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Decomposing World Education Inequality

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DECOMPOSING WORLD EDUCATION INEQUALITY*

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ABSTRACT

We decompose global inequality in educational achievement into within- and between-country components. We find that the former is significantly larger. This is different than results for international income inequality, but similar to results for international health inequality.

JEL Codes: I20, D39

Keywords: Education, Inequality, Decomposition, Global, TIMSS

1. INTRODUCTION

Recent literature has shown a growing interest in global inequality[1] in part because a series of studies have suggested that inequality may be an important determinant of growth (Aghion, Caroli, and Garcia-Peñalosa, 1999; Alesina and Perotti, 1996; Banerjee and Duflo, 2003; and Barro, 2000), and in part because such studies are now possible: the majority of countries have collected the household survey data necessary to conduct them (Milanovic, 2005; Deninger and Squire, 1996; Glewwe and Grosh, 1999). As with most studies of inequality, the focus of the global inequality literature has been *income* inequality.[2] This paper expands the discussion of global inequality beyond income to a different dimension of well-being: education. In particular, we decompose global inequality in performance on standardized tests into shares that are due to within-country inequality and between-country inequality, in exactly the same way that Milanovic (2002, 2005), Schultz (1998), Goesling (2001) and others have done for income.

Our motivation is twofold. From a theoretical perspective, we are persuaded by Sen's argument that income is not a sufficient statistic for the measurement of well-being or deprivation (Sen 1979, 1985, 1987). Many dimensions of well-being cannot be bought, including some aspects of health, education, political freedom, and voice. Sen argues that these characteristics are *intrinsically* important, while income is *instrumentally* significant. As such, it is important to measure well-being in these dimensions as well as income. From a practical perspective, we have already analyzed a within- and between-country decomposition of world inequality in children's health (Pradhan, Sahn, and Younger, 2003). Rather surprisingly, we found that the decomposition of health inequality is quite different from similar decompositions of income inequality. While the latter typically find that about two-thirds of world income inequality is due to inter-country differences in average incomes (Firebaugh and Goesling, 2004), we found that only about one-third of world child health inequality is due to inter-country differences. Our interest here is to compare a third key dimension of well-being to the existing results for income and health.

The specific measures of well-being that we examine are eighth graders' scores on math and science achievement tests collected by the 1999 and 2003 surveys that were conducted by Trends in International Mathematics and Science Study (TIMSS). These scores are strictly comparable across the 38 and 49 countries included in the 1999 and 2003 rounds of the TIMSS, respectively, which comprise one-quarter of the world's population. Furthermore, as continuous, cardinal variables, these scores are suitable for

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[1] See for example Milanovic (2000, 2005), Sala-i-Martin (2002); Firebaugh (1999); Schultz (1998); and Ravallion and Chen (1997); Becker, Philipson, and Soares (2005).

[2] Pradhan, Sahn, and Younger (2003) study global health inequality, using the stature of young children as their measure of health. Several other papers, including Becker, Philipson, and Soares (2005), Firebaugh and Goesling (2004), and Neumayer (2003) study inter-country inequality in a variety of health and education variables, though none use scores on achievement tests.

the standard tools of distributional analysis. We use these scores to calculate total "world" inequality in math and science knowledge, and then decompose that global inequality into within- and between-country components.

The focus of our analysis is the 2003 test score results, both because they are more recent and because of the greater survey coverage. We also compare the results for 1999 and 2003 to address any differences in educational inequality over this (rather short) time interval. When making inter-temporal comparisons based on the common set of countries, we find trivial differences in the extent of global inequality, and the decomposition into within versus between country inequality, over the four year time interval separating the surveys. Using the available data from a recent and comprehensive study of global income inequality (Milanovic, 2005), we compare our decompositions of math and science achievement with income inequality decompositions for the TIMSS countries, finding them to be significantly different. While income inequality is mostly between-country, achievement inequality is mostly within-country, as was the case with our earlier results on health inequality (Pradhan, Sahn, and Younger, 2003), although the difference here is less dramatic. This adds to the evidence that the intra-country component is more important for non-income measures of inequality than it is for income inequality.

The remainder of the paper is organized as follows. Section 2 briefly discusses the TIMSS data. Section 3 presents the measures of inequality and the related decomposition techniques that we employ. Results follow in Section 4, including a comparison of achievement and income inequality. We conclude with a brief discussion of the implications of the results in Section 5.

2. THE TIMSS DATA

In 1999 and 2003, the International Study Center and Boston College conducted the second and third rounds of the Trends in International Mathematics and Science Study.[3] Achievement tests designed to measure cognitive skills and processes were administered to eighth grade students, ages 13 to 14 years. The test in mathematics covered fractions and number sense, measurement, data representation, analysis and probability, geometry and algebra; the science tests included questions on earth science, life science, physics, chemistry, environmental and resource issues, and scientific inquiry and the nature of science. The tests given and the procedures for data collection and quality control were such that the results are comparable across all countries and across the two surveys.

The 1999 data were collected in 38 countries, while 49 were surveyed in 2003. All but five of the countries in the earlier survey were included in the 2003 survey. In each country, the sample was based on the students enrolled in the upper of the two

[3] See http://nces.ed.gov/timss/index.asp

adjacent grades that contain the largest proportion of 13-year-olds at the time of testing, usually the eighth grade. All samples were intended to be nationally representative, although geographical coverage was restricted in some cases, particularly of the most remote regions. Other students attending extremely small schools or schools offering a curriculum that differed dramatically from the mainstream education system may have been excluded from the sample as well. However, the excluded population was not to exceed 10 percent of the national desired population in any case.

The TIMSS data are unique in their breadth of country coverage for a standardized achievement test, but they do have important limitations for our purposes. In the poorest countries included in the sample, secondary schooling is not universal. Since school children (rather than all children) are the population sampled, there is a potential selection bias, the direction and magnitude of which are indeterminate in theory. The other obvious problem with our analysis is that the even the more comprehensive 2003 TIMSS includes only 49 countries, and these countries are disproportionately rich. There are only six countries from Africa, equally divided between north and south of the Sahara. Chile is the only Latin American country in the survey. India and China are also notable for their absence. This clearly detracts from our claim to estimate “global” achievement inequality. Nevertheless, we explore the likely size of these biases and find that they may not be very large. Given that this is the most comprehensive set of test scores available internationally, and given the importance of education as a measure of well-being, we feel that the exercise is worthwhile.

3. MEASUREMENT AND DECOMPOSITION OF EDUCATION INEQUALITY

As in our previous work, it is convenient to use Generalized Entropy (GE) indices because they are sub-group decomposable:

$$GE(\alpha)=\left(\frac{1}{\alpha(\alpha-1)}\right)\left(\frac{1}{n}\sum_{i=1}^{n}\left(\frac{y_i}{\mu}\right)^{\alpha}-1\right) \tag{1}$$

where y_i is student i's test score, μ is the mean test score, and α is a parameter that can take any real value, although, those most commonly employed are α=0 (often referred to as the Theil L or mean log deviation), α=1 (the Theil T), and α=2 (half the square of the coefficient of variation), all of which we use in our analysis. The difference among the values is the sensitivity to changes in different parts of the distribution, with α=0 giving the most weight to the lower tail. Any GE index is easily decomposable into within- and between-group components for k exhaustive and mutually exclusive groups:

$$GE(\alpha) = \left(\frac{1}{\alpha(\alpha-1)}\right)\left(\frac{1}{n}\sum_{i=1}^{n}\left(\frac{y_i}{\mu}\right)^{\alpha} - 1\right) =$$

$$\left(\frac{1}{\alpha(\alpha-1)}\right)\left[\sum_{k=1}^{K}\frac{n_k}{n}\left(\frac{\mu_k}{\mu}\right)^{\alpha}\left(\frac{1}{n_k}\sum_{i=1}^{n_k}\left(\frac{y_i}{\mu}\right)^{\alpha} - 1\right) + \left(\sum_{k=1}^{K}\frac{n_k}{n}\left(\frac{\mu_k}{\mu}\right)^{\alpha} - 1\right)\right] = \qquad (2)$$

$$\sum_{k=1}^{K}\frac{n_k}{n}\left(\frac{\mu_k}{\mu}\right)^{\alpha} GE(\alpha)_k + GE(\alpha)_B = GE(\alpha)_I + GE(\alpha)_B$$

where y_i is the variable of interest for person i; μ is the overall mean of y; μ_k is the mean for the k^{th} group; n_k is the size of the k^{th} group; and $GE(\alpha)_k$ is the index for the k^{th} group. In words, the generalized entropy index of the entire population can be decomposed into a weighted average of each group's generalized entropy index, called the within-group index $(GE(\alpha)_I)$, and a between group index based on each group's mean value of y $(GE(\alpha)_B)$ and sample size n_k. This decomposability enables us to determine what is driving inequality at the global level.

4. RESULTS

Table 1 reports three generalized entropy indices for 38 countries in 1999 and 49 countries in 2003, both for the math and science test scores. In addition, we show their decomposition into the within- and between-country contribution. Given the similarity of the two results, we focus on the 2003 data. For α=0, total inequality is 0.0339 for math and 0.0373 for science. The within-country share of this inequality is 52 and 56 percent for math and science, respectively.[4] We conducted the same analysis for the common 33 countries in the two surveys. When doing so, we find that the decomposition results for the two surveys were identical for science. For math, they differ by less than one percentage point.[5] While apparently close to a 50-50 split, the standard errors for these estimates are quite small, so that each is significantly different from 50 percent, and from the between-country share, at the one percent significance level. Thus, within-country inequality contributes significantly more than half of global inequality for both math and science test scores. The results are not sensitive to the choice of α, so in the remainder of the analysis we will present information only for the mean log deviations (α=0).

To check the extent to which this decomposition might be biased by the fact that only 49 mostly rich countries are included in the TIMSS sample, we repeated the analysis for all countries in the world, assigning the distribution of scores from the most

[4] The similarity of the science and math test decompositions reflects the high correlations in the scores themselves and their dispersions across the countries included in the sample.

[5] More specifically, the within country share was 53 percent in 2003 and 52 percent in 1999.

comparable TIMSS countries to countries for which we have no data.[6] The within-country share for math scores increases from 52 percent to 59 percent, and that for the science results increases from 56 to 59 percent. While this is clearly a very approximate exercise, it does give us some confidence that the bias inherent in using only 49 countries is not that large, and that it does go in a direction that, if anything, strengthens our conclusions.

To check the selection bias due to the fact that not all children are enrolled in school in poorer countries, we simulated adding a sufficient number of observations to the TIMSS samples so that the total number of observations would correspond to a secondary school enrolment rate of 90 percent.[7] In each case, we drew the additional observations from a normal distribution with the same standard deviation as the country's observed distribution but with the mean shifted down by 0.83 standard deviation to reflect that fact that these students are likely to have lower scores than those in school.[8] This simulation yields within-country shares of 55 and 59 percent for math and science scores, respectively, in both 1999 and 2003. So again, this bias does not seem to be very large, and if anything, it goes in a direction that strengthens our principal conclusion about the relative importance of within country inequality.

To make comparisons to world income inequality, we have to account for the fact that the income inequality data are calculated for data aggregated into income quantiles, usually deciles or vigntiles, rather than for individual observations. Table 1 thus reports the mean log deviation for our data, similarly aggregated to within-country deciles. This reduces the within-country inequality only slightly, and consequently leaves the decomposition little changed. For income, we use the Milanovic data for the 49 TIMSS countries and calculate the mean log deviation, reported in the last column of Table 1. The intra-country share is higher for the education decompositions than it is for incomes, for which only 46 percent is due to within-country inequality. This result is consistent with what we observed in our earlier work that compared health and income decompositions (Pradhan, Sahn and Younger 2003). Given that the sample of countries in that study has very little overlap with the TIMSS countries, we cannot directly compare the health and education decompositions. We can only conclude that for

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[6] The correspondence between TIMSS countries and all countries is available upon request. The most important are that we use Chile's results for all Latin American countries in both surveys. Indonesia's inequality numbers are used for India and China. For African countries, we use Ghana's results for the 2003 survey, and South Africa's for all other African countries in the 1999 survey.

[7] The 2005 World Development Indicators give a net enrolment rate of 90 percent for "high income" countries.

[8] We chose these adjustments based on written mathematics tests for children aged 14 to 16 both in and out of school in Senegal and Madagascar. These surveys show that children who are no longer attending school have a distribution of test scores that is 0.83 standard deviations lower than those still attending school, on average, with approximately the same variance as that for children still in school. See Glick and Sahn (2007) and Dumas, Glick, Lambert, Sarr and Sahn (2004) for details in these surveys and testing procedures.

education, like health, the ratio of intra-country to inter-country inequality is greater than it is for income.

A closer look at the country-specific inequality numbers for 1999 and 2003 reveals a wide range of within-country inequality (Table 2). For example, Hong Kong, Singapore, and Tunisia all have low levels of achievement test inequality, in contrast to South Africa, where inequality is extraordinarily high. Chile, Ghana, the Philippines, Indonesia, Jordan, Palestine and Egypt have high inequality as well. We also statistically compare the changes in inequality over time. A positive sign next to the 2003 results denotes a statistically significant increase in inequality, and a negative sign a decline. For math, 10 countries witness an increase in inequality, while inequality declines in 16 countries. The decline in inequality is even more widespread for science, occurring in 23 countries.

One striking feature of these data is the obvious correlation between average test scores and their dispersion: the Spearman coefficient for the mean and the mean log deviation of the math achievement test is -0.7622; the comparable correlation for science is -0.7715 (Table 3).This is another way in which global education inequality differs from income inequality. The lack of correlation between income inequality and average incomes is well-known (Kanbur, 2000).

Despite these strong correlations, for any narrow band of math or science scores, there is a wide range of inequality values. For example, if we look at math scores in five Middle Eastern and North African countries—Bahrain, Egypt, Iran, Jordan, and Tunisia—all have quite similar mean math test scores, ranging between 401 and 423. However, math inequality for those four countries differs markedly, the mean log deviation is 0.0162, 0.0.0238, 0.0140, 0.0209, and 0.0088 respectively. Thus, it is clear that countries with comparable levels of educational achievement can have very different degrees of education inequality, and vice versa, despite the overall high correlation between these two statistics.

The significant correlation of math and science inequality with their respective means suggests that there is something inherent in the process of determining the inequality of education that may contribute to the strong negative correlation with levels of achievement, in contrast to income. One possible explanation for this difference is that the distribution of test scores does not have the long rightward tail that is typical of income distributions. Rich people in rich countries can be (almost) infinitely richer than everyone else – witness Bill Gates. But smart people in smart countries cannot be infinitely smarter. This means that as the mean of the test score distribution increases, it is increasingly likely that it is mostly improvements at the lower end of the distribution that are bringing up the mean. The same is not true for incomes.

Finally, we are also interested in the relationship between our education inequality index numbers and the comparable figures for income inequality, particularly in light of the difference of the within and between-country decomposition results. The rank correlation between the income mean log deviation and those for math and science inequality is 0.2426 for math and 0.3254 for science, and only significant in the case of the latter.[9]

5. CONCLUSION

In this paper we have analyzed education inequality over a broad sample of students 13-14 years of age (generally in 8th grade) throughout the world using the TIMSS data on math and science knowledge. We have done so using data from both the 1999 and 2003 surveys, comparing the results over time. Our results indicate that slightly more than half of total inequality in achievement is attributable to intra-country differences. This is significantly higher than similar calculations for income inequality for the same set of countries. The results are similar to, if less striking than, our earlier work on world health inequality (Pradhan, Sahn and Younger, 2003). Thus, world inequality in at least two important non-income dimensions of well-being is more likely to be within- rather than between-country, in contrast to now standard results for income. Our inter-temporal comparisons of the two surveys suggest no significant change in the decomposition analysis, something not surprising given the relatively short time interval separating the surveys. Although, at the country level there is evidence that education inequality is declining, especially for science.

The sample of TIMSS countries is not random, nor can it make the same claim to fairly represent the world's population of eighth graders that earlier work on income and health can make. In particular, poor and developing countries where performance on achievement tests is likely to be low are under-sampled. It would clearly be of great interest to extend the TIMSS to poorer regions of the world, particularly India, China, and a larger sample of countries in Africa and Latin America. That said, doing so will raise more selection problems because the sample of 13-year-olds that attend school in poor countries is not as representative of 13-year-olds in general as it is in wealthier countries. However, our simulations designed to deal with sample selection and the low shares of enrollees with the existing TIMSS data suggest that neither of these biases is very large for the decomposition analysis.

This research is part of a larger effort to extend inequality and poverty analysis to non-income dimensions of well-being, inspired by Sen's seminal theory. One objection to this effort is that the cognitive skills and processes that are measured by math and science knowledge are not "redistributable" in the same way that income is. The analysis of income distributions is often conducted with an eye to the immediate public policy debate on tax and expenditure policy as a means to *re*distribute income. It is not possible, of course, to think about redistributing knowledge and the performance on achievement tests in the same fashion. This, however, does not negate the role of public policy choices in terms of affecting the distribution of cognitive skills and processes. It is entirely possible for public policy to change the distribution of educational outcomes (while leaving the

[9] Excluding the two obvious outliers, Ghana and South Africa, has little effect on these rank correlations.

mean unchanged). For example, government could choose to place a greater emphasis on primary or secondary schools in remote rural areas where individuals test score achievement are lagging at the expense of urban schools where performance is higher. Such action is not quite analogous to redistributing incomes because, for a given cohort, it does not take away knowledge from some people and distribute it to others. For newer cohorts, however, it does change the distribution of educational outcomes. As a result, we feel that distributional analysis of knowledge and achievement is both interesting and relevant to policy makers.

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TABLE 1. (2003)
Within and Between Country Decomposition of Achievement Test Scores and Incomes

	Individuals						Deciles		Income
	GE(0)		GE(1)		GE(2)		GE(0)		GE(0)
	Math	Science	Math	Science	Math	Science	Math	Science	
Intra-country	0.0177	0.0208	0.0158	0.0162	0.0150	0.0144	0.0194	0.0234	0.2458
share	52%	56%	51%	52%	51%	51%	57%	63%	46%
Inter-country	0.0162	0.0166	0.0152	0.0149	0.0146	0.0137	0.0145	0.0139	0.2851
share	48%	44%	49%	48%	49%	49%	43%	37%	54%
Total	0.0339	0.0373	0.0310	0.0311	0.0295	0.0281	0.0339	0.0373	0.5309

TABLE 1. (1999)
Within and Between Country Decomposition of Achievement Test Scores and Incomes

	Individuals						Deciles		Income
	GE(0)		GE(1)		GE(2)		GE(0)		GE(0)
	Math	Science	Math	Science	Math	Science	Math	Science	
Intra-country	0.0183	0.0209	0.0163	0.0171	0.0154	0.0155	0.0191	0.0223	0.2458
share	54%	56%	52%	54%	52%	54%	56%	60%	46%
Inter-country	0.0158	0.0164	0.0148	0.0145	0.0140	0.0131	0.0150	0.0150	0.2851
share	46%	44%	48%	46%	48%	46%	44%	40%	54%
Total	0.0341	0.0373	0.0311	0.0316	0.0294	0.0286	0.0341	0.0373	0.5309

TABLE 2.
Test Scores, Incomes Per Capita, and Within Country Inequality for Math and Science, 2003

	Math			Science		
Country	Test Score	GE(0)	chg from 1999*	Science	GE(0)	chg from 1999*
Armenia	478.1	0.0148	N/A	461.3	0.0140	N/A
Australia	504.7	0.0127	+	527.0	0.0098	-
Bahrain	401.2	0.0162	N/A	438.3	0.0129	N/A
Belgium (fl.)	536.7	0.0097	N/C	515.5	0.0084	+
Botswana	366.3	0.0158	N/A	364.6	0.0252	N/A
Bulgaria	476.2	0.0150	+	478.8	0.0190	+
Chile	386.9	0.0206	+	412.9	0.0184	N/C
Cyprus	459.4	0.0152	+	441.5	0.0150	N/C
Egypt	406.2	0.0238	N/A	421.1	0.0298	N/A
England	498.5	0.0114	-	543.9	0.0095	-
Estonia	530.9	0.0080	N/A	552.3	0.0063	N/A
Ghana	275.7	0.0448	N/A	255.3	0.1203	N/A
Hong Kong	586.1	0.0076	N/C	556.1	0.0067	-
Hungary	529.3	0.0111	-	542.8	0.0093	-
Indonesia	410.7	0.0222	-	420.2	0.0162	N/C
Iran	411.4	0.0140	-	453.4	0.0111	-
Israel	495.6	0.0141	-	488.2	0.0143	-
Italy	483.6	0.0120	-	490.9	0.0118	-
Japan	569.9	0.0096	N/C	552.2	0.0078	-
Jordan	424.4	0.0209	-	474.8	0.0174	-
Korea	589.1	0.0102	+	558.4	0.0073	-
Latvia	508.3	0.0098	-	512.4	0.0079	-
Lebanon	433.0	0.0105	N/A	393.4	0.0254	N/A
Lithuania	501.6	0.0116	N/C	519.4	0.0082	-
Macedonia	435.0	0.0201	-	449.4	0.0205	N/C
Malaysia	508.3	0.0101	-	510.5	0.0077	-
Moldova	459.9	0.0146	N/C	472.4	0.0110	-
Morocco	386.5	0.0125	-	396.5	0.0121	-
Netherlands	536.3	0.0083	N/C	535.8	0.0062	-
New Zealand	494.0	0.0121	-	519.7	0.0096	-
Norway	461.5	0.0112	N/A	493.9	0.0093	N/A
Palestine	390.5	0.0252	N/A	435.4	0.0217	N/A
Philippines	377.7	0.0235	-	377.4	0.0347	-
Romania	475.3	0.0178	N/C	469.6	0.0182	N/C
Russia	508.0	0.0108	-	513.6	0.0100	-
Saudi Arabia	331.7	0.0238	N/A	397.7	0.0142	N/A
Scotland	497.7	0.0111	N/A	511.5	0.0105	N/A

continued

TABLE 2 *continued*.
Test Scores, Incomes Per Capita, and Within Country Inequality for Math and Science, 2003

	Math			**Science**		
Country	Test Score	GE(0)	chg from 1999*	Science	GE(0)	chg from 1999*
Serbia & Montenegro	476.6	0.0171	N/A	467.7	0.0151	N/A
Singapore	605.5	0.0089	+	577.8	0.0132	-
Slovakia	507.7	0.0129	+	516.8	0.0103	+
Slovenia	493.0	0.0098	-	520.5	0.0075	-
South Africa	263.6	0.0672	+	243.7	0.1332	+
Sweden	499.1	0.0097	N/A	524.3	0.0094	N/A
Syria	357.6	0.0199	N/A	410.6	0.0163	N/A
Taiwan	585.3	0.0151	-	571.1	0.0094	-
Tunisia	410.3	0.0088	+	403.5	0.0087	N/C
United States	504.4	0.0122	-	527.3	0.0114	-

* + means there was a statistically significant increase in inequality between 1999 and 2003
- means there was a statistically significant decrease in inequality between 1999 and 2003
N/C means there was no statatistically significant change in inequality between 1999 and 2003
N/A means data were not available for comparing 1999 and 2003

TABLE 3.
Rank Correlation Matrix between Mean Values and Inequality, All Countries, 2003

	Means					
	Math		Science		Income	
Inequality (GE(0))						
Math						
Rank Correlation	-0.7622	**	–		-0.5749	**
Science						
Rank Correlation	–		-0.7715	**	-0.5759	**

*Indicates significant at 10% level

*Indicates significant at 1% level