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ABSTRACT

Intrahousehold Resource Allocation and Individual Poverty: Assessing Collective Model Predictions against Direct Evidence on Sharing*

Welfare analyses conducted by policy practitioners around the world usually rely on equivalized or per-capita expenditures and ignore the extent of within-household inequality. Recent advances in the estimation of collective models suggest ways to retrieve the complete sharing process within families using homogeneity assumptions (typically preferences stability upon exclusive goods across individuals or household types) and the observation of exclusive goods. So far, the prediction of these models has not been validated, essentially because intrahousehold allocation is seldom observed. We provide such a validation by leveraging a unique dataset from Bangladesh, which contains information on the fully individualized expenditures of each family member. We also test the core assumption (efficiency) and homogeneity assumptions used for identification. It turns out that the collective model predicts individual resources reasonably well when using clothing, i.e., one of the rare goods commonly assignable to male, female and children in standard expenditure surveys. It also allows identifying poor individuals in non-poor households while the traditional approach understates poverty among the poorest individuals.

JEL Classification: D11, D12, D36, I31, J12

Keywords: collective model, Engel Curves, Rothbarth Method, sharing rule

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1 Introduction

Welfare and policy analyses around the world usually rely on per capita or equivalized household expenditure, ignoring the possibility of unequal sharing within families. Increasing evidence, however, points to a large degree of intrahousehold inequality, which explains that poor individuals often live in non-poor households (Brown, Ravallion & van de Walle, 2019). Such a poverty misclassification of individuals' status relative to their household status makes the targeting of social programs especially difficult. A possible solution consists in further efforts to measure "who consumes what" in the household. At the moment, very few datasets of that sort exist because they are costly and difficult to collect (World Bank, 2018). In the absence of direct observation, researchers and policy analysts may be able to use collective models of household decision-making to recover the intrahousehold allocation of resources and measure individual poverty. Following Chiappori (1988), the early literature on collective models has focused on testing the efficiency assumption, which is at the core of this approach. Many integrability results have also been obtained, but they generally provided the identification of the *marginal* sharing rule only, i.e., how an extra dollar is shared among household members (see, for instance, Chiappori, Fortin & Lacroix, 2002).[1] This is obviously of limited practicality for welfare analyses at the individual level.

More recently, we have witnessed a surge of studies aiming at the identification of the full allocation process in collective models of consumption.[2] An increasingly popular approach is the contribution of Browning, Chiappori & Lewbel (2013), in which the complete sharing rule is identified by means of additional information. This approach hinges on a homogeneity assumption, namely that part of individual preferences are stable across marital status, so that individual Engel curves for adults in couples can be estimated using data on singles. While these authors use price variation to recover the degree of joint consumption in the form of Barten scales, Lewbel & Pendakur (2008) make the approach more tractable by suggesting the identification of the sharing rule – and of a composite measure of scale economies – using cross-sectional expenditure data.[3] Bargain

[1] Useful surveys are suggested by Vermeulen (2002), Browning, Chiappori & Weiss (2014) and Chiappori & Donni (2011).

[2] Identification results have also been obtained in the context of labor supply, which is generally more complicated to handle because of non-convexities in budget sets resulting from means-tested benefits (see in particular Laisney, Beninger & Beblo, 2003, Couprie, 2007, Lise & Seitz, 2011, and Bloemen, 2019). We focus here on consumption decisions only.

[3] Note that when price variation is available, applications based on a revealed preference approach can, at the cost of set identification, provide much insights on the intra-household allocation of resources, including in a context that easily incorporates public consumption (Cherchye, De Rock & Vermeulen, 2011).

& Donni (2012) extend this method to households with children while Bargain, Donni & Kwenda (2015) apply it to measure individual poverty in the context of a poor country. All these approaches rely on assignable or exclusive goods – i.e., goods consumed by specific individuals in the household, such as adult women's clothing for instance – and on the use of singles data combined with the preference stability assumption upon the exclusive goods.[4] Because people living alone are not common in the context of developing countries, Dunbar, Lewbel & Pendakur (2013) suggest a method of identification for couples with children that does not require singles data. They propose two alternative identifying approaches based on weaker preference homogeneity assumptions. For a given person type (woman, man, child), the slope of individual Engel curves is first assumed to be stable across household types, i.e., it does not depend upon the number of children (the *Similar Across Type* assumption or SAT). Alternatively, for a given household type, the Engel curves for the three types of individuals (woman, man, child) are presumed to have the same slope (the *Similar Across People* assumption or SAP). Applications and extensions of these approaches are suggested in an increasing number of studies (for instance in Brown, Calvi & Penglase, 2018, Tommasi & Wolf, 2018, Tommasi, 2019, Calvi, 2020, Calvi et al., 2020, Penglase, 2020, and Lechene, Pendakur & Wolf, 2020).

This burgeoning literature brings the promise that collective model estimations will eventually allow practitioners to measure the extent of intrahousehold inequality and to assess individual poverty more systematically. In facing this challenge, researchers must provide some evidence regarding the validity of the current methods to identify resource sharing. In the present paper, we suggest a simple way to conduct such an assessment. We leverage an exceptional dataset from Bangladesh, which provides fully individualized expenditure data. In other words, we observe the detailed consumption of each household member – a relatively rare feature, especially in the context of developing countries (see Cockburn, Dauphin & Razzaque, 2009). First, with individualized consumption, we can suggest fundamental tests including renewed tests of efficiency in the context of households with children, a check on whether sharing rules are independent from total expenditure (the *independence of the base* assumption), and tests of the identifying assumptions of our empirical application (notably SAT and SAP). Subsequently, individualized expenditure leads to a direct measure of individual resource shares, which can be compared to the shares predicted by the collective model identified using recent methods. While assessing the performance of these methods is crucial for the operationalization of the collective

[4] Cherchye, De Rock & Vermeulen (2012a) propose an application to elderly couples, using widows and widowers from the same data source to recover male and female adult preferences, hence making the preference stability assumption less restrictive. A similar strategy was also suggested by Couprie (2007) and Michaud & Vermeulen (2011) for collective labor supply decisions.

model for individual welfare analyses, such a validation exercise also complements the important set of studies, starting with Cherchye, De Rock & Vermeulen (2007), who have refined theory testing using nonparametric approaches. Finally, it adresses the question of whether collective models outperform the standard "equivalence scale" approach when the degree of intrahousehold inequality is large.

Our validation approach is carried out for a series of three models of private resource allocation. Identification is based on the observation of assignable goods, using either clothing or, alternatively, other individualized expenditures from our data. We begin with the traditional "Rothbarth" approach, here embedded in the collective model framework. With this method, welfare analysis focuses on how resources are shared between parents and children, though inequalities based on gender or age may be captured among children. Targeting children's welfare can be an important policy objective, making the Rothbarth approach still of interest. The use of childless couples for identification of adult Engel curves additionally makes estimations stable and easy. We then move to the approach of Dunbar, Lewbel & Pendakur (2013) – referred to as "DLP" hereafter – which has received much attention in the recent literature. It allows modelling resource allocation between the mother, the father and the group of children. If the final objective is to operationalize the collective model for welfare analyses at a country level, one must extend the approach to a broader population than nuclear families. Thus, we suggest a third model of resource allocation within "Complex Households", namely among the groups of men, women and children of any household composition. The validation exercise is again fully justified by the fact that an increasing number of studies apply a DLP-type of approach to complex households for individual poverty analysis.[5]

The results can be summarized as follows. First, we proceed with the series of tests outlined above. We use individualized expenditures for men, women and children to test proportionality conditions imposed by Pareto efficiency and based on distribution factors. These tests are reminiscent of Bourguignon, Browning & Chiappori (2009) but we adapt them to the more general context of households with children. We also tend to accept

[5] These include Lechene, Pendakur & Wolf (2020), who focus precisely on ways to make the model estimation more tractable and operational. Five studies also show how individual poverty is related to age-gender combinations or other specific characteristics. For Bangladesh, Brown, Calvi & Penglase (2019) explore which types of individuals are poor and the nature of the poverty misclassification based on household status. Calvi (2020) points to the dramatic increase in women's poverty rates with age and its correlation with their lower life expectancy in India. Penglase (2020) considers how resource shares may vary across children in Malawi, in particular among foster and orphaned children. Tommasi (2019) assesses the extent to which mothers and children benefit from PROGRESA in Mexico. Calvi et al. (2020) extend the welfare analysis by identifying scale economies benefiting to adults and, originally, to children in the collective approach.

the *independence of the base* assumption used in most of the recent contributions for identification. Finally, individualized expenditures allow us to estimate individual Engel curves for all the potential assignable goods and, hence, to test identifying assumptions for the three alternative models, i.e., the version of SAT specific to the Rothbarth approach and the standard SAT and SAP assumptions for DLP. Tests based on male, female and child clothing as assignable goods are usually not rejected. Given the presence of fully individualized data, we can actually check the sensitivity of our tests to the choice of the identifying good, alternatively using total food expenditures or specific food items (rice or proteins). The latter do not perform so well, possibly because of home production.

Next, we confront observed and estimated resource shares for all three models. We compare mean levels as well as key determinants of observed versus estimated resource shares. The different approaches lead to reasonable predictions of average resource shares. Irrespective of the identification strategy, the collective approach tends to identify correctly the effect of family size and children's age on child shares. Importantly, it also unearths the presence of pro-boy discrimination and broadly captures the role of distribution factors. We then compare the distribution of individual resources as a prelude to individual poverty analyses. While distributions of estimated versus observed resources are not completely aligned, there is relatively little reranking when we group households by vintiles to reduce individual heterogeneity. This is encouraging for the possibility of using model predictions for welfare analyses involving individual ranks. We finally suggest a characterization of individual poverty using the different models. While the traditional approach based on equivalized or per-capita expenditure underestimates poverty among the poorest individuals (mainly children), model predictions come close to true levels of men's, women's and children's poverty. The models are relatively informative about the extent of poverty misclassification when household-level poverty is used (see also Brown, Calvi & Penglase, 2019). Some of the best performances of the structural model are obtained when using clothing as the exclusive good, which is important for practical considerations. This is indeed one of the very few assignable goods commonly available in standard expenditure surveys. While our validation takes place in a relatively limited framework – i.e., a static model of consumption without identification of the scale economies – results are encouraging regarding the possibility to use collective models for welfare analysis at the individual level.

2 Model and Identification

2.1 Set-up and Notations

Since we aim at a validation of the collective approach based on the observation of individual resource shares, we focus on a model of allocation of *private* consumption. The latter represents the large majority of household expenditure in a poor country like Bangladesh (food alone represents 60% of total expenditure on average). The non-individualized expenditures are essentially of a public nature and we treat them as such, assuming the separability of public consumption in individual utility functions (this simplification is used in Chiappori, 1988, Browning et al., 1994, Blundell et al., 1999, or Cherchye et al., 2012b, among others). This implies that each individual demands for private goods are function of individual private spending only. This is not an impediment to welfare analyses: the small fraction of public expenditure can be added to every household member's own resources for poverty analyses at the individual level (as done for instance in Lise and Seitz, 2011). We suggest a broader interpretation of this set-up at the end of this section.

We examine household consumption decisions. Goods are indexed by superscript $k = 1, ..., K$. We suggest three models that are extensively used to assess the poverty of specific groups of people (e.g., children, women). These models are referred to as "Rothbarth", "DLP" and "Complex Households" henceforth. In the first two, we focus on the main nuclear family in the household. For each family, the number of children is denoted by s, the log of private expenditure by x and the relevant observed characteristics are gathered in a vector z. Obviously, we cannot select nuclear households alone: it would reduce sample size too much and would be relatively restrictive in the context of poor countries.[6] Yet, with the data at hand, we can extract detailed consumption information for the main nuclear family in every household with children. We simply assume separability of private consumption between the nucleus and other household members. By abuse of language hereafter, the term "household" will refer to the nuclear family when talking about the Rothbarth/DLP approaches. With the Rothbarth method, we consider resource allocation between the adult parents, indexed by subscript $i = a$, and all their children, $i = c$. With the DLP approach, resource sharing is modelled among the mother, the father and their children, indicated by $i = f, m, c$ respectively ($i = c$ corresponds to a representative child since resource sharing among siblings is not identified). Finally, in the Complex Households approach, we model the resource allocation of the whole household between three groups: the set of women, the set of men and the set of children,

[6] Indeed, couples typically live with other adult relatives. In our data, households composed of only one nuclear family represent only 53% of the sample of households with children.

indicated by subscripts $i = f, m, c$ respectively. In this setting, x denotes the (log) private expenditures of the whole household. The household composition is characterized by the number of individuals in each of the three groups, denoted by s_f, s_m and s_c respectively, which are stacked in a vector $s = (s_f, s_m, s_c)$. Individual resource shares will correspond to representative women, men and children, as we will not identify how resources are shared within each of these groups. Note, however, that we can capture whether older women receive less resources than younger women (e.g., as in Calvi, 2020, for India) or whether boys receive more than girls (as in Dunbar, Lewbel & Pendakur, 2013, for Malawi), simply by making resource shares depend on the relevant characteristics (e.g. women's average age or the proportion of boys).

2.2 Assumptions and Sharing Rule Interpretation

The collective approach assumes the *efficiency* of household choices (Chiappori, 1988). This assumption may be unreasonable when it comes to infrequent decisions that possibly lead to strategic choices in intertemporal settings (for instance, changes in location or professional activities). In the context of poor countries, several studies have rejected the efficiency hypothesis when it comes to production decisions (e.g., Udry, 1996). Yet, efficiency is more defendable and reasonable in the case of frequently repeated decisions such as daily consumption, which has less of a strategic content (see the discussion in Baland & Ziparo, 2017).[7] In addition to efficiency, we must also assume *separability* between the consumption of different groups of individuals in the household.[8] In this setting, the efficient allocation process can be represented as a three-stage budgeting. First, household members agree on a level of public consumption. Second, total private expenditure is allocated between the different groups of individuals i according to a sharing rule, which is the outcome of an (unspecified) decision process. Finally, expenditures on all goods are chosen *as if* each individual solved her own utility-maximization problem subject to her individual budget constraint (determined by the sharing rule).

We denote by $\eta_{i,n}(z^r, d)$ the share of total private expenditure $\exp(x)$ accruing to individual i in household of type s. Resource shares depend upon several determinants, including a vector d of distribution factors, i.e., variables that influence negotiation without directly

[7] Note also that the estimation of demand systems, as the one we suggest to identify resource sharing, may be rationalized by models with inefficiency. Using other data from Bangladesh, Lewbel & Pendakur (2019) show that the departure from efficiency leads to relatively small variation of the resource sharing estimations.

[8] This does not preclude altruism: for instance, the utility of children may enter into the mother's welfare function, in the DLP approach, but as a separable sub-utility (an assumption known as 'caring' in the literature, cf. Bourguignon, Browning & Chiappori, 2009).

affecting individual preferences or the budget constraint. Resource shares also vary with household characteristics z^r, including demographic factors (as indicated, these may comprise the average ages of women, men and children, for instance). Resource shares can also change with prices, but our setting is static so that we ignore time variation in market prices. In principle, resource functions should depend upon (log) total expenditure x. In Dunbar, Lewbel & Pendakur (2013) and in most of the recent contributions cited in the introduction, identification of the sharing rule requires that shares do not depend on total household expenditure. We empirically examine this *independence of the base* (IB) assumption in what follows. With the sharing rule interpretation, each individual is endowed with a level of (log) private resources $x_{i,s} = x + \log \eta_{i,s}$, which can be seen as a money-metric utility (cf. Chiappori & Meghir, 2014) and used for individual poverty analysis.

For the identification of resource shares, some structure is put on household demand functions. Lewbel & Pendakur (2008), for couples, and Dunbar, Lewbel & Pendakur (2013) or Bargain & Donni (2012), for couples with children, apply Roy's identity to the indirect utility of each person in the household to derive a structural expression of the *individual* budget share spent on any good k. For each individual i in a family of type s, this is the fraction of this person's own budget $x_{i,s}$ spent on good k in the last stage of the decentralized process. In a cross-sectional context without price variation, it is written as

$$w_{i,s}^k = \omega_{i,s}^k \left(x + \ln \eta_{i,s}(z^r, d), z^p \right) \tag{1}$$

with function $\omega_{i,s}^k$ representing the individual Engel curve. This function depends on individual resources $x_{i,s} = x + \log \eta_{i,s}$ and a vector of preference factors z^p. With this minimalist structure, we can write *household* budget shares for an assignable good k_i – i.e., a good consumed only by persons of type i – as:

$$W_s^{k_i} = \eta_{i,s}(z^r, d) \cdot \omega_{i,s}^{k_i} \left(x + \ln \eta_{i,s}(d, z^r), z^p \right) \tag{2}$$

in a family of type s. This is all that we need to derive identification results. Household heterogeneity includes variation in log private expenditure x, distribution factors d and household characteristics $z = (z^r, z^p)$.

2.3 Identification of Resource Sharing

To harmonize the upcoming identification approaches for all three models (Rothbarth, DLP and Complex Households), we adopt a semi-parametric identification à la Dunbar, Lewbel & Pendakur (2013). Like them, we implement estimations with the assumption of Piglog indirect utility functions (Deaton & Muellbauer, 1980). It conveniently yields

Engel curves that are linear in the logarithm of individual resources, i.e. the budget share for a good k consumed by person i from her resources $x_{i,s}$ is written:

$$w_{i,s}^{k} = \delta_{i,s}(z^p) + \beta_{i,s}(z^p)x_{i,s}(z^r, d). \tag{3}$$

In what follows, we omit preference shifters z^p and sharing rule determinants (d, z^r) in the notations, for simplicity, but reintroduce them when we detail the empirical specification.

Rothbarth Approach. We begin with a focus on resource sharing between the parents – treated as a 'unitary' couple – and their children. As mentioned above, we will ignore sharing with other household members (if any), using individualized expenditure data to exclude non-nuclear members' consumption from x. In the traditional Rothbarth method, the allocation of resources to the children is estimated using standard expenditure information on adult-specific goods. Since we do not model sharing between spouses, these goods need not be gender-specific (for instance, we can use overall adult clothing). In the original formulation, the preferences of adults upon the exclusive goods are assumed not to change with family size s. Consequently, adult Engel curves can be proxied by those of childless couples, and child resources are inferred from the income effect that depresses adult consumption after the arrival of a child (Rothbarth, 1943). We follow this path but the preference similarity assumption can be less demanding: in the spirit of the DLP approach, we require only stability upon the *shape* of Engel curves. That is, we can estimate household budget shares on the adult good k_a, jointly for childless couples $(s = 0)$ and couples with children $(s > 0)$:

$$\begin{aligned} W_0^{k_a} &= \delta_{a,0} + \beta_{a,0}x \\ W_s^{k_a} &= \eta_{a,s}\left(\delta_{a,s} + \beta_{a,s}(x + \ln \eta_{a,s})\right) \text{ for } s > 0, \end{aligned} \tag{4}$$

while assuming the appropriate version of SAT ("Similarity Across Types"):

$$\text{Rothbarth-SAT: } \beta_{a,s} = \beta_a \text{ for all } s \geq 0. \tag{5}$$

With this assumption, the first expression of system (4) identifies the slope of the adult Engel curves β_a from the sample of childless couples. Then, from the second expression, we directly identify the resource share function $\eta_{a,s>0}$ for adults living with children from the estimate of $\partial W_s^{k_a}/\partial x = \eta_{a,s}\beta_a$. Child resource shares are obtained simply as $\eta_{c,s} = 1 - \eta_{a,s>0}$. The Rothbarth approach does not allow studying gender disparities among adults but it is still a relevant approach, as argued above, especially if we want to focus on child poverty.

DLP Approach. To additionally investigate potential gender inequality in adult consumption, we adopt the DLP approach. We model resource sharing between mother, father and children, now only using observations on couples with children ($s > 0$). We still focus on the main nuclear family and ignore other household members' expenditures in x. We need exclusive goods consumed specifically by women, men and children, or, similarly, a good that is assignable across these three groups. We index the woman's, man's and children's specific consumption by k_f, k_m and k_c respectively. The corresponding household budget shares for these three goods are written as:

$$\begin{aligned} W_s^{k_f} &= \eta_{f,s}(\delta_{f,s} + \beta_{f,s}(x + \ln \eta_{f,s})) \\ W_s^{k_m} &= \eta_{m,s}(\delta_{m,s} + \beta_{m,s}(x + \ln \eta_{m,s})) \\ W_s^{k_c} &= s\eta_{c,s}(\delta_{c,s} + \beta_{c,s}(x + \ln \eta_{c,s})) \\ \text{with:} &\quad \eta_{f,s} + \eta_{m,s} + s\eta_{c,s} = 1. \end{aligned} \tag{6}$$

Thanks to the IB assumption, x appears only once in each row so that $\partial W_s^{k_f}/\partial x = \eta_{f,s}\beta_{f,s}$, $\partial W_s^{k_m}/\partial x = \eta_{m,s}\beta_{m,s}$, and $\partial W_s^{k_c}/\partial x = (1 - \eta_{f,s} - \eta_{m,s})\beta_{c,s}$. The left-hand derivatives are obtained by estimating household budget shares for the assignable goods k_f, k_m and k_c. This gives a system of $3s$ equations and $5s$ unknowns ($\eta_{f,s}$, $\eta_{m,s}$, $\beta_{f,s}$, $\beta_{m,s}$, and $\beta_{c,s}$ for each s).

Identification requires at least one of the two restrictions: preferences for the assignable good are either similar across family types (SAT) for a given person type, or similar across people (SAP) for a given household type. With our notations, SAT is written

$$\text{SAT: } \beta_{i,n} = \beta_i \text{ for } i = f, m, c \text{ and all } s > 0 \tag{7}$$

which leads to $2s+3$ unknowns ($\eta_{f,s}$, $\eta_{m,s}$ for each s and β_f, β_m and β_c). Hence, the model is exactly identified if $s = 3$, which is the case in our application.[9] Note that the first series of papers identifying the complete sharing rule relied on homogeneity assumptions close to SAT (Browning, Chiappori & Lewbel, 2013, Lewbel & Pendakur, 2008, Bargain & Donni, 2012). However, they typically extended SAT to household types such as single individuals, hence allowing a direct identification of individual Engel curves, which is close to the spirit of the Rothbarth approach presented above.[10]

[9] With I types of individuals, it is overidentified when $Is > (I-1)s + I$, hence when there are more household sizes s than member types I, which is 3 in our case. We will refrain from carrying out overidentification tests since the number of households with 4 children or more is very limited in our small dataset. Dunbar, Lewbel and Pendakur (2013) do not reject overidentifying restrictions.

[10] While this is arguably a stronger assumption – because singles may be specific – it allows recovering more structure (indifference scales). Most important, it makes estimations more stable. We further discuss this point below.

Finally, SAP is written as follows:

$$\text{SAP: } \beta_{f,s} = \beta_{m,s} = \beta_{c,s} = \beta_s \text{ for each } s > 0. \tag{8}$$

It leads to $3s$ unknowns in total ($\eta_{f,s}$, $\eta_{m,s}$ and β_s for each s) and, hence, to an exact identification. SAP is a commonly used preference restriction in the demand literature and a weaker version of shape-invariance as defined by Pendakur (1999) and Lewbel (2010). Interestingly, our data provides the actual resource shares so that individual Engel curves can be estimated and the preference restrictions tested.

Complex Households. Finally, to operationalize welfare analyses more broadly, we model resource sharing between all the household members – i.e., between women, men and children ($i = f, m, c$) – in any household configuration and not just within the main nuclear family. We denote by $\eta_{i,s}$ the resource share per person of type $i = f, m, c$ in households of composition s (hence, $s_i \times \eta_{i,s}$ is the total share of resources accruing to individuals of type i). As in previous models, we cannot elicit how resources are shared among siblings and here, in the same way, we cannot identify how resources are shared among men or among women. This would require the observation of exclusive goods that are specific to certain subgroups. Nonetheless, we can specify resource shares $\eta_{i,s}(d, z^r)$ according to a vector z^r including the characteristics of each groups, for instance the average age in the group of women or the proportion of boys in the group of children. By doing so, we can capture the extent of gender or age bias in resource allocation. Household budget shares for women's, men's and children's goods are written

$$\begin{aligned}
W_s^{k_f} &= s_f \eta_{f,s}(\delta_{f,s} + \beta_{f,s}(x + \ln \eta_{f,s})) \\
W_s^{k_m} &= s_m \eta_{m,s}(\delta_{m,s} + \beta_{m,s}(x + \ln \eta_{m,s})) \\
W_s^{k_c} &= s_c \eta_{c,s}(\delta_{c,s} + \beta_{c,s}(x + \ln \eta_{c,s})) \\
\text{with} &: s_f \eta_{f,s} + s_m \eta_{m,s} + s_c \eta_{c,s} = 1.
\end{aligned} \tag{9}$$

The identification results of the DLP approach readily apply. For instance, with SAP, we obtain a system of three derivatives: $\partial W_s^{k_f}/\partial x = s_f \eta_{f,s} \beta_s$, $\partial W_s^{k_m}/\partial x = s_m \eta_{m,s} \beta_s$, and $\partial W_s^{k_c}/\partial x = (1 - s_f \eta_{f,s} - s_m \eta_{m,s})\beta_s$, which exactly identifies, for each s, the three unknowns ($\eta_{f,s}$, $\eta_{f,s}$ and β_s). The same is true if we consider households with two of the three groups (for instance, for childless couples, there are two unknowns and two equations). Note that the DLP approach can be seen as an application of the "Complex household" model to households with only one adult man and one adult woman, while Rothbarth is a restriction of the latter whereby the identifying good is not assignable by gender.

2.4 Discussion

We further discuss the modelling choices and the interpretation of our set-up. First, note that the model presented above simply distinguishes private and public goods for simplicity. Yet its interpretation can be more general. The only assumption we must make for identification is that the assignable good is purely private. We have assumed that the whole set of individualized expenditures is private in order to comply with the fact that these expenditures are effectively associated to specific household members at the time of data collection. The bulk of this consumption is food and, hence, private by nature. However, nothing precludes that these goods – especially non-food ones – generate some degree of publicness if they are also used by other members at some other time.[11] In other words, our model is compatible with a Barten-type consumption technology for these individualized expenditures. For non-individualized expenditure, we have assumed publicness and, given the nature of these goods as we will see in the data section, this is not a very strong restriction put on the original setting of Browning, Chiappori & Lewbel (2013).

Note that recent studies, including Dunbar, Lewbel & Pendakur (2013) or Calvi (2020), also assume the possibility of Barten-type scale economies – in their case for the whole consumption bundle – but, similarly to us, do not identify them. This is not an issue for our validation exercise, which focuses on the allocation of actual expenditures. This is not a problem for individual poverty analyses either, here or in the aforementioned studies, since these are based only on individual resources rather than on the comprehensive consumption – i.e., once scale economies are taken into account – of each household member. Yet, a more comprehensive welfare assessment would attempt to estimate how joint consumption affect these individual consumption levels. To model Barten scales, one would need exogenous price variation, which is beyond the scope of what can be achieved with our data.[12] Moreover, to extend our validation exercise to a more comprehensive framework, we would need to *observe* the degree of joint consumption or, in a pure public good framework, to derive information on the willingness-to-pay of the different household members for the public goods. Finally, most of the recent studies since Lewbel and Pendakur (2008) use single cross-sections and the IB assumption to achieve a more

[11] For instance, if a child shares his toys by playing with his brother half of the time these toys are used, then the consumption of toys in private good equivalents is 1.5 times the purchased quantity at the household level. That is, the Barten scale transforming actual prices into shadow prices is equal to two-thirds. Goods that are not shared – the assignable good, by assumption – will have shadow prices equal to market prices.

[12] Time variation in prices is obtained in Browning, Chiappori & Lewbel (2013) by pooling many years of cross-sectional data. We refrain from using spatial price variation: it is probably endogenous to local markets and preferences, reflecting variation in good quality and measurement errors.

tractable implementation of collective models for welfare analyses. Thus, we pragmatically carry out our validation exercise in this setting, simply based on Engel curve estimations for assignable goods.

3 Empirical Implementation

3.1 Data Sources and Selection

The Bangladeshi Data. Our sample is drawn from a household survey carried out in 2004 under the research project "Capturing Intrahousehold Distribution and Poverty Incidence: A Study on Bangladesh". This project was conducted by the Bureau of Economic Research at the University of Dhaka and supported by the IDRC (Canada). It aimed to improve the estimation and analysis of poverty in Bangladesh by taking into account intrahousehold resource allocation. The survey comprises information on $1,039$ households, randomly drawn from 33 districts. It includes standard household characteristics as well as information on food and non-food expenditures. Most originally, private expenditure is almost entirely individualized across all household members. As argued in the introduction, this is a rare feature because of the cost and difficulty to collect such individualized consumption data.[13]

Individualized Expenditures. Individual dietary intake was recorded mainly by direct observation. A team of specially trained enumerators assessed all meals prepared and consumed within households, weighting food items consumed by each individual in the household. In order not to overestimate food intakes, the survey also considered the amount of food sent outside the home and food waste. To reduce the measurement errors

[13] Individualized expenditure is sometimes collected in rich countries: Denmark (Bonke & Browning, 2011), the Netherlands (Cherchye, de Rock & Vermeulen, 2012b), Japan (Lise & Yamada, 2014) and Italy (Menon, Pendakur & Perali, 2012). For low- or middle-income countries, several surveys investigate intrahousehold inequality in food consumption specifically through the lens of calorie adequacy, i.e., calorie intake relative to standardized calorie requirements by age and sex. In this way, Haddad and Kanbur (1990) suggest that total nutrition inequality among individuals is under-estimated by 30-40% percent in the Philippines when inequality within households is ignored. A more recent assessment is proposed by Brown, Ravallion & van de Walle (2019). Several surveys also individualize some components of consumption such as food, for instance in a survey on Bangladesh that is different from the one used here and that is exploited by Brown, Calvi & Penglase (2019), D'Souza & Tandon (2018) or Lechene, Pendakur & Wolf (2020). Similarly, partially individualized expenditure is used in other settings (Mercier & Verwimp 2017 on Burundi; Santaeulàlia-Llopis & Zheng 2017 on China). Another interesting survey fully individualizes expenditure but across 'cells' rather than individuals within Senegalese households (cells are either the man or different women with their own children in polygamous households, cf. De Vreyer & Lambert, 2021).

associated with recording of food intake – including the bias due to the presence of investigators – enumerators spent three full days with each household. The composition of the teams was carefully designed both in terms of gender allocation[14] and personal knowledge of local customs.[15] All enumerators were trained for two weeks, particularly on methods for socializing within local households, on food preparation and on techniques and tools to measure dietary intake (more on this in online Appendix B1).

For food items (excluding spices), expenditures were calculated using surveyed quantities and local price quotes. Information on food consumption outside the home – both expenditures (in snack places or restaurants) and the items consumed – was gathered by interviewing the relevant persons on the basis of a one-week recall. Information was obtained on the non-food consumption of each household member on the basis of the recall method, largely by interviewing the head of the household or the person who made decisions on such expenditures, using an inventory of goods consumed individually or jointly over the past year. When non-food items were reported by household heads (usually men), most answers were also validated by a woman of the household (usually the head's spouse). For spices and all non-food goods, private or public, we use the direct observation of expenditure (prices can only be constructed indirectly based on the total expenditure in these items and their purchased or consumed quantity). Consumption amounts also include the value of home-produced goods and services imputed at their market value.

Sample Selection. We select monogamous couples with or without children (polygamous households represent only 0.5% of the original sample) and drop couples whose youngest child is above 17 years old (10%) or showing missing values for key variables (0.9%). As explained, Rothbarth and DLP approaches are implemented on a sample of nuclear families, who often live with other household members. Assuming separability between these two groups, we use detailed individual expenditure information to isolate the budget of the nuclear family and model resource sharing within this sphere.[16] We are left

[14]Given that cooking in Bangladesh was mostly done by women, and given that an important segment of the information to be collected would be from practices related to food preparation and distribution, women field workers were deemed more appropriate for the task. A number of male investigators eventually comprised the field survey team, but their role was limited to gathering data on market prices (through the survey of local markets and bazaars) and administering the segment of the questionnaire dealing with general socio-economic information.

[15]Special care was taken to select, in each team of enumerators, at least one person who was native from the region in which the field investigation was carried out, so that their familiarity with the localities and cultural practices would be helpful to conduct the field work.

[16]At the same time, in order to account for possible behavioral differences, we will control for a nuclear-household dummy in the specifications of the Engel curves and of the sharing rule.

with 803 nuclear families, which correspond to 2,163 individual observations for the Rothbarth approach. With DLP, these figures are 701 and 2,966 respectively, i.e., there are less households since childless couples are not used, but more individuals since we depart from 'unitary' adults. For the Complex Households approach, we model resource sharing among all male, female and child members so we could, in theory, include any household composition. In practice, we keep only households with both men and women, whether there are children or not in the household.[17] We avail of 4,157 individual observations for budget-share estimations.

3.2 Data Description and Assignable Expenditures

Table A.1 presents the descriptive statistics of the sample used in the Rothbarth/DLP approaches. The upper panel reports general information on the nuclear families (composition, women's employment, location). We also indicate the level of private expenditure (i.e., individualized expenditure), which represents between 63% (childless couples) and 73% (couples with three children) of total expenditure. The fact that private expenses increase with family size is mainly due to larger budget shares on food in larger families. In our sample, food represents between 50% (childless couples) and 65% (couples with three children) of total expenditure. The lower panel of Table A.1 provides more insight into private consumption patterns. We report both family budget shares of the main groups of private food and non-food goods, as well as the percentage of zero expenditures (in square brackets).

A unique feature of this data is the fact that consumption is individualized as much as possible. The composition of total expenditure across different types of goods is depicted at different points of the total expenditure distribution in Appendix B1. Individualized consumption represents $67-72\%$ of total consumption across expenditure levels. Regarding food, around $90-96\%$ of total consumption could be individualized ("food: individualized" in Figure B.1), i.e., almost everything except spices. Regarding non-food consumption, between 38% and 43% of it was privately allocated ("non-food individualized (1)"), including expenses for health, education, clothing (including footwear) and personal items (e.g., watch, bags, jewelry). Nondurable items whose consumption could not be individualized are mainly of a public nature ("non-food: non-individualized, public (2)"), including energy (fuel and electricity), household equipment, furniture, repair and maintenance. Admittedly, a fraction of non-food expenditures may be only partly public ("non-food: non-individualized, possibly private (3)"), though it represents less than 2% of total expenditures. According to Figure B.1, the food share decreases, from 60% to

[17] Note that households with only adult men or only adult women are very marginal.

50% of total expenditure, conforming with the Engel law. The share of individualized non-food expenditures ranges from 10% to 20% while the share of non-food expenditures that are not individualized – but clearly public by nature – increases from 17% to 23% with expenditure levels.

An interesting aspect with this degree of individualization is that we can opt for alternative assignable goods for identification. The choice set for such goods is usually very limited. Clothing is typically used for the Rothbarth approach (cf. Deaton, 1997) or for collective model estimations (e.g. in Browning et al., 1994, Bourguignon, Browning & Chiappori, 2009) because children's, men's and women's clothing expenditures can generally be distinguished in standard surveys (see Browning et al, 1994). This practical aspect is important for future applications in various countries and various set-ups. Individualized expenditures, as available in the present study or in Brown, Calvi & Penglase (2018), offer alternative options. We will consider the possibility of using total food consumption as well as specific food items such as rice (the main food component of daily diets in Bangladesh, representing between 20% and 30% of private expenditure in our sample) and proteins (meat, fish, eggs, dairy products). If they lead to better identification of the sharing rule, an important recommendation would be to collect data on this type of food item more systematically (see Lechene, Pendakur & Wolf, 2020).

Finally, we discuss how consumption patterns shift when family composition changes. In Table A.1, the share of primary food expenditure, like rice, increases with the presence (and the number) of children, as expected. Total budget shares on clothing, on the other hand, tend to decrease with the second and third child (but the absolute expenditure level increases). For clothing, our main identifying good, we report individual budget shares $w_{i,s}^{cloth_i}$ for $i = f, m, c$. Reassuringly, the rate of zero expenditures is very small.[18] The presence of children reduces the budget devoted by parents to their own private consumption. For instance, men without children allocate 6.5% of their own resources to clothing while this budget share drops to 5.3% when they have one child and to 3.8% when they have two. This pattern is consistent with the Rothbarth's intuition as it reveals the resource shift towards children.

3.3 Specification and Estimation Method

Specification. The semi-parametric approach provides the log-linear specification of Engel curves derived from Piglog preferences, as written in equation (3). Additionally,

[18] Note also that our statistics are relatively comparable with those reported in Table 5.1 of Del Ninno (2001, ed.) that is based on a nationally representative sample. In particular, zero-consumption shares in all our categories are highly comparable with the reported figures.

we model resource shares using logistic functions to guarantee that the shares are below 1 and sum up to 1. To estimate the model, we add error terms to household Engel curves for women's, men's and children's assignable goods in demand systems (4), (6) and (9) while imposing identifying conditions. For instance, in the Complex Households approach with SAP, we estimate the following system:

$$\begin{aligned} W_s^{k_f} &= s_f \eta_{f,s}(z^r, d) \cdot (\delta_{f,s}(z^p) + \beta_s(z^p)(x + \ln \eta_{f,s}(z^r, d))) + \epsilon_{f,s} \\ W_s^{k_m} &= s_m \eta_{m,s}(z^r, d) \cdot (\delta_{m,s}(z^p) + \beta_s(z^p)(x + \ln \eta_{m,s}(z^r, d))) + \epsilon_{m,s} \\ W_s^{k_c} &= s_c \eta_{c,s}(z^r, d) \cdot (\delta_{c,s}(z^p) + \beta_s(z^p)(x + \ln \eta_{c,s}(z^r, d))) + \epsilon_{c,s} \end{aligned} \tag{10}$$

with

$$\begin{aligned} \eta_{f,s} &= \frac{\exp(\gamma_f z^r + \rho_f d)}{1 + \exp(\gamma_f z^r + \rho_f d) + \exp(\gamma_c z^r + \rho_c d)} \\ \eta_{c,s} &= \frac{\exp(\gamma_c z^r + \rho_c d)}{1 + \exp(\gamma_f z^r + \rho_f d) + \exp(\gamma_c z^r + \rho_c d)} \\ \eta_{m,s} &= \frac{1}{1 + \exp(\gamma_f z^r + \rho_f d) + \exp(\gamma_c z^r + \rho_c d)}. \end{aligned} \tag{11}$$

Engel curve parameters $\delta(z^p)$ and $\beta(z^p)$ vary linearly with preference shifters z^p, which include household composition and other characteristics (a urban dummy, adults' age and education). In Rothbarth and DLP, household composition comprises the number of children and a nuclear-household dummy (indicating whether the nuclear family lives alone or with other adults in the household). For the Complex Households approach, household composition is simply the number of children, the number of women and the number of men. For the sharing rule, we specify the logistic form with a set $\boldsymbol{z}^r$ of variables – including household composition (as previously defined), other household characteristics (an urban dummy) and child characteristics (average child age and the proportion of boys), as well as a set d of distribution factors. For all models, the first one, d_1, is the income ratio, i.e., a measure of women's financial power calculated as their income over total household income. For Rothbarth/DLP, the second, d_2, is a "final say" variable, namely whether the mother in the nuclear family has control over expenses regarding education.[19] For the Complex Households approach, the final say measure cannot be computed since it is often missing for women who are not the head's spouse. Instead, we use the "female ratio", calculated as the number of adult women over the total number of adults.[20]

[19] The answers are recorded on a scale from 1 to 4 corresponding to: 1-No, I cannot purchase, 2- I can rarely purchase, 3- I can sometimes purchase, 4- Yes, I can always purchase.

[20] Note that our models are specified more parsimoniously than in Dunbar, Lewbel and Pendakur (2013) because we avail of a much smaller sample.

Estimation Procedure and Endogeneity. Since the error terms of the model are likely to be correlated across equations, each system is estimated using Non-Linear Seemingly Unrelated Regressions (as, for instance, in Calvi, 2020). The SUR estimator is iterated until the estimated parameters and error covariance matrices settle. Iterated SUR is equivalent to maximum likelihood with multivariate normal errors. One source of endogeneity in our setting is the likely correlation between the error terms in each budget-share function and the log total expenditure, especially if total expenditure suffers from measurement errors. Each budget share equation is augmented with the Wu-Hausman residuals (see Banks, Blundell & Lewbel, 1997, Blundell & Robin, 1999). These are obtained from reduced-form estimations of x on all exogenous variables used in the model plus some instruments, namely a quadratic form of the log household disposable income. These instruments are very strong in predicting the log of expenditure (the F statistic on the excluded instruments is 53 with the sample used for the Rothbarth/DLP approaches and 100 with the Complex Households sample). Following Dunbar, Lewbel and Pendakur (2013), we also suggest a treatment of the endogeneity of household size, as explained later.

Estimation of Observed Shares. Individualized expenditures are used to compute observed resource shares $\eta_{i,s}^{obs}$ for each person or group of persons i in household s. Then, for comparison, we can estimate observed shares on the same determinants as in the collective models. This estimation, carried out by Maximum Likelihood, is based on a logistic form and the same specification as in the structural approach, for instance for DLP and Complex Households:

$$\begin{aligned}
\eta_{f,s}^{obs} &= \frac{\exp(\gamma_f^{obs} z^r + \rho_f^{obs} d)}{1+\exp(\gamma_f^{obs} z^r + \rho_f^{obs} d) + \exp(\gamma_c^{obs} z^r + \rho_c^{obs} d)} \qquad (12)\\
\eta_{c,s}^{obs} &= \frac{\exp(\gamma_c^{obs} z^r + \rho_c^{obs} d)}{1+\exp(\gamma_f^{obs} z^r + \rho_f^{obs} d) + \exp(\gamma_c^{obs} z^r + \rho_c^{obs} d)}\\
\eta_{m,s}^{obs} &= \frac{1}{1+\exp(\gamma_f^{obs} z^r + \rho_f^{obs} d) + \exp(\gamma_c z^r + \rho_c^{obs} d)}.
\end{aligned}$$

By using logistic forms, we guarantee that shares are never zero or negative, which would lead to missing values when taking the log of these shares at any iteration of the structural model estimation. In addition, it directly imposes that the shares sum up to one. Estimated coefficients are denoted γ^{obs} and ρ^{obs} to indicate that they stem from the estimation of observed shares. Note that no particular restriction is needed in this setting. This estimation should be able to identify the "true" effect of distribution factors, which is interesting per se and used in proportionality tests of Pareto efficiency below. The direct estimation of the sharing rule also allows us to experiment with other specifications, notably when adding other determinants such as the (log) expenditure x. In this way, as shown below, we can provide an original test of the IB assumption needed for identification in the structural approach.

4 Results: Tests

We present the results of (i) proportionality tests for Pareto efficiency, (ii) tests of the IB assumption and (iii) tests of the different identifying assumptions used in recent collective-model approaches aimed at eliciting resource allocation in multi-person households.

4.1 Testing Efficiency

Context and Approach. This test comes logically first since the Pareto efficiency of household decisions is the core assumption of collective rationality. A large literature has developed different types of efficiency tests (see Browning, Chiappori, and Weiss, 2014, or Chiappori and Donni, 2011). In particular, in a context without price variation, as here, several tests have been suggested that rely on distribution factors. The structure that is put on household demand functions is such that these factors affect demand only through the sharing rule and lead to proportionality restrictions (Browning and Chiappori, 1998). These restrictions are necessary conditions (Bourguignon et al., 1993, Browning et al., 1994) but also sufficient conditions for efficiency (Bourguignon, Browning & Chiappori, 2009).[21] Distribution factors have also been used to achieve the identification of the marginal sharing rule (cf. Bourguignon, Browning & Chiappori, 2009) and, more recently, for the identification of the full resource allocation (Dunbar, Lewbel & Pendakur, 2019). In our setting, distribution factors are *not* required for identification but we mobilize them for efficiency tests and, later, we will simply check how they influence women's and child resource shares.[22]

If we multiply both sides of equation (2) by $\exp(x)$, we obtain an identity between the household demand for good k^i, $Q_s^{k_i} = W_s^{k_i} \times \exp(x)$, and individual demands $q_{i,s}^{k_i} = w_{i,s}^{k_i} \times \{\eta_{i,s} \exp(x)\}$:

$$
\begin{aligned}
Q_s^{k_i}(x,d,z^p) &= q_{i,s}^{k_i}\left(x + \log \eta_{i,s}(x,d,z^p), z^p\right) \\
&= q_{i,s}^{k_i}\left(x_{i,s}(x,d,z^p), z^p\right).
\end{aligned}
\tag{13}
$$

[21] Distribution factor proportionality tests have been widely applied in the literature. See, for instance, Bobonis (2009), Attanasio & Lechene (2014) or LaFave & Thomas (2017).

[22] As stated by Brown, Calvi and Penglase (2018), distribution factors correspond to preference restriction and the validity of this exclusion restriction may be hard to prove (they may actually impact preferences, for instance). Another limitation of an identification approach based on these factors is that they may be difficult to find, especially when children are included in the model.

Taking the derivatives with respect to the two distribution factors, we obtain the condition:

$$\frac{\partial Q_s^{k_i}/\partial d_1}{\partial Q_s^{k_i}/\partial d_2} = \frac{\partial x_{i,s}/\partial d_1}{\partial x_{i,s}/\partial d_2} \text{ for } i = f, m, c. \tag{14}$$

The ratio, on the right, does not depend on the good k^i. Hence, the condition states that the ratio to the left, the relative marginal effects of two distribution factors on household demand, must be equal across goods k^i.[23] In the present setting, it means that the ratio of marginal effects should be equal across assignable goods (clothing, food, rice, proteins) for a given person type $i = f, m, c$.[24] To conduct this test, we first express the equality above in terms of budget shares and using the observed resource shares. The testable condition becomes:

$$\frac{\partial W_s^{k_i}(x, \boldsymbol{z})/\partial d_1}{\partial W_s^{k_i}(x, \boldsymbol{z})/\partial d_2} = \frac{\partial \eta_{i,s}^{obs}/\partial d_1}{\partial \eta_{i,s}^{obs}/\partial d_2}. \tag{15}$$

Results of the Tests. We proceed with the tests using the DLP sample and the distribution factors d_1 and d_2 defined in this case (the income ratio and the final say variable). Table 1 reports the p-value of nonlinear Wald tests. We first test the equality of $\frac{\partial W_s^{k_i}(x,\boldsymbol{z})/\partial d_1}{\partial W_s^{k_i}(x,\boldsymbol{z})/\partial d_2}$ across four assignable goods (clothing, total food, rice, proteins), for each person type $i = f, m, c$. Results in column (1) show that efficiency is never rejected. Bonferroni p-values are reported in column (2) and lead a fortiori to the same conclusion.[25] Note also that these tests are feasible because the data at hand contain several assignable goods thanks to individualized expenditures. Finally, we can also use the observed resource shares to test the equality of equation (15) directly. We do so for the different assignable goods k^i and the different member types ($i = f, m, c$). Columns (3)-(6) confirm that the null hypothesis cannot be rejected at any conventional level of significance for any of the assignable goods, in general or when carrying the tests for specific demographic subgroups.[26]

[23] In the context of childless couples, this leads to the proportionality condition across the male and female exclusive goods, written $\frac{\partial Q_s^{k_f}/\partial d_1}{\partial Q_s^{k_f}/\partial d_2} = \frac{\partial Q_s^{k_m}/\partial d_1}{\partial Q_s^{k_m}/\partial d_2}$, as suggested for instance in Bourguignon, Browning & Chiappori (2009). The extension of this type of test to multiple decision-makers is suggested in Dauphin & Fortin (2001), Dauphin, El Lahga, Fortin and Lacroix (2011) and Dauphin, Fortin & Lacroix (2018). It is not straightforward and requires rank condition test or z-conditional demands as well as the use of more distribution factors.

[24] Brown, Calvi and Penglase (2018) suggest such a test using assignable clothing and food.

[25] These tests involve multiple hypotheses: the likelihood of incorrectly rejecting the null hypothesis (efficiency) increases. The Bonferroni method compensates for it by multiplying p-values by the number of tested equalities.

[26] It should be noted that while tests from efficiency are based on a static definition of rationality, they are also consistent with the intra-household allocation stage of any dynamic household decision

Table 1: Tests of Pareto Efficiency

Household type	Assignable good for:	Joint test	Joint test (corrected)	Clothing	Food	Rice	Proteins
		(1)	(2)	(3)	(4)	(5)	(6)
All	Children	.936	1.000	.866	.871	.856	.633
	Women	.496	1.000	.999	.947	.142	.174
	Men	.277	.831	.862	.323	.812	.072
no children	Women	.897	1.000	.633	.508	.875	.464
	Men	.975	1.000	.38	.577	.723	.516
1 child	Children	.929	1.000	.681	.996	.735	.708
	Women	.925	1.000	.942	.957	.927	.926
	Men	.903	1.000	.873	.475	.647	.336
2 children	Children	.767	1.000	.984	.844	.467	.214
	Women	.735	1.000	.618	.799	.291	.771
	Men	.568	1.000	.229	.535	.796	.153
3 children	Children	.682	1.000	.718	.491	.503	.325
	Women	.726	1.000	.967	.968	.965	.967
	Men	.411	1.000	.463	.899	.900	.167

We report the p-values of proportionality tests of efficiency. If efficiency holds, distribution factors DF1 and DF2 affect demands only through their impact on the sharing rule. As a consequence, the marginal effect of DF1 over the marginal effect of DF2 on the budget share of an assignable good must be the same ratio across the different assignable goods. We test the equality of these ratios across assignable goods in column (1). We report Bonferroni-corrected p-values in column (2). In columns (3)-6), we test the equality between each of these marginal budget share ratios and the 'target ratio', which is the derivative of the resource share with respect to DF1 over its derivative with respect to DF2. DF1 and DF2 are the woman's contribution to total earnings and a 'final say' measure (her control over education decisions), respectively. We present test results overall and for each demographic group.

4.2 Testing the Independence of the Base

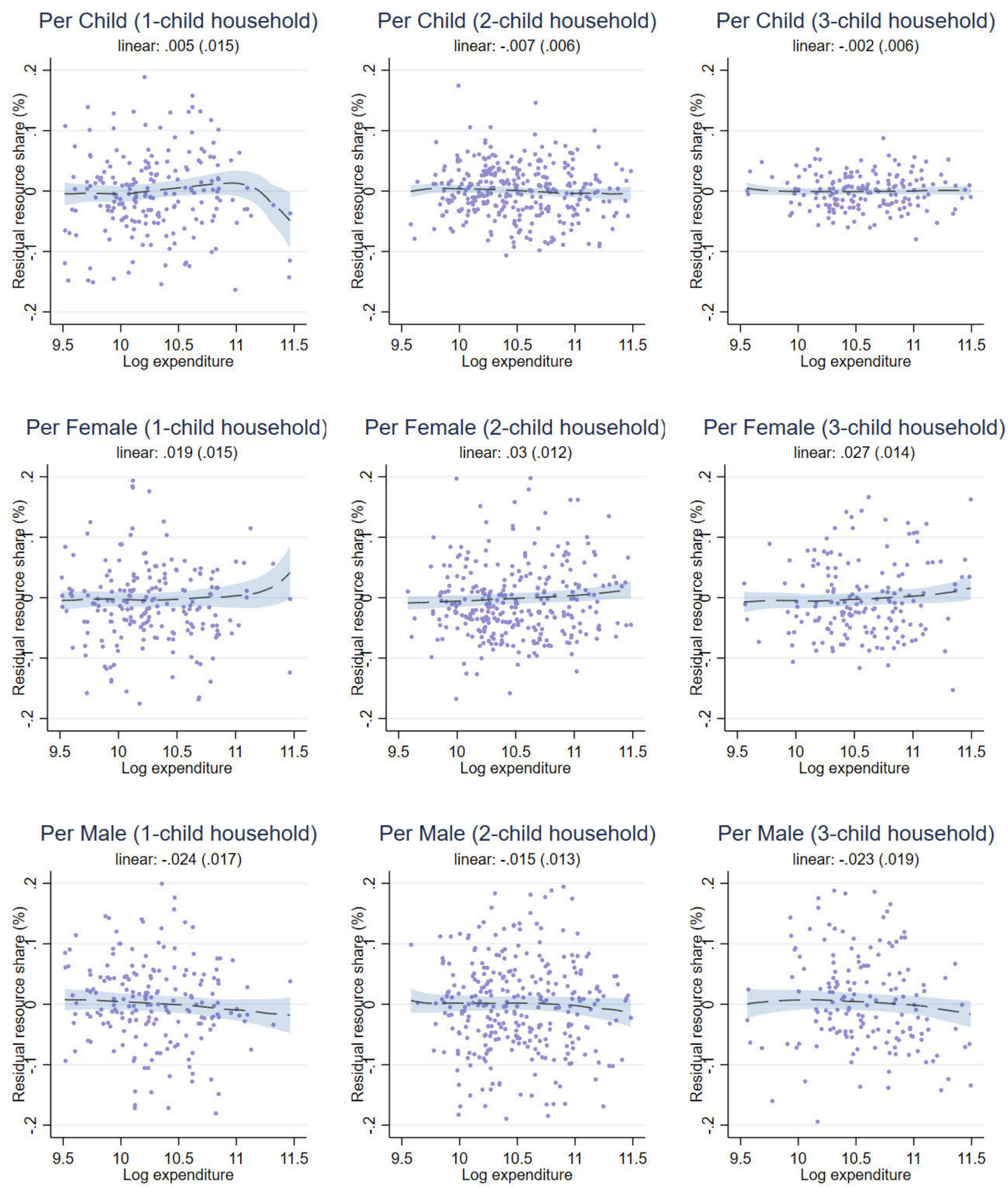
Context and Approach. The IB assumption states that resource shares should not be correlated with total expenditure. This assumption is used for identification in many recent collective-model approaches (e.g., in Browning, Chiappori & Lewbel, 2013, or Dunbar, Lewbel & Pendakur, 2013). Using cross-sectional data, Menon, Pendakur & Perali (2012) and Cherchye et al. (2015) test this restriction for rich countries, Italy and the Netherlands respectively. The former study provides tests for children's shares only while the latter consider labor supply rather than consumption decisions. Nonetheless, these results are interesting as they tend to show that resource shares estimated on cross-sections do not exhibit much dependence on household budgets. In contrast, Botosaru, Muris & Pendakur (2020) use panel data and obtain a more precise estimate of this relationship, detecting a slight decrease of women's resource with household budget levels.

Given the availability of individualized-consumption data, we can uniquely perform a *direct test* of the IB assumption. That is, we carry out separate regressions of the observed shares $\eta_{i,s}^{obs}$ per person type i and household type s on the determinants (z^r, d) of the sharing rules. We use similar specifications as before, for instance as written in equation (12), while adding log expenditure x among sharing rule determinants. Importantly, independence is tested *conditionally* on other variables that enter the sharing rule. We also propose a more flexible test in which we regress resource shares on (z^r, d) and use the residuals for local polynomial regressions on log expenditure x. This allows us to detect in which part of the expenditure distribution we may find dependence. Related to this, the DLP approach requires only that resource shares be invariant over some range of household expenditure. If this invariance holds, say, for the poorest households, we could still identify resource shares for them and consequently identify poverty at the individual level for this subpopulation.

Results of the Tests. Results are reported in Figure (1) for the sample used in the Rothbarth/DLP approaches and in Figure (2) for the Complex Households sample. Coefficients of the linear regressions are reported in the subtitles of each graph while the dashed lines depict nonparametric regressions (with 95% confidence bounds). Results tend to support the IB assumption. Indeed, the relationship between shares and budgets is relatively flat overall. The linear dependence is insignificant in the majority of cases (eight out of twelve). Admittedly, log expenditure is statistically significant in individual share regressions for women in households $s = 2, 3$ of the DLP sample, and for both women and men in $s_c = 2$ of the Complex Households sample. Women's (men's) shares

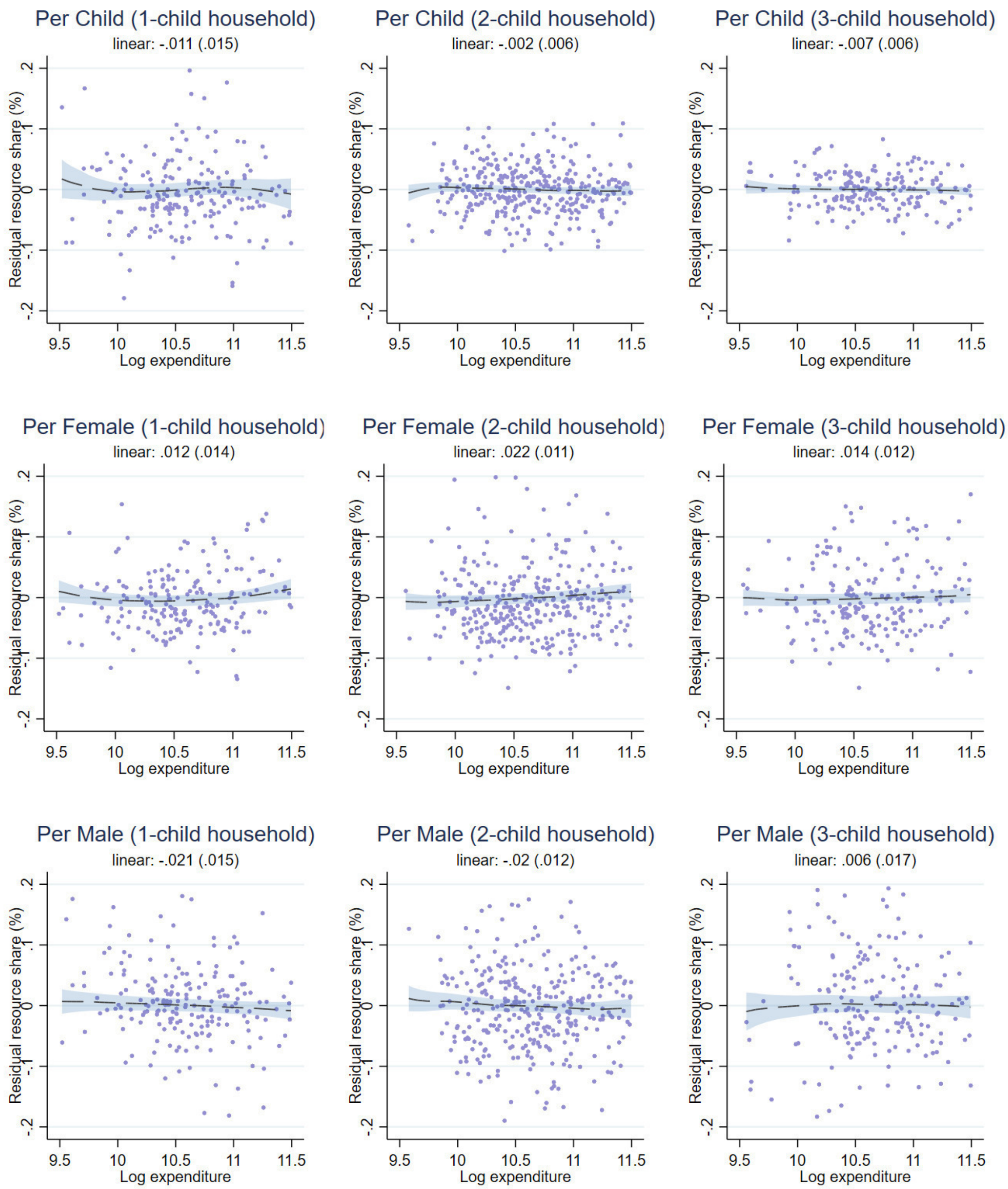
process that assumes within-period efficiency. This includes limited-commitment and full-commitment intertemporal collective models (Chiappori and Mazzocco, 2017).

Figure 1: Conditional Independence of Resource Shares on (Log) Expenditure (Rothbarth/DLP sample)



Test of independence of the base for the different resource shares (per child, per male, per female) and different demographic groups. Dots represent the residuals from a regression of individual shares on the household composition and household characteristics as used in the sharing rule specification of the collective model. The dashed line represents a local polynomial regression of residual resource shares on log expenditure (with a 95% confidence interval in colored area). Subtitles indicate the correlation between residual resource shares and log expenditure, conditional on the covariates used in the structural model (std.err. of this linear estimation in brackets).

Figure 2: Conditional Independence of Resource Shares on (Log) Expenditure (Complex Households sample)



Test of independence of the base for the different resource shares (per child, per male, per female) and different demographic groups. Dots represent the residuals from a regression of individual shares on the household composition and household characteristics as used in the sharing rule specification of the collective model. The dashed line represents a local polynomial regression of residual resource shares on log expenditure (with a 95% confidence interval in colored area). Subtitles indicate the correlation between residual resource shares and log expenditure, conditional on the covariates used in the structural model (std.err. of this linear estimation in brackets).

tend to increase (decrease) with household budgets. Yet, individual shares vary by 2-3 points of percentage at most over the whole range of expenditure levels. Besides, local polynomial regressions indicate that the whole range must be crossed to obtain a significant change in the shares. In fact, if we ignore just the top 10% of the distribution, the linear dependence is no longer significant in the four cases where it was.

4.3 Testing Identifying Assumptions

Individual Engel Curve Estimations and Tests. With the data at hand, we suggest an original test of the identifying assumptions of preference homogeneity used in the recent literature on collective models. We use observed individual resources $x_{i,n}^{obs}$ to estimate individual Engel curves directly – which is usually not possible with standard data – for any private good k_i. With Piglog preferences, we estimate:

$$w_{i,s}^{k_i}(x_{i,s}) = \delta_{i,s}(z^p) + \beta_{i,s}(z^p)x_{i,n}^{obs} \tag{16}$$

for all person types i in all household types s. These estimations directly lead to tests of Rothbarth-SAT, SAT and SAP, i.e., the identifying assumptions defined in equations (5), (7) and (8) above. We conduct the tests for clothing as well as for other potential assignable goods. Just as we did for efficiency tests, we provide detailed results for the different subgroups (person $\times$ household type) in order to investigate where potential rejections may arise. For the Rothbarth approach, then, we test whether $\beta_{a,s} = \beta_{a,0}$ for $s = 1, 2, 3$, since the slopes of the Engel curves for adults are identified thanks to childless couples. For SAT, we test whether $\beta_{i,1} = \beta_{i,2} = \beta_{i,3}$ for each $i = f, m, c$ separately. For SAP, since identification requires shape invariance of all persons (for any household size), we directly test $\beta_{f,s} = \beta_{m,s} = \beta_{c,s}$ for each value of s in the DLP sample.

Results of the Tests. The comprehensive set of p-values for all these tests is reported in columns 1-4 of Table 2. Note also that these tests involve multiple hypotheses. Thus, we also show Bonferroni-corrected p-values in columns 5-8. We begin with the results for SAT. For our main identifying good, i.e. clothing, none of the assumptions are rejected at conventional levels for any of the different individual types (i.e. adults for Rothbarth of f, m, c for DLP). Maybe the most surprising result is that Rothbarth-SAT is not rejected in general and especially for large s, though one may expect that adults with children tend to become less and less similar to childless adults as the family grows. An opposite argument is that childless couples may be young couples who will eventually have children or older couples whose children have left home, two groups whose preferences may not be so different from those of couples with children. This reasoning may greatly vary when it comes to food because parents themselves sometimes change their diets when children are present. We indeed see a rejection of Rothbarth-SAT in the case of food. For similar reasons, SAT is also rejected in some of the cases when using total food or specific food items (rice, proteins). Another possible explanation for the poorer performances of food items is that they are conceivably more subject to self-production than clothing. SAT may be violated if home-production technology (and, thus, the shadow price of rice) varies significantly with family size. As a matter of fact, our dataset contains information on the proportion of self-produced consumption. It is basically zero for clothing. It is more substantial for food and decreases with the number of children, from 32% in couples with one child to 29% in couples with three.[27] In Table B.1 in the Appendix, we replicate the tests for total food while restricting the sample to households whose food consumption is only partly self-produced. We see that the results of the test for SAT improve with lower degrees of home-production of food. When this production corresponds to less than two-third of total food consumption, SAT is rejected only for child Engel curves.[28]

Turning to our main identifying assumption, SAP, we find that it is not rejected for clothing, which is a key result for what follows. Admittedly, we find a relatively smaller p-value for SAP in the case of $s = 2$ but still cannot reject the assumption at less than the 10% significance level (before Bonferroni correction). SAP is rejected in some cases for the other assignable goods and in particular for food. Nonetheless, Table B.1 indicates that when the extent of food home-production is very limited, i.e. when it represents less that a third of total food consumption, SAP is rejected only for very large households. Note that this sensitivity check is only suggestive since the sample size decreases substantially when we exclude households with high levels of home production (as indicated in the last row of Table B.1).

Comparisons with Recent Studies. Our results are broadly consistent with recent evidence, notably with the relatively small literature testing the behavioral restrictions that are required for identification of resource sharing. Existing tests usually hinge on indirect methods. They start from alternative identification approaches, which do not require SAT and SAP, and then test these restrictions. In particular, Dunbar, Lewbel & Pendakur (2019) suggest identification results relying on distribution factors (and not

[27] This is driven mainly by the main food item, rice. Rice from home production contributes about a quarter of energy intake in Bangladesh (Yu, 2012). In our data, the consumption of self-produced rice varies from 34% in couples with one child to 24% in couples with three. This variation may reflect a combination of factors, e.g. lower per-capita land productivity and less time for women with more children to work in rice paddies.

[28] Another aspect regarding food consumption is the potential role of misreporting and measurement errors. Extensive sensitivity checks are performed in Brown et al. (2018, A2), in particular using alternative temporalities on the recording of food expenses.

requiring preference homogeneity assumptions): they show that results are close to those obtained with SAP and additionally test and do not reject this restriction. Brown, Calvi & Penglase (2018) apply the same identification based on distribution factors to test SAT, SAP and original restrictions based on two assignable goods (D-SAP and D-SAT). The authors reject SAT (and D-SAT) but tend not to reject SAP (only in a quarter of the cases) or D-SAP. Dunbar, Lewbel & Pendakur (2013) test if behavioral restrictions are satisfied by single men and single women living alone, arguing that one can have more confidence in preference homogeneity in multi-person household if they are found to hold for single individuals. They test SAP by comparing single men and single women to each other and do not reject this assumption.[29]

Table 2: Tests of Identifying Assumptions: Results

Test of identifying assumptions based on preference similarity		Joint test / Assignable good: Clothing	Food	Rice	Proteins	Joint test (corrected for multiple testing) / Assignable good: Clothing	Food	Rice	Proteins
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Rothbarth, SAT	$\beta_{a0} = \beta_{a1} = \beta_{a2} = \beta_{a3}$	0.64	0.00	0.47	0.17	1.00	0.01	1.00	0.51
DLP, SAT	$\beta_{f1} = \beta_{f2} = \beta_{f3}$	0.77	0.03	0.12	0.00	1.00	0.06	0.23	0.00
	$\beta_{m1} = \beta_{m2} = \beta_{m3}$	0.27	0.49	0.03	0.50	0.53	0.99	0.05	1.00
	$\beta_{c1} = \beta_{c2} = \beta_{c3}$	0.77	0.00	0.08	0.11	1.00	0.00	0.17	0.21
DLP, SAP	$\beta_{f1} = \beta_{m1} = \beta_{c1}$	0.26	0.04	0.00	0.09	0.52	0.07	0.01	0.19
	$\beta_{f2} = \beta_{m2} = \beta_{c2}$	0.10	0.00	0.08	0.00	0.20	0.00	0.16	0.00
	$\beta_{f3} = \beta_{m3} = \beta_{c3}$	0.19	0.00	0.00	0.40	0.38	0.00	0.00	0.80

We report the p-values for tests of the SAT ('Similar Across Types') and SAP ('Similar Across Persons') identifying conditions in columns 1-4 and Bonferroni p-values in columns 5-8 to correct for multiple testing. The tests concern the shape of individual Engel curves captured by the slope β_{is} for person of type i in household of type s. Individual Engel curves are estimated for the different i x s subgroups (as shown in raws) and for the different possible assignable goods (as specified in columns). SAT for the Rothbarth approach means that for adults, the slope is independent from the number of children s=*0,...,3*. SAT for DLP means that for females (f), males (m) or children (c), the slope is independent from the family size s=*1,2,3*. SAP means that for each family size s=*1,2,3*, the slopes are equal across individuals (*f,m,c*). P-value in red at those below significance level of 5%.

Discussion. Arguably, SAT is weaker than the homogeneity assumptions extended to childless couples (as in Rothbarth) or to single individuals (as in Browning, Chiappori, and

[29] While there is a broad support for SAP, including in our own results, at least one study tends to reject it but not SAT. Sokullu and Valente (2019) use panel information and random income shocks due to PROGRESA for identification. They do not need to assume preference similarity assumption and can test both restrictions.

Lewbel, 2013). Indeed, adult preferences may change with the presence of a partner or of children. However, budget-share estimations on these groups help a lot the identification of resource shares because they directly provide the shape of adult Engel curves. This is exactly what we have encountered with the Rothbarth approach in our application. In contrast, DLP estimations based on the strict definition of SAT – i.e., applied to individuals in families with children only – were very unstable. This is acknowledged by Dunbar, Lewbel & Pendakur (2013), who highlight the fact that, since the $\beta_{i,s}$ coefficients are unknown, the only thing that identifies the levels of $\eta_{i,s}$ from the observed budget-share derivatives $\partial W_{i,s}/\partial \ln x = \eta_{i,s}\beta_{i,s}$ for multiple values of s is the restriction that the resource shares $\eta_{i,s}$ sum to 1. Tommasi and Wolf (2018) also state that the model is weakly identified and leads to extreme variability in the estimates of the sharing rule. They suggest a minimal form of the homogeneity assumption, using data on singles with a shrinkage term to govern the strength of the preference restriction.[30]

The main issue with SAP is that it may be deemed far from the philosophy of collective models, which precisely aim to encompass the heterogeneity of individual preferences while SAP partly rules it out. On the other hand, shape invariance is a well documented empirical regularity in the Engel curve literature (see Blundell, Chen & Kristensen, 2007). Moreover, it provides more stable estimations of the resource shares than SAT.[31] These considerations, plus the fact that SAP is rarely rejected in the literature and not rejected for clothing in our tests, justify its choice for the implementation of the DLP and Complex Household approaches in what follows. Note that this is also the pragmatic choice made in most of the recent contributions aimed at recovering resource shares for welfare analyses (e.g., Tommasi, 2019, Calvi, 2020 Penglase, 2020, or Lechene, Pendakur & Wolf, 2020). The results of the tests above also support the use of clothing as assignable good. We will nonetheless report summary information about prediction errors when other assignable goods are used.

4.4 Checking Engel Curves' Slopes

An important empirical aspect for the applicability of the methods at use is that β estimates are statistically significantly different from zero, since identification hinges on

[30] We confirm this variability even for large samples using simulations. Our simulations are based on artificial data generated using the "true" model, i.e., the parameters of the sharing function directly estimated on individual resources (as for instance in equation (12)) and the parameters of individual Engel curves (as stemming from the direct estimation of equation (16)).

[31] SAP basically means that the slopes of the household budget shares for women's, men's and children's clothing provide the resource shares of these persons up to a multiplicative factor β_s. The fact that resource shares sum up to 1 simply provides a normalization of the shares (i.e., it is less critical for identification than in the case of SAT).

restrictions put on β parameters. With Rothbarth-SAT, we calculate the slope of the adults' Engel curve $\beta_a(z^p)$ for each household given its characteristics z^p, which includes the number of children s. With SAP (in the two other approaches), we calculate the slope $\beta_s(z^p)$, common to all the persons of a household of type n, given the household characteristics z^p including its composition s. As explained before, clothing is an interesting good because clothing expenditure is commonly available in an assignable form in standard surveys. Importantly, it passes most of the tests above. However, the drawback with clothing is that it is less frequently purchased than food items. Thus, it leads to less precise estimates (see also the discussion in the concluding section) and bears the risk of insignificant Engel curve slopes. Lechene, Pendakur and Wolf (2020) discuss this point in detail and, in their application on several countries, keep the countries for which β estimates are significantly different from zero in at least 75% of the households. Our results are relatively encouraging in this respect. With clothing, we find that β_a is nonzero for 80% of the households (Rothbarth) while β_s is nonzero in 85% of the cases with DLP and 100% of the cases with the Complex Household approach.[32]

5 Results: Resource Shares and Welfare Analysis

We now present the validation exercise for welfare analyses. We first assess how predicted resource shares replicate observed ones on average, for different demographic subgroups and in terms of distribution. We next focus on individual poverty measures, i.e. measures originally based on the resources accruing to the different family members, as opposed to the standard approach based on equivalized household expenditure.

5.1 Individual Resource Share Comparisons

Mean Shares. We start with our baseline results for the Rothbarth approach (using Rothbarth-SAT), the DLP approach (using SAP) and the Complex Households approach (using SAP), with clothing as the assignable good. We focus on the direct comparison of predicted shares $\widetilde{\eta}_{i,s}$ and observed shares $\eta_{i,s}^{obs}$. Mean levels of per-child shares and adults' shares are shown in Figure 3. All the models based on clothing yield fairly accurate predictions. With Rothbarth and DLP, children's shares are slightly overestimated but nonetheless relatively close to the observed levels regardless of family size. With DLP,

[32] Protein food items (Fish/Meat/Eggs) give the worse results with a nonzero occurrence of only 60%, 44% and 73% for the three models respectively. Rice and total food expenditures lead to significant β estimates for all households and all models. For clothing and food, a 100% rate of nonzeros is also obtained by Lechene, Pendakur and Wolf (2020) using an approach similar to our Complex Households model and for a different Bangladesh sample in which these two goods are assignable.

the shares of men are slightly underestimated for $s = 1, 2$. For Complex Households, estimates are also accurate, with slight underestimations of men's and women's shares in most demographic groups. The different models reproduce well the fact that child shares increase with family size but at a decreasing rate, a pattern found in previous studies (notably Dunbar, Lewbel & Pendakur, 2013, for Malawi and Bargain, Donni & Kwenda, 2015, for Côte d'Ivoire). Collective models also replicate gender asymmetry well, which is similar to Rose (1999), Calvi (2020) or Dunbar, Lewbel & Pendakur (2013). However, as discussed by the latter authors, apparently unequal treatments regarding resource allocation might also reveal differences in caloric requirements across gender or age groups, because a large fraction of total expenditure is devoted to food. That said, other studies point to inequitable intrahousehold resource distribution in Bangladesh.[33]

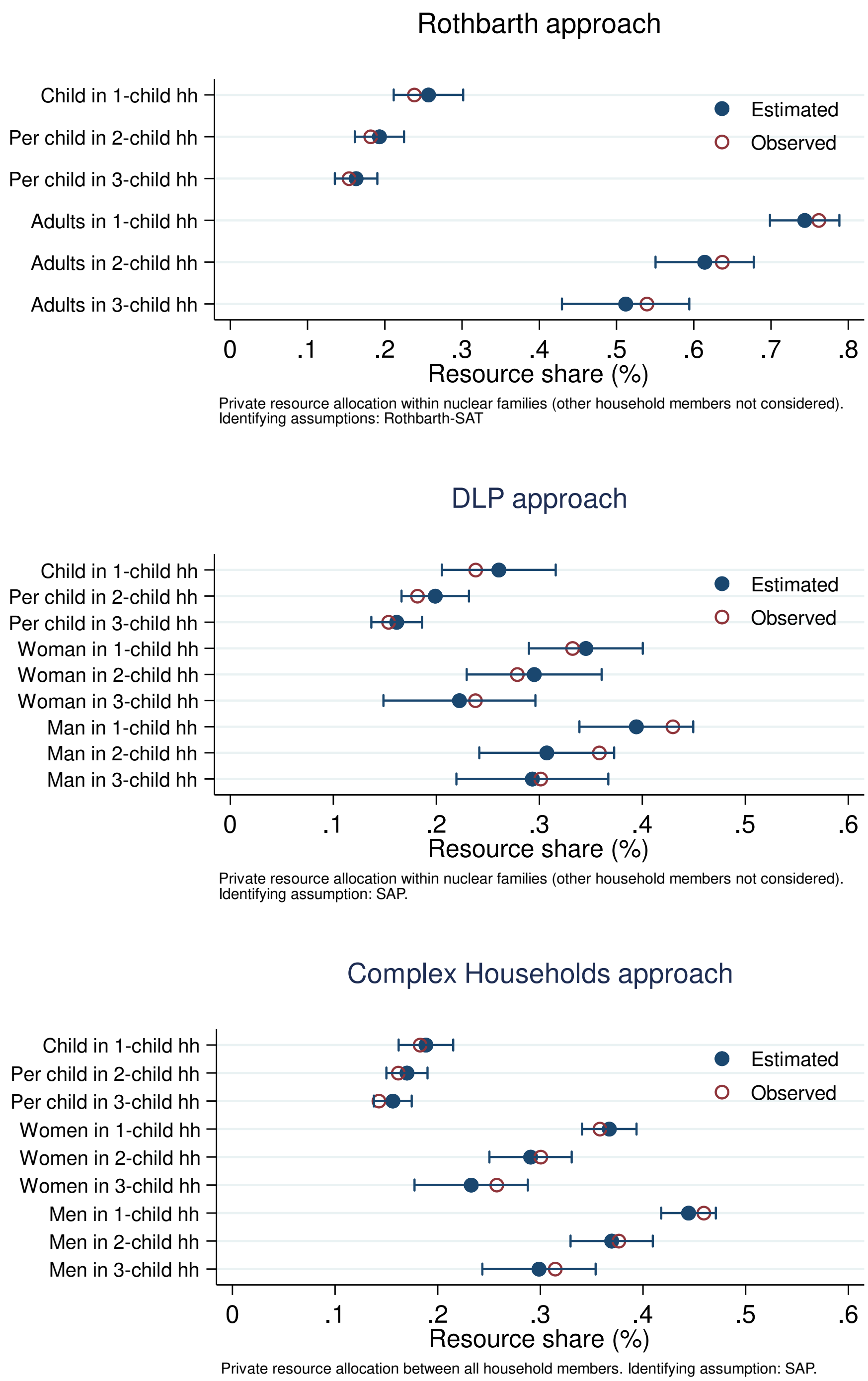
Marginal Effects for Key Variables. In Table 3, we report the marginal effects $\partial\eta_{i,s}/\partial z^r$ of key variables when clothing is used.[34] We compare these to the marginal effects in the observed resource shares $\partial\eta_{i,s}^{obs}/\partial z^r$. Child resource shares logically increase with the age of children while, for DLP and Complex Household samples, women's shares significantly decrease with child age. The comparison between estimated and observed marginal effects shows that these age gradients are well predicted by all three models. Next, child shares are larger when the group of children is predominantly male, a result in line with past evidence on gender discrimination in Bangladesh.[35] Interestingly, this pro-boy bias is also very well predicted by the Rothbarth and DLP approaches based on clothing. If the children are all girls, they absorb about 2.5 percentage points less of household resources than if they were all boys. Living in an urban area has no influence

[33] In particular, D'Souza & Tandon (2018) use the 2011 Bangladesh Integrated Household Survey to explore differences in undernourishment across household members. Their analysis reveals that male heads have much smaller caloric and micronutrient shortfalls than other household members. Brown, Calvi and Penglase (2018) estimate resource allocation and show that differences in needs clearly do not explain the extent of unequal sharing.

[34] As can be seen in equations (11), variables z^r simultaneously enter in the different exponential terms of the logistic functions for resource shares, so their effect on each person's share is unclear. Hence, we calculate and report here their marginal effects on these shares, as well as their standard errors using the delta method.

[35] See Quisumbing & Maluccio (2003) and Murdoch & Stern (1997) among others. Empirical evidence from the Indian subcontinent documents discrimination against girls (see for instance the survey by Behrman, 1987, and Zimmerman, 2012, for new evidence), usually on the basis of nutritional outcomes, mortality and health status, rather than with evidence based on resource allocation by gender. Brown, Calvi and Penglase (2018) and Calvi (2020) bring both types of evidence together for Bangladesh and India respectively using the DLP/Complex Households approach. Dunbar, Lewbel & Pendakur (2013) point to a pro-boy advantage in Malawi. As mentioned above, gender differences may also reflect some differences in needs.

Figure 3: Observed vs. Estimated Resource Shares (Assignable Clothing)



Note: Mean estimated resource shares from collective model approaches (with 95% confidence interval) versus observed shares from fully individualized expenditure. Structural estimations based on clothing expenditure as the assignable good.

in most cases. When they are significant, in DLP, the predicted and observed effects have opposite signs. Results regarding the first distribution factor d_1, the income ratio, tend to go broadly in the expected direction. According to the observed sharing rule, women's financial power has no impact on their own shares of resources but positively and significantly affects children's shares, which is consistent with women's altruism towards children (see, e.g., Duflo, 2003). The sign and order of magnitude of this latter effect are relatively well captured by the structural models. However, contrary to the observed effect, the estimated impact of d_1 is significant only in the third model.[36] The second distribution factor d_2 has no real effect. In the case of DLP, the woman's control upon education expenditure correlates positively with her share (the estimate from the structural model yields the right magnitude but the t-stat is only 1.55). With the Complex Households sample, d_2 is the female ratio (the proportion of women among all adults), which is positively associated with women's resource shares, both observed and estimated.

Alternative Assignable Goods. Similar comparisons are conducted using alternative identifying goods. Regarding mean shares, the results are summarized in Figure A.1 using prediction errors, measured as the estimated share minus the observed share. With this general picture, we confim the good score of clothing. Admittedly, results are more precise when using food and rice as assignable good, simply because zero expenditures are less frequent in this case.[37] Yet, results are not necessarily more accurate with these goods. Resource shares estimated with food tend to give satisfying results with Rothbarth. Discrepancies appear when the negotiation between men and women is accounted for, namely in the DLP and Complete Households approaches. Food leads to an underestimation of women's shares to the benefit of men. These results are broadly consistent with the fact that SAP conditions are rejected in most cases when using food (cf. Table 2). Figure A.1 shows that specific food items perform even more poorly. Using protein goods (fish, meat, eggs), the share of children is massively overstated with Rothbarth and, to a lesser extent, with DLP. Using rice, the results are far off the mark with the Complex Households approach: the share of women is greatly overestimated at the expense of children. Also,

[36] Note that the interpretation of distribution factors in the Rothbarth model is ambiguous. We have left distribution factors in the specification for the sake of symmetry, but arguably, different types of distribution factors would be required here, i.e. factors that improve the position of children vis-à-vis that of their parents (as in Dauphin et al.„ 2011, for instance). In the present case, a positive effect of women's relative income on child allocation in the Rothbarth setting reflect either a high degree of mothers' altruism (as women with more power allocate more to children, i.e. less to adults including themselves) or other household unobserved characteristics.

[37] They represent a large share of household budgets: $76 - 81\%$ for food and $21 - 29\%$ for rice, across demographic groups $s = 0, ..., 3$ (cf. Table A.1).

Table 3: Marginal Effects of Key Determinants of the Sharing Rule

Resource shares	Rothbarth		DLP		Complex households	
	Observed sharing rule	Estimated sharing rule	Observed sharing rule	Estimated sharing rule	Observed sharing rule	Estimated sharing rule
	(1)	(2)	(3)	(4)	(5)	(6)
Marginal effects:	*children's shares*		*children's shares*		*children's shares*	
mean child age	0.015 ***	0.016 ***	0.015 ***	0.015 ***	0.014 ***	0.010 ***
	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)
proportion of boys	0.024 **	0.025 **	0.023 **	0.025 **	0.017 **	0.009
	(0.010)	(0.012)	(0.010)	(0.012)	(0.007)	(0.010)
urban	0.008	0.015	0.008	-0.010	0.009	-0.011
	(0.007)	(0.040)	(0.008)	(0.038)	(0.006)	(0.031)
distribution factor 1 (a)	0.057 ***	0.050	0.056 **	0.035	0.082 ***	0.079 **
	(0.021)	(0.037)	(0.026)	(0.038)	(0.017)	(0.034)
distribution factor 2 (b)	0.001	-0.002	0.001	-0.002	0.006	-0.027
	(0.003)	(0.003)	(0.003)	(0.003)	(0.035)	(0.017)
Marginal effects:	*Adults' share*		*Mother's share*		*Women's share*	
mean child age	-0.015	-0.016	-0.006 ***	-0.006 ***	-0.007 ***	-0.006 ***
	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)
proportion of boys	-0.024	-0.025	-0.006	-0.017	-0.006	0.001
	(0.010)	(0.012)	(0.008)	(0.012)	(0.008)	(0.009)
urban	-0.008	-0.015	-0.015 **	0.132 ***	-0.007	-0.034
	(0.007)	(0.040)	(0.007)	(0.041)	(0.006)	(0.032)
distribution factor 1 (a)	-0.057	-0.050	0.029	-0.014	0.009	-0.014
	(0.021)	(0.037)	(0.021)	(0.029)	(0.031)	(0.028)
distribution factor 2 (b)	-0.001	0.002	0.005 *	0.006	0.029	0.038 **
	(0.003)	(0.003)	(0.003)	(0.004)	(0.019)	(0.016)

Notes: the table reports marginal effects of key covariates on the sharing rule, using estimates of the observed sharing rule (logistic estimation of resource shares) or estimates of the collective models (with clothing as identifying good and using SAT for Rothbarth or SAP for DLP and Complex Households). *, **, *** indicate 1%, 5% and 10% significance levels. Standard errors in parentheses. (a) Distribution factor 1 is the mother's income share (Rothbarth/DLP) or all adult women's income share (Complex Households). (b) Distribution factor 2 is a final say question on education (Rothbarth/DLP approaches) or the female ratio, i.e. the fraction of women among all adults (Complex Households).

this good does not predict well how per-child shares vary with the number of children.[38]

Instrumented Fertility. As a robustness check, we suggest an alternative estimation whereby the number of children is instrumented. We borrow from Dunbar, Lewbel & Pendakur (2013). They comment extensively on the possible correlation between fertility choices and the residuals in the clothing equations, which might be due to unobserved preference heterogeneity affecting both. They use measures of access to medical care and medical information as instruments for household size.[39] In a similar way, we construct variables on the access to health services and vaccination. These are binary variables taking value one if at least one member in the household got any medical treatment over the previous six months and if at least one member received the full doses of vaccines, respectively. As known from the literature, access to medical care affects fertility decisions while it has no reason to be correlated with unobserved heterogeneity in clothing preferences.[40] Summary results are reported in appendix Table A.2 and show similar patterns as in the baseline, even though resource shares are less precisely estimated. Important results, such as the gender bias in children's resources, are preserved.

5.2 Distributional Comparisons

We move to a comparison beyond average levels and address the implication of our results for inter-individual resource distribution. From now on, we focus on individual resources, either estimated ($\widetilde{x}_{i,s} = x + \log \widetilde{\eta}_{i,s}$) or observed ($x_{i,s}^{obs} = x + \log \eta_{i,s}^{obs}$).

Distribution of Individual Expenditure. We consider a semi-aggregated approach in which estimated and observed resource levels $\widetilde{x}_{i,s}$ and $x_{i,s}^{obs}$ are averaged in equal-sized bins of the distribution of $x_{i,s}^{obs}$. We use 20 bins for each type s, which is a large number compared to what is necessary to calculate meaningful inequality indices (Davies and Shorrocks, 1989, show that a limited number of data points is required for Gini indices, for instance). The binned scatterplots are displayed in Figures 4 to 6 for the three approaches. In each set of graphs, we compare estimated and observed resources per child, per woman and per man in each family of $1, 2$ or 3 children. Despite occasional discrepancies, for instance for men in the upper tail of the distribution when using the DLP approach,

[38] The detailed results for the different assignable goods and for different family compositions are gathered in the online appendix (Figures B.2 to B.4).

[39] Precisely, they use the presence in the village of an HIV prevention–oriented NGO office, the distance to a doctor's office and a dummy variable indicating that the woman has a chronic illness.

[40] Admittedly, these instruments do not strongly predict the number of children in the household. Conditional on all the variables contained in the structural model, the F-statistic of the excluded instruments in the first stage is only 7 (similarly, Dunbar, Lewbel & Pendakur, 2013, report a F-statistics of 2.5).

results are encouraging. Most importantly, there is only very limited reranking across groups (vintiles) of households. In other words, the *relative* position of each subgroup of children (resp. women, men) is relatively well explained. This is reassuring for our ability to conduct welfare analyses based on individuals' ranks. We go a bit further hereafter since we explore the implications for *absolute* poverty analysis as well.[41]

Andrews Tests. To assess the overall fit of the models beyond mean values, we use the chi-square goodness of fit test introduced by Andrews (1988). Under the null hypothesis that the model is correctly specified, the distribution of observed resources $x^{obs}_{i,s}$ and the distribution of predicted resources $\widetilde{x}_{i,s}$ should be similar. This asymptotic test requires partitioning the dependent variable into cells of equal size. A sensitivity analysis based on different partitionings is common practice. Focusing on children's resources, we partition their resource levels into 4, 6 or 8 cells, alternatively, and contrast the number of right and wrong cell predictions. Table A.3 reports the p-values of the test, overall and for different demographic subgroups. Results are consistent with the previous analysis comparing the distributions of individual resources estimated using clothing. High p-values indicate that we cannot reject, at standard levels, the null hypothesis that observed and estimated resources are identical. It is usually not rejected except in the overall sample and with a small number of partitions.[42]

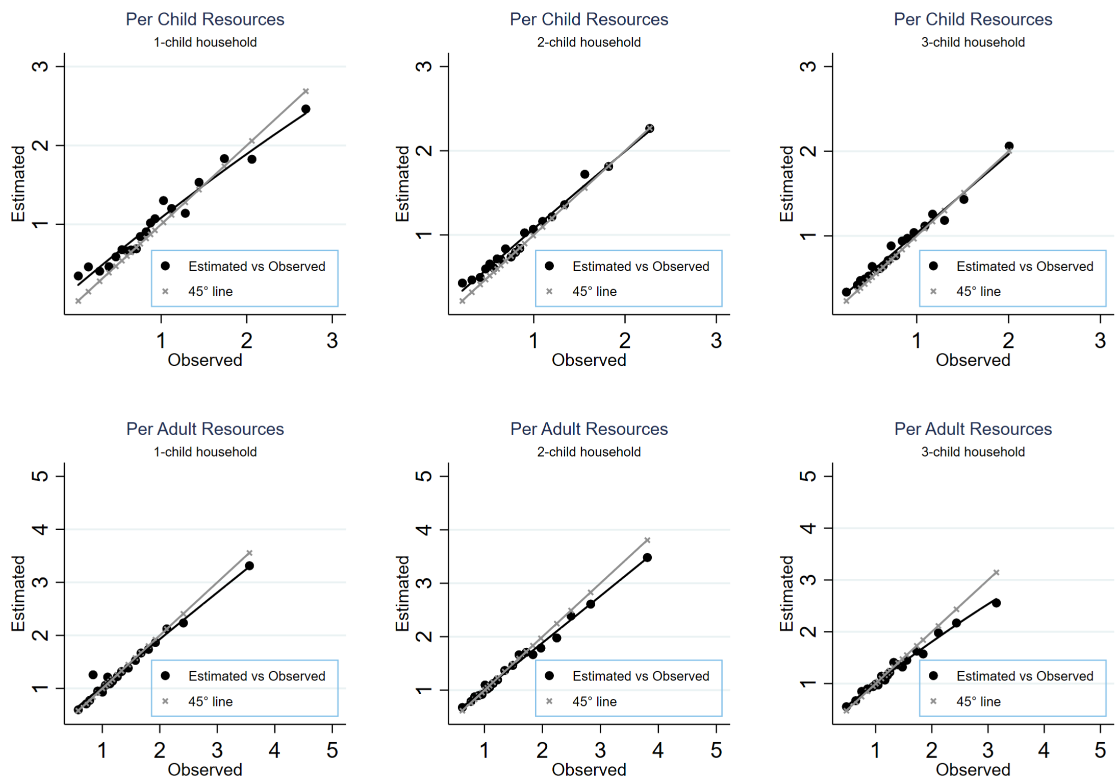
5.3 Individual Poverty Analysis

Individual Poverty Analysis. We finally examine the poverty implications of our analysis. Critically, redistributive policies may fail to reach their targets if undernourished or disadvantaged individuals live in households deemed non-poor according to the standard approach based on household equivalized income (see also Cockburn, Dauphin & Razzaque, 2009, Brown, Calvi & Penglase, 2018, and Brown, Ravallion & van de Walle, 2019). Column 1 in Table 4 reports standard poverty rates, which ignore intrahousehold allocation and are common to children, mothers and fathers. They rely on equivalized expenditures, calculated as the total household consumption deflated by an equivalence scale. To derive standard headcount poverty, equivalized expenditure is compared to an absolute poverty line, i.e. \$1.25 per person per day (2005 PPP), which was the line proposed by the World Bank for the year 2005. Equivalence scales are defined as $2 + sq$ with

[41] Detailed comparisons for each assignable good and each approach are shown in the online appendix (Figure B.5), confirming the good performance of clothing but large discrepancies with proteins and rice.

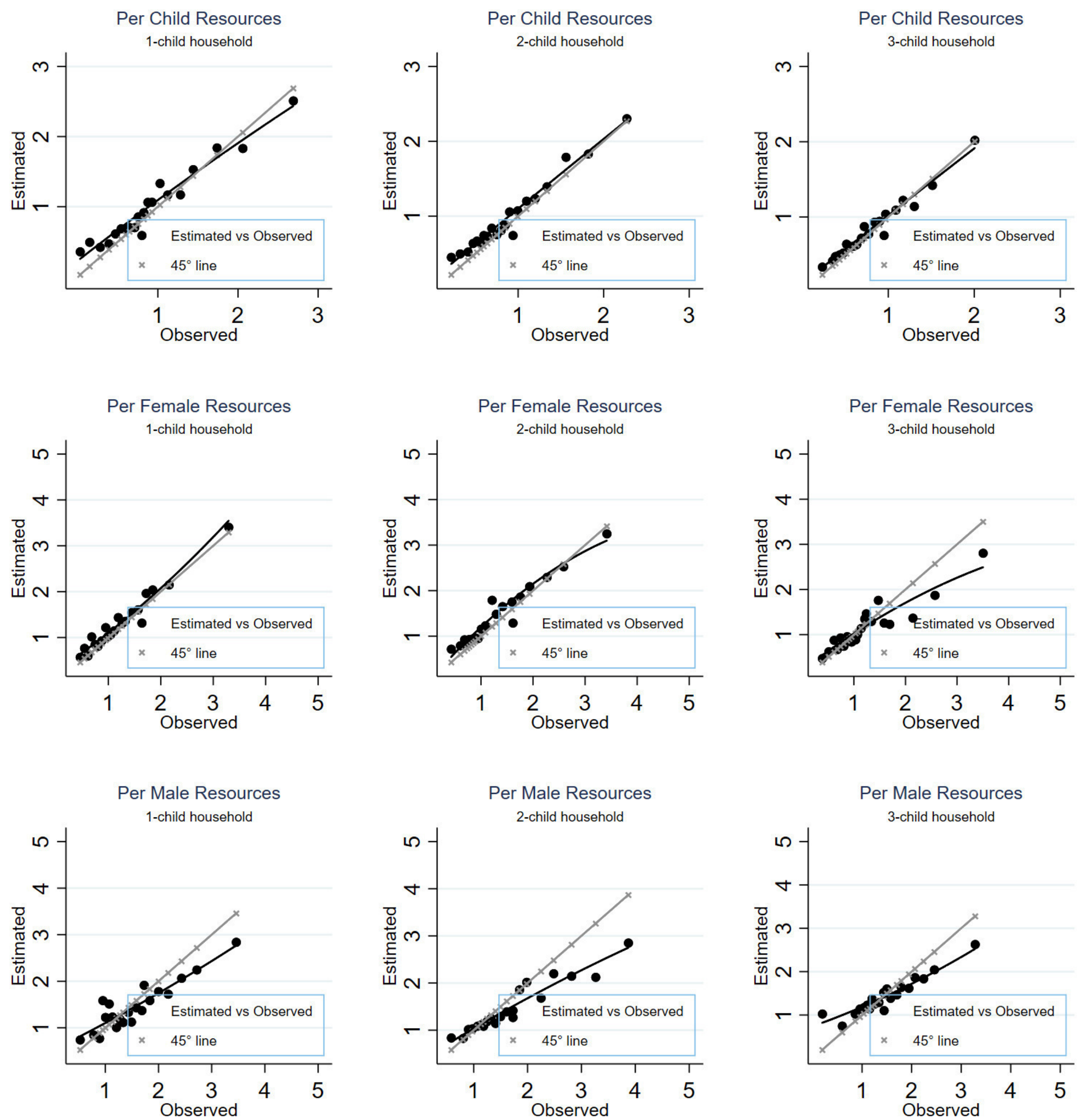
[42] The statistical power of the chi-squared test increases with the degrees of freedom and with sample size (Cohen, 1988). Hence, it decreases when the number of cells increases with our partitioning, since there are fewer observations per cell. This explains why the test passes more easily with 6 and 8 partitions.

Figure 4: Observed vs. Estimated Resources (Equal-Size Bins): Rothbarth Approach



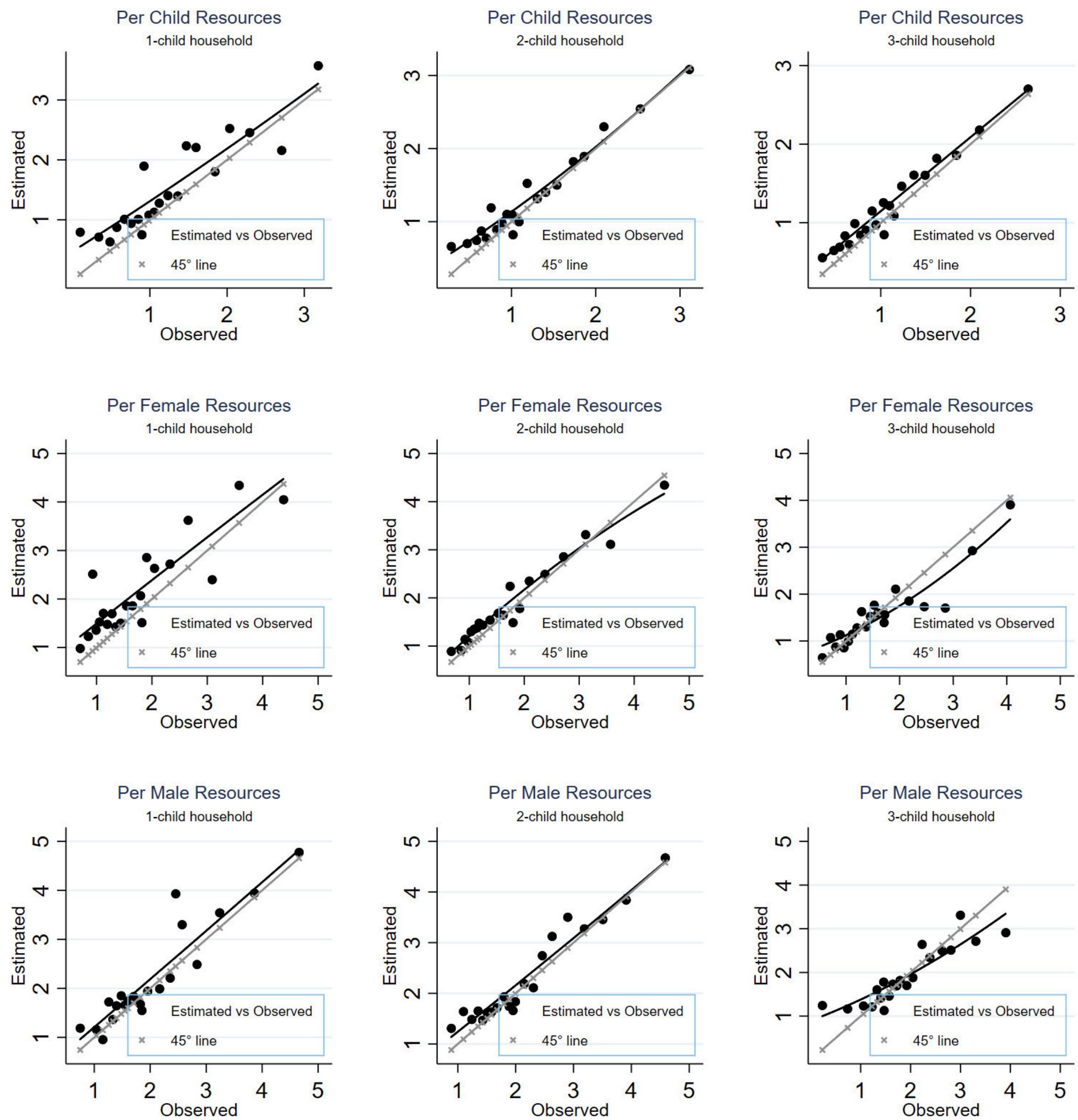
Dots compare mean observed and estimated individual resources, averaged by same-sized bins, corresponding to vintiles of the observed distribution. Observed resources from resource shares estimations based on the **Rothbarth (SAT)** approach using assignable **clothing**.

Figure 5: Observed vs. Estimated Resources (Equal-Size Bins): DLP Approach



Dots compare mean observed and estimated individual resources, averaged by same-sized bins, corresponding to vintiles of the observed distribution. Observed from resource shares estimations based on the **DLP (SAP)** approach using assignable **clothing**.

Figure 6: Observed vs. Estimated Resources (Equal-Size Bins): Complex Household Approach



Dots compare mean observed and estimated individual resources, averaged by same-sized bins, corresponding to vintiles of the observed distribution. Observed from resource shares estimations based on the **Complex Households (SAP)** approach using assignable **clothing**.

priors q representing per-child needs relative to adults'. Two options are suggested. The first posits $q = 1$ and corresponds to the *per capita* approach adopted in most development studies. By assuming that children, especially young ones, have the same needs as adults, we necessarily overstate the extent of poverty. Hence, in the second option, child needs q are proportional to the calorie requirements by age groups and sex, relative to adults, as suggested in FAO/WHO/UNU (1985). Per-adult equivalent poverty must mechanically decrease in this case.

Then, to measure *individual* poverty, we consider observed or estimated individual resources $\widetilde{x}_{i,s}$ and $x_{i,s}^{obs}$, for all the persons in our selected samples, augmented with the level of non-individualized expenditures. We compare them to the individual poverty line ($1.25/day for adults or a fraction q of it for children). Individual poverty rates are reported in column 2 (using observed resource shares) and column 3 (using estimated shares).

Main Results. Let us start with the sample of nuclear families used with the Rothbarth/DLP methods. The traditional approach yields a poverty rate of 36% for men, women and children when using per-capita expenditures ($q = 1$). In contrast, observed individual expenditures point to a poverty rate of 57% among children and 17% among adults. That is, the traditional approach understates child poverty by $57 - 36 = 21$ points and overstates adult poverty by 19 points. The collective model tends to do significantly better. The Rothbarth/DLP approaches yield a child poverty rate of 53% and 51% respectively (an underestimation of $4 - 7$ points only). With Rothbarth, adult poverty reaches 18% (an overestimation of 1 point only). These small discrepancies are due to the slight overestimation of child shares, as previously encountered. With DLP, observed and estimated poverty rates are also very close for women (33% and 32% respectively) or for men (12% and 15% respectively). Gender imbalances in resource shares materialize here in rather sharp contrast in poverty levels between men and women, which is something that the DLP approach tends to predict well.

If we then move to lower child needs (age-specific q-weights), both standard and individual child poverty rates decrease significantly, as expected. Yet, observed child poverty (41%) is still much larger than the standard poverty rate of 26% while collective model predictions come closer ($33\% - 35\%$). Conclusions for adults are unchanged since their poverty rates depend solely upon the adult poverty line (they do not change with the value of q). We notice that, in this case, the traditional approach understates women's poverty (33% with observed resources), which is well predicted by the DLP approach (32%).

The rest of Table 4 provides results for the Complex Households approach. Compared to poverty assessments of individuals in the nucleus (Rothbarth/DLP), the poverty incidence

Table 4: Traditional versus Individual Poverty Analysis

	Per-adult equivalent poverty (ignoring unequal sharing in the family)	Individual poverty, using:		Misclassification: % of poor individuals in nonpoor households, using:	
		Observed shares	Estimated shares	Observed shares	Estimated shares
	(1)	(2)	(3)	(4)	(5)
Poverty rates of:		Rothbarth on nuclear households (SAT)			
Children	(a): 0.36	0.57	0.53	0.24	0.19
Children	(b): 0.26	0.41	0.35	0.18	0.11
Adults	(a): 0.36 / (b): 0.26	0.17	0.18	-	-
Poverty rates of:		DLP on nuclear households (SAP)			
Children	(a): 0.36	0.57	0.51	0.24	0.18
Children	(b): 0.26	0.41	0.33	0.18	0.10
Mothers	(a): 0.36 / (b): 0.26	0.33	0.32	0.07	0.05
Fathers	(a): 0.36 / (b): 0.26	0.12	0.15	0.12	0.12
Adults	(a): 0.36 / (b): 0.26	0.17	0.19	-	-
Poverty rates of:		Complex Households (SAP)			
Children	(a): 0.17	0.39	0.32	0.24	0.16
Children	(b): 0.11	0.27	0.18	0.17	0.09
Women	(a): 0.17 / (b): 0.11	0.19	0.18	0.06	0.04
Men	(a): 0.17 / (b): 0.11	0.07	0.08	0.10	0.09
Adults	(a): 0.17 / (b): 0.11	0.08	0.09	-	-

Column (1): per-adult equivalent poverty rates based on a poverty line of \$1.25/day (2005 PPP) and equivalized expenditure, i.e. household expenditure divided by an equivalence scale with two alternative definitions of child weights:

(a) Per capita approach: child needs are assumed equal to adults'

(b) Age-specific child needs: using a function of calorie requirements per age (FAO/WHO/UNU, 1985)

Next columns: individual poverty rates based on individual resources that are either observed (column 2) or estimated with the structural models (column 3). Individual poverty lines are the adult poverty line (\$1.25/day) or a child poverty line as a fraction of the adult's using the alternative child weights as indicated above. The last columns report misidentification as the % of poor individuals recorded in nonpoor households, according to observed resources (column 4) or estimated resources (column 5). Between 53% and 93% of this mistargeting is captured by the models. Estimations are carried on nuclear families in Rothbarth/DLP and on all households (with and without children) in the Complex households approach.

in the broader household decreases substantially, down to 17%, when using per-capita expenditure.[43] Our poverty measure for complex households is broadly comparable to that reported in Brown et al. (2020) and Lechene, Pendakur and Wolf (2020).[44] Observed resources point to a much higher incidence of child poverty (39%), reasonably approached by the collective model at use (32%). With age-dependent needs for children, overall poverty (11%) still understates child poverty (27%) and women's poverty (19%) while men's poverty is lower (8%). Collective model predictions understate child poverty (18%) but are fairly accurate for adults.

Mistargeting. Many poor individuals may not be reached by anti-poverty programs based on household per-capita or equivalized expenditure. Column (4) of Table 4 reports the degree of misclassification of poor individuals as non-poor (i.e., the proportion of persons with individual resources below the poverty line but who live in non-poor households according to the traditional approach). The potential mistargeting is relatively important, between 18% and 24% for children (across settings) and $6\% - 12\%$ for adults. This is consistent with D'Souza and Tandon (2018) who point to a substantial misclassification of individuals, especially children, relative to their household status in Bangladesh, using nutritional measures. This is also the case in Brown, Calvi and Penglase (2018), who find a slightly larger frequency of mistargeting compared to our results, using recent data from Bangladesh and collective model estimations based on assignable food. This convergence of findings is reassuring. Finally, the collective approach tends to identify the bulk of observed mistargeting. As reported in column (5), between 53% and 93% of the misclassified poor are identified as such using the estimated resource shares. In a context where redistributive programs may miss a large fraction of intended recipients by ignoring individual poverty, collective models may represent a promising tool to improve targeting.

6 Concluding Discussion

Economists and policy practitioners usually measure inequality and poverty using equivalized or per-capita expenditure, thereby ignoring the allocation process taking place within households. At the same time, increasing evidence suggests that in poor and rich

[43] This is consistent with the fact that adult couples with children tend to be overrepresented among the poor (see World Bank, 2018, and Boudet et al., 2018, Fig. 10) while households in more complex arrangements are less poor.

[44] They find an overall poverty rate of 16.5% and 10.9%, respectively. Both studies use data from Bangladesh collected in 2015 and compare per-capita expenditure to the standard international poverty line (which is raised to 1.90 \$PPP for that year, using 2011 prices).

countries alike, within-household inequities can be large. We suggest an assessment of recent methods used to estimate resource sharing within households. Our validation relies on a unique dataset from Bangladesh, which provides the detailed consumption of each household member. Thus, the resource allocation predicted by a collective model of consumption can be compared to the actual allocation rule. When model identification rests on the observation of clothing as an assignable good for men, women and children, homogeneity assumptions used for identification are not rejected and the model performs reasonably well in predicting the resource allocation and, subsequently, the extent of *individual* poverty. In contrast, the traditional approach understates the poverty status of the poorest – i.e. mainly children in our application on Bangladesh – a great deal. The collective approach also provides a relatively good approximation of the size and direction of the errors made.

Even though our validation exercise focuses on one country and a single year, the results are encouraging regarding the possibility of using structural models for welfare analysis at the individual level. They should motivate further data collection for more systematic tests of identifying assumptions and model predictions in different settings. In such a way, the discussion regarding exclusive goods could be pushed further. Among all assignable goods used in our empirical exercise, clothing may be the least subject to the pitfalls attached to the Rothbarth approach (see Deaton, 1997).[45] It is not necessarily subject to large consumption externalities (see the extensive checks in Dunbar, Lewbel & Pendakur, 2013) and, in our data, the reported level of self-production of clothing is extremely limited. However, better data could inform us on the extent to which the good performance of clothing as an exclusive good is context-dependent, i.e., how much it depends on the local culture and social environment. Infrequent purchase and estimation issues that may arise due to zero expenditures are also emphasized by Brown, Calvi & Penglase (2018) and Lechene, Pendakur & Wolf (2020). At the same time, the collection of other individualized expenditure data, such as food, is rare. We have extensively discussed how carefully data collection has to be conducted for credible measures of individualized resources. Nonetheless, we agree with these authors that further efforts at data collection could be made to obtain more precise tests of the identifying assumptions and more precise estimates of the model for validation.[46] Note that comparisons between observed and

[45] These are (i) substitution effects (between own consumption and family size), (ii) the necessity for the relative price of the adult goods not to change across demographic types (the implicit price of food goods may change, for instance, if the returns to scale in food production are not constant), (iii) the requirement for adult goods not to be inelastic with respect to total expenditure (some of the food items are relatively inelastic).

[46] Large datasets would also provide the conditions of external (i.e. out-of-sample) validation using data-splitting approaches, for instance. Note, however, that the internal validation suggested in this

estimates resource shares are relatively encouraging for food in general, less so for specific food items (for which the identifying assumption was also rejected).[47]

Further work should also push the validation exercise toward more complete models and, most of all, more comprehensive welfare assessments. This would incorporate both elements of time and economies of scale in consumption. Regarding time, research efforts are required to simultaneously model time allocation and consumption within the collective framework (see Cherchye, De Rock and Vermeulen, 2012b, or Browning, Donni & Gørtz, 2020). Regarding scale economies, it is possible to build on comprehensive approaches such as Browning, Chiappori & Lewbel (2013) but validations would face the challenge to observe Barten scales (the degree of joint consumption) or, in a more classic public good interpretation, Lindhal prices. Further research could use the model to measure unequal sharing in terms of nutritional quality (calorie/protein content) rather than in terms of pure expenditures. Note that in Brown, Calvi & Penglase (2018), estimates of individual consumption based on assignable food align much more closely with individuals' health and nutritional outcomes than does household per-capita consumption, which can be seen as an indirect validation of the model, completing the direct validation presented here. Finally, some of the intra-household disparity in nutrient in-take may be due to labor market specialization of certain family members in energy-intensive tasks (Pitt, Rosenzweig & Hassan, 1990), which could be further investigated using individualized consumption data.

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paper does not suffer from the usual problem of overfitting, which would be the case if we estimated the model on a particular outcome (observed shares) and checked the prediction of the same outcome. We estimate the model on dependent variables (exclusive good expenditure) that are different from the validation yardstick (resource shares).

[47] As suggested, the self-production of food items, and the fact that it varies with family composition, possibly complicates identification when it is based on these goods.

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A Appendix

Descriptive Statistics

Table A.1: Descriptive Statistics of the Selected Sample

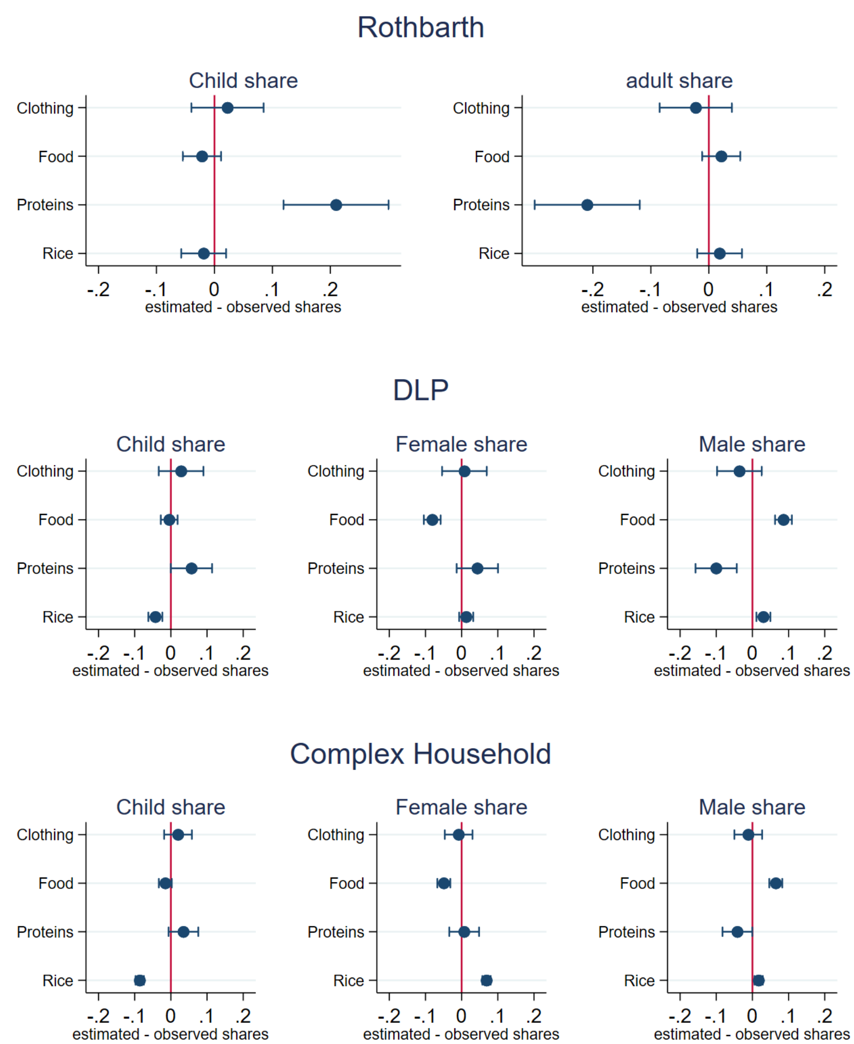
		Childless couple		Couple with 1 child		Couple with 2 children		Couple with 3 children	
Family Characteristics									
Proportion of boys (%)		-		0.531		0.497		0.503	
Average age of children		-		8.4		8.2		9.3	
Average age of the head		51.7		39.7		39.6		41.8	
Working women (%)		0.139		0.188		0.144		0.225	
Urban (%)		0.406		0.329		0.381		0.278	
Annual private expenditure (PPP $)		1,217		1,400		1,802		1,847	
Private goods as % of total expenditure		0.63		0.67		0.69		0.73	
Budget shares of private goods [% of zeros]									
Cereals & pulses		0.060	[0.129]	0.067	[0.085]	0.070	[0.087]	0.070	[0.065]
Fruit & vegetables		0.100	[0.000]	0.113	[0.000]	0.108	[0.000]	0.126	[0.000]
Oils & fats		0.048	[0.010]	0.042	[0.014]	0.042	[0.016]	0.039	[0.018]
Beverages, sweets, tobacco		0.124	[0.089]	0.096	[0.136]	0.095	[0.103]	0.086	[0.030]
Proteins (Fish, meat, eggs, dairy)		0.210	[0.010]	0.205	[0.028]	0.207	[0.019]	0.196	[0.036]
Rice		0.217	[0.010]	0.249	[0.005]	0.261	[0.000]	0.293	[0.000]
Other private non food		0.116	[0.079]	0.101	[0.085]	0.109	[0.038]	0.099	[0.030]
Clothes & shoes	Total	0.125	[0.030]	0.127	[0.005]	0.108	[0.000]	0.092	[0.000]
	Father	0.065	[0.040]	0.053	[0.005]	0.038	[0.009]	0.027	[0.006]
	Mother	0.061	[0.030]	0.047	[0.014]	0.035	[0.006]	0.026	[0.018]
	Children	-	-	0.026	[0.085]	0.035	[0.009]	0.039	[0.012]
# households		101		213		320		169	
# individuals (all children count for 1)		202		639		960		507	

Source: authors' calculation using the 'Capturing Intra-household Distribution and Poverty Incidence' data for Bangladesh.

Note: figures in this table refer to the main nuclear family of the household, i.e. the main couple and up to 3 children. The first panel reports family budget shares and, in square brackets, the percentages of zeros, for all private expenditures. We also show individual expenditure for father, mother and children on two goods (clothing and rice) used as alternative identifying goods. The lower panel reports total annual expenditure, characteristics of the nuclear families (or their head) and the number of observations.

Prediction Errors

Figure A.1: Prediction Errors for Different Models and Assignable Goods



Mean estimated resource share from the collective model (from alternative approaches as indicated) minus the observed share(from individualized consumption), using alternative assignable expenditure.

Instrumented Number of Children

Table A.2: Estimations With Instrumented Number of Children (DLP)

	Observed shares	Estimated sharing rule: Baseline	Estimated sharing rule: Instrumented number of children	Observed shares	Estimated sharing rule: Baseline	Estimated sharing rule: Instrumented number of children
	(1)	(2)	(3)	(1')	(2')	(3')
	Average resource share per child			*Average resource share of the mother*		
1 child	0.238	0.261 ***	0.253 ***	0.332	0.345 ***	0.313 ***
		(0.055)	(0.057)		(0.055)	(0.057)
2-child family	0.182	0.199 ***	0.194 ***	0.279	0.295 ***	0.272 ***
		(0.033)	(0.035)		(0.066)	(0.069)
3-child family	0.154	0.161 ***	0.156 ***	0.238	0.222 ***	0.213 ***
		(0.025)	(0.026)		(0.074)	(0.078)
	Marginal effects on children's share			*Marginal effects on the mother's share*		
mean child age	0.015 ***	0.015 ***	0.014 ***	-0.061 ***	-0.006 ***	-0.005 ***
	(0.001)	(0.002)	(0.002)	(0.008)	(0.002)	(0.002)
proportion of boys	0.023 **	0.025 **	0.024 **	-0.006	-0.017	-0.016
	(0.010)	(0.012)	(0.011)	(0.008)	(0.012)	(0.011)
urban	0.008	-0.010	-0.007	-0.015 **	0.132 ***	0.117 ***
	(0.008)	(0.038)	(0.033)	(0.007)	(0.041)	(0.036)
distribution factor 1	0.056 **	0.035	0.032	0.029	-0.014	-0.008
	(0.026)	(0.038)	(0.036)	(0.021)	(0.029)	(0.027)
distribution factor 2	0.001	-0.002	-0.001	0.005 *	0.006	0.006
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)

Notes: marginal effects of key covariates on the sharing rule from estimates of the observed sharing rule (logistic estimation of resource shares) versus estimates of the collective model using clothing expenditure as assignable good and the DLP approach with SAP. Distribution factors are the woman's income share and a final say question on education. Instruments for the number of children are access to health care and access to vaccination centers. *, **, *** indicate 1%, 5% and 10% significance levels. Standard errors in parentheses.

Andrews Tests

Table A.3: Andrews Test: Estimated versus Observed Child Resources

Household type	# obs.	Rothbarth (SAT)			DLP (SAP)			Complex Households (SAP)		
		Andrews test p-values			Andrews test p-values			Andrews test p-values		
		# of partitions			# of partitions			# of partitions		
		4	6	8	4	6	8	4	6	8
All	702 (779)	0.01	0.39	0.82	0.01	0.37	0.79	0.02	0.36	0.75
1 child	213 (225)	0.40	0.87	0.99	0.47	0.90	0.99	0.25	0.82	0.99
2 children	320 (353)	0.12	0.79	0.96	0.09	0.77	0.95	0.10	0.68	0.95
3 children	169 (201)	0.28	0.83	0.98	0.18	0.81	0.97	0.12	0.72	0.97
Nuclear	375 (375)	0.06	0.63	0.99	0.05	0.58	0.99	0.11	0.68	1.00
Non-nuclear	327 (404)	0.37	0.88	0.99	0.31	0.91	0.98	0.17	0.76	0.95
Urban	239 (257)	0.42	0.97	0.99	0.49	0.96	0.99	0.69	0.95	1.00
Rural	463 (522)	0.04	0.48	0.92	0.02	0.51	0.89	0.04	0.61	0.88

The table reports the p-value of an Andrews' test of the distributional difference between observed and estimated expenditure in clothing, for different sample partitioning of the shares (4, 6 or 8 partitions) and different collective model identification strategies: Rothbarth (SAT), DLP (SAP) and Complex Households (SAP), using clothing as identifying good. The column # obs. indicates the number of observations in the DLP/Rothbarth approches or, in brackets, for the Complex Households model.

B Online Appendix

B.1 Additional Data Information

Survey Components. The dataset is presented in detail in Razzaque et al. (2011).[48] There are five broad survey components. The first one is the standard set of socio-economic information including housing conditions, total household income and main sources of income, the expenditure survey (food and non-food consumption), households' exposure to various crises, saving behavior, possession of different assets. Secondly, it covers individual-specific information, e.g., anthropometric measures, educational attainment, occupational status, time allocation to different daily activities performed, health status and access to health care facilities, individualized expenditures (expenses incurred due to consumption of food and non-food items both within and outside households). The third block contains information on food preparation and intra-household distribution of food. The fourth gathers information on market prices of goods and services consumed by the households. The final one covers information on gender-related matters including women's participation in various household decision making, their physical mobility, being subject to verbal and physical abuse, exposure to domestic violence and/or other maltreatment, participation in income-earning activities (both home-based and off-home), and resources brought at marriage by both spouses. Obtaining data on many of the factors mentioned above required working closely with the households. Administering the questionnaire over a few hours to get the required information was not a possibility. Given the challenge, Razzaque et al. (2011, p.109) indicate: "The anthropological and participatory approaches were combined with the usual technique of recording data using a pre-designed questionnaire. Participatory approaches were critical for observing the food preparation and capturing the intra-household distributional practices, and for getting credible responses on the gender issues. A comprehensive questionnaire, combining individual and household level checklists, both quantitative and qualitative aspects including food preparation and distribution and gender issues, was developed and pre-tested."

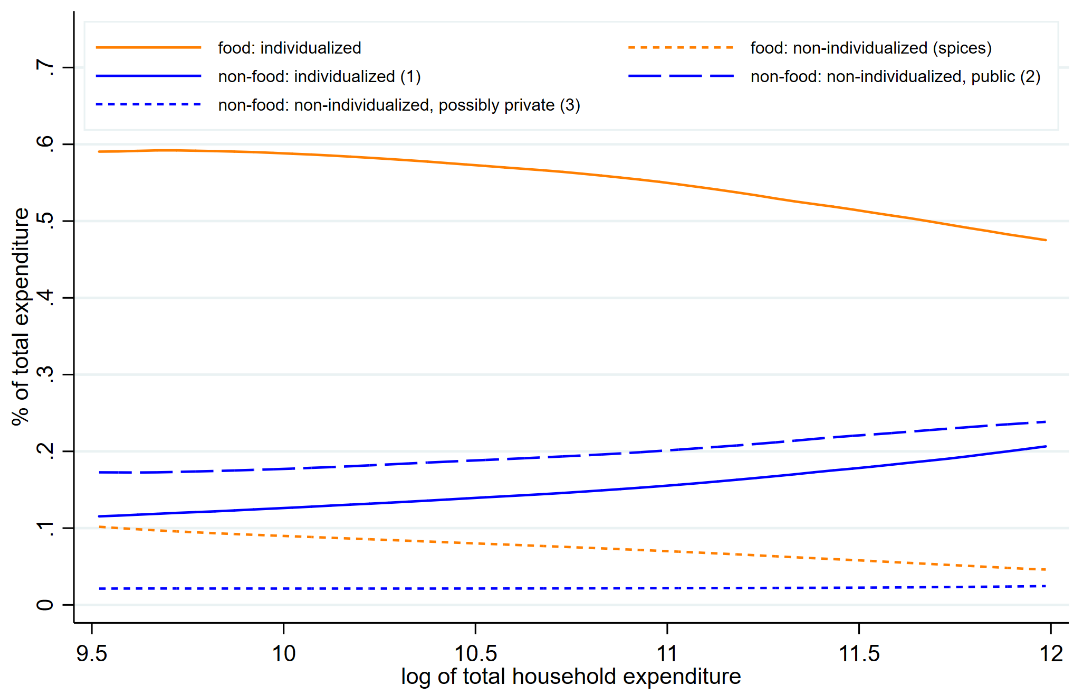
Selection and Training of Enumerators/Field Workers. The questionnaire directed the need for selecting appropriate enumerators/ field workers and their training, as described in the main text. A significant proportion of the field workers in the project came from the Institute of Nutrition and Food Science (INES). One advantage was that they were familiar with the methods of food preparation and measuring the dietary in-

[48] More detailed explanations on the procedure of data collection are also found in Razzaque, Khondker & Raihan (2011). The data is described in detail and used for intrahousehold welfare analysis in Cockburn, Dauphin & Razzaque (2009) and Toufique and Razzaque (2007).

take. Many other field investigators were students of anthropology, sociology and economics departments of Dhaka University. As noted by Razzaque et al. (2011, p.113-114): "An overwhelming majority of the selected enumerators had some experience of undertaking socio-economic surveys. After the selection of the enumerators/ field investigators, they were trained for two weeks. The training programme had mainly four components. First, understanding the objectives of the survey and questionnaire developed. Second, administering the questionnaire for gathering general socio-economic information of the households and data on market prices. Third, using participatory and anthropological approaches to socialise with the households to be surveyed, to understand their practices with food preparation and distribution, and to gather information on gender issues as kept in the questionnaire. Finally, recording food preparation techniques, measuring raw and cooked foods, and determining the amount of various food items consumed by individuals with the help of kitchen scales and other tools. Each enumerator was provided with a kitchen scale and several measuring spoons (for weighing the food items – both cooked and raw), a weighing machine (for taking the physical weights of individual members), and a measuring tape (for taking the height of the household members). Training was provided on the use of these instruments. The training was conducted by researchers with experiences of undertaking participatory research and by dietary experts who had conducted surveys on food and nutrition to determine the calorie intake and nutrient deficiencies of people in Bangladesh. [...] A number of field supervisors were selected to monitor the field work and they also took part in the training and participated in the pretesting of the questionnaire."

Individualization of Food and Non-food Expenditures. Among individualized expenditures, the bulk of expenses coincides with goods of a purely public nature: energy (fuel and electricity), household toiletries/laundries, household equipment (kitchen, bedding, etc), furniture, repair and maintenance. A small share of the expenditures treated as public corresponds to goods that could not be individualized but that may have some private components: tv/audio, cultural goods and cosmetics. Yet, we show that they represent a very small fraction of total expenditures (less than 2%), which is understandable given the luxury nature of these goods and the fact that we are dealing relatively poor households. This is visualized in Figure B.1, where we present the fraction of total expenditure that is individualized (for food and nonfood) and more specifically, among expenditures that could not be individualized, the fraction of expenditures that are deemed public and the fraction of those that might be partly private.

Figure B.1: Individualization of Household Expenditures in the 2004 Bangladeshi Data



(1) Individualized non-food includes tobacco, clothing, health, education, personal goods (ornaments, jewelry, bag, watch, etc.).
(2) Non-individualized non-food of a clear-cut public nature: fuel, electricity, home maintenance, toiletries/laundries, housing material, kitchen & bedding furniture
(3) Non-individualized non-food goods that could be privately consumed to some extent: tv/audio, cultural goods, cosmetics.

B.2 Additional Tables and Figures

Table B.1: Tests of Identifying Assumptions: Results for Food with Limited Self-production

Test of identifying assumptions based on preference similarity		Maximum possible level of self-production in % of total food consumption:			
		100% (baseline)	66%	50%	33%
Rothbarth, SAT	$\beta_{a0} = \beta_{a1} = \beta_{a2} = \beta_{a3}$	0.01	0.00	0.02	0.02
DLP, SAT	$\beta_{f1} = \beta_{f2} = \beta_{f3}$	0.06	1.00	0.71	0.12
	$\beta_{m1} = \beta_{m2} = \beta_{m3}$	0.99	0.22	0.27	0.13
	$\beta_{c1} = \beta_{c2} = \beta_{c3}$	0.00	0.00	0.00	0.01
DLP, SAP	$\beta_{f1} = \beta_{m1} = \beta_{c1}$	0.07	0.93	0.53	0.59
	$\beta_{f2} = \beta_{m2} = \beta_{c2}$	0.00	0.00	0.08	0.39
	$\beta_{f3} = \beta_{m3} = \beta_{c3}$	0.00	0.00	0.00	0.00
Fraction of initial sample		100%	90%	76%	57%

We report the Bonferroni p-values for tests of the SAT ('Similar Across Types') and SAP ('Similar Across Persons') identifying conditions using food as exclusive good. These tests concern the shape of individual Engel curves captured by the slope β_{is} for person of type i in household of type s. Individual Engel curves are estimated for the different i x s subgroups (as shown in raws) for food. SAT for the Rothbarth approach means that for adults, the slope is independent from the number of children s=0,...,3. SAT for DLP means that for females (f), males (m) or children (c), the slope is independent from the family size s=1,2,3. SAP means that for each family size s=1,2,3, the slopes are equal across individuals (f,m,c).

Table B.2: Average Resource Shares for different Household Characteristics (Rothbarth)

Household type	Child share			Adult share		
	Obs.	Est.	S.E.	Obs.	Est.	S.E.
All	0.349	0.371	0.062	0.651	0.629	0.062
1 child	0.238	0.256	0.045	0.762	0.744	0.045
2 children	0.363	0.386	0.064	0.637	0.614	0.064
3 children	0.461	0.488	0.082	0.539	0.512	0.082
Majority of boys	0.356	0.379	0.063	0.644	0.621	0.063
Majority of girls	0.344	0.366	0.062	0.656	0.634	0.062
Rural	0.348	0.369	0.069	0.652	0.631	0.069
Urban	0.351	0.376	0.056	0.649	0.624	0.056
Young children	0.287	0.305	0.057	0.713	0.695	0.057
Older children	0.408	0.434	0.066	0.592	0.566	0.066

Average resource share per child, per female and per male according to direct observation of individual consumption (Obs.) and to model estimations (Est.), using clothing expenditure as assignable good and the Rothbarth approach with Rothbarth-SAT.

Table B.3: Average Resource Shares for different Household Characteristics (DLP)

Household type	Child share			Female share			Male share		
	Obs.	Est.	S.E.	Obs.	Est.	S.E.	Obs.	Est.	S.E.
All	0.349	0.377	0.062	0.285	0.293	0.062	0.366	0.330	0.062
1 child	0.238	0.261	0.055	0.332	0.345	0.055	0.430	0.394	0.055
2 children	0.363	0.398	0.066	0.279	0.295	0.066	0.358	0.307	0.066
3 children	0.461	0.484	0.074	0.238	0.222	0.074	0.301	0.293	0.074
Majority of boys	0.356	0.383	0.063	0.282	0.282	0.063	0.362	0.336	0.063
Majority of girls	0.344	0.373	0.061	0.287	0.300	0.061	0.369	0.327	0.061
Rural	0.348	0.385	0.066	0.288	0.245	0.066	0.364	0.371	0.066
Urban	0.351	0.362	0.057	0.279	0.386	0.057	0.370	0.252	0.057
Young children	0.287	0.313	0.058	0.309	0.323	0.058	0.404	0.364	0.058
Older children	0.408	0.438	0.064	0.262	0.264	0.064	0.330	0.298	0.064

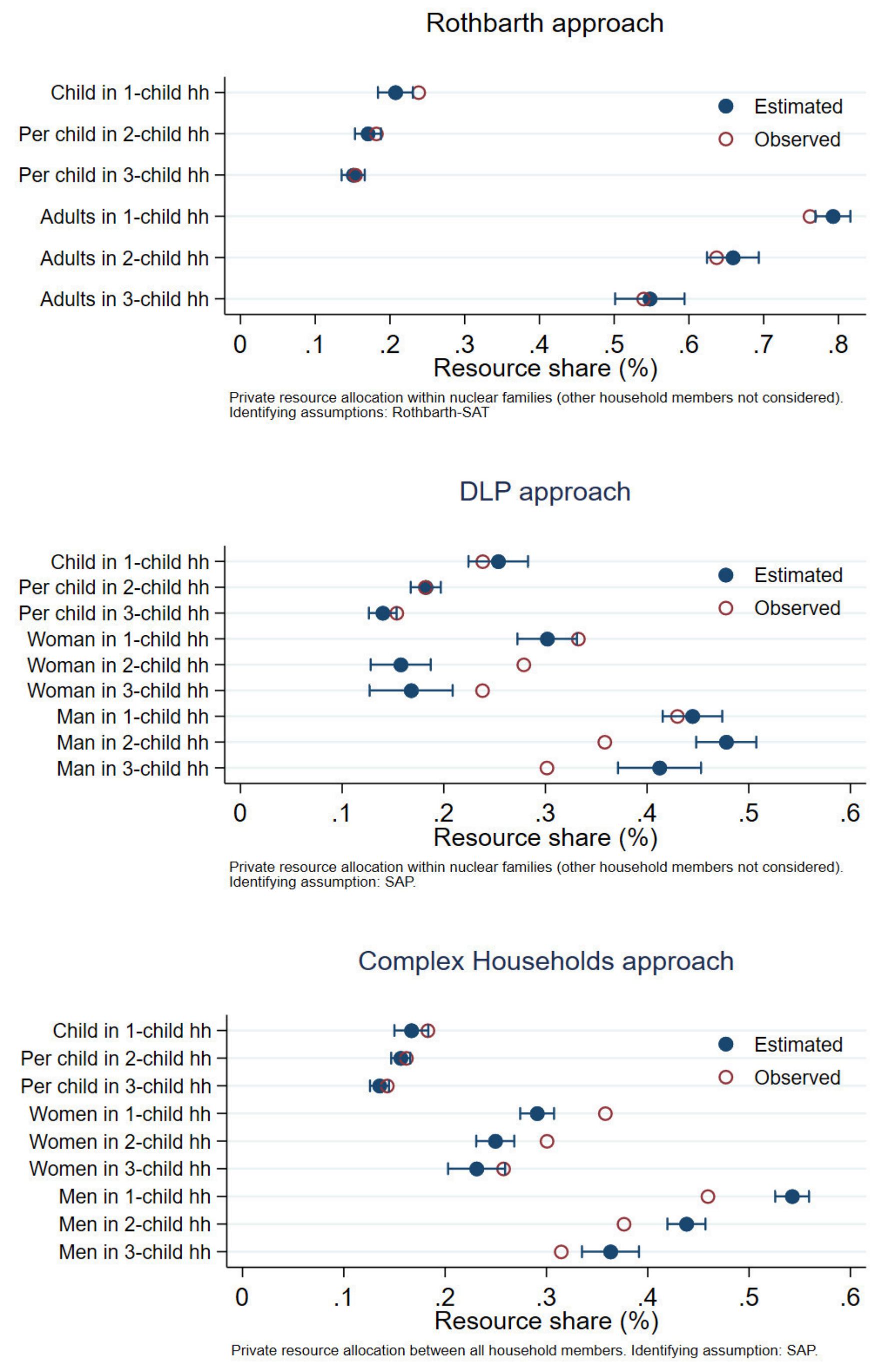
Average resource share per child, per female and per male according to direct observation of individual consumption (Obs.) and to model estimations (Est.), using clothing expenditure as assignable good and the DLP approach with SAP.

Table B.4: Average Resource Shares for different Household Characteristics (Complex Households)

Household type	Child share			Female share			Male share		
	Obs.	Est.	S.E.	Obs.	Est.	S.E.	Obs.	Est.	S.E.
All	0.310	0.329	0.038	0.306	0.298	0.038	0.384	0.373	0.038
No children				0.438	0.436	0.063	0.562	0.564	0.063
1 child	0.183	0.189	0.027	0.358	0.367	0.027	0.459	0.444	0.027
2 children	0.323	0.340	0.040	0.300	0.290	0.040	0.376	0.369	0.040
3 children	0.428	0.469	0.055	0.258	0.233	0.055	0.314	0.299	0.055
Majority of boys	0.317	0.334	0.039	0.295	0.300	0.039	0.388	0.367	0.039
Majority of girls	0.305	0.327	0.038	0.313	0.297	0.038	0.382	0.377	0.038
Rural	0.307	0.334	0.040	0.308	0.308	0.040	0.385	0.358	0.040
Urban	0.315	0.321	0.042	0.302	0.276	0.042	0.382	0.403	0.042
Young children	0.259	0.291	0.037	0.341	0.315	0.037	0.400	0.394	0.037
Older children	0.351	0.361	0.039	0.277	0.284	0.039	0.372	0.356	0.039

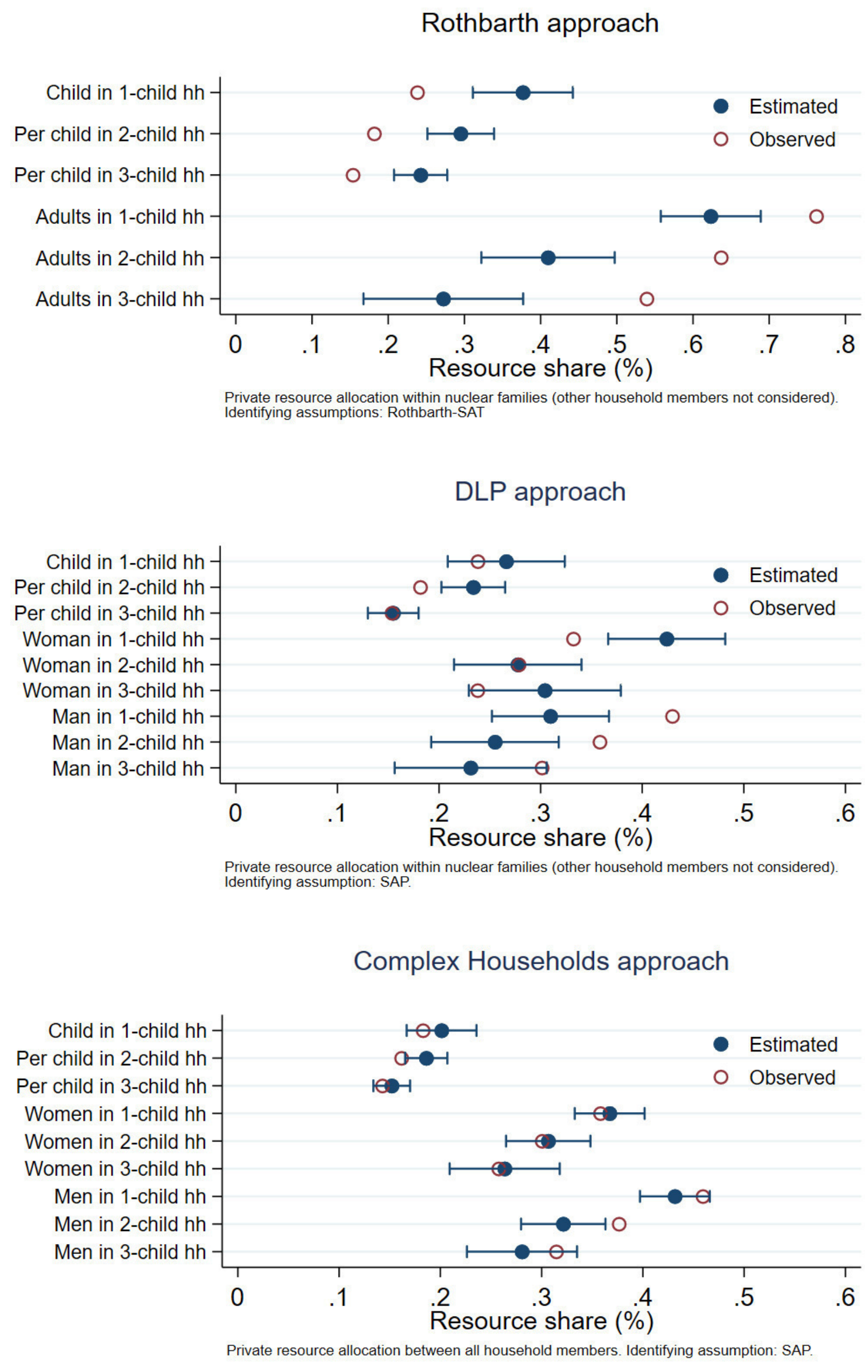
Average resource share per child, per female and per male according to direct observation of individual consumption (Obs.) and to model estimations (Est.), using clothing expenditure as assignable good and the Complex Household approach with SAP.

Figure B.2: Observed vs. Estimated Resource Shares (Assignable Food)



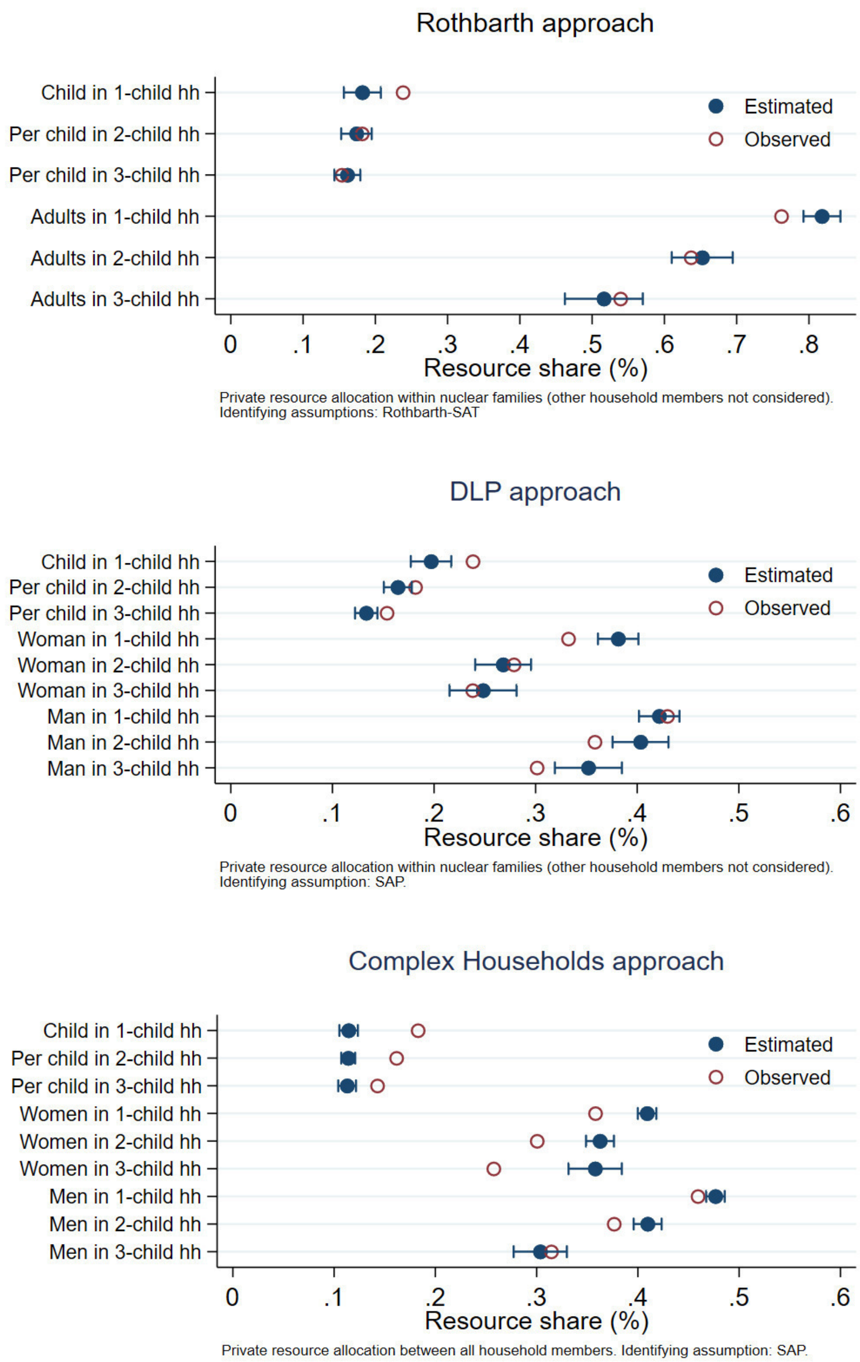
Note: Mean estimated resource shares from collective model approaches (with 95% confidence interval) versus observed shares from fully individualized expenditure. Structural estimations based on food expenditure as the assignable good.

Figure B.3: Observed vs. Estimated Resource Shares (Assignable Proteins)



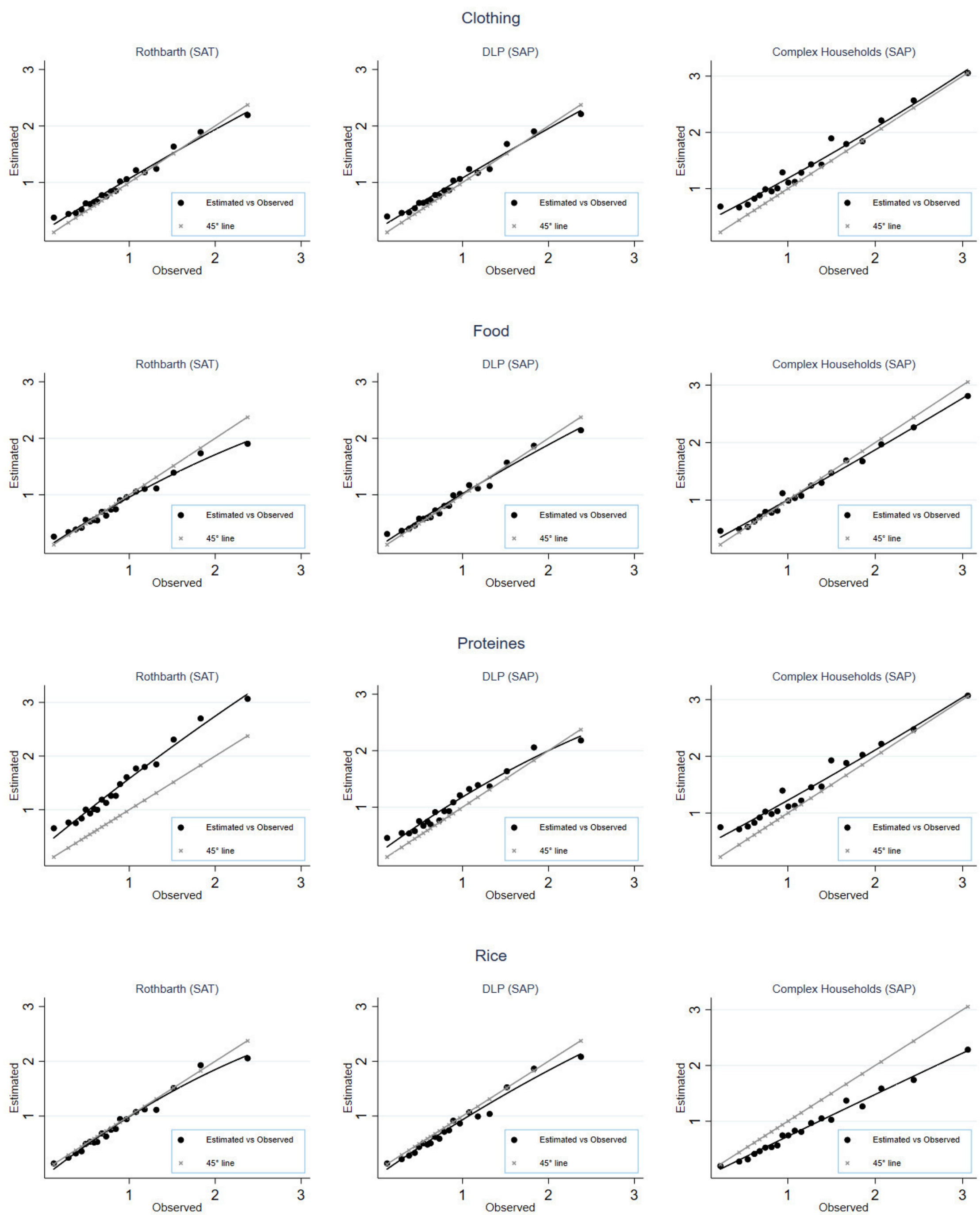
Note: Mean estimated resource shares from collective model approaches (with 95% confidence interval) versus observed shares from fully individualized expenditure. Structural estimations based on protein expenditure as the assignable good.

Figure B.4: Observed vs. Estimated Resource Shares (Assignable Rice)



Note: Mean estimated resource shares from collective model approaches (with 95% confidence interval) versus observed shares from fully individualized expenditure. Structural estimations based on rice expenditure as the assignable good.

Figure B.5: Distribution of Observed vs. Estimated Child Resources



Dots compare mean observed and estimated individual resources, averaged by same-sized bins, corresponding to vintiles of the observed distribution.