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Siblings, Schooling, Work and Drought

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Young Lives
An International Study of Childhood Poverty

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Abstract

In this paper we explore the effect that a recent drought in Andhra Pradesh, India, has had on the school and work patterns of children aged 11 to 12 years. Previous empirical studies have investigated the effect of shocks on outcomes for children but few have allowed for heterogeneous treatment effects across children. Ignoring such heterogeneity might lead to biases in the estimated impact of the shocks. The aim of this paper is to address this lacuna. Using data from Young Lives, a longitudinal cohort study of children, we estimate the average impact of the drought on participation in schooling. We then expand our empirical model to allow for heterogeneous effects across children of different demographic categories – namely gender and birth order. Our analysis shows that ignoring child heterogeneity would underestimate the severity of the effect of the drought on children's welfare and human capital accumulation. In particular, we find that the drought significantly reduced the time spent on schooling by most demographic groups. The exception is the group most likely to have been involved in agricultural work when there is no drought; the schooling participation of eldest sons appears to increase because of the drought. Furthermore, we trace the impact of the drought on child labour and cognitive development, while we rule out the possibility that the uncovered heterogeneous patterns might be driven by social norms or cultural biases in favour of eldest sons.

Keywords: Child labour; Cognitive development; School drop-out; India; Andhra Pradesh

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About Young Lives

Young Lives is an international study of childhood poverty, following the lives of 12,000 children in 4 countries (Ethiopia, India, Peru and Vietnam) over 15 years. **www.younglives.org.uk**

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1 Introduction

Economic shocks, adverse events and risk are phenomena present in all economies; however, both the incidence of shocks and exposure to their negative impact are particularly extensive for households in less-developed economies. In these households, children are particularly vulnerable. Shocks might not only reduce child welfare in the short term, but when occurring at critical stages of a child's development they might also have permanent effects on health, anthropometric and educational outcomes (Alderman et al. 2006; Hoddinott and Dercon 2004).

This paper explores the effect of a recent drought in Andhra Pradesh, India, on human capital formation among a sample of children of school age. While we are interested in the average effect of the drought, our emphasis is on exploring the heterogeneous effects of the shock across children with varying demographic attributes. Previous studies have investigated the effect of shocks on children's welfare, but few allow for heterogeneous treatment effects. Our view is that ignoring this heterogeneity might grossly misrepresent the true welfare impact of shocks against which people are uninsured.

Modelling the process of the acquisition of human capital is notoriously complex. Social norms, economic factors, parental preferences and intra-household time, resource, task and role allocation issues all play important roles. In rural economies such as Andhra Pradesh, recognising the interplay between school and work is particularly important in understanding the mechanisms underpinning this process. In rural households, schooling and study time are often crowded out by the other commitments and responsibilities children face in such a household. Child care and household chores, providing help in the family business or farm, as well as carrying out paid work outside the household, are common examples of such responsibilities.

In this type of context, the incidence of a shock, such as a drought, might affect schooling through a range of different mechanisms. Firstly, the drought might reduce schooling directly by depressing disposable income – the so-called 'profit effect'. Lower expenditure on educational goods – such as school fees, books or uniforms – might reduce school attendance and impair educational performance, and even lead to school drop-out. Secondly, the drought might also affect schooling indirectly through its impact on the demand for child labour. The same negative profit effect could increase the need for children to become involved in economic activities. Indeed, an extensive economics literature has documented the importance of children's work as a coping strategy through which households deal with unexpected income shocks (see for example Townsend 1994; Beegle et al. 2006; Mohonan 2008). The same literature however, has devoted less attention to a third effect, namely the possibility that agricultural shocks could reduce the demand for child labour. *Ceteris paribus*, a drought might lower the productivity of child labour – an example of the 'price effect' – thereby potentially increasing schooling for children who, in the absence of the drought, might have been involved in income-generating or income-supporting activities.

The aim of this paper is to uncover how these contrasting effects might have affected, in varying degrees, children across different demographic groups. To model this range of mechanisms, we set up a theoretical framework based on theories of household agricultural production in a context of imperfect labour markets. While simple in their nature, models of this type explicitly recognise the inter-linkages between household consumption and production and are particularly well suited for modelling decision-making about child labour.

Insights on preferences and social norms prevalent in rural Andhra Pradesh, combined with these models, allow us to make the following predictions. First, for the average child we expect the profit effect to outweigh the price effect, resulting in reduced schooling for children affected by the drought. Secondly, we expect the price effect to be strongest among children more likely to be involved in farming work when there is no drought – in rural Andhra Pradesh 'eldest sons' appear to be this demographic group. Thirdly, the price effect will also be strongest among households involved in labour-intensive economic activities. The demand for child labour in Andhra Pradesh is highest among irrigation farmers, a group primarily focused on the intensive cultivation of rice. A corollary to these predictions is that the impact of the drought will be least pernicious – due to the largest price effects – among the group of eldest sons in irrigation-farming households.

To test the validity of these predictions, we use the sample from Young Lives, a longitudinal cohort study of children from Andhra Pradesh (see section 3 for further details). We borrow from human capital accumulation models (such as Cunha and Heckman 2007) and set up an econometric model where schooling outcomes of children aged 12 are determined by child, household and community characteristics measured four years earlier. Our main variable of interests is a dummy variable that indicates whether an individual household was affected by the 2002–3 drought. In this setting, we test for heterogeneous drought impact by interacting the drought dummy with variables indicating the demographic attributes of the children and the farming practices of the households.

The empirical analysis suggests the following findings. First, children affected by the drought appear to spend fewer hours at school and are more likely to have dropped out of school altogether. These effects are only significant among households involved in farming land they own or occupy; children in landless rural households appear unaffected by the drought. Secondly, when we allow for heterogeneity of impact, we find that the effect of the drought on schooling is significantly different among eldest sons from other types of households. In particular, they increase their schooling time and likelihood of remaining in school – compared to similar children in unaffected households – while other groups decrease them following the incidence of the drought.

While these patterns of impact heterogeneity are consistent with the predictions of our model, they could also be interpreted as positive discrimination towards eldest sons borne out of parental preferences and social norms. In the paper we present evidence to the contrary. On the one hand, the same heterogeneous patterns are not reproduced when estimating the impact of the drought on weight and body mass index of children. We find eldest sons to have suffered nutritionally as much as any other demographic group.

On the other hand, we present evidence supporting the mechanisms suggested by the theoretical model. First, by analysing data on time spent on paid and unpaid work, we find that eldest sons are less likely to work following the drought while other groups increase their involvement in work activities. Secondly, these results are primarily driven by households involved in labour-intensive activities. For households not engaged in irrigation farming, we find only weak evidence of a drought effect and – in opposition to their irrigation-farming counterparts – the increase in work activities appears largest among eldest sons. If discriminatory preferences were behind the demographic idiosyncratic patterns, we would instead expect these patterns to be common across farming practices.

Finally, using data on the educational attainment and cognitive development of individual children, we test whether the patterns of schooling and work uncovered appear to affect these direct measures of human capital accumulation. We find that the drought reduces cognitive development as measured by the Peabody Picture Vocabulary Test (PPVT) for most categories of children. Meanwhile, eldest sons in irrigation-farming households – by virtue of their increased probability of remaining in school – improve counterfactually their reading and writing abilities.

The potential endogeneity of the drought shock implies that average household-level effects should be interpreted with caution. However, our exploration of impact heterogeneity is less open to this criticism; a priori there is no reason to believe that these biases should be distributed across demographic groups other than uniformly. There is also some comfort in the impact heterogeneity we find, since it provides some reassurance that average impact estimates are not exclusively caused by a spurious correlation between the drought incidence and the error term, but are motivated by the economic incentives faced by households.

The evidence presented contributes to the literature on child labour as a coping strategy (see Townsend 1995; Beegle et al. 2006; Mohanan 2008). Households affected by the drought appear to resort to child labour as a means to smoothing consumption. It also contributes to the literature on child labour determinants and household composition, in that we show that birth order, gender and agricultural practices of the households all play an important role in determining school and child work allocations (Edmonds 2006; Behrman 1988; Erjnaes and Portner 2004; Bacolod and Ranjan 2008, among others).

The paper provides a cautionary tale regarding the impact of shocks. Failing to recognise the heterogeneity of the effects of the shock might lead to gross misrepresentations of their true impact. Indeed, our estimates suggest that the effect of the drought on school participation is doubled in magnitude when impact heterogeneity is allowed – the average decrease in the amount of time children spent in school went from less than a third of an hour to approximately half an hour. The drought would account for a movement in schooling hours of approximately 21 per cent of one standard deviation. While these effects appear modest in magnitude, it should be noted that they are mainly driven by children dropping out of school before the age of 12, with the resulting uncertainty about whether they will rejoin later. Furthermore, the reduced schooling hours already appear to have had a significant negative effect on the cognitive development of these children as measured by the PPVT.

The remainder of this paper is structured as follows. In the next section, we discuss more in detail the conceptual context to our analysis and present the theoretical framework underpinning our predictions. Section 3 presents the Young Lives datasets and provides some descriptive statistics that illustrate the mechanisms at work. In section 4, we discuss our econometric methodology. Section 5 reports the main findings of the paper and section 6 concludes.

2 Conceptual and theoretical framework

The effect of the drought on schooling and child work is best analysed using models of household agricultural production in a context of imperfect or missing markets. While simple in their nature, models of this type explicitly recognise household inter-linkages between consumption and production and are particularly well suited for modelling decision-making about child labour. An important feature of these models is that in a context of imperfect labour markets, household consumption and production decisions are not recursive. Consumption and production are linked by the household-specific shadow price of labour. Households will no longer behave as profit maximisers, in the sense that labour input choices will be influenced by both production and consumption factors. This type of model, first formally introduced by Singh et al. (1986), has become part of the standard toolkit for investigating issues of rural households' economics. Most recently Fafchamps and Quisumbing (2003) and Fafchamps and Wahba (2006) have used this type of model in analysing the effect of social norms and market proximity on schooling and children's work.

In this type of theoretical setting, the drought can be modelled as a productivity shock affecting specific economic activities. Presumably during the drought the agricultural productivity of a child will be reduced while the productivity of carrying out household chores might remain unaffected. Such productivity shocks will have two distinct effects. First, the drought will have a profit effect. Lower productivity might reduce household profits and disposable income. As a result households are likely to reduce consumption of educational goods while expanding the supply of labour. In other words, we expect the schooling hours of children in affected households to be reduced and their work hours to expand. At the same time, the drought will affect labour and educational decisions through its impact on the shadow price of labour. This is the price effect. The reduced agricultural productivity due to the drought will depress the demand for child labour in agricultural production while also diminishing the opportunity cost of school attendance. The price effect will therefore increase schooling and depress children' labour.

The overall effect of the drought on education and labour decisions of the household is the combination of both price and profit effects, and its sign is ambiguous. However, while the 'income' effects will affect all siblings in the household, presumably more or less homogenously, the price effect will only affect siblings who counterfactually would have been involved in those activities affected by the drought. For example, social norms in Andhra Pradesh determine that daughters are typically involved in child care and household chores. The drought is likely to have affected the labour productivity in this type of task only marginally, such that decisions about daughters' education and labour will be exposed primarily to the income effect of the drought. Conversely, sons, and eldest sons in particular, are the group most likely to become involved in agricultural activities and will therefore be exposed to both the income and price effects of the drought.

Equipped with the insight from this type of model and the literature on child labour and social norms, we can make the following predictions regarding the impact of the drought. First, given the social norms prevalent in rural Andhra Pradesh, we predict that most demographic groups will be little affected by the 'price' effect – implying that the drought will have primarily a negative effect on schooling and a child's economic involvement. Secondly, we expect the demographic group of eldest sons to be the exception. This group, being first to be used in agricultural production, will be exposed to the largest 'price' effect. In consequence, for eldest sons we expect the effect of the drought to be ambiguous. In fact, if there is a sufficiently large price effect the group, could be better off in the presence of a drought. Finally, we also expect households involved in labour-intensive agricultural activities – such as irrigated cultivation – to experience a more ambiguous effect of the drought than other households. Labour-intensive activities demand a higher involvement of the household's children such that, *ceteris paribus*, households needing more children to work will face stronger price effects. In other words, following the drought, children living in irrigation-farming households are less likely to become involved in work and reduce their schooling hours, vis-à-vis children in households involved in other less labour-intensive agricultural practices. The corollary of our predictions is that the price effect will be strongest – and therefore the pernicious effects of the drought smallest – among the group of eldest sons in irrigation-farming households. Vis-à-vis this group, all other children will experience higher reductions in schooling and higher incidence of working following the drought. In summary, consistent with previous empirical findings we expect the average impact of the drought to be negative. However, at the same time, we expect substantial impact heterogeneity across groups of children, driven by varying magnitudes of the price effect.

3 Data and descriptive statistics

In our analysis we use a sample from Young Lives, a longitudinal cohort study of children across four different countries: Peru, Ethiopia, Vietnam and Andhra Pradesh (India). In 2002, during baseline surveying, two cohorts of children were identified in each country to take part in the 15-year study. The Older Cohort consists of approximately 1,000 children aged 7 to 8 in 2002, and the Younger Cohort consists of approximately 2,000 children aged 6 to 18 months, living in 20 sentinel sites. We use the Older Cohort in Andhra Pradesh for this study. Young Lives was designed to collect detailed information on the children, alongside information from their households, during five different rounds over the 15-year period. This analysis is based on data from 2002 and 2006 when the children were aged around 8 and then 12. A third round of data was collected in 2009.

The Young Lives dataset is an ideal sample in which to explore the effects of the drought on human capital accumulation and the economic activities of children. First, the children in the sample would have been affected by the drought in 2002–3 during a critical period of their lives, namely at the age of 8, and we look here at the impact through to the age 12, just before entering secondary school and at the age when children start acquiring more responsibilities in the household. Secondly, the Young Lives dataset provides information on time allocations for a range of activities, as well as information on school performance for all children. This breadth of information will allow us to test the effect of the drought not only on schooling but also on cognitive skills and actual working hours. Finally, Young Lives was envisaged as a study concerned primarily with issues of poverty and child development. To fulfil this purpose, the sample was designed to be primarily rural and to over-sample households from poor backgrounds. This ensures that our sample of analysis contains those households most likely to have been exposed and vulnerable to the drought.

The drought occurred during the agriculture year of 2002–03 and has been the most severe of all the droughts experienced in Andhra Pradesh since 1985–6. It affected 90 per cent (1,087 out of 1,128) of mandals spread across all the districts of Andhra Pradesh.[1] The effect of this drought has been highly pronounced in all the districts where the Young Lives sample live, which is evident from the fact that nearly 80 per cent of mandals in each of these districts were affected (Revenue Department, Government of Andhra Pradesh 2008). The areas of irrigated and unirrigated crops, yields of these crops, and rural employment have declined considerably

1 A district is the administrative unit below the state in India while a mandal is the administrative unit below the district in Andhra Pradesh.

in all the villages of these mandals. Some of the coping mechanisms adopted in response to the drought include out-migration of household members or whole families for alternative livelihoods, such as construction work; withdrawing children from school to assist women in collecting fuel or fodder, or to help in earning wages; and working at lower wages to generate some income (Department of Disaster Management, Government of Andhra Pradesh, not dated; World Bank 2006). Thus it is evident that a reduction in households' disposable income (profit effect) may increase the incidence of withdrawing children from school; and the reduced demand for labour that results in low shadow wages (price effect) may reduce the opportunity cost of schooling and liberate children to spend more time on schooling.

Our main variable of interests is a dummy that indicates whether an individual household was affected by the drought during the period between the two rounds of data collection, namely between 2002 and 2006.[2] Table 1 provides some basic descriptive statistics of the incidence of the drought across the Young Lives sample. The drought affected a total of 287 households, or 29 per cent of the sample, and was mostly centred in the non-coastal regions, Rayalaseema and Telangana. The table also shows that even within these regions there is substantial variation across sites. It explores how different types of households were exposed differently to the drought.

Table 1. *Incidence of the drought, by location and household type*

Region	YL Site	All HHs	Affected by drought		Urban		Rural		Landless		Land-owning	
			N.	%	None	Drought	None	Drought	None	Drought	None	Drought
Coastal	1	49	1	2.0%	48	1			41	1	7	
	2	49	2	4.1%			47	2	26	1	21	1
	3	45	0	0.0%	45				42		3	
	4	49	8	16.3%			41	8	17	4	24	4
	5	51	3	5.9%			48	3	21	3	27	
	6	50	14	28.0%			36	14	14	6	22	8
	7	50	9	18.0%			41	9	16	2	25	7
Rayalaseema	8	50	2	4.0%			48	2	24		24	2
	9	49	14	28.6%			35	14	15	5	20	9
	10	49	2	4.1%	47	2			45	2	2	
	11	55	46	83.6%			9	46	2	4	7	42
	12	51	41	80.4%			10	41	6	19	4	22
	13	50	39	78.0%			11	39	2	9	9	30
Telangana	14	49	2	4.1%	47	2			39		8	2
	15	50	11	22.0%			39	11	14	2	25	9
	16	50	16	32.0%			34	16	14	1	20	15
	17	50	21	42.0%			29	21	4	1	25	20
	18	52	18	34.6%			34	18	5	2	29	16
	19	50	32	64.0%			18	32	2		16	32
	20	49	6	12.2%	43	6			37	5	6	1
Total		**997**	**287**	**28.8%**	**230**	**11**	**480**	**276**	**386**	**67**	**324**	**220**

2 Specifically, the question included in the Round 2 survey reads as follows: 'Have you experienced any natural disasters in the last four years?' If the answer to this question was positive, multiple options were available, of which 'Drought' was one.

Throughout the paper, our analysis mostly focuses on households that own land and actively cultivate it.[3] As shown in Table 1 not only did the drought affect mostly rural areas, but land-owning households were most affected. This is counter-intuitive as one would expect landless households to be most vulnerable to shocks. However, on the one hand, a large proportion of landless households are located in urban areas, and on the other, in Andhra Pradesh landless rural households – whose members are often employed as agricultural labourers – are free to migrate.

In the context of the Young Lives sample, land-owning households are small-scale farmers mostly reliant on family labour and the odd hired agricultural labourer. It is in this type of household economies, that the question of the impact of the drought on children's schooling and work is most relevant. Table 2 reports some basic statistics that address this question. For land-owning households only, the table reports the number of hours spent at school and on work by children in households affected and unaffected by the drought. We split children into four demographic groups – Eldest girl, Eldest boy, Younger girls and Younger boys[4] – as well as showing whether their households use labour-intensive farming practices such as irrigation farming.

The results are quite striking. On the one hand, we find that across all demographic groups, children in households affected by the drought appear to spend fewer hours at school and more hours working than unaffected children. On the other hand, we note that eldest boys have very distinct patterns from the other demographic groups. Eldest sons appear to benefit from the drought in the sense that they spend more hours in school and fewer working than their unaffected peers. While some of these effects are not significant at a standard level of significance, it is nevertheless striking to find these differences across demographic groups. It should be noted that all the children belong to the same cohort, so that we are comparing here children of a similar age (born 1994 to mid-1995) where their only distinguishing feature is their demographic attribute.

At the same time, the divergence in the effect of the drought is largest among irrigation-farming households. Across all demographic groups, schooling hours are lowest among households involved in irrigation farming, while work hours of eldest sons in irrigation-farming households are the highest of all demographic groups.

The bottom panel in Table 2 explores the extensive margin of these patterns by reporting percentages of children enrolled in school and involved in work activities. The data preview some of our later findings, in that the some of the positive effect of the drought on eldest sons can be explained by lower rates of school drop-out among this demographic group.

3 We define landowners as those households that over the past year have 'owned, rented or borrowed' land.

4 More specifically, the 'eldest boy' dummy takes a value of 1 if the eldest child is a boy and a zero otherwise. Similarly, the 'eldest girl' dummy takes a value of one if the eldest child is a girl. 'Younger girl' and 'younger boy' identify the gender of all other children in the household.

Table 2. *Schooling and work in the time of drought*

		Hours at School			Hours at Work		
		No Drought	Drought	Difference	No Drought	Drought	Difference
All HHs	Girl –Eldest	5.92	5.73	-0.18	0.48	0.88	0.40
	Girl – Younger	6.06	5.71	-0.35	0.60	1.02	0.42
	Boy – Eldest	6.23	6.46	0.23	0.90	0.38	-0.52*
	Boy – Younger	5.95	5.31	-0.65	0.87	1.29	0.42
No Irrigation	Girl – Eldest	6.08	5.79	-0.30	0.54	0.57	0.03
	Girl – Younger	6.00	5.74	-0.26	0.82	1.04	0.22
	Boy – Eldest	6.89	6.04	-0.84	0.17	0.75	0.58
	Boy – Younger	6.15	5.39	-0.76	1.04	1.00	-0.04
Irrigation	Girl – Eldest	5.84	5.69	-0.14	0.45	1.11	0.67
	Girl – Younger	6.14	5.68	-0.45	0.34	1.00	0.66
	Boy – Eldest	5.74	6.82	1.08*	1.46	0.07	-1.39*
	Boy – Younger	5.83	5.19	-0.63	0.76	1.65	0.90
Total		**6.03**	**5.79**	**-0.25**	**0.69**	**0.89**	**0.21**

		% enrolled in school			% involved in work			Sample Size
		No Drought	Drought	Difference	No Drought	Drought	Difference	
All HHs	Girl – Eldest	86.6%	84.6%	-2.0%	10.7%	13.8%	3.1%	177
	Girl – Younger	88.9%	87.8%	-1.1%	9.5%	17.1%	7.5%	104
	Boy – Eldest	90.1%	94.3%	4.2%	12.3%	11.3%	-1.0%	134
	Boy – Younger	89.6%	83.1%	-6.5%	19.4%	23.7%	4.3%	126
No Irrigation	Girl – Eldest	89.5%	86.2%	-3.3%	15.8%	6.9%	-8.9%	67
	Girl – Younger	85.3%	86.4%	1.1%	11.8%	18.2%	6.4%	56
	Boy – Eldest	97.1%	87.5%	-9.6%	2.9%	16.7%	13.8%*	59
	Boy – Younger	88.5%	84.8%	-3.6%	19.2%	18.2%	-1.0%	59
Irrigation	Girl – Eldest	85.1%	83.3%	-1.8%	8.1%	19.4%	11.3%*	110
	Girl – Younger	93.1%	89.5%	-3.6%	6.9%	15.8%	8.9%	48
	Boy – Eldest	84.8%	100.0%	15.22%*	19.6%	6.9%	-12.7%	75
	Boy – Younger	90.2%	80.8%	-9.5%	19.5%	30.8%	11.26%*	67
Total		**88.5%**	**87.2%**	**-1.4%**	**12.7%**	**16.5%**	**3.8%**	**541**

Note: The table includes land-owning households only. Statistics for a total of 541 households are reported. Top panel reports hours spent at school and at work (paid and unpaid) on an average day for all 541 children. The bottom panel reports the percentage of children enrolled in school and involved in work (paid and unpaid).

In the remainder of the paper, we seek to substantiate the patterns documented in Table 2 in a more rigorous setting. For this purpose we set up an econometric model that seeks to estimate the impact of the drought on schooling and child work. In Table A1 in the appendix we provide descriptive statistics for our sample of analysis.

4 Empirical model specification

We develop our empirical model by borrowing heavily from the literature on human capital formation. We follow Cunha and Heckman (2006a) in modelling the acquisition of human capital as a multi-period dynamic process in which the level of skill achieved at a particular point in time is a function of the level of previously accumulated skills (S_{t-1}) and the investments made between the periods (I_{t-1}). This type of model is not only characterised by self-productivity (higher skills leading to higher skill accumulation) but also can model 'critical periods'. Shortfalls in skill investments at critical stages of development might lead to permanent reductions in the skill-accumulation growth path.

$$(1) \qquad S_t = f_t(S_{t-1}, I_t)$$

Another critical feature of these models is that the vector of skills not only includes traditional definitions of human capital, such as cognitive skills and educational attainment, but might also include non-cognitive aspects of human capital formation such as nutrition and health, as well as psychosocial factors.

In our main model specification, we explain children's outcomes (y_{it}) for child *i* at the age of 12 with a vector of controls from the earlier round (X_{it-1}), which include household and child characteristics as well as cluster dummies. We also control for a vector of skills (S_{it-1}) acquired by the child up to the age of 8. Finally, we include our variable of interest (D_{it}), a dummy indicating whether a household was affected by the drought between rounds.

$$(2) \qquad y_{it} = \gamma S_{it-1} + X_{it-1}\delta + \alpha D_{it} + u_{it}$$

As proxies for skills previously acquired by the child we use two measures from Round 1. First, the score achieved by the child on the Raven test, and secondly, the anthropometric z-score measure for height-for-age as a proxy for the health and nutritional status of the child. Both variables will also capture previous parental and environmental investments in health and cognitive skills.

The vector of controls (X_{it-1}) consists of a parsimonious set of household and child characteristics, including mother's education and age, household size and composition, access to services, consumer durables and housing quality index, caste and cluster dummies, as well as age and demographic characteristics of the children.

We estimate the effect of the drought on a range of different outcome variables, including number of hours spent at school, number of hours spent working, school enrolment and measures of cognitive ability – such as tests on reading, writing and mathematical competence. Our model specification can be interpreted as a reduced form of equation (1), the vector (X_{it-1}) of controls and the drought dummy capturing the level of additional investment in child outcomes between rounds.

To test the heterogeneous effect of the drought, we augment our model specification to include interactions between the drought dummy and a set of j demographic categories.

$$(3) \qquad y_{it} = \gamma S_{it-1} + X_{it-1}\delta + \sum \alpha_j (D_{it} \cdot d_j) + u_{it}$$

$$u_{it} = \mu_i + \eta_h + \varepsilon_{it}$$

Estimation of equations (2) and (3) will present a number of econometric challenges. While we take care of some of the worst endogeneity problems using controls measured four years before the outcome variable, issues of unobserved child (μ_i) and household heterogeneity (η_h) remain. More specifically, any correlation between these components of the error term and the drought incidence would render our impact estimates biased and inconsistent.

In our analysis, the exogeneity of the drought dummy is particularly suspect given that our measure of incidence is based on self-reported answers. The concern is that households affected by the drought are different in some unobserved attribute from those unaffected. For a highly correlated shock, such as a drought, it is likely that, in a given site, households reporting having been affected by the drought might be systematically different from their unaffected neighbours – perhaps poorer and more vulnerable.

However, household heterogeneity only becomes a real concern if those differences remain unobserved. To the extent that we have appropriately controlled for any correlates of the drought also affecting the outcome variables, estimates will arguably remain consistent. While we only use a parsimonious set of controls in our model specification, by including Round 1 measures of acquired skill (S_{it-1}), we effectively control for any unobserved heterogeneity affecting the children's cognitive and nutritional status prior to period *t*.

We address issues of endogeneity by isolating the effect of the drought from unobserved heterogeneity. Applying a first-difference (FD) transformation of our main specification would do precisely that. Our two-wave sample does not allow us to implement such a procedure; instead, we estimate a value-added specification (see Todd and Wolpin 2003 and Todd and Wolpin 2007) of the following form:

$$(4) \qquad \Delta y_{it} = \rho y_{it-1} + \gamma S_{it-1} + X_{it-1}\delta + \sum \alpha_j (D_{it} \cdot d_j) + \varepsilon_{it}$$

By differencing between periods, we are able to control for time-invariant child and household unobserved characteristics. Consequently equation (4) constitutes our preferred model specification for identifying the impact of the drought. Unfortunately, our sample only includes consistent measures across rounds for a very limited set of variables, effectively restricting the application of equation (4) to changes in 'school enrolment'.[5]

While the cloud of endogeneity can never be truly dispelled, it should be noted that our exploration of impact heterogeneity is less subject to this caveat. Endogeneity in the shock variable might render the effect of the drought biased and inconsistent, however a priori there is no reason to believe that these biases should be distributed across demographic groups other than uniformly. Indeed evidence of heterogeneity across demographic groups would indicate that drought impact estimates are not exclusively caused by a spurious correlation between the drought incidence and the error term.

A genuine concern however in the interpretation of the child heterogeneity regressions is issues of intra-household task and resource allocation and gender discrimination. A large literature exists on prevalent discrimination against daughters in India. Therefore caution is called for when interpreting differences across gender. However, in our analysis, we tackle this issue head on. Should gender preferences and intra-household discrimination be driving some of our results, the same type of patterns uncovered in schooling and work outcomes

5 It should be noted that estimates of equation (4) will remain suspect if household unobserved investments change between stages of child development. In other words, results from equation (4) should be interpreted with caution if we believe that decision-making about the enrolment of children aged 8 is not a good proxy for decision-making about the enrolment of 12-year-old children.

should be reproduced in nutritional and health outcomes. As a robustness check we re-estimate equation (4) with height-for-age, body mass index for age and child weight in Round 2 as outcome variables.

Before moving on to present the results of our analysis, it is worth discussing a number of technical aspects of our methodology. A central part of our analysis uses time allocation variables, e.g. number of hours a child spends at school or carrying out household chores in an average day. This type of variable typically suffers from data censoring, in that the set of values that they can take are bounded between zero and 24 hours. We use standard Tobit estimation methods to correct for any potential bias arising from such data censoring. Unless otherwise stated, tables report marginal effects for Tobit estimates. Additionally throughout the paper we use cluster-corrected standard errors. We correct inferencing statistics by allowing for arbitrary correlation in the error term across children born and living in the same site.[6]

5 Estimation results

5.1 Baseline results

We proceed to estimate the effect of the drought on time spent at school at the age of 12. Table 3 presents our estimates of equation (3) for the full sample, and for land-owning and landless households. Our core regressions are reported in columns A to C and include a full set of household and child controls as well as caste[7] and cluster dummies. We find that Tobit estimates controlling for data censoring indicate that the incidence of the drought reduces significantly the number of hours spent at school (see column A). As expected the results are driven by land-owning households (column B), indicating that income of landless households is either less exposed to the shock, especially since a substantial proportion of landless households are located in urban areas, or they are better equipped to smooth its negative effects, presumably thanks to temporary or seasonal migrations (column C).

6 As a result from the sample frame, the Andhra Pradesh Young Lives dataset includes children from a single cohort sampled from 20 different sites. We use a clustering weighting matrix to correct for correlation in the error term across children from the same sites.

7 The four caste categories used are Scheduled Castes (SC), Scheduled Tribes (ST), Backward Classes (BC) and Other Castes (OC). These are legal terms used by the Government of India to classify people in order to monitor welfare, prevent discrimination and use positive discrimination to enable disadvantaged groups to overcome social hurdles such as lack of educational and job opportunities.

Table 3. *Drought impact and schooling determinants*

	Dependent variable: hours spent at school (% total hours)					
	Tobit Estimates, Bottom Censoring					
	Full Controls			RestrictedControls		
	Full Sample	Land Owning	Landless	Full Sample	Land Owning	Landless
	A	B	C	D	E	F
Drought Shock, t-1	-0.012*	-0.014*	-0.007	-0.011	-0.013	-0.008
	(0.095)	(0.078)	(0.734)	(0.155)	(0.105)	(0.694)
12 Years Age, (vs 11 yr Olds)	-0.027***	-0.042***	-0.015	-0.031***	-0.045***	-0.016
	(0.002)	(0.000)	(0.206)	(0.000)	(0.000)	(0.124)
Nr Kids <5 Yrs, t-1	-0.010*	-0.017*	-0.001	-0.007	-0.013	0.002
	(0.059)	(0.079)	(0.874)	(0.130)	(0.149)	(0.813)
Nr HH Adults, t-1	0.005**	0.005**	0.006	0.006***	0.006***	0.006
	(0.029)	(0.046)	(0.136)	(0.007)	(0.009)	(0.103)
Male HH Head, t-1	0.013	0.031	-0.003	0.020	0.030	0.011
	(0.213)	(0.180)	(0.784)	(0.154)	(0.198)	(0.331)
ST Caste, (SC default)	-0.005	-0.011	0.007	-0.007	-0.024	0.018
	(0.773)	(0.716)	(0.789)	(0.657)	(0.408)	(0.451)
BC Caste, (SC default)	0.008	0.014	-0.007	0.018	0.022	0.008
	(0.604)	(0.494)	(0.751)	(0.209)	(0.236)	(0.713)
O C Caste, (SC default)	0.022	0.036	-0.003	0.040**	0.053**	0.018
	(0.216)	(0.231)	(0.888)	(0.019)	(0.045)	(0.402)
Age Mother, t-1	-0.002***	-0.002**	-0.002**			
	(0.001)	(0.013)	(0.015)			
Height-for-Age z-score, t-1	-0.009*	-0.012**	-0.007			
	(0.094)	(0.041)	(0.364)			
Ravens Test, t-1	-0.000	0.001	-0.000			
	(0.926)	(0.690)	(0.766)			
Highest Grade Edu - Carer, t-1	0.001	0.002*	0.001			
	(0.173)	(0.057)	(0.494)			
Housing Quality Index, t-1	0.021	0.001	0.045			
	(0.215)	(0.975)	(0.140)			
Consumer Durables Index, t-1	0.056**	0.054	0.033			
	(0.045)	(0.115)	(0.418)			
Services Index, t-1	0.017	0.025	0.021			
	(0.393)	(0.222)	(0.590)			
_cons	0.252***	0.220***	0.260***	0.232***	0.234***	0.237***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Tobit 'Sigma'	0.111***	0.106***	0.112***	0.113***	0.108***	0.115***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Cluster Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	949	517	432	981	535	446
Adjusted R2	-0.251	-0.325	-0.233	-0.223	-0.282	-0.222

Note: Cluster-corrected standard errors. P-values reported in brackets; *, ** and *** denote significance at 10%, 5% and 1% level of confidence. 'Restricted controls' include: age of child, number of children in the household, number of adult household members, gender of household head, and individual caste dummies: SC, ST, BC and OC, as well as site-specific dummies. 'Core controls' include: age of child, number of children in the household, number of adult household members, gender of household head, age of biological mother, height-for-age of child, Raven test of child, education of the child's caregiver, housing quality index, consumer durables index, services index, and individual caste dummies: SC, ST, BC and OC, as well as site-specific dummies.

Nevertheless, these results could be highly misleading. As suggested by the theoretical models, the impact of the drought on schooling and child work might vary significantly across children with different demographic attributes. Results reported in Table 3 might hide this heterogeneity and could lead to the erroneous belief that the incidence of the drought had only a limited effect on time spent at school. Moreover, the potential endogeneity of the drought shock at the household level also calls for caution when interpreting these results.

Before exploring further the heterogeneity of the impact of the drought, it is informative to analyse the determinants of school time allocation in Andhra Pradesh. We find that the demographic structure of the household affects the schooling patterns of children. Children appear to compete for scarce household resources. A higher number of young children in the household reduces schooling time while greater household wealth – as proxied by the number of adult members in the household – increases time allocated to schooling. As expected, schooling hours fall with the age of the child. Similarly, taller, able-bodied, children spend fewer hours at school. Interestingly these effects do not carry over to the sample of landless/urban households, again suggesting that competition for children's time, at least at this early age, is less fierce in non-farming households.

In the context of India, the question of the role of caste groups is a pertinent one. We find that caste dummies are not significant when we use our full set of controls, but become significant when we drop controls for education and socio-economic status of the household – as we do in columns D to F. More specifically, among land-owning households, belonging to the OC caste increases significantly the number of hours a child spends at home compared to children in the SC caste, while ST and BC castes are not significantly different from the default caste (see column E). The evidence suggests that observed differences in time allocations across caste are not driven by caste-specific preferences or cultural norms, but by the prevalence of different levels of education and socio-economic status across caste groups.

5.2 Uncovering impact heterogeneity

In Table 4 we explore the heterogeneity of the drought impact across children with different demographic characteristics. We seek to test whether preliminary findings in Table 2 are robust to econometric methods. We restrict our analysis to land-owning households only. In column (A) we reproduce the average treatment effect from Table 3. Columns B and C explore heterogeneity of the drought impact on schooling hours while Columns D to F estimate equation (4) for school drop-out.

Table 4. *Schooling hours and drop-out rates, by demographic groups*

	Hours at School (% Total)			School Drop-Out		
	Tobit	Tobit	Tobit	LPM	LPM	LPM
	A	B	C	D	E	F
Drought Shock, t-1	-0.014* (0.078)	-0.022** (0.011)	0.012 (0.514)	-0.040** (0.037)	0.065*** (0.006)	-0.040 (0.341)
Eldest Boy		-0.004 (0.800)			0.041 (0.285)	
(Drought x Eldest Boy)		0.033 (0.105)			-0.103* (0.053)	
Eldest Girl			-0.004 (0.826)			-0.015 (0.753)
Younger Girl			0.010 (0.505)			-0.043 (0.351)
Younger Boy			0.014 (0.371)			-0.095** (0.024)
(Drought x Eldest Girl)			-0.033 (0.248)			0.092 (0.191)
(Drought x Younger Girl)			-0.036** (0.042)			0.067 (0.330)
(Drought x Younger Boy)			-0.036 (0.167)			0.156** (0.014)
Implied Combined Effect of Drought						
Drought – Not-Eldest Boy		-0.022** (0.011)			0.065*** (0.006)	
Drought – Eldest Boy		0.012 (0.526)			-0.038 (0.358)	
Drought – Eldest Girl			-0.021 (0.114)			0.052 (0.190)
Drought – Younger Girl			0.024 (0.167)			0.028 (0.607)
Drought – Eldest Boy			0.012 (0.514)			-0.040 (0.341)
Drought – Younger Boy			0.024 (0.214)			0.116** (0.016)
Core Controls	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	517	517	517	521	521	521
Adjusted R2	0.325	-0.332	-0.336	0.062	0.064	0.063

Note: The top half of the table reports interaction and full effects of 'Drought' and 'Demographic Groups'. The bottom half reports the correspoding combined effects of the drought. Cluster corrected standard errors. P-values reported in brackets; *, ** and *** denote significance at 10%, 5% and 1% level of confidence. Core controls include: number of children in the household, number of adult household members, gender of household head, age of biological mother, height-for-age of child, Raven test of child, education of the child's caregiver, housing quality index, consumer durables index, services index, individual caste dummies: SC, ST, BC and OC, as well as site-specific dummies.

Living in a household affected by the drought reduces school hours for an average child by 0.014 per cent of a 24-hour day or approximately half an hour. However, when we allow for heterogeneity of the drought impact by eldest boy, we find that the effect of the drought almost doubles to approximately 50 minutes for the 'not eldest boy' demographic group (see column B). These effects are large since an average child spends approximately six hours at school. More pointedly the drought's effect is equivalent to a movement of 21 per cent standard deviation of schooling hours. Even more marked is the heterogeneity of the drought effects on the likelihood of children dropping out of school. While the average effect of the drought is positive, analysis of the child demographics suggests a more complex pattern (see columns E and F). Drop-out rates are significantly increased among 'not eldest boys' – by 6.5 per cent – while the drop-out rate for eldest boys is reduced, even though the latter effect is insignificant but large in magnitude (3.8 per cent).

The evidence so far would suggest that the drought indeed had differential effects on schooling of children of different demographic groups. Models of agricultural production would suggest that eldest sons are being positively affected by the drought because social norms imply that counterfactually they would be involved in the farming activities of the household as opposed to, for example, the eldest daughters, who would most likely be involved in the child care and household chores. To test this particular mechanism we explore further whether eldest sons in households involved in more labour-intensive activities (irrigation farming) experience a stronger price effect, compared with eldest sons in households in less labour-intensive farming activities (non-irrigated agriculture).

Table 5 reports results of the effect of the drought on hours spent on schooling, work and household chores when the drought is interacted with irrigation-farming and child demographic dummies. In panel A we report main dummy and interaction effects, while in panel B we report full effects for each category. Columns A to C report estimates from a parsimonious model where we create three aggregated categories: 'household affected by the drought', 'child is eldest son and in irrigation-farming household' and the interaction between these two categories. The model tests whether the effect of the drought was different for eldest sons in irrigation-farming households compared to all other categories jointly. In columns D to F, we estimate a more disaggregated model where we split by demographic categories and type of household – in total we estimate eight different drought impact variables.

Results generally support the predictions of the household agricultural model. The effect of the drought becomes more significant when interacted with the 'eldest boy and irrigation-farming household' category. Eldest sons in irrigation-farming households dedicate more hours to household work than any other category; similarly they spend less time on household chores. When affected by the drought, this category of children increase their schooling hours significantly and reduce their work. The overall effect for this group of children (panel B) is that they marginally increase schooling but significantly reduce their working hours. When we disaggregate the drought effect by demographic group and household type, we find evidence of increases in working hours, probably as coping strategies against the drought (see panel B). In particular, among irrigation-farming households, eldest daughters and younger daughters increase their working hours, presumably in work activities unaffected by the drought.

Table 5 also provides an interesting insight into social norms prevalent in rural Andhra Pradesh with regard to schooling and work patterns across different child demographic groups. As expected daughters across all households spend more hours on household chores than the eldest sons, but – although to a lesser extent – younger sons also carry out more household chores. All categories spend fewer hours working than the default eldest son category. Among irrigation-farming households, daughters work significantly fewer hours, while among non-irrigation-farming households, interestingly, it is eldest sons who work least. However, the demographic patterns of child work do not appear to be mirrored by schooling hours. In this Andhra Pradesh sample and with children aged 11 to 12 years, neither do eldest sons appear to be favoured, nor daughters disfavoured regarding time allocated to their schooling.

Table 5. *Mechanisms of drought impact: hours of schooling, work and chores, by farming activity and demographic groups*

	Panel A – Interaction and Full Effects, Tobit Estimates						Panel B – Implied Effects of Drought, Tobit Estimates					
	School	Work	Chores	School	Work	Chores	School	Work	Chores	School	Work	Chores
	A	B	C	D	E	F	A	B	C	D	E	F
Drought Shock, t-1	-0.023***	0.124	0.002									
	(0.003)	(0.127)	(0.826)									
EldestBoy & IrrigationHH	-0.019	0.184**	-0.073***									
	(0.379)	(0.013)	(0.000)									
(Drought x Not Eldest Boy & IrrigationHH)							-0.023***	0.124	0.002			
							(0.003)	(0.127)	(0.826)			
(Drought x Eldest Boy & IrrigationHH)	0.060***	-0.470***	0.025				0.037	-0.346**	0.027			
	(0.007)	(0.000)	(0.259)				(0.106)	(0.011)	(0.197)			
E Girl & No IrrigationHH				0.019	-0.174	0.085***						
				(0.501)	(0.279)	(0.000)						
Y Girl & No IrrigationHH				0.011	-0.140	0.079***						
				(0.593)	(0.178)	(0.000)						
E Boy & No IrrigationHH				0.034	-0.333*	0.032						
				(0.151)	(0.062)	(0.261)						
Y Boy & No IrrigationHH				0.045**	-0.122	0.034*						
				(0.048)	(0.297)	(0.077)						
E G irl & IrrigationHH				0.005	-0.222*	0.092***						
				(0.849)	(0.057)	(0.000)						
Y Girl & IrrigationHH				0.037	-0.349***	0.070***						
				(0.121)	(0.004)	(0.002)						
Y Boy & IrrigationHH				0.018	-0.068	0.046**						
				(0.404)	(0.518)	(0.012)						
(Drought x E Girl & No IrrigationHH)				0.071**	0.308	-0.028				-0.033	-0.044	-0.004
				(0.042)	(0.188)	(0.273)				(0.161)	(0.865)	(0.804)
(Drought x Y Girl & No IrrigationHH)				-0.050	0.415**	-0.029				-0.012	0.063	-0.006
				(0.195)	(0.017)	(0.274)				(0.679)	(0.661)	(0.693)
(Drought x E Boy & No IrrigationHH)				-0.062*	0.650**	-0.016				-0.024	0.298	0.008
				(0.066)	(0.021)	(0.601)				(0.397)	(0.231)	(0.655)
(Drought x Y Boy & No IrrigationHH)				0.074**	0.373**	-0.005				-0.036	0.021	0.018
				(0.015)	(0.039)	(0.797)				(0.265)	(0.872)	(0.263)
(Drought x E Girl & IrrigationHH)				-0.053*	0.584***	-0.006				-0.015	0.232*	0.017
				(0.094)	(0.004)	(0.750)				(0.359)	(0.071)	(0.261)
(Drought x Y Girl & IrrigationHH)				0.076**	0.600***	-0.007				-0.038	0.248	0.016
				(0.017)	(0.005)	(0.820)				(0.251)	(0.170)	(0.516)
(Drought x E Boy & IrrigationHH)										0.038*	-0.352**	0.023
										(0.088)	(0.014)	(0.242)
(Drought x Y Boy & IrrigationHH)				-0.058*	0.397**	-0.047**				-0.020	0.045	-0.023*
				(0.055)	(0.019)	(0.030)				(0.310)	(0.771)	(0.098)
Tobit 'Sigma'	0.106***	0.352***	0.065***	0.105***	0.349***	0.061***	0.106***	0.352***	0.065***	0.105***	0.349***	0.061***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Core Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	517	517	517	517	517	517	517	517	517	517	517	517
Adjusted R2	-0.335	0.251	-0.297	-0.346	0.272	-0.419	-0.335	0.251	-0.297	-0.346	0.272	-0.419

Note: Panel A presents interaction and full effects of Drought' and 'Farming categories' and 'Demogrpahic groups'. Panel B reports the corresponding combined effects of the drought. Cluster-corrected standard errors. P-values reported in brackets; *, ** and *** denote significance at 10%, 5% and 1% level of confidence. Core controls include: number of children in the household, number of adult household members, gender of household head, age of biological mother, height-for-age of child, Raven test of child, education of the child's caregiver, housing quality index, consumer durables index, services index, individual caste dummies: SC, ST, BC and OC, as well as site-specific dummies.

5.3 Discussion

The evidence so far suggests that the drought had a large and significant effect on child schooling. When we allow for heterogeneity of the impact across demographic groups and household types, we find that price effects are largest among eldest sons in irrigation-farming households. The main effect of the drought – for the remaining categories – can therefore be interpreted as the profit or income effect. We find also some evidence that, as a coping strategy against the reduction in disposable income, daughters in irrigation-farming households increase their supply of labour.

How to interpret some of these results is not obvious. In particular, it seems odd to find that work supply is increased among daughters in irrigation-farming households while in the same type of households eldest sons reduce their working hours and increase their school time.

However, recall that we rely on comparisons across households and across children – we only have one child per household. The time allocation impact of the drought on children aged 11 to 12 ought to be interpreted in counterfactual form. That is, we use the sample of unaffected households as the counterfactual evolution for a given demographic group. Namely, patterns of labour supply among unaffected irrigation-farming households show that eldest boys work longer hours than daughters. It is in this context that we can reconcile the overall positive effect among eldest sons with a negative effect among eldest daughters (see column E in Table 5). The drought reduces the work involvement of eldest sons, who counterfactually have the highest labour supply among child demographic categories, but increases the involvement among daughters, who counterfactually have a relatively low involvement in work activities.

While consistent with the predictions of the model, the evidence could also be interpreted as positive discrimination towards eldest sons borne out of parental preferences and social norms. We tackle this issue head on. We re-estimate the models in Table 5 with height-for-age, body mass index and child weight as dependent variables, and find that the same heterogeneous patterns across demographic groups and household types are not reproduced. Indeed, eldest sons appear to have suffered from the drought as much as any other demographic group. Overall, we find no effect of the drought on height-for-age but a marginal negative effect on weight. This is consistent with the fact that these children have long outgrown their nutritional critical period, and only short-term measures of nutrition are likely to be sensitive to shocks at their age (See Table A3).

If we want to understand the medium-term consequences of the drought, an issue of concern is whether the captured changes in schooling are achieved through changes in the intensive or extensive margin of schooling (children dropping out). The assumption is that a child who reduced their schooling hours in the first place could presumably increase their involvement back to full schooling when the lean years are over. Such seamless recovery is unlikely to be available for children who have dropped out altogether. Columns A and F in Table 6, report the results of the heterogeneous analysis on children who have dropped out of school. We find indeed that for most categories of children drop-out rates are substantially increased due to the drought. Similarly eldest sons' drop-out rates are reduced counterfactually. Figure A1 plots kernel densities for the four categories: affected and not affected eldest sons or other siblings. We find that even though the intensive margin effects are substantial as well, the changes in the drop-out rates are most marked. While other siblings affected by the drought have the highest rates of drop-out, affected eldest sons have the lowest drop-out rates among all children.

Finally, Table 6 also includes a number of alternative outcome variables. We are interested in exploring whether the patterns of schooling and work really matter for the potential future welfare of the children. In particular, we analyse the effects of the drought on cognitive development and educational attainment. To the extent that increasing the labour supply of a child does not have any further medium-term and long-term consequences, it would constitute a very effective and cost-free response to the drought. The evidence in Table 6 however points to the contrary. Probably mediated through drop-out patterns, we find that cognitive development as measured by the PPVT scores has been reduced significantly for most children exposed to the drought.

Table 6. *Effect of the drought on cognitive development, by farming activity and demographic group*

	Implied Effects of Drought Only									
	Drop-Out	Read	Write	CDA Score	PPVT Score	Drop-Out	Read	Write	CDA Score	PPVT Score
	LPM	LPM	LPM	OLS	OLS	LPM	LPM	LPM	OLS	OLS
	A	B	C	D	E	F	G	H	I	J
All – 'EldestY Boy AND IrrigationHH'	0.074 (0.155)	-0.067 (0.751)	-0.202 (0.526)	0.224 (0.714)	0.200 (0.243)					
Drought – 'Not Eldest Y Boy AND IrrigationHH'	0.070*** (0.004)	-0.143 (0.474)	0.043 (0.747)	-0.502 (0.170)	-0.271*** (0.001)					
Drought – 'Eldest Y Boy AND IrrigationHH'	-0.119** (0.020)	1.192* (0.061)	1.107** (0.015)	0.699 (0.314)	-0.108 (0.456)					
All – E Girl & NoIrrigHH						-0.005 (0.944)	-0.014 (0.967)	0.070 (0.847)	-0.600 (0.308)	-0.237 (0.246)
All – Y Girl & NoIrrigHH						-0.021 (0.696)	-0.268 (0.445)	-0.105 (0.742)	-0.576 (0.384)	-0.394* (0.091)
All – E Boy & NoIrrigHH						-0.058 (0.337)	0.196 (0.564)	0.395 (0.375)	-0.561 (0.308)	-0.141 (0.515)
All – Y Boy & NoIrrigHH						-0.094 (0.149)	0.533 (0.141)	0.590* (0.099)	0.136 (0.838)	-0.062 (0.793)
All – E Girl & IrrigHH						-0.055 (0.361)	0.129 (0.701)	0.445 (0.192)	-0.126 (0.858)	-0.173 (0.413)
All – Y Girl & IrrigHH						-0.117 (0.147)	0.036 (0.864)	0.105 (0.828)	0.448 (0.533)	-0.087 (0.658)
All – Y Boy & IrrigHH						-0.137** (0.019)	-0.020 (0.960)	-0.174 (0.687)	-0.674 (0.357)	-0.340 (0.213)
Drgt – E Girl & NoIrrigHH						0.054 (0.440)	0.097 (0.842)	0.250 (0.534)	-0.456 (0.422)	-0.153 (0.268)
Drgt – Y Girl & NoIrrigHH						0.028 (0.804)	-0.249 (0.511)	-0.356 (0.161)	-0.810 (0.346)	-0.376** (0.017)
Drgt – E Boy & NoIrrigHH						0.076 (0.320)	-0.047 (0.924)	-0.017 (0.973)	-0.197 (0.786)	-0.367** (0.032)
Drgt – Y Boy & NoIrrigHH						0.086 (0.255)	-0.417 (0.358)	-0.178 (0.574)	-0.959*** (0.008)	-0.492** (0.027)
Drgt – E Girl & IrrigHH						0.057 (0.333)	-0.276 (0.584)	-0.026 (0.945)	-0.249 (0.672)	-0.213 (0.473)
Drgt – Y Girl & IrrigHH						0.055 (0.487)	-0.193 (0.520)	0.191 (0.582)	-0.866 (0.240)	-0.489** (0.010)
Drgt – E Boy & IrrigHH						-0.115** (0.023)	1.203* (0.059)	1.117** (0.015)	0.651 (0.346)	-0.112 (0.450)
Drgt – Y Boy & IrrigHH						0.159*** (0.007)	-0.046 (0.903)	0.167 (0.541)	-0.566 (0.282)	-0.078 (0.654)
Core Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	521	518	511	455	523	521	518	511	455	523
Adjusted R2	0.070	0.152	0.183	0.147	0.181	0.059	0.166	0.206	0.145	0.172

Note: Table reports combined effects of the drought only. See Table A2 in Annex for corresponding interaction effects. Cluster corrected standard errors. Pvalues reported in brackets; *, ** and *** denote significance at 10%, 5% and 1% level of confidence. Core controls include: number of children in the household, number of adults members, sex of household head, age of biological mother, height-for-age of index child, ravens test of index child, education of the child's carer, housing quality index, consumer durables index, services index, individual caste dummies: SC, ST, BC and OC, as well as site specific dummies.

6 Conclusions

Our analysis provides evidence that households in rural Andhra Pradesh reallocate school hours towards work as a response to drought. However, we show that such coping strategies come at a substantial cost. We find that the drought also resulted in high school drop-out rates – with the prospect of children staying out of school after the drought's effects have faded away – and that fewer schooling hours resulted in a slowdown of cognitive development as measured by the PPVT.

We explore and find evidence of substantial impact heterogeneity across child demographics and household types. We use household agricultural models to analyse the heterogenous impact of the drought on child birth order and gender, as well as the labour intensity of the farming activities of the affected households. We find that profit and income effects of the drought dominate price and productivity effects for most demographic groups and activities that are not labour-intense, resulting in reduced schooling and increased child work. However, we also find evidence of a net price effect among the group of eldest sons in labour-intense activities (irrigation farming), resulting in reduced child involvement in work and increased schooling.

Finally, the paper provides a cautionary tale about the impact of shocks. Failing to recognise the coping mechanisms applied by households when faced with shocks might lead to gross misrepresentations of the true impact of the shocks. Indeed, our estimates suggest that the effect of the drought on school participation is doubled in magnitude when impact heterogeneity is allowed for – from less than a half an hour to approximately 50 minutes. When allowing for heterogeneity we find that the effect of the drought on schooling is substantial, amounting to a movement in schooling hours of approximately 21 per cent of one standard deviation for most child demographic groups.

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Appendix: Further tables

Table A1. *Descriptive statistics*

		All	No Land	Own Land	Own Land		No Land	
					No Drought	Drought	No Drought	Drought
		A	B	C	D	E	F	G
Hours Spent at School (% of Total), t	Mean	0.26568	0.27430	0.2585**	0.26433	0.24989	0.27606	0.26433
	Std. Dev.	(0.111)	(0.113)	(0.109)	(0.110)	(0.107)	(0.116)	(0.095)
Hours Spent at Work (% of Total), t	Mean	0.02776	0.02034	0.0339**	0.03046	0.03908	0.02080	0.01779
	Std. Dev.	(0.092)	(0.080)	(0.101)	(0.096)	(0.108)	(0.082)	(0.068)
Hours Spent doing HH C hores(% of Total), t	Mean	0.04804	0.04340	0.0519**	0.05068	0.05374	0.04151	0.05412
	Std. Dev.	(0.057)	(0.058)	(0.056)	(0.057)	(0.055)	(0.058)	(0.059)
Drought Shock, t-1	Mean	0.28759	0.14889	0.4030***	0.00000	1.00000	0.00000	1.00000
	Std. Dev.	(0.453)	(0.356)	(0.491)	-	-	-	-
HH Owns Land, t-1	Mean	0.54591	0.00000	1.00000	1.00000	1.00000	0.00000	0.00000
	Std. Dev.	(0.498)	–	–	–	–	–	–
Child is 12-Years Age, (Default 11-years), t-1	Mean	0.72553	0.70889	0.73937	0.75542	0.71560	0.74674	0.4925***
	Std. Dev.	(0.446)	(0.455)	(0.439)	(0.431)	(0.452)	(0.435)	(0.504)
Nr Kids in HH below 5, t-1	Mean	0.33401	0.29111	0.3697**	0.33437	0.4220*	0.25065	0.5224***
	Std. Dev.	(0.598)	(0.587)	(0.606)	(0.557)	(0.669)	(0.501)	(0.911)
Nr Adults in HH, t-1	Mean	2.85066	2.61111	3.0499***	2.95975	3.18349	2.60313	2.65672
	Std. Dev.	(1.456)	(1.226)	(1.596)	(1.447)	(1.789)	(1.213)	(1.309)
Sex of HH Head, t-1	Mean	0.92028	0.90000	0.9372**	0.94118	0.93119	0.89295	0.94030
	Std. Dev.	(0.271)	(0.300)	(0.243)	(0.236)	(0.254)	(0.310)	(0.239)
Age of Mother, t-1	Mean	30.61140	30.48624	30.71456	30.64465	30.81991	30.68022	29.4179*
	Std. Dev.	(5.612)	(5.413)	(5.773)	(5.717)	(5.870)	(5.565)	(4.363)
Child's Height-for-Age, t-1	Mean	-1.53050	-1.43611	-1.6091***	-1.50876	1.7574***	-1.38097	-1.7513***
	Std. Dev.	(1.046)	(1.021)	(1.061)	(1.014)	(1.113)	(1.010)	(1.040)
Child's Ravens Test, t-1	Mean	22.95233	22.79778	23.08209	22.67610	23.6743**	23.06005	21.2985**
	Std. Dev.	(5.293)	(5.364)	(5.234)	(5.065)	(5.428)	(5.240)	(5.841)
Education of Caregiver, t-1	Mean	2.33502	3.19556	1.6192***	1.81115	1.3349*	3.53786	1.2388***
	Std. Dev.	(3.895)	(4.419)	(3.231)	(3.427)	(2.901)	(4.539)	(3.005)
Househing Quality Index, t-1	Mean	0.40104	0.45791	0.3537***	0.39280	0.2959***	0.48624	0.2960***
	Std. Dev.	(0.285)	(0.290)	(0.273)	(0.289)	(0.236)	(0.285)	(0.261)
Consumer Durables Index, t-1	Mean	0.23979	0.28040	0.2060***	0.22291	0.1810***	0.29812	0.1791***
	Std. Dev.	(0.195)	(0.201)	(0.184)	(0.189)	(0.175)	(0.202)	(0.161)
Services Index, t-1	Mean	0.37790	0.48500	0.2888***	0.31037	0.2569***	0.51958	0.2873***
	Std. Dev.	(0.290)	(0.328)	(0.218)	(0.238)	(0.179)	(0.332)	(0.214)
Caste ST , (Default SC), t-1	Mean	0.10797	0.09111	0.12200	0.15789	0.0688***	0.09661	0.05970
	Std. Dev.	(0.311)	(0.288)	(0.328)	(0.365)	(0.254)	(0.296)	(0.239)
Caste BC , (Default SC), t-1	Mean	0.46519	0.43333	0.4917*	0.45820	0.5413*	0.41253	0.5522**
	Std. Dev.	(0.499)	(0.496)	(0.500)	(0.499)	(0.499)	(0.493)	(0.501)
Caste O C , (Default SC), t-1	Mean	0.21594	0.25111	0.1867**	0.20433	0.16055	0.26632	0.1642*
	Std. Dev.	(0.412)	(0.434)	(0.390)	(0.404)	(0.368)	(0.443)	(0.373)
Number of observations	Mean	991	450	541	323	218	383	67

Note: Standard deviations reported in brackets. Test of equality of means across sub-groups reported between columns (B) and (C), (D) and (E) and (F) and (G) respectively. *, ** and *** denote significance at 10%, 5% and 1% level of confidence.

Table A2. *Effect of the drought on cognitive development, by farming activity and demographic group*

	Interaction and Full Effects									
	Drop-Out	Read	Write	CDA Score	PPVT Score	Drop-Out	Read	Write	CDA Score	PPVT Score
	LPM	LPM	LPM	OLS	OLS	LPM	LPM	LPM	OLS	OLS
	A	B	C	D	E	F	G	H	I	J
Drought Shock, t-1	0.070***	-0.143	0.043	-0.502	0.271***	-0.115**	1.203*	1.117**	0.651	-0.112
	(0.004)	(0.474)	(0.747)	(0.170)	(0.001)	(0.023)	(0.059)	(0.015)	(0.346)	(0.450)
EldestBoy & IrrigationHH	0.074	-0.067	-0.202	0.224	0.200					
	(0.155)	(0.751)	(0.526)	(0.714)	(0.243)					
(Drought x EldestBoy & IrrigationHH)	-0.189***	1.334*	1.063**	1.201	0.163					
	(0.003)	(0.063)	(0.025)	(0.149)	(0.341)					
E Girl & No IrrigationHH						-0.005	-0.014	0.070	-0.600	-0.237
						(0.944)	(0.967)	(0.847)	(0.308)	(0.246)
Y Girl & No IrrigationHH						-0.021	-0.268	-0.105	-0.576	-0.394*
						(0.696)	(0.445)	(0.742)	(0.384)	(0.091)
E Boy & No IrrigationHH						-0.058	0.196	0.395	-0.561	-0.141
						(0.337)	(0.564)	(0.375)	(0.308)	(0.515)
Y Boy & No IrrigationHH						-0.094	0.533	0.590*	0.136	-0.062
						(0.149)	(0.141)	(0.099)	(0.838)	(0.793)
E Girl & IrrigationHH						-0.055	0.129	0.445	-0.126	-0.173
						(0.361)	(0.701)	(0.192)	(0.858)	(0.413)
Y Girl & IrrigationHH						-0.117	0.036	0.105	0.448	-0.087
						(0.147)	(0.864)	(0.828)	(0.533)	(0.658)
Y Boy & IrrigationHH						-0.137**	-0.020	-0.174	-0.674	-0.340
						(0.019)	(0.960)	(0.687)	(0.357)	(0.213)
(Drought x E G irl & No IrrigationHH)						0.169*	-1.106	-0.867	-1.107	-0.041
						(0.061)	(0.163)	(0.145)	(0.192)	(0.841)
(Drought x Y Girl & No IrrigationHH)						0.143	-1.452*	-1.473***	-1.461	-0.264
						(0.285)	(0.054)	(0.002)	(0.180)	(0.215)
(Drought x E Boy & No IrrigationHH)						0.191**	-1.250	-1.134	-0.848	-0.255
						(0.033)	(0.152)	(0.106)	(0.400)	(0.305)
(Drought x Y Boy & No IrrigationHH)						0.201**	-1.620**	-1.295**	-1.610**	-0.380*
						(0.021)	(0.022)	(0.011)	(0.031)	(0.071)
(Drought x E Girl & IrrigationHH)						0.173**	-1.479	-1.143**	-0.901	-0.101
						(0.043)	(0.140)	(0.036)	(0.410)	(0.776)
(Drought x Y Girl & IrrigationHH)						0.170*	-1.395**	-0.926	-1.517	-0.377
						(0.095)	(0.049)	(0.141)	(0.189)	(0.121)
(Drought x Y Boy & IrrigationHH)						0.274***	-1.249	-0.950	-1.218	0.034
						(0.001)	(0.104)	(0.136)	(0.121)	(0.883)
Core Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	521	518	511	455	523	521	518	511	455	523
Adjusted R2	0.070	0.152	0.183	0.147	0.181	0.059	0.166	0.206	0.145	0.172

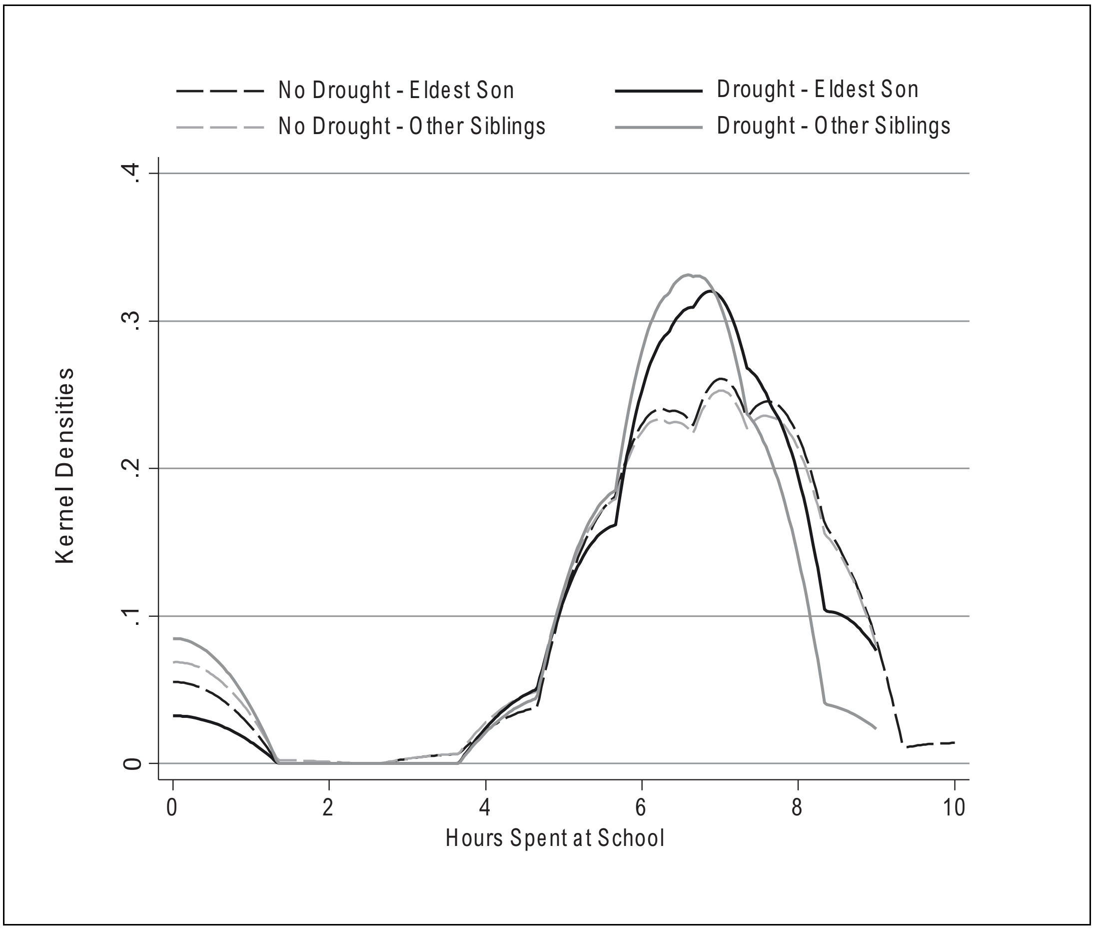
Note: Table reports interaction and full effects of 'Drought' and 'Farming categories' and 'Demogrpahic groups' only. P-values reported in brackets; *, ** and *** denote significance at 10%, 5% and 1% level of confidence. 'Core controls' include: number of children in the household, number of adults members, sex of household head, age of biological mother, height-for-age of child, Ravens test of child, education of the child's caregiver, housing quality index, consumer durables index, services index, individual caste dummies: SC, ST, BC and OC, as well as site-specific dummies.

Table A3. *Testing preferences: nutritional effect of the drought, by demographic group*

	Interaction and Full Effects						Implied Effects of Drought Only					
	Change in BMI z-score	Change in HAZ z-score	Change in weight	Change in BMI z-score	Change in HAZ z-score	Change in weight	Change in BMI z-score	Change in HAZ z-score	Change in weight	Change in BMI z-score	Change in HAZ z-score	Change in weight
	A	B	C	D	E	F	A	B	C	D	E	F
Drought Shock	-0.186	0.022	-1.778	-0.273	0.119	-2.460						
	(0.112)	(0.083)	(1.069)	(0.202)	(0.080)	(1.769)						
All – 'EldestBoy AND IrrigationHH'	-0.009	0.044	-0.576				-0.009	0.044	-0.576			
	(0.136)	(0.072)	(1.660)				(0.136)	(0.072)	(1.660)			
Drought – Not 'EldestBoy AND IrrigationHH'							-0.186	0.022	-1.778			
							(0.112)	(0.083)	(1.069)			
Drought – 'EldestBoy AND IrrigationHH'	-0.072	0.075	-0.538				-0.258	0.097	-2.316			
	(0.232)	(0.117)	(1.374)				(0.210)	(0.079)	(1.703)			
All – E Girl & NoIrrigHH				-0.038	0.183	0.666				-0.038	0.183	0.666
				(0.182)	(0.134)	(2.050)				(0.182)	(0.134)	(2.050)
All – Y Girl & NoIrrigHH				0.200	-0.046	0.928				0.200	-0.046	0.928
				(0.256)	(0.128)	(1.564)				(0.256)	(0.128)	(1.564)
All – E Boy & NoIrrigHH				-0.261	0.086	-1.373				-0.261	0.086	-1.373
				(0.178)	(0.107)	(1.907)				(0.178)	(0.107)	(1.907)
All – Y Boy & NoIrrigHH				-0.072	-0.118	-1.941				-0.072	-0.118	-1.941
				(0.253)	(0.113)	(1.747)				(0.253)	(0.113)	(1.747)
All – E Girl & IrrigHH				0.133	-0.178*	0.204				0.133	-0.178*	0.204
				(0.176)	(0.087)	(1.778)				(0.176)	(0.087)	(1.778)
All – Y Girl & IrrigHH				0.124	-0.063	3.609				0.124	-0.063	3.609
				(0.176)	(0.145)	(3.709)				(0.176)	(0.145)	(3.709)
All – Y Boy & IrrigHH				-0.280*	0.118	0.294				-0.280*	0.118	0.294
				(0.145)	(0.089)	(1.919)				(0.145)	(0.089)	(1.919)
Drgt – E Girl & NoIrrigHH				0.422	-0.272	1.923				0.149	-0.153	-0.537
				(0.271)	(0.184)	(1.946)				(0.152)	(0.163)	(0.710)
Drgt – Y Girl & NoIrrigHH				0.117	-0.396*	-0.273				-0.156	-0.277	2.733**
				(0.373)	(0.221)	(1.618)				(0.253)	(0.224)	(1.162)
Drgt – E Boy & NoIrrigHH				0.152	-0.387	0.238				-0.121	-0.268	-2.222
				(0.298)	(0.229)	(1.962)				(0.254)	(0.219)	(1.643)
Drgt – Y Boy & NoIrrigHH				-0.226	0.310*	2.094				-0.499	0.429***	-0.366
				(0.324)	(0.150)	(1.516)				(0.316)	(0.121)	(1.111)
Drgt – E Girl & IrrigHH				0.217	0.107	2.874				-0.056	0.226	0.414
				(0.353)	(0.162)	(1.799)				(0.253)	(0.135)	(1.412)
Drgt – Y Girl & IrrigHH				-0.343	-0.415	-4.038				-0.616**	-0.296	6.498**
				(0.230)	(0.296)	(2.903)				(0.216)	(0.263)	(3.043)
Drgt – E Boy & IrrigHH										-0.273	0.119	-2.460
										(0.202)	(0.080)	(1.769)
Drgt – Y Boy & IrrigHH				0.251						-0.022	0.042	-2.988
				(0.243)						(0.168)	(0.099)	(2.163)
Core Controls	Yes	Yes	Yes	Yes						Yes	Yes	Yes
Number of observations	514	515	519	514						514	515	519
Adjusted R2	0.168	0.124	0.045	0.188						0.188	0.150	0.041

Note: Panel A presents interaction and full effects of 'Drought' and 'Farming categories' and 'Demographic groups'. Panel B reports the corresponding combined effects of the drought. P-values reported in brackets; *, ** and *** denote significance at 10%, 5% and 1% level of confidence. Core controls include: number of children in the household, number of adult household members, gender of household head, age of biological mother, height-for-age of child, Raven test of child, education of the child's caregiver, housing quality index, consumer durables index, services index, individual caste dummies: SC, ST, BC and OC, as well as site-specific dummies.

Figure A1: *Hours spent at school, by drought status and demographic category, kernel densities*



Young Lives is an innovative long-term international research project investigating the changing nature of childhood poverty.

The project seeks to:

- improve understanding of the causes and consequences of childhood poverty and to examine how policies affect children's well-being
- inform the development and implementation of future policies and practices that will reduce childhood poverty.

Young Lives is tracking the development of 12,000 children in Ethiopia, India (Andhra Pradesh), Peru and Vietnam through quantitative and qualitative research over a 15-year period.

Young Lives Partners

Young Lives is coordinated by a small team based at the University of Oxford, led by Jo Boyden.

Ethiopian Development Research Institute, Ethiopia

Centre for Economic and Social Sciences, Andhra Pradesh, India

Save the Children – Bal Raksha Bharat, India

Sri Padmavathi Mahila Visvavidyalayam (Women's University), Andhra Pradesh, India

Grupo de Análisis para el Desarollo (Group for the Analysis of Development), Peru

Instituto de Investigación Nutricional (Institute for Nutritional Research), Peru

Centre for Analysis and Forecast, Vietnamese Academy of Social Sciences, Vietnam

General Statistics Office, Vietnam

Save the Children, Vietnam

The Institute of Education, University of London, UK

Child and Youth Studies Group (CREET), The Open University, UK

Department of International Development, University of Oxford, UK

Save the Children UK (staff in the Policy Department in London and programme staff in Ethiopia).

Young Lives
An International Study of Childhood Poverty

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