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Human capital and economic growth: an empirical analysis

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1. Introduction

„Wissen ist heute die wichtigste Ressource in unserem rohstoffarmen Land. Wissen können wir aber nur durch Bildung erschließen… Ich verstehe sehr wohl, dass bei der heutigen Spezialisierung von Wirtschaft und Verwaltung keine Ausbildung alles vermitteln kann, was ein junger Mensch auf seinem ersten Arbeitsplatz braucht, und dass daher betriebliche Einweisung unvermeidlich bleiben wird… Schulbildung bereitet oft auf andere Fächer und Bildungswege, nicht unbedingt aber auf die Lebenspraxis vor… Es geht wieder darum, sich wieder auf das Wesentliche zu konzentrieren und allen ein breiteres Grundwissen zu vermitteln". [1]

This short extract of Roman Herzog's „Bildungsrede" from 1997 was a call to reconsider schooling policies. Main target of his speech was to remind the importance to improve economic growth, decrease the unemployment rate and adapt the schooling system (*„international, werteorientiert, praxisbezogen, vielseitig, Wettbewerbszulässig, dass mit der Ressource Zeit vernünftig umgeht"*).

Human Capital is a widespread notion implementing different kinds of investment in humans (for example investments in health or alimentation). For the purpose of this work and to accord with the literature, human capital is treated as a matter of education, schooling and experience at work. Following a definition by de la Fuente and Ciccone (2002) human capital can be distinguished between three components:[2]

- *Common abilities:* abilities enabling a person to absorb and use information and to apply this information to solve problems
- *Intrinsic abilities:* necessary to apply certain technologies and production processes
- *Technical and scientific abilities:* being proficient in organised knowledge and analytical methods, relevant for further developments.

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[1] Roman Herzog, former german President (1997).

[2] de la Fuente and Ciccone (2002).

Through similar classifications as above and growing public interest, the notion of education gained in importance and got an increasingly important role in applied economics.

Following the de la Fuente and Ciccone among other definitions, education therefore can easily be seen as a possibility to "*equip a man to perform certain jobs and functions, or enable a man to perform a given function more effectively*"[3].

Economic growth theory equated human capital for a long time with labour, and so it was thought to be easy to substitute, a workers skills or his education were not been taken into consideration for those theories.

Since the beginning of the 20th century, both micro- and macroeconomics increased their attention toward the influences of human capital and education. Microeconomics focused for example on how education influences wages. Jacob Mincer for example introduced the idea that education could model wages. Therefore, investing in human capital by training or education could create additional social and private returns. On the other side macroeconomics tried to show up a relation between human capital and economic growth and its arising returns. Augmented neoclassical growth theory as in Mankiw, Romer and Weil (1992) see an increase in human capital through education as an increase in labour productivity, leading to a higher equilibrium level of output. Endogenous growth theory as in Lucas (1988) understands education as a possibility to increase a country's innovative capacity. Growth therefore is promoted because of new technologies, new knowledge, processes and products. Finally, education is also seen as facilitating the diffusion of knowledge, necessary to understand and implements new technologies which leads again to economic growth.[4] This last approach follows the idea of Nelson and Phelps (1966) as well as Benhabib and Spiegel (1994) and lays the foundation of the following work.

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[3] Nelson and Phelps (1966).

[4] Hanushek and Wößmann (2007).

1.1. A basic model

During the mid 1960ies, Richard Nelson and Edmund Phelps renewed the common idea on how educational attainments could enter into economic growth.

The neo-classical growth theory proclaims that education affects economic growth primarily through its effects on the rate of human capital accumulation. Another feature of this theory is that human capital enters like an ordinary input in the production function.

By contrast to this common approach Nelson and Phelps thought it would be a misspecification of the productive process to simple include an index of education or human capital to the production function.[5] Therefore they described "*growth as being determined by the consequences of the stock of human capital (or the education level) for a country's ability to innovate or to adapt to more advanced technologies*".[6] *So, h*uman capital enters in first order differences or in levels in growth regression to their model.

Hence, education only has a positive payoff "*if the technology is always improving".*

As their education enables more educated persons to better understand new technologies it seems obvious that *"educated people make good innovators so that education speeds the process of technological diffusion"*[7] which in turn is often stated as a major component for a dynamic economy.

An example cited in Nelson and Phelps (1966) demonstrates the remarkable importance of being a good innovator, true for an agriculturist as well as for scientists or a company's manager. [8]

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[5] Benhabib and Spiegel (1994).

[6] Aghion, Frydman, Stiglitz and Woodford (2001).

[7] Nelson and Phelps (1966).

[8] Example in Nelson and Phelps (1966).

The Nelson and Phelps approach starts with the following basic production function:

$$Q(t) = F[K(t), A(t), L(t)] \quad (1)$$

defined by the following variables:

- capital (K),
- labour (L)
- time (t)
- and an index of technology in practice (A).

Additionally introduced to the model are the variables (T) and (h).
(T) stands for the theoretical level of technology which measures the stock of knowledge available for innovators and increases exogenously at a constant rate λ.
(h) describes the index of average educational attainment, the approximation for human capital for this model[9].

1.1.1. The first approach

In the first model, the time lag (w) between innovation (or the creation of new technologies) and its adoption is a decreasing function of (h).

$$A(t) = T(t - w(h)), w'(h) < 0 \quad (2)$$

Assuming constancy of (h) and putting equation (2) and the definition of (T) together it follows that (A) and (T) grow at the same rate λ and that *"the "level" or path of the technology in practice is an increasing function of h, since an increase of h shortens the lag between T (t) and A (t)"*.[10]
Under the same assumptions as above, it also follows that the faster (T) advances the greater is the return to education. A completely new feature of this model is that only if the growth rate λ of the theoretical technology level is positive, the marginal productivity of education is positive too and an increasing function of *λ.*

[9] T is defined by: $T(t) = T_0 e^{\lambda t}$, and $\lambda > 0$.

[10] Nelson - Phelps (1966)

Even though this first model was a completely new treatment of education at its time, Nelson and Phelps abandon this approach, estimating it not that realistic (in terms of not implemented time lags as well as a not considered impact of profitability of new technologies on the model).

1.1.2. The second approach

The second model seems more realistic and more interesting for the purpose of this work.

Equation (3) shows that through $\phi(h)$ education concentrates a human's capacity to innovate and to adopt existing technologies. Through this capacity, education accelerates diffusion of ideas in an economy. The technological development of a country depends therefore upon the gap of its technology level in practice and its theoretical technology level.

$$\frac{A(t)}{A(t)} = \phi(h)\left[\frac{T(t) - A(t)}{A(t)}\right] \tag{3}$$

True for $\phi'(h) > 0$ and $\phi(0) = 0$

The growth rate of the technology level in practice (A (t) / A (/t)) is an increasing function of educational attainment Φ (h) and proportional to the gap between theoretical level of technology and level of technology in practice: *T (t) – A (t) / A (t)*.

Like in the first approach, (T) advances at a constant exponential rate λ and (h) is constant. Therefore, we could say that if (h) is positive in the long run, the growth rate of the level of technology in practice settles down to the theoretical growth rate λ, independently of the index of educational attainments.

Another result of this second approach by Nelson and Phelps is the equilibrium gap, a decreasing function of educational attainment, given by:

$$\frac{T(t) - A^*(t)}{A^*(t)} = \frac{\lambda}{\phi(h)} \tag{4}$$

If λ equals zero, meaning an economy with a stagnant level of technology, the gap also tends to zero for every (h) greater than zero. Vice versa in a progressive economy with a λ greater than zero, it holds that a positive equilibrium gap exists for every (h) and λ.

$$\frac{\partial A^*(t)}{\partial h}\frac{h}{A^*(t)}=\left[\frac{h\phi'(h)}{\phi(h)}\right]\left[\frac{\lambda}{\phi(h)+\lambda}\right] \tag{5}$$

As can be seen from the elasticity equation from above, the more progressive an economy in terms of technological advances is, the greater the return to education. The authors sum up that "*society should build more human capital relative to tangible capital the more dynamic is the technology*."[11] Further suggestions of this paper are that different factors can influence education. A direct effect could be gained via educational policies. Research and development policies affect education on a more indirect way.

Empirical studies often come to the point that education does not have a positive or significant impact on economic growth rate (Mankiw, Romer and Weil (1992), Pritchett (1996), Bils and Klenow (2000)). Hence, the question comes up if differences in data quality could explain this lack of correlation.
Some recent works by Krueger and Lindahl (2001), de la Fuente and Doménech (2002) or Crespo-Cuaresma (2005) try to clarify the above-mentioned idea. The purpose of those papers is to accentuate the lack of significance on measurement problems. Their results show significant differences for the tested models in dependence of the datasets used.
"*This paper was originally motivated by the view that weak data is likely to be one of the main reasons for discouraging results obtained in the recent empirical literature on human capital and growth. Our results clearly support this hypothesis… and suggest that the contribution of investment in education to productivity growth is sizeable*." [12]

"*This note shows that the answer to the question whether convergence of educational attainment levels across OECD countries happened in the period 1960-1990 depends strongly on the dataset used for the analysis…The three datasets provide contradictory conclusions on both the existence and evolution of convergence of educational attainment in industrialized countries.*"[13]
Therefore, it seems interesting to run different datasets through a single model.

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[11] Nelson – Phelps (1966).

[12] de la Fuente - Doménech (2002)

[13] Crespo - Cuaresma (2005)

2. The Analysis

2.1. The Data

To clarify if data quality is relevant for the correlation between human capital, respectively education, and economic growth, we compare three datasets:

- Barro and Lee (1993),
- de la Fuente and Doménech (2002)
- Cohen and Soto (2001).

Both Barro-Lee and Fuente–Doménech data sets observe educational attainments for adult population over 25 years, Cohen-Soto focuses on population aged over 15 years.

Those three datasets all use average years of schooling as variable for education, which is our approximation for human capital. Even though it seems not to be the best choice, average schooling years seem to catch better than other variables the results of educational policies.

Due to problems with data availability and collection, we analyse the convergence of the variables for a shortened sample. The period concerned starts 1970 and lasts until 1990, using data in steps of ten years (1970, 1980 and 1990) for a range of 21 OECD countries (Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Japan, Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Switzerland, Unites Kingdom, United States).[14]

Some descriptive statistics follow in the tables below.

Table 1: Statistical evidence for average years of schooling in 21 OECD countries, Barro-Lee dataset

Barro-Lee	*1960*	*1970*	*1980*	*1990*
Mean	6,70	7,25	8,22	8,87
Standard deviation	1,98	1,85	2,06	1,83
Median	6,87	7,47	8,28	9,06
Maximum	9,56	10,09	11,91	12,00
Minimum	1,94	2,44	3,27	4,33

[14] For details, see Appendix.

Table 2: Statistical evidence for average years of schooling in 21 OECD countries, Cohen-Soto dataset

Cohen-Soto	*1960*	*1970*	*1980*	*1990*
Mean	8,07	9,12	10,23	10,93
Standard deviation	1,86	1,94	1,90	1,83
Median	8,68	9,87	10,72	11,02
Maximum	10,96	11,81	12,65	13,21
Minimum	3,15	4,11	5,57	5,91

Table 3: Statistical evidence for average years of schooling in 21 OECD countries, Fuente-Doménech dataset

Fuente-Doménech	*1960*	*1970*	*1980*	*1990*
Mean	8,36	9,03	9,87	10,64
Standard deviation	1,96	2,02	2,03	1,90
Median	8,57	9,10	9,94	10,97
Maximum	10,78	11,32	12,41	12,95
Minimum	4,37	4,87	5,73	6,41

The tables above show the meaningful differences for educational attainment data for all the datasets. Figure 1a and 1b support these observations.

The difference of the means of average schooling years over time for 21 countries (see Figure 1a) between the Barro-Lee dataset and the more recent Cohen-Soto or Fuente-Doménech ones suggests that there were significant divergences in the way data was collected. Although average schooling years increase continuously over time for each of the available datasets, Barro - Lee data curve is always below to the Fuente - Doménech data curve (both focussing on adult population over 25 years) and also below the Cohen – Soto curve.

The latter arguments are further supported by the irregularities in standard deviation from the Barro - Lee dataset over the years represented in Figure 1b.[15]

Figure 1a: Mean years of schooling, 1960 - 1990

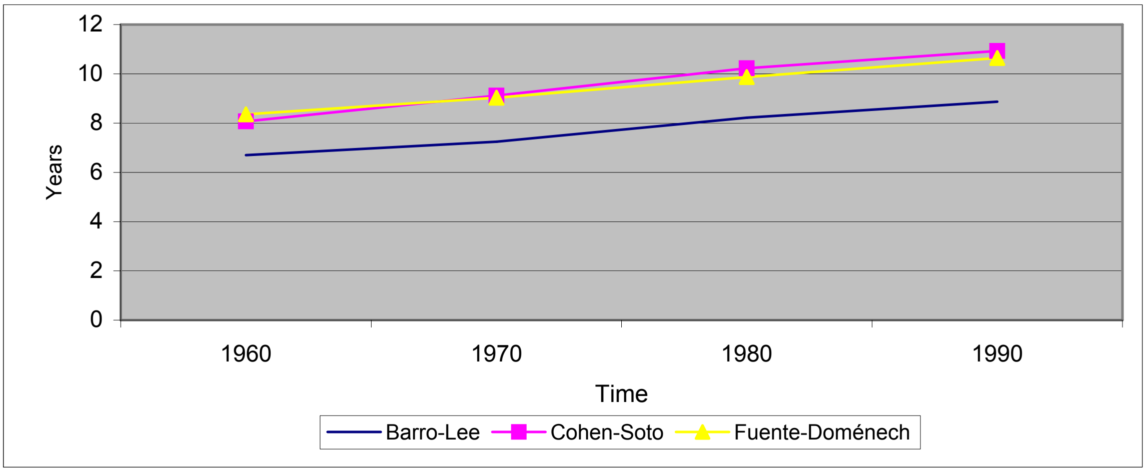
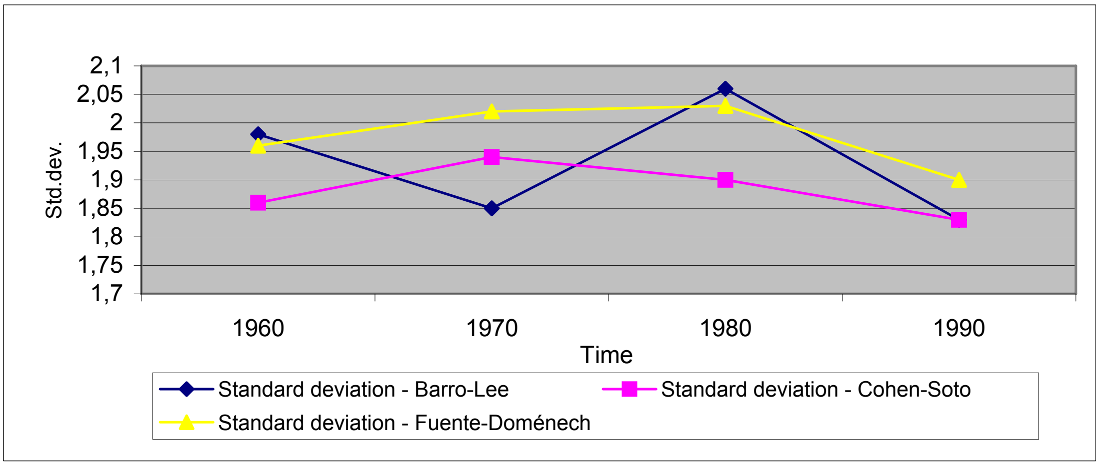


Figure 1b: Development of the standard deviation, 1960 - 1990



[15] Further observations and detailed results concerning the matter of data differences in: de la Fuente - Doménech (2002) or Crespo - Cuaresma (2005).

2.2. The Model

Since the mid 1960ies, the relation between education and economic growth has been subject of many improvements. As already mentioned, empirical attainments often yielded disappointing results.

Following the intention of this work, "*The role of human capital in economic development. Evidence from aggregate cross-country data*" by Jess Benhabib and Mark Spiegel (1994) seems to be the perfect basic approach to implement the datasets. Benhabib and Spiegel treat in a first approach human capital as an ordinary factor of production in a standard Cobb-Douglas function (equation 6) and in a second model, human capital levels can influence GDP growth through two mechanisms (equation 7).

$$\begin{aligned}(\log Y_T - Y_0) = (\log A_T - \log A_0) + \alpha(\log K_T - \log K_0) + \\ \beta(\log L_T - \log L_0) + \gamma(\log H_T - \log H_0) + (\log \varepsilon_T - \log \varepsilon_0)\end{aligned} \tag{6}$$

Benhabib and Spiegel (1994) assume in this first try a Cobb – Douglas technology, take log differences and express long term growth as in equation (6). This first analysis results in a non-significant (even negative) correlation for education and economic growth although they introduced dummies for Latin America, Africa as well as for oil exporting countries. The authors even took account of the size of the middle class and political instability.[16]

Testing the robustness of their results with other datasets (Kyriacou (1991), Summer – Heston) or a specification of another model (Mankiw, Romer and Weil) led to the same, non-significant and disappointing, results.[17]

Nevertheless, Benhabib and Spiegel introduce their second model, following the Nelson and Phelps (1966) approach described in the part above as well as Romer (1990). Human capital therefore influences directly productivity "*by determining the capacity of nations to innovate new technologies suited to domestic production*" and human capital levels are allowed "*to affect the speed of technological catch-up and diffusion*". [18]

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[16] Benhabib - Spiegel (1994).

[17] See Benhabib - Spiegel (1994) for more detailed results.

[18] Benhabib - Spiegel (1994).

The adopted model acts from the assumption that a country takes a leadership position for its advanced technology level and other countries try to catch up to this level. This idea, to catch up another country's technology level, stands for the ability of a country to adopt or implement foreign technology instead of being reduced on its own, national, technology level and so the adoption and implementation of new technologies as well as the speed needed to catch-up the leader country are functions of human capital stocks. And to adopt those specifications equation 6 is replaced by the following:

$$\left(\log Y_T - Y_0\right) = \left(\log A_T - \log A_0\right) + \alpha\left(\log K_T - \log K_0\right) + \beta\left(\log L_T - \log L_0\right) + \gamma\left(1/T\sum_{0}^{T} \log H_T\right) + \left(\log \varepsilon_T - \log \varepsilon_0\right) \tag{7}$$

For equation (7) Benhabib and Spiegel use the average level of human capital over the period instead of log differences of average schooling years.

To be able to better compare the variables, log differences are used. Furthermore, the ordinary least squares method with Whites heteroskedasticity is applied.

GDP data was generated through the product of population and GDP per capita data. As a substitute for physical capital data we use the mean of investment share of GDP from 1970 to 1990 for each country. Technology level is the constant in our model and labour force variable is approximated through population data aged from 15 to 64 years.[19]

[19] For details, see Appendix.

3. The Results

3.1. Model 1: HC as factor in the production function

This first model applies equation 6 where human capital is a simple factor in the production function. While Benhabib and Spiegel gained very disappointing results with this approach (human capital showed no significance at all), the regressions below show surprising outputs.

Starting with Barro – Lee data (Table 4) the results permit to observe a positive and significant coefficient on the log differences for workforce as well as for log changes in years of education, both entering at a 1% confidence level.

Whereas the coefficients for technology level and log changes in the capital stock of GDP (physical capital for the following parts) fail to enter significantly.

A similar trend is detected for Cohen – Soto (Table 5) and de la Fuente – Doménech (Table 6) data.

In both cases, the coefficients for C and physical capital also fail to enter significantly, but the coefficients on log differences of workforce and years of education both have positive signs and enter significantly to the model.

Workforce is significant at a 1% confidence level, years of education at a 5% confidence level for Cohen – Soto and a 10% level for de la Fuente - Doménech data.

R^2 for Barro – Lee and Cohen – Soto has similar values (approximately 0,43) whereas de la Fuente – Doménech is about 0,35. The coefficient estimates for workforce are also quite similar between the different datasets (ranging between 0,69 and 0,79). The coefficient estimates for human capital differs extremely between the different observations. It is about 0.48 for Barro – Lee, 0,77 for de la Fuente – Doménech and about 0,92 for Cohen – Soto data set.

Table 4: Barro – Lee, Model 1

Variable	Coefficient	Std. Error	Prob.
Technology level	0.168819	0.185410	0.3753
Log-changes in the capital stock of GDP	0.006883	0.007164	0.3502
Log-changes in workforce	0.695580	0.233393	0.0084
Log-changes in years of education versus average years of education	0.483536	0.162588	0.0085
R-squared	0.428386		

Table 5: Cohen – Soto, Model 1

Variable	Coefficient	Std. Error	Prob.
Technology level	0.031201	0.202080	0.8791
Log-changes in the capital stock of GDP	0.008873	0.008312	0.3006
Log-changes in workforce	0.799733	0.206796	0.0012
Log-changes in years of education versus average years of education	0.923348	0.356560	0.0191
R-squared	0.431183		

Table 6: Fuente – Doménech, Model 1

Variable	Coefficient	Std. Error	Prob.
Technology level	0.116769	0.179380	0.5238
Log-changes in the capital stock of GDP	0.007868	0.007623	0.3165
Log-changes in workforce	0.685089	0.231743	0.0088
Log-changes in years of education versus average years of education	0.774525	0.431506	0.0905
R-squared	0.351635		

3.2. Model 2: using the average of schooling years

In this second model, the results obtained differ from those above. Instead of treating human capital as a simple factor in the production function, we take equation 7 where human capital enters as an average of schooling years. The observations lead to very different results. Barro - Lee data (Table 7) yields only a single positive and significant coefficient on log differences.

Workforce enters at a 5 % confidence level while the other variables are positive but fail to enter significantly.

Cohen – Soto estimates (Table 8) lead to divergent and more satisfying results. The coefficient for technology level is significant (at a 1% confidence level) but with a negative effect on economic growth. Positive and significant coefficients on log differences are examined for workforce (1% confidence level) as well as for physical capital and years of education (5 % confidence level).

The output for de la Fuente – Doménech data (Table 9) is quite similar to the findings of Cohen – Soto estimates.

The coefficient for technology level enters at a 5% confidence level and a negative effect on economic growth, while the coefficient on log differences of workforce enter significant at a 1% confidence level. Log differences for physical capital enter positive and significantly at a 5 % confidence level whereas log differences of years of education, surprisingly, fail to enter.

R^2 for Barro – Lee (0,21) is in this specification perceivable inferior than for Cohen – Soto and de la Fuente – Doménech, ranging between 0,41 and 0, 44.

Standard errors fit the variables well for each of the data sets.

Additionally it is remarkable that the values of the coefficients differ across the datasets. Barro – Lee coefficient for workforce is 0,672193 whereas the coefficient of Cohen – Soto estimation is 9,252598 and de la Fuente – Doménech is about 8,519316. The physical capital coefficient estimate is about 0,08 for Cohen – Soto and de la Fuente – Doménech, 0,010 for Barro – Lee.

Table 7: Barro – Lee, Model 2 - Equation 6

Variable	Coefficient	Std. Error.	Prob
Technology level	0.185141	0.420874	0.439897
Log-changes in the capital stock of GDP	0.010124	0.007717	0.2070
Log-changes in workforce	0.672193	0.265274	0.0214
Log-changes in years of education versus average years of education	0.006611	0.175812	0.9704
R-squared	0.217639		

Table 8: Cohen – Soto, Model 2 – Equation 6

Variable	Coefficient	Std. Error	Prob.
Technology level	-10.50235	2.988103	0.0027
Log-changes in the capital stock of GDP	0.081811	0.040278	0.0582
Log-changes in workforce	9.252598	2.778442	0.0040
Log-changes in years of education versus average years of education	2.866338	1.329535	0.0457
R-squared	0.447344		

Table 9: Fuente – Doménech, Model 2 – Equation 6

Variable	Coefficient	Std. Error	Prob.
Technology level	-9.332412	3.457355	0.0152
Log-changes in the capital stock of GDP	0.084646	0.036604	0.0335
Log-changes in workforce	8.519316	3.195755	0.0163
Log-changes in years of education versus average years of education	2.408993	1.586724	0.1473
R-squared	0.412119		

3.3. Model 3: adding initial income

Due to Benhabib and Spiegel's disappointing results with model 2, they decided to introduce additionally initial income to the estimation of equation 7.

This introduction is somehow obvious, regarding the numerous theories underlying the correlation between education and income as well as initial income (e.g. Mincer: schooling affects individual earnings, private and social returns[20], Solow).

As Mankiw, Romer and Weil augment the textbook Solow model, they also introduce human capital accumulation into their estimates. In the course of their work, the authors come to the results that in three samples (including initial income, investment, population growth (working-age population) and school enrolment) "*the coefficient on the initial level of income is now significantly negative; that is, there is strong evidence of convergence. … Second, the empirical results including human capital imply a faster rate of convergence than the empirical results without human capital".*[21]

Benhabib and Spiegel follow this theory as initial income enters significantly with the predicted negative sign into the estimations and human capital enters significantly and with a positive sign. Initial income is supposed to accentuate the weight of a country's technological catch-up effect and "*that countries with a higher education tend to close the technology gap faster than others. … The result suggest that the role of human capital is indeed one of facilitating adoption of technology.*"[22]

Following the idea of convergence, the authors interpret the negative coefficient estimate of the initial income levels as a sign of catching up the adoption of technology from abroad instead of diminishing returns.

As our findings in the above part led to quite divergent results, it seemed interesting to adopt the equation and let run the datasets through this modification.

Contrarily to the observations above, similar trends are detected for all of the three datasets. The coefficients for technology level log differences in workforce enter positively and significant at a 1% level for, Barro – Lee (Table 10), Cohen – Soto (Table 11) and de la Fuente – Doménech (Table 12).

[20] Hanushek & Wößmann (2007).
[21] Mankiw, Romer & Weil (1992).
[22] Benhabib & Spiegel (1994).

As in Benhabib and Spiegel, the coefficients for log differences in initial income also enter significant at a 1% level and with a negative effect on economic growth. Unfortunately, log differences in years of education and physical capital fail to enter significantly to the model.
In addition, the values of the coefficient estimates are in a quite comparable range. R^2 is very similar for each of the datasets, ranging between 0,589 (Cohen - Soto / Fuente – Doménech) and 0,596 (Barro – Lee). Standard errors fit the variables very well, except log differences in years of education in the Cohen – Soto specification.
The insignificance of log differences in years of education for each of the three datasets is quite surprising as at least one of the specifications showed significance for model 1 and 2 above. A correlation (as mentioned at the beginning of model 3 analysis) between initial income and the education estimate could be an explanation for this result.

Table 10: Barro – Lee, Model 3

Variable	Coefficient	Std. Error	Prob.
Technology level	5.386413	1.412202	0.0015
Log-changes in the capital stock of GDP	0.009469	0.005652	0.1133
Log-changes in workforce	0.581629	0.181404	0.0055
Log-changes in years of education versus average years of education	0.100649	0.062762	0.1283
Log of initial income, GDP 1970 (Y0)	-0.319149	0.080147	0.0011
R-squared	0.596789		

Table 11: Cohen – Soto, Model 3

Variable	Coefficient	Std. Error	Prob.
Technology level	6.735521	2.152724	0.0065
Log-changes in the capital stock of GDP	0.007293	0.004825	0.1502
Log-changes in workforce	0.623304	0.167663	0.0019
Log-changes in years of education versus average years of education	0.158291	0.162007	0.3431
Log of initial income, GDP 1970 (Y0)	-0.405381	0.144489	0.0127
R-squared	0.589574		

Table 12: Fuente – Doménech, Model 3

Variable	Coefficient	Std. Error	Prob.
Technology level	6.825486	1.900814	0.0024
Log-changes in the capital stock of GDP	0.007351	0.005413	0.1933
Log-changes in workforce	0.572958	0.175952	0.0050
Log-changes in years of education versus average years of education	0.155638	0.121156	0.2172
Log of initial income, GDP 1970 (Y0)	-0.409680	0.123707	0.0044
R-squared	0.589638		

4. Conclusion

The estimations gained in the part above show the importance of good data quality. On the one hand, we got very different results for the diverse datasets but on the other hand, similar trends had been detected. The first model led to identical results and interpretation of data, even though R^2 should not be disregarded in any case. Further similarities were observed for the coefficient of labour force and initial income. The remaining coefficients showed resemblances for the more recent Cohen – Soto and de la Fuente – Doménech datasets, whereas the Barro – Lee data generally differs and leads to contrary interpretations. Introducing initial income to the second specification led surprisingly to similar results for all datasets. Unfortunately, log differences in years of education were not significant, model 1 gained best results for these coefficients.

However, this work proves that data sources and quality should not be ignored in any case.

The quote at the beginning of this work underlines the relevance and diversity that schooling and education take in our thoughts. In most countries, education is said to be a prerequisite for development and so more than ever a subject of interest. Comparing three datasets in the part above, led on the one hand to striking differences and on the other hand to similar trends for the interpretation of educational data and its influence on economic growth.

Nevertheless, a few questions come up. How significant is the use of average schooling years to provide a relation between education and economic growth? Following this idea, a year of schooling in a developing country such as Morocco, Indonesia or Peru is supposed to create the same amount of output and knowledge as in a developed country (for example Japan, France or Sweden). Wouldn't schooling quality be as important as quantity? Even differences in quality between developed countries are noteworthy. German schooling policies for example are a matter of the federal state decisions. Therefore, it comes to differences on the education standards within a single country. The same is true for nearly each country such as for example France with its differentiation on higher education (University is thought to be less worth than a “Classe Préparatoire” or a “Grande École”) or Austria with differing schooling systems (“Real- or Hauptschule”, “Gymnasium”).

Would it make sense to include to the regression measures as student per teacher ratios, investments in education or results of comparative tests as PISA, college admission test or literacy levels (even for adults) for a more significant correlation to economic growth?

Another point to question is, if education should only be modelled as a product of schooling. Which role plays the family or on the job training and how could it be represented? Furthermore, is it really guaranteed that excellent students get innovative and productive workers?

Observing the recent schooling and education debates across Europe, the necessity for changes appears quite clear. Maybe the schooling system itself should be reconsidered. What kind of information should be conveyed? What do individuals really have to achieve? Is it really possible to handle and transmit the fast growing amount of knowledge and information? Education, educational systems and knowledge should always be subject of improvements as emphasises the quote of Derek Bok, former president of Harvard University: “If you think education is expensive, try ignorance”.[23]

[23] Bildung fördern. Europäisierung, Finanzierung und Gestaltung der Hochschulreform (Broschiert), K. Holz, S. Keppler, T. Mundi, page112

5. References

- Aghion, P., Frydman, R., Stiglitz, J., Woodford, M. (2001), *Edmund S. Phelps and Modern Macroeconomics.*
- *Ameco Database:* http://ec.europa.eu/economy_finance/indicators/annual_macro_economic_database/ameco_en.htm
- Barro, R. & Lee, J.W., 1993, *International comparisons of educational attainment*, Journal of Monetary Economics, 32, No. 3, 363-394.
- Barro, R. & Lee, J.W., 2001, *International data on educational attainment: Updates and implications*, Oxford Economic Papers 53, No. 3, 541-563.
- Benahbib, J. & Spiegel, M. (1994), The role of human capital in economic development. Evidence from aggregate cross-country data, Journal of Monetary Economics 34, 143-173.
- Crespo – Cuaresma, J. (2005), Convergence of educational attainment levels in the OECD: More data, more problems? , Economics of Education Review 25, 173-178.
- De la Fuente, A. & Domenéch, R. (2002), *Human capital in growth regressions: how much difference does data quality make? An update and further results*, Journal of the European Economic Association, 4(1), 1-36. March, 2006, http://iei.uv.es/~rdomenec/.
- De la Fuente, A. & Ciccone, A. (2002), *Das Humankapital in der wissensbasierten globalen Wirtschaft – Abschlussbericht,* http://ec.europa.eu/employment_social/news/2002/jul/report_final_de.pdf.
- Hanushek, E. & Wößmann, L. (2007), *The role of education Quality in economic growth,* World Bank Policy Research Paper 4122.

- Heston, A. & Summers, R. & Aten, B., Penn World Table Version 6.2, Center for International Comparisons of Production, Income and Prices at the University of Pennsylvania, September 2006.

- Holz, K., Keppler, S.& Mundi, Th. (2005), *Bildung fördern. Europäisierung, Finanzierung und Gestaltung der Hochschulreform (Broschiert)*, LIT-Verlag

- Krueger, A. & Lindahl, M. (2001), *Education for Growth: Why and for Whom?* Journal of Economic Literature, Volume 39, December 2001, pp. 1101-1136.

- Lucas, R. (1988), *On the mechanis of economic development*, Journal of Monetary Economics 22, 3-42.

- Mankiw, G., Romer, D. & Weil, D. (1992), *A contribution to the empirics of economic growth*, Quarterly Journal of Economics 107, No. 2, 407-437.

$

- Nelson, R. & Phelps E. (1966), *Investment in humans, technological diffusion and economic growth*, American Economic Review 56, 69-75.

- Romer, P. (1990), *Endogenous technological change*, Journal of Political Economy 98, 71-102

6. Appendix

6.1. Abstract

Human capital is a widespread notion within sciences and had therefore changing definitions and meanings during the last decades. Different theories (based on the neoclassical and endogenous growth theory or the Nelson and Phelps approach) treated the correlation between education and economic growth and came often to the same disappointing result: education was slightly or not at all significant or entered with the wrong sign into the estimations.
As similar or identical datasets (or data sources) were used, the question came up if the estimation results could be explained by differences in data quality.
Therefore, we decided to test three datasets (Barro and Lee (1993), de la Fuente and Doménech (2002), Cohen and Soto (2001)) with the 1994 Benhabib and Spiegel model based on the Nelson and Phleps approach.
We gained surprising results and very interesting questions came up.

6.2. Zusammenfassung

Humankapital ist ein weitverbreiteter Ausdruck dessen Bedeutung und Definition sich in den letzten Jahrzehnten stetig gewandelt hat und somit immer wieder in den Fokus der unterschiedlichsten Wissenschaften gerückt ist.
Zahlreiche Theorien (basierend auf neoklassischen Theorien, der „endogenous growth“ Theorie oder dem Nelson und Phelps Ansatz) und Erklärungen über Zusammenhänge zwischen Ausbildung und Wirtschaftswachstum entstanden im Laufe der Jahre. Schlussfolgerung war oft dass es lediglich einen schwachen, einen insignifikanten oder negativen Zusammenhang gäbe.
Einige dieser Studien sind mit identen Datensammlungen oder Sammlungen aus ähnlichen Quellen berechnet worden. Somit ergibt sich die Fragestellung ob womöglich die Qualität der verwendeten Daten nicht auch ausschlaggebend für diese Resultate ist.
Um diese Aussage zu untermauern testeten wir drei Datensammlungen (Barro and Lee (1993), de la Fuente and Doménech (2002), Cohen and Soto (2001)) mit dem Modell von Benhabib und Spiegel (1994) welches auf dem Nelson und Phelps Ansatz beruht. Es ergaben sich überraschende Resultate und weitere interessante Fragestellungen.

6.3. Variables

- A: index of technology in practice
- B.-L.: Barro - Lee
- C.-S.: Cohen – Soto
- F.-D.: de la Fuente – Doménech
- GDP: Gross Domestic Product
- H: index of average educational attainments
- H: human capital
- HC: Human Capital
- K: capital
- L: labour force
- T: theoretical level of technology
- Y: output (GDP)
- w: time lag

6.4. Data

Table 13: Cross-country data: 1970 - 1990 - Average years of schooling. Cohen-Soto, Fuente-Doménech and Barro-Lee data sets.

	C.-S.			*F.-D.*			*B.-L.*		
	1970	*1980*	*1990*	*1970*	*1980*	*1990*	*1970*	*1980*	*1990*
Australia	11,04	12,20	12,76	11,06	12,41	12,88	10,09	10,02	10,12
Austria	9,28	10,31	10,94	9,34	10,28	11,31	7,01	8,42	8,22
Belgium	8,29	9,24	10,03	8,49	9,36	10,08	8,40	7,85	8,43
Canada	10,37	11,59	12,36	11,12	12,13	12,74	8,80	10,23	10,50
Denmark	10,08	11,03	11,54	11,10	11,54	11,73	8,78	9,16	10,13
Finland	7,96	9,49	10,73	8,74	9,94	10,97	6,50	8,33	9,48
France	8,02	9,34	10,36	9,04	9,86	10,45	5,86	6,77	7,56
Germany	11,14	12,65	13,21	10,97	12,01	12,95	8,27	8,41	9,06
Greece	6,74	7,72	8,71	6,18	7,09	7,91	5,19	6,56	7,66
Ireland	8,01	8,94	9,53	7,84	8,49	9,41	6,52	7,60	8,50
Italy	6,78	7,96	9,10	6,19	6,98	8,04	5,22	5,32	6,16
Japan	10,37	11,20	11,93	9,34	10,42	11,24	6,88	8,23	9,22
Netherlands	9,35	10,28	10,72	8,85	9,88	10,95	7,58	7,99	8,61
New Zealand	9,87	10,72	11,02	10,98	11,60	12,11	9,36	11,43	11,18
Norway	10,30	11,56	12,32	10,07	10,57	11,11	7,36	8,28	10,85
Portual	4,11	5,57	5,91	4,87	5,73	6,41	2,44	3,27	4,33
Spain	6,52	7,45	8,44	5,19	5,87	7,10	4,69	5,15	6,09
Sweden	9,97	11,26	12,04	8,57	9,60	10,62	7,47	9,47	9,57
Switzerland	11,81	12,48	12,96	11,15	11,63	12,23	8,28	10,07	9,92
U.K.	10,32	11,57	12,28	9,10	9,77	10,52	7,66	8,17	8,74
United States	11,27	12,19	12,62	11,32	12,15	12,67	9,79	11,91	12,00

Table 14: Workforce (in thousands) Population aged 15 – 64 years, from 1970 - 1990 for 21 OECD countries

Country	*1970*	*1980*	*1990*
Australia	7.946,8	9.571,0	11.417,0
Austria	4.596,8	4.845,1	5.185,7
Belgium	6.084,6	6.471,0	6.673,8
Canada	13.148,0	16.636,0	18.845,0
Denmark	3.175,8	3.316,8	3.462,6
Finland	3.050,8	3.236,4	3.355,9
France	32.438,9	35.196,1	38.313,5
Germany	38.602,0	40.828,0	43.947,0
Greece	5.653,6	6.175,6	6.795,5
Ireland	1.704,5	2.009,1	2.161,4
Italy	34.733,5	36.444,2	38.881,5
Japan	72.119,0	78.835,0	85.904,0
Netherlands	8.155,7	9.362,0	10.305,3
New Zealand	1.681,0	1.985,0	2.209,0
Norway	2.428,0	2.577,0	2.746,2
Portugal	5.368,6	6.142,1	6.606,9
Spain	21.136,8	23.625,4	25.848,1
Sweden	5.266,9	5.328,4	5.501,9
tzerland	4.010,1	4.197,0	4.593,0
U.K.	34.976,0	36.079,0	37.358,0
United States	127.007,0	150.227,0	164.229,0

Source Ameco Database:
http://ec.europa.eu/economy_finance/indicators/annual_macro_economic_datab se/ameco_en.htm

Table 15: Investment share of GDP from 1970 – 1990 for 21 OECD countries

	1970	1980	1990	Mean
Australia	26,4	24,10	21,67	24,06
Austria	26,17	26,22	24,23	25,54
Belgium	25,25	24,38	23,9	24,51
Canada	19,86	22,6	24,2	22,22
Denmark	25,63	19,23	20,37	21,74
Finland	36,19	31,43	31,13	32,92
France	25,63	23,22	24,48	24,44
Germany	30,81	25,72	24,49	27,01
Greece	33,58	23,8	19,68	25,69
Ireland	22,79	22,82	21,92	22,51
Italy	28,67	24,81	22,86	25,45
Japan	35,9	31,14	34,41	33,82
Netherlands	30,53	23,72	22,94	25,73
New Zealand	19,43	16,43	19,5	18,45
Norway	34,47	29,43	22,52	28,81
Portugal	23,33	21,52	21,24	22,03
Spain	25,15	20,82	25,14	23,70
Sweden	26,36	21,75	24,10	24,07
Switzerland	30,81	28,27	31,43	30,17
UK	18,79	14,67	17,79	17,08
US	16,95	18,13	18,23	17,77

Source: Heston, A. & Summers, R. & Aten, B., Penn World Table Version 6.2, Center for International Comparisons of Production, Income and Prices at the University of Pennsylvania, September 2006.

Table 16: Real GDP (in millions) from 1970 – 1990 for 21 OECD countries

Total GDP	1970	1980	1990
Australia	186.761,317	255.528,8842	344.635,2343
Austria	94.755,0573	134.600,0709	171.742,4761
Belgium	120.391,1907	168.220,029	205.775,663
Canada	307.709,9567	458.175,6859	603.095,9217
Denmark	81.167,46042	97.434,80511	114.111,9621
Finland	54.369,36218	75.329,56521	99.146,98218
France	678.448,5997	937.532,1096	1.208.219,91
Germany	1.058.864,787	1.374.233,109	1.690.223,459
Greece	72.452,47347	113.505,0708	121.963,289
Ireland	22.898,32295	36.102,02312	47.315,77071
Italy	623.930,3343	887.444,9295	1.107.827,717
Japan	1.181.609,087	1.812.739,497	2.673.372,808
Netherlands	196.045,5117	256.507,8574	313.582,0271
New Zealand	40.476,31666	48.485,62766	58.566,19055
Norway	51.265,92001	79.756,08258	101.759,5098
Portugal	60.657,45597	97.240,80285	135.986,0683
Spain	31.5061,3309	452.872,1234	605.121,8079
Sweden	126.157,7362	151.015,3677	185.834,0243
Switzerland	130.421,8204	151.936,955	187.578,2763
UK	702.888,1181	859.062,4272	1.127.549,886
US	3.662.234,372	5.006.471,939	6.944.055,117

Source Heston, A. & Summers, R. & Aten, B., Penn World Table Version 6.2, Center for International Comparisons of Production, Income and Prices at the University of Pennsylvania, September 2006.

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