IQ in the Production Function: Evidence from Immigrant Earnings

Garett Jones*
Department of Economics and Finance
Southern Illinois University Edwardsville
and
Department of Economics
University of California, San Diego

W. Joel Schneider
Department of Psychology
Illinois State University

October 2006

Abstract

We show that a country's average IQ score is a useful predictor of the wages that immigrants from that country earn in the U.S., whether or not one adjusts for immigrant education. The coefficient on IQ (where 1 IQ point predicts 1% higher wages) is remarkably close to that derived from numerous microeconomic studies. After putting IQ into a conventional production function, a cross-country development accounting exercise is conducted. We show that about one-sixth of the global inequality in log income can be explained by the effect of large, persistent differences in national average IQ on the private marginal product of labor.

---

*Corresponding Author. E-mail: garett@ucsd.edu. Homepage: www.siue.edu/~garjone. We would like to thank participants at the Missouri Economics Conference, the Southern Economic Association meetings, the Society for Economic Dynamics, and DEGIT XI for helpful comments. We especially thank economists Francesco Caselli, Michael Davis, Petia Stoytcheva, and William Smith for particularly insightful observations, and the Graduate School of Southern Illinois University Edwardsville for financial support. An earlier version of this paper circulated under the title "IQ in the Ramsey Model." The usual disclaimer applies with particular force.

During the 20th century, psychologists provided a variety of evidence that average intelligence differs across countries. Whether one looks at traditional IQ tests, at electroencephalograms, at the time it takes for one to react to a stimulus, or at brain size as measured with an MRI, multiple forms of evidence indicate that there are large, persistent differences in average intelligence across countries.

The serious debate within psychology is not over whether these differences are due to test bias—psychologists responded aggressively to reduce test bias in the 60's and 70's, but found little evidence that such bias had been quantitatively important. Instead, their debate is over what percentage of group differences in intelligence are due to genetic versus environmental factors.

For instance, recent DNA research by Bruce Lahn and coauthors (Evans et al., 2005; Mekel-Bobrov et al., 2005) and Wang et al. (2005), has provided evidence that genes related to brain function have been under evolutionary selection pressure during the last 40,000 or so years; the work of Lahn and his coauthors focused specifically on genetic differences between groups from different countries. This line of research has reinvigorated the question, most prominently raised by Jensen (1969) and Herrnstein and Murray (1994), of why group differences in IQ persist.

This paper will not resolve the genetic vs. environmental IQ debate. What it will do instead is provide evidence that cross-country IQ tests are useful—perhaps crucial—predictors of the average productivity of workers from different countries. The cross-country growth literature (esp. Sala-i-Martin (1997), Sala-i-Martin, Doppelhofer, & Miller (2004)) has found that traditional education measures rarely have a robust relationship with growth and productivity—elementary education being a rare exception. At the same time, a new literature (Lynn & Vanhanen 2002, Weede & Kampf 2002, Weede 2004, Jones & Schneider (2006)) has shown that a nation's average IQ does indeed have a robust relationship with productivity (Figure 1) between countries. Thus, there appear to be good reasons for economists to focus on the microfoundations of the cross-country IQ-productivity relationship. We begin that process in this paper.

We present four main findings:

1. If one knows the average IQ of a nation's citizens as estimated by Lynn and Vanhanen (2002, 2006), one can predict the average wages that immigrants from that country will earn upon their arrival in the U.S.—whether or not one controls for immigrant education. In other words, national average IQ measures part of what Hendricks (2002) calls "unmeasured worker skill."

2. We find that a one point increase in national average IQ predicts one percent higher immigrant wages—precisely the value found repeatedly in microeconometric studies (note that by construction, 1 IQ point $\approx 1/15^{th}$ of a standard deviation within any large national population). Together, points 1 and 2 provide evidence that cross country IQ tests are valid predictors of worker productivity, predictors that measure more than just differences in education.

3. When IQ is added to the production function in the form implied by traditional, externality-free human capital theory, differences in national average IQ are quantitatively significant in explaining cross-country income differences. That said, our productivity accounting exercise does not resolve the puzzle of why high-IQ countries are 15 times richer than low-IQ countries.

4. We provide suggestive evidence that little of the IQ-productivity relationship is due to causality running from income to IQ by demonstrating that the East Asian "miracle" economies had (or in China's case, have) high average IQ's when relatively poor. Thus, economists who wish to explain the IQ-productivity relationship will need to look at deeper causes for the world's IQ inequality, causes such as culture, environment, geography, and genetics.

We begin with an overview of the recent psychological literature on the validity of intelligence tests, and then proceed to our discussion of the link between IQ and immigrant wages. The discussion of IQ and immigrant wages yields a parameter, γ, the IQ semi-elasticity of wages, which we use in our development accounting exercise. We then discuss the questions of reverse causality and trends in the IQ-productivity relationship over the last 40 years, and conclude by discussing how our results fit into the growth literature.

II. IQ: A psychologist's perspective

IIA. Intelligence tests: An overview

It is not possible to have confidence in these or any other IQ-related findings without an adequate understanding of how IQ is measured and why psychologists believe that IQ tests can provide reasonable estimates of intelligence. Many criticisms, some

incisive, some vapid, have been raised regarding IQ-related research. Because it is not possible to anticipate all of the most important concerns in the brief summary of relevant findings that follows, readers wishing for scholarly, balanced, and accessible introductions to intelligence research are advised to consult Bartholomew (2004), Cianciolo & Sternberg (2004), Deary (2001), or Seligman (1992). A more technical, more comprehensive, and perhaps more controversial summary of intelligence research can be found in Jensen (1998). Jensen's research on racial differences in cognitive ability is much disputed but other aspects of his work are widely regarded, even by his critics, as masterful (e.g., Flynn, 1980, Sternberg, 1998).

Although it is true that IQ tests do measure general knowledge, comprehension, and verbal reasoning in ways resembling narrowly-focused ability tests (such as the SAT in the United States), high-quality IQ tests also measure such diverse abilities as abstract reasoning, novel problem solving, spatial reasoning, auditory processing, attention/concentration, short-term memory, long-term retention of new information, fluency of recall, speed of perception, speed of information processing, and many others. Thus, IQ is a summary of how well an individual performs on a wide variety of cognitive ability measures. The advantage of using IQ tests is that a person's idiosyncratic weaknesses on some tests tend to be balanced by the person's idiosyncratic strengths on other tests.

IIB. Culture-Fair IQ Tests

Well-constructed IQ tests are designed to avoid tasks and content taught explicitly in school. Unfortunately, in the case of general knowledge and verbal comprehension tests, it is impossible to eliminate all school-related content. Therefore, care is taken to focus on information that is generally available to all members of the intended population, avoiding specialized knowledge. In cross-cultural studies of IQ such as ours, general information and verbal comprehension tests typically are omitted because it is almost impossible to develop tests of general knowledge that have comparable meaning across cultures (e.g., not knowing why the year 1066 is important means something different if one is from New Guinea rather than from Great Britain). Considerable effort has gone into producing nonverbal IQ tests that can be used in any culture. These

"culture-fair" or "culture-reduced" IQ tests have been shown to predict important life-outcomes with validity coefficients comparable to traditional IQ tests designed for specific populations (Court, 1991; Kendall, Verster, & Von Mollendorf, 1988, Rushton, Skuy, & Bons, 2004).

Unlike traditional IQ tests that measure a very diverse set of cognitive abilities, culture-reduced IQ tests necessarily measure a much smaller number of abilities, focusing on nonverbal reasoning and novel problem-solving. Fortunately, the types of tests that lend themselves to cross-cultural research correlate very highly with the overall scores from traditional IQ tests (Jensen, 1987). Indeed, reasoning and the ability to deal effectively with unfamiliar situations is at the core of most theorists' definitions of intelligence (Gottfredson, 1997). Thus, although many of the IQ tests in the dataset we use lack the breadth and diversity of traditional IQ tests, they focus on perhaps the most important facets of cognitive ability.

IIC. The universal positive correlation among mental abilities

If the separate parts of an IQ test do indeed measure diverse cognitive abilities, the question that naturally arises is why one would want to average the scores from those IQ subtests, recklessly throwing away information. The answer to this question is that it is reasonable to form a composite score (i.e., IQ) because of the unexpected but ubiquitous finding that, in all large and heterogeneous samples, all tests of cognitive abilities positively correlate with all other tests of cognitive abilities (Jensen, 1998). This finding occurs across cultures and even across species (Chabris, 2006). A composite score from a diverse collection of tests tends to correlate highly with a composite of a different set of diverse tests, even if, on the surface, the tests are quite dissimilar. Indeed, different commercially available IQ tests tend to correlate with each other highly (.8 to .9; Roid, 2003).

IID. Environmental effects on intelligence

Although IQ tends to be rather stable throughout the lifespan, given certain events and environmental changes, IQ is quite malleable (Shaie, 2005). Unfortunately, when this malleability is observed within an individual, IQ is more likely to drop than rise. It is

relatively easy to disrupt the delicate processes of the brain with disease, malnutrition, parental abuse and neglect, environmental toxins, and brain injury.

Still, with considerable effort, it is possible to raise IQ somewhat with high-quality personal health care, sound public health policies, adequate nutrition, reasonable parental involvement, and excellent education (Armor, 2003). The fact that IQ scores have been rising .2 standard deviations per decade in most developed countries ever since mass IQ testing started in the 1920's (Dickens & Flynn, 2001; Flynn, 1987) suggests that many societies are doing some of these things. This phenomenon is referred to as the "Flynn effect." Although it is possible that rising IQ is caused by trivial factors such as better test-taking skills, the causes of the increase might include better access to information though education and mass communication, better nutrition, better health care, falling birth rates (leading to more child-focused parenting and more resources per child), heterosis due to increased migration, and less exposure to parasites and environmental toxins (Colom, Font, & Andrés-Pueyo, 2005; Mingroni, 2004).

IIE. What IQ predicts

There is some controversy over whether IQ measures general intelligence--a domain-free ability that can be applied to a wide variety of tasks--or intelligence-in-general, that is, an average of overlapping abilities, each of which are used separately in different tasks (Horn & Blankson, 2005). It is not controversial that, whatever IQ measures, it is a useful predictor of an extraordinarily large number of important life outcomes. IQ correlates positively with important life outcomes such as occupational prestige, job performance, educational attainment, academic skills, creativity, physical health, mental health, and longevity. IQ correlates negatively with criminal status, poverty, chronic welfare dependence, unemployment, divorce, and single-parenthood (Gottfredson, 1997; Herrnstein & Murray, 1994). IQ is also related to a many aspects of the brain including overall brain size, nerve conduction speed, various aspects of cortical electrophysiological activity, aspects of cerebral blood flow, and cerebral glucose metabolism (McDaniel, 2005; Reed et al., 2004; Cianciolo & Sternberg, 2004, pp 13-16).

IIF. IQ: A poor proxy for SES

It is possible to dismiss the importance of IQ scores, claiming they are simply an index of social class or educational opportunity. It is certainly true that socioeconomic status (SES) and IQ are positively correlated but IQ predicts educational and occupational success even after controlling for SES. SES also predicts educational and occupational success after controlling for IQ but its independent effects are much smaller than IQ's (Herrnstein & Murray, 1994).

It could be objected that standard measures of SES are simply too crude to capture the subtle effects of SES. Probably the best way to control for the effects of SES is to use a sibling comparison methodology in which the between-family effects of IQ are separated from the within-family effects of IQ. This is because if IQ were simply an index of SES, then we would expect that siblings, who presumably share the same SES, to have very similar IQ's and very similar life outcomes.

The average IQ difference between random strangers in the U.S. population is about 17 points (1.13 SD) whereas the average IQ difference between U.S. siblings is not that much smaller: about 12 points (.8 SD; Jensen, 1998). Thus, it is common in the psychology literature to note that most of the variance in IQ's occurs *within* families, not *between* families. This is the opposite of what one would likely expect if one held to the IQ-as-SES hypothesis.

Probably the best evidence that IQ is not simply an index of SES is that among siblings who differed substantially in IQ during childhood, the sibling with the higher IQ is much more likely to do well in school, earn more money, and have a higher status job in adulthood (Murray, 1997, 2002).

IIF. Bias in Mental Testing?

Even if IQ tests are broadly predictive of social and economic outcomes, the question still arises of whether the tests are unbiased. Responding to legitimate criticism, IQ test developers have developed sophisticated techniques of identifying test items that are biased against subgroups (e.g., ethnic minorities) of the general population for which the test is intended to be used. Generally these items are eliminated or, less frequently, are counterbalanced by items that are biased in favor of certain subgroups.

In the United States (and probably elsewhere), these procedures designed to address concerns about test bias appear to have been successful. Despite intense scrutiny from researchers whose careers would probably benefit immensely from showing that IQ tests are biased, findings repeatedly fail to find that contemporary IQ tests have meaningful differences in predictive validity of important life outcomes for native-born English-speaking minority groups (Brown, Reynolds, & Whitaker, 1999; Jensen, 1980).

Thus, if IQ tests are biased against minority groups, it is because the criteria by which we validate IQ tests (e.g., educational success, occupational status, job performance, physical and mental health outcomes, longevity, and brain functioning) are measured with equally biased indicators. Note that the issue of test bias is distinct from issues related to the fairness of test use. It is possible to use an IQ test that validly estimates intellectual functioning of a particular group in ways that are unfair. For example, denying a high quality education to people who score poorly on IQ tests would be considered an injustice by most people and might perpetuate low IQ scores among lower scoring subgroups in a population but the IQ tests would be no less valid in their prediction of important life outcomes. IQ tests are merely tools that can be used for good or for ill.

III. IQ as a measure of "unmeasured worker skill."

In this section, we investigate whether the average IQ in the immigrant's home country is a useful predictor of the wages of immigrants from that country. Our estimates of immigrant wages come from Hendricks (2002), who used data on earnings, education, and age from 106,263 immigrants from the 1990 Census of Population and Housing.[1] These immigrants were between the ages of 20 and 69 and worked full-time in the U.S. For further information on the immigrant data, see Section II of Hendricks (2002).

By comparing the earnings of native-born and immigrant workers who have identical ages and identical education levels, Hendricks was able to create adjusted wage

[1] Hendricks census data on "earnings" combine all forms of income, but we will follow Hendricks's practice and treat them as useful proxies of wages. In our case, this will create no econometric biases as long as log non-wage income is uncorrelated with wages at the aggregate level. Further, since we are concerned with estimating γ (the semi-elasticity of wages with respect to IQ) rather than with estimating the intercept, no problems will be created if workers from all countries have the identical log non-wage incomes. Thus, we will, with appropriate caution, refer to wages rather than earnings.

measures that extracted systematic wage differences due to these two factors. After controlling for age and education, he concludes that the only remaining explanation for wage differences between workers from different countries is what he calls differences in "unmeasured worker skill."[2] Hendricks created estimates of unmeasured worker skill for 76 countries.

Perhaps surprisingly, this "unmeasured worker skill" estimate varies widely for immigrants from different countries. The standard deviation of log unadjusted wages is 0.29 across Hendricks's sample of 76 countries, while the standard deviation of log unmeasured worker skill across these countries is still a sizable 0.19. Henceforth we refer to uws_i, the log of "unmeasured worker skill" in country i.

Our goal in this section is to show that national average IQ is a useful predictor of Hendricks's "unmeasured worker skill." We use Lynn and Vanhanen's (2002, 2006) database of national average IQ estimates. We should briefly review how Lynn and Vanhanen (henceforth LV) (2002, 2006) created their datasets: LV (2002) assembled results from 183 conventional IQ tests, both verbal and visual, given in 81 countries across the entire 20th century; they used hundreds of IQ tests from 113 countries across the 20th and 21st centuries in LV (2006). They aggregated these results using best-practice methods to create estimates of "national average IQ" for these countries.[3] LV show in those works as well as in Lynn (2006) that the IQ gaps between regions of the world have not appreciably changed during the 20th century.

Lynn and Vanhanen's 2006 dataset overlaps with 59 of Hendricks's observations. The mean and median IQ across these 59 countries are both 91 and the standard deviation of IQ across these countries is 9. This is a slightly more intelligent, less varied sample than the full 113 countries: The full-sample mean and median are both 87 and the standard deviation is 12. For comparison, we note that within the United Kingdom, mean IQ is defined as equal to 100, and the standard deviation of IQ within the U.K. population is defined as equal to 15.

[2] Hendricks addresses the question of immigrant self-selection in detail, and finds little evidence that this is quantitatively important. We refer interested readers to his valuable analysis.

[3] LV made one noteworthy change between their 2002 and 2006 IQ estimates: In cases where they had more than two IQ estimates for a country, they chose the median as their national average IQ estimate rather than their mean.

In this section, our estimates amount to a regression of log uws_i on the level of national average IQ and a constant. Since one of our goals is to see whether the estimated relationship between immigrant wages and national average IQ is close to microeconometric estimates of the IQ-wage relationship, we should briefly survey the previous literature on the link between wages and IQ within the U.S. Throughout, we denote the IQ semi-elasticity of wages by γ.

The widely-cited work of Zax and Rees (2002) uses data from Wisconsin to estimate the impact of teenage IQ on lifetime earnings. They find that for men in their 50's, $\gamma = 0.7\%$ higher earnings when they control for education, and $\gamma = 1.4\%$ when they do not. Since some education is surely caused by prior IQ, and since that education causes higher wages, Zax and Rees note that we should place some weight on the estimates that do not control for education when trying to determine the impact of IQ on wages. Interestingly, they find that IQ—which was measured when these men were teenagers—does a better job predicting wages in a worker's 50's than in his 20's. Neal and Johnson (1996) similarly find that one IQ point is associated with $\gamma = 1.3\%$, while Bishop (1989) finds $\gamma = 1.1\%$.[4] Cawley et al (1997) find U.S. estimates in a similar range, even when they break the estimates down by ethnic group and gender. Behrman et al. (2004) survey some developing country studies, and find that the mean and median estimates both imply $\gamma = 0.8\%$. We take $\gamma = 1\%$ as reasonable estimate of best-practice labor econometric work; U.S. estimates often run a bit larger, while developing country estimates and estimates that control for education often run a bit smaller.

Note that these estimates imply that large differences in IQ are likely to have only a modest impact on worker wages—a two-standard deviation difference in IQ within a typical nationwide population (i.e., 30 IQ points) will lead to only about a 35% difference in wages. And a move from the 5th to the 95th percentile in IQ will fail to double wages, on average.

Another way to emphasize the relative irrelevance of IQ at the micro level is to note that when Zax and Rees regress wages on just IQ and a constant, the R^2 is about 10%. This replicates a standard result in the labor literature, which is that while prior

[4] With the exception of Zax and Rees (2002), all of these studies used Armed Forces Qualifying Test scores as the measure of cognitive ability. We have made the relevant adjustments to be able to report AFQT scores as IQ scores.

ability likely matters more than any other measurable premarket factor (such as parental socioeconomic status, as Herrnstein and Murray (1994) demonstrated), it still predicts little of a person's labor market outcomes. Thus, IQ's impacts on micro-level wages are statistically significant, but quantitatively modest.

Now, let us return to our main question. Do our 59 observations roughly replicate these intra-country estimates of the IQ-wage relationship, where 1 IQ point predicts about 1 percent higher wages? Yes, they do, as seen in Figure 2. When we run a simple bivariate correlation between uws_i and national average IQ, we find a correlation of +0.47, and OLS yields a regression coefficient of γ=0.95 (White std. error=0.31). This is remarkably close to the coefficient estimates cited above.

Our estimate, which we round to unity, provides a number of insights. First, it shows that LV's national average IQ measures are useful for predicting more than just cross-country productivity differences, cross-country growth rates (both positive correlations), cross-country suicide rates (also a positive correlation: Voracek 2004, 2005), and other cross-country factors. We have now shown that they are also useful for predicting the age-and-education adjusted wages of the average immigrant coming from her home country to the United States.[5] This is surely evidence that national average IQ is an important measure of what Hanushek and Kimko (2000) call "labor quality."

Further, we have shown that estimate is quite close to conventional microeconometric estimates of the IQ-wage relationship. If one thought that workers from low-IQ countries faced enormous hardships, hardships that would impact their level of human capital in ways that wouldn't show up on a so-called "pencil and paper IQ test," then one would expect immigrants from those countries to have much lower earnings upon their arrival in the U.S than an IQ test would predict. In other words, an IQ of 81 for an American citizen would mean something much different than an IQ of 81 for a person from Ecuador. The Ecuadorean 81 would likely come bundled with a history of poor nutrition and education, weak public health services, and other adverse factors. Can a mere "pencil and paper IQ test" capture the impact of all of these various insults on

[5] Vinogradov and Kolvereid (2006) show that Lynn and Vanhanen's national average IQ estimates are good predictors of the self-employment rates of immigrants coming to Norway.

a person's wage-earning ability? The answer appears to be yes, on average. So while one might have expected $\gamma >> 1$ in this cross-country regression, that was not the case.

At the same time, one might have expected the OLS estimate of γ to be smaller than 1: If IQ tests in general were a *Mismeasure of Man* (Gould, 1981), then one would expect cross-country IQ tests that were aggregated to the national level and then imputed to the average immigrant to have multiple levels of errors-in-variables problems. This would bias the IQ coefficient downward, yielding $\gamma << 1$.

But neither turned out to be the case: Our estimated coefficient is quite close to conventional microeconometric estimates. Whatever an IQ test can tell us about worker wages, it appears to be measuring the same thing across countries as within countries. This is confirmatory evidence that cross-country IQ comparisons are in indeed possible, despite the claims of many (e.g., Ehrlich, 2000; Diamond, 1999) to the contrary.

Of course, it may be the case that the upward and downward biases just happen to cancel out, yielding an estimate of $\gamma=1$ that is astonishingly close to conventional microeconometric estimates. We hope that future research can investigate whether that is, in fact, the case. We turn to a few preliminary robustness checks here, and then proceed to our cross-country development accounting exercise.

IV. Immigrant IQ Robustness Check: Endogneous Education and Outliers.

Following Hendricks, we have so far used wage measures that adjusted for an immigrant's education level. As mentioned above, Zax and Rees (2002) note that controlling for education may bias the γ coefficient downward. After all, as they note, IQ is quite likely to have an impact on the quantity of future education a student acquires, so some of the estimated effect of education on earnings is likely to represent IQ's indirect impact on earnings. As a practical solution, they recommend a simple regression of earnings on IQ alone.

In our case, the equivalent regression would involve regressing Hendricks's "log unadjusted earnings" on IQ. This will provide us with an upper bound for IQ's impact on immigrant earnings. In such a regression, the correlation coefficient is +0.42, with an OLS regression coefficient of $\gamma=1.3$ (White s.e., 0.44). This is quite close to the upper

bound of current estimates found in micro-level panel and cross-sectional studies, and is only 30% larger than our baseline estimate of γ=1.

Further, our original uws_i results do not appear to be sensitive to outliers. There are three obvious outliers, and all three tend to push γ downward: high-wage South African immigrants, (IQ=72) and low-wage Chinese (IQ=105) and South Korean immigrants (IQ=106); they are the only three with regression residuals more then 2.5 standard deviations away from zero, and all three are in fact over 4 standard deviations away from zero. Thus, they are not small outliers. But are they driving our results from the previous section? It would appear not. One-at-a-time omission of these outliers has a negligible impact on the γ estimate, and eliminating all three raises the coefficient to just 1.4, at the high end of microeconometric estimates. Overall, our results appear to be robust to endogenous education and to outliers. In our development accounting exercises below, we investigate the implications of imposing various γ values.

It appears that when workers come to the U.S. from around the world, the average earnings of immigrants from a particular country are significantly positively correlated with the estimated average IQ of the residents of their home country. Further, the empirical relationship between IQ and adjusted immigrant earnings can be summarized quite simply: 1 IQ point ($\approx 1/15^{th}$ of a standard deviation within any large population) leads to about 1% higher earnings.

This is quantitatively quite close to the estimates from recent micro-level wage studies both from the U.S. and around the world. We tentatively conclude that cross-country IQ measures, as aggregated by LV, are a useful indicator of the private marginal productivity of workers. LV's national average IQ scores appear to summarize labor quality about as well as conventional, micro-level IQ tests. Cross-country IQ scores pass this "market test" with little difficulty, a result that strengthens our confidence in the validity of cross-country IQ tests as indices of one form of labor quality.

V. IQ in the Production Function

We now turn to the question of whether IQ's impact on the private marginal product of labor can explain the massive differences in living standards we see across countries. We begin by assuming an IQ-augmented Cobb-Douglas production function,

$$Y_i = K_i^{\alpha}(e^{\gamma IQi}A_iL_i)^{1-\alpha} \qquad (1)$$

The subscript *i* is the country subscript, Y, K, A, and L are output, the capital stock, disembodied technology, and the labor supply respectively, and γ is the semi-elasticity of wages with respect to IQ. In other words, γ is the impact of IQ on human capital. Since our concern is with cross-country comparisons, we suppress time subscripts. We reorganize the production function to make it amenable to development accounting:

$$\left(\frac{Y}{L}\right)_i = A_i e^{\gamma IQ_i}\left(\frac{K}{Y}\right)_i^{\frac{\alpha}{1-\alpha}} \qquad (2)$$

This is the equation we use (sometimes in log form) to evaluate the impact of IQ differences on steady-state living standards. IQ appears in the production function just as any other form of human capital would. As such, we can estimate IQ's impact on output in the same way that economists estimate education's impact on output: By looking at microeconometric estimates of the link between wages and this form of human capital. Thus, we will repeatedly reuse our γ=1 estimate from Section 3, but will also consider γ=1.25 as an upper bound and γ=0.5 as a lower bound (Bowles et al. (2001), in a meta-study of the labor literature, find a median estimate of γ=0.5; their meta-study includes all possible studies, without regard to econometric technique).

Before we do so, let us briefly review the power of national average IQ to predict national productivity. Lynn and Vanhanen found a correlation of 0.7 between national average IQ and the level of GDP per worker in 81 countries. Jones and Schneider (2006) found a correlation of 0.82 between national average IQ and log GDP per worker, and also found that national average IQ was statistically significant at the 1% level in 455 cross-country growth regressions that used all of Sala-i-Martin, Doppelhofer, and Miller's (2006) robust growth variables as controls.

But does this strong IQ-productivity correlation depend on the type of IQ test used? Apparently not. For example, looking only at the 25 scores (out of the 163 total) that used Cattell's Culture-Fair test, the correlation with 1998 PPP-adjusted log GDP per capita was 0.74, slightly below the 0.82 in the aggregated sample. For one form of Raven's Progressive Matrices (a non-verbal, visual pattern-finding IQ test), the

correlations were 0.92 (35 tests), and for the other form of the Raven, the correlation was 0.69 (53 tests). These were the only three tests appearing more than 25 times in the LV (2002) database. Clearly, regardless of the type of test used, national average IQ can still predict about half or more of a nation's productivity.

In the results below, GDP per worker estimates are from the Penn World Tables. In total, we have complete data for 87 countries that are broadly representative of the world's economies. Data and software are available upon request, and the raw data underlying Lynn and Vanhanen's IQ estimates are available in table form on the web (Sailer 2004). The Sailer website is especially useful for demonstrating that these IQ differences have been persistent and do not turn on the type of IQ test employed.

VA. IQ differences: Magnitude

In this section, we combine the IQ-augmented production function (2) with conventional parameter values for γ to illustrate how IQ differences can impact steady-state living standards. Consider two countries that differ only in average IQ—i.e., their levels of technology and their capital-output ratios are equal across countries. The ratio of living standards in these two countries would then be:

$$\frac{(Y/L)_{hi}}{(Y/L)_{lo}} = e^{\gamma \Delta IQ} \qquad (3)$$

where ΔIQ is the difference in IQ between the two countries. Lynn and Vanhanen (2006) show that if countries are ranked according to IQ, then the country in the 5th percentile has an estimated average IQ of 66, while the country in the 95th percentile has a median IQ of 104. This yields an IQ gap of 38 points—a bit more than two standard deviations if one were looking within the U.S. population. As noted above, we take $\gamma = 1$ as our preferred estimate; under this assumption a rise of 1 IQ point raises wages (and hence the marginal product of labor) by a modest 1%.

Therefore, as Figure 3 illustrates, if a country moved from the bottom IQ decile to the top IQ decile (a rise of 38 points), steady state living standards would be about 1.5 times greater in the higher-IQ country ($e^{0.38} \approx 1.46$). This compares to the factor of 2 commonly cited for the impact of cross-country differences in education on productivity—some of which may in fact reflect differences in intelligence endogenously

driving education choices. If the true γ were equal to 1.25, toward the high end of current estimates, a 38-IQ-point gap would raise living standards by a multiple of 1.64. And if γ were half our preferred estimate, as denoted in the lowest of the three lines, a 38-point IQ gap would cause living standards to diverge by a factor of 1.23.

But perhaps the 5th and 95th percentiles are outliers, driven by test error or idiosyncratic environmental factors. Therefore we look at the 90/10 and 80/20 ratios. The gap between the 90th and 10th percentiles is 31 IQ points (102 and 71 points), while the gap between the 80th and the 20th percentiles is 21 IQ points (99 and 78 points). In these cases, productivity levels between these countries in the γ =1 case would differ by a bit more than 30% and a bit more than 20%, respectively.

Since living standards across countries differ by perhaps a factor of 30, and since the natural log of 30 is about 3.4, then if γ =1, the channel running from national average IQ to the private marginal product of labor explains perhaps 0.46/3.4, or a bit less than 1/6th of the log difference in living standards across countries.

We should note these development accounting results do not depend on IQ being exogenous. We suggest below that simple reverse causality (running from productivity to IQ) is unlikely to be the main explanation for the strong empirical IQ-productivity relationship. However, even if reverse causality *were* important, the development accounting results would still hold, since microeconomic studies demonstrate convincingly that IQ has an independent impact on the marginal product of labor.

So if the actual causal chain starts with a high level of disembodied technology (A) causing higher output per worker, which in turn causes higher IQ, it is difficult to believe that the causal chain stops there. According to economic theory, the chain continues to a second set of links, where higher IQ-workers cause more productivity. This paper is concerned only with that second set of links. Whether the first set of links is as strong as the second remains to be demonstrated.

VB: Calibration Results

The calibration exercise is quite straightforward: In a regression of log output per worker on IQ (comparable to eq. (3) above), we impose a variety of parameter values for the γ coefficient, and report the accompanying R^2. The resulting R^2 is the percentage of

the global income distribution that can be explained through a single channel: the steady-state impact of differences in national average IQ on labor productivity by way of the private marginal product of labor, γ.

The only coefficient estimated in this regression is the constant, assumed to be identical across countries. The constant collects the non-IQ terms in (3); thus, there are no free parameters to speak of. For reference, note that the R^2 between log GDP per worker in 2000 and Lynn and Vanhanen's (2002) national average IQ estimate is 64%, and in an OLS regression, 1 IQ point is associated with 6.7% higher GDP per worker.

Results are reported in Table 1.[6,7] For the preferred parameter value of γ=1.0, IQ can explain 16% percent of log cross-country income variation. Therefore, IQ's impact on wages would explain 29% (i.e., 16%/58%) of the relationship between IQ and log productivity.

If, instead, IQ has a 25% larger impact on wages (γ=1.25) then IQ's effect on wages can explain 20% of the variance in log productivity and 34% (=20%/58%) of the IQ/log productivity relationship.

And even if γ=0.5--half of our preferred estimate--IQ's impact on wages explains 8% of the log global income distribution. So even under unusually conservative assumptions, IQ's impact on the private marginal product of labor appears to belong on any top 20 list of explanations for cross-country income differences.

VI: Addressing Reverse Causality

The quantitative results of the last two sections imply that differences in national average IQ are substantial drivers of global income inequality. Thus, those who would

[6] Results were substantially unchanged if 2000 log GDP per person was used instead of log GDP per worker. They were also substantially unchanged if national average IQ was windsorized at values of 70, 80 or even 90 IQ points (first recommended by McDaniel and Whetzel (2004)). For example, IQ scores less than 70 were set equal to 70, and the estimates were substantially unchanged when rerun. This windsorizing addresses the concern than IQ scores from the poorest countries are "too low to believe": Even if we bump the lowest scores up a few (dozen) points, the results still hold.

[7] Results were likewise substantially unchanged if we omitted the 8 observations that Jones and Schneider (2005) also omitted. They omitted observations from LV's dataset that were based on fewer than 100 test subjects per country or that relied exclusively on immigrant data. They also omitted two observations (Peru and Columbia) that partially relied on imputing IQ scores based on the average IQ's of residents of nearby countries. Omitting these possibly weaker data points had no substantial effect on the results.

understand the wealth of nations should be concerned with where these differences in national average IQ come from. Are they mostly genetic, as Lynn and Vanhanen (2002) and Rushton and Jensen (2005) conclude? Are they mostly driven by more malleable factors, like education, nutrition, and the physical environment, as we hope they are? Or are they instead driven by differences in culture (cf. Ogbu & Davis (2003)), which may prove to be even more intractable than any genetic differences?

While we leave most of these questions to future research, we will take a moment to address one key question: Can simple reverse causality can explain this relationship? In other words, does a dramatic rise in GDP per worker cause a dramatic rise in national average IQ?

The region of the world that has witnessed the most rapid increases in living standards the world has ever known is unambiguously East Asia. Surely, this region would be an ideal testing ground for the productivity-causes-IQ hypothesis. If most of the IQ-productivity relationship were reverse causality, then we would expect to see the East Asian economies starting off with low IQ's in the middle of the 20th century, IQ's that would rapidly rise in later decades, perhaps even converging to European IQ levels. In short, one would expect to see Solow-type convergence in national average IQ.

But what would we expect the mid-20th-century starting point for IQ to be? Perhaps one should assume that it would be as low as the bottom decile of the global IQ distribution which has a mean of 66, as noted above. That would place such countries more than two standard deviations below the mean IQ within the United States. Or perhaps that assumption is too strong; at the very least, one would expect these poor East Asian economies to have started off with IQ's below the unweighted global mean of 90, and certainly well below the U.K and U.S., which are within a point or two of 100.

However, this is not the case. When Sailer (2004) employs Lynn and Vanhanen's (2002) raw IQ data--based on 183 tests taken over the past 90 years--to create a panel dataset, he reports that average East Asian IQ's were *never* estimated below 100 before the 1980's (Figure 3). From the 1950's and 60's, for example, Lynn and Vanhanen have four IQ tests based on relatively large samples: Two from Japan (1951—based on Japanese immigrants to the U.S.—and another Japanese in Japan from 1967), one from Taiwan (1956, only a few years after the Nationalists were driven there from the

mainland), and one from Hong Kong (1968). We also have a number of estimates from regions of China from the 1980's and 1990's, only one of which is below 100.

Lynn and Vanahen's (2002) data from rapidly growing economies in Southeast Asia, though based on only five observations, support a similar conclusion:

Indonesia, 1959:	IQ = 89
Philippines, 1970:	IQ= 86
Singapore, 1974:	IQ = 103 (A predominantly Chinese population)
Thailand, 1987:	IQ = 91
Malaysia, 1992:	IQ = 92

Average IQ's start about ten points lower than in East Asia, but also end about ten points lower. There have apparently been no twenty-to-thirty-point IQ increases in either East or Southeast Asia as these regions rapidly emerged from dire poverty.[8]

So, where do these cross-country differences in IQ come from? Of course, the answer to such a question is far beyond the scope of any one paper, but already existing models in the economics literature may provide a starting point for future work. Galor and Moav (2002) and Robson and Kaplan (2003) have formally modelled the impact of natural selection on the creation of higher intelligence in human populations. The theorist looking to model differences across *countries* will find much of interest in these papers.

To return to the particular question of Asia: Perhaps there was some unique barrier such massive IQ increases in East and Southeast Asia, or perhaps some unique cultural, environmental, or economic forces enabled these countries to maximize their average IQ while still poor. Of course, addressing all possible explanations for the high average IQ in these regions is beyond the scope of any one paper, but we point the reader to Lynn's (2006) thoughtful and provocative book-length treatment of the question, which reports results from 620 intelligence tests performed in 100 countries.

But while twenty-to-thirty point increases have not been documented, more modest IQ increases *do* occur on a national scale. Indeed, there is a large literature in psychology that studies the rise in IQ's across the developed world, a rise of roughly two

[8] The reader interested in further exploring changes in IQ scores over time for a particular country or region is urged to consult Appendix 2 of Lynn and Vanhanen (2002) or Sailer's (2004) online spreadsheet.

to three points per decade across most of the 20th century. This phenomenon is known as the Flynn effect (after Flynn (1987)), and it has been widely studied and widely debated. Explanations that psychologists have considered for the Flynn effect include better nutrition, better education, and educational television, as well as the possibility that the Flynn effect is merely a "nominal" rise in narrow test-taking ability with little impact on "real" general reasoning and information processing abilities. For helpful reviews of the Flynn effect literature, Neisser (1998) and Jensen (1998, 318-333) are highly recommended.[9]

Unfortunately, economists have not yet brought their powerful econometric tools to bear on the question of what causes the Flynn effect, either within the U.S. or in other countries. Indeed, they have not joined the debate over whether the Flynn effect is "real" or merely "nominal." As economists come to recognize the importance of IQ differences for determining living standards, one can only hope that they will devote substantial resources to determining what causes the Flynn effect within the developed world, as well as whether policy interventions can set off even larger Flynn effects in the world's poorest countries. If economists can collaborate with policymakers to initiate a process of global IQ convergence, they may be able to remove a substantial barrier to riches.[10]

VII. IQ and Productivity, 1960-1990

One question of interest is whether the IQ-productivity relationship has strengthened or weakened over the past few decades. Shocks such as the Great Depression and the Second World War were likely to move nations away from their steady-state paths. Further, many countries have embraced market economies in recent decades, a policy change which is likely to have removed non-IQ-related barriers to

[9] For evidence of a large Flynn effect in rural Kenya in recent decades, see Daley et. al (2003).

[10] An additional way to address reverse causation is to see whether old estimates of national average IQ do a good job predicting current GDP. Using the raw LV IQ and GDP data included in Sailer (2004), the correlation between pre-1960 national average IQ estimates and log 1998 PPP-adjusted real GDP per worker is 0.83, essentially the same as the 0.82 found in the full LV (2002) sample (N=18 countries, 21 tests, multiple observations from every inhabited continent except Australia (one test only)). That these pre-1960 IQ tests—dating as far back as 1914 for the U.S. and 1933 for Guinea--should predict 1998 productivity so well is quite astonishing. Extending to pre-1970 and pre-1980 IQ tests yield similar strong results. Old IQ tests are extremely useful for predicting a nation's present-day worker productivity, perhaps as useful as the old measures of "social capability," (i.e., media penetration) used by Temple and Johnson (1998).

riches.[11] Accordingly, one would expect the IQ-productivity relationship to have strengthened over the decades.

As Figure 5 shows, this indeed appears to be the case. We used LV's 2006 IQ data along with Penn World Table data for on GDP per worker for 1960, 1970, 1980, 1990, and 2000. The correlation between each year's log GDP per worker and the (timeless) IQ estimate is reported, along with ten times the coefficient from a simple regression of that year's log GDP per worker on the (timeless) IQ estimate. It appears that by either measure, IQ is more important than it used to be.

This increasing relevance of IQ could be due to a number of factors. Perhaps as other differences across countries diminish—as market-oriented institutions take hold and as knowledge of science, technology, and management methods diffuse across countries—then persistent IQ differences have become the dominant remaining difference across countries. Another possibility is that modern economies depend much more on cognitive ability than they once did. The simplest possibility would be the one with which we began this section: that the crises of the early and middle 20th century pushed many nations away from their steady-state growth paths, paths toward which they are approaching every year. If this latter explanation is the case, then barring other large shocks, we can predict that differences in national average IQ will become an increasingly important source of global income inequality.

VIII. IQ as a Missing Input

Based on IQ's power to explain a portion of cross-country income differences, it would be reasonable to conclude that IQ is one of the "missing inputs" that Caselli (2004), Easterly (2004), and other growth researchers are looking for. Caselli, for example, considers the possibility that what he calls "schooling quality"—a combination of standardized test scores broadly comparable to IQ—may be a key missing input. However, the conclusions he can draw are limited by the existence of relevant math,

[11] Lynn and Vanhanen (2002) hypothesize that national average IQ and market institutions are the two crucial determinants of GDP per capita. They provide some bivariate regressions supporting this hypothesis; they show that both variables together explain much more—about 75% of the variance in the *level* of GDP per capita--than either variable alone, each of which can explain roughly 50%.

science, and reading scores from only 28 countries. As Jones and Schneider (2006) demonstrate in their consideration of the Barro-Lee (1993) and Hanushek-Kimko (2000) data on cross-country standardized test scores, such math and science scores are quite strongly correlated with IQ scores, and are likely to be measuring many of the same productive mental skills that IQ tests measure.

One strength of IQ data is that they are much more widely available than standardized test scores: Lynn and Vanhanen's (2006) IQ data cover 131 countries, and IQ measures have the benefit of a massive international literature linking cognitive ability to wage outcomes. Further, there is a rich clinical and academic literature within psychology devoted to making scores from different types of IQ tests comparable—something that does not exist for the math and science tests that have, for better or worse, become so popular among economists. So collecting IQ scores for even more countries is clearly possible. It should even be possible to assemble historical data on cross-country IQ differences, since the raw test scores are already sitting in thousands of elementary-school file drawers.

As an empirical matter, then, the merits of considering IQ as a "missing input" are clear: Widely available data combined with large literatures in labor econometrics and empirical psychology on which growth economists can draw. These are merits which international math and science tests such as the TIMMS lack almost entirely.

But what of the possible role for IQ in growth theory? Surely, IQ's impact on the private marginal product of labor is not the only mechanism by which IQ can impact national productivity. More microfoundational channels remain to be explored if economists wish to explain the strong relationship between IQ and log productivity across countries.

As should be clear by now, IQ appears to matter more at the macro level than at the micro level. For example, in our simple bivariate relationship reported in Figure 1, 1 IQ point is associated with 6.7% more output; and in the robust growth regressions of Jones and Schneider (2006) 1 IQ point is associated with an average of 6% more output in steady state. By contrast, at the micro level, 1 IQ point is associated with perhaps 1% more output.

There are more channels to be explored if one wishes to explain why IQ appears to matter so much more at the macro level. The Ramsey-style model of Manuelli and Seshadri (2005) would be a natural extension: In their model, ex-ante differences in total factor productivity of at most 27% interact with the education decisions and fertility choices to *completely* replicate the span of the current global income distribution. In their calibration—less naïve and more complex then the one we present—a 1% rise in TFP (e.g., 1 IQ point) causes a 9% rise in steady-state productivity. Manuelli and Seshadri leave unanswered the question of what those ex-ante differences in TFP might be, but persistent differences in national average IQ are a natural candidate. As we have seen, these differences are readily verifiable and appear to have been persistent for many decades, even in Asian countries that have undergone overwhelming economic and social transformations.

Manuelli and Seshadri themselves refer repeatedly to unspecified differences in the "quality of human capital" between countries. Within the realm of quantitative social science, it would be hard to think of a better candidate for "quality of human capital" than IQ. Indeed, the current span of global IQ differences—38 points between the bottom and top IQ deciles—creates a TFP gap almost double the amount needed in the Manuelli/Seshadri model.[12] Thus, by introducing more decision channels through which persistent underlying "TFP differences" (i.e., IQ differences) impact steady-state productivity, the simple model introduced here could fit the global income distribution even more completely.

As an additional example: Warner and Pleeter (2001) and Fredrick (2005) find that higher cognitive ability is associated with lower discount rates. If these results generalize across countries, then IQ may impact steady-state capital accumulation through yet another channel: via country-specific differences in discount rates.[13] And the possible links between national average IQ and technology innovation and adoption are too obvious to belabor.

---

[12] Note that if $\gamma=1$, then exp(.01*38)=1.46; so a 38-point IQ gap would cause a 46 percent TFP gap.

[13] Indeed, persistent cross-country differences in average cognitive ability could provide a solution to the Feldstein-Horioka (1980) international savings puzzle: High-IQ countries would be both more productive (hence creating a higher demand for investment goods) and more patient (hence creating more private savings with which to meet that demand). Experimental findings of the strong relationship between cognitive ability and patience can be found in Benjamin and Shapiro (2005) and Fredrick (2005).

One can multiply examples, but the point is clear: stylized facts related to IQ and productivity are ready and waiting for the theorist who seeks to explain a large part of the puzzle of cross-country productivity differences. Accordingly, persistent difference in national average IQ—regardless of their source—may play an important role in answering Prescott's (1998) call for a theory of total factor productivity.

XIX. Conclusion

Hendricks (2002) showed convincingly that workers from different countries have different average levels of what he calls "unmeasured worker skill." We have provided evidence that conventional, out-of-the-box IQ tests can measure an important part of that heretofore unmeasured skill. This supports the claims of Lynn and Vanhanen (2002, 2006) that national average IQ is an important determinant of economic outcomes across countries.

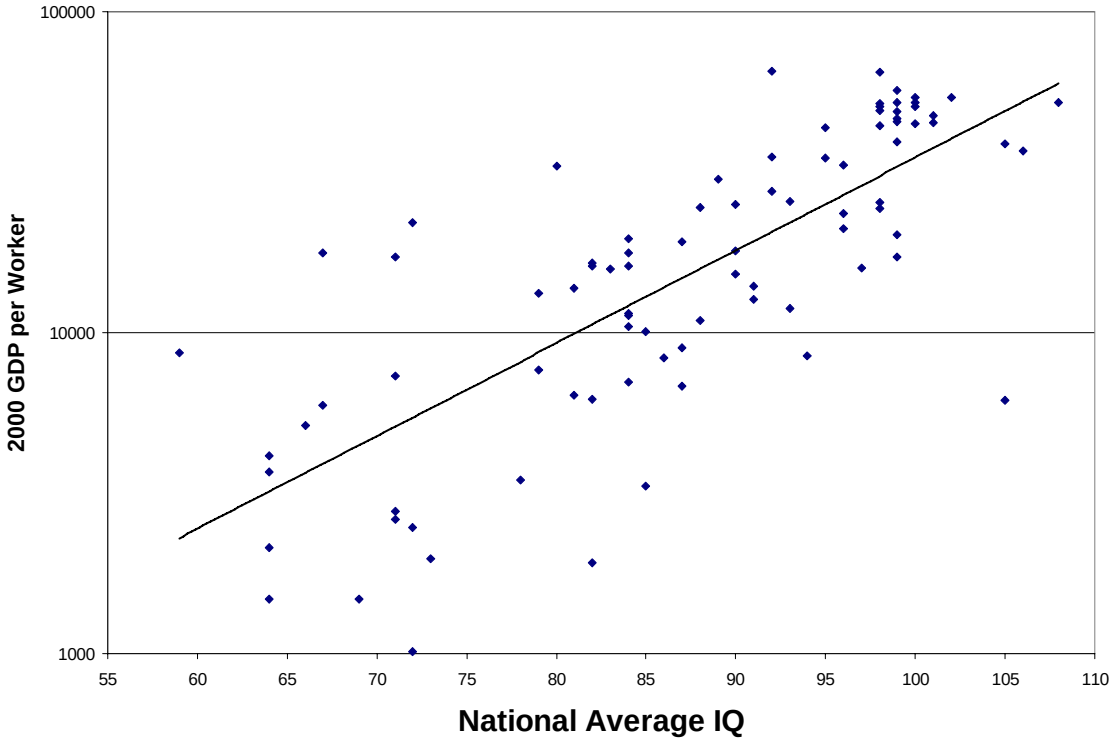
We have further shown that the between-country coefficient on IQ is essentially identical to the within-country coefficient on IQ, and we have used that fact to conduct a conventional, externality-free development accounting exercise. In such an exercise, we found IQ's impact on productivity to be quantitatively modest: It explains about $1/6^{th}$ of the variance in log productivity between countries, and about $1/6^{th}$ of the predicted steady-state relationship between IQ and log productivity.

To put this in perspective, note that if a nation moved from the 5th to the 95th percentile of national average IQ, our development accounting exercise predicts that its output per worker would rise by perhaps 50%. But in reality, these countries have living standards that differ by a factor of 15, not 1.5. We hope that future research investigates why these relatively modest IQ differences between countries predict such massive differences in living standards.[14]

[14] Jones (2006) asserts that one reason for the strong IQ/national productivity relationship may be because higher-IQ groups are better at solving the repeated prisoner's dilemmas that arise in non-market interactions between citizens and their government; in a metastudy of repeated prisoner's dilemma experiments held at various universities, he finds that students at better schools cooperate much more often. His result apparently survives a variety of robustness tests.

We also hope that economists can bring their powerful econometric and theoretical tools to bear on the question of why IQ gaps across poor countries are so large. If economists can find ways to narrow these persistent IQ gaps, the world's poorest citizens may be able to make full use of their productive potential.

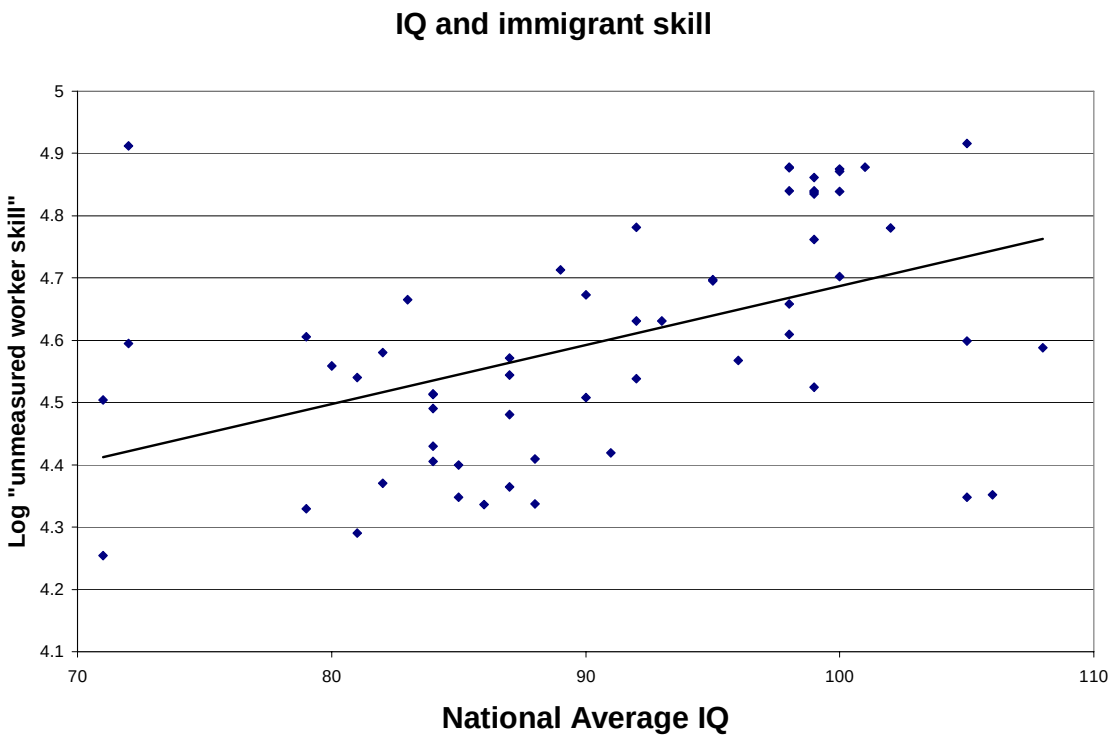
Figure 1: National Average IQ (Lynn & Vanhanen, 2006) and Year 2000 GDP Per Worker



Notes: Y-axis shows GDP per worker in logarithmic scale. In this bivariate regression, the coefficient on national average IQ is 0.067, and the R^2 is 58%. Thus, a one-point rise in IQ is associated with 6.7% higher output per worker. The sample covers 87 countries. The outlier in the lower-right corner is China (IQ=105).

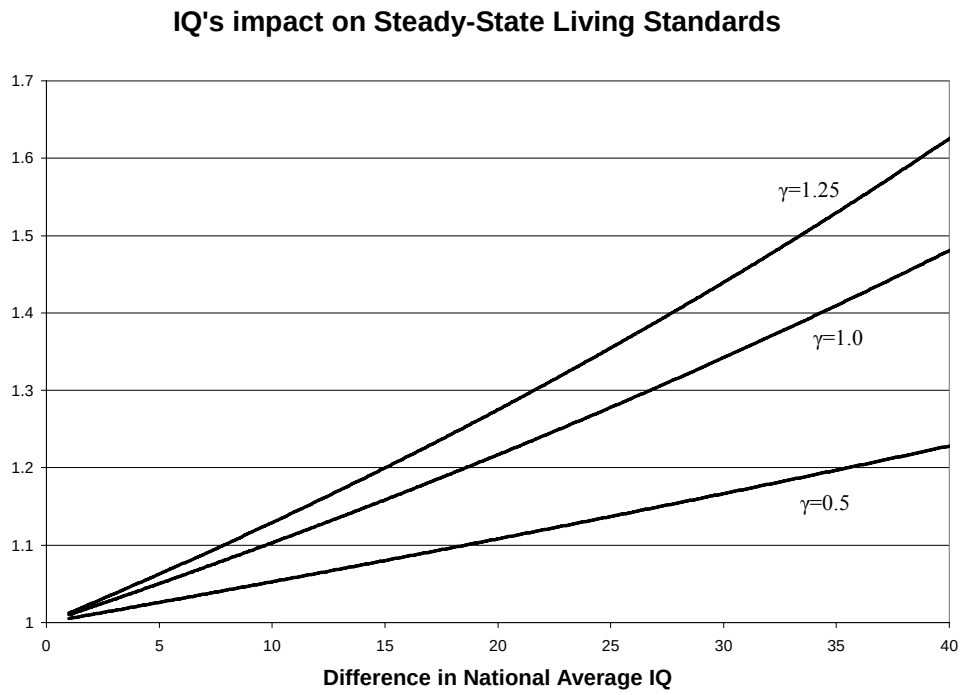
Source: Lynn and Vanhanen (2002) and Penn World Tables 6.1 for IQ and GDP data, respectively.

Figure 2



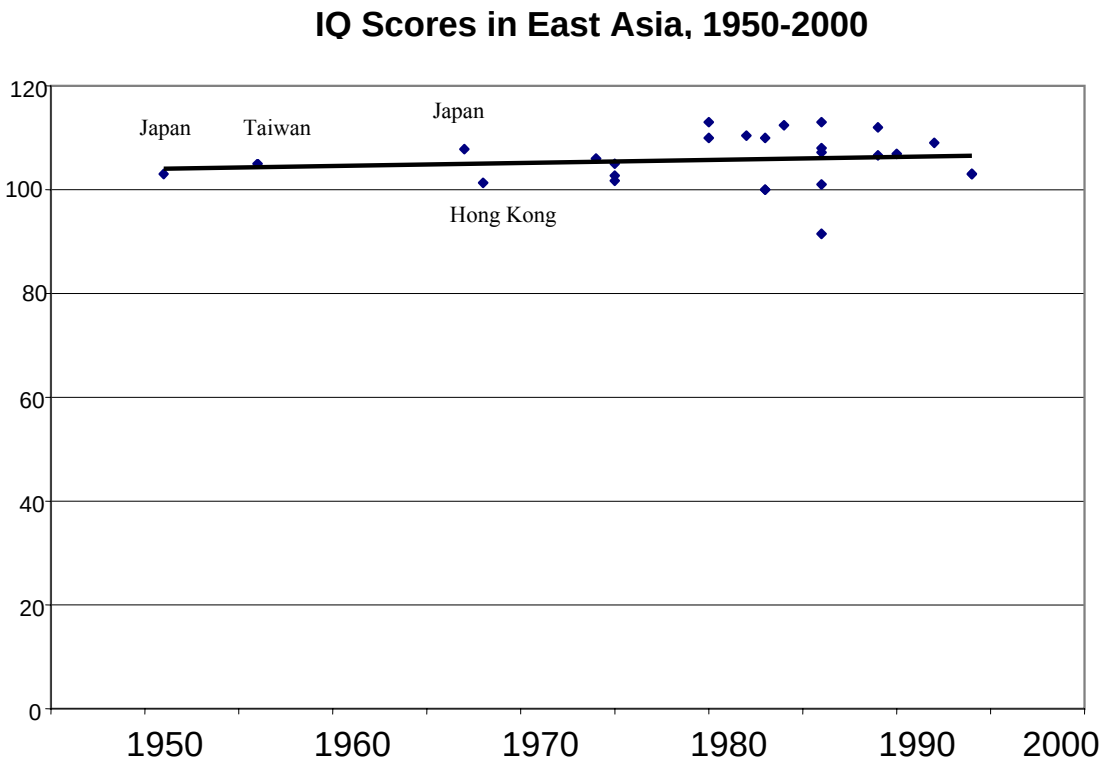
Notes: The x-axis reports estimates for national average IQ for country *i* from Lynn and Vanhanen (2006). The y-axis reports values for uws_i, the unmeasured worker skill estimate for immigrants from country *i*, as estimated in Hendricks (2002). uws_i is the log average wage of immigrants for country *i*, adjusting for age and education. The trendline reflects the OLS coefficient of 0.95 reported in the text, and the R^2 is 22%.

Figure 3



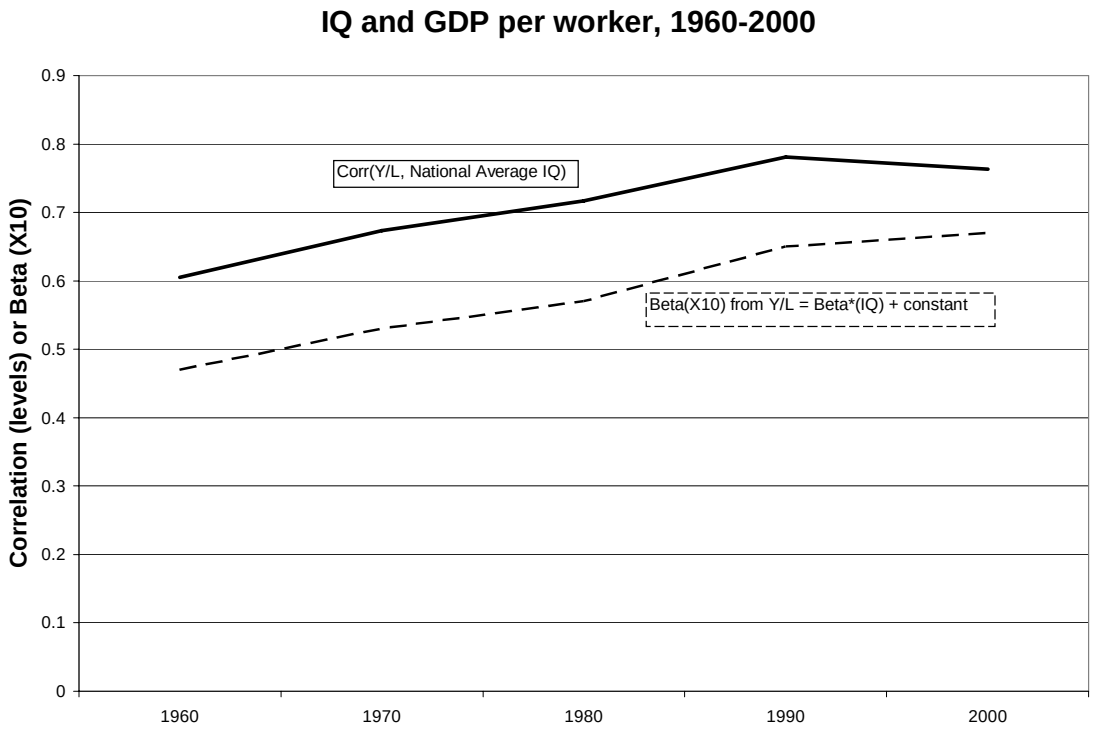
Notes: The value on the y-axis is $(Y/L)_{hi}/(Y/L)_{lo}$, the ratio of living standards in two countries who differ only in national average IQ. This chart is based on equation (3).

Figure 4



Source: Lynn and Vanhanen (2002), as reported online in Sailer (2004).
For descriptions of all datapoints, see Sailer (2004).

Figure 5



Note: This reports the relationship between log GDP per worker in the given year (PWT) and Lynn and Vanhanen's (2006) measure of national average IQ. In all five regressions, t-statistic > 6.5, N>76.

Table 1: Log productivity variance explained by IQ's impact on wages

γ=0.5	γ=1.0	γ=1.25
8%	**16%**	**20%**

Notes: γ is the semi-elasticity of skill/wages with respect to IQ. The percentages indicate the variance in year 2000 log GDP per worker that can be explained by IQ's steady-state impact on the private marginal product of labor, as set forth in equation (3). These calibrations are based on data from 87 countries.

For reference, the R^2 from a simple regression of year 2000 log GDP per worker on national average IQ is 58%. IQ and GDP data are from Figure 1.

Data Appendix

Country	National Average IQ	Log Adjusted Earnings
Argentina	93	4.63
Australia	98	4.88
Austria	100	4.84
Barbados	80	4.56
Belgium	99	4.84
Bolivia	87	4.36
Brazil	87	4.54
Canada	99	4.83
Chile	90	4.51
China	105	4.35
Colombia	84	4.43
Denmark	98	4.88
Dominican Republic	82	4.37
Ecuador	88	4.41
Egypt	81	4.54
Fiji	85	4.40
France	98	4.84
Germany	99	4.76
Ghana	71	4.25
Greece	92	4.63
Guatemala	79	4.33
Honduras	81	4.29
Hong Kong	108	4.59
Hungary	98	4.61
India	82	4.58
Indonesia	87	4.57
Iran	84	4.51
Iraq	87	4.48
Ireland	92	4.78
Israel	95	4.70
Italy	102	4.78
Jamaica	71	4.50
Japan	105	4.92
Jordan	84	4.51
Kenya	72	4.60
Malaysia	92	4.54
Mexico	88	4.34
Netherlands	100	4.70
New Zealand	99	4.84
Norway	100	4.88
Pakistan	84	4.41
Peru	85	4.35
Philippines	86	4.34
Poland	99	4.53
Portugal	95	4.70
South Africa	72	4.91
South Korea	106	4.35
Spain	98	4.66
Sri Lanka	79	4.61
Sweden	99	4.86
Switzerland	101	4.88
Syria	83	4.67
Taiwan	105	4.60
Thailand	91	4.42
Turkey	90	4.67
United Kingdom	100	4.87
Uruguay	96	4.57
Venezuela	84	4.49
Yugoslavia	89	4.71

Notes: National Average IQ data are from Lynn and Vanhanen (2006). Adjusted Earnings data are from Hendricks (2002), and draw on the 1990 U.S. census.

Bibliography

Acemoglu, D., Johnson, S., & Robinson, J. (2001). "The Colonial Origins of Comparative Development: An Empirical Investigation," *American Economic Review, 91*, 1369-1401.

Armor, D. J. (2003). *Maximizing intelligence*. New Brunswick: Transaction Publishers.

Barro, R. J. & Lee, W. (1993). "International Comparisons of Educational Attainment," *Journal of Monetary Economics*, 32, 363-394. Data available at www.nber.org.

Barro, R. J. & Sala-i-Martin, X. (2001) *Economic Growth*, 2nd ed. Cambridge, MA: MIT Press.

Bartholomew, D.J. (2004). *Measuring intelligence: Facts and fallacies*. Cambridge: Cambridge University Press.

Behrman, J., Alderman, H. & Hoddinott, J. (2004). *Copenhagen Consensus – Challenges and Opportunities: Hunger and Malnutrition*. http://www.copenhagenconsensus.com/Default.asp?ID=223

Benjamin, D. J. & Shaprio, J. M. "Does Cognitive Ability Reduce Psychological Bias?" working paper, Harvard University.

Bils, M. & Klenow, P. (2000). "Does Schooling Cause Growth?" *American Economic Review, 90*, 1160-83.

Bishop, J. H. (1989). "Is the Test Score Decline Responsible for the Productivity Growth Decline?" American Economic Review, *79*, March, 178-197.

Bowles, S., Gintis, H. & Osborne, M. (2001). "The Determinants of Earnings: Skills, Preferences, and Schooling," *Journal of Economic Literature*, *39*, 1137–1176.

Brown, R.T., Reynolds, C. R., Whitaker, J. S. (1999). "Bias in mental testing since Bias in Mental Testing," *School Psychology Quarterly, 14*, 208-238.

Cascio, W. F. (2003). *Managing Human Resources: Productivity, Quality of Work Life, Profits*, 6th ed. New York: McGraw-Hill Irwin.

Caselli, F. (2003) "The Missing Input: Accounting for Cross-Country Income Differences," Harvard University working paper. Forthcoming in *Handbook of Economic Growth.*

Castro, R. (2005). "Economic Development and Growth in the World Economy," *Review of Economic Dynamics*, *8*, 1, 195-230.

Cawley, J., Conneely, K., Heckman, J. & Vytlacil, E. (1997). "Cognitive Ability, Wages, and Meritocracy," in B. Devlin, S. E. Fienber, D, P. Resnick, & K. Roeder (Eds), *Intelligence, Genes, and Success: Scientists Respond to* The Bell Curve. New York: Springer-Verlag.

Chabris, C. F. (2006). "Cognitive and Neurobiological Mechanisms of the Law of General Intelligence." In Roberts, M. J. (Ed.) *Integrating the mind.* Hove, UK: Psychology Press.

Cianciolo, A. T. & Sternberg, R. J. (2004). *Intelligence: A brief history*. Malden, MA. Blackwell Publishing.

Colom, R., Lluis-Font, J.M., and Andrés-Pueyo, A. (2005). "The generational intelligence gains are caused by decreasing variance in the lower half of the distribution: Supporting evidence for the nutrition hypothesis." *Intelligence, 33*, 83-91.

Court, J. H. (1991). "Asian applications of Raven's Progressive Matrices," *Psychologia, 34*, 75-85.

Daley, T. C., Whaley, S. E., Sigman, M. D., Espinosa, M. P., Neumann, C. (2003). "IQ on the rise: The Flynn effect in rural Kenyan children," *Psychological Science, 14*, 215-219.

Deary, I. J. (2001). *Intelligence: A very short introduction.* Oxford: Oxford University Press.

Deary , I. J. (2003). "Reaction time and psychometric intelligence: Jensen's contributions," In H. Nyborg (Ed.), *The scientific study of general intelligence: Tribute to Arthur R. Jensen* (pp. 53-75). Amsterdam: Pergamon.

Diamond, J. (1999). *Guns, Germs, and Steel: The Fates of Human Societies.* New York: W.W. Norton.

Dickens, W. T., & Flynn, J. R. (2001). „Heritability estimates versus large environmental effects: The IQ paradox resolved," *Psychological Review, 108*, 346–369.

Doing Business (2005) "Doing Business Economy Rankings," http://www.doingbusiness.org/EconomyRankings

Easterly, W. (2004). "Globalization, Poverty, and All That: Factor Endowment versus Productivity Views." Working paper, NBER Globalization and Poverty Workshop.

Ehrlich, P. (2000). *Human Natures: Genes, Culture, and the Human Prospect.* Washington, DC: Island Press.

Evans P.D., Gilbert S.L., Mekel-Bobrov N., Vallender E.J., Anderson J.R., Tishkoff S.A., Hudson R.R. & Lahn B.T. (2005). "Microcephalin, a gene regulating brain size, continues to evolve adaptively in humans." *Science*, 309:1717.

Feldstein, M. & Horioka, C. (1980). "Domestic Saving and International Capital Flows." *The Economic Journal*, *90*, June, 314-329.

Flynn, J. R. (1980). *Race, IQ and Jensen*. London: Routledge & Kegan Paul.

Flynn, J. R. (1987). "Massive IQ gains in 14 nations," *Psychological Bulletin, 101*, 171-191.

Fredrick, S. (2005). "Cognitive Reflection and Decision Making," *Journal of Economic Perspectives,* Fall 2005, 19(4), 29-42.

Galor, O. and Moav, O. (2002). "Natural Selection and the Origin of Economic Growth," *Quarterly Journal of Economics*, 117 (November), 1133-1191.

Global Lead Network, (2005). "Leaded Gasoline Phase-Out in Africa." www.globalleadnet.org/policy_leg/policy/africa.cfm

Gollin, D. (2002) "Getting Income Shares Right," *Journal of Political Economy*, *110*, 2, 458-474.

Gottfredson, L. (1997). "Why g matters: The complexity of everyday life," *Intelligence, 24,* 79-132.

Gould, S. J. (1981). *The mismeasure of man.* New York:W.W. Norton/Harmondsworth, U.K.: Penguin Books.

Haier, R. J. (1993). "Cerebral glucose metabolism and intelligence," in Philip A. Vernon (Ed.), *Biological Approaches to the Study of Human Intelligence*, Norwood, NJ: Ablex, 313-373.

Hanushek, E. & Kimko, D. (2000). "Schooling, Labor Force Quality, and the Growth of Nations," *American Economic Review*, 90, 1184-1208.

Herrnstein, R. J. & Murray, C. (1994). *The Bell Curve: Intelligence and Class Structure in American Life.* New York: Free Press.

Heston, A., Summers, R. & Aten, B., (2002). *Penn World Table Version 6.1*, Center for International Comparisons at the University of Pennsylvania (CICUP), October 2002.

Horn, J. L. & Blankson, N. (2005). "Foundations for better understanding cognitive abilities," In Flanagan, D. P. & Harrison, P. L. (Eds.), *Contemporary intellectual assessment: Theories, tests, & issues (2nd ed.)* (pp. 41-68). NY: The Guilford Press.

Jcnsen. A. R. (1969). "How much can we boost IQ and scholastic achievement?" *Harvard Educational Review*, 39, 1-123.

Jensen, A.R. (1980). *Bias in mental testing*. New York: Free Press.

Jensen, A.R. (1987) 'The g beyond factor analysis.' In R. R Ronning, J.A. Glover, J. C. Conoley, & J. C. Witt (Eds.), *The influence of cognitive psychology on testing* (pp. 87-142). Hillsdale, NJ: Erlbaum.

Jensen, A. R. (1998). *The g factor: The science of mental ability*. Westport, CT: Praeger.

Jones, G. (2006). "Are Smarter Groups More Cooperative? Evidence from Repeated Prisoner's Dilemma Experiments, 1959-2003." Working Paper, Southern Illinois University Edwardsville.

Jones, G. & Schneider, W. J. (2006). "Intelligence, Human Capital, and Economic Growth: A Bayesian Averaging of Classical Estimates (BACE) Approach," *Journal of Economic Growth*, 11:71-93.

Kendall, I. M., Verster, M. A. & Von Mollendorf, J. W. (1988) Test performance of blacks in Southern Africa. In S. H. Irvine and J. W. Berry (Eds.), *Human abilities in cultural context* (pp. 299-339). Cambridge, UK: Cambridge University Press.

Lacey, M. (2004) "Belatedly, Africa is Converting to Lead-Free Gasoline," *New York Times*, October 31.

Leamer, E. E. (1983). "Let's Take the Con Out of Econometrics," *American Economic Review, 73*, 31-43.

Leamer, E. E. (1985). "Sensitivity Analysis Would Help," *American Economic Review, 75*, 31-43.

Lomborg, B.., ed. (2004). *Global Crises, Global Solutions.* New York: Cambridge UP.

Lynn, R. (2006). *Race Differences in Intelligence: An Evolutionary Analysis*. Washington Summit Publishers.

Lynn, R. & Vanhanen, T. (2002). *IQ and the Wealth of Nations.* Westport, CT: Praeger Publishers.

Mankiw, N. G., Romer, D. & Weil, D. (1992). "A Contribution to the Empirics of Economic Growth," *Quarterly Journal of Economics, 107*, 407-38.

Manuelli, R. & Seshadri, A. (2005). "Human Capital and the Wealth of Nations," Working paper, University of Wisconsin-Madison, June.

McDaniel, M.A. (2005). Big-brained people are smarter: A meta-analysis of the relationship between in vivo brain volume and intelligence. *Intelligence, 33*, 337–346.

McDaniel, M.A. & Whetzel, D.L. (2004). *IQ and the Wealth of Nations: Prediction of GDP Not Dependent on Precise g Estimates*. Working paper, Virginia Commonwealth University.

Mekel-Bobrov N., Gilbert S.L., Evans P.D., Vallender E.J., Anderson J.R., Hudson R.R., Tishkoff S.A. & Lahn B.T. (2005). "Ongoing adaptive evolution of ASPM, a brain size determinant in Homo sapiens." *Science*, 309:1720.

Mingroni, M.A. (2004). "The secular rise in IQ: Giving heterosis a closer look". *Intelligence 32*, 65–83.

Murray, C. A. (1997). "IQ and economic success," *The Public Interest, 128*, 21-35.

Murray, C. A. (2002). "IQ and Income Inequality in a Sample of Sibling Pairs from Advantaged Family Backgrounds," *American Economic Review, 92,* 339-343.

Neal, D. A. & Johnson, W. R. (1996). "The Role of Premarket Factors in Black-White Wage Differences," *Journal of Political Economy*, *104*, 5, 869-895.

Nechyba, T. (2004). *Review of* IQ and the Wealth of Nations, *Journal of Economic Literature*, *42, March,* 220-21

Neisser, U. (1998). *The Rising Curve*. Washington, DC: American Psychological Association.

Ogbu, J. U., & Davis, A. (2003). *Black American Students in an Affluent Suburb: A Study of Academic Disengagement.* Mahwah, NJ: Lawrence Erlbaum Associates.

Parente, S. L. & Prescott, E. C. (2004). "A unified theory of the evolution of international income levels," Staff Report 333, Federal Reserve Bank of Minneapolis.

Parente, S. L. & Prescott, E. C. (2002). *Barriers to Riches*, reprint edition. Cambridge, MA: MIT Press.

Prescott, E. C. (1998). "Needed: A Theory of Total Factor Productivity." *International Economic Review*, *39*, 3, 525-51.

Reed, T. E., Vernon, P. A., & Johnson, A. M. (2004). "Confirmation of correlation between brain nerve conduction velocity and intelligence level in normal adults," *Intelligence, 32*, 563–572.

Robson, Arthur J. and Hillar S. Kaplan (2003). "The Evolution of Human Life Expectancy and Intelligence in Hunter-Gatherer Economies," *American Economic Review*, 93: 1(Mar), 150-169.

Roid, G. H. (2003). Stanford-Binet Intelligence Scales-Fifth Edition: Technical Manual. Itasca, IL: Riverside Publishing.

Rushton, J. P., Skuy, M. & Bons, T. A. (2004). "Construct Validity of Raven's Advanced Progressive Matrices for African and Non-African Engineering Students in South Africa." *International Journal of Selection and Assessment, 12*, 220-229.

Sailer, S. (2004). "IQ and the Wealth of Nations, Lynn and Vanhanen: data table of national mean IQ studies." http://www.isteve.com/IQ_Table.htm

Schaie, K. W. (2005). *Developmental influences on adult intelligence: The Seattle Longitudinal Study*. London: Oxford University Press.

Seligman, D. (1992). *A question of intelligence: The IQ debate in America*. New York: Birch Lane Press.

Sternberg, R.J. (1998). "Costs and benefits of defying the crowd in science," *Intelligence, 26*, 209-215.

Sternberg, R. J. & Grigorenko, E. L. (2001) *Enviromental effects on cognitive abilities.* Mahwah, New Jersey: Lawrence Erlbaum Associates, Publishers.

Temple, J., and Johnson, P.A. (1998). "Social Capability and Economic Growth," *Quarterly Journal of Economics,* Vol. 113, No. 3: 965-990.

Vinogradov, E., and Kolvereid, L. (2006). "Cultural Background, Home Country National Intelligence, and Self-Employment Rates Among Immigrants in Norway," Working Paper, Bodo Graduate School of Business.

Volken, T. (2003). "IQ and the Wealth of Nations. A Critique of Richard Lynn and Tatu Vanhanen's Recent Book," *European Sociological Review, 19,* 411-412.

Voracek, M. (2004). "National intelligence and suicide rate: an ecological study of 85 countries." *Personality and Individual Differences*, 37: 543–53.

Voracek, M. (2005). "National intelligence, suicide rate in the elderly, and a threshold intelligence for suicidality: an ecological study of 48 Eurasian countries." *Journal of Biosocial Science,* 37: 721–40.

Wang, E.T., Kodama, G., Baldi, P., and Moyzis, R.K. (2006). "Global landscape of recent inferred Darwinian selection for *Homo sapiens*." *Proceedings of the National Academy of Sciences,* 103(1):135-40.

Warner, J. T. & Pleeter, S. "The Personal Discount Rate: Evidence from Military Downsizing Programs." *American Economic Review*, *91*, 1, 33-53.

Weede, E. (2004). "Does Human Capital Strongly Affect Economic Growth Rates? Yes, but only If Assessed Properly." *Comparative Sociology*, *3*, 2, 115-134.

Weede, E. & Kampf, S. (2002). "The Impact of Intelligence and Institutional Improvements on Economic Growth," *Kyklos, 55*,361-380.

Winship, C. & Korenman, S. (1997). Does Staying in School Make You Smarter? The Effect of Education on IQ in *The Bell Curve,* in *Intelligence, Genes, and Success: Scientists Respond to the Bell Curve.* New York, NY: Springer-Verlag.

Zax, J. S. & Rees, D. I. (2002). "IQ, Academic Performance, Environment, and Earnings," *Review of Economics and Statistics, 84*, 4, 600-616.