Cognitive Ability and Technology Diffusion: An Empirical Test

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Abstract

Recent economic research has shown that cognitive ability scores are robustly associated with good national economic performance. How much of this is due to high-ability countries doing a better job of absorbing total factor productivity from the world's technology leader? Following Benhabib and Spiegel (*JME* 1994, *Handbook of Economic Growth* 2005) who estimated the Nelson-Phelps technology diffusion model, I use the database of IQ tests assembled by Lynn and Vanhanen (2002, 2006) and find a robust relationship between national average IQ and the conditional rate of total factor productivity growth over the 1960-1995 period. In a horse race between IQ and education, national average IQ performs better as a predictor of TFP growth. The results hold even if only pre-1970 IQ scores are used.

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Recent economic research, including Hanushek and Woessmann (NBER working paper, 2007), Jones and Schneider (*Journal of Economic Growth*, 2006), Weede and Kampf (2002) and Ram (*Economics Letters,* 2006) has shown that cognitive ability scores are robustly associated with good economic performance. They almost invariably find that cognitive ability scores have vastly more predictive power than traditional schooling measures (the sole exception is Volken (2003)).

The question of *whether* intelligence tests and other standardized tests are robust predictors of growth has apparently been settled. The present paper turns to the question of why this is so. Herein, I focus on the following question: How much of the cognitive ability/economic growth relationship is due to high-ability countries being better at absorbing ideas from the world's technology leader?

Benhabib and Spiegel (*JME* 1994, *Handbook of Economic Growth* 2005) estimated the technology diffusion model of Barro and Sala-i-Martin (*Journal of Economic Growth*, 1997); Benhabib and Spiegel used years of education as their measure of human capital, and found a modestly robust relationship that weakened considerably when additional control variables were added.

Instead, I use the database of IQ tests assembled by Lynn and Vanhanen (*IQ and Global Inequality*, 2006), and invariably find a robust relationship between national average IQ and the conditional rate of total factor productivity growth over the 1960-1995 period. In a horse race between IQ and education, national average IQ easily wins under all specifications. The results also hold even if only pre-1970 IQ scores are used.

One reason to use IQ tests rather than the international math and science test scores employed by Hanushek and Kimko (*AER* 2000) and Barro and Lee (*AER* 1996) is that IQ tests are much more widely available. For instance, the former have data from 31 countries, and the latter from 23. Further, the psychological profession has worked to make such test scores comparable across time and space–indeed, a substantial number of the Lynn and Vanhanen observations come from country-wide “standardization samples” that are created when an IQ test is revised. As Jones and Schneider (2007) demonstrate, the positive relationship between IQ and year 2000 output per worker holds whether one uses verbal or visual IQ tests, whether one uses "culture reduced" or traditional IQ tests, and whether one uses pre -1980, pre-1970, or pre-1960 IQ tests.

Arthur Jensen's 1998 book *The g Factor*, provides the best overview of the IQ literature; Ian Deary's *Intelligence: A Very Short Introduction* (2001) provides a more accessible overview written by another prominent intelligence researcher. The psychology literature demonstrates that while environmental effects can explain some of the IQ gap across countries, there is also some evidence in support of genetic sources for this gap, as Jensen as well as Lynn and Vanhanen (2002) discuss. (N.B. On average, East Asian countries routinely outperform European countries on these tests designed by Europeans and their descendants). Accordingly, disentangling this nature-nurture question will likely be of increasing importance to growth economists in the future.

Greg Clark's (2007) book *A Farewell to Alms*, which builds on the theoretical model of Galor and Moav (2002), is one recent attempt at disentangling this important question. In the Galor/Moav framework, some combination of the agricultural revolution and private property begins a process favoring human-capital-investment genes; indeed, one section of their paper is entitled "Evolution of Intelligence and Economic Growth." Since the agricultural revolution has been more thorough in some regions of the world than others (Galor and Moav, 2007), this could provide one possible mechanism explaining some differences in cognitive ability across countries.

At the same time, environmental explanations, including cultural differences across time and space as well as health and nutrition differences, clearly play an economically significant role, and may be the sole explanation for IQ differences across countries. I have summarized this literature elsewhere (Jones and Schneider, 2006), so I will only note here that the long-term rise in IQ's across countries known as the Flynn Effect (2007) provides some reason to believe that cognitive skills respond to changes in the environment.

In all, the results presented below support the hypothesis that abstract tests of reasoning ability given to a random sample of the population can tell us more about an economy's economic potential than measuring years of schooling. Where these differences in reasoning ability come from is a matter of ongoing research in a variety of disciplines; for economists, the main lesson is that these differences appear to be quantitatively significant correlates of TFP. In the conclusion, I point to some literature that might begin to provide a micro-level explanation for this macroeconomic result.

Data

The primary data come from three sources: Benhabib and Spiegel (2005), Lynn and Vanhanen (2006), and Barro and Lee (1996). The latter two sources provide the IQ and the education level data, respectively. Total factor productivity (TFP) data come from Benhabib and Spiegel; I use it since it is the benchmark dataset in this literature. The TFP estimates start with output per person in a given country, and then remove the element of output per person that is explained by differences in capital per person: What is left is, of course, the Solow residual, or total factor productivity. I will occasionally refer to this value simply as "productivity"; since I never need to distinguish between output per worker and TFP in this paper, this slight misuse of the language should come at little cost.

The two education measures I use are the average years of schooling in 1960 only along with the average years of schooling averaged across the years 1960 to 1995; both are used in Benhabib and Spiegel (2005). The latter is more likely to reflect endogeneity running from growth to education, but I still use it since most of the IQ tests likewise come from the post-1960 period. Thus, this helps keep the horse race fair.

For the robustness tests run below, I also use controls from Sala-i-Martin, Doppelhofer, and Miller (2004). Table 1 provides summary statistics, and Table 2 a correlation matrix–note that as is so common in the growth literature, many "causal" variables correlate greater than 0.7 with the "outcome" variables.

Lynn and Vanhanen's data can be briefly summarized: They collected data from hundreds of published intelligence studies given in 113 countries over the last century to create estimates of national average IQ for each country. They are available, with commentary, at Wikipedia. As noted in the previous literature (*inter alia*, Jensen (1998), Lynn and Vanhanen (2002, 2006), Jones and Schneider (2007)), the differences across countries are roughly the same whether one uses traditional IQ tests, non-verbal tests, or culture-reduced tests. Thus, the national average IQ estimates appear similar regardless of what kind of IQ test is used. All estimates used here have been adjusted for the Flynn

Effect, the well-known time trend in IQ. I use three IQ measures: Lynn and Vanhanen's actual IQ data for 113 countries, an expanded database of actual IQ data for 113 countries plus interpolated data for the rest of the world (interpolations based on demographic comparisons with neighboring countries), and a smaller database of countries that uses only pre-1970 scores. Since there is only an imperfect overlap between the Benhabib/Spiegel data and the Lynn/Vanhanen data, sample sizes fall dramatically, leading to effective samples sizes of 68, 84, and 25, respectively.

Model

The Nelson-Phelps (1966) model of technology diffusion has been the workhorse of this literature. As augmented by Barro and Sala-i-Martin (1997), it can tell us not only whether the data favor conditional TFP convergence in *levels*, but even more importantly, whether the data favor conditional TFP convergence in *growth rates.* For instance, using the Nelson-Phelps model, Benhabib and Spiegel found that countries with low-enough levels of education were unlikely to ever catch up to the TFP growth rates of the richest countries.

The Nelson-Phelps model shows how a mathematical formalization of a verbal theory can yield greater insights. In Gerschenkron's (1962) foundational essay, "Economic Backwardness in Historical Perspective" he discusses what it takes to turn backwardness into an advantage. Gerschenkron notes:

> Industrialization always seemed the more promising the greater the backlog of technological innovations which the backward country could take over from the more advanced country. Borrowed technology, so much and so rightly stressed by Veblen, was one of the primary factors assuring a high speed of development in a backward country….(p. 87).

The Nelson-Phelps model formalizes this idea by claiming that human capital yields new ideas through two channels: First, through inventing ideas in ones own country, and second, through adapting ideas from countries at the economic frontier. At the most informal mathematical level, I can write:

$$\%\Delta A_i = \alpha * h_i + \beta * h_i * (\text{distance from frontier}) + \gamma$$

Here, $A_i \equiv$ TFP in country *i*; $h_i \equiv$ human capital in country *i*, $\alpha \equiv$ how productive a country is at producing its own ideas with one unit of human capital, $\beta \equiv$ how productive a country is at adopting the ideas of the economic frontier, and α and β are both strictly positive, while the constant, γ, is a stand-in for omitted variables. The constant can be either positive or negative; as in Benhabib and Speigel (2005), I find that γ is negative. The Gerschenkron assumption is that countries that are far from the frontier will find it easy to adapt ideas from the frontier–it's a "bills on the sidewalk" story, since countries that have used few of the world's best ideas will certainly find *some* useful ideas out there in the frontier economies.

But it turns out that the above equation isn't quite ready to take to the data. There are a variety of ways to mathematize "distance from the frontier," the value that Gerschenkron described as "backwardness." And it turns out that the mathematization matters profoundly. Let's run through the two that are relevant in this paper:

$$\%\Delta A_i = \alpha h_i + \beta h_i \left(1 - \frac{A_i}{A_{leader}}\right) + \gamma \qquad (1)$$

In this formalization, low-growth TFP traps are quite possible, since as $A_i \rightarrow 0$, $\%\Delta A_i \rightarrow \alpha h_i + \beta h_i$. If this number is less than the growth rate of TFP on the frontier, then country *i* will always grow (for $h_i > 0$), but will constantly fall behind the frontier. In an abuse of language, I'll refer to such a situation as a *poverty trap*. Of course, a country in such a situation might become incredibly wealthy, but it will constantly be falling ever-farther behind the living standards of the frontier country.

But this isn't the only way for things to turn out. If the "distance to the frontier" term is mathematized as below, then poverty traps are quite impossible:

$$\%\Delta A_i = \alpha h_i + \beta h_i \left(\frac{A_{leader}}{A_i} - 1\right) + \gamma \qquad (2)$$

In this case, as $A_i \rightarrow 0$, $\%\Delta A_i \rightarrow +\infty$. That means that as TFP goes to zero, the marginal productivity of searching for frontier ideas becomes infinite, regardless of how low the country's level of human capital goes.

Benhabib and Spiegel found that when human capital was measured by the level of formal education, OLS regressions preferred specification (1), the poverty-trap specification. They further listed the countries that within sample were forecasted to grow slower than the frontier country, and used the accuracy of such within-sample forecasts as an informal specification check–and they boldly used year 2000 human capital levels to make out-of-sample forecasts of future TFP growth. I do the same below, using national average IQ estimates instead of education measures.

On the question of logs versus levels: Benhabib and Spiegel focus on logs of education, but for IQ, both in micro-level research, levels are universally used (e.g., Cawley et al., (1996)), and cross-country results find a better fit for a levels specification (Dickerson (2006)). In addition, the Nelson-Phelps model tends to focus on the *level* of TFP, but most empirical work tends to focus on the *log-level*. Below, I tend to report estimates that use the *level* of IQ and the *log* of TFP, as is standard in the cross-country growth literature, but using the reverse had no material impact other than modestly weakening all estimates.

Empirical Results

I. IQ versus education as predictors of TFP performance: A horse race.

Table 3 provides the most elementary regressions, designed to give the reader a sense of the broad picture. I regress TFP growth and the log-level of TFP on education and IQ measures, but specifically *exclude* lagged levels of TFP as explanatory variables. I also report regressions that include both human capital measures simultaneously. As in all my empirical results, I run separate specifications for the three separate IQ measures: IQ (always using IQ data from the country in question), estimated IQ (which interpolates IQ estimates based on IQ tests from nearby countries), and pre-1970 IQ (only using pre-1970 IQ scores in the estimates to minimize endogeneity problems but cutting the sample size down to a maximum of 25). In these atheoretical regressions, IQ and education perform about equally well: both statistically and economically, each has power to predict TFP levels and growth. In the TFP log-level regressions, the inclusion of education drops the IQ coefficients by an average of 1/3, but in the TFP growth regressions, controlling for education actually raises the coefficients by about 1/2. In later regressions, controlling for education *always* has only a minor impact on the size of the IQ coefficient, while the reverse is much less true.

In Table 4, I run Solow-style growth regressions, regressing TFP growth from 1960 to 1995 on log 1960 TFP and one or two human capital variables. Since economists are familiar with such regressions, this gives an intuitive and transparent illustration of IQ's robustness. Under all three definitions of IQ, IQ is statistically significant, but education never is. Unsurprisingly, the convergence variable is negatively signed and usually statistically significant. One IQ point is associated with roughly a persistent 0.09% increase in TFP growth; this implies that a 15 IQ point increase–one standard deviation within the U.S., or about the average difference between Mexico and Singapore–is associated with 1.4% faster TFP growth per year.

One can interpret this as a steady-state relationship by dividing the IQ coefficient by the speed of convergence. Thus, 0.094/0.127 = 0.074; this implies that one IQ point is associated with 7.4% higher steady state total factor productivity, so 15 IQ points are associated with 3 times more productivity in steady state (since $e^{15*0.074}=3$). Since the gap between the 10^{th} and 90^{th} percentiles of the cross-country IQ distribution is 38 IQ points, it's worth noting that 38 points would be associated with 16.6 times greater productivity in steady state.

Turning to the climax of the horse race, in Table 5, I replicate the results of Benhabib and Spiegel (2005) using IQ and education as measures, and including the crucial Nelson-Phelps interaction between IQ and log TFP. The IQ*(log TFP) interaction term is everywhere negative and usually statistically significant. In results not reported here, I found that the interaction term's sign and statistical significance *did not* depend on whether or not I included a non-interacted log TFP term.

Most importantly, I find that IQ is dramatically more statistically significant than the education terms, whether I use the 1960 education level or the 1960-1995 average education measure. The IQ level effect is usually significant at the 0.1% level, while the education level effect is never significant at that level. The interaction effects provide a similar pattern at lower levels of statistical significance.

These horse-race results provide no support for the hypothesis that the quantity of education is more important than the level of IQ in producing and adopting TFP, but instead support the hypothesis that IQ, even pre-1970 IQ, is a robust predictor of total factor productivity growth.

II. Testing for Poverty Traps

The TFP growth convergence hypothesis is quite simple to test. I check for the optimal specification of the interaction term: Does OLS prefer a negative sign on the *level* of TFP (poverty trap) or a positive sign on the *inverse* of TFP (no trap)? Benhabib and Spiegel could show quite clearly that there was little evidence for the no-trap hypothesis, with some statistically-insignificant evidence for the low-education/poverty-trap hypothesis.

The horse races in the previous section were reported using the more typical log TFP format, but in order to provide the clearest test of the Nelson-Phelps growth convergence test, here I use the level of TFP, and to mimic Benhabib-Spiegel as closely as possible, here I use the log of IQ and the log of education rather than the levels, and I always include a constant. The result is sufficiently simple that I omit tables: I just include an exponent term on the TFP interaction term, and check to see if it looks more like positive one or negative one. In the specification that omits education, the exponent on TFP is 1.002 (s.e. 0.47, p=0.04) and when I include education, the exponent on TFP is 0.56 (s.e. 1.24, p=.65). The exponent on the TFP term that is interacted with log education is 0.03 (s.e. 24 (*sic*)).

Varying logs versus levels or using the estimated IQ and pre-1970 IQ measures had no noticeable impact on these results: IQ performs better than education, and the evidence still points clearly *against* the no-trap hypothesis (exponent of –1), but as with Benhabib and Speigel, the statistical support *in favor of* the simplest poverty trap hypothesis (exponent exactly equal to +1) is never overwhelming.

Intuitively, these results aren't surprising: Countries that started off the 1960's with a combination of low TFP and high IQ like East Asia often grew quickly, but as Tsao (1985), Young (1995) and Krugman (1994) have all noted, East Asian TFP growth over this period was largely unremarkable–it certainly didn't support the idea that asympototically low TFP causes infinite TFP growth.

So, if one takes the poverty-trap model of (1) as the empirical framework, then what's the critical value? What is the level of national average IQ at which TFP growth is predicted to be forever slower than that of the frontier country? I take the U.S. to be the frontier country, and its TFP grew at an annual rate of 1.5% (N.B. The rest of economic growth came from capital growth and population growth). Quantitatively, one wants to know when

$$\alpha IQ_i + \beta IQ_i + \gamma < \text{frontier TFP growth} = 1.5\%$$

Note that β is the *negative* of the estimated interaction coefficient. When run in IQ levels and imposing an exponent of unity, and using the coefficients from the first column of Table 5, the critical value is 72. When I instead use log IQ, the critical value rises to 81. Under the 72 cutoff, the complete list includes every country in sub-Saharan Africa for in this dataset (with the exception of Uganda, estimated national average IQ of 73) plus Jamaica. These countries are predicted to constantly fall behind the frontier in steady-state (Table 6).[1] Over the sample period of 1960 to 1995, every one of these countries experienced TFP growth of less than 1.5% with two exceptions: Botswana, an important African miracle economy, discussed in detail in Acemoglu et al (2002), and Zimbabwe, a country that essentially tied the 1.5% average.

III. Other controls

Jones and Schneider (2006) ran thousands of regressions that demonstrated the robustness of national average IQ in predicting economic growth, so extensive testing of IQ's relationship with TFP growth is presumably unneeded. Instead, I run a shorter set of tests, always using the data of Sala-i-Martin et al. (2004) for additional controls: I run one test that replicates as closely as possible Benhabib and Spiegels' own robustness test (Table 7), and then run my own set of 12 TFP growth regressions that employ all 67 growth regressors included in Sala-i-Martin et al. In the results reported below, I use the actual IQ score (omitting interpolated values), yielding a sample size of about 65 across specifications. Using the larger "estimated IQ" dataset had no impact on these results. Using the pre-1970 IQ estimates with a maximum sample size of 25, results

[1] When I look at *all* of the Lynn/Vanhanen countries, including those that lacked TFP data and so were never used in these regressions, the set expands to include all sub-Saharan African countries minus Uganda and Mauritania, plus a small number of Caribbean countries and islands off the African coast.

unsurprisingly weakened, but IQ was still statistically significant at the 1% level in most specifications.[2]

The results can be summarized quite briefly: national average IQ is always statistically significant with a t-statistic of between 6 and 12. In the Benhabib-Spiegel replication (Figures 2 and 3 and Table 7), I use Tropics, a Sub-Saharan Africa dummy, Year 1960 Life Expectancy, Years Open to Trade, and Ethnolinguistic Fractionalization. Of these, only Life Expectancy is statistically significant at conventional levels, and only it and Years Open are "correctly" signed. The signs, significance, and magnitude of the IQ coefficients are similar to those from the previous regressions.

Using the Sala-i-Martin et al. controls, I take the 67 variables 6 at a time, in alphabetical order; this yields a total of 12 regressions. Only the following non-IQ variables are ever statistically significant, but none ever push the IQ-level coefficient below the 0.01% level of significance. The sign of the coefficient and the category of significance (5%, 1% or 0.1%) are reported:

Real exchange rate distortions (–) 5%
Years open (+) 5%
Former British colony (+) 5%
Degree of capitalism (+) 5%
Religious intensity (–) 5%
Landlocked (–) 5%
1960 life expectancy (+) 1%
Average education in 1960 (–) (*sic*) 1%
Primary schooling in 1960 (+) 0.1%

In these regressions, as noted above, the level of national average IQ is always statistically significant with a t-statistic around 7 on average and a range from 6 to 12, and the magnitude of the level and interaction coefficients change little from the previous results. Thus, the overall impression is that IQ is a robust predictor of total factor productivity growth, something that cannot be said for conventional education measures.

[2] There were 3 exceptions out of 12 specifications: Using the Sala-i-Martin et al. (2004) controls, the level of pre-1970 IQ was reduced to statistical insignificance and a small positive size in one specification that included an overwhelmingly significant Confucianism measure, and in another specification that included a 5% significant sub-Saharan African dummy. It was significant at the 6% level with a reasonable coefficient size in a specification that included a significant 1960 primary schooling measure. Again, given the small sample size with a maximum of 25, this fragility is unsurprising.

Conclusion

If IQ tests are indeed "biased," they appear to be biased in favor of productivity growth. Thus, it would be most useful for economists and psychologists to determine just why these highly abstract tests designed by *psychologists* are such useful predictors of a crucial variable measured by *economists.* As part of such an agenda, researchers might take up James Flynn's (2007) call to write the "cognitive history of the 20th century," delving into how the human mind has adapted itself to–and how it helped to create–a high-technology, organizationally-driven society.

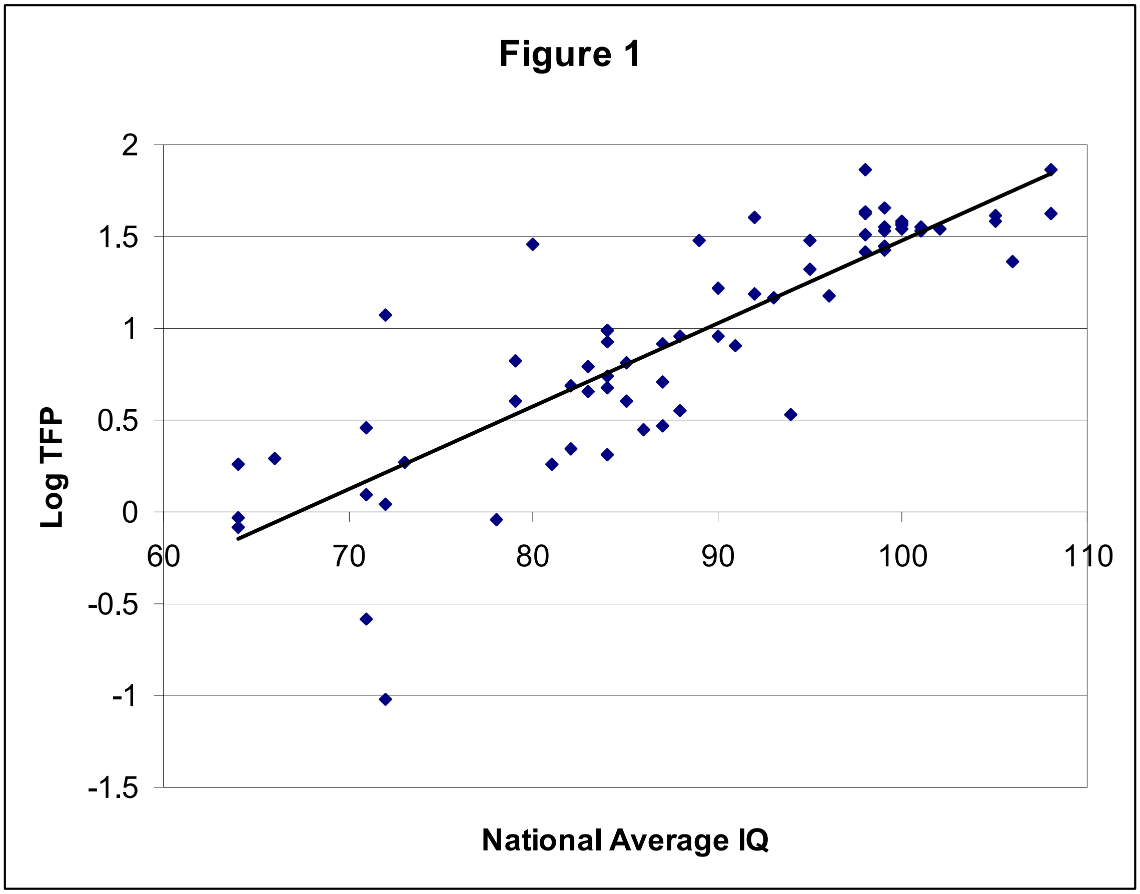
At the same time, economists could tap into the literature on the sources of group IQ differences in order to assess how much of these differences are due to physical environment, social environment, and genetics. This issue has been debated in a scholarly exchange available online in the June 2005 issue of the *Journal of Psychology, Public Policy, and Law*, an American Psychological Association journal.

And of course, the most important question is how IQ differences, which appear to have a modest impact on wages (Jones and Schneider (2007), Cawley et al. (1996)), can apparently be such important drivers of technology adoption. If high-average-IQ workers are so good at adopting frontier technology, then why isn't the IQ/wage premium greater than a mere 1% per IQ point, less than 1/7th of the implied steady-state effect of IQ on aggregate productivity, and only 1/6th of the implied steady-state effect of IQ on GDP per worker?

One possibility is that high-IQ citizens are better at discerning good economic policies: Caplan and Miller (2007) show that citizens who perform better at a simple ability test are more likely to agree with economists one a wide variety of economic issues, even after controlling for education. Since some economic ideas appear to involve high levels of abstraction, high intelligence may be quite useful for understanding the benefits of the division of labor, of comparative advantage, of flexible prices, and of delegating economic policymaking power in order to solve time consistency problems. Thus intelligent citizens may support high-productivity economic policies.

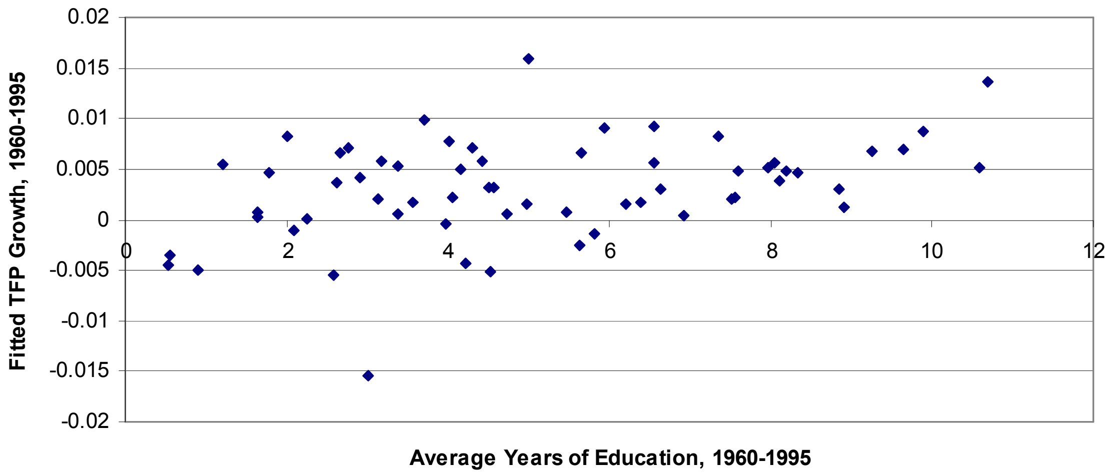
Another possibility is that high-IQ citizens are better at building good political institutions. Jones (forthcoming) provides evidence for this; I show that students at high-SAT schools are more likely to cooperate in a repeated prisoner's dilemma, with 100

SAT points associated with 5% to 8% more cooperation. To the extent that political problem-solving–whether among neighbors, among businesses on the same street, or among members of a party coalition–depends on the ability to cooperate in a dynamic environment, then high national average IQ may be crucial for building the political foundations for productivity growth. Miller's *Managerial Dilemmas* (1992) provides an exceptionally clear argument for the centrality of repeated prisoner's dilemmas in any explanation of economic productivity. If the results presented here are as robust as they appear, then some fraction of cross-country productivity differences may be explained by a short causal chain running from low IQ causing low cooperation in the public and private sectors which in turn causes low aggregate productivity. Quantifying the relative strength of this and other channels running from cognitive ability to aggregate productivity is a question for future work. And one can only hope that economists and other scientists will find strong channels running in the opposite direction as well.

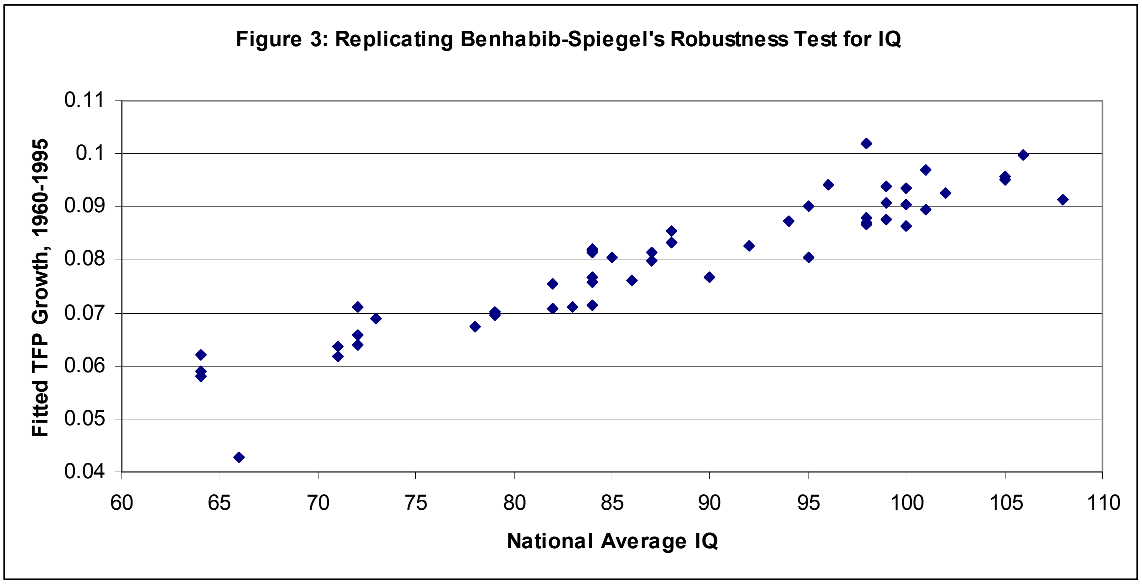


Note: National average IQ estimates are from Lynn and Vanhanen (2006); year 1995 total factor productivity estimates are from Benhabib and Spiegel (2005). The average IQ within the U.K. is defined as 100, and the within-U.K. standard deviation is defined as 15 IQ points. R^2 from a linear regression is 72%, and one IQ point is associated with 4.5% greater total factor productivity.

Figure 2: Replicating Benhabib-Speigel's Robustness Test for Education



Note: The Y-axis equals the residual from the regression in Table 7 plus the predicted effect of years of education on TFP growth implied by that regression. The Y-axis spans a range of about a 3% difference in annual TFP growth across countries.



Note: The Y-axis equals the residual from the regression in Table 7 plus the predicted effect of IQ on TFP growth implied by that regression. The Y-axis spans a range of about a 5% difference in annual TFP growth across countries.

Table 1: Data Description

Summary Statistics

	IQ	Est. IQ	Pre-70 IQ	log TFP60	log TFP95	TFP growth	Avg. Educ. 60	Avg. Educ. 60-95
Mean	88.4	86.4	87.0	0.39	0.85	1.3%	3.5	4.6
Median	88.5	86.5	88.0	0.41	0.92	1.3%	3.1	4.4
Maximum	108.0	108.0	105.0	1.33	1.86	4.3%	9.6	10.7
Minimum	64.0	64.0	61.0	-1.06	-1.02	-1.5%	0.1	0.4
Std. Dev.	11.5	11.8	12.9	0.49	0.65	1.2%	2.5	2.6
Skewness	-0.4	-0.2	-0.5	-0.33	-0.52	0.149	0.7	0.4
Kurtosis	2.4	2.1	2.2	2.79	2.51	3.591	2.6	2.3
Obs.	68	84	25	84	84	84	82	82

Note: “IQ” is the Lynn and Vanhanen estimate of the average IQ score in a country for which they have data. “Est. IQ” includes, in addition, interpolated values based on IQ estimates of geographically proximate countries. Lynn and Vanhanen show that such interpolations have high correlations with actual IQ scores. Years of Schooling from Barro-Lee (2000) (denoted “h” below). IQ data are from Lynn and Vanhanen (2006). TFP data are from Benhabib and Spiegel (2006).

Table 2

Correlation Matrix

	IQ	Est. IQ	Pre-70IQ	log TFP60	log TFP95	TFP Growth	Avg. Educ. 1960	Avg. Educ. 60-95
IQ	1.00	1.00	0.90	0.51	0.85	0.67	0.68	0.74
Est. IQ	1.00	1.00	0.90	0.56	0.84	0.64	0.71	0.76
Pre-70IQ	0.90	0.90	1.00	0.58	0.77	0.60	0.73	0.76
log TFP60	0.51	0.56	0.58	1.00	0.76	0.00	0.75	0.73
log TFP95	0.85	0.84	0.77	0.76	1.00	0.65	0.76	0.82
TFP Growth	0.67	0.64	0.60	0.00	0.65	1.00	0.30	0.40
Avg. Educ. 1960	0.68	0.71	0.73	0.75	0.76	0.30	1.00	0.97
Avg. Educ. 60-95	0.74	0.76	0.76	0.73	0.82	0.40	0.97	1.00

Note: "IQ" is the Lynn and Vanhanen estimate of the average IQ score in a country for which they have data. "Est. IQ" includes, in addition, interpolated values based on IQ estimates of geographically proximate countries. Lynn and Vanhanen show that such interpolations have high correlations with actual IQ scores. Years of Schooling from Barro-Lee (2000) (denoted "h" below). IQ data are from Lynn and Vanhanen (2006). TFP data are from Benhabib and Spiegel (2006).

Table 3: Basic Results

	log TFP95	log TFP95	log TFP95	log TFP95	log TFP95	log TFP95	TFP growth	TFP growth	TFP growth	TFP growth	TFP growth	TFP growth
IQ	0.0454***			0.0319***			0.0663***			0.0960***		
	(0.00353)			(0.00368)			(0.00901)			(0.0114)		
est.IQ		0.0467***			0.0337***			0.0658***			0.0867***	
		(0.00331)			(0.003908)			(0.00864)			(0.000120)	
Pre-1970 IQ			0.0456***			0.026153**			0.0572**			0.0743**
			(0.00785)			(0.00803)			(0.0160)			(0.0239)
h 1960				0.0767***	0.08045***	0.1006*				-0.204***	-0.1479*	-0.1183
				(0.01666)	(0.01875)	(0.03705)				(0.000515)	(0.000576)	(0.1101)
N	68	84	25	66	82	24	68	84	25	66	82	24
R^2	72%	71%	59%	82%	79%	76%	45%	41%	36%	55%	45%	38%

Note: Standard errors in parentheses. *, **, and *** represent statistical significance at the 5%, 1%, and 0.1% levels, respectively. Constant included but not reported.

Table 4: Solovian Convergence Results

	Dependent Variable→	TFP growth	TFP growth	TFP growth	TFP growth	TFP growth	TFP growth
IQ		0.0944***			0.0937***		
		(0.001884)			(0.00918)		
est.IQ			0.0956***			0.0926***	
			(0.00863)			(0.0100)	
Pre-1970 IQ				0.737***			0.0749**
				(0.0192)			(0.0219)
h 1960					0.0335	0.0645	0.101
					(0.0578)	(0.0594)	(0.1414)
log TFP 1960		-1.2743***	-1.271***	-0.654	-1.636***	-1.6392***	-1.58
		(0.1884)	(0.2056)	(0.4408)	0.2767	0.2710	(0.1414)
N		68	84	25	66	82	24
R^2		68%	60%	42%	71%	63%	50%

Note: Standard errors in parentheses. *, **, and *** represent statistical significance at the 5%, 1%, and 0.1% levels, respectively. Constant included but not reported.

Table 5: Benhabib-Spiegel Convergence Results

	TFP growth	TFP growth	TFP growth	TFP growth	TFP growth	TFP growth	TFP growth	TFP growth	TFP growth
IQ	0.1009***			0.0940***			0.0886***		
	(0.00814)			(0.00939)			(0.0102)		
est.IQ		0.1012***			0.0912***			0.0809***	
		(0.00889)			(0.0103)			(0.0111)	
Pre-1970 IQ			0.0769**			0.0686*			0.0577*
			(0.0202)			(0.0253)			(0.0254)
IQ*log TFP 1960	-0.0150***	-0.0150***	-0.00766	-0.0161***	-0.0155**	-0.121	-0.0154**	-0.0142*	-0.00885
	(0.00202)	(0.00231)	(0.00502)	(0.00424)	(0.00463)	(0.0110)	(0.00513)	(0.00540)	(0.0123)
h60				0.1660	0.2163*	0.2986			
				(0.0920)	(0.0927)	(0.2644)			
h60*logTFP60				-0.1106	-0.1374	-0.1825			
				(0.0847)	(0.7563)	(0.2226)			
h 60-95							0.1758*	0.2556**	0.3541
							(0.0805)	(-0.0809)	(0.2080)
h60-95*logTFP1960							-0.0981	-0.1382	-0.2031
							(0.0793)	(0.0838)	(-.1861)
N	68	84	25	66	82	24	66	82	24
R^2	70%	62%	42%	74%	65%	51%	75%	67%	55%

Note: Standard errors in parentheses. *, **, and *** represent statistical significance at the 5%, 1%, and 0.1% levels, respectively. Constant included but not reported.

Table 6: Countries predicted to be in low-TFP growth traps

Botswana
Cameroon
Centr. Afr. Rep.
Ghana
Jamaica
Kenya
Lesotho
Malawi
Mali
Mozambique
Niger
Senegal
South Africa
Tanzania
Togo
Uganda
Zambia
Zimbabwe

Note: This list includes every country in the dataset with a national average IQ less than or equal to 72 (about 1.7 standard deviations below the U.S. mean). This includes every sub-Saharan-African country in the sample (aside from Uganda, with estimated IQ of 73) plus Jamaica. As discussed in the text, 72 is the poverty-trap cutoff when estimated parameters are plugged into equation (1).

Table 7. Replicating Benhabib-Spiegel's Robustness Test

	Dep Var→	TFP growth, 1960-1995
IQ		0.0912*** (0.0135)
IQ*log TFP 1960		-0.0242*** 0.00515
Tropics		-0.0717 0.4037
Sub-Saharan Africa		0.4437 0.2990
Life Exp. 1960		0.0433*** (0.0153)
Years Open		0.4437 (0.2990)
Ethnolinguistic Fract.		-0.0518 (0.4037)
h60-95		-0.0650 (0.0905)
h60-95*logTFP 1960		0.0279 (0.0768)
N		63
R^2		83%

Note: Standard errors in parentheses. *, **, and *** represent statistical significance at the 5%, 1%, and 0.1% levels, respectively. Constant included but not reported.

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