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Gender-Gap in Learning Outcomes under Rainfall Shocks: The Role of Gender Norms

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Abstract

There is mixed evidence in the literature on the effect of rainfall shocks on educational outcomes for children in rural areas, with a limited understanding of how the gender-gap in education evolves in the face of such a shock. We posit that the vulnerability to climatic shocks can vary by the gender institutions of the setting which can have a bearing on the gender-gap in educational outcomes. On one hand, a negative productivity shock can lead to a disproportionate reduction in human capital outcomes for girls, as investments for girls may be more sensitive to income constraints. On the other hand, as the opportunity cost of schooling goes down in the face of a negative shock, it can translate into gains in educational outcomes, which are higher for female children in areas that favour female labour force participation. Leveraging the variation in cropping patterns that guide norms around female labor force participation (FLFP) in rural India, we examine how exposure to contemporaneous and past rainfall shocks affects learning outcomes for girls and boys. We find the widest gaps in outcomes in positive versus negative rainfall shock years for female children in regions that favour FLFP. We provide suggestive evidence that this is driven by increased participation in paid employment and full time domestic work during a positive rainfall shock.

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1 Introduction

The vulnerability to climatic shocks experienced by rural households in developing countries often manifests in the form of disproportionate negative effects on children's school attendance and human capital outcomes (Jacoby & Skoufias, 1997; Jensen, 2000). The impact of shocks is likely to multiply over time through the channels of self-reinforcement and dynamic complementarity (Cunha & Heckman, 2007), especially in the context of developing countries, where shocks experienced in childhood are likely to interact with other health shocks (Currie & Vogl, 2013). The effects of these shocks have been shown to manifest through two contrasting channels and the net effect is ambiguous a priori. First, a negative productivity shock may adversely affect educational investments in children through the income constraint channel. Second, the opportunity cost channel predicts that the child is *less* likely to drop out and put *more* time in education as demand for labour goes down in the face of a negative productivity shock. The susceptibility to these shocks has implications for long run development.

Importantly, the vulnerability to rainfall shocks might vary by the gender institutions of the setting and also have a bearing on the gender gap in learning outcomes. Gendered impacts of shocks on human capital outcomes have far reaching consequences which go beyond equity concerns as they affect fertility choice and intergenerational outcomes (Bloom et al., 2020; Gandhi Kingdon, 2002). Gender gaps in education often emerge as early as primary school, and become wider over time (Bharadwaj et al., 2012; Muralidharan & Sheth, 2016). Male and female children arguably also have different production functions of education, where differences in parent's attitudes, or differences in expected returns to schooling play a major role (Gandhi Kingdon, 2002). A negative income shock can lead to disproportionate reduction in *female* schooling outcomes and educational investments if they are more *elastic* to an income shortfall. The opportunity cost channel, on the other hand, can lead to a relative *gain* in female schooling outcomes in the face of a negative shock, from a greater relaxation of their time from both paid and unpaid work. Additionally, this effect is likely to be even higher in a setting with higher female labour force participation(FLFP). Hence, theoretically, the effect of a negative productivity shock on the gender gap in human capital outcomes is ambiguous. Using exogenous variation in cropping pattern that guides gender norms in the labour market, we examine how a rainfall shock affects the gender-gap in schooling and learning outcomes and explore the mechanisms through studying the labour market dynamics in response to the shock.

In this paper,we use the inter-temporal variation in exposure to rainfall shocks at the district level to study the gendered impact of the shock by crop type, controlling for a range of confounding variables including household fixed effects and district-specific linear time trends. We first show that districts that grow more rice than wheat, or 'rice-dominant' districts, have a larger share of both female adults and children in paid employment (10.3 and 12 percentage points respectively) than 'wheat-dominant' districts. Children in rice-dominant districts, irrespective of their gender, have *better* test scores and schooling outcomes on average. Their reading and math scores are better than their counterparts in wheat dominant districts by around 0.1 standard deviations, they are less likely to have dropped out of school (0.2 percentage points) and are more likely to be in the age-appropriate grade (3.2 percentage points). This aligns with previous findings on how mother's labor force participation can play a role in safeguarding child's educational outcomes (Afridi et al., 2016). Additionally, the gender gap in scores is also *lower* in rice-dominant districts, and in-fact completely reverses in the case of reading scores. On the other hand, in wheat-dominant districts, female children do worse than their male counterparts in both reading and math by much larger margins.

We find that while children of all genders experience a worsening of learning outcomes under positive rainfall shocks, female children in rice-dominant districts are especially affected. We find the widest gaps in outcomes in positive versus negative rainfall shock years for female children in rice-dominant districts, where test scores in negative shock years are better by close to 0.2 standard deviations than in positive shock years. We provide suggestive evidence that this is being driven by increased rates of dropping out during positive shock years. Under a negative rainfall shock, female children in rice-dominant districts are *less* likely to drop out of school by 1.16 percentage points (a 35 percent decline). This appears to be to be driven by increased participation in paid employment and full time domestic work during a positive rainfall shock. We also provide preliminary evidence on how gender norms might mediate the relationship between early life shocks and those experienced in later life. All children except female children in wheat-dominant districts (where there is systematically lower FLFP), who have experienced a positive shock in early life, gain less under a contemporaneous drought (negative) shock than their counterparts who have not. On the other hand, for female children in wheat-dominant districts, a positive shock in early life augments the gains from a negative shock in school-going years.

Our study makes several contributions. First, we add to the broader literature that looks at the impacts of climatic shocks on human capital outcomes. We specifically shed light on the gendered impact of the shock on learning outcomes using granular data on objective learning scores on around 3 million children across multiple years. Second, leveraging the variation in the cropping pattern in a district, we examine the role of the gender norms in the mediation of the shock dynamics. Third, our setting allows us to study how early-life shocks interact with contemporaneous shocks to impact human capital outcomes, thereby examining the role of dynamic complementarities. We build on work such as Shah and Steinberg (2017) and Bau et al. (2020) to show that the impact of early life shocks is also *gendered*. Lastly, using granular data on labour force participation, we are able to look at the possible mechanisms that explain the heterogeneity in the impact of the shock. The rest of the paper is structured as follows: Section 2 provides background and context for our setting. Section 3 describes our data sources and presents summary statistics. Section 4 lays out the empirical strategy and main results. Section 5 concludes.

2 Background and Context

It is well documented that a rainfall shock is also an income shock in rural districts - shocks affect crop production, which is closely linked to agricultural wages (Amare et al., 2018; Auffhammer et al., 2012; Jayachandran, 2006; Kaur, 2019; Mueller & Osgood, 2009; Mueller & Quisumbing, 2011; Shah & Steinberg, 2017; Singh et al., 2011). In the absence of opportunities to smooth consumption, this affects the availability of household resources, which can lead to implications for human capital formation. The impact of shocks on human capital attainment depends on how household-level income losses (or gains) translate into resource allocation within the household. A reduction in household income due to a rainfall shock could lead to reduced educational inputs (Groppo & Kraehnert, 2017; Jensen, 2000), reduced health investments (Lohmann & Lechtenfeld, 2015), and poorer calorific intake (Carpena, 2019).

This change in household resources could affect early and later life investments in male and female children differently (Björkman-Nyqvist, 2013; Cameron & Worswick, 2001; Dinkelman, 2016; Maccini & Yang, 2009; Rose, 1999). In the case of India, Kingdon (2005), Chaudhuri and Roy (2006) and Saha (2013) find evidence of gender discrimination in educational expenditure across most states in the country, even in the absence of a rainfall shock. Zimmermann (2020) show that in India, girls in the 8-10 age range are more likely to be taken out of school than boys in case of adverse rainfall shocks. Additionally, female children could be worse-off even in the absence of direct differential treatment by parents. Son-preference and fertility-stopping behaviour by the household could also lead to female children having more siblings overall, and therefore make them more likely to be in environments where there are less resources available per child (Jayachandran & Pande, 2017; Jensen, 2002), which could further exacerbate the impact of a negative rainfall shock.

The changes in wages caused by a rainfall shock may directly affect the value of the outside option for school-going children. As previously shown in the Indian context, a positive rainfall shock has a negative effect on test scores and enrollment for children in the school going age (Shah & Steinberg, 2017). This is driven by the increased opportunity cost of schooling as the positive shock shifts wages upwards, causing school-going children to drop out and move to the labor force (Atkin, 2016; Dumas, 2020; Kruger, 2007; Shah & Steinberg, 2017; Shah & Steinberg, 2019; Trinh et al., 2020). In contrast, a negative rainfall shock could have the opposite effect on scores and enrollment. There is also reason to expect that the impact of the change in the value of the outside option to schooling is gender sensitive. Child labor varies by context and gender - Gustafsson-Wright and Pyne (2002) show that in rural Brazil, boys are more likely to be employed, while Blunch and Verner (1999) and Zapata et al. (2011) show that in Ghana and Bolivia respectively, girls are more likely to be engaged in paid work. Bau et al. (2020) show that in Indian districts with high prevalence of child labor, a positive rainfall shock in early life reduces educational investment, in particular for girls, while outcomes for oldest sons remain relatively protected from the shock.

Rainfall shocks affect wages and labor market participation of adults in the household, which could alter their time-use patterns, and also have a bearing on children. As Dillon (2013) documents in the case of Northern Mali, children are complementary to adult labor in agriculture, but substitutes for adult labor in care-giving. If a rainfall shock causes labor market options in agriculture for adults to shrink for example, these could be substituted by increases in labor supply in the non-agricultural sector or increases in time spent at home. Chuang (2019) documents that farmers in India increase both agricultural and non-agricultural wage work in the case of a negative rainfall shock. Afridi et al. (2021) present evidence from India that women's workdays reduce to a larger extent than men when faced with a drought shock, as they are more constrained by a lack of opportunities in non-farm work. Maitra and Tagat (2019) show that adults (both men and women) increase participation in non-agricultural labor in the face of *any* rainfall shock. They also find that women tend to also increase time allocated to domestic activities and reduce time attending educational institutions in response to a shock, particularly in districts that cultivate rain-fed rice. In sum, it becomes important to investigate the role gender and associated norms might play in mediating the impact of rainfall shocks on children's human capital attainment.

One crucial determinant of gender norms is the extent of female involvement in agricultural processes, which determines their relative economic value in the labor force, and therefore to the household. Requirements of deep tillage, for example, lead to lower levels of female labor force participation and lower female to male sex-ratios (Alesina et al., 2013; Carranza, 2012, 2014). Historical factors - such as the adoption of intensive agriculture, which further influence patrilocality and land inheritance can determine the relative value of sons compared to daughters. These effects are persistent, and immune to temporal changes in the dependence on land, leading to lower present-day female to male sex ratios in cultures with a higher incidence of patrilocality (Ebenstein, 2021). In this study, we use within-country variation in female labor force participation, linked to the cultivation of rice and wheat. Females have a comparative advantage in weeding and transplanting, making demand for female labor higher in regions that predominantly cultivate rice. On the other hand, in traditionally wheat cultivating areas where the use of the plough is more extensive, demand for female labor is lower (Bardhan, 1974; Chin, 2012).[1] While cultivation of both rice and wheat is positively linked to rainfall, additional benefits accrue to females, particularly in regions that grow rain-fed rice. In these regions, the gender wage gap reduces under a positive rainfall shock relative to normal years (Mahajan, 2016).

We test for how norms surrounding women's work drive impacts of rainfall shocks using data from rural India, where pervasive gender-based discrimination and differences in both human capital attainment and labor force participation are well documented (Jensen & Oster, 2009; Pande, 2003; Sen, 1992). We use granular precipitation data from 1982 to 2016 to capture exogenous variation in district-level rainfall, and classify districts based on whether they experienced below-normal, normal, or above-normal rainfall. In India, below-normal rainfall is considered a negative shock to agricultural productivity, and above-normal rainfall is considered

[1] We also demonstrate empirically that female labor force participation of both adult and children is higher in districts that cultivate more rice than wheat in our study context.

a positive shock to agricultural productivity (Jayachandran, 2006). We estimate the systematic gender difference in the impact of a rainfall shock on a range of measures of human capital and related investments, for a sample of about three million children in 472 districts, collated using seven rounds of ASER data. We use data on test scores collected for all children in the school going age range (5-16 years). These data are collected irrespective of the child's school enrollment status. We also use information on schooling, including school type and extra investments in the form of enrollment in tuition support. We utilize data on rice and wheat cultivation from 1997, to classify districts as predominantly cultivating one of rice or wheat. We do this by comparing the mean area under rice cultivation for each district with the area under wheat cultivation.[2] The crop margin allows us to test for heterogeneity in the impacts of the shock by gender norms surrounding FLFP.

3 Data

3.1 Cognitive Outcomes and Schooling

We use objective data on schooling and learning outcomes on a sample of approximately three million children collected by Annual Status of Education Report(ASER) for the years 2008 through 2012, 2014 and 2016.The ASER survey, conducted annually since 2005, measures schooling and learning outcomes for children aged 5-16. It is a representative household level survey, covering all rural districts in India.[3]. A unique feature of the ASER survey is that children are surveyed at home, meaning that data on test scores is available *irrespective* of school enrollment status.

We use data on reading (in the native language)and math ability.The surveyors code the reading level as a number from 1-5, where 1 indicates the child cannot read anything, 2 indicates the child can identify letters, 3 indicates the child can read words, 4 indicates the child can read a grade 1 level text, and 5 indicates the child can read a grade 2 level text. In the case of Math, 1 indicates inability to do any arithmetic, 2 indicates ability to recognize numbers from 0-9, 3 indicates ability to recognize numbers from 11-99, 4 indicates ability to do simple subtraction and 5 indicates ability to do division. We convert each of these codes into z-scores by the child's age - comparing children's learning level to children in their age cohort. The mean reading and math z-scores in our sample are -0.01 and -0.02 respectively. The mean reading z-score is 0.012 for male children, and -0.012 for female children. The corresponding statistics for the math z-score are 0.040 and -0.045.

In addition to learning outcomes, we also know schooling status (currently enrolled, dropped out or never enrolled), school grade (if enrolled) and whether the child

[2]Means are computed using data spanning 15 years on average.

[3]For more details on ASER, see http://www.asercentre.org/

attends any extra tuition.[4] We use the ASER data to construct an indicator for whether the child is 'on track'. This variable takes value 1 if the difference between the child's age and school grade is less than or equal to 6, and value 0 if this difference is greater than 6. This is similar to the definition used in Shah and Steinberg (2017). 3% of the children in our sample have dropped out of school and 86% are in the age-appropriate grade. The drop-out rate is 3.1% for male children and 3.8% for female children, while 84.4% and 85.9% male and female children are in the age-appropriate grade respectively. 21% of the children in our sample are enrolled in extra tuition support. The enrollment in extra tuition support is slightly higher for male children, at 22.4%, and 19.5% for female children.

We split the ASER sample into two age cohorts - the older cohort includes all children who are aged 11 to 16, and the younger cohort includes all children who are aged 5 to 10. In addition to analysis using the pooled sample, we report all regression specifications for the age sub-samples. This allows us to inspect heterogeneous effects of the interaction of shock and gender norms for children by their age.

We code an indicator "In Government School" that takes value 1 for children that study in public schools (approximately 65% of our sample). We also test for heterogeneity in the effects of shock and gender norms by school type, and these results are available upon request.

3.2 School, Household and Village Level Controls

In our regression specifications, we control for a range of school, household and village characteristics, available in the ASER survey. We also compute a household wealth index, using a principal component analysis of data on household asset ownership - this includes indicators for whether the house is a 'pucca' (fixed) house, a 'kutcha' (temporary) house, owns an electricity connection, a TV or a mobile phone.

3.3 Rainfall

We use rainfall data from the University of Delaware, for the years 1982 to 2016.[5] These data are available in the form of monthly totals, and are gridded by latitude and longitude. We match each geo-point for which data are available with India's district boundaries, calculate the mean rainfall for all the coordinates that lie within each district's boundary, and assign that as the rainfall for the district. We use the intertemporal variation in rainfall shock *within* a district for our analysis. We define the rainfall shock variable by comparing the total annual rainfall in each

[4] Data on monthly tuition expenditure are available, but only for the years 2014 and 2016.

[5] The Willmott and Matsuura (2001) data are available here: https://psl.noaa.gov/data/gridded/data.UDel_AirT_Precip.html

district in a given year to the 20th and 80th percentile for the last 10 years in the *same* district. In other words, we compare the rainfall in each district in the year ASER data was collected to the 20th and 80th percentile for that district computed using district-specific data for the last 10 years. The shock variable takes value -1 (Drought or negative shock) if the rainfall in the ASER year is less than or equal to the 20th percentile, value 1 (Flood or positive shock) if the rainfall in the ASER year is greater than or equal to the 80th percentile, and value 0 (Normal) if rainfall lies between the 20th and 80th percentile. This is similar to the definition used in Jayachandran (2006), Shah and Steinberg (2017), Kaur (2019) and Mahajan (2016). We also construct the shock variable for the year preceding the year when ASER data was collected and indicators for early life shock (rainfall shock in birth year and years when the child was 1-4 years old) in a similar way. The shock indicators for the ASER years are defined at the district-year level, and the indicators for early-life shock are defined at the child level. 25% of the districts in the combined ASER sample are classified as having a drought shock, 26% are classified as having experienced a flood and 49% as having normal rainfall conditions in the year of the ASER survey.

3.4 Crop Data

We use data on district-wise, season-wise crop yield from the Ministry of Agricultural Welfare and Directorate of Economics and Statistics.[6] The data are available for the years 1997-2015, for 640 districts in India, and provide season-wise area sown and production for a range of crops.

We compute district-wise crop share of rice and wheat in terms of total area sown and production for each year, and the mean crop share of rice and wheat using data across all available years.[7]. We code a dummy 'rice dominant district' that takes value 1, if the mean crop share of rice is greater than the mean crop share of wheat in terms of area sown.[8] We will refer to districts for which this variable takes value 1 as 'rice dominant districts' and those for which it takes value 0 as 'wheat dominant districts' hereon. 46% of the districts in our data are rice-dominant. In Figure 1 we show the geographical distribution of rice dominant districts. The dark green area, encompassing most of southern and eastern India, indicates districts that grow more rice than wheat (in terms of area sown).

[6] The data are available here: https://data.gov.in/catalog/district-wise-season-wise-crop-production-statistics

[7] Data are not available for the years 1997 to 2015 for all districts. On average, data are available for 15 years for each district

[8] In the case of 2 districts - Kargil and Leh Ladakh, crop share in terms of area sown under rice and wheat is equal to 0. We drop these districts when looking at variation along the rice versus wheat margin.

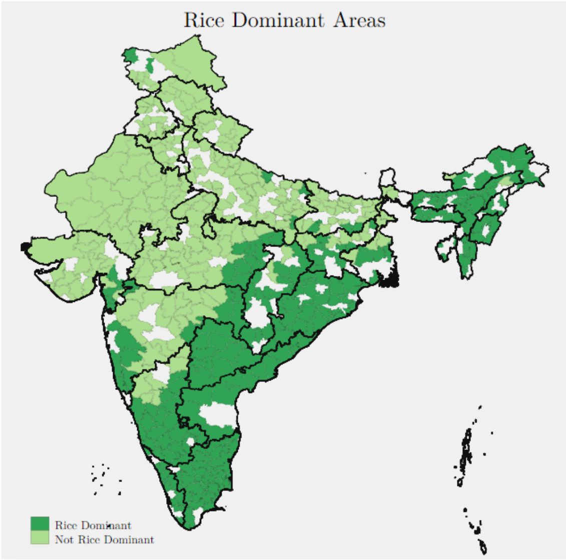

Figure 1: Distribution of Rice Dominant Districts

3.5 National Sample Survey Data

We use data from the 64th, 66th and 68th Employment and Unemployment Surveys of India's National Sample Survey to look at how rainfall shocks affect adult and child labor force participation by gender and crop type.[9] Data are available from households across all of India's districts. We restrict analysis to rural households, and have a combined sample of more than 9,91,000 individuals. We use data on adult and children's 'Usual Principal Activity Status' to create indicators for whether each individual is engaged in paid employment, carries out domestic work or performs unpaid work for a family enterprise. We also define an indicator for whether those in paid employment are engaged in non-agricultural casual labor.

Table 1: Summary Statistics - Main Variables

	N	Mean	S.D.	Min	Max
	ASER DATA (Ages 5-16)				
Female	2796905	0.47	0.50	0.00	1.00
Age	2787464	10.34	3.29	5.00	16.00
Reading : Z-score	2496871	-0.01	1.00	-3.88	3.65
Math : Z-score	2487607	-0.02	1.00	-3.32	3.78
Drop Out	2796905	0.03	0.18	0.00	1.00
On-Track	2446309	0.86	0.35	0.00	1.00
Attends Tuition	2033345	0.21	0.41	0.00	1.00
In Government School	2796905	0.65	0.48	0.00	1.00
Older Age Cohort	2787464	0.47	0.50	0.00	1.00
	RAINFALL DATA				
Negative Shock	2796905	0.25	0.43	0.00	1.00

[9]These data are available here: http://microdata.gov.in/nada43/index.php/catalog/EUE. The data were collected in the years 2007-2008, 2009-2010 and 2011-2012 respectively

Positive Shock	2796905	0.26	0.44	0.00	1.00
Normal Rainfall	2796905	0.49	0.50	0.00	1.00
Negative Shock (Previous Year)	2796905	0.16	0.37	0.00	1.00
Positive Shock (Previous Year)	2796905	0.34	0.48	0.00	1.00
Normal Rainfall (Previous Year)	2796905	0.49	0.50	0.00	1.00
			CROP DATA		
Rice Dominant District	2784952	0.46	0.50	0.00	1.00
			NSS DATA		
Age	643785	27.89	19.27	0.00	98.00
Female	643863	0.49	0.50	0.00	1.00
Paid Employment	379371	0.51	0.50	0.00	1.00
Unpaid Work on HH Enterprise	379371	0.13	0.34	0.00	1.00
Domestic Work Only	643863	0.20	0.40	0.00	1.00
Non-Agricultural Casual Labor	379371	0.20	0.40	0.00	1.00
HH Owns Land	643863	0.95	0.22	0.00	1.00
Agri. Household	643863	0.50	0.50	0.00	1.00
NREGA Operational (District)	643863	0.85	0.36	0.00	1.00
District Grows Rain-Fed Rice	303068	0.09	0.28	0.00	1.00

Note: Table presents the total number of observations (N), mean, standard deviation, minimum and maximum value of key variables used in the analysis. ASER data are from the years 2008-2012, 2014 and 2016. Rainfall data are from the University of Delaware, and shock variables are calculated based on merging with ASER data. NSS data are from rounds 64 (2007-2008), 66 (2009-2010) and 68 (2011-2012) of the Employment and Unemployment Surveys. NSS data only includes the rural sample.

Our primary analysis explores how differences in norms around FLFP mediate the impact of a rainfall shock - where we use the dominance of rice versus wheat cultivation to account for these differences. We show differences between rice and wheat dominant districts in key variables from the ASER and NSS data in Tables 8 and 9 in the Appendix. Table 2 shows mean values of our outcome variables by gender, separately for rice and wheat dominant districts. Interestingly, there appears to be a considerable gap between scores for both male and female children in rice and wheat dominant districts, where children in rice dominant districts do better overall. Mean reading z-scores for children in rice dominant districts are 0.04 for male children, and 0.07 for female children, while those in wheat dominant districts are -0.04 for male children and -0.10 for female children. Math z-scores are 0.06, 0.03, -0.02 and -0.16 for male and female children in rice and wheat dominant districts respectively. As is commonly noted in the gender skill gap literature, female children outperform male children in reading scores in rice dominant districts. However, this is not true for wheat dominant districts where female children fare considerably worse in both reading and math. On average, female children in wheat dominant districts are also more likely to have dropped out of school (4%) than other children, and are the least likely (among the gender-crop groups) to be enrolled in extra tuition support. The gender differences between rice and wheat dominant districts in principal activity status are also stark, and FLFP is lower by 11 percentage points in the latter. Congruently, females in wheat dominant districts are also 7 percentage points more likely to be engaged in domestic work full-time than their counterparts in rice dominant districts. We show gender based differences in children's participation in Table 9. The differences in male children's participation in paid employment and unpaid work on a household enterprise do not vary systematically between rice and wheat dominant districts. However, female children's participation in paid employment is higher in rice-dominant districts by 12 percentage points than in wheat-dominant districts and they are 6.3 percentage points more likely to be engaged in unpaid work on a household enterprise. These differences are statistically significant.

Table 2: Outcomes by Gender for Rice and Wheat Dominant Districts

	Rice Dominant Districts		**Wheat Dominant Districts**	
	Male	Female	Male	Female
		ASER DATA (Ages 5-16)		
Reading: Z-score	0.04	0.07	-0.04	-0.10
	[0.94]	[0.94]	[1.02]	[1.08]
Math: Z-score	0.06	0.03	-0.02	-0.16
	[0.93]	[0.94]	[1.02]	[1.06]
Drop Out	0.03	0.03	0.03	0.04
On-Track	0.87	0.88	0.84	0.85
Attends Tuition	0.22	0.20	0.23	0.19
In Government School	0.67	0.69	0.61	0.65
		NSS DATA		
Paid Employment	0.84	0.25	0.81	0.14
Unpaid Work on HH Enterprise	0.12	0.14	0.16	0.10
Domestic Work Only	0.01	0.38	0.01	0.45
Non-Agricultural Casual Labor	0.29	0.14	0.29	0.08

Note: Table presents means of variables by gender and crop type. Standard deviations are in parentheses. ASER data are from the years 2008-2012, 2014 and 2016. NSS data are from rounds 64 (2007-2008), 66 (2009-2010) and 68 (2011-2012). NSS data only includes the rural sample.

4 Empirical Strategy and Results

We exploit the quasi-random variation of rainfall shock within a district and test for gender differences in shock response by the cropping-pattern margin. Our main outcome variables are test scores, schooling and extra investments on tuition expenses. Additionally, we are able to use within-household variation in shock exposure that addresses selection concerns arising from unobserved heterogeneity between households prone to rainfall shocks. We include a battery of individual, household, school and village level time-varying controls and district-year time trends in addition to household fixed effects. We restrict the analysis to children aged 5 or older, as ASER only records test scores for children in this age bracket. We also run sub-sample analyses for children aged 5-10 and 11-16 respectively. The outcome variables from the ASER data are reading and math z-scores (calculated by age), an indicator for whether the child has dropped-out of school, an indicator for whether the child is 'on-track' in school and an indicator for whether the child is enrolled in paid tuition classes in addition to school. The outcomes from the NSS data are indicators for whether the individual is engaged in paid employment, carrying out unpaid work on a household enterprise, doing domestic work full time, or from within those who are employed - engaged in non-agricultural casual labor. The estimating equation is as follows:

$$\begin{aligned} Y_{ihvdt} &= \alpha_{ihvdt} + \beta_1 Female_{ihvdt} + \beta_2 RainfallShock_{dt} + \beta_3 Female_{ihvdt} * RainfallShock_{dt} \\ &+ \beta_4 RainfallShock_{dt-1} + \beta_5 Female_{ihvdt} * RainfallShock_{dt-1} \\ &+ \delta_1 X_{1ihvdt} + \delta_2 X_{2hvdt} + \delta_3 X_{3vdt} \\ &+ \gamma_h + \mu_d + \pi_{dt} + \epsilon_{ihvdt} \end{aligned} \quad (1)$$

Y_{ihvdt} represents the outcome variable for child i in household h, village v, district d, surveyed in year t. $Female_{ihvdt}$ takes value 1 if child i is a female and 0 otherwise. $RainfallShock_{dt}$ takes value -1 if district d, in the year t faced a negative rainfall shock, 1 if it faced a positive rainfall shock and 0 if it was a year with normal rainfall. Coefficient β_2 is the effect of a one unit increase in the value of the rainfall shock variable on outcome Y for male children. The term $Female_{ihvdt} * RainfallShock_{dt}$ represents the interaction between the indicator that the child is female, and the rainfall shock variable. β_3 is the coefficient representing the differential effect of the shock by gender.

Following Shah and Steinberg, 2017, we also include the rainfall shock in the previous year and its interaction with the child's gender, represented by the terms $RainfallShock_{dt-1}$ and $Female_{ihvdt} * RainfallShock_{dt-1}$ respectively. X_{1ihvdt} is a vector of child-level controls, including school grade, school type,[10], indicators for exposure to a rainfall shock in early life - in the child's birth year and in the years when the child was 1 to 4 years of age, and indicators for whether the child's mother has gone to school. School grade and school type are excluded in the specification where dropping out is the outcome, as these variables are only defined for children who are enrolled in school. X_{2hvdt} is a vector of household level controls, for household h in village v and district d. This includes sibling cohort composition[11], number of children in the household, an indicator for whether the household has a first-born female child, and a household wealth index constructed using a principal component analysis of the following variables - house type,[12] and indicators for whether the household has an electricity connection, a T.V or a mobile device. X_{3vdt} is a vector of village-level controls for village v in district d, and includes indicators for whether the village is connected by a paved road, has electricity supply, a bank, a ration shop, a government primary school, a government middle school and a government secondary school. γ_h, μ_d, represent vectors of household and district fixed effects, and π_{dt} represents district-year time trends.

[10]Categorized as Government, private, Madarsa and other
[11]Defined as 0 = Only Child, 1 = All Female, 2 = All Male, 3 = Mixed
[12]Included as indicators for whether the house is kutcha or pucca

To explore our main margin of interest, we test for heterogeneity in effects by rice and wheat dominant districts. We examine if the effect of a rainfall shock on both male and female children varies by the dominant crop type. We estimate the fully saturated model, including all pairwise interactions between the shock indicator, the dummy for female child and a dummy for rice dominant district[13] in the following equation:

$$\begin{aligned}
Y_{ihvdt} &= \alpha_{ihvdt} + \beta_1 Female_{ihvdt} + \beta_2 RainfallShock_{dt} + \beta_3 RiceDominant_d \\
&+ \beta_4 Female_{ihvdt} * RainfallShock_{dt} + \beta_5 Female_{ihvdt} * RiceDominant_d \\
&+ \beta_6 RainfallShock_{dt} * RiceDominant_d \\
&+ \beta_7 Female_{ihvdt} * RainfallShock_{dt} * RiceDominant_d \\
&+ \beta_8 RainfallShock_{dt-1} + \beta_9 Female_{ihvdt} * RainfallShock_{dt-1} \\
&+ \beta_{10} RainfallShock_{dt-1} * RiceDominant_d \\
&+ \beta_{11} Female_{ihvdt} * RainfallShock_{dt-1} * RiceDominant_d \\
&+ \delta_1 X_{1ihvdt} + \delta_2 X_{2hvdt} + \delta_3 X_{3vdt} \\
&+ \gamma_h + \mu_d + \pi_{dt} + \epsilon_{ihvdt} \qquad (2)
\end{aligned}$$

In equation (2), β_2 captures the impact of a one unit increase in the value of the rainfall shock variable on males in wheat dominant districts[14] and β_4 captures the difference in shock outcomes between males and females in wheat dominant districts. β_6 captures the effect of a one unit increase in the value of the rainfall shock variable on male children in rice dominant districts. β_7 is the triple difference term, that measures the relative difference in gender wise impacts of shocks for male and female children in rice dominant districts. As in equation 1, we include household fixed effects and district-year time trends.

We estimate the interaction of a shock experienced in early life with contemporaneous shocks using the following equation:

$$\begin{aligned}
Y_{ihvdt} &= \alpha_{ihvdt} + \beta_1 Female_{ihvdt} + \beta_2 Drought_{dt} + \beta_3 EarlyLifePositiveShock_{ihvdt} \\
&+ \beta_4 Female_{ihvdt} * Drought_{dt} + \beta_5 Drought_{dt} * EarlyLifePositiveShock_{ihvdt} \\
&+ \beta_6 Female_{ihvdt} * EarlyLifePositiveShock_{ihvdt} \\
&+ \beta_7 Female_{ihvdt} * EarlyLifePositiveShock_{ihvdt} * Drought_{dt} \\
&+ \beta_8 RiceDominant_d + \beta_9 RiceDominant_d * Female_{ihvdt} \\
&+ \beta_{10} RiceDominant_d * Drought_{dt} + \beta_{11} RiceDominant_d * EarlyLifePositiveShock_{ihvdt} \\
&+ \beta_{12} RiceDominant_d * Drought_{dt} * EarlyLifePositiveShock_{ihvdt} \\
&+ \beta_{13} RiceDominant_d * Drought_{dt} * Female_{ihvdt} \\
&+ \beta_{14} RiceDominant_d * Drought_{dt} * Female_{ihvdt} * *EarlyLifePositiveShock_{ihvdt} \\
&+ \delta_1 X_{1ihvdt} + \delta_2 X_{2hvdt} + \delta_3 X_{3vdt} \\
&+ \gamma_h + \mu_d + \pi_{dt} + \epsilon_{ihvdt} \qquad (3)
\end{aligned}$$

[13] The indicator for rice dominant districts, *RiceDominant* takes value 1 for districts where the mean area under rice cultivation, calculated using district-level crop data for the last 15 years on average, is greater than the mean area under wheat cultivation

[14] For whom *RiceDominant* takes value 0

In equation 3, β_2 captures the effect of experiencing a contemporaneous drought (negative) shock. $beta_3$ captures the effect of experiencing a positive shock in early life. The indicator $EarlyLifePositiveShock_{ihvdt}$ takes value one if a positive rainfall shock occurred in the birth year or two years following birth, for child i in household h, village v and district d. We include all pairwise interactions of the gender, drought, early life shock and rice dominant district variables to inspect differences by gender and crop type. As in earlier models, we include a rich set of individual, household, district and village level controls. Household fixed effects and district-year time trends are included.

In Table 3, we present the results of the first specification. Panel A displays the results from the full sample analysis, and panels B and C display results from the sub-sample analyses with older (ages 11-16) and younger (ages 5-10) children respectively. We include household fixed effects in all specifications, and compare siblings. This allows us to account for household level heterogeneity in unobservables. In the full-sample analysis, our results indicate that for male children, test scores as well as the likelihood of being on-track are higher under a negative rainfall shock, while the probability that the child has dropped out of school is lower. All these effects are statistically significant. Reading and math scores of male children tested in a negative shock year are higher by 0.06 and 0.14 standard deviations respectively, than those of male children tested in a positive shock year. The probability of having dropped out of school is lower by 0.32 percentage points (a 9.6 percent decline) while that of being in the age-appropriate grade is higher by 0.9 percentage points respectively. While we do not find effects of a contemporaneous rainfall shock on enrollment in extra-tuition, we find that a positive rainfall shock in the previous year *improves* the probability of being enrolled in tuition support for male children by about 1.9 percentage points (an 8.6 percent increase).

An added advantage accrues to female children in drought (negative shock) years, indicated by the significant coefficients on the interaction of an indicator of being female and the rainfall shock variable (for all outcomes except on-track and enrollment in extra tuition). Female children tested under a negative shock have reading scores that are 0.1 standard deviations higher than female children tested under a positive one. The corresponding effect on math scores is an increase of 0.16 standard deviations, likely due to the fact that female children do worse at math in the absence of any shock. The likelihood of dropping out is lower by 0.7 percentage points (a 21 percent decline) and the likelihood of and being on-track is higher by 0.35 percentage points (although not significant). As with male children, the likelihood of being enrolled in extra tuition support does not appear to change significantly due to a contemporaneous rainfall shock, but is *higher* by 1.24 percentage points if the previous year witnesses a positive shock rather than a negative one.

The results using sub-samples of older children (11-16 years) and younger children (5-10 years) show the same trends as the pooled sample, but effect sizes are slightly different. In negative shock years, reading and math scores of male children in the older cohort are higher by 0.04 and 0.12 standard deviations, probability of dropping-out is lower by 0.8 percentage points and that of being on-track is higher by 0.8 percentage points, as compared to older male children in positive shock years.

As in the pooled sample, contemporaneous rainfall shocks have no impact on enrollment in tuition support, but a positive shock in the previous year improves this likelihood by 2.76 percentage points (10 percent) for male children in the older cohort. Negative shocks lead to improvements to the tune of 0.09 and 0.15 standard deviations in reading and math scores of younger male children. The change in the probability of dropping out is very small (0.1pp) and not statistically significant, and the probability of being in an age appropriate grade is higher by 1.18 percentage points. Neither the contemporaneous shock, nor one in the previous year appears to influence enrollment in tuition for younger children. In the case of female children, those in the older cohort tested during a negative shock have reading and math scores that are 0.08 and 0.16 standard deviations higher than those tested during a positive shock. They are less likely to have dropped out - by about 1.8 percentage points (27 percent), and are more likely to be on-track - by 0.5 percentage points. Their likelihood of being enrolled in paid tuition is higher under a positive shock in the previous year, by 1.24 percentage points (5 percent). Female children in the younger cohort, tested in negative shock years have reading and math scores that are higher by 0.13 and 0.17 standard deviations respectively, compared to their counterparts tested in positive shock years. The change in the probability of having dropped out as with younger male children, is very small (0.01pp, and not significant) and probability of being on-track is greater, by 0.1 percentage points.

Consistent with previous findings from similar contexts (Shah & Steinberg, 2017; Zimmermann, 2020), we find that negative rainfall shocks lead to better human capital and schooling outcomes. Additionally, our results show that female children gain (lose) more in negative (positive) shock years overall. That is to say, that test scores and schooling outcomes for female children are more *elastic* to rainfall conditions than those of male children. Younger children's test scores are more affected than those in the older cohort, but the likelihood of dropping out is considerably higher for older children - especially older female children. We also find suggestive evidence that households spend more on extra investments in education (such as by enrolling children in paid tuition) in cases where there is a positive rainfall shock in the previous year. Notably, there is a gap in the household spending by gender, and suggests households prefer to spend more on male children, especially those in the older age cohort.

Table 3: Impact of Rainfall Shocks by Gender

	Reading: Z-Score	**Math: Z-Score**	**Dropped Out**	**On Track**	**Enrolled in Extra Tuition**
Panel A: Full sample					
Female	0.0075	-0.0527***	0.0014*	0.0012*	-0.0272***
	(1.55)	(-9.90)	(1.76)	(1.91)	(-15.41)
Rainfall Shock	-0.0311***	-0.0684***	0.0016*	-0.0043***	-0.0050
	(-4.00)	(-7.57)	(1.69)	(-2.91)	(-0.92)
Female × Rainfall Shock	-0.0205***	-0.0123***	0.0018**	0.0008	0.0007
	(-4.84)	(-2.76)	(2.30)	(0.87)	(0.45)
Rainfall Shock (Previous Year)	-0.0421***	-0.0659***	0.0003	-0.0019	0.0095**
	(-4.76)	(-6.51)	(0.31)	(-1.15)	(2.18)
Female × Rainfall Shock (Previous Year)	-0.0173***	-0.0185***	0.0030***	-0.0000	-0.0033**
	(-4.07)	(-4.22)	(4.05)	(-0.01)	(-2.03)
Constant	0.0118	-0.0250	-0.0845***	1.8627***	0.0154
	(0.39)	(-0.85)	(-17.59)	(219.86)	(1.31)
Observations	1062777	1059491	1410153	1204388	937749
Mean of Dep. Var.	0.038	0.019	0.033	0.854	0.221
Panel B: Old Cohort: Age 11 - 16					
Female	-0.0054	-0.0744***	0.0048**	-0.0000	-0.0379***
	(-0.92)	(-10.35)	(2.55)	(-0.02)	(-12.97)
Rainfall Shock	-0.0190**	-0.0621***	0.0040**	-0.0039*	-0.0046
	(-2.35)	(-6.13)	(2.05)	(-1.66)	(-0.60)
Female × Rainfall Shock	-0.0192***	-0.0201***	0.0048***	0.0015	-0.0016
	(-3.41)	(-2.97)	(2.70)	(0.90)	(-0.57)
Rainfall Shock (Previous Year)	-0.0390***	-0.0743***	0.0010	-0.0018	0.0138**
	(-4.25)	(-6.34)	(0.52)	(-0.64)	(1.97)
Female × Rainfall Shock (Previous Year)	-0.0154**	-0.0237***	0.0061***	-0.0009	-0.0076***
	(-2.42)	(-3.51)	(3.53)	(-0.54)	(-2.63)
Constant	0.0273	0.0058	-0.3065***	1.9325***	0.0076
	(0.54)	(0.12)	(-22.88)	(152.19)	(0.42)
Observations	408957	407935	546199	477614	364253
Mean of Dep. Var.	0.087	0.070	0.066	0.787	0.245
Panel C: Young Cohort: Age 5 - 10					
Female	0.0182***	-0.0239***	-0.0001	0.0021**	-0.0147***
	(3.24)	(-4.51)	(-0.48)	(2.18)	(-9.47)
Rainfall Shock	-0.0448***	-0.0754***	0.0005	-0.0059***	-0.0140**
	(-4.18)	(-6.52)	(1.03)	(-3.27)	(-2.10)
Female × Rainfall Shock	-0.0186***	-0.0102*	-0.0004	0.0011	0.0025
	(-3.08)	(-1.69)	(-0.81)	(0.82)	(1.23)
Rainfall Shock (Previous Year)	-0.0421***	-0.0562***	0.0002	-0.0010	-0.0006
	(-3.39)	(-4.28)	(0.42)	(-0.51)	(-0.11)

Female × Rainfall Shock (Previous Year)	-0.0148***	-0.0121**	0.0002	0.0000	0.0006
	(-2.60)	(-2.12)	(0.54)	(0.00)	(0.29)
Constant	-0.0461	-0.0688**	-0.0095***	1.6698***	-0.0021
	(-1.31)	(-2.03)	(-5.30)	(98.05)	(-0.13)
Observations	434111	431845	616123	483509	353342
Mean of Dep. Var.	0.006	-0.005	0.005	0.925	0.188

Note: * 0.1 ** 0.05 *** 0.01. t statistics in parentheses. Standard errors are clustered at the district level. Table 3 shows effects of a rainfall shock on educational outcomes, by gender for the combined sample of children aged 5-16 (panel A) and by age cohorts (panels B and C). Rainfall shock defined as -1 = Drought, 0 = Normal, 1 = Flood. Reading and Math scores are z-scores computed by age. Individual level controls include age and early life shocks. Household controls include indicator for whether the mother has gone to school, sibling cohort composition, whether the household has a first born female, number of children and a household wealth index. School controls include grade, school type, and for all outcomes except drop out - an indicator for being enrolled in school. Village level controls include indicators for whether the village has a pucca road, a bank, a ration shop, electricity and a government primary, middle and secondary school. Household fixed effects and district-year time trends are included.

In Table 4 we report results from our main specification. We investigate how differences in gender norms mediate the impact of rainfall shocks on human capital and scores. In Figures 2 and 3, we plot gaps in outcomes between positive and negative shock years for each of the four gender-crop group categories. In other words, the plot shows the magnitude of the difference in the outcomes in positive shock years and negative shock years. It follows that a negative value indicates that outcomes are worse in positive shock years than negative shock years and vice versa.

We find that outcomes for male and female children in wheat dominant districts[15] worsen as rainfall conditions improve, but effect sizes do not vary drastically by gender. When measured in a negative shock year, reading and math scores for male children in wheat dominant districts are higher by 0.04 and 0.1 standard deviations than when measured under a positive rainfall shock. Consistent with scores, probability of having dropped out of school is lower by 0.2 percentage points (although not statistically significant) and that of being on-track is greater by 1.3 percentage points respectively (a 1.5 percent improvement). For female children in wheat dominant districts, a negative shock leads to an improvement in reading and math scores to the tune of 0.3 and 0.1 standard deviations. The corresponding changes in the probability of having dropped out and on-track are a reduction in the former by 0.22 percentage points, and an increase in the latter by 0.6 percentage points. For math scores and dropping out, the coefficients on the interaction of the indicator for female and the contemporaneous shock variable are not significant, but those on the interaction of the indicator with a shock in the previous year shows the same direction of change and are statistically significant. We do not find significant impacts of a contemporaneous rainfall shock on extra investments in the form of enrollment in paid tuition, other than evidence that a positive shock in the previous year increases this likelihood by 2.3 percentage points for male children in wheat dominant areas. We do not pick up differences in extra investments by the gender and crop margin.

[15] For whom the indicator $RiceDominant$ takes value 0

In rice dominant districts, we find considerably larger gaps in the effects of a rainfall shock, particularly for female children. Under a negative shock, improvements in reading and math scores for male children in rice dominant districts are of the magnitude 0.1 and 0.2 standard deviations. Probability of having dropped out of school is lower by 0.6 percentage points, and that of being being on-track is greater by 0.08 percentage points. Reading and math scores of female children, in negative shock years, are greater by 0.17 and 0.2 standard deviations respectively. Their likelihood of dropping-out of school is lower by 1.16 percentage points (a 35 percent decline) and their likelihood of being on-track increases by 0.16 percentage points.

Our results indicate that gender norms that favour higher labor participation of females may in-fact, lead to worse human capital and schooling outcomes in the face of a favourable productivity shock. In districts where norms do not favour higher female labor force participation, rainfall shocks affect scores of male and female children to a similar extent. In contrast, where norms do favour female work, female children are *more* affected by rainfall shocks. Particularly their likelihood of dropping out of school - which improves considerably under a positive rainfall shock. Thus, we find this trade-off between schooling and productive work is stronger in settings that are more gender-equal in the labour market norms.

Looking at the impact of the shock in children of the older and younger children, we find that scores of younger children are more affected as rainfall conditions improve, but older children are more likely to have dropped out. Older male children in wheat dominant districts have reading and math scores that are 0.01 and 0.09 standard deviations higher in negative shock years than years with a positive shock, and that their probability of having dropped out of school is lower by 0.98 percentage points (14.8 percent) while that of being on-track is higher by 1.2 percentage points. They are more likely to be enrolled in paid tuition by 2.8 percentage points, in case of a positive rainfall shock in the previous year as opposed to a negative one. On the other hand, younger male children in wheat dominant districts report reading and math scores that are 0.07 and 0.12 standard deviations higher under a negative shock. The impact on their likelihood of having dropped out is a decline by 0.02 percentage points (although not significant), and on their being on-track is an increase by 1.66 percentage points. We do not find evidence of a significant impact of contemporaneous or lagged rainfall shocks on enrollment in tuition support. For female children in wheat dominant districts, reading scores are better in drought years by 0.03 standard deviations, and math scores are better by 0.05 standard deviations. Their probability of dropping out declines under a negative shock by 0.6 percentage points, and that of being on-track improves by 0.5 percentage points. Younger female children in wheat dominant districts report improvements in reading and math scores, decreases in likelihood of dropping out and increases in likelihood of being on track that are of magnitudes 0.08 and 0.11 standard deviations, 0.05 and 0.7 percentage points.

In rice dominant districts, older male children have reading scores that are 0.09 standard deviations higher under a negative shock than years with a positive shock, and math scores that are 0.21 standard deviations higher. They are less likely to have dropped out in drought years by 0.4 percentage points, and are more likely to be on-track by 0.02 percentage points. For younger male children in rice dominant districts, the impact of a negative shock on reading and math scores is an improvement to the tune of 0.13 and 0.23 standard deviations respectively. The corresponding impact on the probability of having dropped out is a decline of 0.3 percentage points and that on being on-track is an increase of 0.48 percentage points. For older female children in rice dominant districts, reading and math scores are higher in negative shock years by 0.14 and 0.12 standard deviations, the probability of having dropped out is lower by 2.1 percentage points (a 31 percent decline) and the probability of being on-track in school is higher by 0.46 percentage points. Younger female children, between the ages 5 and 10 report reading and math scores that are higher by 0.18 and 0.25 standard deviations in negative shock years when compared to positive shock years. The likelihood that they have dropped out reduces by 0.26 percentage points, and that they are on-track increases by 0.1 percentage points.

Overall, our results indicate that scores of younger female children in rice dominant districts are most affected by positive rainfall shocks, and gaps in the probability of dropping out are largest for older female children - who are 31 percent less likely to have dropped out in years with a negative rainfall shock as compared to a positive one.

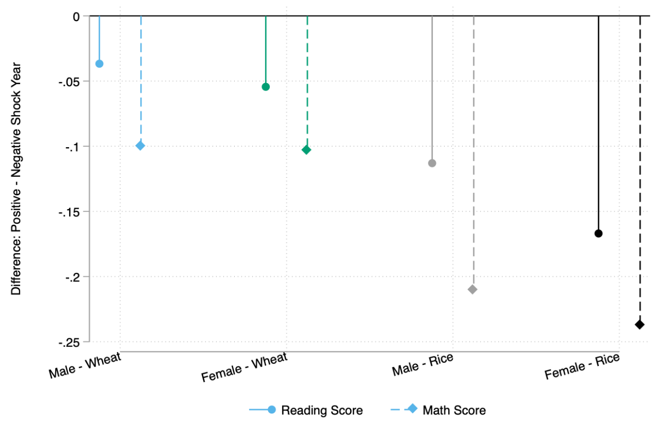

Figure 2: Difference in Scores in Positive versus Negative Shock Years

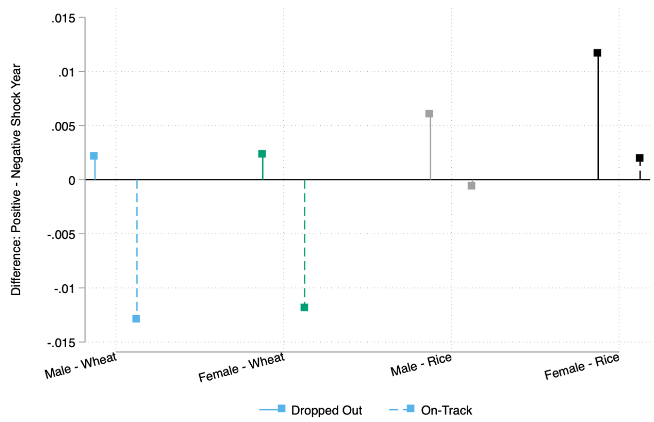

Figure 3: Difference in Schooling in Positive versus Negative Shock Years

Table 4: Impact of Rainfall Shocks by Gender and Crop Share

	Reading: Z-Score	**Math: Z-Score**	**Dropped Out**	**On Track**	**Enrolled in Extra Tuition**
Panel A: Full sample					
Female	-0.0180***	-0.0842***	0.0048***	0.0004	-0.0352***
	(-2.63)	(-11.28)	(3.82)	(0.47)	(-14.43)
Rainfall Shock	-0.0183*	-0.0500***	0.0010	-0.0065***	-0.0006
	(-1.79)	(-4.38)	(0.87)	(-3.47)	(-0.08)
Female × Rainfall Shock	-0.0089	-0.0017	0.0001	0.0005	0.0017
	(-1.57)	(-0.27)	(0.08)	(0.44)	(0.78)
Female × Rice Dominant	0.0552***	0.0686***	-0.0075***	0.0017	0.0180***
	(6.11)	(7.26)	(-4.62)	(1.32)	(6.04)
Rice Dominant × Rainfall Shock	-0.0382**	-0.0551***	0.0020	0.0061*	-0.0106
	(-2.13)	(-2.82)	(1.00)	(1.93)	(-0.99)
Female × Rice Dominant × Rainfall Shock	-0.0181**	-0.0120	0.0027*	0.0007	0.0002
	(-2.24)	(-1.47)	(1.72)	(0.42)	(0.07)
Rainfall Shock (Previous Year)	-0.0499***	-0.0674***	-0.0000	-0.0056***	0.0118**
	(-4.98)	(-5.74)	(-0.00)	(-2.71)	(2.28)
Female × Rainfall Shock (Previous Year)	-0.0091	-0.0131**	0.0035***	-0.0002	-0.0023
	(-1.63)	(-2.27)	(3.44)	(-0.20)	(-1.04)
Rice Dominant× Rainfall Shock (Previous Year)	0.0045	-0.0165	0.0020	0.0116***	-0.0104
	(0.24)	(-0.79)	(1.06)	(3.21)	(-0.94)
Female × Rice Dominant× Rainfall Shock (Previous Year)	-0.0117	-0.0018	-0.0026*	0.0006	0.0024

	(-1.45)	(-0.23)	(-1.79)	(0.31)	(0.80)
Constant	0.0110	-0.0280	-0.0847***	1.8621***	0.0139
	(0.36)	(-0.94)	(-17.58)	(219.55)	(1.17)
Observations	1054462	1051211	1398159	1194839	931307
Mean of Dep. Var.	0.038	0.018	0.033	0.855	0.221
Panel B: Old Cohort: Age 11 - 16					
Female	-0.0354***	-0.1160***	0.0131***	-0.0005	-0.0512***
	(-4.31)	(-11.10)	(4.43)	(-0.31)	(-12.48)
Rainfall Shock	-0.0053	-0.0431***	0.0049*	-0.0060**	-0.0031
	(-0.48)	(-3.32)	(1.92)	(-2.03)	(-0.27)
Female × Rainfall Shock	-0.0082	-0.0119	0.0012	0.0008	-0.0002
	(-1.11)	(-1.28)	(0.42)	(0.34)	(-0.04)
Female × Rice Dominant	0.0640***	0.0909***	-0.0182***	0.0008	0.0296***
	(5.99)	(7.16)	(-4.85)	(0.34)	(5.74)
Rice Dominant× Rainfall Shock	-0.0392**	-0.0606***	-0.0009	0.0059	-0.0037
	(-2.13)	(-2.90)	(-0.22)	(1.27)	(-0.25)
Female × Rice Dominant × Rainfall Shock	-0.0152	-0.0014	0.0052	0.0016	0.0013
	(-1.35)	(-0.11)	(1.44)	(0.47)	(0.25)
Rainfall Shock (Previous Year)	-0.0454***	-0.0720***	0.0011	-0.0065*	0.0144*
	(-4.17)	(-5.46)	(0.48)	(-1.88)	(1.73)
Female × Rainfall Shock (Previous Year)	-0.0066	-0.0171*	0.0073***	-0.0008	-0.0062
	(-0.76)	(-1.96)	(2.93)	(-0.33)	(-1.56)
Rice Dominant × Rainfall Shock (Previous Year)	0.0003	-0.0320	0.0012	0.0139**	-0.0024

	(0.01)	(-1.42)	(0.31)	(2.56)	(-0.16)
Female × Rice Dominant× Rainfall Shock (Previous Year)	-0.0127	-0.0021	-0.0064*	-0.0003	0.0044
	(-1.05)	(-0.17)	(-1.82)	(-0.08)	(0.83)
Constant	0.0291	0.0041	-0.3075***	1.9336***	0.0048
	(0.57)	(0.08)	(-22.87)	(151.63)	(0.26)
Observations	405103	404082	541261	473066	361340
Mean of Dep. Var.	0.087	0.070	0.066	0.788	0.245
Panel C: Young Cohort: Age 5 - 10					
Female	-0.0019	-0.0429***	-0.0001	0.0011	-0.0185***
	(-0.24)	(-5.76)	(-0.28)	(0.81)	(-8.34)
Rainfall Shock	-0.0336**	-0.0541***	0.0001	-0.0083***	-0.0028
	(-2.40)	(-3.66)	(0.12)	(-3.65)	(-0.29)
Female × Rainfall Shock	-0.0089	-0.0021	-0.0006	0.0010	0.0033
	(-1.12)	(-0.26)	(-1.02)	(0.64)	(1.16)
Female × Rice Dominant	0.0457***	0.0430***	-0.0000	0.0024	0.0084***
	(4.23)	(4.27)	(-0.06)	(1.24)	(2.79)
Rice Dominant × Rainfall Shock	-0.0324	-0.0588**	0.0012	0.0059	-0.0222
	(-1.21)	(-2.14)	(1.13)	(1.47)	(-1.57)
Female × Rice Dominant × Rainfall Shock	-0.0173	-0.0117	0.0006	0.0009	-0.0013
	(-1.45)	(-1.00)	(0.67)	(0.31)	(-0.34)
Rainfall Shock (Previous Year)	-0.0547***	-0.0633***	-0.0000	-0.0040*	0.0026
	(-3.94)	(-4.18)	(-0.03)	(-1.78)	(0.43)
Female × Rainfall Shock (Previous Year)	-0.0077	-0.0123	0.0003	-0.0001	0.0035

	(-1.02)	(-1.62)	(0.52)	(-0.03)	(1.32)
Rice Dominant × Rainfall Shock (Previous Year)	0.0200	0.0006	0.0010	0.0096**	-0.0080
	(0.75)	(0.02)	(0.90)	(2.35)	(-0.55)
Female × Rice Dominant × Rainfall Shock (Previous Year)	-0.0107	0.0081	-0.0001	0.0001	-0.0056
	(-0.97)	(0.70)	(-0.15)	(0.03)	(-1.42)
Constant	-0.0492	-0.0741**	-0.0095***	1.6670***	-0.0032
	(-1.39)	(-2.19)	(-5.28)	(98.09)	(-0.21)
Observations	430821	428568	610341	479848	351229
Mean of Dep. Var.	0.005	-0.006	0.005	0.926	0.188

Note: * 0.1 ** 0.05 *** 0.01. *t* statistics in parentheses. Standard errors are clustered at the district level. Table 4 shows effects of a rainfall shock on educational outcomes, by gender and crop type for the combined sample of children aged 5-16 (panel A) and by age cohorts (panels B and C). Rainfall shock defined as -1 = Drought, 0 = Normal, 1 = Flood. Rice dominant districts are those where area under rice cultivation > area under wheat cultivation. Reading and Math scores are z-scores computed by age. Individual level controls include age, sibling cohort composition, whether the household has a first born female, number of children and early life shocks. Household controls include whether the mother has gone to school and a household wealth index. School controls include grade, school type, and for all outcomes except drop out - an indicator for being enrolled in school. Village level controls include indicators for whether the village has a pucca road, a bank, a ration shop, electricity and a government primary, middle and secondary school. Household fixed effects and district-year time trends are included.

In our last set of specifications testing for the impact on human capital attainment, we present results on the role of positive rainfall shocks in early life in Table 5. We find that male children in both rice and wheat dominant districts, and female children in rice dominant districts who have experienced a *positive* shock in early life have *lower* educational gains from contemporaneous negative shocks. In other words, in times of a drought shock, reading and math scores improve to a slightly larger extent for children who have *not experienced a positive shock in early life*; they are less likely to drop out of school and more likely to be on-track than their counterparts who have experienced a positive shock in early life. This applies to male children in both rice and wheat dominant districts and female children in rice dominant districts. For female children in wheat dominant districts, however, the opposite is true. Female children who have experienced a positive shock in early life, gain more in contemporaneous drought years, than those who have not. Their test scores are marginally better, and they are less likely to have dropped out of school. Our results are consistent with Bau et al., 2020 who find that positive investments in early life reduce human capital attainment in districts with high incidence of child labor. We investigate what role gender has to play in this dynamic, and find that indeed, where adult and child FLFP levels are higher, girls are exposed to similar vulnerabilities as their male counterparts. On the other hand, where adult and child FLFP levels are lower, girls who experience positive shocks in early life gain from negative shocks in later life, and experience relatively larger gains to human capital attainment.

Table 5: Impact of Positive Shock In Early Life by Gender and Crop Share

	Reading: Z-Score	**Math: Z-Score**	**Dropped Out**	**On Track**	**Enrolled in Extra Tuition**
Drought	0.0087	0.0401	-0.0008	-0.0002	-0.0097
	(0.39)	(1.51)	(-0.33)	(-0.07)	(-0.95)
Early Life Positive Shock	0.0063	0.0161**	0.0088***	-0.0114***	0.0054**
	(0.87)	(2.10)	(5.55)	(-6.01)	(2.12)
Drought × Early Life Positive Shock	-0.0432***	-0.0149	-0.0013	0.0089**	-0.0001
	(-2.87)	(-1.00)	(-0.40)	(2.23)	(-0.02)
Female	-0.0276***	-0.0925***	0.0068***	0.0005	-0.0366***
	(-4.00)	(-10.41)	(5.19)	(0.36)	(-12.34)
Drought × Female	-0.0073	-0.0171	0.0047	-0.0016	-0.0060
	(-0.62)	(-1.20)	(1.41)	(-0.58)	(-1.26)
Early Life Positive Shock × Female	0.0138	0.0178*	-0.0029*	-0.0002	0.0060*
	(1.51)	(1.78)	(-1.70)	(-0.07)	(1.70)
Drought × Early Life Positive Shock × Female	0.0346**	0.0183	-0.0084**	0.0018	0.0035
	(2.15)	(1.00)	(-2.08)	(0.44)	(0.57)
Drought × Rice Dominant	0.0867***	0.1166***	-0.0015	0.0019	0.0289**
	(2.77)	(3.08)	(-0.42)	(0.36)	(1.98)
Early Life Positive Shock × Rice Dominant	-0.0156	-0.0162	-0.0070***	0.0095***	-0.0088**
	(-1.54)	(-1.46)	(-2.84)	(3.21)	(-2.39)
Drought × Early Life Positive Shock × Rice Dominant1	0.0508**	0.0051	0.0030	-0.0091*	0.0068
	(2.52)	(0.25)	(0.72)	(-1.77)	(1.16)

Female × Rice Dominant	0.0491***	0.0687***	-0.0078***	0.0015	0.0171***
	(4.67)	(5.32)	(-3.83)	(0.71)	(3.75)
Drought × Female × Rice Dominant	0.0468***	0.0307*	-0.0096**	0.0008	0.0060
	(2.92)	(1.73)	(-2.41)	(0.22)	(0.96)
Early Life Positive Shock × Female × Rice Dominant	-0.0045	-0.0127	0.0022	0.0007	-0.0004
	(-0.36)	(-0.91)	(0.92)	(0.22)	(-0.08)
Drought × Early Life Positive Shock× Female × Rice Dominant	-0.0341	-0.0007	0.0099**	-0.0053	-0.0030
	(-1.53)	(-0.03)	(2.00)	(-0.96)	(-0.37)
Constant	0.6441***	0.7896***	-0.0849***	1.8884***	0.1883***
	(10.98)	(11.33)	(-14.49)	(186.10)	(6.15)
Observations	1058002	1054728	1403065	1198933	934167
Mean of Dep. Var.	0.038	0.018	0.033	0.855	0.221

Note: * 0.1 ** 0.05 *** 0.01. t statistics in parentheses. Standard errors are clustered at the district level. Table 5 shows effects of a drought (negative) shock on educational outcomes, by gender and crop type for the combined sample of children aged 5-16 (panel A) and by age cohorts (panels B and C). $Drought$ takes value 1 if the rainfall in district d in year t is less than the 20th percentile computed using the last 10 years' rainfall data for that district. $RiceDominant$ indicates districts where area under rice cultivation > area under wheat cultivation. $EarlyLifePositiveShock$ takes value 1 if child i experienced a positive rainfall shock in their birth year or one of the two years following birth. Reading and Math scores are z-scores computed by age. Individual level controls include age, sibling cohort composition, whether the household has a first born female, number of children. Household controls include whether the mother has gone to school and a household wealth index. School controls include grade, school type, and for all outcomes except drop out - an indicator for being enrolled in school. Village level controls include indicators for whether the village has a pucca road, a bank, a ration shop, electricity and a government primary, middle and secondary school. Household and district fixed effects, and birth year time trends are included.

To understand the mechanisms of our results we examine the effect of the rainfall shock on labor force participation of adults and children by gender, crop type (rice versus wheat) and NREGA work availability in the district, using multiple rounds of the National Sample Survey [16]. We use the data on Principal Activity Status to code up indicators for engagement in paid employment, unpaid work in an household enterprise, non-agricultural casual labor and full time domestic work. We also include the NREGA margin as it appears to mediate the effects on employment. Table 6 shows effects on outcomes for adults in the working age range (ages 18 to 60). We find that male adults in wheat dominant districts where NREGA is not active are less likely to be in both paid employment and unpaid work on a household enterprise under a positive rainfall shock, than under a negative shock (4pp and 6.8pp decline respectively). Their female counterparts, on the other hand, are more likely to work for pay and carry out unpaid work on a family enterprise by 4.6 and 6.2 percentage points respectively under a positive shock. They are also 10 percentage points less likely to be carrying out domestic work full time than under a negative shock. In rice dominant districts where NREGA is not active, both male and female adults are more likely to participate in paid employment (by 1 and 1.4pp respectively) under a positive shock than a negative one. Male adults are also more likely to carry out unpaid work on a family enterprise and non-agricultural casual labor. Female adults on the other hand, increase participation in domestic work by 3.4 percentage points. In wheat dominant districts where NREGA is active, both male and female adults are slightly more likely to work under a positive shock than a negative one (0.4 and 0.6pp increase respectively). Females also increase time spent in domestic work, by 1.15 percentage points. In rice dominant districts, male adults appear to be less likely to be in paid employment (1.6pp lower) under a positive shock, while females are more likely to do so (2.2pp increase). Females are also less likely to be in domestic work full time, by 1.2 percentage points.

[16]Previous literature points to the employment guarantee programs like the National Rural Employment Guarantee Act (NREGA) has had beneficial impacts on safeguarding children's human capital outcomes (Afridi et al., 2016; Dasgupta, 2017) but may have decreased adolescent's outcomes through the opportunity cost channel (Shah & Steinberg, 2019)

Table 6: Impact of Rainfall Shocks on Adult's Work

	Paid Employment	**Unpaid Work In HH Enterprise**	**Non-agri Casual Labor**	**Domestic Work**
Female	-0.684***	-0.079***	-0.216***	0.729***
	(-44.97)	(-7.63)	(-10.36)	(34.92)
Female × Rice Dominant	0.047*	0.084***	0.029	-0.129***
	(1.70)	(5.07)	(1.07)	(-3.48)
Rainfall Shock	-0.020*	-0.034***	-0.016	0.044***
	(-1.72)	(-2.93)	(-1.20)	(2.72)
Female × Rainfall Shock	0.043**	0.065***	0.038**	-0.097***
	(2.29)	(3.94)	(2.06)	(-3.14)
Rice Dominant × Rainfall Shock	0.025*	0.039***	0.041**	-0.059***
	(1.67)	(2.63)	(2.22)	(-3.13)
Female × Rice Dominant × Rainfall Shock	-0.055**	-0.076***	-0.069***	0.129***
	(-2.27)	(-3.91)	(-2.89)	(3.59)
NREGA	-0.021*	-0.011	-0.028*	0.030**
	(-1.88)	(-1.03)	(-1.90)	(2.26)
Female × NREGA	0.012	0.032***	0.014	-0.046**
	(0.74)	(3.03)	(0.63)	(-2.17)
Rice Dominant × NREGA	-0.007	0.006	0.008	0.003
	(-0.33)	(0.36)	(0.39)	(0.13)
Female × Rice Dominant × NREGA	0.034	-0.001	0.035	-0.030
	(1.16)	(-0.07)	(1.16)	(-0.76)

NREGA × Rainfall Shock	0.022*	0.034***	0.030**	-0.049***
	(1.78)	(2.83)	(2.16)	(-2.90)
Female × NREGA × Rainfall Shock	-0.042**	-0.071***	-0.052***	0.105***
	(-2.13)	(-4.13)	(-2.70)	(3.30)
Rice Dominant × NREGA × Rainfall Shock	-0.035**	-0.039**	-0.051***	0.068***
	(-2.10)	(-2.53)	(-2.59)	(3.39)
Female × Rice Dominant × NREGA × Rainfall Shock	0.070***	0.082***	0.077***	-0.147***
	(2.70)	(3.92)	(3.01)	(-3.84)
Constant	0.884***	0.091***	0.623***	-0.109***
	(64.11)	(7.16)	(40.95)	(-7.17)
Observations	339228	339228	339228	365866
Mean of Dep. Var.	0.513	0.130	0.204	0.315

Note: * 0.1 ** 0.05 *** 0.01. *t* statistics in parentheses. Standard errors are clustered at the district level. Only includes rural households. Table shows effects of a rainfall shock on labor market outcomes, by gender and crop type for adults in the working age range (18-60 years). Rainfall shock defined as -1 = Drought, 0 = Normal, 1 = Flood. Indicators are defined using Principal Activity Status codes in the NSS data. The indicator for being in 'Paid Employment' excludes adults that are not in the workforce. Individual level controls include age and marital status. Household controls include whether the household owns land, religion, caste, household size and whether the household is an agricultural household. District level controls include indicators for whether NREGA is operational and whether rice cultivation is rain-fed.

In Table 7 we shows effects on labor market outcomes for children (ages 5 to 17). Once again, we use the NREGA margin as it appears to capture relevant heterogeneity. In wheat dominant districts where NREGA is not operational, female children appear to increase participation in paid employment under a positive rainfall shock (9pp increase), as compared to a negative one. Male children, on the other hand appear to work less under a positive rainfall shock than they do under a negative one. In rice dominant districts where NREGA is not operational, we observe opposite patterns. Male children increase time spent in paid employment under a positive shock, while female children increase time spent on full-time domestic work. In districts where NREGA is optional - male children in wheat dominant districts are less likely to participate in paid employment under a positive rainfall shock (5pp decrease), while their counterparts in rice dominant districts are more likely to do so (1.4pp increase). The same holds true for female children - where those in wheat dominant districts are less likely to work for pay under a positive shock (0.2pp decrease), and those in rice dominant districts are more likely to do so (0.4pp increase). Female children in rice dominant districts are also 1.8 percentage points more likely to be engaged in domestic work full time under positive shocks.

Our results provide suggestive evidence that positive rainfall shocks *increase* the participation of adult females in paid employment. In rice dominant districts this is relatively higher in districts where NREGA is optional, while the opposite is true in wheat dominant districts. Female adults in wheat dominant districts where NREGA is operational, and rice dominant districts where it is not, are also more likely to be engaged in full time *domestic work* under a positive rainfall shock. Positive rainfall shocks increase children's participation in paid employment - particularly for female children in wheat dominant districts where NREGA is not operational, male children in rice dominant districts (both when NREGA is and isn't operational), and female children in rice dominant districts where NREGA is operational. Additionally, female children in rice dominant districts also increase full time engagement in domestic work under positive rainfall shocks, when compared to negative ones (especially when NREGA is not available and they are not as likely to be in paid employment). Taken together, this suggests that adult females increase participation in paid activity. Female children either *complement* adult female labor force participation, or *substitute* for adult time in domestic work.

Table 7: Impact of Rainfall Shocks on Children's Work

	Paid Employment	**Unpaid Work In HH Enterprise**	**Non-agri Casual Labor**	**Domestic Work**
Female	-0.413***	-0.276***	-0.286***	0.125***
	(-13.15)	(-8.52)	(-10.22)	(13.00)
Female × Rice Dominant	0.146***	0.058	0.085**	-0.060***
	(3.59)	(1.28)	(2.19)	(-5.37)
Rainfall Shock	-0.094***	0.005	-0.093***	0.000
	(-3.55)	(0.16)	(-3.09)	(0.10)
Female × Rainfall Shock	0.139***	0.006	0.129***	-0.008
	(4.13)	(0.20)	(3.77)	(-0.84)
Rice Dominant × Rainfall Shock	0.116***	-0.013	0.080**	-0.001
	(3.16)	(-0.31)	(2.04)	(-0.23)
Female × Rice Dominant × Rainfall Shock	-0.162***	0.034	-0.143***	0.021*
	(-3.40)	(0.82)	(-3.13)	(1.78)
NREGA	-0.061	0.034	-0.038	0.019***
	(-1.59)	(0.90)	(-1.15)	(3.66)
Female× NREGA	0.046	0.043	-0.004	-0.045***
	(1.38)	(1.17)	(-0.13)	(-4.70)
Rice Dominant × NREGA	0.073	-0.111**	0.029	-0.012*
	(1.31)	(-2.02)	(0.55)	(-1.75)
Female × Rice Dominant × NREGA	-0.007	0.013	0.037	0.026**
	(-0.16)	(0.25)	(0.86)	(2.25)

NREGA × Rainfall Shock	0.069**	-0.010	0.065**	-0.001
	(2.41)	(-0.29)	(2.06)	(-0.23)
Female × NREGA × Rainfall Shock	-0.115***	-0.024	-0.108***	0.017
	(-3.03)	(-0.70)	(-2.96)	(1.62)
Rice Dominant × NREGA × Rainfall Shock	-0.084*	0.008	-0.055	0.001
	(-1.95)	(0.17)	(-1.21)	(0.21)
Female × Rice Dominant × NREGA × Rainfall Shock	0.133**	-0.030	0.134**	-0.020
	(2.42)	(-0.64)	(2.53)	(-1.50)
Constant	0.331***	0.083*	0.205***	-0.110***
	(7.95)	(1.83)	(5.24)	(-16.26)
Observations	16293	16293	16293	178233
Mean of Dep. Var.	0.303	0.201	0.230	0.040

Note: * 0.1 ** 0.05 *** 0.01. t statistics in parentheses. Standard errors are clustered at the district level. Only includes rural households. Table shows effects of a rainfall shock on labor market outcomes, by gender and crop type for children (5-17 years). Rainfall shock defined as -1 = Drought, 0 = Normal, 1 = Flood. Indicators are defined using Principal Activity Status codes in the NSS data. The indicator for being in 'Paid Employment' excludes adults that are not in the workforce. Individual level controls include age and marital status. Household controls include whether the household owns land, religion, caste, household size and whether the household is an agricultural household. District level controls include indicators for whether NREGA is operational and whether rice cultivation is rain-fed.

5 Conclusion and Discussion

There is contrasting evidence in the literature on the impact of climatic shocks on human capital outcomes. While some studies find negative impacts of drought shocks on schooling outcomes through the channel of reduced household income, (Björkman-Nyqvist, 2013; Jacoby and Skoufias, 1997; Jensen, 2000) others find a positive impact stemming from lower opportunity cost of schooling during such negative productivity shocks (Shah and Steinberg, 2017; Jacoby and Skoufias, 1997 Zimmermann, 2020). We help understand and contribute to this strand of literature by studying how gender norms around labour force participation mediate the impacts of shocks in developing countries. We find that relative outcomes for girls worsen with a positive shock, in areas favouring female labour force participation. In rice dominant districts, positive shocks affect outcomes of female children to a *larger* extent than their male counterparts. Reading and Math scores of female children between 5-10 years are particularly affected - who do better by 0.18 and 0.25 standard deviations in reading and math respectively, when tested under negative shock conditions rather than positive ones. On the other hand, older girls (11-16 years) are 1.6 percentage points (35 percent) less likely to have dropped out of school in negative shock years, rather than years where there is a positive rainfall shock. Our analysis offers support to the relative importance of the opportunity cost channel vis-a-vis the income effect channel, in the mediation of the shock impact. This is particularly strong in areas with higher participation of females in the labour market. While educational outcomes for both boys and girls are better off in these areas at the level, they are more vulnerable to a positive productivity shock, and even more so for girls.

Our results complement the findings from Shah and Steinberg (2019), Zimmermann (2020) and Afridi et al. (2021). While there exists a growing body of literature that looks at the impact of climatic shocks on human capital formation, with evidence from similar contexts (Shah & Steinberg, 2017; Zimmermann, 2020), there is limited understanding on how gender norms play a role in this dynamic. Using variation in cropping patterns that correlate with gender norms on female labor force participation in rural India, we examine how exposure to contemporaneous and previous year's rainfall shocks affects learning outcomes by gender of the child. Our analysis uses a range of educational outcomes, including objective measures such as test scores, school enrollment, investments in private tuition and a measure for being in the age-appropriate grade. We use the quasi-random variation in the exposure to rainfall shock within a household and check how the response varies by the prevalent gender norms in the labour market. Strikingly, we find that on average, *both* male and female children in rice dominant districts perform better at reading and math tests, and are more likely to be 'on-track' in school than their counterparts in wheat dominant districts. Female children in wheat dominant districts, where norms around female labor force participation are less gender-equal, fare worse than the other crop-gender groups on all measures of ability and schooling. This result complements the previous findings of (Carranza, 2014) that finds higher female participation in the labour market improves the economic value of females as manifested by improved sex-ratio in favour of females and the beneficial impacts of mother's work on children's education (Afridi et al., 2016). Our results documenting the relative dominance of the opportunity cost channel, complement the analysis in Afridi et al. (2021), which finds that women's workdays fall by a larger extent than men's in the face of a negative shock due to constraints to their participation in non-agricultural employment. Our results indicate that this may prove beneficial for female children in areas with higher levels of FLFP and child labor, where negative shocks lead to an added gain in learning outcomes and lower rates of dropping out of school. We examine the mechanisms using data on labour force participation from the 64th, 66th and 68th Employment and Unemployment survey rounds from the Indian National Sample Survey (NSS). We find suggestive evidence that increased participation in paid employment and full-time domestic work under a positive rainfall shock drive the disproportionate losses accruing to female children in rice dominant districts.

Lastly, our results on understanding the dynamics of an early life shock are in line with Bau et al. (2020), which finds that higher early life investment leads to a reduction in schooling in districts with high child labor. From our analysis, we see all children, except females in wheat-dominant districts, gain less from negative rainfall shocks if they have experienced a positive shock in early life. For females in wheat dominant districts, where child labor among females is the lowest among the crop-gender groups, a positive rainfall shock in early life adds to the gains from a negative rainfall shock.

Reducing the gender-gap in education outcomes is one of the focus of millennium development goals(MDGs), where there has been substantial progress in terms of bridging the gaps in primary school enrollment (Muralidharan & Sheth, 2016). Previous research documents the importance of timely insurance policies in safeguarding human capital outcomes of very young children. This is even more crucial in the face of increasing climate variability. Our analysis sheds light on the gender dynamics in the household response to climatic shocks and highlights the important pathways through which exposure to early-life and contemporaneous rainfall shocks impacts the gender gap in learning outcomes.

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Appendix

Differences in ASER and NSS outcomes between rice and wheat dominant districts

Table 8: ASER Outcomes: Rice and Wheat Dominant Districts

	(1) Wheat Dominant		(2) Rice Dominant		T-test Difference
Variable	N	Mean/SE	N	Mean/SE	(1)-(2)
Female	1505027	0.457 (0.000)	1279925	0.484 (0.000)	-0.027***
Age	1500639	10.295 (0.003)	1274907	10.388 (0.003)	-0.093***
Reading Z-Score	1348277	-0.066 (0.001)	1138356	0.053 (0.001)	-0.119***
Math Z-Score	1343676	-0.084 (0.001)	1133727	0.047 (0.001)	-0.131***
Dropped Out	1505027	0.034 (0.000)	1279925	0.032 (0.000)	0.002***
On Track	1314494	0.844 (0.000)	1122398	0.875 (0.000)	-0.032***
Attends Extra Tuition	1118696	0.212 (0.000)	906550	0.207 (0.000)	0.005***
Public School	1505027	0.631 (0.000)	1279925	0.683 (0.000)	-0.052***
HH has First-born Female	1505027	0.474 (0.000)	1279925	0.486 (0.000)	-0.012***
Mother Gone to School	1458445	0.444 (0.000)	1222572	0.583 (0.000)	-0.139***
Normal Rainfall	1505027	0.479 (0.000)	1279925	0.511 (0.000)	-0.033***
Negative Rainfall Shock	1505027	0.226 (0.000)	1279925	0.276 (0.000)	-0.050***
Positive Rainfall Shock	1505027	0.295 (0.000)	1279925	0.212 (0.000)	0.083***

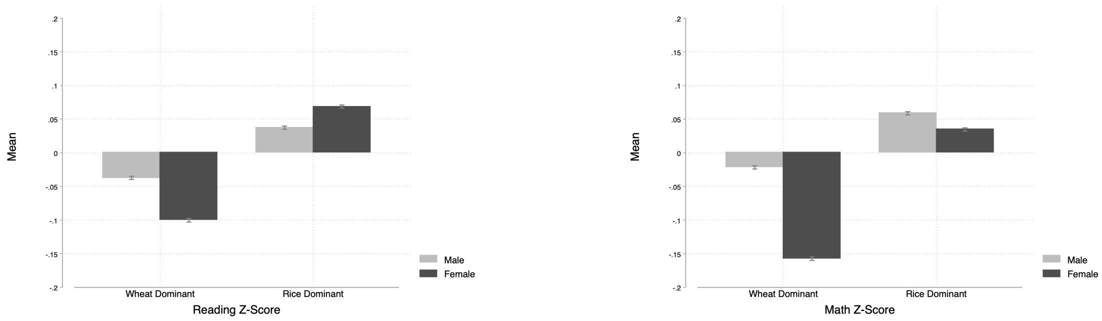
Note: * 0.1 ** 0.05 *** 0.01. The value displayed for t-tests are the differences in the means across the groups. Table 8 shows differences in variables from the ASER data between rice and wheat dominant districts. Standard deviations are in brackets. Rice dominant districts are those where area under rice cultivation > area under wheat cultivation. Reading and Math scores are z-scores computed by age. ASER data from the years 2008-2012, 2014 and 2016 are used.

Table 9: NSS Outcomes: Rice and Wheat Dominant Districts

	(1)		(2)		T-test
	Wheat Dominant		Rice Dominant		Difference
Variable	N	Mean/SE	N	Mean/SE	(1)-(2)
Female	307901	0.482 (0.001)	335962	0.496 (0.001)	-0.014***
Age	307852	26.600 (0.035)	335933	29.066 (0.033)	-2.466***
Adult Paid Employment (M)	81522	0.826 (0.001)	96850	0.852 (0.001)	-0.026***
Adult Paid Employment (F)	83165	0.146 (0.001)	101529	0.249 (0.001)	-0.103***
Child Paid Employment (M)	4045	0.490 (0.008)	3236	0.478 (0.009)	0.012
Child Paid Employment (F)	5097	0.103 (0.004)	3927	0.224 (0.007)	-0.120***
Adult Unpaid Work on HH Enterprise (M)	81522	0.151 (0.001)	96850	0.111 (0.001)	0.040***
Adult Unpaid Work on HH Enterprise (F)	83165	0.104 (0.001)	101529	0.137 (0.001)	-0.034***
Child Unpaid Work on HH Enterprise (M)	4045	0.314 (0.007)	3236	0.319 (0.008)	-0.004
Child Unpaid Work on HH Enterprise (F)	5097	0.081 (0.004)	3927	0.144 (0.006)	-0.063***
Adult Full-time Domestic Work (M)	92864	0.005 (0.000)	110267	0.007 (0.000)	-0.002***
Adult Full-time Domestic Work (F)	91207	0.682 (0.002)	112764	0.540 (0.001)	0.142***
Child Full-time Domestic Work (M)	66695	0.006 (0.000)	59066	0.004 (0.000)	0.002***
Child Full-time Domestic Work (F)	57135	0.072 (0.001)	53865	0.044 (0.001)	0.028***
HH Owns Land	307901	0.950 (0.000)	335962	0.952 (0.000)	-0.002***
Agricultural Household	307901	0.537 (0.001)	335962	0.468 (0.001)	0.069***
NREGA Operational	307901	0.879 (0.001)	335962	0.814 (0.001)	0.065***

Note: * 0.1 ** 0.05 *** 0.01. The value displayed for t-tests are the differences in the means across the groups. Table 9 shows differences in variables from the NSS data between rice and wheat dominant districts. Standard deviations are in brackets. (M) indicates statistics are computed for a sub-sample of males, (F) indicates statistics are computed for a sub-sample of females. Rice dominant districts are those where area under rice cultivation > area under wheat cultivation.

Gender differences in test scores and schooling between rice and wheat dominant districts



(a) Reading Z-Score

(b) Math Z-Score

Figure 4: Gender differences in test scores by dominant crop type
(Note: Figure 4 shows mean reading and math z-scores by gender and dominant crop type.)

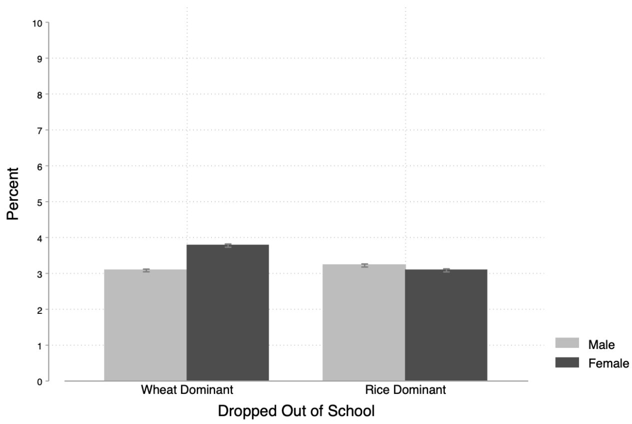


Figure 5: Gender differences in share dropped-out of school by dominant crop type
(Note: Figure 5 shows percent of students that have dropped out of school by gender and dominant crop type.)

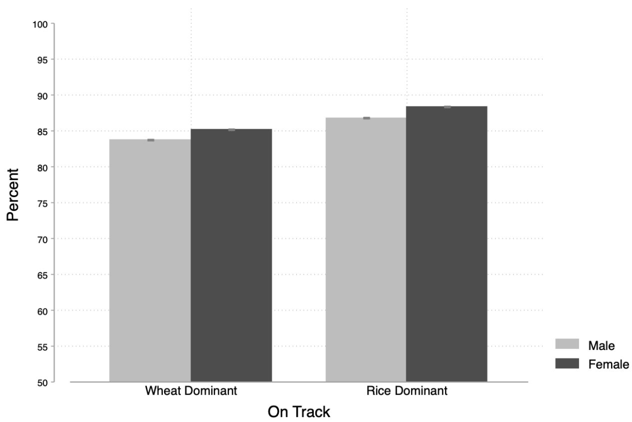


Figure 6: Gender differences in share on-track by dominant crop type
(Note: Figure 6 shows percent of students that are 'on-track' or in the age appropriate grade in school by gender and dominant crop type. Only includes children enrolled in school.)

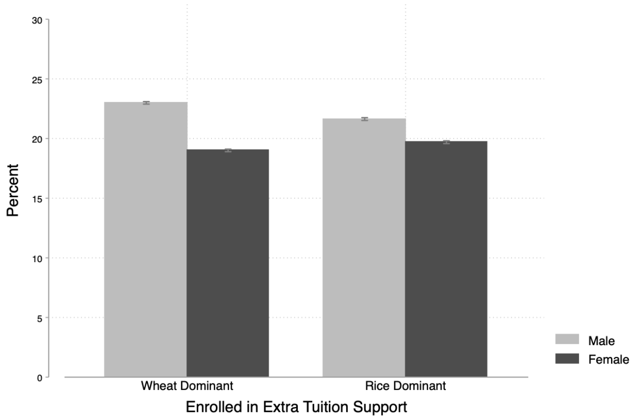


Figure 7: Gender differences in share enrolled in extra tuition support by dominant crop type

(Note: Figure 7 shows percent of students that are enrolled in extra tuition support by gender and dominant crop type.)