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Peer effects and the indigenous/non-indigenous early test-score gap in Peru

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This paper assesses the magnitude of the non-indigenous/indigenous test-score gap for third-year and fourth-year primary school pupils in Peru, in relation to the main family, school and peer inputs contributing to the test-score gap using the estimation method of feasible generalized least squares. The article then decomposes the gap into its constituent components using the traditional Oaxaca–Blinder decomposition method, as well as a modified decomposition method based on the estimation of a cognitive achievement production function. The decomposition results from both decomposition methods suggest that almost all of the test-score gap is explained by various peer, student, family and school characteristics. The peer characteristics used in the regression are the main contributors to the gross test-score gap, comprising between 58% and 71% of the language test gap and 45–62% of the mathematics test-score gap, depending on the decomposition method used.

Keywords: indigenous; education; test scores; peer effects; Peru

Introduction

In Latin America, Bolivia, Peru and Mexico (the last in absolute numbers only) are the major indigenous population centers along with Guatemala and Ecuador. In Peru in the 1990s, approximately 30% of the population was indigenous, speaking different versions of Quechua, which is widespread throughout Peru. In urban areas, most of the indigenous people are bilingual, while the rural indigenous population of Peru is mostly monolingual. The educational achievement of indigenous people in Peru, as well as in the other Latin American countries with significant indigenous minorities, has been lagging behind the Spanish-speaking population.

While in recent years student enrollment in Peru has increased with near universal completion of primary education in the 1990s, the quality of the education system as measured by pupils' scores in international tests remains low and unevenly distributed between urban and rural areas (World Bank 1999; Benavides et al. 2007). In particular, based on results from international achievement evaluations, Peru ranks very low among Latin American countries. For example, in the international achievement evaluation (language and mathematics) for third-grade and fourth-grade students organized by UNESCO, fourth-grade students in Peru ranked 12 while third-grade students ranked 11 among 12 Latin American countries. Similarly, in the first Programme for International Student Assessment (PISA) evaluation, Peru ranked at the bottom (OECD 2003). Additional evidence from national evaluations conducted by the Peruvian Ministry of Education

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suggest deficiencies in mathematics (general problem-solving and the topic of fractions) and that most sixth-grade students score below the cut-off threshold considered acceptable by specialists (Cueto, Ramirez, and León 2006).[1]

As in most Latin American countries, inequity is a major challenge of the education system in Peru, as manifested by low enrollments and higher repetition and dropout rates of children from disadvantaged backgrounds. Socioeconomic background remains an important determinant of educational outcomes in Latin American countries, and – according to Reimers (2000), who analyzed the effect of more family resources (such as parents' education and family income) on education outcomes – educational systems in Latin America have perpetuated, if not increased socioeconomic differences between groups. However, it is worth pointing out that, in the case of Peru, the low quality of education as measured by pupils' scores on international tests is not just an artifact of Peruvian students' lower socioeconomic background. For example, on UNESCO's Latin American Laboratory for the Assessment of the Quality of Education (LLECE) test, Peruvian pupils from higher socioeconomic backgrounds also scored much lower than their counterparts in many other Latin American countries (Benavides et al. 2007).

Willms and Somer (2001) used data from the *Primer Estudio International Comparativo* survey and found that the relationship between schooling outcomes and family background varies among Latin American countries. Across all countries examined, the most effective schools tend to be those with high levels of school resources; those that have classrooms that are not multi-grade; those with students tested frequently; and those that have classrooms with a positive classroom climate, especially with respect to discipline.

Empirical evidence on education production functions exists for both developed countries (for example, Hanushek 1986, 2002) and developing countries (for example, Glewwe 2002). Past empirical research does not always agree on which personal (student), school and family inputs improve children's achievement. Examples are the disagreements on the role of schooling inputs such as class size, teacher experience, teacher education and mother's employment.[2]

Nevertheless, although a child's achievement is inherently individual in nature, a large body of evidence points to the existence of persistence effects in educational achievement across generations (Fertig 2003; Fertig and Schmidt 2002; Currie and Thomas 1999). Consequently, one must control for individual pupil characteristics as well as family background. Finally, one needs to control for characteristics on school environment as well as institutional arrangements.[3]

Recent evidence from the literature on early test-score differentials suggests that differences in children's cognitive ability across families appear at an early age, tend to persist and may even widen with age. In general, 'good' families promote cognitive, social and behavioral skills, while 'bad' families do not. This is important in determining what policy interventions can be successful (Carneiro and Hecknam 2003). Evidence also suggests that socioeconomic and family background variables, such as parent's education and the number of books a child has, are very important determinants of test scores at early ages (Fryer and Levitt 2002). Finally, evidence exists suggesting that peer effects may be significant (see, for example, McEwan 2004).

The objective of this study is to assess the magnitude of the indigenous/non-indigenous test-score gap for third-year and fourth-year primary school pupils in Peru, to identify the main student, family, school and peer characteristics contributing to the test-score gap, and to decompose the gap into its constituent components using the Oaxaca–Blinder decomposition method. In doing so, education production functions will be estimated, using the 1997 *Primer Estudio International Comparativo* survey data.

Methodology and estimation

Methodology

The first step is to specify and estimate cognitive achievement production functions that relate students' achievement to individual, family and school inputs. I then proceed to decompose the indigenous/non-indigenous test gap into an explained component (accounting for family, school and peer characteristics) and an 'unexplained' component, using the traditional Oaxaca (1973)–Blinder (1973) decomposition method as well as a modified decomposition method based on the estimation of a cognitive achievement production function using a pooled sample consisting of both indigenous and non-indigenous students, after including an indigenous dummy in the set of explanatory variables.

Although the two decomposition approaches are expected to provide similar results, at least qualitatively, the traditional Oaxaca–Blinder decomposition allows the estimation and evaluation of the contribution of differences in intercepts in the overall test-score gap. Furthermore, by using both decomposition methods, one can compare results with those from other studies that are not consistent in the decomposition methodology used. The model specification for the estimation of the production function for cognitive achievement is as follows:

$$T_{ija} = T_a\left(F_{ija}, S_{ija}, P_{ija}\right) + \varepsilon_{ija}, \tag{1}$$

where T_{ij} is the observed test score of student i in household j at time a (time of the test), F_{ija} is a vector of individual and parent inputs, S_{ija} is a vector of school-related inputs, P_{ija} is a vector of peer characteristics and ε_{ija} is an additive error, which includes all of the omitted variables including those that relate to the history of past inputs, endowed mental capacity and measurement error.[4]

In its linear specification (after dropping subscript a) the model is given by:

$$T_{ij} = \beta_0 + \beta_1 F_{ij} + \beta_2 S_{ij} + \beta_3 P_{ij} + \varepsilon_{ij}, \tag{2}$$

where β_0–β_3 are coefficients to be estimated.

The standard procedure for analyzing the determinants of the test-score differentials is to fit equations between test scores and observed characteristics. The observed test-score differential can be decomposed as:

$$T_{\mathrm{NI}} - T_{\mathrm{I}} = \left(X_{\mathrm{NI}} - X_{\mathrm{I}}\right)\beta_{\mathrm{NI}} + \mathbf{X}_i\left(\beta_{\mathrm{NI}} - \beta_{\mathrm{I}}\right), \tag{3}$$

where T is the standardized test score (z-score),[5] $\mathbf{X}_i$ is a vector of family, school and peer characteristics for the ith individual, β is a vector of coefficients, and subscripts NI and I are identifiers of indigenous and non-indigenous students. A student is identified as indigenous if that student grew up speaking an indigenous language at home.

The overall test-score gap can therefore be decomposed into two components: one is the portion attributed to differences in characteristics ($X_{\mathrm{NI}} - X_{\mathrm{I}}$) evaluated with the non-indigenous group performance (β_{NI}) as 'price'; the other portion is attributable to differences in effects on performance ($\beta_{\mathrm{NI}} - \beta_{\mathrm{I}}$) of non-indigenous and indigenous students derived from the same characteristics. This second (unexplained) component, while more difficult to interpret in the present context compared with an earnings gap decomposition framework, can be assigned more than one interpretations.

First, an obvious one is that the unexplained portion of the test gap may reflect certain unobserved family characteristics that are correlated with achievement and indigenous status, possibly relating to household wealth. Second, even in the absence of overt discrimination against indigenous students, teachers may view indigenous students as underachievers, and therefore use different teaching standards.[6] Finally, it may be that indigenous and non-indigenous students do not reap the same benefits from equivalent school and classroom resources (McEwan, 2004).

A modified Oaxaca–Blinder decomposition

An alternative decomposition is possible using a modified Oaxaca–Blinder method, in which the unexplained part of the test-score differential is captured by an indigenous indicator taking the value of one for indigenous students and zero otherwise. Consider a production function for cognitive achievement:

$$T_{ija} = T_a\left(INDIG_{ij}, F_{ija}, S_{ija}, P_{ija}\right) + \varepsilon_{ija}, \tag{4}$$

where T_{ij} is the observed test score of student i in household j at time a (time of the test), $INDIG_{ija}$ is a dummy variable equal to one if the student spoke an indigenous language at home and zero otherwise, and $\varepsilon_{\mathrm{ija}}$ is an additive error, which includes all the omitted variables including those that relate to the history of past inputs, endowed mental capacity and measurement error.

In its linear specification (after dropping subscript a) the model is given by:

$$T_{ij} = \beta_0 + \beta_1 INDIG_{ij} + \beta_2 F_{ij} + \beta_3 S_{ij} + \beta_4 P_{ij} + \varepsilon_{ij}, \tag{5}$$

where β_0–β_4 are coefficients to be estimated.

In implementing a modified Oaxaca decomposition of the test-score gap (for an application on Bolivia and Chile, see also McEwan 2004), note that the mean test score of indigenous and non-indigenous students is given by:

$$T^{\mathrm{I}} = \beta_0 + \beta_1 + \beta_2 F^{\mathrm{I}} + \beta_3 S^{\mathrm{I}} + \beta_4 P^{\mathrm{I}} \tag{6}$$

$$T^{\mathrm{NI}} = \beta_0 + \beta_2 F^{\mathrm{NI}} + \beta_3 S^{\mathrm{NI}} + \beta_4 P^{\mathrm{NI}} \tag{7}$$

where T is the mean test score, I and NI indicate indigenous and non-indigenous students, and F, S and P are the mean family (including individual), school and peer characteristics.

Subtracting Equation (6) from Equation (7):

$$\left(T^{\mathrm{NI}} - T^{\mathrm{I}}\right) = \beta_1 + \beta_2\left(F^{\mathrm{NI}} - F^{\mathrm{I}}\right) + \beta_3\left(S^{\mathrm{NI}} - S^{\mathrm{I}}\right) + \beta_4\left(P^{\mathrm{NI}} - P^{\mathrm{I}}\right) \tag{8}$$

where coefficient β_1 is an estimate of the portion of the gap that remains after accounting for the differences in mean characteristics.

Certain of the above coefficient estimates may be subject to biases. For example, if a school characteristic is correlated with unobserved family characteristics that influence achievement (such as family wealth and parents' motivation), the effect of attending a school with such characteristics may be biased.

Concluding, two alternative decompositions are used in order to assess the consistency of results (mainly concerning the size and nature of the unexplained indigenous/non-indigenous test-score gap). Note, however, that the two decompositions are different, as the two estimators actually correspond to different counterfactual situations: one of them corresponds to the comparison of indigenous people with the average of the population, and the other to indigenous people compared with non-indigenous people.

Estimation method

While test scores and individual and family information are at the individual level, school resources and other school-related inputs are at the school level. In choosing the estimation method we recognize that observed test scores are expected to be correlated at the school level due to clustering effects. Therefore, the assumption that disturbances are independently and identically distributed with fixed conditional variance does not hold. The estimation method of feasible generalized least squares (FGLS) (see Greene 2000) is chosen as more suitable than ordinary least squares (OLS) regression, as it allows the disentangling of student from school effects.

Given the generalized regression model:

$$T = X\beta + \varepsilon,$$

and a positive definite variance–covariance matrix Ω assumed not available and estimated as Ω* using a FGLS estimator. The FGLS estimator of the vector of coefficients is:

$$\beta_{\text{FGLS}} = (X'\Omega^{*-1}X)^{-1}X'\Omega^{*-1}T$$

In our case, the panels are the schools. As is common in cross-sectional datasets, the variance for each panel will differ. A heteroskedastic FGLS model is therefore specified in the derivation of the FGLS estimator.

Data

The data used are from the 1997 *Primer Estudio International Comparativo* (First Comparative International Study on Language, Mathematics and Associated Factors) survey, carried out by the LLECE, coordinated by UNESCO and funded by the Inter-American Development Bank, the Ford Foundation, UNESCO and the participating countries. Data were collected in 13 countries, but information is available only for 11 countries[7] (Argentina, Bolivia, Brazil, Chile, Colombia, Honduras, Mexico, Paraguay, Peru, Dominican Republic and Venezuela).

In the process of data collection, more than 50,000 third-grade and fourth-grade students were tested in language and mathematics. A set of questionnaires were also administered to students, their parents (or guardians), teachers and school principals. The data were stratified to ensure sufficient observations of public, private, urban, rural and metropolitan pupils in each country. Private schools were over-sampled, allowing for more precise comparisons between private and public schools. It is also worth noting that the survey's sampling strategy designated rural schools as a single, public sector stratum, reflecting the fact that in rural areas in most Latin American countries schools are overwhelmingly public. On the other hand, urban areas were divided into public and private strata. Furthermore, rural students are poorer in ways that may be unobservable by researchers (Somers, McEwan, and Willms 2004).

Data were collected for 100 schools in each country with 40 children per school. One-half of the students were in the third grade and one-half in the fourth grade. The survey instruments – besides the tests administered to the sample of pupils – were the self-applied questionnaires to school principals, teachers, parents (or legal guardians) of tested pupils and the students themselves. Since the test and questionnaires were administered only to children who attended school (therefore, no information was obtained on children not in school), the results can only be applied to enrolled children. The test consisted of 32 multiple choice questions for mathematics[8] and 19 multiple choice questions for language.

Finally, the tests were developed using the norms model; that is, the tests were designed to produce national averages of about 50% of the maximum possible score. The testing results are therefore appropriate for producing relative scores by groups – such as urban versus rural, boys versus girls, indigenous versus non-indigenous, and so on – rather than evaluating adequacy of learning.

Discussion

Descriptive statistics

Figures 1–4 show the distribution of test scores of indigenous and non-indigenous students in Peru. The language test consisted of 19 questions, while the mathematics test consisted of 32 questions. Generally speaking, the distributions of indigenous students are right-skewed. On the other hand, the distributions of non-indigenous pupils are approximately normally distributed.

Table 1 presents descriptive statistics on a variety of characteristics of third-year and fourth-year pupils. A first observation is that the non-indigenous/indigenous test-score differential is much higher in the language test than the mathematics test. The standardized

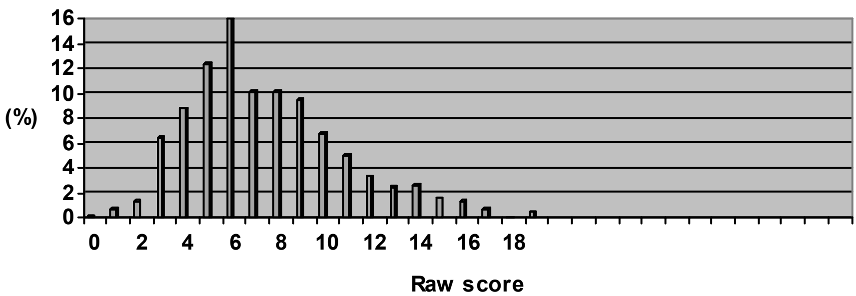

Figure 1. Distribution of language test scores (%): indigenous, Peru 1997.

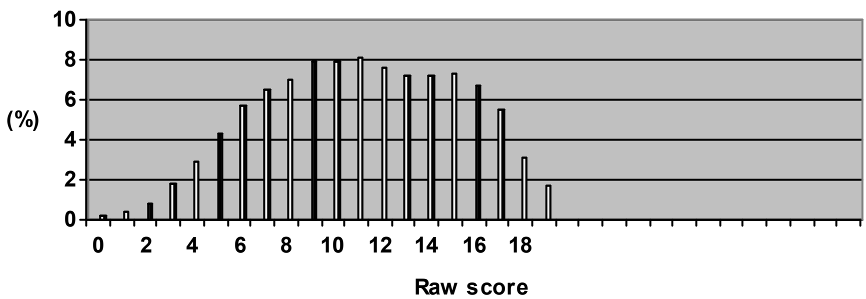

Figure 2. Distribution of language test scores (%): Spanish, Peru 1997.

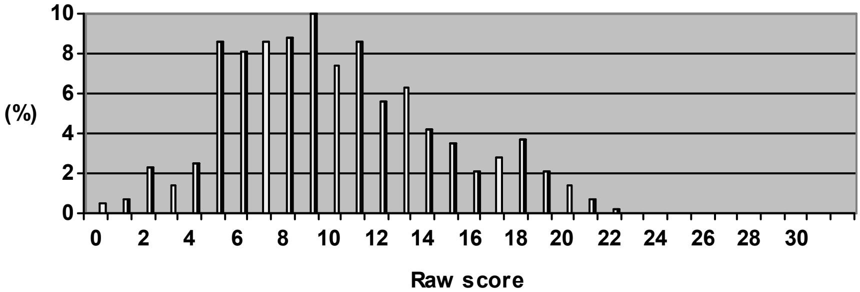

Figure 3. Distribution of mathematics test scores (%): indigenous, Peru 1997.

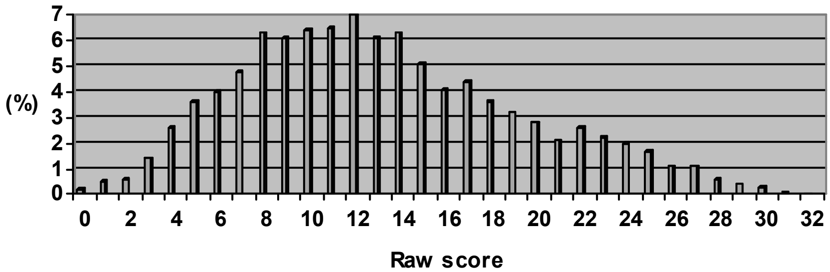

Figure 4. Distribution of mathematics test scores (%): Spanish, Peru 1997.

Table 1. Descriptive statistics, Peru 1997.

	Full sample	Spanish	Indigenous	Difference
Test scores				
Language	10.63 (4.2)	11.03 (4.2)	7.51 (3.4)	3.52** (0.83[a])
Mathematics	12.90 (6.1)	13.27 (6.1)	9.94 (4.5)	3.35** (0.60[a])
Other characteristics (%)				
Indigenous	0.11	–	–	–
Female	0.49	0.49	0.44	0.05**
Fourth grade	0.49	0.49	0.47	0.02
Work activity				
Never works	0.39	0.42	0.16	0.26**
Works sometimes	0.35	0.34	0.46	–0.12**
Works regularly	0.25	0.24	0.38	–0.14**
Repeated first grade	0.16	0.13	0.35	–0.22**
Books at home				
No books at home	0.15	0.14	0.29	–0.15**
< 10 books	0.53	0.51	0.65	–0.14**
> 10 books	0.32	0.35	0.06	0.29**
Attended kindergarten	0.71	0.75	0.37	0.38**

Table 1. *(Continued)*.

	Full sample	Spanish	Indigenous	Difference
Guardian's education				
< primary	0.06	0.04	0.29	–0.25**
Primary	0.40	0.37	0.62	–0.25**
Secondary	0.30	0.32	0.07	0.25**
Higher	0.24	0.27	0.02	0.25**
Teacher female	0.68	0.71	0.46	0.25**
Teacher's years of experience	19.9 (14.5)	19.9 (14.5)	19.3 (14.5)	0.6
Teacher has freedom	0.82	0.82	0.81	0.01
Pupil/teacher ratio	14.25(12.3)	14.72(12.5)	10.03 (9.2)	4.7**
Have Spanish textbook	0.69	0.74	0.30	0.44**
Have mathematics textbook	0.39	0.43	0.11	0.32**
Classroom condition				
Bad	0.18	0.14	0.45	–0.31**
School sector				
Public	0.78	0.75	0.99	–0.24**
Private subsidized	0.09	0.11	0.005	0.10**
Private	0.12	0.14	0.005	0.13**
School location				
Capital city	0.31	0.34	0.03	0.31**
Secondary city	0.20	0.22	0.06	0.14**
Small town	0.30	0.30	0.32	–0.02
Rural	0.20	0.15	0.59	–0.44**
School type				
Morning or afternoon	0.49	0.48	0.57	–0.09**
Whole day	0.10	0.08	0.26	–0.18**
School shift	0.40	0.43	0.17	0.26**
By school				
Mean (indigenous)	0.11	0.05	0.64	–0.59**
Mean (guardian > secondary)	0.51	0.56	0.21	0.35**
Observations	4064	3620	444	

Note: Means of variables using the complete sample. There are differences between the above sample statistics and those used in the regression estimations and decomposition analysis, due to missing observations in various independent variables. **Significance at the 1% level. [a]Standard deviation.
Source: 1997 UNESCO (OREALC) survey.

differential is 0.83 standard deviations in the language test, compared with 0.60 standard deviations in the mathematics test.[9]

Looking at other descriptive statistics, a much larger proportion of indigenous students exhibit some form of work activity while attending school (84%), compared with non-indigenous students (58%). Furthermore, indigenous students predominantly live in rural areas and small towns (91%), while non-indigenous students mostly reside in large cities (56%). In Peru, practically all indigenous students (over 99%) attend public schools, while about 25% of non-indigenous students attend private schools (14% of which are private paying schools). While there is no information on family income, there is hardly any doubt that indigenous students come from a more disadvantaged socioeconomic background; besides their higher incidence of work activity, indigenous students have fathers (or guardians) who are less educated and grow-up with less books at home compared with non-indigenous students.

Estimation results

Before discussing the estimates derived from FGLS regressions, attention is drawn to the consequences of student self-selection on the estimated relationships among student, family, teacher and school characteristics and student outcomes. Two potential sources[10] of student self-selection may be of importance. First, households choose specific schools based on observed arbitrary differences, such as cost and location. Controlling for various socioeconomic and other student characteristics can greatly reduce this potential bias. I therefore control for student background to the full extent permitted by the data. Second, households may choose a school based on unobserved differences, or differences that are hard to measure (Vegas 2002). If, for example, more motivated parents systematically tend to choose, say, private schools, results will overestimate any positive effects associated with private schools.

It should also be noted that, while family income is absent from the set of regressors, certain variables that are present (such as work activity and number of books at home) are expected to capture (at least partly) the effect of family wealth, and therefore the estimated coefficients should be interpreted as such. Furthermore, the *a priori* expectation of the sign of certain (mostly school) variables may be ambiguous; for example, being given a mathematics textbook is certainly preferred to nothing at all – however, students who are given a textbook may perform worse compared with those who are given teacher-compiled notes. Likewise, certain questions in the questionnaire may be misleading; for example, teachers having a lot of freedom at work may be associated with worse student performance, as it may reflect bad management and poor supervision of teachers' performance.

Table 2 presents the regression results using the pooled sample of indigenous and non-indigenous students, which include a dummy for indigenous/non-indigenous status, the coefficient of which is a measure of the effect of indigenous status on student performance after controlling for a variety of student, family, school and peer characteristics. Without controlling for various characteristics, the detrimental effect of being indigenous on test-score achievement is twice as large in the language test compared with the mathematics test. After controlling for such characteristics, the coefficient of indigenous status is small and statistically insignificant.

Looking at the standardized coefficients in the achievement regressions, a number of results emerge. Girls performed better than boys in the language test, while the opposite is true for mathematics. Children who never worked while studying did much better in both tests compared with children who worked regularly. The effect of father's education is important only when it is at the postsecondary level, while having a father with primary or secondary education (compared with less than primary) does not significantly affect the child's achievement. Having access to books at home significantly increases performance in both tests, and the beneficial effect increases with the number of books. However, rather than assigning a causal interpretation to the estimated coefficients, family variables such as the ones considered here are best interpreted as proxies of family wealth and the home educational environment; they may also reflect the influences of unmeasured school variables that are correlated with certain family characteristics.

Table 2. Achievement regressions: All, Peru 1997.

	Dependent variable: language *z*-score		Dependent variable: mathematics *z*-score	
	Column 1	Column 2	Column 3	Column 4
Indigenous	–0.858 (20.5)**	–0.045 (0.7)	–0.442 (11.5)**	–0.084 (1.4)
Female	–	0.66 (2.5)*	–	–0.072 (2.5)*
Fourth grade	–	0.377 (13.8)**	–	0.416 (14.0)**
Work activity (omitted: always works)				
Never works	–	0.261 (7.2)**	–	0.264 (6.6)**
Works sometimes	–	0.091 (2.6)**	–	0.044 (1.2)
Repeated first grade	–	–0.175 (4.6)**	–	–0.128 (3.2)**
Books at home (omitted: no books)				
1–10 books	–	0.028 (0.7)	–	0.180 (4.5)**
> 10 books	–	0.167 (3.3)**	–	0.244 (4.1)**
Attended kindergarten	–	0.041 (1.2)	–	–0.028 (0.8)
Guardian's education (omitted: less than primary)				
Primary	–	0.017 (0.3)	–	0.030 (0.5)
Secondary	–	–0.011 (0.2)	–	–0.011 (0.2)
Higher	–	0.220 (3.3)**	–	0.125 (1.8)
Teacher female	–	–0.115 (3.9)**	–	–0.91 (2.8)**
Teacher's years of experience	–	0.0002 (0.2)	–	0.003 (3.7)**
Teacher has freedom	–	0.022 (0.6)	–	0.025 (0.7)
Pupil/teacher ratio	–	0.003 (2.3)*	–	0.001 (1.9)
Have Spanish/mathematics textbook	–	0.043 (1.2)	–	0.029 (0.9)
Room condition: bad	–	0.090 (2.4)*	–	0.059 (1.4)
School sector (omitted: public school)				
Private subsidized	–	0.287 (5.0)**	–	0.576 (9.1)**
Private	–	0.366 (6.4)**	–	0.779 (11.8)**

Table 2. *(Continued)*.

	Dependent variable: language z-score		Dependent variable: mathematics z-score	
	Column 1	Column 2	Column 3	Column 4
School location (omitted: capital/secondary city)				
Small town	–	–0.145 (3.3)**	–	–0.155 (3.4)**
Rural	–	–0.147 (2.9)**	–	–0.040 (0.9)
School type (omitted: morning or afternoon)				
Whole day	–	–0.012 (0.2)	–	0.107 (1.7)
Shift school	–	0.078 (2.2)*	–	0.111 (2.9)**
Peer effects (by school)				
Mean (indigenous)	–	–0.490 (5.0)**	–	–0.269 (3.0)**
Mean (guardian > secondary)	–	0.651 (6.5)**	–	0.480 (5.0)**
Constant	0.073 (4.8)	–0.823 (8.8)**	–0.039 (2.7)	–0.781 (8.1)**
Log-likelihood	–5478	–3575	–5363	–3013
Wald chi-square	420	2533	133	1664
[*p* value]	[0.000]	[0.000]	[0.000]	[0.000]
Estimated covariances (number of schools)	117	106	117	115
Observations	4064	3089	4029	2572

Note: Data in parentheses are *t*-values. **Significance at the 1% level, *significance at the 5% level. Columns l and 3: controlling for indigenous status only; columns 2 and 4: full set of controls.
Source: 1997 UNESCO survey.

Having a female teacher is associated with a worse student performance in both tests. Longer teacher experience results in better student performance, but only for the mathematics test; however, this variable may also be reflecting the effect of having an older teacher. The effect of teacher freedom at work is not significant, suggesting that enjoying freedom as a teacher (self-reported by the teachers in the survey) has no effect on students' performance. This result may reflect some other unmeasured school quality, such as bad management or inadequate supervision. A higher pupil/teacher ratio, in the case of Peru, is associated with a higher test score. The empirical literature provides inconclusive evidence on the effect of the pupil/teacher ratio on student performance. Textbook availability improves student performance for both language and mathematics, but this result is not significant. Bad condition of the classroom seems to have a perverse effect on student performance, although this effect is significant only in the language test. However, this result may reflect some other effect, such as school location.

School sector and location are significant determinants of student performance. Private school students[11] (in both private subsidized and paying schools) performed much better than their public school counterparts. Finally, students attending school in large cities outperform those in small towns and rural areas.

Peer effects are particularly strong, especially on their effects on the language test. A higher proportion of indigenous students in the school population results in lower test scores. Note, however, that about 90% of students are Spanish speaking. On the other hand, the higher the proportion of students with fathers (or guardians) with higher than secondary school qualifications, the higher the test scores in both language and mathematics (by 0.65 and 0.48 standard deviations, respectively).

Table 3 reports the results of separate achievement regressions for indigenous and non-indigenous students, which were used in the Oaxaca–Blinder decompositions. Regression coefficient estimates are less precise in the indigenous regressions due to smaller sample sizes. This results in a large number of coefficient estimates in the indigenous regressions being statistically insignificant.

Notable differences in estimated regression coefficients between the indigenous and non-indigenous regressions are the effects of no labor market activity – from which non-indigenous students reap benefits while indigenous students do not – and the effects of living in small towns and rural areas, where indigenous students performed worse in the language test and better in the mathematics test while their Spanish-speaking counterparts living in large cities performed better in both tests. Notable also is the finding that a higher pupil/teacher ratio has a beneficial effect on pupil performance, possibly because in Peru the pupil/teacher ratio proxies community size and larger communities enjoy better teacher quality, materials, and other unobservable inputs.

Again, of particular interest are the results on peer effects. A higher proportion of indigenous students in the school actually increases the score (language) or has no effect on the score (mathematics) of indigenous students, while a higher proportion of indigenous students significantly decreases the score of non-indigenous students. On the other hand, attending a school where students' fathers are more educated significantly increases the score of non-indigenous students but does not seem to have a significant effect on the score of indigenous students.

Decomposition results

Table 4 presents the results of decomposing the non-indigenous/indigenous achievement gap using the traditional Oaxaca–Blinder decomposition method (column 2) as well as a

Table 3. Achievement regressions (FGLS), by indigenous/non-indigenous status: Peru 1997.

	Dependent variable: language		Dependent variable: mathematics	
	Indigenous	Non-indigenous	Indigenous	Non-indigenous
Female	–0.044 (1.3)	0.088 (3.1)**	–0.105 (1.7)	–0.071 (2.3)*
Fourth grade	0.214 (3.1)**	0.405 (13.8)**	–0.079 (1.1)	0.472 (14.8)**
Work activity (omitted: always works)				
Never works	–0.070 (0.7)	0.291 (7.5)**	0.135 (1.4)	0.237 (5.6)**
Works sometimes	0.011 (0.2)	0.128 (3.3)**	0.236 (3.5)**	–0.005 (0.1)
Repeated first grade	–0.027 (0.4)	–0.215 (4.9)**	–0.050 (0.7)	–0.113 (2.5)*
Books at home (omitted: no books)				
1–10 books	0.035 (0.4)	0.007 (0.2)	–0.005 (0.1)	0.165 (4.1)**
> 10 books	0.213 (1.5)	0.144 (2.6)**	0.085 (0.2)	0.226 (3.7)**
Attended kindergarten	1.101 (1.4)	0.045 (1.2)	–0.038 (0.6)	–0.009 (0.2)
Guardian's education (omitted: less than primary)				
Primary	0.089 (1.2)	–0.036 (0.5)	0.054 (0.8)	–0.019 (0.2)
Secondary	0.125 (0.9)	–0.063 (0.8)	0.117 (0.8)	–0.059 (0.7)
Higher	0.207 (0.7)	0.161 (2.0)*	0.387 (1.2)	0.101 (1.2)
Teacher female	–0.229 (2.8)**	–0.107 (3.4)**	–0.274 (3.7)**	–0.110 (3.1)*
Teacher's years of experience	–0.002 (0.7)	0.001 (0.6)	–0.009 (4.1)**	0.004 (4.2)**
Teacher has freedom	0.214 (2.8)**	0.008 (0.2)	–0.024 (0.2)	0.044 (1.1)
Pupil/teacher ratio	0.030 (5.4)**	0.001 (0.5)	0.005 (6.5)**	0.001 (1.9)
Have Spanish/mathematics textbook	0.038 (0.5)	–0.005 (0.1)	0.049 (0.8)	0.014 (0.4)
Classroom condition: bad	–0.051 (0.6)	0.101 (2.4)*	–0.613 (8.0)**	0.193 (4.3)**
School location (omitted: capital/secondary city)				
Small town	–1.181 (5.4)**	–0.079 (1.8)	0.579 (2.4)*	–0.154 (3.2)**
Rural	–0.973 (5.2)**	–0.141 (2.6)**	0.558 (2.3)*	–0.038 (0.8)

Table 3. *(Continued)*.

	Dependent variable: language		Dependent variable: mathematics	
	Indigenous	Non-indigenous	Indigenous	Non-indigenous
School type (omitted: morning or afternoon)				
Whole day	–0.861 (5.4)**	–0.014 (0.2)	0.777 (7.1)**	–0.034 (0.5)
Shift school	–0.044 (0.3)	0.032 (0.8)	0.734 (5.5)**	0.059 (1.5)
Peer effects (By school)				
Mean (indigenous)	1.059 (3.6)**	–0.857 (7.2)	0.044 (0.2)	–0.609 (6.1)**
Mean (guardian ≥ secondary)	0.488 (1.1)	0.816 (7.6)**	–0.255 (0.9)	0.491 (5.0)**
Constant	–0.903 (3.0)**	–0.784 (7.3)**	–0.968 (3.3)**	–0.737 (6.6)**
Log-likelihood	–245	–3201	–178	–2741
Wald chi-square	166	1842	261	1450
[*p* value]	[0.000]	[0.000]	[0.000]	[0.000]
Estimated covariances (number of schools)	34	104	33	113
Observations	343	2746	255	2317

Note: Data in parentheses are *t*-values. **Significance at the 1% level, *significance at the 5% level. School sector is not controlled for as only a handful of indigenous students in the sample attended private subsidized or private schools.
Source: 1997 UNESCO (OREALC) survey.

Table 4. Decompositions of non-indigenous/indigenous test-score (z-score) differentials, Peru 1997.

	Decomposition based on pooled regression with indigenous dummy	Oaxaca decomposition
Language test		
Explained	**0.932**	**1.149**
Family	0.229	0.226
School	0.173	0.103
Peer	0.536	0.820
Unexplained	**0.045**	**–0.204**
Family	–	0.079
School	–	0.775
Peer	–	–1.040
Intercept	–	–0.019
Total	**0.983**	**0.945**
Usable observations	3089	3089 (343 indigenous)
Mathematics test		
Explained	**0.662**	**0.788**
Family	0.161	0.152
School	0.200	0.146
Peer	0.301	0.490
Unexplained	**0.084**	**–0.034**
Family	–	0.144
School	–	–0.213
Peer	–	–0.204
Intercept	–	0.238
Total*	**0.746**	**0.754**
Usable observations	2572	2572 (255 indigenous)

Note: Implied totals (sum of decomposition components). Totals from the two decompositions do not coincide, as the two decompositions reflect different counterfactuals. Numbers in bold: Total explained, total unexplained and gross gap for language and mathematics tests.
Source: 1997 UNESCO survey.

modified decomposition method (column 1). The gross standardized gap is approximately one standard deviation for the language test and approximately 0.75 standard deviations for the mathematics test, in favor of non-indigenous (Spanish-speaking) students.

Two issues worth commenting on before proceeding with the presentation of the test-score decomposition results relate to how representative are the survey data available of the indigenous and non-indigenous populations of third-year and fourth-year pupils, as well as the severity of selection bias due to dropping observations with partial background information. With respect to the first, it should be noted that pupils who drop out of school before the third grade are not part of the sample, while the probability of a child dropping out of school is higher among the indigenous population. Furthermore, pupils who are more often absent (and hence more likely to be absent the day of the test) are not part of the sample.

The severity of selection bias due to dropping observations with partial background information can be assessed by comparing the average test-score gap in the original sample with that after dropping observations with partial background information (i.e. the one that appears in the test-score decomposition in Table 4). Based on this comparison, the selection bias seems to be a moderate one, as the test-score differences from the original sample of students who took the tests (0.83, 0.60 for language and mathematics, respectively) are not drastically different from those derived form the decomposition (0.95 and 0.75 respectively).

Using the standard Oaxaca–Blinder decomposition method (Table 4, column 2), the unexplained component is close to zero for the mathematics test and somewhat in favor of indigenous students for the language test. The greatest contribution towards explaining the test-score gap comes from the peer variables. Furthermore, family variables contribute more than school variables to the overall explained component.

Column 1 of Table 4 reports the results of the decomposition using the modified method. The predicted gross test gaps by the two decomposition approaches are broadly similar in magnitude. As in the conventional decomposition, in the modified decomposition the unexplained component represents only a small part of the gross test-score gap (5% and 12% for the language test and the mathematics test, respectively). Peer effects are again the most important contributors, constituting 45–60% of the total gap.

The indigenous population in Peru is predominantly rural. While in the decompositions of Table 4 about 11% of students are indigenous, one-third of the students in the high-poverty rural areas are indigenous, compared with only about 5% in urban areas. There are compelling reasons to expect the school dynamics (and hence, the education production functions) to differ substantially. I therefore estimated education production functions separately for rural and urban areas. The decomposition results using the modified method are presented in Table 5. In this comparison I use the modified decomposition method only, as the small numbers of indigenous students (especially in urban areas) resulted in imprecise estimates in the indigenous education production functions.

Certain coefficient estimates between rural and urban areas are somewhat different. The effect of being indigenous on the standardized test score (unexplained component) is negligent in rural areas, while in urban areas the effect is larger but not statistically significant

Table 5. Decompositions of non-indigenous/indigenous test-score (*z*-score) differentials, based on pooled regression with indigenous dummy: rural versus urban, Peru 1997.

	Rural		Urban	
Language test	Language test	Mathematics test	Language test	Mathematics test
Explained	**0.720**	**0.496**	**1.014**	**0.755**
Family	0.290	0.158	0.235	0.211
School	–0.061	–0.062	–0.063	0.070
Peer	0.492	0.400	0.842	0.474
Unexplained	**–0.037**	**0.054**	**0.160**	**0.136**
Family	–			
School	–			
Peer	–			
Intercept	–			
Total	**0.683**	**0.548**	**1.174**	**0.892**
Usable observations	2491	1825	598	772

Note: Implied totals (sum of decomposition components). Totals from the two decompositions do not coincide, as the two decompositions reflect different counterfactuals.
Source: 1997 UNESCO survey.

at the 5% level. The effect of student gender is significant in urban areas, where female students do better in language but worse in mathematics, while in rural areas there is no gender effect. The detrimental effect of working regularly while studying is much stronger in urban compared with rural areas. This may be because exhibiting work activity while studying is very common in rural areas. Having many books at home is associated with a higher increase in student's performance in urban compared with rural areas. A higher pupil/teacher ratio is found to be associated with a significantly lower mathematics score in urban areas and a higher mathematics score in rural areas. The finding that a higher pupil/teacher ratio has a beneficial effect on pupil performance in rural areas further supports the suspicion that in rural areas class size is correlated with other characteristics such as community size, with students in larger communities enjoying better quality of unobservable inputs. Another possible explanation for the finding that in rural areas large classes do not negatively affect outcomes could be that that students are of similar ability (and perhaps low ability for certain schools such as indigenous schools), resulting in fewer conflicts and disruptions. Notable similarities between rural and urban areas are found in the effect of having a female teacher (consistently resulting in lower scores in both areas and tests) and the effect of peer groups, particularly the strong positive effect on scores from attending schools where peers have more educated parents.

The decomposition analysis by school location confirms the earlier finding that student, family, school and peer characteristics explain almost the entire test-score gap, and more so in rural areas. Peer effects are again the most important determinant, explaining about 73% of the test-score gap in rural areas and 53–72% of the gap in urban areas. Finally, it is worth noting that the gross test-score gap in urban areas is much larger (nearly double that in rural areas).

The results presented in this paper for Peru are qualitatively similar to those obtained by McEwan (2004) for Bolivia and Chile using the modified decomposition approach, who found that the unexplained component varies from about 10% (Chile) to about 25% (Bolivia) of the gross gap. The results for Peru are, however, more conclusive; when peer effects are included, the unexplained component of the test-score gap virtually disappears. The role of peer groups in explaining test-score differences between groups has been also established when comparing public versus private school outcomes. Somers, McEwan, and Willms (2004), using the same set of data as this study, found that while there are substantial and consistent differences in the achievement of private and public schools, after accounting for peer group characteristics the average private school effect across all 10 countries examined is zero.

Conclusions and policy recommendations

The present study assesses the magnitude of the indigenous/non-indigenous test-score gap for third-year and fourth-year primary school pupils in Peru. I identify the main student, family, school and peer inputs contributing to the test-score gap, and decompose the gap into its constituent components.

In choosing the estimation method I recognize that observed test scores are expected to be correlated at the school level due to clustering effects. Therefore, the estimation method of FGLS is chosen, as it allows the disentangling of student from school effects.

The decomposition results from both decomposition methods suggest that, essentially, the entire test-score gap is explained by various peer and characteristics. The two peer characteristics used in the regression (proportion of indigenous students by school and proportion of educated fathers by school) are the main contributors to the gross test-score gap, comprising between 58% and 71% of the language test gap and 45–62% of the mathematics test-score gap, depending on the decomposition method used.

While inequalities among groups are important in national achievement test results, the Peruvian evidence (such as that from Programme for International Student Assessment) confirms that the under-achievement problem is generalized and not just a problem of low-income, rural, or indigenous language-speaking students. Similarly, when the results were adjusted for social class differences, analysis on the LLECE test (1996/97) shows that Peruvian third and fourth graders scored in the bottom five of 12 Latin American countries in language and in the bottom three in mathematics. Peruvian pupils whose parents have a high level of education scored lower than their counterparts in most other Latin American countries (Willms and Somers 2001; Benavides et al. 2007). One may therefore suggest that any interventions specific to indigenous students should be considered in the context of the quality problems faced by the primary education system, as well as the understanding that the poor results of indigenous pupils are characteristic of the low-income, mainly rural population in Peru.

Some promising policy interventions one could consider for reducing the gap have been suggested in the literature (see, for example, Hernandez-Zavala et al. 2006), such as: promoting effective bilingual education instruction designed to provide indigenous children with mastery of the Spanish language before the completion of primary school, although there is some evidence that frequently bilingual education is poorly implemented even within schools designated as indigenous (see, for example, World Bank 2005); compensatory education programs meant to equalize learning opportunities, which have proven to be very effective in closing learning gaps (see, for example, Shapiro and Moreno 2004); finally, and in light of the finding that peer groups are of particular importance, choice of school at least theoretically, could lead to improved learning outcomes (see, for example, Angrist et al. 2002). Cueto et al. (2004) show that students grouped in classrooms of relatively lower socioeconomic status tend to progress less in school than their peers in relatively higher socioeconomic groups.

Evidence also exists that policy reforms, especially at the primary school level, contribute to reducing the indigenous test-score gaps. For example, the 1990 reform in Chile – where the Ministry of Education implemented a range of reforms targeting low-achievement or low-income students (including targeted investments in remedial tutoring and a lengthening of the school day) were successful in increasing mean school test scores, and in particular, some of these education reforms played a role in the observed reduction of the indigenous rest score gaps in the late 1990s within the eighth-grade cohorts. In a relatively short time period, the mean indigenous/non-indigenous test-score gap declined by 0.2 standard deviations in Spanish and 0.1 standard deviations in mathematics (McEwan 2006).

Any policy choices (such as compensatory programs), however, need to be preceded by experiments that are rolled out over time with treatment and control groups and are made on the basis of rigorous impact evaluation results. This is important as there is lack of evidence on what it takes to improve indigenous education in Latin America.

Notes

1. For further insight into issues relating to quality of education in Peru, see also Cueto et al. (2006), Benavides (1998) and Cueto and Aguero (2003).
2. For a survey or related literature, see Todd and Wolpin (2003).
3. While studies that use an education production function approach provide valuable insight into the relationship between inputs and student outcomes, few studies look at what happens inside the classroom and evaluate opportunities to learn. For such a study see Cueto et al. (2006), who attempted to describe opportunities to learn mathematics in Peru, to determine whether these

opportunities were related to the type of school and analyzed whether opportunities to learn were related to student achievement.

4. Todd and Wolpin (2003) discuss in detail the assumptions that would satisfy the application of this specification, in which the achievement test score depends solely on the contemporaneous measures of family, school and other inputs. These assumptions state: that current input measures capture the entire history of inputs or, alternatively, only contemporaneous inputs matter; and that contemporaneous inputs are unrelated to endowed mental capacity.
5. Standardized test scores are used to facilitate the comparison between language and mathematics test results, as the two tests consist of a different number of questions.
6. This may be a contributing factor that helps to sustain, and possibly expand the black–white test-score gap in the United States (Ferguson 1998).
7. Subsequently, Costa Rica and Cuba were excluded; the first due to consistency problems and the second due to missing data on child labor.
8. One hundred percent of pupils' test score in mathematics was in the 0–30 range; that is, no pupil answered 31 or all 32 questions correctly.
9. These test-score differentials are not identical to those reported in the decomposition tables due to missing observations on the right-hand side variables in the estimation of cognitive achievement production function.
10. A third possible source – namely, students (or their parents) choosing a school based on its resources – is probably of lesser importance in countries like Peru (especially in rural areas), as opposed to, say, the United States, where there are substantial differences in resources per student among schools.
11. Note that only a handful of students in private subsidized and private paying schools in the sample are indigenous.

References

Angrist, J., E. Bettinger, E. Bloom, E. King, and M. Kremer. 2002. Vouchers for private schooling in Colombia: Evidence from a randomized natural experiment. *American Economic Review* 92, no. 5: 1535–58.

Benavides, M. 1998. Para explicar las diferencias en el rendimiento en matemáticas de cuarto grado en el Perú urbano: análisis de resultados en base a un modelo básico. Documento de Trabajo 13, Análisis y resultados de las pruebas CRECER 1998, MECEP, Ministerio de Educación, Lima-Perú.

Benavides, M., M. Carnoy, S. Cueto, and A. Gove. 2007. *Evaluation of World Bank's assistancce to primary education in Peru.* Washington, DC: World Bank.

Blinder, A. 1973. Wage discrimination: Reduced form and structural estimates. *Journal of Human Resources* 8, no. 4: 436–55.

Carneiro, P., and J. Hecknam. 2003. Human capital theory. National Bureau of Economic Research (NBER) Working Paper 9495, February, Cambridge, MA.

Cueto, S., and J. Agüero. 2003. *Dime con quién andas y te diré cómo rindes: Peer Effects como determinantes del rendimiento escolar.* Lima-Peru: GRADE-CIES.

Cueto, S., C. Ramirez, and J. Leon. 2006. Opportunities to learn and achievement in mathematics in a sample of sixth-grade students in Lima, Peru. *Educational Studies in Mathematics* 62: 25–55.

Cueto, S., C. Ramírez, J. León, and G. Guerrero. 2004. Oportunidades de aprendizaje y rendimiento en matemática de los estudiantes de tercero y cuarto grados de primaria en Lima y Ayacucho. In *Educación, procesos pedagógicos y equidad: 4 informes de investigación,* ed. M. Benavides. Lima: GRADE.

Cueto, S., C. Ramírez, J. León, and S. Azañedo. 2006. Oportunidades de aprendizaje y rendimiento en comunicación integral de estudiantes en tercer y cuarto grado de primaria en Lima y Ayacucho. In *Los Desafíos de la Escolaridad en el Perú. Estudios sobre los procesos pedagógicos, los saberes previos y el rol de las familias,* ed. M. Benavides, 13–78. Lima: GRADE.

Currie, J., and D. Thomas. 1999. Early test scores, socioeconomic status, and future outcomes. National Bureau of Economic Research (NBER) Working Paper 6943, Cambridge, MA.

Ferguson, R.F. 1998. Teachers' perceptions and expectations and the Black-White test score gap. In *The black–white test score gap,* ed. C. Jencks and M. Phillips. Washington, DC: Brookings Institution Press.

Fertig, M. 2003. Who is to blame? The determinants of German students' achievement in the PISA 2000 study. Institute for the Study of Labour (IZA) Discussion Paper 739, Bonn, Germany.

Fertig, M., and C.M. Schmidt. 2002. The role of background factors for reading literacy: Straight national scores in the PISA 2000 study. Institute for the Study of Labour (IZA) Discussion Paper 545, Bonn, Germany.

Fryer, R., and S. Levitt. 2002. Understanding the black–white test-score gap in the first two years of school. National Bureau of Economic Research (NBER) Working Paper 8975, Cambridge, MA.

Glewwe, P. 2002. Schools and skills in developing countries: Education policies and socioeconomic outcomes. *Journal of Economic Literature* 40, no. 2: 436–82.

Greene, W.A. 2000. *Econometric analysis.* 4th ed. New Jersey: Prentice Hall.

Hanushek, E. 1986. The economics of schooling: Production and efficiency in public schools. *Journal of Economic Literature* 24, no. 3: 1141–77.

———. 2002. Publicly provided education. In *Handbook of public economics,* ed. A.J. Auerbach and M. Feldstein, vol. 4, 2045–2145. Amsterdam: Elsevier.

Hernandez-Zavala, M., H. Patrinos, C. Sakellariou, and J. Shapiro. 2006. Quality of schooling and quality of schools for indigenous students in Guatemala, Mexico and Peru. Policy Research Working Paper 3982, World Bank, Washington, DC.

McEwan, P.J. 2004. The indigenous test score gap in Bolivia and Chile. Working paper. January, Department of Economics, Wellesley College, Wellesley, MA.

———. 2006. Can schools reduce the test score disadvantage of ethnic minorities? Evidence from Chile. *Journal of Development Studies* forthcoming.

Oaxaca, R. 1973. Male–female wages differentials in urban labor markets. *International Economic Review* 14, no. 3: 693–709.

OECD. 2003. *Literacy skills for the world of tomorrow: Further results from PISA 2000.* Paris: UNESCO 7 OECD.

Reimers, F. 2000. *Unequal schools unequal chances. The challenges to equal opportunities in the Americas.* The David Rockefeller Center Series on Latin American Studies. Cambridge, MA: Harvard University.

Shapiro, J., and J. Moreno. 2004. Compensatory education for disadvantaged Mexican students: An impact evaluation using propensity score matching. World Bank Policy Research Working Paper No. 3334, Washington, DC.

Somers, M.A., P. McEwan, and J.D. Willms. 2004. How effective are private schools in Latin America? *Comparative Education Review* 48, no. 1: 48–69.

Todd, P.E., and I. Wolpin. 2003. On the specification and estimation of the production function for cognitive achievement. *Economic Journal* 113(February): F3–33.

Vegas, E. 2002. School choice, student performance and the teacher and school characteristics: The Chilean case. World Bank Policy Working Paper 2833, April, World Bank, Washington, DC.

Willms, J.D., and M.A. Somers. 2001. *Schooling outcomes in Latin America.* Santiago, Chile: UNESCO, LLECE.

World Bank. 1999. Peru education at a crossroads. Challenges and opportunities for the 21st century. Vol. I, Report No. 19066-PE, The World Bank, Washington, DC.

———. 2005. Mexico: Determinants of learning policy note. Report No. 31842-MX, Latin America and the Caribbean, Human Development, The World Bank, Washington, DC.