SEVEN DECADES OF ECONOMETRICS AND BEYOND

A tribute to the life and work of Marc Nerlove

ONLINE APPENDICES

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Chapter 13
The Correlated Random Effects GMM-Level Estimation: Monte Carlo Evidence and Empirical Applications
Online Appendix

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Online Appendix to Chapter 13

A13.1 Monte Carlo Setup

The random components of Equations (**??**) used in Monte Carlo simulations are generated such as:

$$\mu_i \sim iidN(\mu_\mu, \sigma_\mu^2), \tag{A13.1}$$

$$\xi_{it} \sim iidN(\mu_\xi, \sigma_\xi^2), \tag{A13.2}$$

$$\epsilon_{it} \sim iidN(\mu_\epsilon, \sigma_\epsilon^2). \tag{A13.3}$$

The measurable time invariant variable w_i is drawn across the cross-sectional units as $w_i = round(N(\mu_w, \sigma_w^2))$. We assume homoskedasticity in all variances, that is $\sigma_{i\mu}^2 = \sigma_\mu^2, \sigma_{i\xi}^2 = \sigma_\xi^2$ and $\sigma_{i\epsilon}^2 = \sigma_\epsilon^2$. The variance of the random component e_{it} can be defined in two ways. First, it can be fixed so that $V(e_{it}) = \sigma_e^2$, where σ_e^2 is predefined. Then ϵ_{it} in e_{it} is generated as:

$$\sigma_\epsilon = \sqrt{\sigma_e^2 - \gamma_3^2\sigma_\mu^2 - \gamma_4^2\sigma_w^2}. \tag{A13.4}$$

Alternatively the variance of ϵ_{it} can be predefined and then the variance of e_{it} becomes:

$$V(e_{it}) = \gamma_3^2 V(\mu_i) + V(\epsilon_{it}). \tag{A13.5}$$

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There are two ways to control the within variance of $\mathbf{x}_i$. The first is to specify the standard deviation[1] of the random term ξ_{it} so that $V(\mathbf{x}_i) = \sigma_x^2$:

$$\sigma_\xi = \sqrt{\left(1-\vartheta^2\right)\sigma_x^2 - \gamma_1^2\sigma_\mu^2 - \gamma_2^2\sigma_\epsilon^2 - \gamma_5^2\sigma_w^2}. \tag{A13.6}$$

In this case the within variance of the generated $\mathbf{x}_i = (x_{i1}, ..., x_{iT})$ will be σ_x^2. The second way is to specify the standard deviation directly and not fix it. Then the variance of the generated ξ will be σ_ξ^2 and the variance of the generated $\mathbf{x}_i$ will be:

$$V(\mathbf{x}_i) = \frac{1}{1-\vartheta^2}\left(\gamma_1^2 V(\mu_i) + \gamma_2^2 V(\epsilon_i) + V(\xi)\right). \tag{A13.7}$$

The means μ_μ, μ_ξ and μ_ϵ are all set to zero or can be specified. Within the program it is ensured that σ_ξ remains strictly positive, which rules out certain combinations of $\gamma_1, \gamma_2, \vartheta$.

Table A13.1: Variances for x and e - options.

Error component $e_{it} = \gamma_3\mu_i + \gamma_4 w_i + \epsilon_{it}$	
$V(e)$ is fixed $V(e) = \sigma_e^2(=1)$	$\sigma_\epsilon^2 = \sigma_e^2 - \gamma_3^2\sigma_\mu^2 - \gamma_4^2\sigma_w^2$; Eq. (A13.4)
$V(\epsilon)$ is fixed $V(e) = \gamma_3^2 V(\mu_i) + V(\epsilon_{it})$; Eq. (A13.5)	$V(\epsilon) = \sigma_\epsilon^2(=1)$
Error component $x_{it} = \gamma_1\mu_i + \vartheta x_{it-1} + \gamma_2\epsilon_{it} + \gamma_5 w_i + \xi_{it}$	
$V(x)$ is fixed $V(x) = \sigma_x^2(=1)$	$\sigma_\xi^2 = \left(1-\vartheta^2\right)\sigma_x^2 - \gamma_1^2\sigma_\mu^2 - \gamma_2^2\sigma_\epsilon^2 - \gamma_5^2\sigma_w^2$; Eq. (A13.6)
$V(\xi)$ is fixed $V(x) = \frac{1}{1-\vartheta^2}\left(\gamma_1^2 V(\mu_i) + \gamma_2^2 V(\epsilon_i) + V(\xi)\right)$; Eq. (A13.7)	$V(\xi) = \sigma_\xi^2(=1)$

Note: $\sigma_e^2, \sigma_\epsilon^2, \sigma_x^2$, σ_ξ^2, σ_μ^2 and σ_w^2 can be defined (default values in parentheses; for σ_μ^2 the default is 1; for σ_w^2 the default is 2). Under option (A13.4) with $\gamma_3 > 0$, the variance of the idiosyncratic shock, σ_e^2, is lower than the variance of the individual heterogeneity, σ_μ^2.

The Monte Carlo simulations are repeated 1000 times and implemented in Stata; estimations exploit the community contributed command `xtdpdgmm` (Kripfganz, 2019). In both simulations and empirical examples, $t-1$ and $t-3$ lags are used as instruments (Ziliak, 1997; Bun & Kiviet, 2006).

A13.2 Monte Carlo Results

Some detailed results for the PAM-ARDL(1, 0) model are presented in Tables A13.2-A13.10 for the $\rho = 0.5$, $\beta_1 = 1$, $\beta_2 = 0$ and $\beta_3 = 0.1$ case. The Tables report the bias and empirical standard error obtained from the RE, FE, CRE1, CRE2, GL, CRE-GMM-CRE-GMM5, GS, GSC and KS2 estimators of ρ, β_1 and β_3. The γ_1

[1] Let define $V(\mathbf{x}_i)$ the (empirical) variance of the realized draw of $\mathbf{x}_i$, while σ_x^2 is the theoretical variance.

and γ_2 are varied between 0, 0.25 and 0.8, while $\gamma_3 = [0, 0.8]$; $\gamma_4 = \gamma 5 = 0.3$. We focus on three combinations of cross-sectional, N, and time-series, T: longitudinal panel ($N = 1000, T = 10$), macro panels ($N = 25, T = 40$), and multilevel panels ($N = 100, T = 25$).[2]

To help comparison of simulated results for PAM model, Figures A13.1-A13.3 shows the role of alternative values of γ_1, the endogeneity due to heterogeneity, on the bias of ρ, β_1 and β_3 in the considered types of panel datasets and under the case that $\sigma^2_\mu/\sigma^2_\epsilon = 1$, where σ^2_μ is the variance of individual heterogeneity, μ_i, and σ^2_ϵ is the variance of the shocks ϵ_{it}. Figures A13.4-A13.6 shows how the bias changes when the variance of individual heterogeneity is higher than the variance of the shocks, $\sigma^2_\mu/\sigma^2_\epsilon > 1$. Figures A13.7-A13.9 and Figures A13.10-A13.12 compare the cases $\sigma^2_\mu/\sigma^2_\epsilon = 1$ and $\sigma^2_\mu/\sigma^2_\epsilon > 1$ when standard endogeneity, due to the correlation between x_{it} and the idiosyncratic shocks through $\gamma_2 = 0.25$, is added to the endogeneity due to heterogeneity. To extend the landscape of results provided by the Tables, where $\gamma_3 = 0.8$, in the Figures we present the case of $\gamma_3 = 0.25$.

[2] The analyses of the $\rho = 0.8$ case in the PAM-ARDL(1, 0) and the ECM case, with $\beta_1 = 1, \beta_2 = 0.5$ and individual averages of both x_{it} and x_{it-1}, are still in progress. Very preliminary results are in Bontempi and Ditzen (2023).

Table A13.2: MonteCarlo results for ρ, ARDL(1,0) with $\rho = 0.5$, $\beta_1 = 1$ and $\beta_3 = 0.1$

Longitudinal panel N = 1000, T = 10. Parameter ρ														
	RE	FE	CRE1	CRE2	GL	CRE-GMM	CRE-GMM1	CRE-GMM2	CRE-GMM3	CRE-GMM4	CRE-GMM5	GS	GSC	KS2
$\gamma_1 = 0, \gamma_2 = 0, \gamma_3 = [0, 0.8]$														
bias	0.253	-0.080	0.170	0.170	0.010	0.052	0.026	0.024	0.042	0.017	0.019	0.003	0.012	-0.017
ese	0.004	0.007	0.007	0.007	0.017	0.013	0.018	0.021	0.014	0.017	0.016	0.019	0.024	0.042
bias	0.359	-0.038	0.162	0.196	0.053	0.108	0.073	0.071	0.081	0.042	0.047	0.029	0.037	-0.008
ese	0.005	0.005	0.009	0.008	0.031	0.013	0.022	0.030	0.013	0.021	0.019	0.026	0.025	0.031
$\gamma_1 = 0, \gamma_2 = 0.25, \gamma_3 = [0, 0.8]$														
bias	0.188	-0.110	0.108	0.131	0.006	0.051	0.021	0.021	0.037	0.012	0.014	0.001	0.009	-0.029
ese	0.007	0.006	0.009	0.007	0.018	0.014	0.019	0.022	0.014	0.017	0.017	0.020	0.024	0.040
bias	0.336	-0.057	0.131	0.165	0.054	0.110	0.074	0.074	0.080	0.040	0.047	0.026	0.035	-0.015
ese	0.006	0.005	0.008	0.008	0.032	0.013	0.022	0.029	0.014	0.021	0.020	0.025	0.024	0.030
$\gamma_1 = 0, \gamma_2 = 0.8, \gamma_3 = [0, 0.8]$														
bias	-0.002	-0.138	-0.041	-0.016	-0.002	0.050	0.009	0.008	0.022	-0.003	0.001	-0.011	-0.009	-0.056
ese	0.006	0.004	0.006	0.007	0.018	0.014	0.020	0.025	0.015	0.017	0.017	0.019	0.024	0.031
bias	0.230	-0.084	0.051	0.083	0.045	0.116	0.066	0.066	0.077	0.029	0.039	0.020	0.028	-0.027
ese	0.007	0.004	0.007	0.008	0.031	0.014	0.025	0.034	0.015	0.023	0.021	0.025	0.026	0.025
$\gamma_1 = 0.25, \gamma_2 = 0, \gamma_3 = [0, 0.8]$														
bias	0.232	-0.080	0.134	0.138	0.010	0.059	0.053	0.029	0.063	0.059	0.059	0.005	0.017	-0.016
ese	0.004	0.007	0.006	0.006	0.018	0.012	0.013	0.019	0.013	0.013	0.014	0.021	0.023	0.042
bias	0.322	-0.038	0.134	0.167	0.052	0.105	0.106	0.073	0.089	0.099	0.093	0.031	0.040	-0.009
ese	0.004	0.005	0.007	0.007	0.031	0.012	0.012	0.025	0.012	0.012	0.015	0.025	0.023	0.031
$\gamma_1 = 0.8, \gamma_2 = 0, \gamma_3 = [0, 0.8]$														
bias	0.148	-0.080	0.077	0.076	0.010	0.042	0.042	0.030	0.046	0.039	0.039	0.008	0.018	-0.017
ese	0.004	0.007	0.006	0.006	0.017	0.012	0.012	0.016	0.013	0.013	0.013	0.020	0.021	0.044
bias	0.238	-0.038	0.099	0.118	0.051	0.085	0.086	0.067	0.089	0.075	0.073	0.038	0.039	-0.009
ese	0.003	0.005	0.006	0.006	0.028	0.010	0.012	0.019	0.011	0.011	0.014	0.025	0.019	0.032
$\gamma_1 = 0.25, \gamma_2 = 0.25, \gamma_3 = [0, 0.8]$														
bias	0.177	-0.110	0.081	0.091	0.007	0.061	0.054	0.029	0.066	0.061	0.061	0.001	0.012	-0.029
ese	0.005	0.006	0.007	0.006	0.018	0.013	0.014	0.021	0.013	0.014	0.014	0.020	0.023	0.040
bias	0.294	-0.057	0.103	0.135	0.047	0.108	0.107	0.072	0.090	0.100	0.095	0.032	0.041	-0.015
ese	0.004	0.005	0.007	0.007	0.030	0.012	0.013	0.026	0.013	0.013	0.015	0.026	0.023	0.030

Note: Bias and empirical standard error, $ese = 1/R \sum_{r=1}^{R} se_{\rho_r}$, R = 1000 replications for each setting. Estimates are implemented in Stata using `xtdpdgmm` (Kripfganz, 2019), one-step cluster standard errors. Variances are defined by Equations (A13.4) and (A13.7).

Table A13.3: MonteCarlo results for ρ, ARDL(1,0) with $\rho = 0.5$, $\beta_1 = 1$ and $\beta_3 = 0.1$

Macro panel $N = 25$, $T = 40$. Parameter ρ														
	RE	FE	CRE1	CRE2	GL	CRE-GMM	CRE-GMM1	CRE-GMM2	CRE-GMM3	CRE-GMM4	CRE-GMM5	GS	GSC	KS2
$\gamma_1 = 0, \gamma_2 = 0, \gamma_3 = [0, 0.8]$														
bias	0.274	-0.017	0.147	0.104	0.186	0.057	0.056	0.056	0.043	0.043	0.042	0.056	-0.006	-0.073
ese	0.014	0.019	0.035	0.031	0.028	0.030	0.030	0.030	0.028	0.028	0.028	0.035	0.036	0.051
bias	0.421	-0.008	0.194	0.119	0.370	0.070	0.069	0.069	0.050	0.050	0.049	0.252	0.014	-0.043
ese	0.009	0.013	0.040	0.032	0.021	0.029	0.029	0.029	0.026	0.026	0.026	0.032	0.028	0.033
$\gamma_1 = 0, \gamma_2 = 0.25, \gamma_3 = [0, 0.8]$														
bias	0.187	-0.058	0.096	0.054	0.110	0.017	0.016	0.016	-0.002	-0.003	-0.003	0.049	-0.038	-0.107
ese	0.016	0.018	0.032	0.030	0.030	0.030	0.029	0.030	0.027	0.027	0.027	0.033	0.033	0.044
bias	0.400	-0.028	0.177	0.098	0.341	0.052	0.051	0.051	0.031	0.031	0.030	0.159	-0.005	-0.062
ese	0.010	0.012	0.040	0.032	0.023	0.028	0.028	0.028	0.025	0.025	0.025	0.033	0.027	0.032
$\gamma_1 = 0, \gamma_2 = 0.8, \gamma_3 = [0, 0.8]$														
bias	0.094	-0.109	0.029	-0.010	0.032	-0.044	-0.045	-0.045	-0.058	-0.059	-0.059	-0.026	-0.093	-0.146
ese	0.020	0.012	0.030	0.026	0.026	0.025	0.025	0.025	0.022	0.022	0.022	0.028	0.024	0.028
bias	0.351	-0.061	0.141	0.063	0.291	0.019	0.018	0.018	-0.001	-0.001	-0.001	0.206	-0.037	-0.093
ese	0.021	0.010	0.044	0.032	0.026	0.028	0.028	0.028	0.025	0.025	0.025	0.033	0.023	0.026
$\gamma_1 = 0.25, \gamma_2 = 0, \gamma_3 = [0, 0.8]$														
bias	0.212	-0.017	0.099	0.087	0.147	0.047	0.046	0.046	0.053	0.050	0.048	0.096	-0.004	-0.079
ese	0.014	0.019	0.027	0.026	0.026	0.029	0.029	0.029	0.027	0.028	0.028	0.034	0.036	0.051
bias	0.358	-0.008	0.150	0.109	0.329	0.064	0.063	0.063	0.060	0.060	0.059	0.234	0.014	-0.042
ese	0.009	0.013	0.032	0.028	0.019	0.027	0.027	0.027	0.025	0.025	0.025	0.029	0.027	0.033
$\gamma_1 = 0.8, \gamma_2 = 0, \gamma_3 = [0, 0.8]$														
bias	0.155	-0.017	0.058	0.056	0.127	0.030	0.029	0.029	0.044	0.036	0.027	0.081	-0.011	-0.074
ese	0.012	0.019	0.021	0.021	0.022	0.026	0.026	0.026	0.025	0.025	0.026	0.029	0.035	0.049
bias	0.255	-0.008	0.097	0.085	0.249	0.050	0.049	0.049	0.063	0.054	0.047	0.218	0.010	-0.042
ese	0.007	0.013	0.023	0.022	0.016	0.023	0.023	0.023	0.023	0.023	0.023	0.019	0.025	0.033
$\gamma_1 = 0.25, \gamma_2 = 0.25, \gamma_3 = [0, 0.8]$														
bias	0.203	-0.058	0.064	0.048	0.150	0.013	0.013	0.012	0.018	0.014	0.011	0.021	-0.041	-0.109
ese	0.013	0.017	0.028	0.027	0.026	0.028	0.028	0.028	0.027	0.028	0.028	0.032	0.033	0.045
bias	0.311	-0.029	0.127	0.087	0.264	0.044	0.044	0.043	0.041	0.041	0.040	0.251	-0.005	-0.066
ese	0.011	0.012	0.032	0.028	0.022	0.026	0.025	0.026	0.025	0.025	0.025	0.027	0.026	0.032

Note: Bias and empirical standard error, $ese = 1/R \sum_{r=1}^{R} se_{\rho_r}$, $R = 1000$ replications for each setting. Estimates are implemented in Stata using `xtdpdgmm` (Kripfganz, 2019), one-step cluster standard errors. Variances are defined by Equations (A13.4) and (A13.7).

Table A13.4: Monte Carlo results for ρ, ARDL(1,0) with $\rho = 0.5$, $\beta_1 = 1$ and $\beta_3 = 0.1$

Multilevel panel $N = 100$, $T = 20$. Parameter ρ														
	RE	FE	CRE1	CRE2	GL	CRE-GMM	CRE-GMM1	CRE-GMM2	CRE-GMM3	CRE-GMM4	CRE-GMM5	GS	GSC	KS2
$\gamma_1 = 0, \gamma_2 = 0, \gamma_3 = [0, 0.8]$														
bias	0.243	-0.035	0.158	0.142	0.070	0.039	0.038	0.037	0.032	0.031	0.030	0.028	0.005	-0.064
ese	0.009	0.014	0.018	0.018	0.029	0.025	0.025	0.026	0.025	0.025	0.025	0.035	0.034	0.059
bias	0.394	-0.016	0.216	0.186	0.229	0.067	0.065	0.066	0.048	0.047	0.047	0.163	0.027	-0.035
ese	0.010	0.010	0.022	0.019	0.038	0.024	0.024	0.026	0.023	0.024	0.023	0.041	0.028	0.040
$\gamma_1 = 0, \gamma_2 = 0.25, \gamma_3 = [0, 0.8]$														
bias	0.208	-0.073	0.123	0.104	0.054	0.022	0.020	0.020	0.008	0.007	0.007	0.006	-0.015	-0.092
ese	0.010	0.013	0.018	0.018	0.029	0.024	0.024	0.026	0.025	0.025	0.025	0.033	0.032	0.051
bias	0.381	-0.036	0.193	0.170	0.229	0.059	0.057	0.058	0.038	0.037	0.037	0.128	0.015	-0.052
ese	0.013	0.009	0.025	0.019	0.037	0.024	0.024	0.027	0.025	0.025	0.025	0.040	0.026	0.037
$\gamma_1 = 0, \gamma_2 = 0.8, \gamma_3 = [0, 0.8]$														
bias	0.037	-0.117	-0.001	0.010	-0.008	-0.024	-0.026	-0.027	-0.037	-0.037	-0.038	-0.051	-0.065	-0.141
ese	0.019	0.009	0.019	0.019	0.027	0.022	0.022	0.025	0.023	0.023	0.022	0.028	0.026	0.035
bias	0.302	-0.067	0.112	0.108	0.204	0.043	0.041	0.041	0.019	0.018	0.018	0.115	-0.007	-0.084
ese	0.019	0.008	0.025	0.025	0.040	0.024	0.024	0.028	0.025	0.025	0.025	0.040	0.025	0.030
$\gamma_1 = 0.25, \gamma_2 = 0, \gamma_3 = [0, 0.8]$														
bias	0.244	-0.035	0.129	0.126	0.091	0.041	0.040	0.039	0.065	0.048	0.046	0.031	0.006	-0.062
ese	0.009	0.014	0.016	0.016	0.030	0.023	0.023	0.024	0.023	0.025	0.024	0.033	0.033	0.057
bias	0.356	-0.017	0.175	0.164	0.245	0.064	0.063	0.060	0.076	0.065	0.064	0.169	0.026	-0.033
ese	0.007	0.010	0.019	0.016	0.034	0.022	0.023	0.024	0.023	0.024	0.024	0.037	0.027	0.039
$\gamma_1 = 0.8, \gamma_2 = 0, \gamma_3 = [0, 0.8]$														
bias	0.147	-0.035	0.071	0.070	0.063	0.024	0.024	0.022	0.048	0.027	0.023	0.041	0.002	-0.060
ese	0.009	0.014	0.013	0.013	0.025	0.022	0.022	0.023	0.022	0.024	0.023	0.031	0.032	0.056
bias	0.252	-0.016	0.116	0.116	0.204	0.049	0.048	0.046	0.084	0.049	0.046	0.149	0.020	-0.034
ese	0.005	0.010	0.013	0.012	0.026	0.019	0.020	0.020	0.019	0.021	0.021	0.031	0.025	0.040
$\gamma_1 = 0.25, \gamma_2 = 0.25, \gamma_3 = [0, 0.8]$														
bias	0.179	-0.073	0.079	0.076	0.052	0.018	0.018	0.016	0.042	0.027	0.024	0.010	-0.015	-0.094
ese	0.009	0.013	0.016	0.016	0.029	0.023	0.023	0.024	0.023	0.025	0.024	0.033	0.031	0.053
bias	0.327	-0.036	0.148	0.144	0.213	0.054	0.053	0.051	0.067	0.056	0.054	0.148	0.015	-0.053
ese	0.010	0.009	0.021	0.017	0.036	0.022	0.022	0.024	0.022	0.024	0.024	0.039	0.026	0.038

Note: Bias and empirical standard error, $ese = 1/R \sum_{r=1}^{R} se_{\rho_r}$, $R = 1000$ replications for each setting. Estimates are implemented in Stata using `xtdpdgmm` (Kripfganz, 2019), one-step cluster standard errors. Variances are defined by Equations (A13.4) and (A13.7).

Table A13.5: MonteCarlo results for β_1, ARDL(1,0) with $\rho = 0.5$, $\beta_1 = 1$ and $\beta_3 = 0.1$

Longitudinal panel N = 1000, T = 10. Parameter β_1															
	RE	FE	CRE1	CRE2	GL	CRE-GMM	CRE-GMM1	CRE-GMM2	CRE-GMM3	CRE-GMM4	CRE-GMM5	GS	GSC	KS2
$\gamma_1 = 0, \gamma_2 = 0, \gamma_3 = [0, 0.8]$															
bias	-0.168	0.017	-0.119	-0.109	-0.018	-0.065	-0.034	-0.033	-0.108	-0.045	-0.040	-0.002	-0.010	0.013
ese	0.013	0.012	0.013	0.013	0.048	0.043	0.045	0.051	0.041	0.045	0.043	0.045	0.045	0.048
bias	-0.169	0.008	-0.083	-0.108	-0.102	-0.144	-0.098	-0.093	-0.207	-0.107	-0.098	-0.039	-0.040	0.007
ese	0.011	0.007	0.010	0.011	0.066	0.038	0.046	0.049	0.040	0.049	0.043	0.039	0.034	0.035
$\gamma_1 = 0, \gamma_2 = 0.25, \gamma_3 = [0, 0.8]$															
bias	0.046	0.231	0.095	0.078	-0.009	-0.080	-0.031	-0.028	-0.110	-0.033	-0.032	0.004	-0.007	0.041
ese	0.015	0.011	0.014	0.013	0.054	0.048	0.053	0.055	0.048	0.053	0.052	0.049	0.049	0.058
bias	-0.090	0.088	0.001	-0.022	-0.110	-0.164	-0.109	-0.103	-0.219	-0.109	-0.103	-0.037	-0.041	0.019
ese	0.011	0.007	0.009	0.010	0.073	0.040	0.051	0.052	0.043	0.052	0.047	0.040	0.035	0.037
$\gamma_1 = 0, \gamma_2 = 0.8, \gamma_3 = [0, 0.8]$															
bias	0.393	0.464	0.414	0.399	0.017	-0.089	-0.003	-0.000	-0.073	0.016	0.009	0.034	0.026	0.116
ese	0.009	0.008	0.009	0.010	0.054	0.052	0.056	0.056	0.052	0.055	0.054	0.051	0.053	0.061
bias	0.088	0.223	0.163	0.146	-0.102	-0.200	-0.113	-0.107	-0.232	-0.086	-0.095	-0.032	-0.039	0.045
ese	0.009	0.006	0.008	0.008	0.073	0.047	0.059	0.060	0.050	0.058	0.055	0.046	0.042	0.039
$\gamma_1 = 0.25, \gamma_2 = 0, \gamma_3 = [0, 0.8]$															
bias	-0.034	0.017	-0.014	-0.015	-0.006	-0.023	0.003	-0.018	0.017	-0.019	-0.019	-0.002	-0.009	0.010
ese	0.013	0.011	0.012	0.012	0.049	0.041	0.047	0.050	0.040	0.044	0.045	0.043	0.043	0.046
bias	-0.077	0.008	-0.030	-0.051	-0.083	-0.102	-0.073	-0.071	-0.099	-0.079	-0.084	-0.035	-0.035	0.007
ese	0.009	0.007	0.008	0.009	0.061	0.034	0.040	0.042	0.033	0.034	0.035	0.037	0.031	0.035
$\gamma_1 = 0.8, \gamma_2 = 0, \gamma_3 = [0, 0.8]$															
bias	0.061	0.017	0.042	0.042	0.023	0.014	0.014	0.005	0.082	0.000	0.004	0.007	-0.000	0.008
ese	0.012	0.012	0.011	0.011	0.048	0.039	0.043	0.045	0.037	0.042	0.044	0.044	0.044	0.048
bias	0.013	0.008	0.015	0.006	-0.038	-0.047	-0.041	-0.037	-0.030	-0.044	-0.046	-0.028	-0.024	0.007
ese	0.009	0.007	0.008	0.008	0.056	0.030	0.032	0.035	0.030	0.031	0.031	0.037	0.030	0.035
$\gamma_1 = 0.25, \gamma_2 = 0.25, \gamma_3 = [0, 0.8]$															
bias	0.179	0.231	0.199	0.192	0.002	-0.039	-0.007	-0.016	0.000	-0.033	-0.032	0.008	-0.004	0.040
ese	0.014	0.012	0.013	0.012	0.054	0.047	0.052	0.053	0.046	0.049	0.050	0.048	0.048	0.057
bias	0.010	0.088	0.055	0.037	-0.077	-0.118	-0.083	-0.074	-0.108	-0.091	-0.095	-0.039	-0.040	0.019
ese	0.010	0.007	0.008	0.009	0.066	0.038	0.043	0.045	0.037	0.037	0.037	0.043	0.035	0.037

Note: Bias and empirical standard error, $ese = 1/R \sum_{r=1}^{R} se_{\beta_{1r}}$, R = 1000 replications for each setting. Estimates are implemented in Stata using `xtdpdgmm` (Kripfganz, 2019), one-step cluster standard errors. Variances are defined by Equations (A13.4) and (A13.7).

Table A13.6: Mont Carlo results for β_1, ARDL(1,0) with $\rho = 0.5$, $\beta_1 = 1$ and $\beta_3 = 0.1$

Macro panel $N = 25$, $T = 40$. Parameter β_1														
	RE	FE	CRE1	CRE2	GL	CRE-GMM	CRE-GMM1	CRE-GMM2	CRE-GMM3	CRE-GMM4	CRE-GMM5	GS	GSC	KS2
$\gamma_1 = 0, \gamma_2 = 0, \gamma_3 = [0, 0.8]$														
bias	-0.182	0.009	-0.098	-0.067	-0.197	-0.061	-0.060	-0.059	-0.065	-0.064	-0.063	-0.045	0.001	0.030
ese	0.042	0.032	0.041	0.038	0.075	0.065	0.065	0.065	0.065	0.065	0.065	0.074	0.071	0.072
bias	-0.276	0.004	-0.128	-0.076	-0.399	-0.077	-0.076	-0.075	-0.074	-0.073	-0.072	-0.204	-0.013	0.019
ese	0.035	0.019	0.037	0.030	0.062	0.048	0.048	0.047	0.047	0.047	0.047	0.057	0.044	0.041
$\gamma_1 = 0, \gamma_2 = 0.25, \gamma_3 = [0, 0.8]$														
bias	0.030	0.219	0.101	0.136	-0.019	0.100	0.101	0.101	0.102	0.103	0.103	0.062	0.150	0.200
ese	0.042	0.031	0.043	0.039	0.075	0.066	0.067	0.067	0.067	0.067	0.068	0.077	0.069	0.069
bias	-0.213	0.084	-0.058	-0.000	-0.354	-0.017	-0.016	-0.015	-0.011	-0.011	-0.010	-0.104	0.044	0.082
ese	0.036	0.019	0.039	0.031	0.065	0.050	0.049	0.049	0.049	0.049	0.049	0.059	0.046	0.043
$\gamma_1 = 0, \gamma_2 = 0.8, \gamma_3 = [0, 0.8]$														
bias	0.284	0.461	0.341	0.379	0.201	0.316	0.317	0.317	0.327	0.327	0.328	0.258	0.346	0.407
ese	0.038	0.021	0.039	0.035	0.066	0.057	0.057	0.057	0.055	0.055	0.055	0.060	0.052	0.047
bias	-0.092	0.221	0.067	0.130	-0.266	0.090	0.091	0.092	0.100	0.101	0.102	-0.121	0.143	0.194
ese	0.041	0.017	0.044	0.032	0.071	0.052	0.052	0.052	0.049	0.049	0.049	0.061	0.041	0.037
$\gamma_1 = 0.25, \gamma_2 = 0, \gamma_3 = [0, 0.8]$														
bias	-0.029	0.008	-0.012	-0.010	-0.038	-0.009	-0.009	-0.008	-0.005	-0.005	-0.006	0.005	0.020	0.031
ese	0.036	0.032	0.034	0.033	0.070	0.062	0.062	0.062	0.061	0.062	0.062	0.074	0.070	0.069
bias	-0.144	0.005	-0.059	-0.042	-0.245	-0.048	-0.047	-0.047	-0.045	-0.045	-0.044	-0.126	-0.004	0.019
ese	0.031	0.019	0.028	0.026	0.060	0.044	0.044	0.044	0.042	0.042	0.042	0.056	0.044	0.042
$\gamma_1 = 0.8, \gamma_2 = 0, \gamma_3 = [0, 0.8]$														
bias	0.067	0.010	0.030	0.029	0.098	0.027	0.027	0.028	0.037	0.032	0.027	0.081	0.033	0.028
ese	0.033	0.032	0.032	0.032	0.063	0.059	0.059	0.060	0.058	0.058	0.058	0.074	0.071	0.071
bias	-0.014	0.005	-0.003	-0.002	-0.055	-0.009	-0.009	-0.009	-0.011	-0.010	-0.009	-0.032	0.008	0.017
ese	0.025	0.019	0.022	0.021	0.054	0.040	0.040	0.040	0.039	0.039	0.039	0.053	0.043	0.041
$\gamma_1 = 0.25, \gamma_2 = 0.25, \gamma_3 = [0, 0.8]$														
bias	0.171	0.220	0.196	0.199	0.102	0.154	0.154	0.155	0.160	0.160	0.160	0.153	0.171	0.199
ese	0.038	0.031	0.035	0.035	0.076	0.062	0.062	0.062	0.062	0.063	0.063	0.073	0.069	0.069
bias	-0.060	0.085	0.019	0.037	-0.161	0.016	0.017	0.017	0.019	0.020	0.021	-0.109	0.053	0.083
ese	0.032	0.019	0.028	0.026	0.062	0.044	0.044	0.044	0.043	0.043	0.043	0.059	0.044	0.042

Note: Bias and empirical standard error, $ese = 1/R \sum_{r=1}^{R} se_{\beta_{1r}}$, $R = 1000$ replications for each setting. Estimates are implemented in Stata using `xtdpdgmm` (Kripfganz, 2019), one-step cluster standard errors. Variances are defined by Equations (A13.4) and (A13.7).

Table A13.7: Monte Carlo results for β_1, ARDL(1,0) with $\rho = 0.5$, $\beta_1 = 1$ and $\beta_3 = 0.1$

Multilevel panel $N = 100$, $T = 20$. Parameter β_1														
	RE	FE	CRE1	CRE2	GL	CRE-GMM	CRE-GMM1	CRE-GMM2	CRE-GMM3	CRE-GMM4	CRE-GMM5	GS	GSC	KS2
$\gamma_1 = 0, \gamma_2 = 0, \gamma_3 = [0, 0.8]$														
bias	-0.161	0.015	-0.107	-0.092	-0.112	-0.064	-0.062	-0.059	-0.068	-0.065	-0.063	-0.033	-0.011	0.034
ese	0.028	0.024	0.028	0.027	0.080	0.071	0.071	0.071	0.071	0.071	0.071	0.074	0.072	0.072
bias	-0.253	0.007	-0.142	-0.120	-0.367	-0.108	-0.104	-0.101	-0.102	-0.100	-0.097	-0.187	-0.032	0.024
ese	0.026	0.014	0.026	0.022	0.087	0.057	0.056	0.056	0.056	0.056	0.055	0.068	0.051	0.049
$\gamma_1 = 0, \gamma_2 = 0.25, \gamma_3 = [0, 0.8]$														
bias	0.016	0.226	0.079	0.099	-0.053	0.009	0.012	0.014	0.016	0.018	0.021	0.034	0.063	0.144
ese	0.031	0.023	0.030	0.029	0.089	0.076	0.076	0.076	0.077	0.076	0.077	0.078	0.075	0.077
bias	-0.188	0.087	-0.067	-0.050	-0.378	-0.083	-0.080	-0.077	-0.072	-0.069	-0.067	-0.150	-0.006	0.064
ese	0.028	0.014	0.028	0.023	0.096	0.061	0.061	0.061	0.060	0.060	0.060	0.070	0.051	0.049
$\gamma_1 = 0, \gamma_2 = 0.8, \gamma_3 = [0, 0.8]$														
bias	0.343	0.463	0.373	0.363	0.126	0.164	0.167	0.169	0.187	0.189	0.190	0.186	0.209	0.323
ese	0.026	0.015	0.024	0.024	0.077	0.067	0.068	0.068	0.066	0.067	0.067	0.068	0.063	0.061
bias	-0.022	0.222	0.103	0.103	-0.350	-0.032	-0.029	-0.027	-0.008	-0.006	-0.005	-0.141	0.049	0.148
ese	0.027	0.012	0.024	0.025	0.103	0.062	0.063	0.063	0.060	0.060	0.060	0.082	0.049	0.043
$\gamma_1 = 0.25, \gamma_2 = 0, \gamma_3 = [0, 0.8]$														
bias	-0.034	0.015	-0.015	-0.015	-0.041	-0.019	-0.017	-0.017	0.007	-0.009	-0.011	-0.005	0.005	0.034
ese	0.027	0.024	0.025	0.025	0.079	0.068	0.068	0.069	0.068	0.069	0.069	0.074	0.073	0.073
bias	-0.142	0.007	-0.070	-0.066	-0.296	-0.070	-0.068	-0.066	-0.070	-0.067	-0.065	-0.149	-0.021	0.023
ese	0.023	0.015	0.021	0.020	0.080	0.053	0.053	0.053	0.053	0.054	0.054	0.065	0.049	0.048
$\gamma_1 = 0.8, \gamma_2 = 0, \gamma_3 = [0, 0.8]$														
bias	0.061	0.014	0.034	0.034	0.089	0.020	0.020	0.020	0.060	0.027	0.020	0.039	0.016	0.029
ese	0.024	0.024	0.024	0.024	0.070	0.065	0.066	0.066	0.065	0.068	0.068	0.076	0.075	0.076
bias	-0.016	0.007	-0.004	-0.005	-0.099	-0.022	-0.022	-0.021	-0.031	-0.026	-0.023	-0.072	-0.006	0.022
ese	0.018	0.015	0.017	0.017	0.068	0.047	0.047	0.047	0.048	0.047	0.047	0.059	0.049	0.049
$\gamma_1 = 0.25, \gamma_2 = 0.25, \gamma_3 = [0, 0.8]$														
bias	0.173	0.226	0.193	0.193	0.043	0.067	0.067	0.068	0.085	0.079	0.078	0.062	0.078	0.144
ese	0.028	0.024	0.026	0.026	0.081	0.071	0.072	0.072	0.073	0.073	0.073	0.078	0.075	0.077
bias	-0.061	0.087	0.012	0.011	-0.260	-0.041	-0.039	-0.037	-0.041	-0.037	-0.034	-0.133	0.005	0.066
ese	0.024	0.015	0.021	0.020	0.086	0.054	0.054	0.054	0.054	0.054	0.054	0.069	0.050	0.049

Note: Bias and empirical standard error, $ese = 1/R \sum_{r=1}^{R} se_{\beta_{1r}}$, $R = 1000$ replications for each setting. Estimates are implemented in Stata using `xtdpdgmm` (Kripfganz, 2019), one-step cluster standard errors. Variances are defined by Equations (A13.4) and (A13.7).

Table A13.8: Monte Carlo results for β_3, ARDL(1,0) with $\rho = 0.5$, $\beta_1 = 1$ and $\beta_3 = 0.1$

Longitudinal panel $N = 1000$, $T = 10$. Parameter β_3														
	RE	FE	CRE1	CRE2	GL	CRE-GMM	CRE-GMM1	CRE-GMM2	CRE-GMM3	CRE-GMM4	CRE-GMM5	GS	GSC	KS2
$\gamma_1 = 0, \gamma_2 = 0, \gamma_3 = [0, 0.8]$														
bias	-0.263	-	-0.342	-0.335	-0.009	-0.280	-0.134	-0.126	-0.268	-0.098	-0.130	0.297	0.169	0.318
ese	0.011	-	0.011	0.011	0.024	0.014	0.077	0.080	0.014	0.069	0.075	0.026	0.109	0.050
bias	-0.385	-	-0.476	-0.451	-0.041	-0.426	-0.284	-0.275	-0.409	-0.194	-0.268	0.275	0.033	0.310
ese	0.012	-	0.011	0.010	0.040	0.013	0.073	0.078	0.013	0.065	0.069	0.037	0.085	0.042
$\gamma_1 = 0, \gamma_2 = 0.25, \gamma_3 = [0, 0.8]$														
bias	-0.226	-	-0.326	-0.328	-0.005	-0.256	-0.108	-0.104	-0.243	-0.078	-0.105	0.299	0.188	0.327
ese	0.014	-	0.013	0.011	0.023	0.014	0.078	0.081	0.014	0.064	0.075	0.025	0.102	0.042
bias	-0.373	-	-0.481	-0.454	-0.041	-0.418	-0.276	-0.271	-0.401	-0.189	-0.261	0.276	0.053	0.314
ese	0.013	-	0.012	0.011	0.040	0.012	0.073	0.077	0.013	0.065	0.071	0.035	0.082	0.040
$\gamma_1 = 0, \gamma_2 = 0.8, \gamma_3 = [0, 0.8]$														
bias	-0.072	-	-0.225	-0.239	0.000	-0.201	-0.053	-0.049	-0.185	-0.030	-0.049	0.308	0.268	0.346
ese	0.018	-	0.017	0.016	0.022	0.014	0.063	0.066	0.015	0.045	0.058	0.024	0.081	0.033
bias	-0.283	-	-0.462	-0.438	-0.035	-0.389	-0.222	-0.215	-0.372	-0.136	-0.205	0.284	0.108	0.325
ese	0.019	-	0.015	0.013	0.038	0.013	0.071	0.076	0.014	0.060	0.067	0.037	0.082	0.039
$\gamma_1 = 0.25, \gamma_2 = 0, \gamma_3 = [0, 0.8]$														
bias	-0.263	-	-0.305	-0.308	-0.009	-0.282	-0.226	-0.149	-0.285	-0.313	-0.312	0.294	0.142	0.317
ese	0.008	-	0.009	0.009	0.024	0.011	0.054	0.071	0.010	0.019	0.028	0.027	0.092	0.049
bias	-0.360	-	-0.406	-0.405	-0.044	-0.393	-0.346	-0.277	-0.391	-0.377	-0.384	0.270	0.033	0.309
ese	0.009	-	0.009	0.008	0.040	0.010	0.037	0.066	0.010	0.012	0.016	0.037	0.073	0.045
$\gamma_1 = 0.8, \gamma_2 = 0, \gamma_3 = [0, 0.8]$														
bias	-0.183	-	-0.198	-0.197	-0.015	-0.192	-0.193	-0.146	-0.185	-0.226	-0.221	0.289	0.147	0.318
ese	0.007	-	0.007	0.008	0.023	0.010	0.030	0.051	0.010	0.015	0.025	0.026	0.072	0.051
bias	-0.278	-	-0.291	-0.299	-0.053	-0.299	-0.293	-0.242	-0.298	-0.307	-0.311	0.263	0.056	0.311
ese	0.006	-	0.007	0.006	0.038	0.008	0.018	0.045	0.008	0.009	0.013	0.036	0.057	0.045
$\gamma_1 = 0.25, \gamma_2 = 0.25, \gamma_3 = [0, 0.8]$														
bias	-0.237	-	-0.287	-0.293	-0.008	-0.270	-0.208	-0.137	-0.274	-0.303	-0.301	0.297	0.178	0.327
ese	0.011	-	0.010	0.010	0.024	0.011	0.049	0.068	0.011	0.019	0.027	0.025	0.089	0.043
bias	-0.343	-	-0.402	-0.401	-0.040	-0.386	-0.330	-0.259	-0.384	-0.369	-0.376	0.269	0.035	0.314
ese	0.011	-	0.011	0.009	0.039	0.010	0.038	0.064	0.010	0.013	0.016	0.037	0.074	0.041

Note: Bias and empirical standard error, $ese = 1/R \sum_{r=1}^{R} se_{\beta_{3r}}$, $R = 1000$ replications for each setting. Estimates are implemented in Stata using `xtdpdgmm` (Kripfganz, 2019), one-step cluster standard errors. Variances are defined by Equations (A13.4) and (A13.7).

Table A13.9: Monte Carlo results for β_3, ARDL(1,0) with $\rho = 0.5$, $\beta_1 = 1$ and $\beta_3 = 0.1$

Macro panel $N = 25$, $T = 40$. Parameter β_3														
	RE	FE	CRE1	CRE2	GL	CRE-GMM	CRE-GMM1	CRE-GMM2	CRE-GMM3	CRE-GMM4	CRE-GMM5	GS	GSC	KS2
$\gamma_1 = 0, \gamma_2 = 0, \gamma_3 = [0, 0.8]$														
bias	-0.285	-	-0.415	-0.385	-0.179	-0.364	-0.365	-0.367	-0.357	-0.359	-0.359	0.240	-0.031	0.375
ese	0.060	-	0.063	0.063	0.082	0.070	0.079	0.082	0.072	0.081	0.085	0.100	0.102	0.132
bias	-0.439	-	-0.514	-0.451	-0.356	-0.437	-0.437	-0.440	-0.431	-0.432	-0.433	0.041	-0.133	0.342
ese	0.042	-	0.055	0.051	0.064	0.058	0.061	0.062	0.061	0.063	0.065	0.113	0.072	0.230
$\gamma_1 = 0, \gamma_2 = 0.25, \gamma_3 = [0, 0.8]$														
bias	-0.222	-	-0.370	-0.356	-0.123	-0.329	-0.327	-0.329	-0.318	-0.318	-0.318	0.232	-0.056	0.390
ese	0.068	-	0.071	0.071	0.086	0.077	0.085	0.087	0.080	0.087	0.089	0.123	0.107	0.167
bias	-0.427	-	-0.514	-0.449	-0.332	-0.431	-0.430	-0.434	-0.426	-0.425	-0.426	0.132	-0.110	0.355
ese	0.049	-	0.062	0.057	0.074	0.063	0.065	0.066	0.066	0.068	0.070	0.114	0.079	0.178
$\gamma_1 = 0, \gamma_2 = 0.8, \gamma_3 = [0, 0.8]$														
bias	-0.162	-	-0.313	-0.326	-0.074	-0.294	-0.292	-0.294	-0.287	-0.285	-0.287	0.296	-0.022	0.411
ese	0.092	-	0.089	0.085	0.104	0.091	0.098	0.099	0.093	0.099	0.101	0.149	0.124	0.180
bias	-0.392	-	-0.510	-0.445	-0.289	-0.422	-0.422	-0.426	-0.417	-0.417	-0.419	0.091	-0.124	0.391
ese	0.068	-	0.070	0.063	0.089	0.069	0.072	0.074	0.072	0.075	0.077	0.148	0.087	0.279
$\gamma_1 = 0.25, \gamma_2 = 0, \gamma_3 = [0, 0.8]$														
bias	-0.240	-	-0.315	-0.325	-0.162	-0.314	-0.313	-0.314	-0.316	-0.322	-0.324	0.181	-0.034	0.375
ese	0.046	-	0.049	0.049	0.068	0.056	0.062	0.065	0.055	0.060	0.062	0.096	0.079	0.160
bias	-0.392	-	-0.428	-0.415	-0.341	-0.408	-0.408	-0.410	-0.408	-0.408	-0.409	0.052	-0.103	0.348
ese	0.035	-	0.045	0.042	0.054	0.048	0.049	0.050	0.049	0.050	0.051	0.098	0.060	0.224
$\gamma_1 = 0.8, \gamma_2 = 0, \gamma_3 = [0, 0.8]$														
bias	-0.191	-	-0.210	-0.216	-0.164	-0.214	-0.214	-0.214	-0.214	-0.230	-0.219	0.190	0.092	0.381
ese	0.025	-	0.030	0.037	0.037	0.043	0.052	0.054	0.040	0.049	0.052	0.068	0.074	0.180
bias	-0.294	-	-0.302	-0.320	-0.279	-0.322	-0.321	-0.321	-0.322	-0.328	-0.324	0.056	-0.021	0.369
ese	0.023	-	0.031	0.034	0.034	0.040	0.042	0.043	0.037	0.040	0.042	0.062	0.051	0.281
$\gamma_1 = 0.25, \gamma_2 = 0.25, \gamma_3 = [0, 0.8]$														
bias	-0.267	-	-0.331	-0.341	-0.191	-0.334	-0.333	-0.333	-0.335	-0.340	-0.342	0.248	0.008	0.390
ese	0.048	-	0.051	0.054	0.074	0.062	0.065	0.068	0.060	0.064	0.065	0.100	0.091	0.137
bias	-0.354	-	-0.412	-0.404	-0.282	-0.395	-0.394	-0.396	-0.395	-0.394	-0.396	0.028	-0.109	0.363
ese	0.043	-	0.050	0.047	0.066	0.053	0.054	0.056	0.053	0.054	0.056	0.099	0.064	0.268

Note: Bias and empirical standard error, $ese = 1/R \sum_{r=1}^{R} se_{\beta_{3r}}$, $R = 1000$ replications for each setting. Estimates are implemented in Stata using `xtdpdgmm` (Kripfganz, 2019), one-step cluster standard errors. Variances are defined by Equations (A13.4) and (A13.7).

Table A13.10: Monte Carlo results for β_3, ARDL(1,0) with $\rho = 0.5$, $\beta_1 = 1$ and $\beta_3 = 0.1$

Multilevel panel N = 100, T = 20. Parameter β_3														
	RE	FE	CRE1	CRE2	GL	CRE-GMM	CRE-GMM1	CRE-GMM2	CRE-GMM3	CRE-GMM4	CRE-GMM5	GS	GSC	KS2
$\gamma_1 = 0, \gamma_2 = 0, \gamma_3 = [0, 0.8]$														
bias	-0.252	-	-0.355	-0.344	-0.059	-0.291	-0.285	-0.288	-0.287	-0.282	-0.281	0.272	0.010	0.366
ese	0.029	-	0.032	0.031	0.052	0.041	0.074	0.081	0.041	0.075	0.079	0.062	0.102	0.091
bias	-0.411	-	-0.485	-0.451	-0.200	-0.419	-0.416	-0.420	-0.415	-0.413	-0.409	0.146	-0.127	0.338
ese	0.025	-	0.028	0.026	0.055	0.035	0.051	0.058	0.036	0.052	0.055	0.077	0.066	0.112
$\gamma_1 = 0, \gamma_2 = 0.25, \gamma_3 = [0, 0.8]$														
bias	-0.244	-	-0.355	-0.345	-0.053	-0.280	-0.272	-0.276	-0.273	-0.267	-0.264	0.289	0.036	0.384
ese	0.034	-	0.035	0.034	0.052	0.041	0.073	0.078	0.042	0.075	0.079	0.062	0.103	0.084
bias	-0.408	-	-0.493	-0.456	-0.199	-0.417	-0.414	-0.419	-0.413	-0.412	-0.408	0.180	-0.103	0.352
ese	0.029	-	0.031	0.028	0.058	0.037	0.050	0.055	0.039	0.052	0.055	0.077	0.069	0.106
$\gamma_1 = 0, \gamma_2 = 0.8, \gamma_3 = [0, 0.8]$														
bias	-0.104	-	-0.239	-0.262	-0.012	-0.200	-0.185	-0.183	-0.196	-0.184	-0.183	0.326	0.126	0.406
ese	0.049	-	0.047	0.041	0.052	0.044	0.073	0.079	0.045	0.072	0.074	0.061	0.096	0.074
bias	-0.345	-	-0.487	-0.449	-0.171	-0.403	-0.396	-0.399	-0.399	-0.394	-0.390	0.194	-0.096	0.373
ese	0.044	-	0.042	0.035	0.067	0.040	0.053	0.059	0.042	0.056	0.058	0.087	0.073	0.121
$\gamma_1 = 0.25, \gamma_2 = 0, \gamma_3 = [0, 0.8]$														
bias	-0.278	-	-0.325	-0.329	-0.101	-0.307	-0.305	-0.303	-0.314	-0.346	-0.344	0.266	0.030	0.367
ese	0.021	-	0.024	0.024	0.051	0.031	0.050	0.057	0.029	0.039	0.040	0.056	0.084	0.085
bias	-0.388	-	-0.420	-0.414	-0.231	-0.400	-0.398	-0.395	-0.401	-0.408	-0.410	0.130	-0.093	0.332
ese	0.020	-	0.024	0.022	0.055	0.029	0.035	0.043	0.028	0.032	0.033	0.071	0.050	0.112
$\gamma_1 = 0.8, \gamma_2 = 0, \gamma_3 = [0, 0.8]$														
bias	-0.181	-	-0.201	-0.200	-0.088	-0.193	-0.197	-0.194	-0.193	-0.234	-0.214	0.245	0.107	0.364
ese	0.016	-	0.017	0.019	0.038	0.025	0.042	0.046	0.023	0.034	0.039	0.049	0.067	0.088
bias	-0.289	-	-0.298	-0.306	-0.217	-0.305	-0.307	-0.305	-0.307	-0.324	-0.316	0.140	-0.002	0.336
ese	0.014	-	0.017	0.017	0.042	0.023	0.028	0.031	0.020	0.024	0.026	0.055	0.040	0.109
$\gamma_1 = 0.25, \gamma_2 = 0.25, \gamma_3 = [0, 0.8]$														
bias	-0.239	-	-0.298	-0.303	-0.067	-0.278	-0.274	-0.269	-0.287	-0.319	-0.318	0.275	0.041	0.380
ese	0.026	-	0.028	0.027	0.051	0.033	0.052	0.059	0.031	0.043	0.045	0.060	0.083	0.084
bias	-0.369	-	-0.412	-0.407	-0.200	-0.389	-0.386	-0.383	-0.391	-0.399	-0.401	0.155	-0.086	0.355
ese	0.024	-	0.027	0.025	0.056	0.032	0.038	0.046	0.031	0.035	0.035	0.073	0.055	0.114

Note: Bias and empirical standard error, $ese = 1/R \sum_{r=1}^{R} se_{\beta_{3r}}$, $R = 1000$ replications for each setting. Estimates are implemented in Stata using `xtdpdgmm` (Kripfganz, 2019), one-step cluster standard errors. Variances are defined by Equations (A13.4) and (A13.7).

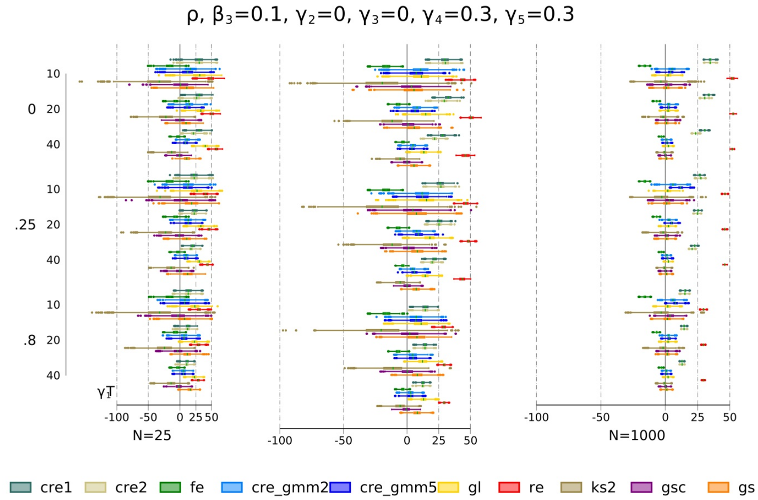

Fig. A13.1: Boxplot - No standard endogeneity, PAM ($\rho = 0.5, \beta_1 = 1, \beta_3 = 0.1$)
Boxplot for bias of ρ with $\gamma_2 = \gamma_3 = 0$ and $\gamma_4 = \gamma_5 = 0.3$.
Vertical axis: $\gamma_1 = [0, 0.25, 0.8]$ and $T = 10, 20, 40$; Horizontal axis: $N = 25, 100, 1000$.

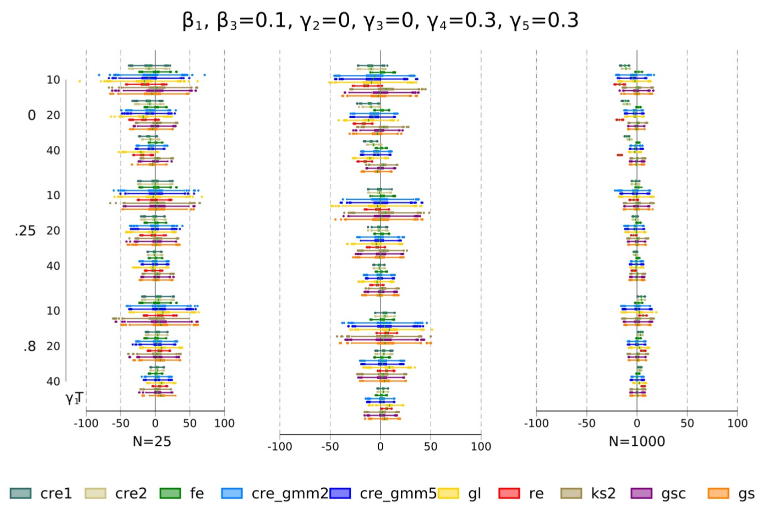

Fig. A13.2: Boxplot - No standard endogeneity, PAM ($\rho = 0.5, \beta_1 = 1, \beta_3 = 0.1$)
Boxplot for bias of β_1 with $\gamma_2 = \gamma_3 = 0$ and $\gamma_4 = \gamma_5 = 0.3$.
Vertical axis: $\gamma_1 = [0, 0.25, 0.8]$ and $T = 10, 20, 40$; Horizontal axis: $N = 25, 100, 1000$.

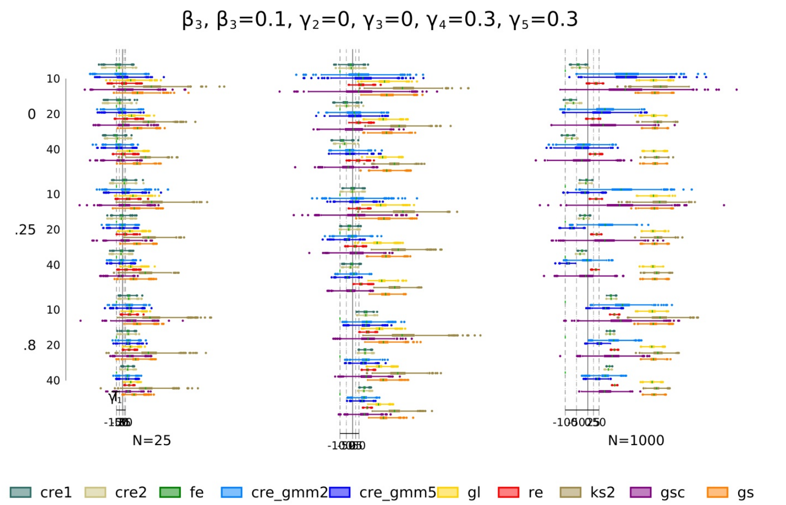

Fig. A13.3: Boxplot - No standard endogeneity, PAM ($\rho = 0.5, \beta_1 = 1, \beta_3 = 0.1$)
Boxplot for bias of β_3 with $\gamma_2 = \gamma_3 = 0$ and $\gamma_4 = \gamma_5 = 0.3$.
Vertical axis: $\gamma_1 = [0, 0.25, 0.8]$ and $T = 10, 20, 40$; Horizontal axis: $N = 25, 100, 1000$.

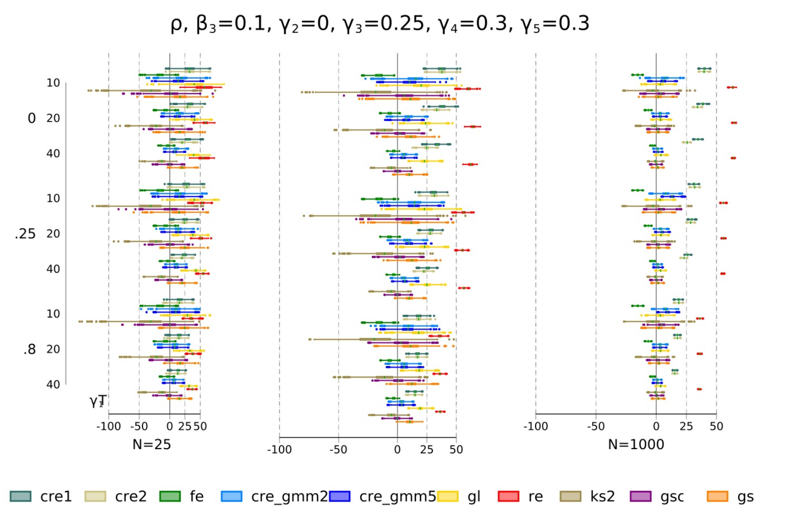

Fig. A13.4: Boxplot - No standard endogeneity, PAM ($\rho = 0.5, \beta_1 = 1, \beta_3 = 0.1$)
Boxplot for bias of ρ with $\gamma_2 = 0, \gamma_3 = 0.25, \gamma_4 = \gamma_5 = 0.3$, and higher variation in μ_i than error component ϵ_{it}, $\sigma_\mu^2/\sigma_\epsilon^2 > 1$.
Vertical axis: $\gamma_1 = [0, 0.25, 0.8]$ and $T = 10, 20, 40$; Horizontal axis: $N = 25, 100, 1000$.

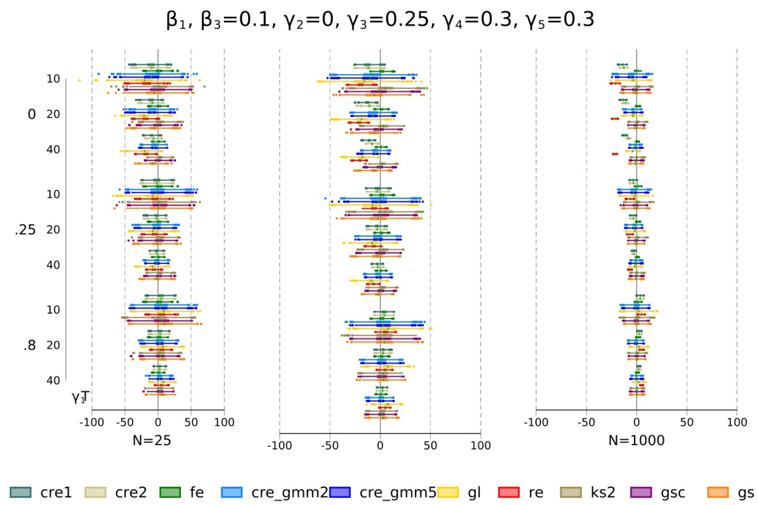

Fig. A13.5: Boxplot - No standard endogeneity, PAM ($\rho = 0.5, \beta_1 = 1, \beta_3 = 0.1$)
Boxplot for bias of β_1 with $\gamma_2 = 0, \gamma_3 = 0.25, \gamma_4 = \gamma_5 = 0.3$, and higher variation in μ_i than error component ϵ_{it}, $\sigma_\mu^2/\sigma_\epsilon^2 > 1$.
Vertical axis: $\gamma_1 = [0, 0.25, 0.8]$ and $T = 10, 20, 40$; Horizontal axis: $N = 25, 100, 1000$.

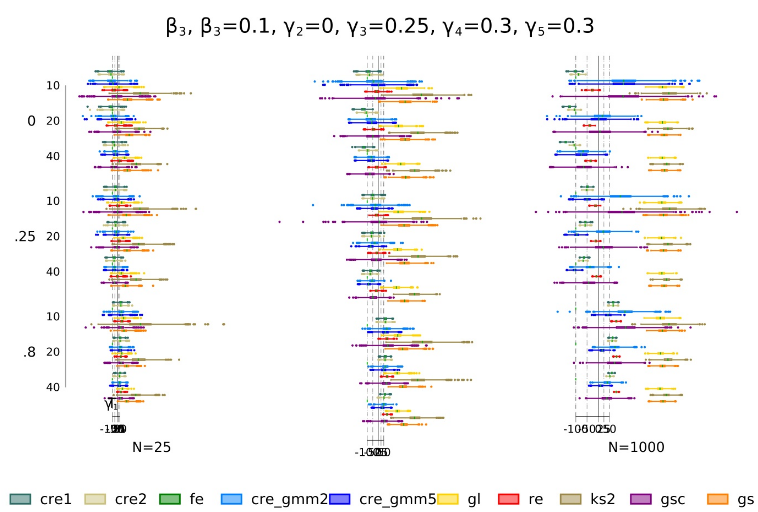

Fig. A13.6: Boxplot - No standard endogeneity, PAM ($\rho = 0.5, \beta_1 = 1, \beta_3 = 0.1$)
Boxplot for bias of β_3 with $\gamma_2 = 0, \gamma_3 = 0.25, \gamma_4 = \gamma_5 = 0.3$, and higher variation in μ_i than error component ϵ_{it}, $\sigma_\mu^2/\sigma_\epsilon^2 > 1$.
Vertical axis: $\gamma_1 = [0, 0.25, 0.8]$ and $T = 10, 20, 40$; Horizontal axis: $N = 25, 100, 1000$

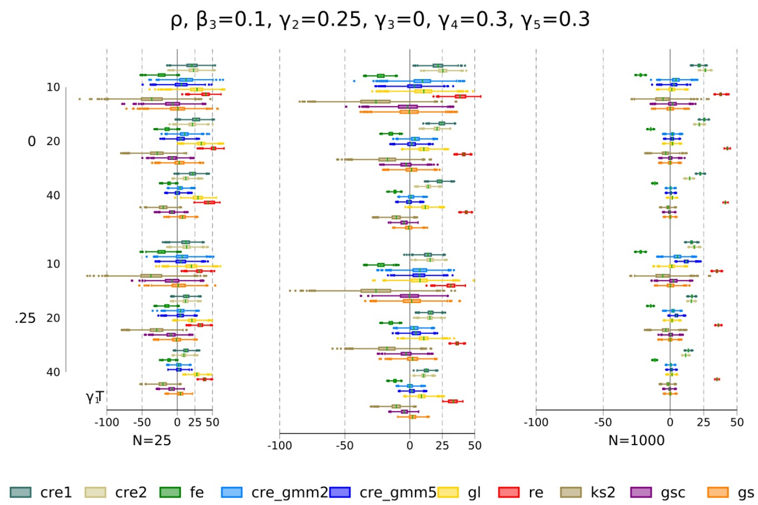

Fig. A13.7: Boxplot - Endogeneity from both sources, PAM ($\rho = 0.5, \beta_1 = 1, \beta_3 = 0.1$)
Boxplot for bias of ρ with correlation between x_{it} and error ϵ_{it}, $\gamma_2 = 0.25, \gamma_3 = 0, \gamma_4 = \gamma_5 = 0.3$.
Vertical axis: $\gamma_1 = [0, 0.25, 0.8]$ and $T = 10, 20, 40$; Horizontal axis: $N = 25, 100, 1000$.

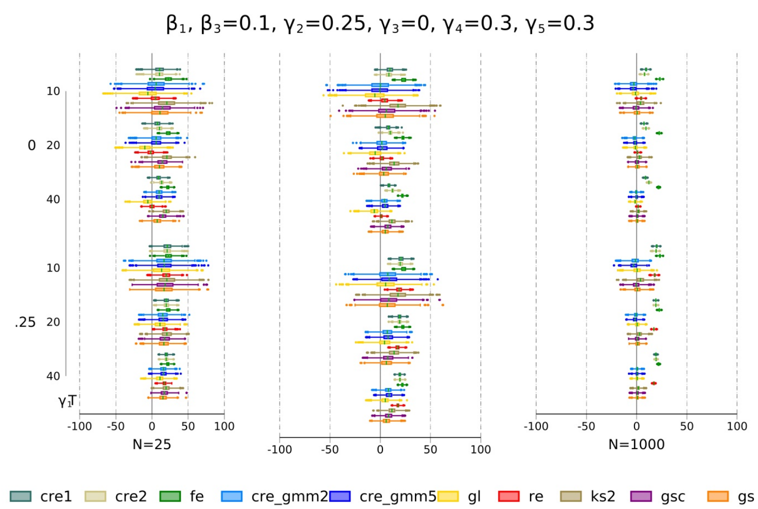

Fig. A13.8: Boxplot - Endogeneity from both sources, PAM ($\rho = 0.5, \beta_1 = 1, \beta_3 = 0.1$)
Boxplot for bias of β_1 with correlation between x_{it} and error ϵ_{it}, $\gamma_2 = 0.25, \gamma_3 = 0, \gamma_4 = \gamma_5 = 0.3$.
Vertical axis: $\gamma_1 = [0, 0.25, 0.8]$ and $T = 10, 20, 40$; Horizontal axis: $N = 25, 100, 1000$

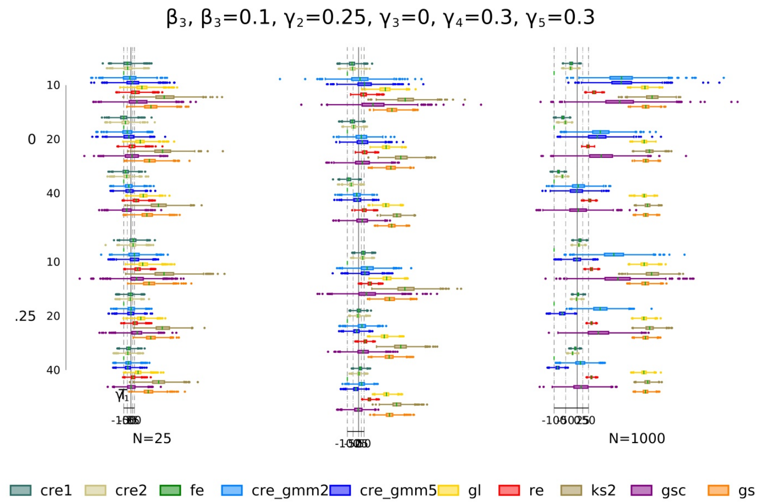

Fig. A13.9: Boxplot - Endogeneity from both sources, PAM ($\rho = 0.5, \beta_1 = 1, \beta_3 = 0.1$)
Boxplot for bias of β_3 with correlation between x_{it} and error ϵ_{it}, $\gamma_2 = 0.25, \gamma_3 = 0, \gamma_4 = \gamma_5 = 0.3$.
Vertical axis: $\gamma_1 = [0, 0.25, 0.8]$ and $T = 10, 20, 40$; Horizontal axis: $N = 25, 100, 1000$

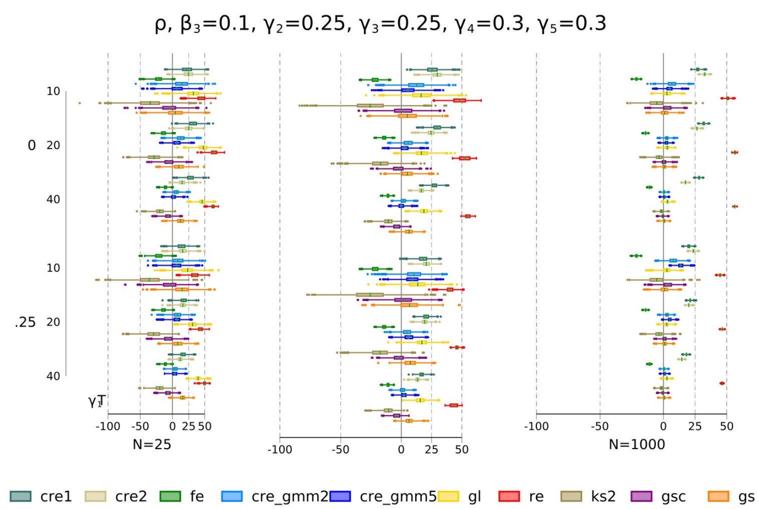

Fig. A13.10: Boxplot - Endogeneity from both sources, PAM ($\rho = 0.5, \beta_1 = 1, \beta_3 = 0.1$)
Boxplot for bias of ρ with correlation between x_{it} and error ϵ_{it}, $\gamma_2 = 0.25, \gamma_3 = 0.25, \gamma_4 = \gamma_5 = 0.3$, and higher variation in μ_i than error component ϵ_{it}, $\sigma^2_\mu / \sigma^2_\epsilon > 1$.
Vertical axis: $\gamma_1 = [0, 0.25, 0.8]$ and $T = 10, 20, 40$; Horizontal axis: $N = 25, 100, 1000$.

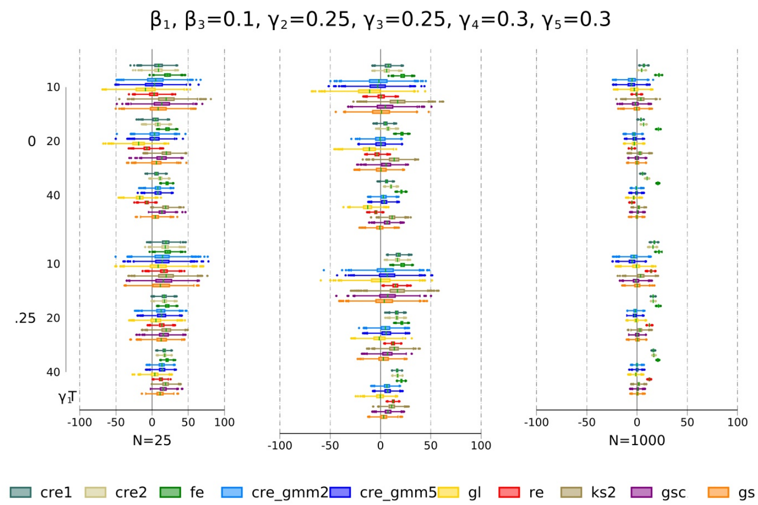

Fig. A13.11: Boxplot - Endogeneity from both sources, PAM ($\rho = 0.5, \beta_1 = 1, \beta_3 = 0.1$)
Boxplot for bias of β_1 with correlation between x_{it} and error ϵ_{it}, $\gamma_2 = 0.25, \gamma_3 = 0.25, \gamma_4 = \gamma_5 = 0.3$, and higher variation in μ_i than error component ϵ_{it}, $\sigma^2_\mu/\sigma^2_\epsilon > 1$.
Vertical axis: $\gamma_1 = [0, 0.25, 0.8]$ and $T = 10, 20, 40$; Horizontal axis: $N = 25, 100, 1000$.

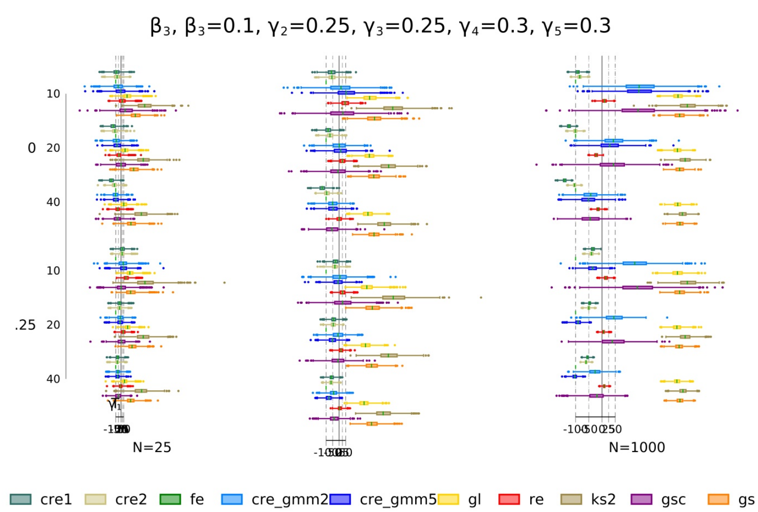

Fig. A13.12: Boxplot - Endogeneity from both sources, PAM ($\rho = 0.5, \beta_1 = 1, \beta_3 = 0.1$)
Boxplot for bias of β_3 with correlation between x_{it} and error ϵ_{it}, $\gamma_2 = 0.25, \gamma_3 = 0.25, \gamma_4 = \gamma_5 = 0.3$, and higher variation in μ_i than error component ϵ_{it}, $\sigma^2_\mu/\sigma^2_\epsilon > 1$.
Vertical axis: $\gamma_1 = [0, 0.25, 0.8]$ and $T = 10, 20, 40$; Horizontal axis: $N = 25, 100, 1000$.

A13.3 Production Functions Estimation

We use the dataset in Blundell and Bond (2000) to estimate a Cobb-Douglas production function in a balanced panel of 509 US manufacturing firms observed through an eight-year period from 1982 to 1989.[3] The series are persistent, which makes the use of level equations preferable. We estimate the $ARDL(1,1,1)$ model:

$$y_{it} = \alpha + \rho y_{it-1} + \beta_1 n_{it} + \beta_2 n_{it-1} + \beta_3 k_{it} + \beta_4 k_{it-1} + \lambda_t + \mu_i + \epsilon_{it},$$

where y_{it} is the logarithm of sales, n_{it} is the logarithm of employment, k_{it} is the logarithm of net capital stock, λ_t captures time effect and α_i is firms' heterogeneity. The individual averages of the five explanatory variables are computed over the years 1982-1983 and the model is estimated over the years 1984-1989. Table A13.11 shows that most of the variability of the dependent variable is between and that the within variability is mostly firm-specific, while common factors (e.g. business cycle and inflation) play a marginal role.

Table A13.11: Variance decomposition for the dependent variable logarithm of sales

Period	1982-1989	1982-83	1984-89
Between variability	98.22%	99.70%	98.87%
Within variability	1.78%	0.30%	1.13%
common to all the units	(0.31%)	(0%)	(0.17%)
unit-specific	(1.47%)	(0.30%)	(0.95%)

Note: Computations implemented by author-written procedure `xtsum3`.

Table A13.12 shows that consistent estimates of persistence should fall within $0.378 < \rho < 0.930$; CRE shows that firm-specific effects μ_i (e.g. CEO skills and product features) are correlated with the explanatory variables. GL and CRE-GMM consider that employment and the capital stock are correlated with the error term (e.g. a positive productivity shock could favour the demand for new workers and the capital stock could be correlated with some omitted financial variables). To complete the comparison, we report maximum likelihood estimates (with and without time dummies, MLtd and ML, respectively) and quasi-maximum likelihood estimates (QML), which are negatively affected by the capital and labour exogeneity assumption.[4] The parameter ρ is estimated consistently by GL and CRE-GMM, while, for n_{it} and k_{it}, CRE-GMM5 produces estimates in line with the macroeconomic

[3] This dataset is the equivalent of the UK data used by Arellano and Bond (1991) and successively largely analysed by the literature on dynamic panel data models.

[4] Another drawback of ML estimations is that they work when panels are strongly balanced, T is small (e.g. less than 10) and there are no missing data, which is not the typical situation we face in modern panels.

Table A13.12: Estimation of production function for US firms.

	RE	FE	CRE1	CRE2	GL	CRE-GMM2	CRE-GMM5	MLtd	ML	QML
y_{it-1}	0.930***	0.378***	0.935***	0.864***	0.667***	0.694***	0.667***	0.928***	0.604***	0.546***
	(0.0094)	(0.0281)	(0.0114)	(0.0175)	(0.0466)	(0.0514)	(0.0491)	(0.0132)	(0.0483)	(0.0757)
n_{it}	0.454***	0.460***	0.453***	0.438***	0.459***	0.688***	0.779***	0.369***	0.520***	0.411***
	(0.0303)	(0.0325)	(0.0302)	(0.0338)	(0.1249)	(0.1630)	(0.1749)	(0.1127)	(0.0534)	(0.0426
n_{it-1}	-0.406***	-0.004	-0.406***	-0.301***	-0.232*	-0.360***	-0.453***	-0.335***	-0.114**	-0.072
	(0.0316)	(0.0368)	(0.0315)	(0.0368)	(0.1265)	(0.1355)	(0.1571)	(0.0529)	(0.0544)	(0.0602)
k_{it}	0.238***	0.200***	0.235***	0.177***	0.573***	0.400**	0.383**	0.219*	0.093*	0.182***
	(0.0373)	(0.0377)	(0.0379)	(0.0431)	(0.1309)	(0.1955)	(0.1649)	(0.1205)	(0.0547)	(0.05489)
k_{it-1}	-0.216***	-0.125***	-0.211***	-0.222***	-0.464***	-0.460***	-0.420***	-0.204***	-0.145***	-0.177***
	(0.0361)	(0.0277)	(0.0371)	(0.0345)	(0.1162)	(0.1329)	(0.1252)	(0.0577)	(0.0370)	0.0530
$\check{y}^1_{i.}$			-0.007	0.079***		0.061	0.087			
			(0.0084)	(0.0175)		(0.0630)	(0.0598)			
$\check{n}_{i.}$				0.026		-0.165*	-0.090			
				(0.0278)		(0.0961)	(0.0748)			
$\check{n}^1_{i.}$				-0.129***		-0.105**	-0.101**			
				(0.0185)		(0.0446)	(0.0485)			
$\check{k}_{i.}$				0.067***		0.215*	0.143*			
				(0.0256)		(0.1213)	(0.0820)			
$\check{k}^1_{i.}$				0.001		0.022	0.006			
				(0.0113)		(0.0487)	(0.0261)			
NT	3054	3054	3054	3054	3054	3054	3054	3054	3054	3054
N	509	509	509	509	509	509	509	509	509	509
$\bar{T}$	6	6	6	6	6	6	6	6	6	6
ar1 pval.		0.00	0.00	0.00	0.00	0.00	0.00			
ar2 pval.		0.29	0.80	0.65	0.53	0.83	0.62			
ar3 pval.		0.35	0.98	0.92	0.59	0.98	0.83			
Hausman pval.			0.417	0.000	0.000	0.007	0.034			
λ_t pval.	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000		

Note: Estimates are implemented using `xtdpdgmm` (Kripfganz, 2019) in Stata, one-step cluster standard errors. The Arellano and Bond (1991) test for autocorrelation is ar#; Hausman is Hausman (1978)'s test. Blundell and Bond (2000) use either $t-2$ or $t-3$ lag and prefer $t-3$ to avoid over-fitting; as for simulations, we use both $t-2$ and $t-3$ lags. ML estimates are from `xtdpdml` (Williams, Allison & Moral-Benito, 2018), QML are from `xtdpdqml` (Kripfganz, 2016). Individual means computed over 1982-1983, estimations run over 1984-1989; as a robustness check, the results estimated over the whole sample 1982-1989 corroborate our findings.

shares of GDP to labour and capital, 70% and 30%. According to the results preferred by Blundell and Bond (2000) in Table III for GMM-sys, the estimates are 0.629 (lag $t-2$) and 0.472 (lag $t-3$) for n_{it}, and 0.361 (lag $t-2$) and 0.398 (lag $t-3$) for k_{it}, with cumulative dynamic multipliers for labour and capital equal to 0.537 and 0.035 (lag $t-2$), and 0.194 and 0.189 (lag $t-3$). Our cumulative dynamic multipliers for labour and capital are more robust at 0.038 and 0.177 in CRE-GMM2, and 0.135 and 0.112 in CRE-GMM5. The decomposition of the within and between effects allowed by CRE-GMM shows that increasing size makes firms able to produce more output, whereas being larger does not mean being more productive; the capital effect is strongest in the long run (the between effect is larger than the within effect).

A13.4 Education and Wage

Here we use the dataset from Vella and Verbeek (1998), a classical example of econometricians and sociologists studying the effect of education on the logarithm of nominal earnings, measured on 8 occasions (level 1) for 545 workers (level 2) in the United States. We divide the period into 1980-1981 to compute pre-sample averages and 1982-1987 to estimate the model. Table A13.13 shows that the variability of the dependent variable is distributed among the three components, between workers and within workers, with common factors (e.g. business cycle and inflation) playing a non-marginal role.

Table A13.13: Variance decomposition for the dependent variable logarithm of wages

Period	1980-1987	1980-81	1982-87
Between variability	53.74%	71.80%	64.79%
Within variability	46.26%	28.20%	35.21%
common to all the units	(7.52%)	(1.19%)	(3.89%)
unit-specific	(38.74%)	(27.01%)	(31.32%)

Note: Computations implemented by author-written procedure `xtsum3`.

The estimated model is:

$$wage_{it} = \alpha + \rho\, wage_{it-1} + \beta_1\, exper_{it} + \beta_2\, exper_{it}^2 + \\ + \beta_3\, union_{it} + \beta_4\, married_{it} + \theta_1\, educ_i + \theta_2\, black_i + \theta_3\, hisp_i + \lambda_t + \mu_i + \epsilon_{it}.$$

The variables in the model include time varying terms, such as years of work experience (which increase over a lifetime), rarely changing variables, such as being married and part of a union, and worker-specific variables, such as years of educations and race dummies.

The results are shown in Table A13.14. As expected, measurable individual characteristics (education, black, Hispanic) cannot be estimated by FE (nor by GMM-dif). Changes in the parameters from FE to CRE2 show that union and married are correlated with individual heterogeneity; union, married and experience may also be endogenous because of the correlation with shocks to wages and should be instrumented; time dummies are important as they capture the effect, common to all workers, of the inflation rate on nominal wages; however, they are collinear with experience, particularly in the FE estimator. The GL estimator overestimates parameter ρ. The GL, GS and KS2 estimators show underestimated effects for educ and black, at least compared to HT and CRE-GMM, and find no significant effects for married and union (except GS for married). It is interesting that the CRE-GMM5 estimates for time-invariant variables are similar to those of HT. Education, assumed to be endogenous due to individual heterogeneity, is instrumented in HT by the within transformation of exogenous (uncorrelated with μ_i) variables. In contrast, in the CRE-GMM approach, this endogeneity is controlled for by the inclusion of pre-sample individual averages. Finally, variables affected by possible standard endogeneity (such as union, married, exper) are not instrumented in the HT approach, whereas they are in the CRE-GMM approach and this explains the differences in the corresponding estimates. Finally, GSC in table A13.14 uses the CRE-GMM5 approach, that is, the system level equation is instrumented with the levels of the $\mathbf{x}_{it}$ variables and performs better than using the first differences of the $mathbfx_{it}$ variables as the instruments for the level equation.

Table A13.14: Estimation of logarithm of nominal wages for US workers.

	FE	RE	CRE1	CRE2	GL	GLC-GMM2	GLC-GMM5	HT	GS	GSC	KS2
$wage_{it-1}$	0.020	0.596***	0.563***	0.560***	0.302***	0.210***	0.218***		0.163***	0.131***	0.156***
	(0.0266)	(0.0304)	(0.0320)	(0.0318)	(0.0353)	(0.0478)	(0.0465)		(0.0357)	(0.0347)	(0.0399)
$educ_i$	-	0.035***	0.029***	0.031***	0.061***	0.100***	0.088***	0.090***	0.075***	0.090***	0.071***
		(0.0058)	(0.0059)	(0.0060)	(0.0088)	(0.0229)	(0.0144)	(0.0048)	(0.0104)	(0.0147)	(0.0136)
$black_i$	-	-0.078***	-0.076***	-0.075***	-0.114***	-0.170**	-0.149***	-0.174***	-0.137***	-0.149***	-0.133**
		(0.0247)	(0.0257)	(0.0259)	(0.0435)	(0.0689)	(0.0488)	(0.0519)	(0.0521)	(0.0517)	(0.0557)
$hisp_i$	-	0.010	0.010	0.007	0.021	0.009	0.009	0.012	0.020	0.000	0.022
		(0.0193)	(0.0195)	(0.0196)	(0.0313)	(0.0546)	(0.0378)	(0.0451)	(0.0358)	(0.0395)	(0.0364)
$union_{it}$	0.074***	0.062***	0.052***	0.052***	0.046	0.142	0.157***	0.075***	0.111	0.194***	0.119
	(0.0238)	(0.0162)	(0.0159)	(0.0189)	(0.0816)	(0.1442)	(0.0606)	(0.0220)	(0.1103)	(0.0733)	(0.1284)
$married_{it}$	0.047**	0.043***	0.036**	0.042***	0.055	0.038	0.099**	0.048**	0.078*	0.099**	0.098
	(0.0218)	(0.0143)	(0.0144)	(0.0156)	(0.0395)	(0.0514)	(0.0410)	(0.0207)	(0.0452)	(0.0426)	(0.0631)
$exper_{it}$	0.090***	-0.002	-0.009	0.031	0.059***	0.071***	0.063***	0.122***	0.058***	0.054**	0.069***
	(0.0218)	(0.0153)	(0.0155)	(0.0269)	(0.0178)	(0.0242)	(0.0233)	(0.0151)	(0.0172)	(0.0208)	(0.0236)
$exper^2_{it}$	-0.004***	0.000	0.000	-0.002**	-0.003***	-0.003***	-0.003***	-0.004***	-0.002***	-0.003***	-0.003***
	(0.0010)	(0.0008)	(0.0008)	(0.0008)	(0.0009)	(0.0009)	(0.0009)	(0.0010)	(0.0008)	(0.0008)	(0.0009)
$\breve{wage}^1_{i.}$			0.096***	0.098***		-0.151**	-0.151**			-0.079	
			(0.0209)	(0.0216)		(0.0711)	(0.0658)			(0.0786)	
$\breve{union}_{i.}$				0.012		0.048	0.090			0.078	
				(0.0223)		(0.1321)	(0.0556)			(0.0858)	
$\breve{married}_{i.}$				-0.018		-0.151	-0.005			0.011	
				(0.0198)		(0.1031)	(0.0491)			(0.0609)	
$\breve{exper}_{i.}$				-0.056**		-0.117	-0.061*			-0.146**	
				(0.0258)		(0.2549)	(0.0324)			(0.0700)	
$\breve{exper^2}_{i.}$				0.005***		0.015	0.008***			0.014**	
				(0.0015)		(0.0273)	(0.0027)			(0.0063)	
NT	3270	3270	3270	3270	3270	3270	3270	3270	3270	3270	3270
N	545	545	545	545	545	545	545	545	545	545	545
$\bar{T}$	6	6	6	6	6	6	6	6	6	6	
ar1 pval.					0.00	0.00	0.00		0.00	0.00	0.00
ar2 pval.					0.02	0.04	0.04		0.07	0.11	0.09
ar3 pval.					0.79	0.60	0.52		0.61	0.45	0.57
Hansen pval.					0.01	0.11	0.11		0.03	0.01	0.03
Hansen df.					47	42	52		55	51	56
Hausman pval.			0.00	0.00		0.22	0.01			0.13	
Hausman df.			1	5		5	5			5	
λ_t pval.	0.13	0.00	0.00	0.68	0.04	0.38	0.33	0.25	0.09	0.49	0.24
R2	0.08	0.47	0.48	0.49	0.42	0.24	0.27	0.14	0.33	0.24	0.28

Note: Estimates are implemented using `xtdpdgmm` (Kripfganz, 2019) in Stata, one-step cluster standard errors. The Arellano and Bond (1991) test for autocorrelation is ar#; Hausman is Hausman (1978)'s test; Hansen is Hansen (1982)'s test. HT (Hausman & Taylor, 1981) estimates are from `xthtaylor` (Amemiya & MaCurdy, 1986 produces similar results as Hausman & Taylor, 1981); time-varying variables correlated with μ_i are experience and squared experience, married and union; education is the time-invariant variables correlated with μ_i. KS2 is from `xtseqreg` (Kripfganz & Schwarz, 2019) where estimates for educ, black and hisp are from the second stage. In CRE-GMM, individual means are computed over 1980-1981, estimations run over 1982-1987; as a robustness check, the results estimated over the whole sample 1980-1987 corroborate our findings.

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