IQ in the Ramsey Model:
A Naïve Calibration

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Abstract

I show that in a conventional Ramsey model, between one-fourth and one-half of the global income distribution can be explained by a single factor: The effect of large, persistent differences in national average IQ on the private marginal product of labor. Thus, differences in national average IQ may be a driving force behind global income inequality. These persistent differences in cognitive ability--which are well-supported in the psychology literature--are likely to be somewhat malleable through better health care, better education, and especially better nutrition in the world's poorest countries. A simple calibration exercise in the spirit of Bils and Klenow (2000) and Castro (2005) is conducted. I show that an IQ-augmented Ramsey model can explain more than half of the empirical relationship between national average IQ and GDP per worker. I provide evidence that little of the IQ-productivity relationship is likely to be due to reverse causality.

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In this paper, I contend that between one-fourth and one-half of the global distribution of income can be explained by a single factor: The effect of large, persistent differences in average national IQ on the private marginal product of labor. These differences in cognitive ability--which are well-supported in the psychology literature--are likely to be at least somewhat malleable through better nutrition, better education, and better health care in the world's poorest countries.

I arrive at this result through a short chain of reasoning: labor econometricians have shown that higher IQ causes higher wages (*inter alia*, Bowles, Gintis, and Osborne (2001), Cawley, Connelly, Heckman, and Vytlacil (1997), Zax and Rees (2002), Neal and Johnson (1996), and developing country estimates cited in Behrman et al., (2004)). In competitive markets, the reason for this higher wage is because higher IQ raises labor productivity. Finally, in a conventional Ramsey growth model, anything that raises labor productivity raises the steady-state capital-labor ratio, thus leading to a multiplier effect of IQ on labor productivity.

Formalizing this chain of thought within a quantitative general equilibrium setting, I use microeconometric estimates of IQ's impact on the marginal product of labor along with macroeconomic estimates of the elasticity of output with respect to capital to calibrate a simple Ramsey model of a nation's economy. This methodology takes into account the possibility of reverse causality, and in this respect is similar to Bils and Klenow (2000), who focused on the possibility of reverse causality in the cross-country education-growth relationship. My use of calibration in a cross-country setting is similar to the innovative work of Castro (2005).

The theoretical model calibrated here helps explain why previous researchers (Lynn and Vanhanen (2002), Weede and Kampf (2002), Weede (2004), Jones and Schneider (2006)) have found strong statistical relationships between national average IQ and economic performance. For reference, I note that the simple correlation between log year 2000 output per worker and national average IQ (as measured by the Penn World Tables and Lynn and Vanhanen (2002), respectively) is 0.82 (Figure 1), which implies that IQ predicts 64% of the global distribution of income.

Multivariate tests have repeatedly demonstrated that this relationship between national average IQ and economic performance is robust (though see Volken (2003) and Nechbya (2004) for contrary views). For example, Jones and Schneider found that in 455 Solow-style growth regressions that included only robust control variables, national average IQ was statistically significant at the 1% level in every one of these regressions, thus comfortably passing Leamer's (1983, 1985) extreme bounds test.

A crucial question is whether IQ differences across countries are a simple case of reverse causation: Do high-income countries simply develop higher IQ's? We address this question in a number of ways, but the most important is likely to be this simple fact: East Asian countries had high average IQ's—at or above the European and U.S. averages—well before they entered the ranks of the high income countries. This is precisely the opposite of what one would expect if the IQ-productivity relationship were merely epiphenomenal. Those wishing to explain the divergence of national average IQ's should cross simple reverse causality off the list, and should instead focus on the possible roles of persistent cross-country differences in culture, nutrition, education, environment, and genetic inheritance on measured cognitive ability.

IQ's correlation with cross-country differences in productivity and productivity growth demands a theoretical explanation: This calibration exercise is the beginning of such an explanation. The results presented here imply that depending on the capital elasticity of output parameter, the IQ-wage relationship can explain more than half of the IQ-productivity relationship. I close by discussing the opportunities for macroeconomists to explore policy interventions that can best narrow this large, persistent IQ gap.

The Relative Reliability of IQ

The crucial question in this line of inquiry is whether cross-country IQ measures are generally reliable. A large line of research in the psychology literature, going back for a hundred years and summarized in Lynn and Vanhanen (2002) demonstrates that when using best-practice psychometric methods, they generally are. After discussing IQ tests in general, I will then discuss cross-country and non-verbal IQ tests.

Tests of general cognitive ability--which I will refer to as IQ (Intelligence Quotient) tests--were originally developed for the Paris school system by Alfred Binet in 1908. Binet's tests were quickly found to be useful in identifying mentally retarded children (Jensen (1998), 15). IQ tests have had this practical orientation ever since: They are used by schools to place students, and they are widely used by the U.S. military to allocate human resources efficiently (Jensen (1998), 282ff.).

In addition, IQ tests are heavily used by firms to hire and promote (Cascio (2003), 250-251), and so it appears that such tests are a valuable source of information for firms about the quality of job applicants. In a meta-analysis reported in Cascio's (2003, 252) widely-used human resources text, such "general mental ability tests" are tied for third out of 19 predictors of job performance, ranking behind actual work samples and tied with structured employment interviews for statistical validity.

The validity of IQ tests in work settings is unambiguous. These scores correlate 0.3 to 0.5 with assessments of worker performance by managers—and are higher when job performance can be measured objectively or when the work tasks are more difficult (Gottfredson (1997)). Additionally, a well-known finding in the labor economics literature is that IQ tests taken at an early age have strong predictive power for wages later in life, even if the test is taken long before a person's education is complete (*inter alia*, Neal and Johnson (1996), Zax and Rees (2002). For example, as we see below, Zax and Rees find that men's high school IQ scores have a larger impact on wages when a worker is in his fifties than when the same worker is in his thirties. And as I demonstrate below, the link between cognitive ability and wages is an extremely robust finding among labor econometricians.

In the last two decades, psychologists have started to investigate how IQ is correlated with brain activity. To give one example: An experimenter flashes a bright light in front of a subject's eyes and measures the speed with which that message is conducted to the vision centers at the back of the brain. This simple measure of nerve conduction velocity is correlated +0.37 with IQ after correction for restriction of range (Jensen (1998), 160ff).

Another example: IQ is correlated by between –0.7 and –0.8 with cerebral glucose metabolism (Haier, (1993), Jensen (1998) 157ff). This sugar-burning process is measured using a PET scan while the test subject is trying to answer questions on an IQ test. This implies a quite astonishing result: Lower-IQ individuals are generally trying harder than higher-IQ individuals to solve the questions. If one believed that IQ differences across individuals were largely driven by social norms in favor of "trying hard" in some groups but not in others, one would instead expect a *positive* correlation between IQ and cerebral glucose metabolism. The nerve conduction velocity results and the cerebral glucose metabolism results both support the view that high-IQ individuals have brains that are, on average, more efficient processors of information. Chapter 8 of Jensen (1998) discusses the wide variety of experiments establishing the link between IQ and information processing, and is highly recommended.

The possibility of studying a key determinant of productivity through brain imaging has important consequences for economists. As microeconomists and financial economists have begun to use brain imaging techniques to study individual decisionmaking--creating the new field of neuroeconomics--it may be time for macroeconomists and productivity researchers to consider similar methods.

One can repeat a number of other examples where objective brain measures are correlated with IQ tests; Jensen (1998, 150-165) is especially useful in this regard. However, these brain activity measures have not to my knowledge been conducted in poor countries, so they shed limited light on whether IQ comparisons from across countries are measuring the same differences that have been found within countries.

Thus, I turn to the Jensen Box. Jensen created a simple test of information processing speed that has been widely used by psychologists interested in intelligence testing. The Jensen box has a home button and between 1 and 8 buttons with lights.

Initially, all of the buttons with lights are turned off. When one of the buttons with lights turns on, the test subject takes her finger off the home button and presses the lighted button as quickly as possible. One might expect this skill to be uncorrelated with IQ, but in fact button-pressing speed (known as reaction time) is correlated by an average of –0.35 (Jensen (1998), 204). The correlation is greater (in absolute value) when there are more buttons to choose from.

Again, one might believe that this correlation simply results from social norms and acculturation: People who try harder on IQ tests might also be people who try harder on button-pressing tests. But if that is the case, it is difficult to explain the following fact: The correlation between reaction time and IQ derives almost entirely from the speed with which one lifts one's finger from the home button (a measure known as decision time). There is little if any correlation between movement time (the time between finger removal and the time when the lighted button is depressed) and IQ (Jensen (1998), 211-214, 230-231, 242). If reaction time were simply a result of "trying harder," one would expect both decision time *and* movement time to be correlated with IQ. And according to a massive psychology literature summarized in Jensen (1998), it is decision time, not movement time, that has a robust correlation with cognitive ability however measured.

A natural question is whether this strong correlation between decision time and IQ holds outside the United States. Psychologist Richard Lynn and his coauthors conducted a series of studies in Britain, Ireland, Hong Kong, Japan, and South Africa to see if the correlation between IQ and decision time held across these countries (reviewed in Lynn and Vanhanen (2002), 66ff). In studies of hundreds of 9-year olds using non-verbal IQ tests, they found that it did. Aggregating to one observation per country, the correlation between national average IQ and national average decision time was always greater than 0.89, regardless of the type of Jensen Box test. The Jensen Box thus appears to verify the value of IQ tests as a measure of information processing speed, a factor that seems likely to influence worker productivity.[1]

This brings us to the question of cross-cultural and nonverbal IQ tests. Because IQ tests are in such demand among educators, businesses, and governments around the world, psychologists have responded by supplying a wide variety of such tests. When a new test is created, its validity is verified by giving both the new and the old test to the same group of people. Further, since the early 1970's, psychologists have responded aggressively to claims that IQ tests were culturally biased in favor of affluent people of European descent. Since the 1980's, there have been no noticeable differences in the validity of IQ tests across racial groups in the U.S. That is, these tests predict non-test outcomes equally well across groups. While we cannot survey this culture-bias question in depth, Jensen ((1998), 360-369) can point the interested reader toward much of the relevant literature.

Of course, one often wants to give IQ tests to children, people who have not learned to read, and people for whom IQ tests do not exist in their language. Non-verbal IQ tests are widely used, such as Catell's Culture-Fair test, Raven's Progressive Matrices, and the Draw-A-Man test. Let us consider the Raven test, since its matrices are a statistically powerful predictor of overall IQ scores, and since similar matrices are part of a conventional IQ test. One is given three visual objects with something in common--a triangle, a square, and a pentagon, perhaps--and is given a set of choices that can

[1] Interestingly, Lynn found that while South African students had slower average decision times than Asian students, they tended to have faster movement times than the Asian students. Thus, the evidence is consistent with the South African students "trying" quite hard to do well on the test.

complete the pattern--four objects, one of which is a hexagon. The patterns one is looking for may include colors, straight lines, complex designs, and the like. For a literate person, scores on the matrices section are heavily correlated with overall IQ as measured via a traditional test--indeed, scores on these matrix-style tests often have the highest correlation with overall mental ability (*inter alia*, Jensen, (1998), 34-38). Thus, if one had to choose just one portion of an IQ test to give, the matrices section would be a reasonable choice. Accordingly, non-verbal IQ tests such as the Raven play a central role in modern IQ testing.

This completes our brief survey of the validity of cross-cultural IQ tests. For the reader interested in the overall validity of IQ tests, Jensen (1998) is highly recommended, as is Lynn and Vanhanen (2002, c. 6) on the question of the cross-national validity of IQ tests.

Environmental Effects on IQ

All major psychological researchers agree that the environment has a major impact on a person's IQ. And while social forces are an important part of a person's environment, "environment" encompasses far more than just social forces. Factors such as childhood caloric intake, lead and mercury exposure, micronutrient levels, and prenatal maternal health can all have sizeable impacts on IQ.

Leading economists have also been convinced of the impact of health and nutrition on IQ. The Copenhagen Consensus project--a panel of prominent economists that included three Nobel laureates--evaluated the costs and benefits of various proposals to improve the well-being of the world's poor (Lomborg (2004)). Their second-highest-ranked recommendation was to include key micronutrients--vitamin and mineral supplements--in the food supply of the world's poorest countries. The impact of nutrition on IQ figured prominently in the arguments in favor the micronutrient policy.

For example, the "challenge paper" on health and nutrition that was presented to the Consensus panelists points to research showing that low-birth-weight babies have IQ's that are roughly 7 points lower than that of full-weight children (Behrman et al., 2004). They also point to research showing that iodine deficiency can reduce IQ by 13.5 IQ points, and that iron deficiency can reduce IQ by 7.5 points. Overall, Behrman et al.'s paper to the Copenhagen Consensus panel had 54 references to the word "cognitive" and 10 references to "IQ." The prominence of IQ in their micronutrient challenge paper and the high ranking given to the micronutrient initiative by the Copenhagen Consensus participants demonstrate that leading thinkers are convinced that the brain health of the world's poorest people is a substantial "barrier to riches" in the sense of Parente and Prescott (2004).

In addition, lead poisoning is a well-known cause of lower IQ's in the U.S., but this is also a problem around the world, particularly in Africa, where leaded gasoline is still widely used (Lacey (2004)). As the Global Lead Network (2005) notes, "Africa is more severely affected by lead poisoning and pollution than any other region of the world. Virtually all countries on the continent still use leaded gasoline in opposition to global trends - and the lead content of that gasoline is the highest in the world."

The possible impact of education on IQ should be noted: While estimates of education's impact on IQ vary, Winship and Korenman (1997) survey the literature of

U.S. and Scandanavian studies—which include some natural experiments—and also perform their own analyses of the U.S. National Longitudinal Surveys of Youth. An additional year of education is estimated to raise IQ by anywhere from 1.0 to 4.2 IQ points according to their literature survey. In their own regressions, point estimates range from 1.8 to 2.7 IQ points per year of education depending on the specification. Neal and Johnson (1996), using quarter-of-birth as an instrument for exogenous education, find estimates toward the upper end of these ranges. So the malleability of IQ through education appears to be an important channel for raising national average IQ.

This just touches on the massive literature demonstrating how environmental forces can impact national average IQ. For further references on the effects of the environment on IQ, Jensen (1998, pps 489-509), Sternberg and Grigorenko (2001), and Armor (2003) are especially useful. This body of literature gives hope that the large IQ differences that exist between countries can be narrowed in the future through environmental improvements.

IQ in the Production Function

To begin a discussion of IQ in the Ramsey model, I begin by assuming an IQ-augmented Cobb-Douglas production function,

$$Y_i = e^{\gamma IQ_i} K_i^{\alpha} (A_{it} L_i)^{1-\alpha}$$

The subscript *i* is the country subscript, and γ is the semi-elasticity of output with respect to IQ (Since my concern is with steady-states, I suppress time subscripts wherever possible). Below, I show that the labor economics literature implies precisely this form for the role of IQ in the production function. Note that national average IQ is implicitly a component of total factor productivity, a point that I will return to later in discussing how my results relate to the work of Manuelli and Seshadri (2005).

As in Mankiw, Romer, and Weil (1992) I assume that $\ln(A_{it}) = \bar{a} + gt + \varepsilon_i$, implying a one-time country-specific shock to the level of technology; *gt* represents the time trend in technology assumed constant across all countries. Mankiw et al. assume that ε_i was uncorrelated with any other parameter in the model; I relax this assumption by assuming only that ε_i has mean zero and is possibly correlated with IQ. Thus, all countries have access to the same global stock of knowledge, plus or minus a country-specific shock to the level of technology.

Since in competitive markets (without externalities) labor and capital earn their marginal products, this model implies that (suppressing subscripts):

$$\text{Real wage} = \frac{\partial Y}{\partial L} = (1-\alpha)e^{\gamma IQ}\left(\frac{K}{L}\right)^{\alpha} A^{1-\alpha}$$

$$\text{Interest Rate} = \frac{\partial Y}{\partial K} = \alpha e^{\gamma IQ}\left(\frac{K}{AL}\right)^{\alpha} \qquad (1)$$

In this section, it is the real wage that concerns us. I take logs and simplify:

$$\text{Log(Real wage)} = \log(e^{\gamma IQ}) + \log[(1-\alpha)\left(\frac{K}{L}\right)^{\alpha} A^{1-\alpha}]$$

$$= \gamma IQ + \log[(1-\alpha)\left(\frac{K}{L}\right)^{\alpha} A^{1-\alpha}] \qquad (2)$$

The first term of equation (2) notes that a one-point increase in IQ raises the real wage by γ percent. Fortunately for our purposes, there is large literature in labor economics devoted to estimating γ: The exogenous impact of a rise in IQ (often referred to as cognitive ability) on the log of real wages. I survey this literature below.

In light of equation (2), I can now explain why I allow the possibility of a correlation between A (often thought of as disembodied technology) and IQ. The focus of this paper is on one particular channel through which IQ impacts output per worker: by raising the private marginal product of labor. IQ surely impacts productivity through other channels—human capital spillovers come immediately to mind, and it seems quite plausible that the level of IQ has important impacts on the efficiency of technology adoption across countries.

Further, the relationship may run in exactly the opposite direction: From higher productivity to higher IQ, perhaps by way of better nutrition, more stimulating educational environments, and the like. The productivity-to-IQ causal chain should be kept in mind as a possibility, since rich countries tend to have healthier, better-educated populations: these would be just the types of populations that would be expected to perform well on IQ tests. This simple calibration exercise allows me to separate out the γ impact (of IQ on output via worker productivity) from any other possible channel through which IQ and productivity could be related.

Therefore, one should keep in mind that of the many possible reasons for the high unconditional correlation (0.82) between national average IQ and log worker productivity, I explore only one possible channel in this paper. If this strong relationship cannot be explained by the channel running from IQ to the private marginal product of labor, then further avenues will need to be explored.

The IQ-augmented Ramsey model

While the same results will obtain whether I use a Ramsey or a Solow growth model, I use the Ramsey model. I assume that aside from differences in IQ and A (the technology parameter), all countries share the same parameter values. Assume the consumer's utility function is

$$V = \sum_{t=0}^{\infty}\left(\frac{1}{1+\rho}\right)^{t} c_t^{1-\theta}$$

Where, as usual, ρ is the rate of time preference and θ is the risk aversion parameter (higher θ→ greater risk aversion). If the depreciation rate of capital = δ, it can be shown that in steady-state:

$$\frac{\partial Y}{\partial K} = \text{gross real interest rate} = \rho + \theta g + \delta$$

(For all Ramsey-related proofs, see, *inter alia*, chapter 2 of Barro and Sala-i-Martin (2004)). This result implies that the steady-state interest rate is determined by the model's deep parameters, ρ, θ, g, and δ. It is not in any way impacted by the level of technology or IQ. Combining this result with (1) and simplifying yields:

$$\left(\frac{K}{L}\right)^{ss} = A\left(\frac{\alpha e^{\gamma IQ}}{\rho + \theta g + \delta}\right)^{\frac{1}{1-\alpha}}$$

So while technology (in its A and IQ forms) has no impact on the steady-state interest rate, it has a dominating impact on the capital-labor ratio. Note that when IQ is higher, steady-state capital per worker is also higher. In a Ramsey framework, this is because a rise in IQ causes a higher non-steady-state interest rate, which generates more saving. This in turn generates more capital per worker in the new steady-state.

My original IQ-augmented production function can be rewritten as:

$$\left(\frac{Y}{L}\right) = A^{1-\alpha} e^{\gamma IQ} \left(\frac{K}{L}\right)^{\alpha}$$

Plugging in steady-state K/L and simplifying yields[2]:

$$\left(\frac{Y}{L}\right) = Ae^{\left(\frac{1}{1-\alpha}\right)\gamma IQ} \left(\frac{\alpha}{\rho + \theta g + \delta}\right)^{\frac{\alpha}{1-\alpha}}$$

Taking logs, substituting out the technology expression *A*, and combining constants into the term μ yields

$$\log\left(\frac{Y}{L}\right)^{ss} = \frac{\gamma}{1-\alpha} IQ + \mu + gt + \varepsilon_i \qquad (3)$$

This is the equation I use to evaluate the impact of IQ differences on steady-state living standards. The $\gamma/(1-\alpha)$ coefficient captures one unique channel through which IQ impacts living standards: by raising the private marginal product of labor and hence steady-state productivity. As noted above, the error term may well be correlated with a nation's IQ, and captures any other channel that could explain IQ's correlation with output per worker.[3]

[2] If I instead used a Solow framework with its accompanying exogenous savings rate, only the $\left(\frac{\alpha}{\rho + \theta g + \delta}\right)$ term would change; it would become $\left(\frac{s}{n + g + \delta}\right)$, with *s* = saving rate and *n*= population growth rate. The IQ-multiplier term, $\gamma/(1-\alpha)$, would be unchanged; this implies that even in a Solow framework higher IQ would have an identical impact, creating a higher steady-state capital stock.

[3] Note that since the parameters relating to the steady-state interest rate are assumed to be the same across countries, this implies that whether each economy is open or closed to capital flows will have no impact on the steady-state capital stock.

Data and Parameters

Two key parameters are needed for this simple calibration exercise: the semi-elasticity of wages with respect to IQ, γ, and the elasticity of output with respect to capital, α. I discuss these in order.

Labor economists have a rich literature estimating the link between cognitive ability and wages. In most cases, the cognitive ability measure is the Armed Forces Qualifying Test (AFQT) given as part of the National Longitudinal Survey of Youth. The AFQT is the test used to measure of cognitive ability in Herrnstein and Murray's *The Bell Curve*, in Neal and Johnson (1996), and in Cawley et al. (1997).

In the labor economics literature, differences in cognitive ability are usually reported as z-scores, that is, as standard deviations away from the mean. However, in the spirit of tying the economics literature closer to the psychology literature, and also to aid interpretation when comparing results from different countries, I will make the necessary conversions in order to report all cognitive scores in terms of IQ points.

As is well known, the mean IQ in the U.S. is typically defined as equal to 100, and the standard deviation of I.Q. in the U.S. population is defined as equal to 15. And this standard deviation of 15 holds in practice: For example, when Zax and Rees (2002) analyzed an actual IQ test (*not* an AFQT) given to male citizens of Wisconsin, they found the standard deviation of their sample was 15.1. Thus, γ equals one-fifteenth of the estimated effect of a one-standard-deviation rise in cognitive ability on wages.

The labor economics literature has used a variety of innovative techniques to estimate the impact of a rise in cognitive ability on wages. Many studies control for a wide variety of variables, such as education, age, and sector of employment. Others use innovative instruments, such as Neal and Johnson (1996) who used quarter of birth as an instrument for exogenous changes in education (and hence, to estimate the effect of exogenous changes in education on IQ). When assessing the vast literature on cognitive ability and wages, I put more weight on estimates that have been widely cited and that appear to use the best econometric techniques.

A crucial question is that of appropriate controls: As Zax and Rees (2002) carefully show, the decision to include education variables in a regression of wages on IQ could bias the IQ coefficient downward. For example, if higher IQ causes more education, then some of the IQ coefficient's true value would be transferred to the education coefficient. Thus, the simplest regressions may well be the best ones. This implies that I should place some weight on results from naïve bivariate regressions of wages on IQ when trying to estimate the true value of γ.

Using a number of controls, Neal and Johnson (1996) estimate γ=1.17, while Bishop (1989) estimates γ=1.27. In regressions that omit non-cognitive control variables, Cawley et al. (1997) find a range of estimates across various racial and gender categories, ranging from γ =1.3 for black females to γ=1.0 for white males. When Zax and Rees omit non-cognitive control variables, their estimates are γ=0.7 for males age 35 and γ= 1.4 for males in at age 53; they consider these to be upper bounds for the true estimate.

When controls are added to the Cawley et al. results, the estimates drop by between one-third to one-half. When Zax and Rees include controls, the estimates drop by roughly half, to 0.3 and 0.7, respectively. This indicates that while including controls does cut the estimated value of γ, it should cut it by no more than one-half. And of course, since education “controls” are well-known to be endogenous in the labor literature, I will place substantial weight on the simple bivariate regression estimates.

In one literature survey that looks at 65 estimates of γ without regard to the quality of the econometric methodology, Bowles et al (2001) find an average estimate of $\gamma=0.5$ over the past four decades, an estimate that has a wide variance but no substantial time trend; their mean and median estimate were nearly identical. The discovery of no trend provides some reason to believe that γ remains relatively stable as nations become richer. The one exception to their no-trend result is a rising trend in γ among African Americans (p.23).

The question of whether γ is roughly similar across countries should be briefly discussed. Within the U.S., Cawley et al. (1997) test for and reject the restriction that γ is equal across gender and racial groups. Their finding that white men's wages are less responsive to IQ than any other demographic group (aside from Hispanic men) provides some preliminary evidence that the wage-IQ link will be at least as strong in poorer countries as it is in the U.S.

Behrman et al. (2004) survey the academic literature on estimates of γ from various developing countries. They report values for Pakistan ($\gamma\approx0.87$), Ghana (0.67), Kenya (1.07), Tanzania (0.67), Columbia (0.47 to 1.53), and Chile (0.4 to 0.67). If I average the Columbia and Chile estimates to create one estimate per country, then the overall mean for these 6 countries is $\gamma\approx0.8$, with a median of 0.77.

I summarize this wide variety of U.S. and international estimates by taking $\gamma=1$ as the preferred estimate. In part, this is because U.S. estimates using modern methodologies rarely find $\gamma<1$, and generally find $\gamma>1$. This is also because if I average the median developing country estimate of $\gamma \approx 0.8$ with the $\gamma \approx 1.2$ found in the U.S. by Neal and Johnson (1996) and Bishop (1989), I arrive at an average of $\gamma=1$. As a robustness check, I also consider $\gamma=1.25$ and $\gamma=0.5$ as alternative estimates.[4]

Now I turn to α, the capital elasticity of output. A conventional estimate of α based on the share of income paid to owners of physical capital would be one-third (*inter alia,* Gollin, 2002). However, there are good reasons to believe that α is substantially larger than that. A basic result in the growth literature is that α is a key determinant of the speed with which an economy converges to its steady-state growth path: The greater the α, the slower is the speed of convergence (*inter alia*, Mankiw, Romer, Weil (1992)). Barro and Sala-i-Martin (2004, 110, 496) note that countries (as well as U.S. states and Japanese prefectures) converge to the steady state growth path much too slowly for a value of α as small as one-third. They find that $\alpha=0.75$ fits the convergence data much better.

Such a large value for α could be due to the important role played by the accumulation of human capital by way of education, as Mankiw, Romer, and Weil (1992) argue. They find that a human-capital augmented Solow model with a coefficient on education-based human capital equal to one-third fits the data well; when they combine this with a physical capital elasticity of one-third, this implies an aggregate model where $\alpha=0.67$.

By contrast, Parente and Prescott (2000, 2004) argue that the key form of "missing capital" is organizational capital. Investment in organizational capital includes activities such as "starting up a new business, learning-on-the-job, training, education,

[4] In a footnote below, I consider the possibility that γ depends on a nation's level of development. Such an assumption improves the calibration's fit.

research and development, and some forms of advertising" (p. 49; note that education is among their forms of missing capital investment). This unmeasured investment ranges from 35% to 55% of GDP, according to Parente and Prescott (2004). In their attempt to match the widely-analyzed catch-up of the East Asian economies, they conclude that "capital share values in the range from 0.55 to 0.65 are consistent with the growth miracles" (p. 47). Recent work by McGrattan and Prescott (2005) uses data from the national income accounts of the U.S and the U.K. to quantify some forms of corporately-held organizational capital, and likewise find that such stocks of intangible capital are too large to ignore.

Thus, if I am trying to explain why some countries are richer than others, an α=1/3 is likely to miss the important roles of human and organizational capital. I use α=1/3, 1/2, and 3/4, but prefer the latter two estimates.

My data sources should briefly be mentioned. As noted above, national average IQ estimates are from Lynn and Vanhanen (2002), and cover 81 countries. These 81 estimates are derived from a database of 163 IQ tests given across the 20th century by a wide variety of researchers. Within-country scores are highly comparable across time—As LV note themselves, the within-country correlation of national average IQ estimates is greater than 0.9. Thus, estimates of national average IQ rarely vary wildly from test to test, as a perusal of Sailer's (2004) online version of the LV database will demonstrate to the reader.

To make scores across decades comparable in a world where the Flynn effect is at work, LV adjusted older scores upward by 2 to 3 points per decade, with the size of the adjustment depending on the type of test. LV thereby “deflated” newer scores and “inflated” older scores. I use this Flynn-adjusted data in my main estimates.

However, my results are essentially unchanged if I instead use raw IQ scores unadjusted for the Flynn effect. Further, as a note below indicates, the results are likewise unchanged if only pre-1960 or pre-1970 IQ tests are used to predict present-day worker productivity.

Likewise, the strong IQ-productivity correlation does not depend on the type of IQ test used. For example, looking only at the 25 scores (out of the 163 total) that used Cattell’s Culture-Fair test (and using LV’s Flynn-adjusted data), the correlation with 1998 PPP-adjusted log GDP per capita was 0.74, slightly below the 0.82 in the aggregated, 81-observation sample. For one form of Raven’s Progressive Matrices, 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 database. Clearly, regardless of the type of test used, national average IQ can still predict about half or more of a nation’s productivity.

GDP per worker estimates are from the Penn World Tables. In total, I have complete data for 67 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 valuable for demonstrating that these IQ differences have been persistent and do not turn on the type of IQ test employed.

Using the Model

In this section, I combine the steady state equation of the IQ-augmented Ramsey model (eq. 3) with conventional parameter values for γ and α to illustrate how IQ differences can have a large impact on steady-state living standards. Consider two countries that differ only in average IQ. The ratio of steady-state living standards in these two countries would then be:

$$\frac{(Y/L)_{hi}^{ss}}{(Y/L)_{lo}^{ss}} = e^{\frac{\gamma}{1-\alpha}\Delta IQ} \qquad (4)$$

where ΔIQ is the difference in IQ between the two countries. Lynn and Vanhanen show that if countries are ranked according to IQ, then the bottom decile has a median IQ of 66 and the top decile has a median IQ of 104. I take γ =1 as my preferred estimate; under this assumption a rise of 1 IQ point raises wages (and the marginal product of labor) by a modest 1%.

Therefore, as Figure 2 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 1.75 times the initial value if α=1/3, and 4.5 times the initial value if α=3/4. In either case, IQ's impact on steady-state living standards would be too large too ignore.

But perhaps my estimates of cross-country IQ differences are exaggerated. If the true IQ gap between the top 10% and the bottom 10% is only half of Lynn and Vanhanen's estimate--19 points--then a move from bottom to top would imply a rise in steady state living standards of between 33% and 110%, depending on the value of α.

The implications are clear: If Lynn and Vanhanen are correct in concluding that IQ differences across countries are substantial, and if labor economists are correct in believing that higher IQ raises the marginal product of labor, then the IQ-augmented

Ramsey model implies that IQ is an important determinant of cross-country income differences. This result holds even if one believes that Lynn and Vanhanen's dataset inaccurately measures national average IQ for particular countries: Large, persistent, between-country IQ differences are all that is needed to reach this result. Whether the role of IQ is overwhelming or merely substantial turns on the preferred value of α.

I should note the results in this section do not depend on IQ being exogenous. I demonstrate below that reverse causality is unlikely to be the main explanation for the strong empirical IQ-productivity relationship. However, even if reverse causality *were* important, the above 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 and hence cause a higher steady-state capital stock. 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.

Finally, I should address the question of slope. In growth economics, it is common to attempt to answer the following question: "Can this model replicate 'most' of the massive gap in living standards that exists between countries?" This is often an ill-formed question, since the meaning of 'most' can be quite counterintuitive in a world of log and exponential factors, as in (3) and (4), respectively.

Consider a factor that, through two separate channels, can explain a 20-times-difference in living standards. For instance, assume that national average IQ has two impacts on productivity: 1. An impact on the private marginal product of labor, γ, and 2. An external impact of IQ on labor productivity, Γ. The latter might reflect human capital spillovers, the better cooperation that might be possible among a higher-average-IQ workforce, or the more efficient government that might result from the same.

In this case,

$$\frac{(Y/L)_{hi}^{ss}}{(Y/L)_{lo}^{ss}} = e^{\frac{\gamma+\Gamma}{1-\alpha}\Delta IQ}$$

If α= 0.75, then all that is needed for a 38-IQ-point gap to replicate a 20-times-difference in living standards is for γ+ Γ to be about 2 (since $e^{.02*38/.25} \approx 20$). In other words, if the true γ were equal to 1, my preferred value, then IQ's impact on the private marginal product of labor could do "half of the work" of getting to twenty.

This is true even though Figure 2 clearly demonstrates that a 38-IQ-point increase would only raise living standards 4.5 times its original level through the γ channel. "Doubling the IQ impact" from γ=1 to γ+ Γ=2 does not raise productivity to 9 times the original value: It raises it to 20 times the original value. Clearly, our linear intuitions can mislead us when considering exponential relationships.

Thus, the best way to evaluate quantitative growth models is probably *not* to ask whether a model can predict "most of the difference in living standards." Instead, one should ask whether it predicts most of the *log* difference in living standards. Or, what is the same thing for the present purpose, one should ask whether it can predict most of the *log slope*.

By this measure, IQ passes the test quite easily. Figure 1 indicates that one IQ point is associated with 7.2% higher living standards. For α= 3/4 and γ=1, the IQ-augmented Ramsey model yields $\gamma/(1-\alpha)$= 4, which is comfortably more than half of 7.2. So this parameterization can predict more than half of the log-slope between IQ and productivity. And even if α=2/3 (the Mankiw-Romer-Weil total capital share) and γ=1.25, we have $\gamma/(1-\alpha)$= 3.75, again more than half the log-slope seen in the data. Thus, using plausible parameter values, the IQ-augmented Ramsey model can explain most of the IQ-productivity relationship.

Calibration Results

The calibration exercise is quite straightforward: In a regression of log output per worker on IQ (comparable to eq. (3) above), I impose a variety of parameter values for the $\gamma/(1-\alpha)$ coefficient, and I 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, I note that the R^2 between log GDP per worker in 2000 and Lynn and Vanhanen's national average IQ estimate is 64%, and in an OLS regression, 1 IQ point is associated with 7.2% higher GDP per worker.

Results are reported in Table 1.[5,6] For the preferred parameter value of γ=1.0, IQ can explain between 24 and 52 percent of cross-country income variation depending on the choice of capital share, α. Therefore, IQ's impact on wages would explain between 38% (i.e., 24%/64%) and 81% (52%/64%) of the relationship between IQ and productivity.

If, instead, IQ has a 25% larger impact on wages (γ=1.25), and if Barro and Sala-i-Martin are correct in their estimate of the "broad capital" share (α=.75), then IQ's effect on wages can explain 91% (=58%/64%) of the IQ/productivity relationship. In such a case, there would be little need to invoke human capital externalities or other factors to explain the strong relationship between national average IQ and GDP per worker.

And even if γ=0.5--half of my preferred estimate--IQ's impact on wages explains at least one-eighth and perhaps more than one-fourth of the global income distribution. So even under the most restrictive assumptions, IQ's impact on the private marginal product of labor appears to belong on any top ten list of explanations for cross-country income differences.[7]

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[5] 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.

[6] Results were likewise substantially unchanged if I omitted 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. For instance, in the two cells of Table 1 where the calibration explained more than 50% of the global income distribution, this restricted sample yielded results that were within 2% of the results reported in Table 1. So even in this restricted sample, adding IQ to the Ramsey model can explain more than half of the global income distribution.

[7] I also considered the possibility that a nation's γ rises as that nation's national average IQ rises. This would be the case, if, for instance, countries are better at sorting workers into more-productive jobs as the national average IQ rises. In particular, I considered the following functional form: $\gamma = 0.8 + 0.0133(\text{IQ}-70)$. This would be the appropriate form if moving from the bottom to the top of the global distribution of

Note that in each of these cases, the coefficient $\gamma/(1-\alpha)$ is always less than the 7.2 that would occur in an OLS regression; for example, in the $\gamma=1$ case, the relevant values for $\alpha=1/3$, 1/2, and 3/4, are 1.33, 2, and 4, respectively. Therefore, in no case does the IQ-augmented Ramsey model overpredict the log-slope relationship between IQ and steady-state productivity per worker: more remains to be explained, though more than half can be explained by the wage channel if the capital share is three-fourths. We now turn to one possible explanation for the remainder of the IQ-productivity relationship.

Addressing Reverse Causality

These theoretical and empirical results imply that differences in national average IQ are important drivers of global income inequality. Thus, those who would 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 I hope they are? Or are they

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IQ raised gamma from 0.8 to 1.2, and is equivalent to adding a quadratic term to the linear model of equation (3). The 0.8 value is the mean γ for developing countries, while the 1.2 value is close to many of the U.S. estimates noted in the text.

Such a model fits the data better than the results reported here. In the case of year 2000 GDP per worker, values of $\alpha=1/3$, 1/2, and 3/4 explain 44%, 54%, and 63%, respectively, of the variance in the global income distribution. This improved fit is robust to changes in the intercepts of the γ equation. The improved fit is not surprising, but it is not tautological. It is not surprising since this endogenous γ equation will tend to depress estimated steady-state productivity in lower-IQ countries and raise it in higher-IQ countries--thus widening the global income distribution. And as noted in the text, the model implied by equation (3) underpredicts the empirical relationship between IQ and living standards. But the improved fit is not tautological: Since there are no free parameters to speak of in the calibration exercises, adding a quadratic term to the calibration will not necessarily improve the model's fit.

Despite the improved fit that results from endogenizing γ in this way, I choose to impose a single value for γ. I do so largely because the growth and labor literatures have, to my knowledge, done no theoretical or empirical work on the appropriate functional form for γ. Since I intend to remain close to the mainstream of these literatures, I leave the question of γ's functional form to future research.

instead driven by differences in culture (cf. Ogbu and Davis (2003)), which may prove to be even more intractable than any genetic differences?

While I leave most of these questions to future research, I will take a moment to address one key question: Whether 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 I 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 I expect the mid-20th-century starting point for IQ to be? Perhaps I 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, I 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 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 and 1967), one from Taiwan (1956, only a few years after the Nationalists were driven there from the mainland), and one from Hong Kong (1968).

Lynn and Vanahen's 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]

But 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 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.

[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.

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 will have removed one of the most substantial barriers to riches.[10]

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 (Flynn-unadjusted) 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 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.

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

As Table 2 shows, I indeed found this to be the case. I used LV's IQ data along with Penn World Table data for each decade from 1960 through 1990 (1950 only had 38 relevant observations, and so is omitted). As before, equation (3) was used to estimate the IQ-productivity relationship, while the IQ-elasticity of wages is assumed to equal 1 for simplicity. Both the unconditional R^2 and the fraction of the variance explained by the IQ-wage relationship increase steadily across the decades. This is true regardless of the capital share parameter in question. Further, the log-slope of the IQ-productivity relationship has also increased.

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 I 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.

[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%.

IQ as a Missing Input

Based on IQ's power to explain such a large 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, 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 IQ data cover 81 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? Here, one can not only point to the IQ-augmented Ramsey model presented here; one can also consider the possibility of a new theoretical literature that spells out the ability of IQ to explain productivity levels as well as productivity growth rates.

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 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 I 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) 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.

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, IQ may play an important role in answering Prescott's (1998) call for a theory of total factor productivity.

Conclusion

The wide divergence we see in living standards across countries is not a puzzle: This divergence is precisely what quantitative general equilibrium theory predicts as long

[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).

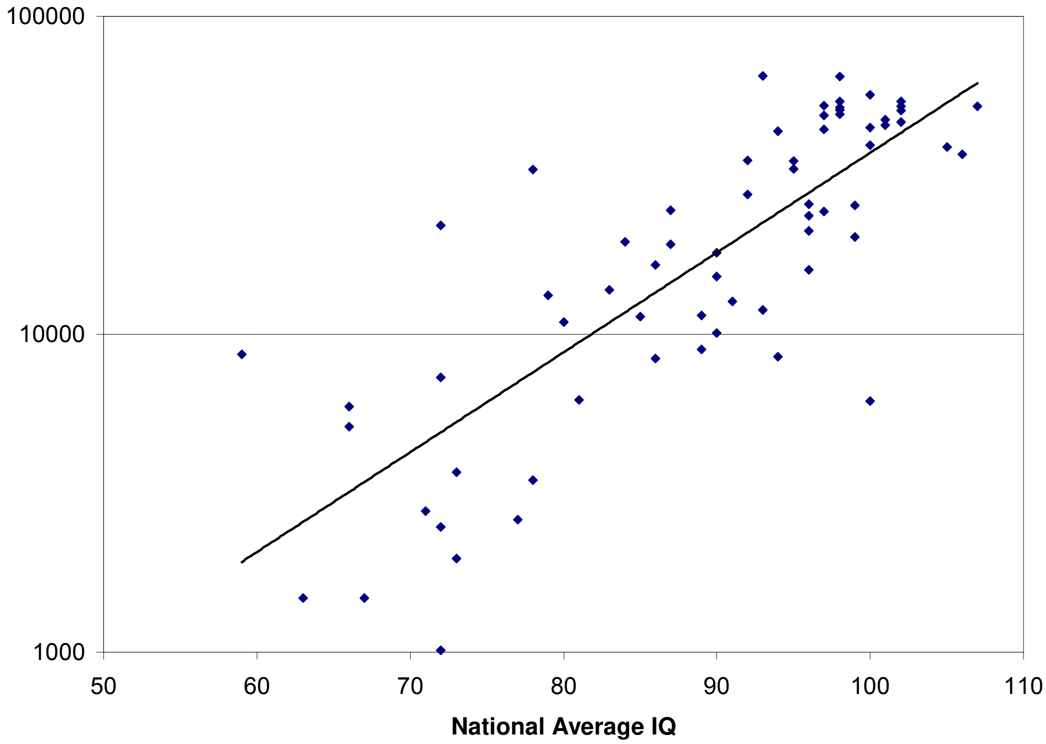
as there are large, persistent differences in general reasoning ability across countries. I have shown that IQ's empirically-well-established impact on the private marginal product of labor, when added to a conventional Ramsey growth model, can explain most of the strong relationship between IQ and worker productivity. The gradual accumulation of more tangible and intangible capital in the world's higher-IQ countries drives this strong result. Thus, even though IQ has only a modest effect on productivity at the micro level, I have explained why it can have a large effect at the macro level.

But what has been left unexplained? I have not explained the *entire* correlation of 0.82 between national average IQ and worker productivity. Perhaps human capital externalities and feedback effects from worker productivity to IQ are part of the story. Perhaps the education and fertility channels emphasized by Manuelli and Seshadri (2005) play an important role. Or perhaps higher-IQ countries tend to create more effective, efficient governments, which would help explain the correlation of 0.7 between national average IQ and the Ease of Doing Business index (*Doing Business*, 2005). Indeed, any non-wage explanation for the IQ-productivity link remains open for exploration. In this paper, I have shown how IQ in the Ramsey model can explain more than half of the IQ-productivity relationship; I leave the rest to future research.

Perhaps most importantly, I have not attempted to fully explain why IQ diverges so much across countries--and diverges even across poor countries, as China's national average IQ of 100 illustrates. Aside from demonstrating that reverse causality from income to IQ is unlikely to be driving these results, I have left this issue untouched. In this respect, these results are similar to those of Kydland and Prescott (1982), who showed that well-documented differences in productivity across *time* could explain a large fraction of the variance of output over time. Similarly, I have shown that well-documented differences in IQ across *countries* can explain a large fraction of the variance of output across countries. And just as Kydland and Prescott left the investigation of the causes of productivity fluctuations to future research, I leave the investigation of the causes of persistent IQ differences to future research.

I hope that economists can bring their powerful econometric 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. If growth economists instead avoid studying differences in national average IQ, the results presented here imply that they may be missing more than half the story.

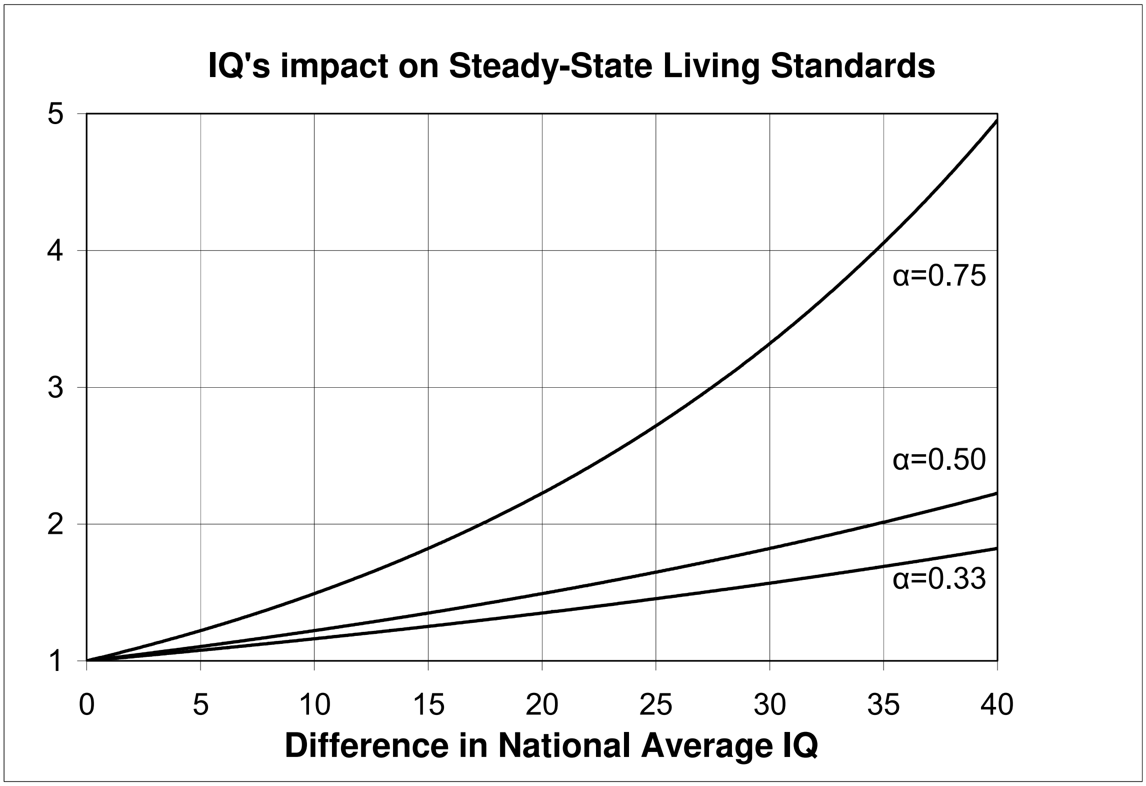
Figure 1: National Average IQ and Year 2000 GDP Per Worker



Notes: Y-axis shows GDP per worker in logarithmic scale. In this bivariate regression, the coefficient on national average IQ is 0.072, and the R^2 is 64%. Thus, a one-point rise in IQ is associated with 7.2% higher output per worker. The sample covers 67 countries. The outlier in the lower-right corner is China.

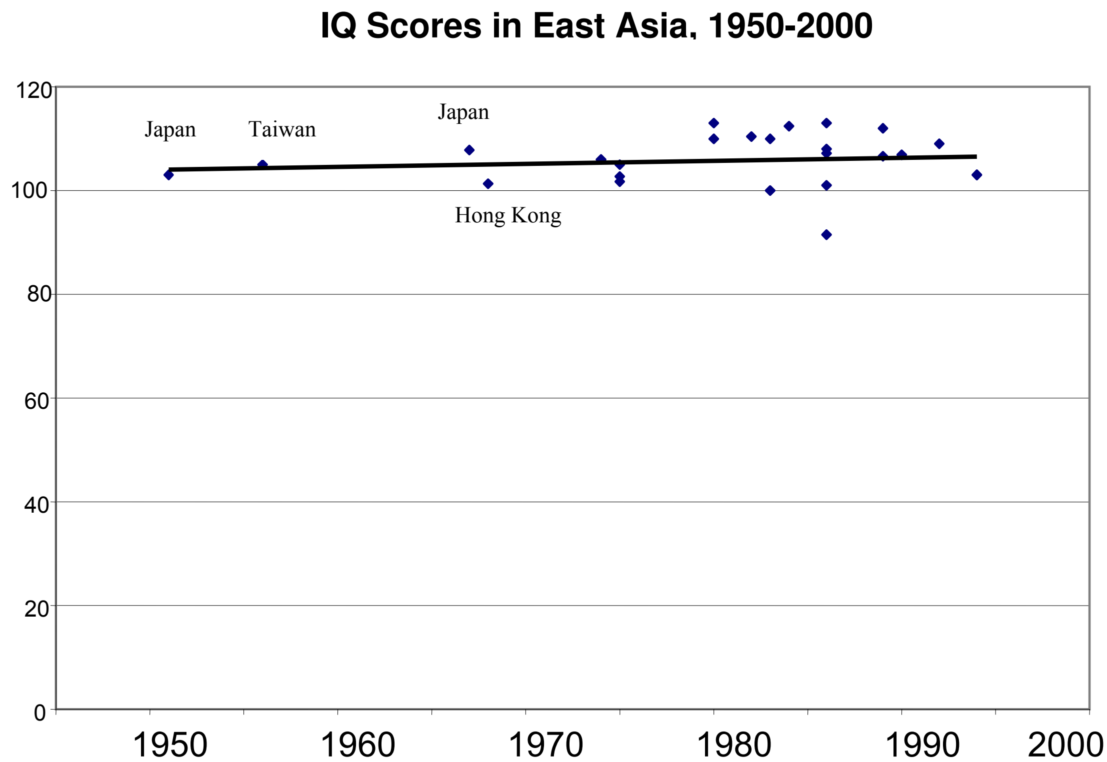
Source: Lynn and Vanhanen (2002) and Penn World Tables 6.1 for IQ and GDP data, respectively.

Figure 2



Notes: The value on the y-axis is $(Y/L)^{SS}_{hi}/(Y/L)^{SS}_{lo}$, the ratio of steady-state living standards in two countries who differ only in national average IQ. This chart is based on equation (4) in the text under the assumption that γ, the semi-elasticity of wages with respect to IQ, equals 1. α is the capital elasticity of output.

Figure 3



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

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

	γ=0.5	γ=1.0	γ=1.25
α=.33	**13%**	**24%**	**29%**
α=.5	**17%**	**31%**	**37% ***
α=.75	**31%**	**52% ***	**58% ***

Notes: γ is the semi-elasticity of output with respect to IQ, and α is the capital elasticity of output. 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 67 countries.

For reference, the R^2 from a simple regression of year 2000 log GDP per worker on national average IQ is 64%. An asterisk (*) indicates that this parameterization explains more than half of the R^2 from the simple regression. IQ and GDP data are from Figure 1.

Table 2: Productivity variance explained by IQ's impact on wages, 1960-1990

	1960	1970	1980	1990
α=.33	**19%**	**21%**	**22%**	**24%**
α=.5	**24%***	**27%***	**28%***	**31%**
α=.75	**38%***	**43%***	**46%***	**52%***
R^2	**40%**	**48%**	**54%**	**65%**
β	5.4% (0.86%)	5.8% (0.79%)	6.9% (0.76%)	7.3% (0.67%)
N	60	62	63	66

Notes: γ, the semi-elasticity of output with respect to IQ, is assumed to be 1, and α is the capital elasticity of output. The percentages indicate the variance in the year's 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). N is the number of countries for which data are available in that year.

For reference, the R^2 from simple regression of the year's log GDP per worker on national average IQ is also reported, as are the slope and the standard errors from the same regression. An asterisk (*) indicates that this parameterization explains more than half of the R^2 from the simple regression. GDP data is from the Penn World Tables.

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

Barro, Robert and Xavier Sala-i-Martin. (2001) *Economic Growth*, 2nd ed.. Cambridge, MA: MIT Press.

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

Benjamin, Daniel J. and Jesse M. Shaprio, "Does Cognitive Ability Reduce Psychological Bias?" working paper, Harvard University.

Bils, Mark and Peter Klenow. (2000). "Does Schooling Cause Growth?" *American Economic Review, 90*, 1160-83.

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

Bowles, Samuel, and Herbert Gintis, and Melissa Osborne (2001). "The Determinants of Earnings: Skills, Preferences, and Schooling," *Journal of Economic Literature*, *39*, 1137–1176.

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

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

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

Cawley, John, Karen Conneely, James Heckman, and Edward Vytlacil. (1997). "Cognitive Ability, Wages, and Meritocracy," in Bernie Devlin, Stephen E. Fienber, Daniel P. Resnick, and Kathryn Roeder, *Intelligence, Genes, and Success: Scientists Respond to* The Bell Curve. New York: Springer-Verlag.

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. (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.

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

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

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

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

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

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

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

Haier, Richard 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, Richard and Charles Murray. (1994). *The Bell Curve: Intelligence and Class Structure in American Life.* New York: Free Press.

Heston, Alan, Robert Summers and Bettina Aten, (2002). *Penn World Table Version 6.1*, Center for International Comparisons at the University of Pennsylvania (CICUP), October 2002.

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

Jones, Garett and W. Joel Schneider. (2006). "Intelligence, Human Capital, and Economic Growth: An Extreme-Bounds Analysis." Forthcoming, *Journal of Economic Growth*.

Kydland, Finn E and Edward C. Prescott. (1982). "Time to Build and Aggregate Fluctuations," *Econometrica*, *50*, 6, 1345-70.

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

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

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

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

Lynn, Richard and Tatu Vanhanen. (2002). *IQ and the Wealth of Nations.* Westport, CT: Praeger Publishers.

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

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

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.

McGrattan, Ellen, and Edward C. Prescott (2005). "Taxes, Regulations, and the Value of U.S. and U.K. Corportaions," *Review of Economic Studies,* July 2005.

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

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

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

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

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

Parente, Stephen L. and Edward C. Prescott. (2002). *Barriers to Riches*, reprint edition. Cambridge, MA: MIT Press.

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

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

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

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.

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

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

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

Winship, C. and 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, Jeffrey S. and Daniel I. Rees. (2002). "IQ, Academic Performance, Environment, and Earnings," *Review of Economics and Statistics, 84*, 4, 600-616.