E C O N O M I C S   B U L L E T I N

Technological Change and Catch-up and Capital Deepening: Relative Contributions to Growth and Convergence: Comment

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Abstract

The empirical results through a fixed effects regression model show that the initial level of productivity has a negative effect on the contribution of efficiency to productivity growth, which implies that technological catch-up has done much to cause economic convergence among countries. Further, we found that if we incorporate year dummy variables the relation between the initial level of productivity and the change in capital accumulation is not negative but positive. These results are contrary to the assertion of Kumar and Russell (2002).

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1. Introduction

A recent article by Kumar and Russell (KR) (2002, p.546) decomposed labor-productivity growth into some components to empirically analyze economic growth. It concluded as follows;

(1) Technological catch-up…this catch-up does not seem to have been a force for convergence as relatively rich as well as poor countries have benefited from catch-up.

(2) Technological change has not been neutral, apparently benefiting rich countries more than poor.

(3) It is primarily capital deepening, as opposed to technological change or catch-up, that has contributed the most to both growth and bipolar international divergence of economies.

KR(2002) suggests that economic growth convergence can be considered as the movements of countries toward a world production frontier. KR(2002) used production-frontier methods to analyze the evolution of the distribution of labor productivity in terms of decomposition into three components; technological change, technological catch-up, and capital accumulation[1]. Through regression analysis, they examined how the initial output per worker has an effect upon these components[2].

In spite of their long term analysis covering over 25-year period, the analysis of KR(2002) conducted a very simple regression model devoid of international time specific, countries' specific, and any socioeconomic variables[3]. Since the lack of these variables results in the omission of variable bias, they are generally included or

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[1] Färe et al.(1994) first applied production-frontier methods to empirical international economic growth. Ray and Desli(1997) used a variable returns to scale technology as a benchmark to analyze. Recently, Kumbhakar and Wang(2005) used a stochastic production frontier approach to estimate the world production frontier.

[2] KR(2002) conducted not only regression analysis but also distribution hypothesis tests for examining the relative contribution of components of productivity changes to changes in the distribution of labor productivity. Here we restrict our attention to their regression results.

[3] Henderson and Russell(2005) added the proxy for human capital, one of the key variables, to the model of KR(2002) to abbreviate the omitted variable bias. Caselli and Coleman(2006) find that there is a skill bias in cross-country technology differences and higher-income countries use skilled labor more efficiently than lower-income countries.

controlled for in the micro economic analysis to reduce the bias[4]. KR(2002, pp.544-45) also recognized that there are caveats; "potentially important variables (e.g., human capital and natural resources) are omitted", "our long-run analysis has not taken short-run economic fluctuations into account".

Our approach to this problem is to construct panel data at the outset. Second, we use the panel data to conduct estimations by a fixed effects model that reduces or eliminates the influence of omitted variables[5].

Our estimation results concerning technological catch-up estimations are robust and strikingly different from those of KR(2002). Technological catch-up plays a more important role in convergence in poor countries than in rich ones.

2. Data and Model

By using Penn World data, KR(2002) decomposed labor-productivity growth into three components to construct a cross section dataset[6]. They conduct a very simple regression model in which independent variables are the output per worker in 1965 and the dependent variables are the percentage change between 1965 and 1990 in output per worker, technology change, efficiency index, and the capital accumulation index. They plotted regression lines in their Figure 4 (KR 2002, p.537). They ignored the unobservable individual or time effects and did not pay attention to the possibility that their estimators suffered from an omission bias. Additionally, if they attempt to reduce omission bias, such unobservable effects cannot be captured by using the cross section dataset they constructed.

To obtain unbiased estimators, first based on the Penn World data, we use the same method as KR(2002) to construct a panel dataset consisted of 57 countries from 1965 to 1990. Second, using this dataset we conduct re-estimations through a fixed effects model to reduce the omitted variable bias caused by time invariant countries' features. We also incorporate the year dummies into this model to capture the time specific effect that is individually invariant[7].

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[4] Kumbhakar and Wang (2005) argued that the catch-up rate tends to be overestimated and the technical progress is likely to be overestimated if country-specific fixed effects are ignored. We need to take such effects into account.

[5] See Baltagi(2005).

[6] Although the structure of Penn World data is panel, KR use only 1965 and 1990 data. In other words, for their study they discarded all information between 1966 and 1989.

[7] This estimator is identical to that of a two-way fixed effects estimator (Baltagi 2005, ch. 3).

3. Results

The estimation results of fixed an effects model without year dummy variables are reported in Table 1[8]. The coefficient of the dependent variable of output per capita change is shown in column (1) and that of the capital accumulation index change in column (3) takes a negative sign, while being statistically significant at the 1% level. The sign of the coefficient of technological change estimation in column (2) is positive and statistically significant at the 1% level. These results conform with KR(2002). Nonetheless, the sign of the coefficient of the efficiency change estimation, in column(4), is negative and statistically significant at the 1% level, which means that poor countries have benefited more from catch-up than have rich ones. This result is distinctly different from that of KR(2002).

Turning to the model to control for international time specific effects, the results of the estimations of a fixed effects model with year dummy variables are reported in Table 2. 1965 is the based year, therefore year dummy variables shows the difference from 1965.

The result of the estimation of output per capita change shown in column (1) of Table 2 is negative and statistically significant, which is almost the same as in column (1) of Table 1. This means that the economic growth convergence can be considered as robust. The sign of the coefficient of technological change estimation is positive in column (2), despite being statistically insignificant[9]. We can interpret this result as supporting the argument of KR(2002) concerning the effect of technological change on the convergence of economic growth.

The coefficient of the estimation of capital accumulation change in column (3) Table 2 takes a positive sign, while being statistically significant at the 1% level. This results are remarkably reverse to that of Table 1 and KR(2002). The coefficients of all year dummies are negative and are almost statistically significant. Furthermore, the larger the absolute value and its t-statistics become, the larger are dummies' years, suggesting the lesser effect that capital accumulation has contributed to economic

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[8] In Tables 1 and 2, the white's robust standard error is used to calculate the t-statistics because the error term is likely to be heteroskedastic.

[9] The method in KR(2002) admits the possibility of an implosion of the technological frontier. Henderson and Russell(2005) preclude an implosion of the frontier over time. The signs of technological change are positive and statistically significant if estimations are conducted using a dataset in which technological degradation is precluded.

growth convergence as time passes. One explanation to bridge the gap between the results with year dummy variables and without is that capital accumulation contributed to economic growth more in the developing stage than in the developed stage in terms of international growth trends.

The sign of the coefficient in the estimation of efficiency change in column(4) of Table 2 is negative and statistically significant at the 1% level; further, the absolute value is the same as the result in Table 1 in column (4), suggesting that the result of the efficiency change estimation is robust. The results of the efficiency change shown in Tables 1 and 2 imply that technological catch-up plays a more important role in poor countries for convergence than rich ones. This is evidently contrary to the argument that "the degree of catch-up appears not to be related to initial productivity."(KR 2002, p529).

Overall, with the exception of technological change, the results of the estimations are opposed to those of KR(2002), if the country specific fixed effects and international year specific effects are controlled for[10]. As a consequence, after controlling for the time trend, only the coefficient signs of output per capita and efficiency changes are negative, which suggests that the growth pattern may have been driven primarily by the pattern of technological catch-up.

4. Conclusions

A major drawback of the KR work is that the results of their estimations are biased because they omitted country specific variables such as human capital, natural resources and the year specific variables capturing international time trends. The empirical results through a fixed effects regression model show that the initial level of productivity has a negative effect on the contribution of efficiency to productivity growth, which implies that technological catch-up has done much to cause economic convergence among countries. Further, we found that if we incorporate year dummy variables the relation between the initial level of productivity and the change in capital accumulation is not negative but positive. These results are contrary to the assertion of KR.

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[10] The fixed effects estimation results with year dummy variables do not change even if we use the dataset in which technological degradation is precluded. KR report "results with two major oil producing countries, Iran and Venezuela, excluded" (KR 2002, p.531). In the case of using 59 countries panel data that includes these two countries, our results with year dummy variables are not influenced.

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Table 1 FIXED EFFECTS ESTIMATES [a]

	OUTPUTCH (1)	*TECHNO* (2)	*CAPITAL* (3)	*EFFICIEN* (4)
OUTPUT	$-0.39*10^{-3}$ **	$0.19*10^{-3}$**	$-0.29*10^{-3}$**	$-0.29*10^{-3}$**
	$(-8.64)^{-}$	$(7.17)^{-}$	$(-14.9)^{-}$	$(-5.99)^{-}$
Groups	57	57	57	57
Samples	1425	1425	1425	1425

[a] Numbers in parentheses are *t*-statistics calculated by white robust standard error. * and ** indicate significance at the 5 and 1 per cent levels, respectively.

Table 2 FIXED EFFECTS ESTIMATES[a]

	OUTPUTCH (1)	*TECHNO* (2)	*CAPITAL* (3)	*EFFICIEN* (4)
OUTPUT	$-0.13*10^{-3}$ *	$0.04*10^{-3}$	$0.10*10^{-3}$**	$-0.29*10^{-3}$**
	(-1.68)$^{-}$	(0.96)$^{-}$	(3.62)$^{-}$	(-3.51)$^{-}$
Y66	-0.24	0.11	0.27	-0.40
	(-0.30)	(0.26)	(0.06)	(-0.41)
Y67	1.33	2.75**	-0.34	-1.23
	(1.65)	(7.29)	(-0.96)	(-1.30)
Y68	2.68**	3.70**	-0.48	-0.68
	(2.80)	(9.12)	(-1.31)	(-0.61)
Y69	2.06*	0.97*	-0.39	1.39
	(1.99)	(1.80)	(-1.08)	(1.25)
Y70	2.18*	2.36**	-0.65*	0.35
	(1.90)	(4.22)	(-1.74)	(0.30)
Y71	0.75	0.92*	-1.01**	0.79
	(0.87)	(2.09)	(-2.90)	(0.76)
Y72	1.06	2.87**	-1.28**	-0.65
	(1.21)	(6.84)	(-3.49)	(-0.63)
Y73	1.46	2.13**	-1.13**	0.39
	(1.28)	(3.83)	(-3.14)	(0.33)
Y74	-2.16*	-1.58**	-1.47**	0.88
	(-2.30)	(-3.85)	(-4.09)	(0.87)
Y75	0.34	3.43**	-1.82	-1.34
	(0.40)	(7.34)	(-4.93)	(-1.35)
Y76	0.32	7.01**	-2.20**	-4.40**
	(0.36)	(15.2)	(-5.88)	(-4.50)
Y77	0.59	4.38**	-2.22**	-1.64*
	(0.71)	(10.8)	(-5.72)	(-1.69)
Y78	0.31	2.65**	-2.37**	-0.03
	(0.35)	(5.00)	(-6.19)	(-0.03)
Y79	-0.49	6.56**	-2.49**	-3.98**
	(-0.46)	(6.11)	(-6.62)	(-2.76)
Y80	-1.83*	2.71**	-3.16**	-1.45
	(-2.03)	(6.46)	(-8.38)	(-1.41)
Y81	-3.43**	-2.39**	-3.24**	2.32*
	(-3.76)	(-4.68)	(-8.42)	(2.12)
Y82	-2.85**	-2.47**	-3.63**	3.57**
	(-2.95)	(-2.75)	(10.0)	(2.87)
Y83	-1.63*	5.08**	-3.86**	-2.83**
	(-1.72)	(8.88)	(-10.3)	(-2.67)
Y84	-1.23	0.73	-3.86**	1.85*
	(-1.46)	(1.55)	(-10.3)	(1.86)
Y85	-0.78	1.77**	-3.99**	1.33
	(-0.82)	(3.82)	(-10.9)	(1.23)
Y86	0.07	7.65**	-3.93**	-3.45**
	(0.08)	(11.0)	(-10.7)	(-3.12
Y87	-0.44	3.33**	-3.77**	-0.03
	(-0.42)	(6.07)	(-9.56)	(-0.03)
Y88	-0.16	3.77**	-3.42**	-0.61
	(-0.16)	(7.21)	(-7.56)	(-0.55)
Y89	-1.21	1.23*	-3.52**	1.07
	(-1.20)	(2.06)	(-7.79)	(0.90)
Groups	57	57	57	57
Samples	1425	1425	1425	1425

[a] Numbers in parentheses are *t*-statistics calculated by white robust standard error. * and ** indicate significance at the 5 and 1 per cent levels, respectively.