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Cognitive skill and technology diffusion: An empirical test

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ABSTRACT

Cognitive skills are robustly associated with good national economic performance. How much of this is due to high-skill countries doing a better job of absorbing total factor productivity from the world's technology leader? Following Benhabib and Spiegel (*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 total factor productivity growth. Controlling for IQ, years of education is of modest statistical significance. If IQ gaps between countries persist and model parameters remain stable, TFP levels are forecasted to sharply diverge, creating a "twin peaks" result. After controlling for IQ, few other growth variables are statistically significant.

1. Introduction

Recent economic research, including Hanushek and Woessmann (2007), Jones and Schneider (2006), Weede and Kampf (2002) and Ram (2007), has shown that cognitive skill scores are robustly associated with good economic performance. The authors invariably find that cognitive skill scores have vastly more predictive power than traditional schooling measures.

The question of *whether* intelligence tests and other standardized tests are robust predictors of economic success has apparently been settled. The present paper turns to the question of why this is so. Herein, I focus on the following questions: How do differences in cognitive skills influence differences in productivity across countries? Is there a cognitive skill cutoff below which countries will fail to even conditionally converge? And after one accounts for differences in average cognitive skill in

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a country, which other conventional growth variables are reliable predictors of long-run productivity growth?

Since, following Benhabib and Spiegel (1994, 2005), estimated total factor productivity (TFP) is my productivity proxy, one should interpret "productivity differences" as including differences in managerial methods, political systems, and productivity-enhancing cultural norms that make one country more productive than another – thus, TFP includes more than just menus of manufacturing processes. Potrafke (2012) provides cross-country evidence that cognitive skills are robust predictors of lower national corruption, and Burks et al. (2009) and Jones (2008, 2011) provide experimental evidence that intelligence is a predictor of cooperative, pro-social behavior; these correlates may explain some portion of the documented relationship between cognitive skills and national productivity.

Benhabib and Spiegel (1994, 2005) estimated the technology diffusion model of Barro and Sala-i-Martin (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 national average IQ estimates assembled by Lynn and Vanhanen (2006) and psychometrically validated in Rindermann (2007a,b), 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 (2000) and Barro and Lee (1996) is that IQ tests are much more widely available. For instance, Hanushek and Kimko have data from 31 countries, Barro and Lee from 23. By contrast, we have IQ scores from well over 100 countries, although limitations on other data shrink the sample considerably below 100. Further, the psychological profession has worked to make IQ 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 (2010) 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. Hanushek and Woessmann (2010) provide a brief review of the literature on national IQ and economic growth.

Where these nation-level differences in reasoning skill 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.

2. Data

The primary data come from three sources: Benhabib and Spiegel (2005), Lynn and Vanhanen (2006), and Barro and Lee (1996); in additional robustness tests, data from Sala-i-Martin et al. (2004, henceforth SDM) are used. Lynn/Vanahanen and Barro/Lee provide the IQ and 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 abuse of the language should come at little cost. Fig. 1 illustrates the relationship between national average IQ and log GDP in 1995.

The two education measures I use are the average years of schooling in the year 1960 along with the average years of schooling averaged across the years 1960–1995; both are used in Benhabib and Spiegel (2005). The latter is more likely to reflect endogeneity running from growth to education, but I

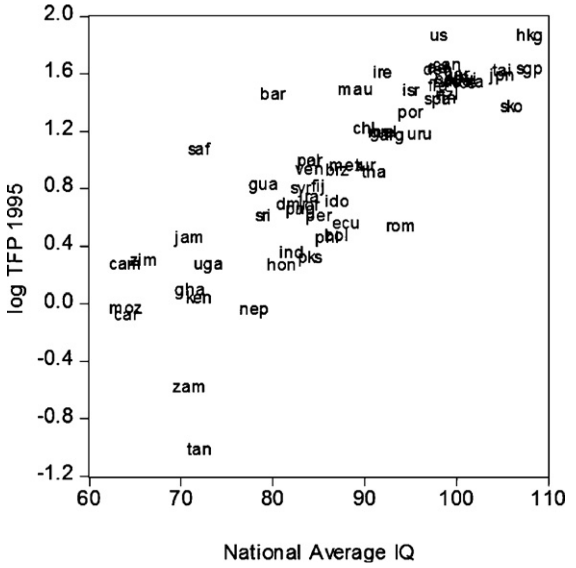

Fig. 1. IQ and TFP. *Note*: National average IQ estimates are from Lynn and Vanhanen (2006); year 1995 total factor productivity estimates are from Benhabib and Spiegel (2005). The average IQ within the U.K. is defined as 100, and the within-U.K. standard deviation is defined as 15 IQ points. R^2 from a linear regression is 72%, and one IQ point is associated with 4.5% greater total factor productivity.

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 et al. (2004). Table 1 provides summary statistics, and Table 2 a correlation matrix – note that, as is so common in the growth literature, many ostensibly causal variables correlate greater than 0.7 with ostensible outcome variables.

Lynn and Vanhanen's data can be briefly summarized: The authors, a psychologist (Lynn) and a political scientist with a background in cross-country databases (Vanhanen), collected data from hundreds of published intelligence studies performed in 113 countries over the last century to create estimates of national average IQ for each country. As noted in the previous literature (inter alia, Jensen, 1998; Lynn and Vanhanen, 2002, 2006; Jones and Schneider, 2010), the differences 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 are from Barro–Lee (2000) (denoted "h" below). IQ data are from Lynn and Vanhanen (2006). TFP data are from Benhabib and Spiegel (2005).

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 are from Barro–Lee (2000) (denoted "h" below). IQ data are from Lynn and Vanhanen (2006). TFP data are from Benhabib and Spiegel (2005).

are roughly the same whether one uses traditional IQ tests, non-verbal tests, or culture-reduced tests.[1] Thus, the national average IQ estimates appear similar regardless of what kind of IQ test is used. All estimates used here have been adjusted by Lynn and Vanhanen for the Flynn Effect, the well-known positive time trend in IQ: They use 1979 as their benchmark year, adjusting older scores on conventional tests upward by 2 IQ points per decade and more recent scores downward by 2 IQ points per decade. For the Ravens Matrices (a visual pattern-completion test, which has seen larger gains over time) they use 3 IQ points as the decade-level adjustment. Since IQ scores from both rich and poor countries exist from both decades before and decades after the 1979 benchmark, the degree of adjustment may matter little for the results; Jones and Schneider (2010) ran their IQ-productivity calibrations with both Flynn-adjusted and Flynn-unadjusted measures, with no substantial influence on the results.

I use three IQ measures: Lynn and Vanhanen's actual IQ data for 113 countries, an expanded database that adds interpolated data for the rest of the world (interpolations created by Lynn and Vanhanen 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 sample sizes of 68, 84, and 25, respectively.

3. Model

The Nelson–Phelps (1966) model of technology diffusion has been widely used in the technology diffusion literature. As augmented by Barro and Sala-i-Martin (1997), it can suggest 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", the author discusses what it takes to turn backwardness into an advantage. Gerschenkron notes:

[1] Wicherts et al. (2010a,b,c) have presented some evidence that Lynn and Vanhanen's scores from sub-Saharan Africa are lower than the true values, although they also state "[t]here can be little doubt that Africans average lower IQs than do westerners" (Wicherts et al., 2010a, p. 17). While this debate has not been settled in the academic literature, the outcome is unlikely to weaken the results presented here: In all prior statistical work that Winsorizes the lowest national average IQ estimates to higher values, national IQ is a weakly more reliable predictor of economic performance after Winsorizing the lowest scores. In results not reported, I rerun every regression here with an additional dummy variable for sub-Saharan Africa: as the results in Table 8 and in Section 4 below would suggest, inclusion of this dummy has no influence on the final results.

> "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 one's own country, and second, through adapting ideas from countries at the economic frontier. At the most informal mathematical level, one can write:

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

Here, A_i≡TFP in country i; h_i≡human capital in country i, α≡how productive a country is at producing its own ideas with one unit of human capital, β≡how productive a country is at adopting the ideas of the economic frontier. Of course, 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, depending in part on the units in which h_i is measured. The Gerschenkron assumption is that countries that are far from the frontier will find it easy to adapt ideas from the frontier – a "bills on the sidewalk" story, since countries that have used few of the world's best ideas (technological, political, cultural, and managerial) will certainly find *some* useful ideas in the frontier economies.

There are a variety of ways to mathematize "distance from the frontier," the value that Gerschenkron described as "backwardness." The form of the mathematization matters profoundly. Nelson and Phelps discuss two. The first is outwardly similar to a conventional growth regression specification, but has quite different implications:

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

In this formalization, low-growth TFP traps are quite possible, since as $A_i \to 0$, $\%\Delta A_i \to \alpha h_i + \beta h_i + \gamma$. 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 refer to such a situation as a *poverty trap*. 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 another mathematization is possible. If the "distance to the frontier" term is represented as below, then poverty traps are quite impossible:

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

In this case, as $A_i \to 0$, $\%\Delta A_i \to +\infty$. 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 becomes.

Benhabib and Spiegel found that when human capital was measured by the log (or 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.

In theoretical and empirical work on the link between TFP diffusion and human capital, there is no uniform preference for logs versus levels for either human capital or TFP, and microfounded theories exist with both log and level specifications. For instance, Benhabib and Spiegel and the models they draw upon imply that the level of TFP is the correct form of technology; Wolff (2000) uses a microfounded model where the log of TFP is the correct functional form with which to interact human capital. He then uses the log of TFP in an empirical specification of the model. Sala-i-Martin (1997) uses a functional form similar to Wolff's in his "two million regressions" economic growth paper: the level of human capital is interacted with starting log GDP per person. Since both theory and empirical work have come to no consensus on the issue, I report key results in two classes of specifications: The level of TFP interacted with the log of human capital (based on Benhabib and Spiegel's microfounded

Table 3
Solovian convergence results.

	Dependent variable→	TFP growth	TFP growth	TFP growth	TFP growth	TFP growth	TFP growth
IQ		0.0944*** (0.01884)			0.0937*** (0.00918)		
Est. IQ			0.0956*** (0.0863)			0.0926*** (0.0100)	
Pre-1970 IQ				0.0737*** (0.0192)			0.0749** (0.0219)
h 1960					0.0335 (0.0578)	0.0645 (0.0594)	0.101 (0.1414)
Log TFP 1960		−1.2743*** (0.1884)	−1.271*** (0.2056)	−0.654 (0.4408)	−1.636*** 0.2767	−1.6392*** 0.2710	−1.58 (0.1414)
N		68	84	25	66	82	24
R^2		68%	60%	42%	71%	63%	50%

Note: Standard errors in parentheses. Constant included but not reported. Dependent variable multiplied by 100:1 IQ point associated with ~0.09% faster TFP growth.
** Statistical significance at the 1% level.
*** Statistical significance at the 0.1% level.

approach), and the log of TFP interacted with the level of human capital (based on Wolff's microfounded approach).

One can interpret these two sets of specifications as an initial case where diminishing returns to human capital are relatively important in slowing the rate of convergence and a second case where diminishing returns to TFP are relatively important in slowing the rate of convergence. Results are little changed across the two sets of specifications.

4. Empirical results

4.1. IQ versus education as predictors of TFP growth

I begin by reporting a set of specifications more transparent and tractable than the diffusion models discussed above. Table 3 reports elementary Solow-style regressions, regressing TFP growth from 1960 to 1995 on log 1960 TFP and the level of either one or two human capital variables. Since economists are familiar with such regressions, this gives an intuitive and transparent illustration of IQ's relationship with TFP. Under all three definitions of IQ, IQ is statistically significant at conventional levels, but education never is. Unsurprisingly, the convergence variable is negatively signed and usually statistically significant.[2] 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, 0.094/1.27 = 0.074; this implies that one IQ point is associated with 7.4% higher steady state total factor productivity, so a difference of 15 IQ points is associated with 3 times more productivity in steady state (since $e^{15*0.074} = 3$).[3]

[2] In a human capital-log, TFP-level specification, IQ has a *t*-statistic greater than 7.5 across all three IQ measures, while human capital has *t*-statistics of 3.01 for the interpolated IQ specification, 1.94 ($p = 0.06$) for the benchmark IQ sample, and 0.81 for the pre-1970 IQ sample. TFP is always negatively signed and significant at the 5% level.

[3] As Jones and Schneider (2006) show, IQ almost always retains its statistical significance in growth regressions when additional controls are added. For example, it was significant at the 1% level in all 455 growth regressions that controlled for various combinations of Sala-i-Martin et al. (2004, henceforth SDM) robust growth variables. Thus, I avoid reporting results with additional controls here, with this illustrative exception: When additionally controlling for SDM's degree of capitalism, absolute latitude, primary schooling in 1960, and East Asia controls, the *t*-statistic for IQ is 6.2. In steady state, IQ point is associated with 4% higher TFP.

Table 4
Poverty traps versus convergence.

	TFP growth	TFP growth	TFP growth	TFP growth	TFP growth	TFP growth
Log(IQ)	0.0845***			0.0693***		
	(0.0067)			(0.0074)		
Log(est. IQ)		0.0831***			0.0698***	
		(0.0074)			(0.0074)	
Log(Pre-1970 IQ)			0.0631**			0.0469**
			(0.0165)			(0.0150)
Potential poverty trap:						
Log(IQ)*(TFP 1960)	−0.0019***	−0.0018***	−0.0011			
	(0.00202)	(0.0003)	(0.0006)			
Conditional convergence:				0.0024***	0.0025***	0.0003
Log(IQ)*(1/TFP 1960)				(0.0006)	(0.0006)	(0.0010)
N	68	84	25	67	84	25
R^2	71%	61%	41%	57%	53%	33%

Note: Standard errors in parentheses. Constant included but not reported. Results little-changed upon joint inclusion of controls for absolute latitude, degree of capitalism, 1960 primary schooling, and East Asia and sub-Saharan Africa dummies: in particular, coefficient on log(IQ) never drops below 0.1% level in IQ and Estimated IQ specifications, coefficient on log(Pre-1970 IQ) never drops below 5% level, and R^2 on each potential poverty trap specification is always higher than on each TFP convergence specification.
** Statistical significance at the 1% level.
*** Statistical significance at the 0.1% level.

4.2. Testing for poverty traps

With this basic evidence in hand, I turn to testing the TFP growth convergence hypothesis. The empirical question is straightforward: Does OLS prefer a negative sign on the *level* of TFP (poverty trap) or a positive sign on the *inverse* of TFP (no trap)?[4] Benhabib and Spiegel showed quite clearly that there is little evidence for the no-trap hypothesis, with some statistically insignificant evidence for the low-education/poverty-trap hypothesis.

I estimate Eqs. (1) and (2) by OLS and compare these non-nested specifications for goodness of fit (Table 4). Since these regressions have identical numbers of parameters, standard information criteria methods will give the same results as the simpler method of comparing R^2 across specifications. In the benchmark case, the potential poverty trap specification has an R^2 of 71%, while the unconditional convergence (inverse TFP) specification has an R^2 of 57%. Including additional controls for geography, institutions, and primary education from Sala-i-Martin et al. (2004) did not substantially change the results, nor did the alternative IQ measures.[5] I include one additional test, directly estimating the following[6] nonlinear equation:

$$\%\Delta A_i = \alpha h_i + \beta h_i A_i^{\delta} + \gamma$$

If there is a poverty trap, then the necessary but not sufficient condition would be $\delta > 0$ and $\beta < 0$ (critical values for sufficiency are calculated below). If low-TFP countries grow infinitely faster as they recede from the TFP frontier, then $\delta < 0$ and $\beta > 0$ is both necessary and sufficient.

Using log of IQ as the measure of human capital, the δ exponent on TFP is 1.002 (s.e. 0.47, $p = 0.04$). The β coefficient is correctly signed, but with $p = 0.2$, it does not rise to statistical significance; the tiny amount of nonlinearity and the additional degree of freedom is apparently enough to widen the

[4] In a cross-sectional specification such as this one, there is no need to model the TFP of the frontier country.
[5] As in n.3, the additional controls include latitude, primary education, an East Asia dummy, and degree of capitalism. The R^2 is 78% in the potential poverty trap specification, and 70% in the convergence specification.
[6] After combining constants, this equation embeds both Eqs. (1) and (2) above; because this is a cross-sectional regression, there is no need to explicitly model the frontier country.

standard errors. The Wald 95% confidence ellipse for these two variables covers no parameter space where β is positive while δ is negative.

The evidence points clearly *against* the no-trap hypothesis because estimates of δ are positive, because 95% confidence intervals exclude $\delta = -1$, and because estimates of β are negative. Thus, evidence points *in favor of* a potential poverty trap, with δ=+1 invariably in the 95% confidence interval. Henceforth, I assume δ=+1 for tractability.

Intuitively, the results from the non-nested and the nonlinear specifications are unsurprising: Countries that started off the 1960s 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 – the East Asian experience fails to support the idea that asymptotically low TFP causes infinite TFP growth.

4.3. Forecasting poverty traps

If one takes the poverty-trap model of (1) as the empirical framework, then what is 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? After all, if that IQ level is well below the observed values, then the possibility of a poverty trap is a mere curiosum. As noted above, Benhabib and Spiegel calculated the critical value for education, and I do the same for IQ. I take the U.S. to be the frontier country, and its TFP grew at an annual rate of 1.5% (N.B. remaining economic growth arose from capital growth and population growth). Quantitatively, one wants to know when (collapsing the unity term into α):

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

Note that β is the *negative* of the estimated interaction coefficient.[7] Using log IQ and the coefficients from the first column of Table 4 (and the omitted constant from that regression), the critical value is 81. When run in the level of IQ, the critical value is 72.[8] Under the 72 cutoff, the complete list includes every sub-Saharan African country 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; I report them as a lower-bound prediction on nations predicted to be in poverty traps (Table 5).[9] Over the sample period of 1960–1995, 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.

4.4. IQ versus education in poverty trap specifications

Tables 6 and 7 report regressions of TFP growth on education and IQ. Table 6 uses the log of human capital and the level of TFP as controls; Table 7 uses the reverse. The two tables present similar findings.[10] Each specification was also rerun a second time including dummies for sub-Saharan Africa and East Asia, as well as measures of absolute latitude and degree of capitalism. As in other

[7] Following Benhabib and Spiegel (2005), we omit other controls in calculating the poverty-trap cutoff; the question of which values to include for the other controls in estimating the cutoff would admit numerous ad hoc judgments. Instead, this estimate is best interpreted as a forecasting exercise: knowing only a country's average IQ, would one predict conditional technological convergence or divergence?

[8] Coefficients from the first column of Table 7 are used, again including the constant.

[9] Looking 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.

[10] Parameter instability is a possible concern, particularly across high- and low-income countries (inter alia, Ram, 2008). Accordingly, I split the IQ specifications into high and low starting TFP subsamples, using median 1960 TFP to divide the sample. Whether in the Solow-style specifications or in regressions with interaction effects, the coefficient on IQ is changed little across these two subsamples. The results are robust to including the above-mentioned controls for geography, economic institutions and primary schooling.

Table 5
Countries predicted to be in low-TFP growth traps.

Botswana
Cameroon
Central African Republic
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 Eq. (1).

specifications, these additional controls had minimal influence on parameter estimates and negligible influence on statistical significance levels; these regression results are omitted for brevity.

Following Benhabib and Spiegel (2005), I use both 1960 years of education and average years of education from 1960 to 1995 in separate specifications; the latter likely contains an endogenous component of education, thereby giving an added advantage to education in the horse race against IQ. In Table 6, after controlling for log IQ, log years of education is never statistically significant, and the interaction term for education is always anomalously signed. In Table 6, years of education is statistically significant in half the specifications, but never at the 0.1% level; interaction terms for education are never significant. Both education terms – level and interaction with TFP – are always correctly signed, even when statistically insignificant.

In both tables, IQ and its interaction term are dramatically more statistically significant than the education terms in each specification, whether using 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 reliable predictor of total factor productivity growth.

4.5. Other controls

Jones and Schneider (2006) (summarized in Hanushek and Woessmann, 2010) ran thousands of regressions that demonstrated the robustness of national average IQ in predicting economic growth; for instance, in 455 cross-country growth regressions using combinations of growth variables found robust in SDM (2004), Lynn and Vanhanen's IQ estimate was significant at the 1% level in every regression. In the interest of brevity, I run a shorter set of tests, always using the data of Sala-i-Martin et al. (2004) for additional controls: I begin by running two tests that replicate Benhabib and Spiegel's own robustness test (Table 8); one specification uses logs of human capital and levels of TFP, and the second uses the reverse. The final set of tests uses all 67 of SDM's growth variables; these tests will illustrate which of SDM's growth variables are statistically significant predictors of productivity growth once one controls for national average IQ.

Table 6
Log(human capital) and TFP.

	TFP growth	TFP growth	TFP growth	TFP growth	TFP growth	TFP growth	TFP growth	TFP growth	TFP growth
Log(IQ)	0.0845***			0.0760***			0.0731***		
	(0.0067)			(0.0077)			(0.0083)		
Log(est. IQ)		0.0831***			0.0706***			0.0651***	
		(0.0074)			(0.0083)			(0.0087)	
Log(Pre-1970 IQ)			0.0631**			0.0544**			0.0483*
			(0.0165)			(0.0180)			(0.0188)
Log(IQ)*TFP60	−0.0019***	−0.0018***	−0.0011	−0.0028***	−0.0030***	−0.0031	−0.0031***	−0.0033***	−0.0034
	(0.00202)	(0.0003)	(0.0006)	(0.0006)	(0.0006)	(0.0016)	(0.0009)	(0.0009)	(0.0021)
Log(h60)				0.0007	0.0015	0.0005			
				(0.0021)	(0.0021)	(0.0042)			
Log(h60)*TFP60				0.0016	0.0020	0.0030			
				(0.0014)	(0.0015)	(0.0034)			
Log(h60–95)							0.0019	0.0034	0.0040
							(0.0033)	(0.0030)	(0.0068)
Log(h60–95)*TFP1960							0.0020	0.0024	0.0032
							(0.0020)	(0.0020)	(0.0045)
N	68	84	25	66	82	24	66	82	24
R^2	71%	61%	41%	73%	65%	50%	74%	67%	52%

Note: Standard errors in parentheses. Constant included but not reported. Additional joint inclusion of controls for sub-Saharan Africa, East Asia, absolute latitude, and degree of capitalism had minimal influence on these estimates.

* Statistical significance at the 5% level.
** Statistical significance at the 1% level.
*** Statistical significance at the 0.1% level.

Table 7
Human capital and log (TFP).

	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)			
h60–95							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. Constant included but not reported. Dependent variable multiplied by 100.
* Statistical significance at the 5% level.
** Statistical significance at the 1% level.
*** Statistical significance at the 0.1% level.

Table 8
Replicating Benhabib–Spiegel's robustness test.

	Dependent variable: TFP growth, 1960–1995	Dependent variable: TFP growth, 1960–1995
Log IQ	0.0777*** (0.0119)	
Log IQ*TFP60	−0.0036*** (0.0008)	
IQ		0.0912*** (0.0135)
IQ*log TFP60		−0.0242*** (0.00515)
Tropics	0.0011 (0.0034)	−0.0717 (0.4037)
Sub-Saharan Africa	0.0063 (0.0033)	0.4437 (0.2990)
Life Exp. 1960	0.0003 (0.00016)	0.0433*** (0.0153)
Years Open	0.0049 (0.0029)	0.4437 (0.2990)
Ethnolinguistic Fract.	−0.0011 (0.0042)	−0.0518 (0.4037)
Log h60–95	−0.0034 (0.0034)	
Log h60–95*TFP60	0.0026 (0.0026)	
h60–95		−0.0650 (0.0905)
h60–95*logTFP 60		0.0279 (0.0768)
N	63	63
R^2	81%	83%

Note: Standard errors in parentheses. Constant included but not reported. Dependent variable in human capital level regression (second column) multiplied by 100.
*** Statistical significance at the 0.1% level.

In the replication of Benhabib and Spiegel's main result (Figs. 2 and 3 and Table 8), I use Tropics, a Sub-Saharan Africa dummy, Year 1960 Life Expectancy, Years Open to Trade, and Ethnolinguistic Fractionalization, all of which appear to be close proxies for Benhabib and Spiegel's original control variables. Of these additional controls, only Life Expectancy is statistically significant at conventional levels (and then only in the IQ level regression) and only it and Years Open are "correctly" signed. Indeed, education is anomalously signed, though statistically insignificant. The signs, significance, and magnitude of the IQ coefficients, by contrast, are similar to those from the previous regressions. The

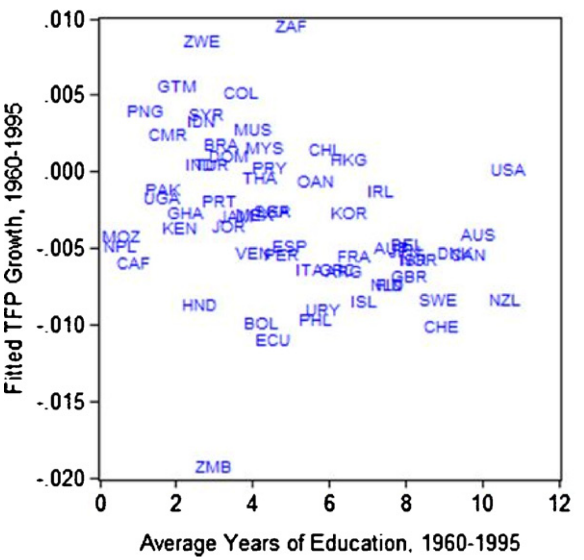

Fig. 2. Replicating Benhabib–Spiegel's Robustness Test for Education. *Note*: The *Y*-axis equals the residual from the regression in Table 8 plus the predicted effect of years of education on TFP growth implied by that regression, omitting the interaction term. Aside from the outlier, Zambia, the *Y*-axis spans a range of about a 2% difference in annual TFP growth across countries. One year of education is associated with a statistically insignificant 0.07% lower (*sic*) TFP growth, and the partial R^2 is 12%.

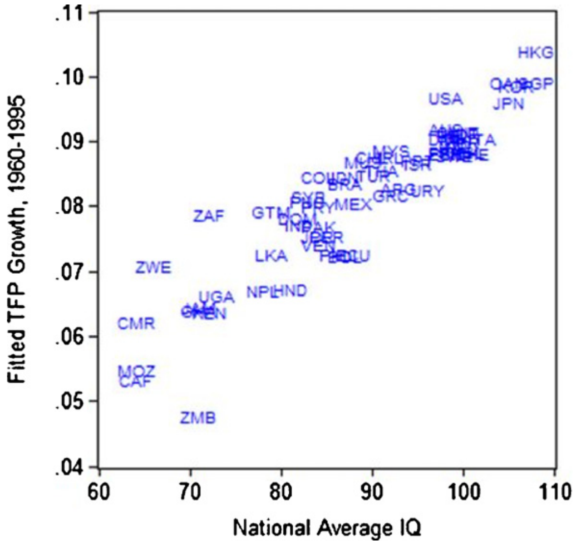

Fig. 3. Replicating Benhabib–Spiegel's Robustness Test for IQ. *Note*: The *Y*-axis equals the residual from the regression in Table 8 plus the predicted effect of IQ on TFP growth implied by that regression, omitting the interaction term. The *Y*-axis spans a range of about a 5% difference in annual TFP growth across countries. One IQ point is associated with 0.09% higher TFP growth, and the partial R^2 is 83%.

partial residual plots (Figs. 2 and 3), created in levels of human capital for ease of interpretation, demonstrate the greater explanatory power of national average IQ when compared to years of education.[11]

I now turn to the final set of regressions: for each of the two human capital specifications (log/level and level/log), I run 22 TFP growth regressions that employ all 66 growth regressors included in SDM (2004) (omitting only log 1960 GDP per capita). I add three of these SDM controls at a time in alphabetical order for five control variables total per specification: IQ, IQ interacted with TFP, and the three rotating controls; a constant is also included. These 66 controls (listed in Table 9) include multiple measures of institutional quality, of geography, of language usage, religion, disease correlates, and many other widely discussed possible drivers of economic growth – no major area is omitted, and no major area includes only one measure. In the results reported below, I use the actual IQ score (omitting interpolated values). This yields a typical sample size of 65 across specifications. Using the larger "estimated IQ" dataset had no substantial impact on these results.

The results can be summarized quite briefly: in the 22 specifications that use combinations of the SDM (2004) variables, national average IQ is always statistically significant with a *t*-statistic always greater than 5. Again, given the Jones and Schneider (2006) result, this is unsurprising. What may be surprising is that only the following non-IQ variables are *ever* statistically significant in and of themselves. The sign of the coefficient and the category of significance (5%, 1% or 0.1%) are reported. Variables significant in both the level and the log specifications are denoted by an asterisk:

IQ level specifications:

Degree of Capitalism (+) 5%
*Former British colony (+) 5%
*Former Spanish colony (–) 5%
*Fraction English Speaking (+) 5%

[11] The partial residuals of log human capital have a similar relationship to that of the level of human capital: log IQ has a correlation of +0.91 with the log specification's partial (non-IQ) residuals, while log years of education has a correlation of −0.36 (*sic*) with the same model's partial (non-education) residuals.

Table 9
Control variables used in Section 4.

Listed in order of robustness in SDM (AER, 2004)
East Asian dummy
Primary schooling 1960
Investment price
Fraction of tropical area
Population density coastal
Malaria prevalence in 1960
Life expectancy in 1960
Fraction Confucian
African dummy
Latin American dummy
Fraction GDP in mining
Spanish colony
Years open
Fraction Muslim
Fraction Buddhist
Ethnolinguistic fractionalization
Government consumption
Population density 1960
Real exchange rate distortions
Fraction speaking foreign
(Imports + exports)/GDP
Political rights
Government share of GDP
Higher education in 1960
Fraction population in tropics
Primary exports in 1970
Public investment share
Fraction Protestant
Fraction Hindu
Fraction population less
Air distance to big cities
Government consumption share
Absolute latitude
Fraction Catholic
Fertility in 1960s
European dummy
Outward orientation
Colony dummy
Civil liberties
Revolutions and coups
British colony
Hydrocarbon deposits
Fraction population over 65
Defense spending share
Population in 1960
Terms of trade growth in
Public education spending/
Landlocked country dummy
Religion measure
Size of economy
Socialist dummy
English-speaking population
Average inflation 1960–1990
Oil-producing country dummy
Population growth rate
Timing of independence
Fraction land area near navigable water
Square of inflation 1960–1990
Fraction spent in war 1960–1990
Land area
Tropical climate zone

Table 9 (*Continued*)

Listed in order of robustness in SDM (AER, 2004)
Terms of trade ranking
Degree of capitalism
Fraction Orthodox
War participation 1960–1990
Interior density

*Inflation, 1960–1990 (−) 5%
*Life expectancy 1960(+) 5%
*Primary schooling in 1960 (+) 0.1%
Revolutions and Coups (−) 5%
*Years open to trade (+) 5%

log(IQ) specifications:

Confucianism (+) 5%
Fertility in 1960s (−) 5%
*Former British colony (+) 5%
*Former Spanish colony (−) 1%
*Fraction English Speaking (+) 1%
Government consumption share, 1961 (−) 5%
*Inflation, 1960–1990 (−) 0.1%
*Life expectancy 1960 (+) 5%
Openness to trade [(Ex+Im)/*Y*] (+) 5%
Primary exports as % of total exports (−) 5%
*Primary schooling in 1960 (+) 0.1%
Revolution/Coup dummy (−) 5%
*Years open to trade (+) 5%

The only coefficient significant at the 0.1% level in both specifications is primary schooling; this is consistent with the results of Jones and Schneider (2006), who found that primary schooling was significant in more specifications than any other human capital measure other than national IQ. It is also consistent with the findings of Glaeser et al. (2004), who report that "human capital is a more basic source of growth than are institutions" (p. 271). And between the two classes of specifications, only 15 of the 66 growth variables – 23% – are *ever* statistically significant. Notably, no geography measure is ever statistically significant in these specifications that control for national average IQ.

Running the same 22 specifications on years of education twice over (once for the level of education and the interacted log of TFP, and again for the log of education and the interacted level of TFP), one sees that when IQ is omitted, other growth variables appear more robust: across these 44 specifications that omit IQ, 24 of the 66 variables are significant at the 5% level at least once, 22 variables are significant in both regressions, and five are significant at the 0.1% level in both regressions (Confucianism, Coastal density, East Asia, Life expectancy, and Years open to trade). Controlling for IQ reduces the statistical significance of other widely used growth regressors when compared to specifications that control for education.

5. Conclusion

If national average IQ estimates 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 for economists is how IQ differences, which appear to have a modest impact on wages (Jones and Schneider, 2010; Cawley et al., 1996; Zax and Rees, 2002), are such important predictors of total factor productivity growth. If high-average-IQ workers are good at adopting frontier technology, then why is not the wage premium for IQ greater than a mere 1% per IQ point, less than 1/7th of the implied steady-state relationship between IQ and aggregate productivity?

One possibility is that high-IQ citizens are better at discerning good economic policies: Caplan and Miller (2010) show that citizens who perform better at a simple IQ test are more likely to agree with economists on 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 noted in the introduction is that high-IQ citizens are better at building good political institutions. Jones (2008) provides evidence for this, showing that students at high-SAT schools are more likely to cooperate in a repeated prisoner's dilemma, with 100 SAT points associated with 5–8% more cooperation. Likewise, Putterman et al. (2010) have found that high IQ predicts more generous contributions in a repeated public goods game, and Burks et al. (2009) found that IQ predicted both trust and trustworthiness in a sequential prisoner's dilemma game run on truck driving school students. 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, high national average IQ may be crucial for building the political foundations for productivity growth.

Finally, in a recent paper in *Psychological Science*, Rindermann (2011) has found that in path analysis models, the estimated cognitive skills of the top 5% of a nation's population are better predictors of scientific achievement and good economic institutions than the mean cognitive skill of the population. Since the mean score and the top 5% score correlate +0.97 across countries, economists would be well-advised to bring their econometric tools to bear on the important question of whether mean scores are more or less important than extreme scores.

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.

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