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The role of family background and school resources on elementary school students' mathematics achievement

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Abstract This article compares the effects of family background and school resources on fourth-grade students' math achievement, using data from the 2011 Trends in International Mathematics and Science Study (TIMSS). In order to ameliorate potential floor effects, it uses relative risk and population attributable risk to examine the effects of family background and low levels of school resources. Four findings stand out: (1) the percentage of vulnerable students decreases as GDP increases, but this relationship weakens at higher levels of GDP; (2) the relative risk associated with low socioeconomic status is positively related to GDP, but the relative risk associated with low school resources is unrelated to GDP; (3) the population attributable risk associated with some of the family and school risk factors tends to fall with rising GDP, but varies considerably amongst countries; and (4) family background effects are stronger than school resource effects in low- and high-income countries.

Keywords Relative risk · Population attributable risk · Mathematics achievement · Family background · School resources

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For nearly half a century, educators have debated the question of whether school resources affect children's academic achievement more than does family background. The landmark Coleman study (Coleman, Campbell, and Hobson 1966) in the United States suggested that the effects of family background far outweigh the effects of school resources, leading to a popular interpretation that "schools do not make a difference". Bowles and Levin (1968) immediately criticized the Coleman study, arguing that family and school effects are confounded and cannot be separated with cross-sectional data. The study spawned two generations of research dedicated to showing that schools do make a difference, and that teaching practices, school organization, and climate account for their effects.

This question of school resources versus family background has important implications for the roles that governments play in funding education and for the relative merits of supply- and demand-side approaches to funding. The debate is especially relevant to the approaches for funding education in low-income countries. In 1983, Heyneman and Loxley argued that the relative strength of the effects of family background and school resources was a function of national economic development. They found that socioeconomic status (SES) was a more powerful determinant of achievement in high-income countries, whereas school resources were a more powerful determinant of achievement in low-income countries. Twenty years later, Baker, Goesling, and LeTendre (2002) found larger family effects across countries regardless of the countries' level of economic development. They concluded that the changes from the 1980s to the 1990s were associated with changes in institutional arrangements, which they called a "spreading Coleman effect". Hanushek and Luque (2003) also found that school resource effects were unrelated to level of national economic development.

In an earlier study, Nonoyama-Tarumi and Willms (2010) examined the school resources versus family background issue using data from the Programme for International Student Assessment (PISA). In most low-income countries, the test score distribution was positively skewed, with many students scoring at or near the bottom end of the test score. According to classical test theory, each student has an underlying "true" score, which is the score he or she would obtain if there were no errors of measurement. The "observed score" is the score the student obtains on the particular occasion of the PISA administration. It is conceived of as the sum of the "true score" plus "measurement error" (Allen and Yen 2002). As a result of floor effects, the observed score of many low-performing students are higher than their "true" score. This results in biased estimates of the effects of family background and school resources on achievement. The authors addressed this issue by using a dichotomous schooling outcome: students were considered *not* vulnerable (or vulnerable) depending on whether (or not) they scored above a critical threshold in their reading performance. They defined "vulnerable students" as those performing at level 0, 1, or 2 on PISA reading tests. They also distinguished between the relative risk of certain risk factors, such as living in a family with low SES, versus the population attributable risk, which gauges the overall impact of a risk factor on the prevalence of vulnerability in the population.

Earlier studies of school effects based on regression approaches typically reported unstandardized regression coefficients, which are the analogues of relative risk or odds-ratios, or the "percentage of variance in achievement explained", which is the analogue of population attributable risk. In this article, we report both relative risk and population attributable risk to describe the effects of family background and school resources using data unfolding the fourth-grade achievement of students in 45 countries that participated in the 2011 Trends in International Mathematics and Science Study (TIMSS).

In using this approach, we shed new light on the question of whether the effects of family background and school resources are associated with the level of national economic development, and whether family effects are larger than school resources effects in high- and low-income countries. In the next section, we review cross-national school effectiveness research pertaining to the effects of school resources. We then describe the TIMSS data and how we calculated the relative risk (RR) and the population attributable risk (PAR). In discussing our findings, we address the prevalence of vulnerability and risk factors, and the relative magnitude of each risk factor across countries and their association with national economic development. We conclude by discussing the implications of these results.

Prior research

Much conversation has taken place cross-nationally on the relative effects that school and family resources have on student achievement. Heyneman and Loxley's (1983) study, noted above, was seminal in testing whether the extent of family effects and school effects differed with the society's level of economic development. They estimated the proportion of variance in achievement explained by school and family variables for each country studied and then considered correlations between the proportion of variance explained by SES or school resources and the GNP per capita of the country. They found that SES was a more powerful determinant of achievement in high-income countries; however, school factors were a more powerful determinant of achievement in low-income countries.

That study had a large impact in cross-national literature at a time when large-scale cross-national studies like PISA and TIMSS were not yet available. However, it was criticized for its methodology, particularly its reliance on a single-level model and its use of R-squared as an indicator of school effects (Riddell 1989a, 1989b). A decade later, advances in statistical techniques allowed Baker et al. (2002) to explore these relationships using a multilevel model. They revisited the Heynemann-Loxley (H-L) hypothesis, using the 1995 TIMSS data, and concluded that the relative effect of school resources or family background on achievement within nations was not associated with the level of national economic development. Ilie and Lietz (2010), using the 2003 TIMSS data and limiting their analysis to European countries, concluded that their results supported the Baker team's findings.

Hanushek and Luque (2003) estimated upper and lower bounds on the proportion of variance explained for school resources using the 1995 TIMSS data and concluded that even the upper-bound estimates were unrelated to a country's level of economic development. Gamoran and Long (2007) reviewed the United States research as well as international research on school effects since the Coleman Report, and highlighted the differences in their contexts. They argued that the limited between-school variation in achievement amongst United States schools made school resources effects theoretically small and difficult to detect. In contrast, between-school variation in achievement is larger in developing countries. As the poorest schools face severe shortages of basic resources, the variation in school resources is also larger. Therefore, the income levels of the selected countries affect the findings in international research. They concluded that, when comparing countries below a certain income threshold, school resources do have a strong effect on student achievement.

Based on their findings, Harris (2007) formally tested the diminishing marginal returns (DMR) of school inputs amongst and within countries; that is, whether school effects are relatively large where school input levels are low, and vice versa. He concluded that DMR could not explain the differences in findings between low- and high-income countries. Chudgar and Luschei (2009) brought a new dimension to the debate by testing whether school effects were a function of a country's level of income inequality. They found significant correlations amongst estimates of school effects (using OLS), estimates of the intra-class correlation coefficient (using HLM), and the GINI coefficient. They concluded that school resources are more important in countries with greater inequalities.

Nonoyama-Tarumi and Willms (2010) brought a new perspective to the debate by arguing that in making these cross-national comparisons, researchers must consider both the effects of a particular risk or protective factor and its relevance in a population. For example, consider the risk of lung cancer associated with regular and prolonged smoking. "Relative risk" would refer to the prevalence of lung cancer amongst smokers compared to that of nonsmokers. One might expect that the increased risk associated with smoking would be similar across countries, after taking account of intensity and duration of smoking, and that any observed differences could be attributed to sampling and measurement issues. If there were observed differences related to a society's level of economic development, the risk may have been compounded by other factors, such as diet or exposure to other toxins. However, even if the relative risk were the same across countries, the population attributable risk would, on average, be greater in low-income countries because the prevalence of smokers tends to be higher in low-income countries (WHO 2011). Therefore, reducing smoking rates in low-income countries would have a greater impact on reducing the prevalence of lung cancer in low-income countries than in high-income countries.

In the Nonoyama-Tarumi and Willms (2010) study, which was based on PISA data, the authors estimated the relative risk and the population attributable risk of low reading achievement for five factors related to family background and school resources. Following the smoking example, one might expect that the relative risk of low parental education would be quite uniform across countries. If it did vary with levels of national economic development, it would suggest that the processes that families use to translate their cultural capital into better achievement for their children also varied amongst countries (Levin and Belfield 2002; Tramonte and Willms 2010).

The relative risk (RR) associated with living in a family with low parental education was on average about 1.65, indicating that the risk of having low reading scores for students in low parental education families was 1.65 times that of students who were not in low parental education families. However, the RR was lower in low-income countries and increased with rising GDP, leveling off where GDP per capita was above $25,000. Turning to the population attributable risk (PAR), its relationship with GDP per capita was curvilinear. In low-income countries, the prevalence of children living in families where parents had little education was high, as expected, but because the relative risk was low, the population attributable risk was also low. In high-income countries, the prevalence of children living in such families was low, while the relative risk of low parental education was high and, therefore, the population attributable risk was low. Hence, Nonoyama-Tarumi and Willms (2010) observed the highest levels of population attributable risk for middle-income countries, which had average levels of both relative risk and prevalence of children living in low parental education families—explaining the curvilinear relationship.

For their measure of school resources, they found that the average RR across countries was 1.16 and did not vary significantly with GDP per capita. However, because the prevalence of children in schools with low levels of school resources is considerably higher in low-income countries, the PAR tended to be higher in low-income than in high-income counties, although the effects varied considerably amongst countries. This might also explain why Heyneman and Loxley (1983) found that larger effects of school resources in low-income countries—as their measure of proportion of variance explained—like population attributable risk, depends on both the "effect" of a risk factor and its prevalence in the population. Finally, consistent with Baker et al. (2002), Nonoyama-Tarumi and Willms (2010) found that the family background effects were larger than school resource effects in most countries. On average, across countries, the relative risk associated with parental education, parental occupation, and educational resources in the home was 1.65, 1.67, and 1.80, respectively, while the relative risk associated with school resources, teacher quality, and pupil-teacher ratio was 1.16, 1.15, and 1.14, respectively.

In this study, we use 2011 TIMSS data describing the mathematics achievement of grade 4 students in 45 countries. Our interest is in whether the effects observed in earlier studies are also apparent for a younger cohort of students. They may differ, as the selection into certain types of schools and school programs typically occurs after grade 4. Also, there may be subtle selection effects. For example, in low-income countries, where a smaller percentage of students make it to secondary school, the sample is a more select group. Finally, the findings may differ because PISA measures the ability of students to apply their knowledge in various real-world contexts, but TIMSS measures more traditional classroom content and students' acquisition of school curricula.

Methods

Data

In this study, we used the data describing fourth-grade students from the 2011 TIMSS. TIMSS is a cross-national achievement study conducted every 4 years since 1995. The 2011 TIMSS fourth-grade study was conducted in 50 countries, which have a large variation in terms of economic development, geographic location, and population size. We used the data from 45 countries, excluding 2 countries (Chinese Taipei and Northern Ireland) whose GDP per capita information was not available, and 3 others (Kuwait, Qatar, and United Arab Emirates) whose GDP per capita did not reflect the population sampled in TIMSS due to high proportions of expatriates.

In each country, a two-stage stratified sample was drawn. In the first stage, schools were sampled by probability proportional to size. In the second stage, a total of two fourth-grade mathematics classes were selected in each school in an equal probability sample, and all students in the sampled classes were selected. We used sampling weights to take into account any disproportional sampling of subgroups and to adjust for nonresponse (Martin and Mullis 2012).

Analytic procedures

In this study, we calculated the relative risk and the population attributable risk of family background and school resource measures separately for each country. These concepts are commonly used in epidemiological studies but have seldom been used in educational research; to the best of our knowledge they were first used in our earlier study based on the

PISA data (Nonoyama-Tarumi and Willms 2010). We used the jackknife repeated replication (JRR) weights and the 5 plausible values to estimate standard errors. This approach entails estimating the statistic of interest 375 times, once for each jackknife replicate for each of the 5 plausible values. We calculated the estimate of the standard error of the statistic using the Fayes formula, which takes account of the variation amongst the 75 replicates and between the 5 plausible values. This approach takes into account the clustering of the data associated with the two-stage sample design.

Plausible values are used rather than students' actual test scores, because the test included a total of 10 hours of assessment items, but each student completed a 90-minute test, with a subset of the assessment items. These plausible values reflect the uncertainty in individual students' scores, thereby providing better estimates of population parameters. We dichotomized the mathematics achievement scores into "vulnerable" or "not vulnerable", depending on whether they were above the intermediate benchmark. We also dichotomized the independent variables and expressed them as risk factors. For example, low parental education is a risk factor based on whether a student's parents had 9 or fewer years of education (exposed) versus more than 9 years of education (unexposed). We acknowledge that in using this approach we lose the richness of the continuous data by dichotomizing the dependent and independent variables, but, as mentioned at the outset, we did so to ameliorate the "floor effect" found in many low-income countries. With a

Table 1 Description of variables

Variables	Definition
Vulnerable factor	
Math achievement	Based on 5 plausible values; dummy variable denoting intermediate and below
Risk factors	
Family background	
Parental education	The higher of either the father's or the mother's education; dummy variable denoting 9 years and below
Parental occupation	The higher of either the father's or the mother's occupation; dummy variable denoting never worked for pay, general laborer, skilled worker, and others
Home possessions	Sum of 6 items related to home possessions: computer; study desk; own books; own room; internet connection; more than 26 books at home; dummy variable denoting 1 standard deviation lower than OECD mean and below
School resources	
School resources	Sum of 6 items related to school facilities and instructional resources: shortage of instructional materials; supplies; school buildings and grounds; heating/cooling and lighting systems; classrooms; computers for instruction; dummy variable denoting 1 standard deviation lower than OECD mean and below
Teacher quality	Sum of 5 items related to teacher quality: low teacher job satisfaction; poor teacher understanding of school's curricular goals; low degree of teacher success in implementing the school's curriculum; low teacher expectations for student achievement; teacher absenteeism; dummy variable denoting 1 standard deviation lower than OECD mean and below
Country factor	
Economic development	GDP per capita (in International US dollars)

Table 2 Percent of students vulnerable and at-risk

Country	GDP per capita 2011 $	Vulnerable Math	Family background			School resources	Teacher quality
			Parental education	Parental occupation	Home possessions		
Yemen	2,333	97.67	–	–	86.28	18.64	53.17
Morocco	4,952	90.40	80.18	76.53	71.08	22.22	68.22
Georgia	5,465	58.74	4.97	29.69	42.57	8.97	36.89
Armenia	5,789	59.08	–	–	59.99	12.21	13.19
Thailand	8,646	56.59	–	–	62.87	60.29	22.74
Tunisia	9,351	88.71	–	–	50.01	26.17	43.78
Azerbaijan	10,067	53.58	13.94	66.60	66.96	68.38	56.24
Iran	11,508	66.78	48.30	46.57	48.55	60.27	10.62
Serbia	11,883	30.27	–	–	10.62	32.82	26.34
Kazakhstan	13,099	38.24	–	–	34.78	32.91	8.01
Romania	15,139	42.97	31.15	46.22	24.13	31.64	17.40
Turkey	17,110	48.98	–	–	46.99	79.96	42.16
Chile	17,310	55.83	–	–	24.69	31.82	31.30
Croatia	19,469	39.58	6.97	22.36	7.43	13.47	4.55
Lithuania	20,321	20.92	0.49	24.10	11.87	18.08	5.29
Russian Federation	21,246	18.18	4.08	17.34	23.78	28.05	11.58
Poland	21,261	44.35	32.21	30.26	19.20	6.30	12.11
Hungary	21,663	29.61	–	23.17	9.46	18.34	16.23
Bahrain	23,645	66.17	–	–	21.77	53.52	15.69
Slovak Republic	23,910	31.20	6.05	20.98	17.70	15.43	14.42
Saudi Arabia	24,268	75.61	29.13	16.29	42.31	52.03	25.43
Portugal	25,372	19.53	31.20	21.04	5.02	35.47	9.61
Czech Republic	26,208	28.21	1.51	18.21	5.74	7.29	21.45
Slovenia	26,954	27.96	3.68	13.55	9.30	.54	15.91
Malta	27,284	36.87	37.79	20.61	9.06	16.43	3.11
Oman	28,684	79.72	19.04	21.20	49.57	73.29	21.33
New Zealand	30,057	41.97	–	–	12.29	4.10	0.00
Korea	30,286	3.37	–	–	11.08	4.12	4.51
Spain	32,045	43.78	24.23	19.79	9.03	9.02	17.59
Italy	32,647	31.27	22.22	24.97	18.12	18.03	39.02
Japan	34,314	6.81	–	–	14.79	15.08	31.74
England	35,657	22.37	–	–	7.55	4.03	7.08
Finland	37,464	15.33	3.94	9.44	5.11	13.63	8.60
Belgium (Flemish)	38,768	10.76	–	–	4.97	4.12	8.63
Germany	39,491	19.28	26.48	10.67	5.36	7.16	14.24
Australia	39,721	29.82	0.18	5.36	8.37	9.05	12.50
Denmark	40,908	18.14	–	–	1.22	18.24	10.06
Sweden	41,467	31.48	0.99	6.38	1.94	10.13	8.56
Ireland	41,682	23.45	3.77	15.79	9.00	7.43	3.16
Austria	42,196	29.57	3.77	15.17	5.24	6.72	5.30

Table 2 continued

Country	GDP per capita 2011 $	Vulnerable Math	Family background: Parental education	Parental occupation	Home possessions	School resources	Teacher quality
Netherlands	42,772	11.57	–	–	2.16	3.04	20.43
United States	48,112	19.03	–	–	13.35	11.01	8.22
Hong Kong	50,551	3.83	29.69	21.52	15.05	81.07	19.70
Norway	60,405	37.28	0.44	6.91	4.75	2.28	6.03
Singapore	60,688	6.13	10.96	8.70	10.36	21.12	20.24
Average across countries		38.02	17.68	23.55	22.70	23.87	18.94
Correlation with GDP per capita		−0.68	−0.40	−0.72	−0.72	−0.29	−0.50

dichotomous outcome and risk factor, relative risk (RR) is calculated with the following formula:

$$\mathrm{RR} = \frac{a/b}{c/d} \tag{1}$$

where a = number of low performers who are exposed to the risk factor, b = total population exposed to the risk factor, c = number of low performers who are not exposed to the risk factor, and d = total population not exposed to the risk factor. RR is the ratio of the proportion of people who are vulnerable amongst those exposed to the risk factor, to the proportion of people who are vulnerable amongst those *not* exposed to the risk factor.

Population attributable risk is calculated with the following formula:

$$\mathrm{PAR} = \frac{e\,(RR-1)}{1+[e\,(RR-1)]} \tag{2}$$

where $e = b/(b + d)$, the proportion exposed to the risk factor in the population. PAR expresses the proportion of the total occurrence of vulnerability that can be attributed to a particular risk factor.

Construction of variables

In this study, the main outcome variable is mathematics achievement. In our preliminary analyses we also examined the relationships for science; however, at the country level the correlation between the percent vulnerable in mathematics and percent vulnerable in science was 0.94, and therefore the science results were very similar to those of mathematics. TIMSS identified four points (625=Advanced, 550=High, 475=Intermediate, 400=Low) on the overall mathematics scales to serve as international benchmarks. We define "vulnerable students" as those who performed below the intermediate international benchmark.

Table 1 outlines the main risk factors for family background, school resources, and teacher quality. As this study is a re-analysis of the study by Nonoyama-Tarumi and Willms (2010), we attempted to make the variables analogous to that study. However, as the parental questionnaires were implemented in only 30 countries, data were missing for both parental education and parental occupation in 15 of the 45 countries. Therefore, our main analyses refer to the risk factors of home possessions, school resources, and teacher quality. Finally, for economic development, we used GDP per capita (in International US dollars) from the World Development Indicators.

Results

Prevalence of vulnerability and risk

In Table 2, we present the prevalence of students who are vulnerable and the percentage exposed to risk factors in each country, with the countries ordered by GDP per capita. One can see that vulnerability—the percentage of low-performing students—is smaller in high-income countries (correlation with GDP per capita is –0.68). To examine these patterns more closely, we regressed the prevalence of vulnerability and risk factors on GDP and GDP-squared. Figure 1 shows the scatter plot for math achievement as a function of GDP per capita. The dot size represents the number of 15-year-old students in the country.

Turning to those exposed to risk factors, for family background measures, the percentage at risk is smaller in high-income countries, and the pattern is stronger for parental occupation and home possessions than for parental education. In Figure 2, we plot the prevalence of low home possessions against GDP per capita; this indicates that the negative relationship levels off at GDP per capita of about $40,000.

Regarding school measures, Figure 3 is a scatter plot for prevalence of low school resources and Figure 4 is a scatter plot for the prevalence of low teacher quality. As expected, the prevalence of low school resources is more severe in lower-income countries, but there are outliers, such as Singapore. Although with the highest GDP per capita, the prevalence of low school resources is about 20%, equivalent to that of Yemen and Morocco. This may be because the school resources measure is based on principals' perceptions of shortages of facilities and resources, and principals in Singapore may have high expectations. We found that teacher quality has a stronger negative correlation with GDP than do school resources. Similar to the family background measures, the prevalence of low teacher quality decreases as a country's GDP per capita increases; this negative relationship levels off when GDP per capita reaches about $40,000. Perhaps the aspects of teacher quality that make up the indicator—teachers' job satisfaction, understanding of the

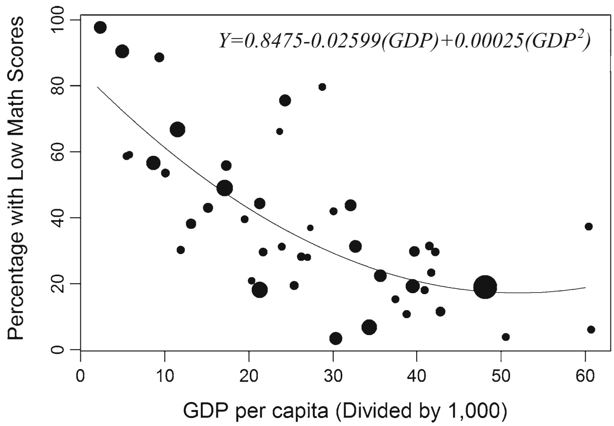

Fig. 1 Percentage with low mathematics scores vs. GDP per capita

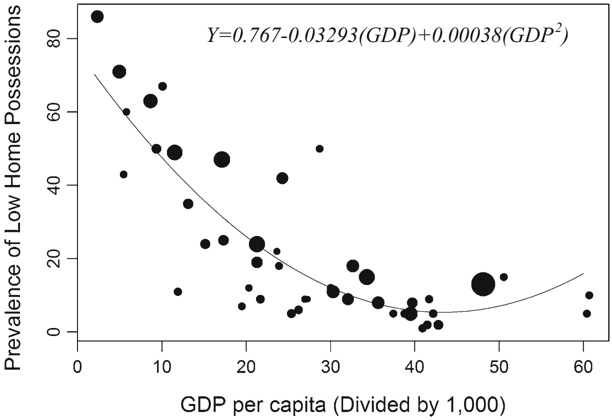

Fig. 2 Prevalence of low home possessions vs. GDP per capita

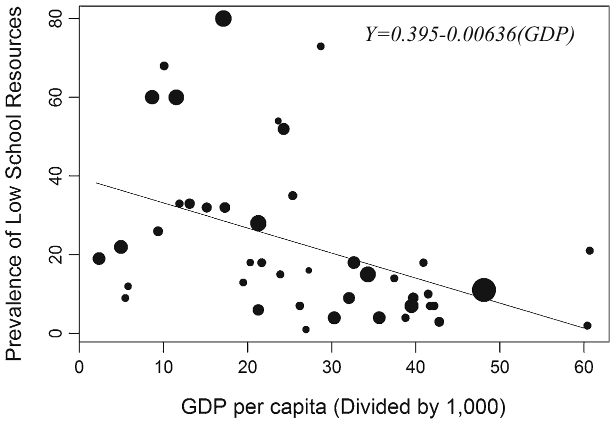

Fig. 3 Prevalence of low school resources vs. GDP per capita

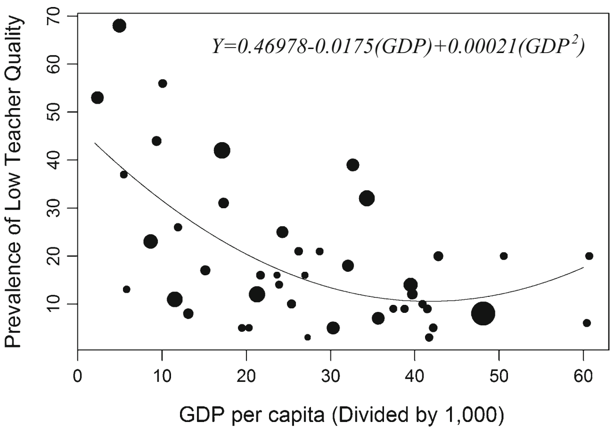

Fig. 4 Prevalence of low teacher quality vs. GDP per capita

Table 3 Relative risk (RR) and population attributable risk (PAR) of low mathematics achievement for family background measures

Country	GDP per capita 2011 $	Parental education		Parental occupation		Home possessions	
		RR	PAR	RR	PAR	RR	PAR
Yemen	2,333	–	–	–	–	1.00 (0.01)	0.00 (0.01)
Morocco	4,952	1.09 (0.02)	0.07 (0.01)	1.08 (0.02)	0.06 (0.02)	1.03 (0.02)	0.02 (0.01)
Georgia	5,465	1.37 (0.07)	0.02 (0.00)	1.23 (0.04)	0.07 (0.01)	1.20 (0.04)	0.08 (0.02)
Armenia	5,789	–	–	–	–	1.06 (0.03)	0.04 (0.02)
Thailand	8,646	–	–	–	–	1.40 (0.07)	0.20 (0.03)
Tunisia	9,351	–	–	–	–	1.06 (0.01)	0.03 (0.01)
Azerbaijan	10,067	1.12 (0.05)	0.02 (0.01)	1.21 (0.06)	0.12 (0.03)	1.19 (0.06)	0.11 (0.03)
Iran	11,508	1.44 (0.05)	0.17 (0.01)	1.28 (0.03)	0.12 (0.01)	1.32 (0.04)	0.14 (0.01)
Serbia	11,883	–	–	–	–	1.61 (0.13)	0.06 (0.01)
Kazakhstan	13,099	–	–	–	–	1.38 (0.10)	0.12 (0.03)
Romania	15,139	1.99 (0.12)	0.24 (0.02)	1.53 (0.10)	0.20 (0.03)	1.63 (0.10)	0.13 (0.02)
Turkey	17,110	–	–	–	–	1.41 (0.06)	0.16 (0.02)
Chile	17,310	–	–	–	–	1.32 (0.04)	0.07 (0.01)
Croatia	19,469	1.76 (0.10)	0.05 (0.01)	1.63 (0.06)	0.12 (0.01)	1.21 (0.08)	0.02 (0.01)
Lithuania	20,321	2.65 (0.63)	0.01 (0.00)	2.02 (0.17)	0.20 (0.03)	1.65 (0.14)	0.07 (0.01)
Russian Federation	21,246	1.58 (0.23)	0.02 (0.01)	1.62 (0.15)	0.10 (0.02)	1.50 (0.13)	0.11 (0.03)
Poland	21,261	1.90 (0.09)	0.22 (0.02)	1.50 (0.07)	0.13 (0.02)	1.35 (0.05)	0.06 (0.01)
Hungary	21,663		–	2.08 (0.11)	0.20 (0.02)	2.19 (0.17)	0.10 (0.02)
Bahrain	23,645		–	–		1.11 (0.03)	0.02 (0.01)
Slovak Republic	23,910	2.24 (0.22)	0.07 (0.01)	1.75 (0.11)	0.14 (0.02)	1.53 (0.11)	0.09 (0.02)
Saudi Arabia	24,268	1.13 (0.03)	0.04 (0.01)	1.08 (0.03)	0.01 (0.00)	1.01 (0.03)	0.00 (0.01)
Portugal	25,372	1.56 (0.12)	0.15 (0.03)	1.34 (0.15)	0.07 (0.03)	1.65 (0.22)	0.03 (0.01)
Czech Republic	26,208	2.41 (0.25)	0.02 (0.00)	1.73 (0.12)	0.12 (0.02)	1.69 (0.17)	0.04 (0.01)
Slovenia	26,954	2.15 (0.18)	0.04 (0.01)	1.79 (0.13)	0.10 (0.01)	1.35 (0.11)	0.03 (0.01)
Malta	27,284	1.37 (0.04)	0.12 (0.01)	1.37 (0.06)	0.07 (0.01)	1.27 (0.08)	0.02 (0.01)
Oman	28,684	1.13 (0.02)	0.02 (0.00)	1.09 (0.01)	0.02 (0.00)	1.09 (0.02)	0.04 (0.01)
New Zealand	30,057		–	–		1.48 (0.07)	0.06 (0.01)
Korea	30,286		–	–		3.63 (0.58)	0.23 (0.04)
Spain	32,045	1.54 (0.07)	0.12 (0.01)	1.40 (0.07)	0.07 (0.01)	1.39 (0.07)	0.03 (0.01)
Italy	32,647	1.62 (0.09)	0.12 (0.02)	1.45 (0.08)	0.10 (0.02)	1.16 (0.08)	0.03 (0.01)
Japan	34,314		–	–		2.05 (0.28)	0.13 (0.03)
England	35,657		–	–		1.50 (0.18)	0.04 (0.01)
Finland	37,464	1.99 (0.26)	0.04 (0.01)	1.61 (0.19)	0.05 (0.02)	1.37 (0.25)	0.02 (0.01)
Belgium (Flemish)	38,768		–	–		2.59 (0.37)	0.07 (0.02)
Germany	39,491	1.52 (0.12)	0.12 (0.02)	1.72 (0.14)	0.07 (0.01)	1.42 (0.19)	0.02 (0.01)
Australia	39,721	2.10 (0.54)	0.00 (0.00)	1.48 (0.12)	0.03 (0.01)	1.50 (0.10)	0.04 (0.01)
Denmark	40,908		–	–		3.10 (0.36)	0.03 (0.01)
Sweden	41,467	2.02 (0.23)	0.01 (0.00)	1.69 (0.12)	0.04 (0.01)	1.69 (0.17)	0.01 (0.00)

Table 3 continued

Country	GDP per capita 2011 $	Parental education		Parental occupation		Home possessions	
		RR	PAR	RR	PAR	RR	PAR
Ireland	41,682	2.46 (0.21)	0.05 (0.01)	1.48 (0.13)	0.07 (0.02)	1.77 (0.14)	0.06 (0.01)
Austria	42,196	2.38 (0.17)	0.05 (0.01)	1.71 (0.11)	0.10 (0.01)	1.53 (0.13)	0.03 (0.01)
Netherlands	42,772		–	–		1.64 (0.39)	0.01 (0.01)
United States	48,112		–	–		1.93 (0.10)	0.11 (0.01)
Hong Kong	50,551	0.86 (0.31)	−0.04 (0.10)	0.74 (0.26)	−0.06 (0.06)	1.17 (0.30)	0.02 (0.04)
Norway	60,405	1.63 (0.39)	0.00 (0.00)	1.35 (0.15)	0.02 (0.01)	1.15 (0.13)	0.01 (0.01)
Singapore	60,688	3.57 (0.32)	0.22 (0.02)	2.61 (0.35)	0.12 (0.02)	3.72 (0.29)	0.22 (0.02)
Average		1.80	0.07	1.52	0.09	1.58	0.07
Correlation with GDP per capita		0.39	−0.11	0.26	−0.42	0.44	−0.09

Note: Standard errors are shown in parentheses.

school's curricular goals, degree of success in implementing the school's curriculum, expectations for student achievement, and absenteeism—reach a ceiling at a certain level of GDP.

Moreover, these indicators of teacher quality are based on school administrators' assessments. This has two important implications. First, this might reflect variance in school administrators' expectations of teachers rather than in teacher quality. Second, the results may reflect cultural differences in expectations and standards, rather than differences in teacher quality in absolute terms. As a result, when we compared with the relationship between family background measures and GDP per capita, we found that the country-level results were more varied. For example, in some East Asian countries, despite the relatively high GDP per capita, a high proportion of students attend schools with low teacher quality: 32% for Japan, 20% for Hong Kong and Singapore. This may be because school principals in these countries may have higher expectations for teachers than do those in other countries.

Relative risk (RR) and population attributable risk (PAR)

Table 3 shows the RR and PAR for the three family background measures for each country, using math achievement as the outcome variable. When making cross-national comparisons of these statistics, it is important to examine the relative and absolute risk simultaneously for each country. The correlations between these two statistics and GDP per capita, which are of primary concern in this study, show that the RR of two family background measures are significantly positively associated with GDP per capita (0.39 for parent education and 0.44 for home possessions), and the PAR of the one family background measure, parental occupation, is significantly negatively associated with GDP per capita (−0.42).

To examine these patterns more closely, we regressed RR and PAR on GDP and GDP-squared. Figure 5 shows the scatter plot for RR; Figure 6 shows the scatter plot for absolute risk of home possessions. The Y-axis shows the effect of family background on achievement and the X-axis shows the level of economic development. Looking at RR, the likelihood that students are in the low-performing group when they do not have minimum home possessions is significantly higher in high-income countries. We do not detect the curvilinear association we found in our earlier study (Nonoyama-Tarumi and Willms 2010), perhaps because of the different grades and ages examined. In older grades, there may be a "threshold" effect of family background. For instance, by grade 8 or 9 the availability of study materials such as computers, calculators, and writing utensils may be similarly essential in both moderate- and high-GDP countries; thus, the achievement gap between children of low SES and average-high SES may be consistent across moderate- and high-GDP countries. In comparison, when examining grade 4 data, a significant linear association between GDP and relative risk of parental education may indicate that no threshold effect exists at this age, and that family background consistently matters more as country GDP increases. For instance, home possessions and the availability of learning resources may increasingly matter, since they can help children focus on learning. As GDP increases, there may be an increased focus on early childhood education and on the role that family background plays in providing a nurturing learning environment for young students. There may be no ceiling effect to this, as higher GDP countries may have more material resources for average and high SES children, resulting in a greater disparity with low SES children.

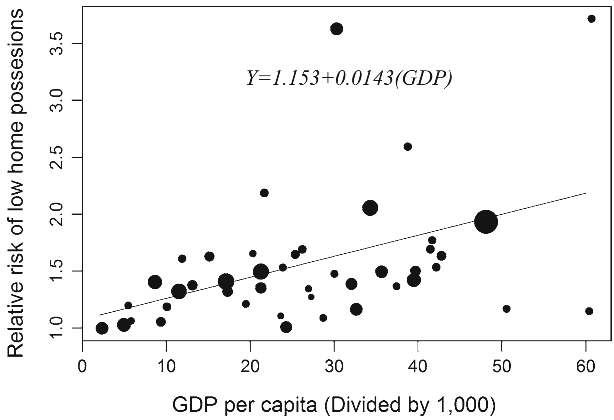

Fig. 5 Relative risk of low mathematics associated with low home possessions vs. GDP per capita

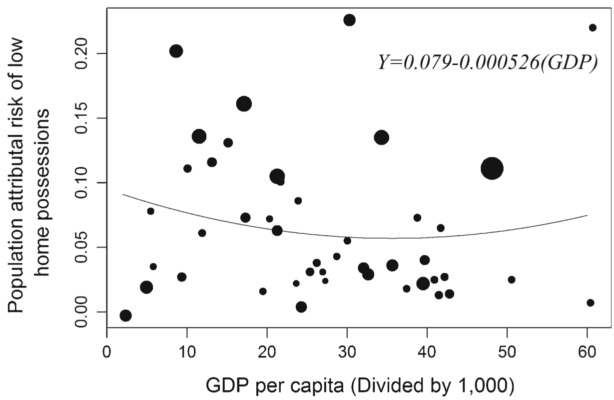

Fig. 6 Population attributable risk of low mathematics associated with low home possessions vs. GDP per capita

In addition, the relative risk of home possessions, as well as parent education and parent occupation, are all above 1.0, with the exception of Hong Kong. This suggests that high SES students outperform low SES students across countries. When we turn to the population attributable risk of low home possessions (Figure 6), there is no clear pattern. Although the prevalence of low home possessions is higher in low-income countries, no significant association exists between PAR and GDP per capita.

In Table 4, we show the relative and population attributable risks for the two school measures for each country, using math achievement as the outcome variable. Only the PAR of attending a school with poor school resources is significantly associated with GDP per capita. Although the RRs of low achievement associated with low teacher quality are quite large in a few countries, such as Romania (1.34) and Japan (1.58), in many other countries the likelihood of low performance is not significantly different whether one's school has low or high teacher quality. Again, this may be due to differences amongst countries in the measures' validity, as the teacher quality index is based on responses from school administrators. Interestingly, when we compared the descriptive statistics with our prior analyses using the PISA data, we found less consistency between the two studies for school resource measures than for family background measures—which illuminates the challenges of measuring the quality of school resources and teachers in cross-national studies.

Figures 7 and 8 show scatter plots for RR and PAR of school resources, and Figures 9 and 10 show the comparable plots for teacher quality.

Discussion

We used data from 45 countries that participated in the 2011 TIMSS to compare the effects of family background and school and classroom resources factors on elementary students' mathematics achievement. Our approach to the analysis was to first identify students who were "vulnerable", in that their achievement test scores were below the intermediate international benchmark, and then to define a set of "risk factors" associated with family background, such as living with parents who had little or no formal education or attending a school with low levels of resources. Although one loses some of the richness of the data by dichotomizing continuous variables, our approach addresses a shortcoming of most international studies—namely, the "floor" effects on the test score distributions evident in most low-income countries. Also, using dichotomous outcomes and risk factors allowed us to examine the relative risk and population attributable risk in a uniform way across countries.

In this section, we highlight some challenges in measuring school resources in cross-national studies. First, when the questions are answered by school administrators, the indicators might reflect the variance in school administrators' expectations of teachers, rather than teacher quality itself. This issue becomes especially severe in cross-national studies, as the results may reflect cultural differences in expectations and standards rather than differences in teacher quality in absolute terms.

Second, test scores in international studies such as TIMSS embody children's capacity to learn at birth plus the cumulative effects of their learning at home and at school since birth. Thus, when we consider children's test scores at the end of fourth grade, we should not expect to observe a strong relationship between their test results and measures describing the quality of teaching during that school year. Another way to think about the explanatory factors in this study is that the contemporary measures of family background

Table 4 Relative risk (RR) and population attributable risk (PAR) of low mathematics achievement for low school resources

Country	GDP per capita 2011 $	School resources		Teacher quality	
		RR	PAR	RR	PAR
Yemen	2,333	1.00 (0.01)	.00 (0.00)	1.00 (0.01)	.00 (0.00)
Morocco	4,952	1.00 (0.03)	.00 (0.01)	1.05 (0.03)	.03 (0.02)
Georgia	5,465	1.01 (0.13)	.00 (0.01)	1.05 (0.07)	.02 (0.03)
Armenia	5,789	1.02 (0.10)	.00 (0.01)	.99 (0.08)	.00 (0.01)
Thailand	8,646	1.18 (0.11)	.10 (0.06)	1.11 (0.11)	.02 (0.03)
Tunisia	9,351	.98 (0.03)	−.01 (0.01)	1.04 (0.02)	.02 (0.01)
Azerbaijan	10,067	1.08 (0.12)	.05 (0.07)	1.02 (0.10)	.01 (0.05)
Iran	11,508	1.10 (0.05)	.06 (0.03)	1.14 (0.05)	.01 (0.01)
Serbia	11,883	1.25 (0.11)	.08 (0.03)	1.23 (0.13)	.06 (0.03)
Kazakhstan	13,099	.91 (0.13)	−.03 (0.04)	1.35 (0.27)	.03 (0.02)
Romania	15,139	1.19 (0.12)	.06 (0.03)	1.34 (0.15)	.06 (0.03)
Turkey	17,110	1.39 (0.16)	.24 (0.07)	1.28 (0.08)	.10 (0.03)
Chile	17,310	1.27 (0.07)	.08 (0.02)	1.23 (0.07)	.07 (0.02)
Croatia	19,469	.99 (0.11)	.00 (0.02)	1.26 (0.15)	.01 (0.01)
Lithuania	20,321	1.13 (0.16)	.02 (0.03)	1.42 (0.39)	.02 (0.02)
Russian Federation	21,246	.91 (0.11)	−.03 (0.03)	.95 (0.22)	−.01 (0.03)
Poland	21,261	1.14 (0.13)	.01 (0.01)	1.25 (0.08)	.03 (0.01)
Hungary	21,663	1.02 (0.17)	.00 (0.03)	1.25 (0.22)	.04 (0.03)
Bahrain	23,645	1.15 (0.06)	.08 (0.03)	1.06 (0.06)	.01 (0.01)
Slovak Republic	23,910	1.03 (0.13)	.00 (0.02)	1.24 (0.16)	.03 (0.02)
Saudi Arabia	24,268	1.03 (0.04)	.01 (0.02)	1.02 (0.05)	.01 (0.01)
Portugal	25,372	1.08 (0.18)	.03 (0.06)	1.31 (0.24)	.03 (0.03)
Czech Republic	26,208	.92 (0.13)	−.01 (0.01)	.97 (0.12)	−.01 (0.03)
Slovenia	26,954	1.51 (0.22)	.00 (0.00)	1.01 (0.13)	.00 (0.02)
Malta	27,284	1.21 (0.06)	.03 (0.01)	1.18 (0.09)	.01 (0.00)
Oman	28,684	.97 (0.02)	−.02 (0.02)	1.08 (0.02)	.02 (0.00)
New Zealand	30,057	1.08 (0.10)	.00 (0.00)		
Korea	30,286	1.17 (0.26)	.01 (0.01)	1.50 (0.43)	.02 (0.02)
Spain	32,045	.99 (0.17)	.00 (0.01)	1.14 (0.11)	.02 (0.02)
Italy	32,647	1.28 (0.11)	.05 (0.02)	.93 (0.10)	−.03 (0.04)
Japan	34,314	1.01 (0.21)	.00 (0.03)	1.58 (0.22)	.15 (0.05)
England	35,657	1.12 (0.44)	.00 (0.01)	1.36 (0.35)	.03 (0.02)
Finland	37,464	1.22 (0.21)	.03 (0.03)	1.68 (0.47)	.06 (0.04)
Belgium (Flemish)	38,768	1.01 (0.14)	.00 (0.01)	.90 (0.20)	−.01 (0.02)
Germany	39,491	1.33 (0.32)	.02 (0.02)	1.20 (0.22)	.03 (0.03)
Australia	39,721	1.13 (0.13)	.01 (0.01)	1.26 (0.14)	.03 (0.02)
Denmark	40,908	.74 (0.15)	−.05 (0.03)	.88 (0.18)	−.01 (0.02)
Sweden	41,467	1.09 (0.12)	.01 (0.01)	1.21 (0.14)	.02 (0.01)
Ireland	41,682	1.20 (0.20)	.01 (0.01)	1.12 (0.55)	.00 (0.02)
Austria	42,196	.99 (0.15)	.00 (0.01)	1.09 (0.19)	.00 (0.01)
Netherlands	42,772	1.84 (1.08)	.02 (0.03)	1.03 (0.22)	.01 (0.05)

Table 4 continued

Country	GDP per capita 2011 $	School resources		Teacher quality	
		RR	PAR	RR	PAR
United States	48,112	1.08 (0.11)	.01 (0.01)	1.40 (0.19)	.03 (0.02)
Hong Kong	50,551	.37 (0.16)	−1.04 (0.61)	2.19 (1.32)	.19 (0.15)
Norway	60,405	.91 (0.47)	.00 (0.01)	1.23 (0.20)	.01 (0.01)
Singapore	60,688	1.02 (0.29)	.00 (0.06)	1.08 (0.22)	.02 (0.04)
Average		1.09	0.00	1.20	0.03
Correlation with GDP per capita		−0.08	−0.30	0.26	0.10

Note: Standard errors are shown in parentheses.

stand as a proxy for the time-varying effects of parenting on children's learning since birth, while the contemporary measures of school resources and teacher quality are proxies for the school resources and the quality of teaching children experienced since starting school at age 5 or 6. We would expect that factors such as parents' education would be relatively stable over a child's life course from birth to age 8; similarly, the level of schools' material resources from kindergarten or grade 1 to grade 4 is probably quite stable. However, one cannot make this claim for teaching quality. A number of studies have shown that the variation in students' achievement amongst classrooms within schools is greater than the variation amongst schools. For example, in a study of Inner London primary schools, Mortimore, Sammons, Stoll, Lewis, and Ecob (1988) found that the variation in mathematics performance amongst classrooms ranged from 2% to 16%, while the variation amongst schools was only 3% to 8%. Similarly, Kyriakides, Campbell, and Gagatsis (2000) found that for students in Cyprus who were in their last year of primary school, 14% of the variation in student achievement was amongst classrooms; about 9% was amongst schools.

These two limitations on the school resources measures may partially explain the relatively small effects of school resources and teacher quality on achievement, both in terms of RR and PAR, and the considerable variation amongst countries. For policy purposes, countries can use data from three types of studies. International studies such as TIMSS provide information on the overall level and variation in school resources vis-à-vis

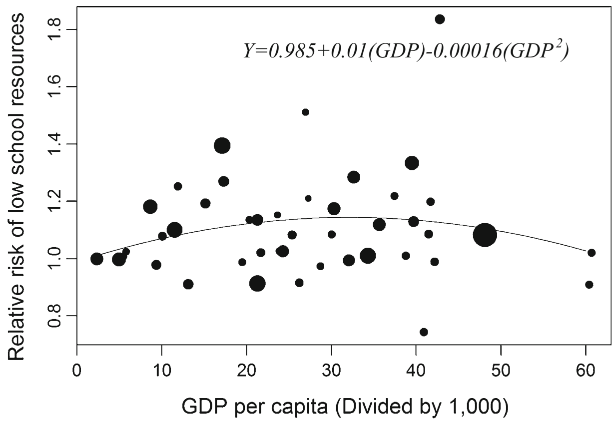

Fig. 7 Relative risk of low mathematics associated with low school resources vs. GDP per capita

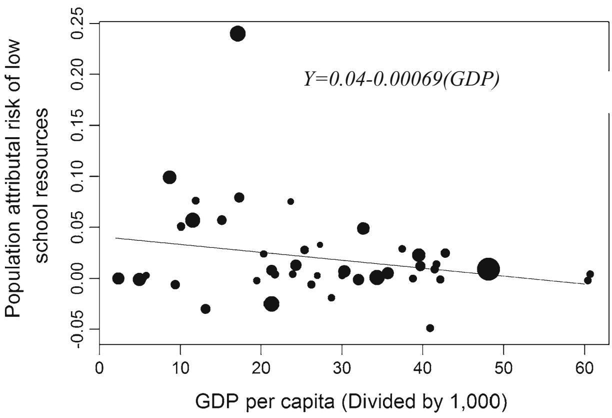

Fig. 8 Population attributable risk of low mathematics associated with low school resources vs. GDP per capita

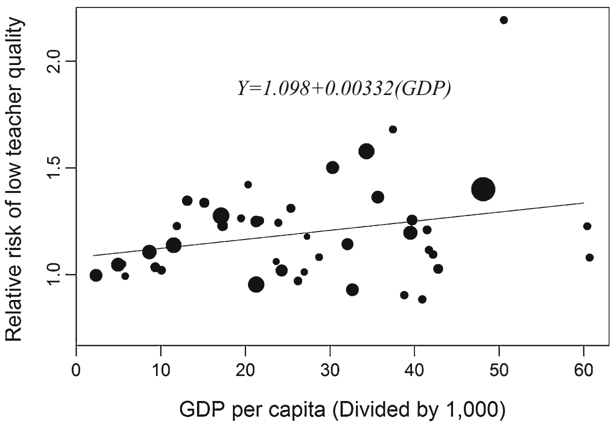

Fig. 9 Relative risk of low mathematics associated with low teacher quality vs. GDP per capita

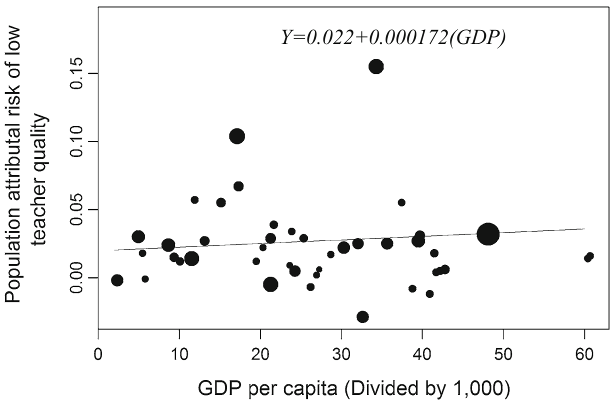

Fig. 10 Population attributable risk of low mathematics associated with low teacher quality vs. GDP per capita

international norms. Results of more focused studies that collect student questionnaire data from all schools and all students across a range of grade levels can provide a more detailed portrait of school resources, which can be used to allocate resources and design interventions. Finally, relatively small, focused intervention studies can be used to assess gains in achievement associated with improved school resources and in-service teacher professional development. This type of study can be piggy-backed on the sampling frame of an international study. A combination of these three types of studies can provide policymakers with direction on how best to allocate school resources and make broader policy decisions.

Next, we discuss our four important findings on the relative and absolute effects of family background and school resources, and how these effects vary between low- and high-income countries. First, vulnerability decreases with increasing levels of GDP per capita, but the relationship is weaker at higher levels of GDP. As one would expect, wealthy countries have fewer vulnerable children than poor countries. However, we found that the prevalence of vulnerability levels off to about 20% at GDP per capita above $40,000. This finding raises the larger question of whether countries can reasonably reduce vulnerability levels to 10%. In four countries—Hong Kong, Japan, Korea, and Singapore – had a prevalence of low mathematics scores below 10%. In addressing this question, one would need to take account of the rates of "exclusions" in each country; that is, the percentage of students excluded from taking the test because they are considered to have special learning needs or limited proficiency in the assessment language.

Second, the relative risk associated with low socioeconomic status (SES) is positively related to GDP, but the relative risk associated with attending a poorly-resourced school is unrelated to GDP. It may seem counterintuitive to state that living in a low SES family in a high-income country has a greater effect on achievement than it does in a low-income one: in higher-income countries we would expect to find a smaller achievement gap between children from low and high SES families. However, this finding emphasizes the need to consider achievement alongside measures of equality. Our results indicate that the gap between low and high SES families is smaller in low-income countries because the achievement scores are uniformly low across all levels of SES. In other words, in many low-income countries, the achievement of students from high SES families is relatively low, and there is less disparity between high and low SES families.

The results also suggest that countries may differ in the ways that the cultural capital associated with parents' levels of education or wealth is translated into their children's academic achievement. For example, in high-income countries, families with relatively higher SES or higher levels of education may spend more time reading to their children or be better able to tutor or mentor them. Tramonte and Willms (2010) distinguished between two types of cultural capital: "static", representing the parents' highbrow activities, and "relational", representing cultural interactions and communication patterns between parents and their children. They suggest that parents' static cultural capital more strongly affects whether a child attends a private or public school, but their relational cultural capital plays a stronger role after the child is "in the door". Given the role that private schooling plays in many low-income countries, the findings of this study call for a more detailed analysis that examines the mediating role that relational and static cultural capital plays in each country.

Third, the population attributable risk associated with some measures of family background and school resources tends to fall with rising GDP, but it varies considerably amongst countries. In the same way that it is important to consider overall levels of achievement alongside measures of equality, such as relative risk, this finding emphasizes the need to consider relative risk and population attributable risk together. Relative risk indicates the magnitude of effects associated with a risk factor, such as living in a family with low parental education, whereas population attributable risk indicates the overall impact that policies to reduce the prevalence of risk will have on the countries' results. When relative risk is high, and the prevalence of those exposed to the risk factor is high, then the overall effect on a country's outcomes are large.

Fourth, in low- and high-income countries alike, the effects of family background are stronger than the effects of school resources. On average, across countries, the relative risks associated with parental education, parental occupation, and home possessions are 1.80, 1.52, and 1.58, respectively; those associated with school resources and teacher quality are 1.09 and 1.20, respectively. These results are consistent with an earlier study based on PISA data (Nonoyama-Tarumi and Willms 2010) and with the Baker et al. (2002) findings. However, one must not conclude that "schools don't make a difference". Indeed, we found positive effects of school resources and teacher quality in the majority of countries, with an average relative risk of 1.09 for the measure of school resources and 1.20 for teacher quality. Also, our findings suggest that the effects are quite variable across countries, possibly due to variation amongst countries in the validity of the measure, as we discussed earlier.

Also, with cross-sectional data one cannot address the longitudinal effects associated with family background nor the extent to which school resources mediate those effects. In most countries, students are segregated into schools with differing levels of socioeconomic status, partly because of residential segregation but also because of other selection processes. Willms (2010) refers to this as "horizontal segregation". Thus, the effects of family background are confounded with those of school resources and teacher quality. We would expect that that the extent to which these effects are confounded would be greater in low-income countries, where levels of school resources are less uniform, between-school segregation is greater, and private schooling plays a bigger role. With longitudinal data, we would be better able to control for this selection effect and thereby tease out the unique effects associated with family background and school resources.

Also, as Baker et al. (2002) suggest, there are interactions between family background and school resources. We believe there are also interactions between teacher quality and school resources. Even the best teachers are unlikely to succeed without a certain level of material resources. A more detailed analysis of the current TIMSS data could give some indication of these interactions; however, detailed analyses of monitoring data collected within countries are likely to be more productive.

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