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The effect of working on students' learning in Latin America: evidence from the learning survey TERCE

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Abstract

There is limited comparable and robust research on the effect of children's work on learning for developing countries. We use matching techniques relying on rich information from the Third Regional Comparative and Explanatory Study (TERCE) for 15 Latin American countries and a bounding approach to account for unobservables. We find that work leads to 9 (math) and 13 (reading) points less in achievement for sixth grade students, with a significant variation within the learning distribution and between countries. Policies should prioritise low achievers, those in paid employment living in large urban areas, and factors driving work allocations within families.

Keywords: working children, learning outcomes, matching, bounding, Latin America, TERCE

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1. Introduction

Although there are well established international regulations restricting child labour through established frameworks such as the International Labour Organization (ILO) conventions¹ and major efforts have been made to reduce its incidence throughout the developing world ([Hindman, 2014](#); [ILO, 2017](#)), child labour is still a persistent problem in developing economies. It is estimated that in poorer countries around one in four children (aged 5 to 17) are engaged in labour that is considered detrimental to their health and development ([UNICEF, 2017](#)). Even though child labour has declined over the last decade by 94 million worldwide, progress stagnated between 2012 to 2016. Latest global estimates for 2016 indicates that there are 152 million children (aged 5 to 17) working, out of which 73 million are carrying out hazardous work that endangers their health, safety, and moral development ([ILO, 2017](#)).

In the Latin American region, in particular, there are 11 million working children (a prevalence rate of around 5%), out of which 5.7 million are still falling into the worst form of child labour.² Worryingly, the progress on the reduction of child labour has been slow considering the rapid economic growth in the region for the 2000-2010 period (between 3.8%-5.8%)³ and even more so now that, due to the recent stagnation of income inequality and the lower rate of growth, there is a pattern of growth that is less pro-poor ([WorldBank, 2015](#)).

Against this backdrop, child labour has been assigned a higher importance in the development agenda explicitly through two sustainable development goals (SDG): Goal 8 (Promote inclusive and sustainable economic growth, employment and decent work for all) and Goal 16 (Promote just, peaceful and inclusive societies).⁴ Specifically, relevant SDG targets are Target 8.7 for child labour: “Take immediate and effective measures to eradicate forced labour, end modern slavery and human trafficking and secure the prohibition and elimination of the worst forms of child labour, including recruitment and use of child soldiers, and by 2025 end child labour in all its forms”, and Target 16.2: “End abuse, exploitation, trafficking and all forms of violence and torture against children”. Critically, child labour is key to the fulfilment of SDG 4 on education as it is strongly linked to achieving an inclusive and equitable quality education. Thus, within Goal 4, Target 4.5 stresses that: “By 2030, eliminate gender disparities in education and ensure equal access to all levels of education and vocational training for the vulnerable, including persons with disabilities, indigenous peoples and children in vulnerable situations”. A 2017 evaluation of monitoring agencies of the SDG agenda for the education Goal 4 highlights that: “Equity issues constitute a major challenge in education according to a recent assessment. In all countries with data, children from the richest 20 per cent of households achieved greater proficiency in reading at the end of their primary and lower secondary education than children from the poorest 20 per cent of households.”⁵

Hence, understanding the impact of child work on education, how this impact varies for different types of work (be it paid or unpaid, and either carried out at home or outside), and how this association is linked to student’s characteristics and

which policies may eliminate the negative impact of child labour on education, are all issues related to the achievement of the sustainable development education agenda. There is a significant body of research on child labour and learning, but mostly this strand of research is country specific and for different regions (e.g., [Emerson et al., 2017](#); [Post and PONG, 2009](#)). There is, however, limited evidence on the role of school factors on the working-learning gap. The only exception is the recent study of [Post \(2018\)](#) which carries out an analysis of the impact of work on learning for the Latin America region.

Therefore, in this paper, using data from 15 Latin American countries we provide new and robust evidence on the impact of student (child) work on learning (math and reading scores) using a recent learning cross-country comparable learning survey for the region (i.e., Third Regional Comparative and Explanatory Study-TERCE). We also provide implications for the role of school’s policies and institutional practices towards narrowing the negative effect of students’ work on their learning, and assess which are the different individual, school and labour market channels of transmission from work to learning.

Furthermore, we offer new methodological insights for child labour-learning research by isolating the effect of students’ characteristics and their environment on their likelihood to work using sub-samples obtained by propensity score matching as well as accounting for unobservables and ability driven heterogeneity on the effect of work on learning achievement. We make use of a bounding approach to assess the robustness of child work-learning associations under different assumptions on the role of unobservables not previously applied in the child labour and learning literature.

A key concern is that child (or student) labour is not a concept that easily translates into a unique statistical indicator ([De Hoop and Rosati, 2014](#)). This is because child labour can affect children in different ways, its consequences for their welfare cannot be captured by a single indicator. Long term damage on learning chances for working students, for instance, would be more detrimental if they engaged in long hours in hazardous activities and occupations. Thus, we employ different measures for student’s work differentiating between where a student works, and whether he/she is being paid for his/her employment.

1.1. How this paper departs from [Post \(2018\)](#)

As mentioned above, [Post \(2018\)](#) is related to our paper as it explores a somewhat similar hypothesis (the impact of work on learning) relying on the same dataset.⁶ However, after reviewing it, we found various differences to our paper, both in terms of scope and methodological approach. Specifically, we employ a wider set of controls allowing us a more precise identification of the student’s work effect on learning (e.g., demographic factors, proxy of previous achievement, and parental educational input at the household level as well as school infrastructure, and proxy for labour market through community sizes) and we rely on a more robust technique (matching) and, additionally, we account for endogeneity. Though, notably, our study departs from [Post \(2018\)](#) in at least three ways. First, further to the regional analysis, we carry out an analysis at the country level too and examine the factors (mirroring policy

interventions and measuring institutional practices) which may reduce the work-learning gap. Second, we are able to evaluate the hypothesis of family assignment of a child based on ability through quantile regression. Thirdly, we provide estimates on the association of student’s work and learning by the quality of labour markets and the educational quality of school of working children. These different and additional analyses, in turn, allow us to derive novel policy implications.

The remainder of the paper is structured as follows. Section 2 includes a review on student’s work and learning, and child work policies. In Section 3 we describe the data used and Section 4 outlines the empirical methods. Results are presented in Section 5 for the whole region (the main results) and for each country in Section 6. A robustness check for the child work-learning association are included in Section 7. We conclude in Section 8. Additional results are displayed in Appendices A to D.

2. Background

2.1. Review of child work and learning

Regional studies for Latin America find that working is detrimental for children’s learning (Gunnarsson et al., 2006; Sánchez et al., 2009; Post, 2018). Only some country specific studies (e.g., Bezerra et al., 2009; Emerson et al., 2017 in Brazil and Dumas, 2012 in Senegal) find that work and learning can be partly complementary goods (if a work activity involves learning-by-doing, for instance) and so working could potentially benefit academic achievement. However, cross-country studies for the region (Post, 2011) find a negative correlation after accounting for the initial socio-economic disadvantage related to a child’s likelihood to be in employment. The leading explanation for the latter finding is based on the economic theory of time allocation where children must divide their time between work and schooling, and more time dedicated to work reduces the amount of time available for attending school, resting and studying at home (Lee and Staff, 2007). The same arguments that validate the negative associations of work and achievement apply to both work carried outside the household and work activities within their families (Post, 2018). The time that students devote to the work and the energy in doing so, reduces the limited reserve of resources (time) that they would otherwise need for a proper development of their academic skills.

In a recent study related to the current paper (also based on the TERCE study for sixth grade students), Post (2018) validates his previous findings for the region. This regional study evaluates the hypothesis that student’s work, be it at home or outside the household, has negative consequences on math and reading achievement, and this effect is also related to the intensity of work and the economic and political context of each country. Using OLS and a multilevel analysis under different controls, Post (2018) finds that work is a source of inequality as working children score significantly less than non-working children in math and reading tests. This negative effect even holds when accounting for the fact a student may live in a country with low quality schools (multilevel analysis).

Other studies suggesting positive effects of work on learning are based on socialisation and development theories (the positive effects of work ethic, independence, etc.) or in the assumption of working hours below a given threshold, but these have not been found to be widely applicable (see, [Byun et al., 2014](#), for a discussion). Yet most studies find strong negative effects on academic performance with working outside the home, regardless of the amount of time spent at work. For example, in Ghana, [Heady \(2003\)](#) finds that work outside the household has a substantial effect on learning achievement because of exhaustion or a diversion of interest away from academic concerns. In Latin America, unpaid work carried out within the family is also widespread and a likely barrier to learning ([Amarante and Rossel, 2018](#)).

Beyond key household factors identified by empirical research (income/wealth and parental education mainly, see [Webbink et al., 2013](#) for an overview) and contextual macro factors (e.g., a country labour market quality: [Basu and Tzannatos, 2003](#)), also related to a student's work decision, could be a child's own educational potential or prospects (as perceived by their parents).

Parents' assessment of a child's education prospect can be another factor. Parents may draw the conclusion that a child's low achievement or motivation for education as a signal to prioritize his/her contribution from work over school attendance. This might be particularly important for families facing binding economic constraints where they need to allocate more able children to full-time study and weaker students to work ([Post, 2011](#)). Parental expectations of a child, thus, will shape whether or not they get involved in employment. Besides economic factors, parental expectations have been found to play a critical role in children's academic success ([Yamamoto and Holloway, 2010](#)). Having lower expectations on the educational level a child would reach will, for instance, affect the quantity and quality of parental investment in his/her schooling ([Pomerantz et al., 2007](#)) and hinder a child's learning. Hence, expectations from parents and its association with the likelihood that a child would end up working are a further plausible mechanism mediating the effect of work on learning.

There is, of course, an additional range of pathways affecting the work-learning association. To pin down a set of main channels, one could focus on relevant factors determining child labour and how they simultaneously affect a child's educational performance. [Webbink et al. \(2013\)](#) contains an exhaustive review of these factors which operate at the child level (e.g., gender, age, birth order), at the household level (e.g., wealth, parental occupation and education, mother's bargaining power, number of siblings, family type), at the district level (e.g., urbanisation, educational infrastructure and quality, community development) and at the national level (e.g., cultural factors such as traditional values, women's position, degree of development, laws).

Urbanisation, particularly in Latin America, has been linked to increasing chances of a child entering the labour market. Latin America has been exposed to a rapid process of urbanisation leading to over-urbanisation (with 80% of its' population living in cities; [Habitat, 2012](#)), especially in non-Caribbean countries.⁷ Because living in a city means to be part of a monetized economy where cash must be generated

to survive (Fay, 2005), resource-constrained households and their children need to integrate to labour markets, mostly on low-skill jobs. Evidence suggests that low skill production makes child labour more likely, with relative expansion of high versus low skilled job opportunities increasing time spent at school (ILO, 2017). Also, the size of a district matters as it frames the type of labour markets which can be accessed. In small, mostly rural communities, with just a few jobs and labour opportunities, child labour is more often an economic decision likely to be made by parents for survival (Basu, 1999). In these communities, there is a high chance that children (particularly boys) will end up doing the same jobs as their parents, such as agricultural and basic jobs (Bass, 2004) and, consequently, returns to formal education would be considerably lower halting education demand.

The stability of work, too, is important (Duryea et al., 2007; Guarcello et al., 2010). In rural Ethiopia, Colmer (2015) finds that uncertainty has an effect on the composition of children’s work; in particular, an increase in uncertainty is linked to an increase in the number of hours children spend working on the farm while reducing the number of hours spent on domestic chores. Furthermore, the quality of education supply will influence parental decisions on a child’s work engagement because the quality of education is linked to the expected returns of education (Bezerra et al., 2009; Guarcello and Rosati, 2007). With regards to the family level, one of the leading household determinants of child labour is mother’s education (Huisman and Smits, 2009). Higher educated mothers are likely to place more importance on their children’s education and to be more empowered to take decisions on children’s educational investment discouraging children’s work.

2.2. *Child work policies*

Policies aiming to weaken the impact that work has on student’s achievement tackle barriers on education supply and demand factors as well as wider social issues (De Hoop and Rosati, 2014). Post (2018) suggests some of the following components of successful policies: to discuss the personal and social benefits of schooling; to foster a demand for quality education both in terms of access and achievement levels; to boost a supply of education where schools are closer to communities and offer a relevant education; public policies alleviating economic and material constraints of families when deciding on the work-learning trade-off increasing students retention. Post (2018) argues that the over-reaching objective of public policies on child labour is to guarantee perfect information for households on the cost and benefits when taking decisions on the assignation of child labour, although he argues that improving educational quality is a necessary condition to raise school attendance.

Household subsidies and economic transfers tend to alleviate demand constraints lowering the opportunity cost of schooling and so they provide a counterbalance to what is known as ”added worker effect” (Basu and Van, 1998) –i.e., an increase in unemployment causes an increase in labour supply and so exacerbates unemployment problems. Basu et al. (2000) show that, if the primary breadwinner in a low-income household has little probability of finding work, the household will send its other family members to seek work as well. These other members could be children, or

adults for whom the children must assume some of the domestic duties (Grimsrud, 2001). Additionally, bringing the children along with themselves to the labour market may also increase the adult's opportunities for work.

There is a vast evidence on the beneficial effects of cash transfers on school participation (Baird et al., 2013; Novella et al., 2012; Saavedra et al., 2012). Unconditional cash transfers provide families with an income transfer that helps to reduce poverty, and encourage household investment in the human capital of their children (De Hoop and Rosati, 2014), which is critical to address vulnerability for families falling into a low wage-high child labour traps (Grimsrud, 2001). Conditional cash transfer programs also provide an income transfer, but on the condition that the members of the households receiving the transfer, adhere to specific behavioural requirements. Policy interventions which are successful to keep children in school while restraining their work activity have the potential of producing a significant improvement in their academic achievement (Emerson et al., 2017). For instance, Ecuador's Bono de Desarrollo Humano had a strong effect, lowering participation in economic activities by 25% percentage points for 11-16-year-old children (Edmonds and Schady, 2012). In our analysis, some of the policy variables we rely on from this group on economic constraints are: family subsidy, feeding programs and programs fostering students' attendance (see Section 6.2).

There are several programs in Latin America targeting indigent and poor families (for a review, see: Novella et al., 2012). For instance, Families in Action in Colombia, the Family Allowance Program in Honduras, Bolsa Família program in Brazil, and the Human Development Grant in Ecuador. But they have come under criticism for not addressing the quality of education; a concern also raised by Post (2018). In some cases teachers do not necessarily show up in the classroom, are not properly trained or programs may be focused on skills which don't match up labour market needs.⁸ In that sense, Holgado et al. (2014) through the analysis of the program the Edúcame Primero in Colombia argue that an effective combination of public policies and specific educational and community-based interventions is the best strategy for addressing child labour. In our analysis, a second set of variables we look at as leverage mechanisms are institutional practices which may be linked to educational quality and, in consequence, could be useful to narrow work-related learning gaps. These are: programs on school management and to support teaching competencies, and practices such as teacher performance evaluations, support and economic incentive.

3. Data and descriptive statistics

3.1. Data source

The analysis is based on the Third Regional Comparative and Explanatory Study (TERCE), a learning survey for 15 Latin American countries (i.e., Argentina, Brazil, Chile, Colombia, Costa Rica, Dominican Republic, Ecuador, Guatemala, Honduras, Mexico, Nicaragua, Panama, Paraguay, Peru and Uruguay) for 2013. TERCE's main goal is to provide information on the education quality in the region and, by

matching students' learning indicators (on maths, reading and writing) to contextual background information, to contribute to effective educational policies (UNESCO-OREALC, 2015e). We focus on students attending sixth grade, which covers around 3,065 schools and 67,000 students (UNESCO-OREALC, 2015b). We concentrate on math and reading learning outcomes as a comparison with other studies looking into the effect of working on achievement (Byun et al., 2014; Gunnarsson et al., 2006; Post and PONG, 2009; Post, 2011, 2018).

Math tests evaluate five domains of knowledge (numeric; geometric; measurement; statistics; and variation) and, for reading, knowledge in comprehension and metalinguistic/theoretical concepts are examined. These two outcomes are presented in two forms: (i) a continuous indicator (with an average of 700 points and a standard deviation of 100), (ii) a discrete four levels indicator that measures what students know and are able to do in each of the levels and grades tested. Furthermore, TERCE contains several background variables which influence student's learning (i.e., students' characteristics and their families and neighbourhoods where they live, teachers' and schools' characteristics, educational resources and classroom practices (UNESCO-OREALC, 2015c).

3.2. *Key explanatory variable - child working status*

Child labour entails work that is mentally, physically, socially dangerous and harmful to children or it interferes with their schooling. According to ILO, the term child labour includes children aged 5 to 17 engaged in following categories of activities: (i) worst forms of child labour, (ii) employment below the minimum age of 15, and (iii) hazardous unpaid household services (ILO, 2008, 2013). Although TERCE does not contain the degree of detail needed to construct exactly this definition of child labour as it does not ask, for instance, whether child work is hazardous or not, there are other questions on working conditions in TERCE.⁹

In particular, we use three questions answered by sixth grade students about the work they do outside of class. In the student's questionnaire, question 26 asks: "Besides attending school, do you work?". The responses to this question are: (a) "No", (b) "Yes, in the house," and (c) "Yes, outside the home". For the children who responded that they work, two follow-up sub-questions are included. One asks if the work is remunerated (in contrast to not being remunerated). The second sub-question asks whether the child works on weekends, worked rarely, or if he/she works when not in school.

Based on this information we define three work indicators, differentiating between where a student works, and whether he/she is being paid for his/her employment. Specifically, we construct: (i) an overall indicator of work which includes either work outside or work at home regardless of payment, (ii) an indicator of work outside and being paid (thereby excluding those receiving non-monetary payments), and (iii) an indicator for work at home but without being paid. It should be noted that the overall work indicator does not add up to the latter two as we are excluding, albeit small, the categories of unpaid students who are working outside ($\approx 4\%$) and those working at home and paid ($\approx 14\%$). We exclude these two informal working

categories from our definition as to highlight the fact that most decisions of working outside the family are driven by households' economic constraints, whereas helping with work at home is largely related to non-pecuniary payments common in less formal and underdeveloped labour markets opportunities.

Table 1 shows the prevalence of child work based on the three working indicators for each of the 15 countries included in TERCE and for the Latin American region.¹⁰ There is a large prevalence of child work in the region: nearly half of children attending grade 6 carry out some kind of work, around one out of ten children are involved in paid-labour outside their homes, and more than a third of students work in unpaid activities at home. Estimates indicate a great disparity within the region, with the probability of undertaking any work being as high as 69% (Paraguay) and as low as 29% (Costa Rica), and children living in lower middle income countries (Guatemala and Nicaragua) in particular have high chances of doing some work ($\approx 60\%$). Poverty is a widespread phenomenon in these countries which leads to a large prevalence of paid work, as well as in other countries such as Paraguay and Dominican Republic. Unpaid work within the household is common regardless of a country's wealth: in high income countries such as Argentina and Uruguay this rate is around 30%.¹¹ For the whole region, there is a lower degree of variation (SD) for the indicator paid work outside the household ($\sigma=0.31$) in comparison to the indicator unpaid work ($\sigma=0.48$). In some countries (Colombia, Costa Rica, Ecuador and Panama) the extent of heterogeneity among students on their chances of working is considerable larger for remunerated than non-remunerated work within the household.

[Table 1 here]

3.3. Learning outcomes by work status and background characteristics

Table 2 contains raw estimates for maths and language scores by working status and by background characteristics. This table shows that working is closely linked to lower learning levels (Panel A). Across the region, the average working child attains between 48 and 57 point less in math and reading than a non-working child. This gap is more pronounced for higher levels of achievement, with working children being less likely to be able to grasp appropriate knowledge for grade 6. For instance, in the case of math, 69%-76% of the group of non-working children reaches levels 3 and 4 but only between 31%-24% reaches levels above 2 of the group of working children.

[Table 2 here]

The lower achievement for working students is related to disadvantages regarding their family background as well as on the characteristics of the schools they attend (Table 2, Panel B). In comparison to non-working students, students who work are slightly older, are 9% more likely to be repeaters and come from larger families, are 5% less likely to have attended preschool and 7% less likely to have a writing book and books at home. Their families are more deprived in terms of wealth and cultural assets and also they have lower chances of being supervised on their studies at home. Working students initial personal and families shortcomings are compounded by a second layer of disadvantage: the school level. Working students attend schools

with worse infrastructure, schools with less computers connected to the web, schools with a lower average socioeconomic level, and schools where teachers have less years of experience and lower qualifications. Also, the prevalence of working students is comparatively larger than non-working students in public schools, in rural areas and small/medium size locations.

4. Empirical methodology

We attempt to obtain robust associations of child work with learning by following different approaches. The different approaches allow us to account for different issues which may bias the work-learning association. The use of these approaches are also framed by our research questions for the regional and country analyses. For the regional analysis, research questions are: (1) what is the impact of students' different types of work for the average performing student?, (2) does the impact of work vary across the learning scores distribution?, (3) what are the main regional pathways mediating the working-learning association? And for the country analysis, these are: (4) which are the salient countries with the most unequal and larger child's work learning gaps, (5) what is the leverage of policies to narrow or eliminate the work-learning gaps?

To answer question 1 we employ OLS with a wide range controls at the individual, family and school level as well as matching techniques. To investigate if there is heterogeneity on the child's work and learning association (question 2), we employ quantile treatment effects. For the analysis of questions 3 and 4 we use OLS, but based on smaller and comparable matched sub-samples (defined by working and non-working students having the same observables characteristics), which are obtained by matching techniques. In addition, as a robustness analysis for the main results, we look at the role of unobservables (e.g., students' ability, parental perception on the value of education) on the working-learning association using a bounding approach.¹²

4.1. Mean effects

An initial estimate for the impact of child work on learning for the whole region is obtained by estimating a null model with OLS, and then sequentially adding controls (first, students' and families' controls, and second a model where schools/head master/teachers controls are added) as well as a model which controls for school heterogeneity through school fixed effects. All models use weighted OLS adjusting standard errors for school-level clustering. The estimated equation by OLS regression for the whole region with full controls for student i of country k ($k=1,...,15$) for the learning score (math and reading) Y_{ik} is:

$$Y_{ik} = \beta_0 + \beta_1 W_{ik} + \beta_2 X_{ik} + \beta_3 X_{hk} + \beta_4 X_{sk} + d_k + \epsilon_{ik} \quad (1)$$

where the key explanatory variable is W_{ik} -a dummy for whether child i works in country k (indicators: any work, work outside and paid, and work at home unpaid), X_{ik} includes a wide range of child's characteristics affecting learning ex-post (e.g., age, gender, repetition/truancy, pre-school attendance), X_{hk} includes

household background covariates (such as family size, parental education and socio-economic and cultural status), and the vector X_{sk} includes school characteristics linked to student’s achievement (e.g., school type, location, infrastructure, average socio-economic status), head-master controls (education and experience) and teacher controls (education, experience, qualifications, working hours) (see Table 2), and d_k is a country dummy to capture country heterogeneity. The specification’s choice follows earlier studies (e.g., Bezerra et al., 2009; Byun et al., 2014; Dumas, 2012; Emerson et al., 2017; Gunnarsson et al., 2006).¹³

However, whether children end up working is not a random event and independent of working children and non-working children’s characteristics. Even if factors driving child work (and their associated learning) are controlled for in a regression analysis, the negative effect of child work on learning might be overstated because the distribution of the characteristics of working children and non-working children differ, as it was shown in Table 2 (Panel B). In other words, selection into work (i.e., the treatment) is not independent of treated and control individuals’ characteristics. To account for this selection bias (on observable characteristics), we employ matching techniques¹⁴ which pair similar individuals from the working group of children group with individuals from the non-working children group in order to estimate the effect of work on test scores.¹⁵

We use two types of matching procedures: propensity score matching and exact matching. Propensity score matching (Rosenbaum and Rubin, 1983, 1984) summarises the pre-treatment characteristics of each subject into a single-index variable (the propensity score) that makes the matching possible, with the index based on the estimation of the probability of being treated (or the event that a child works) conditioned on pre-treatment control variables: $P(X_i = P(W_i = 1|X))$. We estimate the average treatment effect on the treated (ATT), that is, the difference in the expected outcome with and without treatment for cases that received treatment (Caliendo and Kopeinig, 2008):

$$\tau_{ATT} = E[Y_i^1|W = 1] - E[Y_i^0|W = 1] \quad (2)$$

where Y_i^1 and Y_i^0 denote students’ test scores for the working and non-working groups, respectively, and X is the whole set of covariates used to calculate the propensity score by a logit. Note that the second term of (2) is the counterfactual outcome in the absence of the treatment and, thus, is unobservable and must be estimated. The estimator of the ATT relies on two assumptions: unconfoundedness and overlap. The overlap condition states that the probability of assignment into the work treatment is bounded away from zero and one ($P(X_i) \in (0, 1)$) ensuring that any combination of characteristics observed in the treatment group can also be observed among the control group. The unconfoundedness (or conditional independence) assumption states that assignment to treatment is independent of outcomes conditional on covariates: $(Y_i^1 - Y_i^0) \perp (W = 1)|X$.

Though untestable, the latter assumption is vital because, if certain variables (such as parental supervision or lack of good study condition and teaching quality) are not included but are positively correlated with the distribution of potential outcomes,

then our estimates for work’s impact would be biased, yielding an overestimation of the work-learning relationship. We attempt to address this by including a wide range of variables for matching beyond those more closely linked to children’s work decision (as in equation (1)).

Furthermore, it is widely acknowledged in the literature that the likelihood of child work is shaped by the characteristics of the labour market (Basu, 1999; Basu and Tzannatos, 2003). In the TERCE dataset two proxies for labour market features are schools’ area and their location. We attempt to tackle this by employing exact matching (on covariates) where, for each country, we match working children with non-working children living in the same area (rural or urban) or in locations of the same size (small, medium or large).¹⁶ This allows to find better matches among the working and non-working students groups as regional estimates would consider students living in the same country as well as in the same area or living locations of the same size, which, in turn, would be isolating the influence of local labour market features within the work-learning association.

4.2. Quantile treatment effects

It is probable that children enter the labour market or help parents with family work because parents believe their children’s prospects in education are narrow due to their low ability or poor motivation. But it could also be that more able children have better paid opportunities in the labor market (Emerson et al., 2017), especially in Latin American countries where combining work with studying is common. If this is true, whether a student is either a low or high performer could be a risk factor for entering into the labour market leading to lower achievement. In other words, it is probable that the impact of child’s work on learning varies across the test scores distributions.

We investigate the extent of this problem by linking observed ability (given by the position on the τ ’th quantile of the test score score distribution) with the effect of work on learning. Looking at the impact by performing groups may provide an indication on the role of ability within the work-learning association and its heterogeneity. We do so by using quantile treatment effects (QTEs) (see, Firpo et al., 2009; Powell, 2016).¹⁷ QTEs (as matching or OLS in Section 4.1) uses propensity scores based on observed characteristics to match working students with non-working students. Through QTE we are able to explore the effect of work on learning for students of different abilities.

QTE measure the distance on test scores between the treatment (working children) and control (non-working children) groups at any quantile τ using differences on the inverse CDFs:

$$QTE_{\tau} = Y_{T,\tau} - Y_{C,\tau} \quad (3)$$

where $Y_{T,\tau}$ and $Y_{C,\tau}$ are the value of the outcome at the τ ’th quantile of the treatment group and control group distributions, respectively. To estimate the work-learning QTEs we follow Cattaneo (2010) and Cattaneo et al. (2013) where we adapt the multivalued treatment approach for the single work treatment framework of

our application. We run QTE for the three working definitions of the treatment (work, work outside-paid, and work at home-unpaid) using, as benchmarks, the 25th, 50th and 75th quantiles and testing whether the impact of work is similar across these three ability groups, for the bottom and top quartile and for median and top quartile.¹⁸

4.3. Matched sub-samples analysis

Here we base our analysis on a matched sub-sample obtained through propensity score matching. That is, each student in the work treatment group is paired with a student in the control non-working group.¹⁹ These matched subsamples contain fewer observations than the original sample ($N_m < N$) as unmatched comparison units are discarded. Importantly, these smaller sub-samples identify comparable working and non-working students in terms of the observed covariates which are then used to examine if the learning working gap persists, both for a regional and country analyses.

For the regional analysis, we re-run the model for the matched sub-sample and test whether the impact across the three work indicators is the same as for the OLS estimates based on the full sample. Moreover, using matched sub-samples, we investigate the importance of different family and community drivers²⁰ from work to learning. We choose as drivers: mother education, whether a child is indigenous, location combined with its size, and proxies for labour market structure and for school quality.²¹

For the country matched sub-sample analysis we only use the overall work indicator and obtain the matched sub-sample by running a matching analysis for each country. We evaluate the impact of policy variables and institutional practices on the country work-learning gap, be it whether the effect of work on learning is reduced after including them or it becomes statistically insignificant or it remains unmodified. We loosely term this strand of the analysis as country policy channels, highlighting where in Latin America school programs and established educational practices operating within schools are meaningful in reducing the work-driven learning inequality. This is carried out only for the narrower subset of countries where OLS estimates remain significant in the matched-subsamples which allow us to highlight issues around school policies and practices net of observables. Formally, for each country k , we run the following OLS regression:

$$Y_{i'} = \beta_0 + \beta_1 W_i + \beta_2 SP_j + \epsilon_i \quad (4)$$

where $i' = 1, \dots, N_{km}$ (the smaller number of students matched: $N_{km} < N_k$), and the school policy (SP) variables SP_j are defined at the school level (j).

As policy variables we rely on the TERCE dataset information on whether a school has cultural programs, or programs on management and support of students attendance and teacher competencies. For institutional practices related to schools' operation we use variables measuring whether a school has a practice on the evaluation of teachers' performance, whether a school provides economic incentives to teachers, as well as supervision and training on math and language, and whether

head teachers are evaluated through students assessments. As said above, our choice of factors here are holistic containing a mix of programs and institutional practices.

5. Main results - regional estimates

5.1. OLS estimates

Results from OLS estimation²² for the three work indicators are presented in Table 3. In column 1 we report the results from a model in which we do not include any controls.²³ Regardless of the set of controls used, estimates confirm earlier research for the region (Gunnarsson et al., 2006; Post, 2011) that child’s work is negatively associated with academic achievement in Latin America. The effect of work is larger for reading than for math, perhaps underlying this is the fact that math’s performance is more closely linked to unobserved factors such as ability. For the composite work indicator, estimates are reduced from a negative impact of 28.31 to 10.35 (math, columns 1 and 3) and from 40.67 to 15.1 (reading, columns 5 and 7) in the null and full models, respectively, with the two-third estimates’ reduction indicating the importance of background characteristics behind children’s working decisions. School fixed effects estimates (columns 4 and 8) are similar to the full model estimates.²⁴

[Table 3 here]

As expected, the largest impact on learning is given by paid work outside the household. For instance, students being involved in paid employment outside the home achieve 3.86 (7.58) points less in math (reading) than students who are involved in unpaid employment in their households (columns 4 and 8).). Unpaid family work also hinders academic achievement; in many cases working at home comprises arduous physical labour. Overall, the negative estimates of Table 3 reject the hypothesis that certain activities encompassed by any of the working measures are either directly or indirectly beneficial to learning and possible leading to positive impacts of work on learning.²⁵

5.2. Matching estimates

A concern behind the above estimates is selection bias. With matching, a balance in the distributions of covariates between the working and non-working children groups is achieved (see Appendix B), minimising the impact of observables on the causal effect of child work on learning. Propensity score matching seems to perform well. A comparison of the standardized mean differences before and after matching (Figure B1) shows that matching on the propensity score substantially reduce imbalances in the distributions of the explanatory variables. For example, socioeconomic status at the family and school levels (absolute) biases are of 63.7% and 70.3% before matching and only 2.3% and 3.1% among matched units. The bias for whether a student had repeated a grade is also reduced from 23.4% to 1.6%, and for mother’s education from 37.4% to 0.8% in the matched sample. The bias of main drivers of achievement at the school level such as infrastructure are lowered from 65.6% to

3.7% in the matched sample.²⁶ Likewise, common support shows an improvement after matching with the propensity score values for the treated and untreated groups overlapping (Figure B2) and the differences on conditional probabilities of the treatment reducing, especially for the indicator paid work outside the household where densities were quite different before matching.

Table 4 contains estimates for the average treatment on the treated (ATT) based on exact and propensity score matching. For all working indicators and for the two approaches, ATT's estimates confirm that working students academic performance is consistently worse than non-working students, both for math and reading. Recall that the exact matching procedure matches individuals within each country by either rural/urban location or location size, to come up with regional estimates. Estimates for the two exact matching models lead to very similar effects (Table 4, Panel A). Overall work's results (columns 1 and 2) are mainly explained by unpaid household work (columns 5 and 6). Estimates for the impact of work on math, for instance, are around -13 and -12 for unpaid work, while for paid outside work they are around -18. The highest negative effect is for reading for students undertaking paid outside work (approx. -23, column 4). Propensity score estimates (Table 4, Panel B) are slightly lower but similar to exact matching estimates.

[Table 4 here]

Importantly, propensity score matching estimates are in line with OLS's estimates (Table 3, full model, columns 3 and 7), and so equally qualitative conclusions are obtained through each method: work (measured by any of the three indicators) is damaging for students' learning prospects at the regional level. An additional comparison of OLS with matching is shown in Table 5. Here we include OLS estimates (columns 1 and 5) and test whether they are statistically different to estimates based on matched sub-samples. Only one out of the six estimates are significantly different from each set of estimations (at p-values of 5%).

[Table 5 here]

5.3. Heterogenous effects - quantile treatment effect estimates

Here we test the hypothesis of whether the relationship of learning and work varies at different points of test score distributions. Quantile treatment effect (QTE) estimates are included in Panel A of Table 6. This model uses full controls for the outcome equation and a subset of covariates for the treatment equation on the probability that a student works.²⁷ Tests across the three quantiles indicate that how work translates into lower achievement varies by ability as we reject the null hypothesis of equality of the quantile effects at Q25, Q50 and Q75 (and for all three work indicators for the two outcomes). The same holds for the bottom and top performers at 10% level (only the null is accepted for reading, unpaid household work, column 6). A comparison of the tests' results of the bottom and top performers against the average performing working student reveals that previous OLS and matching estimates are more sensitive to heterogeneity at the bottom half of the test score

distribution (i.e., between the very low and medium ability students). Here, out of the six tests, only one is accepted for the equality of effect for Q25 and Q50 quantiles.

[Table 6 here]

From the coefficients across quantiles (top part of Panel A of Table 6) one can see that the negative impact found earlier on (in Tables 4 and 5) for the indicator outside paid-work, seems to be driven by low ability students as coefficients are non-statistically significant for Q50 and Q75 (columns 3 and 4). This might support the hypothesis that poor families allocate low-ability children to do remunerative work. Turning to the estimates for the other two work indicators in Table 6, we find that negative (absolute value) effects are decreasing by ability for math but increasing for reading (indicator any work: columns 1 and 2, respectively), but for home unpaid work (columns 5 and 6) both for reading and math work impacts are increasing with ability. This finding may suggest that math's performance is more closely linked to innate individuals traits which may allow high ability students to counterbalance the less available time for studying due to work, whereas for reading the opposite holds.

In Panel B of Table 6 we present matching estimates using a categorical definition of learning, taking the value of one if a student scores above levels 3 and 4 (reaching a medium or high achievement), and 0 for levels 1 and 2 (not being able to master specific-subject concepts).²⁸

We use double robust matching estimator (Bang and Robins, 2005) which uses the same (full) specification for estimating the propensity score and the outcome model (we use inverse-probability weighting). This estimator has the theoretical advantage that it yields unbiased estimates if either or both the propensity score and outcome equation are correctly specified, a double robust property which offers more protection against misspecification. The first row of Panel B shows the average treatment effect on the treated (ATT) as a percentage of the untreated potential outcome mean. Results from this specification yields negative impacts for the group of working students reaching at least acceptable levels of mastering math and reading concepts -with absolute impacts being larger for the reading. For instance, for the any work indicator (columns 1 and 2), a working child has 16% and 21% less chances to reach at least level 3 in math and reading than a non-working child, respectively. This is somehow different for the work indicator of outside paid-work where we did not find significant effects at the top tail of the distribution.

5.4. Pathways mediating the relationship between work and learning

In this section, we explore some individual and school channels of transmission from work to learning as well as some labour market features as this could shed some light on possible policies that may help to attenuate some existing disparities between these groups. Group heterogeneity is evaluated after controlling for other sources of differences by using matched sub-samples for each work indicator.

We examine whether mother's education (low or high) and student's indigeneity lead to differential effects of student's work on learning. We also assess heterogeneity by labour market opportunities using location (rural and urban) combined with

location size, the role of work stability in the area measured by schools averages of parental employment type (seasonal versus permanent)²⁹ and quality of the labour markets (by combining information on family wealth and parental education averaged across schools). Furthermore, we check if the work-learning relationship is driven by the poor quality of the educational institutions working students attend because household decisions about the extent to which children are engaged in work is related school quality through its' influences on the expected returns to education ([Guarcello and Rosati, 2007](#)).

Table 7 (Panel A) shows that, in general, regional estimates for outside paid-work are mostly driven by the group of lower middle income countries (LMIC) (columns 2 and 5) rather than from the groups of upper middle income countries (UMIC) or high income countries (HIC). For instance, for math, the estimate for LIC is -29.88 (significant at 1%), for UMIC is only -7.44 (significant at 10%), but the estimate for HIC of -12.93 is not significant (this is also the case for math and home unpaid-work, column 3). Yet, for reading, estimates are significant across the three income country groups and larger for HIC than for UMIC (column 5). The impact of the indicator any work (columns 1 and 5) is increasing by income group as well.³⁰ It seems that in poorer Latin American countries where the kind of work undertaken by students is physically and mentally more demanding, students who work outside of school will also suffer academically.

[Table 7 here]

Panel B of Table 7 shows estimates for the sample of students whose mothers have low or higher education. Mothers' education does not seem to matter much as a source of inequality in itself across work indicators once matching in other background variables, except for outside paid work and for math (column 2), where the estimate is not significant for students whose mothers have high education but it is significant for the group of working children with low educated mothers (= -13.52). This result may be explained by the fact that household educational disadvantages of working children are channeled through economic household disadvantage which we matched for in matched sub-samples. Indigenous working children, though, are clearly disadvantaged even after matching on various individual and household variables such as socio-economic status. They are more likely to reach lower achievement in math in comparison to non-indigenous working children, and the learning gap is particularly large for those engaged in outside paid-employment (Panel C, columns 2 and 5).³¹

Results for the impact of the overall indicator for work on learning for urban and rural locations (or schools) in Panel C of Table 7 (columns 1 and 4, first two rows), indicate that the effect is larger in urban locations, and statistically different from rural locations (i.e., we reject the null of equality of effects). Surprisingly, impacts on math and reading for unpaid household work are not statistically significant in rural communities but they are in urban communities (column 3).³² Within urban locations, whether a student lives in a small or large community matters -effects are not significant for small size urban areas only, with the gap on effects of around

5-8 larger for students working in larger urban communities (Panel C, third and fourth rows). These differential estimates by location type and location size, in turn, provide further support to the earlier estimates of exact matching based on these two definitions.

Furthermore, estimates seem to suggest that the structure of labour markets matters for the work-learning gap in terms of the quality of job opportunities (Table 7, second part of Panel E): students living in poorer areas characterised by low family wealth and low parental education, and quite probably with low qualified and low paid jobs too, lose more in achievement through work than students living in richer areas. Although larger household income fluctuation (proxied by the school rate of parents temporary work versus stable work)³³ does not seem to further contribute to the negative working-learning gap (Panel E, first part). School quality (Panel F) shows slightly different results by outcome -that is, for math, impacts for the three work indicators are not significant for low and high quality school (columns 1 to 3) but, for reading, attending a low quality school leads to larger and significant impact for the indicator paid outside work (column 5).

6. Additional results - country estimates

This section contains the country-level policy analysis. We look at whether the remaining (if any) country-specific work-learning gap can either be closed or narrowed through policy variables and institutional practices. We often refer to these two set of variables loosely as school policies. For this analysis we rely on the overall student work indicator.³⁴ Before showing this analysis, we present OLS country estimates for the full sample using previous controls (as those in Table 3, columns 3 and 7) and OLS estimates based on matched sub-samples (a null model including only the work dummy) obtained through propensity score matching for each country. Details on the quality of matching for each country are shown in Appendix C (Table C1, bottom part).

6.1. OLS and matched sub-sample estimates

Country OLS estimates for math and reading are displayed in Figure 1 for full and matched sub-samples. For completeness, we also include in Appendix C exact and propensity score matching estimates for each country (Table C1).³⁵ Figure 1 shows a significant heterogeneity on the effect of student work on achievement across the region. For math, the OLS estimates based on the full sample (x-axis) for the whole sample of -11.79 (highlighted in red, and shown in Table 5) varies between -22.02 (Argentina) and -18.06 (Chile), to -3.30 (Nicaragua) and -2.31 (Peru). Of the 15 countries, only the effects for 10 countries are statistically significant (at 10%) using the full sample and 7 based on matched sub-samples. Most of the significant estimates from the matched sub-samples are considerably lower than those from the full sample. For instance, the sub-sample estimates are around a half of the estimates of the full sample in Colombia (-20.98 and -10.86) and Uruguay (-28.76 and -9.58). This shows the importance of isolating observables characteristics through matching

in the country analysis. For reading, too, there is a between-country variation on the effect of work on achievement, though slightly smaller than for math. The whole sample estimate of -16.27 varies between -30 (Uruguay) to -11.1 (Mexico), with all 15 countries (full sample) and 10 countries (matched sub-sample) showing significant effects.

[Figure 1 here]

6.2. Policy and institutional practices effects on the work learning gap

We now turn to the school policy and institutional practice analysis of the work learning gap for the group of countries where the effect of work on learning is still statistically significant in country matched sub-samples. Table 8 reports results for math and Table 9 for reading.³⁶ For comparison, in Panel A we include the estimate of work for matched sub-samples (null model). Panel B shows the estimates of the work indicator dummy on achievement after controlling for specific policy variables following the specification of equation (4).

[Tables 8 and 9 here]

We find that policy variables lead to non-significant effects of work for those countries where the original association of work with learning scores were at the margin of statistical significance. That is, for math in Chile, Honduras and Uruguay (Table 8, columns 2, 5 and 8) and for Paraguay and Dominican Republic for reading (Table 9, columns 9 and 10). Estimates suggest that school policies are unable to fully close the work-learning gap beyond what it is explained by background individual and household characteristics, which we control for in the matched sub-samples. But in other countries specific school policies can narrow the learning gap. For instance, in Argentina and Colombia, having a school management program in school (Table 8, columns 1 and 3) or a school feeding program in Uruguay (Table 9, column 11) lower the impact of work on learning between 2 and 5 points.

7. Robustness analysis

The main concern of earlier results of Section 5 are that, both the endogeneity of child work and the presence of other unobservables (e.g., parental preferences to send a poor performing child to work) that are potentially correlated with both the decision to engage in work and the aptitude towards learning, could bias the work-learning association. Because OLS and matching rely on observables characteristics, any unobserved variables included in the error term ϵ_{ik} of equation (1) that is correlated with the dummy for student work W_{ik} would bias the estimated OLS coefficient β_1 or the *ATT* (equation 2). Some studies have accounted for potential endogeneity using instrumental variables to overcome this problem (Bezerra et al., 2009; Dumas, 2012; Gunnarsson et al., 2006).

In this section, we use a bounding approach (Oster, 2016) instead, due to its advantage of not needing to identify an instrument (which is often difficult to find and validate). This approach has been increasingly used in recent empirical studies

(see, e.g., [Dahlen, 2016](#); [Nghiem et al., 2015](#)) but, as far as we are aware, it has not been applied to the study of the effect of child work on learning. Bounding allows us to identify the true effect of work on learning within a range taking information from observed covariates to make inferences on the role of the unobserved measures and creating bounds around the estimated effect. If bounds exclude zero, it is an indication of robustness against omitted variable bias.

7.1. Selection on observables and unobservables - bounding

We assess if the work-learning OLS specification is robust to the presence of unobservables by providing estimates' bounds based on assumptions about the degree of selection between observables and unobservables ([Oster, 2016](#)). Define the effect of observables as $O_{ik} = \beta X_{ik}$ and unobservables as U_{ik} , with equation (1) being re-expressed as $Y_{ik} = \beta_0 + \beta_1 W_{ik} + O_{ik} + U_{ik} + \epsilon_{ik}$. The proportional selection relationship δ between unobservables and observables is,

$$\delta = \frac{\text{cov}(U, W)}{\text{var}(U)} \bigg/ \frac{\text{cov}(O, W)}{\text{var}(O)} \quad (5)$$

Following [Oster \(2016\)](#), define the coefficient resulting from the null regression of Y as β^* and the R-squared from that regression as R^* ; from the intermediate regression with additional observables X as $\tilde{\beta}$ and $\tilde{R}$; and, finally, define the R-squared for the regression also including the unobservables as R_{max} . Assuming a degree of selection for β equals to some target value $\hat{\beta}$ leads an approximate value for $\hat{\delta}$:

$$\hat{\delta} = \frac{(\tilde{\beta} - \hat{\beta})(\tilde{R} - R^*)}{(\beta^* - \hat{\beta})(R_{max} - \tilde{R})} \quad (6)$$

We rely on two assumptions to construct the two identified sets for student's work (treatment) effect on learning ([Oster, 2016](#)). The first assumption assumes equal selection (i.e., $\delta = 1$), which is an appropriate upper bound for δ as this implies that unobservables should not be more important than the observables in the treatment effect. The second assumption entails a bounding value for R_{max} and report the value of δ for which the estimator would produce a treatment effect of zero. A large value for δ (i.e., $\delta > 1$) would indicate a robust result because unobservables must be greater than observables to explain away the effect of work on learning, and also if intervals of the work treatment effect do not contain zero.

7.2. Bounding: regional results

As mentioned, the earlier estimated negative relationships of student's work with learning outcomes hinges on the assumption that working and non-working students have the same distribution of unobservables, and if not, results might be driven by unmeasured variables. Therefore bounds in these associations are estimated to check if our results are robust to the presence of unobservables, within limits on the magnitude of the selection on unobservables.

Results for estimates' bounds are shown in Table 10. Under the assumption of equal selection between observables and unobservables for math (Panel A, column 5) bounds estimates do include zero within their intervals, suggesting a null effect of work on learning when the unobserved factors are considered. But, under the assumption of a smaller importance of unobservables (i.e., 30% of observables)³⁷ only intervals include zero for one work indicator, i.e., outside paid-work (Panel A, column 7). Results for reading (Panel B) indicate a more robust association with student's work; out of six estimates only two (work in column 5, and work outside-paid in column 7) include zero within their intervals. It is important to examine the range of potential generated impacts by bounding as well. The upper bounds for work (column 7), for instance, although they don't overlap with zero, they are quite wide -i.e., for math around 14% and for reading around 17%.

[Table 10 here]

Another relevant information from Table 10 to assess the robustness of estimates of work on learning is the estimated value of δ under a null effect ($\beta = 0$). This indicates how much larger the role of unobservables would need to be to make the impact of students' work on their learning zero. If $\delta > 1$ estimates are robust to unobservables and conversely if $\delta < 1$. For math δ varies between 0.70-0.83 (Panel A, column 6) and for reading between 0.99-1.10 (Panel B, column 6), again suggesting that estimates for reading scores are more robust. In general, the bounding exercise for the impact of students' work on learning at regional level, suggests that the true effect of any type of work and home unpaid work is negative in presence of unobservables whereas for outside paid-work this association needs to be interpreted with caution.³⁸

7.3. Bounding: country results

Here we present estimates for the bounding analysis based on the indicator any work for each country. Bounds for math and reading are displayed in Figure 2 and are constructed under the assumption of a null effect of work on achievement scores under a 30% impact of unobservables with respect to observables. First, for math, out of the 15 countries of the total sample, in 10 countries work effects are significant, and from those 10 countries only in 5 countries effects are robust to omitted variable bias. In countries such as Argentina, Chile and Mexico with initial large OLS effects (see Figure 1), estimated bounds include zero and so it cannot be ruled out that a reduction on math achievement is being driven by unobserved factors.

[Figure 2 here]

Second, all estimated OLS coefficients for reading were found to be statistically significant, but after addressing the role of unobserved variables, only in 10 countries there is evidence that the true effect of student's work on reading is different from zero. Furthermore, because in Peru $\delta < 1$ for the two outcomes, the role of unobservables could be less important than the role of observables and still imply that student's work is not having an impact on achievement. All in all, the country bounding analysis suggests that unobservables are important mediating pathways

which have a different bearing on the work and learning association across countries and, importantly, OLS estimates are not robust in half of the countries studied, even after the wide range of covariates employed.

8. Conclusions

In this paper, we presented recent evidence on the effect of different kinds of child (or student) work on learning for Latin America using the TERCE learning survey (2013). The paper aimed to estimate causal links from work to learning, both at the regional and country level. We used alternative methodologies to generate estimates on the impact of child work on learning addressing the influence of observables through matching (and matching sub-samples) and the role of endogeneity by establishing bounds on the results, as well as the influence of ability on work's learning effects through quantile treatment effects. We also investigated the leverage of educational policies on lowering the country's work-learning gap.

Although with limitations due to the information provided in the TERCE dataset, these different kinds of analysis allowed us to put forward alternative hypotheses (e.g., what are the most damaging types of child work for learning and for what types of performing group students, what is the role of labour markets and whether school quality is an important determinant on household decisions on children's work and the impact on their achievement) for the region as a whole and for specific countries which, in turn, could hint towards future analysis. Importantly, results were based on a current cross-country comparable learning dataset. As such, we believe that our results contribute relevant insights to the scarce cross-country literature on child work and learning as to guide education policies in Latin America aimed at narrowing learning inequalities.

We found that student's work is still a significant barrier hampering learning in the region leading to lower math and reading achievement for working students (of around 9-13 points) and, importantly, this work-learning gap remains even after we control for a large set of student, parental, household, and school characteristics. The group of students more affected are those engaged in paid employment outside the household and of low ability. We found no support either for the hypothesis of school quality being a mediating factor on child's work impact on achievement nor that school policies (in general) are able to close the work-learning gap. Policies on school management, on supporting teachers competencies and on supporting student's attendance are useful, yet only for a few countries. But it should be noted that the policies' impacts we obtained are for the average performing working child, as well as net of other background students and family factors in matched sub-samples. This, in turn, may suggest that policies should place more prominence on the first layer of disadvantage of the work-learning relationship given by a child and family characteristics. In addition, for certain deeply entrenched disadvantages, like students' indigeneity, work is a strong barrier for learning. Regional estimates, nonetheless, hide a significant variation with only half (two-thirds) of countries of the regional sample showing significant math (reading) impacts when differences on

characteristics of working and non-working students are accounted for. At the outset, to narrow the regional working learning gap, policies should prioritise low achievers, those in paid employment and students living in large urban areas as well as to focus on factors driving work allocations within families.

When we considered the issue of endogeneity of children’s working decisions and learning outcomes (e.g, driven by parental preferences, a child’s attitudes to learning) in the bounding approach, this only yielded to a few more countries where the effect of work on learning lacked statistical significance. However, estimates controlling for endogeneity have wide bounds and so are less precise. Thus, future work in this direction would also need to rely on labour force datasets ideally having information on work intensity and its interference in students’ study time allocation and habits such as attending class and turning in homework on time.

8.1. Limitations

The paper’s analysis has limitations. Work is self-reported and hence likely to suffer from measurement error. Importantly, several aspects of work which would impact differently on student’s learning are not possible to be measure through the TERCE dataset. The definitions of work used do not include, for instance, the types of jobs students are engaged in (whether it is a more or less physically demanding activity, or an intellectual and complementary task to learning), jobs’ remuneration levels, distance to the workplace, and a robust indicator for work frequency in terms of number of hours. In addition, the dataset lacks accurate country information on labour markets (which is why we used measures averaged at the school level as a proxy for labour market features). A standard limitation of the cross-section nature of the data is that we are unable to control for initial ability. Having a panel data would be beneficial as it could allow us to control for individual time-invariant unobservable characteristics, as well as looking at cumulative effects of child labour on learning and at different ages. However, we lessen this by producing robust coefficient bounds for the impact of work on learning.

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Disclosure statement

No potential conflict of interest was reported by the authors.

Notes

1. For instance, there is the ILO convention 182 on the worst forms of child labour where nearly all children are covered, and convention 138 on the minimum age for admission to employment and work with a coverage of 80% of world's children ILO (2017, p. 22) for details. For details on ILO conventions, see: <http://www.ilo.org/ipec/facts/IL0conventionsonchildlabour/lang--en/index.htm>.
2. For recent child labour information for Latin America, see: <http://www.ilo.org/ipec/Regionsandcountries/latin-america-and-caribbean/lang--en/index.htm>.
3. The latest GDP rate for the LAC region for year 2016 is negative, around 0.69%. Source: World Bank national accounts data, and OECD National Accounts data files: https://data.worldbank.org/indicator/NY.GDP.MKTP.KD.ZG?locations=ZJ&year_low_desc=true.
4. See, <https://sustainabledevelopment.un.org>, for details on goals targets and indicators.
5. See: <https://sustainabledevelopment.un.org/sdg4#progress2017>.
6. We are grateful to one of the referees for directing us to this study, which has been published after our initial submission and we were not aware of.
7. However, In a recent study, Roberts et al. (2017) shows that the although LAC region appears to be over-urbanized relative to their levels of development and the importance of the agricultural sector to their economies, they show that this is an urban myth when relying on a different consistent set criteria without systematic biases in the measurement of levels of urbanization.
8. See: <http://knowledge.wharton.upenn.edu/article/ending-child-labor-in-latin-america/>.
9. See UNESCO-OREALC (2015a, p. 14) for details.
10. Note that TERCE work prevalence estimates are in line with other international surveys. For example in the case of Peru, estimates based on MICS survey are very close to TERCE -the prevalence of child employment is 49.6% for the age group 12-14 (Dayioglu, 2012).
11. There are no large differences on the three indicators by gender, except from paid work (larger for boys) and home work (slightly larger for girls). That is: any work is 49.5% (male) and 43.4% (female); outside paid-work is 16.3% (male) and 5.5% (female); and work at home unpaid is 35.4% (male) and 37.22% (female).
12. This analysis, carried out both at the regional and country level, is included in Section 7 and further in Appendix D.
13. A limitation of our specification is, of course, due to the cross section nature of the dataset and as a result the lack of key driver on the likelihood of work: prior achievement. Whether a student

is a stronger or weaker student at earlier grades would affect his/her chances of both working and his/her later achievement. Although repetition, which is included in the set of covariates X_{ik} of equation (1) is a kind of proxy of prior achievement.

14. As far as we aware, there are only a couple of studies in this area (Lee and Staff, 2007; Staff et al., 2010) which use matching techniques, although they deal with the effect of working intensity on high school dropout in the USA context.
15. Even if children in the two groups are not identical in every way, they are similar in their likelihood to work (the propensity score), so the learning score of non-working children can be used as counterfactual outcome for working children if they had not worked. Unlike OLS, unmatched children are excluded from the analysis and higher weights are assigned to better matches. Thus, in this context, matching reduces bias and improve efficiency of OLS estimates (e.g. Williamson et al., 2014).
16. Note that this modelling approach coincides with one of the factors proposed by Heckman et al. (1998) to reduce selection bias in an evaluation study, that is, both treated and non-treated populations must be in the same geographical area.
17. For recent education applications using QTEs (see, e.g.: Andrews et al., 2016; Cummins, 2017).
18. We are not aware of regional studies looking at the possibility of reverse causality (say, how parental allocation could create negative incentives for students with lower achievement becoming more likely to be employed) either explicitly or using a QTE approach.
19. This is done by applying propensity score matching without replacement for each working indicator and using a caliper of 20% SD of the score, excluding observations outside common support. Examples following this approach in the education field are, for example: Chudgar and Quin (2012) and Delprato et al. (2017).
20. Note that these drivers are not used as covariates in the estimation of the propensity score through which the matched sub-samples are obtained.
21. This analysis sheds light about mediating pathways on the working-learning association at the regional level and so it may offer an insight on which groups to target to reduce the working-learning gap. Importantly, the relevance of these drivers are assessed net of other factors by relying on matched sub-samples. For instance, we look at regional issues around school quality and labour market on the student's work learning gap (Gunnarsson et al., 2006; Sánchez et al., 2009) but after comparing individuals with similar family characteristics.
22. Note that the interpretation of all estimated coefficients throughout the analysis is in terms of impacts on standard deviations (SD), which as said above in TERCE are around 100 for each outcome, with a mean equals of 700.
23. In the regional working sample, we dropped missing observations either math or reading scores being missing (=4,799, 7.61%) and work status (5,780, 9.21%). The correlation on the two set of missing is high, $\rho=0.43$, so not a concern of different missing pattern by the two key variables of the analysis. For the country analysis the rates of missing for work status from students' answers vary between countries – from 3.3% in Costa Rica, to 14.2% in Dominican Republic. Although we could have replaced by mean schools values as an imputation method for the missing of the or the work variable, in the analysis we treated the data as missing as random and so excluded these observations from the analysis. This is validated by comparing estimates. For instance, the OLS estimates differences of using the working sample excluding missing and the sample replacing work status by the school mean for the 15 countries are between -2.5% - 6.7% (math) and 2% and 4% (reading). For the regional analysis differences on estimates are nearly the same. We obtain similar results when replacing covariates by school mean as well.

24. Not following a separate analysis for male and female students is validated by our results. We estimate alternative models to test differences by gender (Appendix A). We do not find differences on the effect of work on learning for any of the three work indicators by gender. All tests on the equality of male and female coefficients are above the 10% significance level (Table A1, Panel A). Further, we check whether work intensity matters and whether its impact is different for male and female students. We find that working at ‘the weekends’ and ‘most of the time’ are significant but, for students who works ‘little’ the impact is non-significant (Table A1, Panel B). A gender test on the work intensity and gender interaction was also found to be non-significant.
25. These activities, such as the use of math, writing or learning by doing could counterbalance and even compensate the time and effort dedicate put into a work activity (Emerson et al., 2017).
26. Mean t-tests for covariates before and after matching lead to similar conclusions (see last row of Table 4, Panel B). Moreover, absolute biases are below the 5% after matching (see Table 4, Panel B). See also Figure B3 for examples on distribution of covariates before and after matching.
27. For details on the specification, see notes of Table 6.
28. See (UNESCO-OREALC, 2015d, Chapters 2 and 3) for details on the subjects domain of each level.
29. Location type and location size may capture small farm households adjusting children work and their schooling to variation on income, and proximity to urban centers may deter working in the household due to specialisation (Fafchamps and Wahba, 2006). Employment type in urban areas can also be linked to unpredictable household head unemployment shocks which in turn increases the probability that a student becomes engaged in work decreasing school attendance and achievement (see: Duryea et al., 2007 for a study on insurances failure and child labour in Brazil).
30. Note, however, that differences on marginal effects are not statistically different (marked in bold) between LMIC and UMIC for paid outside work (Table 7, Panel A, columns 2 and 5).
31. A comparison of estimates of Panels B and C (columns 2 and 5 of Table 7) suggests that the indigenous learning gap is higher than the mother education’s gap. The indigenous work-learning gap is around -10 and -20 points for math and reading achievement, respectively, while for mother education it is around -5 (math) and zero (reading). As shown by Delprato (2019), also using the TERCE dataset, this work learning gap is likely to be related to the low parental education expectations of indigenous parents.
32. In the TERCE sample, the regional prevalence of unpaid household work is of 50% in rural locations (schools), which is 20% higher than in urban locations (schools).
33. We obtain the distribution of labour market jobs stability by using parents’ temporary work (=1) against parents’ permanent work (=0) which is averaged across schools, and then divided the distribution of this indicator into quartiles for the region. Quartile 4 denotes a high work instability in the area (where the indicator is above 73%) and quartile 1 a high stability (school average rate below 8%). See notes of Table 7.
34. The reason why we only focus on this indicator is because the prevalence for the treatment variable outside paid-work is rather small in a few countries, leading to poor matches and some problem on common support. Results are available from the authors upon request.
35. Appendix C also includes quantile regression estimates for each country which are displayed in Figures C1 and C2. In general, these figures show that countries with either constant or increasing effect across quantiles are those which fall into the subset of countries where matched sub-sample estimates for the impact of work on learning are statistically non-significant.
36. Based on matched subsamples, the degree of variation on between-schools policies uptake is quite similar across countries (e.g., for programs supporting teaching competences the SD is around

0.45-0.50) but on the contrary there is a differential across countries on policies' prevalence (e.g., for the same policy the mean is of 0.23 in Mexico but 0.60 in Colombia). There is, too, a large discrepancy on the cultural programs uptake between countries but feeding programs are more country homogenous. Moreover, performance evaluation of teachers are quite significant across the sample, except for Argentina and Uruguay below the average and economic incentives to teachers are rather low in central American countries. More results on these statistics are available from the authors upon request.

37. This cut-off point is derived by [Oster \(2016\)](#) based on larger number of papers using randomised treatment evaluations.
38. In addition, in Appendix [D](#) we include matching estimates controlling for endogeneity (Probit-2SLS), using two instruments formulation alternatives. We find that the effect of work types on math become non-significant and for reading it is downward biased and significant (see: Table [D1](#)). These results are, somehow, in line with the conclusions based on the bound analysis.

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Figure 1: Countries' effects of working on test scores. OLS estimates for full and matched sub-sample

Notes: (1) Same specification as in Table 4. (2) WS denotes estimates for whole sample. (3) The symbol X indicates a country estimate which is not significant both for the full sample and the matched sub-sample, a hollow circle indicates a non-significant effect for matched sub-samples, and a filled circle indicates a significant effect for both samples. (4) Countries' abbreviations are described in Table 1.

Figure 2: Bounds estimates for work's impact equal to zero for each country

Notes: (1) Countries' intervals are derived using the rule $R_{max} = \Pi \times \tilde{R}$ and $\Pi = 1.3$ (see Table 10). (2) Dotted intervals in gray are for countries where the coefficient of work is not statistically significant (at 10%). (3) Intervals in black are for those countries where the coefficient of work is significant (at 10%) in the full model. (4) Intervals in gray are for those countries where the interval excludes zero but $\delta < 1$ indicating cases where the estimate is not considered to be robust against potential omitted variable bias (Oster, 2016). (5) Countries' abbreviations are described in Table 1.

Table 1: Latin American countries prevalence of type of child working - TERCE study, sixth grade students

		Work	Work outside - paid	Work at home - unpaid
		(1)	(2)	(3)
Argentina (ARG)	mean	0.41	0.07	0.30
	sd	0.49	0.25	0.46
Brazil (BRA)	mean	0.47	0.15	0.38
	sd	0.50	0.36	0.49
Chile (CHL)	mean	0.22	0.05	0.15
	sd	0.41	0.22	0.36
Colombia (COL)	mean	0.32	0.05	0.24
	sd	0.47	0.21	0.42
Costa Rica (CRI)	mean	0.29	0.03	0.24
	sd	0.45	0.18	0.42
Ecuador (ECU)	mean	0.39	0.06	0.31
	sd	0.49	0.24	0.46
Guatemala (GTM)	mean	0.64	0.29	0.53
	sd	0.48	0.45	0.50
Honduras (HON)	mean	0.60	0.15	0.52
	sd	0.49	0.35	0.50
Mexico (MEX)	mean	0.42	0.10	0.31
	sd	0.49	0.30	0.46
Nicaragua (NIC)	mean	0.61	0.23	0.53
	sd	0.49	0.42	0.50
Panama (PAN)	mean	0.48	0.07	0.37
	sd	0.50	0.25	0.48
Paraguay (PAR)	mean	0.69	0.19	0.60
	sd	0.46	0.39	0.49
Peru (PER)	mean	0.50	0.16	0.37
	sd	0.50	0.37	0.48
Dominican Rep. (REP)	mean	0.65	0.20	0.56
	sd	0.48	0.40	0.50
Uruguay (URU)	mean	0.39	0.09	0.29
	sd	0.49	0.29	0.45
Latin America	mean	0.46	0.11	0.36
	sd	0.50	0.31	0.48

Notes: (1) Work measures are derived from the TERCE's student questionnaire (question 26). (2) The work category includes either work outside or at home categories regardless of whether students are being paid. (3) The work outside and paid category includes monetary payments only, excluding cases where students' payments are non-pecuniary. (4) Work at home excludes cases when students are being paid.

Table 2: Summary statistics of learning scores and selected covariates by working status. Whole Sample

<i>Panel A - Outcomes</i>	Math		Reading	
	Not working	Working	Not working	Working
Scores	726.6	679.1	730.6	674.1
Level 1	41.0	59.0	32.1	67.9
Level 2	58.0	42.1	49.1	50.9
Level 3	69.3	30.8	66.1	33.9
Level 4	76.0	24.0	75.7	24.3
<i>Panel B - Characteristics</i>				
	Not working	Working		
<i>Student and family characteristics</i>				
Age	12.33	12.57		
Gender - male	0.47	0.53		
Repeated	0.18	0.28		
Missing school	1.94	1.98		
Attended preschool	0.80	0.75		
Nuclear family	0.81	0.80		
Number of kids at home	2.89	3.45		
Study conditions at home - index	0.00	-0.03		
Notebook	0.74	0.67		
Socioeconomic and cultural - index	0.17	-0.35		
Study supervision at home - index	0.07	-0.11		
Number of books	3.45	2.93		
Father's education	3.08	2.74		
Mother's education	2.99	2.66		
<i>School, head master and teacher characteristics</i>				
Public	0.75	0.87		
Urban	0.83	0.62		
Location size	2.30	1.96		
Infrastructure - index	0.34	-0.22		
Number of computers with internet, average	2.89	2.11		
Socioeconomic and cultural average - index	0.13	-0.33		
Years of experience - head master	10.55	9.86		
Education level - head master	3.96	3.70		
Years of experience - teacher	4.61	4.57		
Education level - teacher	3.63	3.43		
Teacher qualification	0.86	0.80		
Sample size	29,277	25,432		

Notes: (1) Performance levels are defined as from basic knowledge (level 1) to highest knowledge of each subject. In particular, for reading: level 1 (score ≤ 611), level 2 ($612 \geq \text{score} \leq 753$), level 3 ($754 \geq \text{score} \leq 809$), level 4 (score ≥ 810); and for math: level 1 (score ≤ 686), level 2 ($687 \geq \text{score} \leq 788$), level 3 ($789 \geq \text{score} \leq 877$), level 4 (score ≥ 878) [UNESCO-OREALC \(2015d\)](#). (2) Based on t-tests, all variables are statistically different (at 1% level) between the non-working and working groups, both outcomes and characteristics. Only the nuclear family dummy is not (p-value ≈ 0.62). (3) For details on covariates' construction see Table [D2](#).

Table 3: Impact of child labour on learning. OLS estimates

Work indicator	Math				Reading			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Work	-28.31***	-13.07***	-11.79***	-10.35***	-40.67***	-18.82***	-16.72***	-15.10***
N	51,804	36,233	30,225	36,233	51,804	36,233	30,225	36,233
Work outside - paid	-35.11***	-14.39***	-10.77***	-13.10***	-57.96***	-24.02***	-20.89***	-20.05***
N	30,178	21,773	18,010	21,773	30,178	21,773	18,010	21,773
Work at home - unpaid	-24.28***	-11.41***	-10.38***	-9.24***	-32.48***	-15.77***	-14.31***	-12.47***
N	43,758	31,177	25,975	31,177	43,758	31,177	25,975	31,177
Student and household controls	No	Yes	Yes	Yes	No	Yes	Yes	Yes
School, head master and teacher controls	No	No	Yes	No	No	No	Yes	No
School fixed effects	No	No	No	Yes	No	No	No	Yes

Notes: (1) Student's controls are: age, gender, a dummy for whether repeated a grade, absent from school, attended pre-primary, or live with parents, number of children and index of study conditions at home, index of computer's use at school, have writing book. (2) Household controls are: socio-economic and cultural status, index of control/study supervision, mother and father education level, number of books at home. (3) School's controls are as follows: dummies for public and urban schools, school location size, number of students, index of infrastructure, library number of books, number of computers with internet, socio-economic and cultural index school average. (4) And school's head master controls included are: years of experience, education level; and teacher controls: number of working hours, years of experience, education level, teaching qualification, further courses in language/math/others. (5) All models account for country heterogeneity by including country dummies. (6) Estimations are weighted by regional-representative weights and standard errors are clustered at the school level. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: Impact of child labour on learning. Matching estimates

	Work		Work outside - paid		Work at home - unpaid	
	Math	Reading	Math	Reading	Math	Reading
	(1)	(2)	(3)	(4)	(5)	(6)
<i>Panel A. Exact matching</i>						
Country and urban/rural location	-13.61***	-17.58***	-18.35***	-22.73***	-12.07***	-14.55***
Country and location size	-12.52***	-16.86***	-17.94***	-23.01***	-11.62***	-13.51***
N	31,485	31,485	18,529	18,529	26,945	26,945
<i>Panel B. Propensity score matching</i>						
Nearest neighbour (k-nn)	-9.43***	-12.55***	-13.52***	-26.42***	-9.15***	-12.18***
N controls	17,408	17,408	16,757	16,757	17,408	17,408
N treated	10,077	10,077	1,649	1,649	8,039	8,039
Off support	4,000	4,000	123	123	1,498	1,498
Caliper	0.037	0.037	0.02305	0.023	0.032	0.032
Bias (median) (%)	1.4	1.4	2.0	2.0	1.3	1.3
t-tests (non sign at 5%) #Xs	2	2	0	0	1	1

Notes:(1) Matching estimates specification contains full controls: student, family, school and head master and teacher covariates as for the OLS specification (3, columns 3 and 7). (2) Exact matching matches observations per country with either location type (urban, rural) or location size. It is carried out by Nearest-neighbor matching with replacement (Stata command: nnmatch), including a bias-correction term for continuous variables (e.g., age, all indices, years of experience, etc.) using [Abadie and Imbens \(2011\)](#) standard errors' correction. (3) Propensity score matching is carried out by Nearest-neighbor matching (K-nn) (Stata command: psmatch) with replacement, keeping observations on common support, and standard errors computed with the correction of [Abadie and Imbens \(2016\)](#). Using Radius and Kernel (Epanechnikov) instead of K-nn leads to similar results. (4) Both matching procedures use a caliper of $0.20 \times \text{SD}$ of the estimated propensity score. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: Impact of child labour on learning. Comparison of OLS estimates - full and matched sub-samples

Work indicator	Maths				Reading			
	Estimate (1)	Estimate (2)	Difference (3)	Test (4)	Estimate (5)	Estimate (6)	Difference (7)	Test (8)
Work	-11.79***	-10.10***	-1.69	2.87	-16.72***	-13.35***	-3.37	10.94
N	30,225	19,314		0.091	30,225	19,314		0.000
Work outside - paid	-10.77***	-11.94***	1.17	0.13	-20.89***	-22.37***	1.48	0.12
N	18,010	3,147		0.714	18,010	3,147		0.732
Work at home - unpaid	-10.38***	-9.19***	-1.19	1.02	-14.31***	-12.21***	-2.10	3.19
N	25,975	15,454		0.312	25,975	15,454		0.074
Student and household controls	Yes	No			Yes	No		
School, head master and teacher controls	Yes	No			Yes	No		
Sample	Full	Matched			Full	Matched		

Notes: (1) Same specification as in Table 3. (2) Estimations are weighted by regional-representative weights and standard errors are clustered at the school level. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 6: Impact of child labour on learning across ability groups

	Work		Work outside - paid		Work at home -unpaid	
	Math	Reading	Math	Reading	Math	Reading
	(1)	(2)	(3)	(4)	(5)	(6)
<i>Panel A- Quantile treatment effects for continuous scores</i>						
Contrast estimates						
Q25	-16.22***	-12.83***	-14.53***	-25.80***	-7.14**	-12.90***
std err	2.22	1.37	3.81	5.04	3.06	1.95
Q50	-5.20***	-16.61***	-3.95	-15.07***	-9.20***	-17.46***
std err	1.85	1.58	4.74	4.61	1.90	2.20
Q75	-11.30***	-17.22***	4.64	-0.43	-15.79***	-16.87***
std err	1.29	1.06	11.86	5.86	2.35	3.85
Tests						
q25=q50=q75: $\chi^2(4)$	138.15	368.91	20.76	38.78	69.25	149.75
p-value	0.000	0.000	0.000	0.000	0.000	0.000
q25=q50: $\chi^2(1)$	14.87	4.23	4.70	3.50	0.39	3.41
p-value	0.000	0.040	0.030	0.062	0.534	0.065
q50=q75: $\chi^2(1)$	9.20	0.13	0.75	6.10	5.95	0.02
p-value	0.002	0.716	0.386	0.014	0.015	0.884
q25=q75: $\chi^2(1)$	3.99	6.86	2.86	12.79	5.46	0.91
p-value	0.046	0.009	0.091	0.000	0.019	0.339
<i>Panel B - Matching estimates for categorical outcomes</i>						
ATT % of PO mean	-0.16***	-0.21***	-0.24***	-0.32***	-0.15***	-0.19***
N	31,485	31,485	18,529	18,529	26,945	26,945

Notes: (1) Treatment equation for quantile treatment effects includes students and household controls (age, gender, repetition and skipping class, whether student attended pre-school and live with parents, number of children in the household, and indicators for household socio-economic status and parental education), and school controls (dummies for school type and school location, location size and average school socio-economic status). (2) Bootstrapped standard errors based on 2000 repetitions (Stata command: `poparms`, Cattaneo et al., 2013). Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 7: Impact of child labour on learning across sub-groups at the regional level. OLS estimates (marginal effects) based on matched sub-samples

	Math			Reading		
	Work	Work outside - paid	Work at home - unpaid	Work	Work outside - paid	Work at home - unpaid
	(1)	(2)	(3)	(4)	(5)	(6)
<i>Panel A - Income group</i>						
LMIC	-9.04***	-29.88***	-8.34***	-16.12***	-46.90***	-14.95***
UMIC	-12.31***	-7.44*	-10.36***	-16.47***	-17.83***	-13.76***
HIC	-12.68**	-12.93	-6.81	-23.20***	-33.89***	-20.74***
<i>Panel B - Mother education</i>						
High	-12.53***	-8.72	-11.62***	-19.49***	-25.44***	-17.67***
Low	-11.63***	-13.52***	-6.98***	-15.42***	-24.30***	-10.98***
<i>Panel C - Indigenous</i>						
No	-10.46***	-6.35	-8.81***	-17.54***	-17.55***	-16.83***
Yes	-13.52***	-17.50***	-10.69***	-13.72***	-38.45***	-7.87
<i>Panel D - Location and size</i>						
Urban	-11.74***	-9.11***	-9.92***	-17.61***	-23.08***	-15.91***
Rural	-7.35***	-13.12**	-3.97	-10.18***	-21.37***	-5.86
Urban small	-5.51	-26.55*	-8.65	-10.20**	-34.34**	-12.59**
Urban large	-13.12***	-6.21	-11.52***	-18.29***	-22.34***	-17.66***
<i>Panel E - Structure of labour market</i>						
Temporay work						
Low	-13.03***	-4.79	-15.44***	-25.06***	-25.13*	-26.78***
High	-8.87***	-14.77***	-4.74	-10.83***	-22.59***	-5.81
Labour market quality						
Low	-10.65***	1.40	-10.07***	-16.93***	-17.69*	-20.03***
High	-8.74***	-10.49**	-5.58*	-9.42**	-16.74***	-5.47
<i>Panel F - School quality</i>						
Low	-1.67	-1.36	-0.64	1.74	-9.30***	4.38*
High	-0.88	3.80	0.49	-3.68**	-1.16	-3.67*
N	29,966	5,099	23,877	29,966	5,099	23,877

Notes: (1) All estimations are based on matched-subsamples for each work indicator at the regional level using students and family covariates (excluding those covariates measured by the sub-groups) as well as country dummies. (2) Lower income countries (LIC) are: GTM and NIC; upper middle income countries (UMIC) are: ARG, CHL, URU and the remaining (10) countries are lower-middle income countries (LMIC). (3) Mother's low education is defined as lower secondary and below and high, upper secondary and above. (4) Location: small (≤ 2000 people) and medium (> 2000 and ≤ 10000). (5) Labour market structure categorical variables are based on the top and bottom quartiles of the distribution school average measures. Temporary work is defined as the school average of an indicator equals to 1 if the father works seasonally or occasionally, and zero if in paid-permanent employment. Labour market quality is defined as a combination of father low education (less than upper secondary) and the negative value of the average school family socio-economic status. (6) School quality is obtained by generating the mean school achievement for math and reading and then dividing into low for the bottom quartile and high for the top quartile of the distribution. (7) Bold estimates indicates significant differences (at 10%) on marginal effects. For Panel A tests are against LMIC, and for Panel D between rural and urban, and between urban small and large size. (8) Estimations are weighted by regional-representative weights and standard errors are clustered at the school level. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 8: Explaining the working math learning gap at the country level. Work OLS estimates for math based on matched sub-samples (countries included: subset of countries with significant effects of work on math based on matched sub-sample)

	ARG	CHL	COL	GTM	HON	MEX	REP	URU
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A - Matched sub-sample	-21.86***	-9.67*	-13.01***	-9.41**	-7.77*	-13.81***	-14.64***	-9.99*
Panel B - Policy variables estimates								
Family subsidy	-24.40***	-9.03	-14.29***	-10.27**	-10.65**	-15.13***	-14.36***	-11.58**
<i>School programs:</i>								
School management	-17.90***	-7.67	-11.73**	-4.32	-6.55	-14.40***	-15.36***	-11.72*
Support teaching competencies	-18.24***	-9.23	-12.22***	-4.21	-7.39	-15.57***	-15.48***	-11.61*
Incentive students attendance	-18.40***	-8.36	-11.75**	-4.46	-8.00*	-13.61***	-15.23***	-11.45*
Feeding	-20.86***	-7.20	-13.58***	-10.83***	-8.01*	-14.44***	-15.41***	-7.98
Cultural	-23.09***	-10.04*	-12.84***	-10.65**	-7.46*	-14.37***	-14.83***	-9.26
<i>Head master:</i>								
There is teacher performance evaluations	-22.52***	-7.79	-12.75***	-10.01**	-9.49**	-15.02***	-15.11***	-8.90
Principal evaluated through students achievement	-22.25***	-9.53*	-13.37***	-9.40**	-7.58*	-13.83***	-14.63***	-10.30*
<i>Teacher:</i>								
Supervision or support	-22.01***	-10.07*	-12.88***	-9.15**	-8.20*	-13.65***	-14.61***	-10.09*
Economic incentive	-21.89***	-9.66*	-13.25***	-9.02**	-8.08*	-13.51***	-14.92***	-9.99*
Language or math training	-22.06***	-9.42*	-13.51***	-9.43**	-8.23*	-12.41**	-14.70***	-10.02*
N	966	1,296	1,536	1,764	1,326	1,574	1,292	1,632

Notes: (1) All estimations are based on matched-subsamples for each country for the work indicator using students, family and school co-variables as in Table 3. (2) Estimations' standard errors are clustered at the school level. (3) Countries included are those where the null model for the OLS impacts of work for the matched sub-sample analysis are significant (see Figure 1, first plot). (4) Estimates highlighted in bold show cases where work dummy coefficient becomes non-significant at 10%. (5) Countries' abbreviations are described in Table 1. Significance levels: * p < 0.10, ** p < 0.05, ***p < 0.01.

Table 9: Explaining the working reading learning gap at the country level. Work OLS estimates for reading based on matched sub-samples (countries included: subset of countries with significant effects of work on reading based on matched sub-sample)

	ARG (1)	CHL (2)	COL (3)	CRI (4)	ECU (5)	GTM (6)	MEX (7)	PAN (8)	PAR (9)	REP (10)	URU (11)
Panel A - Matched sub-sample	-19.43***	-24.24***	-19.35***	-13.11***	-11.28***	-15.70***	-11.88**	-13.94***	-10.78*	-9.34*	-16.19***
Panel B - Policy variables estimates											
Family subsidy	-20.81***	-23.61***	-20.78***	-12.54**	-12.03***	-15.28***	-11.89**	-13.35**	-9.66	-8.33	-16.51***
<i>School programs:</i>											
School management	-15.16**	-22.94***	-18.32***	-13.85***	-10.72**	-12.35**	-13.29***	-16.04***	-8.01	-9.49*	-15.90***
Support teaching competences	-15.35**	-23.83***	-18.80***	-14.41***	-11.97***	-12.16**	-14.32***	-16.28***	-9.50	-9.79*	-15.76***
Incentive students attendance	-15.63**	-23.28***	-18.46***	-13.99***	-11.17***	-12.25**	-11.99**	-16.26***	-8.81	-9.35*	-15.61***
Feeding	-18.35***	-22.03***	-19.98***	-13.45***	-10.62***	-17.37***	-12.55**	-15.24***	-13.21**	-10.48**	-13.85**
Cultural	-20.63***	-24.43***	-19.17***	-14.14***	-10.83***	-17.30***	-12.53**	-15.55***	-13.68**	-9.58*	-15.49***
<i>Head master:</i>											
There is teacher performance evaluations	-20.04***	-22.87***	-19.34***	-13.70***	-11.62***	-16.64***	-12.01**	-14.15***	-9.17	-10.74**	-15.61***
Principal evaluated through students achievement	-19.97***	-24.12***	-19.88***	-13.17***	-11.21***	-15.68***	-11.90**	-14.40***	-10.68*	-9.33*	-16.40***
<i>Teacher:</i>											
Supervision or support	-19.52***	-24.56***	-19.19***	-13.22***	-11.17***	-15.50***	-11.56**	-13.79**	-10.82*	-9.26*	-16.16***
Economic incentive	-19.46***	-24.23***	-19.57***	-12.65**	-11.35***	-15.35***	-11.47**	-15.12***	-10.49*	-9.57*	-16.19***
Language or math training	-19.27***	-24.13***	-19.16***	-12.88**	-11.46***	-15.81***	-11.88**	-13.65**	-10.85*	-9.48*	-15.92***
N	966	1,296	1,536	1,318	2,206	1,764	1,574	1,205	1,042	1,292	1,632

Notes: (1) All estimations are based on matched-subsamples for each country for the work indicator using students, family and school covariates as in Table 3. (2) Estimations' standard errors are clustered at the school level. (3) Countries included are those where the null model for the OLS impacts of work for the matched sub-sample analysis are significant (see Figure 1, second plot). (4) Estimates highlighted in bold show cases where work dummy coefficient becomes non-significant at 10%. (5) Countries' abbreviation are described in Table 1. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 10: Bounds estimates based on the degree of selection between observables and unobservables. OLS estimates for the effect of child work on learning

	Baseline effect			Controlled effect			$\delta = 1$	$\beta = 0$	
	Coeff		R^2	Coeff		R^2	Identified set	δ	Identified set
	(1)		(2)	(3)		(4)	(5)	(6)	(7)
<i>Panel A - Math</i>									
Work	-28.31	***	0.22	-11.80	***	0.362	[-11.80, 2.68]	0.83	[-11.80, -1.61]
Work outside - paid	-35.11	***	0.20	-10.80	***	0.342	[-10.80, 5.10]	0.70	[-10.80, 1.18]
Work home - unpaid	-24.28	***	0.21	-10.39	***	0.353	[-10.39, 2.24]	0.83	[-10.39, -2.09]
<i>Panel B - Reading</i>									
Work	-40.67	***	0.17	-16.74	***	0.354	[-16.74, 0.17]	0.99	[-16.74, -2.87]
Work outside - paid	-57.96	***	0.15	-20.89	***	0.325	[-20.89, -0.48]	1.02	[-20.89, 0.16]
Work home - unpaid	-32.48	***	0.15	-14.32	***	0.334	[-14.32, -1.45]	1.10	[-14.32, -3.71]

Notes: (1) Baseline effects and controlled effects denotes the model without controls and full controls, respectively. (2) The identified set in column (5) lower bound is $\hat{\beta}$ and the upper bound is given by β^{*} based on R_{max} which is assumed to be 30% higher than the R^2 for the model with students controls: $R_{max} = \Pi \times \tilde{R}$ and $\Pi = 1.3$. See [Oster, 2016](#) (Stata command: psacalc). (3) Weighted OLS regression. Significance levels: * p < 0.10, ** p < 0.05, ***p < 0.01.

Appendices

A. Appendix A

Table A1: Working impact by gender (test) and estimates by intensity of work -OLS estimates

	Math			Reading		
	(1)	(2)	(3)	(4)	(5)	(6)
<i>Panel A - tests by gender</i>						
Work						
$\chi^2(1)$	0.17	0.44	0.82	1.56	0.08	0.00
p-value	0.68	0.51	0.37	0.21	0.78	0.94
Work outside - paid						
$\chi^2(1)$	2.61	0.04	1.39	2.16	0.00	0.70
p-value	0.11	0.84	0.24	0.14	0.99	0.40
Work at home - unpaid						
$\chi^2(1)$	1.39	0.13	0.53	11.01	2.18	0.98
p-value	0.24	0.72	0.47	0.00	0.14	0.32
Student and household controls	No	Yes	Yes	No	Yes	Yes
School, head master and teacher controls	No	No	Yes	No	No	Yes
<i>Panel B - Estimates on work intensity and gender interaction</i>						
	coeff	std error		coeff	std error	
i. Work - little						
female	-5.11	4.47		-8.63**	4.01	
male	-7.22	4.81		-7.72	4.74	
test on male = female, p-value	0.63			0.44		
ii. Work - weekends						
female	-22.38***	3.65		-28.36***	3.75	
male	-18.12***	3.51		-24.46***	3.71	
test on male = female, p-value	0.20			0.23		
iii. Work- most of the time						
female	-25.08***	4.22		-28.72***	3.94	
male	-22.92***	4.51		-28.82***	4.12	
test on male = female, p-value	0.36			0.51		

Notes: (1) The model for the gender's test in Panel A includes the same controls as in Table 3. Each model is run separately for the male and female samples (with clustered standard error at the school level) and the equality of the work indicator effect is obtained with a cross-model Wald test. (2) The model in Panel B also use the same controls and replace work explanatory variable in equation (1) by a discrete work intensity indicator (1= work little, 2 = work weekends, 3 = work most of the time) interacted with the gender dummy. Panel B coefficient presents the marginal effects of this interaction terms and standard errors are obtained by the delta method. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

B. Appendix B

Figure B1: Covariates' standardised bias before (unmatched) and after matching (matched)

Notes: (1) The standardised proportional bias is defined as the proportional difference of the sample means in the treated and non-treated (full or matched) sub-samples as a percentage of the square root of the average of the sample variances in the treated and non-treated groups ([Rosenbaum and Rubin \(1985\)](#)). (2) Biases estimates are based on nearest neighbour.

Figure B2: Estimated propensity score for working indicator treatments

Notes: (1) Propensity scores estimated by nearest neighbour.

Figure B3: Distribution of covariates in full and matched sample

C. Appendix C

Figure C1: Quantile regression for each country for indicator (any) work - Math scores

Notes: (1) Quantile point estimates are derived by running QR with a full specification. (2) 95% confidence interval use standard errors clustered at the school level. (3) Countries' abbreviations are described in Table 1.

Figure C2: Quantile regression for each country for indicator (any) work - Reading scores

Notes: (1) Quantile point estimates are derived by running QR with a full specification. (2) 95% confidence interval use standard errors clustered at the school level. (3) Countries' abbreviations are described in Table 1.

Table C1: Impact of child labour on learning. Countries' matching estimates

	ARG	BRA	CHL	COL	CRI	ECU	GTM	HON	MEX	NIC	PAN	PAR	PER	REP	URU
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
<i>Math</i>															
Exact matching	-26.73***	-7.48	-16.11***	-12.60***	-4.21	-8.88*	-11.37***	-6.26	-12.22**	-9.49**	-11.64**	-11.24*	-9.84**	-17.45***	-18.89***
PS matching	-21.53***	-5.13	-18.55**	-14.32***	-14.70**	-7.49	-10.06**	-3.33	-13.47**	-5.21	-9.12	-13.44**	-14.87***	-12.98**	-5.41
<i>Reading</i>															
Exact matching	-33.54***	-13.23*	-29.72***	-14.09***	-12.40**	-15.05***	-20.11***	-13.24**	-16.46***	-14.22***	-25.34***	-22.93**	-0.77	-16.46***	-28.36***
PS matching	-17.95**	0.99	-25.48***	-18.76***	-11.69**	-23.33***	-15.63***	-15.78**	-10.75**	-5.66	-14.26*	-16.30**	-11.95**	-15.37***	-13.57***
N treated	498	540	591	825	654	850	1687	1106	969	1044	656	1134	1532	1087	904
N controls	735	580	2151	1923	1606	1383	1052	840	1473	710	803	544	1553	614	1441
On support	870	710	1128	1428	1180	1478	1638	1120	1558	1232	1032	946	1988	1200	1538
Caliper	0.032	0.050	0.024	0.047	0.039	0.039	0.053	0.055	0.045	0.037	0.042	0.044	0.051	0.023	0.035
Bias (median) (%)	2.3	5.1	2.5	2.2	2.4	2.4	3.7	5.2	2.4	4.4	2.4	6.3	3.3	4.7	1.4
t-tests (sign diff)	0 X	0 X	0 X	0 X	0 X	0 X	1 X	1 X	0 X	0 X	0 X	1 X	1 X	1 X	0 X

Notes: (1) Exact matching by gender and location urban and location size, using nn match with replacement. (2) PS match: propensity score matching without replacement and common support (nn 1 to 1). (3) Same controls and matching approaches as in Table 4. (4) Countries' abbreviations are described in Table 1. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

D. Appendix D

Table D1: Impact of child labour on learning. Matching estimates controlling for endogeneity (Probit, 2SLS)

	Work		Work outside - paid		Work at home - unpaid	
	Math	Reading	Math	Reading	Math	Reading
	(1)	(2)	(3)	(4)	(5)	(6)
<i>Panel A. z_1: opportunity cost</i>						
ATT	-20.07	-50.84**	-10.15	-47.52***	52.38*	-60.86**
std error	22.51	20.20	14.88	15.29	27.30	25.00
N	31,485	31,485	18,529	18,529	26,945	26,945
First-stage	0.226***		0.271*		0.17*	
<i>Panel B. z_2: labour market condition</i>						
ATT	19.88	-26.75	1.15	-39.23***	63.89**	-61.95**
std error	23.44	21.15	14.49	14.41	31.61	27.28
N	31,471	31,471	18,523	18,523	26,932	26,932
First-stage	0.72***		0.67***		0.71***	

Notes: (1) Same specification as in Table 3. (2) Instruments describe opportunity cost and labour market conditions in each country and averaged for each school. The instrument on opportunity cost z_1 is constructed as dummy which equals to 1 if the student is two years older than the median age of the country sample and 0 otherwise, and then averaged across schools. The instrument on labour market condition z_2 is measured by combining information on low father education (uncompleted secondary education) with low household wealth (bottom half of the household wealth distribution), and then average across each school. (3) Robust standard errors based on 400 bootstrapped repetitions and with ATE heterogeneity in age, gender, location and location size. Stata command: `ivtreatreg` (Cerulli et al., 2014). Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table D2: Description of covariates

Variables	Definitions
<i>Panel A - Work indicators</i>	
Work	1=student works anywhere, being paid or not, 0=does not work
Work outside and paid	1=student works outside the home and he/she is being paid, 0=does not work
Work at home - unpaid	1=student works at home the household and he/she is not being paid, 0=does not work
<i>Panel B - Other characteristics</i>	
<i>Student and family characteristics</i>	
Age	student age
Gender - male	1=male, 0=female
Repeated	1=if student repeated, 0 otherwise
Missing school (last 6 months)	1=never, 2=twice in the semester, 3=twice a month, 4=once per week, 5=few days per week
Attended preschool	1=attended preschool between ages 4-6, 0 otherwise
Nuclear family	1=live with parents, 0 otherwise
Number of kids at home	number of children in the household
Study conditions at home - index	based on answers about: quiet place to study, table and chairs, good lighting, etc (q22); derived in dataset
Notebook	1=has notebook for classes, 0 otherwise
Socio-economic and cultural - index	based on variables on assets, education and occupation of parents and income; derived in dataset
Study supervision at home - index	control and supervision of studies - homework, grades (q32); derived in dataset
Number of books	number of (any) books in the households
Father's and mother's education	1=no education, 2=at most lower secondary, 3=upper secondary, 4=post-secondary or short tertiary, 5=tertiary, 6=master or above
<i>School, head master and teacher characteristics</i>	
Public	1=public school, 0 otherwise
Urban	1=urban school, 0 otherwise
Location size	1=small (2,000 or less), 2=medium (2,001-10,000), 3=large (above 10,000)
Infrastructure - index	based on answers about: school installations, # library books, PC, classroom facilities, etc (q14 to q17); derived in dataset
Number of computers with internet, average	number of computers with internet access and available for use for students
Socio-economic and cultural average - index	school average of family socio-economic and cultural index
Years of experience - head master	number of years working as head master (any school)
Education level - head master	1=no education, 2=at most lower secondary, 3=upper secondary, 4=post-secondary or short tertiary, 5=tertiary, 6=master or above
Years of experience - teacher	number of years working as head master (any school)
Education level - teacher	1=no education, 2=at most lower secondary, 3=upper secondary, 4=post-secondary or short tertiary, 5=tertiary, 6=master or above
Teacher qualification	1=has teaching qualification, 0 otherwise

Notes: (1) Questions number refers to the TERCE students and school questionnaires.