

Why Standard Measures of Human Capital are Misleading[†]

By ERIC A. HANUSHEK*

After a long, dormant period, recent attention has turned to a variety of measurement issues surrounding the concept of human capital. The traditional approach of rely entirely on measures of school attainment, while convenient, is almost certainly misleading. The availability of cognitive skills measures greatly improves on these measurements, but there remains also concern about other unmeasured factors, including noncognitive skills. This paper considers alternative approaches to assessing the role of human capital on individual earnings and on economic growth.

Key Word: Human Capital, Returns to Skills, Cognitive Skills,
Earnings Function, Long-run Growth

JEL Code: O15, I25, I26

I. Introduction

For the last half century, economists have been largely content with both the measurement and the empirical importance of human capital. But recently, after this period of dormancy, attention to measurement issues has picked up. The ubiquitous analysis of school attainment has come to the fore, leading to a reconsideration of what skills are important and, implicitly, of what policies should be considered for skill development. This paper focuses on the role of cognitive skills in earnings determination and economic growth, and attempts to understand what might be left out of such measures of human capital.

Historically, the idea of human capital as a useful concept took a significant move forward with the demonstration that school attainment might capture many of the important aspects for empirical work. However, the ubiquitous reliance on school attainment is clearly at odds with other analyses that consider schooling as just one element of skill development.

* Paul and Jean Hanna Senior Fellow, Hoover Institution of Stanford University, Stanford CA 94305.
(Email: hanushek@stanford.edu)

* Received: 2015. 4. 27

* Referee Process Started: 2015. 4. 27

* Referee Reports Completed: 2015. 5. 20

[†] This paper is partly supported by Korea Development Institute. An earlier version was presented at the “International Workshop on Human Capital Policy,” October 2014 in Seoul.

It is now possible to estimate both models of wage determination and of economic growth that include better measures of human capital – namely cognitive skills. In these, it is clear that differences in cognitive skills are very important in describing economic outcomes. At the same time, it is less clear whether measurement problems with these or omitted factors such as noncognitive skills are also important.

By considering alternative estimates of basic models, it is possible to put some bounds on the range of concerns about cognitive skill measures. From these, it is clear that other factors are likely to enter into the individual wage determination, although the exact nature of these other factors is less clear. It is not clear that these other factors are significant in the case of economic growth.

II. A Short History

Today, few economists recognize the conflicts and disagreements that existed in the middle of the last century. There is a long history of economists thinking about the importance of individual skills.¹ Perhaps the earliest economic analysis of skills was introduced by Sir William Petty (1676 [1899]), who thought that the costs of war and the economic power of nations should be directly related to how skilled the relevant individuals were. Adam Smith (1776 [2010]) also delved into ideas of human capital before moving into the areas of trade and specialization. But, Alfred Marshall (1898) called the whole idea into question, because he did not think it was relevant empirically since individuals could not be bought and sold. Because of his influence, Marshall essentially stopped the consideration of human capital.

The reintroduction of the concept of human capital came with Theodore Schultz (1961). His presidential address to the American Economic Association concluded that the much of the difference between growth of national income and the slower increases in labor, physical capital, and land was due to investments in human capital. While providing an overview of various investments that individuals made in human capital, he also felt compelled to address the “deep-seated moral and philosophical issues” against such considerations – a necessity that now seems quaint.

Parallel to the arguments of Schultz comes the broadening and deepening developments of Gary Becker (1964) and Jacob Mincer (1970, 1974). Becker, in a variety of works, developed ideas of individual investments in human capital. But, the most profound development arguably was the development of an empirical approach to understanding human capital investments and the returns on them.

A major obstacle in empirical work was judging the amount of skills, or human capital, that an individual possessed. For physical capital, the well-developed approach was totaling up the expenditures on capital as an indication of the investment. With various allowances for depreciation and quality improvement, the stock of human capital could be calculated from aggregating past investments. But,

¹Kiker (1966, 1968) provides a detailed history of various approaches to incorporating human capital dating back to the seventeenth century.

with human capital, it is less than obvious how individual consumption expenditure can be separated from investments. Schultz (1961) recognized this problem and observed that it might be possible to look at differences in wages as a measure of the returns on skills to an individual. This observation could not, however, adequately drive the measurement of human capital, because arguing that human capital drives wage differences and thus that wage differences indicate the difference in human capital becomes tautological.

Mincer (1974) provided a direct way to circumvent the tautological version of human capital and to proceed with meaningful empirical analysis. His motivation was to develop an empirical approach to understanding the role of human capital investments in wage determination. He made two observations. First, a major function of schools was to develop individual skills that were useful in the market. Thus, if the costs of schooling came entirely from foregone earnings, it was possible to measure the schooling component of investment simply by the time in school, or years of school attainment. Second, building on Becker's analysis about investment in on-the-job (OJT) training, plausible investment plans provided a structure to lifetime investment in OJT and allowed direct estimation of the impact of OJT on investment.²

When these ideas were combined, Mincer (1974) showed that individual wages could be characterized by relating (log) wages to years of schooling and to a quadratic function of experience that captured OJT investments. The standard version is

$$(1) \quad \ln Y_i = a_0 + rS_i + a_1E_i + a_2E_i^2 + \varepsilon_i,$$

where Y_i denotes the earnings of individual i , S_i is years of schooling, E_i is experience, and ε_i is a random error.³ In the standard interpretation, r is the rate of return to schooling.⁴

This formulation of wage determination is perhaps the most successful theoretical/empirical development ever in the history of economics. The "Mincer earnings function" is so common that no reference is needed, and, if any alterations of the measures of human capital or of the functional form are made, they need to be explained.

Importantly, school attainment has been accepted fully as a legitimate and largely complete measure of human capital differences across individuals. In its standard Mincer form, the coefficient of years of schooling is a direct measure of the rate of return to schooling, and thus can summarize the investment value in schooling across time and space.⁵

²The initial development of Becker (1964) argued that while firms might invest in the specific human capital of a worker, they would not invest in general human capital because the worker could take that investment to a different firm, thus inflicting a capital loss on the original firm. This issue has subsequently been reopened by Acemoglu and Pischke (1998, 1999).

³Even more commonly, instead of actual labor market experience, E denotes potential experience equal to $S - \text{age} - 6$.

⁴See, however, Heckman, Lochner, and Todd (2006), who consider problems in the interpretation of r as the rate of return to schooling investment.

⁵Again, however, see the issues that surround such an interpretation in Heckman, Lochner, and Todd (2006,

A driving force in the acceptance of employing school attainment as a measure of human capital is clearly its ready availability. Common census data and household surveys contain all of the data needed to estimate labor market returns to human capital. For example, in the latest of a series of international estimates of Mincer earnings functions, Montenegro and Patrinos (2014) provide comparable estimates across 139 economies.⁶

From these developments, school attainment has been widely accepted as a measure of an individual's human capital. It is incorporated into a wide range of studies beyond just past wage determination, indeed virtually all analyses where it is necessary to identify differences across individuals that might affect their behavior.

Perhaps the only consistent concern with the Mincer development is whether the earnings estimates represent the causal impact of schooling. In the simplest formulation of this concern, one dating from the earliest earnings studies, it is widely accepted that higher ability individuals are likely to continue farther in school.⁷ Thus, if there is a separate return to ability, estimation of the simple Mincer earnings function will represent the combined impact of school and of ability, and not just the causal impact of schooling. These issues have led to a large amount of literature, as described and evaluated by Card (2001). A continuing literature seeks to deepen and extend this work, often introducing new strategies to identify the rate of return to schooling.

The perspective of this paper is that the Mincer formulation has been too successful in driving research. The treatment of school attainment as synonymous with human capital fundamentally distorts economic analysis of human capital and the policy implications that are drawn from this analysis. The primary concern is other omitted factors that directly affect earnings and lead to biased estimates of the return to skills.

III. Distortions in Estimating the Returns to Skills

Two closely related topics suggest a problem with the way that this research into human capital has developed.⁸ First, there has been a long and extensive line of research into educational production functions. This research has sought to investigate directly the determinants of schooling outcomes. Second, from a policy perspective, the concerns center more on the quality of schooling and the policies that might be put in place to improve schooling outcomes. Neither of these topics is compatible with the general Mincer approach to wage determination or the more general proposition that school attainment is an adequate measure of human capital.

A simplified version of a standard human capital production function would be

2008).

⁶Prior estimates in this expanding set of estimates are found in Psacharopoulos (1973) and Psacharopoulos and Patrinos (2004).

⁷See, for example, Hause (1971, 1972).

⁸Discussion of this general set of issues follows that in Hanushek and Woessmann (2008), where the issues were first set out.

$$(2) \quad H_i = \beta_1 F_i + \beta_2 (q_s S_i) + \beta_3 A_i + \beta_4 Z_i + v_i,$$

where human capital (H) is a function of family inputs (F), the quantity and quality of inputs provided by schools ($q_s S$), individual ability (A), and other relevant factors (Z) such as health or peers. Such a function has been estimated innumerable times (Hanushek, 2002). Several aspects are important. While there have been a variety of measures of H , including incomes, college attendance, and the like, the most common measure has been student achievement, or some dimension of cognitive skills. Second, family background (F) invariably affects student outcomes, a consistent finding since the first major investigation along these lines (Coleman *et al.*, 1966). Third, many common input measures – such as expenditures or pupil-teacher ratios – have somewhat surprisingly and somewhat controversially not proven to be reliable measures of school quality (Hanushek, 2003).

Putting analyses on Mincer earnings functions into the context of educational production functions immediately uncovers the fundamental problem. From eq. (2), it would not be possible simply to substitute school attainment into an earnings function and assume that it would adequately measure human capital. Moreover, it goes considerably beyond the idea of ability bias, where some indication of fixed differences among individuals, call it A , must be considered. To the extent that all of the terms in eq. (2) except for S and possibly A enter the error term in eq. (1), all of the past analyses indicate why the standard requirement for an unbiased estimation of r (i.e., $E[\varepsilon|S] = 0$) is very unlikely to hold.

It is also true from these considerations that, even with a consistent estimate of r , it is necessary to go further to understand the returns to quality of schooling. It is not possible simply to assume that the estimated return to quantity of schooling will provide a reliable estimate of the return to various approaches to improve school quality.

IV. Alternative Estimates of the Returns to Individual Human Capital

Considering eq. (1) and eq. (2) together suggests a variety of alternative approaches to the estimation of returns to skills. One appealing approach, however, is suggested by Hanushek *et al.* (2015). Consistent with the estimation of educational production functions, it would seem reasonable to use test scores as a direct measure of appropriate skills, or human capital. In other words, it would be possible to use C_i , the measured cognitive skills of the individual, in a model of earnings determination.

Schools explicitly have a goal of increasing the cognitive skills of the population. In fact, most of the accountability systems and rewards related to schools are geared toward measured student achievement. Thus, it seems natural to consider tests as a measure of human capital. Unfortunately, data on cognitive skills are not nearly as plentiful as data on school attainment, and the evidence on the returns to cognitive skills is much less available and consistent.

The most common set of estimates comes from an augmented Mincer earnings function, where a simple modification is made to add cognitive skills, as in

$$(3) \quad \ln Y_i = \alpha_0 + rS_i + \alpha_1 E_i + \alpha_2 E_i^2 + fC_i + \varepsilon_i,$$

Most of the evidence on the impact of cognitive skills from this extension of the Mincer earnings functions comes from U.S. panel data sets that record test information while the individual is a student and then follow their performance in the labor market.

The results of these estimates for the United States are shown in Table 1. Three parallel U.S. studies provide very consistent estimates of the impact of test performance on earnings (ϕ) for young workers (Mulligan 1999; Murnane *et al.* 2000; Lazear 2003). These studies employ different nationally representative data sets that follow students after they leave school and enter the labor force. When scores are standardized, they suggest that one standard deviation in mathematics performance at the end of high school translates into 10-15 percent higher annual earnings.⁹

Murnane *et al.* (2000) provide evidence from the High School and Beyond and the National Longitudinal Survey of the High School Class of 1972 (NLS72). Their estimates suggest that males obtain a 15 percent increase and females a 10 percent increase per standard deviation of test performance. Lazear (2003), relying on a somewhat younger sample from National Educational Longitudinal Study of 1988 (NELS88), provides a single estimate of 12 percent. These estimates are also very close to those in Mulligan (1999), who finds 11 percent for the normalized AFQT score in the National Longitudinal Study of Youth (NLSY) data. Note that these returns can be thought of as how much earnings would increase with higher skills every year throughout a person's working career. The estimates do, however, come

TABLE 1—EXISTING ESTIMATES OF RETURNS TO COGNITIVE SKILLS

	Data source	Age sample	Return to cognitive skills
Mulligan (1999)	NLSYa	?	0.11
Murnane <i>et al.</i> (2000)	HSBb and NLS72c	27, 31	0.10-0.15
Lazear (2003)	NELS88d	≤27	0.12
Hanushek and Zhang (2009)	IALSE	16-65	0.20
Chetty <i>et al.</i> (2011)	STARf	25-27	0.18
Hanushek and Woessmann (2012)	IPUMSg	25-65	0.14

Note: Each comes from an estimation of a Mincer earning function that adds an achievement measure in units of standard deviations.

Data sets: a. National Longitudinal Study of Youth; b. High School and Beyond; c. National Longitudinal Survey of the High School Class of 1972; d. National Educational Longitudinal Study of 1988; e. International Adult Literacy Survey; f. Project STAR; g. 2000 Census IPUMS.

Source: Hanushek and Woessmann (2015).

⁹It is convenient to convert test scores into measures of the distribution of achievement across the population. A separate review of earlier studies of the normalized impact of measured cognitive skills on earnings by Bowles, Gintis, and Osborne (2001) finds that the mean estimate is only 0.07, or slightly over half of that for the specific studies here.

early in the worker's career, suggesting that the impact may actually rise with experience.¹⁰

In a different set of estimates using data on a sample of workers of all ages within the U.S., Hanushek and Zhang (2009) provide estimates of returns (ϕ) of 20 percent per standard deviation.¹¹ One distinguishing feature of these estimates is that they come from a sample of workers throughout the career, as opposed to the prior estimates that all come from early-career earnings.¹²

Using yet another methodology that relies upon international test scores and immigrants into the U.S., Hanushek and Woessmann (2012) obtain an estimate of 14 percent per standard deviation. That analysis begins with a standard Mincer earnings model but estimates the returns to skills from a difference-in-differences formulation based on whether the immigrant was educated in the home country or in the United States. They find that skills measured by international math and science tests from each immigrant's home country are significant in explaining earnings within the United States.

Finally, Chetty *et al.* (2011) look at how kindergarten test scores affect earnings at age 25-27 and find an increase of 18 percent per standard deviation. These estimates do not control for any intervening school attainment differences but do control for a rich set of parental characteristics.

But there are two problems with this evidence. First, by referring only to young workers (except for Hanushek and Zhang 2009), the results potentially understate the returns to skills. Altonji and Pierret (2001) consider the possibility of statistical discrimination that leads to increased returns to cognitive skills over time. Specifically, when young workers first go to an employer, it is difficult for the employer to judge the skills of the worker. Over time, the employer can more accurately assess the skills of the worker, and, if worker skills are related to cognitive skills as measured by tests, the returns to test scores will rise with experience. Their analysis supports the idea that these estimated returns to skills could be an understatement, with the returns to cognitive skills rising and the returns to school attainment falling with labor market experience.¹³ Related to this, Haider and Solon (2006) show that people with higher lifetime earnings show systematically steeper earnings growth.

Second, a potentially more serious issue is the form of the earnings determination model. If in fact cognitive skills are a good measure of human capital, school attainment would just be an input to human capital (eq. (2)) and

¹⁰These estimates are derived from observations at a point in time. Over the past few decades, the returns to skill have risen. If these trends continue, the estimates may understate the lifetime value of skills to individuals. On the other hand, the trends themselves could change in the opposite direction. For an indication of the competing forces over a long period, see Goldin and Katz (2008). Haider and Solon (2006), from a different perspective, show that the earnings of individuals with higher earnings tend to rise more steeply early in their careers.

¹¹Their estimates of returns to cognitive skills actually include 13 countries, of which the U.S. had the highest estimated returns in the mid-1990s.

¹²The data from the International Assessment of Adult Literacy (IALS) provide both tests of reading and numeracy skills but also assess a range of adult workers. The estimates in Hanushek and Zhang (2009) come, like the previously mentioned studies, from adding cognitive skills to a standard Mincer earnings function, but that paper also discusses alternative ways to obtain estimates of the schooling gradient (r in equation (1)).

¹³When the model was tested across countries, however, it seemed most important for the United States but not for other countries (see Hanushek and Zhang 2009).

should not be included in eq. (3). Thus, the appropriate way to estimate earnings determination would be

$$(4) \quad \ln Y_i = \alpha_0 + \alpha_1 E_i + \alpha_2 E_i^2 + fC_i + \varepsilon_i,$$

Hanushek *et al.* (2015) provide evidence on both of these issues. They employ OECD data from the Programme for the International Assessment of Adult Competencies (PIAAC). This survey, conducted in 2011-2012, has several strengths that permit a new view of the earnings determination process. First, it uses representative samples of the population aged 16-65. Second, it provides consistent information across 23 countries. Third, in addition to labor market data for individuals, it conducted a set of three separate cognitive skills tests: literacy, numeracy, and problem solving in technology-rich environments.¹⁴

With these data, it is possible not only to estimate the returns to skills but also to consider the interpretation of various models of the role of human capital in earnings determination.

V. International Estimates of Returns to Skills

Hanushek *et al.* (2015) provide direct evidence on the range of returns to skills across countries. The most basic estimates focus on eq. (4).¹⁵ In an effort to separate skills from other factors that might enter into the earnings determination, the estimates begin with a sample of full-time workers (≥ 30 hours per week). The initial estimation employs numeracy scores, and there is substantial variation across countries. Figure 1 plots the returns to numeracy estimated by Hanushek *et al.* (2015). The scores have been normalized to mean zero and standard deviation one within each country, implying that the estimated numeracy coefficient is the percentage difference in average earnings that is associated with a one standard deviation difference in numeracy scores.

Two things stand out in this evidence. First, there are very substantial differences in the returns to skill across countries. Second, the returns to a number of countries, including Korea, are very high.

From Figure 1, the overall estimate for pooled data across all countries of the impact of numeracy is that a one standard deviation higher score corresponds to 17.8 percent higher earnings at all years of experience.¹⁶ These estimates for individual countries range from 12 percent for Sweden to 28 percent for the U.S. Six of the 23 countries – including Korea – have returns to numeracy that exceed 20 percent.

¹⁴Participation in the problem-solving domain was optional; Cyprus, France, Italy, and Spain did not participate in this domain.

¹⁵The estimation also includes an indicator variable for gender in addition to experience and experience squared. Females on average in the pooled sample earn 15 percent less than males, but there is no difference in the returns to skills. All other things being equal, females in the U.S. earn on average 18 percent less than males. For Korea, the comparable figure is 38 percent, a female difference exceeded only by Estonia at 40 percent.

¹⁶The pooled estimates include country fixed effects, implying that the returns to skills are estimated from just the within-country variance.

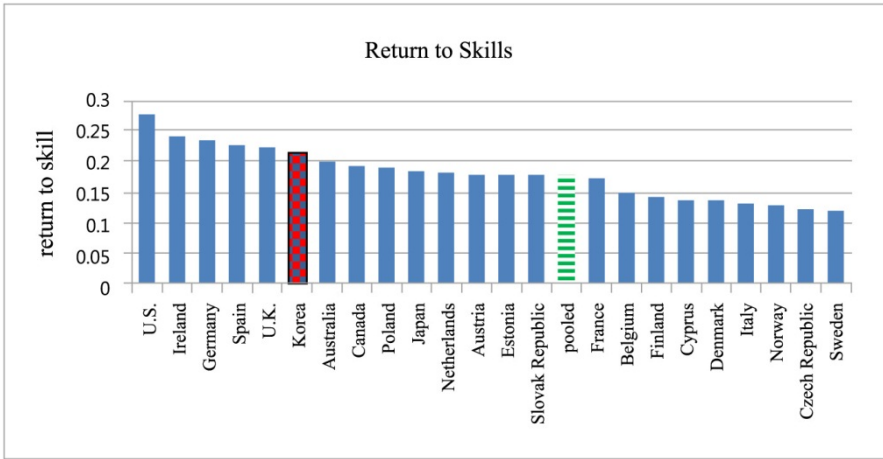


FIGURE 1. ESTIMATED RETURNS TO NUMERACY BY COUNTRY

Source: Hanushek *et al.* (forthcoming).



FIGURE 2. RETURNS TO NUMERACY SKILLS BY PORTION OF WORK LIFE

Source: Hanushek *et al.* (forthcoming).

An interesting aspect of the PIAAC data is the measurement of several dimensions of cognitive skills.¹⁷ The assessment of problem solving in technologically rich environments is an innovative attempt in PIAAC to measure the skills needed to succeed in an information-based economy where information and communication skills are required.¹⁸ Interestingly, these skills, at least as assessed by PIAAC, are systematically less strongly associated with individual earnings than more traditional cognitive skills. In conjunction with numeracy skills,

¹⁷The PIAAC data are actually modeled after the earlier data of IALS (International Assessment of Adult Literacy survey). That survey, including international data from adults in a number of countries, also had multiple tests, but they are all so highly correlated that it was not really possible to separate them. See Hanushek and Zhang (2009).

¹⁸See, for example, the description at: <http://nces.ed.gov/surveys/piaac/problem-solving.asp>.

problem solving has half the estimated return: 6.1 percent on average versus 12.2 percent for numeracy. This aggregate result holds across all countries except for the Czech Republic and Slovak Republic. Further, the point estimates for problem solving are insignificant in Australia, Japan, Korea, and Poland.

Another aspect of this analysis is the insight into the effect of just measuring skills early in the career – as commonly found in the studies shown in Table 1. If eq. (4) is modified to let the impact of skills vary across the work life, it becomes clear that skills have much less of an impact early in a career. Figure 2 show the returns pooled across all 23 countries for work force entry (age 16-34), the prime earnings period (age 35-54), and exit (age 55-65). Over the entry period, returns average 14 percent (per s.d.). They then rise to 18 percent for the remainder of the career.

The pattern for Korea mimics this, although it is everywhere higher. Entry period returns are 18 percent, and returns rise to 23 percent for the remainder of the work life.

VI. Alternative Interpretations

Most prior estimates of the return to skills have come from estimations of the augmented Mincer earnings function in eq. (3). The question from this is how to interpret the estimated impact of schooling on earnings.

Two interpretations of the schooling gradient are possible. The previous estimates of the return to skill assume not only that the tests are accurate but also that they are complete measures of the requisite skills for the labor market.¹⁹ Both of these assumptions are questionable, but consideration of them provides more on the interpretation of the estimated schooling coefficient.

Consider first the case of a simple measurement error in using the test scores to describe the human capital of the individual. In this case, the estimated returns to skills would be biased downward. But also, where school attainment is simply an input to the production of human capital, the true coefficient on schooling in the earnings model would still be zero, but the estimate would be biased upward.²⁰ Thus, estimating an augmented Mincer earnings function will produce a positive coefficient on years of schooling, but it would not have an interpretation of the returns to schooling that is common (e.g., Card 2001; or more nuanced, Heckman, Lochner, and Todd 2008).

The alternative interpretation is that cognitive skills are one proxy for human capital and school attainment is another. In this case, years of schooling is not just an input into the educational production function but is also an error-prone measure of relevant skills, or the output of the educational process. School attainment could, for example, be related to the noncognitive skills that are important for the educational process. Recent work has emphasized the importance of noncognitive skills and claims by some measures that noncognitive skills are as important if not

¹⁹The full requirement is that any unmeasured portions of skills are uncorrelated with the variables included in the model.

²⁰The bias in the simple model is actually a special case of proxy variables; see McCallum (1972) or Wickens (1972).

more important in earnings determination (e.g., Heckman, Stixrud, and Urzua 2006; Cunha and Heckman 2008).²¹ No attempt is made here to measure directly noncognitive skills. Instead we consider the potential impacts through the channel of school attainment.

It is possible to look at the range returns to measured skills from the augmented Mincer function perspective. Figure 3 provides an international comparison of returns to skills after controlling for school attainment. Four of the top six countries in terms of returns to numeracy from Figure 1 remain at the top of the world distribution in the estimates that include schooling, but returns in Spain and Korea drop to the pooled mean across countries. Countries at the low end of returns remain there, although the magnitude of the returns to cognitive skills is estimated to be lower.

The easiest way to think about these estimates is to consider that they provide a set of bounds on the importance (and in some sense usefulness) of cognitive skills measures of skills, or human capital. By any interpretation, however, it is clear that differences in cognitive skills are very important in individual earnings determination. Lacking measures of noncognitive skills, except as correlated with school attainment, implies nonetheless that it is difficult to categorize their role. The drop in the estimates of the returns to cognitive skills could reflect issues of pure measurement errors or could reflect the parallel importance of noncognitive skills.

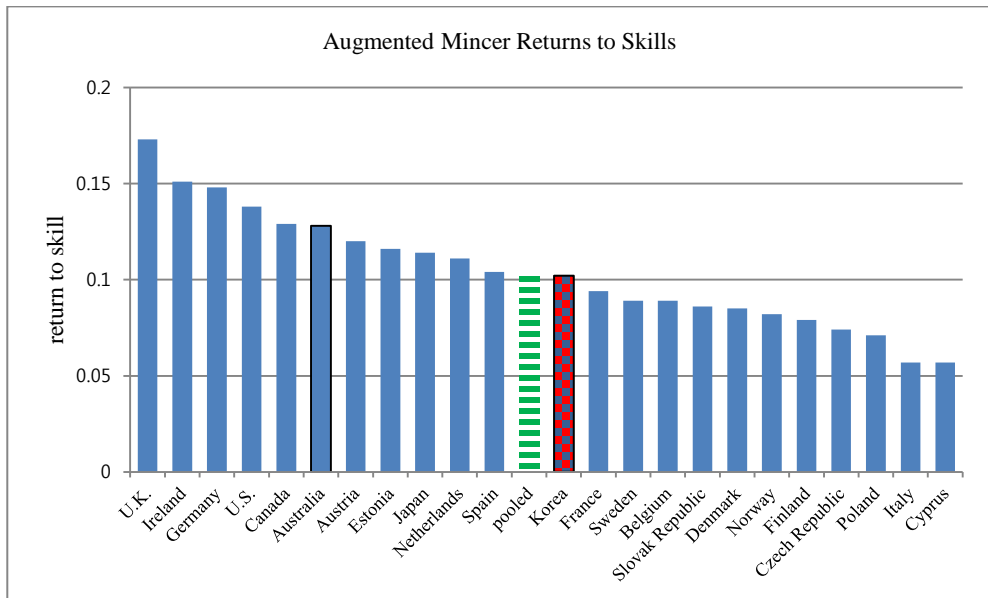


FIGURE 3. RETURNS TO NUMERACY IN AUGMENTED MINCER

Source: Hanushek et al. (forthcoming)

²¹Heckman, Stixrud, and Urzua (2006) develop a very general model of endogenous school choice and error-prone measures of cognitive skills and noncognitive skills. While simple regressions of cognitive skills and noncognitive skills show that cognitive skills explain much more of the earnings variation than noncognitive skills, their simulations of a factor model find larger wage impacts from going across the range of noncognitive skills as compared to the range of cognitive skills.

VII. A Different Viewpoint – Economic Growth

An alternative perspective on the measurement of human capital comes from looking at economic growth. As developed fully in Hanushek and Woessmann (2015), essentially the same measurement questions arising in the models of wage determination reappear when interest turns to empirical models of growth.

In the late 1980s and early 1990s, empirical macroeconomists turned to attempts to explain differences in growth rates around the world. Following the initial work of Barro (1991), hundreds of separate studies – typically cross-sectional regressions – pursued the question of what factors determined the very large observed differences. The widely different approaches tested a variety of economic and political explanations, although the modeling invariably incorporated some measure of human capital.

The typical development is that growth rates (g) are a direct function of human capital (H), a vector of other factors (X), and a stochastic element (ν), as in

$$(5) \quad g = rH + X\beta + \nu,$$

where r and β are unknown parameters to be estimated. The related empirical analysis employs cross-country data in order to estimate the impact of the different factors on growth.²²

From a very early point, a number of reviews and critiques of empirical growth modeling went to the interpretation of these studies. The critiques have focused on a variety of aspects of this work, including, importantly, the sensitivity of the analysis to the particular specification (e.g., Levine and Renelt 1992). They also emphasized basic identification issues and the endogeneity of many of the factors common to the modeling (e.g., Bils and Klenow 2000).

In both the analysis and the critiques, much of the attention focused on the form of the growth model estimated – including importantly the range of factors included – and the possibility of omitted factors that would bias the results. Little attention was given to measurement issues surrounding human capital.

When growth modeling looked for a measure of human capital, it was natural to think of measures of school attainment, building on the prior labor market analyses of Mincer.²³ This initial growth work, much like the common wage determination models, simply substituted S for human capital in eq. (5) and estimated the growth relationship directly.²⁴

²²A detailed discussion of this growth model and of its variants can be found in Hanushek and Woessmann (2008).

²³Initially, even thinking of measuring human capital by school attainment faced data shortcomings, but data construction by Barro and Lee (1993) provided comparable data on school attainment, and the international growth work could proceed to look at the implications of human capital. There were some concerns about the accuracy of the data series, leading to alternative developments (Cohen and Soto 2007) and to further refinements by Barro and Lee (2010).

²⁴A variety of different issues have consumed much of the empirical growth analysis. At the top of the list is whether eq. (5) should be modeled in the form of growth rates of income as the dependent variable, or whether it

Fundamentally, however, using school attainment as a measure of human capital in an international setting presents huge difficulties. In comparing human capital across countries, it is necessary to assume that the schools across diverse countries are imparting the same amount of learning per year in all countries. In other words, a year of school in Japan has the same value in terms of skills as a year of school in South Africa. In general, this is implausible.

A second problem with this measurement of human capital, as pointed out previously, is that it presumes schooling is the only source of human capital and skills. Yet, a variety of policies promoted by the World Bank and other development agencies emphasize improving health and nutrition as a way of developing human capital. These efforts reflect a variety of analyses into various health issues relative to learning, including micro-nutrients (Bloom, Canning, and Jamison 2004), worms in school children (Miguel and Kremer 2004), malaria, and other issues. Others have shown a direct connection of health and learning (Gomes-Neto *et al.* 1997; Bundy 2005). More broadly, as reviewed in Hanushek and Woessmann (2011a), a substantial body of work has recently developed in an international context, where differences in schools and in other factors are related to cross-country differences in achievement.

The analysis of cross-country skill differences used here is made possible by the development of international assessments of math and science (see the description in Hanushek and Woessmann 2011a). These assessments provide a common metric for measuring skill differences across countries, and they provide a method for testing directly the approaches to modeling growth, as found in equation (5).²⁵ Hanushek and Woessmann (2012) show that the achievement of the population is closely related to cognitive skills as measured by international math and science assessments and, importantly, that a casual interpretation is likely warranted.

The fundamental idea is that skills as measured by achievement, C , can be used as a direct indicator of the human capital of a country in eq. (5). And, as described in equation (2), schooling is just one component of the skills of individuals in different countries. Thus, unless the other influences on skills outside of school are orthogonal to the level of schooling, S , the growth model that relies on only S as a measure of human capital will not provide consistent estimates of how human capital enters into growth.

The impact of alternative measures of human capital can be seen in the long-run growth models summarized in Figure 4. The figure presents the result of estimating a simple model of long-run growth (g) over the period of 1960-2000 for the set of 50 countries with required data on growth, school attainment, and achievement (see Hanushek and Woessmann 2015). The underlying regression relates growth to initial levels of GDP and to human capital as measured by school attainment and cognitive skills measured by international test scores.²⁶ Not only is there a

should model the level of income. The former is generally identified as endogenous growth models (e.g., Romer 1990), while the latter is typically thought of as a neoclassical growth model (e.g., Mankiw, Romer, and Weil 1992). The distinction has received a substantial amount of theoretical attention, although little empirical work has attempted to provide evidence on the specific form (see Hanushek and Woessmann 2008).

²⁵This approach to modeling growth as a function of international assessments of skill differences was introduced in Hanushek and Kimko (2000). It was extended in Hanushek and Woessmann (2008) and in a variety of other analyses identified there.

²⁶The inclusion of initial income levels for countries is quite standard in this literature. The typical

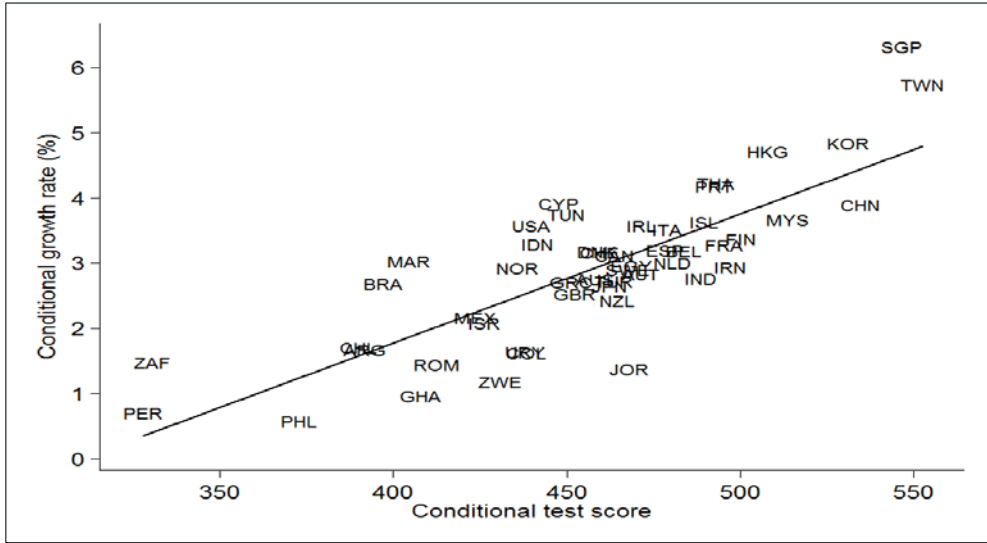


FIGURE 4. KNOWLEDGE CAPITAL AND ECONOMIC GROWTH RATES ACROSS COUNTRIES

Notes: Added-variable plot of a regression of the average annual rate of growth (in percent) of real GDP per capita in 1960-2000 on average test scores on international student achievement tests, average years of schooling in 1960, and initial level of real GDP per capita in 1960 (mean of unconditional variables added to each axis).

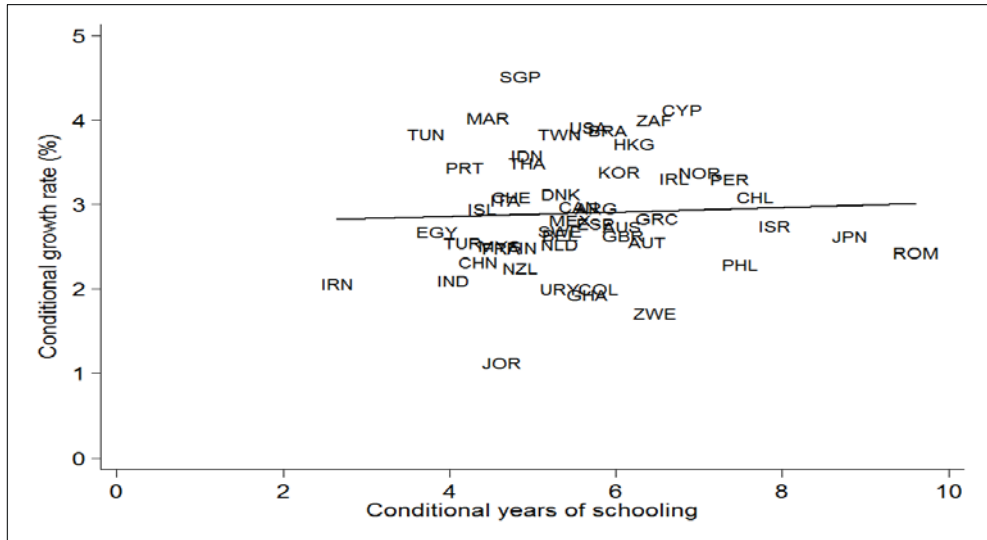


FIGURE 5. YEARS OF SCHOOLING AND ECONOMIC GROWTH RATES AFTER CONSIDERING KNOWLEDGE CAPITAL

Notes: Added-variable plot of a regression of the average annual rate of growth (in percent) of real GDP per capita in 1960-2000 on average test scores on international student achievement tests, average years of schooling in 1960, and initial level of real GDP per capita in 1960 (mean of unconditional variables added to each axis).

Source: Hanushek and Woessmann (2015).

interpretation is that this permits “catch-up” growth, reflecting the fact that countries starting behind can grow rapidly simply by copying the existing technologies in other countries, while more advanced countries must develop new technologies. Estimating models in this form permits some assessment of the differences between the endogenous and neoclassical growth models (see Hanushek and Woessmann 2011b).

significant relationship between cognitive skills and growth, but the simple model can also explain three-quarters of the variance in growth rates.

Importantly, as shown in Figure 5, once direct assessments of skills are included, school attainment is not significantly related to growth, and the coefficient on school attainment is very close to zero. Seen the other way, school attainment by itself can explain just one-quarter of the variation in growth rates across countries. These models do not say that schooling is worthless. They do say, however, that only the portion of schooling that is directly related to skills has any impact on cross-country differences in growth. The importance of skills and conversely the unimportance of schooling that does not produce higher levels of skills have a direct bearing on human capital policies for developing countries.

Finally, the estimated impacts of cognitive skills on growth are very large. The cognitive skills measure is scaled to standard deviations of achievement. Thus, one standard deviation difference in performance equates to two percent per year in average annual growth of GDP per capita.

For the measurement discussions here, two things are important, particularly as related to the prior evidence on wage determination. First, beyond cognitive skills (which in the aggregate we call the knowledge capital of nations) there is not much room for other factors to explain differences in growth rates. Second, while there was some confusion about how to interpret school attainment in the prior wage equations, there is no such confusion here – because only the portion of school attainment that is correlated with cognitive skills counts in the growth models.

VIII. Some Concluding Thoughts

Nobody doubts the role of human capital for either individuals or nations. But being able to measure the underlying skills consistently and accurately remains an issue. It is quite clear that school attainment cannot be a sufficiently accurate measure either for analysis of economic outcomes or for the development of appropriate policies. But the alternative is not fully certain.

Fairly recently there has been the development of data on cognitive skills – both for individuals and for nations – that provide one way to measure human capital. The development of various achievement tests has been going on for some time, so that many issues of internal reliability have been addressed. There still remain some questions about external validity and particularly the range of skills measured, but the prior results show that existing measures are strongly related to economic outcomes.

A parallel discussion of noncognitive skills has not moved to the same place yet. While there is considerable intuition behind the importance of noncognitive skills for individuals, and perhaps nations, there is less background in the measurement and testing of these.²⁷ Thus, for policy purposes, there is not strong guidance on when or how to consider noncognitive skill development.

²⁷See the development of these ideas in Heckman, Stixrud, and Urzua (2006). See also West *et al.* (2014) on the difficulty of measuring noncognitive skills and of understanding how they are produced.

REFERENCES

- Acemoglu, D. and J. S. Pischke.** 1998. "Why Do Firms Train? Theory and Evidence." *Quarterly Journal of Economics* 113 (1): 79-119.
- Acemoglu, D. and J. S. Pischke.** 1999. "Beyond Becker: Training in Imperfect Labour Markets." *Economic Journal* 109 (453): F112-F142.
- Altonji, J. and C. Pierret.** 2001. "Employer Learning and Statistical Discrimination." *Quarterly Journal of Economics* 116 (1): 313-350.
- Barro, R.** 1991. "Economic Growth in a Cross Section of Countries." *Quarterly Journal of Economics* 106 (2): 407-443.
- Barro, R. and Jong-Wha Lee.** 1993. "International Comparisons of Educational Attainment." *Journal of Monetary Economics* 32 (3): 363-394.
- Barro, R. and Jong-Wha Lee.** 2010. "A New Data Set of Educational Attainment in the World, 1950-2010." National Bureau of Economic Research (NBER) Working Paper 15902.
- Becker, G.** 1964. *Human Capital: A Theoretical and Empirical Analysis, with Special Reference to Education.* New York, NY: National Bureau of Economic Research.
- Bils, M. and P. Klenow.** 2000. "Does Schooling Cause Growth?" *American Economic Review* 90 (5): 1160-1183.
- Bloom, D., D. Canning, and D. Jamison.** 2004. "Health, Wealth and Welfare." *Finance and Development* 41 (1): 10-15.
- Bowles, S., H. Gintis, and M. Osborne.** 2001. "The Determinants of Earnings: A Behavioral Approach." *Journal of Economic Literature* 39 (4): 1137-1176.
- Bundy, D.** 2005. "School Health and Nutrition: Policy and Programs." *Food and Nutrition Bulletin* 26 (2): S186-S192.
- Card, D.** 2001. "Estimating the Return to Schooling: Progress on Some Persistent Econometric Problems." *Econometrica* 69 (5): 1127-1160.
- Chetty, R., J. Friedman, N. Hilger, E. Saez, D. Schanzenbach, and D. Yagan.** 2011. "How Does Your Kindergarten Classroom Affect Your Earnings? Evidence from Project STAR." *Quarterly Journal of Economics* 126 (4): 1593-1660.
- Cohen, D. and M. Soto.** 2007. "Growth and Human Capital: Good Data, Good Results." *Journal of Economic Growth* 12 (1): 51-76.
- Coleman, J., E. Campbell, C. Hobson, J. McPartland, A. Mood, F. Weinfeld, and R. York.** 1966. *Equality of educational opportunity.* Washington, D.C.: U.S. Government Printing Office.
- Cunha, F. and J. Heckman.** 2008. "Formulating, Identifying and Estimating the Technology of Cognitive and Noncognitive Skill Formation." *The Journal of Human Resources* 43 (4): 738-782.
- Goldin, C. and L. Katz.** 2008. *The Race between Education and Technology.* Cambridge, MA: Harvard University Press.
- Gomes-Neto, J., E. Hanushek, R. Leite, and R. Frota-Bezerra.** 1997. "Health and Schooling: Evidence and Policy Implications for Developing Countries." *Economics of Education Review* 16 (3): 271-282.
- Haider, S. and G. Solon.** 2006. "Life-cycle Variation in the Association between Current and Lifetime Earnings." *American Economic Review* 96 (4): 1308-1320.
- Hanushek, E.** 2002. "Publicly Provided Education." In *Handbook of Public Economics*, Vol. 4, edited by A. Auerbach and M. Feldstein. Amsterdam: North Holland, 2045-2141.
- Hanushek, E.** 2003. "The Failure of Input-based Schooling Policies." *Economic Journal* 113 (485): F64-F98.
- Hanushek, E.** 2011. "The Economic Value of Higher Teacher Quality." *Economics of Education Review* 30 (3): 466-479.
- Hanushek, E., and D. Kimko.** 2000. "Schooling, Labor Force Quality, and the Growth of Nations." *American Economic Review* 90 (5): 1184-1208.
- Hanushek, E., G. Schwerdt, S. Wiederhold, and L. Woessmann.** 2015. "Returns to Skills around the World: Evidence from PIAAC." *European Economic Review* 73: 103-130.

- Hanushek, E. and L. Woessmann.** 2008. "The Role of Cognitive Skills in Economic Development." *Journal of Economic Literature* 46 (3): 607-668.
- Hanushek, E. and L. Woessmann.** 2011a. "The Economics of International Differences in Educational Achievement." In *Handbook of the Economics of Education*, Vol. 3, edited by E. Hanushek, S. Machin, and L. Woessmann. Amsterdam: North Holland, 89-200.
- Hanushek, E. and L. Woessmann.** 2011b. "How much do Educational Outcomes Matter in OECD Countries?" *Economic Policy* 26 (67): 427-491.
- Hanushek, E. and L. Woessmann.** 2012. "Do Better Schools Lead to more Growth? Cognitive Skills, Economic Outcomes, and Causation." *Journal of Economic Growth* 17 (4): 267-321.
- Hanushek, E. and L. Woessmann.** 2015. *The Knowledge Capital of Nations: Education and the Economics of Growth*. Cambridge, MA: MIT Press.
- Hanushek, E. and L. Zhang.** 2009. "Quality-consistent Estimates of International Schooling and Skill Gradients." *Journal of Human Capital* 3 (2): 107-143.
- Hause, J.** 1971. "Ability and Schooling as Determinants of Lifetime Earnings or If You're so Smart, Why aren't You Rich?" *American Economic Review* 61 (2): 289-298.
- Hause, J.** 1972. "Earnings Profile: Ability and Schooling." *Journal of Political Economy* 80 (3): S108-S138.
- Heckman, J., L. Lochner, and P. Todd.** 2006. "Earnings Functions, Rates of Return and Treatment Effects: The Mincer Equation and Beyond." In *Handbook of the Economics of Education*, Vol. 1, edited by E. Hanushek and F. Welch. Amsterdam: North Holland, 307-458.
- Heckman, J., L. Lochner, and P. Todd.** 2008. "Earnings Functions and Rates of Return." *Journal of Human Capital* 2 (1): 1-31.
- Heckman, J., J. Stixrud, and S. Urzua.** 2006. "The Effects of Cognitive and Noncognitive Abilities on Labor Market Outcomes and Social Behavior." *Journal of Labor Economics* 24 (3): 411-482.
- Kiker, F.** 1966. "The Historical Roots of the Concept of Human Capital." *Journal of Political Economy* 74 (5): 481-499.
- Kiker, F.** 1968. *Human Capital: In Retrospect*. Columbia, SC: University of South Carolina.
- Lazear, E.** 2003. "Teacher Incentives." *Swedish Economic Policy Review* 10 (3): 179-214.
- Levine, R. and D. Renelt.** 1992. "A Sensitivity Analysis of Cross-country Growth Regressions." *American Economic Review* 82 (4): 942-963.
- Mankiw, N., D. Romer, and D. Weil.** 1992. "A Contribution to the Empirics of Economic Growth." *Quarterly Journal of Economics* 107 (2): 407-437.
- Marshall, A.** 1898. *Principles of Economics*, vol. 1. London: Macmillan and Company.
- McCallum, B.** 1972. "Relative Asymptotic Bias from Errors of Omission and Measurement." *Econometrica* 40 (4): 757-758.
- Miguel, E. and M. Kremer.** 2004. "Worms: Identifying Impacts on Education and Health in the Presence of Treatment Externalities." *Econometrica* 72 (1): 159-217.
- Mincer, J.** 1970. "The Distribution of Labor Incomes: A Survey with Special Reference to the Human Capital Approach." *Journal of Economic Literature* 8 (1): 1-26.
- Mincer, J.** 1974. *Schooling, Experience, and Earnings*. New York: NBER.
- Montenegro, C. and H. Patrinos.** Sept. 2014. "Comparable Estimates of Returns to Schooling Around The World." World Bank Policy Research Working Paper 7020.
- Mulligan, C.** 1999. "Galton Versus the Human Capital Approach to Inheritance." *Journal of Political Economy* 107 (6): S184-S224.
- Murnane, R., J. Willett, Y. Duhaldeborde, and J. Tyler.** 2000. "How Important are the Cognitive Skills of Teenagers in Predicting Subsequent Earnings?" *Journal of Policy Analysis and Management* 19 (4): 547-568.
- Petty, W.** 1676 [1899]. "Political Arithmetic." In *The Economic Writings of Sir William Petty*, edited by Charles Henry Hull. Cambridge, UK: Cambridge University Press: 233-313.
- Psacharopoulos, G.** 1973. *Returns to Education: An International Comparison*. San Francisco, CA: Jossey-Bass Inc.
- Psacharopoulos, G. and H. Patrinos.** 2004. "Returns to Investment in Education: A Further Update." *Education Economics* 12 (2): 111-134.
- Romer, P.** 1990. "Endogenous Technological Change." *Journal of Political Economy* 99 (5):

S71-S102.

Schultz, T. 1961. "Investment in Human Capital." *American Economic Review* 51 (1): 1-17.

Smith, A. 1776[2010]. *The Wealth of Nations*. Simon and Brown.

West, M., M. Kraft, A. Finn, R. Martin, A. Duckworth, C. Gabrieli, and J. Gabrieli. Sept. 2014. "Promise and Paradox: Measuring Students' Noncognitive Skills and the Impact of Schooling." CESifo Area Conference on Economics of Education Munich: CESifo.

Wickens, M. 1972. "A Note on the Use of Proxy Variables." *Econometrica* 40 (4): 759-761.