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Explaining urban–rural differences in educational achievement in Thailand: Evidence from PISA literacy data

Kiatanantha Lounkaew *

Faculty of Economics and Research Center, Dhurakij Pundit University, Thailand

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ABSTRACT

Using the Thai PISA 2009 literacy test, this paper offers two contributions to the literature on the achievement gap between students in urban and rural areas. The first contribution relates to the estimation of the student-level education production function at different points along the achievement distributions. With the use of Oaxaca–Blinder decomposition, the second contribution demonstrates how much of the achievement differential between urban–rural students can be explained by unmeasured school characteristics. It has been found that the impact of student, family as well as school characteristics on student achievements vary along the test achievement distributions. Decompositions exercises at the mean find that about 45–48 percent of urban–rural achievement gaps are accounted for by the unmeasured characteristics of schools. The disaggregated decomposition exercise along the achievement percentile shows that these characteristics account for about 12–15 percent low-performing students and increase to about 61–69 percent for high-performing students.

1. Introduction

Thailand implemented the first education reform in 1999. Massive efforts and resources were mobilized to support the initiative. Budget allocated to Ministry of Education doubled within a decade, yet academic achievements of Thai students – i.e. the O-Net,[1] TIMSS,[2] and PISA[3] – had been declining (Siamwalla, Lathapipat, & Tangkitvanich, 2011). In 2008, National Education Standards and Quality Assessment (NESQA) conducted a nation-wide study to examine the quality of schools in Thailand. The study found that 3243 out of 15,515 schools assessed did not pass the minimum quality requirements (NESQA, 2008). It was also found that the majority of these low-performing schools were in rural areas. Such findings, along with continued decline of the O-NET achievements in recent years, resulted in a push for another round of education reform. As a result, in 2012, the Ministry of Education announced a 6-year plan for the second education reform. The Ministry of Education expected the reform to cost around 4.7 billion USD (Ministry of Education, 2011). Many were concerned that this initiative would be a replica of the failure of the first reform attempted a decade earlier.

On the issues of urban–rural student achievement differentials, it has been argued that such differentials exist because schools in urban areas enjoy more endowments than their rural counterparts; their students, therefore, are able to enjoy more benefits from these endowments. To reduce this disparity, therefore, sizable public investment

* Tel.: +66 869983459; fax: +66 25800064.
E-mail addresses: kiatanantha.lou@dpu.ac.th, k.lounkaew@anu.edu.au.

[1] The Ordinary National Educational Test (O-NET) is conducted by the National Institute of Educational Testing Services (NIET). Students at grade 6, 9 and 12 participate in the test. Eight subject areas are assessed: (1) Thai language, (2) mathematics, (3) science, (4) social science, religion and culture, (5) health and physical education, (6) art, (7) career and technology and (8) foreign languages.

[2] Trends in International Mathematics and Science Study.

[3] Programme for International Student Assessment.

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is required. By injecting more money into rural schools, they would be furnished with sufficient resources and staff to bring their students up to the level of those schooled in urban areas. While this line of reasoning may be sound, empirical findings suggest otherwise.

Two recent researches related to education reform in Thailand concluded that the success and failure of Thai education reform is weighted more heavily on management and accountability than the size of the budget allocated (Lathapipat, 2011; Siamwalla, Lathapipat, & Tangkitvanich, 2011). They called for a greater focus on the so-called ''intangible'' aspects – i.e. management, autonomy, leadership, parental participation, accountability, perceptions of staff and students, which are needed to ensure the success of the second reform. This recommendation is consistent with international studies on education reform and school quality. These studies acknowledge that intangible factors are at least as important as tangible factors, or even more so (see for examples, Betts, 1995; Hanushek, 2003, 2005; Brunello & Checchi, 2005; Hanushek & Woesserman, 2011).

In Thailand, as well as many other developing countries in Asia, there is a common lack of empirical evidence to support the claim that intangible aspects matter with regard to school performance, which is commonly measured by the academic achievements of students. When taking into account the need to address academic performance issues in the context of urban–rural differences, the paucity becomes even more pronounced.

In addition, it is a common practice that analyses of student academic achievement are done at the mean of the data. While such endeavor provides valuable insights into how different factors influence student achievement, it is unable to deliver a more critical understanding of how the magnitudes of these influences vary along the achievement distributions. A factor thought to be beneficial to an average student may be insignificant quantitatively for low-performing students; likewise, what matters for high-performing students may be irrelevant to the success of an average student.

Using the Thai PISA 2009 data on literacy test, this paper contributes to the education reform debate and student academic achievements in two ways. The first contribution relates to the estimation of student-level education production function at different points along the achievement distribution. With the use of Oaxaca–Blinder decomposition, the second contribution demonstrates how much of the achievement differential between urban–rural students can be explained by intangible aspects of schools.

The remaining sections of this study are organized as follows. Section 2 reviews selected empirical issues related to determinants of test performance. Descriptive statistics are reported in Section 3. Explanation for the methodology employed is provided in Section 4. Empirical results are shown and discussed on Section 5. Section 6 concludes the study.

2. Literature review

Economic researches that look into what determines students' academic achievement – measured by test performance – as well as the overall success of a school ground their analyses on the concept of the education production function. In essence, the concept posits that academic success is an outcome of a production process where students are considered as an input. School is treated as a factory with teachers and staff being workers, and physical endowments treated as capital. Consequentially, test performance is an output from this production process (Glewwe, 2002; Hanushek, 1979, 2002; Pritchett & Filmer, 1999). Hence empirical estimates of this production function typically include a host of variables to capture the characteristics of students, the household as well as the school.

Association between student and household characteristics is a well-established empirical finding both in developed and developing countries. Schuetz, Ursprung, and Woessmann (2008), using TIMSS data of 54 countries, found that student and household characteristics have significant effects on achievement. Woessmann (2005) also found such strong effects in Singapore, Hong Kong and Thailand. On school characteristics, Harbison and Hanushek (1992), Heneveld and Craig (1996) and White (2004) are examples of studies that highlighted the role of tangible assets. They conclude that minimum basic school facilities are critical to improving achievement outcomes of students in developing countries. International comparisons by Woessmann (2003, 2010), confirm that, apart from physical aspects, such school characteristics as geographical location, class size, instruction time and institutional aspects of schools also matter.

One issue to be noted is the problem of an omitted variable. The prime candidates for omitted variables are innate ability, motivation and past investment in education. In an attempt to take into account innate ability, for example, one may be tempted to use IQ test scores as a proxy. The IQ test score itself, however, may not capture only innate ability but also other contaminating factors related to the past and present environment (Glewwe, 2002; Todd & Wolpin, 2003). The lack of a good proxy for such omitted variables also implies that the IQ technique rarely offers an adequate remedy. An alternative strategy pursued by Berhman, Resenzweig, and Taubman (1994) was to use twins data. Another possible empirical strategy to address the influence of these unobserved inputs is to use fixed-effect estimation. Prerequisites for implementing these two remedies are the availability of suitable data; the first approach requires that we have sufficient data on twins; the second calls for panel data. In developing countries, these two kinds of data are rare. In addition, lack of resources and expertise preclude them carrying out a randomized trial designed specifically for this research purpose.

While challenges to overcome omitted variable bias are recognized by researchers, there is another issue that has long been overlooked: the analysis that goes beyond the mean of the data. Regardless of the estimation strategy employed, the majority of previous exercises have been carried out at the mean of the data (Entorf & Minoiu, 2005; Fertig & Wright, 2005; Fuchs & Woessmann, 2007; Hanushek & Woesserman, 2011; Peterson & Woessmann, 2007). The only study that looks at the impact of school inputs across the distribution is Eide and Showalter (1998). Accepting analysis at the mean is equivalent to accepting that the influence an input has on students at the top end of the class will be the same as the ones at the bottom (Hanushek, 1979; Watts, 1985). For example, reduction in class size may offer considerable benefit to low-performing students who require more attention; students who are already at the top 10 percent of the class may not enjoy much additional benefit beyond what they are already capable of.

There is ample empirical evidence that establishes the link between education performance and labor market outcomes (Angrist & Lavy, 1997; Bedi & Edwards, 2002; Card, 1999; Grogger, 1996; Koedel & Tyhurst, 2012; Murnane, Willett, & Levy, 1995). Studies that look into the determinants of wages and wage inequality typically use education as one of the explanatory variables. In this strand of research, it is commonly accepted that the ability to look beyond the mean is critical to the understanding of wage determination mechanisms (Buchinsky, 1994; Machado & Mata, 2001). If distribution matters for wage studies, then it must also matter for the study of education performance. It is very surprising that this practice has not been adopted as a common practice in the study of academic achievement.

Apart from distributional issue, another under-researched area is what causes the persistence of the achievement gap across geographical locations. Two notable studies that examined this issue explicitly are Krieg and Storer (2006) and Ammermueller (2007). Krieg and Storer's study found that the major causes of the gap between high- and low-performing schools can be attributed to student backgrounds. Ammemueller's finding concluded that the achievement gaps between Finnish and German students cannot be explained by student backgrounds. Students from Finland, however, are able to use educational resources more efficiently. Both studies use Oaxaca–Blinder decomposition to investigate the achievement gap only at the mean of the data. None of the studies mentioned in this section combined analysis beyond the mean with a decomposition method to analyze the achievement gap issues beyond the mean. This study is the first to attempt to fill this gap.

3. Data

The Programme for International Student Assessment (PISA) began in 1997 with an aim of evaluating the education systems worldwide through the assessment of the skills and knowledge of students. More than 70 countries participated in this exercise. The assessment is carried out every three years by conducting a test of randomly selected groups of 15-year-old students. There are three areas to be assessed: literacy, mathematics and science. The test focuses on students' ability to apply their knowledge to real-life situations rather than their technical skills and knowledge of the respective subject. In addition to the collection of test data, school principals and students are requested to fill in background questionnaires to provide additional information about family and school characteristics, respectively. In some countries, parents are also participated by filling in the questionnaire.

Descriptive statistics of Thai students who participated in the test are shown in Table 1.[4] The Thai PISA data contain information on test score, student and family characteristics, student learning styles, and school characteristics. For the purpose of this study, students are divided into four groups according to gender and school location. Locations are divided into two groups: urban and rural. An urban school is defined as a school located in a city or large city. A rural school is defined as a school located in a village, small town or town. In this study, the share of government funding relative to the school's total annual income is used instead of a public-private school proxy. This is because, in Thailand, both types of school are entitled to government funding and indirect support from government funding.

A cursory examination of the statistics points to five important observations relating to urban–rural disparities. First, students in urban areas performed better than their rural counterparts. Second, there are considerable disparities in educational resources between these two locations; students in urban areas enjoy more educational resources, have higher socioeconomic status and have better access to computers at home than rural area students. Third, parents of urban area students are better educated than parents of students in rural areas. Fourth, while schools in these two locations differ in size, their student–teacher and computer per student ratios are similar; the only distinction at school-level is that a greater proportion of schools in rural areas indicated that they had severe shortage of learning materials. Lastly, schools in rural areas have larger shares of government funding relative to their annual income.

4. Methodology

This section illustrates the empirical strategy implemented to estimate the contribution of intangible aspects of a school to the differences in PISA performance of urban and rural area students. It begins by developing an Oaxaca–Blinder decomposition in the context of this exercise. The decomposition will then be used to examine the contribution of measured and unmeasured inputs in explaining differences in test performances of students in urban and rural schools. Subsequently, Unconditional Quantile Regression (UQR) developed by Firpo, Fortin, and Lemieux (2009) will be discussed. Necessary adjustment to take into account the cluster-sampling nature of the data will also be explained.

4.1. The Oaxaca–Blinder decomposition

Typical econometric specification of education production function takes the following form:

$$L_i = \beta_0 + \boldsymbol{\beta}'\mathbf{X}_i + \boldsymbol{\delta}'\mathbf{H}_i + \boldsymbol{\kappa}'\mathbf{S}_i + e_i, \tag{1}$$

[4] We refer interested readers to several technical documents for PISA 2009 for detailed explanation of variables. These documents are available online at http://www.oecd.org/pisa/pisaproducts/pisa2009/.

Table 1
Descriptive statistics.

Variable	Boys		Girls	
	Urban[a]	Rural[b]	Urban[a]	Rural[b]
Dependent variable				
PISA literacy test score	459.770	405.037	489.162	439.375
	(78.077)	(67.612)	(73.33)	(62.834)
Student and family characteristics				
Socioeconomic index	−0.140	−1.362	−0.367	−1.446
	(1.195)	(1.149)	(1.241)	(1.143)
Educational resource index	0.374	−0.465	0.399	−0.326
	(0.966)	(1.037)	(0.958)	(1.042)
Father's occupation-upper white collar	0.489	0.187	0.443	0.203
(dummy)	(0.500)	(0.390)	(0.497)	(0.402)
Father's occupation-lower white collar	0.107	0.082	0.112	0.072
(dummy)	(0.309)	(0.274)	(0.316)	(0.258)
Mother's occupation-upper white collar	0.406	0.169	0.385	0.162
(dummy)	(0.491)	(0.375)	(0.487)	(0.368)
Mother's occupation-lower white collar	0.194	0.111	0.159	0.112
(dummy)	(0.396)	(0.314)	(0.366)	(0.316)
Father's schooling (years)	11.772	8.800	10.857	8.384
	(3.690)	(4.011)	(4.058)	(3.878)
Mother's schooling (years)	11.073	8.404	10.379	7.809
	(4.091)	(3.980)	(4.230)	(3.878)
Computer (dummy)	0.834	0.552	0.814	0.504
	(0.373)	(0.497)	(0.389)	(0.500)
Attitude toward school	0.102	0.076	0.249	0.283
	(0.865)	(0.824)	(0.803)	(0.804)
Attitude toward reading	0.394	0.377	0.728	0.676
	(0.634)	(0.582)	(0.717)	(0.593)
Learning styles				
Elaboration	0.388	0.222	0.291	0.281
	(0.726)	(0.711)	(0.694)	(0.687)
Control	−0.329	−0.524	−0.322	−0.394
	(0.748)	(0.803)	(0.766)	(0.698)
Memorization	0.089	−0.057	0.196	0.173
	(0.742)	(0.776)	(0.732)	(0.728)
Summarizing	−0.524	−0.738	−0.332	−0.589
	(0.974)	(0.950)	(1.013)	(0.978)
Understanding	−0.161	−0.434	0.040	−0.108
	(1.030)	(0.990)	(1.021)	(1.033)
School factors				
School size	583.622	315.006	584.604	303.257
	(400.215)	(269.877)	(380.619)	(250.667)
Students per teacher	20.243	20.785	21.534	20.826
	(5.961)	(6.246)	(5.882)	(6.045)
Computer per student	0.082	0.077	0.084	0.079
	(0.050)	(0.049)	(0.046)	(0.044)
Government funding	64.264	85.584	64.954	84.441
(% of total funding)	(29.453)	(20.505)	(27.894)	(22.365)
Duration of reading class	146.060	158.758	141.904	151.308
(minutes per class)	(57.024)	(56.753)	(51.171)	(53.340)
Teacher shortage (dummy)	0.492	0.502	0.454	0.556
	(0.500)	(0.500)	(0.498)	(0.497)
Learning material shortage (dummy)	0.289	0.476	0.291	0.480
	(0.454)	(0.500)	(0.455)	(0.500)
Ability grouping (dummy)	0.662	0.465	0.720	0.517
	(0.473)	(0.499)	(0.450)	(0.500)
n	571	1236	830	1759

[a] An urban school is defined as a school located in city or large city.
[b] A rural school is defined as a school located in village, small town or town.

where L_i represents log of PISA literacy test achievement of student i; $\mathbf{X}_i$ is a vector of student characteristics; $\mathbf{H}_i$ is a vector of household characteristics; $\mathbf{S}_i$ is a vector of school characteristics; and e_i is an error term such that $e_i \sim N(0, \sigma^2)$. (Hanushek and Woesserman, 2011; Murnane, Maynard, & Ohls 1981; Watts, 1985; Woessmann, 2003, 2010).

If students are classified into two groups depending on whether they are at urban or rural schools, then the difference between average PISA literacy test performance at urban and rural schools can be written as:

$$\bar{L}_{urban} - \bar{L}_{rural} = [\beta_{urban} - \beta_{rural}] + [\boldsymbol{\alpha}'_{urban}\bar{\mathbf{X}}_{urban} - \boldsymbol{\alpha}'_{rural}\bar{\mathbf{X}}_{rural}] + [\boldsymbol{\delta}'_{urban}\bar{\mathbf{H}}_{urban} - \boldsymbol{\delta}'_{rural}\bar{\mathbf{H}}_{rural}] + [\boldsymbol{\kappa}'_{urban}\bar{\mathbf{S}}_{urban} - \boldsymbol{\kappa}'_{rural}\bar{\mathbf{S}}_{rural}] \quad (2)$$

Adding and subtracting $\boldsymbol{\alpha}'_{urban}\bar{\mathbf{X}}_{rural}, \boldsymbol{\delta}'_{urban}\bar{\mathbf{H}}_{rural}$ and $\boldsymbol{\kappa}'_{urban}\bar{\mathbf{S}}_{rural}$ on the right and side of Eq. (2) gives:

$$\bar{L}_{urban} - \bar{L}_{rural} = [\beta_{urban} - \beta_{rural}] + \{\bar{\mathbf{X}}_{rural}[\boldsymbol{\alpha}'_{urban} - \boldsymbol{\alpha}'_{rural}] + \bar{\mathbf{H}}_{rural}[\boldsymbol{\delta}'_{urban} - \boldsymbol{\delta}'_{rural}] + \bar{\mathbf{S}}_{rural}[\boldsymbol{\kappa}'_{urban} - \boldsymbol{\kappa}'_{rural}]\} + \{\boldsymbol{\alpha}'_{urban}[\bar{\mathbf{X}}_{urban} - \bar{\mathbf{X}}_{rural}] + \boldsymbol{\delta}'_{urban}[\bar{\mathbf{H}}_{urban} - \bar{\mathbf{H}}_{rural}] + \boldsymbol{\kappa}'_{rural}[\bar{\mathbf{S}}_{urban} - \bar{\mathbf{S}}_{rural}]\} \quad (3)$$

Eq. (3) is known as the Oaxaca–Blinder decomposition. The technique allows us to decompose differences in the mean PISA score of urban and rural area students (Blinder, 1973; Oaxaca, 1973). This decomposition technique is commonly used in the study of wage discrimination based on race or gender. In such an exercise, a straightforward approach would be to compare differences of average wages between the two groups of interest. Such comparison, however, fails to account for the fact that the average qualification of these two groups may differ; such differences can be manifested in differences in wages. Oaxaca–Blinder decomposition disentangles the effects of qualification variations and discrimination.

For this study, the three groupings on the right hand side of Eq. (3) represent different components disentangled by the decomposition. The first term, $\beta_{urban} - \beta_{rural}$, captures the difference in average performance of the two groups that is independent of characteristics variables included in the regression. In this sense, this term can be interpreted as a pure performance difference caused by unmeasured individual, family as well as school characteristics.

The second term, $\bar{\mathbf{X}}_{rural}[\boldsymbol{\alpha}'_{urban} - \boldsymbol{\alpha}'_{rural}] + \bar{\mathbf{H}}_{rural}[\boldsymbol{\delta}'_{urban} - \boldsymbol{\delta}'_{rural}] + \bar{\mathbf{S}}_{rural}[\boldsymbol{\kappa}'_{urban} - \boldsymbol{\kappa}'_{rural}]$, represents differences in how the measured characteristics of students, family and school are converted into test scores. For example, if an urban school performs better in converting educational input into test scores, then $\boldsymbol{\kappa}'_{urban}$ will be greater than $\boldsymbol{\kappa}'_{rural}$. Thus, holding constant other factors, an identical student attending urban school will do better in the test than the one attending rural school.

The term, $\boldsymbol{\alpha}'_{urban}[\bar{\mathbf{X}}_{urban} - \bar{\mathbf{X}}_{rural}] + \boldsymbol{\delta}'_{urban}[\bar{\mathbf{H}}_{urban} - \bar{\mathbf{H}}_{rural}] + \boldsymbol{\kappa}'_{rural}[\bar{\mathbf{S}}_{urban} - \bar{\mathbf{S}}_{rural}]$, calculates how much variation in average characteristics of student, family and school influence average test scores. This term, therefore, captures differences in test scores of students with different characteristics attending the same school. The larger the size of this term, the more the test score variation is explained by these characteristics. It is a common practice in the use of Oaxaca–Blinder decomposition to label this term the "explained" differences due to endowment differences. The other two components discussed in the preceding paragraphs are, consequentially, called "unexplained" differences. In the context of this exercise, the explained components represent contributions from measured educational inputs; unexplained components refer to unmeasured educational inputs.

It should be noted here that the unexplained differences can also be contaminated by other unmeasured influences apart from unmeasured school inputs. To minimize the influence, as well as to minimize biases introduced by omitted variables, we include such variables as father and mother's schooling, their occupations, attitude toward reading and learning styles. If unobserved ability correlate with these variables, then these coefficients will also be contaminated by the influence from unobserved ability. Additional control for school characteristics such as proportion of government funding and ability groupings are also included to minimize school-level contamination. The greater the contamination in the coefficients, the less is the contamination left in the unexplained portion of the decomposition, allowing for a more precise estimation of the role of unmeasured inputs in explaining the urban–rural achievement gap.

4.2. Unconditional quantile regression

As mentioned in the introductory section, one of the main contributions of this study is beyond-the-mean analysis. The econometric technique that makes possible such endeavor is the Unconditional Quantile Regression. The UQR technique relies on a transformation known as the re-centered influence function (RIF). The RIF for the quantile of interest q_τ is

$$RIF(I; q_\tau) = q_\tau + \frac{\tau - D(I \le q_\tau)}{f_I(q_\tau)}, \quad (4)$$

where $f_I(.)$ is the marginal density function of I where D is an indicator function. In practice $RIF(I; q_\tau)$ is not observed, hence its sample counterpart is used instead:

$$RIF(I; \hat{q}_\tau) = \hat{q}_\tau + \frac{\tau - D(I \le \hat{q}_\tau)}{\hat{f}_I(q_\tau)}, \quad (5)$$

where $\hat{q}_\tau$ is the sample quantile and $\hat{f}_I(q_\tau)$ is the kernel density estimator, with this transformed variable being used in place of the original dependent variable. One crucial distinguishing feature of the UQR is that it provides us with a way to recover the marginal impact of regressors on the unconditional quantile of I; in the context of this study it is the marginal impact of additional unit of input on PISA test performance at a given score percentile. Usual inference procedures of the OLS are also applicable to the UQR estimates. The UQR estimate will be performed across a range of achievement distributions from the 10th to the 90th percentile.

One issue to be accounted for is the nature of two-level clustered sampling procedures used to collect the data. In PISA the first level sampling identifies schools to be sampled from; the second level sampling identifies individuals to be sampled. This means that error terms of students from the same school may correlate due to the

Table 2
Regression results for boys.[a]

Variable	OLS		p30		p50		p70	
	Urban	Rural	Urban	Rural	Urban	Rural	Urban	Rural
Constant	6.200**	5.974**	6.179**	5.847**	6.204**	5.947**	6.315**	6.193**
	(0.118)	(0.085)	(0.121)	(0.128)	(0.106)	(0.087)	(0.159)	(0.061)
Student and family characteristics								
Socioeconomic index	0.032**	3.62×10^{-6}	0.035*	−0.014	0.025*	−0.013	0.056**	−0.008
	(0.011)	(0.012)	(0.019)	(0.019)	(0.016)	(0.012)	(0.016)	(0.009)
Educational resource index	0.023**	0.016**	0.027**	0.030**	0.013	0.013*	0.017	0.005**
	(0.009)	(0.006)	(0.012)	(0.010)	(0.010)	(0.007)	(0.012)	(0.006)
Father's occupation-upper white collar	−0.005	0.016	−0.026	0.038	0.017	0.029*	−0.008	0.020**
(dummy)	(0.016)	(0.016)	(0.022)	(0.027)	(0.021)	(0.017)	(0.022)	(0.016)
Father's occupation-lower white collar	−0.016	0.022	0.013	0.010	0.020	0.032*	−0.028	0.021*
(dummy)	(0.025)	(0.016)	(0.034)	(0.031)	(0.031)	(0.020)	(0.029)	(0.020)
Mother's occupation-upper white collar	0.028*	0.005	0.013	0.016	0.046**	0.032*	−0.011	0.018
(dummy)	(0.017)	(0.016)	(0.026)	(0.024)	(0.022)	(0.020)	(0.020)	(0.023)
Mother's occupation-lower white collar	0.026*	0.003	0.020	0.033	0.024	−0.005	−0.021	0.007
(dummy)	(0.014)	(0.015)	(0.027)	(0.025)	(0.019)	(0.017)	(0.015)	(0.016)
Father's schooling	0.002	−0.0003	0.003	0.0009	−0.001	0.001	−0.0005	0.0004**
(years)	(0.003)	(0.002)	(0.004)	(0.003)	(0.003)	(0.002)	(0.003)	(0.002)
Mother's schooling (years)	−0.003*	0.003*	−0.003	0.005*	−0.003	0.006**	−0.003	0.004
	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)	(0.001)
Computer	−0.004	0.006	0.006	−0.001	0.053**	0.031**	0.019	0.021
(dummy)	(0.020)	(0.013)	(0.031)	(0.021)	(0.025)	(0.015)	(0.027)	(0.012)
Attitude toward school	0.011	0.029**	0.020*	0.045**	0.010	0.023**	0.005	0.007
	(0.007)	(0.005)	(0.012)	(0.009)	(0.008)	(0.006)	(0.010)	(0.006)
Attitude toward reading	0.020**	0.007	0.032**	0.021*	0.034**	0.017*	0.022	0.011**
	(0.010)	(0.008)	(0.015)	(0.013)	(0.014)	(0.010)	(0.015)	(0.008)
Learning styles								
Elaboration	−0.004	0.006	−0.010	0.006	−0.005	−0.003	0.0005	0.004
	(0.010)	0.009	0.014	0.014	0.012	0.010	0.016	0.010
Control	0.006	0.009	0.009	0.005	0.006	0.014	−0.004	0.019
	(0.012)	(0.009)	(0.017)	(0.014)	(0.016)	(0.010)	(0.015)	(0.010)
Memorization	0.018*	0.014*	0.020	0.0251*	0.012	0.015	0.008	0.007*
	(0.011)	(0.008)	(0.014)	(0.013)	(0.012)	(0.010)	(0.016)	(0.009)
Summarizing	0.023**	0.022**	0.014*	0.032**	0.022**	0.016**	0.037**	0.013**
	(0.006)	(0.005)	(0.009)	(0.008)	(0.009)	(0.005)	(0.009)	(0.005)
Understanding	0.021**	0.022**	0.011*	0.023**	0.017**	0.025**	0.031**	0.022**
	(0.005)	(0.004)	(0.007)	(0.008)	(0.008)	(0.005)	(0.009)	(0.004)
School factors								
School size	0.0006	0.0002**	0.0002**	0.0004**	0.00009	0.0002**	−0.00008	0.0002
	(0.00009)	(0.00008)	(0.0001)	(0.0001)	(0.00008)	(0.00007)	(0.0009)	(0.00006)
(School size)^2	-2.07×10^{-8}	-1.97×10^{-7}**	-1.31×10^{-7}**	-3.10×10^{-7}**	-4.15×10^{-8}	-1.98×10^{-7}**	8.35×10^{-8} *	-1.54×10^{-7}
	(5.77×10^{-8})	(6.29×10^{-8})	(5.58×10^{-8})	(9.26×10^{-8})	(4.18×10^{-8})	(6.28×10^{-8})	(5.15×10^{-8})	(4.50×10^{-8})
Students per teacher	0.005	0.003	−0.003	−0.0002	−0.001	−0.002	0.008	−0.003*
	(0.010)	(0.005)	(0.009)	(0.006)	(0.008)	(0.003)	(0.010)	(0.003)
(Students per teacher)^2	−0.0002	−0.00008	−0.00004	−0.00004	−0.00006	-4.35×10^{-6}	−0.0003	0.00001**
	(0.0002)	(0.00009)	(0.0002)	(0.0001)	(0.0002)	(0.00006)	(0.0002)	(0.00005)
Computer per student	1.64**	0.703**	−0.214	0.766*	2.42**	0.808**	3.240**	0.209**

	(0.719)	(0.289)	(0.741)	(0.423)	(0.668)	(0.275)	(0.792)	(0.234)
(Computer per student)^2	−8.335**	−1.616**	−1.500	−2.623**	−12.429**	−2.187**	−14.388**	−0.699**
	(3.337)	(0.645)	(3.212)	(0.977)	(2.952)	(0.603)	(3.447)	(0.552)
Government funding (% of total funding)	−0.003*	−0.002*	−0.0007	−0.003**	−0.004**	−0.002**	−0.005**	−0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.0008)
(Government funding)^2	0.00001	0.00001	-7.66×10^{-7}	0.00002*	0.00003**	0.00001*	0.00004**	0.00001
	(0.00001)	(8.98×10^{-6})	(0.00001)	(0.00001)	(0.00001)	(8.90×10^{-6})	(0.00002)	(7.02×10^{-6})
Duration of reading class (minutes per class)	−0.0006	−0.0002	−0.001	0.00001	−0.0002	−0.00007	0.0001	−0.0004
	(0.0008)	(0.0005)	(0.0009)	(0.0009)	(0.0008)	(0.0005)	(0.001)	(0.0004)
(Duration of reading class)^2	7.27×10^{-7}	6.95×10^{-7}	2.43×10^{-6}	-6.63×10^{-8}	-5.42×10^{-7}	2.99×10^{-7}	-1.22×10^{-6}	6.20×10^{-7}
	(2.36×10^{-6})	(1.44×10^{-6})	(2.59×10^{-6})	(2.46×10^{-6})	(2.21×10^{-6})	(1.48×10^{-6})	(3.16×10^{-6})	(9.87×10^{-7})
Teacher shortage (dummy)	0.026	−0.015	0.057**	−0.012	0.032*	−0.013	−0.002	−0.008
	(0.024)	(0.013)	(0.025)	(0.020)	(0.020)	(0.013)	(0.027)	(0.010)
Learning material shortage (dummy)	−0.104**	−0.026**	−0.104**	−0.014	−0.098**	−0.022*	−0.084**	−0.027
	(0.028)	(0.013)	(0.031)	(0.020)	(0.032)	(0.013)	(0.033)	(0.010)
Ability grouping (dummy)	0.021	0.021	0.077**	0.011	0.014	0.010	−0.009	0.010
	(0.026)	(0.013)	(0.033)	(0.021)	(0.027)	(0.013)	(0.027)	(0.010)
R^2	0.5075	0.2778	0.3310	0.1882	0.3859	0.2420	0.3907	0.2027
N	571	1236	571	1236	571	1236	571	1236

[a] Full regression results for boys and girls are available upon request.
* Statistically significant at 10 percent level of confidence.
** Statistically significant at 5 percent level of confidence.

influence of the school level stochastic factor. As a result, estimates of standard deviation will be biased, invalidating statistical inference. As suggested by Woessmann (2003), we calculate cluster-adjusted standard deviation for the purpose of statistical inference.

5. Empirical results

This section begins with the reports of the OLS and UQR's estimates of student-level education production functions by gender and location. As will be discussed, beyond-the-mean exercises confirm that influences of some inputs vary along the achievement distributions. The following section reports the results from decomposition exercises both at the mean and by achievement percentiles. The section concludes with two policy implications for education reform.

5.1. Estimates of student-level education production function

This section reports the OLS and selected UQR estimates, namely 30th, 50th and 70th percentile for boys and girls in urban and rural areas. Detailed estimates by percentile are available upon request. Results are reported in Tables 2 and 3. Since the findings for boys and girls are quite similar, only the estimates for boys will be discussed.

For boys in urban areas, socio-economic status plays an important role in determining the achievement of students, especially those at the 30th and 70th percentiles. The positive relationship found in the estimates confirms the findings from previous studies (see for example, Woessmann, 2005; Schuetz, Ursprung and Woessmann, 2008). In contrast, the role of educational resources, which is significant for an average student and the 30th percentile, becomes insignificant for urban students at the median and the 70th percentile. One explanation is because there are minimum required educational resources in order to do well in the test. Once the threshold has been reached, marginal gains from additional resources begin to fall. This finding is consistent with Roscigno and Ainsworth-Darnell (1999) and Marks, Cresswell, and Ainley (2006). In rural areas, however, socio-economic factors do not contribute to achievements. This is because families in rural areas are relatively homogeneous in terms of their socio-economic compositions. Educational resources, however, becomes more important, especially for boy students at the 30th percentile.

Another significant variable for an average boy in a rural area as well as the ones in the 30th and 50th percentile is mother's education. This is consistent with Murnane et al. (1981). The results can be explained by two customary practices of parents in Thailand. First, the father and mother of a student in an urban area are more likely to work. Consequentially, they have less time to educate their child. The mother of a child in a rural area is more likely to work in agricultural activities or be engaged in part-time work. Thus they are able to spend more time helping the child to study. The more time a mother with better qualifications has to spend her child, the higher the

Table 3
Regression results for girls.[a]

Variable	OLS		p30		p50		p70	
	Urban	Rural	Urban	Rural	Urban	Rural	Urban	Rural
Constant	6.264**	6.003**	6.040**	5.856**	6.123**	5.890**	6.417**	6.034**
	(0.118)	(0.083)	(0.126)	(0.116)	(0.132)	(0.096)	(0.134)	(0.119)
Student and family characteristics								
Socioeconomic index	0.018*	−0.001	−0.011	−0.010	−0.005	−0.11	0.034**	−0.016
	(0.009)	(0.009)	(0.014)	(0.015)	(0.011)	(0.014)	(0.013)	(0.012)
Educational resource index	0.004	0.025**	0.005	0.038**	0.012	0.019**	−0.009	0.031**
	(0.007)	(0.005)	(0.011)	(0.009)	(0.009)	(0.007)	(0.011)	(0.008)
Father's occupation-upper white collar	0.024**	0.028**	0.032**	0.040**	0.043**	0.037**	0.002	0.049**
(dummy)	(0.012)	(0.010)	(0.014)	(0.017)	(0.016)	(0.016)	(0.023)	(0.017)
Father's occupation-lower white collar	0.012	0.018	−0.009	0.040*	0.028	0.030*	0.004	0.033*
(dummy)	(0.015)	(0.012)	(0.019)	(0.022)	(0.024)	(0.019)	(0.024)	(0.018)
Mother's occupation-upper white collar	0.025**	0.014	0.011	0.020	0.025*	0.025	0.046*	0.014
(dummy)	(0.012)	(0.011)	(0.015)	(0.022)	(0.014)	(0.018)	(0.026)	(0.016)
Mother's occupation-lower white collar	0.003	0.008	0.005	0.003	−0.007	0.030*	0.008	0.014
(dummy)	(0.013)	(0.011)	(0.018)	(0.018)	(0.015)	(0.016)	(0.021)	(0.016)
Father's schooling	−0.001	0.002*	0.0003	0.003	0.002	0.004**	0.001	0.005**
(years)	(0.002)	(0.001)	(0.003)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)
Mother's schooling (years)	0.0009	0.0005	0.0008	0.0004	−0.0005	0.001	−0.002	0.002
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Computer	0.034**	−0.002	0.042*	−0.023	0.067**	0.0006	0.067**	0.003
(dummy)	(0.014)	(0.010)	(0.022)	(0.018)	(0.021)	(0.014)	(0.024)	(0.012)
Attitude toward school	0.001	0.009**	0.015**	0.027**	0.004	0.013**	−0.0006	0.002
	(0.004)	(0.004)	(0.006)	(0.008)	(0.005)	(0.006)	(0.006)	(0.006)
Attitude toward reading	0.032**	0.029**	0.010	0.023**	0.023**	0.031**	0.029**	0.036**
	(0.005)	(0.006)	(0.009)	(0.010)	(0.008)	(0.008)	(0.009)	(0.008)
Learning styles								
Elaboration	0.020**	−0.003	−0.167**	0.012	−0.024**	−0.009	−0.028*	−0.005
	0.007	0.007	0.008	0.011	0.010	0.009	0.016	0.011
Control	0.015**	−0.005	0.013*	−0.017	−0.006	−0.003	0.019	−0.001
	(0.007)	(0.007)	(0.008)	(0.014)	(0.009)	(0.010)	(0.015)	(0.100)
Memorization	0.007	0.020**	−0.002	0.024**	0.019*	0.022**	0.028*	0.017*
	(0.007)	(0.005)	(0.007)	(0.010)	(0.010)	(0.009)	(0.015)	(0.009)
Summarizing	0.018**	0.012**	0.016**	0.009	0.014*	0.016**	0.026**	0.021**
	(0.005)	(0.003)	(0.007)	(0.006)	(0.007)	(0.005)	(0.009)	(0.005)
Understanding	0.028**	0.016**	0.015**	0.014**	0.033**	0.015**	0.038**	0.014**
	(0.005)	(0.003)	(0.008)	(0.005)	(0.007)	(0.005)	(0.008)	(0.005)
School factors								
School size	0.00002	0.0001**	0.0001**	0.0003**	0.0001*	0.0002**	0.00003	0.00003
	(0.00007)	(0.00007)	(0.00008)	(0.0001)	(0.00007)	(0.00009)	(0.0001)	(0.00008)
$(\text{School size})^2$	1.03×10^{-8}	-1.29×10^{-7}**	-8.56×10^{-8}*	-2.11×10^{-7}**	-6.80×10^{-8}*	-1.96×10^{-7}**	7.55×10^{-9}	-2.83×10^{-8}
	(4.26×10^{-8})	(6.38×10^{-8})	(4.45×10^{-8})	(8.82×10^{-8})	(4.01×10^{-8})	(8.56×10^{-8})	(6.18×10^{-8})	(7.33×10^{-8})
Students per teacher	−0.011	0.003	−0.009	0.005	−0.004	0.007*	−0.007	0.007
	(0.010)	(0.004)	(0.012)	(0.006)	(0.012)	(0.004)	(0.010)	(0.004)
$(\text{Students per teacher})^2$	0.0001	−0.00008	0.0001	−0.0001	0.00004	−0.0001**	0.00005	−0.0001**
	(0.0002)	(0.00006)	(0.0003)	(0.00009)	(0.0003)	(0.00006)	(0.0002)	(0.00007)
Computer per student	1.597**	0.597**	0.848	0.634	1.304*	0.477	2.251**	0.721**

	(0.598)	(0.295)	(0.835)	(0.432)	(0.811)	(0.432)	(0.880)	(0.330)
$(\text{Computer per student})^2$	−7.040**	−1.589**	−4.626	−1.808*	−6.409*	−1.302	−10.060**	−2.245**
	(2.612)	(0.788)	(3.691)	(1.150)	(3.528)	(1.218)	(3.583)	(0.894)
Government funding	−0.002*	−0.0006	−0.002*	0.0005	−0.002	−0.0003	−0.003*	−0.002
(% of total funding)	(0.001)	(0.001)	(0.001)	(0.0009)	(0.001)	(0.001)	(0.001)	(0.002)
$(\text{Government funding})^2$	0.00001*	1.04×10^{-6}	9.72×10^{-6}	-6.80×10^{-6}	0.00001	-2.25×10^{-6}	0.00002**	7.70×10^{-6}
	(8.71×10^{-6})	(8.32×10^{-6})	(8.37×10^{-6})	(8.92×10^{-6})	(9.46×10^{-6})	(9.33×10^{-6})	(0.00001)	(0.00001)
Duration of reading class	−0.0005	−0.00005	0.0004	−0.0005	−0.0005	0.0002	−0.001*	0.0002
(minutes per class)	(0.0005)	(0.0004)	(0.0006)	(0.0008)	(0.0007)	(0.0006)	(0.0009)	(0.0005)
$(\text{Reading time})^2$	5.98×10^{-7}	-7.27×10^{-8}	-1.46×10^{-6}	1.61×10^{-6}	9.55×10^{-7}	-1.51×10^{-6}	3.04×10^{-6}	-1.25×10^{-6}
	(1.53×10^{-6})	(1.20×10^{-6})	(1.93×10^{-6})	(2.23×10^{-6})	(2.50×10^{-6})	(1.82×10^{-6})	(2.73×10^{-6})	(1.51×10^{-6})
Teacher shortage (dummy)	0.039	0.002	0.0261	−0.003	0.016	0.014	0.029	−0.002
	(0.025)	(0.011)	(0.042)	(0.016)	(0.032)	(0.016)	(0.024)	(0.015)
Learning material shortage (dummy)	−0.057*	−0.017	−0.032	0.017	−0.033	−0.012	−0.046	−0.019
	(0.029)	(0.011)	(0.048)	(0.017)	(0.037)	(0.016)	(0.034)	(0.014)
Ability grouping (dummy)	0.038*	0.003	0.075**	0.015	0.047	0.005	0.038*	−0.0005
	(0.021)	(0.012)	(0.036)	(0.018)	(0.031)	(0.016)	(0.023)	(0.015)
R^2	0.4951	0.2719	0.1903	0.1292	0.3198	0.1828	0.3637	0.1992
N	830	1759	830	1759	830	1759	830	1759

[a] Full regression results for boys and girls are available upon request.
* Statistically significant at 10 percent level of confidence.
** Statistically significant at 5 percent level of confidence.

achievement the child will attain. This effect, however, disappears for a boy in a rural area who is in the 70th percentile.

Attitude toward school is significant for boy students in urban as well as rural areas in the 30th percentile. The variable remains significant for average and median students in rural areas. The declining marginal effect of this variable along the achievement percentile implies that benefits from any improvement in attitude will not benefit high-performing students. Another variable which exhibits a similar pattern is the attitude toward reading, with the difference being that it is significant only for an average student in urban areas.

On learning style, memorization is a significant variable for average boy students from urban as well as rural areas. Two meta-cognitive variables – summarizing and understanding – are significant for both groups of students at all points along the achievement distribution. It is interesting to note that for students in urban areas, the marginal effects of both variables are increasing along the achievement percentiles. This pattern does not show up for those in rural areas. Thus, helping low-performing students in urban areas to be able to improve their ability to think critically will be beneficial to their achievements.

School-level variables that are significant and important in magnitude for an average student are computers per student and the shortage of learning materials. For boy students in the 30th percentile, shortage of learning materials affects their performance. An interesting result is the coefficient for the teacher shortage variable for low performing student in urban areas; the variable is positive with a marginal effect of approximately 5.7 percent. A straightforward interpretation concludes that teacher shortage is beneficial to a low-performing student and to a lesser extent for an average student. A plausible interpretation relates to the fact that, amidst a shortage, a teacher is more likely to pay greater attention to low-performing students to ensure that such shortage will not have adverse affect on their achievements (Barnett & Ritter, 2008; Barnett, Ritter, Winters, & Greene, 2007).

5.2. Urban–rural achievement gaps: how much do unmeasured characteristics matter?

As discussed in Section 4.1, the unexplained component of the decomposition will be interpreted as the contribution from unmeasured school characteristics to the gap between achievements for urban and rural students. Within a reasonable stretch of the boundary, we can also interpret the contribution from these characteristics as the contribution of school quality. Fig. 1 reports the Oaxaca–Blinder decomposition at the mean. On average, intangible school characteristics can explain about 45–48 percent of the achievement differential (see Tables A1 and A2 in the appendix for details). This confirms the argument set forth in the introductory section on the vital role of intangible school characteristics. Any attempt to narrow the gap without giving due attention to intangible aspects will, at best, reduce the gap by about half.

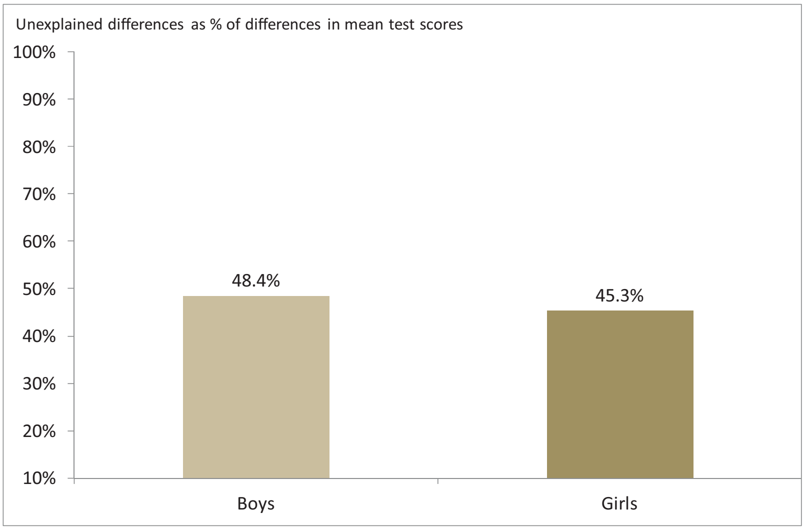

Fig. 1. Average contributions of unexplained components.

To provide more disaggregated pictures, which is the major contribution of this study, we now depart from the standard practice of comparing averages. Fig. 2 reports the contributions of unexplained components by percentile. These results are derived from the UQR estimates. By examining the results across the distribution, it is found that school's intangible characteristics are more beneficial to high-performing students. For example, for students in the 10th percentile of PISA test scores, intangible characteristics explain about 13–17 percent of the achievement gap. For the median performer, about 41–50 percent of the gap can be accounted for by intangible characteristics. For the highest achievers in 90th percentile, intangible characteristics explain about 61–69 percent of the gap. The estimates also show that, for students in 10th to 30th percentile, the contribution from unmeasured characteristics to explain the gap for boys rises faster than for girls: from 12.8 percent to 49.0 percent compared to 17.0 percent to 29.9 percent, respectively. Therefore, by and large, intangible characteristics matter more for boys than girls. To the best of our knowledge, this is the first time such a positive relationship between the urban–rural achievement gap and the contribution from school's intangible characteristics has been explored empirically beyond the mean.

Decomposition estimates suggest that, even after accounting for tangible school resources, achievement differentials still exist. The magnitude to which these differentials affect student performance also changes across the test distribution. Thus the achievement gap between schools in urban and rural areas cannot be reduced simply by putting more financial resources into

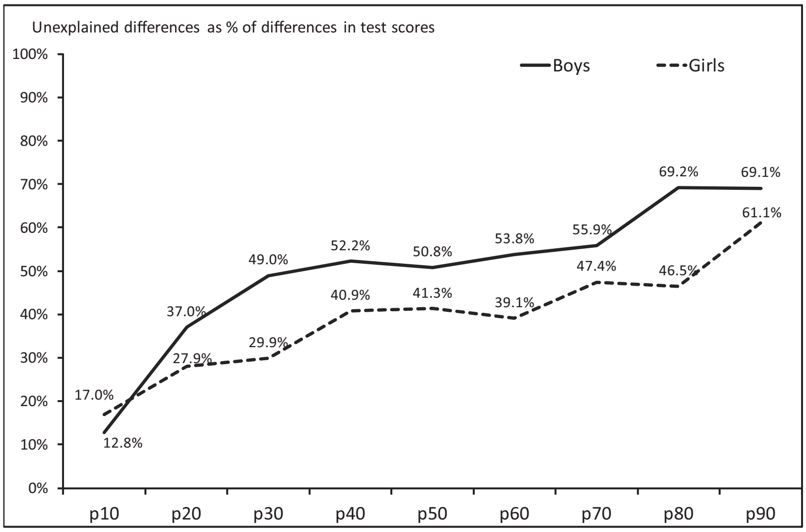

Fig. 2. Contributions of unexplained components by percentile.

schools as the Thai government has done in the past. The findings from this exercise are consistent with Hanushek and Luque (2003) and Woessmann (2010) and a conceptual model developed by De Fraja and Landeras (2006). These studies pointed to the need to devote more attention and resources to the improvement of non-tangible aspects of schools such as incentive structure for teachers, institutional adjustment and a more conducive environment for both students and teachers.

6. Discussions

There is an interesting policy implication to be put forward: reforms of basic education with a one-size-fits-all prescription will not achieve the desired result. The disaggregated decomposition exercise points to a more flexible reform in two aspects. The first aspect relates to the need to develop tailor-made policies to cater for different groups of students (and possibly gender). In order to reduce the achievement gap of low-performing students, more emphasis should be placed on promoting greater access to educational resources and other tangible educational inputs; further financial investment, therefore, can be justified. For high achievers, greater financial resources will be less effective; for them, reducing the gap relies more on non-financial, non-tangible measures.

Thus initiative to address the urban–rural achievement gaps can best be addressed at school level so as to take into account differences in compositions of students. Such an initiative calls for a bottom-up approach of school reform rather than a top-down approach being used in Thailand and many other countries. Judging by the size of coefficients, five key policy initiatives that will improve the achievement of low-performing students in rural areas are educational resources, attitude toward school and reading, appropriate assistance to enhance students' ability to learn and greater access to computers at school.

The second aspect is that the reform should devote similar or, preferably, more attention to improving the non-tangible characteristics of school: realigning incentives to attract qualified teachers and staff, promoting good school governance, revising curricula, revising teaching and learning approaches, and promoting more school accountability and parental involvement. Thus, it is not so much a question of how much money is thrown at the problem, as how the money is spent. Much more fundamental issues have to be addressed, such as teacher training, reducing the power distance between teachers and students, employing better teaching techniques (e.g. learning by doing) to encourage learner autonomy, having better quality teachers and teaching materials and a serious reassessment of the ways students are tested (e.g. practical formative rather than summative testing, with good feedback).

7. Conclusion

This paper sets out to contribute to the debate on the equity in basic education between urban and rural areas. It takes advantage of a vast range of variables available in the Thai PISA data. Unconditional quantile regression estimates of student-level education production functions demonstrate that contributions of student, family as well as school characteristics are not symmetric across achievement distributions and gender. Oaxaca–Blinder decomposition results point to the importance of non-tangible school characteristics in explaining achievement gaps between students in urban and rural areas. Decomposition exercises by achievement percentile reveal the increasing role of these characteristics; the higher the achievement percentile, the greater is the role of these characteristics in explaining the gap.

There are two major policy implications drawn from the empirical findings. First, there is no one-size-fits-all education reform policy. Asymmetrical effects of student, family and school characteristics by achievement percentile call for a bottom-up approach where the reform initiatives are formed at school levels to take into account differences in student compositions. Second, financial resources alone do not guarantee that the reform will succeed; initiatives to enhance non-tangible aspects of schools deserve equal attention. Ultimately, the success of reform in basic education to address inequity in school quality rests on finding the right balance between financial investment and developing a conducive school environment. Thorough investigation of how these proposals can be designed, developed and implemented to fit with the local environment deserve to be explored in a rigorous manner. This is where the issue departs from economic analysis into the hands of education experts.

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Appendix A

See Tables A1 and A2.

Table A1
Oaxaca–Blinder decomposition results for boys.

Estimate	Predicted mean			Differences between groups		
	Urban	Rural	Overall	Endowment	Unexplained	% unexplained
	(1)	(2)	(3) = (1) – (2)	(4)	(5)	(6) = (5)/(3)
OLS	6.116	5.990	0.126	0.065	0.061	48.4%
p10	5.864	5.731	0.133	0.116	0.017	12.8%
p20	5.959	5.832	0.127	0.080	0.047	37.0%
p30	6.032	5.889	0.143	0.073	0.070	49.0%
p40	6.090	5.956	0.134	0.064	0.070	52.2%
p50	6.131	6.003	0.128	0.063	0.065	50.8%
p60	6.182	6.05	0.132	0.061	0.071	53.8%
p70	6.226	6.099	0.127	0.056	0.071	55.9%
p80	6.278	6.148	0.130	0.04	0.090	69.2%
p90	6.325	6.228	0.097	0.03	0.067	69.1%

Table A2
Oaxaca–Blinder decomposition results for girls.

Estimate	Predicted mean			Differences between groups		
	Urban	Rural	Overall	Endowment	Unexplained	% unexplained
	(1)	(2)	(3) = (1) – (2)	(4)	(5)	(6) = (5)/(3)
OLS	6.181	6.075	0.106	0.058	0.048	45.3%
p10	5.940	5.887	0.053	0.044	0.009	17.0%
p20	6.029	5.961	0.068	0.049	0.019	27.9%
p30	6.096	6.009	0.087	0.061	0.026	29.9%
p40	6.142	6.049	0.093	0.055	0.038	40.9%
p50	6.189	6.08	0.109	0.064	0.045	41.3%
p60	6.233	6.118	0.115	0.07	0.045	39.1%
p70	6.285	6.148	0.137	0.072	0.065	47.4%
p80	6.346	6.191	0.155	0.083	0.072	46.5%
p90	6.422	6.26	0.162	0.063	0.099	61.1%

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