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National Income, Income Inequality, and the Importance of Schools: A Hierarchical Cross-National Comparison

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The international and comparative education literature is not in agreement over the role of schools in student learning. The authors reexamine this debate across 25 diverse countries participating in the fourth-grade application of the 2003 Trends in International Mathematics and Science Study. The authors find the following: (a) In most cases, family background is more important than schools in understanding variations in student performance; (b) schools are nonetheless a significant source of variation in student performance, especially in poor and unequal countries; (c) in some cases, schools may bridge the achievement gap between high and low socioeconomic status children. However, schools' ability to do so is not systematically related to a country's economic or inequality status.

KEYWORDS: school, family, income, inequality, cross-national

The international and comparative education literature is not in agreement over the role that school resources play in learning. Beginning with the 1966 Coleman Report, which argued that family background variables are paramount in understanding variations in student performance, many studies have evaluated the impact of family and school factors on student

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achievement. In an influential multicountry study, Heyneman and Loxley (H-L) (1983) challenged the universality of the Coleman Report.[1] They argued that in low-income countries, school quality constitutes the predominant influence on student learning, possibly because scarcity of educational places in lower-income countries leads to a greater educational "push" from families for children to perform well, regardless of their socioeconomic status (SES). Recently, however, studies using different data sets, methods, and measures have questioned the H-L findings (Baker, Goesling, & Letendre, 2002; Hanushek & Luque, 2003; Harris, 2007). For example, Baker et al. (2002) find a "vanishing HL effect" between the 1970s and 1994 and hypothesize that increasing access of children to school through governments' funding of mass schooling has diminished the differentially positive impact of school resources in low-income countries. A potential corollary of the H-L hypothesis is that in developing countries, specific school factors are more uniformly significant in explaining variations in student achievement. But the international literature has not yet reached a consensus on which specific school resources matter and the extent to which they matter (e.g., Fuller, 1987; Hanushek, 1995b; Kremer, 1995).

Thus, in cross-national studies of achievement, we are faced with two related but unresolved questions, each with different policy implications. First, in explaining variations in achievement, does the impact of schools relative to the impact of families decrease as national income increases? Second, independent of the comparison with family factors, do schools matter more in low-income countries than in wealthier countries? With respect to the first question, the key issues are whether, *within countries*, schools outweigh families in terms of their ability to influence achievement and whether the impact of schools *relative to families* varies *across countries* with different income levels. The second question addresses whether the *overall* impact of schools varies *across countries* with different income levels.

These questions are important not only for researchers but also for policy makers, especially in developing nations. Considerable evidence suggests that differences in national educational achievement are strongly related to differences in economic growth (Barro, 2001; Hanushek & Kimko, 2000, Hanushek & Woessman, 2007). Educational achievement, in turn, depends on school and family factors. Within countries, identifying the role of schools relative to families could therefore serve as an important guide for policy makers as they allocate scarce educational resources. With respect to our first question, if research can establish that schools are more important than families in certain countries, policy recommendations must place greater weight on schools in such settings.[2] In response to our second question, information on cross-country patterns in the overall impact of schools can help toward more targeted international aid policies.

To understand the importance of schools vis-à-vis families across countries, this study revisits the H-L hypothesis using 2003 Trends in International Mathematics and Science Study (TIMSS) data from 25 countries.[3] We also revisit the related debate regarding the overall importance of schools in explaining variations in student achievement across countries with different economic conditions. In addition, we argue that previous studies have ignored national income inequality levels in understanding the relative and overall importance of schools. Therefore, unlike earlier cross-national studies, we also examine the impact of schools across different levels of income inequality. Finally, we make a preliminary effort to understand not only if schools matter differently in rich and poor and equal and unequal countries but also if schools play a role in bridging the achievement gap between high and low SES children and if this role of the school varies by country income and inequality levels. Guided by an extensive review of the current literature and its potential limitations, our study departs from the existing literature in several important respects. Specifically, we use fourth-grade rather than conventionally used eighth-grade TIMSS data, we conduct 25 sets of separate country-level hierarchical linear model (HLM) analyses for decomposing variance attributable to schools and family, and we explicitly focus on country inequality levels as an important country-context variable in addition to the traditionally used economic-context measure.

Literature Review

After briefly reviewing the impact of the family on student achievement, we discuss research regarding the role of schools relative to family, as well as the overall impact of schools. We also address inconsistencies in the school resource literature, as well as the importance (and omission) of inequality in these discussions.

Relationship Between Family Background and Achievement

Although different studies use different family background measures (e.g., parental education, family income and occupation, expenditures, and household size), there is little disagreement that family background characteristics profoundly influence children's schooling outcomes. Specifically, children whose families have higher SES, more learning-related resources, and better-educated parents tend to perform better in school (e.g., Buchmann & Hannum, 2001).

In addition to a large literature in the United States, cross-national studies of achievement also support the importance of the family. In their multicountry, three-level hierarchical analysis, Baker et al. (2002) show that a family's SES (indicated by father's education, mother's education, and number of books at home) has a positive and significant relationship with student achievement in both mathematics and science. In their classroom-level analysis of multicountry data, Hanushek and Luque (2003) similarly note the importance of home learning resources and parental education. Using a different international data set, Chiu and Khoo (2005) also find that higher levels of family resources are associated with higher school performance.

Cross-national studies have also examined interactions between country contexts and the impact of the family. Using multilevel analysis of data from 107,834 fifteen-year-olds in 41 countries, Chiu (2007) notes that "family constructs" are particularly strongly linked with achievement in "economically and culturally developed" countries. Schiller, Khmelkov, & Wang (2002) find that the positive effect of family background on math test scores is "remarkably consistent" among the 34 countries studied, but the relative advantage of living with "traditional families" is especially greater in affluent economies. These two studies support the original H-L result that family background is relatively less important in lower-income countries.

Aside from the universally acknowledged importance of family background, a review of the literature also illustrates the difficulties of "controlling for family background" while working with multicountry data. Most studies (including this one) use preexisting international data collected from children across the world. Through standardized questionnaires, such preexisting data aim to provide an accurate snapshot of family SES from different countries. This approach has its own limitations. Fuller and Clarke (1994) argue that studies in developing countries may often use social class measures that are not culturally relevant to the community studied. They therefore caution researchers against putting extensive faith in "Western" measures of SES.

While it is important to acknowledge the limitations of international data, we also note that extensive thought, international consultation, time, pretesting, and attention to detail—including the language and length of questions—go into designing background questionnaires (Martin, Mullis, & Chrostowski, 2004). For instance, in the TIMSS 2003 survey, fourth-grade children are not asked to report on their parents' education level because they are not expected to know it accurately. In a question about number of books at home, children are provided with accompanying visuals of one, two, or more bookcases. Similarly, the student background survey includes questions about home possessions where, rather than using a generic set of variables for all countries, care is taken to identify country-specific indicators of families' SES.

In an extensive review of family background measures, Buchmann (2002, pp. 168) rightly notes that international comparative researchers must walk a "fine line" between sensitivity to local context and concerns about comparability across multiple countries. In this study, we make a sincere attempt to address these concerns, most importantly by estimating separate models for each country in our analysis in the ordinary least squares (OLS) and HLM frameworks. Nonetheless, we must acknowledge that our study is not entirely free from these challenges.

Relationship Between School Resources and Achievement

Before discussing the importance of school resources in developing countries, we must first clarify relevant concepts. As noted earlier, researchers disagree about the relative importance of school and family factors, as well as the overall importance of specific school factors in improving learning outcomes. In part, this may be because various studies and syntheses of studies fail to distinguish between the *relative importance* of school versus family in poor countries and the *overall importance of (specific) school resources* in poor countries. This distinction is important from a policy perspective because while all the specific school variables introduced in a model may be statistically significant in a given country, that does not prove that schools are more important than families. Instead, both school and family factors may be significant, but family factors may be even more important.

This distinction is also important from an analytical standpoint because each question demands a slightly different research method. In the first case (schools relative to families), we decompose the total explained variance in test scores into school (V_{sch}) and family (V_{fam}) and identify the proportion of explained variance attributable to schools ($pr.V_{sch} = V_{sch} / (V_{sch} + V_{fam})$), or ($pr.V_{sch} = (V_{sch} / V_{total})$). In the second instance (overall impact of schools), we identify the variance in test scores attributable to school factors that matter in improving test scores (V_{sch}). Because the first approach examines proportions and the second absolute values, each may produce a different rank ordering of countries in the degree to which schools matter more relative to families and in the overall impact of schools. Finally, the first approach involves two sets of comparisons: (a) comparing the role of school versus family and (b) comparing the relative role of the school in rich versus poor countries. So a researcher may find that in no country does the importance of school exceed that of family, but the relative role of schools in poor countries may still exceed the relative role of schools in rich countries.

Relative Importance of Schools in Poor Countries

In their study using 1970s data from 28 countries—including Africa, Asia, Latin America, and the Middle East—H-L (1983) included an extensive and diverse set of measures. They decomposed the explained variance (adjusted R^2) into variance due to "preschool" factors (family background) and variance due to school and teacher quality variables. They showed that with diminishing GNP per capita, the proportion of variance explained by school and teacher quality variables increased. In fact, in low-income countries, school and teacher variables explained more of the variance in student achievement than family variables; in other words, in poor countries, school was relatively more important than family. While this study had a large impact on both cross-national literature and development aid, it was not without critics. For example, Riddell (1989) argued that H-L ignored the inherently hierarchical structure of the data, with students clustered within schools. Riddell also argued that better measures of school resources may intensify the effect of school variables since the R^2 of an equation is only a reflection of what one is able to measure (Riddell, 1989, pp. 487). In Heyneman's (1989) response to Riddell, he pointed to some of the flaws in Riddell's own approach and noted the relative recency of multilevel techniques and related computing ability. In addition, he argued that differences in methodological approach do not necessarily invalidate the OLS findings.

Subsequent researchers have used large cross-national data sets and different sets of school controls in attempts to duplicate the H-L results. For the most part, these studies have failed to find the H-L effect (Baker et al., 2002; Hanushek & Luque, 2003). Also, while Baker et al. (2002) use multilevel modeling, they do not split variance in student achievement into school and family variables. Instead, they focus on the relationship between country background and the impact of school measures on achievement (which is more akin to studying the "overall" effect of school variables).

Two other studies that employ the multilevel modeling approach to split the variance in student performance found that family variables explain a greater proportion of the variation in student performance relative to school variables in the country studied (see Buchmann & Hannum, 2001, for a summary). However, because these studies are limited to single developing countries, they address only the first part of the comparison (school vs. family) and not the second part (relative importance of schools in rich vs. poor countries).

The Overall Importance of School Resources in Developing Countries

Several studies of developing countries have attempted to identify the role of specific school variables in explaining student achievement. Many of these studies fit within the production function framework of economics, in which researchers see the production of education as a function of several different inputs and attempt to identify important inputs for a given context or country.

Starting with Fuller's (1987) review of 60 studies from developing countries, researchers have attempted to synthesize findings of production function studies from the developing world, most notably, Fuller and Clarke (1994), Hanushek (1995a, 1995b), and Velez, Schiefelbein, and Valenzuela (1993). Notwithstanding concerns about efficiency (Hanushek, 1995b), in general, these studies find that to varying extents, certain school and teacher variables appear to be uniformly important and significant in developing countries. Fuller (1987) notes the importance of material resources; in a later analysis, Fuller and Clarke (1994) argue for the importance of textbooks, teacher quality, instructional time, and the demands placed on students in improving learning outcomes. Similarly, Hanushek (1995a) notes that some school resources tend to have a greater positive relationship with student outcomes in lower-income countries, results that "clearly suggest a possible differentiation by stage of development and general level of resources available" (p. 281). Hanushek (1995a) also found some evidence for the importance of teacher experience and education, as well as basic facilities such as quality of buildings and libraries. Similarly, after an extensive review of research from Latin America, Velez et al. (1993) identified 12 school-based or alterable variables that are related with achievement. The general conclusion from these studies is that basic material resources are relatively more important in contexts that have inadequate or very unequally distributed educational resources (Buchmann & Hannum, 2001, p. 86).

More recent multicountry studies, however, have failed to find that schools matter more in poor countries. Using a three-level HLM analysis, Baker et al. (2002) focused on two specific indicators of whether student background and school resource effects vary according to the level of economic development in a country.[4] They found that neither of these two coefficients was statistically significant for either math or science, leading them to conclude that in the 1990s data, economic development is not related to either the relationship between family background and student achievement or the relationship between school resources and student achievement (p. 304). This approach has been criticized, however, for proposing a single production function for the divergent countries in their analysis (Harris, 2007). In other words, proposing one three-level HLM does not allow for relationships between inputs and outputs to vary across countries. Yet it is difficult to imagine that the relationship between, for example, teachers' experience and student achievement is the same across 25 diverse countries.

In an analysis of 1999 TIMSS data, Harris (2007) explicitly searches for evidence of diminishing marginal returns (DMR) to national income across countries. If, in economically more advanced countries, where school inputs are already higher, incremental increases in school inputs yield smaller gains in learning outcomes, compared to poor countries where school inputs are lower, then such differential impacts would support the possibility of diminishing marginal returns. However, although he implemented various tests and used data from 32 countries, Harris did not find solid evidence in favor of DMR except for some evidence with regard to teacher-related variables.

Similarly, in an analysis of 1995 TIMSS data aggregated to the classroom level, Hanushek and Luque (2003) did not find support for the argument that school resources are more important in poor countries than in wealthier ones. Their results also showed a negative relationship between achievement and expenditure per pupil, proportion of GDP devoted to public education, and pupil-teacher ratio in primary education. Using several relevant background controls, their school factors included total enrollment, teacher degree level and experience, grade level, and class size. In very few countries did they find a significant relationship in the expected direction between a specific school variable and achievement. Furthermore, none of their school variables was especially important in poorer countries. For instance, in plotting coefficient estimates associated with class-size reduction across GNP per capita, they found that these coefficients are not systematically larger in poorer countries.

Finally, two single country studies are worthy of note due to their unique methodology and data use. Heyneman, Jamison, and Montenegro (1984) analyzed the impact of textbook provision in Philippines. Due to the nationwide simultaneous implementation of the project, they used a randomly selected sample of children from the preproject year to serve as the control group. They found that while family background was an important determinant of student performance, the intervention was more effective for children from impoverished backgrounds.

Second, it is valuable to note the findings of a recent experimental study in Kenya. While focused on just one country and one specific school input, the findings are potentially generalizable due to the rigor of research methods used. Glewwe, Kremmer, Moulin, and Zitzewitz (2004) studied flip-chart use in Kenyan schools. While a cross-sectional (or "retrospective") study showed that flip-charts were important in improving student learning, a randomized experiment indicated that providing a flip-chart was not in itself crucial in improving test scores. This discrepancy may arise due to the inability of cross-sectional studies to adequately control for school resources.

The above literature highlights three important points. First, there is an important distinction between research that focuses on decomposing the variance between school and family variables and the research that focuses only on the role of school variables. Second, the literature highlights the lack of consensus about the relative importance of school versus family in developing countries. Finally, this review demonstrates a similar disagreement about the overall importance of school resources in developing countries.

Why These Inconsistencies?

We see several possible explanations for discrepancies among different studies. One relates to the age group of children analyzed by most of these studies over the past several decades. Data sets that sample eighth graders (TIMSS) and 15-year-olds (Program for International Student Assessment [PISA]) represent a fundamentally different population of children than the overall population of children in a given country. In most countries, and especially developing ones, children steadily drop out of school as they grow older.[5] This attrition may lead to greater homogeneity in student background among those who remain in school, which may in turn attenuate the effect of student background on test scores. One could also argue that because younger children spend more time with the family, they may be more prone to family influences. Blossfield and Shavit (1993) use the "life-course hypothesis" in arguing that as children grow older, they grow less dependent on family resources in deciding their course of action (p. 9). Reviewing evidence from 13 countries, Shavit and Blossfield show that with one exception (Switzerland), the effects of "social origin are strongest at the beginning of the educational career and then decline for subsequent educational transitions" (p. 18).

A second challenge plagues these studies: how to effectively measure school-level resources. Various researchers have noted the challenges of measuring or even effectively describing relevant and important school resources, including school context and organization (Fuller, 1987; Hanushek, 1995b). Similarly, the authors of the Kenyan flip-chart study note that the discrepancy between retrospective and randomized trial-based prospective studies may indicate an omitted variable bias where schools with flip-charts tend to do better because of other *unmeasured but* *related school-quality* indicators. Thus, while schools may be important in improving learning outcomes, specific school measures (in this case flip-charts) may not be as crucial in improving learning achievement (Glewwe et al., 2004). Clearly, difficulties in measuring relevant school resources present a fundamental challenge for any study examining the role of schools.

Finally, discrepancies among studies may stem from differences in country samples, which could lead to differences in economic background and income inequality levels. Gamoran and Long (2007) argue that inconsistencies in findings stem from the fact that in contrast to the original H-L data, the TIMSS and PISA samples have typically collected data on the "advantaged populations, compared to the global averages" (p. 12). They compare the global averages for data collection years to show that while H-L sample countries had an average per capita income only 50% greater than the global average, subsequent reanalyses of the H-L hypothesis using TIMSS data have used samples with per capita income 300% greater than the global average. Citing Long's 2006 analysis of *Primer Estudio Internacional Comparativo* (PEIC) data from Latin America, they note that in these relatively poor countries, the percentage of total variance explained by schools is large and comparable to the original H-L findings. Finally, they plot the relationship between per capita income (in 1990 dollars) and percentage variance explained using original H-L (1983) results, Baker et al. (2002) results using TIMSS 1995 data, and Long's (2006) results using PEIC data. Using a simple linear regression to examine the fit between per capita income and variance explained, they find a threshold of $16,000 in per capita income. Below this threshold, the fit between national income and variance explained is higher ($R^2 = 31\%$) than the fit in countries above the threshold ($R^2 = 9\%$). Thus, they argue that in the appropriately sampled low-income countries, H-L results continue to hold.

In addition to varying income levels, it is likely that subsequent samples may have been very different in levels of income inequality. Baker et al.'s (2002) analysis contained fewer Latin American countries than those of H-L, whose data from the early 1970s included Bolivia, Brazil, Chile, Colombia, El Salvador, Mexico, Paraguay, and Peru. Baker et al. point out that the 1970s country sample includes more poor Latin American countries, where inequality is high and a large proportion of children from wealthy families attend private schools, while their own data from 1995 feature a greater proportion of poor countries from the former Soviet Union, which have relatively low levels of inequality and private school attendance. In contrast, greater inequality in school resource distribution in the original H-L sample may have strengthened the statistical power of school resources to predict achievement, thereby enhancing the H-L effect. If inequality influences the relationship between national income and the impact that schools have on achievement, then failure to consider inequality differences in country samples may lead to inaccurate conclusions.

The Importance of Inequality

Despite the possibility that income inequality can mitigate (or exacerbate) the school-student relationship, the studies discussed above, with the exception of Chiu and Khoo (2005) and Chiu (2007), do not consider the role of income inequality. To explain their results, H-L (1983) consider the possibility that in developing countries, social class may be less important because such countries may have greater homogeneity (or less inequality) in social class to begin with, but they discard this idea after a brief analysis. However, income inequality may be important in understanding the relative importance of schools in a country over and above income levels. Chiu (2007) found that students living in countries with more equal income distribution have higher science test scores. In contrast, a high level of income inequality may intensify the level of poverty faced by poor children, especially in developing countries. As a result, access to school resources—albeit rare—may have a large impact on the performance of poor children.

If a country has unequal income distribution (income inequality) but its schools have more equally distributed resources (resource equality), then to some extent schools may be able to mitigate the benefits associated with higher SES. Conversely, in an unequal country, if school resources are skewed toward wealthier children, then schools will exacerbate the disadvantages faced by low-SES children. Chiu and Khoo (2005) refer to this as the "privileged student bias." Furthermore, the DMR hypothesis argues that a poor child would benefit more from an additional unit of school resources than would a rich child. If this is true, then in the first scenario, overall returns for investment in school resources would be higher, and in the second scenario, they would be lower due to greater investment in "low-yield" privileged students. Indeed, Chiu and Khoo (2005) suggest that policies to weaken privileged student bias and redirect school resources toward less advantaged students could boost the overall impact of school resources.

Summary of Literature Review

Our review of the literature points to a few specific limitations in prior studies. With respect to decomposing the variance between school and family factors, prior studies may underreport the importance of family background variables to the extent that attrition makes the older student population more homogenous. Second, while a few individual country studies have used hierarchical models to decompose variance, this approach has not been adopted systematically for multicountry data. Third, while all the studies cited here have used different (and sometimes similar) sets of specific measures of school resources, researchers have also argued that it is difficult to effectively measure relevant school variables. Thus, while schools may matter, a specific set of resources may not adequately reflect the importance of schools, especially if they are not correctly measured, or if they do not vary much across schools. Four, prior studies have not explicitly considered inequality levels across countries in determining the relative importance of schools.

Our study addresses all of these limitations. We work with data from fourth grade both to reduce the potential selection bias in working with older children and to examine the relative impact of schools and families among younger children. Unlike prior studies, we use separate HLMs for each country analyzed to decompose the variance in test score between family and school variables, which allows each country to have a unique relationship between these variables and student achievement. To overcome the challenges of adequately measuring school attributes, we use a different analytical approach compared to prior work: Instead of focusing on the variance explained by specific school factors, we quantify the variance attributable to school factors as a whole. This addresses concerns raised by earlier studies: A given measure of school resources may be limited in itself, and the lack of significance of a specific measure does not indicate that schools overall do not matter. Finally, we explicitly consider cross-country differences in inequality levels and explore how schools may mediate the relationship between family background and student learning outcomes.

Data and Method

In revisiting the results of the H-L hypothesis and extending the analysis beyond that work, our study aims to address the following seven questions:

Schools relative to family

1. Do school differences account for more variance in student achievement than family differences across 25 countries?

Schools relative to family in light of country context

2. Do school differences account for more variance in student achievement relative to variance explained by family differences in poor countries?
3. Do school differences account for more variance in student achievement relative to variance explained by family differences in unequal countries?

Overall role of schools in light of the country context

4. Do schools account for more of the overall variation in student achievement in poor countries relative to wealthier countries?
5. Do schools account for more of the overall variation in student achievement in unequal countries relative to more equal countries?

Schools' role in bridging SES-based achievement gaps

6. Do schools influence the relationship between student family background (SES) and learning achievement?

Schools' role in bridging SES-based achievement gap in light of the country context

7. If schools do influence these relationships, does their ability to do so vary once again by the country's income and inequality levels?

Data: TIMSS 2003, Grade 4

To explore the questions discussed above, we use fourth-grade data from the 2003 application of TIMSS. TIMSS collects test-score data in mathematics and science in the fourth and eighth grades, along with extensive background information on students, principals, math and science teachers, and curriculum. In the 2003 TIMSS, 26 countries participated in the fourth-grade survey and 49 countries in the eighth-grade survey. However, because Yemen did not meet requirements for reporting data in TIMSS documentation, we work with the remaining 25 countries (Gonzales et al., 2004). These countries represent a wide range of national incomes, levels of income inequality, and geographical regions, including two North African countries (Tunisia and Morocco) and five countries classified by the World Bank as having lower-middle incomes (Armenia, Iran, Philippines, Morocco, and Tunisia).

Variables. Table A1 in the Appendix provides a list of all the variables used in this study, and Table A2 lists sample sizes. Our key dependent variables are student test scores on mathematics and science achievement tests as represented by five plausible values. To ensure that our analysis reflects the broader population of each country, we also include sample weights related to the probability of being included in the sample (Martin, 2005).

At the individual student level, we control for students' age and gender and include indices available in TIMSS data that measure students' self-confidence in learning the subject (math or science depending on the dependent variable), the time they spend on subject homework, and their perceptions of whether they are safe in the school.[6] We include these variables to control for characteristics of individual students that may be related to both school resources and student achievement.

At the family level, we take into account whether the student's family speaks the test language at home. Unfortunately, the fourth-grade data do not provide information on parental education, occupation, or income. For our SES measure, we constructed an index of educational capital in the home, or "SESEDCAP," which is based on students' answers regarding family possessions related to learning: dictionary, calculator, computer, desk (1 = *yes* and 0 = *no*), and books in the home (1 = *no or few books* to 5 = *more than 200 books*). This variable ranges from a minimum of 1 to a maximum of 9.[7] We chose this measure of SES as it seemed to be the family status indicator that would be related most closely to educational outcomes and at the same time provide a fair proxy for the family's economic status and parental education.[8]

Measures of country income and inequality levels. In order to measure the overall economic status and inequality levels of our sample countries, we used preexisting (or external) measures and generated country-specific (or internal) measures from the TIMSS data (see Table 1). We used two external

Table 1

Country Background Including Internal and External Measures of Economic and Inequality Status

	External Measures				Internal Measures				
Country	Per Capita GDP (PPP), 2005	Gini Index	Gini Index Source Year	Composite Rank	Mean SES Value	Internal Gini	Composite Rank	TIMSS Math Score	TIMSS Science Score
MDA	2,190	33.20	2003	9.00	4.71	.21	5.0	504	496
PHL	2,956	44.50	2003	1.50	4.24	.23	4.0	358	332
MAR	3,554	39.50	1998-99	5.00	3.41	.24	1.5	347	304
ARM	4,162	33.80	2003	10.00	5.22	.19	6.0	456	437
TUN	6,382	38.90	2000	6.50	4.14	.23	3.0	339	314
IRN	9,314	43.00	1998	4.50	3.57	.30	1.5	389	414
RUS	11,858	39.90	2002	6.50	5.54	.17	7.0	532	526
LVA	13,215	37.70	2003	8.50	6.34	.13	14.0	536	532
LTU	14,084	36.00	2003	10.00	5.72	.15	8.5	534	512
HUN	17,014	26.90	2002	16.50	6.62	.13	16.0	529	530
SVN	22,506	28.40	1998	16.50	6.32	.13	12.5	479	490
CYP	24,534	29.00	2005	16.50	6.25	.13	13.5	510	480
NZL	24,566	36.20	1997	11.50	6.70	.13	21.0	493	520
TWN	26,057	32.60	2000	16.50	6.59	.13	16.5	564	551
ITA	27,750	36.00	2000	13.50	5.86	.15	8.5	503	516
JPN	30,290	24.90	1993	20.50	6.39	.11	19.0	565	543
SCO	31,371	36.00	2000	16.00	6.64	.14	16.0	490	502
ENG	31,371	36.00	2000	15.00	6.80	.12	22.0	531	540
BFL	31,699	33.00	2000	18.50	6.61	.11	21.0	551	518
AUS	34,106	35.20	1994	17.50	7.08	.11	24.0	499	521
NLD	34,492	30.90	1999	20.50	6.70	.12	21.5	540	525
HKG	35,690	43.40	2004	12.00	5.90	.14	10.0	575	542
SGP	41,479	42.50	1998	13.50	6.65	.11	21.5	594	565
USA	41,813	40.80	2000	14.50	6.45	.14	13.0	518	536
NOR	47,538	25.80	2000	24.50	6.64	.13	18.5	451	466

Source. External economic: http://siteresources.worldbank.org/DATASTATISTICS/Resources/WDI08_section1_intro.pdf. External Gini for all except Cyprus and Taiwan: http://siteresources.worldbank.org/DATASTATISTICS/Resources/table2_7.pdf. Cyprus: https://www.cia.gov/library/publications/the-world-factbook/fields/2172.html. Taiwan: http://www.gio.gov.tw/info/taiwan-story/economy/edown/table/table-10.1.htm.

Note. We used the data for the United Kingdom for both England and Scotland. We used the data for Belgium for Flemish Belgium. The table shows only first two digits after decimal for the internal measures. However, we noted first four digit for all our analysis in order to appropriately rank-order countries. PPP = purchasing power parity; SES = socioeconomic status; TIMSS = Trends in International Mathematics and Science Study.

measures, GDP per capita (2005) and the Gini index (various years). As noted elsewhere in the literature, high-income countries tend to also be higher performing countries on TIMSS. However, relationships are not completely congruent. With respect to income inequality levels, the relationship with TIMSS performance is even less clear.

Cross-country comparisons for even well-established indicators such as the Gini index are not free from problems (World Bank, 2005, p. 38). Given these limitations, we developed two internal measures for each country using the TIMSS data: (a) the mean of SESEDCAP for each country and (b) a Gini coefficient based on SESEDCAP for each country, calculated by the Stata command "ineqdeco."[9] It is important to note that our measures of economic status and income inequality do not perfectly match the external measures. However, the internal and external measures are correlated. The correlation between the external economic measure and the internal economic measure is .78; similarly, that between external and internal inequality is .50. Both these correlations are significant at $\alpha = .05$. It is also noteworthy that the internal measure of inequality is generally smaller than the external measure for most countries. This may partly reflect that the internal measure depends on a "subset" of a family's income and thus may vary less than overall income. The lack of perfect correlation between internal and external measures also raises interesting possibilities that these two sets of variables reflect two related but different measures of income and inequality. At the very least, the external measures based on national data reflect the "broad" national conditions, whereas the internal measures reflect the conditions of a subset of families in the nation with fourth-grade children. Arguably, the external measures may be also seen as "public" measures and the internal measures as "private" measures of national well-being.

Finally, there may be an interaction between poverty and inequality levels, such that schools matter especially in countries that are both poor and unequal. In order to investigate this possibility using the external income and inequality measures, we rank countries in order of both poverty and inequality (where higher rank implies a better situation, i.e., less poverty and more equality). Using both these ranks, we generated a "composite rank," which is the average of the two ranks. We also used the two internal measures to generate a composite rank, which we then use to reorder the list of countries by taking into account *both* their income and inequality levels.

Method

To address the questions of interest, we rely primarily on HLM. We also use the OLS approach to replicate the original H-L study with some modifications. All of the models described below are estimated separately for each country to allow for different input-output relationships across countries.

OLS approach. For OLS, we use only the first plausible value as our dependent variable (instead of all five plausible values as we do with HLM).[10]

We conduct the OLS analysis in two steps, and we estimate the models separately for science and math in each of the 25 countries as described in Equation 1. As indicated in Table A2 in the Appendix, the sample size for the OLS analysis ranges from 8,140 in the United States to 1,778 in Tunisia.

$$\text{Model 1: } Y = b_0 + \boldsymbol{\alpha}\textbf{STUDENT} + \boldsymbol{\delta}\textbf{FAMILY} + e \tag{1}$$

The adjusted R^2 from this model is the proportion of variance in test score accounted for by student/family independent variables (R_1).[11] In the second step, we make an important departure from the H-L protocol. Instead of adding specific school variables to examine the change in adjusted R^2, we use school fixed effects (Equation 2), in which a separate indicator variable is included for each school in the dataset (with one school admitted as the reference category):

$$\text{Model 2: } Y = b_0 + \boldsymbol{\alpha}\textbf{STUDENT} + \boldsymbol{\delta}\textbf{FAMILY} + a_i + e, \tag{2}$$

where a_i denotes the school-specific effect, which is unique to each school and does not vary across individuals within a given school. This method amounts to allowing a different intercept for each school, controlling for student background (Wooldridge, 2000). Using school fixed effects allows us to account for all the observed and unobserved school characteristics that may influence student learning. We note the new value of the adjusted R^2, which is the total explained variation in student test scores (R_2) using student, family, and observed and unobserved school characteristics. We next calculate both the relative importance of family versus school as $(R_2 - R_1) / R_2$ and the variance attributable to school, or the gain in adjusted r-square from Step 1 to Step 2 $(R_2 - R_1)$.

Within a country, if schools are more important than family in accounting for variations in student test score, then in the OLS framework, we should find $(R_2 - R_1) / R_2 \geq .50$. In other words, a larger portion of total variance explained is due to all the observed and unobserved school characteristics. Additionally, if schools are more important relative to families in poor countries compared to rich ones, we will find a negative relationship between country economic status and the relative importance of schools, $(R_2 - R_1) / R_2$. If schools are more important overall in poor than in rich countries, we should find a negative relationship between the overall importance of schools $(R_2 - R_1)$ and country economic status.

HLM approach.[12] As noted earlier, the OLS approach has been criticized for its lack of attention to an inherently multilevel phenomenon. To address this concern, we use HLM to analyze two different models for each of the 25 countries in both science and math. For all the HLM models presented here, student and family background are considered as Level 1 and the school is considered Level 2; that is, students are clustered within schools. As indicated in Table A2 of the Appendix, the number of students at Level 1 ranges from 8,140 in the United States to 1,778 in Tunisia. The number of schools at Level 2 ranges from 248 in the United States to 121 in England. Using HLM software also allows us to take into account all of the five plausible values for all our analyses. Once again, we use sample weights to produce nationally representative findings.

First, to decompose the variance between school- and family-level variables, we employ the HLM model equivalent to a one-way analysis of variance with random effects (Raudenbush & Bryk, 2002, p. 23), also referred to as the Null model (Willms & Smith, 2005).

$$\text{Model 3: Level 1: } Y_{ij} = b_{0j} + e_{ij} \quad (3)$$

$$\text{Level 2: } b_{0j} = \gamma_{00} + u_{0j} \quad (4)$$

The Null model partitions variation in the dependent variable (Y_{ij}) into between schools (Var(u_{0j}) = τ_{00}) and within schools (Var(r_{ij}) = σ^2). These variance measures are used to compute the intraclass correlation coefficient ρ.

$$\rho = \tau_{00} / (\tau_{00} + \sigma^2) \quad (5)$$

Intraclass correlation coefficient is the proportion of the total variance in test score that is between schools (Raudenbush & Bryk, 2002; Willms & Smith, 2005). It indicates the extent to which schools (rather than individual student and family background) matter in explaining student achievement. If within a country, school attributes (between-school differences) are more important than student and family attributes, then $\rho \geq .50$. Additionally, if the importance of schools relative to families is greater in poorer countries, then we should expect a negative relationship between the relative importance of school (ρ) and country economic status.

In Model 4, we introduce at Level 1 student and family controls to estimate the variation in student performance attributable to schools (Level 2), and the extent to which schools influence the SES-based achievement gap. The focus of this analysis is to understand how within and across countries, and taken as a whole, schools may be differently important for students. The model is again estimated separately for each country in math and in science.

$$\text{Model 4: Level 1: } Y_{ij} = b_{0j} + b_{1j} SES_{ij} + \boldsymbol{\alpha}\mathbf{STUDENT} + \boldsymbol{\delta}\mathbf{FAMILY} + e_{ij} \quad (6)$$

$$\text{Level 2: } b_{0j} = \gamma_{00} + u_{0j} \quad (7)$$

$$b_{1j} = \gamma_{10} + u_{1j} \quad (8)$$

Level 1 is the student-level equation where for student i in school j, b_{1j} represents the relationship between student SES and achievement in school j. The letters in bold indicate other student/family variable matrices and coefficient vectors. In the Level 2 analysis, the variation in school-level coefficients b_{0j} and b_{1j} is provided by the unconditional variance component for the error terms (u_{0j} and u_{1j}). The variance of u_{0j} represented as τ_{00}, for instance, is the unconditional variance in Level 1 intercepts, or the variance component. The significance of the b_{0j} variance component indicates significant differences in average achievement across schools—that is, schools matter. In this framework, if schools matter more overall in poor countries, then we should find a negative relationship between the overall importance of schools (τ_{00}) and country economic status. The remaining coefficients, not expressed at Level 2, remain fixed at Level 2 without the error term. In other words, we propose a scenario where student gender or age or other family-level variables relate to their achievement in the same fashion no matter which school the student attends.

After generating estimates for unconditional variance components in the model above, we use the actual intercept and the coefficient value along with the variance component to generate a 95% plausible value range for the intercept.

$$\text{95\% plausible value range for the intercept} = \hat{\gamma}_{00} \pm 1.96(\hat{\tau}_{00})^{1/2} \qquad (9)$$

This range will be wider for poor countries than rich ones if we expect that overall schools are more important in poor countries in terms of their impact on test scores.

Finally, we consider whether the SES-achievement relationship differs across schools within each country. In the SES-achievement relationship in the model above, the significance of the variance component for b_{1j} implies that schools influence the relationship between student SES and achievement. In addition, the unconditional variance of the SES coefficient indicates how schools may matter differently across countries in bridging the achievement gap due to SES. We also generate the 95% plausible value range for the SES coefficient:

$$\text{95\% plausible value range for the SES coefficient} = \hat{\gamma}_{s0} \pm 1.96(\hat{\tau}_{ss})^{1/2} \qquad (10)$$

This 95% plausible value range quantifies the set of values that the actual SES coefficient would assume from school to school. A wider range in the beta SES coefficient implies a greater variation in the SES-achievement relationship by schools, indicating that the school a child enrolls in can be crucial in determining how her family's SES relates to her achievement.

Finally, to investigate if this SES-achievement relationship varies by country background, we divide the data into two groups, in which the variance component for SES is and is not significant (for both science and math separately) and conduct a *t*-test analysis to see if the two groups differ in terms of their mean external or internal economic or inequality measures. Another approach to investigate this question is a three-level HLM model in which we compile the 25 country data into one data set and then estimate a model where students are Level 1, schools Level 2, and countries Level 3. At Level 3, this model would include country-level internal and external measures. However, for this article, we chose not to pursue that approach. Our main concern with a three-level model (as noted in our review of Baker et al., 2002) is that unless we allow each coefficient to vary randomly at Level 2, such a model would propose the same input-output relationship between Level 1 and Level 2 variables across 25 countries.

Results

OLS Results

In Table 2, columns 1 and 2, we find that in Singapore (science), Latvia (science), Tunisia, Moldova, the Philippines, Italy, Morocco, Armenia, and Russia, adding school fixed effects explains more than 50% of the total variation in test scores. That is, for these countries, $(R_2 - R_1) / R_2 \geq .50$. Thus, in almost one third of the countries in our sample, schools are more important than family in explaining variance in student performance; H-L found this to be the case in more than half the countries in their sample. However, in most of the countries in our sample, schools explain less than half of the total variance. This finding is fairly consistent for both mathematics and science. With respect to columns 3 and 4 in Table 2, we note that in terms of relative and absolute importance of schools, country listings are not congruent. For instance, in Armenia, schools explain 25% of variation in math scores (column 3), but in the same country, relative to family, schools account for 73% of the explained variation in test scores. These differences provide an important cautionary note against confusing relative and absolute importance of schools. We also note that after including a dummy for each school and potentially accounting for all unobserved school background variables, in some countries like Japan, schools add very little to the total variance explained, while in the Philippines, adding school dummies makes a significant contribution to the total variation accounted for by the model.

Table 3 displays the correlation between columns 1 to 4 in Table 2 and columns 1 to 6 in Table 1. (These correlations are based on a relatively small *n* [25 countries], which limits identification of nonsignificant country-level results. For instance, for a 0.4 effect size at $p = .05$, statistical power = 0.52; Cohen, West, Aiken, & Cohen, 2003). For both math and science, both the relative and the overall importance of schools is negatively related to a country's economic status and positively related to a country's inequality status. The results in Table 3 show that schools matter more, both relatively and overall, in poor and unequal countries. These findings are consistent across science and mathematics, across internal and external measures of economic and inequality status, and even for composite measures of income and inequality. The majority of the findings are significant at $p \leq .01$ and the rest at $p \leq .05$. The correlation coefficients are also fairly large with the smallest coefficient of .44. Not surprisingly, we find that the strongest correlation is obtained in both the internal and the external data when we look at the composite measure of income and inequality. Since both income and inequality levels matter, we find that in countries that are both poor and unequal (lower composite rank), schools matter more, both overall and compared to family.

Table 2

Ordinary Least Squares Estimates of Relative Importance of School Versus Family and Estimates of Overall Variance Attributable to Schools for Math and Science Achievement

	Relative Importance of School Versus Family			Overall Importance of Schools			Importance of Family Background	
Country	Math	Science	Country	Math	Science	Country	Math	Science
JPN	.19	.16	JPN	.05	.02	ARM	.09	.08
NLD	.20	.21	NOR	.06	.05	MAR	.10	.08
TWN	.23	.16	CYP	.07	.07	ITA	.13	.09
NOR	.24	.29	TWN	.07	.03	RUS	.13	.08
CYP	.25	.37	NLD	.08	.05	PHL	.18	.19
BFL	.25	.28	SVN	.09	.10	CYP	.20	.13
SVN	.28	.48	BFL	.10	.07	MDA	.20	.15
HUN	.29	.35	SCO	.11	.10	NOR	.20	.13
SCO	.33	.40	HUN	.13	.10	AUS	.20	.15
ENG	.36	.36	IRN	.15	.13	HKG	.21	.15
USA	.37	.43	ENG	.15	.12	TUN	.21	.19
IRN	.38	.41	USA	.15	.16	JPN	.22	.12
NZL	.39	.40	LTU	.16	.09	SCO	.22	.15
LTU	.41	.41	LVA	.17	.17	SVN	.22	.11
LVA	.41	.59	NZL	.18	.14	LTU	.23	.13
HKG	.46	.49	AUS	.18	.13	LVA	.24	.12
AUS	.48	.46	HKG	.18	.14	IRN	.24	.19
SGP	.49	.53	ARM	.25	.29	TWN	.24	.18
TUN	.54	.52	TUN	.25	.21	USA	.26	.21
MDA	.59	.63	MAR	.27	.22	ENG	.27	.21
PHL	.67	.61	MDA	.28	.26	NZL	.27	.22
ITA	.71	.76	SGP	.30	.30	BFL	.28	.17
MAR	.73	.74	ITA	.31	.29	HUN	.31	.19
ARM	.73	.78	PHL	.36	.30	SGP	.32	.26
RUS	.75	.83	RUS	.41	.38	NLD	.32	.19

Note. Relative importance of school versus family = $(R_2 - R_1) / R_2$. Overall importance of school = $R_2 - R_1$. Importance of family background = R_1.

HLM Results

While the purpose of this study is not to compare analytic techniques, some observations are difficult to ignore. In Tables 2 and 4, it seems that the overall patterns of how much schools matter are similar for math and science in any given country and similar across OLS and HLM models. In general, the models show a similar outcome in terms of countries where schools matter more or less, with some notable exceptions like Armenia. However, HLM estimates generally tend to be slightly smaller in magnitude than OLS estimates.

Table 3

Relationship Between the Ordinary Least Squares Estimates of Relative Importance of School Versus Family and Overall Variance Attributable to School and the Country's Economic and Inequality Status ($n = 25$) by Math and Science

		Relative Importance of School Versus Family		Overall Importance of School	
		1	2	3	4
	Country measure	Math	Science	Math	Science
External	Per capita GDP	−.58***	−.55***	−.50**	−.47**
	Gini index	.59***	.50**	.66***	.59***
	Composite rank	−.73***	−.68***	−.73***	−.69***
Internal	Mean SESEDCAP	−.60***	−.52***	−.52***	−.47**
	Gini coefficient	.55***	.46**	.48**	.44**
	Composite rank	−.65***	−.63***	−.53***	−.53***

**$p \le .05$. ***$p \le .01$.

Examining the HLM estimates in Table 4, columns 1 and 2, we notice that only in the case of the Philippines in math and in Singapore, more than half of the total variance is between schools ($\rho \ge .50$). In other words, in all countries except in these one or two cases, for both science and math, when we use HLM for variance decomposition, we find that a greater proportion of the total variation in test scores is within schools and not between them. However, we do find wide variations across countries in the magnitude of between-school variation in science and math (columns 1 and 2, Table 4).

Columns 3 and 4 present the variance component of the intercept for both math and science, and columns 5 and 6 show the range of plausible intercept values. For both math and science, the coefficient of the variance on the intercept or the variance component (τ_{00}) is statistically significant. This implies that controlling for relevant child- and family-level background variables, average student test scores vary significantly from school to school. In other words, in all the countries in our sample, some school characteristics matter in addition to children's own background in determining their test scores. The range of plausible intercept values uses the variance component information along with the actual size of the intercept to provide related but slightly different information on the range of impacts of school-specific differences on achievement. As noted earlier, a greater magnitude for either of these numbers would mean that overall, schools matter more in a given country compared to a country where the magnitude is smaller.

In order to systematically investigate the relationship between relative and overall school-effect estimates and country background (columns 1–6, Table 4), Table 5 displays the correlation estimates with the internal and external economic, inequality, and composite measures from Table 1 (once

Table 4

Hierarchical Linear Model Estimates of Relative Importance of School Versus Family and Overall Variance Attributable to Schools for Math and Science Achievement

	Intraclass Correlation Coefficient			Variance Component of Intercept		Range of Intercept			Importance of Family Background	
Country	Math	Science	Country	Math	Science	Math	Science	Country	Math	Science
JPN	.05	.03	JPN	224.54	147.57	58.74	47.62	ARM	.09	.08
NOR	.08	.07	NLD	272.36	151.87	64.69	48.31	MAR	.10	.08
CYP	.10	.10	NOR	299.36	262.49	67.82	63.51	ITA	.13	.09
SVN	.11	.12	TWN	301.56	164.34	68.07	50.25	RUS	.13	.08
TWN	.15	.09	BFL	322.68	202.58	70.42	55.79	PHL	.18	.19
BFL	.16	.14	SVN	454.67	570.94	83.59	93.67	CYP	.20	.13
SCO	.16	.16	CYP	509.85	433.73	88.51	81.64	MDA	.20	.15
NLD	.18	.15	SCO	592.32	601.78	95.40	96.16	NOR	.20	.13
HUN	.22	.18	HKG	700.00	504.95	103.71	88.09	AUS	.20	.15
LTU	.22	.13	HUN	741.02	552.07	106.71	92.11	HKG	.21	.15
LVA	.23	.24	LTU	767.18	342.35	108.58	72.53	TUN	.21	.19
AUS	.25	.19	LVA	865.03	860.73	115.29	115.01	JPN	.22	.12
HKG	.25	.21	USA	937.11	1170.85	120.00	134.13	SCO	.22	.15
ENG	.26	.22	ENG	1129.84	782.11	131.76	109.63	SVN	.22	.11
ARM	.27	.34	AUS	1189.27	820.65	135.18	112.30	LTU	.23	.13
USA	.27	.30	IRN	1201.90	1260.14	135.90	139.15	LVA	.24	.12
IRN	.29	.26	NZL	1279.65	980.33	140.23	122.74	IRN	.24	.19
NZL	.31	.29	ARM	1655.71	2454.47	159.51	194.21	TWN	.24	.18
MAR	.32	.25	MAR	2066.51	3122.97	178.20	219.06	USA	.26	.21
ITA	.32	.31	ITA	2108.54	1992.73	180.00	174.99	ENG	.27	.21
MDA	.40	.34	MDA	2136.91	1761.94	181.21	164.54	NZL	.27	.22
TUN	.40	.33	RUS	2479.44	2315.74	195.19	188.64	BFL	.28	.17
RUS	.45	.41	TUN	2594.58	3222.13	199.67	222.51	HUN	.31	.19
PHL	.51	.45	SGP	2811.31	2862.66	207.85	209.73	SGP	.32	.26
SGP	.57	.52	PHL	4902.38	7230.70	274.47	333.33	NLD	.32	.19

Note. The variance component for mathematics and science for each of the 25 countries is statistically significant at $\alpha = .05$. Importance of family background = R_1.

Table 5

Relationship Between the Hierarchical Linear Model Estimates of Relative Importance of School Versus Family and Estimates of Overall Variance Attributable to Schools for Math and Science Achievement and the Country's Economic and Inequality Status (*n* = 25) by Math and Science

		Intraclass Correlation Coefficient		Variance Component of the Intercept		Range of Plausible Intercept Value	
		1	2	3	4	5	6
	Country Measure	Math	Science	Math	Science	Math	Science
External	Per capita GDP	–.38*	–.35*	–.51***	–.53***	–.54***	–.56***
	Gini index	.75***	.73***	.63***	.58***	.67***	.64***
	Composite rank	–.71***	–.69***	–.74***	–.72***	–.78***	–.79***
Internal	Mean SESEDCAP	–.46**	–.41**	–.58***	–.63***	–.59***	–.66***
	Gini coefficient	.45**	.42**	.55***	.59***	.58***	.64***
	Composite rank	–.39*	–.38*	–.51***	–.55***	–.54***	–.60***

*$p \leq .10$. **$p \leq .05$. ***$p \leq .01$.

again, we should remind the readers these correlations are based on a relatively small number of countries). In terms of the overall importance of schools (columns 3–6, Table 5), the findings from Table 5 based on HLM are in agreement with those from Table 3 based on OLS. In other words, for both science and math, using internal and external measures, we find that in countries that are economically advanced or equal, schools overall matter less, and in countries that are poor and unequal, schools overall matter more.

The results from columns 1 and 2 in Table 5, however, are slightly different and hence particularly interesting. We find a relatively weak relationship between the relative importance of school compared to family and the country's economic status, especially when considering external measures of economic status as indicated by the math and science correlation coefficients that are significant only at $p \leq .10$. The relative importance of schools is more strongly related to the internal measures of economic status, as reflected by larger (in absolute terms) correlation coefficients and greater levels of significance. This may stem from the possibility that the internal measure better captures the actual resources that families bring to bear on the education of their children. In cases where this measure is low, the impact of the school relative to families seems to be greater.

But in terms of the relative importance of school versus family, for both science and math, the correlation coefficients are significantly (at $p \leq .001$ or at $p \leq .05$) and positively related to the country's inequality levels. This implies that there is a relationship between the relative importance of school compared to family and inequality levels: The more unequal the country, the more schools matter relative to families. These differences in the significance of correlation coefficients for economic and inequality status may indicate that economic status is indeed important in explaining the overall importance of schools (columns 3–6, Table 5), but to explain the relative importance of schools compared to family, researchers need to more systematically investigate the role of income inequality.[13]

While the HLM analysis shown in Table 4 and the correlation analysis in Table 5 show that schools are important to varying degrees in all 25 countries studied, we now consider whether schools are able to mediate the SES-achievement gap in the countries studied. Table 6 presents the variance components associated with the SES coefficient in the HLM model and the related plausible SES coefficient values. We find that for math in 10 out of the 25 countries and for science in 8 out of the 25, the variance component associated with the SES coefficient is not statistically significant. In these countries, schools do not seem to mediate how a student's SES relates to her achievement. For those countries, it is also not relevant to calculate the plausible values of the SES coefficients since the variation between SES coefficients by school is not different from zero. It is also interesting to note that the relationships for math and science are not absolutely congruent, which may indicate some differences in the underlying mechanisms through which schools mediate the relationship between SES and achievement in science and math. Ignoring Morocco, Russia, and Tunisia, we find a pattern in which countries where schools do not seem to mediate the SES-achievement relationship tend to have higher GDP and be more equal. However, when we divide the data into two groups, in which the variance component for SES is and is not significant (for science and math separately), a simple *t* test reveals no differences between the two sets of countries based on any of the measures: internal or external, economic or inequality. While the smaller sample size of 25 may be partly to blame for the lack of significance in the *t* test, we still prefer to make a conservative conclusion that we cannot argue for a systematic relationship between country background and the role of schools in mediating the SES-achievement relationships.

Discussion and Conclusion

Limitations and Major Findings

We acknowledge that like its predecessors, our study is not free from limitations. To begin with, we must make several assumptions regarding the completeness of the data (at Level 1) and the comparability of data across countries (especially our SES variable). Most importantly, the SES variable could be greatly improved if better data were available and if family background itself were not so difficult to measure. We are also aware that inaccurate measurement of family background could lead to biased estimates of the impact of families or schools on achievement. In particular, if school resources are positively correlated with family SES, then failure to adequately control

Table 6
Estimates of Variation in SES Achievement Relationship Attributable to Schools

	Variance Component of SES Coefficient		Range of Plausible SES Coefficient Values	
Country	Math	Science	Math	Science
LVA	5.44	21.59	9.14	18.21
LTU	7.95	21.87	11.05	18.33
HKG	12.44	10.32	13.83	12.59
NZL	14.08	50.56	14.71	27.87
BFL	17.31	31.07	16.31	21.85
NOR	17.33	28.11	16.32	20.78
AUS	18.96	51.88	17.07	28.24
ARM	31.10	76.87	21.86	34.37
USA	32.68	18.31	22.40	16.77
SCO	38.82	17.11	24.42	16.22
IRN	46.18	72.73	26.64	33.43
HUN	51.81	42.98	28.22	25.70
ENG	84.71	66.73	36.08	32.02
PHL	117.26	107.72	42.45	40.68
MDA	163.13	143.49	50.07	46.96
RUS	NS	29.17	NA	21.17
TUN	NS	92.63	NA	37.73
JPN	NS	NS	NA	NA
SVN	NS	NS	NA	NA
NLD	NS	NS	NA	NA
ITA	NS	NS	NA	NA
MAR	NS	NS	NA	NA
SGP	NS	NS	NA	NA
CYP	NS	NS	NA	NA
TWN	NS	NS	NA	NA

Note. The variance component for SES for mathematics and science for each of the 25 countries is statistically significant at $\alpha = .05$ unless noted as NS.

for family background could inflate estimates of the impact of school resources on achievement.

We also acknowledge that we are unable to make causal claims due to the cross-sectional nature of the data. Multicountry studies are limited in their ability to draw causal inferences, primarily because such studies are constrained to work with cross-sectional rather than longitudinal data. We are aware of few studies that have used multicountry test-score data to draw causal claims. One such study by Schmidt et al. (2001) used data from the first and most ambitious application of TIMSS in 1995. The data were collected at five grade levels, and the same test was administered to two adjacent grades among 9- and 13-year-olds. Schmidt et al. used this information to create a measure of national gain from one grade level to next. They then used structural equation modeling among other techniques to draw causal inferences about the relationship between national curriculum and student performance. West and Woessmann (2008) used an instrumental variables approach (with the size of a country's Catholic population in 1900 as an instrument) to calculate the causal impact of private schooling across 29 countries participating in the 2003 PISA. Unlike Schmidt et al., our study relying on the 2003 application of TIMSS is unable to benefit from estimates of national gain. Unlike West and Woessman, our study does not use a quasi-experimental technique. Consequently, we do not attempt to make causal inferences.

We are therefore cautious about putting too much weight on any one estimate or coefficient. However, what we do find valuable is the systematic and broad pattern that the data display under different methods of scrutiny, which provides us with a reason to trust the overarching patterns. Our results can be summarized as follows: Using fourth-grade science and mathematics test-score data from TIMSS 2003, using the five plausible values for each test score and applying correct sample weights, in most of the 25 countries studied, schools do not matter more than families in explaining student achievement. However, we find no evidence that schools are not important. School-level variations in math and science achievement are significant in all 25 countries after controlling for student and family background variables at Level 1. Furthermore, the importance of schools relative to families is particularly strong in countries with high levels of income inequality. We find weaker support for the possibility that schools relative to family are more important in poor countries (a key finding of the original H-L study). When looking at the overall importance of schools, however, we do find that schools are more important both in poor and in unequal countries. We also find that in some countries, schools may be able to mediate the relationship between children's SES and their achievement. However, we fail to find a systematic relationship between country background and the schools' mediating role.

Comparison With Related Literature

Like Gamoran and Long (2007), we find that the average GDP per capita (purchasing power parity [PPP]) of the TIMSS countries in our sample ($22,799) is much higher than similar figures for the world. The worldwide gross national income per capita (PPP) in 2005 was $8,638.[14] However, unlike Gamoran and Long, we do find a relationship between country economic status and the importance of schools. This may be due to our methodological approach, which focuses on school fixed effects in OLS and total school variance in HLM, rather than select school-level variables.

We also investigated the Gamoran and Long (2007) hypothesis to see if we find a stronger correlation between the importance of school and country resources in countries with GDP per capita less than $16,000 (in 1990 dollars). Applying the appropriate GDP deflator, this equals $28,912 in 2005 dollars.[15] Fifteen countries in our sample are below this level. While this sample is too small to meaningfully run correlation analysis, this truncated sample shows the following patterns: With respect to the internal and external inequality measures, changes in correlation are not consistent; with respect to the internal economic measure, there are some relatively small gains in the correlation coefficient. As expected, the main changes in correlations are with respect to the external economic measure. The correlation between the external economic variable and the HLM estimates is uniformly greater in magnitude. The largest gains occur in the correlation between intraclass correlation coefficients for math and science and the external economic indicator. Correlations between the external economic variable and the OLS estimates of the overall importance of school also gain in magnitude. The only exceptions to this pattern are the correlations with the OLS estimates of the relative importance of school versus family for science and math. In this case, either the correlation coefficient did not change or it actually fell in magnitude and significance.

The overall gain in the magnitude of the correlation coefficients, especially the correlation of the external economic measure with the intraclass correlation coefficient, confirms that schools are especially more important in poor countries, as Gamoran and Long (2007) have argued. These findings once again highlight that external and internal measures of economic status are not congruent. In particular, the generally higher correlation between external measures and the impact of schools may indicate that the social and institutional context of a country, as manifested by its national income and income inequality, may be especially important in explaining differences in the importance of schools across countries. Third, these results again highlight the need to distinguish between the relative and the overall importance of school. Finally, these differences also highlight the potential distinctions between the OLS and the HLM approaches.

Like Baker et al. (2002) and Hanushek and Luque (2003), our results demonstrate the importance of families across diverse national contexts. Unlike these prior studies, our results indicate that school-level factors may also be important in explaining variations in student achievement using both the conventional OLS approach and the two-level HLM approach. Once again, the key differences may be that earlier studies have attempted to understand the importance of schools by using a select set of school variables. The finding that those select factors do not yield a significant relationship with student achievement is then often used to argue that school resources do not matter (or that they do not matter more in developing countries). In contrast, by quantifying the variance attributable to schools, we find distinct patterns indicating that schools are more important in poor countries. Finally, these prior studies have ignored the role of income inequality. Lack of variation in access to resources should lead to relatively lower importance of school factors in more equal countries. Our analysis shows that in fact, school resources are more important in unequal countries.

Contributions of the Study

The study makes three additional contributions. First, while it was not the purpose of our analysis, by setting OLS and HLM findings side by side, we found that in most cases, substantive conclusions are similar across these two methods, except when we decompose the variance explained between schools and families. Compared to HLM, the OLS results identify more countries where schools are more important than family in the proportion of variance explained. Second, our study clarifies the importance of the distinction between relative and overall importance of schools in trying to understand if and how much to invest in schools. Both the OLS and the HLM results show that depending on the question, lists of countries where schools matter more relative to family compared to where schools matter more overall may not be perfectly congruent. Third, this study introduces the yet ignored dimension of country-level inequality, which seems to be crucially important in understanding where schools may be more important. In fact, relative to family, schools appear to be more important in unequal contexts but not in poor ones. The findings imply that even in a rich but relatively unequal country (like the United States or Singapore), schools may have a greater role to play than has yet been acknowledged.

Although this article does not focus on "what about the school" may cause greater variations in student performance in poor and unequal countries, we must make several observations regarding within-school influences. Most importantly, school factors include not just the resources allocated to them in terms of lower class sizes, higher teacher qualifications, or instructional materials. School factors also include the composition of school or the SES of students within the school. Indeed, several studies have argued for the importance of school composition. For instance, Caldas and Bankston (1997) use data from the Louisiana Department of Education to show that the SES of peers in a child's school is important in understanding variations in student performance. To examine similar questions, Chiu and Khoo (2005) generated a "school clustering index," which is the ratio of the variance in school mean SES in a country divided by overall variance in SES in the country, where a higher number indicates greater clustering of students within schools by SES (segregation). Future research must pay much closer attention to evaluating the importance of school composition alongside other school factors that are more conventionally linked with greater resources. For the purposes of this article, however, we note that peers are part of the overall school effect that we assess here. While it is important to examine whether school resources—above and beyond peer influences—influence student achievement, this question is beyond the scope of this analysis. Moreover, just as the degree of school resources can be influenced by policy, peer composition can also be altered, through such programs as desegregation and magnet schools.

Policy Implications

Most importantly, our findings argue for international focus not only on national or personal income but also on income inequality. While the manifestations and mechanisms of inequality must be investigated more thoroughly, particularly in terms of how both income and resources are distributed within schools, we can offer some preliminary implications from this research. First, at the school level, significant differences across schools indicate that contrary to many earlier studies, schools do matter. Schools may also be able to close SES-based achievement gaps, but future research must examine this question more closely. At the country level, our findings argue for a consistent government role in ensuring equitable and adequate schools, especially in poor and unequal regions. Focusing on low-income students in unequal regions may be a particularly high-yield strategy for directing scarce educational resources. Finally, and perhaps most importantly for developing countries, the international aid community must take note of the importance of income inequality. Just as multilateral and bilateral aid organizations target countries suffering from extreme poverty, such organizations must also continue to consider the development of aid targets based on levels of inequality, as potential investments in school resources may yield especially high returns in these contexts.

Appendix

Table A1
Variable Details

Variable	Description
Student mathematics achievement	Five achievement plausible value (HLM), first plausible value (OLS)
Student science achievement	Five achievement plausible value (HLM), first plausible value (OLS)
Student age	Age in years
Student sex	Dichotomous dummy variable
Student self-confidence in math	Categorical variable indicating high, medium, or low level of self-confidence
Student self-confidence in science	Categorical variable indicating high, medium, or low level of self-confidence
Student time spent on math homework	Categorical variable indicating high, medium, or low amount of time
Student time spent on science homework	Categorical variable indicating high, medium, or low amount of time
How often test language spoken at home	Categorical variable indicating always, almost always, sometimes, never
Index of school safety (not available for U.S. data)	Categorical variable indicating high, medium, or low perception of safety
Family Socioeconomic status (SESEDCAP)[a]	Index based on a summation of family possessions related to learning (dictionary, calculator, computer, desk, and books in the home)
Per capita GDP 2005 (PPP)	External measure of country's economic status (Source: World Bank)
Gini index	External measure of country's inequality levels (Source: World Bank, CIA World Fact Book, Taiwan government Web site)
Composite rank, external[a]	We ranked countries in order of both poverty and inequality. Using both these ranks, we generated a "composite rank"

(continued)

Table A1 (continued)

Variable	Description
Mean SESEDCAP[a]	Internal measure of country economic status
Gini based on SESEDCAP[a]	Internal measure of country inequality level calculated by the Stata command "ineqdeco"
Composite rank internal[a]	We ranked countries in order of both poverty and inequality. Using both these ranks, we generated a "composite rank"

Note. The science variables were used for the science models, and the math variables were used for the math models, the remaining variables were used for both the models. HLM = hierarchical linear models; OLS = ordinary least squares; PPP = purchasing power parity; TIMSS = Trends in International Mathematics and Science Study.
[a]Indicates the variable was created by authors, all other variables unless specified otherwise were available in TIMSS 2003. More details about TIMSS 2003 index constructions can be found in Martin, Mullis, and Chrostowski (2004).

Table A2
Sample Sizes

Country	Level 1 and OLS	Level 2
ARM	2,780	143
AUS	3,356	191
BFL	4,214	149
COT	3,690	173
CQU	3,928	192
CYP	3,724	150
ENG	2,992	121
HKG	4,319	132
HUN	2,863	156
IRN	3,508	170
ITA	3,875	171
JPN	3,981	150
LTU	3,818	150
LVA	3,371	139
MAR	1,942	190
MDA	3,486	151
NLD	2,451	128
NOR	3,164	139
NZL	3,528	218
PHL	3,795	135
RUS	3,495	205
SCO	3,311	125
SGP	6,266	182
SVN	2,691	171
TUN	1,778	140
TWN	4,522	150
USA	8,140	248

Note. OLS = ordinary least squares.

Notes

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[1]The literature on the United States also contains unresolved debates about the relative importance of school resources. Examples include Greenwald, Hedges, and Laine (1996) and Hanushek (1997).

[2]In the United States, for instance, a recent discussion and debate surrounding a "Broader Bolder Approach to Education" (http://www.boldapproach.org/statement.html) urges policy makers to look beyond the schools in addressing the achievement gap.

[3]It is important to acknowledge that while we refer to each separate unit as a country while discussing our methods and results, we are aware that several entities participating in Trends in International Mathematics and Science Study (TIMSS) are not separate countries.

[4]Their measure of school resources included a composite score of 11 resource shortage variables estimating the level of educational resources in the school. In addition, they used measures of the teaching environment.

[5]For example, in the 2003 assessment of Program for International Student Assessment, Mexico and Turkey enrolled only 58% and 54%, respectively, of their 15-year-old children in school (Organization of Economic Cooperation and Development, 2004).

[6]This variable is not available for the United States.

[7]There is a wide and varying amount of missing data in the 25 country data sets for science and mathematics. To avoid arbitrary decisions about data imputation, we work only with cases on which information for all the selected variables was available. Exceptions to this approach were the five SESEDCAP variables, for which we used mean imputation. Across the 5 variables in 25 countries (125 cases), in all but 114 cases, this amounts to imputing from 0.1% of values to 5.5%. In eight of the remaining nine cases, we imputed between 6% and 8% of the data; in Morocco, we imputed 12.4% of the values of the books in the home variable.

[8]Other approaches we tried included the first principal component based on the five educational capital variables, the number of books available at home, and a measure of total home possessions. The home possessions measure would have been an ideal candidate, but it is problematic due to large amounts of missing data on the 16 (country-specific) home possession variables in each of our 25 data sets. At the same time, working with just one variable like number of books available in the home ignores a good amount of potential information about family background. The loading of different variables on the first principal components were not consistent across countries (as expected). So we finally settled with a summation of the five variables that make up SESEDCAP.

[9]The Gini index is the Gini coefficient expressed as a percentage and is equal to the Gini coefficient multiplied by 100. World Bank reports use the index, while we use coefficients.

[10]This approach has been adopted by earlier research as well. For instance, after an extensive preliminary analysis, Baker, Goesling, and Letendre (2002) found that substantive analysis remained unchanged whether they used five plausible values or the first plausible value alone.

[11]While we are not reporting individual coefficients or their standard errors, all the standard errors are jackknifed robust standard errors adjusted for sample variance and school-level clustering.

[12]The definitions and terminology for hierarchical linear modeling are based on Raudenbush and Bryk (2002). We also used the manual prepared by Willms and Smith (2005) to guide some parts of the analysis.

[13]Given the correlation of .5 between the two inequality measures, we investigated the possibility that they may be capturing two very different underlying concepts of inequality. Our analysis indicates that while not highly correlated, these measures may not be entirely different.

[14]http://ddp-ext.worldbank.org/ext/DDPQQ/showReport.do?method=show Report.

[15]http://www.measuringworth.com/uscompare/.

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