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Cross-section dependence in nonstationary panel models: a novel estimator*

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Abstract: This paper uses Monte Carlo simulations to investigate the impact of nonstationarity, parameter heterogeneity and cross-section dependence on estimation and inference in macro panel data. We compare the performance of standard panel estimators with that of our own two-step method (the AMG) and the Pesaran Common Correlated Effects (CCE) estimators in time-series panels with arguably similar characteristics to those encountered in empirical applications using cross-country macro data. The empirical model adopted leads to an identification problem in standard estimation approaches in the case where the same unobserved common factors drive the evolution of both dependent and independent variables. We replicate the design of two recent Monte Carlo studies on the topic (Coakley, Fuertes, & Smith, 2006; Kapetanios, Pesaran, & Yamagata, 2009), with results confirming that the Pesaran (2006) CCE approach as well as our own AMG estimator solve this identification problem by accounting for the unobserved common factors in the regression equation. Our investigation however also indicates that simple augmentation with year dummies can do away with most of the bias in standard pooled estimators reported — a finding which is in stark contrast to the results from earlier empirical work we carried out using cross-country panel data for agriculture and manufacturing (Eberhardt & Teal, 2008, 2009). We therefore introduce a number of additional Monte Carlo setups which lead to greater discrepancy in the results between standard (micro-)panel estimators and the novel approaches incorporating cross-section dependence. We further highlight the performance of the pooled OLS estimator with variables in first differences and speculate about the reasons for its favourable results.

Keywords: Nonstationary Panel Econometrics, Common Factor Models, Empirical Analysis of Economic Development

JEL codes: C33, O11

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1. INTRODUCTION

> *"Monte Carlo results should be treated with some caution since the DGP [Data Generating Process] used in the simulation may not reflect factors typical in real applications. This may be the case here [results for the analysis later published in Coakley et al. (2006)], since some of the applications discussed . . . do not show the same features as the Monte Carlo results."* Smith and Fuertes (2007, p.76)

In this paper we consider the estimation of the mean slope coefficient in a linear heterogeneous panel model where unobserved common factors lead to correlations in the disturbances across units and to correlations between the disturbances and the regressors. We employ Monte Carlo experiments to investigate the small sample properties of a number of standard pooled and heterogeneous parameter estimators (POLS, FE, FD-OLS, MG) as well as the recently developed Pesaran (2006) CCE estimators and our own contribution, the Augmented Mean Group (AMG) estimator in various contexts, including variable and factor nonstationarity.

Our investigation is motivated by the range of parameter estimates obtained from empirical investigations of cross-country production functions for manufacturing and agriculture (see Eberhardt & Teal, 2008, 2009). Using sectoral data for manufacturing (UNIDO, 2004) and agriculture (FAO, 2007) respectively, we argued that the combination of technology heterogeneity, variable nonstationarity and cross-section dependence (CSD) led to severe distortions in standard panel estimators, and pointed to various diagnostic test results to support our claims: empirical testing supported the suggestion of nonstationary variable series and the presence of cross-section correlation in these macro datasets. Production function regressions gave evidence of considerable differences in the results for estimators which do and do not account for these matters. In the present paper we seek to provide some further evidence as to the importance of heterogeneity, nonstationarity and cross-section dependence in macro panel data, focusing on the view of the applied econometrician.

In our simulation exercises we first build on the setups presented in two recent papers from the literature on cross-section dependence in nonstationary panels, Coakley et al. (2006) and Kapetanios et al. (2009). We also present our own simulation setup and investigate estimation and inference for panel estimators in a number of scenarios.

The paper makes the following contributions to the literature:

(i) We introduce the Augmented Mean Group (AMG) estimator, which similar to the Pesaran (2006) CCE approach can account for data time-series properties as well as differences in the impact of observables and unobservables across panel groups.

(ii) We compare the small sample properties of the AMG, standard (micro-)panel and Common Correlated Effects estimators in cross-sectionally dependent macro-panels. We are able to identify scenarios in which the performance of the AMG estimators matches that of the Pesaran (2006) CCEMG and CCEP, as well as circumstances under which there is evidence of bias in the former but not the latter.

(iii) Our investigation highlights that in the recent simulation studies by Coakley et al. (2006) and Kapetanios et al. (2009) the 'naïve' pooled estimators (POLS, FE), which ignore cross-section dependence, are not specified in a manner that reflects practical empirical convention. Namely they do not contain year dummies, a standard augmentation in the applied literature to account for 'common shocks' to all units in the panel. Our Monte Carlo results reveal that once augmented with a set of year dummies the bias in these estimators drops dramatically in *all* of the scenarios studied, even if factor loadings on the unobserved common factors are heterogeneous across countries.

(iv) The simulations further highlight the performance of the pooled first difference estimator (FD-OLS). For cases where FD-OLS is biased (which also leads to bias in the AMG estimators) we suggest a simple IV version of this estimator and investigate its resulting performance (and that of the AMG based on first-stage IV estimates). We further briefly speculate on the origins of the good performance of FD-OLS in standard setups and provide some tentative evidence for our suggestion.

The remainder of the paper is organised as follows: Section 2 introduces the empirical framework and the Augmented Mean Group (AMG) estimator first presented in Eberhardt and Teal (2008). Section 3 discusses the Monte Carlo setups by Coakley et al. (2006) and Kapetanios et al. (2009). We replicate their results and show that introduction of year dummies in the 'naïve estimators' wipes out the most serious bias from cross-section dependence.[1] Section 4 then introduces our own simulation setup and the four scenarios for analysis. For the simulation setups which induce biased FD-OLS estimates *by construction* we further investigate an IV version of this estimator. The final section summarises and interprets the results of the various simulation exercises and concludes.

2. THE AUGMENTED MEAN GROUP ESTIMATOR

2.1 Model setup

We adopt the the following empirical model: for $i = 1, \ldots, N$ and $t = 1, \ldots, T$, let

$$y_{it} = \boldsymbol{\beta}_i' \boldsymbol{x}_{it} + u_{it} \qquad u_{it} = \alpha_i + \boldsymbol{\lambda}_i' \boldsymbol{f}_t + \varepsilon_{it} \tag{1}$$

$$x_{mit} = \pi_{mi} + \boldsymbol{\delta}_{mi}' \boldsymbol{g}_{mt} + \rho_{1mi} f_{1mt} + \ldots + \rho_{nmi} f_{nmt} + v_{mit} \tag{2}$$

$$\text{where} \qquad m = 1, \ldots, k \qquad \text{and} \qquad \boldsymbol{f}_{\cdot mt} \subset \boldsymbol{f}_t$$

$$\boldsymbol{f}_t = \boldsymbol{\varrho}' \boldsymbol{f}_{t-1} + \boldsymbol{\epsilon}_t \qquad \text{and} \qquad \boldsymbol{g}_t = \boldsymbol{\kappa}' \boldsymbol{g}_{t-1} + \boldsymbol{\epsilon}_t \tag{3}$$

where $\boldsymbol{x}_{it}$ is a vector of observable covariates. In addition we employ the combination of group-specific fixed effects α_i and a set of common factors $\boldsymbol{f}_t$ with country-specific factor loadings $\boldsymbol{\lambda}_i$. In equation (2) we further add an empirical representation of the k observable regressors, which are modelled as linear functions of unobserved common factors $\boldsymbol{f}_t$ and $\boldsymbol{g}_t$, with country-specific factor loadings respectively. The model setup thus introduces cross-section dependence in the observables and unobservables. As can be seen, some of the unobserved common factors driving the variation in y_{it} in equation (1) also drive the regressors in (2). This setup leads to endogeneity whereby the regressors are correlated with the unobservables of the production function equation (u_{it}), making $\boldsymbol{\beta}_i$ difficult to identify. Equation (3) specifies the evolution of the unobserved factors.

We maintain the following assumptions for the general model and the data it is applied to:

A.1 The $\boldsymbol{\beta}_i$ parameters are unknown random coefficients with fixed means and finite variances. Similarly for the unknown factor loadings, i.e. $\boldsymbol{\lambda}_i = \boldsymbol{\lambda} + \boldsymbol{\eta}_i$ where $\boldsymbol{\eta}_i \sim \text{iid}(0, \Omega_\eta)$.[2]

A.2 Error terms $\varepsilon_{it} \sim N(0, \sigma^2)$, where σ^2 is finite. Similarly for v_{mit} and ϵ_t.

A.3 Observable inputs $\boldsymbol{x}_{it}$ and output y_{it}, as well as the unobserved common factors $\boldsymbol{f}_t$ and $\boldsymbol{g}_t$ are not *a priori* assumed to be stationary variables/processes.

A.4 The unobserved common factors with heterogeneous factor loadings $\boldsymbol{\lambda}_i' \boldsymbol{f}_t$, can contain elements which are common across countries as well as elements which are country-specific.

A.5 There is an overlap between the unobserved common factors driving output and the regressors ($\boldsymbol{f}_{\cdot mt} \subset \boldsymbol{f}_t$), creating difficulties for the identification of the technology parameters $\boldsymbol{\beta}_i$.

The two most important features of this setup are the potential nonstationarity of observables and unobservables (y_{it}, $\boldsymbol{x}_{it}$, $\boldsymbol{f}_t$, $\boldsymbol{g}_t$), as well as the potential heterogeneity in the impact of observables and unobservables on output across countries (α_i, $\boldsymbol{\beta}_i$, $\boldsymbol{\lambda}_i$). Taken together these properties have important bearings on estimation and inference in macro panel data, as pointed out in the recent literature Coakley et al. (2006); Pesaran (2006); Kapetanios et al. (2009).

2.2 Estimator

We now introduce a novel estimator, the Augmented Mean Group (AMG) estimator, which accounts for cross-section dependence by inclusion of a 'common dynamic effect' in the country regression. This variable is extracted from the year dummy coefficients of a pooled regression in first differences and represents the levels-equivalent

[1] Simulations were carried out in `GAUSS` version 9.

[2] The assumption of random coefficients is for convenience. Based on the findings by Pesaran and Smith (1995, footnote 2, p.81) the coefficients could alternatively be fixed but differing across groups.

mean evolvement of unobserved common factors across all countries. Provided that the unobserved common factors form part of the country-specific cointegrating relation, the augmented country regression model encompasses the cointegrating relationship, which is allowed to differ across countries.[3]

$$\text{AMG — Stage (i)} \qquad \Delta y_{it} = \boldsymbol{b}'\Delta \boldsymbol{x}_{it} + \sum_{t=2}^{T} c_t \Delta D_t + e_{it} \tag{4}$$

$$\Rightarrow \hat{\boldsymbol{c}}_t \equiv \hat{\mu}_t^{\bullet}$$

$$\text{AMG — Stage (ii)} \qquad y_{it} = a_i + \boldsymbol{b}_i'\boldsymbol{x}_{it} + c_i t + d_i \hat{\mu}_t^{\bullet} + e_{it} \tag{5}$$

$$\hat{\boldsymbol{b}}_{AMG} = N^{-1}\sum_i \hat{\boldsymbol{b}}_i$$

The first stage represents a standard FD-OLS regression with $T-1$ year dummies in first differences, from which we collect the year dummy coefficients which are relabelled as $\hat{\mu}_t^{\bullet}$. This process is extracted from the pooled regression *in first differences* since nonstationary variables and unobservables are believed to bias the estimates in the pooled levels regressions. There is also some evidence that the identification problem for $\boldsymbol{\beta}$ (Kapetanios et al., 2009) is addressed successfully in the FD-OLS. In the second stage this variable is included in each of the N standard country regressions which also include linear trend terms to capture omitted idiosyncratic processes which evolve in a linear fashion over time. Alternatively (not shown) we can subtract $\hat{\mu}_t^{\bullet}$ from the dependent variable, which implies the common process is imposed on each country with unit coefficient. [4] In either case the AMG estimates are then derived as averages of the individual country estimates, following the Pesaran and Smith (1995) MG approach. Based on the results of our Monte Carlo simulations below we posit that the inclusion of $\hat{\mu}_t^{\bullet}$ allows for the *separate* identification of $\boldsymbol{\beta}_i$ or $\mathbb{E}[\boldsymbol{\beta}_i]$ and the unobserved common factors driving output and inputs ($\boldsymbol{\lambda}_i$), like in the CCE case discussed above.

2.3 Comparing augmented Mean Group estimators

In the following we want to indicate how our own augmented estimators relate to the Pesaran (2006) estimators, which were shown to perform very well in recent Monte Carlo studies. We argue that our augmentation approach uses an *explicit* rather than implicit estimate for $\boldsymbol{f}_t$ from the pooled first stage regression in first differences. From (1) we obtain

$$\Delta y_{it} = \beta_i \Delta \boldsymbol{x}_{it} + \boldsymbol{\lambda}_i' \Delta \boldsymbol{f}_t + \Delta u_{it} \tag{6}$$

Pooled estimation of this model is carried out using a set of as $T-1$ year dummies in first differences ($\sum_{t=2}^{T} \Delta D_t$) to yield the common or mean evolution of unobservables in levels[5] across countries over time $\hat{\mu}_t^{\bullet}$. Our pooled estimate is some function $h(\cdot)$ of the unobserved common factors $\boldsymbol{f}_t$: $\hat{\mu}_t^{\bullet} = h(\bar{\boldsymbol{\lambda}}\boldsymbol{f}_t)$. It is clear from this discussion that as in the Pesaran (2006) CCE approach we require that the average impact of the unobserved common factors across countries is non-zero ($\bar{\boldsymbol{\lambda}} \neq 0$). Plugging this estimate back into the model in equation (1) yields

$$y_{it} = \alpha_i + \boldsymbol{\beta}_i \boldsymbol{x}_{it} + \boldsymbol{\lambda}_i\, h(\bar{\boldsymbol{\lambda}}\boldsymbol{f}_t) + u_{it} \tag{7}$$

From equation (7) we can see that provided there are no issues related to Δu_{it} in the first stage regression the estimate $\hat{\mu}_t^{\bullet}$ obtained can be included in the second stage to account for unobserved common factors $\boldsymbol{f}_t$ and allow for their heterogeneous impact on y_{it}.

[3] This matches the assumption of the Pesaran (2006) CCEMG estimator (Pedroni, 2007).

[4] Note further that unity is also the cross-country average parameter expected for the coefficients on $\hat{\mu}_t^{\bullet}$: $\bar{d} = N^{-1}\sum_i d_i = 1$. The year dummy coefficients which make up $\hat{\mu}_t^{\bullet}$ represent an average of the unobservables *and* their country-specific factor loadings across countries. As an illustration, if we regress y on $Z = (\hat{\beta}'X)$ (with $\hat{\beta}$ estimated earlier) this would yield a parameter estimate of unity on this new 'regressor', since Z represents the combination of a variable *and* its coefficient. If $\hat{\mu}_t^{\bullet}$ is included as a covariate in our first stage regression (instead of the $T-1$ year dummies) it enters with a unit coefficient due to this representation and similarly in the Mean Group averages of the country regressions. The only difference to our $Z = \hat{\beta}'X$ example is that both (latent) elements of $\hat{\mu}_t^{\bullet}$ (factors, loadings) are treated as parameters (Bai & Ng, 2008).

[5] Recall that the differencing of the regression equation is carried out to avoid spurious correlation brought about by nonstationary errors in a misspecified levels model with nonstationary observables and unobservables. If we difference the year dummies as well, their coefficients describe a levels process, rather than year-on-year growth.

3. RECENT MONTE CARLO STUDIES ON MULTIFACTOR MODELS

3.1 Coakley, Fuertes and Smith (2006)

The authors introduce the following Data Generating Process (DGP):

$$\begin{aligned} y_{it} &= \alpha_i + \beta x_{it} + u_{it} \qquad u_{it} = \rho_{ui} u_{i,t-1} + \lambda_i f_t + \varepsilon_{u,it} \\ &\varepsilon_{u,it} \sim \text{i.i.d. } N(0, \sigma_{ui}^2), \text{ where } \sigma_{ui}^2 = 1 \end{aligned} \tag{8}$$

for $i = 1, \ldots, N$ and $t = 1, \ldots, T$, where we adjust the notation to concentrate on the nonstationary observables settings with homogeneous β (Cases A-G). Coakley et al. (2006) do not report any simulation results for heterogeneous β but suggest that findings were rather similar to those for the homogeneous setup. The single regressor is defined as

$$\begin{aligned} x_{it} &= \rho_{xi} x_{i,t-1} + \phi_i f_t + \psi_i \chi_t + \varepsilon_{x,it} \\ &\varepsilon_{x,it} \sim \text{i.i.d. } N(0, \sigma_{xi}^2), \text{ where } \sigma_{xi} = \text{i.i.d. } U[0.5, 1.5] \end{aligned} \tag{9}$$

The unobserved common factors are generated as

$$f_t = \rho_f f_{t-1} + \varepsilon_{ft} \qquad \varepsilon_{ft} \sim \text{iid } N(0, \sigma_f^2), \text{ where } \sigma_f^2 = 1 \tag{10}$$

$$\chi_t = \rho_\chi \chi_{t-1} + \varepsilon_{\chi t} \qquad \varepsilon_{\chi t} \sim \text{iid } N(0, \sigma_\chi^2), \text{ where } \sigma_\chi^2 = 1 \tag{11}$$

Heterogeneous intercepts are distributed $\alpha_i \sim$ iid $U[-0.5, 0.5]$ s.t. $\bar{\alpha} = 0$. Unless indicated the independently drawn factor loadings are heterogeneous across countries: $\lambda_i \sim$ iid $U[0.5, 1.5]$, $\phi_i \sim$ iid $U[0.5, 1.5]$ and $\psi_i \sim$ iid $U[0.5, 1.5]$. Regressors are nonstationary ($\rho_{xi} = 1$) in all the cases presented here, and unless indicated $\rho_f = \rho_\chi = 0$ (stationary common factors). The variation in the regressors (σ_{xi}) differs uniformly across countries. The slope coefficient is common and set to unity ($\beta = 1$).

With reference to our own empirical model in equations (1) to (3), we can highlight the following points of departure: *firstly*, in equation (8) Coakley et al. (2006) allow for serially correlated errors from *other* sources than the presence of unobserved common factors, which includes nonstationary u_{it} (noncointegration) regardless of the nature of the unobserved common factors f_t. *Secondly*, in equation (9) the single regressor x is nonstationary for reasons *other than* the presence of I(1) common factors: this allows Coakley et al. (2006) to focus their investigation on the impact of *stationary common factors* f_t and χ_t on estimation and inference in a model with two *nonstationary observables* which do or do not cointegrate. *Thirdly*, the authors only allow for cointegration between y and x, but not between these observables and the unobservable common factors f — the presence of the latter is treated as a nuisance in the consistent estimation of the slope coefficient β.

As our later analysis shows, none of these issues lead to fundamental differences in the simulation results. With empirical cross-country production functions in mind (Eberhardt & Teal, 2008, 2009) we have highlighted the desirability of modelling unobservables (TFP) as a unit root process, as well as the heterogeneous nature of production technology (β_i) across countries, which will both be addressed in our own simulations as well as those by Kapetanios et al. (2009).

In detail, Coakley et al. (2006) consider the following scenarios:

Case *A*: $\rho_{ui} = 0$, $\lambda_i = \phi_i = \psi_i = 0$: Cointegration between y and x. No common factors and thus no cross-section dependence (CSD).

Case *B*: $\rho_{ui} = 1$, $\lambda_i = \phi_i = \psi_i = 0$: No cointegration between y and x. No CSD.

Case *C*: $\rho_{ui} = 1$, $\phi_i = 0$: No cointegration between y and x. An I(0) factor f_t drives the errors, a different I(0) factor χ_t drives the regressors.

Case *D*: $\rho_{ui} = 1$, $\psi_i = 0$: No cointegration between y and x. An I(0) factor f_t drives both the errors and the regressors.

Case $\tilde{D}$: Like Case D, but $\lambda_i = \phi_i$ for all i — factor loading dependence.

Case *E*: $\rho_{ui} = 0$, $\psi_i = 0$: Cointegration between y and x. An I(0) factor f_t drives both the errors and the regressors.

Case *F*: $\rho_{ui} = 1$: No cointegration between y and x. An I(0) factor f_t drives both the errors and the regressors, a different I(0) factor χ_t drives the regressors.

Case *G*: $\rho_f = \rho_\chi = 1$, $\rho_{ui} = 0$: No cointegration between y and x. An I(1) factor f_t drives both the errors and the regressors, a different I(1) factor χ_t drives the regressors.

By construction the simulations are primarily interested in the cointegrating relationship (or lack thereof) between y and x, and exclude the possibility of a three-way cointegrating relation (y, x, f). Furthermore, in most of the scenarios the unobserved common factors are stationary.

In the present and all the following Monte Carlo simulations we compare the small sample performance of the following estimators:

Pooled estimators: POLS — pooled OLS, FE — pooled OLS with Fixed Effects, CCEP — pooled version of the Pesaran (2006) Common Correlated Effects estimator, FD-OLS — pooled OLS with variables in first differences. The estimation equations are augmented with year dummies as indicated in the results tables.

MG-type estimators: CCEMG — Mean Groups version of the Pesaran (2006) Common Correlated Effects estimator, AMG(i) — Augmented Mean Groups estimator with 'common dynamic process' imposed with unit coefficient, AMG(ii) with 'common dynamic process' included as additional regressor, MG — Pesaran and Smith (1995) Mean Groups estimator. All of these are based on averaged country-regression estimates, and we include linear trends in all but the CCEMG.

We present the simulation results across the sample of 5,000 replications for the panel dimensions $N = 30$, $T = 20$ in Table I in the Appendix. For each estimator we provide the mean, median and ('empirical') standard error of the 5,000 estimates, as well as the sample mean of the standard errors. This replicates the results in Table 3(II) of Coakley et al. (2006).

- In the baseline **Case A** with cointegration and cross-section independence all estimators are unbiased and due to the large variance in the I(1) regressors rather precise.
- The setup with nonstationary errors (**Case B**) represents a 'spurious panel regression' — as established by Phillips and Moon (1999) the pooled estimators in effect average across spurious regressions and provide unbiased estimates, although the empirical standard errors are much larger now, e.g. .1351 instead of .0182 for pooled FE without year dummies ('one-way FE', marked FE†).
- If we introduce cross-section dependence to the non-cointegration scenario (**Case C**) nothing much changes. This is because the omitted factors in the errors and the regressors are independent. The exceptions are the FE estimator without year dummies (FE†) and the MG estimator, for which the factor f_t in the errors leads to a doubling of the empirical standard errors.
- In **Case D** the correlation between the regressors and the errors via the common factor f_t leads to serious bias in the pooled OLS and FE without year dummies (POLS†, FE†) and the MG estimator. POLS is much less biased at .0766 than FE at .4157. In either case the bias virtually disappears once year dummies are included in the estimation equation (POLS‡, FE‡) — we will speculate about the source of this benign correction in the conclusion of this paper. The CCE and AMG estimators are unbiased and remain comparatively precise, though not dramatically more so than the POLS‡ or FE‡.
- Factor loading dependence between the errors and regressors (**Case $\tilde{\boldsymbol{D}}$**) we observe a similar pattern of results across estimators, with the bias in POLS† and FE† slightly elevated. FD-OLS is biased for the first time and this bias naturally carries over to our AMG estimates, although the latter display only mild distortion.
- If y and x are cointegrated any correlation between the regressors and the errors via the common factor f_t leads to only modest bias in FE† and MG (**Case E**), since the correlation between the I(1) regressors and I(0) errors goes to zero with T.
- If several, rather than a single factor drive the regressors in the case of no cointegration between y and x and correlation between regressors and the errors (**Case F**) nothing much changes compared to the single factor scenario in Case D, except that the higher variation in the x leads to more precise estimates.
- Finally, the scenario where the unobserved factors are I(1), residuals are nonstationary and a common factor drives both y and x (**Case G**) we can observe the most serious bias of all cases considered here. The POLS† and FE† are biased by .2273 and .4374 respectively, while the bias for the MG is .5110 —

all of these estimators are further very imprecise. Once we use year dummies for the pooled estimators, however, their bias goes to zero (POLS‡, FE‡) and the estimators are highly efficient. The CCE estimators are unbiased with relative precision, while the bias in the FD-OLS leads to bias in the AMG estimators — this time of similar magnitude.

In summary, our replication of the Monte Carlo results by Coakley et al. (2006) with alternative POLS‡ and FE‡ estimators, as well as our own AMG-type estimators for the cases considered cannot reveal any serious bias in the standard pooled estimators, provided year dummies are added to the estimation equation. The AMG estimators commonly perform similarly well to the Pesaran (2006) CCE estimators, with the notable exception of Case G (noncointegration even after nonstationary factors are accounted for).

3.2 Kapetanios, Pesaran and Yamagata (2009)

The authors introduce the following DGP:

$$y_{it} = \beta_i x_{it} + u_{it} \qquad u_{it} = \alpha_i + \lambda^y_{i1} f_{1t} + \lambda^y_{i2} f_{2t} + \varepsilon_{it} \tag{12}$$
$$x_{it} = a_{i1} + a_{i1} d_t + \lambda^x_{i1} f_{1t} + \lambda^x_{i3} f_{3t} + v_{it} \tag{13}$$

for $i = 1, \ldots, N$ unless indicated below and $t = 1, \ldots, T$, where we adjust the notation by Kapetanios et al. (2009) since we limit our analysis to the case with a single regressor (x).

The common deterministic trend term (d_t) and individual-specific errors for the x-equation are zero-mean independent AR(1) processes defined as

$$d_t = 0.5 d_{t-1} + v_{dt} \qquad v_{dt} \sim N(0, 0.75) \qquad t = -48, \ldots, 1, \ldots, T \qquad d_{-49} = 0$$
$$v_{it} = \rho_{vi} v_{i,t-1} + v_{it} \qquad v_{it} \sim N(0, (1 - \rho^2_{vi})) \qquad t = -48, \ldots, 1, \ldots, T \qquad v_{i,-49} = 0$$

where $\rho_{vi} \sim U[0.05, 0.95]$. The three common factors are nonstationary processes

$$f_{jt} = f_{j,t-1} + v_{ft} \qquad j = 1, 2, 3 \qquad v_{ft} \sim N(0, 1) \qquad t = -49, \ldots, 1, \ldots, T \qquad f_{j,-50} = 0 \tag{14}$$

The authors generate innovations to y as a mix of heterogeneous AR(1) and MA(1) errors

$$\varepsilon_{it} = \rho_{i\varepsilon} \varepsilon_{i,t-1} + \sigma_i \sqrt{1 - \rho^2_{i\varepsilon}} \omega_{it} \qquad i = 1, \ldots, N_1 \qquad t = -48, \ldots, 0, \ldots, T$$
$$\varepsilon_{it} = \frac{\sigma_i}{\sqrt{1 + \theta^2_{i\varepsilon}}} (\omega_{it} + \theta_{i\varepsilon} \omega_{i,t-1}) \qquad i = N_1 + 1, \ldots, N \qquad t = -48, \ldots, 0, \ldots, T$$

where N_1 is the nearest integer to $N/2$ and $\omega_{it} \sim N(0, 1)$, $\sigma^2_i \sim U[0.5, 1.5]$, $\rho_{i\varepsilon} \sim U[0.05, 0.95]$, and $\theta_{i\varepsilon} \sim U[0, 1]$. ρ_{vi}, $\rho_{i\varepsilon}$, $\theta_{i\varepsilon}$ and σ_i do not change across replications. Initial values are set to zero and the first 50 observations are discarded for all of the above.

Regarding parameter values, $\alpha_i \sim N(0, 1)$ and a_{i1}, $a_{i2} \sim$ iid$N(0.5, 0.5)$ do not change across replications. We limit ourselves to *'Experiment 1'* in Kapetanios et al. (2009), where $\beta_i = \beta + \eta_i$ with $\beta = 1$ and $\eta_i \sim N(0, 0.04)$. For the factor loadings the authors consider

$$\lambda^x_{i1} \sim N(0.5, 0.5) \qquad \text{and} \qquad \lambda^x_{i3} \sim N(0.5, 0.5) \tag{15}$$
$$\text{with either} \quad \mathcal{A}: \quad \lambda^y_{i1} \sim N(1, 0.2) \qquad \text{and} \qquad \lambda^y_{i2\mathcal{A}} \sim N(1, 0.2) \tag{16}$$
$$\text{or} \quad \mathcal{B}: \quad \lambda^y_{i1} \sim N(1, 0.2) \qquad \text{and} \qquad \lambda^y_{i2\mathcal{B}} \sim N(0, 1) \tag{17}$$

Since we are interested in consistent estimation of the mean parameter estimate ($\mathbb{E}[\beta_i]$) and therefore did not find considerable differences in the patterns of the results in setup $\mathcal{A}$ and $\mathcal{B}$ we only present the former to save space.[6]

[6]In setup $\mathcal{B}$ the mean $\mathbb{E}[\beta_i]$ can be estimated consistently but not the individual β_i — see Kapetanios et al. (2009, p.6).

With reference to our own empirical model we can state that the points of departure (e.g. the complex structure of innovations in y) are not substantial by any measure and were introduced by the authors to highlight the robustness of their results to a range of alternative sources of heterogeneity.

We investigate combinations of T and N for $T, N = \{20, 30, 50, 100\}$, but with 1,000 instead of the 2,000 replications in Kapetanios et al. (2009) for each case. Our results in Table II in the Appendix replicate those in Table 1 of Kapetanios et al. (2009). In addition to the mean, median, empirical standard errors and mean estimated standard errors we also report the average bias and the root mean squared error (RMSE), in line with the presentation in Kapetanios et al. (2009).[7] We also introduce 'infeasible' estimators, namely for fixed effects and MG — these represent estimators where the unobserved common factors in y are included in the estimation equation to provide a benchmark.

The POLS and FE estimators without year dummies (marked †) indicate serious bias which increases in T but is stable as N increases. In all cases the bias in the one-way FE estimator (marked †) is larger. The standard MG estimator (with linear trend) similarly performs quite poorly, in general no better (or worse) than the FE estimator. In contrast the CCEP and FD-OLS (with $T-1$ year dummies) for the pooled case and the augmented MG-estimators display no bias. In data dimensions investigated the FD-OLS estimator has RMSE closest to the infeasible estimators.

The significant bias in the POLS and FE estimator however is almost entirely absent once these are augmented with $(T-1)$ year dummies (again marked ‡). RMSE are still slightly elevated for the latter two estimators, but on the whole the year dummies in the POLS and FE estimators can accommodate the cross-section dependence (as well as the other data properties) introduced in this setup quite well.

4. NEW SIMULATIONS

Our analysis in the previous section has indicated that under the setups considered the use of 'naïve estimators' such as the pooled OLS or Fixed Effects estimators does not create considerable bias in the estimates provided the estimation equation is augmented with $(T-1)$ year dummies. This is surprising, since these estimators impose *common* factor loadings across countries on all unobserved common factors. Although the CCE and to a lesser extent the AMG estimators provide unbiased and more efficient estimates, the analysis seems to suggest that using estimators which account for cross-section dependence does not yield a dramatically different result from the use of standard pooled estimators that ignore it. This finding is somewhat at odds with our experience from the agriculture and manufacturing data, where we saw vast differences between the pooled OLS, Fixed Effects on the one hand (both augmented with year dummies), and the CCE and AMG-type estimators on the other. In the following we therefore present a new simulation setup and consider a number of alternative scenarios which create results somewhat more in line with those observed in our regressions with real data.

4.1 Our Monte Carlo setup

We define our dependent variable and regressor as

$$y_{it} = \beta_i x_{it} + u_{it} \qquad u_{it} = \alpha_i + \lambda^y_{i1} f_{1t} + \lambda^y_{i2} f_{2t} + \varepsilon_{it} \tag{18}$$

$$x_{it} = a_i + \lambda^x_{i1} f_{1t} + \lambda^x_{i3} f_{3t} + \epsilon_{it} \qquad \epsilon_{it} = \rho\epsilon_{i,t-1} + e_{it} \tag{19}$$

The serially-correlated x-variable is in practice constructed using a dynamic equation

$$x_{it} = (1-\rho)a_i + \lambda^{x_1}_i f_{1,t} - \rho\lambda^{x_1}_i f_{1,t-1} + \lambda^{x_3}_i f_{3,t} - \rho\lambda^{x_3}_i f_{3,t-1} + \rho x_{i,t-1} + e_{it}$$

which we begin with $x_{i,-49} = a_i$ and then accumulate for $t = -48, \dots, 0, 1, \dots, T$, discarding the first 50 time-series observations for all i. The common AR-coefficient is $\rho = .25$.

[7] The bias is computed as $M^{-1}\sum_{m=1}^{M}\hat{\beta}_m - 1$, the average deviation across replications (here $M = 1,000$) of the estimate from the true mean parameter $\beta = 1$. The RMSE is computed as $\{M^{-1}\sum_{m=1}^{M}(\hat{\beta}_m - 1)^2\}^{1/2}$, the average squared deviation across replications of the estimate from the true mean parameter. In case of both statistics we multiplied the results by 100.

The unobserved common factors are nonstationary processes with individual drifts so as to ensure upward evolution over time, as observed in macro production data.

$$\begin{array}{lllll} f_{j,t} = \mu_j + f_{j,t-1} + \upsilon_{fjt} & t = -48, \ldots, 0, 1, \ldots, T & f_{j,-49} = 0 & & \\ \upsilon_{fjt} \sim N\left(0, \sigma^2_{fj}\right) & \sigma^2_{fj} = .00125 & \mu_j = \{0.015, 0.012, 0.01\} & j = 1, 2, 3 & \end{array} \tag{20}$$

The error terms for the y and x equations are defined as

$$\begin{array}{lll} e_{it} & \sim & iid\, N(0, \sigma^2_{e,i}) \qquad \text{where } \sigma^2_{e,i} \sim U[.001, .003] \\ \varepsilon_{it} & \sim & iid\, N(0, \sigma^2_{\varepsilon}) \qquad \sigma^2_{\varepsilon} = .00125 \end{array}$$

The slope coefficient on x is set to $\beta_i = 1 + e^{\beta}_i$ where $e^{\beta}_i \sim U[-.25, +.25]$. The factor loadings are uniformly distributed, with λ^x_{i1} and λ^y_{i1} iid $U[0, 1]$ respectively, and λ^x_{i3} and λ^y_{i2} iid $U[.25, 1.25]$ respectively.

We consider the following cases (as well as combinations of these)

(i) baseline (as above).
(ii) baseline with additional country-specific linear trends.
(iii) feedbacks: an idiosyncratic shock to y feeds back into x with one period lag.
(iv) two 'clubs' of countries with the same β coefficient.

For the linear country trend case, the trends are distributed $U[-.02, +.03]$, s.t. that the mean annual growth rate across countries is non-zero. For the feedback case, the lagged error ε_{t-1} from the y-equation in (18) is included in the x-equation in (19) with coefficient .25 (in practice we enter this term in the same way as the other terms in the dynamic equation as described above to allow for serial correlation in the x-equation). Finally, for the 'two clubs' case 20% of countries have $\beta = 2$, while 80% have $\beta = .75$, s.t. the mean β across all countries is still unity.

4.2 Results

Results for our benchmark specification — **Case (i)** — are presented in Table III. For the remainder of this paper the POLS and FE estimators always contain $(T-1)$ year dummies in their estimation equations. As can be seen both of these estimators are biased (increasing in T, decreasing in N) and in particular the POLS is very imprecise. For $T = 30$, $N = 50$ FE has only limited bias of .0324 with empirical standard error of .0876, compared to .0271 for the infeasible FE estimator. Similarly for the MG estimator, although the magnitude of the bias is higher. For the CCE and AMG estimators, all of which are unbiased, the AMG(ii) commonly is most efficient and very close to the standard errors for the infeasible estimators. The FD-OLS similarly performs very well.

Once we add the country-specific trend terms — **Case (ii)** — as presented in Table IV the bias in the standard pooled estimators does not change by any significant margin, however their imprecision now increases with T. Again for $T = 30$, $N = 50$ FE has a bias of .0277, but a very substantial empirical standard error of .1973 (over twice that of the benchmark case), compared with .0280 for the infeasible FE estimator in the same setup. In contrast the unbiased CCE and AMG estimators are still efficient, although the FD-OLS estimator now emerges as the most efficient feasible estimator. The MG estimator is seriously biased and inefficient.

By construction, the feedback setup — **Case (iii)** — leads to bias in the FD-OLS, which carries over to the AMG estimators, as can be seen in Table V (AMG estimates marked †): due to first differencing the lagged error $\varepsilon_{i,t-1}$ is contained in both the errors and the regressors of the FD-OLS estimation equation, whereas this is not the case in the other (levels-based) estimators which account for common factors. We therefore also present the results for an IV-version of the FD-OLS estimator, where we use growth rates at time $(t-1)$ as instruments for the endogenous growth rates at time t (FD-IV), and AMG estimators which are based on the year dummies from the instrumented regression (AMG estimates marked ‡). The pooled OLS, FE and MG results are virtually unchanged from the baseline results: for $T = 30$, $N = 50$ FE has a bias of .0299 with empirical standard error of .0865 compared with .0271 for the infeasible FE estimator. The augmented estimators all display small bias, albeit very modest in case of the CCE estimators, while the new AMG estimates based on the FD-IV results are unbiased. The latter is unbiased, but inefficient compared with the new AMG estimators.

If we combine the feedback setup with linear country trends (results presented in Table VI) the pattern of bias does not change considerably, although the empirical standard errors for POLS and FE increase by around a third: for $T = 30$, $N = 50$ FE has a bias of .0253 with empirical standard error of .1943 — this is driven by the presence of the additional trend terms, since results for Case (ii) are very similar.
In the setup where β is heterogeneous but only takes two values for different 'clubs' of countries — **Case (iv)** — the results in Table VII show considerable bias for the POLS estimator, while the results for all other estimators remain relatively similar to those presented before. For $T = 30$, $N = 50$ the FE estimator has a bias of .0224 and an empirical standard error of .1375 compared with .0357 for the infeasible FE.
We also ran the simulations for this setup with additional linear country trends, with results in Table VIII. This specification leads to some bias and very serious imprecision in the standard pooled estimators, but hardly has any impact on the CCE and AMG estimators vis-à-vis the setup without country-specific linear trends. For $T = 30$, $N = 50$ the FE estimator has a bias of .0202 and an empirical standard error of .2275 compared with .0364 for the infeasible FE.

5. INTERPRETATION AND CONCLUDING REMARKS

We carried out a range of Monte Carlo simulations to investigate the properties of various standard and novel panel estimators in the face on nonstationary data series and unobserved common factors. Our review of earlier studies with the same aim (Coakley et al., 2006; Kapetanios et al., 2009) and replication of their results shows that the supposed serious bias in standard pooled estimators under the Monte Carlo setup specified by these authors can be reduced substantially by the use of year dummies in the pooled OLS and Fixed Effects estimators — a standard practice in the applied literature. Since our empirical results in previous empirical implementations (Eberhardt & Teal, 2008, 2009) however showed significant differences between these pooled and the alternative heterogeneous CCE and AMG-type estimators, we specified our own simulations so as to identify under which scenario we can observe the same patterns in the simulation results as in the empirical results.

In particular the specification of heterogeneous country trends led to some bias but primarily imprecision in the POLS, FE and MG estimators, while the FD-OLS, AMG and CCE estimators remained unbiased and comparatively precise. Similar bias is present when in addition to heterogeneous country trends our simulated DGP specifies two distinct 'clubs' of countries with differing technology parameter β. Overall, the issues of nonstationarity in observables and unobservables as well as the heterogeneity in their impact that are the focus of this paper seem to lead to inefficiency, rather than serious bias in the standard pooled panel estimators.

From the perspective of an applied economist this finding of serious inefficiency is observationally equivalent to severe bias in the estimator: a single 'draw' from the 1,000 replications carried out during our Monte Carlo simulations would yield a highly distorted parameter estimate in the pooled OLS, Fixed Effects (regardless of year dummy augmentation) and standard MG regression case, but a rather precise estimate in case of the estimators accounting for cross-section dependence. As an illustrative example we compute the 95% confidence interval (CI) of the mean for each estimator in the baseline scenario described above ($T = 30$, $N = 50$). Results are presented in the table below.[8]

We can see that if we ran a single regression with real-world data following this DGP, then with a true β-parameter of unity in 95% of the cases the POLS estimate we would obtain is as likely to be .56 as 1.39, the FE estimate is as likely .87 as 1.20, the MG estimate is as likely .77 as 1.48… while the AMG and CCEMG estimates are as likely to be .94 as 1.06. In each case the t-statistic associated with the obtained estimate would indicate the parameter to be highly significant (due to the uniformly low standard errors across all models, as indicated by their means in our simulation studies) and thus very precisely estimated.[9] The invalidity of

[8]As discussed in Hendry and Nielsen (2007, p.272/3) the mean of the simulated statistic (here: regression coefficient on β) provides an unbiased estimate of the unknown mean of the statistic, and the simulation sample variance is an unbiased estimator of the unknown population variance of the statistic. Note that these authors refer to the 'empirical standard error' as the 'Monte Carlo standard deviation' ($\bar{\omega}$) and use the term 'Monte Carlo standard error' $M^{-1/2}\bar{\omega}$ to refer to a measure of precision of the simulation exercise. See note 9 below.

[9]This result is not due to the imprecision of the Monte Carlo experiment: based on the empirical standard error (the standard

t-statistics and their distortion away from zero in the case where regression residuals are nonstationary has been highlighted in the literature by Kao (1999). Our numerical example indicates that while the unobserved common factor structures we considered here may not lead to biased estimates, inference is severely affected in the cases where these common factors are not accounted for. In order to illustrate this we have computed a measure of 'over-confidence' (OC), which is simply the quotient of the empirical standard error and the averaged regression standard error. If this is close to unity, our individual regression standard errors are a sound reflection of the 'true' standard errors of the estimator — e.g. the infeasible MG estimator has a statistic of unity. We can see that the FD-OLS estimator aside, all estimators which fail to account for heterogeneous cross-section dependence obtain overconfidence statistics far in excess of unity: the standard errors obtained for each of the regressions are thus much smaller than they should be, leading us to believe that our coefficient estimate of β is very precise.

Pooled Estimators						
	mean	*median*	*emp.ste.*	*mean ste.*	95% *CI (mean)*	OC
POLS‡	0.975	0.981	0.214	0.041	[0.556 , 1.395]	5.18
FE‡	1.032	1.031	0.088	0.027	[0.861 , 1.204]	3.26
CCEP	0.999	0.998	0.033	0.022	[0.934 , 1.065]	1.50
FD-OLS‡	1.002	1.002	0.034	0.024	[0.935 , 1.069]	1.44
FE (inf)	1.000	1.000	0.027	0.016	[0.947 , 1.053]	1.69
MG-type Estimators						
	mean	*median*	*emp.ste.*	*mean ste.*	95% *CI (mean)*	OC
CCEMG	0.999	0.998	0.034	0.033	[0.933 , 1.065]	1.03
AMG(i)	1.003	1.001	0.032	0.032	[0.939 , 1.066]	1.01
AMG(ii)	1.002	1.000	0.033	0.030	[0.938 , 1.066]	1.07
MG	1.126	1.114	0.182	0.039	[0.768 , 1.484]	4.70
MG (inf)	1.000	0.999	0.027	0.027	[0.948 , 1.052]	1.00

The estimators accounting for cross-section dependence aside, these simulations particularly highlight the performance of the FD-OLS estimator: with the exception of the feedback case, this estimator is unbiased and has very similar empirical standard errors as the CCE and AMG estimators. This is somewhat puzzling, since the FD-OLS model does not account for unobserved common effects with *heterogeneous* factor loadings: with reference to our own DGP in equation (18) we have $\lambda^y_{i1}\Delta f_{1t}$ and $\lambda^y_{i2}\Delta f_{2t}$ as part of the error term, where $\bar{\lambda}^y_1 = .5$ and $\bar{\lambda}^y_2 = .75$ and Δf_{1t}, Δf_{2t} have non-zero means (due to the presence of the drift terms). This setup thus specifies *non-zero average impact* for the unobserved factors, but in the FD-OLS regressions augmented with year dummies the correlation this induces with the regressors does not seem to create any bias. Thus even though $\boldsymbol{\beta}$ or the mean of the $\boldsymbol{\beta}_i$ is in theory not identified in this case the FD-OLS estimator yields an unbiased and efficient result.

A possible explanation for this phenomenon is that the year dummies lead to a 're-centering' of these factor-loadings around zero, such that the presence of the same factors in the errors and regressors (endogeneity) does not create any problems for consistent estimation of $\mathbb{E}[\beta_i]$, since the correlation between regressor and error terms is on average zero. We can provide the following, tentative evidence for this: adopting the baseline specification — Case (i) — from our own Monte Carlo setup we ran simulations where we dropped the year dummies in the FD-OLS estimators. The resulting bias in the estimates for the case of $\bar{\lambda}^y_1 = .5$ and $\bar{\lambda}^y_2 = .75$ is considerable, e.g. for $T = 30$, $N = 50$ we get a bias of .1159 and an empirical standard error of .0565 (1,000 replications). Recall that the results for the estimator *with* year dummies were unbiased with an empirical standard error of .0342. Still keeping FD-OLS without year dummies, we then re-center the factor-loadings around zero, which yields unbiased estimates and an empirical standard error of .0314. This pattern where FD-OLS is seriously biased if mean factor loadings are non-zero and year dummies are missing, but unbiased if mean factor loadings are zero, points to the year dummies as fulfilling the role described above. Future research may provide further evidence to support this speculative explanation.

The econometric literature on panel time series with cross-section dependence is presently developing quite rapidly — and to some extent in blissful isolation of the *mainstream* applied literature. In this paper we have introduced a very simple approach, the Augmented Mean Group estimator, which has proven surprisingly robust

deviation of the $m = 1,000$ estimates $\hat{b}_i$) we can compute the standard error of the experiment as $m^{-1/2}$ times this value to yield (in case of pooled FE) $2.77 * 10^{-3}$. Thus the *precision of the experiment* is such that the true mean estimate lies between 1.0269 and 1.0379 with 95% confidence.

to a great many empirical setups. The performance matches that of the Pesaran (2006) CCE estimators in a number of setups, but we were also able to indicate when this estimator is biased, thus providing an explanation for the differential performance of these estimators in our previous applied work (Eberhardt & Teal, 2008, 2009). This aside, we highlighted the dramatic change in simulated performance for 'naïve' estimators (POLS, 2FE) once they are augmented with year dummies — a standard practice in the applied literature. Furthermore, we speculated about the strong performance of the pooled FD-OLS estimator in the face of cross-section dependence, which will be investigated further in future work. It is important to highlight a potential short-coming of the estimators discussed in this study, namely that once the heterogeneous factor loadings on the unobservables are correlated with the observable variables the CCE and AMG-type estimators are likely to be biased — note that there is some disagreement about this (Chudik, Pesaran, & Tosetti, 2009), although our own preliminary results seem to support this claim. We will experiment with the 'Chamberlain-Mundlak' extension to the CCE estimators, suggested by Bai (2009) as a remedy for this problem. Most recently Jushan Bai has introduced a number of estimators (Bai & Kao, 2006; Bai, Kao, & Ng, 2009; Bai, 2009) which are suggested to be robust to this setup and in further work we will establish how these fair from a practical point of view in direct comparison to the estimators investigated here. Preliminary results from Chudik et al. (2009) suggest these are subject to serious size-distortions vis-à-vis the CCE estimators.

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Appendix: Monte Carlo simulations

Tables 1 to 8 from overleaf.

Table I: Coakley, Fuertes and Smith (2006)

Monte Carlo Results — replicating Coakley, Fuertes and Smith (2006)

5,000 replications; $N = 30$, $T = 20$; year dummies in the POLS or FE estimation equations: † — no, ‡ — yes; AMG-estimators are constructed from FD-OLS year dummy coefficients

	Case *A*				**Case *B***				**Case *C***				**Case *D***			
	Cointegration, no CSD				No cointegration, no CSD				No cointegration, CSD				No cointegration, CSD, endogenous x			
Pooled Estimators																
	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*
POLS†	1.0001	1.0001	0.0109	0.0055	0.9986	1.0005	0.2155	0.0397	0.9971	1.0013	0.2071	0.0399	1.0766	1.0774	0.2099	0.0397
POLS‡	1.0002	1.0002	0.0088	0.0054	0.9987	0.9995	0.2165	0.0407	0.9981	0.9983	0.2182	0.0409	1.0169	1.0170	0.2185	0.0409
FE†	1.0003	1.0004	0.0182	0.0180	1.0037	1.0038	0.1351	0.0404	0.9973	1.0038	0.2808	0.0410	1.4157	1.4065	0.2012	0.0363
FE‡	1.0004	1.0005	0.0186	0.0185	1.0041	1.0026	0.1381	0.0414	1.0034	1.0009	0.1389	0.0415	1.0208	1.0182	0.1420	0.0416
CCEP	1.0003	1.0003	0.0232	0.0226	1.0049	1.0039	0.1154	0.0421	1.0029	1.0043	0.1137	0.0418	1.0034	1.0041	0.1148	0.0420
FD-OLS	1.0014	1.0006	0.0574	0.0573	1.0010	1.0013	0.0413	0.0405	1.0006	1.0003	0.0413	0.0406	1.0120	1.0124	0.0442	0.0406
MG-type Estimators																
	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*
CCEMG	0.9998	1.0002	0.0335	0.0321	1.0045	1.0062	0.1314	0.1260	1.0027	1.0011	0.1281	0.1239	1.0035	1.0022	0.1303	0.1255
AMG(i)	1.0001	0.9997	0.0392	0.0373	1.0022	1.0031	0.1104	0.1072	1.0009	1.0018	0.0689	0.0727	1.0069	1.0071	0.0695	0.0788
AMG(ii)	1.0000	0.9995	0.0289	0.0273	1.0051	1.0052	0.1410	0.1379	1.0025	1.0022	0.0828	0.0897	1.0056	1.0084	0.1327	0.1319
MG	1.0001	0.9998	0.0283	0.0274	1.0047	1.0039	0.1626	0.1595	0.9985	1.0054	0.3017	0.1338	1.5059	1.4880	0.2196	0.1306

	Case $\tilde{D}$				**Case *E***				**Case *F***				**Case *G***			
	like Case D, factor loading dependence				Cointegration, CSD, endogenous x				like Case D, additional I(0) factor in x				No cointegration, I(1) factors			
Pooled Estimators																
	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*
POLS†	1.1317	1.1288	0.2181	0.0394	1.0072	1.0066	0.0109	0.0071	1.0648	1.0679	0.1938	0.0374	1.2273	1.2128	0.2439	0.0251
POLS‡	1.0088	1.0088	0.2174	0.0408	1.0003	1.0003	0.0106	0.0055	1.0078	1.0098	0.2101	0.0394	1.0016	1.0010	0.0049	0.0010
FE†	1.4437	1.4352	0.2096	0.0356	1.0516	1.0510	0.0345	0.0188	1.2775	1.2685	0.2069	0.0319	1.4374	1.4640	0.5928	0.0217
FE‡	1.0133	1.0123	0.1398	0.0415	1.0015	1.0014	0.0185	0.0185	1.0124	1.0105	0.1352	0.0401	1.0006	1.0004	0.0077	0.0028
CCEP	1.0051	1.0051	0.1147	0.0420	1.0004	1.0006	0.0234	0.0228	1.0035	1.0046	0.1135	0.0416	1.0031	1.0037	0.0934	0.0416
FD-OLS	1.0725	1.0707	0.0477	0.0405	1.0125	1.0122	0.0599	0.0574	1.0111	1.0102	0.0425	0.0392	1.0647	1.0456	0.1323	0.0303
MG-type Estimators																
	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*
CCEMG	1.0056	1.0035	0.1300	0.1256	0.9998	0.9995	0.0336	0.0322	1.0034	1.0029	0.1271	0.1234	1.0021	1.0030	0.1037	0.0988
AMG(i)	1.0381	1.0394	0.0690	0.0782	1.0068	1.0064	0.0447	0.0272	1.0090	1.0101	0.0564	0.0608	1.0627	1.0444	0.1308	0.0490
AMG(ii)	1.0170	1.0180	0.1314	0.1309	1.0071	1.0059	0.0396	0.0186	1.0088	1.0104	0.0806	0.0877	1.0654	1.0479	0.1341	0.0252
MG	1.5057	1.4972	0.2060	0.1238	1.0812	1.0796	0.0456	0.0259	1.3266	1.3134	0.2112	0.1018	1.5110	1.4921	0.7386	0.1585

Notes: For each estimator we report the mean and median for the 5,000 estimates of β. $*$ emp. ste refers to the empirical standard error, the standard deviation of the 5,000 estimates of β; mean ste refers to the sample mean of the estimated standard errors in the 5,000 estimations of β. See main text for simulation setup and detailed description of the cases.
The estimators are: POLS — pooled OLS, FE — Fixed Effects, CCEP — Pesaran (2006) pooled CCE estimator, FD-OLS — pooled OLS with variables in first difference, CCEMG — Pesaran (2006) Mean Group CCE estimator, AMG(i) — Augmented Mean Group estimator, $\hat{\mu}_t^{\bullet}$ imposed with unit coefficient, AMG(ii) — Augmented Mean Group estimator, $\hat{\mu}_t^{\bullet}$ included as regressor, MG — Pesaran and Smith (1995) Mean Group estimator. ‡ (†) We do (not) include $T-1$ year dummies.

Table II: Kapetanios, Pesaran and Yamagata (2009)

Monte Carlo Results — replicating Kapetanios, Pesaran and Yamagata (2009)

1,000 replications; year dummies in the POLS or FE estimation equations: † — no, ‡ — yes; AMG-estimators are constructed from FD-OLS year dummy coefficients

***T* = 20**	***N* = 20**						***N* = 30**						***N* = 50**						***N* = 100**					
	mean	median	emp. ste.*	mean ste.*	Bias x 100	RMSE x 100	mean	median	emp. ste.*	mean ste.*	Bias x 100	RMSE x 100	mean	median	emp. ste.*	mean ste.*	Bias x 100	RMSE x 100	mean	median	emp. ste.*	mean ste.*	Bias x 100	RMSE x 100
Pooled Estimators																								
POLS†	1.028	1.021	0.197	0.046	2.78	19.85	1.038	1.026	0.163	0.037	3.80	16.69	1.050	1.038	0.144	0.029	5.01	15.26	1.047	1.032	0.115	0.020	4.69	12.42
POLS‡	0.989	0.992	0.181	0.040	-1.09	18.15	0.986	0.992	0.142	0.033	-1.45	14.27	0.996	0.999	0.119	0.026	-0.37	11.85	0.995	0.992	0.081	0.018	-0.47	8.13
FE†	1.224	1.201	0.296	0.062	22.37	37.07	1.213	1.194	0.272	0.048	21.28	34.52	1.231	1.218	0.280	0.039	23.11	36.31	1.228	1.213	0.265	0.027	22.84	35.00
FE‡	0.996	0.994	0.107	0.041	-0.41	10.72	0.999	0.995	0.085	0.031	-0.14	8.54	1.000	0.999	0.070	0.026	-0.02	7.04	1.002	1.003	0.046	0.018	0.21	4.56
CCEP	0.998	1.001	0.089	0.044	-0.17	8.89	0.999	0.995	0.073	0.034	-0.11	7.32	1.001	1.000	0.061	0.030	0.13	6.10	1.002	1.001	0.041	0.020	0.21	4.05
FD-OLS	0.998	0.998	0.074	0.042	-0.21	7.41	0.999	1.000	0.058	0.031	-0.11	5.77	1.001	1.002	0.050	0.028	0.06	4.96	1.001	1.001	0.033	0.019	0.13	3.29
FE (inf)	1.002	1.001	0.068	0.034	0.16	6.81	1.000	0.999	0.053	0.025	-0.04	5.30	0.999	0.999	0.045	0.023	-0.13	4.48	1.001	1.002	0.030	0.015	0.09	3.03
MG-type Estimators																								
CCEMG	0.998	0.997	0.088	0.084	-0.25	8.75	1.000	0.997	0.074	0.070	-0.02	7.42	1.002	1.001	0.062	0.059	0.16	6.17	1.001	1.001	0.041	0.041	0.10	4.10
AMG(i)	0.997	0.999	0.080	0.075	-0.31	8.00	0.996	0.997	0.065	0.062	-0.37	6.51	1.001	1.003	0.057	0.053	0.05	5.71	1.000	1.001	0.037	0.036	-0.01	3.69
AMG(ii)	0.997	0.997	0.078	0.075	-0.26	7.79	0.998	0.998	0.066	0.063	-0.19	6.55	1.002	1.002	0.057	0.053	0.18	5.74	1.001	1.001	0.037	0.036	0.06	3.71
MG	1.217	1.184	0.286	0.163	21.74	35.91	1.209	1.187	0.261	0.133	20.88	33.45	1.230	1.208	0.270	0.113	22.99	35.45	1.230	1.211	0.251	0.077	23.00	34.05
MG (inf)	1.003	1.004	0.063	0.063	0.25	6.33	0.999	0.999	0.052	0.052	-0.14	5.22	0.999	0.999	0.047	0.045	-0.09	4.71	0.999	0.999	0.030	0.030	-0.08	3.01

***T* = 30**	***N* = 20**						***N* = 30**						***N* = 50**						***N* = 100**					
	mean	median	emp. ste.*	mean ste.*	Bias x 100	RMSE x 100	mean	median	emp. ste.*	mean ste.*	Bias x 100	RMSE x 100	mean	median	emp. ste.*	mean ste.*	Bias x 100	RMSE x 100	mean	median	emp. ste.*	mean ste.*	Bias x 100	RMSE x 100
Pooled Estimators																								
POLS†	1.064	1.050	0.196	0.038	6.43	20.62	1.066	1.049	0.172	0.030	6.61	18.41	1.054	1.039	0.144	0.023	5.45	15.40	1.061	1.042	0.124	0.016	6.10	13.82
POLS‡	1.015	1.020	0.174	0.032	1.51	17.41	1.006	1.000	0.140	0.026	0.59	13.96	0.994	0.997	0.108	0.020	-0.60	10.82	1.001	1.002	0.074	0.014	0.09	7.37
FE†	1.253	1.240	0.318	0.051	25.34	40.65	1.240	1.216	0.287	0.040	23.96	37.40	1.241	1.224	0.285	0.031	24.14	37.37	1.243	1.226	0.283	0.022	24.26	37.29
FE‡	1.002	1.001	0.113	0.032	0.16	11.24	1.006	1.005	0.087	0.025	0.57	8.68	0.999	1.003	0.069	0.020	-0.10	6.87	1.002	1.000	0.050	0.014	0.16	4.98
CCEP	0.998	1.000	0.093	0.036	-0.17	9.31	1.001	1.001	0.070	0.027	0.07	6.96	1.001	1.004	0.056	0.022	0.10	5.63	1.001	1.002	0.041	0.015	0.08	4.12
FD-OLS	1.001	0.999	0.075	0.038	0.13	7.49	1.003	1.000	0.055	0.026	0.27	5.50	0.998	0.999	0.042	0.021	-0.23	4.21	1.002	1.002	0.032	0.015	0.19	3.17
FE (inf)	1.001	0.998	0.066	0.027	0.11	6.56	1.002	1.003	0.053	0.020	0.16	5.28	0.998	0.997	0.041	0.016	-0.22	4.11	1.001	1.002	0.029	0.011	0.11	2.92
MG-type Estimators																								
CCEMG	0.997	0.997	0.088	0.083	-0.33	8.82	1.000	0.999	0.067	0.065	0.04	6.73	1.001	1.002	0.053	0.052	0.12	5.31	1.003	1.004	0.039	0.038	0.25	3.94
AMG(i)	0.998	1.001	0.084	0.078	-0.22	8.44	1.003	1.004	0.063	0.059	0.34	6.33	0.999	1.000	0.048	0.048	-0.07	4.84	1.002	1.004	0.036	0.034	0.24	3.61
AMG(ii)	0.999	0.998	0.085	0.080	-0.14	8.53	1.002	1.002	0.062	0.061	0.20	6.16	0.999	1.000	0.050	0.049	-0.09	4.97	1.002	1.002	0.036	0.035	0.22	3.60
MG	1.247	1.223	0.320	0.183	24.65	40.36	1.231	1.204	0.275	0.137	23.12	35.95	1.241	1.223	0.270	0.111	24.12	36.17	1.243	1.219	0.263	0.079	24.27	35.77
MG (inf)	0.998	0.997	0.060	0.060	-0.17	6.01	1.001	1.000	0.046	0.046	0.08	4.62	0.999	0.999	0.036	0.037	-0.14	3.60	1.002	1.002	0.026	0.026	0.15	2.58

Continued on the following page.

Kapetanios, Pesaran and Yamagata (2009) — continued

$T = 50$	$N = 20$						$N = 30$						$N = 50$						$N = 100$					
	mean	median	emp. ste.*	mean ste.*	Bias x 100	RMSE x 100	mean	median	emp. ste.*	mean ste.*	Bias x 100	RMSE x 100	mean	median	emp. ste.*	mean ste.*	Bias x 100	RMSE x 100	mean	median	emp. ste.*	mean ste.*	Bias x 100	RMSE x 100
Pooled Estimators																								
POLS†	1.083	1.058	0.207	0.029	8.31	22.25	1.083	1.063	0.183	0.024	8.30	20.10	1.083	1.061	0.165	0.018	8.31	18.48	1.078	1.052	0.147	0.013	7.84	16.69
POLS‡	0.998	0.995	0.167	0.024	-0.25	16.70	1.000	1.003	0.129	0.020	0.02	12.87	1.000	0.998	0.098	0.015	-0.04	9.79	0.997	1.000	0.071	0.011	-0.36	7.10
FE†	1.263	1.239	0.334	0.039	26.27	42.48	1.259	1.240	0.315	0.031	25.85	40.71	1.268	1.257	0.315	0.025	26.84	41.38	1.268	1.253	0.306	0.017	26.79	40.67
FE‡	0.997	0.998	0.114	0.024	-0.28	11.43	0.999	0.998	0.092	0.019	-0.14	9.22	0.999	1.001	0.070	0.015	-0.07	6.96	1.001	0.999	0.051	0.011	0.06	5.08
CCEP	1.006	1.005	0.092	0.025	0.55	9.25	1.000	1.001	0.074	0.019	0.02	7.38	1.002	1.005	0.061	0.016	0.24	6.05	1.001	1.001	0.042	0.011	0.08	4.24
FD-OLS	1.001	0.998	0.067	0.027	0.13	6.70	1.000	0.998	0.053	0.020	-0.01	5.33	1.002	1.004	0.042	0.017	0.22	4.17	1.001	1.002	0.029	0.012	0.08	2.93
FE (inf)	0.999	0.998	0.060	0.017	-0.07	6.02	0.998	1.000	0.050	0.013	-0.17	4.95	1.001	1.002	0.041	0.011	0.08	4.08	1.001	1.001	0.029	0.008	0.10	2.90
MG-type Estimators																								
CCEMG	1.005	1.008	0.087	0.083	0.48	8.71	1.000	1.003	0.070	0.068	-0.03	7.02	1.002	1.003	0.057	0.055	0.23	5.68	1.000	1.000	0.040	0.038	-0.02	3.95
AMG(i)	1.003	0.998	0.077	0.073	0.27	7.70	1.002	1.003	0.063	0.062	0.19	6.27	1.004	1.006	0.053	0.051	0.37	5.30	1.001	1.002	0.036	0.035	0.08	3.58
AMG(ii)	1.005	1.002	0.077	0.075	0.47	7.75	1.003	1.004	0.064	0.063	0.25	6.42	1.003	1.004	0.053	0.052	0.29	5.31	1.001	1.001	0.037	0.036	0.06	3.73
MG	1.263	1.241	0.336	0.180	26.29	42.65	1.266	1.236	0.316	0.148	26.58	41.24	1.277	1.246	0.304	0.123	27.73	41.11	1.277	1.254	0.294	0.083	27.65	40.33
MG (inf)	1.000	1.003	0.051	0.050	0.01	5.06	1.000	1.000	0.042	0.042	0.04	4.15	1.002	1.002	0.035	0.033	0.18	3.46	1.000	1.001	0.024	0.023	0.04	2.41

$T = 100$	$N = 20$						$N = 30$						$N = 50$						$N = 100$					
	mean	median	emp. ste.*	mean ste.*	Bias x 100	RMSE x 100	mean	median	emp. ste.*	mean ste.*	Bias x 100	RMSE x 100	mean	median	emp. ste.*	mean ste.*	Bias x 100	RMSE x 100	mean	median	emp. ste.*	mean ste.*	Bias x 100	RMSE x 100
Pooled Estimators																								
POLS†	1.128	1.106	0.221	0.022	12.77	25.54	1.124	1.100	0.202	0.018	12.41	23.68	1.116	1.091	0.182	0.014	11.61	21.62	1.118	1.089	0.171	0.010	11.80	20.78
POLS‡	1.007	1.004	0.158	0.018	0.72	15.84	1.008	1.003	0.131	0.014	0.81	13.12	0.999	0.999	0.097	0.011	-0.11	9.73	1.001	1.003	0.070	0.008	0.07	7.02
FE†	1.318	1.289	0.346	0.028	31.78	46.97	1.322	1.312	0.337	0.023	32.19	46.61	1.319	1.312	0.324	0.018	31.89	45.47	1.322	1.311	0.320	0.012	32.23	45.40
FE‡	1.001	1.000	0.121	0.017	0.05	12.11	1.002	1.002	0.098	0.014	0.24	9.81	0.998	0.997	0.076	0.010	-0.21	7.63	1.000	1.001	0.053	0.007	-0.01	5.29
CCEP	1.001	0.997	0.103	0.016	0.10	10.27	1.007	1.007	0.088	0.014	0.69	8.79	1.003	1.004	0.065	0.010	0.28	6.50	1.004	1.004	0.047	0.008	0.36	4.72
FD-OLS	1.002	1.002	0.065	0.019	0.22	6.46	1.002	1.002	0.053	0.016	0.16	5.33	1.000	1.003	0.039	0.012	-0.05	3.93	1.001	1.001	0.028	0.008	0.12	2.82
FE (inf)	1.002	1.001	0.064	0.010	0.18	6.41	1.000	1.000	0.057	0.008	0.01	5.68	1.000	1.001	0.042	0.006	0.04	4.21	1.000	1.000	0.029	0.004	0.04	2.91
MG-type Estimators																								
CCEMG	1.003	1.001	0.099	0.090	0.27	9.88	1.007	1.006	0.081	0.076	0.71	8.15	1.004	1.003	0.062	0.059	0.36	6.21	1.003	1.001	0.043	0.043	0.25	4.34
AMG(i)	1.001	1.001	0.081	0.079	0.12	8.04	1.003	1.002	0.067	0.069	0.25	6.73	1.001	1.002	0.053	0.052	0.05	5.32	1.001	1.002	0.037	0.038	0.09	3.72
AMG(ii)	1.003	1.000	0.083	0.080	0.34	8.25	1.007	1.007	0.073	0.070	0.72	7.32	1.002	1.004	0.054	0.054	0.22	5.39	1.002	1.003	0.039	0.039	0.18	3.93
MG	1.334	1.298	0.366	0.207	33.41	49.55	1.351	1.327	0.361	0.181	35.10	50.37	1.338	1.310	0.327	0.137	33.84	47.05	1.343	1.326	0.312	0.099	34.33	46.35
MG (inf)	1.003	1.002	0.049	0.047	0.25	4.90	1.002	1.002	0.042	0.039	0.16	4.16	1.002	1.001	0.031	0.030	0.15	3.08	1.000	1.001	0.022	0.021	0.03	2.18

Notes: See Table I and main text for details. FE (inf) and MG (inf) are ‘infeasible estimators’ where the true unobserved common factors are included in the regression. ‡ (†) We do (not) include $T - 1$ year dummies.

Table III: New Simulations — (i) Baseline setup

Monte Carlo Results — Baseline Setup

1,000 replications; POLS, FE and FD-OLS all have $T-1$ year dummies; AMG-estimators are constructed from FD-OLS year dummy coefficients

$\boldsymbol{T=20}$	$\boldsymbol{N=20}$				$\boldsymbol{N=30}$				$\boldsymbol{N=50}$				$\boldsymbol{N=100}$			
Pooled Estimators																
	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*
POLS	1.0481	1.0618	0.3660	0.0793	1.0448	1.0364	0.2875	0.0618	0.9689	0.9628	0.2142	0.0508	0.9896	0.9845	0.1384	0.0328
FE	1.0543	1.0483	0.1205	0.0499	1.0188	1.0188	0.0934	0.0402	1.0211	1.0201	0.0703	0.0312	1.0093	1.0086	0.0479	0.0218
CCEP	1.0014	0.9994	0.0584	0.0444	0.9999	1.0018	0.0491	0.0365	1.0006	1.0011	0.0370	0.0282	1.0014	0.9998	0.0268	0.0200
FD-OLS	1.0057	1.0054	0.0648	0.0466	1.0016	1.0008	0.0534	0.0377	1.0029	1.0027	0.0396	0.0291	1.0013	1.0005	0.0292	0.0204
FE (inf)	1.0019	1.0028	0.0474	0.0344	1.0003	0.9991	0.0403	0.0281	1.0008	1.0015	0.0309	0.0219	1.0009	1.0001	0.0221	0.0154
MG-type Estimator																
	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*
CCEMG	1.0013	1.0008	0.0598	0.0586	0.9983	1.0003	0.0498	0.0483	1.0004	1.0007	0.0382	0.0376	1.0016	1.0008	0.0277	0.0269
AMG(i)	1.0059	1.0050	0.0598	0.0530	1.0015	1.0021	0.0500	0.0439	1.0040	1.0044	0.0373	0.0344	1.0021	1.0005	0.0271	0.0246
AMG(ii)	1.0046	1.0028	0.0590	0.0499	1.0013	1.0022	0.0492	0.0421	1.0031	1.0041	0.0376	0.0328	1.0023	1.0011	0.0270	0.0233
MG	1.1076	1.1013	0.1651	0.0656	1.1261	1.1160	0.1725	0.0543	1.1128	1.1002	0.1582	0.0421	1.1205	1.1114	0.1656	0.0299
MG (inf)	1.0007	1.0000	0.0488	0.0493	0.9992	0.9981	0.0408	0.0405	1.0003	1.0014	0.0317	0.0314	1.0007	0.9996	0.0224	0.0222

$\boldsymbol{T=30}$	$\boldsymbol{N=20}$				$\boldsymbol{N=30}$				$\boldsymbol{N=50}$				$\boldsymbol{N=100}$			
Pooled Estimators																
	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*
POLS	1.0517	1.0593	0.3582	0.0649	1.0370	1.0269	0.2895	0.0507	0.9754	0.9815	0.2139	0.0413	0.9908	0.9940	0.1406	0.0268
FE	1.0735	1.0703	0.1536	0.0431	1.0258	1.0257	0.1178	0.0346	1.0324	1.0312	0.0876	0.0269	1.0111	1.0069	0.0602	0.0188
CCEP	1.0018	1.0049	0.0514	0.0350	1.0012	1.0007	0.0438	0.0287	0.9995	0.9975	0.0333	0.0222	1.0007	1.0006	0.0241	0.0157
FD-OLS	1.0035	1.0052	0.0552	0.0381	1.0037	1.0045	0.0454	0.0308	1.0021	1.0015	0.0342	0.0237	1.0009	1.0004	0.0248	0.0167
FE (inf)	1.0012	1.0035	0.0438	0.0255	1.0014	1.0023	0.0347	0.0207	1.0000	0.9996	0.0271	0.0161	1.0002	1.0003	0.0197	0.0113
MG-type Estimator																
	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*
CCEMG	1.0007	1.0017	0.0517	0.0497	1.0009	1.0014	0.0436	0.0420	0.9992	0.9975	0.0338	0.0327	1.0003	1.0002	0.0241	0.0237
AMG(i)	1.0064	1.0081	0.0523	0.0488	1.0041	1.0036	0.0435	0.0405	1.0026	1.0008	0.0323	0.0319	1.0024	1.0024	0.0237	0.0229
AMG(ii)	1.0035	1.0036	0.0517	0.0461	1.0043	1.0048	0.0429	0.0386	1.0018	1.0004	0.0326	0.0304	1.0024	1.0023	0.0231	0.0217
MG	1.1284	1.1263	0.1827	0.0604	1.1520	1.1369	0.1864	0.0502	1.1259	1.1143	0.1825	0.0388	1.1378	1.1356	0.1839	0.0278
MG (inf)	1.0012	1.0038	0.0431	0.0419	1.0016	1.0019	0.0336	0.0344	0.9999	0.9989	0.0267	0.0267	1.0002	1.0000	0.0194	0.0190

Continued on the following page.

New Simulations — (i) Baseline setup (continued)

***T* = 50**	***N* = 20**				***N* = 30**				***N* = 50**				***N* = 100**			
Pooled Estimators																
	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*
POLS	1.0502	1.0698	0.3640	0.0504	1.0342	1.0343	0.2919	0.0388	0.9857	0.9825	0.2057	0.0318	0.9893	0.9971	0.1392	0.0209
FE	1.1156	1.1189	0.2044	0.0357	1.0381	1.0356	0.1529	0.0285	1.0451	1.0468	0.1163	0.0221	1.0165	1.0140	0.0823	0.0155
CCEP	1.0024	1.0023	0.0480	0.0264	0.9993	0.9988	0.0405	0.0218	0.9997	1.0001	0.0317	0.0168	0.9996	1.0003	0.0217	0.0119
FD-OLS	1.0055	1.0031	0.0493	0.0295	1.0006	1.0008	0.0387	0.0239	1.0018	1.0022	0.0312	0.0184	1.0003	1.0004	0.0217	0.0129
FE (inf)	1.0009	1.0000	0.0393	0.0172	0.9995	0.9997	0.0324	0.0141	1.0000	1.0001	0.0257	0.0109	0.9997	0.9995	0.0177	0.0077
MG-type Estimator																
	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*
CCEMG	1.0026	0.9999	0.0475	0.0459	0.9982	0.9993	0.0405	0.0387	0.9994	0.9997	0.0310	0.0300	1.0001	0.9999	0.0213	0.0217
AMG(i)	1.0075	1.0064	0.0474	0.0479	1.0024	1.0027	0.0385	0.0398	1.0040	1.0035	0.0301	0.0312	1.0024	1.0023	0.0211	0.0224
AMG(ii)	1.0048	1.0036	0.0464	0.0444	1.0016	1.0020	0.0375	0.0372	1.0024	1.0022	0.0301	0.0290	1.0018	1.0020	0.0207	0.0209
MG	1.1700	1.1564	0.2160	0.0595	1.1761	1.1669	0.2123	0.0499	1.1613	1.1496	0.2088	0.0384	1.1641	1.1584	0.2148	0.0275
MG (inf)	1.0006	1.0017	0.0368	0.0370	0.9996	1.0001	0.0314	0.0300	0.9998	0.9996	0.0241	0.0236	0.9996	1.0005	0.0170	0.0166

***T* = 100**	***N* = 20**				***N* = 30**				***N* = 50**				***N* = 100**			
Pooled Estimators																
	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*
POLS	1.0973	1.1043	0.3540	0.0349	1.0422	1.0282	0.2762	0.0273	0.9990	0.9964	0.2148	0.0221	0.9993	1.0001	0.1434	0.0145
FE	1.1469	1.1565	0.2527	0.0266	1.0446	1.0479	0.1911	0.0212	1.0557	1.0553	0.1433	0.0166	1.0233	1.0196	0.1042	0.0115
CCEP	1.0068	1.0045	0.0535	0.0185	1.0017	1.0011	0.0428	0.0153	0.9999	1.0001	0.0343	0.0119	0.9984	0.9987	0.0260	0.0084
FD-OLS	1.0063	1.0051	0.0427	0.0208	1.0034	1.0033	0.0346	0.0169	1.0021	1.0023	0.0266	0.0130	1.0002	1.0007	0.0195	0.0091
FE (inf)	1.0019	1.0012	0.0375	0.0101	1.0018	1.0019	0.0302	0.0082	0.9997	0.9996	0.0226	0.0063	0.9994	0.9991	0.0171	0.0045
MG-type Estimator																
	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*
CCEMG	1.0044	1.0024	0.0509	0.0478	0.9998	0.9992	0.0415	0.0408	0.9987	0.9986	0.0328	0.0323	0.9996	0.9992	0.0249	0.0229
AMG(i)	1.0089	1.0075	0.0461	0.0503	1.0052	1.0055	0.0363	0.0420	1.0054	1.0042	0.0291	0.0336	1.0032	1.0038	0.0212	0.0238
AMG(ii)	1.0056	1.0039	0.0436	0.0459	1.0049	1.0046	0.0358	0.0387	1.0026	1.0027	0.0280	0.0308	1.0022	1.0031	0.0209	0.0219
MG	1.2078	1.1970	0.2549	0.0617	1.2084	1.2021	0.2516	0.0519	1.1932	1.1815	0.2678	0.0412	1.1944	1.1858	0.2601	0.0295
MG (inf)	1.0010	0.9995	0.0349	0.0337	1.0014	1.0020	0.0279	0.0277	0.9993	0.9992	0.0209	0.0216	0.9997	0.9996	0.0155	0.0152

Notes: See main text for details of Monte Carlo setup.

Table IV: New Simulations — (ii) Additional country trend

Monte Carlo Results — Baseline Setup

1,000 replications; POLS, FE and FD-OLS all have $T-1$ year dummies; AMG-estimators are constructed from FD-OLS year dummy coefficients

$T = 20$	$N = 20$				$N = 30$				$N = 50$				$N = 100$			
Pooled Estimators																
	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*
POLS	1.0517	1.0587	0.4729	0.1068	1.0321	1.0318	0.3800	0.0839	0.9679	0.9616	0.2921	0.0675	0.9914	0.9951	0.1949	0.0441
FE	1.0403	1.0364	0.2249	0.0905	1.0201	1.0226	0.1840	0.0732	1.0210	1.0192	0.1429	0.0563	1.0113	1.0123	0.0998	0.0396
CCEP	0.9986	0.9999	0.0726	0.0526	0.9995	0.9990	0.0595	0.0435	1.0025	1.0022	0.0445	0.0333	1.0015	1.0006	0.0307	0.0236
FD-OLS	1.0050	1.0067	0.0670	0.0497	1.0015	0.9995	0.0536	0.0401	1.0027	1.0006	0.0393	0.0309	1.0008	1.0000	0.0287	0.0217
FE (inf)	1.0023	1.0036	0.0520	0.0384	0.9998	0.9991	0.0427	0.0313	1.0012	1.0017	0.0322	0.0243	1.0008	1.0004	0.0234	0.0172
MG-type Estimator																
	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*
CCEMG	0.9990	0.9994	0.0741	0.0692	0.9981	0.9968	0.0622	0.0582	1.0022	1.0018	0.0456	0.0441	1.0017	1.0015	0.0320	0.0317
AMG(i)	1.0050	1.0065	0.0947	0.0537	1.0035	1.0054	0.0745	0.0445	1.0054	1.0049	0.0603	0.0347	1.0041	1.0033	0.0458	0.0250
AMG(ii)	1.0161	1.0074	0.1054	0.0718	1.0155	1.0143	0.0819	0.0586	1.0152	1.0115	0.0672	0.0446	1.0120	1.0109	0.0505	0.0315
MG	1.1092	1.1037	0.1686	0.0656	1.1254	1.1144	0.1742	0.0544	1.1129	1.0965	0.1579	0.0423	1.1203	1.1148	0.1650	0.0300
MG (inf)	1.0032	1.0017	0.0545	0.0537	1.0016	1.0021	0.0451	0.0436	1.0029	1.0027	0.0357	0.0338	1.0029	1.0028	0.0255	0.0241

$T = 30$	$N = 20$				$N = 30$				$N = 50$				$N = 100$			
Pooled Estimators																
	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*
POLS	1.0654	1.0722	0.4969	0.0893	1.0241	1.0298	0.3888	0.0708	0.9731	0.9688	0.3102	0.0567	0.9948	1.0017	0.2054	0.0371
FE	1.0718	1.0761	0.3278	0.0888	1.0109	1.0138	0.2497	0.0717	1.0277	1.0283	0.1973	0.0552	1.0108	1.0159	0.1400	0.0389
CCEP	1.0028	1.0021	0.0612	0.0431	1.0015	0.9991	0.0553	0.0355	0.9991	1.0003	0.0395	0.0275	1.0003	1.0018	0.0286	0.0194
FD-OLS	1.0036	1.0038	0.0556	0.0402	1.0028	1.0024	0.0473	0.0325	1.0025	1.0031	0.0351	0.0250	1.0009	1.0017	0.0243	0.0176
FE (inf)	1.0009	1.0019	0.0446	0.0282	1.0011	1.0001	0.0372	0.0230	0.9998	0.9995	0.0280	0.0179	1.0004	1.0002	0.0191	0.0126
MG-type Estimator																
	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*
CCEMG	1.0019	1.0017	0.0618	0.0603	1.0007	0.9984	0.0554	0.0508	0.9997	0.9997	0.0404	0.0400	1.0002	1.0008	0.0295	0.0284
AMG(i)	1.0041	1.0044	0.0839	0.0495	1.0058	1.0089	0.0697	0.0405	1.0049	1.0047	0.0506	0.0322	1.0019	1.0014	0.0378	0.0229
AMG(ii)	1.0100	1.0071	0.0894	0.0665	1.0130	1.0144	0.0752	0.0555	1.0090	1.0080	0.0558	0.0432	1.0061	1.0053	0.0412	0.0300
MG	1.1262	1.1248	0.1824	0.0603	1.1506	1.1427	0.1853	0.0502	1.1269	1.1185	0.1848	0.0390	1.1379	1.1361	0.1826	0.0277
MG (inf)	1.0013	1.0005	0.0452	0.0441	1.0028	1.0025	0.0375	0.0361	1.0017	1.0019	0.0286	0.0281	1.0012	1.0011	0.0198	0.0200

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New Simulations — (ii) Additional country trend (continued)

***T* = 50**	***N* = 20**				***N* = 30**				***N* = 50**				***N* = 100**			
Pooled Estimators																
	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*
POLS	1.0407	1.0480	0.5318	0.0724	1.0288	1.0308	0.4090	0.0572	0.9913	0.9831	0.3194	0.0462	0.9868	0.9830	0.2078	0.0304
FE	1.1113	1.1193	0.4462	0.0821	1.0354	1.0517	0.3627	0.0658	1.0486	1.0570	0.2810	0.0512	1.0137	1.0202	0.2003	0.0361
CCEP	1.0053	1.0051	0.0640	0.0356	0.9999	0.9987	0.0511	0.0290	0.9999	1.0007	0.0409	0.0223	0.9991	0.9984	0.0288	0.0159
FD-OLS	1.0058	1.0038	0.0502	0.0309	1.0006	1.0013	0.0395	0.0250	1.0009	1.0012	0.0318	0.0192	1.0007	1.0005	0.0221	0.0135
FE (inf)	1.0015	1.0004	0.0406	0.0192	0.9999	1.0003	0.0330	0.0157	0.9988	0.9998	0.0255	0.0122	1.0001	1.0002	0.0181	0.0086
MG-type Estimator																
	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*
CCEMG	1.0055	1.0051	0.0628	0.0586	0.9989	0.9983	0.0506	0.0482	0.9997	1.0004	0.0398	0.0375	0.9993	0.9992	0.0285	0.0270
AMG(i)	1.0040	1.0080	0.0767	0.0483	0.9991	0.9996	0.0597	0.0395	1.0011	1.0005	0.0461	0.0311	1.0027	1.0021	0.0339	0.0224
AMG(ii)	1.0061	1.0068	0.0829	0.0694	1.0023	1.0013	0.0655	0.0561	1.0027	1.0034	0.0495	0.0437	1.0038	1.0041	0.0360	0.0308
MG	1.1724	1.1591	0.2178	0.0600	1.1755	1.1653	0.2131	0.0496	1.1606	1.1530	0.2088	0.0383	1.1651	1.1605	0.2149	0.0276
MG (inf)	1.0013	0.9999	0.0400	0.0383	1.0002	1.0008	0.0314	0.0311	1.0000	0.9997	0.0245	0.0243	1.0010	1.0011	0.0177	0.0171

***T* = 100**	***N* = 20**				***N* = 30**				***N* = 50**				***N* = 100**			
Pooled Estimators																
	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*
POLS	1.1143	1.1221	0.5645	0.0569	1.0373	1.0306	0.4429	0.0454	0.9945	0.9797	0.3600	0.0359	1.0010	1.0050	0.2425	0.0238
FE	1.1824	1.1952	0.6226	0.0652	1.0394	1.0153	0.4984	0.0537	1.0535	1.0629	0.3844	0.0409	1.0211	1.0263	0.2716	0.0289
CCEP	1.0051	1.0048	0.0673	0.0280	0.9999	0.9996	0.0586	0.0231	1.0017	1.0009	0.0457	0.0179	0.9992	1.0002	0.0314	0.0126
FD-OLS	1.0063	1.0070	0.0429	0.0217	1.0018	1.0014	0.0337	0.0176	1.0032	1.0024	0.0270	0.0135	1.0020	1.0019	0.0188	0.0095
FE (inf)	1.0013	1.0009	0.0364	0.0114	0.9997	1.0004	0.0301	0.0093	1.0002	0.9994	0.0241	0.0072	1.0012	1.0010	0.0166	0.0051
MG-type Estimator																
	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*
CCEMG	1.0038	1.0017	0.0639	0.0619	0.9976	0.9975	0.0524	0.0530	0.9998	0.9999	0.0429	0.0417	1.0005	1.0016	0.0294	0.0295
AMG(i)	1.0013	1.0019	0.0683	0.0508	1.0043	1.0062	0.0516	0.0421	1.0043	1.0049	0.0425	0.0336	1.0049	1.0056	0.0284	0.0238
AMG(ii)	1.0003	0.9993	0.0732	0.0733	1.0040	1.0050	0.0542	0.0602	1.0037	1.0016	0.0448	0.0479	1.0042	1.0050	0.0311	0.0337
MG	1.2072	1.1991	0.2528	0.0621	1.2091	1.2019	0.2514	0.0521	1.1948	1.1830	0.2692	0.0413	1.1966	1.1871	0.2593	0.0295
MG (inf)	1.0012	1.0021	0.0343	0.0345	1.0002	0.9999	0.0279	0.0280	1.0006	1.0004	0.0221	0.0218	1.0017	1.0017	0.0156	0.0154

Notes: See main text for details of Monte Carlo setup.

Table V: New Simulations — (iii) Feedback setup

Monte Carlo Results — Setup with Feedbacks from y to x

1,000 replications; POLS, FE and FD-OLS all have $T-1$ year dummies; AMG-estimators are constructed from † FD-OLS or ‡ FD-IV year dummy coefficients

$T = 20$	$N = 20$				$N = 30$				$N = 50$				$N = 100$			
Pooled Estimators																
	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*
POLS	1.0481	1.0618	0.3660	0.0793	1.0448	1.0374	0.2874	0.0618	0.9688	0.9629	0.2141	0.0508	0.9896	0.9845	0.1384	0.0328
FE	1.0485	1.0427	0.1183	0.0493	1.0140	1.0117	0.0923	0.0397	1.0163	1.0133	0.0691	0.0309	1.0048	1.0036	0.0473	0.0216
CCEP	0.9823	0.9814	0.0578	0.0436	0.9805	0.9833	0.0492	0.0358	0.9812	0.9822	0.0361	0.0277	0.9823	0.9806	0.0265	0.0196
FD-OLS	0.9181	0.9195	0.0631	0.0467	0.9142	0.9127	0.0530	0.0377	0.9154	0.9146	0.0391	0.0291	0.9142	0.9140	0.0287	0.0204
FD-IV	0.9951	0.9876	0.1662	0.0474	0.9963	0.9936	0.1282	0.0381	1.0027	1.0033	0.1036	0.0293	0.9978	0.9981	0.0706	0.0205
FE (inf)	0.9892	0.9902	0.0472	0.0340	0.9875	0.9867	0.0406	0.0278	0.9880	0.9881	0.0304	0.0216	0.9883	0.9879	0.0224	0.0152
MG-type Estimator																
	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*
CCEMG	0.9772	0.9758	0.0589	0.0576	0.9740	0.9764	0.0495	0.0473	0.9762	0.9761	0.0370	0.0368	0.9772	0.9765	0.0271	0.0264
AMG(i)†	0.9585	0.9597	0.0596	0.0526	0.9540	0.9541	0.0508	0.0435	0.9580	0.9576	0.0378	0.0340	0.9569	0.9562	0.0288	0.0244
AMG(i)‡	0.9922	0.9890	0.0877	0.0532	0.9913	0.9931	0.0704	0.0438	0.9939	0.9926	0.0571	0.0343	0.9914	0.9894	0.0432	0.0245
AMG(ii)†	0.9528	0.9534	0.0573	0.0500	0.9508	0.9514	0.0494	0.0419	0.9537	0.9528	0.0375	0.0327	0.9539	0.9535	0.0286	0.0234
AMG(ii)‡	1.0055	0.9958	0.1005	0.0507	1.0030	0.9990	0.0773	0.0422	1.0037	0.9981	0.0663	0.0328	0.9991	0.9974	0.0490	0.0233
MG	1.0918	1.0852	0.1627	0.0648	1.1105	1.1012	0.1692	0.0535	1.0970	1.0828	0.1554	0.0415	1.1048	1.0956	0.1625	0.0295
MG (inf)	0.9829	0.9815	0.0483	0.0490	0.9814	0.9819	0.0410	0.0400	0.9826	0.9834	0.0311	0.0311	0.9831	0.9823	0.0225	0.0220

$T = 30$	$N = 20$				$N = 30$				$N = 50$				$N = 100$			
Pooled Estimators																
	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*
POLS	1.0518	1.0588	0.3581	0.0648	1.0370	1.0271	0.2894	0.0507	0.9754	0.9818	0.2138	0.0413	0.9908	0.9938	0.1406	0.0268
FE	1.0697	1.0647	0.1513	0.0428	1.0232	1.0231	0.1163	0.0343	1.0299	1.0285	0.0865	0.0267	1.0088	1.0055	0.0596	0.0186
CCEP	0.9888	0.9915	0.0507	0.0343	0.9883	0.9892	0.0432	0.0282	0.9867	0.9851	0.0330	0.0219	0.9880	0.9882	0.0238	0.0155
FD-OLS	0.9162	0.9177	0.0547	0.0377	0.9162	0.9165	0.0447	0.0305	0.9149	0.9136	0.0341	0.0235	0.9139	0.9138	0.0243	0.0165
FD-IV	0.9948	0.9924	0.1312	0.0381	1.0009	1.0006	0.1052	0.0308	1.0004	0.9993	0.0813	0.0237	0.9973	0.9989	0.0569	0.0166
FE (inf)	0.9934	0.9963	0.0436	0.0252	0.9938	0.9943	0.0345	0.0205	0.9924	0.9923	0.0271	0.0159	0.9926	0.9926	0.0198	0.0112
MG-type Estimator																
	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*
CCEMG	0.9847	0.9873	0.0510	0.0490	0.9845	0.9855	0.0431	0.0413	0.9828	0.9819	0.0333	0.0322	0.9841	0.9843	0.0238	0.0233
AMG(i)†	0.9581	0.9580	0.0529	0.0485	0.9563	0.9569	0.0442	0.0401	0.9552	0.9541	0.0340	0.0316	0.9560	0.9558	0.0258	0.0227
AMG(i)‡	0.9979	0.9985	0.0801	0.0486	0.9978	0.9968	0.0653	0.0403	0.9959	0.9953	0.0486	0.0317	0.9949	0.9954	0.0375	0.0227
AMG(ii)†	0.9516	0.9520	0.0513	0.0460	0.9528	0.9535	0.0429	0.0385	0.9511	0.9503	0.0338	0.0303	0.9527	0.9532	0.0255	0.0217
AMG(ii)‡	1.0033	1.0008	0.0874	0.0464	1.0061	1.0004	0.0722	0.0386	1.0015	0.9995	0.0542	0.0303	0.9997	0.9991	0.0415	0.0216
MG	1.1179	1.1159	0.1801	0.0596	1.1413	1.1239	0.1839	0.0496	1.1157	1.1043	0.1799	0.0384	1.1274	1.1261	0.1810	0.0274
MG (inf)	0.9901	0.9913	0.0430	0.0416	0.9906	0.9907	0.0336	0.0341	0.9888	0.9884	0.0265	0.0265	0.9892	0.9891	0.0195	0.0189

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New Simulations — (iii) Feedback setup (continued)

$T = 50$	$N = 20$				$N = 30$				$N = 50$				$N = 100$			
Pooled Estimators																
	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*
POLS	1.0501	1.0700	0.3639	0.0503	1.0342	1.0344	0.2919	0.0388	0.9857	0.9823	0.2056	0.0318	0.9893	0.9969	0.1391	0.0209
FE	1.1136	1.1164	0.2024	0.0355	1.0369	1.0349	0.1515	0.0284	1.0439	1.0458	0.1153	0.0220	1.0156	1.0125	0.0816	0.0154
CCEP	0.9947	0.9935	0.0474	0.0260	0.9917	0.9914	0.0400	0.0214	0.9922	0.9925	0.0314	0.0166	0.9921	0.9924	0.0214	0.0117
FD-OLS	0.9179	0.9165	0.0489	0.0290	0.9131	0.9125	0.0385	0.0235	0.9145	0.9143	0.0307	0.0181	0.9132	0.9137	0.0212	0.0127
FD-IV	0.9973	0.9963	0.1028	0.0293	0.9944	0.9924	0.0836	0.0236	0.9977	1.0005	0.0659	0.0182	0.9972	0.9971	0.0439	0.0128
FE (inf)	0.9970	0.9969	0.0392	0.0171	0.9957	0.9960	0.0323	0.0139	0.9962	0.9960	0.0257	0.0108	0.9960	0.9959	0.0177	0.0076
MG-type Estimator																
	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*
CCEMG	0.9927	0.9899	0.0470	0.0453	0.9886	0.9881	0.0399	0.0381	0.9897	0.9895	0.0306	0.0296	0.9903	0.9901	0.0209	0.0214
AMG(i)†	0.9543	0.9541	0.0491	0.0477	0.9503	0.9509	0.0395	0.0395	0.9528	0.9516	0.0318	0.0310	0.9515	0.9512	0.0238	0.0222
AMG(i)‡	1.0001	1.0000	0.0711	0.0477	0.9960	0.9977	0.0564	0.0395	0.9987	0.9990	0.0444	0.0310	0.9978	0.9977	0.0303	0.0222
AMG(ii)†	0.9485	0.9470	0.0469	0.0443	0.9461	0.9459	0.0380	0.0371	0.9477	0.9485	0.0310	0.0290	0.9475	0.9477	0.0236	0.0209
AMG(ii)‡	1.0021	0.9992	0.0774	0.0446	0.9993	0.9978	0.0612	0.0371	1.0007	0.9999	0.0486	0.0290	0.9994	0.9992	0.0327	0.0208
MG	1.1634	1.1486	0.2130	0.0588	1.1694	1.1597	0.2094	0.0493	1.1548	1.1428	0.2061	0.0380	1.1577	1.1515	0.2118	0.0272
MG (inf)	0.9946	0.9958	0.0368	0.0369	0.9938	0.9943	0.0312	0.0299	0.9939	0.9940	0.0242	0.0235	0.9937	0.9943	0.0170	0.0166

$T = 100$	$N = 20$				$N = 30$				$N = 50$				$N = 100$			
Pooled Estimators																
	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*
POLS	1.0973	1.1041	0.3540	0.0349	1.0423	1.0277	0.2761	0.0273	0.9990	0.9964	0.2148	0.0221	0.9993	1.0000	0.1434	0.0145
FE	1.1463	1.1546	0.2518	0.0266	1.0443	1.0476	0.1904	0.0211	1.0554	1.0557	0.1428	0.0165	1.0231	1.0194	0.1039	0.0115
CCEP	1.0031	1.0007	0.0526	0.0182	0.9981	0.9978	0.0423	0.0150	0.9964	0.9967	0.0338	0.0117	0.9949	0.9952	0.0256	0.0083
FD-OLS	0.9189	0.9181	0.0429	0.0204	0.9162	0.9165	0.0346	0.0165	0.9147	0.9146	0.0264	0.0127	0.9132	0.9139	0.0194	0.0089
FD-IV	0.9966	0.9926	0.0807	0.0205	1.0010	1.0005	0.0601	0.0166	0.9988	0.9977	0.0473	0.0128	0.9989	0.9982	0.0327	0.0090
FE (inf)	1.0005	0.9998	0.0375	0.0101	1.0004	1.0009	0.0302	0.0082	0.9983	0.9985	0.0226	0.0063	0.9981	0.9976	0.0171	0.0045
MG-type Estimator																
	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*
CCEMG	0.9997	0.9978	0.0501	0.0470	0.9952	0.9947	0.0410	0.0401	0.9940	0.9947	0.0323	0.0317	0.9948	0.9944	0.0244	0.0225
AMG(i)†	0.9478	0.9458	0.0473	0.0503	0.9447	0.9460	0.0384	0.0418	0.9448	0.9443	0.0315	0.0334	0.9432	0.9429	0.0248	0.0237
AMG(i)‡	1.0011	0.9987	0.0667	0.0501	1.0030	1.0027	0.0497	0.0418	1.0021	1.0019	0.0397	0.0334	1.0011	1.0013	0.0282	0.0237
AMG(ii)†	0.9422	0.9410	0.0447	0.0461	0.9415	0.9413	0.0374	0.0389	0.9388	0.9395	0.0295	0.0310	0.9392	0.9402	0.0239	0.0220
AMG(ii)‡	1.0001	0.9962	0.0689	0.0460	1.0038	1.0026	0.0519	0.0386	1.0007	1.0008	0.0409	0.0307	1.0008	1.0009	0.0294	0.0218
MG	1.2041	1.1925	0.2523	0.0612	1.2048	1.1968	0.2491	0.0514	1.1897	1.1785	0.2651	0.0408	1.1909	1.1814	0.2575	0.0292
MG (inf)	0.9986	0.9970	0.0348	0.0337	0.9990	0.9997	0.0279	0.0277	0.9969	0.9966	0.0209	0.0215	0.9974	0.9971	0.0155	0.0152

Notes: ‡ These use the year dummy coefficients from FD-IV estimator, rather than the FD-OLS estimator.

Table VI: New Simulations — (iii)* Feedback and country trend

Monte Carlo Results — Setup with Feedbacks from y to x

1,000 replications; POLS, FE and FD-OLS all have $T-1$ year dummies; AMG-estimators are constructed from † FD-OLS or ‡ FD-IV year dummy coefficients

$T = 20$	**$N = 20$**				**$N = 30$**				**$N = 50$**				**$N = 100$**			
Pooled Estimators																
	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*
POLS	1.0517	1.0595	0.4728	0.1068	1.0321	1.0324	0.3799	0.0839	0.9678	0.9614	0.2920	0.0675	0.9914	0.9953	0.1949	0.0441
FE	1.0345	1.0289	0.2202	0.0895	1.0157	1.0187	0.1807	0.0724	1.0162	1.0150	0.1402	0.0557	1.0068	1.0107	0.0979	0.0392
CCEP	0.9793	0.9802	0.0714	0.0517	0.9804	0.9789	0.0590	0.0427	0.9827	0.9819	0.0434	0.0327	0.9824	0.9807	0.0303	0.0232
FD-OLS	0.9173	0.9163	0.0656	0.0484	0.9142	0.9141	0.0529	0.0391	0.9153	0.9138	0.0385	0.0301	0.9137	0.9130	0.0283	0.0212
FD-IV	0.9968	0.9981	0.1686	0.0490	0.9954	0.9893	0.1293	0.0395	1.0007	0.9996	0.1034	0.0304	0.9973	0.9964	0.0723	0.0213
FE (inf)	0.9834	0.9840	0.0518	0.0379	0.9808	0.9806	0.0427	0.0309	0.9824	0.9828	0.0317	0.0240	0.9821	0.9820	0.0236	0.0169
MG-type Estimator																
	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*
CCEMG	0.9745	0.9730	0.0726	0.0678	0.9738	0.9747	0.0612	0.0569	0.9776	0.9775	0.0445	0.0432	0.9772	0.9777	0.0313	0.0311
AMG(i) IV	0.9934	0.9922	0.0910	0.0532	0.9912	0.9929	0.0721	0.0440	0.9931	0.9922	0.0585	0.0343	0.9914	0.9908	0.0445	0.0247
AMG(ii) IV	1.0047	0.9966	0.1030	0.0707	1.0035	1.0011	0.0800	0.0577	1.0034	0.9996	0.0657	0.0440	0.9998	0.9976	0.0494	0.0311
MG	1.0933	1.0899	0.1658	0.0648	1.1099	1.0978	0.1711	0.0537	1.0972	1.0782	0.1552	0.0417	1.1045	1.0977	0.1618	0.0296
MG (inf)	0.9789	0.9769	0.0540	0.0530	0.9773	0.9798	0.0451	0.0431	0.9788	0.9793	0.0351	0.0334	0.9788	0.9790	0.0254	0.0238

$T = 30$	**$N = 20$**				**$N = 30$**				**$N = 50$**				**$N = 100$**			
Pooled Estimators																
	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*
POLS	1.0654	1.0724	0.4969	0.0893	1.0241	1.0300	0.3887	0.0708	0.9731	0.9684	0.3101	0.0567	0.9948	1.0020	0.2053	0.0371
FE	1.0680	1.0746	0.3230	0.0880	1.0082	1.0124	0.2460	0.0711	1.0253	1.0278	0.1943	0.0548	1.0083	1.0121	0.1379	0.0386
CCEP	0.9898	0.9902	0.0605	0.0424	0.9885	0.9878	0.0544	0.0349	0.9861	0.9873	0.0387	0.0270	0.9874	0.9887	0.0282	0.0190
FD-OLS	0.9162	0.9168	0.0547	0.0391	0.9153	0.9142	0.0467	0.0316	0.9153	0.9152	0.0347	0.0244	0.9139	0.9145	0.0238	0.0171
FD-IV	0.9965	0.9975	0.1331	0.0395	1.0022	1.0028	0.1072	0.0319	1.0024	1.0029	0.0820	0.0245	0.9968	0.9961	0.0554	0.0172
FE (inf)	0.9893	0.9897	0.0443	0.0278	0.9895	0.9893	0.0371	0.0227	0.9882	0.9879	0.0280	0.0177	0.9889	0.9886	0.0193	0.0125
MG-type Estimator																
	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*
CCEMG	0.9858	0.9848	0.0609	0.0592	0.9842	0.9840	0.0545	0.0498	0.9833	0.9836	0.0392	0.0393	0.9837	0.9841	0.0289	0.0279
AMG(i) IV	0.9978	0.9971	0.0805	0.0490	0.9983	1.0023	0.0663	0.0401	0.9976	0.9973	0.0487	0.0319	0.9945	0.9932	0.0363	0.0227
AMG(ii) IV	1.0041	1.0003	0.0864	0.0658	1.0054	1.0046	0.0725	0.0547	1.0019	1.0013	0.0538	0.0427	0.9988	0.9981	0.0401	0.0296
MG	1.1158	1.1139	0.1797	0.0596	1.1399	1.1316	0.1827	0.0496	1.1167	1.1089	0.1821	0.0386	1.1274	1.1245	0.1797	0.0273
MG (inf)	0.9861	0.9857	0.0448	0.0438	0.9873	0.9869	0.0374	0.0358	0.9862	0.9867	0.0285	0.0279	0.9859	0.9860	0.0199	0.0198

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New Simulations — (iii)* Feedback and country trend (continued)

$T = 50$	**$N = 20$**				**$N = 30$**				**$N = 50$**				**$N = 100$**			
Pooled Estimators																
	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*
POLS	1.0406	1.0486	0.5317	0.0724	1.0288	1.0311	0.4089	0.0571	0.9913	0.9834	0.3193	0.0462	0.9868	0.9831	0.2077	0.0304
FE	1.1093	1.1158	0.4420	0.0817	1.0341	1.0501	0.3591	0.0655	1.0474	1.0540	0.2786	0.0509	1.0127	1.0212	0.1984	0.0359
CCEP	0.9978	0.9964	0.0630	0.0350	0.9921	0.9903	0.0500	0.0285	0.9923	0.9927	0.0403	0.0220	0.9916	0.9906	0.0282	0.0156
FD-OLS	0.9183	0.9183	0.0501	0.0301	0.9132	0.9144	0.0392	0.0243	0.9136	0.9137	0.0312	0.0187	0.9136	0.9131	0.0219	0.0132
FD-IV	0.9979	0.9997	0.1048	0.0303	0.9946	0.9948	0.0858	0.0245	0.9963	0.9984	0.0655	0.0188	0.9988	0.9997	0.0455	0.0132
FE (inf)	0.9954	0.9944	0.0408	0.0191	0.9939	0.9943	0.0330	0.0155	0.9928	0.9936	0.0255	0.0121	0.9942	0.9945	0.0181	0.0085
MG-type Estimator																
	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*
CCEMG	0.9959	0.9963	0.0618	0.0575	0.9892	0.9875	0.0493	0.0473	0.9899	0.9908	0.0391	0.0369	0.9894	0.9889	0.0277	0.0265
AMG(i) IV	1.0009	1.0022	0.0738	0.0479	0.9957	0.9944	0.0572	0.0392	0.9975	0.9975	0.0443	0.0308	0.9987	0.9976	0.0328	0.0222
AMG(ii) IV	1.0030	1.0020	0.0801	0.0686	0.9989	0.9983	0.0632	0.0555	0.9992	0.9993	0.0481	0.0433	1.0000	1.0002	0.0349	0.0304
MG	1.1657	1.1519	0.2148	0.0594	1.1688	1.1590	0.2103	0.0490	1.1542	1.1451	0.2061	0.0379	1.1587	1.1530	0.2120	0.0272
MG (inf)	0.9928	0.9914	0.0400	0.0381	0.9919	0.9927	0.0314	0.0310	0.9916	0.9917	0.0245	0.0242	0.9926	0.9926	0.0177	0.0171

$T = 100$	**$N = 20$**				**$N = 30$**				**$N = 50$**				**$N = 100$**			
Pooled Estimators																
	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*
POLS	1.1143	1.1221	0.5644	0.0569	1.0373	1.0301	0.4428	0.0454	0.9945	0.9799	0.3599	0.0359	1.0010	1.0052	0.2425	0.0238
FE	1.1816	1.1930	0.6203	0.0651	1.0390	1.0171	0.4965	0.0536	1.0534	1.0632	0.3832	0.0409	1.0209	1.0255	0.2706	0.0288
CCEP	1.0014	1.0008	0.0657	0.0275	0.9962	0.9957	0.0575	0.0227	0.9982	0.9970	0.0447	0.0176	0.9957	0.9967	0.0307	0.0124
FD-OLS	0.9190	0.9189	0.0430	0.0211	0.9145	0.9140	0.0333	0.0171	0.9158	0.9151	0.0267	0.0132	0.9148	0.9150	0.0186	0.0093
FD-IV	0.9965	0.9988	0.0820	0.0213	1.0003	1.0026	0.0605	0.0172	1.0002	0.9994	0.0481	0.0133	1.0010	1.0020	0.0332	0.0093
FE (inf)	0.9990	0.9986	0.0363	0.0113	0.9975	0.9973	0.0300	0.0092	0.9980	0.9971	0.0240	0.0071	0.9990	0.9989	0.0165	0.0051
MG-type Estimator																
	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*
CCEMG	0.9990	0.9976	0.0624	0.0606	0.9928	0.9924	0.0516	0.0519	0.9951	0.9948	0.0420	0.0408	0.9958	0.9963	0.0286	0.0289
AMG(i) IV	1.0012	1.0012	0.0663	0.0504	1.0030	1.0044	0.0499	0.0418	1.0031	1.0023	0.0406	0.0334	1.0034	1.0041	0.0273	0.0237
AMG(ii) IV	1.0002	0.9984	0.0710	0.0727	1.0026	1.0026	0.0527	0.0596	1.0025	1.0009	0.0432	0.0475	1.0027	1.0023	0.0298	0.0334
MG	1.2035	1.1962	0.2503	0.0615	1.2054	1.1978	0.2490	0.0516	1.1914	1.1790	0.2665	0.0409	1.1931	1.1835	0.2567	0.0292
MG (inf)	0.9978	0.9987	0.0342	0.0344	0.9968	0.9970	0.0279	0.0280	0.9972	0.9966	0.0221	0.0218	0.9983	0.9983	0.0155	0.0154

Notes: ‡ These use the year dummy coefficients from FD-IV estimator, rather than the FD-OLS estimator.

Table VII: New Simulations — (iv) Two ‘clubs’ for β

Monte Carlo Results — Setup with 2 ‘clubs’ of countries

1,000 replications; POLS, FE and FD-OLS all have $T-1$ year dummies; AMG-estimators are constructed from † FD-OLS or ‡ FD-IV year dummy coefficients

$T = 20$	$N = 20$				$N = 30$				$N = 50$				$N = 100$			
Pooled Estimators																
	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*
POLS	1.8149	1.7937	0.5854	0.2526	0.7037	0.6908	0.4523	0.1948	0.5417	0.5377	0.3662	0.1566	0.6228	0.6079	0.2252	0.1022
FE	1.0311	1.0204	0.1755	0.0691	1.0079	1.0082	0.1450	0.0561	1.0157	1.0144	0.1095	0.0434	1.0079	1.0065	0.0756	0.0308
CCEP	0.9989	0.9977	0.0727	0.0512	0.9974	0.9968	0.0591	0.0421	1.0026	1.0016	0.0450	0.0326	1.0000	0.9995	0.0320	0.0231
FD-OLS	1.0023	1.0036	0.0778	0.0563	1.0006	1.0002	0.0650	0.0455	1.0017	1.0016	0.0481	0.0350	1.0005	0.9997	0.0355	0.0246
FD-IV	0.9953	0.9914	0.2019	0.0569	0.9975	0.9970	0.1587	0.0458	0.9993	0.9996	0.1241	0.0352	0.9971	0.9950	0.0864	0.0247
FE (inf)	1.0004	0.9981	0.0636	0.0431	0.9994	1.0006	0.0515	0.0353	1.0018	1.0010	0.0391	0.0274	1.0003	1.0004	0.0285	0.0193
MG-type Estimator																
	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*
CCEMG	1.0013	1.0017	0.0525	0.1205	0.9980	0.9993	0.0419	0.0993	1.0007	1.0001	0.0329	0.0769	1.0012	1.0006	0.0239	0.0548
AMG(i)	1.0058	1.0104	0.1008	0.1195	1.0051	1.0036	0.0820	0.0980	1.0065	1.0048	0.0647	0.0763	1.0036	1.0037	0.0470	0.0541
AMG(ii)	1.0268	1.0199	0.1172	0.1193	1.0228	1.0140	0.0965	0.0980	1.0182	1.0093	0.0768	0.0755	1.0123	1.0105	0.0545	0.0535
MG	1.1070	1.1008	0.1631	0.1283	1.1257	1.1134	0.1705	0.1047	1.1130	1.1011	0.1571	0.0805	1.1202	1.1128	0.1650	0.0571
MG (inf)	1.0000	1.0013	0.0377	0.1205	0.9988	0.9993	0.0310	0.0978	1.0004	1.0012	0.0248	0.0753	1.0003	1.0002	0.0175	0.0530

$T = 30$	$N = 20$				$N = 30$				$N = 50$				$N = 100$			
Pooled Estimators																
	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*
POLS	1.7897	1.7979	0.6062	0.2051	0.7090	0.7064	0.4695	0.1579	0.5539	0.5537	0.3778	0.1267	0.6332	0.6166	0.2479	0.0830
FE	1.0400	1.0279	0.2265	0.0619	1.0098	1.0028	0.1799	0.0505	1.0224	1.0171	0.1375	0.0388	1.0114	1.0051	0.1015	0.0277
CCEP	1.0008	0.9985	0.0601	0.0405	0.9978	0.9978	0.0505	0.0332	1.0017	1.0000	0.0384	0.0257	1.0007	0.9991	0.0279	0.0182
FD-OLS	1.0008	0.9976	0.0654	0.0455	1.0020	1.0019	0.0541	0.0368	1.0023	1.0009	0.0401	0.0283	1.0015	1.0017	0.0297	0.0200
FD-IV	0.9908	0.9908	0.1610	0.0458	1.0044	1.0068	0.1324	0.0370	1.0011	0.9960	0.0968	0.0284	0.9977	0.9988	0.0692	0.0200
FE (inf)	1.0028	1.0004	0.0578	0.0329	0.9983	0.9979	0.0466	0.0266	0.9999	0.9994	0.0357	0.0207	1.0001	0.9993	0.0259	0.0147
MG-type Estimator																
	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*
CCEMG	1.0002	0.9988	0.0406	0.1177	1.0005	1.0005	0.0354	0.0966	0.9996	0.9991	0.0260	0.0747	1.0002	0.9996	0.0194	0.0533
AMG(i)	1.0033	1.0035	0.0919	0.1185	1.0077	1.0087	0.0766	0.0967	1.0045	1.0018	0.0541	0.0750	1.0019	1.0048	0.0417	0.0533
AMG(ii)	1.0162	1.0082	0.1045	0.1183	1.0220	1.0155	0.0879	0.0966	1.0132	1.0108	0.0625	0.0746	1.0075	1.0075	0.0473	0.0528
MG	1.1273	1.1158	0.1797	0.1262	1.1518	1.1404	0.1830	0.1032	1.1260	1.1166	0.1827	0.0788	1.1377	1.1358	0.1834	0.0559
MG (inf)	1.0000	0.9990	0.0277	0.1181	1.0014	1.0015	0.0232	0.0954	1.0000	1.0003	0.0174	0.0734	1.0001	1.0002	0.0125	0.0518

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New Simulations — (iv) Two ‘clubs’ for β (continued)

$T = 50$	$N = 20$				$N = 30$				$N = 50$				$N = 100$			
Pooled Estimators																
	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*
POLS	1.7581	1.7304	0.6804	0.1555	0.7469	0.7299	0.4968	0.1198	0.5878	0.5711	0.4052	0.0958	0.6544	0.6465	0.2592	0.0632
FE	1.0730	1.0577	0.3102	0.0530	1.0259	1.0188	0.2327	0.0436	1.0308	1.0245	0.1809	0.0331	1.0147	1.0109	0.1342	0.0239
CCEP	1.0003	1.0010	0.0541	0.0306	0.9962	0.9955	0.0432	0.0252	1.0012	1.0000	0.0343	0.0195	0.9997	0.9988	0.0240	0.0138
FD-OLS	1.0036	1.0026	0.0562	0.0350	1.0000	1.0002	0.0441	0.0283	1.0019	0.9999	0.0355	0.0218	0.9999	0.9990	0.0251	0.0154
FD-IV	0.9980	0.9944	0.1261	0.0352	0.9957	0.9896	0.1014	0.0284	0.9988	0.9993	0.0760	0.0218	0.9972	0.9983	0.0521	0.0154
FE (inf)	1.0017	1.0001	0.0539	0.0233	1.0001	0.9993	0.0432	0.0190	1.0013	1.0012	0.0345	0.0148	0.9990	0.9980	0.0244	0.0104
MG-type Estimator																
	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*
CCEMG	1.0030	1.0020	0.0361	0.1160	0.9987	0.9984	0.0295	0.0955	0.9992	0.9991	0.0226	0.0739	1.0004	1.0007	0.0159	0.0525
AMG(i)	1.0061	1.0043	0.0834	0.1179	1.0010	0.9992	0.0669	0.0968	1.0040	1.0040	0.0491	0.0749	1.0017	1.0012	0.0339	0.0532
AMG(ii)	1.0142	1.0067	0.0936	0.1179	1.0080	1.0025	0.0761	0.0962	1.0072	1.0063	0.0547	0.0741	1.0038	1.0031	0.0374	0.0524
MG	1.1699	1.1553	0.2150	0.1256	1.1766	1.1668	0.2104	0.1031	1.1608	1.1480	0.2079	0.0785	1.1644	1.1598	0.2147	0.0560
MG (inf)	1.0005	0.9999	0.0196	0.1162	1.0001	0.9997	0.0152	0.0940	0.9993	0.9993	0.0118	0.0725	0.9999	0.9999	0.0084	0.0509

$T = 100$	$N = 20$				$N = 30$				$N = 50$				$N = 100$			
Pooled Estimators																
	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*
POLS	1.6150	1.5904	0.7539	0.1035	0.8114	0.8097	0.5409	0.0804	0.6528	0.6305	0.4439	0.0634	0.7408	0.7289	0.2888	0.0424
FE	1.0786	1.0545	0.3821	0.0408	1.0371	1.0189	0.2999	0.0335	1.0348	1.0376	0.2320	0.0255	1.0310	1.0327	0.1667	0.0184
CCEP	1.0023	1.0023	0.0563	0.0214	0.9965	0.9964	0.0466	0.0177	1.0015	1.0013	0.0362	0.0137	0.9990	0.9990	0.0274	0.0097
FD-OLS	1.0018	1.0033	0.0453	0.0246	1.0022	1.0010	0.0372	0.0199	1.0023	1.0032	0.0282	0.0153	1.0017	1.0015	0.0217	0.0108
FD-IV	0.9934	0.9927	0.0907	0.0246	1.0008	1.0021	0.0716	0.0200	0.9996	1.0001	0.0554	0.0154	0.9994	1.0006	0.0377	0.0108
FE (inf)	1.0008	0.9949	0.0579	0.0149	1.0034	1.0034	0.0448	0.0122	1.0013	1.0015	0.0383	0.0094	1.0010	1.0002	0.0258	0.0067
MG-type Estimator																
	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*
CCEMG	1.0046	1.0052	0.0379	0.1176	0.9989	0.9989	0.0312	0.0971	0.9994	0.9998	0.0253	0.0751	0.9996	1.0000	0.0195	0.0531
AMG(i)	1.0027	1.0011	0.0748	0.1197	1.0033	1.0018	0.0586	0.0982	1.0056	1.0069	0.0466	0.0762	1.0017	1.0030	0.0316	0.0539
AMG(ii)	1.0055	1.0013	0.0798	0.1191	1.0064	1.0053	0.0627	0.0972	1.0057	1.0053	0.0492	0.0750	1.0022	1.0030	0.0335	0.0529
MG	1.2074	1.1958	0.2524	0.1270	1.2075	1.1975	0.2499	0.1043	1.1937	1.1839	0.2683	0.0802	1.1945	1.1898	0.2602	0.0570
MG (inf)	1.0006	1.0001	0.0108	0.1152	1.0005	1.0002	0.0092	0.0933	0.9998	0.9999	0.0070	0.0717	0.9998	0.9999	0.0050	0.0505

Notes: ‡ These use the year dummy coefficients from FD-IV estimator, rather than the FD-OLS estimator.

Table VIII: New Simulations — (iv)* Two 'clubs', country trends

Monte Carlo Results — Setup with 2 'clubs' of countries and country trends

1,000 replications; POLS, FE and FD-OLS all have $T-1$ year dummies; AMG-estimators are constructed from † FD-OLS or ‡ FD-IV year dummy coefficients

$T = 20$	$N = 20$				$N = 30$				$N = 50$				$N = 100$			
Pooled Estimators																
	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*
POLS	1.8069	1.7834	0.6712	0.2612	0.7184	0.7198	0.5146	0.2032	0.5362	0.5287	0.4150	0.1630	0.6198	0.6131	0.2632	0.1064
FE	1.0184	1.0082	0.2557	0.1025	1.0130	1.0061	0.2168	0.0833	1.0175	1.0129	0.1683	0.0641	1.0075	1.0060	0.1161	0.0454
CCEP	0.9959	0.9960	0.0836	0.0586	0.9975	0.9952	0.0684	0.0484	1.0032	1.0032	0.0507	0.0371	1.0002	0.9998	0.0354	0.0263
FD-OLS	1.0016	1.0017	0.0793	0.0577	1.0013	1.0018	0.0654	0.0467	1.0017	1.0016	0.0478	0.0359	1.0001	0.9986	0.0357	0.0253
FE (inf)	1.0005	1.0008	0.0684	0.0455	1.0006	1.0016	0.0524	0.0371	1.0015	1.0000	0.0397	0.0288	0.9996	0.9999	0.0287	0.0203
MG-type Estimator																
	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*
CCEMG	0.9987	0.9984	0.0677	0.1267	0.9979	0.9964	0.0546	0.1048	1.0020	1.0030	0.0403	0.0806	1.0016	1.0009	0.0285	0.0574
AMG(i)	1.0078	1.0105	0.1029	0.1196	1.0038	1.0026	0.0828	0.0981	1.0058	1.0062	0.0644	0.0763	1.0045	1.0034	0.0477	0.0541
AMG(ii)	1.0274	1.0172	0.1174	0.1307	1.0215	1.0172	0.0918	0.1066	1.0181	1.0140	0.0714	0.0818	1.0141	1.0106	0.0522	0.0578
MG	1.1082	1.0993	0.1640	0.1284	1.1254	1.1132	0.1715	0.1048	1.1127	1.1001	0.1563	0.0806	1.1203	1.1120	0.1650	0.0571
MG (inf)	1.0006	0.9999	0.0428	0.1222	0.9993	0.9975	0.0341	0.0989	1.0004	1.0014	0.0271	0.0762	1.0010	1.0002	0.0192	0.0536

$T = 30$	$N = 20$				$N = 30$				$N = 50$				$N = 100$			
Pooled Estimators																
	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*
POLS	1.8009	1.7707	0.6974	0.2129	0.7297	0.7311	0.5478	0.1663	0.5506	0.5589	0.4528	0.1325	0.6312	0.6313	0.2837	0.0868
FE	1.0403	1.0383	0.3698	0.0994	1.0013	1.0133	0.2795	0.0811	1.0202	1.0222	0.2275	0.0622	1.0077	1.0076	0.1592	0.0441
CCEP	1.0013	0.9991	0.0694	0.0478	0.9994	0.9990	0.0593	0.0393	1.0009	1.0014	0.0445	0.0305	1.0006	1.0011	0.0321	0.0215
FD-OLS	1.0003	0.9970	0.0653	0.0467	1.0019	0.9999	0.0544	0.0378	1.0029	1.0021	0.0405	0.0291	1.0012	1.0015	0.0299	0.0205
FE (inf)	1.0022	0.9988	0.0535	0.0346	1.0016	1.0001	0.0465	0.0282	1.0016	0.9998	0.0364	0.0219	1.0001	0.9992	0.0240	0.0155
MG-type Estimator																
	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*
CCEMG	1.0021	1.0010	0.0548	0.1223	1.0008	0.9994	0.0485	0.1010	0.9997	1.0010	0.0347	0.0784	1.0001	1.0006	0.0261	0.0558
AMG(i)	1.0032	1.0033	0.0946	0.1185	1.0070	1.0094	0.0774	0.0967	1.0053	1.0049	0.0539	0.0750	1.0019	1.0033	0.0415	0.0533
AMG(ii)	1.0160	1.0082	0.1035	0.1286	1.0197	1.0152	0.0859	0.1054	1.0127	1.0104	0.0614	0.0816	1.0077	1.0063	0.0453	0.0571
MG	1.1258	1.1189	0.1801	0.1261	1.1508	1.1381	0.1833	0.1032	1.1267	1.1196	0.1833	0.0789	1.1378	1.1365	0.1830	0.0559
MG (inf)	0.9999	0.9994	0.0305	0.1189	1.0015	1.0018	0.0251	0.0960	0.9999	0.9995	0.0190	0.0739	0.9999	0.9997	0.0134	0.0521

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New Simulations — (iv)* Two 'clubs', country trends (continued)

$T = 50$	**$N = 20$**				**$N = 30$**				**$N = 50$**				**$N = 100$**			
Pooled Estimators																
	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*
POLS	1.7315	1.7307	0.7819	0.1637	0.7518	0.7384	0.5836	0.1268	0.5759	0.5795	0.4862	0.1018	0.6663	0.6606	0.3030	0.0668
FE	1.0674	1.0687	0.4922	0.0913	1.0249	1.0182	0.4090	0.0738	1.0331	1.0291	0.3222	0.0570	1.0165	1.0226	0.2254	0.0405
CCEP	1.0035	1.0035	0.0665	0.0389	0.9969	0.9977	0.0543	0.0317	1.0016	1.0004	0.0429	0.0244	0.9985	0.9988	0.0295	0.0174
FD-OLS	1.0028	1.0028	0.0562	0.0359	0.9998	1.0001	0.0437	0.0291	1.0016	1.0001	0.0357	0.0224	1.0002	0.9991	0.0253	0.0158
FE (inf)	0.9999	0.9972	0.0508	0.0246	0.9994	0.9966	0.0410	0.0201	0.9996	1.0004	0.0316	0.0156	0.9999	0.9996	0.0215	0.0110
MG-type Estimator																
	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*
CCEMG	1.0062	1.0057	0.0521	0.1219	0.9992	0.9994	0.0438	0.1000	1.0001	1.0005	0.0347	0.0774	0.9991	0.9996	0.0239	0.0552
AMG(i)	1.0069	1.0053	0.0843	0.1180	1.0008	1.0002	0.0677	0.0967	1.0039	1.0027	0.0501	0.0749	1.0014	0.9997	0.0352	0.0533
AMG(ii)	1.0144	1.0070	0.0917	0.1311	1.0076	1.0042	0.0753	0.1059	1.0069	1.0043	0.0551	0.0819	1.0032	1.0030	0.0379	0.0577
MG	1.1723	1.1552	0.2146	0.1259	1.1758	1.1663	0.2115	0.1030	1.1608	1.1531	0.2079	0.0784	1.1650	1.1580	0.2149	0.0560
MG (inf)	1.0007	1.0010	0.0213	0.1166	0.9999	0.9998	0.0169	0.0944	0.9994	0.9992	0.0130	0.0727	1.0001	1.0000	0.0093	0.0511

$T = 100$	**$N = 20$**				**$N = 30$**				**$N = 50$**				**$N = 100$**			
Pooled Estimators																
	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*
POLS	1.6429	1.6258	0.8825	0.1122	0.7961	0.7808	0.6623	0.0884	0.6299	0.6197	0.5156	0.0694	0.7340	0.7407	0.3508	0.0464
FE	1.1202	1.1320	0.6789	0.0721	1.0369	1.0160	0.5495	0.0598	1.0245	1.0204	0.4288	0.0453	1.0213	1.0196	0.2998	0.0324
CCEP	1.0014	1.0012	0.0726	0.0301	0.9962	0.9964	0.0598	0.0248	1.0030	1.0012	0.0480	0.0192	0.9985	0.9992	0.0334	0.0135
FD-OLS	1.0023	1.0026	0.0452	0.0252	1.0023	1.0011	0.0382	0.0205	1.0017	1.0019	0.0287	0.0157	1.0012	1.0009	0.0212	0.0111
FE (inf)	0.9999	0.9975	0.0529	0.0157	1.0018	1.0019	0.0435	0.0128	0.9995	0.9990	0.0327	0.0099	1.0000	0.9993	0.0232	0.0070
MG-type Estimator																
	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*	mean	median	emp. ste*	mean ste*
CCEMG	1.0042	1.0038	0.0575	0.1246	0.9981	0.9981	0.0448	0.1036	0.9994	0.9987	0.0381	0.0801	0.9988	0.9995	0.0266	0.0564
AMG(i)	1.0028	1.0048	0.0760	0.1197	1.0052	1.0044	0.0605	0.0982	1.0066	1.0079	0.0471	0.0762	1.0032	1.0046	0.0319	0.0539
AMG(ii)	1.0052	1.0022	0.0818	0.1335	1.0074	1.0060	0.0646	0.1092	1.0070	1.0059	0.0506	0.0845	1.0035	1.0042	0.0345	0.0593
MG	1.2070	1.1939	0.2515	0.1270	1.2097	1.1979	0.2501	0.1043	1.1944	1.1818	0.2689	0.0802	1.1950	1.1825	0.2590	0.0571
MG (inf)	1.0007	1.0006	0.0121	0.1152	1.0004	1.0001	0.0101	0.0934	0.9999	0.9998	0.0075	0.0718	0.9998	0.9997	0.0056	0.0505

Notes: ‡ These use the year dummy coefficients from FD-IV estimator, rather than the FD-OLS estimator.