# 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 some 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 total consumption inequality within families. We apply a novel approach to identify individual-level consumption within a collective household model and use the structural estimates to compute poverty rates separately for women, men, boys, girls, and the elderly. We find that women (especially older women) and children (later-born children in particular) face significant probabilities of living in poverty even in households with per-capita expenditure above the poverty line. This poverty misclassification is severe, as one third of poor individuals in our sample live in non-poor families.

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

**Keywords**: intra-household resource allocation, poverty, collective model, undernutrition, Bangladesh

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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 difficulties are compounded by the presence of intra-household inequality. Standard poverty measures are based on household per-capita consumption, and thus assume an equal allocation of resources among family members.[2] There is substantial evidence, however, suggesting that this is *not* the case. A broad body of work has documented the inferior outcomes of, e.g., widows, orphans, girls, and later-born children.[3] As a result, household-level measures of poverty may underestimate poverty rates for those individuals who have less power within the household. Anti-poverty policies based on household-level 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 assess the scope of such poverty mistargeting. Using a structural model of intra-household consumption allocation and data from the Bangladesh Integrated Household Survey (hereafter BIHS), we provide estimates of *individual* consumption. We find intra-household consumption inequality to be pervasive and show that poverty-targeting based on household per-capita consumption misses a significant fraction of poor individuals. One third of individuals with estimated consumption below the World Bank's extreme poverty line are classified as non-poor based on household per-capita consumption.

We validate our structural estimates by comparing them to established measures of individual deprivation, which has not been done previously. Relative to household per-capita consumption, our estimates of individual consumption align more closely with anthropometric indicators and other measures of nutrition. Another contribution of this paper is the identification of relevant predictors of poverty mistargeting, which may be useful in contexts where individual consumption is not only unavailable, but also difficult or impossible to estimate. We also show that food and non-food goods are shared quite differently, so knowing how food is allocated can offer only a partial understanding of how resources are allocated overall. This may provide guidance for future data collection.

We begin by quantifying the extent of *nutritional* inequality both across and within households. Undernutrition can stem from insufficient caloric and protein intake or from illness, and it often serves as a measure of individual deprivation (Steckel, 1995; Sahn and Younger, 2009; Brown et al., 2019). We find that undernourished individuals in Bangladesh are spread across the household per-capita

[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-testing models have also been developed to improve poverty targeting with imperfect information (see e.g. Grosh and Baker (1995) and Alatas et al. (2012)). Brown et al. (2018) 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] A recent World Bank report, for instance, states that household consumption per capita is the preferred welfare indicator for the World Bank's analysis of global poverty (World Bank, 2015). Household-level poverty indicators have clear practical advantages, such as reducing the costs involved with data collection.

[3] See e.g. Chen and Drèze (1992), Drèze and Srinivasan (1997), Jensen (2005), van de Walle (2013), Djuikom and van de Walle (2018) for evidence on widows; Bicego et al. (2003), Case et al. (2004), Evans and Miguel (2007) for orphans; Subramanian and Deaton (1990), Lancaster et al. (2008), Oster (2009), Jayachandran and Kuziemko (2011) for girls; and 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) for later-born children.

expenditure distribution. We also document the existence of substantial within-household variation in caloric and protein intake, and in individual-level food consumption.[4] 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 in food consumption.

Standard poverty calculations are not based on food consumption only, but rather on *total* consumption. Thus, to correctly measure poverty, one must determine how total (food and non-food) consumption is allocated within families.[5] Measuring the total consumption of each family member is challenging as surveys are typically conducted at the household level and goods can be shared. Even in a dataset as rich as the BIHS, which exceptionally includes individual food consumption, details on the allocation of non-food expenditures are not available. Therefore, we employ a collective household model (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)) to estimate *resource shares*, defined as each member's share of total household consumption (Browning et al., 2013). The model allows us to structurally recover the intra-household allocation of total consumption when individual consumption is only partially observable.[6]

According to our estimates, 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 girl and one boy, the man consumes 36 percent of the total budget, the woman consumes 30 percent, and the boy and girl each consume 17 percent, respectively.[7] 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, 2019). Further, we show that first-born children are allocated disproportionately larger shares of the total household budget relative to later-born children (Jayachandran and Pande, 2017).

Next, we use our estimates of resource shares to compute individual level expenditures that take into account the unequal allocation of household resources. We then compare these expenditures to poverty thresholds and calculate poverty rates for women, men, boys, girls, the elderly, and for children by birth order, and contrast them to those obtained using household per-capita consumption. Two observations stand out. First, household-level measures substantially understate poverty: allowing for unequal resource allocation within the household increases the overall extreme poverty rate (i.e., the share of individuals living below US$1.90/day) from 17 precent to 27 percent. Second, we show

[4]These findings echo early works by e.g. Haddad and Kanbur (1990) and Haddad et al. (1995), who also find evidence of within-household inequality in food consumption in the Philippines. Chen et al. (1981) also document gender biases in intrafamily food distribution and feeding practices in rural Bangladesh. Pitt et al. (1990) find similar results and attribute these to differences in activity levels. We show, however, that differences in needs and activity levels cannot fully explain inequality within families in our sample (see Section A.10 in the Appendix). Our results are also in line with parallel work by D'Souza and Sharad (2019), who use BIHS data to explore the intra-household distribution of food consumption and differences in average shortfalls in nutritional intakes. We depart from previous works by moving beyond nutrition, by quantifying within-household differences in total consumption, and by analyzing the consequences of such differences for poverty calculations.

[5]In our sample, non-food consumption is non-negligible even among the poorest (i.e., the bottom 5 percent of the household expenditure distribution), accounting for one third of total consumption.

[6]Importantly, the observable portion of individual consumption does not need to include food, which is rarely available. Observability of individual expenditures on e.g. clothing or footwear suffices.

[7]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.

that women, children (later-born children in particular), and the elderly (especially older women) 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. First, our results are not driven by differences in nutritional requirements by age and gender, 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. Our results are also confirmed when accounting for possible measurement error in our data, when allowing for unobserved heterogeneity in the resource shares, and when considering alternative poverty measures. Finally, we show that using intra-household allocation of food as a proxy for the allocation of total consumption may, in some instances, lead to erroneous conclusions since food and non-food goods are allocated quite differently.

This paper makes several key contributions. The first is to document the existence and quantify the degree of intra-household inequality in Bangladesh along various dimensions of individual well-being. 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, total consumption, and likelihood of living in poverty. Such comparisons generate a number of policy-relevant insights, while providing an (indirect) validation of the structural model.[8] To our knowledge, we are the first to juxtapose nutritional outcomes and estimates of individual consumption based on a collective household model and to combine structural estimates of individual consumption with machine learning methods to identify the predictors of poverty mistargeting.

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 (2019) for India, and Sokullu and Valente (2018) and Tommasi (2019) for Mexico), we are the first to provide such calculations separately for prime-aged women and men, the elderly, boys, girls, and children by birth order. Moreover, while most of the existing literature has used assignable clothing items to estimate resource shares, we use food instead. Using food has a number of advantages, including eliminating possible estimation issues arising from the infrequency of clothing purchases.

Our third contribution is a new approach to identify the fraction of total household expenditure that is devoted to each household member in the context of a collective household framework. Dunbar et al. (2013) achieve identification by assuming observability of *one* private assignable good for each

[8] An example of direct validation is parallel work by Bargain et al. (2018), who also examine intra-household inequality using a different dataset from Bangladesh that contains private consumption by family member. The details of their analysis and the scope of their paper, however, differ substantially from ours.

individual,[9] and by imposing semi-parametric restrictions on the preferences for such goods either across people within households or across households for a given person type (e.g., women, men, and children). Under these restrictions, resource shares are identified by comparing Engel curves for the assignable goods across people or across households. We provide an alternative identification method that may reduce the restrictiveness of such assumptions by making use of *two* assignable goods. While most consumption surveys do not include assignable food items (e.g., cereals or vegetables, 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 (see Table A4 in the Appendix for a list of relevant surveys).

The policy implications of our findings pertain to poverty measurement and how anti-poverty programs should be targeted when intra-household inequality is present. As highlighted by existing works in the nutrition, economics, and public policy literatures, accounting for intra-household inequality may yield poverty rates that are different from what standard estimates indicate. Here, we go a step further by quantifying the severity of poverty misclassification and by identifying some of its critical predictors. While the existing practice for most large-scale programs is to target poor households, our findings suggest that more finely targeted policies may be required to ensure that individuals who need help actually receive it. Programs that are designed to improve the relative standing of the most vulnerable groups, such as women, children and the elderly, may also be beneficial.

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

## 2 Do Undernourished Individuals Live in Poor Households?

Following the existing literature that has used nutritional outcomes as proxies for individual deprivation, in this section we analyze the relationship between individuals' anthropometric measures and household expenditure, and assess the extent of nutritional inequality within Bangladeshi households. The results of this analysis motivate our later study of intra-household total consumption inequality and set the stage for the investigation of the validity of our consumption-based individual-level poverty estimates, which we discuss in Section 6.

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 in-

[9] 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.

equality. In 2011, 6,500 households were drawn from 325 primary sampling units.[10] Households were interviewed beginning in October 2011, and the first wave was completed by March 2012. Households were then resurveyed in 2015.

The BIHS exceptionally 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 as underweight if their BMI is less than 18.5 according to the World Health Organization classification (WHO, 2006).[11] For children, we construct height-for-age and weight-for-height z-scores.[12] 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. 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.[13]

**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. Concentration curves show the cumulative share of undernourished individuals by cumulative household expenditure percentile and are often used to assess the degree of income-related inequality in the distribution of a health variable (Kakwani et al., 1997; Wagstaff, 2000; Wagstaff et al., 2014; Bredenkamp et al., 2014; Brown et al., 2019). 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 (see Figure A13 in the Appendix for an illustration).

Figure 1 presents concentration curves for adults and children in 2015 (results are similar for 2011). It is striking how close the curves are to the 45-degree line, suggesting that undernourished individuals are spread widely across the per-capita household expenditure distribution. Only around 60 percent of undernourished adults and children, for instance, can be found in the bottom half of the per-capita expenditure distribution. Importantly, only one fifth of undernourished adults and children can be found in poor households (below the 17th percentile of per-capita household expenditure).[14]

In Section A.1 of the Appendix, we subject these findings to further scrutiny. To account for the

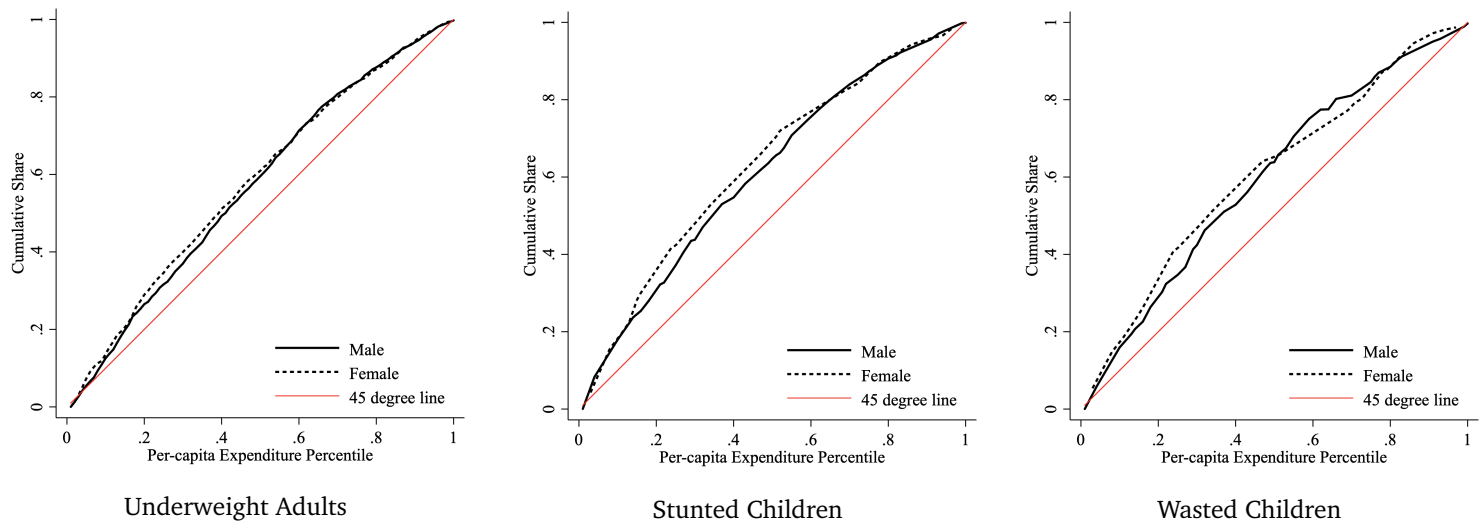
[10] The survey defines households as "a group of people who live together and take food from the same pot," while a household member is "someone who has lived in the household at least 6 months, and at least half of the week in each week in those months" (IFPRI, 2016).

[11] 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.

[12] 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. 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).

[13] Table A5 in the Appendix lists summary statistics for nutritional outcomes for adults and children across both survey rounds. Men and boys are more likely to be underweight and stunted than women and girls, which is in line with existing evidence, e.g. Svedberg (1996), Hazarika (2000), and Wamani et al. (2007). Excluding older (over 49) and young adults (under 20) reduces the overall incidence of undernutrition among adults.

[14] These results are in line with recent work by Brown et al. (2019), who show that in sub-Saharan Africa around one half of undernourished women and children are not found in the poorest 40 percent of households.




Note: BIHS 2015 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. The WB extreme poverty line of US$1.90/day correspond to the 17th percentile. The 10th, 25th, 50th, 75th, and 90th percentiles correspond to 621, 769, 1,000, 1,329, and 1,699 PPP dollars, respectively. 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

possibility that some individuals near the threshold for undernourishment are misidentified as undernourished (or not undernourished), we construct concentration curves for severely undernourished individuals. Relative to Figure 1, we find a higher concentration of severely stunted children in the lower household expenditure percentiles (which is expected), but less so for severely underweight adults and wasted children, suggesting that the role of measurement error in anthropometric outcomes around the relevant cutoffs is limited. We also present concentration curves excluding individuals who have reported suffering from weight-loss due to illness in the four weeks prior to the survey: these figures display higher, but still limited curvature.[15] Lastly, in Figure A4 we plot the relationship between the continuous anthropometric variables (BMI, height-for-age, and weight-for-height) and per-capita expenditure. We find that individuals with low nutritional values are spread across the expenditure distribution and the distance from the undernourishment cutoff values does not appear to be highly correlated with expenditure percentile.[16]

**Food Intake and Inequality.** A key advantage of the BIHS dataset is that, in addition to anthropometric information, it contains a measure of individual food consumption for each household member. This measure is based on a 24-hour recall of individual dietary intakes and food weighing. 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

[15] That exposure to diseases plays a role is indisputable (Coffey and Spears, 2017; Duh and Spears, 2017; Geruso and Spears, 2018), but it does not dismiss our later analysis of intra-household consumption inequality. As postulated in Chen et al. (1981), malnutrition and infections are likely to be "synergistic." 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.

[16] An additional point to mention is the role of age misreporting among children; see, e.g. Agarwal et al. (2017); Larsen et al. (1999). Age-heaping in this paper would predominately affect our stunting results and would be problematic if it were concentrated among, say, the lower end of the expenditure distribution generating an over- (or under-) estimation of stunting for those households. We do not find any evidence of bias due to age-heaping in our data.

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.[17]

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 of 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 by age and gender to allow for more consistent comparisons between individuals.[18] We normalize caloric intake and food consumption using a 2,400 calories per day reference level (which is the average amount recommended for moderately active adults); for example, prime-aged women, whose recommended intake is 2,000 calories/day, are scaled up by a factor of 1.2, while 4 to 5 year old boys are scaled up by a factor of 1.7. We similarly rescale protein intake to 46 grams per day, the recommended amount for most adults.[19]

To quantify the extent of nutritional inequality within Bangladeshi households, we use the Mean Log Deviation measure of inequality (hereafter MLD). Following Ravallion (2016), total 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. Unlike the popular Gini index, MLD is exactly decomposable into between- and within-group components (details of the decomposition are provided in Appendix A.1).

[17]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.

[18]We draw from the 2015-2020 Dietary Guidelines for Americans which contain requirements for males and females by age group. 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 caloric intake (this is not measured by the survey). For simplicity, we here do not account for potential differences in activity levels between individuals. Results are qualitatively confirmed when activity levels are considered (as we do in Section A.10 of the Appendix) and are available upon request.

[19]Table A6 in the Appendix presents descriptive statistics for the actual and scaled caloric intake, protein intake, and individual food consumption variables for adults and children. 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.

**Table 1:** Inequality in Nutritional Intake

| | Caloric Intake | | Protein Intake | | Food Cons. | | Cereal Cons. | | Vegetable Cons. | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Actual | Scaled | Actual | Scaled | Actual | Scaled | Actual | Scaled | Actual | Scaled |
| Total MLD | 0.115 | 0.056 | 0.135 | 0.088 | 0.201 | 0.150 | 0.155 | 0.090 | 0.259 | 0.210 |
| Within share | 0.705 | 0.464 | 0.607 | 0.375 | 0.395 | 0.210 | 0.635 | 0.418 | 0.365 | 0.219 |
| Between share | 0.295 | 0.536 | 0.393 | 0.625 | 0.605 | 0.790 | 0.365 | 0.582 | 0.635 | 0.781 |

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. Cereal cons. and vegetable cons. refer to the value of total cereal and vegetable consumption respectively. Caloric intake and the consumption variables have been scaled using the recommended caloric intake requirements; protein has been scaled using the recommended protein intake requirements.

We implement this decomposition for the two nutrition variables as well as for food consumption 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). Vegetable consumption has the highest overall inequality (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 cereal consumption is also quite substantial, at over 40 percent of total inequality. Within-household inequality for total food and vegetable consumption is less prevalent (but still quite remarkable) and accounts for roughly 20 percent of total inequality once adjusted for requirements by age and gender.[20]

While nutrition and food consumption are clearly important components of individual well-being, other dimensions of consumption (such as healthcare, housing, and education) may matter significantly (Deaton, 2016). In the next section, we use a structural model to estimate how total consumption is divided among family members, allowing us to further investigate the extent of intra-household inequality and to directly assess its implications for the measurement of poverty.

# 3 Theoretical Framework and Identification Results

The starting point of our main analysis is the collective household model of Chiappori (1988, 1992), which assumes that the household is Pareto efficient in its allocation of goods. While this is an important assumption, it is still not sufficient to identify how resources are allocated within the household.[21]

A recent approach for the identification of resource shares (the fraction of total household spending allocated to each family member) exploits 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). Specifically, Dunbar et al. (2013) demonstrate that resource shares can be identified by impos-

[20] The decomposition for protein consumption is almost identical to that for protein intake, so we omit it for brevity. Using data from the first wave of BIHS, D'Souza and Sharad (2019) 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. Chen et al. (1981) and Pitt et al. (1990) similarly find large differences in food intake within Bangladeshi households.

[21] See e.g. Browning et al. (1994), Browning and Chiappori (1998), Vermeulen (2002), Chiappori and Ekeland (2009) for details on this negative result. A growing literature has sought to solve this identification problem by adding more structure to the model and several approaches have been developed. Browning et al. (2013), for instance, demonstrate that if we assume preference stability across household compositions (singles and married couples), we can identify resource shares (or 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 resource shares using axiomatic revealed preference methods (Cherchye et al., 2011, 2015, 2017).

ing semi-parametric restrictions on preferences for a single private good across households or across household members, and under the assumption that resource shares are independent of household expenditure.[22] Recent work by Dunbar et al. (2019) 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.[23]

In what follows, we develop a new approach that extends this recent literature. Like Dunbar et al. (2013, 2019), 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, but we impose weaker preference restrictions. This additional data requirement is satisfied in the BIHS as well as in other popular datasets, such as the PROGRESA dataset and datasets from the World Bank's Living Standards Measurement Study (see Table A4 for examples of such datasets). Finally, unlike Dunbar et al. (2019), we do not require distribution factors.

## 3.1 Collective Households and Resource Sharing

We now set out a collective household model to identify and estimate resource sharing among co-resident family members. Our model builds upon the theoretical framework of Browning et al. (2013) and Dunbar et al. (2013). Since only half of our sample consists of nuclear households (comprising two parents and their children), we extend this framework to accommodate the existence of non-nuclear families with more than two decision makers.

Let households consist of $J$ categories of *people* (indexed by $j$), such as boys, girls, 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 what follows, we also assume all household members of a specific category are the same and are treated equally.[24]

Let $y$ denote the household's total expenditure. Each household consumes $K$ types of goods with 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 let $x_j = (x_j^1, ..., x_j^K)$ be the vector of unobserved quantities of goods consumed by individuals of type $j$ (that is, their *private good equivalents*). We allow for economies of scale in consumption through a Barten type consumption technology, which assumes the existence of a $K \times K$ matrix $A$ such that $z = A\sum_{j=1}^{J} \sigma_j x_j$, and allows the sum of the private good equivalents to be weakly

[22]This assumption needs to be satisfied 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.

[23]In some ways, a distribution factor can be thought of as a preference restriction. 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.

[24]Admittedly, this is a strong assumption that is data-driven. Later on, we rely on cross-sectional variation to estimate the model and this assumption ensures a tractable number of household types. In estimation, we allow preference parameters and resource shares to vary with a wide set of observable attributes (such as age of household members, location, and other socio-economic characteristics), so that, e.g., households with older children may allocate more resources to children than households with younger children. We acknowledge that additional dimensions of heterogeneity may be relevant (e.g., one's disability status or financial independence). For computational tractability, we abstract from these when estimating the model, but we explore them further in Section 6.2.

larger than what the household purchases. If good $k$ is a private good (i.e., not jointly consumed), then the $k$th row of $A$ would be equal to 1 in the $k$th column and zeros elsewhere.[25]

Each household member has a monotonically increasing, continuously twice differentiable and strictly quasi-concave utility function over consumption goods. Let $U_j(x_j)$ denote the consumption utility of individuals of type $j$ over the vector of goods $x_j$. Each member may also care about other family members' well-being so that her total utility may depend on the utility of other household members. We assume that $j$'s total utility is weakly separable over the consumption utility functions of all household members. So, for instance, member $j$ would have a total utility function given by $\tilde{U}_j = \tilde{U}_j(U_1(x_1), \ldots, U_J(x_J))$. As $\tilde{U}_j$ depends upon $x_{j' \neq j}$ only through the consumption utilities they produce, direct consumption externalities are ruled out.

The household chooses what to consume solving the following program:

$$\begin{aligned} &\max_{x_1,\ldots,x_J} U_s^H[U_1(x_1),\ \ldots.\ ,\ U_J(x_J),\ p/y] \\ &\qquad \text{such that} \\ &\qquad y = z_s' p \ \text{ and } \ z_s = A_s \sum_{j=1}^{J} \sigma_j x_j, \end{aligned} \tag{2}$$

where the function $U_s^H$ describes the social welfare function of the household. $U_s^H$ exists because we assume that the household reaches a Pareto efficient allocation of goods.[26]

The solution of the above problem yields bundles of private good equivalents that each household member consumes. Pricing these vectors at 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 $\eta_{js}$.

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 $\eta_{js}$, household members choose $x_j$ as the bundle maximizing their utility subject to a personal shadow budget constraint. By substituting the indirect utility functions $V_j(A'p, \eta_{js} y)$ in Equation (2), the household program simplifies to the choice of optimal resource shares subject to the constraint that total resource shares must sum to one. Note that, since we allow for caring preferences, the choice of optimal resource shares encompasses each person's feelings of altruism towards the other household members. In presence of altruism, resource shares should be thought of as measures of *material* well-being rather than measures of overall welfare.

[25] This framework allows for a simple household production technology with constant returns to scale through where market goods are transformed into household commodities. As in Dunbar et al. (2013), while the model allows for scale economies, these are not identified nor estimated. For this reason, we cannot compute *indifference scales* à la Browning et al. (2013). Doing so would require either detailed price variation and/or observability of consumption decisions of children living alone (Browning et al., 2013; Lewbel and Pendakur, 2008), or more demanding assumptions (Calvi et al., 2019). Following previous work, we also assume consumption is separable from leisure. For a detailed discussion of the data requirements and the complications of relaxing this assumption see Browning et al. (2013).

[26] 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)). Note that most rejections of Pareto efficiency are based on decisions about production, not consumption. Rangel and Thomas (2019) question the validity of this approach. Recent work by Lewbel and Pendakur (2019) develops a collective household model where households behave inefficiently (they engage in domestic violence and do not fully exploit scale economies), but shows that this does not have a large effect on the estimates of resource shares. In Section A.8 of the online Appendix, we provide a formal test of Pareto efficiency using distribution factors: in line with previous work, Pareto efficiency is not rejected in our context.

Define a *private assignable* good to be a good that is consumed exclusively by household members of known category $j$.[27] While the budget share functions for other goods are more complicated, the ones for private assignable goods are simpler and given by:

$$W_{js}(y,p) = \sigma_j \eta_{js}(y,p)\, w_{js}(\eta_{js}(y,p)y,\, A_s' p), \tag{3}$$

where $w_{js}$ 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 $\eta_{js}$ 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 Engel curves for food items for each group $j$. We then implicitly invert these Engel curves to recover the resource shares.

## 3.2 Identification of Resource Shares

The main goal of the model outlined above is to identify and estimate resource shares. In what follows, we describe the methodology developed by Dunbar et al. (2013) (hereafter DLP) and present our new identification results.

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 $\bar{p}$ as the subvector of private non-assignable good prices, and $\tilde{p}$ as the subvector of shared good prices. In the empirical section, we will assume individuals have piglog (price independent generalized logarithmic) preferences over the private assignable goods (Deaton and Muellbauer, 1980). While our identification results *do not* rely on piglog preferences, this functional form facilitates the discussion of identification, so we use it henceforth. In Section A.3 of the Appendix, we present more general identification results based on semi-parametric restrictions.

The standard piglog indirect utility function takes the form: $V_j(p,y) = e^{F_j(p)}(\ln y - \ln a_j(p))$, where $F_j(p)$ and $a_j(p)$ are differentiable functions that are homogenous of degree zero and one, respectively. By Roy's Identity, the budget share functions are as follows: $w_j(y,p) = \alpha_j(p) + \gamma_j(p)\ln y$, with $\gamma_j(p) = -\frac{\partial F_j(p)}{\partial p_j}$. The budget share functions are therefore log-linear in expenditure.[28] Substituting them into Equation (3), and holding prices fixed, results in the following household-level Engel curves:

$$\begin{aligned} W_{js} &= \sigma_j \eta_{js}[\alpha_{js} + \gamma_{js}\ln(\eta_{js}y)] \\ &= \sigma_j \eta_{js}[\alpha_{js} + \gamma_{js}\ln \eta_{js}] + \sigma_j \eta_{js}\gamma_{js}\ln y. \end{aligned} \tag{4}$$

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

[27] In the consumer demand literature, there exists a distinction between assignable and exclusive goods: individual consumptions of an assignable good have the same price, while exclusive goods have different prices. As noted in Browning et al. (2014), however, this distinction is irrelevant in contexts (like ours) that abstract from price variation.

[28] With more complex Engel curves for private assignable goods, identification relies on comparisons of higher-order derivatives, but the intuition behind identification is identical.

**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).[29]

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. Under SAP, Equation (4) is such that $\gamma_{js} = \gamma_s$, and resource shares are identified by comparing the slopes of Engel curves across individuals within the same household. To fix ideas, suppose that the household's total 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 not vary across household types, that is, $\gamma_j(p_j, \bar{p})$ is not a function of the prices of shared goods $\tilde{p}$. Equation (4) can be modified so that $\gamma_{js} = \gamma_j$, and resource shares are identified by comparing the slopes of Engel curves 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. Using data from Malawi, Dunbar et al. (2019) find evidence supporting the use of SAP with clothing expenditures as the assignable good. Bargain et al. (2018) analyze data from Bangaldesh and reject SAP for clothing expenditures, and both SAP and SAT for food expenditures; Sokullu and Valente (2018) find similar results for clothing expenditures in Mexico. Since we observe multiple private assignable goods for each person type, we develop two alternative identification methods that employ these additional data and allow for higher preference heterogeneity. Tests using overidentifying restrictions (which we discuss later on) indicate that our approach may be preferable in our context.

**Differenced SAP (D-SAP).** In our first approach, we show that the SAP restriction of DLP can be modified by using two private assignable goods. Unlike DLP, we do not assume that preferences for the assignable goods are similar across people. Instead, we allow preferences to differ considerably across people, but require them to do so in a similar way for two private assignable goods.[30] For our identification strategy to work, we therefore require the observability of two such goods ($l = 1, 2$) for

[29] 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.

[30] Having a third assignable good (or more assignable goods) would not meaningfully reduce the assumptions necessary for identification. Nonetheless, having additional assignable goods allows for robustness checks and tests of the validity of the identification assumptions (see Section A.6 in the Appendix for details).

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 assumption *Differenced Similar Across People*, or D-SAP.

We begin by placing restrictions on each person's indirect utility function to derive Engel curves that satisfy D-SAP (as above, we use piglog preferences for illustrative purposes; general identification theorems and proofs are in Sections A.3 and A.4 of the Appendix). Recall that with piglog preferences, the indirect utility function takes the following form: $V_j(p,y) = e^{F_j(p)}(\ln y - \ln a_j(p))$. For our assumption to hold, $F_j(p)$ may be as follows: $F_j(p) = b_j(p_j^1 + p_j^2,\ \bar{p},\ \tilde{p}) + r(p)$, where $r(p)$ does not vary across people, and $p_j^1$ and $p_j^2$ are additively separable in $b_j(\cdot)$.[31] Our assumption then results in differences in preferences for the two assignable goods being similar across people, since:

$$\frac{\partial F_j(p)}{\partial p_j^1} - \frac{\partial F_j(p)}{\partial p_j^2} = \frac{\partial r(p)}{\partial p_j^1} - \frac{\partial r(p)}{\partial p_j^2} = \theta(p), \tag{5}$$

where $\theta(p)$ is some function that does not vary across people.

We use Roy's Identity to derive the budget share functions for goods $l = 1,2$. Then, holding prices fixed, we can write Engel curves for person $j$'s two assignable goods as follows:

$$\begin{aligned} W_{js}^1 =& \sigma_j \eta_{js}[\alpha_{js}^1 + (\beta_{js} + \gamma_s^1)\ln \eta_{js}] + \sigma_j \eta_{js}(\beta_{js} + \gamma_s^1)\ln y \\ W_{js}^2 =& \sigma_j \eta_{js}[\alpha_{js}^2 + (\beta_{js} + \gamma_s^2)\ln \eta_{js}] + \sigma_j \eta_{js}(\beta_{js} + \gamma_s^2)\ln y. \end{aligned} \tag{6}$$

Consistent with the SAP restriction, preferences for the assignable goods are allowed to differ entirely across household types in $\gamma_s^l$ and $\alpha_{js}^l$. We weaken the SAP restriction by including an additional preference parameter $\beta_{js}$, which allows preferences for the two assignable goods to differ more flexibly across people. To better understand our assumptions, consider the following example. Suppose we observe assignable cereals and vegetables for the man, the woman and the 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. Instead, with D-SAP we allow his marginal propensity to consume cereals to differ considerably from that of other household members. However, we require that, if there is any difference between his marginal propensity to consume cereals and his marginal propensity to consume vegetables, this difference be the same for the woman and the children.

Let $\lambda_{js} = \beta_{js} + \gamma_s^1$ and $\kappa_s = \gamma_s^2 - \gamma_s^1$. System (6) can be rewritten as follows:

$$\begin{aligned} W_{js}^1 &= \sigma_j \eta_{js}[\alpha_{js}^1 + \lambda_{js}\ln \eta_{js}] \ + \ \sigma_j \eta_{js}\lambda_{js}\ln y \\ W_{js}^2 &= \sigma_j \eta_{js}[\alpha_{js}^2 + (\lambda_{js} + \kappa_s)\ln \eta_{js}] \ + \ \sigma_j \eta_{js}(\lambda_{js} + \kappa_s)\ln y. \end{aligned} \tag{7}$$

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 $\eta_{js} = c_{js}/\kappa_s$. Section A.5 in the Appendix provides a graphical illustration of the D-SAP approach.

[31] Note that the original SAP restriction requires $F_j(p) = r(p)$. DLP requires this to hold for a single good.

**Differenced SAT (D-SAT).** In our second approach, we use two private assignable goods to modify the SAT restriction. 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 for two different private assignable goods. Here, we call our approach *Differenced SAT*, or D-SAT.

With D-SAT, $F_j(p)$ 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.[32] As above, $p_j^1$ and $p_j^2$ are additively separable in $b_j(\cdot)$. Then, differences in preferences for the two assignable goods are similar across household types:

$$\frac{\partial F_j(p)}{\partial p_j^1} - \frac{\partial F_j(p)}{\partial p_j^2} = \frac{\partial r_j(p_j^1,\ p_j^2,\ \bar{p})}{\partial p_j^1} - \frac{\partial r_j(p_j^1,\ p_j^2,\ \bar{p})}{\partial p_j^2} = \theta_j(p_j^1, p_j^2, \bar{p}), \tag{8}$$

where $\theta_j(p_j^1, p_j^2, \bar{p})$ is some function that does not vary across household types.

We again use Roy's Identity to derive the budget share functions for goods $l = 1, 2$. The Engel curves for person $j$'s assignable goods are then written as follows:

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

Preferences for the assignable goods are allowed to differ across people in $\gamma_j^l$ and $\alpha_{js}^l$. Relative to SAT, the additional preference parameter $\beta_{js}$ allows the slopes of the Engel curves to differ more flexibly across household types $s$. 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 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. The same must be true for women and children. With D-SAT, we allow the man's marginal propensity to consume cereals to vary across household types. However, we require that, if there is any difference between his marginal propensity to consume cereals and his marginal propensity to consume vegetables, this difference be the same regardless of the number of children in the household. The same must be true for women and children.

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 (9) as follows:

$$\begin{aligned} W_{js}^1 &= \sigma_j \eta_{js}[\alpha_{js}^1 + \lambda_{js}\ln \eta_{js}] \ + \ \sigma_j \eta_{js}\lambda_{js}\ln y \\ W_{js}^2 &= \sigma_j \eta_{js}[\alpha_{js}^2 + (\lambda_{js} + \kappa_j)\ln \eta_{js}] \ + \ \sigma_j \eta_{js}(\lambda_{js} + \kappa_j)\ln y \end{aligned} \tag{10}$$

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 system of differenced Engel curves that are similar to the SAT system of equations. The slope coefficient for each person type $j$ is identified by linear regression of $W_{js}^1 - W_{js}^2$ on log expenditure. Comparing the slopes of the differenced Engel curves across household types, and

[32] Note that the original SAT restriction requires $F_j(p) = r_j(p_j^1,\ p_j^2,\ \bar{p})$ for one good.

assuming that resource shares sum to one allows us to recover the resource share parameters.[33]

**Discussion.** Our identification results rely on the existence of two private assignable goods for each person-type that satisfy the required preference restrictions. It is important to note that these restrictions do not need to apply to *all* possible pairs of goods; such requirement would be extreme. Nonetheless, the validity of our approaches (as well as of the DLP approaches) clearly depends on the choice of goods.[34] In general, we recommend testing the validity of the identifying assumptions whenever possible (see Sections A.6 and A.8 in the Appendix for details). Note that, as in DLP, we impose preference restrictions across people or across household types, not across goods *per se*. So, e.g., the two private assignable goods could be complements or substitutes, the budget shares for both goods could be increasing or decreasing in expenditure, or one could be increasing and the other decreasing in expenditure (as in Figure A7 in the Appendix).

One advantage of the DLP identification approach over ours is that it requires observability of a single assignable good, while ours needs two. However, DLP impose stronger preference restrictions. By allowing the slopes of the individual-level budget share functions for the assignable goods to vary across people as well as household types, we add flexibility to the model. While SAP and SAT are consistent with the shape-invariance restriction of Pendakur (1999) and Lewbel (2010), D-SAT and D-SAP cannot generally be interpreted through the lenses of standard properties of Engel curves. This may be a limitation. Ultimately, though, the relative merits of each approach is an empirical matter that depends on the context. In Section A.8 in the Appendix, we exploit overidentifying restrictions to test the validity of the four preference restrictions in our setting: the Wald tests never reject D-SAP, the SAP restriction is rejected in some specifications but not others, whereas the D-SAT and SAT are consistently rejected.[35] To ease comparisons, however, in what follows we estimate the model using each of the four identification strategies.

# 4 Estimating Resource Shares and Individual Consumption

## 4.1 Data

As previously discussed, the Bangladesh Integrated Household Survey (BIHS) contains detailed expenditure data, together with information on household characteristics, and demographic and other particulars of household members. Based on information contained in the 7-day recall module of household

[33]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 ($\kappa_j$), or $J(J+1)$ unknowns in total. A proof of the rank condition can be found in Section A.4 of the Appendix.

[34]The following example may help clarify this point. For the sake of brevity, we focus on D-SAP, but the extension to D-SAT is straightforward. Consider a nuclear household without children, and footwear and cereals as the assignable goods. The two household members (e.g., a man and a woman) may have different preferences over all consumption goods, including footwear and cereals. D-SAP, however, requires that, if the man's marginal propensity to consume cereals differs from his marginal propensity to consume footwear, then this difference be the same for the woman too. If, e.g., the man has a higher marginal propensity to consume cereals relative to footwear, but the opposite holds true for the woman, D-SAP will *not* be satisfied. So, estimating Engel curves for footwear and cereals under the D-SAP restriction is not advised. By contrast, other food items may work better in place of footwear if, e.g., both the woman and the man have higher marginal propensities to consume cereals relative to vegetables. Similarly, choosing footwear and clothing would be appropriate if, e.g., both the woman and the man have higher marginal propensities to consume clothing relative to footwear.

[35]We test preference restrictions for cereals and vegetables, which we use in our main specification. Recall that the validity of each restriction is not invariant to the choice of assignable goods.

food consumption, the 24-hour recall module of individual dietary intakes and food weighing, and the annual consumer expenditure module, we compute individual budget shares for different categories of food. For simplicity, we focus on cereals, vegetables, and proteins (meat, eggs, fish, and dairy products), which are the three largest components of food consumption.[36]

We compute the budget shares as follows. For each food category, we first calculate the total value (in taka) of household consumption over the previous 24 hours. We then determine the percentage of that total value consumed by each 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 consumption for each food category over that time period, and extrapolate this value to annual terms. Multiplying total annual household consumption of e.g. cereals by the percentage consumed by each individual household member over the previous 24 hours results in individual consumption of cereals over the previous year. Finally, dividing by total annual household expenditure yields the individual-level budget shares.

For computational reasons, we pool data from the two rounds of the BIHS dataset. We select a sample of 6,417 households as follows. To ensure comparability across household types, we exclude households with zero men, women, or children, or with more than five individuals in any 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 households reporting having guests during the food recall day (1,554 households). A small number of households have individuals with food budget shares that take a value of zero due to illness, fasting, being an infant, or currently being away from the household. Households with such individuals are excluded from the analysis (546 households). Finally, households with missing data for any of the household characteristics or relevant expenditures are dropped from the sample.

Tables 2 contains descriptive statistics for the variables included in the empirical analysis; Table A7 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.[37] The corresponding per-capita expenditure 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). Non-food consumption represents roughly one third of total consumption and includes, among others, expenditures on housing (10 percent), healthcare (5 percent), and clothing (4 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 contain grandfathers. An overwhelming majority of households are Muslim (87 percent) and live in rural areas (83 percent).

[36] Figure A14 in the Appendix provides a clear picture of how individual spending on different food items varies with household expenditure.

[37] We here focus on expenditure on non-durable consumption goods and refer to consumption and expenditure interchangeably.

**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 Share Food | 6,417 | 0.662 | 0.675 | 0.114 |
| Budget Share Cereals | 6,417 | 0.204 | 0.194 | 0.083 |
| Budget Share Vegetables | 6,417 | 0.068 | 0.062 | 0.033 |
| Budget Share 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.

## 4.2 Engel Curve Estimation

We implement the model by adding an error term to each Engel curve in either System (7) or (10).[38] Recall that the empirical implementation of our novel identification approaches (D-SAP and D-SAT) requires two assignable goods. 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. As predicted by the theory, the estimation of resource shares should be invariant to

[38] Alternatively, resource shares can be estimated from a system of four differenced Engel curves, that is $W^1_{js} - W^2_{js}$ (see Section 3.2 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.

the choice of assignable goods. In the Appendix (Table A10), we check that this is indeed the case using proteins (i.e., fish, meat, and milk) as alternative goods.[39]

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

$$\begin{cases} W^1_{js} = \sigma_j \eta_{js}[\alpha^1_{js} + \lambda_{js} \ln \eta_{js}] + \sigma_j \eta_{js}\ \lambda_{js} \ln y + \epsilon^1_{js} \\ W^2_{js} = \sigma_j \eta_{js}[\alpha^2_{js} + (\lambda_{js} + \kappa_{js}) \ln \eta_{js}] + \sigma_j \eta_{js}\ (\lambda_{js} + \kappa_{js}) \ln y + \epsilon^2_{js}, \end{cases} \tag{11}$$

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 $\sigma_j$ 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 $W^l_{js}$, $y$ and $\sigma_j$ are observed in the data.[40]

Let $a$ be a vector of household *type* variables, which includes the number of boys and girls aged 0-5 and 6-14, and the number of men and women aged 15-45 and 46 and above. Let $X$ be a vector containing all other demographic characteristics presented in Table 2. We model resource shares $\eta_{js}$ and preference parameters $\lambda_{js}$, $\alpha^l_{js}$, and $\kappa_{js}$ as linear functions of $a$ and $X$.[41] To achieve identification of resource shares, we impose the preference restrictions discussed in Section 3.2. Given D-SAP, $\kappa_{js} = \kappa_s$ is linear in a constant, $a$ and $X$; given D-SAT, $\kappa_{js} = \kappa_j$ is linear in a constant and $X$ for each person category $j$. For completeness, we provide estimates obtained using the original SAP and SAT restrictions from 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). Results from alternative specifications are available upon request.

Since the error terms may be correlated across equations, we estimate the system of Engel curves using non-linear Seemingly Unrelated Regression (SUR) method.[42] Non-linear SUR is iterated until the estimated parameters and the covariance matrix settle.[43]

[39] Parallel work by Lechene et al. (2019) shows that using food as an assignable good delivers resource share estimates that are similar to those generated from clothing data. Unfortunately, the BIHS does not include assignable clothing and footwear separately for boys and girls, so we cannot extend their interesting comparisons to our setting.

[40] Figure A14 in the Appendix shows the results of non-parametric regressions of $W^l_{js}$ 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. 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.

[41] In line with previous works, for our main analysis, we model resource shares as deterministic functions of observable household characteristics. As a robustness check, we follow Dunbar et al. (2019) and estimate the model allowing for unobserved heterogeneity in the resource shares. The full set of results is presented in Section A.11 in the Appendix.

[42] Dunbar et al. (2013) and other works (Dunbar et al., 2019; Calvi, 2019; Penglase, 2018; Tommasi, 2019; 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.

[43] Iterated SUR is equivalent to maximum likelihood with multivariate normal errors. 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.

## 4.3 Baseline Results

We start by briefly discussing the role of covariates. Point estimates and robust standard errors are reported in Tables A8 (for the D-SAP and D-SAT approaches) and A9 (for SAP and SAT) in the Appendix. For the sake of brevity, the tables present the covariates of resource shares $\eta_{js}$ 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 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). 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.[44] 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. Interestingly, the estimates are quantitatively similar across specifications, despite the results of tests of overidentifying restrictions.[45] Relative to D-SAT and SAT, D-SAP and SAP require fewer parameters be estimated, which is likely contributing to their lower standard errors.

In Section A.2 of the Appendix, we carefully assess the sensitivity of these results to measurement error and to systematic misreporting of food consumption. Results obtained comparing Engel curves for cereals and proteins are similar and presented in Table A10 in the Appendix. Results are also confirmed when accounting for possible endogeneity in total expenditure due to measurement error using total household wealth as an instrument (see Table A11 in the Appendix).[46]

Table 4 (columns (2) to (4)) reports descriptive statistics for the 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

[44] Our results are mostly consistent with estimates from a linearized version of DLP by Lechene et al. (2019) and with the *observed* resource shares found in Bargain et al. (2018), who also study Bangladesh. Bargain et al. (2018) use a different dataset, the Household Income and Expenditure Survey, that exceptionally contains individualized (private only) 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) and 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.

[45] This may not be the case in other contexts or applications.

[46] Unlike expenditure, wealth is measured by enumerating observable assets and may be less susceptible to recall error. For this reason, it is often used to instrument expenditure in the household demand literature.

**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.

household composition variables $a$ and of all other covariates $X$. For simplicity, we here discuss results obtained using the D-SAP restriction. As there can be more than one individual of the same type in each family and because not all 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.[47] 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.[48]

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 indicate that the probability of living in poverty may be non-trivial even for individuals who reside in households with per-capita expenditures above the poverty line (or vice versa). Before further investigating this issue in Section 5, 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, 2019) and to first-born vs. later-born children (Jayachandran and Pande, 2017).[49]

[47] Since we are not imposing any inequality constraints when estimating the model, it is also reassuring that only a very small fraction of individuals in our sample (less than 5 percent) have observed 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.

[48] In Figure A15 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.

[49] 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 1.

**Table 4:** Estimated Resource Shares and Individual Consumption

| | | Resource Shares | | | Individual Consumption (PPP dollars) | | |
|---|---|---|---|---|---|---|---|
| | Obs. | Mean | Median | St. Dev. | Mean | Median | St. Dev. |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| Boys | 4,502 | 0.158 | 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.

## 4.4 Additional Results

**Young vs. Older Adults.** The age structure of the population in Bangladesh is changing rapidly. 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 contains 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 (2019) 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 aged 46 and above, and men aged 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 (11), 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, $\sigma_j$ is the number of household members of category $j$, so that $\sigma_{m^y}\eta_{m^y s} = 1 - \sigma_b\eta_{bs} - \sigma_g\eta_{gs} - \sigma_{w^y}\eta_{w^y s} - \sigma_{w^o}\eta_{w^o s} - \sigma_{m^o}\eta_{m^o s}$.[50]

The resource shares estimates are presented in Panel A of Table A12 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 40 percent lower than those of younger women and 60 percent lower than men aged 46 and older.[51]

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

[51] 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 A12, we estimate the model on a restricted sample that excludes households with widows. These results are presented in Panel A of

**Children by 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.[52] 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.[53] 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 A12 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 A8). However, as we further discuss in Section 5, 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.

# 5 Do Poor Individuals Live in Poor Households?

Based on the model estimates presented in the previous section, we can now calculate consumption-based poverty rates that take into account the *unequal* allocation of resources within households. These are different from standard poverty measures which by construction assume *equal* sharing of household resources.

We focus on the World Bank's extreme poverty line of US$1.90 per day, which is meant to reflect the amount of resources below which a person's minimum nutritional, clothing, and shelter needs cannot be met.[54] Using the same line for everyone, however, may lead to welfare-inconsistent poverty

Table A13. 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.

[52]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).

[53]One 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.7). 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. These results are presented Table A13 in the Appendix and are largely consistent with the results in Table A12.

[54]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).

comparisons if some individuals (such as children) require fewer resources to achieve the same level of welfare as others.[55] To account for differences in needs between individuals, 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 (US$1.14/day).[56] 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 line (US$1.52/day).[57] 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 US$1.90/day to be the average threshold for adults aged 15 to 45. We then rescale individual poverty lines based on the 2015-2020 Dietary Guidelines for Americans (see footnote 18 for details), which set that the average caloric recommendation for adults aged 15 to 45 to 2,400.[58] So, for instance, the poverty line for a young man aged 16 to 25 (with recommended intake of 2,800 calories/day) would be US$2.20/day; for an older woman aged 51 to 79 (with recommended intake of 1,800 calories/day), it would be US$1.40/day. For simplicity, we here abstract from joint consumption and economies of scale. Section 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. As noted before, these estimates encompass the consumption of *both* food and non-food goods. 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 $693.50; that is, the annual amount consumed by an individual who lives on US$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 2, 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 2 for caloric and protein intake (see Table 1).[59] In Panel B, we show estimated individual consumption by household per-capita consumption percentiles. Unsurprisingly, individual consumption increases as per-capita household consumption increases. However, there are significant differences between women, men, boys, and girls, which confirm our previous findings.

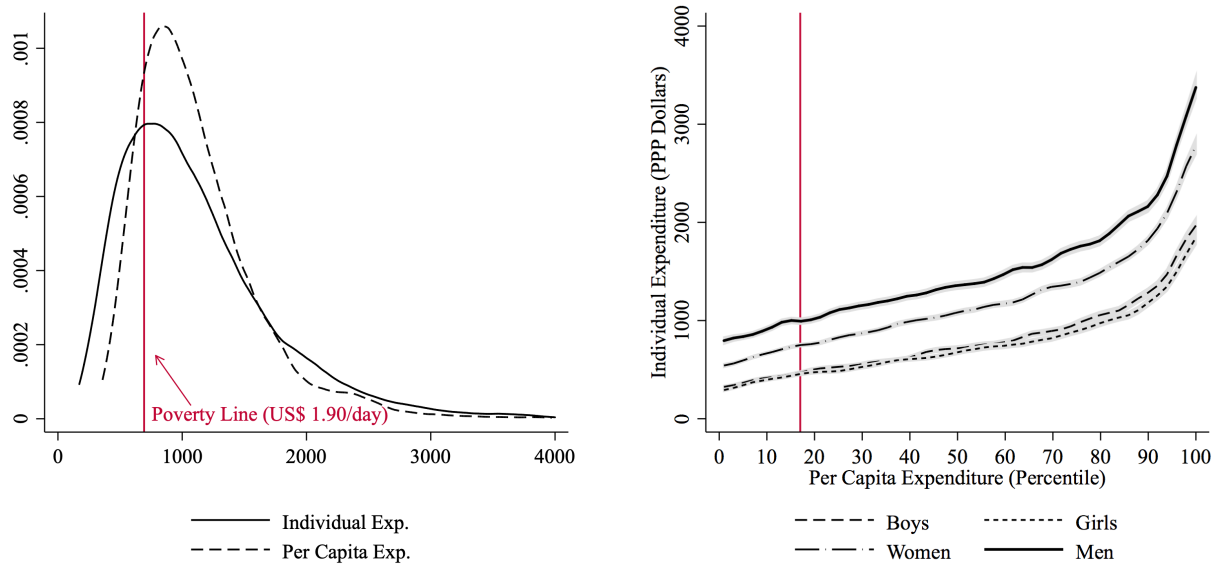
[55] Equivalence scales are sometimes used to adjust for consumption differences between individuals within the household and between household compositions. However, poverty calculations are often highly sensitive to the type of equivalence scale used (Batana et al., 2013; Ravallion, 2015). Moreover, equivalence scales typically lack theoretical foundations and involve untestable assumptions related to welfare comparisons across individuals in different household environments. The deficiencies of equivalence scales has motivated recent work on *indifference scales* (Browning et al. (2013), Chiappori (2016)), which ask how much income an individual would need to reach the same indifference curve as she would were she a member of a different type of household.

[56] We follow previous works (e.g., Dunbar et al. (2013, 2019), Calvi (2019), and Tommasi (2019)) that use the adjustment implied by OECD standard equivalence scales.

[57] 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.

[58] Figure A16 in the Appendix plots the resulting poverty thresholds for by gender and age. Note that this adjustment relies on relative intakes rather than absolute caloric requirements, which mitigates concerns related to the applicability of the US dietary guidelines to Bangladesh. No dietary guidelines are available that are specific to Bangladesh. However, our equivalence scales are analogous to those obtained using guidelines for India, as in D'Souza and Sharad (2019). However, ours allow for a more disaggregated categorization of individuals by age. It also allows us to account for differences in activity levels, as we do in Section A.10 in the Appendix.

[59] These figures are in line with Bargain et al. (2018) (see footnote 44). 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




(A) Empirical Distributions

(B) Individual Expenditures by Per-Capita Expenditure

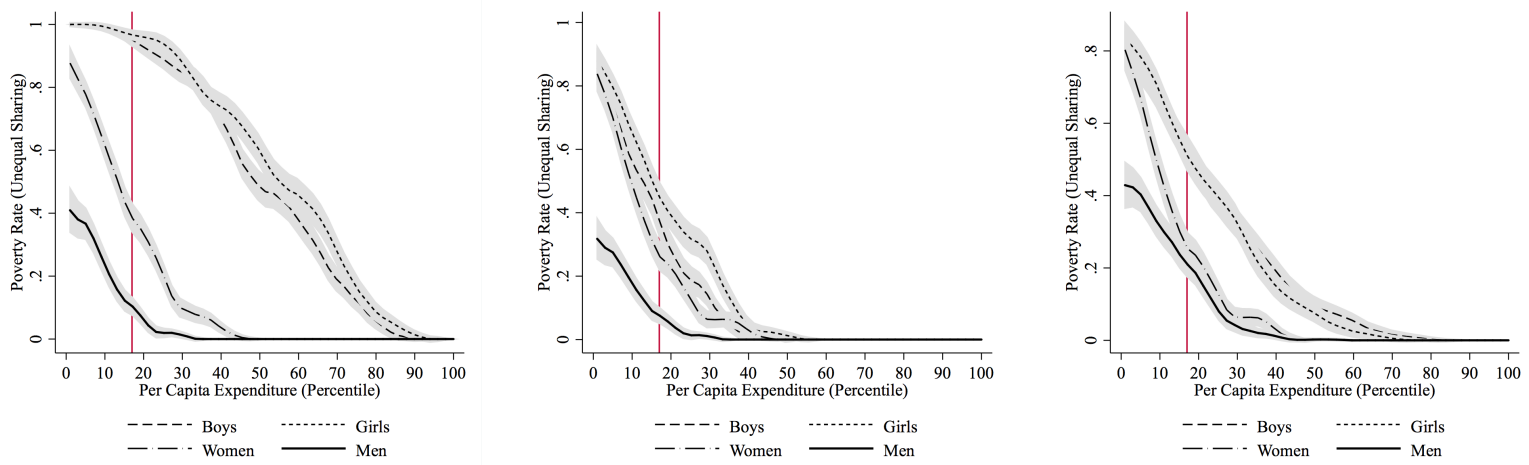
Note: Individual consumption is obtained multiplying total annual household expenditure (PPP dollars) by individual resource shares. Only households surveyed in 2015 are included. The vertical line corresponds to the percentile of the US$1.90/day threshold. Estimates are based on BIHS data and D-SAP identification method with Engel curves for cereals and vegetables (results obtained with the other three identification approaches are similar and available upon request).

**Figure 2:** Per-Capita and Individual Expenditures

Next, we document a large increase in the poverty rate (headcount ratio) once intra-household inequality is accounted for. When using the same line for all individuals, we find that the poverty rate increases from 17 percent using per-capita expenditures to 27 percent using our baseline estimates of individual expenditures (or to 30 percent if we account for unobserved heterogeneity in resource sharing across households; see Section A.11 in the Appendix). Of those who are poor, 57 percent are female and 80 percent are children. Under our rough adjustment equivalence scale, the overall extreme poverty rate increases from 8 to 11 percent when accounting for intra-household inequality; adjusting for differences in caloric needs, the increase is from 9 to 13 percent.

One explanation for the unequal of distribution in resources within the household may be related to differences in activity levels, which may not be fully captured by our caloric intake-based scale. For example, a male adult working in a labor-intensive occupation may need relatively more resources than a similarly-aged sedentary man. Using occupational data available in the BIHS, we generate an additional scale roughly based on activity levels and re-estimate our results (see Section A.10 in the Appendix for details on both the derivation of the scale and the estimates generated). While we find that men's poverty rates increase somewhat, we do not think differences in activity levels fully explain the extent of intra-household inequality we observe. For example, we find that men's daily caloric requirements would need to be 10 percent higher than what we have specified (after the adjustment) in order for men and women to have equal poverty rates. Moreover, for men to have the same poverty rates as boys and girls, men's caloric requirements would need to be 38 percent higher than what is indicated by typical dietary recommendations (see footnote 18). As shown in Table A14 in the Appendix, these results are qualitatively confirmed when computing headcount ratios using the alternative poverty threshold of US$3.10/day. We also consider the impact on the poverty gap index, which is an indicator

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. Only households surveyed in 2015 are included. The vertical line corresponds to the percentile of the US$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

of the *intensity* of poverty, and find sizeable increases in the index when intra-household inequality is accounted for.

More than half of households (53 percent) contain at least one person with estimated consumption below US$1.90/day, suggesting that a sizable number of poor individuals may not reside in non-poor households. Figure 3 shows how individual poverty rates vary over the household per-capita expenditure distribution. Clearly, if individual consumption coincided with household 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 A17 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 household per-capita expenditure percentile. As expected, individual poverty rates decline as per-capita household expenditure increases. However, poverty rates for women are higher than those for men up until the 45th percentile of household per-capita 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 share of poor individuals are still found in non-poor households. As shown in Figure A18 in the Appendix, similar patterns hold when we use the World Bank average poverty line of US$3.10/day.

Using our additional estimates that distinguish between young and older adults and between first-born and later-born children (see Section 4.4), 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 aged 46 and above living with less than US$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. Confirming our previous results, we do not find significant differences by gender among first-born children or among later-born children.[60]

# 6 Some Insights for Policy

The results presented above 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. In this section, we address a few questions that may be relevant for the design of anti-poverty policies and may help guide data collection in the future. Since our considerations stem from estimates based on the BIHS data, any extrapolations beyond the Bangladeshi context should be done with caution.

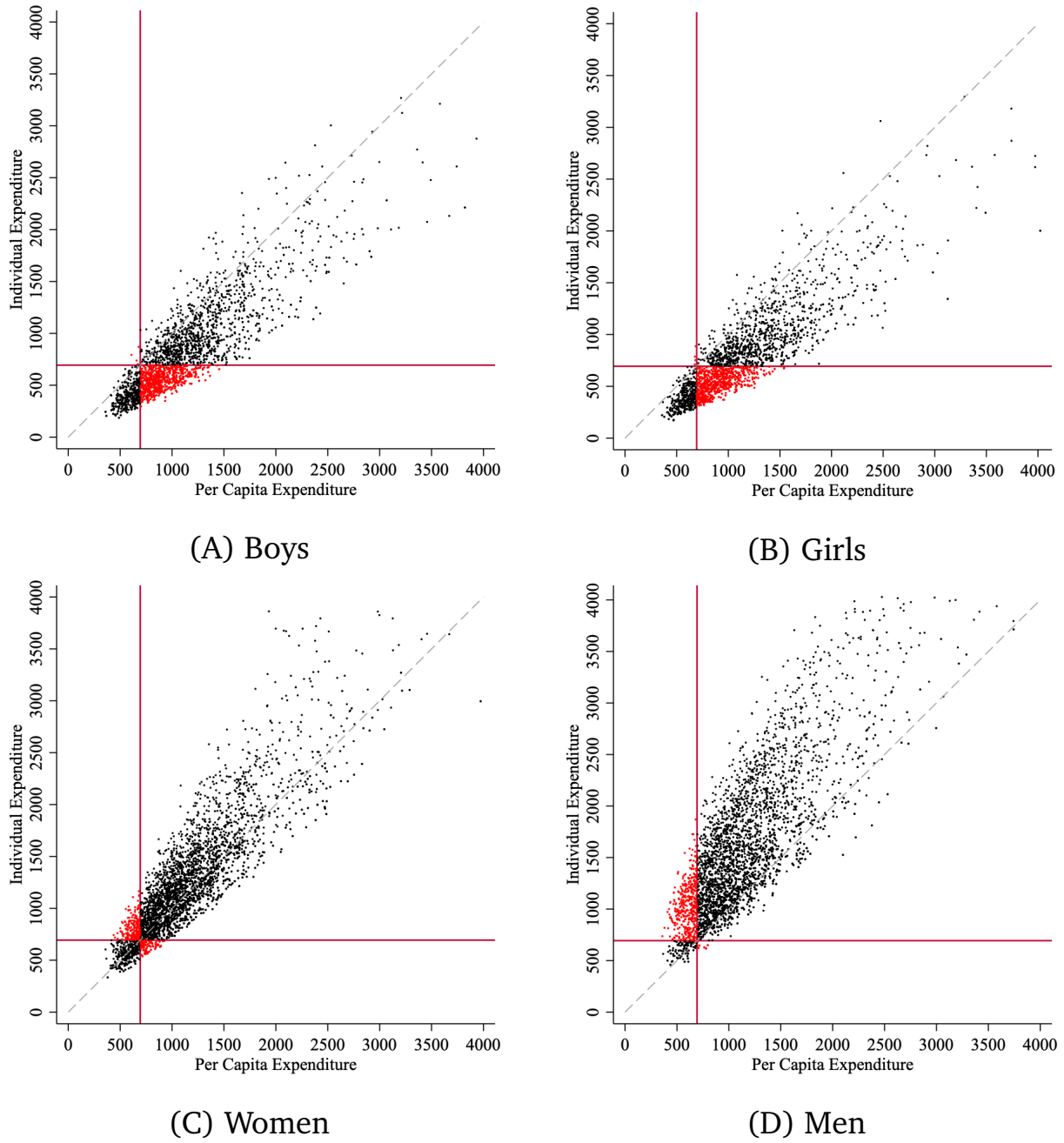
## 6.1 What Is the Extent of Poverty Mistargeting?

As we stressed throughout the paper, 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 *not* be reached by anti-poverty programs that are based on household per-capita expenditure?

We start by plotting individual consumption against household per-capita consumption for men, women, boys and girls. Each dot in Figure 4 corresponds to one individual in our sample. We partition each graph into four regions based on whether one's estimated individual consumption or per-capita consumption is above or below the US$1.90/day poverty threshold. For individuals falling in the lower left or upper right quadrants, the two measures of poverty 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.

Two key features stand out. First, a significant 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. Second, for given per-capita expenditures, there is substantial variation in individual expenditures (and viceversa). This is particularly true for children: several children with estimated consumption below US$1.90/day live in households with per-capita consumption that is two or even three times higher.

[60] Figures A19 and A20 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 US$1.90/day threshold. To avoid clutter in the figures, we do not display graphs for children in Figure A19 and for adults in Figure A20.




Note: Individual consumption is obtained 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. Only households surveyed in 2015 are included. Reference lines correspond to the 1.90 dollar/day poverty line. Dash lines identify the 45 degree lines. 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

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.

## 6.2 What Predicts Poverty Misclassification?

Given that individual consumption is not observable in the majority of surveys (though we have shown it can be estimated under certain conditions and the availability of assignable goods), it is critical to

identify individual or household traits that correlate with one's likelihood to be misclassified as non-poor. To this aim, 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 him or her residing in a household with per-capita consumption above the poverty line (Tibshirani, 1996; Belloni et al., 2014; Athey, 2017).[61] We estimate separate models for boys, girls, men, and women.

Table 6.2 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. First, household size and composition matter: boys, for instance, are more likely to be classified as poor when they represent 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 is 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. Moreover, bargaining power and relative outside options matter, 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.[62]

## 6.3 Can We Compute Poverty Rates Using 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 *not* included in most household surveys. However, most surveys do contain data on one or more assignable goods, which can be used to estimate resource shares. 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' well-being 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.

For the sake of comparison, however, we also compute poverty estimates based on observed individual shares of food consumption (the full set of results is presented in Section A12 of the Appendix).[63] A comparison between poverty calculations based on food sharing and those based on total consumption sharing (that is, based on our estimated resource shares) unveils some interesting features. First, the

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

[62] While we do not present these results for the sake of brevity, our findings are qualitatively confirmed when we apply lasso regularization to predict the difference between individual and per-capita consumption instead of the probability of being misclassified as non-poor.

[63] On average, each man receives a food share of 0.215. Average food shares are 0.188 for a woman, 0.128 for a boy, and a 0.122 for a girl.

poverty rates based on food shares are much higher than our model-based estimates: not adjusting for relative needs, 36 percent of the sample fall below the poverty line; under the rough adjustment, the poverty rate equals 25 percent, while it equals 21 percent under the calorie-based adjustment. This finding is consistent with our estimates of resource shares encompassing the allocation of both food and non-food goods, including public goods or goods that are partially shared. Second, 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, the correlations are quite low otherwise. Thus, 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 among family members may not be well-captured by food allocations.

## 6.4 Comparing Various Measures of Individual Well-Being

One question remains: How well do our estimates of individual consumption align with other indicators of well-being, such as nutritional status and food intakes? To answer this question, we first construct concentration curves based on individual consumption (as opposed to household per-capita consumption; see Figure 1) percentiles. As shown in Figure A21 in the Appendix, with the exception of underweight males, more undernourished individuals are found in the lower percentiles of estimated individual consumption relative to per-capita consumption. Additionally, we find that concentration curves for females that are based on our estimates of individual consumption display a much higher curvature (recall that the further the curve is above the 45 degree line, the more concentrated undernutrition is amongst the poor). Specifically, for females the concentration curves based on our estimates on individual consumption lie everywhere above those based on household per-capita consumption, establishing a relative ranking analogous to Lorenz dominance (Atkinson, 1970; Deaton, 1997).

Next, we calculate the amount of variation in individuals' food intake and nutritional status that is explained by our estimates of individual consumption versus per-capita consumption. For food intake, we estimate linear regression models of nutritional variables on each 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 A16 in the Appendix. 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 our model-based estimates account for about one fifth of its variation, while per-capita consumption explains only 12 percent.[64]

Turning to our measures of underweight, stunting, and wasting, we do not find such impressive differences in terms of explained variation. Other factors such as the health environment, exposure to diseases, sanitation, and access to infrastructure, as well as their idiosyncratic impacts, are therefore

[64] 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.

likely to play a critical role in determining one's nutritional and health status.[65] Nonetheless, for women and children, increases in 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. For children, we find that of those who are stunted, 70 percent are also poor under our estimated consumption, relative to only 24 percent using per-capita consumption. Relatively similar results are obtained for child wasting. For adults, we do less well, though this seems to be driven by underweight men who are no longer deemed poor based on our estimates.

# 7 Conclusion

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 consumption within families and document the extent to which resources are *not* shared equally. To this end, we extend the methodology of Dunbar et al. (2013) to identify and estimate resource shares in collective household models.

We use our model estimates to compute poverty rates that account for potential disparities in resource sharing within households. 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 model assumptions, 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 accounts for a substantial portion of overall consumption inequality. Relative to per-capita household expenditures, our estimates of individual consumption match nutritional outcomes more closely, providing an indirect validation of our structural model.

One important contribution of our work is the identification of households' or individuals' traits that might help predict poverty mistargeting in contexts where individual consumption is not only unavailable but also difficult to estimate (e.g., when assignable goods are not available). We also provide guidance for data collection, showing that knowing how food is allocated may fall short from

[65] See e.g., Banerjee et al. (2004); Guiteras et al. (2015); Coffey and Spears (2017); Duh and Spears (2017); Geruso and Spears (2018)). Brown et al. (2019) provide a number of potential explanations for the why undernourished women and children may not necessarily live in poor households.

helping understand how resources are allocated overall, since food and non-food goods are found to be allocated quite differently.

There are some caveats to our analysis that deserve mention. First, our empirical analysis is primarily 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, consider differences in caloric requirements by age and gender and account for possible differences in activity levels. 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 are the source of our policy recommendations. Third, while we are able to show that our estimates of individual consumption are better indicators of nutritional status for women and children relative to standard per-capita measures, intra-household inequality cannot account for all the variation in nutritional outcomes. Progress has been made in this direction (see e.g., Coffey and Spears (2017); Duh and Spears (2017); Geruso and Spears (2018)), but future research should continue investigating alternative explanations. Finally, as typical in recent works on the identification and estimation of collective models, we do not estimate the full model but focus on recovering a few parameters of interest (that is, resource shares and preferences over the assignable goods). While this approach reduces the assumptions and the data requirements, it unavoidably limits our ability to perform counterfactuals.

While significant progress has been made in reducing extreme poverty as well as in improving the measurement of poverty over the past few decades, much more is still to be done. Our paper adds to recent works arguing that a correct measurement of poverty requires taking into account how resources are allocated among household members (see e.g., Dunbar et al. (2013, 2019); Calvi (2019); Bargain et al. (2018); Lechene et al. (2019)). We also contribute to the discussion on how anti-poverty programs should be targeted. We show that that policies aimed at poor household may not be effective in reaching poor individuals if intra-household inequality is pervasive. However, targeting at the individual-level is challenging and costly. Context-specific cost-benefit analyses of individual versus household targeting are advisable to guide the design of efficient, successful anti-poverty programs. As an alternative, universal untargeted income transfers may be preferable when a significant fraction of poor individuals do not reside in poor households (Ghatak and Muralidharan, 2019). Any transfers (targeted or untargeted) to families, however, would be subject to intra-household allocation and could prove inefficient. In this regard, in-kind transfers (such as school meals for children) may represent a valid alternative. We hope future work will address these important issues.

# Appendix

Our Appendix (available online) contains thirteen sections. In Appendix A.1, we present additional results on nutritional outcomes and food intakes in Bangaldeshi families. In Appendix A.2, we discuss the quality of the 24-hour food recall survey and test the sensitivity of our estimates to measurement error as well as to systematic misreporting error. Our identification assumptions and theorems are presented in Appendix A.3; proofs are discussed in Appendix A.4. In Appendix A.5, we provide a graphical

illustration of the differences between the SAP and D-SAP identification assumptions. In Appendix A.6, we discuss possible benefits of observing three or more private assignable goods for each family member. In Appendix A.7, we describe how we combine available information from various modules of the Bangladesh Integrated Household Survey to determine children's birth order. In Appendix A.8, we provide tests of the preference restrictions required for identification and of the assumption of Pareto efficiency. In Appendix A.9 and Appendix A.10, we check the sensitivity of our poverty calculations to accounting for joint consumption (economies of scale) and for individuals' activity levels, respectively. In Appendix A.11, we present results obtained when we allow resource shares to vary across households for unobserved reasons. In Appendix A.12, we compare our model-based poverty calculations to those based on food shares. Additional figures and tables are in Appendix A.13.

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