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

Caitlin Brown, Rossella Calvi, and Jacob Penglase

A Appendix

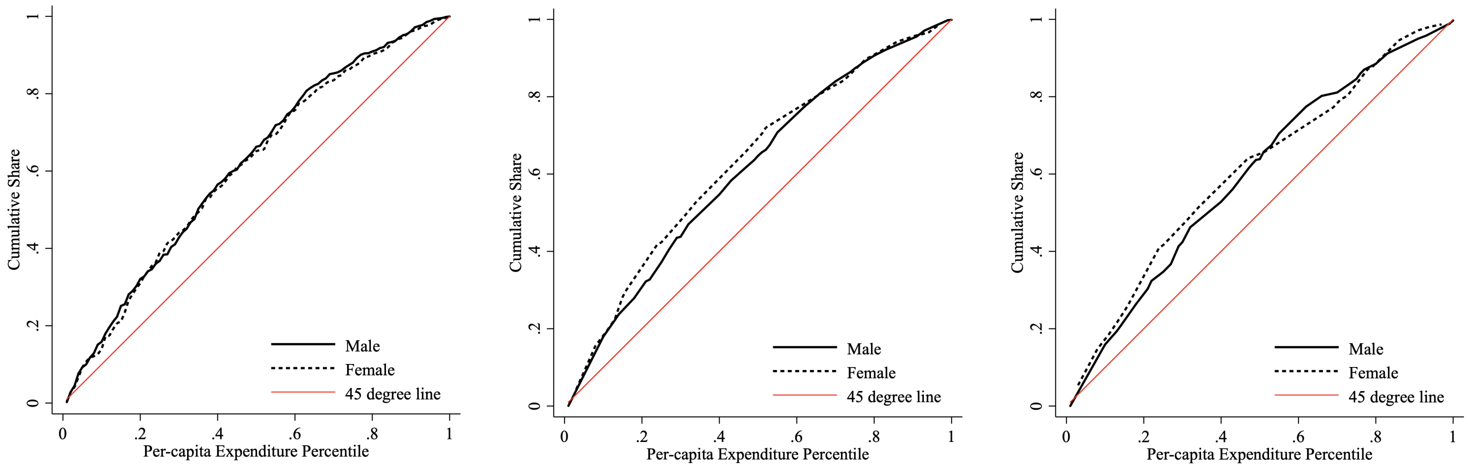
A.1 Nutrition and Inequality: Additional Results and Robustness Checks

Potential Biases. Some potential biases could be influencing our findings regarding the link between household expenditure and individuals' nutritional outcomes (Section 2). First, the relatively weak relationship between household expenditure and undernutrition may be driven by excess mortality among the undernourished; that is, the sample may not include those who are too undernourished to survive.[1] This is particularly true if excess mortality was concentrated among the poor. However, existing studies have found the effect of survivorship bias on estimates of child anthropometric indicators to be marginal; see, for example Boerma et al. (1992); Moradi (2010). In addition, Brown et al. (2019) simulate the potential effect of selective child mortality and find little difference in their results. Nonetheless, we acknowledge that the relationship between household expenditure and nutritional outcomes may be stronger if individuals who did not survive were to be included.

Another possible bias is related to measurement error in the anthropometric outcomes, particularly among very young children. Larsen et al. (1999) and Agarwal et al. (2017), for instance, find evidence of misreporting of child age in DHS surveys, which impacts height-for-age z-scores. Larsen et al. (1999), however, find little resulting impact on estimated rates of stunting. Nevertheless, to account for potential measurement error in the stunting and wasting indicators, we construct concentration curves excluding children younger than 18 months. We also replicate our analysis excluding teenagers (who may still be growing) and older adults (who may be frail or ill and difficult to measure). These concentration curves (shown in Figure A1) look very similar to those shown in Figure 1 in Section 2.

As an additional test, we look at correlations between children's nutritional outcomes and mother's BMI. If there is error in the recorded nutritional measures, we might expect a low correlation be-

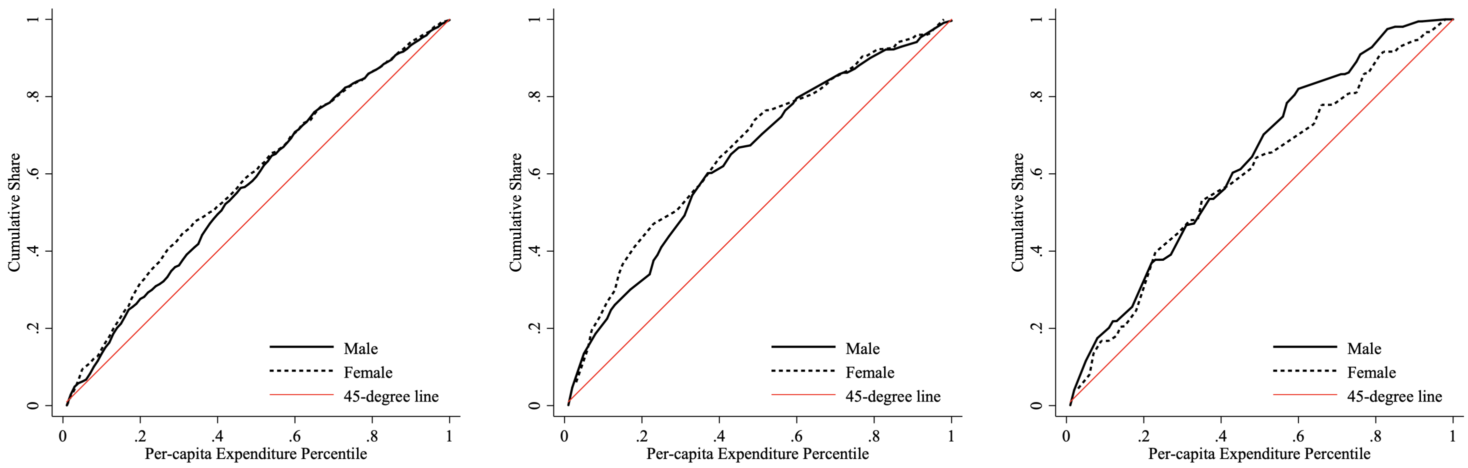
[1]According to World Bank estimates, the mortality rate in Bangladesh for children under 5 in 2015 was 36.3 per 1000 live births (the average for South Asia was 50.3). Male children had a higher mortality rate (38.8) than female children (33.7).



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

Note: BIHS 2015 data. The graphs show concentration curves for the cumulative proportion of women and men aged 20 to 49 who are underweight, and children 18 months or older aged 0-5 who are stunted and wasted at each household per-capita expenditure percentile. Observations with missing values and pregnant or lactating women have been dropped. The Stata command `glcurve` is used to construct the curves.

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



Severely Underweight Adults | Severely Stunted Children | Severely Wasted Children

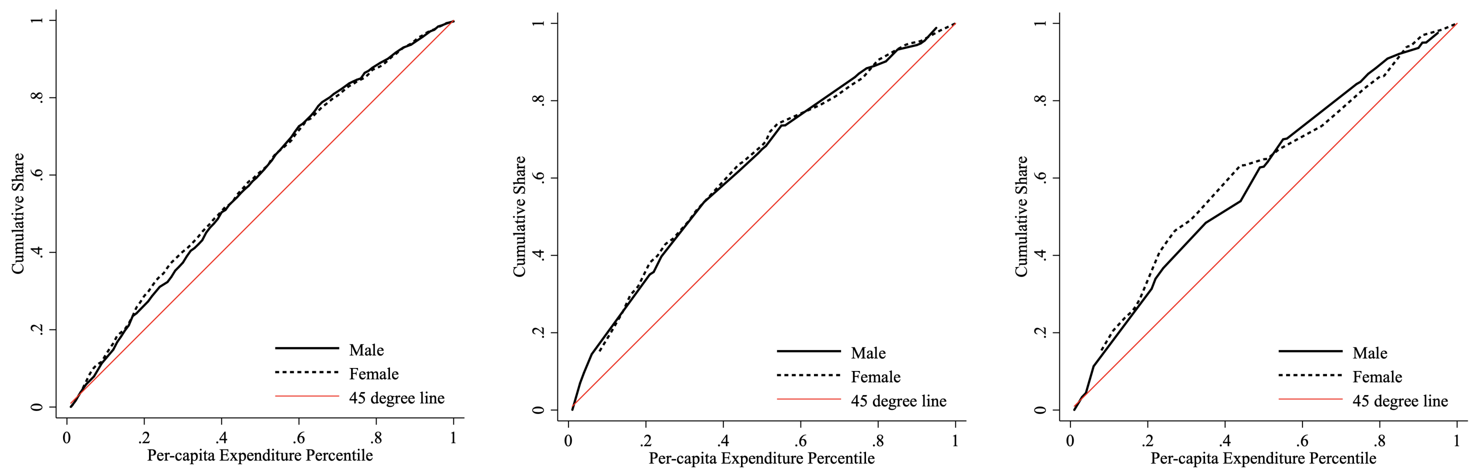
Note: BIHS 2015 data. The graphs show concentration curves for the cumulative proportion of adults aged 15 to 49 and children aged 0-5 who are severely undernourished at each household per-capita expenditure percentile. Severely underweight is defined as a BMI of 17 or lower. Severely stunted and wasted are defined as 3 SDs below the median for height-for-age and weight-for-height respectively. The Stata command `glcurve` is used to construct the curves.

Figure A2: Undernutrition Concentration Curves For Severely Undernourished Individuals

tween a mother's and a child's nutritional status.[2] We find that mother BMI is negatively and significantly correlated with both child stunting and wasting (results are available on request).

Children in Bangladesh may be smaller on average than children in other regions (for example, Africa), and the definition of stunting and wasting may be including children who are not undernourished. To address this concern, we construct concentration curves for severely stunted and wasted children, where severe stunting and wasting is defined as 3 standard deviations below the median height-for-age and weight-for-height scores (see Figure A2). We see a slightly curvature for severely stunted children, but the curves for severely wasted children and severely underweight adults (with BMI below 17) are similar to those in Figure 1, suggesting that the specific definition of undernourishment is not driving our findings.

[2]Existing work has found that mother and child nutritional status is highly correlated; see, for example Jehn and Brewis (2009); Black et al. (2013); Tigga and Sen (2016).



Underweight Adults   Stunted Children   Wasted Children

Note: BIHS 2015 data. Individuals who report having lost weight due to illness in the past four weeks are excluded. The graphs show concentration curves for the cumulative proportion of women and men who are underweight, and children aged 0-5 who are stunted and wasted at each household per-capita expenditure percentile. Observations with missing values and pregnant or lactating women have been dropped. The Stata command `glcurve` is used to construct the curves.

Figure A3: Undernutrition Concentration Curves Excluding Sick Individuals

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

MLD Decomposition. Mean Log Deviation (as discussed in Section 2) can be decomposed into between and within household inequality as follows:

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

where we assume that each individual i belongs to household j has a nutritional intake of c_{ij}. Each household has a total of N_j members and an average household nutritional intake of c_j; J and N are the total number of households and individuals, respectively. The average of all individual nutritional intake is given by $\bar{c}$.

A.2 How Accurate is the BIHS Food Data?

Our empirical analysis relies on the 24-hour food recall module in the BIHS. This data is central to our analysis and therefore its reliability deserves attention. In this section, we describe several aspects of the survey that were designed to ensure its accuracy. We also discuss recent work by D'Souza and Sharad (2019) who extensively analyze potential biases within the BIHS food module. Lastly, we conduct several robustness checks of our own to determine the extent of any measurement error and its relevance for our results.

As discussed in Section 2, a female enumerator surveyed the woman in the household most responsible for preparing and distributing meals. All enumerators had prior experience collecting dietary intake data, including some in Bangladesh. The enumerator asked the respondents recipes, ingredient amounts, the source of the ingredients, as well as the amount of each meal allocated to each person in the household, including guests. The survey also accounted for leftover food and food given to animals. If any individual did not consume a meal, the enumerator found out why.

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

Meals consumed outside the household are also included in the data. One might be worried that these meals are particularly susceptible to measurement error. However, D'Souza and Sharad (2019) analyze differences in food allocation across households where no meals are consumed away from home, and those where some are, and find no qualitative differences.

We conduct additional tests of our own to analyze the quality of the 24-hour food module. First, we compare the per-capita amount households spent on food derived from the 7-day household-level food expenditure module to the individual food consumption aggregate derived from the 24-hour consumption module. In terms of levels, we find a reasonably strong correlation of 0.62. We then determine whether households were being reordered in terms of total consumption across the two survey modules. We compute percentile ranks of household food expenditure for both recall periods and find a correlation between the ranks of 0.74.

Next, we check the robustness of our model estimates along several dimensions. We test the sensitivity of our results to restricting the estimation sample to households where each household member had at least one meal at home during the recall day. Recall that in our main specification we exclude households where either all men, or all women, or all children did not consume any food.

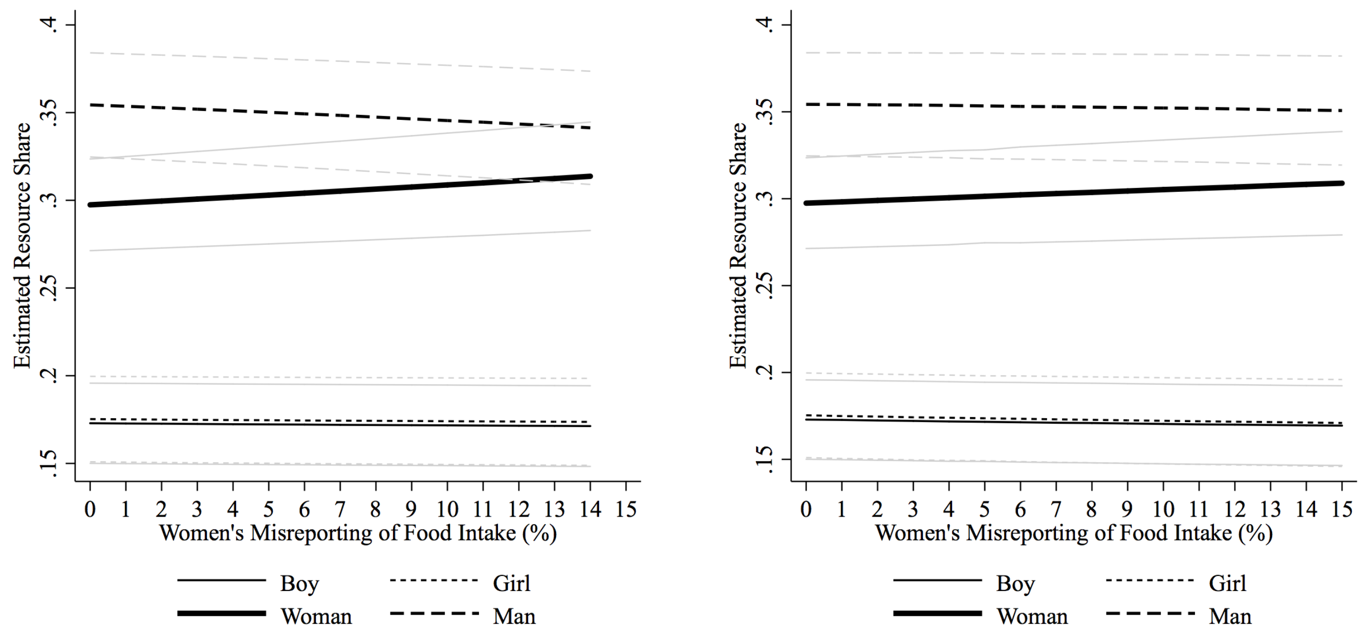
We find that our results are not only qualitatively, but also quantitively confirmed. In addition, for each household we compute the difference between food consumption from the 7-day expenditure module and from the 24-hour food consumption module. We estimate our model excluding those household that display the highest discrepancies (that is, the top 10 percent of the distribution of the difference). The estimated resource shares are very similar to our baseline results (under D-SAP, for example, the average shares equal 0.158, 0.148, 0.245, and 0.337 for boys, girls, women, and men, respectively), which is reassuring. The full set of estimates is available upon request.

In summary, it is possible that measurement error is present in our data (as it is in almost all survey data). Given both the results of the robustness checks discussed above and the results in D'Souza and Sharad (2019), however, we believe that measurement error in our context is not too severe. Nonetheless, it is important to comment on how any measurement error would affect our results, if present. On one hand, if the measurement error in food recalls is random (that is, the respondent was not systematically underestimating the consumption of a certain type of person in the household), then we are confident our results are robust. The above discussion is focused on this type of measurement error. On the other hand, if there exist cultural norms that lead women to report their husbands and children are well-fed, then that may bias our results. While the survey enumerators were aware of these potential biases and were instructed on how to elicit honest responses (D'Souza and Sharad, 2019), some systematic misreporting may have occurred.

To shed light on how relevant women's systematic misreporting is for our results, we consider two different forms of bias. First, if cultural norms push women to report their husbands are well-fed, they may attribute some of their own consumption to their husbands. In this case, the reported consumption of food for men may be higher than what it actually is. Second, if cultural norms lead women to report their husbands and children are well-fed, the reported consumption of food for both men and children may be inaccurate. While we are unable to determine how prevalent this type of bias is in our data, we can examine how sensitive our results are to this type of misreporting. We therefore reestimate the model under the assumption that women underreport (by a certain percentage) how much food they consume and overreport how much men and children consume. For simplicity, we estimate the model using the D-SAP approach and cereals and vegetables as assignable goods.

Figure A4 shows resource shares estimated for a reference household by the degree of possible misreporting of food consumption.[3] In Panel A, we assume women underreport how much food they consume and overreport (by the same amount) how much men consume. In Panel B, we assume women underreport their food consumption and overreport (by an equal fraction of that amount) how much men, boys, and girls consume. It is reassuring that, even when we increase the degree of women's underreporting of their own food intake, the deviation from our baseline estimates (corresponding to no misreporting at all) is minimal. Since identification of the resource

[3] As in section 4.3, a reference household is 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.



(A) Overreporting Husband's Food Consumption

(B) Overreporting Husband's and Children's Food Consumption

Note: The graphs show the estimates of resource shares and associated 90 percent confidence intervals for reference households, (households 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 north-eastern Bangladesh, surveyed in year 2015, with all other covariates at median values) under different degrees of individual food consumption misreporting. Estimates are based on BIHS data, Engel curves for cereals and vegetables, and the D-SAP identification approach. In both panels, we assume that the woman answering the survey is underreporting by a certain percentage (x-axis) how much cereals and vegetables she consumes. In Panel A, we assume that this underreporting inflates the reported consumption of cereals and vegetables by men. In Panel B, we assume that this underreporting inflates the reported consumption of cereals and vegetables by both men and children.

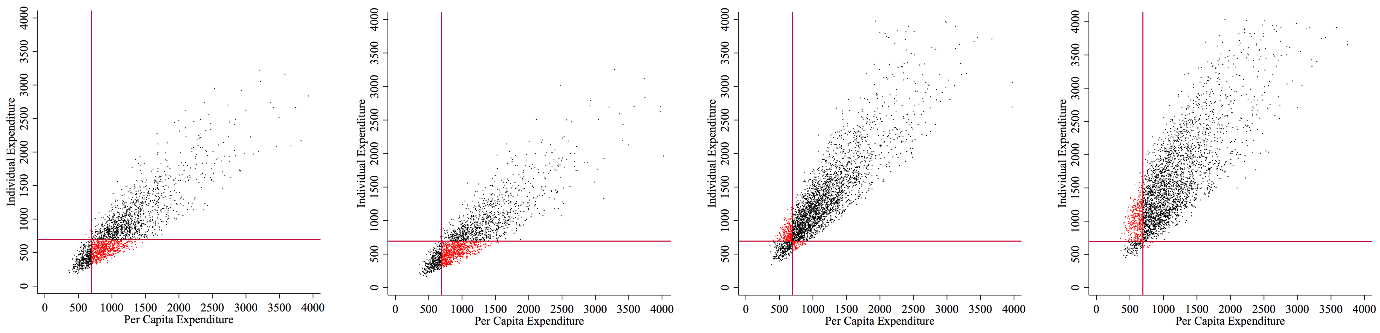
Figure A4: Estimated Resource Shares under Misreporting of Food Consumption

shares comes from how assignable food shares change with total expenditure (and not from the level of the food shares), this is not surprising: any underreporting of food (even if systematic) would be captured by the intercept terms of the Engel curves for cereals and vegetables and would *not* influence their slopes. This is an additional benefit of estimating resource shares the way we do, instead of simply inferring intra-household resource sharing from from allocations (see Section A.12 for a discussion of other benefits)

When looking at the descriptive statistics of the estimated resource shares for all households, we also find little difference when we account for misreporting: with 10 percent misreporting in food consumption, the average shares are 0.156 and 0.148 for boys and girls, and 0.258 and 0.328 for women and men, respectively (detailed results are available on request). Most importantly, the results of our poverty analysis presented in Section 5 are both qualitatively and quantitatively unchanged when we allow for women's systematic reporting bias. Figure A5 is analogous (and very similar) to Figure 4, but considers the case in which women underreport their food consumption by 10 percent and overreport (by an equal fraction of that amount) how much men, boys, and girls consume.

A.3 Theorems

The section provides the two main theorems of the paper. Both are extensions of Theorems 1 and 2 in Dunbar et al. (2013) (hereafter DLP), and therefore share much of the same content. The main



(A) Boys (B) Girls (C) Women (D) Men

Note: Only households surveyed in 2015 are included. Individual consumption is obtained by multiplying total annual household expenditure (PPP dollars) by individual resource shares. Per-capita consumption is obtained by dividing total annual household expenditure (PPP dollars) by household size. Reference lines correspond to the 1.90 dollar/day poverty line. Estimates are based on BIHS data and D-SAP identification method with Engel curves for cereals and vegetables. In all panels, we assume that women answering the survey are underreporting by 10 percent how much cereals and vegetables women consume and that this underreporting inflates the reported consumption of cereals and vegetables by both men and children.

Figure A5: Individual and Per-capita Expenditure under Misreporting of Food Consumption

differences are in the data requirements (we need more) and the assumptions (we need fewer). The key differences can be found in Assumptions A2$'$, A3$'$, B3$'$. Otherwise, we follow DLP.

A.3.1 Theorem 1

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

Let z_s denote the vector of goods purchased by a household of composition s, where the subscript s indexes the household types. Let σ_j denote the number of individuals of type j in the household. From Browning et al. (2013), we write the household's problem as follows:

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

- For $I(y > y^*)$
$$h_j^k(y,p) = -\Big[\partial \Psi_j(y,p)/\partial p_j^k\Big]/\Big[\partial \Psi_j(y,p)/\partial y\Big]$$
- For $I(y \le y^*)$

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

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

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

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

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

A.3.2 Theorem 2

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

A.4 Proofs

A.4.1 Proof of Theorem 1

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

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

$$\lambda_s = \lim_{y\to 0}[y^{\zeta} g^{''}_s(y)/g^{'}_s(y)]^{\frac{1}{1-\zeta}}$$

Case 1: $\zeta \neq 1$

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

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

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

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

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

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

DLP:

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

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

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

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

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

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

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

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

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

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

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

A.4.2 Proof of Theorem 2

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

$$H^k_{js}(y) = a^k_{js} \eta_{js} y + \Big(\tilde{b}_{js} + \tilde{e}^k_j \Big) f_j(\frac{\eta_{js} y}{G_{js}}) \eta_{js} y$$

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

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

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

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

Then since resource shares sum to one,

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

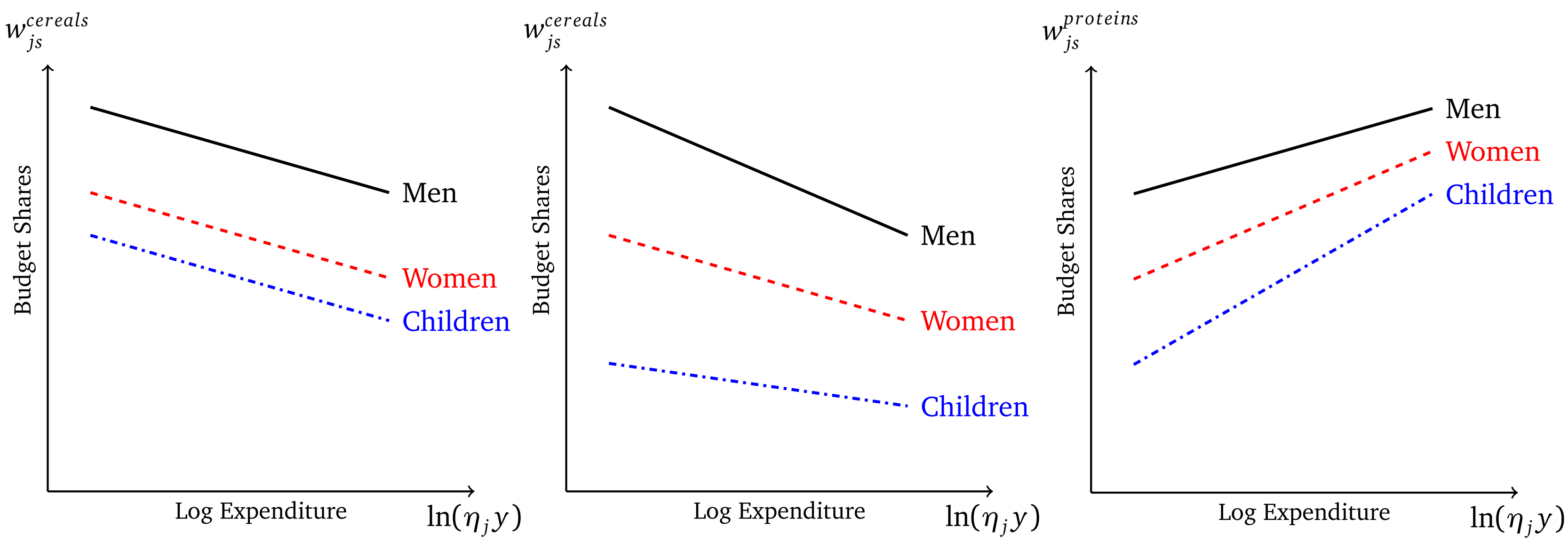
for $s \in \{2, ..., S\}$.

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

A.5 Graphical Illustration for D-SAP

To understand the D-SAP identification results graphically, we plot hypothetical *individual-level* Engel curves for two assignable goods (e.g., cereals and proteins). Recall from Section 3 that these are not observed. Under SAP, Dunbar et al. (2013) assume that preferences for one assignable good (either cereals or proteins) are similar across person types. With piglog preferences, this results in individual-level Engel curves with the same slopes as shown in Panel A of Figure A6. We differ in that we allow preferences for the assignable goods to vary substantially across individuals. Panels B and C of Figure A6 illustrate this point as the slopes are no longer identical across people.

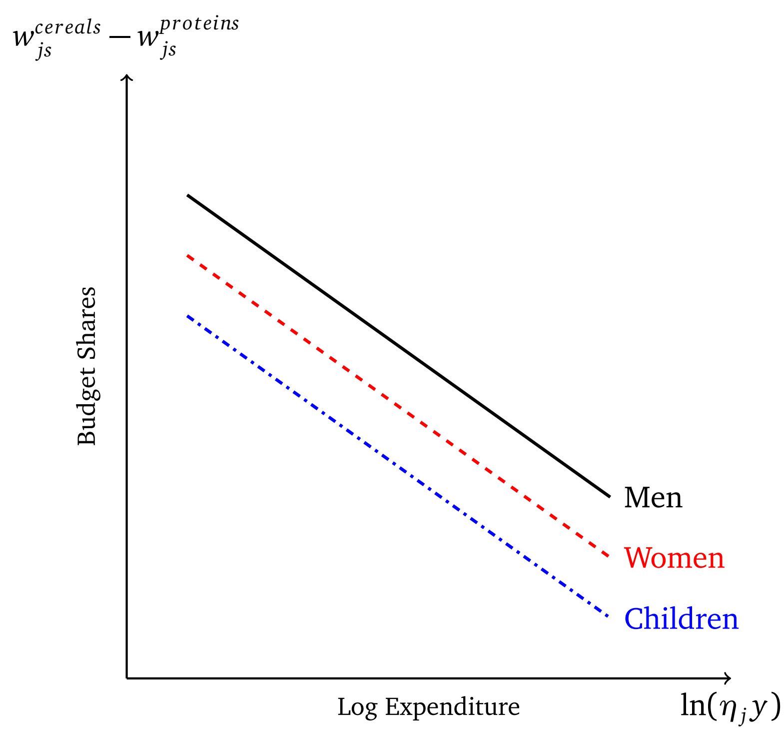
We purpusedly plot hypothetical Engel curves for proteins (positively sloped in our sample) and cereals (negatively sloped) to stress that the two assignable goods needed for our identification strategy may be quite heterogeneous and that we are not imposing specific restrictions on the nature of the goods *per se*. However, we restrict preferences for the two assignable goods to differ in a similar way across people. Intuitively, this means that if women have a higher marginal propensity to consume proteins relative to cereals, this difference needs to be the same for men and children. Under this assumption, if we take the difference between the two Engel curves for each individual, we end up with Figure A7. Here, the differenced *individual-level* Engel curves are parallel, similar



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

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

Figure A6: SAP and D-SAP Comparison



Note: Differences in individual-level Engel curves across assignable cereals and proteins. The Engel curves are derived by taking the difference of Panels B and C from Figure A6. By assumption, the differenced Engel curves will have the same slope and we can therefore use the DLP identification results.

Figure A7: Differenced Engel Curves (D-SAP)

to SAP, and we can therefore use the DLP identification results to recover resource shares. In effect, any difference in the slopes of the *household-level* differenced Engel curves can be attributed to differences in resource shares, as in SAP.

A.6 Identification with More than Two Assignable Goods

Our main identification results rely on the existence of two private assignable goods for each person-type that satisfy either the D-SAP or D-SAT restrictions. It is important to note that these restrictions do not need to apply to *all* possible pairs of goods. In our approach, the identification restrictions apply only to two goods, while preferences for the other assignable and non-assignable goods are free to vary arbitrarily. The question is: What if we observe more than two goods? While there is no obvious way of using additional goods to relax our identification assumptions, there may be some other benefits from having access to additional data. We illustrate some of them below.

One benefit of observing additional goods is that it may help assess the robustness of the estimates. Moreover, it may allow to test the validity of the identification restrictions. If we were to observe $L > 2$ private assignable goods for each person type, we could impose our D-SAP assumption on goods $l = 1$ and $l = 2$, while allowing the preferences for goods $l = 3, ..., L$ to remain unrestricted:[4]

$$\begin{aligned} W_{js}^1 &= \sigma_j \eta_{js} [\alpha_{js}^1 + (\beta_{js} + \gamma_s^1) \ln \eta_{js}] + \sigma_j \eta_{js} (\beta_{js} + \gamma_s^1) \ln y \\ W_{js}^2 &= \sigma_j \eta_{js} [\alpha_{js}^2 + (\beta_{js} + \gamma_s^2) \ln \eta_{js}] + \sigma_j \eta_{js} (\beta_{js} + \gamma_s^2) \ln y \\ W_{js}^3 &= \sigma_j \eta_{js} [\alpha_{js}^3 + \gamma_{js}^3 \ln \eta_{js}] + \sigma_j \eta_{js} \gamma_{js}^3 \ln y \\ \vdots &= \qquad \vdots \qquad\qquad \vdots \\ W_{js}^L &= \sigma_j \eta_{js} [\alpha_{js}^L + \gamma_{js}^L \ln \eta_{js}] + \sigma_j \eta_{js} \gamma_{js}^L \ln y \end{aligned} \tag{A12}$$

Doing so will identify resource shares η_{js}, separately from $\alpha_{js}^1, \ldots, \alpha_{js}^L$, $\gamma_{js}^1, \ldots, \gamma_{js}^L$, and β_{js}. With L goods, we could estimate a system of up to $L \times J$ Engel curves (where J is the number of household member types; e.g., men, women, boys, girls). Clearly, this comes at a cost: the higher the number of assignable goods one decides to include in estimation, the larger is the number of Engel curves and parameters that need to be estimated.

Note that if we observed $L = 3$ goods, we would have three possible pairs of goods that could satisfy the D-SAP assumption. We could sequentially impose the identification assumption on each pair of goods and place no restrictions on the third good, and compare the estimation results from different specifications. More generally, with L goods, there are $\frac{L!}{2(L-2)!}$ potential pairs of goods that can be used for identification. As an illustration, we estimate a system of up to 12 Engel curves (3 assignable goods, 4 person types) using cereals, vegetables, and protein as assignable goods. We restrict the preferences for two goods at a time, while leaving the third good unrestricted. Table A1 reports the resource shares estimated for reference households. In this case, all specifications deliver quite similar estimates. It is important to note, however, that in general different combinations of goods may lead different estimates since not all pairs of goods will satisfy D-SAP (see Section 3.2 for detailed examples).

One could also use the additional Engel curves to test overidentifying restrictions in absence of distribution factors (see Section A.8 for details). For instance, if we observed three assignable goods, we could impose the SAP assumption from Dunbar et al. (2013) on the first good ($l = 1$), and test whether preferences differ across the other two goods ($l = 2$ and $l = 3$) in a similar way across person-types (that is, if our D-SAP is satisfied for goods 2 and 3). Analogously, if we observed

[4] A similar argument applies to our D-SAT assumption. For the sake of brevity, we focus here on D-SAP.

Table A1: Estimated Resource Shares - Three Assignable Goods

	D-SAP on Veg. & Protein, Cereals Unrestricted		D-SAP on Protein & Cereals, Vegetables Unrestricted		D-SAP on Veg. & Cereals, Protein Unrestricted	
	Estimate	Standard Error	Estimate	Standard Error	Estimate	Standard Error
Boy	0.164	0.015	0.176	0.013	0.161	0.012
Girl	0.154	0.013	0.168	0.012	0.154	0.012
Woman	0.299	0.016	0.290	0.013	0.307	0.014
Man	0.383	0.021	0.367	0.017	0.378	0.016

Note: Estimates based on BIHS data and Engel curves for cereals, vegetables, and proteins. 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.

four assignable goods, we could impose D-SAP on goods $l = 1$ and $l = 2$ test whether preferences differ across the other two goods in a similar way across person-types.

A.7 Determining Birth Order

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

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

We also conduct our birth order analysis on a restricted sample where we expect less misclassification. We drop households with mother's who may have adult-age children who have left the household. Specifically, we estimate the model on households without mothers who are above age 35. The reason we choose 35 is that we assume the earliest a woman gives birth is 15, and that the earliest a child moves out is 15. Moreover, we know children who have migrated in the previous five years. It follows that we should be entirely accurate for women age 35 and under ($15+15+5 = 35$). Because women who are 35 in 2011 are 39 in 2015, we drop households with women above 39 in 2015. Results of this exercise are reported in Table A11.

A.8 Testing the Model Assumptions

Preference Restrictions. As discussed in Section 3.2, distribution factors (i.e., variables that affect bargaining power but not individual preferences or the budget constraint) are not required for identification when using our novel strategies (D-SAP and D-SAT) as well as when using the methodologies developed by Dunbar et al. (2013) (SAP and SAT). Recent work by Dunbar et al. (2018), however, shows that when such variables are available the preference restrictions required for identification are no longer necessary. Specifically, if there are a sufficient number of distribution factors (or if there is a distribution factor with enough support points), if one maintains the assumption that resource shares do not depend on total expenditures, and if one observes some assignable goods, then the level of resource shares can be identified. No similarity restrictions on tastes like those discussed in Section 3.2 are needed.

One limitation of this approach is that distribution factors may be difficult to find (especially when children are included in the model) and their validity (that they do not impact preferences or the budget constraint) might be hard to prove. With this caveat in mind, we now apply the Dunbar et al. (2018) approach to test the validity of the D-SAP, D-SAT, SAP, and SAT preference restrictions.[5] Thus, we first estimate an unrestricted system of Engel curves of cereals and vegetables with distribution factors, and then implement Wald tests for the similarity of preferences restrictions. For simplicity, we present tests for a model that comprises four types of individuals (women, men, boys, and girls).

Several recent studies have used relative unearned income or assets as distribution factors (see, e.g., LaFave and Thomas (2017); see Browning et al. (2014) for a discussion of the most widely used distribution factors in the literature). Conveniently, the BIHS data contains information about the ownership of assets, land, and animals. Based on this information, we construct three distribution factors capturing the share of such assets that is owned by women. By ranging between zero and one, these variables satisfy the requirement that the distribution factor must take on as many values as family member types. For example, if $J = 4$ (men, women, boys, girls), then a distribution factors that take on four values are enough. We also consider a fourth distribution factor computed as the first principal component of the other three.

The first panel of Table A2 contains the average resource shares for boys, girls, women, and men estimated using the Dunbar et al. (2018) approach and different distribution factors. It is reassuring to see that the estimates do not deviate significantly from the restricted models discussed in Section 4.3 (Table 4). In the second panel, we report the results of Wald tests for our preference restrictions. Interestingly, D-SAT and SAT are always rejected at conventional levels of significance. The SAP restriction on preferences for cereals (preferences for vegetables are completely unrestricted) is rejected one out of four times, but the generally low p-values are not encouraging. By contrast, the D-SAP restriction is never rejected at at conventional levels.

[5] Looking at the Engel curves for clothing, both Dunbar et al. (2018) and Calvi (2019) find evidence supporting the similarity across people assumption. In contrast, Bargain et al. (2018) mostly reject both SAP and SAT using observed individual-level Engel curves for several different assignable goods, including rice and protein. SAT with clothing, however, is not rejected by Bargain et al. (2018).

Table A2: Testing Preference Restrictions With Distribution Factors

	Share of Assets Owned by Women	Share of Land Owned by Women	Share of Animals Owned by Women	First Principal Component
	(1)	(2)	(3)	(4)
	Resource Shares (Mean)			
Dunbar et al. (2018) Approach:				
Boys	0.149	0.153	0.147	0.150
Girls	0.131	0.132	0.127	0.133
Women	0.286	0.267	0.278	0.268
Men	0.317	0.333	0.319	0.324
	Testing Preference Restrictions			
D-SAP:				
Wald statistic	5.43	4.41	5.09	4.40
p-value	0.1428	0.2200	0.1653	0.2212
D-SAT:				
Wald statistic	13.83	14.04	16.51	17.20
p-value	0.0079	0.0072	0.0024	0.0018
SAP:				
Wald statistic	6.86	5.69	5.78	4.97
p-value	0.0766	0.1278	0.1182	0.1742
SAT:				
Wald statistic	8.14	8.28	8.04	8.22
p-value	0.0865	0.0818	0.0902	0.0839

Note: Estimates based on BIHS data, Engel curves for cereals and vegetables, and the Dunbar et al. (2018) identification approach.

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

Recall from Section 3 that, under the assumption of efficiency, the optimization program can be rewritten as a two-stage process. In the first stage, the household may be treated as if all members pool their income and then re-allocate it among themselves according to some sharing rule. In the second stage, each household member maximizes her own utility given their income share. Under efficiency, distribution factors affect outcomes only through their impact on the first stage sharing rule. As a consequence, the ratio of, e.g., the impact of men's assets to women's assets must be the same across outcomes. This property is known as *distribution factor proportionality*, and it is a sufficient condition for the collective model (Bourguignon et al., 2009).[6]

[6]While this test has been widely applied (e.g. Bobonis (2009), Attanasio and Lechene (2014), Browning et al. (2014), LaFave and Thomas (2017)), recent work by Chiappori and Naidoo (2015) show that demand systems satisfying distribution factor proportionality can be ratio-

Table A3: Testing Pareto Efficiency

	Sample		
	All Households	Nuclear Only	Extended Only
	(1)	(2)	(3)
Test of equality of ratios between:			
1) Men's Food and Clothing Budget Shares			
Wald statistic	0.12	0.07	0.88
p-value	0.7321	0.7912	0.3470
2) Men's Food, Women's Food, and Clothing Budget Shares			
Wald statistic	1.30	0.07	1.74
p-value	0.5219	0.9653	0.4195
3) Men's Food, Women's Food, Children's Food, and Clothing Budget Shares			
Wald statistic	2.10	0.08	2.46
p-value	0.5528	0.9946	0.4819

Note: Tests for proportionality restriction of the effects of distribution factors (share of women's assets and share of men's assets) across outcomes (Browning and Chiappori, 1998). The underlying regression models include the same household level controls as in Tables A7 and A8. Only households with one woman and one man are included in column 2. Only households with more than one woman and more than one man are included in column 3.

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

$$W_i^k = \alpha^k + \beta_w^k y_i^w + \beta_m^k y_i^m + X_h' \gamma^k + \epsilon_i^k \tag{A13}$$

where W_i^k is a budget share for household i, and k is alternatively clothing, or men's, women's, or children's food. y_h^w and y_h^m are the share of household assets owned by women and by men, respectively. As some assets are jointly owned, y_h^w and y_h^m are not perfectly collinear. We use these variables as distribution factors.[7] X_h is a vector of household level characteristics (see Table A7).

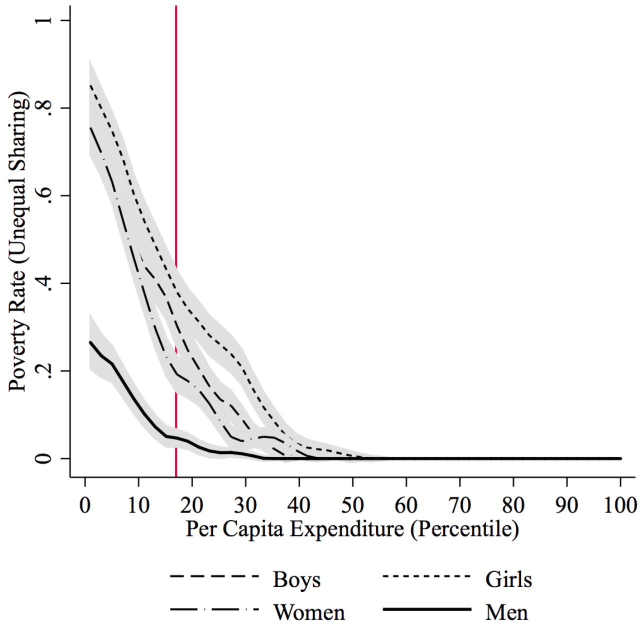
If Pareto efficiency holds, then $\frac{\beta_w^k}{\beta_m^k} = \frac{\beta_w^j}{\beta_m^j}$, for all $k \neq j$. Table A3 reports the results of nonlinear Wald tests for equality of the ratios. We perform tests over our full estimation sample, and separately for nuclear and extended households. The null hypothesis of distribution factor proportionality (Pareto efficiency) cannot be rejected at any conventional levels of significance.

A.9 Economies of Scale and Joint Consumption

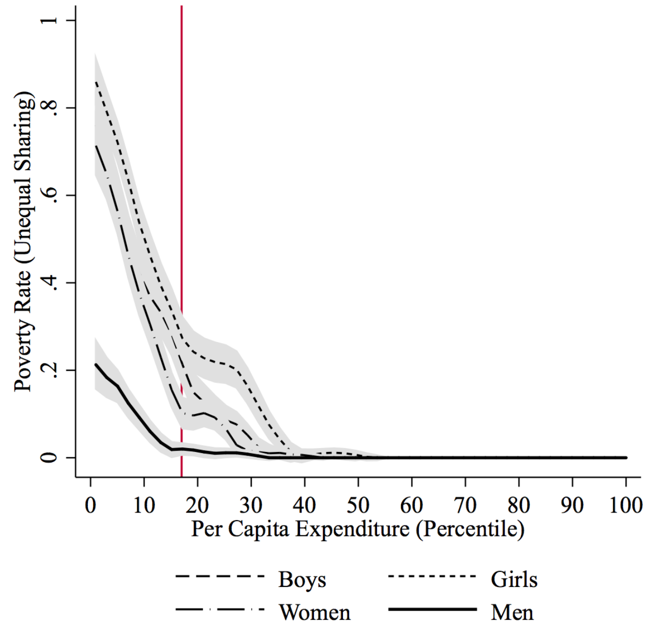
The theoretical model of household consumption presented in Section 3 does allow for economies of scale to consumption through a linear consumption technology function that transforms quantities purchased by the household in quantities consumed by each member. The structural parameters capturing the extent of joint consumption, however, are not estimated (this requires detailed price variation and substantially complicates the empirical exercise; see Browning et al. (2013) for details

nalized either from a collective framework or from a noncooperative one. So, results must be interpreted with caution.

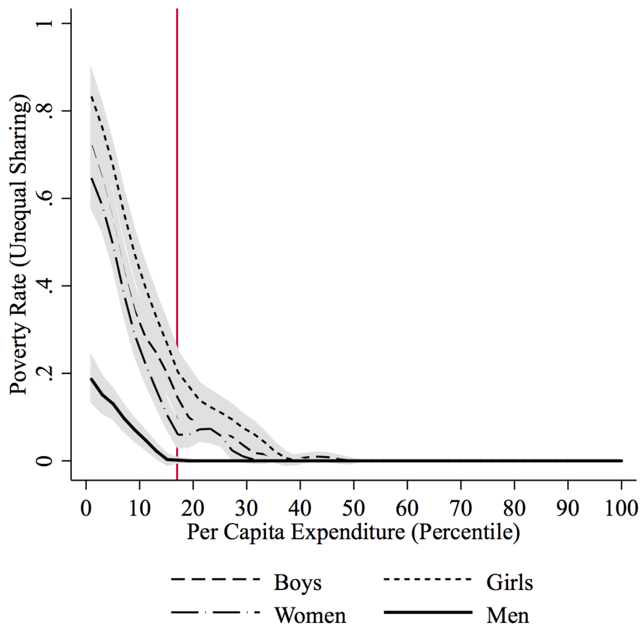
[7] Overall, distribution factors are jointly significant in all specifications. The p-values are below 0.10 for clothing, children's food, and women's food. The p-value equals 0.13 for men's food. These results provide a rejection of the unitary model, as it is inconsistent with the income pooling hypothesis (see Browning et al. (2014) for more details). Tests using alternative distribution factors (such as whether men or women have loans that need to be paid back) deliver analogous results.



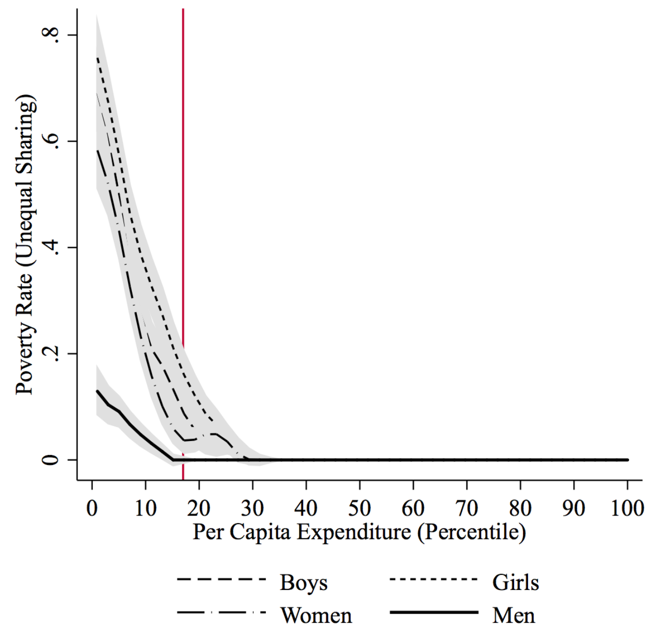
(A) $\alpha = 0.05$



(B) $\alpha = 0.10$



(C) $\alpha = 0.15$



(D) $\alpha = 0.20$

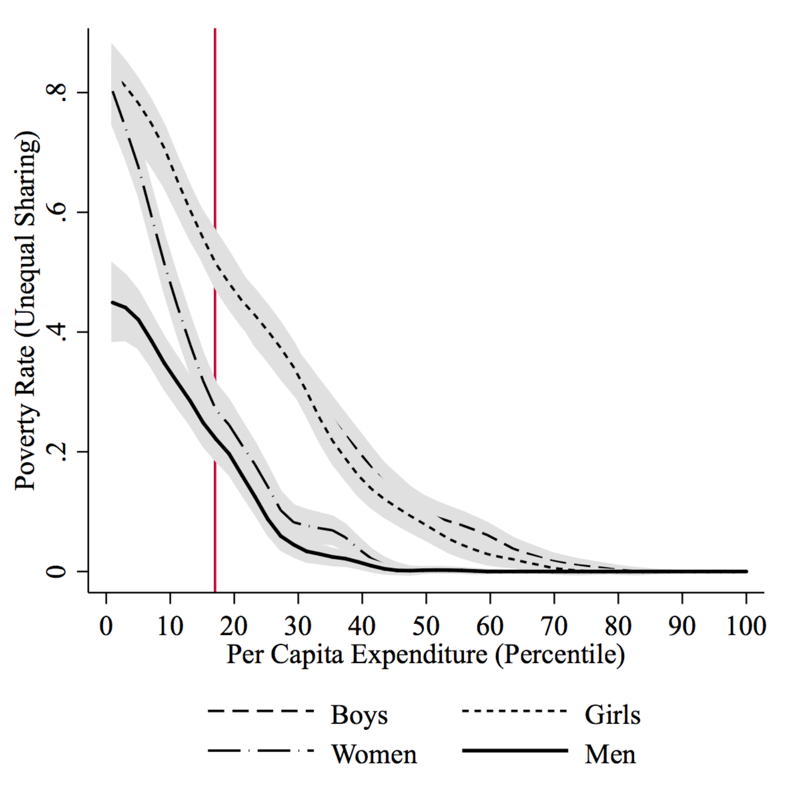
Note: Only households surveyed in 2015 are included. Individual consumption is obtained by multiplying total annual household expenditure (PPP dollars) by individual resource shares. The vertical line corresponds to the percentile of the $1.90/day threshold. Estimates are based on BIHS data and D-SAP identification method with Engel curves for cereals and vegetables. In all panels, the poverty line for children (aged 14 or less) is set to 0.6*1.90 and the poverty line for the elderly (aged 46 plus) is set to 0.8*1.90.Three levels of consumption jointness are obtained by multiplying the household total expenditure by $(1+\alpha)$, with $\alpha = 0.05, 0.1, 0.15, 0.2$.

Figure A8: Scale Economies and Joint Consumption

on point identification). Thus, in Section 5, we provide poverty calculations that ignore the extent of joint consumption (public and shared goods) in Bangladeshi families.

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

Figure A8 shows the results of this analysis. Similarly to Figure 3, we display the fraction of



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

Figure A9: Poverty Rates Adjusted for Activity Levels

individuals with an estimated level of individual consumption below the poverty line by household per-capita expenditure. For simplicity, we present results for year 2015 and obtained using the D-SAP approach. To account for differences in needs, we adjust the poverty lines for children and the elderly following the rough adjustment discussed in Section 5 (unadjusted poverty rates and rates obtained using a calorie-based adjustment are available upon request). Allowing for some degree of joint consumption has clear implications for our poverty calculations since it increases the amount of resources available to each individual. As we increase the extent of scale economies, poverty headcount ratios declines slightly. The relative poverty ranking for men, women, boys, and girls, however, is maintained.

A.10 Accounting for Individuals' Activity Levels

In Section 5, we adjust the $1.90/day poverty line using a rough adjustment or relative caloric requirements to account for differences in needs by age and gender. In that exercise, however, we ignore possible differences in individuals' *activity levels*. Individuals who work in agriculture or construction may expend more energy on a day-to-day basis than individuals who live a more sedentary lifestyle. As a result, more active individuals require more calories, and therefore more resources.

We modify our constructed individual-level poverty lines to account for differences in need by activity level. Using occupational data provided in the BIHS, we classify individuals as high-activity if they work in a strenuous job (e.g., farming, construction, carpentry). We consider an individual as employed in one of these occupations if they worked at least eight hours in the previous week in this job (the BIHS labor module is limited to a 7-day recall). In 2015, 47 percent of adult men worked in a high-activity occupation, whereas only 5 percent of women did. The USDA suggested caloric requirements specify thresholds for sedentary, moderately active, and active adults and children by age. For higher activity levels, the necessary calorie requirements increases by 200 to 400 calories per day. For simplicity we assume that individuals in high-activity occupations require 200 more calories per day than individuals who are not in those occupations.

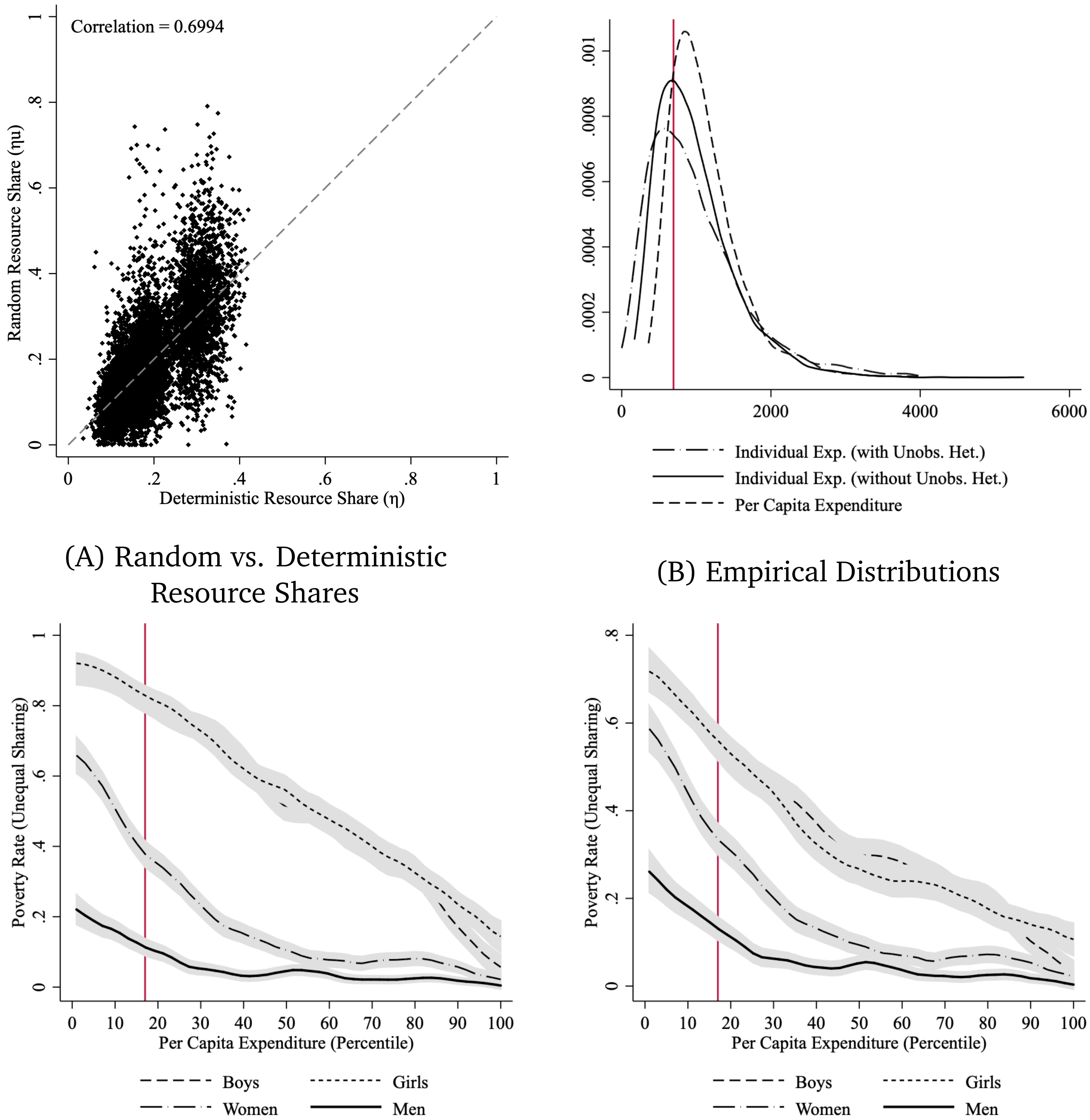
Figure A9 presents poverty rates using this adjustment. A consequence of the adjustment is that, compared to the results presented in Section 5 (Figure 3), poverty rates for men increase slightly. No substantial difference, however, can be detected. While this is the best we can do with the data at hand, it is important to note that this is a crude exercise that does not fully capture differences in needs. First, daily activity levels comprise much more than just employment. There are certain activities, such as fetching wood and fetching water, that require a significant amount of energy that we are unable to account for. These unaccounted for activities may have a gender component that affect the results presented above. Lastly, we only observe work in the previous week and therefore are not able to fully capture highly active individuals.

A.11 Unobserved Heterogeneity in Resource Shares

For our main analysis, we follow previous work and model resource shares as deterministic (linear) functions of observable household characteristics (see Section 4.2 for details). We now exploit recent results by Dunbar et al. (2018) to allow for *unobserved* heterogeneity in resource allocations across households. Note that Dunbar et al. (2018) provide two main theorems. One, which we use to test the validity of our identification assumaptions in Section A.8, shows that resource shares and preference parameters over the assignable goods can be identified without imposing preference restrictions when an adequate distribution factor is available. The other, which we apply in this section, shows identification of the distribution (around an unknown mean) of random resource shares across households.

We apply our D-SAP approach to pin down the means of the distributions of men's, women's, boys' and girls' resource shares, and use the insights provided by Dunbar et al. (2018) to estimate the random variation in the resource shares around this means. This random variation may originate from the presence of unobserved distribution factors that impact the bargaining power of individual household members as well as from measurement error in the household total expenditure. For the sake of brevity, we refer the reader to Dunbar et al. (2018) for more details on the theoretical setup as well as estimation details.

We summarize the results of this analysis in Figure A10. In Panel A, we plot the estimated de-



(A) Random vs. Deterministic Resource Shares

(B) Empirical Distributions

(C) Not Adjusted for Relative Needs

(D) Adjusted for Relative Needs

Note: Only households surveyed in 2015 are included. Individual consumption is obtained by multiplying total annual household expenditure (PPP dollars) by random individual resource shares (resource shares adjusted for unobserved heterogeneity following Dunbar et al. (2018) and then rescaled so that they sum to one). As in the original paper, we trim the data by dropping observations where $\eta_{js} < 0.01$ for any household member. Estimates of the mean of the resource shares distributions are obtained using our D-SAP identification method with Engel curves for cereals and vegetables. The vertical lines in Panels B, C, and D correspond to the percentile of the \$1.90/day threshold. In Panel D, 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 A10: Unobserved Heterogeneity in Resource Shares

terministic resource shares obtained using our D-SAP identification approach against the estimated random resource shares. The former are the individual shares of total household consumption that we have used throughout our poverty analysis in Section 5 (what we have called η_{js} throughout). The latter are calculated as $\eta_{js}u_{js}$, where u_{js} is a structural error term that encompasses both unobserved heterogeneity in the resource shares and measurement error in total household expenditure.[8]

[8] The structural error terms are recovered by numerically minimizing the difference between $E(u_{js} \ln u_{js})$ and the sample average of $u_{js} \ln u_{js}$

Overall, the correlation between the two sets of estimates is quite high. Not surprisingly, however, allowing for unobserved heterogeneity in the resource shares increases their variability. As shown in Panel B, the empirical distribution of individual consumption based on the estimated random resource shares is slightly more skewed relative to the distribution of individual consumption based deterministic resource shares. As a result, the poverty rate increases from 27 percent to 30 percent when unobserved heterogeneity in resource shares is allowed for.[9]

In Panels C and D, we plot individual poverty rates (obtained using our estimates of random resource shares) for women, men, boys, and girls by household per-capita expenditure percentile. These graphs are analogous to those presented in Figure 3 in the main text. Our results obtained using the deterministic resource shares are qualitatively confirmed: a substantial share of poor individuals (especially women and children) are found in non-poor households. In fact, the scope of poverty mistargeting appears to be even larger when we account for unobserved heterogeneity in resource shares, with children facing a positive probability of having estimated levels of consumption below their poverty line even in families in the upper fifth of the household per capita expenditure distribution (above $3.90/day).

A.12 Poverty Rates Based on Individual Food Consumption

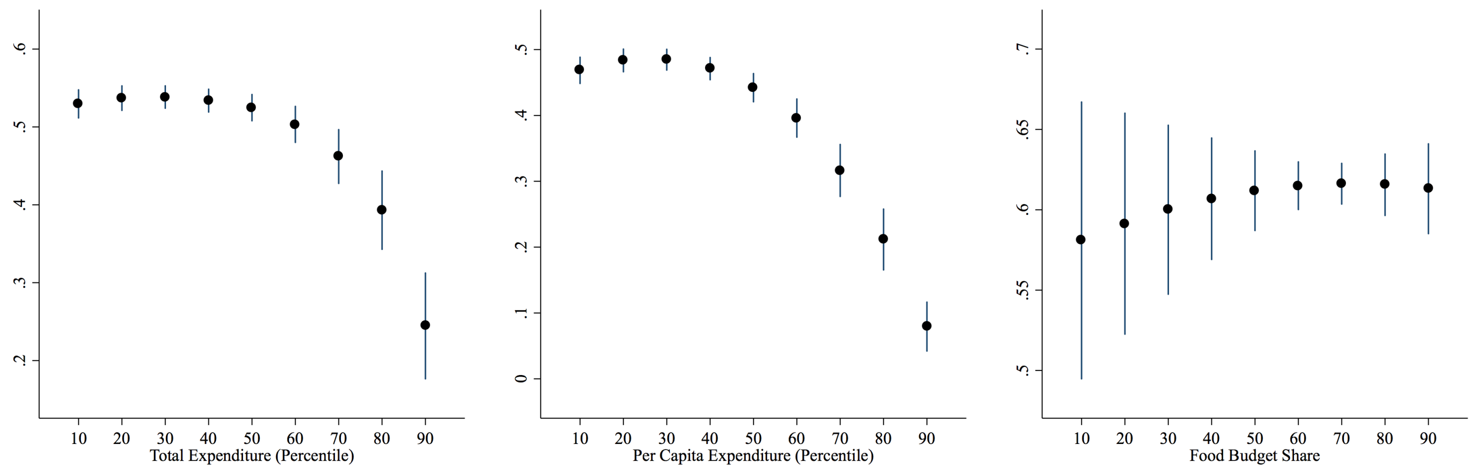
We here compare our poverty calculations (that are based on the estimated resource shares and are presented in Section 5) with calculations based on food allocations. We construct individual food shares as the ratio between reported individual food consumption and household expenditure on food. We then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

The resulting poverty rate is 36 percent, much higher than the poverty rates obtained with per-capita expenditure (17 percent) or our estimates of individual consumption (27 percent). This higher rate could result from individuals in non-poor households consuming a low proportion of food but a high proportion of non-food goods.

The marginal effect from a logistic regression of the probability of having a food-based individual consumption below the poverty threshold on an indicator variable for being poor based on our model estimates equals 0.46 over the entire sample. We expect such association to be stronger in poorer households, where food represents a large portion of the total budget. We compute marginal

(plus a penalty function for deviations from the sample average of u_{js} from one) under the constraint that the structural relation between the observed budget shares on the assignable goods and u_{js} holds for each u_{js} (equation (10) in the original paper).

[9] We recall from Section 5 that the poverty rate increases from 17 percent using per-capita expenditures to 27 percent using estimated individual expenditures based on deterministic resource shares.



(A) By Total Expenditure Percentile (B) By PCE Percentile (C) By Food Budget Share

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

Figure A11: Model-based Poverty vs. Food-based Poverty

effects at different percentiles of household expenditure (or for different values of food budget shares) and find this to be the case (see Figure A11).[10] These results are reassuring as they provide additional validation of our approach: our calculations are closer to the food-based ones exactly in households where food represents a large portion of overall consumption. However, they also suggest that in contexts with possibly high levels of intra-household inequality (where several poor people might reside in non-poor households) looking at food sharing alone may lead to erroneous conclusions.

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

A.13 Additional Tables and Figures

Table A4: BIHS Nutritional Outcomes

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

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

Table A5: Individual Caloric, Protein and Food Intake

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

Note: BIHS data. Statistics are population weighted. Consumption is in local currency units (taka). Children are defined as 14 years and younger. Calories have been scaled to 2,400 calories per day; protein has been scaled to 56 grams per day. Food consumption uses the same scale as caloric intake and is converted to annual values (see section 4.2 for details). Recommended intakes have been taken from the 2015-2020 Dietary Guidelines for Americans.

Table A6: BIHS Food Consumption - Descriptive Statistics

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

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

Table A7: Engel Curves Estimates - Resource Shares (D-SAP and D-SAT)

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

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. BIHS data. NLSUR estimates. Robust standard errors in parentheses. Age variables are divided by 100 to ease computation. We include indicators for the following regions: Barisal, Chittagong, Dhaka, Khulna, Rajshahi, Rangpur. Sylhet is the excluded region. None of the region indicators are statistically different from zero.

Table A8: Engel Curves Estimates - Resource Shares (SAP and SAT)

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

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. BIHS data. NLSUR estimates. Robust standard errors in parentheses. Age variables are divided by 100 to ease computation. We include indicators for the following regions: Barisal, Chittagong, Dhaka, Khulna, Rajshahi, Rangpur. Sylhet is the excluded region. None of the region indicators are statistically different from zero. SAP and SAT restrictions are imposed on the first set of assignable goods (cereals), while the second set (vegetables) is unrestricted.

Table A9: Estimated Resource Shares - Reference Household

	D-SAP		D-SAT		SAP		SAT	
	Estimate	Standard Error	Estimate	Standard Error	Estimate	Standard Error	Estimate	Standard Error
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Boy	0.176	0.014	0.164	0.021	0.169	0.014	0.145	0.019
Girl	0.1676	0.014	0.146	0.016	0.162	0.013	0.135	0.016
Woman	0.2901	0.014	0.273	0.036	0.296	0.014	0.308	0.038
Man	0.3662	0.018	0.417	0.033	0.373	0.018	0.413	0.033

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

Table A10: Estimated Resource Shares: Additional Results

		Resource Shares			Individual Consumption (PPP dollars)		
	Obs.	Mean	Median	St. Dev.	Mean	Median	St. Dev.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
A) Young vs. older adults:							
Boys	4,502	0.130	0.142	0.037	668.85	593.67	333.91
Girls	4,243	0.125	0.135	0.038	653.86	578.30	336.49
Women 46+	1,908	0.123	0.132	0.027	777.47	698.05	346.45
Men 46+	2,398	0.315	0.199	0.179	1,723.37	1,403.33	1,085.79
Women 15-45	6,073	0.210	0.227	0.048	1,070.34	956.80	499.37
Men 15-45	5,403	0.431	0.444	0.127	2,165.45	1,929.09	1,036.70
B) Hhs. with first born boy:							
First born boy	1,885	0.155	0.158	0.019	726.09	659.52	310.55
Higher birth order boys	746	0.128	0.139	0.029	629.39	571.60	286.17
Higher birth order girls	668	0.120	0.130	0.029	599.22	559.14	262.96
Women	1,885	0.252	0.283	0.065	1,152.06	1,031.86	528.86
Men	1,885	0.408	0.408	0.101	1,883.21	1,687.91	891.53
C) Hhs. with first born girl:							
First born girl	1,804	0.146	0.148	0.019	703.85	628.71	322.39
Higher birth order boys	775	0.142	0.155	0.034	726.79	639.89	367.50
Higher birth order girls	768	0.132	0.145	0.034	666.18	590.75	332.97
Women	1,804	0.233	0.261	0.060	1,097.46	961.25	546.05
Men	1,804	0.405	0.408	0.113	1,914.54	1,669.56	962.87

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

Table A11: Estimated Resource Shares: Additional Results (Restricted Samples)

	Obs.	Resource Shares Mean	Resource Shares Median	Resource Shares St. Dev.	Individual Consumption (PPP dollars) Mean	Individual Consumption (PPP dollars) Median	Individual Consumption (PPP dollars) St. Dev.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
A) Young vs. older adults:							
Boys	3,906	0.132	0.145	0.037	664.42	588.21	336.50
Girls	3,653	0.127	0.138	0.037	649.96	577.95	335.65
Women 46+	1,092	0.143	0.144	0.026	871.87	778.39	385.48
Men 46+	2,212	0.314	0.199	0.177	1,704.19	1,395.82	1,062.02
Women 15-45	5,244	0.218	0.236	0.048	1,090.46	972.97	512.40
Men 15-45	4,626	0.434	0.443	0.129	2,125.18	1,893.08	1,019.85
B) Hhs. with first born boy:							
First born boy	1,463	0.157	0.159	0.016	714.99	645.80	310.94
Higher birth order boys	596	0.119	0.129	0.026	567.35	507.94	264.21
Higher birth order girls	535	0.111	0.121	0.027	540.59	501.67	241.41
Women	1,463	0.256	0.281	0.058	1,146.28	1,027.08	530.23
Men	1,463	0.429	0.429	0.093	1,940.28	1,726.89	933.57
C) Hhs. with first born girl:							
First born girl	1,417	0.147	0.150	0.016	698.47	622.06	322.37
Higher birth order boys	625	0.133	0.145	0.032	674.19	601.56	345.46
Higher birth order girls	607	0.124	0.137	0.032	612.00	546.77	305.30
Women	1,417	0.234	0.258	0.055	1,090.68	957.72	542.76
Men	1,417	0.426	0.428	0.107	1,990.65	1,722.85	996.89

Note: Estimates based on BIHS data and D-SAP identification method with Engel curves for cereals and vegetables. Mean and median of resource shares do not need to sum to one because there can be more than one individual of the same type in each family. Individual consumption is obtained multiplying total annual household expenditure (PPP dollars) by individual resource shares. In Panel A, we exclude households with widows. In Panel B and C, we exclude households with mothers older than 35 in 2011.

Table A12: Headcount Ratios and Poverty Gap Indices

	Headcount Ratio: Per-capita Consumption	Headcount Ratio: Individual Consumption	Poverty Gap Index: Per-capita Consumption	Poverty Gap Index: Individual Consumption
No adjustment:				
$1.90 poverty line	0.165	0.273	0.026	0.078
$3.10 poverty line	0.611	0.605	0.173	0.223
Rough adjustment:				
$1.90 poverty line	0.076	0.114	0.016	0.028
$3.10 poverty line	0.392	0.450	0.129	0.143
Caloric adjustment:				
$1.90 poverty line	0.090	0.132	0.013	0.026
$3.10 poverty line	0.430	0.474	0.108	0.134

Note: BIHS data 2015. The table lists the headcount and poverty gap indices for the $1.90 and 3.10$ a day poverty lines. The poverty gap index is the average gap between the poverty line and expenditure weighted by the poverty line for those with expenditures below the line. Estimated individual consumption is obtained multiplying total annual household expenditure (PPP dollars) by individual resource shares. Per-capita consumption is total household consumption divided by household size.

Table A13: Predictors of Poverty Misclassification: Post-LASSO Estimates

	Boys	Girls	Women	Men
	(1)	(2)	(3)	(4)
Household Size	-0.001	0.009		0.078***
	(0.00517)	(0.00555)		(0.000919)
Share of Boys in Household	0.434***			
	(0.0703)			
Share of Men in Household		-0.083***		0.083***
		(0.0956)		(0.0147)
Share of Girls in Household		0.333***		
		(0.0770)		
Share of Women in Household			0.230***	
			(0.0297)	
Average Education Women	-0.224***	-0.212***	-0.074***	0.058***
	(0.00771)	(0.00852)	(0.00324)	(0.00137)
Average Education Men	-0.160***	-0.185***	-0.100***	
	(0.00694)	(0.00746)	(0.00269)	
Age	-0.181***	-0.192***		
	(0.00196)	(0.00213)		
$\mathbb{1}$(Muslim)			-0.034**	
			(0.00950)	
$\mathbb{1}$(Works in Agriculture)			0.079***	
			(0.0292)	
$\mathbb{1}$(Works in Own Farm)			-0.014	
			(0.00738)	
$\mathbb{1}$(Works as Artisan)				0.048***
				(0.00630)
$\mathbb{1}$(Unemployed/Jobless)				0.050***
				(0.0143)
$\mathbb{1}$(Not Household Head)				0.00555
				(0.00396)
$\mathbb{1}$(Disabled)			0.035**	
			(0.0209)	
$\mathbb{1}$(Far Relative or Servant)			0.010	
			(0.0181)	
$\mathbb{1}$(Son or Daughter)				0.029
				(0.00396)
Share Land by Adult Women				0.012
				(0.0164)
Share Homestead Owned by Adult Women				0.069**
				(0.0125)
Share Animals Owned by Adult Women				0.046**
				(0.00385)
Constant	0.249***	0.572***	-0.0224	-0.0503***
	(0.0460)	(0.0619)	(0.0162)	(0.00790)
Observations	2,393	2,301	3,848	2,978
λ	116.142	93.749	37.201	16.817

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

Table A14: R^2 for Estimated Individual Consumption and Per-Capita Consumption

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

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

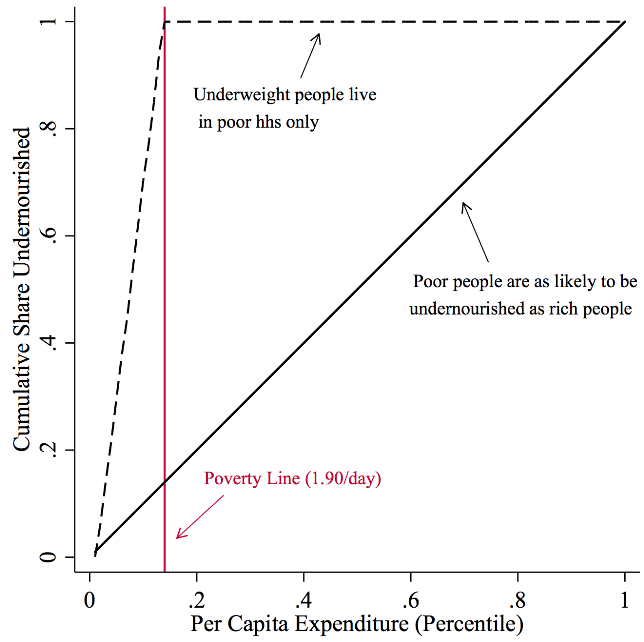
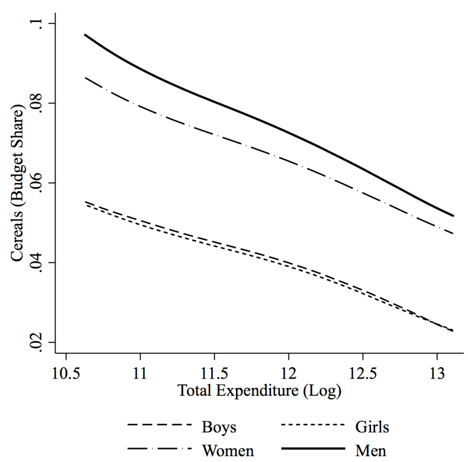
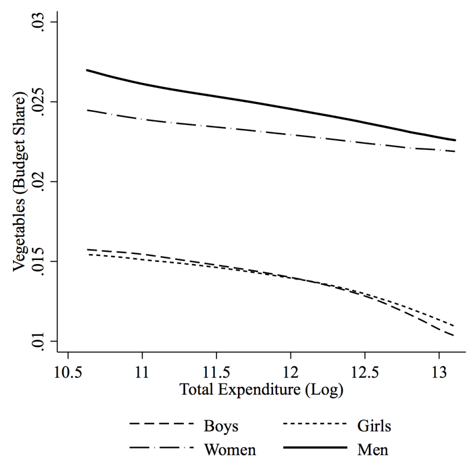


Figure A12: Archetypal Concentration Curve

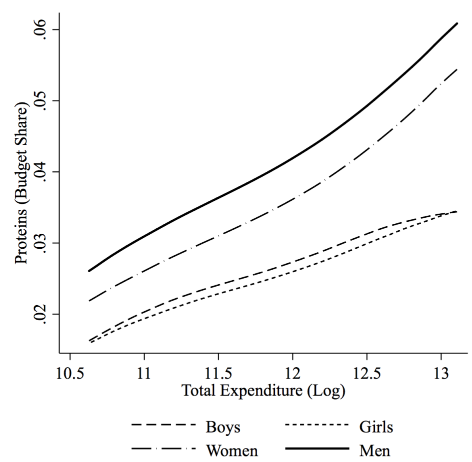
Note: The figure shows example concentration curves under two extreme scenarios: the first is where all undernourished individuals live in poor households, the second where undernourished individuals are found with equal probability across the expenditure distribution. Concentration curves show the proportions of individuals in the population ranked from poorest to richest based on per capita expenditure.



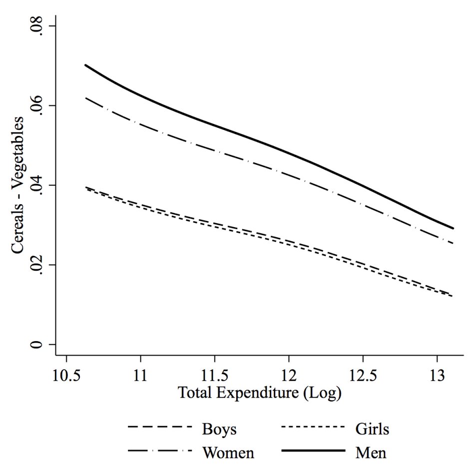
(A) Cereals



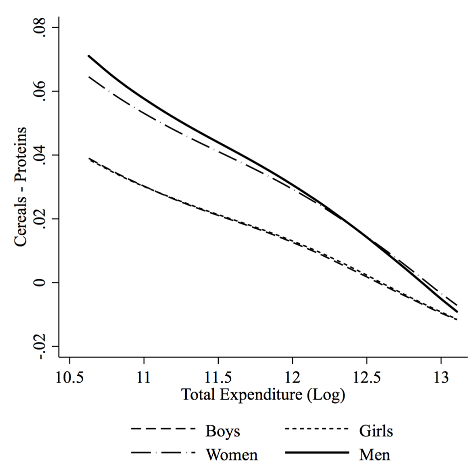
(B) Vegetables



(C) Proteins



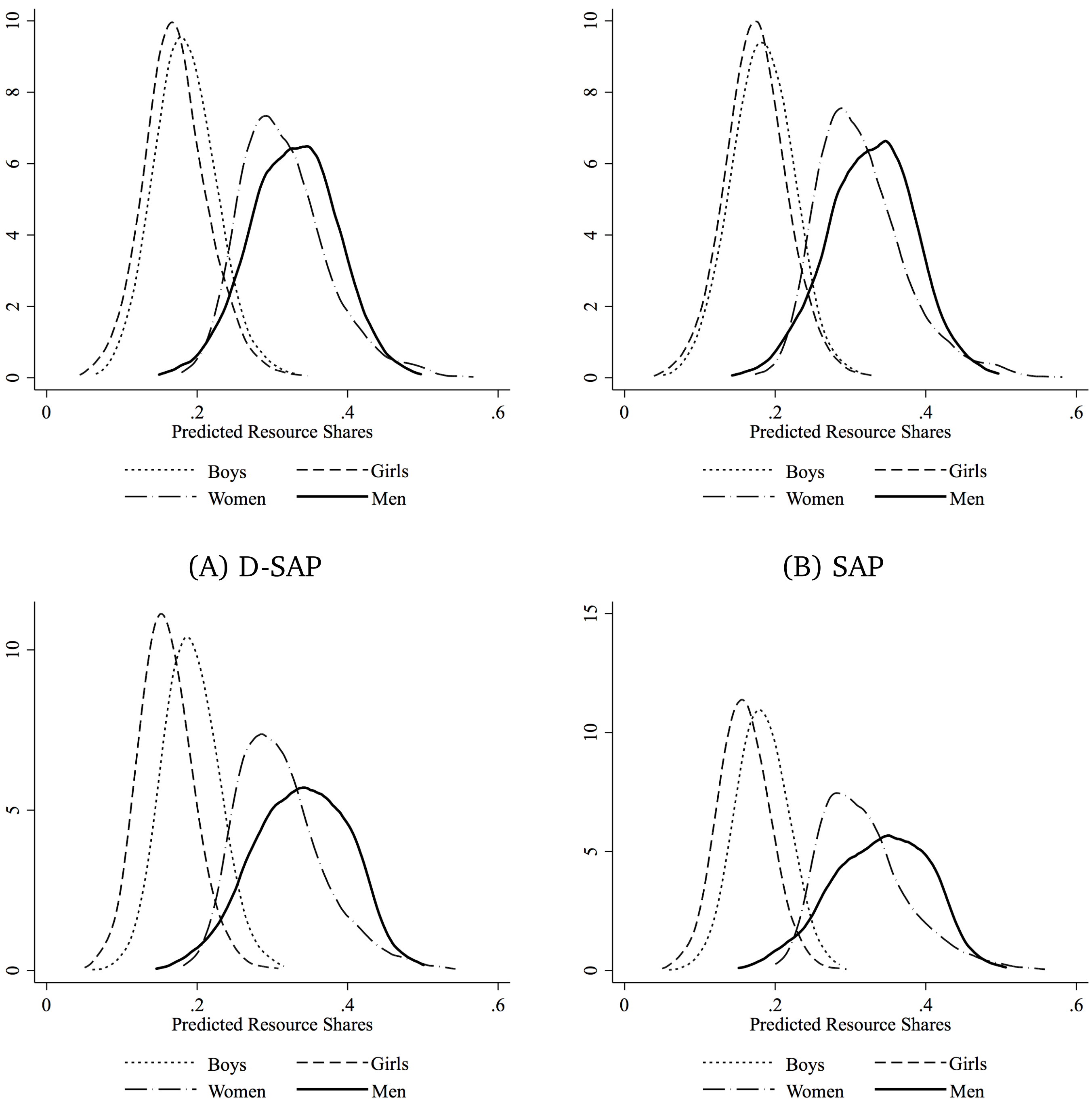
(D) Cereals - Vegetables



(E) Cereals - Proteins

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

Figure A13: Non-Parametric Engel Curves



(A) D-SAP

(B) SAP

(C) D-SAT

(D) SAT

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

Figure A14: Estimated Resource Shares - Empirical Distributions

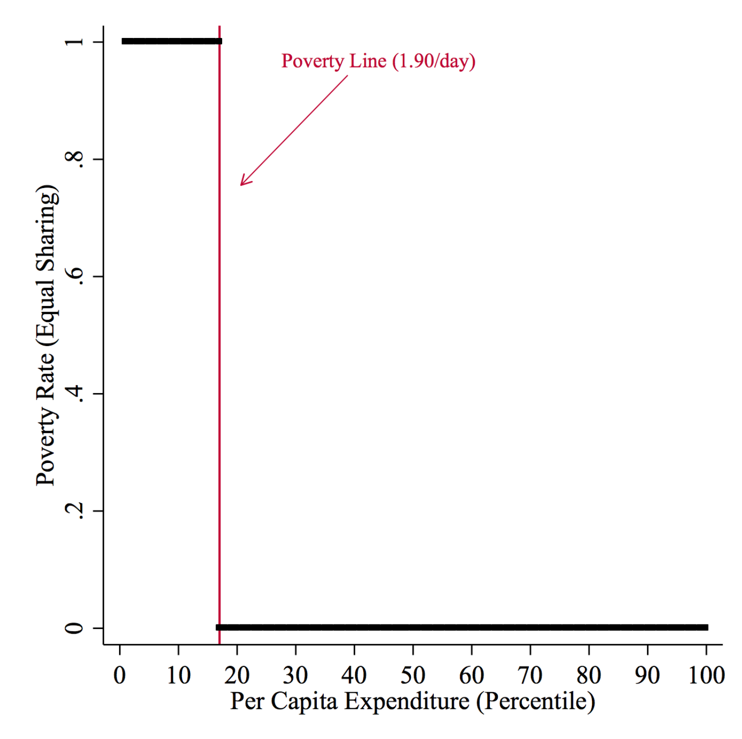
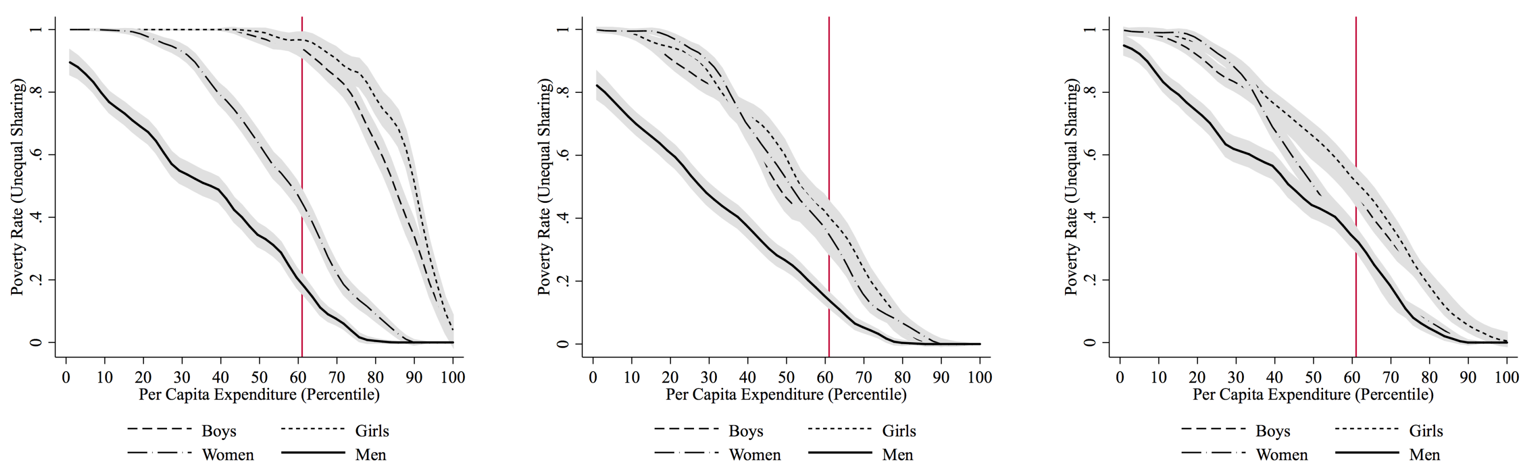


Figure A15: Poverty Rate (Based on Per-Capita Expenditure) by Per-Capita Expenditure Percentile



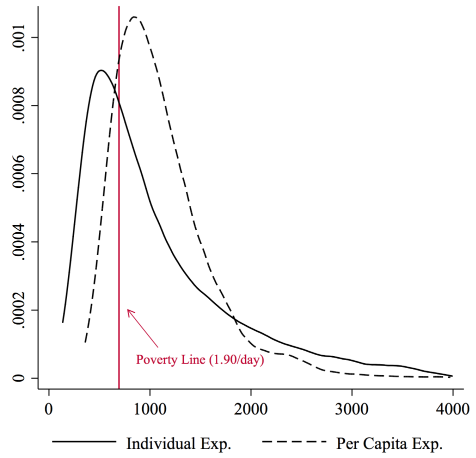
(A) No Adjustment for Relative Needs

(B) Rough Adjustment

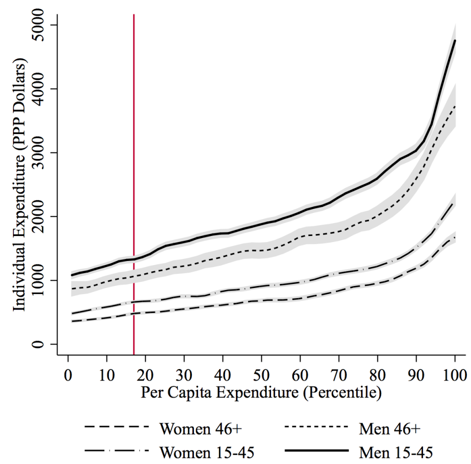
(C) Calorie-based Adjustment

Note: Individual consumption is obtained multiplying total annual household expenditure (PPP dollars) by individual resource shares. The vertical line corresponds to the percentile of the $3.10/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*3.10 and the poverty line for the elderly (aged 46 plus) is set to 0.8*3.10. 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.

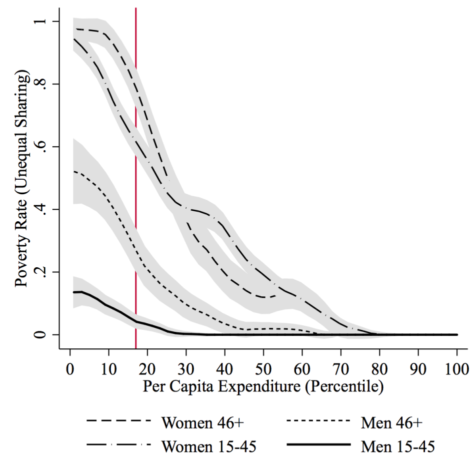
Figure A16: Poverty Rates by Per-Capita Expenditure Percentile (US$3.10/day)



(A) Empirical Distributions



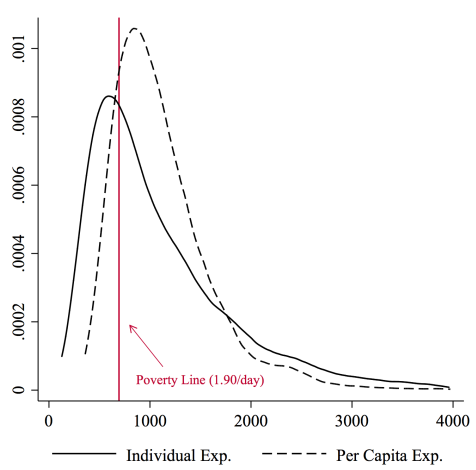
(B) Individual Exp. by Per-Capita Expenditure



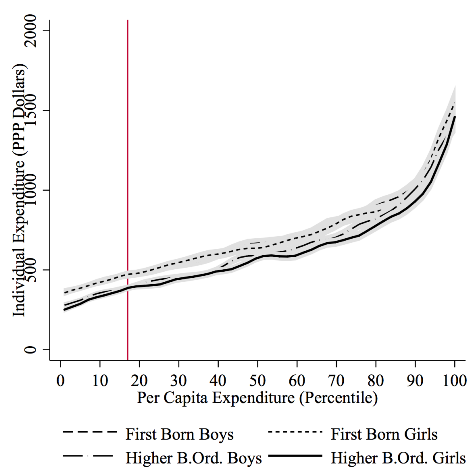
(C) Poverty Rates by Per-Capita Expenditure

Note: Only households surveyed in 2015 are included. Individual consumption is obtained by multiplying total annual household expenditure (PPP dollars) by individual resource shares. The vertical line corresponds to the percentile of the $1.90/day threshold. Estimates are based on BIHS data and D-SAP identification method with Engel curves for cereals and vegetables. In Panel C, we assume poverty lines for the elderly to be proportional to their caloric requirements relative to young adults (aged 15-45). We rely on the daily calorie needs by age and gender estimated by the United States Department of Health and Human Services and assume young adults require 2,400 calories per day.

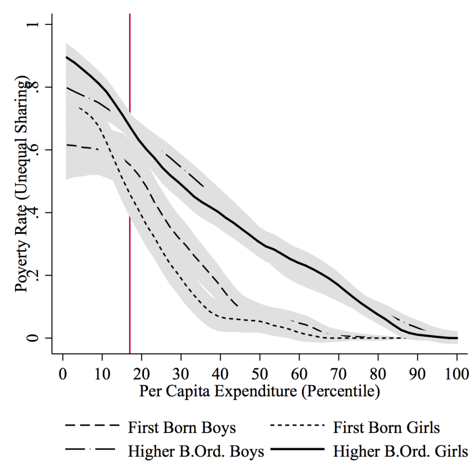
Figure A17: Additional Results - Young vs. Older Adults



(A) Empirical Distributions



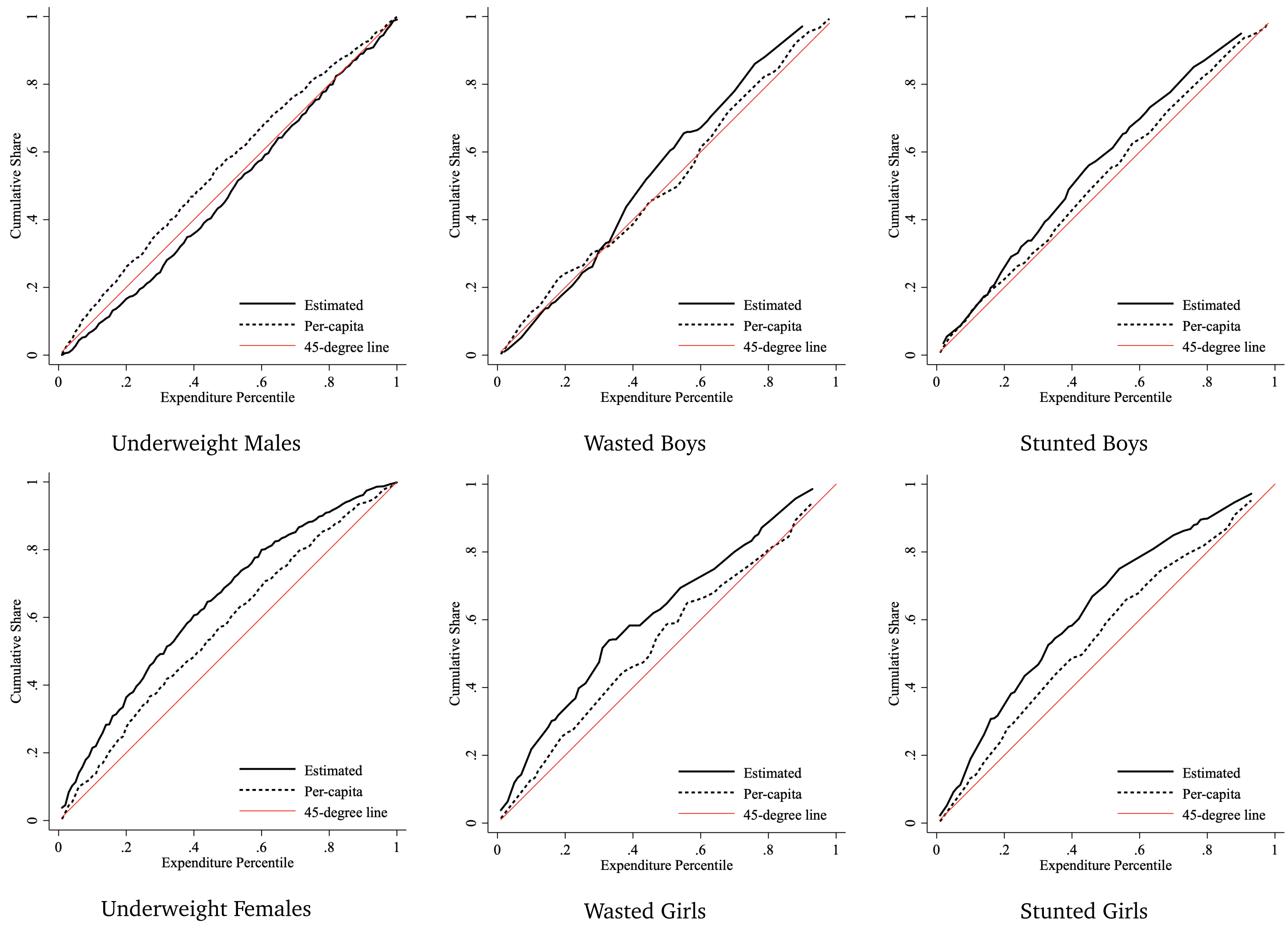
(B) Individual Exp. by Per-Capita Expenditure



(C) Poverty Rates by Per-Capita Expenditure

Note: Only households surveyed in 2015 are included. Individual consumption is obtained by multiplying total annual household expenditure (PPP dollars) by individual resource shares. The vertical line corresponds to the percentile of the $1.90/day threshold. Estimates are based on BIHS data and D-SAP identification method with Engel curves for cereals and vegetables. In Panel C, we assume poverty lines for children to be proportional to their caloric requirements relative to young adults (aged 15-45). We rely on the daily calorie needs by age and gender estimated by the United States Department of Health and Human Services and assume young adults require 2,400 calories per day.

Figure A18: Additional Results - Birth Order



Note: BIHS 2015 data. Individuals who report having lost weight due to illness in the past four weeks are excluded. The graphs show concentration curves for the cumulative proportion of women and men who are underweight, and children aged 0-5 who are stunted and wasted at each household per-capita expenditure percentile (dashed line) and at each individual consumption percentile. To account for the issue that children may be found disproportionately in the lower percentiles due to their lower average consumption levels, we construct percentiles for adults and children separately. That is, when looking at the new concentration curves, we consider the proportion of undernourished adults (children) found among the poorest x percent of adults (children). Note that in Figure 1 the percentiles are at the household level. Individual consumption is estimated using the D-SAP approach and Engel curves for cereals and vegetables. Observations with missing values and pregnant or lactating women have been dropped. The Stata command `glcurve` is used to construct the curves.

Figure A19: Undernutrition Concentration Curves Based on Individual Consumption vs. Per-Capita Consumption

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