

School resources and student achievement: Data from rural India

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Published online: 3 September 2015
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Abstract In addition to basic infrastructure, what school resources are important to improve learning? This question is hard to answer due to lack of availability of appropriate data. Collaboration between researchers at US universities and a large, well-established educational foundation in India enabled this study to overcome the challenge of data availability. The study used a unique 60-item instrument—with data from 88 government

We acknowledge excellent support from the Azim Premji Foundation's Child Friendly School Initiative program team, including its leaders, Rudresha S. and Uma Shankar Periodi. D. D. Karopady, former head of Research and Documentation at the Azim Premji Foundation, also provided invaluable guidance during the course of the study.

Madhur Chandra's time on the project was supported in part by a Pre-doctoral Training Grant from the Institute of Education Sciences, US Department of Education (Award # R305B090011) to Michigan State University. The opinions expressed here are those of the authors and do not represent the views of the Institute, the US Department of Education, or Michigan State University.

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schools—that generated 8 different indices of school resources. The article finds that in schools with more learning-specific facilities and more co-curricular activities children perform well in math, all else being equal. This article discusses the study’s limitations and implications for research, policy and practice.

Keywords School resources · Student achievement · India · Rural education

A well-functioning education system requires adequate educational expenditure and basic infrastructure. Yet, research shows these alone will not ensure higher learning levels (Muralidharan 2013). Schools in India have received increased financial allocations (PAISA 2012), leading to some improvements in woefully inadequate school infrastructure, but student learning has not improved commensurately (ASER 2013). This raises an important question: In addition to basic infrastructure, what other school resources are important to improve learning?

One key challenge in addressing this question is identifying and quantifying relevant school resources. Studies typically rely on limited measures of school resources that capture just the basic infrastructure. When these infrastructure items appear insignificant, researchers may prematurely conclude that schools resources in general cannot make a significant difference to learning levels (see Chudgar and Luschei 2009 for a related discussion); however, they may not be measuring important aspects of school resources.

A related challenge is isolating the importance of school factors on learning. Students attending well-resourced schools likely belong to more affluent families; thus, it is not immediately evident whether higher performance at such schools reflects these schools’ resources or their students’ overall privileged circumstances. In such a case, knowing the students’ prior test scores may be particularly useful, allowing researchers to account for the influence of students’ circumstances on their learning thus far. However, prior test score data are also difficult to obtain from most standard data-collection exercises.

We overcome these data challenges via a collaborative partnership between researchers at universities in the United States and a large, well-established Indian educational foundation. The foundation has an intimate knowledge of school environments and school operations in the study location. Its ongoing and extensive school-based data-collection effort is a primary strength of our study. In consultation with the US-based scholars, the foundation team added a pre-test to its existing protocol of testing students once yearly and added modules to collect background data on students and teachers. These pre-test scores and rich background data are our study’s second core strengths. This partnership resulted in a rich and unique test-score dataset of 2,072 fifth-graders in 88 government schools located in 1 district in a southern Indian state. These data helped us explore this study’s guiding question: What school resources may be associated with improved student achievement?

The challenge of isolating the importance of school resources

The research literature most relevant to our work follows the “production function” framework of economics. Using this framework, researchers attempt to identify the role of such “inputs” as a child’s own characteristics, home background, classroom and school

background, and teachers in “producing” a given educational “output”, usually measured as test scores.

Researchers generally agree that a child’s home background is crucial in explaining his/her educational outcomes: children in more educated and better-resourced families tend to have better educational outcomes. We focus on the role of inputs that policymakers can influence, such as teacher, classroom, and school attributes. Research on these factors is not consistent (e.g., Chudgar and Luschei 2009), as discussed below.

Production-function research in the United States: Identifying and measuring school resources

Extensive research from the United States shows that traditional school resources are not systematically associated with improved learning levels (Hanushek 1996, 1997). This research, however, is not without its critiques (e.g., Greenwald, Hedges, and Laine 1996; Krueger 2003); thus, debate continues about the role of resources and money in improving learning in the US context (e.g., Burtless 1996).

Uneven or inadequate quantification of key educational inputs such as school resources may explain, at least in part, why these debates have remained unsettled. But developing a comprehensive understanding of what is happening inside a school, and the related taxonomy, is a complex task. Cohen, Raudenbush, and Ball (2003) summarize the US-based literature that attempts to address these challenges. They identify three strands of research that aim to understand the role of school resources: one that investigates the “instructional processes and the resources used therein”, a second that focuses on the “schools’ collective characteristics”, and a third that examines “teachers’ and students’ interactions over specific content” (p. 121). The authors note the importance of what they term “personal resources” as a mediator between “conventional resources” and learning. They urge future researchers to pay close attention to “coherent systems of instruction” in order to understand how they influence learning. In other words, they argue in favor of developing a more nuanced understanding of what occurs inside a school.

Norton Grubb’s (2008) empirical research is an example of such a move beyond conventional resources to a more coherent and systemic understanding of school resources. Using a slightly different nomenclature, he identifies conventional school resources as “simple resources” and introduces the notion of “compound resources, complex resources, and abstract resources”. Compound resources become meaningful “in conjunction” with another resource, such as teacher experience and teacher training to teach the particular subject. Complex resources, such as innovative teaching approaches, are important but cannot be easily bought. Finally, abstract resources are “often embedded within a web of relationships and practices in a school” (p. 108); these include factors like positive school climate. Grubb’s (2008) research indicates that using these concepts greatly improves the explanatory power of models elucidating student performance. Thus, the resources he identifies as important for improved learning are not those that traditional measures identify.

Our brief review of the US-based literature underscores the potential limits of what researchers have termed “basic”, “traditional”, “conventional”, or “simple resources” for identifying factors significant for improved learning. We also highlight the value of adequately measuring and accounting for the complexities of school resources to understand

what matters for improved learning. The presence of these challenges is equally unmistakable in the literature from developing countries.

Production-function research in developing countries

Scholars have argued that school resources may be especially important for improving learning outcomes in poor countries (Heyneman and Loxley 1983). Multi-country research following Heyneman and Loxley has questioned these findings (Baker, Goesling, and LeTendre 2002; Hanushek and Luque 2003). Most recently, Chudgar and Luschei (2009) revisited this question and found that schools are, indeed, relatively more important for learning in poor and unequal countries. However, that paper did not identify specific school resources that matter for improving learning, leaving unanswered the question we are interested in.

In terms of “simple” or “conventional resources”, it appears that the most recent and exhaustive review of the literature, from 1990 to 2010 (Glewwe, Hanushek, Humpage, and Ravina 2011), identifies few school resources that matter for learning in developing countries. From a database of 9,000 studies, the authors focus on 43 “high quality” studies. Simple or conventional resource measures in their synthesis include the availability of textbooks, furniture, technology, electricity, blackboards, a library, and other basic infrastructure. Some studies also include measures of the length of a school day, provision of meals, and parent and community participation, which Glewwe et al. group together as measures of “school organization”. The authors find that the impact of most school and teacher characteristics on student learning is statistically insignificant. Their review reveals the potentially limited importance of simple resources in developing countries and also underscores the fact that most studies from developing countries rely on limited school resource measures.

Production-function literature, or literature that aims to identify the role of educational inputs, in the Indian context is limited but growing. A recent exhaustive literature review from India (Muralidharan 2013) notes that this literature emphasizes teacher attributes over school attributes. An important feature of several of these studies (e.g., Atherton and Kingdon 2010; Kingdon and Banerji 2008; Kingdon and Muzammil 2013; Kingdon and Sipahimalani-Rao 2010) is their taking account of extensive student background variables, including prior-test scores.

This approach, also referred to value-added modeling (VAM), uses students’ prior performance as a control in production-function models (Koedel and Betts 2011). This allows researchers to better isolate inputs introduced after prior test–score data. However, researchers debate what are appropriate VAM model specifications; they have examined assumptions underlying various value-added specifications (Guarino, Reckase, and Wooldridge 2012; Harris and Sass 2006) and often critiqued the standard VAM approaches for producing implausible results (Baker et al. 2010; Corcoran 2010; Rothstein 2010). In general, though, agreement is emerging that including a lagged or prior achievement score, as several Indian studies do and as our study proposes to do, may be an adequate value-added model specification (Harris and Sass 2006; Guarino et al. 2012).

Thus, our work is similar to some of the recent production-function studies from India regarding its use of prior-test scores as a control. However, our study differs from this existing work from India in its exploration of school resources as important for

achievement. Existing research as noted above primarily investigates the impact of various teacher attributes on learning.

To summarize: while school resources may play a role in learning (especially in poor and unequal contexts), researchers have not ascertained which are important. Researchers are often limited by their ability to identify and measure relevant and complex aspects of school resources. We have overcome this challenge through a close collaboration between experts in the field and researchers in the US, resulting in the collection of a unique dataset.

The school resources instrument: Development and existing use

Brief note on the administrative hierarchy in the Indian education system

India has a federal system, with 29 states (divided into 600 districts) and 7 union territories. Districts are divided into blocks, and blocks into clusters. The educational infrastructure exists at the national, state, district, block, and cluster levels.

While the national and state levels set agenda, the block- and cluster-level machinery, particularly the Cluster Resource Coordinators (CRC), support the day-to-day functioning of schools within their purview. The CRCs are responsible, on average, for 10–15 schools and are the first point of academic contact for teachers. Their primary responsibility is to provide academic support to teachers by visiting their assigned schools regularly and by conducting regular cluster-level meetings to enable exchange of pedagogic ideas between the teachers.

Foundation's work and development of the school resource instrument

This study is located in a relatively underdeveloped, northeastern region of a southern Indian state, where the foundation has worked in education for over a decade. Its efforts support the state government's work to improve education in this region. The foundation initially recruited 25 school "guides" (SGs) to work closely with schools (SG to school ratio is currently 1:14). The work of SGs is similar to that of CRCs. SGs visit their assigned schools regularly and maintain close contact; they support the teachers, the principals, school organizers, and the community in various educational activities. They also facilitate various foundation interventions. Their long and extensive association with these schools gives SGs a unique understanding of the school context. A key aspect of their work, relevant to our study, is to gather data on their schools.

The foundation has adopted an "integrated and holistic" approach toward education (APF 2013, p. 9). Initially, the foundation identified five areas for work and intervention: school environment, class environment, teaching learning process, teacher development, and community participation. It has launched interventions in each of these areas (APF 2013, p. 29) and regularly evaluates this work through systematic data collection activities.

To gather these data, the foundation team originally developed a 214-question school indicator survey (SIS) that encompassed the 5 key areas of intervention discussed above. It used these data to inform a school-improvement plan that local stakeholders (including parents and community members) developed jointly. SGs participated in these meetings and helped stakeholders interpret data and generate school-improvement plans.

The team recognized, over time, that the 214-item SIS did not track schools effectively. In their own words, "the indicators captured infrastructure and other tangible items rather

than the progress in the teaching-learning process” (APF 2013, p. 26). This group of practitioners thus arrived at a conclusion similar to the literature about the relative importance of simple versus complex and compound resources in understanding what might matter in improving educational outcomes.

They produced a 60-item SIS and began collecting the variables at different time intervals. They collected some information fortnightly and some monthly, quarterly, and even annually. This time frame of data collection became a primary mode of grouping these variables. The 20 fortnightly indicators included variables related to cleanliness, hygiene, food and water provision, and teacher attendance; and other variables where changes occur even on a daily basis. The 6-month indicators included such variables as School Development and Monitoring Committee (SDMC—a parent-teacher body required in all public schools) meetings or teachers’ lesson plans. Quarterly indicators included 8 measures that varied every few months, such as community contributions and student dropout rates. Finally, the SG monitored 26 variables on an annual basis: these included information on whether an SDMC existed, whether teachers had their mandatory annual trainings, whether the required infrastructure was in place, and whether annual events (e.g., sports meet, cultural day) had occurred. This 60-item SIS provides a unique and comprehensive picture of the schools we analyze here.

Data

The study uses data from one rural block in the region where the foundation has been active. The block consists of 190 villages, with over 300,000 people, including the largest proportion of rural population in the district (nearly 87%) and a sizeable minority population. It has high socioeconomic disparity and low female literacy (just under 40%). The foundation, active in over 340 government schools in this block, works with 1,600 teachers and more than 60,000 children. For our study, we excluded lower primary schools (LPS), or schools that teach only up to grade 5. We excluded 7 Urdu medium schools due to lack of Urdu language assessment tools at the time of the survey. Our study uses data from 88 higher primary government schools (HPS) that teach up to grade 7, and from 2,072 fifth-grade students at these schools.

The foundation team entirely managed and carried out data collection for this study; the researchers obtained the data from the foundation in a de-identified format. The team collected data in August–September 2011, toward the beginning of the school year, and again in March 2012, toward the end of the academic year. The SIS formed one of the key questionnaires for data collection; the foundation team and the researchers jointly developed additional questionnaires as needed. SGs administered the questionnaires in their respective schools.

The resultant data had information: (a) from the 60-item SIS; (b) on teachers’ gender, experience, training, and education; (c) on principal-reported school enrolment and principals’ perceptions of their schools’ percentage of children from poor families; (d) on student-reported demographics and home-background; and (e) on student baseline and end-line test-scores in math and environment science (EVS). SG gathered these test data by administering each child with a subject-specific test instrument.

EVS’s inclusion in school curricula in India reflects global educational discourses around environment education (EE) since UNESCO’s Tbilisi Declaration in 1977. In 2003, an order from the Supreme Court of India made the “green curricula” mandatory for all states (see Iyengar and Bajaj 2011). Per the National Curricular Framework 2005, EVS’s aim is to make children aware of environmental issues by helping them to make a

connection with their natural and human-made surroundings (Directorate of State Education Research and Training 2012). The EVS curriculum is action-oriented and project-centered, with participatory approaches to teaching. It envisions multidisciplinary and integrated courses, drawing from the sciences (physical, chemical, and biological), from social studies (history, geography, civics, etc.) and from environmental education (protection and conservation). Thus, the two subjects we have test-score data for—math and EVS—might be particularly divergent: math relies on a formal, codified body of knowledge, while EVS attempts to create a more holistic, experiential learning experience.

Preparing variables for analysis

To prepare the variables for analysis, we collapsed the teacher information at the school level, such that for each school we generated values representing average teacher experience, proportion of female teachers, proportion of teachers with a bachelor's degree or more, and proportion of teachers with a diploma in education. Teacher attributes in our analysis, therefore, do not account for the students' specific teachers but, instead, provide an overall sense of the teachers at a given school.

We next had to group the SIS's 60 items, as it was untenable to use these items separately in a regression framework. We decided to use 57 items, excluding data on total numbers of students and teachers, and information that no students had dropped out that quarter—these variables departed from the more standard “resources” we focused on.

Based on concerns about sample size, we rejected using factor analysis in constructing our composite measures of school resources. The literature's recommendations for item-to-observation ratios for factor analysis were 1:5, 1:10, and even 1:20 (Kline 2013). Researchers have noted that a small sample size where the item-to-observation ratio is as low as 1.5:1 (as in this study) will produce incorrect solutions and misclassify items (Costello and Osborne 2005). Small sample sizes are associated with the data's failure to converge to a solution and the possibility of producing outcomes that do not make practical sense. After extensive discussion and, exploratory analysis we adopted a more organic iterative approach to data reduction, which helped us identify and group variables into eight indices, each based on variables reflecting a similar underlying concept. After grouping these variables, we generated a simple average measure for each of the eight indices, ranging from 0 to 1—where a larger number meant a greater presence of the indicated items.

These data allowed us to produce an extensive set of simple and more complex resources. In addition to measures of basic facilities, we have information on tangible (e.g., learning facility, school organization, mid-day meals) and intangible (teacher preparedness, learning environment) school resources available to children, as well as their parents and community's participation in their schools' day-to-day functioning. We use these school indicators to investigate if, and to what extent, any of these resources matter in understanding variation in student performance.

Method

Given the continuous nature of the dependent variables (math and EVS performance) and the clustering of children within schools, we used an ordinary least squares (OLS) regression analysis with cluster correction at the school level. For both math and EVS, we first conducted regression analyses including student, teacher, and school background as

controls, and excluding any of the eight school resource indices. We then introduced these eight indices one at a time.

$$A_{ijt} = \gamma_1 + \gamma_2 A_{ij(t-1)} + \mathbf{X}_{ij} \gamma_3 + \mathbf{ST}_j \gamma_4 + \varepsilon_{ij} \quad (1)$$

$$A_{ijt} = \pi_1 + \pi_2 A_{ij(t-1)} + \mathbf{X}_{ij} \pi_3 + \mathbf{ST}_j \pi_4 + \pi_5 SC_j + \varepsilon_{ij} \quad (2)$$

where,

A_{ijt} = EVS or math scores for the individual i in school j at time t ;

$A_{ij(t-1)}$ = EVS or math scores for individual i in school j at time $t-1$;

\mathbf{X}_{ij} = vector of background characteristics of individual i in school j ;

\mathbf{ST}_j = vector of teacher and school-related characteristics for school j ;

SC_j = school resource index, introduced one at a time.

Results

Descriptive analysis

Table 1 provides a detailed list of all the child, teacher, and school variables, with their description. The EVS and math baseline and end-line sample sizes reveal a slight discrepancy, since some children might have been absent during tests.

The data indicate an improvement in mean scores between the baseline and end-line testing, though the change is not directly comparable since these two sets of tests had slightly different ranges for both EVS and math. In our sample, 47% of the respondents are girls, their average age is nearly 11 years, and 37% of them reported belonging to the scheduled castes (SC) or scheduled tribes (ST). The average household size is around 5 persons. A majority (68%) of these children report that their mother is illiterate; 46% report an illiterate father; and in 43% of the families no one speaks English at home, where “English at home” is treated as an additional proxy of the family’s ability to access and navigate complex educational choices. Reflecting the overall low economic development of the region, 54% report having a vehicle at home and 66% report regular electricity in the house. Most children’s families have at least one “possession”—mobile phone, land line, or television. In terms of the learning environment: 36% of children receive no homework help at home, 25% report not discussing their schools at home, 80% do not receive private coaching or tuition, 58% report not reading at all at home, and over 60% report not using the library. Overall, thus, these children belong to poor families with limited education. Although it is unremarkable, given the extent of illiteracy among their parents, that most of these children do not read at home or use the library, these numbers are large and striking.

Table 1 also describes the average teachers in this dataset. Only 31% of teachers in our sample are female—not surprising, given that our sample excludes lower primary schools and that we collected these data from a rural block. The literature has associated both these factors with a lower presence of female teachers. In our sample, 28% of teachers have a BA degree or higher, and 70% have a diploma in education. Average teacher experience is approximately 11 years. These schools enroll approximately 300 students on average. According to the principals, on average, 68% of these schoolchildren belong to “economically disadvantaged (economically weaker) sections of society”. Regarding the eight school resource indicators: on average, schools tend to have high levels of basic facility (0.73) and school organization (0.79). Similarly, mid-day meal indicators are also present

Table 1 Student, teacher, and school background characteristics, means, standard deviations, and frequencies

Variable name	No. Obs	Mean	SD	Min	Max
<i>Student background variables</i>					
EVS score (End line)	2060	17.25	5.04	0	30
Math score (End line)	2048	9.99	4.20	0	20
EVS score (Baseline)	2059	13.41	5.40	0	28
Math score (Baseline)	2060	7.68	3.71	0	19
Female	2072	0.47	0.50	0	1
Age	2072	10.73	1.24	0	14
Caste (SC/ST)	2072	0.37	0.48	0	1
Household size	2072	4.79	0.97	2	6
Mother is illiterate	2072	0.68	0.47	0	1
Father is illiterate	2072	0.46	0.50	0	1
No one speaks English at home	2072	0.43	0.49	0	1
Possessions	2072	1.55	0.66	0	3
Household has electricity	2072	0.66	0.47	0	1
Household has vehicle	2072	0.54	0.50	0	1
No homework help	2072	0.36	0.48	0	1
No discussions about school	2072	0.25	0.43	0	1
No tuition	2072	0.80	0.40	0	1
No reading outside school	2072	0.58	0.49	0	1
No library use	2072	0.63	0.48	0	1
<i>Teacher/school variables</i>					
Prop. Female teacher	88	0.31	0.21	0	0.8
Avg. Teacher experience	88	10.54	3.05	4.60	18.6
Prop. Teacher with BA or more	88	0.28	0.22	0	1
Prop. Teacher with Dip. Ed	88	0.70	0.29	0	1
School total enrollment	88	290.38	119.21	41	752
Prop. Children from poor families	88	68.22	19.14	10	100
Basic school facility index	88	0.73	0.14	0.37	1
Learning facility index	88	0.50	0.29	0	1
Community participation index	88	0.48	0.21	0	0.88
Mid-day meal index	88	0.69	0.27	0	1
Co-curricular environment index	88	0.46	0.17	0.14	1
School organization index	88	0.79	0.14	0.4	1
Teacher preparedness index	88	0.57	0.22	0	1
Learning environment index	88	0.60	0.16	0.21	0.98

more widely, on average (0.69). School learning environment and teacher preparedness indicators are, however, less evident, with an average of 0.60 and 0.57, respectively. Finally, the presence of school learning facilities, co-curricular activities, and community participation seems relatively less consistent. On a scale of 0 to 1 (where 1 implies presence and 0, absence) schools, on average, score 0.50 or lower.

Table 2 OLS regression, with baseline test-score

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
		School facility	Learning facility	Community participation	Mid-day meal	Co-curricular environment	School organization	Teacher preparedness	Learning environment
<i>(a) EVS, N = 2,047</i>									
Female student	-0.50*	-0.47	-0.49*	-0.48*	-0.49*	-0.50*	-0.48*	-0.50*	-0.50*
Age	-0.13	-0.13	-0.13	-0.13	-0.13	-0.13	-0.13	-0.13	-0.14
Caste (SC/ST)	0.22	0.25	0.22	0.23	0.23	0.22	0.24	0.22	0.21
Household size	-0.03	-0.01	-0.02	-0.02	-0.02	-0.03	-0.01	-0.03	-0.03
Mother is illiterate	0.17	0.17	0.17	0.17	0.16	0.17	0.17	0.17	0.17
Father is illiterate	-0.43**	-0.41**	-0.40**	-0.43**	-0.41**	-0.43**	-0.43**	-0.43**	-0.43**
No one speaks English at home	-0.34	-0.36	-0.38	-0.41	-0.35	-0.34	-0.38	-0.35	-0.34
Possessions	-0.08	-0.09	-0.07	-0.08	-0.07	-0.08	-0.08	-0.08	-0.08
No electricity	0.40	0.41	0.44	0.38	0.37	0.40	0.40	0.40	0.40
No vehicle	-0.04	-0.04	-0.06	-0.05	-0.06	-0.04	-0.05	-0.04	-0.04
No homework help	-0.28	-0.29	-0.24	-0.30	-0.28	-0.28	-0.28	-0.28	-0.28
No discussions about school	-0.33	-0.27	-0.32	-0.28	-0.31	-0.33	-0.26	-0.33	-0.33
No tuition	0.42	0.35	0.39	0.39	0.44	0.42	0.42	0.42	0.42
No reading outside school	-0.75**	-0.73**	-0.73**	-0.76**	-0.73**	-0.75**	-0.68**	-0.75**	-0.76**
No library use	-0.69*	-0.71**	-0.68*	-0.58*	-0.68*	-0.69*	-0.72**	-0.69*	-0.69*
Prop. female teacher	-1.16	-1.22	-1.39	-1.25	-1.05	-1.16	-1.46	-1.20	-1.13
Avg. teacher experience	-0.02	-0.01	0.00	0.01	-0.01	-0.02	-0.03	-0.02	-0.02
Prop. Teacher with BA or more	0.05	-0.14	-0.17	-0.34	0.01	0.05	-0.12	0.04	0.07
Prop. teacher with Dipl. Ed.	-1.29	-1.21	-1.22	-1.42	-1.45	-1.29	-1.14	-1.29	-1.30
School total enrollment	-0.00**	-0.00**	-0.00*	-0.00**	-0.00**	-0.00**	-0.00*	-0.00**	-0.00**
Prop. Children from poor families	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02
School resource index	0.38***	0.38***	0.38***	0.38***	0.38***	0.38***	0.37***	0.38***	0.38***
EVS (baseline)	0.24	0.24	0.24	0.25	0.24	0.24	0.24	0.24	0.24
Adjusted R-squared									

Table 2 continued

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
		School facility	Learning facility	Community participation	Mid-day meal	Co-curricular environment	School organization	Teacher preparedness	Learning environment
<i>(b) Math, N = 2,037</i>									
Female student	-0.44*	-0.44*	-0.42*	-0.43*	-0.44*	-0.48*	-0.43*	-0.45*	-0.45*
Age	-0.12	-0.12	-0.10	-0.11	-0.11	-0.10	-0.11*	-0.10	-0.11
Caste (SC/ST)	-0.22	-0.22	-0.22	-0.21	-0.20	-0.23	-0.20	-0.21	-0.19
Household size	-0.16	-0.16	-0.13	-0.15	-0.14	-0.15	-0.14	-0.13	-0.14
Mother is illiterate	0.08	0.08	0.08	0.08	0.06	0.07	0.08	0.07	0.06
Father is illiterate	-0.27	-0.28	-0.20	-0.27	-0.25	-0.26	-0.28	-0.23	-0.28
No one speaks English at home	-0.39	-0.39	-0.46**	-0.41*	-0.40	-0.45*	-0.43*	-0.45*	-0.40*
Possessions	-0.04	-0.04	-0.02	-0.04	-0.03	-0.01	-0.03	-0.04	-0.04
No electricity	-0.24	-0.24	-0.13	-0.24	-0.27	-0.24	-0.24	-0.24	-0.25
No vehicle	0.11	0.11	0.04	0.10	0.08	0.05	0.10	0.09	0.11
No homework help	-0.57*	-0.57*	-0.47	-0.58*	-0.57*	-0.52*	-0.58*	-0.53*	-0.59*
No discussions about school	0.11	0.11	0.13	0.14	0.15	0.12	0.18	0.11	0.11
No tuition	0.02	0.03	-0.05	0.01	0.05	0.01	0.03	-0.01	0.02
No reading outside school	-0.51*	-0.52*	-0.46	-0.51*	-0.48*	-0.54*	-0.45	-0.49*	-0.45
No library use	-0.27	-0.27	-0.24	-0.23	-0.26	-0.24	-0.30	-0.26	-0.27
Prop. female teacher	0.17	0.17	-0.39	0.13	0.31	-0.05	-0.17	-0.42	-0.21
Avg. teacher experience	-0.10	-0.10	-0.05	-0.09	-0.09	-0.11	-0.11	-0.08	-0.07
Prop. Teacher with BA or more	1.77	1.78	1.23	1.62	1.68	1.37	1.59	1.64	1.61
Prop. teacher with Dip. Ed	-0.21	-0.21	-0.07	-0.26	-0.44	-0.05	-0.06	-0.28	-0.02
School total enrollment	-0.00**	-0.00**	-0.00*	-0.00**	-0.00**	-0.00**	-0.00*	-0.00**	-0.00*
Prop. children from poor families	-0.03*	-0.03*	-0.03*	-0.03*	-0.03*	-0.02	-0.03*	-0.03**	-0.03*
School resource index	-0.08	-0.08	1.96**	0.74	1.25	2.51*	2.65	1.57	1.73
Math (baseline)	0.38***	0.38***	0.37***	0.38***	0.38***	0.37***	0.37***	0.38***	0.38***

Table 2 continued

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
		School facility	Learning facility	Community participation	Mid-day meal	Co-curricular environment	School organization	Teacher preparedness	Learning environment
Adjusted R-squared	0.20	0.20	0.21	0.20	0.20	0.21	0.20	0.20	0.20

Note: Column title indicates the school index controlled for in the regression.

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$

Correlation analysis (not shown) indicated that these eight school resource indicators are positively and significantly correlated with one another. Yet, the correlation between most of these variables is not so large as to obviate the need for these separate variables. The correlation also signifies that the presence of one school-based advantage makes it more likely that the child will experience other school-related advantages as well.

Regression analysis

Regression results for equations (1) and (2) are presented in Table 2a, b. In both of these analyses controlling for students' prior performance was crucial as indicated by the consistent, positive, and significant coefficients associated with baseline scores. In analysis not shown here we also noted an appreciable increase in the overall model R-square after inclusion of prior student performance.

Focusing first on EVS results, girls seem to perform systematically poorer than boys. Fathers' illiteracy is also statistically significant and negatively associated with EVS performance. A child who receives no help for homework, or has no discussions about school at home, performs poorly, but these relationships are not statistically significant. The negative and significant coefficients associated with a child who does not read and does not use the library are especially striking given that we are also controlling for the child's prior performance. These two variables may be a proxy not just for the child's reading behavior but also for his or her overall learning environment outside of school. Of the school variables, average teacher gender, experience, education, or training do not appear to be significantly associated with EVS performance. However, we do note that children attending large schools tend to perform poorly in EVS.

For math, many of the patterns are similar; we find that girls perform significantly more poorly than boys. Also, receiving no homework help, and not engaging in any out-of-school reading are all associated with negative math performance. Fathers' illiteracy or library use are, however, not associated with math performance. Once again, large school size and also greater presence of children from low-income families is associated with lower math performance.

The remaining columns in each table (Table 2a, b) add different school indices one at a time. The column title in each case indicates the school resource index that was introduced in the model. Before we discuss the role of these specific school resource indices, a few additional observations emerge from this analysis. We note that almost all the child-level variables and even the few school-level variables that were significant in the initial analysis remain significant throughout. Inclusion of these exhaustive school resource indices does not seem to diminish the importance of, say, fathers' illiteracy or household size. However, in case of math, English speaking ability at home actually becomes significant in some of these later cases. Perhaps most striking is the consistent significance of the child's reading habits. A child who does not read at home performs poorly regardless of what other explanatory variables we add to the model, and regardless of the subject. Similarly, in their respective models, library use and homework support both remain important.

In terms of school indices, we observe more significant relationships for math compared to EVS—not altogether surprising, given the distinct nature of these two subjects and the potentially greater role for school-based work in math. For math, we find that basic facilities, teacher preparedness, and learning environment indices remain insignificant. School organization and community participation coefficients are also insignificant. The coefficient associated with provision of the school mid-day meal is insignificant but with a p-value of 0.108. However, for math, after an extensive set of student- and school-

background controls, including prior test scores, we find that having learning facilities in school (e.g., laboratory, library, resource center) and having co-curricular activities are both significantly and positively related to math performance (at $p \leq 0.05$ and $p \leq 0.10$), respectively). The analysis thus provides some support for the argument that some specific, nuanced school resource measures may be important in understanding variation in student performance in math in particular.

Limitations, conclusion, and discussion

In this study we aimed to use a unique school-based dataset to identify school resources associated with student performance.

A key limitation of this study is closely related to its main strengths: having one data source means that the data are not nationally representative or even representative of the state they are gathered from. The data represent schools from one block in India where the foundation is active. Nonetheless, to the extent that these data record school circumstances of relatively disadvantaged children, they provide some insights into such schools and may inform future large-scale analyses.

The other key limitation of our work is our inability to establish causal relationships. Our ability to control for prior test scores helped us to remove some bias in our analysis. But to establish causality, researchers ideally need to benefit from a well-designed experimental or a quasi-experimental study. Our approach using retrospective, cross-sectional data does not allow us to infer such cause-and-effect relationships.

Despite these limitations, the study provides important insights into factors associated with improved student performance. The first is the importance of controlling for prior performance, where possible, which improves the overall explanatory power of the model. Even controlling for prior performance, we found that certain student background and home-level factors were invariably important. If students did not read outside school, they consistently performed lower in both math and EVS, regardless of what other controls we introduced. Reading outside of school potentially indicates the overall learning environment available to a child once he or she leaves school; it means having access to reading material, having quiet time (i.e., not needing to work), and either having sufficient basic reading skills or having an adult at home who can read. Similarly, the importance of library use, receiving homework support at home, and fathers' literacy levels in different models are all noteworthy. Data from these factors indicate what we noted earlier: students' own backgrounds and their home circumstances are crucial to understanding their performance.

Noteworthy and disappointing is the consistent underperformance of female children after accounting for other variables. In India, girls' lesser access to educational opportunities is well documented, but the phenomenon of female underperformance in tests is not well studied. Our results show a need for greater research in this direction.

Within the school, average teacher attributes do not seem to be important. This finding generally aligns with research acknowledging that teachers are important; but asserting that there is less consensus on what aspects of teacher backgrounds matter for improving student performance (e.g., Luschei and Chudgar 2011). Within the school, however, we find that studying in a larger school, or with more low-SES children, is associated with generally poor performance. The literature supports this latter association; and while a separate study by the foundation team in the same block has also revealed a potential association between lower performance and large school sizes, this relationship warrants more attention.

Returning to the question that motivated this study: What school resources may be associated with improved student performance? First, our findings lend support to prior

research that notes that exploring “simple” or “traditional” school resources may not be enough to understand improved student performance. This is not to argue that basic infrastructure such as clean water, functioning toilets, or hygienic learning environments are not important—they are important preconditions for a well-functioning school. But the presence of these infrastructural resources alone does not explain variation in learning performance across schools in this data.

Schools with more learning-specific facilities (library, laboratory, and other resources) and with more co-curricular activities (sports, cultural events) are schools where all else equal, children perform well in math. Similar model specifications for EVS do not yield any significant school resource variables. This may be partly explained by the differences, discussed earlier, in the nature of these two subjects.

An equally, or even more, important “finding” is the challenge of satisfactorily measuring school environments that support learning improvement. This is difficult, even with the benefit of a nuanced, context-specific instrument that has evolved with much thought from experts in the field. So, what lessons emerge from this work for future research, policy, and practice?

For researchers, the perils of looking inside schools with large-scale, standardized datasets are clear. It is not surprising that researchers using standard, large-scale data with traditional school resource measures are unable to identify important school factors for improved performance. Yet, one should not ignore the potential importance of school environments altogether, especially in poor and less developed parts of the world. Rather, this “finding” is a call to improve the current measures of school resources. From a policy and practice perspective, the foundation team’s extensive efforts offer potential guidance for gathering nuanced measures of school resources that go beyond the traditional ones. In the Indian context, the existing CRC system provides a cluster-level infrastructure to gather this form of nuanced school data. Thus, the potential exists to develop and refine similar school-based surveys that can provide valuable data for scholars and practitioners in their efforts to improve student performance.

Finally, perhaps, this study serves as an example of a fruitful and productive partnership between scholars and practitioners. The foundation’s willingness to engage in additional research efforts alongside its existing practices and the technical knowledge of the scholars based in the US created a unique learning opportunity for both groups and has added value to our collective knowledge.

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