Seasonality, Academic Calendar and School Drop-outs in South Asia*

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April 2, 2024

Abstract

Rural families face tradeoffs in deciding whether to retain their children in school or work in the field. School calendars heighten this tradeoff by not accommodating seasonal agricultural labor demand, leading to dropouts. Utilizing Ramadan school holidays as a natural experiment, we find annual exams overlapping with the harvesting season increase school dropout by 6.7–8.3 percentage points in Bangladesh. Age-specific cohort analysis using national household survey confirms these findings. Exploiting state-level academic calendar variation, we execute complementary analysis with India and find supporting evidence. Our paper suggests careful school calendar design in developing countries by adequately addressing local seasonality.

Keywords: Enrollment; child labor; seasonal labor-demand; school calendar; ramadan; drop-out.

JEL Code: O13, O15, O38, O53, J23, J24

*The authors are grateful to IFPRI for sharing the data and Ranjana Roy for the data cleaning support. The authors thank the following people for helpful comments (alphabetically): Ariel BenYishay, Austin Davis, Gary Fields, Hyuk H Son, Jessica A. Goldberg, Jonathan Morduch, Kensuke Kubo, Nobuhiko Fuwa, Seema Jayachandran, Takashi Kurosaki, Tomoki Fujii, Yasuyuki Sawada, and participants at ASSA Meeting, NEUDC, Econometric Society Meeting, Hakone Conference as well as seminar series at Hitotsubashi University, GRIPS-FASID, Waseda University, Singapore Management University, National University of Singapore, NanYang Technological University, World Bank, Washington State University, University of Central Florida, Florida International University and IDE. The authors are responsible for the errors. The findings, interpretations, and conclusions expressed in this paper are the author's own, not of their affiliated institutions.

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1 Introduction

Local agricultural seasonality in developing countries is an integral dimension of rural livelihoods, which can seriously affect numerous poor students in continuing their school education. Low-income families, who are mostly credit-constrained and often dependent on their children's labor, face a fundamental trade-off in deciding whether to retain their children in school or make them work in the field. In agrarian societies, this tension is greatest during the harvesting season, when there is a rise in labor demand and escalating wage rates, leading to students dropping out of school. Education-related policies in developing countries do not typically address this concern with seasonal work. In this study, using a natural experiment (or quasi-experiment framework), we estimate the adverse impact of seasonal labor demand on education, which overlaps with Bangladesh's annual school examination calendar. We find that this overlap contributes to school dropout for students from agricultural households compared to non-agricultural ones. To check the validity of this finding in South Asia with relevant populations (dominant agricultural sector, credit-constrained, and poor smallholder farmers), we conduct a complementary analysis in India and find supporting evidence. These are important findings caused by the inadequacy of addressing local agricultural seasonality in education policy, a lesson for many emerging countries trying to achieve universal education and lower school dropouts.

Bangladesh's schooling system follows the English (Gregorian) calendar for academic activities (January–December) and does not accommodate local agricultural cycles. As a consequence of this misalignment, annual examinations in schools, which are typically held at the end of the calendar year (specifically in December), coincide with the peak harvest period of the major wet season paddy called *Aman*.[1] *Aman* rice harvesting period is between late November and late December, with seasonal labor demand peaking in December.[2] During

[1] *Aman* rice is the largest crop in Bangladesh by area and the second-largest by cereal production.

[2] Please note that along with the harvest period, labor demand also rises during the plantation time. However, the timing of the *Aman* plantation does not overlap with the annual exam to have an adverse effect on academic progression for the children from agricultural households.

harvesting, schooling is routinely interrupted by the active involvement in rice production and post-production processes. Unlike Bangladesh, where a national homogeneous school calendar is utilized, in India, this conflict occurs due to the variation in the state-level school calendar and local primary crop harvesting season, making some states' academic routines unfavorable for students from agrarian families.

Poor agricultural households, who typically cultivate small-hold-tenure land, are generally unable to hire external labor because of labor market imperfections, such as shortage of labor at the harvesting time (Rosenzweig, 1988), liquidity constraints raising the shadow price of labor input owing to cash payment requirements (Singh et al., 1986), and imperfect substitution between hired and family labor (De Janvry et al., 1991).[3] Such households involve their children and other household members in assisting with harvesting and associated post-harvesting tasks (threshing, husking, storage, transportation, and selling end products to the market).[4] Moreover, the opportunity cost of schooling increases during harvesting as the marginal revenue product of child labor increases. Consequently, children in agricultural households remain absent from school for extended periods. In a detailed education assessment study by USAID, 42% of rural students are reported to be absent during the harvesting period in Bangladesh, compared to 6.8% absent during the planting period (Rahman et al. (2004), Table IV.D.9, page 110). This is not a past phenomenon; a recent 2017–18 study on school students in Bangladesh also finds a similar trend in absenteeism among rural children (Fujii et al., 2019).[5] Similarly, high absenteeism is reported in India's rural schools due to

[3]Even if farmers are not constrained, parents may want their children to learn essential farming skills by actively engaging in the harvesting process (Bhalotra and Heady, 2003), or illiterate farmers are myopic to realize the importance of children's human capital formation or return to education (Baland and Robinson, 2000).

[4]In addition, several landless families depend on seasonal agricultural work opportunities. The adults of these families, predominantly male, work extensively during the harvesting period, which requires frequent migration out of the village, while children in the household take care of the livestock and other activities (like fetching water and hay-stacking for fodder).

[5]More recently Primary School Certification Exam (PCSE), which was introduced in 2009, was scheduled in the last week of November in 2010. Unsurprisingly, the Directorate of Primary Education reported a 10% absenteeism on the first day of this largest nationwide public examination, highlighted in the media *the Daily Star* (click here `https://www.thedailystar.net/news-detail-163453`). Interestingly on the same day, the 24th November 2010, the Daily Star reported bumper production of *Aman* paddy in some parts of Bangladesh (click here `https://www.thedailystar.net/news-detail-163434`).

such conflict with the agricultural calendar as reported in the paper by De and Mehra (2016).

Children involved in harvest labor also face a greater risk of injury because of the use of traditional tools such as sickles. This, along with work-related fatigue caused by physically demanding harvesting work, lack of academic support at home to catch up (particularly for first-generation learners), and inadequate night-time lighting at home as these students are required to study in the evening, also hamper their exam preparation.

All these factors result in children achieving lower academic scores or missing exams, leading them to discontinue schooling. The progression to the next grade is usually contingent on satisfactory performance in the annual grade completion written examination at the end of each academic year (Zhongming et al., 2017). Technically, a student can repeat the grade due to unsatisfactory performance in the yearly final exam. However, grade repetition is not encouraged; as a result, failing a grade typically leads to school discontinuation.[6] Previous studies have investigated the role of technology and price changes in agriculture on schooling; however, except by Sabates et al. (2010), the calendar issue has not been discussed or documented in the academic literature.

To address this research gap, we estimate the impact of increased seasonal labor demand during the annual final exam on school continuation. We use a temporary exogenous shift in the annual examination schedule owing to the mandatory school holidays during *Ramadan* in 1999-2001 as an identification strategy. This change in the academic calendar forced schools to bring forward their final examinations to the pre-harvest season in Bangladesh, a time of reduced local agricultural labor demand. Using household and student-level panel data from 1999 and 2002 and employing a difference-in-differences (DID) estimator, we compare changes in school enrollment between children from agricultural and non-agricultural households to assess the differential impacts of seasonal labor demand changes on school continuation. Moreover, we control for time-variant variables, such as local paddy yield and weather. We find that annual exams overlapping with the *Aman* harvesting period decrease

[6]The percentage of repeaters in Primary education is only 4% and 1% for Bangladesh and India, respectively. `https://data.worldbank.org/indicator/SE.PRM.REPT.ZS`

school continuation (increase dropout) for children from agricultural households by 6.7 to 8.3 percentage points (compared with a 32% dropout between 1999–2002 by non-agricultural households). This effect disappears when we use the same specification with later rounds of data, thus supporting the causality of this effect. Moreover, we document that this impact is mostly coming from boys enrolled in secondary school, suggesting the brawn-based interpretation that boys who are more productive in agricultural activities tend to get pulled out of schools (Pitt et al., 2012). To check the impact mechanism, we find suggestive evidence that higher absenteeism during the agricultural season and slower grade progression are plausible factors driving these estimates.

To test the common trend assumption necessary for the consistency of the DID estimator, we show that it is likely to hold using three data sources: One with a later round of the primary sample and the other two with nationally representative household sample surveys of Bangladesh. We also compare our estimates with Muslim and non-Muslim households to disentangle any confounding factors, such as festivity and fasting, and flood-affected and unaffected areas to see if a natural disaster-driven shock is driving the results. We find that these factors have a negligible impact. Our findings survive a series of robustness and placebo tests and maintain low p-values and significant impact sizes. Moreover, we perform a complimentary analysis in India by exploiting state-level academic calendar variations. We find a similar negative impact (5.34 to 6.55 percentage points reduction) of academic calendar mismatch on school continuation for India's agricultural household children, consistent with our findings in Bangladesh.

Furthermore, we examine the overall impact of *Ramadan* induced temporary changes in the academic calendar on educational outcomes in Bangladesh. Using the latest round of the nationally-representative Household Income and Expenditure Survey (HIES 2016), we conduct an age-specific cohort analysis of academic outcomes in rural areas. Our analysis suggests that the school-going age cohort in 1999 significantly benefited from this favorable academic calendar, which reduced the urban-rural education gap by 0.46 years and increased the probability of completing primary, secondary, and higher secondary schools by 5.3, 5.3, and 3.3 percentage points, respectively. This impact generates approximately a three percent economic return (measured with annual wage earnings) for the beneficiary cohort owing to a favorable academic calendar.

Our findings have broader implications and are not limited to Bangladesh or India. In Africa, the temporary withdrawal of children from school during harvesting and times of hungry-season-led migration results in permanent withdrawal from schools (Andvig et al., 1999; Colclough et al., 2000; Hadley, 2010; Kadzamira and Rose, 2003; WorldBank, 1998).[7] This issue becomes even more complicated because of the multiple climatic zones coupled with a country-wide uniform school calendar. Countries such as Tanzania, Brazil, Colombia, and India have multiple climatic zones suitable for different crops, creating academic calendar conflicts with local agricultural seasonality.

Our study contributes to the literature by identifying the demand-side constraints on schooling in developing countries. Research on the demand-side aspects of schooling suggests that the opportunity cost of schooling can be exorbitantly high for children from economically marginalized households. This is due to liquidity constraints (Jacoby and Skoufias, 1997; Beegle et al., 2006), the inability to insure against shocks to income-earning activities (Jensen, 2000; de Janvry et al., 2006; Case and Ardington, 2006), comparative advantages in remunerative physical work (Pitt et al., 2012), and children's inability to become decision-makers for their human capital investments (Baland and Robinson, 2000). The existing literature documents a higher opportunity cost of schooling through positive rainfall shocks, increasing agricultural productivity in India (Shah and Steinberg, 2017), new manufacturing factory openings (Atkin, 2016) and gold mining (Santos, 2018). Our study highlights another important opportunity cost issue caused by a mismatch between the academic calendar and

[7] In Ethiopia, school enrollment begins in September; however, children leave schools in November due to the harvesting labor demand of *meher* season crops, which are Barley, Maize, Wheat, Sorghum, Oats, and Millet. In Kenya, a similar problem occurs, as maize harvesting (October-November) overlaps with the Kenyan Certificate of Secondary Exam (KCSE) in November. We observe such conflict in school schedules and seasonality in other countries such as Malawi, Nigeria, and Nepal.

seasonal agricultural labor demand.

This study also speaks to the literature on the effects of academic calendar reforms, such as all-year schooling (McMullen and Rouse, 2012; Graves, 2010); shorter school week (Anderson and Walker, 2015); early school starting hours (Cortes et al., 2012; Hinrichs, 2011; Edwards, 2012; Carrell et al., 2011); and reduction in compulsory years of schooling (Elsayed and Marie, 2021). One paper close to our setting is Dillon (2021) study in Malawi, documenting mixed evidence on schooling improvement when the government aligns academic session starting time with harvesting to facilitate school fee payments for credit-constrained farmers. Lastly, our study strengthens the literature on the impact of child labor on schooling that documents the presence of concurrence of work and schooling (Ravallion and Wodon, 2000; Edmonds, 2007; Dumas, 2012); and negative correlations between exam scores and work hours (Akabayashi and Psacharopoulos, 1999; Heady, 2003; Gunnarsson et al., 2006).

2 Context and Identification

2.1 School Education and Academic Calendar in Bangladesh

Bangladesh's educational system comprises Primary (grades 1–5), Secondary (grades 6–10), and Higher Secondary (grades 11–12) schooling followed by tertiary and vocational education (Kono et al., 2018). Schooling is compulsory up to grade 8. However, it is not enforced. The academic year in Bangladesh follows the Gregorian calendar, which runs from January to December. Since its independence, Bangladesh's school learning assessment system has mostly followed two pen-and-paper-based exams conducted by schools annually, known as half-yearly (mid-year, conducted in June) and final (year-end, conducted from late November to mid-December) exams. Figure A4 in Appendix A4 presents a typical Ministry of Education (MoE) provided academic calendar that clearly shows the half-yearly and final exam timing for Bangladesh.[8] These assessments are prepared and graded by teachers of the

[8]The Bangladesh National Education Commission has recommended the addition of three exams – first-term, second-term, and third-term, which were introduced later, with the third term acting as the annual

respective schools. The mid-year exam is somewhat formative, while the year-end exam is considered the final evaluation. Students are promoted to the next grade based on their annual exam results and satisfactory performance (Zhongming et al., 2017). End-of-year exams are binding for all grades, and not passing the exam would prohibit grade progression.

2.2 Rice Harvesting and Agricultural Calendar

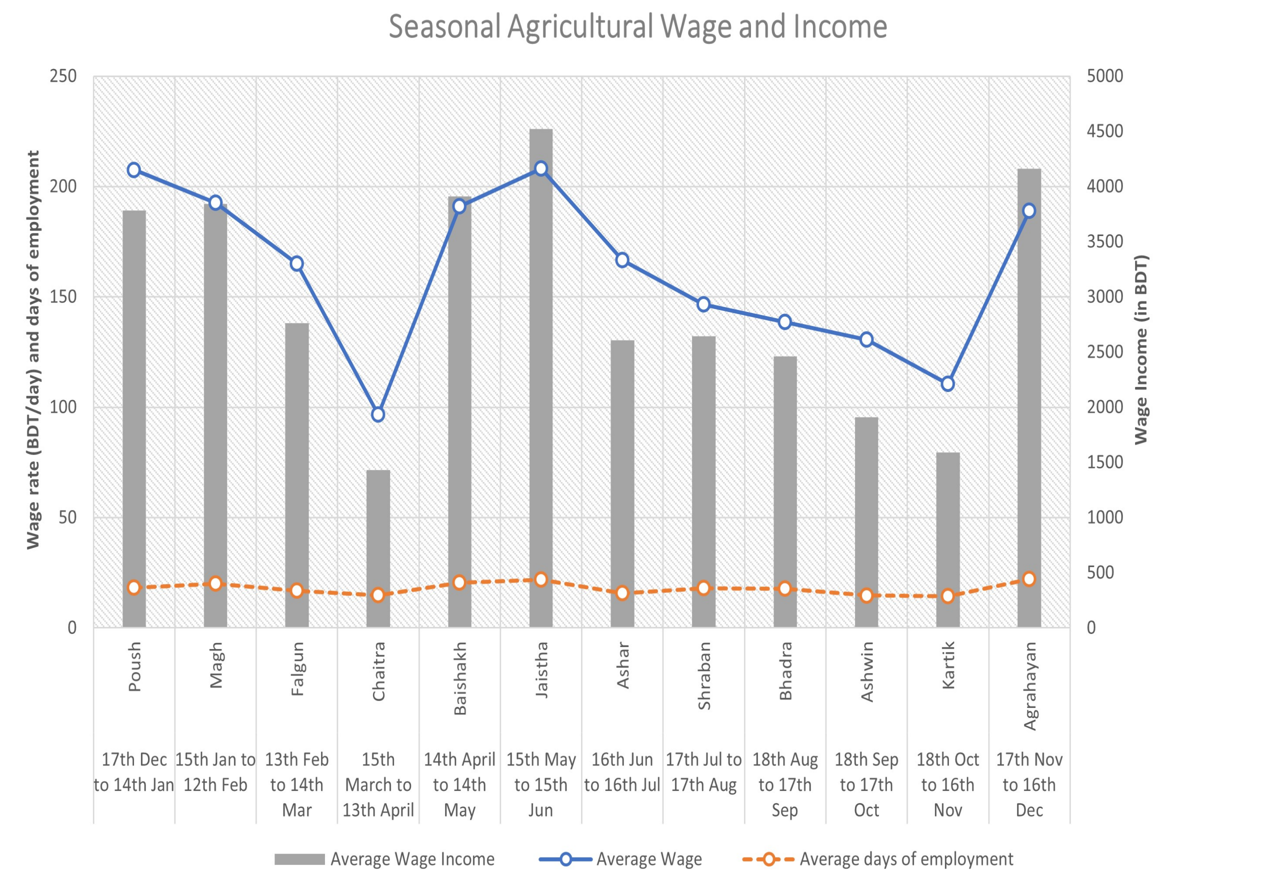
Rice is the principal agricultural product in Bangladesh, accounting for 74% of the gross crop area (Tisdell et al., 2019). Out of three cropping seasons (Boro, Aus, and Aman) of rice production (Laborte et al., 2017), *Aman* is the largest in terms of the amount of area utilized, as mentioned in footnote 1. *Aman* is a traditional rain-fed paddy variety planted in July–August and harvested from late November to mid-December (Shelley et al., 2016).[9] *Aman* intensity varies across regions; however, given the dominance of rice and the lack of agricultural diversity, other crops in any season are very limited, capturing only 2.67 and 1.97% of the gross cropped area in Bangladesh (Tisdell et al., 2019). It is well documented that agricultural wage fluctuates seasonally, peaking during harvesting (and sometimes during plantation). Figure 1 taken from Rahman and Islam (1988) portrays wage variation for agricultural wage laborers across the seasons, with wages peaking during the *Boro* and *Aman* paddy harvesting seasons in April-June and November-December, respectively.

This hike in agricultural wages during harvesting is driven by the rapid rise in local labor demand within a short period of time owing to time-sensitive harvesting (hence, not allowing spatial labor movement) coupled with liquidation demand to pay the bills accumulated throughout the year (Burke et al., 2019). Moreover, the lack of credit access makes it difficult for marginalized farmers to pay for hired labor, forcing agricultural families to depend on family labor. According to the BBS (2003b) National Child Labor survey 2002-

exam. However, currently, primary schools continue with the annual three-examination system, while the Ministry of Education (MOE) has recently switched secondary schools to a two-examination system (half-yearly and annual). These two exams have already been scheduled, and all schools adhere to this new system.

[9] The agricultural calendar is not static, and it may shift by a week or so due to climatic conditions of the year.

Figure 1: Seasonal variation in agricultural wage in Bangladesh



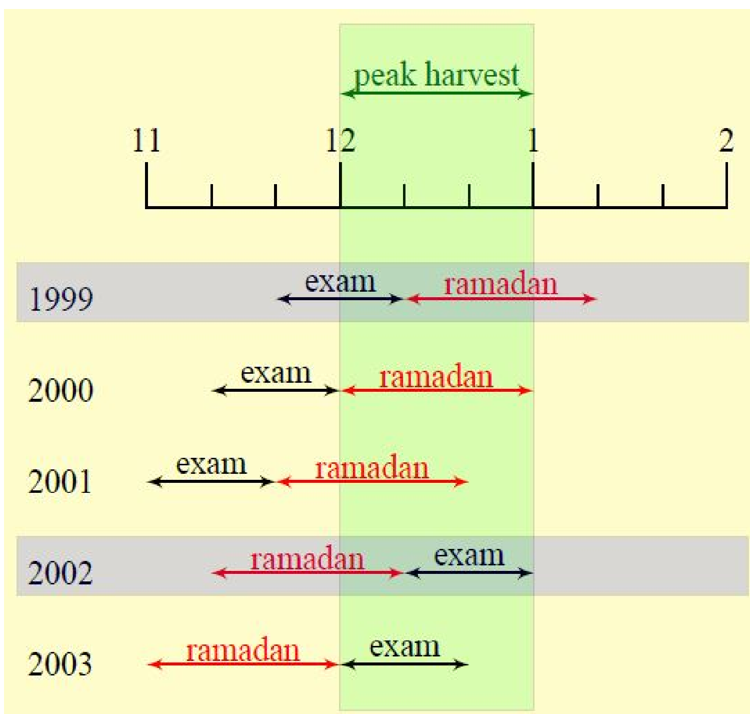
Source: Table IX of Rahman (2017). Data source is BIDS Food Insecuirity Survey, 2008

2003, approximately 7.4 million children in Bangladesh are engaged in child labor, of which 23.5% are in paid work (and another 57% are in unpaid family work). Overall, 56% of all child labor belongs to the agricultural sector. Agriculture remains the dominant sector for child labor, as reported in the later round of the child labor survey, BBS (2003a). The age distribution of child labor overwhelmingly belongs to the 10-18 age category, comprising 96% of all child labor in Bangladesh.

2.3 Ramadan timing as an identification strategy

Bangladesh is predominantly a Muslim country, and *Ramadan* is a compulsory activity for Muslims. During *Ramadan*, schools are instructed by the Ministry of Education to declare holidays to accommodate and encourage religious practices for children. However, the schedule of these holidays is not fixed, as the Islamic months follow the lunar calendar system. Therefore, *Ramadan* drifts 11-12 days per year on the solar calendar. Interestingly, from 1999 to 2001, *Ramadan* was observed in December; consequently, schools had to move their annual final examinations by one month backward to November (which is the off-harvest season for *Aman* rice) to accommodate the completion of the academic schedule and holidays. This created only a small overlap between the peak seasonal labor demand period for *Aman* rice and the final examination period. Three years later, in 2002, owing to shifts in lunar calendar dates to the Gregorian calendar, *Ramadan* was celebrated in November. Schools declared holidays in that month and scheduled final examinations in December, which is the usual schedule that overlapped with the *Aman* harvest season.

Figure 2: Sequence of Events.[a]



[a]Timing of the annual final exams, *Ramadan*, and the peak harvest period for *Aman* rice. *Ramadan* shifts by approximately 11–12 days each year. The starting dates of *Ramadan* in the different years are as follows: December 9, 1999; November 27, 2000; November 16, 2001; November 6, 2002; and October 27, 2003. The years in shaded rows indicate the years compared in this study using a natural experimental framework. This is a simplified schematic representation; the peak harvest season may shift by year and region.

FIGURE 2 depicts the schematic explanation of the timing of these events. In 1999, the annual final examination period partially overlapped with the harvest period. In 2002, the examination and harvest occurred concurrently after the *Ramadan* holidays. For students preparing for the examinations, this implies that they faced a lower marginal product of labor or smaller seasonal labor demand during the 1999 examination period than during 2002. We use this variation in seasonal labor demand during the examination period as the foundation for a simple standard two-period model with a productivity shock in Appendix A1, providing the setting for the natural experimental framework.

We primarily use the 1999-2002 (released in 2000 and 2003) longitudinal data sets to estimate the impact of peak seasonal labor demand and the examination period variation — created by *Ramadan* school vacation — on the school continuation in Bangladesh between the agricultural and non-agricultural households. Our identification strategy is similar to that used by Oosterbeek and van der Klaauw (2013); taking the time difference of the same individual to eliminate individual fixed effects while using differences in exposure to harvest labor demand between households during exam periods to identify its impacts on school continuation.[10]

2.4 Identification challenges

The challenges we face with this identification strategy are threefold. First, there is no natural control group, as school holidays given during *Ramadan* are nationwide phenomenon. Therefore, we use children from agricultural households as the "treated" who face higher exposure to seasonal agricultural labor demand, with non-agricultural household children as the "control." This is based on the assumption that poor agricultural families typically

[10]The *Ramadan* timing variation as a natural experiment has been successfully applied in the economics literature. Almond and Mazumder (2011) employ *Ramadan* as a natural experiment for forcing smaller food intake. They control for its seasonality by exploiting the shifting nature of *Ramadan* that results from its determination according to the lunar calendar. Oosterbeek and van der Klaauw (2013) exploit the same shifting pattern of *Ramadan* over a five-year period as a source of differing exposure to fasting and estimate its impacts on the examination scores of Muslim graduate students in the Netherlands. Campante and Yanagizawa-Drott (2013) examine the impacts of *Ramadan* fasting on the labor market and economy-wide outcomes.

engage their children in farming activities during the harvest season to reduce the cost of harvesting and reap the benefits of greater seasonal labor demand and a higher marginal product of labor. In addition to these supply-side justifications, one can consider the demand-side preference for children from agricultural households because they have stronger ties with the agricultural community, more seasonal agricultural-based job networks, and more experience in agriculture activities, all of which make them more employable.[11]

Second, empirical support for the common trend assumption is necessary for the consistency of estimates. Owing to data limitations, we compare the enrollment changes between the treatment and control groups with later waves of the main data source using the 2002 and 2006 survey rounds. Using birth cohorts and the latest round of the National Representative HIES of Bangladesh, we also test the common trend assumption. All these empirical exercises support that the common trend assumption is satisfied.

Third, because we utilize a natural experiment that lacks fine control of events, there may be other possible confounding factors that have affected only agricultural households in the observed years. For instance, in 1999, the annual final examinations were conducted before the harvest and the *Ramadan* school holidays. In 2002, the examinations were scheduled during the harvest and after *Ramadan* school holidays. Therefore, in our natural experiment framework, there exist two potential "treatments," which are: a) Examination coinciding with vs. avoiding the harvest season, and b) Examination before vs. after the *Ramadan* school holidays. Throughout our analysis, we emphasize the effect of point (a) by comparing the impact of the examination calendar shift on agricultural and non-agricultural households. For point (b), we assume that conducting examinations before or after school holidays similarly affects students in agricultural and non-agricultural households. In 2002, annual exams were conducted after a school break, which could have impacted school continuation (for example, students had adequate opportunities for proper rest, which might have improved academic continuation). However, this is true for students from both agricultural and non-

[11]We also note that non-agricultural households tend to face peak labor demand, if any, at different times of the year, rather than during the harvest season (e.g., during new year celebrations).

agricultural households. We assume that there is no particular reason why having a school break before the exam systematically affects students only from agricultural households to discontinue schooling. We test this assumption using the HIES 2016, employing older cohorts for whom *Ramadan* holidays occurred after the harvest and final exam season. Our estimates indicate no systematic difference in having long holidays before the exam.

In addition to checking the possible advantages of having a holiday before the exam, we also examine the possible disadvantages of having festivity-related holidays that may affect subsequent exam performance. For instance, the home-learning environment during the festival period may differ between agricultural and non-agricultural households, which can systematically affect exam preparation and school continuation. To verify this empirically, we compare Muslim and non-Muslim households in the main sample. Since non-Muslims do not fast and are less prone to be affected by festivities, this exercise helps us disentangle the festivity impact, which is statistically negligible, and our primary findings remain unchanged. This also checks the impact of fasting; non-Muslim students do not fast; therefore, the statistically zero estimates for non-Muslims affirm that fasting is not the source of enrollment rate variations between households.

Finally, one may be concerned that natural disaster-related shocks (such as floods) may have negatively affected disproportionately the schooling of agricultural households in 2002. This can systematically drive children of agricultural households out of schools. To check this possibility, we test the impacts of floods by using a dummy variable of flooded areas at thana level. We find no evidence that floods disproportionately affected the children of agricultural households. More on the robustness checks are given in Section 6.

3 Empirical Strategies and Specification

3.1 Difference-in-differences (DID)

Using a balanced panel of children aged 10-18 in 1999, we consider the following DID equation:

$$y_{i,t} = \delta r_t + \eta D_i + \gamma r_t D_i + \boldsymbol{\beta}' \mathbf{x}_{i,t} + v_i + e_{i,t}, \tag{1}$$

where $y_{i,t}$ is a binary variable indicating the enrollment of an individual i in period t, r_t is a dummy variable for the year 2002 (when the school exam schedule coincides with the harvest season), D_i is a dummy variable for agricultural households, $\mathbf{x}_{i,t}$ is a set of covariates, v_i is the time-invariant individual effect, and $e_{i,t}$ is the error term clustered at *thana* level. $r_t D_i$ picks up any changes in enrollment of agricultural households in 2002 relative to changes of non-agricultural households, and γ gives the magnitude of such changes. Here, γ captures unfavorable school exam schedules that coincide with the seasonal labor demand of the harvest period. The coefficient δ of the year 2002 dummy r_t accounts for all other effects in 2002 while $\mathbf{x}_{i,t}$ includes all relevant exogenous variables that affect future income and effective interest rates faced by individuals that change the schooling decisions.[12]

Given a general tendency observed in low-income countries, enrollment rates decrease as children progress in school, we condition on the baseline observables vector $\boldsymbol{\omega}_i$ to control for heterogeneous trends in enrollment rates. This allows the impacts to be correlated with the baseline characteristics $\boldsymbol{\omega}_i$ through $\boldsymbol{\gamma}_\omega$.[13] Hence, (1) changes to the following:

$$y_{i,t} = (\delta + \boldsymbol{\delta}'_\omega \boldsymbol{\omega}_i)\, r_t + \eta D_i + (\gamma + \boldsymbol{\gamma}'_\omega \boldsymbol{\omega}_i)\, r_t D_i + \boldsymbol{\beta}' \mathbf{x}_{i,t} + v_i + e_{i,t}. \tag{2}$$

For statistical inference, we cluster the standard errors at the thana level. This follows

[12] These are, in general, time-variant variables capturing the characteristics of children and their parents. We use the child's age squared, program membership, paddy yield in the area, and weather variables.

[13] These are initial values of child sex, number of older siblings, head-of-household and spouse education level, per member land holding, per member non-land assets, house conditions (access to piped water and having a structured toilet at home) all observed in 1999. In (2), we also allow heterogeneous trends that are correlated with these variables through $\boldsymbol{\delta}_\omega$.

the convention that one should cluster at the level of cluster sampling (thanas) or treatment assignment (households), whichever is higher, and it is thanas in our case (Abadie et al., 2023). Given that we have only eight clusters, we also report the results using a bias-reduced linearization (Satterthwaite correction, see Bell and McCaffrey, 2002; Imbens and Kolesár, 2016; Pustejovsky and Tipton, 2018) of clustered robust standard errors to guard against type I errors (false positives).[14],[15]

3.2 Control variables in DID

First, even if γ is estimated with precision, agricultural households may share unobservable characteristics that result in a larger decrease in enrollment rates in 2002 compared to non-agricultural households. As we are controlling for individual fixed effects, the remaining unobservable characteristics are the time-varying ones. The most likely candidate is the possibility of incidentally large agricultural labor demand in 2002. Even if *Ramadan* in 1999 had no impact on enrollment, a good harvest in 2002 might have induced greater school discontinuation for agricultural households relative to non-agricultural households, resulting in a larger drop in the enrollment rate. As a proxy for paddy production variability, we include district-specific *Aman* paddy production information in our regressions with primary data collected from the Bangladesh Bureau of Statistics (BBS). We note that BBS reported national production of *Aman* rice did not significantly differ between these two seasons (*Aman* season of 1999 and 2002) within our sample household districts, with 5,010 thousand metric tons produced in 1999 and 5,342 thousand metric tons in 2002, representing only a 6.6 percentage change in production.[16]

Second, in all regressions with primary data, we include the year 2002 dummy as well as

[14] We use R's clubSandwich package developed by Pustejovsky and Tipton (2018).

[15] Wild cluster bootstrap is not generally recommended in a DID setting (Canay et al., 2021). We note that the confidence intervals using wild cluster bootstrap are very similar to those using bias-reduced linearization and are almost always narrower.

[16] If wage elasticity of yield is ψ and labor supply elasticity of wage is ξ, impacts on labor supply in the 30-day harvest period is $0.06 \times \psi \times \xi \times 30 = 1.8\psi\xi$. Even if we assume relatively large elasticity $\psi = 1.5$, $\xi = 1$, we have only a 5.4 percent increase in labor supply per day during the two-month-long harvesting period in 2002. We assume that this magnitude does not change the passing rate for the final examination.

its interaction terms with the location dummies, which capture all other time-variant causes that can affect enrollment (e.g., occurrence of seasonal flood in some riverine sub-districts) that are common at the level of thana.[17] Third, we additionally control for annualized values of temperature (mean high and low temperatures in Celsius) and mean rainfall (measured in millimeters) variations at the sub-district (thana) level, which can simultaneously influence school continuation as well as the agricultural productivity and income of our sample households.[18] Fourth, given that maternal education can play a key role in academic continuation (Behrman et al., 1999), we include parental education variables in our regressions. Finally, we control for variables capturing safety-net access, household hygiene conditions, and asset levels.

Taken together, we control for time-invariant individual characteristics, time-variant aggregate unobservables, time-variant geographical (thana)-level unobservables, and heterogenous trends in our DID framework. We also test for common trends in enrollment rates among agricultural and non-agricultural households in future rounds between 2002 and 2006 using comparable cohorts as part of the placebo tests (as well as using other data sources). In addition, we control for district level *Aman* rice production and sub-district level weather variation. However, one may be concerned about whether there exists any particular issue at the individual level in 2002 relative to 1999 that systematically prompted individuals to drop out from only agricultural households (e.g., household-level productivity shocks that are uncorrelated with aggregate productivity shocks) for which we do not have sufficient data to control for. Except for this, we control a wide range of factors that could affect the enrollment variation of our estimation, which shows the extent of credibility that our analysis conveys.

[17] Thana or sub-district is the second lowest administrative unit in Bangladesh.

[18] Weather data is obtained from Bangladesh Meteorological Association monthly data at the district level.

3.3 Long-term Cohort Analysis with national survey

As the favorable examination calendar shift in 1999 was a country-wide event that benefited children from agricultural households for three years (from 1999 to 2001, see Figure 2), one can expect an overall rise in years of schooling for the affected cohort, nationally. Employing the latest rounds of HIES 2016-17, officially known as HIES 2016, we check this empirically. Our estimation exploits the year of birth as the identification. Here, we assume that parents did not decide on fertility based on the favorable examination calendar of 1999-2001. Given that the HIES does not have the adult household members' parental occupation information, the estimation assumes that the rural population has a greater ratio of agricultural households than the urban population and uses the rural population as a proxy.[19] In this setting, we expect that the exposed rural cohort has more schooling relative to its urban counterpart relative to the unexposed cohort. This necessarily subsumes measurement errors in estimates. We use a proxy variable for agricultural households with a rural population dummy. Therefore, we interpret the results as attenuated from the actual impacts and find that the impacts add to the plausibility of the favorable effects of the final exam rescheduling in 1999.

One potential threat to these estimates is the large national educational interventions to improve schooling, particularly in rural areas. Hence, the positive impact on schooling could be owing to nationwide educational aid and not related to the favorable calendar shift in 1999–2001. Two potential candidates for such confounding factors are the national Food For Education (FFE) and Female Stipend Programs (FSPs). However, the FFE was launched in 1993 as a large-scale national pilot intervention, providing free monthly food grains to economically marginalized families to continue primary schooling (Ahmed and Del Ninno, 2002). Similarly, FSPs targeting secondary education for females started a pilot project in 1982 and were rolled out nationally in 1994 (Xu et al., 2022). Moreover, both programs

[19]Urban and rural definitions for Bangladesh come from the Bangladesh Bureau of Statistics (BBS). The BBS defines an urban area as a developed area (i) around an identifiable central place, (ii) where amenities like Paved roads, communication facilities, electricity, gas, water supply, sewerage connections usually exist, and (iii) which is densely populated and a majority of the population involved in non-agricultural occupations. Non-urban areas are defined as Rural areas.

maintained steady support coverage rates and targeted both rural and urban areas.[20] Hence, these factors are unlikely to explain the cohort impact in rural areas.

We estimate the following equation for individual i, in region j belongs to cohort t:

$$Y_{i,j,t} = \omega_1 \text{Cohort}_t + \omega_2 \text{Rural}_j + \omega_3 \text{Cohort}_t * \text{Rural}_j + \boldsymbol{\omega}_4' \mathbf{x}_i + V_j + \omega_5 Age_i * V_j + e_{i,j,t}, \quad (3)$$

where $Y_{i,j,t}$ is the outcome variable of interest. $\mathbf{x}_i$ is a set of control variables (age dummy capturing both demand and supply side change in education over time, sex, and religion). ω_1 indicates whether an individual belongs to a particular birth-age cohort that is 10-18 years old in 1999 (our cohort of interest). ω_2 captures rural area fixed effect. ω_3 is our co-efficient of interest where we have cohort dummy interacted with the rural dummy, capturing the deviation compared with urban areas. V_j is the regional (district-level) time-invariant fixed effects. We also control for time-variant district effects by interacting the district dummy with the age dummy (capturing disproportionate changes in education supply and demand in a particular year in some areas) captured in ω_5 and $e_{i,j,t}$ is the error term clustered at the district level. We estimate the equation using OLS (for years of education) and the probit for completing different educational qualifications.

4 Data

4.1 Definitions and descriptive statistics

The data set we use is a panel data set collected in 1999, 2002, and 2006 in rural Bangladesh by the International Food Policy Research Institute (IFPRI). It surveyed 600 households from 60 villages in 30 unions (sub-sub-districts in 10 thanas (sub-districts) to investigate the impacts of Food for Education (FFE) programs on school enrollment. The sample was selected using the following protocol: Ten thanas were first randomly selected with

[20] Except for metropolitan areas.

probability proportional to size (PPS) based on thana-level population data from the 1991 census, and two FFE unions and one non-FFE union were selected per thana.[21] From each union, two villages were randomly selected with the PPS using village-level population data from the 1991 census. A complete census of the households was then conducted in each of the selected villages, and ten households that had at least one school-age child were randomly selected in each village from the census list of households. Two thanas were dropped from the 2002 survey by the IFPRI, making the panel data include eight thanas. In total, 3,326 individuals were surveyed.

The survey timing mentioned in the IFPRI data-sets for the 2000, 2003, and 2007 rounds was September-October of the respective years. These survey rounds captured enrollment information after completing the school examinations in the 1999, 2002, and 2006 academic years. Given the enrollment information captured through survey timing, we refer to enrollment information as "school continuation to 2000" and "school continuation to 2003."

In our main DID analysis, we use the balanced portion of the 1999-2002 survey data with an age cut-off of 10-18 years old in 1999, consisting of 626 individual observations. Our sample is built on parent(s)-child tuples (nuclear households) to control for parental characteristics, excluding 56 of the 682 individuals who do not have information about their parents. We set the lower age cutoff at ten years old, based on the definition of child labor used in the Labor Force Survey (LFS) of Bangladesh, capturing both primary and secondary school-enrolled students.[22] We also use different age cutoffs (11-18 and 12-18 years) for robustness checks. Our main results remain qualitatively unchanged if we retain dropped individuals,[23] or if we use different lower-age cutoffs. We also examined if there is any indication of non-random attrition and found no statistical evidence (reported in Table A2 and discussed in Appendix A3).

[21] This indicates that the choice of unions is not random. However, it gives reasonable representative information about rural and economically disadvantaged areas of the country. The sample cannot be regarded as a representation of overall rural Bangladesh.

[22] Compulsory school enrollment for primary education in Bangladesh is from age 6-10. For more information, see http://uis.unesco.org/en/country/bd.

[23] Not reported but available upon request.

For placebo regressions and testing common trends, we use the balanced portion of the 2002-2006 data. When we use the same individuals of the main estimation who were 10-18 in 1999 (1999 cohort), the placebo sample size is 616. When we use individuals aged 10-18 in 2002 (2002 cohort), the placebo sample is 812. A detailed description of the data cleaning, selection process, and descriptive statistics of the variables used in the main and placebo estimation are available in Appendix A3.[24]

In our main DID analysis, we compare the enrollment information of agricultural and non-agricultural households in 1999 and 2002.[25] To define an agricultural household, we consider a range of definitions that regard a household as agricultural if any household member reports his or her primary income source or occupation as agriculture or if a household cultivates agricultural plots. We also use an alternative, narrower definition of agricultural households in which the household head reports his or her primary income source or self-reported occupation as agriculture. Nevertheless, the different definitions are highly correlated, and the estimated results are similar, as reported in the next section and explored more in Appendix A4.[26]

Given that agricultural and non-agricultural households engage in different types of economic activities, we expect their characteristics to differ. The means are compared and tested for differences, as presented in Table 1. These are the covariates we use in our estimation. Only a few spouses of agricultural household heads are likely to have education up to a sec-

[24]The 1999 and 2002 data sets are known as the *Impact Evaluation of Food for Education Program in Bangladesh 2000*, and *Comparing Food versus Cash for Education program in Bangladesh 2003* data set, respectively. The 2016 round data set is known as *Chronic poverty and long-term impact study in Bangladesh*. For more information, see `https://www.ifpri.org/publication/impact-evaluation-food-education-program-bangladesh-2000`, `https://www.ifpri.org/publication/comparing-food-versus-cash-education-program-bangladesh-2003`, and `https://www.ifpri.org/publication/chronic-poverty-and-long-term-impact-study-bangladesh`.

[25]Here, enrollment information confirms the school continuation of each student as the discontinued student does not enroll in school at the beginning of the academic year. Schools typically confirm this by the middle of the academic year in Bangladesh, when they are obligated to report this to the local administration and the education ministry.

[26]We found that 9.7% of reported "occupation as agriculture" is associated with non-agricultural work as its primary income source. Accordingly, our default definition of agricultural household, which is a union of occupation and income-based definitions, gives smaller impact estimates than income source or head's reply-based definitions.

Table 1: Summary Statistics and Contrasts of agricultural and non-agricultural Households

Individual and Household level Variables	Means			p-values (%)	
	Overall	Agri HH	Non-Agri HH	t-test	Satterth-Waite
Age of the child	12.9856	13.0469	12.8884	[41.18]	[44.38]
	(0.061)	(0.141)	(0.194)		
Sex of the child (female = 1)	0.5112	0.4870	0.5496	[12.72]	[15.20]
	(0.024)	(0.040)	(0.038)		
Enrollment status of the child	0.7380	0.7135	0.7769	[7.42]	[13.89]
	(0.035)	(0.033)	(0.037)		
HH Head education: primary	0.1550	0.1641	0.1405	[42.17]	[57.16]
	(0.022)	(0.020)	(0.040)		
HH Head education: secondary	0.2843	0.2057	0.4091	[0.00]	[0.98]
	(0.031)	(0.054)	(0.056)		
HH Head spouse education: primary	0.1709	0.1901	0.1405	[9.93]	[38.41]
	(0.028)	(0.036)	(0.053)		
HH Head spouse education: secondary	0.1661	0.1146	0.2479	[0.00]	[1.96]
	(0.043)	(0.053)	(0.043)		
HH Head sex (female = 1)	0.1278	0.0365	0.2727	[0.00]	[4.88]
	(0.048)	(0.101)	(0.098)		
Number of older brothers	0.5767	0.6484	0.4628	[0.47]	[0.87]
	(0.041)	(0.067)	(0.050)		
Number of older sisters	0.3898	0.3646	0.4298	[25.61]	[47.18]
	(0.060)	(0.101)	(0.085)		
Per-member land holding (decimal)	16.7471	18.9627	13.2316	[1.59]	[10.80]
	(2.029)	(1.361)	(3.073)		
Per-member nonland asset (1000 Tk)	11.2091	9.9168	13.2599	[1.17]	[12.46]
	(1.694)	(2.451)	(1.894)		
HH has piped water	0.3802	0.4010	0.3471	[17.37]	[56.32]
	(0.096)	(0.113)	(0.088)		
HH has Structured toilet	0.2939	0.3229	0.2479	[4.13]	[40.19]
	(0.055)	(0.019)	(0.084)		
HH is Non-Muslim	0.1230	0.1250	0.1198	[84.78]	[92.63]
	(0.062)	(0.082)	(0.054)		
HH Program Membership	0.7396	0.7161	0.7769	[8.65]	[18.87]
	(0.035)	(0.038)	(0.041)		
Sub-District level variables					
Rainfall (in millimeters)	206.6157				
	(33)				
High temperature (in Celsius)	31.1582				
	(0.252)				
Low temperature (in Celsius)	21.6092				
	(0.263)				
Paddy Yield (in '000 metric ton)	0.7859				
	(0.044)				
Flood (dummy)	0.6230				
	(0.187)				
No. of Observations	626	384	242		

Source: Compiled from IFPRI data. All information is from 1999.

Notes:
1. Columns: For each variable, the top rows indicate the mean and p values. The bottom rows indicate the standard errors of the means. Standard errors are clustered at the thana level, and the Satterthwaite correction for degrees of freedom is applied to account for the small number of clusters. Agricultural households are defined as those with at least one adult member claiming that the primary income source or occupation is agriculture (agricultural laborer, tenant, or owner-farmer). The column headed by t indicates p values of zero difference using standard t-tests. The column headed by Satterthwaite implies p values of zero difference with cluster-robust standard errors and Satterthwaite corrections.
2. Rows: Enrolled is an indicator variable for school enrollment. Program is an indicator variable for a household's enrollment in any anti-poverty school support program. Age is defined as the child's age in 1999. Sex (female = 1) is an indicator variable of the child's sex. Head primary, Head secondary, Spouse primary, and Spouse secondary are the indicator variables for highest educational attainment. Head sex (female = 1) is an indicator variable for the household head's gender. The number of older brothers/sisters is the number of older siblings per child. Per-member landholding is the per-member landholding of the household in decimals. The per-member non-land assets are the per-member non-land asset values in 1000 Takas. Piped water and structured toilets are indicator variables for household ownership of each facility. "Non-Muslim" is an indicator variable for households with heads who do not identify themselves as Muslim. Floods are the indicator variables.

ondary level. They have more land holding per member, which is unsurprising as they engage in agriculture. However, there are more female-headed households among non-agricultural households who are more educated. All other characteristics that may potentially be correlated with child schooling seem to be similar between agricultural and non-agricultural households, for example, per-capita non-land asset holding, water access, and structured toilets, once we use cluster robust standard errors with Satterthwaite corrections.

For the long-run cohort analysis, we use the latest round of the Household Income and Expenditure Survey (HIES) 2016-17, officially known as HIES 2016.[27] We utilize the HIES 2016 to create birth cohort and years of education to conduct our analysis.[28] To this end, we create two cohorts, 10-18, and an immediately older cohort of the same age bracket, 19-27 years old in 1999, as cohort 1 and 2, respectively.[29] The details of the sample used in the cohort analysis are given in A13, while the cohort structure is reported in Table A12 of Appendix A4.

5 Testing common trends

5.1 Testing with IFPRI data-set

The DID specification requires a common trend assumption in the enrollment rates of agricultural and non-agricultural households. As our primary data set was collected in three rounds, with the final round collected in 2006,[30] we can use the 2002-2006 panel of the relevant cohorts to check this empirically.

We see that the changes in enrollment rates with the 2002-2006 panel are 24.6% for

[27]HIES 2016 is a nationally representative household survey conducted by the Bangladesh Bureau of Statistics with a sample size of about 46000 households. To know more about this survey, please check the following link `https://catalog.ihsn.org/index.php/catalog/7399/study-description`

[28]Since our cohort of interest is 10-18 years old in 1999, we could not use earlier rounds of HIES surveys for our analysis as many of these age cohorts are continuing education.

[29]We could not use the same age bracket for immediate younger cohort (1-9 years old in 1999), as this cohort is continuing education during the 2016-17 HIES survey (18-26 years old in 2016).

[30]See `http://www.ifpri.org/dataset/chronic-poverty-and-long-term-impact-study-bangladesh`.

agricultural households and 21.9% for non-agricultural households. The proportions test for equal changes in enrollment rates (i.e., testing the null hypothesis of equal changes in enrollment rates) gives a p value of 44.8%. This indicates that the common trend assumption is plausibly valid in our sample.[31]

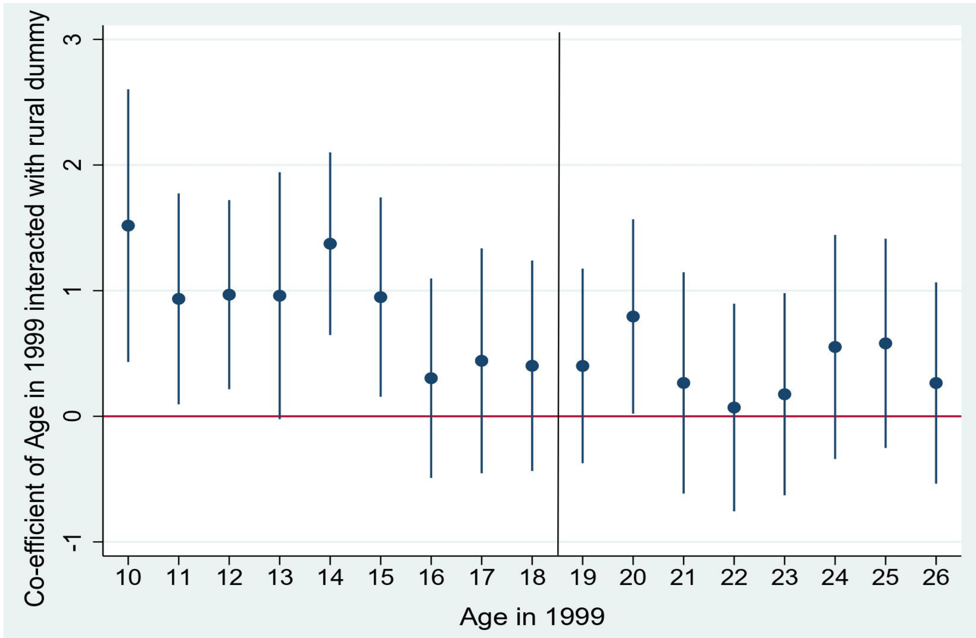
5.2 Testing with HIES 2016 data-set

To test the common trend with the HIES 2016 data, we restricted the sample within the cohort 2 age group (aged 19-27 years old in 1999) who were not exposed to the favorable school calendar shift in 1999-2001. We estimate a regression following equation 3, which is reported in Table A15 in the Appendix, where we use age 19 in 1999 as a reference group to estimate the coefficients of Age interaction with the Rural dummy for the age group of 20-27 to detect any pre-trend in years of schooling or completion of education qualification (primary, secondary or higher secondary). As presented in Table A15, we do not observe any statistical evidence of pre-trend patterns among cohort 2 age groups between rural and urban areas.

Furthermore, We also conduct additional common trend regressions (not reported for brevity, available on request) by restricting the sample between cohort 2 (19-27 years old in 1999) and 3 (28-36 years old in 1999). Similar to the estimates in Table A15, we find that 19-27 years in 1999 (cohort 2) in rural areas had no statistically significant difference in years of schooling, on average, compared to the same cohort located in urban areas, supporting the common trend assumption for our setting. Finally, in Figure 3, we plot the entire cohort 1 and 2 age dummy interacted with the rural dummy to demonstrate this pattern graphically.

[31] When we restrict our sample by shifting to the older cohorts, we obtain more equal changes in enrollment rates; however, the power of the test gets weaker as the sample size becomes smaller with older cohorts. In a separate exercise, we further test the common trends in various sub-samples (cohorts) between 2002 and 2006 and find that all but 11-years-old cohort ($p = 7.1\%$) give large p values against the null hypothesis of common trend.

Figure 3: Coefficient plot of Years of Schooling for age 10-27 in 1999.[a]

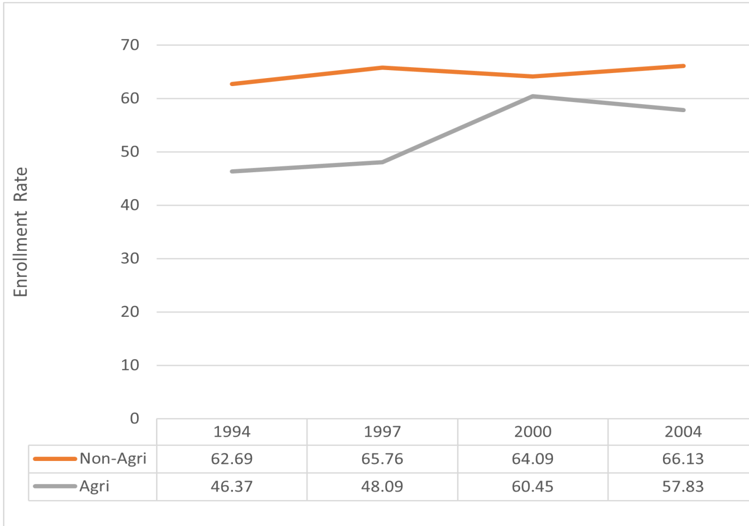


[a]Source: Compiled from HIES 2016 data. Based on a regression estimate of years of schooling regressed against age interacted with rural dummy along with cohort of birth dummy, sex, district and cohort of birth dummy interactions, and religion. Standard errors clustered at *district* level.

5.3 Testing with DHS data

As our data set does not have information before the favorable calendar event in 1999 to test for a common trend, we also check the common trend assumption using another nationally representative data source: The repeated cross-sectional data of the Demographic and Health Survey (DHS) 1994, 1997, 2000, and 2004 rounds with 10-18 years old children of the survey households (see Figure 4 below). We can observe that there exists a clear common trend prior to the 1999 event; the enrollment rates between non-agricultural and agricultural household children were 62.69% and 46.37%, respectively, which slightly increased to 65.76% and 48.09% in 1997 (4.9% and 3.7% change). Moreover, the DHS data-sets indicate empirical support for our identification: An increase in school continuation for children from agricultural households in 2000 (owing to a favorable calendar) and a decreasing continuation rate in 2004, when the calendar was reinstated to an unfavorable one, conflicting with the local agricultural cycle.

Figure 4: Common trend using DHS 1994-2004 rounds



6 DID regressions

6.1 Main estimates

Table 2 presents the estimates of our main coefficient of interest $\hat{\gamma}$ for the sample age of 10-18 years old in 1999. In the first three columns of Table 2 report regressions with the broadest definition of agricultural households, as described in the previous section. In the next three columns, we report regression estimates with a narrower definition of agricultural households (termed as "Agricultural (Head)"). We report the estimates using all the definitions of agricultural households in Table A8 in Appendix A3, and the results are qualitatively similar. Each estimate is followed by two 95% confidence intervals (CI). The first CI in the parentheses is based on the "regular" cluster-robust standard errors of Liang and Zeger (1986), and the second CI in the square brackets is based on the cluster-robust standard errors with a correction for the small number of clusters using bias-reduced linearization (BRL) of Pustejovsky and Tipton (2018).

In Table 2, columns (1) and (4) report the first DID specification, for which we use the interaction term of the year 2002 dummy with the agricultural household, time-varying covariates, and demographic variables interacted with the year 2002 to control for heteroge-

Table 2: Main regression estimates with 10-18 years old in 1999

	Agricultural HHs			Agricultural HHs (head)		
	(1)	(2)	(3)	(4)	(5)	(6)
Agri HHs * year 2002	-0.0673^{**}	-0.0760^{**}	-0.0754^{**}	-0.0827^{**}	-0.0842^{**}	-0.0833^{**}
	(-0.114, -0.021)	(-0.126, -0.026)	(-0.125, -0.026)	(-0.126, -0.039)	(-0.135, -0.033)	(-0.132, -0.034)
	[-0.127, -0.008]	[-0.147, -0.005]	[-0.144, -0.007]	[-0.139, -0.027]	[-0.156, -0.013]	[-0.151, -0.016]
Demographic fixed trends	Yes	Yes	Yes	Yes	Yes	Yes
Other household fixed trends		Yes	Yes		Yes	Yes
Thana fixed trends			Yes			Yes
$\bar{R}^2$	0.4676	0.4830	0.4835	0.4712	0.4829	0.4835
N: Agricultural HHs	384	384	384	346	346	346
N	626	626	626	626	626	626
Mean of control in 1999	0.7135	0.7135	0.7135	0.7312	0.7312	0.7312
Mean of control in 2002	0.3906	0.3906	0.3906	0.3844	0.3844	0.3844

Source: Compiled from IFPRI data.

Notes: 1. Sample of direct offspring of household heads. Agri HHs * year 2002 is an interaction term of agricultural household dummy and year 2002 dummy. All the interaction terms are demeaned. Columns (1) and (4) use time-varying thana level characteristics (yield, mean rainfall, mean high temperature, mean low temperature) and individual level characteristics (age squared, recipient of a poverty program). Demographic fixed trends are interactions of baseline individual and demographic characteristics (sex of individual, household head's education, number of older male/female siblings) with the year 2002 dummy, and sex of individual with the year 2002 * agricultural household dummy. Parental education is highly collinear with agricultural household dummy and is dropped from triple interactions. Columns (2) and (5) add Other household fixed trends that are interactions of other baseline household characteristics (per member land holding, per member non-land assets, household condition (access water through pipe and having structured toilet at home). Columns (3) and (6) add Thana fixed trends, which allow heterogeneous trends at Thana level.

2. Standard errors are clustered at thana level. 95% confidence intervals of cluster robust standard errors using Liang and Zeger (1986) are shown in parenthesis, and bias-reduced linearization (BRL) for a correction of a small number of clusters are shown in square brackets. $*$, $**$, $***$ indicate significance levels at 10%, 5%, 1% under BRL cluster robust standard errors, respectively.

neous trends. Our estimation indicates that the impact of the annual final exam coinciding with seasonal labor demand had a 6.7-8.3 percentage points negative impact on the enrollment rates of students from agricultural households in the three years between 1999 and 2002 (from the base of 10.6-11.6 percentage drop per annum in enrollment rate). Table A9 in Appendix A4, present similar estimations with higher age cutoffs of 11-18 and 12-18 years. Panels B and C of Table A9 indicate a stronger impact for children older than 10-18 years. These estimates suggest that, in 2002, the enrollment rates of children from agricultural households declined more severely than those from non-agricultural households because of conflicting academic and agricultural calendars.

In Columns (2) and (5) of Table 2, we introduce other time-variant controls (Thana-level annual weather characteristics and paddy yield variations, as well as the child's age squared to capture the natural change in education over time) along with individual- and household-level controls, as discussed earlier. The time-invariant variables interact with the 2002 dummy to control for heterogeneous trends. Despite these additional interaction terms, our main coefficient of interest indicates a similar level of impact with a similar level of precision. This is also true when we use different definitions of agricultural household (reported in column (5) in Table 2).

As discussed in Section 2.4, one issue may remain in our identification strategy that is worth further consideration. It is possible that we may be detecting impacts of time-varying productivity shocks (for example, due to weather variations) that may have increased labor demand in 2002. Although the aggregate production of *Aman* rice was not significantly different between the two waves of data, regional-level variation may have existed between these two rounds. To control for possible productivity differences, we use the year 2002 dummy for aggregate productivity shocks and the thana and year 2002 interaction terms for time-variant thana-level productivity shocks (controlling for thana-level fixed trends) as additional regressors, as reported in Columns (3) and (6) of Table 2, which are our richest specifications. Including these interaction terms does not affect the main coefficient of interest. In all specifications, $\hat{\gamma}$ has low p-values and shows the expected sign. From Columns (1) to (6), the point estimates of the year 2002 dummy with agricultural households range from 6.7 to 8.4 percentage points, and all estimates have p-values below 5%.

In Table 3, we estimate the impacts disaggregated by gender. In Columns (1)-(3), the boys' subsample indicates a stronger negative impact than that in Table 2. The conflicting calendar impact implies a -11.4 to -11.7 percentage point decline in enrollment rates for boys from agricultural households. Girls also shows negative point estimates; however, they are all statistically indistinguishable from zero (reported in Columns (4)-(6)).[32] Girls in agricultural and non-agricultural households tend to have similar enrollment rates in both years, and the difference in enrollment rate change is small. Boys from agricultural households have lower enrollment rates, and the reduction between 1999 and 2002 is greater.

This finding suggests that the effects observed in Table 2 mostly come from boys. This

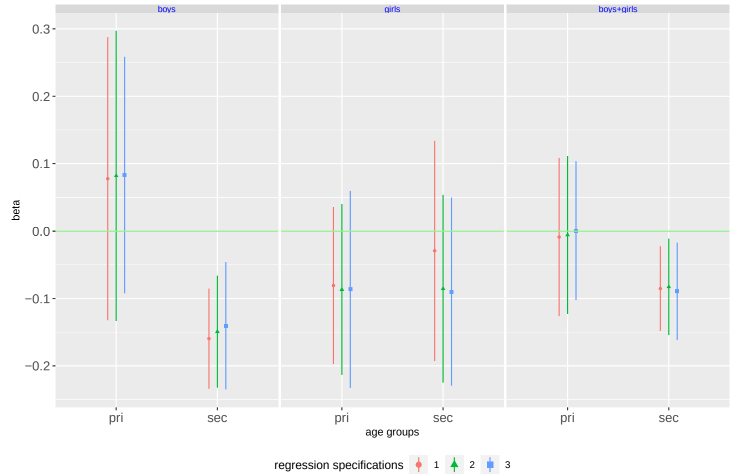
[32] We have qualitatively similar and quantitatively stronger results when we use the alternative, head-based agricultural household definition in Table A8 of the Appendix A3.

Table 3: Main regression estimates with 10-18 years old in 1999 (by gender)

	Boys			Girls		
	(1)	(2)	(3)	(4)	(5)	(6)
Agri HHs * year 2002	-0.1169^{**}	-0.1143^{**}	-0.1161^{**}	-0.0310	-0.0505	-0.0494
	(-0.200, -0.034)	(-0.185, -0.044)	(-0.189, -0.043)	(-0.168, 0.106)	(-0.187, 0.086)	(-0.187, 0.088)
	[-0.225, -0.009]	[-0.213, -0.016]	[-0.215, -0.017]	[-0.212, 0.150]	[-0.245, 0.144]	[-0.243, 0.144]
Demographic fixed trends	Yes	Yes	Yes	Yes	Yes	Yes
Other household fixed trends		Yes	Yes		Yes	Yes
Thana fixed trends			Yes			Yes
$\bar{R}^2$	0.3685	0.4078	0.4096	0.5911	0.6061	0.6101
N: Agricultural HHs	197	197	197	187	187	187
N	306	306	306	320	320	320
Mean of control in 1999	0.6396	0.6396	0.6396	0.7914	0.7914	0.7914
Mean of control in 2002	0.2944	0.2944	0.2944	0.4920	0.4920	0.4920

Source: Compiled from IFPRI data.
Source: Compiled from IFPRI data.
Notes:
1. Sample of direct offspring of household heads. Agri HHs * year 2002 is an interaction term of agricultural household dummy and year 2002 dummy. All the interaction terms are demeaned. Columns (1) and (4) use time-varying thana level characteristics (yield, mean rainfall, mean high temperature, mean low temperature) and individual level characteristics (age squared, recipient of a poverty program). Demographic fixed trends are interactions of baseline individual and demographic characteristics (sex of individual, household head's education, number of older male/female siblings) with the year 2002 dummy, and sex of individual with the year 2002 * agricultural household dummy. Parental education is highly collinear with agricultural household dummy and is dropped from triple interactions. Columns (2) and (5) add Other household fixed trends that are interactions of other baseline household characteristics (per member land holding, per member non-land assets, household condition (access water through pipe and having structured toilet at home). Columns (3) and (6) add Thana fixed trends, which allow heterogeneous trends at Thana level.
2. Standard errors are clustered at thana level. 95% confidence intervals of cluster robust standard errors using Liang and Zeger (1986) are shown in parenthesis, and bias-reduced linearization (BRL) for a correction of a small number of clusters are shown in square brackets. $*$, $**$, $***$ indicate significance levels at 10%, 5%, 1% under BRL cluster robust standard errors, respectively.

Figure 5: Impacts by age group, 1999-2002, 6-17 years old in 1999



Source: Compiled from IFPRI data.

Notes: 1. "pri" and "sec" mean enrolled in primary and secondary grades, aged 6-10 and 11-17 years in 1999, respectively. The coefficients are dummies for agri-HH $\times$ year 2002.

2. Specification 1 uses time-varying thana level characteristics (yield, mean rainfall, mean high temperature, mean low temperature), individual-level characteristics (age squared, recipient of a poverty program), and demographic fixed trends, which are the interactions of baseline individual and demographic characteristics (sex of individual, household head's education, number of older male/female siblings) with the year 2002 dummy and the year 2002 * agricultural household dummy. Specification 2 adds other household fixed trends that are the interactions of other baseline household characteristics (per-member land holding, per-member non-land assets, own piped water, and structured toilet). Specification 3 includes Thana's fixed trends.

3. Error bars are cluster standard errors at thana level with Satterthwaite correction.

supports the brawn-based interpretation by Pitt et al. (2012) that boys who are more productive in agricultural labor tend to get pulled out of school. Consistent with the interpretation, we see a greater dropout rate for boys from agricultural households when there is an exam-harvest overlap in school and agricultural calendars. To explore this in more detail, we estimate the impacts based on different age bandwidths, 10–18, 11–18, and 12–18 samples disaggregated by gender, as reported in Table A9 in Appendix A4. These estimates are consistent with our finding that the negative impact is more pronounced among older boys from agricultural households. In Figure 5, we provide graphical presentation estimates using a larger age range (6–17 years old) separated by primary grade age (6–10 years old in 1999) and secondary grade age (6–10 years old in 1999), with gender segregation (see results in Table A10 in Appendix A4). As one can notice, the negative impacts are observed only among secondary school-aged boys in our estimations.

Table 4: Placebo test results

	Agricultural household			Agri HH (head)		
	Panel A: 1999 cohort					
	(1)	(2)	(3)	(4)	(5)	(6)
Agri HHs * year 2006	−0.0181	−0.0202	−0.0290	−0.0122	−0.0198	−0.0308
	(-0.049, 0.013)	(-0.072, 0.031)	(-0.082, 0.024)	(-0.070, 0.045)	(-0.076, 0.036)	(-0.082, 0.020)
	[-0.062, 0.026]	[-0.099, 0.058]	[-0.113, 0.055]	[-0.087, 0.063]	[-0.097, 0.057]	[-0.104, 0.043]
$\bar{R}^2$	0.3073	0.3193	0.3262	0.3062	0.3196	0.3262
N	616	616	616	616	616	616
Mean of control in 2006	0.1425	0.1425	0.1425	0.1349	0.1349	0.1349
	Panel B: 2002 cohort					
	(7)	(8)	(9)	(10)	(11)	(12)
Agricultural HHs * year 2006	−0.0293	−0.0363	−0.0411	−0.0208	−0.0299	−0.0363
	(-0.098, 0.039)	(-0.116, 0.044)	(-0.127, 0.045)	(-0.094, 0.053)	(-0.103, 0.043)	(-0.112, 0.039)
	[-0.112, 0.053]	[-0.137, 0.065]	[-0.151, 0.069]	[-0.110, 0.068]	[-0.122, 0.062]	[-0.132, 0.059]
$\bar{R}^2$	0.2158	0.2312	0.2352	0.2148	0.2264	0.2301
N	812	812	812	812	812	812
Mean of control in 2006	0.2988	0.2988	0.2988	0.2955	0.2955	0.2955

Notes: 1. Sample of direct offspring of household heads. Agri HHs * year 2006 is an interaction term of agricultural household dummy and year 2006 dummy. All the interaction terms are demeaned. Columns (1) and (4) use time-varying thana level characteristics (yield, mean rainfall, mean high temperature, mean low temperature) and individual level characteristics (age squared, recipient of a poverty program). Demographic fixed trends are interactions of baseline individual and demographic characteristics (sex of individual, household head's education, number of older male/female siblings) with the year 2002 dummy, and sex of individual with the year 2002 * agricultural household dummy. Parental education is highly collinear with agricultural household dummy and is dropped from triple interactions. Columns (2) and (5) add Other household fixed trends that are interactions of other baseline household characteristics (per member land holding, per member non-land assets, household condition (access water through pipe and having structured toilet at home). Columns (3) and (6) add Thana fixed trends, which allow heterogeneous trends at Thana level.

2. Standard errors are clustered at thana level. 95% confidence intervals of cluster robust standard errors using Liang and Zeger (1986) are shown in parenthesis, and bias-reduced linearization (BRL) for a correction of a small number of clusters are shown in square brackets. $*$, $**$, $***$ indicate significance levels at 10%, 5%, 1% under BRL cluster robust standard errors, respectively.

6.2 Placebo tests

In this sub-section, we conduct placebo tests employing 2002–2006 panel data based on the fact that the 1999 favorable calendar returned to a normal (unfavorable) routine in 2002. Hence, the school enrollment rate should follow the common trend between the treatment and control groups. We test this using two cohorts: 10–18 years old in 1999 (1999 cohort) and 10–18 years old in 2002 (2002 cohort).

Table 4 provides the results of two sets of placebo tests. All regression specifications follow those of Table 2. In Panel A, we report the first placebo test with the same individuals (10-18 years old in 1999) with the later rounds of data. This also provides a validity check for the common trend assumption. Since there was no shift in the academic calendar between 2002 and 2006, we do not expect any differential impact on children from agricultural households in these years. Our coefficient of interest $\hat{\gamma}$ has a smaller point estimate relative to the main results with larger standard errors, leading to large p values.[33]

In the second set of placebo tests, we use 10-18-year-old in 2002 (2002 cohort). The results are provided in Panel B. All the estimates are negative but statistically indistinguishable from zero. The estimation results using the 2002 cohort gender subsamples are presented in Table A11 in Appendix A4. All of these results show large p values for the impact of the year 2006 interacted with agricultural households, lending support for our identification assumption under the DID setting.

6.3 Mechanisms

In Table 5, we examine the impacts on other outcomes as potential impact mechanisms related to enrollment continuation: The number of completed grades or grade progression in three years (between 1999-2002),[34] and the mean number of days absent from school in the past two months before the survey interview date (July-August 1999 and 2002). Both outcome measures are estimated for those enrolled in 1999 (panel A of Table 5) and those enrolled in both the 1999 and 2002 rounds (panel B of Table 5). Please note that the sample we used in these exercises is a selected sample containing only regular students; hence, the evidence generated here is suggestive and is likely to provide lower-bound estimates.

Columns (1)-(3) show the negative impacts on grade progression among children from agricultural households in 2002 when the academic calendar was unfavorable. This negative grade progression estimates range from -0.40 to -0.47 years during 1999-2001 (from the base of 2.37 years of progression by the non-agricultural household children), depending on the specification. In Columns (4)-(6) with the panel B sample, the estimates are similar, however

[33]The point estimates are all negative, indicating children from agricultural households tend to drop out earlier even when exam-harvest overlap is absent. Consistent with our brawn-based interpretation that female labor is not a perfect substitute for male labor to work in the field, we obtain negative estimates on the triple interaction terms of the number of older female siblings with p values ranging between 7.2% and 8.9%. This implies that children from agricultural households are naturally disadvantaged in schooling even if there is no change in exam-harvest overlap when the household demographic structure is unfavorable.

[34]Grade progression is defined as the difference in reported grades between 2002 and 1999 for individuals who are not out of school. Out-of-school individuals are those whose schooling is lower than grade 1, who are not enrolled in both 1999 and 2002 rounds, or who are not reporting a change in grade between 1999 and 2002.

smaller in magnitude, which is reasonable given that the sample used in panel A includes dropouts in 2002 who have fewer grade progressions. This implies that agricultural children plausibly struggle to get "passing" scores to continue academic progression, which could be related to inadequate learning owing to school absenteeism, particularly during the peak labor demand season.

Columns (7)–(9) present the cross-sectional estimates of the impacts on the average monthly absent days for students enrolled in both survey rounds. The sample consists of continuing school students and uses only the year 2002 cross-section. Our estimates indicate that children from agricultural households systematically missed more (about 28%) school days, on average, during July–August, which overlaps with the local *Aman* paddy plantation time (see section 2.2). Gender sub-sample estimation (not reported but available on request) shows this absenteeism impact predominantly comes from boys. On average, boys from agricultural households missed school about 2.3-2.6 days more per month in 2002 during the plantation time (from the base of 2.5 absent days for non-agriculture household students, an increment equivalent to 92-100%). Taken together, these results suggest that learning, if measured by regular school attendance, is affected by local agricultural activities. This provides plausible evidence that absenteeism hinders grade progression and school continuation, particularly when the annual exam is held during the harvesting season.

6.4 Testing for alternative mechanisms

In Table 6, we report two tests to check the plausibility of alternative mechanisms that are consistent with the estimated results: one with non-Muslims and the other with floods-affected areas.

It is possible that our estimates primarily capture the impact of fasting and festivities during *Ramadan*, which may diminish children's capacity to learn and pass annual exams. To verify this empirically, we compare Muslim and non-Muslim households. As non-Muslims do not fast and are less prone to be affected by festivities, this exercise helps us disentangle

TABLE 5: GRADE PROGRESSION AND ABSENT DAYS

	Grade progression			Absent days per month		
Panel A: Enrolled in 1999 survey round						
	(1)	(2)	(3)			
Agricultural HHs * year 2002	-0.4139^{**} (-0.694, -0.134) [-0.761, -0.067]	-0.4667^{**} (-0.761, -0.172) [-0.840, -0.093]	-0.3977^{**} (-0.710, -0.086) [-0.795, -0.001]			
Demographic fixed trends	Yes	Yes	Yes			
Household fixed trends		Yes	Yes			
Thana fixed trends			Yes			
$\bar{R}^2$	0.2435	0.2657	0.2863			
N	393	393	393			
Mean of control in 1999	5.0504	5.0504	5.0504			
Mean of control in 2002	7.4202	7.4202	7.4202			
Panel B: Enrolled in both 1999 and 2002 survey rounds						
	(4)	(5)	(6)			
Agricultural HHs * year 2002	-0.3268^{**} (-0.583, -0.071) [-0.636, -0.018]	-0.3472^{**} (-0.564, -0.131) [-0.622, -0.072]	-0.2422^{*} (-0.454, -0.030) [-0.503, 0.018]			
Demographic fixed trends	Yes	Yes	Yes			
Household fixed trends		Yes	Yes			
Thana fixed trends			Yes			
$\bar{R}^2$	0.1621	0.1947	0.2347			
N	260	260	260			
Mean of control in 1999	5.2025	5.2025	5.2025			
Mean of control in 2002	7.2883	7.2883	7.2883			
Panel C: Panel B sample observed in 2002 survey round (cross section)						
				(7)	(8)	(9)
Agricultural HHs				1.1393^{**} (0.325,1.954) [0.117, 2.162]	1.1088^{**} (0.368, 1.849) [0.114, 2.104]	1.0590^{**} (0.315,1.802) [0.040, 2.078]
Demographic fixed trends				Yes	Yes	Yes
Household fixed trends					Yes	Yes
Thana fixed trends						Yes
$\bar{R}^2$				0.0492	0.0525	0.0528
N				263	263	263
Mean of control in 2002				3.75	3.75	3.75

Source: Compiled from IFPRI data.

Notes: 1. Sample of direct offspring of household heads. Agri HHs * year 2002 is an interaction term of agricultural household dummy and year 2002 dummy. All the interaction terms are demeaned. Columns (1),(4) and (7) use time-varying thana level characteristics (yield, mean rainfall, mean high temperature, mean low temperature) and individual level characteristics (age squared, recipient of a poverty program). Demographic fixed trends are interactions of baseline individual and demographic characteristics (sex of individual, household head's education, number of older male/female siblings) with the year 2002 dummy and sex with the year 2002 * agricultural household dummy. Parental education is highly collinear with agricultural household dummy and is dropped from triple interactions. Columns (2), (5) and (8) add Other household fixed trends that are interactions of other baseline household characteristics (per member land holding, per member non-land assets, household condition (access water through pipe and having structured toilet at home). Columns (3),(6) and (9) add Thana fixed trends, which allow heterogeneous trends at the Thana level. Columns (7)-(9) use only 2002 data.

2. Standard errors are clustered at thana level. 95% confidence intervals of cluster robust standard errors using Liang and Zeger (1986) are shown in parenthesis, and bias-reduced linearization (BRL) for a correction of a small number of clusters are shown in square brackets. $*$, $**$, $***$ indicate significance levels at 10%, 5%, 1% under BRL cluster robust standard errors, respectively.

Table 6: Testing for confounding mechanisms

	Non-Muslims			Flooded areas		
	(1)	(2)	(3)	(4)	(5)	(6)
Agri HHs * year 2002	-0.0676^{**}	-0.0763^{**}	-0.0772^{**}	-0.0618^{**}	-0.0718^{**}	-0.0727^{**}
	(-0.114, -0.021)	(-0.128, -0.025)	(-0.128, -0.026)	(-0.108, -0.015)	(-0.123, -0.021)	(-0.122, -0.023)
	[-0.128, -0.008]	[-0.150, -0.003]	[-0.148, -0.006]	[-0.124, 0.001]	[-0.148, 0.004]	[-0.147, 0.001]
Agri HHs * year 2002						
* Non-Muslim	0.0416	0.0297	0.0262			
	(-0.077, 0.160)	(-0.090, 0.149)	(-0.097, 0.149)			
	[-0.196, 0.279]	[-0.195, 0.255]	[-0.215, 0.268]			
Agri HHs * year 2002						
* Flooded				0.0042	0.0293	0.0269
				(-0.075, 0.083)	(-0.055, 0.114)	(-0.063, 0.117)
				[-0.111, 0.119]	[-0.100, 0.159]	[-0.111, 0.164]
Demographic fixed trends	Yes	Yes	Yes	Yes	Yes	Yes
Other household fixed trends		Yes	Yes		Yes	Yes
Thana fixed trends			Yes			Yes
$\bar{R}^2$	0.4695	0.4860	0.4865	0.4684	0.4843	0.4846
N	626	626	626	626	626	626
Mean of control in 2002	0.3906	0.3906	0.3906	0.3906	0.3906	0.3906

Source: Compiled from IFPRI data.

Notes: 1. Sample of direct offspring of household heads. Columns (1) and (4) use time-varying thana level characteristics (yield, mean rainfall, mean high temperature, mean low temperature) and individual level characteristics (age squared, recipient of a poverty program). Demographic fixed trends are interactions of baseline individual and demographic characteristics (sex of individual, household head's education, number of older male/female siblings) with the year 2002 dummy, and sex of individual with the year 2002 * agricultural household dummy. Parental education is highly collinear with agricultural household dummy and is dropped from triple interactions. Columns (2) and (5) add Other household fixed trends that are interactions of other baseline household characteristics (per member land holding, per member non-land assets, household condition (access water through pipe and having structured toilet at home). Columns (3) and (6) add Thana fixed trends, which allow heterogeneous trends at Thana level. Flooded is 1 for Haziganj, Modhupur, Sherpur sadar thanas. Other covariates include interaction terms unflooded/nonmuslim * year 2002.

2. Standard errors are clustered at thana level. 95% confidence intervals of cluster robust standard errors using Liang and Zeger (1986) are shown in parenthesis, and bias-reduced linearization (Satterthwaite correction) for a correction of the small number of clusters are shown in square brackets. $*$, $**$, $***$ indicate significance levels at 10%, 5%, 1% under cluster robust standard errors, respectively.

the impact of festivities. Columns (1)–(3) of Table 6 presents estimates using a non-Muslim dummy and its interaction with the year 2002 and the year 2002*agricultural household. We can observe that our main coefficient of interest does not differ from those in Table 2. For non-Muslims, the statistically imprecise point estimates suggest that *Ramadan* before the exam in 2002, fasting before the final exams, and post-*Ramadan* festivities are not plausible mechanisms leading to lower enrollment rates for children from agricultural households.

Another possible confounding mechanism that can explain the estimated results is the impact of a natural disaster that systematically affected agricultural households in 2002. If this is true, then our estimates capture the impact of natural disasters on school dropouts. In 2002, several districts were affected by the monsoon flash floods.[35] Columns (4)-(6) of Table 6

[35] Flood-affected districts were Chandpur, Sherpur and Tangail. To know more about the flood monsoon based flash flood, please check the following website `https://reliefweb.int/report/bangladesh/bangladesh-monsoon-floods-2004-post-flood-needs-assessment-summary-report`

assess the effects of flooding using a dummy variable of flooded areas and its interaction with the year 2002, and triple interaction with the year 2002 * agricultural household. The triple interaction of flood-affected areas with agricultural households and the year 2002 dummy indicate no statistically discernible impact, suggesting that natural disasters such as floods are not plausible impact mechanisms.

7 Long-term Cohort analysis in Bangladesh

Table 7 reports the estimates of equation 3 using a cohort analysis. Column (1) of Panel A reports the regression estimates for years of education. We noticed that the rural population had less schooling than the urban counterpart, which is a common trend in developing countries. Nevertheless, the negative effect on Rural children was significantly lessened in the 10-18 cohort relative to the older cohort. Our estimates indicate that holding all other things constant, the urban-rural enrollment gap has shrunk by 0.46 years for the 10-18-year-old cohort of 1999. This impact is sizable and ~~statistically significant~~has a low p value. In Panel B, we disaggregate the age bracket into 10-12, 13-15, and 16-18 years old in 1999. Our estimates are consistent, as shown in Panel A, and the impact is greater for the secondary school age (10-12 and 13-15 years old in 1999) in rural areas.

Columns (2)–(4) provide the estimates of the probit regression for different stages of academic qualification, namely Primary, Secondary, and Higher Secondary. Our estimates indicate that the probability of completing primary, secondary, and higher secondary education increased by approximately 5.3, 5.3, and 3.4 percentage points, respectively, for the 10–18-year-old rural cohort in 1999 compared to the base. In Panel B, we similarly disaggregate the age brackets and, consistent with the previous finding, observe that secondary school-aged children benefited the most from this exogenous shift in the examination calendar. To test the robustness of our analysis, we use age-specific interaction with rural dummies, which are reported in Table A14 in Appendix A4. As we can see from Table A14

Table 7: **Cohort Analysis: Aged 10-27 in 1999**

Variables	**Years of Education**	**Primary**	**Secondary**	**Higher Secondary**
Estimation:	**OLS**	**Probit (Marginal Effects)**		
	(1)	(2)	(3)	(4)
Panel A:				
Cohort: Aged 10-18 in 1999	4.278***	0.396***	0.366***	0.317***
	(0.119)	(0.0110)	(0.0113)	(0.00957)
(Aged 10-18 in 1999) X (Rural)	0.462***	0.0532***	0.0531***	0.0334***
	(0.112)	(0.0106)	(0.0106)	(0.00859)
Rural	-2.155***	-0.164***	-0.199***	-0.160***
	(0.174)	(0.0153)	(0.0137)	(0.0105)
Panel B:				
Age 10-12 in 1999	4.188***	0.381***	0.359***	0.312***
	(0.137)	(0.0136)	(0.0116)	(0.0103)
Age 13-15 in 1999	2.322***	0.253***	0.159***	0.146***
	(0.141)	(0.0122)	(0.0124)	(0.0104)
Age 16-18 in 1999	1.414***	0.0796***	0.0197	0.151***
	(0.135)	(0.0140)	(0.0136)	(0.0118)
(Age 10-12 in 1999) X (Rural)	0.587***	0.0718***	0.0628***	0.0401***
	(0.139)	(0.0141)	(0.0118)	(0.0103)
(Age 13-15 in 1999) X (Rural)	0.773***	0.0825***	0.0730***	0.0374***
	(0.141)	(0.0139)	(0.0135)	(0.00981)
(Age 16-18 in 1999) X (Rural)	-0.0272	0.000236	0.0185	0.0201
	(0.143)	(0.0155)	(0.0156)	(0.0134)
Rural	-2.155***	-0.164***	-0.199***	-0.160***
	(0.174)	(0.0152)	(0.0137)	(0.0105)
Mean of older cohort: aged 19-27 in 1999	4.31	0.46	0.27	0.15
Mean of older sub-cohort: aged 19-21 in 1999	4.61	0.50	0.29	0.15
Mean of older sub-cohort: aged 22-24 in 1999	4.23	0.45	0.26	0.15
Mean of older sub-cohort: aged 25-27 in 1999	3.93	0.42	0.25	0.14
Other Control	Yes	Yes	Yes	Yes
District Control	Yes	Yes	Yes	Yes
District $\times$Age Control	Yes	Yes	Yes	Yes
Observations	49165	49129	49128	48987

Source: Compiled from the HIES 2016 data. Notes: 1. Standard errors are clustered at *district* level are reported in parentheses. $*$, $**$, $***$ indicate significance levels at 10%, 5%, 1%, respectively. 2. Regression estimates control for cohort of birth dummy, sex, district and cohort of birth dummy interactions, and religion.

the impact is predominantly limited to 10-15 years of age in 1999, who got the full impact exposure of the academic calendar shift. Older students also benefited, however, only partially and limited to higher secondary completion, as expected.

To understand the economic return of this impact, we estimate the private return of education by employing Mincer's (1974) regression following Montenegro and Patrinos (2014).

We utilize HIES 2016 data for this estimation (reported in Table A16 in Appendix A4). Based on this framework, we regress the natural logarithm of annual wage earnings on years of education, age, age squared, sex, location (rural or urban), and regional dummies (district level) with standard errors clustered at the district level.[36] We find that the economic return from an additional year of education is approximately 6.6 percent. This is consistent with Montenegro and Patrinos (2014) estimates on Bangladesh, which reported an internal rate of return of 5.9 (using estimates of the year 2000) for each additional year of schooling.

Plugging our cohort estimates into the education rate of return calculation indicates that shifting the academic calendar in favor of agricultural households led to an increase of about 3.03 percent in wages (or 2.71 percent if we use Montenegro and Patrinos (2014) estimate). This estimated economic return is comparable to other education-related interventions, such as the Conditional Cash Transfer (CCT) program in Mexico.

8 Estimates using India sample

As mentioned in the introduction, the impact of the seasonal agricultural harvesting period overlapping with the school academic session (particularly the grade completing exam) is an issue faced by several developing countries, particularly agriculture-dominated ones. To check the cogency of this claim, one can conduct an exercise with data from other countries with similar settings. One promising country to conduct such an analysis is India, a country neighboring Bangladesh, where agriculture is the dominant economic sector. Like Bangladesh, India also faces large school dropout rates.

In India, the state-supported public school system is the primary education provider. These state-supported schools are governed by state-level academic calendars in which some states follow academic sessions from January to December, similar to Bangladesh. However, most states follow different academic calendars depending on their locality, history, and

[36]The regression specification used for individual i in district j is the following: $Log(Income)_{i,j} = \beta_1 Education_{i,j} + \beta_2 Age_{i,j} + \beta_3 Age^2_{i,j} + \beta_4 Male_{i,j} + \beta_5 Urban_i + \delta_j + e_{i,j}$.

climatic conditions (e.g., monsoon). Consequently, the academic calendars of most states, particularly the timing of annual exams, overlap with those of the primary crop-harvesting period.

Consider *Madhya Pradesh* as an example, where wheat is the dominant crop of the state. The final examination of the public schools in *Madhya Pradesh* is in March, which overlaps with the wheat harvesting season between February and April. However, several states, such as *Bihar*, experience no such overlap since the dominant crop of the state is rice, which is harvested between September and November, whereas the final examinations are scheduled for March. Hence, we can utilize state-wise academic calendar variations to detect the impact of such an overlap on school continuation for children from agricultural households. This impact mechanism is slightly different from that of the Bangladesh setting, as it tests the cumulative effect of overlapping with examinations on educational attainment, not the one-time impact of the exam shift. However, one should note that this analysis may be non-causal as it requires strong assumptions that the state-level placement of school calendars in India is quasi-random. Nevertheless, the following India analysis provides more suggestive evidence for the external validity of the Bangladesh findings.

To do this analysis, we first generate Table A17 of the Appendix, where we report state-specific dominant crops and their harvesting seasons for India, coupled with school academic sessions, final exam timing, and whether there is an overlap with the harvesting and academic calendar.[37] In Table A17, state-wise agricultural information is obtained from Government of India (GOI, 2017) while academic session information has been taken from the GOI (2014). Second, we employ the panel version of the Indian Human Development Survey (IHDS) data collected in 2004-05 and 2011-12.[38] We begin with those interviewed in both rounds of IHDS (N=150,988) to form the balanced panel. Unlike most education surveys, the IHDS collects information on a range of variables, such as details on children's education, landholding,

[37]We could not use Chandigarh and Sikkim in our analysis due to data limitation.

[38]IHDS-1 interviewed 41,554 households (215,774 individuals) in 1503 villages and 971 urban neighborhoods across India. The second phase of the survey re-interviewed most of the households (N=42152) in 2011-12. To link the dataset from both rounds, we follow the instructions given on the IHDS website.

employment, and economic status. To aid our analysis, we merge other variables, such as rainfall, the area under crops, and major cereal production, with the IHDS data. We obtained state-wise rainfall and cereal production information from the Indian Meteorological Department (IMD) and the Directorate of Economics and Statistics, Government of India (GoI), respectively.

For our analysis, we consider only those children who enrolled in school during the first round of the IHDS survey and were within the age range of 6-14 (and also 5-13 years for robustness checks).[39] To identify agricultural households, we generate an agriculture dummy that takes the value of one if the household head is employed in the agricultural sector during the baseline, as classified in the IHDS survey. We defined an "overlap-state" dummy where the harvesting time of the major crop overlaps with the annual school final exam based on Table A17 in Appendix A3.[40] We consider only the harvesting period of the dominant crop produced in the state, defined by the maximum share of the gross cropped area allotted to that crop. Information on the academic sessions in different states is gathered from the Ministry of Human Resource Development of the GoI. Table A18 in Appendix A3 presents the descriptive statistics of the Indian sample in our study.

We estimate the impact of the state-specific overlapping calendar on school continuation using triple-difference regressions, in which one difference is taken between agricultural and non-agricultural households, one between overlapping and non-overlapping states, and the other between the two survey rounds. Here, the household type and overlapping state dummies are time-invariant by definition.

Specifically, we use a triple-difference specification where $Enroll_{iht}$ is a binary variable indicating enrollment status for individual i, located in household h in period t. Similarly,

[39] Unlike Bangladesh analysis, we could not use age 10-18 as our age cutoff given the difference between the two survey waves is seven years. According to the Eighty-Sixth Amendment Act (2002), the constitution of India provides free and compulsory education to all children in the age group of six to 14 years as a fundamental right.

[40] One caveat is *Kerala* where the major crop is rubber, which does not have a harvesting season in the conventional sense; hence we have taken rice (the second largest crop) as the representative crop for the state.

$YrEdu_{iht}$ captures completed years of education for an individual i, in household h in period t. X_{iht} are covariates and $Year2011_{iht}$ is the Year 2011 dummy. We estimate the following two equations as fixed-effect estimators with household fixed effect, where ε is the error term clustered at the household level. Our main coefficient of interest is a_4 which estimates the triple difference variable of $Year2011_{iht} \times \text{Overlapping-State}_{ih} \times \text{Agri}_{ih}$ in both equations 4 and 5 are given below.

$$\begin{aligned} Enroll_{iht} &= a_1 Year2011_{iht} + a_2 Year2011_{iht} \times \text{Agri}_{ih} \\ &+ a_3 \text{Year2011}_{iht} \times \text{Overlapping-State}_{ih} \\ &+ a_4 Year2011_{iht} \times \text{Overlapping-State}_{ih} \times \text{Agri}_{ih} \\ &+ a_5 X_{iht} + \varepsilon_{ht}, \end{aligned} \tag{4}$$

$$\begin{aligned} YrEdu_{iht} &= a_1 Year2011_{iht} + a_2 Year2011_{iht} \times \text{Agri}_{ih} \\ &+ a_3 \text{Year2011}_{iht} \times \text{Overlapping-State}_{ih} \\ &+ a_4 Year2011_{iht} \times \text{Overlapping-State}_{ih} \times \text{Agri}_{ih} \\ &+ a_5 X_{iht} + \varepsilon_{ht}. \end{aligned} \tag{5}$$

Table 8 represents the regression estimates based on Equation 4. Column (1) reports the estimates of the triple-difference estimator for enrollment with 5-13 years old in 2004. As we can observe, the 2011 dummy and agricultural household interaction with the 2011 dummy indicates negative impacts on enrollment, demonstrating the natural dropout trend and vulnerability of poor agricultural household students.

After controlling for these effects, we see a sizable negative impact on enrollment in 2011 for agricultural household children who were in schools in the overlapping states relative to agricultural households in non-overlapping states or non-agricultural households in overlap-

Table 8: **Estimates with India Data**

Dependent Variable:	Enrollment		Years of Education	
Age group:	5-13 in 2004	6-14 in 2004	5-13 in 2004	6-14 in 2004
	(1)	(2)	(3)	(4)
Year 2011	-0.131***	-0.139***	4.018***	3.878***
	(-0.0322)	(-0.0315)	(-0.156)	(-0.157)
(Agri) X (Yr 2011)	-0.0456***	-0.0558***	-0.106	-0.144**
	(-0.0133)	(-0.0136)	(-0.0672)	(-0.0669)
(Overlapping state) X (Yr 2011)	-0.0236	-0.0283*	0.113	0.0678
	(-0.0152)	(-0.0157)	(-0.083)	(-0.0825)
(Overlapping state) X (Agri) X (Yr 2011)	-0.0655***	-0.0543**	-0.214*	-0.221*
	(-0.022)	(-0.0225)	(-0.113)	(-0.113)
Other Household level Control	Yes	Yes	Yes	Yes
District Control	Yes	Yes	Yes	Yes
Observations	18922	19184	18922	19184
R-Square (within)	0.428	0.452	0.86	0.856
Mean of control group in 2011	0.72	0.69	8	8.24

Source: Compiled from IHDS 2004-05 and 2011-12 data. Notes: 1. Regression estimated using a panel fixed effect estimator with standard errors clustered at the household level.. $*$, $**$, $***$ indicate significance levels at 10%, 5%, 1%, respectively. 2. We used the nuclear households. The regression estimates control for time-variant covariates: Age, age squared, parents' age, education, and the number of household assets. We also control for major state-level crop yields, agricultural areas, and rainfall. 3. Time-invariant variables interact with the year 2011. An agricultural household is an indicator variable for a household whose primary occupation is agriculture. Overlapping State is an indicator variable of the states in which the major harvesting crop of the state overlaps with the schools' annual exam period.

ping states. This impact is ~~highly statistically significant~~estimated precisely, causing about a 6.55 percent decline in enrollment from the mean. We use a different age bandwidth (age 6-14 years old in 2004) in columns (2) of Table 8, which show similar estimates. Given India's population, this estimate is sizable, causing millions of children to discontinue their schooling due to the academic calendar conflicting with the local agricultural cycle.

Columns (3) and (4) of Table 8 present the estimates of equation 5 with years of education as a dependent variable and find similar negative impacts, about 0.20 to 0.22 years of fewer schooling between surveys for agricultural households in overlapping states relative to agricultural households in non-overlapping states or non-agricultural households in overlapping states — supporting our findings with Bangladesh data. However, caution should be exercised in interpreting these results as we do not know the final years of school attainment; these students may be in school at the time of the survey (and students who lag behind may also be able to catch up with time).

9 Conclusion

Seasonality in agrarian societies is an important issue that must be addressed appropriately to formulate effective public policies. Surprisingly, seasonally adjusted policies outside the context of food security and disaster management are rare. Educational reforms in developing countries often focus on teacher incentives, technology adoption, and better curriculum design; however, the adjustment of the academic calendar has not received due attention. This issue is becoming increasingly important as developing countries aim for greater outreach of universal education and education-related Sustainable Development Goals (SDGs), which require precise targeting for rural school-going children.

This study addresses the impact of seasonal labor demand on school continuation in South Asia. The school calendars for both primary and secondary schools in Bangladesh are not seasonally adjusted for local agricultural cycles, whereas in India, some state school calendars are not designed to accommodate the primary crop harvesting period. We empirically assessed the impact of such overlaps between school exams and harvest periods using a panel data from rural Bangladesh. Our estimates indicate that children from agricultural households benefited significantly from school continuation owing to a favorable off-harvest exam schedule in Bangladesh. In other words, a favorable annual examination schedule away from the harvest season helped school children from agricultural households continue their schooling in 1999. However, there was a substantial decline in enrollment due to the typical unfavorable examination schedule that overlaps with harvesting, which was observed in 2002. Exploiting state-level academic calendar variations, we conducted a complementary analysis of school-enrolled children in India and found supporting evidence on this issue.

Employing a nationally representative household survey, we estimated that this temporary favorable shift in the exam calendar for the 10-18-year-old rural cohort increased years of education by 0.46 years in Bangladesh. Moreover, these additional years of education have a substantial economic return of a 3 percent increase in income. To benchmark this effect, the pioneering CCT program of Mexico, "Progresa-Oportunidades" yielded 0.66 additional years of schooling for every eight years of participation in the program (Reimers et al., 2006), while our favorable calendar shift continued for three years. Infrastructural interventions such as large-scale school construction programs in Indonesia yielded an increase of 0.12-0.19 years of education and 3 to 5.4 percent economic return (Duflo, 2001). Compared to these interventions, fixing the academic calendar to avoid seasonal labor demand appears to be a cost-effective intervention with a sizable return.

Beyond seasonality, ample factors hamper education performance in developing countries. However, adjusting school calendars to accommodate local agrarian calendars can reduce the dilemma faced by children from agricultural households. Moreover, such an adjustment involves a relatively small one-off cost for the curriculum change. The United Kingdom implemented a seasonally adjusted school calendar during World War II, and the impacts were favorable, although the results were anecdotal (Moore-Colyer, 2004, 190-191). In early 20th-century Japan, the school calendar was adjusted to accommodate daytime work hours, and some students were allowed to attend night school or take shorter courses (Institute for International Cooperation, 2004, Chapter 3). Even in Bangladesh, non-formal education providers, primarily non-governmental organizations (NGOs), have taken necessary steps to adjust school calendars according to seasonality. For instance, schools run by BRAC, a leading NGO, have begun to use a seasonally adjusted school calendar for non-formal education in Bangladesh.

One can reasonably argue that providing a well-targeted subsidy akin to the CCT is a way to achieve the goal of retaining children from agricultural households in schools. Policymakers may also consider alternative measures, such as targeted CCT during the peak labor demand season, to reduce the pull factor for children from poor agricultural households. However, we argue that a school calendar adjusted for local economic activities is advisable as a policy suggestion for two important reasons. First, children's time use is never dichotomous of schooling or working; on the contrary, a substantial number of children are required to do both, at least in periods of rising seasonal labor demand, such as during harvesting. This reflects the fact that eliminating profitable activities may be costly. Second, adjusting the school calendar to accommodate seasonality is a relatively less expensive and easier administrative solution than providing a well-targeted subsidy. Given these considerations, we expect the results of our empirical analysis to provide a foundation for school calendar reforms that benefit children in agrarian economies, such as Bangladesh, India, and other countries globally.

References

Abadie, A., S. Athey, G. W. Imbens, and J. M. Wooldridge (2023): "When should you adjust standard errors for clustering?" The Quarterly Journal of Economics, 138, 1–35.

Ahmed, A. U. and C. Del Ninno (2002): "The food for education program in Bangladesh: An evaluation of its impact on educational attainment and food security," Tech. rep.

Akabayashi, H. and G. Psacharopoulos (1999): "The tradeoff between child labour and human capital formation: A Tanzanian case study," Journal of Development Studies, 35, 120–140.

Almond, D. and B. Mazumder (2011): "Health Capital and the Prenatal Environment: The Effect of Ramadan Observance during Pregnancy," American Economic Journal: Applied Economics, 3, 56–85.

Anderson, D. M. and M. B. Walker (2015): "Does shortening the school week impact student performance? Evidence from the four-day school week," Education Finance and Policy, 10, 314–349.

Andvig, J. C., S. Canagarajah, and A. Kielland (1999): "Child labor in Africa: The issues," Unpublished mimeo. World Bank, Social Protection Sector.

Atkin, D. (2016): "Endogenous skill acquisition and export manufacturing in Mexico," American Economic Review, 106, 2046–2085.

Baland, J.-M. and J. A. Robinson (2000): "Is Child Labor Inefficient?" Journal of Political Economy, 108, 663–679.

BBS, Ÿ. (2003a): "Child Labour Survey Bangladesh 2013," Dhaka, Bangladesh: BBS.

——— (2003b): "Report on National Child Labour Survey 2002–2003," Dhaka, Bangladesh: BBS.

Beegle, K., R. H. Dehejia, and R. Gatti (2006): "Child labor and agricultural shocks," Journal of Development Economics, 81, 80–96.

Behrman, J. R., A. D. Foster, M. R. Rosenzweig, and P. Vashishtha (1999): "Women's Schooling, Home Teaching, and Economic Growth," The Journal of Political Economy, 107, pp. 682–714.

Bell, R. M. and D. F. McCaffrey (2002): "Bias reduction in standard errors for linear regression with multi-stage samples," Survey Methodology, 28, 169–182.

Bhalotra, S. and C. Heady (2003): "Child farm labor: The wealth paradox," The World Bank Economic Review, 17, 197–227.

Burke, M., L. F. Bergquist, and E. Miguel (2019): "Sell low and buy high: arbitrage and local price effects in Kenyan markets," The Quarterly Journal of Economics, 134, 785–842.

Campante, F. R. and D. H. Yanagizawa-Drott (2013): "Does Religion Affect Economic Growth and Happiness? Evidence from Ramadan," Working Paper 19768, National Bureau of Economic Research.

Canay, I. A., A. Santos, and A. M. Shaikh (2021): "The wild bootstrap with a "small" number of "large" clusters," The Review of Economics and Statistics, 103, 346–363.

Carrell, S. E., T. Maghakian, and J. E. West (2011): "A's from Zzzz's? The causal effect of school start time on the academic achievement of adolescents," American Economic Journal: Economic Policy, 3, 62–81.

Case, A. and C. Ardington (2006): "The impact of parental death on school outcomes: Longitudinal evidence from South Africa," Demography, 43, 401–420.

Colclough, C., P. Rose, and M. Tembon (2000): "Gender inequalities in primary schooling: The roles of poverty and adverse cultural practice," International Journal of Educational Development, 20, 5–27.

Cortes, K. E., J. Bricker, and C. Rohlfs (2012): "The role of specific subjects in education production functions: Evidence from morning classes in Chicago public high schools," The BE Journal of Economic Analysis & Policy, 12.

De, A. and C. S. Mehra (2016): "Estimating the Number of Out-of-School Children: Methodological Problems and Alternative Approaches-India Case Study," .

De Janvry, A., M. Fafchamps, and E. Sadoulet (1991): "Peasant household behaviour with missing markets: some paradoxes explained," The Economic Journal, 101, 1400–1417.

de Janvry, A., F. Finan, E. Sadoulet, and R. Vakis (2006): "Can conditional cash transfer programs serve as safety nets in keeping children at school and from working when exposed to shocks?" Journal of Development Economics, 79, 349 – 373.

Dillon, B. (2021): "Selling crops early to pay for school A large-scale natural experiment in Malawi," Journal of Human Resources, 56, 1296–1325.

Duflo, E. (2001): "Schooling and labor market consequences of school construction in Indonesia: Evidence from an unusual policy experiment," American economic review, 91, 795–813.

Dumas, C. (2012): "Does Work Impede Child Learning? The Case of Senegal," Economic Development and Cultural Change, 60, 773–793.

Edmonds, E. V. (2007): "Chapter 57 Child Labor," in Handbook of Development Economics, ed. by T. P. Schultz and J. A. Strauss, Elsevier, vol. 4 of Handbook of Development Economics, 3607 – 3709.

Edwards, F. (2012): "Early to rise? The effect of daily start times on academic performance," Economics of Education Review, 31, 970–983.

Elsayed, A. and O. Marie (2021): "Less school (costs), more (female) education? Lessons from Egypt reducing years of compulsory schooling," .

Fujii, T., C. Ho, R. Ray, and A. Shonchoy (2019): "Incentivizing School Attendance in Bangladesh: A Loss Aversion Conditional Cash Transfer Design," AEA RCT Registry.

GOI (2014): "Selected Information on School Education 2011-12," .

——— (2017): "Agricultural statistics at a glance 2017," .

Graves, J. (2010): "The academic impact of multi-track year-round school calendars: A response to school overcrowding," Journal of urban Economics, 67, 378–391.

Gunnarsson, V., P. F. Orazem, and M. A. Sánchez (2006): "Child Labor and School Achievement in Latin America," The World Bank Economic Review, 20, 31–54.

Hadley, S. (2010): "Seasonality and Access to Education: the case of primary education in Sub-Saharan Africa," CREATE Pathways to Access Monograph, 31.

Heady, C. (2003): "The Effect of Child Labor on Learning Achievement," World Development, 31, 385 – 398.

Hinrichs, P. (2011): "When the bell tolls: The effects of school starting times on academic achievement," Education Finance and Policy, 6, 486–507.

Imbens, G. W. and M. Kolesár (2016): "Robust standard errors in small samples: Some practical advice," The Review of Economics and Statistics, 98, 701–712.

Institute for International Cooperation (2004): The History of Japan's Educational Development: What implications can be drawn for developing countries today, Tokyo, Japan: Japan International Cooperation Agency.

Jacoby, H. G. and E. Skoufias (1997): "Risk, Financial Markets, and Human Capital in a Developing Country," The Review of Economic Studies, 64, 311–335.

Jensen, R. (2000): "Agricultural Volatility and Investments in Children," American Economic Review, 90, 399–404.

Kadzamira, E. and P. Rose (2003): "Can free primary education meet the needs of the poor?: evidence from Malawi," International journal of educational development, 23, 501–516.

Kono, H., Y. Sawada, and A. S. Shonchoy (2018): "Primary, secondary, and tertiary education in Bangladesh: achievements and challenges," Economic and Social Development of Bangladesh: Miracle and Challenges, 135–149.

Laborte, A. G., M. A. Gutierrez, J. G. Balanza, K. Saito, S. J. Zwart, M. Boschetti, M. Murty, L. Villano, J. K. Aunario, R. Reinke, et al. (2017): "RiceAtlas, a spatial database of global rice calendars and production," Scientific data, 4, 1–10.

Liang, K.-Y. and S. L. Zeger (1986): "Longitudinal data analysis using generalized linear models," Biometrika, 73, 13–22.

McMullen, S. C. and K. E. Rouse (2012): "The impact of year-round schooling on academic achievement: Evidence from mandatory school calendar conversions," American Economic Journal: Economic Policy, 4, 230–52.

Montenegro, C. E. and H. A. Patrinos (2014): Comparable estimates of returns to schooling around the world, The World Bank.

Moore-Colyer, R. (2004): "Kids in the Corn: School Harvest Camps and farm labour supply in England, 1940–1950," The Agricultural History Review, 183–206.

Oosterbeek, H. and B. van der Klaauw (2013): "Ramadan, fasting and educational outcomes," Economics of Education Review, 34, 219–226.

Pitt, M. M., M. R. Rosenzweig, and M. N. Hassan (2012): "Human capital investment and the gender division of labor in a brawn-based economy," American economic review, 102, 3531–60.

Pustejovsky, J. E. and E. Tipton (2018): "Small-sample methods for cluster-robust variance estimation and hypothesis testing in fixed effects models," Journal of Business & Economic Statistics, 36, 672–683.

Rahman, A. and R. Islam (1988): "Labour use in rural Bangladesh—an empirical analysis," The Bangladesh development studies, 1–40.

Rahman, A., S. Spaulding, K. Tietjen, F. Afroze, F. A. M. R. Al Azad, I. A. wlia Chowdhury, P. S. Ghosh, and S. Nizam (2004): "Bangladesh Educational Assessment, Time to Learn: Teachersï¿½ and Studentsï¿½ Use of Time in Government Primary Schools in Bangladesh," Creative Associates International, Inc. Washington, DC Prepared for Basic Education and Policy Support Activity, USAID.

Ravallion, M. and Q. Wodon (2000): "Does Child Labour Displace Schooling? Evidence on Behavioural Responses to an Enrollment Subsidy," Economic Journal, 110, C158–75.

Reimers, F., C. D. Da Silva, and E. Trevino (2006): Where is the" education" in conditional cash transfers in education?, UNESCO Institute for Statistics Montreal.

Rosenzweig, M. R. (1988): "Labor markets in low-income countries," Handbook of development economics, 1, 713–762.

Sabates, R., A. Hossain, and K. M. Lewin (2010): "School Drop Out in Bangladesh: New Insights from Longitudinal Evidence," .

Santos, R. J. (2018): "Blessing and curse. The gold boom and local development in Colombia," World Development, 106, 337–355.

Shah, M. and B. M. Steinberg (2017): "Drought of opportunities: Contemporaneous and long-term impacts of rainfall shocks on human capital," Journal of Political Economy, 125, 527–561.

Shelley, I. J., M. Takahashi-Nosaka, M. Kano-Nakata, M. S. Haque, and Y. Inukai (2016): "Rice cultivation in Bangladesh: present scenario, problems, and prospects," Journal of International Cooperation for Agricultural Development, 14, 20–29.

Singh, I., L. Squire, and J. Strauss (1986): Agricultural household models: Extensions, applications, and policy, The World Bank.

Tisdell, C., M. Alauddin, M. A. R. Sarker, and M. A. Kabir (2019): "Agricultural diversity and sustainability: general features and Bangladeshi illustrations," Sustainability, 11, 6004.

WorldBank (1998): "Ethiopia," Project document, Human Development I, Eastern and Southern Africa, Africa Region.

Xu, S., A. S. Shonchoy, and T. Fujii (2022): "Assessing gender parity in intrahousehold allocation of educational resources: Evidence from Bangladesh," World Development, 151, 105730.

Zhongming, Z., L. Linong, Y. Xiaona, Z. Wangqiang, L. Wei, et al. (2017): "Innovative Strategies for Accelerated Human Resource Development in South Asia: Student Assessment and Examination——Special Focus on Bangladesh, Nepal, and Sri Lanka," .

A1 Theoretical Framework

In this section, we use Baland and Robinson (2000) to show a simple theoretical framework to better our understanding of the impact of seasonal labor demand coinciding with the examination period. Consider an individual living over two periods. In the first period, she faces a trade-off between the optimal schooling hours l, and work $1-l$. If she chooses school for l hours, she receives an income according to the production function $h(1-l)$, and her second-period income y increases at rate $e(l) > 0$ with $e(0) = 1$. We let a multiplicative term $1 + aD$ where $a > 0$ measure the productivity change in production. In harvest seasons, D takes the value of 1, and 0 otherwise for agricultural households. Rewriting $1 + aD = m$, the individual's problem is as follows:

$$
\begin{aligned}
\underset{c_1, c_2, l}{\text{maximize}} \quad & u(c_1) + \beta u(c_2) \\
\text{subject to} \quad & mh(1-l) = c_1 + s, and \\
& e(l)y + Rs = c_2,
\end{aligned}
\tag{A1}
$$

where we denoted c_t as period t consumption with $t = 1, 2$, $\beta \in (0, 1]$ as a discount factor, s as savings, y as second-period base income, and $R > 0$ as an interest rate factor. Upon substitution, this is equivalent to the following:

$$
\max_{\{s,l\}} u[mh(1-l) - s] + \beta u[e(l)y + Rs].
$$

First-order conditions (FOCs) are as follows, assuming positive savings [41]

$$
-u'(c_1) + \beta R u'(c_2) = 0, and
$$

$$
-mh'(1-l)u'(c_1) + \beta e'(l) y u'(c_2) = 0.
$$

[41] Alternatively, one can assume that the interest rate is an effective interest rate that varies according to household wealth and other entitlements.

The second FOC suggests that individuals equate marginal utility loss of income due to schooling in the first period to marginal utility gain due to increased income in the second period. Substituting the first FOC to the second FOC, we have the following:

$$e'(l) = \tfrac{R}{y} m h'(1-l). \tag{A2}$$

If there is a uniform market wage rate w, then at the equilibrium without any factor market imperfection, we must have $w = mh'(1-l)$. Then the above becomes

$$e'(l) = \tfrac{R}{y} w. \tag{A3}$$

Let us assume that the return to schooling e and production h are strictly concave functions. In addition, assume that regularity conditions $\lim_{l\to 0} e'(l) = \infty$ and $\lim_{l\to 0} h'(1-l) = \bar{h} > 0$ hold.[42] There exists $l^* > 0$ that satisfy FOCs, because the left-hand side of (A2) is increasing while the right-hand side is decreasing in l. When $D = 1$, time of harvesting (and $m > 1$), the marginal productivity of labor increases, and l^* decreases.

We can alternatively rewrite (A2) as

$$\begin{aligned} g(l) &= \frac{R}{y} m, \\ g(l) &:= \frac{e'(l)}{h'(1-l)}, \textit{where } g' < 0. \end{aligned} \tag{A4}$$

Taking an inverse function of $\frac{e'}{h'}$, we see that $g(\cdot)$ is nonlinear in l. We approximate (A4) by log-linearization:

$$l_{i,t} \backsimeq l_i^* + \tilde{a}\{(\ln R_t - \ln R_i^*) - (\ln y - \ln y_i^*) + (\ln m_t - \ln m^*)\} + v_i,$$

[42]These assure that $l^* > 0$ to exists. Given that almost everyone attends school to some level and that the Government of Bangladesh introduced compulsory primary education in 1991, these conditions are an effective description of reality.

where $\tilde{a} = \frac{R_i^* m^*}{g''(l^*) y^*}$ and $v_i = -\frac{g'(l_i^*)}{g''(l_i^*)}$. Noting that y is second-period base income and R_t is the person-specific interest rate, these are functions of household and individual characteristics $\mathbf{x}_{i,t}$ with $R_t = R(\mathbf{x}_{i,t})$ and $y = y(\mathbf{x}_{i,t})$. Further approximating these functions will give a linear equation in $\mathbf{x}_{i,t}$. Hence, we arrive at,

$$l_{i,t} - l_i^* \backsimeq \boldsymbol{\beta}'(\ln \mathbf{x}_{i,t} - \ln \mathbf{x}_i^*) + \gamma(\ln m_t - \ln m^*) + v_i, \tag{A5}$$

which provides the basis for the estimating equation (1) in Section 2.

Passing the examination and continuing schooling are critical for students to achieve greater human capital for a future increase in income. The impact of having the annual final examination during the off-peak seasonal labor demand period is equivalent to a decrease in productivity or wage rates in this model. In Bangladesh in 1999, *Ramadan* school holidays resulted in the rescheduling of the annual final exam of schools to the pre-harvest period. Hence, individuals faced a lower marginal labor productivity or wage during the examination period of 1999 than in any typical year. This can be expressed as having a lower value for m. Comparing the favorable final exam schedule of 1999 with the unfavorable one of 2002 – between agricultural and non-agricultural will enable us to identify its impact on enrollment.

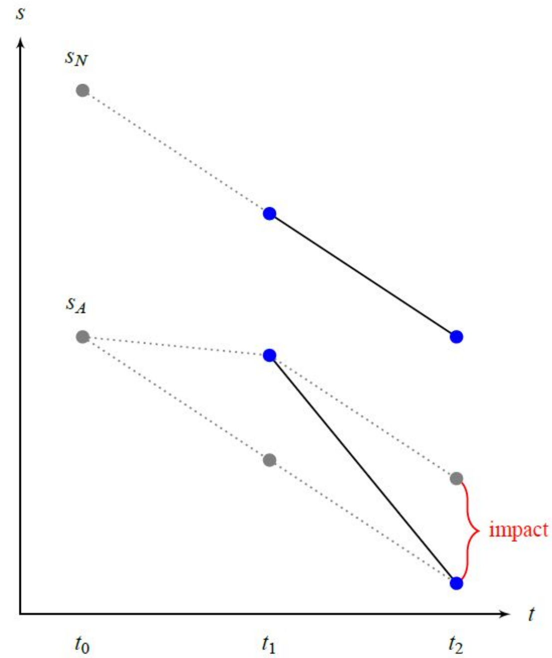
A2 Explanations of DID Framework

The reverse time order of policy and observation requires an additional assumption from regular DID specification. In addition to the common (parallel) trend in the absence of an exam schedule shift, one needs the impact to be one-time and tapering off by the second period. Figure A1 graphically illustrates these two assumptions (and Figure 4 shows empirically with the DHS data). For the ease of exposition, we include the before-baseline period t_0. The *Ramadan* favorable examination schedule happens in the period of t_1 and disappears in period t_2. In the absence of this exogenous shift in exam schedule at period t_1, both agricultural and non-agricultural households should have shared a common trend (depicted with dotted gray lines in Figure A1). With the aid of a favorable exam calendar in t_1, the observed enrollment rate of agricultural households (depicted with the first blue point of s^A in Figure A1) is higher than the counterfactual. However, once it reaches period t_2, with the typical concurrence of the final examination coinciding with the harvest season, we see a disproportionate decrease in the enrollment rate for students in agricultural households relative to students in non-agricultural households. This disproportionate decrease is what we aim to estimate as the impact of an unfavorable examination calendar that coincides with peak harvest season.

One may feel that the one-off impact assumption is too strong. However, this can be justified under a rational schooling decision. If the schooling demand is rational, in the sense that it is optimal given the current conditions and future prospects, then, *cetris paribus*, a student at the margin who stayed in school because the marginal product of labor (MPL) was lower due to no exam-harvest overlap, will drop out in the next period once the MPL increases under exam-harvest overlap. In the absence of any additional schooling policy to improve enrollment (such that it reduces the opportunity cost of schooling), rational students will discontinue schooling, which makes the impact one-off.

The impacts may last more than one period under certain scenarios. The first is when the students are irrational. If they are irrational in the sense that they change their decision

Figure A1: Graphical illustration of identification.[a]



[a]In the diagram s denotes the enrollment rate and t denotes time. Gray points are not observed but assumed. Blue points are observed in our research design. We assume a common trend in the absence of *Ramadan* induced school holidays, and its impacts keep students at school in t_1 who would have otherwise dropped out. Such favorable impact dissipates in t_2.

rule and continue enrollment just because they unexpectedly benefited from schooling. In that case, even if the MPL increases to the level under exam-harvest overlap, as in the case of sunk cost fallacy, the impacts last more than one period. Second is enrollment rate-based policy placement. As exemplified in the above, if policymakers target high enrollment areas to reduce schooling costs, it will induce longer-lasting enrollment rate hikes.

We remain agnostic about the extent to which these two scenarios hold in practice. We also note that longer-lasting impacts can give underestimated impacts. If the impact remains indefinitely, the estimate will be zero because both the treated and the control will follow the common trend. This implies that the impacts will likely be underestimated to the extent that the one-off impact assumption does not hold. In light of this, our estimate potentially gives attenuated impacts if this additional assumption does not hold.

A3 Descriptive statistics of IFPRI Data-set

Data we utilized in our paper is drawn from IFPRI panel surveys of 1999, 2002, and 2006. Data from 1999 and 2002 are used in the main regression estimations. In contrast, the 2006 data set is employed for placebo and common trend tests. Given our focus on those children actively engaged in agricultural work, we set the lowest age limit as ten years of age, following the definition of child labor used in the Labor Force Survey (LFS) of Bangladesh.[43]. Setting the upper age limit for our sample is not as simple as setting the lower age limit. Children are officially supposed to finish high school at the age of 16 years, but as a result of starting late and repeating grades, many individuals remain in school beyond that age. As public primary schools accept children up to the age of 10 years for grade 1 and because many children begin enrolling late, several individuals who may be considered "adults", if judged according by their age alone, are still attending secondary or high schools.

Under these conditions, the oldest individual in our sample was 18 years old in 1999. Hence, the lower and upper age limits of 10-18 years are applied. We exclude individuals whose highest education level in round 2 (2002) is preschool, madrasa (Islamic religious schools), or bachelor's or higher degrees. For our regression exercise, we utilize only the balanced covariate portion of the 1999-2002 panel. When we set the age upper bound to 18, the sample size becomes 689, reduced from 735. We also exclude children who are not sons or daughters (direct offspring) of household heads because, first, one cannot obtain parental information to be used in estimation, and second, their schooling decisions may be affected by their parents who live outside the households. These reduce the sample size from 689 to 626. Table A1 shows that our selected sample is not systematically different from the original sample (except for the child's age).

To check if our regression sample was affected by non-random attrition between the two types of households, we tested it empirically in Table A2. The first two columns under

[43]In Bangladesh, the official age to begin schooling is six years of age. However, some parents choose to begin later. As a result, many of our sample children are still in the primary grades despite their age, which is suitable for the post-primary grades.

Table A1: Original (10-20, all children) vs. regression (10-18, direct offspring) sample contrasts

Variables	Means: Original sample	Means: Study sample	p-values (%): $t-$ test	p-values (%): χ^2 test	p-values (%): Binomial
Agricultural household	0.6027	0.5863	0.5381	0.5747	0.4141
Yield (thana)	0.7851	0.7859	0.8822		
Age	12.2932	12.9856	0.0000		
Sex (female = 1)	0.5007	0.5112	0.6996	0.7400	0.6036
Head education: primary	0.1646	0.1550	0.6273	0.6812	0.5533
Head education: secondary	0.2898	0.2843	0.8248	0.8718	0.7916
Head spouse education: primary	0.1374	0.1438	0.7372	0.7963	0.6423
Head spouse education: secondary	0.1660	0.1629	0.8799	0.9380	0.8721
Number of older brothers	0.8660	0.8482	0.7373		
Number of older sisters	0.4241	0.3946	0.4119		
Per member land holding (decimal)	0.1760	0.1675	0.5700		
Per member nonland asset (1000 Tk)	11.3942	11.2091	0.8077		
Own piped water	0.3687	0.3802	0.6630	0.7038	0.5620
Structured toilet	0.2925	0.2939	0.9545	1.0000	0.9300
Observation	735	626			

Source: Compiled from IFPRI data.

Notes: 1. All information is of the year 1999. The column headed by t shows p values of equal means for both data sets using t tests. Column headed by χ^2 shows p values of equal proportions. The column headed by binomial shows p values of two-sided test for one proportion being equal to another proportion under presumed Bernoulli trials.

2. Agricultural households are defined as at least one adult member claiming that the main income source is agriculture.

Descriptive statistics panel show the attriter's characteristics separated by agriculture and non-agricultural households. All the numbers reported are the means and standard errors (in brackets) in columns (1) and (2), respectively. In column (3), the top rows show mean differences, and the bottom rows (in bracket) show associated p values of mean differences in percentage. As we can see, attrition is not systematically different between the two types of households.

OLS estimation panel shows estimates from a linear probability model of attrition on the agricultural household dummy, baseline variables $\mathbf{x}_i$ and their interaction with the agricultural household dummy D_i: $y_i = \boldsymbol{\beta}'\mathbf{x}_i + \boldsymbol{\gamma}' D_i \mathbf{x}_i + e_i$. The top rows show point estimates, and the bottom rows show standard errors (in brackets). Estimates of household attributes $\boldsymbol{\beta}$ are shown in column (4), and interaction terms $\boldsymbol{\gamma}$ of each variable with agricultural households are shown in (5). Consistent with descriptive statistics, we see no systematic attrition between the agricultural and non-agricultural households, except for agricultural households attrit by the rate of 3% per one acre reduction of land holding (p value = 9.58%).

We consider the negative correlation of agricultural households' attrition and land holding to be inconsequential for enrollment estimation with two reasons. First, implied magnitude is small compared to mean land holding of 1.46 acres by agricultural households. Even if we shrink the land holding drastically by half, we lose 10 agricultural households out of 353. Second, the potential bias it gives to enrollment may cancel out with each other, at least on signs. When smaller landholding has smaller labor demand for children therefore higher enrollment rates, their attrition can understate enrollment rates. When smaller landholders, or less wealthy households, stop schooling early that results in lower enrollment rates, their attrition can overstate enrollment rates. However, to guard against possible biases, we include per member land holding as a covariate in all the estimation.

Table A3 summarizes the data used in the regressions. Based on the age cut-off of 10 years and older in the 1999 survey, we have 626 observations. In our sample, approximately 61 percent of households were categorized as agricultural households. Alternative agricultural household definitions give similar summary statistics, which explains the small difference in estimation. The household head's highest level of education is mostly secondary, 28%, and the primary level comprises 15.5% of our sample. Spousal education is similar for the primary level, 17%, but relatively low for the secondary level, 16.6%. The mean per member landholding is 0.168 acre. Median per member non-land assets are about 11,000 BDT (110 USD), and about 14,000 BDT (140 USD) at the 75th percentile. These non-land asset values indicate that our sample primarily comprises poor rural households.

For the placebo sample, we took 10 to 18 years in 2002 (2002 cohort) to compare with the main data. TABLE A4 presents a summary of the data used in the placebo regressions. Based on the age cutoff of 10 years and older in the 2002 survey, there are 812 observations in the placebo sample. In our placebo sample, we have about 60% agricultural households, which is quite similar to the main sample. Other summary statistics reported in Table A3 show close similarity with Table A4. This demonstrates the validity of a placebo sample, at least observational. The only notable observable difference between these two samples,

Table A2: Attrition comparison between agricultural vs. non-agricultural households

	Descriptive statistics			OLS estimates	
	(1)	(2)	(3)	(4)	(5)
Variable	agHH	nonagHH	Difference	Base	Base×agHH
Attrition	0.2096	0.2186	−0.009		
	(0.408)	(0.414)	[79.23]		
Agri HH				−0.0350	
				(0.0569)	
Total asset holding (BDT1000)	75.8336	74.1008	1.733	0.0006	0.0005
	(72.989)	(71.839)	[89.37]	(0.0009)	(0.0005)
Total landholding (decimal)	106.1092	70.5729	35.536*	0.0001	−0.0003*
	(126.084)	(96.580)	[8.49]	(0.0003)	(0.0002)
Head primary education	0.1486	0.1852	−0.037	−0.0966	0.0749
	(0.358)	(0.392)	[59.04]	(0.0717)	(0.0874)
Head secondary education	0.1757	0.1667	0.009	−0.1218	0.1794
	(0.383)	(0.376)	[89.46]	(0.1054)	(0.1470)
Spouse primary education	0.0541	0.1111	−0.057	−0.0806	−0.1350
	(0.228)	(0.317)	[26.28]	(0.0848)	(0.1166)
Spouse secondary education	0.0405	0.0556	−0.015	−0.1284	−0.0561
	(0.199)	(0.231)	[70.12]	(0.1035)	(0.1121)
F(all interaction terms = 0)					$p = 0.545$

Source: Compiled from IFPRI data.

Notes: 1. Attrition is true if a household is missing in round 2. All covariates are of round 1.

2. Descriptive statistics panel shows attriter's characteristics. The top rows show the means, and the bottom rows show the standard errors in columns (1) and (2), respectively. In column (3), the top rows show mean differences, and the bottom rows show associated p values of mean differences in percentage. OLS estimation panel shows results from a linear probability model of attrition on baseline variables $\mathbf{x}_i$ and their interaction with the agricultural household dummy r_i: $y_i = \boldsymbol{\beta}'\mathbf{x}_i + \boldsymbol{\gamma}' r_i \mathbf{x}_i + e_i$. The top rows show point estimates, and the bottom rows show standard errors. Estimates of non-agricultural HHs $\boldsymbol{\beta}$ are shown in (4), and interaction terms $\boldsymbol{\gamma}$ of each variable with agricultural HH are shown in (5). Number of observations for LPM is 570, $\bar{R} = 0.058$. Standard errors are shown in parentheses, which are clustered at the Thana level with a Satterthwaite correction for a small number of clusters. For column (3), p values of the null of zero difference are shown in square brackets. $*$ indicates a p value between 5% and 10%.

however, is the declining enrollment rate, which is about 11 percentage points lower than the 1999 average.

Table A3: Descriptive statistics of main estimation, 10-18 years old, direct offspring

Variables	Min	25%	Median	75%	Max	Mean	STD	‘0’s	‘NA’s	n
Enrolled	0	0	1	1	1	0.738	0.440	164	0	626
Agricultural household	0	0	1	1	1	0.613	0.487	242	0	626
Agricultural household (head definition)	0	0	1	1	1	0.553	0.498	280	0	626
Agricultural household (income definition)	0	0	1	1	1	0.575	0.495	266	0	626
Agricultural household (occupation definition)	0	0	1	1	1	0.543	0.499	286	0	626
Program	0	0	1	1	1	0.740	0.439	163	0	626
Sex (female = 1)	0	0	1	1	1	0.511	0.500	306	0	626
Head sex (female = 1)	0	0	0	0	1	0.128	0.334	546	0	626
Non-Muslim	0	0	0	0	1	0.123	0.329	549	0	626
Flood	0	0	1	1	1	0.623	0.485	236	0	626
Structured toilet	0	0	0	1	1	0.294	0.456	442	0	626
Own piped water	0	0	0	1	1	0.380	0.486	388	0	626
Head education: primary	0	0	0	0	1	0.155	0.362	529	0	626
Head education: secondary	0	0	0	1	1	0.284	0.451	448	0	626
Head spouse education: primary	0	0	0	0	1	0.171	0.377	519	0	626
Head spouse education: secondary	0	0	0	0	1	0.166	0.372	522	0	626
Age	10	11	13	15	18	12.986	2.351	0	0	626
Yield (thana)	0.607	0.647	0.823	0.906	0.928	0.786	0.110	0	0	626
Number of older sisters	0	0	0	1	4	0.390	0.670	434	0	626
Number of older brothers	0	0	0	1	5	0.577	0.844	376	0	626
Per member land holding (decimal)	0	0.019	0.069	0.196	3.215	0.167	0.287	2	0	626
Per member nonland asset (1000 Tk)	0.373	3.918	7.062	13.623	205	11.209	14.515	0	0	626

Source: Compiled from IFPRI data.

Notes: 1. All information is of year 1999.

2. Agricultural households are defined as at least one adult member claiming that the main income source is agriculture or occupation is agriculture. Program membership is one if holding a membership to anti-poverty programs. STD represents Standard deviation.

Table A4: Descriptive statistics of placebo estimation, 10-18 years old in 2002, direct offspring

Variables	Min	25%	Median	75%	Max	Mean	STD	'0's	'NA's	n
Enrolled	0	0	1	1	1	0.631	0.483	300	0	812
Agricultural household	0	0	1	1	1	0.606	0.489	320	0	812
Agricultural household (head definition)	0	0	1	1	1	0.542	0.499	372	0	812
Agricultural household (income definition)	0	0	1	1	1	0.562	0.496	356	0	812
Agricultural household (occupation definition)	0	0	1	1	1	0.537	0.499	376	0	812
Program	0	0	0	1	1	0.273	0.446	590	0	812
Sex (female = 1)	0	0	1	1	1	0.525	0.500	386	0	812
Head sex (female = 1)	0	0	0	0	1	0.116	0.320	718	0	812
Flood	0	0	1	1	1	0.626	0.484	304	0	812
Structured toilet	0	0	0	1	1	0.282	0.450	583	0	812
Own piped water	0	0	0	1	1	0.376	0.485	507	0	812
Head education: primary	0	0	0	0	1	0.159	0.366	683	0	812
Head education: secondary	0	0	0	1	1	0.281	0.450	584	0	812
Head spouse education: primary	0	0	0	0	1	0.177	0.382	668	0	812
Head spouse education: secondary	0	0	0	0	1	0.166	0.373	677	0	812
Age	10	12	13	16	18	13.631	2.470	0	0	812
Yield (thana)	0.69	0.743	0.838	0.984	1.036	0.848	0.117	0	0	812
Number of older sisters	0	0	0	1	4	0.560	0.793	477	0	812
Number of older brothers	0	0	0	1	5	0.659	0.882	447	0	812
Per member land holding (decimal)	0	0.017	0.063	0.179	3.215	0.160	0.289	2	0	812
Per member nonland asset (1000 Tk)	0.369	3.537	6.963	13.143	205	10.994	14.995	0	0	812

Source: Compiled from IFPRI data.

Notes: 1. All information is of year 2002 except for Enrolled, Yield, Temperature, Rainfall, Program membership.

2. Agricultural households are defined as at least one adult member claiming that the main income source is agriculture or occupation is agriculture. Program membership is one of holding a membership to anti-poverty programs. STD represents Standard deviation.

Table A5: Tabulation of Agricultural vs. Non-Agriculture household Consumption Quartiles

Quartiles	1	2	3	4	'NA's	N
Agricultural households	25.8	27.27	26.54	19.66	0.74	407
Non-agricultural households	23.27	24.36	18.55	33.82	0	275

Notes: Consumption quartiles are based on households.

To assess relative impoverishment, we tabulated agriculture and non-agricultural households based on household consumption information in Table A5. The consumption quartiles are derived based on per-member consumption information in the household. We noticed a higher consumption quartile for non-agricultural households compared to Agricultural households.

The IFPRI panel data set reports reasons for dropping out of school (Table A6). We notice dropout rates are higher for lower consumption quartiles, and their reasons for dropping out primarily include financial difficulties, which is also true for irregular students. Upper-quartile individuals cite non-financial reasons such as marriage as the reason for drop-out. We also summarize the reported reasons for school dropout by household type in Table A7: agricultural or non-agricultural households. Our table indicates that agricultural households cite financial reasons more frequently than non-agricultural ones as the main reason for dropping out and school irregularity.

Figure A2 shows mean enrollment rates by age. Ages under primary and secondary schooling have less than 100% enrollment rates. Age 5, one year before primary schooling begins, reports nonzero enrollment rates. These show that "compulsory schooling" is not enforced strictly.

Figure A3 shows the mean age of starting class 1 for each calendar year. Most years report the mean starting age older than six years old. This also shows that "compulsory schooling" is not enforced strictly. Agricultural households tend to start school later in age than non-agricultural households. This may partly explain why Agricultural households's enrollment rates are higher at some of the later ages.

Table A6: Reported Reasons for Stop Going to School by Consumption Quartiles and by Household Type

Quartile	Group	Financial	Not accepted	School environment	Marriage	Distance	Sickness	NA	Total
1	Irregular 1999	0.52	0.03	0.2	0	0.06	0.02	0.17	65
1	Irregular 2002	0.54	0.01	0.01	0.01	0.01	0	0.43	115
1	Drop outs 2002	0.62	0	0.02	0.02	0	0	0.34	58
2	Irregular 1999	0.48	0	0.23	0	0.14	0	0.14	56
2	Irregular 2002	0.37	0	0.06	0.01	0.02	0.01	0.52	81
2	Drop outs 2002	0.41	0	0.08	0	0.03	0	0.49	37
3	Irregular 1999	0.44	0	0.26	0	0.18	0.09	0.03	34
3	Irregular 2002	0.28	0	0	0.05	0.03	0.03	0.61	64
3	Drop outs 2002	0.26	0	0	0.05	0.03	0.03	0.63	38
4	Irregular 1999	0.45	0.05	0.18	0	0.05	0.05	0.23	22
4	Irregular 2002	0.1	0.01	0.03	0.03	0.01	0.03	0.79	73
4	Drop outs 2002	0.11	0.02	0.02	0.04	0	0.04	0.78	54

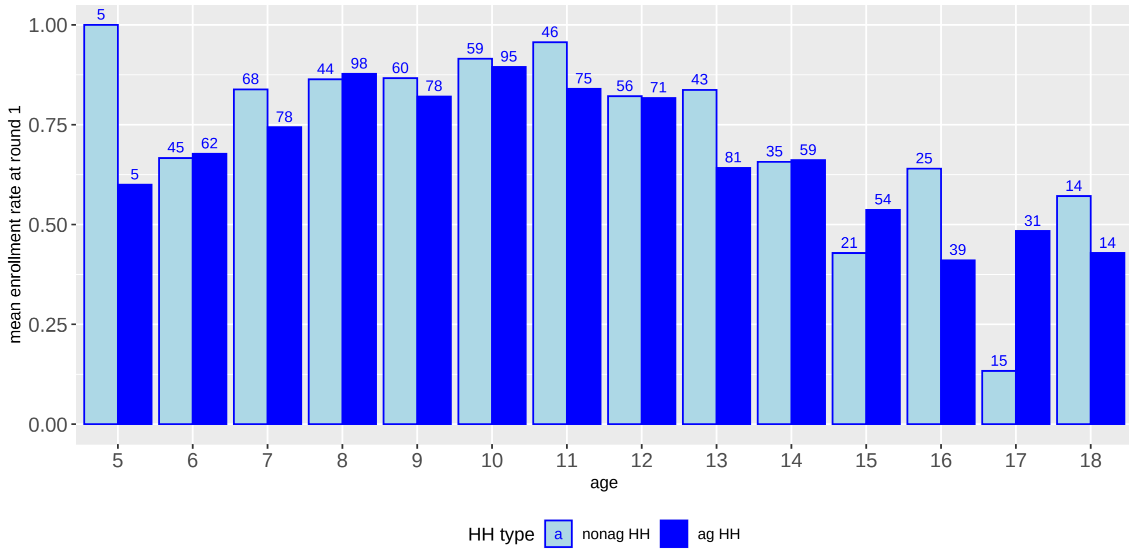
Notes: Numbers are all ratios except totals. “Agri HH” indicates agricultural households. See main text for definition of agricultural households. Irregulars are individuals who were not enrolled in the respective period. Dropouts are individuals who were enrolled in 1999 but not in 2002..

Table A7: Reasons for Not Going to School, Agricultural vs. Non-Agriculture household

HH Type	**Group**	**Financial**	**Not accepted**	**School Environment**	**Marriage**	**Distance**	**Sickness**	**NA**	**Total**
Ag	Irregular 1999	0.55	0.03	0.21	0	0.06	0.05	0.11	66
Ag	Irregular 2002	0.38	0	0.01	0.01	0.01	0.02	0.57	120
Ag	drop outs 2002	0.46	0	0.01	0	0.01	0.01	0.5	70
Non-ag	Irregular 1999	0.46	0.01	0.22	0	0.13	0.02	0.16	112
Non-ag	Irregular 2002	0.33	0.01	0.03	0.03	0.02	0.01	0.56	214
Non-ag	drop outs 2002	0.3	0.01	0.03	0.04	0.01	0.02	0.59	117

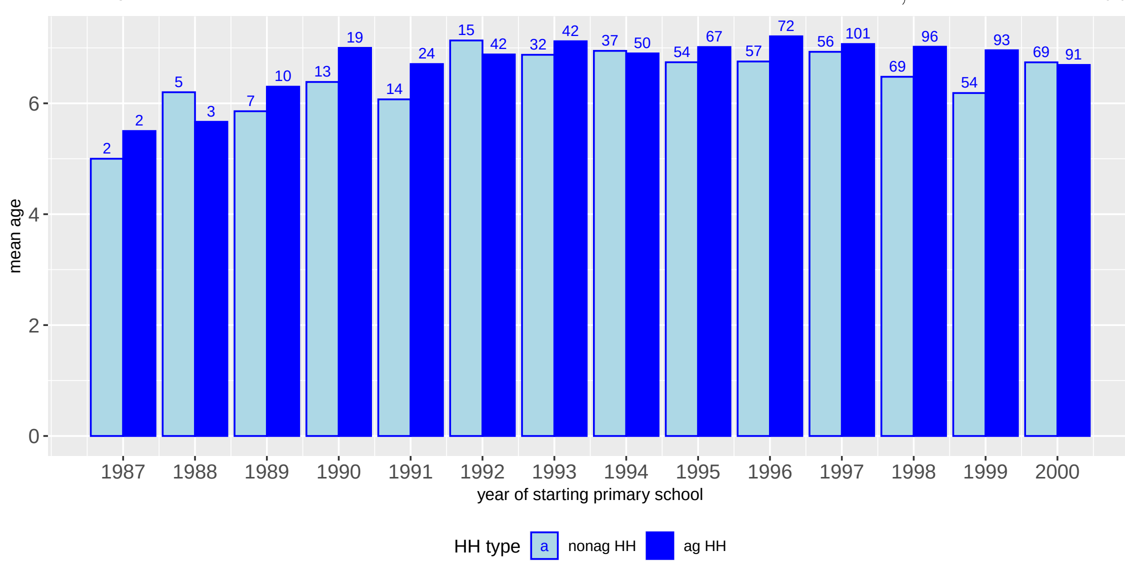
Notes: Numbers are all ratios except totals. “Agri HH” indicates agricultural households. See the main text for the definition of agricultural households. Irregulars are individuals who were not enrolled in the respective period. Dropouts are individuals who were enrolled in 1999 but not in 2002..

Figure A2: Enrollment rates by age and HH type, 1999, 5 years and older



Source: Compiled from IFPRI data. All households, including attrited households, are used.
Notes: Ages are of round 1. Numbers displayed above the bar are cell sample size.

Figure A3: Age starting the primary school by year and HH type, reported in 2000



Source: Compiled from IFPRI data. All households, including attrited households, are used.
Notes: : The Numbers displayed above the bar are cell sample size.

A4 Additional Tables

Figure A4: Government School Calendar in Bangladesh (2019).[a]

Junior and Secondary School Holiday List:

বিষয় : সরকারি/বেসরকারি মাধ্যমিক ও নিম্নমাধ্যমিক বিদ্যালয়সমূহের ২০১৯ শিক্ষাবর্ষের ছুটির তালিকা ও শিক্ষাপঞ্জী অনুমোদন।

সূত্র : মাধ্যমিক ও উচ্চ শিক্ষা অধিদপ্তরের স্মারক নং-ওএম/১৮৮-সম/২০০২/২৯৪৬; তারিখ: ১৮.১১.২০১৮

উপযুর্ক্ত বিষয় ও সূত্রোক্ত পত্রের পরিপ্রেক্ষিতে জানানো যাচ্ছে যে, সরকারি/বেসরকারি মাধ্যমিক ও নিম্নমাধ্যমিক বিদ্যালয়সমূহের ২০১৯ শিক্ষাবর্ষের ছুটির তালিকা ও শিক্ষাপঞ্জী সরকার নিম্নোক্তভাবে অনুমোদন করেছে:

ক্রমিক	পর্বের নাম	তারিখ ও দিন	তারিখ বঙ্গাব্দ	দিন সংখ্যা
১.	শ্রী শ্রী সরস্বতী পূজা	১০ ফেব্রুয়ারি, রবিবার, ২০১৯	২৭ মাঘ, ১৪২৫	০১ দিন
২.	* মাঘী পূর্ণিমা	১৯ ফেব্রুয়ারি, মঙ্গলবার, ২০১৯	০৬ ফাল্গুন, ১৪২৫	০১ দিন
৩.	শহীদ দিবস ও আন্তর্জাতিক মাতৃভাষা দিবস	২১ ফেব্রুয়ারি, বৃহস্পতিবার, ২০১৯	০৮ ফাল্গুন, ১৪২৫	০১ দিন
৪.	শ্রী শ্রী শিবরাত্রি ব্রত	০৪ মার্চ, সোমবার, ২০১৯	১৯ ফাল্গুন, ১৪২৫	০১ দিন
৫.	জাতির পিতা বঙ্গবন্ধু শেখ মুজিবুর রহমান এর জন্ম দিবস	১৭ মার্চ, রবিবার, ২০১৯	০৩ চৈত্র, ১৪২৫	০১ দিন
৬.	শুভ দোলযাত্রা	২১ মার্চ, বৃহস্পতিবার, ২০১৯	০৭ চৈত্র, ১৪২৫	০১ দিন
৭.	স্বাধীনতা ও জাতীয় দিবস	২৬ মার্চ, মঙ্গলবার, ২০১৯	১২ চৈত্র, ১৪২৫	০১ দিন
৮.	* শব-ই-মিরাজ	০৪ এপ্রিল, বৃহস্পতিবার, ২০১৯	২১ চৈত্র, ১৪২৫	০১ দিন
৯.	বৈসাবি	১২ এপ্রিল, শুক্রবার, ২০১৯	২৯ চৈত্র, ১৪২৫	০০ দিন
১০.	বাংলা নববর্ষ	১৪ এপ্রিল, রবিবার, ২০১৯	০১ বৈশাখ, ১৪২৬	০১ দিন
১১.	* শব-ই-বরাত, ইস্টার সানডে	২১ এপ্রিল, রবিবার, ২০১৯	০৮ বৈশাখ, ১৪২৬	০১ দিন
১২.	মে দিবস	০১ মে, বুধবার, ২০১৯	১৮ বৈশাখ, ১৪২৬	০১ দিন
১৩.	গ্রীষ্মকালীন অবকাশ, * পবিত্র রমজান, * বুদ্ধ পূর্ণিমা (বৈশাখি পূর্ণিমা ১৮মে) জুমাতুল বিদা (৩১ মে), * শব-ই-কদর (০২ জুন), * ঈদ-উল-ফিতর (০৫ জুন)	০৬ মে, সোমবার থেকে ১৩ জুন বৃহস্পতিবার, ২০১৯	২৩ বৈশাখ থেকে ৩০ জ্যৈষ্ঠ ১৪২৬	৩৪ দিন
১৪.	* পবিত্র ঈদ-উল-আযহা (১১, ১২, ১৩ আগস্ট), জাতীয় শোক দিবস (১৫ আগস্ট)	০৮ আগস্ট, বৃহস্পতিবার থেকে ১৯ আগস্ট, সোমবার, ২০১৯	২৪ শ্রাবণ থেকে ০৪ ভাদ্র, ১৪২৬	১০ দিন
১৫.	শুভ জন্মাষ্টমী	২৩ আগস্ট, শুক্রবার, ২০১৯	০৮ ভাদ্র, ১৪২৬	০০ দিন
১৬.	* হিজরী নববর্ষ	০১ সেপ্টেম্বর, রবিবার, ২০১৯	১৭ ভাদ্র, ১৪২৬	০১ দিন
১৭.	* আশুরা	১০ সেপ্টেম্বর, মঙ্গলবার, ২০১৯	২৬ ভাদ্র, ১৪২৬	০১ দিন
১৮.	দুর্গাপূজা (বিজয়া দশমী, ০৮ অক্টোবর) * প্রবারণা পূর্ণিমা (১৩ অক্টোবর), শ্রী শ্রী লক্ষ্মী পূজা(১৩ অক্টোবর)	০৪ অক্টোবর, শুক্রবার থেকে ১৩ অক্টোবর, রবিবার, ২০১৯	১৯ আশ্বিন থেকে ২৮ আশ্বিন, ১৪২৬	০৮ দিন
১৯.	* আখেরী চাহার সোম্বা	২৩ অক্টোবর, বুধবার, ২০১৯	০৭ কার্তিক, ১৪২৬	০১ দিন
২০.	শ্রী শ্রী শ্যামা পূজা	২৭ অক্টোবর, রবিবার,২০১৯	১১ কার্তিক, ১৪২৬	০১ দিন
২১.	* ঈদ-ই- মিলাদুন্নবী (সাঃ)	১০ নভেম্বর, রবিবার, ২০১৯	২৫ কার্তিক, ১৪২৬	০১ দিন
২২.	*ফাতেহা-ই-ইয়াজদাহম	০৯ ডিসেম্বর, সোমবার ২০১৯	২৪ অগ্রহায়ণ, ১৪২৬	০১ দিন
২৩.	শীতকালীন অবকাশ, বিজয় দিবস(১৬ ডিসেম্বর), যিশু খ্রিস্টের জন্মদিন (বড় দিন, ২৫ ডিসেম্বর)	১৫ ডিসেম্বর, রবিবার থেকে ২৯ ডিসেম্বর, রবিবার, ২০১৯	৩০ অগ্রহায়ণ থেকে ১৪ পৌষ, ১৪২৬	১৩ দিন
২৪.	প্রধান শিক্ষকের সংরক্ষিত ছুটি			০৩ দিন
		মোট =		৮৫ দিন

* চাঁদ দেখার উপর নির্ভরশীল।

পরীক্ষার সময়সূচি-২০১৯ খ্রি:

পরীক্ষার নাম	তারিখ	দিন সংখ্যা	ফলাফল প্রকাশ
অর্ধ-বার্ষিক/প্রাক নির্বাচনী পরীক্ষা	২২ জুন, শনিবার থেকে ০৪ জুলাই, বৃহস্পতিবার পর্যন্ত ২০১৯	১২ দিন	২০ জুলাই, শনিবার, ২০১৯
নির্বাচনী পরীক্ষা	১৪ অক্টোবর, সোমবার থেকে ২৯ অক্টোবর, মঙ্গলবার পর্যন্ত ২০১৯	১২ দিন	০৭ নভেম্বর, বৃহস্পতিবার ২০১৯
বার্ষিক পরীক্ষা	২৭ নভেম্বর, বুধবার থেকে ১১ ডিসেম্বর, বুধবার পর্যন্ত ২০১৯	১২ দিন	৩০ ডিসেম্বর, সোমবার ২০১৯

[a] Above is the Ministry of Education (MoE) Bangladesh provided examination and annual holiday calendar for the secondary and higher secondary schools (in Bangla). The bottom table of this notice contains the exam calendar, which instructed all the schools to hold annual exams from November 27 to December 11.

Table A8: Main results by gender and by agricultural household definitions

	Specification 1			Specification 2			Specification 3		
	Boys	Girls	Boys+Girls	Boys	Girls	Boys+Girls	Boys	Girls	Boys+Girls
				A. Agricultural household					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
AgriHH * year 2002	−0.1169**	−0.0310	−0.0673**	−0.1143**	−0.0505	−0.0760**	−0.1161**	−0.0494	−0.0754**
	(-0.20, -0.03)	(-0.17, 0.11)	(-0.11, -0.02)	(-0.18, -0.04)	(-0.19, 0.09)	(-0.13, -0.03)	(-0.19, -0.04)	(-0.19, 0.09)	(-0.12, -0.03)
	[-0.22, -0.01]	[-0.21, 0.15]	[-0.13, -0.01]	[-0.21, -0.02]	[-0.25, 0.14]	[-0.15, -0.01]	[-0.22, -0.02]	[-0.24, 0.14]	[-0.14, -0.01]
$\bar{R}^2$	0.3685	0.5911	0.4676	0.4078	0.6061	0.4830	0.4096	0.6101	0.4835
N: Agricultural HHs	197	187	384	197	187	384	197	187	384
N	306	320	626	306	320	626	306	320	626
Mean of control in 2002		0.4679			0.4920			0.4959	
				B. Agricultural household (head)					
	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
AgriHH * year 2002	−0.1448**	−0.0293	−0.0801**	−0.1390***	−0.0498	−0.0878**	−0.1418***	−0.0524	−0.0887**
	(-0.23, -0.06)	(-0.16, 0.10)	(-0.13, -0.03)	(-0.19, -0.08)	(-0.18, 0.08)	(-0.13, -0.04)	(-0.20, -0.08)	(-0.19, 0.08)	(-0.13, -0.04)
	[-0.25, -0.04]	[-0.20, 0.14]	[-0.14, -0.02]	[-0.22, -0.06]	[-0.24, 0.14]	[-0.15, -0.02]	[-0.22, -0.06]	[-0.24, 0.13]	[-0.15, -0.03]
$\bar{R}^2$	0.3755	0.5910	0.4707	0.4119	0.6073	0.4859	0.4139	0.6121	0.4865
N: Agricultural HHs	189	171	360	189	171	360	189	171	360
N	306	320	626	306	320	626	306	320	626
Mean of control in 2002		0.4786			0.4912			0.5000	
				C. Agricultural household (income)					
	(19)	(20)	(21)	(22)	(23)	(24)	(25)	(26)	(27)
AgriHH * year 2002	−0.1454**	−0.0329	−0.0827**	−0.1381***	−0.0444	−0.0842**	−0.1412***	−0.0448	−0.0833**
	(-0.22, -0.07)	(-0.16, 0.09)	(-0.13, -0.04)	(-0.19, -0.08)	(-0.17, 0.09)	(-0.14, -0.03)	(-0.19, -0.09)	(-0.18, 0.09)	(-0.13, -0.03)
	[-0.25, -0.05]	[-0.19, 0.13]	[-0.14, -0.03]	[-0.21, -0.07]	[-0.22, 0.14]	[-0.16, -0.01]	[-0.21, -0.07]	[-0.23, 0.14]	[-0.15, -0.02]
N: Agricultural HHs	177	169	346	177	169	346	177	169	346
N	306	320	626	306	320	626	306	320	626
Mean of control in 2002		0.4419			0.4793			0.4893	
				D. Agricultural household (occupation)					
	(28)	(29)	(30)	(31)	(32)	(33)	(34)	(35)	(36)
AgriHH * year 2002	−0.1019**	−0.0047	−0.0485*	−0.0974*	−0.0180	−0.0523*	−0.0951*	−0.0197	−0.0515**
	(-0.18, -0.02)	(-0.13, 0.12)	(-0.09, -0.01)	(-0.18, -0.01)	(-0.13, 0.10)	(-0.09, -0.02)	(-0.18, -0.01)	(-0.14, 0.10)	(-0.09, -0.02)
	[-0.20, -0.00]	[-0.16, 0.15]	[-0.10, 0.00]	[-0.21, 0.02]	[-0.18, 0.14]	[-0.11, 0.00]	[-0.21, 0.02]	[-0.18, 0.14]	[-0.10, -0.00]
$\bar{R}^2$	0.3662	0.5902	0.4665	0.3961	0.6018	0.4780	0.3980	0.6060	0.4786
N: Agricultural HHs	180	160	340	180	160	340	180	160	340
N	306	320	626	306	320	626	306	320	626
Mean of control in 2002		0.4444			0.4875			0.4860	

Source: Compiled from IFPRI data.

Notes: 1. Sample of direct offspring of household heads. AgriHH * year 2002 is an interaction term of agricultural household dummy and year 2002 dummy. All the interaction terms are demeaned. Specification 1 uses time-varying thana level characteristics (yield, mean rainfall, mean high temperature, mean low temperature), individual-level characteristics (age squared, recipient of a poverty program), and Demographic fixed trends that are interactions of baseline individual and demographic characteristics (sex of individual, household head's education, number of older male/female siblings) with the year 2002 dummy, and sex of individual with the year 2002 * agricultural household dummy. Parental education is highly collinear with agricultural household dummy and is dropped from triple interactions. Specification 2 add other household fixed trends that are interactions of other baseline household characteristics (per member land holding, per member non-land assets, own piped water, structured toilet). Specification 3 adds Thana fixed trends, which allow heterogeneous trends at the Thana level.

2. Standard errors are clustered at thana level. 95% confidence intervals of cluster robust standard errors using Liang and Zeger (1986) are shown in parenthesis, and bias-reduced linearization (Satterthwaite correction) for a correction of a small number of clusters are shown in square brackets. $*$, $**$, $***$ indicate significance levels at 10%, 5%, 1% under BRL cluster robust standard errors, respectively.

Table A9: Main results by gender and by age lower-bound definitions

	Specification 1			Specification 2			Specification 3		
	Boys	Girls	Boys+Girls	Boys	Girls	Boys+Girls	Boys	Girls	Boys+Girls
A. 10 - 18									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Agri HH * year 2002	−0.1169**	−0.0310	−0.0673**	−0.1143**	−0.0505	−0.0760**	−0.1161**	−0.0494	−0.0754**
	(-0.20, -0.03)	(-0.17, 0.11)	(-0.11, -0.02)	(-0.18, -0.04)	(-0.19, 0.09)	(-0.13, -0.03)	(-0.19, -0.04)	(-0.19, 0.09)	(-0.12, -0.03)
	[-0.22, -0.01]	[-0.21, 0.15]	[-0.13, -0.01]	[-0.21, -0.02]	[-0.25, 0.14]	[-0.15, -0.01]	[-0.22, -0.02]	[-0.24, 0.14]	[-0.14, -0.01]
$\bar{R}^2$	0.3685	0.5911	0.4676	0.4078	0.6061	0.4830	0.4096	0.6101	0.4835
N: Agricultural HHs	197	187	384	197	187	384	197	187	384
N	306	320	626	306	320	626	306	320	626
Mean of control in 1999	0.6278	0.7750	0.6971	0.6278	0.7750	0.6971	0.6278	0.7750	0.6971
Mean of control in 2002	0.2944	0.4875	0.3853	0.2944	0.4875	0.3853	0.2944	0.4875	0.3853
B. 11 - 18									
	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
Agricultural * year 2002	−0.1464***	−0.0243	−0.0749**	−0.1303***	−0.0488	−0.0788*	−0.1340***	−0.0482	−0.0822**
	(-0.21, -0.09)	(-0.15, 0.10)	(-0.13, -0.02)	(-0.18, -0.08)	(-0.17, 0.08)	(-0.14, -0.02)	(-0.19, -0.08)	(-0.18, 0.08)	(-0.14, -0.03)
	[-0.22, -0.07]	[-0.19, 0.14]	[-0.14, -0.01]	[-0.20, -0.06]	[-0.22, 0.13]	[-0.16, 0.00]	[-0.21, -0.06]	[-0.23, 0.13]	[-0.16, -0.00]
$\bar{R}^2$	0.4233	0.6232	0.5181	0.4709	0.6406	0.5326	0.4720	0.6430	0.5344
N: Agricultural HHs	159	158	317	159	158	317	159	158	317
N	244	269	513	244	269	513	244	269	513
Mean of control in 1999	0.5664	0.7388	0.6498	0.5664	0.7388	0.6498	0.5664	0.7388	0.6498
Mean of control in 2002	0.1958	0.4403	0.3141	0.1958	0.4403	0.3141	0.1958	0.4403	0.3141
C. 12 - 18									
	(19)	(20)	(21)	(22)	(23)	(24)	(25)	(26)	(27)
Agricultural * year 2002	−0.1305*	−0.0171	−0.0603*	−0.1229**	−0.0474	−0.0697**	−0.1360**	−0.0468	−0.0776**
	(-0.24, -0.02)	(-0.13, 0.09)	(-0.11, -0.01)	(-0.20, -0.05)	(-0.15, 0.06)	(-0.12, -0.02)	(-0.23, -0.04)	(-0.15, 0.06)	(-0.12, -0.03)
	[-0.27, 0.01]	[-0.15, 0.12]	[-0.13, 0.01]	[-0.23, -0.02]	[-0.19, 0.10]	[-0.14, -0.00]	[-0.26, -0.01]	[-0.20, 0.11]	[-0.14, -0.02]
$\bar{R}^2$	0.4721	0.6222	0.5399	0.5190	0.6538	0.5598	0.5233	0.6547	0.5623
N: Agricultural HHs	138	124	262	138	124	262	138	124	262
N	208	217	425	208	217	425	208	217	425
Mean of control in 1999	0.5366	0.7048	0.6140	0.5366	0.7048	0.6140	0.5366	0.7048	0.6140
Mean of control in 2002	0.1626	0.3333	0.2412	0.1626	0.3333	0.2412	0.1626	0.3333	0.2412

Source: Compiled from IFPRI data.

Notes: 1. Sample of direct offspring of household heads. AgriHH * year 2002 is an interaction term of agricultural household dummy and year 2002 dummy. All the interaction terms are demeaned. Specification 1 uses time-varying thana level characteristics (yield, mean rainfall, mean high temperature, mean low temperature), individual-level characteristics (age squared, recipient of a poverty program), and Demographic fixed trends that are interactions of baseline individual and demographic characteristics (sex of individual, household head's education, number of older male/female siblings) with the year 2002 dummy, and sex of individual with the year 2002 * agricultural household dummy. Parental education is highly collinear with agricultural household dummy and is dropped from triple interactions. Specification 2 add other household fixed trends that are interactions of other baseline household characteristics (per member land holding, per member non-land assets, own piped water, structured toilet). Specification 3 adds Thana fixed trends, which allow heterogeneous trends at the Thana level.

2. Standard errors are clustered at thana level. 95% confidence intervals of cluster robust standard errors using Liang and Zeger (1986) are shown in parenthesis, and bias-reduced linearization (Satterthwaite correction) for a correction of a small number of clusters are shown in square brackets. $*$, $**$, $***$ indicate significance levels at 10%, 5%, 1% under BRL cluster robust standard errors, respectively.

Table A10: Main results by gender and age group

	Boys			Girls			Boys+Girls		
				A. Primary school ages					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Agricultural HHs * year 2002	0.0776	0.0701	0.0831	−0.0807	−0.0916	−0.0864	−0.0088	−0.0148	0.0005
	[-0.13, 0.29]	[-0.13, 0.27]	[-0.09, 0.26]	[-0.20, 0.04]	[-0.22, 0.04]	[-0.23, 0.06]	[-0.13, 0.11]	[-0.13, 0.10]	[-0.10, 0.10]
___ * Older sisters		0.0351	0.0273		0.0597	0.0665		0.0482	0.0471
		[-0.13, 0.20]	[-0.14, 0.20]		[-0.15, 0.27]	[-0.16, 0.29]		[-0.10, 0.20]	[-0.10, 0.20]
___ * Older brothers		−0.0949*	−0.1002*		−0.0089	−0.0127		−0.0510	−0.0545
		[-0.21, 0.02]	[-0.20, 0.00]		[-0.16, 0.14]	[-0.16, 0.13]		[-0.15, 0.05]	[-0.16, 0.05]
Demographic fixed trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other household fixed trends		Yes	Yes		Yes	Yes		Yes	Yes
Thana fixed trends			Yes			Yes			Yes
$\bar{R}^2$	0.4123	0.4439	0.4602	0.3916	0.4060	0.4151	0.4130	0.4239	0.4303
N: Agricultural HHs		154			295			141	
N		253			507			254	
Mean of treated in 1999		0.8586			0.8255			0.7965	
Mean of treated in 2002		0.7778			0.8302			0.8761	
Mean of control in 1999		0.7792			0.8000			0.8227	
Mean of control in 2002		0.7922			0.8000			0.8085	
				B. Secodary school ages					
	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
Agricultural HHs * year 2002	−0.1595***	−0.1388***	−0.1403**	−0.0293	−0.0930	−0.0897	−0.0853**	−0.0873**	−0.0894**
	[-0.23, -0.09]	[-0.22, -0.06]	[-0.23, -0.05]	[-0.19, 0.13]	[-0.23, 0.04]	[-0.23, 0.05]	[-0.15, -0.02]	[-0.16, -0.01]	[-0.16, -0.02]
___ * Older sisters		−0.1265*	−0.1252*		0.0361	0.0385		−0.0271	−0.0282
		[-0.27, 0.02]	[-0.28, 0.03]		[-0.24, 0.32]	[-0.25, 0.33]		[-0.18, 0.12]	[-0.18, 0.13]
___ * Older brothers		0.0164	0.0135		−0.1237	−0.1207		−0.0692	−0.0704
		[-0.13, 0.17]	[-0.15, 0.17]		[-0.31, 0.06]	[-0.32, 0.08]		[-0.22, 0.08]	[-0.22, 0.08]
$\bar{R}^2$	0.4032	0.4586	0.4597	0.5046	0.5215	0.5235	0.6135	0.6434	0.6453
N: Agricultural HHs		148			301			153	
N		228			486			258	
Mean of treated in 1999		0.6750			0.7459			0.8000	
Mean of treated in 2002		0.4625			0.4649			0.4667	
Mean of control in 1999		0.5878			0.6877			0.7843	
Mean of control in 2002		0.2230			0.3455			0.4641	

Source: Compiled from IFPRI data.

Notes:
1. Sample of direct offspring of household heads. Agricultural households * year 2002 is an interaction term of agricultural household dummy and year 2002 dummy. All the interaction terms are demeaned. Columns (1), (4), (7), (10) use time-varying thana level characteristics (yield, mean rainfall, mean high temperature, mean low temperature), individual-level characteristics (age squared, recipient of a poverty program), and Demographic fixed trends that are interactions of baseline individual and demographic characteristics (sex of individual, household head's education, number of older male/female siblings) with year 2002 dummy $\mathbf{x}_i r_t$, and with year 2002 * agricultural household dummy $\mathbf{x}_i r_t D_i$. Parental education is highly collinear with agricultural household dummy and is dropped from triple interactions. Columns (2), (5), (8), (11) add Other household fixed trends that are interactions of other baseline household characteristics (per member land holding, per member non-land assets, own piped water, structured toilet). Columns (3), (6), (9), (12) add Thana fixed trends, which allow heterogeneous trends at the Thana level.
2. Standard errors are clustered at thana level. 95% confidence intervals of cluster robust standard errors using (Liang and Zeger, 1986) are shown in parenthesis, bias-reduced linearization (Satterthwaite correction) for a correction of a small number of clusters are shown in square brackets. $*$, $**$, $***$ indicate significance levels at 10%, 5%, 1% under BRL cluster robust standard errors, respectively.

Table A11: Placebo test results by gender

	Boys			Girls		
	A. 1999 cohort					
	(1)	(2)	(3)	(4)	(5)	(6)
Agri HHs * year 2006	−0.0016	0.0093	−0.0034	−0.0313	−0.0422	−0.0515
	(-0.069, 0.065)	(-0.071, 0.090)	(-0.082, 0.075)	(-0.131, 0.069)	(-0.141, 0.057)	(-0.149, 0.046)
	[-0.083, 0.080]	[-0.107, 0.125]	[-0.117, 0.111]	[-0.166, 0.104]	[-0.190, 0.106]	[-0.198, 0.095]
$\bar{R}^2$	0.1176	0.1557	0.1653	0.5227	0.5328	0.5430
N: Agricultural HHs		196			183	
N		304			312	
Mean of control in 2002		0.2908			0.4863	
Mean of control in 2006		0.1173			0.1694	
	B. 2002 cohort					
	(7)	(8)	(9)	(10)	(11)	(12)
Agri HHs * year 2006	−0.0433	−0.0340	−0.0324	−0.0336	−0.0492	−0.0445
	(-0.101, 0.015)	(-0.088, 0.020)	(-0.086, 0.021)	(-0.125, 0.058)	(-0.156, 0.057)	(-0.165, 0.076)
	[-0.113, 0.027]	[-0.103, 0.035]	[-0.100, 0.035]	[-0.147, 0.080]	[-0.189, 0.090]	[-0.204, 0.115]
$\bar{R}^2$	0.1336	0.1720	0.1724	0.3572	0.3710	0.3839
N: Agricultural HHs		243			249	
N		386			426	
Mean of control in 2002		0.5391			0.6506	
Mean of control in 2006		0.2840			0.3133	

Source: Compiled from IFPRI data.

Notes: 1. Sample of direct offspring of household heads. Agricultural households * year 2002 is an interaction term of agricultural household dummy and year 2002 dummy. All the interaction terms are demeaned. Columns (1), (4) use time-varying thana-level characteristics (yield, mean rainfall, mean high temperature, mean low temperature), individual-level characteristics (age squared, recipient of a poverty program), and Demographic fixed trends that are interactions of baseline individual and demographic characteristics (sex of individual, household head's education, number of older male/female siblings) with the year 2002 dummy, and sex of individual with the year 2002 * agricultural household dummy. Parental education is highly collinear with agricultural household dummy and is dropped from triple interactions. Columns (2), (5) add other household fixed trends that are interactions of other baseline household characteristics (per member land holding, per member non-land assets, own piped water, structured toilet). Columns (3), (6) add Thana fixed trends, which allow heterogeneous trends at the Thana level.

2. Standard errors are clustered at thana level. 95% confidence intervals of cluster robust standard errors using Liang and Zeger (1986) are shown in parenthesis, and bias-reduced linearization (Satterthwaite correction) for a correction of the small number of clusters are shown in square brackets. $*$, $**$, $***$ indicate significance levels at 10%, 5%, 1% under BRL cluster robust standard errors, respectively.

Table A12: Descriptive Statistics: HIES (2016) with 10-27 years old in 1999

Variables	Mean	STD	Max	Min
Income (in taka)	12562.64	14940.05	480000	0
Years of education	4.634214	4.560333	18	0
Education completed: Primary	0.505697	0.499971	1	0
Education completed: Secondary	0.293591	0.45541	1	0
Education completed: Higher Secondary	0.155453	0.362339	1	0
Age (in years)	37.41189	7.633799	52	26
Gender: Male	0.48575	0.499801	1	0
Residency: Rural	0.683457	0.465131	1	0
Religion: Muslim	0.859788	0.347209	1	0
No. of Observation	66,528			

Notes: All information is based on the HIES (2016) data-set. STD represents Standard deviation.

Table A13: Cohort Analysis Data on Bangladesh: HIES (2016)

Age Classification	Number of Observation
Cohort 1 (Age 10-18 in 1999)	26100
Age 10 in 1999	3,387
Age 11 in 1999	2,650
Age 12 in 1999	3,929
Age 13 in 1999	1,978
Age 14 in 1999	4,533
Age 15 in 1999	2,068
Age 16 in 1999	3,754
Age 17 in 1999	1,889
Age 18 in 1999	1,912
Cohort 2 (Age 19-27 in 1999)	23120
Age 19 in 1999	4,944
Age 20 in 1999	2,974
Age 21 in 1999	1,841
Age 22 in 1999	2,698
Age 23 in 1999	1,416
Age 24 in 1999	3,676
Age 25 in 1999	1,619
Age 26 in 1999	2,577
Age 27 in 1999	1,375

Table A14: **Cohort Analysis 2: (Aged 10-27 in 2016)**

Variables	**Years of Education**	**Primary**	**Secondary**	**Higher Secondary**
Estimation:	**OLS**	**Probit**		
	(1)	(2)	(3)	(4)
(Aged 10 in 1999) X (Rural)	1.067***	0.368***	0.370***	0.296**
	(0.343)	(0.108)	(0.108)	(0.120)
(Aged 11 in 1999) X (Rural)	0.873**	0.213*	0.230**	0.330***
	(0.412)	(0.119)	(0.117)	(0.123)
(Aged 12 in 1999) X (Rural)	0.910**	0.278***	0.283***	0.345***
	(0.366)	(0.101)	(0.106)	(0.128)
(Aged 13 in 1999) X (Rural)	0.933*	0.335**	0.351***	0.230
	(0.487)	(0.138)	(0.131)	(0.150)
(Aged 14 in 1999) X (Rural)	1.339***	0.360***	0.364***	0.371***
	(0.357)	(0.0979)	(0.106)	(0.116)
(Aged 15 in 1999) X (Rural)	0.897**	0.228**	0.233*	0.257*
	(0.386)	(0.110)	(0.133)	(0.132)
(Aged 16 in 1999) X (Rural)	0.261	0.116	0.147	0.218*
	(0.391)	(0.117)	(0.117)	(0.125)
(Aged 17 in 1999) X (Rural)	0.417	0.0876	0.184	0.272*
	(0.443)	(0.127)	(0.117)	(0.139)
(Aged 18 in 1999) X (Rural)	0.416	0.0561	0.182	0.241*
	(0.406)	(0.121)	(0.123)	(0.146)
Other Control	Yes	Yes	Yes	Yes
District Control	Yes	Yes	Yes	Yes
District ×Age Control	Yes	Yes	Yes	Yes
Observations	49165	49129	49128	48987

Source: Compiled from HIES 2016 data. Notes: 1. Regression estimated using OLS with standard . errors clustered at *district* level reported in the parenthesis. $*$, $**$, $***$ indicate significance levels at 10%, 5%, 1%, respectively. 2. Regression estimates control for the cohort of birth dummy, sex, type of location (rural or urban), district and cohort of birth dummy interactions, and religion.

Table A15: **common trend test with HIES 2016: (Aged 19-27 in 1999)**

Variables	**Years of Education**	**Primary**	**Secondary**	**Higher Secondary**
Estimation:	**OLS**	**Probit**		
	(1)	(2)	(3)	(4)
(Aged 20 in 1999) X (Rural)	0.395	0.0924	0.0722	-0.0198
	(0.26)	(0.07)	(0.08)	(0.09)
(Aged 21 in 1999) X (Rural)	-0.189	0.0623	-0.0514	-0.210**
	(0.31)	(0.08)	(0.08)	(0.09)
(Aged 22 in 1999) X (Rural)	-0.349	-0.184**	-0.0539	-0.0289
	(0.30)	(0.08)	(0.09)	(0.09)
(Aged 23 in 1999) X (Rural)	-0.181	-0.0822	-0.0223	-0.121
	(0.37)	(0.10)	(0.11)	(0.12)
(Aged 24 in 1999) X (Rural)	0.131	0.0214	-0.0387	-0.078
	(0.24)	(0.06)	(0.07)	(0.07)
(Aged 25 in 1999) X (Rural)	0.133	0.0177	-0.0272	0.0177
	(0.34)	(0.09)	(0.11)	(0.11)
(Aged 26 in 1999) X (Rural)	-0.136	0.0198	-0.0374	-0.161*
	(0.29)	(0.07)	(0.09)	(0.09)
(Aged 27 in 1999) X (Rural)	-0.364	-0.0928	-0.122	-0.213*
	(0.38)	(0.10)	(0.11)	(0.12)
P-value for joint significance test for age and rural interaction terms	0.39	0.13	0.54	0.25
Other Control	Yes	Yes	Yes	Yes
District Control	Yes	Yes	Yes	Yes
District ×Age Control	Yes	Yes	Yes	Yes
Observations	23100	23087	23063	22986

Source: Compiled from HIES 2016 data. Notes: 1. Standard errors clustered at *district* level reported in the . parenthesis. $*$, $**$, $***$ indicate significance levels at 10%, 5%, 1%, respectively. 2. Regression estimates control for cohort of birth dummy, sex, district and cohort of birth dummy interactions, and religion.

Table A16: **Education Return: Dependent variable: log of income**

Variables	**Co-efficient**
Years of education	0.0663***
	(0.00356)
Age	0.0313
	(0.0280)
Age Squared	-0.000280
	(0.000412)
Male	0.525***
	(0.0412)
Rural	-0.0640**
	(0.0315)
Muslim	0.0611
	(0.0388)
District Control	Yes
Observations	6698

Source: Compiled from HIES 2016 data. Notes: Regression estimated using OLS with standard . errors clustered at *district* level reported in the parenthesis. $*$, $**$, $***$ indicate significance levels at 10%, 5%, 1%, respectively.

Table A17: India State Wide Academic and Agricultural Calendar

States	Major Crop	Area under crop (% of cropped area)	Academic Session	Final Exam	Harvest Period of major crop	Final Exam timing overlaps with Harvesting period
Andhra Pradesh	Rice	30%	June to April	April/May	November December	No
Arunachal Pradesh	Rice	47%	July to April	February	November-December	No
Assam	Rice	62%	January to December	December	November December	Yes
Bihar	Rice	44%	April to March	March	September to November	No
Delhi	Wheat	45%	April to March	March	March-April	Yes
Goa	Rice	29%	June to April	March	September-October	No
Gujarat	Cotton	23%	June to May	March	October to April	Yes
Haryana	Wheat	39%	April to March	Feb-March	April-May	No
Himachal Pradesh	Wheat	38%	April to March	March	April-June	No
Jammu-Kashmir	Wheat	26%	November to October	October-November	April-June	No
Jharkhand	Rice	69%	April to June	January-March	September to November	No
Karnataka	Pulse	18%	May to April	March	November-January	No
Kerala	Rice	8%	June to March	March	September-October	No
Madhya Pradesh	Wheat	23%	July to April	March	February-April	Yes
Maharashtra	Cotton	19%	June to May	March	Nov-Jan	No
Manipur	Rice	61%	Feb to Jan	December-January	October-November	No
Meghalaya	Rice	32%	Feb to Jan	October	October-December	Yes
Mizoram	Rice	26%	Jan to Dec	November-December	October-December	Yes
Nagaland	Rice	38%	Jan to Dec	November-December	September-November	Yes
Odisha	Rice	83%	April to March	March	September-October	No
Puducherry	Rice	63%	June to April	March-April	September-October	No
Punjab	Wheat	45%	April to March	March	April-May	No
Rajasthan	Pulse	16%	July to June	March	Feb-March	Yes
Tamil Nadu	Rice	33%	June to April	March-April	September-October	No
Tripura	Rice	53%	Jan to Dec	November-December	September-November	Yes
Uttar Pradesh	Wheat	38%	July to June	February-March	March-April	Yes
Uttarakhand	Wheat	31%	April to March	March-April	March-April	Yes
West Bengal	Rice	58%	Feb to Dec	November-December	August-November	Yes

Table A18: Descriptive Statistics: India sample (2004)

Variables	Mean	STD	Max	Min
Enrolled	1.00	0.00	1	1
Completed Years of education	2.82	2.18	0	12
Agricultural Households	0.385	0.485	0	1
Overlapping State	0.352	0.477	0	1
Age	9.10	2.38	5	13
Mother's Age	33.95	6.32	18	80
Father's Age	38.79	7.03	21	88
Father's Education	2.15	3.43	0	15
Mother's Education	4.44	4.44	0	16
No. of Assets	8.78	4.55	0	25
Household Size	6.67	2.72	2	38
No. of Observation	24378			

Notes: All information is based on the first round of the data set, which was collected in 2004. Agricultural household is an indicator variable for a household whose primary income is agriculture. Agricultural household (head) is defined as head is claiming that main income source is agriculture. STD represents Standard deviation.