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Abstract

Individuals that reside in the highest social stratum of intelligence (i.e., those that have a high IQ) have been shown to generate relatively more national income and are more innovative, with those that have the lowest levels of IQ being less influential on economic development. However, the degree to which all levels of IQ influence economic growth and technological innovation remains unclear. By assuming that the IQ of a population is modeled based on a bell curve, we arrange IQ into three strata, namely intellectual class, average ability citizens, and non-intellectual class, which are represented by the 95th, 50th, and 5th percentiles of cognitive ability, respectively. Our multiple hierarchical regression analysis of a sample of over 60 countries shows that the intellectual class has the greatest impact on economic growth followed by average ability citizens and the non-intellectual class in that order. Moreover, we find evidence that the impact of the intellectual class on technological progress is exceptionally more significant than even the number of professional researchers engaged in R&D activities, with average ability citizens and the non-intellectual class not significant. These findings allow us to suggest that the government and private institutions should not only employ professionals with good experiences and high academic credentials, but also those who has excellent IQ levels to work in their R&D sectors. However, in order to foster economic growth, governments should invest into facilities that benefit all societal groups of intelligence level, with highest priority given to the intellectual class, followed by the average ability citizens and the non-intellectual class respectively.

Keywords: economic growth; innovation; intellectual class; national IQ; non-intellectual class; patent

JEL Classifications: I25, J24, O3, O47, Z13

1. Introduction

Empirical studies have found that intellectual people, namely those that have a high IQ, contribute more to socioeconomic development in a society as compared to the average ability citizens. For example, assuming that the IQ of a population is modeled based on a normal distribution or bell curve (Herrnstein & Murray, 2010), Rindermann and Thompson (2011) found that the smartest proportion (i.e., those at the 95th percentile on the IQ scale) is more significant in raising cross-national income and technological achievement as compared to the citizens that have an average IQ (50th percentile). This finding implies that although the size of this "intellectual class" as it is termed in this paper is relatively small in the population, they are able to benefit society to a greater degree than society contributes to their lives.

In a similar vein, Rindermann, Sailer, and Thompson (2009) found that the IQ of the non-intellectual class (i.e., those at the 5th percentile) is less influential at generating national income and technological progress compared with the 50th and 95th percentiles. However, neither of these studies employed standard models that consists of important control variables to measure how IQ affects their well-established determinants of technological achievement and national income. Moreover, although some prominent economists such as Hanushek and Woessmann (2012), Mankiw, Romer, and Weil (1992), and Furman, Porter, and Stern (2002) have identified the major determinants of economic growth and technological progress (e.g., GDP/GDP per capita, government investment, number of scientists and engineers, R&D expenditure, population growth rates), the degree to which all levels of IQ influence economic growth and technological innovation remains unclear.

In order to bridge this gap in the body of knowledge on this topic, the present study uses a standard estimation model to examine the influence of IQ at the 95th, 50th, and 5th percentiles on economic growth and technological achievement. For example, when formulating long-term plans for improving economic development, how should governments organize their human resources development policies? Should policymakers concentrate on small groups of brilliant people or provide an equal (moderately good) education for all citizens, as manifested by the United Nations (UNESCO, 2005). Identifying which classes of IQ are more or less important for boosting economic development will thus assist in the formulation of education, development, and R&D policies at the national level.

This paper contributes to the literature in two important ways. First, it employs an econometric approach using standard growth model (Mankiw et al., 1992; Ram 2007) in examining the relative impact of different IQ classes on economic growth. This includes specific control variables, i.e., initial GDP per capita, population growth, proportions of government investments, and society education level. Secondly, it employs ideas production model (Furman et al., 2002) in measuring the impact of the IQ level of societal groups on technological progress, where the IQ-impact is controlled for population size, total GDP, and the number of professional researchers in R&D.

2. Literature Review

The centuries-old relationship between cognitive ability and technological achievement has recently been explored. Lynn (2012), for example, examined 120 countries in order to assess the degree to which technological achievement over millennia at the national level has been significantly correlated with variation in IQ. Variation in IQ was borrowed from the approach taken by Meisenberg and Lynn (2011) and the measures of technological achievement were derived from the study by Comin, Easterly, and Gong (2010). Based on this analysis, Lynn (2012) verified their correlation at r=.42 for 1000 BCE, r=.63 for 1500 AD, and r=.75 for 2000 AD. High-IQ nations have further been shown to demonstrate extraordinary expansion in their economic growth and productivity (Hanushek & Kimko, 2000; Jones & Schneider, 2006, 2010; Lynn & Vanhanen, 2002, 2006), arising from relatively high levels of technological achievement (Davies, 1996; Jamison, Jamison, & Hanushek, 2007; Rindermann, 2012). Similarly, Hart (2007, p. 23) showed that the most notable inventions and innovations throughout history have been formulated by individuals with substantially above-average intelligence.

The studies by Rindermann (2012) and Hanushek and Woessmann (2008, 2012) both showed that societal progress is mostly attributed by those that have an exceptional IQ. By employing the internationally renowned scholastic achievement scores (SAS), they found that economic growth and technological progress are accelerated in countries in which a larger proportion of the population has high cognitive skills (SAS≥600 points, or IQ≥115) compared with basic cognitive skills (SAS≥400 points, or IQ≥85).[1,2] Moreover, the impact of the intellectual class on growth is four times that of basic performers, indicating that the size of the former is relatively more important for expanding economic growth.

Other studies have verified the significant role of the intellectual class in coping with the increasing complexity of technology in daily life. The comprehensive European study of the determinants of innovation by Furman et al. (2002) found that the impact of scientists and engineers (β=1.407) and size of the economy (i.e., GDP) (β=1.034) on technological innovation were significantly positive, whereas population size (β=-1.337) was significantly negative.[3] Ciccone and Papaioannou (2009) confirmed that a larger number of highly skilled people contributes to the more rapid adoption of new technologies and production processes, resulting in faster productivity growth in sophisticated skill-intensive industries. On the contrary, increasing population size hampers innovation rate, as similarly found in growth studies (e.g., Mankiw et al*.,* 1992; Ram, 2007). However, unfortunately, Furman et al. (2002) neglected to examine the role of IQ in technological progress, thus leaving a large unanswered question regarding this IQ–innovation relationship.

Gelade (2008) proved that countries that have a higher percentage of high-IQ individuals engineer a greater number of patents per capita compared with other nations. In a study of 112 countries, the author discovered a correlation of .51 between average IQ at the national level and number of patents per capita. Surprisingly, however, when investigating

[1] Previous studies found high correlations between SAS scores and Lynn and Vanhanen's (2002, 2006) national IQs, with r=.92–1.00 (Lynn & Meisenberg, 2010; Lynn, Meisenberg, Mikk, & Williams, 2007; Lynn & Mikk, 2007, 2009), hence they are equivalent and sufficiently similar to be alternative measures of the same construct (Meisenberg & Lynn, 2011; Rindermann, 2007).

[2] The Programme for International Student Assessment (PISA) 2003 science and math test establishes the threshold of 400 points as the lowest bound for a basic level of achievement and 600 points for high performance (OECD, 2010). These values are comparable to an IQ level of 85 and 115, respectively.

[3] Accordingly, a 1% raise in GDP and the number of scientists and engineers will raise the number of patents by 1.034% and 1.407%, respectively. A 1% decrease in population size will raise the number of patents by 1.337%.

the influence of the intelligent class (IQ≥140), the correlation only increased to .64. Despite these findings, it could be argued that setting an IQ threshold level of 140 is vague since it is purely based on assumptions and it lacks strong justification. Additionally, because Gelade's analysis does not include major control variables such as those employed in Furman et al. (2002), it is hard to determine whether IQ does indeed have a substantial influence the rate of technological achievement across countries.

In contrast to the procedures adopted by Hanushek and Woessmann (2008, 2012) and Gelade (2008), Rindermann and Thompson (2011) suggested that it is not the *percentage* of the high-IQ population that is crucial but rather the *absolute* IQ of this population. In Rindermann et al. (2009), the authors employed SAS data on cognitive ability for 90 countries to compare the relative strength of the 95th, 50th, and 5th percentiles of IQ level on an array of economic outcomes. Their findings suggested that the IQ of the intellectual class is most significant at determining cross-country variations in GDP per capita and scientific-technological achievement. To our knowledge, this is the only study that considers the low impact of the non-intellectual class on national income and scientific-technological achievement. Rindermann et al.'s (2009) conclusion that cross-country income inequality and the variation in scientific-technological achievement depend mostly on differences in IQ is similar to their subsequent findings in Rindermann and Thompson (2011). In this paper, they demonstrated that each point of national average IQ is found to raise GDP per capita by US$229, increasing to US$468 per IQ point for the brightest 5%. Further, they found considerable differential impact between the 95th percentile (β=.70), national average IQ (β=-.19), and eminent-scientists rate from 800 BC to 1950 (β=.37) on high scientific-technological achievement today. While these findings confirm the fact that high- and low-IQ individuals do not play an equal role in the economic development of a country, these two studies did not use standard models that included other major factors or control variables. Thus, we use standard models of economic growth and technological progress in order to examine the relative impact of different IQ classes.

3. Methodology

3.1. Measuring intellectual and non-intellectual classes

As discussed in Section 2, previous studies have examined the effect of intelligence level by measuring either the proportion of the population that exceeds a given threshold (e.g., IQ or SAS level) or the IQ of an upper-level group, for instance at the 95th percentile of the population. Following Rindermann and Thompson (2011), we used the second approach because the absolute IQ of the intellectual class enables society-wide progress, not the percentage of the population in a higher stratum (i.e., the right-hand tail of the bell curve). In order to measure how the intellectual and non-intellectual classes affect economic development, we examined the data on cognitive ability used by Rindermann et al. (2009) and Rindermann and Thompson (2011). These authors presented an aggregate cognitive ability value for 90 countries by using the 95th, 50th, and 5th percentiles from the Trends in International Mathematics and Science Study (1995–2007), PISA (2000–2006), and the Progress in International Reading Literacy Study (2001–2006). In their study, they also transformed the data into an IQ scale, because psychologists are more familiar with the IQ scale than the SAS scale. Since the IQ level was taken from the distribution of a society (students) at 95%, 50%, and 5% achievement levels, therefore a limitation in our study; that is, we don't analyze the impact of the intellectual classes themselves since we haven't looked at the intelligent people and then analyze their work and impact on economic growth and technological achievement. However, this kind of procedure was defended by previous studies e.g., Hanushek and Woessmann (2008, 2012) and Rindermann and Thompson (2011).

3.2 Model specifications

We used the augmented Mankiw et al. (1992) growth model with the IQ measure employed by Ram (2007, Table 2 (4)) in order to estimate the impact of the 95th, 50th, and 5th percentiles on economic growth:

$$GROWTH_{\mathrm{i}} = \beta_0 + \beta_1 \log(Y_{1970})_{\mathrm{i}} + \beta_2 (I/Y)_{\mathrm{i}} + \beta_3\,(POPGR)_{\mathrm{i}} + \beta_4\,(SCHOOL)_{\mathrm{i}} + \beta_5\,(IQ)_{\mathrm{i}} + e_{\mathrm{i}}$$

where *GROWTH* is the annual growth rate of real GDP per capita over the 1970–2010 period, β is a constant, and Y_{1970} is the initial per capita income at the beginning of the sample period. The data on *GROWTH* and Y_{1970} were obtained from the Penn World Table 7.1 (Heston, Summers, & Aten, 2012). *I/Y* is the investment as a percentage of annual GDP averaged over 1970–2010 obtained from the World Development Indicators 2013 (World Bank, 2013). *POPGR* is the growth rate of the population obtained from the United States Census Bureau (USCB, 2013) database.[4] *SCHOOL* is the average percentage of the working-age population (those aged 15–19) in secondary schools over 1970–2010 obtained from Barro and Lee's (2010) dataset.[5] *IQ* is the cognitive ability at the 95th, 50th, and 5th percentiles and e_i is the error term. The data on *IQ* were obtained from Rindermann et al. (2009).[6]

The next stage was to examine the impact of IQ on technological achievement. We added the IQ of the intellectual class, mean ability, and non-intellectual class into Furman et al.'s (2002, Table 4 (4.1)) ideas production function. The model structure takes the following form:

$$\log(PATENTS)_{\mathrm{i}} = \beta_0 + \beta_1\log(GDP)_{\mathrm{i}} + \beta_2\log(POP)_{\mathrm{i}} + \beta_3\log(RESEARCHER)_{\mathrm{i}} + \beta_4(IQ)_{\mathrm{i}} + e_{\mathrm{i}}$$

where *PATENTS* is the average annual number of patents granted in the United States to establishments in country i within 2000–2009, which serves as a proxy for innovative output. Patent data were obtained from the database of the World Intellectual Property Organization (WIPO, 2009). *GDP* (real GDP in billions of PPP-adjusted 2005 US$) and *POP* (population (thousand persons)) were both obtained from the Penn World Table 7.1 (Heston et al., 2012) and their annual values were averaged for 2000–2009. *IQ* is the cognitive ability at the 95th, 50th, and 5th percentiles and e_i is the error term.

Furman et al. (2002) used the full-time equivalent scientists and engineers in all sectors obtained from the OECD's science and technology indicators database in order to

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[4] This variable is equal to (n + δ + g), namely population growth (n) plus the depreciation rate of capital (δ) plus the growth rate of total factor productivity (g), which is assumed to be exogenously growing at an exponential rate. Since δ and g are assumed to remain equal to .05 over time and identical across countries, (n + δ + g) is equal to the population growth rate, n (Mankiw et al., 1992).

[5] Population aged 15–19 is considered as a working-age group. Thus, Mankiw et al. (1992) suggested that percentage of this working-age population that is in secondary school can be used to proxy for the rate of human capital accumulation that benefits long-term economic growth. They found that the impact of initial GDP per capita, *I/Y*, *POPGR*, and *SCHOOL* were significant on economic growth over the 1960–1985 period.

[6] A similar dataset was employed by Rindermann and Thompson (2011).

proxy for a common innovation infrastructure. However, the unavailability of data on non-OECD countries forced us to instead use *RESEARCHER*, namely the number of professional researchers (per million people) engaged in R&D, which was obtained from the World Development Indicators 2013 (World Bank, 2013). As before, its annual values were averaged for 2000–2009. Researchers in R&D are defined as professionals engaged in the invention of new knowledge, processes, products, methods, or systems and in the supervision of the projects involved. This includes postgraduate PhD students engaged in R&D. Table 1 shows the list of countries ranked by selected variables.

[Insert Table 1 here]

4. Results

Tables 2 and 3 present correlation matrices for variables.

[Insert Table 2 here]

[Insert Table 3 here]

In Table 4, we find that *POPGR* (Model 1) is inversely correlated with *GROWTH*, implying that increasing population growth rates negatively affect economic growth, as described by Mankiw et al. (1992) and Ram (2007). *SCHOOL* is not significant in all models (1, 5, 6, and 7), while IQ alone (Models 2, 3, and 4) is also insufficient to explain the economic growth rate in 1970–2010 as the R^2 values of these models are very small, ranging from .060 to .067. Therefore, IQ-only regressions are not a good test of IQ-growth theory.

[Insert Table 4 here]

However, when IQ is added into Model 1, it substantially raises the adjusted R^2 values from .336 to .573 (Model 5), .574 (Model 6), and .524 (Model 7). This trend is associated with beta-convergence of growth process, as evidenced by the negative sign of Y_{1970} (Models 1, 5, 6, 7), showing that poor countries grow faster than rich ones and thus able to catch up on them, because decreasing returns to capital are not as strong as in capital-rich countries (Barro & Sala-i-Martin, 1997; Mankiw et al., 1992). With specific amount of human capital (e.g., IQ), the poorer countries gain advantages of relative backwardness due the ability to imitate the production methods and technologies of advanced countries with lower cost, and then enjoying a more rapid growth than developed countries (Gerschenkron, 1962; Howitt, 2005). Therefore, the rate of convergence estimates (Model 5, 6, 7) becoming higher ($|\beta|>|-1.693|$) especially when IQ is included in the regression, given that long-run steady state level of income per capita is partially determined by human capital (Mankiw et al., 1992).

IQ at the 95th, 50th, and 5th percentiles is found to be positively significant at the 1% level. Indeed, the impact of IQ is so strong that it greatly eliminates the influence of the major control variables (i.e., *I/Y* and *POPGR*) in the growth models. Of these three percentiles, we find that the magnitude of the 95th percentile is the largest (β=.104), followed by the 50th (β=.088) and 5th (β=.066) percentiles in that order. The result presented here, interpreted causally, imply that a 1 point increase in national IQ at 95th, 50th, and 5th percentiles correspond to a total more growth of 3.8%, 3.11%, and 2.46%, correspondingly, within 1970–2010 period.[7] Therefore, these results suggest that the intellectual class is the most relevant for increasing the economic growth rate followed by those categorized as mean ability and the non-intellectual class.

As Table 5 shows, we find that the ideas production function (Model 1) explains 86.7% of the variation in the average number of patents across the 66 sample countries. The control variables of *GDP*, *POP*, and *RESEARCHER* are also significant at the 1% level in Model 1. Accordingly, increasing GDP and the number of professional researchers as well as reducing population size will promote a greater technological achievement, as similarly found by Furman et al. (2002). We also show that *GDP* and *RESEARCHER* alone are strong enough to explain the average number of patents, with R^2 values of .737 (Model 2) and .405 (Model 3), respectively. In contrast to the growth regression, the three percentiles' IQ alone (Models 4, 5, and 6) is better at determining national innovative capacity across countries, with higher R^2 values (.246–.366). When the percentile-based classification is added into Model 1, we further find that IQ at the 95th percentile (Model 7) maintains its significance at the 1% level, whereas the 50th (Model 8) and 5th (Model 9) percentiles are not significant. 1 IQ of the intellectual class indicates .041% more patents within 2000–2009. Furthermore, Model 7 shows that the impact of the 95th percentile on technological progress is stronger than that of the number of professional researchers in R&D, which is in turn more significant than the 5th percentile.

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[7] To determine the long-run level effect of IQ on economic growth, we adopted Jones and Schneider's (2006) procedure, where the IQ coefficient is divided by 1/100th of the lagged GDP variable (log Y_{1970}). This shows how much 1 IQ point raises steady-state living standards.

[Insert Table 5 here]

5. Conclusion

The present study examined how different levels of IQ affect economic growth and technological progress at the national level. Overall, the resulted presented herein lent support to earlier studies of this topic. Consistent with the intellectual class theory advocated by Rindermann and Thompson (2011) and Rindermann et al. (2009), our research findings showed strong evidence that those people that have high IQ are the most relevant influence on economic development. Although our results suggested that all three examined IQ categories promote higher economic growth, the intellectual class has the highest impact followed by the mean ability and non-intellectual classifications. Similarly, the intellectual class also has a highly significant effect on generating technological progress, whereas the influence of the other two groups is immaterial.

IQ in this study is represented by cognitive skills, in which the raise in IQ level brings about more efficiencies, thus potentially producing a higher productivity with the same amount of resources (i.e., doing more with less). This justifies our finding that all three IQ classes have a significantly positive effect on economic growth, suggesting that intelligence level is a fundamental component of all economic activities, embracing both the high- and low-skilled labor forces, with the high-skilled labors have largest impact on productivity. Moreover, we found that the large differential impact between the 95th and 5th percentiles on economic growth occurs as an outcome of the increasing returns to scale in human capital accumulation (Acemoglu, 1996; Romer, 1986, 1990). For that reason, even a small difference between individual IQ could magnify into large income inequalities across countries (e.g., Hanushek & Kimko, 2000; Jones & Schneider, 2010).

On the relationship between IQ and technological progress, our findings on intellectual class concur with those in the literature. Initiating and formulating innovation and invention demand exceptionally high cognitive skill levels. Indeed, even when other factors are controlled for, the impact of the intellectual class on technological progress is so strong that it largely eliminates the influence of professional researchers employed in the R&D sector. These findings allow us to suggest that the role of excellent IQ levels on technological progress outperforms the importance of people’s professional experience and academic credentials especially in R&D. Nonetheless, the role of professional researchers was still shown to be of greater importance than the non-intellectual class. Moreover, the impact of GDP on technological progress maintains its exceptional significance, since larger economies can invest greater amounts into facilities that support long-term R&D activities (Furman et al., 2002).

Based on these findings, we can recommend two main development policies. First, in order to foster economic growth, governments should invest into facilities that benefit all societal groups of intelligence level (UNESCO, 2005). Even though the intellectual class adds most value to GDP at the national level, other social classes still play a substantial role in this process, implying that development and human resources policies should focus on people of average and low IQ as well. Therefore, other than focusing on identifying low-income high-IQ individuals to foster their educational and economic mobility (Pritchett & Viarengo, 2009), governments should enhance public investment in societal and intellectual development of non-intellectual class to prevent criminal activities and risky behaviors such as teenage pregnancy, school dropouts, and alcohol or drug abuse which actually have detrimental effects to wider society. Second, in order to achieve the highest technological achievement growth rate, we suggest that the government and private institutions should not only employ professionals with good experiences and high academic credentials, but also those who has excellent IQ levels to work in their R&D sectors. IQ is so significant that it does not only predict differential creative potential in scientific and technological innovation within populations that have a master's or doctoral degree (Park, Lubinski, & Benbow, 2008), but also to determine whether billionaires could occupy themselves in science, technology, engineering, and mathematics (STEM) sectors, or earn less in non-STEM sectors (Wai, 2013). A useful development approach would not merely increase the average education levels of the society, but would rather enhance the IQ level of the top percentile. Pritchett and Viarengo's (2009) ideas on education policy are worth listening to, where the importance should be on "discovering the discoverers" by improving the educational system on high-IQ individuals, and promoting international standards of cognitive performance. This focus would ensure that the resulting innovation and invention would be of the finest quality and thereby generate the highest economic value.

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References

Acemoglu, D. (1996). A microfoundation for social increasing returns in human capital accumulation. *The Quarterly Journal of Economics*, *111*, 779–804.

Barro, R. J., & Lee, J. W. (2010). *A new data set of educational attainment in the world, 1950–2010* (NBER Working Papers 15902). Cambridge, MA: National Bureau of Economic Research.

Barro, R. J., & Sala-i-Martin, X. (1997). Technological diffusion, convergence, and growth. *Journal of Economic Growth, 2*, 1–26.

Ciccone, A., & Papaioannou, E. (2009). Human capital, the structure of production, and growth. *Review of Economics and Statistics, 91*, 66–82.

Comin, D. A., Easterly, W., & Gong, E. (2010). Was the wealth of nations determined in 1000 BC? *American Economic Journal: Macroeconomics, 2*, 65–97.

Davies, H. (1996). High IQ and low technology: Hong Kong's key to success. *Long Range Planning, 29,* 684–690.

Furman, J. L., Porter, M. E., & Stern, S. (2002). The determinants of national innovative capacity. *Research Policy*, *31,* 899–933.

Gelade, G. A. (2008). IQ, cultural values, and the technological achievement of nations. *Intelligence*, *36,* 711−718.

Gerschenkron, A. (1962). *Economic backwardness in historical perspective. A book of essays.* Cambridge: Harvard University Press.

Hanushek, E. A., & Kimko, D. D. (2000). Schooling, labor-force quality, and the growth of nations. *American Economic Review, 90,* 1184–1208.

Hanushek, E. A., & Woessmann, L. (2008). The role of cognitive skills in economic development. *Journal of Economic Literature*, *46,* 607–668.

Hanushek, E. A., & Woessmann, L. (2012). Do better schools lead to more growth? Cognitive skills, economic outcomes, and causation. *Journal of Economic Growth*, *17,* 267–321.

Hart, M. (2007). *Understanding human history*. Augusta, GA: Washington Summit Publishers.

Herrnstein, R. J., & Murray, C. (2010). *Bell curve: Intelligence and class structure in American life*. New York, NY: Simon and Schuster.

Heston, A., Summers, R., & Aten, B. (2012). Penn World Table Version 7.1, Center for International Comparisons of Production, Income and Prices at the University of Pennsylvania, November 30, 2012.

Howitt, P. (2005). Health, human capital, and economic Growth: A Schumpeterian perspective. In G. Lopez-Casasnovas, B.Rivera, & L. Currais (Eds), *Health and economic growth: Findings and policy implications* (pp. 19–40). Cambridge, MA: MIT Press.

Jamison, E. A., Jamison, D. T., & Hanushek. E. A. (2007). The effects of education quality on mortality decline and income growth. *Economics of Education Review, 26,* 772–789.

Jones, G., & Schneider, W. J. (2006). Intelligence, human capital, and a Bayesian Averaging of Classical Estimates (BACE) approach. *Journal of Economic Growth*, *11,* 71–93.

Jones, G., & Schneider, W. J. (2010). IQ in the production function: Evidence from immigrant earnings. *Economic Inquiry*, *48,* 743–755.

Lynn, R. (2012). IQs predict differences in the technological development of nations from 1000 BC through 2000 AD. *Intelligence, 40,* 439–444.

Lynn, R., & Meisenberg, G. (2010). National IQs calculated and validated for 108 nations. *Intelligence*, *38,* 353–360.

Lynn, R., Meisenberg, G., Mikk, J., & Williams, A. (2007). National IQs predict differences in scholastic achievement in 67 countries. *Journal of Biosocial Science, 39,* 861–874.

Lynn, R., & Mikk, J. (2007). National differences in intelligence and educational attainment. *Intelligence, 35,* 115–121.

Lynn, R., & Mikk, J. (2009). National IQs predict attainment in math, science and reading across 56 nations. *Intelligence, 37,* 305–310.

Lynn, R., & Vanhanen, T. (2002). *IQ and the wealth of nations*. Westport, CT: Praeger.

Lynn, R., & Vanhanen, T. (2006). *IQ and global inequality.* Augusta, GA: Washington Summit.

Mankiw, N. G., Romer, D., & Weil, D. N. (1992). A contribution to the empirics of economic growth. *The Quarterly Journal of Economics*, *107,* 407–437.

Meisenberg, G., & Lynn, R. (2011). Intelligence: A measure of human capital in nations. *Journal of Social, Political & Economic Studies, 36,* 421–454.

OECD (2010). *PISA 2009 at a glance*. Paris: OECD Publishing. Available online at http://www.oecd.org/pisa/46660259.pdf.

Park, G., Lubinski, D., & Benbow, C. P. (2008). Ability differences among people who have commensurate degrees matter for scientific creativity. *Psychological Science, 19,* 957–961.

Pritchett, L., &, Viarengo, M. (2009). Producing superstars for the economic mundial: The Mexican predicament with quality of education. In R. Hausmann, E. L. Austin, & I. Mia (Eds), *The Mexico competitiveness report 2009* (pp. 71–89). Genf/Harvard: World Economic Forum.

Ram, R. (2007). IQ and economic growth: Further augmentation of Mankiw–Romer–Weil model. *Economics Letters*, *94*, 7–11.

Rindermann, H. (2007). The g-factor of international cognitive ability comparisons: The homogeneity of results in PISA, TIMSS, PIRLS and IQ-tests across nations. *European Journal of Personality*, *21,* 667−706.

Rindermann, H. (2012). Intellectual classes, technological progress and economic development: The rise of cognitive capitalism. *Personality and Individual Differences, 53,* 108–113.

Rindermann, H., Sailer, S., & Thompson, J. (2009). The impact of smart fractions, cognitive ability of politicians and average competence of peoples on social development. *Talent Development & Excellence, 1,* 3–25.

Rindermann, H., & Thompson, J. (2011). Cognitive capitalism: The effect of cognitive ability on wealth, as mediated through scientific achievement and economic freedom. *Psychological Science, 22,* 754–763.

Romer, P. M. (1986). Increasing returns and long-run growth. *Journal of Political Economy, 94,* 1002–1037.

Romer, P. M. (1990). Endogenous technological change. *Journal of Political Economy*, *98*, 71–102.

UNESCO (2005). *Education for all: The quality imperative (EFA Global Monitoring Report 2005).* Paris: UNESCO. Available online at: http://unesdoc.unesco.org/images/0013/001373/137333e.pdf

USCB (2013). *International Database.* United States Census Bureau. Available only at: http://www.census.gov/ population/international/data/idb/informationGateway.php.

Wai, J. (2013). Investigating America's elite: Cognitive ability, education, and sex differences. *Intelligence, 41,* 203–211.

WIPO (2009). *Patent applications by patent office (1883- 2007), by resident and non-resident*. Geneva: World Intellectual Property Organization. Available online at: http://www.wipo.int/ipstats/en/statistics/patents.

World Bank (2013). *World development indicators 2013*. Washington, DC: World Bank. Available online at: http://data.worldbank.org

Table 1

List of countries with top- and bottom-10 rankings for selected variables.

	GROWTH **(*N*=61)**	***PATENTS*** **per 100,000 people (*N*=66)**	***RESEARCHER*** **(*N*=66)**	***GDP*** **(*N*=66)**	***IQ*** **95th (*N*=66)**	***IQ*** **50th (*N*=66)**	***IQ*** **5th (*N*=66)**
10 Countries at Highest Ranking	S. Korea: 5.89	USA: 28.369	Finland: 7507	USA: 11697	Singapore: 127.22	S. Korea: 106.37	S. Korea: 86.11
	Macau: 5.68	Japan: 26.712	Iceland: 7445	Japan: 4440	S. Korea: 125.25	Singapore: 104.56	Finland: 84.96
	Singapore: 5.36	Switzerland: 16.434	Sweden: 5463	Germany: 2567	Japan: 124.3	Japan: 104.55	Macau: 84.43
	Botswana: 5.27	Finland: 15.647	Japan: 5221	UK: 2032	N. Zealand: 122.65	Hong Kong: 103.66	Estonia: 84.40
	Malaysia: 4.65	Sweden: 14.806	Singapore: 5219	France: 1923	Australia: 121.94	Finland: 102.91	Hong Kong: 83.32
	Malta: 4.60	Germany: 12.273	Denmark: 5210	Italy: 1600	UK: 121.92	Estonia: 102.26	Japan: 82.85
	Hong Kong: 4.49	S. Korea: 10.849	Norway: 4842	Canada: 1003	Hong Kong: 121.54	Netherlands: 101.89	Netherlands: 82.74
	Thailand: 4.28	Canada: 10.563	USA: 4688	Spain: 982	Finland: 120.92	Canada: 101.75	Canada: 79.59
	Indonesia: 4.11	Singapore: 8.682	Luxembourg: 4509	Brazil: 850	Estonia: 120.75	Australia: 101.12	Sweden: 79.21
	Egypt: 3.70	Luxembourg: 7.970	N. Zealand: 4148	Mexico: 773	Canada: 120.32	Macau: 101.11	Australia: 79.06
10 Countries at Lowest Ranking	Argentina: 1.32	Colombia: .022	Mexico: 328	Cyprus: 15.11	Albania: 103.56	Egypt: 81.14	Brazil: 58.43
	N. Zealand: 1.28	Turkey: .022	Thailand: 294	Iceland: 12.87	Colombia: 101.38	Albania: 81.10	Colombia: 58.15
	Algeria: 1.22	Philippines: .022	Algeria: 170	Ghana: 12.51	Philippines: 101.02	Tunisia: 80.81	Albania: 55.84
	Peru: 1.21	Tunisia: .017	Kuwait: 168	Estonia: 12.33	Indonesia: 100.93	Colombia: 80.61	Argentina: 54.72
	El Salvador: 1.11	Egypt: .009	Indonesia: 166	Macau: 10.89	Tunisia: 100.63	Algeria: 80.56	Egypt: 53.73
	S. Africa: .96	Morocco: .008	Colombia: 150	Bosnia: 9.82	S. Africa: 100.06	Kuwait: 75.72	Kuwait: 53.10
	Ghana: .90	Ghana: .005	Albania: 147	Albania: 7.00	Algeria: 97.94	Philippines: 73.55	Morocco: 47.48
	Switzerland: .80	Algeria: .004	Bosnia: 113	Macedonia: 5.53	Kuwait: 97.77	Morocco: 71.02	Philippines: 46.61
	Iran: .63	Iran: .004	Philippines: 77	Malta: 5.53	Morocco: 95.36	S. Africa: 63.26	S. Africa: 35.69
	Bahrain: .51	Indonesia: .003	Ghana: 17	Moldova: 2.70	Ghana: 89.38	Ghana: 61.25	Ghana: 32.86

[a] *GROWTH* is the annual growth rate (%) of real GDP per capita (averaged 1970–2010).

[b] *PATENTS* per 100,000 people is the annual number of patents per 100,000 people granted in the USA to the establishments in country *i* (averaged 2000–2009).

[c] *RESEARCHER* is the number of researchers (per million people) engaged in R&D (averaged 2000–2009).

[d] *GDP* is the real gross domestic product (in billions of PPP-adjusted 2005 US$) (averaged 2000-2009).

[e] *IQ* is cognitive ability at the 95^{th}, 50^{th}, and 5^{th} percentiles.

Table 2

Correlation matrix for variables in growth model (N=61).

		1	2	3	4	5	6	7
1	***GROWTH***	-						
2	**log(Y_{1970})**	-.396**	-					
3	***I/Y***	.426**	-.185	-				
4	***POPGR***	-.008	-.449**	.229	-			
5	***SCHOOL***	-.031	.543**	-.093	-.449**	-		
6	***IQ* 95th**	.245	.642**	.110	-.567**	.563**	-	
7	***IQ* 50th**	.258*	.635**	.164	-.561**	.515**	.966**	-
8	***IQ* 5th**	.256*	.595**	.203	-.507**	.429**	.902**	.975**

Note: *$p < .05$; **$p < .01$

[a] *GROWTH* is the annual growth rate (%) of real GDP per capita (averaged 1970–2010).

[b] Y_{1970} is the GDP per capita in 1970.

[c] *I/Y* is the investment as a percentage of annual GDP (averaged 1970–2010).

[d] *POPGR* is the percentage of population growth rate (averaged 1970–2010).

[e] *SCHOOL* is the percentage of the working-age population (those aged 15–19) in secondary schools (averaged 1970–2010).

[f] *IQ* is cognitive ability at the 95th, 50th, and 5th percentiles.

Table 3

Correlation matrix for variables in ideas production function (N=66).

		1	2	3	4	5	6
1	**log (*PATENTS*)**	-					
2	**log (*GDP*)**	.858**	-				
3	**log (*POP*)**	.410**	.740**	-			
4	**log (*RESEARCHER*)**	.636**	.384**	-.158	-		
5	***IQ* 95th**	.605**	.291*	-.216	.837**	-	
6	***IQ* 50th**	.548**	.267*	-.237	.815**	.965**	-
7	***IQ* 5th**	.496**	.257*	-.223	.773**	.906**	.979**

Note: *p < .05 ; **p < .01

[a] *PATENTS* is the annual number of patents granted in the USA to the establishments in country *i* (averaged 2000–2009).

[b] *GDP* is the real gross domestic product (in billions of PPP-adjusted 2005 US$) (averaged 2000-2009).

[c] *POP* is the population size (thousand persons) (averaged 2000–2009).

[d] *RESEARCHER* is the number of researchers (per million people) engaged in R&D (averaged 2000–2009).

[e] *IQ* is cognitive ability at the 95th, 50th, and 5th percentiles.

Table 4

The relative impact of the 95th, 50th, and 5th percentiles on economic growth rates.

Dependent Variable: *GROWTH* (GDP Growth Rates, % (1970–2010))							
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
log (Y_{1970})	-1.693** (-.536)				-2.740** (-.867)	-2.832** (-.896)	-2.680** (-.848)
I/Y	.130** (.403)				.058 (.181)	.043 (.132)	.051 (.158)
POPGR	-.336* (-.260)				.014 (.011)	.045 (.035)	-.034 (-.027)
SCHOOL	.017 (.181)				.002 (.026)	.008 (.080)	.015 (.154)
***IQ* 95th**		.033 (.245)			.104** (.773)		
***IQ* 50th**			.029* (.258)			.088** (.783)	
***IQ* 5th**				.026* (.256)			.066** (.649)
N	61	61	61	61	61	61	61
R^2	.380	.060	.067	.065	.608	.610	.564
Adjusted R^2	.336	.044	.051	.050	.573	.574	.524

Note: Unstandardized and standardized (in parentheses) β coefficients.

[a] * $p < .05$

[b] ** $p < .01$

Table 5

The relative impact of the 95th, 50th, and 5th percentiles on national innovative capacity.

Dependent Variable: ***PATENTS*** **(log (Total Number of Patents (averaged 2000–2009)))**									
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
log (*GDP*)	1.591** (.999)	1.367** (.858)					1.505** (.945)	1.544** (.970)	1.579** (.991)
log (*POP*)	-.511** (-.297)						-.394* (-.229)	-.443* (-.258)	-.493** (-.287)
log (*RESEARCHER*)	.450** (.206)		1.393** (.636)				.020 (.009)	.247 (.113)	.399* (.183)
***IQ* 95th**				.090** (.605)			.041** (.272)		
***IQ* 50th**					.067** (.548)			.016 (.135)	
***IQ* 5th**						.053** (.496)			.004 (.036)
N	66	66	66	66	66	66	66	66	66
R^2	.867	.737	.405	.366	.300	.246	.888	.872	.867
Adjusted R^2	.860	.733	.396	.356	.289	.234	.880	.864	.858

Note: Unstandardized and standardized (in parentheses) β coefficients.

[a] * $p < .05$

[b] ** $p < .01$