THE ROLE OF HUMAN CAPITAL IN ECONOMIC GROWTH: SOME EMPIRICAL EVIDENCE ON THE 'LUCAS vs. NELSON-PHELPS' CONTROVERSY

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ABSTRACT

It is argued that the usual interpretation of the Nelson-Phelps approach to the modelling of human capital in growth regressions is biased, distracting from Nelson and Phelps' main contribution. It is shown that for OECD economies, both our interpretation of the Nelson-Phelps approach, as well as the Lucas approach, are supported when outliers are deleted from the data.

Keywords: Growth, human capital, Lucas approach, Nelson-Phelps approach, outliers.

JEL classification: O15, O40

* I thank Jess Benhabib for supplying data and Mark Spiegel for clarifying some of the model specifications used in their paper.

1. INTRODUCTION

The modelling of human capital in economic growth is controversial. Aghion and Howitt (1998, chapter 10) distinguish two major frameworks within the endogenous growth literature, i.e. the 'Lucas' approach and the 'Nelson-Phelps' [NP] approach. The former, based on Lucas (1988) and shared by neo-classical growth theory, assumes that growth is driven by the accumulation of human capital. It treats human capital like an ordinary input in the production function. In particular, differences in growth rates across countries are assumed to be primarily due to differences in the rates of human capital accumulation. The second approach, based on Nelson and Phelps (1966), relates growth to the stock of human capital which affects a country's ability to innovate and catch-up with more advanced countries (Aghion and Howitt, 1998, p. 327).

It is argued here that the characterisation of Nelson and Phelps (1966) adopted by the NP approach is biased and driven by the controversy whether human capital should be entered in 'first differences or in levels' in growth regressions. Nelson and Phelps' original hypothesis related to education speeding the process of technology *diffusion* and catch-up, not to the advance of the technological frontier (domestic innovation), which they assumed to occur at a constant exponential rate (ibid., p. 71).[1] However, they did conclude their paper by suggesting "the usual, straightforward insertion of some index of educational attainment in the production function may constitute a gross misspecification of the relation between education and the dynamics of production" (ibid., p. 75).

This statement seemed to have been confirmed by Benhabib and Spiegel [BS](1994) and many others since then, i.e. economic growth seems to be unrelated to increases in educational attainment. Instead, BS found that their version of the Nelson and Phelps model, which included human capital in levels (the innovation component) as well as human capital levels interacted with a technology lag factor (the technology

[1] Making technology diffusion/catch-up, instead of innovation, the centrepiece of the NP approach also counters Cannon's (2000) criticism that Aghion and Howitt's (1998) suggestion of how to distinguish between the two approaches does not work. Cannon focuses solely on the 'first differences versus level' controversy of the modelling of human capital.

diffusion/catch-up component), was preferable and confirmed a positive role for human capital in growth. It seems fair to say that in their discussion, BS emphasized the 'first differences versus levels' controversy of the specification of human capital, rather than the technology diffusion/catch-up factor, thereby distracting from the arguably major contribution of Nelson and Phelps (1966).

BS's results are suspect for a number of reasons. In particular, Temple (1999) has shown that their major result concerning the negative and statistically insignificant point estimate for human capital in first differences is due to the inclusion of unrepresentative observations. When outliers are deleted from the data, human capital becomes positive and statistically significant in a standard production function specification, supporting the Lucas approach. Temple's contribution concerning the importance of robustness tests of cross-country growth regressions is important and can potentially overturn many of the empirical results reported in the literature.[2] Second, BS found the technology diffusion variable to have the expected sign and/or be statistically significant for their complete data sample and their poorest third of countries, but not for the middle and richest third of countries. The latter finding seems to contradict the spirit of Nelson and Phelps (1966) as well as the many empirical macro- and micro-level studies that confirm an important role for R&D-related knowledge spillovers amongst developed economies (for example Coe and Helpman, 1995, Engelbrecht, 1997, Irwin and Klenow, 1994). Third, there are the well-known problems of reverse causation (simultaneity) and measurement error (data quality) in this type of study.

This short paper re-examines the BS results, arguing that their model does support the NP approach for developed economies once outliers are deleted. Moreover, if it is accepted that technology diffusion and catch-up, rather than 'human capital in levels', is the key feature of the NP approach, one has to conclude that the data support *both* major approaches to the modelling of human capital.

[2] There are, of course, many other reasons why economic growth may appear unrelated to increases in educational attainment (see Temple, 1999).

2. EMPIRICAL RESULTS

The empirical analysis is conducted in two parts. First, BS's results for their Nelson-Phelps style model (BS, 1994, table 5) are re-examined. The focus is on their total sample of countries, as well as on their 'rich' group of economies (the richest, but still very mixed, third of countries in their data sample), and their limited number of OECD economies. Second, by adding human capital stock data from Barro and Lee (2000) to the BS data set, it is possible to estimate their model for the group of OECD economies. Throughout, the importance of correcting for data outliers is emphasized.

Regression 1, table 1, is taken from BS (1994, model 1, table 5). This model for their complete data sample of developed and developing economies appears to favour the diffusion/catch-up component over the domestic innovation component (ibid.). Using trimmed least squares and deleting 10 outliers does not change BS's conclusions (regression 2, table 1).[3]

Regression 3, table 1, reports BS's estimates for the richest third of countries. It seems to indicate that, for these countries, the diffusion/catch-up component is relatively unimportant, whereas the innovation component is positive and statistically significant. Again, using trimmed least squares does not overturn their results (regression 4, table 1). However, one has to be careful not to put too much weight on this finding. BS's rich country sample is determined by initial (i.e. 1965) per capita income levels. It is not the same as the OECD group of economies. In fact, their data set excludes many OECD economies (i.e. Austria, Belgium, Czech Republic, Hungary, Iceland, Norway, Netherlands, Finland, Poland, Switzerland), but it includes countries like Nicaragua, Fiji, Argentina, Chile, Iraq, Venezuela, etc. The latter are not commonly regarded as belonging to the group of rich economies.

[3] All trimmed least squares regressions reported in this paper have been performed with the trimming proportion TRIM set at 0.005, 0.01, 0.025, 0.05, 0.1. Only the results for TRIM=0.01 are reported. All other results were very similar.

Temple (2000) has emphasized the importance of differences between the developed countries, proxied by OECD membership, and the 'rest'. In general, the former group of countries have very similar institutions, and the quality of their data is much higher. Regressions 5 and 6, table 1, are for the OECD member countries contained in the 78-country BS data set. In regression 5, neither the innovation component nor the technology diffusion/catch-up component is statistically significant. There are only 11 observations left once outliers are deleted. However, the trimmed least squares regression (regression 6) does give a first indication that BS's rich county results may not apply to the OECD group of economies. The innovation component remains statistically insignificant, whereas the diffusion component becomes statistically significant, which is the reverse of the BS results for rich economies.

The reason why BS exclude many OECD economies from their data sample is lack of human capital stock data. This has since been remedied. Combining the latest Barro and Lee (2000) schooling data with the other data used by BS, one can estimate their models for a sample of 25 OECD economies. The only OECD economies excluded are Luxembourg (due to lack of human capital stock data), and the former socialist countries Poland, Hungary, and the Czech Republic (due to their very different institutional frameworks during the period of analysis).

Regressions 1 and 2, table 2, indicate that even when the OECD data sample is used, H is either negative and statistically insignificant (using OLS) or negative and statistically significant (using trimmed least squares). However, the diffusion/catch-up component is positive and statistically significant in both regressions.[4]

The use of 'total years of schooling' in the NP framework can be criticised for being less appropriate than some schooling sub-categories. In particular, Aghion and Howitt (1998, p. 339) suggest focusing on secondary and higher education that better reflect the number of potential researchers/developers in an economy. Re-running regressions 1 and 2, table

2, with ‘average years of secondary schooling in the total population’ and ‘average years of higher schooling in the total population’ from Barro and Lee (2000) does not produce any qualitatively different results, nor does inclusion of a separate Y_{max}/Y variable.[5] However, it does result in a much larger parameter estimate for the diffusion/catch-up component, especially for higher schooling. Also, deleting influential observations greatly increases the parameter estimate (from 0.111 to the 0.306 reported in regression 3, table 2). The estimate for H, the innovation component, also becomes larger, but it remains negative and highly statistically significant.

Temple (2000, p. 19) has commented that studies for the OECD that relate growth to both human capital in initial levels and in changes have yet to appear. Here we explore his suggestion in the context of the BS model specification, which identifies the innovation component with the average level of human capital over the period analysed. DH is added to the specification used in regressions 1 to 3, table 2. Only the trimmed least squares estimates are reported (regression 4, table 2). The parameter estimate for human capital in first differences is positive, but not statistically significant (using OLS without deleting outliers, the estimate for DH was negative and statistically insignificant).

The negative and statistically significant estimate for the innovation component in regressions 1 to 4, table 2, might only seem counter-intuitive. There are a number of possible explanations. First, in terms of the NP approach, technological innovation, mainly concentrated in a handful of economies, is important for shifting the world technological frontier, but it seems too much to expect it to show up as a significant and positive factor in explaining differences in development levels in a cross-section study. The main factor in such a setting, even for OECD economies, is surely technological diffusion and catch-up. The results for the innovation term might be different if a panel data set were used. Second, even if panel data were used, it is possible that the human capital stock data are not precise enough as proxies for innovation (but they might proxy

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[4] These results do not change when Y_{max}/Y is included as a separate variable alongside H* Y_{max}/Y to control for the possibility that the estimates for the later might simply be driven by a neoclassical convergence effect. Like BS (1994, model 5, table 5), we find this variable to be statistically insignificant.

for other ‘learning’). In fact, there is evidence that when human capital (average years of schooling) is included alongside separate R&D capital stock variables, both types of variables are statistically significant and have the expected sign.[6]

The second of the above arguments is not explored here. However, following the first argument, a hybrid model is estimated which includes human capital in first differences as well as the technology diffusion/catch-up component of the NP approach, but not human capital in levels. The trimmed least squares estimates (regression 5, table 2) indicate that both human capital in first differences and the diffusion/catch-up component play important roles in the context of OECD economies. The largest estimate for the diffusion/catch-up component is obtained when human capital is proxied by ‘average years of higher schooling in the total population’ (regression 6, table 2). Also, in that case, the estimate for DH becomes much smaller.

It should be noted that when OLS is used to estimate the hybrid model, the estimates (not reported in table 2) for both human capital in first differences as well as technology diffusion/catch-up are much smaller and statistically insignificant. This again emphasizes the importance of robust estimation in growth regressions.

3. CONCLUDING COMMENTS

It is argued in this paper that the usual interpretation of the Nelson-Phelps approach to the modelling of human capital in growth regressions is biased due to the prominence of the ‘first differences versus level’ controversy. Emphasizing the technology diffusion/catch-up component over the domestic innovation component, it is shown that at least for OECD economies both our interpretation of the Nelson-Phelps approach as well as the Lucas approach are supported, when outliers are deleted from the data. The findings

[5] Only the trimmed least squares estimates for the regression using higher schooling as the human capital proxy are reported in table 2.
[6] See Engelbrecht (1997) and Frantzen (2000). To the best of my knowledge, these are the only empirical growth studies, so far, that include both domestic and foreign R&D capital variables as well as a human capital variable side-by-side.

support Temple's view that robust estimation methods should be used routinely in empirical growth research.

Of course, the relative importance of the NP approach vis-à-vis the Lucas approach still has to be determined. In common with many other cross-country growth studies, issues of simultaneity and data quality are not addressed. Moreover, the findings, obtained from only one cross-country data set, need to be confirmed with a wide variety of other data sets and model specifications. However, if they should stand up to further scrutiny, it would indicate that we have to refine our tests of the different approaches to modelling the relationship between human capital and growth, and/or that we have to focus more on the development of hybrid models.

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Table 1: OLS and robust cross-country growth regressions, 1965-1985 (using Benhabib and Spiegel's human capital stock data)[a]

Regression	1	2	3	4	5	6
Constant	0.163	0.235	-0.227	-0.152	0.232	0.007
	(0.114)	(0.096)	(0.282)	(0.127)	(0.122)	(0.045)
H	-0.014	-0.016	0.044	0.030	-0.015	0.001
	(0.014)	(0.011)	(0.022)	(0.010)	(0.010)	(0.005)
$H(Y_{max}/Y)$	0.0011	0.005	0.0003	0.003	0.003	0.0055
	(0.0002)	(0.0008)	(0.001)	(0.003)	(0.002)	(.0013)
DK	0.472	0.478	0.508	0.429	0.516	0.504
	(0.072)	(0.040)	(0.094)	(0.063)	(0.088)	(0.046)
DL	0.188	0.131	0.172	0.371	0.193	0.376
	(0.164)	(0.141)	(0.233)	(0.106)	(0.136)	(0.054)
R^2	0.71	0.71	0.57	0.56	0.92	0.91
N	78	68	26	16	19	11

[a] The dependent variable is DY, the log difference of end and initial period per capita incomes. Standard errors are in parentheses. Regressions 1, 3, 5 have been estimated by OLS, regressions 2, 4, 6 by trimmed least squares (with TRIM=0.01).

Regression 1 is taken from Benhabib and Spiegel [BS] (1994, model 1, table 5). It is for their full data sample. Regression 2 is for BS's full sample, excluding Botswana, Jordan, Mozambique, Rwanda, Sudan, Nicaragua, Uruguay, India, Israel and Italy.

Regression 3 is taken from BS (model 2, table 5). It is for their wealthiest third of countries. Regression 4 uses the same data, but excludes Nicaragua, Syria, Uruguay, Chile, Iraq, Italy, Israel, France, Luxembourg, New Zealand.

Regression 5 is for the sub-group of OECD countries included in BS's sample. Regression 6, also for the sub-group of OECD countries, excludes Mexico, Korea, Ireland, Italy, Luxembourg, Turkey, Australia, New Zealand.

Table 2: OLS and robust cross-country growth regressions for OECD economies, 1965-1985 (using Barro and Lee human capital stock data)[a]

Regression	1	2	3	4	5	6
Constant	0.217	0.173	0.137	0.142	0.037	-0.007
	(0.105)	(0.051)	(0.053)	(0.044)	(0.022)	(0.027)
H	-0.017	-0.016	-0.443	-0.012	-	-
	(0.009)	(0.005)	(0.095)	(0.004)		
$H(Y_{max}/Y)$	0.005	0.012	0.306	0.0094	0.0066	0.110
	(0.002)	(0.002)	(0.051)	(0.0011)	(0.0015)	(0.026)
DK	0.486	0.353	0.386	0.389	0.430	0.565
	(0.080)	(0.051)	(0.066)	(0.034)	(0.045)	(0.032)
DL	0.305	0.524	0.675	0.464	0.400	0.236
	(0.094)	(0.051)	(0.076)	(0.042)	(0.053)	(0.050)
DH				0.086	0.222	0.061
				(0.061)	(0.071)	(0.019)
R^2	0.91	0.89	0.89	0.90	0.89	0.90
N	25	16	16	14	16	16

[a] The dependent variable is DY, the log difference of end and initial period per capita incomes. Standard errors are in parentheses. Regression 1 has been estimated by OLS. All other regressions have been estimated by trimmed least squares (with TRIM=0.01). The observations are: (1) Canada, (2) Mexico, (3) USA, (4) Japan, (5) Korea, (6) Austria, (7) Belgium, (8) Denmark, (9) Finland, (10) France, (11) Germany, (12) Greece, (13) Iceland, (14) Ireland, (15) Italy, (16) Netherlands, (17) Norway, (18) Portugal, (19) Spain, (20) Sweden, (21) Switzerland, (22) Turkey, (23) UK, (24) Australia, (25) New Zealand.
Regression 1 uses 'average schooling in the total population over age 25' from Barro and Lee (2000) for human capital stocks. Regression 2 uses the same human capital stock data as regression 1 but excludes observations 2, 4, 5, 14, 15, 17, 21, 24, 25. Regression 3 uses 'average years of higher schooling in the total population over age 25' from Barro and Lee (2000) and excludes observations 1, 2, 4, 5, 6, 14, 15, 24 25. Regression 4 uses 'average schooling in the total population over age 25' from Barro and Lee (2000) and excludes observations 2, 4, 5, 9, 14, 15, 17, 19, 21, 24, 25. Regression 5 uses the same human capital stock data as regression 4 and excludes observations 2, 4, 5, 9, 15, 17, 24, 25. Regression 6 uses 'average years of higher schooling in the total population over age 25' from Barro and Lee (2000). The excluded observations are 2, 5, 13, 14, 15, 17, 21, 24, 25. Data other than human capital stock data are from Benhabib and Spiegel (1994).