Birth Endowments and Intrahousehold Resource Allocation: Structural Estimates from a Collective Household Model

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ABSTRACT

This paper investigates how parents allocate household consumption resources in response to children's initial birth endowments, specifically examining whether they compensate for or reinforce endowment differences. Departing from the focus on traditional human capital investments, this study uses a structural collective household model to estimate children's resource shares, the fraction of household expenditure consumed by each child. The analysis leverages exogenous variation in birth endowments due to exposure to in utero drought shock, using primary survey data in southern India. The findings suggest that parents exhibit compensatory behavior, allocating a larger share of household consumption to children born under adverse weather conditions. This is observed both when comparing households with different proportions of in utero drought-exposed children and directly between exposed and nonexposed siblings within the same household. Furthermore, the study demonstrates that individual child poverty rates are significantly higher among siblings who were not exposed to drought in utero in households where both groups are present. This highlights the importance of considering intra-household inequality and the long-term welfare implications of early life shocks for all children in the household.

1 INTRODUCTION

Understanding parental responses to early life advantages or disadvantages is crucial given the well-documented long-lasting consequences of fetal conditions and early childhood experiences on health, education, cognitive ability and wages[1]. Parents face a critical choice when one child has a favorable or adverse early life 'endowment' (e.g., health at birth or innate ability): do they compensate for the weaker child or reinforce the advantages by investing in the stronger child?[2] There is no consensus in the literature on parental responses to differences in children's endowments[3]: in some cases, parents choose an efficiency-driven path, reinforcing initial advantages by allocating more input to the child who is already better endowed. In other cases, parents exhibit equity motives, compensating for a disadvantaged child by giving them additional investments to help close the gap.

Most studies examining parental responses to child endowment shocks have concentrated on three primary types of human capital investments: education, health-related inputs, and parental time. However, a significant gap remains in our understanding of parental responses through consumption expenditures, particularly per-child consumption spending. This paper aims to fill this gap by examining whether parents adjust the share of the household budget allocated to each child in response to their initial birth endowments. This approach is particularly relevant, as children are vulnerable to intra-household inequality in consumption (Dunbar et al. (2013), Bargain et al. (2011)). Such inequalities may be magnified in resource-constrained settings, where limited resources can potentially intensify competition among household members.

[1]See Almond and Currie (2011) and Almond et al. (2018) for a review of this literature

[2]It is common in this literature to refer to the stock of capacities at birth as the birth endowment. An exogenous component of birth endowments can be isolated by examining prenatal shocks. If postnatal investments in human capital are positively correlated with shock, they are said to be reinforcing. They are considered compensating if the correlation is negative.

[3]Almond and Mazumder (2013) review article offers a summary of the work in this field.

Following Dunbar et al. (2013), I set up a collective household consumption model to structurally estimate the level of resource shares for each member of the household. Then, I use these predicted resource shares to analyze consumption differences between children born with different levels of endowment using the fact that, conditional on household consumption, higher resource shares translate into higher individual consumption. Specifically, I compare resource shares across siblings within the same household who differ in their unobserved endowments, exploiting rainfall shocks as an exogenous source of variation in the unobservable endowment measure. In my study population in rural India, weather plays a critical role, as livelihoods and employment are highly dependent on rainfed agriculture.

I show that exposure to a negative rainfall shock (drought) during the year before a child's birth significantly increases the likelihood of low birth weight (LBW) by 8 percentage points, an effect statistically significant at the 5% level. Put differently, experiencing a drought shock in utero is associated with a 50% higher probability of low birth weight compared to the average. I also find that these early-life health disadvantages persist into later life. The analysis reveals that exposure to drought during the year before birth significantly reduces a child's height-for-age z (HAZ) score. This reduction in the HAZ score results in a statistically significant increase in the probability that a child is stunted by about 9% points. These findings provide credence to my empirical strategy of using prenatal drought exposure as a proxy for the child to be born with a low initial endowment.

The results of my structural estimation show that, on average, a child who experienced in utero drought conditions receives 16% of household resources, compared to 14% for a child who had no such exposure in the household. Another way of interpreting this result is that parents allocate approximately 15% more resources to a child who experienced a negative shock around birth relative to a child born under ordinary weather conditions. I perform a test for equality of means and find that the test rejects the null hypothesis of equal resource allocation at the 1% significance level.

I also use the model estimates to calculate poverty rates for children (and other members) taking into account the *unequal* allocation of resources within households. Using this approach, I find that in households where both children experienced in utero drought conditions and those who did not are present, individual child poverty rates are substantially higher among non-drought-exposed siblings: approximately 42% of them live in extreme poverty, compared to only 6% of children who were exposed to drought in utero. This clearly demonstrates that the incidence of poverty among children is heterogeneous, with major shocks experienced around the time of birth leading to significant long-term welfare implications, not only for directly affected children, but also potentially for their siblings.

As an alternative but complementary approach, I examine a larger set of households which differ by the proportion of children who experienced in utero drought conditions. I find that if all children in the household were exposed to in utero drought conditions (instrument for low endowment), on average, the share of children's resources is 7 percentage points higher compared to households with no such exposure. Taking advantage of the cross-sectional variation in children's ages, I provide suggestive evidence that children in households with at least one child exposed to in utero drought conditions receive a greater share of resources throughout childhood compared to those households where children had no such exposure. Consistent with this finding, I observe lower child poverty rates among children in households with at least one in utero drought-exposed child relative to households without any exposed children.

In summary, my results suggest that parents exhibit compensatory behavior by allocating a larger share of household consumption resources to children born under adverse weather conditions. This compensatory response is evident both in comparisons between households with varying proportions of children exposed to in utero drought conditions as well as in households where direct comparisons can be made between exposed and unexposed children. My results confirm the importance of environmental shocks experienced around the time of birth in shaping children's resource shares and their subsequent welfare outcomes.

The proposed structural framework is compelling because it combines insights from two different strands of literature: the literature on collective household models and intra-household resource allocation, and the literature on fetal origins and parental responses to children's initial endowments. Exploring children's resource shares is advantageous because it provides a holistic view of resource allocation decisions within households by considering the entire consumption bundle. Moreover, these resource shares enable the estimation of individual-level poverty rates, including those specifically for children, thereby naturally facilitating welfare analysis. In addition, this method offers a useful way to directly investigate resource reallocations and potential spillover effects among siblings.

The analysis utilizes primary data collected from 1,409 households in 240 villages in two southern states of India, Karnataka and Andhra Pradesh. This survey was specifically designed to capture a wide array of parental investments and assignable consumption expenditures for each household member, including children. The paper also uses historic rainfall data from NASA's Precipitation Measurement Program to define rainfall shocks. The empirical context is also appealing because of the relatively high potential for external validity. Adverse rainfall is the most common type of shock experienced by poor households in much of the developing world and has long-term and short-term consequences.[4]

The remainder of the paper is structured as follows: Section 1.2 provides an overview of the related literature and further discusses the contributions of this paper.

[4]See Maccini and Yang (2009); Bobonis (2009).

Section 1.3 describes the data. Section 1.4 discusses the impact of early life rainfall on birth endowment and child health. Section 1.5 outlines the collective household model and the identification strategy for resource shares. Section 1.6 presents the results of the structural estimation of the resource shares. Section 1.7 provides the poverty analysis for children, and Section 1.8 contains conclusion and policy implications.

2 LITERATURE

There are two competing theories regarding how parents respond to differences in their children's observed endowments, each rooted in theoretical frameworks developed over four decades ago. According to Becker and Tomes (1976), parents tend to reinforce differences by allocating more resources to the better endowed child, driven by the assumption that returns on investment are greater for children with higher endowments, thus prioritizing efficiency over equity. In contrast, Behrman et al. (1982) argue that parents compensate for endowment differences to achieve equality among children, and parents' inequality aversion preferences outweigh efficiency concerns.

Whether parents choose to reinforce or compensate for children's endowments has important long-term implications for disparities both within families and across the broader population. In response, a burgeoning empirical literature has investigated how children's initial endowments influence parental responses. Yet, findings from this literature are mixed, indicating overall either that there is no consistent direction of parental response on child endowment, or that the response depends heavily on context. In developing countries, the evidence is similarly mixed: some studies indicate reinforcing parental responses (Adhvaryu and Nyshadham (2016); Datar et al. (2007)), others report compensating behaviors (Cabrera-Hernandez (2016); Leight (2017), Fan and Porter (2020)), and still others find mixed responses (Ayalew (2005)).[5]

[5]Even in developed countries, results from the literature have been mixed. Several studies doc-

Methodologically, most evidence is derived from: (a) within-twin comparisons, which control for genetic and prenatal environment differences while varying birth endowments (e.g., Abufhele et al. (2017); Bharadwaj et al. (2018)); (b) sibling fixed-effects comparisons, which compare siblings within the same family to remove household-level factors (e.g.,Abufhele et al. (2017); Bharadwaj et al. (2018); Del Bono et al. (2012); Cabrera-Hernandez (2016); Datar et al. (2010); Hsin (2012); Restrepo (2016); Rosales-Rueda (2014)); or (c) instrumental variable strategies that utilize quasi-random variation in children's early endowments— such as exposure to programs, rainfall shocks, or famines (e.g.,Adhvaryu and Nyshadham (2016); Leight (2017); Fan and Porter (2020)). In this paper, I exploit the rainfall shocks occurring during the in utero period as a source of exogenous variation in a child's birth endowment. This approach aligns with several previous studies that have similarly utilized rainfall shocks. For instance, Maccini and Yang (2009) use rainfall shocks in early life to document the negative effects of adverse weather on child health and human capital formation. Fan and Porter (2020) employ sibling fixed effects along with rainfall during early life as a source of variation in cognitive ability, finding that Ethiopian parents allocate greater cognitive investments toward the child with lower ability. Similarly, Leight (2017) uses natural variations in weather (including rainfall and grain yield shocks) to instrument for the early life nutritional inputs, thereby examining how these exogenous shocks affect parental investments in children's cognitive development, and finds evidence for compensatory behavior. These studies underscore that in settings where environmental variability is high, weather shocks can serve as a powerful tool to isolate causal parental responses to endowment differences (see Almond et al. (2018) for a review).

ument reinforcing parental responses (Aizer and Cunha (2012);Behrman et al. (1994);Datar et al. (2010);Frijters et al. (2013);Grätz and Torche (2016);Hsin (2012);Rosales-Rueda (2014)), while others report compensating behaviors (Behrman et al. (1982);Bharadwaj et al. (2018);Del Bono et al. (2012);Frijters et al. (2009);Griliches (1979);Halla and Zweimüller (2014)). Some studies have identified mixed patterns (Hsin (2012);Restrepo (2016);Yi et al. (2015), and yet others found no evidence of any parental response (Abufhele et al. (2017)).

Most research on parental responses to child endowment shocks has focused on human capital investments in three main categories: educational investments (educational expenses, schooling inputs), health-related inputs (medical expenditures, medical visits, breastfeeding, immunizations, prenatal care), and occasionally parental time investments (time spent on child care and stimulating activities)[6]. However, to the best of my knowledge, none of the existing literature examines parental responses through spending on consumption goods or per-child consumption expenditures.

The main contribution of my paper is to expand this literature by evaluating whether parents respond to initial birth endowments by varying the share of the household budget allocated to each child. Children differ from other members of a household in that they do not enter households by choice and have limited ability to leave (DLP). Hence, they are potentially very vulnerable to intra-household inequality in consumption allocations. Moreover, in a low-income country context, parental resource constraints are likely to be more binding, increasing the likelihood of consumption gaps between children. Typically, surveys do not collect consumption information at the individual level; they only record household-level consumption or expenditures. To overcome this limitation, a thriving literature has applied a structural approach based on the collective household model (Chiappori (1988); Chiappori (1992)). This approach combines observable household-level expenditures on assignable goods (goods that are consumed exclusively by, e.g., women, men or children) with preference restrictions to recover individual-level consumption from household-level data (DLP).[7] Specifically, the structural approach allows researchers

[6]Studies examining educational investments include Yi et al. (2015), Leigh (2017), and Bharadwaj et al. (2018), who focus specifically on educational expenses, and Ayalew (2005), who explores schooling inputs. In terms of health investments, examples include Datar et al. (2007) and Adhvaryu and Nyshadham (2016), who study breastfeeding and immunizations; Bharadwaj and Lakdawala (2013), who investigate prenatal care; and Yi et al. (2015), who analyze medical expenditures. Research on parental time investments, such as Hsin (2012) and Leigh (2017), examines how parents adjust the time spent on child care and stimulating activities in response to shocks.

[7]This approach has been used to study inequality between spouses or between parents and children (Dunbar et al. (2013); Bargain et al. (2022) Tommasi (2019); Sokullu and Valente (2022); Lechene et al. (2022); Casco (2024); Hernandez-de Benito (2022)), the well-being of older women in

to identify and estimate resource shares (the fraction of total household consumption allocated to each family member including children), which are otherwise unobserved.

The resource shares can be used to compute consumption and poverty rates at the individual (rather than the household) level. Such individual-level poverty estimates are fundamentally different from standard poverty rates, which are based on observed household per-capita consumption and implicitly assume an equal distribution of resources among family members. This brings me to the second contribution of the paper. The structural model enables me to estimate child poverty at the individual level, a topic that has not yet been explored in either the fetal origins literature or the related literature on parental responses. Several recent works have shown that accounting for intra-household inequality is critical for poverty measurement (see, for instance, Dunbar et al. (2013); Brown et al. (2021); Lechene et al. (2022)). Individual-level poverty measures are ALSO recommended by a recent World Bank report, which outlines the key considerations for monitoring global poverty (Atkinson (2019)).

Third, I contribute to the strand of recent studies that show that parental responses to an adverse early life shock experienced by a child can have significant spillover effects on their siblings. Spillovers can occur through several channels, including reallocating resources among children, epidemiological externalities, behavioral peer effects, parental learning about the effectiveness of various inputs, and economies of scale in investments. For example, if households tend to compensate for the negative effects of an early life intervention while keeping their total investment unchanged, the improved welfare of one child could come at the expense of reduced resources for his siblings. In contrast, if parents value equity and strive to treat their children more uniformly, a policy that enhances the endowment of one child could lead to increased investments in all children in the home (Adhvaryu and Nyshadham

India (Calvi (2020)), the treatment of foster children in Malawi (Penglase (2021)), and the allocation of resources among prime-aged adults, the elderly, and children by sex and birth-order in Bangladesh (Brown et al. (2021)).

(2016)[8]). I examine how parental responses in resource share allocations towards children born with low endowment affect other siblings in the household.

While the primary contribution of this paper is situated within the literature examining parental responses to children's birth endowments, it also makes a secondary contribution to the literature on fetal origins hypothesis by joining the handful of studies that have examined the effects of environmental shocks in early life on both health at birth and child health in later life. Previous studies in this area include Maccini and Yang (2009), which showed that adverse rainfall shocks during pregnancy in Indonesia reduce birth weight and have lasting effects on adult height, education, and income. Currie and Vogl (2013) reviewed similar evidence in developing countries, linking weather-induced health shocks in early life with low birth weight and long-term physical growth impairments. More recently, Abiona (2024)demonstrated that prenatal drought exposure in African settings increases low birthweight incidence and leads to gender-differentiated postnatal growth outcomes. However, the literature remains sparse, particularly for South Asia. This study addresses this gap by examining how early life weather shocks influence birth weight and subsequent anthropometric outcomes, providing evidence on the lasting impacts of adverse environmental shocks experienced in utero on health.

3 DATA

3.1 Primary Survey Data

The primary source of data comes from a field experiment in two southern states of India- Karnataka and Andhra Pradesh. The sample covers 1409 households from 20

[8]Adhvaryu and Nyshadham (2016) document that in Tanzania, an exogenous shock—implemented via variation in iodine supplementation—leads parents to adjust their investments, sometimes increasing health inputs such as vaccinations not only for the directly affected child but also indirectly benefiting the untreated sibling.

village taluks or subdistricts.[9]

Table 1: Descriptive Statistics on Household Characteristics

Variable definitions	(1) Mean	(2) S.D.
Household size	5.98	2.20
No. of adult males	1.84	1.02
No. of adult females	1.96	0.98
No. of children	2.18	1.10
No. of children who were exposed to in-utero drought	0.41	0.56
No. of children who were not exposed to in-utero drought	1.77	1.14
Fraction of female children	0.48	0.37
Avg. age of adult men	37.88	8.59
Avg. age of adult women	35.05	8.24
Avg. age of children	7.53	3.86
Avg. age of children who were exposed to in-utero drought	7.81	5.59
Avg. age of children who were not exposed to in-utero drought	7.36	3.43
Avg. education of adult men	2.28	1.70
Avg. education of adult women	1.62	1.36
Working share of adult men	0.85	0.24
Working share of adult women	0.43	0.41
Indicator if household has below poverty line status	0.87	0.33
Log of consumption expenditure	11.84	0.40
Budget Shares (Assignable clothing and footwear)		
Adult males	0.05	0.04
Adult females	0.05	0.03
Children	0.05	0.03
Children who were exposed to in-utero drought	0.03	0.02
Children who were not exposed to in-utero drought	0.05	0.03
Geographic Regions		
I(Andhra Pradesh)	0.13	0.33
I(Belgavi region, Karnataka)	0.27	0.45
I(Kalaburagi region, Karnataka)	0.45	0.50
I(Bangalore region, Karnataka)	0.15	0.36
N	1,409	

Table 1 shows the descriptive statistics at the household level. The average household size in my sample is 5.98 and the average number of children in a household is 2.18 with almost 48% of them being girls. It confirms the widespread existence of extended families in the region. On average, a household has 0.41 children who experienced drought conditions during the in-utero period and 1.77 children who were

[9]Data was collected for 2880 households for the field experiment, but for this article, we restrict the sample to households where at least one adult male, one adult female and one child is present at the time of survey. This is due to data requirements for the DLP model. I also drop any households with a missing value on any of the variables mentioned in Table 1, giving a total of 1409 households.

born under ordinary rainfall conditions.[10] At the time of the survey, the children were approximately 7.53 years old, on average. The participation of women in the labor force (work outside of home) is low only at 43%, compared to the corresponding male rate at 85%. This is consistent with the generally low female labor force participation rates documented in India. An overwhelming majority of households are poor, 87% having below the poverty line. I collected information on private assignable consumption expenditures.[11] These expenditures are typically hard to identify because consumption is measured at the household level and goods can be shared. However, in the survey, I collect this information on private assignable goods (clothing and footwear) for each member of the household, including each child. This data set is ideal for the structural estimation of the collective household model as outlined by DLP. Clothing and footwear expenditures account for 16% of total household budget. I group the villages into 4 regions-Andhra Pradesh, Belgavi, Kalaburgi, and Bangalore-based on geographical proximity.

In our reduced-form analysis, to identify and isolate the impact of rainfall variation on child health outcomes, I incorporate factors related to an infant's biology, the socioeconomic characteristics of her or his parents, and the household. In Table 2, I describe the summary statistics for the relevant outcome variables as well as the control variables.

- Child characteristics: About 49% of the children are female. The mean age of the children in our sample is 7.6 years. The mean order of birth is 2. The average spacing between births is reasonably high (34 months), and the number of siblings is 1.82.

[10]The definition of drought year will be explained in detailed later in this section under Rainfall data

[11]A good is said to be private if it is not shared, and assignable if it is consumed exclusively by a person of known type t (e.g. typically clothing and footwear).

[13]Child birth weight was collected on all living children aged 0–10 years.

[13]Height related anthropometric outcomes was collected on living children aged 0–15 years. Anthropometric weight-related results were collected in all living children 0–10 years

Table 2: Descriptive Statistics on Child characteristics, Parental characteristics and Health outcomes measures

Variable	Definition/Units	Mean	S.D.	N
Child characteristics				
Indicator if girl		0.490	0.50	3,212
Age in years		7.610	4.33	3,212
Birth order		2.055	1.06	3,212
Preceding birth spacing	(in months)	34.030	16.49	3,212
No. of siblings of each child		1.820	1.08	3,212
Parental characteristics				
Mother's age at birth of child		23.470	4.85	3,212
Mother's labor force participation		0.420	0.49	3,212
Mother's education level		1.440	0.63	3,212
Father's education level		1.550	0.75	3,212
Child's health outcomes at birth[12]				
Birth weight	(in kgs)	2.830	0.59	1,970
Indicator for low birth weight	($\leq 2.5\,$kg)	0.160	0.37	1,970
Anthropometrics[13]				
Height for age z-score	(HAZ)	-1.500	1.47	2,481
Indicator if stunted	(HAZ ≤ -2sd)	0.350	0.48	2,481
Indicator if severe stunted	(HAZ ≤ -3sd)	0.140	0.34	2,481
Weight for age z-score	(WAZ)	-1.920	1.12	1,670
Indicator if underweight	(WAZ ≤ -2sd)	0.470	0.50	1,670
Indicator if severe underweight	(WAZ ≤ -3sd)	0.160	0.37	1,670

- Parental characteristics: The mothers were 23.5 years old on average when they gave birth. Only 42% of the mothers had participated in any economic activity during the previous 12 months. Fathers were more educated than mothers in my sample.

- Child health outcomes at birth: I collect information on the child's birth weight for all living children aged 10 years or under. As shown in Table 1, the average birth weight is 2.83 kilograms (kg). Each child with a recorded birth weight is classified as low birth weight (LBW) or non-LBW using the WHO 2500 grams cutoff.[14] In my sample, 16% of the children are classified as LBW. These numbers are similar to those found in the National Family Health Survey- Round

[14]The medical literature has identified 2500 gms as the threshold over which the probability of perinatal mortality and morbidity, inhibited growth and cognitive development, and chronic diseases later in life drops substantially.

4 (NFHS-4) conducted in 2015–16.[15] Both the recorded birth weight and the categorical measure of LBW will be used as dependent variables to examine the impact of rainfall shocks on health at birth.

- Anthropometric outcomes: Anthropometric measures are commonly used measures that reflect the nutrition and growth status of children. I collect height and weight for the children in the study sample and calculate the height-for-age z score (HAZ)[16] and weight-for-age z-score (WAZ) using the the World Health Organization's growth standards. I also define four indicator variables for malnutrition. A child whose HAZ < -2 is considered stunted and a child whose HAZ < -3 is severely stunted. Likewise, a child whose WAZ < -2 is considered underweight and a child whose WAZ < -3 is severely underweight. As Table 2 shows, HAZ and WAZ on average are -1.5 and -1.92 standard deviations, respectively. The negative values on HAZ and WAZ reflect that the average child in my sample is considerably shorter and with lower weight than the WHO reference populations. More than one third of the children in my sample are stunted and nearly half of them are underweight.

3.2 Rainfall data

In addition to data from the primary survey, I also use historic rainfall data from NASA's Precipitation Measurement Program. This publicly available data set consists of interpolated (on a 0.5-degree latitude-longitude grid) global monthly rainfall data.

[15] According to NFHS-4 (2015–16), the overall prevalence of low birth weight (LBW, defined as a birth weight less than 2.5 kg) in India was estimated to be around 18%. In Karnataka and Andhra Pradesh, the overall prevalence of LBW was slightly lower than the national average - around 17% in general

[16] HAZ is a standardized measure that compares a child's height with that of healthy children of the same age, living under conditions likely to favor achievement of their full genetic growth potential. In other words, the height-for-age z score captures how much a child's height deviates from an international standard of healthy children of the same age. A similar definition is used for calculating WAZ as well.

3.2.0.1 Definition of rain shock:

Using the latitude and longitude information, I identified all weather stations within a radius of 62 km of each household.[17] Using an inverse distance weighting method, weights were assigned to each station's observed annual precipitation value, where the weight was the inverse of the distance between the station and the household. For each household, annual rainfall was imputed for each year during the 1970–2017 period. This gave the historical distribution of the rainfall for each household.

To capture rainfall shocks, I constructed two indicator variables based on the historical, local imputed precipitation distribution around the time of the child's birth. The positive rain shock variable equals 1 if the imputed rainfall in the year prior to the birth of the child was above the 80th percentile and 0 otherwise. The negative rain shock variable equals 1 if the rainfall in the year prior to the birth of the child was below the 20th percentile and 0 otherwise. These definitions of rain shocks have been widely used in the literature on the Indian subcontinent (Shah and Steinberg (2017); Kaur (2019); Jayachandran (2006)).

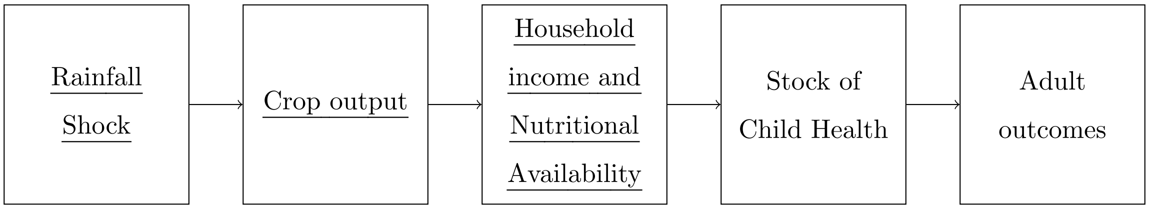
3.2.0.2 Impact of Rainfall on Crop Yield and Wages:

In rural India, agriculture is the dominant source of income for the majority of households, either through their own agricultural production or through casual agricultural employment. According to the National Sample Survey Office, approximately 58.3% of rural households in India reported agricultural activities as their main source of income in 2019[18]. The wages and employment levels in this sector are strongly influenced by the rainfall conditions (Jayachandran (2006); Kaur (2019)), and agricultural income has been well

[17] A radius of 62 km ensured that each household was matched to at least 3 weather stations. I have also used an alternative radius of 53 km which implied that each household was matched to at least two weather stations, as well as matched each household to its nearest weather station. The results are similar and are available on request.

[18] Data derived Situation Assessment of Agricultural Households and Land and Livestock Holdings of Households in Rural India, 2019, conducted by the National Sample Survey Office (NSSO). `https://mospi.gov.in/`

established to be inherently risky. I will use rainfall shocks as the source of exogenous variation in the unobservable endowment of the child with the following underlying intuition.



To test the first part of the proposed intuition (see underlined), I estimate the relationship between the log wage and log crop yield using rainfall shocks as an instrument for log crop yield. I follow an approach very similar to that of Jayachandran (2006). Detailed results are available in the Appendix Table A1. I find that droughts are particularly pertinent in my study areas. A negative rainfall shock causes a 6 percent (negative) change in crop yield and a 4% fluctuation in agricultural wages. Both results are significant at 1 percent level. A decline in earning power of even this magnitude is likely to be economically important to those who are poor, and the rare events when crop yield and the wage fall sharply would have more severe consequences. I do not find that positive rain shocks have statistically significant impacts on crop yield or wages. Furthermore, Karnataka ranks second in terms of arid and semi-arid areas. The state is highly vulnerable to drought compared to its neighboring states. About 80 percent of the geographical area is prone to drought. The distribution of rain in space and time in the state is highly erratic.[19] Data from the National Disaster Management System suggest that in 12 of the 15 years (2002–2014), one or other parts of the Karnataka state have been subjected to drought conditions.

[19] A possible issue with using rain shocks as quasi-random shocks is that they may be correlated over time. There are definitely some areas in which droughts are more frequent across all years, but this should not affect my results because I use subdistrict fixed effects. However, if it is the case that droughts this year are correlated with droughts next year, then it is difficult to tell to what extent we are picking up the effects of a single shock or multiple years of rainfall. I test for serial correlation, and find that the coefficient is negative and statistically significant; however, the magnitude is very small. It is unlikely that such a small amount of negative rainfall correlation will affect our results. However, in all regressions I include indicators for rain shocks around the focal year.

This period overlaps with the birth period for the majority of the children in the study sample. In my study areas, over 32% of the households report agriculture as their only source of income, and about 53% of households state that they have grown at least one crop in the last 12 months.

My analysis establishes that weather shocks, specifically droughts, negatively impact households due to the high share of the population working directly or indirectly in the agricultural sector, and the high dependence of agriculture on rainfall. Several other studies in the literature have also found evidence in support of the income effect of rain shocks for India.[20] Lower incomes may make it difficult for pregnant mothers to afford sufficient food supplies, medical services, vaccines and vitamin supplements, all of which are crucial for healthy fetal development.

In addition to agricultural production and household income, there may be other channels linking in utero rainfall to child nutrition and health. One such channel is the change in the local disease environment. The evidence on how drought affects the prevalence of diseases is mixed. On the one hand, deficient rainfall can lead to a scarcity of clean drinking water and deteriorating sanitation conditions. Studies in sub-Saharan Africa suggest that water shortages during dry seasons are linked to a higher incidence of diarrhea and infectious diseases due to the consumption of unsafe water and reduced hygiene practices (Bandyopadhyay et al. (2012); Rocha and Soares (2015)). This, in turn, can compromise maternal health, affecting fetal growth and development. On the other hand, drought may may have a positive impact on health by reducing the prevalence of waterborne diseases.

Finally, droughts can also impact child health through changes in labor demand and time use patterns for women. For example, facing food and water insecurity,

[20]For example, Kumar et al. (2016) find that Indian households in drought years have fewer assets, suggesting that households sell assets to cope with the income shock of a drought, indicating financial pressure that would likely affect nutrition. Jayachandran (2006) finds that negative rainfall shocks reduce agricultural production by approximately 7%, causing agricultural wages to fall with an elasticity of approximately 0.17.

pregnant women can be forced to undertake more physically demanding tasks to secure resources for their families. The allocation of parental time, for example, between agricultural work and leisure, can also be a function of precipitation.

Although I do not explicitly test the other channels through which rainfall shocks can impact child health in my data (aside from income effects), Mendiratta (2015) examined three key pathways and provided evidence that the income channel is the dominant mechanism in rural India.

In the next section, I examine whether rain shocks around the time of birth affect an individual's biological endowment, as measured by birth weight, and later-life health outcomes, as captured by anthropometric indicators.

4 IMPACT OF EARLY LIFE RAINFALL ON BIRTH ENDOWMENT AND CHILD HEALTH

4.1 Early life Rainfall and Birth Endowment

It is most common to refer to the use of birth weight as a measure of the stock of capacities at birth (or the endowment at birth). Both medical and economic studies have provided strong evidence in support of a robust relationship between birth weight and short-term and long-term health risks and welfare outcomes (see Behrman and Rosenzweig (2004) and Black et al. (2007) for extensive discussions).

I use a reduced-form econometric model for this part of my analysis.[21]To estimate the effects of exposure to abnormal rainfall deficit around birth on birth weight outcomes for the child, I employ the following model:

$$y_{ihsmt} = \alpha + \beta_1 \, \text{NegRainShock}_{h,t-1} + \beta_2 X_{ih} + \gamma_s + \delta_y + \lambda_m + \epsilon_{ihst} \qquad \text{(Eq. .1)}$$

[21]Similar models have been extensively applied to assess the effects of weather shocks on early life human capital outcomes, such as health and education, and have also been used in studies examining the impact of weather shocks on birth outcomes (Grace et al. (2015),Andalón et al. (2014),Rocha and Soares (2015),Abiona and Ajefu (2023) and Le and Nguyen (2022)).

where, y_{ihsmt} is the birth weight outcome for child i belonging to household h born in the sub-district s in month m and year t. I use both the birth weight (in kg) and the LBW indicator measure as dependent variables. $\text{NegRainShock}_{h,t-1}$ is an indicator variable that equals 1 if the imputed rainfall for the household h in the year prior to birth of child is below the 20^{th} percentile of its historical distribution and zero otherwise. The main coefficient of interest is β_1, which captures the impact of drought in the year prior to birth of the child on the birth weight of the child.

I use a suite of variables to control for variation in birth weight. X_{ih} is the set of child, parental, and household controls-sex, age, birth order of the child and preceding birth interval[22], number of own siblings[23]; parental characteristics like mother and father's education levels[24], indicators for mother's labor force participation, mother's age at birth, and its squared[25]. I also include household level controls such as household's annual consumption expenditure; an indicator if the household has cultivated crops in the previous 12 months and an indicator if at least one member of the household is involved in wage employment.

To explicitly control for the effects of seasonality, the birth month was included as a fixed effect, λ_m. I also include year of birth fixed effects δ_y to capture aggregate shocks that impacted entire region and sub-district fixed effects γ_s to capture policies and other factors at the sub-district level which may influence maternal health.

Table 3 presents the results of the estimation of Equation (.1) using the LBW indicator as the outcome variable, with the sample restricted to children aged 5 years

[22]I control for birth order and birth interval, with the assumption that children of higher birth order and those born within a short interval following the preceding birth may be smaller than their counterparts (Rutstein (2005), Jayachandran and Pande (2017)).

[23]I control for the number of siblings for each child, since there might be fewer resources per person in a household with more children and caregiver's time might be limited by the increase in childrearing responsibilities that come with more children.

[24]Parents with higher education levels are likely to have better access to healthcare care and a clearer understanding of nutritional needs during pregnancy, factors that can promote a healthier pregnancy

[25]Maternal age is related to the size of the infant as babies born to older women are more likely to weigh than babies born to younger women (Swamy et al. (2012)).

or under.

Table 3: Impact of negative rainfall shock around birth on low birth weight indicator

Variables	Whether the child had birthweight < 2.5 kgs (1)	(2)	(3)	(4)
Neg Rain shock during Year −2		0.004		0.012
		(0.043)		(0.045)
Neg Rain shock during Year −1	0.084**	0.082*	0.114*	0.109*
	(0.035)	(0.047)	(0.060)	(0.063)
Neg Rain shock during Year 0			−0.035	−0.039
			(0.057)	(0.059)
Child's gender is girl	0.031	0.031	0.030	0.030
	(0.024)	(0.024)	(0.024)	(0.024)
Birth order	−0.012	−0.012	−0.012	−0.012
	(0.022)	(0.022)	(0.022)	(0.022)
Birth spacing	0.000	0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)
Child's age	−0.116**	−0.116**	−0.116**	−0.116**
	(0.057)	(0.057)	(0.057)	(0.057)
Mother's education level	−0.018	−0.018	−0.018	−0.019
	(0.019)	(0.019)	(0.019)	(0.019)
Mother's age at birth	−0.015	−0.015	−0.016	−0.015
	(0.020)	(0.020)	(0.020)	(0.020)
Mother's age at birth squared	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Mother's labor force participation	−0.039	−0.039	−0.039	−0.040
	(0.028)	(0.028)	(0.028)	(0.028)
Father's education level	−0.007	−0.007	−0.008	−0.008
	(0.016)	(0.016)	(0.016)	(0.016)
Number of siblings	−0.010	−0.010	−0.010	−0.009
	(0.021)	(0.021)	(0.021)	(0.021)
Whether household has cultivated crops in the last 12 months	0.020	0.019	0.021	0.020
	(0.025)	(0.025)	(0.025)	(0.025)
Log of consumption expenditure	−0.016	−0.016	−0.016	−0.016
	(0.027)	(0.027)	(0.027)	(0.027)
Constant	1.341**	1.340**	1.356**	1.356**
	(0.533)	(0.533)	(0.534)	(0.534)
Observations	909	909	909	909
R-squared	0.09	0.09	0.09	0.09

Notes: Sample is restricted to children aged 5 years or below. Dependent variable is an indicator if the child's birth weight is < 2.5 kgs and 0 otherwise. Year 0 is birth year. Year 0–1 is year prior to birth year and Year 0–2 is two years prior to birth year. Neg Rain Shock during Year-1 is an indicator variable that equals 1 if the imputed rainfall for the household in the year prior to birth of child is below the 20th percentile of its historical distribution and zero otherwise, and the main covariate of interest. I also include negative rain shocks two years prior to birth and during year of birth for robustness. All regressions include year of birth, month of birth and sub-district fixed effects. Robust standard errors are in parentheses. Significance: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

In Table 3, the primary coefficient of interest, β , is reported in the row labeled

"Neg rain shock in Year - 1". Column 1 shows that the incidence of drought during the year before birth of the child increases the probability of delivering a child with LBW by 8 percentage points and the coefficient is statistically significant at the level 5%. In other words, an incidence of drought shock in the year before birth is associated with a 50% higher probability of low birth weight compared to the average.[26]

An important concern in our specification is that rainfall during the year before birth might be correlated with rainfall in other periods, before conception or after birth, and it is rainfall in these other periods that affects health outcomes. For example, maternal nutrition in the year before conception can have an impact on the health of the mother and the local environment of disease. So, from Columns 2–4, I perform an important robustness exercise by analyzing whether rainfall variation during the year before birth is not, in reality, capturing the effect of rainfall in other periods. In order to tackle this issue, I control for rainfall shocks in the period 2 years prior to birth and in the year of birth (or first year of life). These additional rainfall variables are relatively small in magnitude and none are statistically significant. The results are similar if I include each of these variables separately, one at a time (Columns 2 and 3), or I include them together in Column 4. In Column 4, the coefficient on the rain shock during the year before birth increases in magnitude and remains strongly significant. It does seem to be the amount of rain during the year before birth that affects the birth weight, rather than the rainfall in other time periods.[27]

Robustness tests: I also estimate Equation (.1) using birth weight as the outcome

[26]My estimates are very similar to those found by Abiona and Ajefu (2023). They found that the incidence of drought increases the likelihood of low birth weight by 7.9 percentage points in Sierra Leone, or an increase in 57% the probability of LBW compared to the mean

[27]A potential issue in my analysis is that of fetal selection driven by adverse weather, since I only observe birth outcomes for surviving fetuses. If shocks eliminate weaker fetuses, then this would lead me to underestimate the true effect of negative rain shock on birth weight. I would have a real threat to results only if there was an explicit decision on the part of parents to avoid pregnancy and if those pregnancies being avoided were of better quality. Given the data limitations, I am unable to test this.Rocha and Soares (2015) explore the impact of rainfall fluctuations during the gestational period on health at birth in the semi-arid Brazilian. They examined the selection channel in detail and found no evidence that parents actively make fertility choices in anticipation of a rain shock.

variable. The results are presented in Table A2 of the Appendix. Although I find a negative relationship between birth weight and negative rain shock during the year before birth, the effects are small and not statistically significant.[28] I also estimate Equation (.1) for all children aged 10 years or under, and look at both birth weight outcome measures. The results are remarkably similar to Table 3 and are available in Table A3 of the Appendix.

In an earlier analysis, I showed that in my study states, droughts have a larger impact on the rural population through their negative effects on wages and agricultural production, while positive rain shocks did not have any significant impacts on crop yield or wages. In Table A4 of the Appendix, I show the results of my estimation of Equation (.1), replacing $\text{NegRainShock}_{h,t-1}$ by $\text{PosRainShock}_{h,t-1}$.I find that while a positive rain shock in the year prior to birth is positively correlated with birth weight and reduces the likelihood of low birth weight, the estimated effects are very small in magnitude and not statistically significant. Given this, in my structural estimation, I focus solely on negative rain shocks during the year before birth.

4.2 Early life Rainfall and Anthropometric outcomes

In this sub-section, I examine the impact of negative rainfall shocks experienced around the time of birth on anthropometric outcomes. The motivation for this exercise is to assess whether the health disadvantages that originate at birth continue through later life. This echoes the "fetal origins" hypothesis, which posits that shocks in the womb or infancy can permanently impair human development.

I use the regression framework as described in Equation (.1) with dependent variables such as the six anthropometric measures-HAZ, stunting, severe stunting, WAZ,

[28]The relationship between birth weight and health outcomes is often nonlinear. Although birth weight is continuous, the risks of mortality, respiratory distress, infections, and neurodevelopmental problems increase disproportionately below certain cut-off points. Also, Blanc and Wardlaw (2005) note that threshold-based binary indicators are preferable to the continuous birthweight variable in low-resource settings because the latter is prone to measurement challenges, particularly those arising from heaping and missing data.

underweight, and severe underweight. The results of the estimation for HAZ, stunting, and severely stunting as dependent variables are shown in Table 4.[29]

Table 4: Impact of negative rainfall shock around birth on anthropometric outcomes

	HAZ score		Stunting		Severe stunting HAZ < -3	
	(1)	(2)	(3)	(4)	(5)	(6)
Neg Rain shock during Year -2		-0.309^{***}		0.067^{*}		0.029
		(0.102)		(0.036)		(0.024)
Neg Rain shock during Year -1	-0.368^{***}	-0.290^{***}	0.090^{***}	0.075^{**}	0.069^{***}	0.052^{**}
	(0.080)	(0.097)	(0.028)	(0.034)	(0.019)	(0.023)
Neg Rain shock during Year 0		-0.276^{***}		0.076^{**}		0.015
		(0.092)		(0.032)		(0.022)
Neg Rain shock during Year 1		-0.233^{**}		0.037		0.022
		(0.098)		(0.035)		(0.024)
Observations	2,259	2,129	2,259	2,129	2,259	2,129
R-squared	0.11	0.14	0.09	0.09	0.09	0.09

Notes: Sample is restricted to children aged 15 years or below. Dependent variable in Columns 1 and 2 is height-for-age z score, in Columns 3 and 4 is an indicator for stunting if HAZ < -2, and in Columns 5 and 6 is an indicator for severe stunting if HAZ < -3. Year 0 is birth year. Year 0–1 is year prior to birth year and Year 0–2 is two years prior to birth year. Year 1 is year after birth year. Neg Rain Shock during Year-1 is an indicator variable that equals 1 if the imputed rainfall for the household in the year prior to birth of child is below the 20th percentile of its historical distribution and zero otherwise, and the main covariate of interest. I also include negative rain shocks two years prior to birth, year of birth and one year after birth year for robustness. All regressions include year of birth, month of birth and sub-district fixed effects. Robust standard errors are in parentheses. Significance: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

As before, the primary coefficient of interest, β , is reported in the row labeled "Neg rain shock in Year-1" of Table 4. In Columns 1, 3 and 5, I include only the "Neg rain shock in Year-1" variable. Column 1 shows that the occurence of drought during the year before birth of the child reduces the HAZ score by 0.37 standard deviations. The reduction of HAZ translates into increased probabilities of being stunted. The probability of stunting increases by about 9 percentage points (Column 3) and the probability of severe stunting increases by 7 percentage points (Column 5) if the child is exposed to drought in the year before birth. All effects are statistically significant

[29]The full results with all coefficients are available in Table A5.

at the 1% level. In Columns 2, 4 and 6, I estimate the model by including negative rain shocks for each year, starting from two years prior to birth to one year after the birth year. This is to address the potential concern of serial correlation in rainfall, as well as the strong correlation of deprivation across the vulnerable periods in the life cycle (Glewwe and King (2001)). The coefficients on the "Neg rain shock in Year 1" decrease slightly in magnitude after inclusion in the regressions of rainfall in adjacent years, but remain statistically significant through all models. In Table A5, I present the results of the entire model, with estimated coefficients on all covariates.

In Table A6 of the Appendix, I show the impact of negative rainfall shocks on WAZ, underweight, and severe underweight measures. I find that negative rainfall shocks during the year before birth decrease WAZ, increase the likelihood of being underweight and severely underweight, but the effects are not statistically significant. It is important to note that while weight is a measure of short-term health status, height, on the other hand, is a stock variable and has long been considered a long-term predictor of nutrition and good health (Dearden et al. (2017)). The prior literature also suggests that HAZ largely reflects the history of nutrition or health before age 3, as after this age, catch-up for a child stunted in infancy is limited (Alderman et al. (2006)).

By integrating high-resolution weather data with detailed records of birth and child growth, my findings in this section confirm that adverse weather conditions, specifically occurence of droughts during the prenatal period are associated with lower birthweight and reveal that these early-life shocks have enduring consequences on child growth, as evidenced by significant deficits in height-for-age and increased likelihood of stunting.

5 COLLECTIVE MODEL

Browning et al. (2013) (hereafter BCL) provide a general efficient collective household model with preference heterogeneity across people, scale economies in consumption, and possibly unequal distributions of household resources. Dunbar et al. (2013) (hereafter DLP) take that model and impose sufficient restrictions on it to make it implementable with real world data via non-linear estimation of household-level Engel curves for assignable goods. In this section, I first present the structural model of households using the DLP framework and then outline the identification strategy that is used to estimate resource shares for family members, including children by birth endowment.

5.1 Collective Model of the Household

Collective households are households comprised of a collection of individuals with separate utility functions. Households can be thought of as economic environments in which these individuals live. In line with the standard characterization of collective households, I make no assumptions about the bargaining process which determines intra-household resource allocation. I only assume that in the eventual allocation, household members are assumed to reach the (household) Pareto frontier. This assumption of Pareto efficient is very strong and has been analyzed in different contexts and usually cannot be rejected.[30]Pareto efficiency implies that the collective household allocation problem is observationally equivalent to a decentralized person-level allocation problem. In this decentralized allocation, each household member demands a vector of consumption quantities given their preferences and a personal (shadow)

[30]While some papers provide evidence in favor of Pareto efficiency (see e.g. Attanasio and Lechene (2014) for Mexico and Brown et al. (2018) for Bangladesh), some others cast doubt on this assumption (see, e.g., Udry (1996) and De Vreyer et al. (2020)). Most rejections of Pareto efficiency are based on decisions about production, not consumption. As discussed in Rangel and Thomas (2019), confounding these two aspects may be misleading. They find that in more complex household structures, efficiency in allocations is not rejected in models that allow for more than two decision makers(e.g. extended households, similar to my context). Finally, Lewbel and Pendakur (2019) develop a collective household model in which households behave inefficiently but show that this does not have a large effect on the estimates of resource shares in Bangladesh.

budget constraint[31], and the household purchases the sum of these demanded quantities (adjusted for shareability or economies of scale).

Now, we present the formal model. Let households consist of T categories of people (indexed by $t = 1, \ldots, T$).[32] Let the number of household members of category t be denoted by σ_t. In practice, households can differ according to a wide range of observable characteristics, such as demographic composition, age, and education level of members, location, and other socioeconomic attributes. These characteristics may affect both preferences and bargaining power within the household. To reduce notational clutter, I omit these household characteristics for this subsection. I will introduce it explicitly in the estimation.

Let y denote the total expenditure of the household. Each household consumes K types of goods at market prices $p = (p_1, \ldots, p_K)$. Let $z = (z_1, \ldots, z_K)$ be the vector of observed quantities of goods purchased by the household and $x_t = (x_1^1, \ldots, x_t^K)$ be the vector of unobserved quantities of goods consumed by individuals of type t (ie, *private good equivalents*). Following DLP, I allow for economies of scale in consumption through a Barten-type consumption technology. This technology assumes the existence of a $K \times K$ matrix A which converts the quantities purchased by the household into private good equivalents, $z = A \sum_{t=1}^{T} x_t$. This technology allows the sum of private good equivalents to be weakly larger than what the household purchases.[33]

[31]Each member's budget constraint is characterized by a shadow budget and a shadow price vector. They are "shadow" budgets and prices because they determine each person's consumption demands but they are not observed. They are not the same as the observed household budget or market prices.

[32]In section6.1, I first consider three types of individuals in the household- men, women and children. Later, in section 6.2 I estimate the model with four types of household members: men, women, children born in drought year(s) and children born in non-drought years in a more restricted sample.

[33]A practical example often used in the literature to explain this type of consumption technology function is the following: Suppose that a household consists of only two adults. They ride in the car half the time, in which case they share the cost of gasoline by half. However, when one of them rides alone, he or she pays the full cost of gasoline. Then the consumption of gasoline, in equivalents of private goods, is 1.5 times higher than the quantity of gasoline purchased at the household level. If I assume that the consumption of gasoline does not depend on the consumption of other goods, then the kth diagonal element of matrix A would be $\frac{2}{3}$ and zero otherwise such that: $z_k = \frac{2}{3} * (x_m + x_f)$

For a private good, which is never jointly consumed, $A_k = 1$, and all off-diagonal elements of row or column k are equal to 0. This means that private goods, by definition, do not have economies-of-scale in consumption.

Each household member has a monotonically increasing, twice continuous differentiable, and strictly quasi-concave utility function over the K goods. Let $U_t(x_t)$ denote the subutility function of an individual of type t on the vector of goods x_t. This utility function is assumed to be separable from leisure, savings, or any other goods not included in the commodity bundle. Each member may also care about the well-being of other family members, so that their total utility may depend on the utility of other household members, but we assume it to be weakly separable over the subutility functions of goods.

Each household maximizes a Bergson–Samuelson social welfare function, U_H defined as

$$U_H(\tilde{U_1}, \ldots, \tilde{U_T}, y, p) = \sum_{t=1}^{T} \mu_t \tilde{U_t} \qquad \text{(Eq. .2)}$$

where $\mu_t = \mu_t(p/y)$ are the Pareto weights[34] that depends on prices, individual characteristics, and household expenditure. The form of the household utility function (.2) is different from the unitary model of the household, where choices are generated by maximizing a single well-behaved utility function. Following DLP, the household optimization program is as follows:

$$\max_{x_1,\ldots,x_T} \sum_{t=1}^{T} \mu_t \tilde{U_t} \qquad \text{(Eq. .3)}$$

$$\text{such that } z = A \sum_{t=1}^{T} x_t \text{ and } y = z'p$$

The solution to this optimization program above yields the quantities of private

[34] Pareto weights are traditionally interpreted as measures of intrahousehold bargaining power: the larger the value of μ_t, the more the weight that individual t's preferences is attributed in the household program. BCL show that there exists a monotonic correspondence between μ_t and η_t.

good equivalents x_t. After pricing these vectors at the within household shadow prices $A'p$, we get the resource share η_t, i.e., the fraction of household total resources devoted that are devoted to individuals of type t.

Following the standard characterization of efficient collective models and using the second welfare theorem, the household program can be represented as a two-stage process. In the first stage, resources are optimally allocated among household members. In the second stage, each individual maximizes their own individual utility function subject to the shadow budget constraint. That is, conditional on knowing η_t, household members choose x_t as the bundle that maximizes her own utility function subject to a Lindahl-type shadow budget constraint $\sum_k A_k p_k x_t^k = \eta_t y$. When the indirect utility function is substituted back into Equation (.3), the household program simplifies to the choice of optimal resource shares subject to the constraint that total resource shares must add up to 1. For simplicity, we assume all household members of a specific type are the same and interpret resource share being equally divided within all individuals of a particular type.

Much work on consumer demand estimation models the Engel curves[35] for private assignable goods.[36] Typical such goods used in literature are clothing and footwear because it can be assumed that e.g. men do not consume women's clothing and vice versa. Although demand functions for goods that are not private are more complicated, household demand functions for private assignable goods have much

[35] An Engel curve describes the relationship between the proportion of household expenditure spent on a good (budget share) and total expenditure, holding prices constant.

[36] I define a private good to be a good that does not have any economies of scale in consumption and an assignable good to be a private good consumed exclusively by household members of known type t.

simpler forms[37] and are given by:

$$W_t(y,p) = \eta_t \omega_t(A'p, \eta_t y) \tag{Eq. .4}$$

where W_t is the share of total household expenditure spent on member t's private assignable goods; η_t is the resource share attributed to that member and ω_t is the (unobserved) demand function of each household member of type t when facing her personal shadow budget constraint. In other words, ω_t is the amount of private assignable good that a person of type t would hypothetically demand had they lived alone with income $\eta_t y$ facing the shadow price vector $A'p$.

In the equation system (.4), W_t and y are observable, and the aim is to identify the share of resources η_t. The challenge in identifying the system is that for each equation, there are two unknowns (the resource shares and the individual demand functions are unobservable). Hence, the system is not identified without more assumptions. In the next subsection, I describe how to identify the parameters of interest using the DLP framework.

5.2 Identification of Resource Shares

The main goal of the collective model outlined in the previous subsection is to estimate resources shares. DLP provide sufficient restrictions on the model such that the resource shares can be identified using Engel curves of private assignable goods facing a single price vector.

To achieve identification, resource shares are assumed to be independent of household expenditures. This is an important identification assumption.[38] This implies,

[37]Intuitively, household-level demand for children's clothing will behave similarly to children's demand for clothing. On the other hand. the household's demand for non-private goods, depends on the degree to which such goods are shared within the household, and also on each person's preferences for that good.

[38]There is empirical support for this restriction. Menon et al. (2012) show that for Italian households, resource shares do not exhibit much dependence on household expenditure, and therefore find this assumption quite reasonable. Cherchye et al. (2015) use a revealed preference approach

for example, that all else equal, if a household gets richer, the relative consumption distribution will not change. However, resource shares can depend on variables highly correlated with expenditure, e.g. wealth, remittances, and household member wages. In the empirical application, I assume that individuals have PIGLOG (price-independent generalized logarithm) preferences over private assignable goods (Deaton and Muellbauer (1980)). The standard PIGLOG indirect utility function takes the form: $V_j(y,p) = e^{F_j(p)}(\ln y - \ln a_j(p))$. By Roy's identity, the budget share functions can then be written as follows:

$$w_t(y,p) = \delta_t(p) + \beta_t(p)\ln y \qquad \text{(Eq. .5)}$$

Thus, it conveniently yields Engel curves that are linear in the logarithm of household expenditures. An example of such a function is the popular, almost ideal demand system of Deaton and Muellbauer (1980). Substituting the budget share functions from (.4) into (.5)and holding prices fixed, results in the following household level Engel curves for private assignable goods consumed by people category type t:

$$W_t = \alpha_t\eta_t + \beta_t\eta_t \ln\frac{\eta_t}{\sigma_t} + \beta_t\eta_t \ln y \qquad \text{(Eq. .6)}$$

Identification of resource shares is achieved by imposing similarity of preferences for private assignable goods across household members. Given this additional assumption, resource shares can be identified by comparing household demands for assignable clothing across people within households, which the DLP authors call SAP ("Similar Across People"). In particular, I assume that $\beta_t = \beta \; \forall \, t$ and then identify the slopes of the Engel curves in equations (.6) by estimating linear regressions of the assignable clothing and footwear budget shares on a constant term and $\ln y$. This gives the

to impose bounds on resource shares. They find that although resource shares depend on variables such as relative wages and education, they do not vary much with household budgets.

slope or observable budget semi-elasticity of the Engel curves at the household level for assignable goods, $\frac{\partial W_t(y)}{\partial \ln y} = \beta\eta_t$. It is proportional to the unobservable resource share, with the factor of proportionality set by the constraint that the resource shares must add up to 1 (i.e. $\sum_{t=1}^{T} \eta_t = 1$). Given the adding-up constraint, the sum of this semi-elasticity across all types is β. Consequently, the relative magnitude of budget semi-elasticities determines resource shares. To fix ideas, suppose that the household receives a positive income shock (i.e. $\ln y$ increases). If the household response is a larger increase in the budget share for men's clothing than for women's clothing, then I can infer that it is because men's resource share is larger. It is worth reiterating that it is budget responses, not levels, that identify resource shares. Furthermore, in estimation, the intercepts and slopes of the Engel curves are allowed to vary with several observable household characteristics.

Before concluding this section, two remarks are in order. First, it is important to note that the budget shares in private assignable goods W_t and the resource shares η_t are not the same objects. Different household members may have very different tastes for their private assignable good. For example, a woman might consume the same amount of resources as her husband but less food because she derives less utility from it (e.g. she has lower calorific requirements). Second, identification in the model assumes separability between consumption, and other critical aspects of household behavior (e.g., labor supply, savings, and home production). In other words, it assumes that consumption and non-consumption decisions are made independently. This is typically not the case in the real world.

6 STRUCTURAL ESTIMATION RESULTS

The key data requirement for identification strategy under DLP framework is to observe household-level expenditure on a private assignable good for each person type within the household. The consumption module of the survey was designed to capture the expenditure of each member on clothing and footwear items in the year before the survey. This allows me to have great flexibility in how I define the types of members in the household. For instance: to get assignable expenditures incurred on children, I add up the expenditures on items of clothing and footwear for each child in the household. Instead, if I am interested in defining the person type as children born in drought years, I can add up the clothing and footwear expenditures incurred on only those children. The unique survey design offers significant advantage as compared to previous studies using the DLP framework which did not record individual expenditure and hence were restricted in how their categorization of person types, most often limiting to adult men, women and children. Similarly to other studies, I impose an additional assumption that preferences are the same for all household members of a specific type.

I estimate the system of Equation (.6) empirically by appending an error term to each equation and by imposing the assumption of similarity of preferences over private assignable goods: $\beta_t = \beta$.

For the estimation of resource shares, I do two types of exercises presented sequentially in the sub- sections that follow.

First, to compute resource shares for people living in households with men, women and children, I run regressions on observations with at least 1 adult man, 1 adult woman and 1 child in each household. I include the proportion of children born during drought year(s) in a household as a variable that affects both preferences and, more crucially, the resource share parameters. This allows me to use a larger sample of 1409 households. I call this "Approach 1" and discuss this in Section 6.1.

As a second exercise, I restrict to households that have at least 1 adult man, 1 adult woman, 1 child born in a drought year, and 1 child born in a non-drought year. Then I estimate resource shares accrued by each member type in such households and test if the resources allocated to children differ by shocks around the time of birth (proxy for birth endowment). I refer to this as "Approach 2" and discuss it in Section 6.2.

6.1 Approach 1: Variation in the proportion of children exposed to in utero drought conditions

Here, I restrict to households with at least 1 adult man, 1 adult woman and 1 child. In line with other studies, I allow preference parameters and resource shares to vary according to a broad set of household characteristics. This vector includes, among other things, household composition (for example, number of women, men and children; the proportion of female children), quadratic polynomial for women and children's average age respectively, average age difference between the genders. I also control for a set of economic and demographic household characteristics (e.g., average education level and average labor force participation shares of adult household members separately by gender). I group my 20 subdistricts into 4 geographic regions and include regional indicators to capture area-specific characteristics such as price levels and account for unobserved geographical heterogeneity. Importantly, for this study, the proportion of children who experienced an in-utero drought (instrument for low endowment children) is included as a covariate that affects both preference parameters and resource share. Thus, my model accounts for considerable heterogeneity across households by this characterization of preference and resource share parameters.[39] The descriptive statistics on these variables have been presented earlier in Table 1.

The demand functions for assignable clothing and footwear in households with M

[39]For example, children's resource shares will depend on the types of children who are living together. Ceteris paribus, resource shares will be different depending on the fraction of female children, etc.

men, F women and C children can be written in Engel form as follows:

$$\begin{aligned} W_m &= \alpha_m\eta_m + \beta\eta_m \ln\left(\frac{\eta_m y}{M}\right) + \epsilon_m \\ W_f &= \alpha_f\eta_f + \beta\eta_f \ln\left(\frac{\eta_f y}{F}\right) + \epsilon_f \\ W_c &= \alpha_c\eta_c + \beta\eta_c \ln\left(\frac{\eta_c y}{C}\right) + \epsilon_c \end{aligned} \qquad \text{(Eq. .7)}$$

where:

$$\begin{aligned} \alpha_m &= \delta^0_{\alpha_m} + \delta^1_{\alpha_m} X_1 + \cdots + \delta^{n-1}_{\alpha_m} X_{n-1} + \delta^n_{\alpha_m} \,\text{Prop LE} \\ \alpha_f &= \delta^0_{\alpha_f} + \delta^1_{\alpha_f} X_1 + \cdots + \delta^{n-1}_{\alpha_f} X_{n-1} + \delta^n_{\alpha_f} \,\text{Prop LE} \\ \alpha_c &= \delta^0_{\alpha_c} + \delta^1_{\alpha_c} X_1 + \cdots + \delta^{n-1}_{\alpha_c} X_{n-1} + \delta^n_{\alpha_c} \,\text{Prop LE} \\ \beta &= \delta^0_{\beta} + \delta^1_{\beta} X_1 + \cdots + \delta^{n-1}_{\beta} X_{n-1} + \delta^n_{\beta} \,\text{Prop LE} \\ \eta_f &= \delta^0_{\eta_f} + \delta^1_{\eta_f} X_1 + \cdots + \delta^{n-1}_{\eta_f} X_{n-1} + \delta^n_{\eta_f} \,\text{Prop LE} \\ \eta_c &= \delta^0_{\eta_c} + \delta^1_{\eta_c} X_1 + \cdots + \delta^{n-1}_{\eta_c} X_{n-1} + \delta^n_{\eta_c} \,\text{Prop LE} \\ \eta_m &= 1 - \eta_f - \eta_c \end{aligned}$$

where W_m, W_f and W_c are the budget shares spent on men's, women's and children's assignable clothing and footwear and y is the total household expenditure, excluding durable(s). α_t and β, $\forall t = \{m, f, c\}$ are combinations of the underlying preference parameters. η_m, η_f and η_c are the resource shares devoted to men, women and children respectively and the main object of interest. Lastly, as previously noted, I allow the proportion of children exposed to in utero drought conditions (Prop LE) to affect both the resource share and preference parameter functions. I take this equation system .7 to the data. For the sake of brevity, Table 5 presents the estimated coefficients of the covariates of children's resource share only.

Table 5 indicates that the shares of children's resources depend on the composition of the household. As expected, they increase with the number of children in

Table 5: Determinants of Children's Resource Shares (Approach 1)

All households with at least one adult man, one adult woman and one child.

	(1)
Number of women	−0.02**
	(0.01)
Number of men	−0.03***
	(0.01)
Number of children	0.02*
	(0.01)
Fraction of female children	0.00
	(0.03)
Average age of women	−0.30
	(0.87)
Average age of women^2	0.46
	(1.18)
Average age difference (men-women)	−0.04
	(0.13)
Average age of children	6.03***
	(1.29)
Average age of children^2	−35.95***
	(8.55)
Average education of men	−0.02**
	(0.01)
Average education of women	0.00
	(0.01)
Share of working men	−0.06
	(0.05)
Share of working women	−0.02
	(0.03)
Proportion of children born with in-utero drought experience	0.07**
	(0.03)
I(Andhra Pradesh)	−0.09**
	(0.04)
I(Belgavi region,Karnataka)	−0.08**
	(0.04)
I(Kalaburagi region,Karnataka)	−0.09***
	(0.03)
Constant	0.36**
	(0.17)
N	1,409

Notes: Nonlinear seemingly unrelated regression estimates based on survey data. Household consists of three types of people: men, women and children. Age variables are divided by 100 to ease computation. Sub-districts in the Bangalore region are taken as excluded region. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

the household and decrease with the number of adult members in the household. Unlike Calvi (2020) and DLP, the coefficient on the fraction of female children is not statistically significant. This is not a surprising finding because the southern states of Karnataka and Andhra Pradesh are known to have relatively favorable and equitable gender norms. In Appendix Table A7, I present the covariates of adult members' resource shares, both women and men.[40] The children's age terms are statistically significant. All else being equal, a 1-year increase in child's age is associated with a 5.3 percentage point increase in their resource shares. Households with high adult male education surprisingly devote less resources to children. The estimated model confirms the importance of environmental shocks around the time of birth in determining children's resource shares. If all children in the household experienced in-utero drought conditions (instrument for low birth endowment), then children's resource shares are 7 percentage points higher. This provides suggestive evidence that parents might be responding by compensating for the child's initial birth endowments by providing children with a greater share of intra-household consumption allocations.

Next, I use this model estimates to predict resource shares for each category of person-type estimated for a reference household, as well as mean of resource shares across all households. The results are reported in Table 6.

In Column 1 of Table 6, I present the predicted share of resources that accrues to women, men, and children in a reference household and the corresponding standard errors. A reference household is defined as one with exactly 1 adult man, 1 adult woman and 1 child who experienced in-utero drought conditions residing in Andhra Pradesh with all other covariates set equal to their mean values. Columns (2) and (3) show the mean and standard deviation of the predicted resource share estimates across all households, and therefore these account for the distribution of covariates. The averages of the resource shares are 36% for women, 35% for men, and 30% for

[40] Parameters related to the men's resource shares are calculates off of the estimated values for children's and women's resource share parameters, based on the constraint that sum of resource shares across all types equals 1.

Table 6: Descriptive Statistics for the Estimated Resource Shares (Approach 1)

Sample: All households with at least one child under Age 15 years.

		All households		$I(.) = 0$	$I(.) = 1$	
	Reference household	Mean	Std. Dev	Mean	Mean	Difference
Person-type	(1)	(2)	(3)	(4)	(5)	(4)–(5)
Women	0.30	0.36	0.09	0.35	0.38	–0.03***
	(0.04)					(0.01)
Men	0.37	0.35	0.11	0.36	0.32	0.04***
	(0.05)					(0.01)
Children	0.33	0.30	0.09	0.29	0.30	–0.01***
	(0.04)					(0.00)
N		1,409		883	526	

Notes: Reference household has 1 man, 1 woman and 1 child who experienced in utero drought conditions living in Andhra Pradesh region with all other covariates are equal to the mean values. Col.(4) shows the mean resource shares across households where no children experienced in utero drought conditions. Col.(5) shows the mean resource shares across households that have at least one child exposed to in-utero drought conditions. The last column has the results from equality of means t-tests between the two sub-samples of households. Standard errors in parentheses. $^{***}p < 0.01$.

children, respectively.

In columns (4) and (5), I divide my households into two subsamples depending on the presence of at least one child who experienced in utero drought conditions in the household, and calculate the mean predicted children's resource share for each subsample. In households where at least one child experienced in utero drought conditions, children's resource shares are on average 30% and higher by 1 percentage point (or around 3.4 percent higher) when compared to households where all children were born under normal weather conditions. Finally, in the last column I conduct a formal test of equality of means across these two types of households and find that the tests reject the null hypothesis for all three types of people- adult females, adult males, and children. Higher resources are devoted to children when a child is present in the household who experienced a negative rain shock during in utero period and the difference is statistically significant at the 1% level. This pattern is also confirmed by the two-sample Kolmogorov-Smirnov tests of the equality of distributions. Surprisingly, it is the adult men in the households (the group includes fathers) who have a lower resource share in the presence of a child born during adverse weather circumstances.

However, an important caveat applies to the interpretation of these results: households with at least one child exposed to in utero drought conditions may differ systematically from those without such children. In Appendix Table A8, I examine whether the two types of households differ across observable household characteristics that are allowed to affect preference parameters and resource share functions. I find that three out of twelve characteristics show significant imbalance, namely the number of adult males, the number of children, and the share of working women. To address this concern, I compare the resource shares across the two types of households, restricting the sample first to households with only one child and then to households with two children in the Appendix Table A9. Among households with one child, I find that if the child was exposed to in utero drought conditions, his/her resource share is 1.8 percentage points higher, and this difference is statistically significant. This higher share comes at the expense of male members, who receive a lower share of resources. These patterns are consistent with those reported in Table 6. In contrast, for two-child households, I find no statistically significant difference in children's resource shares between the two household types.

Next, following a similar approach to Calvi (2020), I take advantage of the cross-sectional variation in the age of the children to plot the average predicted child resource share by age. For each age, $a = 1, 2, \ldots, 14$ years, I calculate the mean predicted resource shares for children among all households with children's average age equal to a. For simplicity, I restrict the sample to households with only two children. Fig.1 shows the average predicted resource shares for a child versus the average age of the children for two different groups of households: households with at least one child who experienced drought conditions in utero (red solid curve) and households where no child was exposed to in utero drought conditions (blue dotted curve). The red curve lies above the blue curve at nearly all ages, providing suggestive evidence that children in households with at least one in utero drought exposed child receive a greater share of resources than those in households without a drought exposed child across all ages. It provides suggestive evidence for the theory that parents can view children who experienced poor conditions in utero as more at risk of health and nutritional deficits and, therefore, spend more in them to offset early disadvantages (compensatory behavior). However, several other factors may be at play as well. For instance, this analysis does not account for potential differences in household income, labor contributions, or unobserved household behaviors, which could influence observed patterns.

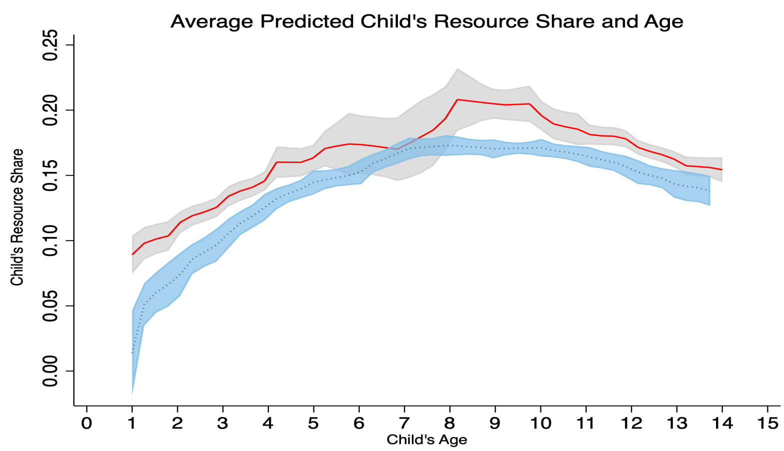


Figure 1: Average Predicted Resource Share for a Child and Age

Figure 1 shows the mean predicted resource share for a child among households with average child's age equal to $a = 1, 2, \ldots, 14$. Sample is restricted to all households with exactly two children. I stratify these households- with at least one child born under drought (red solid curve) and households with no children born under drought (blue dotted curve), and then plot the graph for each type separately. The solid red curve and the blue dotted curve are running means, and the shaded areas are the 95% confidence interval for the smoothed values

Robustness tests- I perform a series of robustness checks to test the sensitivity and validity of the structural estimates. All results are included in the Appendix.

First, I repeat the estimation by replacing the proportion of low endowment children by an indicator variable that assumes the value 1 if at least one child in the household experienced in utero drought conditions and is zero otherwise. The results are very similar and are presented in TableA10. In households where at least one child experienced in utero drought conditions (instrument for low endowment children), the share of resources of children is greater by 5 percentage points.

Second in Table A11, I show that my results are confirmed even when estimating the system of Engel curves with a different negative rain shock variable. Specifically, I match each household to its closest weather station. The rainfall deviation (or *z-score*) in year before birth is calculated as the difference between the actual precipitation during the year before birth from its long-run mean and scaled by the long-run standard deviation. The long-run average and standard deviation are calculated using data from the 10 years prior to the year of birth. I consider it a drought year if the rainfall deviation in the year before birth is less than two standard deviations below the local norm. I find that if all children are born with in utero drought exposure (instrument for low endowment), then children's resource shares are 8 percentage points higher.

Third in Table A12, I include the proportion of children of low birth weight in my resource share function. Birth weight is considered a significant indicator not only of immediate infant health, but also of a broader health trajectory that extends into childhood and adulthood (Walker et al. (2007), Victora et al. (2008), Almond et al. (2005)). Column 1 in Table A12 reports the determinants for the children resource shares the same as in Table 5. In column 2, I also include the proportion of children of low birth weight in my resource share function. Comparing columns 1 and 2, I find that the estimated coefficient on the proportion of children born under drought conditions has decreased in magnitude from 0.07 to 0.04 and becomes insignificant (p-value 0.12), while the coefficient on the proportion of low-birth weight children is 0.07

and statistically significant at the level 1%. This provides suggestive evidence that a large part of the positive correlation between the drought variable and child's resource shares is mediated by the low birth weight variable. In other words, controlling for birth weight (an imperfect proxy of the health endowment at birth[41]) diminishes the estimated direct effect of the drought shock on resource shares, implying that at least one of the channels through which the shock affects resource shares is largely through its impact on birth weight (and related health channel).

A key assumption here is that resource shares do not depend on household expenditure. However, in this setting, this assumption may be problematic, as children born under drought conditions may live in households with expenditure levels systematically different from the remainder of households. However, Dunbar et al. (2013) points out that resource shares can vary with variables closely linked to household expenditure, such as household wealth or individual wages. Given that the data set includes information on total household assets, I use this as a proxy for household wealth in resource share functions. Resource shares now only have to be independent of household expenditure, conditional on household wealth. These results are presented in Table A13 in the Appendix. The results are statistically similar to the main estimation results, and log total assets do not have a statistically significant relationship with children or womens' resource shares.

Obtaining similar findings across various specifications does not by itself guarantee robustness: in theory, the results could be incorrect in a similar way across specifications. Although I have not been able to examine every facet of the model, recent work by **?** and Brown et al. (2021) gives credence to several of the assumptions that underpin Dunbar et al. (2013) and its more recent extensions.

[41]Not all health effects are fully captured by birth weight – for instance, Currie and Rossin-Slater (2013) suggests stress in utero can affect newborn health in ways not reflected in birth weight (e.g., respiratory problems at birth despite normal weight).

6.2 Approach 2: Households with both in utero drought-exposed and non-exposed children

As a second exercise, I define my household as consisting of four types of members: M men, F women, L children who experienced in utero drought conditions, and H children who were not exposed to in utero drought conditions. The sample is restricted to households that have at least one member of each of the four aforementioned types. I have 366 such households in the data. The demand functions for assignable clothing and footwear in these households can be written in Engel form as follows:

$$
\begin{aligned}
W_m &= \alpha_m \eta_m + \beta \eta_m \ln\left(\frac{\eta_m y}{M}\right) + \epsilon_m \\
W_f &= \alpha_f \eta_f + \beta \eta_f \ln\left(\frac{\eta_f y}{F}\right) + \epsilon_f \\
W_l &= \alpha_l \eta_l + \beta \eta_l \ln\left(\frac{\eta_l y}{L}\right) + \epsilon_c \\
W_h &= \alpha_h \eta_h + \beta \eta_h \ln\left(\frac{\eta_h y}{H}\right) + \epsilon_c
\end{aligned}
\qquad \text{(Eq. .8)}
$$

where W_m, W_f, W_l and W_h are the clothing and footwear budget shares spent on men, women, children who experienced in utero drought and children born in normal rain conditions respectively. α_t and β, $\forall t = \{m, f, l, h\}$ are combinations of the underlying preference parameters. Crucially, the main objects of interest are η_l and η_h which denote the resource shares devoted to children exposed to in utero drought conditions and those not exposed to in utero drought conditions. This model allows me to test directly whether the consumption resources allocated to children differ by shocks around the time of birth by comparing per child measures of η_l and η_h.I take this equation system .8 to the data. Then I estimate resource shares accrued by each member type in such households and test if the per-child resource share is different for children who were exposed to in utero drought and otherwise.

As before, I allow preference parameters and resource shares to vary according to the following characteristics- number of members of each type; the proportion of female children), average age of women and children, average age difference between men and women, average education level and average labor force participation shares of adult household members separately by gender, and finally regional indicators. Table A14 in the Appendix presents the estimated coefficients of the covariates of the share of resources of children for both types.

Table 7: Descriptive Statistics for the Estimated Resource Shares (Approach 2)

Sample: All households with at least- one adult man, one adult woman, one child who experienced in utero drought and one child who no such exposure.

Person-type (1)	Mean (2)	Median (3)	Std. Dev. (4)	Min (5)	Max (6)
Woman	0.18	0.17	0.09	0.03	0.45
Man	0.20	0.17	0.08	0.03	0.50
Child exposed to in utero drought	0.16	0.16	0.08	0.01	0.33
Child not exposed to in utero drought	0.14	0.13	0.08	0.03	0.38
N			366		

I use my model estimates to calculate descriptive statistics of predicted resource shares for each type of person in all households. The results are presented in Table 7. Note that I report resource shares allocated at the individual level[42]- a man, woman, child who had in utero drought exposure and a child who did not have in utero drought exposure. This is important because in my data, on average these 366 households have 1.08 children of type l and 1.8 children of type h. So, comparing the resources going to all children of type l with the resources going to all children of type h is misleading. As Col.(2) indicates, on average, a child who was exposed to in utero drought receives 16% of the household resources compared to 14% allocated to a child who did not have any such exposure. Alternatively, parents allocate 15% more resources to a child

[42]While estimating the model, I assume all household members of a specific type are the same and interpret resource share being equally divided within all individuals of a particular type. So, the share of resources accruing to a person of type t is simply $\frac{\eta_t}{\sigma_t}$, where σ_t is the count of persons of type t in household.

who experienced a negative shock around the time of birth compared to a child who was born in more ordinary circumstances. I perform a test of the equality of means and find that the tests reject the null hypothesis at the 1% level. The difference in resource shares of 2 percentage points is stark. The pattern is also confirmed by two-sample Kolmogorov-Smirnov tests of the equality of distributions.

7 POVERTY ANALYSIS

I will now use the model estimates presented in the previous section to calculate poverty rates for children (and other members) that take into account the *unequal* allocation of resources within households.[43] This is in contrast to standard poverty measures, which commonly assume equal resource sharing within the household and ask whether or not per-capita household income falls below a threshold. This conventional approach mischaracterizes poverty levels, as there is strong evidence of substantial inequality in domestic consumption as presented in the previous sections.

Standard poverty line used by the World Bank and other international institutions concerned with poverty is US $1.9/day per person per day (using PPP adjusted values[44]). This poverty line is meant to capture the amount of resources below which a person's minimum nutritional, shelter and clothing needs cannot be met. Similarly to other papers in the literature[45], I set poverty rates for adult men and women to be the same and for children 60% of adult poverty rates. This is an adjustment implied by the OECD standard equivalence scales and takes into account the fact that children likely have different needs relative to adults. Typically, children require fewer resources to reach the same level of welfare as adults. I calculate each person's expenditures as the product of total household expenditure and the individual resource shares

[43]Note that the absolute levels of poverty discussed in this section are based on our estimation sample and on specific modeling assumptions. For these reasons, I do not want to emphasize the levels too much. Instead, I would like readers to focus on relative poverty.

[44]Since October 2015, the World Bank has updated the international poverty line of US $1.9/per day in 2011 PPP. The same has been used for the empirical work presented

[45]DLP, Calvi (2020), Tommasi (2019)

predicted by the model. Then, I construct poverty head count ratios by comparing these person-level expenditures with poverty lines.

First, I want to gauge the level of poverty among men, women and children in my study region. I use the model estimates from my *Approach 1* discussed in Section 6.1 and look at the set of 1409 households wherein there is at least one member of each type- men, women and children. I stratify my sample into two groups- households where at least one child exposed to in utero drought conditions is present, and households where all children had no such exposure.

Table 8: Poverty Rates (Approach 1)

All households with at least one adult man, one adult woman and one child.

	Model Predictions			Equal Sharing	N
	Women f (1)	Men m (2)	Children c (3)	(4)	(5)
Panel A: Household Level Poverty Rates					
Hhlds. with at least 1 drought child	0.08	0.11	0.04	0.07	526
Hhlds. with no drought child	0.12	0.06	0.06	0.07	883
Panel B: Individual Level Poverty Rates					
Hhlds. with at least 1 drought child	0.11	0.13	0.06	0.09	526
Hhlds. with no drought child	0.16	0.07	0.08	0.08	883

Panel A of Table 8 shows the proportion of households living in extreme poverty. Columns 1 to 3 report the fraction of households with each person-type that live below the poverty line while allowing for possible unequal allocation of resources within the household. Column 4 states the poverty rates calculated under the assumption that equal resources are allocated to each household member. The poverty estimates in Column 3 of Panel A indicate that among households in which at least one child experienced in utero drought conditions, 4% have children living in extreme poverty, whereas among households in which no child was exposed, 6% have children living in extreme poverty. In Panel B, I present individual-level poverty rates, i.e., the fraction of all individuals- women, men, or children separately-who live under poverty. This distinction is important because the type of household that has a child born after utero drought conditions may be different from the type of household that does not have any such children. In terms of individual head counts, among households in which at least one child was exposed to in utero drought, 6% of the children live in extreme poverty. Among households in which no child was exposed to drought, 8% of the children live in extreme poverty. Both panels A and B provide suggestive evidence that child poverty is likely lower for children exposed to in utero drought conditions compared to those born under nondrought conditions.

Now, I focus attention on households that have at least one member of each type-women(f), men (m), children who experienced in utero drought conditions (l) and children who did not have such experience (h). This is based on the model estimation discussed as *Approach 2* in Section 6.2. The results of the poverty estimation are reported in Table 9.

Table 9: Poverty Rates (Approach 2)

All households with at least one adult man, one adult woman, one child born under drought conditions and one child born under non-drought conditions.

	Model Predictions (Unequal Sharing)					Equal Sharing
	Women	Men	Children		Poverty Ratio	
	f	m	l	h	$\frac{h}{l}$	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Household Level Poverty Rates						
US $1.9/day	0.07	0.15	0.06	0.27	4.67	0.08
US $3.1/day	0.42	0.41	0.22	0.53	2.38	0.57
Panel B: Individual Level Poverty Rates						
US $1.9/day	0.14	0.16	0.06	0.42	7.26	0.09
US $3.1/day	0.51	0.44	0.24	0.69	2.89	0.61
N			366			

Taking into account column 3 and 4 in Table 9, 42% of children who did not have exposure to drought in utero live below the extreme poverty limit, while only 6% of children who were exposed to drought conditions live below the threshold. In Col.

5, I show the poverty ratio calculated as the ratio of poverty rates of type l over type h and the number is much larger than 1. Results remain similar when using the moderate poverty line of US $3.10 per day—another common threshold employed by the World Bank—rather than the international poverty line of US $1.90 per day.[46] It clearly shows that the incidence of poverty for all children is not the same, and major shocks around the time of birth can result in long-term welfare implications for both children born under adverse circumstances and their siblings living in the same household.

Finally, I would like to discuss an important limitation of the structural model used in the paper. The DLP collective household model used in this paper offers a promising framework for estimating poverty rate at the individual level while accounting for both inequality within the household and economies of scale in consumption. However, the model cannot pin down what the utility threshold is really or exactly what the amount of resources each individual needs to attain it is. To address this issue, the poverty line for children was set to a fraction of adults'. An alternative way could have been to rescale to account for calorific requirements. However, either approach is ad hoc.

8 CONCLUSION

In many ways, the household remains a black box for economists. Understanding its internal workings is challenging, and measuring how children are treated within households is far from straightforward. Building upon work by Dunbar et al. (2013), I structurally estimate resource shares in a collective household model using expenditures on private assignable goods and consequently measure consumption inequality among children. Although there may be several dimensions of inequality among chil-

[46]The US $3.10 per day per day reflects moderate poverty or a slightly improved standard of living. Individuals below this cutoff may have basic subsistence covered, but often face significant hardships in other basic human needs (nutrition, health, education

dren, I focus on shocks around the time of birth and parental responses to children's endowment.

This study contributes to the literature on parental responses to children's birth endowments, a strand of research which has not previously explored whether parents allocate consumption resources differently based on initial endowment differences. My findings show that parental behavior in response to these endowment differences is compensatory rather than reinforcing. I demonstrate that in rural South India, the allocation of household resources tends to favor children who experienced adverse in utero weather shocks and associated health consequences. A consequence of this pattern is that child poverty rates are different within the household and early life shocks constitute an important source of this inequality.

Policies aimed at increasing children's consumption typically target resources at the household level. Even when transfers are intended for a specific child, effective monitoring and enforcement prove challenging. My analysis provides nuanced insights into the welfare implications of such household-level interventions. Specifically, I demonstrate that since parents in rural South India tend to allocate more resources toward children who experienced adverse in utero shocks, external transfers intended to benefit vulnerable children might indeed reach their intended recipients. However, these transfers could inadvertently reduce the resources available to other children within the same household. Policymakers should therefore recognize that parental responses can either magnify or mitigate a program's impact on child inequality. A clear understanding of whether households tend to compensate or reinforce disparities among children can help better predict and shape the overall effectiveness of policy interventions. Child-specific interventions may be necessary to ensure equitable outcomes for all children in the family.

My analysis also underscores the lasting effects of early life shocks, specifically prenatal exposure to drought, on child health outcomes. I find that negative rainfall shocks during pregnancy significantly increase the probability of low birth weight and these early health disadvantages persist into childhood, as reflected in lower anthropometric outcomes. By integrating both immediate and long-term health measures, my study offers a comprehensive view of how weather-induced shocks disrupt early development and continue to influence growth and nutritional status throughout childhood. Given projections that climate change will increase the frequency and severity of extreme weather events worldwide, including in South Asia, these findings imply that increasingly unpredictable environmental shocks may undermine food security, increase health risks, and consequently exacerbate child malnutrition and adverse health outcomes throughout the region.

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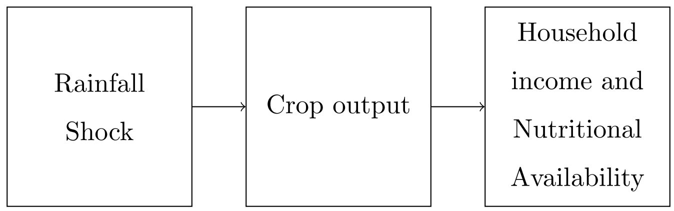
A APPENDIX

B RAINFALL SHOCK, CROP YIELDS AND AGRICULTURAL WAGES



To test the proposed mechanism (see above), I estimate the relationship between the log wage and log crop yield using rainfall shocks as an instrument for log crop yield. The method followed is very similar to Jayachandran (2006). India differs from other settings in which either below or above normal rainfall might hurt agricultural productivity. The rainfall shocks variable are constructed accordingly, with excess rain treated as a good shock and a shortfall as a bad shock.

$$\log(w_{dt}) = \beta_1 \log(\text{Yield}_{dt}) + \delta_t + \alpha_d + \epsilon_{dt}$$

First stage:

$$\log(\text{Yield}_{dt}) = \beta_2 \,\text{PosRainShock}_{dt} + \beta_3 \,\text{NegRainShock}_{dt} + \lambda_t + \mu_d + \epsilon_{dt}$$

The unit of observation for the above regressions is a district in my study states (Karnataka and Andhra Pradesh) in a given year. The dependent variable, w_{dt} is the male agricultural wage for district d in year t. Yield_{dt} refers to crop yield. It is calculated as the revenue-weighted average of log(volume of crop produced/area cropped) for the 5 major crops by revenue. They are taken from the World Bank India Agriculture and Climate dataset. Each district matched to closest point closest point on a 0.5 latitude by 0.5 longitude grid, and rainfall shock is constructed district specific. PosRainShock_{dt} equals one if the annual rainfall is above the eightieth percentile for the district, zero otherwise. NegRainShock_{dt} equals one if the annual rainfall is below the twentieth percentile for the district, zero otherwise. Results are shown in Table A1.[47]

Table A1: Relationship between Agricultural Wage and Crop Yield, Instrumented with Rainfall

Model	OLS (1st stage)	IV	
OLS	Dependent Variable		Log agricultural
	Log Crop Yield	wages	wages
	(1)	(2)	(3)
Positive Rain Shock	0.041		
	(0.0260)		
Negative Rain Shock	**−0.062****		
	(0.030)		
Log Crop Yield		**0.045****	**0.193****
		(0.0215)	(0.098)
District and Year Fixed Effects	Yes	Yes	Yes
Instruments			Positive and Negative Rain shocks
N	608	608	608
R-squared	0.74	0.92	0.89

Column 1 of Table A1 shows the first stage relationship between log crop yield and rainfall. A negative rainfall shock causes a 6-percent (negative) change in crop yield and is significant at 1 percent level. In contrast, the coefficient on the positive rain shock is not significant. Because there maybe spatial correlation in rainfall, standard errors allow for clustering within a region year, where a region comprises seven districts on average. The regression includes fixed effects for districts and years. Column 2 presents the OLS relationship between the wage and the crop yield. The coefficient on logarithmic crop yield, which represents the elasticity of the wage with respect to the yield, is 0.045. Higher productivity seems to lead to a higher wage. However, OLS estimates are expected to be biased downward. Hence, we move

[47]The data used is collected by the University of Delaware. The distribution of rainfall used to construct the variables pertains to the period 1956–87.

to column 3 which presents the instrumental variable estimates, where rainfall is instrumenting for crop yield. The elasticity of the wage with respect to productivity is 0.19.

Estimated elasticity of the wage with respect to crop yield allows us to calculate the magnitude of typical wage fluctuations caused by productivity shock. The logarithmic crop yield is regressed on the district-specific linear time trends and year effects. The standard deviation of the residual is 21 logarithmic points. A 21% shock, given the estimated elasticity of 0.19 (column 3), corresponds to a fluctuation in wages 4%. A decline in earning power of even this magnitude is likely to be economically important to those who are poor, and the rare events when crop yield and the wage fall sharply would have more severe consequences.

In these analyses, I explored both positive and negative rain shocks. However, it is obvious that negative rain shocks or droughts are more pertinent in my study areas. Hence, for structural estimation, I focus only on droughts.

Table A2: Impact of negative rainfall shock around birth on birth weight (children aged 5 years or below)

	Birthweight in kgs			
Variables	(1)	(2)	(3)	(4)
Neg Rain shock during Year −2		−0.012		0.004
		(0.069)		(0.072)
Neg Rain shock during Year −1	−0.074	−0.065	−0.008	−0.009
	(0.056)	(0.075)	(0.095)	(0.100)
Neg Rain shock during Year 0			−0.078	−0.079
			(0.091)	(0.094)
Child's gender is girl	−0.089**	−0.089**	−0.090**	−0.090**
	(0.039)	(0.039)	(0.039)	(0.039)
Birth order	0.065*	0.065*	0.065*	0.064*
	(0.035)	(0.035)	(0.035)	(0.035)
Birth spacing	−0.001	−0.001	−0.001	−0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Child's age	0.131	0.131	0.129	0.129
	(0.091)	(0.091)	(0.091)	(0.091)
Mother's education level	0.027	0.027	0.026	0.026
	(0.030)	(0.030)	(0.030)	(0.030)
Mother's age at birth	0.034	0.033	0.033	0.033
	(0.032)	(0.032)	(0.032)	(0.032)
Mother's age at birth squared	−0.001	−0.001	−0.001	−0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Mother's labor force participation	−0.034	−0.034	−0.036	−0.036
	(0.045)	(0.045)	(0.045)	(0.045)
Father's education level	0.013	0.013	0.012	0.012
	(0.026)	(0.026)	(0.026)	(0.026)
Number of siblings	0.001	0.001	0.002	0.002
	(0.033)	(0.033)	(0.033)	(0.033)
Whether household has cultivated	−0.061	−0.061	−0.059	−0.059
crops in the last 2 months	(0.041)	(0.041)	(0.041)	(0.041)
Log of consumption expenditure	0.054	0.053	0.053	0.053
	(0.043)	(0.043)	(0.043)	(0.043)
Constant	0.696	0.698	0.730	0.730
	(0.851)	(0.852)	(0.852)	(0.853)
Observations	909	909	909	909
R-squared	0.11	0.11	0.11	0.11

Notes: Sample is restricted to children aged 5 years or below. Year 0 is birth year. Year 0–1 is year prior to birth year and Year 0–2 is two years prior to birth year. Dependent variable is the birth weight measured in kilograms. Neg Rain Shock during Year-1 is an indicator variable that equals 1 if the imputed rainfall for the household in the year prior to birth of child is below the 20th percentile of its historical distribution and zero otherwise, and the main covariate of interest. All regressions include year of birth, month of birth and sub-district fixed effects. Robust standard errors are in parentheses. Significance: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table A3: Impact of negative rainfall shock around birth on birth weight outcomes (children aged 10 years or below)

	Whether the child had birthweight < 2.5 kgs		Birthweight in kgs	
Variables	(1)	(2)	(3)	(4)
Neg Rain shock during Year −2		−0.003		0.017
		(0.041)		(0.065)
Neg Rain shock during Year −1	0.045	0.097*	−0.026	−0.048
	(0.032)	(0.059)	(0.050)	(0.094)
Neg Rain shock during Year 0		−0.058		0.012
		(0.054)		(0.087)
Child's gender is girl	0.021	0.021	−0.063**	−0.063**
	(0.017)	(0.017)	(0.027)	(0.027)
Birth order	0.001	0.001	0.033	0.033
	(0.013)	(0.013)	(0.020)	(0.020)
Birth spacing	0.000	0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)
Child's age	−0.058	−0.059	0.113*	0.113*
	(0.041)	(0.041)	(0.065)	(0.065)
Mother's education level	−0.016	−0.017	0.003	0.003
	(0.014)	(0.014)	(0.023)	(0.023)
Mother's age at birth	−0.023**	−0.023**	0.031*	0.032*
	(0.011)	(0.011)	(0.018)	(0.018)
Mother's age at birth squared	0.000**	0.000**	−0.001*	−0.001*
	(0.000)	(0.000)	(0.000)	(0.000)
Mother's labor force participation	−0.011	−0.012	−0.005	−0.004
	(0.019)	(0.019)	(0.030)	(0.030)
Father's education level	−0.008	−0.009	0.018	0.018
	(0.012)	(0.012)	(0.019)	(0.019)
Number of siblings	−0.020	−0.020	0.020	0.020
	(0.012)	(0.012)	(0.020)	(0.020)
Whether household has cultivated crops in the last 12 months	0.000	0.001	−0.019	−0.020
	(0.018)	(0.018)	(0.028)	(0.028)
Log of consumption expenditure	−0.005	−0.006	0.038	0.038
	(0.019)	(0.019)	(0.031)	(0.031)
Constant	1.328**	1.342**	0.471	0.470
	(0.538)	(0.538)	(0.861)	(0.862)
Observations	1,970	1,970	1,970	1,970
R-squared	0.05	0.05	0.06	0.06

Notes: Sample is restricted to children aged 10 years or below. Year 0 is birth year. Year 0–1 is year prior to birth year and Year 0–2 is two years prior to birth year.In Column 1, the dependent variable is an indicator if the child's birth weight is < 2.5 kgs and 0 otherwise. In Column 2, the dependent variable is birth weight measured in kilograms. Neg Rain Shock during Year-1 is an indicator variable that equals 1 if the imputed rainfall for the household in the year prior to birth of child is below the 20th percentile of its historical distribution and zero otherwise, and the main covariate of interest. All regressions include year of birth, month of birth and sub-district fixed effects. Robust standard errors are in parentheses. Significance: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table A4: Impact of positive rainfall shock around birth on birth weight outcomes (children aged 10 years or below)

	Whether the child had birthweight < 2.5 kgs		Birthweight in kgs	
Variables	(1)	(2)	(3)	(4)
Pos Rain shock during Year -2		0.053		−0.084
		(0.056)		(0.089)
Pos Rain shock during Year -2	−0.011	−0.023	0.040	0.056
	(0.046)	(0.070)	(0.073)	(0.112)
Pos Rain shock during Year 0		−0.017		0.032
		(0.054)		(0.086)
Child's gender is girl	0.022	0.022	−0.063**	−0.063**
	(0.017)	(0.017)	(0.027)	(0.027)
Birth order	0.001	0.001	0.033*	0.034*
	(0.013)	(0.013)	(0.020)	(0.020)
Birth spacing	0.000	0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)
Child's age	−0.059	−0.060	0.114*	0.115*
	(0.041)	(0.041)	(0.065)	(0.065)
Mother's education level	−0.016	−0.017	0.004	0.004
	(0.014)	(0.014)	(0.023)	(0.023)
Mother's age at birth	−0.022**	−0.022**	0.031*	0.031*
	(0.011)	(0.011)	(0.018)	(0.018)
Mother's age at birth squared	0.000*	0.000*	−0.001*	−0.001*
	(0.000)	(0.000)	(0.000)	(0.000)
Mother's labor force participation	−0.011	−0.011	−0.005	−0.005
	(0.019)	(0.019)	(0.030)	(0.030)
Father's education level	−0.008	−0.008	0.018	0.018
	(0.012)	(0.012)	(0.019)	(0.019)
Number of siblings	−0.020	−0.020	0.020	0.020
	(0.012)	(0.012)	(0.020)	(0.020)
Whether household has cultivated crops in the last 2 months	0.000	0.000	−0.020	−0.020
	(0.018)	(0.018)	(0.028)	(0.028)
Log of consumption expenditure	−0.007	−0.007	0.038	0.039
	(0.019)	(0.019)	(0.031)	(0.031)
Constant	1.346**	1.362**	0.465	0.439
	(0.538)	(0.539)	(0.861)	(0.861)
Observations	1,970	1,970	1,970	1,970
R-squared	0.11	0.11	0.11	0.11

Notes: Sample is restricted to children aged 10 years or below. in Columns 1 and 3, the dependent variable is an indicator if the child's birth weight is < 2.5 kgs and 0 otherwise. In Columns 2 and 4, the dependent variable is birth weight measured in kilograms. Pos Rain Shock during Year-1 is an indicator variable that equals 1 if the imputed rainfall for the household in the year prior to birth of child is above the 80th percentile of its historical distribution and zero otherwise, and the main covariate of interest. All regressions include year of birth, month of birth and sub-district fixed effects. Robust standard errors are in parentheses. Significance: $***p < 0.01$, $**p < 0.05$, $*p < 0.1$.

Table A5: Impact of negative rainfall shock on height-related anthropometric outcomes

	HAZ score		Stunting		Severe stunting HAZ< -3	
	(1)	(2)	(3)	(4)	(5)	(6)
Neg Rain shock during Year -2		−0.309***		0.067*		0.029
		(0.102)		(0.036)		(0.024)
Neg Rain shock during Year -1	−0.368***	−0.290***	0.090***	0.075**	0.069***	0.052**
	(0.080)	(0.097)	(0.028)	(0.034)	(0.019)	(0.023)
Neg Rain shock during Year 0		−0.276***		0.076**		0.015
		(0.092)		(0.032)		(0.022)
Neg Rain shock during Year 1		−0.233**		0.037		0.022
		(0.098)		(0.035)		(0.024)
I(child is a girl)	−0.091	−0.098*	0.014	0.012	−0.010	−0.010
	(0.059)	(0.058)	(0.020)	(0.021)	(0.014)	(0.014)
Birth Order – Alive	−0.018	−0.023	0.028*	0.028*	0.003	0.000
	(0.042)	(0.041)	(0.014)	(0.014)	(0.010)	(0.010)
Birth Spacing – Alive	0.008***	0.008***	−0.001**	−0.001**	−0.001*	−0.001**
	(0.002)	(0.002)	(0.001)	(0.001)	(0.000)	(0.000)
Age of child (in yrs)	−0.084	−0.029	0.046	0.042	0.082**	0.077**
	(0.137)	(0.138)	(0.047)	(0.048)	(0.033)	(0.033)
Mother's education level	0.096*	0.106**	−0.023	−0.032*	−0.006	−0.008
	(0.054)	(0.054)	(0.018)	(0.019)	(0.013)	(0.013)
Mother's age at birth (in yrs)	0.054	0.051	−0.018	−0.015	0.001	−0.001
	(0.036)	(0.035)	(0.012)	(0.012)	(0.009)	(0.008)
Mother's age at birth squared	−0.001	−0.001	0.000	0.000	0.000	0.000
	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
I(Mother's LFP)	−0.145**	−0.134**	0.051**	0.049**	0.003	0.000
	(0.064)	(0.064)	(0.022)	(0.022)	(0.015)	(0.015)
Father's education level	0.056	0.045	−0.013	−0.010	−0.011	−0.008
	(0.043)	(0.042)	(0.015)	(0.015)	(0.010)	(0.010)
No. of Siblings	−0.029	−0.032	−0.001	0.002	0.012	0.013
	(0.040)	(0.039)	(0.014)	(0.014)	(0.010)	(0.009)
Whether household has cultivated crops in the last 12 months	0.125**	0.132**	−0.022	−0.024	−0.012	−0.013
	(0.061)	(0.061)	(0.021)	(0.021)	(0.015)	(0.015)
Log of consumption expenditure	0.077	0.088	−0.034	−0.034	0.003	−0.006
	(0.069)	(0.069)	(0.024)	(0.024)	(0.016)	(0.017)
Constant	−1.878	−2.823	0.184	0.182	−1.166*	−0.949
	(2.582)	(2.600)	(0.885)	(0.916)	(0.620)	(0.625)
Observations	2,259	2,129	2,259	2,129	2,259	2,129
R-squared	0.11	0.14	0.09	0.09	0.09	0.09

Notes: Sample is restricted to children aged 15 years or below. Dependent variable in Columns 1 and 2 is height-for-age z score, in Columns 3 and 4 is an indicator for stunting if HAZ < -2 , and in Columns 5 and 6 is an indicator for severe stunting if HAZ < -3. Year 0 is birth year. Year 0–1 is year prior to birth year and Year 0–2 is two years prior to birth year. Year 1 is year after birth year. Neg Rain Shock during Year-1 is an indicator variable that equals 1 if the imputed rainfall for the household in the year prior to birth of child is below the 20th percentile of its historical distribution and zero otherwise, and the main covariate of interest.I also include negative rain shocks two years prior to birth, year of birth and one year after birth year for robustness. All regressions include year of birth, month of birth and sub-district fixed effects. Robust standard errors are in parentheses. Significance: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table A6: Impact of negative rainfall shock on weight-related anthropometric outcomes

	WAZ score		Underweight		Severe underweight	
	(1)	(2)	(3)	(4)	(5)	(6)
Neg Rain shock during Year −2		−0.063		0.089		0.012
		(0.177)		(0.084)		(0.061)
Neg Rain shock during Year −1	0.055	−0.069	−0.031	0.041	−0.009	0.015
	(0.091)	(0.146)	(0.043)	(0.069)	(0.031)	(0.050)
Neg Rain shock during Year 0		−0.144		0.097*		0.007
		(0.106)		(0.050)		(0.036)
Neg Rain shock during Year 1		−0.090		0.043		0.010
		(0.096)		(0.046)		(0.033)
I(child is a girl)	0.064	0.069	−0.017	−0.021	−0.018	−0.021
	(0.057)	(0.060)	(0.027)	(0.028)	(0.020)	(0.020)
Birth Order – Alive	0.028	0.016	−0.012	−0.009	0.021	0.023
	(0.043)	(0.044)	(0.020)	(0.021)	(0.015)	(0.015)
Birth Spacing – Alive	0.006***	0.006***	−0.002**	−0.002*	−0.001**	−0.002**
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Age of child (in yrs)	0.052	0.151	−0.087	−0.091	0.029	−0.007
	(0.133)	(0.141)	(0.063)	(0.067)	(0.046)	(0.049)
Mother's education level	0.113**	0.105**	−0.046**	−0.044*	−0.025	−0.018
	(0.048)	(0.051)	(0.023)	(0.024)	(0.017)	(0.018)
Mother's age at birth (in yrs)	0.002	0.003	−0.007	−0.008	0.000	−0.003
	(0.038)	(0.039)	(0.018)	(0.018)	(0.013)	(0.013)
Mother's age at birth squared	0.000	0.000	0.000	0.000	0.000	0.000
	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
I(Mother's LFP)	−0.033	0.014	0.023	−0.001	−0.030	−0.040*
	(0.063)	(0.065)	(0.029)	(0.031)	(0.022)	(0.022)
Father's education level	0.071*	0.071*	0.002	0.000	−0.025*	−0.020
	(0.040)	(0.042)	(0.019)	(0.020)	(0.014)	(0.014)
No. of Siblings	−0.047	−0.043	0.020	0.015	−0.004	0.002
	(0.043)	(0.044)	(0.020)	(0.021)	(0.015)	(0.015)
Whether household has cultivated crops in the last 12 months	−0.005	0.016	0.009	0.008	0.005	0.001
	(0.060)	(0.063)	(0.028)	(0.030)	(0.021)	(0.022)
Log of consumption expenditure	0.089	0.104	−0.054*	−0.047	−0.013	−0.026
	(0.066)	(0.069)	(0.031)	(0.033)	(0.023)	(0.024)
Constant	−4.051	−6.260**	2.892**	3.121**	0.086	0.955
	(2.567)	(2.763)	(1.209)	(1.307)	(0.886)	(0.951)
Observations	1,471	1,336	1,471	1,336	1,471	1,336
R-squared	0.11	0.12	0.07	0.08	0.09	0.10

Notes: Sample is restricted to children aged 10 years or below. Dependent variable in Columns 1 and 2 is weight-for-age z score, in Columns 3 and 4 is an indicator for underweight if WAZ < -2 , and in Columns 5 and 6 is an indicator for severe underweight if WAZ < -3. Year 0 is birth year. Year 0–1 is year prior to birth year and Year 0–2 is two years prior to birth year. Year 1 is year after birth year. Neg Rain Shock during Year-1 is an indicator variable that equals 1 if the imputed rainfall for the household in the year prior to birth of child is below the 20th percentile of its historical distribution and zero otherwise, and the main covariate of interest.I also include negative rain shocks two years prior to birth, year of birth and one year after birth year for robustness. All regressions include year of birth, month of birth and sub-district fixed effects. Robust standard errors are in parentheses. Significance: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table A7: Determinants of Men's and Women's Resource Shares (Approach 1)

All households with at least one adult man, one adult woman and one child.

	Women (1)	Men (2)
No. of women	0.04***	−0.07***
	(0.01)	(0.01)
No. of men	−0.05***	0.06***
	(0.01)	(0.01)
No. of children	0.02	−0.02***
	(0.01)	(0.01)
Fraction of female children	−0.07***	0.02
	(0.03)	(0.03)
Avg. age of women	−0.70	−0.97
	(0.93)	(0.98)
Avg. age of women^2	1.32	−1.72
	(1.23)	(1.29)
Avg. age difference (men-women)	0.57***	−0.34***
	(0.13)	(0.14)
Avg. age of children	−5.33**	−2.64
	(1.46)	(1.71)
Avg. age of children^2	29.85***	13.56
	(9.28)	(11.22)
Average education of men	0.01	0.00
	(0.01)	(0.01)
Average education of women	−0.02**	0.02*
	(0.01)	(0.01)
Share of working men	0.04	0.10**
	(0.05)	(0.05)
Share of working women	−0.02	−0.03
	(0.03)	(0.03)
Proportion of children born during a drought	0.01	0.00
	(0.03)	(0.04)
I(Andhra Pradesh)	0.02	0.00
	(0.05)	(0.05)
I(Belgavi region,Karnataka)	0.06	−0.01
	(0.04)	(0.04)
I(Kalaburagi region,Karnataka)	0.00	0.04
	(0.03)	(0.04)
Constant	0.57***	0.32**
	(0.18)	(0.19)
N	1,409	

Notes: Nonlinear seemingly unrelated regression estimates based on survey data. Household consists of three types of people: men, women and children. Age variables are divided by 100 to ease computation. Sub-districts in the Bangalore region are taken as excluded region. Robust standard errors in parentheses. $^*p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A8: Balance Tests: Households With vs. Without In-Utero Drought Exposure Children

	$I(.) = 1$ (1)	$I(.) = 0$ (2)	Difference Col (2) − Col (1) (3)	P value (4)
Adult males	1.94	1.79	−0.15	0.042
Adult females	2.02	1.92	−0.09	0.274
Children	2.39	2.05	−0.33	0.000
Proportion of girls	0.49	0.48	−0.01	0.769
Average Age Men	37.76	37.96	0.20	0.598
Average Age Women	35.24	34.93	−0.31	0.878
Average Age Children	7.70	7.43	−0.27	0.131
Share of working men	0.84	0.86	0.02	0.287
Share of working women	0.37	0.46	0.08	0.002
Average education men	2.26	2.30	0.05	0.546
Average education women	1.61	1.63	0.02	0.883
Log of consumption expenditure	11.84	11.83	−0.01	0.299
N	556	883		

Notes: This table reports subsample means and tests of balance for key household covariates that affect both resource share functions and preference parameters in the emprical model of Approach 1. P-values are derived from linear regressions that regress the variable of interest on an indicator if at least one child exposed to in utero drought is present in the household and 0 otherwise, controlling for region fixed effects.

Table A9: Descriptive Statistics for Estimated Resource Shares for 1 child and 2 child households

Panel A: Descriptive Statistics of Estimated Resource shares (Approach 1) Sample is restricted to households with exactly 1 child

	Mean $I(.) = 0$ (1)	Mean $I(.) = 1$ (2)	Difference Col (2) − Col (1) (3)	p value Col (2) − Col (1) (4)
Women	0.338	0.377	0.039	0.001
Men	0.421	0.363	−0.057	0.000
Children	0.241	0.259	0.018	0.029
N	281	128		

Panel B: Descriptive Statistics of Estimated Resource shares (Approach 1) Sample is restricted to households with exactly 2 children

	Mean Both children unexposed (1)	Mean 1 child exposed; 1 child unexposed (2)	Mean Both children exposed (3)	Difference Col (2) − Col (1) (4)	p value Col (2) − Col (1) (5)
Women	0.349	0.376	0.342	0.027	0.001
Men	0.347	0.323	0.363	−0.024	0.008
Children	0.304	0.301	0.295	−0.003	0.648
N	365	171	17		

Table A10: Determinants of Children's Resource Shares (with an indicator if a child exposed to in-utero drought is present in hhld)

Sample: All households with at least 1 child under Age 15 years.
I replaced proportion of children born under drought by an indicator that assumes value 1 if such a child is present in the household and 0 otherwise.

	(1)
Number of women	−0.02**
	(0.01)
Number of men	−0.03***
	(0.01)
Number of children	0.01*
	(0.01)
Fraction of female children	0.00
	(0.02)
Average age of women	−0.21
	(0.88)
Average age of women^2	0.32
	(1.19)
Average age difference (men-women)	−0.04
	(0.13)
Average age of children	6.37***
	(1.24)
Average age of children^2	−38.21***
	(8.32)
Average education of men	−0.02**
	(0.01)
Average education of women	0.00
	(0.01)
Share of working men	−0.06
	(0.05)
Share of working women	−0.02
	(0.03)
Indicator if a child is born during a drought	0.05**
	(0.02)
I(Andhra Pradesh)	−0.09**
	(0.04)
I(Belgavi region,Karnataka)	−0.08**
	(0.04)
I(Kalaburagi region,Karnataka)	−0.09***
	(0.03)
Constant	0.35**
	(0.17)
N	1,409

Notes: Nonlinear seemingly unrelated regression estimates based on survey data. Household consists of three types of people: men, women and children. Age variables are divided by 100 to ease computation. Sub-districts in the Bangalore region are taken as excluded region. Robust standard errors in parentheses. $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

Table A11: Determinants of Children's Resource Shares (with alternative definition of negative rain shock)

Sample: All households with at least 1 child under Age 15 years.
I used an alternative definition of rainfall shock based on z-score.

	(1)
Number of women	–0.02*
	(0.01)
Number of men	–0.03***
	(0.01)
Number of children	0.02*
	(0.01)
Fraction of female children	0.01
	(0.02)
Average age of women	–0.31
	(0.81)
Average age of women^2	0.38
	(1.09)
Average age difference (men-women)	–0.12
	(0.13)
Average age of children	3.36***
	(1.15)
Average age of children^2	–19.32***
	(7.52)
Average education of men	–0.02**
	(0.01)
Average education of women	0.00
	(0.01)
Share of working men	0.00
	(0.04)
Share of working women	–0.01
	(0.03)
Proportion of children born during a drought	0.08**
	(0.06)
I(Andhra Pradesh)	–0.12**
	(0.04)
I(Belgavi region,Karnataka)	–0.06**
	(0.04)
I(Kalaburagi region,Karnataka)	–0.09***
	(0.03)
Constant	0.36**
	(0.17)
N	1,409

Notes: Nonlinear seemingly unrelated regression estimates based on survey data. Household consists of three types of people: men, women and children. Age variables are divided by 100 to ease computation. Sub-districts in the Bangalore region are taken as excluded region. Robust standard errors in parentheses. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

Table A12: Determinants of Resource Shares: Accounting for Low Birthweight

All households with at least one adult man, one adult woman and one child.

	Child (1)	Child (2)
No. of women	0.35**	0.51***
	(0.17)	(0.19)
No. of men	−0.02**	−0.01
	(0.01)	(0.01)
No. of children	−0.03***	−0.04***
	(0.01)	(0.01)
Fraction of female children	0.02*	0.01
	(0.01)	(0.01)
Avg. age of women	−0.28	−1.00
	(0.87)	(0.95)
Avg. age of women^2	0.44	0.90
	(1.18)	(1.27)
Avg. age difference (men-women)	−0.04	−0.15
	(0.13)	(0.13)
Avg. age of children	6.02***	4.43***
	(1.29)	(1.41)
Avg. age of children^2	−35.90***	28.42***
	(8.55)	(9.15)
Average education of men	−0.02***	−0.01
	(0.01)	(0.01)
Average education of women	0.00	0.01
	(0.01)	(0.01)
Share of working men	−0.06	−0.05
	(0.05)	(0.05)
Share of working women	−0.02	−0.02
	(0.03)	(0.02)
Proportion of children born during a drought	0.07**	0.04
	(0.03)	(0.02)
Prop of low birth weight children	–	0.07***
	–	(0.02)
I(Andhra Pradesh)	−0.09**	−0.12***
	(0.04)	(0.04)
I(Belgavi region,Karnataka)	−0.08**	−0.07**
	(0.04)	(0.04)
I(Kalaburagi region,Karnataka)	−0.09***	−0.09***
	(0.03)	(0.03)
Constant	0.35**	0.51***
	(0.17)	(0.19)
N	1,409	

Notes: Nonlinear seemingly unrelated regression estimates based on survey data. Household consists of three types of people: men, women and children. Robust standard errors in parentheses. $^*p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A13: Determinants of Resource Shares: Accounting for Wealth

All households with at least one adult man, one adult woman and one child.

	Child (1)	Women (2)
No. of women	−0.02*	0.04***
	(0.01)	(0.01)
No. of men	−0.04***	−0.04***
	(0.01)	(0.01)
No. of children	0.02	0.01
	(0.01)	(0.01)
Fraction of female children	0.02	−0.08***
	(0.03)	(0.03)
Avg. age of women	−0.46	−0.52
	(0.92)	(0.92)
Avg. age of women^2	0.56	1.10
	(1.25)	(1.22)
Avg. age difference (men-women)	−0.07	0.58***
	(0.14)	(0.13)
Avg. age of children	6.08***	−5.02***
	(1.39)	(1.48)
Avg. age of children^2	−35.89***	27.45***
	(9.14)	(9.37)
Average education of men	−0.02***	0.01
	(0.01)	(0.01)
Average education of women	0.01	−0.02*
	(0.01)	(0.01)
Share of working men	−0.06	0.04
	(0.05)	(0.05)
Share of working women	−0.01	−0.03
	(0.03)	(0.03)
Proportion of children born during a drought	0.04*	−0.01
	(0.02)	(0.02)
Wealth Index	0.02	0.00
	(0.01)	(0.01)
I(Andhra Pradesh)	−0.12	0.03
	(0.05)	(0.05)
I(Belgavi region,Karnataka)	−0.06	0.07*
	(0.04)	(0.04)
I(Kalaburagi region,Karnataka)	−0.07	0.01
	(0.03)	(0.03)
Constant	0.41**	0.53***
	(0.18)	(0.18)
N	1,409	

Notes: Nonlinear seemingly unrelated regression estimates based on survey data. Household consists of three types of people: men, women and children. Robust standard errors in parentheses. $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

Table A14: Determinants of Children's Resource Shares by Endowment

All households with at least one adult man, one adult woman, one child born under drought conditions and one child born under non-drought conditions

	Children born during drought year(s) (1)	Children born during non-drought year(s) (2)
No. of women	–0.03**	0.02**
	(0.01)	(0.01)
No. of men	–0.01	–0.02**
	(0.01)	(0.01)
No. of children born during drought year(s)	0.00	–0.02
	(0.02)	(0.02)
No. of children born during non-drought year(s)	0.00	–0.01
	(0.01)	(0.00)
Avg. age of women	–0.16	–0.15
	(0.12)	(0.10)
Avg. age difference (men-women)	0.12	0.01
	(0.09)	(0.09)
Avg. age of children born during drought year(s)	3.45***	0.41
	(0.90)	(0.77)
Avg. age of children born during non-drought year(s)	–18.65***	–0.87
	(5.63)	(5.06)
Average education of men	0.00	0.00
	(0.00)	(0.00)
Average education of women	0.00	–0.01
	(0.00)	(0.01)
Share of working men	0.02	–0.10***
	(0.04)	(0.04)
Share of working women	0.06***	–0.01
	(0.02)	(0.02)
I(Andhra Pradesh)	–0.16**	0.12***
	(0.04)	(0.05)
I(Belgavi region,Karnataka)	0.00	–0.05
	(0.03)	(0.03)
I(Kalaburagi region,Karnataka)	–0.02***	0.34***
	(0.07)	(0.08)
Constant	0.21***	0.34***
	(0.07)	(0.08)
N	366	

Notes: Nonlinear seemingly unrelated regression estimates based on survey data. Household consists of four types of people: men, women, children born during drought year(s) and children born during non-drought year(s). Age variables are divided by 100 to ease computation. Sub-districts in the Bangalore region are taken as excluded region. Robust standard errors in parentheses. $^*p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.