Does the timing of the school year affect child labor decisions in developing countries?*

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Abstract

In developing countries, agricultural productivity shocks are an important predictor of the opportunity cost of time for children. This can lead to children dropping out of school to work during good rainfall years. However, this trade-off between current and future income is most salient only when the agricultural season and the school year overlap. In this paper, I show that this overlap is an important mediator of the effect of agricultural productivity shocks on both child labor and school enrollment. A long overlap between the harvest season and the school year leads to a lower elasticity of child labor with respect to agricultural productivity shocks relative to harvest season that does not overlap with the school year. The entirety of the effect is driven by self-employment, which is consistent with a story of children working on household farms.

Keywords: child labor, education, agriculture
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1 Introduction

In 2016, an estimated 152 million children engaged in child labor across the world (ILO, 2017). Worryingly, higher levels of child labor are correlated with lower levels of educational attainment (Beegle et al., 2009), meaning that child labor may not just be a moral issue, but also an economic development issue (Mankiw et al., 1992). The prevalence of child labor, however, varies substantially across regions. In Africa, for example, almost 20 percent of children are estimated to engage in child labor, while the number in Asia and the Pacific is around seven percent. This suggests that local context is an important predictor and mediator of child labor and education.

What causes children to engage in employment or drop out of school? There are many possible explanations, many of which conflict with one another. For example, household income can be an important determinant of child labor, with lower levels of income leading to a higher incidence of child labor and lower educational attainment (Jensen, 2000; Bharadwaj et al., 2020). Additionally, given the costs associated with schooling, income risk also plays an important role, with some households using schooling – or lack thereof – to help smooth consumption (Jacoby and Skoufias, 1997). More generally, there are good theoretical reasons to think that households may use child labor to help overcome a minimum-consumption constraint (Basu and Van, 1998).

On the other hand, the opportunity cost of time can also play an important role. For many children, there is a trade-off between employment and education (Beegle et al., 2009). While employment increases household income now, education increases expected income in the future. As such, this trade-off is essentially one between current and future income. If this is true, higher wages and more job opportunities can lead to higher levels of child labor, which is also empirically true (Atkin, 2016; Duryea and Arends-Kuenning, 2003; Shah and Steinberg, 2017; Bau et al., 2020; Shah and Steinberg, 2021). In all of these explanations, however, context is important. Children in poorer households, for example, are often more likely to work, and reallocation of labor within these households in response to shocks may be more pronounced (Kruger, 2007; Bharadwaj et al., 2020), as can changes in school attendance (Thomas et al., 2004).

In this paper, I provide evidence of how an additional facet of local context – the overlap of the agricultural season and the school year – mediates child labor decisions. Since children play an important role in household agricultural production (Rosenzweig and Evenson, 1977), children are often involved in the agricultural sector (ILO, 2017). Importantly, this means that the effective wage – whether an actual market wage or the shadow wage within the household – is a function of agricultural productivity shocks, like rainfall (Jayachandran, 2006). In this paper, I use labor survey data from dozens of developing countries, collected by IPUMS International,[1] and match information on rainfall, agricultural production, and the timing of planting and harvest to the labor data. I show that the degree of overlap between the harvest period and the school year is an important mediator of how child labor responds to agricultural productivity shocks, proxied by rainfall, which reinforces recent evidence that the timing of the agricultural season has important knock-on effects (Montero and Yang, 2021).

I develop a simple model of labor allocation and education choices, and derive comparative statistics based on whether there is overlap between the working season – the agricultural season – and the school year. The key driver of effects is that children who live in areas without overlap are able to work and attend school in the same year. Nonetheless, not all children work every year, since parents would prefer that the children not work (this is similar in spirit to the argument put forth in Basu and Van (1998)), but the probability of a child working in a given year is increasing in rainfall, driven by wage effects. However, children who live in areas of overlap between the agricultural season and the school year face a trade-off: they can either work or attend school, but not both. This adds an additional cost to current work and attenuates the relationship between rainfall and child labor.

[1]https://international.ipums.org/international/

I then take the predictions from the model to the survey data. The data comprises tens of millions of children across almost 30 developing countries. Using variation derived from differences in rainfall across years in the same geographic area, I first show that child labor in this sample responds strongly to rainfall, with higher levels of current rainfall leading to higher levels of labor. However, an interaction between the length of overlap between harvest and the school year attenuates this relationship, supporting predictions from the model. In other words, the additional cost of future income makes children less likely to work in response to increases in agricultural productivity. Interestingly, this attenuation only comes from harvest overlap; planting overlap has no effect on labor allocation. This is likely due to the fact that rainfall is not yet realized at the time of planting, meaning yearly rainfall shocks have not yet been realized. Attenuation in absolute terms is similar for younger children (9-14 years of age) and older children (15-17). Importantly, the effect appears to be driven by a reallocation of time into self employment, not wage employment. This is consistent with a story in which children are working within households, which is consistent with previous literature on the most common types of child labor.

A key additional analysis adds credence to the identification strategy. One major concern is that endogenous differences in the timing of the agricultural season and the school year lead to different labor market conditions. If this is true, we might also expect to see large effects of overlap on adult labor, despite the fact that overlap should primarily affect children.[2] However, the effects for adults are much smaller than for children, at less than one-third the magnitude.

This paper contributes to the broad literature on child labor in developing countries. Child labor responds differently in diverse contexts, including differences in access to credit (Dehejia and Gatti, 2005), poverty (Contreras, 2008; Basu and Van, 1998; Jacoby and Skoufias, 1997; Edmonds and Schady, 2012), and local legislation (Basu and Tzannatos, 2003). Perhaps most salient to the current paper is the literature that explores how household shocks affect child

[2] If there is intrahousehold substitution of labor, this need not be true. Instead, the argument I put forth is simply that the effect on adults should be less than the effects on children.

labor. Beegle et al. (2006) and Duryea et al. (2007), for example, show that negative shocks lead to increases in child labor, while Colmer (2021) argues that higher income volatility for households decreases child labor. Other work, however, also shows that higher rainfall in agricultural areas leads to increased child labor (Nordman et al., 2022). Perhaps closest to this paper is Allen (2022), who looks at a change in school timing in Malawi and its effects on child labor and schooling, finding similar results to the results presented here. One drawback to all the previous studies, however, is the focus on a single country. In this paper, I used data from dozens of developing countries across several decades.

There are many reasons for setting the school year to start and end on certain dates, but this paper contributes additional evidence that the timing of the agricultural season is a salient consideration. The results found here come from data that spans almost 30 countries and comprises tens of millions of children. As such, it appears that the importance of the timing of the agricultural season with respect to the school year is relatively widespread, even if it does not hold in all countries.

2 A simple model of labor and schooling

A household lives for three periods. In each of the first two periods, the household makes child labor and education decisions. The child can work for a wage, $w_t\left(\delta_t\right)$, which is a function of rainfall, δ_t, and $\frac{\partial w_t}{\partial \delta_t} > 0$. If the child works, $L_t = 1$ and the household faces a cost, c. This cost can be thought of in different ways, but the intuition is that the household does not want the child to work (e.g. Basu and Van (1998)) and, as such, incurs a cost when the child does work. The household also receives income $Y_t\left(\delta_t\right)$, which is also a function of rainfall. This means that the utility the household receives in each of the first two periods is

$$U_t\left[L_t w_t\left(\delta_t\right) - c + Y_t\left(\delta_t\right)\right]. \tag{1}$$

In the third period, the household receives income from the child's education decisions, where the total income is $I(e)$, education is $e \in \{0, 1, 2\}$, and $\frac{\partial I}{\partial e} > 0$.

Thus, the household's total utility over the three periods is

$$U_1\left[L_1 w_1(\delta_1) - c + Y_1(\delta_1)\right] + \beta U_2\left[L_2 w_2(\delta_2) - c + Y_2(\delta_3)\right] + \beta^2 U_3\left[I(e)\right], \tag{2}$$

where β is the discount rate.

The key concern in this paper is how education and child labor decisions vary with overlap between the agricultural season and the school year. When there is no overlap, there is no trade-off between labor and schooling.[3] This means that someone can work and attend school in the same year. For these families, there is no trade-off between current income (working) and future income (education). As such, the decision in each period is separable, and the child works if and only if

$$w_t(\delta_t) - c > 0 \tag{3}$$

Since c is fixed, the probability of this happening is increasing in rainfall.

However, when there is overlap between the agricultural calendar and the school year, children can either work or attend school, that is, either $e_t = 1$ or $L_t = 1$. Moreover, if the child does not attend school in period one, they cannot attend school in period two. As such, we proceed in turn for each period.

In period one, there is now a trade-off between current income and future income. Recall that when there was no trade-off, the only relevant comparison for a household was whether the income from child labor is large enough to offset the costs of child labor. However, now there is an additional cost: lower income in period three. As such, the total cost is higher

[3] This assumes that there is no work available during the agricultural off season. We can relax this constraint and the comparative statics will remain unaffected, as long as the off season provides lower wages/opportunities.

when there is overlap than when there is not, leading to an attenuated effect of rainfall, or:

$$\left.\frac{\partial L_t}{\partial \delta_t}\right|_{overlap} < \left.\frac{\partial L_t}{\partial \delta_t}\right|_{no\ overlap} \tag{4}$$

In period two, we see the same attenuated effect of rainfall on the probability of working.

There are two additional considerations that are difficult to model. First, a big question is what type of agricultural overlap matters. Two obvious possibilities are planting and harvesting. It seems reasonable to think that harvest labor shows larger changes in response to rainfall, since rainfall is generally unknown at the time of planting (Rosenzweig and Udry, 2014). If this is the case, then harvest overlap with the school year could matter more than planting overlap with the school year, at least as it relates to the effect of rainfall shocks.

Second, the fact that educational attainment in period 2 is conditional on having attended school in period 1, there can be differential effects of rainfall on schooling at earlier and later ages. However, the direction of these effects is hard to know a priori, since many children in developing countries who are likely to complete the full years of schooling are less likely to drop out in response to rainfall shocks.[4] This means that, even though older children may have higher returns to work (higher wages), older children may be less moved into labor by rainfall because the dropping out decision was made earlier in their school career.

These considerations can be modelled such that any outcome is possible. As such, these are empirical questions that we can test with data.

3 Data and methodology

The labor data come from IPUMS International. IPUMS International has collected labor force survey data from across the world and put them together in a single location. This labor force data includes information on age, gender, and work status, including for younger

[4]For example, children from richer families are more likely to graduate from secondary school and are less likely to work.

children. Importantly for this project, the IPUMS team has also harmonized shapefiles across time for these countries. Specifically, they create "admin2" areas that are harmonized over time, taking into account things like administrative splits and merges. I use these consistent admin2 boundaries in two ways. First, using their provided shapefiles, I can match additional geospatial data in a consistent way over time. Second, I have a consistent geographic fixed effect I can use in estimation. I discuss both of these issues more below. Unfortunately, the labor force surveys do not have an indicator for school attendance in a given year. As such, I focus here on labor.

I am primarily interested in the role of the timing of the agricultural season relative to the school year. To do this, I first collect data on school timing for the countries in the data. I find this information on the internet, using official government websites wherever possible. As it is difficult to know about small differences in school calendars in different areas of a country – especially when the data may be difficult to find or in different languages – I generally assume the same school year for each country. This means much of the variation in overlap comes from small differences in the agricultural season within each country.

It is important to note that there is likely measurement error in the school calendar data. In addition to the fact that school calendars can vary slightly within countries, they can also vary across time. In Malawi, for example, the school year was changed to better align with the agricultural season (Dillon, 2020). In the results section, I consider only estimates using more recent data and confirm that this measurement error is likely leading to a lower bound in the main effects.

The data on agricultural timing is from Sacks et al. (2010). The authors provide publicly available maps of the estimated planting and harvest dates for different crops across the world. I overlay these maps with the harmonized shapefiles from IPUMS in order to match agricultural timing with the survey data. Importantly, the exact timing of the cropping season can differ across crops in the same area. As such, I take the most commonly grown crop in each harmonized admin2 and use that for the timing of the agricultural season using maps on planted crop area from earthstat.org (Monfreda et al., 2008). There are many countries that have two rainy seasons. In this paper, I only consider the main rainy season for these analyses.

Figure A1 in the appendix gives a graphical representations of how the overlap variables are created. I create four separate variables: one for the number of days of the season that overlaps with the school year and another for the number of days of the season that do not overlap with the school year, and I create these separately for planting and harvest. In the figure, harvest overlaps the beginning of the school year, so both overlap and non-overlap will be non-zero. For planting, however, note that the entirety of the season overlaps with the school year, so non-overlap days are zero.

Harvest length tends to be much longer than planting length, likely due to differences in growing patterns for different crops even when planted at the same time, and even for differences in varieties of the same crop planted simultaneously. This is exacerbated by the fact that these seasons are defined as the length between the estimated last day and estimated first day of each season. The mean number of days of total harvest time is around 120 days while the mean number of days of total planting time is around 50 days. While harvest length is likely longer than the true harvest for any given household, this should not bias results unless there are systematic measurement errors in the underlying data and the elasticity of child labor with respect to rainfall. However, this seems unlikely, given that Sacks et al. (2010) created their estimated dates using models of true dates without any reference to demographics.

Finally, rainfall data – which is used as a proxy for agricultural productivity shocks – is from Terraclimate (Abatzoglou et al., 2018).[5] I construct z-scores using the mean and standard deviation from the previous 15 years of data (excluding the current year) for each admin2 geographic area.

Figure A2 in the appendix shows the sample status for admin2 areas, after matching

[5]http://www.climatologylab.org/terraclimate.html

available data across all data sources. The samples are dominated by sub-Saharan Africa and South/Southeast Asia. After matching across different datasets and keeping only the surveys that have the requisite variables and time frame – one requirement, for example, is that at least two waves of data exist due to the use of admin2 fixed effects – the labor data includes 4,528 admin2 areas and 549 admin1 areas across 26 countries.

3.1 Methodology

The main focus of this paper is how child labor responds to rainfall shocks, which are a proxy for agricultural productivity, and how the overlap between the agricultural season and the school year mediates this relationship. I focus on child labor due to data limitations. The principal specification is

$$\begin{aligned} y_{iat} = \beta_1 \text{rainZ} + \beta_2 \left(\text{overlap} \times \text{rainZ}\right) + \beta_2 \left(\text{nonoverlap} \times \text{rainZ}\right) \\ + \gamma_1 \text{age} + \gamma_2 \text{age}^2 + \gamma_3 \text{male} + \alpha_a + \delta_t + \varepsilon_{iat}, \end{aligned} \tag{5}$$

where y_{iat} is the outcome of interest y for individual i in admin2 a in year t, rainZ is the rainfall Z score during the year of the survey, overlap is the length in days of overlap between the relevant season variable – either planting or harvest – and the school year, nonoverlap is the length in days of the relevant season that does *not* overlap with the school year, α_a is admin2 fixed effects, δ_t is year fixed effects, and ε_{iat} is an error term. Since the rainfall and crop data is merged at the admin2 level, I cluster standard errors at the admin2 level throughout.

The primary outcome variable is whether a child is working. I include both the length of overlap and the length of non-overlap to help control for the overall length of the agricultural season. In other words, it is possible that a longer agricultural season affects the probability of child labor. However, any direct effects of season length should be in both the overlap and non-overlap lengths. Any difference in effects across these two variables should be driven primarily by whether there is overlap with the school year or not. In other words, the model above makes predictions about the *relative* effect of non-overlap and overlap lengths, but not each individually.

With the inclusion of both overlap and non-overlap, the effects of overall length should be the same for each variable, with any differences driven primarily by whether there is overlap with the school year or not. Since the type of overlap could be important, I check for effects using both planting and harvest overlap, the latter of which is more likely to be affected by rainfall shocks (since rainfall shocks are not known at the time of planting).

I focus on child labor mainly due to issues with the schooling variable. While there is an attendance variable, it does not capture immediate enrollment in the same way the labor variable does. Specifically, it asks about whether children have attended school at all, not whether they are currently in school. Labor, on the other hand, captures whether the child is contemporaneously working. Finally, I split results into three age groups: 9-11, 12-14, and 15-17. This will allow me to look at heterogeneity by age across specifications.

4 Results

I first show the relationship between rainfall and the probability of working for children in Table 1. In all three columns, the left-hand variable is a simple dummy for whether the child works. The three columns separate children by age, with the first column including the youngest children and the third column including the older children. Across all three columns, there is a strong, consistent, positive relationship between rainfall and child labor. In the first column, for example, a one-standard-deviation increase in rainfall leads to an almost 16-percentage-point increase in the probability of working for the youngest children and a 19-percentage-point increase for the older children. For our entire sample, it is clear that higher levels of rainfall lead to more child labor.

It appears that children in the middle age bracket are most likely to work in response to

Table 1: Rainfall

	(1)	(2)	(3)
	9-11	12-14	15-17
Rainfall (z)	0.159***	0.235***	0.191***
	(0.010)	(0.015)	(0.013)
Male	0.004***	0.009***	0.025***
	(0.001)	(0.001)	(0.001)
Observations	17,747,729	17,413,792	15,700,867

Standard errors, clustered at the admin2 level, are in parentheses. Column titles indicates the ages of children in each regression.
* p<0.10 ** p<0.05 *** p<0.01

higher rainfall; the effect is almost 50% larger than the effect in the youngest group and around 23% larger than the effect in the oldest age group. Why is the middle group most affected by rainfall? One possibility is that the youngest children are too young to work, at least in a meaningful way. On the other hand, the oldest group may have the largest returns to working, but the children who are still in school are less likely to work due to productivity shocks because they would have already dropped out if they were at risk of doing so.

On the other hand, the relative effects are largest for younger children. A one-standard-deviation-increase in rainfall increases the probability of working by twice the mean. The middle-aged children have the second-largest relative effect, at around 1.7 times the mean, while the oldest children have the smallest relative effect, at around 80 percent of the mean.

Table 2 shows how overlap between the school year and different parts of the agricultural season moderate the effect of rainfall on the probability of child labor. The first column includes overlap with the entire agricultural season, pooling planting, harvest, and the growing season together. One additional day of the agricultural season that *does not* overlap with the school year has essentially no impact on the relationship between child labor and rainfall (second row). However, we see that an additional day of the agricultural season that overlaps with the school years leads to a slightly more negative effect of rainfall on the probability of child labor. Importantly, however, this difference is small and magnitude and

Table 2: School-agriculture overlap and child labor

	(1) All	(2) Planting	(3) Harvest
Overlap (10s) times rainfall	-0.010***	0.048***	-0.012***
	(0.004)	(0.006)	(0.002)
Non-overlap (10s) times rainfall	-0.000	0.036***	0.021***
	(0.005)	(0.011)	(0.007)
Rainfall (z)	0.322***	-0.068**	0.214***
	(0.041)	(0.032)	(0.017)
overlap - non-overlap	-0.010	0.012	-0.033
p-value	0.199	0.320	0.000
Observations	50,862,395	50,862,395	50,862,395

Standard errors, clustered at the admin2 level, are in parentheses. Column titles indicates the type of overlap: entire season, planting only, or harvest only. Only children between 9 and 17 years of age are included.
* p<0.10 ** p<0.05 *** p<0.01

is not significant.[6]

We see no differences in the effect of overlap and non-overlap days during planting. In fact, the coefficient on rainfall is actually higher during overlap days than non-overlap days. However, the difference in the coefficient does not approach significant, regardless of whether we use a one-tailed or two-tailed test. Recall that the model does not make predictions about how a longer growing season (or school year) will affect child labor. Instead, the focus here is on the difference between overlap and non-overlap. When it comes to the planting season, it seems that the effects of the two variables are similar.

Finally, column three looks at the effects of overlap during harvest. Here, we see very strong evidence that overlap days during harvest lead to a much more negative effect of rainfall on the probability of child labor. For each additional ten days of overlap between harvest and the school year, the effect of rainfall on the probability of child labor is actually 0.033 more negative than for each additional ten days of the harvest season that do not overlap with the school year. In other words, moving ten days of non-overlap to ten days

[6]Note that theory predicts a more negative effect of overlap days than non-overlap days. This is, essentially, a one-tailed test, which means that the two-tailed p-value at the bottom of the first column would be marginally significant at the ten-percent level for a one-tailed test.

Table 3: School-harvest overlap and child labor

	(1) 9-11	(2) 12-14	(3) 15-17
Panel A: Current rainfall			
Overlap (10s) times rainfall	-0.010***	-0.014***	-0.012***
	(0.002)	(0.003)	(0.003)
Non-overlap (10s) times rainfall	0.020***	0.024***	0.019***
	(0.006)	(0.008)	(0.007)
Linear combination:			
overlap - non-overlap	-0.030	-0.038	-0.031
p-value	0.000	0.000	0.001
Panel B: Lagged rainfall			
Overlap (10s) times rainfall	-0.001	-0.000	0.000
	(0.000)	(0.001)	(0.001)
Non-overlap (10s) times rainfall	0.001	-0.002	-0.006**
	(0.001)	(0.002)	(0.003)
Linear combination:			
overlap - non-overlap	-0.001	0.002	0.007
p-value	0.433	0.605	0.059

Standard errors, clustered at the admin2 level, are in parentheses. Column titles indicates the ages of children in each regression.
* $p<0.10$ ** $p<0.05$ *** $p<0.01$

of overlap decreases the probability of child labor by around 23 percent of the mean. These three columns indicate show that harvest appears to be particularly salient when looking at the overlap between the school year and the agricultural season.

Panel A of Table 3 breaks down the effects of overlap with the harvest season by age of the child. The first column includes the youngest children (9-11 years of age) while the last column includes the oldest children (15-17 years of age). Interestingly, the overall effects of overlap and rainfall are relatively consistent across the three columns. While we might expect rainfall to have the largest effect on the oldest children, there is likely also a selection effect at play. The children still in school at the older ages likely have a lower propensity to drop out due to higher wages driven by agriculture. This means that, although older children may be more likely to work, they are not necessarily more likely to be driven to work by higher levels of rainfall. As before, the effect for middle-aged children is actually

Table 4: School-harvest overlap and type of work, by age

	(1) Self	(2) Wage	(3) Unpaid
Overlap (10s) times rainfall	-0.013***	0.000	0.001
	(0.003)	(0.000)	(0.001)
Non-overlap (10s) times rainfall	0.023***	0.001*	-0.003**
	(0.007)	(0.001)	(0.001)
overlap - non-overlap	-0.035	-0.001	0.004
p-value	0.000	0.186	0.040
Observations	50,862,395	50,862,395	50,862,395

Standard errors, clustered at the admin2 level, are in parentheses. Column titles indicates the outcome variables..
* p<0.10 ** p<0.05 *** p<0.01

the largest, consistent with this story.

As a robustness check, Panel B includes lagged rainfall instead of current rainfall. The estimates in the first two columns support the identifying assumptions; lagged rainfall does not appear to interact with overlap/non-overlap in any way that predicts child labor. The estimate in the third column is marginally significant. However, importantly, the magnitude of the coefficient is quite small, at less than one-quarter the size of the magnitude of the relevant coefficient in Panel A.

In the last set of main results, Table 4 breaks down effects across different types of employment. The first column includes self employment and the second column includes wage employment. If children are mostly dropping out of school to help the household with labor in agricultural, we would expect to see much more negative effects of rainfall based on overlap days in self employment than in wage employment. This is exactly what we see. In fact, we have no evidence that there are any differences in the effects of rainfall on the probability of wage employment based on the number of overlap or non-overlap harvest days. In self employment, on the other hand, there is a significantly more negative effect of rainfall when harvest overlap is higher than when harvest non-overlap is higher, which is consistent with the model.

As a placebo check, Table A1 in the appendix shows the effects of (harvest) overlap and rainfall on the probability of working for adults. The table tests for whether there is something structural about the economy that leads to the effects we see for children; essentially, if we see the same effects for adults as we do for children, then it might not be due to overlap, per se, but something else about the structure of the labor markets. While the first column of Table A1 is marginally significant, it is worth noting two things. First, this is the youngest set of adults, some of whom may still be in school (i.e. high school or college) and are thus still affected by rainfall shocks. Second, the difference in the effect of rainfall between non-overlap and overlap days is much smaller even for this subset of adults than it is for children. For example, the difference in the effect of rainfall based on a day of overlap is just one-third as large in the first column of Table A1 as it is for children in Table 3. Overall, this is consistent with opportunity costs of schooling leading to larger differences for children.

The final check is for measurement error. As discussed in the methods section, the school calendar variable likely suffers from measurement error. In particular, it was not possible to find school calendars for many of the countries going back in time. This means that the school calendar variable may be more accurate for more recent data. If the measurement error is random, it may be attenuating coefficients towards zero, meaning the estimated effects are actually the lower bound. To test this, I split the sample into two, looking at the same main effects with harvest overlap for 1995 or earlier versus after 1995. It is worth noting that this is not a perfect solution; this also affects how many times we observe different countries in the data. Nonetheless, it should shed some light on possible measurement error.

I present these results in Table 5. The first column is for all survey years from 1995 or earlier. Here, we see no evidence that either overlap nor non-overlap days has any mediating effect on child labor. Since we do not see any effect of either and both are quite close to zero, this is evidence that random measurement error in the school calendar variable – which is used to construct the overlap variables – may be attenuating estimated coefficients. This is

Table 5: School-harvest overlap and type of work, by year of survey

	(1) 1995 or earlier	(2) After1995
Overlap (10s) times rainfall	0.001	-0.011***
	(0.002)	(0.002)
Non-overlap (10s) times rainfall	-0.005	0.057***
	(0.003)	(0.017)
Rainfall (z)	0.028***	0.200***
	(0.010)	(0.032)
overlap - non-overlap	0.007	-0.068
p-value	0.182	0.000
Observations	17,871,053	32,991,342

Standard errors, clustered at the admin2 level, are in parentheses.
The first column includes countries with above median child labor.
The second column includes country with below median child labor.
* p<0.10 ** p<0.05 *** p<0.01

corroborated by the results in column two, which show much larger effects consistent with the main effects above; in fact, the difference between non-overlap and overlap harvest days is now 0.068, much higher than any of the previous results.

However, there is another possible explanation besides measurement error. Specifically, it may be that few children were pushed into child labor in earlier years because so many children were already working, either due to necessity or because there were fewer schooling options. The coefficient on rainfall suggests this may be the case; rainfall significantly predicts child labor in the earlier years, but much less so than in the later years.[7] Unfortunately, it is difficult to cut the data in too many ways. Further restrictions on years, for example, greatly reduce the number of countries contributing to identification of the coefficients due to the admin2 fixed effects. As such, I am not able to further disentangle the exact causes of differences across years. Nonetheless, the more recent results – which, if nothing else, are less likely to be contaminated by measurement error in the academic calendar variable – support the main conclusions of the paper.

[7]Regressions with only rainfall and admin2/year fixed effects confirm this is the case, even without the overlap interactions.

5 Conclusion

In a world of no overlap between the school year and the season of peak labor demand, there is no trade-off between school and labor decisions; a child can work outside of the school year, but then attend school once it restarts. Of course, not all children work, as parents may prefer children stay out of the labor force (Basu and Van, 1998). Nonetheless, higher rainfall makes them more likely to work, as higher rainfall means higher wages but without a trade-off between school attendance and work. However, as the overlap between the agricultural season and the school year increases, the trade-off between current and future income becomes more salient. A child can no longer do both, but instead must choose between schooling and work. This attenuates the effects of rainfall, which is exactly what we observe in the labor results.

These results point to important policy decisions vis-à-vis the timing of the school year. There is a clear trade-off facing families, but this trade-off is only salient when the school year coincides with the peak agricultural season, in this case harvest. Of course, this does not immediately imply that changing school years is necessary or even ideal. There are many aspects to these decisions, including heterogeneity within and across countries as well as a desire to align school years with other countries. Moreover, countries already consider the timing of the agricultural season when creating school calendars.[8] As such, the effects in this paper are inclusive of any endogenous effects of school timing across countries.

In spite of these caveats, the results nonetheless improve our understanding of the trade-offs facing households when it comes to the child labor/schooling decision, at least in one respect. The opportunity cost of schooling remains an important predictor of child labor. This paper shows that the opportunity cost is mediated by the timing of the school year with respect to agricultural calendar, in particular with respect to the timing of harvest, and this mediation is seen in data spanning dozens of developing countries.

[8] Dillon (2020), for example, looks at effects of a change in the school year in Malawi, a change made ostensibly to bring the school year closer to harvest.

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Appendix

Table A1: School-harvest overlap and work, adults

	(1) 18-39	(2) 40-59	(3) 60+
Overlap (10s) times rainfall	0.001	0.004	-0.001
	(0.003)	(0.003)	(0.003)
Non-overlap (10s) times rainfall	0.012***	0.011**	0.009*
	(0.004)	(0.004)	(0.005)
Rainfall (z)	0.007	-0.041***	0.080***
	(0.014)	(0.015)	(0.014)
Male	0.140***	0.174***	0.148***
	(0.006)	(0.006)	(0.006)
overlap=non-overlap	0.060	0.329	0.153
Observations	89,586,462	40,843,540	17,434,855

Standard errors, clustered at the admin1 level, are in parentheses. Column titles indicates the ages of adults in each regression.
* p<0.10 ** p<0.05 *** p<0.01

Figure A1: Defining overlap and non-overlap

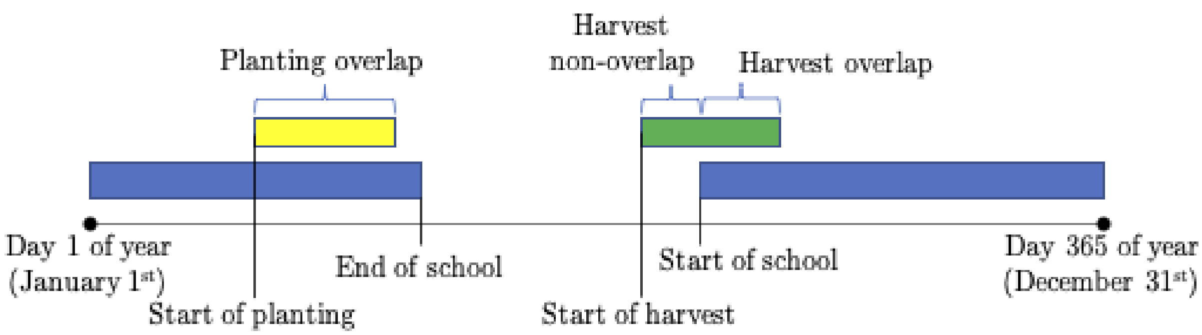

Figure A2: Sample status by admin2