Human Capital and Growth in a Panel of OECD Countries

Zvi Eckstein[*], Assaf Sarid[†‡], and Yuli (Yael) Tamir[§]

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Abstract

Recent research has shown that an increase of one standard deviation in the aggregate level of human capital – as measured by a quality-based index based on standardized international tests-will lead to an increase of 2% in the growth rate of GDP per capita. This result, based on a cross-section of countries, had a significant impact on educational policies recommended by the OECD and the World Bank. We use a panel of OECD countries in order to analyze the robustness of this result using stronger measures of human capital that better identify the impact of human capital on the level and/or growth rate of GDP per capita. The main finding is that human capital has a positive and significant level effect but a zero effect on the growth of GDP per capita, and therefore the long-run predictions for the effect of an increase in human capital remain positive but are significantly more modest.

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[*]The Interdisciplinary Center (IDC), Israel
[†]The University of Haifa, Israel
[‡]Corresponding Author
[§]Shenkar College, Israel

The impact of human capital on economic growth has been studied extensively in the economic literature, with emphasis on the measurement of human capital at the individual (micro) and aggregate (macro) levels.[1] In most empirical studies, years of schooling on the individual level and average years of schooling on the aggregate macroeconomic level are the standard measures of human capital. Recently, Hanushek and Woessmann (2012, 2015, henceforth: HW) convincingly showed that using a quality-based measure for aggregate human capital based on international standardized tests produces a closer empirical fit for the impact of human capital on the aggregate per-capita GDP growth rate than average years of schooling.[2] HW constructed a measure of aggregate human capital based on the average achievements of students aged 10, 14 and 15 on international standardized tests, such as PISA and TIMSS.[3] Using standard cross-section regressions to explain the per-capita growth rates of 52 countries from 1960 to 2000 with the average HW measure of human capital as the main dependent variable, they showed that their measure produces a better fit than average years of schooling in explaining the cross-section variation in per-capita GDP growth and that a rise of one standard deviation in the quality-based measure of aggregate human capital according to these tests leads to an increase of 2% in the growth rate of GDP per capita. This latter result had a significant impact on educational policies recommended by the OECD and the World Bank.[4]

A simple macroeconomic model shows that human capital can have an impact on either the level of GDP per capita or its rate of growth or on both.[5] Thus, an increase in the level of human capital can generate an increase in the growth rate of GDP per capita in either the short run or the long run or both.

While theoretical arguments have been made for both the level and growth effects of human capital, the question is still open from an empirical standpoint. Simple specifications of human capital in the production function can have either level or growth effects or both. HW's empirical specification assumes that human capital has a direct impact only on the growth rate – they did not consider the alternative specification according to which human capital affects only the level of GDP per capita. Other empirical studies, however, have presented conflicting results. Mankiw et al. (1992), for example, provided empirical evidence for a level effect, while Benhabib and Spiegel (1994) found empirical evidence for a growth effect. (Both studies used quantity-based measures of human capital.) Recently, Sunde and Vischer (2015) provided empirical evidence for a cross-section of countries that both effects exist.

We endeavor to contribute to this strand of the literature by estimating a simple growth model using panel data, which makes it possible to estimate the two effects separately. We argue that panel data is better able to identify the growth and level effects for two reasons: First, by using panel data we can control for unobserved time-invariant heterogeneity, which, if correlated with either one of the effects, generates endogeneity and thus biases the results in a cross-section of countries. Second, by using panel data we can track the dynamics of both human capital and GDP per capita, which can be very different depending on whether human capital has a growth effect or a level effect.

We use a panel of 13 advanced economies to jointly estimate the potential level and growth impacts of human capital on growth of GDP per capita. The panel includes the most advanced economies in the OECD, and therefore, if human capital indeed has a growth effect due to a higher return on investment in R&D, it should be observable in those countries. We construct a quality-based measure of human capital following HW, based on the average achievements of 10, 14 and 15-year-old students on standardized international tests in math and science. The only difference between our measure and that of HW is that we construct a series for this measure, while HW used the simple mean for the entire period they analyzed. We use data for the period 1970-2010 from Penn World Tables (Feenstra et al., 2013) for GDP per worker and the stocks of other factors of production.

The measure we construct is depicted in Figure 1 and it is clear that human capital has evolved differently in different countries. Thus, some of the countries have experienced an increase in their human capital stock over the entire period, while others have experienced a decline. In a few, the stock of human capital has been volatile with no specific trend. Thus, we will attempt to determine whether the countries that experienced an upward trend in their stock of human capital also experienced an upward trend in the growth rates of GDP per capita or only in its level.

We estimate a standard growth model with country-specific and time fixed effects and show that the data support the level effect, but not the growth effect. In fact, the growth effect appears to be negatively correlated with the GDP per worker growth rate, whereas the level effect is positively correlated with it and is statistically significant at the 5%. Furthermore, this result holds for various robustness checks.

Finally, we run a simulation of an education reform, as in HW, which increases the average achievements of students in the PISA tests by one standard deviation, and find that the impact of the reform is much less than that reported by HW. Thus, GDP per capita will exceed that in the no-reform case by 6% after 90 years according to our results, as compared to the result of 26% in HW, in which human capital had only a growth effect.

The rest of the paper is organized as follows: Section 1 specifies the standard aggregate production function in which human capital has both a growth and a level impact on GDP per capita. Section 2 presents the panel data and section 3 the estimation results. Section 4 discusses the results and section 5 concludes.

1 The Aggregate Production Function

We construct a standard aggregate production model that accommodates panel data, in order to jointly estimate the level and growth effects of human capital on GDP per capita. The model consists of a Cobb-Douglas production function and an equation that connects the GDP growth rate to the level of human capital through total factor productivity (TFP).

Aggregate GDP per worker in country i at time t, $y_{i,t}$, is given by the following technology:[6]

$$\ln y_{i,t} = \alpha \ln k_{i,t} + \beta \ln h_{i,t} + (1 - \alpha - \beta) \ln A_{i,t}, \tag{1}$$

where $k_{i,t}$ is the physical capital per worker employed in production in country i at time t, $h_{i,t}$ is the human capital level per worker employed in production in country i at time t, and $A_{i,t}$ is TFP in country i at time t. We also assume that $0 < \alpha, \beta < 1$, $\alpha + \beta < 1$ and that the TFP growth rate, $g_{A_{i,t}}$ depends on human capital as follows:

$$g_{A_{i,t}} = \phi + \chi \cdot h_{i,t}, \tag{2}$$

where ϕ is a common constant for all countries and the impact of human capital on the TFP growth rate is linear and common to all i and measured by χ. This equation is a reduced form of two economic forces that can generate a growth effect: the effect of human capital on the development of new technologies (Ha and Howitt, 2007) and on the assimilation of new technologies (Nelson and Phelps, 1966a; Rubinstein and Tsiddon, 2004). Fully differentiating with respect to time, adding a country time-invariant fixed effect, Δ_i, and an error term, $\epsilon_{i,t}$, generates our estimated equation:

$$g_{y_{i,t}} = \alpha g_{k_{i,t}} + \beta g_{h,i,t} + (1 - \alpha - \beta)(\phi + \chi h_{i,t}) + \gamma_1 \Delta_i + \gamma_2 \delta_2 + \epsilon_{i,t}, \tag{3}$$

where $g_{x_{i,t}}$ is the growth rate of variable x in country i at period t. A long-run growth effect is captured by a positive estimate for χ, whereas a short-run level effect is captured by a positive estimate for β.

Note that if only cross-section data is used with a sample of countries, then consistency of estimation requires the assumption that the time-invariant country-specific heterogeneity, Δ_i, not be correlated with either the level of human capital or its change. But there are reasons to suspect this is not the case. First, human capital is acquired based on local labor market conditions, which are almost by definition country-specific. Second, investment in education may also be affected by cultural characteristics (Figlio et al., 2018), which are of course country-specific. If this is the case, then in a cross-section analysis the estimated β becomes:

$$\hat{\beta} = \beta + \gamma_1 \frac{\text{cov}(h_{i,t}, \Delta_i)}{\text{var}(h_{i,t})}, \tag{4}$$

and the coefficient of the level effect will be biased. Since when using panel data we control for country-specific fixed effects, the estimated coefficients are not biased and thus yield a better identification of the level and growth effects since they are being jointly estimated.

2 Data

2.1 A Quality-Based Measure of Human Capital

One of the contributions of this paper is in extending HW by means of time series data for a quality-based measure of human capital.[7] This measure is based on average achievements on international tests in math and science. The data used is only for countries that participated in those tests in the first year they were given, i.e. 1964, or the second year, i.e. in 1970.[8]

During the sample period (1964-2003), the tests in math and science were written by students aged 9, 10, 13, 14 and 15. The tests are designed to identify a common set of expected skills and are conducted in the country's native language. In earlier tests, i.e. the First International Mathematics Study (FIMS) and the First International Sciences Study (FISS), only a few countries participated. In contrast, the number of countries participating in the TIMSS and PISA tests grew from 13 to more than 50 during the 1990s.[9]

The estimation uses annual panel data for the sample countries and follows the HW methodology, which will be briefly explained. In order to construct a reliable measure of human capital that makes it possible to compare results from across tests and across time, HW took advantage of the fact that the US has participated in all the tests, and that it also conducts independent national testing called NAEP (National Assessment of Educational Progress) in the same subjects.[10] HW derive the pattern of US results in the international tests by normalizing the US results for each international test according to those obtained in the NAEP tests of the same year. This produces standardized scores for the US on all the international tests. HW then construct a distance metric that can be used to compare each country's average achievements to that of the US for each test. The metric is based on calibrating the variance of each country's achievement on the PISA 2000 test, since all 13 OECD countries, which served as a standardization group for HW and which we use as our sample, participated in those tests. Hence, HW construct a normalized measure of the average achievements of students for each country and for each test the country participated in.

Up to this point, we have adhered to the HW methodology. HW then calculate a simple mean of each country's average scores over the entire period of 1960-2000. In contrast, we construct a time series of this measure. In other words, we use the mean of each country's average scores each time the country participated in the test.[11] Finally, we linearly interpolate the results for missing years, either because the tests did not take place in those years, or because the countries did not participate in those years.

The tests are given at the ages of 10, 14 and 15.[12] Most of the exams (76%) are given at the ages of 14 and 15.[13] Since we are attempting to capture how variation in the test scores affects growth, this measure is used with a lag of 5 years, such that the individuals who took the exams 5 years earlier are now 15, 19 and 20 years old, respectively. To check robustness, we tested other lags as well, but the results were hardly affected.

Figure 1 and Table 1 provide a first glance at the data, which shows that the evolution of human capital differs significantly between counries. Human capital in France and Netherlands, for example, has mainly been characterized by an upward trend, whereas Italy and New Zealand have mainly experienced a downward trend. Other countries (such as the US) do not show any identifiable trend. Furthermore, the mean average achievement on the international tests varies across countries, from 4.804 (US) to 5.216 (New Zealand), a difference of almost 9%. Furthermore, the volatility of these scores, as captured by the standard deviation, also varies substantially across countries, ranging from 0.097 (Belgium) to 0.27 (Sweden). Interestingly, one might argue that the more volatile countries are the ones with the highest scores, simply because their score levels are higher and have more room to fluctuate. However, this is not the case, which can be seen in the example of Sweden which has the highest volatility but is ranked second to last in human capital. Furthermore, Belgium and Germany have very similar mean scores, but Germany is much more volatile than Belgium. In short, the dataset we construct introduces a time dimension, which facilitates a panel analysis of the impact of human capital on the growth rate of GDP per capita.

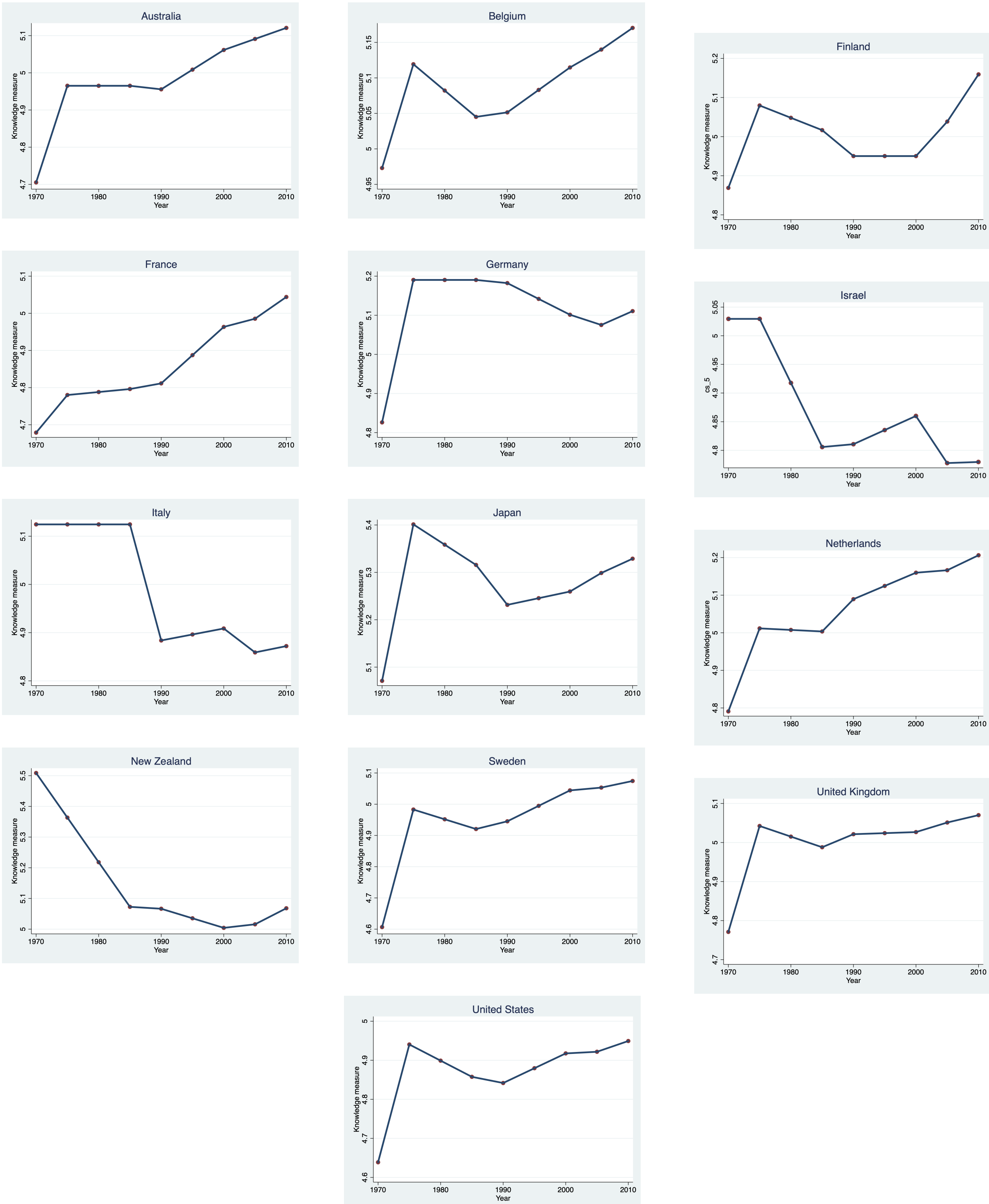

Figure 1: The evolution of the quality-based measure of human capital for the countries in the sample. Source: authors' calculations based on the HW methodology, as explained above.

Table 1: Summary Statistics for the Quality-Based Measure of Human Capital during the Sample Period

Country	Observations	Mean	Std.	Min	Max
Australia	9	4.907	0.204	4.445	5.091
Belgium	9	5.048	0.097	4.827	5.14
Finland	9	4.951	0.128	4.658	5.08
France	9	4.808	0.129	4.578	4.985
Germany	9	5.04	0.246	4.462	5.19
Israel	9	4.9	0.105	4.778	5.029
Italy	9	5.019	0.126	4.859	5.125
Japan	9	5.214	0.2	4.741	5.401
Netherlands	9	4.992	0.195	4.57	5.166
New Zealand	9	5.216	0.24	5.004	5.654
Sweden	9	4.859	0.27	4.23	5.053
United Kingdom	9	4.938	0.185	4.5	5.051
United States	9	4.804	0.197	4.337	4.94
Overall	117	4.976	0.218	4.23	5.64

2.2 Other Data

We also use data from Penn World Tables (PWT).[14] to compute the real stock of capital, number of workers, and real GDP per worker for the period 1970-2010. The sample period is divided into 5-year-long sub-periods such that the time dimension, t, is in five-year units. For each sub-period, the average annual growth rate of GDP per worker and of the stock of capital per worker is calculated, following the convention in the literature.[15][16]

3 Estimation Results

Table 2 presents the estimation results. Columns (1) and (2) provide the estimates for determining whether human capital has only a growth effect. Column (1) provides an estimate for the unconditional correlation between the growth effect of human capital and GDP per worker growth rate, while column (2) also controls for the rate of investment in physical capital. The coefficient of the level of human capital, χ, is negative and only somewhat statistically significant. Columns (3) and (4) provide the estimates for determining whether human capital has only a level effect. Again, the first column presents the unconditional correlation between the level effect and the growth rate of GDP per worker, while the second column also controls for the rate of investment in physical capital. In both columns, the coefficient is positive and statistically significant at the 5% and 1% level, respectively.

Columns (5) and (6) provide the estimates for simultaneously testing the growth and level effects. Only the level effect is statistically significant at the 10% and 5% levels, respectively. In column (7), we add initial GDP per worker for each sub-period as a control, in response to the concern that the initial level of human capital captures the effect of initial GDP per worker, rather that its direct effect on growth. The results remain similar to those in the other columns. It is possible to conclude from this table that the data support the existence of a short-run level effect on GDP per worker but not a long-run effect.

Table 2: Growth and Level Effects

	Annual Growth in GDP per Worker						
	Growth Effect Alone		Level Effect Alone		Both Effects		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$(1-\alpha-\beta)\chi$	-0.04*	-0.03*			-0.03	-0.02	-0.02
	(0.02)	(0.02)			(0.02)	(0.02)	(0.02)
β			1.22**	1.31***	0.93*	1.07**	1.07**
			(0.40)	(0.41)	(0.45)	(0.45)	(0.45)
α		0.07*		0.09**		0.08*	0.08*
		(0.04)		(0.04)		(0.04)	(0.04)
Adjusted-R^2	0.06	0.10	0.07	0.13	0.09	0.14	0.14
Observations	117	117	117	117	117	117	117

The results differ from those of Sunde and Vischer (2015) who found empirical evidence for both the growth and level effects. The difference has several explanations: First, we use a quality-based measure of human capital rather than years of schooling. This kind of measure provides a better fit for growth in GDP per capita, as was shown convincingly by HW. Moreover, it is also because our estimates are potentially less sensitive to standard endogeneity problems, since they are not affected by labor market responses to changes in growth.[17] Second, estimating fixed effects in a panel setting should eliminate any bias generated by unobserved country fixed effects.

Our main result is consistent with those reported in who in a cross-section analysis found that average years of schooling among OECD countries is negatively correlated with growth in GDP per worker. Our results are also consistent with those of Altinok and Aydemir (2017) who found that in high-TFP OECD countries, the effect of quality-based measures of human capital on growth is smaller than that of quantity-based measures.

Robustness The first robustness test is based on columns (1), (3) and (5) in Table 2 in which capital is omitted in order to overcome a potential endogeneity problem that arises because investment in human capital that changes the stock of capital will be pro-cyclical. The second is based on Table B.1 and B.2, which show similar results to those in Table 1 when we use a lag between our measure of human capital and the growth rate of GDP per worker of 3 or 6 years, respectively, instead of 5 years. The third is based on Table B.3 which shows that almost identical results are obtained from a random effects model. The fourth is based on Table B.4 which shows that the results remain unchanged if we use only the data up to 2005 in order to exclude the period of the Great Recession.

Finally, in an earlier and extended version of this study (Eckstein et al., 2018) we constructed a neoclassical growth model á la Mankiw et al. (1992) with an added assumption similar to equation (2). In this setup, we linearize around the steady state and estimate the short-run level and long-run growth effects using only cross-section data for the countries, as in HW.[18] The estimates are close to those obtained here: the long-run growth impact was not significantly different from zero and the short-run level impact was significant and close to the value reported in Table 1. Thus, our results are also robust to a larger set of countries and to the cross-section data, which is potentially subject to bias, as explained above.

4 Discussion

To illustrate the importance of the results, we simulate the evolution of GDP per capita following an educational reform that increases human capital by one standard deviation and compare it to a similar simulation conducted by HW.[19]

Following HW, we assume that all individuals work for 40 years of their lives and that in the absence of an educational reform GDP per capita grows at a constant rate of 1.5%. We also follow HW by assuming that the economic impact of the educational reform consists of four phases: (i) The first twenty years: During this period, the level of human capital gradually increases by one standard deviation, which is equivalent to a 25-point increase in the PISA test scores (1.25 points per year). During this period, students who only partially benefited from the reform begin replacing older workers who had already been in the labor force prior to the reform. (ii) The subsequent 20 years: Once the educational reform has been fully implemented, students with the highest level of human capital start replacing the aforementioned older workers. (iii) Forty to sixty years following the reform: Students with the highest level of human capital replace the initial group of students who only partially benefited from the educational reform. Hence, during this period, the labor force's average level of human capital continues to rise, until all the workers are at the highest level of human capital. (iv) Sixty years following the reform: The economy has now completed the transition, and all the workers now have the higher level of human capital.

Figure 2 presents the simulation of such a reform. The horizontal axis represents time, starting from the beginning of the educational reform, while the vertical axis represents the ratio of GDP per capita with the reform relative to no reform. The three periods of the reform are also shown. The graph presents three simulations: the HW long-run simulation, our simulation and the HW short-run simulation. Our simulation is based on the results in Table 2 Column 6 and differs from the HW long-run simulation in two aspects: First, the coefficient of the impact of such a reform on (short-run) growth is 1.07, as compared to a value of 2 in HW. Second, the growth rate of GDP per capita converges towards 1.5% at a rate of 2%, consistent with Barro and Sala-i Martin (1992) and Mankiw et al. (1992).

The significant differences between our results and those of HW raise the question of whether they are due to the difference in the coefficient or because HW assume that human capital has a growth effect, whereas we find only evidence of a level effect. To answer this question, we added a third simulation, which we have labeled as the HW short-run simulation. It adopts HW's coefficient, but interpreted as a short-run effect (rather than a long-run growth effect, as assumed by HW). If the results of this simulation are similar to ours, then human capital has a level effect, a fact that should play a key role in the design of educational policies that target economic prosperity.

Figure 2 shows the large differences between the impact of an educational reform according to HW and according to our results. Thus, forty years after the reform, as the second phase of the reform's impact ends, there are major differences between the three simulations: HW predicts an increase in GDP per capita of 0.7%, while our results predict a change of 0.3% (and the HW short-run simulation predicts 0.5%). However, the differences diverge after that. Sixty years after the reform (when the third phase of the impact ends), the HW simulation predicts an increase of almost 5% in GDP per capita, while our results predict only 2.3% (and the HW short-run simulation predicts 4%). Ninety years after the reform, the HW simulation predicts that GDP per capita will exceed the no-reform level by about 26% while our results show only a 6% increase (and the HW short-run simulation predicts only 10%).

5 Conclusions

Most economists predict that the growth rate of US GDP per capita will in the future decline to about 1.0-1.4 percent.[20] One suggested remedy is to invest in an educational reform to increase average human capital, as indicated by HW's results. We show that such a reform

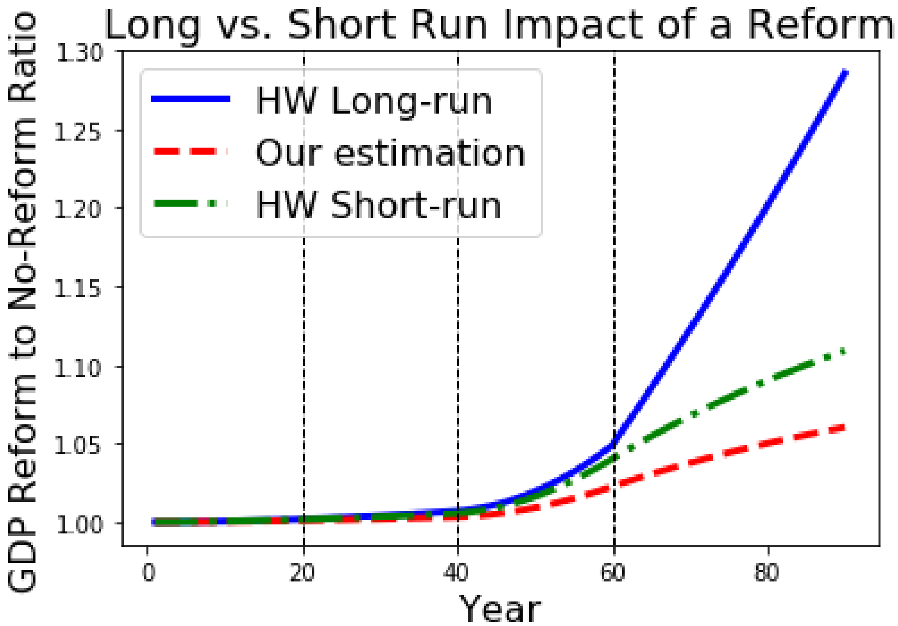

Figure 2: Growth vs. level effect of an educational reform

will raise the level of GDP per capita and its growth rate only in the short run. This is based on the estimation results of a standard aggregate production function, using panel data for 13 advanced economies and a quality-based measure of human capital, as in HW.

Future research based on the HW measures of human capital will most likely conclude that the aggregate level of human capital is bounded from above conditional on ability at birth. If so, then policies that attempt to raise the average level of human capital by increasing the human capital of all students might overshoot the target. Instead, targeting education policies to reduce the dispersion of student achievement on the international tests, with the goal of raising the scores of disadvantaged students, may produce a better outcome. In other words, reforms should aim to increase the average and median level of human capital – and therefore stimulate economic prosperity – by focusing more on the less able students.

The question of the growth effect vs. the level effect of human capital is becoming increasingly important for two reasons: First, many economies, including several OECD countries, have been experiencing lower growth rates since the Great Recession and it is widely believed that growth rates will decline to well below those of the second half of the

20$^{\text{th}}$ century.[21] Second, new technologies developed during the past two decades suggest that many tasks that are currently carried out by workers will become automated in coming decades.[22] Thus, understanding whether human capital has a growth effect or a level effect may have significant implications for educational and distributional policies.

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Notes

[1]For a comprehensive survey of the literature, see Krueger and Lindahl (2001).

[2]This measure was first introduced in Hanushek and Kimko (2000).

[3]These are standardized international tests that designed to evaluate students' skills in math and science. For more details, see section 2.

[4]In the introduction to Hanushek and Wößmann (2007), Bourguigono, the former Chief Economist of the World Bank, wrote as follows: "The Bank will contribute to ensuring that the measurement of learning achievements is undertaken in a more systematic way and is properly taken into account in the Bank's dialogue with partner countries."

[5]In particular, the level effect result may be due to the fact that a more educated labor force produces more effectively (as in Becker (1962) or Galor and Zeira (1993), whereas the growth effect may be due to the fact that better-educated workers invent and assimilate new technologies more easily, a result originally suggested by Nelson and Phelps (1966b) and used extensively thereafter (e.g., Galor and Tsiddon (1997).

[6]Following the literature, we assume that the proportion of workers in the population is constant.

[7]See Section 3 and Appendix B in Hanushek and Woessmann (2012) for a detailed explanation of the methodology, as well as for the sources.

[8]Table 1 presents the countries in our sample.

[9]PISA is the OECD's Program for International Student Assessment. Every three years it tests 15-year-olds in a large number of countries in reading, mathematics and science. The tests are designed to gauge how well the students have mastered key subjects in order to prepare for real-life situations in the adult world (see `http://www.oecd.org/pisa/`). TIMSS (Trends in International Mathematics and Science Study) is conducted by the International Association for the Evaluation of Educational Achievement and monitors trends in mathematics and science achievement every four years at the fourth and eighth grade levels (see `https://timssandpirls.bc.edu/timss-landing.html`). Prior tests, such as FIMS and FISS were conducted at the ages of 9, 10 and 14.

[10]For further details on NAEP, see `https://nces.ed.gov/nationsreportcard/`.

[11]Ideally, the mean we use should be based on the results for the last 40 years of testing, which is the average working life of each cohort. However, since the test score data is for a period of less than forty years, this is unnecessary.

[12]See Table 10 in Hanushek and Woessmann (2012) for a full list of all the tests and ages used in the construction of their measures. We use all the data they do and add from later tests (2000-2003). These data are available from the aforementioned PISA and TIMSS websites.

[13]Most of the exams for 10-year-old students were given towards the end of the 1990's and as such they constitute only a small part of the sample.

[14]The Penn World Tables is a database of information on relative levels of income, GDP, input and productivity for 182 countries starting from 1950.

[15]For a comprehensive survey of the literature on using panel data in growth regressions, see Section VI.ii in Durlauf and Johnson (1995).

[16]Table C.1 provides the summary statistics for all of the variables used in the panel data analysis.

[17]In Eckstein et al. (2018), we replicate the result showing that HW's measure of human capital more accurately captures the impact of human capital on GDP than does years of schooling.

[18]Hence, unlike HW, we do not assume that human capital has a growth effect but no level effect.

[19]For further details on HW's methodology in constructing the simulation and a discussion of their results, see Chapter 7 in Hanushek and Woessmann (2015).

[20]See, for example, the prediction of between 1.7 and 2.1 percent by a member of the FOMC for the long-run growth rate of GDP. (`https://www.federalreserve.gov/monetarypolicy/files/fomcprojtabl20190918.pdf`) Given the current US population growth rate of 0.7, that translates into a growth rate per capita of between 1 and 1.4 percent.

[21]Gordon (2014) and Summers (2014) make a prediction of secular stagnation in post-2009 advanced economies.

[22]Frey and Osborne (2013) suggest that about 47% of all jobs will become automated in the next few decades.

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Appendix

A The Countries in the Sample, and Their Participation in International Tests

Table A.1: Countries with Early Participation in International Tests & Average Years of Schooling, 1970, 1990

Country	Year of First Participation	No. of Times Participated	Avg. Years of Schooling, 1970	Avg. Years of Schooling, 1990
Australia	1964	8	11.44	11.97
Belgium	1964	7	9.5	11.57
United Kingdom	1964	9	8.48	9.05
Finland	1964	7	8.66	10.15
France	1964	6	7.41	10.03
Germany	1964	5	4.2	11.35
Israel	1964	5	10.39	12.31
Italy	1970	6	7.38	10.74
Japan	1964	9	10.72	12.41
Netherlands	1964	8	9.1	11.43
New Zealand	1970	7	13.13	12.55
Sweden	1964	6	9.9	12.16
United States	1964	9	12.53	12.89

B Robustness Checks for the Panel Data Analysis

Table B.1: Growth Rate vs. Level Effect Analysis Using a 3 Yead Lag

	Annual GDP per Worker Growth, 1970-2010					
	Growth Effect Alone		Level Effect Alone		Both Effects	
	(1)	(2)	(3)	(4)	(5)	(6)
$\chi(1-\alpha-\beta)$	-0.03	-0.03			-0.01	-0.01
	(0.03)	(0.03)			(0.03)	(0.03)
β			1.86***	1.80***	1.72**	1.66**
			(0.58)	(0.53)	(0.76)	(0.73)
α		0.08*		0.07*		0.07*
		(0.04)		(0.04)		(0.04)
Adjusted-R^2	0.03	0.08	0.10	0.15	0.10	0.14
Observations	117	117	117	117	117	117

Table B.2: Growth Rate vs. Level Effect Analysis Using a 6 Year Lag

	Annual GDP per Worker Growth, 1970-2010					
	Growth Effect Alone		Level Effect Alone		Both Effects	
	(1)	(2)	(3)	(4)	(5)	(6)
$\chi(1-\alpha-\beta)$	-0.04**	-0.04**			-0.03	-0.02
	(0.02)	(0.02)			(0.02)	(0.02)
$\beta)$			1.18***	1.25***	0.77*	0.90**
			(0.38)	(0.40)	(0.41)	(0.41)
α		0.07*		0.08**		0.08*
		(0.04)		(0.04)		(0.04)
Adjusted-R^2	0.07	0.11	0.07	0.13	0.09	0.14
Observations	117	117	117	117	117	117

Table B.3: Growth Rate vs. Level Effect Analysis: Random Effects Model

	Annual GDP per Worker Growth, 1970-2010						
	Growth Effect Alone		Level Effect Alone		Both Effects		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\chi(1-\alpha-\beta)$	-0.01	-0.01			-0.00	0.00	-0.00
	(0.01)	(0.01)			(0.01)	(0.01)	(0.01)
β			1.22**	1.34***	1.26***	1.36***	0.96*
			(0.40)	(0.44)	(0.45)	(0.45)	(0.53)
α		0.08*		0.09**		0.09**	0.10***
		(0.04)		(0.04)		(0.04)	(0.04)
y_0							-0.01**
							(0.01)
Adjusted-R^2	0.07	0.08	0.07	0.14	0.08	0.14	0.21
Observations	117	117	117	117	117	117	117

Table B.4: Growth Rate vs. Level Effect Analysis Excluding The Great Recession

	Annual GDP per Worker Growth, 1970-2005						
	Growth Effect Alone		Level Effect Alone		Both Effects		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
HC Level (5 year lag)	-0.04*	-0.03			-0.02	-0.01	-0.01
	(0.02)	(0.02)			(0.02)	(0.02)	(0.02)
HC Growth (5 year lag)			1.20**	1.30***	0.95*	1.15**	0.84*
			(0.42)	(0.42)	(0.45)	(0.43)	(0.40)
Capital Growth		0.08**		0.10***		0.10**	0.11**
		(0.04)		(0.03)		(0.03)	(0.04)
Initial GDP per Worker							-0.01
							(0.01)
Adjusted-R^2	0.05	0.10	0.07	0.16	0.08	0.16	0.17
Observations	104	104	104	104	104	104	104

C Summary Statistics

Table C.1: Summary Statistics

Variable		**Mean**	**Std. Dev.**	**Min.**	**Max.**	**Observations**	
GDP per capita growth	overall	0.019	0.017	-0.23	0.076	N=	117
	between		0.007	0.006	0.029	n=	13
	within		0.016	-0.024	0.066	T=	9
knowledge	overall	5.01	0.16	4.607	5.509	N=	117
	between		0.124	4.836	5.273	n=	13
	within		0.108	4.68	5.359	T=	9
knowledge change	overall	0.001	0.004	-0.007	0.014	N=	117
	between		0.002	-0.002	0.004	n=	13
	within		0.004	-0.005	0.011	T=	9
Physical capital change	overall	-0.007	0.049	=0.122	0.106	N=	117
	between		0.011	-0.022	0.015	n=	13
	within		0.048	-0.108	0.1	T=	9