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IS AGE-GRADE DISTORTION IN BRAZIL'S PRIMARY PUBLIC EDUCATION SYSTEM MORE CLOSELY ASSOCIATED TO SCHOOL INFRASTRUCTURE OR TO FAMILY CHARACTERISTICS?

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Abstract

Different economic studies have shown the importance of education in improving the quality of life of individuals. Thus, in the 90's, the public education system was reformed to enhance the quality of public education in Brazil and motivate student interest. This paper participated in this discussion by suggesting an assessment of the impact that school infrastructure and family characteristics have on age-grade distortions in primary education. Probit and ordered probit models were used for public schools in urban areas in the states of Sao Paulo and Pernambuco, using databases from the demographic census and the school census and National Fund for School Development (FNDE) transfers for 2000. Interactions between family characteristic and school infrastructure variables were explored to determine the most effective ways to retain students and ensure student promotion. Simulations were also made to assess the impact of enhancing school quality versus improving the socioeconomic status of families on lagging students. Results showed that Sao Paulo students from families headed by less educated heads of household and/or low income families would benefit more from public policies oriented towards improving school infrastructure. Reaching low income children in Pernambuco would require investments in policies aimed at improving both family socioeconomic status and school infrastructure. In addition, improving family characteristics has a greater impact on age-grade distortion in both states, but these are long term policies. Even though their impact is lower, policies oriented towards improving school infrastructure would achieve more immediate results.

Key words: age-grade distortion, school infrastructure, family characteristics, primary education, government policy.
Classification JEL: I28.

Introduction

For decades, national and international literature has been concerned with proving the significance of education in improving the quality of life of individuals. In a study for developing countries, Behrman and Wolfe (1984) concluded that investing in education has a positive socioeconomic impact on income generation.

Studies using Brazilian data show that one year of education increases individual income as much as 16% (Ueda and Hoffmann, 2002; Kassouf, 2001; Barros and Ramos, 1992). Another study shows that if the educational level of illiterate mothers were at the primary or secondary level, pre-school student malnutrition would be reduced between 25% and 15% (Kassouf and Senauer, 1996). An International Labor Organization study (ILO, 1998) has shown that more educated individuals are more aware of their rights and raise more educated and healthy children, reducing child labor in the long term.

Increasing school attendance levels and retaining students is the first step to raising average education levels in a country. Based on this fact, an increasing number of studies, such as Case and Deaton (1999) and Binder (1999), have assessed the impact of family's income per capita, parents' education and place of residence on the probability of a student entering or remaining in school. On the other hand, some studies have added variables representative of school quantity and school quality to study their influence on returns to basic education. Summers and Wolfe (1977), for example, showed that investing in school infrastructure had an impact on black student and low income student outcomes. In addition, Card and Krueger (1992) showed that lowering teacher/student ratios and/or raising teacher salaries increased the rate of return on North American students' wages. Glewwe and Jacoby (1993) showed that both mother's education and teacher education and experience had a significant impact on student performance in Ghana. Angrist and Lavy (2001) suggested investing in training for teachers to improve student education outcomes in Jerusalem because the average cost of this initiative would be lower than reducing class sizes, for example.

In Brazil, taking into account the different political and educational changes that took place during the last decade, the purpose of some studies has been to understand the determinants of basic education. Ribeiro (1991) showed that in the 80's, repetition rates in Brazil were extremely high and represented an obstacle to universal basic education in the country. Recently, Barros et al. (2001) showed that the number of grades completed by an individual is strongly influenced by parents' education and/or family income per capita. Vasconcellos (2003) analyzed age-grade distortion in Brazilian primary education between 1981 and 1999, concentrating on exploring a potential causal relationship between family income and education indicators. Using National Basic Education Assessment System (Saeb) data, Ferrao, Beltrao and Santos (2002) explored whether differences in the academic performance of those who had completed their basic education could be attributed to non-repetition policies. Albernaz, Ferreira and Franco (2002) also used Saeb data to determine if different school variables are good measures of efficiency and/or equity in the Brazilian education system.

This paper aims to contribute to this bibliography by including both individual and family characteristics as well as characteristics associated to school infrastructure and enhanced quality of education in the analyses of age-grade distortion among urban public school primary students. Micro data from the Demographic Census 2000, collected by IBGE (Brazilian Institute of Geography and Statistics), and Ministry of Education and Sports (MEC) data banks, such as the School Census and FNDE (National Education Development Fund) transfers, were used, constraining the study to the States of Sao Paulo and Pernambuco.

School quality was measured as the number of students per class, teacher's education and remuneration, public expenditure on direct school transfers, in addition to the number of schools in the municipality with IT laboratories, micro computers and libraries. Factors representative of individual and family characteristics included family income per capita, education, sex and age of head of household and student's age, sex and color. In addition to analyzing the individual effects that each variable has on a student's probability of falling behind in school and the number of years over age for his/her grade, simulations were made by comparing school infrastructure variables to student family characteristics to determine which type of intervention would have a greater impact on selected dependent variables. The interaction between education of the head of household and family income per capita was also estimated using school infrastructure variables to determine how to better allocate resources targeted to the neediest. In this case, a complementary effect between income and school infrastructure indicates that investments in school improvement benefit the rich more than the poor. Similarly, a substitution effect between school infrastructure and education of head of household reveals that students from families with less educated heads of household would benefit the most from school improvements. In addition to estimating a probit model to measure the impact of these variables on the probability of a student falling behind in school, an ordered probit model was also estimated to determine whether these same variables affect the severity of the age/grade gap. Based on results obtained, public policy recommendations were made to help government leaders make decisions when implementing social programs on education.

1. Theoretical and Econometric Model

1.1 Model

This study is based on the theoretical model developed by Becker and Tomes (1979), which aims to understand why parents maximize their returns by investing in their children's and in other family members' human and non human capital. They assume a utility function of parents that depends not only on their own expenditure but also on the number of children and on these children's aggregate wealth. Thus, the authors show that parents are capable of modifying their children's wealth patterns by investing in factors that will augment their children's human and non human capital accumulation. To do so, parents must give up personal expenses in the present, that is, by investing in the student's quality of life, the family compares direct costs and opportunity costs with expected future benefits. They will continue making these investments as long as the marginal rate of return exceeds the costs associated to improving the student's quality of life.

One of the most important empirical approximations to the Becker-Tomes model is the work of Holmes (1999), who analyzed the determinants of demand derived from investments in education using a probit model. Marope (1996) explored the impact of interventionist educational policies on age/grade gaps in Botswana. The impact of qualitative teacher characteristics, physical school characteristics and family characteristics on primary and secondary student performance in Pakistan was analyzed by Behrman et al. (1997). Also using a probit model, Handa (2002) studied the impact of school characteristics and family variables on the decision to enroll a child in primary education.

To model academic gaps, the estimating method used in this study is the probit model, which is generally used with binary dependent variables (Greene, 2003). In this case, the probability of an individual with certain **x** characteristics falling behind in school was analyzed, that is:

$$A^* = \mathbf{x}'\gamma + u \qquad (1)$$

where A^* is not observed but a binary variable A is observed, defined as:

$A = 1$ if $A^* > 0$ and

$A = 0$ otherwise,

for students with and without age/grade gaps, respectively. **x** includes the vector of individual student characteristics ($\mathbf{x}_c$), which includes control variables for ethnical and regional differences; the vector of each student's family characteristics ($\mathbf{x}_f$); the vector of school infrastructure characteristics ($\mathbf{x}_e$) and the vector of family and school infrastructure characteristic interaction ($\mathbf{x}_i$). In addition, γ are parameters to be estimated and u is the error term that represents non observable factors.

Variables representative of school infrastructure were repeated for each student in each municipality analyzed and this could cause dependency and correlations between the observations. Attempting to minimize this issue, a variance correction factor was used in every equation using STATA's robust cluster variance estimator.

Even though the age-grade distortion variable takes the value of 1 or 0 for students with or without age/grade gaps, in our sample the age/grade gap may range from 0 to 8 years. Thus, students who have never fallen behind in school have a 0 age/grade gap while students with serious age-grade distortion may have age grade gaps of 8 years. To determine how the above mentioned explanatory variables affect the age/grade gap, the ordered probit model was adopted. For this model, based on Greene (2003) and Maddala (1983), consider the following equation:

$$y^* = \mathbf{x}'\boldsymbol{\beta} + \varepsilon \qquad (2)$$

where y^* is not observed but we know the J category it belongs to. Thus, we observe:

$$\begin{aligned} y &= 0 \quad \text{if} \quad y^* \leq 0, \\ y &= 1 \quad \text{if} \quad 0 \leq y^* \leq \mu_1, \\ y &= 2 \quad \text{if} \quad \mu_1 \leq y^* \leq \mu_2, \\ &\vdots \\ y &= J \quad \text{if} \quad \mu_{J-1} \leq y^*. \end{aligned}$$

where $\boldsymbol{\beta}$ and μ are parameters to be estimated, **x** are exogenous variables observed and ε is the error term for non observable factors.

Assuming ε has a normal distribution, we have the following probabilities:

$$
\begin{aligned}
&\Pr(y=0|\mathbf{x}) = \Phi(-\mathbf{x}'\boldsymbol{\beta}),\\
&\Pr(y=1|\mathbf{x}) = \Phi(\mu_1-\mathbf{x}'\boldsymbol{\beta})-\Phi(-\mathbf{x}'\boldsymbol{\beta}),\\
&\Pr(y=2|\mathbf{x}) = \Phi(\mu_2-\mathbf{x}'\boldsymbol{\beta})-\Phi(\mu_1-\mathbf{x}'\boldsymbol{\beta}),\\
&\vdots\\
&\Pr(y=J|\mathbf{x}) = 1-\Phi(\mu_{J-1}-\mathbf{x}'\boldsymbol{\beta}).
\end{aligned}
$$

For the probabilities to be positive, the following is required:

$$0<\mu_1<\mu_2<\cdots<\mu_{J-1}.$$

Considering $z_{ij}=1$ if y^* falls in the jth category and $z_{ij}=0$ otherwise, for $i=1,2,\dots,n$ and, $j=1,2,\dots,J$ therefore:

$$\Pr(z_{ij}=1|\mathbf{x}) = \Phi(\mu_j-\mathbf{x}'\boldsymbol{\beta})-\Phi(\mu_{j-1}-\mathbf{x}'\boldsymbol{\beta})$$

And the log-likelihood function will be:

$$\log L=\sum_{i=1}^{n}\sum_{j=1}^{J} z_{ij}\log\left[\Phi(\mu_j-\mathbf{x}'\boldsymbol{\beta})-\Phi(\mu_{j-1}-\mathbf{x}'\boldsymbol{\beta})\right]$$

Once the parameters have been estimated, marginal effects are obtained as follows:

$$
\begin{aligned}
&\frac{\partial \Pr(y=0|\mathbf{x})}{\partial \mathbf{x}} = -\phi(\mathbf{x}'\boldsymbol{\beta})\boldsymbol{\beta},\\
&\frac{\partial \Pr(y=1|\mathbf{x})}{\partial \mathbf{x}} = \left[\phi(-\mathbf{x}'\boldsymbol{\beta})-\phi(\mu_1-\mathbf{x}'\boldsymbol{\beta})\right]\boldsymbol{\beta},\\
&\vdots\\
&\frac{\partial \Pr(y=J|\mathbf{x})}{\partial \mathbf{x}} = \phi(\mu_{J-1}-\mathbf{x}'\boldsymbol{\beta})\boldsymbol{\beta}.
\end{aligned}
$$

Selected data bases used to obtain the above mentioned variables are described below.

1.2 Data

To obtain the results that will be presented later, the study used the Demographic Census, collected by the Brazilian Institute of Geography and Statistics (IBGE) as well as the School Census and FNDE transfers made by the Ministry of Education and Sports (MEC).

The Demographic Census takes place every 10 years and in 2000 it took place from August 1 to November 30. Selected variables from this data bank were student´s personal and family characteristics and teacher´s income and average education.

The goal of the School Census is to provide information to allow researchers to evaluate the reality of the Brazilian education system. In 2000, the School Census took place in April and included 266.7 thousand schools, 52.7 million students registered in the system (early childhood education, primary education and middle education) and 2.2 million Teaching Functions. Based on information from the School Census, variables regarding the number of schools with libraries, IT laboratories and micro computers available to students were selected, in addition to the number of students per class in each municipality in both states. [1]

The National Fund for the Development of Education (FNDE) has been the MEC body responsible for student aid policies and basic education financing. [2] The National School Meal Program (PNAE) and the Direct Transfers to Schools Program (PDDE) are some of the programs for which FNDE is responsible. In 2000, PNAE distributed afternoon snacks to over 37 million students in the education system. Financial resources transferred by PDDE benefited more than 31 million students from different schools in the country (Ministério da Educação e Desporto, 2001). These two programs were chosen because they are national programs and the number of students who benefit from these programs is almost equal to the total number of students enrolled in primary education. The programs were included in the model as a proxy for the most relevant government investments in the education system in order to analyze their impact on student performance.

2. Empirical Outcomes

To conduct the analysis suggested in this paper, individuals between the ages of 8 and 23 who had not completed primary education were identified. From this total, individuals who answered that they were not in school were eliminated to be able to focus our analysis only on students. In Sao Paulo, these individuals represented 98% of the total number of students and in Pernambuco they represented 95%. Students who responded that they were the head of the household were excluded since head of household characteristics had already been included in the study as explanatory variables. We know that the most important education policies adopted during the 90's were mainly oriented towards primary public schools, so from the total number of students, only those who said that they were studying in public schools were selected.

The variable that represents the age-grade gap was obtained by taking into consideration MEC's criteria to calculate the age-grade distortion rate, which represents the percentage of students older than the recommended age. This criterion assumes that students who were apparently below the correct grade for their age when the School Census took place could have been in the right age

[1] The first question in the School Census questionnaire refers to school facilities, including whether IT laboratories are available to students. In another question, the school has to describe IT equipment available at the time. In this case, the school answers whether there are any micro computers in the school, which must not necessarily be made available to students; they might be in the conference room, teachers' lounge, etc..

[2] In Brazil, basic education includes early childhood education, primary education (basic education) and middle education.

when they were enrolled. The Demographic Census considered as reference the week from July 23 to July 29, 2000 and only asked respondents their age but did not inquire about their date of birth. Thus, students aged 9 in July 2000 who answered that they were in the second grade could have been 8 years old at the beginning of 2000 and this would not have been considered an age/grade gap. Taking this fact into account, this study adopted the following criteria: only 1st grade students over 8, second grade students over 9 and so on, ending with 8th grade students over 15 are considered to be lagging. Thus, in the probit model, the variable for age/grade gaps is a binary variable identified as 1 if a student is one or 2 years behind the correct grade for his/her age and identified as 0 if the student is in the right grade according to his/her age. The age/grade gap in the ordered probit model is the number of years the student has fallen behind, which varies from 0 to 8.

The explanatory variables selected were: teachers' average level of education in number of years and average teacher salaries. Individuals from both states who said that they were primary school teachers were identified. Then average years of schooling and average income were calculated for each municipality in both states. This information was then cross referenced with selected student and family data, repeating the information on variables representing teacher characteristics for each student in the same municipality.

The variables regarding the number of schools with IT laboratories and computers, as well as average students per group were obtained using school census data. For the first two variables, the total number of schools in each municipality and the number of schools with IT laboratories or micro computers was verified. The proportion of schools with infrastructure improvements of this kind and the average number of students per group were then calculated for each municipality. In addition, FNDE program amounts are transferred directly to municipalities or eligible schools and this study obtained information on transfers made in 2000 to each municipality in the states of Sao Paulo and Pernambuco. Based on these data, average transfers per student/grade were calculated. For the analysis, school census and FNDE data were repeated for each student in each municipality.

An econometric analysis of age-grade distortion equations was only conducted for urban areas in the states of Pernambuco and Sao Paolo. The maximum likelihood test showed significant differences between urban and rural areas, but due to the peculiar characteristics of rural areas affecting student performance, such as: distance between student's place of residence and school, which is not available in the data bank, high teacher turnover in rural areas, physical school characteristics, which are rather poor in terms of IT laboratories, libraries and other, we limited our research to urban areas.[3]

In addition to variables representing individual, family and school infrastructure characteristics, the analyses also included the interaction between education of the head of household and family income per capita with school infrastructure variables. These interactions could be indicating substitution between the observed variables or revealing complementarity. If education of the head of the household and school infrastructure were substitute goods, raising the education level of the head of the household would reduce problems associated to poor

[3] In the demographic census, urban areas include cities or districts regardless of size, while rural refers to areas outside these boundaries. But in the school census, the definition of urban or rural depends on the school representative, whose answer regarding the location of the school is based on information provided by the land registry. Due to the above, the definition of urban and rural might be different in the demographic census and in the school census.

school infrastructure. On the other hand, if these goods were complementary, students from families with highly educated heads of household would benefit more from improved school infrastructures. A similar analysis can be made for family income per capita.

The regressions that will be analyzed in this paper were estimated by weighing the data using the demographic census sample expansion factor.[4] The weighted averages of the variables used can be found in appendix Table A.1. The following section will discuss the results of the econometric analysis of age-grade distortion, including simulations, to help target public policies. Then interactions and ordered probit results will be presented.

2.1 Probit model analysis

2.1.1 Results

Appendix tables A.2 and A.3 show the marginal effects of the probit model for the states of Sao Paulo and Pernambuco, respectively. The first column shows the results for selected variables, not including interactions. The second column includes interactions with the variable for education of the head of household and the third column shows interactions with the variable for family income per capita. We decided to make three separate regressions because the regression that included all the variables presented multicolinearity issues. Variables representative of meso-regions were included to control for cultural and price differences and for any other potential non-controllable factors in the state.[5]

Results in column 1 show that in both states the coefficients of the variables related to student characteristic were highly significant. In addition, in both states families with higher income per capita are better equipped to look for alternate solutions (such as private tutoring) when a student is having problems keeping up in school, thus reducing the student's probability of falling behind in school. Likewise, more educated household heads are more aware of these difficulties and are even able to help their children by solving any doubts they might have on school subjects. The positive effect that parents' education and the purchasing power of families have on raising the education of individuals was also mentioned by Holmes (1999) in his study for Pakistan. Vasconcellos (2003) confirms the tendency of variables associated to family characteristics in Brazil. Using the Monthly Employment Survey (MEP) for 1984-1997, Lopez de Leon and Menezes-Filho (2002) also stressed the importance of the education of the head of the household. Analyzing 4^{th} and 8^{th} grade primary students, as well as 3^{rd} grade middle education students, these authors observed that the average education of the head of the household was lower among failing students. The authors also found a negative correlation between age/grade gaps and student socioeconomic status.

In the analysis for Sao Paulo, among the variables of school infrastructure, the coefficients of the number of schools with IT laboratories and micro computers were significant and had the

[4] Regressions were examined including the Human Development Index in the Municipalities (HDI-M) as an explanatory variable, but this variable was not significant and did not modify other coefficients. Thus, we decided to present the results not including the HDI-M.

[5] Methodological notes in the demographic census explain that a meso-region is a group of micro-regions, while a micro-region is made up by a group of municipalities, grouped according to natural resources, product organization and integration. Therefore, it is assumed that if a student moves from one municipality to another to study, it will probably be within the same meso-region.

correct sign. In this case, improving the physical condition of schools with equipment that allows students access to technology, could contribute to reducing age-grade distortion. Using data from the demographic census 2000, Rios-Neto, Riani and Cesar (2003) analyzed the probability of 1st and 5th grade primary students making academic progress. In their study, class size had a negative effect while the percentage of teachers with college education, as well as school infrastructure, had a positive impact on the probability of making academic progress in primary education.

In the case of Pernambuco, teacher training reduces age-grade distortion. In addition, concentrating PDDE resources in initiatives oriented towards improving learning conditions in schools also reduces the probability of age-grade gaps. The variables for average number of students per class and the logarithm of average teacher income were significant, but the sign was not the one we had anticipated. Compared to Case and Deaton (1999), these authors argue that students advance more in the education system when there are more teachers per student. Thus, both variables might be affected by variables not observed in the sample.

Econometric problems resulting from the omission of relevant variables are common in this type of analysis. For example, non-controlled effects such as student's cognitive skills, price of goods (such as school material), school distance, etc. could influence results. According to Glewwe (2002), the production function of human capital can include non-observable factors such as student, parents and teachers skill and motivation, as well as management capabilities of those responsible for the school. These omitted variables tend to be correlated with the exogenous variables included and with age/grade gaps, producing tendency and inconsistency in parameter estimates. Another issue is the fact that the variables representing school quality may be endogenous. This happens when high performing students with more educated parents choose high performing schools. Therefore, this research acknowledges the limitations of the available data.

2.1.2 Simulations for public policy purposes

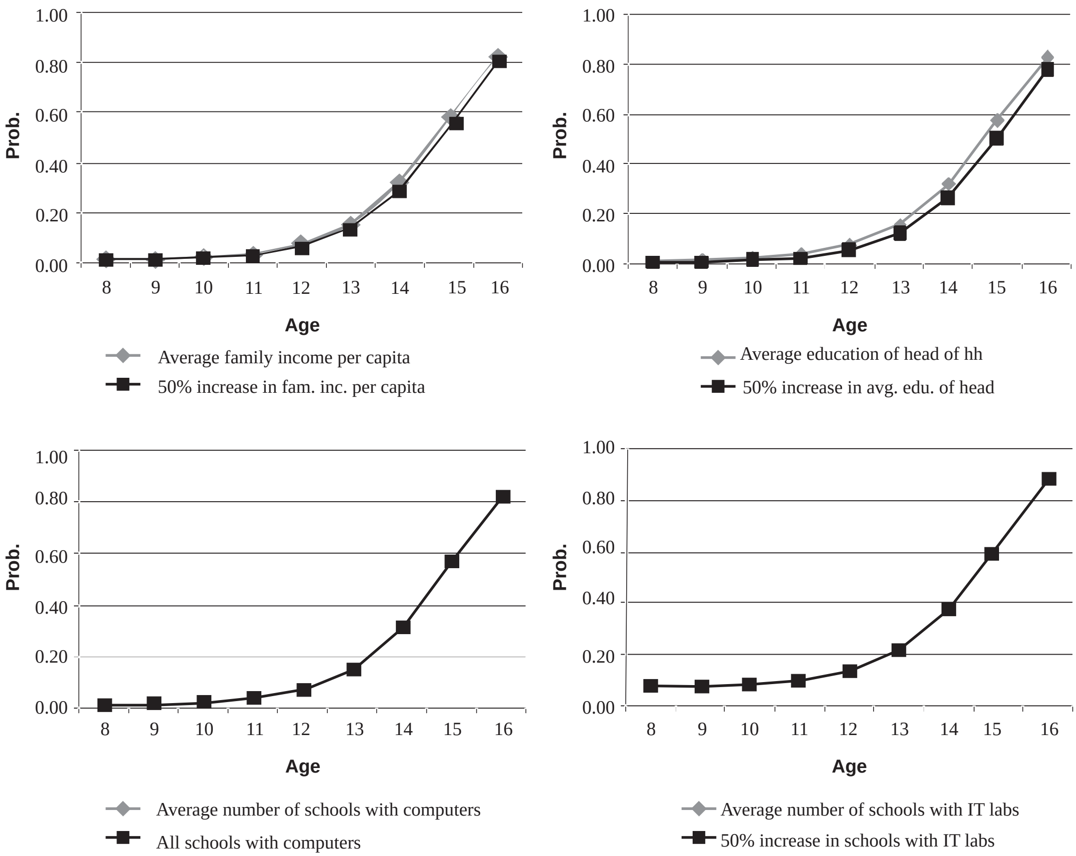
Recent Educational policies show that fighting grade distortion in primary education has become a priority issue in improving the quality of education. In view of the above, this section attempts to analyze the impact of family characteristics and school infrastructure on age-grade distortion, both in Sao Paulo and in Pernambuco. The education of the head of the household will be used to represent family characteristics, based on policies oriented towards the education of young people and adults adopted in the country. Another variable used is family income per capita, representing income transfer programs in Brazil. Variables with significant coefficients and with the correct signs in the first column of the previously described probit models were chosen to represent school infrastructure.

We are aware that as students get older, their probability of falling behind in school increases. Thus, using the coefficients of the probit model, we analyzed the variation in the probability of students being below the correct grade for their age as a function of their age. To do that, the average value of the explanatory variables was used, simulating variations only in the average value of the explanatory variable of interest. We must mention, however, that we considered variations in age/grade gaps that occurred when students were between 8 and 16 years of age because after age 16, all students are below the correct grade for their age.

Simulations in Figure 1 shows the change in the probability of age-grade distortion among Sao Paulo students resulting from variations in family income per capita, average education of the head of household, number of schools with micro computers and IT laboratories. In this case, the grade distortion curve shows a positive slope between the ages of 8 and16, indicating that the older the student, the greater the probability of age-grade distortion. However, this relationship becomes more visible at older ages because the age-grade gap widens. This result could also be influenced by the continuous progress regime, implemented in the state in 1997 (Sao Paulo/CEE, 2004). In view of the above, the number of younger students included in the program is larger than the number of older students.

Family income per capita seems to be a relevant variable in the potential changes a student can go through during his school life. Using age 14 as an example, we can see that the probability of a student falling behind in school decreases from 0.322 to 0.288 when average family income per capita increases 50%. Therefore, this probability varies by 10.4%. Raising the average education

Figure 1
Changes in the Probability of Age-Grade Distortion among Sao Paulo Students after Modifying Four Explanatory Variables

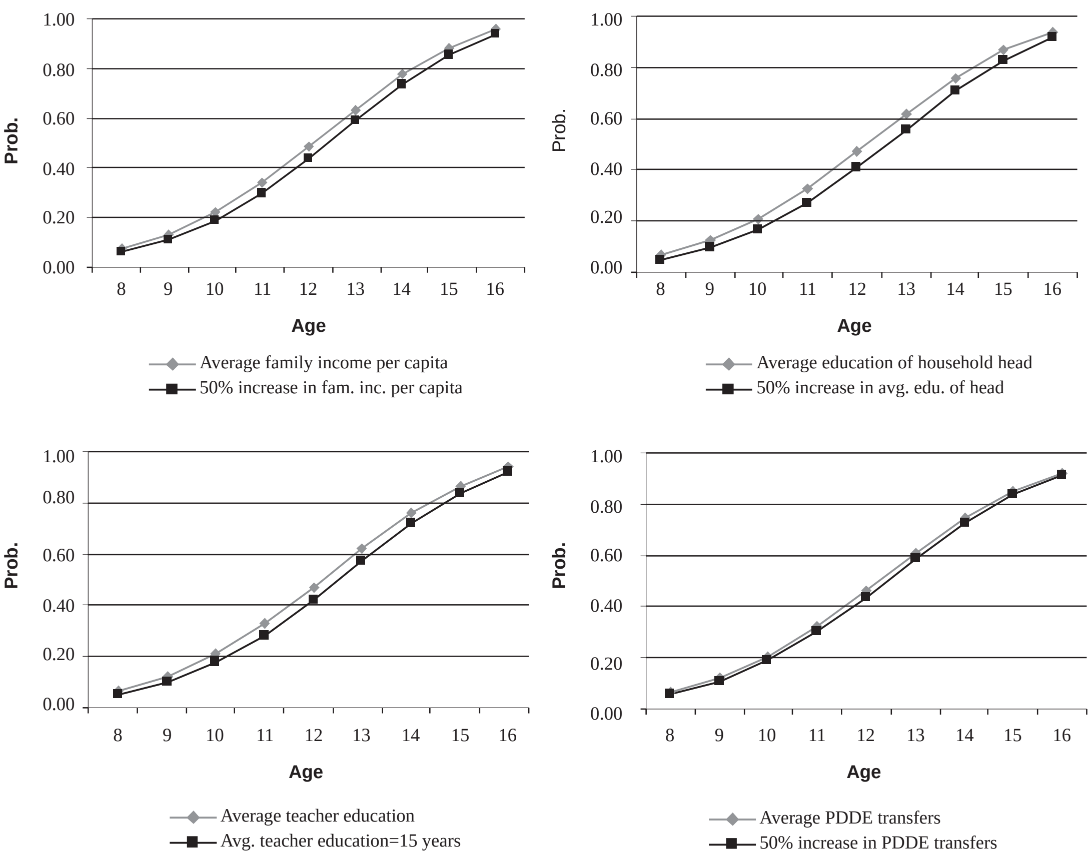


of the head of household by 50% produces changes that are more pronounced than in the previous case. In this case, the average years of schooling of the head of household increase from 5.84 to 8.76 years. This variation reduces age grade/gaps in 14 year old students by 19.7% and potentially to 0.258.

Changes in school infrastructure variables have very little impact on the probability of grade distortion among students. The number of schools with micro computers is now relatively high in Sao Paulo, 0.92 in average. So we simulated all schools had computers. In this case, grade distortion among 14 year old students would only decrease 1.41%. For the number of schools with IT laboratories, assuming the average value of this variable were to increase 50% (from 0.36 to 0.54), there would be a 1.9% fall in age-grade gaps among 14 year old students.

The changes in the probability of age-grade distortion in the state of Pernambuco are a little different from those observed for Sao Paulo (Figure 2). We can see that if average family income

Figure 2
Changes in the Probability of Age/Grade Gaps among Pernambuco Students after Modifying Four Explanatory Variables



per capita increases, grade distortion decreases. While in Pernambuco, percentage variation is lower than the one observed in Sao Paulo, reaching 4.86% among 14 year old students (it falls from 0.757 to 0.72).

Policies oriented towards improving the average education of the head of the household have greater impact in reducing age-grade distortion among students in Pernambuco. We simulated that the average value of this variable increased from 3.9 to 5.9 years of education. Thus, age/grade gaps among 14 year old students would decrease to 0.705, equivalent to a 6.85% reduction.

If primary teachers complete 15 years of school or completed higher education, average teacher education would increase 23%. This change would result in a 5.5% reduction in the probability of 14 year old students falling behind in school. With respect to PDDE transfers, we observed that simulating a 50% increase in average available resources for this program decreased the probability of age/grade gaps among 14 year old students by 2.5%, a percentage that is lower than results observed for other variables.

In the simulations presented in this study, increasing family income per capita by 50% impacts the school indicator that is being analyzed. However, improving the education of the head of the household modifies even more the probability of age/grade gaps. Handa (2002) found similar results in simulations made for Mozambique. In the study by this author, raising the education level of the head of the household increased school enrollment rates by up to 15%, a higher percentage than in other variables observed. Lopez de Leon and Menezes-Filho (2002) observed that family variables (head of household's education and income) gain importance throughout the school cycle when compared to individual student characteristics, particularly when entering higher education. We must point out, however, that these authors did not include infrastructure variables in their regressions.

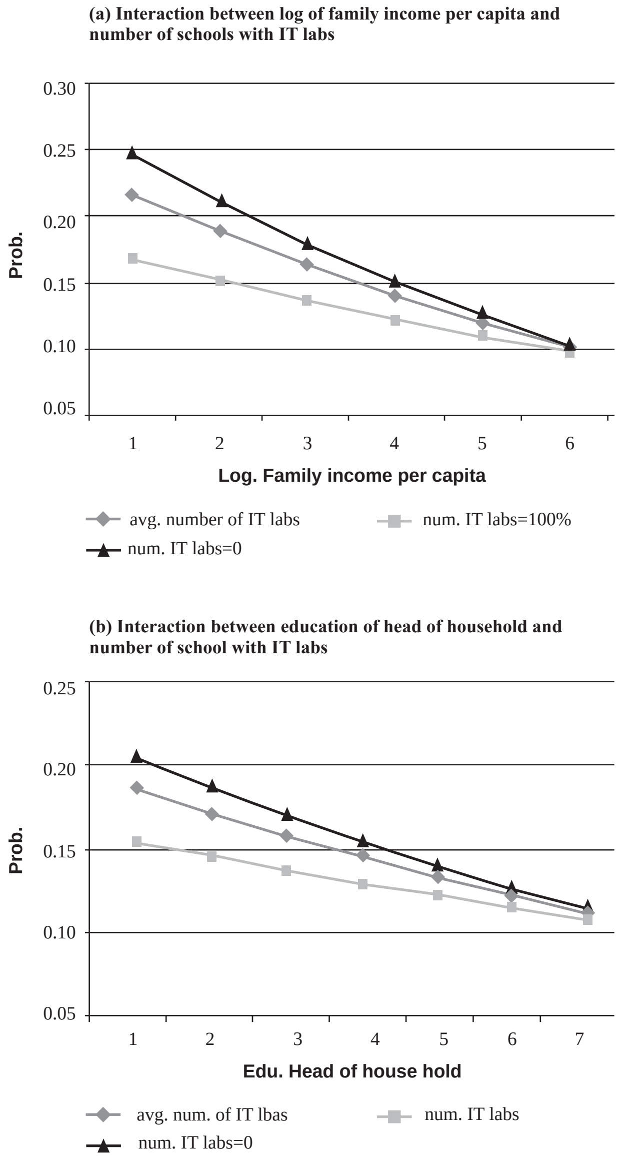
2.2 Interaction results

For interactions, we selected significant school infrastructure variables in regression 1 for both states. These variables were number of schools with IT laboratories and micro computers, for Sao Paulo, and PDDE average transfers and average teacher education for Pernambuco. With respect to coefficient signs, if the sign of the interaction is positive, both are substitute variables in reducing age/grade gaps. A negative sign indicates that both variables are complementary.

Column 2 in Table A.2 shows outcomes for Sao Paulo, including interactions with the education of the head of the household. Only interactions with the number of schools with IT laboratories were significant and they had a positive sign, indicating substitution. In this case, students from families with poorly educated heads of household would benefit the most from public policies on digital inclusion oriented toward ensuring academic success. The interaction between school infrastructure in Sao Paulo and the logarithm of family income per capita can be seen in column 3 of Table A.2. Only the coefficient of interaction with the number of schools with IT laboratories was significant and had a positive sign, indicating that these are substitute goods. Therefore, income transfer programs for poor families could prove to be effective instruments to ensure student promotion, particularly in places where physical school infrastructure is below the desired level.

Figure 3 shows the impact of the interaction between the number of schools with IT laboratories and family income per capita on age-grade distortion among Sao Paulo students

Figure 3
(a) Effects of the Interaction between the Logarithm for Family Income Per Capita and the Number of Schools with IT Laboratories on Age Grade Retardation in Sao Paulo; (b) Effects of the Interaction between the Education of the Head of the Household and the Number of Schools with IT Laboratories on Age Grade Retardation in Sao Paulo



(panel *a*). Panel *b* shows the interaction between the number of schools with IT laboratories and the education of the head of the household. In this case, the horizontal line in panel *a* represents the logarithm of family income per capita, while in panel *b*, this line represents the years of schooling of the head of the household. In both panels, the line in the middle represents the outcomes for the average number of schools with IT laboratories. All variables constant, reducing the number of schools with IT laboratories increases the probability of grade distortion. On the contrary, increasing this number reduces the probability of grade distortion. However, the impact of these changes depends on family income per capita and on the education of the head of the household.

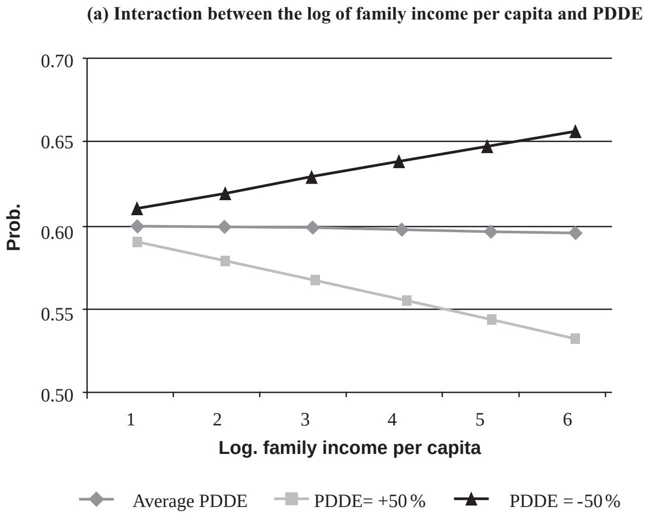
As we can see in panel *a*, when the logarithm of family income per capita is lower, increasing the number of schools with IT laboratories reduces the probability of age/grade gaps more than when the logarithm of family income per capita is higher. If all schools had IT laboratories, age/grade gaps would decrease 14.1% at the lowest income level and 1.5% at the highest income level. The same can be observed in the interaction with the education of the head of the household (panel *b*), where age-grade distortion decreased 10.6% at the lowest education level (1 year) and 1.9% at the highest education level (7 years). This confirms that students from poor families and/or poorly educated parents benefit the most from public policies oriented towards improving school infrastructure.

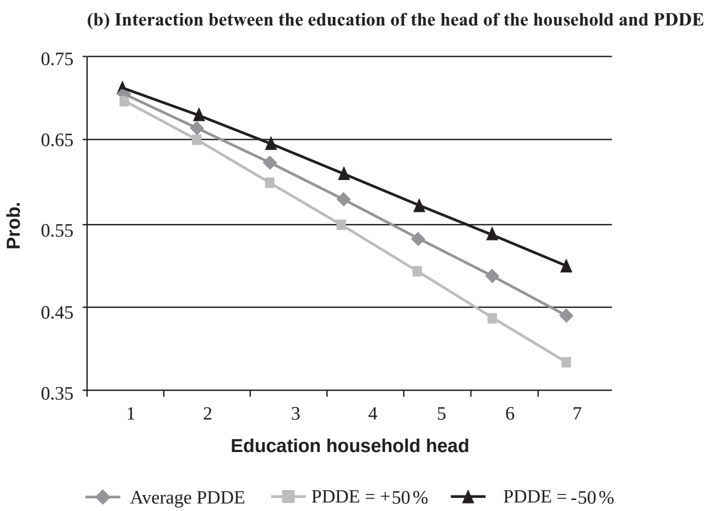
For Pernambuco, interactions between school infrastructure and both the education of the head of the family and the logarithm of family income per capita are presented in the regressions in columns 2 and 3 of Table A.3. In both cases, interaction with PDDE transfers was significant at the 1% level and had a negative sign. This indicates that the variables observed are complementary goods. In this case, public policies targeting the State of Pernambuco should simultaneously invest in improving the income level and the education of the head of the household and in programs oriented towards providing additional financial resources to schools and improving school infrastructure if the goal is to improve the academic performance of the poorest students.

Interaction effects for the state of Pernambuco can be seen in Figure 4. The logarithm of family income per capita and the years of schooling of the head of the household are presented in the horizontal line in panels *a* and *b*, respectively. The center line represents average PDDE transfer outcomes and changes are observed when transfer amounts are increased or red uced by 50%. Since these variables are complementary, in panel *b*, for example, when the education of the head of the household is the lowest possible (1 year), increasing PDDE transfers reduces the probability of age-grade distortion by approximately 1%. For heads of household with 7 years of schooling, increasing PDDE transfers reduces the probability of age/grade gaps by 13%. Notice that increasing the education of the head of the household magnifies the impact of increased PDDE transfers on age-grade distortion among Pernambuco students. A similar analysis can be conducted for results shown in panel *a*.

Using 1998 PNAD data for Brazil, Rios-Neto, Cesar and Riani (2002), showed that the variables for average teacher education and mother's education were substitute goods in the probability of grade promotion. However, these authors did not cross reference data with the MEC data bank to explore other school infrastructure characteristics as this study does.

Figure 4
(a) Effects of the Interaction between the Logarithm of Family Income Per Capita and PDDE Transfers on Age-Grade Distortion in Pernambuco; (b) Effects of the Interaction between the Education of the Head of the Household and PDDE Transfers on Age-Grade Distortion in Pernambuco





2.3 Ordered probit analysis

Table 1 shows the number and the percentage of students with age/grade gaps, by number of years above the correct grade for their age, in both states selected for the analysis. In this table we can see that 46.6% of the students in Pernambuco showed no grade distortion. In Sao Paulo, this percentage increases to 80.7%. In addition, in both states, the largest number of individuals is concentrated in the first two levels, that is, 12.6% of the students in Sao Paulo had an age grade gap of between 1 and 2 years, while among Pernambuco students this percentage was 28%. We can also see that the number and the percentage of students with age/grade gaps decreases as the number of years above the correct grade for their age increases.

Considering the econometric analysis so far, we question whether the explanatory variables used to explain the probability of students falling behind in school would have the same impact on the magnitude of the age/grade gap, measured as the number of years above the correct grade for their age. In this case, the ordered Probit model was used to test whether age-grade distortion determinants also determine its severity.

Ordered Probit results for the state of Sao Paulo can be seen in Table 2. The regression was ran using the same explanatory variables used in the Probit model. However, since we are trying to focus on variables associated to family characteristics and school infrastructure, only their coefficients are presented. Table 2 shows that, for Sao Paulo, the coefficients of variables representative of family income per capita and education of the head of the household remained significant and had a negative sign. With respect to the two variables representing school infrastructure, only the number of schools with micro computers remained significant. Thus, increasing the education of the head of the household by one year decreases the probability of a student being, for example, two years above the correct grade for their age (j=2) by approximately 0.25%.

Table 1
Number and Percentage of Individuals with Age-Grade Distortion in the States of Sao Paulo and Pernambuco, by Number of Years above the Correct Grade for their Age

Number of Years Overage	State			
	São Paulo		Pernambuco	
	Number	%	Number	%
0	354,097	80.68	42,537	46.58
1	35,962	8.19	14,512	15.89
2	19,335	4.41	11,059	12.11
3	12,106	2.76	8,634	9.45
4	6,333	1.44	5,637	6.17
5	3,637	0.83	3,771	4.13
6	2,392	0.54	2,429	2.66
7	3,032	0.69	1,633	1.79
8	2,010	0.46	1,106	1.21

Source: Own elaboration using Demographic Census/2000-IBGE data.

Table 2
Ordered Probit Marginal Effects for Age-Grade Distortion in Primary Public Schools in Urban Areas in Sao Paulo for each *j* Gap (Selected Variables)[1]

Age/Grade Gap	Explanatory Variables			
	Log of family income per capita	House head's education	Number of schools with micro computers	Number of schools with IT laboratories
j = 1	-0.0099421*	-0.0060246*	-0.0156885***	-0.0087567
j = 2	-0.0041055*	-0.0024878*	-0.0064785***	-0.003616
j = 3	-0.0015539*	-0.0009416*	-0.0024521***	-0.0013687
j = 4	-0.0004887*	-0.0002501*	-0.0006582***	-0.0012987
j = 5	-0.0001328*	-0.0000679*	-0.0001788***	-0.0003528
j = 6	-0.0000417*	-0.0000213*	-0.0000562***	-0.0001108
j = 7	-0.0000219*	-0.0000112*	-0.0000295***	-0.0000581
j = 8	$-2.27x10^{-6}$*	$-1.16x10^{-6}$*	$-3.05x10^{-6}$***	$-6.03x10^{-6}$

Source: Estimation results.
[1] Control variables presented in the Probit model were included but not all were presented.
*Significant at the 1% level; **significant at the 5% level; ***significant at the 10% level.

We found that the absolute value of the impact of the explanatory variables on the dependent variables decreases as the age/grade gap increases. Keep in mind that grade distortion is directly linked to the individual's age. Thus, individuals that are six, seven or eight years above the correct grade for their age are older and other economic and social factors might be affecting their academic performance.

Regarding Pernambuco, Table 3 shows that both variables for family characteristics and variables for school infrastructure remain significant and negative.[6] It is therefore confirmed that increasing family income per capita or the education of the head of the household, or the average years of teachers, or average PDDE transfers, could reduce the probability of age-grade distortion at any level.

Notice that, unlike Sao Paulo, the absolute value of the marginal effects increases between the age/grade gap of 1 to 2 years and remains almost constant between the age/grade gap of 2 to 3 years, and only then does it start to fall until it reaches the age/grade gap of 8 years. Thus, a 1% increase in the logarithm of family income per capita would reduce, for example, the probability of students being 3 years above the correct grade for their age by 1.2 percentage points.

[6] The variables for school infrastructure included in Tables 2 and 3 are those which were significant and had the correct sign in Probit regressions. The results for other school infrastructure variables in the ordered probit model were similar to those in the probit model, shown in Tables A.1 and A.2 in the Appendix.

Table 3
Ordered Probit Marginal Effects for Age-Grade Distortion in Primary Education in Urban Public Schools in Pernambuco, for each *j* Age/Grade Gap (Selected Variables) [1]

Age/Grade Gap	Explanatory Variables			
	Log of family income per capita	Education of household head	Average teacher's education in years	PDDE transfers (average)
$j = 1$	-0.0023521*	-0.0017602*	-0.0012260**	-0.0002316**
$j = 2$	-0.0121494*	-0.0090919*	-0.0063325**	-0.0011961*
$j = 3$	-0.0120483*	-0.0090163*	-0.0062798**	-0.0011862*
$j = 4$	-0.0062643*	-0.0046878*	-0.0032650**	-0.0006167*
$j = 5$	-0.0024545*	-0.0018368*	-0.0012793**	-0.0002417*
$j = 6$	-0.0006996*	-0.0005235*	-0.0003646**	-0.0000689*
$j = 7$	-0.0001595*	-0.0001193*	-0.0000831**	-0.0000157*
$j = 8$	-0.0000192*	-0.0000144*	-0.0000100**	-1.89x10-6*

Source: Estimation results.
[1] Control variables presented in the Probit model were included but not all were presented.
*Significant at the 1% level; **significant at the 5% level; ***significant at the 10% level.

3. Conclusion

This paper assesses the impact of family characteristics and school infrastructure on age/grade gaps in primary education in public schools. Comparative analysis was performed between Sao Paulo and Pernambuco, taking into account the socioeconomic differences between both regions. To achieve our objective, both a probit model and an ordered probit model were estimated for urban areas in both states. In the first case, the dependent variable was whether students were above the correct grade for their age or not and in the second case, the number of years above the correct grade for their age.

Probit estimates showed that in both states individual and family characteristics affect age-grade distortion. Thus, we can conclude that improving the socioeconomic status of families contributes to reducing age/grade gaps. It must be pointed out, however, that the magnitude of the coefficients associated to family characteristics was greater in the state of Sao Paulo than in Pernambuco, indicating that these variables have a greater impact on the academic performance of Sao Paulo students.

School infrastructure variables include the number of schools with micro computers and the number of schools with IT laboratories, for Sao Paulo. For Pernamubco, the variables that impact age-grade distortion the most were number of schools with IT laboratories and average PDDE transfers (government income transfer to school). These results indicate that investing in improving these variables could reduce age-grade gaps among primary students in the states analyzed.

Policy simulations compared the impact of improving school infrastructure versus improving the variables for family characteristics on age-grade distortion among students in Pernambuco and Sao Paulo. Both in Pernambuco and Sao Paulo, raising the level of education of the head of the household had a greater impact on the dependent variable than investing in improving the other variables analyzed in this study, but family income per capita simulations were also significant. This result indicates that existing income transfer programs in both states could be effective. Thus, we can conclude that public initiatives concerned with reducing age-grade distortion in the states analyzed in this study should be oriented towards improving the socioeconomic status of families since this has a positive impact on primary students.

Even though they have a greater impact on age/grade gaps, investments to improve the socioeconomic status of families only produce effective results in the long term. For example, to raise the average level of education of the head of the household, incentives for parents to complete primary education would be required. Since these individuals are already working and the opportunity cost of their time is higher than for students, their motivation to study may diminish over the years, leading them to abandon their studies. In this case, efforts could be directed towards inserting and retaining students in school so that they may become better educated adults capable of earning better salaries in the labor market and encouraging their own children to study. But for this to be possible, students should be able to access quality education capable of ensuring that they will absorb basic knowledge. Thus, we believe that in the short term, public policies oriented towards improving school infrastructure are more effective and should be adopted in both states.

Interactions were used to explore substitution or complementarity effects between family and infrastructure characteristics. Outcomes for the state of Sao Paulo lead us to conclude that the lower the education level of the head of the household and/or family income per capita, the greater the effect of increasing the number of schools with IT laboratories has on the probability of age-grade distortion. In interactions used for Pernambuco, complementarity was observed between the variables for family income per capita and education of the head of the household and PDDE resources. Thus, we can conclude that to encourage Pernambuco students to acquire knowledge, investments in public policies oriented towards improving both family characteristics and available school infrastructure resources are required.

The ordered probit model confirmed the results observed in the probit model, indicating that variables for family characteristics and school infrastructure impact age-grade gap rates. Thus, improving family and school conditions would not only reduce the probability of age-grade distortion among students but would also reach individuals with different age-grade gaps.

On the other hand, decisions regarding the best policy to adopt depend on the relative costs of each investment. Thus, we suggest taking into account the costs associated to the socioeconomic improvements mentioned in this paper.

Appendix

Table A.1
Average and Standard Deviation in Variables to be used in the Regressions for Age Grade Retardation in Sao Paulo and Pernambuco

Variables	São Paulo		Pernambuco	
	Average	Standard Deviation	Average	Standard Deviation
Age grade retardation	0.199	0.395	0.534	0.499
Age/grade gap	0.473	1.252	1.522	1.956
Age	11.784	2.626	12.665	3.103
Age square	145.764	66.321	170.021	83.802
Sex (student = 1)	0.519	0.499	0.517	0.499
Colo or race				
White	0.648	0.477	0.344	0.475
Black	0.043	0.203	0.046	0.21
Yellow	0.004	0.065	0.001	0.032
Brown	0.297	0.457	0.6	0.489
Sao Paulo Meso-regions				
Metropolitan	0.522	0.499		
Sao Jose de Rio Preto	0.034	0.182		
Ribeirao Preto	0.059	0.237		
Aracatuba	0.016	0.125		
Bauru	0.035	0.184		
Araraquara	0.019	0.137		
Piracicaba	0.034	0.182		
Campinas	0.088	0.283		
President Prudente	0.019	0.138		
Marilia	0.01	0.101		
Assis	0.014	0.117		
Itapetininga	0.019	0.137		
Macro-regiao	0.059	0.237		
Vale do Paraiba	0.056	0.233		
Litoral Sul	0.011	0.105		
Pernambuco Meso-regions				
Metropolitan			0.467	0.499
Sertao Pernambucano			0.099	0.299
Sao Francisco			0.054	0.226
Agreste Pernambucano			0.216	0.411
Zona da Mata			0.163	0.369

Table A.1 (continued)

Variables	São Paulo		Pernambuco	
	Average	Standard Deviation	Average	Standard Deviation
Family Characteristics				
Family income per capita	210.597	275.427	84.328	233.819
Log of family income per capita	4.793	1.368	3.761	1.439
Age of head of household	41.309	9.339	44	11.796
Education of head of household	5.843	3.678	3.904	3.548
Sex of head of household (male = 1)	0.772	0.419	0.689	0.463
School infrastructure characteristics				
Average teacher education (number of years)	13.259	0.487	12.194	0.608
Average teacher salary	858.349	156.199	344.647	82.553
Log of average teacher salary	6.729	0.341	5.814	0.238
Number of schools with micro computers	0.923	0.098		
Number of schools with IT laboratories	0.359	0.159	0.068	0.07
Average students per class	34,902	2,523	34,539	0,149
PDDE transfers (average)	21.192	24,084	12,073	3,080

Table A.2
Marginal Effects of Probit Regressions for Age Grade Retardation in Public Primary Schools in Urban Areas in Sao Paulo

Variables	Regression 1	Regression 2	Regression 3
Age	-0.18061*	-0.18053*	-0.18057*
Age square	0.01079*	0.01078*	0.01079*
Sex (male = 1)	0.04729*	0.04728*	0.04730*
Color or race (White was omitted)			
Black	0.05705*	0.05701*	0.05700*
Yellow	-0.02733*	-0.02753*	-0.02719*
Brown	0.03631*	0.03636*	0.03633*
Meso-regions (Metropolitan area was omitted)			
Sao José do Rio Preto	-0.01794**	-0.01768**	-0.01768**
Ribeirao Preto	-0.00368	-0.00353	-0.00341
Aracatuba	-0.02435**	-0.02435**	-0.02403**
Bauru	-0.0027	-0.00249	-0.00242
Araraquara	-0.02463*	-0.02431*	-0.02437*
Piracicaba	-0.00729	-0.00697	-0.00685
Campinas	0.00899	0.00911	0.00928
Presidente Prudente	-0.03649*	-0.03627*	-0.03633*
Marilia	-0.00611	-0.00584	-0.00583
Assis	-0.0131	-0.01288	-0.01283
Itapetininga	0.00832	0.00832	0.00845
Macro-regiao	-0.01239**	-0.01223**	-0.01217**
Vale do Paraiba	-0.01006	-0.0097	-0.00989
Litoral Sul	0.00396	0.00408	0.00412
Family characteristics			
Log of family income per capita	-0.02048*	-0.02049*	-0.02388*
Age of head of household	-0.00115*	-0.00115*	-0.00115*
Education of head of household	-0.01304*	-0.01313*	-0.01305*
Sex of head of household (male = 1)	-0.02239*	-0.02238*	-0.02239*
School infrastructure characteristics			
Average teacher education (number of years)	-0.00179	-0.00177	-0.00176
Log of average teacher salary	0.01815	0.01804	0.01794
Number of schools with micro computers	-0.03408**	-0.02406	-0.03169
Number of schools with IT laboratories	-0.01950***	-0.04643*	-0.06781*
Average students per class	-0.00037	-0.00033	-0.00034
PDDE transfers (average)	0.00024*	0.00023*	0.00024*

Table A.2 (continued)

Variables	Regression 1	Regression 2	Regression 3
Interaction between school infrastructure and education of head of household			
Number of schools with micro computers X Education of head of household		-0.00218	
Number of schools with IT laboratories X Education of head of household		0.00572*	
Interaction between school infrastructure and log of family income per capita			
Number of schools with micro computers X Log of family income per capita			-0.00045
Number of schools with IT laboratories X Log of family income per capita			0.01049*
Number of observations	435,044	435,044	435,044
Likelihood Ratio Test	76,871.24*	77,630.84*	80,561.37*

Source: Estimation results.
*Significant at the 1% level; **significant at the 5% level; ***significant at the 10% level.
Note: Variance correction using STATA's robust cluster command.

Table A.3
Marginal Effects of Probit Regressions for Age Grade Retardation in Public Primary Schools in Urban Areas in Pernambuco

Variables	Regression 01	Regression 02	Regression 03
Age	0.08854*	0.08867*	0.08864*
Age square	0.00237*	0.00237*	0.00237*
Sex (male = 1)	0.15153*	0.15162*	0.15150*
Color or race (White was omitted)			
Black	0.08746*	0.08717*	0.08733*
Yellow	-0.0505	-0.05109	-0.05015
Brown	0.04087	0.04074*	0.04081*
Meso-regions (Metropolitan area was omitted)			
Serrato Pernambucano	0.03139	0.03319	0.03298
Agreste Pernambucano	0.03869*	0.04023*	0.04041*
Zona da Mata	0.01453	0.01497	0.01534
Sao Francisco	-0.01347	-0.00997	-0.01167
Family characteristics			
Log of family income per capita	-0.04080*	-0.04059*	-0.01997
Age of head of household	-0.00049**	-0.00052**	-0.00047**
Education of head of household	-0.03135*	-0.02921*	-0.03131*
Sex of head of household (male = 1)	-0.04646*	-0.04739*	-0.04670*
School infrastructure characteristics			
Average teacher education (number of years)	-0.01780**	-0.02039**	-0.00595
Log of average teacher salary	0.04807**	0.04194***	0.04840**
Number of schools with IT laboratories	-0.05526	-0.06256	-0.05736
Number of schools with libraries	-0.00818	-0.00935	-0.00827
Average students per class	-0.00049***	-0.00049***	-0.00049***
PDDE transfers (average)	-0.00382*	-0.00004	-0.0021
Interaction between school infrastructure and education of head of household			
Average teacher years of education X education of head of household		0.00114	
PDDE X Education of head of household		-0.00135*	
Interaction between school infrastructure and log of family income per capita			
Average teacher education (number of years) X log of family income per capita			-0.00328
PDDE X log of family income per capita			-0.00173*
Number of observations	79,930	79,930	79,930
Likelihood Ratio Test	50,176.03*	51,824.16*	51,111.79*

Source: Research results.

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