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CEE Policy Series
Number 31
2018

Measuring Human Capital Across Countries: IQ and the Human Capital Index

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EXECUTIVE SUMMARY

It has been shown that country-level IQ and aggregated performance by school-age children on international assessment tests in math and science are by-in-large capturing analogous indicators of the cognitive human capital. We expand that analysis by comparing country-level IQ to the World Economic Forum's Human Capital Index (HCI). This index, comprised of several dozen separate indicators, accounts for inputs and outcomes to measure human capital, across age profiles and gender. Two outcomes are of note. First, there is a positive, significant correlation between IQ and the vast majority of the component indicators in the HCI across all age cohorts. Second, because the HCI's interpretation of educational attainment extends beyond formal education by including indicators such as on-the-job learning and other work-related skills, our finding that IQ is positively correlated with these measures suggests a deeper connection between national average IQ and the fundamental factors of what constitutes the cognitive side of human capital development.

1. INTRODUCTION

There is a large (and expanding) body of work investigating the role that IQ plays in helping to explain economic and social outcomes. The breadth of this work is well-represented by Lynn and Vanhanen's (2012) exhaustive

survey. Over the past several years, researchers have continued to expand the boundaries of previous work. A small selection of work done in the past few years—for sake of brevity, we focus on economic fields—includes evaluating IQ's ability to empirically explain national differences in entrepreneurial activity (Hafer & Jones, 2015; Hafer, 2017); corruption (Potrafke, 2012); financial development (Kodila-Tedika & Asongu, 2015; Hafer, 2017); economic welfare (Hafer, 2017); happiness (Stolarski, et al., 2015; Noklaev & Salahodjaev, 2016); and cognitive capitalism (Coyle, et al, 2016). The gist of the evidence is that countries with higher national average IQ tend to be more successful economically, have greater levels of entrepreneurial activity (in general and among women), less corruption, and a propensity toward more democratic institutions.

Especially in economics, attempts to measure human capital have generally focused on either educational inputs (e.g., years in school) or outcomes (e.g., test scores). In terms of assessing the role of human capital in explaining differences in economic growth, Mankiw, Romer and Weil's (1992) inclusion of the rate of secondary school enrollment in their empirical growth model was an initial step to better understand how human capital affects economic growth. Their work was followed by many similar studies: A good example is Sala-i-Martin's (1997) analysis

wherein he tried eight different measures of education-based human capital to explain economic growth across countries. Of these he found that the rate of primary school enrollment was empirically the most robust in his exhaustive search process. In contrast to using input-oriented measures of education, others have argued that output-based measures—e.g., average scores on international math and science tests, such as TIMMS and PISA—were more appropriate to capture the cognitive development of labor. Representative work in this area include Hanushek and Kimko (2000), Hanushek and Woessmann (2008, 2015), and Hanushek, et al. (2017). Wobmann (2003) offers an assessment of how human capital often is calculated, though he makes no mention of Lynn and Vanhanen’s national IQ measure.

The use of national IQ in an economic growth context was introduced by Weede and Kampf (2002). They found that Lynn and Vanhanen’s national IQ has a large and statistically significant effect on economic growth, even after controlling for other input-type education measures. It wasn’t until Jones and Schneider (2006) that IQ was tested rigorously against other quantitative-based education variables which had heretofore been used as proxies for human capital. Jones and Schneider found that when pitted against a large battery of other variables, IQ was one of the most important variables in explaining differences in economic growth across a large sample of countries. Even though primary school enrollment survived their testing procedure and had a positive and significant effect on economic growth, the number of times this variable achieved significance was sharply reduced when IQ was added

to the set of explanatory variables. “This dramatic decline in the statistical significance of primary school enrollment,” Jones and Schneider note, “makes the performance of IQ—statistically significant in 99.8% of the same regressions—all the more surprising. Not only is IQ robustly correlated with economic growth in this sample: it is also the most robust human capital measure in this dataset.” (p. 88)

The current paper is in the spirit of Lynn and Meisenberg (2011), who show that country-level IQ and aggregated performance by school-age children on international assessment tests in math and science are by-in-large capturing analogous indicators of the cognitive human capital. Our purpose here is to further consider the ability of national-average IQ to represent a broad concept of cognitive human capital. To do this we compare country-level IQ to a new human capital construct that includes a cognitive component of human capital development and accounts for actual labor market outcomes. Not only does this measure, the World Economic Forum’s Human Capital Index (hereafter, HCI), thus consider inputs and outcomes to measure human capital, it also provides information about these aspects across a wide spectrum of age profiles and across gender. Comprised of several dozen separate indicators, the Forum’s country-level index is constructed to “serve as a tool for capturing the complexity of education and workforce dynamics so that various stakeholders are able to take better-informed decisions.” (Report, p. 3) Thus, it offers a useful benchmark against which to compare IQ across countries.

In what follows, we address the following questions:

- How closely correlated are IQ and the HCI?
- Given the structure of the HCI, is it possible to identify specifically areas with which IQ is more closely related than others? That is, can we glean any information from correlating IQ with the disaggregated parts of the HCI, across indicators and across age profiles?
- How closely is real GDP related to each of the two series?

The *Report* also provides additional information on other social indicators—e.g., business perceptions of education, the innovation environment in a country, and the vulnerability of workers in the labor market—that we also correlate with IQ. These “other” measures are not part of the HCI, but they allow us to further gauge the ability of IQ to explain observed differences in social and economic conditions across countries.

The point of our paper is to consider as many facets of the social and economic environment that may influence human capital development and, in the end, worker productivity. Our analysis, we think, provides a useful extension to current understanding of what national IQ captures. In the end, our task is not to determine whether IQ or the HCI “beats” the other in some statistical horserace: we leave that exercise to others.

The format of the paper is as follows. Section II provides a brief overview of the two series. Our statistical analysis is found in

Section III where we examine the link between IQ and the HCI indicators, the “other” indicators provided in the Report, and to real GDP. Summary remarks close the paper in Section IV.

2. DATA

2.A. National IQ

The national average IQ data are taken from Lynn and Vanhanen (2012) (hereafter, LV). These data are the most recent version of their original IQ series (Lynn & Vanhanen; 2002, 2006), and include adjustments due to Lynn and Meisenberg (2010a, b). These data have been discussed in detail elsewhere, so ours will be brief. The IQ data are an aggregation of existing cognitive testing scores from around the world, including journal articles and actual samples of cognitive scores from individual countries. These inputs are used to create an IQ “profile” for a country. When there are multiple estimates for a given country, LV use an average. When there are multiple inputs over time, LV account for any potential Flynn Effects by adjusting the raw data for the upward trend in nation-level IQ scores. To control for this, LV adjust the IQ scores to bring them into alignment at a point in time. For example, a country’s IQ score in 1960 is adjusted to make it “equivalent” to the outcome from a similar British test given in 1979. In our sample of 124 countries, the mean IQ score is 86 with a standard deviation of 11.

Though the LV data have been used widely across disciplines, it is not without criticism. One important issue concerns the accuracy of the IQ statistics generated for Sub-Saharan African countries. Wicherts, et al (2009, 2010a, b) create an

alternative IQ series that focuses on healthy Sub-Saharan populations of normal socio-economic status. This approach yields an average IQ of 80 for this sample, which is significantly higher than that found in the LV data. Lynn and Meisenberg (2010b) and Lynn and Vanhanen (2012) provide counter arguments, and Jones and Potrafke (2014) note that the sampling bias inherent in Wicherts, et al. approach could just as easily yield an over-estimate of the average human capital level. Rindermann’s (2013) recent analysis of African cognitive measurement is worth noting in this regard.

Partly to validate the IQ measure and to put it into the broader perspective as a measure of human capital, there has been much work comparing the Lynn-Vanhanen IQ to other indicators of cognitive development, such as standardized test results (Lynn & Meisenberg, 2010; Jones & Potrafke, 2014; and Rindermann, 2007). These results (and others) suggest that IQ should be considered an indicator of a nation’s labor quality—its human capital—in the spirit of Hanushek and Kimko’s (2000) use of international standardized test scores.

2.B. The Human Capital Index

The Human Capital Index (hereafter, HCI) is compiled and published annually by the World Economic Forum. The first index was published in 2013, though we use the 2015 index and its components in this study. The HCI focuses on both outcomes and demographics. In terms of outcomes, the index accounts for both learning and employment inputs to the development of human capital. Half of the indicators (23) used to measure the

educational side of human capital development account for such factors as school enrollment, quality of education, and workplace learning. The other half (23) are labor market indicators, dealing with labor market participation, such as participation rates, and how well educational attainment and knowledge—skills—are matched to employment.

What makes the HCI distinctive is that on top of this input-output coverage it overlays a generational reflection by reporting the learning and employment themes across specific age groups. In their terminology, the “horizontal themes” of learning and employment are deployed across age “pillars.” The Report assembles its index using data for the age groups Less Than 15; 15-24; 25-54; 55-64; and More Than 65. The HCI is thus constructed to account for the multidimensional nature of how human capital is developed and used: the accumulation of skills acquired formally—through education—and informally—through workplace learning—that aggregate into what can be considered a quantitative measure of human capital. Thus, unlike IQ, the HCI is a broader measure of human capital, one that encompasses more than just the cognitive development component.

Using data from a variety of public sources and from survey responses, the World Economic Forum takes the raw data series and converts them into a common metric with a 0 to 100 scale: the higher the value the closer to the “ideal” for that indicator. Each age group’s score is an unweighted average of all the indicators in that age pillar. The overall index is then constructed by weighting each age pillar according to its percentage share of the global

population in 2015. For example, the 2015 weighting scheme is, by age group: Under 15 (26%); 15-24 (16%); 25-54 (41%); 55-64 (9%); and 65 and over (8%).

3. STATISTICAL ANALYSIS

Comparing the HCI and the IQ data, we have 124 countries with both in common. The list of countries included in our sample along with their respective values for IQ and the HCI is provided in Appendix A. Table 1 provides summary statistics for the two series. The mean IQ score is 86 and ranges from a low of 60 (Malawi) to a high of 107 (Singapore). For the HCI the mean value is 67 out of 100 possible points, with a range from 41 (Yemen) to 86 (Finland).

Figure 1 provides a quick visual answer to the question posed in the introduction: How closely are IQ and the HCI related? The scatter plot in Figure 1 shows that the two series are positively related with a fair degree of closeness; that is, the scatter of points—each representing a country’s IQ-HCI pair—lie fairly close to the imposed best-fit regression line. The regression is significant ($adj-R^2 = 0.69$), and the estimated slope coefficient (0.831) is not statistically different from one.

Table 1
Summary statistics and correlations

	Summary statistics	
	<u>IQ</u>	<u>HCI</u>
Mean	86.54	67.22
Std Dev	10.65	10.64
Median	86.25	67.61
Minimum	60.10	40.72
Maximum	107.10	85.78
N	124	124

As noted earlier, even though the broad measures are related, it is of interest to understand why. To do this we investigate the question “How IQ is correlated with the many indicators that comprise the HCI?”

The correlation between IQ and HCI Components

Table 2 provides the evidence to answer that question. There we report the correlations between IQ and each of the 46 individual indicators included in the HCI. This is useful both to see where IQ is or is not related to the component parts of the HCI, and get a feel for whether such links are influenced by age. To facilitate reading Table 2, we adopt the convention of reporting those correlations that are not significant at the five-percent level of significance (or better) in bold and underlined.

Looking across the five age groups (the columns) and the components

of each age-specific group (rows) in Table 2, we see that the vast majority of the correlations with IQ are positive and statistically significant. Looking specifically at the set of variables that comprise the “Learning Component” theme of the HCI, it is notable that IQ has a positive and statistically significant correlation with all the education-related components, measures of enrollment and attainment alike. This is consistent with previous work, which generally has found IQ and various educational metrics, whether it is raw enrollment or scores on standardized exams, are positively correlated. It also is notable that IQ is positively correlated with other less formal types of learning measures, those being the quality components found in the under-15 age group and the 15-24 age group. It may not be surprising to see that countries with higher IQs also have higher quality educational systems. But the evidence in Table 2 shows that higher IQ countries tend to have, as evidence by the results for

Figure 1
IQ and HCI

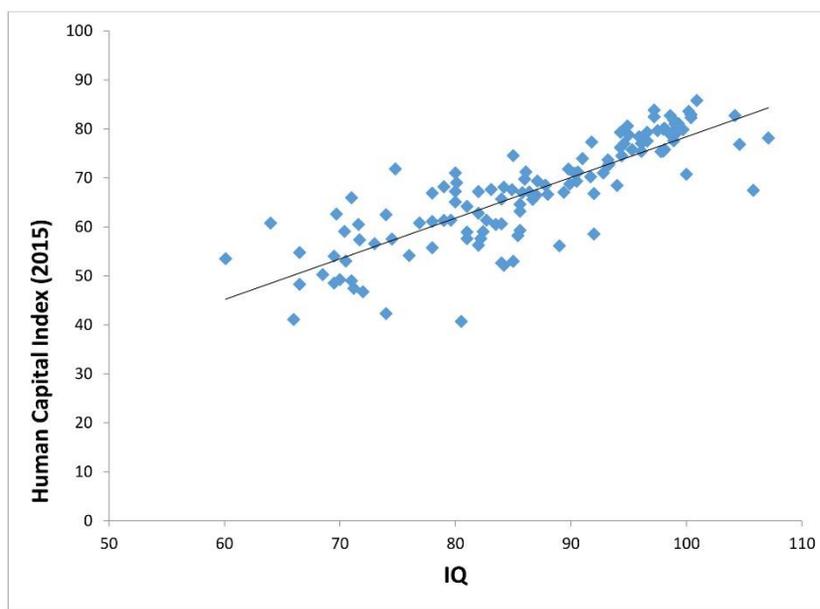


Table 2
Correlations between IQ and components of the Human Capital Index (2015)
Correlations NOT significant at 5% are shown in bold and underlined

LEARNING COMPONENT									
	Correlation		Correlation		Correlation		Correlation		Correlation
Under 15 Age Group	with IQ	15-24 Age Group	with IQ	25-54 Age Group	with IQ	55-64 Age Group	with IQ	65 and Older Age Group	with IQ
Enrollment in Education		Enrollment in Education		Educational Attainment		Educational Attainment		Educational Attainment	
Primary enrollment rate	0.624	Tertiary enrollment rate	0.795	Primary educational attainment rate	0.611	Primary educational attainment rate	0.677	Primary educational attainment rate	0.694
Secondary enrollment rate	0.783	Vocational enrollment rate	0.484	Secondary educational attainment rate	0.771	Secondary educational attainment rate	0.749	Secondary educational attainment rate	0.702
Basic education survival rate	0.477	Primary education	0.581	Tertiary education attainment rate	0.699	Tertiary education attainment rate	0.638	Tertiary education attainment rate	0.636
Secondary Enrollment Rate gender gap	0.444	Secondary education	0.712						
Quality of education		Quality of education		Workplace learning					
Quality of primary schools(1)	0.658	Quality of educational system (1)	0.446	Staff training services (1)	0.434				
		Youth literacy rate	0.665	Economic complexity (3)	0.794				
EMPLOYMENT COMPONENT									
	Correlation		Correlation		Correlation		Correlation		Correlation
Under 15 Age Group	with IQ	15-24 Age Group	with IQ	25-54 Age Group	with IQ	55-64 Age Group	with IQ	65 and Older Age Group	with IQ
Vulnerability		Economic Participation		Economic Participation		Economic Participation		Economic Participation	
Incidence of child labor	-0.756	Labor force participation rate	-0.213	Labor force participation rate	0.058	Labor force participation rate	-0.394	Labor force participation rate	-0.704
		Unemployment rate	0.078	Unemployment rate	-0.027	Unemployment rate	0.168	Unemployment rate	-0.122
		Underemployment rate	-0.254	Underemployment rate	-0.484	Underemployment rate	-0.375	Underemployment rate	-0.374
		Not in employment, ed., etc.	-0.249	Employment gender gap	0.315	Healthy life expectancy at birth	0.846	Healthy life years beyond 65	0.683
		Long-term unemployment rate	-0.149						
		Skills		Skills					
		Incidence of overeducation	0.032	High-skilled employment share	0.787				
		Incidence of undereducation	-0.485	Medium skilled employment share	0.268				
		Skill Diversity (2)	-0.475	Ease of finding skilled employees (2)	0.301				
Notes:									
1. Based on survey responses on a 1 (worst) to 7 (best) scale.									
2. Based on data on a 0 (best) to 1 (worst) scale.									
3. Based on data from -1.854 (worst) to 2.235 (best) score.									
All other series based on percentage rates for the corresponding age group, rounded to one decimal place.									

the 25-54 age group, better staff training services and greater economic complexity. This suggests that in high-IQ countries it is recognized (and implemented) that continuing sources of human capital improvements are beneficial to human capital development.

The evidence in Table 2 indicates that the eight correlations that are not statistically significant are located exclusively in the “Employment Component” of the HCI. This is somewhat surprising given previous findings that IQ and broad measures of economic activity, such as real GDP, tend to be positively related: Chapter 4 of

Lynn and Vanhanen (2012) provides an overview. Using the HCI data we find that the IQ-unemployment rate correlations—again by age group—tend not to be significant, and when significant often exhibit negative signs.

But the evidence also indicates that higher IQ countries have more

“effective” labor markets. The evidence shows that IQ is negatively related to the underemployment rate across age groups.

Underemployment is based on the number of people in involuntary part-time employment; that is, individuals who cannot find full-time employment, because of some mismatch in skills or unavailability of full-time opportunities. The negative correlation with IQ suggests that countries with higher average IQ have labor markets that are able to more effectively match workers with full-time jobs. In addition, for the 15-24 age group, higher levels of IQ are associated—again, negatively—with the measure of “not in employment.” For those countries with a higher average IQ we would expect to find that those in the 15-24 age group tend to be “employed,” either it is in work-related fields or in education. This again suggests better functioning labor markets in higher IQ countries. Finally, for the two groups encompassing the ages 15-54, the results indicate that higher IQ countries are more likely to have a lower incidence of under-education (this no doubt reflects the positive relationship between IQ and the various measures of education in the upper portion of Table 2) but also economies that require a more skilled workforce (see high-skilled and medium skilled employment shares). This would suggest that higher levels of IQ are associated with higher levels of worker productivity, exactly what a human capital measure should show.

Finally, the results in Table 2 show IQ and a crude measure of overall health—life expectancy at birth—are positively related for the 55 and above age groups. This is what a number of previous studies have

found: Lynn and Vanhanen (2012), Chapter 6, provide an overview.

What might be surprising is finding that IQ and the employment gender gap are negatively and significantly related in our sample. This means that, on average, in high IQ countries the ratio of female to male employment (see the appendix for a more detailed description) is lower than in relatively low-IQ countries. Wouldn't one expect that in countries with higher average IQ that women would not face workplace disadvantages that lead to a larger gender gap? It turns out that this result is consistent with the findings of Lynn and Vanhanen (2012, pp. 150-152) where they correlated IQ with the Gender Inequality Index (GII), which gauges the relative disadvantages that women face in human development. As they note, finding of no correlation between GII and IQ would imply that the disadvantages women might face in human development are not based on differences in national average IQ. So, our negative correlation suggesting that, on average, there is less parity—fewer women employed relative to men—in high average IQ countries, is not without precedent.

The results in Table 2 identified the areas most closely related to IQ: The indicators included under the Learning Component heading. This result provides more evidence of the strength of the IQ-education link. If educational attainment—not just enrollment or years of schooling—is an important ingredient to improving human capital which in turn raises worker productivity, then country-level IQ is a feasible measure to capture this connection. The results in Table 2 show that IQ is related to several important education-related areas found in the HCI's Employment Component. If

areas such as “skills acquired on the job” or “staff training services” are related to increasing human capital and worker productivity, as suggested by Heckman (2000), then the positive correlation between them and IQ further substantiates the finding why IQ helps predict economic growth across countries.

The correlation between IQ and “other” indicators

To further assess the value of IQ as a broad gauge of human capital development, it is informative to make use of the “other” indicators that are found in World Economic Forum's Report. These indicators are not part of the HCI, but they offer an additional glimpse into why a high-IQ country may exhibit relatively better social and economic outcomes. One such set of indicators is a collection of responses to a survey of businesses people about their country's educational system, training and talent. Though the descriptions in Table 3 are fairly self-explanatory, more complete descriptions and sources of these business perceptions data are found in Appendix C. The correlations between IQ and these different assessments of the business-educational environment reported in Table 3 again indicate that those in business tend to have rate the quality of education, and specifically of business schools, higher in those countries with higher levels of IQ. This may be a post hoc ergo propter hoc result, but it builds upon previous findings that suggests a causal link from higher average IQ to a country's educational outcomes. In high-IQ countries businesspeople generally believe that their economy is characterized by better specialized training services which should enhance worker productivity. And there is a positive relation between

Table 3
Correlations between IQ and business perceptions

<u>Business Perceptions Measure</u> ¹	<u>Correlation</u> ²
Quality of math/science education	0.573
Quality of business schools	0.469
Specialized training services	0.596
Capacity to attract talent	0.206
Capacity to retain talent	0.292

¹ The measures used are based on survey responses, utilizing a score from 1 (best) to 7 (poor). More complete definitions are found in the data appendix.

² The two-tailed probability for these correlations (N = 124) is 0.20 at the five-percent level of significance.

Table 4
Correlations between IQ and additional measures

<u>Component</u>	<u>Innovation Ecosystem</u>	<u>Correlation</u>
State of cluster development ¹		0.415
University-business R&D collaboration ¹		0.575
Ease of starting a business ²		-0.510
	<u>Vulnerability</u>	
<u>Component</u>		<u>Correlation</u>
Workers in informal employment		-0.433
Workers in vulnerable employment		-0.689
Social safety net ¹		0.574
	<u>Public Investment</u>	
<u>Component</u>		<u>Correlation</u>
Internet access in schools ¹		0.782
Public spending on education (%of GDP)		0.102

1. The measures used are based on survey responses, utilizing a score from 1 (worst) to 7 (best). More complete definitions are found in the data appendix.

2. Based on rank out of 189 countries.

IQ and business perceptions of business' ability to attract and retain talented employees. Since these latter two responses are couched in terms of being able to attract and/or retain talent from outside their

country, they suggest that higher average IQ countries, presumably with relatively more successful economies, are more likely to attract and retain more talented individuals. Thus, undertaking policies to raise

IQ in one country could, all else the same, create the positive externality of improving worker productivity, which leads to greater economic success, which attracts the more productive workers from other countries.

In Table 4 we report another set of correlations using more non-HCI indicators found in the Report. These are Innovation Ecosystem, Worker Vulnerability, and Public Investment. Descriptions and sources of these indicators are found in Appendix C. The first set of correlations under the heading of Innovation Ecosystem—state of cluster development and university-business R&D collaboration—are positively and significantly related. The positive correlation found between IQ and the perceptions of university-business R&D collaboration is similar in sign to that reported by Lynn and Vanhanen (2012) where they correlated national IQ with the number of researchers in R&D per one million of population. Although there are obviously other factors at work, they argue that national IQ is a dominant factor. Their finding, and ours, reflects the underlying relation between IQ and countries' educational success: High-IQ countries are more likely to have greater technological innovation and use of university-generated research outcomes. In contrast, we find that it is harder to start a business, on average, in higher-IQ countries. This result, which seems counter-intuitive, is not without precedent, however. Hafer and Jones (2015) investigated the role that IQ plays in explaining differences in entrepreneurial activity across countries. One measure of entrepreneurship that they used is a series on new incorporations, part of the World Bank's Entrepreneurship Survey.

They found “new incorporations” and IQ are positively related. But once a broad set of controls are added to the regression, this relationship is reduced to statistical insignificance.

The second batch of correlations in Table 4 deals with worker vulnerability. In effect, these three indicators are an attempt to gauge the degree to which workers in a country are subject to discontinuous employment, which leads to increased income uncertainty. For the first two indicators that relate directly to worker vulnerability, countries with higher average IQ exhibit lower levels of worker vulnerability: The higher is IQ, the less likely workers will find themselves in informal and/or discontinuous employment situations. And it is more likely that workers living in a relatively high-IQ country also live in a country with a social safety net—e.g., unemployment insurance—that reduces the economic burden of unemployment and the income insecurity that accompanies it. The results in Table 4 corroborate the belief that higher IQ countries are more likely to be characterized by working conditions that enhance worker productivity.

The last section of Table 4 considers the link between IQ and public investment in two areas related to education. One is the availability of Internet access in schools. The positive correlation between IQ and Internet access reflects the fact that there is probably a greater appreciation of the need for access to modern information systems in countries with higher levels of IQ. Of course, this may just be proxying for the fact that higher IQ countries also tend to be more successful economically; that is, this correlation reflects a relation between income

and Internet access. Given the findings that IQ helps explain faster economic growth, it may be possible that IQ precedes income growth which then leads to greater Internet access.

Finally, the correlation between IQ and public spending on education is positive, though statistically insignificant. Wouldn't one expect high-IQ countries to spend more of their aggregate income on education relative to lower-than-average IQ countries? One possible answer is the finding that the level of public spending on education often is not a good predictor of educational success. That is, spending more on each pupil (in absolute or relative terms) does not ensure that educational attainment is greatly improved after some basic level of learning. Thus, this result could signify that higher IQ countries, while not skimping on education, recognize the diminishing marginal returns to more dollars spent relative to greater demand for educational excellence for public dollars spent.

To summarize the evidence to this point, higher IQ countries also have a higher level of human capital as measured by the HCI. The main reason for this, as our disaggregated look at the HCI suggests, is that IQ and the various education-related indicators used to comprise the HCI are highly correlated. A new finding is that this correlation occurs across the age spectrum of the population. We also find that high-IQ countries are more likely to have more informal, on-the-job types of training and skill development opportunities for workers. And looking at the non-HCI indicators available in the Report, higher average IQ countries have environments in which business uses technology more, there is a

higher regard for the educational systems, technological innovation occurs at a higher level, and worker vulnerability is lower. All these conditions arguably contribute to improving worker productivity. Correlations between IQ, HCI, and Real GDP

We thus far have demonstrated that IQ and the HCI are closely related: the correlation between the two overall series is strong, and a closer examination indicates a high degree of correlation between IQ and the vast majority of the individual indicators, across age groups, that comprise the HCI. As a final note, we address the question: What is the relation between our two human capital measures and total economic output? If IQ and the HCI are human capital measures, then we should expect to find that each exhibits a strong, positive correlation with output: higher levels of human capital lead to greater productivity and higher levels of output.

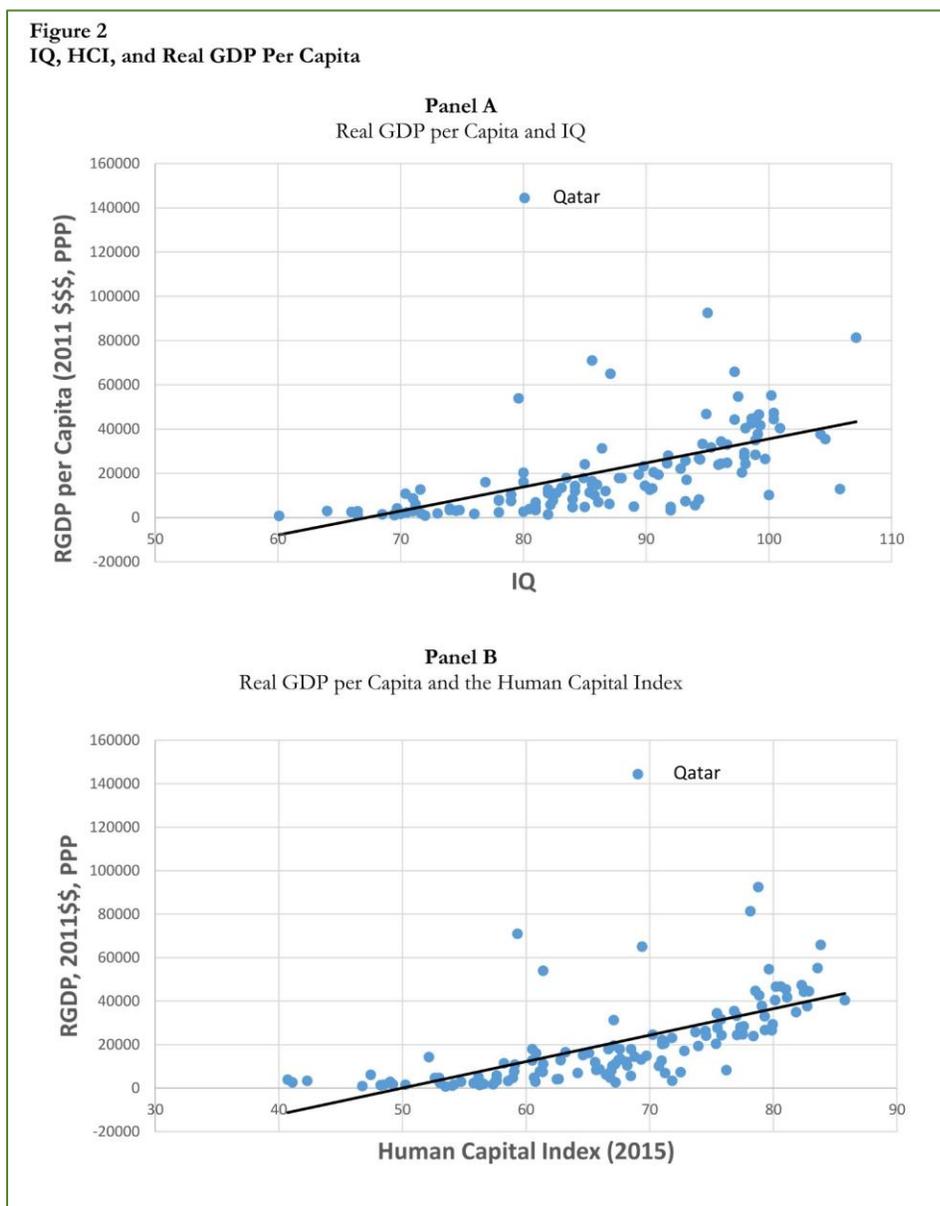
We use each country's output using real GDP per capita, in constant US (2011) dollars measured on a PPP basis. We use this measure for sake of consistency: It is what is reported in the Report (2015) where our other data come from. For our sample of countries, the mean value of output is \$20,965, with a large standard deviation of \$21,565. The standard deviation indicates the wide dispersion in the data: From a low of \$781 for Malawi to a high of \$144,427 for Qatar. Given this dispersion, the median value of \$14,350 probably is more representative of the average.

We note at the outset that the results from this analysis should be viewed with caution. This is because both the HCI and the real GDP per capita (hereafter, RGDP)

data are based on current observations: The HCI uses data around 2013-2015 and the RGDP data are for 2011. This means that both are products of an historical economic growth process that gets each country to its current state. Indeed, we would be surprised if RGDP and HCI are not highly correlated. The IQ data, on the other hand, are standardized to the early 1980s, so its relation to current RGDP may reflect more of a causal relationship.

With those caveats in mind, how is RGDP related to IQ and HCI for our sample of 124 countries? Figure 2 provides the answer. The upper panel is a scatter plot using IQ and RGDP. There is a general positive correlation, though the deviations from the superimposed regression line suggest that the relationship is not nearly as tight as that found earlier comparing IQ and the HCI. The estimated value of the slope coefficient is 1,086 ($t = 7.02$) which suggests that a one-unit increase in IQ is associated with a \$1,086 increase in RGDP. The dispersion of points around the regression line—indicated by the adj-R2 of .28—arises because of countries with relatively a low national IQ and a high level of RGDP. For example, Qatar has a below-average IQ score of 80, but the highest RGDP (\$144,427). The effect of this one country is notable in the underlying statistics: The correlation between IQ and RGDP is 0.537 when the sample includes Qatar, but 0.662 when Qatar is excluded. Still, in general the correlation between IQ and RGDP is positive and significant, a finding that holds with much previous works (see Lynn & Vanhanen (2012), Chapter 4).

The lower panel of Figure 2 plots RGDP and the HCI. The scatter is



similar to that using IQ. Once again there is a positive relationship between the two series, and once again there is a relative loose fit. In this regression the slope coefficient on HCI is 1,215 ($t = 8.29$). The estimated adj-R2 of 0.36 indicates that the relationship between RGDP and the HCI is slightly tighter than that using IQ. And again this statistical fit improves once Qatar is omitted (adj-R2 = 0.47).

These results do not reveal which is the preferred measure of human capital. They do suggest that nation-level IQ and the HCI are both statistically viable constructs of human capital. The more rigorous test of how well each does in explaining economic growth patterns across countries is, unfortunately, impossible: The fact that the HCI data are current observations means that we are unable to exogenize the data when trying to explain economic growth over the past. While the HCI

provides a useful metric to gauge the current distribution of human capital across countries—a measure of where countries stand in relative terms—it is less useful in analyzing economic growth patterns, something for which the IQ series has proven able.

4. SUMMARY

We find that it is highly correlated with the Human Capital Index, a measure that was developed by the World Economic Forum in recent years explicitly for the specific purpose of providing an overall representation of human capital development across countries. Not only are IQ and the HCI positively correlated, by disaggregating the HCI into its component parts, we also find that IQ is mostly highly correlated with the educational indicators of the HCI, which should not be too surprising. Two outcomes of this analysis are of note. First, the positive, significant correlation between IQ and the educational indicators holds across all the age cohorts used to create the HCI. Second, the HCI's interpretation of educational attainment extends beyond formal education, including such indicators as on-the-job learning and other work-related skills. Our results show that such “educational” factors are positively related to national IQ. This suggests an even deeper connection between national average IQ and the fundamental components of what constitutes the cognitive side of human capital development. Finally, we also found that each series has a strong, positive relation with real GDP per capita. Further analysis is needed to determine if there is independent information in the HCI and IQ series that could better explain differences in output across countries.

The bottom line is that our results corroborate and extend earlier work in which IQ was tested against a variety of education-based measures of the cognitive component of human capital development. As a measure of human capital, the evidence once again points to the positive returns to country policies aimed at raising the average IQ of their citizens. While this is difficult in already high IQ countries, it does suggest that countries with lower-than-average IQ could improve the well-being of their citizens by engaging in policies that improve the quality and quantity of education, reduce poverty, and improve overall health conditions, among others, also will improve the economic welfare of their populations in years to come.

Acknowledgements

We would like to thank Garrett Jones, Oasis Kodila-Tedika, Richard Lynn, Heiner Rindermann for comments and suggestions on an earlier draft, and Carlos Cabral for his research assistance. We remain responsible for all errors and omissions.

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NOTES

¹ Data on US and state RGDP come from the Bureau of Economic Analysis (the BEA), “Real GDP by state (millions of chained 2009 dollars),” downloaded from the BEA website January 16 2018.

² Data on state-level civilian noninstitutionalized population

(“population”), civilian labor force (“labor force”), and civilian labor force employment (“employment”) are from the Bureau of Labor Statistics document “States and selected areas: Employment status of the civilian noninstitutionalized population, 1976 – 2016 annual averages,” downloaded January 16 2018. Data for the USA is from the St. Louis Federal Reserve’s Federal Reserve Economic Data (FRED) database, and is the civilian noninstitutionalized population (series CNP16OV), the civilian labor force (CLF16OV), and civilian employment level (CE16OV), downloaded January 16 2018.

³ Here we refer to data from 2015, because we will be discussing growth of RGDP along with growth of the labor force and the capital stock in the various states, and our capital stock series is only available up to 2015.

⁴ The NCES Comparable Wage Index describes the prevailing wage for college-educated workers who are not educators for the period 1997 to 2005. One of the authors (Lori Taylor) has extended that series through 2015 [here](#):

⁵ The capital stock data is supplied by Steven Yamarik based on methods he developed in two paper. These are “Regional Convergence: Evidence from a New State-by-State Capital Stock Series” (with Gasper Garofalo), *The Review of Economics and Statistics* 84 (May 2002): 316-323, and “State-Level Capital and Investment: Updates and Implications,” *Contemporary Economic Policy* (January 2013): 62-72. Professor Yamarik updated and extended his capital stock series to 2015 and provided it to one of us (Dennis Jansen). A copy of that data is available upon request.

⁶ Author calculations based on state-level RGDP, employment, and capital. The assumed capital share of output is .38 and the labor share .62.

⁷ Data from the American Community Survey (ACS) Public Use Microdata Sample (PUMS) File.

⁸ Data from the American Community Survey (ACS) Public Use Microdata Sample (PUMS) File.

⁹ We define STEM degrees, as consisting of the natural sciences, computer sciences, and engineering degrees.

¹⁰ Data from the American Community Survey (ACS) Public Use Microdata Sample (PUMS) File. Some numbers differ slightly

from those reported by the Bureau of Labor Statistics.

¹¹ For example, see Luc Anselin, Attila Varga, and Zoltan Acs. "Local geographic spillovers between university research and high technology innovations." *Journal of Urban Economics*, 42(3) (1997). 422-448.

¹² Bruce A. Weinberg, Jason Owen-Smith, Rebecca F. Rosen, Lou Schwartz, Barbara McFadden Allen, Roy E. Weiss and Julia Lane. "Science Funding and Short-Term Economic Activity." *Science*, 344(6179) (2014). 41-43. Nikolas Zolas, Nathan Goldschlag, Ron Jarmin, Paula Stephan, Jason Owen-Smith, Rebecca F. Rosen, Barbara McFadden Allen, Burce A. Weinberg, Julia I. Lane. "Wrapping it up in a person: Examining employment and earnings outcomes for Ph.D. recipients." *Science*, 350(6266) (2015). 1367-1371. Nathan Goldschlag, Sefano Bianchini, Julia Lane, Joseba Sanmartin Sola, Bruce Weinberg,. "Research Funding and Regional Economies." NBER Working Paper Series, Working Paper 23018 (2017). 1-25.

¹³ Downloaded January 18, 2018 [here](#).

¹⁴ Shawn Kantor and Alexander Whalley. "Knowledge Spillovers From Research Universities: Evidence From Endowment Value Shocks." *Review of Economics and Statistics*, 96(1) (2014), 171-188.

¹⁵ Data on appropriations come from the Digest of Education Statistics, 2016, US Department of Education. Data on the CPI-U come from the US Bureau of Labor Statistics.

¹⁶ Joseph H. Haslag and Michael Austin. "Was Missouri Always Like This? A comparison of Missouri's Growth with that of The United States." Show-Me Institute Essay, (2017). 1-13.

¹⁷ See the starting salary at step 1 of the base tier in the following. For Unified School District 500 (Kansas City, Kansas Public Schools), see [here](#), (page 22). For the Kansas City School District in Kansas City, MO, see [here](#). For St Louis Public Schools in St. Louis, MO see [here](#). For the East St. Louis School District in East St. Louis, IL see [here](#), (page 6)

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APPENDIX A

<u>Country</u>	<u>IQ</u> ¹	<u>HCI</u> ²						
Albania	82	67.2	Israel	94.6	77.03	South Africa	71.6	60.5
Algeria	84.2	52.14	Italy	96.1	75.44	Spain	96.6	79.3
Argentina	92.8	71.01	Jamaica	71	65.95	Sri Lanka	79	68.19
Armenia	93.2	72.5	Japan	104.2	82.74	Sweden	98.6	82.73
Australia	99.2	80.22	Jordan	86.7	65.59	Switzerland	100.2	83.58
Austria	99	81.02	Kazakhstan	85	74.56	Tajikistan	80	67.24
Azerbaijan	84.9	67.58	Kenya	74.5	57.54	Tanzania	73	56.56
Bangladesh	81	57.62	Korea, Rep.	104.6	76.84	Thailand	89.9	68.78
Barbados	80	65.09	Kuwait	85.6	59.31	Trinidad/Tobago	86.4	67.1
Belgium	99.3	81.12	Kyrgyz Rep.	74.8	71.82	Tunisia	85.4	58.21
Bhutan	78	61.11	Lao	89	56.16	Turkey	89.4	67.09
Bolivia	87	66.46	Latvia	95.9	78.39	Uganda	71.7	57.34
Botswana	76.9	60.81	Lesotho	66.5	54.74	Ukraine	94.3	76.21
Brazil	85.6	64.6	Lithuania	94.3	79.33	United Arab Emirates	87.1	69.39
Bulgaria	93.3	72.81	Luxembourg	95	78.79	United Kingdom	99.1	79.07
Burkina Faso	70	49.22	Macedonia	90.5	69.31	United States	97.5	79.64
Burundi	72	46.76	Madagascar	82	56.25	Uruguay	90.6	71.18
Cambodia	92	58.55	Malawi	60.1	53.49	Venezuela	83.5	60.51
Cameroon	64	60.75	Malaysia	91.7	70.24	Vietnam	94	68.48
Canada	100.4	82.88	Mali	69.5	48.51	Yemen	80.5	40.72
Chad	66	41.1	Malta	95.3	75.77	Zambia	74	62.5
Chile	89.8	71.8	Mauritania	74	42.29			
China	105.8	67.47	Mauritius	88	66.66			
Colombia	83.1	67.63	Mexico	87.8	68.5			
Costa Rica	86	69.75	Moldova	92	66.81	Sources:		
Côte d'Ivoire	71	49.02	Mongolia	100	70.75	IQ: Lynn and Vanhanen (2012)		
Croatia	97.8	75.37	Morocco	82.4	59.04	HCI: World Economic Forum (2015)		
Cyprus	91.8	77.33	Mozambique	69.5	54.04			
Czech Rep	98.9	77.6	Myanmar	85	52.97			
Denmark	97.2	82.47	Namibia	70.4	59.09			
Dominican Rep.	82	62.79	Nepal	78	55.77			
Egypt	82.7	61.38	Netherlands	100.4	82.3			
El Salvador	78	66.89	New Zealand	98.9	81.84			
Estonia	99.7	79.88	Nicaragua	84	60.65			
Ethiopia	68.5	50.25	Nigeria	71.2	47.43			
Finland	100.9	85.78	Norway	97.2	83.84			
France	98.1	80.15	Pakistan	84	52.63			
Germany	98.8	78.55	Panama	80	71.01			
Ghana	69.7	62.63	Paraguay	84	65.68			
Greece	93.2	73.7	Peru	84.2	68.13			
Guatemala	79	61.34	Philippines	86.1	71.24			
Guinea	66.5	48.25	Poland	96.1	77.06			
Guyana	81	64.17	Portugal	94.4	74.5			
Honduras	81	58.93	Qatar	80.1	69.04			
Hungary	98.1	75.82	Romania	91	73.94			
Iceland	98.6	78.86	Russia	96.6	77.54			
India	82.2	57.62	Rwanda	76	54.17			
Indonesia	85.8	66.99	Saudi Arabia	79.6	61.38			
Iran	85.6	63.2	Senegal	70.5	53.04			
Ireland	94.9	80.59	Serbia	90.3	70.97			
			Singapore	107.1	78.15			
			Slovak Rep	98	75.48			
			Slovenia	98	79.95			

APPENDIX B

This appendix provides a description of the HCI components, by age group. More detailed descriptions can be found in the *Report*, pp. 52 - 56, from which this is taken. Descriptions of sources are provided at the end of this table.

<u>AGE GROUP/ MEASURE</u>	<u>DESCRIPTION OF MEASURE</u>	<u>ORIGINAL SOURCE</u>
UNDER 15 AGE GROUP		
<u>Enrolment in Education</u>		
Primary enrollment rate	Percentage of children in official primary school age range enrolled in primary or secondary.	<i>UNESCO</i> , 2013
Secondary enrollment rate	Percentage of children in official age range enrolled in secondary education.	<i>UNESCO</i> , 2013
Basic education survival rate	Percentage of students enrolled in lower secondary education in given school year expected to reach last grade lower secondary education.	<i>UNESCO</i> , 2012
Secondary enrollment gender gap	Female-to-male ratio of enrollment rate in lower secondary education. Value of 100 indicates gender parity; less than 100 indicates disparity toward males.	<i>UNESCO</i> , 2012
<u>Quality of Education</u>		
Quality of primary schools	Response to "How would you assess the quality of primary schools in your country?" 1 = poor; 7 = excellent.	<i>EOS</i> , 2014-2015
<u>Vulnerability</u>		
Incidence of child labor	Percentage of children 5-14 years in child labor, including unpaid household services.	<i>UNICEF</i> , latest data
15-24 AGE GROUP		
<u>Enrollment in Education</u>		
Tertiary enrollment rate	Total enrollment in tertiary as percent of total population of age group that has left secondary school.	<i>UNESCO</i> , 2013
Vocational enrollment rate	Tech/vocational enrollment as a percentage of total enrollment in secondary school.	<i>UNESCO</i> , 2013

Quality of Education

Quality of educational system Survey response to “How well does the educational system in your country meet the needs of a competitive economy?” (1 = not well; 7 = very well) *UNESCO, 2012 or latest*

Youth literacy rate Percentage of those 15-24 who can read and write a short statement of their everyday life; also includes ability to make simple math calculations. *UNESCO, 2015 or latest*

Educational Attainment

Primary educational attainment rate Percentage of the population with at least a primary education, both sexes age 15-24. Data is cumulative: those with secondary education and above are counted in the primary education figures. *Lutz; Barro-Lee*

Secondary education attainment rate Percentage of the population with at least a secondary education, both sexes age 15-24, both sexes. Data is cumulative: those with secondary education and above are counted in the primary education figures. *Lutz; Barro-Lee*

Economic Participation

Labor force participation rate Percentage of population engaged in working or looking for work, both sexes aged 15-24. *ILOSTAT, 2014 or latest*

Unemployment rate Number of unemployed as a percentage of the total number of labor force, both sexes age 15-24. *ILOSTAT, 2014 or latest*

Underemployment rate People in involuntary part-time employment as a percentage of the total number in employment, both sexes age 15-24. *ILOSTAT, 2013 or latest*

Not in employment, education or training Proportion of people age 15-24 not in employment; not in education or training. *ILOSTAT, 2013 or latest*

Long-term unemployment rate Number of people 15-24 unemployed for more than 12 months as a percentage of total unemployed. *ILOSTAT, 2013 or latest*

Skills

Incidence of overeducation Mismatch between the qualification requirements of jobs held by workers and the qualifications these workers possess. *ILO, 2011 or latest*

Incidence of undereducation	Mismatch between the qualification requirements of jobs held by workers and the qualifications these workers possess.	<i>ILO</i> , 2011 or latest
Skill diversity	A Herfindahl-Hirschman Index (HHI) of concentration of graduates among nine broad fields of study.	<i>Report</i> , 2015
25-54 AGE GROUP		
<u>Educational Attainment</u>		
Primary education attainment rate	Percentage of population with at least primary education, both sexes age 25-54. Data is cumulative: those with secondary education and above are counted in the primary education figures.	<i>Lutz</i> ; <i>Barro-Lee</i>
Secondary education attainment rate	Percentage of the population with at least secondary education, both sexes age 25-54. Data is cumulative: those with tertiary education counted in the secondary education figures.	<i>Lutz</i> ; <i>Barro-Lee</i>
Tertiary education enrollment rate	Percentage of the population with at least tertiary education, both sexes age 25-54.	<i>Lutz</i> ; <i>Barro-Lee</i>
<u>Workplace Learning</u>		
Staff training services	Response to the question, “To what extent do companies in your country invest in training and employee development? (1 = hardly at all, 7 = to a great extent)”	<i>EOS</i> , 2014-2015
Economic complexity	From the Atlas of Economic Complexity. Attempts to measure the amount of country productive knowledge and skills, as embodied in the sophistication of its exports.	<i>Hausman</i> , et al, 2012
<u>Economic Participation</u>		
Labor force participation rate	Percentage of population actively engaged in either by working or looking for work, both sexes age 25-54.	<i>ILOSTAT</i> , 2014 or latest
Unemployment rate	Number of unemployed as a percentage of the total number of labor force, both sexes age 25-54.	<i>ILOPSTAT</i> , 2014 or latest

Underemployment rate People in involuntary part-time employment *ILOSTAT*, as a percentage of the total number in 2013 or latest employment, both sexes age 25-54.

Employment gender gap Ratio of female employment-to-population *ILOSTAT*, ratio over male value, people age 25-54, 2013 or latest expressed as a percentage. Value of 100 indicates gender parity.

Skills

High-skilled employment share Number of all persons employed in occupations with tertiary education requirements as a percentage of the total number of employed people. *ILOSTAT*, 2014 or latest

Medium-skilled employment share Number of all persons employed in occupations with at least secondary education requirements as a percentage of the total number of employed persons. *ILOSTAT*, 2014 or latest

Ease of finding skilled employees Response to “In your country, how easy is it for companies to find employees with the required skills for their business needs? (1 = extremely difficult, 7 = extremely easy) *EOS*, 2014-2015

55-64 AGE GROUP

Educational attainment

Primary education attainment rate Percentage of population with at least primary education, both sexes age 55-64. Data is cumulative: those with secondary education and above are counted in the primary education figures. *Lutz; Barro-Lee*

Secondary education attainment rate Percentage of the population with at least secondary education, both sexes age 55-64. Data is cumulative: those with tertiary education counted in the secondary education figures. *Lutz; Barro-Lee*

Tertiary education enrollment rate Percentage of the population with at least tertiary education, both sexes age 55-64. *Lutz; Barro-Lee*

Economic Participation

Labor force participation rate	Percentage of population actively engaged in either by working or looking for work, both sexes age 55-64.	<i>ILOSTAT</i> , 2014 or latest
Unemployment rate	Number of unemployed as a percentage of the total number of labor force, both sexes age 55-64.	<i>ILOPSTAT</i> , 2014 or latest
Underemployment rate	People in involuntary part-time employment as a percentage of the total number in employment, both sexes age 55-64.	<i>ILOSTAT</i> , 2013 or latest
Health life expectancy	Health-adjusted life expectancy developed by the World Health Organization; attempts to capture a more complete estimate of health than standard life expectancy rates. Capped at 65.	<i>WHO</i> , 2013

65 AND OVER AGE GROUPEducational attainment

Primary education attainment rate	Percentage of population with at least primary education, both sexes age 65 and over. Data is cumulative: those with secondary education and above are counted in the primary education figures.	<i>Lutz</i> ; <i>Barro-Lee</i>
Secondary education attainment rate	Percentage of the population with at least secondary education, both sexes age 65 and over. Data is cumulative: those with tertiary education counted in the secondary education figures.	<i>Lutz</i> ; <i>Barro-Lee</i>
Tertiary education enrollment rate	Percentage of the population with at least tertiary education, both sexes age 65 and over.	<i>Lutz</i> ; <i>Barro-Lee</i>

Economic Participation

Labor force participation rate	Percentage of population actively engaged in either by working or looking for work, both sexes age 65 and over.	<i>ILOSTAT</i> , 2014 or latest
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Unemployment rate	Number of unemployed as a percentage of the total number of labor force, both sexes age 55-64.	<i>ILOSTAT</i> , 2014 or latest
Underemployment rate	People in involuntary part-time employment as a percentage of the total number in employment, both sexes age 65 and over.	<i>ILOSTAT</i> , 2014 or latest
Health life expectancy beyond 65	The number of years by which a country's health-adjusted life expectancy exceeds value of 65 years, if any.	<i>WHO</i> , 2013

Original Sources:

Barro –Lee: Barro, R. and J.W. Lee, “A New Dataset of Educational Attainment in the World, 1950–2010”, NBER Working Paper 15902, The National Bureau of Economic Research, 2013, <http://www.nber.org/papers/w15902>.

EOS: World Economic Forum, *Executive Opinion Survey*, 2014-2015.

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ILOSTAT: International Labour Organization, *Annual Indicators*, various years.

Lutz: Lutz, W. et al. “Validation of the Wittgenstein Centre Back-projections for Populations by Age, Sex, and Six Levels of Education from 2010 to 1970”, IIASA Interim Report IR-15-008, International Institute for Applied Systems Analysis, April 2015. http://www.iiasa.ac.at/publication/more_IR-15-008.php.

Report: World Economic Forum, *The Human Capital Report*, 2015.

UNESCO: United Nations Educational, Scientific and Cultural Organization, Institute for Statistics.

UNICEF: *Statistics by Topic, Child Protection*

WHO: World Health Organization, Global Health Observatory, World Health Statistics.

APPENDIX C

This appendix provides a description of the additional indicators as found in the *Report*, pp. 56-57, from which this is taken. Descriptions of sources are provided at the end of this table.

<u>MEASURE</u>	<u>DESCRIPTION OF MEASURE</u>	<u>SOURCE</u>
<u>Business perceptions</u>		
Quality of math/science education	Response to question, “How would you assess the quality of math and science education in your country’s schools? (1 = poor; 7 = excellent, among the best in the world)	<i>EOS</i> , 2014-2015
Quality of business schools	Response to question, “How would you assess the quality of management or business schools in your country? (1 = poor; 7 = excellent, among the best in the world)	<i>EOS</i> , 2014-2015
Specialized training services	Response to the question, “In your country, to what extent are high-quality, specialized training services available? (1 = not at all available, 7 = widely available)	<i>EOS</i> , 2014-2015
Capacity to attract talent	Response to question, “Does your country attract talented people from abroad? (1 = not at all, 7 = attracts the best and brightest from around the world)	<i>EOS</i> , 2014-2015
Capacity to retain talent	Response to question, “Does your country retain talented people? (1 = the best and brightest leave to pursue opportunities in other countries, 7 = the best and brightest stay and pursue opportunities in the country)	<i>EOS</i> , 2014-2015
<u>Innovation Ecosystem</u>		
State of cluster development	Response to question, “In your country, how prevalent are well-developed and deep clusters (geographic concentrations of firms, suppliers, producers of related products and services and specialized institutions in a particular field)? (1 = non-existent, 7 = widespread in many fields)	<i>EOS</i> , 2014-2015

University-business R&D Collaboration	Response to question, “To what extent do business and universities collaborate on research and development (R&D) in your country? (1 = do not collaborate at all, 7 = collaborate extensively)	<i>EOS</i> , 2014-2015
Ease of starting a business	Country rank (out of 189) on the Starting a Business pillar of the World Bank’s Doing Business report.	<i>World Bank</i> , 2014
<u>Vulnerability</u>		
Workers in informal employment	Employment in the informal sector as percentage of total non-agricultural employment.	<i>ILO</i> , latest year
Workers in vulnerable employment	Share of own-account workers, who don’t hire paid employees on a continuous basis, but may have assistance from contributing family workers (unpaid employed who usually live in same household and are related to family members) as a percentage of all persons employed.	<i>ILOSTAT</i> , 2013
Social safety net	Response to question, “In your country, does a formal social safety net provide protection from economic insecurity in the event of job loss or disability? (1 = not at all, 7 = fully)	<i>EOS</i> , 2014-2015
<u>Public Investment</u>		
Public spending on education (% of GDP)		<i>World Bank</i> , 2013
Internet access in schools	Response to question, “In your country, how widespread is Internet access in schools? (1 = non-existent; 7 = extremely widespread)	<i>EOS</i> , 2014-2015

Sources:

EOS: World Economic Forum, *Executive Opinion Survey*.

ILO: *Women and Men in the Informal Economy: A Statistical Picture*, Second Edition (2013).

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