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Family background and students' achievement on a university entrance exam in Brazil

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This paper examines the determinants of students' performance on the entrance test at Universidade Federal de Pernambuco, Brazil. Particular attention is paid to the importance of family background variables, such as parents' education and family income, on students' performance and how they relate to the probability of attending public schools and private tutoring classes. Results suggest that parents' education and study environment are key determinants of students' achievements. Also, they are positively related to the probability of attending private schools and private tutoring classes, which are both estimated to have a positive effect on test scores. Finally, the quantile regression estimation shows that the effect of parents' education and family income varies across the conditional score distribution. These results highlight the need for developing policies that seek to improve the equality of opportunities in access to higher education. They are of special importance for a developing country like Brazil, in which not only the level of inequality is among the highest in the world but also the level of social intergenerational mobility is among the lowest compared to international standards.

Keywords: academic achievement; family background; quantile regression; Brazil

JEL Codes: J01; J24; C13

1. Introduction

Over the past decades researchers have examined the key determinants of students' performance on standardized achievement tests. Data from England, the USA, and Australia with information on student performance, their family background, and school characteristics have provided researchers with a true live laboratory to answer questions such as the effect of income, work hours, and school characteristics, among others, on students' achievement. This area of study is still new in Brazil. There are few studies evaluating students' performance in test scores, especially in higher education.

In Brazil, according to Emilio, Belluzzo, and Alves (2004), income inequality is strongly related to differences in years of schooling among individuals. Barros and Mendonça (1996), for example, estimate that if the differences in earnings arising from individuals with different levels of education were eliminated, income inequality could be reduced by one half to 1/3. Fernandes and Menezes-Filho (2000) provide

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additional evidence that for each additional year of education acquired at the university, wages increase on average by 20%.[1] Hence, it is crucial to have a better knowledge about the barriers some students face to get into higher education and proceed with their studies.

In this paper we address the question of 'what are the main factors explaining the variation on standardized test scores in Brazil.' We pay particular attention to variables related to family background, such as family income, parents' schooling, among others, in order to understand the obstacles faced by students coming from disadvantaged background to acquire an acceptance letter from a university. For this purpose we use a unique dataset on students' entrance test scores at the Universidade Federal de Pernambuco (UFPE), which is the major university in the Northeast of Brazil.[2] The dataset brings detailed information on students' personal characteristics, such as age, gender, race, religion, family background, high school attended, and their standardized test scores. We use ordinary least squares (OLS) and quantile regression (QR) to estimate not only the mean effect but also the effect of the explanatory variables of interest on different quantiles of the conditional score distribution. The conditional quantile function provides a more complete characterization of the relationship between test scores and students' characteristics, compared to the one given by OLS regression, which concentrates on the first conditional moments.

The paper provides interesting results to both the academic community and policymakers. We document how factors such as parents' education, family income, for instance, affect the average scores of students on entrance tests for the university. We also investigate the interaction between income and the probability of attending public schools and private tutoring classes. From the best of our knowledge this is the first paper in Brazil to address questions such as the connection and the effect of family background, private tutoring, and public schools on the performance of students in entrance tests. In addition to that, we also look at how different the family background effect is across the conditional score distribution. Understanding the relationship between variables related to family background and university entrance test scores is an essential topic to help guiding the development of policies that seek to improve the equality of opportunities in access to higher education. These results are of particular importance to a developing country like Brazil, in which not only the level of inequality is among the highest in the world but also the level of social intergenerational mobility is among the lowest compared to international standards (see Bourguignon, Ferreira, and Menendez 2003; Ferreira and Veloso 2006).

After this brief introduction, Section 2 presents a review of the literature on the effect of family background on educational outcomes. Section 3 describes the methodology and Section 4 presents the data. Section 5 presents the least squares and the QR estimates, and Section 6 concludes.

2. Literature review

Back in 1960s Blau and Duncan (1967) published *The American Occupational Structure*, in which they examined the contribution of fathers' education and occupational status on the achievement of their children. Several studies devoted to analyze the parental influence on kid's educational attainment followed, however, only after a few years, economists tried to fill the gap on the empirical literature by developing models that would rely on utility-maximizing behavior by all participants (see, e.g., Becker and Tomes 1986). The process of children's attainment was then considered within the framework of family behavior, where the family is viewed as a production unit which employs real inputs in order to maximize utility of its members. Adults would make decisions regarding the generation of family resources and also their use, for instance, consumption, asset accumulation, or investment in children. Choices such as fertility, neighborhood in which they raise their children, and the number of location moves are also known to affect the amount invested in children and as a result their attainment.

Parents can also affect the economic position of their children by transferring gifts or bequests to them. Arleen Leibowitz (1974) also considered the fact that the genetic endowments of parents to be passed along to children. Becker and Tomes (1986) considered the inheritability of genetic endowment and cultural endowments as well (e.g., a commitment to learning music). According to them, any decision by parents to alter endowment is described by a Markov process in which the degree of 'inheritability' is taken to be greater than 0, but less than 1. This inheritance will translate into human capital and into earnings on the labor market. Basically, children's ability and the levels of parental income and home investments in time and goods would determine schooling performance and, trough schooling, the level of post-school investment.

Haverman and Wolf (1995) considered a more comprehensive framework where children attainment would depend on basically three primary factors – the choices made by society (or government) that determines the opportunities available to both children and parents (the social investment in children); the choice made by parents regarding the quantity and quality of family resources devoted to children (the parental investment in children); and the choices that children make, given the investments in and opportunities available to them.

In this framework the process of children's attainment would be a sequential one. The government would act first, making some direct investment in children and setting the environment in which both children and parents operate. Parents will then act afterwards in this environment, choosing how much to work and earn, consequently how much time to spend with their children and how much income to devote to them. Also, they make decisions regarding location to live and size of the family, which affect directly the investment in their children. After that, given their ability and resources invested in them, children make their own choices regarding their education, fertility, family structure, and their work effort, that is observed trough their attainment.

It is not our goal to set up a theoretical model here. Instead, we will rely on previous well-established literature, such as Becker and Tomes (1986), Acemoglu and Pischke (2001), and Cunha, Heckman, and Schennack (2010), among others, and test their findings empirically with data on university entrance test scores in Brazil. As mentioned before, we will focus on the role of family background which, according to the models, affects the parental decisions regarding the investment in their children.

Haverman and Wolf (1995) in their comprehensively review of the literature point out the most common findings since early 1970s. Among the determinants of children performance, the most commons are those related to human capital of parents. It is usually statistically significant, no matter how the variables are defined. Most of all, the human capital of the mother is usually more closely related to the attainment of the child than is of the father. Parental completion of high school and one or two years of postsecondary schooling are typically found to have a later effect on children schooling than years of parental schooling beyond this level. According to their review, for the same time span, the income level of the family is positively associated with the education attainment of the child, and the variable is statistically significant in more than half of all cases. Growing up in a family in which the mother chooses to work appears to have a modest adverse effect on education attainment due to loss of childcare time. However, mother's work decision seems to contribute to prevent teenage pregnancy among other risk behavior in early adulthood for girls. With regards to family structure, in all the studies that included proxies for that, the fact that the children is growing up in a one-parent family (or experiencing divorce) is negatively related to the level of schooling attained. Moreover, the number of siblings, the number of geographical moves during childhood, religiousness, schooling, and the presence of books at home are found to have large and significant effect on children performance.

More recent literature such as Carneiro, Meghir, and Perey (2007) show that mother's education increases the child's performances in both math and reading at ages 7–8, but theses effects are not seen at ages 12–14. They also find that, maternal education also reduces the incidence of behavioral problems and reduces grade repetition, but they find no effect on obesity. More educated mothers are more likely to invest in their children through books, providing musical instruments, special tutoring, or availability of computer. Even though they work more, more educated mothers do not spend less time with their children, breast feeding, reading, or taking them on outings.

Acemoglu and Pischke (2001) find that family income, rather than other factors related to family background, explains 27 percentage points of the 36 percentage point difference in the enrollment rates of children in a four-year college. These effects are different between rich and poor family.

Woessmann (2004) estimates how different family background variables may affect students' scores in several European countries and the USA. His main conclusions are that family background has strong and similar effects on both Europe and the USA. France and Flemish Belgium appear to achieve the most equitable performance for students coming from different family backgrounds, while Britain and Germany appear to be the least. He also estimates the model using a QR approach where he concludes that there is weak evidence of variation in the family background influence.

Following these theoretical and empirical findings, we set up our empirical model and estimate it to data on entrance test scores at a university in Brazil.

3. Methodology

In this paper we are particularly interested in estimating the relationship between family background variables and students' achievement on college entrance test scores. Thus, we proceed by estimating the following equation:

$$Y_{is} = a + \beta' X_{is} + \Theta' Z_{is} + \varepsilon_{is} \tag{1}$$

where Y_{is} is student i from school s entrance test score, X_{is} is a vector of family background variables, Z_{is} is a vector of control variables (including school characteristics), and ε_{is} is an error term. The parameters of interest are represented by the vector β.

We also estimate the model without any of the control variables, that is, only including parents' education and/or family monthly income. Thus, we follow Woessmann (2004) that considers the estimated coefficient from this regression without controls as the 'total impact of family background on student performance, including any effect that might work through families' differential access to schools or their influence on school policies' (p. 7). Also, β represents the joint impact of unobservable variables that are correlated with parents' education, such as parents' ability.[3] In the Section 5, we discuss parents' schooling choice decision and other related choices such as private tutoring classes that are shown to significantly affect students' performance.

The estimations are performed using both OLS and QR.[4] In the same way that $\hat{\beta}_{\text{OLS}}$ minimizes the sum of the loss function $(Y_i - X'_i\,\beta)^2$; $\hat{\beta}(\tau)$ minimizes the sum of the following linear loss function $\rho_\tau\,(Y_i - X'_i\,\beta)$.[5] Thus, the τ^{th} conditional quantile function is given by

$$Q_{y_i(\tau|X)=X'\beta(\tau)} \tag{2}$$

The conditional quantile function will give a family of functions, one for each quantile τ, which provides a more complete characterization of the relationship between Y_i and X_i (scores and students' background) compared to the one given by OLS regression, which concentrates on the first conditional moments (Arias, Hallock, and Sosa-Escudero 2001). In addition, Koenker and Portnoy (1997) show that the quantile functions have, in general, the same robustness properties to outlying observations as the ordinary sample quantiles. These robustness properties are very important when the distribution of the disturbance term deviates from the Gaussian distribution. With the quantile model the entrance test scores can be influenced by personal characteristics in different ways at different parts of the distribution. For instance, family income seems to influence student's performance positively. Although the influence of family income is stronger for conditional higher scores than for lower score students, QR has been used extensively in economics to analyze several issues such as gender wage differentials, returns to education and income inequality, and recently to examine students' achievements.[6]

Two important caveats must be mentioned before we proceed to the description of the data and results. The first is that the available dataset includes only students that actually sat for the university entrance exam. Since the decision to take the exam is likely to be correlated with a student's potential score, the estimates of Equation (1) would not reflect the true family background effect. We argue that our estimated parameters are a lower bound for the true effect we interested in estimating. This is because students coming from wealthier families are probably the ones more likely to take the exam when compared to students coming from poorer families. Thus, if, for example, our independent variable is a dummy equal to 1 when mothers have a college degree and 0 otherwise, our hypothesis would imply that the students' ability distribution for the less educated environments would be left censored while the students' ability distribution for the more educated environments would not, or at least not as censored as the distribution for the less education ones. If this is the case, then our results would underestimate the positive impact of parents' education. Emilio, Belluzzo, and Alves (2004) provide, in fact, evidences that our hypothesis is correct. They use data for the University of São Paulo to estimate the probability of being accepted for higher education. To correct for the selection bias arising from the fact that only those individuals taking the entrance exams are observed, they use a Heckman selection type of model. The results show that the effect of fathers' and mothers' education estimated, considering the selection problem, are greater or equal to the ones estimated without the selection correction. Thus, we take our estimates as being a lower bound for their true values.

The second caveat is that rigorously the analysis should be carried out with the dependent variable transformed to reflect the nature of the weighted average score, which is bounded by 0 and 10.[7] Notice, however, that the OLS is not equivariant to monotonic transformation and therefore we cannot recover from the transformed model the true effect of each independent variable on the ETS (see Papke and Wooldridge 1996). Nevertheless, due to the equivariance property of the quantiles, estimation of QR function for continuous fractional data is relatively simple (see Powell 1986; Machado and Silva 2006), specially when there are no mass point at 0 and 10, which is the case of our sample. Since the estimations with the transformed variable, however, did not differ widely from the ones analyzed in this section, and they are easier to interpret, we just report the results for the non-transformed model.

4. The data

In this paper we use a unique dataset on students' entrance test scores at UFPE which is the major university in the Northeast of Brazil. The students were taking the entrance test (*vestibular*) in 2005. University student records data are very rich in characteristics of individuals, the colleges they are applying for, and their previous school. Our dependent variable is their scores on the entrance test.

The explanatory variables can be divided into *personal information and family background* such as age, gender, race, religion, number of siblings, parents' schooling, parents' employment status, family income; *academic history or family investment* such as information on school attended (so we can identify the type of school if private or public, for instance), if had lab classes, foreign language classes, preparation classes to the entrance test, the presence of computer at home, and access to internet; and others account for *Students' Choices* such as the major they choose, if they like reading, if they are working, and how many hours, marital status, and the number of children. We should emphasize that most of these variables will be used as controls in our estimations and we will not give a detailed interpretation for it. Our variables of interest are related to background variables such as, for example, fathers' and mothers' schooling, income, and if parents are working or not. The last one is slightly more difficult to give a causal interpretation since parents' decision to work when the student is finishing high school might be related to other unobservable measures that might influence students' performance. Thus, we will focus on parents' education and income.

4.1. Summary statistics

Table 1 presents summary statistics of the variables used in the analysis. Data on 56,723 students who took the entrance test at the UFPE in 2005 were collected. Cases with missing values of variables included in the study were omitted. This leaves 54,877 students in the sample used in the statistical analysis covering more than 95% of all students with roughly equal numbers of males and females. The dependent variable is the students' achievement on the entrance test, which is a continuous variable that ranges from 0 to 10.

Table 1. Summary statistics.

Variables	Mean	SD
Entrance test scores	4.379	(1.381)
Father education		
Illiterate	.034	(.182)
Incomplete primary	.177	(.382)
Complete primary	.099	(.299)
Incomplete high school	.064	(.246)
Complete high school	.367	(.482)
College degree	.208	(.406)
Master/doctor degree	.05	(.219)
Income		
≤300	.161	(.367)
300–1000	.352	(.478)
1001–1500	.15	(.357)
1501–2000	.111	(.314)
2001–3000	.093	(.290)
3001–5000	.069	(.254)
≥5000	.059	(.236)
Working mother	.507	(.500)
Working father	.615	(.487)
Public school		
Part of high school	.07	(.254)
Complete high school	.332	(.471)
Part of primary	.105	(.306)
Complete primary	.318	(.466)
Private tutoring classes	.413	(.492)
Public tutoring classes	.113	(.316)
Hours worked		
4-hour shift	.123	(.329)
8-hour shift	.134	(.341)
Reading habit	.281	(.449)
Internet user	.359	(.480)
Female	.568	(.495)
Age	20.134	(4.714)
Number of children		
Only one	.033	(.177)
More than one	.024	(.153)
Family size	4.212	(1.163)
Number of entrance tests taken		
One	.287	(.452)
Two	.143	(.350)
More than two	.088	(.283)

Table 1. (*Continued*).

Variables	Mean	SD
Laboratory classes	.364	(.481)
Foreign language	.042	(.201)
Supletivo	.028	(.165)
Religion		
Catholic	.582	(.493)
Protestant	.216	(.411)
Atheist	.111	(.314)
Jewish	.002	(.040)
Race		
White	.466	(.499)
Asian	.048	(.214)
Native Brazilian	.017	(.130)
Pardo (Brown)	.381	(.486)
Black	.087	(.282)
Trial exam	.035	(.183)
	$N = 54,877$	

Our sample consists of students whose average age is 20 years. Around 3% of them have one child and about 2.4% have more than one child. On average 12% of the students are working around four hours per day and 13% on a eight-hour shift. The majority of them classify themselves as white or *pardos*, with only about 9% of blacks.[8] More than 50% of the students are Catholics, 21% are Protestants, 11% declared themselves as atheists, and less than 1% are Jewish.

Notice, however, that the income distribution across families is very unequal as shown by the density of low-income people living with less than R$1000 a month (Table 1).[9] It is worth to stress that this is a reflection of the unequal income distribution in the state and country wise. Most of the students' fathers have either a college degree or have completed high school. Almost 62% of students' fathers are working, while 51% of their mothers have paid jobs. With regards to family size, we can observe that families have about four people in each household on average.

Students were queried about their access to educational resources. In our sample 36% of the students have access to internet, 36% have additional lab classes, and only 4% of the students have extra foreign languages classes. Families may invest in extra private tutoring classes that cover extensively the entrance exam material. In our sample 41% of the students attended private extra tutorial classes and 11% attended tutorial offered by state or local authorities. Only 28% of the students admitted they like reading.

In Brazil, the Education Ministry offers an alternative education method for those individuals who had either dropped off or did not have the chance to go to school at school age. Those are individuals that have usually a large distortion age/grade, sometimes even illiterate adults. This alternative method is called *Supletivo* (Supplementary) and offers short-term courses with a condensed material for different grades. The students can have, for instance, middle school diploma in a one-year course. In our dataset we have the information if the student graduated from *Supletivo* or not, 3% of our sample got a high school *Supletivo* degree.

Students take the entrance exam usually in the year they finish high school. However, if not accepted in their first try, students may take as many exams as they like until being accepted or deciding to go directly to the labor market. Thus, some students try for many years to be admitted at the university, especially in more competitive areas such as medicine or law. In our sample 52% of students have done the exam at least once before the present year we analyze.

When it comes to the education system, 51% of the sample comes from private schools while 24.2% of them studied on the public education system. The rest, 24.4%, acquired part of their schooling in private schools and another part in the public system. Public school students have lower scores compared to private ones, 3.7 against 4.7 (Table 2). They are usually older and from low-income families (e.g., only 3.8% of the students from the private system have income lower than R$300, while in the public system this percentage is about 40%). Public school parents have on average no more than high school degree, i.e., only about 5% of the students' parents have college or a master/doctor degree. For the private school parents, this percentage is about 43%. The students on state-sector schools are more prompt to work more hours and have a slightly higher chance to have more children, compared to private school

Table 2. Summary statistics – public and private school students.

Variables	Private	Public
N =	28,204	13,294
Test score	4.716 (1.405)	3.732 (1.111)
Age	19.321 (4.185)	22.320 (6.284)
Number of children	.06 (.324)	.185 (.573)
Hours Worked		
4-hour shift	.109 (.311)	.157 (.363)
8-hour shift	.084 (.278)	.228 (.420)
Mother education		
Illiterate	.015 (.121)	.084 (.277)
Incomplete primary	.057 (.231)	.376 (.484)
Complete primary	.047 (.211)	.165 (.372)
Incomplete high school	.054 (.226)	.077 (.266)
Complete high school	.4 (.490)	.249 (.433)
College degree	.333 (.471)	.041 (.198)
Master/doctor degree	.095 (.293)	.008 (.088)
Income		
≤300	.038 (.192)	.398 (.490)
300–1000	.225 (.417)	.454 (.498)
1001–1500	.164 (.370)	.075 (.264)
1501–2000	.138 (.345)	.035 (.185)
2001–3000	.13 (.336)	.018 (.134)
3001–5000	.105 (.307)	.008 (.086)
≥5000	.097 (.296)	.003(.055)

Note: Standard deviation in parenthesis.

students. We will not focus on differences between public and private schooling. However, we should emphasize that it is very likely that income is an important channel affecting children schooling choice and consequently their achievement and acceptance for higher education.[10]

5. Results

In this section we analyze the OLS and the QR estimates.

5.1. OLS results

We start by providing estimates for our main variables of interest, i.e., the ones related to family background such as parents education and income. We then discuss and present results for other variables included in our estimated equations.

Not surprisingly, family background is a key determinant of student performance. In Table 3 we present estimates for our three main variables: mothers' and fathers' education and family monthly income. In Columns 1 through 3 we use only mothers' education while in Columns 4 through 6 we use only fathers' education. In Column 7 we include both. In Column 1 we observe that mothers' schooling and students' scores are highly correlated. These results highlight the importance of family characteristics on determining access to higher education and, as a consequence, future wages. As emphasized by Woessmann (2004), understanding how family background affects students' performance and the different channels it might be working through is crucial to help design policies to achieve more equal educational opportunities. This discussion is also related to the literature on intergenerational earnings mobility, which is extremely important for Brazil, a country whose level of inequality is among the highest in the world and whose level of social intergenerational mobility is among the lowest compared to international standards (see Bourguignon, Ferreira, and Menendez 2003; Ferreira and Veloso 2006).

The positive correlation we observe in Column 1 still holds when family monthly income is introduced in the equation (Column 2). In Column 3 we add a few other controls such as age, family size, type of school attended (public or private), among others, and the correlation between mothers' education becomes statistically insignificant for families whose mothers have at most completed high school. On the other hand, for mothers with at least a college degree, a positive and statistically significant effect still exists. The positive correlation between monthly income and performance becomes weaker with the introduction of other control variables but is still large and significant. This reduction in the education and income coefficients is due to the fact that other variables (such as type of school attended, access to internet, or extra tutoring classes, for example) might be capturing part of the education/income effect. We will shortly discuss how income and education are related to the choices made by parents regarding type of school and extra tutoring classes and the impact they might have on students' outcomes.

We decided to investigate if the inclusion of fathers' education instead of mothers' education would modify our results. As expected, the correlation between fathers' education and students' performance is statistically the same as the correlation between mothers' education and students' performance. We do, however, observe a different pattern for fathers' and mothers' if we look at the correlation between

Table 3. Ordinary least squares (OLS) regressions – family background variables.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Mother education							
Incomplete primary	.151***	.059	−.052				−.039
	(.037)	(.036)	(.032)				(.034)
Complete primary	.292***	.122**	−.043				−.035
	(.039)	(.039)	(.034)				(.037)
Incomplete high school	.387***	.161**	−.079**				−.081**
	(.041)	(.041)	(.036)				(.039)
Complete high school	.654***	.324***	−0.01				−.023
	(.035)	(.036)	(.033)				(.035)
College degree	1.214***	.600***	.184***				.135***
	(.037)	(.038)	(.035)				(.038)
Master/doctor degree	1.415***	.685***	.231***				.156***
	(.440)	(.045)	(.042)				(.044)
Father education							
Incomplete primary				.141***	.038	−0.053	−.039
				(.035)	(.035)	(.031)	(.033)
Complete primary				.263***	.094***	−0.04	−.028
				(.038)	(.037)	(.033)	(.035)
Incomplete high school				.398***	.153***	−0.051	−.037
				(.041)	(.040)	(.036)	(.038)
Complete high school				.621***	.277***	0.002	.006
				(.034)	(.035)	(.031)	(.034)
College degree				1.183***	.547***	.189***	.152***
				(.036)	(.037)	(.034)	(.037)
Master/doctor degree				1.585***	.768***	.343***	.290***
				(.046)	(.048)	(.044)	(.046)

Table 3. (*Continued*).

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Income							
300–1000		.321***	.203***		.343***	.207***	.197***
		(.017)	(.016)		(.017)	(.016)	(.016)
1001–1500		.622***	.371***		.649***	.375***	.354***
		(.022)	(.022)		(.022)	(.022)	(.022)
1501–2000		.770***	.462***		.797***	.465***	.434***
		(.025)	(.025)		(.025)	(.025)	(.025)
2001–3000		.964***	.611***		.975***	.602***	.563***
		(.027)	(.028)		(.027)	(.028)	(.028)
3001–5000		1.239***	.809***		1.226***	.784***	.736***
		(.032)	(.032)		(.032)	(.033)	(.033)
≥ 5000		1.350***	.895***		1.321***	.856***	.798***
		(.035)	(.035)		(.035)	(.036)	(.036)
Working mother			.012				.013
			(.012)				(.012)
Working father						.035***	.036***
						(0.012)	(.012)
Controls	No	No	Yes	No	No	Yes	Yes
R^2	.092	.154	.318	.096	.153	.319	.321
				$N = 54{,}877$			

**$p < 0.05$; ***$p < 0.01$.
Note: All regressions include a constant. The dependent variable is the student entrance test score. Controls include students' age, gender, if living with parents, family size, if is working and how many hours, if has access to internet, race, religion, type of school attended (public or private) during primary and secondary schooling, if attended extra tutoring classes, and if had lab classes in high school. Standard deviation presented in parentheses.

students' performance and occupational status. It appears that fathers who are working have, on average, better performing children when compared to other students whose fathers are unemployed. We should emphasize, however, that this variable might be capturing the effect of other unobservable variables (such as fathers' motivation or inherited ability) that we are not able to control for using this dataset.

In Table 4 we investigate three issues related to the influence of family background and two possible channels where inequality of educational opportunity may arise. In Column 1 we present a regression similar to the ones showed in Table 3; however, we include all estimated parameters. We decided to use fathers' education given our results just presented in Table 3.[11] In Column 2 we look at the correlation between fathers' education and income (among a few other covariates included in the regression) and the probability of attending a private tutoring class, and in Column 3 we look at the same correlations but the dependent variable being a dummy indicating if the student attended a public school during his/her primary and secondary education. If both private tutoring classes and public schools are significantly affecting performance (below we discuss causal effects in more details), and if the probability of attending both are affected by income, then one can interpret this as a barrier faced by poorer families that are financially constrained in obtaining a college degree.[12]

Before looking at how fathers' education and income affect the probability of attending a public school or a private tutoring class, let us first look at other considered student characteristics that are related to students' performance. A first important, however, expected result is that publicly operated schools perform worse than private ones. Figure 1 shows the empirical density estimate of the entrance test score for students coming from private and public schools. It shows that public school students' score distribution is located to the left of that for private school students, showing that they perform worse for all quantiles of the empirical score distribution. Moreover, the longer the student remains at the public school system, the worst he/she will perform, i.e., students who spent their entire schooling years (primary and secondary) in a public school are the ones more damaged when compared to students who partially or never studied in a publicly operated establishment.[13] As showed by the World Bank, in Latin America 'private schools offer up to twice as many hours of instruction as public schools, and generally cover the full official curriculum, which ironically, only about 50 percent of the official curriculum is covered in official schools … It is also not surprising that high-income families turn away from public education' (Inter-American Development Bank 1999). This is also the case in Brazil.

Regarding the effect of private and public tutoring classes, it appears that students that had extra private tutoring classes increased their scores significantly as also did students that had public tutoring classes (Column 1, Table 4). However, the effect was twice as large for private tutoring classes when compared to publicly operated ones. This is a key result since it highlights the importance of providing public tutoring classes, which was a policy implemented just a few years ago in attempt to compensate the large advantage students coming from wealthier families had over students coming from poorer environments. One should, however, take both coefficients with caution if causal interpretations are to be derived. For the dummy variable identifying private tutoring classes, it might be the case that it is not only capturing the causal effect of the class itself but other unobservable variables that are determining attendance, such as students' motivation. For the publicly offered classes, local authorities in fact use an exam as a selection process in which the best students enrolled in public schools are selected to participate. This, if not properly accounted for, could bias our

Table 4. Ordinary least square (OLS) regressions.

Variables	**ETS**	**Tutoring Classes**	**Public School**
	(1)	**(2)**	**(3)**
Father education			
Incomplete primary	–.055 (.031)	.018 (.012)	.013 (.012)
Complete primary	–.041 (.033)	.023 (.013)	–.044*** (.013)
Incomplete high school	–.054 (.036)	.016 (.014)	–.123*** (.014)
Complete high school	–.004 (.032)	.010 (.012)	–.160*** (.012)
College degree	.180*** (.034)	.042*** (.013)	–.203*** (.012)
Master/doctor degree	.324*** (.044)	.050*** (.016)	–.175*** (.014)
Income			
300–1000	.204*** (.016)	.120*** (.007)	–.224*** (.006)
1001–1500	.371*** (.022)	.187*** (.009)	–.413*** (.008)
1501–2000	.465*** (.025)	.196*** (.010)	–.451*** (.008)
2001–3000	.609*** (.028)	.218*** (.010)	–.469*** (.008)
3001–5000	.791*** (.033)	.267*** (.012)	–.472*** (.008)
≥ 5000	.860*** (.036)	.346*** (.013)	–.469*** (.008)
Working mother	.043*** (.012)	.034*** (.005)	–.040*** (.004)
Working father	.028** (.012)	.016*** (.005)	–.014*** (.004)
Public school			
Part of high school	–.062*** (.024)	–.007 (.010)	
Complete high school	–.102*** (.019)	–.037*** (.007)	
Part of primary	–.099*** (.021)	.007 (.008)	
Complete primary	–.085*** (.019)	.004 (.007)	
Private tutoring classes	.287*** (.013)		
Public tutoring classes	.140*** (.018)		
Hours worked			
4-hour shift	–.231*** (.017)	–.032*** (.007)	.015** (.006)
8-hour shift	–.321*** (.017)	–.014 (.008)	.088*** (.007)
Reading habit	.264*** (.013)		
Internet user	.200*** (.015)		
Female	–.222*** (.012)	.046*** (.004)	–.017*** (.004)
Age	–.047*** (.002)	–.005*** (.001)	.017*** (.001)
Laboratory classes	.162*** (.013)	.016*** (.005)	–.070*** (.004)
Foreign language	.544*** (.033)	.004 (.012)	–.038*** (.008)
Supletivo	–.390*** (.035)	.079*** (.015)	–.110*** (.013)
Religion			
Catholic	–.247*** (.020)	.038*** (.008)	–.008 (.007)
Protestant	–.192*** (.022)	.021*** (.009)	.073*** (.008)
Atheist	.087*** (.026)	.014 (.010)	.042*** (.009)
Race			
Asian	–.057** (.027)	.002 (.011)	–.003 (.009)
Native Brazilian	–.304*** (.042)	.009 (.017)	.037** (.016)
Pardo (Brown)	.031** (.013)	–.007 (.005)	.044*** (.004)

Table 4. (*Continued*).

Variables	ETS	Tutoring Classes	Public School
	(1)	(2)	(3)
Black	−.080*** (.020)	−.004 (.008)	.096*** (.008)
Controls	Yes	Yes	Yes
R^2	.308	.174	.351
		$N = 54{,}877$	

**$p < 0.05$; ***$p < 0.01$.
Note: All regressions include a constant. The dependent variable in Column 1 is students' entrance test score. In Columns 2 and 3 we run linear probability models in which the dependent variable in Column 2 is a dummy indicating if the student attended extra private tutoring classes and in Column 3 is a dummy indicating if the student studied in a public school. Additional controls include family size, number of exams taken before the present one, and number of kids. Standard deviation presented in parentheses.

estimates of the causal effect of these tutoring classes. One way to assess the potential size of any bias due to unobservables in the equation is to use the methodology proposed by Altonji, Elder, and Taber (2005). In their paper they propose the idea that 'selection on observables is the same as selection on unobservables,' which is equivalent to the condition that $\frac{Cov(u,PC)}{Var(u)} = \frac{Cov(\beta X,PC)}{Var(\beta X)}$ where PC is a dummy equal to 1 if the students attended a private tutoring class, X is a vector of observables characteristics, and u is the error term potentially correlated with PC. As a consequence,

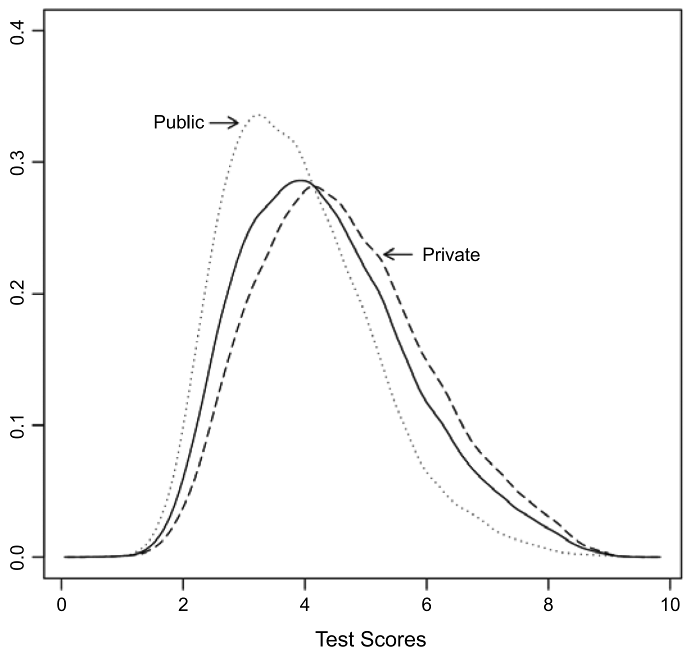

Figure 1. The above plot presents the unconditional densities estimations for student test scores in public (dotted) and private (dashed) schools compared to the density for the entire sample (solid).

the bias from OLS, $\frac{Cov(u,\tilde{P}C)}{Var(\tilde{P}C)}$, where tildes denote the residuals from a regression of *PC* on *X*, can be assessed by the following equation:

$$\frac{Cov(u,\tilde{P}C)}{Var(\tilde{P}C)} = \frac{Cov(u,PC)}{Var(\tilde{P}C)} = \frac{Cov(u,PC)}{Cov(\beta X,PC)}\frac{Var(\beta X)}{Var(u)}\frac{Cov(\beta X,PC)}{Var(\beta X)}\frac{Var(u)}{Var(\tilde{P}C)}$$
$$= \frac{Cov(\beta X,PC)}{Var(\beta X)}\frac{Var(u)}{Var(\tilde{P}C)}$$

where the first equality follows if u and X are orthogonal. The estimated bias we obtain is −.081, which points in the direction that the bias is negative and suggests that the effect of private tutoring classes on ETS is indeed positive. Similar result is obtained for public-operated tutoring classes. Hence, besides any selection problems, the size of the bias due to unobservables appears to be smaller than the estimated coefficients, indicating that classes are indeed effective in improving students' marks.

When it comes to other individual characteristics, female students, on average, have marks that are 2.5 percentage points lower than their male counterparts. This result is not consistent with previous findings in the empirical literature on the determinants of academic success (see, e.g., Birch and Miller 2006). Older students apparently score on average worse than younger students. This result, however, might be a consequence of the fact that less able kids are more likely to repeat grades while in primary and secondary education,[14] which implies that less able children are more likely to finish high school older. Thus, the existence of a correlation between ability and age implies that OLS will deliver biased estimates of the causal effect of age on the outcomes of interest.[15]

Not surprisingly, variables that reflect educational resources such as access to internet, extra laboratory classes, preparation and foreign language classes that are all good proxies for a better study environment, matter for students' performance. Students who reported having access to internet scored higher than student who declared not having access to it. This was also the case of students who reported having lab classes and foreign language classes. Students that declared having reading habits also had higher marks on average.

It is interesting to notice that students' scores are inversely related to the family size. This result reinforces Becker's (1960) idea of quantity versus quality tradeoff. Our estimates show that bigger families are detrimental to students' scores. Li, Zhang, and Zhu (2008) using dataset for China found that the tradeoff is more pronounced for developing countries where the welfare state cannot provide good quality education and health care. In fact, their estimates show that the tradeoff is even more pronounced in rural areas in China. Moreover, this can also be correlated to the fact that the probability of being held back on performance increases very significantly with the number of persons per room in the house, as showed by Goux and Maurin (2005) for data on children in France. Their results holds true regardless of the size of the family or the socioeconomic status of the parents. Although we do not control for house sizes, the family size variable can in fact be capturing this effect.

Asians, native Brazilians, and blacks tend to perform worse than white students. This is not true for *pardos* (brown), who tend to have a higher achievement, when compared to whites. When it comes to religious beliefs, Catholics and Protestants performed worse on average than the ones who declared having other creeds (Jewish, afro-religion, or other). It is interesting to notice that those that declared having no religious beliefs, atheists, scored higher compared to those that declared having some kind of religious beliefs.

There is no consensus on the literature about the effect of hours worked during school on students' current and future performance (Stinebrickner and Stinebrickner 2003). Here we found that work jeopardizes students' achievements. In fact, the higher the number of working hours, the lower the student performance on the test on average. A four-hour shift lowers students' score in 1.7 percentage points, while an eight-hour shift decreases their score by 2.2 percentage point.

As mentioned by Lefebvre and Merrigan (1998), it is already a known fact that child's well-being is strongly related to families' socioeconomic background, the latter consisting of financial resources, human capital (such as innate or learned skills, educational attainment, and health status), personal and psychological resources (such as resilience, positive outlook, and motivation), and social capital (such as community ties, relation with neighbors and friends). It is important to notice that in our model we control for proxies of most of the variables that would compose families' socioeconomic background, and most important, they are all positively related to students' scores. Students who graduated with a *supletivo* degree had, as expected, lower performance on average. Moreover, we controlled for the fact that the student is taking the entrance test just for experience, and it turns out that these students perform worse than the ones taking the test for real.[16]

Now we turn to the analysis of Columns 2 and 3 of Table 4. Let us first look at the relationship between fathers' education and family income and the probability of attending a private tutoring class. As one can observe, fathers' education and family monthly income is highly correlated with attending tutoring classes.[17] Thus, besides the benefits of having educated parents and availability of educational resources, such as access to internet, students coming from wealthier families benefit also from having the opportunity of attending additional tutoring classes, which are extremely effective in increasing students' performance. The same conclusions can be drawn if we look at the probability of attending a public school during primary and secondary education. As shown before, students enrolled in public schools have less educated fathers and are from poorer families when compared to students enrolled in private schools. These evidences are consistent with the common view that the Brazilian educational system is extremely unequal in terms of opportunities and is an important channel through which inequality may persist across generations.

Some of the above results differ for other parts of the distribution, different from the mean. The QR estimates bellow will show the major differences.

5.2. *Quantile regression results: do effects vary across the conditional score distribution?*

In this subsection we analyze the QR estimates from the quantile function $Q_{Y_i}(\tau \mid X) = X'\beta(\tau)$ given by $\beta_i(\tau), i = 1,\ldots, k$ and $\tau \in (0,1)$. We follow the specification presented in Column 5 of Table 3, including only fathers' education and family monthly income as covariates in the regression. Also, in order to make the interpretation of the results easier, we decided to impose two additional strong restrictions on the functional form of the regression to be estimated by linearizing both fathers' education and income.

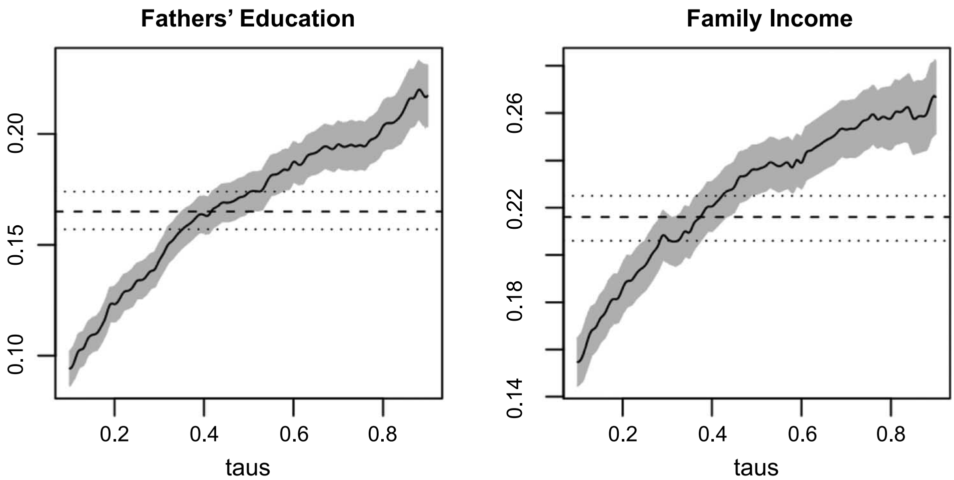

Figure 2. The above plots present the quantile regression estimates for each covariate indicated. The solid lines are the quantile estimates and the shade the 95% confidence intervals. The dotted line presents the ordinary least square estimates and its respective confidence interval.

This restriction should not affect significantly the quantile results given the coefficients presented in Table 3.

The results are displayed in Figure 2. The plots show the QR estimates as well as the 95% confidence intervals. The least square estimates are presented together with its confidence interval as the dotted horizontal lines.

These plots tell a different story from the least square results. Looking first at fathers' education we can observe that at the beginning of the conditional score distribution students do benefit from having a more educated father; however, this effect is twice as large once we move to the other end of the conditional score distribution. This same pattern is observed if we look at family monthly income, where coefficients vary from .15 to .27. This result was also obtained by Woessmann (2004), however, in a much smaller scale. His results show that family background effects do not vary strongly across the conditional score distribution, with a slight increase observed in countries such as Austria, Ireland, Norway, Spain, Sweden, and the USA. One exception, however, is England where coefficients almost doubled in size when moving from the lowest quantile (.10) to the highest (.90). Thus, it seems Brazil is different from most European countries and the USA in terms of how different family background affects students along the conditional score distribution.

6. Conclusions

In this paper we use a unique dataset on students' academic scores at UFPE, which brings information on their standardized entrance tests scores, personal characteristics, such as age, gender, race, religion, family income, parents' education and family size, school attended, tutoring classes, among others. Our goal was to analyze the effect of family background and family investment on students' performance at university entrance test. From the best of our knowledge this is the first paper in Brazil to address questions such as the connection and the effect of family background, private tutoring, and public schools on the performance of students in entrance tests.

Using least squares and QR we found some very interesting results. Following the ones previously obtained in the international literature, we found that family background and study environment are key determinants of student performance. Parental schooling impacts positively students' scores. In a first instance we analyzed the relationship between mothers' schooling and test scores, which are found to be positively and highly correlated. This result is robust to the inclusion of other variables such as family income and students' personal characteristics. The correlation between fathers' education and students' performance is statistically the same as the correlation between mothers' education and students' performance. We do, however, observe a different pattern for fathers and mothers if we look at the correlation between students' performance and occupational status. It appears that fathers who are working have, on average, better performing children when compared to other students whose fathers are unemployed.

The analysis of private and public tutoring classes shows that students that had extra private tutoring classes increased their scores significantly. This is also true for students that had public tutoring classes. The effect, though, was twice as large for private tutoring classes when compared to publicly operated ones. Due to potential selection bias in the process of enrollment, we used the methodology proposed by Altonji, Elder, and Taber (2005) to assess the potential size of bias due to unobservables. This showed that the size of the bias appears to be smaller than the estimated coefficients, indicating that classes are indeed effective in improving students' marks. This is a key result since it highlights the importance of providing public tutoring classes, which was a policy implemented just a few years ago in attempt to compensate the large advantage students coming from wealthier families had over students coming from poorer environments. The effect of attending public schools is also estimated to be negative, that is, scores are reduced for every additional year spent at the public system.

Another result that reinforces the view of an unequal access to higher education in Brazil is the fact that fathers' education and family monthly income are, as expected, highly correlated with attending private schools and tutoring classes. Thus, besides the benefits of having educated parents and availability of educational resources, students coming from wealthier families also benefit from having the opportunity of attending private schools and additional tutoring classes.

Our quantile estimates concentrated on father schooling and family income. With regards to fathers' education, we can observe that at the beginning of the conditional score distribution students do benefit from having a more educated father; however, this effect is twice as large once we move to the other end of the conditional score distribution. This same pattern is observed if we look at family monthly income, where coefficients vary from .15 to .27. This result was also obtained by Woessmann (2004), however, in a much smaller scale.

Above all, the evidences presented here contribute not only by quantifying the effect of family background, public schools, and tutoring classes on test scores, but also by highlighting how the Brazilian educational system, which is similar to several other developing countries, is designed in a way that inequality tends to persist across generations.

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Notes

1. See also Curi and Menezes-Filho (2005) for evidences on how test scores affect wages in Brazil.
2. Established in 1946, the Universidade Federal de Pernambuco is, according to the Education Ministry, the major university on the North/Northeast regions of Brazil. The degrees are offered by 10 colleges of four different areas which consist of 67 departments. The university offers 62 different undergraduate courses, 17 of them are ministered at night. The university also has 108 postgraduate courses, among masters, PhDs and MBAs. In 2004 the university had 25,000 students registered (20,500 were undergrads and 4500 were graduate students) and 1647 professors.
3. This dataset does not allow a separation of these effects.
4. We do not discuss quantile regression in detail. Instead we will just comment on some important properties of this approach, which are useful for this study. We suggest the works of Koenker and Basset (1978), Koenker and Portnoy (1997), and Hallock and Koenker (2001) as comprehensive sources of how to understand quantile regression.
5. $\rho_\tau(u) = u\tau - uI\,(u \leq 0)$ where $I\,(u \leq 0)$ is an indicator function.
6. See, for instance, Edie and Showalter (1998), Ng and Pinto (2003), Bassett, Tam, and Knight (2002), Kremer and Levy (2003), Smith and Naylor (2005), and Birch and Miller (2006).
7. The transformation ensure that estimations will not exceed 10 or far below 0. The transformation of the dependent variable goes as follows:

$$y_{transformed} = \log\left(\frac{y}{10-y}\right) \tag{3}$$

   Marginal effects may be calculated from the estimates obtained with this dependent variable using:

$$\frac{\partial y 1}{\partial x\, y} = \beta(10-y) \tag{4}$$

   These partial effects are usually evaluated at the mean value of the dependent variable $\bar{y}$.
8. Due to interbreeding of races (blacks and whites, natives and whites, and blacks and natives) which happens to be stronger in the Northeast, the individual classifies himself (herself) as brown or *pardo*.
9. The Real/Dollar exchange rate by the time the data were collected was 2.856 which means families are living with less than US$ 350.14 a month.
10. See Cavalcanti, Guimaraes, and Sampaio (2010) for evidences on the effect of studying in a public or a private school in Brazil.
11. All results remain unchanged if we switch to mothers' education instead of using fathers' education.
12. According to empirical evidence provided by Banerjee (2006), credit access and borrowing interest rates depend on wealth and social status.
13. One should, however, take this coefficient carefully when interpreting it as a causal effect since selection may be driving the negative coefficient obtained. Cavalcanti, Guimaraes, and Sampaio (2010) used the technique developed by Altonji, Elder, and Taber (2005) to address the issue of unobserved selectivity when instrumental variables are unavailable. They find that although selection may play an important role, test scores of public school students are on average about 4.2–17% lower than those taken by private school students.
14. In Brazil, the problem of grade retention is very pronounced. In 2004, for the age cohort of 11–14, which should be enrolled in Grades 5–8, 29% were still in Grades 1–4 (Soares 2006; Love and Baer 2009). On the other side, there is little or no grade promotion in Brazilian school, thus more able children are not skipping grades.
15. See Bedard and Dhuey (2006) for more on that.

16. Some students decide to take the test on their junior high school year just to have an idea on how they will perform on their senior year and to gain experience on dealing with test anxiety, for example. Hence, we expected to obtain a negative and significant effect for this variable.
17. This result is also obtained by Tansel and Bircan (2005) who estimate a similar equation using data from Turkey.

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