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Technical change: It should be positive and make sense!

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ABSTRACT

We present the results of eight models that differ with respect to the time behavior of technical inefficiency and the presence of country heterogeneity. When taken into account, heterogeneity raises average technical change estimates, however technical progress rankings become counter-intuitive.

1. Introduction

The stochastic frontier literature has recently presented some important contributions with respect to the measurement of technical change and technological catch-up of nations. Nonetheless the results obtained in economic growth studies using such techniques are so far counter-intuitive, showing negative average rates of technical change (Kneller and Stevens, 2003; Kumbhakar and Wang, 2005). Using the stochastic frontier framework, this paper discusses how technical change estimates vary in sign and magnitude according to different econometric specifications. We present and discuss the results from the estimation of eight models that differ with respect to assumptions related to the time behavior of technical inefficiency and the presence or not of country heterogeneity. The inclusion of such heterogeneity control is necessary in order to compare the results with those of Kumbhakar and Wang (2005), one of the few studies that deal with economic growth data. We estimate average rates of world technical change and produce rankings of countries according to their individual performance with respect to this indicator. These rankings differ according to the model used and the plausibility of them is discussed on intuitive grounds.

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2. Models

The models considered here share a common translog production frontier specification in a cross-country panel given by Eq. (1):

$$y_{it} = \alpha_i + \lambda_t t + \alpha_k k_{it} + \alpha_l l_{it} + \frac{1}{2}\cdot\lambda_{tt} t^2 + \frac{1}{2}\cdot\alpha_{kk} k_{it}^2 + \frac{1}{2}\cdot\alpha_{ll} l_{it}^2 + \frac{1}{2}\cdot\alpha_{kl} k_{it} l_{it} + \alpha_{kt} k_{it} t + \alpha_{lt} k_{it} t + v_{it} - u_{it} \quad (1)$$

They differ from one another according to the behavior of the inefficiency term which can be assumed to be one of Eqs. (2), (3), (4) or (5):

$$u_{it} = u_i \cdot \exp[-\eta(t-T)],\ u_i \sim \text{i.i.d.}\, N^{+}(\mu,\ \sigma_u^2) \quad (2)$$

$$u_{it} = z_{it}\delta + \varepsilon_{it},\ \text{with}\ E[u_{it}] = \mu_{it} = z_{it}\delta\ \text{and}\ \varepsilon_{it} \sim N(0,\ \sigma_\varepsilon^2) \quad (3)$$

$$u_{it} \sim \text{i.i.d.}\, N + (\mu,\ \sigma_u^2) \quad (4)$$

$$u_{it} \sim \text{i.i.d.}\, N + \left(\mu_{it},\ \sigma_{u_{it}}^2\right),\ \text{with}\ \hat{u}_{it} = w_{it}\delta \quad (5)$$

Low case variables y, k and l represent the natural logarithms of output, capital, and labor force, respectively. Subscripts i and t refer to country and year, respectively; the isolated t is a time trend.

Technical inefficiency u_{it} is assumed to be nonnegative and to measure the distance of a country to the frontier; v_{it} is a stochastic noise component that allows for random errors affecting the frontier, that is, $v_{it} \sim$ i.i.d. $N(0,\sigma_v^2)$. The term z_{it} stands for a vector of observed explanatory variables for the behavior of inefficiency, namely: the natural log of the capital-labor ratio and the time distance relative to the initial period, that is, $t-t_0$; δ is a vector of unknown parameters to be estimated. The error component term ε_{it} is a random variable with normal distribution truncated at $-z_{it}\delta$. The term w_{it} stands for a vector of observed explanatory variables used to correct for heteroscedastic behavior of u_{it} (which are the same as mentioned for z_{it}). Eq. (2) follows the specification of Battese and Coelli (1992); Eq. (3), relates to Battese and Coelli (1995); Eqs. (4) and (5), follow Aigner et al. (1977), the last one of which adds heteroscedasticity correction of u_{it}. All these four models are estimated with and without country-specific intercepts. Therefore, we have a total of eight models.

3. Data and results

Data employed in the estimations are from Penn World Table 6.1 (PWT 6.1)(Heston et al, 2002). The output series is GDP in constant 1996 US$ with purchasing power parity (PPP) adjustments. The aggregate physical capital stock series was constructed following Nehru and Dhareshwar (1993) using the investment series available in PWT 6.1, and was also converted into constant 1996 US$ with PPP adjustments. The labor force series comes directly from PWT 6.1 "as is". All variables used in the estimations are expressed in deviations from their sample means. The data set is an unbalanced panel with annual observations for a sample of 104 countries over the period 1950–2000, with a total of 4818 observations. All estimations were obtained using the maximum likelihood method.

Results are reported in Tables 1a and 1b in the Appendix. In Table 1a all countries share the same intercept. Table 1b brings the estimation results controlling for country heterogeneity. In the models without country heterogeneity (models 1–4), all the estimated parameters are statistically significant at 1%, except for λ_t, α_{kt} and α_{lt} in model 2, which are statistically significant at 5%. The signs of the parameters in models 3 and 4 are the same, that is, α_{kk}, α_{ll}, α_{lt} and λ_{tt} are negative, while the other parameters are positive. Model 2 shows a positive sign for α_{kk} and α_{ll}. Model 1 shows negative signs for α_{kl}, α_{lt} and λ_{tt}. For models 3 and 4 the negative signs imply that the production factors have decreasing returns, and that technical change is labor saving and decreases over time.

With the introduction of country heterogeneity (models 5–8), some parameters turned to be not significant at 10% and more important, their signs diverge from those of the models without country heterogeneity. For instance, in model 5, λ_t is negative. Notice also that the estimated coefficients of α_k and α_l present considerable changes with respect to models 1–4, with great impact on the calculated elasticities of capital and labor.

We can compare models 1–4 with models 5–8 using likelihood ratio (LR) tests, since the former are nested in the later. The test statistics are, respectively, $\chi^2_{103}=3744.4$, $\chi^2_{103}=7486.8$, $\chi^2_{103}=7684.2$, and $\chi^2_{103}=7653.1$, all significant at the 1% level. Therefore, the data provide evidence of cross-country heterogeneity, as the results found in Kumbhakar and Wang (2005) also do. However, these tests and the remarks made in the previous paragraphs have serious implications for the economic interpretation of the estimates of total factor productivity and its components, as we shall see.

Following Orea (2002), we obtained total factor productivity change (TFPC) from a frontier production function as the sum of three components, namely: technical efficiency change (TEC), technical change (TC) and scale efficiency change (SEC). Eq. (6) specifies the TC indicator which is central to all the analysis done in this paper.

$$\frac{\partial y_{it}}{\partial t} = \lambda_t + \lambda_{tt}t + \alpha_{kt}k_{it} + \alpha_{lt}l_{it} \tag{6}$$

Table 2 in the Appendix shows our estimates for each of these components. It also shows an alternative way to measure the productivity change (TFPC1), ignoring the scale component, as in Kumbhakar and Wang (2005). The estimated TFPC is positive only in models 2, 3 and 4. For all models, except model 2, SEC is negative and larger in absolute terms with country heterogeneity (as compared with models 1, 3 and 4). The estimated components TEC, TE and TC from model 5 do not seem to make sense at all in economic grounds.

Models 2, 3 and 4 show plausible results, not only with respect to signs but also to magnitudes. It is quite reasonable to say that the world average annual technical change rate was about 0.474% (model 2), 0.122% (model 3) or 0.299% (model 4) over the period 1950–2000, and that TC had a important role in this—one can see the share of TC in TPFC is greater in models 3 and 4. Notice that, for estimations made without the SEC component, TFP changes are positive for all models (TFPC1); this could mean that scale efficiency is overestimated in models with country heterogeneity. The introduction of country heterogeneity makes TPF change numbers less intuitive and reduces the contribution share of TC in TFP change.

From Eq. (6), we were able to estimate the annual average TC for each of the 104 countries (for all eight models). Results for model 2 show a rank order of countries which seems very intuitive, with nations such as Germany (1.215% per year), Switzerland (1.173%), USA (1.129%), Norway (1.090%), Netherlands (1.078%), France (1.071%), Sweden (1.062%), Denmark (1.047%), Japan (1.042%) and Belgium (1.037%) at the top, and Sub-Saharan African countries at the bottom of the list: Mozambique (−0.264% per year), Burundi (−0.364%) and Sierra Leoa (−0.367%). Developing countries such as Brazil, South Korea and Mexico come all close together at the 33rd, 34th and 35th positions, and with annual average TC rates of 0.638%, 0.634% and 0.632%, respectively. The rankings obtained according to the estimates produced by models 3 and 4 do not differ considerably from the previous ranking.[2]

Considering models 6–8, as observed by Kumbhakar and Wang (2005), country heterogeneity in fact raises the world average TC estimates, but on the other hand the rankings are completely modified. It almost seems as they were turned upside down, with USA, Germany, Japan, Switzerland, for example, appearing among the countries with the smallest rates of TC. And worst: Sub-Saharan African and other developing nations appear at the top of the ranking. That simply does not seem plausible on intuitive grounds. The reasons why this happened are simple and can be inferred from the estimated coefficients in each model. When fixed-effects are introduced in models 2, 3 and 4, λ_t and λ_{tt} become larger, making world average TC also larger. On the other hand, α_{kt} becomes much smaller, reducing TC in countries with large amounts of capital stock. Also, the α_{lt} coefficients in models 5, 6 and 7 are bigger than in models 1, 2 and 4, making TC larger in countries with vast labor forces. The net effect of these changes is to raise technical change estimates in poor nations that present little capital per worker, making them even bigger than in rich countries.

It should be noted that there is no asymptotic theory that clearly justifies the inclusion of fixed effects in nonlinear models like the one we use here[3], although some significant progress has been done in the analysis of heterogeneity by Greene (2005a,b) in the context of stochastic frontiers. The root causes of the changes mentioned above on the estimated parameters (when we introduce heterogeneity control) may well be related to the problem of incidental parameters as argued by Greene (2005b). In fact, heterogeneity control means 103 extra parameters to be estimated in models 5–8, for a sample of 4818 observations.

The more intuitive results of models 2 and 4 are corroborated by the fact that the rates of TC obtained from them are highly correlated with R&D indicators and also with industrial performance indicators from the World Development Indicators 2005 (World Bank, 2005). In fact, Table 3 illustrates that the efforts nations make to develop and diffuse technology seem to be better represented in the models without heterogeneity control, when comparing with models including them.

[2] Rankings are available to readers upon request from the authors.

[3] We are grateful to an anonymous referee for pointing this out to us.