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Abstract

Intelligence quotient (IQ) scores are normally distributed within a nation's population. In a cross-country regression, Burhan et al. (2014, *Intelligence*, 46, 1–8) had statistically proven that intellectual class represented by the 95th percentile IQ had contributed most to economic growth. Those with average ability (50th percentile IQ) contributed second most, followed by the non-intellectual class (5th percentile IQ). Also, the researchers found that only the intellectual class was significant for technological progress. This paper reanalyzed their dataset using robust regressions. After eliminating some outliers, the IQs of the intellectual class and average ability group were found to have equal impacts on economic growth, and the impacts were larger than that of non-intellectual's. Furthermore, the IQ of the average ability group was significant on technological achievement although not as strong as the intellectual class. Nevertheless, the number of professional researchers employed in research and development (R&D) sector did not give the same paramount effects as the impact of the average ability IQ in generating technological progress. Based on the conclusions drawn, it will be better for R&D sectors to employ professionals who possess not only high academic qualifications, but also exceptional levels of cognitive skills to develop new innovations.

Keywords: economic growth; technological achievement; intelligence; social class; robust regression

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

1. Background of the Study

Economics and psychology literatures have established that intelligence quotient (IQ) or cognitive ability is fundamental to numerous aspects of socioeconomic development and well-being of people. For example, individuals with higher IQs are said to be healthier (Batty, Der, Macintyre & Deary, 2006; Gottfredson & Deary, 2004; Whalley & Deary, 2001). In addition, high IQ individuals retain positive attitudes such as patience, ambitious and do not seek instant gratification and are more likely to be a team player (Gill & Prowse, 2016; Jones, 2008; Robalino & Robson, 2016; Shamosh & Gray, 2008). These qualities affects the country as a whole, in which societies with higher average IQs experience higher quality of life and health (Lynn &Vanhanen, 2012, pp. 163–165, pp. 177–187; Madsen, 2016; Nikolaev & McGee, 2016; Nikolaev & Salahodjaev, 2016). The countries also enjoy higher levels of savings rates, gender equality, democracy and globalization (Burhan, Sidek, Kurniawan & Mohamad, 2015; Jones, 2012b; Salahodjaev, 2015a; Salahodjaev & Azam, 2015), as well as lower levels of corruption and crime rates (Beaver & Wright, 2011; Potrafke, 2012; Rushton & Templer, 2009; Rushton & Whitney 2002; Salahodjaev, 2015b). Furthermore, individuals with high IQ thrive in work settings as excellent cognitive abilities are indispensable for tasks that involve advanced technologies, knowledge, and skills. In particular, higher cognitive ability and skills are associated with greater working memory capacity and information-processing speed in individuals (Deary & Ritchie, 2016; Fry & Hale, 1996, 2000; Sheppard & Vernon, 2008; Tourva, Spanoudis & Demetriou, 2016). For that reason, individuals with higher IQs are more efficient in calculating financial risk and making choices (Fang, Keane & Silverman, 2008; Grinblatt, Ikäheimo, Keloharju & Knüpfer, 2015; Grinblatt, Keloharju & Linnainmaa, 2011, 2012). Intellectuals are also found to be more competent in learning and applying new knowledge, skills, and experiences across occupations, which make them more productive, and therefore obtain higher earnings than those with lower cognitive abilities (Ceci & Williams, 1997; Lynn & Vanhanen 2012, pp. 70–72, p. 74; Nyborg & Jensen, 2001; Schmidt & Hunter, 2004; Schmidt, Hunter, Outerbridge & Goff, 1988; Zagorsky, 2007; Zax & Rees, 2002). Consequently, cross-country achievement is strengthened, where nations with higher average IQ attain higher levels of gross domestic product (GDP) per capita (Jones, 2013; Jones & Schneider, 2010; Lynn & Vanhanen, 2002, 2006, 2012), financial development (Hafer, 2016; Kodila-Tedika & Asongu, 2015), economic (GDP per capita) growth rate (Hanushek & Kimko 2000; Jones & Schneider, 2006; Ram, 2007; Weede & Kämpf, 2002), and technological progress (Davies, 1996; Gelade, 2008; Jones, 2012a; Lynn, 2012) than lower IQ countries.

In a globalized world such as today, intelligent individuals are a country's capital for advanced progression. IQ can be measured through a series of tests, and the scores are normally distributed within a nation's population. As such, the test scores can be modelled in a bell-shaped graph that allows the study of the cause-effect relationship between IQ and socioeconomic development across countries. While positive association between national average IQ and the level of economic development has been well-discussed in literature, a few recent empirical studies suggested that national level of income and economic growth are mostly contributed by intellectual class, particularly the group of people with higher than the average IQ. Although the population size of the intellectual class is smaller than the average ability group, IQ of the intellectual class has contributed most to the well-being of nation than the average ability group, especially on economic growth and technological progress (Ciccone & Papaioannou, 2009; Gelade, 2008; Hanushek & Woessmann, 2008, 2012; Rindermann, 2012; Rindermann & Thompson, 2011; Rindermann, Sailer & Thompson, 2009). The most recent study on the impact of social classes of IQ on economic growth and technological progress was conducted by Burhan, Mohamad, Kurniawan, and Sidek (2014). In Burhan et al.'s study, the independent variables of interest are respectively the intellectual, average ability, and non-intellectual classes IQ at the 95th, 50th, and 5th percentiles of the normal distribution of population IQs. The researches employed Rindermann et al.'s (2009) cognitive ability dataset for 90 countries that is based on the data on three international scholastic achievement test scores. The tests were the Trends in International Mathematics and Science Study (TIMSS) (1995–2007), the Programme for International Student Assessment (PISA) (2000–2006), and the Progress in International Reading Literacy Study (PIRLS) (2001–2006). The data from those test scores were then converted into IQ scale. Using Rindermann et al.'s dataset, Burhan et al. performed regression analyses and verified that all IQ measures were significant at 99 per cent level, where the effect of the 95th percentile IQ on the GDP per capita growth rate was the highest, followed by the 50th and 5th percentiles' IQ. Furthermore, after controlling other factors, only the 95th percentile IQ was found to be significant (p<.01) on technological achievement, measured by the number of patents produced. In contrast, both 50th and 5th percentiles of IQ were non-significant even at 90 per cent level in the regressions. These prove that the IQ of the smartest group adds more to a nation's wealth as compared to national average IQ.

Burhan et al.'s (2014) study employed three percentiles of IQ, allowing the relative effect of each IQ classes on economic development to be determined, after controlling other factors. The study is based on economic growth model (Ram, 2007; Mankiw, Romer & Weil, 1992) and technological achievement model, namely 'ideas production function' (Furman, Porter & Stern, 2002) that acts as the proxy for innovative output. So far, Burhan et al. (2014) is the only study that examined the impacts of 95^{th}, 50^{th}, and 5^{th} percentiles' IQ on economic growth and technological achievement using regression analyses through the use of econometric models. However, the Ordinary Least Squares (OLS) model employed by Burhan et al. (2014) claimed that the data are homoscedastic - the expected value of all error terms when squared are assumed equal at any specified point. However, in cross-sectional models, when the variances of the error terms are not the same, the data suffers from heteroskedasticity. The regression coefficients of an OLS estimate are still unbiased, but standard errors and confidence intervals obtained from the regression are inaccurate (Engle, 2001). For example, in Burhan et al.'s cross-section regressions of economic growth and technological achievement on IQs, the error terms may be larger among countries with high achievement than low achievement, or vice versa. Therefore, in the present study, White's (1980) covariance-matrix estimator is employed. This allows for the computation of heteroskedasticity-robust standard errors to correct for possible heteroskedasticity in the residuals as the skedastic function is unknown (Rodriguez & Rodrik, 2001).

Other than White's heteroskedasticity correction, robust regression methods are also applied to deal with potential outliers in the data samples. Temple (1999b) asserted that it is very important to identify outliers in the cross-country regression, especially when samples are inclusive of a large number of heterogeneous countries. Robust regression methods frequently give different results than using OLS especially in the presence of extreme outliers in the samples. For instance, Jappelli and Pagano (2002) found that significance level and the size of the regression coefficients are reduced in the Huber-weighted robust regressions. Furthermore, many economics studies have shown that the significance levels of independent variables have slightly changed after down weighting outliers, and substantially changed after removing even a single outlier (e.g., De Haan & Sturm, 2003; Temple & Johnson, 1998; Temple & Woessmann, 2006; Sturm & De Haan, 2005). Studies conducted by Ding and Knight (2009) and Zaman, Rousseeuw, and Orhan (2001) found that omitting the outliers from samples has resulted in a rise of the R^2 of OLS and a decline in the estimated standard errors of most independent variables, both of which imply improved goodness of fit of the regressions. One of the advantages of robust regression approach is that it can cope with large number of outliers. Hence, this approach is better than single-case diagnostics such as Cook's distance measure, the Studentized residuals, and DFITS that are likely to overlook group of outliers (e.g., masking effect) or mistakenly identify representative points as outlying observations, as advocated by Sturm and De Haan (2001) and Temple (1999a). In contrast, a robust analysis fits a regression model to the data, and attempts to identify points that have large residuals of so-called outliers. Therefore, two types of robust regression method are utilized in this study. The first was OLS with Huber-weight option that gives less weight to high-leverage observations (Huber, 1973). This is to ensure that extremely large or small observational values will not bias to the regression estimates, without removing outliers from the samples. Robust regression uses 'ROBUSTREG' command using the M-estimation technique and the Huber-weight option, which follows procedure recommended in Huber's (1973) work. Secondly, in addition to Huber's, the growth regression is estimated using OLS with Bisquare-weight option, a method formulated by Beaton and Tukey (1974) to mitigate the biasing effects of outliers in the regression. Also, if necessary, it removes outliers from the observations. Robust solutions provide high resistance to outliers, and give better predictions.

2. Robust Regression Analyses

This study is an analysis based on these two linear regression models shown in the first row of Table 1 and Table 2. Definition for each dependent and independent variables are presented as footnotes of those tables. As shown in Table 1, the average annual economic growth rates (GROWTH) for the 1970–2010 period are the dependent variable, while in Table 2, the number of patents (PATENTS) averaged for the 2000–2009 period are the dependent variable. The effect of the variables of interest, which are a set of IQ variables on GROWTH and PATENTS, are controlled for other factors as specified in Table 1 and Table 2, respectively. Each IQ variables is entered separately into the regression models to avoid serious multicollinearity problem. In particular, the correlations between IQs at the 95^{th}, 50^{th}, and 5^{th} percentiles, namely $IQ95^{th}$, $IQ50^{th}$, and $IQ5^{th}$ are reported at r=.90–.98 where their VIF values are very high, ranging from 5.3 to 24.4. Furthermore, the VIF between other independent variables are less than 4.0, indicating an absence of multicollinearity among variables. See Table A1 and Table A2 in Appendix A for details on the correlations and VIF for all variables employed.

[Insert Table 1 here]

[Insert Table 2 here]

Table 1 summarizes the regression results for economic growth model. Model 1 is the result of a basic growth regression, which shows that SCHOOL was non-significant on economic growth during 1970–2010 period. This finding is in contrast to Mankiw et al.'s (1992) and Ram's (2007) who reported a positive and significant effect of the variable on economic growth during 1960–1985 period. Hence, SCHOOL may be a crude measure of education quantity of the society, and its effect on economic growth is diminishing over time.

Model 2 to Model 4 are the results of regression after we incorporated IQ into the growth model, as reported in Burhan et al. (2014). Model 5 to Model 7 show the regression results when the standard errors were corrected for heteroskedasticity, a procedure suggested by White (1980). There was no difference in significance level (p<.01) of IQ variables in Model 5 to Model 7 compared to Model 2 to Model 4. Across Model 1 to Model 7, including the IQ variables has increased the adjusted R^2 from .336 to .524–.574. All measures of IQ were significant at p<.01 level, where IQ95th (β=.104) has the largest effect on GROWTH, followed by IQ50th (β=.088) and IQ5th (β=.066). An increase in the magnitude of log(Y_{1970}) from β=|-1.693| to β=|-2.681|–|-2.832| demonstrates that higher rate of convergence occurred when IQ is included into the growth model. Therefore, human capital (i.e., IQ) is a fundamental determinant of steady state level of per capita income in the long-run (Mankiw et al., 1992).

For robustness check, Model 2 to Model 7 were re-estimated by using robust regression methods. Robust regressions are very useful when dealing with outliers. For example, using Huber and Bisquare-weight techniques has increased the adjusted R^2 from .524–.574 in Model 2 to Model 7 to .585–.789 in Model 8 to Model 13. All measures of IQ remained significant at p<.01 level across all models. There is a reduction in the number of observations to N=59 and N=60 in Model 11 and Model 12, respectively, showing that there are severe outliers that have been removed from the regression by Bisquare-weight method. Moreover, adjusted R^2s of the models are the largest after the Bisquare-weight technique were applied in the regression analyses. In Model 2 to Model 4, the difference in the β-coefficients of IQ95th (β=.104) and IQ5th (β=.066) was 58 per cent. After removing outliers, the effects of IQ95th (β=.119) on GROWTH intensified, raising the difference in coefficients of IQ95th (β=.119) and IQ5th (β=.064) to 86 per cent. Across Model 11 to Model 12, there is almost no difference in the effect of IQ95th (β=.119) and IQ50th (β=.112) as compared to that of Model 2 to Model 4 (IQ95th: β=.104; IQ50th: β=.088). On the other hand, the differential effects of IQ50th and IQ5th had increased significantly from 33 per cent in Model 3 to Model 4 (IQ50th: β=.088; IQ5th: β=.066) to 75 per cent in Model 12 to Model 13 (IQ50th: β=.112; IQ5th: β=.064). These findings demonstrate the impacts of IQ95th and IQ50th on economic growth are almost equal. On the other hand, the effect of IQ5th is 75–80 per cent smaller than the other two, a finding that is in contrast to those reported in Model 2 to Model 7 (i.e., Burhan et al., 2014).

Table 2 presents the summary of regression results for technological achievement model. Model 1 is the basic model of 'ideas production function', where GDP and RESEARCHER were positively significant (p<.01) on PATENTS. The summary shows that national level of income and the number of professional engaged in research and development (R&D) are substantial to raise the number of patents produced across countries. The adjusted R^2 of the model was distinctive, which is reported at .86. Across Model 2 to Model 7, IQ95th (β=.041) was significant at p<.01 level when it was added into the basic model, while IQ50th (β=.017) and IQ5th (β=.004) were non-significant at p<.10 level, such as found by Burhan et al. (2014). Furthermore, RESEARCHER was significant at 95 per cent level in the presence of IQ5th (Model 4 and Model 7), but non-significant at 90 per cent level in the presence of IQ95th (Model 2 and Model 5) or IQ50th (Model 3 and Model 6).

To determine the robustness of IQ classes on technological achievement, Model 2 to Model 7 were re-estimated using robust regression methods, the same procedure applied previously to the growth regression. Model 8 to Model 10 and Model 11 to Model 13 show the results of OLS with Huber-weight and Bisquare-weight techniques, correspondingly. Unlike the growth regressions reported in Table 1, there was no difference in the number of observations (N=66) after using the Bisquare-weight method, which indicates an absence of extreme outliers in the samples. With reference to Model 8 and Model 11, the coefficients of IQ95th persisted at β=.041 and significant at 99 per cent level. RESEARCHER remained significant at the p<.05 level in the presence of IQ5th (Model 10 and Model 13), which was non-significant at 90 per cent level. In contrast to Model 3 and Model 6, IQ50th was significant at p<.05 in Model 9 and Model 12. After giving less-weight to high-leverage observation(s), the β-coefficient of IQ50th has increased from β=.017 to β=.021–.026 in Model 9 and Model 12, leaving RESEARCHER non-significant on PATENTS in both models. The adjusted R^2 for Model 12 was reported as high as .90.

3. Conclusions and Policy Implications

This paper attempted to determine the robustness of Burhan et al.'s (2014) empirical findings on the effects of social classes of IQ on economic growth and technological progress at a cross-country level. Based on the results of robust regression, there are two important findings that need to be highlighted. Firstly, consistent with Burhan et al., the robust analysis had verified that all IQ classes were significant at 99 per cent level on economic growth. In Burhan et al.'s study, the researchers had found that intellectual class (IQ95th) has the largest effect on economic growth rate, followed by the average ability (IQ50th) and non-intellectual (IQ5th) classes. In contrast to Burhan et al., this report established that the effects of both IQ95th and IQ50th on economic growth were almost equal, while the effect size of IQ5th was about 80 per cent smaller than the other two (i.e., IQ95th and IQ50th). Furthermore, the average ability class were comprised mostly of working class citizens, and hence the contribution of this group to productivity growth is greater than the non-intellectual class. Also, the average ability group has the most members, and therefore this group have significant cumulative contribution to economic growth that is equivalent to the small-size intellectual-class. In conclusion, all IQ classes within a national society play significant role to generate higher rate of economic growth.

Secondly, consistent with Burhan et al. (2014), the robust analysis has confirmed that IQ at 95th percentile was exceptionally significant at 99 per cent level on the technological achievement, while the effect of 5th percentile IQ was non-significant even at 90 per cent level after controlling other factors. It is confirmed that 95th percentile IQ is more important than the number of professional researchers engaged in R&D in raising the number of patents produced across countries. This shows that merely high number of researchers in R&D is not crucial, but an exceptional level of cognitive ability in order to invent and innovate on new technologies is. However, it is still more resourceful to utilize more professional researchers (p<.05; R^2=.89) than non-intellectual class into the R&D activities, since the IQ of the non-intellectual class was non-significant and might not be adequate to match to the advance technological knowledge and innovation. On the other hand, the findings differ from Burhan et al. in the way that a significant effect of the 50th percentile IQ (p<.05; R^2=.91) on technological achievement was found. This finding has not been uncovered in their study through the use of non-robust OLS regression. Although the IQ-effect of this average ability group was much smaller than intellectual class, our robust analysis has demonstrated a thought provoking evidence. It was found that the number of professional researchers employed in R&D was non-significant for generating technological progress as compared to the effect of the average ability group. Based on these findings, it can be argued that at a cross-country level, people of average IQ are critically more productive than professional researchers to R&D. Hence, if cognitive skills are essential for generating new technologies, it could be that most of professional researchers employed in R&D were drawn from people with cognitive abilities that is less than 50th percentile of the bell curve distribution of IQ, although they do have IQs higher than the non-significant 5th percentile IQ group. In this study, it is unexpected to observe that the average IQ group rather than the number of professional researchers was significant on technological achievement, especially because those professional researchers have been qualified with high academic credentials (e.g., second stage of tertiary education) before they were employed in the R&D sector. However, this proves that high academic qualification does not guarantee that they have the highest level of cognitive skills gained through their education years. Therefore, public and private R&D sectors should employ professionals who possess not only high academic qualifications such as masters or doctoral degrees, but they must also have exceptional levels of cognitive skills, in order to accelerate the generation of new technological knowledge and innovation. Finally, to fulfil the industrial needs, national education system and curriculum need to be reformed to provide future generations with higher-order thinking skills. This enhances the societal level of IQ and warrants higher economic growth and technological achievement in the future.

[Insert Table A1 here]

[Insert Table A2 here]

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Table 1

The effects of the 95th, 50th, and 5th percentiles IQ on economic growth rates.

Linear regression model:

$$\mathrm{GROWTH}_i = \beta_0 + \beta_1 \log(\mathrm{Y}_{1970})_i + \beta_2 (\mathrm{I/Y})_i + \beta_3 (\mathrm{POPGR})_i + \beta_4 (\mathrm{SCHOOL})_i + \beta_5 (\mathrm{IQ})_i + e_i$$

	Ordinary Least Squares (OLS)				OLS with White heteroskedasticity-consistent standard errors			OLS with Huber-weight option			OLS with Tukey's Bisquare-weight option		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12	Model 13
$\log(\mathrm{Y}_{1970})$	-1.693***	-2.740***	-2.832***	-2.681***	-2.740***	-2.832***	-2.680***	-2.862***	-2.971***	-2.676***	-2.863***	-3.139***	-2.632***
	(.414)	(.380)	(.387)	(.406)	(.344)	(.384)	(.403)	(.310)	(.317)	(.369)	(.307)	(.293)	(.391)
I/Y	.130***	.058*	.043	.051	.058	.043	.051	.046*	.030	.044	.036	.002	.039
	(.035)	(.031)	(.032)	(.034)	(.036)	(.040)	(.047)	(.025)	(.026)	(.031)	(.025)	(.024)	(.033)
POPGR	-.336**	.014	.045	-.034	.014	.045	-.034	.040	.071	-.050	.006	.079	-.076
	(.161)	(.143)	(.145)	(.150)	(.167)	(.173)	(.168)	(.116)	(.119)	(.136)	(.116)	(.010)	(.144)
SCHOOL	.017	.002	.008	.015	.002	.008	.015	-.002	.005	.013	-.003	.003	.012
	(.013)	(.010)	(.010)	(.011)	(.008)	(.008)	(.009)	(.008)	(.008)	(.010)	(.008)	(.008)	(.010)
IQ95th		.104***			.104***			.116***			.119***		
		(.018)			(.023)			(.015)			(.015)		
IQ50th			.088***			.088***			.099***			.112***	
			(.016)			(.022)			(.013)			(.012)	
IQ5th				.066***			.066***			.066***			.064***
				(.014)			(.018)			(.012)			(.013)
N	61	61	61	61	61	61	61	61	61	61	59	60	61
R^2	.380	.608	.610	.564	.608	.610	.564	.759	.741	.624	.786	.807	.620
Adjusted-R^2	.336	.573	.574	.524	.573	.574	.524	.737	.717	.590	.766	.789	.585

Note: Regression coefficients are unstandardized betas. Standard errors are in parentheses; *** p<.01, ** p<.05, and * p<.10

[a] GROWTH is the annual growth rate (%) of real GDP per capita in country *i* (averaged 1970–2010). Source: Heston, Summers, and Aten (2012).

[b] Y_{1970} is the GDP per capita in 1970. Source: Heston, Summers, and Aten (2012).

[c] I/Y is the investment as a percentage of annual GDP (averaged 1970–2010). Source: World Bank (2013).

[d] POPGR is the percentage of population growth rate (averaged 1970–2010). Source: USCB (2013).

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

[f] IQ95th, IQ50th, and IQ5th are the 95th, 50th, and 5th percentiles' IQ, respectively. Source: Rindermann, Sailer, and Thompson (2009).

Table 2

The effects of the 95th, 50th, and 5th percentiles IQ on technological achievement.

Linear regression model:

$$\log(\text{PATENTS})_i = \beta_0 + \beta_1 \log(\text{GDP})_i + \beta_2 \log(\text{POP})_i + \beta_3 \log(\text{RESEARCHER})_i + \beta_4 (\text{IQ})_i + e_i$$

	Ordinary Least Squares (OLS)				OLS with White-heteroskedasticity correction			OLS with Huber-weight option			OLS with Tukey's Bisquare-weight option		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12	Model 13
log(GDP)	1.591*** (.167)	1.505*** (.157)	1.544*** (.168)	1.579*** (.170)	1.505*** (.172)	1.544*** (.190)	1.579*** (.202)	1.557*** (.149)	1.578*** (.161)	1.640*** (.176)	1.575*** (.157)	1.567*** (.165)	1.634*** (.176)
log(POP)	-.511*** (.169)	-.394** (.160)	-.443** (.172)	-.493*** (.174)	-.394** (.161)	-.443** (.176)	-.493** (.186)	-.427*** (.152)	-.458*** (.165)	-.534*** (.179)	-.441*** (.160)	-.448** (.169)	-.530*** (.180)
log(RESEARCHER)	.450*** (.157)	.020 (.193)	.247 (.197)	.399** (.190)	.020 (.185)	.247 (.203)	.399** (.195)	.067 (.183)	.249 (.190)	.406** (.196)	.082 (.193)	.240 (.194)	.410** (.197)
IQ95th		.041*** (.012)			.041*** (.011)			.041*** (.011)			.041*** (.012)		
IQ50th			.017 (.010)			.017 (.013)			.021** (.010)			.026** (.010)	
IQ5th				.004 (.008)			.004 (.009)			.004 (.008)			.004 (.008)
N	66	66	66	66	66	66	66	66	66	66	66	66	66
R^2	.867	.888	.872	.867	.888	.872	.867	.912	.899	.884	.915	.906	.886
Adjusted-R^2	.860	.880	.864	.858	.880	.864	.858	.907	.892	.877	.910	.900	.878

Note: Regression coefficients are unstandardized betas. Standard errors are in parentheses; *** p<.01, ** p<.05, and * p<.10

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

[b] GDP is the real gross domestic product (in billions of PPP-adjusted 2005 US$) (averaged 2000-2009). Source: Heston, Summers, and Aten (2012).

[c] POP is the population size (thousand persons) (averaged 2000–2009). Source: Heston, Summers, and Aten (2012).

[d] RESEARCHER is the number of professional researchers (per million people) engaged in the invention of new knowledge, processes, products, methods, or systems and in the supervision of the R&D projects involved (averaged 2000–2009), including postgraduate PhD students (ISCED97 Level 6: The second stage of tertiary education). Source: World Bank (2013).

[e] IQ95th, IQ50th, and IQ5th are the 95th, 50th, and 5th percentiles' IQ, respectively. Source: Rindermann, Sailer, and Thompson (2009).

Appendix A: Table A1

Correlation matrix and variance inflation factor (VIF) for all variables in growth model (*N*=61).

		1	2	3	4	5	6	7	8
1	GROWTH	1.000							
2	log(Y_{1970})	-.396*** (1.184)	1.000						
3	I/Y	.426*** (1.221)	-.185 (1.035)	1.000					
4	POPGR	-.008 (1.000)	-.449*** (1.253)	.229* (1.055)	1.000				
5	SCHOOL	-.031 (1.001)	.543*** (1.417)	-.093 (1.009)	-.449*** (1.253)	1.000			
6	IQ95th	.245* (1.064)	.642*** (1.701)	.110 (1.012)	-.567*** (1.473)	.563*** (1.464)	1.000		
7	IQ50th	.258** (1.071)	.635*** (1.675)	.164 (1.027)	-.561*** (1.460)	.515*** (1.361)	.966*** (15.13)	1.000	
8	IQ5th	.256** (1.070)	.595*** (1.548)	.203 (1.043)	-.507*** (1.346)	.429*** (1.225)	.902*** (5.342)	.975*** (20.01)	1.000

Note: VIF values are in parentheses; ***p < .01, **p < .05, *p < .10

Appendix A: Table A2

Correlation matrix and variance inflation factor (VIF) for all variables in ideas production function (*N*=66).

		1	2	3	4	5	6	7
1	log(PATENTS)	1.000						
2	log(GDP)	.858*** (3.802)	1.000					
3	log(POP)	.410*** (1.202)	.740*** (2.212)	1.000				
4	log(RESEARCHER)	.636*** (1.681)	.384*** (1.174)	-.158 (1.026)	1.000			
5	IQ95th	.605*** (1.577)	.291** (1.093)	-.216* (1.049)	.837*** (3.344)	1.000		
6	IQ50th	.548*** (1.429)	.267** (1.076)	-.237* (1.059)	.815*** (2.985)	.965*** (14.49)	1.000	
7	IQ5th	.496*** (1.326)	.257** (1.071)	-.223* (1.053)	.773*** (2.488)	.906*** (5.556)	.979*** (24.39)	1.000

Note: VIF values are in parentheses; ***$p < .01$, **$p < .05$, *$p < .10$