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STATISTICS AND INTELLIGENCE IN DEVELOPING COUNTRIES: A NOTE

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Summary. The purpose of this study is to assess the relationship between intelligence (or human capital) and the statistical capacity of developing countries. The line of inquiry is motivated essentially by the scarce literature on poor statistics in developing countries and an evolving stream of literature on the knowledge economy. A positive association is established between intelligence quotient (IQ) and statistical capacity. The relationship is robust to alternative specifications with varying conditioning information sets and control for outliers. Policy implications are discussed.

Introduction

Incorrect national statistics negatively affect government effectiveness (Kodila-Tedika, 2014a) and might potentially lead to debates in policy circles because of substantial disparities between reality and what is reported as factual evidence based on statistics. An example of a contemporary policy debate related to evidence-based findings is Africa's failure to attain the Millennium Development Goal (MDG) extreme poverty targets (see Asongu & Nwachukwu, 2016a, b). Whereas an April 2015 World Bank report revealed that since the 1990s extreme poverty has been declining in all regions of the world, with the exception of sub-Saharan Africa where 45% of countries are still substantially off-track from achieving the MDGs extreme poverty target, Pinkivskiy and Sala-i-Martin (2014) had earlier established that, with the exception of the Democratic Republic of Congo, all African countries had achieved this target in 2014 or one year ahead of time. This debate aligns with the pros (Leautier, 2012) and cons (Obeng-Odoom, 2015) of the 'Africa rising' narrative.

The debate, which has been articulated with fundamental growth issues in Africa, has coincided with the publication of some notable works on data revision, *inter alia*: Jerven (2013a), Devarajan (2013) and Harttgen *et al.* (2013). While Jerven (2013b) clearly outlined the issues in a new book, Young (2012) established that some indicators

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of Africa's development are growing by about 4 times compared with those reported in international datasets. This has motivated a growing stream of literature on the subject, notably: (i) a recent book premised on whether Africa's recent growth resurgence is a reality or a myth (Fosu, 2015a, b) and (ii) another book by Kuada (2015) which suggested a paradigm shift to 'soft economics' or human capability development in order to understand development trends in developing countries.

In the light of the above, it is important to establish why good statistics may be present in some countries and not in others. To the best of the authors' knowledge, very little is covered in the literature, essentially because this is a relatively new debate; only Kodila-Tedika (2013) has attempted to investigate this concern of statistical quality in African countries. The present line of inquiry aims to extend the literature from a human capital angle: notably, on the role of intelligence or the Intelligence Quotient (IQ) in statistical capacity. It is interesting to note that intelligence is not best described by the Intelligence Quotient. In essence, whereas the abbreviation is currently employed in the English language, the modern IQ is a standardized *z*-score and not a ratio. Moreover, the motivation for wanting developing countries to achieve high-quality statistics is to help governments enhance economic development and the living standards of their citizens.

The positioning of this line of inquiry on human capital aligns well with an evolving stream of African development literature documenting the imperative for African countries to catch up with the rest of the world by enhancing their transition from product-based economies to knowledge-based economies (Anyanwu, 2012; Oluwatobi *et al.*, 2015; Andrés *et al.*, 2015; Asongu, 2015a). It is important to note that these recommendations have been emphasized based on the knowledge that it is more feasible for African countries to engage in reverse engineering because their current technologies are more imitative and adaptive in nature (Tchamyou, 2015).

The study's theoretical hypothesis is founded on the following arguments. Educated persons tend to be good and well-informed citizens (Reynal-Querol & Besley, 2011; Besley *et al.*, 2011). Consistent with Botero *et al.* (2012), nations with better-educated citizens are associated with higher government quality because their citizens are more likely to report official misconduct. In essence, for the underlying reporting of corruption and crime to be credible, it should be based on 'reliable data'. Lynn *et al.* (2007) and Lynn and Milk (2007) have shown that IQ is highly correlated with education. People with high IQs can easily use their education for various purposes. Within the framework of this inquiry, societies enjoying relatively high IQs should be associated with a higher demand for accurate information, collected as statistics.

Studies by Jauk *et al.* (2013) have established the relationship between creativity and intelligence. According to the authors, individuals with high intelligence are likely to be more creative. Hence, intelligence within this context may be an essential condition for creativity (see Park *et al.*, 2008; Robertson *et al.*, 2010). On the other hand, other studies take the view that the underlying relationship between intelligence and creativity depends on certain thresholds (see Batey & Furnham, 2006; Kim *et al.*, 2010). Meanwhile, according to Silvia (2008), many of the established relationships are underestimated.

In the light of the above, it is logical to postulate that intelligent persons can improve statistics or even new statistical indices. It is within this framework of intelligence that Henderson *et al.* (2012) suggested that economic growth can be measured through space (e.g. spatial regressions). Moreover, Furnham and Chamorro-Premuzic (2004) established that intelligent people are more at ease with statistics. Accordingly, the authors found that there was a positive relationship between an intelligent group within a sample and grade achieved in statistics exams. Whereas the scope of this inquiry is at the country level, the intuition for the relationship to be estimated is broadly consistent with the bulk of the literature on personality and individual differences (Vickers *et al.*, 2004; Preckel *et al.*, 2006; Silvia, 2008; Martin-Raugh *et al.*, 2016). It is important to note that the relationship between intelligence and statistical capacity is contingent on institutional quality and other dimensions of the knowledge economy (Asongu, 2014; Andrés *et al.*, 2015).

Based on the above theoretical postulations, the testable hypothesis in this study is as follows: on average, countries with a high IQ present better statistics compared with their low-IQ counterparts. It is important to note that concern about the quality of statistical data is not exclusively limited to developing countries. Accordingly, the IQ data employed have been collected across diverse locations worldwide, including several developed countries (Meisenberg & Lynn, 2011; Lynn & Vanhanen, 2012). The study focuses exclusively on developing countries because the indicator of statistical capacity is not available for developed countries.

Methods

The statistics indicator is obtained from the Bulletin Board on Statistical Capacity (BBSC) of the World Bank's Development Data Group. The BBSC focuses on improving the monitoring and measuring of 'statistical capacity' of countries in the International Development Association (IDA), in close collaboration with users and countries. The database embodies information on a plethora of aspects of national statistical systems and provides a country-level statistical capacity indicator based on a set of criteria that are consistent with international recommendations. The World Bank's statistical capacity measurement is a composite score that examines the capacity of a nation's system of statistics. It is based on a framework of diagnosis that examines the following areas: timeliness, periodicity, data sources and methodology. Hence, nations are evaluated against 25 criteria in these areas with the help of country input and publicly available information. Ultimately, the overall score is computed as a simple average of scores in the assessed areas, on a scale of 0–100, with higher values denoting better capacity. In the light of these assessment insights, statistical capacity represents a country's ability to collect, analyse and disseminate data of high quality about its economy and population. It is important to note that statistical quality is essential for all stages of evidence-based decision-making. This includes: (i) informing the international donor community on policy formulation and programme design, (ii) guiding private sector investment, (iii) allocating government sources and political representation and (iv) monitoring economic and social indicators.

The data on intelligence are from Meisenberg and Lynn (2011) and Lynn and Vanhanen (2012). Previous versions can be found in Lynn and Vanhanen (2002, 2006). This dataset is a compilation of hundreds of average national IQ tests observed over the 20th and 21st centuries using best-practice methods. Average IQ is a measure of

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general-purpose human capital as well as a measure of a nation's labour quality (Hanushek & Kimko, 2000; Jones & Schneider, 2006; Hanushek & Woessmann, 2008).

The choices of statistical indicator and intelligence measurement are broadly consistent with recent economic development and intelligence literature (Weede & Kämpf, 2002; Jones & Schneider, 2006; Ram, 2007; Potrafke, 2012; Kodila-Tedika, 2014b; Kodila-Tedika & Mustacu, 2014; Kodila-Tedika & Bolito-Losembe, 2014; Kodila-Tedika & Asongu, 2015a, b; Rindermann *et al.*, 2015). It is interesting to note that data from Hanushek on the one hand, and from Lynn and Vanhanen on the other hand, are continuously being improved upon (Meisenberg & Lynn, 2011, 2012).

In accordance with recent literature on statistical capacity (Kodila-Tedika, 2013, 2014a), the study controls for GDP *per capita*, trade openness, state fragility, ethnic fractionalization and government effectiveness. While data on GDP *per capita* and trade are sourced from the Penn World Tables, ethnic fractionalization is from Alesina *et al.* (2003). The 'state fragility' variable is from the International Monetary Fund (IMF, 2011) and based on the World Bank classification, while the 'government effectiveness' measurement is provided by Kaufmann *et al.* (2010). The expected signs of the control variables are engaged simultaneously with the discussion of the empirical results.

The sampled countries include: Afghanistan; Angola; Albania; United Arab Emirates, Argentina; Armenia; Azerbaijan; Burundi; Benin; Burkina, Bangladesh; Bulgaria; Bahrain; Bosnia and Herzegovina; Belarus, Belize, Bermuda; Bolivia; Brazil; Barbados, Brunei; Bhutan; Botswana, Central African Republic; Chile, China, Cote d'Ivoire, Cameroon, Congo, Colombia, Comoros, Cape Verde; Costa, Cuba, Cyprus, Czech Republic; Denmark; Dominican Republic, Algeria, Ecuador, Egypt, Eritrea, Estonia, Ethiopia; Fiji; Gabon, Georgia, Ghana; Guinea, Gambia. The, Guinea-Bissau, Equatorial Guinea; Guatemala, Guyana, Hong Kong, Honduras, Croatia, Haiti, Hungary, Indonesia, India, Ireland, Iran, Iraq; Iceland; Israel; Italy, Jamaica, Jordan, Japan, Kazakhstan, Kenya, Kyrgyzstan, Cambodia, Kuwait, Laos, Lebanon, Liberia, Libya, Sri Lanka, Lesotho, Lithuania, Latvia, Morocco, Republic of Moldova, Madagascar, Maldives, Mexico, Madagascar, Macedonia, Mali, Malta, Myanmar, Montenegro, Uganda and Ukraine.

Consistent with recent human capital or intelligence (Kodila-Tedika & Asongu, 2015a, b) and development (Asongu, 2013) literature, the specification in Eqn (1) assesses the correlation between human capital and statistical capacity:

$$SC_i = \alpha_1 + \alpha_2 HC_i + \alpha_3 C_i + \varepsilon_i \quad (1)$$

where SC_i (HC_i) represents a statistical capacity (human capital) indicator for country i, α_1 is a constant, C is the vector of control variables, ε_1 is the error term. The term HC is the *human capital* variable, while C involves: *GDP per capita*, *trade openness*, *state fragility*, *ethnic fractionalization* and *government effectiveness*. In harmony with the engaged human capital literature, the objective of Eqn (1) is to estimate if intelligence affects statistical capacity by Ordinary Least Squares (OLS) using standard errors that are corrected for heteroscedasticity. The sampled developing countries are as above.

The descriptive statistics of the variables are presented in Table 1 and the correlation matrix in Table 2. The descriptive statistics enable the following to be assessed: (i) if the variables are comparable, and (ii) whether, from corresponding standard deviations, we

Table 1. Descriptive statistics of study countries' statistical capacity and associated factors

Variable	*n*	Mean	SD	Minimum	Maximum
Statistical capacity	118	68.43	15.81	21.67	94.44
IQ	177	84.30	10.93	61.2	106.9
State fragility	184	0.15	0.36	0	1
Ethnic fractionalization	166	0.46	0.27	0	0.98
Government effectiveness	139	0.11	0.99	− 1.75	2.22
Trade openness	140	95.42	57.16	26.65	446.06
GDP *per capita* (log)	140	8.87	1.19	5.90	11.17
Cognitive ability	192	81.79	14.32	55	108
Cognitive skill	77	4.56	.57	3.09	5.45

Table 2. Correlation matrix to mitigate potential issues of multicollinearity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Statistical capacity (1)	1								
IQ (2)	0.61	1							
State fragility (3)	−0.48	−0.48	1						
Ethnic fractionalization (4)	−0.31	−0.45	0.26	1					
Government effectiveness (5)	0.59	0.61	−0.52	−0.26	1				
Trade openness (6)	0.08	0.30	−0.06	−0.14	0.33	1			
GDP *per capita* (log) (7)	0.60	0.73	−0.47	−0.36	0.73	0.34	1		
Cognitive ability (8)	0.40	0.98	−0.46	−0.58	0.41	0.30	0.53	1	
Cognitive skill (9)	0.01	0.81	−0.03	−0.43	0.08	0.66	0.19	0.86	1

can be confident that reasonable estimated linkages would emerge. The purpose of the correlation matrix is to mitigate potential issues of multicollinearity. The underlying multicollinearity issues were mitigated by employing different covariates in alternative specifications.

Results

Main results

The empirical findings are reported in Table 3. The dependent variable is the 'statistical capacity indicator'. Ordinary Least Squares (OLS) estimates are presented in columns 2 to 7, and Iteratively Weighted Least Squares (IWLS) regressions are presented in Table 4 as a robustness check. In the final column of Table 3 a Variance Inflation Factor (VIF) test was carried out; the results are well below 10 suggesting that multicollinearity is not an issue (Neter *et al.,* 1985). In the OLS modelling exercise, one covariate (listed in column 1) is consistently added to the model on moving from one specification to the next.

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Table 3. Ordinary Least Squares (OLS) estimates with statistical capacity as the dependent variable

	OLS	OLS	OLS	OLS	OLS	OLS	VIF
IQ	0.80***	0.53***	0.57***	0.43***	0.52***	0.42**	3.72
	[0.515]	[0.346]	[0.378]	[0.327]	[0.398]	[0.325]	
	(0.11)	(0.11)	(0.13)	(0.16)	(0.16)	(0.18)	
State fragility		−17.78***	−17.21***	−9.50**	−9.55**	−9.47**	2.97
		[−0.467]	[−0.451]	[−0.253]	[−0.259]	[−0.256]	
		(3.60)	(3.73)	(4.34)	(4.52)	(4.48)	
Ethnic fractionalization			3.65	−0.76	−0.81	−0.48	1.66
			[0.061]	[−0.015]	[−0.015]	[−0.009]	
			(5.26)	(4.53)	(4.71)	(4.78)	
Government effectiveness				5.45**	4.82**	3.35	3.58
				[0.270]	[0.240]	[0.166]	
				(2.53)	(2.37)	(2.81)	
Trade openness					−0.05*	−0.05**	1.50
					[−0.125]	[−0.137]	
					(0.03)	(0.02)	
GDP *per capita* (log)						2.48	3.14
						[0.171]	
						(2.08)	
Constant	3.75	29.90***	24.49*	40.60***	37.70**	24.39	
	(9.70)	(9.38)	(12.73)	(14.72)	(15.04)	(18.67)	
N	115	110	107	91	90	90	
Adjusted R^2	0.27	0.47	0.46	0.50	0.53	0.54	

Standard errors in parentheses; β-coefficients in square brackets.
VIF, Variance Inflation Factor.
$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

The IQ estimates confirm the expected positive correlation between intelligence and statistical capacity. Hence, intelligence is positively correlated with statistical capacity. Columns 3 to 7 assess the relationship conditional on other covariates (control variables). From the results, the positive correlation is broadly confirmed across specifications in terms of the significance of the estimated human capital (or intelligence) coefficient. The estimated coefficients vary between 0.8 and 0.3 and the degree of adjustment (or explanatory power) of the estimated coefficients varies between 26.5% and 59.3%. It is logical to expect R^2 to increase when more control variables are added to the model. Ultimately, it could be inferred from the baseline estimations that countries with high IQs are associated with higher degrees of statistical capacity.

Robustness check

Robustness with respect to influential observations. Given that the estimations by the OLS technique may be weak in the presence of outliers, the robustness of the corresponding estimates is verified by employing an estimation technique that controls for the presence of such outliers. For this purpose IWLS is used (Huber, 1973). The robustness check process is as described by Kodila-Tedika and Asongu (2016). The findings presented in Table 4 are consistent in sign and significance with the OLS results, although they have a relatively lower magnitude. The corresponding lower magnitude implies that outliers influence the investigated nexus between statistical capacity and intelligence.

Table 4. Robustness check for the presence of outliers using IWLS analysis

	IWLS[a]
IQ	0.26*
	(0.14)
State fragility	−14.70***
	(3.22)
Ethnic fractionalization	2.50
	(4.08)
Government effectiveness	1.54
	(2.30)
Trade openness	−0.05*
	(0.03)
GDP *per capita* (log)	4.49**
	(1.77)
Constant	19.47
	(15.05)
N	90
Adjusted R^2	0.59

Standard errors in parentheses; [a]IWLS, Iterated Reweighted Least Squares.
***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

Hence, the corresponding lower magnitude is also a justification for the robustness check. It is important to note that the effect of IQ on statistical capacity is above and beyond that of other country characteristics.

Most of the significant control variables have the expected signs. (i) 'State fragility' should intuitively be negatively related to the ability of governments to collect good data because some regions in a given country may be affected by political strife, civil conflicts and wars, hence rendering data collection very difficult. (ii) 'Government effectiveness' has been documented to be positively associated with statistical capacity (Kodila-Tedika, 2014a). (iii) 'Trade openness' may decrease the ability to collect good data in inherently corrupt developing countries because underlying trading activities are very likely to be associated with mis-invoicing, bribery and unfair lobbying. (iv) The positive nexus of the dependent variable with GDP *per capita* essentially builds on the intuition that wealthier countries are endowed with more financial resources for good data collection, relative to their less-wealthy counterparts.

Alternative measures of cognitive human capital. Cognitive human capital has been measured in different ways in the human capital literature. As discussed in the Methods section, its measurement has experienced an evolution. Rindermann (2007) defined cognitive ability as student achievement plus intelligence, primarily measured by common cognitive ability at the macro-social level. This ability entails: (i) intelligence (the capacity to think) and (ii) knowledge (degree of relevant and true knowledge and the capacity to acquire and use knowledge). Hanushek and Woessmann (2009) suggested an appreciation of cognitive skills. They defined cognitive skills as the average test results in maths and sciences, at primary level through all years until the end of secondary school (scaled to the Programme for International School Assessment (PISA) divided by 100).

These indicators have been exploited here to confirm the baseline findings in Table 3. The results in Table 5 broadly confirm a positive correlation between intelligence and statistical capacity. The result for 'cognitive skill' is not significant, but the sign remains positive. This is probably due to the significant reduction in degree of freedom.

Discussion

The purpose of this note has been to assess the relationship between intelligence or human capital and a nation's statistical capacity. The line of inquiry has been essentially motivated by the scarce literature on poor statistics in developing countries and an evolving literature on the knowledge economy. The study has established a positive association between intelligence quotient (IQ) and statistical capacity. The relationship is robust to the employment of alternative specifications with varying conditioning information sets and the control for outliers.

The findings imply that as average levels of IQ in developing countries increase, we should expect to see countries revising their national statistics substantially. This has been the recent experiences of Nigeria and Kenya in Africa. Given the leading roles of these countries on the continent in education, innovation and information and communication technology (ICT) (Tchamyou, 2015), the intuition for associating higher IQs with better statistical capacity is sound. This is essentially because the highlighted variables are three of the four dimensions of the World Bank's knowledge economy index: the fourth being 'economic incentives and institutional regime'. Accordingly, for better statistics to be collected, broad-based ICTs are essential to facilitate exchanges and accuracies between the data collector and data provider (institutions and civil societies). Moreover, with improvements in educational levels, more-skilled researchers will be available to refine and improve techniques of data collection, simulation, aggregation and computation, *inter alia*.

It is important to note that a substantial percentage of the variance in statistical capacity is not explained by intelligence. This implies that there are other factors explaining statistical capacity that have been left unexplained, even after improving the conditioning information set. Hence, policy measures devoted to enhancing statistical capacity in developing countries should go beyond education and be implemented in conjunction with improvements in other environments, such as capacity building and infrastructural development. Accordingly, such initiatives, which are complementary to the acquisition of intelligence, would improve the ability of sampled developing countries to acquire new technologies and knowledge, essential for 21st century economic development, which is centred on the knowledge economy (Asongu, 2015b). In a nutshell, measures aimed at improving intelligence in order to directly and/or indirectly promote statistical capacity should not be limited to education, but also extended to addressing longstanding issues in developing countries, like, *inter alia*: limited support for Research & Development, depleting knowledge infrastructure, brain-drain, outdated curricula and dwarfed linkages between industry and science.

While government statistics are collected by only a tiny section of the population, the quality and accuracy of the collected data, which are usually based on surveys and interviews, depends on the overall country-average IQ. In essence, interviewees and survey respondents from whom the data are collected across the country need a certain level of intelligence (required for the understanding of questions and the disclosure of accurate answers) to provide the information that is collected. Hence, the data collection process is contingent on country-average IQ. Therefore, increasing country-average IQ has a substantial effect on statistical capacity because the data collection process (and hence the quality of data collected) depends on the intelligibility of respondents.

Ultimately, the findings are consistent with intuition and the empirical literature. The average IQ as reported by Lynn and colleagues (based on Raven's matrices scores) is validated by the high correlation between these matrix scores in areas like arithmetic. Unfortunately, as a caveat, the concern of whether the IQ compilations from Lynn *et al.* represent 'best practice' for estimating 'intelligence' is still open to debate in scholarly circles. Though some researchers continue to interpret underlying outcomes as reflecting biological disparities in intelligence (Kodila-Tedika & Asongu, 2015a, b), others are of the view that IQ scores may be affected by continental specificity (Lynn & Meisenberg, 2010).

Given that Africa is in a comparatively volatile position, compared with other regions of the world, it is relevant to highlight that there are some concerns about Lynn *et al.*'s IQ measurement for the continent. According to Lynn and Meisenberg (2010), for a more representative African sample the average IQ is low (61), but high (80) for an elitist sample. Rindermann (2013) has suggested that controlling some continent-specific factors such as higher schooling age and lower school enrolment could lead to an average IQ of about 75. More insight into issues surrounding the validity of IQ measurements for developing countries can be found in Wicherts *et al.* (2010a, b), Meisenberg and Woodley (2013) and Rindermann *et al.* (2014). Furthermore, as documented by Irving *et al.* (2008) and Klauer and Phye (2008), intelligence training could also be considered as a means of improving intelligence.

Table 5. Ordinary Least Squares (OLS) estimates with alternative measures of cognitive human capital

	OLS	OLS
Cognitive ability	0.54***	
	(0.14)	
Cognitive skill		5.20
		(3.50)
Constant	30.42	24.20***
	(14.49)	(51.59)
N	91	36
Adjusted R^2	0.60	0.47
β-coefficient for IQ	0.51	0.28

Standard errors in parentheses; all control variables used in Tables 3 are included in the estimations.
***$p<0.01$.

Future lines of inquiry could improve the extant literature by examining: (i) the reverse correlation, (ii) channels via which IQ improves statistical capacity and (iii) which dimensions of the knowledge economy drive IQ on the one hand and a nation's statistical capacity on the other. Moreover, a recurring issue with national IQ measures is spatial autocorrelation. Hence, assessing the extent to which this issue can affect established linkages is also an interesting future research direction.

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