Faculdade de Economia,
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Universidade de São Paulo


# Texto para Discussão

## Série Economia

TD-E 02 / 2017

# Evidence of the Impact of Children´s Domestic and Market Labor on Learning from School Census Data in Brazil

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**Evidence of the Impact of Children´s Domestic and Market Labor on Learning from School Census Data in Brazil**

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**Abstract:** This study contributes to the literature by analyzing the direct impact of child labor on the academic progress of students, as measured by standardized achievement tests in Portuguese and Mathematics in Brazil. In contrast to previous studies, our study differentiates the work performed by children into household tasks and labor market activities, and a combination of the two. Also, analyses are performed separately, for boys and girls, in order to observe any differences or discrimination according to gender.

The impact of child labor on learning may be negative if children divide their time between studying and working long hours in jobs that require substantial physical effort, which can harm their school achievement. On the other hand, the impact of child labor on learning may be positive if the job involves tasks that result in learning and skills improvement. Thus, the direction of the expected impact of child labor on learning is unclear.

The estimates are based on students from urban public schools, and come from census data called “Prova Brasil”, which was collected in 2007 and 2011. Children in 5$^{th}$ Grade in 2007 were merged with students in 9$^{th}$ Grade in 2011 to create panel data.

The richness of the data allows us to control for individual, parent, teacher and principal characteristics, as well as school infrastructure. Moreover, having two years of panel data allows us to control for students’ unobserved effects that do not vary in time.

We also correct for attrition bias using the inverse probability weights, as weaker students that may repeat the year or abandon school dropout from the 2007 to 2011 sample. Moreover, the merging may be imperfect for some observations, due to missing data in the merging variables or duplicate observations. We also address the endogeneity of child labor using an instrumental variable approach proposed by Lewbel (2012).

The results show decreases in school performance in Portuguese and Mathematics for boys and girls in 5$^{th}$ and 9$^{th}$ Grade in Brazil when children perform either household tasks or labor market activities. The largest effect occurs when children work only in the market, followed by working both in the market and at home, and finally performing only household tasks. Working in the market may be more detrimental to educational learning than performing household tasks, due to heavy work load, absence of parents, time spent on public transportation, and more stress from the pressure of producing to earn money.

**JEL:** I21, J13, C23, C26, C36

**Keywords:** schooling performance, child labor, instrumental variable, probabilistic linkage, Brazil

**Acknowledgements**
This research work was carried out with financial and scientific support from the Partnership for Economic Policy (PEP) (www.pep-net.org) with funding from the Department for International Development (DFID) of the United Kingdom (or UK Aid), and the Government of Canada through the International Development Research Center (IDRC) (grant number 15-RG-12769). The authors would like to thank Paul Glewwe, Guy Lacroix, Safa Ragued and Rodolfo Hoffmann for excellent technical suggestions as well as an anonymous referee for the insightful comments, and the participants to the PEP annual meeting in Manila (June, 6-7) for useful inputs. We also thanks Michelle Baker for excellent proofreading.

## 1. Introduction

In recent years, Brazil has experienced an impressive decline in child and youth labor. According to the national household survey (PNAD), in 1992, about 23% of Brazilian children and youths aged 10 to 15 worked, compared to 7% in 2014 (IBGE, 2014). The Brazilian law prohibits children under the age of 16 from working, except for in apprenticeships, in which case the minimum age is 14.

With respect to educational indicators such as illiteracy rates and years of schooling, Brazil still lags behind other Latin American countries. However, during the 1990s, school enrollment increased, mainly in primary school and for students aged 7 to 14. In 1992, 87% of the children aged 7 to 14 were enrolled in schools. By 2014, this increased to 98%.

One of the reasons why Brazil continues to lag behind other countries in student learning despite the increases in school enrollment may be that a high percentage of students work while attending school. According to the 2014 PNAD data, of more than 26.5 million Brazilian children aged 10 to 17, 81% study only, 3.2% work outside their homes and do not study, 11.8% combine work with study, and 4.1% neither work nor study. These statistics reveal over three million children and adolescents who continue to divide their time between working and studying, which can harm their school achievement by restricting time spent on assignments, or by not allowing them to make efficient use of their time in school, as their work makes them tired.

This study contributes to the literature by analyzing the direct impact of child labor on the academic progress of students, as measured by standardized achievement tests in Portuguese and Mathematics. In contrast to previous studies, our study differentiates the work performed by children into household tasks and labor market activities, and a combination of the two. Also, analyses are performed separately, for boys and girls, in order to observe any differences or discrimination according to gender.

Authors such as Gunnarsson, Orazeman and Sanchez (2006), Psacharopoulos (2007), Heady (2003), Akabayashi and Psacharopoulos (1999), Stinebrickner and Stinebrickner (2003), Bezerra, Kassouf and Arends-Kuenning (2009), Dumas (2012), and Emerson, Ponczek and Souza (2017) among others, studied the effect of early child labor on student achievement test scores in different countries. However, this present study differs from previous ones in that it uses richer and more updated census data, which allows us to create a panel and better control for observed and unobserved effects, as well as for potential endogeneity of child labor, and reverse causality between child labor and learning at school. Also, this study distinguishes between the effects of labor market and domestic work.

There are some studies in the literature which examine the effect of the work performed by children on their enrollment rate rather than on performance, such as Ravallion and Wodon, (2000), Assaad, Levison and Zibani (2001), Canals-Cerda and Ridao-Cano (2004), Beegle, Dehejia, and Gatti (2009) and Edmonds (2008). However, in Brazil, it is common to see children combining work and school, and therefore, examining the effect of child labor on learning is even more important than examining its effect on school enrollment.

The impact of child labor on learning may be negative if children divide their time between studying and working long hours in jobs that require substantial physical effort, which can harm their school achievement. On the other hand, the impact of child labor on learning may be positive if the job involves tasks that result in learning and skills improvement. Thus, the direction of the expected impact of child labor on learning is unclear (see the discussion provided in Emerson et al., 2017).

Therefore, the main objective of this study is to measure the impact of child labor force participation (here treated as domestic work, labor market work, and both domestic and market work) on learning outcomes. The estimates are based on students from urban public schools, and come from census data called “Prova Brasil”, which was collected in 2007 and

2011. Children in 5th Grade in 2007 were merged with students in 9th Grade in 2011 to create panel data.

The richness of the data allows us to control for individual, parent, teacher and principal characteristics, as well as school infrastructure. Moreover, having two years of panel data allows us to control for students' unobserved effects that do not vary in time.

We also correct for attrition bias using the inverse probability weights, as weaker students that may repeat the year or abandon school dropout from the 2007 to 2011 sample. Moreover, the merging may be imperfect for some observations, due to missing data in the merging variables or duplicate observations. We also address the endogeneity of child labor using an instrumental variable approach proposed by Lewbel (2012).

The results show decreases in school performance in Portuguese and Mathematics for boys and girls in 5th and 9th Grade in Brazil when children perform either household tasks or labor market activities. The largest effect occurs when children work only in the market, followed by working both in the market and at home, and finally performing only household tasks. Working in the market may be more detrimental to educational learning than performing household tasks, due to heavy work load, absence of parents, time spent on public transportation, and more stress from the pressure of producing to earn money.

## 2. Literature Review

Research on the impact of child labor on school performance in developing economies is scarce. In this section we present a short summary of the main studies analyzing the effect of children´s work on their performance in school in recent years. We focused on research using data from Brazil, but we also present relevant studies from other countries.

One of the most recent studies in this area was conducted by Emerson et al. (2017). The researchers investigated the impact of child labor on Portuguese and Mathematics standardized tests for children in 2nd and 8th Grade of elementary public schools in São Paulo from 2007 to 2010, using the Difference in Differences approach. The annual dataset used – "Prova São Paulo" - allowed the authors to create a panel and to explore the causality between the work performed by children and its effect on their test scores. The authors observed that performing some sort of work while studying had a harmful effect on students´ scores in Portuguese and Mathematics.

Mavrokonstantis (2011) investigated the impact of child labor on mathematics test scores over seven year period in Vietnam. Using an instrumental variables strategy, he showed that the impact of child labor was negligible in rural areas, but in urban areas, child labor significantly impeded educational attainment. The instruments used were rice prices, assets, and area of land owned by the household.

Gunnarsson et al. (2006) studied the impact of child labor on children´s test scores (Mathematics and Language) at 3$^{rd}$ and 4$^{th}$ Grades of elementary school in 9 Latin American countries. The results showed negative impacts of child labor on languages (Portuguese for Brazil, and Spanish for eight other countries) and mathematics test scores. To control for potential endogeneity of child labor they used the country's school starting age or truancy age as instruments. They claim that most children were involved in unpaid jobs and, because of that, labor market wages would not adequately capture the value of time outside school even if such information were available.

Edmonds (2008), who analyzed school enrollment and children´s work environments found that the school attendance of children working outside their houses was lower when compared to those working inside their houses. Also, children who worked in both places (in the house and outside) had higher school attendance than those who worked only outside their houses. The author claims that children who worked outside their houses tended to spend more hours working than those who helped in household tasks. Moreover, school attendance declined gradually with the increase in working hours and it became dramatically lower for children who worked between 35 and 45 hours per week. Causal studies of the impact of child labor on schooling face the challenge of isolating some factors that affect child labor without simultaneously affecting schooling. This is difficult, as Edmonds (2008) points out, because child labor, schooling and leisure are not decisions that are mutually exclusive. According to the author, it is hard to imagine how one can be affected without all other decisions being affected. “Panel data on child labor histories is rarely available, so studies typically compare current labor supply to current attainment. … this is hard, because current work status necessarily depends on past education and work histories as these affect the value of child time and whether it's valuable for the child to work. This makes interpretation difficult, but studies typically find that attainment is lower for working children …” (p. 3646).

Using data from the Monthly Employment Survey in six metropolitan regions of Brazil, in the period 1984-1997, Cavalieri (2002) evaluated the impact of child work on school performance, measured by repetition and dropout rates. To estimate such effects, the author used the Propensity Score Matching method and estimated the difference in the average probability of grade advancement in the series between the control and treatment groups (i.e., children who did not work compared to children who worked). The results showed that child labor increased the dropout rates and decreased grade advancement rates in school for children between 10 to 14 years old.

Beegle, Dehejia, Gatti and Krutikova (2008) used panel data from Tanzania to evaluate the impact of child labor on education outcomes. They used the occurrence of crop and rainfall shocks as instruments for child labor. They found negative effects of child labor on school years and on the probability of completing primary school.

Dumas (2012) estimated the impact of working during childhood on proficiency tests between 1995 and 2003 in Senegal. The author found that children working under 17 hours a week had slightly better performance than the others. However, work had a detrimental effect when it was over 17 hours a week.

Bezerra et al. (2009) analyzed the impact of child labor on school achievement using Brazilian school achievement test data from the 2003 Siatema de Avaliação da Educação Básica (SAEB). The authors tried to control for the endogeneity of child labor using the average wage for unskilled male labor in the state as an instrument. The results showed that children and adolescents who did not work had better school performance than students who worked. Up to two hours of work per day did not have a statistically significant effect on school performance, but additional hours decreased students' achievement. Moreover, working in the labor market had a higher negative effect on school performance than working in the household.

The studies discussed above emphasize the importance of having good instruments to identify the models due to the endogeneity of child labor. At the same time, most researchers remark how difficult it is to find such instruments, given the available data. Recently, panel data analyses have provided tools to improve these results, but there are still concerns related to attrition and reverse causality that need to be addressed. In using a large data set that covers the whole of Brazil, and by taking advantage of the panel structure, we add to this literature by accounting for attrition bias using inverse probability weights, and by accounting for the endogeneity of child labor using an instrumental variable approach proposed by Lewbel (2012).

## 3. Methodology: basic model

In this study we created a panel dataset using data from 2007 and 2011. We selected children who were in the 5th Grade in 2007, then we found their counterparts (the same students or students with similar characteristics) in the same school who were 4 years older in

2011, using variables such as gender, and month and year of birth. More details on the procedure followed to construct the panel dataset is provided below in section 4.2.

In the literature, it is well known that there is a reverse causality between child labor and schooling, as when students do not perform well in school it can lead their families to decide that they should invest more time in work. At the same time, children spending time on work activities in their own houses, or in the labor market might do poorly in school.

Creating a two-year panel with students' information, and using a fixed effect model allows us, to a certain degree, to control for both the endogeneity of child labor and the presence of other unobservables (for example, children's ability and parental preferences) that, potentially, are correlated with the decision to work, and performance in school. We also tried to control for student, parent, and teacher characteristics, as well as school infrastructure, using a rich set of variables available from the Prova Brasil data.

Consider the variable of interest *y*, such as children´s performance in school, then,

$$y_{it} = \alpha_i + \gamma_t + \delta S_i T_t + \lambda w_{it}^e + \beta x_{it} + \varepsilon_{it}$$

where $\alpha$ is the individual fixed effect, $\gamma$ is the time fixed effect, $\delta$ is the vector of parameters of the 27 states (*S*) time trends (*T*), $\lambda$ is the coefficient of our main explanatory variable $w_{it}^e$ (*i.e.*, children's work status), $\beta$ is the vector of parameters of the exogenous variables *x* and $\varepsilon$ is the error term. The *x* variables include children, parent, and teacher characteristics, and school infrastructure, children´s work status, and others.

### 3.1 Inverse Probability Weights

The dataset we use suffers from attrition, as many individuals drop out of school, repeat the school year, or change schools. Due to this reason, the remaining students were not representative of the original population and the results may have been affected by attrition bias. The reason is that the individuals who drop out of a panel differ systematically from those who stay in it.

Consider a panel dataset having $N$ individuals surveyed into two different years ($t$ = 1, 2). Let $s_{it}$ denote the selection indicator for each time period, where $s_{it}$ = 1 if both $y_{i1}$ and $y_{i2}$ are observed, and zero when $y_{i2}$ is not observed. Consider ($x_{it}$, $y_{it}$) are observed.

Wooldridge (2002) states that the sequential nature of attrition makes first differencing a natural choice to remove the unobserved effect:

$$\Delta y_{it} = \Delta x_{it}\beta + \Delta u_{it} \qquad t = 2,\ldots,T \qquad (1)$$

In our case, $t$ = 2 (year 2007 and 2011). Let the score for individual $i$ in the second year be $y_{i2}$, and in the first year $y_{i1}$, and let the exogenous variables in the first year be $x_{i1}$, and in the second year be $x_{i2}$. Then, $y_{i2}$ is observed only if there is no attrition. With attrition on observables, we can estimate the Inverse Probability Weights (IPW) to solve the problem of sample attrition. This method relies on an auxiliary observed variable that needs to be related to the attrition and to the outcome variable (Fitzgerald, Gottschalk and Moffitt, 1998).

It follows that we can write an attrition equation as:

$$s_{it}{}^{*} = \gamma x_{i1} + \delta z_{i1} + v_i \qquad (2)$$

We do not observe $s_{it}{}^{*}$, but we do observe $s_{it}$, which takes the value 1 when both $y_{i1}$ and $y_{i2}$ are observed, and zero when $y_{i2}$ is not observed[1].

Following Wooldridge (2002), ideally, at each $t$ we would observe ($y_{it}$, $x_{it}$) for any unit that was in the random sample at $t$ = 1. Instead, we observe ($y_{it}$, $x_{it}$) only if $s_{it}$ = 1. According to Wooldridge (2012) "we can easily solve the attrition problem if we assume that, conditional on observables in the first time period, say, $z_{i1}$, ($y_{it}$, $x_{it}$) is independent of $s_{it}$" (p. 587), that is

$$\Pr(s_{it} = 1|y_{it}, x_{it}, z_{it}) = \Pr(s_{it} = 1|z_{it}) \qquad (3)$$

[1] Note that, for simplicity, in this subsection $x_{it}$ identify all explanatory variables, including child labour.

This assumption is called “selection on observables” because we assume that conditional on $z_{i1}$, selection is independent of ($y_{it}$, $x_{it}$) or that the distribution of $s_{it}$ given [$z_{i1}$, ($y_{it}$, $x_{it}$)] does not depend on ($y_{it}$, $x_{it}$).

There are two steps to obtain the Inverse Probability Weights. First we estimate a probit model of $s_{it}$ on $z_{i1}$ and let $\hat{p}_{it}$ be the fitted probabilities from this model. In the second step the score function in year 2 is weighted by $\left({}^{1}/_{\hat{p}_{it}}\right)$, while in year 1 the weight is one (for $t = 1$, $s_{it} = \hat{p}_{it} = 1$ for all $i$).

The reasoning behind this procedure is that it gives more weight to individuals, who have similar initial characteristics, to individuals that subsequently attrite than to individuals with characteristics that make them more likely to remain in the panel.

The most frequent choice of the auxiliary variable in panel data is a lagged value of $y$ according to Wooldridge (2002) and Fitzgerald et al. (1998). According to Moffit, Fitzgerald and Gottschalk (1999), who also studied sample attrition in panel data, “assuming serial correlation in the $y$ process, such lagged variables will be related to current values of $y$ conditional on $x$. If attrition is related to lagged $y$, least squares projection of $y$ on $x$ using the non-attriting sample will yield biased and inconsistent coefficient estimates. Estimation of attrition probabilities and subsequent weighted least square estimation yields consistent estimation instead” (p. 136). In this study we use the score in Portuguese and Mathematics in 2007 as the $z_{i1}$ variable.

### 3.2 The Lewbel´s Approach

Estimating the relationship between child labor and schooling is complicated because students who work might do poorly in school, but poor performance in school can also lead families to decide that their children should invest more time in work. Also, although we control for students’ unobserved fixed effects, time-varying unobserved heterogeneity might both still bias our results. A way to correct for the endogeneity of child labor, as a right hand side variable, is to use an instrumental variable approach. However, we do not have a good outside instrument, correlated with child labor and not correlated with the outcome variable of test scores.[2] To circumvent this problem we used the Lewbel (2012) approach, which consists of creating instrumental variables from the model, and on identifying the coefficients in the model based on heteroscedasticity (see Fortin and Ragued, 2017, for a nice application of this approach to explain the wage penalty of temporary interruption of secondary education). The Lewbel approach seems particularly appropriate in cases when the error covariances across equations are due to unobserved common factors, such as individual abilities and learning motivation, which is indeed the case in school/work choice modelling (see, for example, Edmonds, 2008).

Following Lewbel (2012), consider the structural equation[3]

$$y = x'\beta_1 + w\mu + \varepsilon_1 \tag{4}$$

where

$$w = x'\beta_2 + \varepsilon_2 \tag{5}$$

In our study, $y$ represents test scores; $x$ are exogenous variables, such as children, parents, teacher and school characteristics; $w$ measures working status of children and $\varepsilon_1$ and $\varepsilon_2$ are unobserved errors.

If we have exclusion restrictions, that is, one or more elements of $\beta_1$ equal zero and the corresponding elements of $\beta_2$ nonzero, we can identify the model using two stage least squares, in which we estimate equation (5) to obtain the fitted values $\widehat{w}$ and then we estimate equation (4) on $\widehat{w}$ and on the subset of $x$ that has nonzero coefficients. However, very often

[2] We did try to include the wage rates by sex, states, educational level etc. from the National Household surveys (PNADs) as instruments. However, the tests and results showed that these were weak instruments and we decided to discard them from this analysis.

[3] For simplicity we present the logic with just one endogenous explanatory variable, but the case with multiple endogenous regressors can be easily extended.

we do not have exclusion restrictions and therefore instruments to identify the model. In general, variables affecting *y* also affect *w*.

Let *z* be a vector of observed exogenous variables, possibly being a subvector of *x* or even equal to *x*. In this case, Lewbel (2012) shows that under the assumptions

$$E(x\varepsilon_1) = 0,\ E(x\varepsilon_2) = 0,\ cov(z, \varepsilon_1\varepsilon_2) = 0 \text{ and } cov(z, \varepsilon_2^2) \neq 0 \tag{6}$$

along with heteroskedasticity of the errors $\varepsilon_1$ and $\varepsilon_2$, the structural equation can be identified. In particular, $cov(z, \varepsilon_1\varepsilon_2) = 0$ assures that the error terms are uncorrelated conditionally to z.

Defining matrices $\Psi_{zx}$ and $\Psi_{zz}$ by

$$\Psi_{zx} = E\left[\begin{pmatrix} x \\ [z - E(z)]\varepsilon_2 \end{pmatrix}\begin{pmatrix} x \\ w \end{pmatrix}'\right],\ \Psi_{zz} = E\left[\begin{pmatrix} x \\ [z - E(z)]\varepsilon_2 \end{pmatrix}\begin{pmatrix} x \\ [z - E(z)]\varepsilon_2 \end{pmatrix}'\right]$$

and let $\Psi$ be any positive definite matrix that has the same dimension as $\Psi_{zz}$, Lewbel shows that,

$$\beta_2 = E(xx')^{-1}E(xw)$$

$$\begin{pmatrix} \beta_1 \\ \mu \end{pmatrix} = (\Psi'_{zx}\Psi\Psi_{zx})^{-1}\Psi'_{zx}\Psi\left[\mathrm{E}\begin{pmatrix} x \\ [z - E(z)]\varepsilon_2 \end{pmatrix} y\right]$$

This result means that $\beta_2$ and $\mu$ can be obtained by two stage least squares regression of *y* on *x* and *w* using *x* and [z - E(z)]$\varepsilon_2$ as instruments. Importantly, the assumption that *z* is uncorrelated with $\varepsilon_1\varepsilon_2$ means that the generated instrument $[z - E(z)]\varepsilon_2$ is exogenous (since uncorrelated with $\varepsilon_1$) and, so, a valid instrument for *w*; also, larger the degree of heteroskedasticity of $\varepsilon_2$ with respect to *z* stronger the instrument$w$, since its correlation with $w$ is proportional to the covariance of $z$ and $\varepsilon_2$.

The estimation procedure is as follows. The coefficient $\beta_2$ is estimated by linearly regressing *w* on *x* to obtain the residuals $\hat{\varepsilon}_2$. Then $\beta_1$ and $\mu$ can be estimated by regressing *y* on *x* and *w* using $x$ and $(z-\bar{z})\hat{\varepsilon}_2$ as instruments, where $\bar{z}$ is the sample mean of $z$. Let over bars denote sample averages, the resulting estimators are

$$\hat{\beta}_2 = (\overline{xx'})^{-1}\overline{xw}, \quad \hat{\varepsilon}_2 = w - x'\hat{\beta}_2$$

and

$$\begin{pmatrix}\hat{\beta}_1\\ \hat{\mu}\end{pmatrix} = (\hat{\Psi}'_{zx}\hat{\Psi}_{zz}^{-1}\hat{\Psi}_{zx})^{-1}\hat{\Psi}'_{zx}\hat{\Psi}_{zz}^{-1}\begin{pmatrix}\overline{xy}\\ \overline{(z-\bar{z})\hat{\varepsilon}_2 y}\end{pmatrix}$$

## 4. Data

### 4.1 Microdata of Prova Brasil.

Prova Brasil is a census dataset for students in their 5th and 9th Grades in urban public schools, collected by the Ministry of Education every 2 years. The great majority of students in Brazil, being mainly from lower income families, attend public schools. Students are expected to start school at the age of 6, so they are 10 or 11 years old in Grade 5, and 14, or 15 years old in Grade 9.

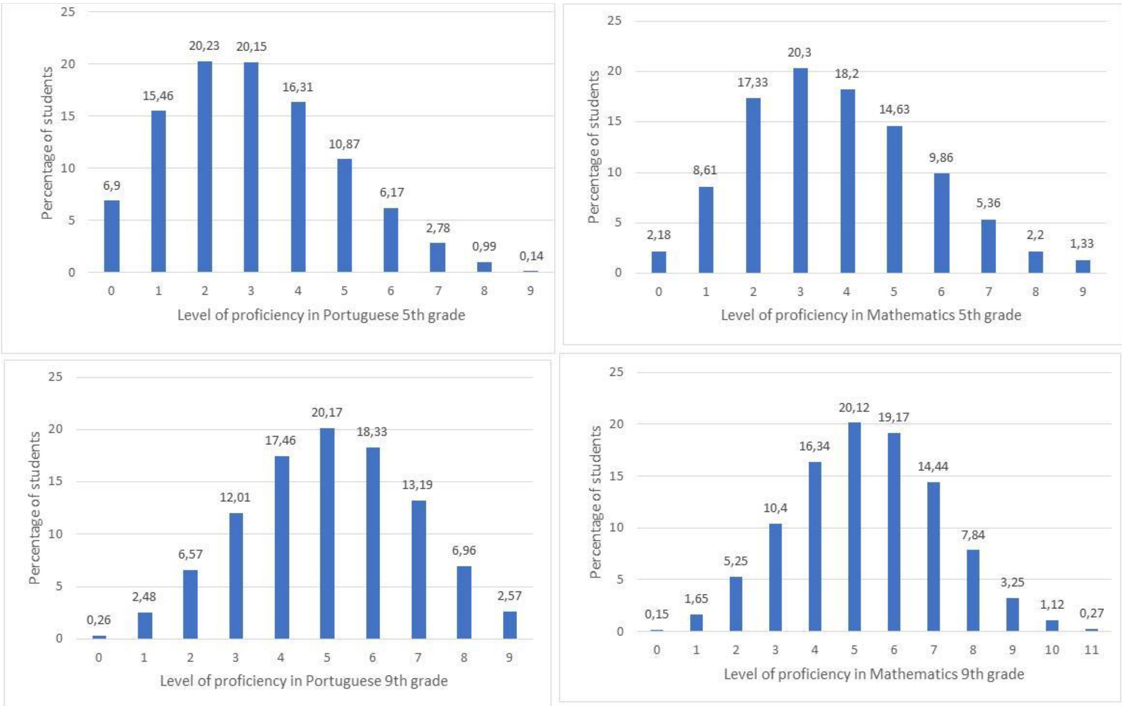
The Prova Brasil data set contains information on test scores and employment of students. The exams administered are standardized, multiple-choice designed to measure students' abilities and capacities in Portuguese (with a focus on reading comprehension) and Mathematics. As a way to compare different students throughout the years, the reading and Mathematics tests administered to students use Item Response Theory. The scores are mapped into cumulative performance scales, which means that students who are placed at a given level are competent in the skills required at the previous levels of the scale. Based on percentage scales, test scores classify students into levels of achievement in Portuguese and in Mathematics. The highest is the level reached, the best is the student´s performance. Level zero is a critical point where students are not able to read, calculate or understand the contents of the test. The scales are different for Portuguese and Mathematics, as well as for 5th and 9th Grades.

In the appendix, Table A1 summarizes all possible levels of achievement in Portuguese and Mathematics tests for students in 5th and 9th Grades. The scales go from 0 to 8 or 9, according to the students´ scores in the tests.

Figure 3.1 shows the percentage of students in 5th and 9th Grade by each level of proficiency in Portuguese and Mathematics described above. Observe that more students were concentrated in the lower levels of proficiency, and a small percentage of children were in the higher levels of proficiency.

The scales of proficiencies differ from Portuguese and mathematics test scores. The scale for Portuguese goes from level 0 (0-125) to level 9 (325-350), while the scale in mathematics goes from level 0 (0-125) to level 12 (400-425).

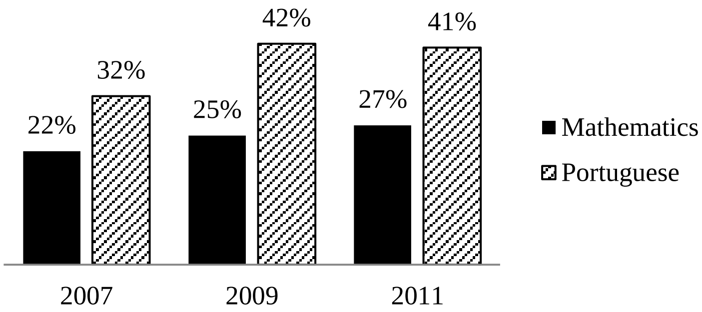
Figure 3.1 - Percentage of students in 5th and 9th Grade in urban public schools in Brazil by level of proficiency in Portuguese and Mathematics.




Source: Microdata of Prova Brasil 2011.

In the beginning of 2000, the National Institute of Educational Studies and Analyses (INEP), from the Ministry of Education, created a classification of the proficiency levels divided into four levels: very bad, bad, fair or basic, and adequate. Figure 3.2 shows the percentage of students in the 9th Grade with basic or adequate test scores in Portuguese and Mathematics. In 2007, 32% of the students were at a basic or adequate level in Portuguese, increasing to 42% in 2009, and remaining almost the same in 2011 at 41.3%. This means almost 60% of the students were at the bad and very bad levels. In 2007, 22% of the students had acceptable levels in Mathematics, increasing to 25% in 2009 and 27% in 2011. Mathematics was even lower than Portuguese with more than 70% of the students at a critical level.

Figure 3.2 - Percentage of students in the 9th Grade of primary education in urban public schools in Brazil with Portuguese and Mathematics test scores at basic or adequate levels.




Source: Microdata of Prova Brasil

### 4.2 Creating a Panel Data Set.

First, we should say that we were interested in retaining students in 5th and 9th Grades since they were the only ones for which our data allowed us to construct a panel dataset, i.e., the information available in the data set is only for 5th and 9th grade. We will start by explaining how the panel dataset was constructed from the original data. In 2007, there were 48,745 schools in the data set, from which 16,121 had both 5th and 9th Grade students. Many schools had only primary level (1st to 5th Grade) while others had only lower secondary level

(6$^{th}$ to 9$^{th}$ Grade). Since we had to merge 5$^{th}$ Grade students in 2007 with 9$^{th}$ Grade students in 2011, we only worked with schools that had both 5$^{th}$ and 9$^{th}$ Grades. There were 1,815,010 students in the 16,121 schools, but only 975,065 students were in 5$^{th}$ Grade in 2007. Similarly, in 2011 there were 16,586 schools with 5$^{th}$ and 9$^{th}$ Grades out of a total of 56,222 schools. There were 2,161,355 students in the 16,586 schools, but only 1,092, 237 were in 9$^{th}$ Grade in 2011. It is good to point out that we need only 5$^{th}$ grade students in 2007 and 9$^{th}$ grade students in 2011. Unfortunately, our data did not provide student identification codes. Hence, to merge 5$^{th}$ Grade students in 2007 with 9$^{th}$ Grade students in 2011, we used the following four time-invariant variables, namely the school code, year and month of birth and sex. Practically no missing values were found in the school code variable, while the other three merging variables showed some missing values.

Once the observations with missing values in all merging variables were dropped, the sample size decreased to 948,951 in 2007 and 858,300 in 2011. Next, we dropped the observations with missing variables in at least one of the variables entering in models (4) and (5) (since these observations would be discarded by the individual fixed-effects estimations), as well as in the sex variable (as our analysis below is run separately by gender). Such data cleaning was necessary in order to generate merging weights whose by individual sum was 1 (that is, to make sure that one individual is merged with one full individual, and not a share of the individual) for all observations included in the estimations. This step reduced our sample down to 615,785 in 2007 and 616,421 in 2011. We implicitly assumed that missing values in the explanatory variables are randomly distributed. At this point, the sample still showed some observations with missing values in one or two merging variables. In the 2007 sample, the month of birth showed 8,619 missing values and the year of birth showed 7,176. In 2011, among 9$^{th}$ Grade students in complete schools, the month of birth had 774 missing values and the year of birth had 1,583. Due to this, we faced two problems: first, some of our observations with missing values could not be merged and then dropped out of the sample. Secondly, and more importantly, our merging variables were not always able to identify for a 2007 student a unique 2011 correspondent individual (i.e., for such equivocal cases, more than one 2011 individual is associated to one 2007 student).

In order to show the nature of these problems, let us demonstrate by taking one individual in 2007, John (whose name or identification code is unknown from the dataset). According to our merging variables, he was merged with 3 individuals in 2011 (John – his correct pair – Peter, William and Julio). For two of them (John and Peter), all merging variables were not missing, while for William the month of birth was unknown and for Julio the month and year of birth were missing. Our repeated observations (as many times as the number of duplicates – 4 in our example) should then be weighted by $W$,[4] defined as:

$$W_{i,j} = \frac{1}{\sum_j p_{i,j}} p_{i,j}$$

where $p_{i,j}$ is the proportion of non-missing merging variables for 2007's observation *i* (John) and his presumed 2011's pair *j*. Of course, the sum of weights by *i* should give one (John should indeed be represented by one individual which, in some particular cases as this one, may be the sum of a proportion of different individuals). In our example, we would then have

$W_{i,1} = \frac{1}{3}1 = 0.333;\ W_{i,2} = \frac{1}{3}1 = 0.333;\ W_{i,3} = \frac{1}{3}0.66 = 0.222; W_{i,4} = \frac{1}{3}0.33 = 0.111$

It is worth noting that 57.3% of our final sample had no missing values in the merging variables, nor duplicated observations. For such cases, the weight is 1.

After the merging, the individual panel dataset had 795,508 observations (397,754 in each year). Henceforth, during the creation of the panel data set in 2007 and 2011 there was a large drop in the number of observations in the merging process, by around a third (from slightly more than 600,000 to around 400,000). Students who changed school, repeated the

[4] Such approach takes some inspiration from the probabilistic linkage literature. One example is Ridder and Moffit (2005).

school year, or dropped out of school were not found in the subsequent survey year. Also, part of the attrition was due to measurement error in birthdate, or the difficulties in matching individuals across a four-year span using the available merging variables (month and year of birth, and sex), as described above. A summary of all the steps in merging the data as well as the number of observations in each step is presented in table 4.1.

Table 4.1 –Construction of the panel dataset.

| Steps | 2007 | 2011 |
|---|---|---|
| Total number of schools | 48,745 | 56,222 |
| Schools with 5th and 9th Grades | 16,121 | 16,586 |
| All students in schools with 5th or 9th Grades | 1,815,010 | 2,161,355 |
| Students in 5th Grade (in 2007) and in 9th Grade (in 2011) | 975,065 | 1,092,237 |
| Same as above without missing values in merge variables | 948,951 | 858,300 |
| Same as above without missing in explanatory variables | 615,785 | 616,421 |
| After merging (individual panel dataset) | 397,754 | 397,754 |

Source: Authors' estimation based on Microdata of Prova Brasil.

The data show that 30.5% of the 5th Grade students, and 33.9% of the 9th Grade students claimed that they repeated at least one school year, while around 7.6% of the 5th Grade students, and 5.9% of the 9th Grade students dropped out of school at least once (Table 4.2). Notice that the student may drop out from school and come back in.

Table 4.2 - Number and percentage of 5th and 9th Grade students who repeated at least one Grade in the past, or dropped out of school.*

| Grade Failure | 2007 5th Grade | | 2011 9th Grade | |
|---|---|---|---|---|
| | number | % | number | % |
| No | 1,441,009 | 69.54 | 1,290,644 | 66.13 |
| Yes | 631,302 | 30.46 | 661,154 | 33.88 |
| Drop out | | | | |
| No | 1,880,736 | 92.43 | 1,839,692 | 94.05 |
| Yes | 154,138 | 7.58 | 116,323 | 5.94 |

Source: Microdata of Prova Brasil.
* The overall sample of children in 5th and 9th Grade in complete schools is used. The observations can vary from variable to variable because of missing values.

Besides data on test scores and work performed by children in the market and household tasks, Prova Brasil has information on student, teacher, principal and school characteristics. Some of the available information is: children´s age, gender and race, mother´

education, father´ education, family size, family possession of goods (TV, washing machine, refrigerator, computer, etc.), reading habits, encouragement of the family towards children´s education, teacher's age, gender, education, wage, number of years of experience, number of hours teaching per week, use of didactic equipment, principal´s age, gender, education, number of years of experience, school maintenance status, school infrastructure, presence of computer, internet, libraries, sports facilities, music, and science labs. Some of these were excluded from the estimations because they showed a large number of missing values.

Table 4.3 shows the description of all the variables used in the econometric models, as well as the mean and standard deviation of each variable calculated based on the 795,508 observations retained as explained above, and separated by gender.

The minimum required level of proficiency (basic level) differs from 5$^{th}$ to 9$^{th}$ Grade and from Portuguese to Mathematics. A child supposedly has a basic level of Portuguese if he or she gets 200 points at Grade 5 and 225 at Grade 9. Similarly, in Mathematics, the minimum score to reach a basic level is 275 at Grade 5 and 300 at Grade 9. In 5$^{th}$ Grade, the average score in Portuguese was 183, and in Mathematics it was 200, while in 9$^{th}$ Grade it was 248 in Portuguese and 254 in Mathematics. These numbers show that on average students were below the basic level. Although presenting the mean and standard deviation of the scores, we used standardized test scores in the econometric models (mean zero and standard deviation 1).

Table 4.3 - Description of the variables, weighted mean and standard deviation in 2007 and 2011. Retained observations only.

| Variables | Description of the Variables | 2007 | | | | 2011 | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | girls | | boys | | girls | | boys | |
| | | mean | s.d. | mean | s.d. | mean | s.d. | mean | s.d. |
| Scores_Portuguese | Portuguese test Score | 187.07 | 40.67 | 178.99 | 41.64 | 254.47 | 42.88 | 240.71 | 46.24 |
| Scores_Mathematics | Mathematics test Score | 198.07 | 41.61 | 202.22 | 45.32 | 250.45 | 44.27 | 258.18 | 46.95 |
| Not_working | don't work | 0.57 | 0.50 | 0.60 | 0.49 | 0.43 | 0.50 | 0.58 | 0.49 |
| Work_hh | Work only in the hh | 0.37 | 0.48 | 0.25 | 0.44 | 0.47 | 0.50 | 0.21 | 0.41 |
| Work_market | Work only in the market | 0.03 | 0.17 | 0.08 | 0.28 | 0.04 | 0.20 | 0.15 | 0.36 |
| Work_both | Work in both | 0.03 | 0.18 | 0.06 | 0.24 | 0.06 | 0.23 | 0.06 | 0.24 |
| Grade_failure | N. years repeat school year | 0.20 | 0.48 | 0.28 | 0.55 | 0.19 | 0.45 | 0.30 | 0.57 |
| Hh_member | Number of people in hh | 4.94 | 1.50 | 4.94 | 1.49 | 5.94 | 1.67 | 5.95 | 1.64 |
| Car | Number of cars in hh | 0.53 | 0.70 | 0.60 | 0.75 | 0.59 | 0.72 | 0.70 | 0.78 |
| floor_sch | 1 if floor in school | 0.60 | 0.49 | 0.59 | 0.49 | 0.63 | 0.48 | 0.64 | 0.48 |
| Start_maternal | 1 if child starts 2 to 4 years | 0.39 | 0.49 | 0.39 | 0.49 | 0.31 | 0.46 | 0.34 | 0.47 |
| Start_preschool | 1 if child starts 4 to 6 years | 0.36 | 0.48 | 0.37 | 0.48 | 0.47 | 0.50 | 0.44 | 0.50 |
| Start_Grade1 | 1 if starts school at 6 or 7 | 0.19 | 0.39 | 0.18 | 0.39 | 0.19 | 0.40 | 0.20 | 0.40 |
| Age_teacher | Age of the teacher | 40.77 | 8.72 | 41.01 | 8.70 | 42.37 | 8.54 | 42.48 | 8.55 |
| Experience_teacher | Number of years teaching | 14.33 | 6.70 | 14.40 | 6.68 | 14.79 | 6.94 | 14.83 | 6.94 |

Source: Authors' estimation based on Microdata of Prova Brasil.

Note: the number of retained girls is 216,206 in 2007 and 2011; the number of retained boys is 181,548 in 2007 and 2011.

Table 4.4 - Weighted number and percentage of 5th and 9th Grade students, according to their work status,° by gender

| Work Status | 2007 - 5th Grade number | % | Average hours/day spent in domestic work | 2011 – 9th Grade number | % | Average hours/day spent in domestic work |
|---|---|---|---|---|---|---|
| | | | *Girls* | | | |
| Do not work* | 122282 | 56.6 | 0. 77 | 92758 | 42.9 | 0.83 |
| Work only in the hh | 80607 | 37.3 | 2.69 (20.9) | 102194 | 47.3 | 2.55 (13.4) |
| Work only in the market | 6193 | 2.9 | 0.80 | 8828 | 4.1 | 0.80 |
| Work in both | 7124 | 3.3 | 2.93 (32.3) | 12426 | 5.8 | 2.74 (22.4) |
| Total | 216206 | 100.0 | 1.55 (8.9) | 216206 | 100.0 | 1.75 (7.6) |
| | | | *Boys* | | | |
| Do not work* | 109063 | 60.1 | 0.64 | 104437 | 57.5 | 0.64 |
| Work only in the hh | 46027 | 25.4 | 2.64 (19.4) | 37917 | 20.9 | 2.40 (9.8) |
| Work only in the market | 15286 | 8.4 | 0.72 | 27895 | 15.4 | 0.59 |
| Work in both | 11172 | 6.2 | 2.81 (27.5) | 11300 | 6.2 | 2.61 (20.5) |
| Total | 181548 | 100.0 | 1.29 (6.7) | 181548 | 100.0 | 1.12 (3.3) |

Source: Authors' estimation based on Microdata of Prova Brasil.
*Considered not working if worked 1 hour or less in the household per day.
º Numbers in parentheses show the share of observations spending 4 hours or more per week in domestic work.

Children responded if they worked or not outside their house and if they took part in household tasks. Moreover, if they performed household tasks, they reported the number of hours spent on those activities. Table 4.4 shows the number and percentage of girls and boys in the 5th and 9th Grade, according to their work status in 2007 and 2011.

In 5th Grade, close to 57% of girls and 60% of boys worked neither in the household, nor in the labor market. Girls worked more in the household (37%), compared to boys (25%). On the other hand, 8.4% of boys worked only in the labor market compared to 2.9% of girls. The percentage of boys working in both the household and the labor market (6.2%) was also larger than girls (3.3%). The average hours spent in domestic work per day was larger when the children worked in both the household and the labor market, spending around 2.8 hours per day. When they worked in the household only, girls spent 2.7 and boys spent 2.6 hours per day. The percentage of students working increased with age (or Grade) as it can be observed in Table 4.4: for 9th Grade students, 15% of boys worked in the labor market, and 6% in both the household and labor market.

The number of hours a child spent working in their own household per day is presented in Table 4.5. It should be noticed that girls, not only worked more in the household than boys, but they also spent more hours doing household tasks. In the 9th Grade, 23% of girls worked 3 or more hours a day in household activities, compared to 9% of boys. Some studies show that giving children household chores helps to form accountability and self-confidence and that they are more likely to succeed in adulthood (Rossmann, 2002). However, if a child is overloaded with household chores, working a large number of hours per day can harm his or her future life as less time is allocated to studying and doing homework. Due to this reason, when a child claimed to be performing household tasks for one hour or less per day, we considered that he/she was not working. From our data, about 53% of girls in 9th Grade spent 2 or more hours a day on domestic activities.

Table 4.5 - Weighted number and percentage of 5th and 9th Grade students, according to the number of hours per day they worked in their household by gender.

| Hours working hh/day | 2007 – 5th Grade | | | | 2011 – 9th Grade | | | |
|---|---|---|---|---|---|---|---|---|
| | Boys | | Girls | | Boys | | Girls | |
| | number | % | number | % | number | % | number | % |
| not work in hh | 41,881 | 23.07 | 29,107 | 13.46 | 48,277 | 26.59 | 17,385 | 8.04 |
| 1 or less hr/day | 80,458 | 44.32 | 97,055 | 44.89 | 84,018 | 46.28 | 84,162 | 38.93 |
| 2 hours/day | 30,970 | 17.06 | 44,608 | 20.63 | 33,183 | 18.28 | 65,082 | 30.10 |
| 3 hours/day | 15,159 | 8.35 | 24,817 | 11.48 | 10,026 | 5.52 | 33,112 | 15.31 |
| 4 or more hr/day | 13,080 | 7.20 | 20619 | 9.54 | 6,044 | 3.33 | 16,465 | 7.62 |
| Total | 181,548 | | 216,206 | | 181,548 | | 216,206 | |

Source: Authors' estimation based on Microdata of Prova Brasil.

## 5. Results

The first step was to estimate the IPW as described earlier. The estimation results are reported in Table A2. It is worth remarking that the coefficients of the score variables were highly statistically significant, indicating that attrition bias might be present when estimating children´s school performance models.[5] Also, the larger the children's test scores were, the larger the probability of staying in school, and therefore in the sample, as we expected.

The final weight used in the descriptive and econometric estimations below is then the product of the inverse probability weight and the weight defined in section 4.2. As mentioned earlier, the inverse probability weight in 2007 is 1.

Table 5.1 shows the effect of child labor on standardized test scores in Portuguese and mathematics, stratified by gender, using fixed effect models. Columns (1) to (5) show the coefficients for girls and columns (6) to (10) for boys. All regressions have year fixed effects, individual fixed effects, and state level time trends. Every column, except (1) and (6), include 13 exogenous variables which are presented in table A3 in the appendix.

The first column is the simplest specification, excluding even the direct effects of child, parents, teacher and school variables. The estimated impacts for the two outcomes were highly significant, with the expected signs. For test scores in Portuguese, girls working both in the household and in the labor market had lower results by 0.25 standard deviation (s.d.) while those working in the labor market only had their scores reduced by 0.24 s.d. points, and those working in the household only had their scores reduced by 0.04. Similarly, the reduction in Mathematics test scores was 0.19 s.d. when working in the household and in the labor market, or when working only in the labor market, and 0.04 s.d. when working only in the household. Similar results were found for boys. Adding control variables (columns (2) and (7)) yielded estimates of child labor impacts a little smaller in magnitude, as expected, but still very similar to the first and sixth columns. Most of these variables were significant, with the expected signs (see table A3). One can claim that there are other important variables affecting test scores that were not included in the model, such as parents´ and teachers´ education. However, we chose to use only the 13 variables described in Table 5.1 to avoid

[5] This is also confirmed by the BGLW attrition test (available upon request) according to which the equality of coefficients estimated on the full and the non-attriting samples is strongly rejected.

dropping even more observations due to missing values observed in those exogenous variables.

Estimates in columns (1) and (2), as well as (6) and (7) of table 5.1 may be biased due to attrition as described before. Columns (3) and (8) present new estimates using the weights described earlier. As such weights take into account both the typical attrition bias and the issues related to the matching procedure, it is hard to anticipate clearly the direction of such potential biases. The new estimates for the working variables are a little smaller in absolute values than the ones presented in columns (2) and (7). Despite the fact that we included individual fixed effects, control variables and controlling for attrition bias, one can still claim that the estimates in columns (3) and (8) are biased due to the endogeneity of child labor or reverse causality. Trying to take the endogeneity problem into account we use an instrumental variable (IV) approach developed by Lewbel (2012), whose results are presented in columns (4) and (5) for girls and (9) and (10) for boys. Before moving to the estimation results, we start with presenting the different tests about the validity of our generated instruments. First, we found heteroskedasticity of the errors as required in the Lewbel's methodology. Also, as reported in Table 5.1, according to the Kleibergen-Paap LM statistic, we strongly reject the underidentification for all estimations (boys and girls). Similarly, we reject the weak identification test (based on the Kleibergen-Paap Wald *F* statistic) as it always shows a sufficiently large value (higher than the Stock-Yogo critical values). In addition, according to the Hansen *J* statistic (which tests the hypothesis of overidentification of all instruments), we do not reject the overidentification restriction. Among the generated instruments, we selected a subsample of instruments such that the overidentification, weak identification and underidentification conditions were respected.

For comparison reasons, results in columns (4) and (9) include IV and exclude IPW, while in columns (5) and (10) include both IV and IPW. When including IV, all the children's work coefficients are negative and significant as before, but the magnitudes of the coefficients change. The larger negative impact in column (5) is when girls worked only in the labor market (-0.88 for Portuguese scores and -0.70 for Mathematics scores) followed by when they worked in both (-0.28 for Portuguese scores and -0.29 for Mathematics scores) and lastly when they worked only in the household (-0.24 for Portuguese scores and -0.19 for Mathematics scores). Similar results were observed for boys in column (10), with the exception that, for the scores in Mathematics, the effect was larger when boys worked in both.

It is reasonable to assume that children working in the labor market are more exposed to harm and to more demanding activities when compared to those working in their households and close to their families. Also, they probably face more working hours on average as they need extra traveling time to go to work. Children working only in the market might spend such a large number of hours working that they do not even have time to work in the household. Due to this reason, we expect the negative impact of working in the market on children´s school performance to be higher than the impact of working in both, and this to be larger than working only in the household, as our results showed.

The change in the magnitude of the work coefficients when using the IV approach reflects the effects of unobserved variables, or the reverse causality between child labor and the test scores. We believe that we cannot define *a priori* the direction of the bias, but it strongly depends on specific dynamics that might affect the bias upward or downward. Our results show that the direction of the bias is downward. This is in conformity with Beegle et al. (2009), in which parents seemed to prefer to send more academically talented children to work, probably because they were more productive. A similar conclusion is also found in Horowitz and Wong (2004) in situations where "talent differential" across children is large. More specifically, and in relation to our results, the largest increase in the magnitude of the coefficients was observed for the variable "work only at home", in which case the coefficient increased almost six times for Portuguese and Mathematics test scores, comparing the columns with and without IV. This would suggest that the inherent biases of OLS estimations apparently vary across child labor alternatives. In our case we can argue that there is more flexibility in household tasks, as children work in their own household and under the supervision of their parents. So, parents being aware of the fact that their children are not doing well in school can immediately prevent them from working, or reduce their hours of work at home. On the other hand, when working in the labor market, besides the need of income, there are contracts and third parties involved, making changes less flexible. Based on these arguments, we can say that working in the household is more flexible than working in the labor market, and this is the reason why there was a larger change in the magnitude of the work in the household coefficient, reflecting endogeneity. Finally, the difference in the coefficients' magnitude may also be due to the error measurement in the child work variable.

Emerson et al. (2017) also found negative effects of child work on test scores, using a micro panel dataset of students in the São Paulo municipal school system. According to the authors "the magnitude of these effects range from 3% of a standard deviation in test scores to 8% which represents from one quarter to one half of a year of lost learning." (p. 3).

In the following paragraphs, we briefly analyze each of the control variables included in the models (results are reported in Table A3).

The variable capturing past repetition (Grade*_failure*) reflects the number of times a child repeated the school year in the past; once, twice, or more. These variables negatively affect test scores, since they reflect students that had the worst academic performance.

The larger the number of people in the student´s household (*hh_member*), the lower his or her test scores were. Studies show that in large families, the provision of goods may be scarce, and often older children work to help the family budget (Emerson & Souza, 2008).

Students in higher income families are expected to have a better performance in school. However, the data used in this study did not have individual or family income information. To circumvent this problem, we used the number of cars owned by families as a proxy for family income. Three binary variables represent families possessing one car, two cars or three or more cars (car_1, car_2, car_3). There are other family possessions available in the data set, such as, VCRs, color TVs, or computers, as well as the number of bathrooms, and whether the household has a housekeeper. We tried to use principal components to create an income index with all these variables. However, due to a large number of missing values, the coefficients were not significant at the 10% level or less, and so we chose to use only the variable of cars as a proxy of income. Close to 50% of the children did not have car in their households, but the average scores for those with cars was higher than for those without cars. As expected, the coefficients for those owning more cars were positive.

Children starting to attend school before the age of 6 or 7 (*start_preschool and start_maternal*) had better academic performance than those who started after 7 years of age (omitted). In Brazil, children from 2 to 4 years old are expected to attend maternal schools, while children from 4 to 6 years old attend preschool. According to the law, a six-year-old child should be in 1st Grade. However, many children actually start school after becoming 7 years of age. It is not mandatory to start school before 1st Grade, but the effect of starting school, at 4, 5, or 6 years old, on test scores was the largest. Similarly, although having less effect than in preschool, those that started between 2 to 4 years old (*start_maternal*) and those who started between 6 or 7 years old (*start_Grade1*) had better test scores than those who started school later. World Bank (2001) analyzed the impact of pre-school and kindergarten on different outcomes. They cited a large number of studies in Colombia, Peru, Jamaica, and Turkey, showing that early childhood development has positive effects on physical, mental and economic wellbeing of a person. Specifically, they cited that interventions, such as, health and nutrition services, in children between 0 and 6 years of age improve health, nutrition and cognitive development, increase enrollment and decrease dropout rates.

School infrastructure was measured by the variable *floor_sch*, if there is a good floor condition in the school. The coefficient is positive and significant as expected.

It seems plausible that teachers have an important task in improving students´ academic performance. In order to measure these effects, we included teachers´ age and experience in the regressions. The inclusion of age squared allowed a parabolic curve and the signs of the coefficients showed a downward concaving parabolic curve. Experience had a positive impact on test scores. Glewwe et al. (2016) reviewed 43 higher quality studies to investigate which specific school and teacher characteristics have strong positive impacts on learning. According to the authors, "there is little evidence that teachers' level of education has any impact on student test scores" (p. 30). Also, teacher gender had an ambiguous impact. On the other hand, they concluded that teacher experience showed a positive effect on test scores. Hanushek and Rivkin (2006) also reviewed studies on teacher quality and concluded that teachers´ advanced degrees did not have systematic relationship to student outcomes. Glewwe and Kremer (2006), after reviewing retrospective studies of the determinants of learning, concluded that "there are no general results regarding which teacher and school variables raise learning in developing countries" (p. 987).

Table 5.2 shows a summary of the impacts of the working variables on test scores in Portuguese and Mathematics for boys and girls. The impacts were calculated based on the coefficients of columns (5) and (10) of Table 5.1 with the average and standard deviation of the scores for boys and girls. For example, in column (5) of Table 5.1, the impact of working only in the labor market on Portuguese test scores for girls was 0.885 s.d.. This value was multiplied by the standard deviation of 40.7 and then divided by the mean of the score for girls in 5th Grade, which was 187.1 (both reported in table 4.3), resulting in a Portuguese score decrease of 19.2%.

The largest observed impact was for girls in 5th Grade who suffered a reduction of 19.2% in their Portuguese test scores when they worked only in the labor market. The largest impact for boys was a reduction of 13.1% in their 5th Grade Portuguese test scores when they also worked only in the labor market. The impacts were larger for 5th Grade students when compared to 9th Grade students. The smallest impacts were observed for boys and girls working only in the household, where the magnitudes varied from 3.3% (9th Grade girls – Math) to 4.4% (9th Grade boys – Mathematics).

Note that although we tried to control for some of the data attrition resulting from children dropping out of school, or repeating the year, we might not have fully achieved our goal, or completely solved the problem of external validity. However, since we focused on the impact of working on the learning of children who stay in school and make normal progress, we can affirm that we found a lower bound of the negative results of working on learning; that is, the magnitudes of the coefficients of the work variables might be even higher.

One important contribution of this paper is that we distinguished between different types of child labor. As per results from the Wald test implemented on specifications (5) and (10), we strongly reject the null hypothesis of equality of the child labor coefficients for most of the combinations. The only exceptions for which we cannot reject the equality of coefficient concern domestic work *versus* both types of work (Portuguese and Mathematics for girls), and for labor market *versus* both types of work (Portuguese and Mathematics for boys). We therefore conclude that domestic work, market labor, and the combination of the two should be treated separately.

Finally, as a robustness check, we ran the estimations on the sample for which a unique match was possible, and without any missing values in the merging variables, which corresponded to 57.3% of the sample used in the estimations above. Although the magnitude of the child work effect slightly changes, the results were quite robust; that is, all statistically significant; the relative contribution of the three alternatives and the direction of the bias are unchanged.

Table 5.1 – Coefficients of the fixed-effect models with and without IPW and IV for test scores in Portuguese and Mathematics in the 2007/ 2011 panel, girls and boys

| Variables | ***Girls*** | | | | | ***boys*** | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | W/out IPW and w/out IV | | With IPW and W/out IV | W/out IPW and With IV | With IPW and With IV | W/out IPW and w/out IV | | With IPW and W/out IV | W/out IPW and With IV | With IPW and With IV |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| ***Panel A: Portuguese*** | | | | | | | | | | |
| Work only at home | -0.044*** | -0.047*** | -0.046*** | -0.317*** | -0.247*** | -0.080*** | -0.073*** | -0.053*** | -0.366*** | -0.269*** |
| | (0.004) | (0.004) | (0.004) | (0.016) | (0.015) | (0.005) | (0.005) | (0.005) | (0.015) | (0.016) |
| Work only in the market | -0.241*** | -0.236*** | -0.200*** | -1.156*** | -0.885*** | -0.291*** | -0.263*** | -0.233*** | -0.690*** | -0.561*** |
| | (0.010) | (0.010) | (0.010) | (0.062) | (0.074) | (0.007) | (0.007) | (0.007) | (0.057) | (0.077) |
| Work in both | -0.249*** | -0.237*** | -0.190*** | -0.580*** | -0.269*** | -0.344*** | -0.316*** | -0.281*** | -0.647*** | -0.523*** |
| | (0.009) | (0.009) | (0.009) | (0.066) | (0.068) | (0.008) | (0.008) | (0.009) | (0.027) | (0.030) |
| R-squared | 0.569 | 0.575 | 0.657 | -0.024 | -0.005 | 0.555 | 0.563 | 0.662 | 0.000 | 0.020 |
| underidentification test (Kleibergen-Paap rk LM statistic) | | | | | 347.006*** | | | | | 389.102*** |
| weak identification test (Kleibergen-Paap Wald F statistic) | | | | | 18.204 | | | | | 19.819 |
| Hansen J statistic (overidentification test)° | | | | | 27.201 | | | | | 30.349 |
| ***Panel B: Mathematics*** | | | | | | | | | | |
| Work only at home | -0.037*** | -0.025*** | -0.026*** | -0.220*** | -0.189*** | -0.071*** | -0.059*** | -0.054*** | -0.308*** | -0.241*** |
| | (0.004) | (0.004) | (0.004) | (0.015) | (0.015) | (0.005) | (0.005) | (0.005) | (0.015) | (0.016) |
| Work only in the market | -0.193*** | -0.179*** | -0.142*** | -0.906*** | -0.690*** | -0.181*** | -0.183*** | -0.155*** | -0.483*** | -0.358*** |
| | (0.010) | (0.010) | (0.010) | (0.055) | (0.066) | (0.007) | (0.007) | (0.007) | (0.040) | (0.054) |
| Work in both | -0.194*** | -0.170*** | -0.127*** | -0.535*** | -0.267*** | -0.292*** | -0.271*** | -0.228*** | -0.604*** | -0.452*** |
| | (0.008) | (0.009) | (0.008) | (0.061) | (0.065) | (0.009) | (0.008) | (0.009) | (0.026) | (0.029) |
| R-squared | 0.576 | 0.583 | 0.672 | -0.013 | 0.002 | 0.571 | 0.579 | 0.663 | 0.005 | 0.013 |
| underidentification test (Kleibergen-Paap LM statistic) | | | | | 354.321*** | | | | | 793.114*** |
| weak identification test (Kleibergen-Paap Wald F statistic) | | | | | 18.592 | | | | | 21.788 |
| Hansen J statistic (overidentification test)° | | | | | 27.443 | | | | | 60.433 |
| States x Trend | yes | yes | yes | yes | yes | yes | Yes | yes | yes | yes |
| Individual fixed effect | yes | yes | yes | yes | yes | yes | Yes | yes | yes | yes |
| Year fixed effect | yes | yes | yes | yes | yes | yes | Yes | yes | yes | yes |
| Exogenous variables[#] | no | yes | yes | yes | yes | no | Yes | yes | yes | yes |
| Observations | 432,412 | 432,412 | 432,412 | 432,412 | 432,412 | 363,096 | 363,096 | 363,096 | 363,096 | 363,096 |

Source: Authors' estimation based on Microdata of Prova Brasil.

Note: ***, **, * significant at 1% level, 5% and 10% level respectively.

[#]In (2), (3), (4), (5), (6), (7) and (8) we also included the variables in table A2.Given the large size of the sample, such test was performed on a random 10% sample selection through bootstrapping (with 100 replications).

Table 5.2 – The impact of the working variables on test scores in Portuguese and Mathematics by percentage for the whole sample and for girls and boys.

| | Portuguese 5th Grade | Mathematics 5th Grade | Portuguese 9th Grade | Mathematics 9th Grade |
|---|---|---|---|---|
| | | GIRLS | | |
| Work only at home | -5.37 | -3.97 | -4.18 | -3.34 |
| Work only in the market | -19.24 | -14.50 | -14.96 | -12.20 |
| Work in both | -5.85 | -5.61 | -4.55 | -4.72 |
| | | BOYS | | |
| Work only at home | -6.26 | -5.40 | -5.18 | -4.38 |
| Work only in the market | -13.05 | -8.02 | -10.79 | -6.51 |
| Work in both | -12.17 | -10.13 | -10.06 | -8.22 |

Source: Authors' estimation based on Microdata of Prova Brasil.
Notes: elasticities are estimated from coefficients reported in tables 5.1 and the means and standard deviations in 4.3.

## 6. Conclusions.

Using Prova Brasil census data collected in 2007 and 2011, we created a panel data of 5$^{th}$ and 9$^{th}$ Grade students to measure the impact of child labor force participation on learning outcomes, measured by Portuguese and Mathematics test scores.

The fixed effect models controlling for year, states and student effects, were weighted by the inverse probability weights to account for possible attrition bias, and an instrumental variable approach proposed by Lewbel (2012) was used to account for the endogeneity of child domestic and market labor in the test score models. Individual, parents, teachers and principal characteristics, as well as school infrastructure were used as control variables.

The estimated parameters were, in general, statistically significant and revealed a negative effect of child labor on school achievement. Students who worked inside the home only experienced a negative impact on their achievement test scores, but the negative impact was greater for students who only worked outside the house, and for those who worked in both inside and outside their home. Students who worked outside their home had possibly a heavier work load, and thus, were possibly physically tired, and encountered greater difficulty coming to class regularly. Furthermore, they were more tired during class, and had less time and energy to devote to their studies than students who did not work, or who only worked in the home.

It seems from these analyses that younger 5th Grade children suffered more harm from work compared to 9th Grade children, and that girls working only in the labor market presented the worst scenario in terms of lowering school achievement.

Our results indicate that domestic work, which is often not counted in social statistics and not considered dangerous, should be included in policies designed to combat child labor. Contrary to the ILO vision, our research shows that domestic work has a negative effect on children´s school performance. According to ILO[6] "Household chores undertaken by children in their own homes, in reasonable conditions, and under the supervision of those close to them are an integral part of family life and of growing up, therefore something positive." As a policy to reduce the amount of time children spend in household activities, we can suggest extending the school day.

Child labor, whether it occurs inside or outside the home, causes a decrease in school achievement. Policy makers will have to make efforts to prohibit child labor, through social programs, enforcement of the law and labor inspections, or by raising awareness about the importance of education and the hazard of early entrance into the job market. A difficult issue for policymakers who would like to eradicate child labor is that families might rely upon the earnings of children and adolescents to meet basic needs. In this case, conditional cash transfer programs, such as Bolsa Familia and PETI are important sources of income allowing for children to stop working.

[6] http://ilo.org/ipec/areas/Childdomesticlabour/lang--en/index.htm

Our results also suggest that Brazilian students might benefit from early entrance into school, from better school infrastructure and from more experienced teachers. Delays in starting school are responsible for a great deal of the weak performance of students. Solving these problems requires educational policies that address the issues of school repetition and drop out, late entry into schools, incentives to improve school quality, and the poor school infrastructure that is found in some regions of the country.

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**APPENDIX**

Table A1 - The students´ level of performance in the Portuguese and Mathematics test scores, according to their scores.

| Level | 5th Grade | | | | 9th Grade | | | |
|---|---|---|---|---|---|---|---|---|
| | Portuguese | | Mathematics | | Portuguese | | Mathematics | |
| | Lower limit | Upper limit | Lower limit | Upper limit | Lower limit | Upper limit | Lower limit | Upper limit |
| level 0 | 0 | 125 | 0 | 125 | 0 | 200 | 0 | 200 |
| level 1 | 125 | 150 | 125 | 150 | 200 | 225 | 200 | 225 |
| level 2 | 150 | 175 | 150 | 175 | 225 | 250 | 225 | 250 |
| level 3 | 175 | 200 | 175 | 200 | 250 | 275 | 250 | 275 |
| level 4 | 200 | 225 | 200 | 225 | 275 | 300 | 275 | 300 |
| level 5 | 225 | 250 | 225 | 250 | 300 | 325 | 300 | 325 |
| level 6 | 250 | 275 | 250 | 275 | 325 | 350 | 325 | 350 |
| level 7 | 275 | 300 | 275 | 300 | 350 | 375 | 350 | 375 |
| level 8 | 300 | 325 | 300 | 325 | 375 | 400 | 375 | 400 |
| level 9 | 325 | 350 | 325 | 375 | - | - | 400 | 425 |

Source: Prova Brasil.

Table A2 – Coefficients of the Probit Model.

| Variables | Coefficients of the Probit Model | |
|---|---|---|
| | Dependent variable is equal to 1 if student is in 2007 and in 2011 and 0 otherwise | |
| Scores_portuguese | 0.230*** | - |
| | (0.0012) | - |
| Scores_mathematics | - | 0.204*** |
| | - | (0.0012) |
| | -0.383*** | -0. 383*** |
| Constant | (0.0012) | (0.0012) |
| Pseudo $R^2$ | 2.41% | 1.91% |
| Observations | 615,785 | 615,785 |

Source: Authors' estimation based on Microdata of Prova Brasil.

Table A3 – Coefficients of the fixed-effect models, full specification with IPW and IV for test scores in Portuguese and Mathematics, by gender

| Variables | Portuguese | | Mathematics | |
|---|---|---|---|---|
| | girls | boys | girls | boys |
| | (5) | (10) | (5) | (10) |
| Work only at home | -0.247*** | -0.269*** | -0.189*** | -0.241*** |
| Work only in the market | -0.885*** | -0.561*** | -0.690*** | -0.358*** |
| Work in both | -0.269*** | -0.523*** | -0.267*** | -0.452*** |
| car_1 | -0.040*** | 0.045*** | -0.045*** | -0.013 |
| car_2 | 0.016 | 0.066*** | 0.017 | 0.025* |
| car_3 | 0.022 | 0.062*** | 0.022 | 0.031** |
| Hh_member | -0.053*** | -0.050*** | -0.042*** | -0.045*** |
| Start_maternal | 0.239*** | 0.216*** | 0.208*** | 0.197*** |
| Start_pre_school | 0.267*** | 0.287*** | 0.250*** | 0.267*** |
| Start_Grade_1 | 0.138*** | 0.168*** | 0.113*** | 0.159*** |
| floor_sch | 0.011*** | 0.005 | 0.019*** | 0.011** |
| Age_teacher | 0.002 | 0.006** | -0.001 | 0.006*** |
| age_teacher2 | -0.000 | -0.000** | 0.000 | -0.000*** |
| Experience_teacher | 0.001*** | 0.001*** | 0.001*** | 0.002*** |

Source: Source: Authors' estimation based on Microdata of Prova Brasil.

Notes: **significant at 1% level, ** at 5% level, * at 10% level