Sharing the Pie: Undernutrition, Intra-household Allocation, and Poverty

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Abstract

Anti-poverty policies often aim to reach poor individuals by targeting poor households. However, intra-household inequality may mean many poor individuals reside in non-poor households. Using Bangladeshi data, we first show that undernourished individuals are spread across the household per-capita expenditure distribution. We then quantify the extent of food and total consumption inequality within families. Based on a collective model, we develop a new methodology to compute individual-level poverty rates that account for intra-household inequality. 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.

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1 Introduction

Anti-poverty programs are a major focus of governments and international development organizations. A key component of successful anti-poverty policy is the accurate identification of poor individuals. This task is especially hard in developing countries, where income is difficult to observe and consumption data is onerous to collect (Deaton, 2016).[1] These problems are compounded by the presence of intra-household inequality. Standard poverty measures are based on household per-capita consumption and assume an equal distribution of resources among family members.[2] As a result, they may underestimate poverty rates for individuals who have less power within the household. Anti-poverty policies based on such measures may fail to reach their intended targets, particularly if disadvantaged individuals live in households with per-capita consumption above the poverty threshold.

In this paper, we provide estimates of *individual* consumption that account for intra-household inequality to assess the scope of such poverty mistargeting. We verify the validity of these estimates by comparing them to established measures of individual nutritional deprivation. For our analysis, we rely on a unique dataset from Bangladesh that contains anthropometric indicators for each household member as well as individual-level records of food intake and detailed recalls of household-level expenditure.

We begin by quantifying the extent of nutritional inequality both across and within Bangladeshi households. Next, we develop a structural model of intra-household allocation to estimate how *total* consumption is divided among family members. We show that a large share of the variation in nutritional status and consumption is *within* households. Using the model estimates, we calculate poverty rates that take into account intra-household inequality. We demonstrate that programs based on household consumption miss a significant fraction of poor individuals: in our sample, one third of individuals with estimated levels of consumption below the World Bank's extreme poverty line are in fact classified as non-poor based on household per-capita consumption.

Undernutrition can stem from insufficient caloric and protein intakes or from illness, and is one important dimension of individual welfare. For these reasons, it often serves as a proxy of individual poverty. Inspired by recent work by Brown et al. (2018a) and using data from the Bangladesh Integrated Household Survey (hereafter BIHS), we show that undernourished individuals are spread across the household per-capita expenditure distribution. For instance, we find that only two thirds of undernourished adults and children are in the bottom half of the distribution. We also document the existence of substantial within-household variation in caloric and protein intakes, and in individual-level food consumption. Even when we adjust for differences in needs by age and gender, we find that within-household inequality accounts for almost half of the total inequality in caloric intake, for roughly 40 percent of the total inequality in protein intake, and for one fifth of inequality

[1] To overcome this issue, many social programs are targeted using proxies for household income or consumption, such as the demographic composition of the household or household assets. Proxy means test models have also been developed to improve poverty targeting with imperfect information. Brown et al. (2018b) discuss possible limitations of these methods. For reviews of targeting and social programs see Coady et al. (2004), Del Ninno and Mills (2015), and Ravallion (2016).

[2] For instance, the World Bank regularly uses consumption per-capita in its poverty analyses; see World Bank (2015) for details.

in food consumption.

To obtain consumption-based measures of individual poverty, we study the allocation of total consumption within the household. Measuring the extent of consumption inequality within families is challenging as consumption surveys are conducted at the household level and goods can be shared. Even in a dataset as rich as the BIHS, individual consumption is not observed in its entirety. We therefore develop a household model to structurally estimate the intra-household allocation of total resources, when the researcher observes only a portion of individual consumption. We rely on the *collective* household framework, where each family member has a separate utility function over goods and the intra-household allocation of goods is Pareto efficient (see Chiappori (1988, 1992) and Apps and Rees (1988) for seminal papers). The goal of the model is to estimate *resource shares*, defined as each member's share of total household consumption (Browning et al., 2013).

Resource shares are not identified without adding more structure to the model (see e.g., Browning et al., 1994; Browning and Chiappori, 1998; Vermeulen, 2002; Chiappori and Ekeland, 2009). Dunbar et al. (2013) achieve identification by assuming observability of one private assignable good for each individual and by imposing semi-parametric restrictions on the preferences for such goods.[3] Under these restrictions, resource shares are identified by comparing Engel curves for the assignable goods across people within households or across households for a given person type. We provide a new identification method that can reduce the restrictiveness of such assumptions by making use of *multiple* assignable goods for each individual. Based on the BIHS 24-hour food module that records detailed food consumption for each household member, we construct individual-level expenditures on several food groups (e.g., cereals and vegetables). We then apply our novel approach to study intra-household resource sharing in Bangladeshi families.

Our estimates indicate that men consume a larger share of the budget relative to women, who in turn consume relatively more than boys and girls. Interestingly, we do not find substantial evidence of gender inequality among children. For instance, in households comprising one man, one woman, one daughter and one son, the man consumes 36 percent of the budget, the woman consumes 30 percent, and the boy and girl each consume 17 percent, respectively.[4] We also assess inequality in access to household resources *among* adults by age and find that older men and women consume significantly less than younger adults (Calvi, 2017). Further, we document the existence of preferential treatment for first-born children relative to later-born children (Jayachandran and Pande, 2017). Our model-based estimates of individual consumption prove to be much better indicators of nutritional outcomes than household per-capita consumption (which assumes resources are allocated equally within the household).

We use these estimates to calculate poverty rates that account for intra-household inequality and compare them to those obtained using household per-capita consumption. Two observations stand out. First, household-level measures substantially understate poverty: allowing for unequal

[3]A good is *private* if it is not shared or consumed jointly. A good is *assignable* if it appears in just one (known) household member's utility function, and so is only consumed by that household member.

[4]These are estimates for a reference household, defined as one comprising one working man of age 15 to 45, one non-working woman aged 15 to 45, one boy 6 to 14, one girl 6 to 14, living in rural northeastern Bangladesh, surveyed in year 2015, with all other covariates at median values.

resource allocation within the household increases the overall extreme poverty rate from 17 precent to 27 percent. Second, we show that women, children (later-born children in particular), and the elderly face significant probabilities of living in poverty even in households with per-capita expenditure above the poverty line. By contrast, men living in poor households are not necessarily themselves poor. We apply machine learning methods to identify relevant predictors of this misclassification. We find, for instance, that lower education and relatively worse outside options are strongly correlated with poor individuals residing in non-poor households.

We verify the robustness of our findings along several dimensions. We demonstrate that our results are not driven by differences in needs or by differences in activity levels across individuals. We also test the sensitivity of our poverty calculations to accounting for joint consumption within families. Unsurprisingly, allowing for joint consumption and economies of scale reduces poverty rates. However, the relative poverty ranking of men, women, children, and the elderly is maintained. Lastly, we show that our results are confirmed when accounting for possible measurement error in our data.

This paper makes several key contributions. The first is to document the existence and quantify the degree of intra-household inequality in Bangladesh along several dimensions of individual welfare. The richness of the BIHS dataset combined with the intra-household allocation model allows for direct comparisons between one's nutritional status, access to food, consumption, and likelihood of living in poverty. Such comparisons generate a number of policy-relevant insights, while providing a validation of the structural model. Our second contribution is to compute individual-level poverty rates for Bangladesh that account for the unequal allocation of goods within the household. While the use of collective models to improve poverty measures in developing countries has recently received some attention (see e.g., Dunbar et al. (2013) and Penglase (2018) for Malawi, Bargain et al. (2014) for Côte d'Ivoire, Calvi (2017) for India, and Sokullu and Valente (2018) and Tommasi (2018) for Mexico), we are the first to provide such calculations separately for prime-aged women and men, the elderly, boys, girls, and by birth order. Moreover, we are the first to evaluate the extent of poverty mistargeting using the collective approach. Our third contribution is a new methodology to identify the fraction of total household expenditure that is devoted to each household member in the context of a collective household framework. Our strategy exploits the observability of two assignable goods. While most consumption surveys do not include assignable food (which we use in this paper), they do contain data on more than one assignable good (such as clothing and footwear). Our approach is therefore applicable to a variety of contexts.

The policy implications of our findings pertain to poverty measurement and how anti-poverty programs should be targeted when intra-household inequality is present. Accounting for intra-household inequality may yield poverty rates that are much higher than what standard estimates indicate, particularly for vulnerable groups such as women, children, and the elderly. While the existing practice for most large-scale programs is to target poor households, our findings suggest that more finely targeted policies are required to ensure that individuals who need help actually receive it. Programs that are designed to improve the relative standing of the aforementioned vulnerable groups within the household may also be beneficial.

The rest of the paper is organized as follows. Section 2 provides an overview of the related literature and further discusses the contributions of this paper. In Section 3, we show that undernourished individuals do not necessarily reside in poor households. In Section 4, we set out a collective model for extended families and present our novel identification approach. In Section 5, we describe estimation and the structural results. In Section 6, we demonstrate that poor individuals do not necessarily reside in poor households. Section 7 further discusses poverty mistargeting and compares various measures of individual welfare. Section 8 concludes. Proofs and additional material are in the online Appendix.

2 Related Literature

Our study pertains broadly to research on measuring intra-household inequality in individual welfare. Within this large literature, we contribute to recent work on the identification and estimation of consumption allocation within the household. We also relate to research on poverty measurement, health, and nutrition.

Standard poverty measures typically rely on household-level indicators to draw inferences on individual welfare. A recent World Bank report, for instance, states that consumption per-capita is the preferred welfare indicator for the World Bank's analysis of global poverty (World Bank, 2015, p.31). Household-level indicators have a number of practical advantages, such as reducing the costs involved with data collection and avoiding assumptions regarding the sharing of public goods within the household. These measures, however, implicitly assume that household resources are distributed evenly across all household members.[5]

There is substantial evidence to suggest that this is not the case. A broad body of works have examined, for instance, the unequal treatment of widows (Chen and Drèze, 1992; Drèze and Srinivasan, 1997; Jensen, 2005; van de Walle, 2013; Djuikom and van de Walle, 2018), orphans (Bicego et al., 2003; Case et al., 2004; Evans and Miguel, 2007), and first and later-born children (Behrman and Tubman, 1986; Behrman, 1988; Black et al., 2005; Price, 2008; Booth and Kee, 2009; De Haan, 2010; Black et al., 2011; Jayachandran and Pande, 2017). Brown et al. (2018a) document that in sub-Saharan Africa around one half of undernourished women and children are not found in the poorest 40 percent of households. Other works have also found evidence of intra-household inequality in caloric intake (Pitt et al., 1990), body-mass index (Sahn and Younger, 2009), non-food expenditures (De Vreyer and Lambert, 2018) and multidimensional poverty indices (Klasen and Lahoti, 2016). Closest to our analysis is parallel work by D'Souza and Sharad (Forthcoming), who use BIHS data to explore the intra-household distribution of food consumption and differences in average shortfalls in nutritional intakes. We depart from their work by moving beyond nutrition and focusing on within-household differences in total consumption, and by analyzing the consequences

[5] Adult equivalence scales are sometimes used to account for differences in needs due to age or gender, as well as economies of scale that larger households may benefit from. These, however, do not account for intra-household inequality.

of such differences for poverty calculations.

The starting point of our analysis is the collective household model of Chiappori (1988, 1992), which assumes that the household reaches a Pareto efficient allocation of goods. While this is an important assumption, it is still not sufficient to identify how resources are allocated within the household (Browning et al., 1994; Browning and Chiappori, 1998; Vermeulen, 2002; Chiappori and Ekeland, 2009). A growing literature has sought to solve this identification problem by adding more structure to the model. Several approaches have been developed. Browning et al. (2013) demonstrate that if we assume preference stability across household compositions (singles and married couples), we can identify the sharing rule. Studies using this type of identification restriction include Lewbel and Pendakur (2008), Bargain and Donni (2012), and Lise and Seitz (2011). Preference stability assumptions between individuals living alone versus living together, however, are somewhat unattractive. Other studies relax such restrictions and achieve set-identification (as opposed to point-identification) of the sharing rule using axiomatic revealed preference methods (Cherchye et al., 2011, 2015, 2017).

A different strand of the identification literature that closely relates to our approach obtains point-identification of the sharing rule via comparisons of Engel curves of goods that are not shared and are consumed by specific household members known to the researcher (that is, private assignable goods). The key assumption is that resource shares are independent of total household expenditure.[6] This assumption is quite powerful, but still requires additional restrictions to identify resource shares. Dunbar et al. (2013) use this assumption along with semi-parametric restrictions on individual preferences for a single assignable good to identify resource shares. No price variation is needed and the only data requirement is an assignable good for each person within the household. Recent work by Dunbar et al. (2017) modifies this approach and shows that the preference restrictions of Dunbar et al. (2013) are no longer necessary if there are a sufficient number of distribution factors (variables affecting how resources are allocated, but not preferences nor budget constraints) in the data.[7]

Our approach extends this recent literature. Like Dunbar et al. (2013, 2017), we analyze Engel curves of assignable goods and require that resource shares be independent of household expenditure. Unlike Dunbar et al. (2013), we require two assignable goods for each household member (which are available in the BIHS as well as in other popular datasets, such as the PROGRESA dataset and the World Bank's Living Standards Measurement Study), but we impose weaker preference restrictions. Specifically, we allow preferences for the assignable goods to differ quite flexibly across people within households and across households for a given person type, but require these differences to be similar across goods. Unlike Dunbar et al. (2017), we do not require distribution

[6]This assumption needs to be satisfied at least at low levels of household expenditure. Menon et al. (2012) show that for Italian households resource shares do not exhibit much dependence on household expenditure, therefore supporting identification of resource shares based on this particular assumption. Bargain et al. (2018) find similar results in Bangladesh. Moreover, Cherchye et al. (2015) use detailed data on Dutch households to show that revealed preferences bounds on women's resource shares are independent of total household expenditure. Finally, this restriction still permits resource shares to depend on other variables related to expenditure, such as measures of wealth.

[7]In some ways, a distribution factor can be thought of as a preference restriction. One possible limitation of this approach is that distribution factors may be difficult to find (especially when children are included in the model) and their validity (that they do not impact preferences or the budget constraint) might be hard to prove.

factors.

A growing literature applies Engel curve comparisons to quantify intra-household inequality. These methods have been used to study inequality between children and adults (Bargain and Donni, 2012; Dunbar et al., 2013; Bargain et al., 2014, 2017; Dunbar et al., 2017; Calvi et al., 2017; Tommasi, 2018; Sokullu and Valente, 2018; Lechene et al., 2018), the wellbeing of older women in India (Calvi, 2017), and the treatment of foster children in Malawi (Penglase, 2018). We add to this literature in two ways. First, we analyze several new dimensions of inequality within the household. We are the first, to our knowledge, to study the extent of consumption inequality among children by gender and birth order. Second, the existing literature has used assignable clothing to identify inequality within the household. Recent work by Bargain et al. (2018) suggests that clothing functions quite well as a means to identify consumption inequality. However, using food instead of clothing has several estimation advantages that we discuss in more detail in Section 5.1.

3 A Descriptive Analysis of Nutrition and Inequality

Household surveys often collect data on nutritional status using anthropometric measures. This data can serve as a proxy for individual-level poverty, which is significantly more difficult to observe (see previous sections for details). Combating undernutrition in developing countries has been a key component of the Millennium Development Goals and features prominently in the Sustainable Development Goals (World Bank, 2008). Bangladesh has seen a large decrease in 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. Nevertheless, recent figures show that 36 percent of children under age five are stunted, 14 percent are wasted, and 19 percent of women are underweight (NIPORT, 2016).

In this section, we follow the existing literature and measure individual deprivation using nutritional outcomes. We analyze the relationship between nutritional outcomes and household expenditure, and assess the extent of nutritional inequality *within* households.[8] This analysis sets the stage for an investigation of the validity of our consumption-based individual-level poverty estimates, which we discuss in Section 7.

We use data from the first two waves of the Bangladesh Integrated Household Survey (BIHS) conducted in 2011/12 and 2015 (we will later use the same data to estimate the structural model). 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 intra-household inequality. In 2011, 6,500 households were drawn from 325 primary sampling units.[9]

[8] The evidence regarding the impact of income on nutritional outcomes is mixed, particularly in South Asia. Well known is the *Asian enigma*: children in South Asia are shorter on average relative to children who are poorer on average (Ramalingaswami et al., 1997). Furthermore, Deaton and Drèze (2009) find that higher per capita incomes in India do not translate into higher caloric intake or better nutritional outcomes on average. However, Hong et al. (2006) finds that children in the poorest 20 percent of households in Bangladesh are more than three times as likely to suffer from stunting as children from the top 20 percent of households. This echoes similar findings from Headey et al. (2015) that wealth accumulation is one of the biggest drivers behind the reduction in undernutrition in Bangladesh.

[9] The survey defines households as "a group of people who live together and take food from the same pot," while a household member is "someone who has lived in the household at least 6 months, and at least half of the week in each week in those months" (IFPRI, 2016).

Households were interviewed beginning in October, 2011 and the first wave was completed by March, 2012. Households were then resurveyed in 2015.

The BIHS collected anthropometric measures for *all* household members in both survey rounds. For individuals of age 15 and over, we calculate their body-mass index (hereafter BMI), defined as weight (in kilograms) divided by height (in meters) squared. We categorize adult individuals to be underweight if their BMI is less than 18.5 according to the WHO classification (World Health Organization, 2006).[10] For children of age 5 or younger, we construct height-for-age and weight-for-height z-scores.[11] A child is considered stunted if her height-for-age is two standard deviations below the median of her reference group, and wasted if her weight-for-height is less than two standard deviations below the median. These key indicators 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.

Among individuals 15 and older, we find that 27 percent are underweight in 2015, while 36 percent of children are stunted and 18 percent are wasted. Men and boys are more likely to be underweight and stunted than women and girls, which is in line with existing evidence.[12] Table A3 in the Appendix lists summary statistics for nutritional outcomes for adults and children across both survey rounds. Adult undernutrition and child stunting has improved over time, while wasting in the 2015 round is higher than in the earlier round.

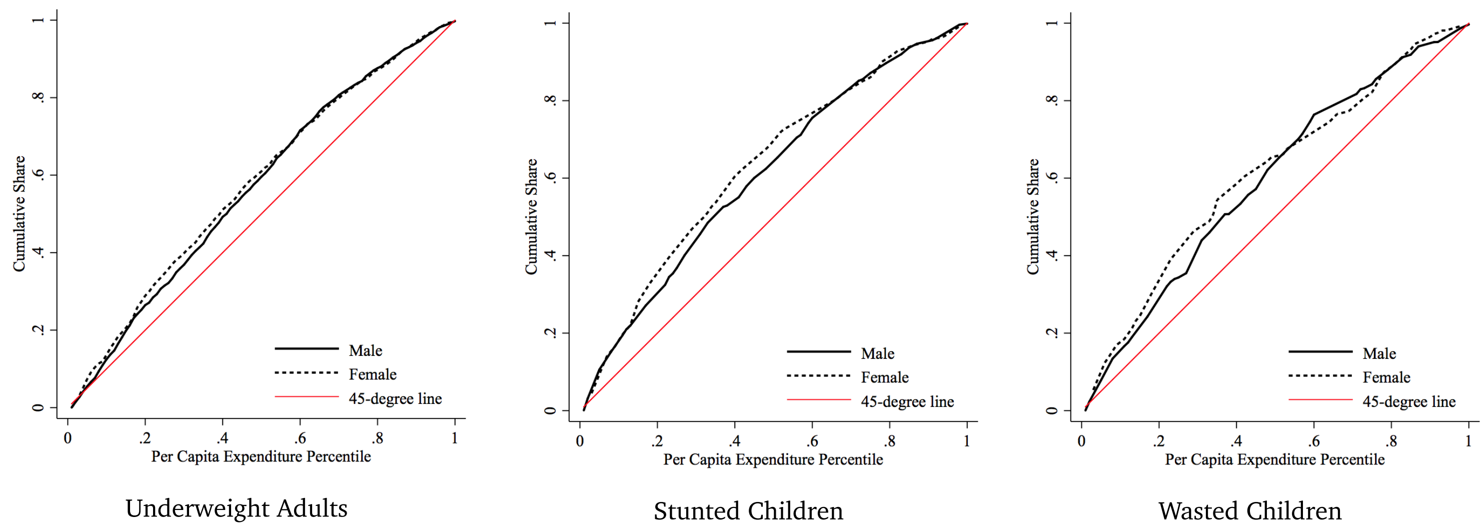
Undernutrition and Household Expenditure. To examine how the incidence of undernutrition among adults and children varies with per-capita household expenditure, we construct concentration curves using an approach similar to Brown et al. (2018a). These curves show the cumulative share of undernourished 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, the concentration curve would coincide with the 45-degree line.

Figure 1 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 some concavity across adults and children as well as by gender, it is striking how close the curves are to the 45-degree line, particularly for underweight adults and wasted children. For example, only around 60 percent of undernourished adults and children are found among the bottom 50 percent of house-

[10]We exclude women who are pregnant or lactating at the time of the survey; this equals 12 percent of women in 2011 and 10 percent of women in 2015. We also exclude individuals who have a BMI value smaller than 12 or greater than 60 as these values are almost certainly due to measurement error. This follows Demographic and Health Surveys (DHS) convention.

[11]The Stata command `zscore06` is used to convert height (in centimeters) and weight (in kilograms) along with age in months into a standardized variable using the WHO 2006 classification. We do not include nutritional indicators for children between 6 and 14 years of age given known problems with accurate anthropometric measurement for this age group; see e.g. Woodruff and Duffield (2002).

[12]Svedberg (1990), Svedberg (1996), Wamani et al. (2007) and Brown et al. (2018a) show similar findings for sub-Saharan Africa. For Pakistan, Hazarika (2000) finds that girls are as nourished (or better) than boys. Excluding older (over 49) and young adults (under 20) reduces the overall incidence of undernutrition among adults.



Note: BIHS data. The graphs show concentration curves for the cumulative proportion of women and men who are underweight, and children age 0-5 who are stunted and wasted at each household per-capita expenditure percentile. Observations with missing values and pregnant or lactating women have been dropped. The Stata command `glcurve` is used to construct the curves.

Figure 1: Undernutrition Concentration Curves (2015)

holds.[13] 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. In the Appendix, we discuss potential biases that could be driving the results: namely, the role of excess mortality among the undernourished and measurement error in anthropometric outcomes. We do not find these to significantly affect our findings.[14]

The question is, how much variation in nutritional status is there *within* households? To facilitate comparisons across family members, we create an indicator variable equal to 1 if an adult is underweight or if a child is either stunted or wasted, and zero otherwise. For each household, we then compute the share of household members who are undernourished. With no intra-household inequality, we should expect this number to equal either 0 or 1; that is, either all household members are adequately nourished or they are all undernourished. We find instead that 55 percent of households in 2015 (60 percent in 2011) have some intra-household inequality in nutritional status. Only 7 percent of households (9 percent in 2011) contain members who are all undernourished.[15]

Caloric Intake, Food Consumption and Inequality. A key advantage of the BIHS is that, in addition to anthropometric data, it contains a measure of individual food consumption for each

[13] Brown et al. (2018a) find similar results when using household wealth as given by the DHS wealth index. They compare these results with those obtained using household consumption data and find consumption to be a slightly better indicator of nutritional status. For this reason, we do not present wealth-based concentration curves in this paper.

[14] In the Appendix, we also include concentration curves for severely undernourished individuals and find a higher concentration of severely stunted children in the lower household expenditure percentiles relative to Figure 1, but less so for severely underweight adults and wasted children. We also present results that exclude individuals who have reported suffering from weight-loss due to illness in the past four weeks and find that these figures display more curvature. That exposure to diseases plays a role is indisputable and to some extent reassuring. This, however, does not dismiss our later analysis of intra-household consumption inequality. In effect, it might be the case that individuals are exposed to diseases exactly because they do not receive enough resources (or vice versa). Given the data at hand, it is hard to assess how illness and resource sharing interact. We leave the answer to this interesting question to future research.

[15] In households with at least one undernourished member (and excluding those with all undernourished members), 42 percent of household members are undernourished on average. Figure A9 in the Appendix plots the average rate of undernourishment within households by household expenditure percentile, excluding households with no intra-household inequality in nutritional outcomes. Poorer households with nutritional intra-household inequality have a slightly higher proportion of members who are undernourished than wealthier ones; however, it is also the case that around 40 percent of individuals in the wealthiest households are undernourished. In line with evidence from the concentration curves, we see that there is substantial within-household variation in nutritional outcomes, and this persists across expenditure percentiles.

household member. This measure is based on a 24-hour recall of individual dietary intakes and food weighing. In conducting the individual dietary module, a 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. Next, the enumerator would ask what share of that meal was consumed by each household member.[16]

Note that in calculating individual food consumption this way, we implicitly assume that food consumption over the previous day is representative of food consumption in general. This could be problematic, e.g., if the 24-hour recall coincided with a special occasion or a festivity. In response to this, several precautions were taken by IFPRI to ensure the accuracy of the data collected. First, households were asked if the previous day was a "special day;" if so, they were asked about the most recent "typical day." No household was surveyed during Ramadan. Second, during the 2015 wave of the BIHS, a 10 percent subsample of households completed the 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 recorded the number of guests the household fed during the recall day. In our analysis, we err on the side of caution and exclude households with guests. In Section A.2 in the Appendix, we summarize several tests we conduct to determine the extent of measurement error in our data, and its relevance for our results.

From the individual records of food consumption, we are able to derive a person's caloric intake. We can also derive other measures of nutritional adequacy such as protein intake, which is often used to indicate the quality of calories consumed. Given that nutritional requirements for maintaining a healthy weight clearly differ across individuals (for example, adult males require a higher caloric intake than young children), we rescale caloric and protein intake to allow for more consistent comparisons between individuals. We draw from the 2015-2020 Dietary Guidelines for Americans which contain requirements for males and females by age group.[17] We normalize caloric intake and food consumption using a 2,400 calories per day reference level (which is the amount typically recommended for moderately active adult males). We similarly rescale protein intake to 46 grams per day, the recommended amount for most adults. Table A4 in the Appendix presents descriptive statistics for the actual and scaled caloric intake, protein intake, and individual food consumption variables for adults and children using data from the two waves of the survey.[18]

[16]The survey accounts for food given to guests, animals, food that was left over, and meals outside of the home. If a household member did not have the meal, the enumerator determined the reason.

[17]We acknowledge that caloric requirements may differ between the United States and Bangladesh due to physiological, environmental, and societal differences; however, we believe the relative differences between ages and genders should be similar. The Dietary Guidelines for Americans are put together by the Department of Health and Human Services and the Department of Agriculture. Specifically, we use Table A2-1 and the caloric requirements for moderately active adults. The file can be accessed here: `https://health.gov/dietaryguidelines/2015/guidelines/`. We exclude children younger than 12 months of age, since many of those will rely on breast milk as part of their calorie intake (this is not measured by the survey). For simplicity, we here do not account for potential differences in activity levels between individuals.

[18]As expected, all three measures are increasing in household per-capita expenditure; the elasticities are 0.14, 0.22 and 0.52 for scaled caloric intake, protein intake and the value of food consumption, respectively, and statistically significant at the 1 percent level (for the unscaled versions, the elasticities are 0.22, 0.33, and 0.60).

Table 1: 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 share	0.705	0.464	0.607	0.375	0.395	0.210
Between share	0.295	0.536	0.393	0.625	0.605	0.790

Note: BIHS data 2015. Within and between components of MLD are given as share of total MLD. Scaled values account for recommended dietary intake by age and gender.

To separate the contributions of within-household inequality and between-household inequality to overall inequality in nutritional intake, we use the Mean Log Deviation measure of inequality (hereafter MLD). Unlike the more popular Gini index, MLD is exactly decomposable into between- and within-group components. Following Ravallion (2016), the MLD 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 nutritional intake, $\bar{c}$ is average nutritional 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 nutritional intake of c_j, Equation (1) can be decomposed as follows (see the Appendix for details):

$$MLD = \underbrace{\frac{1}{N}\sum_{i=1}^{N}\ln\left(\frac{\bar{c}_j}{c_{ij}}\right)}_{\text{Within}} + \underbrace{\frac{1}{N}\sum_{j=1}^{N}N_j\ln\left(\frac{\bar{c}}{c_j}\right)}_{\text{Between}} \tag{2}$$

We implement this decomposition for each of the three nutritional intake variables using both the unscaled and scaled versions of the variable. Results for 2015 are presented in Table 1 (results for 2011 are similar and available upon request). Food consumption has the highest overall inequality relative to caloric and protein intake (for both scaled and unscaled). For caloric and protein intakes, within household inequality represents almost 50 percent and 40 percent of total inequality, respectively. Within-household inequality for individual food consumption is less prevalent (but still quite remarkable) and accounts for 21 percent of total inequality once adjusted for age and gender.[19]

While nutrition and food consumption are clearly important components of individual welfare, other dimensions of consumption, such as housing, health, and education, also matter significantly (Deaton, 2016). In the next section, we develop a new methodology to estimate how total consumption is divided among family members. This will allow us to further investigate the extent of intra-household inequality and its implications for the measurement of poverty.

[19] Our findings are consistent with D'Souza and Sharad (Forthcoming). Using data from the first wave of BIHS, the authors show that household heads have a much smaller calorie shortfall than other members. Moreover, they demonstrate that, conditional on being undernourished, non-heads consume significantly below their minimum daily energy requirement. Pitt et al. (1990) similarly find large differences in caloric intake within Bangladeshi households. Note that the lower share of within-household inequality for food consumption may be driven in part by regional differences in prices, which are not accounted for.

4 Theoretical Framework and Identification Results

We now set out a collective household model to identify and estimate resource sharing among co-resident family members. Since only half of our sample consists of nuclear households (comprising two parents and their children), we develop a flexible theoretical framework for extended families that can account for the presence of multiple decision makers.

4.1 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 $\sigma_j \in \{\sigma_1, ..., \sigma_J\}$. Households differ according to their composition or *type*, defined by the number of people in each category. We denote a household type by s. In practice, households also differ along a wider set of observable attributes, such as age of household members, location, and other socio-economic characteristics. Such characteristics may affect both preferences and resource shares. To reduce notational clutter, we omit household characteristics for now. We will introduce them explicitly in estimation.

Each household consumes K types of goods with market prices $p = (p^1, ..., p^K)$. Let $z = (z^1, ..., z^K)$ be the vector of observed quantities of goods purchased by each household and $x_j = (x_j^1, ..., x_j^K)$ be the vector of *private good equivalents*, which is then divided among the household members. Following Browning et al. (2013) and Dunbar et al. (2013), 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 $z_s = A_s \sum_{j=1}^{J} \sigma_j x_j$, and allows the sum of the private good equivalents to be weakly larger than what the household purchases. All members face the same shadow price vector $A_s^{'} p$. If good k is a private good (which is never jointly consumed) the kth row of A would be equal to 1 in the kth column and zeros elsewhere.[20]

Each household member has a monotonically increasing, continuously twice differentiable and strictly quasi-concave utility function. Let $U_j(x_j)$ be the sub-utility function of an individual of type j over their 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 following maximization program:

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

where the function $\widetilde{U}_s$ describes the social welfare function of the household. $\widetilde{U}_s$ exists because we

[20]This framework also allows for a simple household production technology with constant returns to scale through which market goods are transformed into household commodities.

assume that the household reaches a Pareto efficient allocation of goods.[21]

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 into 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 personal shadow budget constraint. 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 are the same, and interpret resources as being divided equally within categories. In estimation, however, we allow preference parameters and resource shares to vary according to a set of household characteristics, including demographic composition, so that, e.g., households with older children may allocate more resources to children than households with younger children.

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. While the budget share functions for goods that are not private are more complicated, the ones for private assignable goods, W_{js}^k, 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 ω_{js}^k is the budget share function of each household member when facing their personal shadow budget constraint. 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 as her husband but less food because she derives less utility from it (e.g., she has lower caloric requirements). We instead estimate food Engel curves for each group j. We then implicitly invert these Engel curves to solve for resource shares.

4.2 Identification of Resource Shares

The main goal of the model outlined above is to estimate resource shares. Resource shares, however, are not point-identified without additional structure. In this section, we summarize the methodology developed in Dunbar et al. (2013) (hereafter DLP) and discuss two new identification approaches that expand upon the DLP identification results.

[21] While some papers provide evidence in favor of the collective model (see e.g. Attanasio and Lechene (2014)), some others works have cast doubt on the assumption that households behave efficiently (see e.g. Udry (1996)). In Section A.7 of the online Appendix, we provide a formal test of Pareto efficiency using distribution factors. Pareto efficiency is not rejected in our context.

We first introduce some notation. Let $p = [p_j,\ \bar{p},\ \tilde{p}]$, where p_j are the prices of the private assignable goods for each person type $j = 1, ..., J$. 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. In the empirical section, we assume individuals have piglog (price independent generalized logarithmic) preferences over the private assignable goods (Deaton and Muellbauer, 1980). This functional form facilitates the discussion of identification, so we use it henceforth. In the Appendix, we discuss identification in a more general framework.

The standard piglog indirect utility function takes the form: $V_j(p,y) = e^{F_j(p)}(\ln y - \ln a_j(p))$. By Roy's Identity, the budget share functions are as follows: $w_j(y,p) = \alpha_j(p) + \gamma_j(p)\ln y$. Thus, the budget share functions are linear in $\ln y$. Substituting them into Equation (4), and holding prices fixed, results in the following household-level Engel curves:

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

The identification results in DLP are (at least partially) based on semi-parametric restrictions on the shape parameter γ_{js}, where γ_{js} can be interpreted as each person's marginal propensity to consume the private assignable good as their expenditure increases.

Similarity Across People (SAP) and Similarity Across Types (SAT). When (at least) one assignable good is observable for each person type, 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 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).[22]

The indirect utility function under SAP is $V_j(p,y) = e^{F(p)}(\ln y - \ln a_j(p))$, with budget share functions $w_j(y,p) = \alpha_j(p) + \gamma(p)\ln y$. Notice that $F(p)$ and $\gamma(p)$ do not have a j subscript, and therefore they do not vary across family members. Using this budget share function, Equation (5) is modified such that $\gamma_{js} = \gamma_s$, and 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 by 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.

The alternative preference restriction DLP impose is SAT, which is consistent with the following indirect utility function: $V_j(p,y) = e^{F_j(p_j,\bar{p})}(\ln y - \ln a_j(p))$. 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

[22] A household type is determined by the household composition, which is similar, though not the same as the household size. In a slight abuse of terminology, we refer to household type and household size interchangeably henceforth.

not vary across household types, that is $\bar{\gamma}_j(p_j, \bar{p})$ is not a function of the prices of shared goods $\tilde{p}$. Equation (5) can be modified so that $\gamma_{js} = \gamma_j$, and resource shares are identified by comparing the Engel curve slopes across household types.

Both SAP and SAT are practical ways to recover resource shares using demand functions for a single private assignable good. However, evidence on the validity of these restrictions is mixed. Dunbar et al. (2017), Calvi (2017), and Bargain et al. (2018) find evidence supporting the use of SAP or SAT with clothing expenditures as the assignable good. Bargain et al. (2018) rejects both SAP and SAT using food expenditures. 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. SAP and SAT are not nested in our approaches (or vice versa). Thus, the choice of one approach over another varies by context and is driven by data availability.

Differenced SAT (D-SAT). In our first approach, we demonstrate that the SAT restriction can be weakened by using multiple (two) private assignable goods. Unlike DLP, we do not assume that preferences for the assignable goods are similar across household types. Rather, we allow preferences to differ considerably across household types, but require them to do so in a similar way across two different private assignable goods.[23] For our identification strategy to work, we therefore require the observability of 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.

Using the piglog indirect utility function $V_j(p, y) = e^{F_j(p)}(\ln y - \ln a_j(p))$, our assumption requires that

$$\frac{\partial F_j(p)}{\partial p_j^1} - \frac{\partial F_j(p)}{\partial p_j^2} = \theta_j(p_j^1, p_j^2, \bar{p}) \tag{6}$$

where $\theta_j(p_j^1, p_j^2, \bar{p})$ does not vary across household types. 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 type. Moreover, p_j^1 and p_j^2 are additively separable in $b_j(\cdot)$.

We use Roy's Identity to derive the budget share functions for goods $k = 1, 2$:

$$\frac{h_j^k(p, y)}{y} = \Big(\frac{\partial b_j(p_j^1 + p_j^2,\ \bar{p},\ \tilde{p})}{\partial p_j^k} + \frac{\partial r_j(p_j^1\ , p_j^2,\ \bar{p})}{\partial p_j^k}\Big) \ln y + \alpha_j^k(p) \tag{7}$$

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

$$\begin{aligned} W_{js}^1 =& \sigma_j \eta_{js}[\alpha_{js}^1 + (\beta_{js} + \gamma_j^1) \ln \eta_{js}] + \sigma_j \eta_{js}(\beta_{js} + \gamma_j^1) \ln y \\ W_{js}^2 =& \sigma_j \eta_{js}[\alpha_{js}^2 + (\beta_{js} + \gamma_j^2) \ln \eta_{js}] + \sigma_j \eta_{js}(\beta_{js} + \gamma_j^2) \ln y \end{aligned} \tag{8}$$

Consistent with the SAT restriction, preferences for the assignable goods are allowed to differ

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

across people in γ_j^k and α_{js}^k. We weaken the SAT restriction by including an additional preference parameter β_{js}, which allows preferences for the assignable goods to differ more flexibly across household types. However, we restrict preferences to differ across household types in a similar way across goods; that is, β_{js} is the same for both goods.

To better understand our assumptions, consider the following example. Suppose we observe assignable cereals and vegetables 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 types. However, we require the difference in the man's preferences for cereals across household types be the same as the difference in his preferences for vegetables. The same must be true for women and children. Note that we do not require the two goods be complements or substitutes, or have any other similarity of that nature.

To show that resource shares are identified, first let $\lambda_{js} = \beta_{js} + \gamma_j^1$ and $\kappa_j = \gamma_j^2 - \gamma_j^1$. Then, we can rewrite System (8) as follows:

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

with $j = 1, ..., J$. If we subtract person j's budget share function for good 2 from her budget share function for good 1, we are left with a set of differenced Engel curves that are similar to the SAT system of equations from DLP (i.e., Equation (5) with $\gamma_{js} = \gamma_j$). An OLS-type regression of $W_{js}^1 - W_{js}^2$ on log expenditure identifies the slope coefficient for each person type j. Comparing the slopes of the differenced Engel curves across household types, and assuming that 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 differenced 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.

Differenced SAP (D-SAP). In our second approach, we show that the SAP restriction of DLP can also be weakened by using two private assignable goods. Unlike DLP, we do not assume that preferences for the assignable goods are similar across people. We allow preferences to differ considerably across people, but require them to do so in a similar way across two 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. 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. As above, p_j^1 and p_j^2 are additively separable in $b_j(\cdot)$.

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

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

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

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

Consistent with the SAP restriction, preferences for the assignable goods are allowed to differ entirely across household types in γ_s^k and α_{js}^k. We weaken the SAP restriction by including an additional preference parameter β_{js}, which allows preferences for the assignable goods to differ more flexibly across people. However, we restrict preferences to differ across people in a similar way across goods.

We can again use an example to illustrate the differences between DLP and our method. Suppose we observe assignable cereals and vegetables for men, women and children in a nuclear household. The SAP restriction would require that the man's marginal propensity to consume cereals be the same as the woman's and the children's. With our assumption, we allow his marginal propensity to consume cereals to differ considerably from that of other household members. However, we require these differences in the marginal propensity to consume cereals be the same as the differences in the marginal propensity to consume cereals.

Let $\lambda_{js} = \beta_{js} + \gamma_s^1$ and $\kappa_s = \gamma_s^2 - \gamma_s^1$. System (12) can be rewritten as follows:

$$\begin{aligned} W_{js}^1 &= \sigma_j \eta_{js}[\alpha_{js}^1 + \lambda_{js} \ln \eta_{js}] \ + \ \sigma_j \eta_{js} \lambda_{js} \ln y \\ W_{js}^2 &= \sigma_j \eta_{js}[\alpha_{js}^2 + (\lambda_{js} + \kappa_s) \ln \eta_{js}] \ + \ \sigma_j \eta_{js}(\lambda_{js} + \kappa_s) \ln y \end{aligned} \tag{13}$$

Subtracting person j's budget share function for good 2 from her budget share function for good 1 yields a set of differenced Engel curves that is similar to the SAP system. Identification of resource shares is then straightforward. An OLS-type regression of $W_{js}^1 - W_{js}^2$ on log expenditure identifies the slope coefficients $c_{js} = \eta_{js}\kappa_s$. 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.5 in the Appendix provides 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 approach over ours: they require observability of a single assignable good, while we need two. However, the DLP approach imposes stronger preference similarity restrictions. The relative merits of each approach is an empirical matter that depends on the context. In some situations, preferences for certain goods may be mostly identical across people, in which case SAP is preferable.

Alternatively, D-SAP may be the correct method if preferences differ across people, but demands for two relatively similar goods are available to the researcher. The same considerations apply to preference differences across household types (SAT, D-SAT). In our context, we find D-SAP to be the preferred approach, as we consistently fail to reject the D-SAP assumptions but not the others (see Section A.7 in the Appendix for details). Nonetheless, in what follows we estimate the model on a sample of Bangladeshi households using each of the four identification approaches.

5 Estimating Resource Sharing and Individual Consumption

5.1 Empirical Strategy

Data. The Bangladesh Integrated Household Survey (BIHS) contains detailed data on expenditure, together with information on household characteristics, and demographic and other particulars of household members. To estimate the model, we rely on three main components of the 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 proceed as follows. 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 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.

Given the richness of the dataset, we can 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 clear picture of how individual spending on different food items varies with household expenditure (see Figure A10 in the Appendix) 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. In our empirical analysis, we focus on cereals, vegetables, and proteins (meat, eggs, fish, and dairy products), which are the three largest components for food consumption.

For computational reasons, we pool data from the two rounds of the BIHS dataset. We select a sample of 6,417 households. To ensure comparability across household types, 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, we drop from the analysis households reporting to have had guests during the food recall day (1,554 households). A small number of households have individuals with

Table 2: Descriptive Statistics

	Obs.	Mean	Median	Std. Dev
Household Expenditures:				
Total Expenditure (PPP dollars)	6,417	5,302	4,654	2,599
Per Capita Expenditure (PPP dollars)	6,417	1,132	1,018	503
Budget Shares Cereals	6,417	0.204	0.194	0.083
Budget Shares Vegetables	6,417	0.068	0.062	0.033
Budget Shares Proteins	6,417	0.107	0.090	0.089
Household Composition:				
Boys 0-5	6,417	0.349	0.000	0.551
Girls 0-5	6,417	0.338	0.000	0.558
Boys 6-14	6,417	0.623	1.000	0.711
Girls 6-14	6,417	0.611	0.000	0.723
Adult Males 15-45	6,417	1.021	1.000	0.628
Adult Females 15-45	6,417	1.151	1.000	0.553
Adult Males 46+	6,417	0.380	0.000	0.498
Adult Females 46+	6,417	0.307	0.000	0.482
Household Characteristics:				
Average Age Boys	4,502	7.385	7.500	3.195
Average Age Girls	4,243	7.437	7.500	3.053
Average Age Men	6,417	38.768	37.000	11.281
Average Age Women	6,417	34.700	33.000	9.301
$\mathbb{1}$(Muslim)	6,417	0.875	1.000	0.331
Working Men (share)	6,417	0.869	1.000	0.270
Working Women (share)	6,417	0.632	1.000	0.415
Average Education Men	6,417	1.420	1.000	1.338
Average Education Women	6,417	1.444	1.500	1.211
$\mathbb{1}$(Rural)	6,417	0.826	1.000	0.380
$\mathbb{1}$(Barisal)	6,417	0.096	0.000	0.294
$\mathbb{1}$(Chittagong)	6,417	0.128	0.000	0.333
$\mathbb{1}$(Dhaka)	6,417	0.305	0.000	0.460
$\mathbb{1}$(Khulna)	6,417	0.157	0.000	0.364
$\mathbb{1}$(Rajshahi)	6,417	0.102	0.000	0.302
$\mathbb{1}$(Rangpur)	6,417	0.091	0.000	0.287
$\mathbb{1}$(Sylhet)	6,417	0.123	0.000	0.329
Log Distance to Shops	6,417	-1.053	-1.347	1.345
Log Distance to Road	6,417	-0.166	0.000	1.709
Year=2011	6,417	0.528	1.000	0.499

Note: BIHS data. Expenditure data based on annual recall. Per capita expenditure is defined as total expenditure (PPP dollars) divided by household size. Individual education ranges from 0 (no schooling) to 5 (completed secondary school). Indicators for employment equal 1 if individuals worked for pay during the week prior to the survey.

food budget shares that take a value of zero due to illness, fasting, being an infant, or currently being away from the household. Households with such individuals are excluded from the analysis (546 households). Finally, households with missing data for any of the household characteristics are dropped from the sample.

Tables 2 contains descriptive statistics for the variables included in the empirical analysis; Table A5 in the Appendix describes 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 corresponds to 5,302 PPP dollars.[24] The corresponding per-capita expenditure

[24]We here focus on expenditure on non-durable consumption goods. In what follows, we refer to consumption and expenditure interchange-

amounts to 28,931 taka on average. Cereals account for 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 perfect. 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.[25] An overwhelming majority of households are Muslim (87 percent) and live in rural areas (83 percent).

Estimation. To estimate the model, we add an error term to each Engel curve in either System (9) or (13) depending on the set of identification assumptions. 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. The estimation of resource shares, however, should be invariant to the choice of assignable goods. In the Appendix, we check the robustness of our estimates to using different food categories (e.g., milk, fish, and meat).

For households with children of both genders, we take the following system of eight equations to the data:

$$\begin{cases} W^1_{js} = \sigma_j \eta_{js}[\alpha^1_{js} + \lambda_{js} \ln \eta_{js}] + \sigma_j \eta_{js}\ \lambda_{js} \ln y + \epsilon^1_{js} \\ W^2_{js} = \sigma_j \eta_{js}[\alpha^2_{js} + (\lambda_{js} + \kappa_{js}) \ln \eta_{js}] + \sigma_j \eta_{js}\ (\lambda_{js} + \kappa_{js}) \ln y + \epsilon^2_{js} \end{cases} \tag{14}$$

where W^1_{js} and W^2_{js} ($j = b, g, w, m$) are budget shares for boys', girls', women's, and men's cereals and vegetables consumption, 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 $\sigma_m \eta_{ms} = 1 - \sigma_g \eta_{gs} - \sigma_w \eta_{ws}$. Note that W^k_{js}, y and σ_j are observed in the data.

Figure A10 in the Appendix shows the results of non-parametric regressions of W^k_{js} on $\ln y$. While Engel curves are negatively sloped for cereals and vegetables, the share of expenditure devoted to proteins increases with total expenditure. No substantial non-linearity can be detected in these relationships, providing support to the appropriateness of our empirical specification.[26]

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

ably.

[25] This can partly attributed to the high average spousal age difference. According to our 2015 sample, the average age difference between head husbands and their wives is 8 years, which is consistent with the 2014 Bangladesh Demographic and Health Survey.

[26] Tommasi and Wolf (2018) shows that if the data exhibit relatively flat Engel curves in the consumption of the private assignable goods, then the DLP model can be weakly identified. In our dataset, households display a large variation in the consumption of private assignable goods as well as in the budget shares differences. Hence, we do not appear to have a weak identification problem with our data.

containing all other demographic characteristics presented in Table 2. We model resource shares η_{js} and preference parameters λ_{js}, α_{js}^{k}, and κ_{js} as linear functions of a and X.[27] To achieve identification of resource shares, we impose the preference restrictions discussed in Section 4.2. 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 Dunbar et al. (2013). 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 set of assignable goods only (cereals).

Since the error terms may be correlated across equations, we estimate the system of Engel curves using non-linear Seemingly Unrelated Regression (SUR) method.[28] Non-linear SUR is iterated until the estimated parameters and the covariance matrix settle. Iterated SUR is equivalent to maximum likelihood with multivariate normal errors.[29] Alternatively, the model can be estimated as a system of four differenced Engel curves, that is $W_{js}^{1} - W_{js}^{2}$ (see Section 4.2 for more details). While this is a more parsimonious approach and might be preferable in some situations, it has important limitations. First, it does not allow us to recover preference parameters for the assignable goods. Moreover, it might reduce the efficiency gains stemming from the correlation of errors across equations.

5.2 Estimation Results

We start by briefly discussing the role of covariates. Point estimates and robust standard errors are reported in Tables A6 (for the D-SAP and D-SAT approaches) and A7 (for SAP and SAT) in the Appendix. For the sake of brevity, the tables present the covariates of resource shares η_{js} only (analogous tables for the covariates of preference parameters are available upon request). We find that household composition matters. As expected, women's resource shares increase with the number of women in the household, and decrease as the numbers of men, boys, and girls increase. The same holds true for boys and girls. With the exception of women's and men's education, no statistically significant association is found between the sharing rule and other socio-economic characteristics, even though the sign of the estimated coefficients is as expected.

Based on these estimates, we compute women's, men's and children's resource shares for each household as linear combinations of the underlying covariates. In Table 3, we present the estimated resource shares for reference households. We define a reference household as one comprising one working man aged 15 to 45, one non-working woman aged 15 to 45, one boy aged 6 to 14, and

[27] That resource shares change linearly with the household composition variables is due to computational reasons. Adding indicator variables for each possible household composition (as in Dunbar et al. (2013)) would result in an intractable increase in the number of parameters needed to be estimated.

[28] Dunbar et al. (2013) and other works (Dunbar et al., 2017; Calvi, 2017; Penglase, 2018; Tommasi, 2018; Sokullu and Valente, 2018) use similar approaches. They all estimate resource shares using Engel curves of private assignable clothing. Clothing purchases, however, may be infrequent and estimation issues may arise due to zero expenditures. In our sample, for example, assignable clothing shares equal 0.8 percent for children, 1.3 for women, and 1.1 for men. Moreover, the BIHS does not allow us to identify assignable clothing for boys and girls separately, for children by birth order, or for prime-aged adults versus the elderly. We overcome these issues by looking at assignable food consumption instead. Parallel work by Lechene et al. (2018) develops an alternative approach that reduces the non-linearity of the estimation problem.

[29] The sum-of-squared residuals function has multiple local minima. We therefore performed a grid search over 300 starting values and selected the estimates corresponding to the minimum sum-of-squared residuals.

Table 3: 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	0.173	0.014	0.167	0.025	0.178	0.015	0.161	0.023
Girl	0.175	0.015	0.163	0.019	0.172	0.015	0.163	0.019
Woman	0.297	0.016	0.306	0.045	0.286	0.015	0.303	0.042
Man	0.355	0.018	0.364	0.036	0.364	0.019	0.373	0.036

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. SAP and SAT restrictions are imposed on the first set of assignable goods (cereals), while the second set (vegetables) is unrestricted.

one girl aged 6 to 14, living in rural northeastern Bangladesh (Sylhet division), surveyed in year 2015, with all other covariates at median values. In such households, 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, which is in line with encouraging trends in gender equality in Bangladesh (Talukder et al., 2014).[30] Under D-SAP, for instance, we find that the man consumes 36 percent of the budget, the woman consumes 30 percent, and the boy and girl each consume around 17 percent.[31] The difference between women's and men's predicted shares is statistically significant at the 5 percent level; the difference between adults' and children's share is significant at the 1 percent level. Our findings are consistent across specifications (that is, across identification restrictions), with little variation between them. Relative to D-SAT and SAT, D-SAP and SAP require fewer parameters be estimated, which is likely contributing to their lower standard errors. Results obtained comparing Engel curves for cereals and proteins are similar and presented in Table A8 in the Appendix.

Table 4 (columns (2) to (4)) 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. Contrary to the estimates reported in Table 3, these figures take into account the empirical distributions of the household composition variables a and of all other covariates X. For simplicity, we here discuss results obtained using the D-SAP restriction. This choice is not arbitrary. Using an alternative identification approach introduced by Dunbar et al. (2017), we test the four preference restrictions. Specifically, we estimate the model without preference restrictions and use women's command of household assets as distribution factors (see Section 2 for details). The Wald tests never reject the D-SAP restriction, whereas it rejects D-SAT, SAP, and SAT. Section A.7 in the Appendix contains the full analysis.

As there can be more than one individual of the same type in each family and because not all

[30]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.

[31]These results are mostly consistent with the *observed* resource shares found in Bargain et al. (2018), who also study Bangladesh. They use a different dataset, the Household Income and Expenditure Survey, that exceptionally contains individualized expenditure for all the members of 1,039 households in year 2004. The main difference between our results and theirs is that we do not find evidence of a pro-boy bias in resource allocation. It is important to note that Bargain et al. (2018) do not separately estimate resource shares for boys and girls, but model the proportion of boys in a family as a covariate of resource shares.

Table 4: Estimated Resource Shares and Individual Consumption

	Obs.	Resource Shares			Individual Consumption (PPP dollars)		
		Mean	Median	St. Dev.	Mean	Median	St. Dev.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Boys	4,502	0.158	0.162	0.042	829.70	724.15	443.75
Girls	4,243	0.149	0.152	0.041	792.49	693.02	423.09
Women	6,417	0.251	0.270	0.068	1,263.21	1,122.05	607.40
Men	6,417	0.333	0.340	0.115	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.

households have both boys and girls, the mean and median of the estimated resource shares do not need to sum to one. 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' (girls') resource shares are on average 48 (45) percent of men's and 63 (60) percent of women's. In Figure A11 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, the results indicate that there is substantial inequality in resource allocation inside the family, with men commanding the majority of household resources.

We compute individual consumption as the product of total household expenditure and the individual resource shares predicted by the model. In columns (5) to (7) of Table 4, we present mean, median, and standard deviations of the estimated individual consumption in PPP dollars. It is interesting to compare these estimates to per-capita consumption, which we reported in Table 2. 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. Interestingly, women's average individual consumption is similar to the average per-capita level of consumption.

Such discrepancies between per-capita consumption and our estimates of individual consumption suggest that the probability of living in poverty may be non-trivial even for individuals that reside in households with per-capita expenditures above the poverty line (or vice versa). Before further investigating this issue in Section 6, we briefly discuss some additional results related to recent findings in the literature. Specifically, we analyze the differences in the resources allocated to young vs. older adults in extended families (Calvi, 2017) and to first-born vs. later-born children (Jayachandran and Pande, 2017).[32]

[32] These studies focus on India, not Bangladesh. We recognize the existence of clear and important differences between the two countries. However, no dataset containing assignable goods by age and birth order is available for India. For a list of other papers looking at the unequal treatment of specific household members, see Section 2.

5.3 Additional Results

Young vs. Older Adults. Life expectancy at birth in Bangladesh is 71 years, with women having slightly longer lifespans than men. The age structure of the population is changing rapidly, too. For instance, the proportion of population under age 15 declined from 43 percent in 1989 to 34 percent in 2014 (Bangladesh Demographic and Health Survey, 2014). By contrast, populations of age 15-59 and of age 60 and over have increased substantially (by 14 percent and 44 percent, respectively). Roughly half of households in our sample are non-nuclear families, where young and older adults likely coexist (one out of five households comprise women or men aged 46 and older). Assessing the difference in access to household resources by gender and age is therefore of primary importance.

Studying resource sharing in Indian households, Calvi (2017) shows that women's resource shares relative to men's decline steadily at post-reproductive ages (that is, at age 45 and above), where on average women get as low as 65 percent of men's resources. Due to data availability, however, her analysis requires younger and older women within the same family to have identical preferences (even though preferences can vary across families). Given the richness of the BIHS dataset, we can here overcome this limitation. Specifically, we consider young and older men and women as separate household members, with their own preferences and resource shares. We categorize adults into four groups: women aged 15 to 45, men aged 15 to 45, women 46 and above, and men 46 and above. As before, we maintain the distinction between adults and children. We take to the data a system of (up to) twelve Engel curves analogous to (14), where W^1_{js} and W^2_{js} ($j = b, g, w^y, m^y, w^o, m^o$) are now budget shares of cereals and vegetables for boys, girls, prime-aged women and men, and older women and men, respectively. Again, σ_j is the number of household members of category j, so that $\sigma_{m^y}\eta_{m^y s} = 1 - \sigma_b\eta_{bs} - \sigma_g\eta_{gs} - \sigma_{w^y}\eta_{w^y s} - \sigma_{w^o}\eta_{w^o s} - \sigma_{m^o}\eta_{m^o s}$.[33]

The estimates are presented in Panel A of Table A9 in the Appendix. Consistent with our main results, we find that men consume more than women regardless of their age. The average resource share of men aged 15-45 is more than double that of women in the same age range (43 percent to 21 percent). Moreover, resource shares for women aged 46 and older are on average 41 percent lower than those of younger women and 60 percent lower than men aged 46 and older.[34]

Birth Order. Motivated by recent work by Jayachandran and Pande (2017), who find that later-born children in India are substantially more likely to be stunted relative to first-born children, we analyze the importance of children's birth order in intra-household resource allocation.[35] We categorize children aged 14 and under into four groups: first-born boys, first-born girls, later-born boys, and later-born girls. We denote these categories by b^f, g^f, b^l, and g^l, respectively. One

[33] While theoretically possible, given the size of our dataset, including more than six categories is computationally intractable.

[34] Resource shares for older women may decline due to widowhood. Existing research has highlighted the plight of widows in a variety of different contexts (van de Walle, 2013; Chen and Drèze, 1992; Drèze and Srinivasan, 1997; Jensen, 2005). To examine the role of widowhood in driving the results in Table A9, we estimate the model on a restricted sample that excludes households with widows. These results are presented in Panel A of Table A10. The resource share for non-widowed women aged 46 and above is 14 percent, on average, which is above the 12 percent we find using the full sample. This result suggests that widowhood is indeed a potential factor in the declined consumption for older women.

[35] Consistent with the Hindu-Muslim difference in eldest son preference, Jayachandran and Pande (2017) show that the birth order gradient for children's height in India exceeds that in Bangladesh and Pakistan. Nevertheless, they find that the height disadvantage of later-born children is statistically significant and economically relevant for these countries too (see online Appendix of Jayachandran and Pande (2017), Table 4).

complication for our analysis is that birth order is not directly provided in the BIHS. We work around this limitation using additional sections of the survey, including the household roster and a migration module that provides information of non-resident family members. Details of how we back out birth order from the available information can be found in Appendix A.6.

By construction, households can have either one first-born boy, or one first-born girl, but not both (we drop households that have first-born twins, or both a first-born grandchild and a first-born child). Households, however, can have multiple later-born children. As before, we categorize adults into men and women, which results in a system of up to ten Engel curves. We restrict resource shares to sum to one so that resource shares for adult men are defined as $\sigma_m\eta_m = 1-\eta_{b^f}-\sigma_{b^l}\eta_{b^l}-\sigma_{g^l}\eta_{g^l}-\sigma_w\eta_w$ in households with one first-born boy, and as $\sigma_m\eta_m = 1-\eta_{g^f}-\sigma_{b^l}\eta_{b^l}-\sigma_{g^l}\eta_{g^l}-\sigma_w\eta_w$ in households with one first-born girl.

Consistent with Jayachandran and Pande (2017), we find evidence that households favor first-born children. However, gender differences seem less pronounced in our setting. Panel B of Table A9 in the Appendix presents the results for households with a first-born boy. In these households, we find that the first-born boy consumes on average 16 percent of the total budget, whereas later-born boys and girls consume 13 and 12 percent, respectively. In households with a first-born girl (Panel C), the first-born girl consumes 15 percent of the budget, and later-born boys and girls consume 14 and 13 percent on average, respectively. We should note that first-born children are older on average than later-born children, and older children have higher consumption (see Table A6). However, as we further discuss in Section 6, this alone is not enough to account for the difference in resource shares and individual consumption we document between first-born and later-born children.[36]

6 Do Poor Individuals Live in Poor Households?

Based on the model estimates presented in the previous section, we calculate poverty rates (headcount indices) that take into account the *unequal* resource allocation within the household.[37] These are different from standard poverty measures which by construction assume *equal* sharing of household resources. Typically, a household is categorized as poor if its per-capita expenditure is below the World Bank's extreme poverty line of US$1.90 per day. This threshold is meant to reflect the amount of resources below which a person's minimum nutritional, clothing, and shelter needs cannot be met.[38]

Using the same line for everyone may lead to welfare-inconsistent poverty comparisons if some individuals (such as children) require fewer resources to achieve the same level of welfare as others. Equivalence scales are sometimes used to adjust for consumption differences between individuals

[36]Because our measure of birth order may be imperfect, we also estimate the model on a restricted sample of households with mothers aged 35 and under (see section Appendix for details). These results are presented Table A10 and are largely consistent with the results in Table A9.

[37]Note that the absolute levels of poverty discussed in this section are based on our estimation sample and on specific modeling assumptions. For these reasons, we do not wish to emphasize them too much, but rather focus on the relative levels of poverty.

[38]The international poverty line is ultimately based on the national poverty lines of the poorest countries in the world in 2005. Since October 2015, the World Bank uses updated international poverty line of US$1.90/day in 2011 PPP, which incorporate new information on differences in the cost of living across countries (Ferreira et al., 2017).

within the household and between household compositions. Some limitations of these scales, however, have been documented. For instance, poverty calculations are often highly sensitive to the type of equivalence scale used (Batana et al., 2013; Ravallion, 2015). Moreover, equivalence scales typically lack theoretical foundations and involve untestable assumptions related to welfare comparisons across individuals in different household environments.[39]

To account for differences in needs between individuals (but acknowledging the limitations discussed above), we adjust the poverty line for children and the elderly in two distinct ways. In a first approach, which we refer to as the *rough adjustment*, we fix the poverty line for children (individuals 14 and younger) at 60 percent of the extreme poverty line ($1.14/day).[40] Recognizing that elderly adults may have different consumption needs relative to working-age adults, we set the poverty line for adults over the age of 45 at 80 percent of the extreme poverty threshold of $1.90/day ($1.52/day).[41] In a second approach, which we call the *calorie-based adjustment*, we create an equivalence scale based on relative caloric requirements by age and gender. Specifically, we assume $1.90/day to be the relevant threshold for adults aged 15 to 45, and rescale individual poverty lines based on the 2015-2020 Dietary Guidelines for Americans (see footnote 17 for details). For simplicity, we here abstract from joint consumption and economies of scale. We also ignore differences in the activity levels of individuals. Sections A.8 and A.9 in the Appendix discuss sensitivity tests along these dimensions. We do not find these factors to significantly affect our findings.

We start by further exploring the differences between per-capita household consumption and our estimates of individual consumption. For simplicity, we discuss results obtained by imposing the D-SAP restriction and focus on the year 2015 (results obtained with the other three identification approaches and for 2011 are similar and available upon request).

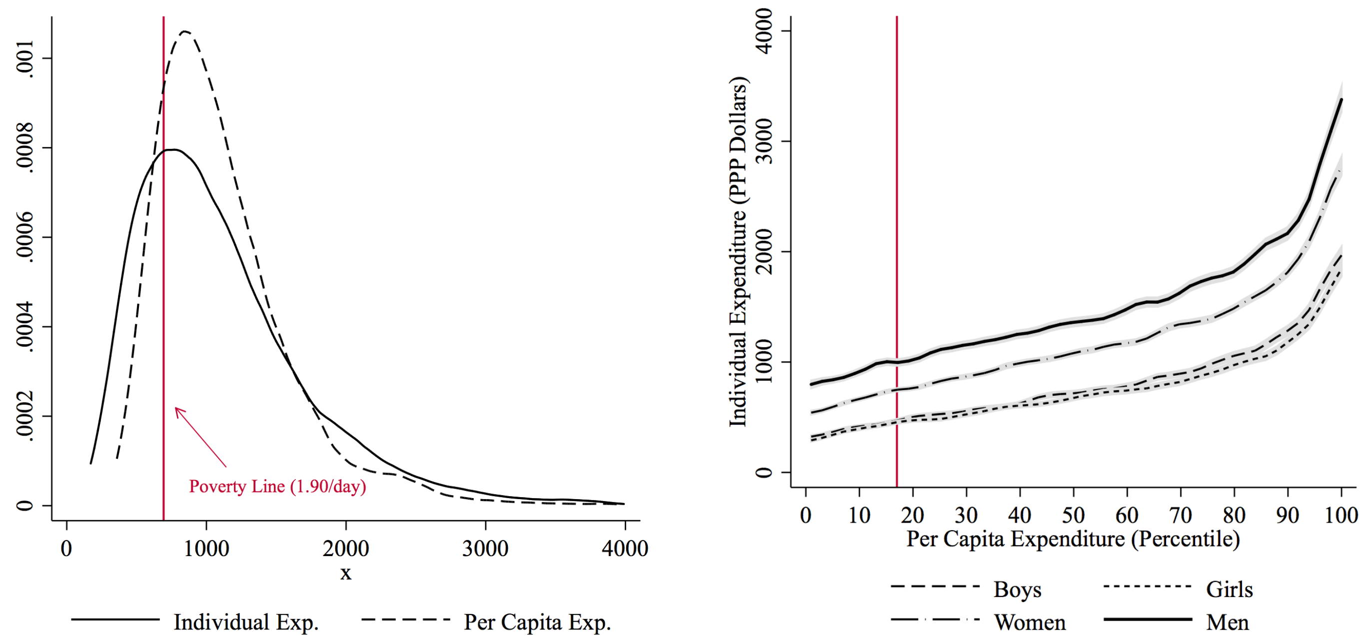
Panel A of Figure 2 shows the empirical distributions of annual individual expenditure and per-capita expenditure (expressed in PPP dollars). The vertical line equals $693.5; that is, the annual amount consumed by an individual who lives on $1.90/day for 365 days. When intra-household inequality is accounted for, the expenditure distribution becomes more skewed and significantly more unequal. Using the Mean Log Deviation measure of inequality described in Section 3, we find that overall inequality almost doubles once we allow for intra-household inequality, from 0.08 under the per-capita measure to 0.15 using individual-level estimates. Within-household inequality represents about 45 percent of total inequality in individual consumption, which is similar to the contribution found in Section 3 for caloric and protein intake (see Table 1).[42]

[39]The deficiencies in equivalence scales has motivated recent work on *indifference scales* (Browning et al. (2013), Chiappori (2016)). Introduced by Browning et al. (2013), 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 of utility 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.

[40]We follow previous works (e.g., Dunbar et al. (2013, 2017), Calvi (2017), and Tommasi (2018)) that use the adjustment implied by OECD standard equivalence scales.

[41]We acknowledge the arbitrariness of such adjustment. Health care expenses associated with age might in effect lead to higher (not lower) consumption needs. If this is the case, our estimates will underestimate poverty for the elderly.

[42]Our figures are again in line with Bargain et al. (2018). Based on observed individual consumption available for a small sample of Bangladeshi households, they find that 40 to 50 percent of total individual inequality is due to within-household inequality (see footnote



(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. The vertical line corresponds to the percentile of the \$1.90/day threshold. Estimates are based on BIHS data and D-SAP identification method with Engel curves for cereals and vegetables.

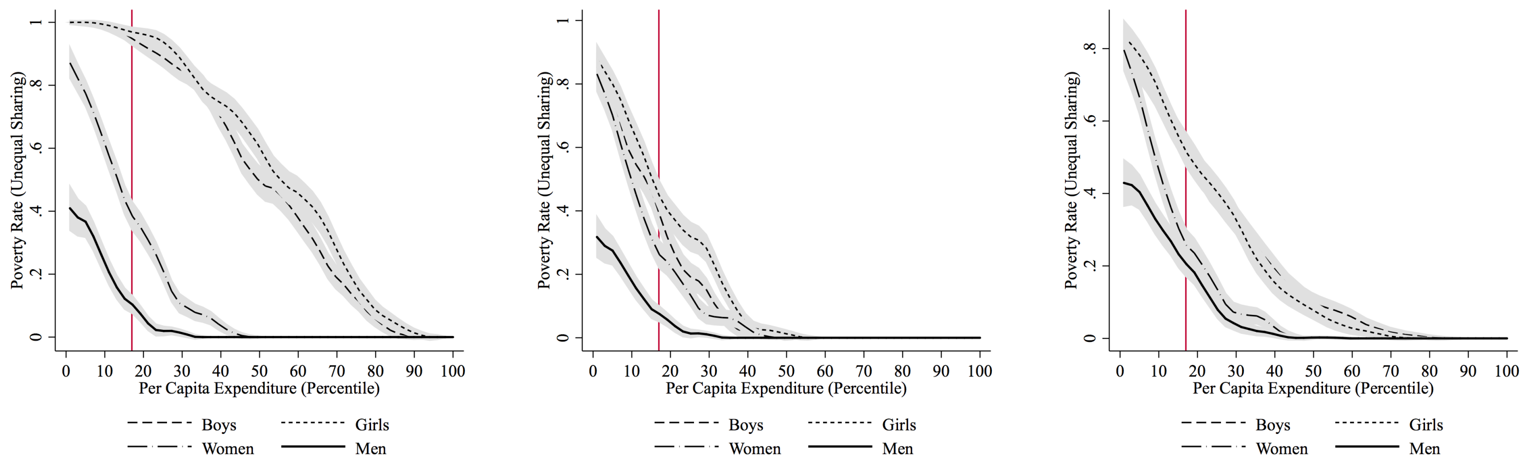
Figure 2: Per-Capita and Individual Expenditures

In Panel B, we show estimated individual consumption by household per-capita consumption percentiles. Individual consumption increase as per-capita household consumption increases. However, there are significant differences between women, men, boys, and girls, which confirm our previous findings. Notice that in our model resource shares are not allowed to vary with household expenditure (this restriction is required for identification; see footnote 6 and Section 4.2). Thus, it is not surprising that the lines are roughly parallel to each other.

We document a large increase in the poverty rate once intra-household inequality is accounted for. This is primarily driven by higher poverty among women and children. When differences in needs are ignored, we find that the poverty rate increases from 17 percent using per-capita expenditures to 27 percent using estimated individual expenditures. Of those who are poor under the model-based estimates, 57 percent are female and 80 percent are 14 years and younger. Under the per-capita-based estimates, 52 percent are female and 45 percent are 14 and younger. Using our rough adjustment equivalence scale, the overall poverty rate falls to 11 percent, while adjusting for differences in caloric needs yields a poverty rate of 15 percent. The proportion of children among the poor falls to 61 percent and 64 percent under the rough and calorie-based adjustments, respectively.

Almost 70 percent of households contain at least one poor person under the \$1.90/day poverty line. Results are similar for the lines based on the rough and caloric-based adjustments. In households with poor and non-poor members, around 50 percent of members are poor, on average. Strikingly, of the households considered poor based on per-capita expenditures, only 10 percent have all

31). The contribution of within-household inequality to overall consumption inequality is larger than that found in De Vreyer and Lambert (2018) in Senegal. However, De Vreyer and Lambert (2018) do not include inequality in food consumption, which we find to be non-negligible.



(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. The vertical line corresponds to the percentile of the \$1.90/day threshold. 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 young adults require 2,400 calories per day.

Figure 3: Poverty Rates by Per-Capita Expenditure Percentile

poor household members.

Figure 3 shows how individual poverty rates vary over the household per-capita expenditure distribution. If individual consumption corresponded exactly to per-capita consumption, then everyone would be poor below the percentile corresponding to the poverty line and no one would poor above that threshold (see Figure A12 in the Appendix). We find this not to be the case. In Panel A, we plot individual poverty rates for women, men, boys, and girls by percentiles of the per-capita expenditure distribution. These poverty rates ignore any differences in relative needs. As expected, individual poverty rates decline as per-capita household expenditure increases. Poverty rates for women are higher than men's up until the 45th percentile of per-capita household expenditure, and children's rates are higher up until the 90th percentile. Adjusting for differences in needs (Panels B and C) reduces the proportion of poor children (and to a lesser extent women) found in non-poor households. Nonetheless, a substantial portion of poor individuals is still found in non-poor households.

Based on our additional estimates that account for differences between young and older adults and between first-born and later-born children (see Section 5.3), we compute poverty rates for adults by age and gender, and for children by gender and birth order. When we use our estimates of individual consumption instead of per-capita consumption, the share of women 46 and above living with less than \$1.90/day increases from 16 percent to 52 percent. Even when we account for differences in needs, we find older women to be three times more likely to live in poverty than older men, who in turn are four times more likely to live in poverty that prime-aged men. Turning to poverty rates for children by birth order, our calculations indicate that later-born children are about 50 percent more likely to live below the poverty threshold than first-born children. This is true both for boys and girls and when we adjust the poverty lines by relative calorie requirements (such adjustment accounts for the fact first-born children are older than later-born children). Confirming our previous results, we do not find significant differences by gender among first-born children or among later-born children.[43]

Taken together, these results indicate that women, children (later-born children in particular), and the elderly (older women in particular) face significant probabilities of living in poverty even in households with per-capita expenditure above the poverty line.

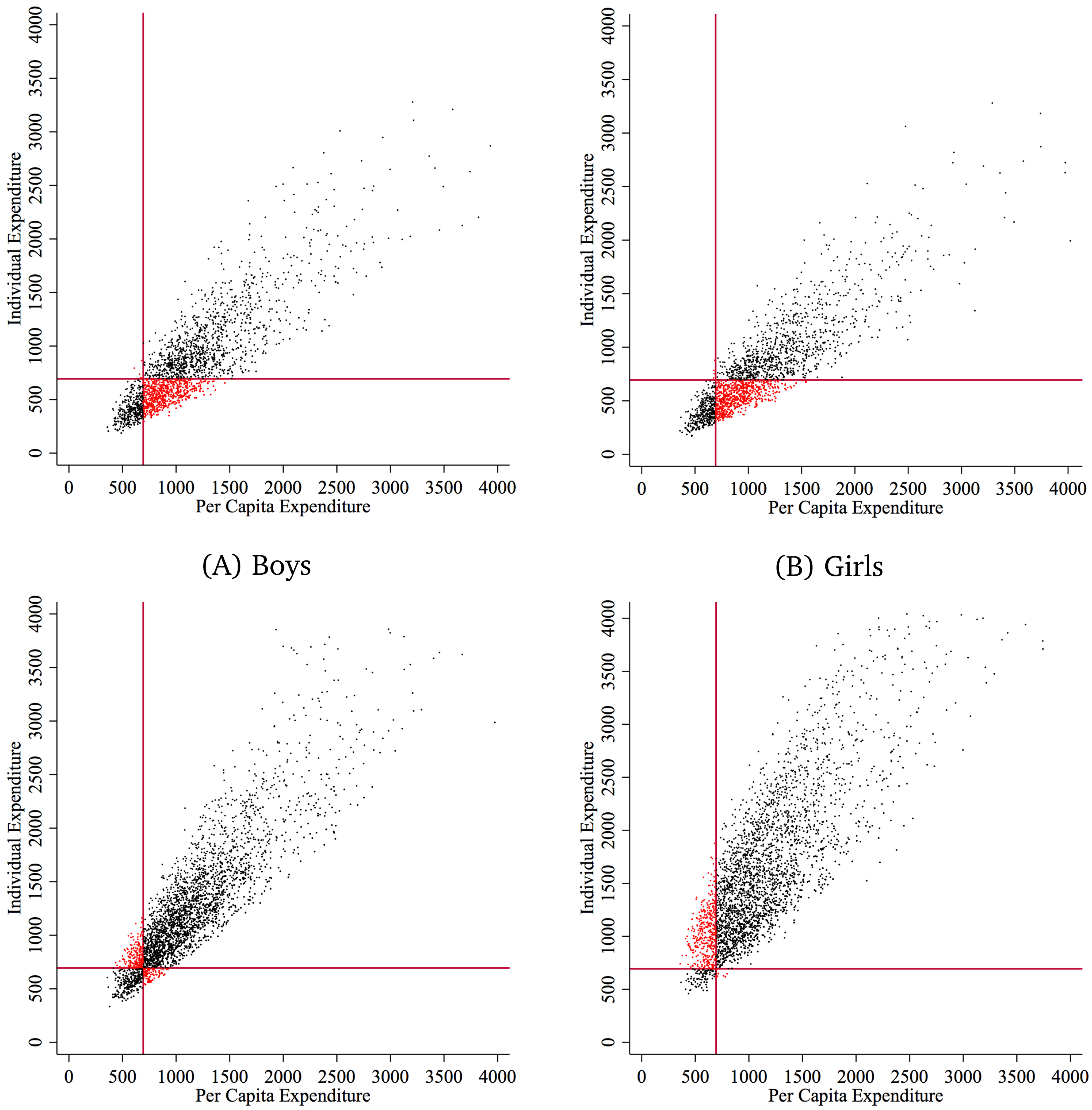
Poverty Rates Based on Food Shares. One might wonder why we compute poverty rates based on the structural model estimates instead of directly using the available information on food allocation. We do so for a number of reasons. First, while the BIHS provides details on individual food consumption, this information is usually not included in household surveys. However, most surveys do contain data on one or more assignable goods. Our approach is therefore more general and applicable to various contexts. Second, using food shares implicitly assumes that households allocate non-food consumption in the same way as they allocate food consumption. As the importance of food (and non-food) consumption for individuals' welfare may vary substantially by age and gender, this assumption can be quite restrictive. Instead, our approach allows us to identify preferences separately from sharing while accounting for substantial heterogeneity across individuals.

Nonetheless, we provide poverty estimates based on observed individual shares of food consumption. The full set of results is presented in Section A8 of the Appendix. The comparison between poverty calculations based on food sharing and those based on total consumption sharing (that is, based on our model estimates) unveils some interesting features. We find high correlations between the model-based and the food-based poverty classifications for those individuals who live in households with large food budget shares, which is reassuring. However, our analysis suggests that using food shares to compute poverty rates may, in some instances, lead to erroneous conclusions. This is particularly true in contexts with high levels of both household consumption and intra-household inequality, where the allocation of non-food expenditure (such as expenditure on healthcare and education) among family members may not be well represented by food allocations.

7 Some Insights for Policy

The Scope of Poverty Mistargeting. Our findings thus far indicate that accounting for intra-household inequalities is crucial for a comprehensive assessment of poverty and inequality. Relatedly, we have stressed throughout the paper that in presence of intra-household inequality, anti-poverty policies based on household consumption may fail to reach their targets if disadvantaged individuals live in households with per-capita consumption above the poverty line. Based on the poverty calculations discussed in the previous section, we now quantify the extent of this *mistargeting*. Specifically, we provide an answer to the following question: how many poor individuals would

[43]Figures A13 and A14 in the Appendix show the empirical distribution of the estimated individual consumption (Panel A), estimated individual consumption by per-capita household expenditure percentile (Panel B), and poverty calculations adjusted for relative calorie requirements by per-capita household expenditure percentile (Panel C). As before, the vertical line corresponds to the percentile of the \$1.90/day threshold. To avoid clutter in the figures, we do not display graphs for children in Figure A13 and for adults in Figure A14.



(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 4: Individual Expenditure and Per-Capita Expenditure

not be reached by anti-poverty programs that are based on household per-capita expenditure?

In Figure 4, we plot estimated individual consumption against household per-capita consumption for men, women, boys and girls. Each dot corresponds to one individual in our sample. As before, we focus on year 2015 and use estimates for individual consumption based on the D-SAP approach. We partition each graph into four regions based on whether one's estimated individual consumption or per-capita consumption is above or below the $1.90/day poverty threshold. For individuals falling in the lower left or in upper right quadrants, the two measures of poverty (unadjusted for relative needs) coincide. In other words, accounting for intra-household inequality does not impact their categorization as living above or below the poverty threshold. By contrast, individuals falling in the lower right quadrant would be considered non-poor according to household per-capita measures despite having an estimated level of individual consumption below the standard poverty line. Analogously, individuals in the upper left quadrant would be considered poor according to household per-capita measures despite having an estimated level of individual consumption above the standard poverty line. A substantial fraction of boys and girls are found in the lower right quadrant, while a number of men fall in the upper left area. Interestingly, women seem to be as likely to be in the lower right as in the upper left quadrant.

Overall, when we adjust poverty lines for relative caloric needs, we find that 37 percent of individuals in our sample with estimated levels of consumption below the poverty line are in fact considered non-poor based on household per-capita expenditure. This figure is much higher (58 percent) for unadjusted figures. As expected, children face the highest mistargeting probabilities: 45 percent of boys and 41 percent of girls who consume less than their own poverty threshold would not be reached by anti-poverty programs based on per-capita consumption. For women, this probability equals 24 percent. By contrast, only 33 percent of men who are categorized as poor based on household per-capita expenditure have levels of estimated individual consumption below the poverty line.

Given that individual consumption is not observable in the majority of surveys (though we have demonstrated it can be estimated under certain conditions), it is critical to identify individual or household traits that correlate with one's likelihood to be misclassified as non-poor. The choice of the relevant variables, however, is not straightforward. For this reason, we perform lasso regressions of one's probability of having (estimated) levels of individual consumption below the poverty line on a wide set of covariates (such as education, occupation, location, religion, age, gender, relationship to the household head, and other measures of wealth), conditional on residing in a household with per-capita consumption above the poverty line (Tibshirani, 1996; Belloni et al., 2014; Athey, 2017).[44] We estimate models separately for boys, girls, men, and women.

Table A11 in the Appendix reports the estimated marginal effects for the variables selected from the lasso regularization (Belloni et al., 2013). Clearly, no causal conclusions can be drawn. However, some interesting features emerge. The results suggest that household size and composition matters. For example, boys are more likely to be classified as poor when they comprise a larger share of the household. This finding may be due to consumption sharing among person types, in which case our resource share estimates would understate individual consumption. We also find that the higher the education level of men and women, the lower is one's likelihood of being misclassified as non-poor, suggesting that more educated households may have more equitable distributions of resources towards women and children. Bargaining power and relative outside options seem to matter too, particularly for adults. Women, for instance, are more likely to be misclassified as non-poor if they work in agriculture or if they are disabled, and less likely if they work on their own farm. Lastly, men's likelihood to be misclassified as non-poor positively correlates with the share of household agricultural assets that is owned by women and with them being unemployed.

[44]Lasso (least absolute shrinkage and selection operator) is a regularized regression method that estimates a regression model with an added constraint that enforces parsimony.

Comparing Measures of Individual Welfare. One final question remains: how much overlap is there between estimated individual consumption and other indicators of welfare, such as nutritional status and food intake? To answer this question, we assess whether our estimates of individual consumption are a better indicator of nutritional outcomes relative to per-capita consumption. First, we construct concentration curves based on individual consumption percentiles, which we present in Figure 5 (note that in Figure 1 the percentiles are at the household level). To account for the issue that children may be found disproportionately in the lower percentiles due to their lower average consumption levels, we construct percentiles for adults and children separately. That is, when looking at the new concentration curves, we consider the proportion of undernourished adults (children) found among the poorest x percent of adults (children).

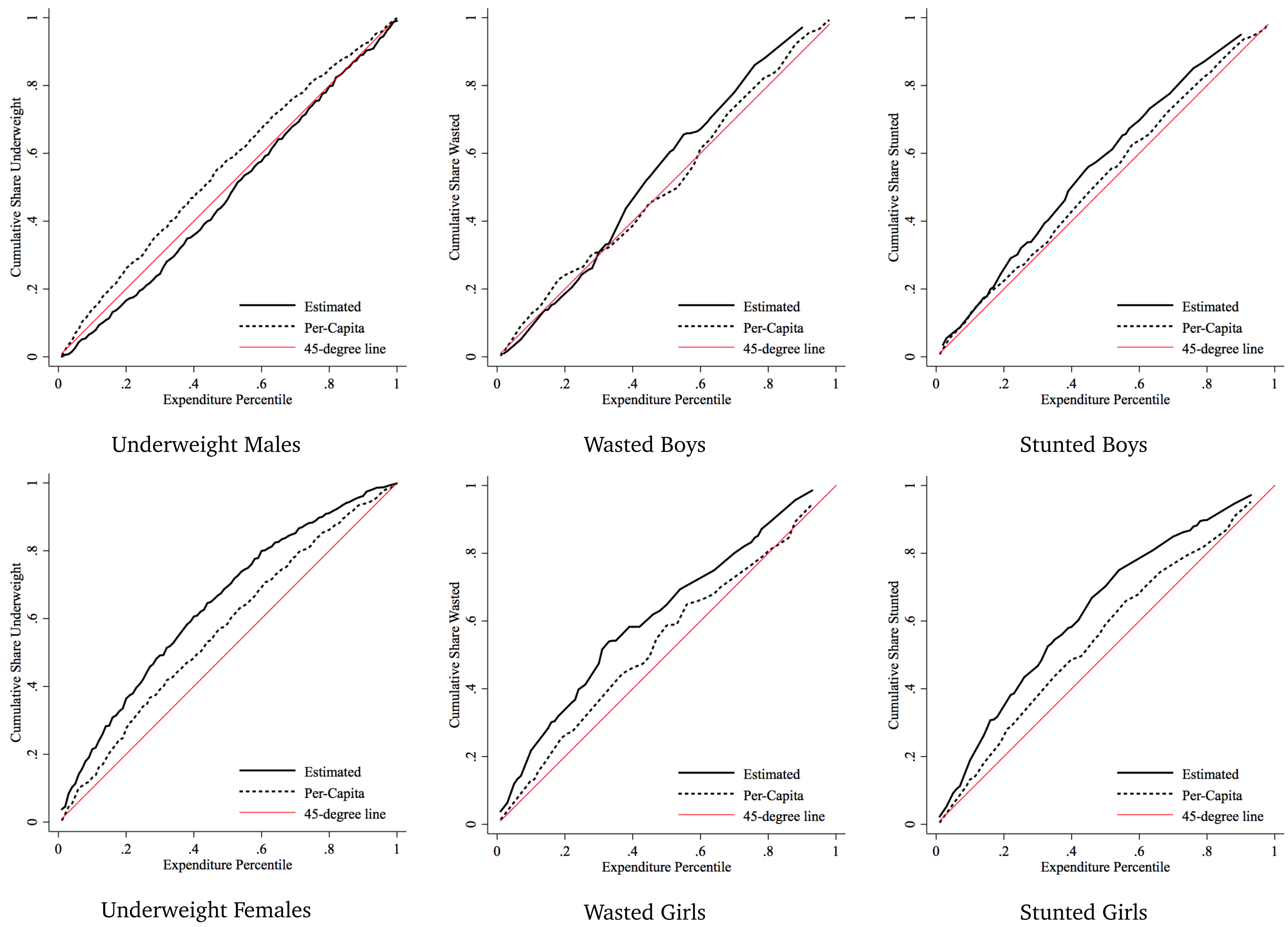
There are at least two features to note in Figure 5. First, with the exception of underweight males, more undernourished individuals are found in the lower percentiles of estimated individual consumption relative to per-capita consumption. Second, concentration curves based on individual expenditures for females display much more curvature than those for males. Taken together, these findings indicate that individual expenditure may be a better indicator of one's nutritional status and a better measure of welfare, especially for those individuals who have less power within the household.[45]

Next, we calculate the amount of variation in individuals' food intake and nutritional status that is explained by the estimated individual consumption versus per-capita consumption. For food intake, we estimate linear regression models of nutritional variables on either of the two measures of consumption (in logarithms). For the binary measures of undernutrition, we estimate logistic regressions. The corresponding R^2 values (pseudo R^2 values for the logistic regressions) are reported in Table A12. For simplicity we report results for year 2015 (results for year 2011 are similar).

Our analysis shows that, relative to per-capita consumption, individual consumption accounts for substantially more variation in caloric intake, protein intake, and food consumption. For caloric intake, the R^2 values are 0.21 and 0.02 for individual consumption and per-capita consumption, respectively; for protein intake, they equal 0.21 and 0.05. When we look at individual food consumption, we find that estimated individual total consumption accounts for about one fifth of its variation, while per-capita consumption explains only 12 percent. We also estimate regression models separately for men, women, boys, and girls. Even within category (with the exception of men), our estimates of individual consumption explain more variability in food intake than per-capita consumption.

Turning to our measures of underweight, stunting, and wasting, we do not find such substantial differences in terms of explained variation. It should be noted, however, that the R^2 values are quite low overall. Other factors such as the health environment, exposure to diseases, sanitation, and access to infrastructure are therefore likely to play a critical role in determining one's nutritional and

[45]Figure A15 in the Appendix compares concentration curves for nutritional outcomes as well as poverty status based on individual-level consumption estimates. Those curves are constructed using household-level per-capita expenditure percentiles and are therefore more easily compared to those in Figure 1 relative to Figure 5. Any differences in the concentration curves for undernutrition should be attributed to the use of a restricted sample for the estimation of the model. We find that concentration curves based on estimated individual consumption are closest to the concentration curves for nutritional outcomes. This is particularly true for children, even when accounting for differences in needs.



Note: BIHS data. Individuals who report having lost weight due to illness in the past four weeks are excluded. The graphs show concentration curves for the cumulative proportion of women and men who are underweight, and children aged 0-5 who are stunted and wasted at each household per-capita expenditure percentile (dashed line) and at each individual consumption percentile. Individual consumption is estimated using the D-SAP approach and Engel curves for cereals and vegetables. Observations with missing values and pregnant or lactating women have been dropped. The Stata command `glcurve` is used to construct the curves.

Figure 5: Undernutrition Concentration Curves with Estimated and Per-Capita Individual Consumption

health status (see e.g., Banerjee et al. (2004); Guiteras et al. (2015); Coffey and Spears (2017); Duh and Spears (2017); Geruso and Spears (2018)). Nonetheless, for women and children, increases in their individual consumption are associated with much larger decreases in their likelihood to be undernourished as compared to increases in their household per-capita consumption. For instance, for women, the average marginal effect of individual consumption is about fifteen times larger than that for per-capita consumption (-0.15 vs. -0.01). For children, even conditional on household per-capita consumption, a one percent increase in their individual consumption is associated with a statistically significant 12 percentage points decrease in their likelihood to be undernourished.

8 Conclusions

Policies aimed at reducing poverty in developing countries often target poor households under the assumption that they will reach poor individuals. However, intra-household inequality in resource allocations 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 also find substantial variation in caloric intake, protein intake, and food consumption within households. We then study the allocation of total resources within families and document that resources are *not* shared equally. 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 model estimates to compute consumption-based poverty rates at the individual level that account for disparities within families. Specifically, we assess the relative consumption (and therefore the relative poverty risk) of prime-aged and older men and women, boys and girls, and first-born and later-born children. Women, children, and the elderly face significant probabilities of living in poverty even in households with per-capita expenditure above the poverty threshold. Under the assumptions of the model, we find that the poverty rate almost doubles once intra-household inequality is accounted for. Consistent with our findings for nutritional outcomes and food intake, we show that within household consumption inequality comprises a substantial portion of overall consumption inequality.

There are some caveats to our analysis that deserve mention. First, our empirical analysis is entirely descriptive. We estimate how resources are allocated within households, but refrain from taking a stand on *why* certain types of individuals consume less. We do, however, find some evidence that education, family composition, and relative outside options are correlated with poor women and children residing in non-poor households. Second, while our poverty estimates improve upon existing household-level per-capita measures, we are unable to quantify the extent of joint consumption within the household, which may bias our poverty estimates upwards. This issue, however, is mostly irrelevant for *relative* poverty measures, which is the source of our policy recommendations. Finally, while we are able to show that estimated individual-level consumption is a better indicator of nutritional status for women and children than the per-capita measure, much of the variation in nutritional outcomes is still unexplained.

While significant progress has been made in reducing extreme poverty as well as in improving the measurement of poverty over the past few decades (Deaton, 2016), our work suggests that much more is still to be done. Based on our findings, we argue that a correct measurement of poverty may require taking into account how resources are allocated among household members. Policies aimed at poor households may not be sufficient in reaching poor individuals, and in particular, poor women, children, and elderly adults. Targeting individuals, however, can be challenging and costly. Thus, context-specific cost-benefit analyses of individual versus household targeting are necessary to guide the design of efficient, successful anti-poverty programs. We hope future work will address these issues.

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On-line Appendix for
"Sharing the Pie: Undernutrition, Intra-household Allocation, and Poverty"

Caitlin Brown, Rossella Calvi, and Jacob Penglase

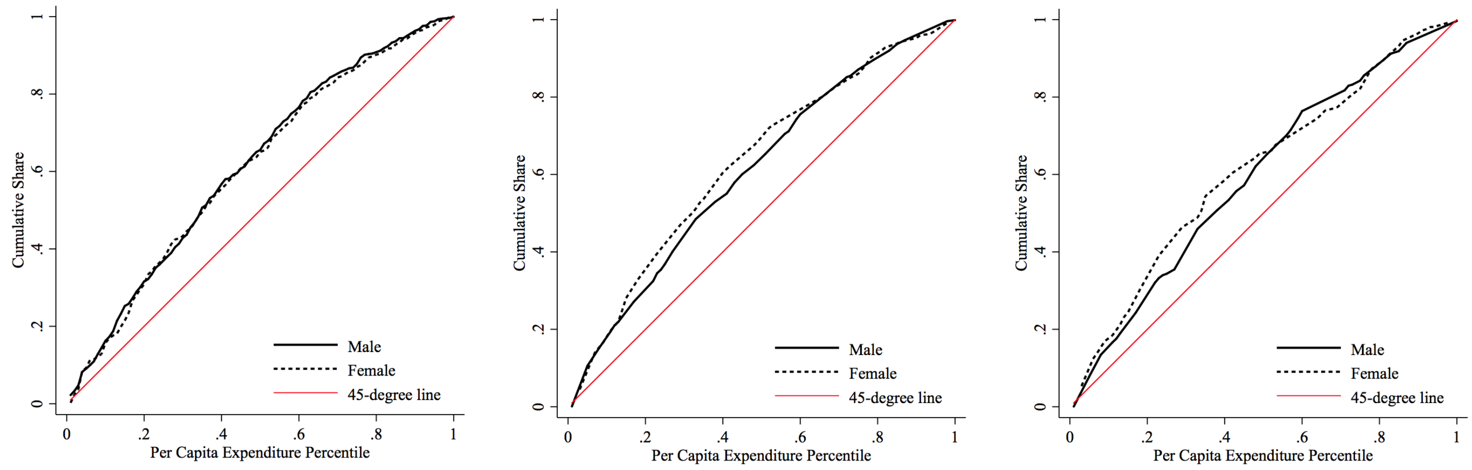
A Appendix

This Appendix contains eleven sections. Additional details and results on nutritional outcomes and food intake are discussed in Appendix A.1. In Appendix A.2 we discuss the quality of the 24-hour food recall survey and the possibility of measurement error. Our identification assumptions and theorems are presented in Appendix A.3; proofs are discussed in Appendix A.4. Appendix A.5 contains a graphical illustration of the D-SAP identification approach. In Appendix A.6, we discuss how we determine birth order from the information included in the Bangladesh Integrated Household Survey. In Appendix A.7, we provide tests of the preference restrictions required for identification and of Pareto efficiency of household allocations. In Appendix A.8 and Appendix A.9, we check the sensitivity of our poverty calculations to accounting for joint consumption and for individuals' activity levels, respectively. In Appendix A.10, we compare our model-based poverty calculations with those based on food shares. Additional figures and tables are in Appendix A.11.

A.1 Nutrition and Inequality: Additional Results

Potential Biases. Some potential biases could be influencing our findings regarding the link between household expenditure and individuals' nutritional outcomes (Section 3). The first is that the relatively weak relationship between household expenditure and undernutrition could be driven by excess mortality among the undernourished; that is, the sample may not include those who are too undernourished to survive.[46] This is particularly true if excess mortality was concentrated among the poor. However, Boerma et al. (1992) report that the effect of survivorship bias on the estimates of child anthropometric indicators is marginal; Moradi (2010) also finds little evidence of such bias. Finally, Brown et al. (2018a) simulate the potential effect of selective child mortality and find little difference in their results. Nonetheless, we acknowledge that the relationship between household expenditure and nutritional outcomes may be stronger if individuals who did not survive were to be included.

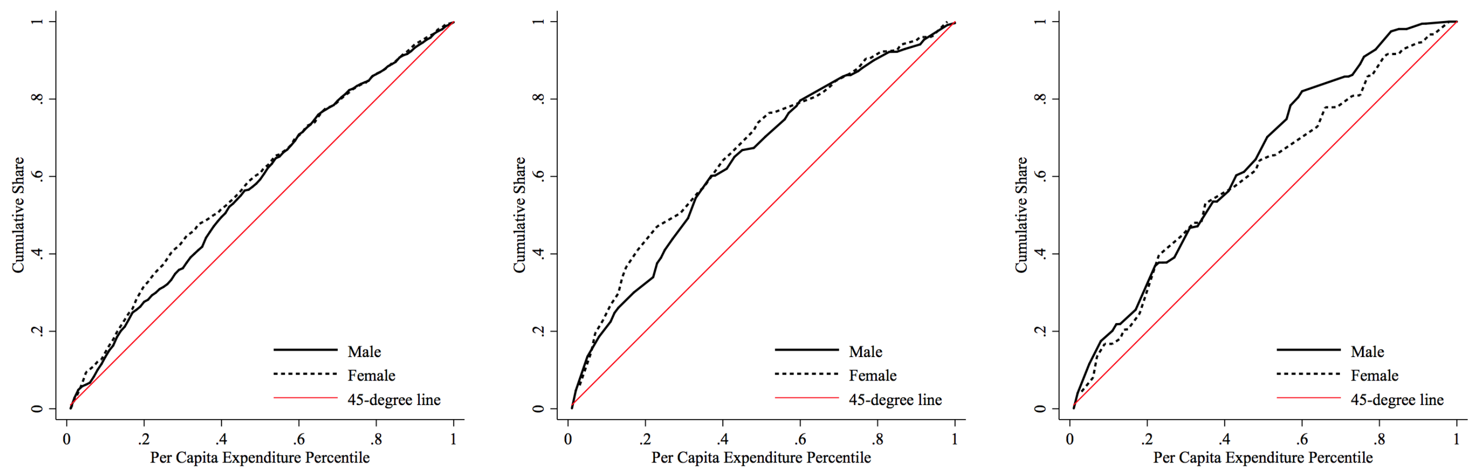
[46] According to World Bank estimates, the mortality rate in Bangladesh for children under 5 in 2015 was 36.3 per 1000 live births (the average for South Asia was 50.3). Male children had a higher mortality rate (38.8) than female children (33.7).



Underweight Adults 20 to 49 | Stunted Children 18 Months and Over | Wasted Children 18 Months and Over

Note: BIHS data. The graphs show concentration curves for the cumulative proportion of women and men aged 20 to 49 who are underweight, and children 18 months or older aged 0-5 who are stunted and wasted at each household per-capita expenditure percentile. Observations with missing values and pregnant or lactating women have been dropped. The Stata command `glcurve` is used to construct the curves.

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



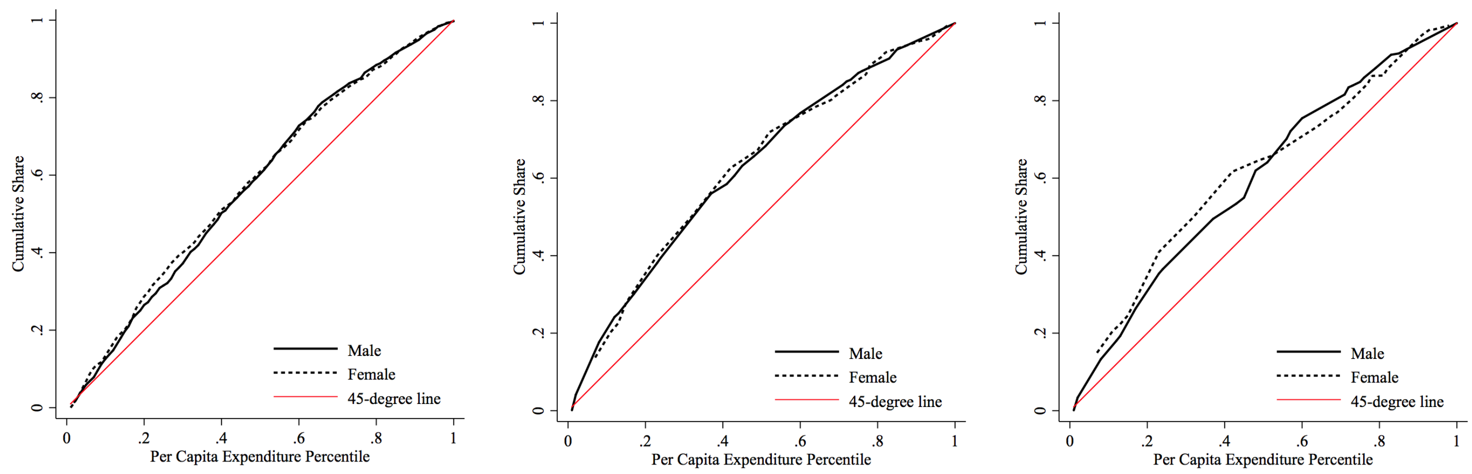
Severely Underweight Adults | Severely Stunted Children | Severely Wasted Children

Note: BIHS data. The graphs show concentration curves for the cumulative proportion of adults aged 15 to 49 and children aged 0-5 who are severely undernourished at each household per-capita expenditure percentile. Severely underweight is defined as a BMI of 17 or lower. Severely stunted and wasted are defined as 3 SDs below the median for height-for-age and weight-for-height respectively. The Stata command `glcurve` is used to construct the curves.

Figure A2: Undernutrition Concentration Curves For Severely Undernourished Individuals (2015)

Another possible bias is related to measurement error in the anthropometric outcomes, particularly among very young children. Larsen et al. (1999) and Agarwal et al. (2017), for instance, find evidence of misreporting of child age in DHS surveys, which impacts height-for-age z-scores. Larsen et al. (1999), however, find little resulting impact on estimated rates of stunting. Moreover, 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. Nevertheless, to account for potential measurement error in the stunting and wasting indicators, we construct concentration curves excluding children younger than 18 months. We also replicate our analysis excluding teenagers (who may still be growing) and older adults (who may be frail or ill, and difficult to measure). These concentration curves (shown in Figure A1) look very similar to those shown in Figure 1 in Section 3.

Children in Bangladesh may also be smaller on average than children in other regions, for ex-



Underweight Adults Stunted Children Wasted Children

Note: BIHS data. Individuals who report having lost weight due to illness in the past four weeks are excluded. The graphs show concentration curves for the cumulative proportion of women and men who are underweight, and children aged 0-5 who are stunted and wasted at each household per-capita expenditure percentile. Observations with missing values and pregnant or lactating women have been dropped. The Stata command `glcurve` is used to construct the curves.

Figure A3: Undernutrition Concentration Curves Excluding Sick Individuals (2015)

ample Africa, and the definition of stunting and wasting may be including children who are not undernourished. We also include concentration curves for severely stunted and wasted children, where severe stunting and wasting is defined as 3 standard deviations below the median height-for-age and weight-for-height scores (see Figure A2). We see slightly more curvature for stunted children, but the curves for wasted children are not dissimilar from those in Figure 1. While it does seem that poorer households are more likely to contain severely undernourished children, we still find these children across the expenditure distribution. We do not think that the definition of stunting and wasting is necessarily inappropriate for Bangladesh or is driving the results found in Figure 1.

Finally, we construct concentration curves excluding individuals who report having lost weight due to illness in the past four weeks (see Figure A3). Particularly among children, we find a higher concentration of the undernourished in the poorer percentiles (that is, higher curvature). This suggests that health shocks may affect both poor and non-poor households and may partly responsible for some of the heterogeneity in nutritional outcomes across the expenditure distribution. That exposure to diseases plays a role is indisputable and to some extent reassuring. This, however, does not dismiss our analysis of intra-household consumption inequality. In effect, it might be the case that individuals are exposed to diseases exactly because they do not receive enough resources (or vice versa). Given the data at hand, it is hard to assess how illness and resource sharing interact. We leave the answer to this interesting question to future research.

MLD Decomposition. Mean Log Deviation (as discussed in Section 3) can be decomposed into between and within household inequality as follows:

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

A.2 How Accurate is the Food Data?

Our study relies on the 24-hour food recall module in the BIHS. This data is central to our analysis and therefore its reliability deserves attention. In this section, we describe several aspects of the survey that were designed to ensure its accuracy. We also discuss recent work by D'Souza and Sharad (Forthcoming) who extensively analyze potentially biases within the BIHS food module. Lastly, we conduct several robustness checks of our own to determine the extent of any measurement error.

As discussed in Section 3, a female enumerator surveyed the woman in the household most responsible for preparing and distributing meals. All enumerators had prior experience collecting dietary intake data, including some in Bangladesh. The enumerator asked the respondents recipes, ingredient amounts, the source of the ingredients, as well as the amount of each meal allocated to each person in the household, including guests. The survey also accounted for leftover food and food given to animals. If any individual did not consume a meal, the enumerator found out why.

Several precautions were implemented by IFPRI to ensure the accuracy of the survey. First, households were asked if the previous day was a "special day", and if so, they were asked about the most recent typical day. In addition, no households were surveyed during Ramadan. Any households with large inconsistencies in the data were revisited to ensure no mistakes were made. Moreover, for the 2015 wave, 10 percent of households were resurveyed to analyze the consistency of the responses across visits, and the data suggest that they were. For example, the difference in individual food allocation shares across visits is within 3.5 percentage points for half of the revisit sample, and within 10 percentage points for 83 percent of the revisit sample.

Meals consumed outside the household are also included in the data. One might be worried that these meals are particularly susceptible to measurement error. However, D'Souza and Sharad (Forthcoming) analyze differences in food allocation across households where no meals are consumed away from home, and those where some are, and find no qualitative differences. We conduct additional tests of our own to analyze the quality of the 24-hour food module. First, we compare the per-capita amount households spent on food derived from the 7-day household-level food expenditure module to the individual food consumption aggregate derived from the 24-hour consumption module. In terms of levels, we find a reasonably strong correlation of 0.62. We then determine whether households were being reordered in terms of total consumption across the two survey modules. We compute percentile ranks of household food expenditure for both recall periods and find a correlation between the ranks of 0.74.

We check the robustness of our model estimates along several dimensions. We test the sensitivity of our results to restricting the estimation sample to households where each household member had at least one meal at home during the recall day. Recall that in our main specification we exclude households where either all men, or all women, or all children did not consume any food. We find that our results are not only qualitatively, but also quantitively confirmed. In addition, for each household we compute this difference between food consumption from the 7-day expenditure module and from the 24-hour food consumption module. We estimate our model excluding those household that display the highest discrepancies (that is, the top 10 percent of the distribution of the difference). The estimated resource shares are very similar to our baseline results (under D-SAP, for example, the average shares equal 0.158, 0.148, 0.245, and 0.337 for boys, girls, women, and men, respectively), which is reassuring. The full set of estimates is available upon request.

To summarize, measurement error is likely present in our data, as it is in almost all survey data. We believe measurement error in our context is not too severe, given both the results of the above robustness checks and the results in D'Souza and Sharad (Forthcoming). Nonetheless, it is important to comment on how any measurement error would affect our results. If the measurement error in food recalls is random, that is, the respondent was not systematically underestimating the consumption of a certain type of person in the household, then we are quite confident our results are robust. The above discussion is focused on this type of measurement error. On the other hand, if there are cultural norms that lead women to claim their husband is well-fed, or that they treat their children equally, then that may bias our results. How worried should we be about cultural norms affecting the survey responses? The survey enumerators were aware of these biases and instructed on how to still elicit honest responses (D'Souza and Sharad, Forthcoming). Furthermore, while we cannot directly examine the extent of cultural and social norms affecting the interview process, we can examine whether the 24-hour food recall is consistent with the anthropometric data. We discuss this in Section 7 and find that the observed health measures do validate our structural results.

A.3 Theorems

The section provides the two main theorems of the paper. Both are extensions of Theorems 1 and 2 in Dunbar et al. (2013) (hereafter 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.3.1 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 Browning et al. (2013), 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 composition 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

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

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.

We 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 $I(y \leq y^*)$

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

For $I(y \leq y^*)$, 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:

$$H^k_{js}(y) = a^k_{js}\eta_{js}y + \left(\tilde{b}_{js} + \tilde{e}^k_s\right)g_s\left(\frac{\eta_{js}y}{G_{js}}\right)\eta_{js}y \tag{A5}$$

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^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.3.2 Theorem 2

Let $\tilde{p}$ be the price of the goods that are not both private and assignable. Let p^k_j 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

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

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 v 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 $u_j(\frac{y}{G_j(p)}) + b_j(p^1_j + p^2_j, \bar{p}, \tilde{p}) + e_j(p^1_j, p^2_j, \bar{p})$. 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: $\partial b_j(\cdot)/\partial p^1_j = \partial b_j(\cdot)/\partial p^2_j$. This holds since the prices for goods 1 and 2 enter $b_j(\cdot)$ in an additively separable way.

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

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

$$h^k_j(y, p) = -\Big[\partial\Psi_j(y, p)/\partial p^k_j\Big] / \Big[\partial\Psi_j(y, p)/\partial y\Big]$$

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

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

For $I(y \leq y^*)$, 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:

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

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_{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.4 Proofs

A.4.1 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

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

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

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

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

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

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

$$\rho^2_{js}(y) - \rho^1_{js}(y) = \hat{\rho}_{js}(y) = (\tilde{e}^2_s - \tilde{e}^1_s) g^{'}_s(\frac{y}{\lambda_s})\frac{\eta_{js}}{\lambda_s} = \phi_s \eta_{js}$$

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.4.2 Proof of Theorem 2

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

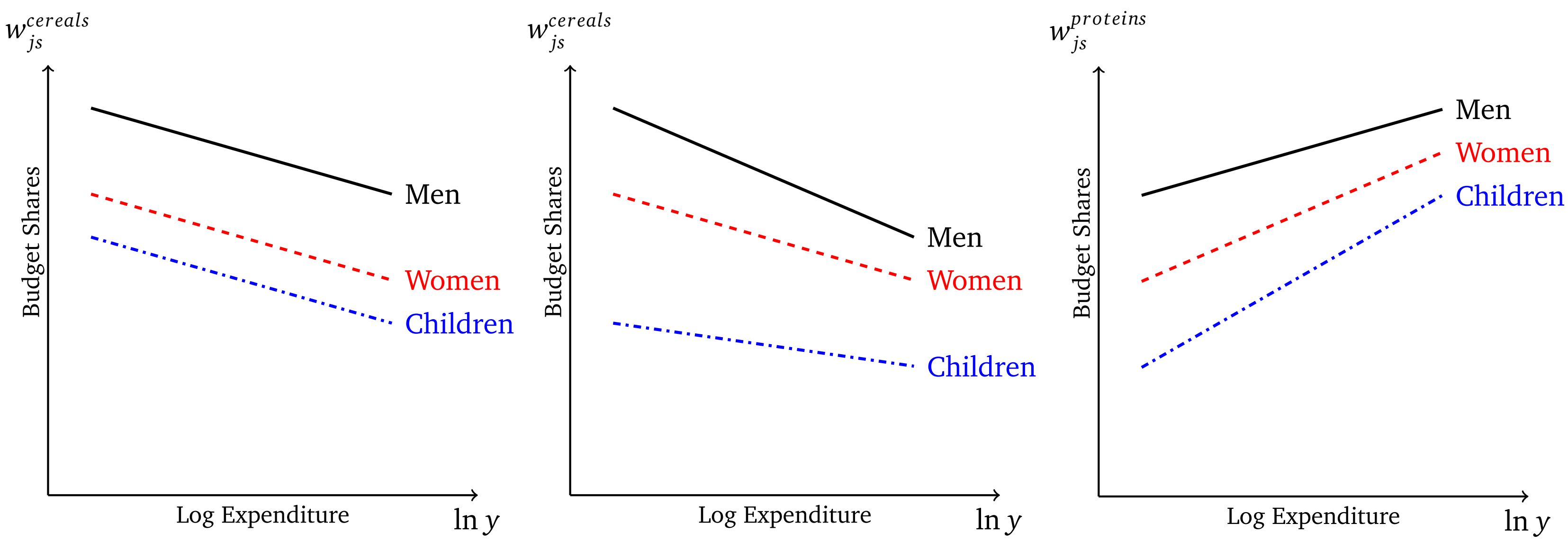
$$H_{js}^k(y) = a_{js}^k\eta_{js}y + \Big(\tilde{b}_{js} + \tilde{e}_j^k\Big)f_j(\frac{\eta_{js}y}{G_{js}})\eta_{js}y$$

For each $j \in \{1, ..., J\}$ take the difference of the Engel curves for private, assignable goods $k = 1$ and $k = 2$.

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

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

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



(A) SAP-Cereals (B) D-SAP-Cereals (C) D-SAP-Proteins

Note: Individual-level Engel curves for assignable cereals and proteins. Figure (A) illustrates Engel curves under the SAP restriction (on cereals). The Engel curves in Figures (B) and (C) do not exhibit shape invariance, however, the difference in slopes across men, women, and children differ in the same way across goods.

Figure A4: SAP and D-SAP Comparison

Then since resource shares sum to one,

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

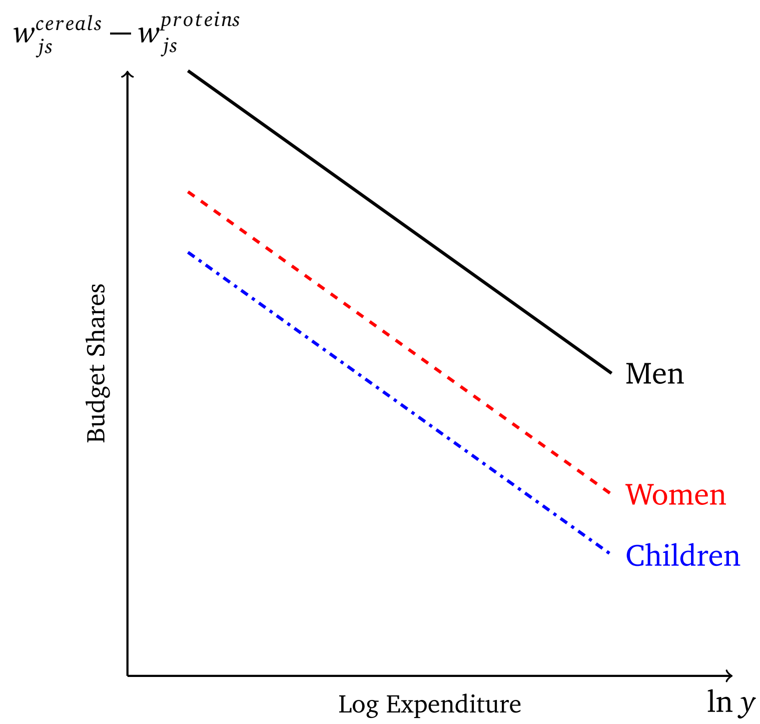
for $s \in \{2, ..., S\}$.

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.5 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., cereals and proteins). Under SAP, DLP assume that preferences for one assignable good (either cereals or proteins) are similar across person types. With piglog preferences, this results in individual-level Engel curves with the same slopes as shown in Panel A of Figure A4.

We differ in that we allow allow preferences for the assignable goods to vary substantially across



Note: Differences in individual-level Engel curves across assignable cereals and proteins. The Engel curves are derived by taking the difference of Panels C and B from Figure A4. By assumption, the difference across Engel curves will have the same slope and we can therefore use the DLP identification results.

Figure A5: Differenced Engel Curves (D-SAP)

individuals. Panels B and C of Figure A4 illustrate this point as the slopes are no longer identical across people. However, we restrict preferences to differ across people in a similar way across goods. Intuitively, this means that if women have a higher marginal propensity to consume cereals than men, then they also have a higher marginal propensity to consume proteins than men. Under 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, and we can therefore use the DLP identification results to recover resource shares. In effect, any difference in the slopes of the *household-level* differenced Engel curves can be attributed to differences in resource shares, as in SAP.

A.6 Determining Birth Order

To determine birth order, we begin by sorting children, grandchildren, and nephews and nieces by their age. This allows us to determine the *relative* birth order of children currently residing in the household. To determine the actual birth order this is not sufficient, since it is likely that for some households the first or second born children have already moved out. We use several different aspects of the survey to correct this measure.

First, the BIHS provides information on any household member who has left the household in the previous five years. So, if we see that a child has moved out, we adjust the birth order of the children currently residing in the household to reflect this. Second, the BIHS does include birth order for children age zero to two in 2011, and also for children age zero to five in 2015. We combine this data with our existing "best guess" measure of birth order to again update the data. If we see that a child's stated birth order is one higher than our existing guess, we increase each child's birth order by one. We do this for children, grandchildren, and nephews and nieces separately. We are left with a measure of birth order that combines all the information available to us in the survey.

We also conduct our birth order analysis on a restricted sample where we expect less misclassification. We drop households with mother's who may have adult-age children who have left the household. Specifically, we estimate the model on households without mothers who are above age 35. The reason we choose 35 is that we assume the earliest a woman gives birth is 15, and that the earliest a child moves out is 15. Moreover, we know children who have migrated in the previous five years. It follows that we should be entirely accurate for women age 35 and under ($15+15+5=35$). Because women who are 35 in 2011 are 39 in 2015, we drop households with women above 39 in 2015. Results of this exercise are reported in Table A10.

A.7 Testing Model Assumptions

Preference Restrictions. As discussed in Section 4.2, distribution factors (i.e., variables that affect bargaining power but not individual preferences or the budget constraint) are not required for identification when using our novel strategies (D-SAP and D-SAT) as well as when using the methodologies developed by Dunbar et al. (2013) (SAP and SAT). Recent work by Dunbar et al. (2017), however, shows that when such variables are available the preference restrictions required for identification are no longer necessary. Specifically, if there are a sufficient number of distribution factors (or if there is a distribution factor with enough support points), if one maintains the assumption that resource shares not depend on total expenditures, and if one observes some assignable goods, then the level of resource shares can be identified. No similarity restrictions on tastes like those discussed in Section 4.2 are needed.

One limitation of this approach is that distribution factors may be difficult to find (especially when children are included in the model) and their validity (that they do not impact preferences or the budget constraint) might be hard to prove. Nonetheless, we here exploit this alternative approach to test the validity of the D-SAP, D-SAT, SAP, and SAT preference restrictions. Looking at the Engel curves for clothing, both Dunbar et al. (2017) and Calvi (2017) find evidence supporting the similarity across people assumption. In contrast, Bargain et al. (2018) mostly reject both SAP and SAT using observed individual-level Engel curves for several different assignable goods, including rice and protein. SAT with clothing, however, is not rejected by Bargain et al. (2018). Thus, we first apply the Dunbar et al. (2017) approach to estimate an unrestricted system of Engel curves of cereals and vegetables and then implement Wald tests for the similarity of preferences restrictions. For simplicity, we present tests for a model that comprises four types of individuals (women, men, boys, and girls).

Several recent studies have used relative unearned income or assets as distribution factors (see, e.g., LaFave and Thomas (2017); see Browning et al. (2014) for a discussion of the most widely used distribution factors in the literature). Conveniently, the BIHS data contains information about the ownership of assets, land, and animals. Based on this information, we construct three distribution factors capturing the share of such assets that is owned by women. By ranging between zero and

Table A1: Testing Preference Restrictions With Distribution Factors

	Share of Assets Owned by Women	Share of Land Owned by Women	Share of Animals Owned by Women	First Principal Component
	(1)	(2)	(3)	(4)
	Resource Shares (Mean)			
Dunbar et al. (2017) Approach:				
Boys	0.149	0.153	0.147	0.150
Girls	0.131	0.132	0.127	0.133
Women	0.286	0.267	0.278	0.268
Men	0.317	0.333	0.319	0.324
	Testing Preference Restrictions			
D-SAP:				
Wald statistic	5.43	4.41	5.09	4.40
p-value	0.1428	0.2200	0.1653	0.2212
D-SAT:				
Wald statistic	13.83	14.04	16.51	17.20
p-value	0.0079	0.0072	0.0024	0.0018
SAP:				
Wald statistic	6.86	5.69	5.78	4.97
p-value	0.0766	0.1278	0.1182	0.1742
SAT:				
Wald statistic	8.14	8.28	8.04	8.22
p-value	0.0865	0.0818	0.0902	0.0839

Note: Estimates based on BIHS data, Engel curves for cereals and vegetables, and the Dunbar et al. (2017) identification approach.

one, these variables satisfy the requirement that the distribution factor must take on as many values as family member types. For example, if $J = 4$ (men, women, boys, girls), then a distribution factors that take on four values are enough. We also consider a fourth distribution factor computed as the first principal component of the other three.

The first panel of Table A1 contains the average resource shares for boys, girls, women, and men estimated using the Dunbar et al. (2017) approach and different distribution factors. It is reassuring to see that the estimates do not deviate significantly from the restricted models discussed in Section 5.2 (Table 4). In the second panel, we report the results of Wald tests for our preference restrictions. Interestingly, D-SAT and SAT are always rejected at conventional levels of significance. The SAP restriction on cereals preferences (preferences for vegetables are completely unrestricted) is rejected one out of four times, but the generally low p-values are not encouraging. By contrast, the D-SAP restriction is never rejected at at conventional levels. We recall from Section 4.2 that D-SAP allows one's marginal propensity to consume cereals to differ considerably from other family members. However, it requires these differences to be similar to the difference in their preferences for vegetables.

Pareto Efficiency. Our model relies on the assumption that households achieve Pareto efficient allocations (if any household member can be made better off, someone else in the household must be worse off). In other words, we recognize that the allocation of resources within the household will depend on the members respective bargaining weights (therefore departing from unitary household models), but require that no matter how resources are allocated, none are left on the table. We now follow existing literature to provide a formal test of this assumption (Browning and Chiappori, 1998; Browning et al., 2014; LaFave and Thomas, 2017). As above, the test relies on the availability of distribution factors. Thus, similar caveats apply.

Recall from Section 4 that, under the assumption of efficiency, the optimization program can be rewritten as a two-stage process. In the first stage, the household may be treated as if all members pool their income and then re-allocate it among themselves according to some sharing rule. In the second stage, each household member maximizes her own utility given their income share. Under efficiency, distribution factors affect outcomes only through their impact on the first stage sharing rule. As a consequence, the ratio of e.g., the impact of men's assets to women's assets must be the same across outcomes. This property is known as *distribution factor proportionality*, and it is a sufficient condition for the collective model (Bourguignon et al., 2009).

We test this restriction empirically by estimating a set of linear regression models of the form:

$$W_i^k = \alpha^k + \beta_w^k y_i^w + \beta_m^k y_i^m + X_h' \gamma^k + \epsilon_i^k \tag{A12}$$

where W_i^k is a budget share for household i, and k is alternatively clothing, or men's, women's, or children's food. y_h^w and y_h^m are the share of household assets owned by women and by men, respectively. As some assets are jointly owned, y_h^w and y_h^m are not perfectly collinear. We use these variables as distribution factors.[47] X_h is a vector of household level characteristics (see Table A6).

If Pareto efficiency holds, then

$$\frac{\beta_w^k}{\beta_m^k} = \frac{\beta_w^j}{\beta_m^j} \quad \forall k \neq j. \tag{A13}$$

Table A2 reports the results of nonlinear Wald tests for equality of the ratios. We perform tests over our full estimation sample, and separately for nuclear and extended households. The null hypothesis of distribution factor proportionality (Pareto efficiency) cannot be rejected at any conventional levels of significance.

A.8 Economies of Scale and Joint Consumption

The theoretical model of household consumption presented in Section 4 does allow for economies of scale to consumption through a linear consumption technology function that transforms quantities purchased by the household in quantities consumed by each member. The structural parameters capturing the extent of joint consumption, however, are not estimated (this requires detailed price variation and substantially complicates the empirical exercise; see Browning et al. (2013) for details

[47] Overall, distribution factors are jointly significant in all specifications. The p-values are below 0.10 for clothing, children's food, and women's food. The p-value equals 0.13 for men's food. These results provide a rejection of the unitary model, as it is inconsistent with the income pooling hypothesis. See Browning et al. (2014) for more details.

Table A2: Testing Pareto Efficiency

	Sample		
	All Households	Nuclear Only	Extended Only
	(1)	(2)	(3)
Test of equality of ratios between:			
1) Men's Food and Clothing Budget Shares			
Wald statistic	0.12	0.09	0.89
p-value	0.7277	0.7701	0.3443
2) Men's Food, Women's Food, and Clothing Budget Shares			
Wald statistic	1.35	0.09	1.78
p-value	0.5091	0.9580	0.4098
3) Men's Food, Women's Food, Children's Food, and Clothing Budget Shares			
Wald statistic	1.94	0.11	1.87
p-value	0.5849	0.9907	0.5997

Note: Tests for proportionality restriction of the effects of distribution factors (share of women's assets and share of men's assets) across outcomes (Browning and Chiappori, 1998). The underlying regression models include the same household level controls as in Tables A6 and A7. Only households with one woman and one man are included in column 2. Only households with more than one woman and more than one man are included in column 3.

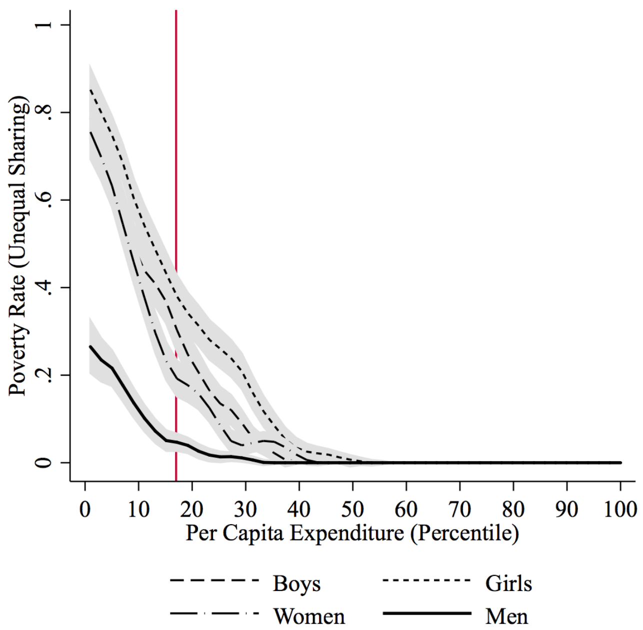
on point identification). Thus, in Section 6, we provide poverty calculations that ignore the existence and the extent of joint consumption (public and shared goods) in Bangladeshi families.

Deaton and Zaidi (2002) recommend low levels of scale economies in poor countries when incorporating joint consumption in poverty calculations (around 7 percent of the total budget): when the budget share of food is high, there is not much scope for economies of scale. We here consider varying levels of consumption jointness in the family by allowing the sum of individual resources to be larger than the observed total household expenditure. Four levels of consumption jointness are obtained by multiplying the household total expenditure by $(1+\alpha)$, with $\alpha = 0.05, 0.1, 0.15, 0.2$.

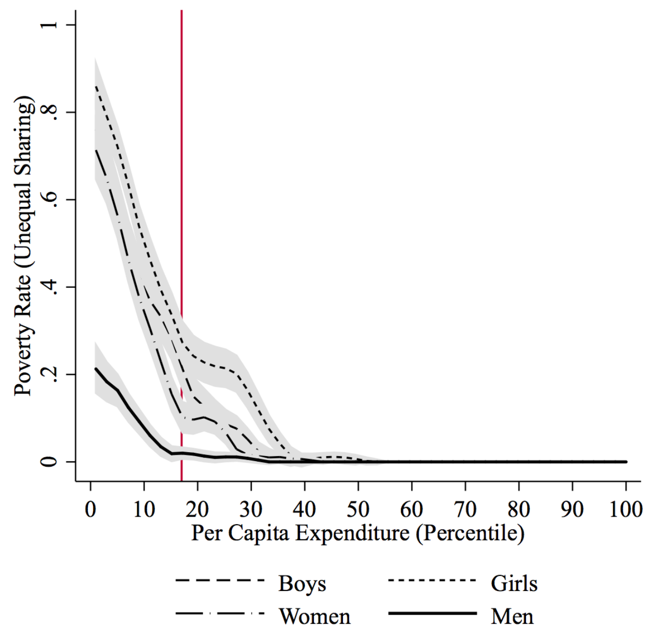
Figure A6 shows the results of this analysis. Similarly to Figure 3, we display the fraction of individuals with an estimated level of individual consumption below the poverty line by household per-capita expenditure. For simplicity, we present results for year 2015 and obtained using the D-SAP approach. To account for differences in needs, we adjust the poverty lines for children and the elderly following the rough adjustment discussed in Section 6 (unadjusted poverty rates and rates obtained using a calorie-based adjustment are available upon request). Allowing for some degree of joint consumption has clear implications for our poverty calculations since it increases the amount of resources available to each individual. As we increase the extent of scale economies, poverty headcount ratios declines slightly. The relative poverty ranking for men, women, boys, and girls, however, is maintained.

A.9 Accounting for Individuals' Activity Levels

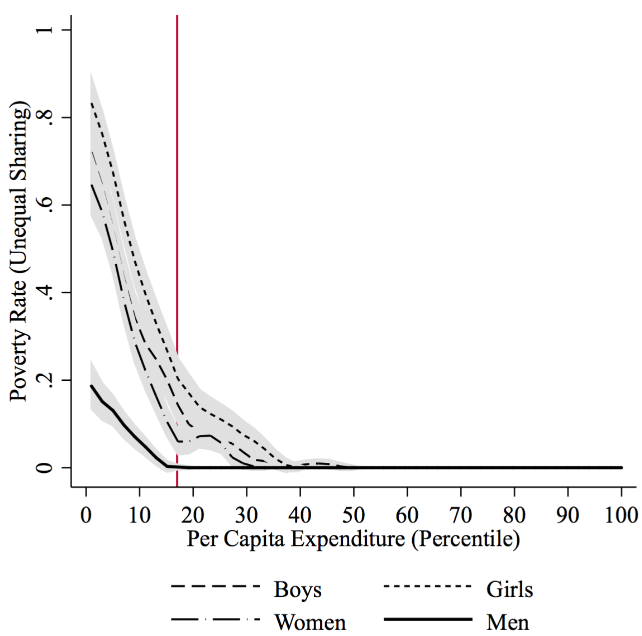
In Section 6, we adjust the \$1.90/day poverty line using relative caloric requirements to account for differences in needs by age and gender. In that exercise, however, we ignore possible differences



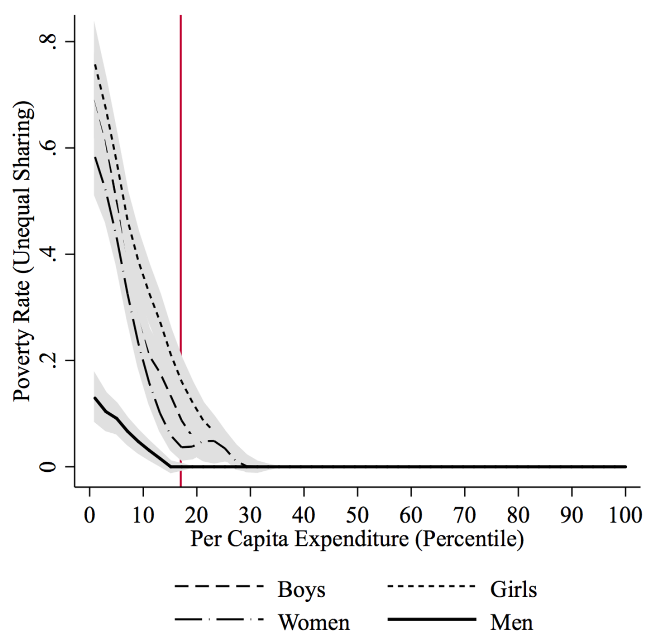
(A) $\alpha = 0.05$



(B) $\alpha = 0.10$



(C) $\alpha = 0.15$



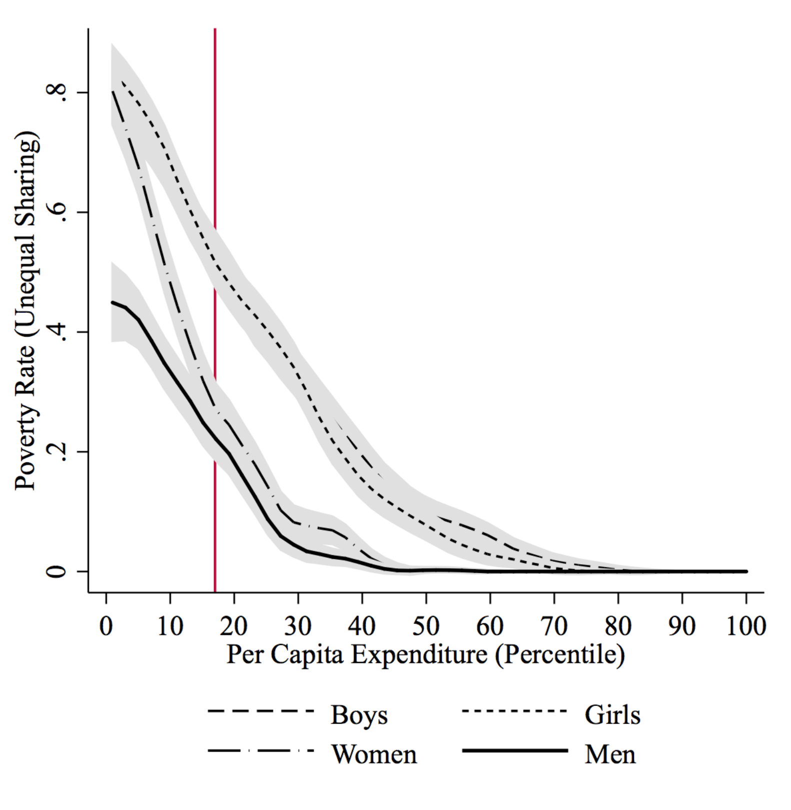
(D) $\alpha = 0.20$

Note: Only households surveyed in 2015 are included. Individual consumption is obtained by multiplying total annual household expenditure (PPP dollars) by individual resource shares. The vertical line corresponds to the percentile of the $1.90/day threshold. Estimates are based on BIHS data and D-SAP identification method with Engel curves for cereals and vegetables. In all panels, 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.Three levels of consumption jointness are obtained by multiplying the household total expenditure by $(1+\alpha)$, with $\alpha = 0.05, 0.1, 0.15, 0.2$.

Figure A6: Scale Economies and Joint Consumption

in individuals' *activity levels*. Individuals who work in agriculture or construction may expend more energy on a day-to-day basis than individuals who live a more sedentary lifestyle. As a result, more active individuals require more calories, and therefore more resources.

We modify our constructed individual-level poverty lines to account for differences in need by activity level. Using occupational data provided in the BIHS, we classify individuals as high-activity if they work in a strenuous job (e.g., farming, construction, carpentry). We consider an individual as employed in one of these occupations if they worked at least eight hours in the previous week in this job (the BIHS labor module is limited to a 7-day recall). In 2015, 47 percent of adult men worked in a high-activity occupation, whereas only 5 percent of women did. The USDA suggested caloric



Note: Only households surveyed in 2015 are included. Individual consumption is obtained by multiplying total annual household expenditure (PPP dollars) by individual resource shares. The vertical line corresponds to the percentile of the $1.90/day threshold. Estimates are based on BIHS data and D-SAP identification method with Engel curves for cereals and vegetables. We assume poverty lines to be proportional to their caloric requirements relative to young adults (aged 15-45) and we adjust them for the one's likely activity level. We rely on the daily calorie needs by age and gender estimated by the United States Department of Health and Human Services and assume that young adults that do not perform high-activity work require 2,400 calories per day. We classify individuals as high-activity if they work in a strenuous job (e.g., farming, construction, carpentry).

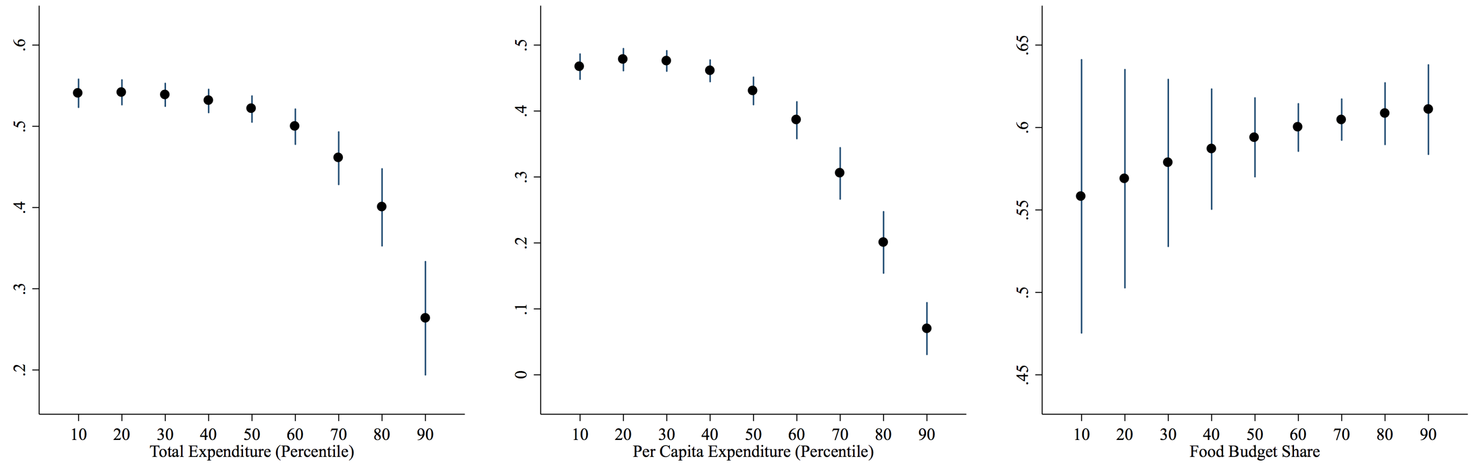
Figure A7: Poverty Rates Adjusted for Activity Levels

requirements specify thresholds for sedentary, moderately active, and active adults and children by age. For higher activity levels, the necessary calorie requirements increases by 200 to 400 calories per day. For simplicity we assume that individuals in high-activity occupations require 200 more calories per day than individuals not in those occupations.

Figure A7 presents poverty rates using this adjustment. A consequence of the adjustment is that, compared to the results presented in Section 6 (Figure 3), poverty rates for men increase slightly. No substantial difference, however, can be detected. It is important to note that this is a crude exercise that does not fully capture differences in needs. First, daily activity levels comprise much more than just employment. There are certain activities, such as fetching wood and fetching water, that require a significant amount of energy that we are unable to account for. These unaccounted for activities may have a gender component that affect the results presented above. Lastly, we only observe work in the previous week and therefore are not able to fully capture highly active individuals.

A.10 Poverty Rates Based on Individual Food Consumption

We here compare our poverty calculations (that are based on the estimated resource shares and are presented in Section 6) with calculations based on individual food shares. Using information on household food expenditure and individual food consumption, we construct individual food shares.



(A) By Total Expenditure Percentile

(B) By PCE Percentile

(C) By Food Budget Share

Note: BIHS data. The graphs show the marginal effects from logistic regressions (at different percentiles of total expenditure, per-capita expenditure and food budget share) of an indicator variable for being poor based on sharing of food on an indicator variable for being poor based on our model estimates of individual consumption.

Figure A8: Model-based Poverty vs. Food-based Poverty

We then compute an alternative measure of individual consumption as the product between these shares and a household's total expenditure. In other words, we assume that individuals consume non-food goods in the same proportion that they consume food. Since we are not imposing any inequality constraints when estimating the model, it is reassuring that only a very small fraction of individuals in our sample (less than 5 percent) have food consumption larger than our estimates of individual consumption (and that they are concentrated in households where food budget shares are high). These slight inconsistencies are likely due to estimation error and to the identification assumption that individuals in the same category are treated equally.

The resulting poverty rate is 38 percent, much higher than the poverty rates obtained with per-capita expenditure (17 percent) or our estimates of individual consumption (27 percent). This higher rate could result from individuals in non-poor households consuming a low proportion of food but a high proportion of non-food goods.

The marginal effect from a logistic regression of the probability of having a food-based individual consumption below the poverty threshold on an indicator variable for being poor based on our model estimates equals 0.46 over the entire sample. We expect such association to be stronger in poorer households, where food represents a large portion of the total budget. We compute marginal effects at different percentiles of household expenditure (or for different values of food budget shares) and find this to be the case (see Figure A8).[48] These results are reassuring as they provide additional validation of our approach: our calculations are closer to the food-based ones exactly in households where food represents a large portion of overall consumption. However, they also suggest that in contexts with possibly high levels of intra-household inequality (where several poor people might reside in non-poor households) looking at food sharing alone is not enough.

Table A3: BIHS Nutritional Outcomes

	2011			2015		
	Adults	Children		Adults	Children	
	Underweight	Stunting	Wasting	Underweight	Stunting	Wasting
Male	31.372	45.585	13.721	29.517	37.784	17.234
Female	30.428	45.180	13.981	25.224	33.975	18.588
Total	30.912	45.382	13.851	27.370	35.974	17.878

Note: BIHS data. The table lists the incidence of undernutrition for adults and children. Adults are defined as 15 years and older; children as 5 years and younger. Statistics are population weighted.

Table A4: Individual Caloric, Protein and Food Intake

	2011				2015			
	Adults		Children		Adults		Children	
	Actual	Scaled	Actual	Scaled	Actual	Scaled	Actual	Scaled
Caloric Intake (kcal):								
Male	2,635	2,464	1,456	2,221	2,415	2,268	1,360	2,082
Female	2,243	2,682	1,407	2,270	2,084	2,516	1,302	2,100
Total	2,427	2,579	1,431	2,246	2,237	2,401	1,331	2,091
Protein Intake (grams):								
Male	64.482	53.391	35.631	66.358	59.215	49.093	33.649	62.265
Female	54.771	54.771	34.300	55.910	50.965	50.965	32.232	52.897
Total	59.331	54.123	34.955	61.048	54.779	50.100	32.943	57.563
Food Consumption (taka):								
Male	50,367	47,130	27,152	41,046	55,530	52,184	30,649	46,793
Female	42,489	50,830	26,016	41,356	48,246	58,265	30,063	48,486
Total	46,188	49,093	26,576	41,204	51,614	55,453	30,035	47,643

Note: BIHS data. Statistics are population weighted. Consumption is in local currency units (taka). Children are defined as 14 years and younger. Calories have been scaled to 2,400 calories per day; protein has been scaled to 56 grams per day. Food consumption uses the same scale as caloric intake and is converted to annual values (see section 5.1 for details). Recommended intakes have been taken from the 2015-2020 Dietary Guidelines for Americans.

A.11 Additional Tables and Figures

[48] On average, food comprises 66 percent of total consumption; the 5th percentile is 45 percent, the 95th percentile is 82 percent.

Table A5: BIHS Food Consumption - Descriptive Statistics

	Obs.	Mean	Median	Std. Dev
Boys:				
Total Food	4,502	0.118	0.105	0.069
Cereals	4,502	0.043	0.035	0.033
Vegetables	4,502	0.014	0.011	0.012
Proteins	4,502	0.025	0.016	0.031
Girls:				
Total Food	4,243	0.116	0.103	0.068
Cereals	4,243	0.041	0.034	0.032
Vegetables	4,243	0.014	0.011	0.012
Proteins	4,243	0.024	0.016	0.030
Women:				
Total Food	6,417	0.182	0.171	0.072
Cereals	6,417	0.069	0.063	0.034
Vegetables	6,417	0.023	0.020	0.014
Proteins	6,417	0.034	0.025	0.034
Men:				
Total Food	6,417	0.205	0.195	0.078
Cereals	6,417	0.077	0.070	0.040
Vegetables	6,417	0.025	0.022	0.015
Proteins	6,417	0.039	0.030	0.039

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

Table A6: 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)
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. We include indicators for the following regions: Barisal, Chittagong, Dhaka, Khulna, Rajshahi, Rangpur. Sylhet is the excluded region. None of the region indicators are statistically different from zero.

Table A7: 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)
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. We include indicators for the following regions: Barisal, Chittagong, Dhaka, Khulna, Rajshahi, Rangpur. Sylhet is the excluded region. None of the region indicators are statistically different from zero. SAP and SAT restrictions are imposed on the first set of assignable goods (cereals), while the second set (vegetables) is unrestricted.

Table A8: 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	0.176	0.014	0.164	0.021	0.169	0.014	0.145	0.019
Girl	0.1676	0.014	0.146	0.016	0.162	0.013	0.135	0.016
Woman	0.2901	0.014	0.273	0.036	0.296	0.014	0.308	0.038
Man	0.3662	0.018	0.417	0.033	0.373	0.018	0.413	0.033

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. SAP and SAT restrictions are imposed on the first set of assignable goods (cereals), while the second set (proteins) is unrestricted.

Table A9: 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	0.130	0.142	0.037	668.85	593.67	333.91
Girls	4,243	0.125	0.135	0.038	653.86	578.30	336.49
Women 46+	1,908	0.123	0.132	0.027	777.47	698.05	346.45
Men 46+	2,398	0.315	0.199	0.179	1,723.37	1,403.33	1,085.79
Women 15-45	6,073	0.210	0.227	0.048	1,070.34	956.80	499.37
Men 15-45	5,403	0.431	0.444	0.127	2,165.45	1,929.09	1,036.70
B) Hhs. with first born boy:							
First born boy	1,885	0.155	0.158	0.019	726.09	659.52	310.55
Higher birth order boys	746	0.128	0.139	0.029	629.39	571.60	286.17
Higher birth order girls	668	0.120	0.130	0.029	599.22	559.14	262.96
Women	1,885	0.252	0.283	0.065	1,152.06	1,031.86	528.86
Men	1,885	0.408	0.408	0.101	1,883.21	1,687.91	891.53
C) Hhs. with first born girl:							
First born girl	1,804	0.146	0.148	0.019	703.85	628.71	322.39
Higher birth order boys	775	0.142	0.155	0.034	726.79	639.89	367.50
Higher birth order girls	768	0.132	0.145	0.034	666.18	590.75	332.97
Women	1,804	0.233	0.261	0.060	1,097.46	961.25	546.05
Men	1,804	0.405	0.408	0.113	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 A10: 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	0.132	0.145	0.037	664.42	588.21	336.50
Girls	3,653	0.127	0.138	0.037	649.96	577.95	335.65
Women 46+	1,092	0.143	0.144	0.026	871.87	778.39	385.48
Men 46+	2,212	0.314	0.199	0.177	1,704.19	1,395.82	1,062.02
Women 15-45	5,244	0.218	0.236	0.048	1,090.46	972.97	512.40
Men 15-45	4,626	0.434	0.443	0.129	2,125.18	1,893.08	1,019.85
B) Hhs. with first born boy:							
First born boy	1,463	0.157	0.159	0.016	714.99	645.80	310.94
Higher birth order boys	596	0.119	0.129	0.026	567.35	507.94	264.21
Higher birth order girls	535	0.111	0.121	0.027	540.59	501.67	241.41
Women	1,463	0.256	0.281	0.058	1,146.28	1,027.08	530.23
Men	1,463	0.429	0.429	0.093	1,940.28	1,726.89	933.57
C) Hhs. with first born girl:							
First born girl	1,417	0.147	0.150	0.016	698.47	622.06	322.37
Higher birth order boys	625	0.133	0.145	0.032	674.19	601.56	345.46
Higher birth order girls	607	0.124	0.137	0.032	612.00	546.77	305.30
Women	1,417	0.234	0.258	0.055	1,090.68	957.72	542.76
Men	1,417	0.426	0.428	0.107	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. In Panel A, we exclude households with widows. In Panel B and C, we exclude households with mothers older than 35 in 2011.

Table A11: Poverty Misclassification: Relevant Variables

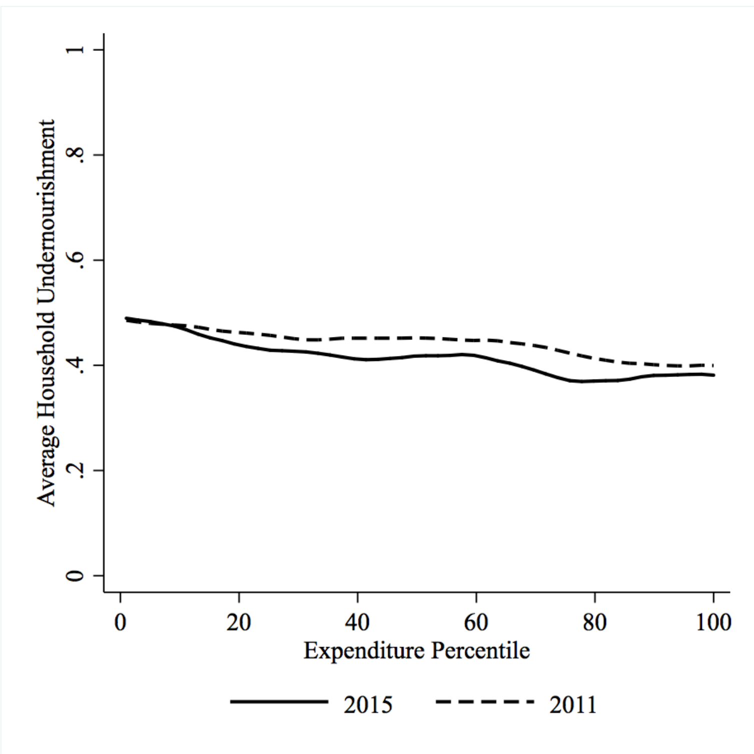
	Boys	Girls	Women	Men
	(1)	(2)	(3)	(4)
Household Size	0.00130	0.00273		0.00382***
	(0.00516)	(0.00555)		(0.000919)
Share of Boys in Household	1.773***		-0.0579***	
	(0.0702)		(0.0221)	
Share of Men in Household		-0.384***		0.0606***
		(0.0956)		(0.0147)
Share of Girls in Household		1.327***		
		(0.0770)		
Share of Women in Household			0.420***	
			(0.0306)	
Average Education Women	-0.0919***	-0.0909***	-0.0139***	0.00437***
	(0.00770)	(0.00852)	(0.00326)	(0.00137)
Average Education Men	-0.0598***	-0.0696***	-0.0165***	
	(0.00693)	(0.00746)	(0.00272)	
Age	-0.0206***	-0.0233***		
	(0.00196)	(0.00213)		
𝟙(Muslim)			-0.0230**	
			(0.00954)	
𝟙(Works in Agriculture)			0.186***	
			(0.0293)	
𝟙(Works in Own Farm)			-0.00691	
			(0.00740)	
𝟙(Works as Artisan)				0.0165***
				(0.00630)
𝟙(Unemployed/Jobless)				0.0389***
				(0.0143)
𝟙(Not Household Head)				0.00555
				(0.00396)
𝟙(Disabled)			0.0570***	
			(0.0210)	
𝟙(Far Relative or Servant)			0.00904	
			(0.0182)	
Share Land by Adult Women				0.00663
				(0.0164)
Share Homestead Owned by Adult Women				0.0284**
				(0.0125)
Share Animals Owned by Adult Women				0.00980**
				(0.00385)
Constant	0.249***	0.572***	-0.0224	-0.0503***
	(0.0460)	(0.0619)	(0.0162)	(0.00790)
Observations	2,393	2,301	3,848	2,978
λ	116.142	93.749	37.201	16.817

Note: OLS estimates. Regressions of an indicator variable for being poor based on estimated individual consumption on a series of characteristics and traits. Estimation samples include only individuals with per-capita expenditure above the poverty line and surveyed in 2015. Variables selected out of 43 variables for children, 54 variables for women, and 52 variables for men. Selection is made using lasso regularization. λ is the penalty parameter corresponding to the minimum BIC information criterion. Since lasso performs variable selection in a linear model, we report estimates for a linear probability model. Logistic regression estimates are available upon request.

Table A12: R^2 for Estimated Individual Consumption and Per-Capita Consumption

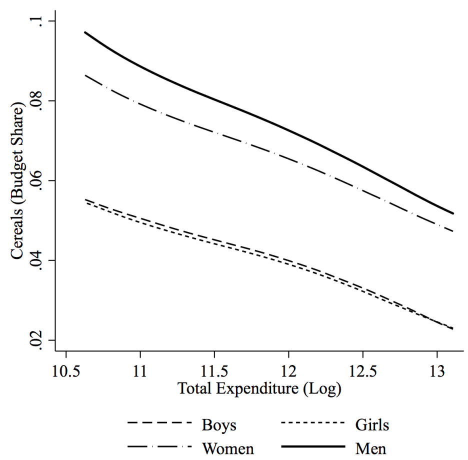
	Caloric Intake		Protein Intake		Food Consumption		Underweight		Stunting		Wasting	
	Ind.	PC	Ind.	PC	Ind.	PC	Ind.	PC	Ind.	PC	Ind.	PC
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Total	0.205	0.021	0.205	0.049	0.210	0.124	0.013	0.015	0.009	0.007	0.003	0.002
Men	0.019	0.013	0.040	0.045	0.085	0.113	0.015	0.014				
Women	0.039	0.021	0.077	0.059	0.140	0.135	0.021	0.016				
Boys	0.040	0.018	0.057	0.036	0.157	0.135			0.007	0.004	0.001	0.001
Girls	0.057	0.027	0.083	0.057	0.138	0.143			0.011	0.011	0.005	0.004

Note: BIHS data 2015. Adults are defined as 15 years and older. For the nutritional outcomes, children are 5 years and younger. For the nutritional intake variables, children are 14 years and younger. Nutritional intake variables are unscaled. Columns (1) to (6) report R^2 for linear regressions of food intake on estimated individual consumption (log) or per-capita consumption (log). Columns (7) to (12) report pseudo-R^2 for logistic regressions of nutritional status on estimated individual consumption (log) or per-capita consumption (log). Regressions are run separately for estimated individual consumption and per-capita consumption. Odd-numbered columns refer to the estimated individual consumption (Ind.); even-numbered columns refer to per-capita consumption (PC).

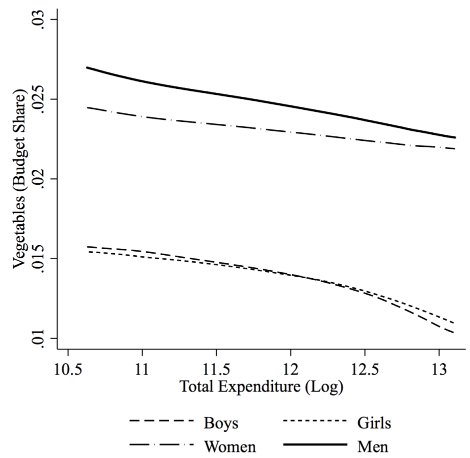


Note: BIHS data. The figure shows the rate of undernourishment within households by expenditure percentile, where a household member is defined as undernourished if he or she is underweight (for adults), stunted or wasted (for children). Adults are defined as 15 years and older; children as 5 years and younger. Households with no intra-household inequality in nutritional outcomes, i.e. those with either all nourished or undernourished members, are excluded.

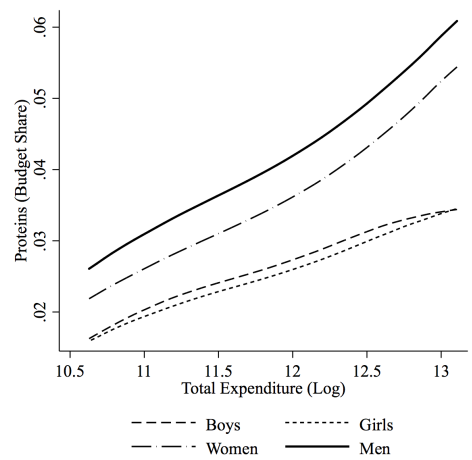
Figure A9: Within Household Inequality in Nutritional Outcomes by Household Expenditure Percentile



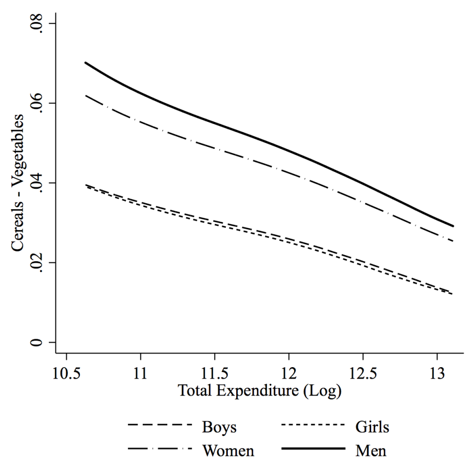
(A) Cereals



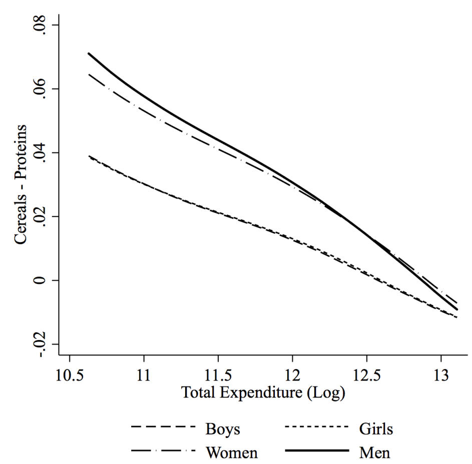
(B) Vegetables



(C) Proteins



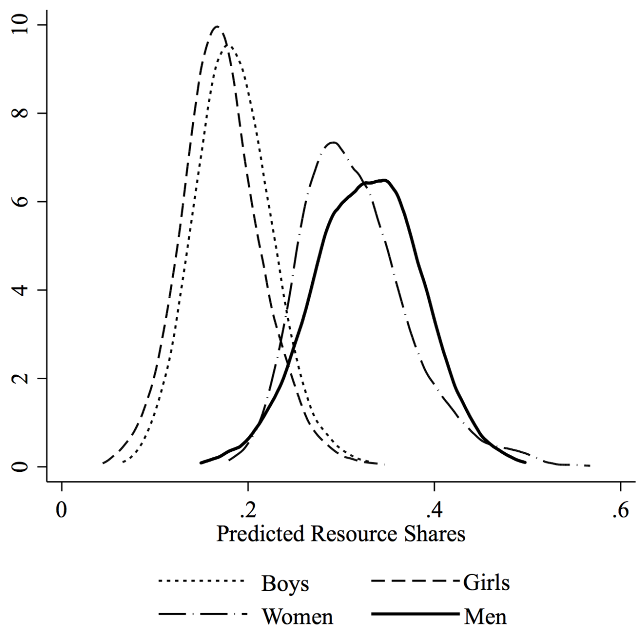
(D) Cereals - Vegetables



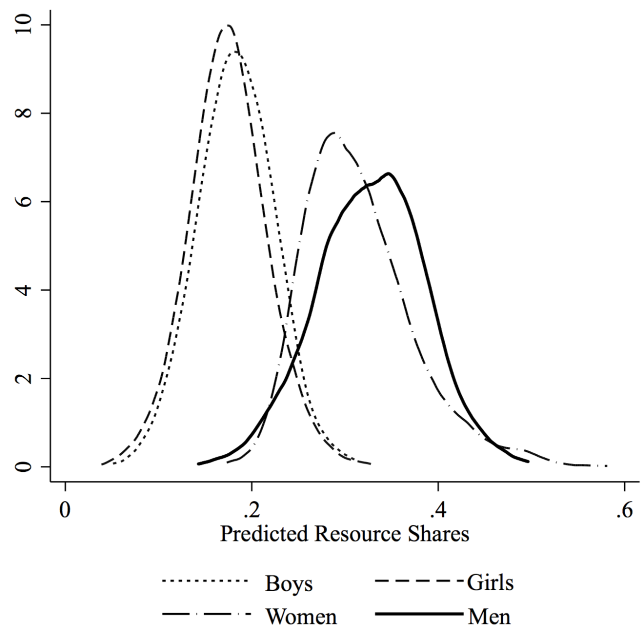
(E) Cereals - Proteins

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

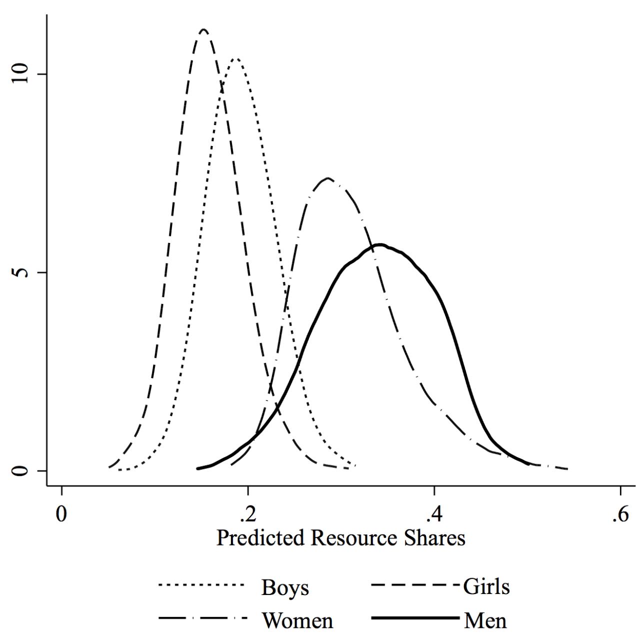
Figure A10: Non-Parametric Engel Curves



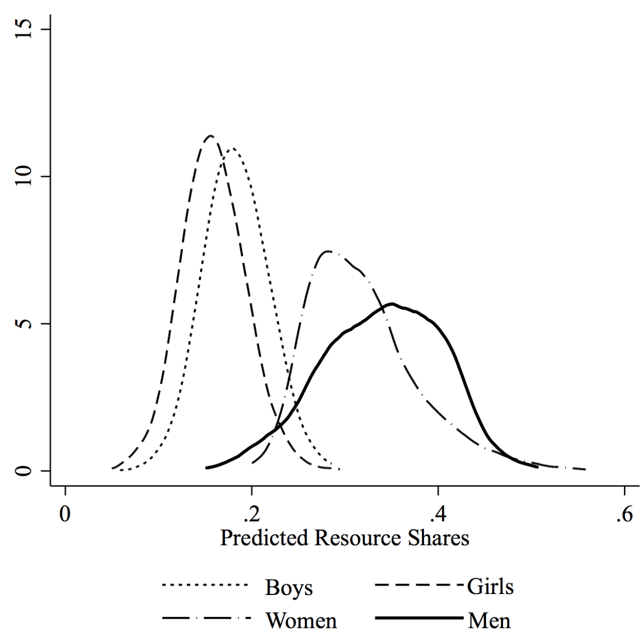
(A) D-SAP



(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 A11: Estimated Resource Shares - Empirical Distributions (2015)

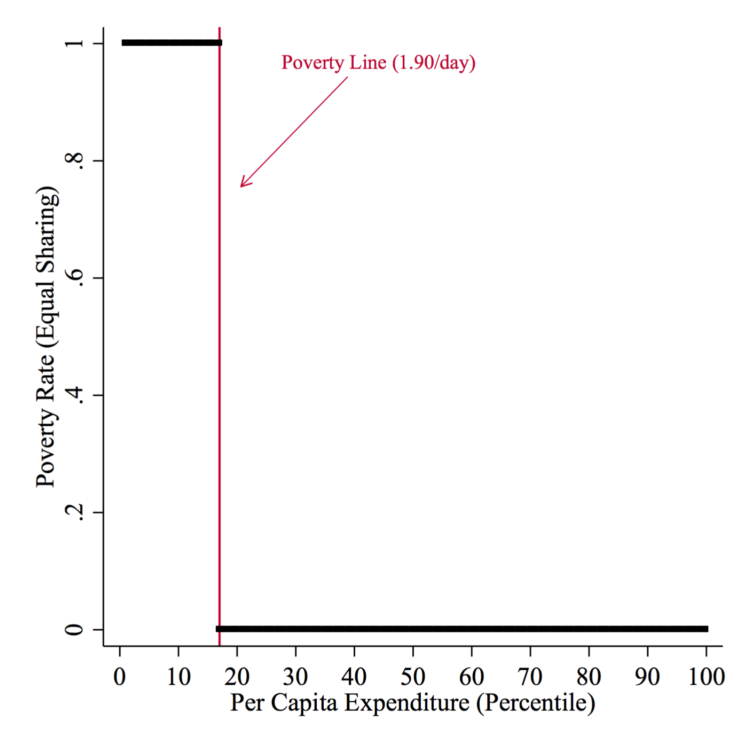
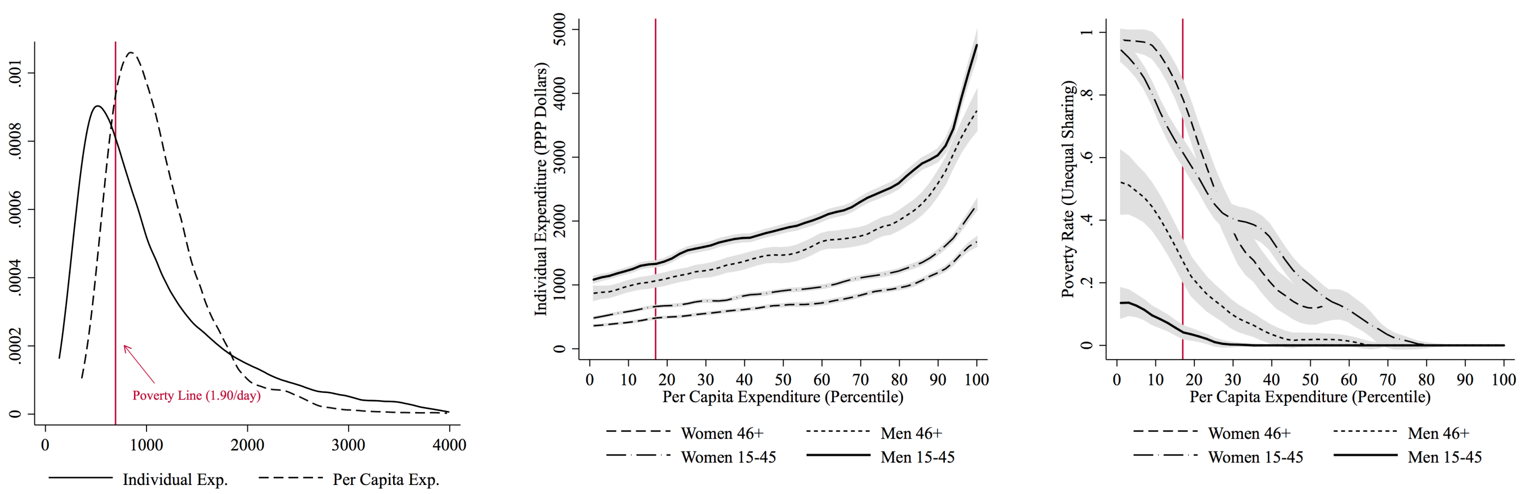


Figure A12: Poverty Rate by Per-Capita Expenditure Percentile



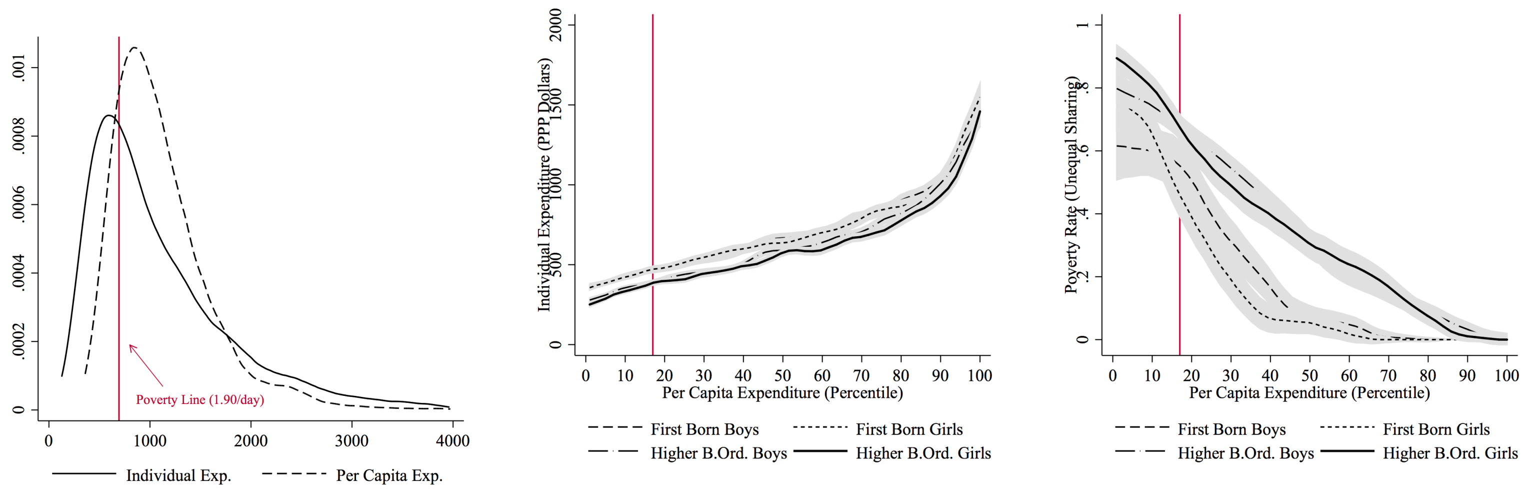
(A) Empirical Distributions

(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. The vertical line corresponds to the percentile of the $1.90/day threshold. 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 A13: Additional Results - Young vs. Older Adults



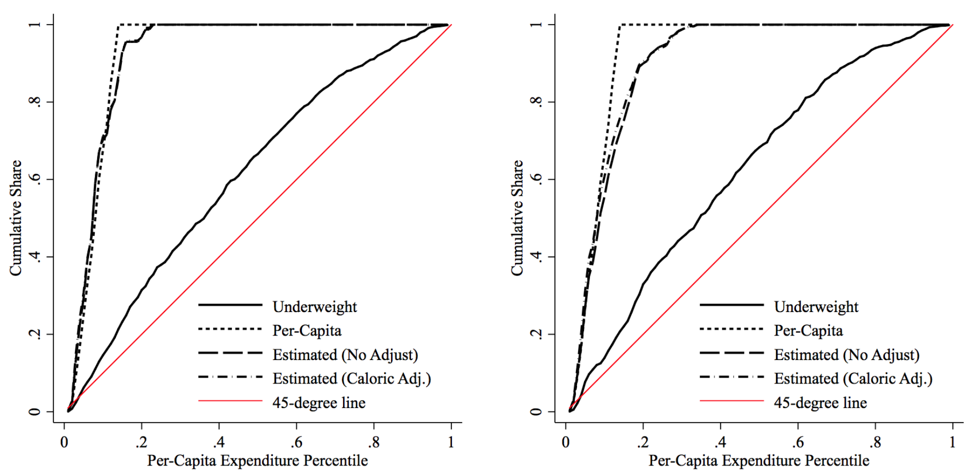
(A) Empirical Distributions

(B) Individual Exp. by Per-Capita Expenditure

(C) Poverty Rates by Per-Capita Expenditure

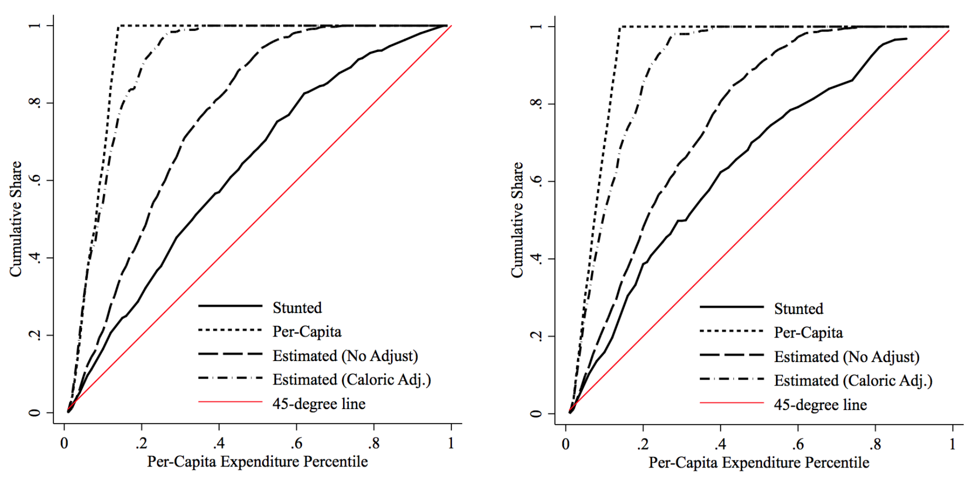
Note: Only households surveyed in 2015 are included. Individual consumption is obtained by multiplying total annual household expenditure (PPP dollars) by individual resource shares. The vertical line corresponds to the percentile of the $1.90/day threshold. Estimates are based on BIHS data and D-SAP 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 A14: Additional Results - Birth Order



(A) Men

(B) Women



(C) Boys

(D) Girls

Note: BIHS data. Individuals who report having lost weight due to illness in the past four weeks are excluded. The graphs show concentration curves for the cumulative proportion of adults and children by gender who are undernourished and poor according to per-capita household consumption and estimated individual consumption, with no adjustment for differences in needs and adjusted for differences in caloric requirements. Individual consumption is estimated using the D-SAP approach and Engel curves for cereals and vegetables. Observations with missing values and pregnant or lactating women have been dropped. The Stata command `glcurve` is used to construct the curves.

Figure A15: Undernutrition and Individual Poverty Concentration Curves (2015)