Child labor and school performance in Mexico

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Abstract

This article analyzes the relationship between child labor and school performance in mathematics in Mexican elementary and junior high school students at a national level. The analysis employs the instrumental variables method, given that the joint modeling of child labor and school performance can generate endogeneity. Even after controlling for household poverty, educational modality, and the degree of marginalization of the community, findings show that the effect of child labor on school performance is negative, regardless of whether a child is employed in a family enterprise or not, at both school levels. Analysis of gender reveals that there is evidence that this effect is more pronounced in girls than in boys.

Keywords: child labor; school performance; basic education; instrumental variables.

1. INTRODUCTION

Child labor is a complex phenomenon occurring for a variety of causes associated to the child's economic, social, and family context. Empirical evidence shoes that some of the most consistent determinants for child labor are the head of the family's level of education and the household's poverty level (López-Calva and Madrid, 2006). According to the National Institute of Statistics and Geography (National Institute of Statistics and Geography [INEGI], 2020), 21.5 million children and adolescents between the ages of 5 and 17 in Mexico are involved in economic activity, equivalent to 7.54% of the Mexican child population. 48.75% of children working state that they do so due to financial need, 26.6% by choice or to help out, and the rest to learn a trade.

Working children have fewer available hours to take care of school activities and sometimes have to give up their rest or leisure time to fulfil school obligations. In Mexico, children who do not work study an average of 34.2 hours a week, while those who work study 28.5 hours a week (INEGI, 2020). This implies a greater challenge for working children to acquire the skills and competencies taught in schools. Reading, writing and basic arithmetic skills are the foundation on which future technical and professional qualifications are built. These skills are obtained during elementary school and are honed during middle and high school.

Therefore, child labor reduces the probability of school attendance in the long-term as well as the number of years students obtain passing grades (Beegle *et al.,* 2009). This, in turn, affects future income because it also causes a reduction in the skills obtained during formal education (Ilahi *et al.,*2009). However, various effects have been found; in the case of male students, there is evidence that joining the workforce at a very young age has a negative impact on future salaries. However, joining the workforce between the ages of 12 and 14 shows a positive impact on salaries (Emerson and Souza, 2007).

The relationship between child labor and health, education, capital markets and conditional transfer programs are studied in specialized literature (Acevedo *et al.,* 2011). Estimates show that child labor increases inequities in income and gender and reduces the accumulation of human capital (Galli, 2001).

This article aims to analyze the relationship between child labor and academic achievement in basic education in Mexico. According to Sánchez *et al.* (2009), when looking at indicators and statistical significance, the most reliable predictor in academic achievement is child labor. The literature on child labor in Mexico is vast and varied. However, there are few current studies that look at child labor in relation to academic achievement.

Using data from 1993, Binder and Scrogin (1999) found no significant negative impact of hours worked on academic performance. Blanco (2008 and 2011) studied a comprehensive set of factors linked to academic achievement, including work, and found that the negative impact on performance increased as the workload was greater. Cervini (2015) shows that child labor has a negative impact on academic performance. It addresses the issue in 16 Latin American countries, and in the case of Mexico only has information about the state of Nuevo León.

The status of data needs using the latest national standardized tests needs to be updated. It should be noted that the joint analysis of the variables of child labor and academic performance imply the possibility of simultaneity, reverse causality, and omitted variables, which are a source of endogeneity.

This is because low academic achievement can influence the parents' decision-making process in sending their children to school (Gunnarsson *et al.,* 2006). When looking at older students, low academic achievement can also motivate them to spend time that they had earmarked for study in ways they perceive to be more advantageous, such as working (Warren and Lee, 2003; Bozick, 2007). Conversely, high academic achievement can incentivize students to both study and work (Sibaja, 2009). The estimates of econometric models affected by endogeneity are biased and inconsistent (Angrist and Pischke, 2009; Wooldridge, 2010). Post and Pong (2009) found that their study sample, using ordinary least squares (OLS), underestimates the real effect of child labor.

This research article seeks to contribute to a greater understanding of the subject matter by analyzing the case of Mexican elementary and middle school education. The goals of this study are: *1)* to estimate the meaning and magnitude of the relationship between child labor and academic achievement in elementary and middle school; *2)* to show if gender affects the impact of child labor on academic achievement differently, and *3)* to see if there are differences in academic achievement when children and adolescents work in a family business versus a non-family business. To achieve the objectives put forward, an econometric analysis was developed using instrumental variables (IV) to present empirical evidence taken from the most recent data available in Mexico for mathematics.

The article is organized in the following manner. The second section looks at the data, variables and the type of child labor that is being analyzed. Arguments and justification for the use of econometric models that support the study are also put forward. The third section presents the results. At the beginning of this section the statistical testing that validates these findings is shown. Later, the effects that child labor has on school grades is shown and, moreover, these results are shown both by gender and whether the business is family run or not. The final section contains research findings.

2. METHOD

Data and variables

The main variables in this study are academic performance and child labor. The first is measured by scores obtained on national standardized tests for mathematics. The educational levels studied are elementary and middle school and the database from the Evaluation of Achievement of the National Education System (ELSEN) designed by the National Learning Assessment Plan (PLANEA). The tests are given to a random and representative sample of students throughout Mexico. The data analyzed corresponds to the math tests results of 91,050 sixth grade elementary students during the 2017-2018 school year (National Institute for the Evaluation of Education [INEE]) and 108, 921 students from third grade of middle school during the 2016-2017 school year (INEE, 2018).

The International Labor Organization (ILO) and the United Nations Children's Fund (UNICEF, 2021, p.18) defines child labor as follows:

> Child labor is work undertaken by children, for which the child is too young and/or the work, either due to its nature or the circumstances in which it is carried out, is likely to harm the health, safety, or morals of children. In more technical terms, child labor includes work done by children in any type of employment, with two important exceptions: light work for children within the permitted age range and work that is not classified among the worst types of child labor for children above the minimum general age for working, particularly work that puts children at risk. A broader statistical definition includes hazardous unpaid household services that are dangerous, commonly known as hazardous household chores.

Román and Murillo (2013) identify five types of child labor: family, household, for third parties, illicit or clandestine and in dangerous conditions. However, the light work that is often assigned to children within the family is not perceived to be a limiting factor in a child's activities. According to Basu and Tzannatos (2003), recognizing what is meant by child labor varies among regions, countries, and sectors. There is also research showing some of the consequences of child labor. Ray and Lancaster (2005) conclude that child labor, even if it only lasts for one hour or a few hours, is detrimental to a child's academic learning. Moreover, Ray and Lancaster (2004) argue that the first hour of child labor reduces the probability of attending school by 50%; whilst He (2016) shows that more than one hour of work has undesirable effects on school performance.

The type of child labor discussed here is that performed by students after attending school. In the model presented in the next section, child labor is a dichotomous variable which takes the value of one when the student reported working at least one hour a day as an employee in a family or nonfamily business. Examples of this type of work include farming, animal husbandry, working in a garage or repair shop, working in a shop, packing supermarket bag products, or undertaking other tasks on the streets.

Students, teachers, and principals previously answered context surveys within the National Evaluation of Learning Plan (PLANEA) framework, with the objective of gathering information on personal, family and school characteristics. Using this survey from the National Institute for the Evaluation of Education [INEE] (2018-2019) database, it is possible to determine whether children work. In this our study sample, 57% of elementary school children and 50.5% of middle school children reported working. Table 1 shows the descriptive statistics with a hypothesis test of means equality between the groups of students who reported that they worked or did not work. At elementary school level, 44% of working students are female, whilst 60% of the group of students who don't work, is female. In middle school 62.3% of non-working students are female, as are 39.4% of the group of working students. This demonstrates that male students report working more in both educational levels.

Table 1. Descriptive statistics of the sample

	Elementary			Middle School		
	Doesn't work	*Works*	*t-stat*	*Doesn't work*	*Works*	*t-stat*
Age	12.06	12.10	-7.78***	15.11	15.21	-16.57***
% Females	59.96	44.13	29.33***	62.28	39.37	51.69***
% Speak an indigenous language	5.46	14.81	-25.16***	3.12	10.79	-30.94***
% Repeated a grade	5.81	12.84	-19.54***	6.74	12.74	-20.09***
%Attend an indigenous school	1.54	5.78	-19.20***			
% Attend a distance learning School				14.33	31.40	-41.63***
% Attend a community school	0.24	0.85	-12.28***	0.19	0.99	-18.18***
% Attend a private school	13.32	6.91	21.37***	13.77	6.93	33.39***
School infrastructure	0.44	0.39	21.31***	0.68	0.59	26.28***
% Attend a multigrade classroom	5.71	11.23	-15.48***	4.81	5.90	-5.43***
Poverty score	-0.47	-0.19	-33.18***	-0.47	-0.20	-50.55***
% In a rural area	14.39	29.56	-30.90***	13.67	31.31	-45.23***
% In a highly marginalized area	27.11	44.66	-32.26***	25.11	45.38	-43.97***
Math grade	532.42	489.85	26.37***	517.46	487.52	22.46***
Observations	39 163	51 887		53 899	55 097	

Note: significant differences to ***1%, **5%, *10%

Source: Compiled by authors.

One piece of data that stands out in Table 1 is that male or female students who work –relative to those who do not work– live in households that are poorer than average; a higher percentage live in highly marginalized areas; a greater percentage speak an indigenous language and are twice as likely to have repeated a grade. On average, they also attend schools with worse infrastructure and take classes in multigrade classrooms, with one teacher teaching different grades simultaneously. Regarding test results, working elementary students obtain 42.6 points less in math tests than those who do not work. In the case of middle school students, there is a 32.63 difference. This represents an 8 and 6% difference, respectively.

Table 2 shows the differences in students' school performances considering some socioeconomic categories included in the analysis. 83% of students live in poverty work while they are studying elementary school, as opposed to 56.4% of students who do not. In the difference column for school performance, we see that students living in poverty get lower test scores, with a 64.42 point difference between these groups. Moreover, we can see that the higher the percentage of students who are working, the lower the grade on the national standardized test for math, except in middle school for both males and females. This allows us to observe the descriptive element of the relationship between socioeconomic status-work-school performance.

Table 2. Work status and differences in school performance according to social variables

	Elementary			Middle School		
	Work %	Performance	Diff.	Work %	Performance	Diff.
Females	51.29	510.37	6.28***	39.96	498.48	-7.28***
Males	66.63	504.09		62.86	505.77	
Speak an indigenous language	79.53	463.88	-48.74***	78.45	453.64	-52.12***
Do not speak an indigenous language	56.31	512.62		49.23	505.76	
Live in poverty[a]	83.09	448.72	-64.42***	77.47	460.43	-45.27***
Do not live in poverty	56.43	513.14		49.03	505.69	
Live in a rural area	74.61	479.91	-35.67***	70.70	483.16	-24.48***
Live in an urban area	54.07	515.59		45.60	507.64	
Live in a highly marginalized area	70.21	481.62		65.55	482.36	
Live in an area with an average level of marginalization	56.17	508.57	+	48.72	501.58	+
Live in an area with a low level of marginalization	47.91	536.84		39.06	522.40	

Note: Dif. Shows the difference in school performance between groups. Significant differences at ***1%. + A mean equality hypothesis test according to the degree of marginalization was undertaken for all three groups, this test is rejected at 1% of significance. [a]Living in poverty considers those living at 0.69 on the poverty index.

Source: Compiled by authors.

Models

One of the objectives of this study was to calculate the sense and magnitude of the relationship between children and adolescents participating in economic activities both in and out of their homes, and their academic achievement. Given the nature of the variables studied, the possibility of simultaneity or inverse causality exists, as the variable of child labor cannot be seen as predetermined, because it depends on decisions taken within the home. Therefore, one of the OLS principles would be violated, namely, that the covariance between the error term and the variable of child labor is zero. Therefore, it is impossible to isolate the effect of child labor on school performance. This means that the OLS principles would be biased and inconsistent, as on average the value of the estimators will not be equal to the value of demographics and this bias persists even if the sample size is increased. This can be corrected using the IV method. Hence the econometric analysis is performed by comparing the estimations between two models. The first ignores the presence of endogeneity and is resolved using OLS and the second corrects endogeneity and is solved using IV.

The equation proposed for the model using OLS is:

$$y_i = \beta_0 + \beta_1 T_i + \alpha X_i + u_i \qquad (1)$$

y_i, to the left of (1) represents the score obtained by the *i*th student expressed in standard deviation (SD). PLANEA presents the students' scores with five plausible values. The plausible values are extracted from an *a posteriori* distribution of the students' abilities, using an imputation method; this is necessary because not all the students answer the same test questions and sufficient answers for each question must be guaranteed (Córdoba, 2016). Thus, (1) is calculated for each plausible value in a particular model, and the magnitude reported is the average of all five models. To the right of (1), T_i is a dichotomous variable that takes the value of one if the student i works at least one hour a day; X_i is a an observable characteristics vector –see below for an explanation of this vector-, u_i is an error term that, among other things, requires the covariance between u and (X,T) to be zero.

There are several ways to resolve the problem of endogeneity. In this case the IV model was used, and the second model is shown below.

$$y_i = \beta_0 + \beta_1 \hat{T}_i + \alpha X_i + u_i \qquad (2)$$

$$T_i = \gamma_0 + \gamma_1 Z_i + \pi X_i + v_i \qquad (3)$$

The left side of the equation (2) is identical to (1). On the right-hand side, u_i is an error term that requires the covariance between u and $X, \hat{T}$ to be zero; $\hat{T}_i$ are the adjusted values obtained after completing the first stage of the method, that is to say once the equation has been estimated (3). To the left of (3), T_i is the indicator variable that the student works, and on the right v_i is an error term that requires the covariance between v and (X, Z) to be zero. Z_i is an IV vector used to solve endogeneity. In both equations X_i is a vector of control variables.

The X_i vector contains variables for the following: age, gender, living in poverty, living in a rural area, level of marginalization, classroom climate, school infrastructure, repeating a grade, attending pre-school, attending multi-grade classrooms, class size above 30 students, and educational modality. Including these variables is justified given the need to consider observable factors available from the database as controls and that have also been identified in literature on this subject to explain the determinants of child labor (López-Calva,2006) as well as factors associated with the variation in school performance among students (Blanco, 2011). Information regarding the definition and construction of the variables can be found in table A1 of the Appendix. The components of vector X_i are known as included instruments in equation (3).

Identifying an admissible instrument is the main challenge when using the IV method. Specialized literature on the subject uses different variables as instruments. Bezerra *et al.* (2009) use low-skilled workers' salaries. Le and Homel (2014) use the average salary of women in a commune. Ray and Lancaster (2004) use household income, access to services and household assets as instruments. Gunnarson *et al.* (2006) use the variation in laws pertaining to school-starting age, regulation, and implementation of child labor laws, as well as salaries for children in the local market. As can be seen, the instruments are varied and specific to the available information of the case studied.

A valid instrument is one which is both exogenous and relevant (García, 2008). The first requires the covariance between the instrument and the error term of the regression in the second stage to be zero, in other words, that the instrument has no relationship with the dependent variable. Therefore, the instruments used must not be related to school performance. Moreover, to comply with relevance, the covariance between instruments and the endogenous variable must have a value other than zero, in this case the aforementioned variable is child labor.

The Z_i instruments used here are household size and suffering a family *shock*; this is made operational with a variable indicating that the student has no parents. The underlying hypothesis is that a child from a large family will have a greater need to work, but that the size of the home in and of itself does not affect school performance. Pörtner (2016) found that a father's absence increases the number of hours worked by children. Cuesta (2018) uses the *shocks* that occur in households as part of his instruments, as he believes that they can modify the way children's time is allocated.

Verifying that the instruments have the required characteristics provides evidence that the estimates are consistent and unbiased. The instruments used here, as we will show, surpass both tests. Proof of this is provided in the next sections, and the estimates obtained are compared with the OLS and IV methods.

2. RESULTS

Relevance and exogeneity tests

Statistics of the relevance and exogeneity tests of the excluded instruments, as well as their respective values p are shown in table 3. In both samples the combined significance test showing that the instruments have no effect on the probability of working, is rejected. An F test was used for the relevancy test. The hypothesis test to show low relevance of the instruments was rejected at 1% level of significance. With regards to exogeneity, the Hansen J statistic was used. This considers the null hypothesis that the instruments are not correlated to the error term and the excluded instruments were excluded correctly from the second stage equation. The statistics of this test are calculated as nR^2, where R^2 is a measure of the goodness of fit of the adjustment of an IV residuals regression, with included and excluded instruments; n is the number of observations. Under the null hypothesis of this statistical test, chi-squared tests with $L – k$ degrees of freedom where L is the number of excluded instruments and k is the number of endogenous regressors. Rejecting this test raises doubts of the instruments' validity. In all the cases analyzed here, this test cannot be rejected to the level of 1% significance.

Table 3. Proof of relevance and exogeneity of excluded instruments

	Null Hypothesis	*Elementary*	*Middle school*
Relevance tests			
F in the first stage	All the coefficients of excluded instruments equal zero	23.574	55.730
		(0.000)	(0.000)
Kleibergen-Paap rk Wald test	Underidentification/low relevance of the instruments	45.951	103.492
		(0.000)	(0.000)
Exogeneity test			
Hansen J statistic	The instruments are not correlated with the error term and the excluded instruments were correctly from the main equation	1.402	0.715
		(0.236)	(0.398)
Significance of the endogenous regressor			
Anderson-Rubin Wald test	The coefficient of the endogenous regressor in the main equation is zero	26.847	40.165
		(0.000)	(0.000)

Note: The value of the statistical test is shown. P-values in brackets

Source: Compiled by authors.

First Stage

The probability that a student works is obtained in the first stage of the IV model. To achieve this, the equation (3) is estimated from the previous section with a linear probability model (LPM). According to Angrist (2011), this kind of model is more suitable than the *logit* or *probit* type models in developing the first stage of IV to describe the relationship in question when the endogenous variable is binary, because the possibility exists that the IV second stage estimations of these models will be inconsistent if the functional form of the first stage is not correct, but this does not occur with an LPM.

The results of the estimation of the coefficients of this stage are presented in table 4. In elementary school- with the rest of the variables remaining constant- a one point increase in poverty is shown to increase the probability of students working by 5.5%. In middle school there is a 3.4% increase. When looking at age we can see that in elementary school there is an inverse relationship to the tendency to work, whilst in middle school the relationship is direct. Specifically, if all the other variables remain constant, a one-year increase reduces the probability of working by 1.6% in elementary students and increases the tendency to work by 0.8% in middle school students. On average, in both elementary and middle school students, male students, those who speak an indigenous language and those who have repeated a grade are more likely to work than their respective counterparts.

Table 4. Estimated coefficients of the equation (3)

	Elementary		*Middle school*	
Excluded instruments				
Household size	0.011***	(0.001)	0.014***	(0.001)
1= Has no parents	-0.005	(0.014)	-0.002	(0.012)
Included instruments				
Poverty Index	0.055***	(0.005)	0.034***	(0.005)
Age	-0.016***	(0.006)	0.008**	(0.004)
1= Female	-0.147***	(0.005)	-0.222***	(0.004)
Classroom climate	-0.009***	(0.003)	-0.001	(0.002)
1= Speaks an indigenous language	0.129***	(0.007)	0.145***	(0.008)
1= Has repeated a grade	0.097***	(0.008)	0.049***	(0.009)
1=Attended pre-school	-0.023*	(0.012)	-0.046***	(0.013)
1=Attends an indigenous school	-0.006	(0.011)		
1=Attends a technical middle school			0.007	(0.005)
1= Attends a distance learning school			0.036***	(0.008)
1= Attends a community school	0.018	(0.019)	0.085***	(0.017)
1= Attends a private school	-0.086***	(0.010)	-0.079***	(0.007)
School infrastructure	0.001	(0.012)	-0.004	(0.007)
1= Attends a multigrade classroom	0.025**	(0.011)	0.009	(0.010)
1=Has more than 30 students per class	-0.008*	(0.005)	-0.032***	(0.006)
1=Lives in a rural area	0.058***	(0.008)	0.079***	(0.008)
1= High marginalization	0.117***	(0.007)	0.138***	(0.006)
1= Average marginalization	0.057***	(0.006)	0.070***	(0.005)
Constant	0.746***	(0.068)	0.388***	(0.066)
Observations	91 050		108 921	
R^2	0.097		0.137	

Note: significant coefficient to ****1%; **5%: *10%. Standard errors are shown in brackets, these were calculated in a robust manner and were grouped by school.

Source: Compiled by authors.

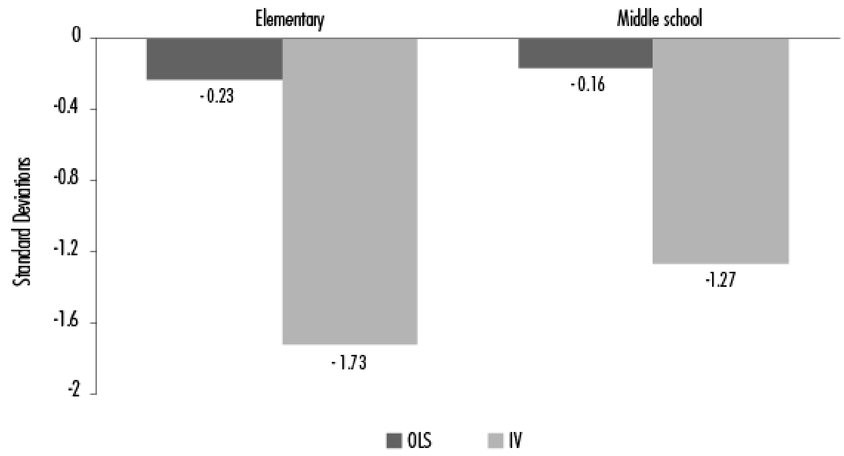
In so far as the effect of school variables, in elementary school a one-point increase in classroom climate reduces the tendency to work by 0.9%. In middle school, this variable does not have a statistically significant effect. The educational modality of attendance is also an associated factor for finding employment. On average, attending a private school reduces the probability of working relative to other students in public schools, for both elementary and middle school students. The community school model only shows a positive and significant relationship with the probability of working for middle school students. School infrastructure does not affect the probability of working in either educational level and classroom size has a negative association to the tendency to work for both elementary and middle school students.

The area that students live in has a significant impact on whether they will work or not. An elementary student living in a rural area is 5.8% more likely to work than one living in an urban area; in middle school, the impact increases to 7%. Living in highly marginalized areas increases the probability that students will work, relative to those living in low-level marginalization.

Second Stage

Figure 1 shows the estimated relationship with OLS and IV between child labor and academic achievement in elementary and middle school math students. [1] In spite of socioeconomic factors and the type of school students attend, child labor has a negative relationship to test scores for both elementary and middle school. OLS results show that a working elementary student scores on average 0.23 SD lower than a student who does not work. When estimations are made using IV, the result is -1.73 SD between a student who works and one who does not. Results are similar for middle school students, on average, the significance of the work effect on academic performance is -0.16 SD using OLS and -1.27 SD using IV. The negative correlation between child labor and school performance is often established with empirical studies. Neyt *et al.* (2019) reviewed research from the last two decades on this subject, and in general found that the effect of child labor on academic performance was not positive. However, their review did not include results for developing countries, such as Mexico.

Figure 1. The effect of child labor on math test scores



Note: the effects are statistically significant at 1%. OLS shows the estimations by minimum ordinary least squares and IV represents the estimations with instrumental variables.
Source: Compiled by authors.

Table 5 shows the difference in the estimated effect of child labor on academic performance for elementary and middle school, using each method. Using OLS, the middle school effect is smaller than for elementary school and there is a significant difference. However, when using IV there is no difference between elementary or middle school; there is no statistical evidence showing that child labor affects students at different measures of magnitude. It is important to note that given data availability, two different school years were studied for elementary and middle school: 2017-2018 for elementary school and 2016-2017 for middle school. However, no structural events were found between these time periods that could impact on the comparison's results.

Table 5. The difference in the estimated effect of child labor on academic performance according to school level

	OLS		*IV*	
Difference	-0.07***	(-4.46)	-0.46	(-1.2)

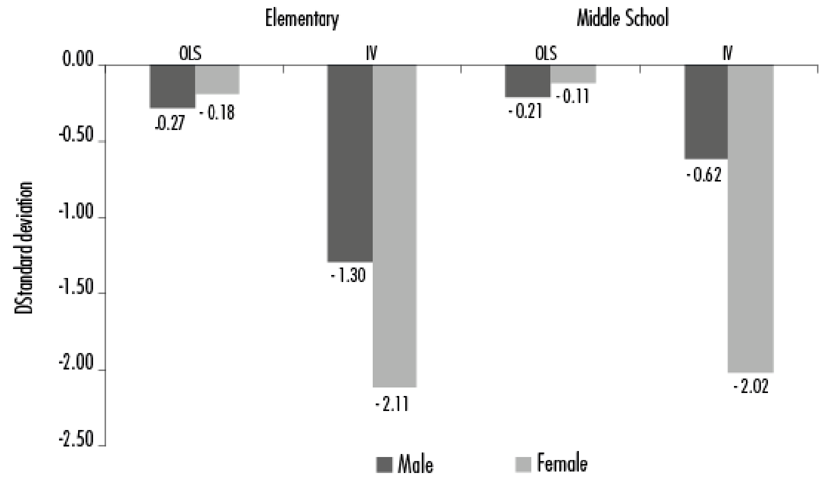
Note: the statistic t is shown in brackets. Significant difference to ***1%. OLS shows estimations for minimum ordinary least squares. IV represents estimations made using the instrumental variables method.

Source: Compiled by authors.

Effects by Gender

This section looks at child labor and academic performance by gender. There is evidence that girls who work do so in worse conditions than boys (ILO, 2009). The results of estimations made by gender are shown in figure 2.[2] Calculated using OLS, female students are shown to be less impacted by child labor than male students with a difference of 0.09 and 0.1 SD in elementary and middle school, respectively. The estimates using IV show that, in the case of male elementary students, the average effect of child labor on academic achievement is -1.3 SD and in middle school it is -0.62 SD. For female elementary students the average effect of child labor on grades is -2.11 SD, and -2.02 SD in middle school. This finding is similar to that of Le and Homel (2014).

Figure 2. The effect of child labor by gender on math test grades



Note: all the effects are statistically significant at 5%. OLS indicates estimates using ordinary least squares. VI represents estimates using instrumental variables.
Source: Compiled by authors

Sim *et al.* (2017) also found results akin to our findings; they found that working female students suffered greater adverse effects on their math studies than boys. The negative effect for girls is important because it could increase gender inequity in education (Galli, 2001). Knaul (2006) puts forward evidence regarding the use of time by gender and shows that young women spend more time on housework. When this is added to work undertaken outside of their household, it means that female students work between five and seven hours more a week than their male counterparts. Therefore, the hypothesis that female students work a double day can be considered to explain the differences in academic performance in math. Female students have less time to dedicate to school as well as homework. The time and energy that they spend working are resources that they cannot channel to develop their academic abilities.

Effects by type of business ownership

Table 6 shows the estimations according to whether the student works in a family or non-family business. [3] The results indicate that the relationship between type of ownership and academic performance is negative, for both elementary and middle school students. Using OLS, working in a family business is seen to have a greater impact than a non-family business, however, when using IV the findings show that there is no significant difference in the estimated magnitude, which implies that the business being family owned or not affects students similarly. Román and Murillo (2013) show that working, whether in or out of the home, affects children's academic performance. Post (2018) has similar findings; all types of work whether paid or unpaid, were shown to be associated with significant learning deficiencies in math and reading skills, across the 15 countries studied.

Table 6. The effect of child labor on math test scores according to the type of business ownership

	Family	*Non-family*	*Difference*
OLS			
Elementary	-0.08***	-0.23***	0.145***
	(0.015)	(0.017)	(0.023)
Middle School	-0.07***	-0.18***	0.105***
IV	(0.011)	(0.012)	(0.016)
Elementary			
Middle School	-2.17***	-2.62***	0.451
	(0.441)	(0.927)	(1.026)
Middle School	-1.48***	-1.68***	0.201
	(0.344)	(0.483)	(0.593)

Note: standard errors are shown in brackets. OLS indicates estimates using ordinary least squares. IV represents estimates using instrumental variables. Statistical significance to ***1%, **5%, *10%

Source: Compiled by authors.

CONCLUSIONS

The empirical evidence from this study shows that child labor has a negative relationship with academic achievement for Mexican elementary and middle school students. Developing the econometric analysis using two methods and comparing the results highlighted the bias in estimations when the issue of endogeneity is not addressed. This is only supported for the Mexican case studied.

The results support the fact that gender differentiated effects exist. The negative association between work and academic performance is more pronounced for female students than male students. These findings suggest that, at least for math, there is a greater negative impact on school performance for working female students than their male counterparts. The result obtained is important as it contributes to future explanations of gender inequity in education. However, there is no evidence to show that the business being family-owned or not affects students differently. There is also no evidence that they are differently impacted in elementary or middle school.

One of the study's limitations was that multiple level statistical analysis was not used and it is therefore not possible to understand the interaction of variables at different levels. The research agenda that follows, therefore, is to develop multilevel models able to solve the issue of endogeneity.

APPENDIX

Table A1. The construction of variables used in modeling

Variable	*Data source*	*Construction*
Dependent		
Academic performance	PLANEA	This is represented by five plausible values that are imputations of the students' ability to answer the test correctly. Each plausible value is standardized, with zero mean and a variance of one.
Instruments		
1 = Has no parents	SCS	Variable indicating that the student reports not having a father or mother. The data is obtained by asking the question: "To what level did your dad (mom) study?" "I don't have a dad (mom)"
Household size	SCS	In answer to the question: "How many people live in your house, including you?"
Independents		
Works in a family run business	SCS	Indicator variable for the student that spends at least one hour a day helping family with their job or business. For example: agricultural work (sowing, harvesting), caring for farm animals, helping in a workshop, or working in a home-based store, making products at home for sale, etc.
Works in a non-family business	SCS	Indicator variable for the student that spends at least one hour a day working for themselves or as an employee for someone outside the family. For example: agricultural work (sowing, harvesting), caring for farm animals, helping in a workshop, or working in a store, packing bags in supermarkets, carrying bags in markets, selling products or other tasks on the streets, etc.
Works	SCS	Indicator variable for the student that spends at least one hour working in family or non-family business.
Poverty Index	SCS	The methodology for the Single Score System (SUP) used to identify beneficiaries of the Oportunidades program (Campos-Vásquez et al.,2013). This included parents' education, assets and services in the household, level of overcrowding, type of area and region the home is located. In the case of lost information, the imputation established by SUP was used.
Age	PLANEA	Age is considered in years completed.
1=Female	PLANEA	Variable that is worth one if the student is female and zero if male.
Classroom climate	SCS	This index is created using principal components; it includes questions measuring the frequency with which the teacher takes into account a student's opinions, the frequency with which they encourage students to express what they think, the frequency with which they encourage them to ask questions about doubts they might have, how often the teacher organizes activities so that students can share their opinions and listen to their classmates', how often students' opinions on classroom rules are heard by the teacher, and how often the student is encouraged to speak their mind if they feel upset with a classmate.
1= Speaks an indigenous language	SCS	Dichotomous variable which is worth one if the answer is Yes to the question: 'Can you speak an indigenous language?'
1= Has repeated a grade	SCS	Indicator variable that the student reports having repeated a grade or school year since entering elementary school.
1= Attended preschool	SCS	Dichotomous variable that is worth zero if the answer to the question 'How many years did you go to preschool?' is 'I didn't go'.
Educational modality	PLANEA	Variable indicators of the type of school the student attended. For elementary, the following modalities were included: public, indigenous, community and private. For middle school the following modalities were included: public, technical public, distance learning, community and private.
School infrastructure		This variable is constructed with an average of indicator variables regarding the existence and quantity of water, restrooms, drainage, electrical power, classrooms, library, computer room, labs, furniture, chalkboards, reading material for students, internet, and computers for students' use.
1=Attends a multilevel classroom	SCSt	Dichotomous variable indicating that the teacher answers Yes to the question: 'Do you teach different student grades simultaneously in this group (multi-level classroom)?'
1= Is in class with more than 30 students	SCSt	Indicator variable that the teacher reports that there are at least 30 students enrolled in the class.
1=Lives in a rural area	SCS	Indicator variable that the area the student lives in has fewer than 2499 inhabitants.
Degree of marginalization	SCS	Variable indicating the degree of marginalization of the area the student lives in. There are three categories: high, average, and low marginalization.

Note: SCS refers to the student context survey. SCSp refers to the principal's context survey. SCSt refers to the teacher's context survey. PLANEA indicates that the data was obtained from the data base for each student with their test scores.
Source: Compiled by authors

Table A2. Estimated Coefficients by OLS and IV for equations (1) and (2)
Results for elementary and middle school

	Elementary		*Middle School*	
	OLS	*IVI*	*OLS*	*IV*
Child labor	-0.227***	-2.414***	-0.161***	-1.212***
Poverty	-0.226***	-0.093***	-0.096***	-0.053**
Age	0.055***	0.023	-0.026**	-0.017
1=Female	-0.051***	-0.370***	-0.144***	-0.376***
Classroom climate	0.202***	0.182***	0.106***	0.105***
1= Speaks an indigenous language	-0.162***	0.121**	-0.206***	-0.053
1=Has repeated a grade	-0.481***	-0.270***	-0.387***	-0.335***
1=Attended preschool	0.154**	0.103*	0.134***	0.085*
1=Attends an indigenous school	0.126*	0.118		
1= Attends a technical school			-0.006	0.000
1=Attends distance learning school			0.186***	0.225***
1=Attends a community school	0.031	0.073	-0.152*	-0.058
1=Attends a private school	0.427***	0.226***	0.633***	0.543***
School infrastructure	0.138***	0.144**	0.153***	0.150***
1=Attends a multigrade school	-0.045	0.007	-0.034	-0.025
1=Has more than 30 classmates per class	0.033	0.015	0.179***	0.146***
1=Lives in a rural area	0.174***	0.290***	0.096**	0.176***
1=High marginalization	-0.193***	0.074	-0.092***	0.058
1=Average marginalization	-0.140***	-0.008	-0.07***	0.006
Constant	-0.734***	0.989***	0.109	0.598***

Note: significant coefficient to ***1%, **5%, *10%. The models were estimated with standard robust errors and grouped by school.
Source: Compiled by authors.

Table A3. Relevance and exogeneity tests for the gender differentiated model

		Elementary		*Middle School*	
	Null Hypothesis	*Males*	*Females*	*Males*	*Females*
Relevance Test					
F in the first stage	All the coefficients of excluded instruments are equal to zero	20.309	12.586	40.573	21.904
		(0.000)	(0.000)	(0.000)	(0.000)
Kleibergen-Paap rk Wald test	Underidentification/low relevance of the instruments	38.379	24.422	72.833	42.500
		(0.000)	(0.000)	(0.000)	(0.000)
Exogeneity test					
Hansen J statistic	The instruments are not correlated with the error term and the excluded instruments were correctly excluded from the main equation	0.715	0.386	1.817	0.172
		(0.398)	(0.534)	(0.178)	(0.678)
Significance of the endogenous regressors					
Andersen-Rubin Wald test	The coefficients of the endogenous regressors in the main equation are zero	9.520	30.907	9.602	50.945
		(0.009)	(0.000)	(0.008)	(0.000)

Note: The table shows the value of the statistical test. P-values in brackets

Source: Compiled by authors.

Table A4. Relevance and exogeneity tests for the differentiated model according to ownership of the business where job takes place

		Elementary		*Middle School*	
	Null hypothesis	*Family run*	*Not family run*	*Family run*	*Not family run*
Relevance tests					
F in the first stage	All the coefficients of excluded instruments are equal to zero	10.088	17.641	28.857	34.593
		(0.000)	(0.000)	(0.000)	(0.000)
Kleibergen-Paap rk Wald test	Underidentification/low relevance of the instruments	18.930	32.260	53.586	62.688
		(0.000)	(0.000)	(0.000)	(0.000)
Exogeneity test					
Hansen J statistic	The instruments are not correlated with the error term and the excluded instruments were excluded correctly from the main equation	1.421	0.276	4.648	0.167
		(0.233)	(0.599)	(0.031)	(0.682)
Significance of the endogenous regressors					
Andersen-Rubin Wald test	The coefficients of the endogenous regressors in the main equations are zero	26.808	26.847	39.708	40.165
		(0.001)	(0.001)	(0.009)	(0.000)

Note: The table shows the value of the statistical test. P-values in brackets

Source: Compiled by authors.

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[1] The model's total estimated coefficients are shown in table A2 of the Appendix

[2] Table A3 of the Appendix shows proof of relevance and exogeneity of the gender-differentiated model.

[3] Table A4 of the Appendix shows model relevance tests and exogeneity, differentiated by the type of business ownership