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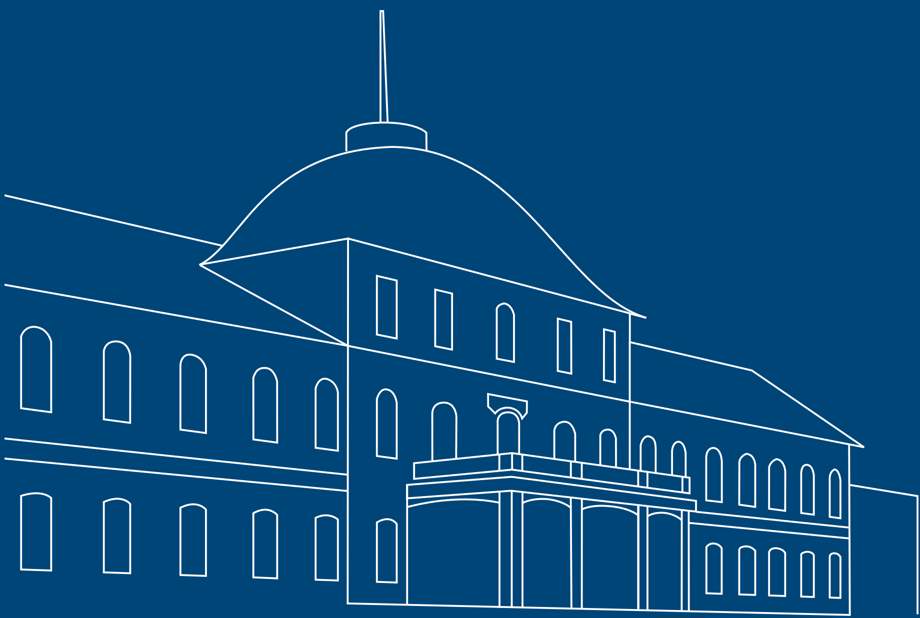
YOU CAN'T ALWAYS GET WHAT YOU WANT? ESTIMATOR CHOICE AND THE SPEED OF CONVERGENCE

Vadim Kufenko

University of Hohenheim

Klaus Prettner

University of Hohenheim



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You can't always get what you want? Estimator choice and the speed of convergence

Vadim Kufenko[a] and Klaus Prettner[b]

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a) University of Hohenheim
Institute of Economics
Schloss, Osthof-West
70593 Stuttgart, Germany
email: vadim.kufenko@uni-hohenheim.de

b) University of Hohenheim
Institute of Economics
Schloss, Osthof-West
70593 Stuttgart, Germany
email: klaus.prettner@uni-hohenheim.de

Abstract

We propose theory-based Monte Carlo simulations to quantify the extent to which the estimated speed of convergence depends on the underlying econometric techniques. Based on a theoretical growth model as the data generating process, we find that, given a true speed of convergence of around 5%, the estimated values range from 0.2% to 7.72%. This corresponds to a range of the half life of a given gap from around 9 years up to several hundred years. With the exception of the (very inefficient) system GMM estimator with the collapsed matrix of instruments, the true speed of convergence is outside of the 95% confidence intervals of all investigated state-of-the-art estimators. In terms of the squared percent error, the between estimator and the system GMM estimator with the non-collapsed matrix of instruments perform worst, while the system GMM estimator with the collapsed matrix of instruments and the corrected least squares dummy variable estimator perform best. Based on these results we argue that it is not a good strategy to rely on only one or two different estimators when assessing the speed of convergence, even if these estimators are seen as suitable for the given sources of biases and inefficiencies. Instead one should compare the outcomes of different estimators carefully in light of the results of Monte Carlo simulation studies.

Keywords: Speed of Convergence, Panel Data, Monte-Carlo Simulation, Estimator Bias, Estimator Efficiency, Economic Growth.

JEL classification: C13, C23, O47.

1 Introduction

Since the publication of Islam (1995), panel data estimators have became a very popular tool in the empirical analysis of economic growth (see Durlauf et al., 2005, for an overview of the literature and a very detailed discussion of the problems that arise in these types of growth regressions). While it seems that there is a broad consensus in the profession that a reasonable estimate for the speed of convergence lies around 2%, the results of different econometric studies vary wildly: Abreu et al. (2005) analyze 48 articles with 619 estimated values for the speed of convergence and show that the estimates range from negative values to the maximum of 65.59%. This huge dispersion can be attributed partly to the use of different specifications, different control variables, and different sample sizes, the presence of measurement errors, and to endogeneity issues (see, for example, Durlauf, 2001; Durlauf et al., 2005). However, purely methodological aspects also seem to play an important role: Abreu et al. (2005, p. 410) note that generalized method of moments (GMM) estimators and the corrected least squares dummy variable (LSDVC) technique yield substantially higher estimates than other approaches and Hsiao et al. (2002) show in Monte-Carlo studies that the biases of GMM-based estimators can be large.

From the perspective of growth economics, the large differences in the results delivered by the different estimation techniques urge for a thorough analysis of the biases and inefficiencies of the different state-of-the-art estimators that are used in growth econometrics. In a sample taken from the real world, one can only speculate about the true speed of convergence because of the issues described in the previous paragraph. However, simulations based on a theoretical model as the "true" and known data-generating process offer an interesting opportunity to put the different econometric techniques to a test. Such an approach allows to abstract from complications that emerge in the real world such as measurement errors, omitted variables, different sample sizes, and endogeneity by performing essentially a controlled experiment. Hauk and Wacziarg (2009) were the first to provide a systematic analysis of the different biases involved with panel data estimators in growth regressions. Our study differs from theirs along the following lines: i) while Hauk and Wacziarg (2009) simulate data based on estimated fixed effects, we simulate different trajectories of per capita GDP for different countries based on a Solow (1956) type of growth model with different deep parameters (such as the savings rate and the population growth rate). This yields simulated country-specific fixed effects without the need to rely on estimations and allows us to infer the true underlying speed of convergence by design;[1] ii) we do not only analyze the extent of the bias of different estimators but also their confidence intervals. This yields the surprising insight that the true speed of convergence is outside of the 95% confidence intervals of all estimators, except for the system GMM (SYSGMM) estimator with a collapsed matrix of instruments, which, however, delivers very inefficient estimates; iii) we include the LSDVC estimator that has been proposed most recently as an alternative to GMM-based estimators as a remedy for the Nickell (1981) bias in our analysis.

[1] Note that we do not need to simulate "realistic" convergence processes. In fact, all we need is that the underlying true speed of convergence is known and that there are enough available data points for estimation.

In our paper we explicitly address the biases of the pooled least squares (POLS) estimator, the random effects (RE) estimator, the between estimator (BE), the fixed effects (FE) estimator, the difference GMM (DIFFGMM) estimator, the system GMM (SYSGMM) estimator, and the LSDVC estimator.[2] Knowing the true speed of convergence from the simulations, we compare the different estimators and their confidence intervals for identifying those estimators that are most promising for estimating the rate of convergence in practical applications. Since even allegedly unbiased estimators perform badly, we argue that researchers should not rely on only one estimator when assessing the speed of convergence, even if this estimator is deemed to be suitable for the different sources of biases involved in the given specifications and in the corresponding data set. A better strategy would be to compare the outcomes of different estimators in light of the results of Monte Carlo studies. Furthermore, we propose to use the information of different available estimators by computing a simple average over the implied speeds of convergence and to report this average in addition to the estimates that are directly obtained from the different econometric methods.

The paper is organized as follows. In Section 2 we provide a short discussion of important articles on convergence and we briefly describe known biases of panel data estimators and the state-of-the-art solutions to cope with them. In Section 3 we provide a detailed explanation of the data-generating process and the different scenarios and trajectories that we simulate. In Section 4, we employ our generated data set to estimate the autoregressive coefficient of the dynamic panel data model with the different state-of-the-art methods. We report the point estimates and their confidence intervals for the different estimators and we compute the implied speed of convergence and the squared percent error for each estimator. This allows us to assess the biases of the estimators in terms of the deviations from the true speed of convergence and the efficiency of the estimators in terms of the range of their confidence intervals. Finally, in Section 5 we summarize our findings and conclude.

2 Panel data estimators and their known biases

While earlier studies of convergence relied on cross-sectional data (cf. Barro, 1991, 1997; Sala-i-Martin, 1997), progress has been made toward the use of panel data in the mid 1990s (cf. Caselli et al., 1996; Islam, 1995).[3] The main advantages of the use of panel data in this context are that i) the number of available observations increases substantially, ii) it becomes possible to control for unobserved heterogeneity that stays constant over time, and iii) dynamic relationships can be captured in a more accurate way by including the lagged dependent variable as a regressor (see, for example, Baltagi, 2013; Hsiao, 2014; Pesaran, 2015, for detailed discussions).

While the inclusion of the lagged dependent variable in panel data growth regressions is

[2] For the conceptual details of the different estimators and their advantages and disadvantages see Hurwicz (1950), Nickell (1981), Arellano and Bond (1991), Blundell and Bond (1998), Judson and Owen (1999), Wooldridge (2002), Bun and Kiviet (2003), Bruno (2005), Hauk and Wacziarg (2009), Baltagi (2013), Hsiao (2014), Pesaran (2015), Durlauf et al. (2005).

[3] For recent applications see, for example, Esposti (2007), Gehringer and Prettner (2014), Crespo-Cuaresma et al. (2014), Hauk and Wacziarg (2009), Brückner (2013), Irmen and Litina (2016), and Cohen and Soto (2007).

crucial for the calculation of the speed of convergence, its introduction comes with a substantial cost: the estimation of dynamic models is subject to the Hurwicz (1950) bias and endogeneity between fixed effects and the lagged dependent variable in FE estimation gives rise to the Nickell (1981) bias. While the Hurwicz (1950) bias can only be mitigated by increasing the time dimension of the panel data set, a number of estimators have been proposed to deal with the endogeneity between fixed effects and the lagged dependent variable: difference GMM (Arellano and Bond, 1991; Arellano and Bover, 1995), system GMM (Blundell and Bond, 1998) and the LSDVC estimator (Bruno, 2005; Bun and Kiviet, 2003; Judson and Owen, 1999). In spite of the fact that the new panel data estimators offer promising improvements over older ones (such as POLS, FE, and BE), there are still a number of known biases arising from these estimators. The sources of those biases that are relevant in our analysis are summarized in Table 1. Of course, the extent of the bias may be different from case to case.

Table 1: Biases of panel data estimators that we address in our study

Biases	POLS	FE	RE	BE	LSDVC	DIFFGMM	SYSGMM
Non-random heterogeneity	x		x				
Omitted group effects	x		x	x			
Endogeneity of y_{t-1}	x	x	x				
Validity of instruments					x	x	x

Sources: Buddelmeyer et al. (2008); Fernández-Val and Vella (2011); Hauk and Wacziarg (2009); Hayakawa (2007); Roodman (2009); Wooldridge (2002).

With regards to POLS and RE estimators, Wooldridge (2002, pp. 249 and 257) notes that, if the country-specific fixed effect denoted by μ_i is correlated with the explanatory variables, then both estimators are biased. A very insightful overview of known biases of well-established panel data estimators is provided by Hauk and Wacziarg (2009): among other biases, they note that the omitted country-specific fixed effect may create a bias for BE and RE estimators and endogeneity of the lagged dependent variable would cause a bias for FE and RE estimators. Another issue is the problem of weak instruments as also noted by Hauk and Wacziarg (2009): this problem is particularly severe in SYSGMM estimation because two types of instruments are used, lagged levels and lagged differences. Even if the instruments are not weak, there can simply be too many of them – this is described by Roodman (2009) for DIFFGMM and SYSGMM and referred to as instrument proliferation. In general, the validity of instruments is often not guaranteed in case of GMM-based estimators.[4]

[4] In our study we focus on the biases described in Table 1. However, there are other known sources for biases the analysis of which would require a different underlying data-generating process. For example, all of the estimators involved are exposed to the bias that arises because of measurement errors (Wooldridge, 2002, p. 311) and to the serial correlation of the error term (see Wooldridge, 2002, pp. 282–283 and 307).

3 The data-generating process

This section provides the detailed information on the data-generating process and the parameters that we use in the Monte-Carlo simulations. We proceed in the following manner: First, we generate a time series of per capita output for one country over a pre-specified number of years according to a dynamic process based on a Solow (1956) type of growth model. Note that this is the simplest framework for simulating a convergence process of which we know the true underlying speed and which we can use to assess the biases and the confidence intervals of our different estimators. Nothing – except for additional complexity – would be gained by using more sophisticated growth models with endogenous saving rates (as, for example, Cass, 1965; Diamond, 1965; Koopmans, 1965; Ramsey, 1928) or endogenous technological progress (as, for example, Howitt, 1999; Jones, 1995; Romer, 1990; Segerström, 1998) as baseline frameworks. Second, we introduce unobserved heterogeneity, μ_i, by the means of a randomization of the parameters of the Solow model to generate time series of per capita output for a pre-specified number of different countries (the cross-country dimension, N). Third, we introduce idiosyncratic distortions by means of stochastic shocks to account for the fact that there are deviations from the output series that are not explained by the underlying theoretical framework.

Suppose that time $t = 1, 2 \ldots, T$ evolves discretely and that we are observing $i = 1, 2, \ldots N$ different economies. Aggregate output of these economies is described by a Cobb-Douglas production function of the form

$$Y_{i,t} = AK_{i,t}^{\alpha} L_{i,t}^{1-\alpha},$$

where $Y_{i,t}$ is aggregate output of country i at time t (which, by the national accounts identity, is equal to aggregate income), A refers to the total factor productivity (TFP), $K_{i,t}$ is the physical capital stock (machines, production facilities, office buildings, etc.), $L_{i,t}$ is the amount of aggregate labor input, and α is the elasticity of aggregate output with respect to physical capital input. Households save a constant fraction s_i of their income $Y_{i,t}$ in each year, which implies that physical capital accumulation is given by the dynamic equation

$$K_{i,t+1} = s_i Y_{i,t} + (1 - \delta) K_{i,t},$$

where δ is the rate of depreciation that does not differ between countries. We denote per worker variables with lowercase letters such that per worker capital is given by $k_{i,t} = K_{i,t}/L_{i,t}$ and per worker output pins down to

$$y_{i,t} = Y_{i,t}/L_{i,t} = k_{i,t}^{\alpha}. \tag{1}$$

Altogether, we can derive the following approximation of the fundamental equation of the Solow (1956) model in terms of the evolution of capital per worker

$$k_{i,t+1} \approx s_i A k_{i,t}^{\alpha} + (1 - \delta - n_i) k_{i,t}, \tag{2}$$

where n_i is the growth rate of the workforce. Since we abstract from unemployment, childhood, and retirement, per worker variables and per capita variables coincide, such that n_i is equivalent to the population growth rate. Note that, in continuous time, the differential equation counterpart to Equation (2) holds with equality. The approximation in case of discrete time becomes better the lower the population growth rate and the smaller the time step between t and $t+1$. In our case, where t is measured in yearly terms, this is a reasonable approximation. It would be more difficult to defend this approximation in an overlapping generations framework in which a time step refers to one generation and therefore lasts for around 25 years.

The steady-state capital stock can be determined by setting $k_{i,t+1} = k_{i,t}$ in Equation (2) and is given by

$$k_i^* = \left(\frac{s_i A}{n_i + \delta} \right)^{\frac{1}{1-\alpha}}. \tag{3}$$

Steady-state output per capita is then equal to

$$y_i = (k_i^*)^\alpha = \left(\frac{s_i A}{n_i + \delta} \right)^{\frac{\alpha}{1-\alpha}}. \tag{4}$$

From now on we normalize $A \equiv 1$ for all countries, which does not impact on our qualitative results.

The true speed of convergence $\lambda_{true,i}$ can easily be derived for each country as (see Romer, 2006, pp. 25-26):

$$\lambda_{true,i} = (1-\alpha)(n_i - \delta). \tag{5}$$

The average values of $\lambda_{true,i}$ over all countries are compared to the estimated speed of convergence from the different estimation methodologies in Section 4. The variable that is crucial for generating convergence is the initial level of capital, $k_{i,0}$. In case that we set $k_{i,0}$ to a small value, we generate a poor country i that has a strong catch-up potential and will grow fast initially. By contrast, if we set $k_{i,0}$ close to the steady-state value, we generate a rich country with a low catch-up potential that will grow sluggishly. To rule out the situation of convergence to the steady state from above (i.e., with negative growth rates)[5], we initialize the simulation by setting $k_{i,0}$ to a level below the steady-state according to

$$k_{i,0} = D_i k_i^*,$$

where $D_i \in (0, 0.3]$ is the distance to the steady state as drawn from a truncated normal distribution (see Tables 2 and 3 for an overview of the parameter values used in the different simulation scenarios). We set the upper bound of the relative position of the initial capital stock at 30% to ensure catch-up growth over a considerable time period.

Instead of generating the data set for different countries by relying on estimated fixed effects from empirical specifications as in Hauk and Wacziarg (2009, p. 116), we create artificial countries, where we follow the theoretical limitations that are imposed on the parameters by

[5] It is often argued that the negative growth rates in the former countries of the Soviet Union in the 1990s can be attributed to a shrinking capital stock. While the Soviet Union had a very high forced investment rate that could not be sustained anymore after the communist system collapsed, in our simulations the question would arise how a country could have built up a capital stock that is larger than its steady-state capital stock in the first place.

the structure of the Solow (1956) model in the simulation of the unobserved heterogeneity, μ_i. Although it is not required to use plausible parameter values — because we could generate any data set we want and use it as our data-generating process as long as we can compute the true underlying speed of convergence — we think it is more comprehensible to use parameter values that are familiar from growth theory and/or that are empirically plausible. Most of the parameters of the Solow model are bounded in some way, for example, $s_i \in (0,1)$, $k_0 > 0$, $\alpha \in (0,1)$, and $\delta > 0$ cannot attain negative values and some cannot exceed 1. This provides theoretical restrictions that we impose on the parameter space by truncating the corresponding simulated distributions (see Robert, 1995; Robert and Casella, 2005). Second, we use mean values of the parameters that are reasonably close to the data observed in reality. We assume that α and δ are fixed and equal across countries and set $\alpha = 0.35$, which is broadly in line with the literature (cf. Acemoglu, 2009; Jones, 1995), and $\delta = 0.06$, which follows from the findings of Fraumeni (1997). We introduce country-specific heterogeneity via the savings rate s_i and the population growth rate n_i. In so doing we rely on World Bank (2016) data for 214 countries over the years 1966 to 2014 to get the mean population growth rate of 1.83% and the mean gross savings rate of 27.97%.[6] While we could easily introduce additional country-specific heterogeneity in A, α, and δ, this would merely complicate the analysis without leading to additional insights.[7]

We simulate four scenarios, two deterministic and two stochastic ones, for 150 countries and 100 time steps. In contrast to the deterministic scenarios, which result in smooth and concave trajectories of output as it converges toward its steady-state level, the stochastic scenarios feature additional shocks over time on output, denoted by ε_y, on the savings rate, denoted by ε_s, and on the population growth rate, denoted by ε_n. Doing so introduces time-varying savings rates and population growth rates $s_{i,t}$ and $n_{i,t}$ (see Table 3, Scenario 4) without altering the underlying speed of convergence in a systematic way. The stochastic shocks ε_y, ε_s, and ε_n are simulated from a normal distribution such that these shocks can be considered as stochastic perturbations similar to unsystematic measurement errors or transient exogenous shocks. We leave out the first 5 time steps from the resulting series because the convergence effects are very strong for countries with a low value of D_i. We also drop the last 45 time steps because most countries are already very close to their steady states after 50 years (see Figure 1 for the simulated time paths of output per capita in the four scenarios). Out of the resulting time series variables, we generate five-year averages to mimic the estimation strategy that is often employed to average out business-cycle effects in real-world data (cf. Crespo-Cuaresma et al., 2014; Islam, 1995). As a consequence, we have an artificial data set for 150 countries and 10 time periods (as five year averages) such that $N = 150$ and $T = 10$ are the dimensions of our panel data set. These values are quite common for panel data growth regressions.

The first scenario involves a limited randomization relying on a truncated normal distribution only for D_i and s_i, whereas in the second scenario we also randomize the population growth

[6] Countries with negative average values for s and n over this time period were left out of the consideration.

[7] Altogether, the distributions from which we draw the underlying parameters for the simulation are independent from each other. It is possible to build in collinearity between the variables and to analyze the extent to which different estimators can cope with multicollinearity. While this is outside of the scope of our paper, it is surely a promising avenue for further research.

rate n_i. In the third scenario we introduce stochastic shocks to Equation (1) for the dynamics of output, while the fourth scenario also features stochastic shocks on the savings rates and on the population growth rates such that $s_{i,t}$ and $n_{i,t}$ enter Equation (2) and the model dynamics in a time-varying manner.

In the next section we estimate the AR(1) coefficient, which is required to determine the speed of convergence, with different state-of-the-art panel data methods. We use the resulting coefficient estimates to calculate the implied speed of convergence, $\lambda_{implied}$, for each method. The resulting value is compared to the true underlying speed of convergence, λ_{true}, such that we can assess the direction and the extent of the bias of the different estimators. Furthermore, we provide information on the confidence intervals of the different estimators to assess their efficiency in a comparative way.

Table 2: Fixed parameter values and distributions from which the remaining parameters are drawn for the deterministic scenarios

Scenario	1	2
Distance to the steady state	$D \sim N(0.1, 0.15^2)$ $D \in [0.001, 0.3]$	$D \sim N(0.1, 0.15^2)$ $D \in [0.001, 0.3]$
s	$s \sim N(0.2797, 0.0919^2)$ $s \in [0.0266, 0.6109]$	$s \sim N(0.2797, 0.0919^2)$ $s \in [0.0266, 0.6109]$
n	0.0183	$n \sim N(0.0183, 0.0117^2)$ $n \in [0, 0.0837]$
α	0.35	0.35
δ	0.06	0.06
λ_{true}	0.0509	0.05208

Table 3: Fixed parameter values and distributions from which the remaining parameters are drawn for the stochastic scenarios

Scenario	3	4
Distance to the steady state	$D \sim N(0.1, 0.15^2)$ $D \in [0.001, 0.3]$	$D \sim N(0.1, 0.15^2)$ $D \in [0.001, 0.3]$
s	$s \sim N(0.2797, 0.0919^2)$ $s \in [0.0266, 0.6109]$	$s \sim N(0.2797, 0.0919^2)$ $s \in [0.0266, 0.6109]$
n	$n \sim N(0.0183, 0.0117^2)$ $n \in [0, 0.0837]$	$n \sim N(0.0183, 0.0117^2)$ $n \in [0, 0.0837]$
α	0.35	0.35
δ	0.06	0.06
ε_y	$\varepsilon_y \sim N(0, 0.006^2)$	$\varepsilon_y \sim N(0, 0.006^2)$
ε_s	-	$\varepsilon_s \sim N(0, 0.0008^2)$; $s.t.\ s > 0$
ε_n	-	$\varepsilon_n \sim N(0, 0.00008^2)$; $s.t.\ n > 0$
λ_{true}	0.05208	0.0508

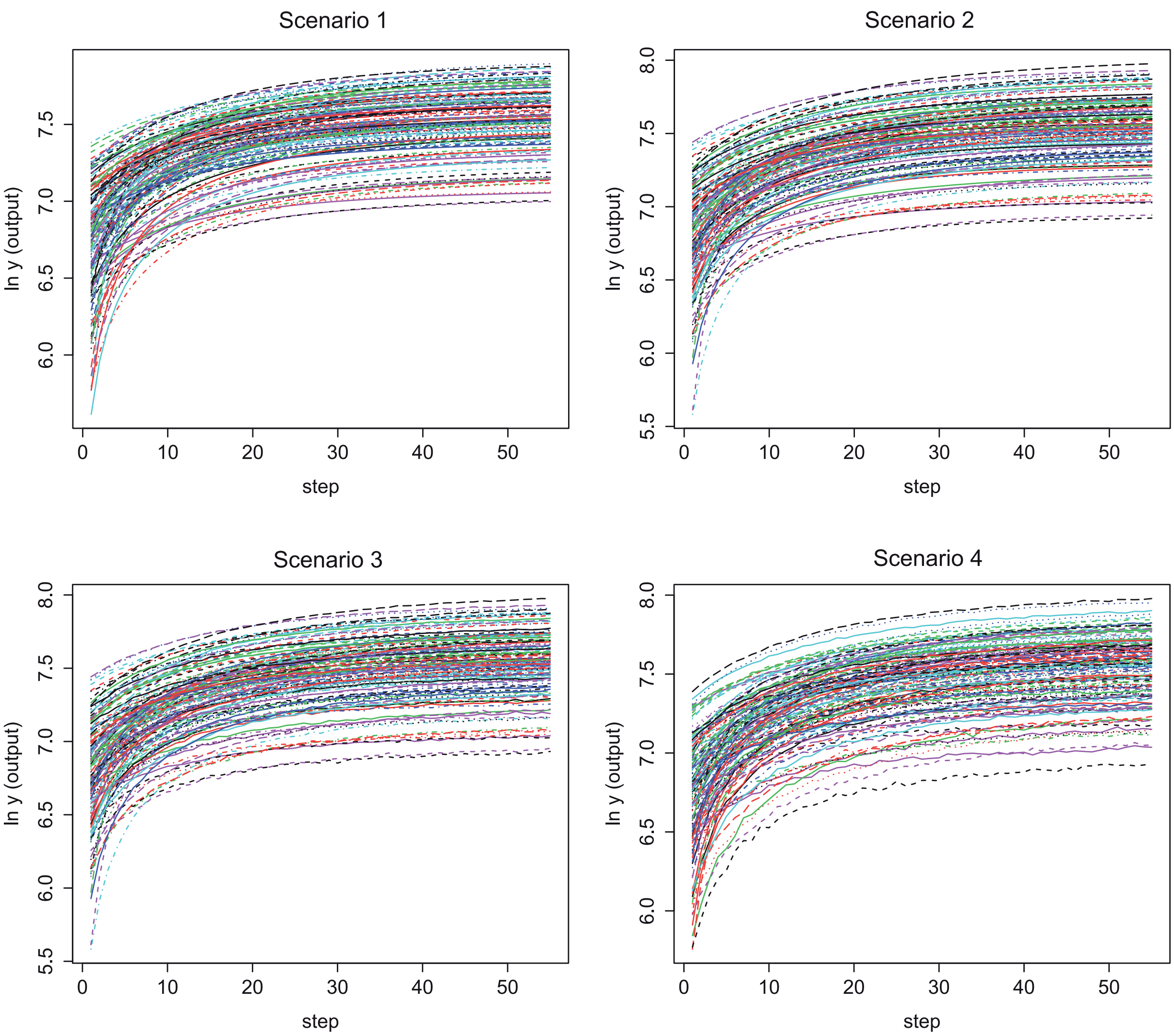

Figure 1: Convergence paths for 150 countries from the different simulated scenarios of the Solow (1956) model over 55 years (we excluded the first 5 years from the sample in the estimation part; see Section 3 for details). Scenario 1 considers deterministic paths, where D_i and s_i are allowed to differ between the different countries. In Scenario 2 also the population growth rate n_i is country-specific. Scenario 3 introduces a stochastic shock ε_y on the per capita output series. Scenario 4 allows for stochastic shocks also on the savings rate (ε_s) and on the population growth rate (ε_n).

4 Estimation and comparative assessment of the results

In this section we estimate the speed of convergence that is implied by the different parameter estimates of the AR(1) term in the dynamic panel data growth regressions ($\lambda_{implied}$). We compare the resulting value to the true value (λ_{true}) that we know for each scenario from the simulations. Based on these values, we measure the error of each estimated value as captured by the relative distance of the implied estimated speed of convergence from the corresponding true speed of convergence. This allows us to compare the extent of the biases of the different estimators. Furthermore, we provide the confidence intervals for the different estimates of the AR(1) term and assess whether or not its true value is captured by them. Finally, we assess the efficiency of the different estimators by comparing the size of their confidence intervals. The equations that we estimate are described in detail by Bond et al. (2001, p. 15) and Islam (1995, p. 1136):

$$y_{i,\bar{t}} = \gamma y_{i,\bar{t}-1} + \phi_{\bar{t}} + \mu_i + \upsilon_{i,\bar{t}},$$

$$\gamma = e^{-\lambda_{implied} \cdot \tau},$$

$$\lambda_{implied} = -\frac{\log(\gamma)}{\tau}.$$

where $y_{i,\bar{t}}$ is average per capita output of country i between time t and $t-4$, $y_{i,\bar{t}-1}$ refers to the corresponding lagged variable, $\phi_{\bar{t}}$ is a vector of time-specific fixed effects, μ_i is a vector of country-specific fixed effects, $\upsilon_{i,\bar{t}}$ is an idiosyncratic error term, γ refers to the auto-regressive coefficient, $\lambda_{implied}$ is the implied speed of convergence obtained via the estimate for γ, and τ is the number of periods captured by each time step, which is 5 in our case.

The POLS, FE, RE, and BE estimators are applied without the implementation of additional corrections/options. In case of LSDVC, DIFFGMM, and SYSGMM, we had to make further decisions. For both, DIFFGMM and SYSGMM, standard errors have been estimated with the small-sample correction proposed by Windmeijer (2005). In DIFFGMM and SYSGMM, the 5-year period dummies were used as variables and as instruments. In addition, for SYSGMM, we implemented two versions, one with the full matrix of instruments and one with the matrix of instruments collapsed, which reduces the number of instruments from 64 to 20. In this context, instrument proliferation (or "too many instruments") can lead to various problems as described in detail by Roodman (2009). Both versions of the estimates are presented here. The ones obtained with the collapsed matrix on instruments are marked by 'col'. In the initialization of the LSDVC estimator we use the SYSGMM estimator with the collapsed matrix of instruments. Furthermore, we implement bias correction up to the third order as proposed by Bruno (2005) and we report bootstrapped standard errors for this estimator based on 50 replications.

Before displaying the values of $\lambda_{implied}$ as obtained from our estimates, we first plot the AR(1) coefficients with the corresponding confidence intervals in Figure 2. Since we know λ_{true}, we can derive the true AR(1) coefficient, which is indicated by the green dotted line for each scenario. Even if the estimated AR(1) coefficient is close to the true value, the confidence intervals can be very large such that even the cases of no convergence [with the AR(1) coefficient being equal to 1] and immediate convergence [with the AR(1) coefficient being equal to zero] are inside the confidence interval.

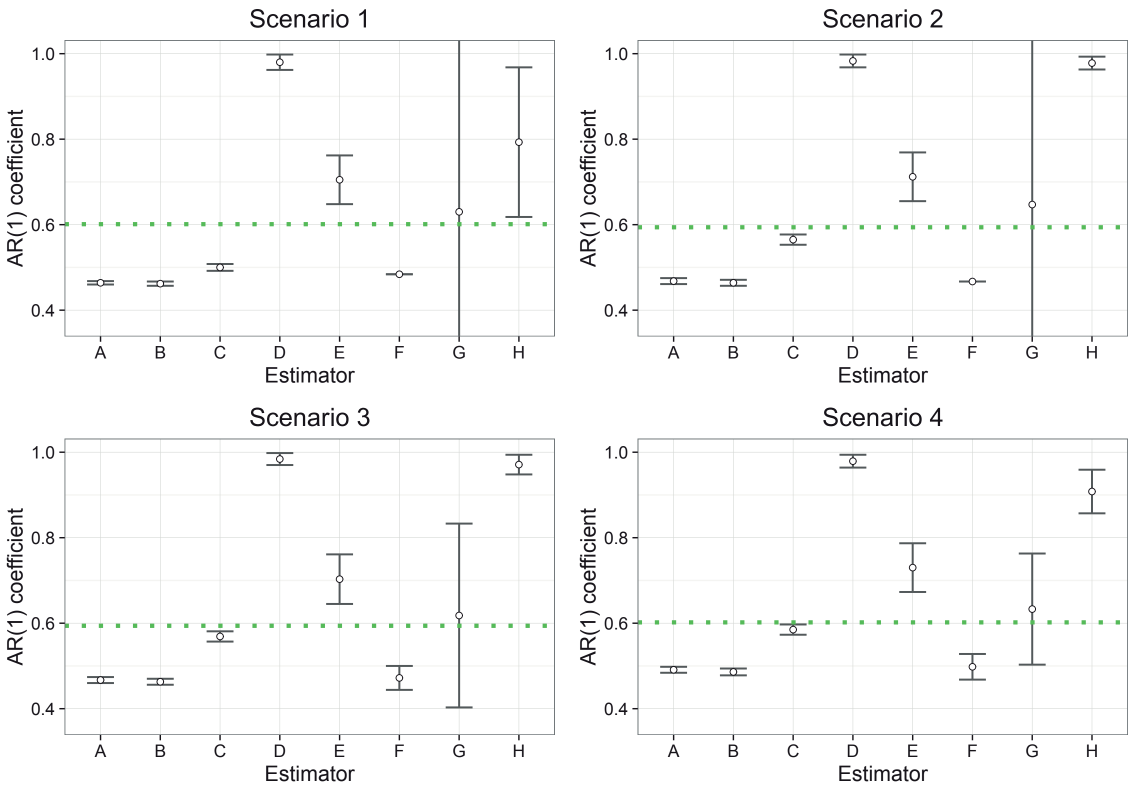

Figure 2: Estimated values of the AR(1) coefficient, γ. Note: The dotted green lines refer to the true value (γ_{true}) as calculated from the known speed of convergence (λ_{true}). The different estimators are denoted by the following list of letters A = POLS, B = FE, C = RE, D = BE, E = LSDVC, F = DIFFGMM, G = SYSGMM col, and H = SYSGMM. The circles indicate the point estimates for the corresponding parameters, while the whiskers refer to the 95% confidence intervals.

Let us first discuss the results for the deterministic Scenarios, 1 and 2. Our expectations regarding the different forms of biases and their direction (see Table 1) are met in case of the POLS, FE, and BE estimators. The first two underestimate the true value of the AR(1) coefficient, whereas the latter overestimates it. Note that the BE estimator performs badly, which contrasts with the findings of Hauk and Wacziarg (2009) – in their analysis BE performs reasonably well.

In general, the RE estimator performs surprisingly well in Scenarios 2, 3, and 4. Whereas in Scenario 1 only D_i and s_i are randomized, in Scenario 2, n_i is randomized as well and we have additional random shocks in Scenarios 3 and 4. By the design of our simulations, the variables that are responsible for the country-specific heterogeneity (D_i, s_i, and n_i) were sampled from truncated normal distributions with the mean being different from zero. At first glance it might seem that this construction provides an advantage for the RE estimator. However, the key assumption of the RE estimator is that $E(\mu_i|x_i) = E(\mu_i) = 0$ (Wooldridge, 2002, p. 257), or that the country-specific effects are orthogonal to the explanatory variables. This is not the case in our generated data set. By the design of our simulations, the dynamics of $y_{i,\bar{t}}$ are related to its lagged level, which is a regressor. The latter can also be seen in Table 4, which illustrates three facts that are common for all of our scenarios: i) the country-specific effects correlate with the regressors; ii) the F test rejects the null of $\mu_i = 0$; and iii) the Hausman test indicates that the parameter estimates of the RE specification differ from the ones of the FE specification (which does not need to be problematic because we know that the FE estimator is biased in the given setting). For Scenarios 1-4 in Table 4 the Hausman test is conducted for the basic model with time dummies. In case of "Scenario 4, expanded", we additionally control for $s_{i,t}$ and $n_{i,t}$ because they are allowed to vary over time in Scenario 4. Even for the expanded specification, the Hausman test indicates that the parameter estimates of the RE specification differ from the ones of the FE specification. Therefore, while the results of the RE estimator are close to the target, this should be interpreted cautiously.

Table 4: A closer look at the fixed effects

Fixed effects inference	corr(μ_i, Xβ)	F test, H_0: $\mu_i = 0$ (p-values)	Hausman FE vs. RE (p-values)
Scenario 1	0.5855	0.0000	0.0000
Scenario 2	0.6290	0.0000	0.0000
Scenario 3	0.6279	0.0000	0.0000
Scenario 4	0.6098	0.0000	0.0000
Scenario 4, expanded	0.6661	0.0000	0.0000

The GMM methods tend to yield estimates for the AR(1) coefficient that are quite far off the mark. DIFFGMM underestimates the true value, whereas SYSGMM overestimates it. As we see in Figure 4, these discrepancies have direct implications for $\lambda_{implied}$: DIFFGMM yields a higher speed of convergence than the true value, whereas SYSGMM yields a substantially lower one. SYSGMM with the collapsed instrument matrix gives a coefficient estimate that is close to the true coefficient, yet, the confidence intervals are extremely wide, which indicates that the estimator might not be useful from a practical point of view. The LSDVC estimator overestimates the true AR(1) coefficient, but, in general, the estimator performs better than the others in Scenario 1 (see Figure 3) when bearing the confidence intervals for SYSGMM with the collapsed instrument matrix in mind.

For the deterministic Scenarios 1 and 2, the worst three performers in terms of the squared percent error are the BE, SYSGMM (with the full matrix of instruments), and the FE estimators. The best three performers are the SYSGMM (with the collapsed matrix of instruments), LSDVC, and RE. Recalling the mentioned problems with the RE estimator and that the SYSGMM estimator with the collapsed matrix of instruments yields extremely wide confidence intervals, LSDVC again performs reasonably well.

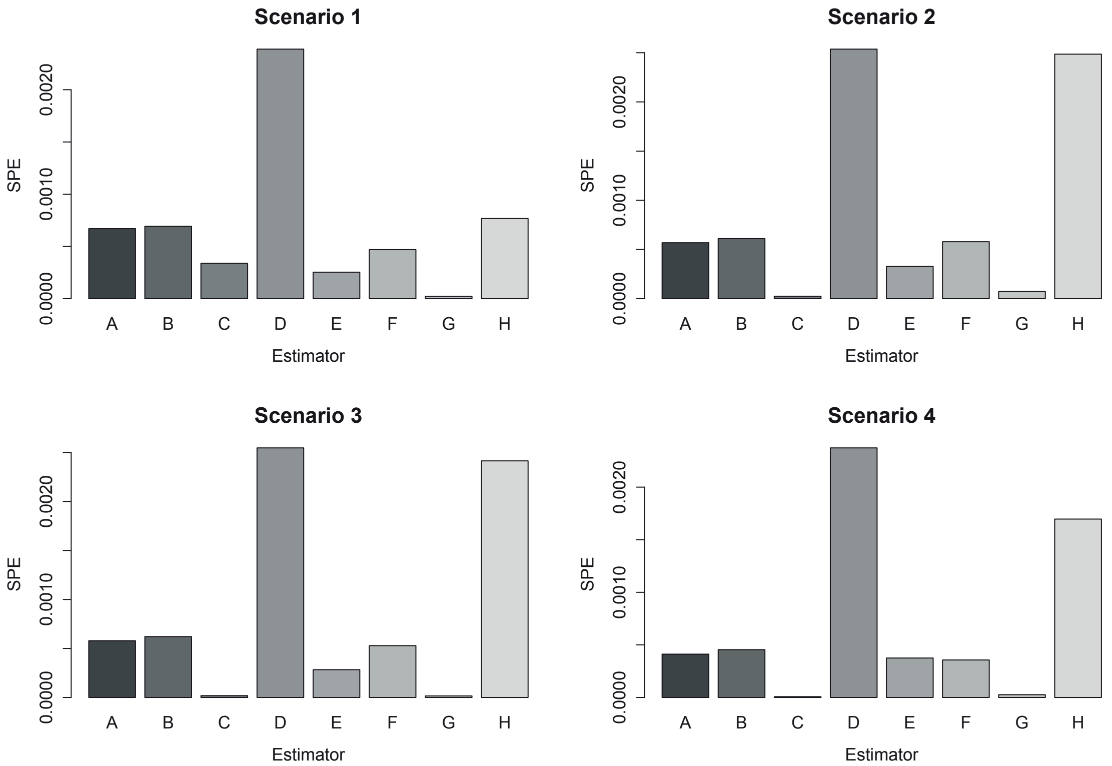

Figure 3: Squared Percent Error of the different estimators. Note: The estimators are referred to by the following letters; A = POLS; B = FE; C = RE; D = BE; E = LSDVC; F = DIFFGMM; G = SYSGMM, col; H = SYSGMM.

The stochastic Scenarios 3 and 4 offer interesting information on the performance of the estimators after the introduction of stochastic shocks. In Scenario 3 only the time series for output is perturbed, while, in Scenario 4, s and n are also affected by shocks (see Table 3). For these scenarios, the POLS, FE, and BE estimators perform as poorly as in the deterministic scenarios. The DIFFGMM estimator still underestimates the true coefficient, whereas the SYSGMM estimator with the full matrix of instruments overestimates it. Yet, both estimators perform slightly better in terms of the error than for the deterministic cases (see Figure 3). The worst performers remain the BE, the SYSGMM (with full matrix of instruments), and the FE estimators. For Scenario 3, SYSGMM with the collapsed matrix of instruments, RE, and LSDVC yield the best results. However, the confidence interval of the SYSGMM estimator with the collapsed matrix of instruments is still the widest among all estimators. For Scenario 4 the situation is similar: RE and SYSGMM with the collapsed matrix of instruments have the lowest error. However, DIFFGMM slightly outperforms the LSDVC estimator, which contrasts with the other scenarios. For the exact values see Table 5, which contains the squared percent error as described above.

Finally, Table 6 provides the numerical values obtained by the different estimators for the implied speed of convergence and the true speed of convergence for comparison, while Figure 4 illustrates the discrepancies graphically. We observe that the implied speed of convergence ranges from barely above 0 in case of the BE and the SYSGMM estimators to almost 8% in case of the POLS, FE, and DIFFGMM estimators. Consequently, depending on the estimator that is used in a certain study, the half life (the time it takes until half of the gap between current per capita GDP and steady-state per capita GDP is closed), ranges from around 9 years in case of the FE estimator to several hundred years in case of the BE estimator. Finally, we also compute the mean over the values for the estimated speed of convergence for all of the involved estimators. The result is surprisingly close to the true speed of convergence.

The central conclusion of our paper is therefore immediately clear. One should never rely on only one or two different estimators when assessing the speed of convergence, even if they are deemed to be suitable for the different sources of biases involved in the empirical specification and in the corresponding data set. A better strategy is to compare the outcomes of different estimators and to keep their biases and inefficiencies from Monte Carlo studies in mind when drawing conclusions based on them. Our computations of the mean over the estimated speed of convergence for all of the involved estimators suggests that this mean is surprisingly close to the true speed of convergence. It might therefore be good strategy in applications to also provide the averages of estimated parameter values.

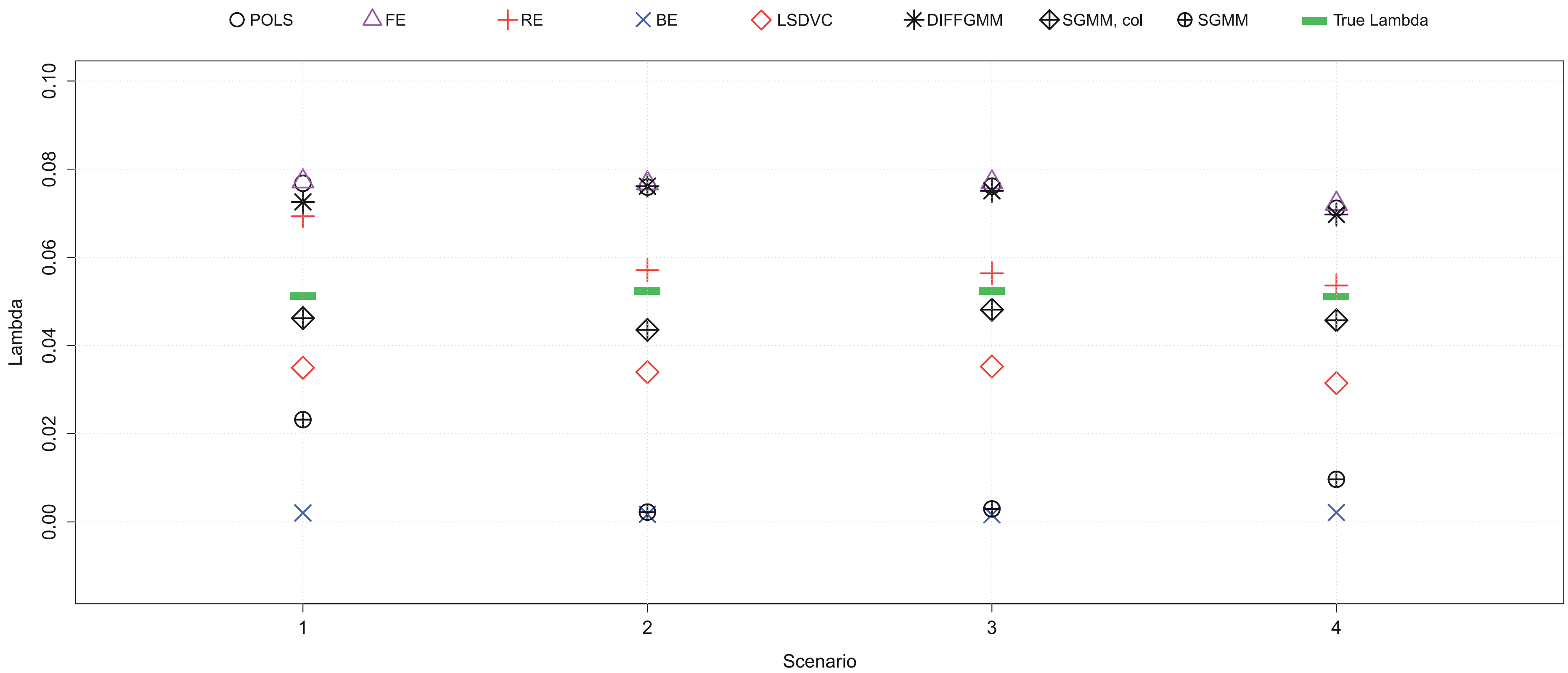

Figure 4: The estimated speed of convergence and the true value. Note: the green lines indicate the true speed of convergence, while the other signs refer to the different values obtained by the different estimators.

Table 5: Squared percent error (Fig. 3)

Estimator	Scenario 1	Scenario 2	Scenario 3	Scenario 4
PA	0.0006704	0.0005688	0.0005790	0.0004119
FE	0.0006930	0.0006105	0.0006212	0.0004545
RE	0.0003393	0.0000251	0.0000186	0.0000772
BE	0.0023887	0.0025366	0.0025469	0.0023729
LSDVC	0.0002541	0.0003280	0.0002836	0.0003750
DIFFGMM	0.0004697	0.0005790	0.0005289	0.0003565
SYSGMM, col	0.0000220	0.0000729	0.0000156	0.0000261
SYSGMM	0.0007674	0.0024855	0.0024144	0.0016961

Table 6: Estimates of the implied speed of convergence (Fig. 4)

Estimator	Scenario 1	Scenario 2	Scenario 3	Scenario 4
POLS	0.0768	0.0759	0.0761	0.0711
FE	0.0772	0.0768	0.0770	0.0722
RE	0.0693	0.0571	0.0564	0.0536
BE	0.0020	0.0017	0.0016	0.0021
LSDVC	0.0350	0.0340	0.0352	0.0315
DIFFGMM	0.0726	0.0761	0.0751	0.0697
SYSGMM, col	0.0462	0.0435	0.0481	0.0457
SYSGMM	0.0232	0.0022	0.0029	0.0097
True lambda	0.0509	0.0521	0.0521	0.0508
Simple average over all estimators	0.0503	0.0459	0.0466	0.0445

5 Conclusions

We generated an artificial data set from the simulated growth trajectories of a Solow (1956) model for 150 countries over a time span of 100 years to construct a panel data set with the dimensions $N = 150$ and $T = 10$ (with the data being averaged over 5 years). This is a typical sample size of panel data growth regressions used to assess the speed of convergence. The resulting trajectories exhibit a rate of convergence that can be calculated and used as the true underlying rate of convergence in a controlled experiment to assess the biases and inefficiencies of different panel data methods against each other. In the simulation exercise we considered two deterministic scenarios, where the first assumes differences in initial capital stocks and savings rates between the different countries, the second allows for different population growth rates, the third introduces stochastic shocks on the per capita output series, and the forth allows for stochastic shocks on savings rates and population growth rates. We use a battery of standard estimators to assess the speed of converge and find that the estimated speed of convergence is typically far off the true speed of convergence. With the true rate being around 5% throughout the 4 scenarios, the estimated rate of convergence ranges from barely above 0% to almost 8%. This means that, while the true half life is around 14 years, the estimated half life ranges from 9 years to several hundred years.

Our analysis sheds some light on the performance of different estimators in certain underlying stylized environments. This is crucial, given that the results of different econometric techniques regarding the analysis of panel data vary widely. For the sake of clarity, we did not include additional complications such as autocorrelated disturbances, multicollinearity, problems with small samples, and systematic measurement errors. These would have required a more elaborate simulation design with some additional arbitrary choices involved, which is outside the scope of the present paper. We think that analyzing these issues is a promising area for further research.

The immediate conclusion from our results is that it might not be a good strategy to rely on only one or two different estimators when assessing the speed of convergence in empirical growth regressions, even if these estimators are seen as suitable for the given sources of biases and inefficiencies. It seems to be a better strategy to compare the outcomes of different estimators carefully in light of the results of Monte Carlo simulation studies. Furthermore, it could be useful to compute and report also the mean over the different estimated parameter values derived from the different estimators.

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University of Hohenheim
Dean’s Office of the Faculty of Business, Economics and Social Sciences
Palace Hohenheim 1 B
70593 Stuttgart | Germany
Fon +49 (0)711 459 22488
Fax +49 (0)711 459 22785
E-mail wiso@uni-hohenheim.de
Web www.wiso.uni-hohenheim.de