Resource Sharing, Undernutrition, and Poverty: Evidence from Bangladesh

Caitlin Brown*[1], Rossella Calvi†[2], and Jacob Penglase‡[3]

[1]Georgetown University

[2]Rice University

[3]Boston College

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Abstract

Policies aimed at reducing poverty in developing countries often assume that targeting poor households will be effective in reaching poor individuals. However, intra-household inequality in resource allocation may mean many poor individuals reside in non-poor households. Using a dataset from Bangladesh that contains detailed expenditure data and anthropometric outcomes for all household members, we first show that undernourished individuals are spread across the distribution of household per capita expenditure. We then test whether this pattern is driven by the unequal allocation of food and overall resources within families. To this aim, we develop a new methodology to identify and estimate the fraction of total household expenditure that is devoted to each household member in the context of a collective household model. Our approach exploits the observability of multiple assignable goods to weaken the assumptions required by existing identification methods. We use our structural estimates to compute individual-level poverty rates that account for disparities within families. We show that women, children, and the elderly face significant probabilities of living in poverty even in households with per capita expenditure *above* the poverty threshold.

JEL Codes: D1, I31, I32, J12, J13, O12, O15

Keywords: intrahousehold resource allocation, poverty, collective model, undernutrition, Bangladesh

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*Georgetown University, Department of Economics, 37th & O St, N.W., Washington, D.C. 20057 (e-mail: cb575@georgetown.edu).

†Rice University, Department of Economics, Backer Hall 274, 6100 Main Street, Houston, TX 77005, USA (e-mail: rossella.calvi@rice.edu).

‡Boston College, Department of Economics, Maloney Hall 315, 140 Commonwealth Avenue, Chestnut Hill, MA 02467, USA (e-mail: jacob.penglase@bc.edu).

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1 Introduction

Measuring poverty is a major focus of government and international development organizations. This task is challenging for a variety of reasons, but it is especially difficult in developing countries where the necessary data are often unavailable; income is difficult to observe as most individuals are self-employed, and consumption data is onerous to collect. These problems are compounded further in the presence of intra-household inequality. Poverty rates for specific groups that may have less power within the household (e.g., women and children) are likely underestimated using household-level measures. As a result, policies designed to reduce poverty that are based on per capita expenditure may fail to reach their intended targets. In this paper, we provide measures of poverty at the individual level in terms of both nutritional status and consumption. We rely on a novel dataset that contains anthropometric measures for every household member, as well as individual-level measures of food consumption to study inequality within Bangladeshi households.

We begin our analysis by quantifying the extent of health inequality. Using the Bangladesh Integrated Household Survey (BIHS), we show that undernourished individuals are spread across the expenditure distribution. Our results suggest that only around 60 percent of undernourished adults and children are found in the bottom 50 percent of household expenditure per capita, which is consistent with recent work by Brown, Ravallion, and van de Walle (2017).

Motivated by this finding, we test whether this pattern is driven by the unequal allocation of resources within the household. Identifying the existence *and extent* of consumption inequality within the household, however, is challenging as consumption surveys are conducted at the household level and goods are shared among family members. We therefore develop a new identification method using a structural model of intra-household resource allocation. The goal of the model is to identify resource shares, defined as the share of total household expenditure allocated to each household member. We use the collective household framework of Chiappori (1988; 1992) where the key assumption of the model is that the household reaches a Pareto efficient allocation of goods. A well-known non-identification result in the collective household literature is that resource shares are not identified without adding more structure to the model.[1] Recent work by Dunbar et al. (2013) (DLP) has overcome this identification problem by using Engel curves for a single assignable good, where a good is assignable if it is consumed exclusively by a particular person type (e.g., men's clothing is assignable to men). DLP demonstrate that resource shares can be identified by imposing similarity restrictions on tastes for these assignable goods, either across individuals or across types of households.

In this paper, we extend the DLP identification results and provide a new method that substantially weakens the similarity assumptions required to identify resource shares. We are able to reduce the restrictiveness of the identification assumptions by making use of *multiple assignable goods*. In particular, we use individual-level expenditure on several food groups (e.g., cereals and vegetables). While most consumption surveys do not contain assignable food, they do contain data on multiple

[1] See Browning et al. (1994), Browning and Chiappori (1998), Vermeulen (2002), and Chiappori and Ekeland (2009).

assignable goods, such as clothing and shoes. Our approach is therefore applicable to a variety of contexts.

We apply this method to study intra-household resource sharing in Bangladesh. Our analysis makes use of the BIHS, which contains a 24-hour food module that measures individual-level food consumption for each household member. We combine this data with an annual expenditure module to construct individual-level budget shares for several different food groups. We therefore observe multiple assignable goods for each individual in the household. Building upon our identification framework, we estimate a system of Engel curves with cereals and vegetables as our assignable goods. The richness of the dataset allows us to compare the estimated *sharing rule* to individual food consumption, providing an empirical validation of the Engel curve approach.

We use our structural results to analyze inequality between men, women, boys, and girls. We find that men consume a larger share of the budget relative to women, who in turn consume relatively more than boys and girls. We do not find substantial evidence of gender inequality among children. In a household with one individual of each person type, the man consumes 35.6 percent of the budget, the woman consumes 29.4 percent, and the boy and girl each consume 17.5 percent. Our results are consistent across identification assumptions. We also study inequality between adults by age and find that older men and women consume significantly less than younger adults. Lastly, we find evidence of preferential treatment for firstborn children.

Using the structural estimates, we conduct a poverty analysis. Traditional household-level measures of poverty implicitly assume resources are allocated equally within the household. We deviate from this assumption using our predicted resource shares which account for inequality within the household. We find that household-level measures of poverty substantially understate poverty for children and women. This finding is robust to accounting for differences in need by age and gender, and is consistent with recent work by Dunbar et al. (2013), Brown et al. (2017), and Calvi (2017). Moreover, we find that men living in poor households are not necessarily themselves poor.

The policy implications of our results pertain to how anti-poverty programs should be targeted. The existing practice is to target programs at the household level. This approach is attractive since collecting data at the individual level is time consuming, costly, and possibly intrusive. Moreover, there is evidence of a wealth effect, that is, poorer households are more likely to contain undernourished individuals. So while there are several reasons for targeting anti-poverty programs in this way, our results suggest that policymakers should be more cognizant of intra-household inequality. We find that women and children are likely to be living in poverty, even in non-poor households. Anti-poverty programs that are designed to improve the relative standing of women and children in the household may be beneficial as a result.

Overall, this paper has several contributions. First, we use a novel data set to provide descriptive evidence of the extent of intra-household inequality in Bangladesh along several dimensions of welfare. Using detailed anthropometric and individual-level food data, we measure health and nutritional inequality both across and within Bangladeshi households. We then proceed to study the source of this inequality using a structural model of intra-household resource allocation. We develop a new identification method using the collective household framework to identify consumption inequality within the household. The identification results provided in this paper allow us to estimate a measure of individual-level consumption. We use the estimates of the structural model to compute individual-level poverty rates, and compare them to our health and nutritional measures of poverty. Taken together, this paper provides a complete picture of inequality in Bangladesh, and highlights the importance of effectively targeting anti-poverty programs in reaching poor individuals.

The rest of the paper is organized as follows. In Section 2, we study whether undernourished individuals concentrate in poor households. In Section 3, we present our model and identification results. In Section 4, we discuss estimation and present our structural results. A comparison between individual and household poverty rates is provided in Section 5. Section 6 concludes.

2 A Descriptive Analysis of Nutrition, and Intra-household Inequality

Bangaldesh has seen a large reduction in child undernourishment over the past two decades: Headey (2013) reports reductions of more than 1 percentage points per annum in the proportion of underweight and stunted children. However, undernutrition still remains a serious concern: recent figures find that 36% of children under 5 are stunted, 14% are wasted, and 19% of women are underweight (NIPORT, 2016). Undernutrition can stem from poor dietary intake (such as low caloric intake or protein deficiencies) or disease (which oftentimes results in poor dietary intake), and is usually a consequence of food insecurity or poor health environments. It is also an important dimension of individual poverty: combating undernutrition in developing countries has been a key component of the Millennium Development Goals and also features prominently in the Sustainable Development Goals.

For the following analysis as well as for the estimation of the structural model, we use the first two waves of the Bangladesh Integrated Household Survey (BIHS) conducted in 2011/12 and 2015, respectively. This nationally-representative survey was implemented by the International Food Policy Research Institute (IFPRI) and was designed specifically to study issues relating to food security and intrahousehold inequality. In 2011, 6,500 households were drawn from 325 villages. Households were interviewed beginning in October, 2011 and the first wave was completed by March, 2012. Households were then resurveyed in 2015.[2]

The BIHS collected anthropometric measures for all household members in both survey rounds. For individuals aged 15 years and over, we calculate the body-mass index (BMI), defined as weight (in kilograms) divided by height (in meters) squared.[3] We categorize adult individuals to be underweight if their BMI is less than 18.5 according to the WHO classification (World Health Organization,

[2]Attrition was relatively low at 1.26 percent per year. The survey team included a male and female enumerator for each household. Over a two day period, the male enumerator interviewed the head adult male in the household, and the female enumerator interviewed the head adult female, who was typically the wife of the male household head. These interviews were closely monitored by the field supervisor and extensive measures were taken to ensure a high survey quality.

[3]Following DHS convention, we exclude women who are pregnant or lactating at the time of the survey. In our sample, 12% of women in 2011 and 10% of women in 2015 are pregnant or lactating.

Table 1: BIHS Nutritional Outcomes

	2011			2015		
	Adults	Children		Adults	Children	
	Underweight	Stunting	Wasting	Underweight	Stunting	Wasting
Male	31.4	45.6	13.7	29.5	37.8	17.2
Female	30.4	45.2	14.0	25.2	34.0	18.6
Total	30.9	45.4	13.9	27.4	36.0	17.9

Note: BIHS data. Statistics are population weighted.

2006). We exclude individuals who have a BMI value smaller than 12 or greater than 60 as these values are almost certainly due to measurement error.

For children 5 years and younger, we construct height-for-age and weight-for-height z-scores which are used to indicate stunting or wasting respectively.[4] A child is considered stunted if her height-for-age z-score is two standard deviations below the median of the reference group, and wasted if her weight-for-height z-score is less than two standard deviations below the median. While both key indicators of undernutrition for children, stunting and wasting arise out of different circumstances: the former is typically an indicator of chronic nutritional deficiencies and has more severe consequences for long-term outcomes, while the latter is often due to short-term deprivations or illnesses.

Table 1 lists summary statistics for nutritional outcomes for adults and children across both survey rounds. Among all adults 15 years and older, 27 percent are underweight in 2015, while 36 percent of children are stunted and 18 percent are wasted. Mirroring existing findings, adult undernutrition and child stunting has improved over time, while wasting in the 2015 round is substantially higher than in the earlier round.[5] Men and boys are more likely to be underweight and stunted than women and girls.[6] Excluding older (over 49) and young adults (under 20) reduces the overall incidence of undernutrition among adults to 24 percent in 2011 and 20 percent in 2015.

2.1 Nutritional Outcomes and Intra-household Inequality

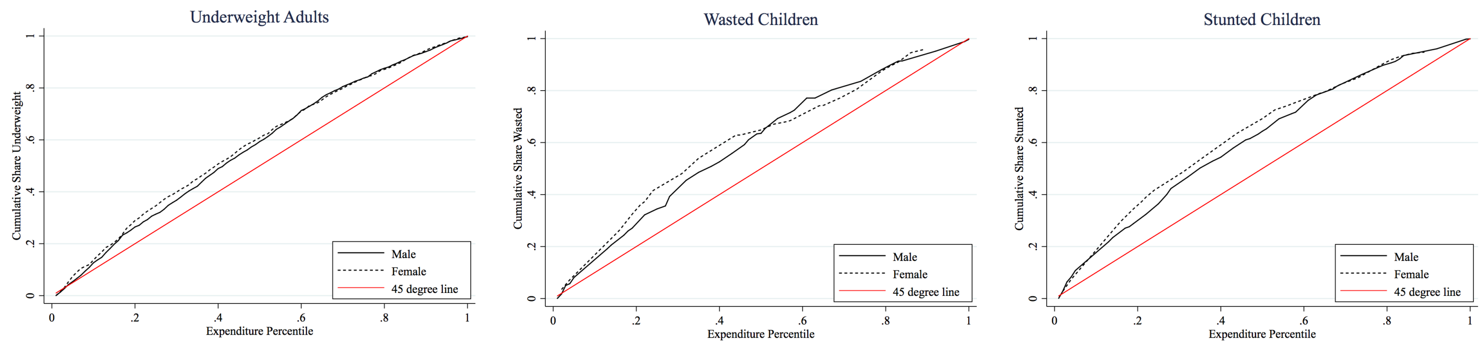
To examine how the incidence of undernutrition among adults and children varies with per capita household expenditure, we construct concentration curves. These curves show the cumulative share of undernourished individuals by cumulative household expenditure percentile (that is, households ranked from poorest to richest). A higher degree of concavity implies that a larger share of undernourished individuals are found in the poorest households. For example, if all undernourished individuals lived in poor households, the concentration curve would reach its maximum (equal to 1) at the poverty rate and become flat for the remaining expenditure percentiles. If individuals faced the same probability of being underweight at any point of the per capita expenditure distribution,

[4] The Stata command zscore06 is used to convert height (in centimeters) and weight (in kilograms) along with age in months into a standardized variable. These z-scores are standardized using the WHO 2006 classification and follow practice used by major health surveys.

[5] This is consistent with Headey et al. (2015), who find a large reduction in child stunting between 1997 and 2011. NIPORT (2016) report similar levels of stunting and wasting using DHS 2014 data.

[6] Svedberg (1990), Svedberg (1996), Wamani et al. (2007) and Brown et al. (2017) demonstrate similar findings for sub-Saharan Africa, while Klasen (1996) finds an anti-female bias in the same region. For Pakistan,Hazarika (2000) finds that girls are as nourished (or better) than boys.

then the concentration curve would coincide with the 45-degree line.



Underweight Adults | Wasted Children | Stunted Children

Figure 1: Undernutrition Concentration Curves (2015)

Figure A3 presents concentration curves for adults and children. Given the similarity of the curves between the two survey waves, we focus here on the 2015 sample only. While there is concavity across adults and children as well as by gender, it is striking to note how close the curves are to the 45-degree line. For example, only around 65 percent of undernourished adults and children are found among the bottom 50 percent of households. Stunted and wasted girls tend to be found in poorer households than boys (though this is true only up until the 60th percentile), while the difference between men and women is negligible.

There are potential biases that could be driving the above results.[7] The first is that the relatively weak relationship between household expenditure and undernutrition, particularly among poorer households, could be driven by excess mortality among the undernourished; that is, the sample does not include those who are too undernourished to survive (also often known as survivorship bias).[8] However, Boerma et al. (1992) report that the effect is marginal unless the mortality rates between the cohorts is very large; Moradi (2010) also finds little evidence of survivorship bias. If excess mortality is concentrated among the poor, then we expect that the relationship between undernutrition and household expenditure to be weaker. However, given that we find undernourished individuals across the expenditure distribution, we do not believe it fully explains our findings.[9]

Another possible bias is that there is measurement error in the anthropometric outcomes, particularly among very young children.[10] To account for potential measurement error in the stunting and wasting indicators, we re-estimate the concentration curves excluding children younger than 18 months. We also re-estimate the curves excluding teenagers, who may still be growing, and older adults, who may be frail (or ill) and diffiult to measure. The results are similar (see Appendix).

Given that undernourished individuals are found across the expenditure distribution, how much variation in nutritional status is there within households? Since the measures of nutritional status differ for adults and children, we create an indiciator variable set equal to 1 if an adult is under-

[7]See Brown et al. (2017) for a summary.

[8]According to World Bank estimates, the mortality rate in Bangladesh for children under 5 in 2015 was 36.3 per 1000 live births (the average for South Asia was 50.3). Male children had a higher mortality rate (38.8) than female children (33.7).

[9]Brown et al. (2017) simulate the potential effect of selective child mortality and find little difference in their results.

[10]Larsen et al. (1999) and Agarwal et al. (1999) find evidence of misreporting of child age in DHS surveys, which impacts height-for-age z-scores. Larsen et al., however, find little impact on estimated rates of stunting. Additionally, Ulijaszek and Kerr (1999) note that height and weight are least susceptible to measurement error, while Jamaiyah et al. (2010) concludes that height and weight measurements for children under 2 are reliable.

weight or if a child is either stunted or wasted and zero otherwise.[11] Using a Bernoulli distribution to calculate the mean and variance, we find that on average 35% of individuals within a household are undernourished in 2011, and 31% in 2015. The variance in household undernutrition is 0.14 and 0.13 in 2011 and 2015 respectively.

Figure 2 plots the average rate of household undernourishment by household expenditure percentile for 2015 (the Appendix provides the same figure for 2011). As expected, poorer household have a higher average rate of undernourishment than wealthier ones. However, it is also the case that around 20% of household members in the wealthiest households are undernourished. In line with evidence from the concentration curves, we see that there is substantial within households variation in nutritional outcomes, and this persists across expenditure percentiles.

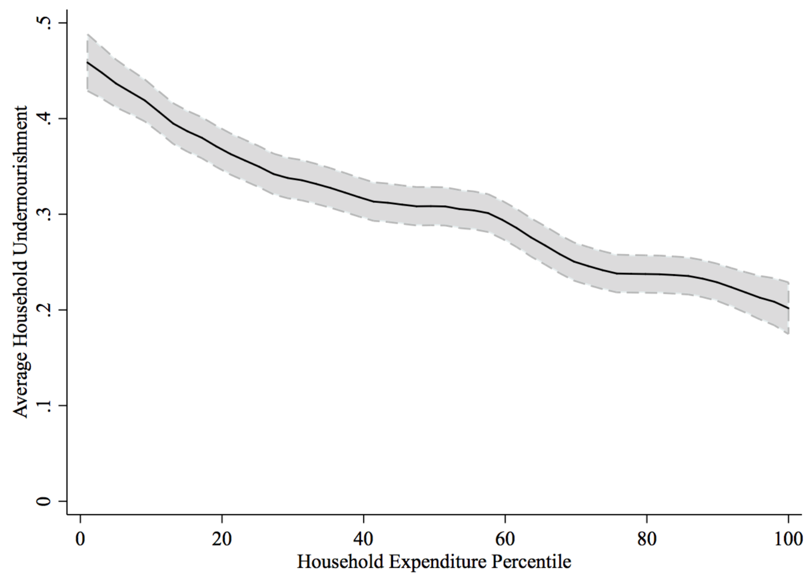


Figure 2: Average Household Undernourishment by Household Expenditure Percentile

2.2 Caloric Intake, Individual Food Consumption and Intra-household Inequality

A key advantage of the BIHS is that it contains a measure of individual food consumption for each household member. This measure is based on a 24 hour recall of individual dietary intakes and food weighing.[12] In conducting the individual dietary module, the female enumerator visited each household and surveyed the woman most responsible for the household's food preparation. The enumerator first collected information regarding the food items consumed by the household the previous day. This information included both the raw and cooked weights of each ingredient. For example, the respondent would tell the enumerator that the household had jhol curry for lunch, and would then provide the weight of each ingredient (onions, potatoes, fish, etc.) used in the recipe.

[11] Sahn and Younger (2009) normalize BMI by age and gender to achieve a comparable measure across individuals. However, given that BMI for children younger than 15 can be quite unreliable, we prefer to exclude this age group and use an indicator variable for underweight, stunting, and wasting. We also follow DHS convention, as DHS surveys do not include anthropometric measures for household members between 6 and 14 years of age.

[12] Other large-scale household surveys have been conducted in Bangladesh to study household-level food consumption, such as the Household Income and Expenditure Survey, but no nationally representative survey has collected both individual-level food consumption and anthropomorphic measurements.

Next the enumerator would ask what share of that meal was consumed by each household member. If a household member did not have the meal, the enumerator determined the reason. Lastly, the survey accounted for food given to guests, animals, or food that was left over.

An assumption we are implicitly making in the following analyses is that the measure of individual food consumption over the previous day is representative of that individual's food consumption over the year. Several precautions are taken in the survey design to mitigate concern about this assumption. First, households are asked if the previous day was a "special day" in terms of the types of food eaten. If yes, then the respondent was asked to describe the most recent "normal day". Moreover, in the 2015 wave of the BIHS, a 10 percent subsample of households completed the 24 hour food recall module on multiple visits. Comparing the computed shares across days reveals little variation, suggesting the 24 hour food recall data is mostly representative. Lastly, the female enumerator counts the number of "guests" the household fed during the specified day. If this figure is above one, we drop the household from the estimation sample.

From the measure of individual food consumption, we are able to derive a person's caloric intake. We can also derive other measures of nutritional adequecy such as protein intake, which is often used to indicate the quality of calories consumed. For example, an individual may have a high caloric intake but consisting of foods with low nutritional value, such as foods with a high fat or sugar content. These are important measures of individual welfare in Bangladesh: for official poverty measures, the poverty line is based on the cost of a fixed bundle of food goods that provides minimum nutritional requirements for the average individual, to which a non-food allowance is then added (World Bank, 2008).[13] Nutritional intake is also directly related to the nutritional outcomes detailed in the previous section.

Nutritional requirements, and hence food consumption, will differ among individuals. Young children, for example, will require lower required caloric intake than adult males. In standard data sources, caloric intake and food consumption are measured at the household level, then divided by household size to obtain a per capita measure that typically ignores differences in needs between individuals.[14] Given that our data is at the individual level, to allow for more consistent comparisons across individuals we scale caloric and protein intake to acount for age and gender.[15] We exclude children younger than 12 months of age, since many of those will rely on breast milk as part of their caloric intake (this is not measured by the survey). For food consumption, we use the scale based on caloric requirements. We do not account for potential differences in activity levels between individuals, and for food consumption, we do not adjust for household size. Table 2 presents descriptive statistics for the actual and scaled caloric intake, protein intake, and individual

[13] This is also known as the cost of basic needs (CBN) method. In the past, alternative methods of poverty measurement have been used in Bangladesh, such as the food-energy intake (FEI) method. Ravallion and Sen (1996) and Wodon (1997) review the two methods and their resulting impact on poverty estimation. More recent work has evaluated the use of multidimensional poverty indices - see, for example, Bhuiya et al. (2012), Chowdhury and Mukhopadhaya (2012) and (Chowdhury and Mukhopadhaya, 2014).

[14] Previously, Bangladesh used a threshold of 2122 calories per day and person, with a household deemed poor if the household per capita caloric intake was below this threshold Wodon (1997).

[15] We draw from the 2015-2020 Dietrary Guidelines for Americans which contain recommended caloric intake for males and females by age group. We scale to 2000 calories per day, which is the amount typically recommended for moderately active adults. We similarly scale protein intake to 46 grams per day, the recommended amount for most adults.

food consumption variables for adults and children using data from the 2015 survey.[16]

Table 2: Individual Caloric and Protein Intake

	Adults		Children	
	Actual	Scaled	Actual	Scaled
Caloric Intake				
Male	2415	1889	1360	1738
Female	2084	2097	1302	1750
Total	2237	2001	1331	1744
Protein Intake				
Male	59.2	49.1	33.6	62.3
Female	51.0	51.0	32.2	52.9
Total	54.8	50.1	32.9	57.6
Food Consumption				
Male	55530	43475	30649	39057
Female	48246	48554	30063	40411
Total	51614	46206	30357	39737

Note: BIHS data 2015. Statistics are population weighted. Consumption is in local currency units

As expected, all three measures are increasing in household per capita expenditure: the elasticities are 0.142, 0.215 and 0.524 for scaled caloric intake, protein intake and food consumption respectively.[17] While this suggests that overall inequality in each of these measures is likely to be high, we are particularly interested in the differences between individuals within a household. To separate the contributions of within-household inequality and between-household inequality to overall inequality, we use the Mean Log Deviation measure of inequality.[18] Unlike the more popular Gini index, MLD is exactly decomposable into between- and within-group components. Following Ravallion (2016), the MLD in caloric intake is equal to:

$$MLD = \frac{1}{N}\sum_{i=1}^{N} \ln\left(\frac{\bar{c}}{c_i}\right) \tag{1}$$

where c_i is individual caloric intake, $\bar{c}$ is average caloric intake among all individuals, and N is the total number of individuals. Assuming that each individual i belongs to household j that has a total of N_j members and an average household caloric intake of c_j, we can decompose (1) as

[16]We have data on individual caloric and protein intake along with individual food consumption for all household members. Adults are defined as a household member 15 years or older, and children as 14 years or younger.

[17]For the unscaled versions, the elasticies are 0.217, 0.325, and 0.601 respectively. All are significant at $p < 0.001$.

[18]First proposed by Theil (1967) as part of the "generalized entropy measures".

follows:

$$
\begin{aligned}
MLD &= \ln \bar{c} - \frac{1}{N}\sum_{j=1}^{N}\sum_{i=1}^{N_j} \ln c_{i,j} \\
&= \frac{1}{N}\sum_{j=1}^{N} N_j \ln \bar{c_j} - \frac{1}{N}\sum_{j=1}^{N}\sum_{i=1}^{N_j} \ln c_{i,j} + \ln \bar{c} - \frac{1}{N}\sum_{j=1}^{N} N_j \ln \bar{c_j} \\
&= \frac{1}{N}\sum_{j=1}^{N}\left(N_j \ln \bar{c_j} - \sum_{i=1}^{N_j} \ln c_{i,j}\right) + \frac{1}{N}\left(\sum_{j=1}^{N} N_j \ln \bar{c} - \sum_{j=1}^{N} N_j \ln \bar{c_j}\right) \\
&= \underbrace{\frac{1}{N}\sum_{i=1}^{N} \ln\left(\frac{\bar{c_j}}{c_{i,j}}\right)}_{\text{Within}} + \underbrace{\frac{1}{N}\sum_{j=1}^{N} N_j \ln\left(\frac{\bar{c}}{c_j}\right)}_{\text{Between}}
\end{aligned}
\tag{2}
$$

We estimate (2) for the three nutritional intake variables using both the unscaled and scaled versions of the variable. Given the properties of MLD, we exclude individuals with zero values. Results are presented in Table 3. Food consumption has the highest overall inequality relative to caloric and protein intake (for both scaled and unscaled). For caloric and protein intake, within household inequality represents around 70% and 60% of total inequality, and almost 50% and 40% once differences in regards to age and gender are accounted for. Within-household inequality is less prevalent for individual food consumption, at 40% of total inequality and 20% once adjusted for age and gender.

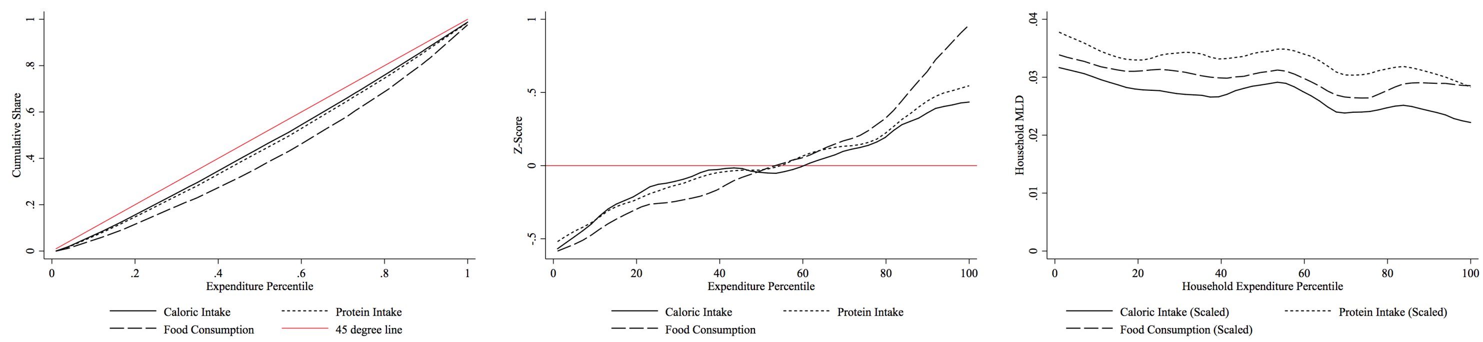
Table 3: Inequality in Nutritional Intake

	Caloric Intake		Protein Intake		Food Consumption	
	Actual	Scaled	Actual	Scaled	Actual	Scaled
Total MLD	0.115	0.056	0.135	0.088	0.201	0.150
Within (%)	70.5	47.6	60.4	37.5	38.7	20.0
Between (%)	30.0	52.2	39.2	59.0	60.1	76.7
Household MLD	0.072	0.024	0.073	0.030	0.070	0.028

Note: BIHS data 2015. Within and between components of MLD are given as percentages of total MLD.

How does inequality vary across the expenditure distribution? For between-household inequaltiy, we construct concentration curves for the household averages of caloric intake, protein intake, and food consumption; that is, the cumulaitve share of average household nutritional intake at each household per capita expenditure percentile. For within-household inequality, we use equation (1) to calculate a household-level MLD for the three variables; the last line in Table 3 lists the average values. Figure **??** shows the results for the scaled variables (the corresponding figure for the actual values can be found in the Appendix).

Following Table 3, we see the lower between household inequality in average household caloric and protein intake relative to average individual food intake, particularly at the lower end of the expenditure distribution. For within-household inequality (Panel B), protein intake has the highest



A) Between Inequality A2) Between Inequality - Z-scores B) Within Inequality

Figure 3: Between and Within Inequality by Expenditure Percentile (Scaled)

levels of intra-household inequality at virtually all household expenditure percentiles; caloric intake the lowest. We also see a negative relationship between household MLD and household expenditure for all three indicators.[19] In other words, wealthier households tend to have less within-household inequality in nutritional intake than poorer households. Nevertheless, on average, household MLD is far from zero at every level of household expenditure: similar to Figure 2, we find intra-household inequality across the expenditure distribution.

3 Theoretical Framework and Identification Results

In this section, we set out a collective household model to identify and estimate resource sharing among co-resident family members. Since only half of households in our sample comprise nuclear households (i.e., consisting of two parents and their children), we develop a flexible theoretical framework for extended families that can account for the presence, e.g., of grandparents, aunts, uncles, and cousins.

3.1 Collective Households and Resource Sharing

Let households consist of J categories of *people* (indexed by j), such as children, men, women, and the elderly. Denote the number of household members of category j by $\sigma_j = 0, ..., N_j$, with $\sigma_j \in \{\sigma_1, ..., \sigma_J\}$. Households differ according to their composition or *type*, that is the number of people in each category. We denote a household type by s. In practice, households differ also along a wider set of observable attributes, such as age of household members, location, and other socio-economic characteristics. While household characteristics may affect both preferences and resource shares, we omit household characteristics and distribution factors while discussing the model to reduce notational clutter.[20]

Each household consumes K types of goods with market prices $p = (p^1, ..., p^K)$. Let $z = (z^1, z^2, ..., z^K)$ be the vector of observed quantities of goods purchased by each household and $x_j = (x_j^1, x_j^2, ..., x_j^K)$ be the vector of *private good equivalents* which is then divided among the household members. As

[19]The elasticities are -0.166, -0.144, and -0.135 for caloric, protein and food intake respectively.

[20]Any characteristics affecting bargaining power and how resources are allocated within the household, but neither preferences nor budget constraints, are called *distribution factors* (Browning et al. (2014)). Since such variables are not required for identification, we exclude them from our discussion.

in Browning et al. (2013) (hereafter BCL) and Dunbar et al. (2013) (hereafter DLP), we 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_s such that $z = A_s \sum_{j=1}^{J} \sigma_j x_j$, therefore allowing for the sum of the private good equivalents to be weakly larger than what the household purchases due to the sharing of goods.[21]

Each household member has a monotonically increasing, continuously twice differentiable and strictly quasi-concave utility function over a bundle of K goods. Let $U_j(x_j)$ be the sub-utility function of individual j over her consumption. Each individual's total utility may depend on the utility of other household members, but we assume it to be weakly separable over the sub-utility functions for goods.

The household chooses what to consume using the maximization program:

$$\begin{gathered} \max_{x_1,\ldots,x_J} \widetilde{U}_s[U_1(x_1),\ \ldots.\ ,\ U_J(x_J),\ p/y] \\ \text{such that} \\ y = z_s^{'} p \ \text{ and } \ z_s = A_s \sum_{j=1}^{J} \sigma_j x_j \end{gathered} \tag{3}$$

where the function $\widetilde{U}$ describes the social welfare function or bargaining process of the household. A function $\widetilde{U}$ exists because the we assume the intra-household allocation to be Pareto efficient.

The solution of the problem above yields the bundles of private good equivalents that each household member consumes. Pricing these vectors at within household shadow prices $A_s^{'} p$ (which may differ from market prices because of the joint consumption of goods within the household) yields the fraction of the household's total resources that are devoted to each household member, i.e., their resource share η_{js}.

Following the standard characterization of collective models (based on duality theory and decentralization welfare theorems), the household program can be decomposed in two steps: the optimal allocation of resources across members and the individual maximization of their own utility function. Conditional on knowing η_{js}, household members choose x_j as the bundle maximizing U_j subject to a Lindahl type shadow budget constraint $\sum_k A_k p^k x_j^k = \lambda_t y$. By substituting the indirect utility functions $V_j(A'p, \eta_{js} y)$ in equation (3), the household program simplifies to the choice of optimal resource shares subject to the constraint that total resources shares must sum to one. For simplicity, we assume all household members of a specific category to be the same (i.e., common to all men, all women, boys, and girls) and interpret resources to being divided equally among within categories. In estimation, however, we allow preference parameters and resource shares to vary according to a set of household characteristics, including family composition and the age of the household members, so that, e.g., households with older children may allocated more resources to children than households with younger children.

[21] Note that each household member?s resource share may differ from those of other members, but all members face the same shadow price vector $A_s^{'} p$. For a private good, which is never jointly consumed, $A_{sk} = 1$. Also note that this framework also allows for a simple household production technology with constant returns to scale through which market goods are transformed into household commodities.

Define a *private* good to be a good that does not have any economies of scale in consumption – e.g., food – and an *assignable* good to be a private good consumed exclusively by household members of known category j – which we observe in the BIHS data. While the demand functions for goods that are not private are more complicated, the household demand functions for private assignable goods have much simpler forms and are given by:

$$W_{js}^{k}(y,p) = \sigma_j \eta_{js}(y,p)\ \omega_{js}^{k}(\eta_{js}(y,p)y,\ A_s^{'}p) \tag{4}$$

where W_{js}^{k} is the demand function of each household member when facing her personal shadow budget constraint, η_{js} is her resource share, and σ_j is the number of individuals in group j. Note that one cannot just use W_{js} as a measure of η_{js}, because different household members may have very different tastes for their private assignable good. For example, a woman might consume the same amount of resources than her husband but less food because she derives less utility from it (e.g., she has lower caloric requirements). Following and expanding on a methodology developed in DLP, we instead estimate food Engel curves for each group j. We then implicitly invert these Engel curves to solve for resource shares.

3.2 Identification of Resource Shares

The main goal of the model outlined above is to identify resource shares. We follow the methodology of DLP who identify resource shares by comparing Engel curves for private assignable goods across either people, or household sizes.

Let $p = [p_j,\ \bar{p},\ \tilde{p}]$ for $j \in \{1,...,J\}$ where p_j are the prices of the private assignable goods for each person type j. We define $\bar{p}$ to correspond to the subvector of private non-assignable good prices, and $\tilde{p}$ to correspond to the subvector of shared good prices.

We assume individuals have piglog (price independent generalized logarithmic) preferences over the private assignable goods in the empirical section and this functional form facilitates a discussion of identification so we use it henceforth.[22] In the Appendix, we discuss identification with a more general functional form. The standard piglog indirect utility function takes the following form: $V_j(p,y) = e^{F_j(p)}\Big(\ln y - \ln a_j(p)\Big)$. By Roy's Identity, the budget share functions are written as follows: $w_j(y,p) = \alpha_j(p) + \gamma_j(p)\ln y$, where the budget share functions are linear in $\ln y$. The identification results in DLP are (at least partially) based on semi-parametric restrictions on the shape parameter $\gamma_j(p)$. Below we briefly summarize the DLP approach. We then discuss in detail how the richness of the our dataset allows us to weaken these restrictions.

3.2.1 Similarity Across People (SAP) and Similarity Across Types (SAT)

DLP make two key assumptions for the identification of resource shares. First, they assume that resource shares are independent of household expenditure, and secondly, they impose one of two

[22] Jorgenson et al. (1982) Translog demand system and the Deaton and Muellbauer (1980) Almost Ideal Demand System have Engel curves of the piglog form, and piglog Engel curves were also used in empirical collective household models estimates by DLP.

semi-parametric restrictions on individual preferences for the assignable good: either preferences are *similar across people* (SAP), or preferences are *similar across household types* (SAT).[23]

The indirect utility function for SAP takes the following form: $V_j(p,y) = e^{F(p)}(\ln y - \ln a_j(p))$, with budget share functions $w_j(y,p) = \alpha_j(p) + \gamma(p)\ln y$.[24] Notice that $F(p)$ and $\gamma(p)$ do not have a j subscript, they does not vary across family members. Substituting this budget share function into Equation (4) results in the following household-level Engel curves:

$$W_{js} = \eta_{js}[\alpha_{js} + \gamma_s \ln \eta_{js}] + \gamma_s \eta_{js} \ln y. \tag{5}$$

Thus, resource shares are identified by comparing the Engel curve slopes across individuals within the same household. To fix ideas, suppose that the household receives a positive income shock (i.e., log expenditure increases). If as a result men's food consumption increases by a lot, and women's food consumption be relatively less, then we can infer that the man in the household *controlled* more of the additional expenditure, and therefore has a higher resource share. More formally, note that from an OLS-type regression of the assignable good budget shares on log expenditure, the product $c_j = \gamma_s \eta_{js}$ is identified. Then, since resource shares sum to one, it follows that $\sum_j c_j = \sum_j \gamma_s \eta_{js} = \gamma_s$, which allows to solve for $\eta_{js} = c_{js}/\gamma_s$.

The alternative preference restriction DLP impose is SAT, which is consistent with the following indirect utility function: $V_j(p,y) = e^{F_j(p_j,\tilde{p})}(\ln y - \ln a_j(p))$ with budget share functions $w_j(y,p) = \alpha_j(p) + \bar{\gamma}_j(p_j,\bar{p})\ln y$. Substituting this budget share function into Equation (4) results in the following household-level Engel curves:

$$W_{js} = \eta_{js}[\alpha_{js} + \gamma_j \ln \eta_{js}] + \gamma_j \eta_{js} \ln y. \tag{6}$$

Unlike SAP, preferences differ relatively flexibly across individuals. However, SAT restricts how the prices of shared goods enter the utility function. In effect, it restricts changes in the prices of shared goods to have a pure income effect on the demand for the private, assignable goods. With SAT, the shape preference parameter does not vary across household types since $\bar{\gamma}_j(p_j,\bar{p})$ is not a function of the prices of shared goods $\tilde{p}$, and therefore does not vary with household size. Resource shares are identified by comparing the Engel curve slopes across household sizes. We can use a simple counting exercise to demonstrate that the order condition holds. Suppose there are three types of individual's j with three household sizes s. Then there are nine total Engel curves (three for each household size). There are nine unknowns: three preference parameters γ_j and six resource shares.[25] So the order condition is satisfied.

Both SAP and SAT are practical ways to recover resource shares using expenditure on a single

[23]An alternative way to identify resource shares within this framework is to use distribution factors ((variables affecting the decision process without affecting preferences or the budget constraint) in place of semi-parametric restrictions on the assignable goods (Dunbar et al. (2017)). Identification comes from observing that resource shares must some to one for different values of the distribution factor. This results in additional equations in the model which yields identification without restricting the preference parameter $\gamma_j(p)$. Note that valid distributions factors may be difficult to identify and might not be available from household expenditure data. Nevertheless, in section **??** we apply this approach to test our identifying preference restrictions.

[24]This is a weaker form of shape invariance. See Pendakur (1999) for details.

[25]Since resource shares sum to one, we only have to identify $j-1$ resource shares for each household type s.

private assignable good. Since we observe *multiple* private assignable goods for each person type, we develop two new approaches that employ this additional data to weaken the necessary preference restrictions.

3.2.2 Differenced SAT (D-SAT)

In the first approach, we demonstrate that the SAT restriction of DLP can be substantially weakened by using multiple private assignable goods. Unlike DLP, we do not assume that preferences for the assignable goods are similar across household sizes, but rather, we allow preferences to differ considerably across household sizes, but require them to do so in the same way across two different private assignable goods.[26] For our identification strategy to work, we therefore require observability of at least two such goods ($k = 1, 2$) for each person type j, with prices denoted by p_j^1, and p_j^2, respectively. For reasons that will become clear later on, we call our approach *Differenced SAT*, or D-SAT.

We can rewrite the piglog indirect utility function $V_j(p, y) = e^{F_j(p)}(\ln y - \ln a_j(p))$. Our assumption requires that

$$\frac{\partial F_j(p)}{\partial p_j^1} - \frac{\partial F_j(p)}{\partial p_j^2} = \theta_j(p_j^1, p_j^2, \bar{p}) \tag{7}$$

where $\theta_j(p_j^1, p_j^2, \bar{p})$ does not vary across household sizes.[27]

D-SAT holds if $F_j(p)$ takes the following form: $F_j(p) = b_j(p_j^1 + p_j^2,\ \bar{p},\ \tilde{p}) + r_j(p_j^1,\ p_j^2,\ \bar{p})$, where $r_j(\cdot)$ does not depend on the prices of shared goods, and therefore does not vary by household size. Moreover, p_j^1 and p_j^2 are additively separable in $b_j(\cdot)$ which results in preferences that differ across households sizes in the same way across goods.

We can use Roy's Identity to derive the budget share functions for goods $k \in \{1, 2\}$:

$$\frac{h_j^k(p, y)}{y} = \Big(\frac{\partial b_j(p_j^1 + p_j^2,\ \bar{p},\ \tilde{p})}{\partial p_j^k} + \frac{\partial r_j(p_j^1\ , p_j^2,\ \bar{p})}{\partial p_j^k}\Big) \ln y + \alpha_j^k(p) \tag{8}$$

The household-level Engel curves for person j's two assignable goods can then be written as follows:

$$\begin{aligned} W_{js}^1 &= \eta_{js}[\alpha_{js}^1 + (\beta_{js} + \gamma_j^1) \ln \eta_{js}] + (\beta_{js} + \gamma_j^1)\eta_{js} \ln y \\ W_{js}^2 &= \eta_{js}[\alpha_{js}^2 + (\beta_{js} + \gamma_j^2) \ln \eta_{js}] + (\beta_{js} + \gamma_j^2)\eta_{js} \ln y \end{aligned} \tag{9}$$

If we compare equations (6) and (9), we can see how we weaken the SAT restriction. As in DLP, preferences for the assignable goods are allowed to differ across people, both in α_{js}^k and in γ_j. Unlike DLP, we also allow preferences to differ across household sizes in the slope parameter β_{js}.[28] However, we restrict preferences to differ across household sizes in the same way across goods,

[26] Having a third assignable good would not meaningfully reduce the assumptions necessary for identification.

[27] DLP impose a stronger version of this with $\partial F_j(p)/\partial p_j^1 = \tilde{\theta}_j(p_j^1, \bar{p})$.

[28] DLP do not require preferences for the assignable good to be identical across household size, as the intercept parameter α_{js} does vary with household size.

that is, β_{js} is the same for both goods. SAT with one good is therefore a special case of D-SAT with $\beta_{js} = 0$.

To better understand our assumptions, consider the following example. Suppose we observe assignable cereals and proteins (meat, dairy, and fish) for men, women, and children in a sample of nuclear households with one to three children. The SAT restriction would require that the man's marginal propensity to consume cereals be the same regardless of the number of children in the household. With D-SAT, we allow his marginal propensity to consume cereals to differ considerably across household sizes. However, we require that the difference in the man's preferences for cereals across household sizes be similar to the difference in his preferences for proteins across household sizes. The same must be true for women and children.

Our identification assumption can be understood a different way by rewriting equation (9); let $\psi^1_{js} = \beta_{js} + \gamma^1_j$ and $\psi^2_{js} = \beta_{js} + \gamma^2_j$ be the shape preference parameters for goods 1 and 2, respectively. With the SAT restriction, DLP implicitly assume that $\psi^1_{js} - \psi^1_{js+1} = 0$. Our alternative restriction allows this quantity to be nonzero, however, it has to be the same for both goods. Stated differently: $\psi^1_{js} - \psi^1_{js+1} = \psi^2_{js} - \psi^2_{js+1}$. Preferences for these goods should differ in the same way across household sizes.

To show that resource shares are identified, first let $\lambda_{js} = \beta_{js} + \gamma^1_j$ and $\kappa_j = \gamma^2_j - \gamma^1_j$. Then we can rewrite system (9) as follows for $j \in \{1, ..., J\}$:

$$W^1_{js} = \ldots + \eta_{js}\, \lambda_{js} \ln y$$
$$W^2_{js} = \ldots + \eta_{js}\, (\lambda_{js} + \kappa_j) \ln y$$

If we then subtract person j's budget share function for good 2 from their budget share function for good 1, we are left with a set of equations that are identical to the SAT system of equations from DLP: $W^1_{js} - W^2_{js} = \ldots + \eta_{js}\, \kappa_j \ln y$. An OLS-type regression of the observable budget shares on log expenditure identifies the slope coefficient for each person type j. Comparing the slopes of the Engel curves across household sizes, and assuming resource shares sum to one allows us to recover the resource share parameters.

The order condition is satisfied with J household types. To see this, first note that there are J Engel curves for each of the J household types, resulting in J^2 equations. Moreover, for each household type resource shares must sum to one. This results in $J(J+1)$ equations in total. In terms of unknowns, there are J^2 resource shares, and J preference parameters (κ_j), or $J(J+1)$ unknowns in total. A proof of the rank condition can be found in the appendix.

3.2.3 Differenced SAP (D-SAP)

In the second approach, we demonstrate that the SAP restriction of DLP can also be substantially weakened by using multiple private assignable goods. Unlike DLP, we do not assume that preferences for the assignable goods are similar across people, but rather, we allow preferences to differ considerably across people, but require them to do so in the same way across two different private assignable goods. Here, we call our assumption *Differenced Similar Across People*, or D-SAP. Under this assumption we require that

$$\frac{\partial F_j(p)}{\partial p_j^1} - \frac{\partial F_j(p)}{\partial p_j^2} = \theta(p) \tag{10}$$

where $\theta(p)$ does not vary across people.[29]

Our assumption holds if $F_j(p)$ takes the following form: $F_j(p) = b_j(p_j^1 + p_j^2,\ \bar{p},\ \tilde{p}) + r(p)$, where $r(p)$ does not vary across people. Moreover, p_j^1 and p_j^2 are again additively separable in $b_j(\cdot)$ which results in preferences that differ across people in the same way across goods.

We again use Roy's Identity to derive the budget share function for goods $k \in \{1,2\}$:

$$\frac{h_j^k(p,y)}{y} = \Big(\frac{\partial b_j(p_j^1 + p_j^2,\ \bar{p},\ \tilde{p})}{\partial p_j^k} + \frac{\partial r(p)}{\partial p_j^k}\Big) \ln y + \alpha_j^k(p) \tag{11}$$

The household-level Engel curves for person j's two assignable goods can then be written as follows:

$$\begin{aligned} W_{js}^1 &= \eta_{js}[\alpha_{js}^1 + (\beta_{js} + \gamma_s^1)\ln \eta_{js}] + (\beta_{js} + \gamma_s^1)\eta_{js} \ln y \\ W_{js}^2 &= \eta_{js}[\alpha_{js}^2 + (\beta_{js} + \gamma_s^2)\ln \eta_{js}] + (\beta_{js} + \gamma_s^2)\eta_{js} \ln y \end{aligned} \tag{12}$$

If we compare equations (5) and (12), we can see how we weaken the SAP restriction. As in DLP, preferences for the assignable goods are allowed to differ entirely across household sizes, both in α_{js}^k and in γ_s. Unlike DLP, we also allow preferences to differ across people in the slope parameter β_{js}.[30] However, we restrict preferences to differ across people in the same way across goods, that is, β_{js} is the same for both goods. SAP with one good is therefore a special case of our set of assumptions with $\beta_{js} = 0$.

We can again use an example to illustrate the differences between DLP and our method. Suppose we observe assignable cereals and proteins (meat, dairy, and fish) for men, women, and children in a sample of nuclear households with one to three children. The SAP restriction would require that the man's marginal propensity to consume cereals be the same as the woman's.[31] With our assumption, we allow his marginal propensity to consume cereals to differ considerably from hers. However, we require that this difference in the man's and woman's preferences for cereals be similar to the difference in their preferences for proteins.

Once again, our identification assumption can be understood a different way using the above system of equations; let $\psi_{js}^1 = \beta_{js} + \gamma_s^1$ and $\psi_{js}^2 = \beta_{js} + \gamma_s^2$ be the shape preference parameters for goods 1 and 2, respectively. With the SAP restriction, DLP implicitly assume that $\psi_{js}^1 - \psi_{j's}^1 = 0$. Our alternative restriction allows this quantity to be nonzero, however, it has to the the same for both goods. Stated differently: $\psi_{js}^1 - \psi_{j's}^1 = \psi_{js}^2 - \psi_{j's}^2$.

[29] DLP impose a stronger version of this with $\partial F_j(p)/\partial p_j^1 = \tilde{\theta}(p)$.

[30] DLP do not require preferences for the assignable good to be identical across people, as the intercept parameter α_{js} does across people.

[31] In DLP, the SAP restriction is imposed on the function $F_j(p)$ with $\partial F_j(p)/\partial p_j = \theta(p)$. Instead, we assume $\partial F_j(p)/\partial p_j^1 - \partial F_j(p)/\partial p_j^2 = \tilde{\theta}(p)$.

To show that resource shares are identified, first let $\lambda_{js} = \beta_{js} + \gamma_s^1$ and $\kappa_s = \gamma_s^2 - \gamma_s^1$. Then we can rewrite system (12) as follows:

$$W_{js}^1 = \ldots \; + \; \eta_{js} \, \lambda_{js} \ln y$$
$$W_{js}^2 = \ldots \; + \; \eta_{js} \, (\lambda_{js} + \kappa_s) \ln y$$

If we then subtract person j's budget share function for good 2 from their budget share function for good 1, we are left with a set of equations that are identical to the SAP system of equations for j: $W_{js}^1 - W_{js}^2 = \ldots \; + \eta_{js} \; \kappa_s \ln y$. Identification of resource shares is straigthforward. An OLS-type regression of the observable budget shares on log expenditure identifies the slope coefficients $c_{js} = \eta_{js}\kappa_s$. Then since resource shares sum to one, $\sum_{j=1}^{J} c_{js} = \sum_{j=1}^{J} \eta_{js}\kappa_s = \kappa_s$ is identified. It follows that $\eta_{js} = c_{js}/\kappa_s$. To fix ideas, section A.4 in the Appendix we provide a graphical illustration of the D-SAP approach.

In comparing our identification approach to DLP, it is important to note one advantage of their identification assumptions over ours: They make their preference restriction for only a single assignable good whereas we place structure on preferences of two assignable goods. Stated differently, we impose a weak preference restriction on two goods, whereas DLP make a stronger preference restriction on one good. Alternatively, with two assignable goods one could assume SAP or SAT for the first good, and place no structure on preferences for the second assignable good. As an example, System (13) presents how resource shares could be identified with two goods using SAP. Note that SAP is assumed to hold for good $k = 1$ as $\gamma_{js}^1 = \gamma_s^1$, and no restrictions are imposed on γ_{js}^2 for good 2.

$$\begin{aligned} W_{js}^1 &= \eta_{js}[\alpha_{js}^1 + \gamma_s^1 \ln \eta_{js}] + \gamma_s^1 \eta_{js} \ln y \\ W_{js}^2 &= \eta_{js}[\alpha_{js}^2 + \gamma_{js}^2 \ln \eta_{js}] + \gamma_{js}^2 \eta_{js} \ln y \end{aligned} \tag{13}$$

The relative merits of each approach is an empirical question that depends on the context.

4 Intrahousehold Resource Allocation and Individual Poverty

4.1 Data and Estimation Strategy

The first two waves of the Bangladesh Integrated Household Survey (BIHS) contain detailed data on expenditure, together with information on household characteristics, and demographic and other particulars of household members. In our empirical application, we pool data from the two rounds and rely on three main components of the BIHS survey: the 7-day recall of household food consumption, the 24-hour recall of individual dietary intakes and food weighing, and the annual consumer expenditure module.

To compute individual food budget shares, we combine the data from the individual-level 24 hour recall module with the household-level 7-day food consumption module. Specifically, we first calculate the total value in taka of household food consumption over the previous 24 hours. We then determine the percentage of that total value consumed by each individual household member; this is the main output of the 24-hour recall module. Next, we use the household-level 7-day food consumption module to calculate the total value in taka of household food consumption over that time period, and extrapolate this value to annual terms. Multiplying total annual food household consumption by the percentage of the total value consumed by each individual household member over the previous 24 hours results in individual food consumption over the previous year. Finally, dividing by total annual household expenditure results in individual-level food budget shares.[32]

Given the richness of the dataset, we can also compute individual food-group budget shares. The different food groups include cereals, pulses, vegetables, fruit, meat and dairy, fish, spices, and drinks. This breakdown provides a clearer picture of how individual spending on different food items varies with household expenditure and allows for the observation of more than one private assignable good per individual, which is required for the implementation of D-SAP and D-SAT.

From the pooled waves of the BIHS dataset, we select a sample of 6,417 households for the estimation. We exclude households with zero men, women, and children, or with more than five individuals in each category (4,247 households). To eliminate outliers, we exclude any households in the top or bottom one percent of total household expenditure (172 households). To avoid issues related to special events and food consumption (see footnote 32), we drop from the analysis households reporting to have had guests during the the food consumption recall day (1,554 households). A small number of households have individuals with food budget shares that take a value of zero due to illness, fasting, being an infant, or currently being away from the household.[33] Households in which these individuals reside are excluded from the analysis (546 households). Finally, households with missing data for any of the household characteristics are removed from the sample.

Tables 4 contains some descriptive statistics for the variables included in the empirical analysis. Table A1 in the Appendix describe the budget shares of specific food groups consumed by men, women, boys, and girls. On average, households report consuming 135,727 taka over the year prior to the survey, which correspond to 5,302 PPP dollars. The corresponding per capita expenditure (obtained dividing total expenditure by household size) amounts to 28,931 taka on average. Cereals account a substantial fraction of household expenditure (20 percent), followed by proteins (11 percent) and vegetables (7 percent). The descriptive statistics related to household composition confirm the widespread existence of extended families. The average household size in our sample is 4.80 and the average number of adults (household members aged 15 and older) equals 2.86. For simplicity and tractability, we categorize household members based on their gender and age. There is a link between this categorization and members' specific roles in the family, but that is not per-

[32]Note that in calculating individual food consumption this way, we implicitly assume that food consumption over the previous day is representative of that food consumption over the year. This could be problematic, e.g., if the 24-hour recall coincided with a special occasion or a festivity, which however does not seem to be too much of a concern in our setting. Conveniently, survey respondents were asked whether the previous day was a "special day" in terms of the types of food eaten. If the answer to such question was "yes", then the respondent was asked to describe the most recent "normal day" instead. Moreover, during the 2015 wave of the BIHS, a 10 percent subsample of households completed the 24 hour food recall module on multiple visits. A comparison of the computed shares across visits reveals little variation in reporting , suggesting the 24 hour food recall data is quite representative. Finally, survey enumerators record the number of "guests" the household fed during the recall day. We erred on the side of caution and excluded from the analysis households guests.

[33]Infants frequently also have zero food budget shares because they consume only breastmilk.

Table 4: Descriptive Statistics

	Obs.	Mean	Median	Std. Dev
Household Expenditures:				
Total Expenditure (PPP dollars)	6,417	5,301.95	4,654.18	2,598.55
Per Capita Expenditure (PPP dollars)	6,417	1,132.11	1,018.04	502.88
Budget Shares Cereals	6,417	0.2038	0.1935	0.0829
Budget Shares Vegetables	6,417	0.0676	0.0619	0.0332
Budget Shares Proteins	6,417	0.1069	0.0903	0.0893
Household Composition:				
Boys 0-5	6,417	0.3491	0.0000	0.5507
Girls 0-5	6,417	0.3375	0.0000	0.5582
Boys 6-14	6,417	7.3850	7.3850	3.1954
Girls 6-14	6,417	0.6110	0.0000	0.7225
Adult Males 15-45	6,417	1.0206	1.0000	0.6281
Adult Females 15-45	6,417	1.1505	1.0000	0.5525
Adult Males 46+	6,417	0.3796	0.0000	0.4977
Adult Females 46+	6,417	0.3072	0.0000	0.4822
Household Characteristics:				
Average Age Boys	6,417	7.3850	7.3850	3.1954
Average Age Girls	6,417	7.4373	7.4373	3.0527
Average Age Men	6,417	38.7680	37.0000	11.2810
Average Age Women	6,417	34.7001	33.0000	9.3012
$\mathbb{1}$(Muslim)	6,417	0.8749	1.0000	0.3309
Average Men Working	6,417	0.8692	1.0000	0.2695
Average Women Working	6,417	0.6324	1.0000	0.4148
Average Education Men	6,417	1.4204	1.0000	1.3375
Average Education Women	6,417	1.4437	1.5000	1.2106
$\mathbb{1}$(Rural)	6,417	0.8255	1.0000	0.3796
$\mathbb{1}$(Barisal)	6,417	0.0955	0.0000	0.2940
$\mathbb{1}$(Chittagong)	6,417	0.1273	0.0000	0.3334
$\mathbb{1}$(Dhaka)	6,417	0.3050	0.0000	0.4604
$\mathbb{1}$(Khulna)	6,417	0.1569	0.0000	0.3638
$\mathbb{1}$(Rajshahi)	6,417	0.1016	0.0000	0.3022
$\mathbb{1}$(Rangpur)	6,417	0.0905	0.0000	0.2870
$\mathbb{1}$(Sylhet)	6,417	0.1231	0.0000	0.3286
Log Distance to Shops	6,417	-1.0534	-1.3471	1.3450
Log Distance to Road	6,417	-0.1661	0.0000	1.7085
Year=2011	6,417	0.5281	1.0000	0.4992

Note: BIHS data. Expenditure data based on annual recall. Per capita expenditure is defined as total expenditure (PPP dollars) divided by household size.

fect. For instance, grandmothers are present in 79 percent of households with women aged 46 and older, but only 46 percent of households with older men comprise grandfathers.[34] An overwhelming majority of households are muslim (87 percent) and live in rural areas (83 percent).

To estimate the model, we add an error term to each Engel curve equation. Recall that the empirical implementation of our novel identification approaches, D-SAP and D-SAT, requires two assignable goods, $k = 1, 2$. In our main specification, we include four categories of family members j (boys (b), girls (g), men (m), and women (w)) and focus on cereals and vegetables as private assignable goods.[35] For households with children of both genders, we take the following system of eight equations to the data:

$$\begin{cases} W_{js}^1 = \sigma_j \eta_{js} [\delta_{js}^1 + \lambda_{js} \ln \eta_{js}] + \sigma_j \eta_{js} \, \lambda_{js} \ln y + \epsilon_{js}^1 \\ W_{js}^2 = \sigma_j \eta_{js} [\delta_{js}^2 + (\lambda_{js} + \kappa_{js}) \ln \eta_{js}] + \sigma_j \eta_{js} \, (\lambda_{js} + \kappa_{js}) \ln y + \epsilon_{js}^2 \end{cases}$$

where W_{js}^1 and W_{js}^1, with $j = b, g, w, m$, are budget shares for boys', girls', women's, and men's cereals and vegetables consumptions, respectively. y is the total household expenditure and σ_j is the number of household members of category j, so that $\sigma_m \eta_{ms} = 1 - \sigma_b \eta_{bs} - \sigma_g \eta_{gs} - \sigma_w \eta_{ws}$. For households with only boys or only girls, the system comprises six Engel curves and either $\sigma_m \eta_{ms} = 1 - \sigma_b \eta_{bs} - \sigma_w \eta_{ws}$ or $\sigma_m \eta_{ms} = 1 - \sigma_g \eta_{gs} - \sigma_w \eta_{ws}$. Figure A6 in the Appendix shows the results of non-parametric regressions of W_{js}^k on $\ln y$. While Engel curves are negatively sloped for cereals and vegetables, the share of expenditure devoted to meat, fish, eggs, and dairy increases with total expenditure. No substantial non-linearity can be detected in these relationships, providing support to the appropriateness of our empirical specification.

Let a be a vector of household size variables, which includes the number of boys and girls aged 0-5 and 6-14, and the number of men and women aged 15-45 and 46 and above. Let X be a vector containing all other demographic characteristics presented in table 4. We model resource shares η_{js} and food preference parameters λ_{js}, δ_{js}, and κ_{js} as linear functions of a and X. We then impose the four alternative identifying restrictions discussed in section 3.2. Given D-SAP, $\kappa_{js} = \kappa_s$ is linear in a constant, a and X; given D-SAT, $\kappa_{js} = \kappa_j$ is linear in a constant and X for each person category j. For completeness, we provide estimates obtained using the original SAP and SAT restrictions from DLP. We recall that SAP and SAT can be implemented using a single assignable good. To improve efficiency and to ease comparability, however, we here include Engel curves for both assignable goods in the system, but impose SAP and SAT restrictions on the first assignable good only.

Since the error terms may be correlated across equations, we estimate the system of eight Engel curves using non-linear Seemingly Unrelated Regression (SUR) method. Non-linear SUR is iterated until the estimated parameters and the covariance matrix settle. Iterated SUR is equivalent to max-

[34] This can partly attributed to the quite high average spousal age difference. According to the 2014 Bangladesh demographic and health survey, husbands are on average 9 years older than their wives.

[35] Note that the estimation of resource shares should be invariant to the choice of assignable goods. We check the robustness of our estimates to using different food categories (e.g., milk, fish, and meat) as assignable goods. Results are confirmed and reported in table A4 in the Appendix. In section 4.3, we discuss results obtained when considering six person categories instead. While theoretically possible, given the size of our dataset, including more than six categories is not feasible in practice. Doing so renders the empirical exercise computationally intractable.

Table 5: Estimated Resource Shares - Reference Household

	D-SAP		D-SAT		SAP		SAT	
	Estimate	Standard Error	Estimate	Standard Error	Estimate	Standard Error	Estimate	Standard Error
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Boy	0.1728	0.0139	0.1669	0.0249	0.1779	0.0153	0.1613	0.0233
Girl	0.1750	0.0148	0.1628	0.0188	0.1724	0.0148	0.1626	0.0193
Woman	0.2973	0.0159	0.3059	0.0449	0.2859	0.0150	0.3027	0.0420
Man	0.3550	0.0181	0.3644	0.0362	0.3639	0.0191	0.3734	0.0364

Note: Estimates based on BIHS data and Engel curves for cereals and vegetables. The reference household is defined as one with 1 working man 15-45, 1 non-working woman 15-45, 1 boy 6-14, 1 girl 6-14, living rural northeastern Bangladesh (Sylhet division), surveyed in year 2015, with all other covariates at median values

imum likelihood with multivariate normal errors. Alternatively, the model can be estimated as a system of four differenced Engel curves, that is $W^1_{js} - W^2_{js}$ (see section 3.2 for more details). While it is more parsimonious, this latter approach has a couple of important limitations. First, it does not allow to recover preference parameters for the assignable goods. Moreover, it might reduce the efficiency gains stemming from the correlation across equations.

4.2 Estimation Results

Our estimates indicate that all the household composition variables matter substantially (see tables A2 and A3 in the Appendix). By contrast, with the exception of women's and men's years of education, no statistically significant association is found between resource sharing and socio-economic characteristics. Based on these estimates, we retrieve women's, men's and children's resource shares for each household as linear combinations of the underlying covariates.

In table 5, we present the predicted resource shares for reference households. We define a reference household as one comprising one working man 15-45, one non-working woman 15-45, one boy 6-14, one girl 6-14, living rural south Bangladesh, that was surveyed in year 2015, with all other covariates set at their median values. We find that men consume a larger share of the budget relative to women, who in turn consume relatively more than boys and girls. Interestingly, our estimates do not reveal the existence of gender inequality among children.[36] Under D-SAP, for instance, we find that the man consumes 35.6 percent of the budget, the woman consumes 29.7 percent, and the boy and girl each consume 17.3 and 17.5 percent, respectively. The results are consistent across specifications (that is, across identification assumptions), with very little variation between them.

Columns (2) to (4) of table 6 reports descriptive statistics for the individual estimated resource shares, that is the fraction of household resources that is consumed by each boy, girl, woman, or man. For simplicity, we discuss results obtained using the D-SAP restriction. Contrary to the estimates reported in table A5, these figures take into account the empirical distributions of the household

[36] This result is in line with existing evidence of low daughter discrimination among Muslims (see e.g. Jayachandran and Pande (2017)) and with encouraging trends in gender equality among children in Bangladesh (Talukder et al. (2014)). According to the 2014 Bangladesh Demographic and Health Survey, for instance, the difference between the ideal number of boys and the ideal number of girls for women aged 15 to 19 is roughly 80 percent lower than the difference for women aged 45 to 49.

Table 6: Estimated Resource Shares and Individual Consumption

		Resource Shares			Individual Consumption (PPP dollars)		
	Obs.	Mean	Median	St. Dev.	Mean	Median	St. Dev.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Boys	4,502	0.1582	0.1624	0.0418	829.70	724.15	443.75
Girls	4,243	0.1491	0.1515	0.0411	792.49	693.02	423.09
Women	6,417	0.2505	0.2698	0.0679	1,263.21	1,122.05	607.40
Men	6,417	0.3327	0.3402	0.1152	1,620.19	1,461.49	737.28

Note: Estimates based on BIHS data and D-SAP identification method with Engel curves for cereals and vegetables. Mean and median of resource shares do not need to sum to one because there can be more than one individual of the same type in each family. Individual consumption is obtained multiplying total annual household expenditure (PPP dollars) by individual resource shares.

composition variables a and of all other covariates X. The reader should note that the mean and median of the estimated resource shares do not need to sum to one because there can be more than one individual of the same type in each family and because not all households have children of both boys and girls. It is reassuring that the minima and maxima of the estimated resource shares do not fall outside the 0 to 1 range, despite them being modeled as linear (and hence not bounded) functions of household characteristics. Women's resource shares are on average 75 percent of men's; when present, boys' resource shares are on average 48 percent of men's and 63 percent of women's. These comparisons are slightly gloomier for girls, whose resource shares are on average 1 percentage point (6 percent) lower than boys'.[37]

Finally, we compute individual consumption as the product of the total household expenditure and the individual resource shares predicted by the model. To ease comparison, in columns (5) to (6) of table 6 we present mean, median and standard deviations of the estimated individual expenditures in PPP dollars. It is interesting to compare these estimates to the per capita expenditure figures presented in table 4, which implicitly assume that individuals within a family share resources equally. On average, men consume 43 percent more than what per capita calculations would indicate, while boys and girls consume 27 and 30 percent less, respectively.

This substantial discrepancy between per capita expenditures and our estimates of individual consumption suggests that the probability of living in poverty may be non-trivial even for individuals that residing in households with per capita expenditure above the poverty line. Before further investigating this issue in section 5, we briefly present some additional results related to the presence of young vs. older adults, differences between first born and higher birth order children, and the role of sickness and diseases.

[37] In Figure A7 in the Appendix, we show the empirical distributions of the estimated resource shares for year 2015 and for households with children of both genders (to avoid including households with zero resource shares for either boys or girls). While there is considerable variation in the sample, our analysis indicates that there is substantial inequality in allocation of resources inside the family, with men commanding the majority of household resources.

4.3 Additional Results: Young vs. Older Adults, Birth Order, and Diseases

5 Do Poor Individuals Live in Poor Households?

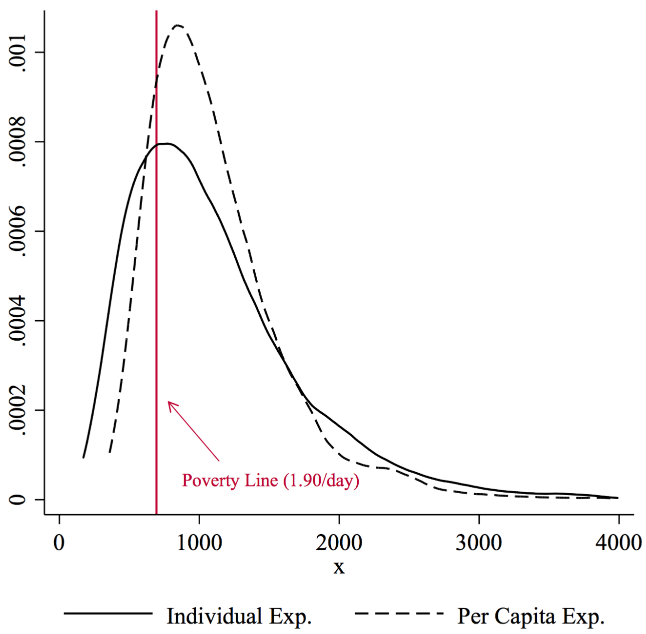
We use the model estimates to construct poverty rates that take into account *unequal* resource allocation within the household. These are different from standard poverty measures which by construction assume *equal* sharing of household resources. Specifically, based on our estimated of individual consumption discussed in section 4.2, we construct poverty headcount ratios by comparing these person level expenditures to poverty lines.

We start by further exploring the differences between per capita expenditure and our estimates of individual consumption. Panel A of Figure 4 shows the empirical distributions of annual individual expenditures and per capita expenditures, expressed in 2015 PPP dollars. The vertical line equals 693.5, that is, the annual amount consumed by an individual who lives on 1.90$/day for 365 days. When intra-household inequality is accounted for, the expenditure distribution becomes more skewed and significantly more unequal. The coefficient of variation (i.e., the ratio between the standard deviation and the mean) equals 0.44 for per capita expenditure, while it equals 0.58 for individual expenditure. In Panel B, we show the individual expenditures by household per capita expenditure. Individual expenditures increase as household expenditure increases. However, there are significant differences between women, men, boys, and girls, which confirm our previous findings. Notice that resource shares are not allowed to vary with household expenditure (this restriction is required for identification). Thus, it is not surprising that the lines are roughly parallel to each other.

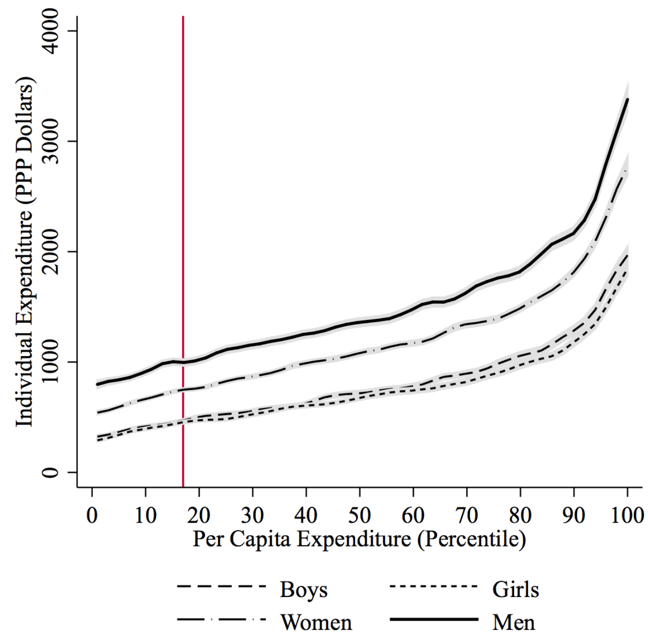
We classify adults as poor using a US$1.90 a day poverty line.[38] Following Penglase (2018), we consider several different poverty lines for children, based on their age and gender. Specifically, we assume the child poverty line to be proportional to the caloric requirements for children of that age relative to adults. We rely on the daily calorie needs by age and gender estimated by the United States Department of Health and Human Services and assume adults require 2,400 calories per day. So, if a six-year-old girl requires half as many calories as an adult, their poverty line would be half of the adult.

Figure 5 shows poverty rates based on per capita expenditure. The interpretation of Panel A is straightforward. When per capita expenditure is used for poverty calculations, everyone is poor below the percentile corresponding to the poverty line and no one is poor above that threshold. Interestingly, this is not the case when poverty rates are based on individual expenditure. In Panel B, we plot individual poverty rates for women, men, boys, and girls by percentiles of per capita expenditure distribution. As expected, individual poverty rates decline as household expenditure increases. However, for certain levels of household expenditure, women's and children's poverty rates are significantly higher than men's. This result suggests women and children often live below

[38] Since October 2015, the World Bank uses updated international poverty line of US$1.90/day, which incorporate new information on differences in the cost of living across countries (2011 PPP). The new lines preserve the real purchasing power of the previous line of 1.25US$/day in 2005 prices.



(A) Empirical Distributions



(B) Individual Expenditures by Per Capita Expenditure

Note: Individual consumption is obtained multiplying total annual household expenditure (PPP dollars) by individual resource shares. Estimates are based on BIHS data and D-SAP identification method with Engel curves for cereals and vegetables.

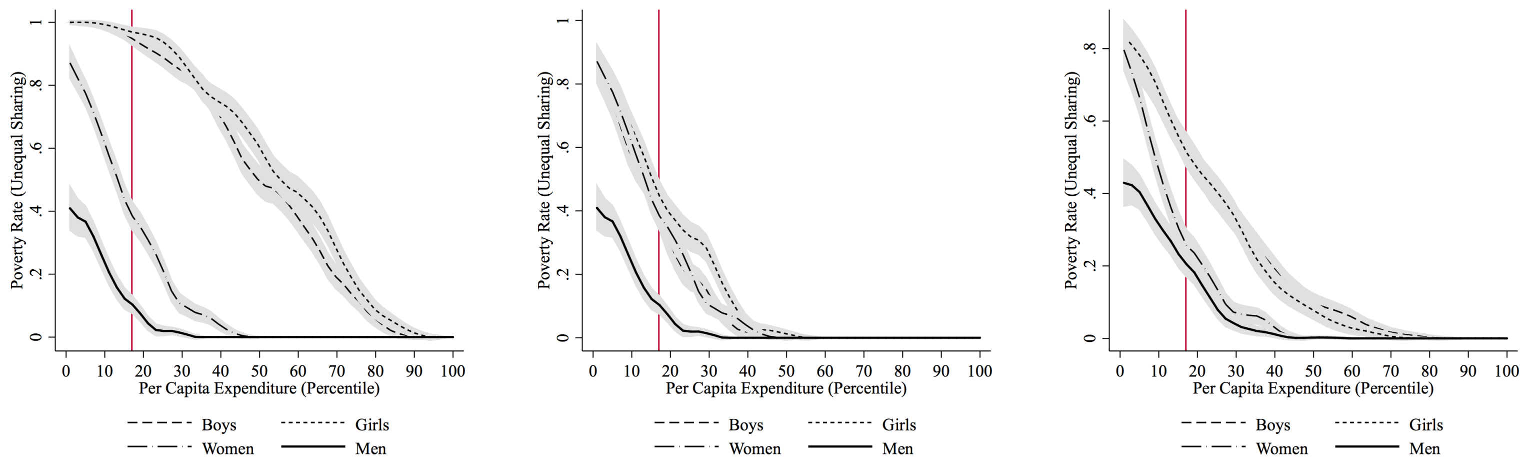
Figure 4: Per Capita and Individual Expenditures

the poverty line, despite living in households that are not considered poor. In effect, household-level measures of poverty are likely to misclassify women and children as non-poor more frequently than men.

6 Conclusions

Policies aimed at reducing poverty in developing countries often assume that targeting poor households will be effective in reaching poor individuals. However, intra-household inequality in resource allocation may mean many poor individuals reside in non-poor households. Using a detailed dataset from Bangladesh that contains both individual-level food consumption and anthropometric outcomes for all household members, we first show that undernourished individuals are spread across the distribution of household per capita expenditure. We then test whether this pattern is driven by the unequal allocation of food and overall resources within families. To this aim, we develop a new methodology to identify and estimate the fraction of total household expenditure that is devoted to each household member in the context of a collective household model. Our approach exploits the observability of multiple assignable goods to substantially weaken the assumptions required by existing identification methods.

We use our structural estimates to compute individual-level poverty rates that account for disparities within families. Specifically, we assess the relative consumption (and therefore the relative poverty risk) of men and women, boys and girls. We show that women and children face significant probabilities of living in poverty even in households with per capita expenditure above the poverty threshold. Our analysis indicates that more focused and targeted polices (that account for within



(A) No Adjustment for Relative Needs

(B) Rough Adjustment

(C) Calorie-based Adjustment

Note: Individual consumption is obtained multiplying total annual household expenditure (PPP dollars) by individual resource shares. Estimates are based on BIHS data and D-SAP identification method with Engel curves for cereals and vegetables. No adjustment for relative needs in Panel A. In Panel B, the poverty line for children (aged 14 or less) is set to 0.6*1.90 and the poverty line for the elderly (aged 46 plus) is set to 0.8*1.90. In Panel C, we assume poverty lines for children and the elderly to be proportional to their caloric requirements relative to young adults (aged 15-45). We rely on the daily calorie needs by age and gender estimated by the United States Department of Health and Human Services and assume adults require 2,400 calories per day.

Figure 5: Poverty Rates by Per Capita Expenditure Percentile

family disparities) can substantially improve the efficacy of anti-poverty programs.

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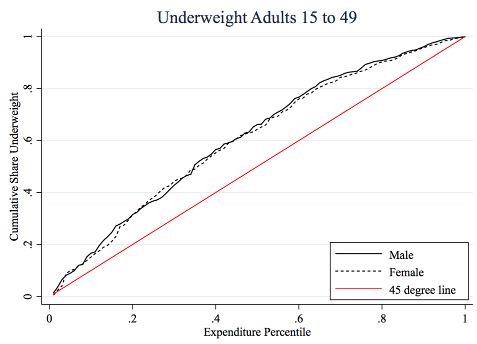
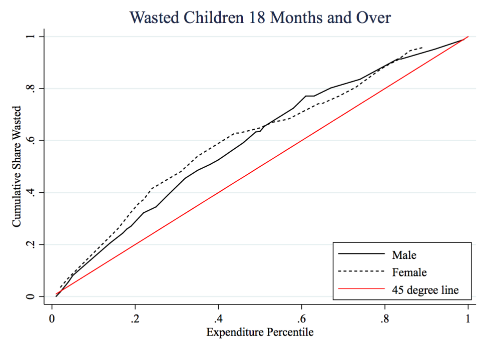
A Appendix

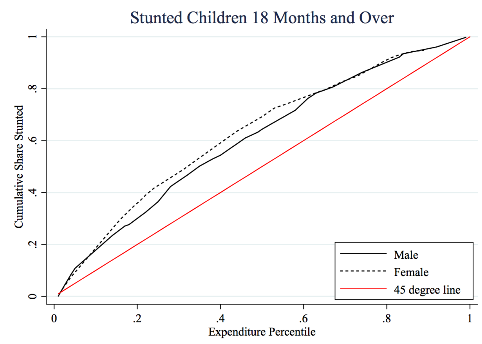
A.1 Additional Results for Nutritional Outcomes, Caloric Intake, and Intra-household Inequality



Underweight Adults 20 to 49



Wasted Children 18 months and Over



Stunted Children 18 months and Over

Figure A1: Undernutrition Concentration Curves For the Restricted Sample (2015)

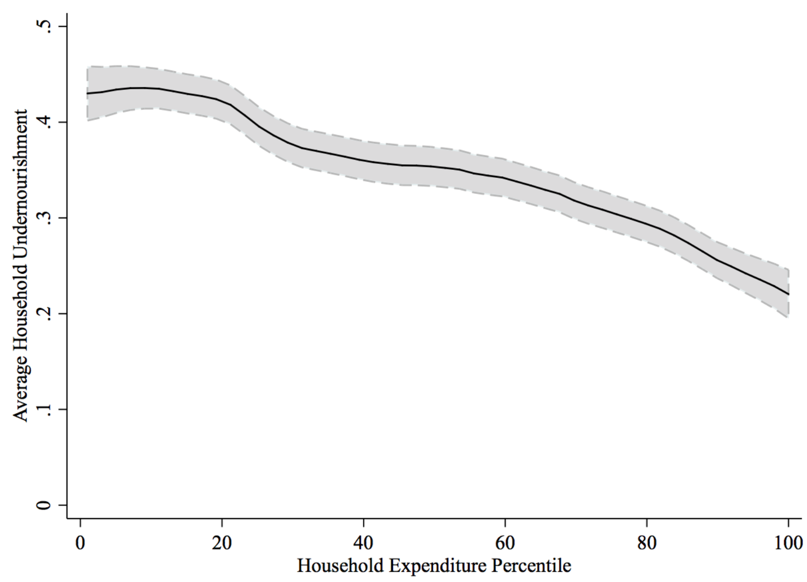
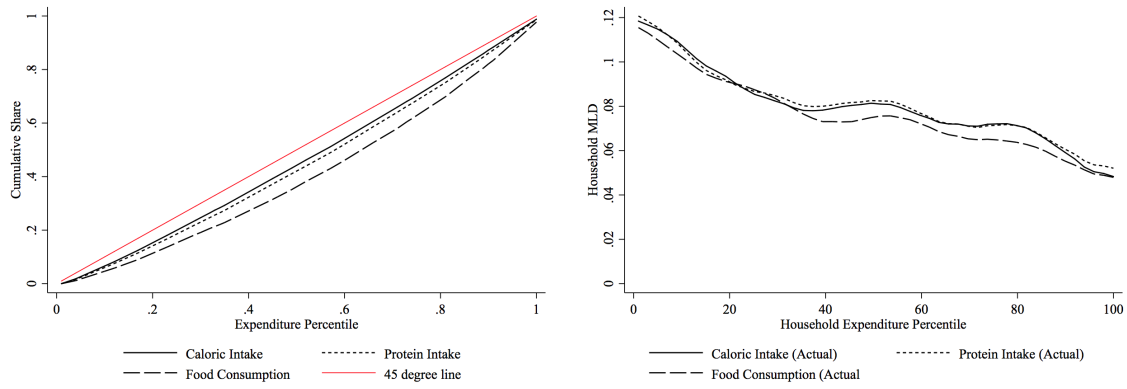


Figure A2: Average Household Undernourishment by Household Expenditure Percentile (2011)



Between Inequality　　　　Within Inequality

Figure A3: Between and Within Inequality by Expenditure Percentile (Actual Values)

A.2 Theorems

The section provides the two main theorems of the paper. Both are extensions of Theorems 1 and 2 in DLP, and therefore share much of the same content. The main differences are in the data requirements (we need more) and the assumptions (we need fewer). The key differences can be found in Assumptions A2$^{'}$, A3$^{'}$, B3$^{'}$. Otherwise, we follow DLP.

A.2.1 Theorem 1

Let j denote individual person types with $j \in \{1,...,J\}$. The Marshallian demand function for a person type j and good k is given by $h_j^k(p,y)$. Each individual chooses x_j to maximize their own utility function $U_j(x_j)$ subject to the budget constraint $p^{'}x_j = y$, where p is vector of prices and y is total expenditure. Denote the vector of demand functions as $h_j(p,y)$ for all goods k. Let the indirect utility function be given by $V_j(p,y) = U_j(h_j(p,y)$.

Let z_s denote the vector of goods purchased by a household of composition s, where the subscript s indexes the household types. Let σ_j denote the number of individuals of type j in the household. From the BCL, we write the household's problem as follows:

$$\max_{x_1...,x_J,z_s} = \tilde{U}[U_1(x_1),...,U_J(x_J),p/y] \tag{A1}$$

$$\text{such that } z_s = A_s\Big[\sum_{j=1}^{J}\sigma_j x_j\Big] \text{ and } y = z_s^{'}p$$

where A_s is a matrix that accounts for the sharing of goods within the household. From the household's problem we can derive household-level demand functions $H_s^k(p,y)$ for good k in a household of size s:

$$z_s^k = H_s^k(p,y) = A_s^k\Big[\sum_{j=1}^{J} h_j(A_s^{'}p, \eta_{js}y)\Big] \tag{A2}$$

where A_s^k denotes the row vector given by the k'th row of matrix A_s, and η_{js} is the resource share for a person of type j in a household of size s. Lastly, resource shares sum to one:

$$\sum_{j=1}^{J} \sigma_j \eta_{js} = 1 \tag{A3}$$

ASSUMPTION A1: Equations (A1), (A2), and (A3) hold, and resource shares are independent of household expenditure at low levels of household expenditure.

Definition: A good k is a private good if the Matrix A_s takes the value one in position k, k and has all other elements in row and column k equal to zero.

Definition: A good k is assignable if it only appears in one of the utility functions U_j.

ASSUMPTION A2$'$: Assume that the demand functions include at least 2 private, assignable goods, denoted as goods j^1 and j^2 for each person type.

DLP require a single assignable good for each person j. We differ in that we require at least 2 different goods for each person.

Let $\tilde{p}$ be the price of the goods that are not both private and assignable. Let p_j^k be the prices of the private assignable goods, with $k \in \{1, 2\}$.

ASSUMPTION A3$'$: For $j \in$ {1,...,J} let

$$\begin{aligned} V_j(p, y) = I(y \leq y^*(p))\psi_j\Big[\, \nu(\frac{y}{G_j(p)}) + F_j(p), \tilde{p}\,\Big] + \\ I(y > y^*(p))\Psi(y, p) \end{aligned} \tag{A4}$$

where $F_j(p) = b_j(p_j^1 + p_j^2, \bar{p}, \tilde{p}) + e(p)$, and y^*, ψ_j, Ψ, ν, b_j e, and G_j are functions with y^* is strictly positive, G_j is nonzero, differentiable, and homogenous of degree one. The function ν is differentiable and strictly monotonically increasing. The functions b_j and e are homogenous of degree 0. Lastly, Ψ and ψ are differentiable and strictly increasing in their first arguments, differentiable, and homogenous of degree zero in their remaining arguments.

This assumption differs from Assumption A3 in DLP in the function $F_j(p)$. DLP restrict $F_j(p)$ to not vary across people with $\partial F_j(p)/\partial p_j = \phi(p)$. Here, we allow $F_j(p)$ to vary across people in the function $b_j(\cdot)$. However, the way $F_j(p)$ varies across people is restricted to be the same across goods 1 and 2: $\partial b_j(\cdot)/\partial p_j^1 = \partial b_j(\cdot)/\partial p_j^2$. This holds since the prices for goods 1 and 2 enter $b_j(\cdot)$ in an additively separable way. The function $e(p)$ does not vary across people.

Use Roy's Identity to derive individual-level demand functions for goods $k \in \{1, 2\}$:

- For $I(y > y^*)$

$$h_j^k(y,p) = -\Big[\partial \Psi_j(y,p)/\partial p_j^k\Big]/\Big[\partial \Psi_j(y,p)/\partial y\Big]$$

- For $I(y \le y^*)$

$$\begin{aligned}
h_j^k(p,y) =& -\frac{\frac{\partial V_j(p,y)}{\partial p_j^k}}{\frac{\partial V_j(p,y)}{\partial y}} \\
=& \frac{y}{G_j(p)}\frac{\partial G_j(p)}{\partial p_j^k} + \Big(\frac{\partial b_j(p_j^1 + p_j^2, \bar{p}, \tilde{p})}{\partial p_j^k} + \frac{\partial e(p)}{\partial p_j^k}\Big)\frac{1}{\nu'(\frac{y}{G_j(p)})}G_j(p) \\
=& \frac{y}{G_j(p)}\frac{\partial G_j(p)}{\partial p_j^k} + \Big(\frac{\partial b_j(p_j^1 + p_j^2, \bar{p}, \tilde{p})}{\partial p_j^k} + \frac{\partial e(p)}{\partial p_j^k})\Big)\frac{1}{\nu'(\frac{y}{G_j(p)})}\frac{y}{y/G_j(p)} \\
=& a_j^k(p)y + \Big(\frac{\partial b_j(p_j^1 + p_j^2, \bar{p}, \tilde{p})}{\partial p_j^k} + \frac{\partial e(p)}{\partial p_j^k}\Big)g(\frac{y}{G_j(p)})y
\end{aligned}$$

For $I(y \le y^*)$, we can then write the household-level Engel curves for the private, assignable goods for $j \in \{1,...,J\}$ in a given price regime p:

$$H_{js}^k(y) = a_{js}^k s_j \eta_{js} y + \Big(\tilde{b}_{js} + \tilde{e}_s^k\Big)g_s(\frac{\eta_{js}y}{G_{js}})s_j\eta_{js}y \tag{A5}$$

ASSUMPTION A4: The function $g_s(y)$ is twice differentiable. Let $g_s^{'}(y)$ and $g_s^{''}(y)$ denote the first and second derivatives of $g_s(y)$. Either $\lim_{y\to 0} y^\zeta g_s^{''}(y)/g_s^{'}(y)$ is finite and nonzero for some constant $\zeta \neq 1$ or $g_s(y)$ is a polynomial in $\ln y$.

Theorem 1: *Let Assumptions A1, A2, A3, and A4 hold. Assume the household-level Engel curves for the private assignable goods H_{js}^1 and H_{js}^2 are identified for $j \in \{1,...,J\}$. Then the resource shares η_{js} are identified for $j \in \{1,...,J\}$.*

A.2.2 Theorem 2

Let $\tilde{p}$ be the price of the goods that are not both private and assignable. Let p_j^k be the prices of the private assignable goods, with $k \in \{1,2\}$ and $j \in \{1,...,J\}$. Let $\bar{p}$ be the price of the private goods that are not assignable.

ASSUMPTION B3$^{'}$: For $j \in$ {1,...,J} let

$$\begin{aligned}V_j(p,y) = I(y \le y^*(p))\psi_j\Big[u_j\Big(\frac{y}{G_j(p)}\Big) + b_j(p_j^1 + p_j^2, \bar{p}, \tilde{p}) + e_j(p_j^1, p_j^2, \bar{p}), \tilde{p}), \tilde{p}\Big] + \\ I(y > y^*(p))\Psi(y,p)\end{aligned} \tag{A6}$$

where y^*, ψ_j, Ψ, u_j, b_j e, and G_j are functions with y^* is strictly positive, G_j is nonzero, differentiable, and homogenous of degree one. The function ν is differentiable and strictly monotonically increasing. The functions b_j and e are homogenous of degree 0. Lastly, Ψ and ψ are differentiable and strictly increasing in their first arguments, differentiable, and homogenous of degree zero in their remaining arguments.

This assumption differs from Assumption B3 in DLP as follows: We replace $u_j(\frac{y}{G(\tilde{p})}, \frac{\bar{p}}{p_j})$ with $u_j(\frac{y}{G_j(p)}) + b_j(p_j^1 + p_j^2, \bar{p}, \tilde{p}) + e_j(p_j^1, p_j^2, \bar{p})$. The function $u_j(\cdot)$ is still restricted to not depend on the prices of shared goods, however, we have included the function $b_j(\cdot)$ which is allowed to depend on the prices of shared goods, and therefore varies across household size. However, the way in which $b_j(\cdot)$ varies across household size is restricted to be the same across goods 1 and 2: $\partial b_j(\cdot)/\partial p_j^1 = \partial b_j(\cdot)/\partial p_j^2$. This holds since the prices for goods 1 and 2 enter $b_j(\cdot)$ in an additively separable way.

Use Roy's Identity to derive individual-level demand functions for goods $k \in \{1,2\}$:

- For $I(y > y^*)$

$$h_j^k(y,p) = -\Big[\partial \Psi_j(y,p)/\partial p_j^k\Big] / \Big[\partial \Psi_j(y,p)/\partial y\Big]$$

- For $I(y \le y^*)$

$$\begin{aligned}
h_j^k(p,y) =& -\frac{\frac{\partial V_j(p,y)}{\partial p_j^k}}{\frac{\partial V_j(p,y)}{\partial y}} \\
=& \frac{u_j'(\frac{y}{G_j(p)})\frac{y}{G_j(p)^2}\frac{\partial G_j(p)}{\partial p_j^k} + (\frac{\partial b_j(p_j^1+p_j^2,\bar{p},\tilde{p})}{\partial p_j^k} + \frac{\partial e_j(p_j^1+p_j^2,\bar{p})}{\partial p^k)j})}{u_j'(\frac{y}{G_j(p)})\frac{1}{G_j(\tilde{p})}} \\
=& \frac{y}{G_j(p)}\frac{\partial G_j(p)}{\partial p_j^k} + \Big(\frac{\partial b_j(p_j^1+p_j^2,\bar{p},\tilde{p})}{\partial p_j^k} + \frac{\partial e(p_j^1,p_j^2,\bar{p})}{\partial p_j^k})\Big)\frac{1}{u_j'(\frac{y}{G_j(p)})}\frac{y}{y/G_j(p)} \\
=& a_j^k(p)y + \Big(\frac{\partial b_j(p_j^1+p_j^2,\bar{p},\tilde{p})}{\partial p_j^k} + \frac{\partial e(p_j^1,p_j^2,\bar{p})}{\partial p_j^k}\Big)f_j(\frac{y}{G_j(p)})y
\end{aligned}$$

For $I(y \le y^*)$, we can then write the household-level Engel curves for the private, assignable goods for $j \in \{1,...,J\}$ in a given price regime p:

$$H_{js}^k(y) = a_{js}^k s_j \eta_{js} y + \Big(\tilde{b}_{js} + \tilde{e}_j^k\Big) f_j(\frac{\eta_{js} y}{G_{js}}) s_j \eta_{js} y \tag{A7}$$

We take the ratio of resource shares for person j across two different household types, which results in the following equation:

$$\frac{\eta_{j1}}{\eta_{js}} = \zeta_{js} \tag{A8}$$

for $j \in \{1,...,J-1\}$ and $s \in \{2,...,S\}$. In total, this results in $(S-1)(J-1)$ equations. Moreover, in the proof we will use that resource shares sum to one to write the following system of equations:

$$\sum_{j=1}^{J-1}(\zeta_{js} - \zeta_{Js})\eta_{js} = 1 - \zeta_{Js} \tag{A9}$$

for $s \in \{2,...,S\}$. Equation (A9) results in $S-1$ equations.

We can stack the system of equations given by Equations (A8) and (A9). This results in a system of $J(S-1)$ equations. In matrix form, let E be a $J(S-1)\times 1$ vector of η_{js} for $j \in \{1,...,J-1\}$ and $s \in \{1,...,S\}$ such that $\Omega \times E = B$, where Ω is a $J(S-1)\times J(S-1)$ matrix, and B is a $J(S-1)\times 1$ vector.

ASSUMPTION B4: The matrix Ω is finite and nonsingular, and $f_j(0) \neq 0$ for $j \in \{1,...,J\}$.

Theorem 2: *Let Assumptions A1, A2, B3, and B4 hold. Assume there are $S \geq J$ household types. Assume the household-level Engel curves for the private assignable goods H^1_{js} and H^2_{js} are identified for $j \in \{1,...,J\}$. Then the resource shares η_{js} are identified for $j \in \{1,...,J\}$.*

A.3 Proofs

A.3.1 Proof of Theorem 1

The proof will consist of two cases. In the first case, we assume g_s is not a polynomial of degree λ in logarithms. In the second case we assume that it is. Define

$$\tilde{h}^k_{js}(y) = \partial[H^k_{js}(y)/y]/\partial y = \left(\tilde{b}_{js} + \tilde{e}^k_s\right) g'_s\left(\frac{\eta_{js} y}{G_{js}}\right)\frac{\eta^2_{js}}{G_{js}}$$
$$\lambda_s = \lim_{y\to 0}[y^\zeta g''_s(y)/g'_s(y)]^{\frac{1}{1-\zeta}}$$

Case 1: $\zeta \neq 1$
Then since $H^k_{js}(y)$ are identified, we can identify $\kappa^k_{js}(y)$ for $y \leq y^*$:

$$\begin{aligned}
\kappa^k_{js}(y) &= \left(y^\zeta \frac{\partial \tilde{h}^k_{js}(y)/\partial y}{\tilde{h}^k_{js}(y)}\right)^{\frac{1}{1-\zeta}} \\
&= \left(\left(\frac{\eta_{js}}{G_{js}}\right)^{-\zeta}\left(\frac{\eta_{js} y}{G_{js}}\right)^{\zeta}\left[(\tilde{b}_{js} + \tilde{e}^k_s) g''_s\left(\frac{\eta_{js} y}{G_{js}}\right)\frac{\eta^3_{js}}{G^2_{js}}\right]/\left[(\tilde{b}_{js} + \tilde{e}^k_s) g'_s\left(\frac{\eta_{js} y}{G_{js}}\right)\frac{\eta^2_{js}}{G_{js}}\right]\right)^{\frac{1}{1-\zeta}} \\
&= \frac{\eta_{js}}{G_{js}}\left(y^\zeta_{js}\frac{g''(y)}{g'(y)}\right)^{\frac{1}{1-\zeta}}
\end{aligned}$$

Then we can define $\rho^1_{js}(y)$ and $\rho^2_{js}(y)$ by

$$\rho^1_{js}(y) = \frac{\tilde{h}^1_{js}(y/\kappa^1_{js}(0))}{\kappa^1_{js}(0)} = (\tilde{b}_{js} + \tilde{e}^1_s) g'_s\left(\frac{y}{\lambda_s}\right)\frac{\eta_{js}}{\lambda_s}$$
$$\rho^2_{js}(y) = \frac{\tilde{h}^2_{js}(y/\kappa^2_{js}(0))}{\kappa^2_{js}(0)} = (\tilde{b}_{js} + \tilde{e}^2_s) g'_s\left(\frac{y}{\lambda_s}\right)\frac{\eta_{js}}{\lambda_s}$$

Taking the difference of the above two equations, we derive the following expression similar to

DLP

$$\rho_{js}^{2}(y)-\rho_{js}^{1}(y)=\hat{\rho}_{js}(y)=(\tilde{e}_{s}^{2}-\tilde{e}_{s}^{1})g_{s}^{'}(\frac{y}{\lambda_{s}})\frac{\eta_{js}}{\lambda_{s}}=\phi_{s}\eta_{js}$$

Then since resource shares sum to one, we can identify resource shares as follows:

$$\eta_{js}=\frac{\hat{\rho}_{js}}{\sum_{j=1}^{J}\hat{\rho}_{js}}$$

Case 2: g_s is a polynomial of degree λ in logarithms

$$g_{s}(\frac{\eta_{js}y}{G_{js}})=\sum_{l=0}^{\lambda}\Big(\ln\Big(\frac{\eta_{js}}{G_{js}}\Big)+\ln y\Big)^{l}c_{sl}$$

for some constants c_{sl}. We can then identify

$$\tilde{\rho^{1}}_{js}=\frac{\partial^{\lambda}[H_{s}^{1}(y)/y]}{\partial(\ln y)^{\lambda}}=(\tilde{b}_{js}+\tilde{e}_{s}^{1})d_{s\lambda}^{1}\eta_{js}$$
$$\tilde{\rho^{2}}_{js}=\frac{\partial^{\lambda}[H_{s}^{2}(y)/y]}{\partial(\ln y)^{\lambda}}=(\tilde{b}_{js}+\tilde{e}_{s}^{2})d_{s\lambda}^{2}\eta_{js}$$

Taking the difference of the above two equations, we derive the following expression similar to DLP

$$\tilde{\rho}_{js}^{2}(y)-\tilde{\rho}_{js}^{1}(y)=\hat{\rho}_{js}(y)=(\tilde{e}_{s}^{2}d_{s\lambda}^{2}-\tilde{e}_{s}^{1}d_{s\lambda}^{1})\eta_{js}=\phi_{s}\eta_{js}$$

Then since resource shares sum to one, we can identify resource shares as follows:

$$\eta_{js}=\frac{\hat{\rho}_{js}}{\sum_{j=1}^{J}\hat{\rho}_{js}}$$

A.3.2 Proof of Theorem 2

The household-level Engel curves for person $j\ \epsilon\ \{1,...,J\}$ and good k:

$$H_{js}^{k}(y)=a_{js}^{k}\eta_{js}y+\Big(\tilde{b}_{js}+\tilde{e}_{j}^{k}\Big)f_{j}(\frac{\eta_{js}y}{G_{js}})\eta_{js}y$$

For each $j\ \epsilon\ \{1,...,J\}$ take the difference of the Engel curves for private, assignable goods $k=1$

and $k = 2$.

$$\tilde{H}_{js}(y) = H^2_{js}(y) - H^1_{js}(y) = \tilde{a}_{js}\eta_{js} + \tilde{e}_j\tilde{f}_j(\frac{\eta_{js}y}{G_{js}})\eta_{js}y$$

Let s and 1 be elements of S. Since the Engel curves are identified, we can identify ζ_{js} defined by $\zeta_{js} = \lim_{y\to 0}\tilde{H}_{j1}(y)/\tilde{H}_{js}(y)$ as follows for $j \in \{1,...,J\}$ and $s \in \{2,...,S\}$

$$\zeta_{js} = \frac{\tilde{e}_j\tilde{f}_j(0)\eta_{j1}y}{\tilde{e}_j\tilde{f}_j(0)\eta_{js}y} = \frac{\eta_{j1}}{\eta_{js}} \tag{A10}$$

Then since resource shares sum to one,

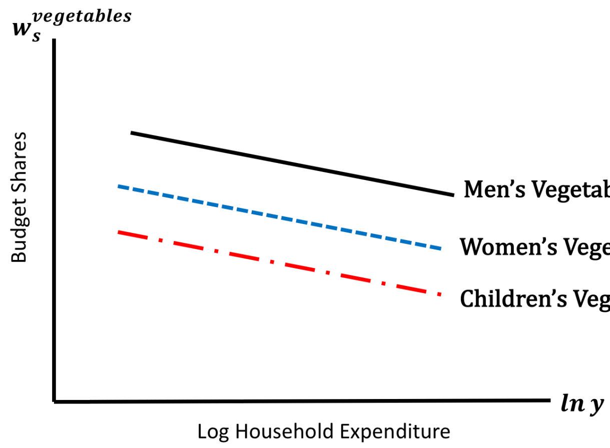
$$\begin{aligned}
&\sum_{j=1}^{J}\zeta_{js}\eta_{js} = \sum_{j=1}^{J}\eta_{j1} = 1 \\
&\sum_{j=1}^{J-1}\zeta_{js}\eta_{js} + \zeta_{Js}\Big(1 - \sum_{j=1}^{J-1}\eta_{js}\Big) = 1 \\
&\sum_{j=1}^{J-1}(\zeta_{js} - \zeta_{Js})\eta_{js} = 1 - \zeta_{Js} \qquad \text{(A11)}
\end{aligned}$$

for $s \in \{2,...,S\}$.

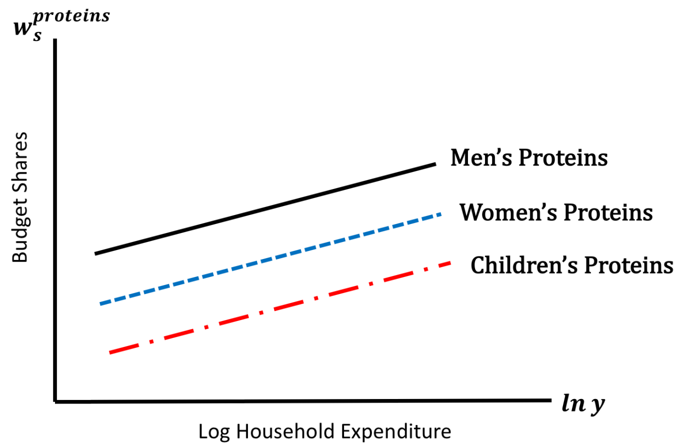
We then stack Equation (A10) for $j \in \{1,...,J-1\}$ and $s \in \{2,...,S\}$ and Equation (A11) for $s \in \{2,...,S\}$. This results in a system of $J(S-1)$ equations. In matrix form, this can be written as the previously defined system of equations $\Omega \times E = B$, where E is a $J(S-1)\times 1$ vector of η_{js} for $j \in \{1,...,J-1\}$ and $s \in \{1,...,S\}$, Ω is a $J(S-1)\times J(S-1)$ matrix, and B is a $J(S-1)\times 1$ vector. By Assumption B4, Ω is nonsingular. It follows that for any given household type s, we can solve for $J-1$ of the η's. Then since resource shares sum to one, we can solve for η_{Js}.

A.4 Graphical Illustration for D-SAP

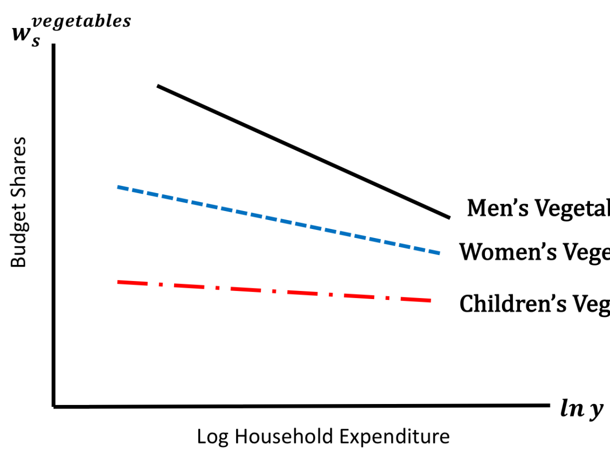
To understand the D-SAP identification results graphically, we first plot hypothetical *individual-level* Engel curves for two assignable goods (e.g., vegetables and proteins). Under SAP, DLP assume that preferences for the assignable good are similar across person types. With piglog preferences, that results in individual-level Engel curves with the same slopes as seen in Figure (A4a) and (A4b).[39]



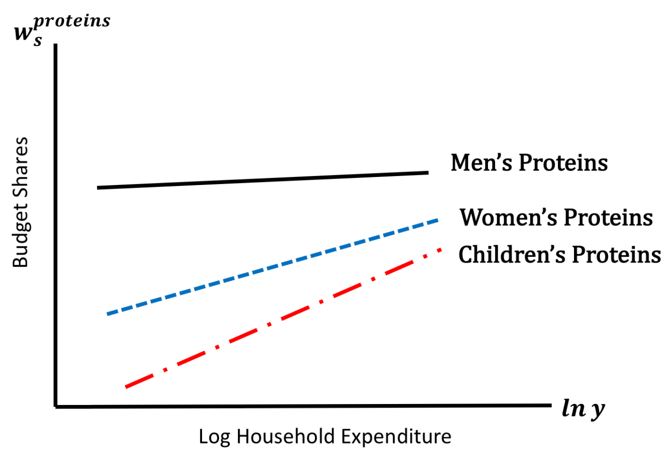
(a) SAP-Vegetables



(b) SAP-Proteins



(c) D-SAP-Vegetables



(d) D-SAP-Proteins

Figure A4: Individual-level Engel curves for assignable clothing and shoes. Figures (A4a) and (A4b) illustrate Engel curves under the SAP restriction. Figures (A4c) and (A4d) illustrate Engel curves under the D-SAP restriction. The Engel curves in Figures (1c) and (1d) do not exhibit shape invariance, however, the difference in slopes across men, women, and children differ in the same way across goods.

We differ in that we allow allow preferences for the assignable goods to differ completely across individuals. Figures (A4c) and (A4d) illustrate this point as the slopes are no longer identical across people. However, we restrict preferences to differ across people in the same way across goods. Intuitively, this means that if women have a higher marginal propensity to consume vegetables than men, then they also have a higher marginal propensity to consume proteins than men. Moreover, this difference in preferences between person types is the same across goods.

It is important to note that DLP also implicitly impose some similarity across goods. Relating to our example, DLP impose that men and women have the same marginal propensity to consume vegetables *and* men and women have the same marginal propensity to consume proteins. In that

[39]The following individual-level Engel curves satisfies SAP: $w_j(y,p) = \delta_j(p) + \beta(p) \ln y$ since $\beta(p)$ does not vary across people.

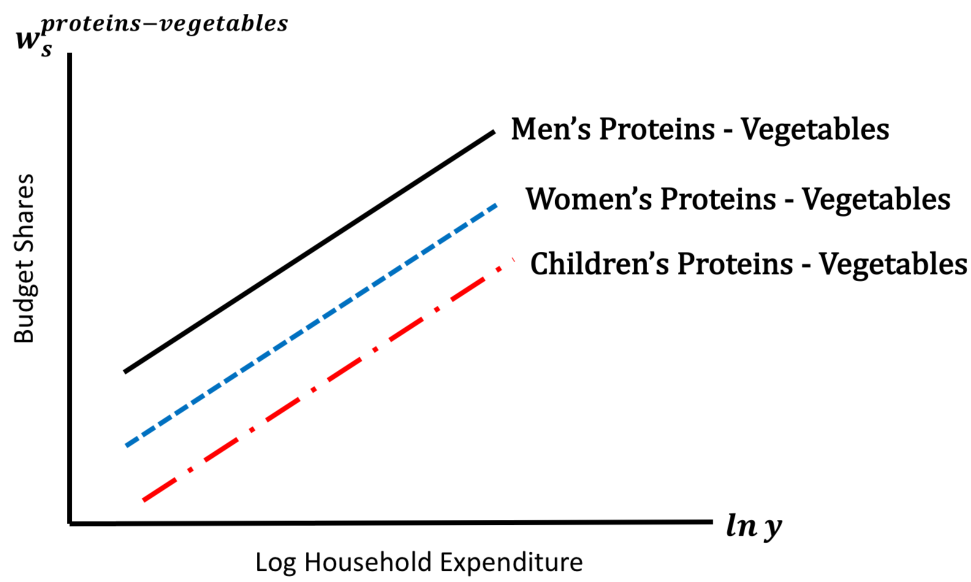


Figure A5: Differences in individual-level Engel curves across assignable clothing and shoes. The Engel curves are derived by taking the difference of Figures (1d) and (1c). By assumption, the difference across Engel curves will have the same slope. Any difference in the slopes of the *household-level* differenced Engel curves can then be attributed to differences in resource shares, as in SAP.

sense, the difference in marginal propensities to consume vegetables across men and women is the same as it is for proteins, in that it does not differ.

With this assumption, if we difference the Engel curves we end up with Figure (A5). Here, the differenced *individual-level* Engel curves are parallel, similar to SAP. Essentially the differenced Engel curves are shape invariant. We can therefore use the DLP identification results to recover resource shares.

A.5 Testing Preference Restrictions

A.6 Scale Economies

Setting an appropriate poverty line is a difficult task (see, for example, Ravallion and Sen (1996) and Wodon (1997) for a comparison of different poverty lines used in Bangladesh). Typically, poverty rates are based on household per capita expenditure; a recent World Bank stated that "consumption per capita is the preferred welfare indicator for the World Bank's analysis of global poverty" (World Bank 2015, 31). Per capita expenditures are then compared to the World Bank's extreme poverty line of \$1.90 per day.[40]

However, simply dividing household consumption by household size does not take into consideration differences in household composition or economies of scale in consumption generated by larger households. Equivalence scales are sometimes used to scale consumption of children (and sometimes women) and adjust for household size. However, these scales are often ad hoc and extremely sensitive to the type of scale used (see, for example, Batana et al. (2013) and Ravallion (2015)). Moreover, equivalence scales lack any theoretical foundation and involve untestable assumptions related to comparing utility across individuals in different household environments.[41] Nevertheless, we use the OECD equivalence scale given by $1+0.7(N_{aj}-1)+0.5N_{cj}$, where N_{aj} is the number of adults in household j and N_{cj} is the number of children. We do not adjust for economies of scale in consumption. We also create an additional equivalence scale based on relative caloric needs, which accounts for the differences in needs between ages and genders. Recognizing that scales may not fully capture the differences in needs across household members, the per capita estimates are our preferred results, and we compare these to the results generated by the equivalence scales.

Following Deaton and Zaidi (2002) and Ravallion (2015), we rescale our consumption estimates around the average characteristics of households at the per capita poverty line.[42] We find that, on average, these households have 2 children (14 and under) and three adults (15 and older), with a

[40] Since October 2015, the World Bank uses updated international poverty line of US\$1.90/day, which incorporate new information on differences in the cost of living across countries (2011 PPP). The new lines preserve the real purchasing power of the previous line of US\$1.25/day in 2005 prices (Chen and Ravallion, 2010).

[41] The deficiencies in equivalence scales has motivated recent work on *indifference scales* (BCL, Chiappori (2016)). Introduced by BCL, indifference scales improve upon equivalence scales in a number of ways. Unlike equivalence scales, which seek to determine the level of income an individual living alone would need to attain the same level as a family with a certain composition, indifference scales ask how much income an individual would need to reach the same indifference curve as they would were they a member of a different type of household. To analyze poverty using indifference scales, we would need to estimate the extent of consumption sharing in Bangladeshi households. We leave that for future work.

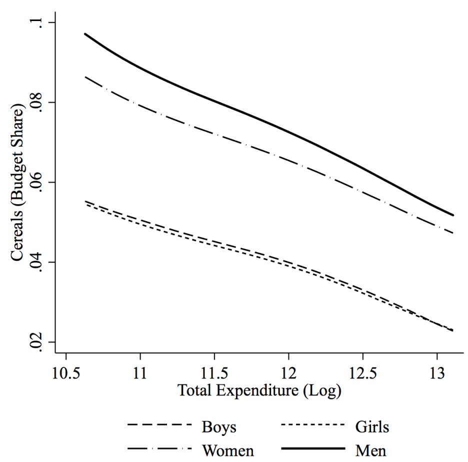
[42] As Deaton and Zaidi (2002) explains, simply dividing total expenditure by the equivalence scale (such as the OECD scale) automatically lowers expenditure per person for every household except those with one adult. If households below the poverty line are disproportionately more likely to have more adults and children, the poverty rate will necessarily be lower. To account for this, the scale is pivoted around characteristics of a "representative" household. Ravallion (2015) suggests choosing the reference household to be the average household at the poverty line, and we follow his advice.

total of 5 household members. Adult equivalent household expenditures are therefore scaled to:

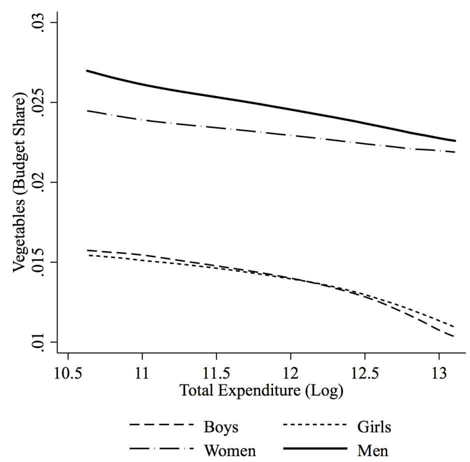
$$
\begin{aligned}
y_j^{AE} &= \frac{y_j}{1+0.7(N_{aj}-1)+0.5N_{cj}} \frac{1+0.7(N_a^r-1)+0.5N_c^r}{N^r} \\
&= \frac{y_j}{1+0.7(N_{aj}-1)+0.5N_{cj}} * 0.68
\end{aligned} \tag{A12}
$$

where y_j is total household expenditure for household j, N_a^r and N_c^r are the number of adults and children in the reference household and N^r is the total number of household members. We also follow a similar method when rescaling individual consumption.[43]

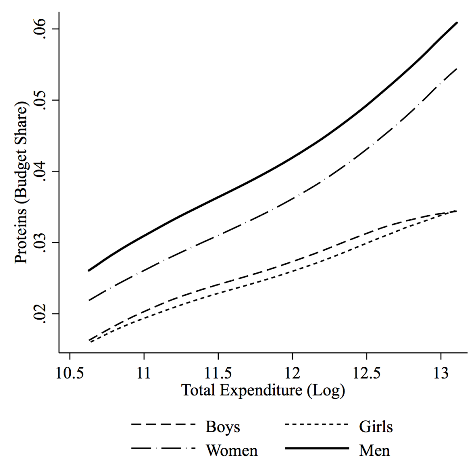
A.7 Additional Figures and Tables



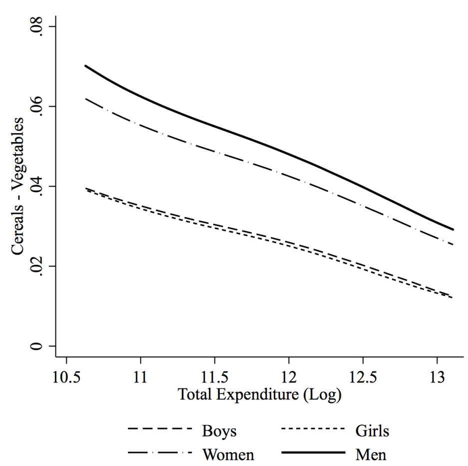
(A) Cereals



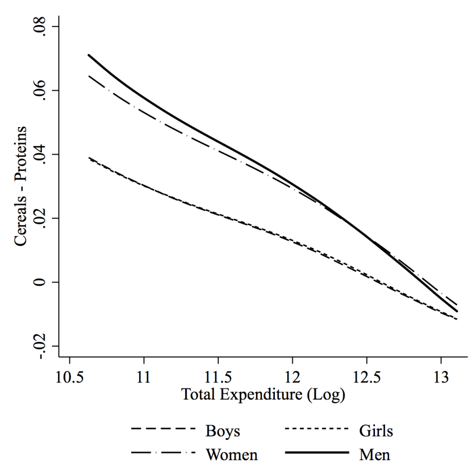
(B) Vegetables



(C) Proteins



(D) Cereals - Vegetables

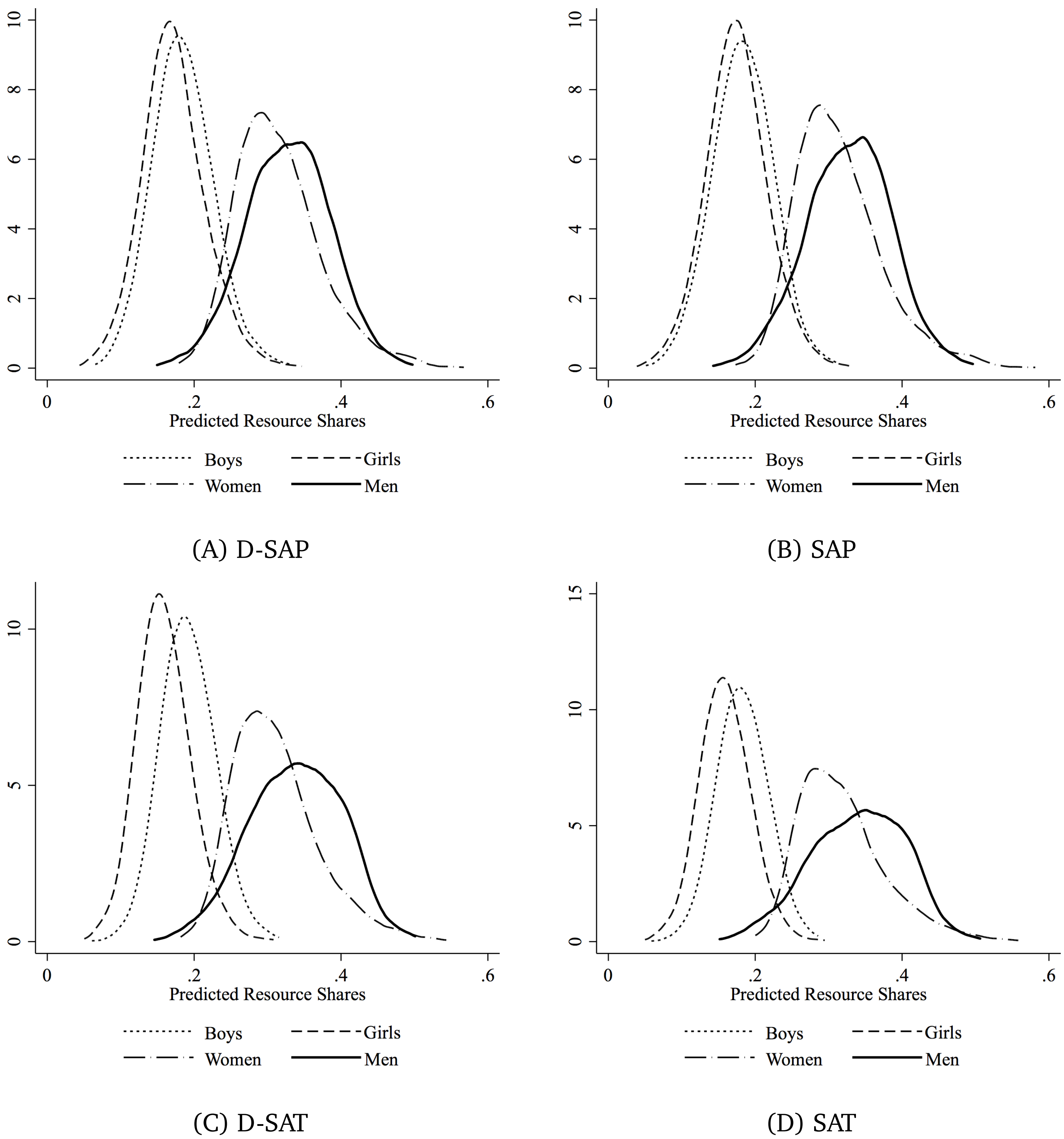


(E) Cereals - Proteins

Note: BIHS data. Proteins include meat, fish, milk, and eggs.

Figure A6: Non-Parametric Engel Curves

[43]For example, a child's expenditure $y_i j$ would be scaled by $\frac{y_j}{0.5} * 0.68$.



(A) D-SAP

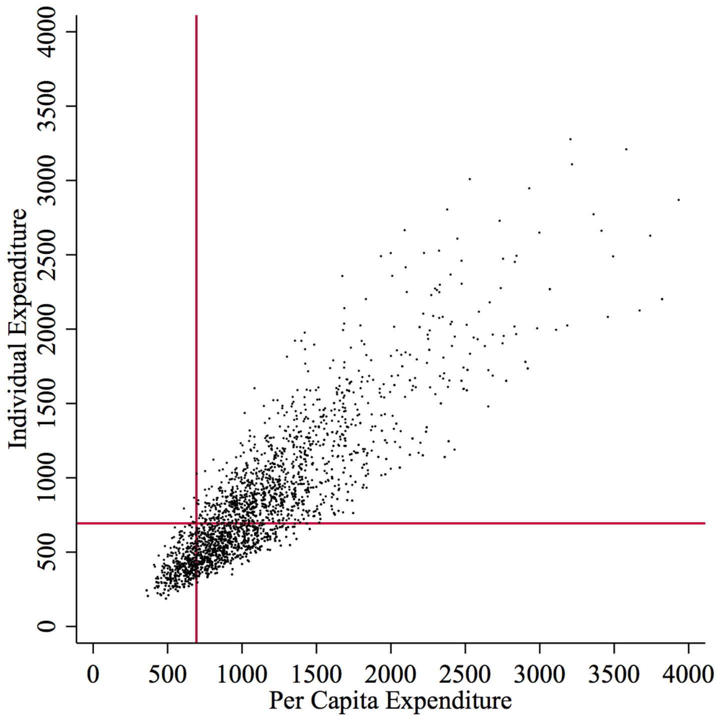
(B) SAP

(C) D-SAT

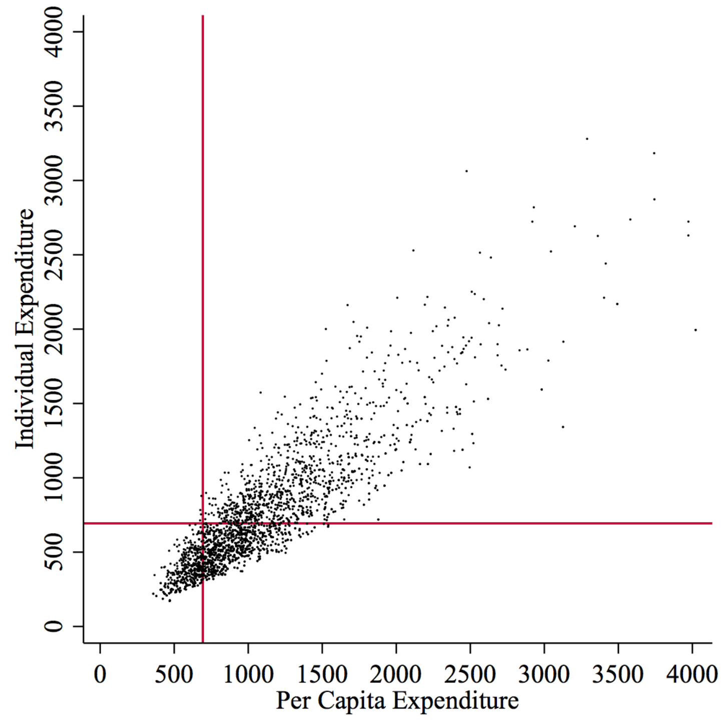
(D) SAT

Note: Estimates based on BIHS data. Only households with both boys and girls and surveyed in 2015 are included. Graphs for 2011 are similar and available upon request.

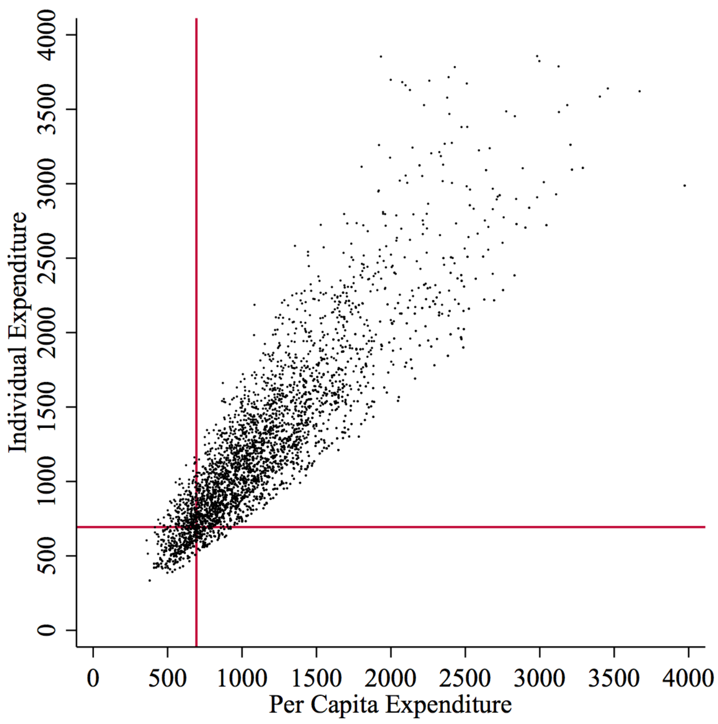
Figure A7: Estimated Resource Shares - Empirical Distributions (2015)



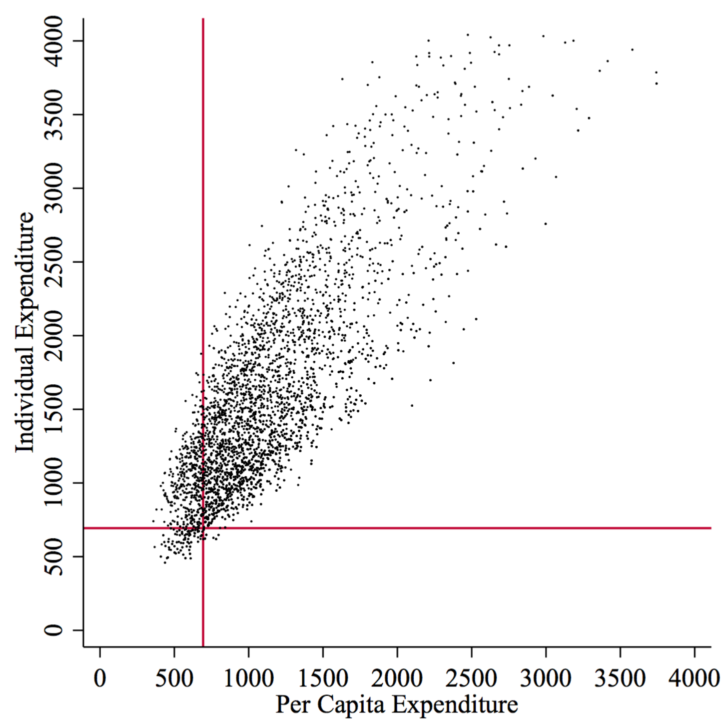
(A) Boys



(B) Girls



(C) Women



(D) Men

Note: Only households surveyed in 2015 are included. Individual consumption is obtained by multiplying total annual household expenditure (PPP dollars) by individual resource shares. Per capita consumption is obtained by dividing total annual household expenditure (PPP dollars) by household size. Reference lines correspond to the 1.90 dollar/day poverty line. Estimates are based on BIHS data and D-SAP identification method with Engel curves for cereals and vegetables.

Figure A8: Individual Expenditure and Per Capita Expenditure

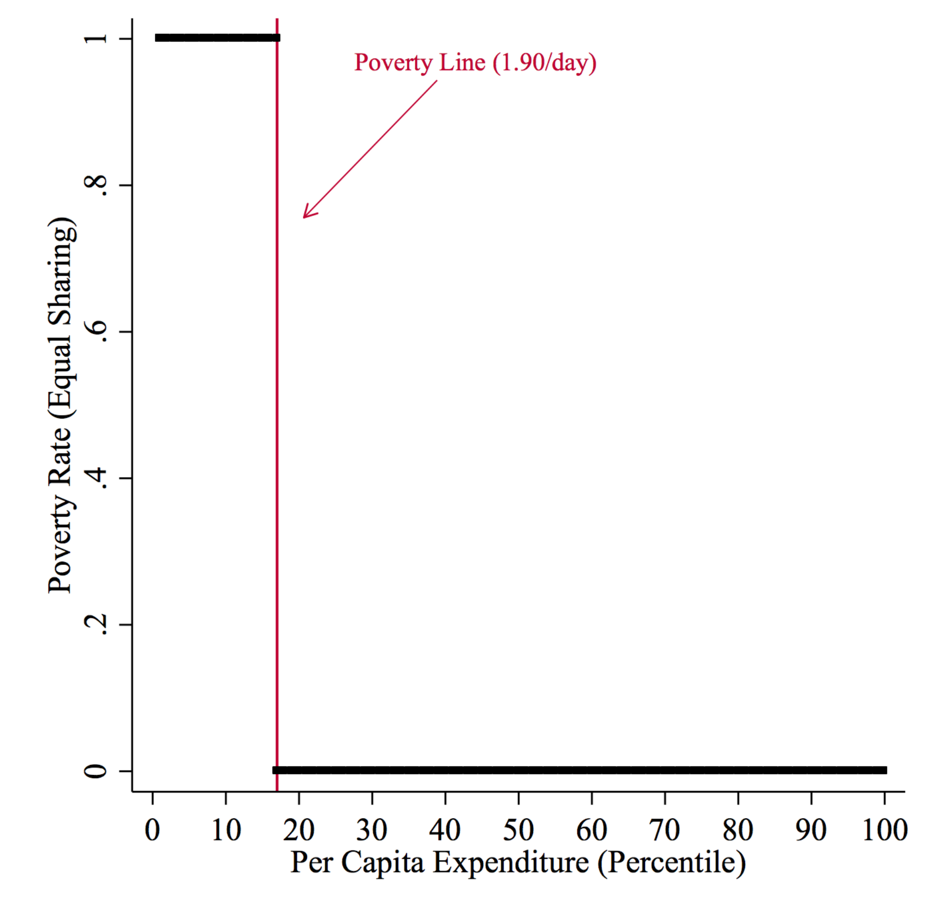
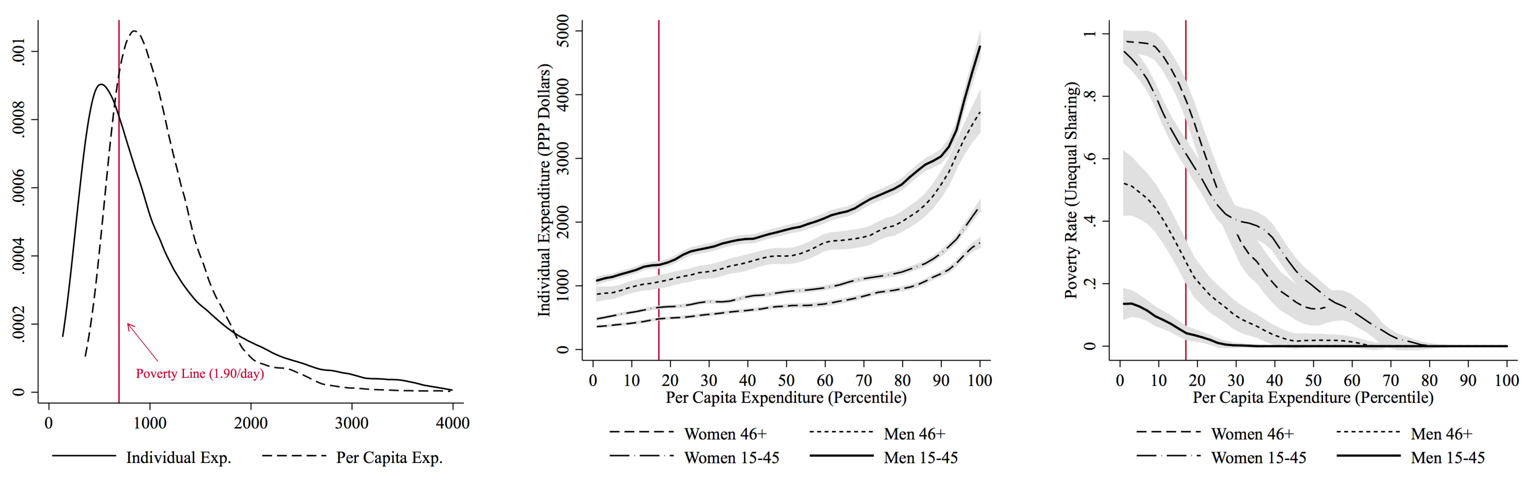


Figure A9: Poverty Rate by Per Capita Expenditure Percentile



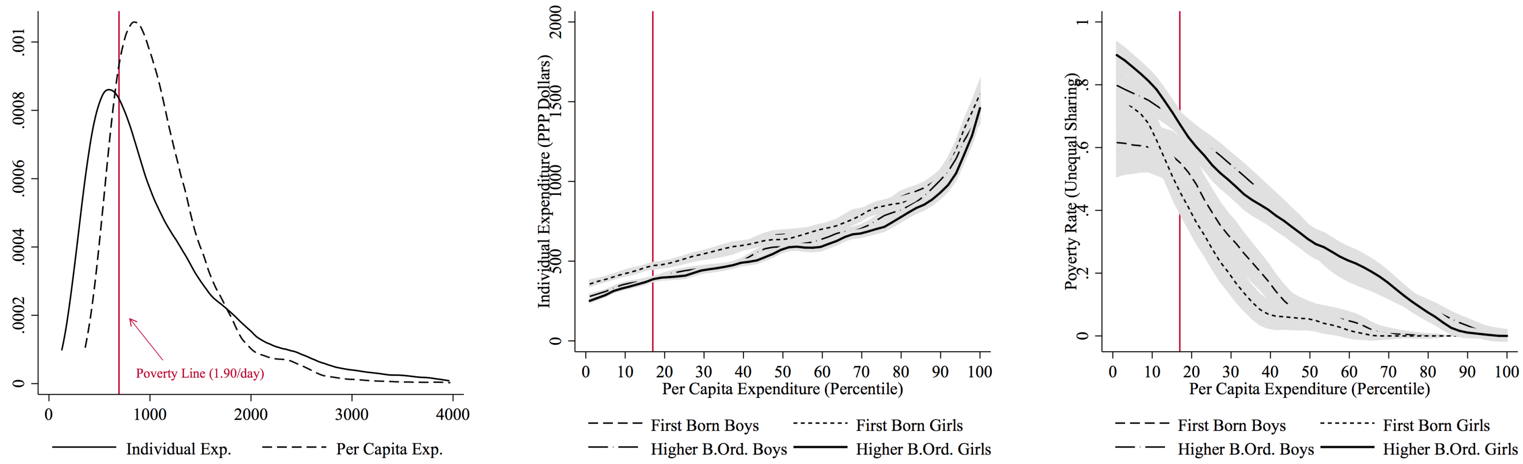
(A) Empirical Distributions

(B) Individual Exp. by Per Capita Expenditure

(C) Poverty Rates by Per Capita Expenditure

Note: Only households surveyed in 2015 are included. Individual consumption is obtained by multiplying total annual household expenditure (PPP dollars) by individual resource shares. Estimates are based on BIHS data and D-SAP identification method with Engel curves for cereals and vegetables. In Panel C, we assume poverty lines for the elderly to be proportional to their caloric requirements relative to young adults (aged 15-45). We rely on the daily calorie needs by age and gender estimated by the United States Department of Health and Human Services and assume young adults require 2,400 calories per day.

Figure A10: Additional Results - Young vs. Older Adults



(A) Empirical Distributions

(B) Individual Exp. by Per Capita Expenditure

(C) Poverty Rates by Per Capita Expenditure

Note: Only households surveyed in 2015 are included. Individual consumption is obtained by multiplying total annual household expenditure (PPP dollars) by individual resource shares. Estimates are based on BIHS data and D-SAP identification method with Engel curves for cereals and vegetables. In Panel C, we assume poverty lines for children to be proportional to their caloric requirements relative to young adults (aged 15-45). We rely on the daily calorie needs by age and gender estimated by the United States Department of Health and Human Services and assume young adults require 2,400 calories per day.

Figure A11: Additional Results - Birth Order

Table A1: BIHS Food Consumption - Descriptive Statistics

	Obs.	Mean	Median	Std. Dev
Boys:				
Total Food	4,502	0.1180	0.1054	0.0688
Cereals	4,502	0.0425	0.0349	0.0326
Vegetables	4,502	0.0142	0.0113	0.0117
Proteins	4,502	0.0253	0.0162	0.0305
Girls:				
Total Food	4,243	0.1155	0.1029	0.0680
Cereals	4,243	0.0414	0.0337	0.0318
Vegetables	4,243	0.0141	0.0114	0.0120
Proteins	4,243	0.0243	0.0156	0.0302
Women:				
Total Food	6,417	0.1818	0.1711	0.0716
Cereals	6,417	0.0694	0.0628	0.0341
Vegetables	6,417	0.0232	0.0202	0.0144
Proteins	6,417	0.0338	0.0253	0.0341
Men:				
Total Food	6,417	0.2046	0.1946	0.0777
Cereals	6,417	0.0773	0.0704	0.0399
Vegetables	6,417	0.0250	0.0222	0.0147
Proteins	6,417	0.0393	0.0300	0.0391

Note: BIHS data. Budget shares reported in the table, ranging between 0 and 1. Proteins include meat, fish, milk, and eggs.

Table A2: Engel Curves Estimates - Resource Shares (D-SAP and D-SAT)

	D-SAP			D-SAT		
	Boys	Girls	Women	Boys	Girls	Women
	(1)	(2)	(3)	(4)	(5)	(6)
Adult Males 15-45	-0.0112**	-0.0117**	-0.0288***	-0.0109*	-0.0123***	-0.0266***
	(0.00544)	(0.00507)	(0.00662)	(0.00660)	(0.00477)	(0.00653)
Adult Females 15-45	-0.0185***	-0.0151***	0.0682***	-0.0207***	-0.0149***	0.0702***
	(0.00527)	(0.00513)	(0.00887)	(0.00613)	(0.00494)	(0.00801)
Adult Males 46+	-0.00931	-0.00447	-0.0324***	-0.00755	-0.00629	-0.0311***
	(0.00840)	(0.00754)	(0.0116)	(0.00944)	(0.00678)	(0.0114)
Adult Females 46+	-0.0122	-0.0196**	0.0648***	-0.0105	-0.0191***	0.0618***
	(0.00794)	(0.00811)	(0.0108)	(0.00907)	(0.00723)	(0.00994)
Boys 0-5	0.0445***	-0.0154**	-0.0225**	0.0405***	-0.0145**	-0.0196**
	(0.00977)	(0.00733)	(0.00981)	(0.0114)	(0.00719)	(0.00943)
Girls 0-5	-0.0160**	0.0411***	-0.0171*	-0.0146*	0.0372***	-0.0153*
	(0.00794)	(0.0114)	(0.00896)	(0.00844)	(0.0124)	(0.00866)
Boys 6-14	0.0544***	-0.0176***	-0.0226***	0.0507***	-0.0163***	-0.0217***
	(0.00801)	(0.00474)	(0.00622)	(0.0117)	(0.00472)	(0.00681)
Girls 6-14	-0.0142***	0.0524***	-0.0209***	-0.0119**	0.0409***	-0.0157***
	(0.00483)	(0.00675)	(0.00566)	(0.00579)	(0.00810)	(0.00572)
Men's Age (avg.)	-0.0526	-0.0820	0.0128	-0.0781	-0.0761	-0.0367
	(0.125)	(0.122)	(0.162)	(0.129)	(0.109)	(0.209)
Men's Age (avg) Sq.	0.0859	0.0874	0.0321	0.0948	0.0860	0.0513
	(0.128)	(0.119)	(0.167)	(0.133)	(0.117)	(0.213)
Women's Age (avg.)	0.109	-0.00804	-0.0464	0.0378	-0.0422	0.230
	(0.195)	(0.162)	(0.180)	(0.173)	(0.148)	(0.276)
Women's Age (avg.) Sq.	-0.159	-0.00882	0.0809	-0.0868	0.0391	-0.206
	(0.244)	(0.175)	(0.207)	(0.198)	(0.171)	(0.321)
Boys' Age (avg.)	0.331	-0.0390	-0.596	-0.755	0.111	-0.184
	(0.379)	(0.385)	(0.438)	(0.806)	(0.398)	(0.594)
Boys' Age (avg.) Sq.	-0.223	-0.312	2.932	4.211	-0.955	1.685
	(2.163)	(2.153)	(2.579)	(4.289)	(2.231)	(3.539)
Girls' Age (avg.)	-0.341	0.442	-0.229	-0.458	0.221	-0.0430
	(0.428)	(0.400)	(0.437)	(0.531)	(0.416)	(0.577)
Girls' Age (avg.) Sq.	0.521	-1.022	0.394	2.030	-1.326	-0.421
	(2.420)	(2.174)	(2.532)	(3.670)	(2.185)	(3.468)
$\mathbb{1}$(Muslim)	0.000762	0.00839	0.00475	-0.00285	0.00751	0.00769
	(0.00948)	(0.00816)	(0.00916)	(0.0101)	(0.00925)	(0.0132)
Working Women (share)	0.00950	0.00372	0.000322	0.0140	0.00424	-0.00556
	(0.00769)	(0.00787)	(0.00737)	(0.00957)	(0.00683)	(0.0111)
Working Men (share)	0.00604	0.00720	-0.00773	0.00517	0.00454	-0.00376
	(0.0116)	(0.0131)	(0.0137)	(0.0144)	(0.0117)	(0.0181)
Women's Education (avg.)	0.00861***	0.00608*	0.00761**	0.00933**	0.00677**	0.0107**
	(0.00325)	(0.00313)	(0.00309)	(0.00373)	(0.00310)	(0.00478)
Men's Education (avg.)	0.00518*	0.00556**	0.00777***	0.00596*	0.00712***	0.00824**
	(0.00271)	(0.00253)	(0.00275)	(0.00341)	(0.00255)	(0.00405)
$\mathbb{1}$(Rural)	0.00917	0.00549	-0.00275	0.00745	0.00444	-0.00776
	(0.00765)	(0.00975)	(0.0102)	(0.00874)	(0.00789)	(0.0140)
$\mathbb{1}$(Barisal)	-0.00336	-0.00563	-0.00707	0.000960	-0.00450	-0.0173
	(0.0126)	(0.0124)	(0.0154)	(0.0132)	(0.0108)	(0.0193)
$\mathbb{1}$(Chittagong)	-0.00266	-0.0155	0.0132	0.00170	-0.0114	0.00392
	(0.0110)	(0.0105)	(0.0146)	(0.0109)	(0.00937)	(0.0156)
$\mathbb{1}$(Dhaka)	0.00375	-0.00830	0.00242	0.00878	-0.00679	0.000595
	(0.0102)	(0.00890)	(0.0111)	(0.0121)	(0.00844)	(0.0151)
$\mathbb{1}$(Khulna)	0.00421	-0.0109	-0.00653	0.0104	-0.0120	-0.00847
	(0.0116)	(0.0104)	(0.0125)	(0.0125)	(0.0114)	(0.0178)
$\mathbb{1}$(Rajshahi)	0.0113	0.00210	-0.00589	0.0128	0.000547	0.00460
	(0.0123)	(0.0117)	(0.0128)	(0.0136)	(0.0106)	(0.0194)
$\mathbb{1}$(Rangpur)	-0.00721	0.00600	-0.00346	-0.0121	0.00502	-0.00717
	(0.0131)	(0.0129)	(0.0134)	(0.0138)	(0.0118)	(0.0202)
Distance to Shops (log.)	-0.000211	-0.000739	0.000970	0.000176	-0.000205	0.000187
	(0.00210)	(0.00233)	(0.00235)	(0.00297)	(0.00206)	(0.00328)
Distance to Road (log.)	0.000823	0.000366	0.00146	0.00110	0.000190	0.000736
	(0.00166)	(0.00171)	(0.00174)	(0.00186)	(0.00186)	(0.00252)
$\mathbb{1}$(2011)	0.00328	0.0135**	0.00185	0.00180	0.0123**	0.00739
	(0.00609)	(0.00629)	(0.00704)	(0.00824)	(0.00581)	(0.0102)
Constant	0.125**	0.135***	0.327***	0.206***	0.150***	0.235**
	(0.0536)	(0.0512)	(0.0593)	(0.0600)	(0.0466)	(0.0923)

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. BIHS data. NLSUR estimates. Robust standard errors in parentheses. Age variables are divided by 100 to ease computation. Sylhet is the excluded region.

Table A3: Engel Curves Estimates - Resource Shares (SAP and SAT)

	SAP			SAT		
	Boys	Girls	Women	Boys	Girls	Women
	(1)	(2)	(3)	(4)	(5)	(6)
Adult Males 15-45	-0.0126**	-0.0138***	-0.0273***	-0.0114*	-0.0130**	-0.0252***
	(0.00550)	(0.00532)	(0.00631)	(0.00597)	(0.00510)	(0.00654)
Adult Females 15-45	-0.0179***	-0.0145***	0.0724***	-0.0189***	-0.0158***	0.0721***
	(0.00565)	(0.00512)	(0.00772)	(0.00581)	(0.00509)	(0.00741)
Adult Males 46+	-0.0122	-0.00601	-0.0286***	-0.0108	-0.00752	-0.0279***
	(0.00859)	(0.00751)	(0.0100)	(0.00808)	(0.00693)	(0.0101)
Adult Females 46+	-0.0168*	-0.0199**	0.0621***	-0.0135*	-0.0194***	0.0601***
	(0.00873)	(0.00794)	(0.0106)	(0.00814)	(0.00737)	(0.0102)
Boys 0-5	0.0424***	-0.0172**	-0.0163*	0.0370***	-0.0156*	-0.0125
	(0.00904)	(0.00774)	(0.00874)	(0.0101)	(0.00798)	(0.00891)
Girls 0-5	-0.0147*	0.0373***	-0.0164**	-0.0132	0.0326***	-0.0136*
	(0.00829)	(0.0110)	(0.00772)	(0.00827)	(0.0123)	(0.00805)
Boys 6-14	0.0441***	-0.0159***	-0.0209***	0.0396***	-0.0141***	-0.0185***
	(0.00726)	(0.00493)	(0.00534)	(0.00765)	(0.00498)	(0.00605)
Girls 6-14	-0.0139***	0.0449***	-0.0189***	-0.0104**	0.0345***	-0.0140**
	(0.00516)	(0.00660)	(0.00510)	(0.00521)	(0.00707)	(0.00552)
Men's Age (avg.)	-0.0531	-0.110	-0.0123	-0.0605	-0.0874	0.0180
	(0.132)	(0.126)	(0.143)	(0.131)	(0.120)	(0.207)
Men's Age (avg) Sq.	0.0821	0.112	0.0546	0.0794	0.0934	0.00355
	(0.134)	(0.125)	(0.146)	(0.135)	(0.126)	(0.212)
Women's Age (avg.)	0.0519	0.0563	-0.0517	0.0170	0.0121	0.218
	(0.215)	(0.159)	(0.182)	(0.193)	(0.156)	(0.275)
Women's Age (avg.) Sq.	-0.0608	-0.0692	0.0837	-0.0400	-0.0164	-0.202
	(0.278)	(0.173)	(0.217)	(0.234)	(0.173)	(0.310)
Boys' Age (avg.)	0.741*	-0.192	-0.519	-0.479	-0.114	-0.0491
	(0.447)	(0.415)	(0.436)	(0.716)	(0.504)	(0.620)
Boys' Age (avg.) Sq.	-1.900	0.603	2.091	2.861	0.373	0.916
	(2.584)	(2.304)	(2.521)	(3.926)	(2.737)	(3.739)
Girls' Age (avg.)	-0.0359	0.545	-0.445	-0.360	0.111	-0.236
	(0.465)	(0.366)	(0.399)	(0.520)	(0.466)	(0.609)
Girls' Age (avg.) Sq.	-1.339	-1.216	1.635	1.485	-0.402	0.950
	(2.754)	(2.050)	(2.344)	(3.544)	(2.507)	(3.705)
$\mathbb{1}$(Muslim)	0.00299	0.00658	0.00364	-0.00410	0.00646	0.00963
	(0.0103)	(0.00827)	(0.00853)	(0.0105)	(0.0117)	(0.0142)
Working Women (share)	0.00685	0.00405	0.00535	0.0132	0.00513	-0.00611
	(0.00798)	(0.00755)	(0.00685)	(0.00921)	(0.00773)	(0.0118)
Working Men (share)	0.00964	0.0153	-0.0179	0.00652	0.00812	-0.0138
	(0.0117)	(0.0142)	(0.0131)	(0.0144)	(0.0132)	(0.0194)
Women's Education (avg.)	0.00884***	0.00632**	0.00524*	0.00936***	0.00803**	0.00840*
	(0.00330)	(0.00318)	(0.00288)	(0.00362)	(0.00338)	(0.00481)
Men's Education (avg.)	0.00580**	0.00573**	0.00810***	0.00617*	0.00647**	0.0113***
	(0.00277)	(0.00242)	(0.00260)	(0.00340)	(0.00284)	(0.00432)
$\mathbb{1}$(Rural)	0.0114	0.00896	-0.00477	0.00817	0.00352	-0.00433
	(0.00746)	(0.0102)	(0.00970)	(0.00901)	(0.00901)	(0.0149)
$\mathbb{1}$(Barisal)	-0.00361	-0.000725	0.000233	0.00150	-0.00253	-0.0174
	(0.0133)	(0.0121)	(0.0139)	(0.0130)	(0.0124)	(0.0205)
$\mathbb{1}$(Chittagong)	-0.00404	-0.00651	0.0150	0.00162	-0.00805	0.00223
	(0.0109)	(0.0108)	(0.0133)	(0.0109)	(0.0112)	(0.0175)
$\mathbb{1}$(Dhaka)	0.00293	-0.00230	0.00283	0.00919	-0.00588	0.00183
	(0.0108)	(0.00915)	(0.0105)	(0.0119)	(0.0103)	(0.0171)
$\mathbb{1}$(Khulna)	-0.000224	-0.00260	-0.00109	0.00902	-0.0102	-0.00779
	(0.0124)	(0.0104)	(0.0121)	(0.0125)	(0.0124)	(0.0190)
$\mathbb{1}$(Rajshahi)	0.0102	0.00377	0.000921	0.0121	0.00118	0.00633
	(0.0129)	(0.0115)	(0.0123)	(0.0137)	(0.0116)	(0.0209)
$\mathbb{1}$(Rangpur)	-0.00162	0.00825	0.00218	-0.0119	0.00355	-0.00155
	(0.0135)	(0.0124)	(0.0129)	(0.0141)	(0.0132)	(0.0221)
Distance to Shops (log.)	-0.000314	-0.000276	0.00105	-0.0000215	0.000127	0.000625
	(0.00224)	(0.00227)	(0.00222)	(0.00303)	(0.00239)	(0.00350)
Distance to Road (log.)	0.00153	0.00138	0.000822	0.00160	0.000412	0.0000340
	(0.00172)	(0.00173)	(0.00165)	(0.00195)	(0.00250)	(0.00272)
$\mathbb{1}$(2011)	0.00402	0.0114*	0.000588	0.00154	0.0118*	0.00987
	(0.00616)	(0.00628)	(0.00636)	(0.00788)	(0.00683)	(0.0111)
Constant	0.110*	0.125**	0.336***	0.188***	0.156***	0.223**
	(0.0563)	(0.0494)	(0.0534)	(0.0595)	(0.0492)	(0.0902)

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. BIHS data. NLSUR estimates. Robust standard errors in parentheses. Age variables are divided by 100 to ease computation. Sylhet is the excluded region.

Table A4: Estimated Resource Shares - Reference Household

	D-SAP		D-SAT		SAP		SAT	
	Estimate	Standard Error	Estimate	Standard Error	Estimate	Standard Error	Estimate	Standard Error
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Boy	0.1761	0.0141	0.1642	0.0206	0.1690	0.0140	0.1445	0.0190
Girl	0.1676	0.0139	0.1455	0.0164	0.1623	0.0127	0.1353	0.0158
Woman	0.2901	0.0137	0.2734	0.0362	0.2956	0.0142	0.3076	0.0379
Man	0.3662	0.0182	0.4170	0.0325	0.3731	0.0181	0.4126	0.0329

Note: Estimates based on BIHS data and Engel curves for cereals and proteins (meat, fish, dairy). The reference household is defined as one with 1 working man 15-45, 1 non-working woman 15-45, 1 boy 6-14, 1 girl 6-14, living rural northeastern Bangladesh (Sylhet division), surveyed in year 2015, with all other covariates at median values.

Table A5: Additional Results

		Resource Shares			Individual Consumption (PPP dollars)		
	Obs.	Mean	Median	St. Dev.	Mean	Median	St. Dev.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
A) Young vs. older adults:							
Boys	4,502	0.1302	0.1416	0.0368	668.85	593.67	333.91
Girls	4,243	0.1251	0.1354	0.0380	653.86	578.30	336.49
Women 46+	1,908	0.1298	0.1320	0.0274	777.47	698.05	346.45
Men 46+	2,398	0.3148	0.1988	0.1789	1,723.37	1,403.33	1,085.79
Women 15-45	6,073	0.2097	0.2269	0.0477	1,070.34	956.80	499.37
Men 15-45	5,403	0.4312	0.4441	0.1271	2,165.45	1,929.09	1,036.70
B) Hhs. with first born boy:							
First born boy	1,885	0.1549	0.1581	0.0194	726.09	659.52	310.55
Higher birth order Boys	746	0.1280	0.1393	0.0288	629.39	571.60	286.17
Higher birth order Girls	668	0.1199	0.1298	0.0291	599.22	559.14	262.96
Women	1,885	0.2520	0.2831	0.0649	1,152.06	1,031.86	528.86
Men	1,885	0.4075	0.4077	0.1009	1,883.21	1,687.91	891.53
C) Hhs. with first born girl:							
First born girl	1,804	0.1458	0.1484	0.0185	703.85	628.71	322.39
Higher birth order Boys	775	0.1417	0.1552	0.0340	726.79	639.89	367.50
Higher birth order Girls	768	0.1322	0.1448	0.0335	666.18	590.75	332.97
Women	1,804	0.2325	0.2608	0.0604	1,097.46	961.25	546.05
Men	1,804	0.4046	0.4084	0.1129	1,914.54	1,669.56	962.87

Note: Estimates based on BIHS data and D-SAP identification method with Engel curves for cereals and vegetables. Mean and median of resource shares do not need to sum to one because there can be more than one individual of the same type in each family. Individual consumption is obtained multiplying total annual household expenditure (PPP dollars) by individual resource shares.

Table A6: Additional Results - Restricted Samples

		Resource Shares			Individual Consumption (PPP dollars)		
	Obs.	Mean	Median	St. Dev.	Mean	Median	St. Dev.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
A) Young vs. older adults:							
Boys	3,906	0.1319	0.1449	0.0367	664.42	588.21	336.50
Girls	3,653	0.1266	0.1380	0.0374	649.96	577.95	335.65
Women 46+	2,212	0.3135	0.1988	0.1774	1,704.19	1,395.82	1,062.02
Men 46+	1,092	0.1428	0.1437	0.0262	871.87	778.39	385.48
Women 15-45	5,244	0.2181	0.2356	0.0478	1,090.46	972.97	512.40
Men 15-45	4,626	0.4342	0.4431	0.1291	2,125.18	1,893.08	1,019.85
B) Hhs. with first born boy:							
First born boy	1,463	0.1565	0.1589	0.0156	714.99	645.80	310.94
Higher birth order Boys	596	0.1187	0.1286	0.0259	567.35	507.94	264.21
Higher birth order Girls	535	0.1107	0.1205	0.0267	540.59	501.67	241.41
Women	1,463	0.2563	0.2806	0.0580	1,146.28	1,027.08	530.23
Men	1,463	0.4291	0.4291	0.0934	1,940.28	1,726.89	933.57
C) Hhs. with first born girl:							
First born girl	1,417	0.1471	0.1496	0.0159	698.47	622.06	322.37
Higher birth order Boys	625	0.1328	0.1454	0.0320	674.19	601.56	345.46
Higher birth 0rder Girls	607	0.1240	0.1370	0.0318	612.00	546.77	305.30
Women	1,417	0.2343	0.2576	0.0550	1,090.68	957.72	542.76
Men	1,417	0.4263	0.4280	0.1070	1,990.65	1,722.85	996.89

Note: Estimates based on BIHS data and D-SAP identification method with Engel curves for cereals and vegetables. Mean and median of resource shares do not need to sum to one because there can be more than one individual of the same type in each family. Individual consumption is obtained multiplying total annual household expenditure (PPP dollars) by individual resource shares.