Li}\boldsymbol{Z}_{Di}][\sum_i \boldsymbol{Z}'_{Di}\widehat{\boldsymbol{w}}_{Li}\widehat{\boldsymbol{w}}'_{Li}\boldsymbol{Z}_{Di}]^{-1}[\sum_i \boldsymbol{Z}'_{Di}\boldsymbol{y}_{Li}]\},$$

$$(10) \qquad \widetilde{\boldsymbol{\gamma}}_D = \{[\textstyle\sum_i \boldsymbol{X}'_{Di}\boldsymbol{Z}_{Li}][\sum_i \boldsymbol{Z}'_{Li}\widehat{\boldsymbol{w}}_{Di}\widehat{\boldsymbol{w}}'_{Di}\boldsymbol{Z}_{Li}]^{-1}[\sum_i \boldsymbol{Z}'_{Li}\boldsymbol{X}_{Di}]\}^{-1} \times \{[\sum_i \boldsymbol{X}'_{Di}\boldsymbol{Z}_{Li}][\sum_i \boldsymbol{Z}'_{Li}\widehat{\boldsymbol{w}}_{Di}\widehat{\boldsymbol{w}}'_{Di}\boldsymbol{Z}_{Li}]^{-1}[\sum_i \boldsymbol{Z}'_{Li}\boldsymbol{y}_{Di}]\},$$

where $\widehat{\boldsymbol{w}}_{Li}$ and $\widehat{\boldsymbol{w}}_{Di}$ are residual vectors from the related 'step-one' estimation; see Davidson and MacKinnon (2004, Sections 9.2–9.3).

3 Design of simulations

In the *simulation framework* now to be described, $K = 2$ exogenous variables are assumed. The processes generating $(\boldsymbol{\eta}_{it}, \nu_{it}, u_{it})$ are specified as (Vector) Moving Average ((V)MA), the signal vector $\boldsymbol{\xi}_{it}$ is a time invariant vector plus a VMA process:

$$(11) \qquad \boldsymbol{\xi}_{it} = \boldsymbol{\chi}_i + \textstyle\sum_{s=0}^{N_\xi} \boldsymbol{\psi}_{i,t-s}\boldsymbol{A}_s, \quad \begin{array}{l} \boldsymbol{\psi}_{it} \sim \mathsf{IIN}_K(\boldsymbol{0}, \boldsymbol{\Sigma}_{\boldsymbol{\psi}}),\ \boldsymbol{\Sigma}_{\boldsymbol{\psi}},\ \boldsymbol{A}_0, \dots, \boldsymbol{A}_{N\eta} \text{ diagonal}, \\ \boldsymbol{\chi}_i \sim \mathsf{IIN}_K(\bar{\boldsymbol{\chi}}, \boldsymbol{\Sigma}_{\boldsymbol{\chi}}),\ \boldsymbol{\Sigma}_{\boldsymbol{\chi}} \text{ non-diagonal}, \\ \qquad i = 1, \dots, N;\ t = 1, \dots, T, \end{array}$$

where IIN denotes 'identically independently normal' and subscript K indicates the distribution's dimension. Measurement errors and disturbances are generated by

[2] In the model versions actually used in the simulations this assumption will be modified, as $\boldsymbol{\xi}_{it}$ is generated as the sum of a moving average component with memory N_ξ and a time-invariant component. The memory of $\Delta\boldsymbol{\xi}_{it}$ then becomes $N_\xi + 1$, as differencing removes any time-invariant component.

[3] Only the use of q-IVs will be considered in this study.

$$
(12) \quad \begin{aligned}
\boldsymbol{\eta}_{it} &= \textstyle\sum_{s=0}^{N_\eta} \boldsymbol{\epsilon}_{i,t-s}\boldsymbol{B}_s, \quad \boldsymbol{\epsilon}_{it} \sim \mathsf{IIN}_K(\mathbf{0}, \boldsymbol{\Sigma_\epsilon}), \quad \boldsymbol{\Sigma_\epsilon}, \quad \boldsymbol{B}_0, \dots, \boldsymbol{B}_{N\eta} \text{ diagonal},\\
\nu_{it} &= \textstyle\sum_{s=0}^{N_\nu} \delta_{i,t-s}d_s, \quad \delta_{it} \sim \mathsf{IIN}_1(0, \sigma_\delta^2),\\
u_{it} &= \textstyle\sum_{s=0}^{N_u} v_{i,t-s}c_s, \quad v_{it} \sim \mathsf{IIN}_1(0, \sigma_v^2), \qquad i=1,\dots,N;\ t=1,\dots,T.
\end{aligned}
$$

Heterogeneity in the equation, assumed fixed in the original model, is generated *as if* random, $\alpha_i \sim \mathsf{IIN}_1(0, \sigma_\alpha^2)$, and assumed uncorrelated with χ_i and $\boldsymbol{\psi}_{it}$.[4]

Table 1: Baseline parameter sets for simulations

Coefficients:	$(\beta_1, \beta_2, \lambda) = (0.6, 0.3, 0.8)$.
Auxiliary matrices:	$\boldsymbol{I}_2 = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \quad \boldsymbol{J}_2 = \begin{bmatrix} 1 & \frac{1}{2} \\ \frac{1}{2} & 1 \end{bmatrix}$
$\boldsymbol{\xi}_{it}$ *process:*	$(\bar{\chi}_1, \bar{\chi}_2) = (5, 10)$;
	$\sigma_\chi^2 = 0.1; \quad \boldsymbol{\Sigma}_\chi = \sigma_\chi^2 \boldsymbol{J}_2$;
	$\sigma_\psi^2 = 1; \quad \boldsymbol{\Sigma}_\psi = \sigma_\psi^2 \boldsymbol{I}_2$;
	$N_\xi = 4: \quad \boldsymbol{A}_s = (1 - \frac{s}{5})\boldsymbol{I}_2, \quad s = 0, 1, \dots, 4.$
	$N_\xi = 6: \quad \boldsymbol{A}_s = (1 - \frac{s}{7})\boldsymbol{I}_2, \quad s = 0, 1, \dots, 6.$
	$\Longrightarrow \text{diag}[\mathsf{V}(\boldsymbol{\xi}_{it})]: \quad \sigma_{\xi 1}^2 = \sigma_{\xi 2}^2 = \begin{cases} \sigma_\chi^2 + \sigma_\psi^2 \times 2.200, & N_\xi = 4. \\ \sigma_\chi^2 + \sigma_\psi^2 \times 2.857, & N_\xi = 6. \end{cases}$
$\boldsymbol{\eta}_{it}$ *process:*	$\sigma_\epsilon^2 = 0.1; \quad \boldsymbol{\Sigma}_\epsilon = \sigma_\epsilon^2 \boldsymbol{I}_2$;
	$N_\eta = 0: \quad \boldsymbol{B}_0 = \boldsymbol{I}_2$;
	$N_\eta = 1: \quad \boldsymbol{B}_0 = \boldsymbol{I}_2, \quad \boldsymbol{B}_1 = \frac{1}{2}\boldsymbol{I}_2$;
	$N_\eta = 2: \quad \boldsymbol{B}_0 = \boldsymbol{I}_2, \quad \boldsymbol{B}_1 = \frac{2}{3}\boldsymbol{I}_2, \quad \boldsymbol{B}_2 = \frac{1}{3}\boldsymbol{I}_2$;
	$\Longrightarrow \text{diag}[\mathsf{V}(\boldsymbol{\eta}_{it})]: \quad \sigma_{\eta 1}^2 = \sigma_{\eta 2}^2 = \begin{cases} \sigma_\epsilon^2 \times 1.000, & N_\eta = 0. \\ \sigma_\epsilon^2 \times 1.250, & N_\eta = 1. \\ \sigma_\epsilon^2 \times 1.556, & N_\eta = 2. \end{cases}$
α_i *process:*	$\sigma_\alpha^2 = 0.1$.
u_{it} *process:*	$\sigma_v^2 = \sigma_u^2 = 0.1$;
	$N_u = 0, \ c_0 = 1$.
ν_{it} *process:*	$\sigma_\delta^2 = 0.1$;
	$N_\nu = 0: \quad d_0 = 1; \quad \sigma_\nu^2 = \sigma_\delta^2 \times 1.000.$
	$N_\nu = 1: \quad d_0 = 1, \quad d_1 = \frac{1}{2}; \quad \sigma_\nu^2 = \sigma_\delta^2 \times 1.250.$
	$N_\nu = 2: \quad d_0 = 1, \quad d_1 = \frac{2}{3}, \quad d_2 = \frac{1}{3}; \quad \sigma_\nu^2 = \sigma_\delta^2 \times 1.556.$

Combining (1) and (2) with (11) and (12) it follows that

$$
(13) \qquad \boldsymbol{q}_{it} = \boldsymbol{\chi}_i + \textstyle\sum_{s=0}^{N_\xi} \boldsymbol{\psi}_{i,t-s}\boldsymbol{A}_s + \sum_{s=0}^{N_\eta} \boldsymbol{\epsilon}_{i,t-s}\boldsymbol{B}_s,
$$

$$
(14) \qquad (1 - \lambda\mathsf{L})(y_{it} - \nu_{it})\mu_{it} = \alpha_i + (\boldsymbol{\chi}_i + \textstyle\sum_{s=0}^{N_\xi} \boldsymbol{\psi}_{i,t-s}\boldsymbol{A}_s)\boldsymbol{\beta} + \sum_{s=0}^{N_u} v_{i,t-s}c_s,
$$

$$
(15) \qquad w_{it} = \textstyle\sum_{s=0}^{N_u} v_{i,t-s}c_s + \sum_{s=0}^{N_\nu} (1 - \lambda\mathsf{L})\delta_{i,t-s}d_s - (\sum_{s=0}^{N_\eta} \boldsymbol{\epsilon}_{i,t-s}\boldsymbol{B}_s)\boldsymbol{\beta}.
$$

Since $\boldsymbol{\chi}_i$ and α_i enter the model asymmetrically and the variables in levels and in differences fill opposite roles in $\widetilde{\boldsymbol{\gamma}}_L$ and $\widetilde{\boldsymbol{\gamma}}_D$, changes in the degree of heterogeneity, measured by σ_χ^2 and σ_α^2, impact the estimators' distribution in quite different ways. For example, changes in $\bar{\boldsymbol{\chi}}$ or in σ_χ^2 affect both $\boldsymbol{q}_{it}$ and y_{it}, but neither of $\Delta\boldsymbol{q}_{it}$ or Δy_{it}, since differencing eliminates any time-invariant variable, while an increase in σ_α^2 affects only the distribution of the level y_{it}.

The design parameters in the baseline simulations are $N = 100$, $T = 10$ and $K = 2$, and $R = 500$ replications are performed. The latent exogenous variable vector has memory

[4]Since these assumptions for generating α_is are not exploited by the GMM procedures, the fixed effects assumption may be viewed as equivalent with conditioning on the α_i values drawn.

$N_\xi = 4$ (exceptionally 6), while the memory of the errors is alternatively set to $N_\eta = 0, 1, 2$ and $N_\nu = 0, 1, 2$. The disturbance memory is set to $N_u = 0$ and its variance to $\sigma_u^2 = \sigma_v^2 = 0.1$. Table 1 displays the parameter set.[5]

4 Simulation results

We next discuss MC simulation results[6] with focus on, *inter alia*, comparing the performance of GMM with respect to the impact of changes in the noise and signal pattern (spread and memory length) on the estimated short-run versus long-run coefficient estimates, the impact on bias of increased time-invariant heterogeneity, and of changed panel design, including panel size and 'shortness'.

First, we consider a benchmark case with an *error-free AR(1) model* ($\sigma_\delta^2 = \sigma_\epsilon^2 = 0 \Longrightarrow \sigma_\nu^2 = \sigma_{\eta k}^2 = 0,\ k = 1, 2$). *Table 2* gives the means of the GMM estimators for $N_\xi = 4$ and $(\sigma_\chi^2, \sigma_\psi^2) = (0.1, 1.0)$ ($\Longrightarrow \sigma_{\xi 1}^2 = \sigma_{\xi 2}^2 = 2.3$) and $(\sigma_\chi^2, \sigma_\psi^2) = (0.1, 0.5)$ ($\Longrightarrow \sigma_{\xi 1}^2 = \sigma_{\xi 2}^2 = 1.2$); see Table 1. For the equation in levels a small bias occurs, negative for (β_1, β_2) and positive for λ, smaller when $\sigma_\psi^2 = 1$ (denoted as the large signal spread case) than when $\sigma_\psi^2 = 0.5$ (denoted as the small signal spread case). The equation in differences gives negatively biased coefficient estimates, and again the bias is smaller when the signal spread is large than when it is small.

Table 2: Benchmark model: No measurement error. Mean of estimates

$(\beta_1, \beta_2, \lambda) = (0.6,\ 0.3,\ 0.8)$. $(\bar{\chi}_1, \bar{\chi}_2) = (5, 10)$. $(N, T) = (100, 10)$

$N_\xi = 4$. $\sigma_\delta^2 = \sigma_\epsilon^2 = 0$, $\sigma_u^2 = \sigma_\chi^2 = \sigma_\alpha^2 = 0.1$

Eq.	*IV*	σ_ψ^2	β_1	β_2	λ
Lev	Diff	1.0	0.5850	0.2688	0.8130
Diff	Lev	1.0	0.5727	0.2879	0.7046
Lev	Diff	0.5	0.5680	0.2369	0.8265
Diff	Lev	0.5	0.5482	0.2782	0.6317

Next, we let the dynamics and the measurement errors interact. *Table 3* illustrates the impact on the mean of the estimates of changes in the measurement error pattern, starting from the *no measurement error case* ($\sigma_\epsilon^2 = \sigma_\delta^2 = 0$). For the equation in levels with large signal spread ($\sigma_\psi^2 = 1$) there is a small negative bias in (β_1, β_2) and a small positive bias in λ. The bias increases, but is still small, when the equation is taken to differences, and then the bias of λ changes sign.

Introducing measurement error in the exogenous variables only, $(\sigma_\epsilon^2, \sigma_\delta^2) = (0.1, 0.0)$, leads, for the level version of the equation, to an increased bias, while doing the same for the *endogenous* variable $(\sigma_\epsilon^2, \sigma_\delta^2) = (0.0, 0.1)$, reduces the bias. Again, there is a notable contrast between level and the difference versions. While for the former, mismeasured exogenous variables only gives an increased bias, a similar experiment for the endogenous variable now also magnifies the bias, and the impact of the latter may exceed the impact of the former. The configuration $\sigma_\psi^2 = 1$, $(N_\xi, N_\eta, N_\nu) = (4, 0, 0)$ gives for example a simulated mean of λ of 0.70 in the absence of measurement error, and 0.67 and 0.51 for $(\sigma_\epsilon^2, \sigma_\delta^2) = (0.1, 0.0)$ and $(\sigma_\epsilon^2, \sigma_\delta^2) = (0.0, 0.1)$, respectively. Interestingly, for the level version

[5] The μ_{it} process is initialized by using as start values the 'long-run expectation' $\mu_{i0} = \mathsf{E}[\mu_{it}/(1-\lambda\mathsf{L})] = \bar{\boldsymbol{\chi}}\boldsymbol{\beta}/(1-\lambda)$.

[6] The simulations are performed by a computer program in the Gauss software code; see Gauss (2006), constructed by the authors. The standard errors are calculated from the GMM formulae, as described in Biørn and Krishnakumar (2008, Section 10.2.5).

it is the combination of exogenous variable error-free and endogenous variable error-ridden, $(\sigma_\epsilon^2, \sigma_\delta^2) = (0.0, 0.1)$, that gives the smallest bias (lowest estimate of λ, highest estimate of β_1, β_2) – also relative to the case with no measurement (Table 3, rows 1–9), while for the difference version the smallest bias occurs in the no measurement case.

For the large signal spread case we find that the level version outperforms the difference version, giving smallest bias for all parameters. The same is the case under small signal spread, except that for β_2 the difference version outperforms the level version when there is no error or error in the exogenous variable only (Table 3, rows 4–5 vs. 13–14). Unsurprisingly, the estimates from the large signal spread experiment ($\sigma_\psi^2 = 1$) have smaller bias than those from the small signal spread ($\sigma_\psi^2 = 0.5$). Our tentative recommendations therefore are: For estimation, give in general preference to the equation in levels. Only exceptionally (exemplified by β_2 with error in the exogenous variable only or no measurement error at all) the equation in differences is preferable.[7]

Table 4 (which is an extract of Appendix Table A.1) supplements Table 3 by illustrating the impact of *inflating measurement error spread* $(\sigma_\epsilon^2, \sigma_\delta^2)$ stepwise from (0.1,0.1) to (0.5,0.5). The primary findings are: *For the equation in levels*: [a] An increased σ_δ^2 (increasing spread of the error in the endogenous variable ν) induces an increase in the mean of the estimated β_1, β_2 (reduced negative bias), and the bias may disappear and become positive, while it induces a reduction of λ (reduced positive bias). [b] An increased σ_ϵ^2 (increasing spread of the error in the exogenous variables $\boldsymbol{\eta}$) induces a reduction of the mean of the estimated β_1, β_2 (increased negative bias) and an increase of λ (increased positive bias). Note, for example, the very small (positive or negative) bias for $(\sigma_\epsilon^2, \sigma_\delta^2) = (0.1, 0.5)$. *For the equation in differences*: [a] An increased σ_δ^2 (increasing spread of the error in the endogenous variable ν) induces a reduction of the mean of the estimated β_1, β_2 (increased negative bias) as well as a reduction of λ (increased negative bias). [b] An increased σ_ϵ^2 (increasing spread of the error in the exogenous variables $\boldsymbol{\eta}$) gives reduced mean of the estimated β_1, β_2 (increased negative bias), while λ is also reduced (increased negative bias). Therefore increased spread of ν only contributes to reducing bias for the equation in differences. [c] For $(\sigma_\epsilon^2, \sigma_\delta^2) = (0.5, 0.5)$, the bias is severe, in particular for λ.The impact of *increased signal memory*, from 4 to 6 (which extends the IV set, see (5)–(6)), is illustrated by comparing columns 4–6 with 7–9 in Table A.1.

The impact of changed degree of *time-invariant heterogeneity* – the ubiquitous type of heterogeneity considered in applied panel data analysis – is illustrated in *Table 5* (which is an extract of Appendix Table A.2). It exemplifies the impact on the mean of the simulated estimates when inflating stepwise, from 0.1 to 0.5, the variance of the *heterogeneity in the equation*, σ_α^2, and of the *heterogeneity in the exogenous variable*, σ_χ^2. The main findings are: *For the equation in levels*: [a] An increased equation heterogeneity σ_α^2 has an ambiguous impact on the mean of the estimated β_1, β_2, but its bias is still negative. It also has an ambiguous effect on λ, but its bias is still positive. [b] An increased signal heterogeneity σ_χ^2 leads to reduced (mean of the estimated) β_1, β_2 (negative bias increased), while λ is increased (positive bias increased) in most cases. [c] A reduced signal spread, through reduced σ_ψ^2, leads to reduced (mean of the estimated) β_1, β_2 (negative bias increased)

[7] The general validity of these conclusions should not be overstated, however, *inter alia* because they rest on the assumed distributional pattern of for the heterogeneity variables $\boldsymbol{\chi}_i$ and α_i; cf. Table 1.

and increased λ (positive bias increased). [d] The impact of increased error memory is ambiguous. *For the equation in differences*: [a] An increased equation heterogeneity, σ_α^2, leads to increased (mean of the estimated) β_1, β_2 (negative bias reduced) and increased λ (positive bias reduced). [b] An increased signal heterogeneity σ_χ^2 leads to increased mean of the estimated β_1, β_2 (negative bias reduced) and increased λ (negative bias reduced). [c] A reduced spread of the signal ξ through a reduced σ_ψ^2, leads to reduced (mean of the estimated) β_1, β_2 (negative bias increased) and reduced (mean of the estimated) λ (positive bias increased). [d] The impact on the (mean of the estimated) $\beta_1, \beta_2, \lambda$ of increased error memory is an increased bias.

Persistence and contrasts between short-run and long-run responses are often given attention in applied panel data studies. *Tables 6 and 7* illustrate the impact on the means of the estimates of $(\beta_1, \beta_2, \lambda)$ and their implied long-run coefficients $[\beta_1/(1-\lambda), \beta_2/(1-\lambda)]$ when the AR parameter λ varies. The (β_1, β_2) estimates (Table 6) are negatively biased in all examples (for both the static case, $\lambda = 0$, and the weak and strong autoregression cases, $\lambda = 0.2$ and $= 0.8$), with one exception: β_2 is approximately unbiased (mean estimate 0.3004) for $\sigma_\psi^2 = 1$ and $(N_\xi, N_\eta, N_\nu) = (4, 0, 0)$. For λ, the sign of the bias differs between the two versions of the equation. For the *equation in levels* there is a positive bias, which is increased when an error memory is introduced or the signal variance is reduced. For example, with $(\beta_1, \beta_2, \lambda) = (0.3, 0.6, 0.0)$, the mean $\lambda = 0.0178$ for $(N_\xi, N_\eta, N_\nu) = (4, 0, 0)$ under large signal spread, increased to 0.0381 under small signal spread; or increased to 0.0661 under large signal spread for $(N_\xi, N_\eta, N_\nu) = (4, 1, 0)$. For the *equation in differences* there is a negative bias, whose magnitude mirrors the equation in levels. For the long-run coefficients (Table 7) the results depart in several respects from the results for the short-run coefficients. First, the conclusion that biases become smaller under large ($\sigma_\psi^2 = 1$) than under small signal spread ($\sigma_\psi^2 = 0.5$) does not hold invariably for the long-run coefficients. An example is provided for the equation in levels for $(\beta_1, \beta_2, \lambda) = (0.3, 0.6, 0.0)$ and $(N_\xi, N_\eta, N_\nu) = (4, 2, 0)$. Secondly, the systematic negative biases for (β_1, β_2) in all examples do not hold. For example, $(\beta_1, \beta_2, \lambda) = (0.3, 0.6, 0.0)$ and $\sigma_\psi^2 = 1$ give, for the equation in levels, $\beta_1/(1-\lambda) = 0.3010$ (*i.e.*, very small positive bias) when $(N_\xi, N_\eta, N_\nu) = (4,1,0)$ and $\beta_1/(1-\lambda) = 0.2990$ (*i.e.*, very small negative bias) when $(N_\xi, N_\eta, N_\nu) = (4, 2, 0)$. Finally, for the equation in differences we still find negative biases in the long-run coeffcients. The biases increase when an error memory is introduced or the signal variance is reduced. A comparison of Tables 6 and 7 indicates that when estimation of long-run effects of exogenous variables is our main concern, the advantages of keeping equations in levels are strengthened. Therefore when analyzing genuine data in cases where long-run impacts are parameters of crucial interest, the better choice seems to be to keep equations in levels and use IVs in differences.

Table 3: Introducing measurement errors. Mean of estimates

$(N,T) = (100,10)$. $(\beta_1,\beta_2,\lambda)=(0.6,\ 0.3,\ 0.8)$. $(\bar{\chi}_1,\bar{\chi}_2)=(5,10)$. $\sigma_u^2=\sigma_\chi^2=\sigma_\alpha^2=0.1$

	(exog.) σ_ϵ^2	(endog.) σ_δ^2	$(N_\xi,N_\eta,N_\nu)=$ (4,0,0)	(4,1,0)	(4,2,0)	(4,2,2)	$(N_\xi,N_\eta,N_\nu)=$ (4,0,0)	(4,1,0)	(4,2,0)	(4,2,2)
			Eq. in levels; σ_ψ^2 *= 1.0*				*Eq. in levels;* σ_ψ^2 *= 0.5*			
β_1	0.0	0.0	0.5850	0.5857	0.5837	0.5814	0.5680	0.5702	0.5718	0.5718
	0.1	0.0	0.5612	0.5501	0.5478	0.5468	0.5285	0.5193	0.5046	0.5078
	0.0	0.1	0.5893	0.5926	0.5876	0.5908	0.5767	0.5793	0.5705	0.5862
β_2	0.0	0.0	0.2688	0.2658	0.2633	0.2680	0.2369	0.2343	0.2295	0.2371
	0.1	0.0	0.2587	0.2572	0.2529	0.2510	0.2261	0.2243	0.2221	0.2198
	0.0	0.1	0.2752	0.2738	0.2774	0.2794	0.2582	0.2508	0.2555	0.2707
λ	0.0	0.0	0.8130	0.8141	0.8152	0.8141	0.8265	0.8271	0.8288	0.8260
	0.1	0.0	0.8203	0.8228	0.8245	0.8256	0.8365	0.8387	0.8421	0.8423
	0.0	0.1	0.8104	0.8101	0.8096	0.8082	0.8178	0.8202	0.8197	0.8126
			Eq. in differences; σ_ψ^2 *= 1.0*				*Eq. in differences;* σ_ψ^2 *= 0.5*			
β_1	0.0	0.0	0.5727	0.5714	0.5654	0.5659	0.5482	0.5433	0.5501	0.5430
	0.1	0.0	0.5391	0.5243	0.5117	0.5120	0.4867	0.4701	0.4461	0.4497
	0.0	0.1	0.5165	0.5097	0.5073	0.4810	0.4703	0.4592	0.4510	0.4257
β_2	0.0	0.0	0.2879	0.2851	0.2839	0.2845	0.2782	0.2735	0.2706	0.2704
	0.1	0.0	0.2651	0.2655	0.2538	0.2565	0.2453	0.2329	0.2260	0.2287
	0.0	0.1	0.2593	0.2560	0.2538	0.2415	0.2393	0.2328	0.2279	0.2179
λ	0.0	0.0	0.7046	0.6958	0.6923	0.6897	0.6317	0.6165	0.6094	0.6067
	0.1	0.0	0.6664	0.6459	0.6228	0.6196	0.5734	0.5393	0.5104	0.5071
	0.0	0.1	0.5146	0.4957	0.4827	0.3919	0.3574	0.3386	0.3175	0.2059

Table 4: Changing noise variances and noise memory. Impact on estimate mean

$(N,T) = (100,10)$. $(\beta_1,\beta_2,\lambda)=(0.6,\ 0.3,\ 0.8)$. $(\bar{\chi}_1,\bar{\chi}_2)=(5,10)$. $\sigma_\psi^2=1,\sigma_u^2=\sigma_\chi^2=\sigma_\alpha^2=0.1$

	(exog.) σ_ϵ^2	(endog.) σ_δ^2	$(N_\xi,N_\eta,N_\nu)=$ (4,0,0)	(4,1,0)	(4,2,0)	(4,2,2)	$(N_\xi,N_\eta,N_\nu)=$ (4,0,0)	(4,1,0)	(4,2,0)	(4,2,2)
			Equation in levels				*Equation in differences*			
β_1	0.1	0.1	0.5655	0.5594	0.5536	0.5591	0.4839	0.4687	0.4610	0.4415
	0.5	0.1	0.4896	0.4641	0.4426	0.4463	0.3867	0.3529	0.3392	0.3107
	0.1	0.5	0.5865	0.5749	0.5717	0.5942	0.3767	0.3655	0.3487	0.3296
	0.5	0.5	0.5087	0.4921	0.4631	0.4794	0.3091	0.2870	0.2641	0.2384
β_2	0.1	0.1	0.2674	0.2682	0.2653	0.2687	0.2401	0.2350	0.2300	0.2219
	0.5	0.1	0.2430	0.2298	0.2242	0.2260	0.1949	0.1777	0.1690	0.1611
	0.1	0.5	0.3009	0.3070	0.3027	0.3189	0.1879	0.1917	0.1729	0.1615
	0.5	0.5	0.2766	0.2644	0.2623	0.2736	0.1548	0.1423	0.1256	0.1233
λ	0.1	0.1	0.8168	0.8175	0.8195	0.8174	0.4840	0.4525	0.4333	0.3547
	0.5	0.1	0.8376	0.8462	0.8513	0.8504	0.3811	0.3293	0.2904	0.2056
	0.1	0.5	0.8019	0.8016	0.8039	0.7945	0.1117	0.0777	0.0442	-0.0538
	0.5	0.5	0.8227	0.8300	0.8350	0.8285	0.0489	0.0153	-0.0158	-0.1229

Table 5: Changing equation and signal heterogeneity. Impact on estimate mean

$(N,T) = (100,10)$. $(\beta_1,\beta_2,\lambda)=(0.6,\ 0.3,\ 0.8)$. $(\bar{\chi}_1,\bar{\chi}_2)=(5,10)$. $\sigma_u^2=\sigma_\delta^2=\sigma_\epsilon^2=0.1.\sigma_\psi^2 = 1.0$

	(eq.) σ_α^2	(exog.var.) σ_χ^2	$(N_\xi,N_\eta,N_\nu)=$ (4,0,0)	(4,1,0)	(4,2,0)	(4,2,2)	$(N_\xi,N_\eta,N_\nu)=$ (4,0,0)	(4,1,0)	(4,2,0)	(4,2,2)
			Equation in levels				*Equation in differences*			
β_1	0.5	0.1	0.5676	0.5610	0.5586	0.5536	0.5009	0.4874	0.4805	0.4543
	0.1	0.5	0.5163	0.5164	0.5079	0.5155	0.4916	0.4751	0.4720	0.4481
	0.5	0.5	0.5185	0.5157	0.5085	0.5182	0.4990	0.4928	0.4804	0.4678
β_2	0.5	0.1	0.2691	0.2653	0.2604	0.2736	0.2495	0.2435	0.2340	0.2319
	0.1	0.5	0.1719	0.1678	0.1634	0.1635	0.2490	0.2404	0.2353	0.2163
	0.5	0.5	0.1701	0.1718	0.1690	0.1692	0.2502	0.2501	0.2433	0.2383
λ	0.5	0.1	0.8155	0.8182	0.8203	0.8163	0.5320	0.5139	0.5059	0.4308
	0.1	0.5	0.8572	0.8592	0.8617	0.8601	0.5048	0.4763	0.4589	0.3777
	0.5	0.5	0.8579	0.8578	0.8602	0.8586	0.5368	0.5353	0.5190	0.4594

So far sample size $(N,T)=(100,10)$ has been assumed in the simulations. As these parameters may crucially influence the size and other properties of the IV sets (see Section 2), and very short panels are quite common, experiments with alternative values are interesting both to assess sensitivity and to guide the choice of approach when using genuine data, which will be exemplified in Section 5. *Table 8* (which is an extract from Appendix Table A.3) illustrates the impact on the simulated mean when N is reduced from 100 to 50 and T is reduced from 10 to 6. Overall, the sensitivity of the means is dramatic within the intervals considered. When the equation is in levels, the bias tends to be smaller for $N=100$ than for $N=50$, a result that does not invariably hold for the equation in differences; examples are the memory configurations $(N_\xi, N_\eta, N_\nu)=(4,1,0)$ and $(4,2,0)$. Neither does the bias tend to vary monotonically with T for a fixed N. Corresponding values of the kurtosis and the skewness of the estimates, for the equation in levels only, are shown in *Table 9* (which is an extract from Appendix Table A.4). Overall, it is the no error memory case (column 1) that comes out with shape parameters in closest agreement with the values under normality (kurtosis=3, skewness=0). This holds for both versions of the equation and both for large and small signal spread. However – maybe contrary to intuition – when assuming large signal spread, the score, by these criteria, is better than when assuming small signal spread; the memory configuration $(N_\xi, N_\eta, N_\nu)=(4,2,0)$ provides a clear example.

The orthogonality conditions underlying the GMM estimation have been tested for, respectively, (7) and (8), by

$$\mathcal{J}_L = [\textstyle\sum_i \widehat{\boldsymbol{w}}'_{Li}\boldsymbol{Z}_{Di}][\sum_i \boldsymbol{Z}'_{Di}\widehat{\boldsymbol{w}}_{Li}\widehat{\boldsymbol{w}}'_{Li}\boldsymbol{Z}_{Di}]^{-1}[\sum_i \boldsymbol{Z}'_{Di}\widehat{\boldsymbol{w}}_{Li}],$$
$$\mathcal{J}_D = [\textstyle\sum_i \boldsymbol{w}'_{Di}\boldsymbol{Z}_{Li}][\sum_i \widehat{\boldsymbol{Z}}'_{Li}\widehat{\boldsymbol{w}}_{Di}\widehat{\boldsymbol{w}}'_{Di}\boldsymbol{Z}_{Li}]^{-1}[\sum_i \boldsymbol{Z}'_{Li}\widehat{\boldsymbol{w}}_{Di}],$$

see Hansen (1982), Newey (1985) and Arellano and Bond (1991), considering all experiments with simulated means reported in Tables 3 through 7. Under the null $\mathcal{J}_L$ and $\mathcal{J}_D$ are asymptotically distributed as χ^2 with a number of degrees of freedom equal to the number of overidentifying restrictions (equal to the number of orthogonality conditions minus the number of unrestricted coefficients under the null). Also $\mathcal{F}$-tests for 'IV-strength', based on an extension of the Bun and Windmeijer (2010) suggestion of using a concentration parameter to measure IV strength for a model with one endogenous regressor, are conducted; see Biørn and Han (2013) for a description of this extension. All tests indicated non-rejection of the orthogonality conditions and 'acceptable strength' of the IV set for sample size $(N,T)=(100,10)$, and are excluded for space reasons. Table 10 reports, as the only example, the p-values for such tests related to the mean estimates in Table 8. We see that the $\mathcal{J}$-tests indicate non-rejection in all alternatives and acceptable IV-strength in all alternatives except the level version with two-period error memory and time series length $T=6$ (p-values around 0.2).

Table 6: Changing autoregression and error memory. Impact on mean $(\beta_1, \beta_2, \lambda)$ estimates $(N,T) = (100, 10)$. $(\bar{\chi}_1, \bar{\chi}_2) = (5, 10)$, $\sigma_u^2 = \sigma_\delta^2 = \sigma_\epsilon^2 = \sigma_\chi^2 = \sigma_\alpha^2 = 0.1$

	Input values			$(N_\xi, N_\eta, N_\nu) =$					
	β_1	β_2	λ	(4,0,0)	(4,1,0)	(4,2,0)	(4,0,0)	(4,1,0)	(4,2,0)
				Eq. in levels; $\sigma_\psi^2 = 1.0$			*Eq. in levels; $\sigma_\psi^2 = 0.5$*		
β_1	**0.3**	0.6	0.0	0.2952	0.2812	0.2779	0.2892	0.2580	0.2644
	0.6	0.3	0.0	0.5791	0.5647	0.5571	0.5652	0.5371	0.5318
	0.3	0.6	0.2	0.2916	0.2793	0.2761	0.2844	0.2720	0.2599
	0.6	0.3	0.2	0.5785	0.5662	0.5529	0.5604	0.5389	0.5273
	0.3	0.6	0.8	0.2836	0.2758	0.2720	0.2600	0.2572	0.2559
	0.6	0.3	0.8	0.5640	0.5609	0.5534	0.5407	0.5310	0.5110
β_2	0.3	**0.6**	0.0	0.5885	0.5598	0.5588	0.5761	0.5366	0.5283
	0.6	**0.3**	0.0	0.3004	0.2757	0.2812	0.2969	0.2658	0.2604
	0.3	**0.6**	0.2	0.5832	0.5615	0.5571	0.5697	0.5306	0.5182
	0.6	**0.3**	0.2	0.2967	0.2787	0.2755	0.2905	0.2611	0.2547
	0.3	**0.6**	0.8	0.5587	0.5520	0.5438	0.5221	0.5132	0.4951
	0.6	**0.3**	0.8	0.2697	0.2648	0.2636	0.2427	0.2400	0.2350
λ	0.3	0.6	**0.0**	0.0178	0.0661	0.0710	0.0381	0.1120	0.1189
	0.6	0.3	**0.0**	0.0176	0.0690	0.0663	0.0322	0.1098	0.1241
	0.3	0.6	**0.2**	0.2218	0.2528	0.2593	0.2404	0.2887	0.3086
	0.6	0.3	**0.2**	0.2186	0.2510	0.2647	0.2384	0.2923	0.3092
	0.3	0.6	**0.8**	0.8134	0.8162	0.8190	0.8259	0.8289	0.8339
	0.6	0.3	**0.8**	0.8165	0.8185	0.8199	0.8293	0.8315	0.8365
				Eq. in diff.; $\sigma_\psi^2 = 1.0$			*Eq. in diff.; $\sigma_\psi^2 = 0.5$*		
β_1	**0.3**	0.6	0.0	0.2819	0.2695	0.2624	0.2687	0.2385	0.2376
	0.6	0.3	0.0	0.5673	0.5319	0.5237	0.5346	0.4831	0.4756
	0.3	0.6	0.2	0.2813	0.2604	0.2554	0.2611	0.2342	0.2238
	0.6	0.3	0.2	0.5594	0.5218	0.5089	0.5220	0.4680	0.4446
	0.3	0.6	0.8	0.2400	0.2342	0.2222	0.2062	0.2037	0.1910
	0.6	0.3	0.8	0.4843	0.4732	0.4560	0.4167	0.4061	0.3774
β_2	0.3	**0.6**	0.0	0.5662	0.5296	0.5213	0.5290	0.4854	0.4719
	0.6	**0.3**	0.0	0.2833	0.2675	0.2620	0.2659	0.2392	0.2393
	0.3	**0.6**	0.2	0.5564	0.5209	0.5119	0.5260	0.4585	0.4461
	0.6	**0.3**	0.2	0.2796	0.2612	0.2534	0.2567	0.2312	0.2125
	0.3	**0.6**	0.8	0.4827	0.4676	0.4506	0.4170	0.4002	0.3839
	0.6	**0.3**	0.8	0.2421	0.2321	0.2323	0.2106	0.1969	0.1868
λ	0.3	0.6	**0.0**	-0.0338	-0.1272	-0.1322	-0.0621	-0.2086	-0.2245
	0.6	0.3	**0.0**	-0.0297	-0.1304	-0.1339	-0.0621	-0.2143	-0.2023
	0.3	0.6	**0.2**	0.1439	0.0351	0.0073	0.0972	-0.0772	-0.1088
	0.6	0.3	**0.2**	0.1486	0.0328	0.0120	0.0997	-0.0745	-0.1027
	0.3	0.6	**0.8**	0.4782	0.4489	0.4047	0.3162	0.2665	0.2503
	0.6	0.3	**0.8**	0.4887	0.4460	0.4274	0.3113	0.2736	0.2375

Table 7: Changing autoregression and error memory. Impact on mean of long-run effects $(N,T) = (100, 10)$. $(\bar{\chi}_1, \bar{\chi}_2) = (5, 10)$, $\sigma_u^2 = \sigma_\delta^2 = \sigma_\epsilon^2 = \sigma_\chi^2 = \sigma_\alpha^2 = 0.1$

	Input values					$(N_\xi, N_\eta, N_\nu) =$					
	β_1	β_2	λ	$\frac{\beta_1}{1-\lambda}$	$\frac{\beta_2}{1-\lambda}$	(4,0,0)	(4,1,0)	(4,2,0)	(4,0,0)	(4,1,0)	(4,2,0)
						Eq. in levels; $\sigma_\psi^2 = 1.0$			*Eq. in levels; $\sigma_\psi^2 = 0.5$*		
$\frac{\beta_1}{1-\lambda}$	0.3	0.6	0.0	**0.3**	0.6	0.3006	0.3010	0.2990	0.3006	0.2905	0.3007
	0.6	0.3	0.0	**0.6**	0.3	0.5897	0.6082	0.5992	0.5848	0.6065	0.6115
	0.3	0.6	0.2	**0.375**	0.750	0.3748	0.3736	0.3729	0.3747	0.3827	0.3771
	0.6	0.3	0.2	**0.750**	0.375	0.7409	0.7585	0.7573	0.7368	0.7662	0.7720
	0.3	0.6	0.8	**1.5**	3.0	1.5199	1.5017	1.5029	1.4933	1.5081	1.5427
	0.6	0.3	0.8	**3.0**	1.5	3.0870	3.1140	3.1240	3.2066	3.2028	3.2312
$\frac{\beta_2}{1-\lambda}$	0.3	0.6	0.0	0.3	**0.6**	0.5992	0.5996	0.6017	0.5989	0.6043	0.5996
	0.6	0.3	0.0	0.6	**0.3**	0.3056	0.2954	0.3001	0.3064	0.2971	0.2952
	0.3	0.6	0.2	0.375	**0.750**	0.7495	0.7517	0.7523	0.7499	0.7460	0.7490
	0.6	0.3	0.2	0.750	**0.375**	0.3795	0.3710	0.3723	0.3809	0.3666	0.3644
	0.3	0.6	0.8	1.5	**3.0**	2.9936	3.0039	3.0053	2.9994	2.9982	2.9813
	0.6	0.3	0.8	3.0	**1.5**	1.4631	1.4480	1.4403	1.4024	1.3989	1.3876
						Eq. in diff.; $\sigma_\psi^2 = 1.0$			*Eq. in diff.; $\sigma_\psi^2 = 0.5$*		
$\frac{\beta_1}{1-\lambda}$	0.3	0.6	0.0	**0.3**	0.6	0.2729	0.2404	0.2342	0.2535	0.1993	0.1970
	0.6	0.3	0.0	**0.6**	0.3	0.5515	0.4732	0.4665	0.5042	0.4013	0.4007
	0.3	0.6	0.2	**0.375**	0.750	0.3291	0.2724	0.2612	0.2903	0.2200	0.2067
	0.6	0.3	0.2	**0.750**	0.375	0.6583	0.5448	0.5254	0.5821	0.4407	0.4115
	0.3	0.6	0.8	**1.5**	3.0	0.4728	0.4467	0.4023	0.3087	0.2898	0.2762
	0.6	0.3	0.8	**3.0**	1.5	0.9699	0.8909	0.8714	0.6200	0.5817	0.5321
$\frac{\beta_2}{1-\lambda}$	0.3	0.6	0.0	0.3	**0.6**	0.5482	0.4727	0.4648	0.4992	0.4053	0.3910
	0.6	0.3	0.0	0.6	**0.3**	0.2754	0.2381	0.2332	0.2509	0.1987	0.2020
	0.3	0.6	0.2	0.375	**0.750**	0.6513	0.5445	0.5237	0.5845	0.4315	0.4112
	0.6	0.3	0.2	0.750	**0.375**	0.3290	0.2725	0.2619	0.2864	0.2175	0.1966
	0.3	0.6	0.8	1.5	**3.0**	0.9493	0.8949	0.8135	0.6272	0.5710	0.5555
	0.6	0.3	0.8	3.0	**1.5**	0.4852	0.4364	0.4396	0.3128	0.2818	0.2621

Table 8: Changing panel design. Impact on estimator mean
$(\beta_1, \beta_2, \lambda) = (0.6,\ 0.3,\ 0.8)$. $(\bar{\chi}_1, \bar{\chi}_2) = (5, 10)$. $\sigma^2_\psi = 1$. $\sigma^2_u = \sigma^2_\delta = \sigma^2_\epsilon = \sigma^2_\chi = \sigma^2_\alpha = 0.1$

			$(N_\xi, N_\eta, N_\nu) =$				$(N_\xi, N_\eta, N_\nu) =$			
	N	T	(4,0,0)	(4,1,0)	(4,2,0)	(4,2,1)	(4,0,0)	(4,1,0)	(4,2,0)	(4,2,1)
			Equation in levels				*Equation in differences*			
β_1	50	6	0.5648	0.5867	0.5687	0.5623	0.4758	0.4601	0.4697	0.4323
	50	10	0.5620	0.5555	0.5500	0.5528	0.4670	0.4543	0.4445	0.4427
	100	6	0.5692	0.5596	0.5594	0.5667	0.4856	0.4690	0.3902	0.5105
	100	10	0.5642	0.5577	0.5550	0.5575	0.4818	0.4686	0.4575	0.4426
β_2	50	6	0.2776	0.2738	0.2787	0.2841	0.2405	0.2395	0.2133	0.1905
	50	10	0.2687	0.2647	0.2585	0.2657	0.2381	0.2275	0.2235	0.2219
	100	6	0.2792	0.2648	0.2879	0.2828	0.2423	0.2415	0.0654	0.1900
	100	10	0.2685	0.2680	0.2620	0.2645	0.2429	0.2382	0.2339	0.2218
λ	50	6	0.8141	0.8109	0.8124	0.8114	0.4619	0.4268	0.3586	0.3569
	50	10	0.8168	0.8193	0.8223	0.8195	0.4339	0.4056	0.3965	0.3675
	100	6	0.8117	0.8184	0.8107	0.8112	0.5070	0.4525	0.4363	0.4462
	100	10	0.8166	0.8177	0.8200	0.8186	0.4845	0.4536	0.4207	0.3754

Table 9: Changing panel design. Impact on estimator kurtosis and skewness
$(\beta_1, \beta_2, \lambda) = (0.6,\ 0.3,\ 0.8)$. $(\bar{\chi}_1, \bar{\chi}_2) = (5, 10)$. $\sigma^2_\psi = 1$. $\sigma^2_u = \sigma^2_\delta = \sigma^2_\epsilon = \sigma^2_\chi = \sigma^2_\alpha = 0.1$. *Eq. in levels*

			$(N_\xi, N_\eta, N_\nu) =$				$(N_\xi, N_\eta, N_\nu) =$			
	N	T	(4,0,0)	(4,1,0)	(4,2,0)	(4,2,1)	(4,0,0)	(4,1,0)	(4,2,0)	(4,2,1)
			Kurtosis				*Skewness*			
β_1	50	6	3.2130	3.9024	15.2166	5.8204	0.0124	0.2100	-1.2840	0.1052
	50	10	3.0628	3.4429	3.5627	3.1895	0.0239	-0.1351	0.1126	-0.0692
	100	6	3.9867	3.8795	6.1599	4.4225	-0.4309	0.1094	-0.2658	-0.1308
	100	10	3.3495	2.9267	3.2543	3.2395	-0.2088	-0.0641	-0.1296	-0.0954
β_2	50	6	4.2630	4.1719	9.4146	6.3879	-0.3177	-0.1377	1.0640	0.0413
	50	10	3.5539	2.9700	2.9294	3.3819	0.0338	0.0432	0.1765	-0.1490
	100	6	3.1785	4.1242	7.8837	15.5332	-0.0591	-0.1471	-0.3890	1.4773
	100	10	3.4851	3.3548	3.3736	3.3325	0.0883	0.1011	-0.1333	- 0.1513
λ	50	6	3.9074	4.1632	6.0577	5.2854	0.2513	-0.1218	-0.7680	-0.4497
	50	10	2.9577	2.7043	3.0343	3.7450	0.0584	-0.0439	-0.0676	0.1925
	100	6	3.1860	3.6477	7.3511	7.6515	0.0828	0.0191	0.5333	-0.5346
	100	10	3.0391	3.4376	3.4329	3.0237	-0.0277	-0.0802	0.0499	0.1344

Table 10: Changing panel design. Impact on $\mathcal{J}$- and $\mathcal{F}$-tests
$(\beta_1, \beta_2, \lambda) = (0.6,\ 0.3,\ 0.8)$. $(\bar{\chi}_1, \bar{\chi}_2) = (5, 10)$. $\sigma^2_\psi = 1$. $\sigma^2_u = \sigma^2_\delta = \sigma^2_\epsilon = \sigma^2_\chi = \sigma^2_\alpha = 0.1$

		$(N_\xi, N_\eta, N_\nu) =$				$(N_\xi, N_\eta, N_\nu) =$			
N	T	(4,0,0)	(4,1,0)	(4,2,0)	(4,2,1)	(4,0,0)	(4,1,0)	(4,2,0)	(4,2,1)
		Equation in levels							
		p-value for $\mathcal{J}$-test (orthogonality)				*p-value for $\mathcal{F}$-test (IV-strength)*			
50	6	0.4501	0.4230	0.1657	0.1538	0.0000	0.0000	0.2278	0.2218
50	10	0.9991	0.7328	0.4168	0.4033	0.0000	0.0000	0.0000	0.0000
100	6	0.5260	0.4585	0.1622	0.1664	0.0000	0.0000	0.1973	0.1964
100	10	0.4028	0.4460	0.4960	0.4850	0.0000	0.0000	0.0000	0.0000
		Equation in differences							
		p-value for $\mathcal{J}$-test (orthogonality)				*p-value for $\mathcal{F}$-test (IV-strength)*			
50	6	0.4052	0.5102	0.6625	0.6446	0.0336	0.0185	0.0406	0.0437
50	10	0.9980	0.7291	0.3850	0.3953	0.0000	0.0000	0.0000	0.0000
100	6	0.4253	0.5518	0.6695	0.6549	0.0219	0.0172	0.0257	0.0268
100	10	0.3608	0.3683	0.4488	0.4273	0.0000	0.0000	0.0000	0.0000

5 Application: FDI impact on economic growth

Our application is concerned with measuring the contribution of FDI on growth. We employ the dynamic model used by, *inter alia*, Basu and Guariglia (2007) and Doytch and Uctum (2011) and a panel data set for 131 countries, and for examining specific issues (see below) sets of only 25–30 countries. The empirical mode is specified as

$$Y_{it} = \alpha_i + Y_{i,t-1}\lambda + X_{it}\beta + Z_{it}\gamma + \varepsilon_{it}, \tag{16}$$

corresponding to (3) and (14), with $(y_{it}, \boldsymbol{q}_{it})$ and w_{it}, as given by (2) and (15), in the simulation model, corresponding to (Y_{it}, X_{it}, Z_{it}) and ε_{it}. The dependent variable for country i at time t, Y_{it}, is the log of real GDP per capita, X_{it} is the share of FDI in GDP, and Z_{it} is a vector of control variables: an indicator of political stableness, an indicator of economic openness and the share of the population which belongs to the working age, while ε_{it} is the disturbance term. The measurement error problem has been given attention in the literature on the relationships between FDI and countries' economic performance. For example, Razin and Sadka (2012) noted that since different countries have different recording and accounting practices relating to FDI measurement, measurement errors are likely to arise when such data are compiled in a country panel. Neuhaus (2006) pointed out that measurement error is a prevalent problem in a transition country when the FDI impact on its economic growth is investigated. Some authors have tried to accommodate persistence in the errors in this kind of study, *e.g.*, Samad (2009) introduced an error-correction mechanism in examining the causal relation between the FDI share in GDP and per capita GDP.

Therefore, motivated by the increasing popularity of GMM in FDI-economic-growth analysis, and our simulation results in section 4, we apply our AR-EIV-GMM approach on a country panel data set in order to shed more light on this issue. The data set is from the years 1996–2010. It is not a full 15-year panel, however, since for the years 1996–2002 only biannual observations are available (1997, 1999 and 2001 are missing). For 2002–2010 (9 years) annual observations exist. Removing the countries with time series shorter than 12 observations, we have compiled a balanced data set of 1572 observations ($N = 131$ countries observed in $T = 12$ years, although, as remarked, only the last 8 years are contiguous). All observations are compiled from World Development Indicators, published by the World Bank, including real GDP per capita in 2005 PPP, FDI and GDP in current USD, the degree of openness, defined as the total share of export and import in GDP, and finally, working age population, defined as the share of the persons in the population with ages 15–64 years. The political stability index is extracted from the World-Wide Governance Indicators (WGI) dataset.

We first, as a benchmark estimation, run a fixed effect OLS regression with the aggregate FDI share as one of the regressors. The result, presented in Table 11, columns 1 and 2, gives a FDI equation with an estimated autoregression parameter as high as, 0.85, which is close to the value assumed in the above simulation experiments. Motivated by our simulation results that estimation is likely to be less biased when based on an equation in levels than on a corresponding equation in differences, we in the following prefer, in making inference on the coefficient of the FDI share, to give priority to the equation in levels. To handle the endogeneity problem we in addition use the GMM version suggested by Blundell and Bond (1998), in which the equation is transformed to first differences, including the lagged left-hand side variables for selected periods in the IV set.[8]

Our dataset specifically allows testing hypotheses about the contributions of manufacturing FDI to GDP growth in both the manufacturing sector and the service sector, and symmetrically, the contributions of service FDI to GDP growth in both sectors, including *cross-effects*. However, at this disaggregate level the data is more limited with respect to both country coverage and time series length. For examining the effects of manufacturing FDI, data from $N=32$ countries and $T=8$ years are available, while for examining the effects of service FDI, the data set includes $N=29$ countries and $T=8$ years.

As pointed in the previous literature, a problem with system GMM estimators is that there is little guidance to determine whether or not the IV set is 'excessive'. For example, Doytch and Uctum (2011) had to experiment with different lags from the potential IV set to obtain their final estimates. An advantage of the strategy proposed in the present paper and used in compiling Tables 12–15 is that we from the different combinations of the noise and signal memories assumed can first deduct potentially valid IV sets which next in confrontation with the results of the $\mathcal{J}$- and $\mathcal{F}$-tests can lead us to the preferred estimator.

As indicated by our MC simulations results in Section 4, the equation in difference and IVs in levels tend to produce more negatively biased coefficient estimates for β_1, β_2, a conclusion also suggested by Blundell and Bond (1998) for a model with no measurement error. As shown in Table 12, for GMM estimates based on different memory lengths, the estimate of the FDI coefficient for the equation in differences is much lower than those for the equation in levels. Based on the recommendation from our MC simulation, we stick to the equation in levels and only lags and leads of independent variables as the working IVs to obtain the more reliable coefficient estimates. Among the combinations presented in Table 12, we choose the one which best fits the data. We can use the $\mathcal{J}$-test as well a goodness-of-fit R^2 measure for equations estimated by IVs based on prediction errors (PS-R^2), see Pesaran and Smith (1994), to make the judgment. Figures 1 and 2 visualize comparisons between different versions. The combination $(N_\xi, N_\eta, N_\nu) = (4,0,0)$ is the dominating case with highest PS-R^2 statistic along with an acceptable p-value from the $\mathcal{J}$-test.

Compared with the FDI coefficient estimate in Table 11, 0.017, the memory constellation $(N_\xi, N_\eta, N_\nu) = (4,0,0)$ for the level version in Table 12 gives a much higher estimate, 0.0388, also higher than the fixed-effect OLS estimate. This illustration therefore shows how dynamic GMM estimation without considering memory in errors can bias the results. An alternative estimation of Table 12 with observations from 2002–2010 gave largely similar results.

To specifically investigate the effects of FDI on GDP growth, we have extracted the subsample of Asian developing countries.[9] The impacts of aggregate FDI, in Table 13, are

[8] The results in Table 11 are obtained by the 'R' software; R being a language and environment for statistical computing and graphics, available as Free Software under the terms of the Free Software Foundation's GNU General Public License in source code form. See `http://www.r-project.org/`.

[9] The 24 Asian developing countries include: Azerbaijan, Bangladesh, Cambodia, China, Fiji, Georgia, India, Indonesia, Kazakhstan, Korea, Rep., Lao PDR, Malaysia, Maldives, Mongolia, Nepal, Pakistan, Papua New Guinea, Philippines, Samoa, Sri Lanka, Tajikistan, Thailand, Uzbekistan, Vietnam. This gives a balanced panel data set for the years 2002–2009.

much stronger than implied by the above results; its coefficient estimate increases from 0.0388 to 0.1674 and, with a standard error of 0.0595, the latter is clearly significant.

Recent studies, *e.g.* Doytch and Uctum (2011), have tended to disaggregate the effects of FDI into different sectors. Following the line, we apply our Dynamic GMM to revisit the effects at the disaggregated level. At a disaggregate level, however, the data sets are much limited compared to the set used for analyzing the above aggregated FDI effects.[10] Table 14 presents the estimated effects of manufacturing FDI on manufacturing GDP growth (section A) and on service GDP growth (section B), modifying the interpretation of X and Y in (16), accordingly. While the similar analysis in Doytch and Uctum (2011) yields no significant effects of manufacturing FDI on GDP growth in either of the sectors at the world wide level, our analysis shows a very different picture: the memory combination $(N_\xi, N_\eta, N_\nu) = (4, 1, 0)$ has the highest fit along with acceptable $\mathcal{J}$-test results. Manufacturing FDI comes out with significant positive effects on GDP growth in both sectors. However, the cross-effect, also called spill-over effects, is much smaller, 0.3614 (section B) against 0.6003 (section A). Next, we extend the analysis to represent the impact of service FDI on both service and manufacturing GDP growth. Because of limited data availability for Chile, Malaysia, and Slovenia we exclude these countries from the 32 countries previously examined. The results are reported in Table 15, sections A and B, respectively, again with the modified interpretation of X and Y in (16). A surprising difference from the above results is that for the impact of the service FDI, when using the equation in difference with memory combination $(N_\xi, N_\eta, N_\nu) = (2, 0, 0)$, the equation yields the best fit. Also contrary to the findings of of Doytch and Uctum (2011), we observe no negative spill-over effect from the service FDI to manufacturing GDP growth. In our findings, both the effects are significantly positive. However, both effects are much lower than the effects of the manufacturing FDI. The contribution of the service FDI to the manufacturing GDP growth is much lower than its contribution to the service GDP growth.

By comparing the memory combination $(N_\xi, N_\eta, N_\nu) = (4, 1, 0)$ for the contribution of manufacturing FDI and $(N_\xi, N_\eta, N_\nu) = (2, 0, 0)$ for the service FDI, we conclude that the 'cyclical pattern' or 'persistence' in the behavior of the service FDI is much weaker than that of the manufacturing FDI, which is consistent with the common expectation. Failing to incorporate such an important feature in the GMM estimation might severely bias the results, for example, the negative effects of service FDI on the manufacturing GDP growth documented by Doytch and Uctum (2011).

As exemplified in our simulations the equation in difference with IVs in levels tends to give more negatively biased coefficient estimates than the opposite constellation. Table 12 shows estimates for the dynamic FDI model under different assumptions about the memory lengths, using IVs based on the exogenous variables. The coefficient estimate of FDI in the equation in differences is much lower than in the equation in levels, which is consistent the simulation results. Drawing on our simulation results, we use the equation in levels and using as IVs only values of the assumed exogenous variables as the working horse in

[10] For examining the effects of manufacturing FDI on both GDP growth in manufacturing sector and service sector, we have for the 8 years 2002–2009 observations for 32 countries, including Australia, Austria, Cambodia, Chile, Czech Republic, Denmark, Estonia, Finland, France, Germany, Hungary, Iceland, Indonesia, Ireland, Japan, Lao PDR, Malaysia, Mexico, Netherlands, Norway, Philippines, Portugal, Singapore, Slovak Republic, Slovenia, Spain, Sweden, Thailand, Turkey, the United Kingdom, the United States, and Viet Nam.

coefficient estimation, giving the results in Table 12. Among the combinations presented, we choose the combination which best fits the data, using the $\mathcal{J}$-test and P&S R^2 to judge. Figure 1 visualize comparisons between different combinations. The constellation $(N_\xi, N_\eta, N_\nu) = (4, 0, 0)$ gives the highest P&S R^2 along with an 'acceptable' $\mathcal{J}$-test result.

Table 11: FDI equation. OLS vs. GMM, 1572 obs

	Fixed Effects, OLS Est. (S.e.)	Fixed effects, GMM Est. (S.e.)
ln(GDP(-1))	0.846 (0.010)	0.650 (0.061)
FDI share	0.029 (0.013)	0.017 (0.013)
Political Stability	0.022 (0.004)	0.031 (0.011)
Openness	0.000 (0.000)	0.001 (0.000)
Working Age Population Share	0.006 (0.001)	0.029 (0.008)
Sargan Test:		123.52 (p=0.1784)
Second-order Autocorrelation Test:		−0.4572 (p=0.3237)
Wald Test for Coefficients:		1062.84 (p=0.0000)

Motivated by results from Sargan tests and tests for second-order disturbance autocorrelation.
IVs: All values of X and Z lagged 5 periods.

Table 12: FDI coefficient GMM estimates from equation (16)
$N = 131,\ T = 12$ *(years 1996,1998,2000,2002–2010)*

	$(N_\xi, N_\eta, N_\nu) =$					
	(4,0,0)	(4,1,0)	(4,2,0)	(3,0,0)	(3,1,0)	(2,0,0)
	Equation in levels					
Est.	0.0388	0.0361	0.0288	0.0408	0.0392	0.0302
S.e.	0.0276	0.0274	0.0213	0.0280	0.0295	0.0209
PS-R^2	0.6674	0.6144	0.5572	0.6346	0.5779	0.5903
$\mathcal{J}$-test	1.0000	0.9690	0.0921	0.9993	0.2033	0.4836
	Equation in differences					
Est.	0.0198	0.0271	0.0235	0.0198	0.0250	0.0236
S.e.	0.0136	0.0221	0.0205	0.0149	0.0220	0.0176
PS-R^2	0.4216	0.4322	0.4097	0.4227	0.4301	0.4179
$\mathcal{J}$-test	1.0000	0.9788	0.0606	1.0000	0.2424	0.4836

Table 13: FDI coefficient GMM estimate. Asian Developing Countries
$N = 24,\ T = 9$ *(years 2002–2010)*

	$(N_\xi, N_\eta, N_\nu) =$			
	(2,0,0)	(2,1,0)	(3,1,0)	(4,1,0)
	Equation in levels			
Est.	0.1881	0.1920	0.1650	0.1674
S.e.	0.0884	0.0639	0.0644	0.0595
PS-R^2	0.8390	0.7403	0.8142	0.8580
$\mathcal{J}$-test	1.0000	0.9197	1.0000	1.0000
	Equation in differences			
Est.	-0.3385	-0.5877	-0.4716	-0.3296
S.e.	0.2971	0.4061	0.3618	0.3141
PS-R^2	0.5708	0.6053	0.5930	0.5803
$\mathcal{J}$-test	1.0000	0.9197	1.0000	1.0000

Table 14: COEFFICIENT GMM ESTIMATES OF MANUFACTURING FDI

$N = 32$, $T = 8$ *(years 2002–2009)*

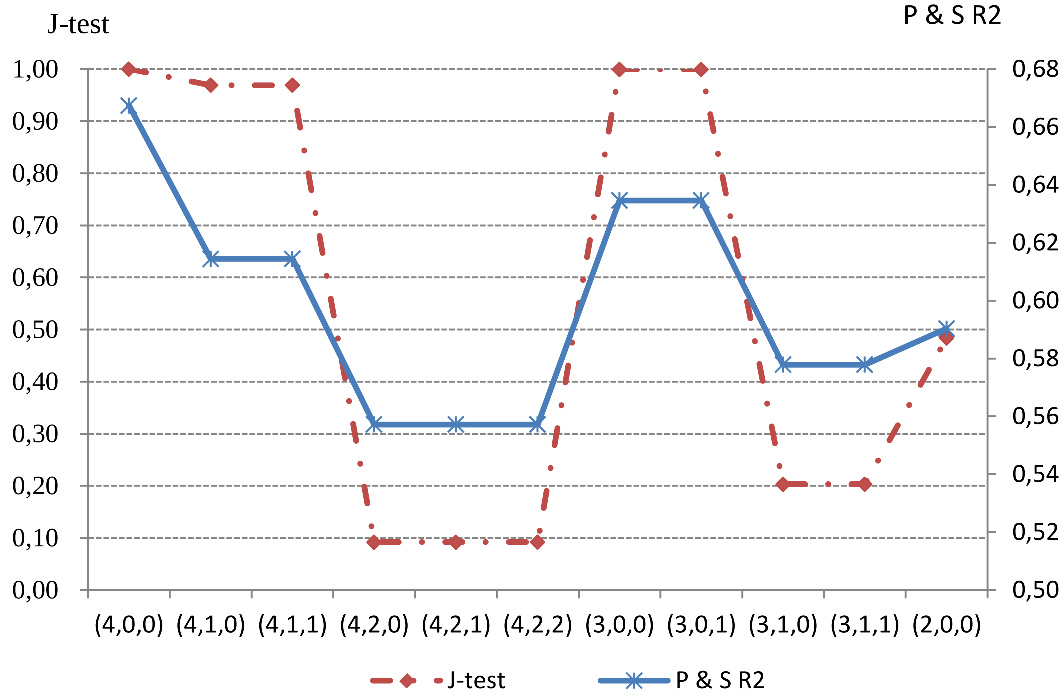
	$(N_\xi, N_\eta, N_\nu) =$ (2,0,0)	(2,1,0)	(3,1,0)	(4,1,0)	(2,0,0)	(2,1,0)	(3,1,0)	(4,1,0)
	A. IN EQUATION EXPLAINING MANUFACTURING GDP							
	Equation in levels				*Equation in differences*			
Est.	0.2672	0.3961	0.6713	0.6003	0.2946	0.2046	0.1646	0.2244
S.e.	0.2001	0.3051	0.3292	0.3469	0.1703	0.2089	0.1753	0.1558
PS-R^2	0.6444	0.4260	0.6063	0.6874	0.6910	0.6851	0.6742	0.6822
$\mathcal{J}$-test	0.9999	0.2321	0.9828	0.9999	0.9999	0.2321	0.9837	0.9999
	B. IN EQUATION EXPLAINING SERVICE GDP							
	Equation in levels				*Equation in differences*			
Est.	0.1684	0.5018	0.5159	0.3614	-0.1702	-0.1452	-0.1580	-0.1759
S.e.	0.1249	0.3660	0.2227	0.2100	0.3907	0.3783	0.3475	0.3550
PS-R^2	0.6422	0.4232	0.6039	0.6846	0.7372	0.7281	0.7252	0.7261
$\mathcal{J}$-test	0.9999	0.2321	0.9828	0.9999	0.9995	0.2321	0.9830	0.9999

Table 15: COEFFICIENT GMM ESTIMATES OF SERVICE FDI

$N = 29$, $T = 8$ *(years 2002–2009)*

	$(N_\xi, N_\eta, N_\nu) =$ (2,0,0)	(2,1,0)	(3,1,0)	(4,1,0)	(2,0,0)	(2,1,0)	(3,1,0)	(4,1,0)
	A. IN EQUATION EXPLAINING SERVICE GDP							
	Equation in levels				*Equation in differences*			
Est.	0.0780	0.1851	0.1127	0.0356	0.2686	0.2766	0.2607	0.2379
S.e.	0.0404	0.0872	0.0839	0.0745	0.0926	0.0860	0.0827	0.0810
PS-R^2	0.6460	0.4319	0.6214	0.7016	0.7605	0.7418	0.7337	0.7302
$\mathcal{J}$-test	0.9999	0.3609	0.9944	0.9999	1.0000	0.3609	0.9944	0.9999
	B. IN EQUATION EXPLAINING MANUFACTURING GDP							
	Equation in levels				*Equation in differences*			
Est.	0.0481	0.1985	0.1594	0.0842	0.1489	0.2186	0.1689	0.1364
S.e.	0.0614	0.1045	0.0774	0.0612	0.0674	0.0921	0.0659	0.0655
PS-R^2	0.6470	0.4326	0.6221	0.7034	0.6951	0.6840	0.6975	0.6982
$\mathcal{J}$-test	0.9999	0.3609	0.9944	0.9999	1.0000	0.3609	0.9938	1.0000

Figure 1. Trends of J-test and P & R Squared with Different Memory Combinations



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Appendix A: Supplementary tables

Table A.1: Changing noise variances and noise memory. Impact on estimate mean
$(N, T) = (100, 10)$. $(\beta_1, \beta_2, \lambda) = (0.6,\ 0.3,\ 0.8)$. $(\bar{\chi}_1, \bar{\chi}_2) = (5, 10)$. $\sigma_\psi^2 = 1, \sigma_u^2 = \sigma_\chi^2 = \sigma_\alpha^2 = 0.1$

	(exog.) σ_ϵ^2	(endog.) σ_δ^2	$(N_\xi, N_\eta, N_\nu) =$ (4,0,0)	(4,1,0)	(4,1,1)	(4,2,0)	(4,2,1)	(4,2,2)	(6,2,0)	(6,2,1)	(6,2,2)
			Equation in levels								
β_1	0.1	0.1	0.5655	0.5594	0.5631	0.5536	0.5519	0.5591	0.5629	0.5620	0.5637
	0.5	0.1	0.4896	0.4641	0.4704	0.4426	0.4464	0.4463	0.4710	0.4799	0.4774
	0.1	0.5	0.5865	0.5749	0.5790	0.5717	0.5668	0.5942	0.5787	0.5866	0.5799
	0.5	0.5	0.5087	0.4921	0.4888	0.4631	0.4728	0.4794	0.4904	0.4898	0.4920
β_2	0.1	0.1	0.2674	0.2682	0.2674	0.2653	0.2633	0.2687	0.2713	0.2700	0.2835
	0.5	0.1	0.2430	0.2298	0.2336	0.2242	0.2253	0.2260	0.2334	0.2342	0.2397
	0.1	0.5	0.3009	0.3070	0.3157	0.3027	0.3191	0.3189	0.2990	0.3026	0.3177
	0.5	0.5	0.2766	0.2644	0.2755	0.2623	0.2665	0.2736	0.2620	0.2692	0.2754
λ	0.1	0.1	0.8168	0.8175	0.8170	0.8195	0.8207	0.8174	0.8161	0.8162	0.8116
	0.5	0.1	0.8376	0.8462	0.8437	0.8513	0.8505	0.8504	0.8440	0.8420	0.8403
	0.1	0.5	0.8019	0.8016	0.7981	0.8039	0.7990	0.7945	0.8035	0.8006	0.7967
	0.5	0.5	0.8227	0.8300	0.8263	0.8350	0.8316	0.8285	0.8304	0.8283	0.8256
			Equation in differences								
β_1	0.1	0.1	0.4839	0.4687	0.4640	0.4610	0.4461	0.4415	0.4800	0.4671	0.4521
	0.5	0.1	0.3867	0.3529	0.3502	0.3392	0.3223	0.3107	0.3618	0.3650	0.3511
	0.1	0.5	0.3767	0.3655	0.3391	0.3487	0.3313	0.3296	0.3725	0.3569	0.3508
	0.5	0.5	0.3091	0.2870	0.2705	0.2641	0.2550	0.2384	0.3007	0.2772	0.2633
β_2	0.1	0.1	0.2401	0.2350	0.2278	0.2300	0.2230	0.2219	0.2385	0.2311	0.2316
	0.5	0.1	0.1949	0.1777	0.1736	0.1690	0.1580	0.1611	0.1801	0.1789	0.1766
	0.1	0.5	0.1879	0.1917	0.1738	0.1729	0.1668	0.1615	0.1845	0.1735	0.1708
	0.5	0.5	0.1548	0.1423	0.1293	0.1256	0.1346	0.1233	0.1479	0.1408	0.1359
λ	0.1	0.1	0.4840	0.4525	0.4205	0.4333	0.3847	0.3547	0.4753	0.4422	0.3954
	0.5	0.1	0.3811	0.3293	0.3050	0.2904	0.2554	0.2056	0.3438	0.3233	0.2814
	0.1	0.5	0.1117	0.0777	0.0130	0.0442	-0.0087	-0.0538	0.1014	0.0453	0.0055
	0.5	0.5	0.0489	0.0153	-0.0581	-0.0158	-0.0707	-0.1229	0.0466	-0.0127	-0.0771

Table A.2: Changing equation and signal heterogeneity. Impact on estimate mean
$(N, T) = (100, 10)$. $(\beta_1, \beta_2, \lambda) = (0.6,\ 0.3,\ 0.8)$. $(\bar{\chi}_1, \bar{\chi}_2) = (5, 10)$. $\sigma_u^2 = \sigma_\delta^2 = \sigma_\epsilon^2 = 0.1$

	(eq.) σ_α^2	(exog.var.) σ_χ^2	$(N_\xi, N_\eta, N_\nu) =$ (4,0,0)	(4,1,0)	(4,1,1)	(4,2,0)	(4,2,1)	(4,2,2)
			Equation in levels; $\sigma_\psi^2 = 1.0$					
β_1	0.5	0.1	0.5676	0.5610	0.5671	0.5586	0.5549	0.5536
	0.1	0.5	0.5163	0.5164	0.5065	0.5079	0.5020	0.5155
	0.5	0.5	0.5185	0.5157	0.5132	0.5085	0.5122	0.5182
β_2	0.5	0.1	0.2691	0.2653	0.2671	0.2604	0.2618	0.2736
	0.1	0.5	0.1719	0.1678	0.1700	0.1634	0.1660	0.1635
	0.5	0.5	0.1701	0.1718	0.1658	0.1690	0.1772	0.1692
λ	0.5	0.1	0.8155	0.8182	0.8168	0.8203	0.8201	0.8163
	0.1	0.5	0.8572	0.8592	0.8598	0.8617	0.8613	0.8601
	0.5	0.5	0.8579	0.8578	0.8598	0.8602	0.8568	0.8586
			Equation in levels; $\sigma_\psi^2 = 0.5$					
β_1	0.5	0.1	0.5479	0.5404	0.5356	0.5308	0.5236	0.5296
	0.1	0.5	0.4648	0.4525	0.4578	0.4317	0.4390	0.4369
	0.5	0.5	0.4860	0.4710	0.4694	0.4705	0.4717	0.4661
β_2	0.5	0.1	0.2468	0.2452	0.2501	0.2421	0.2420	0.2494
	0.1	0.5	0.0957	0.0853	0.0947	0.0923	0.0828	0.0913
	0.5	0.5	0.0968	0.0936	0.0972	0.1006	0.0912	0.1090
λ	0.5	0.1	0.8263	0.8284	0.8274	0.8305	0.8324	0.8285
	0.1	0.5	0.8912	0.8968	0.8929	0.8978	0.9003	0.8976
	0.5	0.5	0.8876	0.8915	0.8904	0.8885	0.8919	0.8867
			Equation in differences; $\sigma_\psi^2 = 1.0$					
β_1	0.5	0.1	0.5009	0.4874	0.4844	0.4805	0.4644	0.4543
	0.1	0.5	0.4916	0.4751	0.4661	0.4720	0.4552	0.4481
	0.5	0.5	0.4990	0.4928	0.4809	0.4804	0.4744	0.4678
β_2	0.5	0.1	0.2495	0.2435	0.2389	0.2340	0.2372	0.2319
	0.1	0.5	0.2490	0.2404	0.2326	0.2353	0.2249	0.2163
	0.5	0.5	0.2502	0.2501	0.2398	0.2433	0.2424	0.2383
λ	0.5	0.1	0.5320	0.5139	0.4843	0.5059	0.4782	0.4308
	0.1	0.5	0.5048	0.4763	0.4394	0.4589	0.4187	0.3777
	0.5	0.5	0.5368	0.5353	0.4919	0.5190	0.4925	0.4594
			Equation in differences; $\sigma_\psi^2 = 0.5$					
β_1	0.5	0.1	0.4602	0.4541	0.4395	0.4392	0.4295	0.4212
	0.1	0.5	0.4325	0.4082	0.4007	0.3995	0.3841	0.3657
	0.5	0.5	0.4614	0.4571	0.4391	0.4564	0.4342	0.4271
β_2	0.5	0.1	0.2269	0.2287	0.2182	0.2143	0.2075	0.2051
	0.1	0.5	0.2184	0.2009	0.2004	0.2068	0.1889	0.1856
	0.5	0.5	0.2303	0.2234	0.2216	0.2248	0.2239	0.2161
λ	0.5	0.1	0.4629	0.4706	0.4321	0.4719	0.4383	0.4029
	0.1	0.5	0.3674	0.3205	0.2781	0.3081	0.2601	0.2091
	0.5	0.5	0.4842	0.4882	0.4526	0.5009	0.4603	0.4156

Table A.3: Changing panel design. Impact on estimate mean
$(\beta_1, \beta_2, \lambda) = (0.6,\ 0.3,\ 0.8)$. $(\bar{\chi}_1, \bar{\chi}_2) = (5, 10)$. $\sigma_u^2 = \sigma_\delta^2 = \sigma_\epsilon^2 = \sigma_\chi^2 = \sigma_\alpha^2 = 0.1$

			$(N_\xi, N_\eta, N_\nu) =$						$(N_\xi, N_\eta, N_\nu) =$					
	N	T	(4,0,0)	(4,1,0)	(4,1,1)	(4,2,0)	(4,2,1)	(3,1,1)	(4,0,0)	(4,1,0)	(4,1,1)	(4,2,0)	(4,2,1)	(3,1,1)
			Equation in levels; $\sigma_\psi^2 = 1$						*Equation in levels;* $\sigma_\psi^2 = 0.5$					
β_1	50	6	0.5648	0.5867	0.5694	0.5687	0.5623	0.5438	0.5457	0.5499	0.5262	0.5492	0.5411	0.5313
	50	8	0.5688	0.5580	0.5655	0.5492	0.5468	0.5638	0.5375	0.5258	0.5273	0.5270	0.5102	0.5256
	50	10	0.5620	0.5555	0.5592	0.5500	0.5528	0.5573	0.5349	0.5240	0.5288	0.5198	0.5280	0.5096
	100	6	0.5692	0.5596	0.5741	0.5594	0.5667	0.5703	0.5448	0.5291	0.5382	0.5550	0.5405	0.5301
	100	8	0.5670	0.5584	0.5646	0.5546	0.5573	0.5567	0.5361	0.5207	0.5238	0.5120	0.5285	0.5234
	100	10	0.5642	0.5577	0.5590	0.5550	0.5575	0.5576	0.5325	0.5268	0.5303	0.5145	0.5179	0.5191
β_2	50	6	0.2776	0.2738	0.2705	0.2787	0.2841	0.2722	0.2543	0.2485	0.2666	0.2734	0.2817	0.2628
	50	8	0.2700	0.2693	0.2667	0.2700	0.2655	0.2630	0.2463	0.2492	0.2442	0.2419	0.2496	0.2511
	50	10	0.2687	0.2647	0.2707	0.2585	0.2657	0.2639	0.2419	0.2352	0.2462	0.2382	0.2373	0.2379
	100	6	0.2792	0.2648	0.2875	0.2879	0.2828	0.2805	0.2619	0.2542	0.2623	0.3057	0.2716	0.2437
	100	8	0.2705	0.2668	0.2667	0.2646	0.2704	0.2708	0.2587	0.2463	0.2476	0.2352	0.2419	0.2501
	100	10	0.2685	0.2680	0.2696	0.2620	0.2645	0.2638	0.2464	0.2395	0.2431	0.2343	0.2411	0.2330
λ	50	6	0.8141	0.8109	0.8149	0.8124	0.8114	0.8188	0.8246	0.8255	0.8235	0.8173	0.8157	0.8240
	50	8	0.8154	0.8173	0.8170	0.8183	0.8204	0.8188	0.8284	0.8294	0.8310	0.8314	0.8317	0.8292
	50	10	0.8168	0.8193	0.8166	0.8223	0.8195	0.8190	0.8306	0.8342	0.8297	0.8342	0.8328	0.8361
	100	6	0.8117	0.8184	0.8085	0.8107	0.8112	0.8115	0.8215	0.8269	0.8228	0.8055	0.8194	0.8304
	100	8	0.8156	0.8182	0.8171	0.8192	0.8171	0.8171	0.8244	0.8310	0.8302	0.8365	0.8312	0.8296
	100	10	0.8166	0.8177	0.8172	0.8200	0.8186	0.8196	0.8292	0.8323	0.8309	0.8361	0.8335	0.8359
			Equation in differences; $\sigma_\psi^2 = 1$						*Equation in differences;* $\sigma_\psi^2 = 0.5$					
β_1	50	6	0.4758	0.4601	0.4599	0.4697	0.4323	0.4423	0.4130	0.3919	0.4002	0.4534	0.4328	0.3639
	50	8	0.4680	0.4559	0.4554	0.4503	0.4297	0.4419	0.4065	0.3907	0.3782	0.3863	0.3752	0.3592
	50	10	0.4670	0.4543	0.4545	0.4445	0.4427	0.4368	0.4014	0.3884	0.3811	0.3856	0.3673	0.3610
	100	6	0.4856	0.4690	0.4733	0.3902	0.5105	0.4478	0.4333	0.4163	0.3936	0.4076	0.3958	0.3987
	100	8	0.4798	0.4649	0.4641	0.4568	0.4502	0.4445	0.4224	0.3906	0.3851	0.3782	0.3799	0.3646
	100	10	0.4818	0.4686	0.4592	0.4575	0.4426	0.4497	0.4142	0.3959	0.3908	0.3796	0.3680	0.3734
β_2	50	6	0.2405	0.2395	0.2245	0.2133	0.1905	0.2135	0.2076	0.1930	0.2123	0.2034	0.1699	0.1944
	50	8	0.2347	0.2336	0.2197	0.2327	0.2082	0.2160	0.2082	0.1932	0.1919	0.1891	0.1867	0.1822
	50	10	0.2381	0.2275	0.2240	0.2235	0.2219	0.2228	0.2074	0.1964	0.1881	0.1897	0.1878	0.1843
	100	6	0.2423	0.2415	0.2341	0.0654	0.1900	0.2241	0.2161	0.2178	0.1934	0.1597	0.1890	0.1967
	100	8	0.2449	0.2317	0.2307	0.2270	0.2182	0.2227	0.2174	0.2009	0.1905	0.1907	0.1824	0.1886
	100	10	0.2429	0.2382	0.2274	0.2339	0.2218	0.2192	0.2078	0.2066	0.1884	0.1898	0.1900	0.1821
λ	50	6	0.4619	0.4268	0.4002	0.3586	0.3569	0.3459	0.3101	0.2716	0.2408	0.3126	0.2464	0.2108
	50	8	0.4392	0.4182	0.3809	0.3982	0.3550	0.3509	0.2735	0.2486	0.1955	0.2458	0.1990	0.1600
	50	10	0.4339	0.4056	0.3785	0.3965	0.3675	0.3336	0.2569	0.2418	0.1920	0.2273	0.1713	0.1585
	100	6	0.5070	0.4525	0.4260	0.4363	0.4462	0.3763	0.3497	0.2874	0.2771	0.2963	0.2162	0.2312
	100	8	0.4865	0.4479	0.4147	0.4237	0.3961	0.3909	0.3263	0.2639	0.2383	0.2518	0.2242	0.1956
	100	10	0.4845	0.4536	0.4107	0.4207	0.3754	0.3881	0.3109	0.2679	0.2244	0.2410	0.1926	0.1875

Table A.4: Changing panel design. Impact on estimator kurtosis and skewness
$(\beta_1, \beta_2, \lambda) = (0.6,\ 0.3,\ 0.8)$. $(\bar{\chi}_1, \bar{\chi}_2) = (5, 10)$. $\sigma_u^2 = \sigma_\delta^2 = \sigma_\epsilon^2 = \sigma_\chi^2 = \sigma_\alpha^2 = 0.1$. *Eq. in levels*

			$(N_\xi, N_\eta, N_\nu) =$						$(N_\xi, N_\eta, N_\nu) =$					
	N	T	(4,0,0)	(4,1,0)	(4,1,1)	(4,2,0)	(4,2,1)	(3,1,1)	(4,0,0)	(4,1,0)	(4,1,1)	(4,2,0)	(4,2,1)	(3,1,1)
			Kurtosis; $\sigma_\psi^2 = 1$						*Skewness;* $\sigma_\psi^2 = 1$					
β_1	50	6	3.2130	3.9024	4.1109	15.2166	5.8204	3.1704	0.0124	0.2100	0.2318	-1.2840	0.1052	-0.2438
	50	8	3.3029	3.3626	3.2671	3.7996	3.0529	3.4255	-0.2490	0.0402	0.0977	0.0603	-0.1599	-0.2708
	50	10	3.0628	3.4429	2.7467	3.5627	3.1895	2.9626	0.0239	-0.1351	-0.0804	0.1126	-0.0692	-0.2246
	100	6	3.9867	3.8795	3.9570	6.1599	4.4225	3.5931	-0.4309	0.1094	0.2740	-0.2658	-0.1308	-0.2720
	100	8	3.0816	2.9307	3.4479	3.4187	3.2840	3.3587	-0.0612	0.0163	-0.0644	-0.0866	0.1018	0.1802
	100	10	3.3495	2.9267	3.0394	3.2543	3.2395	3.0127	-0.2088	-0.0641	0.0918	-0.1296	-0.0954	-0.1198
β_2	50	6	4.2630	4.1719	4.5439	9.4146	6.3879	3.8502	-0.3177	-0.1377	0.3430	1.0640	0.0413	0.0462
	50	8	3.4231	3.5442	3.2667	3.8120	3.5242	3.4093	-0.0367	0.3113	-0.0261	0.0568	-0.0337	0.1358
	50	10	3.5539	2.9700	2.7906	2.9294	3.3819	3.1476	0.0338	0.0432	-0.1399	0.1765	-0.1490	-0.2083
	100	6	3.1785	4.1242	3.6586	7.8837	15.5332	4.0948	-0.0591	-0.1471	0.0504	-0.3890	1.4773	-0.1311
	100	8	2.7475	3.0782	3.8561	3.2647	2.9940	3.2049	0.0217	-0.0517	0.1223	0.0891	0.0437	0.0481
	100	10	3.4851	3.3548	3.0746	3.3736	3.3325	2.9374	0.0883	0.1011	-0.0492	-0.1333	- 0.1513	-0.1137
λ	50	6	3.9074	4.1632	4.7096	6.0577	5.2854	3.3926	0.2513	-0.1218	-0.4913	-0.7680	-0.4497	0.1350
	50	8	2.9992	3.1523	3.0108	4.1339	3.5685	3.3069	0.1825	-0.0852	-0.1168	-0.1327	0.0296	0.0203
	50	10	2.9577	2.7043	2.9417	3.0343	3.7450	3.5791	0.0584	-0.0439	0.0560	-0.0676	0.1925	0.1911
	100	6	3.1860	3.6477	3.6690	7.3511	7.6515	4.2126	0.0828	0.0191	-0.0628	0.5333	-0.5346	0.2350
	100	8	3.1628	2.9396	3.9672	3.3431	3.1359	3.0791	-0.0087	0.0706	0.0925	-0.0183	0.0533	-0.0179
	100	10	3.0391	3.4376	3.1346	3.4329	3.0237	2.8965	-0.0277	-0.0802	-0.1091	0.0499	0.1344	0.1687
			Kurtosis; $\sigma_\psi^2 = 0.5$						*Skewness;* $\sigma_\psi^2 = 0.5$					
β_1	50	6	3.2997	3.4037	3.5205	4.8552	12.8315	4.1596	0.1140	-0.1698	0.0975	-0.1243	-1.5710	0.2381
	50	8	3.0225	3.0056	3.6066	3.1203	3.6236	3.1489	0.1335	-0.0428	0.0359	-0.1073	-0.2083	0.0345
	50	10	2.8139	2.8669	2.9632	3.1138	3.2494	3.3134	0.0390	-0.0462	0.0862	0.0130	0.0523	-0.1500
	100	6	3.2377	4.1899	4.7088	5.0447	12.5917	4.3113	-0.0005	-0.0070	0.2919	-0.2938	-1.4124	0.1176
	100	8	3.0087	3.0061	3.0802	3.2459	3.8318	3.0765	-0.1318	0.0075	-0.0370	-0.0865	0.1473	-0.0675
	100	10	3.6313	3.2869	2.9435	3.3155	3.0677	3.0735	-0.0692	0.0686	0.1086	0.0180	0.0508	-0.0533
β_2	50	6	3.2536	3.3063	4.4908	4.6090	3.8464	3.2458	-0.0198	0.0591	0.3829	0.1373	-0.1657	-0.1794
	50	8	3.0864	3.3442	3.3378	3.3633	3.0543	2.9220	-0.1221	-0.0804	-0.1096	0.2036	0.0768	0.1690
	50	10	2.6795	2.6608	2.8581	3.7753	2.9201	3.5063	-0.0484	-0.1052	0.1513	-0.2758	-0.0954	0.0024
	100	6	3.4091	3.8649	3.7824	5.0174	7.8856	3.5579	0.0322	0.2198	-0.2808	0.5211	-0.4455	-0.0641
	100	8	2.9934	3.0532	3.0011	3.6663	3.1277	4.3054	0.0383	-0.0427	0.2615	0.2238	0.0218	0.3535
	100	10	2.8199	3.0009	2.9323	3.0590	2.9597	2.9141	-0.0398	-0.1237	-0.0156	0.0651	0.0900	0.0777
λ	50	6	3.1886	4.6926	5.6037	4.5917	5.7766	3.2719	0.0622	0.0765	-0.4407	-0.0574	0.5147	0.1211
	50	8	3.2587	3.3976	2.9753	3.6810	3.1351	2.9083	0.1962	0.1344	-0.0930	-0.2459	-0.1737	-0.1147
	50	10	2.6542	2.6079	3.0096	3.5442	3.0225	3.2975	0.0939	0.0351	-0.0743	0.2960	-0.0121	0.0099
	100	6	3.2311	3.8872	3.1932	4.3967	6.3012	3.8167	0.0339	-0.0755	0.1297	-0.2084	0.5436	-0.0753
	100	8	3.1009	3.2616	2.8959	3.2205	3.1877	3.7831	0.0238	-0.0706	-0.1019	-0.2163	-0.0206	-0.2669
	100	10	2.8978	3.1876	2.5711	3.0006	3.1844	3.1158	0.0982	0.0162	0.0470	0.0946	-0.0758	-0.0209