YOUNG LIVES STUDENT PAPER

The Whims of Indian Monsoons: Long-term Health Consequences of Early Childhood Exposure to the Indian Drought of 2002

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Paper submitted in part fulfilment of the requirements for the degree of MSc in Economics for Development at the University of Oxford, UK.

The data used come from Young Lives, a longitudinal study of childhood poverty that is tracking the lives of 12,000 children in Ethiopia, India (Andhra Pradesh), Peru and Vietnam over a 15-year period. **www.younglives.org.uk**

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Young Lives

An International Study of Childhood Poverty

The Whims of Indian Monsoons: Long-Term Health Consequences of Early Childhood Exposure to the Indian Drought of 2002

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I dedicate this essay to the memory of my paternal grandparents, who remained enthusiastic about my academic aspirations till the end of their lives.
All errors are my own. I would like to receive comments and feedback at sourovi_de@hotmail.com.

Abstract

Droughts are recurrent features of the Indian climatic fabric. A single month's failure (or delay) of the annual monsoon can wield a debilitating blow—in varying degrees—to Indian agriculture and the livelihoods of people, particularly the rural populace. In 2002, large parts of the country experienced one of the most intense droughts recorded in India in the last 25 years. While losses in agricultural income and man-days of rural employment have been widely acknowledged, the long-term health consequences of the drought remain unknown.

Combining Young Lives' longitudinal data from Andhra Pradesh in India, with district-level rainfall data from the Directorate of Economics and Statistics, Government of Andhra Pradesh; this essay provides the first estimates of the long-term impact of the drought on the height attainment of a sub-sample of young individuals from below-poverty line households, who experienced this rainfall shock at the ages of 0-18 months (younger cohort), or 7-8.5 years (older cohort). This essay also examines the role of a large-scale rural poverty alleviation program—*Indira Kranthi Patham*—in mitigating the health impact of the drought for 'poor' children.

Using WHO anthropometric z-scores of height-for-age as the outcome variable in static and dynamic specifications, this essay employs several estimation strategies to correct for econometric issues: first-difference estimator for solving endogeneity arising from time-invariant, unobserved heterogeneity; and an instrumental variables strategy (difference generalised method of moments, or difference GMM) to solve the endogeneity arising from lagged height-for-age scores in the dynamic specification.

Our estimates indicate a loss of 0.8 standard deviations in height-for-age z-scores for the younger, drought-affected cohort of 'poor' children; while their older counterparts suffer a decline of 0.4 standard deviations in height-for-age z-scores. While the program under consideration had a positive and significant impact on the height-attainment of our sub-sample of 'poor' children, this impact is not large enough to mitigate the perils of the drought. It is hoped that these findings will not merely highlight the importance of nutrition and care in the sensitive period of early childhood, but will also bring children to the centre-stage of poverty debates in developing countries; while underlining the paramount need to protect children against shocks through welfare programs.

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1 Introduction

There is no single, all-encompassing definition of drought. According to NASA's Earth Observatory[1], a drought is an extended period—a season, a year or more—of deficient rainfall, relative to the statistical multi-year average for a region. While there is no unique, universally-accepted measure of "deficient rainfall", droughts—in most contexts—refer to drier-than-average rainfall conditions extending over weeks, months or even years. Having

[1] Information accessed on May 5, 2011 via: *http://earthobservatory.nasa.gov:81/Library/DroughtFacts/index.html*

said so, it is important to differentiate droughts from famines. The latter refers to shocks characterised by widespread scarcity of food and mass-scale starvation deaths, arising out of natural and/or man-made calamities such as warfare, acute shortage of rainfall, poor food distribution systems, etc. These causal events of famine generally occur over several consecutive years or affect a region acutely over a short period of time.

Droughts, on the other hand, are mostly caused by climatic or hydrological reasons occurring over a season, a year or more. In most cases, droughts do not result in mass-scale starvation deaths. The earliest evidence of the onset of drought is generally noticed in the annual actual rainfall record, vis-à-vis the region's historical average; generally measured over a 30-year period (NDMC, 2010).

The major Indian droughts during the last 150 years occurred in 1877, 1899, 1918, 1972, 1987 and 2002 (PACS, 2008). However, observing strict terminological differences between droughts and famines, the shocks of 1877 and 1899 should be termed as famines because they were marked by mass-scale starvation deaths to the tune of 4.5 and 5.5 million (Fagan, 2009; Anon., 1908) respectively. Similarly, 150 million people were affected by the "drought" of 1918 (Anon., 1919); while 130,000 people perished in the state of Maharashtra alone in 1972 (Drèze, 1991). The drought of 1987 was localised to Saurashtra in the west-Indian state of Gujarat; while the drought of 2002—though affecting more than half of the country's meteorological districts—was not marked by mass-scale starvation deaths and was one of the shortest droughts in recorded history.

In India, the south-west monsoon or "summer monsoon" refers to the rainfall received during the months of June-September and accounts for approximately three-quarters of rainfall received by the country annually (PACS, 2008). Rainfall during these months has a strong grip over Indian agriculture and the livelihoods of people, especially the rural populace. According to the Indian Meteorological Department, 68% of India's landmass is drought-prone, of which 50% is chronically so. Most of these chronically drought-prone areas are confined to the western and peninsular districts of India—especially the arid, semi-arid and sub-humid regions.

However, India has regrettably done little to drought-proof the country from erratic rainfall conditions. This is especially due to: a) poor water-harvesting practices; b) exponential increase in water usage for industrial purposes; and c) large-scale and relentless use of groundwater resources since the Green Revolution in Indian agriculture between 1965 and the early 1980s (Agarwal and Narain, 1997). Take the example of the north-Indian state of Punjab—the 'epicentre' of the Revolution. Since the movement began in 1965, over a million tubewells have been installed, thus putting relentless pressure on the groundwater resources of the state. Presently, more than 605 of the state's hydrological blocks have been declared "dark" or overexploited, meaning that groundwater extraction has surpassed the natural recharge potential (Agnihotri, 2004). In addition, owing to rapid industrialisation in the last few decades, the positive association between forest cover and rainfall has also been thwarted.

Needless to say, the most immediate impact of a drought is experienced by the agricultural sector. Subsequently, the effect is transmitted to other sectors of the economy including industry, through forward (shortage of raw material supplies to agro-based industries) and backward (reduced demand for industrial and consumer products, due to reduced agricultural incomes) linkages. In addition, droughts also exert pressure on public sector resources—diverting them away from investment expenditure, towards drought relief measures. Till the 1980s, major droughts in India were accompanied by negative GDP growth rates (Patnaik, 2004). However, since the 1990s, the overall impact of droughts on the industrial sector and Indian economy has been relatively subdued. The foremost reason for this is the shrinking share of agriculture in the country's GDP: from 57% in 1961 to 22% in 2002 (PACS, 2008). According to the Department of Agriculture and Cooperation (under the Ministry of Agriculture), the share of agro-based industries within the manufacturing sector has declined from 44% in 1961 to 11% in 2002. However, given that nearly 45% of the country's working population is employed in agriculture and allied activities (Nanda, 2010), a drought year is no mean crisis.

This essay examines what has happened to a sub-sample of young people from 'poor' households who experienced the drought of 2002 in the south-eastern state of Andhra Pradesh as infants (0-18 months) by tracking their height attainment seven years after the calamity. Methodologically, we use WHO anthropometric z-scores of height-for-age as the outcome variable in static and dynamic specifications and employ several estimation strategies to correct for econometric issues: first-difference for solving endogeneity arising from time-invariant, unobserved heterogeneity; and an instrumental variables strategy (difference GMM) to solve the endogeneity arising from lagged height-for-age scores in the dynamic specification.

Our estimates indicate a loss of 0.8 standard deviations in height-for-age z-scores for the younger, drought-affected cohort of 'poor' children; while their older counterparts suffer a decline of 0.4 standard deviations in height-for-age z-scores. Access to a safety net in the form of *Indira Kranthi Patham* had a positive and significant impact on the height attainment of recipients in our sub-sample of 'poor' children, but this impact is not large enough to mitigate the effect of the drought.

Apart from focussing on the impact of the Indian drought of 2002 on poor households and contributing to the growing literature on the long-term impacts of shocks experienced during early childhood, the principal contribution of this essay is that it adds to the small body of existing research on the long-term impacts of brief, non-extreme shocks in the context of developing countries. It is hoped that these findings will not merely highlight the importance of nutrition and care in the sensitive period of early childhood, but will also bring children to the centre-stage of poverty debates in developing countries; while underlining the paramount need to protect children against shocks through welfare programs.

The remaining essay is organised as follows: a detailed discussion of the Indian drought of 2002 and the poverty-alleviation program under study are included in section 2. Existing, relevant literature on the impacts of famines and droughts reviewed in section 3. This section also discusses outstanding research questions. Section 4 provides a conceptual framework, while section 5 describes the data, econometric strategy, model specification and econometric issues. Section 6 discusses the essay's main results, while section 7 concludes the essay.

2 Background

2.1 The Drought of 2002

The drought of 2002 was singular in terms of it intensity, duration and geographical coverage. The Indian Meteorological Department (IMD) declares a year as an all-India drought year when the average rainfall over the monsoon season of June-September is more than 10% below its long-period average and this deficiency covers more than 20% of the country's area. By this yardstick, since the last country-wide drought in 1987, the rainfall shock of 2002 was the first all-India drought year after 14 normal monsoon seasons.

According to the Indian Meteorological Department's End-of-Season Report (released on 4 October, 2002); in 2002, the seasonal rainfall during June-September failed by 19% below its long-period average, covering more than 29% of the country's landmass. In the state of Andhra Pradesh, where our sample of young people experienced this crisis, the monsoon from June-September was 33% below its long-period average, with the meteorological districts of Coastal Andhra Pradesh and Rayalaseema facing deficiencies of 26% and 33% respectively (IMD, 2002). Comparing the actual annual rainfall with their long-period averages from 1960 to 2004, the drought of 2002 was Andhra Pradesh's driest monsoon season.

It is important to note that while the overall monsoon rainfall from June-September may have fall short of the long-period average by 19%, the month-wise deficiency was far more acute. Rainfall received during the month of July—typically, the rainiest month of the monsoon season—is critical for agriculture, with approximately a third of the season's rain being received during this month. In particular, July 2002 experienced the worst rainfall deficiency in recorded history, with the shortfall being 49% below its long-period average. According to the aforementioned report of the Indian Meteorological Department, only in 1911 and 1918 (both famine years) have the July rainfall records come close to 2002's deficiency levels.

Regrettably, the Indian Meteorological Department's annual rainfall forecasts failed to provide early warning for the drought that was to come. June 1 is generally considered as the day for the onset of the monsoon in India. On 25 May 2002, the Indian Meteorological Department's forecasts showed that the country was expecting 101% of its long-period average rainfall (with a model error of ±4%). Several other national and global meteorological forecasting centres similarly failed to predict the crisis—allowing for little ex-ante drought-management activity.

In addition, the drought of 2002 was short and acute—marked by failure of monsoon rainfall over June-September—while previous (2001) and successive years (2003) received 'normal' rainfall. According to the Department of Agriculture and Cooperation, the loss of rural employment due to the collapse of agricultural activities during the drought months of 2002 was estimated at 1,250 million man-days, with loss in annual agricultural income to the tune of INR 400 billion (US$ 8,800 million). According to PACS (2008), the foodgrain production during 2002 fell by 29 million tonnes, compared to 2001. Rains received during the monsoon months are also used to inaugurate the sowing of the *kharif* (autumn) harvest. In 2002, 18 million hectares of *kharif* cropped area were left unsown.

In addition, agricultural GDP declined by 3% in 2002-03, while the overall GDP growth rate fell by 1%. There were no drought-related, mass-scale starvation deaths reported in any form of the media or government reports. However, there were recurring reports of farmer suicides in several states in India (including Andhra Pradesh). The subject of farmer suicides is vast, and a discussion is beyond the scope of this essay. For a detailed understanding of this recent and distressing phenomenon in Indian agriculture, see Sainath (2009).

2.2 The Program: *Indira Kranthi Patham* (IKP)

As mentioned above, this essay aims to understand the impact of the drought of 2002 on a sub-sample of young people from 'poor' households who experienced this drought in the state of Andhra Pradesh as infants (0-18 months), by following their height attainment seven years after the shock. Apart from assessing the impact of the aforementioned rainfall shock, this essay also attempts to understand if drought-time access to one of the largest rural poverty-alleviation and gender empowerment schemes in the state could mitigate the long term impact of the drought on the height attainments of the drought-exposed young individuals.

Started in October 2000, IKP is a World Bank-funded and state government-sponsored initiative, providing a gamut of services including credit and savings facilities to rural, 'poor' women in Andhra Pradesh, India. The program uses the state's existing and vast infrastructure of self-help groups (SHGs)[2] to extend services such as credit and thrift facilities. Potential participants are identified on the basis of the country's poverty line established by the 2001 census (routinely used to identify target populations for several large-scale government welfare projects) (Deininger & Liu, 2008). Founded on the belief that every poor household has a strong desire and potential to emerge out of poverty, this program seeks to provide such rural, 'poor' families with the requisite institutional support for unleashing their potential. Along with credit and thrift services, the program also pursues other initiatives such as—marketing and food security programs; community-managed insurance and initiatives for sustainable agriculture; social action programs (day-care and immunisation booths; nutrition centres; community-managed family counselling centres; early child education centres, etc.), among others. Some of these initiatives—especially, nutrition programs for both mother and child, and immunisation booths—have the potential of mitigating nutritional insults arising due to rainfall shocks experienced in early-childhood.

According to the program's latest progress report released in March 2011, IKP has over 11 million members organised under approximately 100,000 self-help groups, run exclusively for women. During the last financial year, INR 71 billion (US$ 1.6 billion) worth of loans were given to program participants under its bank linkages program, while the total savings of the program's participants stood at INR 34 billion (US$ 760 million). Interestingly, in October 2000, the program was rolled out in six of the state's poorest[3] districts (Chittoor, Srikakulam, Adilabad, Vizianagaram, Mahbubnagar, and Anantapur). The second phase of the program—launched in July 2003—covered the remaining 16 districts of Andhra Pradesh. Thus, when the drought of 2002 occurred, rural-poor families of young individuals who were residing in the 16 districts covered by the program's second phase did not have access to the program. This gives us an opportunity to check if access to

[2] 'Poor' women residing in rural areas, who weren't erstwhile members of SHGs, were encouraged to organise themselves under existing or newly-formed SHGs. SHGs were revived wherever they were defunct or dormant. (Deininger & Liu, 2008)

[3] According to World Bank (2000), geographic targeting was carried out on the basis of weighted socio-economic criteria such as: a) percentage of population below the poverty line; b) infant mortality and hospital beds/100,000 of population; c) female literacy and female school drop-out rate; d) ratio of scheduled caste/tribe in the population; and e) ratio of gross irrigated area to gross cropped area.

credit in drought-time allowed these families to mitigate the impact of drought on their children's health.
Having described the drought and program characteristics in the above section, the essay reviews existing and relevant literature on the impact of famines and droughts in the next section.

3 Literature Review

Most existing studies focussing on the long-run impacts of natural shocks have concentrated on famines which, as explained above, are usually marked by mass-scale hunger and starvation deaths. Droughts, which extend over shorter time periods and are relatively weaker in intensity than famines, have received little attention in empirical research.
Stanner *et al.* (1997) find that intrauterine exposure to 872 days of the Leningrad Siege (1941-44) which resulted in unparalleled disruption of food supplies and mass-scale starvation deaths had no impact on glucose intolerance, hypertension or coronary heart ailments in adulthood. Long-run impacts of the Dutch famine or "Dutch Hunger Winter" (1944-45) have been studied by several epidemiologists. Hulshoff *et al.* (2000) have established an association between prenatal exposure to the Dutch famine and specific brain abnormalities in schizophrenia during adulthood. Medical studies have also established associational links between exposure to the Dutch famine and long-run impacts on glucose intolerance (Ravelli *et al.*, 1998) and coronary heart disease (Bleker *et al.*, 2005).

China's Great Famine (1959-61) has been studied extensively to understand its long-term impact on health outcomes. Chen and Zhou (2002) use a difference-in-differences (DD) identification strategy to compare exposed cohorts to unexposed cohorts. They find that adults who were between 1-2 years of age during the famine were shorter, on average. Clair *et al.* (2005) replicate the Dutch famine epidemiological study conducted by Hulshoff *et al.* (2000) for the Great Famine of China, by comparing the risk of schizophrenia in adulthood for those born before, during and after the famine. Among those who were born during the famine years, the adjusted risk of developing schizophrenia was significantly higher (than those born before or after the famine) by 0.84 - 2.15%. Similarly; after performing quintile regression for adjusting the attenuation bias caused by selection for survival, Meng and Qian (2006) find that in-utero and early-childhood exposure to the famine had significant negative impacts on height, weight, educational attainment and labour supply outcomes among surviving adults. Luo *et al.* (2006) find that impact of exposure to the famine (during prenatal and infancy stages) on obesity in adulthood is gender-specific and is more pronounced for women than men.

Maccini and Yang (2009), using longitudinal data from the Indonesian Family Life Survey, find that higher early-life rainfall had positive effects on adult outcomes of women, but not men. Women who experienced 20% higher rainfall in their year and location of birth were less likely to self-report poor health and were more likely to be taller and have higher schooling attainment. Debilitating long-term impacts of other shocks endured in-utero or in early childhood such as epidemics (Almond, 2006; Banerjee *et al.*, 2007) or orphanhood (Dercon *et al.*, 1996) have also been studied extensively. In fact, Martorell *et al.* (1994) posits that the opportunity of growth missed during the first three years of life is difficult to compensate through later-life health investments, i.e. so-called "catch-up" is limited. On balance, the existing literature on the long-term impact of shocks suggests that in-utero and childhood environment is critical for early-child development and shocks experienced during this critical period may have encumbering effects on adult-life outcomes, including health and educational attainments.

As is evident from the above discussion, the existing literature on long-term impacts of shocks endured in early-life is skewed against non-extreme shocks (such as droughts), which often result in below-average rainfall over a few months (Maccini and Yang, 2009 may be cited as an exception). However, as discussed under section 1, in India—where agriculture accounts for approximately a quarter of the country's GDP and has little less than half the country's working population employed in agriculture or allied activities—a substantial deficiency in even a single month's rainfall can have a crippling impact on foodgrain production and livestock population. It would be a gargantuan mistake, therefore, to perceive the gradual dwindling of agriculture's share in India's GDP as an indication of droughts' weakening impact on the country.

This is the principal contribution of the essay. Apart from focussing on the aforementioned specific drought and contributing to the growing literature on the long-term impacts of shocks experienced during early childhood on subsequent childhood outcomes; this essay contributes to the small body of existing research on non-extreme shocks, in the context of developing countries. While I concentrate on health outcomes of young individuals from poor families (proxy for health being height-for-age anthropometric scores calculated by the WHO[4]), impacts of non-extreme shocks on other outcomes of interest such as educational attainment, non-cognitive development, labour supply decisions, marriage market outcomes etc. are outstanding research questions that remain to be explored and are potential subjects for future versions of this essay.

[4] Height-for-age z-scores (HAZ) have been recommended by the WHO as a measure of child development and a good indicator of the cumulative investments in child nutrition. An HAZ score of zero indicates that the child has the average height for his/her age and sex, while a negative HAZ score signifies that the child is shorter than an average and healthy child of his/her age and sex. For a more nuanced scale description and discussion on the international reference group, see World Health Organisation (2006).

4 Theoretical Framework

The conceptual framework developed in this section is inspired from Grossman (1972), and Cunha and Heckman (2007). An individual's health production function in time period *t* is specified as:

$$H_t = f_t(H_0, I_1, \dots, I_t, \gamma, C_1, \dots, C_t, D_1, \dots, D_t) \quad (1)$$

where H_t is an individual's stock of health at time t; H_0 is the initial health endowment; $I_1, \dots, I_t$ is a historical description of investments in health; γ includes time-invariant child, parental and household characteristics that determine health; $C_1, \dots, C_t$ is a historical description of community infrastructure; and $D_1, \dots, D_t$ is a historical description of disease environment. The initial health endowment H_0 is, in turn, specified as:

$$H_0 = g_0(G, R_0, I_0, C_0, D_0) \quad (2)$$

where G is one's genetic endowment; R_0 refers to environmental conditions such as rainfall deficiency or famine experienced in-utero or in early childhood, I_0 refers to health investments in-utero or during early childhood; C_0 is in-utero or early childhood community infrastructure; and D_0 is a vector of early-life or in-utero disease environment. In sum, Grossman (1972) formalises an individual's current period health attainment as a function of the initial health endowment—determined by genetic factors, as also in-utero or early childhood environmental conditions—and subsequent determinants such as time histories of health inputs, time-invariant demographic factors and time-varying community infrastructure and disease environment.

Thus, exposure to an environmental shock in early-life is expected to affect H_t through one's initial health attainment H_0. Working through first principles, an environmental shock such as famine may reduce the provision of food (or induce consumption of inferior nutritional substitutes). Such shocks can negatively impact investment in health inputs, impose excess burden on community health and food distribution infrastructure and worsen the disease environment—especially in the event of mass-scale starvation deaths of humans and animals. In the case of in-utero shocks, these influences of environmental conditions will be transmitted to the foetus through the mother.

However, in light of Barker and Hales (1992)[5] and Cunha and Heckman (2007); one should refrain from conceptualising childhood as a single, homogenous period before adulthood, but rather look at childhood as a multi-period model of health attainment which includes

[5] The *thrifty phenotype hypothesis* (Barker and Hales, 1992) expands on the critical role of in-utero health on later-life health outcomes. This hypothesis proposes the epidemiological associations between poor foetal (and infant) growth and permanent changes in glucose-insulin metabolism, subsequently developing into type-2 diabetes (popularly term as "programming the foetus").

sensitive and critical periods for acquiring skills, abilities and good health. Thus, impacts of positive or negative shocks experienced in early childhood (in-utero or pre-school age, especially 0-36 months) should not be considered equivalent to shocks experienced in later childhood.

The nature of the health production function $f_t(.)$ will determine the complementarity or substitutability of investments in different time periods over the course of one's life. Applying the idea of *dynamic complementarity* from Cunha and Heckman (2007) to equation (1), $\partial^2 f_t(.)/\partial H_{t-1}\partial I_t > 0$ refers to a situation where stocks of health acquired till period $t-1$ make health investments in period t (i.e. I_t) productive. This might explain parents' decision to invest in pre-school learning to augment returns from educational investment in later childhood, such as primary school. On the other hand, *self-productivity* arises when $\partial f_t(.)/\partial H_{t-1} > 0$, i.e. when higher health stocks in one period creates a higher stock of health in the next period. In the extreme situation of perfect complementarity, investments in t cannot compensate for lack of investments in period $t-1$. In this case, the period $t-1$ is said to be a "critical period". In sum, Cunha and Heckman (2007) explain that stages that are more effective than others in producing certain health outcomes are called "sensitive periods" for the acquisition of those faculties or skills. However, if one stage alone is effective in producing a skill (or health outcome), it is called a "critical period" for that outcome[6].

The theoretical framework outlined in this section—which is the inspiration for the empirical analysis that follows—elucidates how an environmental shock (in our case, deficient rainfall resulting in drought) can lead to persistent lower health attainments. As mentioned above, in this essay, we have used height-for-age anthropometric z-score as a proxy for health attainment.

5 Econometric Section

5.1 The Data

The data used in this essay comes from Young Lives, a longitudinal dataset collected through surveys conducted over three waves (mid-2002, early-2007 and June 2009-March

[6] For instance: Hopkins and Brecht (1975) have found that IQ scores among 20,000 students in a school in Colorado, USA became stable by age ten or so. Thus, in this particular context, ages 0-10 are the sensitive phases for development of IQ. However, Cunha and Heckman (2007) mention that a child born with cataract becomes blind if the cataract is not removed within the first year of life; thus, age 0-1 being the critical period in this case.

2010) in the state of Andhra Pradesh[7] in India. The surveys follow approximately 3000 children, spread over two cohorts: a younger cohort of approximately 2000 children born between January 2001 and June 2002; and an older cohort of approximately 1000 children born between January 1994 and June 1995. The number of respondents tracked under each wave of the survey is mentioned in table 1 below:

Table 1: Attrition Levels in Young Lives data (by cohort and round)

Cohort	Round 1	Round 2	Round 3
Older	1008	994	977
Younger	2011	1950	1930

Econometric analysis using longitudinal data can be potentially constrained by a bias induced by attrition. For the first two waves, Outes-Leon and Dercon (2008) note that Young Lives data shows evidence of non-random attrition (attrition chiefly being an urban phenomenon and attriting households are generally poorer and less educated than non-attriting households). However, the data—when tested on child anthropometrics—shows very limited evidence of attrition bias. Observing the small absolute attrition levels in the third round, as such, we do not perceive our empirical inference to be mired by an attrition bias.

In all three rounds, extensive questionnaires covering child-, household-, caregiver- and community-level details were administered to the respondent-children, their caregivers and households. These details include child anthropometrics (including length/height-for-age, our outcome variable of interest) for an appropriate period pertaining to the study of the drought of 2002. Being carried out in mid-2002, the first round data pre-dates the drought and gives us a neat pre-drought baseline—given that the drought set in in July 2002. In any case, given that we are concerned with height-for-age—a measure of long-term nutritional status (unlike, weight-based anthropometrics which measure short-term health and nutritional status)—a few months' overlap between interview dates and the onset of drought should not induce a contamination of the baseline scores. Subsequent rounds of data (in 2007 and 2009-10) are distant enough from the drought to capture any long-term impacts of nutritional abuse endured due to the drought. Moreover, given the longitudinal nature of the data, we can model dynamics into our specification. This wouldn't have been possible with a repeated cross-sectional design.

As mentioned above (section 2.2), a woman from a rural, 'poor' household is eligible for *Indira Kranthi Patham* (IKP) loans. We can identify eligibility (all three rounds) for *Indira Kranthi Patham* since we have data on possession of below-poverty line card, rural/urban setting of household and presence of a female, adult member in the household. However, direct participation details in *Indira Kranthi Patham* are available for the last two rounds only. These details, when combined with information on district of residence, gives us a full understanding of whether the household had access to the first phase (launched in October

[7] The surveys cover 7 districts of Andhra Pradesh: Anantapur, Mahboobnagar, Srikakulam, Cuddapah, Karimnagar, West Godavari and Hyderabad. The survey design ensures a uniform distribution of sample districts across the three geographical regions of Andhra Pradesh (Coastal Andhra Pradesh, Rayalseema and Telangana). For a more informative read on the sampling strategy of Young Lives in India, see Kumra (2008).

2000 in Young Lives sample districts of Anantapur, Mahboobnagar, and Srikakulam) or second phase (launched in July 2003 in sample districts of Cuddapah, Karimnagar, West Godavari, and Hyderabad) of the program.

While the questionnaires do ask about natural calamities and other shocks experienced at the household-level, we are unable to utilise this data because the periodization of the question does not suit our requirements. In round 2 (surveyed during January-July 2007), the questionnaire asks, "In the last *four* years, has the household suffered a drought?" (author's emphasis). However, the drought we are interested in occurred during June-September 2002. While there was no drought of an equal or larger magnitude in Andhra Pradesh since 2002, we refrain from using the responses to this question. Instead, we combine district-wise rainfall data with the existing household-level data to discern if the household concerned was located in a drought-hit district or not. Implications of using a broad, district-level variable (instead of household level measures) have been discussed in section 6 below.

The district-level rainfall data is obtained from the Directorate of Economics and Statistics, Government of Andhra Pradesh[8]. For each meteorological sub-division within the country, the Indian Meteorological Department uses the following criteria to declare rainfall as excess, normal, deficient or scanty:

Table 2: Criteria for Drought Assessment

	Excess	**Normal**	**Deficient**	**Scanty**
Deviation from Long-Period Average (LPA)	+20% or more	+19 to -19%	-20 to -59%	-60% or less

Source: South-West Monsoon 2002, End-of-Season Report; Indian Meteorological Department

Given data for both actual and long-period average levels of rainfall for June-September 2002, we can identify if a district was hit by the drought by using the above yardstick. Table 3 gives a district-level disaggregation of drought-intensity, according to the drought assessment criteria outlined in table 2 above.

Table 3: District-wise actual and long period average (LPA) rainfall in Andhra Pradesh (June-September, 2002)

[8] This data was accessed via *http://www.indiastat.com/02/andhrapradeshstat/meteorologicaldata/22/rainfall/238/stats.aspx* (table titled: "District-level actual and normal rainfall in Andhra Pradesh, 2001-2006") on 26 March, 2011.

Districts	Actual *(in mm)*	LPA *(in mm)*	% Deviation	Drought-hit[9]
Anantapur	157	338	-54%	Yes
Cudappah	201	393	-49%	Yes
Hyderabad	472	562	-16%	No
Karimnagar	548	795	-31%	Yes
Mehboobnagar	360	447	-19%	No
Srikakulam	557	706	-21%	Yes
West Godavari	414	785	-47%	Yes
Andhra Pradesh	417	624	-33%	

Source: Ministry of Agriculture, Government of India

5.2 Descriptive Statistics

Basic summary statistics for below-poverty line (BPL) families are reported by cohort, in table 4 below. All variables are obtained from the Young Lives survey data collected from Andhra Pradesh in India, except the district-level drought intensity variable which has been obtained from the Directorate of Economics and Statistics, Government of Andhra Pradesh.

As mentioned above, we have restricted our sample to below poverty-line (BPL) families[10] only. In this essay, we have used WHO's anthropometric measure for long-term nutritional investment—namely, height-for-age (HAZ)—as the outcome variable. The average HAZ score is -1.56 for the entire cohort of 'poor' children, compared to -1.11 for 'noon-poor' children (not shown in the table). More than 74% of our sample resided in drought areas. As far as eligibility for *Indira Kranthi Patham* (IKP) is concerned, around 65% of our sample of 'poor' households were residing in rural areas and have at least one adult female member in the household, making the household eligible for a loan under the IKP. However, only close to 45% of the sample households were covered in the first round of the program (launched in October 2000) and therefore, had access to the benefits of the program during the drought.

Table 4: Descriptive Statistics (Poor households only)

Variables	Total Sample	Younger Cohort	Older Cohort

[9] See table 2 for drought-assessment criteria

[10] We do this on the basis of the household-level question: "Does your family have a BPL card?". Implications of exclusively focusing on the 'poor' have been discussed below (in section 6).

	Mean	Std. Deviation	Mean	Std. Deviation	Mean	Std. Deviation
Health Status (Outcome variable)						
Height-for-Age, Round 3	-1.56	1.05	-1.46	1.05	-1.71	1.04
Child and Household-level variables						
Dummy variables						
Female	48.52%	0.50	46.94%	0.49	51.10%	0.50
Rural	88.02%	0.33	88.24%	0.32	87.66%	0.33
Caregiver is literate	41.63%	0.49	45.04%	0.50	36.28%	0.48
Wealth Index[11]	0.50	0.17	0.49	0.17	0.51	0.16
Drought	74.42%	0.44	0.74	0.44	0.75	0.43
Eligible for IKP	65.31%	0.476	65.37%	0.476	65.21%	0.477
Eligible for IKP during drought	45.08%	0.498	44.32%	0.497	46.26%	0.499
Other variables						
Mother's Height (cm.)	151.07	7.98	151.45	5.90	150.45	10.47
Household size	9.18	2.99	9.45	2.86	8.76	3.15
Observations	2061		1259		802	

'Poor' households constitute 91.6% of our total sample of 'poor' and 'non-poor' households.

5.3 Econometric Specification

[11] The wealth index is the main indicator used in Young Lives surveys to capture the economic standing of households. Its values lie between 0 and 1 (a higher wealth index indicates a higher economic status). It is computed as a uniformly weighted arithmetic mean of three individual indices: housing quality, consumer durables and access to services.

Guided by the theoretical model of dynamic health production functions presented in Section 4, the basis of our econometric analysis is the following specification:

$$H_{it} = \alpha_0 + \beta H_{it-1} + \sum \alpha_1 X_{it} + \sum \alpha_2 X_{ht} + \sum \alpha_3 X_{ct} + \gamma_i + \delta_h + \tau_c + e_{it} \quad (3)$$

where X_{it}, X_{ht}, and X_{ct} capture time-varying characteristics at the child-, household- and community-level. We also account for time-invariant child-, household- and community-level characteristics through γ_i, δ_h, and τ_c respectively. An important econometric concern is that some of these time-invariant characteristics may be unobserved (and therefore, captured by the error term) but correlated with the observed variables; thus, leading to endogeneity due to time-invariant, unobserved heterogeneity. Our strategy to tackle this concern is through a first-difference estimator to remove individual, household and community level time-invariant factors.

The main variables of interest for us are: *Drought* ("Was the family residing in a rainfall deficient district during the drought of 2002?"); Eligible for *IKP* ("Was the family eligible for a loan under the *Indira Kranthi Patham* program?"; *IKP*Drought* ("Did the family have access to the program at the time of drought?"); and finally, *Cohort * Drought* ("Was the child less than 36 months old in 2002?", interacted with the "drought" variable. While the first three of these variables are included in the vector of household characteristics X_{ht}; the *Cohort * Drought* variable is included in the vector of child-level variables X_{it}. In addition, H_{it} and H_{it-1} are height-for-age child anthropometrics for the current and previous period.

5.4 Econometric Concerns

A number of econometric issues glare at us and threaten to potentially bias our results. These issues must be tackled before we can convincingly argue for the robustness of our results. Sound econometric strategies have been employed to solve these issues wherever possible, within the given data constraints. These issues and proposed solutions are explained in this section.

Unobserved, time-invariant heterogeneity

As mentioned in Section 5.3, we suspect the presence of unobserved child-, household- and community-level characteristics included in the error term, which may be correlated with one or more explanatory variables. If this is the case, then our specification will suffer from a bias arising from time-invariant heterogeneity. We solve this by means of a first-difference estimator[12] which eliminates all time-invariant individual, household and

[12] The first-difference estimator operates as follows—we take a simplified version of our specification (3) by including only child-level characteristics: $H_{it} = \sum \alpha_1 X_{it} + (\gamma_i + e_{it})$. The corresponding specification for period $t-1$: $H_{it-1} = \sum \alpha_1 X_{it-1} + (\gamma_i + e_{it-1})$. Subtracting these two equations gives us: $(H_{it} - H_{it-1}) = (\sum \alpha_1 X_{it} - \sum \alpha_1 X_{it-1}) + (e_{it} - e_{it-1})$ or $\widetilde{H_{it}} = \sum \alpha_1 \widetilde{X_{it}} + \widetilde{e_{it}}$, where $\widetilde{H_{it}}$ denotes the first-differenced height-for-age scores (similarly, for $\widetilde{X_{it}}$ and $\widetilde{e_{it}}$). Having eliminated γ_i, we can now estimate the vector α_1 consistently, provided there is no other form of endogeneity entailed in our specification.

community variables. Provided that any time-varying unobservable included in the error term is not correlated with the observed explanatory variables (and there is no other form of endogeneity), we should be able to yield unbiased, consistent results.

Endogeneity of lagged dependent height-for-age variable

While the first-difference estimator helps us rid the specification of time-invariant unobserved variables, differencing leads to the problem of endogeneity of lagged dependent height-for-age scores. To be clear, a theoretically sound model of health status is difficult to justify if it is a static model. We have seen under section 4, that current health attainment is determined by health status in the previous period, among other factors (Strauss and Thomas, 2008; Grossman 1972). However, going ahead with the dynamic specification is problematic under the first-difference estimator, since the differenced lagged health status $(hfa_{it-1} - hfa_{it-2})$ is correlated with the differenced error term $e_{it} - e_{it-1}$, leading to endogeneity. To solve this particular issue, we turn to a difference generalised method of moments or 'difference-GMM' estimator, where we use twice lagged health status (hfa_{it-2}, i.e. height-for-age in wave 1) as an instrument for $(hfa_{it-1} - hfa_{it-2})$.

Self-Selection

Econometric analysis of means-tested welfare programs are often thwarted by self-selection because participation is not by random assignment, but rather through certain observed and unobserved characteristics. In our case, the program was rolled out and made available to eligible households in some districts in October 2000; and thus, allowed them to have access to a source of credit during the time of the drought. However, neither individual eligibility nor assignment of the program's first phase was by random design— households had to be poor, rural households with an adult female member, to be eligible for an *Indira Kranthi Patham* loan; and the initial six districts were the most backward districts of the state, as recognised on the basis of a matrix of socioeconomic parameters (see footnote 3, pg. 7).

To the extent that these district-level characteristics (determining backwardness) were time-invariant, they can be sufficiently taken care of through the first-difference estimator, as has been explained above. We have attempted to take care of self-selection in participation by looking at individual eligibility criteria, rather than the participation variable. This has been prompted by the fact that eligibility (determined on the basis of observable characteristics which we can control for) is less prone to self-selection than participation (several unobserved characteristics will ultimately determine whether a household will take-up a program or not). In addition, we are also constrained by data since we do not have information for program participation for the first round. However, using eligibility criteria rather than program participation data does not purge out the problem of self-selection entirely. It is still possible to self-select into and become *eligible* for the program, for instance—by migrating to the first-phase districts during the drought, a poor person who was erstwhile residing in an urban area (and was ineligible for the program) will now be counted as eligible for the program.

To control for time-varying unobservables which are correlated with eligibility, it is difficult to find instruments that affect the household's poverty status (and region of residence) but does not affect the child's health status. These are serious data constraints which limit our ability to find a credible instrument. Hence, the most suitable method to circumvent this

	Pooled OLS	First-Difference[13]	Diff-GMM

issue of self-selection, it seems, is to use eligibility and not participation to reduce the extent of the endogeneity; and then use a complete set of controls in the specification under consideration.

6 Results & Discussion

Table 5 (below) shows the impact of the drought of 2002 on young individuals from poor households. We run the specification mentioned in equation 3. In this table, we have reported results from both static and dynamic specifications for OLS, first-difference (FD) and difference-GMM estimators. As is evident, we have controlled for any variation in height-for-age z-score arising from location of residence (rural/urban), gender of the child, wealth of the household, caregiver's literacy and mother's height.

Across all specifications and estimators, being affected by drought has a negative and significant (except for the first-difference estimator under the dynamic specification) impact on height-for-age z-scores for children from poor households who were affected by the drought. Further, the slope coefficient for the cohort-drought interaction dummy is negative and significant across specifications and estimators (barring the static-OLS specification). This implies that poor children who were at a younger and more vulnerable age (0-18 months in our sample) suffered more losses in height attainment than older, drought-affected children. For instance, our difference-GMM estimator indicates a loss of -0.8 standard deviations loss in height-for-age z-scores for the younger and affected cohort, which is approximately 0.4 standard deviations less than the loss in height attainment for the older, affected cohort.

The table also shows that being eligible for loans under the IKP program has a positive, significant impact on height-for-age for children across cohorts and districts. However, the coefficients (for the first-difference and GMM estimators) are not large enough to offset the effect of the drought. Further, we notice that the coefficient on the interaction of program-eligibility and drought variables shows positive (yet insignificant) effects of access to the program during the drought. Thus, those who had access to the program at the time of drought did not benefit additionally over-and-above those who had access to the program after the drought.

The p-values of 34% and 64% for the Sargan and Hansen-J tests respectively indicate that our instrumenting strategy under the GMM estimator—whereby, we have used height-for-age lagged twice (from wave 1) as an instrument for the differenced, dependent regressor, i.e. $(hfa_{it-1} - hfa_{it-2})$—is not fraught with the problem of endogenous instruments.

Table 5 : Estimates of Drought Impact on Height-for-Age Z-Score

	Static	Dynamic			
Height-for-age in previous wave		0.55***		0.378***	0.51**
		(0.012)		(0.009)	(0.028)
Drought	-0.158***	-0.08**	-0.44***	-0.277	-0.39**
	(0.046)	(0.039)	(0.083)	(0.229)	(0.151)
Eligible for IKP	0.272**	0.44***	0.209**	0.233***	0.273***
	(0.124)	(0.133)	(0.099)	(0.102)	(0.086)
IKP x Drought	0.0937	0.083	0.22	0.13	0.088
	(0.089)	(0.064)	(0.147)	(0.061)	(0.119)
Cohort (younger=1, older=0)	0.022***	0.026***			
	(0.049)	(0.035)			
Cohort x Drought	-0.094	-0.332***	-0.354**	-0.258***	-0.42***
	(0.072)	(0.053)	(0.071)	(0.066)	(0.045)
Gender (female=1, male=0)	0.067**	0.058*			
	(0.034)	(0.032)			
Rural	-0.269***	-0.24***			
	(0.068)	(0.058)			
Wealth Index	0.017**	0.65***	0.012**	0.59*	0.53***
	(0.006)	(0.193)	(0.005)	(0.319)	(0.161)
Mother's Height	0.002***	0.0017***			
	(0.0005)	(0.0004)			
Care-giver is literate	0.251***	0.121***			
	(0.036)	(0.029)			
Constant	-1.37***	-0.7***	-1.06 ***	-1.7 ***	--
	(0.11)	(0.15)	(0.07)	(0.293)	
Adj-R^2	0.12	0.40	0.20	0.23	
Sargan test					0.34
Hansen J test					0.64
N	2061	2061	2061	2061	2061

[13] To remove fixed-effects, we have two alternatives—namely, fixed effects estimator and first-difference estimator. When the data set contains only two waves, the fixed-effects and first-differenced estimators are identical. However, this is not so for waves more than (or equal to) three. Under the assumption that the model is correctly specified, we would expect these two estimators to differ only by virtue of sampling error. We also run a fixed-effects estimator, but results have not been included in the table above due to space constraints. The fixed-effects and first-difference results are not significantly different.

*** p<1%, ** p<5%, * p<10%; Standard errors are in parentheses. Blank cells against variables such as gender, rural, etc. are due to these variables being time-invariant. These were naturally omitted in the first-differenced and difference-GMM specification

Having presented results for a variety of estimators across static and dynamic specifications, we are now in a position to pursue a discussion to consolidate these results.

First, one must realise that owing to district-level drought identification (rather than measuring the intensity of the drought at the household-level), we have introduced a source of measurement error (and resultant attenuation bias) in capturing the intensity of the crisis. As has been explained above (section 5.1), district-level rainfall data has been used due to lack of household-level data pertaining to the specific drought we are interested in. Even though droughts are categorised as covariate shocks which simultaneously affect households over large geographical areas, they are unlikely to affect all households (in a given district) equally. The precise household-level impact of a drought will depend on the type and diversity of occupations among household members, availability of alternative irrigation sources, type of crops grown, access to safety nets, etc. Thus, akin to Dercon and Porter (2010), we would have preferred to use household-level measures of drought intensity to obtain more precise results; but as discussed above, unavailability of data prevents us from doing so.

Second, we have used the possession of a below-poverty line card to identify poor households. However, lousy targeting is a worrisome feature of most welfare programs in India and has resulted in problems of both 'inclusion' and 'exclusion'. 'Inclusion' has led to non-eligible—mostly non-poor—households being covered under programs originally designed for 'poor' households, while the opposite has been noticed under targeting errors of 'exclusion'. Swaminathan (2010) assesses the issue of targeting and social exclusion for India's food distribution system. In the case of our essay, if some families which report having a BPL card are indeed non-poor, we should expect a downward bias in the estimates of program impact; while we expect to observe an upward bias in the case of exclusion of 'poor' households from the program. However, on balance, it is difficult to conclusively comment on the direction of the net bias, since we do not possess information on household income.

Third, as has been mentioned above, we have focussed our sample on 'poor' households only. The identification of a 'poor' household has been carried out on the basis of possession of a below-poverty line (BPL) card, used regularly for determining eligibility for welfare programs in India. However, as we have just discussed, the allocation of these cards is often mired by targeting lapses. For our purposes, the crucial question is whether such sample restriction biases our results. To the extent that possession of a BPL card is determined randomly and exogenously, we have no reason to suspect a sample selection bias. However, this is a naive assumption to posit, given our previous discussion on targeting problems of inclusion and exclusion. More concretely—in contexts where households can possess BPL cards (and thus get selected into our sample) by virtue of social and political capital (an unobservable in our specification), we clearly have a problem of endogenous sample selection. In this case, there are two options available to us: a) we can include as controls the socio-political variables that lead to sample selection. These desired controls, however, may be unobserved and hence, unavailable; b) use the Heckit method, attributable to Heckman (1979). In our case, using the Heckit model is difficult because an exclusion restriction is required to generate credible estimates. Arguing for an instrument that appears with a non-zero coefficient when determining a household's selection into the pool of BPL families, while not appearing in the specification explaining health status of that household's children is clearly difficult to accomplish. Here, we are constrained by the unavailability of such an instrument.

Fourth, our results are not based on an opportunistic definition of the drought variable and its periodisation. The chief concern here is that merely controlling for drought in 2002 may miss out on the fact that the state of Andhra Pradesh had a drought (though of a reduced magnitude) in 2004 too. Thus, if we do not control for rainfall conditions in the subsequent years from 2002 onwards, our parameters might indeed be capturing the combined impact of rainfall shocks in 2002 onwards, and not just the impact of the drought of 2002. To check if this is the case, we have run robustness checks by including controls for district-level rainfall deviations (from long-period averages) for years 2003, 2004, 2005, 2006 and 2007. We find the coefficients on these variables to be largely insignificant across all specifications. These insignificant coefficients have not been displayed in table 5 above due to space constraints.

Finally, a word on the GMM estimator used in this essay to purge the endogeneity arising due to the differenced lagged, dependent variable being correlated with the differenced error term. As mentioned above, we resorted to the first-difference estimator to rid our specification of unobserved, time-invariant factors. However, the first-difference estimator introduces a new source of endogeneity due to correlation between the transformed, lagged dependent variable and the transformed error term. In the absence of an IV within our data set for the (differenced) lagged dependent variable, we try to solve this endogeneity by using the GMM estimator which uses the twice-lagged dependent variable as an instrument for the (differenced) lagged, dependent regressor. Though the *p*-value of the Sargan and Hansen tests accept the null of exogenous instruments, the GMM results can hold credibly only when there is no serial correlation between the residual terms. Evidently, if the residual terms are serially correlated, the twice-differenced height-for-age z-score (our instrument for the differenced lagged, dependent regressor) will be correlated with the differenced regressor, causing our GMM estimators to be biased.

6 Conclusion

Health investments in early childhood have a strong impact on child health (O' Connor *et al.*, 2000). Further, child health is a compelling determinant of a person's health in adolescence (Porter, 2010) and adulthood (Dercon and Porter, 2010); which, in turn, has implications for a variety of outcomes ranging from labour market prospects to educational attainment (Meng and Qian, 2006).

In this essay, we have analysed the impact of the Indian drought of 2002 on a sample of young people from below-poverty line households who experienced the drought of 2002 in the state of Andhra Pradesh as infants (0-18 months) by following their height attainment seven years after the drought. This essay has also tried to investigate if access to one of the largest rural, poverty-alleviation and gender empowerment schemes in the state—namely, *Indira Kranthi Patham* (IKP)—could mitigate the long-term impact of drought on the height attainments of drought-exposed young individuals. The principal contribution of this essay is that apart from focussing on the impact of the aforementioned drought on poor households and contributing to the growing literature on the long-term impacts of shocks experienced during early-childhood; this essay contributes to the small body of existing research on the long-term impacts of brief and non-extreme shocks (such as droughts), in the context of developing countries.

While we acknowledge that our analysis has been marred by econometric issues—the most formidable being non-random program placement and self-selection—we have tried to solve these issues as much as possible, within the given data constraints. As long as these issues remain unresolved, causal attribution of height-for-age variation to program impacts will be econometrically unsound. However, we cannot deny that our efforts to purge out endogeneities have led us to some interesting results. We find that while the drought had a significant and negative impact on the height attainments of both cohorts, the younger cohort of children from below-poverty line families (who were at a more vulnerable age at the time of the drought than the older cohort) endured a significantly greater impact than did the older cohort. We also note that while having access to *Indira Kranthi Patham* had a positive and significant impact on the height-attainment of children whose households were eligible for the program, it did not additionally benefit families who had access to the program *during* the drought (rather than after the calamity).

Our results are in line with existing empirical literature on the impact of serious shocks endured in early childhood on later-life outcomes. For instance, Dercon and Porter (2010) find that children who were younger than 36 months at the peak of the Ethiopian famine of 1984 were at least 3 cm shorter (significantly) than their older counterparts, by adulthood. It is hoped that the findings of this essay will not merely highlight the importance of nutrition and care in childhood (especially during the first three years of one's life), but will also bring children to the centre-stage of poverty debates in developing countries; while underlining the paramount need to protect children against shocks through welfare programs. A number of interesting issues related to effects of drought on educational attainment, labour market outcomes, self-reported measures of subjective well-being, etc. could not be pursued in this essay due to time constraints, and form possible ideas for future versions of this essay.

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