GMAT Scores as a Proxy for National IQ

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This study develops a straightforward transformation of Graduate Management Admissions Test (GMAT) scores into an equivalent IQ score using countries for which both measures are available; and, validates the same for countries for which direct measurements of National IQ are not available. The GMAT is an aptitude test used for admission into many MBA and other graduate programs in business. National average GMAT scores are found to be positively correlated with well-established measures of cognitive ability provided the GMAT scores are corrected for participation rate. Even though GMAT scores are indicated to be prone to measurement error, they drive ethnic-based proxies of National IQ to insignificance in regression analysis of GDP per capita.

INTRODUCTION

While National IQs have been validated as predictors of many variables of interest (Lynn and Vanhanen, 2012), National IQs are missing for many countries even when IQ data are supplemented by internationally-standardized scholastic achievement test results (Hanushek and Woessmann, 2015; Rindermann, 2018). Among the imaginative proxies that have been proposed for National IQ have been results of the International Mathematical Olympiad (Rindermann, 2011), the capabilities of agencies responsible for national economic statistics as assessed by the World Bank (Kodilla-Tedika, et al. 2017) and "middle responding" in opinion surveys (Minkov, 2017). The availability of Graduate Management Admission Test (GMAT) scores for almost every country in the world invites consideration of their use as a proxy for National IQ.

THE GMAT

The GMAT is a widely-used, standardized test designed for candidates for the Master of Business Administration (MBA) and for other graduate education programs in business. The GMAT is an aptitude test, as distinct from an intelligence test. It covers skills considered by its sponsor, the Graduate Management Admissions Council, to be important for academic success as well as for success in the real world of business. Currently, the test covers four skills: analytical writing, integrative reasoning, quantitative reasoning and reading comprehension. However, what is called the total score is based only on quantitative reasoning and reading comprehension.

Other than being written in English, the GMAT is not a knowledge test. That the GMAT is written in English may explain the substantially better performance of citizens of China, India and South Korea, and the moderately better performance of citizens of Canada, France and Germany on the quantitative subscale, relative to their performance on the verbal subscale, when compared to the performance of citizens of the United Kingdom and the United States (Graduate Management Admission Council, 2017, p. 22).

Nowadays, about half of the approximately 250,000 annual test-takers indicate their country of citizenship to be other than the United States. Since 2000-01, the number of test-takers by country of citizenship has been reported, as has the average total score for countries with at least four test-takers in a particular academic year. During the years 2009-12, national average GMAT scores were reported for 169 countries; and, during 2013-16, 168. Included are national average GMAT scores for many small and developing countries for which national IQ and school achievement test data are not normally available. It may be important to note that the country of residence of a test-taker may differ from country of citizenship.

Something like a Flynn Effect has been observed in GMAT scores. According to data filed with *U.S. News*, the trend of higher scores has been isolated to test-takers seeking admission to elite schools (Kowarski, 2017). The Graduate Management Admissions Council (2017) attributes rising scores to changing demographics in global test-takers and to adoption of an option for test-takers to not publish test scores.

Average test scores vary significantly by country of citizenship. Among countries with at least 1,000 test-takers during the five-year period 2008-09 to 2012-13, national averages ranged from 324 to 595, where 544 is the global average and about 100 is the individual standard deviation. The United States, at 532, had a national average a little below the global average. This slightly lower average score may reflect a high participation rate.

GMAT test-takers are generally young adults who have successfully navigated to the tertiary level of schooling, often have real-world experience relevant to business management, and choose to take the exam presumably weighing the costs and benefits involved. While GMAT test-takers can be presumed mostly from the upper tail of the general population, Rindermann, et al. (2009, p. 15) have shown that there is a 97 percent correlation between the 95th percentile scores and the mean scores of internationally-standardized student achievement tests.

Because of self-selection, it may be important to correct for participation rate when comparing GMAT scores across countries just as should be done when comparing SAT scores across the states of the United States, and when comparing internationally-standardized achievement test scores across countries. Getting the structural form of this correction is important because of the intent to use data from a tail of a distribution to project a value at the center of the distribution.

THE MODEL

From the definition of the Z score, $Z = (X - \mu)/\sigma$, where μ and σ are the mean and standard deviation of a normal distribution. Assuming GMAT scores are normally distributed and that only those who would do better take the test, a little manipulation gives

$$\mu = X - \sigma Z(P) \qquad (1)$$

Equation [1] has the form of a regression equation, where:

- μ is the (true but unobserved) National (average) IQ (based on contemporary UK norms),
- X the (measured) National (average) GMAT score (converted to contemporary UK norms [i.e., $100 + (X - X_{UK})*(15/100)$]),
- σ the standard deviation of IQ,
- P the GMAT participation rate, and
- Z(P) the Z score associated with the GMAT participation rate.

In fact, it is not known how participation rates should be mapped onto Z scores. The mapping might not be exactly as envisioned. Part of this exercise, while rooted in the theory of the distribution of intelligence, involves curve-fitting. Recognizing this,

$\mu = a + bX + cZ(\ 0.5*(1 + (P_{UK} - P)/P_{UK})$ if $P_{UK}-P > 0$ and 0.5 otherwise) (2)

where *a, b* and *c* are parameters to be estimated by regression reflecting in part the fitting of a curve to the relation between X (National GMATs) and μ (National IQs) when both are observed. Hopefully, *a, b* and *c* are close to if not exactly equal to zero, 1 and -15. If *b* is close to 1 and if *c* is negative, Equation [2] would effectively adjust GMAT-based projections of National IQ down for countries that have low participation rates. Because of possible curve-fitting, it may be important that the resultant model is validated.

REGRESSION ANALYSIS

Table 1 reports the results of regressions of National IQ against National GMAT score converted to an IQ scale and a second variable, Z(P), designed to correct the GMAT scores for countries with low participation rates. National IQs are taken as the weighted average IQs and Achievement Test (AT) scores converted to an IQ scale from Lynn and Meisenberg (2010), with weights equal to the numbers of IQ and AT surveys used to calculate those averages. GMAT scores are weighted averages over the period 2008-09 to 2011-12, with the weights equal to the number of test-takers in each year (Graduate Management Admissions Council, 2012, pp. 19-24). Participation rates are equal to the number of test-takers over the same four-year period relative to the general population aged 20 to 24, from the World Bank database. The sample consists of all countries for which both National IQ and National GMAT score are observed, a total of 94 countries.

TABLE 1
REGRESSION ANALYSIS OF NATIONAL IQs
Dependent Variable - L&M 2010 National IQs, 94 countries

Independent Variables	Unweighted -1-	Unweighted -2-	Weighted -3-	Weighted -4-
CONSTANT	46.59		50.60	
	[6.83]		[5.29]	
GMAT IQ	0.53	1.02	0.51	1.04
(2009-12)	[7.20]	[98.24]	[4.98]	[137.44]
Z(P)	-6.11	-2.22	-15.00	-15.40
(2009-12)	[-6.02]	[-2.17]	[-7.83]	[-7.08]
R^2 {1}	65.7%	58.1%	61.4%	52.2%

t-statistics in brackets. Observations weighted by the square root of the number of GMAT test-takers.

{1} between predicted Y (dependent variable) and actual Y

The regression reported in the first column of Table 1 shows that National IQ is strongly correlated with National GMAT score, and that National GMAT scores tend to be higher in countries with low participation rates. However, the parameters of the model are far from their theoretical values. In particular, the coefficient on the GMAT score (*b*) is much less than its theoretical value (1) and the constant (*a*) much higher than its theoretical value (zero). This combination of results can be indicative of measurement error in the GMAT score due to the inclusion of many national average GMAT scores based on small numbers of test-takers.

The regression reported in the second column of Table 1 constrains the value of the constant to be zero. Subject to this constraint, the parameters of the regression appear reasonable. In particular the coefficient on the GMAT score is close to 1 and the coefficient on the term correcting for a low participation rate is negative. Even so, the latter coefficient is far from -15 and cautions against projections far from the locus of the sample (that is, from a tail of the distribution to its center).

The regression results reported in the third and fourth columns of Table1 correct for the problem of heteroscedasticity due to the inclusion of data based on large and small numbers of test-takers. These regressions otherwise parallel those for which results are reported in the first two columns with one notable exception. The exception is that the coefficient on the term correcting for low participation rates (*c*) is now approximately equal to its theoretical value (-15).

Table 2 presents the results of regressions of national average scores on the internationally-standardized scholastic achievement tests compiled and homogenized by Altinok, et al. (2018) against national GMAT scores accumulated over the period of 2012-13 to 2015-16 (Graduate Management Admissions Council, 2016, pp. 4-25). Notice that the GMAT data in the two sets of regressions are completely different, and that the measures of cognitive ability overlap only insofar as Altinok et al. rely on some vintage achievement test scores previously used by Lynn and Meisenberg. Notice also the increase in the number of countries for which measures of cognitive ability are available, from 94 to 131.

TABLE 2
REGRESSION ANALYSIS OF NATIONAL ACHIEVEMNET TEST SCORES
Dependent Variable - AA&P 2018 National Scholastic Achievement Test Scores, 131 countries

Independent Variables	Unweighted -1-	Unweighted -2-	Weighted -3-	Weighted -4-
CONSTANT	328.72		436.99	
	[8.10]		[10.41]	
GMAT	0.28	0.86	0.11	0.89
(2013-16)	[3.79]	[42.62]	[1.51]	[103.67]
Z(P)	-64.05	-23.04	-111.54	-90.08
(2013-16)	[-7.66]	[-2.65]	[-11.30]	[-6.90]
R^2 {1}	59.1%	44.3%	56.6%	33.9%

The achievement tests are scaled so that the global average is approximately 500 and standard deviation 100. These are approximately the mean and standard deviation of GMAT scores. Accordingly, the parameters *a*, *b* and *c* of the model described in equation [2] should be approximately zero, 1 and -100. To be precise, the parameter *b* is expected to be 88, equal to the ratio of the UK achievement test score to the UK GMAT score.

The results reported in Table 2 roughly correspond to those reported in Table 1. In particular, when the intercept is constrained to be zero, the estimates of *b* and *c* approximate their expected values. As discussed above, the reason for the need for this constraint can be taken to be measurement error.

Thus far it has been determined that GMAT scores are positively correlated with available measures of cognitive ability at least when corrected for low participation rates and that the form of their relation is at least approximately that implied by theory. These two findings give some hope for using GMAT scores as a proxy for National IQ. On the other hand, measurement error is indicated, questioning the usefulness of GMAT scores as a proxy. Accordingly, this investigation now turns to an attempt to validate the use of GMAT scores as a proxy for National IQ.

VALIDATION

As mentioned above, National IQs are missing for many countries, even when Achievement Tests are used to infer National IQs. Lynn and Vanhanen (2002) use ethnic origins to interpolate IQ for countries for which National IQ is not directly observed. Their data including the interpolations and updates have been widely used in subsequent research. In the continuing absence of local data for many countries, it is important to determine if proxy data can improve upon the interpolations.

The first column of Table 3 presents the results of a regression of the natural logarithm of GDP per capita against Lynn and Vanhanen's ethnic-based interpolations of National IQ. The estimates of GDP per capita are the averages of the International Monetary Fund and World Bank estimates for 2012, on a PPP (or "international dollar") basis, or a CIA Factbook estimate if necessary. The sample consists of all countries for which Lynn and Verhanen's National IQ is an ethnic-based interpolation (i.e., not based on local data) and for which GMAT data are available, a total of 75 countries. Almost all of these countries are small or developing countries. Notice, in Column 1, that the Lynn and Vanhanen (2002) ethnic-based data are shown to be significantly correlated with GDP.

TABLE 3
REGRESSION ANALYSIS OF 2012 GDP PER CAPITA

Dependent Variable - Natural logarithm of 2012 GDP per capita {2}, 75 countries in which L&V 2002 National IQs are ethnicity-based interpolations

Independent Variables	Unweighted -1-	Unweighted -2-	Weighted -3-	Weighted -4-
CONSTANT	4.64	7.07	4.96	7.14
	[7.08]	[7.27]	[8.14]	[6.82]
GMAT IQ		0.04		0.04
(2009-12)		[5.43]		[3.96]
Z(P)		-0.79		-0.77
(2009-12)		[-7.27]		[-5.77]
L&V (2002)	0.05	-0.01	0.05	0.00
IQ	[6.29]	[-0.67]	[6.39]	[-0.29]
R^2 {1}	35.2%	63.7%	35.2%	45.3%

{2} Avg. of IMF and World Bank estimates or CIA estimate if necessary, PPP basis

Column 2 presents the results of a regression in which the GMAT score and the correction term for low participation are included as additional explanatory variables. These GMAT data are from the period 2009-12. Reflecting the mix of countries included in the sample, the number of test-takers in many cases is modest. The median number of test-takers is only 135. The GMAT data enter the regression significantly and with the expected signs. They very substantially increase the explanatory power of the regression as measured by R^2. What is more, including the GMAT score and the correction term for low participation reduces the ethnic-based interpolations of IQ to insignificance. Even though there is reason to suspect that cognitive ability is measured with error by GMAT scores, there is no marginal predictive power in ethnicity once the GMAT-based proxy is taken into account.

Table 4 reports the results of a similar exercise to that reported in Table 3, using 2016 GDP per capita and GMAT data of the period 2013-16. The number of countries is unchanged reflecting the loss of one country and the gain of another. The number of test-takers in particular countries is, again, often modest, with the median now equal to only 100.

TABLE 4
REGRESSION ANALYSIS OF 2016 GDP PER CAPITA
Dependent Variable - Natural logarithm of 2016 GDP per capita {2}, 75 countries in which L&V 2002 National IQs are ethnicity-based interpolations.

Independent Variables	Unweighted -1-	Unweighted -2-	Weighted -3-	Weighted -4-
CONSTANT	4.85	7.62	5.66	9.03
	[7.31]	[10.17]	[8.36]	[9.99]
GMAT IQ		0.04		0.03
(2013-16)		[5.68]		[3.04]
Z(P)		-0.76		-0.77
(2013-16)		[-7.47]		[-5.39]
L&V (2002)	0.05	-0.01	0.04	-0.02
IQ	[5.92]	[-1.57]	[4.59]	[-1.88]
R^2 {1}	32.4%	62.2%	22.4%	32.4%

Column 1 of table 4 reports a regression of GDP per capita on the ethnic-based interpolations of National IQ. These ethnic-based interpolations perform well in predicting GDP per capita. This result is impressive since these GDP data are many years following the study by Lynn and Vanhanen. This seems to be strong evidence that ethnicity is a determinate of National IQ. However, the ethnic-based interpolations are again driven to insignificance upon the introduction of the GMAT data into the regressions. As flawed as the GMAT data appear to be, there is no information in ethnicity beyond what is in the GMAT data.

CONCLUDING REMARKS

National average GMAT scores are strongly correlated with well-established measures of cognitive ability if they are corrected for differences in participation rates. They are available for many small and poor countries for which national IQ and school achievement data are often unavailable. Unfortunately, the national average GMAT scores are often based on small numbers of test takers, resulting in measurement error.

While the proxy for national IQ developed in this study is subject to measurement error, it may be possible to construct a better proxy from a combination of GMAT scores and other sources of information, even if the other sources are themselves subject to measurement error. The important thing would be that there is at least some independence in these measurement errors. Further work in this area is called for.

There may be no good substitute for direct measures of intelligence such as IQ tests and their near kin achievement tests. Continuing efforts to recover the results of past IQ tests and to administer new tests are to be commended. The embrace of internationally-standardized achievement tests by global and regional associations is an important part of promoting economic development.

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