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Equity and Educational Performance

Improving education has become widely recommended as crucial for policies to promote growth and improve income distribution.[1] Most of the studies carried out in Latin America reveal problems with both quality and equity in education. This has led governments to implement a range of educational policies and to significantly increase the resources going to education. However, they have not always obtained the hoped-for results.

Interest in improving education has thus produced a far-reaching debate about the policies most suitable to improving its quality. At the same time, the implementation of standard educational performance tests in several Latin American countries has permitted the development of a growing body of literature that attempts to quantify the effects of specific policies on the quality of education. Nonetheless, these studies, along with those carried out in developed countries, often produce conflicting results.

In this paper, we review the main issues under discussion in the field of economics of education, with a special focus on Latin America. We seek to organize the debate about educational policies by showing how these policies respond to different models based on different assumptions and hypotheses about how the educational system functions. Methodological and informational problems make it difficult to test the validity of the results of different policies. This would explain the enormous number of studies in the field that conclude with conflicting policy prescriptions.

Mizala and Romaguera are both with the Universidad de Chile. We acknowledge the support of Fondecyt, Project 1000936. We wish to thank Omar Arias, Nora Lustig, and Miguel Urquiola for their helpful comments.

1. Panel studies for a group of countries support the existence of a relationship between output (GDP) and the quantity and quality of education (see, for example, Barro, 2001; Hanushek and Kimko, 2000). On the other hand, a number of studies point out that educational differences are the most important factor behind workers' income inequality in Latin America (IDB, 1998; Fiszbein and Psacharopoulos, 1995; Bouillon, Legovini, and Lustig, 2001; Legovini, Bouillon, and Lustig, 2001).

This paper is organized as follows. We begin by discussing the quality of education in Latin America. We then review the main educational policy issues and the different models under which we can group the educational policies currently being discussed. This same section examines the extent to which the different policy prescriptions are supported empirically. In an effort to explain the enormous range of conflicting results, the next section discusses the methodological difficulties facing empirical studies that attempt to determine the factors affecting educational outcome and evaluate the results of specific policies. We then use data from Chile to analyze the importance of the school in educational outcome and to explore the heterogeneous impacts of student and school characteristics on educational achievement. The final section summarizes our main conclusions.

The Quality of Education in Latin America

One of the first clues that Latin America's educational level was lagging behind involved the stagnation in the population's average years of schooling. Barro and Lee point out that while in the 1960s Latin American countries averaged more years of schooling than other developing countries, by 1990 the countries of eastern Asia and the Pacific were averaging almost one year more of schooling than Latin American countries.[2] The latest data from Barro and Lee confirm this trend (see table 1).[3]

The implementation of standardized student achievement tests at national and international levels has confirmed that tendency. Over the past twenty years, many Latin American countries have established national systems for measuring the quality of education.[4] UNESCO has applied comparative tests in several of the region's countries, and it is

2. Barro and Lee (1996).
3. Barro and Lee (2001).
4. Chile has applied achievement tests since 1982, starting with the PERT test and, since 1988, the SIMCE test (an educational quality measurement system). In 1990, Brazil gave its first periodic student achievement test, the Sistema Nacional de Avaliação da Educação Básica (SAEB). Colombia implemented its national system for evaluating the quality of education (SABER) in 1991. Argentina began testing education quality in 1993, using the national system for evaluating the quality of education. In 1996, Ecuador's national system for evaluating the quality of education (SIMLA) began giving the Aprendo tests, but there have been interruptions in their application. Bolivia has given achievement

TABLE 1. Educational Attainment of the Population Aged Twenty-Five and Over
Mean school years

Year	*Middle East/ North Africa*	*Latin America/ Caribbean*	*East Asia/ Pacific*	*Developed countries*
1960	1.14	3.13	2.26	6.97
1970	1.51	3.49	3.29	7.50
1980	2.47	4.07	4.39	8.67
1990	3.77	4.97	5.35	9.25
1995	4.46	5.38	6.03	9.57
2000	5.08	5.73	6.50	9.80

Source: Barro and Lee (2001).

precisely in the context of the UNESCO laboratory that some of the systems for measuring educational performance in Latin America have been developed. More recently, some Latin American countries have started participating, although shyly, in international tests for measuring educational results.

All these evaluations have led to a single result: the quality of education in Latin America is low and unequal. Latin American countries perform below average on international tests; a high percentage of students are low achievers on their national performance tests; there is a high variance in educational performance within each country, where the richest income decile of the population mainly attends private paid schools, with better results.[5]

International Test Results

Only two Latin American countries have participated in international tests: Colombia and Chile.[6] The results of these tests support the hypothesis of the poor quality of education in Latin America. In the third international mathematics and science study (TIMSS), applied between 1994 and 1995, Colombia placed second to last. Chile took part in the TIMSS in 1999, ranking thirty-fifth out of thirty-eight countries. The Chilean scores were

tests since 1997, using the system for measuring and evaluating the quality of education (SIMECAL).

5. A study by the Inter-American Development Bank, which examines household surveys in five Latin American countries, shows how public sector participation in education decreases according to the household's socioeconomic decile (IDB, 1998).

6. Mexico participated in the TIMSS test applied in 1994–95, but its results were not published.

substantially lower than the international average and lower than those obtained by other countries with a similar per capita income.

UNESCO's Experience

At the regional level, a comparative study of the quality of education in seven Latin American countries took place in 1992.[7] The results point to poor student achievement, major differences among students depending on their socioeconomic levels, and major differences among countries (see table 2). Students answered correctly only half of the questions in the language and math tests; just 8.5 percent of students performed better than 75 percent (the expected score); and more than 60 percent of students at the low socioeconomic level performed very poorly.[8]

Later, in 1997, the UNESCO Latin American laboratory for evaluating the quality of education gave language and mathematics tests to third and fourth grade students in thirteen Latin American countries.[9] About 55,000 students took the test (0.3 percent of total students in the corresponding countries and grades). In each country, sample sizes were similar, with twenty students at each level selected from around a hundred schools.

Study results revealed deficiencies in the quality of education in almost all participating countries and significant differences between Cuba and the rest of the region, with Cuba performing much better than other countries. Table A1 in the appendix shows the percentage of students who achieved the expected minimum performance for the different levels of the test; results were particularly poor for more complex mathematics. The results also show that private school students scored better than public school students, although differences were small.[10] This result may be influenced by the sample (small number of schools) and the Cuban results, where all schools are public.

7. See OREALC (1994). The countries are Argentina, Bolivia, Chile, Costa Rica, the Dominican Republic, Ecuador, and Venezuela.

8. The econometric analysis also shows a low significance of teacher variables for students' achievement.

9. The countries that participated in the study are Argentina, Bolivia, Brazil, Chile, Colombia, Costa Rica, Cuba, the Dominican Republic, Honduras, Mexico, Paraguay, Peru, and Venezuela.

10. Classification of public and private schools refers to the type of management, regardless of the source of financing. In the case of Chile, subsidized private schools are thus classified as private schools.

TABLE 2. Average Performance According to Socioeconomic Level for Selected Latin American Countries[a]

	Socioeconomic level			
Indicator	*Low*	*Middle*	*High*	*Total*
Test results (percentage achievement)				
Language	47.9	58.4	71.9	54.7
Mathematics	43.8	49.8	59.0	47.9
Average	46.0	54.1	65.5	51.4
Distribution of test scores by performance quartile				
0–25	8.9	3.1	1.4	4.1
26–50	60.6	40.0	15.3	47.2
51–75	26.4	48.0	55.1	40.2
76–100	2.2	8.9	28.1	8.5
Total	98.1	100.0	99.9	100.0

Source: OREALC (1994, tables 20, 21, 31, and 32).

a. The expected test score was 75 points. The countries are Argentina, Bolivia, Chile, Costa Rica, the Dominican Republic, Ecuador, and Venezuela.

Studies of Latin American Countries

At the country level, there is ample evidence that the quality of education is deficient and is not progressing as required. The analysis is limited, however, because not all countries test educational performance, studies are not applied on a regular basis, and even those countries conducting them regularly do not test the same students at different points in time.[11]

Llach, Montoya, and Roldán analyze the Argentine SINEC tests.[12] The results for the 1993–98 period fluctuate around an average of 55 points, a deficient score compared with the expected test results of 100 points for complying with the minimum curriculum requirements. Their analysis indicates that school variables (such as infrastructure, equipment, and teacher characteristics) are less important than family variables for explaining student results.[13] They also found that private schools perform better than public schools, especially at the elementary school level.

11. We only review evidence regarding student achievement test results. Other studies focus on different indicators of education quality. For example, Barros (2000) uses the returns on education in Brazil to show the poor quality of education in that country.

12. Llach, Montoya, and Roldán (1999).

13. However, if school fixed effects are added to the model, the explained variance increases by 40 to 50 percent. According to the authors, this result is explained by the fact that school-related factors are important in explaining student achievement, but these school factors are different from those included in the regression.

Bolivia began implementing school performance tests (SIMECAL) in 1997. The results of the tests show the need to improve teaching levels, particularly as one goes up in the school system. Table A2 in the appendix shows the high percentage of students with an at-risk performance (50 percent), particularly in the sixth grade tests. Private schools score higher than public ones, even when the analysis takes into account family and student characteristics.[14] Mizala, Romaguera, and Reinaga find that home-related variables have a significant effect on children's educational achievement.[15] In Bolivia's case, parental education is not the only important factor in students' results: other statistically significant variables include the indigenous origin of many students, which reflects the specific context of a developing country, and school-related variables such as teachers' experience, infrastructure, daily homework assignments, and school size. Urquiola, who uses an empirical strategy to identify the effects of class size, finds negative and significant class size effects on test scores in Bolivia.[16]

Brazil has applied the Sistema Nacional de Avaliação da Educação Básica (SAEB) since 1990. For each evaluation, 3,000 schools are chosen randomly and evaluated in mathematics, science, and Portuguese. Paes de Barros and Silva Pinto de Mendonca studied school management's impact on student achievement, as measured by the SAEB test and other indicators.[17] The results show no improvement in test results from 1990 to 1993, as well as large regional differences in the quality of education.

Piñeros and Rodriguez analyzed Colombia's results using the ICFES test, which provides information on students finishing the eleventh grade in 1997.[18] A comparison of test results for private and public schools indicates that the former initially performed better. Table A3 in the appendix presents the results of school mean achievement for each sector, with private schools posting slightly higher scores than public schools. When

14. The raw differential was 24.95 points versus 17.03 points, respectively, falling to 4.57 points in favor of private schools when student and family characteristics were considered.

15. Mizala, Romaguera, and Reinaga (1999).

16. Urquiola (2000).

17. Paes de Barros and Silva Pinto de Mendonca (1997).

18. Piñeros and Rodriguez (1998). Changes in these tests from 1985 to 1995 point to a significant increase in the participation of low-performance schools, together with a reduced participation from average- and high-performance schools. These data have been cited as a sign of the ongoing decline in the quality of education in Colombia.

families' socioeconomic level is taken into account, however, public schools score slightly higher than private schools. Regarding educational resources, school facilities (namely, infrastructure such as sports facilities, science and language laboratories, and full-day school sessions) positively influence students' academic performance. Other variables such as textbooks and workshop availability had little or no effect on school performance.

Chile was the first Latin American country to implement school performance tests. However, the results of the different tests cannot easily be used to assess the evolution of the quality of education.[19] Only the most recent results from the SIMCE test for fourth and eighth grade students can be compared with the same tests applied immediately before, using an equating technique. The results show no changes in students' performance between 1996 and 1999 for fourth grade and between 1997 and 2000 for eighth grade (see table A4).

Educational Study and Policy Review

The data and studies reviewed in the previous section reveal that Latin America faces a serious problem with the quality of the education provided to children and young people. Growing awareness of this situation has led several Latin American countries to apply different educational policies in recent decades. These policies address a range of issues associated with improving the quality of education.

This section first discusses the main policy issues in education, suggesting that there are basically three broad visions of the educational system, each of which responds to different assumptions on how the system functions. We then review empirical evidence related to the factors influencing educational achievement. Finally, we review the empirical evidence with regard to the role that could be played by increased competition in education, particularly the possibility that parents can choose whether to send their children to public or private schools.

19. Most difficulties with this comparison arise from a methodology change introduced in 1998. The SIMCE test applied since 1998 differs from previous tests in that it uses an unlimited scale to measure students' abilities: the previous test used a score ranging from 0 to 100, whereas the new test uses a mean of 250 points and a standard deviation of 50 points.

Educational Policy Issues and Models

The educational policies applied in Latin American countries in recent years have, to a greater or lesser degree, addressed a number of issues. These policy issues include decentralization; the introduction of standardized achievement tests and better student achievement indicators; the improvement of educational inputs; teacher and school incentives; and increased private participation in providing educational services through private school choice.[20] Below, we summarize some basic points of debate on each of these issues.

Discussion on decentralization centers on whether school management should be conducted at a central level (ministerial or municipal), or whether schools should be given greater independence in decisionmaking. Several related questions have also been raised. Should spending decisions be made at the central or school level? How should the school budget be used? Should the school receive inputs or funds for buying inputs? Who should select the school principals?

The debate on the importance of educational achievement tests as indicators of school quality (output) and the relevance of publishing test results has raised two main questions. Should the results of achievement tests be used basically as an input to improve educational policies? Or should the information be published (that is, made available to parents and the community at large)?

With regard to educational inputs, the basic issues are how resources should be allocated and who should make the decision. Alternatives to be considered include increasing teachers' salaries, equipping libraries, decreasing class size, improving teaching methods, implementing curriculum changes, and improving infrastructure. This is probably one of the most widely discussed topics in the literature. Nonetheless, as we discuss in the next section, the results of numerous studies are inconclusive owing to the methodological problems involved in empirically analyzing the relation between educational results and input factors.

The root of the debate on incentives lies in whether to provide fixed resources per school (or according to school size) or to use resources as a

20. Latin America has always seen private involvement in education, but it represents a relatively low percentage of total registration because it involves fees. Only parents who are willing and able to pay send their children to private schools. The idea of school choice is that parents can choose between sending their children to public or private schools without having to pay extra.

performance incentive. Several questions are being debated. Should school resources be a function of school results as measured by student performance tests? Should incentives be a management tool within the educational system? Should teachers' salaries include some variation according to student results?

Finally, efforts to increase access to private schools have given rise to the debate on whether parents should be allowed to choose among public schools or, more important, between public and private schools. A related issue is whether private providers should receive public funds through the introduction of school vouchers. This debate has probably been more important in the United States than in Latin America. Nonetheless, the broadest applications of this approach are to be found in Latin America: Chile has instituted a nationwide voucher system that allows parents to choose their children's schools, and Colombia has partially implemented a plan to develop a private school sector using public funds.[21]

Underlying this general debate on policy options are at least three models for how educational systems function and how they should function. First, the traditional paradigm assumes a completely centralized educational system headed by an education ministry, which is responsible for both setting policies and providing teaching. In this system, most of the population gets its education in the public schools, teachers bargain collectively through their union, and teachers' wages are strongly linked to teaching experience and working conditions. This view is based on the assumption that it is possible to identify a set of characteristics that make a school effective and, consequently, that a central unit (such as a ministry or an international agency) can set up patterns for schools to follow in order to improve the quality of education. The underlying hypothesis is that input factors and educational processes can influence educational results and that those with the most significant effect on educational achievement can be singled out and promoted. We call this paradigm the centralized-effective model.

The second paradigm holds that it is difficult to know what makes one school better than another; that is, why some learning processes and input factors work better in some places than in others. It is therefore not possible to centrally design specific policies to improve the educational

21. On Chile, see Mizala and Romaguera (2000); Hsieh and Urquiola (2001). On Colombia, see Angrist and others (2001).

results. Education units themselves must implement actions and policies, while authorities should provide the right incentives.[22] We call this view the decentralized-incentive model. It can be understood as the simulation of incentives that in other activities are provided by competition in the market.

The third paradigm is based on the assumption that even if it were possible to identify the factors that influence the learning process, doing so would not make a difference. Instead, the right policy is to generate an educational market in which educational units compete for students in an independent and decentralized way, thus promoting the quality of education. To generate this market, students should no longer be required to attend public schools but could, for instance, attend private schools using a government-supplied voucher or tuition subsidies to offset the costs. Underlying this view is the belief that private schools respond to competition in ways public schools do not, and they are consequently superior to public schools in providing educational services. We call this view the decentralized-market model.

All three of these models require some form of pressure (either coercion or incentives) to ensure that the educational system will tend to improve its quality. In the centralized-effective model, a strong authority pushes schools to adopt the right policies and achieve the right quality standards. Here the assumption is that central authorities know what the schools must do, and their decisions will be suitably enforced using standards, requirements, penalties, and rewards. In the decentralized-incentive system, the authorities' role is to indicate the right incentive mechanism that will motivate schools to adopt the right policies. The assumption is that enforcement through incentives is more suitable than other policies. Finally, in the decentralized-market model, a market—operating competitively and with full information—applies the necessary pressure by allocating incentives, rewards, and penalties. As in any other market, however, the market cannot guarantee educational quality if competition and the right information are not guaranteed.[23]

22. See Hanushek (1994).

23. Another problem that may arise in an educational market, which is discussed at length in the U.S. literature, is the potential discrimination that would be produced in an educational system operating on the basis of choice and vouchers. See, for example, Hening (1994).

The next two sections review empirical evidence regarding two issues central to the above models: the impact of inputs on educational results and the comparative performance of private and public schools.

A Review of the Factors That Influence Educational Results

Intense debate surrounds the issue of which factors influence educational results. As discussed below, the assumptions and the methodology used seem to influence the results.

Initial studies, which became popular after the pioneering work by Coleman and others, involved estimations of an educational production function that linked output (achievement results) with educational inputs (teacher characteristics, class size, infrastructure, and so forth) and family and student characteristics.[24] Good literature reviews include Hanushek for developed countries and Fuller, Fuller and Clarke, and Hanushek for developing countries.[25]

For developed countries, Hanushek reviews first thirty-eight studies and later 377 studies, applied mostly to the United States.[26] His two studies examine the impact of input factors such as teacher-student ratio, teacher training, teacher experience, teacher salaries, teacher testing, and infrastructure. He points out that input factors do not have a significant effect on educational achievement: generally the coefficients are either low or not statistically significant.

Greenwald, Hedges, and Laine and Kremer criticize Hanushek's results.[27] Their studies are based on a meta-analysis, which is a review of previous studies, eliminating those that have methodological deficiencies and combining the statistical significance and magnitude measurements of the estimated effects. These authors are more optimistic about the effect of increasing educational input factors on student performance, and they insist that the hypothesis that input factors positively affect student performance cannot be rejected.[28] Greenwald, Hedges, and Laine, in particular, find that per-pupil expenditure, smaller schools, smaller classes, and

24. Coleman and others (1966).

25. Hanushek (1989, 1997); Fuller (1990); Fuller and Clarke (1994); Hanushek (1995).

26. Hanushek (1989, 1997).

27. Greenwald, Hedges, and Laine (1996); Kremer (1995).

28. In response to Greenwald, Hedges, and Laine (1996), Hanushek (1996) strongly criticizes the methodology of studies based on meta-analysis.

the quality of teachers (as measured through teacher ability, education, and experience) are positively related to student achievement.[29]

In the case of developing countries, Fuller and later Fuller and Clarke conclude that one cannot assume that family characteristics are the only thing that matters or that the school has little to do with student achievement.[30] On the contrary, empirical evidence seems to show that some input factors are significant, including instruction time, availability of textbooks, and certain teaching methods.

Hanushek reviews ninety-six studies that estimate the effects of educational input factors on student performance in developing countries.[31] The results do not support the idea that smaller classes, more experienced teachers, and better salaries have a positive and significant effect on student performance. The most important input factors in terms of student performance are school infrastructure and resources, such as textbook availability, some teaching methods, and instruction time.[32]

Velez, Schiefelbein, and Valenzuela review the studies for Latin America. They confirm that in the case of developing countries, educational input factors (particularly reading materials, infrastructure, and teacher experience) make a positive contribution to student performance.[33]

Further estimations of the effects of various input factors on educational achievement followed the reviews cited here.[34] Much of this recent literature discusses the methodological problems affecting empirical studies and the difficulties involved in obtaining robust estimations on inputs' effect on educational achievement.

Some studies also analyze the link between the quality of education and labor market performance. In particular, Card and Krueger use a Mincer functions framework to examine the impact of school inputs on future earnings.[35] This study concludes that input-based educational quality proxies positively influence earnings and the return to education. Heckman, Layne-Farrar, and Todd show, however, that the effect of school resources

29. Greenwald, Hedges, and Laine (1996).

30. Fuller (1990); Fuller and Clarke (1994).

31. Hanushek (1995).

32. In cross-country studies, although the importance of family variables is confirmed, several input factors positively influence the quality of education. See Lee and Barro (1997).

33. Velez, Schiefelbein, and Valenzuela (1993).

34. See Pritchett and Filmer (1999), Betts (1999), and the papers cited in the next section.

35. Card and Krueger (1992).

breaks down when some of the identifying assumptions (namely, linear education) are relaxed.[36] Moreover, omitted relevant variables bias the estimated results. Card and Krueger later present evidence that school resources matter in an analysis of the vast differences in resources for blacks and whites attending schools in the segregated states of North and South Carolina.[37] The available evidence on school resources and earnings thus remains ambiguous, so we cannot conclude beyond a reasonable doubt that school resources matter.

In summary, considerable controversy surrounds the effect of increased school input factors on educational performance. While positive effects predominate over negative effects, there are many situations in which the results are not conclusive. In general, results tend to suggest that adding more inputs does not guarantee that students will achieve more. The effects also seem to vary depending on specific conditions at schools and other contextual variables generally omitted from this type of analysis.[38]

A Comparison of Private and Public Schools' Performance

An important part of the debate on the advantages and disadvantages of school choice centers on the relative academic performance of public and private schools. In particular, it is claimed that if choice were available through, for example, a voucher system, students from public schools would transfer to private schools, which provide a better quality of education; this would lead to an improvement in average quality. Furthermore, the existence of competition per se would imply a competitive pressure that would improve all schools, both public and private.

The school choice debate addresses different issues. One involves the question of whether private schools' better results reflect not the quality of the schools per se, but the fact that they serve a population with a higher socioeconomic level, that is, a population that is easier to teach.

A second issue deals with the so-called peer effect, whose impact on educational achievement is unclear. One hypothesis is that low achievers get better results if they are in an environment in which their peers have more knowledge; a massive transfer of students from public to private

36. Heckman, Layne-Farrar, and Todd (1996).

37. Card and Krueger (1996).

38. For example, Pritchett and Filmer (1999) point out that "since the learning gain from additional inputs is not constant, the contribution of an input depends on the rate of input utilization at which it is assessed."

schools would cause the peer effect to be lost for those students left behind, and the average effect on the quality of education would be uncertain. An opposite hypothesis is that teaching is easier if the student population is more homogeneous, such that low achievers benefit from being in a group with similar peers.

A third issue related to school choice has to do with the objectives and values of the educational system. Some claim that the educational system must act as a melting pot. This role would be threatened in a school choice system: the possibility of choice would lead to segmentation of the system, increasing the differences in the quality of education within countries.

Numerous empirical studies examine the relative performance of private and public schools in the United States, starting with Coleman, Hoffer, and Kilgore.[39] In general, the early studies use cross-sectional information only, and they are criticized for failing to include an initial achievement indicator among the explanatory variables in the educational production function.[40] A second group of U.S. studies, which have tried to control for these omitted variables more effectively, reports mixed evidence on each type of school's relative performance. For example, Hoffer, Greely, and Coleman and Chubb and Moe find evidence favoring private schools, whereas Willms; Alexander and Pallas; and Sander find no difference between school types.[41] Hoxby finds evidence that public schools can and do react to competition by improving students' test scores, educational attainment, and wages.[42] A more recent study by Figlio and Stone reviews the evidence and concludes that the mixed results may stem from differences in dependent variables, particular samples, or the instruments used by the different authors to identify sector selection.[43]

The studies for Latin America presented in the previous section do not support unequivocal conclusions. Neither UNESCO nor Piñeros and Rodríguez find achievement differences between public and private schools.[44] In the case of Bolivia, however, the private sector achieved higher scores, and the results were robust under different sets of controls.[45]

39. Coleman, Hoffer, and Kilgore (1981).

40. Coleman, Hoffer, and Kilgore (1981); Cain and Goldberger (1983); Noell (1982).

41. Hoffer, Greely, and Coleman (1985); Chubb and Moe (1990); Willms (1985); Alexander and Pallas (1985); Sander (1996).

42. Hoxby (1994, 1996).

43. Figlio and Stone (1999).

44. UNESCO (2000); Piñeros and Rodríguez (1998).

45. Mizala, Romaguera, and Reinaga (1999).

In Chile, raw test results indicate that private schools have a clear advantage over municipal (public) schools. However, there is much controversy about the respective results when students with similar socioeconomic characteristics are compared. There is also considerable debate as to whether students from different socioeconomic levels show different results in public and private schools, that is, whether some types of schools enjoy an advantage over others when it comes to teaching specific kinds of students, such as low achievers or low-income students.

The empirical studies reviewed here, with regard to both the effects of inputs on educational performance and the relative performance of public versus private schools, reveal that we do not have robust results on these issues.

Methodological Aspects

This section looks more closely at the methodological difficulties affecting studies in the economics of education, which explain the range of results reported in the previous section. Methodological problems also make it difficult to test the hypotheses on which the different educational policies are based or to evaluate their results. We sort these difficulties into three groups: omitted variables and self-selection, general equilibrium effects and inefficiencies, and heterogeneous effects.

Omitted Variables and Self-Selection

The conceptual model generally used to analyze the educational product presents the student's achievement at a point in time as a function of cumulative inputs from family, peers, school, and teachers. These input variables interact with each other and the student's innate skills or learning potential.[46] The educational production function can be written as[47]

$$(1) \qquad A_{it} = \alpha_t S_{it} + \beta_t F_{it} + \sum_{i=1}^{T-1} \alpha_t S_{it} + \sum_{i=1}^{T-1} \beta_t F_{it} + \sum_{i=1}^{T} \varepsilon_{it},$$

where A_{it} is the achievement of student i in school year t, parameters α_t and β_t are the marginal effects on student achievement of different school

46. Some studies incorporate the interactions between the variables as an additional explanatory variable within the production function.

47. Hanushek and Taylor (1990).

inputs in various past school years and in the current school year, and ε_{it} represents the unmeasured factors that contribute to achievement. These unmeasured factors have two components: a systematic component (δ_i), which varies from individual to individual and represents differences in intelligence, motivation, unmeasured family inputs, and so forth, and a random component (θ_{it}), which varies over individuals and time.

$$\varepsilon_{it} = \delta_i + \theta_{it}. \tag{2}$$

One of the problems of empirical studies is that only information on the current period is available, and therefore the following model is estimated:

$$A_i = a_T S_i + b_T F_i + e_i. \tag{3}$$

Since we are not estimating the true model, the error term is

$$e_i = f(S_1, \ldots, S_{T-1}, F_1, \ldots, F_{T-1}, \theta_i, \ldots, \theta_T, \delta). \tag{4}$$

Insofar as there is a correlation between the error defined by equation 4 and the contemporary variables that measure family and school factors, the estimation of equation 3 will lead to biased estimations of the marginal effect of school resources on achievement.

One way of dealing with this problem is to estimate a value-added model. This specification, which is shown in equation 5, assumes that all past educational input factors are captured in the score obtained by the student in the test of a previous period, thus removing any unmeasurable school or family factors that do not vary over time and minimizing any specific individual differences.[48]

$$A_{iT} = \alpha_T S_{iT} + \beta_T F_{iT} + \gamma A_{iT-1} + \mu_i. \tag{5}$$

An additional problem found in econometric estimations seeking to evaluate the impact of different input factors on educational achievement is the endogeneity of some inputs. These variables are correlated with unobservable factors that also influence educational achievement and can bias estimations of the marginal effects of the various educational inputs.

48. This type of model has been estimated by, for example, Jiménez, Lockheed, and Wattanawaha (1988); Hanushek and Taylor (1990); Ehrenberg and Brewer (1994); Goldhaber (1996); Meyer (1997).

The value-added model reduces this problem to the degree that it allows us to control for individual fixed effects. Nonetheless, part of the problem remains to the degree that some nonobservable factors are not fixed over time.[49]

One example of this problem is the estimation of the impact of class size on educational achievement. Education researchers are particularly interested in class size, because it is one of the few variables that administrators can change from term to term. The literature includes highly different results for this effect. In Hanushek's more recent study, 15 percent of the papers find that class size has a positive and significant effect on educational achievement, 13 percent find a negative and significant impact, and 72 percent report that class size does not significantly affect educational achievement.[50] Among the studies for developing countries, some find that class size has a positive and significant effect on educational achievement, others find that it has a significant negative effect, and yet others conclude that there is no significant effect (see table 3).

These conflicting results can be explained by the existence of biases in the ordinary least squares (OLS) estimation, owing to a correlation between the class size variable and some other unobserved variable.[51] To reach a conclusion on the impact of class size or other input factors that may be correlated with unobserved variables, we need a strategy that can identify the exogenous variation of the input. Angrist and Lavy use Maimonides' rule to construct instrumental variable estimates for the effect of class size on scholastic achievement in Israel.[52] They conclude that reductions in class size lead to a significant increase in standardized achievement tests for fifth graders and a smaller increase for fourth graders. Levin uses a similar approach to construct an instrumental variable based on a rule applied by the Dutch ministry of education, linking

49. For instance, the nonobservable variable "educational support at home" may vary according to the age of the children.

50. Hanushek (1997).

51. An overestimation of the influence that class size has on educational achievement may occur when parents interested in their children's success in school enroll them in schools with few students per class. This happens when the estimation does not control for the "educational support at home" variable, which also has an impact on educational achievement. In contrast, an underestimation of the class size effect can be obtained if the parents of children with learning problems enroll them in schools with a smaller number of students per class so that they can get more personalized attention. In this case, there is a correlation between the smaller class size and student achievements.

52. Angrist and Lavy (1999).

TABLE 3. Estimated Effect of Class Size on Student Performance in Developing Countries

Source	Number of studies	Statistically significant: Positive	Statistically significant: Negative	Statistically insignificant
Velez, Schiefelbein, and Valenzuela (1993)	21	2	9	10
Fuller and Clarke (1994)	48	—	11	37
Hanushek (1995)	30	8	8	14
Llach, Montoya, and Roldán (1999)	29	3	10	16

total school enrollment to the number of teachers.[53] He concludes, using a quantile regression approach, that the class size effect is rarely significant in explaining students' achievement. The only study using this methodology for a less developed country is Urquiola's paper on Bolivia, which applies two research designs.[54] First, it uses teacher allocation patterns in rural Bolivia as an instrumental variable, and second, it focuses on remote schools having a single class per grade and a monopoly in their area of influence, thereby ensuring that enrollment and socioeconomic status are not related. As we pointed out above, Urquiola finds that class size significantly and negatively affects test scores. We thus get different results even when we use research specifically designed to identify exogenous variation in input. One possible explanation for these findings is that the same input can have different impacts in different educational and cultural contexts.

Another methodological issue related to estimating educational production functions is the comparison of the performance of different kinds of schools, particularly public versus private schools. This involves comparing the results that the same student would obtain in different types of schools. To determine causality, assignment to the two kinds of schools must be random. The treatment effect on the treated is given by the difference in the average outcomes between public and private schools, and we do not observe the outcome of private (public) students if they go to public (private) schools. Student self-selection or sorting may result from two main processes. First, insofar as the parents can choose the school to which they send their children, family and school characteristics will be systematically correlated. Parents with a higher socioeconomic level will

53. Levin (2001).
54. Urquiola (2000).

tend to invest more in choosing the school and will have more information about it. Second, schools may choose their students, either through entrance examinations or interviews with the parents. Both behaviors generate a nonrandom assignment.[55]

OLS achievement models are thus unsuitable because we cannot determine whether differences between public and private school students' performance are due to genuine differences in achievement attributable to school type or to underlying differences in motivation, home environment, or peer group effect. This implies that the issue of selection is central to the debate on school quality.

Several studies attempt to address selection using a two-stage procedure.[56] The school sector selection is modeled in the first stage; an inverse mill's ratio is calculated from this equation and included as an additional regressor in the second-stage estimation of student achievement. This procedure's empirical effectiveness rests on the identification of suitable instrumental variables included in the first stage but excluded from the second stage, as well as on the appropriateness of the statistical assumptions of normality and homoskedasticity.[57]

In response to criticisms of the simple two-step correction procedure, due to its reliance on distributional assumptions and the lack of robustness when dealing with departures from normality, some researchers have recently tried to adopt a more robust approach by identifying and estimating various treatment parameters without imposing strong distributional assumptions.[58]

Other studies take advantage of small-scale experiments with school choice in the United States to obtain experimental or quasi-experimental data examining whether children benefit from attending private schools.[59]

55. Another source of bias arises from the fact that estimations only consider those students who passed the grade and not those who had to repeat it. The age for starting school may also be a source of bias in rural areas in poor countries (Glewwe and Jacoby, 1993). According to Hanushek (1986), the selection bias problem associated with failing is reduced in the value-added model.

56. Heckman (1979); Sander (1996); Glewwe and Jacoby (1993); Jiménez, Lockheed, and Wattanawaha (1988).

57. Figlio and Stone (1999) summarize the instruments normally used in studies of private versus public school performance.

58. Heckman, Tobias, and Vytlacil (2000). These methodologies require suitable instruments.

59. See Rouse (1998) and Goldhaber and others (1999) for analysis of the Milwaukee experiment.

General Equilibrium Effects and Inefficiencies

The experimental focus is suitable for analyzing small-scale school choice experiments, in which a randomly chosen student is transferred from a public to a private school. It is not useful, however, for determining the impact of a comprehensive school choice system such as Chile's. In this case, analysis cannot be limited to a partial equilibrium, because if the choice results in a greater segregation among schools, then that must be taken into account when evaluating the effect of school choice on educational results. In particular, three effects must be distinguished: the production effect generated by greater competition, which would cause public schools to improve; the student composition or sorting effect, through which public schools lose their higher-income students; and the peer effect, which causes student performance in public schools to change in response to the drop in "quality" of their classmates.[60] If we want to estimate the impact of competition on the quality of public schools, we need to control for sorting and peer group effects.

Another relevant methodological difficulty is the presence of technical inefficiencies in the educational productive process.[61] Because some schools are not using their resources to their full potential, we are empirically estimating not the production frontier itself, but rather a point within the frontier. This problem can be solved by estimating an efficient production frontier. One possibility is to use a likelihood function that allows the estimation of a coefficient λ, which, if statistically significant, proves the existence of inefficiencies. An alternative methodological approach is to use data envelopment analysis (DEA), which allows us to identify schools' efficient production frontier nonparametrically.[62]

Heterogeneous Impacts on Student Performance

The possibility that the impact of input factors on student performance may vary for different kinds of schools (for example, public and private) or for different student groups (such as low and high achievers or low- and high-income students) is another methodological element that must be taken into account. This issue has been tackled by including interaction

60. Hsieh and Urquiola (2001).

61. See Deller and Rudnicki (1993); Bonesronning and Rattso (1994); Ruggiero (1996).

62. Using a stochastic production frontier and data envelopment analysis (DEA), Mizala, Romaguera, and Farren (2002) analyze the technical efficiency of schools in Chile.

terms among the explanatory variables of an educational production function. This approach allows different returns to school inputs for students of different socioeconomic levels, increases flexibility, and allows for heterogeneous treatment effects.[63]

The heterogeneous effects of school inputs on student performance have also been addressed using quantile regression analysis, which allows one to determine how school resources affect achievement differently at different points in conditional test score distribution. Eide and Showalter find that some school resources appear to have no effect on average test score gains but strong effects at other points of the distribution of test score gains.[64] This is the case of per pupil expenditures, which increase math scores for low achievers, and a longer school year, which improves math scores for high achievers. Levin uses quantile regression analysis to investigate the impact of class size and peer effects on student achievement in the Dutch educational system.[65] He finds little support for the conventional wisdom that reducing class size improves learning, but concludes that there is a large positive effect of similar peers on learning for those in the lower portion of achievement distribution.

Another methodological approach that makes it possible to detect heterogeneity is hierarchical linear modeling, although this is only one of the issues that this methodology addresses. When working with multilevel data, the different levels should be modeled separately. In the case of studies that explore the impact of school resources on students' educational achievement, this means differentiating between students and schools, to account for the fact that the level-1 units (students) are not independent, but are nested within the level-2 units (schools). Hierarchical linear models (HLMs), deal with three typical problems encountered when working with multilevel data: heterogeneity of regression, aggregation bias, and misestimated standard errors.[66] Heterogeneity of regression occurs when the relationships between individual characteristics and outcomes vary across organizations (schools). HLMs estimate a separate set of regression coefficients for each organizational unit (a school) and then model variation among the organizations in their set of coefficients as multivariate outcomes to be explained by organizational factors (school resources).

63. Tokman (2001).
64. Eide and Showalter (1998).
65. Levin (2001). He controls for the potential endogeneity in the class size variable.
66. Bryk and Raudenbush (1992).

Aggregation bias can occur when a variable takes on different meanings and therefore may have different effects at different organizational levels.[67] HLMs address aggregation bias by decomposing any observed relationship between variables, such as achievement and social class, into separate level-1 and level-2 components. Misestimated standard errors occur with multilevel data when the dependence among individual responses within the same organization is not taken into account. HLMs solve this problem by incorporating into the statistical model a unique random effect for each organizational unit.

Given the above elements, HLMs are more efficient than OLS for estimating fixed effects, primarily when each school has a different number of students.

In summary, researchers must address several important methodological issues if they are to obtain robust results in empirical work. Many of the available empirical results depend on the assumptions and methodological approaches that the studies employ. More research is thus needed in Latin America to improve general knowledge about the effects of different educational policies on student performance.

Heterogeneous Effects on Student Achievement: An Illustration with Data from Chile

This section uses data for Chile to explore how important schools are to educational outcomes and the existence of heterogeneous impacts of student and school characteristics on educational performance. We briefly describe the main characteristics of the Chilean educational system and then present the empirical results. These include estimates of educational production functions that include interaction variables to capture the differential impact of socioeconomic level on educational achievement at different kinds of schools; estimations of quantile regressions that allow us to determine whether different variables affect low and high achievers differently; and estimations of a hierarchical linear model.

67. For example, the average social class at a school may affect student achievement above and beyond the effect of the individual child's social class. At the student level, social class provides a measure of the intellectual and tangible resources in a child's home environment.

Beginning in the early 1980s, far-reaching reforms were implemented in the Chilean educational system, involving the decentralization of the public school system and the handing over of school management to local government authorities. The reforms also instituted public financing of private schools through a per-student subsidy mechanism. The per-student subsidy, which is equal for public and private schools, is intended to cover running costs and, at the same time, generate competition among schools to attract and retain students, thereby promoting more efficient, better quality educational services.[68]

One outcome of this policy was the creation of a system featuring three types of schools: fee-paying private schools that operate on the basis of fees paid by parents and guardians, which represent 9.5 percent of the enrollment of children and young people; subsidized private schools financed by the per-student subsidy provided by the state, but owned and operated by the private sector, which account for 33.4 percent of enrollment; and municipal schools financed through the per-student subsidy and run by municipalities, which make up 55.6 percent of the enrollment.[69]

A number of studies interpret the results obtained by schools in Chile. In general, they all conclude that families' socioeconomic characteristics are statistically significant when it comes to explaining the performance of students in the different types of schools. The conclusions differ, however, when the performance of public and private schools is compared.[70]

The debate about the effectiveness of private and public schools in Chile faces the same methodological issues discussed in the last sec-

68. This is a voucher-type system in which funds are allocated to the school according to students' and parents' choices. The reform also introduced the SIMCE test; however, test results were only made public in 1995.

69. Fee-paying private schools, which have always existed, do not compete with public schools, since they require a fee that is, on average, about five times the per-student subsidy. Subsidized private schools may also be financed by contributions from parents (shared financing), a practice instituted in the mid-1990s. The three types of schools together account for 98.5 percent of all enrollment. The remaining 1.5 percent of schoolchildren attend schools run by educational corporations linked to business organizations.

70. See Rodríguez (1988); Aedo and Larrañaga (1994); Aedo (1997); McEwan and Carnoy (2000); Mizala and Romaguera (2000, 2001); Bravo, Contreras, and Sanhueza (1999); Tokman (2001); Sapelli and Vial (2001); Gallego (2002). These studies differ in the tests used (year and course), the size of the school samples, and the methodology used to evaluate the performance of different types of schools.

tion.[71] Moreover, the comparison between public and private education in Chile is further complicated by the fact that the regulations for admitting and expelling students are different in public and private schools. While municipal schools must admit all their applicants (as long as there are vacancies) and have serious restrictions for expelling students, private schools are free to establish their own admission and expulsion policies.

In what follows, we analyze the Chilean data for tenth grade using the 1998 SIMCE test. This is the earliest SIMCE test that allows work with student-level data, since along with the general test it collected socioeconomic data on the families of students taking the test.

The raw test scores give private fee-paying schools an advantage over subsidized private and municipal schools. When an educational production function similar to those of equation 3 is estimated, the differentials drop markedly, but they are still statistically significant. A summary of the results is given in table 4, and the complete regression is presented in table A5 in the appendix.

We estimate a cross-sectional equation because as with most Latin American countries, Chile does not give tests to the same students at different times, since policymakers are not aware of the importance of panel data. Therefore, it is not possible to estimate a value-added model such as the one represented by equation 5 in the last section.

As pointed out earlier, a set of problems affects the econometric estimations of educational production functions. One is the structure of the data from students and schools. The assumption behind OLS estimations is that each observation is independent. Student test results, however, present a clustered data structure: the data are not independent within groups, but independent between groups. That is, the observations of students within a school (or a class) correlate.

The methodological alternatives for approaching this problem include using a robust variance estimator that recognizes the cluster structure of the data, such as White-corrected standard errors in the presence of heteroskedasticity. This affects the estimated standard errors and variance-covariance matrix of the estimators, but not the estimated coefficients. When this correction is implemented in model 3 of table A5 in the appen-

71. Hsieh and Urquiola (2001) point out that the Chilean school choice system leads to sorting, as middle-class students transfer from public to voucher-funded private schools; therefore, sorting cannot be ignored when measuring the effect of choice on school performance.

TABLE 4. Test Scores of Public and Private Schools in Chile: SIMCE Language Test, Tenth Grade, 1998[a]

	Type of school		
Indicator	*Private fee-paying*	*Private subsidized*	*Municipal*
SIMCE average score	298.34	256.70	238.87
Differentials with respect to the municipal sector			
Without controls	59.47*	17.83*	—
With controls	17.44*	13.30*	—

* Statistically significant at 1 percent.
a. Full results are given in table A5 (models 1 and 2).

dix, some variables associated with input factors lose their statistical significance.

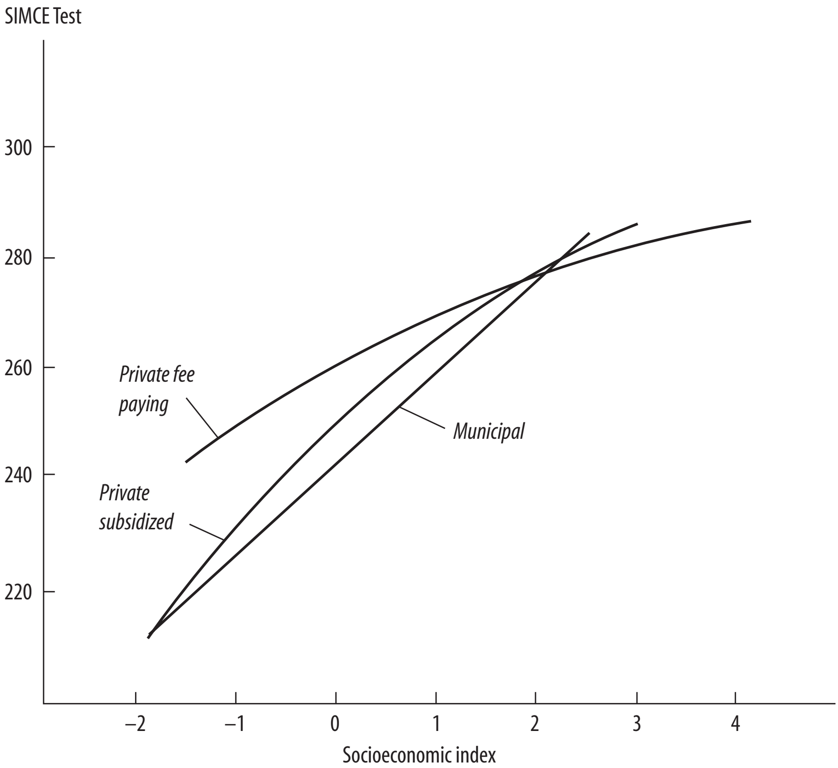
The panel estimation technique with the inclusion of fixed or random effects also attempts to solve the problem that the observation variable is indexed per student and per school.[72] The random effects model assumes that the individual effects are uncorrelated with the other regressors. The results are presented in models 4 and 5 of table A5. In the random effects model, more inputs are statistically significant, although the assumption that the random effects are uncorrelated with the regressors is not fulfilled according to the Hausman test.

The results of the fixed effects model permit us to conclude that schools are important for explaining students' achievement. The *F* test for the joint contribution of the school effect is statistically significant at the 1 percent level. However, the specific contribution of any input variables cannot be identified in this model.

The above models assume that a school dummy captures performance differences between public and private schools, while other independent variables are assumed to have a homogeneous effect on both school types. We now explore the existence of heterogeneous effects on student achievement.[73] We estimate a model with interaction terms for socioeconomic variables; the fitted equations are presented in figure 1, and the complete results are in model 6 of table A5. The effect of socioeconomic level

72. HLMs also deal with this problem.
73. On the basis of 1996 SIMCE aggregate school results, Tokman (2001) points out that Chile's municipal schools have comparative advantages when it comes to teaching low-income students.

FIGURE 1. Student Achievement by School Type, According to Student Socioeconomic Level (with Socioeconomic Interactions)



Source: Authors' calculations (table A5, model 6).

differs across types of schools.[74] The main advantage of fee-paying private schools appears to be for low-income students, while results for high-income students' achievements at the three school types are more alike.

Quantile Regressions

A quantile regression exercise can provide a complementary analysis of heterogeneity. OLS estimations allow us to determine the average effect of

74. The socioeconomic index was obtained using factorial analysis, with a weighted average for the variables mother's education, father's education, and family income. These data were obtained from a household survey of children taking the SIMCE test.

various school input factors or characteristics on educational achievement. However, we want to know how school resources affect achievement at different points in conditional test score distribution. For example, some school characteristics strongly affect low achievers, while others can improve high achievers' educational results. To explore this issue, we estimated quantile regressions for the results of the SIMCE language test given to tenth graders in 1998.

The specification follows the standard educational production function, which relates student achievement to student and school characteristics. The variables considered include the kind of school, its modality (whether it is humanistic-scientific, technical-professional, or both), its size and its square (measured by its total enrollment), student gender, student-teacher ratio, teacher experience, students' socioeconomic level and its square, and two peer effects, one measuring the percentage of students having similar results in the tests and the other measuring the percentage of students of similar income levels.[75] We estimate the model first by OLS and then at the 0.10, 0.25, 0.50, 0.75, and 0.90 quantiles.

The results appear in table 5. Practically all the explanatory variables are statistically significant at 1 percent, with the sole exception of the socioeconomic peer effect, which does not affect the achievement of students in the 0.90 quantile, that is, the top distribution level.[76] We find differences, however, in the magnitudes of coefficients estimated by the different quantiles. Private fee-paying and private subsidized schools' effect on educational achievement decreases as we move to the top of the conditional distribution of language score. The humanistic-scientific schools do not seem to have very different results in the various quantiles, but this is not the case for those schools that are simultaneously humanistic-scientific and technical, which have better results at the bottom of the distribution, mainly the 0.10 quantile.

It is interesting to stress the impact of the peer effect on student achievement, as it measures the degree of homogeneity of students' educational results for a given school. This effect appears to be much more important in the case of individuals in the lowest two quantiles of the conditional

75. Similar refers to those observations that are within the range defined by the mean plus or minus 0.5 standard deviation. Table A6 in the appendix provides the descriptive statistics of the variables.

76. We do not comment on inputs such as the student-teacher ratio because in this estimation we have not corrected for its possible endogeneity.

TABLE 5. Quantile Regressions for Language Achievement in Chile, Tenth Grade, 1998[a]

Variable	*OLS*	*Q10*	*Q25*	*Q50*	*Q75*	*Q90*
Dummy private subsidized	18.974	24.204	21.838	18.709	17.114	15.162
	(0.425)*	(0.959)*	(0.685)*	(0.448)*	(0.383)*	(0.544)*
Dummy private fee-paying	26.251	37.090	31.313	25.332	22.428	19.219
	(0.887)*	(2.061)*	(1.146)*	(1.032)*	(0.926)*	(0.900)*
Humanistic and scientific schools	16.127	15.679	16.125	16.541	17.273	17.614
	(0.438)*	(0.728)*	(0.603)*	(0.557)*	(0.636)*	(0.600)*
H&S schools + technical schools	2.152	4.071	2.924	1.488	2.029	1.919
	(0.505)*	(1.245)*	(0.955)*	(0.555)*	(0.593)*	(0.505)*
Total enrollment	0.007	0.007	0.005	0.007	0.008	0.010
	(0.0009)*	(0.001)*	(0.0008)*	(0.001)*	(0.001)*	(0.001)*
Total enrollment squared	−1.39E−6	−1.62E−6	−9.60E−7	−1.31E−6	−1.58E−6	−1.95E−6
	(2.69E−7)*	(4.16E−7)*	(2.69E−7)*	(3.39E−7)*	(3.18E−7)*	(4.22E−7)*
Gender	5.452	9.246	6.053	4.760	3.611	3.676
	(0.329)*	(0.813)*	(0.476)*	(0.473)*	(0.375)*	(0.441)*
Student/teacher ratio	−0.201	−0.209	−0.193	−0.215	−0.183	−0.169
	(0.023)*	(0.034)*	(0.032)*	(0.027)*	(0.027)*	(0.033)*
Teacher experience	0.703	0.889	0.885	0.727	0.632	0.500
	(0.039)*	(0.902)*	(0.071)*	(0.061)*	(0.037)*	(0.044)*
Student socioeconomic level	17.868	17.443	19.142	19.029	17.802	16.130
	(0.254)*	(0.533)*	(0.343)*	(0.258)*	(0.280)*	(0.368)*
Student socioeconomic level squared	−2.407	−1.582	−2.509	−2.751	−2.824	−2.518
	(0.114)*	(0.208)*	(0.180)*	(0.106)*	(0.106)*	(0.125)*
Achievement peer effect	0.388	0.669	0.630	0.319	0.145	0.154
	(0.028)*	(0.046)*	(0.031)*	(0.028)*	(0.028)*	(0.028)*
Socioeconomic peer effect	0.097	0.136	0.128	0.092	0.053	0.027
	(0.022)*	(0.050)*	(0.036)*	(0.025)*	(0.023)*	(0.031)
Constant	206.705	130.512	166.032	213.329	248.793	273.054
	(1.599)*	(3.743)*	(2.496)*	(1.923)*	(1.479)*	(2.029)*
(Pseudo) R^{2b}	0.2509	0.1080	0.1346	0.1503	0.1572	0.1493
No. observations	67,549					

Source: Authors' estimations.

* Statistically significant at 1 percent.

a. Excluded dummy variables: municipal schools, technical schools, coeducational schools. Asymptotic standard errors in parentheses. Heteroskedasticity robust for OLS, bootstrapped for quantiles.

b. $\text{Pseudo } R^2 = 1 - \dfrac{\text{sum of weighted deviations around estimated quantile}}{\text{sum of weighted deviations around raw quantile}}.$

achievement distribution. Something similar, although less marked, occurs with the socioeconomic peer effect, which is also most pronounced on achievement at the bottom of the conditional distribution.

The above results suggest that school composition in terms of cognitive ability is more closely related to the achievements of individuals at the lower end of the achievement distribution. This result is similar to that of Levin, who concludes that in the Netherlands students at the lower end of the achievement distribution benefit more from learning with classmates of similar ability than with those at the upper end.[77]

Hierarchical Linear Models (HLM)

To continue to explore the existence of heterogeneous impacts of school and student characteristics on educational achievement, we estimated a hierarchical linear model (HLM) using tenth grade data for Chile.[78] The use of this kind of model derives from the multilevel data with which we work, that is, data at the student and school levels, with students nested into schools.[79]

As already mentioned in our discussion on methodology, HLMs make it possible to approach the conceptual and technical problems that arise when working with multilevel data: (i) aggregation biases, which result from variables that have different meanings at the different levels at which the data are generated; (ii) misestimated standard errors, which reflect the failure to take into account the dependence among individual responses within the same organization (school); and (iii) heterogeneity of regression, which occurs when the relationships between individual characteristics and outcomes vary across organizations (schools).

Questions about how organizations affect the individuals within them can be formulated as two-level HLMs. In our case, at the first level the units are students, and each student's outcome (test) is represented as a function of a set of individual characteristics. At the second level the units are schools. The regression coefficients in the level-1 model for each school are conceived as outcome variables that are hypothesized to depend on specific organizational characteristics.

We use this model to investigate the effects of student (and school) socioeconomic level on the educational results, distinguishing the impact of this variable on the different types of schools. This aspect is related to the ability of a given type of school to achieve better learning for low-income students. We thus use the model to pursue the question of whether some kinds of schools enjoy advantages in educating low-income students.

The first model is the following:

77. Levin (2001).
78. For further details on hierarchical linear models, see Bryk and Raudenbush (1992).
79. We work only at the student and school levels because we do not have information at the classroom level.

—Level 1:[80]

$$Y_{ij} = \beta_{0j} + \beta_{1j}\,\text{SES}_{ij} + \beta_{2j}\,\text{SES}^2_{ij} + r_{ij},$$

where SES_{ij} is the socioeconomic status of student i in school j, with the variable centered on the level-2 mean, which implies that β_{0j} is the mean achievement in school j; and where r_{ij} is a level-1 random effect, $r_{ij} \sim n\,(0, \sigma^2)$, in which σ^2 represents the residual variance at level 1.[81]

—Level 2:

$$\begin{aligned}\beta_{0j} = {} & \gamma_{00} + \gamma_{01}\text{DPS} + \gamma_{02}\text{DPFP} + \gamma_{03}\text{DH\&S} + \gamma_{04}(\text{DH\&S} + \text{TECH})\\ & + \gamma_{05}\ln\text{TOTALENROLL} + \gamma_{06}\text{BOYS} + \gamma_{07}\text{GIRLS}\\ & + \gamma_{08}\,\text{SCHOOLSES} + \gamma_{09}\,\text{STUDENT/TEACHER}\\ & + \gamma_{010}\text{TEACHEREXP} + \gamma_{011}\text{ACHIEVPEER} + \mu_{0j}\end{aligned}$$

$$\begin{aligned}\beta_{1j} = {} & \gamma_{10} + \gamma_{11}\text{DPS} + \gamma_{12}\text{DPFP} + \gamma_{13}\text{DH\&S} + \gamma_{14}(\text{DH\&S} + \text{TECH})\\ & + \gamma_{15}\text{SCHOOLSES} + \gamma_{16}\text{SESPEER} + \mu_{1j}\end{aligned}$$

$$\beta_{2j} = \gamma_{20}$$

where $\gamma_{00}, \gamma_{01}, \ldots \gamma_{20}$ are level-2 coefficients (also called fixed effects); and μ_{0j} and μ_{1j} are level-2 random effects that are assumed to be multivariate normally distributed with mean 0 and with variance τ_{qq} and covariance $\tau_{qq'}$ between any two random effects q and q'.[82] The coefficient corresponding to the students' socioeconomic level squared was modeled as a constant because it has a high correlation with coefficient β_{1j}. This implies that the two random effects are carrying the same variation across level-2 units, in which case it is better to specify one of them as fixed.

The description of variables is presented in table 6 and the results in tables 7 and 8. Estimations of fixed effects show that a school's socioeconomic level strongly influences its mean achievement. Once a correction has been made for the effect of socioeconomic level, there seem to be no significant differences in the average scores of private fee-paying schools

80. The variables included in level 1 are the only ones available at the student level.

81. In HLM, the intercept and slopes in the level-1 model become outcome variables at level 2, so they must have a clear meaning. For instance, we must be clear about the meaning of $\text{SES}_{ij} = 0$.

82. The descriptive statistics of each variable are found in table A6 in the appendix.

TABLE 6. Description of Variables

Variable[a]	*Description*
DPS	Dummy private subsidized school
DPFP	Dummy private fee-paying school
DH&S	Dummy humanistic and scientific school
DH&S+TECH	Dummy humanistic and scientific school and technical school
ln TOTALENROLL	Natural log of the number of students enrolled in the school
GIRLS	Schools for girls only
BOYS	Schools for boys only
SCHOOLSES	Average socioeconomic level of school
STUDENT/TEACHER	Student-teacher ratio
TEACHEREXP	Teachers' years of experience
ACHIEVPEER	Percentage of students with similar achievement in the school (that is, percentage of students getting test scores within the range given by the mean plus or minus 0.5 standard deviation)
SESPEER	Percentage of students with similar socioeconomic level in the school (that is, percentage of students with a socioeconomic level within the range given by the mean plus or minus 0.5 standard deviation)

a. Variables that are not dummies have been centered around their grand mean.

and municipal schools, although there are differences between subsidized private schools and municipal schools. Also, the fact that a school has a greater percentage of children with similar scores (achievement peer effect) has a positive impact on the school's mean achievement, which makes sense because it is easier to teach a homogeneous group of students.

The regression of the SES-achievement slope (β_{1j}) gave interesting results. Schools with a high mean socioeconomic level tend to have a weaker association between student SES and language achievement than do schools with a low mean socioeconomic level ($\gamma_{15} = -2.487$). Also, private subsidized schools and private fee-paying schools have a weaker association, on the average, between student SES and achievement than municipal schools ($\gamma_{11} = -2.520$ and $\gamma_{12} = -2.509$). These results are shown graphically in figure 2. The relationship between socioeconomic level and language achievement is displayed for high-, medium-, and low-income schools. Figure 2 shows that within schools, language SES slopes are less steep in the private sector than in the municipal (public) sector, while low SES schools have steeper slopes than do high SES schools. Solid lines indicate the impact of the school's average socioeconomic level on achievement; in both cases these have positive slopes.

TABLE 7. HLM of Language Achievement in Chile, Tenth Grade, Fixed Effects[a]

Variable	*Coefficient*	*Standard error*	P *value*
For Intercept β_0 (school mean achievement)			
Intercept	243.793	2.005	0.000
Dummy private subsidized	13.592	1.400	0.000
Dummy private fee-paying	–2.910	3.244	0.370
Humanistic and scientific schools	10.595	1.611	0.000
H&S schools + technical schools	3.534	1.574	0.025
Ln total enrollment (size)	1.867	0.941	0.047
Boys school	4.692	2.444	0.055
Girls school	12.479	1.476	0.000
School socioeconomic level	28.822	1.370	0.000
Student/teacher ratio	–0.013	0.075	0.867
Teacher experience	0.109	0.123	0.375
Achievement peer effect	0.185	0.070	0.009
For slope β_1 (student socioeconomic level)			
Intercept	7.012	0.783	0.000
Dummy private subsidized	–2.520	0.686	0.000
Dummy private fee-paying	–2.509	1.361	0.065
Humanistic and scientific schools	4.272	0.809	0.000
H&S schools + technical schools	4.245	0.921	0.000
School socioeconomic level	–2.487	0.726	0.001
Socioeconomic peer effect	–0.113	0.033	0.001
For slope β_2 (student socioeconomic level squared)			
Intercept	–0.608	0.225	0.007

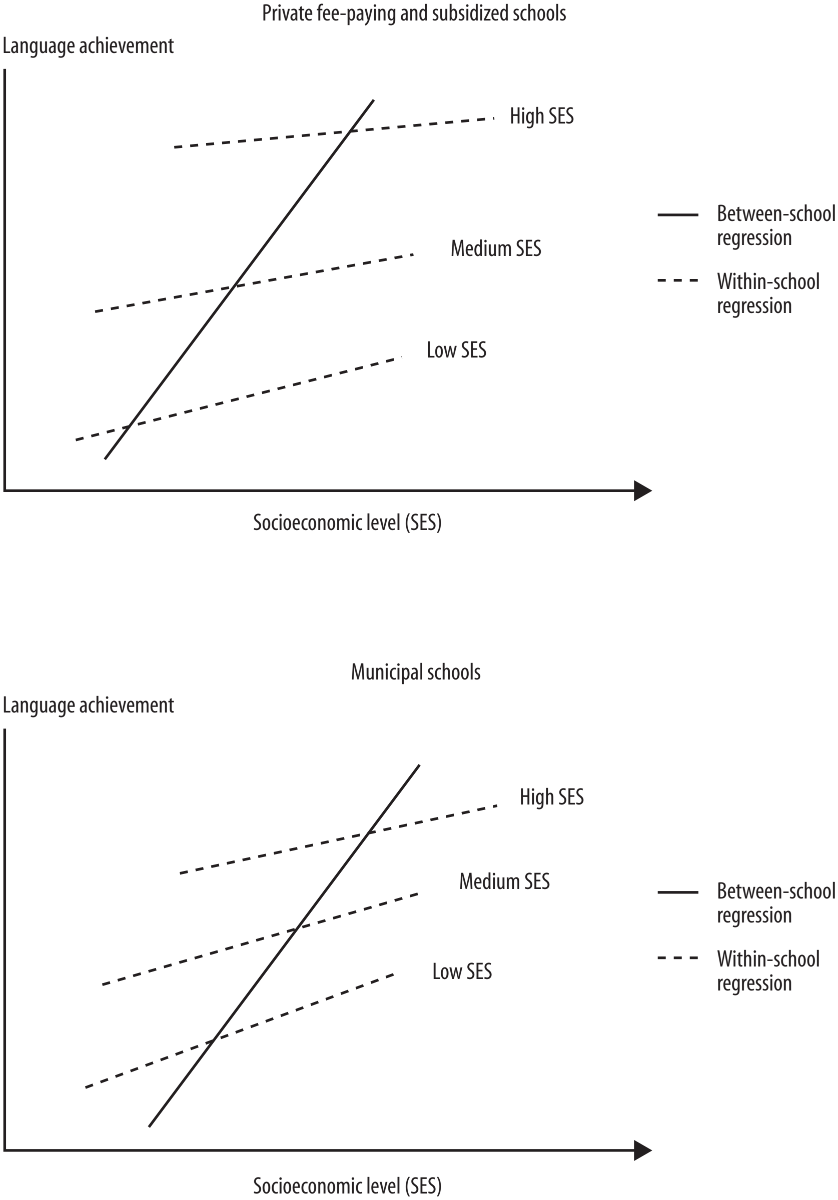
a. Reference dummy variables: municipal schools, technical schools, coeducational schools.

These results also let us calculate the proportion of variance in random coefficients (intercept and slopes) in the level-1 model, explained at level 2. To do so, we must compare the variance component obtained in this model (conditional or residual variance) with the variance component obtained from a model with the same level-1 regression, but with level-2 coefficients (β_{0j}, β_{1j}) equal to a constant plus a random error

TABLE 8. HLM of Language Achievement in Chile, Tenth Grade, Random Effects

Variable	*Variance component*	*df*	*Chi-squared*	P *value*
Intercept (μ_0)	286.077	1354	14499.9	0.000
Slope β_1 (μ_1)	4.294	1359	1647.6	0.000
Level-1 effects, r_{ij}	1472.795			

FIGURE 2. Interaction Results in the HLM Model



Source: Authors' estimation.

(unconditional variance).[83] This explains 74.2 percent of the variance in average achievement and 34.9 percent of the SES-achievement slope.[84]

To more deeply explore socioeconomic impacts on educational achievement and their interaction with the type of school, we estimate an HLM with the same equation from level 1, but with a different specification for level 2. In this second model the equations to be estimated in level 2 are as follows:

$$\begin{aligned}\beta_{0j} = {} & \gamma_{00} + \gamma_{01}DPS + \gamma_{02}DPFP + \gamma_{03}DH\&S + \gamma_{04}(DH\&S + TECH) \\ & + \gamma_{05}\ln TOTALENROLL + \gamma_{06}BOYS + \gamma_{07}GIRLS \\ & + \gamma_{08}STUDENT/TEACHER + \gamma_{09}TEACHEREXP \\ & + \gamma_{010}SCHOOLSES \times DPS + \gamma_{011}SCHOOLSES \times DPFP \\ & + \gamma_{012}SCHOOLSES \times DMUN + \gamma_{013}ACHIEVPEER \times DPS \\ & + \gamma_{014}ACHIEVPEER \times DPFP + \gamma_{015}ACHIEVPEER \times DMUN \\ & + \mu_{0j}\end{aligned}$$

$$\begin{aligned}\beta_{1j} = {} & \gamma_{10} + \gamma_{11}DPS + \gamma_{12}DPFP + \gamma_{13}DH\&S + \gamma_{14}(DH\&S + TECH) \\ & + \gamma_{15}SCHOOLSES \times DPS + \gamma_{16}SCHOOLSES \times DPFP \\ & + \gamma_{17}SCHOOLSES \times DMUN + \gamma_{18}SESPEER \times DPS \\ & + \gamma_{19}SESPEER \times DPFP + \gamma_{110}SESPEER \times DMUN + \mu_{1j}\end{aligned}$$

$$\beta_{2j} = \gamma_{20}$$

The results of this model appear in tables 9 and 10. Significant and positive interaction terms are obtained for the school's socioeconomic level and type, with the socioeconomic level having the most effect on the school's mean achievement in subsidized private schools, followed by municipal schools and fee-paying private schools.

The impact of the achievement peer effect on the school's mean achievement also varies among the different types of schools. The most significant effect is seen in subsidized private schools, where the fact that a higher percentage of the students have similar scores on the standardized tests has a greater positive impact on average achievement. The peer effect

83. Level-2 regressions are as follows: $\beta_{0j} = \gamma_{00} + \mu_{0j}$; $\beta_{1j} = \gamma_{10} + \mu_{1j}$; and $\beta_{2j} = \gamma_{20}$. This model, which is known as the random-coefficient regression model, allows us to conclude that each of the level-1 predictors (SES and SES^2) had, on average, a significant relationship with language achievement.

84. The chi-squared statistics in table 8 are consistent with the hypothesis that the residual variation in these two school effects is zero.

TABLE 9. HLM of Language Achievement in Chile, Tenth Grade, Fixed Effects (with Interaction Terms)[a]

Variable	*Coefficient*	*Standard error*	P *value*
For Intercept β_0 *(school mean achievement)*			
Intercept	246.028	4.357	0.000
Dummy private subsidized (PS)	11.122	5.832	0.056
Dummy private fee-paying (PP)	26.342	5.998	0.000
Humanistic and scientific schools	4.437	1.574	0.005
H&S schools + technical schools	1.145	1.581	0.469
Ln total enrollment (size)	2.031	0.921	0.027
Boys school	3.526	2.173	0.104
Girls school	12.191	1.330	0.000
Student/teacher ratio	–0.013	0.068	0.848
Teacher experience	0.021	0.111	0.849
School socioeconomic level × PS	43.251	1.832	0.000
School socioeconomic level × PP	12.514	2.018	0.000
School socioeconomic level × Municipal	34.484	2.261	0.000
Achievement peer effect × PS	0.291	0.107	0.007
Achievement peer effect × PP	0.064	0.119	0.590
Achievement peer effect × Municipal	0.220	0.099	0.026
For slope β_1 *(student socioeconomic level)*			
Intercept	10.606	2.890	0.000
Dummy private subsidized	–2.258	3.558	0.525
Dummy private fee-paying	–8.266	3 .869	0.032
Humanistic and scientific schools	5.096	0.876	0.000
H&S schools + technical schools	4.615	0.928	0.000
School socioeconomic level × PS	–4.602	1.040	0.000
School socioeconomic level × PP	–0.339	0.890	0.703
School socioeconomic level × Municipal	–2.701	1.420	0.057
Socioeconomic peer effect × PS	–0.136	0.053	0.011
Socioeconomic peer effect × PP	–0.054	0.053	0.300
Socioeconomic peer effect × Municipal	–0.119	0.067	0.074
For slope β_2 *(student socioeconomic level squared)*			
Intercept	–0.567	0.227	0.013

a. Excluded dummy variables: municipal schools, technical schools, coeducational schools.

TABLE 10. HLM of Language Achievement in Chile, Tenth Grade, Random Effects (with Interaction Terms)

Random effects	*Variance component*	*df*	*Chi-squared*	P *value*
Intercept (μ_0)	248.390	1350	12773.5	0.000
Slope β_1 (μ_1)	18.495	1355	1636.5	0.000
Level-1 effects, r_{ij}	1472.891			

also has a positive impact in municipal schools, but not in fee-paying private schools, where its impact is statistically nil.

To analyze, ceteris paribus, the effect of the school type on mean language achievement, we consider different school socioeconomic levels and different percentages of students with similar test scores. Table 11 summarizes these results for two exercises: one using the total average school socioeconomic level (school SES = 0) and the total average school achievement peer effect (37.68) and one using the average socioeconomic level (–0.277, 1.482, and –0.709) and the average school achievement peer effect (37.78, 38.33, and 37.25) of each of the three types of schools—subsidized private schools, fee-paying private schools, and municipal schools, respectively. The table shows that when averages of all schools are used (for SES and achievement peer effect), the gaps between schools' mean language achievement get smaller compared to the average scores obtained when the individual average for each kind of school is used.

The above results are consistent with those obtained for the SES-achievement slope (β_1). On average, fee-paying private schools show a weaker association between student SES and language achievement than do municipal and subsidized private schools. This association is similar for fee-paying private schools having different socioeconomic levels. In contrast, subsidized private schools show a weaker association between student SES and achievement in the case of those schools of higher socioeconomic level, and something similar occurs with municipal schools, although to a lesser extent. These results point to a different conclusion from that obtained by Tokman for the 1996 fourth grade test.[85]

As with the previous model, we calculate the percentage of the explained variance for each of the coefficients. The results indicate that 77.6 percent of the variance in average achievement and 36.3 percent of the variance in the SES-achievement slope have been explained. This implies a 4.6 percent increase in the explained variance of the school mean achievement compared with the previous model, together with a 4 percent increase in the explained variance in the SES-achievement slope.

To summarize, the HLM provides evidence that the school has a significant impact on educational results. These effects are heterogeneous among the different kinds of students, showing that low-income students would benefit most from a change from a public to a private school. This

85. Tokman (2001).

TABLE 11. Mean Language Achievement by School Type under Different School Socioeconomic Levels and Achievement Peer Effects

School type	*Total average school SES and total average school achievement peer effect*	*Average SES for each school type and average achievement peer effect for each school type*
Private subsidized	268.1	256.2
Private fee-paying	272.4	290.9
Municipal	254.3	229.8

conclusion, however, is valid for a marginal student; it does not necessarily apply to massive changes between schools since these would substantially alter the composition of public and private schools.

Finally, this analysis considers educational achievement only, not schools' economic efficiency. This is important because the resources available to schools are different. Preliminary estimations show that fee-paying private schools have five times more resources than subsidized schools, while a comparison of municipal and subsidized private schools shows that, on average, they are much more similar, but vary greatly depending on municipal districts.

Concluding Remarks

This paper has attempted to organize the recent debate about educational policies, revealing that these policies respond to different models with different assumptions and hypotheses about how the educational system functions. Clarifying this issue enriches the debate. Knowledge remains weak, however, despite a significant increase in the field of economics of education, given that most of these studies yield conflicting policy prescriptions. Informational and methodological problems explain the absence of robust results.

Every policy recommendation is implicitly derived from a model with assumptions and hypotheses about the behavior of the educational system. In this paper we have identified three models: the centralized-effective model, the decentralized-incentive model, and the decentralized-market model. The centralized-effective model of the educational system is based on the assumption that it is possible to identify the factors that affect student achievement and that modifying these factors (or inputs) will improve the quality of education. Nevertheless, as we point out, the empirical research has not been able to show a robust and stable relationship between educational inputs and quality.

Likewise, the decentralized-market model is based on the assumption that the creation of an educational market in which schools compete for students would improve educational quality by forcing schools to work to attract students. The educational services provided by private, state-financed schools are assumed to be better than those of public schools, which would generate pressure to raise quality within the system. A review of the empirical literature comparing the two, however, is not conclusive.

Methodological and informational problems have made it difficult, to date, to discriminate between the different hypotheses behind the models. Nor can we develop unambiguous evaluations of the results of the policies applied. It is necessary, therefore, to continue to investigate these issues using new methodologies that produce robust results. This would help improve educational policies, insofar as a consensus can be reached on the variables that are relevant to increasing the quality and equity of education and to selecting between specific policies in given contexts. This challenge requires a substantial improvement in the information available in the region: we need better information on student socioeconomic characteristics and school characteristics, and we need to develop panel data by giving standardized tests to the same students at different points in time.

With regard to the analysis of the Chilean data, the results obtained in this study of the tenth grade allow us to conclude that the school plays a very important role in explaining educational achievement. This does not rely exclusively on students' socioeconomic level, although we still cannot identify the specific school characteristics that are most relevant.

Empirical analysis also shows that the effect of student socioeconomic level varies according to school type. Specifically, the marginal effect of socioeconomic level on language achievement is lower in the subsidized and private fee-paying schools than in the municipal (public) schools. The marginal effect of socioeconomic level on language achievement is also lower in the case of high-income versus low-income schools. Moreover, when we model the joint effects of school type, average school socioeconomic level, and peer effect, the magnitude of the school-type effect on schools leads us to conclude that achievement depends on the school's socioeconomic level, while in the case of private subsidized and municipal schools it also depends on the achievement peer effect. These results show that low-income students stand to benefit the most from attending a private school. However, this conclusion is valid for a marginal analysis and does not necessarily apply to a massive reallocation of students among schools, because massive changes would substantially alter the composition of public and private schools.

From a policymaker's perspective, the results described in this paper reveal that there is no stable, robust relationship between educational inputs and output. Policymakers should be cautious about the policies they plan to implement, first ensuring that suitable information is available to periodically evaluate them.

Similarly, the analysis indicates the importance of incentives in education. While no one knows exactly what favors improvements to the educational product, policymakers can design incentives that lead schools to improve the quality of the education they impart. It is known that schools do matter, although the specific factors that make one school achieve better results than another are unknown. In this sense, incentives should focus on educational results (performance incentives) rather than on the processes and inputs to achieve these results.

Appendix: Supplemental Tables

TABLE A1. Results of UNESCO Laboratory, 1997[a]
Percent of students

	Test levels[b]		
Test and type of school	*Level I*	*Level II*	*Level III*
Language			
Public	90.47	64.91	44.52
Private	93.96	75.06	54.56
Mathematics			
Public	91.07	48.20	14.94
Private	93.70	56.14	15.01
Percent considered appropriate	90.00	75.00	50.00

Source: UNESCO (2000).
a. The countries included in the study are Argentina, Bolivia, Brazil, Chile, Colombia, Costa Rica, Cuba, the Dominican Republic, Honduras, Mexico, Paraguay, Peru, and Venezuela.
b. In the language test, the levels are as follows: I: Literal reading—primary; II: Literal character reading in paraphrase mode; III: Inferential character reading. In the mathematics test, the levels are the following: I: Recognition and use of basic mathematical facts and relations; II: Recognition and use of simple mathematical structures; III: Recognition and use of complex mathematical structures.

TABLE A2. Student Performance in Bolivia, Third and Sixth Grades, 1997
Percent of population

Performance level	*Third grade*	*Sixth grade*
At-risk performance	27	51
Average performance	40	32
Satisfactory performance	33	16

Source: SIMECAL (1998).

TABLE A3. Student Performance in Public versus Private Schools in Colombia, ICFES Test Results, 1997
Test scores (points)

Test and models	*Private (unofficial)*	*Public (official)*
School mean achievement		
Science	48.29*	46.50*
Language	48.69*	46.41*
Mathematics	50.05*	48.47*
School mean achievement after controlling for school socioeconomic level		
Science	35.47*	37.82*
Language	35.53*	36.20*
Mathematics	37.70*	39.29*

Source: Piñeros and Rodriguez (1998).
* Statistically significant at 1 percent.

TABLE A4. Student Performance in Chile, SIMCE Test Results, 1996, 1997, 1999, and 2000[a]

Test scores (points)

	Fourth grade				*Eighth grade*			
	Mathematics		*Language*		*Mathematics*		*Language*	
Type of school	*1996*	*1999*	*1996*	*1999*	*1997*	*2000*	*1997*	*2000*
Municipal	239	239	241	238	238	239	236	239
Private subsidized	253	256	257	258	258	256	255	257
Private fee paying	292	298	296	298	301	299	291	295
Total	248	250	251	250	250	250	247	250

Source: Ministerio de Educación de Chile (2000, 2001).

a. Differences in student performance for each grade between two years are not statistically significant. Comparisons between tests for different years are based on an equating technique.

TABLE A5. Effect of School Type: Models with and without Interactions[a]

						Model 6		
Explanatory variable	*Model 1*	*Model 2*	*Model 3 (cluster)*	*Model 4 (random effects)*	*Model 5 (fixed effects)*	*Municipal*	*Private subsidized*	*Private fee-paying*
Constant	238.873	238.321	238.321	227.766	252.531		242.594	
	(0.350)	(1.070)	(4.082)	(2.980)	(0.257)		(1.240)	
Dummy subsidized private schools	17.830	13.304	13.304	16.309				
	(0.350)	(0.465)	(1.716)	(1.449)				
Dummy private fee-paying schools	59.469	17.445	17.445	28.297				
	(0.549)	(0.917)	(2.817)	(2.092)				
Dummy school type							7.846	17.948
							(0.919)	(1.752)
Socioeconomic index		16.004	16.004	10.696	10.048	16.192	17.263	10.004
		(0.112)	(0.521)	(0.254)	(0.256)	(0.371)	(0.399)	(1.681)
Socioeconomic index, squared		−1.959	−1.959	−1.545	−1.592	0.109	−1.857	−0.894
		(0.259)	−(0.172)	(0.114)	(0.118)	(0.284)	(0.271)	(0.423)
Vulnerability index		−0.311	−0.311	−0.321		−0.427	−0.242	—
		(0.011)	−(0.042)	(0.030)		(0.018)	(0.013)	
Female student		5.471	5.471	3.528	3.135	4.502	5.916	9.249
		(0.323)	(0.938)	(0.344)	(0.350)	(0.459)	(0.501)	(1.052)
Humanistic and scientific school (H&S)		12.483	12.483	15.550			11.948	
		(0.444)	(1.863)	(1.427)			(0.447)	
H&S with technical education		1.858	1.858	5.859			1.924	
		(0.500)	(1.788)	(1.689)			(0.501)	
Full-day school		4.540	4.540	4.694			4.201	
		(0.479)	(1.596)	(1.414)			(0.481)	
School size (no. students)		1.54E−03	1.54E−03	6.00E−03			1.04E−03	
		(8.93)E−04	(3.18)E−03	(3.17)E−03			(9.03)E−04	

School size, squared		3.93E−07	3.93E−07	−1.43E−06		3.01E−07
		(2.70)E−07	(1.04)E−06	(1.22)E−06		(2.70)E−07
Student/teacher ratio		−0.170	−0.170	0.007		−0.147
		(0.022)	(0.113)	(0.058)		(0.023)
Teacher experience		0.754	0.754	0.777		0.741
		(0.038)	(0.134)	(0.112)		(0.038)
Summary statistic						
Adjusted R^2	0.135	0.259	0.259		0.392	0.261
F statistic	6069.80	1867.87	350.47		527.290	1225.250
Chi-squared				4726.26		
No. observations	77,796	69,402	69,402	69,402	69,402	69,402

Source: Authors' estimations.

a. The dependent variable is the SIMCE language test, tenth grade, 1998. Standard errors are in parentheses.

TABLE A6. Descriptive Statistics for Chile, SIMCE Test Results, Tenth Grade, 1998

Variable	*N*	*Mean*	*Standard deviation*	*Minimum*	*Maximum*
Student-level descriptive statistics					
SIMCE Test	70,695	251.82	49.22	101.34	410.56
SES	67,549	−0.05	0.96	−1.86	4.18
SES2	67,549	0.92	1.95	0.00	17.51
School-level descriptive statistics					
SIMCE Test	1,366	256.37	34.70	175.92	335.76
ENROLLMENT	1,366	532.39	473.90	26.00	3,449.00
DPS	1,366	0.43	0.50	0.00	1.00
DPFP	1,366	0.19	0.39	0.00	1.00
DMUN	1,366	0.38	0.49	0.00	1.00
DH&S	1,366	0.61	0.49	0.00	1.00
DH&S+TECH	1,366	0.15	0.36	0.00	1.00
STUDENT/TEACHER	1,366	20.88	10.15	1.73	94.40
TEACHER EXP	1,366	12.39	4.88	0.00	32.02
SCHOOLSES	1,366	−0.10	0.93	−1.76	2.92
BOYS	1,366	0.07	0.26	0.00	1.00
GIRLS	1,366	0.11	0.32	0.00	1.00
COED SCHOOLS	1,366	0.82	0.39	0.00	1.00
ACHIEVPEER	1,366	37.68	7.95	7.69	70.00
SESPEER	1,366	37.51	9.68	0.00	80.00