Intelligence, Human Capital, and Economic Growth:
An Extreme-Bounds Analysis

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Human capital plays an important role in the theory of economic growth, but it has been difficult to measure this abstract concept. We survey the psychological literature on cross-cultural IQ tests, and conclude that modern intelligence tests are well-suited for measuring an important form of a nation's human capital. Using a new database compiled by Lynn and Vanhanen (2002), we show that national average IQ has a robust positive relationship with economic growth. Using a methodology derived from Sala-i-Martin (1997a), we show that in growth regressions that include only robust control variables, IQ is statistically significant in 99.7% of these 1330 regressions. A strong relationship persists even when OECD countries are excluded from the sample. A 1 point increase in a nation's average IQ is associated with a persistent 0.16% annual increase in GDP per capita.

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The concept of human capital holds an important place in the theory of economic growth. However, the question of just how to measure a nation's stock of human capital is an unresolved issue in empirical growth research. Mankiw, Romer, and Weil (1992) kindled interest in empirically testing a Solow model that included human capital. They used a nation's average years of secondary education as their proxy for human capital. Other researchers, most notably Sala-i-Martin (1997a,b), have considered primary school enrollments as one reasonable measure of human capital.

While economists commonly use education as a proxy for human capital, this widespread practice has coexisted with longstanding doubts about using school enrollments as a measure of human capital. This is because it is widely believed that educational *outcomes* are ultimately what matter for producing human capital, not just the quantity of educational *inputs*.

The ability to solve problems, to think creatively, to recall facts and to reinterpret those facts in the light of changing circumstances: these are some of the key elements that economists seem to be thinking of when we think about "human capital." In describing human capital this way, we are setting aside discussion of job-specific human capital, the creation of which is analyzed in theoretical labor market models. General-purpose human capital has been the focus of growth research, and it is here that we place our focus in this paper.

Fortunately for economists, psychologists spent the 20th century putting a great deal of energy into refining and improving upon one valuable technique for measuring this particular type of human capital: The intelligence test.

We use a new database of IQ tests from 70 countries in growth regressions that evaluate the explanatory power of IQ. These regressions include combinations of the 21 growth variables that passed Sala-i-Martin's (1997) robustness test. Out of these 1330 regressions, IQ was statistically significant in 99.7% of them.

We also evaluate the explanatory power of IQ in growth regressions that include Sala-i-Martin's education measures. Among these 56 education-related regressions, IQ was statistically significant in every one, thus passing not only Sala-i-Martin's robustness test, but also Leamer's (1983, 1985) extreme bounds test. By comparison, in Sala-i-Martin's original paper, only one education measure–average primary school enrollment–passed a robustness test. While one might expect that at least *some* linear combination of primary, secondary, and higher education measures could eliminate the statistical significance of IQ, we did not find this to be the case.

As final robustness check, we also show strong results for IQ when OECD countries are completely excluded from the sample. This evidence helps to address the concern that IQ tests are culturally biased in favor of people living in the developed world. We also show that, in all cases, including IQ in the regressions appears to diminish the robust statistical and economic significance of primary school enrollment.

Our IQ-based results bolster the conclusions of Hanushek and Kimko (2000), who found that international mathematics and science test scores from 31 countries were strongly positively correlated with growth; the authors use interpolation methods to expand the sample to a total of 80 countries, with similar results. Hanushek and Kimko consider the math and science scores to be indications of "labor quality." It appears that IQ should likewise be considered as another robust measure of a nation's labor quality.

The results presented here imply that a 10-point increase in national IQ will persistently raise a nation's average growth rate by 1.6%. The relationship between IQ and growth appears to be economically large and statistically robust, and provides more reliable results than other education measures. Therefore, risk-averse policymakers would do well to include changes in IQ as a reliable measure of changes in their nation's stock of productivity-enhancing human capital. We discuss below some of the policies--including improvements in early childhood nutrition, a healthier environment, and parental literacy--that appear to be effective at increasing this measure of human capital in developing countries.

Cross-cultural tests of intelligence and human capital formation

In a country such as the United States in which the average person rates his or her own intelligence at roughly one standard error above the mean (Furnham, 2001), IQ tests are bound to be regarded by many with suspicion and ill-will. More seriously, egalitarians are skeptical of the validity of IQ tests when group differences in cognitive ability are reported. Undoubtedly, there are few topics within the discipline of psychology that have generated as much controversy as have IQ tests. Criticisms of IQ tests found in public discourse range from the subtle and sophisticated to the misinformed and absurd. It is not our purpose to address every objection that can be made about the validity of IQ tests. In a sense, controversial matters such as to what degree individual differences in IQ are genetically mediated or to what degree IQ tests are biased against people of various groupings (e.g., by sex, class, race, or ethnicity) are irrelevant to our thesis: As we demonstrate below, differences in IQ, whatever their origins and influences, appear to reflect differences in a type of human capital strongly associated with long-term economic growth.

IQ--short for Intelligence Quotient--refers to one's relative average performance compared to one's same-age peers on a wide variety of tests of cognitive ability. Compared to tests such as the SAT or ACT (which have components that are similar to components of IQ tests), the range of tasks and problems in IQ tests is extremely broad. Although the public tends to conceptualize intelligence as primarily consisting of verbal knowledge and high academic performance (Flugel, 1947; Shipstone & Burt, 1973), IQ tests measure a wide variety of cognitive abilities with general knowledge and verbal reasoning given equal status with other important capacities such as spatial reasoning, inductive and deductive reasoning, quantitative reasoning, verbal fluency, memory retrieval fluency, short-term memory, long-term memory, phonological awareness, reasoning speed, perceptual speed, simple decision speed, and many others. The advantage of including a wide variety of tasks in an IQ test is that a person's score will not be unduly influenced by idiosyncratic strengths and weaknesses on specific tasks.

Although it can be helpful to consider the peaks and valleys of a person's performance of the different tasks, vast quantities of research indicate that it is the mean elevation of the profile (which is reflected in the Full Scale IQ) and not the specific patterns of strengths and weaknesses that account for virtually all of an IQ test's predictive validity (Ree, Carretta, & Green, 2003). Thus, although it is certain that intellectual performance is multidimensional (Carroll, 1993), the Full Scale IQ is by far the most useful measurement to consider in most situations in which an IQ test is administered.

The Full Scale IQ is one way to operationalize the theoretical construct of *g*. Originally *g* was so named for the *general* factor of intelligence. Some researchers prefer not to use the term "intelligence" because the term has acquired so many different meanings that scientific discourse is hampered by its use (Jensen, 1998). The earliest identified and most persuasive evidence in favor of *g* is the startling (and unexpected) observation that every single test of cognitive ability is positively correlated with every other test of cognitive ability so far identified. Psychologists have sought diligently for cognitive abilities that are unrelated to other cognitive abilities but have thus far failed. The fact that all tests of cognitive ability are positively correlated guarantees that factor analysis will extract a general factor that loads on all tests in the test battery. Depending on the nature of tests in the battery and the particular method of factor analysis used, other factors will emerge in a factor analysis as well (e.g., verbal, numerical, spatial, motor speed, perceptual speed, and phonological awareness). These smaller factors often have their uses in conjunction with *g* in narrow applications (e.g., prediction of musical ability, dyslexia, and typing speed) but rarely do these smaller factors of ability by themselves approach the predictive validity of *g* (Ree, Carretta, & Green, 2003). Despite the claims of some critics (e.g., Gould, 1981), the scientific foundation of *g* does not depend solely on the statistical procedure of factor analysis (Jensen, 1998).

The range of outcomes that IQ can predict with varying degrees of precision is very broad. For example IQ's correlation with tests of academic achievement is about .6 to .7 in elementary school, .5 to .6 in high school, .4 to .5 in college, and .3 to .4 in graduate school (Jensen, 1980, p. 319). IQ's correlation with grade point averages is about .1 to .2 lower than the correlations with academic achievement tests (Jensen, 1980, p. 320). Across all job types in the U.S. economy, the average correlation of IQ and supervisor ratings of job performance is about .3 to .5 (and the correlation is higher when job performance is measured objectively). Furthermore, IQ predicts performance better in complex occupations ($r = .56$) than simple ones ($r = .23$; Gottfredson, 1997). IQ correlates positively with occupational prestige, educational attainment, creativity, physical health, mental health, lifespan, and brain size and negatively with criminal status, poverty, chronic welfare dependence, unemployment, divorce, and single-parenthood (Herrnstein & Murray, 1994). The correlations for some of these outcomes is low enough that IQ has little accuracy for predicting outcomes of specific individuals and leave much variance unexplained but it should be noted that no other psychological trait has a predictive validity even close to that of IQ for such a broad array of outcomes (Gottfredson, 1997).

Some have speculated (hoped?) that IQ's predictive validity derives mainly from its ability to predict the low educational and occupational achievement of individuals with genetic abnormalities that cause mental retardation (e.g., Down's Syndrome). If this were the case, IQ would act as a step function in which higher IQ would predict diminishing or no returns for people with higher IQ. It appears, however, that the relation between IQ and most outcomes is linear at all levels of IQ. For example, the achievement differences between children with an average IQ of 146 and children with an average IQ of 165 are roughly the same as the achievement differences between children with an average IQ of 100 and children with an average IQ of 120 (Jensen, 1980, p. 319).

Is IQ simply an index of socioeconomic status? If so, it is difficult to explain many findings such as the fact that people with higher IQ's than their siblings (who, presumably, share the same socioeconomic status) tend to perform better in school, have higher status jobs, and earn higher incomes than their siblings (Murray, 1997).

Are IQ tests biased against women, poor people, and ethnic minorities? It is certainly true that early IQ test designers were less sensitive to such issues and included some test items that were biased against lower status individuals. However, even the earliest test developers removed any type of test item that gave a significant advantage to either sex. Responding to legitimate criticism, contemporary test developers have worked hard to develop statistical tools and common sense procedures to detect and eliminate most types of bias in IQ tests. Statistical tools to detect bias are necessary because casual inspection of test items does not reveal bias reliably. Numerous studies have found that test items identified by experts as most culturally loaded are not more difficult (and are often easier) for minority groups (Jensen, 1980, p. 528-529). Since the 1970's, research has repeatedly failed to demonstrate meaningful bias in terms of predictive and construct validity in major contemporary IQ tests for native-born English-speaking minority groups in the United States (Brown, Reynolds, & Whitaker, 1999; Jensen, 1980). That is, IQ predicts important outcomes equally well for these groups. If IQ tests are biased against these groups, then the criteria we use to detect such bias such as educational and occupational performance must be equally if not more biased.

Do IQ tests simply reflect the biases of Western Civilization? If they do, it is difficult to explain why East Asians (even from poor countries such as China) slightly outperform Europeans on IQ tests designed by Western scientists. If IQ tests are hopelessly biased against non-Westerners, it is difficult to explain why individual differences in IQ have moderate correlations with brain size (r=.4) in every society in which both brain size and IQ have been measured (Rushton & Rushton, 2003). It is even more difficult to explain why IQ correlates (r = .37 after correction for attenuation) with nerve conduction velocity in the visual pathways of the brain (Reed & Jensen, 1992). IQ correlations with nerve conduction velocity is especially difficult to explain from an "IQ is merely bias" perspective because the procedure requires no active response on the part of the examinee.

If IQ does not measure anything substantive about the performance of the brain, it is difficult to explain the robust correlations of IQ tests with elementary cognitive tasks.

Elementary cognitive tasks are extremely simple tasks that everyone, including the mildly to moderately mentally retarded can perform with near perfect accuracy. One such elementary cognitive task is a reaction time task called the Jensen Box. In this task a person is shown an array of 1 to 8 buttons. Whenever a button lights up, the person lifts his or her hand from a home button and taps the lighted button. The correlation of performance on the Jensen Box and IQ is about .3 to .4 (Deary, 2003). The hypothesis that the correlation simply reflects greater motivation to perform on the Jensen task and on IQ tests is belied by the fact that IQ correlates more strongly with Reaction Time (the interval between the onset of the light and lifting of the hand from the home button) than with Movement Time (the interval between lifting the hand from the home button and hitting the lighted button).

Another promising elementary cognitive task uses the Inspection Time paradigm in which a person is shown 2 lines on a computer screen; the lines are then masked quickly afterward. The person is asked which line was longer. The task is so simple that everyone can understand it and perform it perfectly and no motor response is required. The only parameter that is manipulated to make the task more difficult is the number of milliseconds the person is shown the lines before they are covered up by the mask. The interval in which the person is allowed to inspect the lines decreases until the person no longer can reliably indicate which line is longer. Thus, the task measures the speed of perception rather than the speed of response. The correlation between performance on inspection time tasks and IQ tests is about .5 (Nettelbeck, 2003).

Although the elementary task and biological correlates of IQ are impressive, it is important not to be lulled into believing that all things biological are genetically determined and immutable. It is certain that there are many environmental effects on IQ and the brain (Sternberg

& Grigorenko, 2001). No major theorist claims otherwise. It is thus reasonable that a society could make changes to maximize the cognitive abilities of its population. Indeed, it appears that many societies have been doing so successfully for several decades. Among the group of countries for which there exist time-series data on that nation's average IQ, measured IQ's appear to rise an average of two to three points per decade, a phenomenon known as the *Flynn Effect*, after Flynn (1987).

Although the meaning of the Flynn effect is still hotly debated in the psychology literature, especially over whether it reflects a genuine increase in the problem-solving ability of the population, or some trivial factor such as teachers' greater tendency to "teach to the test," some lessons have been learned. For example, results for the U.S. demonstrate that the rise in average IQ's comes more from a rise in the bottom half of the nation's IQ distribution, and less from a rise in the top half. In fact, it appears that the overall IQ distribution is becoming *more equal* over time (in contrast to the U.S. income distribution), even as the mean rises (Seligman, 1992, p. 180).

As psychologists have given a wider variety of intelligence tests over a longer period of time in more countries, the Flynn effect continues to turn up in the data. Especially interesting results, with possible Solow-like convergence implications, have been found in Kenya. In Kenya, average IQ scores increased by 11 points over the 14-year period of 1984 to 1998 (almost 3 times the average rate of increase in industrialized countries); the factors positively associated with IQ gains appeared to be parental literacy, shrinking family size, and improved childhood nutrition and health (Daley, Whaley, Sigman, Espinosa, & Neumann, 2003). Unfortunately, as this is still an area of active debate, integrating country-specific Flynn effects would be beyond the scope of this paper.

Although within a society it is useful to measure verbal knowledge (e.g., What does "imply" mean? What is the capital of China?) and comprehension (e.g., Why are people accused of a crime in some countries given the right to remain silent? Why do banks pay interest to people with savings accounts?), language and cultural differences make such measurements problematic for purposes of cross-cultural research. Psychologists have developed many types of tests that measure reasoning ability using visual figures and patterns that minimize the effects of language and cultural differences. These tests, so-called "Culture-Fair" or "Culture-Reduced" intelligence tests, have roughly the same validity coefficients in predicting important outcomes as more culturally loaded tests (Court,1991). The best-known of the IQ exams for non-literate persons are Catell's Culture-Fair Intelligence Test and Raven's Progressive Matrices, both of which ask the respondent to find patterns in groups of abstract objects. Psychologists have also worked to ensure that a literate person's estimated IQ will not change markedly if she takes one type of intelligence test rather than another.

This brief review of the validity of IQ tests only scratches the surface of a voluminous literature that is virtually univocal in its support of the utility and validity of IQ tests (Neisser et al., 1996). For a non-technical explanation of intelligence the reader is referred to Seligman (1992); for a more technical summary of the literature on the physiological, genetic, and behavioral observations supporting the existence of *g*, Jensen (1998) is especially valuable. In addition, Gottfredson (1997) has written a comprehensive yet accessible review of the occupational correlates of IQ.

Data

As noted above, we borrow much of our data from Sala-i-Martin's "I Just Ran Two Million Regressions." His dataset--available at his website, www.columbia.edu/~x23 --was chosen because it is widely known and widely used. Further, given the fact that we introduce one entirely new variable into the empirical growth literature, it would have been cumbersome to explain and justify the details of an entirely untested set of growth data. One especially valuable feature of Sala-i-Martin's dataset is that he made every effort to use values estimated at the beginning of the period (1960) to limit the endogeneity problems that are endemic to empirical growth research. The names of the variables we use—the 21 variables that passed his robustness test, the three variables used in all regressions, and his education measures—are included in Table 1. For further information on the Sala-i-Martin dataset, as well as for a methodological critique of Sala-i-Martin's methodology, Hoover and Perez (2000) is invaluable.

Our IQ data come from Lynn and Vanhanen (2002, henceforth LV). Lynn, a psychologist, and Vanhanen, a political scientist, assembled a database of IQ tests from 81 different countries. These scores were derived from a variety of different types of intelligence tests given between the 1950's and the 1990's, using "Culture-Fair" or "Culture-Reduced" tests where possible.

According to LV, the world's average IQ (not weighted by population) was 88.2 and the standard deviation of world IQ was 11.4. As a point of reference, note that the average British IQ is defined as equal to 100, and within Great Britain, the population standard deviation within Great Britain is 15. The reader who is interested in further detail regarding the database is encouraged to consult Appendix 1 of Lynn and Vanhanen (2002).

Lynn and Vanhanen, in their original work, reported the results of a univariate regression of the level of a nation's GDP per capita in 1998 (not the more common log-level) on IQ and a constant for 81 countries, and report that one additional IQ point is associated with a $519 increase in 1998 GDP per capita; this regression had an R^2 of 53%.

LV also performed some simple multivariate analyses using measures of political and economic freedom as additional explanatory variables; however, these multivariate analyses used interpolated IQ data for 104 additional countries, to create an artificial "dataset" of 185 countries.

These interpolations were often based on methods that we do not endorse (e.g., assuming that members of a specific racial group have the same average IQ regardless of the country they live in), and therefore we exclude all of LV's interpolated data from our study. Two of LV's 81 original observations (for Peru and Columbia) also relied heavily on a form of interpolation, and so we exclude these observations from our dataset.

We discard another nine of Lynn and Vanhanen's 79 non-interpolated observations, either because the sample size in the particular country was not stated or was less than 100, or because the IQ estimate relied solely on the scores of emigrants. This leaves us with 70 usable observations. Table 2 provides a complete list of these 70 estimated national average IQ's by country.

Because some of the countries included in LV dataset are not included in Sala-i-Martin's dataset, our regressions include a maximum of 51 countries. The mean IQ in this dataset is 90.2 and the standard deviation of IQ is 11.4. As noted above, this sample of 51 is notably larger than Hanushek and Kimko (2000), who relied upon math and science tests from 31 countries.

The national IQ estimate used in our research is the same used by LV: an average of all same-country IQ studies. However, for 36 of LV's 81 countries, LV rely on just one IQ study to estimate that nation's average IQ. This raises the question of whether one study is enough to estimate a nation's average IQ. LV answer this question by analyzing the distribution of IQ scores across various studies of the same country. In these cases, the within-country correlation between each study's average IQ scores for that country is 0.939. This high intra-country correlation across studies provides some confidence that one study alone provides a reasonable estimate of a nation's average IQ. We look forward to reassessing our results as more comprehensive databases of world IQ estimates become available.

Two published studies have used LV's data in growth regressions: Weede and Kampf (2002) and Volken (2003). However, both studies used LV's interpolated data as well as the authentic data, which may distort their results. Weede and Kampf report the results of 14 regressions, some of which include the Barro-Lee (1993) education measures along with other education measures. They find that national IQ has a large and statistically significant relationship with growth, even controlling for education measures, similar to our results. Volken, using a similar dataset focusing on education, reports results from 10 regressions, and finds that the relationship between IQ and growth becomes unstable once certain education variables are included. We believe that these inconsistent results probably reflect the decision to use LV's interpolated data.

We follow the practice of LV, who assume a Flynn effect of 2 or 3 points per decade, depending on which exam was given. For example, the Iranian average IQ, based on a 1957 test, was estimated as equal to an 80 when compared to the a similar British test given in 1979. Because of the Flynn effect, LV assume that Iranian IQ's have risen by an average of two points per decade since 1957, so Iran's average estimated IQ is inflated to 84 in LV's dataset. This adjustment, while not ideal, follows the best practice of the psychological profession. Further, it allows us to treat all national IQ scores listed in Table 2 as being in what economists might think of as "Real 1979 IQ."

In summary, while LV's dataset has its problems, theirs is the first comprehensive attempt to assemble studies of IQ from around the world in such a way as to allow direct, international comparisons. We hope that the results we present will encourage others to delve more deeply into these intelligence tests. A comprehensive time-series database of such tests would be a natural next step.

To give an overall impression of how these IQ data compare with test scores used by other growth economists, Figure 1 shows the relationship between these IQ measures and the Barro-Lee (1993) national educational achievement scores for math, science, and reading from 23 countries, and Figure 2 compares IQ to Hanushek and Kimko's (2000) two indices of national labor quality, based upon math and science examinations. Hanushek and Kim (1995) describe how these labor quality measures were constructed. Our IQ observations overlap with 27 of Hanushek and Kimko's 31 observations.

Note that the Barro-Lee math and science scores have a particularly strong relationship with national average IQ, and both of Hanushek and Kimko's measures correlate positively with IQ. These correlations provides some reason to believe that all of the exams measure a similar set of mental abilities, however imperfectly. This strong positive correlation would come as no surprise to cognitive psychologists, who, as noted above, have found that outcomes on tests of mental ability invariably positively correlate with each other, with the correlation strongest when the test performance relies on what psychologists refer to as "general intelligence." Figure 3 is a simple plot of IQ against real GDP per capita in 1992, measured in Summers-Heston purchasing-power adjusted dollars.

Finally, note that to the extent that our IQ data mismeasure the actual human capital of the population, and to the extent that such mismeasurements come in the form of independently distributed error terms, the resulting errors in variables will generally tend to bias our coefficient estimates downward. Therefore, if IQ is a "Mismeasure Of Man," in Gould's formulation (1981), then our estimates of IQ's impact on growth may well be too small.

Methodology

Since so many variables could plausibly have an impact on economic growth, the 1990's witnessed a flood of articles that each introduced and tested the statistical significance of a "new" variable, such as a nation's land mass, percent Protestant, or percent of GDP devoted to equipment investment. Many variables were found to have a positive relationship with growth, but economists were skeptical about whether any causal relationship was underlying the regressions results, and were also concerned that perhaps the statistical significance was an artifact of which control variables happened to be included in the regression.

To address these concerns, our methodology is in the spirit of--and, as noted above, uses data from--Sala-i-Martin's "I Just Ran Two Million Regressions"(1997a). Sala-i-Martin's general approach is to start with a sizable set of variables plausibly related to growth, and to then run every single possible regression with that set of variables. Sala-i-Martin then presents summary statistics designed to give the reader of sense of how often and to what degree a particular variable was correlated with growth. Sala-i-Martin judges a variable to be statistically significant if more than 95% of a variable's "cumulative distribution function" was greater than zero. In practice, this closely corresponds to the case where the average coefficient value across all regressions is two standard errors away from zero (where the standard error, likewise, is an average across all regressions).

We broadly follow Sala-i-Martin's approach in order to demonstrate that the relationship between IQ and economic growth is not a mere coincidence, and that it is a relationship as strong as that between such canonical growth variables as equipment investment and number of years the economy has been open to trade. In so doing, we implicitly run a stricter Leamer-style (1983, 1985) "extreme bounds test" on IQ, the results of which we also report.

The key question we want to ask is whether IQ has a robust statistical relationship with a nation's average growth rate from 1960 to 1992, the time period studied by Sala-i-Martin.

We run four sets of regressions, all of which use the average growth rate of per capita GDP from 1960 to 1992 as the dependent variable. Following Sala-i-Martin, each regression includes a total of seven explanatory variables: log per capita GDP in 1960, percent of the age-relevant population enrolled in primary school in 1960, life expectancy in 1960, the nation's estimated average IQ (the variable of interest), and three additional control variables.

The three additional control variables are drawn from one of two sets: the 21 variables that passed Sala-i-Martin's robustness test, or the eight measures of human capital included in Sala-i-Martin's original dataset. Note that none of these eight education measures passed Sala-i-Martin's robustness test; the aforementioned primary school enrollment variable was the sole education variable to meet the 95% threshold value.

We run a separate regression for every possible combination of these variables. This implies that there are 1330=21!/(18!3!) regressions in the 'top 21' set, and 56=(8!/(5!3!)) regressions in the second set. As noted in the introduction, we rerun all results excluding the

OECD countries, in order to address the concern that perhaps IQ tests are biased in favor of the world's developed Western countries.

To summarize our regression results for IQ, we slightly modify one of Sala-i-Martin's summary methods, that of estimating the cumulative distribution function of the coefficient for IQ. We create a weighted average of the IQ coefficient estimates, β_{IQ}, over all estimates in each set of regressions. The β_{IQ} from each regression is weighted by the R^2 from that regression, and then divided by the sum of all R^2's from all regressions. Therefore, if R^2_i is the percent of variance in growth rates explained by regression *i*, then in the regression using the top 21 variables

$$\overline{\beta}_{IQ} = \left(\left(\sum_{i=1}^{1330} \beta_{IQ,i} R_i^2\right) / \sum_{i=1}^{1330} R_i^2 \right).$$

The standard error of $\overline{\beta}_{IQ}$ is calculated similarly. This differs from Sala-i-Martin's approach in that he weights the averages by the likelihood of the regression rather than the R^2. Since we used OLS estimators, R^2 was more readily available. The effect of the R^2 weighting is to give a greater weight to regressions that do a better job explaining the data. We also report unweighted averages of the coefficients and standard errors.

By comparing the weighted and unweighted results, we will be better able to determine whether IQ is a variable that matters most when it is paired with a strong set of control variables or with a weak set. If the latter holds, this could raise some questions about IQ's robustness: It would imply that IQ matters most (in the sense of having a larger coefficient) when other regressors matter little.

The other statistics we report are the minimum value of the lower end of the 95% confidence interval, β_{IQ}-1.96*σ_{IQ}, across all regressions in that set. We also report the percent of regressions in that set where β_{IQ} was statistically significant. As noted above, due to the lack of complete data on some countries, we have a total of 51 observations in our dataset.

Results

Table 3 reports our main results. The first two rows report information on the IQ coefficient using data from all countries, while the third and fourth rows repeat these regressions, while omitting observations from the OECD countries. We focus attention on the weighted results, in part because the methodology used in these results is closest Sala-i-Martin's.

Consider the first row of results: Using data from all countries, and including all possible 3-variable combinations of Sala-i-Martin's top 21 growth variables as explanatory variables (along with log GDP per capita in 1960, primary school enrollment in 1960, average lifespan in 1960, and a constant), IQ was statistically significant in 99.7% of the 1330 regressions. Thus, it failed to reach statistical significance (at the 95% confidence level) in four of these 1330 regressions.

The third column reports the lowest value of the lower end of the confidence interval from the 1330 regressions; this is the value that must be strictly positive in order to pass Leamer's extreme bounds test. The value, -0.0214, means that IQ fails Leamer's rigorous test in this case.

However, IQ passes Sala-i-Martin's less-demanding test quite easily: The weighted average IQ coefficient is more than five weighted average standard errors from zero, so not only can we be extremely confident that the true coefficient is not zero, but we can also be 95%

confident that the true value lies between 0.0947 and .2173. Thus, raising a nation's IQ by 10 points is estimated to add between 0.95% and 2.17% to a nation's annual growth rate, with a point estimate of 1.56%.

Considering all the results from Table 3, the coefficient on average IQ is at least two standard errors away from the mean, so even the weakest results for IQ pass Sala-i-Martin's 95% confidence-interval test. The results that exclude the OECD countries are weaker (likely due to restriction of range), but still above the two standard error cutoff.

R^2 weighting appears only to strengthen our key results. The fact that the weighted average yields higher coefficients than the unweighted average means that the highest β_{IQ} estimates tended to occur in the regressions that also had the highest R^2. This has an important econometric and economic implication: IQ does a better job explaining growth when the other control variables also do a better job explaining growth. IQ is not a variable that only matters when the regression contains weak explanatory variables; in fact, just the opposite appears to be the case. Thus, it would appear that if we had run our regressions using all of Sala-i-Martin's 62 variables—for 30,856 total regressions—our results would be only stronger.

We also note that IQ easily passes a Leamer-style extreme bounds test when regressed along with this particular set of education measures: Out of our 56 education regressions using data from all 51 countries, the extreme lower bound was still positive. Thus, the support for β_{IQ} appears to be strictly positive when other education variables are included as explanatory variables in the full-country dataset. It is noteworthy that no three-variable combination of education measures can eliminate the statistical robustness of IQ. So whether regressed along with Sala-i-Martin's top 21 or against other human capital variables, IQ performs extremely well.

Table 4 reports a comparison between IQ and Sala-i-Martin's best-performing education variable, primary school enrollment. IQ appears to eliminate the statistical significance of primary school enrollment in a growth regression: In no case is the primary school enrollment coefficient twice the size of the standard error, and in most cases it is smaller than the standard error. Some of the decline in statistical significance of primary school enrollment is likely due to the fact that the control variables are limited here to Sala-i-Martin's top 21 variables (a robust set of regressors) or other education variables (with which primary enrollment is collinear). However, these econometric problems apply with just as much force to IQ as to primary school enrollment, but IQ is extremely robust while primary school enrollment loses much of the robustness it had. [1]

While statistical significance is surely not economic significance, it is reasonable to wonder what these results mean. One might interpret these results as indicating that IQ measures a key output of the education, socialization, and child-rearing process—an output called general reasoning ability—while primary school enrollments are a measure of one key input. Inputs are likely to have a noisy relationship with outputs, so the weak relationship between schooling and growth is little surprise.

What is a surprise, at least from the point of view of much growth research, is that a heretofore overlooked measure of educational output—the IQ test—is so robustly related to growth. Growth economists may know little about how a nation's stock of human capital is

[1] In results not reported here, we estimated sets of regressions similar to those reported in Table 4, but used education measures other than primary school enrollment as the schooling variable. We also estimated separate versions that excluded IQ entirely, in order to assess the marginal importance of IQ in the growth regressions. However, as in Sala-i-Martin's work, primary school enrollment was the most robust variable among all of the education-related measures we tested. The other education measures were so weakly correlated with growth that we do not report the results here.

produced, but it appears that we at least have a tool for measuring a critical portion of that stock of human of capital.

Further research can now be done to determine exactly what role this form of human capital plays in the growth process. Is IQ an engine of growth, part of the technology production function? Or is a high national IQ more critical as a resource for *adapting* the technologies that are developed elsewhere? Developing and testing such models is far beyond the scope of this paper, but we hope that our results spur others to wrestle with these questions.

Finally, for an overall assessment of how IQ compares to other common growth variables, consider Sala-i-Martin's original results, which used combinations of 62 growth variables in over two million regressions. Among his top 21 regressors--the ones which he considered robust--the median regressor was statistically significant in 76.4% of cases, with a range from 100% (for fraction Confucian) to 2.81% (for revolutions and coups). Fraction Confucian was the only regressor that passed an extreme bounds test. Only eight of the top 21 had coefficients over three standard errors from zero, while in our full-sample results using his top 21 growth variables, IQ's coefficient is over five standard errors away. For his overall best performing variable, equipment investment, the coefficient estimate was 5.32 standard errors away from zero. IQ would thus appear to fit comfortably in the top half of Sala-i-Martin's top 21 growth variables.

Conclusion

If human capital accumulation is important in economic development, then it would be valuable to have a reliable measure of this stock of human capital. The evidence presented here indicates that general intelligence, as measured by IQ tests, is a reliable indicator of such human capital, and that such general human capital is an extremely important component of economic growth. IQ outperforms the best-performing measure of human capital in Sala-i-Martin's widely used dataset—primary school enrollment—and is statistically significant in all but four out of 1330 full-sample growth regressions. Even when OECD countries are excluded from the sample, IQ appears to have an economically large and statistically significant positive relationship with growth.

It would, of course, be extremely valuable to have data from more countries over a longer time period, and we hope that these encouraging results encourage the collection of cross-country IQ data in the future.

There is one critical issue we have mentioned here but have not fully addressed: The endogeneity of IQ over time. We mention the Flynn effect, the 2 to 3 points-per-decade increase in IQ found in developed countries, an increase that appears to come mostly from a rise in the bottom of a population's IQ distribution. This effect gives researchers some reason to believe that increases in education, reductions in poverty, and increases in overall literacy can increase a nation's average IQ.

Our estimates of IQ account for the Flynn effect, but do so imperfectly. In particular, psychologists are just beginning to understand why the Flynn effect is higher in some countries rather than others, so we do not make country-specific Flynn effect adjustments to our IQ data. But as the structure of the Flynn effect becomes clearer, economists and psychologists may uncover Solow-type convergence results for national average IQ. We hope that the results presented here will encourage growth economists to join this area of research.

And while the endogeneity between IQ and growth is undoubtedly real, our results raise the question: Since so many growth variables are contaminated by endogeneity problems, why don't these other contaminated variables perform at least as well as IQ?

The robust relationship between IQ and growth requires an explanation, but a complete explanation is beyond the scope of this paper. The simplest explanation may turn out to be the best: National average IQ is a better measure of general human capital than any of the other measures tested here.

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Table 1: Variables from Sala-i-Martin (1997a,b)

Twenty-one variables passing Sala-i-Martin's "Two Million Regressions" test, in rank order:

1. Equipment Investment +
2. Number of Years Open Economy +
3. Fraction Confucian +
4. Rule of Law +
5. Fraction Muslim +
6. Political Rights +
7. Latin America Dummy –
8. Sub-Saharan Africa Dummy –
9. Civil Liberties +
10. Revolutions and Coups –
11. Fraction of GDP in Mining +
12. Std. Dev. of Black Market Premium –
13. Fraction of GDP in Primary Exports in 1970 –
14. Degree of Capitalism +
15. War Dummy –
16. Non-Equipment Investment +
17. Absolute Latitude +
18. Exchange Rate Distortions –
19. Fraction Protestant –
20. Fraction Buddhist +
21. Fraction Catholic –

Variables Included in all Sala-i-Martin Regressions

Log (GDP per capita, 1960) +
Rate of Primary School Enrollment, 1960 +
Life Expectancy, 1960 +

Other Education Measures

Rate of Secondary School Enrollment –
Rate of Higher Education Enrollment –
Average Years of Primary Education in Total Population –
Average Years of Secondary Education in Total Population +
Average Years of Higher Education in Total Population –
Average Years of Overall Education in Total Population –
Average Years of Overall Education in Total Population*(log(GDP per capita, 1960) –
Percent of GDP Spent on Education +

Note: + and – signs indicate whether more of that value is good or bad for economic growth in the 1960-1992 period, according to Table 1 of Sala-i-Martin (1997b).
Source: Sala-i-Martin (1997a, b)

Table 2: Estimated National Average IQ

	IQ		IQ
Argentina*	96	Kenya*	72
Australia*	98	Korea, South*	106
Austria*	102	Lebanon	86
Barbados	78	Malaysia*	92
Belgium*	100	Marshall Islands	84
Brazil*	87	Mexico*	87
Bulgaria	93	Morocco*	85
Canada*	97	Nepal*	78
China	100	Netherlands*	102
Congo (Brazzaville)*	73	New Zealand*	100
Congo (Zaire)*	65	Nigeria	67
Croatia	90	Norway*	98
Cuba	85	Philippines*	86
Czech Republic	97	Poland	99
Denmark*	98	Portugal*	95
Ecuador*	80	Puerto Rico	84
Egypt*	83	Qatar	78
Fiji*	84	Romania	94
Finland*	97	Samoa (Western)	87
France*	98	Singapore*	103
Germany*	102	Slovakia	96
Ghana*	71	Slovenia	95
Greece*	92	South Africa*	72
Guatemala*	79	Spain*	97
Guinea	66	Sudan	72
Hong Kong*	107	Sweden*	101
Hungary	99	Switzerland*	101
India*	81	Taiwan*	104
Iran*	84	Tanzania*	72
Iraq*	87	Turkey*	90
Ireland*	93	Uganda*	73
Israel*	94	United Kingdom*	100
Italy*	102	United States*	98
Jamaica*	72	Uruguay*	96
Japan*	105	Zambia*	77

Note: Asterisk indicates inclusion in regression results reported below.
Source: Lynn and Vanhanen (2002)

Table 3: IQ's relationship with economic growth, 1960-1992

	$\overline{\beta}_{IQ}$ (unweighted)	$\overline{\beta}_{IQ}$ (weighted)	β_{IQ}-1.96σ_{IQ} Lower Bound	Percent Significant	No. of Regressions
All Countries, Controls: Top 21	0.1229 (0.0245)	0.1560 (0.0313)	-0.0214	99.7%	1330
All Countries, Controls: Educ	0.1499 (0.0228)	0.1926 (0.0293)	0.0919	100%	56
Non-OECD, Controls:Top 21	0.1030 (0.0479)	0.1339 (0.0624)	-0.1660	62.8%	1330
Non-OECD, Controls: Educ	0.1308 (0.0429)	0.1665 (0.0545)	-0.0056	96.4%	56

Note: $\overline{\beta}_{IQ}$ represents the average across all regressions of the effect of a one-point increase in a nation's average IQ on average annual economic growth, in percent. Standard errors (unweighted and weighted averages across all regressions) are in parentheses. "Lower Bound" is the minimum value of lower bound of the 95% confidence interval across all regressions. "Percent significant" is the percent of regressions where IQ was statistically significant at the 95% level. In all regressions, log GDP per capita in 1960, primary school enrollment in 1960, and average lifespan in 1960 are included as additional explanatory variables.

Table 4: Explaining Growth: IQ versus Primary School Enrollment

	$\overline{\beta}_{IQ}$ (unweighted)	$\overline{\beta}_{IQ}$ (weighted)	$\overline{\beta}_{PS\%}$ (unweighted)	$\overline{\beta}_{PS\%}$ (weighted)	No. of Regressions
All Countries, Controls: Top 21	0.1229 (0.0245)	0.1560 (0.0313)	1.5185 (1.2572)	1.9183 (1.5954)	1330
All Countries, Controls: Educ	0.1499 (0.0228)	0.1926 (0.0293)	0.7164 (1.3154)	0.9033 (1.6889)	56
Non-OECD, Controls:Top 21	0.1030 (0.0479)	0.1339 (0.0624)	0.8836 (2.0569)	1.1323 (2.6838)	1330
Non-OECD, Controls: Educ	0.1308 (0.0429)	0.1665 (0.0545)	0.1198 (2.1241)	0.1347 (2.6967)	56

Note: $\overline{\beta}_{IQ}$ represents the average across all regressions of the effect of a one-point increase in a nation's average IQ on average annual economic growth, in percent. $\overline{\beta}_{PS\%}$ represents the average across all regressions of the effect on growth of moving from 0% to 100% enrollment of the primary-school-aged population. Standard errors (unweighted and weighted averages across all regressions) are in parentheses. In all regressions, log GDP per capita in 1960, primary school enrollment in 1960, and average lifespan in 1960 are included as explanatory variables.

Figure 1

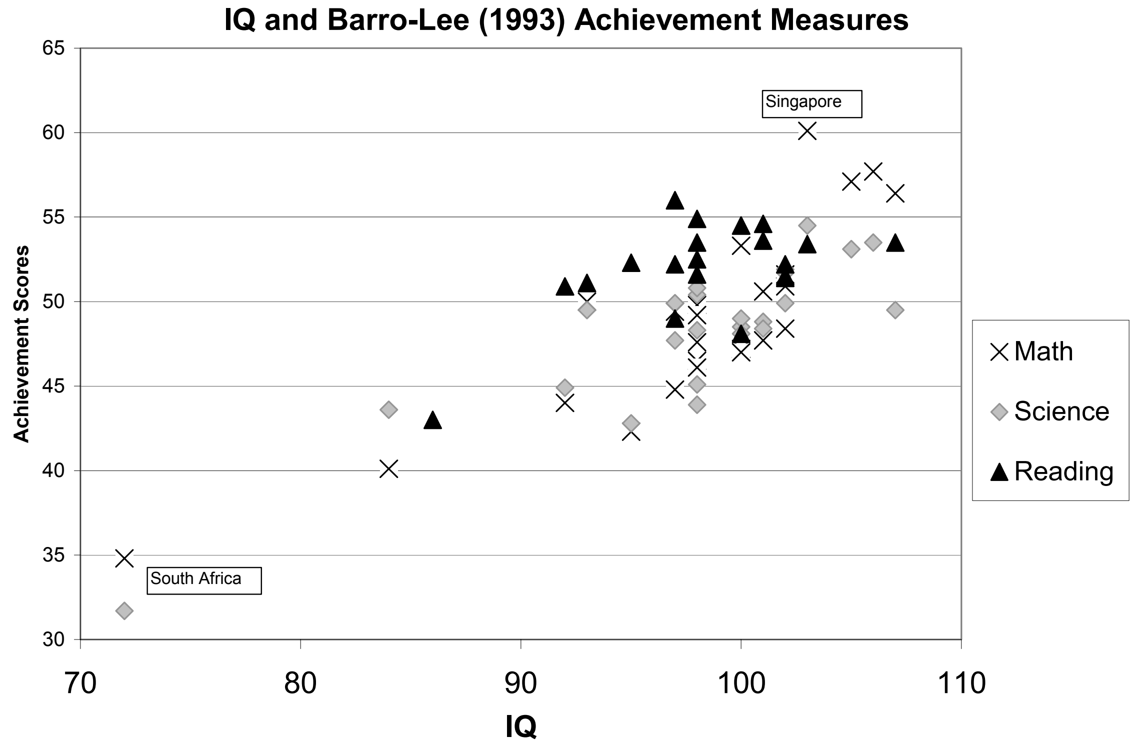
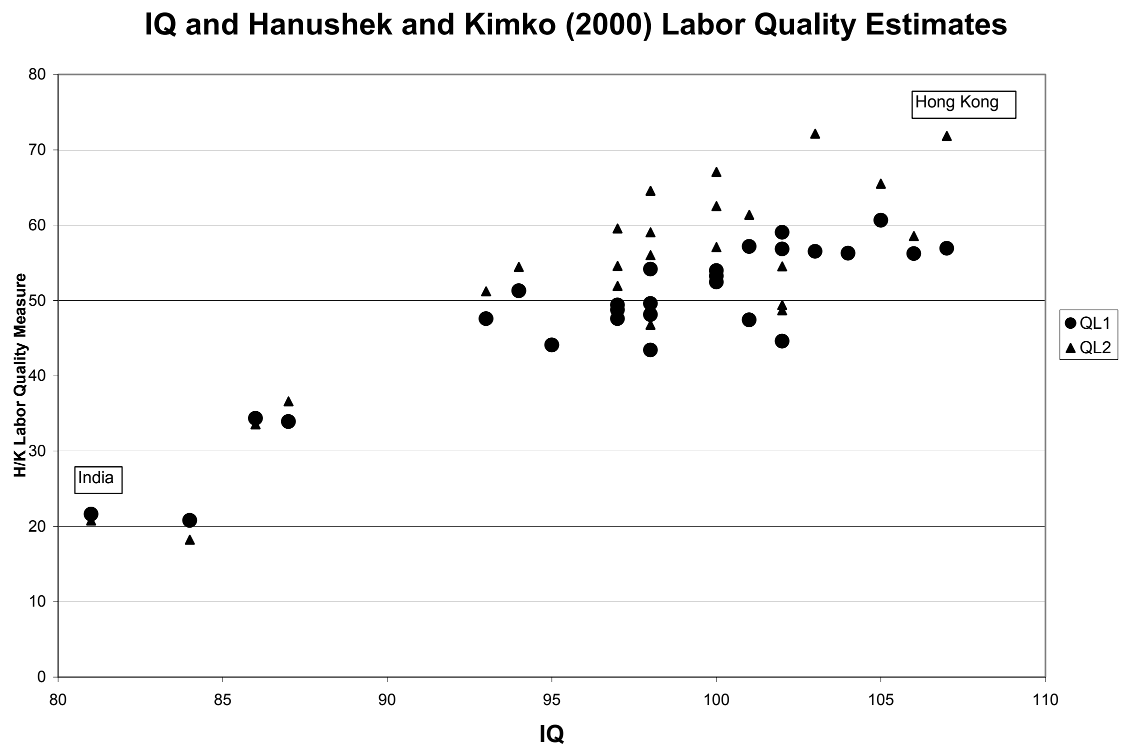
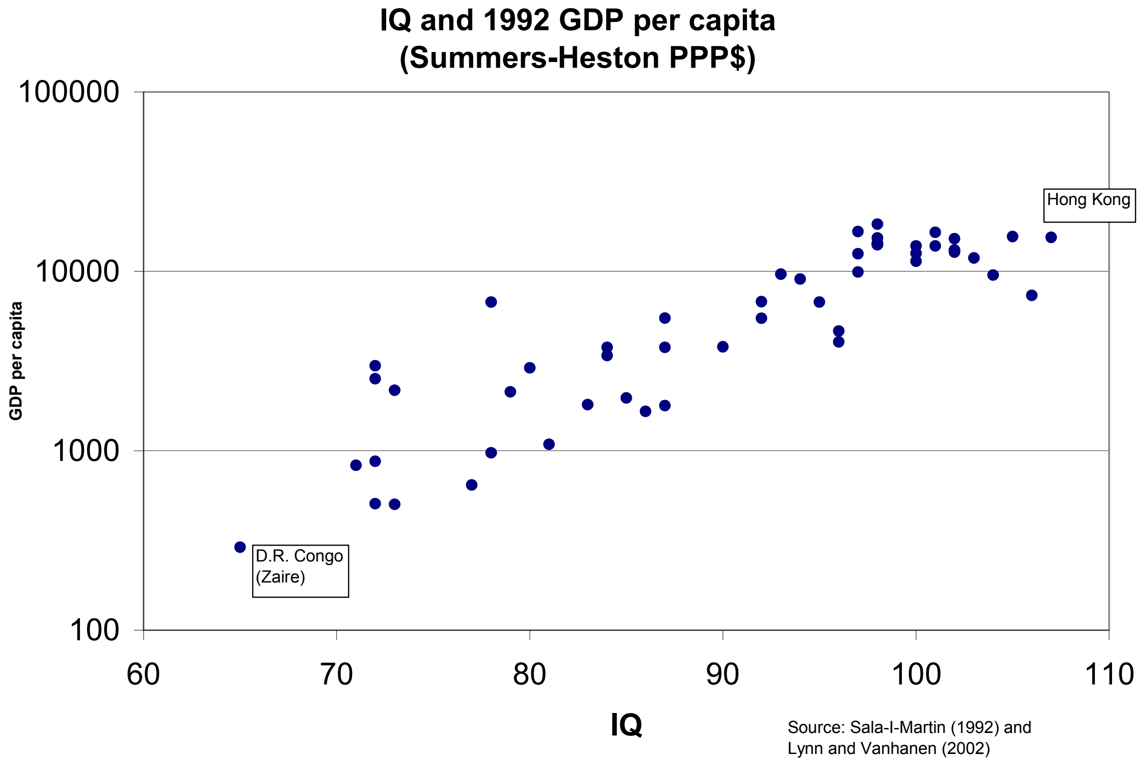

IQ and Barro-Lee (1993) Achievement Measures
Achievement Scores
65
60
55
50
45
40
35
30
70
80
90
100
110
IQ
Singapore
South Africa
Math
Science
Reading

Figure 2



Note: QL1 and QL2 are indices of labor quality used in Hanushek and Kimko (2000) and developed in Hanushek and Kim (1999).

Figure 3


IQ and 1992 GDP per capita
(Summers-Heston PPP$)
100000
10000
1000
100
GDP per capita
Hong Kong
D.R. Congo
(Zaire)
60
70
80
90
100
110
IQ
Source: Sala-I-Martin (1992) and
Lynn and Vanhanen (2002)