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Separating Catch-up and Technical Change in Stochastic Frontier Models. A Monte Carlo Approach

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SEPARATING CATCH-UP AND TECHNICAL CHANGE IN STOCHASTIC FRONTIER MODELS. A MONTE CARLO APPROACH[*]

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Abstract: In the empirical analysis of economic growth an interesting topic is whether backward countries move towards the technological frontier (what it is known as technological catch-up). A common approach to testing for the existence of catching-up is the estimation of stochastic frontiers. However, it is not clear under which conditions technological catch-up can be disentangled from technical change in stochastic frontier models. We try to fill this gap in the literature using Monte Carlo techniques.

Key words: Monte Carlo analysis, stochastic frontier models, technological catch-up, technical change.

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1. Introduction

In the last two decades, we have seen a renewed interest in the study of the determinants of long-run economic growth. It is widely accepted nowadays that factor accumulation can explain only a small fraction of cross-country differences in growth rates. For this reason macroeconomists are looking at Total Factor Productivity (TFP) as the main source of economic growth. Although since Solow technical change has been considered the main driver of TFP growth, more emphasis has been placed recently on the role of international diffusion of knowledge and technology. That is, follower countries do not need to produce innovations in order to grow, rather they can adopt the best-practice technologies developed by leader countries.

When backward countries adopt new technologies they move towards the technological frontier. This is known as "technological catch-up" effect. In fact, the absence of technological catch-up has been considered the main factor responsible for non-convergence or slow convergence in output per worker (Quah, 1997). Therefore, some of the recent macroeconomic literature is interested in the relative importance of technological catch-up and technical change as determinants of economic growth. Given that both effects are unobservable, it is interesting to know the ability of models to disentangle these two effects.

The empirical approach to testing for the existence of catching-up has traditionally followed the path-breaking article by Nelson and Phelps (1966) which implies the use of proxies for the technology gap. More recently, some papers have identified catch-up with inefficiency change (*i.e.*, with the reduction of the distance to the frontier). Part of this literature has used non-parametric techniques to estimate inefficiency change (*e.g.*, Färe *et al*., 1994). On the other hand, other papers (e.g., Koop *et al*., 1999) have used the stochastic frontier methodology developed by Aigner, Lovell and Schmidt (1977).

However, even though it has been recognized that "it may be difficult to disentangle the separate effects of technical change and technical efficiency change when both effects are proxied by the passage of time" (Kumbhakar and Lovell, 2000; pp. 107), to the best of our knowledge, we are not aware of papers that have studied the ability of models to disentangle technical change from efficiency change.

For this reason, in this paper we use Monte Carlo techniques in order to study the ability of several stochastic frontier models to correctly identify these two effects based on macroeconomic data from the Penn World Table 6.2. Specifically, the following models are compared: the traditional pooled stochastic frontier as well as the models suggested by Battese and Coelli in 1992 (BC92) and in 1995 (BC95). The Monte Carlo experiments are based on three alternative data generating processes. In the first one, we generate the data imposing that there is catch-up but no technical change. In the second one, we generate the data assuming that there is only technical change. Finally, in the third one we impose that there are both catch-up and technical change. Given that results can be sensitive to the relative importance of inefficiency over statistical noise, we present the results under different scenarios concerning this parameter.

The rest of this paper is organized as follows. The next section deals with the modelling of catching-up. It is followed by a description of the Monte Carlo study. Then the results are presented. Finally some conclusions are drawn.

2. Modelling catching-up

The idea behind technological catch-up is that backward countries are able to absorb the technology developed by leading countries. This is due to a process of technological diffusion which depends on the absorptive capacity of the country, that is, on the ability to assimilate and apply new knowledge.

The first empirical models to investigate the existence of technological catching-up were based on the model developed by Nelson and Phelps (1966). They specified the rate of growth of the technology as:

$$\frac{\dot{A}_i}{A_i} = \phi(z) \cdot \left[\frac{A_w}{A_i} \right] \qquad (1)$$

where subscript i refers to country and subscript w denotes the world frontier. The function φ(z) models the absorptive capacity of the country, which depends on a set of variables (z). The state of the technology, A, is unobservable and therefore must be proxied. For example, Hansson and Henrekson (1994) used the initial income gap (Y_i/Y_w) as a proxy for the technological gap (A_i/A_w).

Nelson and Phelps (1966) considered that the rate of growth of the technology is an increasing function of education attainment. Other variables that have been used to capture absorptive capacity are Trade Openness, Foreign Direct Investment (FDI), Human Capital or Domestic R&D. For instance, Kneller and Stevens (2006) have used a stochastic frontier model to investigate whether differences in absorptive capacity help to explain cross-country differences in the level of technical efficiency using panel data from nine manufacturing industries in 12 OECD countries.

Since technological catch-up is defined as a movement toward the frontier, the frontier methods, which are able to identify the frontier and the distance of each country to the frontier (inefficiency) seem to be appropriate to study this issue. Färe *et al.* (1994) was one of the first studies to apply frontier techniques. This paper analyzed productivity growth in 17 OECD countries over the period 1979-1988 using a nonparametric programming method to compute Malmquist productivity indexes which were decomposed into technical change and efficiency change. Later, Kumar and Rusell (2002) using a similar approach decomposed the growth of labour productivity into technical change, efficiency change and capital accumulation (i.e. movements along the frontier). Similar studies are Taskim and Zaim (1997), Henderson and Russell (2005) or Henderson and Zelenyuk (2007).

Koop *et al.* (1999) pointed out that stochastic frontier methods have several advantages over nonparametric methods in the presence of noisy data sets such as those typically used in the growth literature. Hence, in order to separate the components of output growth, namely efficiency change, technical change and input change, they estimated a stochastic frontier model. Other papers that have estimated different versions of stochastic frontier models in order to obtain an estimate of efficiency change are Kneller and Stevens (2003); or Kumbhakar and Wang (2005).

In this paper we are concerned with the parametric approach to frontier measurement. Stochastic Frontiers were first developed by Aigner, Lovell and Schmidt (1977). A stochastic frontier production function may be written as:

$$ln\, y_{it} = f(x_{it}) + v_{it} - u_{it} \qquad (2)$$

where *y* represents the output of each country, *x* is a vector of inputs, *f(x)* represents the technology, *v* captures statistical noise and it is assumed to follow a distribution centered at zero, while *u* is a non-negative term that reflects technical inefficiency and it is assumed to follow a one-sided distribution.

In this model a reduction in inefficiency (u_{it}) implies an approximation to the technological frontier and, therefore, this can be interpreted as evidence that countries are "catching-up". The statistical methods employed to estimate stochastic frontiers, such as maximum likelihood, can only provide an estimate of the composed error term. However, using the conditional expectation of u_i on v_i-u_i $E(u_i/v_i-u_i)$ a predictor for u_i can be obtained. This allows us to compute a measurement of catch-up in the sample by comparing the evolution of average inefficiency for every period.

In this framework Kumbhakar (2000) describes the procedure to decompose TFP change into its components using the production function approach. In particular:

$$T\dot{F}P = TC + (e-1)\sum_{j=1}^{n}\frac{e_j}{e}\dot{x}_j + EC \qquad (3)$$

Where *TC* is technical change, *e* is the scale elasticity, e_j are the input elasticities and *EC* is the efficiency change. The technical change is measured as $TC = \partial\, ln\, f(x)/\partial t$ and the efficiency change is calculated as $EC = -(\hat{u}_{it} - \hat{u}_{it-1})$.

3. The Monte Carlo Design

Similarly to Greene (2005) our experiments are based on a realistic configuration of the right-hand side of the estimated equation, rather than simply simulating some small number of artificial regressors. To do so we take both output (GDP) and input variables (capital and labor) from the Penn World Table 6.2[1]. The number of countries considered is 91 while the number of years considered is 31 (1970-2000)[2]. The number

[1] The monetary variables are measured in 1996 US$ with purchasing power parity adjustment.
[2] See further details about the data in the appendix

of replications in each experiment is 1000. First, we estimate a Cobb-Douglas fixed effects model:

$$ln\, y_{it} = \beta_i + \beta_K \, ln\, K_{it} + \beta_L \, ln\, L_{it} + v_{it} \quad (4)$$

where *y* is output, *K* is capital, *L* is labor, β_i are individual effects and *v* is a error term. In order to generate the replications in the Monte Carlo we use the estimated parameters rounded off to the second decimal as the true values in the model. Likewise we use the real values of capital and labor as regressors. However, since we are not interested in the individual effects we take their average as intercept. Specifically, we generate the output data from three different versions of the following stochastic production frontier:

$$ln\, y_{it} = 0.16 + 0.63 \cdot ln\, K_{it} + 0.20 \cdot ln\, L_{it} + \phi \cdot t + v_{it} - u_{it} \quad (5)$$

where *t* is a time trend, *v* is a random error term which is drawn from a normal distribution with zero mean, while *u* is a non-negative random error term, which is drawn from a truncated-normal distribution. In this simple model the passage of time may cause two effects: one is to change the distance of each country to the frontier (u_{it}), while the other effect is shifting the frontier.

In order to observe how the estimates depend on the relative importance of inefficiency over noise the simulations were carried out under three different scenarios by varying the parameter *γ*, which is equal to $\sigma_u^2 / (\sigma_u^2 + \sigma_v^2)$, where σ_u^2 and σ_v^2 are the variances of the inefficiency term and random error term respectively. In particular *γ* will be equal to 0.2, 0.5 and 0.8. Moreover, in order to keep the variance of the error term constant in the different scenarios we consider the denominator of *γ* equal to 0.1. Hence it can be obtained the σ_u and σ_v for each *γ* setting.

Next we present the three experiments:

a) Experiment 1

In this case we generate the data assuming that there is no technical change (ϕ=0) but there exists catch-up, that is, countries improve their efficiency level over the years. To do so the mean of the pre-truncated normal distribution (μ_t) decreases over time, as follows:

$$u_{it} \sim N^{+}(\mu_t, \sigma_u) \; ; \quad \mu_t = 0.2 + 0.01(\bar{t} - t) \qquad (6)$$

where $\bar{t}$ is the average of the years (i.e. 16, as we have data for 31 years) and t is a time trend. Hence, μ_t decreases from 0.35 in the first year of the sample to 0.05 in the last year of the sample. Therefore, the data generating model is:

$$ln\, y_{it} = 0.16 + 0.63\, ln\, K_{it} + 0.20\, ln\, L_{it} + v_{it} - u_{it} \qquad (7)$$

b) Experiment 2

In this experiment we assume that the countries' efficiency level stays constant over time (on average) but there is technical change. To do so, μ_t is fixed over time (equal to 0.2), while technical change is assumed to be 2% every year. Therefore, the data generating model is:

$$ln\, y_{it} = 0.16 + 0.63\, ln\, K_{it} + 0.20\, ln\, L_{it} + 0.02 \cdot t + v_{it} - u_{it} \qquad (8)$$

where $u_{it} \sim N^{+}(0.2, \sigma_u)$.

c) Experiment 3

This is the most general case. Now we include both technical change and technological catch-up in the data generating model. We generate the inefficiency term *u* using equation (5) while technical change is assumed to be 2% every year. Therefore, the data generating model is:

$$\begin{aligned} &ln\, y_{it} = 0.16 + 0.63 \cdot ln\, K_{it} + 0.20 \cdot ln\, L_{it} + 0.02 \cdot t + v_{it} - u_{it} \\ &u_{it} \sim N^{+}(\mu_t, \sigma_u) \\ &\mu_t = 0.2 + 0.01 \cdot (\bar{t} - t) \end{aligned} \quad (9)$$

Next we explain in some detail the models that we estimate. The models differ in the way they accommodate time varying inefficiency. The models are: the traditional pooled Stochastic Frontier model (SFTN), as well as the models suggested by Battese and Coelli in 1992 (BC 92) and in 1995 (BC 95). The three models have in common the composed error term feature. In fact, the three models are different versions of the general stochastic frontier model:

$$y_{it} = f(x_{it}) + \phi \cdot t + v_{it} - u_{it} \quad (10)$$

Model 1: Pooled Stochastic Frontier Model

We assume that *u* follows a truncated normal distribution[3]. It is important to note that in this model inefficiency is allowed to vary over time but around a time-invariant mean (μ). Therefore, mean inefficiency is constant over time and for this reason we do not expect these models to perform well in experiments 1 and 3.

Model 2: Battese and Coelli (1992)

This model allows for time-varying inefficiency, which is modelled as a truncated-normal random variable multiplied by a deterministic function of time. The idiosyncratic error term is assumed to follow a normal distribution centered at zero. The only panel-specific effect is the random inefficiency term. Therefore the model can be expressed as:

[3] Other distributions that can be used are half-normal or exponential. See Kumbhakar and Lovell (2000) for further details about these models.

$$u_{it} = exp(-\eta(t-T)) \cdot u_i \ ; \ u_i \sim N^+(\mu, \sigma_u) \qquad (11)$$

where η is a parameter to be estimated which captures the rate of decline in technical inefficiency, t is the actual period and T is the total number of periods in the sample. Note that this model is rather restrictive in the way that accommodates the variation pattern of inefficiency. In fact the BC92 model imposes that all firms increase or decrease inefficiency and that they do so at the same rate.

Model 3: Battese and Coelli (1995)

This is probably the most popular model among those which attempt to model explicitly the determinants of inefficiency. In this model the parameters of the technology as well as the parameters of the inefficiency explanatory variables are estimated in one stage. The model assumes that the inefficiency effects are obtained by truncation (at zero) of a normal distribution.

$$u_{it} \sim N^+(\mu_{it}, \sigma_u); \quad \mu_{it} = g(z_{it}, \delta) \qquad (12)$$

where z_{it} is a vector of some exogenous variables that are believed to explain differences in inefficiency. Following Kneller and Stevens (2003) we use a time trend as the only explanatory variable for the technical inefficiency. So, the mean of the pretruncated normal distribution is:

$$\mu_{it} = \delta_0 + \delta_1 \cdot t \qquad (13)$$

where δ_0 and δ_1 are parameters to be estimated.

4. Simulation Results

In this section we report the results of the three experiments described above. In order to report the results we use three tools. First, tables 1-3 present the arithmetic mean of the estimates across the replications in each experiment. Second, additional insight is gained by examining kernel density estimates for the distribution of the time trend estimator over the 1000 Monte Carlo trials. Finally, we study the ability of the models to disentangle technical change and efficiency change using the decomposition of TFP growth in technical change, scale change and efficiency change in our experiments. To do so, we calculate the average of each TFP component throughout replications, years and countries. We compare them with the TFP decomposition true values that emerge from the neutral technical change of the data generating model, the true input parameters together with the change in inputs used across countries and the changes in the inefficiency from the generated inefficiency. The simulation procedures have been carried out using the econometric package STATA 9.0. All models were estimated by maximum likelihood.

In tables 1-3, each cell corresponds to the arithmetic mean of the estimates. Likewise the percentage of significant estimates (t-stat greater than 1.96) across the replications is shown in parentheses. It can be seen that some results are common to the three experiments. Specifically, the input parameters in all models are both estimated accurately and significant in almost all replications. This is not surprising since the two random terms are generated independently of the inputs. On the other hand, the constant term (α) is clearly biased in almost all models.

In experiment 1 the data generating process assumes that there is no technical change (ϕ=0) but there exists catch-up. Table 1 presents the results of the Monte Carlo analysis for the experiment 1. In these models we have included the possibility to estimate technical change, though we have generated the data without technical change. In fact, in most of the estimated models the coefficient on the time trend is positive and significant. As the data was generated in the absence of technical change and imposing catch-up, a positive, significant trend parameter in the model indicates that efficiency improvements are partially absorbed by technical progress. This result is reinforced in Figure 1, 2 and 3 in which kernel density estimates of the technical change parameter are shown for experiment 1. The vertical line indicates the true value of the parameter. It can be seen that both the pooled model and the Battese and Coelli (1992) model clearly overestimates this parameter. Actually there is no trial in which this parameter is estimated accurately in the latter models. However the Battese and Coelli (1995) model estimates this parameter accurately if gamma equals to 0.5, and rather accurately in the case of gamma equals to 0.8, but it fails to estimate the parameter accurately if gamma is 0.2. Moreover, it is worth pointing out that the bigger γ the closer the coefficient on the technical change to the true parameter. Hence, as γ gets larger, the ability of the models to distinguish these effects is enhanced.

Finally, Table 4 presents the TFP decomposition under experiment 1. Since all models estimate accurately the input parameters there is no difference between the calculated scale change and the true scale change. However, the true efficiency change is very similar to the calculated technical change in the pooled model and Battese and Coelli 1992 model. This result suggests that these models fail to distinguish between technical change and catch-up. Actually they consider the efficiency change as technical change. Opposite, the Battese and Coelli (1995) model is the only model that does not seem to confuse technical change and efficiency change in some scenarios. Specifically, when gamma is higher than 0.2, the TFP is decomposed fairly well.

Regarding the variances estimates, the Battese and Coelli (1992) is the only model performing poorly.

Table 2 shows the results for experiment 2 in which there is technical change but no efficiency change. The results show that likewise the estimation of the input parameters is unbiased. The constant term seems to be unbiased when γ is equal to either 0.5 or 0.8, with the exception of the Battese and Coelli (1992). Furthermore all models estimate accurately the parameter of technical change. This result can also be seen in Figures 4, 5 and 6. Moreover, the larger gamma the larger the dispersion of the distributions of the time trend parameters. In Table 5 it can be seen that the TFP change components is well decomposed in all models. So if the data doest not hold efficiency change the considered models estimate accurately all the components of TFP change. Hence, unlike experiment 1, in which the changes in the efficiency are considered in some models as technical change, the changes in the technology are not measured as efficiency changes. Regarding the variances estimates, this table reinforces the results obtained in Table 1 since the Battese and Coelli (1992) does not estimate accurately the variances in contrast to the other models that seem to perform relatively fine.

Finally in the Experiment 3 we describe the most general case in which there is efficiency change as well as technological change. The results of experiment 3 basically confirm the results obtained in the experiment 1. An interesting issue is that in the pooled model and the Battese and Coelli 1992 model the percentage of replications in which the time trend is significant is higher in the experiment 1 than in experiment 3.

This fact is rather surprising since in experiment 1 the data is generated without technical change while in experiment 3 the data is generated with technical change.

5. Conclusions

In this paper we have performed Monte Carlo simulation in order to study whether several versions of the stochastic frontier model are able to correctly distinguish between technical change and efficiency change (catch-up). We estimated several models: the pooled Stochastic Frontier Model with the composed error term following a Normal-Truncated Normal model, as well as the models suggested by Battese and Coelli in 1992 and 1995.

The results show that most models fail to correctly distinguish between technical change and efficiency change. In fact, most models estimate significant technical change when the data were generated without it. An important finding is that this problem seems to disappear as γ increases. Furthermore, the Battese and Coelli (1995) model seems to be able to disentangle these two effects when γ is larger than 0.2; nonetheless, when γ is equal to 0.2 it does not perform so well.

Obviously, the results obtained in this paper represent just a first step which must lead to further research in order to know the consistency of these results under alternative scenarios. Moreover, it would be also interesting to analyze the differences between the econometric approach, namely stochastic frontier models and the non-parametric approach (DEA) in order to disentangle the TFP growth components: scale change, technical change and efficiency change.

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APPENDIX

Table 1. Monte Carlo mean estimates under experiment 1 (no technical change)

	γ = 0.20				γ = 0.50				γ = 0.80			
	True value	SF T-N	SF BC92	SF BC95	True value	SF T-N	SF BC92	SF BC95	True value	SF T-N	SF BC92	SF BC95
α	0.160	-0.071 (6%)	-0.179 (72%)	0.046 (17%)	0.160	0.041 (10%)	-0.185 (82%)	0.184 (44%)	0.160	0.096 (43%)	-0.200 (94%)	0.187 (91%)
β_k	0.630	0.630 (99%)	0.630 (99%)	0.630 (99%)	0.630	0.630 (100%)	0.630 (100%)	0.630 (100%)	0.630	0.630 (99%)	0.630 (99%)	0.630 (99%)
β_l	0.200	0.200 (99%)	0.200 (99%)	0.200 (99%)	0.200	0.200 (100%)	0.200 (100%)	0.200 (100%)	0.200	0.200 (99%)	0.200 (99%)	0.200 (99%)
φ	0.000	0.008 (99%)	0.009 (97%)	0.003 (50%)	0.000	0.006 (100%)	0.007 (97%)	-0.001 (8%)	0.000	0.004 (99%)	0.006 (98%)	-0.001 (15%)
δ_0	0.360			0.182 (28%)	0.360			0.345 (83%)	0.360			0.306 (14%)
δ_t	-0.010			-0.010 (40%)	-0.010			-0.015 (93%)	-0.010			-0.013 (99%)
σ_u	0.141	0.144	0.098	0.156	0.224	0.248	0.099	0.248	0.283	0.309	0.160	0.306
σ_v	0.283	0.293	0.307	0.286	0.224	0.229	0.281	0.222	0.141	0.142	0.249	0.139
μ		0.00	-0.34			0.07	-0.49			0.10	-1.48	
η			-0.17				-0.21				-0.28	
γ		0.21	0.12	0.24		0.54	0.14	0.55		0.82	0.28	0.83

Table 2. Monte Carlo mean estimates under experiment 2 (no catch-up)

	$\gamma = 0.20$				$\gamma = 0.50$				$\gamma = 0.80$			
	True value	SF T-N	SF BC92	SF BC95	True value	SF T-N	SF BC92	SF BC95	True value	SF T-N	SF BC92	SF BC95
α	0.160	0.069 (8%)	-0.072 (8%)	0.082 (10%)	0.160	0.166 (50%)	-0.078 (22%)	0.169 (46%)	0.160	0.173 (86%)	-0.142 (54%)	0.175 (85%)
β_k	0.630	0.630 (91%)	0.627 (91%)	0.630 (91%)	0.630	0.630 (87%)	0.630 (87%)	0.630 (87%)	0.630	0.630 (94%)	0.631 (94%)	0.630 (94%)
β_l	0.200	0.200 (91%)	0.204 (91%)	0.200 (91%)	0.200	0.200 (87%)	0.200 (87%)	0.200 (87%)	0.200	0.200 (94%)	0.200 (94%)	0.200 (94%)
φ	0.020	0.020 (91%)	0.023 (91%)	0.020 (90%)	0.020	0.020 (87%)	0.020 (86%)	0.020 (87%)	0.020	0.020 (94%)	0.020 (94%)	0.020 (94%)
δ_0	0.200			0.011 (2%)	0.200			0.090 (17%)	0.200			0.309 (14%)
δ_t	0.000			0.000 (8%)	0.000			0.000 (4%)	0.000			0.000 (5%)
σ_u	0.141	0.150	0.094	0.155	0.224	0.258	0.123	0.258	0.283	0.309	0.201	0.309
σ_v	0.283	0.293	0.313	0.291	0.224	0.222	0.282	0.221	0.141	0.137	0.248	0.137
μ		0.00	-0.53			0.08	-1.09			0.11	-2.96	
η			-0.16				-0.12				-0.30	
γ		0.22	0.10	0.23		0.57	0.17	0.57		0.83	0.36	0.83

Table 3. Monte Carlo mean estimates under experiment 3 (catch-up and technical change)

	$\gamma = 0.20$				$\gamma = 0.50$				$\gamma = 0.80$			
	True value	SF T-N	SF BC92	SF BC95	True value	SF T-N	SF BC92	SF BC95	True value	SF T-N	SF BC92	SF BC95
α	0.160	-0.075 (5%)	-0.180 (67%)	0.055 (18%)	0.160	0.048 (10%)	-0.183 (76%)	0.180 (40%)	0.160	0.096 (41%)	-0.199 (89%)	0.187 (87%)
β_k	0.630	0.630 (91%)	0.630 (91%)	0.630 (90%)	0.630	0.630 (91%)	0.630 (91%)	0.630 (91%)	0.630	0.630 (94%)	0.630 (94%)	0.630 (94%)
β_l	0.200	0.200 (91%)	0.200 (91%)	0.200 (91%)	0.200	0.200 (91%)	0.200 (91%)	0.200 (91%)	0.200	0.200 (94%)	0.200 (94%)	0.200 (94%)
φ	0.020	0.028 (91%)	0.029 (90%)	0.023 (85%)	0.020	0.026 (91%)	0.027 (91%)	0.019 (90%)	0.020	0.024 (94%)	0.026 (94%)	0.019 (94%)
δ_0	0.360			0.197 (26%)	0.360			0.337 (74%)	0.360			0.306 (14%)
δ_t	-0.010			-0.010 (38%)	-0.010			-0.015 (87%)	-0.010			-0.013 (94%)
σ_u	0.141	0.144	0.097	0.157	0.224	0.250	0.103	0.250	0.283	0.309	0.163	0.306
σ_v	0.283	0.293	0.307	0.284	0.224	0.228	0.281	0.223	0.141	0.142	0.249	0.139
μ		0.00	-0.45			0.07	-0.47			0.10	-1.72	
η			-0.18				-0.19				-0.28	
γ		0.21	0.12	0.25		0.54	0.14	0.55		0.82	0.28	0.83

Table 4. Monte Carlo TFP decomposition under experiment 1

	$\gamma = 0.2$				$\gamma = 0.5$				$\gamma = 0.8$			
	True Value	SF T-N	SF BC92	SF BC95	*True Value*	SF T-N	SF BC92	SF BC95	*True Value*	SF T-N	SF BC92	SF BC95
$T\dot{C}$	*0*	0.008	0.009	0.003	*0*	0.006	0.007	-0.001	*0*	0.004	0.006	-0.001
$S\dot{C}$	*-0.007*	-0.007	-0.007	-0.007	*-0.007*	-0.007	-0.007	-0.007	*-0.007*	-0.007	-0.007	-0.007
$E\dot{C}$	*0.008*	0.000	0.000	0.004	*0.006*	0.000	0.000	0.007	*0.005*	0.001	0.000	0.006
$T\dot{F}P$	*0.001*	0.001	0.003	0.001	*-0.001*	-0.001	0.001	-0.001	*-0.002*	-0.002	-0.001	-0.002

TC- Technical change; SC- Scale change; EC- Efficiency change

Table 5. Monte Carlo TFP decomposition under experiment 2

	$\gamma = 0.2$				$\gamma = 0.5$				$\gamma = 0.8$			
	True Value	SF T-N	SF BC92	SF BC95	*True Value*	SF T-N	SF BC92	SF BC95	*True Value*	SF T-N	SF BC92	SF BC95
$T\dot{C}$	*0.020*	0.020	0.023	0.020	*0.020*	0.020	0.020	0.020	*0.020*	0.020	0.020	0.020
$S\dot{C}$	*-0.007*	-0.007	-0.007	-0.007	*-0.007*	-0.007	-0.007	-0.007	*-0.007*	-0.007	-0.007	-0.007
$E\dot{C}$	*0.000*	0.000	0.000	0.000	*0.000*	0.000	0.000	0.000	*0.000*	0.000	0.000	0.000
$T\dot{F}P$	*0.013*	0.013	0.016	0.013	*0.013*	0.013	0.014	0.013	*0.013*	0.013	0.014	0.013

Table 6. Monte Carlo TFP decomposition under experiment 3

	$\gamma = 0.2$				$\gamma = 0.5$				$\gamma = 0.8$			
	True Value	SF T-N	SF BC92	SF BC95	*True Value*	SF T-N	SF BC92	SF BC95	*True Value*	SF T-N	SF BC92	SF BC95
$T\dot{C}$	*0.020*	0.028	0.029	0.023	*0.020*	0.026	0.027	0.019	*0.020*	0.024	0.026	0.019
$S\dot{C}$	*-0.007*	-0.007	-0.007	-0.007	*-0.007*	-0.007	-0.007	-0.007	*-0.007*	-0.007	-0.007	-0.007
$E\dot{C}$	*0.008*	0.000	0.000	0.005	*0.006*	0.000	0.000	0.007	*0.005*	0.001	0.000	0.006
$T\dot{F}P$	*0.021*	0.021	0.023	0.021	*0.019*	0.019	0.021	0.019	*0.018*	0.018	0.019	0.018

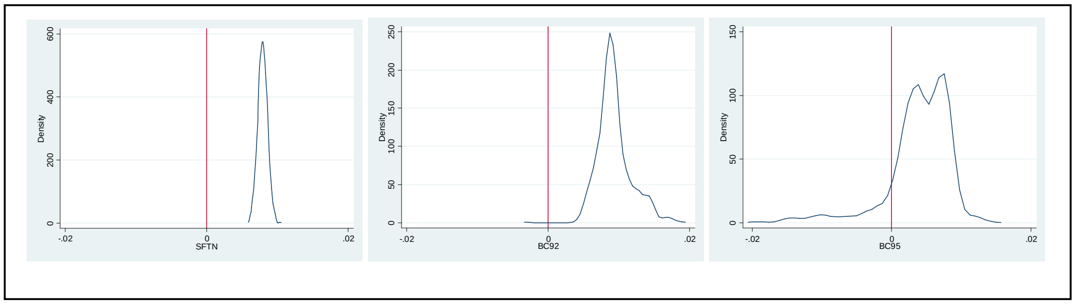

Figure 1. Kernel densities of time trend coefficient under experiment 1 (γ= 0.2)

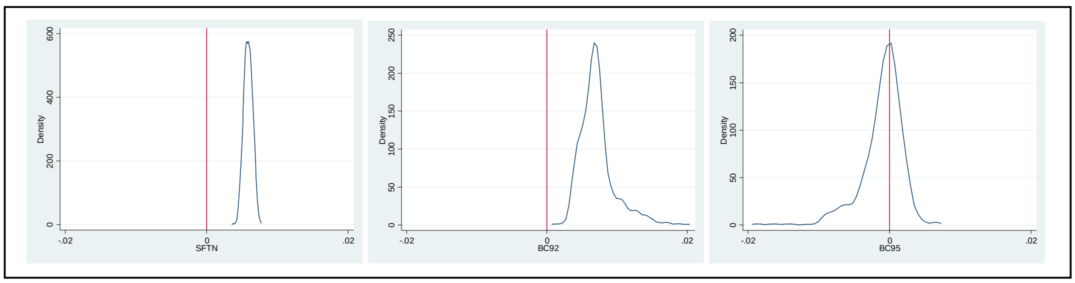

Figure 2. Kernel densities of time trend coefficient under experiment 1 (γ= 0.5)

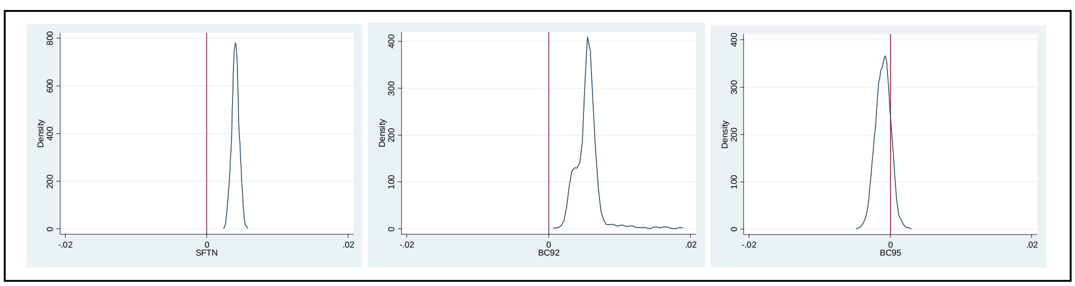

Figure 3. Kernel densities of time trend coefficient under experiment 1 (γ= 0.8)

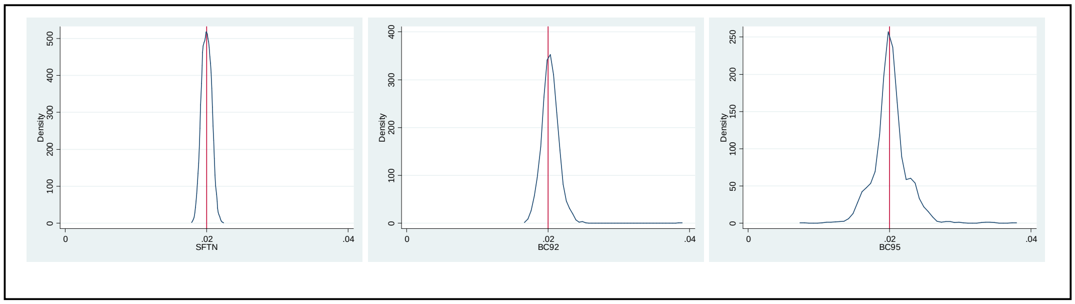

Figure 4. Kernel densities of time trend coefficient under experiment 2 (γ= 0.2)

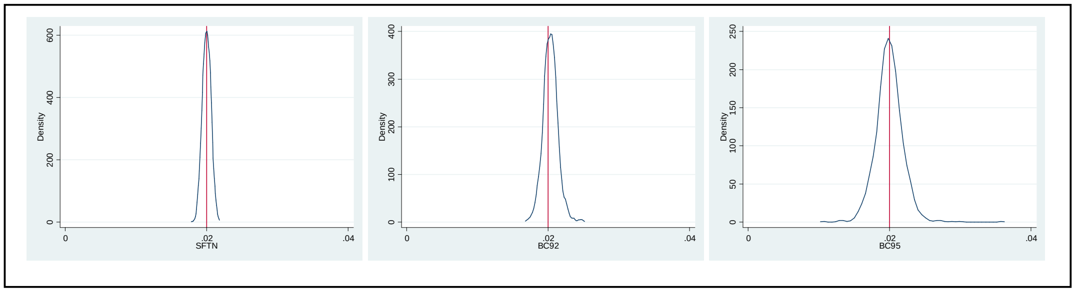

Figure 5. Kernel densities of time trend coefficient under experiment 2 (γ= 0.5)

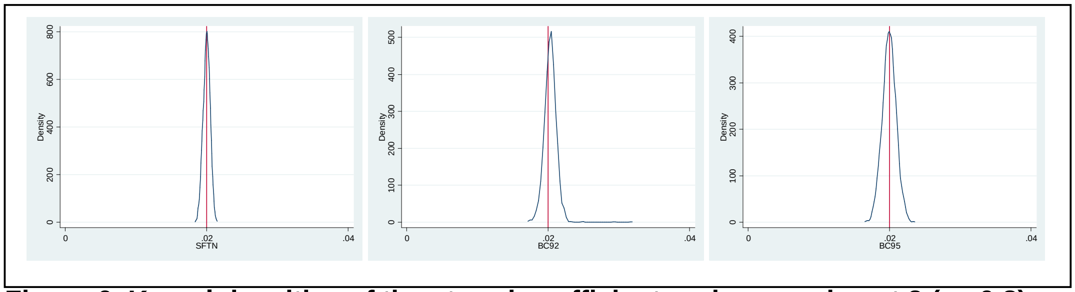

Figure 6. Kernel densities of time trend coefficient under experiment 2 (γ= 0.8)

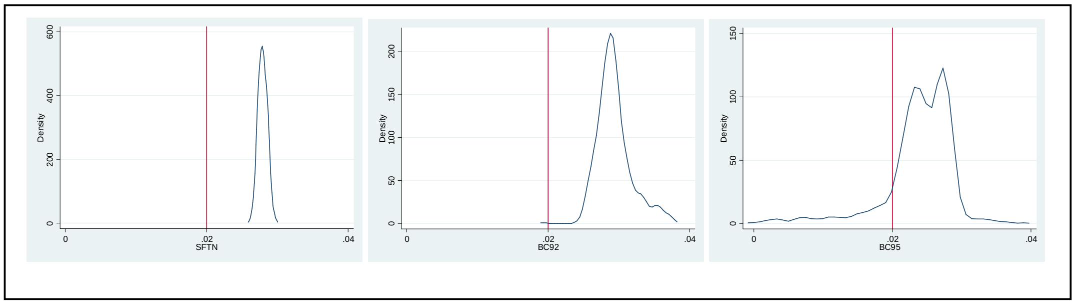

Figure 7. Kernel densities of time trend coefficient under experiment 3 (γ= 0.2)

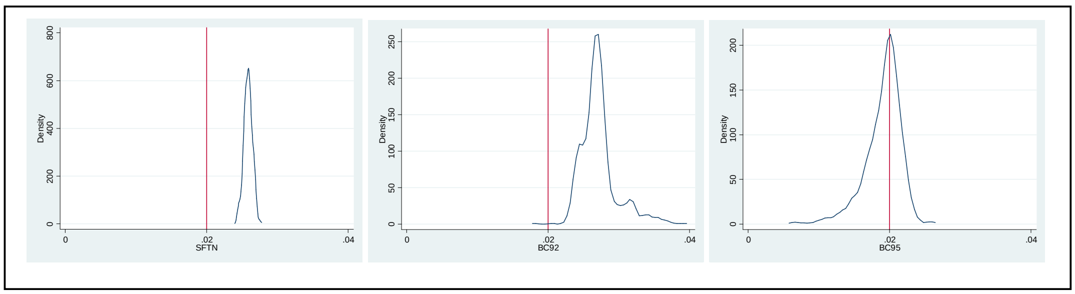

Figure 8. Kernel densities of time trend coefficient under experiment 3 (γ= 0.5)

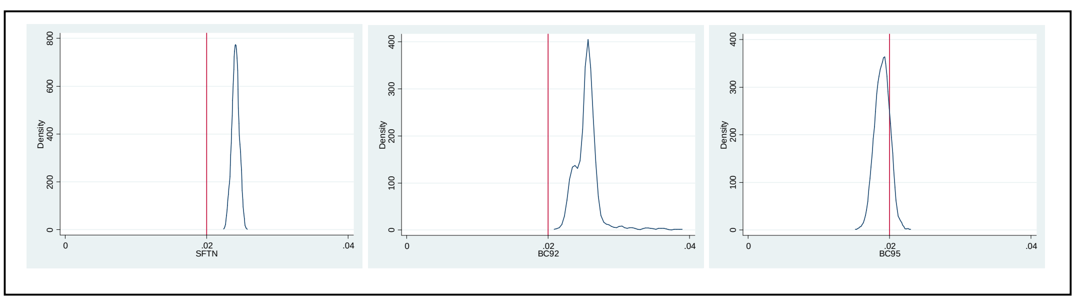

Figure 9. Kernel densities of time trend coefficient under experiment 3 (γ= 0.8)

Countries:

Algeria
Argentina
Australia
Austria
Barbados
Belgium
Benin
Bolivia
Botswana
Brazil
Cameroon
Canada
Central African Rep.
Chile
China
Colombia
Congo
Costa Rica
Cote d'Ivoire
Denmark
Dominican Rep.
Ecuador
El Salvador
Fiji
Finland
France
Gambia
Germany, West
Ghana
Greece
Guatemala
Haiti
Honduras
Hong Kong
Hungary
Iceland
India
Indonesia
Iran, I.R. of
Ireland
Israel
Italy
Jamaica
Japan
Jordan
Kenya
Korea
Lesotho
Malawi
Malaysia
Mali
Mexico
Mozambique
Nepal
Netherlands
New Zealand
Nicaragua
Niger
Norway
Pakistan
Panama
Papua New Guinea
Paraguay
Peru
Philippines
Poland
Portugal
Rwanda
Senegal
Sierra Leone
Singapore
South africa
Spain
Sri Lanka
Sweden
Switzerland
Syria
Taiwan
Tanzania
Thailand
Togo
Trinidad & Tobago
Tunisia
Turkey
Uganda
United Kingdom
United States
Uruguay
Venezuela
Zambia
Zimbabwe

Data

Output: GDP measured at constant prices (1996 US$), with purchasing power parity (PPP) adjustment. We multiplied the *real GDP per capita chain series (RGDPPCH)* by total population for each country.

Labor: this variable was proxied by population of equivalent adults. This population measure used here assigns a weight of 1.0 to all persons over 15, and 0.5 for those under age 15. In order to calculate such a measure, we divided real GDP per capita chain series (*rgdpch*) by real GDP per equivalent adult (*rgdpeqa*) and then we multiplied it by the population (*pop*).

Capital: the physical capital stock series of each country in the sample was obtained using the perpetual inventory method. To compute the investment series we followed the methodology followed by Oliveira and Garcia (2004). We multiplied the GDP, in constant 1996 local currency, by the "current" investment rate, and then we converted it to US$ using the 1996 exchange rate. To obtain the GDP in 1996 local currency units we added up all the components available in the *nafinalpwt* spreadsheet of PWT. The current investment rate was obtained dividing the value of investment in current local currency by the current GDP. In addition, an estimate of the initial capital stock is required so that the perpetual inventory method may be applied. We estimated the initial capital stock using the investment series. Using the assumption that at the beginning of the sample period countries are in steady state (so capital stock growth can be proxied by output growth), an estimate of the country's initial capital stock can be obtained as follows:

$$K_0 = I/(g+d)$$

where:

K_0 = initial capital stock

I = average investment (calculated over the starting three-year period; in our case 1970, 1971, 1972)

g = average growth rate of output for the three-year period

d = average depreciation rate for the 3-year period (which is taken to be the same for all countries; in our database d is equal to 2%).