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Abstract

This paper investigates the impact of working while in school on learning outcomes through the use of a unique micro panel dataset of Brazilian students. The potential endogeneity is addressed through the use of difference-in-difference and instrumental variable estimators. A negative effect of working on learning outcomes in both math and Portuguese is found. The effects of child work range from 3% to 8% of a standard deviation decline in test score which represents a loss of about a quarter to a half of a year of learning on average. We also explore the minimum legal age to entry in the labor market to induce an exogenous variation in child labor status. The results reinforce the detrimental effects of child labor on learning. Additionally, it is found that this effect is likely due to the interference of work with the time kids can devote to school and school work.

JEL classification: J13,I21. *Keywords*: Child Labor; Learning; Proficiency; Education.

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1 Introduction

Though the global trend is downward, the incidence of child labor remains very high in developing countries. For example, in 2000 the International Labour Organization estimated that 246 million, or almost 16 percent, of the world's children between the ages of 5 and 17 were child laborers. By 2008 this had fallen to 215 million - a dramatic decline but still representative of 13.6 percent of the world's children. In response, many governments have proposed or implemented policies designed to reduce the incidence either in their own countries, through labor laws that restrict or prohibit children working, or in other countries, through policies such as restricting the importation of goods that use children in some part of their production.

However, much of this policy discussion has taken place in an information scarce environment. While much is known about the incidence and the determinants of child labor, surprisingly little is known about the consequences of child work on participants. Important policy questions such as how young is too young to work, are some work activities better or worse than others, does work impair the health of children and does combining work and school hinder learning remain largely unanswered. This paper seeks to provide an answer the last of these questions and contributes to the literature by assessing the impact of working while in school on learning as measured by the proficiency of students in the São Paulo municipal school system through their performance on standardized exams.

Perhaps the main reason for the dearth of received evidence on the impact of child work is the inherent difficulty in uncovering causal linkages between the activities of children and their subsequent outcomes. The effects of confounding and unobserved variables are persistent problems that are difficult to overcome. In this study, we utilize a unique panel data set of the standardized test scores of Brazilian children in the metropolis of São Paulo that allow us to explore the causal link between the work activity of children and its effect on their exam performance.

We find that, controlling for individual time-invariant unobservable characteristics, working while remaining in school has a depressing effect on their proficiency test scores. 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. Additionally, we find that the magnitude of the negative impact increases with a students ability and that there are both lingering and cumulative negative effects from working while in school. These results provide valuable information to policy makers who wish to understand what types of child work to target for elimination and the effect of child labor on human capital accumulation. The results are robust to idiosyncratic preferences and we perform robustness checks to show that the results are not due to idiosyncratic trends or shocks at the household level. We implement placebo tests and control for idiosyncratic economic shocks at the household level. Moreover, we implement a LATE strategy using the minimum legal age to entry in the labor market to induce an exogenous variation in child labor status. The robustness check results are consistent with our main findings. Finally, we find possible channels through which child labor can impact learning as participants in the labor market are more likely to report that they miss school days, turn homework in late and complete homework while in school rather than at home.

In recent years, a large body of theoretical and empirical research has emerged that has studied the economics of child labor (see Edmonds, 2008; Edmonds and Pavcnik, 2005; Basu and Tzannatos, 2003; Basu, 1999, for extensive literature reviews). Much of the received empirical work has focused on the determinants of child labor while questions of the consequences of child labor have been largely contained in the theoretical literature (see e.g.

Edmonds, 2008; Edmonds and Pavcnik, 2005; Basu and Tzannatos, 2003; Basu, 1999; Emerson and Knabb, 2007, 2006, 2008; Horowitz and Wang, 2004; Ejrnæs and Pörtner, 2004; Basu, 2002; Dessy and Pallage, 2001; Baland and Robinson, 2000; Dessy, 2000; Basu and Van, 1998). The theoretical literature has long emphasized the trade-off between child labor and human capital accumulation to justify policy interventions assuming depressing impacts from child labor. As noted above, the empirical foundations to support these assumptions are weak. [1]

Though evidence of the effects of child work on participants is still relatively scarce, there is a new and growing literature that has begun to fill in the lacuna. Beegle et al. (2009), studies a five year panel of school children in Vietnam and finds that child labor has negative consequences on school participation and educational attainment. Orazem and Lee (2007) uses Brazilian household data to examine the impact of working as children on self-reported health outcomes and finds negative impacts of child labor. Emerson and Souza (2011) examines retrospective data from Brazil and finds that child work before 13-14 years old negatively affects adult incomes, but that this affect turns positive after these ages. Interestingly, this study finds that the effect of child work on earnings remain even when controls for years of education are included, raising the possibility that child labor may affect the learning of those workers who remain in school, which provides a motivation for the current study.

Research on the consequences of child work on education have mainly focused on attendance rather than learning (e.g. Ravallion and Wodon, 2000; Assaad et al., 2001; Canals-Cerda and Ridao-Cano, 2004; Beegle et al., 2008, 2006; Assaad et al., 2005) and have found modest negative effects of child work. But as Emerson and Souza (2011) suggest, school

[1](See also Ponczek and Souza, 2012; Emerson and Souza, 2003; Ilahi et al., 2001; Psacharopoulos and Patrinos, 1997)

enrollment may not be the only important measure, especially in countries like Brazil where combining work and school are common.

The direction of the expected impact of child work on learning is unclear. Working requires time and energy that could hamper a student's ability to learn, but some work activities could involve tasks that are either directly related to learning (like reading, writing and math) or indirectly related but still involve use of these skills. If a work activity involves learning-by-doing or is otherwise positively correlated to learning the skills tested in school (in our case math and Portuguese), work could, in fact, have a positive impact. In the end the true nature of the relationship between work and learning, if the two are substitutes or complements, is an empirical issue.[2] Understanding this relationship is extremely important as previous research has shown a very strong connection between educational proficiency and adult income and economic growth, and that proficiency is a stronger determinant than completed years of schooling [see, e.g. Hanushek and Zhang (2009) and Hanushek and Kimko (2000)].

We are aware of three previous studies that have examined the impact of child work on student proficiency. The first paper, closely related to the present study is Bezerra et al. (2009), which uses cross-sectional Brazilian data to test the impact of working on the performance on similar exams. The authors find that working has a negative impact on the performance of participants. Another closely related study is Dumas (2012) which exploits retrospective data from Senegal to examine the effects of child work on the test scores of Senegalese children and finds some evidence of positive effects of child work. Finally Gunnarsson et al. (2006) uses data from nine Latin American countries (including Brazil) and finds negative and significant impacts of working on student test scores. All three studies are

[2]We use the terms 'learning' and 'proficiency' synonymously, but for both we are referring specifically to only those aspects of learning that are measured by standardized tests in Portuguese and Math.

constrained by the inherent difficulties in overcoming the potential endogeneity of child labor and both implement instrumental variables strategies in an attempt to overcome the problem. In all three cases, the challenge of finding sources of variation that are correlated with the decision to work but uncorrelated with the unexplained variation in school performance is severe, leading to questions of the validity of the instruments themselves and thus the results. In our case the use of time-series data presents a huge advantage in our ability to control for both the endogeneity of child labor and the presence of other unobservables (e.g. parental preferences) that are potentially correlated with both the decision to work and the aptitude for, and attitude toward, school. We are also able to explore the lingering and cumulative impacts of child labor as well as explore the heterogeneous effects on student of different ages and abilities. In addition, through the time-use information available to us, we are able to explore the potential channels through which child labor may interact with the process of learning and we are thus able to shed light on the mechanisms involved.[3]

This paper proceeds as follows: In section 2 we describe the data used in the study. In section 3 we describe the general child labor and educational environment in the City of São Paulo. In section 4 we explain the empirical strategy, how we identify our model and the robustness checks we employ. In section 5 we present and discuss the results of the empirical investigation. In section 6 we summarize the paper and discuss the policy implications of the results of the empirical investigation.

[3]Also related are studies from cross sectional data such as Heady (2003) which finds large and negative impacts of child work on educational achievement and Akabayashi and Psacharopolous (1999) which examines the correlation between work and subjective measures of ability, and finds a negative impact from child work.

2 Data, Sample Selection and Descriptive Statistics

In 2007, the City of São Paulo started an evaluation system for students enrolled in municipal schools involving a set of proficiency exams in mathematics and Portuguese. These exams were accompanied by a questionnaire that was given to each student taking the exams as well as an additional questionnaire that was given to the parents of the students taking the exams about the socio-economic characteristics of the family, although the parents questionnaire was not administered in 2008.[4] The exam is called the *Prova São Paulo* (São Paulo Exam) and was implemented annually until 2013 when it was discontinued. The microdata from the 2007 to 2010 exams are available and used in this paper. In 2007 all students in the even grades ($2^{nd}, 4^{th}, 6^{th}$ and 8^{th}) took the exam. In 2008, all students in the $2^{nd}, 4^{th}$ and 6^{th} grades took the exam, and randomly selected students in $3^{rd}, 5^{th}$, 7^{th} and 8^{th} grades took the exam (one class per grade per school was randomly selected to take the exam). From 2009 and on, all students in the even grades and randomly selected students in the odd grades (35 students per grade per school) took the exam.[5] In each year, around 500,000 students in 8,000 classes in 500 schools took the exam. Importantly, the São Paulo Exam was structured based on the Item Response Theory (IRT) so that the results are comparable across grades and across years.

We have information from the students' questionnaires for all years on the students' working status. Only students in the fifth grade and above answer the question about child labor, which restricts the population of analysis.[6] The precise wording of the question about

[4] Questionnaires were also given to the principals which asked them to answer questions about themselves, their school, the teachers and supervisors, and the student population, but it was not administered in 2009.

[5] All students in the fifth grade who scored below 150 points in the previous year are also included in sample.

[6] In 2008, students in the fifth grade answered a version of the questionnaire that was distributed to the younger students in second to fourth grade. In this questionnaire, there is no question about the child labor status. Together with the fact that fifth graders are not randomly selected, we decided to exclude them from

working status is as follows (translation ours):

"During school days, do you work?

(A) Yes, outside of the house; (B) Yes, at home helping with the chores; (C) No, I only study."

Respondents were limited to one answer only. We set the indicator variable $MarketLabor$ equal to 1 whenever a student answered "A", and to 0 otherwise so we are comparing those that work outside of the home to those who work at home on chores and those who do not work at all.

From the parent's questionnaire we collected information about the father's employment status for 2007, 2009 and 2010.

The student questionnaire also asks students about their studying habits such as whether they miss classes, hand in homework late, prepare for exams in advance, and complete homework at school. From the responses to these questions we created four indicator variables.

We construct three different samples for this study. The first includes all observations of students in the 6^{th}, 7^{th} and 8^{th} grades in 2007, 2008, 2009 and 2010. This sample constitutes an unbalanced panel of 473,051 observations of 313,297 students (158,180 boys and 155,117 girls).[7] We call this the "full sample". The second sample encompasses all students that were in 6^{th} grade in 2007 or in 2008 and were found two years later from the first observation. Therefore, we have exactly two observations for each student. This balanced panel has 48,009 boys and 48,161 girls. We call this the "paired sample". The third sample also encompasses all that were in 6^{th} grade in 2007 or in 2008, but we include only those who were also found in

our sample.

[7]We also dropped 994 students aged nine years old or below. We believe those are measurement error, since the regular age for the 6^{th} grade in Brazil is 12 years old. Nevertheless, none of the deleted students appear more than once in the sample, therefore the trimming does not change the estimate of the parameter of interest in the fixed effect specification.

next two consecutive years after the first observation. Depending on the exercise, we use the first and third observations or the first and second observation for each students. Therefore, we have exactly two observations for each student. The sample contains observations on 6,563 boys and 6,630 girls and we call this the "3 period sample."[8]

Tables 1 to 3 presents some descriptive statistics of the three samples separately for boys and girls. The incidence of child labor in the full sample is around 12% for boys and 6% for girls. The average age is 14 years old and, on average, boys outperform girls in math and the reverse occurs in Portuguese.

[INSERT TABLES 1 AND 2 AND 3 AROUND HERE]

Since we use fixed effect estimators, it is necessary for identification to have transitions into and out of market labor. Table 4 shows the transition matrix of the market labor variable. We can see that for both boys and girls we have a sufficient number of students transiting in and out of working status. For instance, 4,500 boys and 2,300 girls change their status from not working to working in one year.

[INSERT TABLE 4 AROUND HERE]

It is worth noting here that we observe only those who are enrolled in the São Paulo municipal school system and who remain in the school system. There is no forced repetition of grades in São Paulo municipal schools for the $6^{th}, 7^{th}$ and 8^{th} grades, but there can be drop-out, movement to state or private schools or movement out of the area. As drop-out and delay are likely two other important effects of child labor, it is important to note that we are not examining these ancillary effects of child labor.

[8]No student was age trimmed in the paired and 3 period samples

3 Child Labor and Students in the City of São Paulo

This section describes the incidence of child labor and school attendance in the City of São Paulo.[9] The data used in this study come from the *2010 Demographic Census* collected by the Brazilian Census Bureau (IBGE). It contains information on socio-demographic characteristics, fertility, migration, and time allocation for all individuals sampled. It is a sample of the entire population representative at the municipality level. Most important for the present study, it contains information about school attendance, labor force participation and occupation in the reference month of the survey (July). The information for labor market outcomes are available for individuals aged 10 years old and above.

3.1 Child Laborers

Table 5 below presents the figures for the time allocation of individuals aged 10 to 17 living in São Paulo City in 2010 for male and female individuals, separately. There are around 1.4 million individuals in this category and the majority attend school. In fact, 85.4% (86.6%) of boys (girls) attend school only; and 6.2% (5.4%) of the boys (girls) divide their time between school and work. Thus around 92% (93%) of boys (girls) attend school. Conversely, 2.5% (1.7%) of boys (girls) work only; and 5.9% (6.3%) of boys (girls) neither work in the labor market nor attend school. Summing up those that work only and those that work and attend school, the incidence of child and adolescent work among boys is 8.7% and among girls it is 7%. Note that of all boys working in the labor market, 71% attend school, and for girls the figure is 76%. On the other hand, of all boys attending school, 6.8% work in the labor market, and of all girls attending school, 5.8% work in the labor market.

[9] São Paulo is the name of both the City and the State in which it resides and there are both state and municipal schools inside the City of São Paulo

[INSERT TABLE 5 HERE]

3.2 Students

Our data encompass students enrolled in the $6^{th}, 7^{th}$ and 8^{th} grades at São Paulo municipal schools. According to the *2010 Educational Census* from the Brazilian Ministry of Education, there are around 580,000 students enrolled in these grades in the City of São Paulo in 2010. Table 6 shows their distribution across grades and school systems. Of all of them, 49.6% are enrolled in the public municipal schools, 31.5% are enrolled in public state schools and 18.8% are enrolled in private schools and these proportions are similar for all grades. Since our data are of municipal school children only, we observe roughly half of the $6^{th}, 7^{th}$ and 8^{th} grade students in São Paulo City, a population of around 290,000 students.

[INSERT TABLE 6 HERE]

The IBGE Demographic Census has information about the type of school system in which the student is enrolled as well. It classifies schools as public or private but does not distinguish between municipal and state public schools. Table 7 below presents the distribution of $6^{th}, 7^{th}$ and 8^{th} grade students across public (municipal and state) and private schools. These figures are presented for students who work and who do not work separately.

[INSERT TABLE 7 HERE]

According to the census, there are around 540,000 individuals living in the City of São Paulo in 2010 that reported that they attend $6^{th}, 7^{th}$ and 8^{th} grades. Of all of them, 82% attend public schools. Of all middle school students, around 11% work in the labor market. However, these figures are sharply different between public and private school students. Among public school students, 12.8% work in the labor market, whereas among private school students, 2.4% work in the labor market. As expected, the incidence of child and adolescent work increase with grade. Among $6^{th}, 7^{th}$ and 8^{th} graders in public schools, the incidences of working the labor market are 7%, 12.6%, and 20.4%, respectively.[10]

If the proportion of child workers among $6^{th}, 7^{th}$ and 8^{th} grade students is similar between municipal and state school students, then there are roughly 37,000 municipal middle school students working in the labor market of the City of São Paulo in 2010.

What do these working students do? Table 8 below presents the occupational distribution of the working public school students in $6^{th}, 7^{th}$ and 8^{th} grade in the City of São Paulo according to the *2010 Demographic Census*.

[INSERT TABLE 8 HERE]

Most students who work, work in the service sector. Indeed, 26.1% of them work as domestic servants, street vendors, car washers, and others; 25.4% work as service and retail vendors; 14.8% are in office work; and 10.2% are in military service occupations.

4 Empirical Strategy

The main challenge in estimating the impact of child labor on learning is overcoming the potential endogeneity of child labor. The decision about the child's time allocation could be made based on unobservable characteristics of the individual that also determine her proficiency. It is very likely that *ability* is correlated with proficiency and the parents' perception of the value of education which determines the child's time allocation. In this case, a simple OLS estimator for child labor and proficiency will be biased. Depending on the correlation between the unobservables and time allocation decisions and between the unobservables and proficiency, the OLS estimator could be upward or downward biased.

[10] In our pooled sample the averages (across all three grades) for the market labor variable are 12% for boys and 6% for girls.

In the above example, if there is a positive relationship between *ability* and the perception of the value of education, meaning parents with high ability children are more likely to prioritize schooling, we would expect that a naive approach would overestimate the actual impact of child labor on proficiency. On the other hand, one can imagine that more able children have better opportunities in the labor market. In this case, the OLS estimator would underestimate the effect of child labor on proficiency.

Therefore controlling for such unobservable characteristics is essential to consistently estimate the impact of child labor on proficiency. The longitudinal dataset of *Prova São Paulo* allows us to control for unobservable characteristics that are fixed over time.

Our 'benchmark' strategy is, therefore, a fixed effect estimator, we run the following regression separately for boys and girls and for math and Portuguese:

$$T_{igt} = \beta_0 + \beta_1 Market\ Labor_{igt} + \beta_2 Age_{igt} + \beta_3 Age^2_{igt} + \theta_i + \lambda_t + \gamma_g + \epsilon_{igt} \qquad (1)$$

where T_{igt} is the math or Portuguese language proficiency test score of student i in grade g, and year t. $Market\,Labor_{igt}$ is an indicator variable that assumes 1 if the student i, in grade g is working at year t. θ_i is the individual fixed effect, λ_t is a time-specific effect, and γ_g is the grade fixed effect; ϵ_{isct} is the error term with school clustered variance-covariance matrix. In this case, β_1 is the parameter of interest. Note that by including both and age and grade fixed effects we are estimating the impact of working on students who are the same age and in the same grade, thus we are deliberately netting out the potential effects of drop out and delay as mentioned previously.

This strategy is consistent even if there are unobservable attributes that simultaneously determine child labor and proficiency as long as those characteristics are constant over time.[11]

[11]Indeed, we need only that the variation of the unobservable attributes is not jointly correlated with the

We run the benchmark specification using both full and paired samples.

The identification strategy in our panel structure requires some individuals to transit in and out of the labor market. In the above estimations we implicitly assume that the effects of these transits are the same for all individuals regardless of age, ability, and whether they are entering into child labor or exiting out of child labor. It is likely that these effects are not the same - that there is heterogeneity based on age ability and the direction of the transit - and we therefore conduct four tests of the possibility of heterogeneous effects using the paired sample.

First, we test if younger students suffer more from working than older students.[12] Second, we test if students with different ability levels, as measured by first year test scores, suffer differential impacts of working while studying.

To conduct these two tests we estimate the two specifications below:

$$T_{igt} = \beta_0 + \beta_1 MarketLabor_{igt} + \beta_2 MarketLabor_{igt} \times Age_{ig1} + \beta_3 Age_{igt} + \beta_4 Age^2_{igt} + \theta_i + \lambda_t + \gamma_g + \epsilon_{igt} \tag{2}$$

$$T_{igt} = \beta_0 + \beta_1 MarketLabor_{igt} + \beta_2 MarketLabor_{igt} \times T_{ig1} + \beta_3 Age_{igt} + \beta_4 Age^2_{igt} + \theta_i + \lambda_t + \gamma_g + \epsilon_{igt} \tag{3}$$

where $MarketLabor_{igt} \times Age_{ig1}$ and $MarketLabor_{igt} \times T_{ig1}$ are interaction terms between child labor status and age and test score at the first year the student is observed in the sample, respectively. A negative coefficient estimate associated with the interaction between child

child labor and proficiency variation.

[12]Emerson and Souza (2011) have shown the presence of heterogeneous effects of child labor on adult labor market outcomes depending the age the child enter in the labor market in Brazil.

labor and age suggests that child labor effects younger students more than older students; while a negative coefficient associated with the interaction between test score indicates that higher scoring students are more harmed by working.

In order to account for the possibility of heterogeneous transition effects, we estimate specification (1) separately for those entering and those exiting the labor market using the paired sample. Thus our third test of heterogeneous effects is on those who enter into child labor compared to those who never worked, and our fourth test is on those who exit out of child labor compared to those who work in both periods. Notice that this is a different comparison to the benchmark test which compares those who transit into or out of market labor to those who not change their status (both not working in all periods and working in all periods of observation).

Next, we ask whether child labor has cumulative and lingering effects. To test for these, we analyze whether the impact of work on learning depends on the length of time spent working. For these exercises, we use the 3 period sample restricted to students that were not working in the first observation t.

To check for the presence of cumulative effects we compare the evolution of test scores between t and $t+2$ among three groups of students. Students in the comparison group have not worked in all three periods. Students of group 1 work at period $t+2$ only. Students of group 2 started working in $t+1$ and remain working in $t+2$. Therefore, we run the following specification:

$$T_{igt} = \beta_0 + \beta_1 MarketLabor^1_{igt} + \beta_2 MarketLabor^2_{igt} + \beta_3 Age_{igt} + \beta_4 Age^2_{igt} + \theta_i + \lambda_t + \gamma_g + \epsilon_{igt} \quad (4)$$

where $Market\ Labor^1_{igt}$ indicates whether the student has been in the labor market for one year (started worked in $t+2$) and $Market\ Labor^2_{igt}$ indicates whether the student has been in the labor market for two years (started worked in $t+1$ and remains working in $t+2$). We then test if $\beta_1 = \beta_2$.

To test for the presence of lingering effects we compare the evolution in scores from t to $t+2$ between two groups of students: a comparison group (worked in no periods), and a treatment group of students who have only worked in $t+1$ and have stopped working in $t+2$.

If the time variation of the relevant unobservables is correlated with the child labor and proficiency variations, the fixed-effect estimator is inconsistent.[13] Therefore, we perform several robustness checks in order to validate our identification assumption. The robustness checks use information from students that appear at least three years in our sample. We compare students with the same working history in the first two years we observe them, but with a different working status in the third year. The idea is that the outcome in the second year should not be impacted by a future (third year) working event. If this were so, then the assumption of identical trend for treatment and comparison groups would be invalid. Therefore, we estimate specification (1) for the students that: (i) are in the 3 Period sample (i.e. appear in three consecutive years); and (ii) have the same working status history in the first two years in the sample.

Though our empirical strategy allows us to control for all time-invariant individual and family characteristics there may still be some time-variant characteristics that are important. For example, it is likely that transitions into and out of child labor are correlated with idiosyncratic transitory shocks at the household level and, if so, there may be a direct effect

[13]Ideally, we would observe the same individual's proficiency at the same time: working and not working. In this hypothetical situation, the mean proficiency differential would be a clear and immediate indicator of the impact of child labor on proficiency.

of such shocks on learning.[14] In this case our estimates would be biased upward as we would attribute to child labor the effect of the shock itself. We believe that it is likely that most of the impact of a shock that causes a child to enter the labor market is through the interference that the labor itself has on the time allocation of the student leading to less studying, fatigue, etc. Nevertheless, we are able to perform a robustness check to see if such transitory shocks are biasing our estimates by including a control for the employment status of the father. Since we do not have this information from 2008 we estimate our benchmark model on a sample from 2007, 2009 and 2010 for observations that include the father's employment status with and without the father's employment status included as a control. Moreover, other sources of shocks may be both correlated to child labor transitions and changes in learning. For instance one can imagine that changes of the parents marital status or health problems of a family member may explain our findings. Therefore, we use a IV strategy to circumvent this potential problem. More specifically, we explore the transitions in child labor status induced by the change in age that turn the individual eligible to work. In Brazil the minimum legal age to participate in the labor market is sixteen years old. Therefore, we will estimate a Local Average Treatment Effect (LATE) as explained by Imbens and Angrist (1994).

Finally, if child labor does have a significant effect on learning it would be useful to understand the nature of this effect. To do so we identify some channels through which working could affect student performance that are related to the time use and study habits of the students. Specifically, we use the full sample and run specification (1) to test the impact of child labor on four different outcomes: missing classes, preparing for exams in advance, completing homework at school, and turning in homework late.

[14]For instance Duryea et al. (2007) finds that household economic shocks are important determinants of transit into and out of child labor in metropolitan Brazil.

All regressions use robust standard errors.

5 Results

5.1 Benchmark model

To assess the impact of working while in school on the learning outcomes of São Paulo city school children we begin by estimating the benchmark model on both the full pooled sample (an unbalanced panel) and the paired sample (a balanced panel).

Table 9 presents the results of these regressions. The first four columns present the pooled sample estimation results for the math and Portuguese test scores for boys and girls separately. The second four columns present the same estimation results for the paired sample. In all eight regressions the coefficient estimate on the child labor dummy variable is negative and significant at the one percent level. The point estimates range from -1.278 (boys math) to -3.951 (girls Portuguese). The results suggest that working while in school negatively impacts the students' performance on standardized exams in both math and Portuguese. For math for boys and girls and for Portuguese for boys the coefficient estimates translate to around 3% to 3.5% of a standard deviation decrease in test scores. For Portuguese for girls the coefficient estimates translate to a 6.7% of a standard deviation decrease in the pooled sample and an 8.1% decrease in the paired sample. We can interpret those coefficients with the average proficiency gain a student obtain of one extra year of schooling. The average annual increase is 11 points in math and 12 in Portuguese which suggests the impact is a loss of from around 10% to 40% of a year of learning.

The students' age coefficients are all positive and significant except for boys and Portuguese suggesting that the older a child is (in a given grade) the better he or she generally does on standardized tests with the exception of boys and Portuguese. The squared age coefficient estimates are all negative and significant but very small suggesting that the age effect is slightly non-linear but not enough to turn the net effect negative.

[INSERT TABLE 9 AROUND HERE]

5.2 Heterogeneity

Tables 10 through 13 present the results of the tests of heterogeneity, all of which use the paired sample.

5.2.1 Marginal impacts of age and proficiency

Table 10 presents the results of the estimation with the child labor indicator variable interacted with age at the first observation. The results from this regression suggest that, after controlling for grade and year, the effect of child labor does not significantly change with the student's age.

Table 11 presents the results of the estimation with the child labor indicator variable interacted with test score. In contrast to age, the effect of child labor does vary depending on test score: students are more negatively impacted by child labor the higher their initial test score. This may be perhaps because better students are more prone to study at home where child labor might interfere more or perhaps fatigue has a larger marginal impact on better students.[15]

[INSERT TABLE 10 AND 11 AROUND HERE]

[15] The negative effect dominates for those whose test scores are above: 171.1 for boys math; 187.9 for girls math; 173.1 for boys Portuguese; 113.8 for girls Portuguese. All well below their respective means.

5.2.2 Isolating transitions into and out of child labor

Tables 12 and 13 present coefficient estimates on the paired sample that attempt to isolate the effect of a child starting to work and a child stopping working. In order to accomplish this, the estimation presented in Table 12, 'Ins', selects all those who did not work in the first period of observation (t) and compares those that continued without working in the next window of observation ($t+2$) to those were working in the next window of observation ($t+2$). Table 13, 'Outs', does the opposite: it considers all those that were observed to be working in the first period (t) and compares those that remained working in the next period of observation ($t+2$) to those that were no longer working in the next period of observation. The coefficient estimates for the child labor variable presented in Table 12 for the 'ins' are all negative and significant at the one percent level, similar to Table 9, but the point estimates are larger.[16] The marginal impact of these new estimates now range from 6.2% (girls math) to 10.6% (girls Portuguese) of a standard deviation decline in test score. Interpreting these in terms of average annual increases in test scores reveals that the impact of starting to work is equivalent to roughly one half to a whole year of learning loss. The coefficient estimates for the child labor variable presented in Table 13 for the 'outs' are all negative and significant at the one percent level, similar to Table 9, but again the point estimates are larger. The marginal impact of the estimates now range from 6.7% (boys math) to 19.0% (girls Portuguese) of a standard deviation decline in test score of roughly one half to almost two years of learning loss for those that remain in the labor market compared to those who exit.

[INSERT TABLE 12 AND 13 AROUND HERE]

[16] It is important to understand that these estimates are from an entirely different model and are thus not directly comparable. Whereas the baseline model imposes homogeneous effects and estimates the average impact, this model estimates the impact of working conditional on not working in period t.

The 'In' and 'Out' coefficient estimates have similar magnitudes and we cannot reject that they are statistically equal to each other. Therefore there is not evidence of heterogeneity between moment into or out of the labor market. This could suggest that transitions into and out of the labor market may be due to individual idiosyncratic shocks that are orthogonal to proficiency.

5.3 Exposure and lingering effects of child labor

We now turn to two questions that demand the use of the third 'three period' sample. Recall that this sample takes all of the children we observe in 6^{th} grade in either 2007 or in 2008 and whom we observe in the next two consecutive years (regardless of progression through the grades) and we compare scores in t and $t+2$. Table 14 presents estimates of 'exposure effects' and takes all children who are not working in the first observation year and compares those who only work in the third year (group 1) to those who work in the second and third years (group 2) to see if consecutive years of exposure have increasing or decreasing marginal effects on the students' test scores. For boys math scores the coefficient estimates on both the indicator variable for one year working and two years working are negative and significant. Interestingly, the two year indicator variable coefficient is almost double the one year estimate, suggesting that the effect is essentially linear. Each year of working leads to about a 3.1 point drop in test scores. For the other regressions the effects could not be separately identified perhaps due to the fairly small sample size we are now working with.

[INSERT TABLE 14 AROUND HERE]

Another question we seek to address using the three period sample is the question of 'lingering effects.' In Table 15 we present coefficient estimates of regressions where we again start with those that initially do not work and compare those that remain not working for all three years to those that work in the second year but do not work in the third. The question is if having worked in the past continues to depress a child's test score or do they 'catch up?' From the results in Table 15 we find some evidence that the effects do linger for boys as for math and Portuguese the coefficient estimates are negative and significant (at the 10% level for math). For girls the point estimate for the math coefficient is negative and of a similar magnitude to previous regressions but has a large standard error and is not statistically significant while the Portuguese coefficient estimate is both very small and insignificant.

[INSERT TABLE 15 AROUND HERE]

5.4 Robustness checks

5.4.1 Preexistent different trends

We next conduct a series of robustness checks. The first set are described in Table 16: using the three period sample we conduct a series of difference-in-difference estimates on the relative test score increase over the first two years for kids with identical work experiences and condition on their third year (post evaluation) work experience. We expect to find no impact of working in the third year for those with identical work histories.[17] Below we show the four subsamples we use to conduct the robustness checks. Those who did not work in year t or $t+1$ (Treatment 001), those who worked in both year t and year $t+1$ (Treatment 111), those who worked in year t but did not work in year $t+1$ (Treatment 101)and those that did not work in year t but did work in year $t+1$ (Treatment 011). We will compare

[17]We can only identify those with identical *observed* previous work histories, therefore we cannot completely exclude the possibility that unobserved work histories are correlated with future work histories. This could happen for children in households particularly sensitive to income shocks, for example.

the score trajectory between t and $t+1$ for all subsamples.[18]

[INSERT TABLE 16 AROUND HERE]

In each case we estimate our model for both boys and girls and for both math and Portuguese for a total of 16 robustness tests. The results for boys are presented in Table 17 and the results for girls are presented in Table 18. In all cases but one the robustness test yields the expected result: no difference in the test score progression. In one case the math scores for boys is negative and significant. This could suggest that there could be some selection on trends in scores: boys who observe their score progressing slowly select into child labor or perhaps some correlation with unobserved prior work history.

[INSERT TABLE 17 AND 18 AROUND HERE]

5.4.2 Idiosyncratic shocks

The difference in difference estimators may be biased if there are time variant idiosyncratic shocks correlated to both child labor transitions and variation in test scores. We have information of the time-variant employment status of the father. As there are many missing observations and we do not have information on the parents for 2008, the sample size has decreased considerably from the benchmark case on the full pooled sample. For this reason we estimate the benchmark regression both without and with the father's employment status variable as a control using this sample in order to gauge the extension of this potential bias.

Table 19 presents the result of the estimations of the benchmark model on the sample of observations for which we have information on the employment status of the father both including and excluding the father's employment status as proxy for idiosyncratic economic shocks to the household. We find that for boys the point estimates for both math and

[18]Note that all 16 regressions are robustness checks of the baseline regressions but only some are relevant to the ins and outs regressions.

Portuguese are statistically significant and larger than in the benchmark regression on the pooled sample when father's employment status is not included as a control. However, there is almost no change in the size or significance of the variable when we control for father's employment status suggesting the fixed-effect estimator is not biased upward. For girls the change in sample size causes the point estimates for both math and Portuguese to shrink and loose significance relative to the benchmark case on the full sample, but again, there is virtually no difference between the coefficient estimates from the regressions where father's employment status is excluded and included. These results suggest that our coefficient estimates are not biased due to correlation with time variant idiosyncratic employment shocks to the household.[19]

[INSERT TABLE 19 AROUND HERE]

5.5 IV estimator

One my argue that these robustness checks are not sufficient since unobservable individual characteristics or other time variant idiosyncratic shocks beyond father´s unemployment may be both correlated to labor market transitions and changes in test scores. For instance, a family break up or health problems of a family member.

In order to further investigate the potential bias of our fixed effect estimators, we proceed with an instrumental variable strategy. Brazilian law establishes a minimum legal age to participate in the labor market.[20] No firm can formally hire a worker younger than sixteen years old and parents are also subject to legal punishments if an under age child works

[19] We have information on the mother's employment status as well and we ran regressions using mother's employment status and both mother's and father's employment status and found similar results, but using mother's employment status reduces sample size even further.

[20] Constitutional Amendment No. 20 on December 16th, 1998 which increased the minimum legal age for entry to labor market from 14 to 16.

in the labor market. Because of this Brazilian firms rarely hire formal workers under age of sixteen. However, due to lax enforcement in the informal sector there remains much employment of children younger than sixteen. Hence, our instrumental variable of the labor market transition is a variable the indicates whether the individual is legally allowed to work (older than 192 months old). We estimate the following system of equations:

$$Market\ Labor_{igt} = \alpha_0 + \alpha_1 Minimum\ Age_{igt} + \alpha_2 Age_{igt} + \eta_i + \nu_t + \pi_g + \upsilon_{igt}$$

$$T_{igt} = \beta_0 + \beta_1 Market\ Labor_{igt} + \beta_2 Age_{igt} + \theta_i + \lambda_t + \gamma_g + \epsilon_{igt}$$

Where $Minimum Age_{igt}$ is the indicator variable that it is equal to one if the individual is sixteen years or older at time t and zero otherwise. Note that we are controlling for individual i, year t, and grade g fixed effects, and also for age measured in months. Therefore, our identification strategy comes from the variation on age from not allowed to allowed to work over and above the direct effect of age on the probability of working. The identification assumption is that there is no direct effect of turning sixteen on learning over and above a directly linear effect of age. This is the Local Average Treatment Effect (LATE) described by Imbens and Angrist (1994) and this is the effect of child labor on proficiency among a sub-population of those students induced to work due to changing their legal status of work (i.e., turning sixteen years old). We perform this exercise with the paired sample. In this sample, around 8.7% of the individuals move from not allowed to allowed to work within two years.

The LATE estimator requires that the instrument is valid plus the monotonicity assumption. The instrumental variable is correlated with the potential endogenous variable (this is shown in Table 20 below). Also, it must not be correlated with the error term of the outcome equation. This seems reasonable once we control for the individual fixed effect and age in months. Finally, the monotonicity assumption looks reasonable as well. It requires that all individuals change their probability to work in the same direction when they turn sixteen. It does not seem likely that some individual will decrease their probability to work because they turned sixteen.

Table 21 below presents the results for boys and girls separately. The first stage regressions show that boys and girls are more likely to work when they turn sixteen over and above the linear age effect. In fact, boys (girls) are around 6.5 (4.0) percentage points more likely to work when they became sixteen years of age. The results of the second stage regressions show strong negative impacts on proficiency. A working boy (girl) decreases his proficiency in math by 94.7 (39.4) proficiency points. For Portuguese, the effects are -91 and -137 proficiency points for boys and girls, respectively. The standard deviations of the proficiency scores among individuals aged sixteen years or older ranges from 73.6 for boys in Portuguese to 80.2 for boys in Math. The standard deviations for girls are 76.7 and 76.8 for math and Portuguese, respectively. The results implies that the child labor effect for this subpopulation ranges from 0.5 (1.2) of a standard deviation for girls (boys) in math to 1.8 (1.2) of a standard deviation for girls (boys) in Portuguese.

The IV estimators are (negatively) stronger than the difference in difference estimators. This may suggest that the fixed effect estimators are attenuated (in absolute terms) due to measurement error of the market labor variable. Alternatively, the IV estimators are LATE estimators. The effects are for a subpopulation of those induced to work due to becoming able to work legally thus there could be heterogenous effects such that the impact of child labor on this subpopulation is much stronger than for working students in general. It is important to notice that this specific subpopulation is composed of students that are older than the correct expected age for 6^{th} to 8^{th} graders.

5.6 Channels

Finally we explore potential channels through which child labor could be causing the suppression of test scores. Table 22 has the results of the regression of the answers to the four channels questions on the child labor indicator variable. For three of the variables there is a positive and significant coefficient estimate for both boys and girls: missing classes, completing homework at school, and turning in homework late. Boys (girls) are 6.4 (3.9) percentage points more likely miss classes if they work while in school compared to students who do not work, which translates to 29% (14%) more likely to miss classes. Similarly both boys and girls are 2.2 percentage points more likely to complete their homework at school (rather than at home) if they work, which translates to 8% (10%) more likely to complete homework at home. Finally, boys (girls) are 3.1 (4.4) percentage points more likely to turn in homework late if they work while in school, which translates to 5% (9%) more likely to turn in homework late. These results suggest that the time burden of working while in school is interfering with attendance and the careful and timely completion of assignments.

[INSERT TABLE 22 AROUND HERE]

6 Discussion and Conclusion

Working while in school has negative and lasting consequences for children who participate in the labor market compared to those who do not. This paper finds negative and significant impacts of working while in school on the math and Portuguese proficiency scores of children enrolled in São Paulo municipal schools. The impacts are economically significant. The lower bound of the average effects of working while in school hovers around 3 percent of a standard deviation in math scores for boys and 6% for girls, and 5% for Portuguese for boys and 7% for girls. When we isolate the effects for just those students who transition into child labor we find negative effects of over 6% to over 10%. Extrapolating from the year to year average gain in proficiency scores the average effect of transitioning to work while in school the effect of working is equivalent to one quarter to an entire year of learning.

We show that these results are robust to idiosyncratic preferences and perform robustness checks to rule out selection on idiosyncratic trends and shocks at the household level. We find some evidence that the effect of working while in school is cumulative and that the effect lingers over time. We also find evidence that the negative effect of child labor while in school operates through the interference in students' study time allocation and habits such as attending class, doing homework outside of class and turning in homework on time.

This is not to say that students that work are not optimizing. Their behavior could be the consequence of an optimal decision including the cases where they have large discount rates, are myopic about the future returns and simply prioritize current consumption as some sociologists in Brazil have suggested. It is also possible that students lack information about the true returns to learning in the adult labor market. Another explanation could be that individuals are credit constrained and are unable to borrow against future earnings. However, this individually rational (or boundedly rational) behavior of working while in school is likely inefficient in the sense that the real cost to the individual exceeds the benefits particularly in developing countries like Brazil where returns to education are very high. Whatever the reason as student learning is highly correlated with adult outcomes as well as economic growth, working while in school is likely inefficient.

Though it is tempting to suggest that the policy prescription is to prohibit working for students, one must proceed with caution. It is possible that without the ability to work while in school these students would drop out of school entirely. In general the findings of this paper show that while learning is impaired by working, learning still occurs even when the child works at the same time. This suggests that working and going to school is better than not going to school at all. We are also unable to comment on other effects of working while in school such as grade repetition and dropping out as we are able to study only those that remain in school. Nevertheless, policy interventions that manage to keep kids in school while curtailing their work activity have the potential of producing a dramatic improvement in their academic achievement.

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Tables

Table 1: Full Sample - Descriptive Stats

Boys				
	Min	Max	Mean	SD
Proficiency Math	0	411.87	219.00	43.63
Proficiency Portuguese	0	380.02	204.42	51.05
Market Labor	0	1	0.12	0.33
Chores	0	1	0.32	0.47
Age in Months	128	250	166.86	15.15
6th grade	0	1	0.53	0.50
7th grade	0	1	0.10	0.30
8th grade	0	1	0.37	0.48
Late Homework	0	1	0.58	0.49
Homework at School	0	1	0.27	0.45
Prepare for exam	0	1	0.70	0.46
Miss Classes	0	1	0.22	0.41
Father's Unemployment	0	1	0.11	0.32
Girls				
	Min	Max	Mean	SD
Proficiency Math	0	409.97	216.50	40.55
Proficiency Portuguese	0	381.03	218.60	49.20
Market Labor	0	1	0.06	0.23
Chores	0	1	0.56	0.50
Age in Months	119	249	164.64	14.45
6th grade	0	1	0.54	0.50
7th grade	0	1	0.10	0.29
8th grade	0	1	0.36	0.48
Late Homework	0	1	0.51	0.50
Homework at School	0	1	0.22	0.42
Prepare for exam	0	1	0.71	0.45
Miss Classes	0	1	0.27	0.44
Father's Unemployment	0	1	0.12	0.33

Table 2: Paired Sample - Descriptive Stats

Boys				
	Min	Max	Mean	SD
Proficiency Math	99.79	411.86	221.40	41.73
Proficiency Portuguese	0	380.0234	206.3126	49.98
Market Labor	0	1	0.11	0.32
Chores	0	1	0.32	0.46
Age in Months	128	241	167.35	14.75
6th grade	0	1	0.51	0.50
7th grade	0	1	0.0054	0.074
8th grade	0	1	0.48	0.49
Girls				
	Min	Max	Mean	SD
Proficiency Math	108.13	409.97	218.96	38.63
Proficiency Portuguese	0	381.03	220.86	48.90
Market Labor	0	1	0.055	0.22
Chores	0	1	0.558999	0.49651
Age in Months	124	246	165.70	14.26
6th grade	0	1	0.51	0.50
7th grade	0	1	0.004	0.061
8th grade	0	1	0.48	0.49

Table 3: 3 Period Sample - Descriptive Stats

Boys				
	Min	Max	Mean	SD
Proficiency Math	113.57	391.26	220.88	41.90
Proficiency Portuguese	0	352.60	206.61	48.39
Market Labor	0	1	0.07	0.26
Chores	0	1	0.34	0.47
Age in Months	135	232	170.94	16.27
6th grade	0	1	0.50	0.50
7th grade	0	1	0.01	0.08
8th grade	0	1	0.50	0.50
Girls				
	Min	Max	Mean	SD
Proficiency Math	108.13	395.50	217.22	38.77
Proficiency Portuguese	0	380.02	218.75	46.93
Market Labor	0	1	0.04	0.19
Chores	0	1	0.58	0.49
Age in Months	131	267	169.18	15.42
6th grade	0	1	0.50	0.50
7th grade	0	1	0.00	0.07
8th grade	0	1	0.49	0.50

Table 4: Transition Matrix - Market Labor - Full Sample

Boys				
		t+1		
		Not Working	Working	Total
t	Not Working	30,592	4,412	35,004
		87.40%	12.60%	
	Working	2,734	1,690	4,424
		61.80%	38.20%	
	Total	33,326	6,102	39,428
		84.52%	15.48%	
Girls				
		t+1		
		Not Working	Working	Total
t	Not Working	32,906	2,267	35,173
		93.55%	6.45%	
	Working	1,251	485	1,736
		72.06%	27.94%	
	Total	34,157	2,752	36,909
		92.54%	7.46%	

Table 5: School Attendance and Child Labor - City of São Paulo 2010

Number and Proportion of 10 to 17 Year Olds			
	Boys	Girls	Total
Only School	590.19	591.004	1,181,194
	85.39%	86.63%	86.01%
Only Work	17.146	11.37	28.516
	2.48%	1.67%	2.08%
School and Work	43.084	36.674	79.758
	6.23%	5.38%	5.81%
No School and No Work	40.773	43.155	83.928
	5.90%	6.33%	6.11%
Total	691.193	682.203	1,373,396
	100%	100%	100%

Source: IBGE Demographic Census 2010.

Table 6: School Enrollment by Grade and School System - City of São Paulo 2010

	Municipal Schools	State Schools	Private Schools	Total
6th Graders	94.532	64.243	37.893	196.7
	48.07%	32.67%	19.27%	100%
7th Graders	92.125	60.03	36.572	188.7
	48.81%	31.81%	19.38%	100%
8th Graders	100.742	58.46	34.698	193.9
	51.96%	30.15%	17.89%	100%
Total	287.399	182.733	109.163	579.3
	49.61%	31.54%	18.84%	100%

Source: INEP/MEC, Censo Escolar 2010.

Table 7: School Attendance by Grade and School System - City of São Paulo 2010

	Public		Private		Total	
	Not Work	Work	Not Work	Work	Not Work	Work
6th Graders	132.838	9.529	33.448	346	166.286	9.875
	93.31%	6.69%	98.98%	1.02%	94.39%	5.61%
7th Graders	117.233	12.628	28.962	658	146.195	13.286
	90.28%	9.72%	97.78%	2.22%	91.67%	8.33%
8th Graders	132.808	34.124	34.742	1.404	167.55	35.528
	79.56%	20.44%	96.12%	3.88%	82.51%	17.49%
Total	382.879	56.281	97.152	2.408	480.031	58.689
	87.18%	12.82%	97.58%	2.42%	89.11%	10.89%

Source: IBGE Demographic Census 2010.

Table 8: Occupational Distribution (%) - 2010

Sao Paulo Public School Students: 6th, 7th, and 8th Graders	
Office Work	14.83%
Services and Retail Vendors	25.35%
Industry	23.53%
Domestic services, street vendors, car washers, and others	26.08%
Military Service Occupations	10.21%

Source: IBGE Demographic Census 2010.

Table 9: Benchmark Regressions

	Full Sample				Paired Sample			
	Math		Portuguese		Math		Portuguese	
	Boys	Girls	Boys	Girls	Boys	Girls	Boys	Girls
Market Labor	-1.278***	-1.464***	-1.811***	-3.348***	-1.506***	-1.566***	-1.592***	-3.951***
	(0.347)	(0.458)	(0.463)	(0.630)	(0.445)	(0.568)	(0.583)	(0.774)
Age in Months	2.127***	1.654***	1.631**	1.686***	2.350***	1.381***	1.346*	1.373***
	(0.561)	(0.347)	(0.729)	(0.470)	(0.590)	(0.392)	(0.758)	(0.522)
Squared Age in Months	-0.006***	-0.005***	-0.003***	-0.005***	-0.006***	-0.005***	-0.002***	-0.005***
	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)
F	1938.69	1449.57	334.15	426.14	1870.48	1371.13	301.01	382.21
N	191,494	190,067	186,035	185,860	80,260	82,485	78,109	80,693

Table 10: Interacting with age - first observ.

	Math		Portuguese	
	Boys	Girls	Boys	Girls
Market Labor	-5.098	-0.278	-7.167	6.879
	(7.086)	(9.341)	(9.379)	(12.786)
Age in Months	2.367***	1.378***	1.372*	1.348***
	(0.591)	(0.393)	(0.759)	(0.523)
Squared Age in Months	-0.006***	-0.005***	-0.002***	-0.005***
	(0.000)	(0.000)	(0.001)	(0.001)
Market Labor×Age (1st Obs.)	0.023	-0.008	0.035	-0.069
	(0.045)	(0.060)	(0.060)	(0.082)
F	1662.64	1218.75	267.60	339.82
N	80,260	82,485	78,109	80,693

Table 11: Interacting with proficiency score - first observ.

	Math		Portuguese	
	Boys	Girls	Boys	Girls
Market Labor	8.393***	20.479***	20.265***	5.121
	(2.744)	(3.577)	(2.636)	(3.688)
Age in Months	2.377***	1.401***	1.391*	1.380***
	(0.590)	(0.392)	(0.757)	(0.522)
Squared Age in Months	-0.006***	-0.005***	-0.002***	-0.005***
	(0.000)	(0.000)	(0.001)	(0.001)
Market Labor× Port. Score			-0.117***	-0.045**
			(0.014)	(0.018)
Market Labor× Math Score	-0.049***	-0.109***		
	(0.013)	(0.017)		
F	1664.29	1224.03	276.18	340.47
N	77,007	79,623	75,825	78,773

Table 12: Ins - effect of entering the labor market

	Math		Portuguese	
	Boys	Girls	Boys	Girls
Market Labor	-3.337***	-2.392***	-3.330***	-5.190***
	(0.584)	(0.695)	(0.760)	(0.944)
Age in Months	2.484***	1.379***	1.258	1.424***
	(0.619)	(0.396)	(0.792)	(0.527)
Squared Age in Months	-0.006***	-0.005***	-0.002***	-0.005***
	(0.000)	(0.000)	(0.001)	(0.001)
F	1751.92	1331.87	284.25	372.13
N	62,662	69,405	61,237	68,118

Table 13: Outs - effect of leaving the labor market

	Math		Portuguese	
	Boys	Girls	Boys	Girls
Market Labor	-2.765**	-5.318**	-3.784**	-9.312***
	(1.336)	(2.164)	(1.819)	(2.906)
Age in Months	-0.108	-12.921**	0.776	-14.027*
	(1.975)	(5.953)	(2.612)	(7.759)
Squared Age in Months	-0.003**	-0.004**	-0.000	0.000
	(0.001)	(0.002)	(0.002)	(0.002)
F	126.04	47.43	20.71	15.44
N	5,908	2,515	5,725	2,442

Table 14: Exposure effects

	Math		Portuguese	
	Boys	Girls	Boys	Girls
One year in the labor market	-3.240**	-1.174	-3.341**	-3.288
	(1.389)	(1.695)	(1.644)	(2.046)
Two years in the labor market	-6.206***	-3.817	0.248	-6.950
	(2.271)	(3.632)	(2.703)	(4.340)
Age in Months	3.967**	1.239**	1.349	0.715
	(1.940)	(0.622)	(2.265)	(0.731)
Squared Age in Months	-0.005***	-0.003***	-0.003**	-0.003***
	(0.001)	(0.001)	(0.001)	(0.001)
F	251.90	182.68	74.66	93.72
N	13,154	13,287	12,815	12,995

Table 15: Lingering effects

	Math		Portuguese	
	Boys	Girls	Boys	Girls
In the market in the previous year	-3.507*	-3.869	-4.649**	-0.431
	(1.905)	(2.446)	(2.211)	(2.896)
Age in Months	4.461*	1.139*	3.356	0.897
	(2.578)	(0.636)	(2.979)	(0.744)
Squared Age in Months	-0.005***	-0.003***	-0.003**	-0.004***
	(0.001)	(0.001)	(0.001)	(0.001)
F	250.33	193.17	79.74	102.55
N	11,235	12,300	10,954	12,041

Table 16: Robustness check samples

Treatment 001				Treatment 111			
Periods	t	$t+1$	$t+2$	Periods	t	$t+1$	$t+2$
Treatment	Not Working	Not Working	Working	Treatment	Working	Working	Working
Comparison	Not Working	Not Working	Not Working	Comparison	Working	Working	Not Working

Treatment 101				Treatment 011			
Periods	t	$t+1$	$t+2$	Periods	t	$t+1$	$t+2$
Treatment	Working	Not Working	Working	Treatment	Not Working	Working	Working
Comparison	Working	Not Working	Not Working	Comparison	Not Working	Working	Not Working

Table 17: Robustness checks - Boys

	Treatment 001		Treatment 111		Treatment 101		Treatment 011	
	Math	Portguese	Math	Portguese	Math	Portguese	Math	Portguese
Treatment 001	-2.846**	-1.786						
	(1.350)	(1.668)						
Treatment 111			-2.978	1.991				
			(4.367)	(5.896)				
Treatment 101					-0.674	-3.313		
					(3.527)	(4.323)		
Treatment 011							-2.633	3.919
							(2.539)	(3.168)
Age in Months	2.279***	2.760***	4.545	-2.924	2.710	1.356	2.809	-0.054
	(0.808)	(1.011)	(3.169)	(4.578)	(2.131)	(2.617)	(1.935)	(2.424)
Squared Age in Months	-0.006***	-0.009***	-0.010	-0.009	-0.008	-0.009	-0.008	-0.003
	(0.002)	(0.003)	(0.008)	(0.011)	(0.006)	(0.007)	(0.005)	(0.007)
F	76.46	29.91	3.75	1.46	4.20	2.65	6.70	2.36
N	11,829	11,514	500	482	947	915	1,236	1,187

Table 18: Robustness checks - Girls

	Treatment 001		Treatment 111		Treatment 101		Treatment 011	
	Math	Portguese	Math	Portguese	Math	Portguese	Math	Portguese
Treatment 001	-0.849	-2.116						
	(1.591)	(1.997)						
Treatment 111			2.653	2.262				
			(8.165)	(10.173)				
Treatment 101					4.326	-3.024		
					(5.197)	(7.150)		
Treatment 011							-2.506	1.152
							(4.178)	(6.054)
Age in Months	3.139***	2.613***	4.167	-7.944	5.495*	-0.739	-0.422	4.044
	(0.760)	(0.972)	(5.237)	(6.538)	(3.008)	(4.958)	(3.073)	(4.569)
Squared Age in Months	-0.009***	-0.009***	-0.012	0.022	-0.018**	-0.003	0.003	-0.006
	(0.002)	(0.003)	(0.015)	(0.019)	(0.008)	(0.011)	(0.008)	(0.011)
F	38.64	45.57	1.33	0.48	3.55	0.58	2.04	0.82
N	12,672	12,411	166	162	460	441	548	535

Table 19: Robustness Check - Father's Employment Status

	Math		Portuguese		Math		Portuguese	
	Boys	Girls	Boys	Girls	Boys	Girls	Boys	Girls
Market Labor	-2.232**	-1.527	-2.443**	-0.633	-2.217**	-1.518	-2.443**	-0.634
	(0.949)	(1.192)	(1.131)	(1.536)	(0.950)	(1.192)	(1.131)	(1.535)
Age in Months	1.137	3.059**	-0.099	2.229	1.109	3.083**	-0.100	2.226
	(1.652)	(1.341)	(1.966)	(1.734)	(1.652)	(1.341)	(1.966)	(1.734)
Squared Age in Months	-0.004***	-0.006***	0.001	-0.004**	-0.004***	-0.006***	0.001	-0.004**
	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)
Father Unemployed	-2.223**	0.953	-0.076	-0.100				
	(1.075)	(0.979)	(1.284)	(1.253)				
F	149.00	149.70	43.66	47.04	169.61	170.96	49.90	53.77
N	89,647	94,976	88,614	94,040	89,647	94,976	88,614	94,040

Table 20: IV - Minimum Age Labor Law

	Math		Portuguese	
	Boys	Girls	Boys	Girls
First Stage				
Allowed to work	0.065***	0.040***	0.066***	0.037***
	(0.008)	(0.007)	(0.008)	(0.007)
Age in Months	0.002	-0.002	0.000	-0.002
	(0.007)	(0.003)	(0.007)	(0.003)
Second Stage				
Market Labor	-94.723***	-39.382***	-91.044***	-137.220***
	(15.454)	(14.167)	(25.533)	(38.725)
Age in Months	0.583	0.606	-0.441	-0.550
	(0.865)	(0.780)	(0.472)	(0.657)
N	80260	78109	82485	80693

Table 21: IV - S Minimum Age Labor Law - Second Stage

	Boys		Girls	
	Math	Portuguese	Math	Portuguese
Second Stage				
Market Labor	-94.723***	-39.382***	-91.044***	-137.220***
	(15.454)	(14.167)	(25.533)	(38.725)
Age in Months	0.583	0.606	-0.441	-0.550
	(0.865)	(0.780)	(0.472)	(0.657)
First Stage				
Allowed to work	0.065***		0.040***	
	(0.008)		(0.007)	
Age in Months	0.002		-0.002	
	(0.007)		(0.003)	

Table 22: Channels

	Miss Classes		Prepare for exam		Homework at school		Late homework	
	Boys	Girls	Boys	Girls	Boys	Girls	Boys	Girls
Market Labor	0.064***	0.039***	0.003	-0.003	0.022***	0.022***	0.031***	0.044***
	(0.006)	(0.008)	(0.006)	(0.008)	(0.006)	(0.008)	(0.007)	(0.009)
Age in Months	0.003	0.012**	0.006	-0.005	0.008	0.006	0.008	0.013*
	(0.009)	(0.006)	(0.009)	(0.006)	(0.010)	(0.006)	(0.011)	(0.007)
Squared Age in Months	-0.000***	-0.000***	0.000	0.000***	-0.000**	-0.000***	-0.000	-0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
F	125.09	794.06	1715.58	1701.32	185.65	156.31	130.36	97.16
N	188,051	187,216	186,432	186,591	187,017	186,965	186,487	186,528

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